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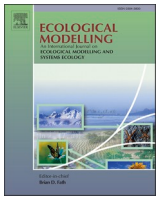

The application of a plant community model to evaluate adaptation strategies for alleviating climate change impacts on grassland productivity, biodiversity and forage quality

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ABSTRACT

Grasslands are environments characterized by an elevated biodiversity in plant species, which dynamically evolves over time as a function of management practices, soil properties, and climate conditions. Climate change can locally affect grassland growth and floristic composition and, in turn, the quality and quantity of provided ecosystem services. We show how the use of the plant community model CoSMo allows to explicitly account for the dynamics of floristic composition as response to environmental variables. This, in turn, allows quantifying climate change impacts on grasslands growth and composition and evaluating alternative strategies to improve adaptation in the mid-term. As a case study, we focused on mountain areas in the northern Apennines (Italy), where temporary alfalfa (*Medicago sativa* L.)-dominated grasslands are sown for the production of Parmesan cheese. Five sites and four alternative climate scenarios (RCP4.5 and RCP8.5 projections as provided by the HadGEM2 and GISS general circulation models) were considered, to explore a wide range of agro-environmental conditions. Results showed that the observed dynamics of floristic composition and biomass accumulation were successfully simulated, with a mean absolute error lower than 10% for floristic composition and less than 1 t ha^{-1} for total biomass. Climate change impacts were globally negative, with a clear decrease of forage production as compared to the baseline (from -3.6% to -14.3% according to the climate scenario). The biodiversity of the plant community also declined (12.5% average decrease in the inverse Simpson index) due to the increase in alfalfa dominance. The latter, however, led to preserve the forage crude protein content (+0.9% on average). Guidelines for optimizing grassland productivity and forage protein under future climate were defined, mainly focused on reducing the alfalfa field duration, sowing grass-legume mixtures, and delaying the last cut of the season. These practices can be easily adopted under operational farming conditions to support the adaptation of temporary grasslands to climate change. According to our knowledge, this is one of the first study of climate change impact that uses a plant community model to explicitly considers phytocoenosis dynamics, biodiversity, and their effect on forage production (quantity and quality). Considering the role of grasslands as providers of key ecosystem services – especially in marginal areas – we believe that our modelling approach can support the identification of effective adaptation strategies to address future climate challenges.

1. Introduction

Grasslands play a key role in the context of ecosystem services by providing material products and services that affect a variety of human activities, including economy, health, and quality of life (Tribot et al., 2018).

Grasslands are crucial for biodiversity conservation, carbon and nitrogen sequestration, pollination, improvement of landscape value for tourism and recreational activities, and for protecting soil from erosion (Marriott et al., 2004; Giustini et al., 2007; Schulze et al., 2009; Argenti et al., 2011; Cong et al., 2014; Hao et al., 2017; Pulina et al., 2017; van Oijen et al., 2018; Bengtsson et al., 2019, 2020; Viira et al., 2020). Despite temporary grasslands are less effective than permanent ones in providing some ecosystem services (e.g., carbon sequestration,

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protection from erosion), they ensure agronomical and environmental benefits when introduced in arable lands rotations. One of the most important ecosystem service that permanent and temporary grasslands provide is forage production (Suttie et al., 2005), which is often linked to the production of local and traditional delicacies. As an example, temporary grasslands dominated by alfalfa (*Medicago sativa* L.) are the main forage source for more than 100 dairy farms that produce local Parmesan cheese in the hilly and mountain areas of northern Apennine, Italy (Mancini et al., 2019). In fact, alfalfa-dominated temporary grasslands cover more than 50% of the total surface cultivated with forage crops in the area, whereas permanent pastures and meadow represent less than 30% (ISTAT, 2023). Alfalfa is amongst the forage species that are better adapted to the local environmental conditions and its capability to provide forage with high nutritional value (high crude protein content, e.g., Aponte et al., 2019) and stable yields even in low-input contexts makes it fundamental to improve the economic and environmental sustainability of dairy farms in the area (Tabacco et al., 2018; Kic, 2019).

Grasslands are environments characterized by the potential coexistence of a large number of herbaceous species and, therefore, by a high biodiversity (Habel et al., 2013). This richness of species has a large influence on the type and quality of ecosystem services that grasslands provide (Oliver et al., 2015), to the point that grassland floristic composition can be used as a proxy of codominance and resilience of grassland ecosystems (Simpson, 1949; Mackie et al., 2018) and, when evaluated in terms of percentage of legumes species, as a reliable indicator of forage quality (Argenti et al., 2021).

Grassland floristic composition is highly variable as function of multiple factors, which include climate conditions, soil properties, and management regimes (Buxton and Fales, 1994; Jeangros et al., 1999; Ziliotto et al., 2004). Agronomic practices play a relevant role especially in case of temporary grasslands, where different species are sown for hay production. These grassland evolve over time due to the settlement of wild species and, for this reason, they are periodically renewed to ensure satisfactory production and quality of forage. Crop management markedly affects the dynamics of these plant communities, through the increase of water and nutrients availability (irrigation and fertilization), the frequency of mowing, the composition of the sown mixture, and the field duration before renewal (Matches, 1992; Ren et al., 2012; Argenti et al., 2021).

Variation in climate may also deeply affect grassland growth and floristic composition (Mooney and Hobbs, 2000), although the impacts can largely vary as a result of the heterogeneity in plant communities and local climates. By conducting an extensive meta-analysis on European pastures, Dellar et al. (2018) expected an increase in aboveground biomass as response to climate change in northern and alpine areas, but a decrease in continental regions.

Despite crop models are widely used for estimating the effects of climate change on multiple crops (e.g., Tubiello et al., 2007), only few of them can explicitly reproduce the floristic composition of plant communities and its dynamics over time (Confalonieri, 2014; Moulin et al., 2021). Modelling approaches accounting for interspecific competition and plant community change in response to environmental drivers would allow to analyse climate change impacts on grasslands floristic composition and related ecosystem services. By explicitly considering management factors, they would also allow to identify strategies to improve the adaptation of these important agro-ecosystems to the climate expected in the coming decades (Franke et al., 2022).

The objective of this study was to present a novel application of the plant community model CoSMo (Confalonieri, 2014) to evaluate the impact of climate change on temporary alfalfa-dominated grasslands by explicitly considering their floristic composition. Adaptation strategies to optimize forage production and quality under future climate conditions were also evaluated and discussed, to provide farmers with guidelines allowing to preserve grasslands productivity and biodiversity in the mid-term. As a case study, we focused on temporary grasslands in the northern Apennines.

2. Materials and methods

2.1. The modelling approach

The CoSMo (Community Simulation Model; Confalonieri, 2014) plant community model was used to dynamically simulate the floristic composition of the plant community as response to environmental and management factors and – coupled with the generic crop model CropSyst (Stöckle et al., 2003) – the grassland productivity (Movedi et al., 2019). CoSMo estimates on a daily basis the variation in the relative abundance of the different species in the community (floristic composition) according to their suitability to environmental and management drivers, which account for both continuous variables (e.g., global solar radiation, soil water content) and events (e.g., cut, grazing). Drivers and the characteristics of each species in the community are used to estimate species-specific suitability factors to the conditions explored at each time step. The overall suitability of each species is then calculated by aggregating the suitability factors estimated for each driver through a hierarchical weighting procedure, which allows to differentiate the drivers according to their actual impact on the overall species suitability. Drivers representing grazing or cutting are top-ranked given the marked effect of these events on grassland composition due to the heterogeneity in species ability to restart after these disruptive events. Phenological development is the second-ranked driver because after maturity annual self-seeding species do not compete anymore until the germination and emergence of the next generation of individuals. The remaining drivers are ranked in decreasing order (air temperature, global solar radiation, soil water and nitrogen availability) in line with other modelling approaches dealing with inter-specific competition (Confalonieri, 2014). The overall suitability of each species is then used to estimate the relative abundance of the different species at the following time step. Each day, the relative abundance of each species allows to weight the crop growth model (CropSyst in this case) parameters describing the features of each species in monoculture, in order to derive the parameters of the crop growth model describing the plant community as a whole. Community parameters are thus dynamic, evolving as a function of changes in the plant community composition. The crop growth model uses these parameters to simulate biophysical processes at the level of plant community at each time step, providing key variables for grassland productivity (e.g., aboveground biomass, leaf area index). Further details on the CoSMo model and on the way it is linked to generic crop growth models are available in Confalonieri (2014) and Movedi et al. (2019).

CropSyst estimates the daily accumulation of aboveground biomass (AGB) with a net photosynthesis approach, based on the minimum between the AGB values calculated as a function of radiation use efficiency and of a vapour pressure deficit-corrected transpiration use efficiency. Green leaf area expansion is derived from the daily-accumulated AGB, the early-stages specific leaf area, and an empiric stem/leaf partition coefficient. The Beer's analogy is used to estimate the radiation intercepted as a function of leaf area index (LAI) and of the light extinction coefficient. Phenological development is simulated according to the mean air daily temperature and parameters defining minimum and optimum thermal requirements, with an option to account for photoperiod. In this study, soil water dynamics were simulated using a cascading model with travel time approach (Neitsch et al., 2002). More details on CropSyst can be found in the reference literature (Stöckle et al., 2003).

Concerning the simulation of forage quality in terms of crude protein content on AGB (CP, %), the empirical model proposed by Argenti et al. (2021) for the same study area was used, which derives forage CP as a function of the relative abundance of legumes in the grassland. This model does not explicitly consider species-specific CP contents. However, it has been considered as suitable for the study context given the

markedly higher content of CP in legumes as compared to other species (e.g., Aponte et al., 2019) and the prevalence of alfalfa amongst the legumes detected in all study sites and sampling events (ranging from 88.3–100%, see Table S3). In this study, CP was estimated based on the relative abundance of wild or sown legumes (alfalfa and *Trifolium* spp.) simulated by CoSMo.

2.2. Model parameterization

Field data for model evaluation were collected at five sites (Table 1) in the northern Apennine (Emilia–Romagna region) on temporary alfalfa-dominated grasslands as described by Argenti et al. (2021). In this mountain and unfavourable area, temporary grasslands and meadows represent a key support for the production of local Parmesan cheese by the about 100 farms of the consortium "Terre di Montagna" (Mancini et al., 2019). The five sites were chosen as representative of the heterogeneity characterizing the area in terms of environmental conditions, presence of wild species, and age of the meadows. Three sampling events were carried out at each site during 2019 before mowing (Appendix A). Measured variables were the floristic composition (visual method; Boob et al., 2019), AGB (t dry matter ha^{-1}), LAI (measured using a ceptometer), and CP (Kjeldhal method) as a key component of forage quality. Concerning floristic composition, three sampling plots of 0.25 m^2 were randomly identified in each field, and the botanical composition assessed visually as the percentage contribution of each species to the vegetation mass according to the method of Klapp/Stählin described in Voigtländer and Voss (1979) and Boob et al. (2019). More details on the field survey can be found in Argenti et al. (2021) and in Table S1, S2 and S3.

For each site, daily minimum and maximum temperature, global solar radiation and rainfall were retrieved from the weather service of the University of Milan Cassandra Lab, which provides historical daily weather data for the whole Europe with a spatial resolution of 0.016° × 0.016° This weather service is based on the spatial downscaling of data from international (NOAA-GSOD, METAR, and SYNOP) and regional networks carried out by using dedicated geo-statistical and modelling techniques also accounting for the effect of elevation (USGS Gtopo30). Reference evapotranspiration was estimated at runtime based on the Penman–Monteith method (Allen et al., 1998).

Simulations were performed under conditions limited by water availability (rainfed grasslands), whereas nutrients were considered as fully able to satisfy plant requirements given the experimental sites were fertilized – especially with manure due to the prevalence of cereal-livestock farms in the study area – and because of the presence of legumes (symbiotic N fixation).

Data from the first sampling event were used for initializing the model (community LAI, AGB and floristic composition). For observed floristic composition, only species with a mean relative abundance higher than 2% over the three sampling events were considered to reduce uncertainty in model initialization and parameterization (Piseddu et al., 2022). Concerning soil moisture, field capacity was assumed at the beginning of the simulation, because of melting snow and of the abundant rainfall that characterize the sites in early spring.

Table 1
Description of the experimental fields (from Argenti et al., 2021).

Site	Elevation (m a.s.l.)	Latitude N (°)	Longitude E (°)	Sown crop	Years since sowing
A	740	44.313808	11.031986	Alfalfa	2
B	870	44.331032	10.987424	Mixture [a]	2
C	750	44.285525	10.946268	Alfalfa	4
D	780	44.234906	10.922269	Alfalfa	8
E	740	44.218132	10.909049	Alfalfa	12

[a] grasses-legumes mixture: Lotus corniculatus L. (7%), Medicago sativa L. (30%), Trifolium pratense L. (13%), Dactylis glomerata L. (22%), Festuca arundinacea Schreb. (23%), Lolium perenne L. (5%).

Root depth were initialized at 150 cm. Concerning management, the observed mowing schedule was used as input in the model. Parameter sets were available from previous studies (see Appendices B and C) for all species but three (*Bromus hordeaceus* L., *Rumex obtusifolius* L. and *Trifolium pratense* L.), for which parameter values were defined using information from literature (Longo et al., 2021) and from Argenti et al. (2021), the latter used to minimize the error between simulated and observed values (trial and error method). Model evaluation was carried out using the coefficient of determination (R^2), the slope and the *p*-value of the linear regression between observed and simulated data, and the following agreement metrics: relative root mean square error (RRMSE, from 0 [optimum] to +∞; Jørgensen et al., 1986), mean absolute error (MAE, from 0 [optimum] to +∞; Jørgensen et al., 1986), and modelling efficiency (EF, from -∞ to 1 [optimum]; Nash and Sutcliffe, 1970).

2.3. Evaluation of climate change impacts on grassland productivity and floristic composition

Future climate projections for two representative concentration pathways (RCPs, RCP4.5 and RCP8.5; IPCC 2013) as provided by two general circulation models (GCMs), i.e., HadGEM2 (Collins et al., 2011) and GISS (Schmidt et al., 2006), were used to assess climate change impact on grasslands productivity and floristic composition. The use of multiple RCP × GCM combinations allowed to handle the uncertainty in future climate projections. This was achieved by considering alternative pathways of CO_2 emissions in the mid-term – RCP4.5 assumes the implementation of policies for curbing GHGs emission while RCP8.5 envisages business as usual storylines – and GCMs with a different equilibrium climate sensitivity that can lead to different climate projections for the same RCP. The uncertainty in the downscaling process (Vesely et al., 2019) was accounted for by using two stochastic weather generators (WGs), LARS-WG (Semenov and Barrow, 1997) and CLIMAK (Danuso, 2002). Historical weather series for the baseline (1986–2005, IPCC 2013) were retrieved from the ECMWF database (Hennessy, 1986). For each of the eight climate scenarios (2 RCPs × 2 GCMs × 2 WGs), 20-year weather series centred on 2040 were generated at each site in order to properly account for the variability amongst seasons. For each site and weather series, independent simulations were run with sowing set on October 1st of each of the first 16 seasons in the series and meadow duration of five years (Argenti et al., 2021).

Regarding management, three main mowing events were considered (June 1st, July 20th and October 1st), as representative of early, medium, and late mowing periods, respectively.

The impact of climate change on grassland productivity and floristic composition was evaluated by comparing the model outputs (mean of the 16 simulated meadows) obtained for the baseline and for the future climate projections. Seven synthetic output variables were analysed: the total AGB harvested each season (AGB_{year}, t ha^{-1}) and its distribution over the different mowing events (AGB_j, t ha^{-1}, AGB harvested on the *j*-th mowing event), the days when the vegetative restart and dormancy occur, the relative abundance of plant species (p_i, from 0 to 1, *i* representing the *i*th species in the community), the Simpson diversity (the inverse of the Simpson concentration index $D = 1/\lambda$, the larger the value of *D*, the highest the diversity, with λ calculated according to Eq. (1); Simpson, 1949; Jost, 2006), and the forage CP, estimated according to Eq. (2) (Argenti et al., 2021).

$$\lambda = \sum_{i=1}^{n} (p_i)^2 \quad (1)$$

where λ is the Simpson concentration index; *n* is the number of herbaceous species in the grassland; *i* is the *i*th herbaceous species.

$$CP = 4.9085 \cdot \ln(x) + 0.8017 \quad (2)$$

where *x* (%) is the relative abundance of legumes in the grassland, which

was derived according to Eq. (3) to account for the effect of the dynamics of legume presence on forage CP at different mowing events.

$$x = \frac{\sum_{j=1}^{m} p_{ij} \cdot AGB_j}{AGB_{year}} \quad (3)$$

where m is the number of mowing events (three in this study), j is the j-th mowing event, and p_{ij} is the relative abundance of legumes (*Medicago sativa* L. and *Trifolium* spp.).

Since the analysis concerned temporary alfalfa-dominated grasslands (in most case sown in purity, the only exception being site B, and then allowed to evolve with the settlement of wild grass species), the initial value of the relative abundance of alfalfa was set to 100% on 1st of October and that of the other relevant species initialized at 0%.

Plant dormancy was simulated according to the approach proposed by Confalonieri and Bechini (2004). The entire plant community is considered dormant after seven consecutive days with mean air temperature below a given threshold (8 °C; Movedi et al., 2019) and night length longer than 13 h. In spring, plant community restarts growing when night length is lower than 13 h and mean air temperature is higher than the dormancy threshold for more than seven consecutive days. In case other factors interfere with plant growth (e.g., water stress), the restart day is postponed until conditions become favourable.

2.4. Adaptation strategies

Four possible adaptation strategies were tested, by considering only those highly feasible under operational farm conditions: (i) modifying the mowing schedule, by testing all the possible combinations of 5-, 10- and 15-day variation (before and after the events used for the baseline scenario) for each of the three mowing events and by adding a fourth cut; (ii) testing different mixtures of sown species (60% *Medicago sativa* L., 20% *Dactylis glomerata* L. and 20% *Lolium multiflorum* L.; 100% *Medicago sativa* L.; 70% *Medicago sativa* L., 15% *Dactylis glomerata* L. and 15% *Lolium multiflorum* L., named Mix1, Mix2, and Mix3, respectively); (iii) testing different meadow durations (four and five years), and (iv) all the possible combinations of the aforementioned strategies.

3. Results

3.1. Model evaluation

Model parameterization (Appendices B and C) allowed achieving a good agreement between observed and simulated values for all the variables analysed (Table 2). Concerning the dynamics at the level of plant community, the model correctly reproduced the grassland floristic composition, with a MAE lower than 10% and both EF and R^2 equal to 0.87. Although the RRMSE was slightly higher than 50%, the good performance obtained for the Simpson index underlines how the error mainly affects non-dominant species with a very low abundance in the community. This is clear in Fig. 1, where the model capability of reproducing the floristic composition is evaluated by comparing observed and simulated relative abundance of single species. In general, relative abundance was well simulated, most of the values being close to the 1:1 line (solid line in Fig. 1) that indicates perfect agreement.

Grassland growth was successfully reproduced by the model, both for the accumulation of AGB during the season and for the AGB harvested at each cut event. MAE was less than 1 t ha^{-1} in both cases, EF was always positive and the average R^2 was equal to 0.67 (Table 2). Similar considerations apply to the model performance for leaf area index, although in this case the modelling efficiency was negative. However, this is due to the fact that the variability in observations was very low (standard deviation was equal to 0.95), which makes the mean of observations a very good estimator of single values. This, in turn, led to negative EF values even for small error in the simulations (e.g., MAE lower than 1 m^2 m^{-2}).

3.2. Climate change impact on forage production, quality and floristic composition

A clear increase in mean temperature was projected for all GCM × RCP combinations, regardless of the weather generator used (Fig. 2). The HadGEM2 projections showed the highest mean temperature increase, close to 2.1 °C for RCP4.5 and 2.4 °C for RCP8.5, whereas the GISS realizations were milder for both RCPs, with values ranging from 1.0–1.2 °C (Fig. 2a and b). The variability due to the weather generator was clear in terms of rainfall patterns, with precipitations distributed more evenly in the case of CLIMAK (Fig. 2c) and larger heterogeneity between months in case of LARS-WG (Fig. 2d).

The general increase in mean temperature reflected on grassland dormancy patterns (Fig. 3), with an extension of the period of active growth (+22 days on average) due to both an earlier spring restart (Fig. 3, left panels) and a later dormancy onset in winter (Fig 3, right panels). A clear variability was found amongst climate scenarios, with the highest impact observed for the HadGEM2 realizations of the RCP8.5 scenario. On average, the spring restart occurred 10 days earlier than for the baseline (Fig. 3a), with values ranging from 4 to 13 days for, respectively, the mildest (RCP4.5-GISS) and the warmest scenario (RCP8.5-HadGEM2). A similar pattern was found for the dormancy onset, which on average was postponed by 12 days, with values ranging between 9 (RCP4.5-GISS) and 16 (RCP8.5-HadGEM2) days. Results highlighted a marked variability amongst season (height of the boxes in Fig. 3), whereas no clear differences amongst sites were observed (mean variability due to the site was less than 2%). These patterns were not affected by the weather generator (variability in mean values due to this factor were less than 5%), which instead largely affected the heterogeneity amongst season, although without a clear pattern (Fig. 3).

Concerning the impact of climate change on grassland growth, the increase in mean temperature was not beneficial for total biomass accumulation (Fig. 4a), which showed an average reduction of 5.7% under future scenarios as compared to the baseline. The extent of the negative impact markedly varied across climate scenarios, ranging from −3.6% (RCP4.5-GISS) to −7.4% (RCP4.5-HadGEM). However, the decrease in biomass accumulation was not evenly distributed over mowing events. The anticipated spring restart (Fig. 3) turned indeed into more biomass harvested at the first cut (Fig. 4b) with an average increase of +17.7% (mean of results for all the climate scenarios). On the contrary, biomass available at the second and third cuts (Figs. 4c and 4d, respectively) under future climate projections was markedly lower than

Table 2
Agreement between measured and simulated variables describing grasslands floristic composition and growth.

Variable	Units	MAE	RRMSE (%)	EF	R^2	Slope	*p*-value
Floristic composition	(%)	6.04	55.84	0.87	0.87	0.99	<0.001
Simpson Index	(-)	0.38	22.03	0.78	0.79	1.03	<0.001
AGB_{cut} [a]	(t ha^{-1})	0.83	41.39	0.00	0.57	0.53	0.01
AGB_{year} [b]	(t ha^{-1})	0.96	23.09	0.57	0.76	1.23	0.05
Leaf area index	(m^2 m^{-2})	0.94	34.84	−0.70	0.61	0.46	0.01

[a] Aboveground biomass harvested at each cut.
[b] Total aboveground biomass harvested during the year.

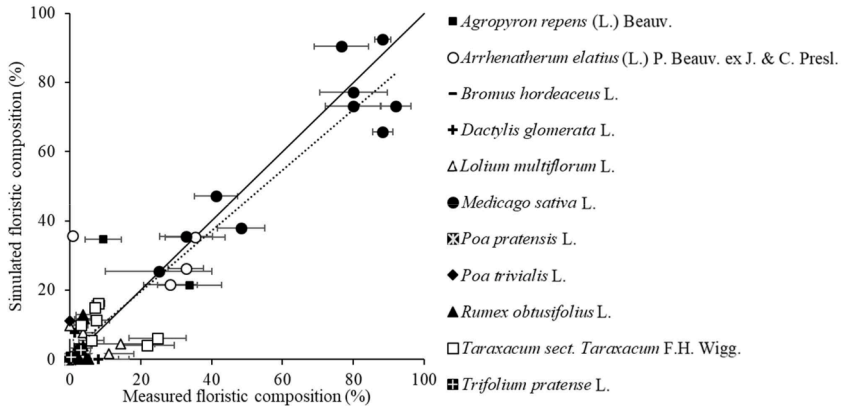

Fig. 1. Comparison between observed and simulated relative abundance (%) for the species detected in the five sites. Only species with a relative abundance higher than 2% were considered.

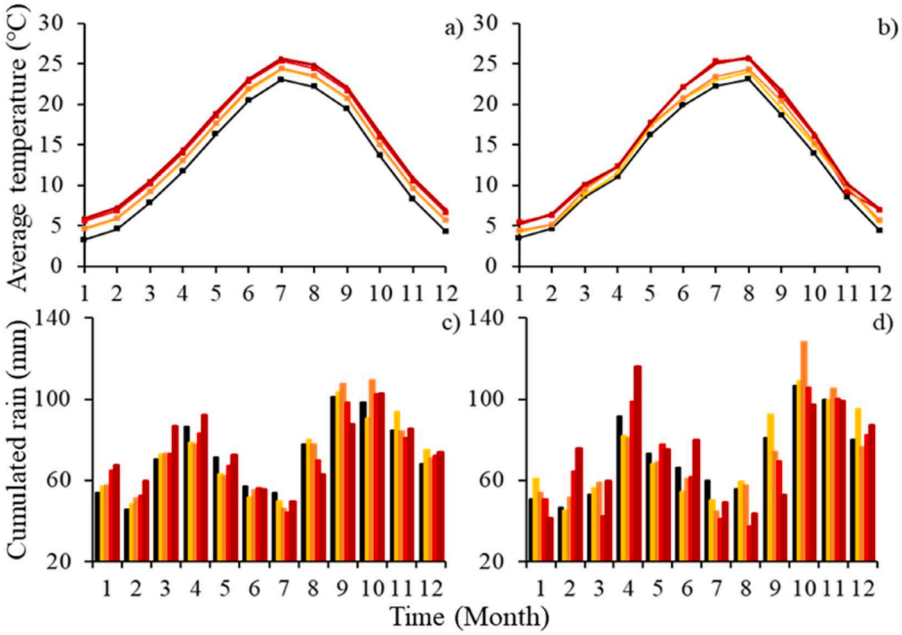

Fig. 2. Monthly average air temperature and cumulated rainfall for the baseline (black) and each GCMs × RCPs combinations (yellow: RCP4.5-GISS, orange RCP8.5-GISS, red: RCP4.5-HadGEM2, dark red: RCP8.5-HadGEM2) as downscaled with the stochastic weather generator CLIMAK (a, c) and LARS-WG (b, d).

for the baseline, likely due to the higher temperatures and lower rainfall during the summer months projected for 2040 (Fig. 1). The average reduction for all the climate scenarios was equal to 29.4% and 31% for the second and the third cuts, respectively. Low variability amongst sites was found, whereas differences due to the weather generator clearly affected biomass accumulation, although to a limited extent compared to the variability due to the different climate scenarios.

The analysis of plant community dynamics in response to climate change highlighted a clear reduction of the grassland biodiversity, with a general decrease in Simpson diversity (−11.7%; Fig. 5a). As expected, alfalfa increased its relative biomass (+6.8% on average for all scenarios; Fig. 5b), thanks to the higher thermal requirements compared to other species and to the deeper root system that prevented drought stress during summer months. Species with lower thermal requirements (mainly *Dactylis glomerata* L., *Poa pratensis* L. and *Lolium multiflorum* Lam.) (see Appendix B) were instead negatively affected (−8.2% on average, Fig. 5c), although a marked variability induced by the weather generator was found (average for all climate scenarios equal to −12% for CLIMAK and –4.4% for LARS-WG). Despite the increase in the relative abundance of alfalfa, the seasonal forage CP improved only slightly (+ 1.5% on average for all scenarios, Fig. 5d). This is due to the fact that the increased abundance of alfalfa in summer was counterbalanced by the general reduction of biomass harvested at the second and third cuts. These results highlight the importance of dynamically simulating both the grassland biomass accumulation and its floristic composition to properly evaluate the effect of climate change on biodiversity and forage quality.

The heterogeneity amongst sites in terms of floristic composition was larger than observed for other variables (e.g., biomass accumulation, Fig. 4). This is consistent with the variability in the plant communities that characterises the five sites in the baseline scenario, which turns into different dynamics of relative abundance according to the species-specific responses to temperatures and water availability.

3.3. Identification of adaptation strategy

Amongst all the tested adaptation strategies (35 combinations of mowing schedule × initial mixture of sown species × meadow duration), only those that provided the best results in terms of forage production and quality are reported and discussed (Table 3).

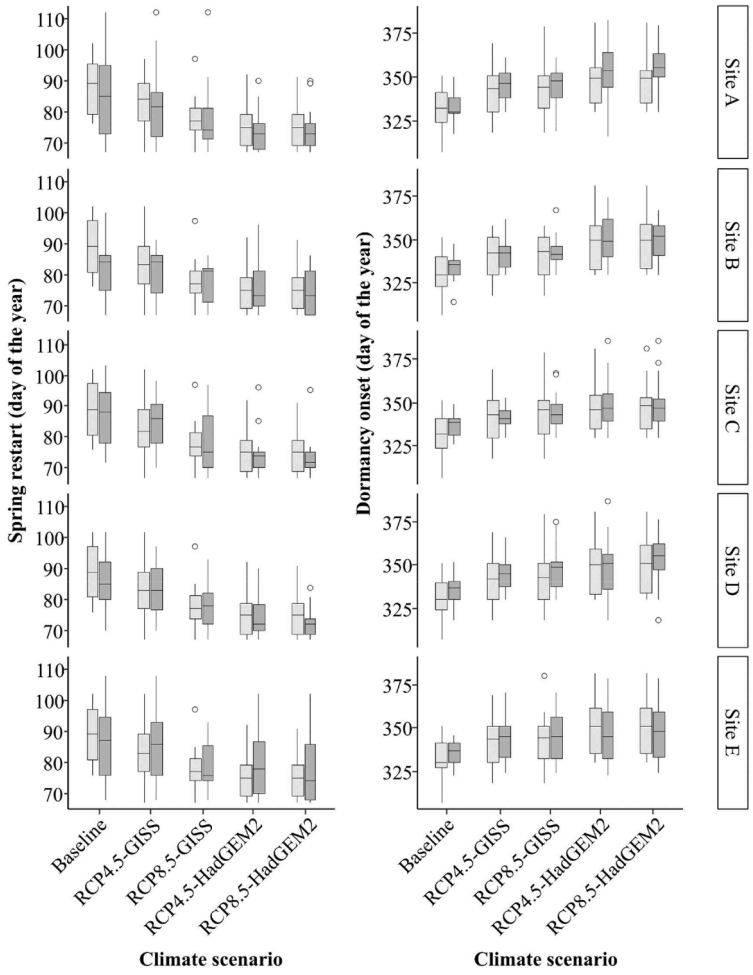

Fig. 3. Effect of climate change on spring restart (left panels) and dormancy onset (right panels) for each site and climate scenario (RCP × GCM combination) as downscaled by the two weather generators, CLIMAK (light grey) and LARS-WG (dark grey). The baseline is reported for sake of comparison. The dispersion of values around the median is due to the variability amongst seasons.

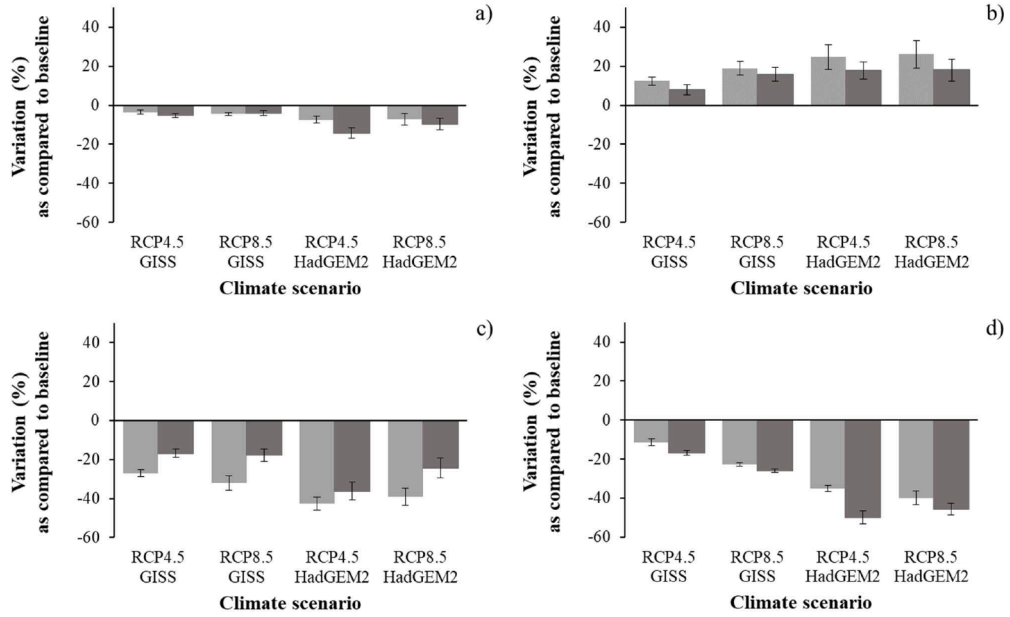

Fig. 4. Effect of climate change on grasslands growth. Percentage variation as compared to the baseline of the aboveground biomass accumulated during the entire season (a) and that harvested before the first (b), second (c), and third (d) cut. Results are reported for each climate scenario (RCP × GCM combination) as downscaled by the two weather generators, CLIMAK (light bars) and LARS-WG (dark bars). Error bars represent the variability (standard deviation) amongst sites.

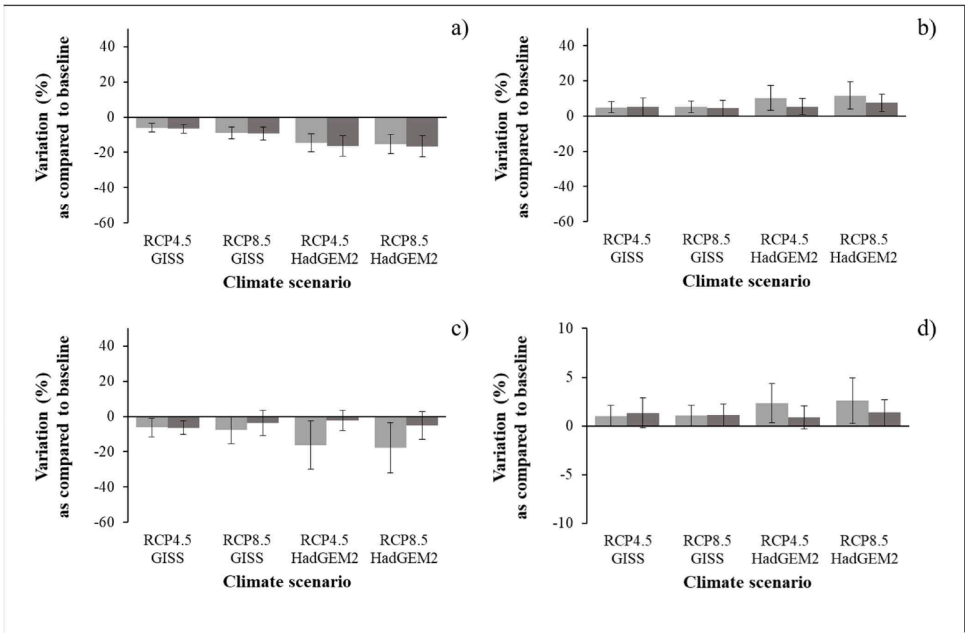

Fig. 5. Effect of climate change on grassland floristic composition and forage quality for each RCP × GCM combination as downscaled by two weather generators, CLIMAK (light grey) and LARS-WG (dark grey). Results are reported as percentage variation as compared to the baseline of the Simpson diversity (a), the relative abundance of alfalfa (b), the relative abundance of other species (c), and the forage crude protein (d). Error bars represent the variability (standard deviation) amongst sites.

Table 3
Adaptation strategies to alleviate climate change impacts on forage production and quality. AGB_{year}: seasonal aboveground biomass accumulation; CP: crude protein content. Data are reported for both current (baseline) management and the best adaptation strategies identified for each climate scenario (RCP × GCM combination) and weather generator (WG). Values are averaged over the five sites.

WG	Climate scenario	Target variable for adaptation	Adaptation strategy			Variation (%) as compared to baseline			
			Meadow duration (years)	Change in mowing schedule (days)[a]	Sown mixture[b]	CP	AGB_{year}	Simpson diversity	Alfalfa relative abundance
CLIMAK	RCP4.5 GISS	Current (baseline) management				0.71	−3.55	−5.83	4.76
		AGB	4	0/0/+10	Mix1	−9.04	1.41	18.46	−27.7
		CP	4	−5/+5/+10	Mix2	1.97	−3.13	−5.86	11.08
	RCP8.5 GISS	Current (baseline) management				0.71	−4.54	−9.02	5.05
		AGB	4	0/0/+10	Mix1	−8.09	−0.08	14.76	−24.72
		CP	4	−5/+5/+10	Mix2	1.89	−3.75	−8.78	10.99
	RCP4.5	Current (baseline) management				1.72	−7.44	−15.52	9.98
	HadGEM2	AGB	4	0/0/+10	Mix1	−5.65	−4.40	7.14	−16.46
		CP	4	−5/+5/+10	Mix2	2.48	−6.87	−14.95	14.1
	RCP8.5	Current (baseline) management				2.00	−7.16	−16.72	11.3
	HadGEM2	AGB	4	0/0/+10	Mix1	−5.73	−4.97	6.03	−16.71
		CP	4	−5/+5/+10	Mix2	2.65	−6.92	−15.92	14.91
LARS-WG	RCP4.5 GISS	Current (baseline) management				0.63	−5.18	−6.70	5.29
		AGB	4	−5/+5/+10	Mix1	−9.81	−0.11	15.28	−28.01
		CP	4	−5/+5/+10	Mix2	1.87	−3.90	−6.28	11.55
	RCP8.5 GISS	Current (baseline) management				0.26	−4.04	−9.03	4.31
		AGB	4	−5/+5/+10	Mix3	−9.71	0.61	11.77	−27.43
		CP	4	−5/+5/+10	Mix2	1.42	−3.00	−8.44	10.06
	RCP4.5	Current (baseline) management				0.24	−14.23	−18.78	5.36
	HadGEM2	AGB	4	0/0/+10	Mix1	−9.02	−11.37	4.76	−25.28
		CP	4	−5/+5/+10	Mix2	1.58	−13.85	−18.18	12.1
	RCP8.5	Current (baseline) management				0.70	−9.70	−18.74	7.47
	HadGEM2	AGB	4	−5/+5/+10	Mix1	−6.78	−7.03	1.63	−17.54
		CP	4	−5/+5/+10	Mix2	2.02	−8.71	−18.51	14.22

[a] slash-separated values refer to variation in the day of first, second and third cuts, respectively, as compared to the current (baseline) schedule.
[b] Mix1: 60% *Medicago sativa* L., 20% *Dactylis glomerata* L. and 20% *Lolium multiflorum* L.; Mix2: 100% *Medicago sativa* L.; Mix3: 70% *Medicago sativa* L., 15% *Dactylis glomerata* L., and 15% *Lolium multiflorum* L.

Given the negative correlation between AGB accumulation and CP, it was not possible to identify a unique strategy able to optimize both factors simultaneously. Nevertheless, results were always better than those achievable with the management adopted within the baseline scenario (also reported in Table 3 for sake of comparison). This supports their adoption to alleviate the negative impact of climate change in the coming decades.

Regardless of the climate scenario, sowing Mix2 (100% alfalfa) at the beginning of the temporary grasslands and varying the mowing schedule (anticipating the first cut and postponing the second and third ones)

allowed to markedly increase the forage CP. Indeed, CP increased by 2% (average for all climate scenarios) with adaptation, the same value being 0.9% with current management practices). Moreover, adaptation strategies targeting high CP values did not penalize the grassland productivity and biodiversity compared to the current management, the mean values of AGB_{year} and CP being −6.3% and −12.1% with adaptation and −7% and −12.5% with current management. As expected, a clear correlation between forage CP and relative abundance of alfalfa was found (Pearson's r was 0.99), given the primary role of *Medicago sativa* L. amongst the legume species detected in the five sites. For the same reason, CP was negatively correlated with the Simpson diversity (Pearson's r equal to −0.91), since the increase in alfalfa dominance turned into a reduction of community biodiversity due to a lower species evenness.

Adaptation strategies aimed at minimizing the negative effects of climate change on forage production (total biomass) were mainly based on sowing mixtures that includes *Dactylis glomerata* L. and *Lolium multiflorum* L. (Mix1 and Mix2) and on the postponement of the last cut (Table 3). This allowed to alleviate the seasonal AGB reduction simulated under future climate conditions for more than a half (−3.2% with adaptation compared to −7% without adaptation, average for all scenarios). The same adaptation strategies allowed reversing the decline in biodiversity expected for the coming decades (mean value of the Simpson index was −12.5% without adaptation and +10% with adaptation), thanks to the introduction of multi-species sowing mixtures.

Regardless of the target variable for the adaptation (seasonal biomass production or forage CP), the optimal duration of the meadow was lower than the current one (4 years instead of 5), although the effect of meadow duration was limited as compared to variations in the mowing schedule and in the sown mixture.

4. Discussion

4.1. Model performance

We presented a novel application of the plant community model CoSMo (Confalonieri, 2014) to analyse the impact of climate change on temporary alfalfa-dominated grasslands by explicitly considering their floristic composition. The climate-driven dynamics observed in the phytocoenosis composition and the related effects on forage production and quality highlighted the benefits of using modelling approaches for simulating multi-species plant communities in climate change impact studies, in line with findings from other authors (Moulin et al., 2021; Movedi et al., 2023). The reliability of CoSMo for simulating variables involved with both grassland growth and floristic composition – as well as its parsimony in terms of data needed to run simulations (e.g., number of species-specific parameters) – highlight the model suitability for operational contexts, given the presence of a large number of species-specific parameters (like in the case of individual-centred models, e.g., Soussana et al., 2012) often represents a severe limit to model applicability (Paleari et al., 2017). Moreover, it supports the extension of this modelling approach to other regions or agro-climatic contexts, given the generic nature of CoSMo allows its application to different types of multi-species plant communities (Movedi et al., 2022; Movedi et al., 2023). Nevertheless, the parameterization for three out of eleven species (*Bromus hordeaceus* L., *Rumex obtusifolius* L. and *Trifolium pratense* L.) was performed using a limited dataset. Further studies involving the collection of new observations will be carried out to improve the parameterization.

The model error in estimating floristic composition and AGB was similar to that observed in other studies, both those where the same model was used (Movedi et al., 2019) and studies carried out using different models for the simulation of plant community dynamics, including complex approaches based on individual-centred models (Soussana et al., 2012) and approaches developed for simpler communities, like those represented by a crop and one weed (e.g., Kropff et al., 1993; Movedi et al., 2022). Moreover, the model error for the relative abundance of species (mean MAE < 7%) was comparable with the uncertainty found in the observations themselves (average standard deviation of observation was equal to 5.2%, with maximum value of 27.8%). The uncertainty in observations likely explains also the lower agreement between simulated and observed values for the dynamics of *Agropyron repens* (L.) P. Beauv. and *Arrhenatherum elatius* (L.) P. Beauv. ex J. Presl. & C. Presl.. Indeed, the similarity between the two species, in particular during the vegetative phase (when reproductive organs are not present), could explain the large coefficient of variation in eye-detected relative abundance for these species (77% and 56% for *A. elatius* and *A. repens*, respectively).

The only variable for which model performance were not satisfactory was LAI. The larger uncertainty in the simulation of this variable was already observed for crop (e.g., Yu et al., 2006; Confalonieri et al., 2009; Tartarini et al., 2019) and crop-weed interaction (Deen et al., 2003; Movedi et al., 2022) models. The reasons for the lower accuracy in LAI simulation compared to other variables can be different, ranging from the intrinsic uncertainty in the methods used for estimating LAI (often using indirect approaches based on the inversion of light transmittance models) to the concurrence – during a large part of the plant cycle – of algorithms for processes leading to positive (emission of new green LAI units) and negative (senescence, self-shading) LAI rates that act on the same state variable. Moreover, in this study, LAI observations fluctuated only slightly around their average, this partly explaining the poor values achieved for EF (Criss and Winston, 2008).

4.2. Climate change impacts and adaptation strategies

The negative impact of climate change on grassland growth found in this study is in agreement with the meta-analysis carried out by Dellar et al. (2018), who found a general reduction of pasture aboveground biomass accumulation in continental and southern European regions as results of reduced summer rainfall and increased temperatures. Similar results were achieved in other studies performed in temperate environments (e.g., Cullen et al., 2009; Kalaugher et al., 2017) and explicitly focused on forage crops (Dono et al., 2016). In our study the largest reduction in biomass production was observed in the summer cuts (the second and the third mowing events). This reduction was due to the increase in temperatures and the limited water availability that characterized the summer months, in particular July, which led to a clear reduction in biomass accumulation rates. This turned into an increase in the relative abundance of alfalfa regardless of the climate change scenario, because of the higher tolerance of this species to high temperature and water stress (deeper root systems) (Tang et al., 2014; Huang et al., 2018; Moot et al., 2000) as compared to the other species such as *Poa pratensis* L. and *Lolium multiflorum* L. (Abraha and Savage, 2008; Vankoughnett et al., 2016). The increase in the relative abundance of alfalfa had positive effects on the quality of forage (higher CP; Argenti et al., 2021) but also a negative effect on biodiversity (quantified here through the Simpson diversity) because of less diversified plant communities. Moreover, another potential negative effect of the increased presence of alfalfa is related to the lower soil capability to withstand erosion, because species with tap roots are less effective in reducing soil detachment compared to fibrous root-ones (Wang and Zhang, 2017; Mackie et al., 2018).

Despite the large availability of modelling studies aimed at finding solutions to alleviate the negative effects of climate change through changes in crop management – e.g., by optimizing the cultivar (Zabel et al., 2021) or the crop selection (Cappelli et al., 2015), the sowing window (Zhang et al., 2012) or the irrigation technique (Wang et al., 2021) – studies targeting the optimization of grassland management are still scarce. The adaptation strategies identified in this study demonstrated the potential to largely reduce climate change impact on grassland productivity and forage quality. Moreover, beside their effectiveness, the adaptation measures we tested (e.g., anticipating or

postponing mowing events, changing the sown mixture) are highly feasible, and thus easily applicable under operational contexts. An important issue is that such adaptation strategies demonstrated their effectiveness without any shift in grassland areas, this representing a key aspect in contexts where production systems are relevant for the economy of specific production districts, like those where Parmesan cheese is produced in the mountain areas of northern Apennines. Our results further demonstrated the great potential of management to counterbalance the negative impacts of climate change on agricultural systems (Franke et al., 2022). Nevertheless, the adaptation strategies we identified might have drawbacks that should be considered before adoption in light of context-specific criticalities. The reduction of the field duration, indeed, leads to more frequent field renovations with potential negative effects on community biodiversity, top-soil carbon sequestration and protection from soil erosion (Haddaway et al., 2017).

Another key result achieved in this study deals with the role of downscaling in affecting the uncertainty of climate change impact studies. Indeed, the use of two different stochastic weather generators led to different quantifications of climate change impacts on grassland productivity and forage quality. This aspect should be considered with more attention in climate change studies, given the scientific community is used since years to manage uncertainty in climate projections by using more RCPs and GCMs, whereas the role of downscaling in generating uncertainty in climate change analysis is – with few exceptions (Vesely et al., 2019) – mostly ignored.

5. Conclusions

The CoSMo plant community simulation model demonstrated its suitability for analysing the dynamics of growth and floristic composition of temporary alfalfa-dominated grassland as response to the changes in climate projected for the mid-term in the northern Apennine. This allowed to estimate some grassland-related ecosystem services (forage production and quality, conservation of biodiversity) and to suggest adaptation strategies to preserve them in the future. Results of the simulations carried out using future climate projections highlighted a clear decline in forage production and in biodiversity, mainly because of the increase in alfalfa dominance, in turn likely explained by the higher suitability of this species to warm and dry conditions (Moot et al., 2000). Given the key role of grasslands for forage production in local dairy farms involved with the production of Parmesan cheese, adaptation strategies were evaluated by prioritizing the applicability of the proposed solutions in real farming contexts. According to our results, guidelines for optimizing grassland productivity and forage quality under future climate projections can be summarised in three key points: reducing the duration of alfalfa meadows by one year, sowing mixtures including grass species and changing the mowing schedule (anticipating the first cut and postponing the summer ones). These are practices that can be easily adopted by farmers to support the adaptation of this peculiar agricultural systems to a changing climate.

The reliability of the CoSMo modelling approach and its parsimony in terms of data needed to run simulations encourage the extension of this kind of analysis to other regions and plant communities, to support the identification of grassland management strategies targeting the exploitation of their role as providers of key ecosystem services, especially in marginal areas.

CRediT authorship contribution statement

Ermes Movedi: Conceptualization, Data curation, Formal analysis, Software, Writing – original draft. **Livia Paleari:** Conceptualization, Formal analysis, Methodology, Writing – original draft. **Giovanni Argenti:** Data curation, Investigation, Writing – review & editing. **Fosco M. Vesely:** Data curation, Methodology. **Nicolina Staglianò:** Data curation, Methodology. **Silvia Parrini:** Data curation, Methodology. **Roberto Confalonieri:** Conceptualization, Funding acquisition, Methodology, Supervision, Writing – review & editing.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ecolmodel.2023.110596.

Appendices

Appendix A
Mowing and sampling events.

Site	A	B	C	D	E
Sampling 1	5/30/2019	5/30/2019	5/30/2019	5/31/2019	5/31/2019
Mowing 1	6/15/2019	6/15/2019	6/4/2019	6/6/2019	6/15/2019
Sampling 2	7/16/2019	7/16/2019	7/15/2019	7/15/2019	7/15/2019
Mowing 2	8/1/2019	7/20/2019	7/20/2019	7/20/2019	8/1/2019
Sampling 3	8/29/2019	8/28/2019	8/28/2019	8/28/2019	8/28/2019
Mowing 3*	-	9/14/2019	-	9/2/2019	9/2/2019

* not available for site A and site C.

Appendix B

CropSyst parameters for different species (A: Agropyron repens (L.) Beauv., A1; Arrhenatherum elatius (L.), P. Beauv. ex J. Presl & C. Presl., B: Bromus hordeaceus L., D: Dactylis glomerata L., L: Lolium multiflorum L., M: Medicago sativa L., P: Poa pratensis L., P1: Poa trivialis L., R: Rumex obtusifolius L., T: Taraxacum sect. Taraxacum F.H. Wigg., T1: Trifolium pratense L.)

Parameters	Species											Units	Description
	A[a]	A1[a]	B[b]	D[c]	L[c]	M[c]	P[a]	P1[a]	R[b]	T[a]	T1[b]		
BT	4	2	2	3	2	5	2	5	6	5	5	°C	Minimum temperature to development
OT	22	16	13	14	15	25	15	11	16	19	16	°C	Optimal temperature to development
K	0.35	0.35	0.4	0.45	0.4	0.5	0.5	0.45	0.5	0.9	0.5	-	Light extinction coefficient
CF	0.95	0.95	0.95	0.95	0.8	1	0.95	0.9	1	0.9	0.95	-	Full canopy coefficient
MWU	8	8	8	8	8	7	8	8	8	9	8	mm d^{-1}	Maximum water uptake
LAIini	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	m^2 m^{-2}	Initial LAI
LeafLife	600	550	500	500	1500	400	1000	400	900	800	500	°C-d	Growing degree days to end single leaf
RUE	2.5	2.5	2.7	2.7	3	3.3	2.7	2.2	3	2.9	4	g MJ^{-1}	Radiation use efficiency
SLA	20	20	27	23	26	28	20	26	30	30	30	m^2 kg^{-1}	Specific leaf area
STP	4.5	2.5	3	4.5	1.2	3.5	1.5	3	2	0.2	1.5	-	Steam/leaf coefficient
GDDf	1000	1400	650	650	600	800	1200	1200	900	1200	800	°C-d	Growing degree days to flowering
TBC	4	4.5	4	4	4	4	4	5	4	4	4	kg m^{-2} kPa m^{-1}	Transpiration coefficient to biomass

[a] Parameterization available; it was derived from Piseddu et al. (2022) and Hadj Saadi (2019).
[b] Derived from information available in Longo et al. (2021) and from Argenti et al. (2021).
[c] Parameterization available; it was derived from Movedi et al. (2019).

Appendix C

CoSMo parameters for different species (A: Agropyron repens (L.) Beauv., A1; Arrhenatherum elatius (L.) P. Beauv. ex J. Presl. & C. Presl., B: Bromus hordeaceus L., D: Dactylis glomerata L., L: Lolium multiflorum L., M: Medicago sativa L., P: Poa pratensis L., P1: Poa trivialis L., R: Rumex obtusifolius L., T: Taraxacum sect. Taraxacum F.H. Wigg., T1: Trifolium pratense L.).

Parameters	Species											Units	Description
	A[a]	A1[a]	B[b]	D[c]	L[c]	M[c]	P[a]	P1[a]	R[b]	T[a]	T1[b]		
WCC	1	0.2	0.4	0.7	0.4	0.88	0.8	0.4	0.8	0.75	0.65	-	Drought tolerance: 1 tolerant, 0 sensible
RT	0	0	0	0	0	1	0	0	1	1	1	-	Root type 1 tap root; 0 fibrous root
MinT	4	2	2	3	6	5	2	5	6	5	5	°C	Minim temperature to competition
MaxT	38	33	25	28	30	38	27	24	30	33	29	°C	Maximum temperature to competition
GDDres	0	0	100	0	0	0	0	0	0	0	0	°C-d	Growing degree days to emergence after resowing
GDDdie	-	-	2000	-	-	-	-	-	-	-	-	°C-d	Growing degree days to die
LAImax	5	4	4	7.5	6.5	5	5	4	3.5	5	4	m^2 m^{-2}	Maximum LAI
MaxH	1.2	1.6	1.3	1.5	1	1	0.8	0.9	0.7	0.35	0.8	m	Maximum plant height
OptT	22	16	13	14	15	25	15	11	16	19	16	°C	Optimal temperature
MaxRD	160	140	120	140	100	180	80	40	140	100	160	cm	Maximum rooting depth
Common													
I	80											-	Inertia coefficient of species replacement
WFMin	0.15											m^3 m^{-3}	Minimum water available for fibrous roots growth
WFMax	0.5											m^3 m^{-3}	Maximum water available for fibrous roots growth
WTMin	0.1											m^3 m^{-3}	Minimum water available for tap roots growth
WTMax	0.4											m^3 m^{-3}	Maximum water available for tap roots growth
DWT	8											°C	Average air temperature to reach after winter to restart to growth

[a] Parameterization available; it was derived from Piseddu et al. (2022) and Hadj Saadi (2019).
[b] Derived from information available in Longo et al. (2021) and from Argenti et al. (2021).
[c] Parameterization available; it was derived from Movedi et al. (2019).

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