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Temperature-based Climate Projections of Pinot noir Suitability in the Willamette Valley American Viticultural Area

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ABSTRACT

In this study, we consider the complete archive of the 32 Coupled Model Intercomparison Project Phase 5 (CMIP5) daily Localized Constructed Analogs (LOCA) downscaled historic datasets and their observational data that were used for downscaling and bias corrections to develop an ensemble that optimises calculation of the growing season average temperature (GST) viticulture climate classification index throughout the Willamette Valley (WV) American Viticultural Area (AVA). Ensemble directed spatiotemporal calculations, using LOCA CMIP5 historic and RCP4.5 future datasets of minimum and maximum daily temperature, were performed throughout the WV AVA for the GST index and Pinot noir specific applications of the grapevine sugar ripeness (GSR) model at a 220 g/L target sugar concentration. The GST index and GSR model evaluations were calculated on a mean decadal basis from the 1950s to the 2090s for the WV AVA. The GST index and GSR model calculations both revealed a warming trend with time for the WV AVA. A 3.1 °C increase in the GST index is predicted from the 1950s to the 2090s. The GSR model indicated a rate advance of 2.9 days a decade from the 1960s to the 2080s. However, the application of the GST index and the GSR model portray markedly different characterisations about the suitability of Pinot noir throughout the WV AVA with time. A strong invertible relationship between the GST index and GSR model calculations is observed and exploited to update the Pinot noir specific lower and upper bounds (14.8 °C, 17.6 °C) for the GST index throughout the WV AVA. Pinot noir specific applications of the GSR model or the GST index with updated bounds indicate that the percent of the WV AVA area suitable for Pinot noir production is currently at or near its peak value in the upper 80s to the lower 90s.

KEYWORDS: downscaled CMIP5, ensemble, growing season average temperature, bioclimatic index, Grapevine Sugar Ripeness phenology model, Pinot noir, suitability

INTRODUCTION

Air temperature is the key driver of grapevine phenology and a significant environmental factor impacting yield and quality for a grapevine growing region (Parker *et al.*, 2011; van Leeuwen *et al.*, 2019). In cool to intermediate climate regions, high-quality vintages were linked to warmer than normal growing seasons for the cultivar Pinot noir (Blank *et al.*, 2019). Recent studies have developed, calibrated, and validated temperature-based models that predict the timing of budbreak, flowering, veraison, and predetermined sugar ripening concentration levels using historical phenological observations across wine regions and cultivars (Parker *et al.*, 2013; Parker *et al.*, 2020a; Piña-Rey *et al.*, 2021; Reis *et al.*, 2020; Zapata *et al.*, 2017). The ability to model grapevine phenology by cultivar supports the selection of plant material compatible with a growing area's climatology (Parker *et al.*, 2020b; van Leeuwen *et al.*, 2019).

Parker *et al.* (2020a) introduced the Grapevine Sugar Ripeness (GSR) model, which predicts the day of the year to reach fixed target sugar concentrations across sixty-five cultivars. Its development was motivated by the observation that results from its application could serve as a surrogate for evaluating maturity by cultivar and that this could be particularly useful for assessing cultivar suitability when coupled with future climate projections (Parker *et al.*, 2020a; Parker *et al.*, 2020b). Its application to date has demonstrated that it models harvest dates well for Merlot, Cabernet-Sauvignon, Cabernet franc, and Sauvignon blanc in Bordeaux for two historical periods (1951-1980; 1981–2010) and that Sauvignon blanc and Merlot are forecasted to ripen too early when a one-degree Celsius increase is added to the latter historical period temperature data (van Leeuwen *et al.*, 2019). In a separate study, Parker *et al.* (2020b) demonstrated a rate advance of two days a decade for Chardonnay in Champagne to reach a 170 g/L sugar concentration when the GSR model was applied using a Representative Concentration Pathways (RCP 4.5) future climate scenario temperature dataset from a single downscaled Coupled Model Intercomparison Project Phase 5 (CMIP5) model.

A notable observation about the temperature based GSR model, determined through a sequential calibration, sensitivity, and validation exercise using a comprehensive database of target sugar concentrations, is that it closely resembles the definition of the growing season average temperature (GST) viticulture climate classification index (Jones, 2006). The GST climate index is the mean of the observed maximum and minimum daily surface air temperature values from the first of April through the end of October (for the Northern Hemisphere). Based on a summary of empirical observations associated with multiple wine regions, Jones (2006) proposed that wine grape growing climates can be ordered and labelled as "Cool", "Intermediate", "Warm", and "Hot" based on the GST index and corresponding varietal ripening potential. Various cultivars have their individual optimal GST value range (Jones, 2006). For example, for optimum suitability of Pinot noir, GST values range from 14.0-16.0 °C (Jones *et al.*, 2005; Jones, 2007). It has been proposed that there is a high likelihood that changes to these bounds do not exceed 0.6 °C (Jones, 2007). Van Leeuwen *et al.* (2013) have shown using continuous data decomposed into two distinct historical periods (1971-1999; 2000-2012) that the upper limits of the GST index are underestimated, at least for the Rheingau (Germany, Pinot gris), Burgundy (France, Pinot noir) and Rhone Valley (France, Syrah). Since its introduction, the GST index has been used to classify historical and future viticulture climates and evaluate cultivar suitability (Jones *et al.*, 2009; Jones *et al.*, 2010; Jones and Alvez, 2012; Ramos *et al.*, 2008).

The GSR model, on the other hand, is the linear sum of daily mean temperatures above zero, from the 91st day of the year in the Northern Hemisphere to an optimised cultivar specific thermal time that is associated with predetermined sugar concentration levels. We hypothesise that results from applications of the GSR model and the GST index strongly correlate, particularly for the higher target sugar concentration levels that were considered by Parker *et al.* (2020a) for the development of the GSR model. Parker *et al.* (2020b) retrieved only two publications in their topic search of peer-reviewed literature published between 1980-2020 that included consideration of the following terms: grape, grapevine, grapes, temperature, temperatures, bioclimate, bioclimatic, phenology, phenological, model, models, classification, variety and varieties. By exploring similarities and differences of predictions from applications of the GSR phenology model and the GST bioclimatic index for a wine grape growing region, we contribute to an area where there has been limited research.

Application of future climate projections requires location and cultivar specific evaluations of the GSR model (Parker *et al.*, 2020b). Skahill *et al.* (2021) computed viticulture climate classification directed optimal ensemble compositions and weights for the Willamette Valley (WV) American Viticultural Area (AVA) for six bioclimatic indices, one being the GST. Their study was based on a comprehensive evaluation of the complete archive of the thirty-two CMIP5 daily Localized Constructed Analogs (LOCA) downscaled historic datasets and their observational data that were used for downscaling and bias corrections (Pierce *et al.*, 2015a; Pierce *et al.*, 2015b; Livneh *et al.*, 2013). Their work was motivated by recent contributions, which underscored the need for prediction and location-specific downscaled CMIP5 ensembles that account for archive model skill and similarity (Massoud *et al.*, 2019; Massoud *et al.*, 2020; Sanderson *et al.*, 2017) and further study to address ensemble subset selection (Herger *et al.*, 2018; Yang *et al.*, 2020). It was also motivated by recent and consistent observed warm to hot vintages and the lack of previous studies of climate change impacts on viticulture in the WV AVA (Wine Spectator, 2020; Schultze and Sabbatini, 2019). The LOCA CMIP5 ensemble compositions and weights computed by Skahill *et al.* (2021) varied by viticulture climate classification index. Of the thirty-two models which constitute the entire LOCA CMIP5

archive, ten of its members composed the unique ensemble for optimal computation of the GST index throughout the WV AVA.

In this study, the optimal ensemble for computing the GST index will be used to spatially compute on a decadal basis from the 1950s to the 2090s predictions of the GST index and the GSR model, for a 220 g/L target sugar concentration level for Pinot noir, throughout the WV AVA using LOCA CMIP5 historic and RCP4.5 future datasets of minimum and maximum daily temperature. In so doing, we will explore spatiotemporal trends of the GST climate classification index and Pinot noir specific applications of the GSR phenology model for the WV AVA. To our knowledge, this is the first study to produce future projections of the GST index and Pinot noir specific GSR model applications for the WV AVA. Our focus herein differs from past studies in that our calculations are based on a consideration of the complete archive of the thirty-two LOCA CMIP5 downscaled datasets rather than an arbitrary and subjective selection or a small sampling of climate projections, or an ensemble weighting strategy that does not account for model archive skill and interdependence (Skahill *et al.*, 2021). Spatiotemporal computations of the GST climate index and Pinot noir specific applications of the GSR model enable the opportunity to explore relationships between their computed values, with one intent being to provide updated GST ranges that better align with current temperature-based modelling understanding of Pinot noir grapevine phenology (Parker *et al.*, 2020a; Parker *et al.*, 2020b; van Leeuwen *et al.*, 2013) and the viticultural application of LOCA CMIP5 climate projections for the WV AVA (Skahill *et al.*, 2021).

MATERIALS AND METHODS

1. Study region

The study region is the Willamette Valley AVA which lies in the Willamette River Basin in the northwestern part of the State of Oregon (OR) in the U.S. (Figure 1). Its area is approximately 13,913 square kilometres. The WV AVA includes the entire main stem of the Willamette River, including parts of its Middle Fork and Coastal Fork, which join near Springfield, just south of Eugene, OR (Figure 1 (a)). The Willamette River flows north to its confluence with the Columbia River in Portland, OR. The WV AVA is bounded to its west by the Oregon Coastal Range and to its east by the Cascade Range. Elevations in the WV AVA range from a minimum of 2.4 meters to a maximum of 717 meters. The median elevation in the AVA is approximately 120 meters, and only ten percent of the AVA is greater than 286 meters. Figure 1 (b) plots the spatial distribution of elevation within and surrounding the WV AVA. The study area includes 553 model-observation comparison points covering the WV AVA (Figure 1 (a)).

2. Time series data

The entire archive of daily Localized Constructed Analogs (LOCA) Coupled Model Intercomparison Project phase 5 (CMIP5) multi-model historic (1950–2005) and RCP4.5 future (2006–2100) scenario datasets (Pierce *et al.*, 2015a; Pierce *et al.*, 2015b) of the minimum and maximum surface air temperature were collected from the Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections archive (https://gdo-dcp.ucllnl.org/downscaled_cmip_projections/).

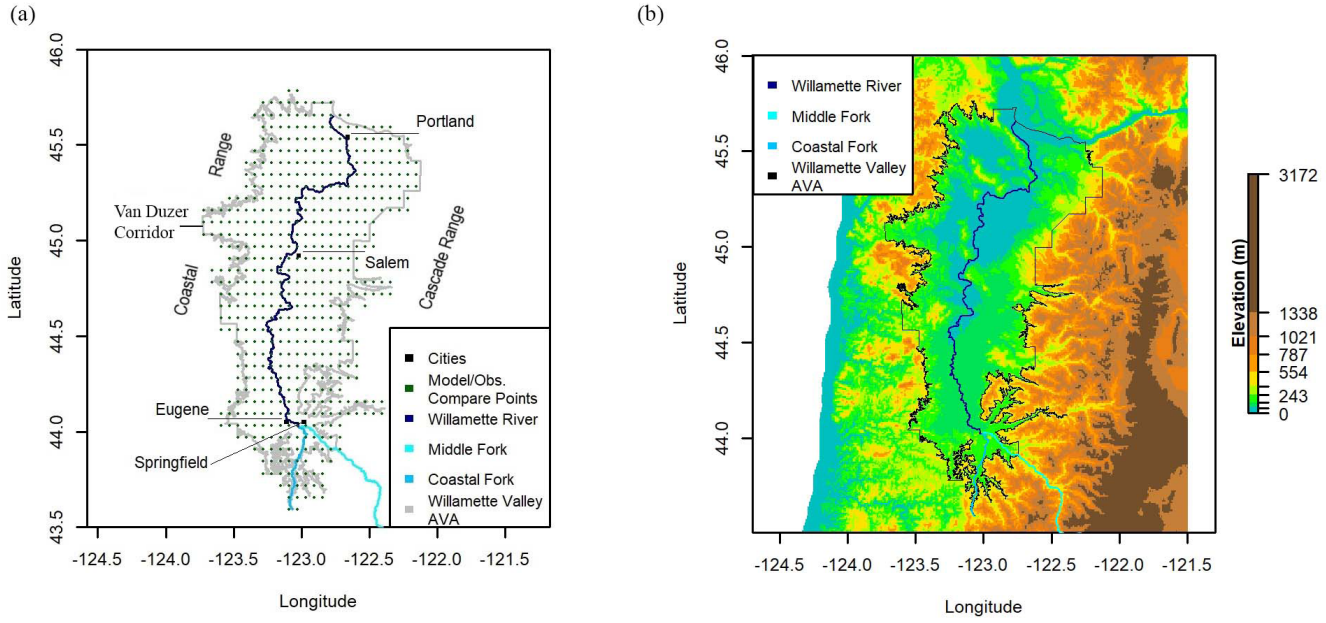


FIGURE 1. (a) The Willamette Valley American Viticultural Area (AVA), which includes the entire main stem of the Willamette River, including parts of its Middle Fork and Coastal Fork, and is covered by 553 model-observation data locations that were used to develop a LOCA CMIP5 multi-model ensemble that optimally computes the growing season average temperature (GST) index throughout the AVA. (b) Spatial distribution of elevation within and surrounding the Willamette Valley AVA (m = meters).

TABLE 1. Viticulture climate classifications with values of the growing season average temperature (GST) index (Hall and Jones, 2009).

GST	
Class interval (°C)	Class of viticulture climate
< 13	Too cool
13-15	Cool
15-17	Intermediate
17-19	Warm
19-21	Hot
21-24	Very hot
> 24	Too hot

The 32 models and modelling groups that provided the data used in this study are listed in Table S1. The observation-based 1/16° longitude-latitude gridded Livneh data product (Livneh *et al.*, 2013), with an approximate resolution of 5 kilometres east-west and 7 kilometres north-south in the study region, was used to train and downscale the daily LOCA CMIP5 historical datasets (Pierce *et al.*, 2015a). Version 1.2 of the Livneh dataset at the 553 grid locations indicated in Figure 1 functioned as the observation dataset. It was processed and compared with its corresponding model counterparts, i.e., the LOCA CMIP5 multi-model processed historic datasets (Wootten *et al.*, 2020). In this study, computed model-observation comparisons are based on growing season average temperature (GST) index calculations throughout the WV AVA for the LOCA CMIP5 historical period. Model-to-measurement evaluations enable computation of the weight assigned to each LOCA CMIP5 model listed in Table S1, which results in the optimal calculation of the GST index throughout the Willamette Valley AVA. The CMIP5 RCP4.5 future scenario dataset collected and used for this study is a radiative forcing stabilisation scenario containing the majority of the scenarios assessed in the Intergovernmental Panel on Climate Change's Fourth Assessment Report (Thomson *et al.*, 2011). It was used rather than CMIP5's low forcing level peak and decline mitigation scenario that assumes full participation of all countries to achieve an emission pathway that limits radiative forcing at 2.6 W/m^2 by 2100 (RCP2.6) (van Vuuren *et al.*, 2011) or its very high baseline scenario that does not include any specific climate mitigation target (RCP8.5) (Riahi *et al.*, 2011).

3. GST climate index and temperature-based GSR phenology model

The growing season average temperature index, GST (Jones, 2006), is defined in Equation 1.

$$\mathrm{GST} = \frac{1}{n}\sum_{Apr\ 1}^{Oct\ 31}(T_{max} + T_{min})/2, \qquad \text{(Eq. 1)}$$

where $n = 214$, the number of days for the northern hemisphere growing season, and T_{max} and T_{min} are the maximum and minimum daily surface air temperature data values in °C, respectively. Its associated viticulture climate classifications are listed in Table 1 (Hall and Jones, 2009).

Application of the temperature-based GSR phenology model (Parker *et al.*, 2020a) involves solving the following equation for t_s (Equation 2):

$$\sum_{t_o=91}^{t_s} x_t \geq F^*, \qquad \text{(Eq. 2)}$$

wherein the daily summation starts on 1 April ($t_o = 91$), x_t denote daily mean temperature values greater than zero and t_s is the day of the year from 1 January, which satisfies the inequality for a predetermined thermal summation value, F^*, which is associated with a cultivar specific fixed sugar concentration level. Parker *et al.* (2020a) reported a threshold value of 2933 for Pinot noir at a 220 g/L target sugar concentration (12.2-13.3 % potential alcohol and 13.1 % using the European conversion ratio (Cowey, 2016)), the highest sugar concentration value considered in their study.

4. Optimal LOCA CMIP5 ensemble selection for the GST index

In this study, we compute a LOCA CMIP5 ensemble that optimises evaluations of the GST index throughout the WV AVA. The specified model is a general linear model without intercept,

$$M = \sum_{i=1}^{32} w_i M_i, \qquad \text{(Eq. 3)}$$

where M_i and w_i represent the i-th LOCA CMIP5 model and its assigned non-negative weight, respectively (Eq. 3). The modelling objective is to minimise model-

to-measurement misfit using the elastic net penalty (Zou and Hastie, 2005) configured in the same manner as it was applied in Skahill *et al.* (2021).

RESULTS AND DISCUSSION

1. A comparison of two LOCA CMIP5 multi-model ensemble weights to optimally compute the GST index throughout the Willamette Valley AVA

Quénol *et al.* (2017) emphasised the importance of accounting for model uncertainty when applying future climate projections. Simulations from the CMIP5 (Taylor *et al.*, 2012) archive are no longer necessarily considered as equally likely independent realisations of the future climate (Eyring *et al.*, 2019; Knutti *et al.*, 2017; Sanderson *et al.*, 2017). It is now understood that assuming archive model independence results in a multi-model mean that is biased by the duplicative information that is contributed by the similar models (Sanderson *et al.*, 2015; Herger *et al.*, 2018), which can confound assessments of model agreement about changes in future climate and alter the statistics of identified correlations (Sanderson *et al.*, 2015). One can address the knowledge uncertainty associated with model choice by applying methods that account for model skill and interdependence, wherein skill is measured by comparison with observed data (Massoud *et al.*, 2019; Massoud *et al.*, 2020; Sanderson *et al.*, 2017; Skahill *et al.*, 2021). Ensemble weight assignment depends on the modelling objective (i.e., the prediction) and study location (Sanderson *et al.*, 2017).

Skahill *et al.* (2021) calculated LOCA CMIP5 ensemble weights that optimally compute the GST index throughout the WV AVA. Their calculations were based on model-observation comparisons that included maximum and minimum temperature datasets that support GST calculations rather than the GST index itself, as is considered in this study. For the computation of the GST index, an individual LOCA CMIP5 model might possess better skill relative to the remaining members of the archive in summing daily maximum surface air temperatures from April through October but poor skill relative to the remaining members of the multi-model ensemble with summing the daily minimum surface air temperatures from April through October. The LOCA CMIP5 model root mean squared error (RMSE) information presented in Table 3 and Figure 2 in Skahill *et al.* (2021) underscore this point. For example, the five best models for calculating the GST climate index throughout the WV AVA, as measured by their median skills (Sanderson *et al.*, 2015; Sanderson *et al.*, 2017; Massoud *et al.*, 2019), rank second, fifth, first, nineteenth and sixth among the thirty-two models which constitute the entire LOCA CMIP5 archive with respect to modelling the sum of the daily maximum surface air temperatures from the beginning of April to the end of October, respectively, and third, second, sixteenth, first, and tenth with modelling the sum of the daily minimum surface air temperature values. Figure S1 includes four plots which compare the best and worst-performing models, as measured by their RMSEs, from among the entire thirty-two member LOCA CMIP5 archive with respect to simulating summed daily maximum and minimum surface air temperature values from 1 April to 30 October across the 553 model-observation comparison points shown in Figure 1 (a) for the historical period (1950-2005). Percent bias computations were low for these calculations. Across all thirty-two LOCA CMIP5 models, the range was [0,0.1] for the summed daily maximum temperature comparisons and [-0.3,0] for the summed daily minimum temperatures. Skahill *et al.* (2021) encouraged further study that seeks to find optimal ensemble subsets using the computed viticulture climate classification indices instead. This section briefly compares two LOCA CMIP5 ensemble compositions and weights developed in two different ways to compute the GST index throughout the WV AVA optimally.

Table 2 lists the LOCA CMIP5 ensemble weights developed to compute the GST index throughout the WV AVA optimally. The ensemble was obtained by applying the elastic net penalty configured in the same manner as described in Skahill *et al.* (2021). The second column of Table 2 lists the ensemble weights obtained when model-observation comparisons involved direct calculations of the GST index. The original ensemble calculated by Skahill *et al.* (2021), wherein model-observation comparisons involved the GST's underlying processed maximum and minimum temperature data, includes ten LOCA CMIP5 archive model members with non-zero weights. When calculations of the GST index are used for model-observation comparisons, the optimal ensemble size is twelve. Eight LOCA CMIP5 models are shared by the two ensembles. Interestingly, the two ensembles poorly correlate ($R = 0.577$). However, the application of the two ensembles developed for the optimal calculation of the GST index throughout the WV AVA correlates well (Figure 2; correlation, $R = 0.993$). Figure 2 is a scatter plot of historical and future projections (RCP4.5) of the GST index throughout the WV AVA using the two LOCA CMIP5 ensembles developed to optimise GST calculations throughout the WV AVA.

The results of this brief exploratory comparison of two approaches to develop LOCA CMIP5 ensembles that optimise GST calculations throughout the WV AVA is encouraging from the practical perspective that it is far easier to determine an optimal ensemble for a compute-intensive index such as the dryness index (Riou *et al.*, 1994) by considering model-observation comparisons of its underlying meteorological data, rather than the index. While either of the two ensembles could be applied, the index-based optimal ensemble listed in Table 2 is used to calculate historical and future projections of the GST index and Pinot noir specific applications of the GSR phenology model for the WV AVA.

2. Spatiotemporal calculations of the GST index and the GSR phenology model

Figure 3 depicts computed decadal means from the 1950s through the 2090s of the GST index climate classification for the WV AVA. The GST calculations were based on applying the historic and RCP4.5 future model datasets associated with the index-based optimal LOCA CMIP5 ensemble listed in

TABLE 2. Localized Constructed Analogs (LOCA) Coupled Model Intercomparison Project phase 5 (CMIP5) multi-model ensemble weights that optimise the calculation of the growing season average temperature (GST) index (Jones, 2006) throughout the Willamette Valley American Viticultural Area when model-observation comparisons are the GST index for the defined historic period (1950-2005).

LOCA CMIP5 Model	Weight
ACCESS1-0	0.1136
ACCESS1-3	0
bcc-csm1-1-m	0.0669
bcc-csm1-1	0.1367
CanESM2	0.0269
CCSM4	0
CESM1-BGC	0
CESM1-CAM5	0
CMCC-CM	0.1830
CMCC-CMS	0
CNRM-CM5	0.0377
CSIRO-Mk3-6-0	0
EC-EARTH	0.0075
FGOALS-g2	0
GFDL-CM3	0
GFDL-ESM2G	0
GFDL-ESM2M	0
GISS-E2-H	0.1039
GISS-E2-R	0
HadGEM2-AO	0
HadGEM2-CC	0
HadGEM2-ES	0
inmcm4	0.1645
IPSL-CM5A-LR	0
IPSL-CM5A-MR	0
MIROC-ESM-CHEM	0
MIROC-ESM	0.1037
MIROC5	1.0470E-05
MPI-ESM-LR	0
MPI-ESM-MR	0
MRI-CGCM3	0.0000
NorESM1-M	0.0555

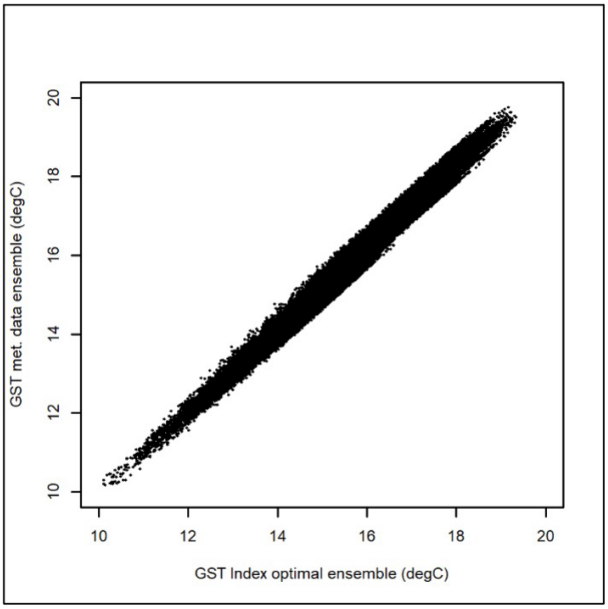


FIGURE 2. Scatter plot of historical (1950-2005) and future (2006-2100) projections of the growing season average temperature (GST) index throughout the Willamette Valley American Viticultural Area based on applications of the GST specific LOCA CMIP5 ensembles listed in Table 2 and Table 5 of Skahill et al. (2021), respectively (met. = meteorological).

Table 2. The GST index climate classification system places Pinot noir as a cool to low intermediate climate cultivar (Jones *et al.*, 2005; Jones, 2006). The classified GST index values presented in Figure 3 indicate a progressive spatiotemporal variable warming trend for the WV AVA. The computed GST climate indices for the 1950s and 1960s classify the WV AVA as mostly cool and intermediate, with the intermediate climate classification covering northern parts of the AVA and, to a lesser degree, the area in the southern section of the AVA. For the next four decades, the generally observed pattern throughout the WV AVA is that the intermediate climate class progressively replaces the area previously classified as cool climate. By the 1980s, the previously separate northern and southern intermediate climate classified areas connected to cover the entire length of the WV AVA from north to south. By the 2000s, the WV AVA is mostly classified as a GST index intermediate climate. A similar spatiotemporal warming pattern repeats from the 2010s to the 2090s, wherein previously classified intermediate climate areas are replaced with a warm climate classification.

Table 3 lists summary statistics across the WV AVA of the computed decadal means from the 1950s through the 2090s of the GST climate index (Jones *et al.*, 2006) values presented in Figure 3. A 3.1 °C increase in the GST index median value is observed from the 1950s to the 2090s. This equates to an approximate 0.21 °C increase for the GST index by decade for the WV AVA. Accounting for the observation that GST values are stable at the beginning of the historical period and also the end of the projected future period, the decadal increase in the GST index median value across the AVA is calculated to be 0.28 °C based on the linear fit of the decadal values for the 120-year period from the 1970s to the 2080s. Similar warming trends to those presented in Table 3 have been reported for other wine regions in previous GST-directed viticulture climate change impacts studies applying RCP4.5 future scenario datasets (Cabré and Nuñez, 2020; Irimia *et al.*, 2019; Teslic *et al.*, 2019).

Approximately 75 % of the WV AVA supports the optimal production of cool to low intermediate climate Pinot noir from the 1950s to the 1970s based on the application of the GST index (Jones, 2006), GST-based guidance for optimal Pinot noir suitability wherein GST values range from 14.0-16.0 °C (Jones *et al.*, 2005; Jones, 2007), and its first quartile and maximum values reported in Table 3. By the 2010s, less than 50 percent of the AVA supported the optimal production of cool to low intermediate climate Pinot noir based on the calculated minimum, first quartile, and median GST values reported in Table 3. From the 2030s to the 2090s, less than 25 percent of the WV AVA supports optimal Pinot noir production based on the application of the GST index and its minimum and first quartile values reported in Table 3 (Jones *et al.*, 2005; Jones, 2006; Jones, 2007). If one accounts for the reported maximum uncertainty of 0.6 °C in the bounds specified for GST-based Pinot noir suitability (Jones, 2007), then greater than 75 percent of the WV AVA supports the optimal production of cool to low intermediate climate Pinot noir from the 1950s–1990s and by the 2030s/2050s, less than 50/25 percent, respectively, based on the calculated GST values reported in Table 3.

Figure 4 includes maps that classify the decadal mean day of year for Pinot noir to reach a 220 g/L sugar concentration level throughout the WV AVA from the 1950s through the 2090s based on the application of the grapevine sugar ripeness model (Parker *et al.,* 2020a) using historic and RCP4.5 future LOCA CMIP5 model datasets and the

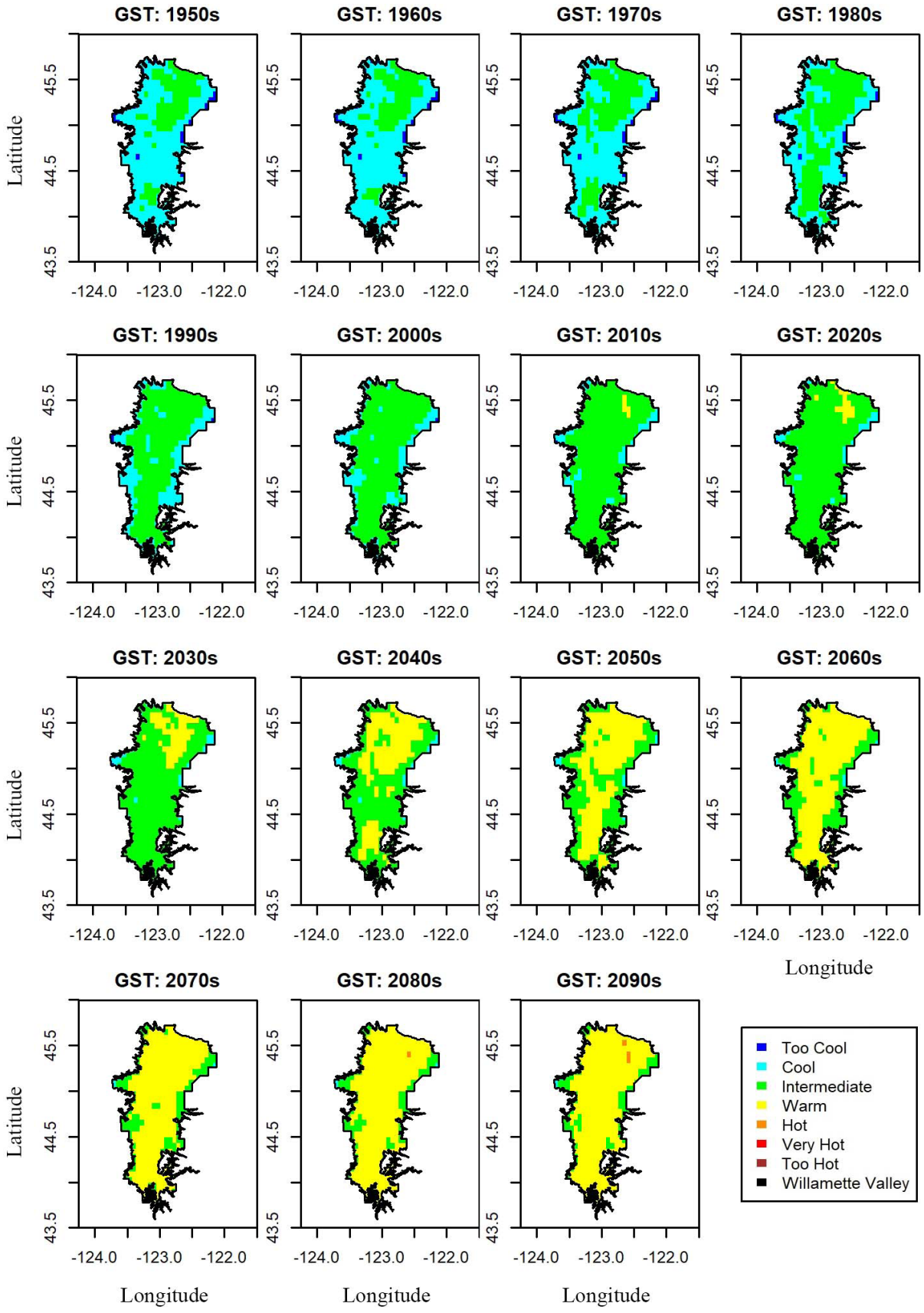


FIGURE 3. Decadal mean GST index climate classification throughout the Willamette Valley American Viticultural Area from the 1950s through the 2090s. Historic and RCP4.5 future LOCA CMIP5 model datasets and the ensemble listed in Table 2 were used to compute the values of the GST index.

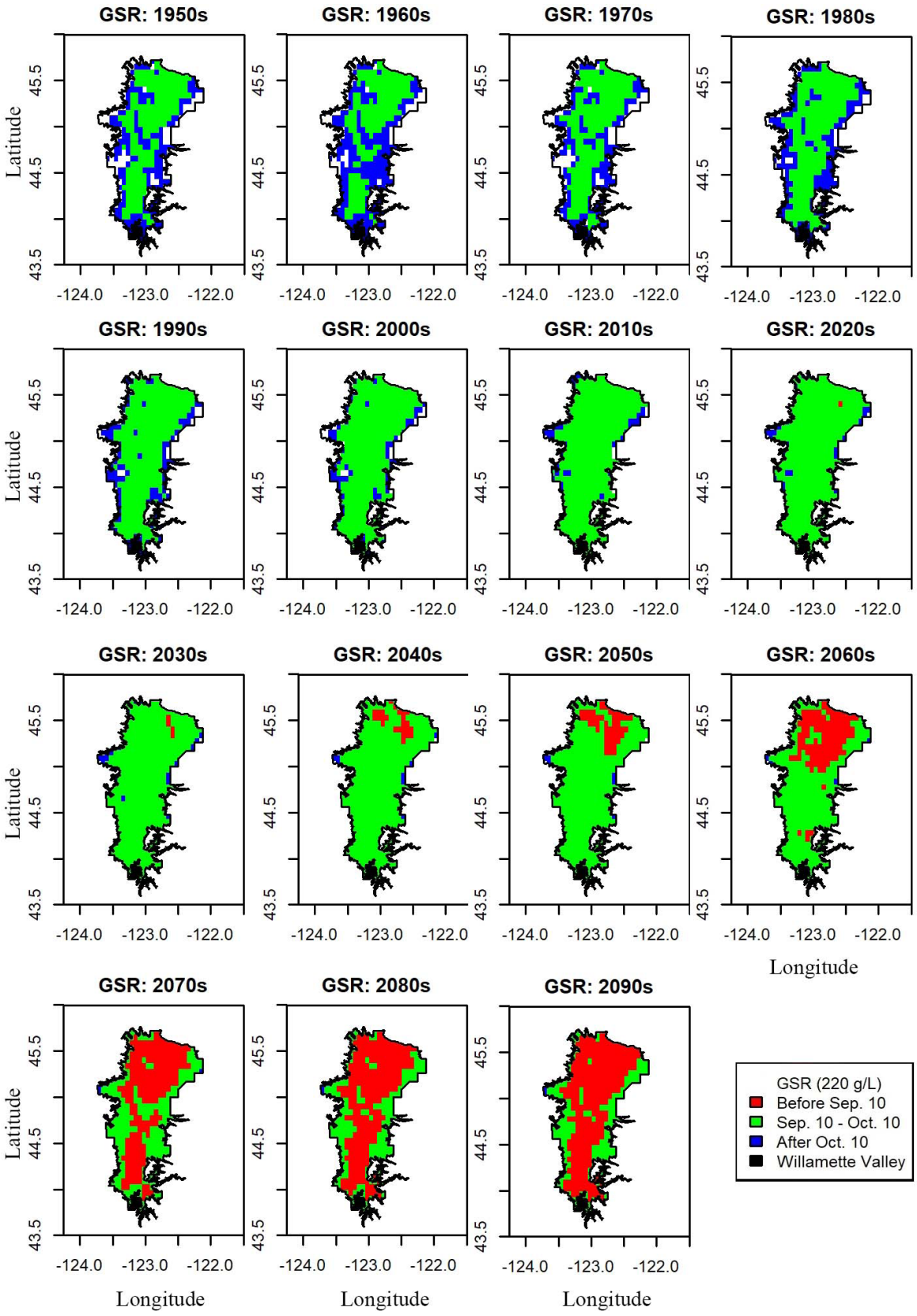


FIGURE 4. Classification of the decadal mean day of year for Pinot noir to reach a 220 g/L sugar concentration level throughout the Willamette Valley American Viticultural Area from the 1950s through the 2090s based on the application of the grapevine sugar ripeness model using historic and RCP4.5 future LOCA CMIP5 model datasets and the ensemble listed in Table 2.

TABLE 3. Summary statistics for the Willamette Valley (WV) American Viticultural Area (AVA) of computed decadal means from the 1950s through the 2090s of the growing season average temperature (GST) climate index and Pinot noir specific applications of the grapevine sugar ripeness (GSR) model, which predict the day of the year from 1 January to achieve a 220 g/L sugar concentration level. Historic and RCP4.5 future LOCA CMIP5 model datasets and the ensemble listed in Table 2 were used to compute the values of the GST index and applications of the GSR phenology model for the WV AVA.

	1950s	1960s	1970s	1980s	1990s	2000s	2010s	2020s	2030s	2040s	2050s	2060s	2070s	2080s	2090s
GST Index (°C)															
Min.	10.4	10.4	10.5	10.6	11.0	11.2	11.6	11.8	12.1	12.4	12.5	12.7	13.0	13.1	13.1
1st Qu.	14.2	14.1	14.2	14.4	14.7	15.0	15.4	15.7	15.9	16.3	16.5	16.8	17.1	17.2	17.3
2nd Qu.	14.8	14.7	14.8	15.0	15.3	15.6	16.0	16.3	16.5	16.9	17.1	17.4	17.6	17.8	17.9
3rd Qu.	15.0	15.0	15.1	15.2	15.6	15.8	16.3	16.5	16.8	17.1	17.3	17.6	17.9	18.1	18.2
Max.	16.1	16.1	16.2	16.3	16.7	16.9	17.3	17.5	17.8	18.1	18.4	18.6	18.9	19.0	19.1
GSR (220 g/L): Pinot noir (Day of year from 1 January)															
Min.	267.7	267.6	266.6	264.8	260.6	258.4	254.4	252.9	250.1	248.2	247.1	244.1	242.7	241.7	240.9
1st Qu.	279.6	280.4	278.5	277.3	272.3	269.5	265.0	262.7	259.6	256.9	255.5	252.2	250.2	249.0	248.2
2nd Qu.	283.0	284.2	282.0	280.5	275.5	272.6	268.1	265.7	262.4	259.8	258.5	255.2	252.9	251.5	250.9
3rd Qu.	288.9	291.2	287.7	288.1	283.1	279.3	274.7	272.5	268.6	265.3	263.8	260.5	257.9	256.4	255.7
Max.	308.2	311.8	305.7	317.0	311.1	300.6	312.2	307.6	308.8	303.7	298.9	291.6	308.9	306.2	304.3

Min.: Minimum. 1st Qu.: First quartile. 2nd Qu.: Second quartile (median). 3rd Qu.: Third quartile. Max.: Maximum.

ensemble listed in Table 2. Use of the GST ensemble is deemed reasonable for GSR application at the 220 g/L target sugar concentration given it results in a calculated day of year that covers the majority, approximately 75-90 percent, of the period from April 1-October 31 (Table 3). The decadal mean GSR computed day of year to achieve a 220 g/L sugar concentration was classified as either early ("Before 10 September"), on time ("10 September-10 October"), or late ("After 10 October") wherein the assumption associated with the classification is that harvest for Pinot noir in the WV AVA occurs at the 220 g/L sugar concentration level (12.2-13.3 % potential alcohol, and 13.1 % using the European conversion ratio (Cowey, 2016)). Historical records of harvest dates and sugar observations for Pinot noir collected from producer data located within the WV AVA support our assumption. Several studies have suggested that optimal terroir expression coincides with a harvest window between 10 September and 10 October (for the Northern Hemisphere) (van Leeuwen and Seguin, 2006; van Leeuwen, 2010; van Leeuwen *et al.*, 2019; Rienth *et al.*, 2020).

The maps displayed in Figure 4 illustrate that the WV AVA land area available for the optimal cultivation and harvest of Pinot noir increases from its value in the 1950s and 1960s, where it mostly covers the AVA's lower elevations, to a maximum, which includes most of the AVA, that is achieved during the 2010s/2020s/2030s. From the 1950s to the 2010s, there was a decreasing but noticeable amount of land area in the AVA, mostly at elevation, that does not support the achievement of a 220 g/L sugar concentration level. From the 2040s to the 2090s, the WV AVA floor progressively becomes less suitable for growing Pinot noir. During the last two decades of the twenty-first century, the optimal LOCA CMIP5 ensemble RCP4.5 forced GSR phenology model predictions indicate that only the high elevations and the western portion of the Van Duzer corridor in the Coastal Range of the WV AVA support Pinot noir production.

Table 3 lists summary statistics across the WV AVA of the computed decadal mean day of year values presented in Figure 4 for Pinot noir to reach a 220 g/L sugar concentration level from the 1950s through the 2090s that are derived from the application of the grapevine sugar ripeness model (Parker *et al*. 2020a). The GSR modelled day of year values reported in Table 3 indicates that greater than 75/50 % of the AVA would achieve a 220 g/L sugar concentration level for Pinot noir between 10 September and 10 October during the 2020s/2060s, and approximately 25–50 % during the 2070s (van Leeuwen and Seguin, 2006; van Leeuwen, 2010; van Leeuwen *et al.*, 2019; Rienth *et al.*, 2020). The linear fit of the median GSR computed day of year values listed in Table 3 indicates a rate advance of 2.7 days a decade when all fifteen decades are included, and no alteration of training or management system, scion rootstock combination or seasonal adaptation practices such as manipulating the leaf area to fruit weight ratio will be implemented. The rate advance is 2.9 days a decade from the 1960s to the 2080s. Parker *et al*. (2020b) reported a rate advance of two days a

decade for Chardonnay in Champagne to reach a 170 g/L sugar concentration when the GSR model was applied using an RCP4.5 future climate scenario.

3. Comparisons of predictions from applications of the GST index and the GSR phenology model for the Willamette Valley American Viticultural Area

Evaluations of the GST index and GSR model results encapsulated in Figures 3 and 4, respectively, and Table 3, result in different general summary assessments of the suitability for Pinot noir in the WV AVA over time. Figure 5 presents a side-by-side comparison of calculated footprints throughout the WV AVA for the 2020s to the 2050s by decade, based on applications of the GST climate index (Jones, 2006) and the GSR phenology model for Pinot noir for a target sugar concentration level of 220 g/L (Parker *et al.*, 2020a) using the RCP4.5 future LOCA CMIP5 model datasets and the ensemble listed in Table 2. The two footprints shown in Figure 5, which are associated with the GST climate index, are based on its original specified lower and upper bounds for Pinot noir, i.e., 14.0-16.0 °C (Jones, 2006), and the upper bound increased to account for its maximum specified uncertainty, i.e., 14.0-16.6 °C (Jones, 2007). The GSR phenology model footprints in Figure 5 are the WV AVA land area that achieves a Pinot noir specific 220 g/L sugar concentration level between 10 September and 10 October (van Leeuwen and Seguin, 2006; van Leeuwen, 2010; van Leeuwen *et al*., 2019; Rienth *et al*., 2020). It is clear from examining the maps in Figure 5 that applications of the GST climate index (Jones, 2006; Jones, 2007) and the GSR phenology model (Parker *et al*., 2020a), while using the same forcing data, portray markedly different assessments of the suitability of Pinot noir throughout the WV AVA over time. The GSR model application shows that a large amount of the WV AVA would support Pinot noir berry ripening to a 220 g/L sugar concentration level between 10 September and 10 October from the 2020s through the 2050s. By contrast, the GST index application, even when accounting for its maximum reported uncertainty (Jones, 2007), indicates a much smaller amount of the AVA would support optimal Pinot noir production.

However, interestingly, the functional definitions of the GST climate index and the GSR phenology model are quite similar. While not necessarily apparent from Figure 3 and Figure 4, the GST climate index values and the day of year values obtained from the Pinot noir specific application of the GSR phenology model for the 220 g/L target sugar concentration do strongly correlate (Figure 6). By decade, their correlation coefficient is consistently -0.99 across all 15 decades. In addition, the curve that best captures their observed nonlinear relationship across all fifteen decades is invertible (Figure 6).

With the application of the GST climate index and the GSR phenology model, the only parameters to adjust include their cultivar specific values, i.e., the lower and upper bounds for the GST index and for the GSR model the thermal summation value, F^*, that is associated with a cultivar specific fixed sugar concentration level (Equation 2). The originally specified upper bounds of the GST index have been shown to be too low (Van Leeuwen *et al.*, 2013). In addition, the cultivar and concentration-specific values for F^* provided by Parker *et al.* (2020a) encapsulate a comprehensive assessment of current knowledge regarding the temperature-based modelling of grapevine phenology. The invertibility of the curve that best captures the nonlinear relationship between the mean decadal computed values of the GST climate index and the GSR phenology model throughout the WV AVA across all fifteen decades provides the opportunity to update the GST climate index ranges for Pinot noir in the WV AVA. Following the application of updated GST climate index lower and upper bounds for Pinot noir, the GST climate classification scheme (Table 1) can subsequently be applied to define the WV AVA area suitable for growing Pinot noir as a cool, low intermediate, high intermediate, or (low) warm climate.

Updated GST climate index values for Pinot noir throughout the WV AVA that correspond with 10 September and 10 October, obtained from a computed quadratic fit ($R^2 = 0.998$, Table S2) to calculations of the GST index and GSR model across all fifteen decades (1950s–2090s) using the GST index-based optimal LOCA CMIP5 ensemble listed in Table 2, are approximately 17.6 and 14.8 °C, respectively (Figure 6 and Table S2). The quadratic model fits calculations of the GST index and GSR model throughout the WV AVA were also computed for decadal periods of sizes 1 to 14, with each starting from the 1950s (Table S2). For each of the fourteen additional model fits, the computed R^2 was 0.998 (Table S2). Across all fifteen separate quadratic model fits, the lower bound of the GST index for Pinot noir in the WV AVA was consistently computed to be 14.8 °C (Figure 6 and Table S2). The upper bound of the GST index for Pinot noir demonstrated a minimum value of 17.4 °C (associated with the 1950s-1990s period) and an upper bound of 17.6 °C (associated with the 1950s–2090s period) (Figure 6 and Table S2). The values reported in Table S2 for the upper bound of the GST index for Pinot noir in the WV AVA increase with time from the 1990s and plateau at approximately 17.6 °C the last five decades of the twenty-first century (i.e., the 2050s-2090s).

An independent gridded daily meteorological dataset developed for northwestern North America for the period 1945-2012 (PNWNA) (Werner *et al.*, 2019) was collected and processed as a source to compare with the updated Pinot noir specific lower and upper bounds for the GST climate index in the WV AVA, which were computed using LOCA CMIP5 historical and RCP4.5 future data. A quadratic model was fit ($R^2 = 0.993$) (Figure 6 and Table S2) to values of the GST climate index and the GSR phenology model for Pinot noir at a 220 g/L target sugar concentration level, computed on a mean decadal basis for the 1950s through the 1990s, using the PNWNA gridded daily meteorological dataset (Werner *et al.*, 2019). Associated lower and upper bounds of the GST climate index for Pinot noir in the WV AVA were 14.8 and 17.18 °C (Figure 6 and

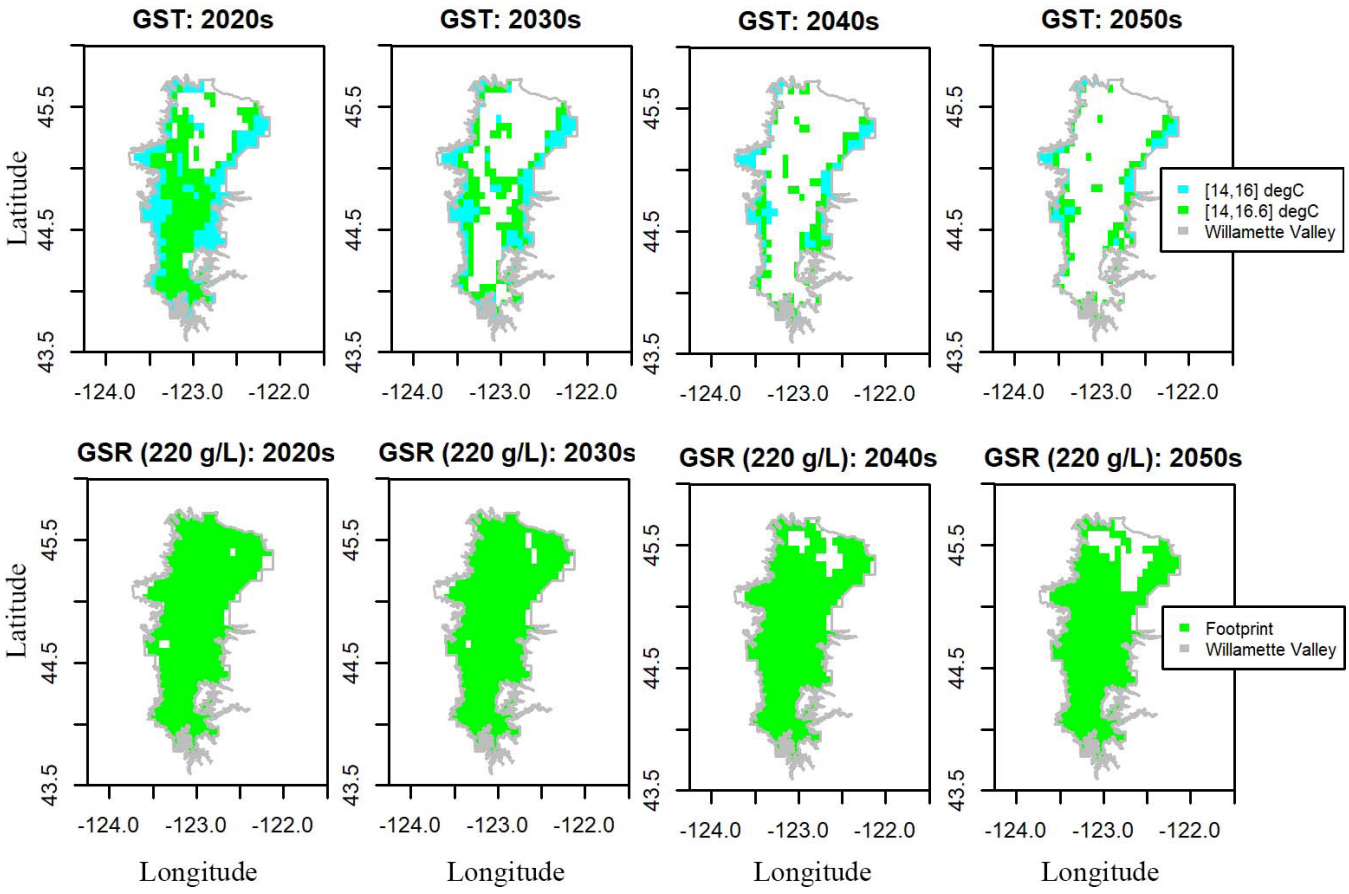


FIGURE 5. Footprints of the Willamette Valley American Viticultural Area land area calculated as suitable for Pinot noir production for the 2020s, 2030s, 2040s and 2050s based on applications of the GST climate index and the GSR phenology model, to achieve a 220 g/L sugar concentration level between 10 September and 10 October for Pinot noir. The GST climate index and GSR model applications used historic and RCP4.5 future LOCA CMIP5 model datasets and the ensemble listed in Table 2.

Table S2). The value for the lower bound of the GST climate index for Pinot noir in the WV AVA agrees with the lower bound computed using the LOCA CMIP5 data, whereas the corresponding upper bounds differ by 0.18 °C (Figure 6 and Table S2).

An additional comparison was made using the LOCA CMIP5 CanESM2 modelled historical and RCP8.5 future data. Skahill *et al.* (2021) determined the CanESM2 model to be the best performing model from among the entire daily LOCA CMIP5 archive with computing the GST index throughout the WV AVA. A quadratic model was fit ($R^2 = 0.995$) (Figure S2 and Table S2) to values of the GST climate index and the GSR phenology model for Pinot noir at a 220 g/L target sugar concentration level, computed on a mean decadal basis for the 1950s through the 2090s using the CanESM2 modelled data. Associated lower and upper bounds of the GST climate index for Pinot noir in the WV AVA were determined to be 14.7 and 17.6 °C, respectively (Figure S2 and Table S2).

The updated WV AVA Pinot noir specific lower and upper bounds for the GST climate index reported herein were obtained from one-to-one mappings between computed values of the GST climate index and the GSR modelled day of year associated with the characterised thermal summation value reported by Parker *et al.* (2020a) for a Pinot noir 220 g/L target sugar concentration. They were found to be consistent regardless of whether the LOCA CMIP5 RCP4.5 or RCP8.5 future climate scenario was considered and agreed well with an independent gridded historical meteorological dataset. However, uncertainties exist with the selection of the GSR model target sugar concentration. Several other environmental and management factors influence ripening (Parker *et al.*, 2020a), including, among others, water availability (van Leeuwen *et al.*, 2009), physical and chemical properties of the soil (van Leeuwen *et al.*, 2018), rootstock interaction (Blank *et al.*, 2022) and canopy management (Smart *et al.*, 1990). The uncertainties reported by Parker *et al.* (2020a) for cultivar and sugar concentration-specific thermal summation values encapsulate other environmental and management factors relevant to sugar accumulation (Parker *et al.*, 2020a and references cited therein). Further related applied research could use the uncertainties reported for by Parker *et al.* (2020a) to determine confidence

intervals for updated location and cultivar specific GST climate index bounds.

Figure 7 includes four plots that depict the percent of the WV AVA that would support Pinot noir production by decade based on applications of the GST climate index and GSR model. The first plot applies the GST climate index with its originally specified value range of 14.0-16.0 °C (Jones *et al.*, 2005; Jones, 2006; Jones, 2007). The second plot is another application of the GST index with its upper bound increased to account for its maximum specified uncertainty of 0.6 °C (Jones, 2007). The third plot is based on the GSR modelled (Parker *et al.* 2020a) day of year values between 10 September and 10 October that reach a 220 g/L sugar concentration level for Pinot noir. The fourth plot applies the GST index with its bounds adjusted to 14.8–17.6 °C based on the one-to-one relationship between the GST index and GSR model across all fifteen decades, which is displayed in Figure 6 (also Table S2 and Figure S2). Historic and RCP4.5 future LOCA CMIP5 (Pierce *et al.*, 2015a; Pierce *et al.*, 2015b) model datasets and the ensemble listed in Table 2 were used to compute the values of the GST index and applications of the GSR phenology model for the WV AVA presented in Figure 7 (a). Historic and RCP8.5 future LOCA CMIP5 CanESM2 modelled data were used to compute the values from applications of the GST index the GSR phenology model for the WV AVA that are presented in Figure 7 (b). The relationship shown in Figure 6 (also Table S2 and Figure S2) between the GST index and GSR model computations throughout the WV AVA enables an updating of the GST climate index ranges that align with Pinot noir phenological data as encapsulated in the temperature-based GSR model (Parker *et al.*, 2020a). With the updated ranges, results from the application of the GST climate index align with those from the application of the GSR phenology model, as is shown in Figure 7.

Application of the historic and RCP4.5 future LOCA CMIP5 model datasets and the ensemble listed in Table 2 result in an approximate bell-shaped GSR modelled suitability curve (Figure 7 (a)). The GSR modelled suitability curve depicts the percent of the area of the WV AVA, by decade, that supports Pinot noir production from the 1950s through the 2090s. Peak values, approximately in the mid-80s to low-90s, are achieved during the 2010s through the 2050s. Percentages in the high to low-40s and mid-30s to low-40s are computed for the first and last two decades of the fifteen decades period, respectively. Application of the historic and RCP8.5 future LOCA CMIP5 CanESM2 modelled data results in a GSR modelled suitability curve (Figure 7 (b)) with a comparable

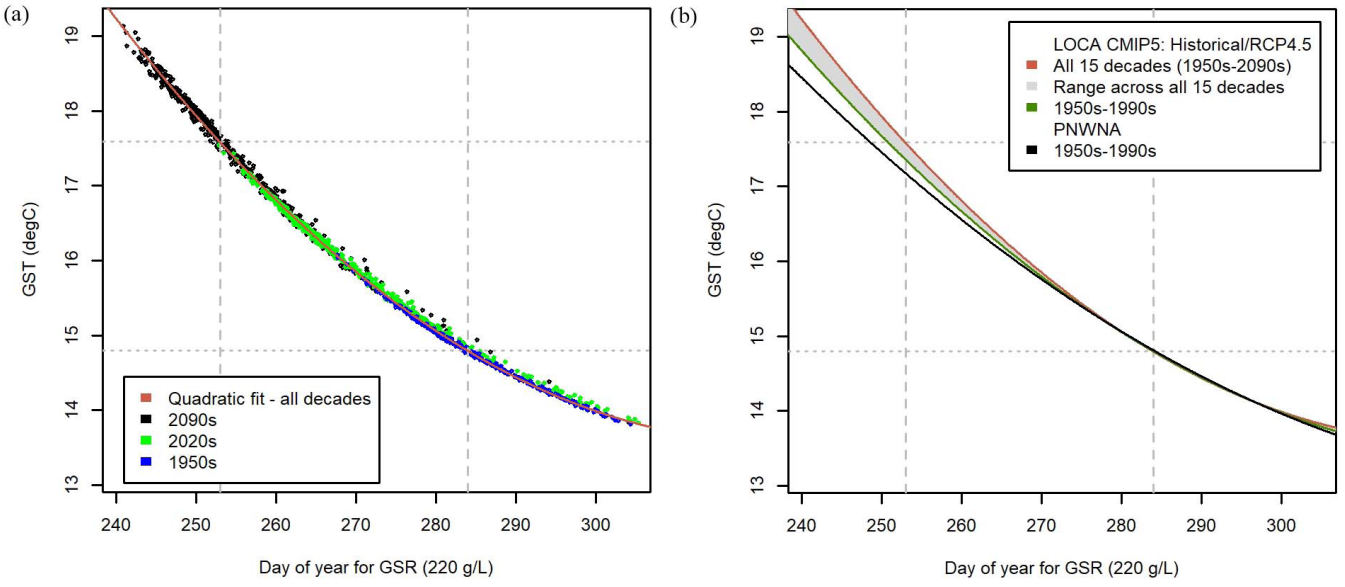


FIGURE 6. (a) Scatter plot of the decadal mean grapevine sugar ripeness (GSR) model day of year from 1 January for Pinot noir to reach a 220 g/L sugar concentration level and the growing season average temperature (GST) index throughout the Willamette Valley (WV) American Viticultural Area (AVA). Values were computed for the 1950s, 2020s and 2090s using historic and RCP4.5 future LOCA CMIP5 model datasets and the ensemble listed in Table 2. Also shown is the quadratic model fit (R2 = 0.998) to the GSR and GST decadal mean calculations across all fifteen decades (1950s–2090s) and the fitted model GST index values that correspond to 10 September and 10 October (i.e., the dashed lines). (b) For the WV AVA, the range of quadratic model fits (each R2 = 0.998, Table S2) to the GSR and GST decadal mean calculations across all 15 decades using historic and RCP4.5 future LOCA CMIP5 model datasets and the ensemble listed in Table 2, with upper and lower bounds defined by the 1950s–2090s and 1950s–1990s periods, respectively. For comparison, the quadratic fit (R2 = 0.993) to the GSR and GST decadal mean calculations throughout the WV AVA using the independent gridded daily meteorological dataset developed for northwestern North America (PNWNA) for the 1950s–1990s period.

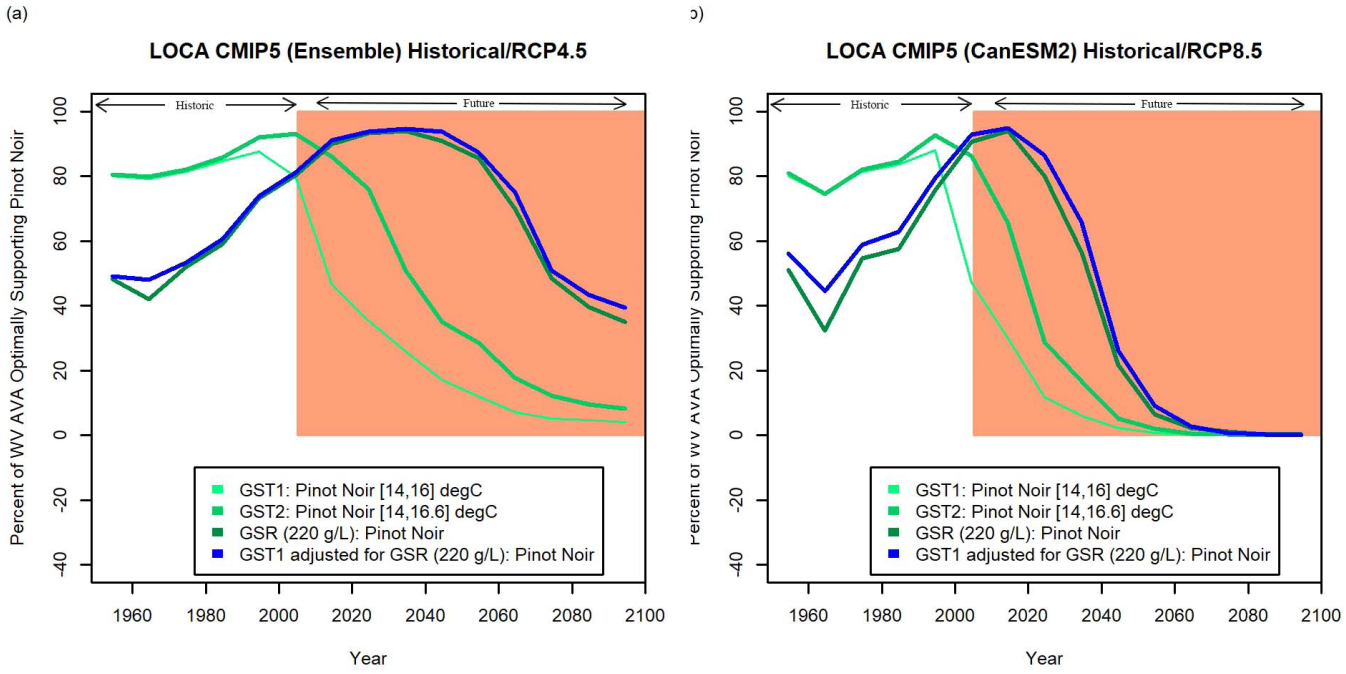


FIGURE 7. Percent of the Willamette Valley (WV) American Viticultural Area (AVA) that would support Pinot noir production based on the application of the GST index with its original bounds of 14.0-16.0 °C, the GST index with its upper bound increased to account for its maximum reported uncertainty of 0.6 °C (Jones, 2007), the grapevine sugar ripeness (GSR) modelled (Parker et al. 2020a) day of year values between 10 September and 10 October that reach a 220 g/L sugar concentration level for Pinot noir, and the GST index with its bounds adjusted to 14.8–17.6 °C based on the relationship between calculations of the GST index and the GSR model, for Pinot noir at 220 g/L, displayed in Figure 6 ((a) Historic and RCP4.5 future LOCA CMIP5 model datasets and the ensemble listed in Table 2 were used to compute the values of the GST index and applications the GSR phenology model for the WV AVA. (b) Historic and RCP8.5 future LOCA CMIP5 CanESM2 modelled data were used to compute the values of the GST index and applications of the GSR phenology model for the WV AVA).

rise (but slightly different as they are based solely on CanESM2 modelled data; whereas Figure 7 (a) is based on the GST index-based optimal LOCA CMIP5 ensemble listed in Table 2), peak value and peak value timing, with a more rapid and severe decline relative to the GSR modelled suitability curve shown in Figure 7 (a). The modelled declines in Pinot noir suitability throughout the WV AVA coincides with GST index values exceeding 17.6 °C. When GST values are greater than this upper threshold in the WV AVA, Pinot noir moves out of the ideal ripening window, and the fruit is overripe and out of balance (Coombe, 1987; van Leeuwen and Seguin, 2006). In this case, alternate cultivars more compatible with the increased temperatures could be selected for planting, for example, by using the GSR model and data from Parker *et al.* (2020a). The updated GST climate index upper bound of 17.6 °C suggests how much warming would be too much for Pinot noir in the WV AVA (Gambetta & Kurtural, 2021). The peak and decline phases of the GSR modelled suitability curves that are presented in Figure 7 suggest a timing window envelope for the location of a tipping point for Pinot noir in the WV AVA (Gambetta & Kurtural, 2021). Until then, the profile of Pinot noir wines from the WV AVA will most likely gradually change (Adelsheim *et al.*, 2016) based on the projected future temperature increases (Figure 3 and Table 3).

CONCLUSIONS

We demonstrated that LOCA CMIP5 ensembles for optimally calculating the GST index throughout the WV AVA could either be formed by considering each of its distinct meteorological components or based on a direct calculation of the climate index. The results of the comparison are promising from a practical perspective, particularly when considering the development of an optimal ensemble for a computationally intensive viticulture climate classification index, such as the dryness index.

Computed values of the GST climate index and the temperature-based GSR phenology model were observed to strongly correlate throughout the WV AVA, consistently over time, while using the same forcing data (i.e., historic and RCP4.5 future LOCA CMIP5 data and the ensemble listed in Table 2). However, the application of the GST climate index and the GSR model result in widely different portrayals of suitability for Pinot noir throughout the WV AVA over time. The relationship between calculated values of the GST

climate index and the GSR model for the WV AVA is observed to be nonlinear and invertible. It can be used to update the originally specified GST lower and upper bounds for Pinot noir throughout the WV AVA. The updated GST lower and upper bounds for Pinot noir suitability throughout the WV AVA are approximately 14.8 and 17.6 °C, respectively. The GST climate classification scheme (Table 1) can subsequently be applied to define the WV AVA area suitable for growing Pinot noir as a cool, low intermediate, high intermediate, or (low) warm climate Pinot noir.

Based on the application of historic and RCP4.5 future model data, the WV AVA suitable for Pinot noir production is currently at or near its peak value in the upper 80s to lower 90 percent of the total WV AVA area. Continued production of Pinot noir in the WV AVA will mostly be limited to higher elevations or the western portion of the Van Duzer corridor in the Coastal Range starting in the 2070s. GSR modelled values currently indicate a rate advance of approximately 2.9 days a decade from the 1960s through the 2080s.

The GST climate index is simple to compute and more accessible for the generalist to apply than the GSR phenology model. Further related applied research that focuses on the development of updated or altogether new location and cultivar specific GST index suitability bounds by leveraging spatial analysis and resultant GSR-GST relations, as illustrated herein, is encouraged.

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