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Research Note

Prediction of berry sunburn damage with machine learning: Results on grapevine (*Vitis vinifera* L.)

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ABSTRACT

Due to climate change, heatwaves and prolonged periods of drought are more frequent and cause serious consequences to yield and berry composition of grapevine (*Vitis vinifera* L.). In response to this challenge, machine learning model was built to predict sunburn damages on the berries. The trial was conducted over two years (2022–2023) in a not irrigated vineyard of cv. Sangiovese, trained to vertical shoot positioning (VSP) spur pruned cordon. The vineyard was monitored from veraison to harvest with a weather station and thermocouples connected to a wireless sensor network (WSN). The evolution of the sunburn damages was visually evaluated twice a week. The damages appeared soon after veraison and the severity of the symptoms increased when heatwaves occurred. Weather station data including air temperature, solar radiation and relative humidity were analysed and used to build prediction models for sunburn damage. Ten parameters were derived from raw data to supply the prediction models of neural network (NN) and Support Vector Machine (SVM) optimised with gamma tuning. The NN achieved 90.32% accuracy in cross-validation, followed by SVM with 86.22% using radial kernel. The machine learning model was created using TensorFlow framework and it is available in the mobile phone application SHEET which will alert grape growers about the risk of sunburn damages on their orchards.

Nomenclature table

Symbol	Description
$A_{0\text{-}24}$	Average value of preceding 0–24 h
$A_{24\text{-}48}$	Average value of preceding 24–48 h
C	Control (without treatment)
DOY	Day of the year, index number in the range of 1–365
LDA	Linear discriminant analysis
LR	Leaf removal treatment
$M_{0\text{-}24}$	Maximum value of preceding 0–24 h
$M_{24\text{-}48}$	Maximum value of preceding 24–48 h
ML	Machine learning
NN	Neural network
NW	North-west
PAR	Photosynthetic active radiation
r	Correlation coefficient
SE	South -east
SVM	Support vector machine
VSP	Vertical shoot positioning
WSN	Wireless sensor network

1. Introduction

Grapevine (*Vitis vinifera* L.) is a relevant crop cultivated worldwide in temperate climates, playing a key socioeconomic role in many countries. One of the most important challenge for modern viticulture, is facing threats coming from climate change. Indeed, global climatic records have shown a significant intensification of extreme weather events such as heatwaves, droughts, and anomalies in both the frequency and

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intensity of rainfall (Droulia & Charalampopoulos, 2022). The Earth surface temperature increased about 0.74 °C during the last century (Gutiérrez-Gamboa et al., 2021) and climate projections foreseeing the global average temperature increase to reach or exceed 1.5 °C within the next few decades (IPCC, 2023). Altogether, they are profoundly altering the viticulture sector worldwide. In particular, prolonged periods of unusual heat are more frequent (IPCC, 2023) and might affect yield and quality of grapevines (Allegro et al., 2020; De Orduna, 2010; Fraga et al., 2016). Together with flowering, grape ripening is the most critical phase for heat stress (Teixeira et al., 2013). Temperatures above 35 °C lead to detrimental and irreversible effects on vineyards, impairing the vegetation activity (Marañón et al., 2023; Venios et al., 2020), accelerating the sugar accumulation and at the same time decreasing grape acidity (Coombe, 1987), modifying secondary metabolites, aroma and colouration of grapes (Pastore et al., 2017). Additionally, the combination of prolonged high-light intensities, high temperature and UV radiation might result in a damage of berry skin called sunburn (Rustioni et al., 2014). Sunburn necrosis symptoms start with bronze-reddish discolouration followed by brown necrotic spots on the epidermis of berries and might cause the complete desiccation of berries (Gambetta et al., 2021), while berry shrivel appears as the partial dehydration of the berries (Bondada & Keller, 2012; Somogyi et al., 2021). The intensity and frequency of sunburn mainly depends on the phenological stage of the plant, on the cultivar and on the row orientation (Gambetta et al., 2021). Although sunburn effects on grape quality need to be fully understood, impacts of berry necrosis and shrivel on yield (Allegro et al., 2024), sugar and malic acid concentration (Bondada & Keller, 2012), and wine sensory characteristics have been observed. As highlighted by Gambetta et al. (2021) the prediction of sunburn events by modelling approaches on canopy level is necessary for the successful implementation of the mitigation strategies such as the use of foliar mineral treatments (e.g. kaolin and zeolites; Petoumenou, 2023), the use of sprinkler misting system that affect microclimate temporarily (Valentini et al., 2024), and the use of shading nets (Oliveira et al., 2014).

From this perspective, precision agriculture, which has been defined as "doing the right thing, in the right place at the right time" (Pierce & Nowak, 1999) might be a powerful approach in order to early warn viticulturists for sunburn risk. The starting point of the modelling process is the data collection, which can be performed through proximal or remote sensors (Ammoniaci et al., 2021). The established models can be used in standalone applications or can be integrated into large software systems to improve their functionality (Madeira et al., 2022). Sunburn predictions typically estimate fruit surface temperature and above a threshold consider the damage (Cola et al., 2009; Ranjan et al., 2020). The BerryTone model (Cola et al., 2009) uses estimated weather data and geographical location for adjusting radiation. Ranjan et al. (2020) used ambient air temperature and solar radiation measurement with 5 days temperature history to predict the current fruit surface temperature.

In the presented work, we selected an optimum set of parameters used in artificial neural network model to link weather conditions with sunburn. The climate and output data are provided with SHEET (Leibniz-Institut für Agrartechnik und Bioökonomie, 2024), a free mobile application that warns growers to sunburn risk in a specific field site. Altogether, this will contribute to help farmers to mitigate heat-stress effects, supporting climate change adaptations in viticulture.

2. Materials and methods

2.1. Field site and vineyard description

The study took place in an 11-year-old not irrigated experimental vineyard of the University of Bologna, located in Cadriano, Italy (44°32′N, 11°22′E). Vines were *Vitis vinifera* L. cv. Sangiovese, clone 12 T grafted onto SO4 rootstock, spaced 1 m within the row (oriented North-East to South-West) and 3 m between rows, and trained to a VSP spur pruned cordon. Vines were cut to 6 two-bud spurs and the canopy was thinned to 12 shoots per vine. Due to the row orientation, both the North-West and the South-East side of the canopy were monitored with sensors.

The experiment was conducted over two years (2022–2023), on 30 vines. Each treatment consisted of 15 vines. Treatments were: a) removal of main and lateral leaves from the eight basal nodes of each shoot (LR) at the beginning of veraison (to favour the appearance of the sunburn symptoms); b) no leaf removal as control (C).

2.2. Weather data and berry temperature acquisition

A weather station (Davis Instruments, Hayward, CA, USA) installed close to the vineyard provided data about air temperature (°C), relative humidity (%), wind direction (°), precipitation (mm) and solar radiation (W m^{-2}) over the two vegetative seasons (2022–2023). Wind direction was excluded from further investigations because of the large fluctuation and lack of wind speed. Precipitation was omitted due to the very low number of rainy days. Ten parameters were finally selected to describe weather and its timely behaviour (Table 1). Parameters were selected according to prior thermodynamic calculations and the commonly available information of weather stations or online weather services (OpenWeather, London, UK).

Listed parameters describe the preceding 24 h timeframe ($A_{0\text{-}24}$ and $M_{0\text{-}24}$), the tendency based on 2 days change ($M_{0\text{-}24}$ – $M_{24\text{-}48}$) and the accumulated stress of 2 days ($A_{0\text{-}24} + A_{24\text{-}48}$). These 10 parameters of the field were used in statistical analysis to predict probability of sunburn damage in the next 3 days. The model output is binary by means of issued or no warning. The evaluated seasons had 53 and 51 days for 2022 and 2023, respectively.

The temperature of 12 berries per treatment was recorded from veraison to harvest with thermocouples connected with a Wireless Sensor Network (Winet Srl, Cesena, Italy). The thermocouples were carefully inserted under the berry skin both on the South-East (SE) and North-West (NW) side of the canopy. Being punctured by the thermocouple, berries may dehydrate or be attacked by rot. Thus, thermocouples were checked twice a week and relocated to adjacent exposed berries if necessary.

2.3. Sunburn damage assessment

The incidence and severity of berry shrivel (Fig. 1A) and berry necrosis (Fig. 1B) were assessed by visual inspections on the clusters with thermocouples. The proportion of damaged clusters (incidence) and the percentages of berries showing the symptoms (severity) were recorded twice a week from veraison to harvest. Sunburn damage assessment scale was 0–100% in 1% steps. Any observed damage was considered as positive case that shall trigger warning.

2.4. Light incidence on cluster

The light incidence was measured at solar midday of a clear sky day (August 18, 2023, day of the year - DOY 230). Incident photosynthetic active radiation (PAR) measurements were taken with a pyranometer (Skye Instruments Ltd, Powys, UK) on two clusters of each tagged vine.

Table 1
Selected weather parameters.

Calculation[a]	Temperature	Solar radiation	Relative humidity
$A_{0\text{-}24}$ = past average	Yes	Yes	Yes
$M_{0\text{-}24}$ = past maximum	Yes	Yes	Yes
$M_{0\text{-}24} - M_{24\text{-}48}$ = change	Yes	Yes	–
$A_{0\text{-}24} + A_{24\text{-}48}$ = summary	Yes	Yes	–

[a] A (average) and M (maximum) parameter indexes show preceding timeframe in hours (0–48).

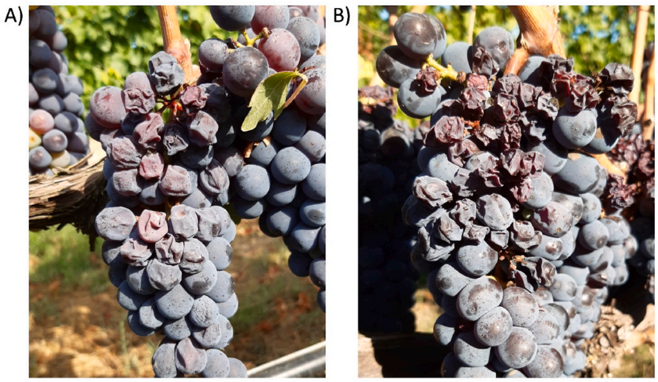

Fig. 1. – Berry shrivel (A) and necrosis (B) damages are shown on cv. Sangiovese clusters.

The shading factor of leaves was calculated to obtain the solar radiation of control fruit from weather station data.

2.5. Statistical analysis

The free software of R (version 4.2.3, R Foundation for Statistical Computing, Vienna, Austria) was used for data pre-processing and package e1071 (version 1.7–13) was used to perform Support Vector Machine (SVM) classification (Meyer et al., 2023), while package mda (version 0.5–3; Hastie et al., 2009) was used for Linear Discriminant Analysis (LDA). The SVM prediction was tested with multiple kernel functions as linear, polynomial, radial and sigmoid. The effect of gamma (γ) modification with $\pm$20% was also tested to optimise results. Polynomial kernel with degree of 3 was used. The LDA can be considered as reference, while together with linear kernel function of SVM they are limited to linear problems. Sigmoid kernel is typically used as proxy to neural network (NN) and best fit to data with symmetric distribution. Polynomial kernel can handle asymmetry, but oscillation may ruin its effectiveness in validation. Radial kernel is commonly used for nonlinear problems, but it also assumes symmetry of distribution.

Machine learning (ML) was applied as well to predict sunburn damage using the artificial neural network of TensorFlow (version 2.13.0, Google Ireland Ltd., Dublin, Ireland) running in Python (version 3.11.2). The NN was built with an input normaliser layer, followed by 2 hidden layers with 5 neurons in each, and one output neuron. The activation function of ReLU (Rectified Linear Unit) was selected. The network was trained with the stochastic gradient descent (SGD) algorithm and the learning rate of 0.01. While NN can learn complex patterns, each NN has unique decision rules due to the random initialisation. On the other hand, over fitting may occur with oversized network and excessive learning beyond optimum.

Both SVM and ML output predicted the future damage (in the next 3 days) what was compared to the observations during the season. All data were merged into a single dataset and split randomly to 80% training and 20% cross-validation subsets. Ten-fold cross validation results were used to compare models. The overall correct classification rate was calculated from the confusion matrix.

3. Results and discussion

3.1. Weather data

The daily maximum temperature and solar radiation data of 2022 showed decreasing tendency for both parameters and fruit sunburn damage were assessed 8 times in the season (Fig. 2A). Large fluctuation of these parameters was observed in 2023 without clear tendency and sunburn damage was assessed 11 times (Fig. 2B). Similar fluctuation of temperature within the season was observed by Cola et al. (2009) at 6

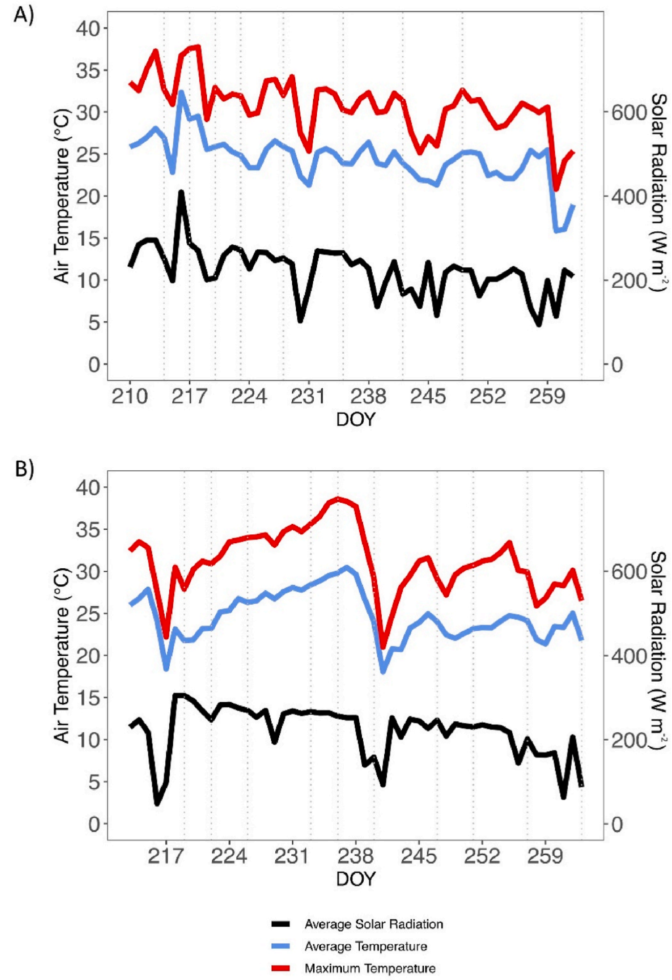

Fig. 2. – Average and maximum air temperature and solar radiation daily average data for 2022 (A) and 2023 (B). Vertical lines mark days when sunburn damage was assessed.

locations in Italy. On average the daily temperatures of 2022 and 2023 seasons were similar, whereas the maximum daily temperature was of one degree higher in 2023 in respect to 2022 (Fig. 2A and B). The average shading factor of leaves was found to be 16.2. This factor was used to obtain $A_{0\text{-}24}$, $A_{24\text{-}48}$, $M_{0\text{-}24}$ and $M_{24\text{-}48}$ of the parameter solar radiation of the control samples.

The correlation test among parameter groups revealed that there was strong relationship between maximum temperature and average humidity ($r = -0.668$, $p < 0.001$). The negative correlation value related to relative humidity support the assumption that hot and dry weather induces sunburn in fruits. Temperature and radiation data achieved high correlation values $r > 0.9$ among their average, maximum and cumulative parameters (see Annex, Table A1). Although these high correlation values suggest potential redundancy, they were all utilised in the model. Similarly, the grape specific BerryTone model (Cola et al., 2009) relies on measured air temperature, but calculation utilises estimated solar radiation (longwave, global, and net), relative humidity, and daily wind as well.

The daily profiles of air temperature and solar radiation are presented in Fig. 3, together with temperatures of NW and SE exposed berry. Average solar radiation curve follows an expected profile with peak value at 14 h. The observed temperature profiles have different peaks according to the orientation. It was found that the surface of differently exposed berries reached peak values at specific time during the day. LR berries on the SE side followed the solar radiation and fruit

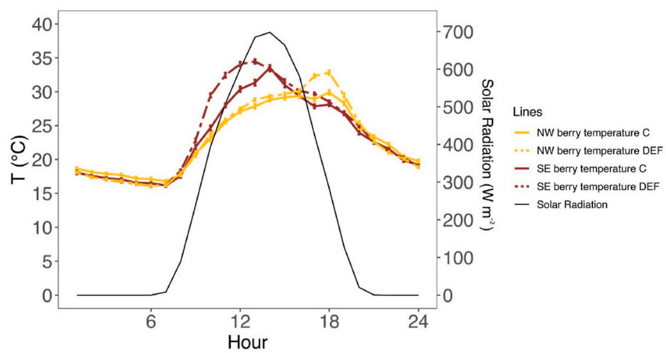

Fig. 3. – Average daily profiles of berry temperature of North-West (NW) and South-East (SE) exposed berries for control (C) and defoliated (LR) berries for the season 2022 (53 days). Vertical bars indicate standard errors. Black line indicates hourly radiation (registered every 15 min, the hourly mean is the average of 4 points).

temperature increased rapidly in the morning. Differently, the LR berries on the NW side reached the maximum temperature about 19 h. Control berries followed the trend of LR berry temperatures but showing lower values. Measured fruit surface temperature exceeded air temperature on both sides due to the solar radiation energy. Similar observations were reported earlier for grape (Cola et al., 2009) and apple (Ranjan et al., 2020).

3.2. Evolution of the sunburn damage

During both 2022 and 2023, berry shrivel and necrosis symptoms were visually assessed from veraison to harvest, differentiating between NW and SE exposed clusters (Fig. 4). Appearance and evolution of both shrivel and necrosis behaved differently in the two years due to different climatic conditions. Indeed, in 2022 an intense heatwave lasting 3 days with the air temperature above 35 °C occurred from DOY 216 to 218 (Fig. 2A), whereas in 2023 air temperature did not reach 35 °C until DOY 231 (Fig. 2B). Altogether, this resulted in shrivel (Fig. 4A) and necrosis (Fig. 4B) damages started from veraison in 2022, whereas in 2023 shrivel appeared on clusters from DOY 233 (Fig. 4C). In 2023, a heatwave lasting six days occurred from DOY 233 to DOY 238 (Fig. 2B) which resulted in a higher percentage of shrivel and a lower percentage of necrosis in respect to 2022 (Fig. 4D). It can be assumed that, due to the late occurrence of the 2023 heatwave, grape berries had sufficient time, by implementing temporary thermotolerant strategies, like apples (Naschitz et al., 2015), to gradually adapt to heat and thus prevent complete berry necrosis.

In both years, at harvest, necrosis percentage was significantly different between NW and SE exposed clusters, whereas for shrivel this was observed only for 2023. In 2022, at harvest, NW clusters reached an average of 7.6% necrosis whereas in 2023 this value was 3.0%, which might be attributed to the lower number of hours when berry temperature exceeded 35 °C (data not shown). Indeed, high air temperature has been demonstrated to play a key role in causing sunburn damages in controlled environments, whereas the effect of light intensity in determining appearance of damages was supposed to be smoother (Hulands et al., 2014; Rustioni et al., 2020). The water demand of grapevine increases within the growing period and further increase is forecasted with climate change (Jagosz et al., 2022). This demand coincides with the warmest time of the year (July–August) and a sudden poor water status induces stress which might increase susceptibility of plants to damages (Marañón et al., 2023). In grapevine, it is unlikely that water status influences sunburn incidence via berry transpiration (Gambetta et al., 2021). However, in berries, limited water supply worsens the incidence of cell death (Carvalho et al., 2016) and thus it might accelerate sunburn damages appearance. However, drought stress priming during the season can lead to a better acclimated canopies and thus to less sensitive berries (Gambetta et al., 2021). Additionally, it has been observed (Allegro et al., 2024) that irrigated vines present lower sunburn damages in respect to non-irrigated one, suggesting that regular water supply during ripening could represent a promising solution.

3.3. Prediction of sunburn damage

According to the accuracy of training, NN achieved the best performance followed by SVM and LDA (Table 2). The SVM linear kernel obtained smaller accuracy in both training and cross-validation than LDA. The SVM sigmoid kernel resulted in the lowest accuracy of cross-validation (74.19%). During γ tuning, the SVM with polynomial kernel was unstable and its efficiency fluctuated the most. The SVM with radial kernel and increased γ achieved the best performance, closest to that of NN. The Type II error (false negative) of the cross-validation was the lowest for the NN and SVM with radial kernel, while the highest value was obtained with the sigmoid kernel of SVM. Besides the best accuracy of NN, it is able to learn with data feedback and adapt to local conditions.

The suggested NN model uses weather data to predict visually confirmed sunburn damage. This approach is different from previously published models, where fruit surface temperature is estimated (Cola et al., 2009; Ranjan et al., 2020). Instead of a threshold of fruit surface temperature, presented technique is based on visually confirmed sunburn damage. The proposed direct estimation of ground truth damage does not require additional measurement from the farmers, only visual evaluation of fruit is enough for validation. Additionally, the model considers the evolution of damages with 3 days window.

The created NN model was saved in TensorFlow Lite format for later use. Since the main goal of the presented work was to create a warning application for growers, the TensorFlow Lite model is built into a mobile application. Volunteer data upload from farmers via this application can help improvement of the model. The open framework also enables easy integration into farm management software systems (Madeira et al., 2022) and their extension with sunburn risk prediction.

4. Conclusions

The effect of cluster exposition on berry temperature and sunburn damage on cv. Sangiovese vines were evaluated in two consecutive years. Sunburn damages of berry shrivel and necrosis appeared following critical weather conditions. Ten parameters were selected to describe temperature, solar radiation and relative humidity of the preceding two days so that prediction models could be created for the forthcoming three days. According to the daily temperature profile, the risk of sunburn damage depends on row orientation as well. The NN model achieved the best accuracy in cross-validation with 90.32%, followed by SVM with 86.29%. The classification results confirmed the potential of the selected parameters and the cross-validation using two years data showed the robustness of the models. Considering the data feedback opportunity and the ability of future learning, NN model is recommended in long term application. The proposed solution is available as a TensorFlow Lite model for developers and in a mobile application[1] for grape growers who may promptly apply the mitigations strategies against sunburn.

CRediT authorship contribution statement

Allegro Gianluca: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Data curation, Conceptualization. **Ilaria Filippetti:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Data curation,

[1] SHEET, https://play.google.com/store/apps/details?id=com.atb.sheet.

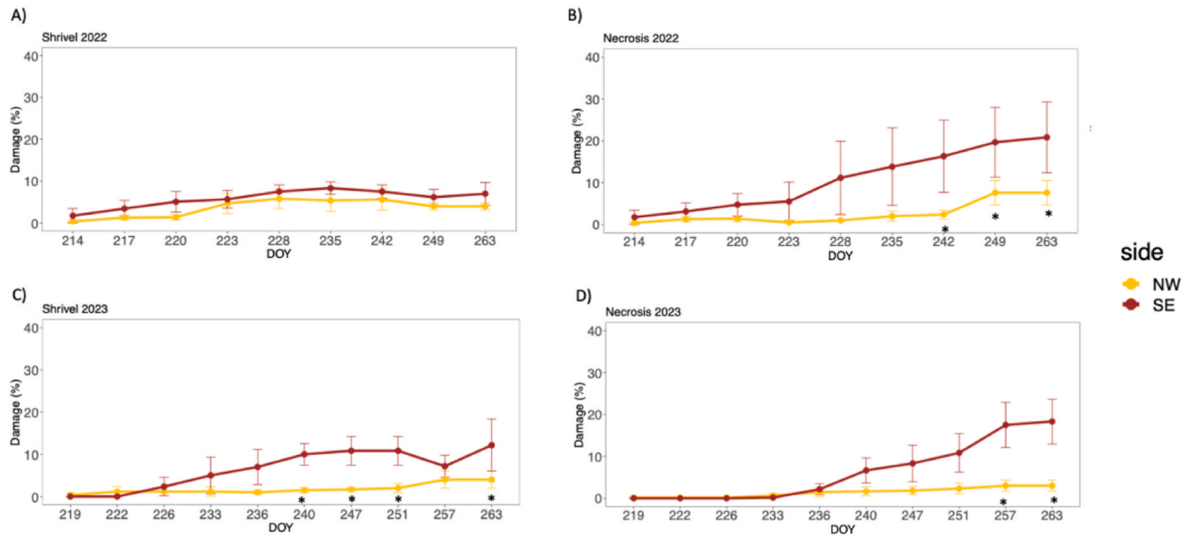

Fig. 4. – Sunburn damage evolution in differently exposed clusters for 2022 and 2023, expressed as berry shrivel (A, C) and berry necrosis (B, D). Asterisks indicate significant differences between NW and SE side according to Student's t-test ($p < 0.05$). SE = South-East exposition; NW = North-West exposition.

Table 2
Classification accuracy of different models on the merged dataset of 2022 and 2023 (%).

Model	Training	Cross-validation	Type II error
Linear discriminant analysis	87.10	82.26	6.45%
Support vector machine - linear	80.65	79.84	6.45%
Support vector machine - radial	93.55	86.29	2.91%
Support vector machine - polynomial	87.10	85.48	3.23%
Support vector machine - sigmoid	83.87	74.19	19.35%
Neural network (2 hidden layers)	96.77	90.32	2.91%

Conceptualization. **Chiara Pastore:** Writing – original draft, Formal analysis, Data curation. **Daniela Sangiorgio:** Writing – review & editing, Writing – original draft, Visualization, Investigation, Formal analysis, Data curation. **Gabriele Valentini:** Writing – original draft, Validation, Methodology, Formal analysis, Data curation. **Gianmarco Bortolotti:** Writing – original draft, Visualization, Software, Investigation, Formal analysis, Data curation. **István Kertész:** Software, Methodology, Investigation, Formal analysis, Data curation. **Lien Le Phuong Nguyen:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation. **László Baranyai:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, 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.

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Annex I.

Table A1
Correlation matrix of weather parameters.

	TempAVG	TempMAX	TempDIFF	TempSUM	RadAVG	RadMAX	RadDIFF	RadSUM	HumidAVG	HumidMAX
TempAVG		0.933	0.243	0.929	0.165	0.039	0.012	0.159	−0.590	−0.399
TempMAX	0.000		0.402	0.839	0.201	0.058	0.027	0.194	−0.668	−0.385
TempDIFF	0.002	0.000		−0.075	0.222	0.074	0.214	0.103	−0.376	−0.105
TempSUM	0.000	0.000	0.353		0.088	0.014	−0.067	0.130	−0.465	−0.338
RadAVG	0.040	0.012	0.006	0.278		0.948	0.148	0.972	−0.188	0.011
RadMAX	0.626	0.476	0.358	0.862	0.000		0.171	0.949	−0.031	0.080
RadDIFF	0.885	0.735	0.007	0.408	0.066	0.033		−0.001	−0.079	0.001
RadSUM	0.048	0.016	0.201	0.107	0.000	0.000	0.989		−0.157	0.020
HumidAVG	0.000	0.000	0.000	0.000	0.019	0.702	0.328	0.051		0.714
HumidMAX	0.000	0.000	0.193	0.000	0.896	0.322	0.995	0.809	0.000	

Upper triangle: Pearson's correlation coefficient values. Lower triangle: p values.

References

Allegro, G., Pastore, C., Valentini, G., & Filippetti, I. (2020). Post-budburst hand finishing of winter spur pruning can delay technological ripening without altering phenolic maturity of Merlot berries. *Australian Journal of Grape and Wine Research, 26*(2), 139–147. https://doi.org/10.1111/ajgw.12427

Allegro, G., Valentini, G., Sangiorgio, D., Pastore, C., & Filippetti, I. (2024). Zeolite application and irrigation during ripening reduced berry sunburn damage and yield loss in cv. Sangiovese (*Vitis vinifera* L.). *Frontiers in Plant Science, 15*, Article 1427366. https://doi.org/10.3389/fpls.2024.1427366

Ammoniaci, M., Kartsiotis, S.-P., Perria, R., & Storchi, P. (2021). State of the art of monitoring technologies and data processing for precision viticulture. *Agriculture, 11* (3). https://doi.org/10.3390/agriculture11030201. Article 3.

Carvalho, L. C., Coito, J.l., Gonçalves, E. F., Chaves, M. M., & Amâncio, S. (2016). Differential physiological response of the grapevine varieties Touriga Nacional and Trincadeira to combined heat, drought and light stresses. *Plant Biology, 18*, 101–111. https://doi.org/10.1111/plb.12410

Cola, G., Failla, O., & Mariani, L. (2009). BerryTone—a simulation model for the daily course of grape berry temperature. *Agricultural and Forest Meteorology, 149*(8), 1215–1228. https://doi.org/10.1016/j.agrformet.2009.01.007

Coombe, B. G. (1987). Influence of temperature on composition and quality of grapes. *Acta Horticulturae, 206*, 23–36. https://doi.org/10.17660/ActaHortic.1987.206.1

De Orduna, R. M. (2010). Climate change associated effects on grape and wine quality and production. *Food Research International, 43*(7), 1844–1855.

Droulia, F., & Charalampopoulos, I. (2022). A review on the observed climate change in europe and its impacts on viticulture. *Atmosphere, 13*(5). https://doi.org/10.3390/atmos13050837. Article 5.

Fraga, H., García de Cortázar Atauri, I., Malheiro, A. C., & Santos, J. A. (2016). Modelling climate change impacts on viticultural yield, phenology and stress conditions in Europe. *Global Change Biology, 22*(11), 3774–3788. https://doi.org/10.1111/GCB.13382

Gambetta, J. M., Holzapfel, B. P., Stoll, M., & Friedel, M. (2021). Sunburn in grapes: A review. *Frontiers in Plant Science, 11*. https://www.frontiersin.org/articles/10.3389/fpls.2020.604691.

Gutiérrez-Gamboa, G., Zheng, W., & Martínez de Toda, F. (2021). Strategies in vineyard establishment to face global warming in viticulture: A mini review. *Journal of the Science of Food and Agriculture, 101*(4), 1261–1269. https://doi.org/10.1002/jsfa.10813

Hastie, T., Tibshirani, R., & Friedman, J. (2009). Support vector machines and flexible discriminants. In T. Hastie, R. Tibshirani, & J. Friedman (Eds.), *The elements of statistical learning* (pp. 417–458). New York: Springer. https://doi.org/10.1007/978-0-387-84858-7_12.

Hulands, S., Greer, D. H., & Harper, J. I. (2014). The interactive effects of temperature and light intensity on *Vitis vinifera* cv. 'Semillon' grapevines. II. Berry ripening and susceptibility to sunburn at harvest. *European Journal of Horticultural Science, 79*(1), 1–7.

Jagosz, B., Rolbiecki, S., Rolbiecki, R., Ptach, W., Sadan, H. A., Kasperska-Wołowicz, W., Pal-Fam, F., & Atilgan, A. (2022). Effect of the forecast air temperature change on the water needs of vines in the region of bydgoszcz, northern Poland. *Agronomy, 12* (7). https://doi.org/10.3390/agronomy12071561. Article 7.

IPCC. (2023). In H. Lee, & J. Romero (Eds.), *Climate change 2023: Synthesis report, summary for policymakers. Contribution of working groups I, II and III to the sixth assessment report of the intergovernmental panel on climate change [core writing team.* Geneva, Switzerland: IPCC.

Leibniz-Institut für Agrartechnik und Bioökonomie. (2024). *SHEET version 1.0.2. [software] Google Play*. https://play.google.com/store/apps/details?id=com.atb.sheet. (Accessed 26 April 2024).

Madeira, R. N., Santos, P. A., Java, O., Priebe, T., Graça, E., Sárközi, E., Asprion, B., & Gómez, R. P.-B. (2022). Towards digital twins for multi-sensor land and plant monitoring. *Procedia Computer Science, 210*, 45–52. https://doi.org/10.1016/j.procs.2022.10.118

Marañón, M., Fernández-Novales, J., Tardaguila, J., Gutiérrez, S., & Diago, M. P. (2023). NIR attribute selection for the development of vineyard water status predictive models. *Biosystems Engineering, 229*, 167–178. https://doi.org/10.1016/j.biosystemseng.2023.04.001

Meyer, D., Dimitriadou, E., Hornik, K., Weingessel, A., Leisch, F., Chang, C. C., & Lin, C. C. (2023). Misc functions of the department of statistics. *Probability theory group (formerly: E1071), TU wien*. CRAN. Online https://CRAN.R-project.org/package=e1071.

Naschitz, S., Naor, A., Sax, Y., Shahak, Y., & Rabinowitch, H. D. (2015). Photo-oxidative sunscald of apple: Effects of temperature and light on fruit peel photoinhibition, bleaching and short-term tolerance acquisition. *Scientia Horticulturae, 197*, 5–16. https://doi.org/10.1016/j.scienta.2015.11.003

Oliveira, M., Teles, J., Barbosa, P., Olazabal, F., & Queiroz, J. (2014). Shading of the fruit zone to reduce grape yield and quality losses caused by sunburn. *OENO One, 48*(3), 1579. https://doi.org/10.20870/oeno-one.2014.48.3.1579

Pastore, C., Dal Santo, S., Zenoni, S., Movahed, N., Allegro, G., Valentini, G., Filippetti, I., & Tornielli, G. B. (2017). Whole plant temperature manipulation affects flavonoid metabolism and the transcriptome of grapevine berries. *Frontiers in Plant Science, 8*. https://www.frontiersin.org/articles/10.3389/fpls.2017.00929.

Petoumenou, D. G. (2023). Enhancing yield and physiological performance by foliar applications of chemically inert mineral particles in a rainfed vineyard under mediterranean conditions. *Plants, 12*(7), 1444. https://doi.org/10.3390/plants12071444

Pierce, F. J., & Nowak, P. (1999). Aspects of precision agriculture. In D. L. Sparks (Ed.), *Advances in agronomy* (Vol. 67, pp. 1–85). Academic Press. https://doi.org/10.1016/S0065-2113(08)60513-1.

Ranjan, R., Khot, L. R., Peters, R. T., Salazar-Gutierrez, M. R., & Shi, G. (2020). In-field crop physiology sensing aided real-time apple fruit surface temperature monitoring for sunburn prediction. *Computers and Electronics in Agriculture, 175*, Article 105558. https://doi.org/10.1016/j.compag.2020.105558

Rustioni, L., Fracassetti, D., Prinsi, B., Geuna, F., Ancelotti, A., Fauda, V., Tirelli, A., Espen, L., & Failla, O. (2020). Oxidations in white grape (*Vitis vinifera* L.) skins: Comparison between ripening process and photooxidative sunburn symptoms. *Plant Physiology and Biochemistry, 150*, 270–278. https://doi.org/10.1016/j.plaphy.2020.03.003

Rustioni, L., Rocchi, L., Guffanti, E., Cola, G., & Failla, O. (2014). Characterization of grape (*Vitis vinifera* L.) berry sunburn symptoms by reflectance. *Journal of Agricultural and Food Chemistry, 62*(14), 3043–3046. https://doi.org/10.1021/jf405772f

Somogyi, E., Kun, Á., Lázár, J., Bodor-Pesti, P., & Sárdy, D.Á. N. (2021). Quantitative analysis of the berry size in grapevine cultivar 'Italia' ●: Digital image analysis of the grapevine. *Progress in Agricultural Engineering Sciences, 17*(S1), 53–60. https://doi.org/10.1556/446.2021.30007

Teixeira, A., Eiras-Dias, J., Castellarin, S. D., & Gerós, H. (2013). Berry phenolics of grapevine under challenging environments. *International Journal of Molecular Sciences, 14*(9), 18711–18739. https://doi.org/10.3390/ijms140918711

Valentini, G., Allegro, G., Pastore, C., Sangiorgio, D., Noferini, M., Muzzi, E., & Filippetti, I. (2024). Use of an automatic fruit-zone cooling system to cope with multiple summer stresses in Sangiovese and Montepulciano grapes. *Frontiers in Plant Science, 15*, Article 1391963. https://doi.org/10.3389/fpls.2024.1391963

Venios, X., Korkas, E., Nisiotou, A., & Banilas, G. (2020). Grapevine responses to heat stress and global warming. *Plants, 9*(12), 1754. https://doi.org/10.3390/plants9121754

Bondada, B. R., & Keller, M. (2012). Not all shrivels are created equal—morpho-anatomical and compositional characteristics differ among different shrivel types that develop during ripening of grape (*Vitis vinifera* L.) berries. *American Journal of Plant Sciences, 3*(7), 879–898. https://doi.org/10.4236/ajps.2012.37105