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Seasonal climate forecasts show skill in predicting winter chill for specialty crops in California

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Prakash Kumar Jha [1] ✉ & Tapan B. Pathak [1,2]

Many fruits and nuts crops in California require sufficient winter chill to break dormancy, and insufficient chill can harm fruit quantity and quality. Early information on winter chill forecast can help growers prepare for a low chill year. Here we evaluate use of dynamic climate models for chill accumulation forecast in California. Using temperature forecasts from seasonal prediction systems, we found that the multimodel forecasts can predict chill. This is evident from the anomaly correlation coefficients exceeding 0.5 between the model-predicted and reference chill values for most California regions. The forecasts correctly identified chill categories in over 50% instances in more than 40% of the Central Valley and southern parts of California. The forecasts also demonstrated skill in capturing the interannual variability of chill, especially during years with substantial decrease in chill. Additionally, the seasonal forecast can provide potentially useful crop specific chill sufficiency prediction. However, forecasts beyond a one-month lead time showed reduced forecast skills.

About three-quarters of the United States' fruits and nuts are grown in California and the southwestern state is a global leader in production and supply of some of these products[1]. Some of these crops such as walnut, pistachio, cherry, pear, and plum require high amounts of winter chill[2]. Although impacts associated with insufficient chill vary with species and cultivars[3], common symptoms include delayed flowering and uneven bud break[4] causing extended flowering period resulting into lack of uniform fruit ripeness, poor fruit quality and extended harvest date[4,5]. More importantly, exposure to low temperatures is necessary in some species for the initiation of female reproductive parts and proper fruit set, to develop proper shape, size and quality fruits[4,6,7], and prevent reduction in yield[8]. Impacts of low chill are not only limited to the reproductive performance but also in reducing plant vigor and vegetative growth[9], inhibiting lateral buds and causing domination of apical buds[9].

Previous studies have indicated that chill accumulation is expected to decline significantly in the future[10,11]. According to these studies, insufficient chill has already been observed in the Central Valley of California, which is one of the main production regions for fruits and nuts in California. Inter-annual prediction of chill anomalies (above average, normal, and below average) can help farmers to manage risks under adverse chill conditions. An important question arises: Is there a reliable method to forecast interannual variability in chill accumulation? Zhang et al.[12] assessed the relationship between chill accumulation and various modes of climate variability including the Oceanic Niño Index (ONI), Pacific-North American teleconnection pattern (PNA), and Pacific Decadal Oscillation (PDO) for three major growing regions of California (Central Coast, Sacramento Valley, and San Joaquin Valley). Results from this study showed that these teleconnections can explain very small part (on average, less than 16%) of the interannual variability in chill accumulation for these regions over the period 1979–2019. Therefore, using these indices to predict chill accumulation will be less reliable due to the lack of a strong association between chill accumulation and these indices.

There is a need to explore alternate approaches. One such approach could be to use inter-annual temperature prediction from dynamic climate models. Then the question is whether climate models have skill to predict temperature for the growing season of these crops over these regions before the season starts. Our goal was to evaluate the potential use of seasonal forecasts from climate models for November, December, January, and February (NDJF), referred to as NDJF, for predicting chill accumulation, commencing from various lead times. Since, chill is derived from temperature, the first question is whether climate models have good skill to forecasts temperature over California, mainly during the winter season. There are some studies conducted earlier in this regard. Zhang et al.[13] found that the North American Multi Model Ensemble (NMME)'s skill to forecast temperature for the interior regions of California is better than the persistence forecasts. The anomaly correlation coefficients ranged from 0.4 to 0.6 for the zero-lead seasonal forecasts of DJF and MAM for two inland locations (Tahoe City

[1]Division of Agriculture and Natural Resources, University of California, 2801 2nd St., Davis, CA, 95618, USA. [2]Department of Civil and Environmental Engineering, University of California, Merced, 5200 N. Lake Rd, Merced, CA, 95343, USA. ✉e-mail: prajha@ucanr.edu

and Parker Dam). Slater et al.[14] found that the correlation coefficients between NMME's temperature forecasts and PRISM (Parameter elevation Regression on Independent Slopes Model) data for the Southwest regions of the US varied from 0.1 to 0.5 between November and March. The ensemble mean has better skill than individual models in all regions and months, with the highest skill found in the shortest lead time (0.5 months) and declining rapidly thereafter. Shukla et al.[15] evaluated skill of the NMME, comprising six models, to forecast air temperature in California using a set of hindcasts from 1982–2010 for each grid cell at a resolution of 1°x1°. They found that models have some skill (correlation coefficient between 0.2 and 0.4) to predict temperature over December, January, February, and March (DJFM) at a zero-month lead time, when forecasts are issued at the start of the season. In general, these studies concluded that the dynamic models exhibit limited skill in predicting temperature at the sub-seasonal to seasonal timescale in California. This is evident from the anomaly correlation coefficient (ACC) values, which range from 0.1 to 0.5 in forecasts with zero or one-month lead time. Even though, models are not good at predicting day-to-day variability in temperatures at seasonal-to-sub-seasonal timescale, given that we are interested in predicting total chill accumulation over a season, our hypothesis is that the skill in predicting daily variability in temperature is different than the skill to predict total chill accumulation in a way that we are not interested in predicting which day will be exactly warmer or cooler, rather we are interested in overall chill accumulation in a season. Therefore, our assumption is that even though models are not good at predicting day-to-day variability in temperature, they might be better at predicting the overall chill accumulation over a season.

Although there are some studies for projecting chill under climate change scenarios in the future[10,16], we did not find any peer-reviewed studies to predict chill on an interannual time scale in California. The objective of this study is to assess potential of state-of-the-art global climate models to predict winter season (NDJF) chill anomalies and chill sufficiency for important specialty crops of California at different lead times. Early information on chill sufficiency can help growers prepare for dealing with insufficient chill. Given that the aim of this research is to help growers in decision-making by providing them with winter season chill sufficiency information, it is important to determine the level of concern among California farmers regarding the decline in chill accumulation. Hence, the study also investigates the extent to which farmers in California are concerned about the observed diminishing trend in chill accumulation over recent decades.

Results

Extent of concern among farmers regarding decreasing chill accumulation

From the survey data, it became evident that a significant majority of the farmers are concerned about the declining chill accumulation. Specifically, out of the 341 farmers who participated in the survey, a notable 70% voiced their concerns about the observed decreasing trend in chill accumulation over the past few decades[17]. These farmers represent diverse regions across California, encompassing a spectrum of agricultural landscapes and cultivating a variety of crops. Nearly half (47%) of them hailed from San Joaquin Valley, while one-quarter quarter (25%) were from the Superior region, with the rest spread throughout California (see Fig. 2 in ref. 17). The majority were white (75.5%) males (82%) aged between 22 and 87 years, and almost all (95.3%) were fruit and nut producers[17]. With California's agricultural sector being renowned for its cultivation of a wide array of crops, ranging from fruits like cherries and apples to nuts like almonds and walnuts, the implications of diminishing chill accumulation reverberate across multiple facets of the farming industry. Notably, crops such as stone fruits (e.g., cherries, plums) and certain varieties of berries are particularly sensitive to the availability of chill hours during their dormant periods, crucial for their subsequent flowering and fruit set. By providing farmers with comprehensive insights into chill accumulations projected for the upcoming season, they gain a strategic advantage in mitigating risks. Armed with this foresight, they can adeptly leverage favorable conditions or brace for challenges during low-chill years.

Correlation between model predicted and observed chill accumulation

We computed anomaly correlation for total Chill Portions (CP) and Chill Hours (CH) during the NDJF season, using temperature forecasts from the models at different lead months and the same estimated using reference data for the period between 1993 and 2015.

Overall, the anomaly correlation coefficients (ACCs) for CP (CH) in the multimodel average of 1-month lead forecasts exceeded 0.5 in 82% (81%) areas of California, 84% (88%) within the Central Valley (combined San Joaquin and Sacramento Valley), and 98% (77%) in the southern parts of California including San Diego, Los Angeles, and Inland South (Figs. 1, 6). Additionally, ACCs for CP (CH) in the multimodel average of 1-month lead forecasts exceeded 0.5 across 84% to 89% (90% to 94%) of regions where these five crops are grown (Figs. 1, 7). However, the ACC gradually decreased with lead time, and values higher than 0.5 were limited to 32% (35%), 19% (20%) and 12% (18%) of California for CP (CH) in forecasts with lead times of 1–4 months, 2–5 months, and 3–6 months (Fig. 1). Similarly, the ACC declined with lead time within the five crop-growing regions, with values surpassing 0.5 found in only 30% to 47% (21% to 35%), 5% to 15% (21% to 33%) and 1% to 12% (19% to 22%) of areas in forecasts with lead times of 1–4 months, 2–5 months, and 3–6 months (Figs. 1, 7).

Across individual models, in 1-month lead forecasts, the areas of California with ACC values greater than 0.5 varied from 34% to 81% (Figs. S1, S2). Notably, GloSea6-GC3.2, SPSv3, and SEAS5 demonstrated superior performance compared to CFSv2 and CanCM4. Conversely, for predictions with lead times extending beyond one month, areas of California with ACC exceeding 0.5 were limited to less than 43%, with CFSv2 exhibiting relatively better performance compared to other models. Relatively bigger areas with ACCs higher than 0.5 were in multimodel prediction than the individual model, indicating improved prediction accuracy when using multiple models.

Prediction of categorical forecasts

Our results revealed that for the NDJF season, multimodel forecasts for the CP (CH) category from a 1-month lead were accurate more than 50% of the time in 40% (43%) of California areas, 41% (52%) in the Central Valley (combined San Joaquin and Sacramento Valley), and 83% (59%) in the southern parts of California including San Diego, Los Angeles and Inland South (Figs. 2, 6). The multimodel forecasts for the CP (CH) category from a 1-month lead were accurate more than 50% of the time in 42% to 50% (54% to 57%) of the areas where walnut, pistachio, cherry and plum are grown (Figs. 2, 7). The corresponding figures for pear were lower, 0.23% (0.32%). However, these are the forecasts of chill category, and do not provide the actual values. It is important to get an idea about how the forecast of chill category translates into the actual values of chill for effective chill management. For a given location, within the same category of chill forecast, the difference between model predicted and actual chill amount varies from year to year. We found that, when a chill category forecast is accurate, it is 71% (78%) likely that the difference between reference PRISM data and model predicted NDJF aggregated CP (CH) will be limited to less than 20% in California (Fig. S3). In the Central Valley, the corresponding probabilities of experiencing less than a 20% bias are 61% (88%) (Fig. S3).

As the lead time increased, the accuracy of forecasts declined, and areas with values surpassing correct forecasts more than 50% of the time were less than 17% in forecasts with lead times exceeding one month (Fig. 2). Specifically, within regions where the five crops are cultivated, the proportion of areas with correct forecasts more than 50% of the time was less than 30% for CP and less than 42% for CH in forecasts with lead times exceeding one month (Figs. 2, 7). In 1-month lead forecasts, the areas of California with correct forecasts of the CP (CH) category more than 50% of the time ranged

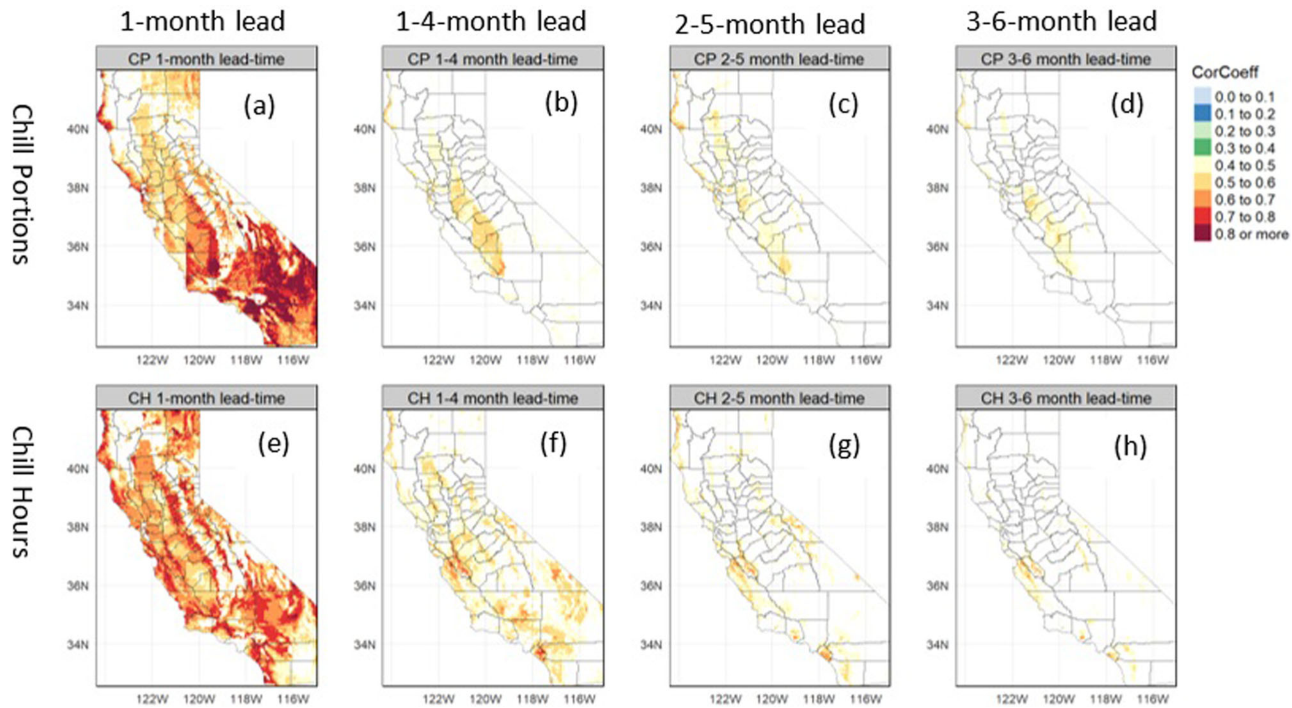

Fig. 1 | Anomaly correlation coefficients between reference and multimodel-averaged Chill Portions and Chill Hours. CP and CH were aggregated for the November-December-January-February (NDJF) season, across various lead times spanning from 1993 to 2015. The first row includes CP forecasts at lead times of (**a**) 1-month, **b** 1–4-months, (**c**) 2–5-months, and (**d**) 3–6-months. The second row contains CH forecasts at lead times of (**e**) 1-month, (**f**) 1–4-months, (**g**) 2–5-months, and (**h**) 3–6-months. The multimodel includes NCEP's CFSv2, CMCC's SPSv3, UKMO's GloSea6-GC3.2, ECMWF's SEAS5 and CCCma's CanCM4. Only statistically significant ($p < 0.05$) correlation is shown here.

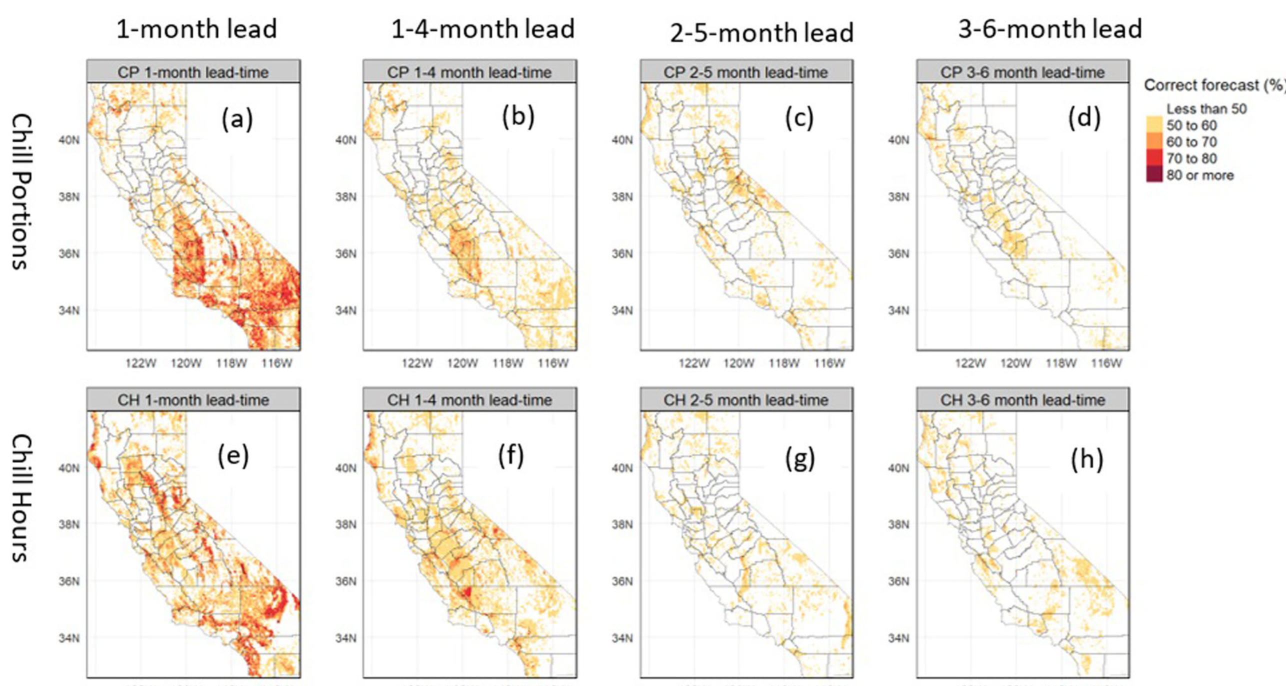

Fig. 2 | Percentage of correct prediction of Chill Portions and Chill Hours category during the November-December-January-February season total out of total predictions from 1993 to 2015 for multimodel forecasts. The first row includes CP forecasts at lead times of (**a**) 1-month, (**b**) 1–4-months, (**c**) 2–5-months, and (**d**) 3–6-months. The second row contains CH forecasts at lead times of (**e**) 1-month, (**f**) 1–4-months, (**g**) 2–5-months, and (**h**) 3–6-months. The predictions were categorized into above-normal, normal, and below-normal categories for the standardized normal variate (SNV) of Chill Portions in a particular year above 1, between −1 and 1, and less than 1. The SNV of CP (CH) was calculated by subtracting mean of CP (CH) and dividing by the standard deviation of CP (CH).

from 12% to 51% across individual models. Similar to ACC forecasts, GloSea6-GC3.2, SPSv3 and SEAS5 demonstrated superior performance in the 1-month period; however, their performance was inconsistent in forecasts with higher lead times (Figs. S4, S5).

Prediction of crop-specific chill sufficiency

Our findings indicated that the multimodel forecasts correctly predict whether the NDJF season total CH would be above or below walnut thresholds more than 50% of the time, covering almost all walnut-growing regions in California regardless of the lead times (Fig. 3). Similarly, for pistachios, cherries, plums, and pears, corresponding percentages ranged from 86–99%, 74–99%, and 97–99%, and 96–99%, respectively, contingent upon lead times (Fig. 3). Despite the large regional variability in forecast accuracy, the influence of lead time on accuracy was limited to less than 16%. All models correctly predicted CH thresholds 50% of the time in all walnut-growing regions, with the differences in percentage areas among models being less than 16% in the case of the remaining four crops (Figs. S6–S9). While these types of forecasts demonstrated improved accuracy in predicting crop-specific chill sufficiency, a limitation lies in their ability to quantify the extent of increase or decrease in chill.

Observed vs. predicted chill

The one-month lead predictions from multiple models demonstrate accurate forecasting of interannual fluctuations in Chill Portions (CP or CH), particularly during the years characterized by a sharp decline in chill, such as 1995, 2005, and 2014–2015 (Figs. 4, 5). The cumulative season CP, as per the reference PRISM data, consistently falls within the multimodel prediction's minimum and maximum range across different crops and counties, more than half of the time (Fig. 4). Nevertheless, there are instances (pistachio and plum in Fresno; walnut and cherry in San Joaquin and Stanislaus) where the CH in the reference data lie outside the predicted range of models more than half of the time (Fig. 5). The anomaly correlation coefficients for county-averaged CP (or CH) predictions from multimodel versus reference data ranged from 0.4 to 0.8 (0.5 to 0.7) for forecasts with a one-month lead time (Table 1). The correlation coefficients for multimodel chill (CP or CH) prediction at one-month lead time were significant ($p < 0.05$) across almost all crops and counties, except for pear in Lake County.

The predictive spread of multimodels for chill (CP or CH) declined in forecasts with longer lead times, evident in the widening range between the maximum and minimum predictions, accompanied by a reduction in ACCs values along with their statistical significance (Figs. S10–S15, Table S2).

Discussion

Insufficient winter chill prevents some specialty crops from realizing their full potential yield along with lowering their fruit quality. Farmers in California are concerned about the impact of decreasing chill accumulation observed in the recent decades. Advance information on the coming season's winter chill can help growers to manage low chill to minimize such losses. This study identified the potential to forecast the category of chill amount (above, below, normal) for the forthcoming winter months one month in advance. Accurate predictions, more than half of the time, are attainable for the majority of the Central Valley and southern parts of California by leveraging temperature predictions from multimodel forecasts. Additionally, we have proved that cumulative CP for the NDJF season in the reference PRISM data, averaged across different locations where a specific crop is grown in a county, falls within the range of multimodel predictions more than half of the time for forecasts made one month in advance. The forecasts for CH were inaccurate more often than those for CP. Given that farmers still prefer using CH over CP due to their simplicity, further research, outreach, and educational efforts to improve CH forecasts may be warranted.

However, the predictive skill diminishes beyond the one-month timeframe. The low skill of models to predict temperature might be associated with their limited skill to predict precipitation considering temperature is modified by the occurrence of precipitation[18]. The low skill of dynamic models in capturing interannual variability in precipitation may be attributed to their inadequacy in capturing circulation anomalies independent of the El Niño–Southern Oscillation, which accounts for only 25% of interannual variability in California's precipitation[19].

Despite the preference for forecasts covering the entire winter season for effective chill management, the current approach, though limited, might serve as a valuable tool in the absence of more sophisticated alternatives, particularly given the low skill of seasonal forecasts in predicting temperatures. We have prioritized multimodel predictions over individual models, as our results showed that no single model consistently outperformed others across all lead time and spatial regions in California. The variations in the performance of models to predict chill, a parameter derived from temperature forecasts, across California can be attributed to a combination of factors, including proper representation of physical processes, slowly varying boundary conditions, initial conditions, complex topography, vegetation dynamics, and models' spatial resolution and parametrizations[20]. Zhang et al.[13] also found that temperature forecasts errors in models varied across different locations in California, with inland regions demonstrating comparatively higher accuracy than coastal areas, primarily due to inadequate representation of low cloudiness conditions in all the models. Additional information regarding these elements in the models is available in https://confluence.ecmwf.int/display/CKB/Description+of+the+C3S+seasonal+multi-system and model specific reference can be found in Table 2.

Another important question is what the added value of this prediction is compared to climatology. As we can see in Fig. 4, the climatology of CP cannot tell whether there will be enough chill in the coming season, but the model prediction can. A prediction that can inform growers, in a particular year, that the chill amount is going to be very low, can be useful. For example, in 2015, the pistachio industry in California was hit hard by insufficient winter chill[21]. By planning early and starting applications of Kaolin clay spray on dormant pistachio trees starting from late November, Doll et al.[22] were able to increase chill portions by 5–7 units, resulting into higher yield in the orchard near Coalinga California. Jarvis-Shean[23] examined the efficacies of different chemicals including hydrogen cyanamide to advance bud break in terminal and lateral branches in "Chandler" variety of walnut in Sacramento Valley and observed that in some cases these treatments were able to hasten bud break.

The reduction in chill accumulation is not only a problem for California but has also been observed in other parts of the world[16,24]. In the tropics, where the temperate fruits are cultivated in mountainous areas, the declining trends in chill accumulation might cause insufficient chill most frequently[25]. There are several examples of successful application of rest breaking chemicals such as hydrogen cyanamide spray to promote bud-break in different regions which are experiencing insufficient chill[26–28]. Other chemicals, such as plant growth regulators comprising thidiazuron[29], which contribute to rest breaking and are considered as relatively less toxic for human health. Alternatives to chemicals include overhead irrigation systems to reduce bud temperature through evaporative cooling[30], pruning during late season[31], and inducing dormancy by artificially defoliating trees after harvest[32]. For new orchards, selecting a combination of cultivars and rootstocks that require lower chill[33], and selecting sites with sufficient winter chill not only in present but also in future climates are some options. While it might be possible to substantially reduce chill requirements for some crops in future as a result of the sustained breeding efforts (e.g. modern blueberry; Rowland et al.[34]), for other temperate fruits trees developing a low-chill variety might take extremely long due to various constraints including cost and time commitments and lack of specific knowledge on key genetic markers related to a specific environmental stress[35].

We have predicted CH and CP, with a focus on a few specialty crops of California, using temperature forecasts from the state-of-the-art

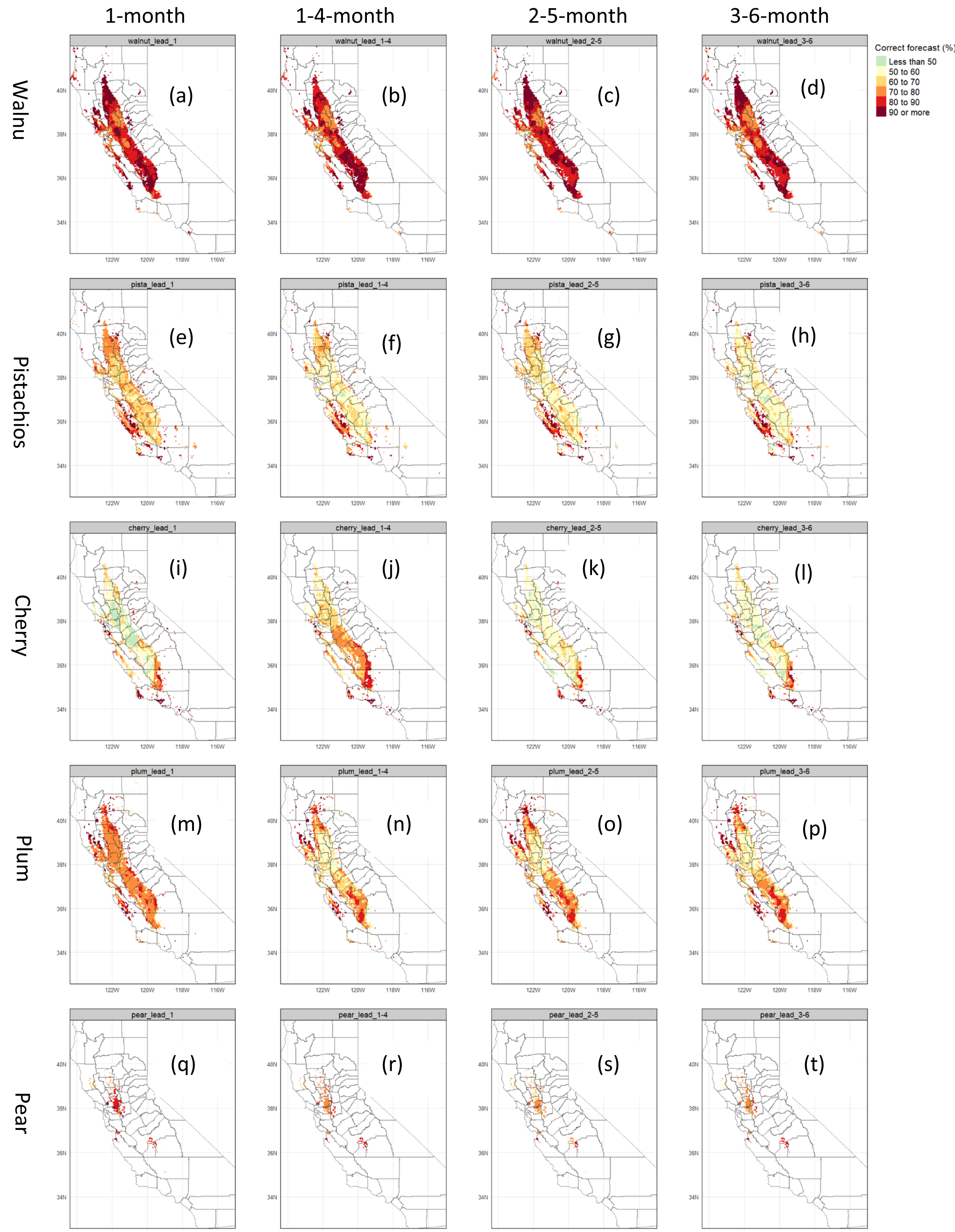

Fig. 3 | Percentage of correct prediction of November-December-January-February season total crop-specific chill sufficiency. The 1st row includes forecast of walnut at lead times of (**a**) 1-month, (**b**) 1–4-months, (**c**) 2–5-months, and (**d**) 3-6-months. Similarly, the 2nd row (**e**–**h**), 3rd row (**i**–**l**) 4th row (**m**–**p**), and 5th row (**q**–**t**) contain the corresponding forecasts for pistachio, cherry, plum, and pear respectively. The forecast was considered correct if total chill accumulation in the forecast and actual NDJF season, estimated using the reference PRISM data, both were in the same direction — either above or below the Chill Hours threshold of the corresponding crops— in each year from 1993 to 2015.

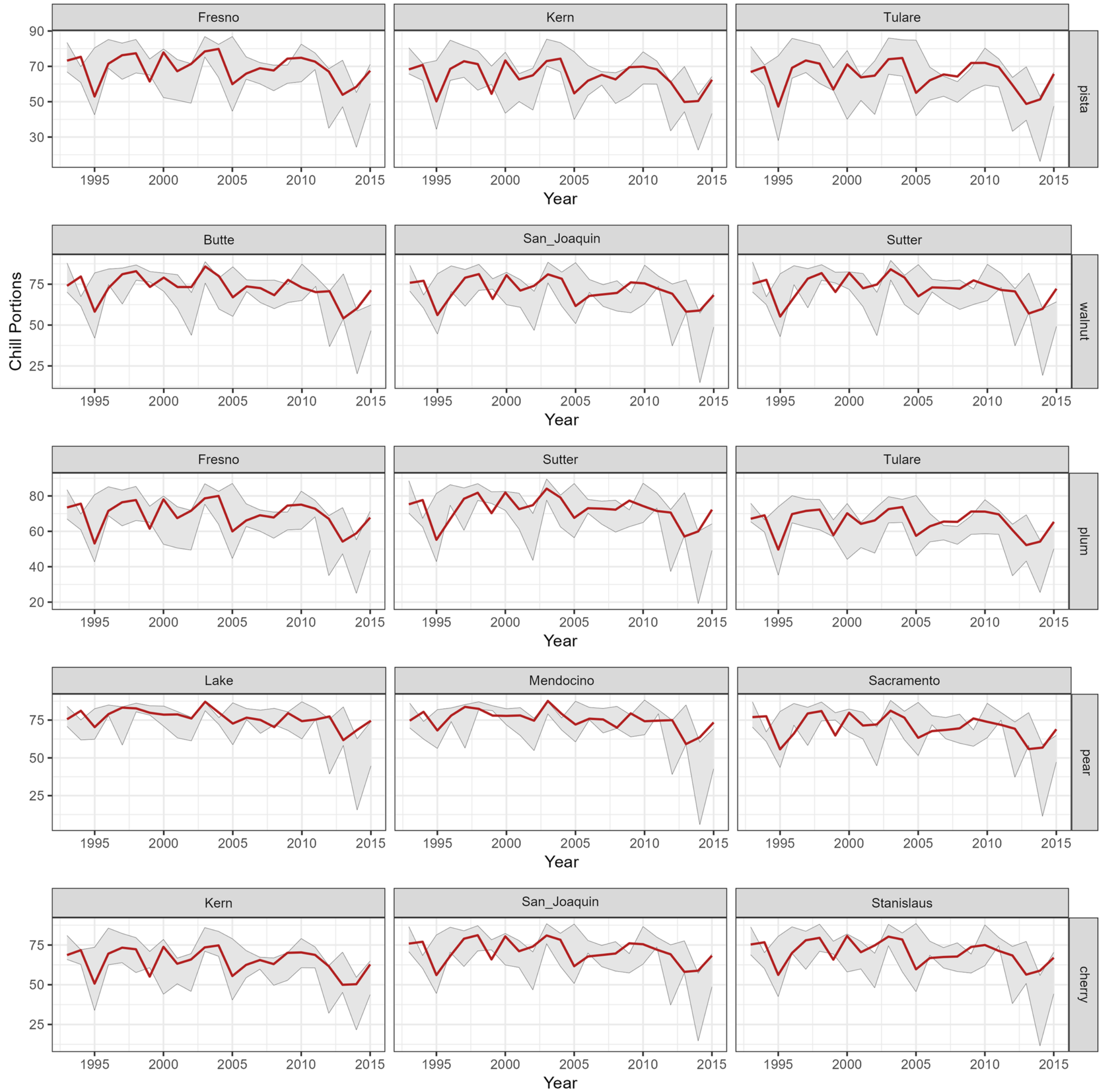

Fig. 4 | Total crop-specific county-averaged Chill Portions during November, December, January, and February from 1993 to 2015 in reference PRISM data (red lines) compared to the prediction from multimodel range (grey shadowing) for different counties of California. Only the top 3 counties in terms of cultivation for each crop were selected. The multimodel prediction includes the range (maximum and minimum) of Chill Portions from 5 models predicted from October (one-month lead time).

climate models available for subseasonal and seasonal predictions, which are openly accessible. It may be possible to extend similar approaches to other regions of the world and crops facing insufficient winter chill. However, there are some caveats. First, the chill requirements of a crop determined for a given location may not be valid elsewhere, and therefore, chill requirement of a species should always be verified using data from a specific location[36]. Second, the prediction accuracy of climate models in forecasting temperatures for the study area must be evaluated, as their predictive performance can vary across different regions of the world[37,38]. It is advisable to repeat this analysis using daily data from climate models. If daily data demonstrate superior predictive capabilities compared to the current approach, adjustments to the methodology should be made, incorporating the use of daily data.

Conclusion

This study explored the potential use of seasonal forecasts from global dynamic climate models for predicting winter season chill before the season starts. We found that while models differ in their skill to predict chill, the multimodel forecasts of temperatures demonstrate the potential to predict chill (CP or CH) one month ahead during the winter season (NDJF). The ACC between the model-predicted and reference PRISM chill values exceeded 0.5 for most parts of California and the Central Valley for predictions with a one-month lead time. These forecasts accurately identified the chill category (CP or CH) in over 50% of instances, covering more than 40% of the Central Valley and Southern California. The use of these forecasts extends to anticipating interannual variations in chill (CP or CH), especially during years characterized by a sharp decrease in chill. Notably, the forecasts demonstrated a relatively

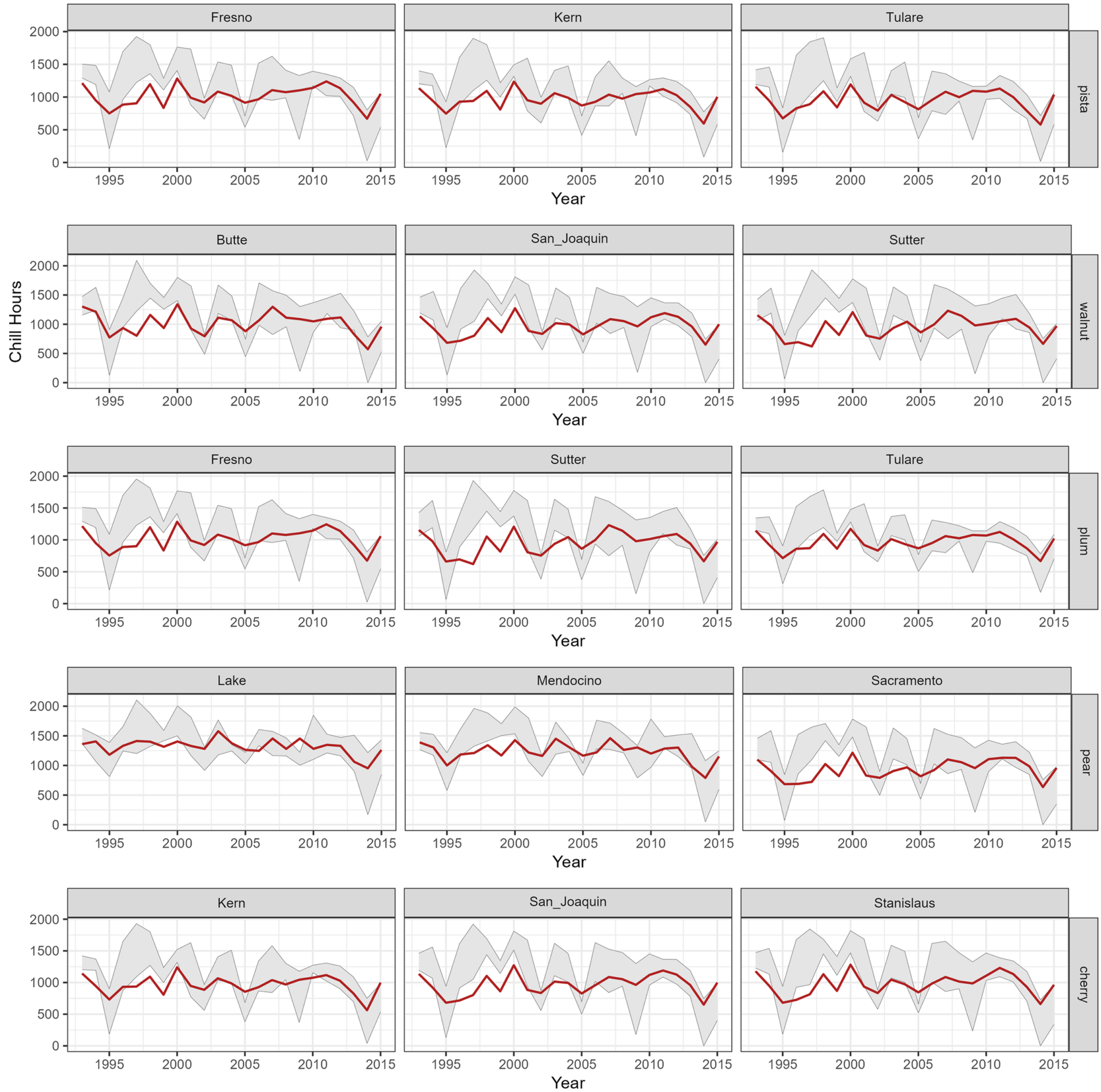

Fig. 5 | Total crop-specific county-averaged Chill Hours during November, December, January, and February from 1993 to 2015 in reference PRISM data (red lines) compared to the prediction from multimodel range (grey shadowing) for different counties of California.

stronger ability to predict a crop-specific chill threshold (a single value) compared to forecasting interannual variability. Forecasts beyond a one-month lead time exhibited limited potential, as evidenced by decreased ACC, diminished predictability of chill category and a weaker ability to capture interannual variability in chill amount compared to forecasts with a one-month lead time.

Materials and Methods

Study Area

While, the study encompassed the entire California region, our analysis specifically targets various ecoregions within California (Fig. 6), as well as counties where the majority of cultivation for these five crops takes place (Fig. 7). We presented the results of chill sufficiency specific to the location of each crop separately. To identify locations where cultivation of these crops occurs, we used 30 m CDL from the USDA-NASS for the year 2022 (https://croplandcros.scinet.usda.gov/). For each crop, masks were generated by aggregating the 30-meter CDL data to match the 4 km resolution of the PRISM grid. Subsequently, chill sufficiency forecasts were presented for these crop-specific masked regions at the 4 km resolution of the PRISM grid.

Farmers' survey to understand their concern regarding chill accumulation

We extracted the information about farmers' concern regarding decreasing chill accumulation and its impact on the future of farming in California from a survey conducted as a part of the United States Department of Agriculture (USDA) National Institute of Food and Agriculture (NIFA) project[17]. The survey aimed to gather insights from farmers regarding their perspectives, experiences, and knowledge regarding the impacts and vulnerabilities of climate change, as well as assessing their needs for tools, resources, and extensions programs. The exact question was "To what extent are you concerned about climate-related impacts for the future of your agricultural

Table 1 | Total crop-county-specific Chill Portions (Hours) in reference CP_o (CH_o), in multimodel 1-month lead CP_1 (CH_1) and 1–4-month lead CP_{1-4} (CH_{1-4}) along with correlation coefficients between reference and multimodel 1-month lead r_{1P} (r_{1H}) and 1-4-month lead r_{1-4P} (r_{1-4H})

Crop	County	CP_o	CP_1	CP_{1-4}	r_{1P}	r_{1-4P}	CH_o	CH_1	CH_{1-4}	r_{1H}	r_{1-4H}
Pista	Kern	64	63	63	0.79	0.54	968	1043	1054	0.69	0.48
Pista	Fresno	69	67	67	0.67	0.52	1015	1112	1120	0.59	0.43
Pista	Tulare	65	63	63	0.78	0.52	950	1017	1025	0.65	0.41
Walnut	San Joaquin	71	69	69	0.58	0.48	964	1104	1106	0.62	0.45
Walnut	Butte	73	70	70	0.54	0.44	1018	1132	1130	0.66	0.55
Walnut	Sutter	72	70	70	0.5	0.41	942	1090	1088	0.47	0.33
Plum	Sutter	72	70	70	0.5	0.41	942	1090	1088	0.47	0.33
Plum	Tulare	65	62	63	0.75	0.49	960	1024	1029	0.62	0.37
Plum	Fresno	69	67	67	0.67	0.52	1017	1116	1124	0.58	0.42
Pear	Sacramento	71	69	69	0.54	0.42	932	1091	1097	0.56	0.39
Pear	Lake	76	73	73	0.41	0.21	1318	1330	1328	0.66	0.41
Pear	Mendocino	75	72	72	0.49	0.25	1230	1292	1305	0.72	0.5
Cherry	San Joaquin	71	69	69	0.57	0.48	963	1104	1106	0.62	0.44
Cherry	Kern	65	63	63	0.78	0.54	963	1040	1050	0.7	0.5
Cherry	Stanislaus	70	68	68	0.6	0.49	972	1101	1109	0.64	0.51

The underlined Pearson correlation coefficients are significant at a significance level of 5%.

Table 2 | Description of the climate models used in this study

Forecasting Center	System	Hindcasts length	Hindcasts ensemble size	Hindcast period	Reference
ECMWF	SEAS5	215 days	51	1981–2016	Johnson et al.[59]
CMCC	SPSv3	6 calendar months	40	1993–2016	Gualdi et al.[60]
UKMO	GloSea6-GC3.2	215 days	28	1993–2016	MacLachlan et al.[61]; Williams et al.[62]
NCEP	CFSv2	215 days	28	1993–2016	Saha et al.[63]
CCCma	CanCM4	214 days	10	1993–2020	Merryfield et al.[64]

operations (select ALL that apply)?" Reduced chill accumulations were one of the climate-related impacts. Responses were grouped into multiple choices Likert-type scales: Not at all concerned, Somewhat concerned, Concerned, and Very concerned. The entire questionnaire was 39 pages. We have provided the portion used in this article in Supplementary Table S1.

The survey was distributed through Qualtrics using 12,933 emails purchased from MarketID. To maximize participation, five reminders were sent. Subsequently, responses underwent meticulous screening to eliminate potential AI-generated or fraudulent submissions, employing criteria devised by the project team. Ultimately, 341 responses from farmers were deemed valid and included in the analysis. For this study, we extracted information related to chill reported by farmers to better understand their overall concerns related to chill accumulations and to translate these concerns into meaningful actions.

Data and model for chill quantification

Daily maximum (T_{max}) and minimum (T_{min}) temperatures from reference PRISM at a spatial resolution of 4 km are available from 1982 to 2018 (https://www.prism.oregonstate.edu/). Monthly hindcasts of temperature were obtained from global climate models participating in NMME along with the models which are available in the Copernicus Climate Data Store (https://cds.climate.copernicus.eu/ #!/home). We selected the Climate Forecasting System version 2 (CFSv2) of the National Centers for Environmental Prediction (NCEP) and Canadian coupled general circulation model version 4 (CanCM4) of the Canadian Centre for Climate Modelling and Analysis (CCCma), as earlier assessment by ref. 13, has shown that these systems (SPSs) have relatively better performance in predicting sub-seasonal to seasonal temperature over the California region. Also, we used European Center for Medium Range Weather Forecasting (ECMWF)'s SEAS5, Euro-Mediterranean Center on Climate Change (CMCC)'s SPS version (v) 3, and United Kingdom Met Office (UKMO)'s GloSea6-GC3.2. Table 2 describes each model's hindcast length, initial conditions, ensemble size, period and model-specific reference. Further details descriptions about the atmospheric and ocean components of these models are available in ECMWF's C3S seasonal multi-system (https://confluence.ecmwf.int/display/CKB/Description+of+the+C3S+seasonal+multi-system). We used hindcasts of monthly T_{max} and T_{min} from each model for the period 1993–2016 to be consistent in time period across models. We used the ensemble average of all members of these models. In order to understand the possible use of seasonal forecasts, our initial step involved evaluating hindcasts for the NDJF season with a one-month lead time. This entails using hindcasts initialized at the start of each month, such as initializing November hindcasts on the 1st of November, December hindcasts on the 1st of December, and so forth. However, from an application standpoint, one-month lead forecasts prove to be of limited value, as they do not provide sufficient time for growers to manage chill requirements effectively. Consequently, we extended the assessment to include hindcasts for the entire NDJF season, initialized from November 1st, referred to hereafter as 1-4-month lead time. Similarly, we evaluated hindcasts for NDJF seasons initialized from October 1st and September 1st, denoted as 2-5-month and 3-6-month lead times, respectively.

The hindcasts from climate models are available at a spatial resolution 1°x1° (~ 111 km). However, these model data at 1° x 1° resolution lack the ability to accurately represent the temperature variations influenced by topography, coastlines, and other meso-climatic factors. In contrast, the reference PRISM data can capture such small-scale variability. These small-scale variabilities in temperature are important

Fig. 6 | Map of California counties along with the ecoregions. The county boundaries are represented by thin black lines, while the ecoregion boundaries are indicated by thick blue lines. The numbers on the map correspond to each county, with the county names listed alongside their respective numbers (ID) in the legend.

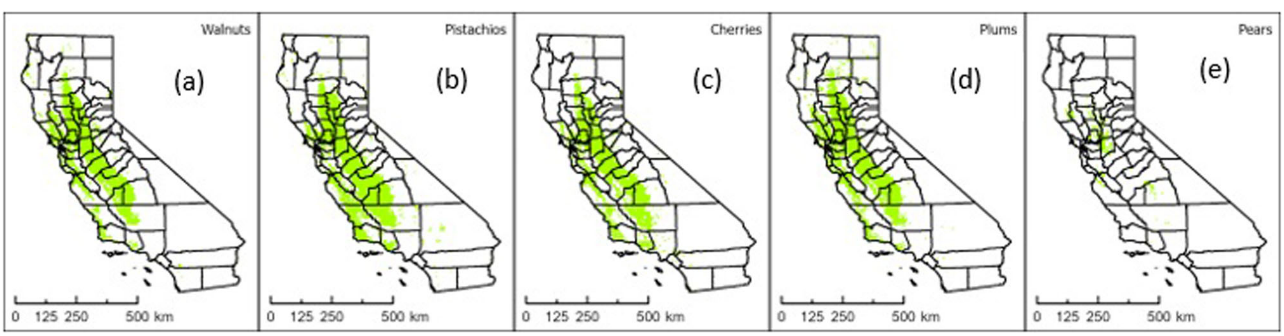

Fig. 7 | Cultivation locations for specific crops in California. This figure displays the geographic distribution of (**a**) walnut, (**b**) pistachio, (**c**) cherry, (**d**) plum, and (**e**) pear cultivation across California, with colored areas representing the regions where each crop is grown.

for realistic prediction of winter chill. We wanted to predict seasonal anomaly of chill by using monthly hindcasts from models and daily climatology of the reference PRISM data. We used PRISM data to ensure preservation of the small-scale temperature variability embedded in the PRISM data. Various previous studies[39–41] have used similar approaches. This approach is pragmatic because accessing and processing daily hindcasts from these models would require relatively more computational resources. To compute CH or CP, we needed hourly temperature data, which was derived from daily T_{max} and T_{min}. First, we downscaled models' monthly T_{max} and T_{min} to their daily values by using PRISM's daily climatology of T_{max} and T_{min} along with the models' monthly temperature anomalies using the following equation.

$$T_{\max} = \mathrm{T}_{\max(\mathrm{obDcl})} + \mathrm{T}^{1}{}_{\mathrm{mx\,(mdM)^{*}}}\sigma_{\mathrm{mdMTmx}}/\sigma_{\mathrm{ObMTmx}}$$

$$T_{\min} = \mathrm{T}_{\min(\mathrm{obDcl})} + \mathrm{T}^{1}{}_{\min(\mathrm{mdM})^{*}}\sigma_{\mathrm{mdMT\,min}}/\sigma_{\mathrm{ObMT\,min}}$$

Where T_{max} and T_{min} are the daily maximum and minimum temperatures respectively from a model. $T_{max\ (obDcl)}$ and $T_{min\ (obDCl)}$ are daily climatology of T_{max} and T_{min} from reference PRISM data. $T^{1}_{mx\ (mdM)}$ and $T^{1}_{min\ (mdM)}$ are monthly anomalies of T_{max} and T_{min} from a model. σ_{mdMTmx}, $\sigma_{mdMTmin}$, σ_{ObMTmx} and $\sigma_{ObMTmin}$ are the monthly standard deviations of T_{max} and T_{min} from a model and reference data respectively.

The daily climatology of T_{max} and T_{min} in the reference PRISM data were derived by simple averaging of their daily values for each day from 1993 to 2016. Monthly anomalies of T_{max} and T_{min} were computed by subtracting the climatological average from the monthly hindcasts. Similarly, the standard deviations of T_{max} and T_{min} in both models and observations were computed from their respective monthly values in the models and reference data.

This method produces T_{max} and T_{min} hindcasts of a model at a daily frequency at a spatial resolution of the PRISM data, 4 km for each lead time. Thus, within each grid of hindcasts, there were many grids of PRISM. We transformed hindcasts from models to 4 km grid by repeating the value present in 4 km grid. To calculate chill hours and portions, temperature data needs to be in an hourly time step. The hourly temperature was derived from the daily T_{max} and T_{min}, latitude, sunrise and sunset hours using a sine curve for the daytime warming and a logarithmic function for nighttime cooling, using the ChillR package developed by Luedeling et al.[42].

Approaches to quantify chill

One chill unit is defined as an hour of exposure to the optimum temperature required to meet the chilling requirement of a species or cultivar[43]. The total chilling requirement for a species is defined as the number of hours of exposure to a specified temperature range, which may vary depending on species and cultivars[44,45]. Consequently, the chill models used for calculating chill accumulation need different temperature ranges, where accumulation is negative or zero above below certain specified limits[43,46,47]. In California, growers commonly use the Chilling Hours Model[48,49]. However, an increasing number of them have begun to embrace CP using the Dynamic Model[16,50,51].

In this study, Chill Hours were calculated using the Chilling Hours model[48,49] by accumulating number of hours within the temperature range of 0–7.2 °C and discarding the rest. The model treats all temperature ranges equally. We used the 'Chilling_Hours' function from the ChillR package to compute Chill Hours. On the other hand, Chill Portions were computed using the 'Dynamic_Model' function in the ChillR package. The Dynamic Model computes CP in a two-step process: initially, cold temperatures result in the formation of an intermediate product, which can either be destroyed by subsequent warm temperatures or augmented by moderate temperatures[52]. Once a specific amount of this intermediate product has amassed, it is irreversibly stored as a CP, impervious to subsequent temperatures. It needs hourly temperature in degree Celsius between two time periods as an input and uses experimentally derived constants in an exponential equation to obtain cumulative CP over the entire duration. The Dynamic Model is deemed particularly suitable for a warming climate such as in California[16]. This is due to its incorporation of the mechanism for negating chilling effects by high temperatures, a phenomenon extensively documented in controlled chilling experiments[53–55], along with its consideration of the impact of moderate temperatures on chill accumulation[56].

Although, CP quantifies chill more accurately than CH under California conditions, we used both CP and CH because large portions of growers in California still use CH because of its simplicity. We computed CH and CP for the NDJF season from different lead times using reference PRISM data and hindcasts from models for the period 1993–2015. Chill computation of 2016 was not possible, given that we needed January and February data of next year, 2017, which were not available in our dataset.

Evaluation of chill forecasts

We evaluated the skill of individual models, along with the multimodel average, to predict CH and CP from different lead months. Rather than using individual ensemble members from the hindcasts, we used the average of all members, assuming equal probability for each ensemble member within the model. Subsequently, we determined the multimodel average by assigning equal weight to each model .

We used the ACC between NDJF seasonal anomalies of these indices for each year and same from the reference data. The NDJF seasonal anomalies were derived from the actual values of these indices by subtracting their respective climatology. We computed statistical significance of this correlation using the Pearson method.

Apart from these deterministic predictions, we also evaluated the potential of chill forecasts in the form of categories. To examine the potential of categorical chill prediction, we categorized each year from 1993 to 2015 into above normal, normal, and below normal chill year depending on the values of the standardized anomaly of the accumulated CP or CH in reference PRISM data and the models, separately.

The standardized anomalies of accumulated CH or CP were computed separately for NDJF season by subtracting the climatology from the actual chill of the season and dividing by the interannual standard deviation. Years with above average chill accumulation (standardized CH or CP > 0.5), were categorized as above-normal chill years. Similarly, years with below average chill accumulation (standardized CH or CP < −0.5) were defined as below-normal chill years, while years with chill accumulation within the standardized chill accumulation (−0.5 to 0.5) were considered as normal years.

Thus, each year was categorized as above-normal, normal, and below-normal years in terms of chill accumulation based on CH and CP in both reference (PRISM data) and in the models. We calculated the percentage of correct forecast by counting number of years in which the model's predicted chill categories matched the reference chill categories out of the total years. Forecasts were considered useful only if they were correct more than half (50%) of times, otherwise it would cause more harm than good.

Each crop differs in terms of its chill requirement. For example, the amounts of CH (CP) required for satisfactory growth of walnut, pistachio, plum, pear and cherry are approximately 700 (38–54), 1000 (36–65), 900, 1350, 1200 (30–70) respectively[11,57].

Nut yields increase exponentially by the increase in chill accumulation until these thresholds are reached, after which yields remain unaffected by the further increase in chill accumulation[58]. We examined models' skill to predict crop-specific chill sufficiency, in a specific year, for these five specialty crops as they require relatively higher amounts of chill compared to other crops.

A model's forecast was considered correct if the model was able to predict NDJF season total chill accumulation above (below) a crop-specific threshold in a specific year if the actual chill accumulated in that particular year, estimated using the reference PRISM data, was indeed above (below) the threshold of that crop. We used crop-specific CH for this purpose, as CP threshold for all five crops was not available. We calculated the percentage of correct forecast out of total forecasts. Given that each crop requires different chill thresholds, we repeated this analysis for each crop separately.

We compared the NDJF season total chill (CP and CH) in reference PRISM data during 1993–2015 with the model-predicted chill at various lead times for top three counties in California in terms of cultivation of walnut, pistachio, plum, pear and cherry. The selection of these top three counties was based on data from the 30 m Cropland Data Layer (CDL) from the National Agricultural Statistics Service (NASS) of the U.S. Department of Agriculture (USDA-NASS) for the year 2022 (https://croplandcros.scinet.usda.gov/).

It is important to highlight that, we aggregated November-December (ND) forecasts of a given year with the January-February (JF) forecasts of the next year. As a result, the CP or CH for 1993 comprised the ND forecasts for 1993 along with the JF forecasts for 1994, and so on. Accordingly, the CP or CH forecasts for 2015 encompassed the ND forecasts of 2015 along with the JF forecasts of 2016. The county-specific chill for each crop was computed by averaging chill across all points within a county where the crop is grown. Subsequently, we computed correlation between observed and predicted county-averaged chill for each crop.

Data availability

All data used in this study are available online. PRISM data are publicly available at: https://www.prism.oregonstate.edu/. Monthly hindcasts of temperature from NCEP CFSv2, ECMWF's SEAS5, CMCC's SPSv3, UKMO's GloSea6-GC3.2 are publicly available at the Copernicus Climate Data Store (https://cds.climate.copernicus.eu/#!/home). We obtained CanCM4's hindcasts from the International Research Institute for Climate and Society (IRI) available at http://iridl.ldeo.columbia.edu/SOURCES/.Models/.NMME/, since it was not available in the Climate Data Store of ECMWF.

Code availability

The data in this study were analyzed using publicly available libraries in the R programming languages. All figures were created by the authors using R as well, except Fig. 6 which was produced using ArcMap. Scripts are available upon requests.

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Author contributions

P.J.: Conceptualization, Methodology and First draft preparation, Data analysis, Visualization and Investigation; T.P.: Supervision, manuscript reviewing and editing.

Competing interests

The authors declare no competing interests.

Additional information

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Correspondence and requests for materials should be addressed to Prakash Kumar Jha.

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