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ABSTRACT

Climate change exerts mounting pressure on major agroecosystems, jeopardizing both their productivity and long-term sustainability. Vineyards, as multi-layer cropping systems, require effective inter-row management to improve grape production and sustain the provision of ecosystem services. Crop models predict the dynamics of the distinct vegetation layers in the system and support the optimization of inter-row practices. In this study, the original UNIFI.GrapeML vine growth model was integrated with a new module to simulate the daily inter-row grass growth in conjunction with the development of the main crop. The model was calibrated and validated in two vineyards located in the Piedmont region. The results showed satisfactory performance simulating grass growth (r = 0.79, RMSE = 31.3 g d.m. m^{-2}) and fractional transpirable soil water (r = 0.93, RMSE = 0.17), for grassed and tilled inter-rows. Moreover, the UNIFI.GrapeML showed satisfactory performance in simulating vine phenology (r = 0.69, RMSE = 6.7 days, on average among all phenological phases), pruned shoot weight (r = 0.74, RMSE = 39.0 g d.m. m^{-2}) and yield (r = 0.55, RMSE = 66.1 g d.m. m^{-2}), in both vineyards. Once validated, the integrated model was applied to assess grass growth in SSP1 2.6, SSP2 4.5 and SSP5 8.5 scenarios. Under future climates, the model demonstrated that the onset of grass growth occurred earlier, and the frequency of required cuts between March and November increased from a minimum of + 4.2 % in SSP2 4.5 to a maximum of + 5.7 % in SSP1 2.6 compared to the present. Furthermore, simulated grass growth trends revealed different redistribution of operating costs and CO_2 emissions for mowing throughout the season. This study demonstrates that UNIFI.GrapeML could guide inter-row management within vineyards under future climates, optimizing production and mitigating the environmental impact of viticulture.

1. Introduction

Climate change is exerting adverse impacts on the agricultural sector across the Mediterranean region, affecting agro-ecosystems and threatening food security (Dibari et al., 2015; MedECC et al., 2020; Moriondo et al., 2021; Semeraro et al., 2023). In this context, the heightened vulnerability of the agricultural sector increasingly requires the implementation of targeted European policies (e.g. The European,

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Deal, 2019) to support the transition towards a more sustainable agricultural system (Boix-Fayos and De Vente, 2023). These policies aim to promote the implementation of adaptation and mitigation strategies to cope with the effects of climate change (Fraga et al., 2020, Santos et al., 2020).

Among European agricultural sectors, viticulture, which accounts for 45 % of the global vineyard area and 60 % of world wine production (Eurostat, 2022, 2023), is among the production sectors most highly exposed to climate change, with repercussions for production, quality, and the suitability of areas for cultivation (Moriondo et al., 2013; Zhu et al., 2016). Beyond production-related aspects, viticulture provides a multitude of services, including those related to the environment (i.e. the maintenance of the territory and biodiversity, and the increase of soil organic carbon), cultural and social aspects (i.e. the enhancement of the life quality, cultural heritage and the support of local communities, (Garcia et al., 2018; Visconti et al., 2024; Winkler et al., 2017).

Proper agronomic management of vineyards, aimed at improving both economic and environmental sustainability, can safeguard the provision of ecosystem services. In this context, inter-row management plays an important role in improving soil hydraulic properties, reducing soil erosion and preserving soil organic carbon content (Bordoni et al., 2019; Liebhard et al., 2024). Effective inter-row management promotes biomass production, enhances biodiversity, controls weeds and provides essential nutrients (e.g. nitrogen) to the soil and vines (De Bernardi et al., 2025; Sulas et al., 2017). Furthermore, proper inter-row management plays a key role in mitigating the impacts of ongoing climate change, contributing in some cases to the reduction of greenhouse gas (GHG) emissions or even facilitating carbon sequestration (Burg et al., 2025; Dencső et al., 2024).

When inter-row practices are not optimized, they can be associated with high GHG emissions leading to inefficient resource use and increased production costs, alongside reducing the system's positive environmental externalities (Giffard et al., 2022; Volanti et al., 2022). As a result, numerous studies on vineyards have focused on evaluating different inter-row management strategies (e.g., spontaneous grass vs. sown cover crops, or grass cover vs. bare soil, etc.), while assessing the competitive effects on water and nutrients, alongside the productive and environmental benefits of proper management (Gatti et al., 2022; Griesser et al., 2022).

Considering the important role of inter-row management in agricultural systems, monitoring and prediction tools (i.e., vine growth models) have been implemented to take into account the contribution of this component to soil water, nutrient dynamics, and plant growth (Celette et al., 2010; Ripoche et al., 2011; Tournebize et al., 2012; Vezy et al., 2023). These models, simulating inter-row management, have been developed to better understand the complex interactions within the agroecosystem, to enhance management and improve the sustainability of production. In particular, some modelling approaches (e.g. WaLIS; Celette et al., 2010) have been developed to simulate inter-row grass growth at vineyard level, by accounting for the water and nutrient competition among the main crop and the inter-row. These models have gradually been improved to achieve increasingly sophisticated modelling solutions (e.g. STICS, Beaudoin et al., 2023), which integrate new formalisms to take into account key interactions between the plant components of the system (Vezy et al., 2023). Although these latter solutions have been specifically adapted to simulate the growth of individual intercrops, the presence of multi-species spontaneous grass cover complicates their calibration and application, as they must account for the seasonal alternation of the inter-row vegetation. Consequently, simpler approaches such as the one proposed in this study, which can simulate the seasonal dynamics of generic grass cover, are more practical for managing spontaneously grassed inter-rows (e.g. changes in number of cuts). Moreover, considering that few modelling solutions have so far been applied to assess the impact of cover crop management in Mediterranean orchards (Ripoche et al., 2011; López-Bernal et al., 2023), and to our best knowledge, none have explored changes in inter-row cuts under future climate scenarios in vineyards.

Although the advance of the grass growing season has already been shown in other studies on alpine and Mediterranean grasslands under future climates (Leolini et al., 2025; Petersen et al., 2021), the inter-row grass growth dynamics in a vineyard should be assessed considering its impact on the overall economy of an agro-ecosystem focused on grape and wine production. In this context, simulating the shift in the growing season, changes in the number of cuts, and the overall role of inter-row grass within the vineyard system can support farmers' decisions by helping them to assess economic and environmental constraints in the future management (e.g. higher operating costs and CO_2 emissions).

This study addresses this gap by integrating an existing grass module (Bellini et al., 2023; Leolini et al., 2025) into the UNIFI.GrapeML grapevine model. This simplified yet effective modeling approach was proposed to address the complexity of the multilayer vineyard system and to evaluate inter-row vineyard management practices under both present and future climate conditions. The adopted modeling approach enables the evaluation of inter-row grass growth dynamics using relatively limited external inputs, including key daily weather variables, soil characteristics, management practices, and a small set of calibratable parameters. Based on this framework, the objectives of this study are twofold: (i) to test the robustness of the improved version of UNIFI.GrapeML in simulating the dynamics of vegetation layers of a vineyard, specifically inter-row grass and vine growth, and grapevine parameters in two experimental sites located in Piedmont (Italy); and (ii) to apply the UNIFI.GrapeML model to assess future inter-row grass growth under present and three projected climate scenarios (SSP1–2.6, SSP2–4.5, and SSP5–8.5). The model simulations will be used for calculating the operational costs and CO_2 emissions associated with mowing operations to provide guidance for adaptive management of vineyard rows under climate change conditions.

2. Materials and methods

2.1. Study areas

The study was carried out in the hilly vine-growing area in the north-western part of Italy (Piemonte region, Fig. 1) at Tenuta Cannona Experimental Vine and Wine Center of Agrion Foundation (44°40'N, 8°37'E, 296 m a.s.l.; site A) and Vezzolano Experimental Farm of the Accademia di Agricoltura di Torino (45°08'N, 7°96'E, 426 m a.s.l.; site B). In both sites, the Institute of Sciences and Technologies for Sustainable Energy and Mobility of the National Research Council (CNR-STEMS) has been conducting research since 1980, with a particular focus on the impact of soil management in sloping vineyards on soil and water conservation (Tropeano, 1984). In this regard, study sites were selected based on the availability of dry grass biomass, soil water, pruned and grape production data, taking into account the numerous experimental trials conducted in both vineyards throughout the year. Table 1 includes information about location, climate, soil and vineyard management in the two sites. Temperature and precipitation patterns during the respective study periods of A and B sites are reported in Appendix 1 (Fig. A1.1).

2.2. Data collection & processing

In site A, grass above-ground biomass (AGB) was sampled during 2021–2022 using a 25 cm× 25 cm frame in GC and CT inter-row. Twenty samples of grass AGB were collected (11 in GC and 9 in CT) in 2021, while 16 samples of grass AGB were collected (8 per treatment) in 2022. The dry matter (d.m.) was extracted by drying the grass AGB in the oven at 65°C for 48 h. The soil surface covered by grass (%) was evaluated using another 50 cm × 50 cm frame characterized by reticules of 100 cm^2, as proposed in the evaluation-per-sectors method of Agrela et al. (2003). The percentage of grass cover was assessed in each

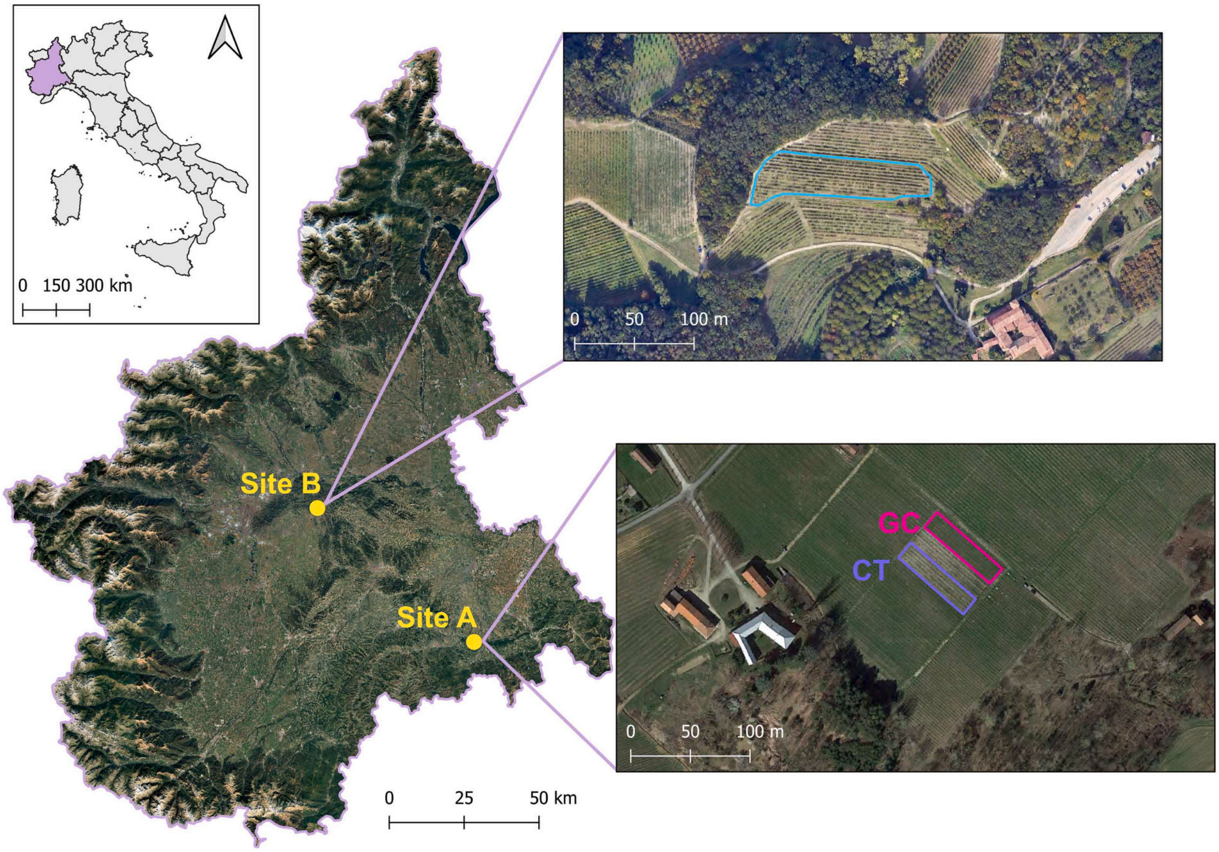

Fig. 1. Study area. A) Tenuta Cannona experimental vine and wine centre; B) Vezzolano vineyard.

reticle of the frame on a rank ranging from 0 (no grass cover) to 5 (maximum grass cover; Palazzi et al., 2022). Moreover, the grass growth and senescence dynamics were evaluated from images captured in GC and CT inter-rows at different time points during the season. The observed grass AGB values were re-scaled to extract the grass green biomass, enabling comparison with model simulations (Appendix 1).

Soil water content (SWC) values were continuously measured in both inter-rows during the period 2021–2022, using 15 capacitance/frequency domain sensors (ECH2O-5TM sensors, Meter, Pullman, WA, USA) installed from 10 to 50 cm under the tractor track in the center of the inter-row in site A. For this study, only data from probes located at 20 cm depth were used to consider the maximum water absorption by the grass roots. The available water capacity (AWC) calculated from field capacity and wilting point measured with soil probes was 0.11 cm cm^{-1} for GC and 0.21 cm cm^{-1} for CT in site A. On the other hand, the AWC values, 0.19 cm cm^{-1} and 0.17 cm cm^{-1} for GC and CT, respectively, were calculated from soil texture in site B. Soil water content data from soil probes were linearly converted into Fractional Transpirable Soil Water (FTSW) values to be comparable with the model variable.

Vine, phenology, pruned shoot weight and yield data were collected in sites A and B. In site A, phenological data (Day Of the Year, DOY) on budbreak (BBCH 8), flowering (BBCH 63–69), veraison (BBCH 81), and ripening (BBCH 89) were collected from 2016 to 2022, with the exception of 2018 and 2020, during which no phenological data were available. The data pertaining to the pruned shoot weight (kg plant $^{-1}$) and grapevine yield (kg plant^{-1}) in fresh matter were collected on six vine rows (6 plants per vine row, on average), with three vine rows in each inter-row management, during the 2021–2022 period. The data were rescaled to g m^{-2} using a planting density of 2.75 m^2 and converted from fresh to dry matter using a fixed coefficient obtained in previous study on vines (Leolini et al., 2023). The coefficient accounts for the presence of 26 % d.m. in harvested grapes.

The data collected in site B exclusively concern phenology, pruned shoot weight and grapevine yield data, considering that no d.m. data on grass growth were available. The phenological data (DOY) of budbreak, flowering, veraison, and ripening were collected from 1993 to 2002. The pruned shoot weight (g plant $^{-1}$) and grapevine yield (kg plant^{-1}) data in fresh matter were collected from 1985 to 1994 (Lisa and Parena, 1994), in the Guyot trellis-trained plot. The data were rescaled to g m^{-2} by considering an area occupied by a single plant of 2.2 m^2. The observed data were then converted from fresh to dry matter to allow the comparison with the simulated d.m. pruned shoot weight. For conversion, we used a fixed coefficient (70 % d.m. in pruned shoot weight) estimated from field data collected in another vineyard (data not shown). Weather data on daily maximum and minimum air temperature (°C) and daily precipitation (mm) were collected from the weather stations located in A (2020–2022) and B (1984–1994) sites. Daily global solar radiation (MJ m^{-2} d^{-1}) was estimated in both vineyards using the Hargreaves method (Hargreaves and Samani, 1982).

2.3. Model description

UNIFI.GrapeML (Leolini et al., 2018, 2023) is a crop model with a mechanistic approach that simulates vine development and growth under different pedo-climatic conditions on a daily time step. In its original version, the vine biomass accumulation (g d.m. m^{-2}) is estimated from the fraction of photosynthetically active radiation (fPAR), either simulated or derived from proximal and/or remote sensors, and potential radiation use efficiency (RUE, g MJ^{-1}), which is reduced to its actual value according to air temperature (Ritchie and Otter, 1984; Van Keulen and Seligman, 1987) and soil moisture. Soil water dynamics are calculated according to a soil water balance module that considers the positive inputs (precipitation and irrigation) and losses (plant

Table 1
Climate, soil and management information of A and B sites. The reference list is reported at the bottom of the Table.

Site	A) Tenuta Cannona Experimental Vine and Wine Center of Agrion Foundation	B) Vezzolano Experimental Farm of the Accademia di Agricoltura di Torino
Location and elevation	Carpeneto (AL), 296 m a.s.l. 44°40'N, 8°37'E	Albugnano (AT), 426 m a.s.l. 45°08'N, 7°96'E
Climate (Köppen–Geiger classification)	Csa, warm temperate with dry and hot summer	Cfa, warm temperate with hot summer and no dry season
Mean Annual Precipitation (mm) 1991–2020	869	777
Average minimum air temperature (°C) 1991–2020	8.5	7.5
Average maximum air temperature (°C) 1991–2020	17.4	16.8
Soil texture (%)	fine-loamy (sand = 24.5, silt = 46.4, clay = 29.1)	silt loam (sand = 30.3, silt = 58.1, clay = 11.6)
Average slope gradient (%)	15	15–35
Inter-row management	Two treatments: GC = permanent grass cover, managed with multiple mowings during the growing season CT = conventional tillage, tilled at 0.25 m depth using chisel plow in spring and autumn	Two treatments: GC = grass cover mowed and chopped three times per year. CT = conventional tillage with autumn ploughing and two summer hoeing;
Vine variety	*Vitis vinifera* L. cv. Barbera	*Vitis vinifera* L. cv. Barbera
Vineyard plots	2 plots including 7 vine rows aligned along the slope for a total surface of 1221 m^2 (74 m long and 16.5 m wide).	Randomized blocks with 4 repetitions, with vine rows along contour lines. Rows at 2.75 m across the hillslope arranged with longitudinal slope

*Arpa Piemonte (2025); Kottek et al. (2006); Palazzi et al. (2022); Rubel, Kottek (2010)

transpiration and soil evaporation) of water from the soil (Soltani and Sinclair, 2012). Plant transpiration is simulated by considering that a nearly linear relationship exists between biomass production and transpired water, expressed through the concept of transpiration efficiency (Tanner and Sinclair, 1983). Potential soil evaporation is calculated based on global radiation reduced by the amount intercepted radiation, albedo and considering the saturated vapour pressure relative to the temperature. Soil evaporation (mm d^{-1}) is estimated by adjusting potential evaporation considering the number of days since the last precipitation event when evaporation occurs under dry conditions (Rivington et al., 2013). Biomass partitioning is limited to a distinction between vegetative and reproductive phases, which are separated by the flowering stage. Before flowering, biomass is allocated entirely to vegetative structures (no distinction between the biomass allocated in leaves and shoots), whereas after flowering, a portion of the biomass is directed toward fruit development in proportion to the total cumulated biomass and the daily increase in the harvest index (dHI/dT).

In the new version of UNIFI.GrapeML (v.3, after 2018, 2023), the model simulates vine growth by dynamically partitioning the accumulated biomass into vegetative (leaf and shoot), reproductive (fruit) and perennial (roots and trunk) organs. In addition, the model simulates the interaction between the main crop and the inter-row vegetation, through the integration of a grass module that estimates grass growth during the season as well as the competition for water and light between the vine and grass components in the system. The grass module simulates the daily actual biomass accumulation, then partitioned in AGB (g d.m. m^{-2}) and belowground biomass (BGB; g d.m. m^{-2}), based on leaf area index (LAI), fPAR and thermal and water stresses, as described in Bellini et al. (2023). Differently from Bellini et al. (2023), daily LAI is simulated using a prognostic approach based on temperature, leaf lifespan and specific leaf area rather than derived from remote sensing data (Leolini et al., 2025). The grass fPAR is calculated considering the impact of vine canopy on the grass inter-row (Eqs. 1, 1.1).

$$k_{grass} = -a \bullet LAI_{grass} + b \tag{1}$$

$$fPAR_{grass} = 1 - e^{(-k_{grass} \bullet LAI_{grass}) \bullet (1 - fPAR_{vine})} \tag{1.1}$$

where k_{grass} is the light extinction coefficient which increases linearly as LAI_{grass} increases during the growing season and *a* and *b* are the empirical coefficients of the equation (Bellini et al., 2023; Zhang et al., 2014).

The thermal stress is estimated using the T_{cor} function depending on daily minimum temperature, which ranges from 0 (no vegetation growth) to 1 (optimal vegetation growth; Bellini et al., 2023). Water stress is calculated using a new version of the soil water balance already used in other orchards (Moriondo et al., 2019), which includes the upper and lower grass and vine roots layers, respectively. The soil water dynamics are calculated in two layers: one characterised by the presence of vine and grass roots and another in which only vine roots are present. In

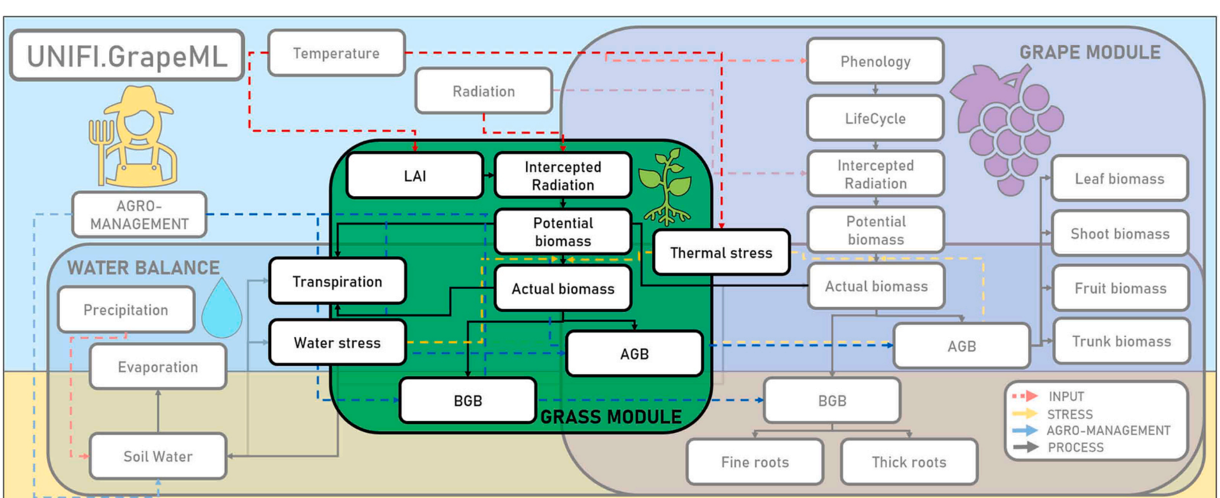

Fig. 2. UNIFI.GrapeML workflow. Integration with the grass module.

this context, the competition for water between the two plant components occurs in the first layer, where the initial value of total transpirable soil water (TTSW) is calculated based on the ratio between $Root_{grass}/Root_{vine}$ and AWC (cm cm^{-1}), between field capacity and wilting point. In the layer characterised exclusively by the vine root component, the TTSW is calculated based on the maximum length of the vine roots and the AWC.

As described above, the daily actual transpirable soil water ($ATSW_d$, mm d^{-1}) is updated at the end of the day based on positive precipitation (Prec, mm d^{-1}) and irrigation (Irr, mm d^{-1}) and negative soil evaporation (SE, mm d^{-1}) and plant transpiration (Tr, mm d^{-1}) water balance items (Eq. 2).

$$ATSW_d = ATSW_{(d-1)} + (Prec + Irr) - (Tr - SE) \tag{2}$$

Where $ATSW_{d-1}$ refers to the ATSW of the previous day. However, to consider saturation conditions in this new model version, when the ATSW of the first layer (layer 1) exceeds the TTSW, the amount of excess water (ATSW-TTSW) passes from the surface layer to the deeper layer (layer 2; Eq. 2.1).

$$ATSW_{d(layer2)} = ATSW_{d-1(layer2)} + ATSW_{d(layer1)} - TTSW_{d(layer1)} \tag{2.1}$$

The FTSW is the ratio between ATSW and TTSW varying between 0 and 1, with 0 representing maximum stress (wilting point) and 1 representing no stress (field capacity). In this study, FTSW is calculated on a homogeneous soil layer occupied by 50 % of the herbaceous root and 50 % of the vine root. In this context, the ATSW value is thus influenced by the transpiration of both herbaceous and vine species in the soil layer where roots compete (Eq. 3).

$$Tr_{vine/grass} = \frac{NPP_{vine/grass} \bullet VPD}{TEC} \tag{3}$$

Where Tr is calculated for vine and grass, respectively. The $NPP_{vine/grass}$ is the net primary production of vine and grass components, respectively, VPD is the vapor pressure deficit (kPa) calculated based on maximum and minimum air temperature (°C) and TEC is the specific transpiration efficiency coefficient for each specific species (Pa; Tanner and Sinclair, 1983). Soil evaporation is calculated from soil potential evaporation (SPE, mm d^{-1}) based on the Penman equation reported in Soltani and Sinclair (2012); Eqs. 4, 4.1), as described in the original model version:

$$SPE = GSR \bullet SALB \bullet (1 - fPAR) \bullet \frac{DELT}{DELT + 0.68} \tag{4}$$

$$DELT = \frac{5304}{(273 + T_{\max})^2} \bullet e^{\left(21.255 - \frac{5304}{273 + T_{\max}}\right)} \tag{4.1}$$

where GSR is the global solar radiation (MJ m^2 d^{-1}), SALB is the soil albedo, fPAR is the fraction of the photosynthetically active radiation, DELT is the slope of saturated vapour pressure versus temperature calculated according to Soltani and Sinclair (2012). The soil potential evaporation is rescaled to actual soil evaporation (SE, mm d^{-1}) as a function of the square root of time since the start of the dry spell (DYSE, days) by considering that the evaporation in the first soil layer is different from a wet surface (Eq. 5).

$$SE = SEP \bullet \sqrt{DYSE + 1} - \sqrt{DYSE} \tag{5}$$

The evapotranspiration rate (mm d^{-1}) is calculated as the sum of SE (mm d^{-1}) and grass and Tr (mm d^{-1}).

Finally, to investigate the grass and vine trends under current and future climates, the impact of CO_2 on RUE was evaluated considering the equations proposed by Soltani et al. (2007) and Kellner et al. (2017). The same approach was used for estimating the impact of CO_2 on TEC (Eq. 6).

$$VAR_{CO2} = VAR_{ref}\left[1.0 + b1_{vine/grass} \bullet \ln\left(\frac{CO_{2meas}}{CO_{2ref}}\right)\right] \tag{6}$$

where VAR_{co2} refers to RUE and TEC variables at elevated CO_2 concentration, VAR_{ref} refers to RUE and TEC variables at reference atmospheric CO_2 concentration, b1 is a constant regulating the response of VAR to elevated CO_2 for vine and grass respectively, CO_{2ref} is the reference atmospheric CO_2 concentration (μmol mol^{-1}) and CO_{2meas} is measured/estimated atmospheric CO_2 concentration (μmol mol^{-1}).

With regard to the impact of grass and vine management on the species, this is quantified in the model by specifying, in external tables, the type of management, the day of the event (DOY) and the reduction percentage of the plant organs (e.g. leaves, shoots, grapes).

2.4. Model calibration & validation

The UNIFI.GrapeML model was calibrated against observed grass and vine data using the CroptimizR package within the R software environment (version 4.5.0, R Core Team, 2024 ; Buis et al., 2020). The calibration/validation strategy adopted in this study is described below. With regard to grass, which represent the main focus of our study, model calibration and validation were performed at site A. With regard to vines, phenology calibration was initially performed using data from both sites, while pruned weight and grape production were first calibrated at site A and then validated at site B.

With the focus on grass growth, the model was calibrated and validated against grass AGB (g d.m. m^{-2}) data collected in the GC and CT inter-rows of site A. The methodology used during these procedures consists of the random distribution of the observed data in GA and GB datasets, 17 data points each. Initially, the model was calibrated on dataset GA and validated on the independent observed GB dataset. The inverse procedure is then applied by calibrating in GB and validating in GA dataset, and the mean of both parameterisations was applied to the entire dataset. Regarding vine, the UNIFI.GrapeML was calibrated and validated against phenology (DOY). The budbreak, flowering, veraison and maturity stages (DOY) of the Barbera vine variety from A and B sites were randomly distributed in two datasets: PA and PB with 7 and 6 observed data, respectively. The model was calibrated on the PA dataset and validated on the PB dataset, and then the inverse procedure was applied (calibration on PB and validation on PA). Once the procedure was repeated on both PA and PB datasets, the two parameterizations were averaged and applied on the entire dataset. Subsequently, UNIFI. GrapeML was calibrated for fruit biomass (g d.m. m^{-2}) and pruned shoot weight (g d.m. m^{-2}) site A and validated on site B. The calibrated parameters are shown in Table S1 (in bold). In our study, we considered that grass and vine development was mainly driven by parameters related to phenology and biomass partitioning. Finally, FTSW dynamics were validated against observed FTSW data in site A, where observed soil water content data were available. The FTSW simulation do not require specific model calibration using only AWC values as input data and by setting the depth of grass and vine roots as parameters (Leolini et al., 2023; Moriondo et al., 2019).

2.5. Statistical analysis

The performance of the UNIFI.GrapeML model was evaluated by comparing observed and simulated values using five statistical indicators: Pearson's correlation coefficient (r, Eq. 7), the root mean squared error (RMSE, Eq. 8), the relative root mean squared error (RRMSE, Eq. 9), the Nash-Sutcliffe modelling efficiency (EF, Eq. 10) and the Akaike information criterion (AIC, Eq. 11):

$$r = \frac{\sum_{i=1}^{n}(O_i - \overline{O}) \bullet (P_i - \overline{P})}{\sqrt{\sum_{i=1}^{n}(O_i - \overline{O})^2 \bullet \sum_{i=1}^{n}(P_i - \overline{P})^2}} \tag{7}$$

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(P_i - O_i)^2}{n}} \tag{8}$$

$$RRMSE = \frac{\sqrt{\sum_{i=1}^{n}\frac{(P_i - O_i)^2}{n}}}{\overline{O}} \bullet 100 \tag{9}$$

$$EF = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \overline{O})^2} \tag{10}$$

$$AIC = 2 \bullet k - 2 \bullet \ln(\widehat{L}) \tag{11}$$

Where O_i is the observed value, $\overline{O}$ is the average of the observed values, P_i is the predicted value, $\overline{P}$ is the average of the predicted values, n is the number of observations, k is the number of estimated parameters and $\widehat{L}$ is the maximum value of the likelihood function in the model.

2.6. Model application

2.6.1. Climatic scenarios and grass management

The climate scenarios have been generated using the stochastic downscaling weather generator LARS-WG 8.0 (Semenov and Barrow, 2002). LARS-WG simulates future daily temperature and precipitation time series based on the analysis of statistical distributions of the observed daily data for each month (e.g., frequency of dry and rainy days and precipitation). To perform the study on a consistent time series, we selected the Ovada weather station, located approximately 5 km from site A with 26 years of daily maximum and minimum air temperature (°C; Arpa Piemonte, 2025). The simulated historical data maintain the frequency of dry and wet spell, seasonal consistency and interannual variability of the original observed data. On the other hand, "delta changes" on future climate averages and variability have been applied to statistical parameters to derive climate scenarios from global climate models (GCMs) from the CMIP6 set of the IPCC's Sixth Assessment Report (AR6; IPCC et al., 2023). In this study, the CESM2 GCM was adopted due to its highest accuracy in southwestern Europe (Palmer et al., 2023; Pellicone and Caloiero, 2025). Three future Shared Socio-economic Pathways (SSPs) have been selected to cover the range of possible future developments in the anthropogenic factors that determine climate change. In detail, the SSP1 2.6, SSP2 4.5 and SSP5 8.5 scenarios have been chosen representing the optimistic, intermediate and pessimistic pathways of the AR6 (IPCC et al., 2023). For each scenario, 300 synthetic years of daily air temperature (°C) and daily precipitation (mm) were generated by LARS-WG representing the expected climatic variability within the time slice 2041–2060, based on the observed weather at the Ovada's station as baseline. Daily GSR (MJ m^{-2} d^{-1}) was instead calculated based on Hargreaves method (sirad R package; Bojanowski et al., 2013; Hargreaves and Samani, 1982). The impact of atmospheric CO_2 on grass and vine (Eq. 6) was calculated based on different concentrations for present (416.41 ppm), SSP1 2.6 (469.3 ppm), SSP2 4.5 (506.9 ppm) and SSP5 8.5 (562.8 ppm) centered in 2050, according with NOAA, 2025 and Meinshausen et al. (2019).

The model was applied to the present and future scenarios generated, considering only GC treatment and vine pruning, since grass and vine cutting can be correlated with LAI and leaf biomass growth of both components in the vineyard. The model was not applied for CT treatment considering that some impacts related to soil aeration and structure could not be simulated under the current version. In the climate scenarios, grass cutting and vine pruning are simulated when certain thresholds are exceeded. For grass, seasonal cuts are simulated in accordance with the vine cycle (from budbreak to complete leaf fall). In addition, mowing is simulated when LAI exceeds 1.6 m^2 m^{-2} (~ 97 g d. m. m^{-2}) to achieve an average of three cuts per year, as is traditionally done in Italian vineyards characterized by spontaneous grass growth (Magni et al., 2020; Mercenaro et al., 2014; Monteiro and Lopes, 2007). For vines, green pruning is simulated when LAI > 1.6 m^2 m^{-2} and DOY < 180, while thinning is simulated when LAI > 1.4 m^2 m^{-2} and DOY > 180. Winter pruning is fixed on DOY 29.

2.6.2. Operational costs and CO_2 emissions

A summary analysis of the costs of mowing operations and CO_2 emissions from the machinery used for inter-row management was applied to the results of the model simulations describing the different grass growth dynamics. Here below we highlight how the costs and CO_2 emissions were calculated. The annual costs of the cutting operations were calculated based on the hourly costs of the iron track tractor (€ 107.90 per hour), the mowing machine (€ 20 per hour), fuel costs (€ 0.93 per liter of diesel for agriculture use; Camera di Commercio Cuneo, 2025) and personnel costs (€ 13 per hour). In this context, we also considered 4.34 kg of diesel consumed per hour per cut and 3 h per hectare of mowing. CO_2 emissions from the tractor (New Holland TK, iron track) were calculated by considering the number of cuts, the hours the tractor was used for inter-row management and the kg of diesel per hour for inter-rows with low biomass (Assandri et al., 2025), as previously described. The kg of diesel was then converted in litres by considering 1 kg equals approximately 1.17 liters of diesel. Finally, the CO_2 emitted from the combustion process was calculated as 2.641 kg of CO_2 emitted for each litre of diesel fuel burnt (Howey et al., 2011; Martelli et al., 2023).

3. Results

3.1. UNIFI. GrapeML model performances under present conditions

The results of final UNIFI.GrapeML model parameterisation for AGB grass, vine phenology, shoot pruned weight and yield are shown in Table A2.1. Regarding inter-row grass growth, the calibrated parameters are mainly related to the leaf cycle and the impact of temperature on photosynthesis. The parameters related with the leaf cycle were calibrated to identify the development of the grass at the study site, where the floral composition during the season is typical of a Mediterranean environment (LeafLife = 635 °C d^{-1}; LAI.Life.ini = 3829 °C d^{-1}; LAI.stop.sen = 0.48 m^2 m^{-2} and Tb = 5.03 °C). Similarly, the parameters related to the impact of temperature on photosynthesis have been calibrated to capture inter-row grass development under the specific site conditions (GT.min = −3.99 °C and GT.opt = 14.25 °C). Moreover, RUE and TEC values of the grass layer were set at 1.6 g MJ^{-1} and 5 Pa respectively, considering an atmospheric CO_2 concentration of 416.41 ppm as recorded in 2021 (NOAA, 2025).

As for the inter-row grass growth, the calibration of vine phenological parameters for the Barbera cultivar is reported in Table A2.1. Moreover, the parameters related to leaf development (LeafLife = 200 °C d^{-1}), biomass growth (RUE = 1.25 g MJ^{-1} and Harvest Index = 0.0058 d^{-1}) and transpiration (TEC = 6.8 Pa) have been calibrated considering the reference CO_2 concentration as reported for grass growth. The parameters related to the impact of water stress on leaf area development and photosynthesis were maintained fixed (PHO1 = 12.9, PHO2 = 14.1, SLN1 = 25.9 and SLN2 = 17.3, unitless). Finally, the maximum depth of the vine roots was set at 150 cm.

The performance from model calibration and validation for grass and vine are shown in Table 2 and Fig. 3. The model satisfactorily simulated the annual AGB grass trend in site A during the seasons 2021 and 2022. The model showed higher performances in CT compared to GC inter-

Table 2
Evaluation of the performance (R, RMSE, RRMSE, EF, AIC) of the UNIFI.GrapeML model in simulating grass and vine components. For vine phenology, pruned shoot weight and yield, the model calibration and validation performances are reported considering both A and B sites.

Layer	Output variable	Unit of measurement	Slope	Intercept	R	RMSE	RRMSE	EF	AIC
Grass	AGB, GC inter-row	g d.m. m^{-2}	1.12	−6.21	0.79	36.93	56.57	0.23	186.62
	AGB, CT inter-row	g d.m. m^{-2}	0.94	−1.74	0.79	25.72	59.72	0.45	154.68
Vine	Budbreak	DOY	0.27	77.28	0.60	5.74	5.52	0.27	54.58
	Flowering	DOY	0.36	100.44	0.55	4.92	3.12	0.29	62.56
	Veraison	DOY	0.28	163.67	0.74	9.34	4.12	0.41	62.39
	Maturity	DOY	0.56	122.03	0.87	6.97	2.59	0.63	65.58
	Yield	g d.m. m^{-2}	0.69	95.10	0.55	66.14	20.09	−0.19	250.79
	Pruned shoot weight	g d.m. m^{-2}	0.43	87.89	0.74	39.01	19.13	−0.06	202.84
Soil	FTSW, GC inter-row	unitless	0.99	0.07	0.90	0.18	34.82	0.74	−407.81
	FTSW, CT inter-row	unitless	0.86	0.08	0.95	0.12	19.82	0.89	−793.88

*r = unitless; RMSE = unit of measurement of the output variable; RRMSE = %; EF = unitless; AIC = unitless

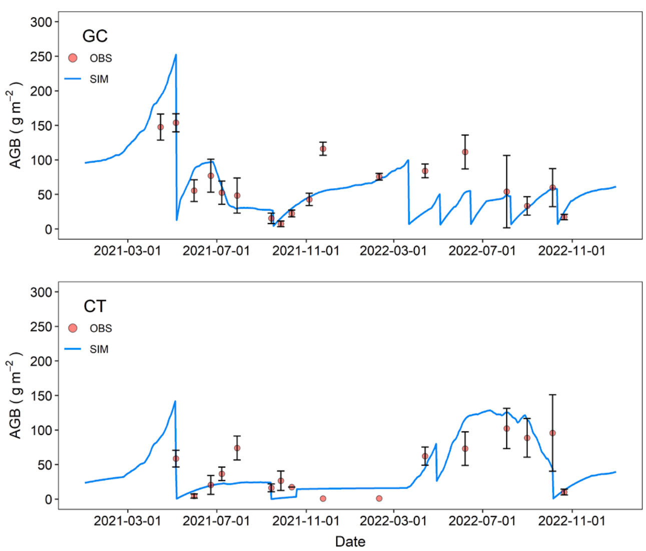

Fig. 3. Comparison of observed and simulated AGB grass trend in GC and CT inter-rows during 2021 and 2022 in site A. AGB grass is expressed in g m^{-2} of dry matter.

rows in terms of RMSE (-44 %), EF (+49 %) and AIC (-21 %) values. Conversely, the RRMSE value showed higher performance in GC compared to CT inter-row (RRMSE = −5 %). In terms of absolute values, the high RRMSE in both inter-rows was determined by the low values of the observed data.

On the other hand, the performances of vine growth model calibration and validation are reported in Table 2 and Figs. A2.1.-A2.2. The model satisfactorily simulated the four phenological phases (r = 0.68, RMSE = 6.7 days, RRMSE = 4 %, EF = 0.4, AIC = 61.30, on average). The lowest RMSE was found for flowering (RMSE = 4.9 days) while highest RMSE was obtained during the simulation of the veraison phase (RMSE = 9.3 days). On the other hand, the highest r and EF values were obtained during the simulation of the maturity phase (r = 0.87, EF = 0.63). Finally, UNIFI.GrapeML obtained the lowest AIC and the highest RRMSE during the budbreak simulation (AIC = 54.58, RRMSE = 6 %; Fig. A2.1.). Furthermore, the model showed good performance in simulating pruned vine weight and yield (Fig. A2.2). The comparison between observed and simulated data during model calibration (only 4 observed data available) showed good calibration results for pruned shoot weight (r = +26 %, RMSE = −70 %, RRMSE = −5 %, EF = +217 %, AIC = −24 %) compared with grapevine yield in both the calibration and validation performances. Finally, the simulation of the FTSW trend showed satisfactory performance on both GC and CT inter-rows (Table 2, Fig. 4). The results showed higher performance in the CT compared to GC inter-rows (r = +6 %; RMSE = −50 %; RRMSE = −76 %; EF = +17 %; AIC = −48 %).

3.2. UNIFI. GrapeML model application under climatic scenarios

The increase of LAI and AGB of inter-row grass in different periods of the growing season (MAM = March-April-May; JJA = July-June-August; SON = September-October-November) is shown in Figs. 5 and A2.3. Comparing the three main periods of the growing season, the highest peak of LAI and AGB was observed, on average among all simulations, in the MAM. In this period, the highest peak of LAI and AGB was observed in SSP5 8.5 (2.97 m^2 m^{-2} and 199.9 g d.m. m^{-2} at DOY 95) while the lowest peak of LAI and AGB was observed in the present period (2.54 m^2 m^{-2} and 170.5 g d.m. m^{-2} at DOY 97). On the other hand, similar LAI and AGB trends were observed between the present scenario (1.17 m^2 m^{-2} and 72.4 g d.m. m^{-2} at DOY 158) and SSP5 8.5 scenario (1.16 m^2 m^{-2} and 69.7 g d.m. m^{-2} at DOY 187) when the JJA period was analyzed. Finally, the highest peak of LAI and AGB was observed in the SSP5 8.5 scenario (1.49 m^2 m^{-2} and 85.9 g d.m. m^{-2} at DOY 334) during the SON period. The lowest peak of LAI and AGB was instead recorded in the present scenario (1.37 m^2 m^{-2} and 80.3 g d.m. m^{-2} at DOY 334) during the same period.

According to the increase in LAI and AGB, the number of cuts per year increased on average by + 5.7 % in SSP1 2.6, + 4.2 % in SSP2 4.5 and + 4.6 % in SSP5 8.5 scenario compared to the present at the middle of the century (Table 3). This increasing trend is also highlighted by the probability density functions of inter-row cuts (Fig. 6). Here, all three future scenarios (SSP1 2.6, SSP2 4.5 and SSP5 8.5) showed a higher probability of cutting compared to the present scenario. In detail, the probability of cuts increased in MAM from the SSP1 2.6 (+1.1 %) to SSP5 8.5 (+8.7 %) scenarios, compared to the present scenario. On the other hand, the probability of cuts increased in JJA, especially in SSP1 2.6 scenario (+19.1 %) while the lowest increase was recorded in the SSP5 8.5 scenario (+9.4 %) compared to the present scenario. Finally, the probability of cuts decreased significantly in the SSP5 8.5 scenario (-18.2 %) during the SON period and remained unchanged in SSP1 2.6 (0 %).

An increased frequency of cuts led to higher operational costs and CO_2 emissions. In the present period, the annual cost for cutting (3.35 cuts per year) is evaluated at approximately 1443 €. This cost includes the hourly cost of a tractor and mowing machine, the cost of fuel and the personnel cost for all cuts performed during the year, by considering the number of hours for each cut and the fuel consumption as reported in Section 2.6.2. In future scenarios, the operational costs increase from + 3.6 % of SSP2 4.5 to + 4.8 % SSP1 2.6 scenario, while an intermediate behaviour was maintained for SSP5 8.5 (+4.1 %).

Regarding CO_2 emissions, the annual mowing activity is estimated to emit 135.6 kg of CO_2 in site A during the present period. According to the increase in the number of cuts (Table 3) in future scenarios, CO_2 emissions increased from 4.2 % (SSP2 4.5) to 5.7 % (SSP1 2.6) compared to the present.

Finally, for vine, shoot biomass and yield were simulated to occur earlier and to increase in all future scenarios (Figs. A2.4 and A2.5).

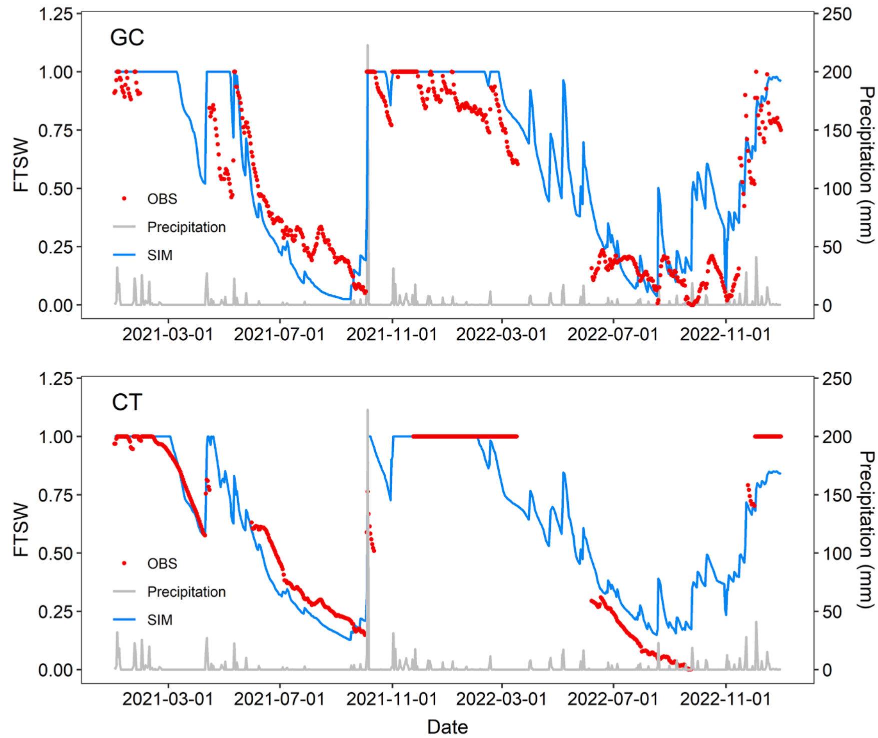

Fig. 4. Comparison between observed and simulated FTSW values in GC and CT inter-rows during 2021 and 2022 in site A.

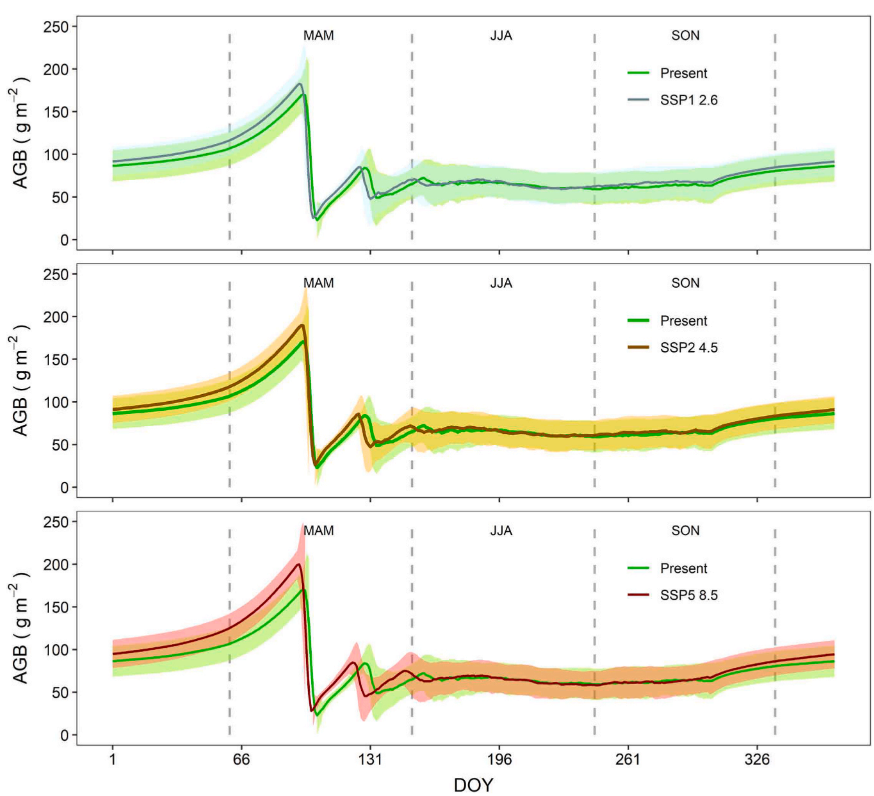

Fig. 5. AGB grass simulations under present and future scenarios (SSP1 2.6, SSP2 4.5 and SSP5 8.5) in site A. AGB grass is expressed in g m^{-2} of dry matter. Legend: MAM = March-April-May; JJA = July-June-August; SON = September-October-November.

Compared with the present period (max 138.5 g d.m. m^{-2}), the shoot biomass the highest increase was in SSP5 8.5 (+16.1 %), while it increased similarly in the SSP1 2.6 and SSP2 4.5 scenarios (+9 %, on average). This increase also coincides with an increase in the amount of pruning during the growing season, ranging from + 4.8 % in SSP2 4.5 to + 40.1 % in SSP5 8.5 scenario, while SSP1 2.6 showed an intermediate trend (+10.9 %). Similarly, fruit biomass (216.1 g d.m. m^{-2} maximum value during the present period) showed the highest increase under the

Table 3
Number and percentage variation of grass cuts and amount of CO_2 emitted by the machine (kg of CO_2) in SSP1 2.6, SSP2 4.5 and SSP5 8.5 climate scenarios compared to the present. MAM = March-April-May; JJA = July-June-August; SON = September-October-November.

Scenario	N. cuts (MAM)	N. cuts (JJA)	N. cuts (SON)	N. cuts (March-November)	Δ% MAM	Δ% JJA	Δ% SON	Δ% March-November	CO_2 emissions (kg of CO_2)
Present	1.94	0.89	0.53	3.35	-	-	-	-	135.6
SSP1 2.6	1.96	1.06	0.53	3.54	+ 1.1	+ 19.1	+ 0.0	+ 5.7	143.3
SSP2 4.5	1.99	1.00	0.50	3.49	+ 3.0	+ 13.2	−6.5	+ 4.2	141.3
SSP5 8.5	2.10	0.97	0.43	3.51	+ 8.7	+ 9.4	−18.2	+ 4.6	141.9

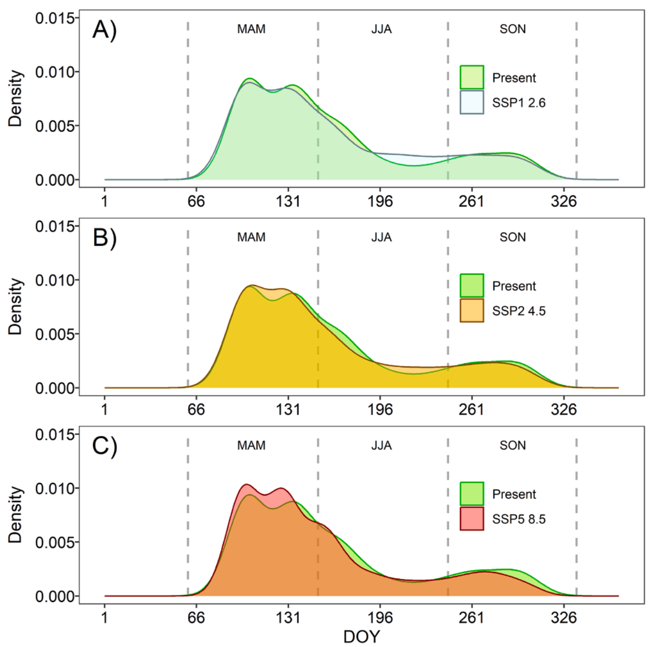

Fig. 6. Probability of the occurrence of inter-row cuts under present and future scenarios SSP1 2.6 (A), SSP2 4.5 (B) and SSP5 8.5 (C), expressed as a probability density function. Legend: MAM = March-April-May; JJA = July-June-August; SON = September-October-November.

SSP5 8.5 scenarios (+7.8 %). On the other hand, similar trends were observed for SSP1 2.6 and SSP2 4.5 (+5.7 %, on average). Jointly with the increase of fruit biomass, the advancement in the harvest date (264 DOY at present time) is evident when moving from the SSP1 2.6 (-4.2 days) to the SSP5 8.5 (-8.7 days) scenario.

4. Discussion

Inter-row grass growth has been demonstrated to play a pivotal role in vineyards, influencing vine production and system sustainability (Giffard et al., 2022; Liebhard et al., 2024). Consequently, the development of modelling solutions that encompass the dynamics and interaction among inter-row grass and vines can represent effective tools for optimising and adapting vineyard agronomic management to changing climate scenarios (Beaudoin et al., 2023; Celette et al., 2010). In the present study, the UNIFI.GrapeML model, when implemented with the grass growth module, demonstrated a satisfactory performance in simulating grass growth in the presence of both GC and CT treatments. The simulated grass growth trend was consistent with other studies, in which AGB is mainly concentrated during the wetter periods of spring and autumn (Moriondo et al., 2019; Ripoche et al., 2011). This type of modeling tools can be particularly useful for estimating the number of interventions required to handle the components of the system (e.g. mowings, prunings, etc.), thereby providing a foundation for an economic and environmental assessment of the operational costs and CO_2 emissions under different climatic and management conditions. In this context, UNIFI.GrapeML represents a promising modelling solution for supporting agronomic management in vineyard. Although it is designed for estimating the growth of generic grass, its minimal input requirements and limited parameterization enhance its practical applicability. As such, it offers a streamlined and accessible alternative to more complex modeling frameworks. The latter, when able to represent the succession of individual species throughout the season, may improve the accuracy of the estimates for diverse floristic compositions, although it may require a larger parameterisations (Movedi et al., 2019; Soussana et al., 2012). While further testing of the model is warranted, the parameterisation obtained in this study was found to be consistent with that reported in previous works, simulating grass development and growth under different environmental conditions (see Table 2; Bellini et al., 2023; Leolini et al., 2025; Moriondo et al., 2019). In this study, grass growth is the result of the modeled growth and senescence patterns as influenced by the applied agronomic management. Grass cutting is simulated taking into account the impact on AGB, whereas tillage affects both AGB and BGB (Balogianni et al., 2014; Buivydiene et al., 2024). To capture these dynamics and estimate grass regrowth, the model assumes that a portion of BGB is reallocated to the AGB after cutting and tillage, thereby enhancing grass regrowth under conditions of severe stresses (e.g., water or heat; Jing et al., 2012).

Correctly simulating grass growth trends is important for evaluating the impact on vine growth dynamics. Although this study did not explicitly address water competition between grass and vines, the model performed well in simulating pruned shoot weight and yield at site A (see Section 2.2). With this calibration, the model was applied to site B, where performance was lower (Table 2; Fig. A2.2). This is due to the limited information (e.g. soil water content and grass biomass) available on site B. Improving model performance in simulating the interactions among inter-row growth and vine requires site-specific calibration that accounts for local situ conditions, crops and management practices since these factors strongly influence both the main crop and the overall system (Abad et al., 2021; Zalai et al., 2025). Furthermore, it may be appropriate to quantify the impact of different types of agronomic operations on the components of the system to improve the accuracy of the model in simulating the effects on plant species growth and development.

Both grass and vine growth dynamics are further influenced by soil water regime. In this context, UNIFI.GrapeML demonstrated good accuracy in simulating soil water dynamics (Figs. 3–4), consistent with findings from previous research (Celette et al., 2010; Moriondo et al., 2019). The available soil water content was simulated based on the initial available water capacity, derived from soil moisture measurements obtained from field probes in both GC and CT inter-rows of site A, within a homogeneous intermediate soil layer equally occupied by vine and grass roots. Under this configuration, low FTSW (water stress) values were more frequent from mid-August to mid-September, while high FTSW (no water stress) values occurred during winter and early spring (October to May), when rainfall is more abundant (Fig. 4). During the wet period of the season, soil water content was higher in GC inter-row where vegetation cover is persistent on the soil compared to CT inter-rows. By providing protective cover and a well-distributed root layer, grassed inter-rows enhance soil structure and reduce the vulnerability of the layer to erosion and loss of organic matter and nutrients during extreme rainfall events, in contrast to tilled soils (Capello et al., 2019, 2020).

Although further improvements are possible in the simulation of both plant components, UNIFI.GrapeML represents an important step forward in the modelling of multi-layer systems (Fig. 2), allowing the evaluation of grass growth trends and agronomic management strategies. Using UNIFI.GrapeML, it was possible to simulate inter-row grass within the management cycle of a mature vineyard, where grass and vine operations are generally coordinated. Under future climate scenarios, the model projected an increase in the number of cuts during the March-November period, particularly within the SSP1 2.6 scenario compared to the present (Table 3). The increase in the associated shifts in mowing seasonality aligns with trends observed in previous studies aimed at assessing the impact of climate change in different agro-pastoral systems (Bellini et al., 2022; Brilli et al., 2023; Leolini et al., 2025). Although vineyards are not traditional pastoral systems, the spontaneous vegetation between the rows behaves similarly, with mowing being the main agronomic intervention. Alterations in mowing seasonality were also observed across different periods. During MAM, the increase in mowing frequency was likely driven by the fertilising effect of high CO_2 concentrations combined with optimal water and temperature conditions early in the beginning of the season. The increase in the number of cuts during the driest season (JJA) was particularly evident in SSP1 2.6, while less so in the SSP2 4.5 and SSP5 8.5 scenarios due to a shift in the growing season. Conversely, the decrease in mowing frequency during SON appears to be linked to more intense summer drought and lower rainfall under the SSP2 4.5 and SSP5 8.5 scenarios compared to the SSP1 2.6 scenario. These results are undoubtedly subject to the limitations of using of fixed cutting thresholds for both grass mowing and vine pruning. Any variation in these thresholds could therefore alter the simulations related to the cost and emissions analysis. Nevertheless, our findings are supported by previous studies that predict an earlier growing season and an increased mowing frequency under future scenarios in similar systems (Bellini et al., 2022; Brilli et al., 2023 Leolini et al., 2025).

The estimation of inter-row growth in present and future climate scenarios also enabled a preliminary evaluation of the economic and environmental costs associated with machinery interventions, including operational expenses and CO_2 emissions (Figs. 5–6, A2.3, A2.4, A2.5). From an economic point of view, even though mowing represents only one of several key viticultural operations (e.g. pruning, fertilisation, pesticide application, harvesting; Giffard et al., 2022), its increased frequency under future scenarios is expected to lead to a significant increase and seasonal redistribution of costs. Although fuel and labour costs were assumed constant in this study, their projected trends indicate a growing economic burden for wine-growing regions exposed to climate change (Ashenfelter and Storchmann, 2016; Bernetti et al., 2012). Beyond economic implications, the associated increase in CO_2 emissions from agronomic operations is also a critical concern. In this context, Callesen et al. (2023) highlighted the important role played by grass cover between vine rows in regulating carbon fluxes. Although grass between rows has a shorter life cycle than perennial species such as vines, it contributes significantly to biomass accumulation and carbon uptake in the system (60.4 %)of the system's NPP in Callesen et al., 2023). Despite its recognised importance in providing numerous ecosystem services such as biodiversity maintenance, soil improvement, carbon storage, etc., maintaining grass cover between rows may not be sustainable in the wine-growing economy (e.g. irrigation, weeding, etc.). Some studies are currently evaluating the sustainability and environmental impact of agronomic practices in vineyards, taking into account the positive aspects related to low-emission productivity (Marras et al., 2015; Rouault et al., 2020) and their impact on consumer preferences (Fantechi et al., 2025). In this regard, the use of prediction tools (e.g., crop models) could play a key role in integrating these methodologies to enhance estimates of carbon uptake and GHG emissions from cropping systems (Launay et al., 2021). Overall, this study encourages the use of decision support tools, based on modelling approach such as UNIFI.GrapeML, to simulate system vegetation dynamics and optimise agronomic management. This approach can facilitate the design of adaptation strategies to cope with climate change while improving the economic and environmental sustainability of vineyard systems.

5. Conclusions

The new UNIFI.GrapeML modelling solution, which accounts for the complex interactions between vines and inter-row grass through the implementation of a dedicated grass growth module, showed satisfactory performance in estimating the growth of both layers, as well as in simulating soil water dynamics during the present period. Moreover, its application under future climate scenarios indicated an earlier onset and an increase in biomass accumulation, as well as a higher cutting frequency compared to present period. The mowing seasonality was also altered, with evident differences from March to November between present and SSPs scenarios. These changes led to higher operational costs associated with mowing and CO_2 emissions from machinery, which are expected to have important economic and environmental implications for the vineyard management. Although vineyard agronomic management should be considered as a whole (e.g., fertilization, pesticide application), this study provides a foundation for the dynamic assessment of vineyard sustainability from both economic and environmental perspectives. In this context, future research should aim to further enhance existing models by incorporating emerging technologies and data sources, thereby improving the estimation of grass and vine growth and supporting adaptive agronomic management strategies under present and future climates.

CRediT authorship contribution statement

L. Leolini: Conceptualization, Methodology, Formal analysis, Software, Writing–original draft. **S. Costafreda-Aumedes:** Conceptualization, Methodology, Formal analysis, Software, Writing–review & editing. **M. Biddoccu:** Methodology, Data curation, Investigation, Writing–review & editing. **R. Rossi:** Methodology, Investigation, Writing–review & editing. **G. Padovan:** Investigation, Writing–review & editing. **M. Moretta:** Investigation, Writing–review & editing. **AR. Balingit:** Investigation, Writing–review & editing. **M. Coli:** Investigation, Writing–review & editing. **L. Brilli:** Investigation, Writing–review & editing. **N. Staglianò:** Investigation, Writing–review & editing. **G. Argenti:** Investigation, Writing–review & editing. **G. Capello:** Data curation, Writing–review & editing. **E. Paradivino:** Data curation, Writing–review & editing. **S. Bussotti:** Data curation, Writing–review & editing. **C. Dibari:** Writing–review & editing; **M. Bindi:** Supervision, Writing–review & editing. **K. Ratković:** Writing–review & editing; **M. Simeunovic:** Writing–review & editing. **M. Moriondo:** Conceptualization, Methodology, Software, Writing–review & editing.

Declaration of Competing Interest

Authors declare no conflict of interest

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ijagro.2025.100059.

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