Agricultural and Forest Meteorology 248 (2018) 240–250

Contents lists available at ScienceDirect

Agricultural and Forest Meteorology

journal homepage: www.elsevier.com/locate/agrformet

Research paper

Assessing spring frost effects on beech forests in Central Apennines from remotely-sensed data

Marco Bascietto[a], Sofia Bajocco[b,*], Francesco Mazzenga[c], Giorgio Matteucci[d]

[a] Council for Agricultural Research and Economics (CREA), Research Centre for Engineering and Agro-Food Processing, Rome, Italy
[b] Council for Agricultural Research and Economics (CREA), Research Centre for Agriculture and Environment, Rome, Italy
[c] National Research Council, Institute of Agro-Environmental and Forest Biology (CNR-IBAF), Monterotondo, Italy
[d] National Research Council, Institute for Agricultural and Forestry Systems in the Mediterranean (CNR-ISAFOM), Ercolano, Italy

ARTICLE INFO

Keywords:
Spring frost
Common beech forest
MODIS EVI
Net ecosystem exchange

ABSTRACT

In common beech forests the most damaging frosts are those that occur at the end of spring. At that time the fresh new leaves are at a vulnerable stage and risk to be readily killed by the freezing temperatures. The ability to identify late spring frost spatial dynamics is a key issue for understanding forest patterns and processes linked to such extreme event. The aim of this study is to detect, map and quantify the vegetation anomalies that occurred in the mono-specific beech forest of the Lazio, Abruzzo and Molise National Park (Italy) after an exceptional spring frost recorded on the 25th of April 2016. Results showed that, beech forests at lower elevations that had an early greening process were subject to spring frost damage (SFD pixels) and their productivity performance strongly decreased with respect to the previous 15 years; to the contrary the beech forests located at higher elevations did not suffer the spring frost effects (NSFD pixels) thanks to their delayed leaf unfolding phase. The duration of the effects of freezing stress for the SFD pixels was about two months, until the end of June, confirmed by Net Ecosystem Exchange measurements. This greening hiatus led to an average 14% loss of productivity compared to the previous 15 years. Elevation had a significant role on the probability of occurrence of SFD pixels. Productivity loss in SFD pixels was more severe at elevations in the range 1500–1700 m, on steeply terrains and North aspects. This study represents a step forward the systematic use of automated techniques to study areas subject to stress or anomalies from multitemporal satellite imagery and to identify break points and recovery of the greening process.

1. Introduction

With climate change, in Central Europe, the start of the growing season has advanced over the last decades (Badeck et al., 2004); over three decades, leaf unfolding has started 6 days earlier (Menzel and Fabian, 1999; Muffler et al., 2016). The frequency of cold spells in spring is likely to decrease (Menzel et al., 2015); however, leaf unfolding is also projected to occur much earlier (Rosenzweig et al., 2008) with potential negative impacts to productivity (Kim et al., 2014).

Extreme cold events after an earlier growing season onset are increasing the risk of frost damage in the temperate zone (Inouye, 2000; Hufkens et al., 2012; Augspurger, 2013; Muffler et al., 2016). The timing of spring phenological development plays a crucial role, not only at the species level, but also at the individual and population level (Menzel et al., 2015).

Common beech (*Fagus sylvatica* L.), the naturally dominant forest tree species of Central Europe over a wide range of environmental conditions (Leuschner et al., 2006), can tolerate very cold conditions over winter, but is sensitive to late frost events (Ningre and Colin, 2007; Kreyling et al., 2012a) more than other tree species due to the earlier onset of leaf unfolding (Dittmar et al., 2006). The ability to identify spring frost spatial dynamics and quantify their damages in term of productivity loss is hence crucial for understanding climate-driven altitudinal shifts.

While probabilistic field measurements of forest productivity may optimise sampling times (Bascietto et al., 2012), remotely-sensed vegetation indices like NDVI (Normalized Difference Vegetation Index) and EVI (Enhanced Vegetation Index) are regarded as reliable indicators for estimating productivity and monitoring vegetation conditions globally (see, e.g., Myneni and Williams, 1994; Cuomo et al., 2001; Lanfredi et al., 2003; Bajocco et al., 2012). NDVI is the most common vegetation index used to monitor vegetation; however there are still some limitations in the NDVI product related to the index saturation in densely-vegetated areas, and to the effect of canopy

* Corresponding author.
E-mail address: sofia.bajocco@crea.gov.it (S. Bajocco).

http://dx.doi.org/10.1016/j.agrformet.2017.10.007
Received 29 May 2017; Received in revised form 26 September 2017; Accepted 5 October 2017

background (Wang et al., 2003).EVI was hence proposed as a modified NDVI allowing more responsiveness to canopy structural variations, including leaf area index (LAI) in forests (Huete et al., 2002).EVI is useful for monitoring seasonal and inter-annual dynamics of vegetation (Huete et al., 2002), for predicting net primary production in ecosystem modeling applications (Potter et al., 2007; Maeda et al., 2014); for quantifying the extent of the shifts in vegetation phenology between rural and urban areas (Dallimer et al., 2016); for examining the relationships between seasonal rainfall fluctuations and phenological parameters (Suepa et al., 2016).

In remote sensing, the analysis of anomalies associated to environmental stress has been performed by means of many different approaches. Anomaly regions in satellite images can reflect unexpected variations of vegetation cover caused by land use changes, fire, landslide, drought, disease, etc.

Zhou et al. (2016), in order to identify land cover dynamic processes, proposed a method for detecting anomaly regions in each NDVI time series image based on seasonal autocorrelation analysis. Yool (2001) enhanced fire scar anomalies by applying the Z-transform on NDVI time-series data; the multi-temporal Z (MTZ) score image thus depicts any deviation of a given pixel, for a specific step in the series, relative to the mean for that pixel across the time series. Fraser and Latifovic (2005) developed a logistic regression model based on satellite change metrics to map insect-induced defoliation and mortality over a coniferous forest region in Quebec (Canada) by means of NDVI and other VIs. Olsson et al. (2016), in order to monitor insect disturbances in Finnish forests, used a damage detection method based on z-scores of seasonal maximums of the 2-band EVI data. Mildrexler et al. (2007) developed a pixel-based algorithm based on the consistent radiometric relationship between Land Surface Temperature and EVI to automatically and systematically detect disturbance at global scale. Menzel et al. (2015) analyzed the greenness time series by a Bayesian multiple change point modeling. Van Hoek et al. (2016) applied a Fourier method to model NDVI time series affected by gaps and outliers (iHANTS). Finally, Lasaponara (2006) focused on the extraction of vegetation inter-annual anomalies from a NDVI temporal series (1999–2002) by applying principal component analysis as a data transformation to enhance regions of localized change in multi-temporal data sets.

In this study, to exploit the EVI capabilities of measuring phenological anomalies in densely-vegetated regions, we developed an automated approach to detect areas of late frost damage from EVI satellite imagery based on machine learning (ML) techniques. ML is a method of data analysis that automates analytical model building, using algorithms that iteratively learn from data.

The investigation focuses on a mono-specific common beech forest of the Lazio, Abruzzo and Molise National Park, Central Apennines (Italy), where an unprecedented severe spring frost occurred on 25th April 2016. The main objectives of this study therefore are: (i) to identify all the areas within the study region where the spring frost anomaly occurred based on EVI annual profiles; (ii) to estimate how topographic factors influenced the occurrence of the damages; (iii) to quantify the productivity loss of 2016 compared to the previous 15 years.

2. Study area

Lazio, Abruzzo and Molise National Park (LAMNP) is an Italian national park founded in 1922 (Fig. 1). The majority of the park is located in the Abruzzo region though it is not constrained by regional boundaries and also includes territory in Lazio and Molise. The park currently covers 496.80 km^2. The morphology is predominantly mountainous, with the highest peak at 2249 m (Petroso Mtn.) The flora of the park is extremely rich with more than 2000 species. European common beech (*Fagus sylvatica* L.) forest covers 60% of the area and dominates the park between 1400 and 1900 m.

A Long-Term Ecosystem Research site (Collelongo-Selvapiana LTER_EU_IT_031, lat. 41.84936 N, long. 13.58814 E, 1560 m asl) is located in the protection belt of LAMNP. The site performs flux measurements with eddy covariance since 1995 in a mono-specific common beech forest (https://data.lter-europe.net/deims/site/lter_eu_it_031) and, on the 25th April 2016, it experienced an anomalous spring frost that damaged nearly 100% of developing shoots and expanding leaves of canopy trees (Fig. 2). The spring frost followed an unprecedented warm period, as detected by 8-day MODIS Terra Nighttime Land Surface Temperature (LST)/Emissivity (MOD11A2) product. The comparison of the LST of 2016 versus the previous 15 years (2001–2015) highlighted that an anomalous early spring warm period occurred since DOY 81 (March, 21st) followed by a sudden below zero drop in temperature on DOY 113 (April, 22nd) (Fig. 3).

3. Data

3.1. MODIS vegetation index

The 16-day MODIS Terra 250 m EVI maximum value composite product (MOD13Q1) was downloaded from the MODIS SOAP Web Service, covering the whole LAMNP and its protection belt for the 15 year-long period 2001–2016. Winter data revealed several low quality, noisy or out of valid range value regions, therefore the late-autumn and winter data of each year were excluded from the analysis. We focused only on the EVI temporal profiles starting from day of year (DOY) 81 (21st of March) to 305 (1st of November), which encompasses the growing season of the European beech forest.

4. Methods

4.1. Training of the SFD-NSFD classifier

A support vector machine (SVM) was used to detect pixels of spring frost damage in EVI data. SVM is a supervised learning model that works as a discriminative classifier formally defined by a separating hyperplane. The training data consist of a set of training examples. Given labeled training data, the algorithm outputs an optimal hyperplane which categorizes new examples into one class or the other (James, 2003; Campbell and Ying, 2010).

A region of 33 × 33 pixels centered at the LTER_EU_IT_031 site (4 km on the right and 4 km on the left from the site pixel) was identified as "training site" for the SVM classifier; this size was chosen in order to be consistent with the LTER_EU_IT_031 site information about the 2016 spring frost occurrence and to avoid the inclusion of adjacent non-forested areas.

To extract only the pure (phenologically homogeneous) beech forest pixels within the training site, a k-means clustering was performed on the 2001–2015 (no spring frost events detected) EVI profiles data.

The k-means clustering is an unsupervised classification technique; it calculates initial class means evenly distributed in the data space, then iteratively clusters the pixels into the nearest class using a minimum distance technique. This process continues until the number of pixels in each class changes by less than the selected pixel change threshold or the maximum number of iterations is reached (MacQueen, 1967; Bajocco et al., 2012). The k-means clustering procedure was used to cluster the vegetation of the training site into k homogeneous groups in terms of annual EVI profile; k was selected according to an iterative to convergence reallocation method starting with 2–5 clusters that resulted in an optimal number of 3 clusters. Given that the LTER_EU_IT_031 site is located in a mono-specific beech forest, the cluster that included LTER_EU_IT_031 site pixel was labeled as "beech forest" and the other two clusters as "non-beech forest" and excluded from the following analysis.

For the "beech forest" cluster of the training site, the EVI profile of the pixels for the year 2016 was taken as representative of the pixels