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ORIGINAL PAPER

Variations in trends of temperature and its influence on tree growth in the Tuscan Apennines

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Abstract
The evidence of climate change occurred in the last century, causes significant alterations to the environment. The adaptation of plants is a particularly important aspect of it and contributes to assess the variations in biodiversity to expect in the near future in the attempt of understanding the possible consequences. In this research, some significant forest areas of the Tuscan Apennines, which are featured by a complex and varied territory from a climatic point of view, have been taken into consideration. Four historical weather stations were considered, in order to verify climate trends and their mutual correlations. In-depth analyses were carried out to identify climate trends and check whether there are recurring periods in the climate, as seemed to be highlighted by previous studies on silver fir forests. The results were surprising as inhomogeneous distribution of temperatures during time between the different sites sampled was observed, and clustering of the sites showed variability through space and time. In addition, a return period of 6–7 years was identified in the historical temperature series through Fourier analysis, outlining a cyclical trend of the same; that could be reflected in the growth trends of trees. Furthermore the analysis revealed that the use of master series of the climate variable as representative of trends across the study area can lead to not detecting relevant information relating to climate/tree growth relationships both at the forest landscape level and at the forest unit level, thus affecting the accuracy and validity of forest management plans.

Keywords Climate change · Tree growth · Agglomerative hierarchical clustering · Fourier spectral analysis

Introduction

The correlation between climate and vegetation growth is attracting increasing interest, especially in the light of the fast climate changes that take place both worldwide (Scholze et al. 2006; Costinot et al. 2016) and in Italy (Gentilucci et al. 2019a, 2020). Changes in trends of mean temperature (Tm) took place at the Northern Hemisphere scale during the period 1850–2000 (i.e. years 1901, 1914, 1942, 1963, and 1975) (Matyasovszky 2011); abrupt changes in Tm have occurred also in the years 825, 1296, 1387, 1656, 1749, and 1883 according to Jones and Wigley (2010a, b). However, abrupt changes may somehow differ at the scale of smaller areas. The variability in climate change trends influences the response of tree growth (Andreu et al. 2007; Ponocná et al. 2016; Schippers et al. 2015). At the local level, the impacts of these changes can reflect on tree growth in different ways (Wilson and Elling 2004; Gallucci and Urbinati 2009; Carrer et al. 2010). In mountain environments, the dominant climate signal tends to be more pronounced at high-elevation sites with extreme conditions (Rolland et al. 1998). For example, changes in the relationships between climate variables and tree-ring growth in silver fir have been detected in the Pyrenees (Macias et al. 2006), in the Lower Bavarian region (Wilson and Elling 2004), in southern-eastern France (Lebourgeois and Mérian 2011), and in Italy (Gentilesca and Todaro 2008; D'Aprile et al. 2012) during the twentieth century. At the regional level, master series of Tm may be used to investigate tree-ring growth if similarity in Tm trends between sites

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is high. Otherwise, low similarity in trends of Tm series among sites over time can reflect on differences in forest tree growth at the site level. This suggests verifying the presence of temperature variations at the single site level to check whether tree growth response differs among sites and/or from the master series of the climate variable. In this study, the presence of long-term trends in seasonal Tm and monthly Tm series in the Tuscan Apennine Alps (Middle Italy) among sites during the twentieth century, their associations, and variations in similarity of both the seasonal and monthly Tm series are investigated. The aim is to understand whether seasonal and monthly Tm trends can be grouped and effectively represented by master series or whether they vary to an extent that addresses to analyse potential effects of Tm changes on tree growth at the site level. In this study, all statistical computations were undertaken by using two different software, and the results were compared to verify if they are similar.

Methods

Regional setting and dataset

The Tuscany Region (Central Italy) shows high variability in climate patterns due to its diversified topography. This region is located on the Tyrrhenian side of Central Italy and stretches over 22,987.04 km^2 with a population of 3,733,897 people. Its landscape is 67% hilly with small flat areas covering only 8% of the region, with mountain massifs reaching 25% of the total surface. This study focuses on the mountainous part of the region, the Apennine Alps, where large forests grow. In this area, the traditional climate pattern is normally Mediterranean montane (Maracchi et al. 2005) with relatively mild summer, and rainfall tends to provide moisture enough to minimize or even avoid drought. Winter is cold and frequently snowy, and the permanence of snow varies from weeks to months; climate change modifies this ‘traditional’ pattern. Four montane forest sites near to the tops of the Apennine Alps were selected in places close to the meteorological stations. The uniqueness of those forests, which is due to their historical, religious, cultural, landscape, touristic, and bio-ecological features, explains why the administrations that succeeded over time installed meteorological stations at Abetone (ABE) and La Verna (LAV) at the beginning of the twentieth century and at the end of the nineteenth century at Camaldoli (CAM) and Vallombrosa (VAL) (Fig. 1).

The data of the four weather stations functional to the analysis were extracted from both the Annals of the former ex-Hydrographic Office of Pisa, Ministero dei Lavori Pubblici (Ministry of Public Works) and the Settore Idrologico e Geologico Regionale (Regional Hydrological and Geological Sector; S.I.R.) of the Tuscan Regional Government. The rainfall and temperature data of CAM were provided by the former Research Centre of Silviculture in Arezzo, Tuscany (today CREA-Research Centre for Forestry and Wood). Data published both in the Annals and the S.I.R. are official and validated; they are regarded as a reliable source of climate data records. The time series of climate data used for statistical analysis start in 1928 (Table 1).

The statistics

At the regional level, time series of Tm may be utilized to investigate tree-ring growth if similarity in Tm trends among sites is high. Otherwise, low similarity in trends of Tm series over time among sites may cause differences in forest tree growth at the site level. Therefore, the analysis of similarity in trends of Tm among sites is essential to assess whether there are differentiated response in tree growth among sites. Thus, the stationarity in similarity of trends in Tm in the study area has been tested. At first, homogeneity of seasonal Tm data was explored in all the Tm series through normality, similarity, and equality of variance tests in the distributions of Tm data by using both parametric and nonparametric tests (Kolmogorov-Smirnov test, Lilliefors test, Shapiro-Wilk test, Anderson-Darling test, Chi-square test, Student’s test, one-way Kruskal-Wallis test, Bartlett’s test, and Levene’s test) to check whether the seasonal Tm series are statistically homogeneous at all the study sites during the twentieth century. Descriptive analysis of seasonal and monthly Tm series was applied to all sites; the average of the maximum Tm, the average of the minimum Tm, Tm (°C), and the standard deviation (SD) of Tm at the seasonal and monthly level were calculated. The patterns and variability in the distribution of the residual error in trends of seasonal Tm were also analysed by linear regression modelling to explore the amount of variability, which corresponds to the real meteorological events, contained in each series of seasonal Tm in the study area. In this case, the seasonal Tm of all study sites was used as a dependent variable with respect to the seasonal Tm series at each site as independent variables. The nonparametric Mann-Kendall trend test (M-K) was used to verify if any trend occurs in the seasonal Tm series (Dawood 2017). This test has been frequently used in climatological research to verify the presence of trends in series of seasonal and monthly climate variables (Crisci et al. 2002; Önöz and Bayazit 2003; Brunetti et al. 2006; Bartolini et al. 2008; Toreti and Desiato 2008; Mavromatis and Stathis 2011). The possible presence of periods with similar length in the seasonal Tm series at all the study sites was tested through spectral (Fourier) analysis. Potential effects of variability in seasonal Tm and/or monthly Tm on tree growth are expected to be similar among sites. In that case, different trends in seasonal Tm or monthly Tm between sites can affect the growth response of trees in different ways. Hence, the level of similarity between seasonal Tm trends across all study sites was estimated by applying both

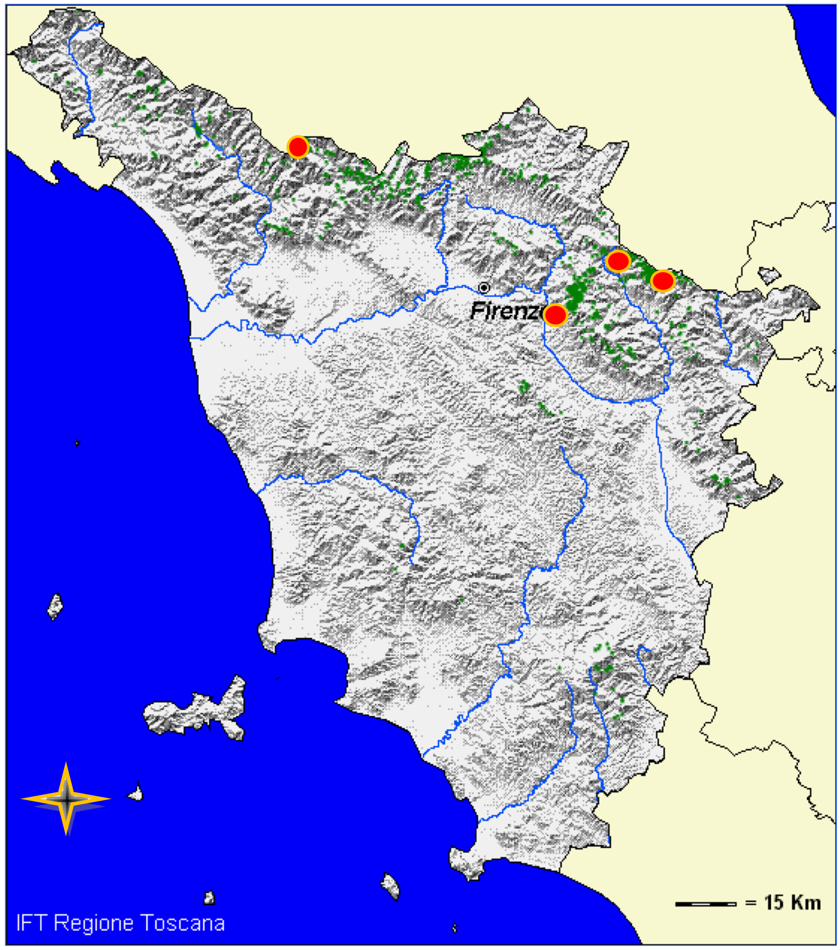


Fig. 1 Location of the meteorological stations on tops of the Tuscan Apennine Alps. A is ABE (1340 m a.s.l.), C is CAM (1120 m a.s.l.), L is LAV (1111 m a.s.l.), and V is VAL (955 m a.s.l.)

matrix correlation (Pearson, Spearman, and Kendall) (Santos and Leite 2009) and agglomerative hierarchical clustering (AHC) (Bartolini et al. 2008). However, because of the underlying rationale, matrix correlation and AHC are statistics that show average levels of similarity between Tm series, but they do not provide information on its variability over time, which may influence tree growth in ways otherwise unknown. A common statistical technique used to reduce the influence of high-frequency variability in time series is moving averages (or running means), which smooth high-frequency variability and highlight low-frequency variability (or enhance long-term trends). Thus, it was assessed whether the similarity in trends of seasonal and monthly Tm among sites is stationary during the twentieth century by applying Pearson's correlations of moving averages (Biond 1997; Kristoufek 2014) to all the Tm series. In other words, to verify if and how the similarity in the trends of Tm is stationary during the twentieth century, the moving averages of Pearson's r were applied between the paired series of monthly Tm, where the length of the 'windows' of the moving averages was defined by the results of the spectral (Fourier) analysis.

The theory of the statistics mentioned above is easily accessible online and in manuals, books, and texts. Here, the main statistics applied are described in the next paragraphs. Computations were made by using the programs Statistica (StatSoft) and XL-Stat (Addinsoft).

Table 1 Periods of climate data available of the meteorological stations in the Tuscan Apennine Alps

Weather station	Temperature	Precipitation
ABE	1934–1996	1931–2000
LAV	1956–1990	1924–2006
CAM	1885–1993 (1) 1925–1996 (2)	1885–1993 (1) 1931–1996 (2)
VAL	1872–1989 (1) 1933–2006 (2)	1872–1989 (1) 1932–2006 (2)

The climate data series cover different time periods. Notation (1) **is for CRA-SEL;** notation (2) is for the Annals

The Mann-Kendall trend test

The Mann-Kendall test is used to determine whether a time series has a monotonic upward or downward trend. It does not require that the data be normally distributed or linear. It does require that there is no autocorrelation. The null hypothesis for this test is that there is no trend, and the alternative hypothesis is that there is a trend in the two-sided test or that there is an upward trend (or downward trend) in the one-sided test. For the time series x_1, ..., x_n, the M-K test uses the following statistic:

$$S = \sum_{i=1}^{n-1}\sum_{j=k+1}^{n} sign(xj - xi)$$

Note that if $S > 0$, then later observations in the time series tend to be larger than those that appear earlier in the time series, while the reverse is true if $S < 0$.

The variance of S is given by

$var = (1/18)[n\ (n-1)\ (2n+5) - \sum_t f_t\ (f_t - 1)(2f_t + 5)\ ]$

where t varies over the set of tied ranks and f_t is the number of times (i.e. frequency) that the rank t appears.

The M-K test uses the following test statistic:

$$z = \begin{cases} \frac{S-1}{se}, & S > 0 \\ 0, & S = 0 \\ \frac{S+1}{se}, & S < 0 \end{cases}$$

where se is the square root of var. If there is no monotonic trend (the null hypothesis), then for time series with more than 10 elements, $z \sim N(0, 1)$, i.e. z has a standard normal distribution.

In addition to the classical Mann-Kendall test, the seasonal Mann-Kendall was calculated. It takes into account the seasonality of the series, in this case 12 months, in order not to find out if there is a trend in the overall series, but if from one month of January to another, and from one month of February to another, and so on, there is a trend.

The Mann-Kendall statistic for the gth season is calculated as:

$$S = \sum_{i=1}^{n-1}\sum_{j=i+1}^{n} sign\left(X_{jg} - X_{ig}\right), \quad g = 1, 2, \ldots, m\ (12)$$

According to Hirsch et al. (1982), the seasonal Mann-Kendall statistic, Sˆ, for the entire series is calculated according to:

$$\widehat{S} = \sum_{g=1}^{m} S_g$$

Matrix correlation

Matrix correlation measures the relationship between two or more variables. Coefficients have a range of −1 to 1, where −1 is the perfect negative correlation while +1 is the perfect positive correlation. Matrix correlation is also called 'multiple correlation coefficient'. The most common correlation coefficient is Pearson's correlation coefficient, which compares two interval variables or ratio variables. But there are many others, depending on the type of data you want to correlate. The following table shows some of the common choices for correlation coefficients:

	Quantitative	Ordinal	Nominal
Quantitative	Pearson	Biserial	Point biserial
Ordinal	Biserial	Spearman rho/tetrachoric	Rank biserial
Nominal	Point biserial	Rank biserial	Phi, Goodman and Kruskal's lambda

In this study, we used the Wilk's approach, which consists in driving the stochastic weather generator with serially independent and spatially correlated random numbers. Each set of serially independent random numbers is then used to generate precipitation occurrence and amounts at a particular station. In essence, Wilks approach concentrates on the bi-variate description of the precipitation field at given rain gauges, expressed by the correlation matrices of both precipitation occurrence and amounts at weather stations.

Therefore, let n be the number of precipitation recording stations and m the length of the synthetic precipitation time series to be generated.

Multiple linear regression

Multiple linear regression attempts to model the relationship between two or more explanatory variables and a response variable by fitting a linear equation to observed data. Every value of the independent variable x is associated with a value of the dependent variable y. The population regression line for p explanatory variables $x_1, x_2, \ldots, x_p$ is defined to be $\mu_y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p$. This line describes how the mean response μ_y changes with the explanatory variables. The observed values for y vary about their means μ_y and are assumed to have the same standard deviation σ. The fitted values b_0, b_1, ..., b_p estimate the parameters $= \beta_0, \beta_1, \ldots + \beta_p$ of the population regression line.

Since the observed values for y vary about their means μ_y, the multiple regression model includes a term for this variation. In words, the conceptual model is expressed as *Data = Fit + Residual*, where the *fit* term represents the expression $= \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p$. The *Residual* term represents the deviations of the observed values y from their means μ_y, which are normally distributed with mean 0 and variance σ. The notation for the model deviations is ε. Formally, the model for multiple linear regression, given n observations, is $y_i =$ $= \beta_0 + \beta_{1xi1} + \beta_{2xi2} + \ldots + \beta_{pxip} + \varepsilon_i$ for $i = 1, 2, \ldots n$. In the least-squares model, the best-fitting line for the observed data is calculated by minimizing the sum of the squares of the vertical deviations from each data point to the line (if a point lies on the fitted line exactly, then its vertical deviation is 0). Because the deviations are first squared, then summed, there are no cancellations between positive and negative values. The least-squares estimates b_0, b_1, ... b_p are usually computed by statistical software.

The values fit by the equation $b_0 + b_1x_{i1} + ... + b_px_{ip}$ are denoted ${}_i$, and the residuals e_i are equal to y_i - ${}_i$, the difference between the observed and fitted values. The sum of the residuals is equal to zero.

The variance σ^2 may be estimated by $s^2 = \sum e_i^2 / (n - p - 1)$, also known as the mean-squared error (or MSE).The estimate of the standard error s is the square root of the MSE. Linear regression is, without doubt, one of the most frequently used statistical methods. A distinction is usually made between simple regression (with only one explanatory variable) and multiple regression (several explanatory variables) although the overall concept and calculation methods are identical. The linear regression hypotheses are as follows: the errors e_i follow the same normal distribution $N(O,s)$ and are independent. The way the model with this hypothesis added is written means that, within the framework of the linear regression model, the γ_i are the expression of random variables with mean μ_ι and variance s^2, where

$$\mu_i = \beta_0 + \sum^p{}_{j=1} \beta_j x_{ij}$$

The estimator of the β coefficients and of their covariance matrix is given by:

$$\widehat{\beta} = (X^tX)^{-1} X^tY \text{And } Var\left(\widehat{\beta}\right) = \widehat{\sigma}^2 (X^tX)^{-1}$$

Conceptually, $T_{mAV} (T_{mJ} + T_{mF} + ... + T_{mD}) = \beta_0 + \beta_J T_{mJ} + \beta_F T_{mF} + ... + \beta_D T_{mD} + \varepsilon)$

where T_{mAV} is the average of monthly $T_m s$ as dependent variable

$T_{mJ} + T_{mF} + ... + T_{mD}$ are monthly mean temperature of January (J), February (F), …, December (D) as explanatory variables

β_0 = y-intercept (constant term)

$\beta_{J, F, ..., D}$ = slope coefficients for each explanatory variable

ϵ = the model's error term (also known as the residuals)

Agglomerative hierarchical clustering

Agglomerative hierarchical clustering (AHC) is a classification method which allows to work from the dissimilarities between the objects to be grouped together. A type of dissimilarity can be chosen which is suited to the subject studied and the nature of the data. One of the results is the dendrogram which shows the progressive grouping of the data. It is then possible to gain an idea of a suitable number of classes into which the data can be grouped. The disadvantage of this method is that it is slow. Furthermore, the dendrogram can become unreadable if too much data is used. Agglomerative hierarchical clustering (AHC) is an iterative classification method whose principle is simple. The process starts by calculating the dissimilarity between the N objects. Then two objects which when clustered together minimize a given agglomeration criterion are clustered together thus creating a class comprising these two objects. Then the dissimilarity between this class and the N-2 other objects is calculated using the agglomeration criterion. The two objects or classes of objects whose clustering together minimizes the agglomeration criterion are then clustered together. This process continues until all the objects have been clustered. These successive clustering operations produce a binary clustering tree (dendrogram), whose root is the class that contains all the observations. This dendrogram represents a hierarchy of partitions. It is then possible to choose a partition by truncating the tree at a given level, the level depending upon either user-defined constraints (the user knows how many classes are to be obtained) or more objective criteria. The proximity between two objects is measured by measuring at what point they are similar (similarity) or dissimilar (dissimilarity). The similarity coefficients are co-occurrence, cosine, covariance (n-1), covariance (n), dice coefficient (also known as Sorensen coefficient), general similarity, Gower coefficient, inertia, Jaccard coefficient, Kendall correlation coefficient, Kulczynski coefficient, Ochiai coefficient, Pearson's correlation coefficient, Pearson Phi, percent agreement, Rogers and Tanimoto coefficient, Sokal and Michener coefficient (or simple matching coefficient), Sokal and Sneath coefficient, and Spearman correlation coefficient. The dissimilarity coefficients are Bhattacharya's distance, Bray and Curtis' distance, Canberra's distance, Chebyshev distance, Chi^2 distance, Chi^2 metric, chord distance, squared chord distance, dice coefficient, Euclidian distance, geodesic distance, Jaccard coefficient, Kendall dissimilarity, Kulczynski coefficient, Mahalanobis distance, Manhattan distance, Ochiai coefficient, Pearson's dissimilarity, Pearson's Phi, general dissimilarity, Rogers and Tanimoto coefficient, Sokal and Michener coefficient, Sokal and Sneath coefficient, Sokal and Sneath coefficient (2), and Spearman dissimilarity. The quality of an agglomerative hierarchical clustering can be assessed by the cophenetic correlation coefficient. It uses a measure of distance called the cophenetic distance that can be estimated on the dendrogram obtained from a classification. The cophenetic distance separating 2 observations is given by the height of the dendrogram at which the 2 observations belong to the same cluster. Finally, the cophenetic correlation is estimated as the Pearson correlation coefficient between the dissimilarity matrix used for the AHC and the cophenetic distance matrix. The closer to 1 the correlation, the better the quality of the clustering. To calculate the dissimilarity between two groups of objects A and B, different strategies are possible, for example, *Simple linkage*: the dissimilarity between A and B is the dissimilarity between the object of A and the object of B that are the most similar. Agglomeration using simple linkage tends to contract the data space and to flatten the levels of each step in the dendrogram. As the dissimilarity between two elements of A and of B is sufficient to link A and B, this criterion can lead to very long clusters (chaining effect) while they are not homogeneous. *Complete linkage*: the dissimilarity between A and B is the largest dissimilarity between an object of A and an object of B. Agglomeration using complete linkage tends to dilate the data space and to produce compact clusters. *Unweighted pair-group average linkage*: the dissimilarity between A and B is the average of the dissimilarities between the objects of A and the objects of B. Agglomeration using unweighted pair-group average linkage is a good compromise between the two preceding criteria and provides a fair representation of the data space properties. *Weighted pair-group average linkage*: the average dissimilarity between the objects of A and of B is calculated as the sum of the weighted dissimilarities, so that equal weights are assigned to both groups. As with unweighted pair-group average linkage, this criterion provides a fairly good representation of the data space properties. *Flexible linkage*: this criterion uses a â parameter that varies between −1 and +1; this can generate a family of agglomeration criteria. For â = 0, the criterion is weighted pair-group average linkage. When â is near to 1, chain-like clusters result, but as â decreases and becomes negative, more and more dilatation is obtained. *Ward's method*: this method aggregates two groups so that within-group inertia increases as little as possible to keep the clusters homogeneous. This criterion, proposed by Ward Jr (1963), can only be used in cases with quadratic distances, i.e. cases of Euclidian distance and Chi-square distance.

Spectral Fourier analysis

Fourier analysis is a method of defining periodic waveform s in terms of trigonometric functions. Many waveforms consist of energy at a fundamental frequency and also at harmonic frequencies (multiples of the fundamental). The relative proportions of energy in the fundamental and the harmonics determines the shape of the wave. The wave function (usually amplitude, frequency, or phase versus time) can be expressed as of a sum of sine and cosine functions called a Fourier series, uniquely defined by constants known as Fourier coefficients. If these coefficients are represented by $a, a_1, a_2, a_3, ..., a_n, ...$ and $b_1, b_2, b_3, ..., b_n, ...$, then the Fourier series $F(x)$, where x is an independent variable (usually time), has the following form:

$$F(x) = a/2 + a_1 \cos x + b_1 \sin x + a_2 \cos 2x + b_2 \sin 2x + \ldots + a_n \cos nx + b_n \sin nx + \ldots$$

In Fourier analysis, the objective is to calculate coefficients $a, a_1, a_2, a_3, ..., a_n$ and $b_1, b_2, b_3, ..., b_n$ up to the largest possible value of n . The greater the value of n (i.e. the more terms in the series whose coefficients can be determined), the more accurate is the Fourier-series representation of the waveform. Spectral analysis allows to discover underlying periodicities. First, data are transformed from time domain to frequency domain. The technical details of spectral Fourier analysis go beyond the scope of this study notes, but there are plenty of works in the literature. In brief, the covariance of the time series can be represented by a function known as the *spectral density*. The spectral density can be estimated using on object known as a *periodogram*, which is the squared correlation between our time series and sine/cosine waves at the different frequencies spanned by the series. For large numbers, the periodogram is approximately independent for distinct frequencies. This independence can be improved—as can the visual quality and interpretability of the plot—by smoothing the periodogram using a kernel smoother, which is frequently some kind of weighted of moving mean. In this study, spectral analysis is used to identify the presence of regular periodicities in the chronologies of the seasonal Tm series at all the study sites. Cyclicity is a factor of variability that may reduce the possibility to detect trends and is taken into account when trends in series of climate variables are investigated. Spectral (Fourier) analysis was applied to all the seasonal Tm series to verify whether periods with similar length occur among sites given the potential presence of cycles in seasonal Tm. If one or more cycles in the Tm trends were found in the study sites, they would indicate an objective span of years—or more spans—by which to set the moving averages to smooth the Tm series. This is important because it shows whether, when, and to what extent similarity in seasonal and monthly Tm series varies among sites in the study area, especially when climate/tree-growth relationships are investigated. So, smoothing of all Tm series by moving averages was used to enhance medium-long-term variability and reduce the influence of high-frequency variability, which is usually due to factors other than climate.

Pearson's *r* correlation of moving means

In statistics, a moving average (rolling average or running average) is a calculation to analyse data points by creating a series of averages of different subsets of the full dataset. It is also called a moving mean (MM)[1] or rolling mean and is a type of finite impulse response filter. Given a series of numbers and a fixed subset size, the first element of the moving average is obtained by taking the average of the initial fixed subset of the number series. Then the subset is modified by 'shifting forward', that is, excluding the first number of the series and including the next value in the subset. A moving average is commonly used with time series data to smooth out short-term fluctuations and highlight longer-term trends or cycles. The threshold between short-term and long-term depends on the application, and the parameters of the moving average will be set accordingly. Mathematically, a moving average is a type of convolution, and so it can be viewed as an example of a low-pass filter used in signal processing. Viewed simplistically it can be regarded as smoothing the data. The period selected (lag) depends on the type of movement of interest, such as short, intermediate, or long-term. If the data used are not centred around the mean, a simple moving average lags behind the latest datum point by half the sample width. A simple moving average can also be disproportionately influenced by old datum points dropping out or new data coming in. One characteristic of the simple moving average is that if the data have a periodic fluctuation, then applying a simple moving average of that period will eliminate that variation (the average always containing one complete cycle). However, a perfectly regular cycle is rarely encountered. For a number of applications, it is advantageous to avoid the shifting induced by using only 'past' data. In this case, a *central moving average* can be computed, using data equally spaced on either side of the point in the series where the mean is calculated. Thus, simple moving average (or running means) is a common statistical technique used to reduce the influence of high-frequency variability in time series, which smooth high-frequency variability to highlight low-frequency variability or enhance long-term trends. In this study, moving averages are featured by lags of years that work as temporal windows over chronologies; normally they smooth time series by yearly shifts. Although the lag of moving average can be chosen subjectively, more objective results are expected when the moving average lags over the length of periods or cycles that have been identified objectively. Therefore, moving means of the Pearson's r between paired series of monthly Tm were used to verify whether and how their similarity is stationary during the twentieth century. For example, simple moving average was calculated over lags of 15 years (7 years + 1 year + 7 years) for each year (central moving average) of the monthly Tm series, which produced a correspondent series of r values each averaged from 7 years before to 7 years after (TA_7). The Pearson's r correlation was computed between the paired series of each monthly TA_7 against the other monthly TA_7s.

Results

Exploratory analysis

A simple visual approach shows that the time series of annual Tm at all the study sites (Fig. 2) are discontinuous in some periods and can vary in similarity of patterns among sites such as ABE in the 1960s and CAM and VAL from the late 1910s to the early 1940s.

Annual Tm at the study sites shows high inter-annual variability and non-stationary trends that increase from the mid-1950s onward and grow even faster from the 1980s until the late 1990s–early 2000s at all the study sites (Fig. 2). This pattern has been observed at the northern hemisphere scale also (Brunetti et al. 2000a, b; Matyasovszky 2011). At first sight, in the study area, correlation between annual Tm series is not stationary during the twentieth century, and the time series show the presence of changes in trends every of 6–7 years, which could influence tree growth. In other words, trends in annual Tm seem to differ among sites in the study area in some periods, and fast changes in the slope of trends occur at relatively regular intervals. However, annual Tm may be of little help in investigating effects of temperature on tree growth, which develops mainly at the seasonal and monthly levels. Table 2 shows the seasonal averages of temperatures in the meteorological stations investigated; ABE is the coldest site, and VAL is the hottest. The example of Fig. 3 shows that summer Tm and winter Tm decrease from the late 1870s and increase after the mid-1950s. In both seasons, the period from the late nineteenth century to the mid-twentieth century shows some cooling (Table 3).

Matrix correlation

In this research, Pearson, Spearman, and Kendall matrix correlation tests of seasonal Tm series were applied to check for possible differences in the level of association among the seasonal Tm series. Different types of coefficients were used on the assumption that the similarity of the results in different tests strengthens the validity of the correlations between matrices. Table 4 and Table 5 summarize the results of the correlation tests; the association of ABE's seasonal Tm with those at CAM, LAV, and VAL (Table 4) is frequently weaker than the associations among CAM, LAV, and VAL (Table 5).

In general, the statistical significance (p-values <0.0001) is good. The level of association between CAM, LAV, and VAL is lower in summer and autumn and higher in winter. In summer, ABE shows the lower level of association with CAM, LAV, and VAL. In spring, CAM, LAV, and VAL show strong association in Tm, and even ABE is more like their Tm. In autumn and spring, the correlation of ABE's Tm with Tm at CAM, LAV, and VAL is moderately good (Table 4). Overall results show that the association in seasonal Tm series varies with season and site, in particular at ABE. This suggests that the seasonal Tm series are likely to have different patterns or trends that vary with site and/or time in some periods during the twentieth century. At the level of monthly Tm series, matrix correlation shows that the level of association between the series varies with month and site from moderately good to high (Table 6). In all months, the correlation coefficients of the monthly Tm series between ABE and CAM, LAV, and VAL are lower than

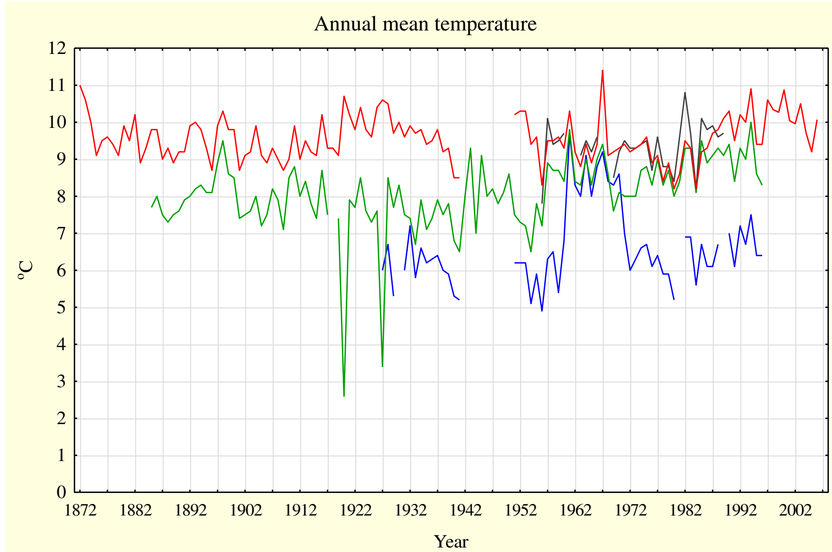


Fig. 2 Annual Tm series at all sites in the study area. Gaps are missing data. ABE is blue, CAM is green, LAV is black, and VAL is red

the correlation coefficients between CAM, LAV, and VAL. Similarity in the monthly Tm series among sites is lower in summer and higher in winter except December at ABE, which shows lower correlation with CAM-LAV-VAL. The interval between the values of the correlation coefficients is greatest in June, July, and September. For example, the correlation coefficients (r) between CAM, LAV, and VAL vary from 0.65 to 0.94 in June and between 0.84 and 0.87 in December. All this variability may derive from differences in trends of monthly Tm that could influence the response in tree growth in different ways.

Agglomerative hierarchical clustering

Similarity-based grouping of meteorological stations in seasonal and monthly Tm patterns was assessed by agglomerative hierarchical clustering (AHC). The AHC results confirm the presence of a moderately higher similarity in the seasonal Tm series to CAM, LAV and VAL, being the seasonal Tm of ABE a relatively separate cluster from CAM, LAV, and VAL in all seasons (Table 7).

It can be noted that:

- CAM and LAV are the most similar only in 3 months (Apr, Jun, and Jul) out of twelve despite they have similar elevation and are at short distance (ca. 13 km).
- CAM and VAL are the less 'statistically' distant in 6 months out of 12.
- CAM's similarity is intermediate between ABE and LAV-VAL in 3 months (Jan, Feb, and Sep) out of twelve.

Thus, clustering of monthly Tm varies somehow with month among sites in the study area. This phenomenon suggests the presence of differences in the variability of trends during the twentieth century. Therefore, verifying if similarity in trends of monthly Tm among sites is stationary during time is a necessary and important step to ascertain as it can reflect on tree growth.

Linear regression modelling

In this context, linear regression analysis of seasonal Tm averaged from all sites in the study area (dependent variable) against the seasonal Tm series of each site (independent variables) has contributed a further insight into data distribution.

Table 2 Maximum Tm, minimum Tm, Tm, and standard deviation (SD) of the winter, spring, summer, and autumn temperature series (°C) at all study sites.

	Winter				Spring				Summer				Autumn			
	Mean	SD	Max	Min	Mean	SD	Max	Min	Mean	SD	Max	Min	Mean	SD	Max	Min
ABE	−0.7	1.4	2.3	−4.9	4.9	1.4	8.8	1.5	14.8	1.3	17.3	12.3	7.7	1.5	11.1	5.0
LAV	1.4	1.3	3.5	−1.9	7.8	1.2	9.6	4.9	18.1	1.0	20.2	16.1	10.3	1.0	12.1	8.2
CAM	0.4	1.5	3.6	−3.4	6.5	1.1	8.9	4.2	16.4	1.0	18.9	14.1	9.3	1.2	11.7	3.3
VAL	2.2	1.1	4.3	−1.0	7.9	1.0	10.0	5.6	17.5	1.1	21.8	15.3	10.6	1.0	13.5	8.0

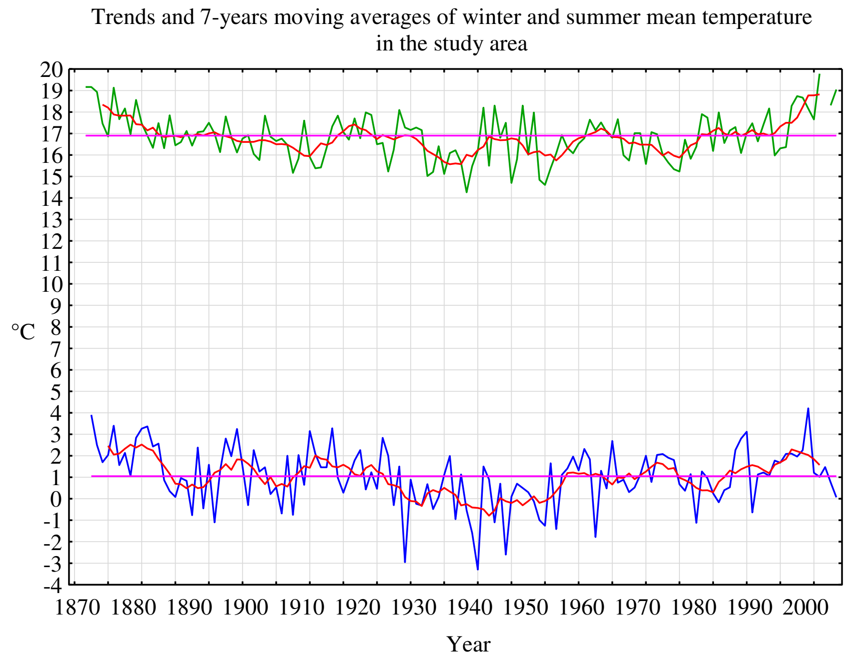


Fig. 3 Winter Tm (blue line) and summer Tm (green line) in the study area as averages from the four study sites; relative 7 years moving averages (red lines) and long-term means (magenta lines).

The patterns of residual errors have shown the presence of different types of data distribution among sites, where the regression models fit well and are statistically significant. Since the residual errors and their distribution represent the real seasonal Tm events that influence climate/growth relationships, they may retain amounts of variability that could reflect on tree growth by ways that are not shown by the regression model. Therefore, the values and possibly trends modelled by linear regression may not show differences in the relationships between climate and tree growth between forest-level sites, to the extent that this type of information is held back by residual errors.

The Mann-Kendall trend tests

The presence of trends in the seasonal Tm series was tested in all sites through the Mann-Kendall (M-K) trend test; in general, no trends were detected. For example, Table 8 shows the results of M-K relative to summer Tm and autumn Tm at ABE and VAL.

The statistical normality of the Tm series was tested; however, the results of different types of tests are controversial. The M-K test, which is a non-parametric test, was used to assess the presence of trends in the historical series of monthly Tm. The series tested start in the year 1928 at all sites except LAV, which shows a relatively short series of data (Table 1); their Tm, SD, maximum Tm, and minimum Tm are shown in Table 2. As the Tm series at CAM and VAL go back respectively to the years 1885 and 1872 (long-term series), these data have been used to verify whether any change in trends of monthly Tm occur before the late 1920s by applying the M-K test to all the monthly Tm series at the study sites. The M-K test does not detect any trend in autumn Tm at ABE (Table 8). However, autumn Tm is 7.0°C in the period 1928–1960 and 7.3°C in the period 1971–1998; normally, autumn Tm (Table 2) is greater than 6.2°C and less than 9.2°C except in the 1960s, when a warmer period (10.1°C) occurs. These results suggest that variability in monthly Tm in different months at different elevation may find trees in different ecophysiological stages, and therefore, it can have different influence on tree growth among sites.

Spectral (Fourier) analysis

The presence of recurrences in the historical series was analysed by performing periodograms and spectral density of the seasonal Tm chronologies. The analysis has shown the presence of periods of (2–4), 6–7, 9–11, 14–16, 18–19, 22–23, 27–28, 34–36, 45, 55, 67–70, and 110–112 years of length in all the study sites. In particular, the periods (2–3), 6–7, 22–23, 34–36, 67–70, and 110 years result the most frequent in the seasonal Tm series (Table 9). It was also noted that the harmonic mean of all the periodogram values varies little among sites in all seasons, and the 7-year period, which derives from a harmonic mean that varies between 5.5 and 7.5, is the most frequent interval between all of them. This suggests that the 7-year period approximates the harmonic mean of the peak periodicities over the entire series of seasonal Tm in the study area, which is a sub-dividend of longer periodicities that occur with regularity.

Table 3 Monthly Tm (°C), SD, maximum Tm, and minimum Tm at all sites in the study area

	ABE (1928–1998)						LAV (1956–1990)						CAM (1928–1996)						VAL (1928–2006)					
	Mean	SD	Max	Year	Min	Year	Mean	SD	Max	Year	Min	Year	Mean	SD	Max	Year	Min	Year	Mean	SD	Max	Year	Min	Year
Jan	−1.3	2.0	2.5	1962	−6.4	1985	0.8	1.9	4.6	1974	−3.0	1985	−0.3	2.3	5.2	1974	−5.4	1954	1.7	1.7	5.1	1932	−1.9	1985
Feb	−1.0	2.6	4.8	1966	−9.9	1956	1.3	2.6	5.4	1990	−6.6	1956	−0.3	2.5	5.3	1990	−8.5	1956	2.1	2.0	5.7	1990	−4.6	1956
Mar	1.5	1.9	6.4	1961	−3.1	1987	3.8	2.3	8.2	1989	−2.4	1956	2.9	2.0	7.9	1994	−0.4	1932/71	4.5	1.7	8.4	1994	0.9	1971
Apr	4.4	1.8	9.4	1961	0.9	1929	7.2	1.4	9.9	1981	4.6	1980	6.2	1.5	9.9	1961	2.1	1938	7.4	1.3	11.7	1961	4.7	1938
May	8.8	1.9	12.7	1969	4.4	1984	12.6	1.8	16.7	1986	8.6	1980	10.5	1.6	14.7	1986	6.6	1941	11.8	1.6	15.1	2003	8.2	1991
Jun	13.0	1.9	21.0	1932	9.3	1933	16.1	1.3	18.7	1982	13.4	1969	14.4	1.4	17.7	1931	9.8	1933	15.4	1.5	20.4	2003	13.0	1933
Jul	15.9	1.5	19.5	1967	12.6	1954	19.3	1.4	22.7	1983	17.5	1978	17.7	1.4	21.2	1983	14.3	1948	18.4	1.3	22.0	2006	15.4	1980
Aug	15.7	1.7	19.5	1962	12.3	1959	19.0	1.7	22.5	1971	15.4	1976	17.6	1.6	21.6	1994	14.7	1976	18.4	1.6	23.6	2003	15.2	1976
Sep	12.1	2.0	17.3	1961	6.4	1931	15.3	1.9	19.5	1985	11.5	1972	14.2	1.8	18.8	1997	10.0	1931	15.0	1.5	19.3	1932	11.9	1976
Oct	7.6	1.9	12.1	1967	2.0	1974	10.4	1.7	13.8	1967	5.0	1974	9.5	1.6	13.2	1942	4.6	1974	10.7	1.3	13.3	2001	5.6	1974
Nov	3.3	2.0	8.8	1928	−0.6	1998	5.3	1.7	7.8	1967	0.3	1979	4.8	1.4	8.5	1994	1.9	1952	6.1	1.3	8.7	1994	3.4	1966
Dec	−0.2	1.7	2.8	1965	−5.7	1940	2.0	1.6	4.9	1985	−2.1	1969	1.3	1.9	5.7	1958	−4.7	1940	2.6	1.5	5.7	2000	−1.7	1940

Table 4 Values of Pearson, Spearman, and Kendall coefficients (*r, ρ, τ*) in the correlation of the seasonal Tm series at ABE with those at CAM, LAV, and VAL

	Pearson		Spearman		Kendall	
	r	p-value	r	p-value	r	p-value
Winter						
Casewise	0.45	0.010	0.39	0.029	0.32	0.012
Pairwise	0.69	<0.0001	0.58	<0.0001	0.44	<0.0001
Spring						
Casewise	0.70	<0.0001	0.73	<0.0001	0.57	<0.0001
Pairwise	0.65	<0.0001	0.70	<0.0001	0.52	<0.0001
Summer						
Casewise	0.48	0.035	0.47	0.006	0.34	0.006
Pairwise	0.54	<0.0001	0.57	<0.0001	0.43	<0.0001
Autumn						
Casewise	0.73	<0.0001	0.76	<0.0001	0.58	<0.0001
Pairwise	0.68	<0.0001	0.69	<0.0001	0.53	<0.0001

The matrix correlations (at the alpha level 0.05) were computed by both 'casewise deletion' and 'pairwise deletion' of missing observations

Table 6 Upper and lower values of Pearson's r in the correlations of the paired series of monthly Tm between ABE and CAM-LAV-VAL and between CAM, LAV, and VAL

		ABE/CAM-LAV-VAL	CAM/LAV/VAL
	Dec	0.61< *r* <0.75	0.84< *r* <0.87
Winter	Jan	0.76< *r* <0.83	0.82< *r* <0.94
	Feb	0.84< *r* <0.86	0.86< *r* <0.96
	Mar	0.74< *r* <0.80	0.84< *r* <0.95
Spring	Apr	0.72< *r* <0.77	0.81< *r* <0.92
	May	0.64< *r* <0.77	0.78< *r* <0.88
	Jun	0.49< *r* <0.69	0.65< *r* <0.94
Summer	Jul	0.60< *r* <0.66	0.68< *r* <0.92
	Aug	0.52< *r* <0.69	0.74< *r* <0.79
	Sep	0.72< *r* <0.81	0.70< *r* <0.90
Autumn	Oct	0.67< *r* <0.78	0.76< *r* <0.81
	Nov	0.73< *r* <0.75	0.71< *r* <0.88

All correlations are statistically significant at the alpha 0.05 level (p-values <0.0001)

Moving averages

Graphs were elaborated by calculating the moving average over 7 years (TA_7) of all seasons to first identify possible cyclical periods. For example, Fig. 4 shows negative trends in winter Tm at CAM and VAL from the late 1910s to the late 1940s; in this period, winter Tm is −0.12 °C at CAM (SD is 1.4) and 2.4 °C at VAL (SD is 1.1). The Tm data start in 1928 at ABE; winter Tm is −1.2°C (SD is 1.4) in the period 1928–1940; and −0.6 °C (SD is 1.1) at ABE, 1.3 °C at CAM (SD is 1.3), and 2.4 °C at VAL (SD is 1.3) in the period 1980–1998. The time series at LAV is short, and no long-term trend could be detected, but it can be noted that the LAV time series is close to CAM.

Table 5 Values of Pearson, Spearman, and Kendall coefficients (*r, ρ, τ*) in the correlation of the seasonal Tm series among CAM, LAV, and VAL

	Pearson		Spearman		Kendall	
	r	p-value	r	p-value	r	p-value
Winter						
Casewise	0.89	<0.0001	0.88	<0.0001	0.75	<0.0001
Pairwise	0.78	<0.0001	0.79	<0.0001	0.60	<0.0001
Spring						
Casewise	0.86	<0.0001	0.84	<0.0001	0.68	<0.0001
Pairwise	0.64	<0.0001	0.64	<0.0001	0.49	<0.0001
Summer						
Casewise	0.65	<0.0001	0.68	<0.0001	0.49	0.000
Pairwise	0.56	<0.0001	0.57	<0.0001	0.41	<0.0001
Autumn						
Casewise	0.77	<0.0001	0.72	<0.0001	0.57	<0.0001
Pairwise	0.54	<0.0001	0.50	<0.0001	0.37	<0.0001

The matrix correlations were computed by both 'casewise deletion' and 'pairwise deletion' of missing observations

The trend in winter TA_7 at ABE differs from those at CAM, LAV, and VAL, which are more similar each to the other (Fig. 4). In spring, Tm at ABE (Fig. 5) is normally higher than 2.0°C and smaller than 6.2°C except in the 1960s (spring Tm is 7.1°C) and in the year 1930 (spring Tm is 1.6°C). As in winter, spring Tm in the 1960s is higher than in all the previous and following decades observed, it decreases during the 1970s and increases after the mid-1980s. In the late 1970s–mid 1980s, a trough in spring Tm occurs at ABE while a peak emerges in the same years at the other study sites. The TA_7 series in spring (Fig. 5) show trends that differ from those in winter TA_7 (Fig. 4). For example, spring TA_7 shows a peak at all the study sites in the 1960s, while winter TA_7 shows troughs in the same period at the same sites except ABE, which peaks instead. Spring Tm from the early 1910s to the mid-1920s increases at VAL and decreases at CAM in spring (Fig. 5) although these trends seem more similar in winter.

At ABE, summer Tm is never greater than 12°C or smaller than 17.3°C in the span of time observed. In winter Tm and in spring Tm, the 1960s is the warmest period in summer at ABE; before the 1960s, summer Tm at ABE is lower (14.0°C) than after the 1960s (15.3°C). Indeed it decreases going back from the 1960s and increases after the late 1970s. Although the M-K test does not show trends in

Table 7 Grouping of monthly Tm series in the study area as shown by AHC. Decrease in the order of cluster corresponds to reduction in similarity among sites. Coloration indicates similar level of hierarchical clustering

		1st Cluster	2nd Cluster	3rd Cluster
Winter	Dec	CAM-VAL	LAV	ABE
	Jan	LAV-VAL	CAM	ABE
	Feb	LAV-VAL	CAM	ABE
Spring	Mar	CAM-VAL	LAV	ABE
	Apr	CAM-LAV	VAL	ABE
	May	CAM-VAL	LAV	ABE
Summer	Jun	CAM-LAV	VAL	ABE
	Jul	CAM-LAV	VAL	ABE
	Aug	CAM-VAL	LAV	ABE
Autumn	Sep	LAV-VAL	CAM	ABE
	Oct	CAM-VAL	LAV	ABE
	Nov	CAM-VAL	LAV	ABE

summer Tm at ABE (Table 8), the pronounced peak during the 1960s is likely to alter or confound the result.

At VAL, summer Tm decreases from the late 1800s to the mid-1910s, while a warm period takes place from the late 1910s to the early 1930s (Fig. 6). Summer Tm at VAL is normally greater than 15°C and less than 19°C but reaches temperature greater than 20.5°C in some years (i.e. 1928, 1952, and 2003). In the period 1990–2006, summer Tm is 18.3°C, similar to summer Tm in the 1920s–1930s; however, this value is mainly due to the summer Tm of the year 2003 (21.8°C). Although summer Tm at VAL increases from the early 1980s and 5 years in the period 1995–2006 show summer Tm higher than upper SD (18.6°C), there had been other periods with summer Tm higher than upper SD. For example, 5 years with summer Tm greater than 18.6°C were noted in the period 1872–1881 and five years in the decade 1921–1930. Warmer summer Tm occurs frequently before the 1990s–2000s, such as in the years 1928 (20.5°C), 1947 (20.0°C), and 1952 (20.0°C). However, results of the M-K test relative to the presence of trends in the summer Tm series indicate the absence of trends at VAL (Table 8). In summer, CAM shows a trend in Tm that decreases from the end of the 1800s to the late 1920s and turns into positive that starts in the 1930s. The presence of a trend is confirmed by the M-K (*p*-value <0.004) test. Summer Tm at CAM shows a hot period in the 1960s (16.5 °C), but this is not the hottest period in the series like at ABE. For example, summer Tm at CAM is 16.7°C in the 1940s and 17.3°C in the 1980s. At LAV, summer Tm increases from the mid-1970s after a moderate trough; however, the data series at LAV is short to detect long-term trends. The M-K test suggests that trends in summer Tm are not present at LAV, once the trends in the summer Tm series are smoothed by 7-year moving averages, CAM and VAL show similar trends before the late 1920s. As the TA_7 trends at ABE and VAL miss data from the 1940s to the early 1950s, comparison with the other study sites could not be done over this period. In the mid-1960s, a pronounced hot period occurs at ABE and, quite at a lower extent, at CAM. From the late 1960s to the 1970s, summer TA_7 at ABE is declining, at CAM it decreases at first and becomes positive in the early 1970s, while at LAV and VAL, it is slightly rising or flat and becomes negative in the second half of the 1970s.

Table 8 Results of M-K test of summer Tm and autumn Tm at ABE and VAL

Season	Summer Tm	Summer Tm	Autumn Tm	Autumn Tm
Weather station	ABE	VAL	ABE	VAL
Kendall's tau	0.013	0.00	0.044	0.01
S	25.000	7.00	82.000	67.00
p-value	0.88	0.99	0.62	0.89
Risk	88.4%	99%	62.2%	89%

The significance level is 0.95, where the null hypothesis (H0) is 'there is no trend in the series' and the alternative hypothesis (Ha) is 'there is a trend in the series'. A *p*-value greater than 0.05 suggests accepting H0; the risk of rejecting H0 while it is true is expressed as a percentage

Table 9 Results of the spectral analysis relating to the summer Tm series at CAM and the winter Tm series at VAL

Spectral analysis							
Summer Tm at CAM				Winter Tm at VAL			
Frequency	Period (years)	Periodogram	Density	Frequency	Period (years)	Periodogram	Density
0.00				0.00			
0.01				0.01	134.00	0.74	1.71
0.01	110.00	3.39	2.48	0.01	67.00	5.27	3.19
0.02	55.00	3.04	2.98	0.02	44.67	2.37	2.97
0.03	36.67	3.24	2.63	0.03	33.50	2.51	2.09
0.04	27.50	0.79	2.28	0.04	26.80	0.22	2.54
0.05	22.00	3.83	2.86	0.04	22.33	4.32	6.90
0.05	18.33	3.21	2.92	0.05	19.14	20.01	10.11
0.06	15.71	2.08	2.13	0.06	16.75	0.12	5.75
				0.07	14.89	2.63	2.74
0.07	13.75	1.03	1.49	0.07	13.40	2.29	3.51
0.08	12.22	1.16	1.74	0.08	12.18	7.60	4.25
0.09	11.00	3.73	2.09	0.09	11.17	0.48	2.89
0.10	10.00	0.07	1.57	**0.10**	10.31	2.87	2.18
				0.10	9.57	1.92	1.94
0.11	9.17	2.44	1.40	0.11	8.93	1.35	1.51
0.12	8.46	0.38	1.38	0.12	8.38	1.26	1.27
				0.13	7.88	1.00	1.52
0.13	7.86	2.01	2.16	0.13	7.44	2.04	2.81
0.14	7.33	3.66	3.57	0.14	7.05	6.54	3.68
0.15	6.88	5.69	3.97	0.15	6.70	0.93	2.20
0.15	6.47	1.97	2.54	0.16	6.38	0.28	1.11
0.16	6.11	0.08	1.78	0.16	6.09	1.75	1.81
0.17	5.79	3.98	2.62	0.17	5.83	3.05	3.10
0.18	5.50	3.11	2.42	0.18	5.58	5.38	3.30
0.19	5.24	0.02	1.35	0.19	5.36	0.28	1.80
				0.19	5.15	1.05	0.99
0.20	5.00	1.84	1.03	**0.20**	4.96	0.46	1.51
0.21	4.78	0.27	0.77	0.21	4.79	4.29	2.24
0.22	4.58	0.78	0.57	0.22	4.62	0.23	2.00
				0.22	4.47	3.23	2.14
0.23	4.40	0.31	0.48	0.23	4.32	1.98	1.73
0.24	4.23	0.45	0.68	0.24	4.19	0.25	0.71
0.25	4.07	0.96	1.55	0.25	4.06	0.01	0.27
0.25	3.93	4.04	2.33	0.25	3.94	0.24	0.68
0.26	3.79	0.86	1.93	0.26	3.83	2.26	1.27
0.27	3.67	2.01	1.73	0.27	3.72	0.48	1.49
0.28	3.55	1.32	2.31	0.28	3.62	2.36	2.30
				0.28	3.53	4.29	2.66
0.29	3.44	4.59	3.15	0.29	3.44	0.53	1.61
0.30	3.33	2.93	2.50	**0.30**	3.35	0.82	1.03
0.31	3.24	0.11	1.05	0.31	3.27	1.52	1.13
				0.31	3.19	0.51	1.60
0.32	3.14	0.41	0.84	0.32	3.12	3.18	3.05
0.33	3.06	0.99	2.54	0.33	3.05	5.95	3.67
0.34	2.97	8.03	4.26	0.34	2.98	0.59	2.46
0.35	2.89	1.52	3.02	0.34	2.91	2.50	1.81
0.35	2.82	1.35	1.57	0.35	2.85	1.22	1.60
0.36	2.75	1.31	0.98	0.36	2.79	1.35	1.74
0.37	2.68	0.03	0.42	0.37	2.73	2.88	2.09
				0.37	2.68	1.68	1.82
0.38	2.62	0.15	0.22	0.38	2.63	0.74	1.91
0.39	2.56	0.21	0.48	0.39	2.58	4.33	2.39
0.40	2.50	1.23	0.99	**0.40**	2.53	0.81	1.66

Values in red are statistically significant with p <0.0001. Periods <2.5 years are not shown as their frequency is very high and may cause 'red noise'. Green cells are prevalent periods and yellow cells show secondary periods

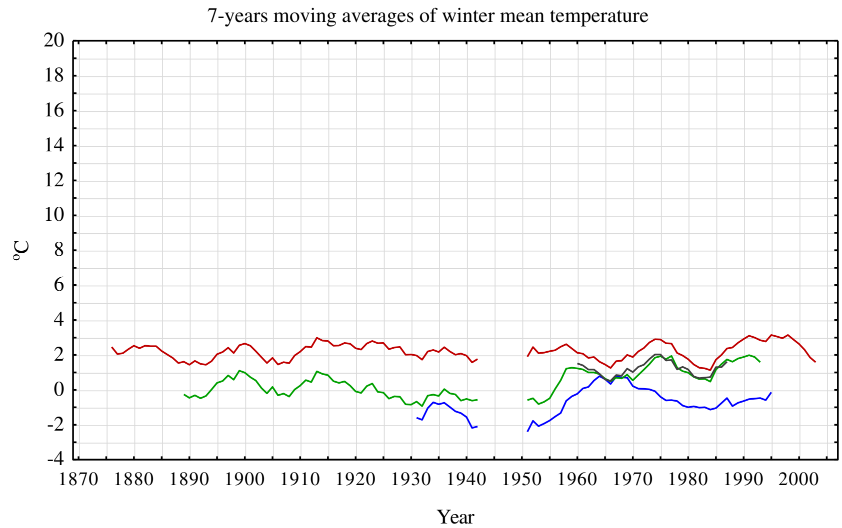


Fig. 4 Winter TA_7 at all sites during the twentieth century at all sites. Blue is ABE, green is CAM, black is LAV, and red is VAL. Gaps in the 1940s are missing data.

However, summer TA_7 trends become positive at all study sites after the early 1980s (Fig. 6). Trends in autumn TA_7 are positive at ABE and CAM, and negative at LAV and VAL from the 1950s to the mid-1970s (Fig. 7). A peak period is observed in the 1960s at all sites. It is pronounced at ABE, moderate at CAM, and small at LAV and VAL. After the mid-1980s, trends in autumn TA_7 are negative also at ABE and CAM, while VAL's trend is only slightly negative. Trends in TA_7 at LAV and VAL are similar from the 1960s to the early 1980s. In autumn, Tm at CAM (Fig. 7) is 9.1°C from the mid-1880s to the 1920s; it is slightly lower (9.0°C) than the long-term mean (9.3°C) from the early 1920s to the early 1950s and increases moderately after the early 1950s (9.7°C in the period 1953–1996). Autumn Tm normally ranges from greater than 7 to less than 11.7°C as lower and upper values, respectively, instead a warmer period takes place in the 1960s at CAM but it is not as pronounced as at ABE; CAM's autumn Tm (10.3°C) in the 1960s is higher than in the previous periods, followed by a decrease. In the 1980s, autumn Tm is 10.5°C. The M-K (p-value <0.001) test suggests the presence of a trend in autumn Tm at CAM. The short time

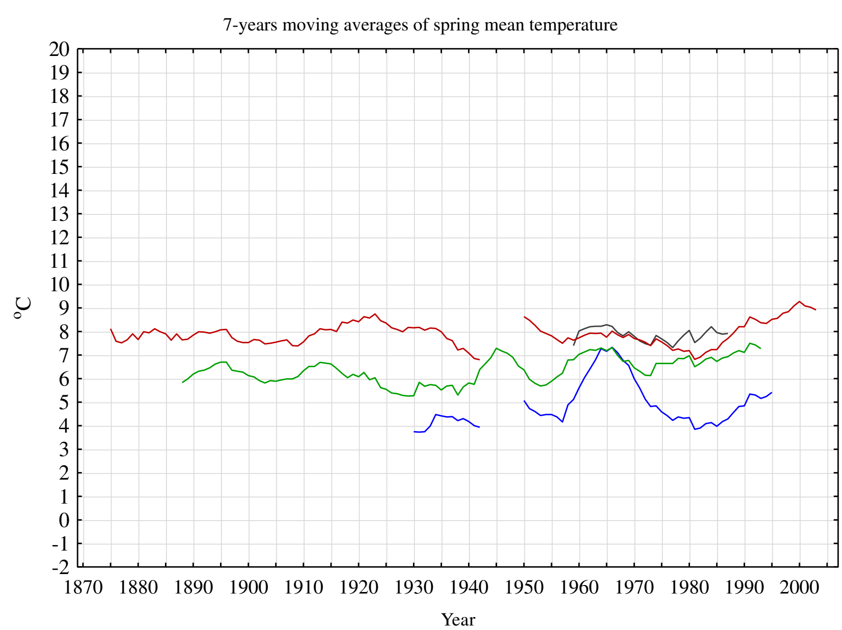


Fig. 5 Spring TA_7 at all sites during the twentieth century at all sites. Blue is ABE, green is CAM, black is LAV, and red is VAL. Gaps in the 1940s are missing data

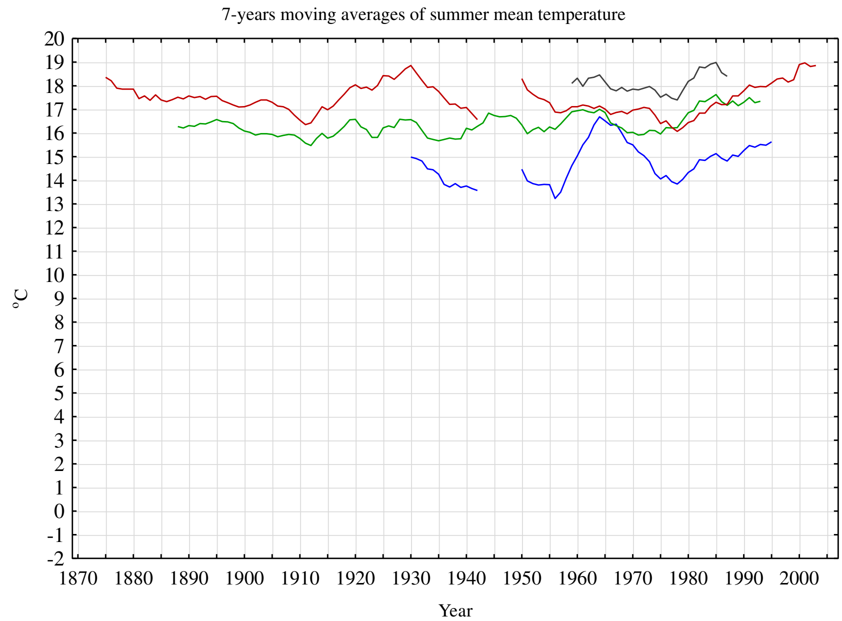


Fig. 6 Summer TA_7 during the twentieth century at all study sites. Blue is ABE, green is CAM, black is LAV, and red is VAL. Gaps in the 1940s are missing data.

series (33 years) at LAV shows that autumn Tm is greater than 8.2°C and less than 12.1°C, while in the 1960s (10.8°C) are warmer than the following years (10.1°C from the year 1971 to the year 1989). At CAM and VAL, the 7-year moving averages trends of the fall Tm series are relatively similar before the mid-1930s and from the late 1950s to late 1980s (Fig. 7). At VAL, autumn Tm is normally greater than 9.0°C and less than 12.5°C except in few years; in fact the long-term mean is 10.6°C (1872–2006). The warmest autumnal period occurs in the 1920s (11.4°C), while the 1970s (9.8°C) and the period 1905–1915 (10.1°C) are the coldest; autumn is smaller than 9.0°C in the years 1884, 1912, 1915, and 1974, while it is higher than 12.5°C in the years 1886, 1898, and 1932.

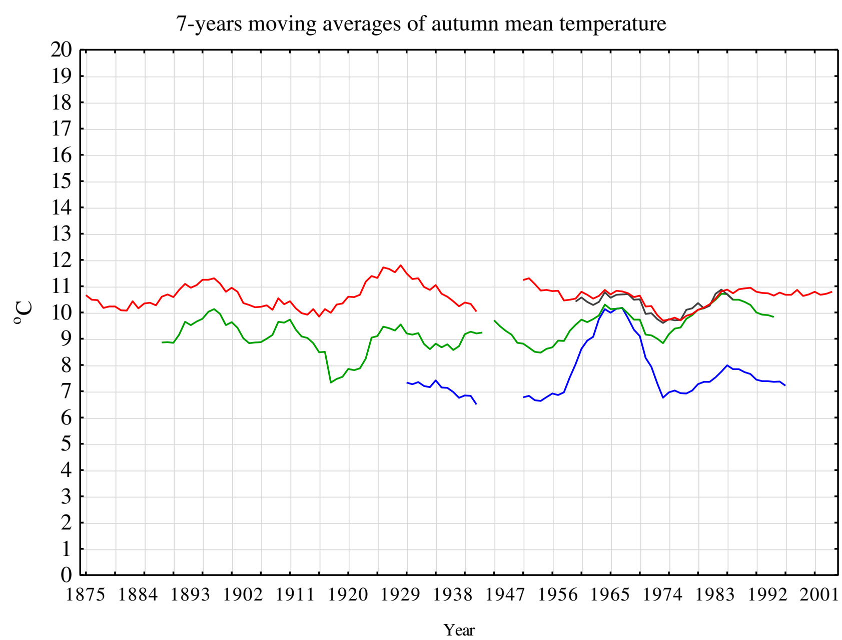


Fig. 7 Autumn TA_7 at all sites. Blue is ABE, green is CAM, black is LAV, and red is VAL. Gaps in the 1940s are missing data

The sharp increase and decrease observed in autumn Tm at ABE respectively in the early 1960s and in the 1970s rise the question whether some artificial change such as temporary reallocation of the meteorological station and/or change of the type of device or else, may have occurred. However, it can be noted that:

– Autumn Tm peaks in the same years also in CAM, although it is not as pronounced as in ABE, and slightly in VAL. This is likely to indicate that the warmer period in the 1960s is not a local feature at ABE.
– Two series of meteorological data of ABE (Boscolungo) are shown in the Annals from the early 1920s to the late 1930s; one is Boscolungo Town, and the other is Boscolungo Forest. Values of monthly Tm in the 'Town' series are normally 1–3°C higher than those in the 'Forest' series. If a change in the temperature data was caused artificially (e.g. displacement of a weather station), the data series would show it.

Pearson's *r* of moving averages

Pearson's *r* correlation coefficients of 7-year moving averages between paired series of monthly Tm was finally used to test if the associations in monthly Tm series are stationary during the twentieth century among sites in the study area. As shown in the examples of Fig. 8, similarity in trends of monthly Tm is non-stationary during the 20th in the Tuscan Apennine Alps; variations in monthly Tm do not necessarily occur in the same months at all sites. In particular, the analysis reveals that there are periods when trends in monthly Tm show dissimilarity among the study sites. This variability can reflect on tree growth and unlikely can be highlighted by master series of climate variables.

Summary of results

Descriptive analysis of monthly Tm shows differences in trends that may influence the response of tree growth among sites in the study area. The AHC of monthly Tm series shows that the associations of monthly MT series among sites vary with month and/or site. However, this type of test does not show if and how similarity in trends varies over time, which is a key point to understand if relationships with tree growth are stationary over time and/or among sites. It has been recalled that changes in trends or differences in the seasonal Tm patterns among sites that may occur in some periods are likely to influence tree growth in unpredicted ways among sites. This phenomenon, which takes place even between sites at short distance and similar elevation such as CAM and LAV, highlights that master series of seasonal Tm can be of little utility to analyse climate/tree-ring relationships in case if the objective of the analysis is to verify the response of tree growth to variations in Tm at the forest site level, at least in the Tuscan Apennine Alps. Still, the seasonal level may not show or highlight what occurs at the monthly level that can influence the tree growth response. Results of the analysis of trends in seasonal Tm and monthly Tm during the twentieth century at the study sites in the Tuscan Apennine Alps are summarized below:

• Distributions of data are not homogenous among sites.

• Standard deviation of Tm is pronounced in all seasons and months and varies irregularly over time.

• Inter-annual variability of Tm is high in all seasons and months.

• Some peaks and troughs occur in different periods among sites and more markedly at ABE in comparison to the other study sites. The ABE seasonal and monthly Tm series form a cluster different from that formed by CAM, LAV, and VAL.

• Clustering within the group CAM-LAV-VAL varies also with season. The similarity in the seasonal Tm series of the CAM-LAV-VAL cluster is lower in summer; this season VAL shows a marked dissimilarity between CAM and LAV.

• The similarity in seasonal and monthly Tm trends is not stationary between study sites during the twentieth century in the Tuscan Apennines, even when the sites are short distances and have similar elevations such as CAM and LAV.

• The similarity varies from high to small or even negative values of the correlation coefficients over time. In other words, trends in monthly Tm can differ greatly and even be opposite over time between sites.

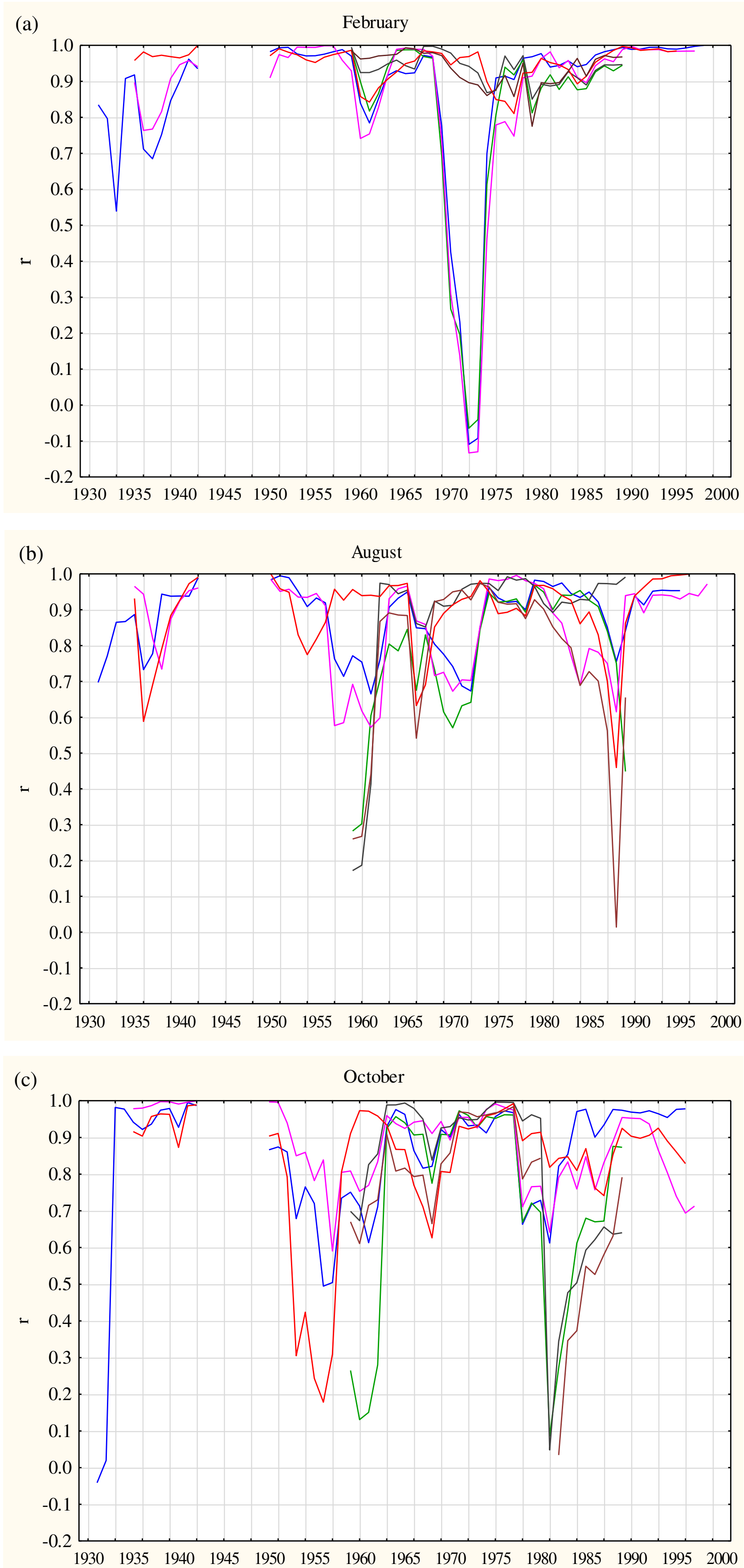
Although Tm at the regional level can show some prevailing tendency (i.e. warming), it can be noted that:

• Regional or higher scale trends in Tm smooth variability at the local level, which may have relevant effects on tree growth and health, however.

• Master series of seasonal Tm do not show variations that occur at the monthly level, which are important to identify possible effects in tree growth instead.

• In the Tuscan Apennines, non-stationary similarity in trends of seasonal Tm and monthly Tm among sites is present even between sites at short distance.

Fig. 8 Variability of the Pearson's *r* in the correlation of 7-year moving averages of monthly Tm in February (a), August (b), and October (c) between paired sites in the study area during the twentieth century. ABE-CAM is shown by the blue line, ABE-VAL is magenta, ABE-LAV is green, CAM-VAL is red, LAV-VAL is brown, and CAM-LAV is dark grey.


(a)
February
r
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
-0.1
-0.2
1930 1935 1940 1945 1950 1955 1960 1965 1970 1975 1980 1985 1990 1995 2000
(b)
August
r
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
-0.1
-0.2
1930 1935 1940 1945 1950 1955 1960 1965 1970 1975 1980 1985 1990 1995 2000
(c)
October
r
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
-0.1
-0.2
1930 1935 1940 1945 1950 1955 1960 1965 1970 1975 1980 1985 1990 1995 2000

Discussion

At the annual scale, a general increase of temperature trend is observed in the mid-1950s that accelerate even faster from the 1980s. Summer Tm and especially winter MT decrease from the late 1870s and turn into an increase from the mid-1950s. This resembles the trends observed during the twentieth century in the Mediterranean area and Italy (Orlandini et al. 2009; Brunetti et al. 2000a, b; Camuffo et al. 2010; Gentilucci et al. 2019a). In the study area, seasonal trends in Tm confirm the occurrence of warming detected throughout South Europe and in the Mediterranean area and Italy (Toreti and Desiato 2008; Gentilucci et al. 2019b). However, months with increasing trends in Tm can differ among sites. For example, in the study area, the clustering of monthly Tm trends by season shows that winter warming occurs only at CAM, although on a regional and higher scale, winter is indicated as the most warming season. Reduction in both the maximum annual Tm and the minimum annual Tm was also observed in some other areas of Tuscany (Maracchi et al. 1998); the period from the late nineteenth century to the mid-twentieth century is cooling in the study area. Increases of summer Tm at all the study sites are also observed at the Tuscan regional scale (Bartolini et al. 2008). In the study area, warming occurs in spring and autumn at CAM and slightly at VAL during the period observed. This variability supports the thesis that differences in trends of seasonal and monthly Tm can either stimulate or reduce tree growth among sites and/or at different elevation. This may reflect on strategies and/or planning to adapt forest management and biodiversity conservation to changing climate conditions (Bolte et al. 2009; Borghetti et al. 2012; Jandl et al. 2019). For example, seasonal variability in Tm suggests that the length of summer and/or winter may extend or shorten over time; this can affect the length of the growing season and/or the growth rate of trees in different ways between sites and/or at different altitudes. In some tree species, a higher summer Tm can promote tree growth at higher elevations and reduce it at lower elevations or even cause a depressing effect on growth at both higher and lower elevations.

Conclusions

This study helps to understand the temperature variability in the Tuscan Apennines (Bartolini et al. 2008; Toreti and Desiato 2008; Scorzini and Leopardi 2019) and provides a more peculiar approach to the evaluation of climate-growth relationships of trees for adaptive (sustainable) forest planning and management. Moreover, the results promote the need for more detailed information on local and regional climate patterns of climate change (Solomon et al. 2007; IPCC 2007, 2014, 2018) and on temperature trends in seasons other than summer in Tuscany (Centro Italy) (Bartolini et al. 2008). In fact, the monthly level is a key factor in gaining a more accurate understanding of the actual influence of climate variability and change on tree growth. A relevant result of this study is the identification of a recurring average period of 6–7 years in the Tm series, for which the smoothing trends of the seasonal and monthly Tm over time tend to coincide with a periodicity that results to be a dividend of various longer periodicities. At the preliminary level, the results seem to support what Dutilleul and Till (2011) observed on *Cedrus atlantica* in Morocco. In this light, the analysis of climate-growth relationships of trees is likely to provide more accurate results that can be used to improve forest planning and management. For example, the identification of a recurring period makes it possible to better highlight the trends of the Tm series by reducing the influences of global circulation or solar activity and to better identify periods where the growth trend is positive or negative. Indeed, the observed 6–7-year period can divide both the lengths of the Tm periods in the study area and the AMO, Hale, NAO, and LNC cycles, where the Atlantic multidecadal oscillation (AMO) has an approximate cycle of 70 years, the Hale cycle is 22 years, the North Atlantic Oscillation (NAO) shows a period of 18–19 years, and the lunar nodal cycle (LNC) is 18.6 years (Yndestad 2006; Dutilleul and Till 2011). Therefore, this analysis contributes to understanding the weight of local variability in relation to the influence of Tm on the responses of forest growth to climate variability in the Mediterranean area. Actually the relationships between climate and forests are a key point to develop adaptive sustainable forest management. For example, it contributes to identify periods when silvicultural interventions can harvest more or less wood mass on the basis of the rate of growth ongoing (D'Aprile et al. 2015). Another relevant use of this approach in forest planning and management is the possibility to adapt the objectives and methods of management in accordance with trends of climate variables expected in the medium term, which provides relevant help in keeping management within the carrying capacity of the forest ecosystem.

Declarations

Conflict of interest The authors declare that they have no competing interests.

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