Modelling olive trees and grapevines in a changing climate

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ABSTRACT

The models developed for simulating olive tree and grapevine yields were reviewed by focussing on the major limitations of these models for their application in a changing climate. Empirical models, which exploit the statistical relationship between climate and yield, and process based models, where crop behaviour is defined by a range of relationships describing the main plant processes, were considered. The results highlighted that the application of empirical models to future climatic conditions (i.e. future climate scenarios) is unreliable since important statistical approaches and predictors are still lacking. While process-based models have the potential for application in climate-change impact assessments, our analysis demonstrated how the simulation of many processes affected by warmer and CO2-enriched conditions may give rise to important biases. Conversely, some crop model improvements could be applied at this stage since specific sub-models accounting for the effect of elevated temperatures and CO2 concentration were already developed.

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1. Introduction

Grapevine and olive tree represent worldwide key economic activities with Europe representing the largest vineyard area in the world (38%, Fraga et al., 2012) and olive tree widespread cultivated around the Mediterranean basin (Vossen, 2007). Besides their economic importance, the cultivation of these species provides a number of services for the society, including landscape maintenance and improvement, enhancement of the quality of life, and ecological and environmental services (Loumou and Giourga, 2003; Nieto et al., 2010).

Centuries of experience in the cultivation of these crops have resulted in a strong association of both olive and grapevine growing with geographically distinct regions in European countries (Jones et al., 2005; Moriondo et al., 2013a,b). Over these areas, olive trees and grapevines are confined to specific climatic niches that put them at greater risk from temperature and rainfall changes. For instance, rising temperatures, as predicted in future climate scenarios, could have a strong impact on grape growth and wine quality (Jones et al., 2005), especially if they occur during the growing season (Jones and Davis, 2000).

Olive grove and grapevine productivity, and consequently profitability, depend on several factors including soil fertility, management practices, climate and meteorology. Since the profitability of a crop is a prerequisite for its cultivation, there is a subsequent need for a reliable assessment of the effects of a changing climate on its yield and quality. This would help to define the possible economic impact on the areas where they are currently cultivated, as well as on the regions in which cultivation could become viable in the future.

In this context, crop models are essential tools for investigating the effects of climate change on crop development and growth via the integration of existing knowledge of crop physiology relating to changing environmental conditions. This approach could provide a unique opportunity to assess possible effects of a warmer climate on crop yield and quality, as well as to evaluate different adaptation options for reducing or exploiting the effects of a changing climate. As such, crop models were extensively applied to assess the potential of various crops on farm, regional and national scales. In

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particular, during the last 20 years, these tools were applied at different time and spatial scales to assess the potential impact of climate change on crop productivity, thereby providing a reliable benchmark to establish relevant adaptation options (White et al., 2011).

Despite their widespread use in studying crop productivity for both the present and future scenarios, crop models have shown limitations, which may simply be represented by the fact that when applied in similar conditions, different models often provide different results (Palosuo et al., 2011; Röter et al., 2012; Asseng et al., 2013). These differences are usually related to the specific approach used to describe a certain process that may be either over-simplified or even incorrectly outlined (Eitzinger et al., 2013).

Based on these premises, this paper provides a review of different models, either generally adapted to, or specifically developed for simulating grapevine and olive tree growth and development by focussing on the major limitations of these models, especially in their application to climate change impact and adaptation assessments.

The analysis first considers the type of modelling approach, i.e. empirical or process-based by detailing the level of their parameterization. Differences in the approaches adopted for the simulation of the main processes such as photosynthesis, leaf area growth, phenology, biomass accumulation and partitioning, and water and nutrient stress were further analysed for the process-based model. The strengths and weaknesses of each simulated process were evaluated and discussed in view of the recent advances in crop modelling. The analysis specifically outlined the following: i) the processes that are not yet simulated but may play an important role in climate-change impact assessment (e.g. the effect of increased CO2 on radiation and water-use efficiency, RUE, WUE) (Tubiello and Ewert, 2002); ii) the effects of extreme events on crop yield (Moriondo et al., 2011a); iii) the impact on yield quality.

2. Modelling approaches

The models selected for this analysis can be divided into two categories, namely (i) empirical and (ii) process-based. In the first category, statistical methods are used to generally describe a linear relationship between the dependent (e.g. crop yield) and predictor variables accounting for the fact that climate (e.g. climate indices such as cumulated rainfall or average temperature of a certain month) is one of the key factors influencing yield quantity and quality (Jones et al., 2005). Conversely, other processes like plant development, Leaf Area Index (LAI) growth, and nitrogen dynamics in the soil are not considered. These models may be summarized according to the following linear equation:

\[ Y_j = \alpha T_j + \beta R_j + \cdots + \delta \]

where \( Y \) is the yield quantity or quality, \( T \) and \( R \) are predicting variables aggregated at different time scales (i) usually monthly, seasonal or yearly) in the year \( j \), \( \alpha, \beta \) are the regression co-efficients, and \( \delta \) is the intercept.

As such, empirical models need a limited amount of input data to produce an output but cause-effects mechanisms between climate and yield are not explicitly described and this limits the applicability of this approach to the specific regions or environmental conditions for which the relationships were calibrated.

Conversely, in process based models, crop behaviour is defined by a range of relationships describing the main plant processes. Crop models working at different levels of detail basically include the simulation of 1) crop development, which indicates the period by which crop growth should get started, the priorities in dry matter partitioning, and the maturity; 2) biomass accumulation, which is a function of the amount of Photosynthetically Active Radiation (PAR) intercepted by the canopy and the efficiency via which the intercepted PAR is converted into dry matter. Depending on the model, potential biomass accumulation may then be reduced by water, nitrogen stress, or heat stress; 3) biomass partitioning to the different organs, (leaves, stem, fruit, and roots) according to the priorities during the plant life cycle, providing a feedback for updating the simulation of leaf area extension and the growth of stem, fruit and roots (Fig. 1). A specific sub-class of these models include functional models that are oriented to simulate specific plant processes such as daily CO2 exchange or water dynamics in the soil while sketching or neglecting other processes such as phenology, biomass partitioning or abiotic stresses.

Further, process-based models, originally designed to work on field scale (Sinclair and Seligman, 1996), explicitly includes non-climatic factors, such as management practices (e.g. sowing dates, fertilization) or soils type, as determinants of crop yield.

As such, process based models, may be easily applied to simulate crop yield on a local scale, provided that climatic and non-climatic information are available at the required scale.

Based on these premises, the different approaches used to simulate plant growth and development were compared separately for each category of model, emphasizing the relevant limitations in the light of new findings in the specific approach.

2.1. Empirical models

The driving variables used to fit empirical models for yield prediction are generally temperature (\( T \)) and rainfall (\( R \)) aggregated on a monthly timescale (Table 1). Despite the large variability of the environments where these models were parameterized, there is a generally good agreement regarding the variables selected as the best predictors of final yield. This implies that these models are able to detect the importance of critical stages in determining final yield, even when there is a rough resolution of the input variables.

Under this context, Nemani et al. (2001) correlated the positive trend in grapevine yield of the Napa valley (1963–1996) to the
increasing minimum temperature (Tmin) observed in spring. Santos et al. (2011) found that high precipitation in early spring as well as relatively low precipitation together with high temperatures in late spring increased grapevine yield in the Porto wine region (Portugal). These findings partially overlap those of Jones and Davis (2000) that showed an increase in precipitation during the budburst-flowering and veraison–harvest periods to be associated with lower yields. These responses are generally attributed to favourable/non-favourable events during the critical stages of the grapevine developmental cycle, which in turn determine a positive/negative impact on crop yield. For example, high precipitation during anthesis were reported to have a detrimental impact on yield, due to the effect of a lower fruit set and inflorescence differentiation (Jones and Davis, 2000).

Other studies demonstrated that climate conditions of previous year may play a role as well in determining the final yield of the following year. Lobell et al. (2006) found that minimum temperatures in April and cumulated rainfall in June and September prior to harvest are positively correlated to grapevine yield anomalies in California. The influence of the previous year, also observed by Quiroga and Iglesias (2009) is consistent with the Mediterranean environments and is related to the accumulation of soil moisture during the wet period that assures vegetative vigour at the onset of the season. Interestingly, Lobell et al. (2006) introduced a corresponding negative quadratic term for each predictive variable, accounting for the non-linear response of grape yield to environmental variables. This can play a fundamental role, especially for impact assessment studies, when these empirical models are coupled to climate scenarios in which temperature and rainfall exceed those generally observed in the area.

Quiroga and Iglesias (2009) introduced an empiric model considering both climate and technological variables (consumption of nitrogen fertilizers, farm-machinery power, irrigation) in estimating grapevine yield. Climatic data were introduced in the model using both monthly and seasonal aggregation periods. Yearly drought explained a significant component of the inter-annual variability of grapevine yield, with high temperatures having a general negative effect.

For olive trees, the same study pointed out that both management practices (irrigation and fertilization) and precipitation around anthesis (April) and during fruit development have a positive impact on final yield.

In addition to the meteorological variables, other studies also used air pollen concentration of olive trees as an explicative variable of yield formation (e.g. Moriondo et al., 2001; Galán et al., 2004, 2008). The pollen quantities can in fact be considered a proxy variable of the potential productivity of olive groves located around the pollen traps (Moriondo et al., 2001), and in many cases pollen quantity acts as the most important predictive parameter of olive yield. Additional climatic information, recorded during the olive tree growth cycle, acts either to reduce or increase yield, but with a lower predictive capacity compared to the biological variable expressed by the pollen emitted.

For grapevines, climate undoubtedly plays a major role in determining berry composition, and simple relationships between yield quality and climate parameters were exploited in several papers. Both temperature and rainfall have demonstrated to be primary determinants of berry composition and grape quality. Quality itself in modelling approaches was defined in different ways, ranging from vintage quality, i.e. a quality score scaled between a minimum and a maximum value, to wine ratings, and sugar and acid concentrations (Barnuud et al., 2013).

Nemani et al. (2001) pointed out how the decreasing trend in frost events in the 1963–1996 period was strongly associated with increasing wine ratings. For the Bordeaux wine region, Jones and Davis (2000) used a numeric vintage quality rating as a dependent variable versus meteorological variables (i.e. cumulated R, averaged T and radiation) over each phenological-phase duration.

Table 1
Predictors of yield and quality of grapevine and olive tree according to different empirical models.

<table>
<thead>
<tr>
<th>Author</th>
<th>Crop</th>
<th>Region</th>
<th>Meteorological variables</th>
<th>Output</th>
<th>Season</th>
<th>CC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Santos et al. (2011)</td>
<td>Grapevine</td>
<td>Porto (PT)</td>
<td>T</td>
<td>Yield</td>
<td>Winter</td>
<td>1</td>
</tr>
<tr>
<td>Jones and Davis (2000)</td>
<td></td>
<td>Bordeaux (FR)</td>
<td>T</td>
<td>Yield</td>
<td>Spring</td>
<td>0</td>
</tr>
<tr>
<td>Nemani et al. (2001)</td>
<td></td>
<td>Napa Valley</td>
<td>T</td>
<td>Yield</td>
<td>Summer</td>
<td>0</td>
</tr>
<tr>
<td>Lobell et al. (2006)</td>
<td></td>
<td>California</td>
<td>T*</td>
<td>Yield</td>
<td>Fall</td>
<td>1</td>
</tr>
<tr>
<td>Quiroga and Iglesias (2009)</td>
<td>Olive tree</td>
<td>Mediterranean basin</td>
<td>T*</td>
<td>Yield</td>
<td></td>
<td>0</td>
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<tr>
<td>Nemani et al. (2001)</td>
<td></td>
<td>Napa Valley</td>
<td>T</td>
<td>Qual.</td>
<td></td>
<td>0</td>
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<tr>
<td>Jones et al. (2000)</td>
<td>Grapevine</td>
<td>Bordeaux (FR)</td>
<td>T</td>
<td>Qual.</td>
<td></td>
<td>0</td>
</tr>
<tr>
<td>Jones et al. (2005)</td>
<td>Olive tree</td>
<td>Global scale</td>
<td>T</td>
<td>Qual.</td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Moriondo et al. (2011b)</td>
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<td>Chianti (IT)</td>
<td>T*</td>
<td>Qual.</td>
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<td>Quiroga and Iglesias (2009)</td>
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<td>Mediterranean basin</td>
<td>T*</td>
<td>Yield</td>
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<td>T*</td>
<td>Yield</td>
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</tr>
<tr>
<td>Moriondo et al. (2001)</td>
<td>Grapevine</td>
<td>Tuscany (IT)</td>
<td>T</td>
<td>Yield</td>
<td></td>
<td>0</td>
</tr>
</tbody>
</table>

Signs + and – refers to correlation sign of the relationship between predictor variables and quality/yield; T – temperature, R – cumulated rainfall, C – grapevine, O – olive tree; * – non-linear model equation. The last column (CC) indicates whether the model was developed for climate change impact assessment (0 = not; 1 = yes).
(e.g. from bud break to anthesis, from anthesis to veraison) along with the number of events where a variable was above or below a threshold. High radiation levels during the bud break interval had a positive impact on yield quality, as well as the number of events with temperatures higher than 30 °C during the anthesis-veraison phase. Conversely, rainfall during veraison caused a reduction in quality. The positive effect of radiation (RAD) and temperature during the bud break-veraison stage may be ascribed to high levels of photosynthetic activity that induce complete maturation, while the negative impact of rainfall may be due to berry dilution and/or moisture-related problems.

Similar results were obtained by Jones et al. (2005) and Moriondo et al. (2011b), indicating that the average T of the growing season is a valid predictor of vintage quality in many parts of the world, and in many cases this relationship is not linear. Moreover, Moriondo et al. (2011b) refined the approach for the Chianti region (Italy) emphasizing how the negative effect of rainfall in the months prior to harvest is possibly related to the dilution of berries during the ripening phase and the onset of fungal diseases triggered by high humidity.

2.2. Process-based models

Different kinds of process-based models were developed for grapevines and olive trees, ranging from crop models, which aim at simulating the entire crop growth cycle, to functional models, which focus on specific processes such as plant gas exchange and water dynamics in the soil. For grapevines, we cited Gutierrez et al. (1985), Wermeling et al. (1991), Bindi et al. (1997), Pallas et al. (2011), STICS (Brisson et al., 2009), Cropsyst (Stöckle et al., 2003) and SUCROS (as modified for grapevines in Nendel and Kersebaum, 2004), VineLogic (Godwin et al., 2002) and Cola et al. (2014). For olive trees, a few models were found in literature. These range from crop models (Abdel-Razik, 1989; Gutierrez et al., 2006; Maselli et al., 2012), or are unbalanced with regard to the functional approach (Viola et al., 2012) which describe in detail leaf gas exchange.

Despite the heterogeneity in the model structure (Table 2), some comments and specific recommendations for each process may be made, especially in view of the increasing temperatures and atmospheric CO₂ concentrations.

2.2.1. Crop development

The simulation of crop development is a fundamental step for correct simulation of plant growth, where the timing of each developmental stage corresponds to a change in carbon assimilation, transpiration, partitioning of carbohydrates and nutrients. As such, the simulation of phenology is included in all the crop models analysed (Bindi et al., 1997; Cropsyst; STICS; Abdel-Razik, 1989; Nendel and Kersebaum, 2004), for ensuring a reliable simulation of growth of single plant organs or merely for setting the start of anthesis (Maselli et al., 2012). Conversely, it is often neglected in models focussing on single processes such as light interception (Villalobos et al., 2013), leaf gas exchange (Poni et al., 2006; Viola et al., 2012), or water dynamics in the soil (Lebon et al., 2003; Celette et al., 2010).

The occurrence of each phenological stage (basically bud burst, anthesis and maturation) is based on the accumulation of temperatures above a threshold calculated on a daily (degree day accumulation, DDA) or hourly time step (e.g. Normal Heat Hours, NHH) up to a fixed amount, which is variety dependent. In Bindi et al. (1997), Ben-Asher et al. (2006), Abdel-Razik (1989) and Cola et al. (2014) the thermal forcing of DDA to bud burst starts on a fixed day of the year. In STICS, and SUCROS for grapevine and Maselli et al. (2012) for olive the accumulation of temperature only starts after the end of dormancy and is triggered when a specific number of chill units has accumulated during winter. Cropsyst uses the same approach but the end of dormancy occurs after seven consecutive days with temperatures above 10 °C (Fig. 2).

2.2.1.1. Issues related to climate change. Reviewed literature indicates that robust phenological models are required to give more certainty to extrapolations of global-change scenarios (Chuine, 2000; Caffarra and Eccel, 2010) since adaptation relies also on phenological performances in response to a warmer climate (Duchêne et al., 2010). Until now, great efforts were taken to develop and test models to predict bud-break for both grapevines and olive trees. This stage, while representing the beginning of the growing season and hence the accumulation of biomass, is also important as an indicator of variety earliness and therefore, adaptability to different climates (Jones et al., 2005; Garcia de Cortazar-Atauri et al., 2009; Webb et al., 2007). For grapevines, the results of Caffarra and Eccel (2010) which compare the performance of a number of phenological models in predicting bud burst, indicated that process-based models accounting for the effect of the chilling unit on dormancy release (Unified Model for Bud Burst, Chuine, 2000) provide the highest performance for the Chardonnay variety in Northern Italy. In particular, rises in temperature after fulfillment of the critical chill requirement help delay the bud-burst stage by increasing the sum of accumulated forcing units.

These results partially overlap those of Garcia de Cortazar-Atauri et al. (2009, 2010), which conclude that even though the calculation of dormancy release using chill units is not a critical factor for improving model performance in this period, it may assume more importance given the expected rise in temperature in the future. A similar approach based on chill days and a subsequent forcing stage was described as effective for olive trees in predicting both bud burst (Cesaraccio et al., 2004) and bud burst and anthesis (De Melo-Abreu et al., 2004).

According to these findings, a warmer climate would give rise to a postponing rather than a advancing of the bud burst date. In any case the advance of this phase would not be proportional to the increase in temperature. Conversely, phenological models based solely on a thermal time accumulation (i.e. Bindi et al., 1997; Ben-Asher et al., 2006; Abdel-Razik, 1989), would undoubtedly overestimate this effect in a warmer climate due to being linearly related to temperature. When applying these models in future climate scenarios, increasing temperatures would gradually bring the occurrence of the phenological stages forward to unrealistic dates (Fig. 2). This, in turn, would further reduce the time for biomass accumulation, overestimating the expected impact of climate change on yield.

2.2.2. Leaf-area growth and intercepted radiation

In many cases, leaf area is empirically simulated as dependent on temperature. Bindi et al. (1997) calculates leaf emission rate as related to average daily temperature and finally simulates total leaf area using an empirical relationship between the number of appeared leaves and the shoot-leaf area. Similarly, in STICS, the leaf-growth rate is dependent on the temperature and phenological stages. Lebon et al. (2003) used a simplified grapevine canopy model consisting of a parallelepiped, the vertical sides of which can be penetrated by the light, where the increase in canopy dimensions and the relevant intercepted radiation are linearly related to cumulative thermal time. Cola et al. (2014) used the same approach as modified in Oyarzun et al. (2007). In Poni et al. (2006), the leaf-area expansion rate is dependent on the degree days and accounts for the effect of the management practices (trimmed shoots). Gutierrez et al. (1985), Wermeling et al. (1991), Nendel
### Table 2
List of models under analysis for olive tree and grapevine.

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<td></td>
<td>Briisson et al., 2009</td>
<td>3/3D</td>
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<td>Prt/B</td>
<td>S/F/L/R/Tr</td>
<td>T/DC/CU</td>
<td>EXP</td>
<td>LIN</td>
<td>W/N/S/T/Tr</td>
<td>P</td>
<td>CN/P/4/B</td>
<td>RUE/WUE</td>
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<td>P/TS</td>
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<td>Prt/B</td>
<td>F</td>
<td>T</td>
<td>LIN</td>
<td>W/Trp</td>
<td>C</td>
<td>P</td>
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<td>3D</td>
<td>P-R</td>
<td>Prt/B</td>
<td>S/L/R/T</td>
<td>T/DC/CU</td>
<td>EXP</td>
<td>LIN</td>
<td>W/N/Trp/CC</td>
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<td>S</td>
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<td>LIN</td>
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"a Light interception model. S, simple approach (e.g. LAI); D, detailed approach (e.g. canopy layers); 3D, three dimensions model.

"b Conversion of intercepted radiation into dry matter. RUE, radiation use efficiency approach; P-R, gross photosynthesis — respiration; WUE, water use efficiency.

"c Conversion of biomass into final yield. HI, fixed harvest index; B, total (above-ground) biomass; Prt, partitioning during reproductive stages; HI_mw, harvest index modified by water stress.

"d Biomass partitioning. Dry matter is allocated to: S, stem; L, leaves, F, fruit; R, storage organs.

"e Phenology driving variables. T, temperature; DL, photoperiod (day length); CU, chill units to the end of dormancy; O, other water/nutrient stress effects considered.

"f Model describing root growth. LIN, linear, EXP, exponential, SIG, sigmoidal, Call, carbon allocation; O, other approaches.

"g Stress factors reducing potential biomass. W, water limitation; N, nitrogen limitation; A, aeration deficit stress; H, heat stress; Trp, temperature response of photosynthesis (or RUE) and respiration; S, salinity; CC, cloud coverage.

"h Description of water dynamics in the soil. C, capacity approach; R, Richards approach.

"i ET models. P, Penman; PM, Penman-Monteith; PT, Priestley–Taylor; R, Ritchie, SW, Shettleworth and Wallace.

"j CN model; N, N model; P(x), x number of organic matter pools; B, microbial biomass pool.

"k Effect of high CO₂ on physiological parameters. RUE, radiation use efficiency; WUE, water use efficiency; P, Photosynthesis model.

"l Climate variables driving the model. Cl, cloudiness; R, rainfall; Tx, maximum daily temperature; Tn, minimum daily temperature; Ta, average daily temperature; Td, dew point temperature; Rd, radiation; e, vapour pressure; RH, relative humidity; W, wind speed; CC, cloud coverage.

"m Crop management. D planting density; P, pruning; T shoot trimming with a feedback to leaf area growth; TS, trellis system; I, intercropping.

"n Number of varieties calibrated.

"o Application of the model elsewhere than in the calibration site: 1) Webb et al. (2007); Zhang et al. (2002); 2) Garcia de Cortazar Atauri (2006); Valdés-Gómez et al. (2009); 3) Wermelinger et al. (1991); 4) Williams et al. (1985); 5) Orlando et al. (2008); 6) Ponti et al. (2014).

"p Programming language used (when applicable). F, Fortran, C, C++; S, Stella environment; E, Excel; G, GreenLab environment.
season in response to water stress or to a strong competition. Lebon et al. (2004) suggest that this rate may decrease during the growing season as a consequence of water stress and increased competition. The relationship is valid under a wide range of temperatures. However, models have never simulated the effects of extreme weather events such as prolonged heat waves or drought periods that are likely to increase both in frequency and intensity in the near future. Future climate conditions will likely result in reduced RUE. Similarly, nitrogen limiting conditions may cause a reduction in leaf gas exchange and also in CO2 exchange, results in reduced RUE. Similarly, nitrogen limiting conditions may also represent an important source of variation in RUE (Sinclair and Muchow, 1999). These effects must be taken into account especially when designing the cultivation of olive trees and grapevines in the future, where increasing temperatures and reduced rainfall are predicted over most of the grapevine and olive growing areas (Moriondo et al., 2013a,b).

2.2.2.1. Issues related to climate change.

The use of RUE was extensively applied in the models under analysis. This coefficient is conservative in non-limiting conditions but when the plants are outside this range, the RUE was found to be reduced: water stress, causing a reduction in leaf gas exchange and also in CO2 exchange, results in reduced RUE. Similarly, nitrogen limiting conditions may also represent an important source of variation in RUE (Sinclair and Muchow, 1999). These effects must be taken into account especially when designing the cultivation of olive trees and grapevines in the future, where increasing temperatures and reduced rainfall are predicted over most of the grapevine and olive growing areas (Moriondo et al., 2013a,b).

2.2.3. Biomass accumulation

Biomass accumulation is calculated according to the amount of active photosynthetic radiation (PAR) intercepted by the canopy that is translated into biomass (B) using a parameter or function describing the efficiency of this process. The light or Radiation Use Efficiency (RUE, g dry matter m⁻² MJ⁻¹) is a simple empirical coefficient describing the linear dependence of B on PAR, providing an efficient way to estimate the net dry matter production per unit of absorbed energy (i.e., gross primary production — (maintenance and growth respirations)]. This approach was extensively applied in semi-empirical crop modelling approaches, including grapevines (Bindi et al., 1996; Pallas et al., 2011; Gutierrez et al., 1985; Wermelinger et al., 1991) and olive trees (Villalobos et al., 2006; Maselli et al., 2012).

RUE is also used in complex models such as STICS (Brisson et al., 2003). Other approaches, such as CropSyst (Stöckle et al., 2003) relies on the use of Water Use Efficiency, i.e., the amount of biomass assimilated per unit of water transpired (WUE, g dry matter m⁻² MJ⁻¹).

Poni et al. (2006) calculated the net photosynthetic rate as the difference between the gross daily integral of canopy photosynthesis and the respiration rates for leaves, stems and clusters. The same scheme is applied in Nendel and Kersebaum (2004) for grapevines and Abdel-Razik (1989) for olive trees. In Viola et al. (2012) biomass accumulation is obtained by applying the photosynthetic model proposed by Farquhar et al. (1980).

2.2.3.1. Issues related to climate change.

The use of RUE was extensively applied in the models under analysis. This coefficient is conservative in non-limiting conditions but when the plants are outside this range, the RUE was found to be reduced: water stress, causing a reduction in leaf gas exchange and also in CO2 exchange, results in reduced RUE. Similarly, nitrogen limiting conditions may also represent an important source of variation in RUE (Sinclair and Muchow, 1999). These effects must be taken into account especially when designing the cultivation of olive trees and grapevines in the future, where increasing temperatures and reduced rainfall are predicted over most of the grapevine and olive growing areas (Moriondo et al., 2013a,b).
At the same time, higher CO₂, as expected in the future, was observed to increase both RUE and WUE (Tognetti et al., 2001; Bindi et al., 2001) (Table 2). Therefore, the interaction between the positive and negative effects of a changing climate should be considered for reliable simulations.

Simple models partially reproduce the balance between the positive and negative effects of climate change on photosynthetic efficiency. For grapevines, Bindi et al. (1997) found that RUE decreases for suboptimal temperatures and water in the soil, whereas the RUE is set to +30% due to a doubling of the CO₂ concentration (700 ppm) (Fig. 3a). In non-limiting water conditions, Poni et al. (2006) only set a reduction in assimilation starting from 31 °C whereas the effect of higher CO₂ was not included. The effect of water stress was considered in Lebon et al. (2003), Bindi et al. (1997) and Viola et al. (2012) where the assimilation efficiency is dependent on the water available in the soil according to a bilinear response function. A similar approach was used in Maselli et al. (2012) based on a simplified water balance for olive trees, where a CO₂ fertilization factor (Veroostraete et al., 2004) was used to account for the effect of increased CO₂ on the RUE. In all these cases, no specific adjustment was found for nutrient-limiting conditions. Complex crop models have different approaches where the interaction between high CO₂ and water/nitrogen stress is organized more efficiently. In CropSyst, unstressed biomass accumulation previously calculated using increased RUE/WUE is then corrected for water or Nitrogen limitation. In STICS, the effect of stress conditions directly affects plant growth by reducing the maximum RUE (Brisson et al., 2003) whereas the effect of increased CO₂ is accounted for by increasing the RUE with specific coefficients (Tubiello et al., 2000; Brisson et al., 2003) (Fig. 3b). In Nendel and Kersebaum (2004), photo-assimilation can be restricted either by water stress, determined by the ratio of actual to potential transpiration, or by nitrogen deficiency.

The interaction between rising temperatures combined with high CO₂ adds to the complexity in simulating the plant responses in future scenarios (Schultz and Stoll, 2010) since these variables were shown to have a synergistic effect on photosynthesis (Sage and Kubien, 2007). This was confirmed for grapevines in Schultz (2000) and Salazar-Parra et al. (2012a, b), where the optimum temperature for photosynthesis shifted in response to higher CO₂ concentrations (Fig. 4 and Table 3).

2.2.4. Biomass partitioning

In semi-empirical models, biomass partitioning to different plant organs (root, stems, leaf and fruit) is generally poorly simulated or even neglected. For instance, for grapevines, Bindi et al. (1997) only considered biomass partitioned daily to fruits, while for olive trees Villalobos et al. (2006), Maselli et al. (2012) and Viola et al. (2012) only used a fixed HI to be applied to the total cumulated biomass at the end of the season.

In functional models that focus more on the simulation of a particular process rather than on the entire plant growth (i.e. gas exchange in Poni et al., 2006; or water dynamics in the soil in Ben-Asher et al., 2006; Celette et al., 2010; Lebon et al., 2003), only the daily biomass accumulation is calculated and the growth of single plant organs is not considered.

In complex models, partitioning is simulated with different approaches. In CropSyst and Nendel and Kersebaum (2004), dry matter is partitioned amongst the various organs according fixed partitioning factors that are function of phenological development stage of crop. Gutierrez et al. (1985), Wermelingler et al. (1991) and Abdel-Razik (1989) STICS and Pallas et al. (2011) used source/sink approach where biomass is partitioned to different organs according to the relevant ability to attract available assimilated from source.

2.2.4.1. Issues related to climate change. Biomass partitioning to single organs may be implemented via fixed proportions that only

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**Fig. 3.** a. Effects of a rise in temperature on the photosynthetic efficiency according to different models (see Table 1 for references). b. Effects of increasing water stress on leaf transpiration as in Lebon et al. (2003), Bindi et al. (1997) and STICS (Brisson et al., 2009) assuming transpiration to be proportional to the gas exchange capability of the plant, used the same model to modify RUE in relation to water stress. FTSW = fraction of total soil water, i.e. the amount of water in the soil with respect to the water available between the filed capacity and the wilting point.

**Fig. 4.** Effects of increasing leaf temperature coupled with a different CO₂ concentration on the grapevine leaf photosynthetic rate (Schultz, 2000). Data were fitted to a second order polynomial equation. The analysis of the first derivative of these equations indicated that the optimum temperature for photosynthesis rises from 31.4 °C (CO₂ = 364 ppm) to 33 °C (CO₂ = 605 ppm).
varying according to the phenological stage. Conversely, the change in distribution of resources amongst different plant organs in response to stress plays a key role in the fitting capacity of plants (Grechi et al., 2007). As observed for many species (Keller and Koblet, 1995; Zerihun and Treeby, 2002), plants provide more resources to the organs responsible for the uptake of a limiting resource compared to non-limiting conditions. This was observed in limiting water and nitrogen conditions for both grapevines and olive trees. For grapevines, Bota et al. (2004) found that water stress may alter the assimilate distribution pattern especially towards the trunk and roots with a reduced contribution to clusters. Grechi et al. (2007) provided evidence that suboptimal nitrogen application affected leaf canopy development while a larger portion of available assimilates translocated from the leaves into the root system (i.e. the organ responsible for balancing the correct plant C/N ratio). Similar results were obtained in Rodíguez-Lovelle and Gaudillère (2002), who observed an increased root/shoot ratio in grapevines in low nitrogen conditions.

In olive trees, Boussadja et al. (2010) observed that limiting nitrogen conditions promote biomass allocation to favour root elongation. In drought conditions, Bongi (1994) concluded that water shortage increases carbon partitioning used for root formation, thereby reducing the carbon available for aboveground canopy growth. These results are confirmed in Celano et al. (1997) and Sofo et al. (2008) who found an increasing root/canopy ratio that was usually greater in non-irrigated plants as a mechanism to enhance water uptake efficiency.

Crop growth simulation models should therefore be improved using dynamic allocation rules, especially in view of the expected future climate. From this point of view, the models using a source-sink approach provide a better framework to implement the dynamics in biomass partitioning according to the specific growing conditions.

The effect of CO₂ concentration on biomass partitioning in grapevines and olive trees is an additional issue. For instance, Norby et al. (2002) indicated that in FACE experiments on a forest ecosystem, the biomass partition coefficients changed in response to higher CO₂. In these conditions, the extra carbon is mainly allocated to leaves and fine roots, as also suggested by other authors for different ecosystems (e.g. Luo et al., 1996). The results of Bindi et al. (2001) highlight a significant effect of CO₂ enrichment on biomass partitioning of grapevines, where plants at 700 ppm showed a higher efficiency of carbon partition to leaves compared to control (350 ppm) conditions (Fig. 5).

### 2.2.5. ETP and water stress

PET is generally calculated according to the approaches of Penman-Monteith as reported in Allen et al. (1998) that is converted into evapotranspiration in compliance with the coefficients accounting for the crop development stages (e.g. cultural coefficients Kc or the fraction of intercepted crop radiation; Fig. 6A). In STICS, PET is calculated using the Penman-Monteith model separately applied for the soil and crop surfaces (Shuttleworth and Wallace, 1985), accounting for the fact that grapevine do not provide a close and uniform canopy. Similarly, in some model, PET is empirically partitioned into daily transpiration and soil evaporation which are converted into actual ET according to specific thresholds which reduces the process from the relevant compartments. (e.g. Lebon et al., 2006; Cellette et al., 2010).

Bindi et al. (2001), assuming WUE as invariant for a wide range of environmental conditions (e.g. Amir and Sinclair, 1991), calculated crop transpiration as the product of WUE and daily simulated biomass accumulation.

In those models considering the effect of water stress, crop ETP is converted into actual transpiration using reducing factors that are dependent on soil moisture conditions relating to available plant water (roughly the amount of water included between the field capacity and the wilting point).

#### 2.2.5.1. Issues related to climate change

Increasing CO₂ concentrations and warmer temperatures have an opposite effect on ETP. While higher CO₂ causes a decrease in stomatal conductance, transpiration per unit surface is decreased. By contrast, higher air temperatures increase transpiration by increasing the vapour pressure deficit (VPD), i.e. the differences between the actual

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**Table 3**

<table>
<thead>
<tr>
<th>Treat.</th>
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<tr>
<td>Moutinho-Pereira et al. (2006), Salazar-Parra et al. (2012a, b)</td>
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<tr>
<td></td>
<td></td>
<td>Grapevine (var. Tempranillo)</td>
<td>PI</td>
</tr>
<tr>
<td>Bindi et al. (2001)</td>
<td>Grapevine (var Sangiovese)</td>
<td></td>
<td>1.0 g MJ⁻¹</td>
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</tr>
<tr>
<td></td>
<td>Olive (var. Picual)</td>
<td></td>
<td>21.08 μmol CO₂ m⁻²s⁻¹</td>
</tr>
</tbody>
</table>

WI = well irrigated; PI = partially irrigated; (4) = -4 °C with respect to control treatment at 350 ppm.

* Significantly different from the control at 350 ppm. In Melgar et al. (2008) and Salazar-Parra et al. (2012a,b) the maximum differences between treatments during the season were reported.

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**Fig. 5** Leaf mass in relation to total above ground grapevine biomass grown at 350 ppm and 700 ppm (Bindi et al., 1997; unpublished data). Treatment and control follow the same trend until the beginning of fruit growth. Afterwards, plants growing at 700 ppm partitioned more biomass to leaves compared to the control plant. This may be the effect of a reduced fruit sink strength in grapevine var. Sangiovese, that is limited to 2 grapes per shoot. The excess of carbon is then stored in leaves and, likely, in roots. The regression slopes are significantly different for $P < 0.05$.
The approach presented in Villalobos et al. (2013) allows for overcoming the missing effect of carbon dioxide on transpiration WUE and is more easily implementable due to a reduced number of input parameters compared to the FAO approach. This model presents the transpiration rate as dependent on the ratio between canopy-intercepted radiation, radiation-use efficiency and CO2 concentration in the boundary layer. Accordingly, the proposed model could consider both the changes in canopy conductance by modifying the relevant coefficients in proportion to the atmospheric CO2 concentration and the expected changes in radiation-use efficiency (Fig. 6b).

2.2.6. Grape quality

The general overview shows that while the simulation of yield quality should be a highly desirable model output for grapevines, this is not considered in grapevine simulation models but only in STICS, which exploits an empirical relationship between berry-water content and sugar concentration (Garcia de Cortazar-Atauri et al., 2009). Conversely, additional process-based approaches specifically developed to simulate berry quality (i.e. sugar content, reviewed in Dai et al., 2010), were not yet dynamically included into a crop growth simulation model. The general framework of these models, focuses on the simulation of processes involved in sugar importing, partitioning, and accumulation in berries.

2.2.6.1. Issues related to climate change

While the berry sugar content has a genetic fingerprint (Liu et al., 2007), the climatic environment and management practices (pruning, fruit thinning, green tipping, leaf removal, and fertilization) also play an important role and the interaction between these components is a challenge for grapevine growers, especially in the context of global change. For example, leaf removal during ripening may increase the temperature of the grape leading to early sugar ripeness, whereas acids are depleted, causing unbalanced wines. This trend is likely to be exacerbated in a warmer climate where the effect of increased CO2 should also be considered since it was demonstrated to have a significant effect on the concentration of sugar and acid in the grape (Bindi et al., 2001). From this point of view, the empirical model such as in Garcia de Cortazar-Atauri et al. (2009) (included in STICS), that links sugar content directly to berry water status, may fail to reproduce the effects of increased CO2 assimilation on assimilate partitioning to the fruit and the expected increase in berry sugar content.

The use of functional models, linking biological responses to climate factors, is therefore recommended to obtain a reliable prediction of climate change impact on grape quality (Dai et al., 2009) in a warmer, CO2-enriched environment. As outlined in Dai et al. (2009), the hypothesis of coupling quality models to those predicting final yield does not seem to be realistic at the present time given the mismatch between the complexity of the processes simulated in crop growth and the functional models.

2.2.7. Canopy management practices

For grapevines, different management practices can easily be introduced in growth models by modifying the number of shoots per plant and the number of plants per square metres, which in turn modifies intercepted crop radiation. Models accounting for the three-dimensional shape (i.e. STICS, Lebon et al., 2003, Cola et al., 2014; Celette et al., 2010) may provide a better benchmark to test the effects of different trellis systems on crop growth as they allow for selecting different widths to height ratios of the crop and the relevant effect on the shadowing among rows. For olive trees, these effect were studied e.g. in Conner (2006), but such an approach was not yet included in a crop growth model.
The simulation of trimmed grapevine shoots was considered in Poni et al. (2006) while the same model was modified in Orlandini et al. (2008) to account for the effect of different trellis systems on grapevine biomass accumulation, while the effect of crown shape of olive tree was given a little attention in literature.

2.2.7.1. Issues related to climate change. The manipulation of crop shape according to different training systems has an influence on many processes such as carbon assimilation and water balance, and the study of these responses as well as their modelling may provide more insight into the adaptation of olive trees and grapevines to a warmer, drier climate.

Intercepted radiation, as influenced by grapevine geometry, is in fact a major determinant of grapevine water status (Williams and Ayars, 2005), where the systems intercepting more radiation (e.g. a canopy arranged on two parallel wires) generally result in a higher transpiration rate with respect to those arranged on a single curtain (Candolfi-Vasconcelos et al., 1994; Orlandini et al., 2008). The same may apply to the CO2 exchange rate of the whole canopy, which was found to be directly related to the amount of canopy light interception (Poni et al., 2003), where trellis systems with higher intercepted radiation tend to have a higher assimilation rate and a higher yield per vine (Orlandini et al., 2008). Accordingly, the modelling of these responses would allow for selecting a training system to balance water loss in relation to carbon gain in a climate change scenario.

Olive trees have a different canopy structure and planting strategy that in any case aim at maximising the interception of solar radiation with an appropriate distribution of radiation within the tree canopies.

The models presented in this review, while having the potential to include the effect of different shapes on canopy light interception and evapotranspiration, may fail to reproduce the effects that these changes have on grapevine growth. The only attempt to compare the effects of different trellis systems on grapevine growth was found in Orlandini et al. (2008), demonstrating that the crop model was not able to reproduce higher biomass accumulation as observed in the lyre trellis system (double curtain) versus the single curtain.

According to these observations, an important part of the modelling should be geared towards studying the effects of changes in canopy shape on photosynthetic rate, water relations and canopy microclimate, with particular attention to the new approaches developed in the last few years (Matese et al., 2014). The use of structural-functional models that integrate a virtual representation of the canopy considering its shape and leaf and shoot orientation, may simulate the physiological space-plant processes such as transpiration or photosynthesis. This coupled representation, already available for grapevines (Louarn et al., 2008), makes it possible to study the effects of a different canopy architecture on light interception, and thus on canopy energy balance, providing the expected feedback on carbon assimilation and water demand (Schultz and Stoll, 2010).

2.2.8. Soil organic carbon

More complex models, STICS, Cropysy and SUCROS, include the simulation of soil organic matter dynamics by considering the contribution of crop residue in the soil and the mineralisation of soil organic matter. In general the rate of crop residue decomposition is negatively dependent on the C/N ratio, while the mineralisation rate of soil organic matter is positively dependent on soil moisture and temperature.

2.2.8.1. Issues related to climate change. The implementation of sub-models to describe the dynamics of soil organic matter in crop models mainly focuses on assessing the kinetics of nitrogen to provide a feed-back on plant growth while the effects of soil organic matter on soil structure and properties are not usually considered. In a climate change context, the effects of soil organic matter on soil structure and consequently on soil hydraulic properties should be considered fundamental for improving the performance of the models.

More importantly, an increase in CO2 concentration is likely to change not only the total biomass of plants and their relevant residue, but also the composition of this material. FACE experiments on woody plants indicated that N concentration of leaves tends to decrease at high CO2 concentrations (Kimball et al., 2002), thus increasing the C/N ratio. This effect should be included in the simulation of residue decomposition as the C/N ratio affects its mineralization rate.

3. Discussion

3.1. General overview

Under the present review, empirical and process-based models were considered as mutually exclusive because these are developed for different purposes and therefore there is a mismatch between their underlying approaches.

Empirical models, do not require a heavy load of input parameters, and the final yield or quality are the only outputs required for these models. They can be easily calibrated by regression approaches with climate over large areas and are applicable on a large spatial scale using gridded climatic datasets. Conversely, since the underlying mechanisms that transform climatic input into yield or quality are not explicitly described, the use of these models should be restricted to the range of climate data from which they are developed (Landau et al., 2000).

The description of physiological processes provides good predictive performance especially on a local scale, where all required inputs should be available and environmental conditions (soil type, rainfall pattern, agricultural practices, e.g. irrigation, fertilization) are usually well defined.

While it should be noticed that these approaches cannot actually be completely separated since in any case process-based models contains a certain degree of empirism (e.g. related to the approximation of specific processes or fitting of equation coefficients), for olive tree and grapevine empirical and process based modelling represent two different lines of research with any mutual inter-relationship.

Conversely, some examples in the literature provide the evidence that empirical and process based approaches may find a common field of application, where the results of one may improve the simulation of the other one. Challinor et al. (2003) developed a combined system where the successful fitting of an empirical model, which links seasonal weather to yield, to a specific spatial scale, provide information on which scale a process based model should operate. Landau et al. (2000) used a multi-regressive approach to predict wheat yield as function of climate variables, which were aggregated over five phenological stages as determined by a phenological sub-model.

Interestingly, Challinor et al. (2003) highlight that the level of complexity of process-based model (i.e. the number of processes considered and their modelling approach) is inherently related to the working scale where this model is intended to be used. When looking at climate change impact assessment, whose spatial scale ranges from regional to continental areas, the use of complex process-based models is particularly unrealistic given the large input data required for these models. Conversely, the use of simplified process-based models, i.e. considering only the
processes having an impact on yield, are more appropriate to work on larger scale reducing, at the same time, the gap between approaches with high (i.e. process-based) and low (i.e. empiric approach) input data requirements.

However, so far large area process-based models for olive tree and grapevine is missing, and this reduces the applicability of these models for climate change impact assessment over wide scales. An exception is represented by the models of Bindi et al. (1996) and Gutierrez et al. (2009) that simulating the basic processes involved in olive and grapevine yield, matches the indications of Challinor et al. (2003) for a low-input process-based model to be applied for impact studies on large scales. These simulations are of a particular interest specifically for climate change impact assessment from regional to continental scale, where the outputs of the process-based models (i.e. crop yield) are used in turn input data to outline possible shift in cultivated area (Ferrise et al., 2015), or to feed economic models (Moriondo et al., 2011a,b; Zhu et al., 2014; Ponti et al., 2014). This kind of framework allowed to outline possible effects of a warming climate on farmer’s income and to propose reliable adaptation options. These studies represent a first step towards an integrated environmental modelling approach for grapevine and olive tree, where crop modelling is a part of a more comprehensive system, which in a holistic fashion, include the formulation of an environmental issue, the identification of the social-economic-environmental components of the relevant system, and an integrated modelling methodology to provide information synthesis (Laniak et al., 2013).

3.2. Specific recommendation

Our analysis showed how the formulation of empirical models is still lacking in important statistical approaches and predictors, especially when applied in a warmer climate. Major drawbacks include the following:

1) Yield quantity and quality are closely related to climatic indices calculated over specific phenological phases. Since the development of grapevines and olive trees is a predominantly temperature-driven process, it is expected that in a changing climate, warmer temperatures will likely shift the occurrence of phenological stages, as well as shortening the duration of the growing cycles (Webb et al., 2007; Ferrise et al., 2013). This may affect or even invalidate the significance of the models calibrated for this period and the empirical models could fail to simulate the correct impact of a warmer climate. The coherence of the approach could be improved by using a phenological model simulating for each scenario the shift of phenological events (e.g. Landau et al., 2000).

2) The effect of extreme weather events should be carefully considered when empirical models are applied to estimate yield in future decades. Temperature and rainfall aggregated on a monthly time step may fail to reveal information on extreme daily atmospheric events, i.e. events falling outside the range generally experienced by the crop during its growing cycle. Extremely high or low temperatures as well as intense rainfall or hail, in particular during sensitive growth stages, may limit yield and yield quality even with general favourable weather conditions for the rest of the season. For instance, temperatures above 35°C during flowering and throughout the growth of the grape berries were reported to have a detrimental impact on final quality due to premature veraison, high grape mortality, and partial or total failure of flavour compound formation (Mullins et al., 1992). In addition, Santos et al. (2011) ascribed the poor simulation of grapevine yield in the Douro region in particular years to missing information about extreme events such as frost or hail occurrence.

3) Prediction of the impact of a warmer climate may be biased by the linear approach used to model the effect of explanatory climatic variables on yield and quality. Jones et al. (2005) and Moriondo et al. (2011b) offer evidence that in many cases an optimum temperature threshold for ripening exists, above which final quality starts decreasing. The same approach was applied by Lobell et al. (2006) to model grapevine yield. To date, these are the only attempts to introduce a non-linear relationship between climate and yield or quality in grapevines, although these dynamics were already demonstrated for a number of crops including corn and soybean (Schlenker and Roberts, 2009), wheat, maize and barley (Lobell and Field, 2007).

4) Finally, the projected increase in CO2 concentration is expected to have a positive effect on grapevine growth and yield (e.g. Bindi et al., 2001), and also olive yield (e.g. Tognetti et al., 2001). Therefore, it should be included as a predictive variable. However, the fertilization effect of CO2 together with the increased water use efficiency was never considered in statistical approaches at least for grapevine and olive.

For process based models, we noticed that the perennial nature of olive trees and grapevines is rarely considered and therefore biomass partitioning to different organs and the relevant contribution of old wood or roots in simulating the growth process is not well represented. Conversely, perennial structures must be considered as they provide reserves of carbon and nutrients that may play a role in plant recovery or support initial growth. As such, these buffering reserves may be particularly important in a warmer climate, where extreme drought or heat events can lead to leaf loss and the recovery process plays a fundamental role in assuring the final yield. More generally, when considering perennial crops, each year growth and yield are dependent in several ways on the previous year’s growing conditions. By way of example, drought or heat stress during anthesis in olive trees may result in a reduced floret fertility or fruit set. While reducing crop yield in the current year, this gives rise to increased production in the following year, triggering alternate (fruit) bearing for many years. In this perspective, more developed models such as STICS and SUCROS, as modified by Nendel and Kersebaum (2004) or Pallas et al. (2011), may provide more insight into the issue of climate change by including the carry-over effects in their simulation.

In any case, the effects of increasing temperatures and CO2 concentration as expected in the near future are generally poorly represented in the models under analysis. Major concerns may be summarized as follows:

1. Phenology is usually poorly described and this affects reliable simulations of crop cycle duration (i.e. the time for biomass accumulation) in a warmer climate in the processes depending on phenology (e.g. changes in biomass partitioning). Chill unit requirements for dormancy release are generally not considered, or modelled with too simple an approach (CropSyst) for both olive trees and grapevines, leading to a progressive advancement of phenological stages that may actually not occur in response to increasing temperatures. Despite the importance of this traits for climate change adaptation, observed data of dormancy break are still lacking thus limiting the development of or refining of specific modelling approaches (Garcia de Cortazar-Atauari et al., 2009). Moreover, the lengthening of the growing period (i.e. the time from bud break to leaf fall or dormancy) as observed in response to increasing temperatures of plants...
(Menzel et al., 2006), is not currently considered even though it could play a role in increasing the capacity of crops to store biomass in perennial organs.

2. While the effects of increased CO2 and temperature on photosynthetic efficiency are accounted for in most models or may easily be implemented by modifying RUE or the value of photosynthetic efficiency, their positive interaction on assimilation is neglected especially because there is a lack of experimental results on these specific crops. This may lead to a systematic underestimation of biomass accumulation in a future climate scenario.

3. Evapotranspiration models currently implemented may fail to reproduce the combined effects of increases in temperature and CO2. While a rise in temperature would lead to a higher evapotranspiration rate, this trend may be counterbalanced by a decrease in canopy conductance in response to higher CO2. Furthermore, when using the FAO approach, changes in KCs should be accounted for because of the effect of a change in the occurrence of phenological stages and in the new ratio between ETo and ETP.

4. Drought stress or nitrogen stress may play a role in changing the biomass partitioning pattern to increase root growth but in most cases biomass partitioning consists of fixed coefficients to plant organs. In addition, an increase in CO2 was demonstrated to change biomass partitioning in woody plants but further experiments in should be performed for grapevine and olive tree, however further experiments should be performed to assess new partitioning coefficients to perennial organs. Change in canopy management practices such as pruning and trellis systems may help to reduce the impact of increasing temperature and reduced soil moisture and models may easily be modified to account for different shapes and plant distances. However, current modelling approaches might be not able to fully reproduce the actual crop physiological responses.

5. Vintage quality is a pre-requisite to obtain premium wines to compete on international markets. The simulation of most important grape quality traits (i.e. sugar and acid concentration) should be therefore pursued to test the impact on climate change.

6. The simulation of soil organic carbon may provide more insight into the analysis of the impact of olive tree and grapevine agro-ecosystems on the accumulation/depletion of soil organic carbon. Agricultural management of perennial crops such as grapevines and olive trees has the potential to increase the accumulation of soil organic matter, thereby capturing CO2 from the atmosphere (Nieto et al., 2010). The simulation of soil organic matter dynamics is therefore of maximum importance in evaluating the impact of these crops on the global carbon cycle in future scenarios.

7. To improve the reliability of process-based models in a warmer climate, the uncertainties related to the use of different models as applied for different varieties or cultivation areas, should be firstly evaluated for the present period. Frameworks like those presented in COST 734 for model intercomparison should be therefore adopted for a first evaluation of olive tree and grapevine model performances under various climatic conditions. However, comprehensive experimental datasets to compare observed and simulated data are scarce. Experimental data as presented in Bindi et al. (1997) (Free Air CO2 Enrichment) and Sadras and Soar (2009) (large scale open-top heating system) for grapevine, while providing more insight the effect of a warmer climate on this crop, may represent, at the same time, a robust dataset to test the reliability of crop modelling in a future climate.

4. Conclusions

The present critical review of empirical and process-based models for grapevines and olive trees highlighted the main weak points in each group, especially in view of possible application to future scenarios. The mere assumption on which empirical models rely, namely, that the climate is driving the growth process and can be used as a predictor of yield and quality is true, have only a local validity. Furthermore, they are generally unreliable for their possible application in a changing climate unless to consider additional predictive variables and improved statistical approaches. Conversely, process-based models may be improved to account for the effect of higher temperatures and CO2, but the high level of details required to run these models restricts their use to a local scale. Further, the missing or poor simulation of olive tree and grapevine agro-ecosystems carbon balance does not allow to study the possible beneficial effects of these cultivations to the global carbon cycle, which conversely is an information highly required to evaluate the capacity of these ecosystems to capture C thus contributing to the mitigation strategies.

As a matter of fact, these limitations reduce the applicability of these tools for impact studies that at the moment is limited to a few cases where crop and economic modelers are merged to provide a comprehensive evaluation of the impact of climate change from regional to sub-continental scale. A model intercomparison would be therefore highly recommended for testing the applicability of process-based models in different regions and in response to a warmer climate.

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