Agricultural and Forest Meteorology 376 (2026) 110905

Contents lists available at ScienceDirect

Agricultural and Forest Meteorology

journal homepage: www.elsevier.com/locate/agrformet

Climate variability and perennial fruit crop yields: insights from Trentino-Alto Adige, Northern Italy

Anna Rita Scorzini [a,*], Mario Di Bacco [b], Vincenzo Guerriero [a], Marco Tallini [a]

[a] Department of Civil, Environmental and Architectural Engineering, University of L'Aquila 67100 L'Aquila, Italy
[b] Department of Civil and Environmental Engineering, University of Florence 50139 Florence, Italy

ARTICLE INFO

Keywords:
Climate variability
Yields
Apple
Grape
Regression
Random Forest
Trentino-Alto Adige

ABSTRACT

Effective adaptation planning for perennial crops, particularly in mountain contexts with climate-sensitive agroecosystems, requires a robust understanding of yield responses to climatic variability. Based on long-term data and a methodological framework covering both linear regression and machine learning techniques, the present study investigates the influence of interannual variability in agro-climatic indices on apple and grape yields in Trentino-Alto Adige, an alpine region in northern Italy. Results reveal that apple yields are more consistently influenced by climate variability than grape yields, with frost occurrence and heat-related indices emerging as key predictors. The machine learning approach, through variable importance metrics and individual conditional expectation plots, provides insights into nonlinear yield responses to critical climatic thresholds, such as sharp declines beyond a certain number of frost days or plateauing gains under sustained heat accumulation. Conversely, grape yields exhibit more heterogeneous and buffered responses, reflecting more complex interactions with climatic conditions. Overall, the study highlights the added value of data-driven approaches with physical interpretability for capturing intricate climate–yield relationships. In regions increasingly exposed to climate pressures, such as the alpine valleys, these tools can support the development of targeted strategies to sustain long-term crop productivity.

1. Introduction

Climate change, characterized by temperature rise, altered precipitation patterns and increased frequency of extreme weather events, poses a significant threat to global agriculture. Agricultural systems are indeed highly sensitive to climate variability and change, which can affect crop yields, quality and overall productivity. This is particularly critical for perennial crops, like orchards and grapes, which are dependent on specific climatic conditions throughout their growth cycles.

The Intergovernmental Panel on Climate Change (IPCC, 2023) has projected that global temperatures will continue to rise, with significant regional variability. In this context, regions that are economically dependent on agriculture are highly vulnerable to the impacts of climate change, making it crucial to assess and understand their implications for long-term resilience and sustainability.

Numerous studies have examined the sensitivity of crop yields to climate variables, highlighting the complex interplay between temperature, precipitation and extreme weather events. For instance, Lobell and Field (2007) analyzed global crop yields and climate data, revealing that temperature increase tends to have a negative effect on the productivity of major crops. Their findings also suggest that growing season temperature and precipitation account for approximately 30 % or more of the year-to-year variability in global average yields for the world's six most widely cultivated crops. Schlenker and Roberts (2009) demonstrated that crop yields in the United States are highly sensitive to temperature extremes, with nonlinear effects showing severe yield reductions beyond optimal temperature ranges. Olesen et al. (2011) reviewed the impacts of climate change on European crop production systems, emphasizing that increased temperatures and altered precipitation patterns could lead to both positive and negative effects depending on location and crop type, with northern areas potentially benefiting from longer growing seasons, whereas southern parts of Europe are more likely to face reduced yields due to heat stress and water scarcity.

Given their substantial share of global agricultural output and value (Alston and Sambucci, 2019; Galbraith, 2023; Muder et al., 2022), as

* Corresponding author.
E-mail addresses: annarita.scorzini@univaq.it (A.R. Scorzini), mario.dibacco@unifi.it (M. Di Bacco), vincenzo.guerriero@univaq.it (V. Guerriero), marco.tallini@univaq.it (M. Tallini).

https://doi.org/10.1016/j.agrformet.2025.110905
Received 8 May 2025; Received in revised form 29 September 2025; Accepted 17 October 2025

well as their strong dependence on climatic conditions (Larue and Ker, 2024; Schultz and Jones, 2010), perennial crops warrant focused investigation into the factors that could affect their productivity and economic stability, in order to inform strategies that safeguard their long-term sustainability.

Among perennial crops, apples and grapevines are particularly sensitive to climatic variability, due to their long growing cycles and the presence of well-defined phenological stages that are each influenced by specific temperature and moisture conditions. For apples, the cycle begins with a period of winter dormancy, during which trees require a certain number of chilling hours – typical temperatures between 0 °C and 7 °C – to ensure uniform bud break in spring. A lack of winter chilling, increasingly common in warmer years, can result in irregular flowering and reduced fruit set. The timing of bud break and flowering is also closely linked to cumulative heat units (i.e.., growing degree days), and early onset can expose flowers to spring frosts, a major risk in temperate and mountain climates. During fruit development, both temperature and water availability are critical: temperatures above 30 °C can induce heat stress, compromising cell expansion and fruit size, while excess rainfall may favor fungal diseases and reduce fruit quality. The maturation phase is sensitive to thermal conditions as well, with excessively high temperatures accelerating ripening, leading to poorer texture, premature softening or sunburn damage (Atkinson et al., 2013; Campoy et al., 2011; Chen et al., 2025; Chitu and Paltineanu, 2020; Dalhaus et al., 2020; Darbyshire et al., 2014; Delgado et al., 2021; El Yaacoubi et al., 2014, 2020; Eccel et al., 2009; Han et al., 2023; Li et al., 2018; Luedeling, 2012; Pfleiderer et al., 2019).

Grapevines follow a similar climate-driven pattern, though with some physiological differences. While their chilling requirement is generally lower than in apples, grapevines are nonetheless vulnerable to early bud break and the resulting frost damage. Flowering and fruit set in grapes are highly sensitive to both heat stress and water conditions; high temperatures and drought during this phase can severely reduce fruit set, resulting in poor cluster formation. During veraison and ripening, heat accumulation is essential to reach adequate sugar and phenolic development. However, excessive heat can cause imbalances in sugar/acidity ratios, accelerated maturation, or dehydration, particularly in white grape varieties. Similarly, water stress during ripening can reduce berry size and yield, while heavy rains may increase the risk of splitting, rot, or reduced flavor concentration (Camps and Ramos, 2012; Di Carlo et al., 2019; Gladstones, 2011; Hannah et al., 2013; Jones et al., 2005; Keller et al., 2010; Palliotti et al., 2015; Rogiers et al., 2022; Santos et al., 2020; Schultz, 2000; Teslić et al., 2018; Tomasi et al., 2011; van Leeuwen et al., 2024; Webb et al., 2007).

Despite growing awareness of climate impacts on perennial cropping systems, there is still limited empirical understanding of how interannual climate variability has historically influenced yield patterns in specific regional contexts, particularly in complex mountain environments, where climatic gradients, topographic heterogeneity and local management practices may modulate crop responses (Moriondo et al., 2011; Santos et al., 2020).

In this context, the alpine region of northern Italy, and in particular Trentino-Alto Adige, offers a valuable case study. The two provinces of the region, Trento and Bolzano, represent one of the most productive fruit-growing districts in Europe, specializing in apples and grapes and significantly contributing to Italy's agricultural output (Muder et al., 2022). The region's unique topography, which includes valleys, mountain slopes and the influence of Lake Garda, creates a diverse range of microclimates suitable for different types of agriculture. By integrating long-term yield records with a set of temperature- and precipitation-based indices, this study explores the impact of interannual climate anomalies on crop performance, with a particular focus on the role of extreme events (e.g., frost, heatwaves, dry spells, etc.) across different sites in the region. The approach combines the analysis of trends in key agro-climatic indices – calculated from homogenized daily temperature and precipitation data from eight meteorological stations representative of the region's main agricultural areas – with the evaluation of their relationship to historical yield variability, using both simple linear regression and machine-learning based (Random Forest) techniques.

By shedding light on the magnitude and dynamics of climate variability effects on apple and grape yields in complex mountain environments, which are particularly vulnerable to climate change (Beniston, 2003; Pepin et al., 2022), this study contributes to the broader effort of developing region-specific adaptation strategies for perennial crops under ongoing and projected climate scenarios.

2. Data and methods

2.1. Study area

This study focuses on Trentino-Alto Adige (comprising the autonomous provinces of Trento and Bolzano (Fig. 1)), a region in northeastern Italy characterized by a complex topography, with elevations ranging from the Adige Valley (below 200 m a.s.l.) to alpine peaks above 3900 m.

The climate reflects both continental and alpine influences, resulting in strong temperature gradients and pronounced precipitation variability (Di Bacco and Scorzini, 2020; Eccel et al., 2016; Panziera et al., 2015). Together, the two provinces form one of Europe's most concentrated and economically important fruit belts, supplying a substantial share of the European apple and wine production. Trentino-Alto Adige is indeed the leading apple-producing area in Italy, accounting for more than 60 % of national production (ISMEA, 2024). The Province of Bolzano alone produces about twice as much as Trento, with both areas characterized by high-density orchard systems and modernized marketing structures based on large cooperative networks. Viticulture also plays a key role, with Trento specializing in sparkling wine production (Trentodoc) and Bolzano focusing on premium-quality, terroir-driven still wines.

2.2. Climatic data and computation of agro-climatic indices

The agro-climatic indices used in this study were derived from daily meteorological records, including maximum and minimum temperatures, and precipitation. These data were extracted from an original dataset compiled by Di Bacco and Scorzini (2020), sourced from regional monitoring networks, including the Hydrographic Service of the Autonomous Province of Bolzano and the Functional Centre of the Civil Protection of Trentino. In total, these networks provided records from 132 meteorological stations. To ensure consistency and reliability of the long-term records, only data from the period 1981–2016 were considered in the analysis. The homogenization of the temperature series was carried out through the combined use of the R-packages 'HOMER' (Mestre et al., 2013) and 'SPLIDHOM' (Mestre et al., 2011), which allowed for the correction of possible inhomogeneities due to station relocation, changes in instrumentation or observational practices. From the filtered dataset of 50 stations compiled by Di Bacco and Scorzini (2020), we selected those best suited to the objective of this study, which focuses on the potential impacts of climate variability on crop yields. The key selection criterion was the location of the stations, in terms of their proximity to agricultural zones – and in particular to those devoted to apple orchards and vineyards (Fig. 1) – to ensure that the derived agro-climatic indices would accurately reflect the environmental conditions experienced by the crops. This approach resulted in a final subset of 8 stations, all situated in valley areas, at elevations below 600 m (Table 1).

For each station, from the selected daily meteorological records, a series of agro-climatic indices was computed to characterize the thermal and precipitation conditions most relevant to apple and grape development (Camps and Ramos, 2012; Chitu and Paltineanu, 2020; Han et al., 2023; Li et al., 2018; Teslić et al., 2018). These indices include

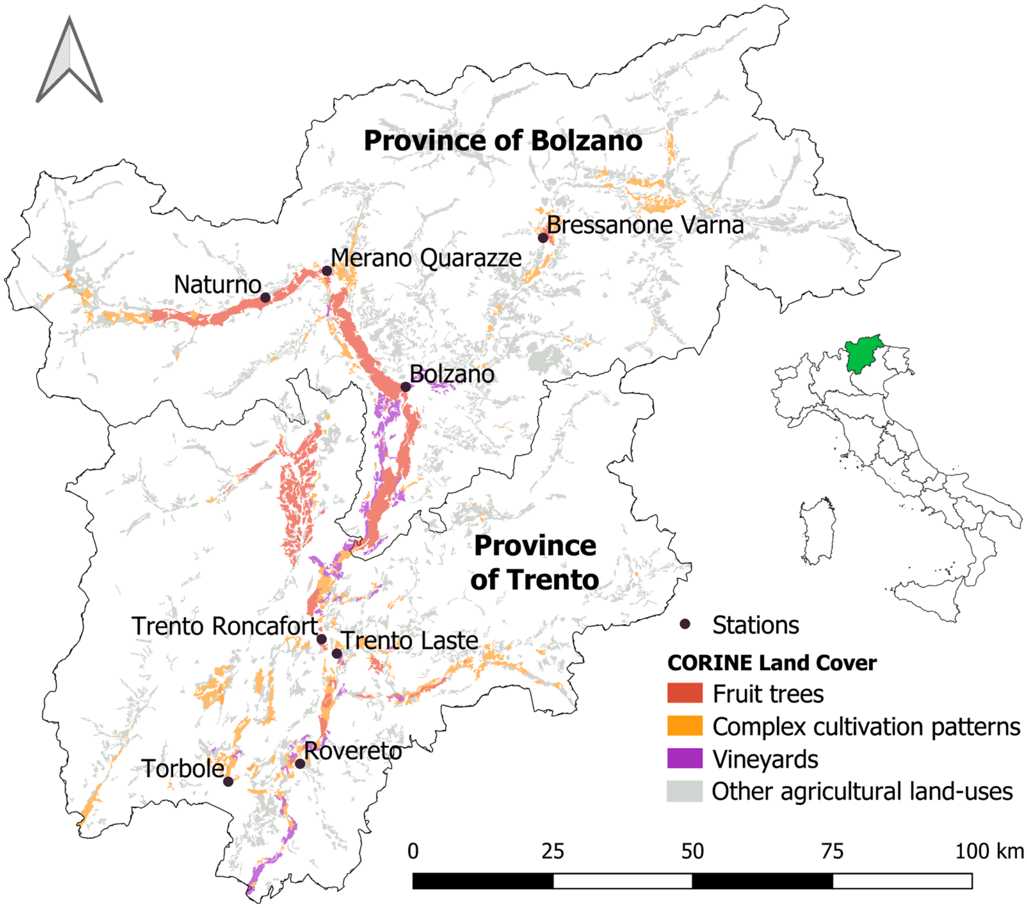

Fig. 1. Study area, with indication of agricultural areas and selected meteorological stations in the provinces of Trento and Bolzano.

Table 1
Selected meteorological stations representative of apple and grape cultivation zones in Trentino-Alto Adige.

Province	Station	Latitude N	Longitude E	Altitude [m a.s.l.]
Bolzano	Bolzano	46°29'52"	11°18'46"	254
	Bressanone Varna	46°43'50"	11°38'39"	590
	Merano Quarazze	46°41'17"	11°08'12"	330
	Naturno	46°38'52"	10°59'28"	541
Trento	Rovereto	45°53'46"	11°02'38"	203
	Torbole	45°52'12"	10°52'39"	90
	Trento Laste	46°04'19"	11°08'08"	312
	Trento Roncafort	46°05'44"	11°06'05"	194

cumulative measures, such as total precipitation during the growing season (Pgs) and the Winkler (Wi) and Huglin (Hu) indices for heat accumulation (important for grapes), as well as threshold-based counts, such as the number of rainy days (ndPgs) during the growing season, dry spell duration (DrSp), and the frequency of frost and heat stress events. Specifically, indices based on minimum and maximum temperature thresholds – e.g., number of frost days (ndTNy<0, on annual basis; ndTNmm<0, between March and May), number of days with maximum temperature above 30 °C (on annual basis, ndTXy>30) or above 20° (over the growing season, ndTXgs>20) – capture the occurrence of potentially damaging extreme events, while seasonal mean temperatures (e.g., mean temperature during the growing season (Tmgs) or mean maximum temperature in summer (TXsum)) provide a general overview of the thermal regime experienced by the crops. Precipitation-based indices characterize both the total water input (Pgs, over the growing season) and the distribution of rainfall (ndPgs, DrSp), which are critical for understanding drought risk and disease pressure during key phenological phases. The full list of indices considered in this study, along with their definitions, is summarized in Table 2, while their descriptive statistics (mean and standard deviation) for the selected stations over the period 1981–2016 are provided in Table S1 of the supplementary material.

Table 2
Description of annual agro-climatic indices used in the analysis.

Index	Definition
Pgs	Total precipitation accumulated during the growing season
ndPgs	Number of days with daily precipitation ≥ 0.1 mm during the growing season
DrSp	Maximum duration of dry spell (maximum annual number of consecutive days with daily precipitation <0.1 mm)
Wi	Winkler index (Winkler et al., 1974): cumulative sum of daily growing degree days (GDD), where GDD is the daily mean temperature exceeding 10 °C, accumulated from April to October
Hu	Huglin index (Huglin, 1978): sum of the daily average of mean and maximum temperatures exceeding a base threshold of 10 °C, accumulated from April to September, and multiplied by a latitude-dependent coefficient accounting for day length (K = 1.04 in this study)
ndTNy<0	Number of frost days (number of days with daily minimum temperature < 0 °C – annual)
ndTNmm<0	Number of frost days (number of days with daily minimum temperature < 0 °C – March to May)
ndTXy>30	Number of days with daily maximum temperatures > 30 °C – annual
ndTXgs>20	Number of days with daily maximum temperatures > 20 °C during the growing season
Tmgs	Mean daily temperature during the growing season
TNmm	Minimum of daily minimum temperatures from March to May
TXsum	Mean daily maximum temperature during summer (June to August)

* Growing season: April to September.

2.3. Trend analysis

The evolution of the selected agro-climatic indices over the period 1981–2016 was analyzed by applying the Mann-Kendall (MK) test (Mann, 1945; Kendall, 1975), a nonparametric method particularly suitable for climate-related time series because of its robustness to outliers and its independence from assumptions of data normality. The test evaluates whether a statistically significant monotonic (either increasing or decreasing) trend is present in the data series. Statistical significance was assessed at the 5 % level. For trends deemed statistically significant, their magnitude was estimated using the Theil-Sen slope estimator (Sen, 1968), which provides a robust and unbiased measure of the median rate of change over the study period.

2.4. Crop yield data

To evaluate the response of agricultural yields to climate variability in Trentino-Alto Adige, this study incorporated yield data for the two main crops cultivated in the region, apples and grapes. Annual data on harvested production and cultivated area were obtained from official statistics provided by the Italian National Institute of Statistics (ISTAT), covering the period 1981–2016 to align with the available homogenized climatic dataset. The data were retrieved at the provincial scale (Trento and Bolzano), which represents the smallest administrative unit with consistent records throughout the study period. For each crop, specific annual yield was calculated as the ratio between total harvested production and cultivated area (Fig. 2a) and c)).

Although aggregated at provincial level, these data offer a reliable proxy for analyzing temporal trends in crop productivity in relation to climate variability, given the spatial concentration of orchards and vineyards within well-defined agricultural zones of each province.

2.5. Data detrending and simple linear correlation analysis

Yield data were subsequently coupled with the agro-climatic indices (Table 2) to assess crop performance in response to interannual climate fluctuations, focusing on thermal and precipitation stressors during key phenological stages.

To focus the analysis specifically on the interannual variability – i.e., year-to-year fluctuations unrelated to long-term directional change (i.e., trend) – both yield and agro-climatic time series were detrended prior to correlation analysis (Guerriero et al., 2023; Iler et al., 2017; Meng and Quian, 2024; Potopova et al., 2016). Indeed, it is acknowledged that crop yield is influenced by multiple factors, including technological advancements, evolving agronomic practices and broader socioeconomic changes that may affect crop management strategies. In parallel, agro-climatic indices often exhibit long-term trends due to ongoing climate change. Detrending then minimizes the risk of detecting spurious correlations that could arise simply from the shared presence of underlying trends rather than from true cause-effect relationships. By removing the long-term component from the data, detrended yield values reflect short-term anomalies, likely attributable to variable seasonal conditions, while detrended indices capture interannual climate variability independent of progressive global or regional climate change. This ensures that the resulting climate-yield relationships more accurately reflect the sensitivity of crops to seasonal climatic anomalies, rather than to coincident but unrelated temporal trends in yield and climate.

In this study, detrending was performed by fitting a linear least squares regression to each annual time series and calculating the residuals, defined as the differences between observed values and the corresponding values predicted by the fitted trend line.

Residuals were used in a subsequent correlation analysis based on the Pearson's correlation coefficient as the metric for assessing the strength and direction of a linear relationship between yields and the agro-climatic variables. The statistical significance of the correlation coefficients was assessed using a two-tailed t-test, with thresholds set at the 5 % and 10 % significance levels. Correlations with p-values below 0.05 were considered statistically significant, while those with p-values between 0.05 and 0.10 were interpreted as marginally significant. This

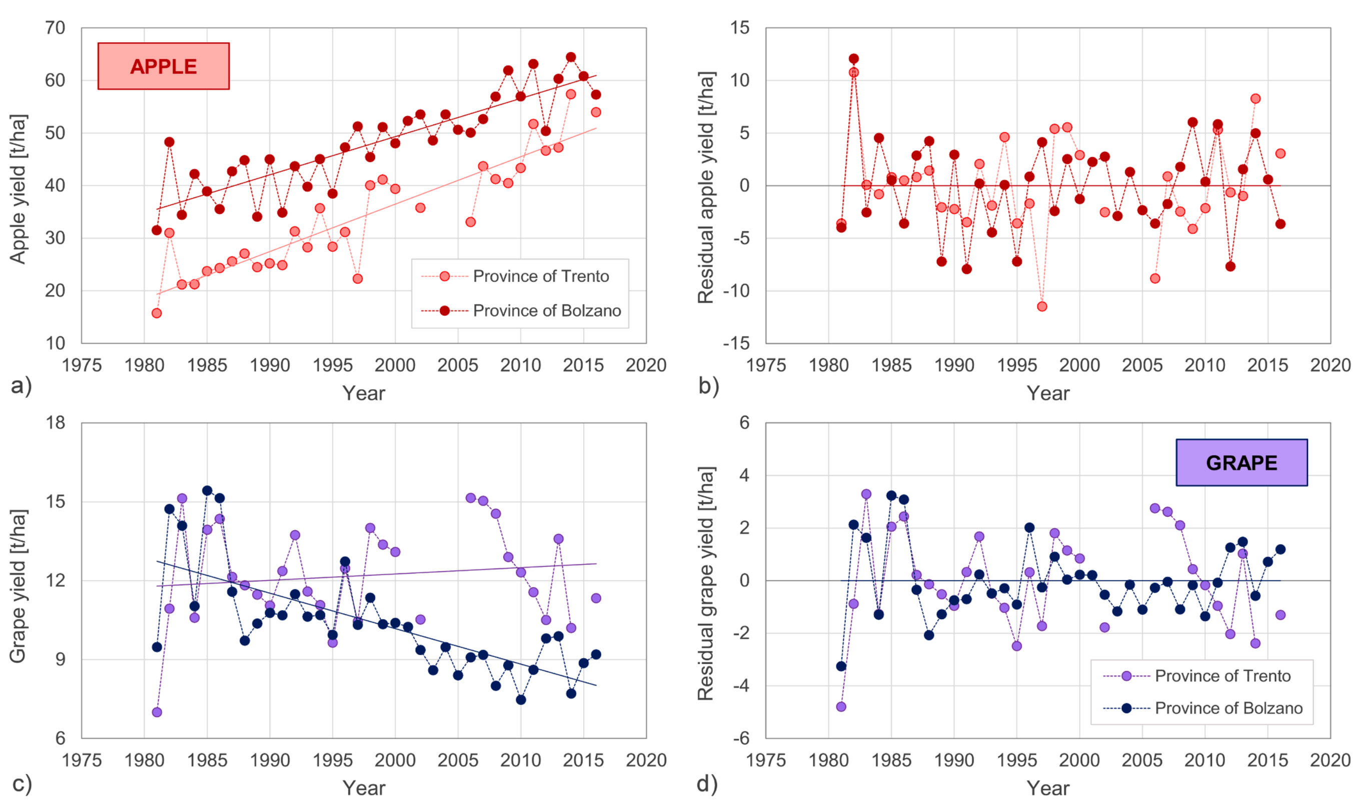

Fig. 2. Yield data for apple and grape production in Trentino-Alto Adige: original (left panels, a) and c)) and detrended (right panels, b) and d)) time series.

first analysis allowed for the identification of agro-climatic indices most strongly associated with yield variability under the hypothesis of a linear relationship, thereby supporting a preliminary interpretation of key climatic drivers affecting apple and grape productivity in the region.

2.6. Random forest regression and variable importance analysis

To further explore the relationship between crop yields and climatic conditions, a Random Forest (RF) regression model was applied separately for each crop and meteorological station. RF is a non-parametric ensemble learning method that constructs multiple decision trees during training and outputs the average prediction across trees (Breiman, 2001). It is particularly suited for capturing nonlinear interactions and complex dependencies among variables, without requiring prior assumptions about the form of the relationship.

In this study, the RF model was employed primarily as an exploratory tool to assess the relative importance of the agro-climatic variables in explaining interannual yield variability, rather than for predictive purposes. Given the limited length of the records, the model was trained on the entire time-series for each station (i.e., without splitting into training and testing subsets) and its performance was assessed on the training data using standard metrics, including the coefficient of determination (R^2), the Root Mean Squared Error (RMSE) and the Mean Absolute Percentage Error (MAPE). R^2 quantifies the proportion of variance in yield that is explained by the model (i.e., reflecting the extent to which climatic indices account for the observed variability in crop yield). RMSE measures the average magnitude of residuals between observed and predicted yield values, giving more weight to larger errors, and thus providing an indication of overall model accuracy. MAPE expresses the average model error relative to the magnitude of the observed values, offering an intuitive metric of how closely the model estimates reproduce yield variability.

While the implemented training approach does not enable out-of-sample validation and predictive assessment, it can still provide meaningful insights into the most influential climatic drivers as well as into the nature of their relationship with yield variability. In model training, all climatic indices were included as predictor variables in the RF configuration, with no restrictions on tree depth or growth. The number of trees in the ensemble was optimized to balance model stability and computational efficiency.

The resulting trained models for apple and grape yields then formed the basis for the subsequent variable importance analysis, performed using a permutation-based approach. The analysis relied on evaluating the deterioration in model performance when the values of a specific input variable are randomly shuffled, thereby breaking its relationship with the target while keeping all other predictors unchanged. This method enables the assessment of each variable's explanatory power within the full multivariate context of the model, accounting for nonlinear interactions and potential redundancies among predictors. As such, it complements the correlation analysis presented in Section 2.5 and helps uncover more complex relationships that may not emerge through simpler, conventional linear regression models. More specifically, in this study, the mean decrease in the coefficient of determination (ΔR^2) was used as a metric of variable importance. For each index, 20 random permutations were applied to the corresponding values, and the model's R^2 was recalculated at each step. The importance score was then computed as the average decrease in R^2 across all permutations, relative to the original model performance.

Moreover, to further refine the interpretation of variable importance results and gain deeper insights into the model's behavior, Individual Conditional Expectation (ICE) plots were generated for the considered agro-climatic indices. Introduced by Goldstein et al. (2015), ICE plots provide a detailed, instance-level visualization of how changes in a single variable affect the model's output across all individual observations, while keeping the remaining variables fixed at their observed values. The investigation of ICE plots served to enhance the interpretability of the RF model by revealing potential nonlinear effects, thresholds or interactions that influence the relationship between agro-climatic indices and yield in Trentino-Alto Adige over the study period.

3. Results and discussion

3.1. Trends in apple and grape yields

Fig. 2 displays the long term evolution of apple and grape yield per hectare for the Provinces of Trento and Bolzano over the period 1981–2016, together with the corresponding detrended residuals.

For apples, both provinces show a clear upward trajectory – with average decadal increases of roughly +7 t/ha in Bolzano and +5 t /ha in Trento – resulting from the structural improvements (such as the introduction of high density orchards, clonal rootstocks, enhanced pest control and post harvest innovations (FAO, 2014)) implemented in the region in the last decades.

Conversely, grape yields exhibit a weakly negative trend in Bolzano and a slight positive tendency in Trento. Such opposing trends reflect differing varietal portfolios and market-driven shifts from high volume to higher quality and lower yield viticulture in Bolzano in recent years. Indeed, since the early 2000s, the local consortia in Bolzano have pursued an explicitly quality oriented model, emphasizing premium, site specific wines and stricter yield limits. They introduced cluster thinning protocols and payment schemes that reward must quality instead of delivered tonnage (Pomarici et al., 2021; Schamel, 2014). Coupled with stricter DOC yield caps – on 10–14 t/ha, depending on grape varieties – this strategy has intentionally lowered specific yield figures in favor of flavor concentration (MIPAAF, 2014). By contrast, Trento dedicates a larger share of vineyards to Trentodoc base wine production, where moderate to high yields – up to 15 t/ha, under the Trentino DOC specification (MIPAAF, 2011) – remain economically advantageous; this different strategy, coupled with recent gains in canopy efficiency and mechanization (Garini et al., 2017), has then produced a modest upward trend in yields in the province.

The long-term trends observed in Fig. 2 then clearly reflect the influence on yields of factors unrelated to climate variability, highlighting the importance of detrending the time series prior to regression analysis with agro-climatic indices, as discussed in Section 2.5. Consequently, the right panels of Fig. 2 represent the true target variables for the climate-yield modelling results presented in the following section, ensuring that the inferred sensitivities are both robust and meaningful.

3.2. Trends in agro-climatic indices

Fig. 3 illustrates the spatial distribution of trends in selected agro-climatic indices across the eight monitoring stations included in this study.

A clear contrast emerges between temperature- and precipitation-related indices, with the former displaying more consistent and spatially coherent patterns. In particular, a general tendency toward warmer conditions during the growing season is evident across the region (Fig. 3). Both the Winkler (Wi) and Huglin (Hu) indices, which capture cumulative heat availability critical for grape development and ripening, show significantly increasing trends at nearly all stations. The magnitude of these trends is particularly marked in the southern portion of the region, where some stations register increases exceeding +10 GDD (growing degree days, in °C) per year. These findings confirm a substantial shift in the thermal conditions of the area (Di Bacco and Scorzini, 2020), with likely implications for varietal suitability and phenological timing (Alikadic et al., 2019; Eccel et al., 2016).

Consistent warming signals are also observed in the indices related to extreme heat events (Fig. 3). The number of days with maximum temperature above 30 °C (ndTXy>30) and the number of days with maximum temperature above 20 °C during the growing season

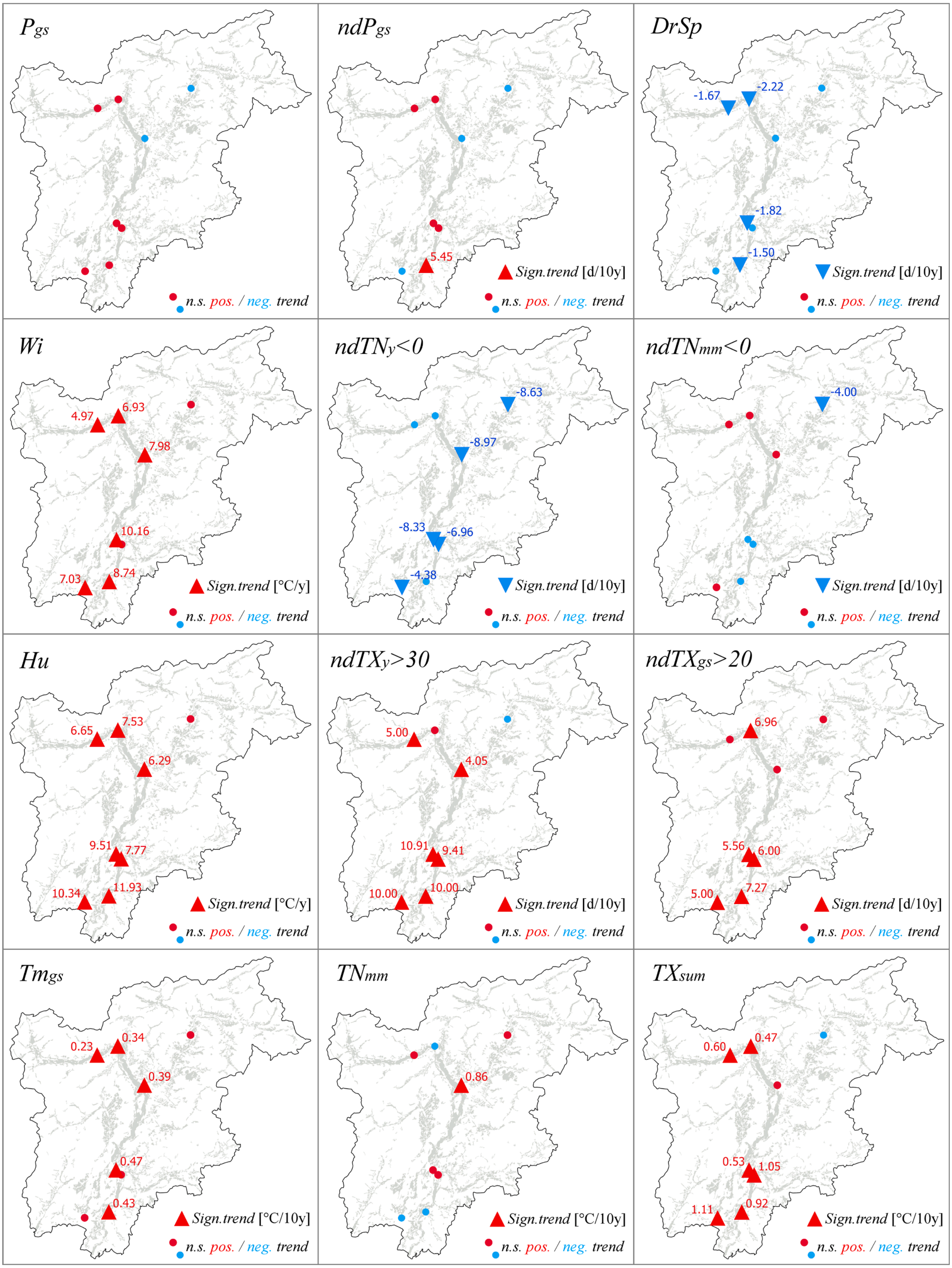

Fig. 3. Spatial distribution and magnitude of observed trends in the agro-climatic indices (Table 2) over the period 1981–2016.

(ndTXgs>20) both exhibit widespread and significant increases. Similarly, mean temperatures during the growing season (Tmgs) and mean maximum temperatures in summer (TXsum) show upward trends at nearly all stations. Collectively, these patterns indicate a progressive intensification of heat stress conditions, which could have adversely affected fruit quality via sunburn, dehydration or accelerated maturation.

While the annual number of frost days (ndTNy<0) has clearly decreased over 1981–2016, especially at northern stations, frost occurrence and minimum daily temperature during the critical early-season period (March-May, ndTNmm<0 and TNmm) have shown weak and spatially inconsistent trends (Fig. 3). As a result, despite the overall reduction in annual frost risk, cold-related hazards may have still played a role in affecting crops during sensitive phenological phases (e.g., bud break and flowering) over the studied period.

Total precipitation (Pgs) and the number of rainy days (ndPgs) during the growing season exhibit very limited changes (Fig. 3). Among the precipitation-related indices, only the Dry Spell index (DrSp) shows a more consistent pattern, with 50 % of the selected stations indicating a significant reduction (at a rate of about −1.8 days/decade), potentially reflecting slight improvements in intra-seasonal water availability over the analyzed period.

Overall, the observed trends highlight a substantial warming of the thermal regime in the region over the past decades, accompanied by less consistent changes in precipitation patterns. These climatic shifts provide important context for understanding the conditions under which apple and grape production in Trentino-Alto Adige has evolved over the last decades. Indeed, although reductions in frost risk and increases in heat accumulation might initially seem beneficial for crop development, sustained future warming trends could lead to significant changes in varietal suitability, phenological timing and fruit quality, ultimately posing challenges for the sustainability of crop production (Alikadic et al., 2019; Eccel et al., 2016; Moriondo et al., 2011) and requiring targeted adaptation strategies.

3.3. Relationships between agro-climatic indices and crop yields

Building on the background outlined in the previous section, the analysis now focuses on examining how interannual climate variability – rather than long-term trends – has shaped annual yield fluctuations. To this end, the relationships between crop yields and agro-climatic indices are explored, staring from simple linear regression to more complex RF models.

3.3.1. Simple linear regression

Fig. 4 summarizes the results of the linear correlation analysis, showing for apple and grape the number of stations where a significant positive or negative association was found between yield and each climatic index.

The results reveal that apple yields are more strongly and consistently influenced by temperature-based indicators than by precipitation-based ones, suggesting that thermal conditions are among the primary drivers of interannual yield variability in Trentino-Alto Adige (Fig. 4a). In particular, the annual number of frost days (ndTNy<0) shows a strong and negative correlation with apple yields across most of the stations. This highlights the persistent role of frost events as a limiting factor for apple production, particularly in areas exposed to colder microclimates. Conversely, the number of frost days during the early growing season (March-May, ndTNmm<0) displays mostly weak or non-significant correlations, thus suggesting that isolated spring frost events, although potentially damaging – as exemplified by the 1997 episode (visible in Fig. 2a, with a pronounced yield drop in the province of province of Trento), which caused around 20 million euros in losses (Eccel et al., 2009) – have exerted a less systematic, linear influence on yield variability over the study period. Temperature accumulation indices, such as Wi and Hu, display positive correlations that are statistically significant only at a few scattered stations in southern areas, such as Rovereto and Trento Laste (Fig. 4a). Although originally developed for viticulture, these indices effectively capture cumulative heat availability during the growing season, and their positive association with apple yield suggests that greater thermal accumulation can enhance fruit development and ripening, provided that excessive heat stress is avoided. Mean growing season temperature (Tmgs) also shows positive correlations across multiple sites in the south (Fig. 4a), supporting the idea that moderate warming can favor apple productivity by accelerating phenological stages without compromising fruit quality. In contrast, heat stress indicators, including ndTXy>30, ndTXgs>20, the minimum daily temperature during spring (TNmm) and the mean maximum summer temperature (TXsum) generally exhibit weak, non-significant correlations with apple yields. Thus, within the limits of a simple linear regression model, heat-related stressors do not appear to have represented a dominant constraint for apple yields in the region during the analyzed period.

Precipitation-related indices (Pgs, ndPgs, DrSp) demonstrate weak and mostly non-significant correlations with yield (Fig. 4a), likely reflecting the widespread adoption of irrigation systems in apple orchards, which effectively buffer the impact of rainfall variability on crop

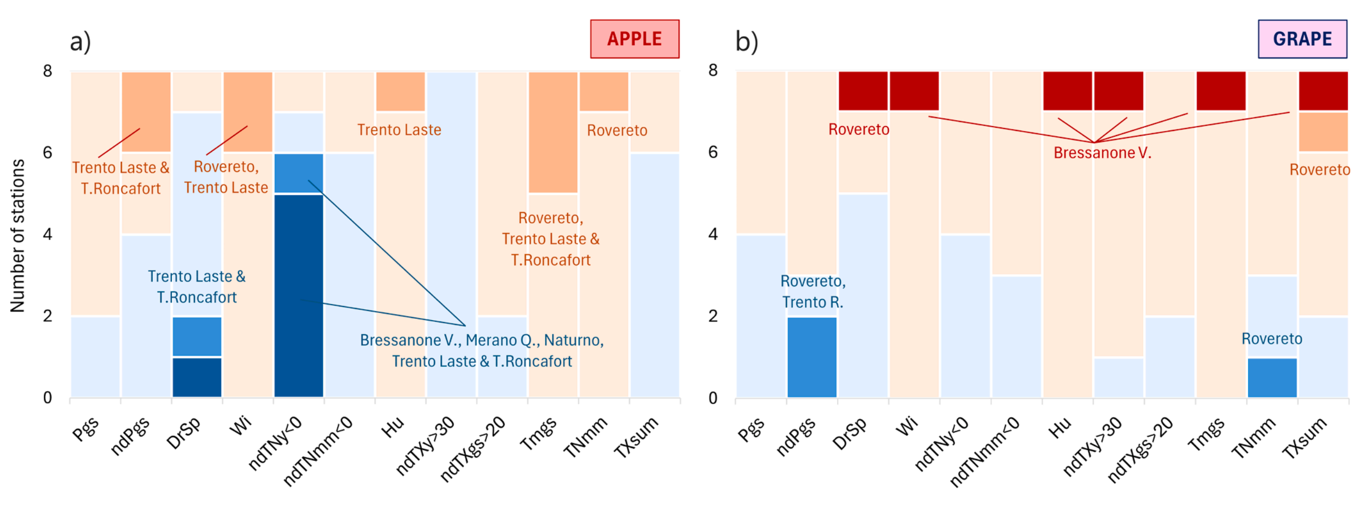

Fig. 4. Summary of the results from the linear correlation analysis between crop yields and agro-climatic indices. For apple (a) and grape (b), the panels show the number of stations exhibiting positive (red) or negative (blue) associations with each index, Eccel et al., 2009differentiated by significance level.

performance. However, the only statistically significant relationships are recorded at two southern stations (Trento Laste and Trento Roncafort), where positive correlations with ndPgs and negative correlations with DrSp are observed, potentially indicating that in specific areas – possibly due to local soil characteristics or less efficient irrigation coverage – a more regular distribution of rainfall during the growing season could have contributed to maintaining adequate plant water status, enhancing fruit set and growth.

Unlike apples, grape yields do not exhibit a clear or widespread sensitivity to frost-related indicators (Fig. 4b). Both ndTNy<0 and ndTNmm<0 show mostly weak or non-significant correlations, suggesting that grapevines, which sprout later and possess greater frost tolerance, are less vulnerable to frost events. Positive correlations, although only occasionally significant, are observed for cumulative temperature indices (Wi, Hu) and for Tmgs, pointing out the role of thermal accumulation in promoting grapevine productivity by supporting fruit maturation.

Indicators of extreme heat (ndTXy>30, ndTXgs>20) display weak and mixed patterns (Fig. 4b). In some locations, positive, although non-significant, correlations suggest that moderate heat exposure may even enhance ripening without imposing significant physiological stress, while the absence of widespread negative correlations indicates that, during the study period, extreme heat did not constitute a major constraint for grape production in the region.

Also regarding precipitation, correlations for grape appear generally weak (Fig. 4b), with only ndPgs exhibiting some significant negative associations (at 10 % s.l.) at Trento Laste and Trento Roncafort. This pattern may suggest that a higher frequency of rainy days, even with moderate daily amounts, could lead to persistently moist conditions during critical phenological stages, potentially favoring disease pressure, hampering fruit set, or delaying ripening, thereby negatively impacting grape yields.

3.3.2. Random forest regression and analysis of the variable importance

To investigate the relationships between crop yields and climatic variability in greater depth, a RF regression model was trained separately for apple and grape datasets at each meteorological station.

The performance metrics summarized in Table 3 indicate a generally strong explanatory power of the developed RF models. For both crops, accuracy values are consistently high across all stations, suggesting that the selected agro-climatic indices account for a substantial portion of the observed interannual yield variability. More specifically, RF models for apple yield achieve higher R^2 (ranging from 0.86 to 0.94) than those obtained for grape (R^2 between 0.81 and 0.89), reinforcing previous indications – already observed in the linear correlation analysis – of greater complexity and heterogeneity in the climate-yield relationships for grapevine. This interpretation was further supported by the results of hyperparameter tuning, which showed that RF models for grape generally required a larger number of trees (up to 20 in some cases) compared to those for apple (typically 10 or fewer), implying that more intricate decision structures were needed to capture the underlying climatic patterns affecting grape yield.

It should be noted, however, that performance metrics shown in Table 3 reflect in-sample fit, as the RF models were trained on the full dataset without a holdout validation set. While this choice was consistent with the exploratory scope of the study, aimed at detecting non-linear relationships and relevant thresholds rather than producing predictive forecasts, the reported explanatory strength should be interpreted with caution, since out-of-sample performance would likely be lower.

Building on the trained RF models, the analysis was extended to examine the role of individual agro-climatic variables in explaining crop yield variability through the assessment of variable importance scores and the interpretation of individual conditional expectation (ICE) plots.

Fig.s 5 and 6 summarize the results for apple (in pink) and grape (in violet) across the meteorological stations located in the Provinces of Bolzano and Trento, respectively.

The bar charts in the left panels show the relative importance of the agro-climatic indices, ranked by their contribution to model performance based on the mean reduction in R^2 following random shuffling (averaged over 20 permutations), which reflects the amount of lost explanatory power when the specific contribution of each predictor is removed from the model. While informative, the variable importance rankings alone do not provide any indication on the type (positive or negative) and functional form of the underlying relationship between explanatory variables and the target. To overcome this limitation and enrich the interpretation of the results, ICE plots in the right panels of Fig.s 5 and 6 were used to visualize the effect of the most important indices on the predicted yield. In these plots, the grey lines represent the individual conditional expectation curves for each observation, illustrating how predictions change as the selected predictor varies while all others are held fixed. The thicker line shows the average trend, providing a summary of the overall direction and shape of the relationship.

Results shown in Fig.s 5 and 6 reveal a clear different pattern for apple and grape in terms of the strength and consistency of their climatic yield drivers. For apples (pink plots), a few variables stand out for their markedly higher explanatory power (often with ΔR^2 values exceeding 0.4). In particular, frost-related variables emerge as the dominant predictors of apple yield variability in both provinces, in agreement with the preliminary linear correlation analysis. The annual number of frost days (ndTNy<0) ranks as the top feature in several stations, especially in the province of Bolzano (Fig. 5). The corresponding ICE plots highlight a clear step-wise negative relationship, with yields sharply decreasing above a threshold at approximately 100 frost days per year, indicating that persistent frost exposure has a detrimental effect on apple productivity. In addition to frost occurrence, heat accumulation indices are also found to play a key role for yield prediction. Variables such as the Huglin (Hu) and Winkler (Wi) indices, as well as the mean maximum summer temperature (TXsum), frequently rank among the most relevant features. Their ICE plots generally reveal a positive effect on yield, often exhibiting either step-wise or saturating trends. For instance, yields are predicted to increase with Wi up to ~1600–1800 GDDs (or ~2500 GDDs for Hu), after which the marginal benefit stabilizes, thus suggesting that moderate heat accumulation promotes phenological development and fruit maturation, while excessive warm may reduce marginal benefits or interact with other limiting factors (e.g., water stress, sunburn, fruit softening).

A similar trend is observed for TXsum, where positive impacts on yield reach a plateau at ~30 °C in Rovereto and Trento Laste, and slightly earlier (~28 °C) in Torbole. Variables associated with prolonged exposure to high temperatures appear among the top-ranked predictors in a few locations. In Merano Quarazze, for instance, apple yield shows a strong, step-wise positive relationship with ndTXgs>20, likely reflecting the regional climatic context where additional warm days promote crop development without surpassing harmful thresholds.

Table 3
RF models' performance across examined meteorological stations for apple and grape yields.

Station	Apple			Grape		
	RMSE [t/ha]	MAPE [-]	R^2 [-]	RMSE [t/ha]	MAPE [-]	R^2 [-]
Bolzano	2.86	0.05	0.89	0.66	0.05	0.89
Bressanone V.	2.76	0.05	0.90	0.68	0.05	0.88
Merano Q.	3.12	0.06	0.86	0.75	0.05	0.83
Naturno	3.14	0.05	0.87	0.83	0.06	0.82
Trento Laste	3.32	0.08	0.90	0.79	0.06	0.81
Trento Roncafort	2.64	0.06	0.94	0.81	0.06	0.81
Rovereto	3.01	0.08	0.92	0.71	0.05	0.85
Torbole	3.25	0.08	0.91	0.76	0.05	0.83

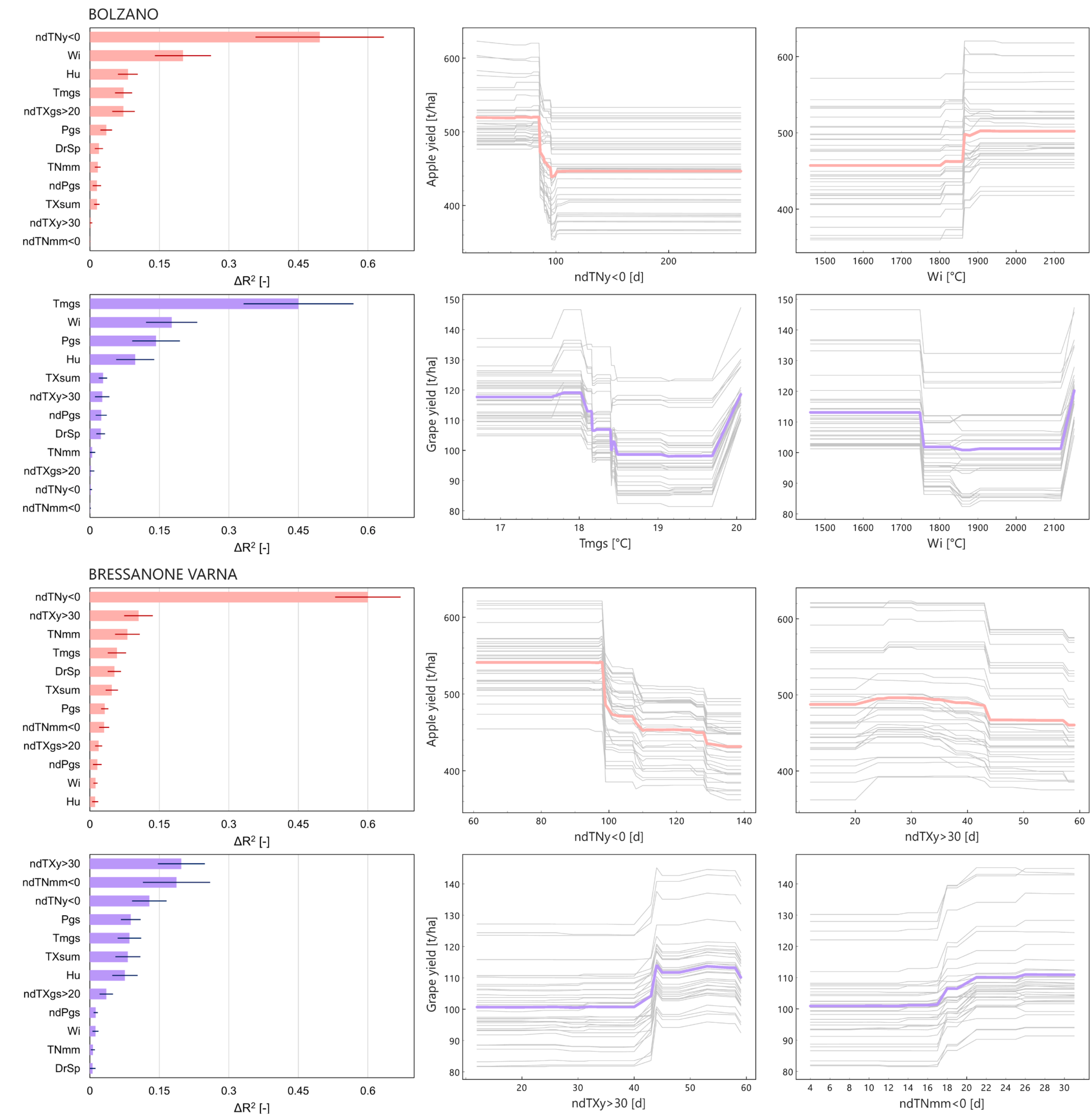

Fig. 5. Results of the RF regression for apple (pink) and grape (violet) – province of Bolzano: (left) variable importance scores (mean R^2 reduction across 20 permutations, with corresponding standard deviation); (right) ICE plots for the two most influential variables.

By contrast, in Bressanone Varna, ndTXgs>30 ranks second, but with limited explanatory power ($\Delta R^2 \sim 0.10$ and nearly flat ICE curves), indicating only a marginal influence on yield variability, which is instead predominantly driven by frost occurrence (ndTNy<0).

On the other hand, Fig.s 5 and 6 show that precipitation-related indices generally play a minor role in explaining apple yield variability, as they tend to rank lower or contribute only modestly to model performance. The latter case occurs in Torbole, where the maximum duration of dry spells (DrSp) is ranked as the second most important variable, but with limited explanatory power ($\Delta R^2 \sim 0.10$), coherently with the agricultural context of Trentino-Alto Adige, where irrigation systems are widely used to buffer precipitation deficits, reducing the potential impact of drought-induced stress on apple yield.

In contrast to apple, grape yields exhibit greater spatial heterogeneity and a generally lower sensitivity to specific climatic variables (Fig.s 5 and 6, violet plots), with no single predictor clearly and consistently standing out across the stations. This apparent buffering of grape yield against climate variability may be attributed to varietal diversity and site-specific management strategies (such as canopy regulation, irrigation scheduling or adaptive harvest timing) that modulate the crop's response to climatic stressors.

Among the predictors most frequently selected by the RF models, and

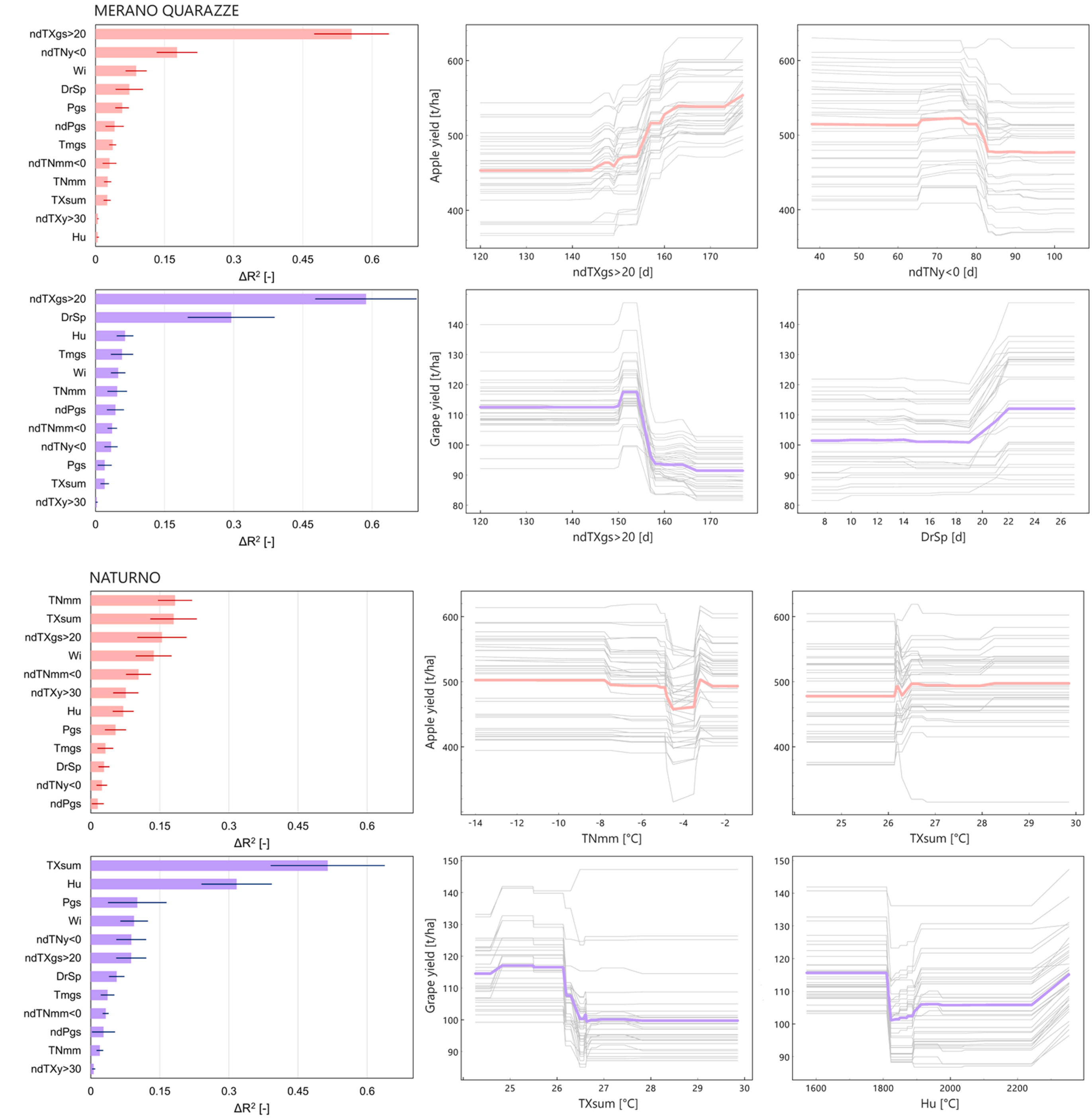

Fig. 5. (*continued*).

contributing more robustly to yield estimation in a few stations, are thermal indicators which capture either heat exposure during the growing season or nighttime temperatures during early phenological stages (TXsum, Tmgs, ndTXy>30, ndTXgs, Wi or Hu, TNmm, ndTNmm<0). The associated ICE plots for warm-related indices – for stations such as Bolzano, Merano and Naturno – display asymptotic behavior, with yield reductions occurring beyond specific threshold values of the indices. These patterns are consistent with physiological stress induced by excessive heat in grapevine, particularly during sensitive phases such as flowering and fruit set, when elevated temperatures can compromise pollen viability and fertilization success, ultimately reducing the number of berries per cluster.

Similarly, prolonged heat during berry development may result in smaller berries, due to accelerated cell expansion that is not accompanied by sufficient water uptake or assimilate accumulation (Costa et al., 2023; Keller et al., 2010; Santos et al., 2020; Webb et al., 2007).

As for apple, precipitation-related indices generally play a marginal role in explaining grape yield variability (Fig.s 5 and 6). However, an exception emerges for Rovereto, where the number of rainy days during the growing season (ndPgs) ranks as the most important predictor, with a relatively high explanatory power ($\Delta R^2 \sim 0.30$). The corresponding ICE plot well reflects the potential negative impact of persistently moist conditions on grape (fostering disease, interfering with fruit set, or delaying ripening) as shown by the abrupt decline in yield around 85–90 rainy days.

Taken together, these findings highlight both consistencies and

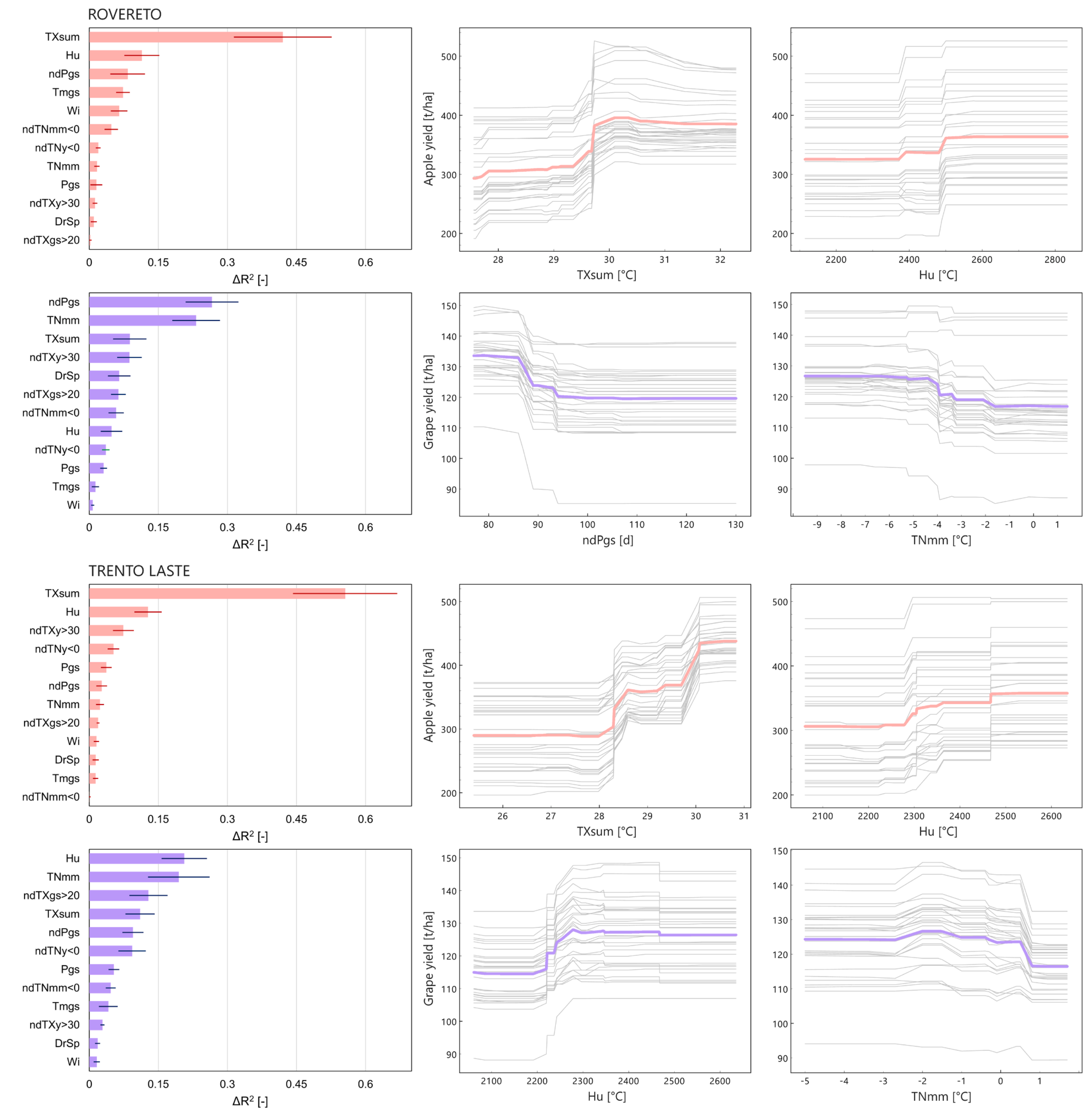

Fig. 6. Results of the RF regression for apple (pink) and grape (violet) – province of Trento: (left) variable importance scores (mean R^2 reduction across 20 permutations, with corresponding standard deviation); (right) ICE plots for the two most influential variables.

extensions between the two approaches. The RF models largely corroborate the linear analysis, confirming the central role of frost for apple yields and the weaker, more heterogeneous sensitivity of grape yields to climatic variability. At the same time, RF results reveal important non-linear dynamics that could not be captured by linear correlations alone (e.g., threshold-driven declines under persistent frost, or plateauing benefits from cumulative heat accumulation). Thus, the RF analysis not only strengthens the robustness of the linear findings, but also provides a more insightful view of climate-yield linkages, helping to contextualize nonlinear effects within a framework that remains physically interpretable.

4. Conclusions

This study investigated the relationships between interannual climate variability and crop yields for apple and grape in Trentino-Alto Adige (northern Italy) over the 1981–2016 period. By combining long-term yield records with a suite of agro-climatic indices derived from homogenized daily temperature and precipitation data, we analyzed both climatic trends and their associations with crop performance across representative agricultural sites in the region. More specifically, while linear regression analyses offered useful preliminary insights into the climate-yield associations, the integration of a machine learning

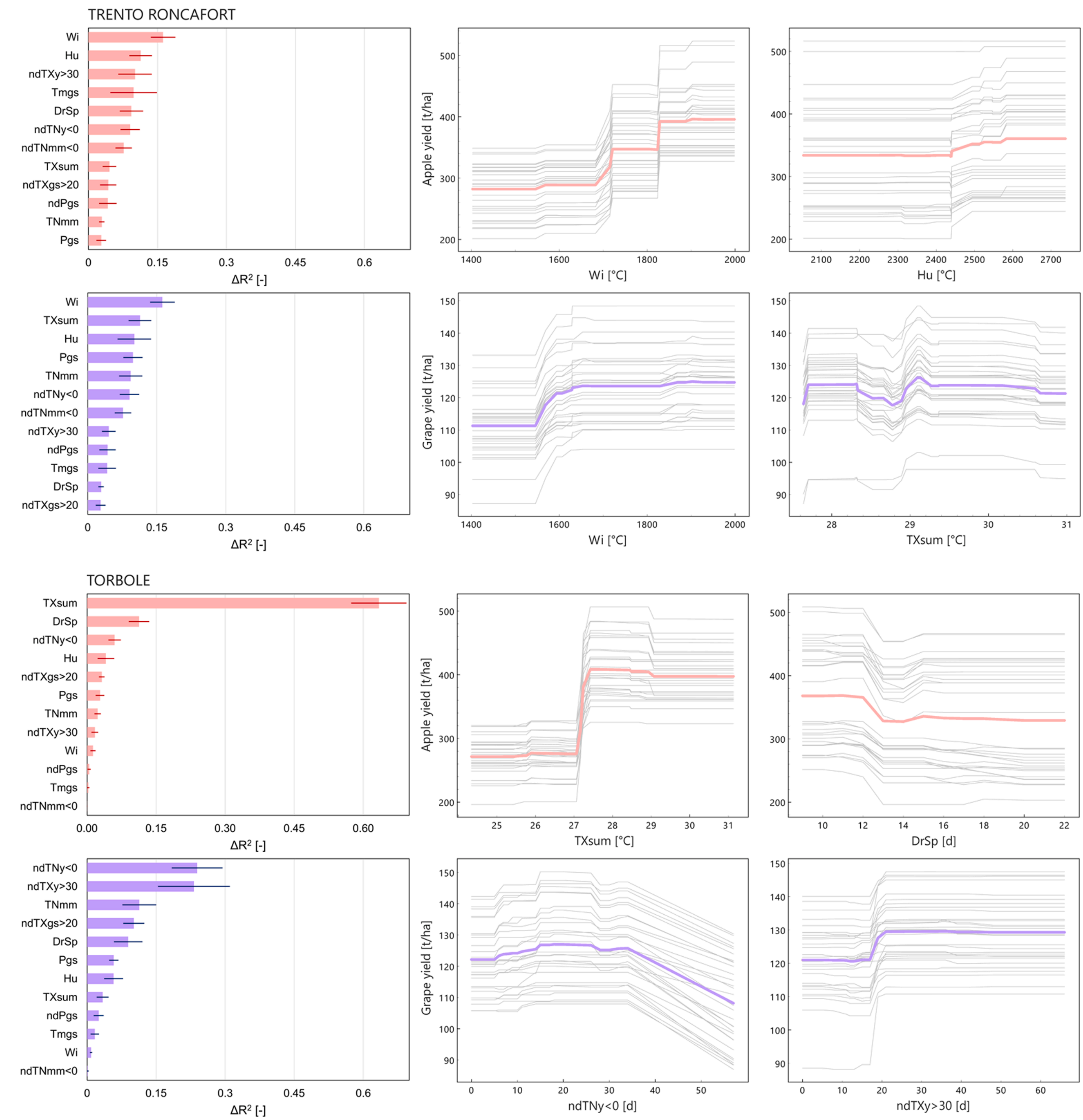

Fig. 6. (*continued*).

approach (i.e., Random Forest) provided a more powerful framework for exploring nonlinear and multivariate interactions.

Consistent with broader trends across Europe, the results revealed a clear warming across the region, with substantial increases in heat accumulation and a general decline in frost events. These thermal changes have occurred in the absence of major shifts in seasonal precipitation, indicating a growing decoupling between thermal and hydrological regimes, which offer both opportunities and challenges for fruit production, depending on the crop and site-specific context.

The linear correlation and RF regression analyses revealed that apple yields are more tightly and consistently affected by climate variability than grape yields, with frost indices and warm-related variables emerging as the dominant predictors. The interpretability of RF outputs, through variable importance scores and individual conditional expectation plots, allowed for the identification of distinct relationships between yields and the agro-climatic indices. For example, apple yield showed sharp reductions beyond critical frost day counts or diminishing gains at high levels of heat accumulation, pointing to nonlinear physiological constraints. In contrast, grape yields exhibited more spatially heterogeneous and buffered responses, likely reflecting greater varietal diversity and climatic sensitivity, as well as adaptive management practices.

Overall, the findings from this study emphasized the added value of machine-learning based models in offering agronomically relevant insights into climate-yield dynamics by capturing complex and nonlinear relationships which often characterize such relationships. Moreover, their ability to handle high-dimensional input spaces and detect complex patterns makes them a promising tool for informing adaptation planning and crop management under future scenarios. However, to ensure reliable extrapolation performance, it is crucial to train such models on very long-term time series that can adequately capture variability and extremes. For the same purpose, relying on plot-level yield observations would be highly beneficial, as they provide an accurate representation of local crop responses. Unfortunately, such level of detail in yield data is rarely available, while information is often accessible only at more aggregated spatial scales. To this aim, as in the present study, a thorough selection of meteorological stations representative of the local agro-climatic context can help in reducing potential spatial biases in climate–yield analyses and ensure that the climatic indices used in the models effectively reflect the environmental conditions experienced by the crops. Future work could usefully explore alternative machine-learning approaches (e.g., ANN, SVR, ExtraTrees, XGBoost) as complementary tools, thereby enabling a more comprehensive assessment of model robustness while also capturing the potential variability in outcomes across methods.

Ultimately, these findings reinforce the importance of adopting integrated data-driven modeling strategies with physical interpretability. In fruit-growing regions increasingly shaped by climate variability, such approaches can enhance the robustness of agro-climatic assessments and support evidence-based decision-making aimed at ensuring long-term crop sustainability.

CRediT authorship contribution statement

Anna Rita Scorzini: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mario Di Bacco:** Writing – review & editing, Investigation, Data curation. **Vincenzo Guerriero:** Writing – review & editing, Investigation. **Marco Tallini:** Writing – review & editing, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This study has been developed in the framework of the research project “National Centre for HPC, Big Data and Quantum Computing” – PNRR Project, funded by the European Union-Next Generation EU – and has been partly funded by the Italian Ministry of Economic Development (MiSE) under the project “SICURA - Casa intelligente delle tecnologie per la sicurezza”.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.agrformet.2025.110905.

Data availability

The datasets used are publicly available. Yield data were obtained from the Italian National Institute of Statistics. Meteorological data were provided by the Hydrographic Service of the Autonomous Province of Bolzano and the Functional Centre of the Civil Protection of Trentino.

References

Alikadic, A., Pertot, I., Eccel, E., Dolci, C., Zarbo, C., Caffarra, A., De Filippi, R., Furlanello, C., 2019. The impact of climate change on grapevine phenology and the influence of altitude: a regional study. Agric. Meteorol 271, 73–82. https://doi.org/10.1016/j.agrformet.2019.02.030.

Alston, J.M., Sambucci, O., 2019. Grapes in the world economy. In: Cantu, D., Walker, M. A. (Eds.), The Grape Genome. Springer Cham, Switzerland, pp. 1–24. https://doi.org/10.1007/978-3-030-18601-2. ISBN: 978-3-030-18601-2.

Atkinson, C.J., Brennan, R.M., Jones, H.G., 2013. Declining chilling and its impact on temperate perennial crops. Env. Exp. Bot 91, 48–62. https://doi.org/10.1016/j.envexpbot.2013.02.004.

Beniston, M., 2003. Climatic change in mountain regions: a review of possible impacts. Clim. Change 59 (1), 5–31. https://doi.org/10.1023/A:1024458411589.

Breiman, L., 2001. Random forests. Mach. Learn. 45 (1), 5–32. https://doi.org/10.1023/A:1010933404324.

Campoy, J.A., Ruiz, D., Egea, J., 2011. Dormancy in temperate fruit trees in a global warming context: a review. Sci. Hortic. 130 (2), 357–372. https://doi.org/10.1016/j.scienta.2011.07.011.

Camps, J.O., Ramos, M.C., 2012. Grape harvest and yield responses to inter-annual changes in temperature and precipitation in an area of north-east Spain with a Mediterranean climate. Int. J. Biometeorol. 56, 853–864. https://doi.org/10.1007/s00484-011-0489-3.

Chen, R., Wang, J., Wang, B., Li, Y., Bai, R., Huang, M., Qu, Z., Liu, L., 2025. Flowering delay in apple could alleviate frost-induced yield loss under climate change in China. Agric. Meteorol. 360, 110313. https://doi.org/10.1016/j.agrformet.2024.110313.

Chitu, E., Paltineanu, C., 2020. Timing of phenological stages for apple and pear trees under climate change in a temperate-continental climate. Int. J. Biometeorol. 64 (8), 1263–1271. https://doi.org/10.1007/s00484-020-01903-2.

Costa, J.M., Egipto, R., Aguiar, F.C., Marques, P., Nogales, A., Madeira, M., 2023. The role of soil temperature in mediterranean vineyards in a climate change context. Front. Plant Sci. 14, 1145137. https://doi.org/10.3389/fpls.2023.1145137.

Dalhaus, T., Schlenker, W., Blanke, M.M., Bravin, E., Finger, R., 2020. The effects of extreme weather on apple quality. Sci. Rep. 10 (1), 7919. https://doi.org/10.1038/s41598-020-64806-7.

Darbyshire, R., Webb, L., Goodwin, I., Barlow, E.W.R., 2014. Challenges in predicting climate change impacts on pome fruit phenology. Int. J. Biometeorol. 58, 1119–1133. https://doi.org/10.1007/s00484-013-0705-4.

Delgado, A., Egea, J.A., Luedeling, E., Dapena, E., 2021. Agroclimatic requirements and phenological responses to climate change of local apple cultivars in northwestern Spain. Sci. Hortic. 283, 110093. https://doi.org/10.1016/j.scienta.2021.110093.

Di Bacco, M., Scorzini, A.R., 2020. Recent changes in temperature extremes across the north-eastern region of Italy and their relationship with large-scale circulation. Clim. Res. 81, 167–185. https://doi.org/10.3354/cr01614.

Di Carlo, P., Aruffo, E., Brune, W.H., 2019. Precipitation intensity under a warming climate is threatening some Italian premium wines. Sci. Total. Environ. 685, 508–513. https://doi.org/10.1016/j.scitotenv.2019.05.449.

Eccel, E., Rea, R., Caffarra, A., Crisci, A., 2009. Risk of spring frost to apple production under future climate scenarios: the role of phenological acclimation. Int. J. Biometeorol. 53 (3), 273–286. https://doi.org/10.1007/s00484-009-0213-8.

Eccel, E., Zollo, A.L., Mercogliano, P., Zorer, R., 2016. Simulations of quantitative shift in bio-climatic indices in the viticultural areas of Trentino (Italian Alps) by an open source R package. Comput. Electron. Agric. 127, 92–100. https://doi.org/10.1016/j.compag.2016.05.019.

El Yaacoubi, A., Malagi, G., Oukabli, A., Hafidi, M., Legave, J.M., 2014. Global warming impact on floral phenology of fruit trees species in Mediterranean region. Sci. Hortic. 180, 243–253. https://doi.org/10.1016/j.scienta.2014.10.041.

El Yaacoubi, A., El Jaouhari, N., Bourioug, M., El Youssfi, L., Cherroud, S., Bouabid, R., Chaoui, M., Abouabdillah, A., 2020. Potential vulnerability of Moroccan apple orchard to climate change–induced phenological perturbations: effects on yields and fruit quality. Int. J. Biometeorol. 64, 377–387. https://doi.org/10.1007/s00484-019-01821-y.

FAO (2014). Apple-producing family farms in South Tyrol: an agriculture innovation case study. de Meyer, J. (Ed.). 31p ISBN 978-92-5-108365-9.

Galbraith, S., 2023. Fresh Apples, Grapes, And Pears: World Markets And Trade. United States Department of Agriculture. https://www.fas.usda.gov/data/fresh-apples-grapes-and-pears-world-markets-and-trade-12122023.

Garini, C.S., Vanwindekens, F., Scholberg, J.M.S., Wezel, A., Groot, J.C., 2017. Drivers of adoption of agroecological practices for winegrowers and influence from policies in the province of Trento, Italy. Land. Policy. 68, 200–211. https://doi.org/10.1016/j.landusepol.2017.07.048.

Goldstein, A., Kapelner, A., Bleich, J., Pitkin, E., 2015. Peeking inside the black box: visualizing statistical learning with plots of individual conditional expectation. J. Comput. Graph. Stat. 24 (1), 44–65. https://doi.org/10.1080/10618600.2014.907095.

Gladstones, J., 2011. Wine, Terroir And Climate Change. Wakefield Press, Adelaide, Australia. ISBN: 9781862549241.

Guerriero, V., Scorzini, A.R., Di Lena, B., Iulianella, S., Di Bacco, M., Tallini, M., 2023. Impact of climate change on crop yields: insights from the Abruzzo region, Central Italy. Sustainability 15 (19), 14235. https://doi.org/10.3390/su151914235.

Han, X., Chang, L., Wang, N., Kong, W., Wang, C., 2023. Effects of meteorological factors on apple yield based on multilinear regression analysis: a case study of Yantai Area, China. Atmosphere 14 (1), 183. https://doi.org/10.3390/atmos14010183.

Hannah, L., Roehrdanz, P.R., Ikegami, M., Shepard, A.V., Shaw, M.R., Tabor, G., Zhi, L., Marquet, P.A., Hijmans, R.J., 2013. Climate change, wine, and conservation. Proc. Natl. Acad. Sci. 110 (17), 6907–6912. https://doi.org/10.1073/pnas.1210127110.

Huglin, M.P., 1978. Nouveau mode d'évaluation des possibilités héliothermiques d'un milieu viticole. C. R. Seances Acad. Agric. Fr. 64, 1117–1126.
Iler, A.M., Inouye, D.W., Schmidt, N.M., Høye, T.T., 2017. Detrending phenological time series improves climate–phenology analyses and reveals evidence of plasticity. Ecology. 98 (3), 647–655. https://doi.org/10.1002/ecy.1690.
IPCC, 2023. Climate Change 2023: synthesis report. In: Core Writing Team, Lee, H., Romero, J. (Eds.), Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. IPCC, Geneva, Switzerland, p. 184. https://doi.org/10.59327/IPCC/AR6-9789291691647.
ISMEA, 2024. Report ISMEA: tendenze e dinamiche recenti. https://www.ismeamercati.it/flex/cm/pages/ServeBLOB.php/L/IT/IDPagina/13346 last access: April 2024.
Jones, G.V., White, M.A., Cooper, O.R., Storchmann, K., 2005. Climate change and global wine quality. Clim. Change 73 (3), 319–343. https://doi.org/10.1007/s10584-005-4704-2.
Keller, M., Tarara, J.M., Mills, L.J., 2010. Spring temperatures alter reproductive development in grapevines. Aust. J. Grape Wine Res. 16 (3), 445–454. https://doi.org/10.1111/j.1755-0238.2010.00105.x.
Kendall, M.G., 1975. Rank correlation methods. Griffin, London, UK.
Larue, B., Ker, A.P., 2024. Climate change, production and trade in apples. Can. J. Agric. Econ./Rev. Can. Agroecon. 72 (3), 325–346. https://doi.org/10.1111/cjag.12367.
Li, M., Guo, J., Xu, C., Lei, Y., Li, J., 2018. Identifying climatic factors and circulation indices related to apple yield variation in main production areas of China. Glob. Ecol. Conserv. 16, e00478. https://doi.org/10.1016/j.gecco.2018.e00478.
Lobell, D.B., Field, C.B., 2007. Global scale climate–crop yield relationships and the impacts of recent warming. Environ. Res. Lett. 2 (1), 014002. https://doi.org/10.1088/1748-9326/2/1/014002.
Luedeling, E., 2012. Climate change impacts on winter chill for temperate fruit and nut production: a review. Sci. Hortic. 144, 218–229. https://doi.org/10.1016/j.scienta.2012.07.011.
Mann, H.B., 1945. Nonparametric tests against trend. Econometrica 13 (3), 245–259. https://doi.org/10.2307/1907187.
Meng, H., Qian, L., 2024. Performances of different yield-detrending methods in assessing the impacts of agricultural drought and flooding: a case study in the middle-and-lower reach of the Yangtze River, China. Agric. Water. Manage 296, 108812. https://doi.org/10.1016/j.agwat.2024.108812.
Mestre, O., Domonkos, P., Picard, F., Auer, I., Robin, S., Lebarbier, E., Stepanek, P., 2013. HOMER: a homogenization software–methods and applications. Q. J. Hung. Meteorol. Serv. 117 (1), 47–67.
Mestre, O., Gruber, C., Prieur, C., Caussinus, H., Jourdain, S., 2011. SPLIDHOM: a method for homogenization of daily temperature observations. J. Appl. Meteorol. Climatol. 50 (11), 2343–2358. https://doi.org/10.1175/2011JAMC2641.1.
MIPAAF - Ministero delle Politiche Agricole, Alimentari e Forestali. (2011). Disciplinare di produzione del vino a denominazione di origine controllata "trento". Gazzetta Ufficiale della Repubblica Italiana, Serie Generale N. 295/2011.
MIPAAF - Ministero delle Politiche Agricole, Alimentari e Forestali. (2014). Disciplinari di produzione dei vini a Denominazione di Origine Controllata e Garantita e Denominazione di Origine Controllata dell'Alto Adige/Südtirol. Gazzetta Ufficiale della Repubblica Italiana, Serie Generale N. 229/2014.
Moriondo, M., Bindi, M., Fagarazzi, C., Ferrise, R., Trombi, G., 2011. Framework for high-resolution climate change impact assessment on grapevines at a regional scale. Reg Env. Change 11 (3), 553–567. https://doi.org/10.1007/s10113-010-0171-z.
Muder, A., Garming, H., Dreisiebner-Lanz, S., Kerngast, K., Rosner, F., Kličková, K., Kaçal, E., 2022. Apple production and apple value chains in Europe. Eur, J. Hortic, Sci 87 (6), 1–22. https://doi.org/10.17660/eJHS.2022/059.
Olesen, J.E., Trnka, M., Kersebaum, K.C., Skjelvåg, A.O., Seguin, B., Peltonen-Sainio, P., Rossi, F., Kozyra, J., Micale, F., 2011. Impacts and adaptation of European crop production systems to climate change. Eur. J. Agron. 34 (2), 96–112. https://doi.org/10.1016/j.eja.2010.11.003.
Palliotti, A., Tombesi, S., Frioni, T., Silvestroni, O., Lanari, V., D'Onofrio, C., Matarese, F., Bellincontro, A., Poni, S., 2015. Physiological parameters and protective energy dissipation mechanisms expressed by grapevines (cv. Sangiovese) under different types of summer stress. Am, J. Enol, Vitic 65 (3), 269–276. https://doi.org/10.1016/j.jplph.2015.07.007.
Panziera, L., Giovannini, L., Laiti, L., Zardi, D., 2015. The relation between circulation types and regional Alpine climate. Part I: synoptic climatology of Trentino. Int. J. Climatol. 35 (15), 4655–4672. https://doi.org/10.1002/joc.4314.
Pepin, N.C., Arnone, E., Gobiet, A., Haslinger, K., Kotlarski, S., Notarnicola, C., Palazzi, E., Seibert, P., Serafin, S., Schöner, W., Terzago, S., Thornton, J.M., Vuille, M., Adler, C., 2022. Climate changes and their elevational patterns in the mountains of the world. Rev. Geophys. 60 (1), e2020RG000730. https://doi.org/10.1029/2020RG000730.
Pfleiderer, P., Menke, I., Schleussner, C.F., 2019. Increasing risks of apple tree frost damage under climate change. Clim. Change 157 (3), 515–525. https://doi.org/10.1007/s10584-019-02570-y.
Pomarici, E., Corsi, A., Mazzarino, S., Sardone, R., 2021. The Italian wine sector: evolution, structure, competitiveness and future challenges of an enduring leader. Ital. Econ. J. 7 (2), 259–295. https://doi.org/10.1007/s40797-021-00144-5.
Potopova, V., Boroneanţ, C., Boincean, B., Soukup, J., 2016. Impact of agricultural drought on main crop yields in the Republic of Moldova. Int. J. Climatol. 36 (4), 2063–2082. https://doi.org/10.1002/joc.4481.
Rogiers, S.Y., Greer, D.H., Liu, Y., Baby, T., Xiao, Z., 2022. Impact of climate change on grape berry ripening: an assessment of adaptation strategies for the Australian vineyard. Front. Plant Sci. 13, 1094633. https://doi.org/10.3389/fpls.2022.1094633.
Santos, J.A., Fraga, H., Malheiro, A.C., Moutinho-Pereira, J., Dinis, L.T., Correia, C., Schultz, H.R., 2020. A review of the potential climate change impacts and adaptation options for European viticulture. Appl. Sci. 10 (9), 3092. https://doi.org/10.3390/app10093092.
Schamel, G.H., 2014. Wine quality, reputation, denominations: how cooperatives and private wineries compete?. In: BIO Web of Conferences, 3, 03008. https://doi.org/10.1051/bioconf/20140303008.
Schlenker, W., Roberts, M.J., 2009. Nonlinear temperature effects indicate severe damages to US crop yields under climate change. Proc. Natl. Acad. Sci. 106 (37), 15594–15598. https://doi.org/10.1073/pnas.0906865106.
Schultz, H., 2000. Climate change and viticulture: a European perspective on climatology, carbon dioxide and UV-B effects. Aust. J. Grape Wine Res. 6 (1), 2–12. https://doi.org/10.1111/j.1755-0238.2000.tb00156.x.
Schultz, H.R., Jones, G.V., 2010. Climate induced historic and future changes in viticulture. J. Wine Res. 21 (2–3), 137–145. https://doi.org/10.1080/09571264.2010.530098.
Sen, P.K., 1968. Estimates of the regression coefficient based on Kendall's tau. J. Am. Stat. Assoc. 63 (324), 1379–1389. https://doi.org/10.1080/01621459.1968.10480934.
Teslić, N., Zinzani, G., Parpinello, G.P., Versari, A., 2018. Climate change trends, grape production, and potential alcohol concentration in wine from the "Romagna Sangiovese" appellation area (Italy). Theor. Appl. Clim. 131, 793–803. https://doi.org/10.1007/s00704-016-2005-5.
Tomasi, D., Jones, G.V., Giust, M., Lovat, L., Gaiotti, F., 2011. Grapevine phenology and climate change: relationships and trends in the Veneto region of Italy for 1964-2009. Am. J. Enol. Vitic. 62 (3), 329–339. https://doi.org/10.5344/ajev.2011.10108.
van Leeuwen, C., Sgubin, G., Bois, B., Ollat, N., Swingedouw, D., Zito, S., Gambetta, G.A., 2024. Climate change impacts and adaptations of wine production. Nat. Rev. Earth. Environ. 5 (4), 258–275. https://doi.org/10.1038/s43017-024-00521-5.
Webb, L.B., Whetton, P.H., Barlow, E.W.R., 2007. Modelled impact of future climate change on the phenology of winegrapes in Australia. Aust, J. Grape Wine Res 13 (3), 165–175. https://doi.org/10.1111/j.1755-0238.2007.tb00247.x.
Winkler, A.J., Cook, J.A., Kliere, W.M., Lider, L.A., 1974. General viticulture. University of California Press, Berkley, p. 740. ISBN 0-520-02591-1.