How the interplay between management and interannual climatic variability influences the NDVI variation in a sub-Mediterranean pastoral system: insight into sustainable grassland use under climate change

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Abstract

The modification of precipitation regimes and the increase in summer aridity under the predicted climate change scenarios are hypothesized to have repercussions on the semi-extensive pastoral systems of Mediterranean grasslands, leading to change in forage quantity/quality, increased interannual variability in phytomass production, reduction of the carrying capacity of rangelands, and worsening of animal welfare. The research aims were to find what climatic features affect changes in the annual peak of Aboveground Net Primary Production (ANPP), and how topographic variables and management conditions influence these variations in a pastoral system of central Apennines (Italy).

We monitored Normalized Difference Vegetation Index (NDVI) variations at the peak of phytomass production using Landsat satellite images, used as a proxy for ANPP changes in the most productive phase of the growing season, when herds are carried to pastures and hay-meadows are mown, on a dataset of 10,000 randomly sampled pixels (30 x 30 m), in the years 2003, 2007, 2009, 2010, and 2013-2015. We investigated the relation between NDVI and climatic variables, topographic parameters, vegetation physiognomy, and management type, using generalized linear mixed-effects modeling, variation partitioning, and correlation analysis.

We observed an increase in average yearly temperatures and high variability in the rainfall seasonal distribution pattern, particularly of spring precipitation. Climatic fluctuations influenced the overall amount of forage production more than management and topographic conditions. The spring variation of climatic variables (precipitation in March, drought stress in April and May), the drought and cold stress intensities in the previous year and the cold stress in the preceding winter were the main drivers of NDVI change. The landform factors interacted with climate variability in determining the amplitude of NDVI changes, which were the widest in semi-flat mountain tops and flat valley bottoms and the smallest in south-facing slopes. The effect of the climatic variables on NDVI was different depending on the management condition, suggesting that grassland management partially filters the climatic drivers of changes in forage production. Based on our results, the most productive grassland communities and the areas used for grazing by domestic herbivores could be the most impacted by the predicted climate changes for the Mediterranean basin, potentially reducing the economic sustainability of semi-extensive farming in the Apennine mountains.

KEYWORDS: Aboveground Net Primary Production; bioclimatic indices; climatic fluctuations; grassland management; remote sensing

1. Introduction

Forage production, namely the Aboveground Net Primary Production (ANPP), is one of the most important ecosystem services provided by semi-natural grasslands (Peeters, 2009), and depends on several factors. ANPP is strongly influenced by macro-climate features, especially by the amount of rainfall and its seasonal distribution (Knapp et al., 2001; Nippert et al., 2006), particularly in water-limited environments, like the Mediterranean-type ecosystems (Miranda et al., 2011). Therefore, global warming and the associated expected increase in dryness (IPCC, 2019) will represent a significant challenge to the economic sustainability of livestock breeding and one of the most relevant factors threatening the Mediterranean pastoral systems (Scocco et al., 2018). Impact due to global warming may accelerate the abandonment of mountain farming (Nardone et al., 2010) with a dramatic loss of cultural heritage and aesthetic values of mountain areas (Catsadorakis, 2007). Moreover, climate-driven variability in grassland ANPP influences the global carbon balance, the provision of ecosystem services including biodiversity, and the sustainability of grassland resources utilization (Grime et al., 2000; Guo et al., 2012; Sala et al., 2012). Consequently, quantifying and modelling the effects of variability related to climate change on the forage production of pastoral systems is a key issue to draw up management plans and implement adaptation strategies to face the effects of global warming (Nardone et al., 2010).

Previous research on climate change highlighted that the Mediterranean basin will be one of the most affected areas in the world, with a large reduction of average precipitation (Stocker et al., 2013) and an increase of their interannual variability (Planton et al., 2016), especially during spring and summer (Bugalho and Milne, 2003; Shafran-Nathan et al., 2013). This may lead to an increase of intensity and frequency of drought events (Giorgi and Lionello, 2008; Giorgi and Coppola, 2009). Modification of the existing regimes of precipitation and temperature will cause the shift of functional and coenological structure of grasslands (Tardella et al., 2016), the worsening of forage features, and the reduction of grassland carrying capacity and animal welfare (Scocco et al., 2016b), even if the complexity of the vegetation mosaic may originate a context-dependent ANPP response (Wellstein et al., 2014, Chelli et al., 2016). In Mediterranean mountains, winter cold stress and summer drought stress intensities are in fact extremely variable in space, depending on elevation, aspect, and slope angle gradients (Somot et al., 2008). Consequently, the vegetation types are variously adapted to overcome different drought stress intensities (Tardella et al., 2016) being landform features a major driver in determining the coenological and functional characteristics, as well as the productivity of grasslands (Catorci and Gatti, 2010; Burrascano et al., 2013). As a matter of fact, it was proved that in south-facing slopes, where vegetation normally experiences a higher summer drought stress, grasslands are less sensitive to climate variations in terms of phytomass production, while the amplitude of differences is higher in more productive conditions (e.g., flat areas and north-facing slopes - Scocco et al., 2016a). Regardless of the land morphology context, the ANPP of sub-Mediterranean grasslands is characterized by a bimodal curve with the main peak in end of June-early July and a secondary peak in autumn, with a stagnation of the regrowth capacity in summer, sometimes associated with the drying of the grass cover (Cesaretti et al., 2009). Analogously, the low temperature, frost and the snow cover of the winter period inhibit the plant growth (Cesaretti et al., 2009). Since the herds are carried to the mountain pastures between the end of May and the beginning of October, the peak of phytomass production between the end of June and early July is crucial for the sustainability of semi-extensive farming in the Mediterranean mountains and variation in the amount of phytomass at its main annual peak due to climate change represents a key issue.

Despite the importance of understanding the effect of global changes on Mediterranean pastoral systems, most of the studies on variation in grassland productivity focused on small scales (e.g., Golodets et al., 2013; Chelli et al., 2016; Nogueira et al., 2017), but overlooked the landscape scale, which is the most suitable level of analysis for the implementation of restoration and conservation plans and sustainable policies (Irwin et al., 2001; Jobin et al., 2010). It was proved that low to moderate levels of grazing may increase production over the absence of grazing, but that the level of grazing that maximizes production depends upon the climatic conditions of the considered year (Patton et al., 2007). Thus, a further key factor to consider for understanding the response of pastures to climate change is the interplay of management conditions and interannual climatic variability. The effect of previous-years' climate on the degree of interannual variation in primary production is another important aspect. It was stated in fact that this effect is buffered if wet, more productive years alternate with dry, less productive years, and is amplified in the case of consecutive wet or dry years (Oesterheld et al., 2001).

To fill the current lack of knowledge for Mediterranean-type pastoral systems, we performed a study at the landscape scale in an Apennine pastoral district of central Italy, with a millennial history of pastoralism. In recent decades, this district underwent a partial cessation of shepherding, resulting in a mosaic of grazed (with different intensities), mowed, and abandoned grasslands. Mediterranean pastoral systems are a biodiversity hotspot (Dengler et al., 2014) and a cultural heritage because they are a very ancient human-shaped landscape (Brown et al., 2013). They are still an important economic element for mountain populations, especially because of the increasing interest in high-quality foods (Martins et al., 2017).

The specific aims of our study were to find what climatic features affect the ANPP at its peak (basic factor for semi-extensive farming in the Mediterranean mountains) and how topographic variables and management conditions influence these variations. To achieve these goals, we used the remote sensing approach. Remote sensing has proven to be a practical and affordable tool for rapidly quantifying important biophysical characteristics of grasslands (Kallenbach, 2015; Primi et al., 2016) from local to global scale (Xie et al., 2008), overcoming some of the problems involved in large-scale field surveys (Nagendra et al., 2013). In particular, the 30 x 30 m pixel resolution of the publicly available Landsat TM data (Nagendra et al., 2013) can allow for relatively fast mapping of biomass patterns, using well-known indices such as the Normalized Difference Vegetation Index (NDVI) obtained from a spectral transformation of the red and near infrared bands. NDVI showed to be well correlated to aboveground phytomass, especially in grassland ecosystems (Muñoz et al., 2010; Mangiarotti et al., 2012), hence the multi-annual variations of NDVI can be considered a good proxy to study changes in ANPP (Rezende et al., 2020).

We hypothesized that the effect of climatic variation is context-dependent and the net result on productivity is given by the interactions between climatic and topographic/management factors. We expected that NDVI variations depend both on current and previous year climatic trends and that the effect of the climatic variables on NDVI is influenced by landform and management regime.

To test such hypotheses, we addressed the following questions: i) How does interannual climatic variability affect NDVI variation? ii) How do topographic features affect NDVI variation, and how do they influence the NDVI response to climate trends? iii) How does management type affect NDVI variation, and how does it influence the NDVI response to climate trends?

2. Materials and methods

2.1 Study area

The study area is a farming system of about 3,000 ha, located along the mountain ridge of the Umbria-Marche Apennines of central Italy (central coordinates 42°57’20’’N; 13°01’00’’E, Fig. 1), between 760 and 1,570 m a.s.l., characterized by limestone lithotypes. In general, the landforms consist of deep and buried valleys, delimited by very steep slopes (maximum slope angles of 45/50°), which in the summit areas, or the areas corresponding to karstic-tectonic plateaux, soften to form flat or not very steep plateaux. The soil has a neutral-sub acid pH, and its depth ranges from 10 (steep south-facing slopes) to more than 100/120 cm (flat bottom of the valleys).

Following Pesaresi et al. (2017), the study area belongs to the Temperate sub-Mediterranean bio-climatic unit, with a weak sub-Mediterraneity and extends within the lower supra-temperate belt with an upper humid ombrotype. It is characterized by the alternation of winter cold stress and summer drought stress (Rivas-Martínez and Rivas-Saenz, 2016). The mean annual rainfall is about 1,100 mm, and the average annual temperature 10-11°C. Soil summer water deficit is usually present in both south- and north-facing slopes. South-facing slopes are characterized by a longer period of water scarcity (from the beginning of June to the end of September), shallow soils, covered by xerophilous communities with open canopy interrupted by patches of bare soil. These plant communities are rich in annual and chamaephyte species, and with a mostly early spring blooming period. North-facing slopes are covered by semi-mesophylous communities dominated by hemicryptophytes and forbs with a prolonged and late blooming period. They have a short and less intense soil water shortage from early/mid-July to the end of August (Catorci et al., 2012, 2017).

The growing season (number of days with minimum temperature over 6 °C) lasts 150–180 days yr^{-1} (Catorci et al., 2009). The plant landscape is composed of different secondary grasslands, interrupted by small beech copses (ancient groups of centuries-old beech trees once used to shelter the herds under the shade in the hottest hours of the day) and croplands. From a phytosociological viewpoint, the pastoral landscape is referred to *Erysimo-Jurineetalia bocconei* S. Brullo 1984 order (*Festuco hystricis-Ononidetea striatae* Rivas-Martínez et al. 2002 class *sensu* Mucina et al., 2016) and *Arrhenatheretalia elatioris* Tx. 1931 order (*Molinio-Arrhenatheretea* class).

The entire study area is characterized by livestock activity, but also by sites with low disturbance intensity or totally abandoned like the slopes within the "Montagna di Torricchio" Nature Reserve. Farming activities are based on sheep and cattle breeding. Cattle are free to graze, while sheep are herded by shepherds. The grazers have different feeding behaviors and vegetation preferences: cattle opt for flat or semi-flat landforms (see also Putfarken et al., 2008), while sheep graze mainly on the slopes. Flat areas covered by meadows are mowed once a year in July and then grazed by cattle.

In the last two decades, the surface area occupied by grasslands did not change significantly, and shrub encroachment (*Juniperus* sp. pl. and *Cytisophyllum sessilifolium* (L.) O.Lang) affected only some slopes that were excluded from the study area. No data are available to ascertain taxonomic changes of grasslands during the considered period of the research.

2.2 Data collection and pre-processing

2.2.1 Climatic data

We gathered climatic data (average monthly temperatures and monthly precipitations) referred to the years 2001-2015 from the meteorological station of Cupi di Visso (Macerata), at 978 m a.s.l., which borders the study area. Prior to data processing, we adjusted mean temperature values using the correction by Cerquetti and Cruciani (1987), that is 0.43 °C decrease every increase in elevation of 100 m. Then, we calculated the following climatic indices: Mitrakos' Monthly Drought Stress (MDS), Summer Drought Stress (SDS), Yearly Drought Stress (YDS), Monthly Cold Stress index (MCS), Winter Cold Stress index (WCS), Yearly Cold Stress (YCS) (Mitrakos, 1980, 1982), positive yearly precipitation (PYP), positive yearly temperature (PYT), and ombro-thermal index (Io) (Rivas-Martinez and Rivas-Saenz, 2016).

We calculated the MDS index for March, April, May, and June of the observation year, to include the period from the start of the growing season to the month before the acquisition of the satellite images, and of all the months of the previous year, using the formula MDS = $2 \times (50 - P)$, where P is the monthly rainfall (mm); the index value is null when $P \geq 50$ mm. We calculated the SDS of the previous year using the formula SDS = $2 \times (50\text{-}P_s)$, where P_s is the average of the monthly rainfall of the summer months (June, July, and August), and the YDS of the previous year, summing the MDS values of all the months of the year. In addition, we calculated the MDS values of the spring months (March, April, and May) in the year in which the satellite images were acquired, and calculated a Spring Drought Stress index (SpDS) using the same formula used to calculate the SDS index, but using precipitation of the spring months. We calculated the Monthly Cold Stress index of the year of image acquisition and of the year before using the formula MCS = $8 \times (10 - t)$, where t is the average monthly minimum temperature (°C) (MCS is null if $t \geq 10$ °C, and is 100 if $t \leq -2.5$ °C), to obtain the WCS by the sum of the MCS values of the winter months (December, January and February), an index of spring cold stress (SpCS) by the sum of the MCS values of the spring months (March, April, and May) immediately before image acquisition, and YCS by the sum of all the MCS values of the year before. Using data of the year before the image acquisition, we calculated the average yearly temperature (YT, °C), the yearly precipitation (YP, mm), the PYP (mm) as the total precipitation of months whose average temperature was higher than 0 ºC, the PYT (tenths of °C) as the sum of the monthly average temperature of months whose average temperature was higher than 0 ºC, and the Io, which is ten times the PYP/PYT ratio.

Average monthly and yearly temperatures (minimum, maximum, and mean temperatures) and mean monthly and yearly precipitation values in the period 1971-2000 are reported in Supplementary data (Table A), along with temperature and precipitation values of the years in the period 2001-2015.

2.2.2 NDVI data set

We acquired Landsat 5 TM images from July 1st to July 15th (since during this period plant communities reach the peak of phytomass production – Cesaretti et al., 2009) of the years 2003, 2007, 2009, 2010 and Landsat 8 Operational Land Imager (OLI) images of the years 2013, 2014, and 2015. These dates were selected to obtain the minimum cloud cover within the ideal period for vegetation growth (phytomass peak). The use of the peak of phytomass as a proxy for ANPP assumes that: minimum phytomass is zero or close to zero; it increases up to a peak after which senescence starts; and there is no carryover from one growing season to the next (Sala et al., 2000). This method may underestimate ANPP because it assumes a single maximum, overlooking other possible phytomass peaks during the growing season, and because part of the phytomass produced may replace tissues that senesced during the same period (Sala et al., 2000). However, we were chiefly interested in the main peak of phytomass production, since it is strictly related to the sustainability of semi-extensive farming practices, as described above. We discarded the images of the years 2000-2002, 2004-2006, 2008, 2011, and 2012 because of the presence of a significant cloud cover. Landsat 5 TM provides orthorectified multispectral images with 30 m pixel resolution and five spectral bands. Landsat 8 OLI provides orthorectified multispectral images with 30 m pixel resolution and nine spectral bands. All the selected images were pre-processed by performing topographic correction based on an illumination model obtained from the NASA Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) mission website (http://asterweb.jpl.nasa.gov/gdem.asp), and then elaborated to obtain top-of-atmosphere reflectance values, which were used for all the analyses described below.

The NDVI was computed from the remote sensing data obtained for the analyzed periods. NDVI is obtained from a spectral transformation of the Red (RED) and Near Infrared (NIR) bands (Rouse et al. 1974). The NDVI is calculated using the formula (NIR-R) / (NIR + R), where the R and NIR stand for the spectral reflectance measurements acquired in the visible regions (red band) and near-infrared. According to the definition, the NDVI values vary between -1 and +1. These spectral reflectances are themselves ratios of the radiation reflected on the incoming one for each spectral band, and consequently take values between 0 and 1.

We made a preliminary physiognomic map of grasslands (scale 1: 10,000), including pastures, meadows, and abandoned pastures, and excluding uncultivated lands and fallow fields, through visual interpretation of the physiognomic types on the Landsat image of 2015. All the abandoned pastures were inside the "Montagna di Torricchio" Nature Reserve. We verified the reliability of this map by performing a field survey during summer 2015. We classified as grasslands those areas whose shrub cover was lower than 20% in 2015. The areas with beech copses, extensive rocky outcrops, bare soil, roads, and around livestock watering points were not included in the map. To exclude that any part of the grasslands mapped in 2015 had undergone vegetation dynamic processes in the previous years, we compared the map with the satellite images of 2003 and the vegetation map of the Marche Region, whose surveys were carried out in the years 2005-2006 (Catorci et al., 2007).

Then, we randomly extracted a total of 10,000 pixels to select a sample as much representative as possible of the combination of topographic features, vegetation physiognomy and management types in the study area. We calculated NDVI values on the same pixels for each considered year.

We used QGIS 2.14.0 (QGIS.org 2016) and GRASS 7.0.3 (GRASS Development Team, 2016) to produce the map of grasslands and for elaborations of the remote sensing images.

2.2.3 Topographic features, vegetation physiognomy and management data

We used the Global Digital Elevation Model with 30 m pixel resolution obtained from the NASA ASTER mission website to obtain georeferenced data of landform features, elevation, aspect angle (azimuth degrees), and slope angle (vertical degrees). We produced aspect, slope and raster maps, using *r.param.scale* module in GRASS GIS. We categorized landform in four categories: north-facing slopes (from west-north-west to east-south-east clockwise); south-facing slopes (from east-south-east to west-north-west clockwise); mountain semi-flat top (semi-flat or gently sloping mountain tops); and flat and semi-flat lands in plateaux and along valley bottoms.

On the map of grasslands previously generated, we identified and mapped three vegetation physiognomies through photointerpretation, i.e. grassland (< 5% of shrub cover), shrubby grassland (shrub cover ranging from 5 to 20%), and meadow.

We categorized management type in four classes: i) absence of grazing (ungrazed turf; grasslands characterized by the spread of competitive tall grasses); ii) low-intensity grazing (turf not completely consumed by grazing herbivores at the end of the growing season); iii) optimal grazing (turf completely consumed by grazing herbivores at the end of the growing season, with turf height less than 3 cm); iv) mowing followed by grazing (the turf is mown once a year and removed, and then grazed by cattle). We mapped these categories based on interviews to farmers, field observations, and the management plan of the "Montagna di Torricchio" Nature Reserve. The management type did not undergo substantial changes during the studied period, although small changes may have happened in optimally and low-intensity grazed grasslands, due to possible local-scale interannual modifications in the number and type of grazing herbivores and timing of grazing.

2.3 Data elaboration

The data matrix was composed of 70,000 records (10,000 pixels per considered year) per 26 variables. Landform, vegetation physiognomy, and management type were treated as categorical variables, while the other ones (elevation, slope angle, and the climatic variables) as continuous variables (Table 1).

Preliminarily, we calculated the overall mean NDVI (± Standard Deviation) and the mean NDVI for each year on the overall dataset and for northerly slopes, southerly slopes, semi-flat tops, flat valley bottoms, optimal grazing intensity, low grazing intensity, mowing and grazing, and grazing cessation.

To understand the drivers of NDVI variation, we used generalized linear mixed-effects models, using as random intercept pixel identity and as fixed effects elevation, slope angle, landform, vegetation physiognomy, management type, monthly precipitation and mean monthly temperature (March-June of the observed year), MDS (March-June of the observed year), SpDS and SpCS (March-May of the observed year), YDS, YCS, SDS, and WCS of the year/summer/winter before image acquisition; YT, YP, PYP, PYT, and Io of the year before image acquisition.

To select the variables that best explained the NDVI variability, we fitted five sub-models including different groups of variables: i) spatial variables (elevation, slope angle, landform, vegetation physiognomy, and management type); ii) monthly precipitation and mean monthly temperature (March-June of the observed year); iii) MDS (March-June of the observed year); iv) YDS, YCS, SDS, and WCS of the year/summer/winter before image acquisition; v) YT, YP, PYP, PYT, and Io of the year before image acquisition.

To perform all statistical analyses we used R software, Microsoft R 3.5.3 (R Foundation for Statistical Computing, Vienna, Austria, http://www.R-project.org). We computed each sub-model using the lmer function (lme4 R-package, version 1.1-21) with the explanatory variables in turn. As a first step, we selected the explanatory variable with the highest marginal R^2 if that variable was also significant ($P < 0.05$) (significance assessed by running a log-likelihood test). We calculated models' R^2 using the r.squaredGLMM function (MuMIn R-package, version 1.43.6). Then, we looked for a second variable to include in the model by computing the model containing the previously selected variable plus the variable among the remaining ones that formed the model with the highest R^2, only if the partial contribution of that variable was significant and if it did not inflate the model's variance. The significance of one model over the previous one, and thus of every added variable, was tested running a log-likelihood test (anova function of the stats R-package). We checked possible collinearities calculating the Variance Inflation Factor, in case of continuous variables, or the

Generalized Variance Inflation Factor for categorical variables, using the vif function of the car R-package (version 3.0-2). Variables whose VIF or squared GVIF^(1/2Df) was higher than 5 were not included in the model. This procedure was repeated until a candidate variable did not improve significantly the model or increased the adjusted R^2 over that of the full model. Given that the observations were collected over time, prior to further elaborations, we explored the presence of temporal autocorrelation in the models' residuals using the acf function (stats package, version 3.5.3), which calculates the degree of correlation associated with increasing lags. As each pixel had the same position over time, after having checked the model linearity assumptions using the gvlma function (gvlma package, version 1.0.0.3), we fitted one linear model per pixel (lm function, stats package), where NDVI was the response variable and a climatic variable in turn, the predictor. Then, estimates of the autocorrelation function were computed and plotted using the acf function, applied to every fitted model. We did not detect any temporal autocorrelation.

The selected variables were used as fixed effects in a new model, which was subjected to the same procedure to obtain the most parsimonious model. Finally, to ascertain the absence of a statistically significant difference between the reduced and the full model, we compared them using a log-likelihood test (anova function).

To quantify the relative contribution of variables that emerged from the model selection procedure, we calculated marginal and conditional R^2 for each of the four sub-models including the selected climatic variables, the selected topographic variables, vegetation physiognomy, and management type, if significant. Finally, we calculated marginal and conditional R^2 for each variable separately.

We analyzed the interactions between topographic variables/management type and single climatic variables that emerged from the selection procedure, by fitting linear mixed-effects models, using as fixed effects "topographic variable*climatic variable" or "management type*climatic variable" and pixel identity as a random intercept. Prior to the analysis of interactions between climatic and topographic variables, the continuous variables were scaled (scale function, center = T, scale = F).

To understand how much variability was explained in each considered year by elevation, slope angle, landform, vegetation physiognomy, and management type singly considered, by the overall set of topographic variables, and the joint contribution of topographic variables and vegetation physiognomy, topographic variables and management type, and vegetation physiognomy and management type, we performed variation partitioning (Borcard et al., 2011) of the NDVI data set. We calculated *adjusted* R^2 values to produce unbiased estimates of the contributions of the independent variables to the explanation of the response variables (Peres-Neto et al., 2006). To test whether each independent fraction exhibited a significant influence on NDVI data, we applied a permutation test with 999 permutations (Legendre and Legendre, 2012). To perform variation partitioning, we used vegan R-package, version 2.3-4 (*varpart* function); to perform permutation tests, we used the *rda* function of the vegan package and the *anova* function of the stats package, version 3.5.3.

To understand whether the NDVI variability explained by topographic factors, management type and vegetation physiognomy in the considered years was related with climatic variation, using the overall data set and the partial data sets composed of pixels inside different management types, vegetation physiognomies, and landforms, we calculated the correlation (Spearman's rho) between the values of each climatic variable/index that emerged from model selection and the NDVI variability explained by: topographic variables, vegetation physiognomy, and management type (overall dataset); topographic variables and vegetation physiognomy (inside each management type); topographic variables and management type (inside each physiognomy); elevation, slope angle, vegetation physiognomy, and management type (inside each landform).

To perform correlation analysis, we used the stats package, version 3.5.3 (*cor.test* functions).

Table 1. Variables used as fixed effects in the models, with their respective label, unit of measurement, and type, associated to each of the 10,000 pixels every considered year.

Variable	Label	Unit of measurement	Type
Elevation		m a.s.l.	Numeric
Slope angle		Vertical degree	Numeric
Landform		-	Categorical
Vegetation physiognomy		-	Categorical
Management type		-	Categorical
[+ a]Average temperature in March	T_{Mar}	° C	Numeric
[+ a]Average temperature in April	T_{Apr}	° C	Numeric
[+ a]Average temperature in May	T_{May}	° C	Numeric
[+ a]Average temperature in June	T_{Jun}	° C	Numeric
[a]Precipitation in March	P_{Mar}	mm	Numeric
[a]Precipitation in April	P_{Apr}	mm	Numeric
[a]Precipitation in May	P_{May}	mm	Numeric
[a]Precipitation in June	P_{Jun}	mm	Numeric
[a]Drought stress index in March	MDS_{Mar}	-	Numeric
[a]Drought stress index in April	MDS_{Apr}	-	Numeric
[a]Drought stress index in May	MDS_{May}	-	Numeric
[a]Drought stress index in June	MDS_{Jun}	-	Numeric
[a]Spring Drought stress index	SpDS	-	Numeric
[+ b]Average yearly temperature	YT	°C	Numeric
[b]Yearly precipitation	YP	mm	Numeric
[+ b]Ombro-thermal index	Io	-	Numeric
[+ b]Positive yearly temperature	PYT	tenths of °C	Numeric
[b]Positive yearly precipitation	PYP	mm	Numeric

[+c]Winter cold stress	WCS	-	Numeric
[a]Sum of cold stress values in March, April, and May	SpCS	-	Numeric
[+b]Yearly cold stress	YCS	-	Numeric
[b]Summer drought stress	SDS	-	Numeric
[b]Yearly drought stress	YDS	-	Numeric

[a] Referred to the same year in which the NDVI data were gathered

[b] Referred to the year before the NDVI data were gathered

[c] Referred to the winter before the growing season in which the NDVI data were gathered

[+] Data adjusted using the correction by Cerquetti and Cruciani (1987), that is 0.43 °C decrease every increase in elevation of 100 m

3. Results

3.1 Climatic trends and NDVI variation

Average yearly temperatures and mean minimum temperatures in the considered period increased by about 1.5 and 2.7 °C, respectively, compared to the previous 30 years, while the mean yearly precipitation remained substantially unmodified. However, the seasonal distribution pattern of rainfall changed (Table A, Supplementary data); in particular, mean spring rainfall showed a higher decrease (-14%) than summer precipitation (-5%). This trend was highly heterogeneous over time and intensified in some years: -49% and -38% of spring rainfall in 2003 and 2007; -75%, -68%, and -49% of summer rainfall in 2001, 2007, and 2012 compared to the 30-year mean value.

The interannual trends of climatic parameters and indices were very changeable during the studied period (Supplementary data, Table B). In particular, among the considered years, 2003 showed the lowest T_{Apr} and P_{May}, and the highest T_{Jun}, with a drought stress period in May; 2007 showed two drought stress periods in April and June, when the highest mean monthly temperature and the lowest monthly precipitation in the studied period were recorded, and the highest YCS in the year before. The year 2009 had the highest T_{May} and P_{Jun}, while 2010 the lowest P_{Mar}, and the lowest SDS and

YDS, and the highest WCS during the year before. The year 2013 showed the lowest T_{Mar}, T_{May} and T_{Jun}, the highest P_{May} and no spring drought stress, as well as the highest SDS, YDS, PYT, and YT in the year before. The year 2014 had the highest T_{Mar} and PYP, and the lowest WCS in the year before, whereas 2015, the highest P_{Mar} and the lowest P_{Apr}, being April the month whose drought stress was the highest among the considered years, and the lowest YCS in the year before.

Mean NDVI values (Table 2) showed an increasing trend from 2003 (0.43) to 2015 (0.67). This trend was consistent across all the landforms and management types. Semi-flat tops had higher average values (0.59) than north-facing slopes (0.55), flat valley bottoms (0.54), and south-facing slopes (0.53). Among management types, abandoned grasslands showed the highest mean NDVI value (0.58), while low grazing intensity the lowest (0.52) (Table 2).

3.2 How does inter-annual climatic variability affect NDVI?

Climatic variables emerging from the model selection procedure were P_{Mar}, MDS_{Apr}, MDS_{May}, PYP, YDS, WCS, and YCS (Table 3). They explained 45.30% of NDVI variation in all. P_{Mar}, MDS_{Apr}, PYP, and YCS of the preceding year were positively related to NDVI, while MDS_{May}, WCS, and YDS of the previous year, were negatively related (Table 3). Drought stress indices and YCS, singly considered, explained the highest percentage of variance, ranging between 14 and 17% (Table 3).

3.3 How do topographic features affect NDVI variation and how do they influence the NDVI response to climate trends?

All the considered topographic features (elevation, slope angle and landform) were selected in the best model (Table 3), explaining the 4.87% (P = 0.001) of NDVI variance. Elevation singly considered, accounted for the 2.83% (P = 0.001), followed by slope angle (2.82%, P = 0.001), and landform (2.19%, P = 0.001).

The proportion of variance significantly explained by the topographic variables changed considerably over time (Table 4, Supplementary data - Table C), ranging from 0.85% (2013) to

18.18% (2007). The portion of NDVI variability explained by the slope angle positively correlated with MDS_{Apr} (0.80^{*}) in the overall dataset, in both north- and south-facing slopes; that explained by elevation correlated with YDS (-0.79^{*}) in flat valley bottoms. NDVI variability explained by landform positively correlated with YCS (0.82^{*}) in the overall dataset.

Increasing elevation reduced the positive effect of P_{Mar} on NDVI and increased the negative effects of MDS_{May}, YDS, and WCS (Table 5). Increasing slope angle reduced the influence of MDS_{Apr}, MDS_{May}, YDS, and WCS. The different landforms interacted in the same direction with climatic variables, but the effects of drought stress (MDS_{Apr}, MDS_{May}, YDS) and WCS were lower in south-facing slopes than in the other landforms and higher in mountain tops (Table 5).

3.4 How does management type affect NDVI variation and how does it influence the NDVI response to climate trends?

Management type explained the 5.33% ($P = 0.001$) of variance of the NDVI data. Yearly variance explained ranged from 4.12 (2009) to 11.90 (2014).

The effects of MDS_{Apr}, MDS_{May} on NDVI were amplified under optimal and low grazing intensity, while the positive effect of P_{Mar} was the highest in low grazing intensity (Table 6). The positive influence of PYP diminished and in every managed condition, while negative effects of WCS and YCS were both mitigated in mowing/grazing condition; the negative effect of YDS was exacerbated under optimal grazing and mowing/grazing conditions (Table 6).

In optimal grazing intensity grasslands, NDVI variability explained by elevation (Supplementary data, Table C) correlated with MDS_{Apr} (0.76^{*}). In low grazing intensity grasslands NDVI variability explained by slope angle positively correlated with MDS_{Apr} (0.80^{*}). In mown and grazed grasslands, NDVI variability explained by landform positively correlated with MDS_{Apr} (0.88^{**}) and PYP (-0.79^{*}), which explained by elevation and slope angle correlated with PYP (0.82^{*}) and YCS (-0.80^{*}), respectively. In abandoned grasslands, the NDVI variability explained by elevation correlated with

P_{Mar} (0.79*), while that explained by the slope angle showed a negative correlation with YDS (-0.93**).

Table 2. Mean values and standard deviation (SD) of the Normalized Difference Vegetation Index (NDVI), calculated, for seven years between 2003 and 2015, from an overall data set of 10,000 randomly selected pixels. Mean and SD values were disaggregated into different landforms and management types.

	Year	2003	2007	2009	2010	2013	2014	2015	All
Overall dataset	Mean	0.4304	0.5224	0.5569	0.5412	0.4743	0.6281	0.6671	0.5461
	SD	0.0616	0.0927	0.1028	0.0844	0.0803	0.0895	0.0884	0.1153
Northerly slopes	Mean	0.4295	0.5306	0.5657	0.5470	0.4832	0.6305	0.6695	0.5510
	SD	0.0635	0.0893	0.0965	0.0819	0.0837	0.0878	0.0849	0.1138
Southerly slopes	Mean	0.4257	0.4968	0.5322	0.5235	0.4693	0.6096	0.6477	0.5307
	SD	0.0621	0.0933	0.1108	0.0873	0.0813	0.0919	0.0941	0.1158
Semi-flat tops	Mean	0.4504	0.5850	0.6112	0.5859	0.4642	0.6818	0.7223	0.5853
	SD	0.0514	0.0719	0.0709	0.066	0.0611	0.0662	0.0549	0.1127
Flat valley bottoms	Mean	0.4332	0.5276	0.5725	0.5387	0.4594	0.6172	0.671	0.5433
	SD	0.0487	0.0612	0.0645	0.0641	0.0701	0.0532	0.0537	0.0972
Optimal grazing intensity	Mean	0.4496	0.5623	0.5843	0.5724	0.4806	0.6685	0.7014	0.5734
	SD	0.0547	0.0863	0.1059	0.0754	0.0732	0.0761	0.0738	0.1150
Low grazing intensity	Mean	0.4103	0.4910	0.5342	0.5127	0.4642	0.5945	0.6389	0.5219
	SD	0.0603	0.0881	0.0968	0.0821	0.0818	0.0861	0.0897	0.1114
Mowing and grazing	Mean	0.4518	0.5167	0.5764	0.536	0.4375	0.6502	0.7310	0.5361
	SD	0.0201	0.0492	0.0696	0.0658	0.0519	0.0566	0.0207	0.0900
Grazing cessation	Mean	0.4773	0.5468	0.5803	0.5912	0.5209	0.6727	0.7023	0.5849
	SD	0.049	0.0723	0.0907	0.0644	0.0873	0.0716	0.0704	0.1047

Table 3. Parameters' estimates and significance level (*P*) of NDVI model built using a forward selection procedure. Marginal and conditional R^2 values of each single variable is also indicated.

Model variables	Estimate	*P*	*Marginal* R^2	*Conditional* R^2
Intercept	0.1624			
Low grazing intensity	-0.0723			
Mowing_Grazing	-0.0460	***	0.05	0.37
Optimal grazing intensity	-0.0289			
Flat valley bottom	-0.0031			
North-facing slope	0.0047	*	0.02	0.37
South-facing slope	0.0006			
Elevation	0.0001	***	0.03	0.37
Slope angle	-0.0020	***	0.03	0.37
Vegetation physiognomy - Shrubby grassland	0.0639	***	0.00	0.37
Vegetation physiognomy - Meadow	-0.0089			
P_{Mar}	0.0005	***	0.10	0.48
MDS_{Apr}	0.0091	***	0.14	0.54
MDS_{May}	-0.0177	***	0.17	0.56
PYP	0.0002	***	0.03	0.40
YDS	-0.0003	***	0.14	0.53
WCS	-0.0001	***	0.04	0.44
YCS	0.0002	***	0.16	0.62
AIC	-224862.5			
P	$< 2.2\ 10^{-16}$			
Model's marginal R^2	0.5642			
Model's conditional R^2	0.8849			

*** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$

Table 4. Amount of spatial variation (%) explained in the observed years at the peak in phytomass production by the topographic variables in all and by the topographic variables singly considered, vegetation physiognomy, and management type.

Year	2003	2007	2009	2010	2013	2014	2015
Elevation^{+}	6.77***	6.81***	5.76***	5.28***	0.59***	6.13***	5.76***
Slope angle^{+}	0.47***	4.12***	1.83***	2.58***	0.00$^{n.s.}$	3.05***	6.08***
Landform^{+}	0.24**	0.40***	0.25***	0.13**	0.12***	0.06*	0.10**
Vegetation physiognomy^{+}	5.72***	5.50***	6.98***	5.89***	11.82***	5.92***	5.79***
Management type^{+}	11.76***	8.74***	4.12***	11.35***	5.61***	11.90***	7.99***
Topographic variables^{+} (elevation, slope angle and landform)	8.18***	18.18***	12.91***	12.26***	0.85***	13.66***	17.07***
Topographic variables and vegetation physiognomy^{++}	-4.34	-4.43	-4.55	-4.11	1.46	-4.3	-4.37
Topographic variables and management type^{++}	3.11	6.07	3.26	4.12	0.44	6.93	5.82
Vegetation physiognomy and management type^{++}	-1.2	-1.1	-0.94	-1.26	-1.26	-1.39	-1.03
All the variables	23.23***	32.97***	21.05***	27.91***	17.76***	32.49***	31.00***

*** $P < 0.001$, ** $P < 0.01$, ** $P < 0.01$, n.s. not significant

$^{+}$ Single portion of variability explained by variables; $^{++}$ joint portion of variability explained by variables (negative values are considered as null)

Table 5. Parameters' estimates of models including each topographic variable and climatic variables emerged from a model selection procedure, in turn. Models include the main effects (topographic and climatic variable) and their interaction. Continuous variables have been scaled. All predictors were significant ($P < 0.001$), except those whose estimate is indicated in italics. Climatic variables included in the models are indicated by $X_{1\text{-}7}$. The value in a cell under the header $X_{1\text{-}7}$ or topographic variable : $X_{1\text{-}7}$, refers to the climatic variable or to the interaction between topographic and climatic variable indicated in the first column.

Climatic variable ($X_{1\text{-}7}$)	Elevation*Climatic variable			Slope*Climatic variable			Landform* Climatic variable						
	Elevation	$X_{1\text{-}7}$	Elevation : $X_{1\text{-}7}$	Slope	$X_{1\text{-}7}$	Slope : $X_{1\text{-}7}$	North	South	Flat	$X_{1\text{-}7}$	North: $X_{1\text{-}7}$	South : $X_{1\text{-}7}$	Flat : $X_{1\text{-}7}$
P_{Mar}	1.3×10^{-4}	1.1×10^{-3}	-8.80×10^{-7}	-2.28×10^{-3}	1.10×10^{-3}	1.0×10^{-5}	-0.0343	-0.0546	-0.0420	9×10^{-4}	1.9×10^{-4}	2.9×10^{-4}	-6.0×10^{-5}
MDS_{Apr}	1.3×10^{-4}	7.7×10^{-3}	4.38×10^{-6}	-2.28×10^{-3}	7.71×10^{-3}	-1.2×10^{-4}	-0.0343	-0.0546	-0.0420	0.0094	-0.0019	-0.0021	-1.8×10^{-3}
MDS_{May}	1.3×10^{-4}	-0.0260	-6.12×10^{-6}	-2.28×10^{-3}	-2.60×10^{-2}	3.0×10^{-4}	-0.0343	-0.0546	-0.0420	-0.0303	0.0030	0.0067	5.57×10^{-3}
PYP	1.3×10^{-4}	9.0×10^{-5}	5.40×10^{-8}	-2.28×10^{-3}	9.0×10^{-5}	*-6.0×10^{-8}*	-0.0343	-0.0546	-0.0420	0.0001	-2×10^{-5}	-1.0×10^{-5}	-2.0×10^{-5}
YDS	1.3×10^{-4}	-5.3×10^{-4}	-5.99×10^{-7}	-2.28×10^{-3}	-5.3×10^{-4}	1.0×10^{-5}	-0.0343	-0.0546	-0.0420	-7.2×10^{-4}	2.0×10^{-4}	2.3×10^{-4}	1.7×10^{-4}
WCS	2.0×10^{-4}	-0.0009	-5.02×10^{-7}	-2.53×10^{-3}	-7.8×10^{-4}	2.0×10^{-5}	-0.0456	-0.0682	-0.0633	-0.0011	3.4×10^{-4}	3.5×10^{-4}	3.1×10^{-4}
YCS	4.0×10^{-4}	-0.0011	*9.34×10^{-8}*	-3.15×10^{-3}	-9.8×10^{-4}	*-1.58×10^{-6}*	-0.0685	-0.0940	-0.1059	-0.0011	9.0×10^{-5}	9.0×10^{-5}	1.6×10^{-4}

North: North-facing slope; South: South-facing slope; Flat: flat valley bottom; Slope: slope angle

Table 6. Parameters of models built to highlight the interaction between management types and different scaled climatic variables emerged from the variable selection procedure in the overall model. All predictors were significant (*P* < 0.001). Climatic variables included in the models are indicated by $X_{1\text{-}7}$. The value in a cell under the header $X_{1\text{-}7}$ (or management type : $X_{1\text{-}7}$), refers to the climatic variable (or to the interaction between management type and climatic variable) indicated in the first column.

Climatic variable	Management type			Climatic variable	Management type : Climatic variable		
$X_{1\text{-}7}$	Optimal grazing	Low grazing	Mowing Grazing	$X_{1\text{-}7}$	Optimal grazing : $X_{1\text{-}7}$	Low grazing : $X_{1\text{-}7}$	Mowing Grazing : $X_{1\text{-}7}$
P_{Mar}	-0.0116	-0.0631	-0.0489	0.0374	-0.0039	0.0003	-0.0208
MDS_{Apr}	-0.0116	-0.0631	-0.0489	0.0395	0.0078	0.0021	-0.0003
MDS_{May}	-0.0116	-0.0631	-0.0489	-0.0439	-0.0066	-0.0016	0.0096
PYP	-0.0116	-0.0631	-0.0489	0.0221	-0.0014	-0.0033	-0.0013
YDS	-0.0116	-0.0631	-0.0489	-0.0441	-0.0052	0.0059	-0.0018
WCS	-0.0058	-0.0634	-0.0514	-0.0256	-0.0046	0.0037	0.0071
YCS	0.0039	-0.0707	-0.0622	-0.0545	0.0080	-0.0007	0.0077

4. Discussion

4.1 Drivers of NDVI variation and main climatic trend

The overall model explained 56.4% of the observed NDVI variability (Table 3), the 80% of which was accounted for by climatic variables and 20% by spatial variables (topographic factors, management type, and vegetation physiognomy). These results are in accordance with Milchunas et al. (1994), who found that magnitude of forage production was more sensitive to rainfall fluctuations than to management conditions. The unexplained portion of variability, about the 32% (difference between conditional and marginal R^2 in the overall model), may be due to climatic parameters or other factors that have not been considered in this study, such as heterogeneity of soil characteristics, fluctuations in the timing of the biomass peak or the variation in number/type of grazers.

We observed an increase in average yearly temperatures and high variability in the rainfall seasonal distribution pattern, particularly of spring precipitation. The interannual variations of precipitation have often gone beyond the normal range of the Mediterranean climate, which tends to fluctuate with variations of 25 percent (Ramos, 2001). This is in line with the predicted climate change for the Mediterranean region, involving high variations both in the quantity and timing of rainfall events (Bolle, 2012).

4.2 Effect of interannual climatic variability on NDVI

Our results did not show a straightforward relation between NDVI and yearly average temperatures and rainfall. Consistently, it was demonstrated that changes in precipitation or temperature during certain parts of the year are more relevant drivers of primary production than annual changes (Chou et al., 2008; La Pierre et al., 2011; Robinson et al., 2013). We found in fact that the spring variation of climatic parameters and indices, and the stress intensities of the previous year were the major drivers of the NDVI variability.

As regards seasonal variations, the main drivers were rainfall in March and drought stress in April and May (Table 3). This is consistent with Chelli et al. (2016), who highlighted the relation between changes in rainfall pattern and phytomass production in sub-Mediterranean grasslands, and with Zavaleta et al. (2003), who found that the timing of rainfall events and midseason droughts influence species productivity in Mediterranean pastures. However, we found a contrasting effect of water availability during spring. Consistently with Ma et al. (2010) and Robinson et al. (2013), who asserted that the increasing spring rainfall fosters primary production, we found that the higher the March rainfall, the higher the NDVI values. To some extent, this finding in the sub-Mediterranean climate might be a by-product of climate change. In fact, the reduction of winter snow cover, lasting from December to March in the past decades and likely providing sufficient soil water reserves for plant growth in early spring, might enhance the importance of spring rainfall nowadays (see also Guo et al., 2017).

In apparent contrast to the effect of rainfall in March, drought stress in April positively influenced the overall NDVI as well (Table 3). We might speculate that it delays the growing period of the early-flowering species (Catorci et al., 2017), producing a higher ANPP peak due to the overlap of the maximum presence of photosynthetic tissue of all species in a limited period (Aguirrezabal et al., 2006). In fact, the initial growth reduction due to drought stress can be compensated by a longer cell proliferation and/or expansion time, a phenomenon denominated ‘growth extension’, allowing reaching the normal dimension of leaves but with some weeks of delay (Pereyra-Irujo et al., 2008). Thus, the NDVI increase with the mid-spring drought might be only an artefact.

As regards the effect of climatic conditions of the previous years on NDVI, we observed that cold stress in the previous winter and drought stress in the previous year were inversely related to NDVI (Table 3). Probably, winter cold stress, jointly with the low temperatures in the early spring, delay the start of the growing season, which is assumed to be related to the threshold of the average daily temperature of 6 °C (see Bonan, 2008). Contrariwise, winter and early spring warming reduces cold temperature constraints on the plant (Chen and Weber, 2014; Chollet et al., 2014), and appears to advance spring greening, which leads to a longer growing season and higher productivity for grasslands (Menzel et al., 2001; Piao et al., 2006).

Drought stress in the previous year (high YDS and low PYP values) showed an important negative effect on grasslands productivity as well. This might depend on a set of factors. First, for the current year's crop, the stored water available for plant growth includes precipitation stored since the end of the previous year's growing season (crop year's precipitation - see Angell et al., 1990). Moreover, drought in previous years likely reduces structural attributes such as tiller density, leaf area or root biomass (Oesterheld et al., 2001) and the accumulation of resources inside storage organs of perennial species (Wang et al., 2008).

The importance of the climate regime of previous years is also demonstrated by the fact that the occurrence in consecutive years (e.g., 2014 and 2015) of a combination of favorable conditions (higher precipitation in early spring, low cold stress in the previous winter and low drought stress in the previous year, see Supplementary data, Tables B and C) reflected on the overall productivity, increasing NDVI values (Table 2), as confirmed by the model outputs (Table 3). Very low spring precipitation or high levels of drought stress in consecutive years (i.e., 2002-2003 and 2012-2013 respectively, see Supplementary data, Tables A, B, and C) led to the decrease of mean NDVI, especially in the most productive landform (semi-flat tops), approximating to values of the least productive grassland communities (Table 2).

4.3 How do topographic features affect NDVI variation and how do they influence the NDVI response to climate trends?

The same interannual NDVI trends were recorded across all the landforms, but the amplitude of changes was not homogeneous, being the widest in semi-flat mountain tops and flat valley bottoms (conservative landforms allowing the accumulation of soil and nutrients) and the smallest in south-facing slopes (Table 2). This is consistent with Scocco et al. (2016c). The same pattern had been already observed in relation to inter-seasonal canopy height variations (Catorci et al., 2017). Probably, in grassland communities these patterns are mediated by plant functional traits. For instance, species growing in stressful habitats (i.e. south-facing slopes in the study area) display stress-tolerant strategies, involving traits such as scleromorphic leaves and storage organs (de Bello et al., 2006; Tardella et al., 2016). Species with these traits have an inherently lower growth rate and lower tissue turnover (Chapin et al., 1990, 1993) and, thus, are subjected to lower shifts in phytomass than species growing in non-stressful habitats. The effect of increased precipitation in March on NDVI was weaker in semi-flat tops and flat valley bottoms than in south-facing slopes (Table 5). This is consistent with Vázquez de Aldana et al. (2008), who found that in the Mediterranean climate, communities of drier slopes are more susceptible to variations in precipitation at certain critical times, such as in early spring, while those of more productive conditions are less affected by these variations. Moreover, we observed a homogenization of phytomass production across topographic gradients under severe stress, as suggested by the very low variance explained by topographic factors in 2013 (Table 4), the year with the lowest mean temperature in March, the highest YDS in the previous year, and one of the highest WCS values in the previous winter (Supplementary data, Table B). In the same year, the percentage of variability explained by vegetation physiognomy increased, likely due to the increased weight gained by shrubby grasslands in explaining NDVI variation (Table 4), probably because shrubs are more resistant than herbs to changes in phytomass production, as they are mainly composed of slow-growth species such as *Juniperus communis*, *J. deltoides*, and *Cytisophyllum sessilifolium* (Ballelli et al., 2020).

Higher drought stress in April was also associated with increased NDVI variability along the slope angle gradient both in northerly and in southerly slopes, reducing its effect towards the steepest slopes (Table 5). The increasing slope angle reduced the negative effects also of MDS_{May}, YDS, and WCS. The apparent coincidence of the influence of slope angle on the variation of the NDVI response to drought stress in both aspects could be due to two different factors. The increase in the effect of the slope angle in south-facing slopes reflects in the increase in abundance of chamaephytes and other species with strong adaptations to tolerate water shortage (e.g., succulence, prostrate habit, and annual life span) and in a decrease in hemicryptophytes (Tardella and Catorci, 2015; Tardella et al., 2016), which amplify the resistance of the system to interannual climatic variation. Species composition in fact may be highly effective in modulating the response of aboveground phytomass in relation to changes in precipitation (Bai et al., 2008). Similarly, in very steep north-facing slopes, where the snow melt occurs later and the soil temperature remains low for a longer period, the growing season and the phenological phases are delayed (Catorci et al., 2017) and the community, dominated by hemicryptophytes, may not be affected by aridity at the beginning of spring.

Our results confirm that herbage production from different plant communities undergoing the same climate inputs may not necessarily respond in the same way (Smart et al., 2007) and the statement by Briggs and Knapp (1995) that at site level, topographic factors, along with soil depth and available water content, largely explain the variability of aboveground productivity due to climate interannual variability. Moreover, variation in composition of plant functional types among different communities may exert a role in modulating the effects of climate and herbivores on soil parameters and, thus, on grassland productivity (Debouk et al., 2020).

4.4 How does management type affect NDVI variation and how does it influence the NDVI response to climate trends?

Overall, the mean NDVI was the highest in abandoned and optimally grazed grasslands than in the other management types (Table 2). The highest mean NDVI value in abandoned grasslands was probably due to the invasion by competitive tall grasses (Malatesta et al., 2019), thickening and closing the sward canopy (Tardella et al., 2020). The high NDVI values found in optimally grazed grasslands may be related to the positive effect on ANPP of complete consumption of leaves (McNaughton, 1985; Hik and Jefferies, 1990; Pandey and Singh, 1992; Frank and McNaughton, 1993; Olofsson et al., 2001) even if there is no general consensus about such relationship (Milchunas and Lauenroth, 1993).

There is still a considerable debate about the response of grassland ANPP to the combined effect of climate variation and livestock grazing (Addison et al., 2012). Patton et al. (2007) asserted that grazing intensity and site climate condition (i.e., plant growth conditions) interact with a complex pattern, and in particular that low to moderate levels of grazing can increase production over no grazing, but that the level of grazing that maximizes production depends upon the growth conditions of the current year.

We found that the amount of variability explained by management type positively correlated to early-spring temperatures (T_{Mar}), suggesting that high early-spring temperatures could amplify differences in productivity among different management conditions. Guo et al. (2017) asserted that high early-spring temperature may have a positive effect on productivity and our results seem to indicate that management might profoundly interact with the increasing trend of temperatures, highlighting the importance of grassland utilization (likely involving both timing and intensity of disturbance) for an aware management of pastoral systems. Such idea is supported also by the observation that the effect on NDVI of the climatic variables selected as significant predictors depend on the management condition (Table 6). In fact, optimally grazed grasslands were the most prone to the positive effects of MDS_{Apr} and the negative effects of MDS_{May}, YDS, and WCS on NDVI (Table 6). It should be underlined that WCS and YDS, being referred to the previous winter and the previous year, are particularly important in forecasting ANPP variations. As the increase of both could greatly reduce the ANPP of optimally grazed grasslands, it follows that knowing their values in advance compared to the start of the grazing period would help in making timely management decisions year by year, so that it seems to be one of the most suitable predictors to face the short-term effect of climate change.

The behavior of low-intensity grazed and abandoned grasslands was similar in that they were less responsive than optimally grazed grasslands to changes, especially of spring drought and winter cold stress, but were fostered to a higher degree by increasing precipitation in March (Table 6). Contrarily, mown and grazed grasslands were the most resistant to the effects of winter cold stress and MDS_{May}, while were the least responsive to the increase in MDS_{Apr} and precipitation in March (Table 6).

Such results suggest that grassland management type partly filters the effects of climatic drivers on forage production. For example, according to our results, in undergrazed and abandoned pastures a decrease in winter cold stress would result in a lower increase in productivity than in an optimally grazed grassland; however, the increase of yearly drought stress would have less negative effects and the increasing trend of precipitation in March would produce higher benefits.

5. Conclusions and general model

We found that semi-natural mountain grasslands characterized by a Mediterranean-type climate give rise to very complex response patterns to interannual climatic variation. Our results showed that the overall amount of forage production was more influenced by climatic fluctuations than by management and topographic conditions. In particular, the spring variation of climatic parameters and indices, the intensities of stresses of the previous year, and the occurrence of consecutive years characterized by high or low levels of stress, chiefly affect the NDVI variability. We may hypothesize that the decrease in winter snow could accentuate the importance of the variability of spring precipitation, but this issue deserves further investigation. Climate interannual fluctuations may relieve the effect of some environmental stresses, such as cold and drought stress; thus, the productivity is the net result of positive and negative effects, and this outcome is context-dependent. The landform factors interact with climate variability in determining the amplitude of ANPP changes, being widest in semi-flat mountain tops and flat valley bottoms (productive conditions), and smallest in south-facing slopes (low-productive systems). Moreover, we found that the effect on NDVI of the climatic variables selected as significant predictors was different depending on the management condition, suggesting that the climatic drivers of changes in forage production are partially filtered by grassland management, which accounts singly and jointly with topographic variables, for about half of the explained NDVI spatial variability.
Ultimately, the net result on productivity is given by the interactions among climatic, topographic, and management factors.

Based on such results, we can infer that the forecasted scenario of climate change for the Mediterranean basin will impact on grassland systems. These changes seem to have a negative influence on the most productive plant communities and the areas used for grazing by domestic herbivores. This relationship could potentially reduce the economic sustainability of semi-extensive farming. This phenomenon could be fatal, especially in consideration of the progressive replacement in recent decades, of sheep breeding with the cattle husbandry (Marchigiana breed used for meat production) in the Apennine mountains. Because of this, our study highlighted how it is increasingly urgent to explore the possible adaptation systems of semi-extensive farming in the Mediterranean mountains. In this perspective, knowing the WCS and YDS values before the start of the growing season would help in making timely management decisions year by year, so that they seem to be possible indicators that can be used for an aware and adaptive mountain farming management.

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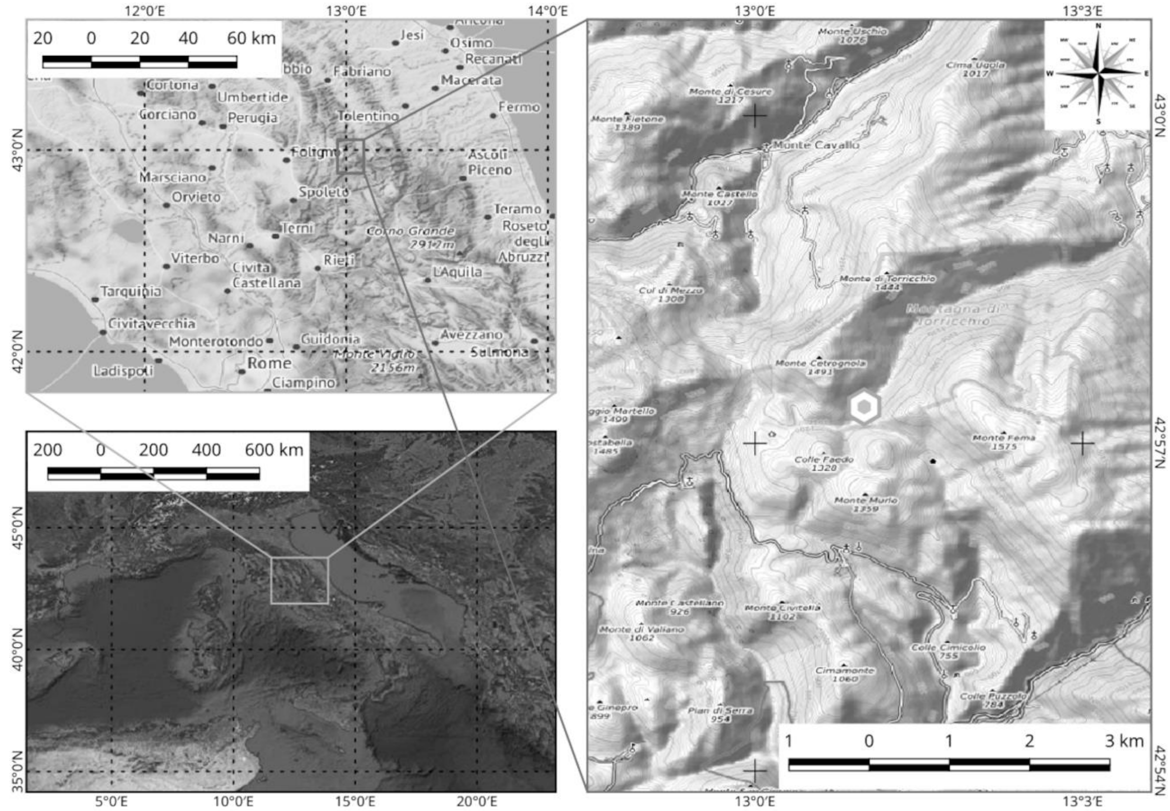
Competing interests Authors declare no competing interests.

Figure caption

Figure 1. Location of the study area.



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