Warming winters, changing springs: cold hardiness dynamics predict budbreak and associated low temperature threats on an intercontinental scale

Running Title: Cold hardiness dynamics predict budbreak

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Abstract

Temperate woody perennial plants form buds during late summer that contain leaves and flowers that emerge in the following growth season. To survive winter, dormant buds must attain cold hardiness, and timely lose it in spring to break bud while avoiding damage from low temperatures and late frosts. Here, we use an untrained process-based model to predict bud cold hardiness of three grapevine varieties (*V. vinifera* 'Cabernet-Sauvignon' and 'Riesling', and *V. hybrid* 'Concord') from historical temperature records of eight different locations in North America and Europe (n = 329). Based on those predictions, and thresholds of cold hardiness at budbreak from literature, timing of budbreak was extracted. Despite being untrained to the data, the RMSE of budbreak predictions was 7.3 days (Bias=–0.83). Based on cold hardiness estimations and air temperature records, low temperature damage was quantified and validated through newspapers and extension records. In years × location where damage was predicted, corrections to budbreak based on delays expected resulted in improvements of predictions (RMSE=7.2d, Bias=0.58). Predictions of instances of freeze damage risk demonstrate genotypic adaptation to different environments. At the species level, increasing or decreasing trends in freeze damage risk are predicted, depending on the range of mean dormant season temperature (MDST; 1 Nov – 30 Apr) present in each location. Sensitivity analysis of predicted time to budbreak based on MDST shows a general advancement of phenology at –5.8d/°C. However, in much warmer locations, delays can be expected as temperatures continue to increase (+1.9d/°C for MDST>10ºC). Through cold hardiness dynamics, the estimation of chilling accumulation appears as an important source of error for predictions of spring phenology across environments. Cold dynamics represents an advancement in phenological modeling that provides information for the entirety of the dormant season, as well as budbreak.

Keywords (6-10)

Budbreak, climate change, cold hardiness, dormancy, grapevine, phenological modeling, plant phenology, spring phenology, *Vitis*, winter physiology

Introduction

Across ecosystems, fluctuations and extremes in temperature, photoperiod, precipitation, and numerous other environmental variables determine the distribution and adaptation of species worldwide[1]. In temperate ecosystems, low temperature is considered one of the most significant factors influencing the distribution of woody perennial species, particularly in the cold range edge[2–4]. Seasonal fluctuations in temperature drive phenological events – the timing of which impacts the length of the growing season, overall productivity, and nutrient cycles[5–7]. Understanding the timing of life cycle events such as budbreak has significant practical and ecological implications, as it informs management practices and climate adaptation strategies[5]. Predicting timing of spring phenology is also an essential component of Earth system models, which help us understand and forecast ecosystem responses to climate change, including carbon sequestration potential of plants[8]. Despite the importance of budbreak, accurately forecasting this critical phase remains a challenge due to our general lack of understanding of temperature responses associated with this phase in plants[9]. This is particularly relevant in the face of rapidly changing climates and the emergence of non-analogous environmental conditions[10–12]. Therefore, new models that deviate from standard and incorporate physiologically derived temperature responses may improve our predictive ability for budbreak.

Buds are formed in the late summer and early fall and remain dormant [with little developmental activity[13]] throughout winter prior to growth resumption in the spring. Typical phenological models use the experimentally demonstrated negative relationship between accumulation of chill ('chilling') – cumulative exposure to low temperatures – and the accumulation of heat ('forcing') – cumulative exposure to warm temperatures – to predict budbreak[14]. However, given the likely overlap in temperature ranges where chilling and forcing occur[15], the timing when the transition from chill to heat accumulation is an important step in models. In most phenology models, the transition from dormant to a growth-responsive state is either classified as sequential or overlapping[16]. In a sequential approach, both chill and heat accumulation occur in separate phases—chilling and forcing—without accounting for their interaction[17]. During the first phase, dormancy release is modulated by exposure to low temperatures (chilling accumulation)[18]. The second phase involves exposure to warm temperatures—accumulation of growing degree

days/hours[19]. However, delays in the transition between phases can significantly impact the calculation of chill and heat units, as transition dates are often arbitrary[18,20]. These models are therefore inherently vulnerable to shifting climatic conditions. Warming temperatures may increase the time exposed to forcing conditions in winter and spring, which would by itself lead to advances in spring phenology. However, the warming conditions will also decrease chill accumulation in fall and spring, which can delay spring phenology. Therefore, variable outcomes in phenological timing can be expected based on future warming[21,22]. As a result, there is considerable interest in developing generalizable models which can accurately describe phenology under a wide range of conditions, especially considering the growing body of evidence supporting both phenological advancement and delay in woody perennials due to climate warming[23].

Previous work has shown that budbreak can be significantly influenced by cold hardiness dynamics[24–27]. Cold hardiness, here the minimum (usually negative) temperature a bud can survive, is a plastic trait within a genotype mainly influenced by air temperature, with gains (acclimation) occurring in autumn and early winter and losses (deacclimation) in late winter and early spring. Rates of acclimation, deacclimation, and maximum levels of cold hardiness achieved in a given location vary by genotype and yearly weather conditions[24,28–31]. Thus, cold hardiness has been shown to be an important barrier to plant survival in cold regions, contributing to the suitability of different species and ecotypes to different climates[2,32–35]. Deacclimation always proceeds budbreak in springtime, with most cold hardiness lost by budbreak[3,25,26,36–38]. Therefore, it is possible that measuring or predicting the cold hardiness phenotype and its dynamics can be used to deliver predictions of budbreak for species across varying climates.

The focus of this study was to test a process-based cold hardiness model for grapevine, NYUS.1[31], for predicting budbreak phenology and exploring low temperature-related growth risks for three different cultivars across eight intercontinental locations. Grapevine (*Vitis* spp.) is both a horticulturally and historically significant crop grown throughout the world, with areas of cultivation present on all continents except Antarctica. Critically, viticultural regions also contain the same clonally propagated genotypes (i.e., cultivars or varieties), facilitating evaluation of plasticity across different climates. The considerable genotypic variability in climatic adaptation among commonly grown grapevines[39] makes it an interesting model to understand the connections

between cold hardiness predictions and estimation of budbreak timing. Without reparameterization, the NYUS.1 model was applied to historical daily temperature records in each location and predictions were validated using longstanding records of phenology observations. Additionally, we used cold hardiness trajectories to predict instances of freeze damage across cultivars and locations that were validated using newspaper and extension records. Using model outputs, we assessed patterns in freeze risk over both thermal and temporal scales, and estimated phenological sensitivity as a product of dormant season temperatures.

Results

Cold hardiness dynamics predict budbreak phenology

Cold hardiness predictions were produced for all locations, for every year in which weather data was collected, and projected cold hardiness was used to predict budbreak (**Figs. 1,2**). The initial budbreak predictions produced across cultivars and locations are reflective of a phenology model which can be used to accurately predict budbreak (n=329, RMSE=7.3 days, bias=-0.83 days, r^2=0.87; **Fig 3a**). Given that cold hardiness trajectories were used to determine budbreak timing, it was also possible to group predictions based on the presence or absence of freeze damage to buds. Although our initial predictions did not account for effects of cold damage, given the known delay that occurs in budbreak when cold damage occurs in buds[3,40,41] we produced corrected budbreak predictions whenever damage occurred prior to initially predicted budbreak. A freeze damage event was predicted to occur when the minimum air temperature dropped below (i.e., was more negative than) the 10th percentile cold hardiness prediction on a given day. For each individual freeze event, a simple linear interpolation was used to determine the percent of buds damaged, and a new 90% confidence interval was calculated to represent the cold hardiness of the remaining population of living buds. Based on the greater cold hardiness in the remaining buds, budbreak predictions shifted to a later date following freeze damage, with the estimated delay dependent on the magnitude of cumulative freeze damage throughout the dormant season (**Fig. 3b**).

Grouping of model residuals based on predictions of freeze damage revealed that errors were significantly influenced by the presence or absence of such damage (No damage vs. Damaged uncorrected; **Fig. 3c**). In years where damage was predicted to occur, uncorrected budbreak predictions were on average 2.68 days earlier than observed budbreak, significantly contrasting from years where no damage was predicted ($Bias_{no\ damage}$=+0.37 days). After accounting for damage in budbreak predictions, error in years where damage was corrected did not significantly differ from years without damage (No damage vs. Damaged corrected; p = 0.591). As a result of incorporating a method for predicting and accounting for damage in the budbreak predictions, overall model outputs improved (RMSE=7.2 days, bias=0.58 days, r^2=0.88; **Fig. 3d**).

Because cold hardiness data was not available to validate predictions of bud damage, a pseudo-validation was performed. This approach used local newspapers and extension documents in which the presence of damage reports was classified as a binary outcome (**Fig. 3e**). Years were classified as either "damage" or "no damage", where any mention of damage to grapevine buds was determined to be a "damage" year, and years where damage was not mentioned were recorded as "no damage" years. The analysis was performed using Concord cold hardiness predictions in Portland, NY, US over the time period of 1926-2023 (n=97). The binary validation of damage predictions over the time period where cold hardiness predictions were made (1926-2023) resulted in model sensitivity of 0.75, specificity of 0.72, precision of 0.57, and accuracy of 0.73 (**Supplementary Fig. S1**).

Based on the evidence that (i) damage-corrected budbreak predictions better reflect phenological observations and (ii) predictions of damage are also reflected in historical records, corrected predictions were incorporated into all further analyses presented. Hereafter, these are then referred to as freeze damage-corrected budbreak (FDC budbreak).

Observational habits and chilling as significant sources of error

Using FDC budbreak, we explored the effect of different factors contributing to uncertainty in the model outputs using partial residual plots. We found observer (**Supplementary Fig. S2**) and chill accumulation (**Supplementary Fig. S3**) to be the most significant sources of uncertainty, while

183 year, minimum yearly temperature in any given location, and maximum predicted cold hardiness
184 to not contribute, or contribute little to model error (**Supplementary Fig. S3**). Observed date of
185 budbreak in Bordeaux, FR between 1981-2008 were recorded based on the date of first bud to
186 BBCH05, or first disclosed bud, differing from the rest of the record in which dates were recorded
187 based on 50% budbreak to either BBCH05 or BBCH07. We accounted for these differences by
188 decreasing the cold hardiness threshold at budbreak, allowing predictions to better reflect the
189 earlier stage of development that better corresponds the observations made, reducing this factor to
190 a non-significant source of error (**Supplementary Fig. S2**).
191
192 Lower chilling accumulation—calculated via the Dynamic Model (portions) and used to modulate
193 both acclimation and deacclimation responses—led to a tendency for late predictions ($p<0.001$;
194 **Supplementary Fig. S3d**). Chill portions are accumulated when temperatures fall within a given
195 range, with the amount of chilling accumulated dependent on the frequency and relative
196 contribution of those temperatures to chilling (**Fig. 4a**). Therefore, chilling accumulation
197 throughout the dormant season varies based on the climate of a region and yearly weather patterns.
198 We explored shifting the range of temperatures contributing to chilling to test whether a simple
199 correction would reduce the model residuals. Both increasing and decreasing the temperature range
200 for chill accumulation increased the RMSE of predictions across all regions (**Fig. 4b**). These
201 changes, however, are uneven when observed within climates. In colder locations, where high
202 levels of chill accumulate within a season due to wide temperature distributions, small shifts in
203 chill accumulation range cause virtually no change in predictions (Portland, NY, US in **Fig. 4c,d**).
204 However, in warmer locations where chill accumulation is lower, small shifts towards colder range
205 of chill accumulation results in significant delays in predicted budbreak (Marseillan-Plage, FR in
206 **Fig. 4c,d**). Large shifts towards colder temperature greatly reduce the amount of chill accumulated
207 in warmer locations, significantly affecting budbreak predictions in warmer locations, whereas
208 these effects remain minor in cold areas (**Fig. 4e**).
209
210 **Cold hardiness as a driver of climate suitability**
211 Because cold hardiness is a plastic trait that responds to temperature, shifting temperature regimes
212 will influence cold hardiness dynamics to varying degrees, leaving some genotypes more

vulnerable to freeze risk during the winter and early spring months. Therefore, we sought to examine the ways in which a cold hardiness model (here NYUS.1) can be utilized to explore low temperature-related growth risks among the three cultivars. To do so, we expanded cold hardiness and budbreak predictions beyond the year:location:cultivar combinations in which phenology observations were available. Instead, for all locations, we estimated cold hardiness and budbreak for the three cultivars, over the range of time for which weather data was available for each location (1950-2023 for European locations; 1926-2023 for Portland, NY, US; and 1980-2022 for all other North American locations).

We first examined predicted freeze risk amongst the three cultivars over the season for a cold location where the longest range of predictions were available (97 seasons; Portland, NY), and where cold damage is often reported (**Supplementary Fig. S1**). This was done based on safety margin calculations as the difference between the minimum temperature and the CH_{50} in any given day (Safety margin = $T_{min} - CH_{50}$). Instances of both predicted damage [Safety margin ≤0)] and near damage (0<Safety margin ≤2) were calculated for each cultivar. All seasons were aligned based on each cultivar's specific FDC budbreak for a given year, resulting in different patterns in freeze risk for each cultivar (**Fig 5a**). Cabernet-Sauvignon faced a higher risk of winter damage (i.e., ~120 to 80 days before budbreak) and a reduced risk of spring damage (i.e., 10 days prior to and after budbreak) when compared to other cultivars. Conversely, Concord displayed low risk of winter damage, but a greater susceptibility to spring damage compared to the other two cultivars. Riesling showed an intermediate risk for both winter damage and spring damage.

To more easily generalize responses to current and future climates, we explored the influence of dormant season temperature (November-April) on freeze damage risk as the number of days within a season where CH_{50} was predicted to crossed by minimum temperatures (negative safety margin). For this, predicted cold hardiness for the three cultivars across the eight locations and for all years was used. Cultivar-dependent patterns in risk became evident: colder dormant seasons (mean temperature below ~2.5ºC) resulted in a greater freeze risk for Cabernet-Sauvignon and (to a slightly lesser degree) Riesling, while Concord exhibited negligible risk (**Fig. 5b**). With moderate temperatures (e.g., 5ºC), all cultivars exhibited some level of freeze risk, with risk being highest for Concord, and lower for Riesling, and Cabernet-Sauvignon. When evaluating all cultivars

together, we can separate freeze risk broadly into four different temperature bands (**Fig. 5c**). Mean winter and spring temperatures below 1ºC were considered high freeze damage risk temperatures. Moderate freeze damage risk was assigned to mean temperatures ranging from 1ºC to 3ºC. Increased freeze damage risk was identified for temperatures ranging from 3ºC to 8ºC, and temperatures above 8ºC were classified as low freeze damage risk.

We also analyzed the sensitivity of simulated budbreak based on mean temperature of the dormant season using the predicted FDC budbreak for all cultivar:year:location points (**Fig. 6a**). At any mean dormant season temperature, Concord has earlier budbreak, followed by Riesling, and by Cabernet-Sauvignon. Date of budbreak advances with increasing mean dormant season temperatures, with sensitivity of –5.8 days/ºC (i.e., budbreak advances) for all cultivars combined. At the cultivar level, Concord has a slightly faster advancement compared to Riesling and Cabernet-Sauvignon (–6.0 days/ºC, –5.1 days/ºC, and –5.7 days/ºC, respectively). However, the overall response appears to be non-linear, with varying patterns across different temperature ranges and locations. To highlight these differences, mean winter and spring temperatures in Portland, NY, US (one of the coldest locations in our study) and Marseillan-Plage, FR (the warmest locations in our study) were explored (**Fig. 6b**). Portland shows an overall phenology advancement of only –3.3 days/ºC, with mean dormant season temperatures ranging from -1ºC to 5ºC (Fig 6B). This contrasts with Marseillan-Plage, FR, where mean dormant season temperatures range from 8ºC to 12ºC, showing a shifting pattern within its temperature range. There is a phenology advancement of –6.7 days/ºC when mean dormant season temperatures ranges from 8ºC to 10ºC. However, as mean temperatures increase further in that location, phenology starts to delay at a rate of +3.8 days/ºC when mean dormant season temperatures are above 10ºC (**Fig. 6b**). When data for all locations is split into three separate groups, sensitivity is highest in moderate temperatures (–6.3 days/ºC for 3-10ºC), and lowest and negative for warmest temperatures (+1.9 days/ºC for 10-12ºC; Fig. 6A).

Discussion

For temperate woody perennials, spring phenology (here budbreak) occurs after plants have been released from an annual period of winter dormancy[42]. Time spent in cold temperatures, quantified as chilling accumulation, is required for dormancy release. Then, to break bud and resume growth, time spent in warm temperatures (forcing) is required[42,43.] Many attempts to model budbreak rely at least partially on this relationship, using quantifiable thermal time metrics to elucidate the time required to reach the stage[16]. Here, the negative chilling and forcing relationship is substituted by winter dynamics of cold acclimation and deacclimation, thus incorporating a third temperature response –cold hardiness– to accurately predict spring phenology while allowing for better understanding of cold temperature-related suitability. Our findings demonstrate that a process-based cold hardiness model for grapevine (NYUS.1[31]) is generalizable to predict spring phenology across a wide range of global climates (**Figs. 2,3**). Our analysis also shows that the NYUS.1 model effectively predicts freeze events (**Supplementary Fig. S1**), while highlighting genotypic differences in damage patterns across locations and climatic conditions (**Fig. 5**). These results emphasize the importance of incorporating cold hardiness as a predictable trait within a phenology model, offering valuable insights beyond just predicting budbreak that will be consequential as global climate conditions continue to rapidly change.

Cold hardiness has a u-shaped pattern (**Fig. 1**), where its level at any point depends on prior temperatures experienced and specific species or cultivar. Here we use a cold hardiness threshold to predict budbreak. Given that colder climates can elicit greater cold hardiness (**Supplementary Fig. S4**), different locations can require different degrees of deacclimation (or forcing) to reach budbreak. This variation helps explain why the same genotypes show different chilling and heat requirements across locations. Additionally, reacclimation is possible if colder temperatures occur after a period of deacclimation (i.e., **Fig. 1**, see deacclimation period in late February, followed by reacclimation in early March[44,45]). In this context, reacclimation could be considered analogous to what would be negative forcing, or negative growing degree-days in ordinary spring phenology models – a concept contrary to growth, and thus never used, yet applicable within a cold hardiness dynamics framework.

The suitability of woody perennial species to local climates is shaped by numerous interacting environmental factors and phenotypic plasticity[34]. Among these, exposure to low temperatures

requires particular attention, especially in light of the unprecedented rise in global temperatures[46]. Increasing temperatures have been shown to cause increased risk of late frosts in some areas[47–49]. Our study found that all cultivars exhibited advancement in phenology with warmer dormant season temperatures (**Fig. 6**), consistent with broader trends in Northern Hemisphere populations[11,22,50,51]. However, it is important to note that warmer winter temperatures can also lead to increases in freeze damage potential, and the trends depend on cultivar (**Fig. 5b**; or similarly provenance[52]) and where a location lies in terms of mean dormant season temperature (**Fig. 5c**). Our study found that a general pattern occurs, where risk generally decreases with increasing mean temperatures, but a "bump" appears between ~3ºC and 8ºC. This "bump", represents a mismatch between phenology advances due to warmer springs and the potential for significant late frosts, increasing the freeze damage risk. When looking at each cultivar separately, the phenology-temperature mismatch places Concord at a greater risk for spring frost damage, including the timing right before budbreak, whereas Riesling and Cabernet-Sauvignon have lower risk (**Fig. 5a,b**). This furthers demonstrate the advantage of using a cold hardiness model to predict spring phenology, allowing for simultaneous assessments of both phenology advances and freeze damage risk that includes pre-budbreak damage.

In addition to risks related to freeze damage, excessive warming reduces chilling accumulation and delays budbreak based on our predictions (**Figs. 4,6**). Recent work supports these findings, suggesting that delays in phenology are also possible due to reduced exposure to temperatures which contribute to chilling accumulation[22,53–56], something often observed in areas with marginal chilling conditions where temperate woody perennial crops are introduced[57–60] and empirically determined in general chilling-forcing experiments [e.g.,[15,25]]. As changing global temperatures shift spring phenology, woody perennials will face novel risks in their current distributions[34,61–63]. The degree to which phenology shifts among the different genotypes in a given location is ultimately an effect of their plasticity and adaptive capacity on separate aspects of winter physiology: cold hardiness, chilling, and forcing. This highlights the importance of expanding empirical work with cold hardiness and chilling to include diverse genotypes and populations, particularly in warm range edges of natural ecosystems and marginal agricultural conditions, where plants will be more strongly affected (**Fig. 4**).

Grapevine cultivars possess a great diversity in traits that affect responses to climatic conditions[15,64]. This diversity is evident when exploring cold hardiness dynamics across the cultivars presented in this study. Across all locations, predicted patterns in acclimation and deacclimation reflected known genotypic differences in hardiness and development, and are therefore reflective of current distributions of the genotypes studied (**Fig. 2**). Cabernet-Sauvignon and Riesling—both cultivars of *V. vinifera*—exhibit low and intermediate mid-winter freeze tolerance (**Figs. 5a,S4**), respectively. These cultivars are thus best suited to climates with moderate to mild winters and longer growing seasons that are presently characteristic of many temperate climates with winters moderated by large bodies of water and western European locations. Concord, a cultivar of the more cold hardy *V. labruscana,* showed the greatest freeze tolerance among the three genotypes here, making it best adapted to regions with the cold winters and shorter growing seasons, presently characteristic of many viticultural regions in Northeastern North America. When freeze risk is evaluated based on mean dormant season temperature, Concord shows higher risk at moderate temperatures due to its faster deacclimation and advanced budbreak compared to the other cultivars (**Figs. 5c,6a**). Genotypic adaptation to local climates has allowed for successful grapevine cultivation in a wide range of climates, and our assessment of spring damage risk supports these known differences. Understanding the degree to which cold hardiness dynamics respond to fluctuations in dormant season temperatures —and, ultimately, how this influences budbreak phenology— will be imperative to making informed management and planting decisions as local climates continues to change.

Although the framework presented here removes subjectivity in determining the transition between chilling and forcing temperatures, exploring alternative approaches to chill calculation could be beneficial to further improve model outputs. The Dynamic Model has been shown to be one of the best models for comparing chilling across regions[65], and particularly without acknowledging cold hardiness[27]. Here, small shifts in temperature for chilling accumulation cause large increases in error (**Fig. 4b**). Chilling accumulation is a crucial component of most phenology models, and in NYUS.1, chilling accumulation modulates the magnitude of acclimation and deacclimation responses throughout the season. Given the significance of chilling to the model variability and the expected future declines in chill accumulation in regions like southern France (**Fig. 4c-e**)[22], improving existing chill models or developing new ones is necessary to better reflect physiological

responses to cold temperatures[27,53]. Our work thus adds to a growing body of literature showing that cold hardiness is likely an important factor to be acknowledged in studies of chilling and dormancy.

Although there was no parameter optimization for the cold hardiness model, predictions of budbreak resulted in very good statistics – particularly after correcting for cold damage (RMSE=7.2 days, Bias=0.58 days, r^2=0.88; **Fig. 3**). The NYUS.1 model was developed using only grapevine bud cold hardiness data obtained in Geneva, NY, US[31], while the dormancy parameters were obtained from a cold hardiness dynamics study of 15 unrelated woody perennial species grown in Boston, MA, US (**Fig. 2** in[25]). This demonstrates that process-based models that use physiologically-derived parameters can be used across climates. Our metrics are comparable to or better than studies using different models that included calibration based on budbreak data. Ferguson et al.[29] found a general RMSE of 7.3 days (n=152) for budbreak predictions of 23 grapevine cultivars in Washington state, USA using the WAUS.2 cold hardiness model. However, their predictions had a low coefficient of determination (r^2=0.45), likely due to the little variability in dates of budbreak for a single region. Considering the poor performance for the WAUS.2 model to predict cold hardiness in different locations[31,66], we can speculate that budbreak predictions would also be poor. Cortázar-Atauri et al. (2008) found RMSE ranging from 9.2 to 18.3 days for three models (one with two parameter sets) for Cabernet-Sauvignon (n=63) and Riesling (n=64) in four regions in France. Sgubin et al. (2018) found RMSEs between 9.7 and 11.1 days for Cabernet-Sauvignon (n=71) and Riesling (n=65) using two different phenological models in four regions in France. The RMSE is assessed by comparing model outputs with observed budbreak dates. Standardized methods for recording phenology observations, such as EL and BBCH scales, are widely used. However, some degree of subjectivity is unavoidable when the phenotyping is based on observations of characteristics that cannot be easily discretely quantified. In multi-decadal phenology records spanning multiple locations with different observers, inconsistencies observation methods are inevitable[67]. Here we demonstrated that depending on observation habits, different threshold can be used for the NYUS.1 model to increase accuracy of predictions for budbreak (**Supplementary Fig. S3**). As has been previously described in other organisms[68], our results reinforce that observations using 50% occurrence of different phenological stages have better results than using first observations – even with corrections. With expansion of phenology

modeling, the development of standardized, quantifiable methods for observing budbreak, including the use of imaging [e.g., PhenoCam[69]], would enhance model accuracy across locations, observers, and species—advances that will likely contribute to a deeper understanding of dormant season physiology.

Previous modeling work on climate suitability for grapevines only included a mid-winter threshold[64]. However, dynamics of weather are extremely important in midwinter cold hardiness, and therefore some of the potential viticultural expansion into colder climates predicted may be overestimated. Our predictions included a significant amount of years and locations with some level of cold damage (129 out of the 329 total observations). We demonstrated that correcting for cold damage can improve predictions of budbreak. It is possible that this was simply changing the trajectory of cold hardiness predictions to delay budbreak for these observations, thus resulting in better predictions. However, we validated our predictions of damage using historical records in the location with the most extensive temperature record (Portland, NY, US; **Figs. 3,S1**). Though this analysis does suggest that NYUS.1 can accurately predict damage, further subjectivity exists in the historical records, with variable language used to describe the damage and the degree to which damage was observable. For example, NYUS.1 predicted some instances of only slight damage when records of damage were not found. A likely explanation is that the damage was light and localized, and thus not widely reported, resulting in the more conservative nature of the model based on higher false positive predictions (**Supplementary Fig. S1**). To further improve these predictions, experiments may be required, including defining minimum cold hardiness thresholds for different tissues[70,71], and measuring mid-winter cold hardiness in multiple locations – particularly warmer climates where this trait is often easily ignored. It is important to note, however, that cold damage is known to delay spring phenology[3,41,72], and ordinary budbreak models have trained on phenology datasets that contain varying levels of cold damage. Thus, shifts in damage patterns that are expected depending on increasing temperatures [e.g., **Fig. 5** in our study, and[73]] may be a cause of failure for such models as climate changes, while that is unlikely to affect a model using cold hardiness as its basis.

Here, a novel method of spring phenology prediction is presented, with which we produced accurate budbreak predictions without calibration of model parameters to the dataset used in this

study. Through instances where reacclimation occurs, we use a physiological basis to introduce the equivalent of negative forcing into phenological modeling. Beyond budbreak, our framework for predictions includes cold hardiness, allowing for corrections of predictions based on damage incurred, as well as assessments of cultivar suitability to different locations and climates, both presently and in future conditions based on winter physiology. Improvements of winter physiological responses are still possible, such as better defining chilling accumulation effects. Therefore, empirical determination of dormancy and cold hardiness in different climatic gradients are warranted. Continued work in measuring cold hardiness of many species and in varied climates (e.g.,[25,74,75]) will allow for expansion of cold hardiness and budbreak modeling using a framework such as the one presented here. Future work may then integrate cold hardiness dynamics into large-scale predictive models to improve forecasts of plant responses to climate change and niche modeling. These efforts can ultimately enable more reliable predictions in earth system models, and better understanding of climatic feedbacks in shifting spring phenology of woody perennials.

Materials and Methods

Phenological Records

The phenology dataset used in this study includes three grapevine cultivars: *Vitis vinifera* cvs. Cabernet-Sauvignon and Riesling, and *Vitis labrusca* cv. Concord (hereon referred to by cultivar name only). Phenology data was retrieved from eight different locations across Europe and North America (**Fig. 2**): Niagara-on-the-Lake, ON, CA[76], Portland, NY, US, Lewisburg, PA, US[77], Bordeaux, FR[78], Bergheim, FR, Montreuil-Bellay, FR[79], Marseillan-Plage, FR[78], and Veitschöhheim, DE[80]. For Bordeaux, FR, we included additional phenology data collected in the same plot for the years 2012-2023. For Veitschöhheim, DE, budbreak data were extracted from figure 2a[80] in RStudio using metaDigitiseR version 1.0.1[81].

The full phenology dataset contains a total of 329 observations–recorded as the Julian day of year (DOY) of budbreak–spanning a cumulative total of 68 seasons (1955-1956 to 2022-2023). An exhaustive list of locations, cultivars, and observational timespans for each location can be found in **Supplementary Table S1**. In most cases, phenology data was explicitly reported as the day of year to reach 50% of buds at BBCH 07 [Biologische Bundesanstalt, Bundessortenamt und Chemische Industrie[82]], or the equivalent stage 4 in the Eichorn-Lorenz scale for grapevines[83]. Occasionally, observations were made of 50% of buds at stage BBCH 05 (and in one location, observations by one observer as first bud at stage BBCH 05).

Phenology predictions

To predict phenology, we first predicted cold hardiness using the NYUS.1 grapevine cold hardiness model[31]. This model uses temperature data as inputs to generate cold hardiness predictions as outputs.

Weather Data and Chill Accumulation

Daily maximum and minimum temperature values were retrieved for all eight locations in this study through publicly available databases. For European locations (Bordeaux, FR; Bergheim, FR; Montreuil-Bellay, FR; Marseillan-Plage, FR; and Veitschöhheim, DE), high-resolution (1 km) downscaled temperature data were obtained from WorldClim version 2.1[84] and accessed via

easyclimate version 0.2.1[85] for the period of 1950-2022, which was the most broad timespan available using these resources. In Bordeaux, FR, additional temperature data were accessed from a nearby weather station (station ID: 335500003) for the time period of 1 January 2023 – 30 June 2023.

For two of the three North American locations (Niagara-on-the-Lake, ON, CA; and Lewisburg, PA, US), high resolution (1 km) temperature data were obtained from Daymet version 4[86] and accessed via *daymetr* version 1.7.1[87] for the period of 1980-2022, the broadest timespan available. For Portland, NY, US, temperature data from the weather station located at the Cornell Lake Erie Research and Extension Laboratory were used (available through the Lake Erie Regional Grape Program) for the time period of 1926-2023.

For evaluations using general yearly weather, such as sensitivity (see below), we characterized each location:year combination using the mean temperature for the dormant season calculated by obtaining the average temperature from 1 November to 30 April for each season within each location. This is referred to simply as mean dormant season temperature.

Modeling Cold Hardiness

The model utilized in this study is based on the NYUS.1 cold hardiness prediction model[31]. It integrates acclimation (1) and deacclimation (2) processes over daily time steps from bud set to any given point during the dormant season, using temperature records as an input.

1. Acclimation: The rate of acclimation for buds at any given time is a function of chilling accumulation, modulated by the difference between the daily minimum temperature, and the maximum temperature that elicits chilling accumulation on any given day.
2. Deacclimation: The rate of deacclimation is determined by a temperature response curve and modulated by a chilling response curve. The maximum possible rate of deacclimation for a given day is ultimately modulated by the amount of chilling received by an individual.

The responses to chilling accumulation are based on chill portions calculated through the Dynamic Model[88,89], which therefore serves as a sub-model. Chilling accumulation was calculated in

RStudio using *chillR* version 0.75[90]. Since the Dynamic Model calculates chill portions in hourly timesteps, daily minimum and maximum temperatures were transformed into hourly data using the "*stack_hourly_temps*" function in *chillR*. Chilling accumulation for each location was calculated continuously from 1 July to 30 June for every year where temperature data was available. To summarize, the cold hardiness of buds at any given time is calculated as an integration of functions of temperature over time, which are modulated by chilling accumulation, which is itself a response to temperature. In this process, acclimation is the strongest driving force for cold hardiness during the fall, and deacclimation is the strongest driving force during spring, resulting in a general U-shaped curve for cold hardiness.

Parameters for the 50th percentile cold hardiness predictions were used based on field data collected in Geneva, NY, US as detailed in [31]. To provide additional detail regarding potential damage, we used the same calibration and validation datasets to obtain parameters for the 10th and 90th percentiles for cold hardiness predictions, which were used to estimate a 90% confidence interval for the cold hardiness predictions. These parameters are described in **Supplementary Table S2**.

Spring Cold Hardiness

Minimum cold hardiness thresholds during spring are not set within the NYUS.1 model, allowing for the projection of cold hardiness freely towards positive temperature values, which here we use for predictions of budbreak (see below). For analyses concerning the estimation of frost damage risk and safety margins, we limited the cold hardiness to thresholds which describe the minimum cold hardiness of growing tissue, obtained from the literature. Here, we used the same 10th, 50th, and 90th percentile values measured in 'Pinot Noir' for the "fourth leaf" stage (i.e., stage 14 of BBCH scale or 11 in the modified EL scale) for the three cultivars[70]: -0.82 °C, -1.2 °C, -1.6 °C, respectively.

Cold Hardiness at Budbreak

Projected cold hardiness trajectories for each cultivar were used to predict the day of year by which 50% of buds reached the BBCH 07 ("beginning of bud burst: green shoot tips just visible") stage[91]. Two different thresholds for the cold hardiness at budbreak were applied, based on cultivar: a

predicted cold hardiness of +10ºC was used for Cabernet-Sauvignon and Riesling, and +5ºC was utilized for Concord. Thresholds were determined from data within [24] in which rates of cold hardiness loss in forced deacclimation assays were related to different bud developmental stages.

Additional threshold adjustments were made to account for differences in observational habits within phenological records. The first adjustment was used to account for years and locations where phenology observations were determined at the 50% BBCH 05 stage ("wool stage"), a threshold of +5ºC was applied for Riesling and Cabernet-Sauvignon predictions. An additional adjustment was made specifically for predictions in Bordeaux, FR over the 1981-2008 period. During this time, the phenological record for budbreak was the day of year when the first bud for each cultivar reached BBCH 05 (as opposed to 50% of buds at a certain stage as in other locations and years). A threshold of 0ºC was therefore used for Cabernet-Sauvignon and Riesling predictions in Bordeaux from 1981-2008 to account for the observational habit differences.

Accuracy and reliability of the budbreak prediction model was evaluated through determination of Bias, Root Mean Square Error (RMSE), and Coefficient of determination (r^2). Bias was determined to assess the average deviation between the predicted and observed cold hardiness values ($Bias = CH_{observed} - CH_{predicted}$), providing insight into any systematic errors present in the model. RMSE was calculated to quantify the overall prediction error, reflecting both the variance and bias of the model. These statistical analyses were performed using RStudio.

Adjustment of Cold Hardiness Predictions to Account for Damage

In years where low temperature damage to buds was predicted, a correction was applied to the cold hardiness of the remaining buds based on an estimate of the degree of damage (as a percentile value). This was achieved through a simple linear interpolation. Damage estimates were performed for days within each season where the minimum air temperature was lower than the predicted cold hardiness. In seasons where multiple instances of damage were predicted, percentile values for damaged buds were calculated for each event, based on the existing population immediately prior. The cold hardiness of the remaining buds was calculated after each damage event, dependent on both the existing cold hardiness percentile values preceding the event as well as the percentile estimation of buds damaged from the freeze event.

When the minimum air temperature fell between the 10th and 50th percentile cold hardiness values, the following equation was used to estimate the percent of buds damaged from the existing population:

$$Damage = \left(\frac{50-10}{CH_{50}-CH_{10}}\right) \times (T_{min} - CH_{10}) + 10; \text{ (Eq. 1)}$$

where T_{min} is the minimum temperature of the day, and CH_{10} and CH_{50} are the 10th and 50th percentile cold hardiness values. When the minimum air temperature fell between the 50th and 90th percentile cold hardiness values, the following equation was used to estimate the percent of buds damaged from the existing population:

$$Damage = \left(\frac{90-50}{CH_{90}-CH_{50}}\right) \times (T_{min} - CH_{50}) + 50; \text{ (Eq. 2)}$$

where CH_{50} and CH_{90} are the 50th and 90th percentile cold hardiness values. After calculating the estimated percent of buds that were damaged, cold hardiness percentile values were adjusted to account for the buds remaining in the undamaged population using the following equations:

$$CH_{10}^{*} = CH_{10} + \left(\frac{CH_{50}-CH_{10}}{40}\right) \times (((100 - \%\, damage) \times 0.1 + \%\, damage) - 10; \text{ (Eq. 3)}$$

$$CH_{50}^{*} = CH_{50} + \left(\frac{CH_{90}-CH_{50}}{40}\right) \times (((100 - \%\, damage) \times 0.5 + \%\, damage) - 50; \text{ (Eq. 4)}$$

$$CH_{90}^{*} = CH_{90} + \left(\frac{CH_{90}-CH_{50}}{80}\right) \times (((100 - \%\, damage) \times 0.9 + \%\, damage) - 90; \text{ (Eq. 5)}$$

Where CH_{10}^{*}, CH_{50}^{*}, and CH_{90}^{*} are the damage-adjusted predicted cold hardiness for the 10th, 50th, and 90th percentiles, respectively. Damage-adjusted cold hardiness predictions were used in all analyses presented unless otherwise mentioned.

Validation of Damage Predictions

Given the absence of long, publicly available records of empirically determined cold hardiness measurements, we validated our predictions of cold damage by comparing them with historical reports. To do so, we performed this analysis based on Concord cold hardiness modeled in one

location (Portland, NY) over the entire time period of cold hardiness predictions (1926-2023). Our analysis focused on Concord in the Lake Erie region given its local economic importance, guaranteeing mentions of cold damage in a local news source, and the availability of searchable news reports in English. The historical records used were obtained from two sources: *The Erie Daily Times* (1927-2006) – a local newspaper – and *Veraison to Harvest* (2007-2023) – an extension publication by Cornell University which reports on New York State's grapevine production. For newspaper articles, the archival search was done using the keywords 'grape+frost'. In order to be included in the analysis, the articles and extension reports had to meet the following criteria: (i) there was a mention of any degree of frost damage to the grapevine crop or (ii) articles explicitly mentioned that the crop escaped damage. If no records of damage were found for a given year, it was assumed that no damage occurred to the buds.

A positive detection of damage for a season was considered when at any day of the season the daily minimum temperature was lower than the predicted 10th percentile cold hardiness for that day. A binary outcome was then applied to all years in this analysis, regardless of level of damage, or number of damage events, where 1 indicated damage occurrence during a season, and 0 indicated no damage. A binary outcome was also applied to the mention of damage in records, wherein 1 indicated presence (records indicated damage occurred within a season) and 0 indicated absence (records indicated no damage had occurred, or no records of damage were discovered for a given season). These binary outcomes were then used to construct a confusion matrix to evaluate prediction performance and calculate sensitivity, specificity, precision, and accuracy of the model.

Effect of Chilling Temperature Range

To examine potential errors associated with chilling range on the budbreak predictions, both as a whole and by location, we applied a series of phase shifts to change the relative contribution of temperatures to chilling accumulation in the Dynamic Model. The chilling range was thus shifted by 1ºC intervals, from -6ºC to +6ºC during chill accumulation estimation (e.g., chill is maximized at 7.5 ºC within the Dynamic Model, and we shifted this maximum to occur between 1.5 ºC and 13.5 ºC). Budbreak predictions were then produced using the model without any other adjustments. RMSE for predictions at each phase shift step were then calculated.

Indicators for Climate Suitability and Sensitivity

To evaluate the temporal nature of freeze risks within a season, we used temperature records and phenology predictions from Portland, NY, over the time period of 1926-2023, we used cold hardiness predictions to estimate the frequency of freeze events and potential freeze damage. Safety margins defined as the difference between the minimum registered air temperature (T_{min}) and the 50th percentile cold hardiness prediction were calculated daily (CH_{50}):

$$Safety\ margin = T_{min} - CH_{50}; \text{(Eq. 6)}$$

Where a safety margin below zero indicates at least 50% freezing damage is predicted, and positive values indicate different levels of safety. We defined freeze risk as the number of days when the safety margin dropped below zero for each cultivar in all locations for all years in which weather data was available (n=1626 location:cultivar:year combinations). Therefore, safety margin calculations were also used to determine the number of freeze risk injury days over the range of mean dormant season temperatures experienced (November-April), providing an overall measure of how many days during the season there was a risk of damage:

$$N_{days} = \Sigma_{i=1}^{n} I(Safety\ margin_i \leq 0)\ ; \text{(Eq. 7)}$$

The potential effects of temperature changes on phenological timing (sensitivity) were evaluated by studying the relationship between the predicted day of budbreak and the mean dormant season temperatures over all locations, years and cultivar combinations (n= 1626). Differences in responses to different mean dormant season temperatures for the entire dataset, and also in three temperature segments (a) -1ºC to 3ºC, b) 3.01ºC to 10ºC, and c) 10.01ºC to 12ºC) were calculated in RStudio using the *rms* package, version 6.8-1[92].

652 **Figure Legends**

653

654 **Figure 1. Conceptual overview of the cold hardiness model to predict budbreak.** The NYUS.1
655 cold hardiness model[31] is used to predict the time to budbreak for *V. labrusca* 'Concord' grapes
656 grown in Portland, NY, US in the 1983-1984 dormant season. Cold hardiness (blue ribbon) is
657 gained and lost in response to seasonal fluctuations in air temperature (grey ribbon). Two different
658 end trajectories are shown for the cold hardiness prediction: real cold hardiness values that remain
659 negative in value, where CH stops decreasing once it reaches minima extracted from [70] (blue
660 ribbon); and a second, projected cold hardiness where values are calculated into non-freezing
661 temperatures (red ribbon and dashed line). When the projected cold hardiness reaches a threshold
662 determined for cold hardiness at budbreak (established from data in [24]), budbreak is predicted to
663 occur.

664

665 **Figure 2. Locations and cultivars in the phenology dataset and cold hardiness model**
666 **development.** The phenology dataset used here contains eight locations: four in France (Bergheim,
667 Bordeaux, Marseillan-Plage, and Montreuil-Bellay), one in Germany (Veitschöhheim), two in the
668 United States (Lewisburg, PA, and Portland, NY), and one in Canada (Niagara-on-the-Lake, ON).
669 The NYUS.1 cold hardiness model was developed using grapevine bud cold hardiness data from
670 Geneva, NY (Kovaleski et al., 2023), and used dormancy parameters from 15 unrelated woody
671 perennial species grown in Boston, MA – both in the United States.

672

673 **Figure 3. Comparison of budbreak predictions from cold hardiness model with observations.**
674 **a,** Relationship between initial predictions and observations of budbreak. **b,** Based on expected
675 cold damage prior to budbreak, predictions of budbreak can be corrected, shifting to a later date as
676 the cold hardiness of the surviving bud population is greater. **c,** Distribution of residuals based on
677 five different groupings, from left to right: initial predictions (years uncorrected for damage +
678 years where damage was not predicted n = 329); years where no damage was predicted (n = 200),
679 uncorrected predictions in years with predicted damage (n = 129), predictions corrected to account
680 for damage (n = 129), and full, corrected predictions (predictions corrected to account for damage
681 + predictions in years where damage is not predicted, n = 329). **d,** Comparison of predictions to
682 observations after accounting for the consequences of freeze damage. **e,** Sample article from

historical records used to qualitatively validate damage predictions (Erie Daily Times, 5 May 1977). In (**a,b**), thin solid black line represents 1:1 ratio between observations and predictions, and dotted lines represent an interval of +/- 7 days from 1:1 line. Heavy black line shows linear relationship between predicted and observed points.

Figure 4. Phenology predictions in different sites are differentially affected by shifts in how chilling accumulation is calculated. a, Density plot of recorded temperatures in Portland, NY, US and Marseillan-Plage, FR, and the relative contribution of temperatures to chilling accumulation in the Dynamic Model under unaltered and two sample phase-shift scenarios (-2ºC and -6ºC). **b,** RMSE of budbreak phenology predictions under a range from -6ºC to +6ºC of phase shift scenarios. **c,d,e,** Phenology predictions compared to observations and average chilling accumulation in a cold location (Portland, NY) and warm location (Marseillan-Plage, FR) under (**c**) unshifted conditions, (**d**) a -2ºC phase shift, and (**e**) a -6ºC phase shift scenario. In (**c,d,e**), thin solid black line represents 1:1 ratio between observations and predictions, and dotted lines represent an interval of +/- 7 days from 1:1 line. Heavy black line shows linear relationship between predicted and observed points. Horizontal dashed line at DOY 150 in (**c,d,e**) to highlight change in axis in (**e**).

Figure 5. Freeze risk shows temporal, temperature, and cultivar effects. a, Damage risk density plot over time within a season, based on cold hardiness predictions for three grapevine cultivars in Portland, NY, US over the time period of 1927-2023 shows two instances of higher probability of damage: midwinter (120-80 days before budbreak) and around budbreak (15 days before and after budbreak). Red curve represents predicted instances of freeze damage (safety margin less than or equal to 0), and the yellow curve represents instances where there is a narrow safety margin (between 0ºC and 2ºC). Horizontal axis shows "0" as the mean day of budbreak for each cultivar over the time period. **b,c,** Number of predicted freeze damage risk days based on mean dormant season temperature (1 November–30 April), for (**b**) each of three grapevine cultivars grown in eight locations and (**c**) for all cultivars combined. Point sizes (**b,c**) are proportional within each decimal mean dormant season temperature. Risk of damage was separated in four temperature bands based on mean dormant season temperature: [1; blue] high freeze risk injury, particularly for *V. vinifera* cultivars, due to low mid-winter temperatures; [2;

green] cool spring days delay budbreak until last frost; [3; orange] risk of freeze damage increases as spring phenology advances faster than date of last frost; [4; red] temperatures are too warm for low temperature injury to be significant. Horizontal colored lines (**c**) show mean dormant season temperature ranges in datasets from each of the eight locations studied.

Figure 6. Sensitivity of phenology to temperature is uneven across the range of climates studied. a,b, Freeze damage corrected predicted day of budbreak for all cultivars as a response to mean dormant season temperatures (1 November–30April) for (**a**) all eight locations combined and (**b**) separately for Portlant, NY, US and Marseillan-Plage, FR. (**a**) Budbreak advances at an overall rate of 5.8 days/ºC for all cultivars, while showing different magnitudes and directions at different temperature intervals, (**b**) which is also affected by local temperature dynamics.

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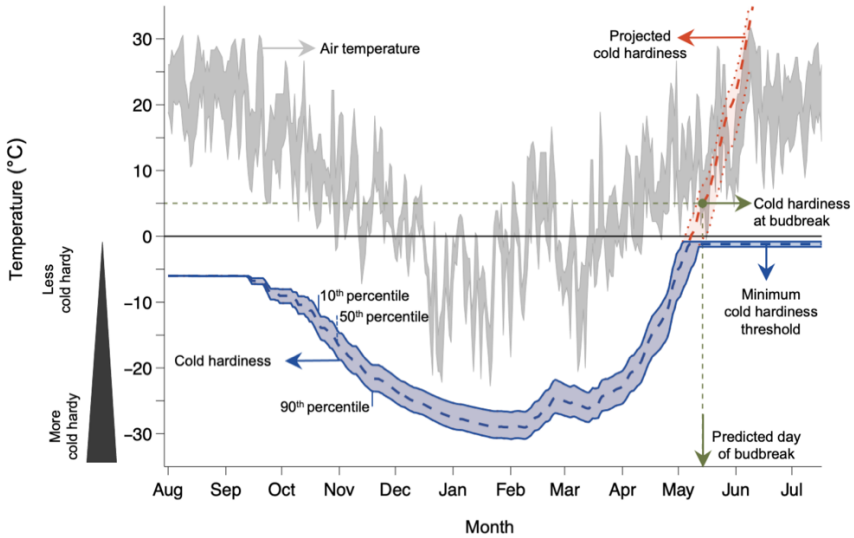


Figure 1. Conceptual overview of the cold hardiness model to predict budbreak. The NYUS.1 cold hardiness model[31] is used to predict the time to budbreak for *V. labrusca* 'Concord' grapes grown in Portland, NY, US in the 1983-1984 dormant season. Cold hardiness (blue ribbon) is gained and lost in response to seasonal fluctuations in air temperature (grey ribbon). Two different end trajectories are shown for the cold hardiness prediction: real cold hardiness values that remain negative in value, where CH stops decreasing once it reaches minima extracted from [70] (blue ribbon); and a second, projected cold hardiness where values are calculated into non-freezing temperatures (red ribbon and dashed line). When the projected cold hardiness reaches a threshold determined for cold hardiness at budbreak (established from data in [24]), budbreak is predicted to occur.

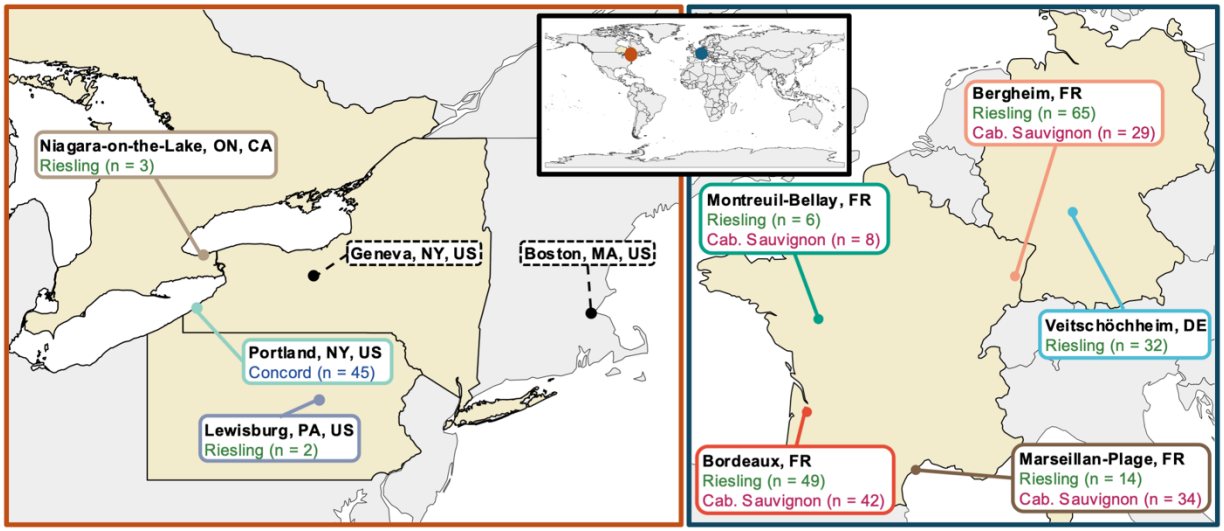
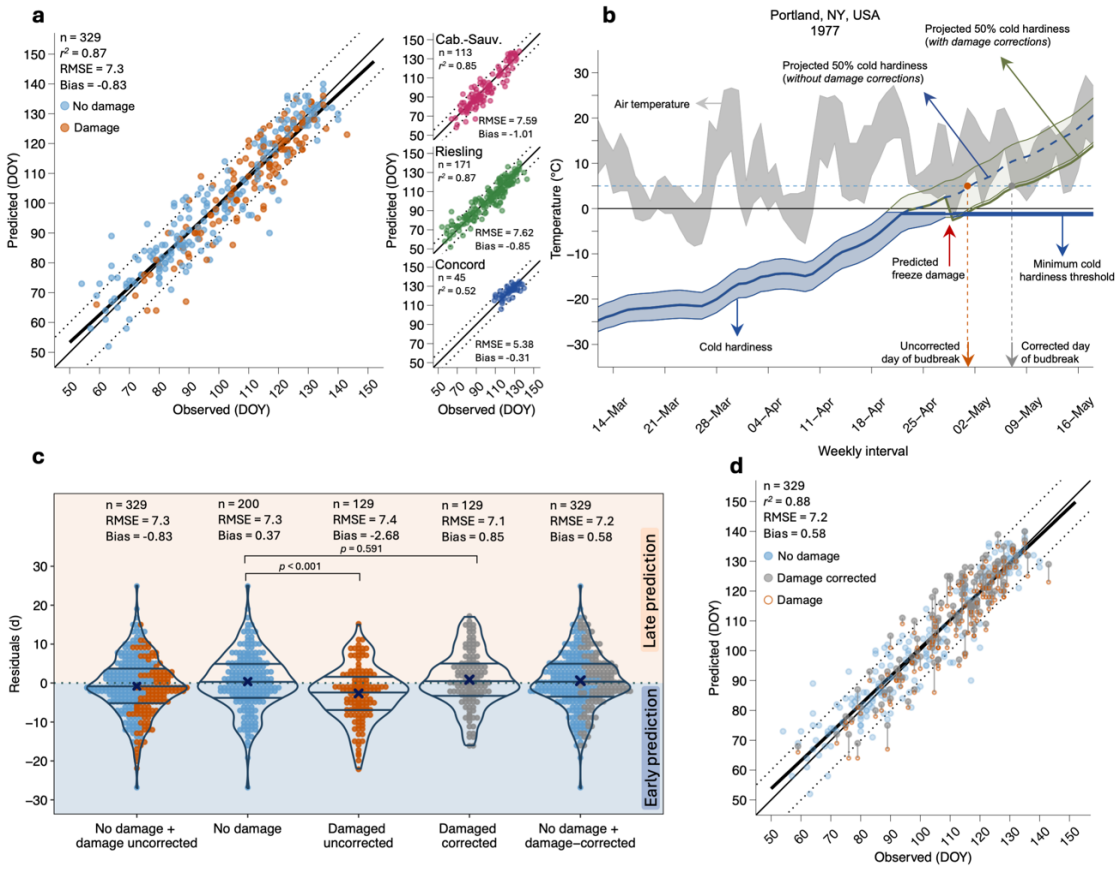


Figure 2. Locations and cultivars in the phenology dataset and cold hardiness model development. The phenology dataset used here contains eight locations: four in France (Bergheim, Bordeaux, Marseillan-Plage, and Montreuil-Bellay), one in Germany (Veitschöhheim), two in the United States (Lewisburg, PA, and Portland, NY), and one in Canada (Niagara-on-the-Lake, ON). The NYUS.1 cold hardiness model was developed using grapevine bud cold hardiness data from Geneva, NY (Kovaleski et al., 2023), and used dormancy parameters from 15 unrelated woody perennial species grown in Boston, MA – both in the United States.



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IN FRIDAY'S RECORD COLD

MAY 5TH, 1977

$ 3 MILLION IN FRUIT LOSS

Estimates of Erie County fruit crop losses range between $3 to $4 million as a result of a record low 22 degree temperature last Friday.

U.S. Rep. Marc Lincoln Marks, 24th Dist., has indicated he will attempt to get federal disaster aid for area farmers.

The loss estimates were made Wednesday by the Erie County U.S. Department of Agriculture emergency board.

According to the board, there was a 40 per cent loss of grape crops, near a 100 per cent loss of cherry and apple blossoms and a 50 per cent loss of peach blossoms.

Losses to Erie area grape crops was placed at more than $2 million.

The board said pears and prune crops were also affected by the frost.

Erie County commissioners next week are expected to ask Gov. Milton J. Shapp to contact the Carter administration to ask for emergency aid.

The aid will come from low interest loans through the Farmer's Home Administration.

More than 400 producers of fruit in Erie County were affected by the frost, according to Joe Burawa, executive director of the Agricultural Stabilization and Conservation Service. He is also chairman of the USDA emergency board.

Erie's grape crop accounts for 90 per cent of the state's total production.

Concorde grapes appeared to suffer the heaviest losses. Burawa said that Erie County will probably be declared a natural disaster area by the Carter administration, once Shapp makes the aid request.

A Marks spokesman confirmed that Marks is seeking passage of a bill that would reduce disaster loan interest to 3 per cent with a grant and 1 per cent without a grant.

The bill, however, is not expected to gain immediate approval and it was unknown Wednesday if there is a retroactive provision.

Figure 3. Comparison of budbreak predictions from cold hardiness model with observations. a, Relationship between initial predictions and observations of budbreak. **b,** Based on expected cold damage prior to budbreak, predictions of budbreak can be corrected, shifting to a later date as the cold hardiness of the surviving bud population is greater. **c,** Distribution of residuals based on five different groupings, from left to right: initial predictions (years uncorrected for damage + years where damage was not predicted n = 329); years where no damage was predicted (n = 200), uncorrected predictions in years with predicted damage (n = 129), predictions corrected to account for damage (n = 129), and full, corrected predictions (predictions corrected to account for damage + predictions in years where damage is not predicted, n = 329). **d,** Comparison of predictions to observations after accounting for the consequences of freeze damage. **e,** Sample article from historical records used to qualitatively validate damage predictions (Erie Daily Times, 5 May 1977). In (**a,b**), thin solid black line represents 1:1 ratio between observations and predictions, and dotted lines represent an interval of +/- 7 days from 1:1 line. Heavy black line shows linear relationship between predicted and observed points.

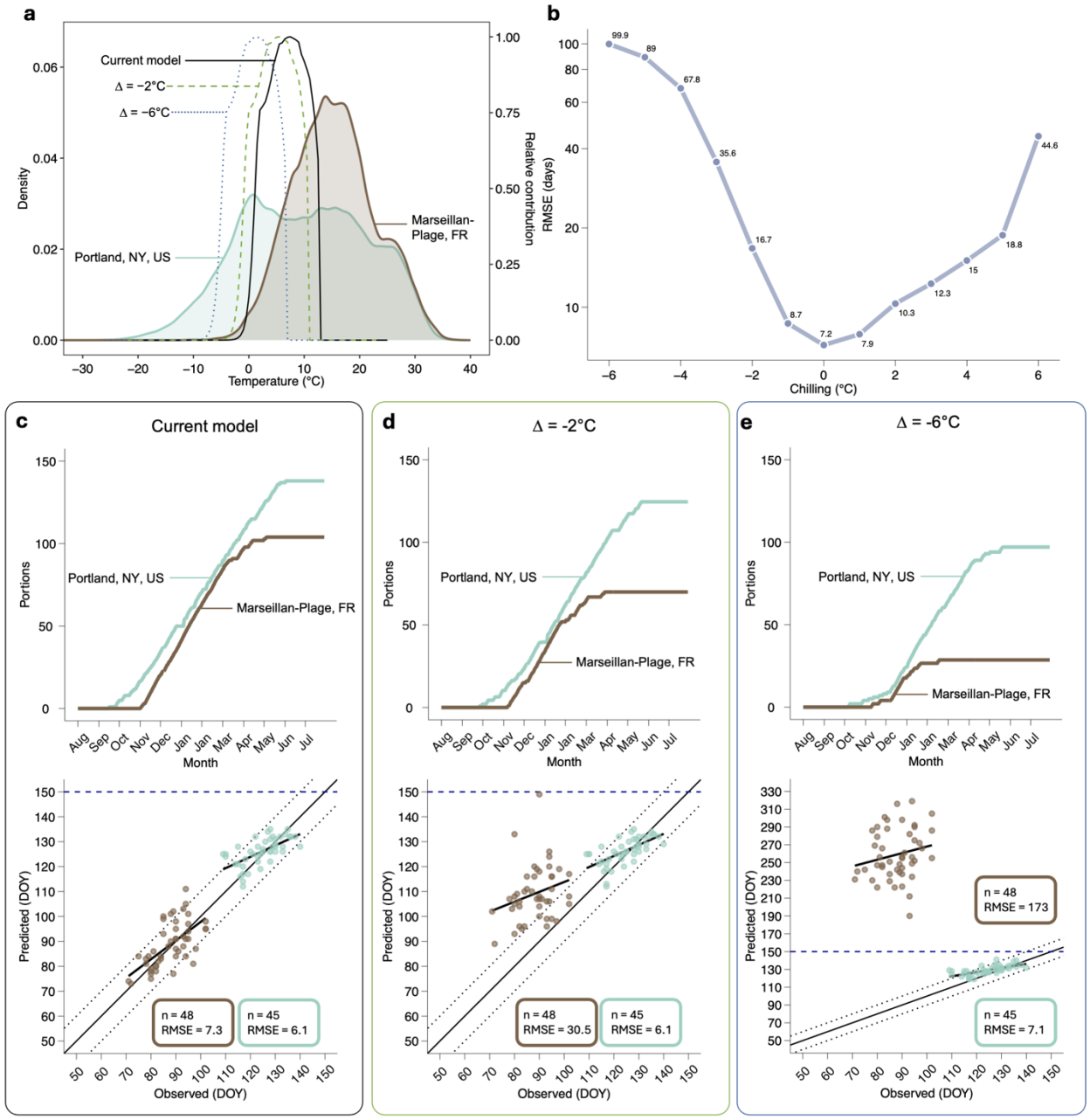

Figure 4. Phenology predictions in different sites are differentially affected by shifts in how chilling accumulation is calculated. a, Density plot of recorded temperatures in Portland, NY, US and Marseillan-Plage, FR, and the relative contribution of temperatures to chilling accumulation in the Dynamic Model under unaltered and two sample phase-shift scenarios (-2ºC and -6ºC). **b,** RMSE of budbreak phenology predictions under a range from -6ºC to +6ºC of phase shift scenarios. **c,d,e,** Phenology predictions compared to observations and average chilling accumulation in a cold location (Portland, NY) and warm location (Marseillan-Plage, FR) under (**c**) unshifted conditions, (**d**) a -2ºC phase shift, and (**e**) a -6ºC phase shift scenario. In (**c,d,e**), thin solid black line represents 1:1 ratio between observations and predictions, and dotted lines represent an interval of +/- 7 days from 1:1 line. Heavy black line shows linear relationship between predicted and observed points. Horizontal dashed line at DOY 150 in (**c,d,e**) to highlight change in axis in (**e**).

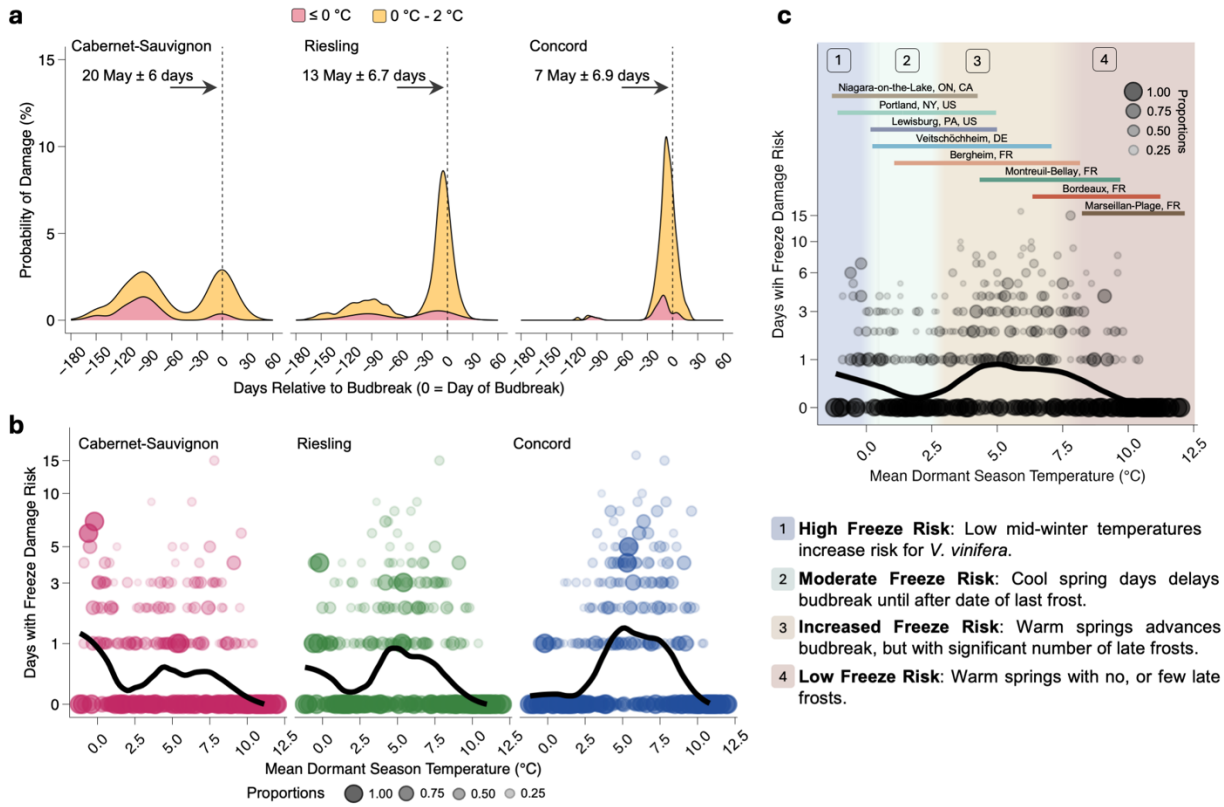

Figure 5. Freeze risk shows temporal, temperature, and cultivar effects. a, Damage risk density plot over time within a season, based on cold hardiness predictions for three grapevine cultivars in Portland, NY, US over the time period of 1927-2023 shows two instances of higher probability of damage: midwinter (120-80 days before budbreak) and around budbreak (15 days before and after budbreak). Red curve represents predicted instances of freeze damage (safety margin less than or equal to 0), and the yellow curve represents instances where there is a narrow safety margin (between 0ºC and 2ºC). Horizontal axis shows "0" as the mean day of budbreak for each cultivar over the time period. **b,c,** Number of predicted freeze damage risk days based on mean dormant season temperature (1 November–30 April), for (**b**) each of three grapevine cultivars grown in eight locations and (**c**) for all cultivars combined. Point sizes (**b,c**) are proportional within each decimal mean dormant season temperature. Risk of damage was separated in four temperature bands based on mean dormant season temperature: [1; blue] high freeze risk injury, particularly for *V. vinifera* cultivars, due to low mid-winter temperatures; [2; green] cool spring days delay budbreak until last frost; [3; orange] risk of freeze damage increases as spring phenology advances faster than date of last frost; [4; red] temperatures are too warm for low temperature injury to be significant. Horizontal colored lines (**c**) show mean dormant season temperature ranges in datasets from each of the eight locations studied.

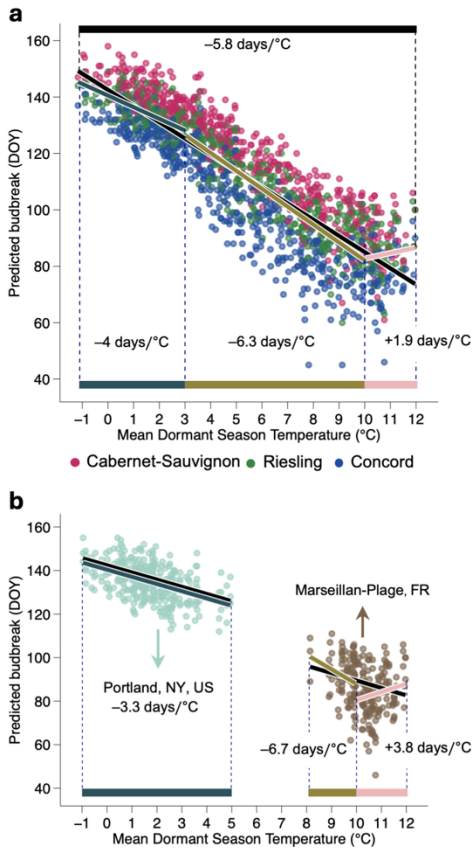

Figure 6. Sensitivity of phenology to temperature is uneven across the range of climates studied. a,b, Freeze damage corrected predicted day of budbreak for all cultivars as a response to mean dormant season temperatures (1 November–30April) for (**a**) all eight locations combined and (**b**) separately for Portlant, NY, US and Marseillan-Plage, FR. (**a**) Budbreak advances at an overall rate of 5.8 days/ºC for all cultivars, while showing different magnitudes and directions at different temperature intervals, (**b**) which is also affected by local temperature dynamics.