MANAGING DOUGLAS FIR STANDS IN ITALY: CALIBRATION AND VALIDATION OF FOREST VEGETATION SIMULATOR (FVS) AND ANALYSIS OF CLIMATE SENSITIVITY FOR FUTURE CALIBRATION OF CLIMATE-FVS AGR/05

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Pianta alberi, che gioveranno in un altro tempo.

(Marco Porcio Catone)
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ABSTRACT

In Italy, Douglas fir (Pseudotsuga menziesii (Mirb.) Franco) has a high potential in terms of wood production and drought tolerance. Testing exotic tree species in Italy dates back to the early years of the last century with the valuable work done by Aldo Pavari. Distinctively, Douglas fir has provided the most satisfactory results in terms of growth and yield. However, a growth reference for mature stands is lacking. We calibrated and validated the Pacific Northwest variant of FVS to Douglas fir plantations in Italy and ran the calibrated model to test management alternatives. We calibrated the height-diameter, crown width, crown ratio, and diameter increment submodels of FVS using multipliers fitted against tree measurements (n=704) and increment cores (180) from 20 plots across the Apennine range. Validation was carried out on tree-level variables sampled in 1996 and 2015 in two independent permanent plots (275 trees). Multiplier calibration improved the error of crown submodels by 7-19%; self-calibration of the diameter growth submodel produced scale factors of 1.0 – 5.2 for each site. Validation of 20-years simulations was more satisfactory for tree diameter (-6% to +1% mean percent error) than for height (-10% – +8%). Calibration reduced the error of predicted basal area and yield after 50 years with respect to yield tables. Simulated response to thinning diverged depending on site index and competition intensity. FVS is a viable option to model the yield of Douglas fir plantations in Italy, reflecting current understanding of forest ecosystem dynamics and how they respond to management interventions. First large-scale experimental plantations of Douglas fir were established between 1922-1938, with the surviving stands now exceeding conventional rotation ages (50-60 years). These stands offer a great opportunity to carry out research on sensitivity of tree growth with respect to climate by this non-native tree species for the purpose of adaptive forest management in the Mediterranean area. To this end, we have carried out dendroclimatic analyses in two 80-90 years old Douglas fir stands: the northern most (Tuscany) and the southern most (Calabria) ones among the oldest plantations. We sampled twenty dominant trees per stand and built a standardized mean ring-width chronology for each site. We tested bootstrap correlations between site chronologies and minimum temperature, maximum temperature, precipitation and standardized precipitation index (SPI) from the database ClimateEU. We used the global correlation function across the entire lifetime of the stands, and the moving correlation function to analyze periodic growth trends. The two sites share a positive correlation between tree growth and winter-spring temperatures, and
a negative correlation with summer minima and maxima. Precipitation and SPI of the previous autumn are negatively correlated with tree growth at both sites. Spring-summer precipitation and water balance have a positive effect on growth in the northernmost site only, although the southernmost site displayed a summer dry period. Differences in correlation strength and significant months are likely due to the different latitude of the two sites, continentality (distance from the sea), and adaptive physiologic activity (e.g., stopping cambial activity during the summer dry period). A shift and increase in summer temperature and precipitation sensitivity in the later period of analysis may be indicative of the effect of climate warming. Douglas fir in Southern Europe has thus been proved to be sensitive to winter frost and spring water balance, but can tolerate summer drought, and has potential to be planted extensively as a supplementary timber resource under mountain Mediterranean climate.
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INTRODUCTION

Forest management must be adapted in order to respond effectively to climate change challenges and mitigation opportunities. In line with expected changes in the climatic conditions (Schar et al. 2004), Douglas-fir is discussed to be part of forest management strategies in Germany (Spiecker 2010). Under favorable climatic conditions, Douglas-fir growth exceeds that of other softwood species and also under dry conditions indicated a clear advantage over native species such as Scots pine and European larch (Larix decidua Mill.) (Eilmann and Rigling 2012). In general, site characteristics have a large influence on the occurrence of water stress (Bauwe et al. 2011). Carnwath et al. (2012) considered site condition as an important silvicultural option and showed that basal area of Douglas fir was more sensitive to water availability on xeric sites. There is still much debate as to how stand density or individual competitive situations, regulated by thinning or initial spacing, modify the growth reaction patterns of trees in dry years. For instance, thinning enhanced Douglas-fir growth of individual trees as a result of a longer growing period due to the absence of summer drought and higher rates of growth (Aussenac and Granier 1988). Hence, more locally explicit information is needed on how species respond to climate variability and projected climate change.

In Italy, Douglas fir was introduced in 1882 (Pucci 1882) using seeds from the Pacific Northwest Coast of the United States (Pavari and De Philippis 1941). Between 1922 and 1938, the “Stazione Sperimentale di Selvicoltura” established 98 experimental plantations (Pavari 1916; Pavari and De Philippis 1941; Nocenti 2010). These trials demonstrated that a variety of sites in central and northern Italy was suitable for the species (Pavari 1958). Nowadays, Douglas fir plantations cover an area of about 0.8 million ha in Europe (Forest Europe 2015). In Tuscany (Central Italy), Douglas fir covers 3,360 hectares in pure stands and 2,112 hectares in mixed stands (Regional Forest Inventory of Tuscany 1998).

In Italy, a growth assessment reference for Douglas fir stands older than 50 years is currently lacking.

In the lights of this, this work tries to answer the following questions:

- how Douglas firs grow after 80-90 years from its establishment in Italy?
- which Model can be used for simulating its growth in Italy?
- which are climatic variables most affecting the growth of Douglas fir in Italy?

In the following flowchart the thesis structure is shown.
Managing Douglas fir stands in Italy:
calibration and validation of Forest Vegetation Simulator (FVS) and analysis of climate sensitivity for future calibration of Climate-FVS

**MATERIALS & METHODS**
- 20 plots (1257 m$^2$); Dbh, Ht, Cr, Cw
- Height-Diameter submodel
- Crown Width submodel
- Crown Ratio submodel
- Large Tree Diameter Growth

**RESULTS**
- Comparison PN-FVS and Cantiani’s Yield Table
- Thinning with different management choices
- Validation of PN-FVS

**DISCUSSION**
- SDImax lower in Italy
- CW > in Pacific NW Coast (Paine & Hann 1982)
- CRNMULT (keyword PN-FVS) 1,22)
- PN-FVS overpredicts (26%)
- Validation: MBE, RMSE, MPE lower in DBH than Height

**CONCLUSION**
- Douglas fir shows increased susceptibility to temperature, rather than precipitation (heat stress and frost)
- Opportunities for Douglas fir in a changing climate
- Calibrated tree level age and distance independent growth model simulator for Douglas fir for Central Italy
- FVS is suitable tool for forest management
- Maintaining existing local networks of permanent plots

**FUTURE PERSPECTIVES**
- Isotopic analyzes and efficiency of water use for phenotypic plasticity
- Use of local climate DB for detailed analysis
- Improve genetic study of the provenance in Italy
- Additional components of FVS (Climate-FVS, Fire and Fuels Extension (FFE), Insect and Disease Extensions)
- Development of IT-FVS (Italy Variant)
SECTION I: MODELING

A model is a simplified illustration of reality. According to a definition of Jørgensen (1997), a model can be regarded as a summary of the elements of a system knowledge. Instead according to Eykhoff (1974) is a representation of the fundamental characteristics of a system, which produces the knowledge of that system in a usable form.

A multivalent use of the term is frequent (Bouchon, 1995). For instance, models are presented for the tree volume in dendrometry or for successional simulation in ecology as well as for forest management normative guidelines, such as the so-called ‘normal forest management reference models’ of European forestry tradition (the ‘normal forest’, Ciancio et al., 1994).

Although a scientific model may have an actual normative content (as prescriptions/rules to be applied or, more relaxingly, as something worthy of being imitated), such a content is not relevant to the adopted point of view. The consequences are not marginal. From such a view, for instance, forest growth and yield models and ‘normal forest management reference models’ involve quite a different concept of modelling. The first are simulation tools which provide answers to questions such as ‘what-if?’, e.g. they allow us to analyze stand reaction to more or less heavy thinnings. Instead, ‘normal forest management reference models’ are characterized by the objectives to be reached: they are rules to be applied which answer questions such as ‘what-for?’ (Houllier et al., 1991).

The quality and the real validity of a model thus depend on the quality of information and data by which to describe and study the structure and the evolution of any hierarchical system, which can be natural or artificial. The most likely models will return results not too reliable if a low amount of data was provided (Acollalti 2011). If you have a good amount of data and a working knowledge of the system, the component parts and processes that control it, then it will be possible to model such a system and its evolutionary dynamics through numerical simulations (quantitative analysis) and graphics (qualitative analysis) able to achieve a high degree of accuracy. Therefore, the greater the amount of data, but above all, the knowledge of the processes that underlie the dynamics of a system, the greater and more reliable will be the result that the model will return. Thus, a model is a simplified representation of a phenomenon by means of mathematical algorithms. Application fields of a model are extensive and range from economics,
sociology, engineering, physics to ecology at any scale and hierarchical (cell, organism, population, community, ecosystem and biosphere).

Ecology modeling has contributed significantly to the development itself and to its statement as an independent discipline. Both the time scale (i.e. hundreds of years) and spatial (i.e. thousands of hectares) on which it works is often not reproducible in the laboratory, even for very simple systems (Acollalti 2011). Also in the field study the problems you go against are many. In field work conditions both inside and the boundary can not be controlled, so there is no guarantee that we can repeat observations of a given phenomenon under the same conditions (Acollalti 2011). By the nineteenth century comes the need to create mathematical models to capture the complexity of environmental problems and to move forward theories that allow to obtain predictions responsive to field testing.

However, it is only with the emergence of a vision of ecological processes based on the analysis of energy flows, between the 40s and 60s, that the use of mathematical models in ecology is spreading, not only in forecasting purposes, but mainly as a research tool and synthesis of knowledge. A model can not contain all aspects of the real system, it is not the mathematical image of nature and thus do not express the real essence of the phenomenon; it is rather to be understood as a conceptual sensor immersed in reality, able to provide an interpretation of the observed phenomenon (Israel, 1994).

Two fundamental kinds of models can be distinguished in relation to how the structure of processes is represented: **Deterministic vs. stochastic models** (Corona 1996).

For deterministic models, outputs are unequivocally determined by inputs: the same results are produced when running conditions (initial state, environment, etc.) do not change. On the contrary, stochastic models may produce different outputs even when running conditions are equal: what is modelled is just the probability distribution of the outputs; a single estimate from a stochastic model is of little use, as a whole series of estimates is necessary to provide useful information of the variability of the outputs. Only models of the deterministic kind appear to be largely applied in forestry. The reason is operational in nature (stochastic models are much more difficult to handle), and primarily conceptual in nature (consider the cultural foundation).

The above mentioned classes are not mutually exclusive, i.e. a model can be dynamic-stochastic-descriptive, static-deterministic-explicative, dynamic-stochastic-descriptive, etc. Another distinction that has some prominence in the forestry context is that between empirical and ecophysiological-based growth and yield models. Both kinds of models
aim to estimate forest growth and yield. Empirical modelling is fundamentally management-based and management-oriented, aiming to extrapolate useful predictions for management purposes on the basis of a limited set of field observations. These models are targeted to the outcome of the numerous, and extremely complex, processes in the growth of trees and their interactions. The most common approach is that of pragmatic prediction through systems of integral equations which express tree and stand variables, such as height, diameter, crown width, etc., as explicit functions of age/size class (Corona, 1989).
I.1 FOREST MODELS

Forest models can be described in two principal category: process-based and empirical models. They make it possible to predict the present value of a variable of interest (biomass, C sequestration, biodiversity, stem growth, etc.) from simultaneous values of other driving variables (climate, soil, stand density, etc.). By assuming that processes hold across time (Pickett & Kolasa 1989), ecologists use models developed and validated for current conditions to make predictions of future system directions. In this perspective, it is possible to define models as quantitative tools that predict the future probability distribution of an ecological variable, conditional upon initial conditions, parameter distributions and the choice of mathematical or statistical methods used to make the calculations (Carpenter 2002). Simulators refer to computer programs resulting from the conversion of such models into a part of software for scenario calculation, and often visualization (Pretzsch et al. 2006).


The increasing interest in forest ecosystem modeling in Europe is reflected by the activation of two EU-COST1 projects: FP0603 - “Forest models for research and decision support in sustainable forest management”, aiming to enhance the quality and consistency of forest growth models to simulate the responses of forests to alternative management and climate scenarios (Bugmann et al. 2010); and FP0804 - “Forest Management Decision Support Systems (FORSYS)”, that will define a European-wide framework and requirements for forest decision support systems (DSS) in a sustainable multifunctional forest management environment. FP0603 called for the identification and description of forest growth models available in Europe. Fifteen out of 23 nations have provided a country report (Palahí 2008).
The first meeting of the Working group for Forest ecosystem modeling of the Italian Society for Silviculture and Forest Ecology (SISEF) in 2009, produced an overall overview of the current state of the art in simulating and forecasting forest ecosystem models in Italy.
I.2 Empirical models

Statistical stand models, i.e. yield tables, have been developed over the past fifty years for the most productive forests of Italy (e.g., Bernetti et al. 1969, Bianchi 1981, Castellani 1982, Amorini et al. 1998, Cantiani et al. 2000, Ciancio & Nocentini 2004) but, like all empirical models, are not always applicable in sites other than those they were calibrated for and they do not consider climate changes. Furthermore, some yield tables are now outmoded, because they do not reflect the changes occurred since they were developed in site conditions or management operations. Empirical stand-scale models may still be useful as decision support systems (DSS) which can help the development of stand structure and the arrangement of related forest services over well-defined areas and short to medium period.

Size distribution models, on the other hand, have never obtained much practical relevance in Italy. As a notable exception, Markovian models of the transition probability between diameter classes (Bruner & Moser 1973) have been suggested for mixed, uneven-aged forests of the eastern Alps (Virgilietti & Buongiorno 1997, Gasparini et al. 2000).

Individual tree models explicitly simulate the development of single trees considering their interactions within a spatial-temporal system, and account for feedback loops between stand structure and individual growth. This enables them to simulate pure and mixed stands of all age structures and intermingling patterns equally well. Stand level data for forestry management are finally provided by aggregation of the single tree results (Pretzsch et al. 2008). Individual tree empirical models have previously been designed for alpine Beech (Fagus sylvatica L.) forests (Cescatti & Piutti 1998), Douglas fir and hybrid poplar plantations (Scotti et al. 1995, Corona et al. 1997, 2002) and are currently being developed to forecast yield in plantations for quality timber such as common walnut (Juglans regia L.). Morani (2009) showed the potential of UFORE, an individual-tree growth model for predicting the dynamics and air-quality benefits of planted trees in an urban context.

Depending on the modeling purpose, several individual growth and yield simulators might be available from the international literature, e.g., CAPSIS (Dreyfus & Bonnet 1996), MOSES (Hasenauer 1994), SILVA (Pretzsch & Kahn 1996) and the Forest Vegetation Simulator (FVS - Dixon 2003, based on early work by Stage 1973). Issues of accuracy and scale have been associated to the use of empirical growth and yield models in Europe (Corona & Scotti 1998).
However, there are two problems: (1) the availability of repeated forest inventories for the focus landscape that provide the input and output variables needed for calibrating empirical growth equations; (2) the inclusion of the impact of climate and site changes on future productivity (Fontes et al. 2010).
I.3 GAP, HYBRID AND LANDSCAPE MODELS

Gap models (Bugmann 2001) and landscape models (He 2008), explicitly include site and climate drivers for predicting forest composition, structure and biomass. Small-area or gap models reproduce the growth of single trees in forest patches (e.g., 100 m2) in relation to the prevalent growth conditions at the site (Botkin et al. 1972, Shugart 1984, Leemans & Prentice 1989). However, physiological processes are not explicitly accounted for, requiring statistical fitting procedures between each environmental factor and observed growth.

The combination of knowledge on specific ecophysiological process with stand or single tree management models and with long-term growth measurements results in the hybrid growth models (Kimmins 1993). In Italy, no developments of either gap or hybrid models have been proposed to date; SORTIE-ND (Pacala et al. 1993) might represent a suitable simulator for future adaptations.

Landscape models comprise a broad class of spatially explicit models that incorporate heterogeneity in site conditions, neighborhood interactions and feedbacks between different spatial processes (Pretzsch et al. 2008).

The role of these models is to develop scenarios for the sustainability of forest or landscape functions (natural resources, habitat, hydrology, socioeconomic), to forecast their response to disturbances and potential environmental change (climate, N deposition, land use), to analyze the relationship between landscape structure and regionally distributed risks, and to assess regional-scale matter fluxes, e.g., water, carbon and nutrients.

One example is the mesoscale SILVA Land Surface Model (Alessandri & Navarra 2008) that represents the momentum, heat and water flux at the interface between land-surface and atmosphere, and has been coupled to a general circulation model (GCM) to estimate the rate of forcing by existing vegetation on precipitation patterns.

At a different scale, other examples of spatially explicit landscape modeling presented at the FMWG meeting are calibrated of fire spread and behavior simulators to a Mediterranean ecosystem by Arca et al. (2007) and eco-hydrological models currently used to forecast water (runoff, snowmelt, evapotranspiration, uptake) and energy (heat, radiation) budgets at the plot and catchment scale (Marletto et al. 1993, Rigon et al. 2006, Bittelli et al. 2010).
Landscape models should be distinguished from models based on spatial data layers at the landscape or regional scale, but without the explicit representation of neighborhood interactions. These should be rather viewed as local models embedded into geographic information systems (GIS). Output variables are predicted based on their relationship with topographic, climatic, biometric or ecophysiological information, either ground-based or remotely-sensed. The link between input and output variables is often based on empirical relationships or multivariate and multicriteria analysis. Examples were given in the fields of fire risk prediction (e.g., Ventura et al. 2001, Laneve & Cadau 2007, Camia 2009), habitat suitability (Boitani et al. 2002, Fiorese et al. 2005, Brugnoli & Brugnoli 2006), and plant species distribution in response to climate change scenarios (Attorre et al. 2008).

Alternatively, GIS-based models can incorporate detailed information on ecophysiological processes, as for the development of the 3PG-s model presented by Nolé at the FMWG meeting (Coops et al. 1998, Nolé et al. 2009).
The Forest Vegetation Simulator (Wykoff et al., 1982; Dixon, 2006) is used extensively throughout the United States in a variety of ways to support contemporary forest management decision making. It was developed as a model to predict stand dynamics in the mixed forests of the Inland mountains of northern Idaho and western Montana: 2Prognosis Model for Stand Development” (Stage, 1973), FVS was chosen as a common modeling platform in the United States Department of Agriculture, Forest Service in 1980 (Crookston and Dixon, 2005). Twenty geographically-specific versions of FVS, called variants, have since been calibrated on local inventory data and currently cover most forested areas of the conterminous 48 states and southeast Alaska (Figure 1).

An FVS variant is a growth and mortality model calibrated to a specific geographic area of the United States. There are 20 different FVS variants. Users select an appropriate FVS variant for their area. FVS variants are calibrated for each of the major tree species within a geographic region. FVS have some extensions that function interactively with the base FVS geographic variant to simulate the effects of various forest ecological disturbances on forest growth and mortality. The insect and disease extensions incorporate the effects of insects and forest pathogens on forest stands (e.g. Douglas-fir Beetle Model, White Pine Blister Rust Model, Western root disease model). The Fire and Fuels Extension
(FFE) links the FVS variant with models of fire behavior, fire effects, fuel loading, and snag dynamics. Model outputs include predictions of potential fire behavior and effects and estimates of snag levels and fuel loading over time. The Climate Extension to the Forest Vegetation Simulator (Climate-FVS) provides forest managers a tool for considering the effects of climate change on forested ecosystems.

FVS belongs in the distance-independent, individual-tree class of models (Munro, 1974). The key state variables for each tree are density, species, diameter, height, crown ratio, diameter growth, and height growth. Key variables for each sample point, or plot, include slope, aspect, elevation, density, and a measure of site potential. The same information is available at the stand level. In addition, the model computes the percentile rank in the distribution of tree basal areas both among trees growing at the same plot and again among all trees in the stand. Time steps, or growth cycles, are generally between 5 and 10 years long, and the total projection is between a few years and several hundred years.

Two input files are generally used when running FVS. The first, a keyword record file, is required to enter stand level parameters, describe management treatments, control the printing of output, compute custom variables, and adjust model estimates. Keywords come with associated data providing information necessary and specific to the keyword action. For a list of available keyword-based operations, see Van Dyck (2006). The second input is the a tree data file, that is composed of records containing tree level information. Tree list variables include:

- plot identifier (integer)
- tree count (number of trees represented by the sample tree)
- species (two letter code)
- DBH
  - DBH increment; period of this increment should correspond to the growth increment of the variant
- height
- height to topkill
- height increment; period of this increment should correspond to the growth increment of the variant
- crown ratio (integer code from 1-9)
- damage code(s)
Species and diameter at breast height are required on each tree record; crown ratio, crown width and tree height may be filled in by the simulator. A projection begins by reading the inventory records (treelist file) and the keyword-based descriptions of site and selected management options (Crookston, 1990). Input tree records with missing heights or crown ratios have these dubbed in; the inventory is then compiled to produce tables that describe initial stand conditions. When this summary is complete, the first projection cycle begins (Figure 2):

![Figure 2: Flowchart of FVS processing sequence (Dixon 2006).](image)
In this work it was used “The Pacific Northwest Coast” (PN) variant. It was developed in 1995 and covers an area bounded by a line between Coos Bay and Roseburg, Oregon on the south; the northern shore of the Olympic Peninsula in Washington on the north; the shore of the Pacific Ocean on the west; and the eastern slope of the Coast Range and Olympic Mountains on the east. Data used to build the PN variant came from forest inventories and silviculture stand examinations.
Dendrochronology (from the Greek dendron = tree, kronos = Time and logos = speech) was established in North America in the early '900, thanks to intuition astronomer Andrew Ellicott Douglass. Douglass was convinced there was a close dependence between the growth of the trees and the availability of water in a given area and this was also convinced that he can obtain, through the study of trees, information about the rainfall occurred in a given period of a specific area.

With these assumptions, dendrochronology is born as a science that studies the growth of the trees in relation to the factors that have determined the same growth (climatic factors, geopedologic, anthropogenic influences, etc.).

The biological process that has enabled the development of this discipline concerns mode of growth of the plants. The tree's growth is characterized by a radial increase: each year forms a woody ring on the outside of the stem. In temperate regions the growing season of a plant it is limited to the period spring and summer; the growth period is stopped at the first sign autumn chills. In spring we have the early wood: it characterized by a light color and made up with wall cells thin and wide lumen. The late summer instead brings to the production of late wood: dense and dark. It formed by cells with little lumen and thick cell wall. Once the annual growth period is therefore visible tree a ring formed from a clear part (early wood) and one part dark (late wood) in sequence. The following year, the arrival of the favorable season, you will have the formation of new early wood. In regions with a tropical climate you can not establish an alternation of seasons and the tree grows continuously throughout the year, without the formation of rings. Sometimes in climates with dry season can be found variations in tree growth due to periods of drought or heavy rainfall.

By means of special tools it is possible to measure the amplitude of each single ring (ring width) and then reconstruct the pattern of tree growth over time. If you know the year of sampling you can then go back to the age of trees and can identify, based on the amplitude of the rings, periods of growth more or less favorable for the plant. Ring widths were measured to 1/100 mm precision using a LINTAB6® measuring table and TSAP-WIN software (Rinntech).

A different approach uses radiodensitometrical analysis. This methodology consists in cutting the wood samples in thin strips which are then subjected to radiograph. The slabs produced are examined with a densitometer which measures the density along the radius.
Among the various parameters that are obtained with the use of this technique is deemed important the maximum density (for the reconstruction of temperatures in temperate areas), the minimum density (to derive the trend of precipitation in areas dry) and the ring width. The variations of intra-annual density are important for determine the scale of short climate change during the growing season (Schweingruber, 2007). Dendrochronology is applicable in many research fields. The continuous development in the various sectors of this main branch led to the formation of a whole range of sub-disciplines, each of which, by studying tree rings, can provide ecological and environmental information valuable.
I.6 DENDROCLIMATOLOGY

The dendroclimatology is the sub-discipline of dendroecology who is interested the study of climate trends in relation to the performance of the ring chronologies obtained by sampling the trees.

Research carried out in this field are based on two fundamental principles:

1. Trees of the same species, living in the same geographical area, produce in the same period of time, similar annular series: the thickness of these rings, in fact, changes each year depending on the weather conditions;

2. It can compare the annular sequences of trees lived in the same geographic area in the same period of time.

Thanks to dendroclimatology is possible to obtain information on the past and present climatic conditions and then draw the basis for future projections. Using time series obtained from trees of different ages and species, on different sampling areas, it is possible, in fact, extend series of meteorological data (Fig. 5.4).

Figure 3: Reconstruction of a long history through the use of numerous samples taken in different areas (Fritts, 1976).
Furthermore, the analysis of considerably long annular series can provide a valuable assistance in understanding the causes of long-term climate fluctuations (Schweingruber, 1988).

If on the one hand the tree responds to climatic variations, it is also true that records in his rings variations from other origins, coming both from the evolution of potential biological tree i.e. age and by external factors unrelated to climate parameters (soil changes, human interventions, etc...). To be able to extrapolate from the plant and to analyze the greatest number of information related to climate trends is therefore necessary to isolate the signal produced. Having established this, you can think of a chronological series as an aggregation of different signals, each of which, according to the purpose of the research, it can become the signal to isolate and analyze (Cook & Briffa, 1990).

The information contained in the thickness of a ring in a certain year (Rt) can expressed as the sum of:

\[ Rt = At + Ct + \delta D1t \delta D2t + Et \]

where
- \( Rt \) = thickness of the ring in year \( t \);
- \( At \) = radial growth trend in function on age;
- \( Ct \) = common climatic signal to all the trees of a site;
- \( \delta D1t \) = disorder caused by an endogenous agent on a small scale (eg. cut);
- \( \delta D2t \) = disorder caused by an exogenous agent on a larger scale, involving all trees of a site (eg. fire, pest attack);
- \( Et \) = random signal distinctive of each elementary series.

For the dendroclimatological analysis the objective it is to isolate the climate signal (Ct) and then delete all the other signals which act, in this specific case, by the disorder.
The cross-dating is a procedure used to check and validate the measurements of the ring widths.

The annular series were examined first by visual cross-dating, then through the use of TSAP-WIN software (Rinntech) and the dplR package (Bunn 2008) with the treeclim package (Zang and Biondi 2015) from R® were used for tree ring series management and analysis of climate-growth relationships.

The chronologies for each individual sample were plotted. The visual comparison is made by placing two chronologies one above the other, over a light plane, so as to be able to appreciate the trends of both series, analyzed in backlight. The analysis is first carried out between the two elementary histories of a same plant. During the phase of dating, for each plot is chosen chronology of reference on the basis of ease of measurement and the linearity and clearness of the rings. All the plot histories are then compared with the reference.

The actual cross-dating process consists primarily of establishing concordance between the performance of the two time series analyzed from time to time, that is, in searches of coincidences between the curves. It is not unusual to find two time series which present a sequence of characteristic rings of one or more years shifted relative to one another. Once identified, such sequences are back to the beginning of the discrepancy that can be due to errors during measurement or missing links in one of the two series.

Either way you go to the correction by adding or subtracting to the history of one or more years, or if it is deemed necessary, re-measuring the sample believed inaccurate and subjecting it again to the comparison process.

The operator operates a quality control on a set of data that is provided input. The program automatically creates a master series and compare all others with this reference chronology.

The critical years are identified as years causing a strong variation, positive or negative, in the value of the correlation between the analyzed series and the reference chronology. The anomalies that are found in a history are reported individually in the output of the program.

In addition to the indications of possible measurement errors, the program also provides a range of statistical parameters, the value of which can be taken as a reference to assess the quality of dating. The values of these parameters are described and shown below, inserted...
inside of a statistical analysis that takes into consideration also other quantities than those provided by the program.

The time series were analyzed statistically through the use of some parameters including: medium (M); standard deviation (STD), coefficient of variation (CV), mean sensitivity (MS), autocorrelation coefficient (AC) and expressed population signal (EPS).

**Mean (E), standard deviation (STD) and coefficient of variation (CV):**
The mean expresses an estimate of the central ring amplitude value recorded within a population.

The standard deviation provides an estimate of the deviation from the mean and then provides information on the degree of homogeneity of the data considered in the context of chronology. Because the relationship between the average and the corresponding standard deviation, the coefficient of variation allows a comparison between different chronologies.

**Mean sensitivity (STD):**
According to Fritts (1976) the mean sensitivity is measured as a coefficient medium sensitivity:

\[
\bar{S} = \frac{\sum_{i=1}^{n-1} |S_i + 1|}{n - 1}
\]

where

- \(x_i\) = ring width in year \(i\);
- \(x_{i+1}\) = ring width in the following year;
- \(n\) = number of years considered.

indicating the difference between two successive values in a series.

The mean sensitivity coefficient expresses the changes in higher frequency (Garcia-Suarez et al., 2009) by measuring the importance of short-term changes (Van der Maaten, 2012). By means of sensitivity analysis it is possible to determine to what extent the growth of a species in a particular area is influenced by environmental factors.

The higher the value of the sensitivity, the greater the influence on the species, employed by climatic factors and therefore also the higher the content of information within chronology (Pellizzari et al. 2014). A species is defined sensitive if it has more than 0.25 values. Otherwise it defines complacent. The average sensitivity is calculated both for the elementary series that for those individual and plot level. However, the incidence of
climatic factors is evaluated on plot chronology. Higher values for individual chronology may correspond to asynchronous fluctuations from one series to another, linked to a stational or genetic heterogeneity and can lead to erroneous conclusions about the species sensitivity (Tessier, 1984). In summary chronology rather the contributions of each individual are mitigated and then get a more homogeneous series and with lower sensitivity values. From these considerations arises the need to use other statistical parameters.

**Autocorrelation coefficient (AC):**

The Pearson correlation coefficient (R) calculated on two series is a useful method to obtain information about the timing of the same series. Its value varies between -1 and +1. These two values are to indicate an indirect link and perfect link respectively. In the case in which the parameter assumes the value 0, the two analyzed series are perfectly independent. The autocorrelation coefficient is a correlation coefficient calculated on the same chronological series.

From each time series it is possible to create new series simply translating the original data for a number of years 1 to k. If k = 1 we will have a coefficient of autocorrelation of the first degree. This makes it possible to assess any existing links between the ring and the ring at time t to time t + 1. In this way, the profile analysis of the correlation coefficients is an excellent method of study of the within each time series signal complex content (Tessier, 1984): the cyclical variations, the low frequency variations and trends due to age.

The values calculated for sample plots are quite high, to testify to the existence of retroactive effect on growth of the previous year of the current year.
I.8 MOVING CORRELATION FUNCTION (MCF)

The Moving Correlation function calculates the statistical correlation between two arrays of data over a moving window defined by (Period) positions.

On the development of DENDROCLIM2002, a software package that computes bootstrapped response and correlation functions for single and multiple intervals, MCF is established. The interval periods (Figure 4) are defined using either a constant length progressively slid by one year (moving intervals) or a length that is incremented by one starting from the most recent year (backward evolutionary intervals) or from the least recent year (forward evolutionary interval) (Biondi, 1997, 2000). The data matrix must includes all available years, so the analysis is repeated on multiples intervals. Evolutionary intervals are generated by adding 1 years to the base length at each iteration. Moving intervals are generated by shifting the base length 1 year at each iteration. The process stops when all available years have been used. Moving intervals begin with the oldest year in common to all variables and they are shifted progressively forward in time up the most recent year in common to all variables. Response and correlation functions from each iteration (or interval) are stored in an r x q matrix, with r = number of intervals, and q = number of climatic variables (or predictors) (Biondi and Waikul 2004).

Figure 4: Graphical representation of multiple intervals available in DENDROCLIM2002 between 1950 and 1996 using a base length (or minimum interval) of 42 yr (Biondi and Waikul 2004).
SECTION II: PROJECTING DOUGLAS FIR GROWTH AND YIELD IN SOUTHERN EUROPE BY THE FOREST VEGETATION SIMULATOR

II.1 FRAMEWORK

Plantations are a resource with global importance for wood and pulp production (Forest Europe 2015). In Europe, Douglas fir (*Pseudotsuga menziesii* (Mirb.) Franco) has been planted on a large scale and is now the most economically important exotic tree species (Schmid et al. 2014; Ducci 2015). Douglas fir has usually a high growth rate in comparison with other forest tree species in Europe, has a higher resistance to drought (Eilmann and Rigling 2012), and may provide high added-value timber (especially after the first thinning) (Monty et al. 2008). In Southern Europe, no indigenous conifer has similar characteristics of productivity and timber quality (Corona et al. 1998).

In Italy, Douglas fir was introduced in 1882 (Pucci 1882) using seeds from the Pacific Northwest Coast of the United States (Pavari and De Philippis 1941). Between 1922 and 1938, the “Stazione Sperimentale di Selvicoltura” established 98 experimental plantations (Pavari 1916; Pavari and De Philippis 1941; Nocentini 2010). These trials demonstrated that a variety of sites in central and northern Italy was suitable for the species (Pavari 1958). Nowadays, Douglas fir plantations cover an area of about 0.8 million ha in Europe (Forest Europe 2015). In Tuscany (Central Italy), Douglas fir covers 3,360 hectares in pure stands and 2,112 hectares in mixed stands (Regional Forest Inventory of Tuscany 1998).

The key to successful management of productive Douglas fir plantations is a proper understanding of growth dynamics in relation to tree characteristics, stand structure, and environmental variables. The productivity of Douglas fir stands in Italy was studied by Pavari and De Philippis (1941) and, distinctly, by Cantiani (1965) who established a yield table for stands up to 50 years old, based on 115 plots of different ages.

Growth and yield models simulate forest dynamics through time (i.e., growth, mortality, regeneration). They are widely used in forest management because of their ability to support the updating of inventories, predict future yield, and support the assessment of management alternatives and silvicultural options, thus providing information for decision-making (Vanclay 1994). Much research has been carried out to model the
growth of Douglas fir throughout its home range (Newnham and Smith 1964; Arney 1972; Mitchell 1975; Curtis et al. 1981; Wykoff et al. 1982; Wykoff 1986; Ottorini 1991; Wimberly and Bare 1996; Hann and Hanus 2002; Hann et al. 2003). In Italy, a growth reference for Douglas fir stands older than 50 years is currently lacking. Here, we propose the use of Forest Vegetation Simulator (FVS) to simulate the growth of such stands.

FVS is an empirical, individual tree, distance-independent growth and yield model originally developed in the Inland Empire area of Idaho and Montana (Stage 1973). FVS can simulate many forest types and stand structures ranging from even-aged to uneven-aged, and single to mixed species in single to multi-story canopies. There are more than 20 geographical variants of FVS, each with its own parameterization of tree growth and mortality equations for a particular geographic area of the United States. In addition, FVS incorporates extensions that can simulate pest and disease impacts, fire effects, fuel loading and regeneration (Crookston 2005).

FVS has been rarely used in Italy (Vacchiano et al. 2014). The aims of this work are: (1) calibrating and validating the Pacific Northwest Coast variant of FVS to Douglas fir plantations in Italy, (2) comparing predictions from the calibrated model against available yield tables for Douglas fir in Italy, and (3) using the calibrated model to test silvicultural alternatives for Douglas fir plantation management.
II.2 MATERIALS AND METHODS

Data for this work were measured in 20 stands of Douglas fir planted between 1927 and 1942 over a 2000 km$^2$ wide area in the northern Apennines, mostly within and nearby Tuscany region (Figure 5), at elevations ranging between 770 and 1260 m a.s.l.

For each stand, Table 1 reports climatic data derived from ClimateEU (Hamann et al. 2013) and Ecopedological Units (EU) from the Ecopedological Map of Italy (Costantini et al. 2012).

For each stand Table 2 reports aspect, slope, and site index, i.e. the top height at 50 years assessed according to Maetzke and Nocentini (1994).

Tree measurements were carried out in a 20-m radius circular plot located at the center of each sampled stand, except Pietracamela that had a radius of 10 m. For each living tree (for a total of 704 trees) we measured: stem diameter at 130 cm height (DBH), total height (HT), crown length (CL), and crown width (CW) as the average of two orthogonal crown diameters. From a sub-sample of 8-10 trees per plot, we extracted an increment core at 130 cm above the ground. Tree cores were prepared for measurement in the lab and analyzed with LINTAB and TSAP-WIN software; from each core (for a total of 180 cores) we measured the radial increment from the last 10 annual rings to the nearest 0.01 mm.
Table 1. Climatic and geographic parameters of the sampled stands: MAT=mean annual temperature, MWMT=mean warmest month temperature, MCMT=mean coldest month temperature, MAP=mean annual precipitation, MSP=mean summer precipitation, EU=ecopedological units.

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Table 2. Main site and dendrometric characteristics of the study areas: SDI=stand density index, CCF=crown competition factor, PCC=percent of canopy cover, QMD=quadratic mean diameter, TH=top height, SI=site index.

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II.3 CALIBRATION

In order to adjust FVS to local growing conditions, the model components (hereafter “submodels”) need to undergo calibration against observed data. FVS submodels include height-diameter equations, crown width equations, crown ratio equations, tree diameter growth equations, tree height growth equations, mortality equations, and bark ratio equations. Due to the lack of repeated field measurements, this paper focuses on the first four submodels, leaving the others unchanged.

Since the considered populations of Douglas fir come from the Pacific Northwest coast of the United States (Pavari and De Philippis 1941), the Pacific Northwest (PN) variant of FVS (Keyser 2014) was used as a basis for model calibration and runs. The original range considered by this variant covers from a line between Coos Bay and Roseburg, Oregon in the south to the northern shore of the Olympic Peninsula in Washington, and from the Pacific coast to the eastern slope of the Coast Range and Olympic Mountains (Keyser 2014).

FVS includes two options to calibrate model performance to local growing conditions (Dixon 2002): (i) automatic scaling by the model, and (ii) user-defined multipliers of model output entered by the user by specific input scripts or “keywords” (Van Dyck and Smith-Mateja 2000). For the height-diameter and large tree diameter growth submodels we analyzed the performance of automatic calibration, while for crown width and crown ratio submodels we fitted user-defined multipliers. The following paragraphs illustrate, for each of the four submodels, the adopted calibration strategy and its results.

All the variables in the FVS equations are expressed in imperial units; conversion to and from the metric system was carried out outside the calibration algorithms. The simulation cycle is 10 years.

To check whether each submodel needed calibration, we fitted FVS submodels to the observed data and computed 95% confidence intervals for all regression coefficients. If default FVS coefficients were outside of locally-calibrated confidence intervals, model adjustment was deemed necessary. Additionally, we compared the fit of non-calibrated versus calibrated submodels against observed data, using coefficient of determination ($R^2$), root mean square error (RMSE), mean bias (MBE), mean absolute bias (MABE) and mean percent bias (MPE) as goodness-of-fit metrics (Rehman 1999).
II.3.1 **Height-Diameter submodel**

Height-Diameter relationships in FVS are used to estimate missing tree heights in the input data. By default, the PN variant uses the Curtis-Arney functional form as shown in Equation [1] (Arney 1985; Curtis 1967). Height-Diameter submodel (HT) uses an internal self-calibration method; if users don’t provide all stem heights, but more than three, the height-diameter equation is calibrated.

\[
HT = 4.5 + p_2 \times \exp(-p_3 \times DBH^{p_4}) \quad [1]
\]

where \(p_2-\ p_4\) are species-specific parameters (default values for the PN variant: 
\(p_2=407.1595; \ p_3=7.2885; \ p_4=-0.5908\)).

When fitted against observed tree heights from all the plots here considered, Equation (1) had two parameters whose confidence intervals did not include the FVS default values (Table 3): submodel adjustment was therefore needed.

The fit of the uncalibrated submodel against observations (Figure 6) produced a R\(^2\) of 0.6 and MPE equal to 1.18%, corresponding to MBE equal to 33 cm and RMSE of 4.86 m. The new coefficients (\(p_2-p_4\)) were calculated by nonlinear regression: \(p_2=199.4300348, \ p_3=8.9860045, \ p_4=-0.9680623\). The calibrated HT submodel produced an MBE equal to -0.3 cm and an RMSE of 4.16 m.

<table>
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<tr>
<th>Submodel</th>
<th>Statistical parameters</th>
<th>Confidence interval</th>
<th>PN-FVS default</th>
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<td>97.5%</td>
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<td></td>
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<tr>
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<tr>
<td></td>
<td>a3</td>
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Table 3. Confidence intervals of HT - CW - CR - ln(DDS) submodel parameters (bold: default PN-FVS value within 95% c.i. of the uncalibrated submodel).
<table>
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<td></td>
<td>b4</td>
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<td>b14</td>
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<td></td>
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</table>
Figure 6: Observed versus predicted tree heights by default PN-FVS Height-Diameter submodel.
II.3.2 CROWN WIDTH SUBMODEL

In PN-FVS, crown width (CW) is computed as a function of tree and stand characteristics (Equation 2: Crookston 2005) and bound to <=24 m:

$$CW = (a1 \times BF) \times DBH^{a2} \times HT^{a3} \times CL^{a4} \times (BA + 1.0)^{a5} \times (exp(EL))^{a6}$$

where BF is a species- and location-based coefficient (default BF for Douglas fir= 0.977), BA is stand basal area, EL is stand elevation in hundreds of feet, and a1–a6 are species-specific parameters (a1=6.02270; a2= 0.54361; a3= -0.20669; a4= 0.20395; a5=-0.00644; a6=-0.00378). When Equation [2] was fitted against observed data, only two parameters were inside the 95% confidence intervals of the uncalibrated equation (Table 3): submodel adjustment was therefore needed.

To this end, we used the CWEQN keyword that allows to enter user-defined coefficients for a new species-specific crown width model (Equation 3):

$$CW = s0 + (s1 \times DBH) + (s2 \times DBH^{s3})$$

where the coefficients s0 - s3 were determined by nonlinear regression: s0=6.701, s1=0, s2=0.111, s3=1.502. Calibration improved model fit: MPE decreased from 31% to 12%, MBE from 83 cm to 0.2 cm and RMSE from 2.12 m to 1.87 m.
II.3.3 Crown Ratio Submodel

Crown ratio (CR), i.e. the ratio of crown length to total tree height, is a commonly used predictor of diameter increment both in United States (Wykoff 1990) and Europe (Monserud and Sterba 1996). It is an indicator of the joint effects of stand density, tree size and vigor, and social position of each tree in the stand. Crown ratio equations are used for three purposes by FVS: (i) to estimate tree crown ratios missing from the input data for both live and dead trees; (ii) to estimate change in crown ratio for each simulated cycle for live trees; and (iii) to estimate initial crown ratios for regenerating trees established during a simulation (Keyser 2014).

PN-FVS uses a Weibull-based model to predict crown ratio for all live trees with DBH >2.5 cm (Dixon 1985). First, the average stand crown ratio (ACR) on a 1-100 scale is estimated as a function of stand density (Equation 4: Johnson and Kotz 1995):

\[ ACR = d_0 + d_1 \times RELSDI \times 100 \] [4]

where \( d_0 \) - \( d_1 \) are species-specific coefficients (\( d_0 = 5.666442 \); \( d_1 = -0.025199 \)) and RELSDI = relative Stand Density Index, i.e., the ratio between measured (SDI) and species-specific maximum SDI (SDImax). SDI is a measure of relative density based on the self-thinning rule (Yoda et al. 1963) i.e., the inverse relationship between the number of plants per unit of area and the mean size of the individuals (Comeau et al. 2010; Pretzsch and Biber 2005; Shaw 2006; Vacchiano et al. 2005). SDI (Reineke 1933) is calculated according to Equation (5):

\[ SDI = TPA \left( \frac{Q_{md}}{25} \right)^{1.605} \] [5]
where TPA is the number of trees per acre. Maximum SDI is provided as species-specific default (SDImax for Douglas fir = 950). Maximum SDI also controls FVS mortality equations; by default, density related mortality begins at RELSDI = 55% (Dixon 1986).

ACR is then used to estimate the parameters A, B, and C of the Weibull distribution of individual CRs (Equations 6-10):

\[ A = A_0 [6] \]

\[ B = B_0 + B_1 * ACR \text{ (bound to } B > 3) [7] \]

\[ C = C_0 + C_1 * ACR \text{ (bound to } C > 2) [8] \]

\[ SCALE = 1 - \left(0.00167 + (CCF - 100)\right) [9] \]

\[ CR = A + B * \left( -\log \left(1 - \left(SCALE * \frac{RANK}{N}\right)\right)^{1/C} \right) [10] \]

where \( a_0, b_0 - b_1, c_0 - c_1 \) are species-specific coefficients (Keyser 2014) \( (a_0=0; b_0=-0.012061; b_1=1.119712; c_0=3.2126; c_1=0) \), \( N \) is the number of trees in the stand, RANK is a tree’s rank in the stand DBH distribution \( (1 = \text{the smallest}; \ N = \text{the largest}) \), SCALE is a density-dependent scaling factor (Siipilehto et al. 2007) bound to \( 0.3 < SCALE < 1.0 \), and CCF is stand crown competition factor (Krajicek et al. 1961), computed as the summation of individual CCF \( (CCF_t) \) from trees with DBH > 2.5 cm (Equation 11: Paine and Hann 1982).

\[ CCF_t = r_1 + (r_2 * DBH) + (r_3 * DBH^2) [11] \]

where \( r_1 - r_3 \) are species-specific coefficients \( (r_1=0.0387616; r_2=0.0268821; r_3=0.00466086) \).
When fitted against observed data, confidence interval of Equation [10] included the PN-FVS default values only in one case (Table 3), therefore calibration was needed.

The fit of the uncalibrated crown ratio model against observed data was very poor ($R^2 = 0.08$, MPE = 14%, MBE = -2.64 m, RSME = 4.47 m).

Crown ratio calibration was attained by a keyword (CRNMULT) that multiplies simulated crown ratios by a specified proportion (Hamilton 1994). The value of CRNMULT (=1.22) was determined by nonlinear regression using observed CR as dependent variable and the independent variables from Equations [4]-[10].

CRNMULT improved the fit of the CR submodel: $R^2$ from 0.08 to 0.91, MPE from -14.02% to 5.13%, MBE from -2.64 to -0.49 m and RMSE from 4.47 to 3.89 m.
II.3.4 LARGE TREE DIAMETER GROWTH SUBMODEL

The large (DBH > 7.62 cm) tree diameter growth model used in most FVS variants predicts the natural logarithm of the periodic change in squared inside-bark diameter (\(\ln(DDS)\)) (Equation 12: Stage 1973) as a function of tree, stand and site characteristics:

\[
\ln(DDS) = b_1 + (b_2 \times EL) + (b_3 \times EL^2) + (b_4 \times \ln(SI)) + (b_5 \times \sin(ASP) \times SL)
\]
\[
+ (b_6 \times \cos(ASP) \times SL) + (b_7 \times SL) + (b_8 \times SL^2) + (b_9 \times \ln(DBH))
\]
\[
+ (b_{10} \times CR) + (b_{11} \times CR^2) + (b_{12} \times DBH^2)
\]
\[
+ \left(b_{13} \times \frac{BAL}{\ln(DBH + 1.0)}\right) + (b_{14} \times CCF) + (b_{15} \times RELHT)
\]
\[
+ (b_{16} \times \ln(BA)) + (b_{17} \times BAL) + (b_{18} \times BA) [12]
\]

where BAL is total basal area in trees larger than the subject tree, RELHT is tree height divided by the average height of the 40 largest diameter trees in the stand, \(b_1\) is a location-specific coefficient that defaults to -0.1992, and \(b_2\)-\(b_{18}\) are species-specific coefficients \((b_2=-0.009845; b_3=0; b_4=0.495162; b_5=0.003263; b_6=0.014165; b_7=-0.340401; b_8=0; b_9=0.802905; b_{10}=1.936912; b_{11}=0; b_{12}=-0.0000641; b_{13}=-0.001827; b_{14}=0; b_{15}=0; b_{16}=-0.129474; b_{17}=-0.001689; b_{18}=0)\) (Keyser 2014).

When fitted against the observations, confidence interval analysis showed that only two parameters of Equation [12] were inside the 95% confidence intervals of the uncalibrated equation (Table 4), therefore the model needed calibration. This was attained by enabling self-adjustment of growth predictions by scale factor calculation.

When five or more observations of periodic increment for a species are provided for a plot, FVS can adjust the increment models to reflect local conditions (Stage 1981). This automatic calibration computes a species-specific scale factor that is used as a multiplier to the base growth equations, bound to a range of 0.08-12.18, and applied at the plot level. The scale factors are attenuated over time. The attenuation is asymptotic to one-half the difference between the initial scale factor value and one. The rate of attenuation is dependent only on time, and has a half-life of 25 year (Dixon 2002).

In order to check for bias, we disabled the self-calibration and randomization algorithms of the large tree diameter growth model using the NOCALIB and NOTRIPLE keywords, and scrutinized scale factors for \(\ln(DDS)\) automatically calculated against observed periodic increments.
These scale factors ranged from 1 to over 5, showing a large variety of growing conditions unaccounted for by the default growth equation (Table 4). The high heterogeneity of growth is also shown by the ratio of the standard deviation of the residuals for the growth sample to the model standard error, which is consistently higher than 1.0. Bayes weights (Krutchkoff 1972) are an expression of confidence that the growth sample represents a different population than does the original data used to fit the model (in this case, PN-FVS data). In other words, a value of 0.90 would indicate a 90% certainty that the growth sample represents a different population than the database used to fit the model (Dixon 2002).
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</table>
II.4 MODEL VALIDATION

We used independent datasets from two of the oldest permanent plots in Italy (Mercurella: 85 years, 39.336°N, 16.081°E; Vallombrosa: 90 years, 43.749°N, 11.577°E) to validate the calibrated PN-FVS for a total of 275 trees. Using the the TIMEINT keyword, we ran a simulation from 1996 to 2015 with a cycle length of 5 years. We compared predicted vs. observed DBH and height (Mercurella: year 2012, Vallombrosa: year 2015). Initial stem heights in Mercurella (1996) were calculated with Curtis-Arney function (Curtis 1967). The value of \( R^2 \) between predicted and observed data for DBH was high in both sites (Table 5), especially for Vallombrosa (0.96), while \( R^2 \) for height was lower (0.54 in Mercurella and 0.72 in Vallombrosa).

Table 5. Results of calibrated PN-FVS model validation at Mercurella and Vallombrosa sites.

<table>
<thead>
<tr>
<th>Statistical parameter</th>
<th>Mercurella</th>
<th>Vallombrosa</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DBH</td>
<td>Height</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.89</td>
<td>0.54</td>
</tr>
<tr>
<td>MBE</td>
<td>-4.36 cm</td>
<td>3.17 m</td>
</tr>
<tr>
<td>RMSE</td>
<td>6.15 cm</td>
<td>4.44 m</td>
</tr>
<tr>
<td>MPE</td>
<td>-6.76%</td>
<td>8.85%</td>
</tr>
<tr>
<td>MABE</td>
<td>4.79 cm</td>
<td>3.53 m</td>
</tr>
</tbody>
</table>
II.5 COMPARISON WITH YIELD TABLES

We ran the locally-calibrated PN variant of FVS 50 years into the future using site characteristics referred to the measured 20 plots and starting from bare ground. Initial plantation density was set at 2745 trees per hectare, i.e. similar to the initial density of the yield table by Cantiani (1965), using the PLANT keyword. We instructed FVS to reproduce the same treatments prescribed by the Cantiani yield table, by using the THINBTA keyword (Thinning from below to trees per acre target); thinnings were scheduled after 20 years (20% basal area removal), 30 years (30% removal), 40 years (25% removal), and 50 years (25% removal). We compared basal area simulated by the uncalibrated and calibrated PN-FVS (mean across all stands) against the Cantiani yield table.

In all stands, simulated basal area was higher than the one predicted by the yield table with a MBE 9.23 m² ha⁻¹, RMSE 13.05 m² ha⁻¹, and MPE 26%.

Calibration reduced the difference between the Cantiani yield table established for Douglas fir plantations in Tuscany and simulated mean basal area (Figure 7) and volume (Figure 8) across all stands.
Figure 7: Basal area predicted by PN-FVS default, by calibrated PN-FVS and by Cantiani yield table (1965.)

Figure 8: Volume predicted by PN-FVS default, by calibrated PN-FVS and by Cantiani yield table (1965.)
Finally, in order to evaluate management alternatives for mature Douglas fir plantations in Italy, we used the calibrated PN-FVS to simulate the results of thinning in two plots with comparable site index but different competition intensity. SDI controls FVS mortality model, and density related mortality begins when the stand SDI is above 55% of SDImax (Dixon 1986). We chose plots Acquerino58 (relative SDI 60.94%, Site index 31m) and Campamoli (relative SDI 48.15%, Site index 37 m) as test sites with similar fertility but different competition intensity. Data from both stands were run for 50 years into the future, starting from year 2013, and prescribing a thinning from below at the beginning of the simulation using the THINBTA keyword with three different management choices (type A 10%, type B 30%, type C control = no thinning). Simulation results diverged depending on site index and current competition intensity. For all thinning regimes, both basal area and volume increased linearly in the low-competition stand (Campamoli: relative SDI =48%). In the high competition stand (Acquerino58: relative SDI = 60%) basal area decreased under the no thinning and 10% thinning regimes because of high competition mortality (Figure 9).

![Figure 9: Simulation of the response of stand basal area (above) and volume (below) to thinning from below in the Campamoli (left) and Acquerino58 (right) stands.](image-url)
II.7 Discussion

FVS can be calibrated by self-calibration (e.g., the height-diameter and large tree diameter growth) or growth multipliers (e.g., crown width and crown ratio submodels). These multipliers allow the user to simulate growth patterns outside the region of first model calibration, i.e., in the presence of growth bias for any given species, geographic area, site, or forest type (Dixon 2002).

Height-Diameter self-calibration reduced from of 0.328 to -0.003 m, indicating that the functional form of this allometric equation is adequate to represent dimensional relationships of Douglas fir outside of its native range. A slightly different approach was followed to calibrate the crown width submodel, i.e., fitting a simplified equation with a different functional form. The analysis of maximum CW by Paine and Hann (1982) shows crowns larger than observed in Italy, probably because of the different thinning regimes and growing conditions in the two countries. Nevertheless, the new equation of crown width (Equation [3]) reduced MBE by 80 cm and MPE by 20 %, showing a satisfactory adjustment for this submodel.

Crown ratio is generally the second most important predictor of tree growth, after DBH. The uncalibrated CR submodel underestimated crown ratio in our plots. Observed crowns were 22% deeper than those predicted by default PN-FVS, possibly as a result of different forest management in these plots than in geographic range of origin (e.g., more intense thinning), altered competitive relationships (no inter-specific competitors in plantations), or improved growing conditions and soil fertility (site index in the upper part of the range provided by, e.g., McArdle et al. 1949). After calibration, the CR submodel improved considerably, although MBE remained negative: (-2.64 m default and -0.49 m calibrated).

Tree diameter growth or basal area growth equations have traditionally been used as one of the primary types of growth equations for individual tree growth models (Holdaway 1984; Ritchie and Hann 1985; Wykoff 1986; Wensel et al. 1987; Dolph 1988). A variety of equation forms and covariates have been used in diameter increment models. Wykoff (1990) indicated that three types of covariates need to be considered in a diameter increment model: tree size, competition and site. FVS includes them all: tree (DBH, height), stand (crown competition factor, basal area, basal area in larger tree) and site (aspect, slope, elevation, site index) characteristics are incorporated in a single equation (Equation [12]). Self-calibration of the large-tree diameter increment model occurs if, for a given species, there are at least five large (DBH >7.62 cm) tree records with measured
diameter increments. Correction scale factors relating measured to predicted increment are then added to the simulations as multipliers. Scale factors higher than one, like the one computed by this calibration study, imply that the default model is underpredicting diameter growth. The amount of underprediction was major (up to 5-fold), but we could find no apparent relationship between scale factor and topographic or site variables in our sample plots. Actual growth performance might be related to unknown provenance differences, local soil water deficit (Sergent et al. 2014a), or soil nitrogen content, which was found important in tree growth recovery after drought spells (Sergent et al. 2014b). Previous calibrations of the FVS empirical diameter growth submodels found the a 18-parameter functional form too complicated to calibrate reliably and to discern ecological effects of individual predictors, suggesting replacement by much simpler model forms (Shaw et al. 2006) following sensitivity analysis of the most influential parameters (Vacchiano et al. 2008).

In this study it was not possible to calibrate other dynamic submodels of FVS, namely the height increment and mortality components, due to the lack of repeated measures as a calibration dataset. We acknowledge that mortality is an especially important component, as FVS has been previously found to be highly sensitive to small differences in the self-thinning algorithm (De Rose et al. 2008). More research and monitoring are needed to understand both density-dependent and density-independent mortality in the non-native range of Douglas fir, especially regarding tree susceptibility to drought stress (Ruiz Diaz Britez et al. 2014) or extreme weather events.

The validation against independent data from Mercurella and Vallombrosa stands showed that the DBH was predicted with a higher accuracy than height, probably due to the lack of measured heights and, consequently, the absence of height-diameter self-calibration for Mercurella in the initial simulation year (1996), and possibly to the lack of calibration of the height growth submodel. The validation against these independent dataset showed that the calibrated model generally had a much lower prediction error than the original PN-FVS models, in particular for predicting DBH at Vallombrosa.

Even after calibration, PN-FVS overpredicted stand basal area at 50 years by 26% to a local yield table (Cantiani 1965). With only one direct measurement in time, it is impossible to ascertain whether this might be related to differences in species-specific carrying capacity (maximum SDI), or altered growing conditions as a consequence of e.g., climate change and/or higher nitrogen deposition relative to when the original yield table was fitted. However, biological validation of model behavior was successful, as
simulated stands responded to different thinning (type A 10%, type B 30%) in a manner that was highly sensitive to their current site index and competition intensity. Where competition was higher, the benefit of thinning was greater.

In this work, our goal was to illustrate a model calibration procedure that could be replicated by forest managers starting from one-time tree size measurements compounded by an increment sampling. Calibration by multipliers is rigid in the sense that it does not allow for changing or simplifying model forms, e.g., dropping unused predictors or altering the shape of allometric curves (e.g., Russell et al. 2013), which could be attained only by rewriting the simulator code. However, our work was successful in providing a statistically validated decision support tool to project growth and yield of mature non-native Douglas fir plantations some decades into the future. Notwithstanding the inherent limitation of an empirical approach to forest modeling (Pretzsch 2009), the wealth of management options, model extensions, open access, and continuity of support by the developers make FVS an attractive option to managers and forest owners wishing to implement their management plans with scientifically based decision support tools.
SECTION III: CLIMATE SENSITIVITY OF DOUGLAS FIR (*PSEUDOTSUGA MENZIESII* (MIRB.) FRANCO) IN MOUNTAIN MEDITERRANEAN AREA

III.1 FRAMEWORK

Forest management must be adapted in order to respond effectively to climate change challenges and mitigation opportunities. A variety of empirical and experimental approaches has been used to reveal plant response to climate variability and climate change over large geographic scales. Examples are provenance trials, common garden experimental plantations over a wide range of environments (Matyas, 1994; Rehfeldt, 1989, Ducci 2015), analysis of growth and mortality in forest inventory plots (Van Mantgem & Stephenson, 2007), remote sensing of net primary productivity (Boisvenue & Running, 2006; Maselli et al., 2010; Chirici et al., 2015). Another possibility is to detect growth limitations due to climatic conditions by analysing tree rings and using correlative analysis of growth responses to climate (Biondi 1997; Barber et al., 2000; Rigling et al. 2002; Weber et al. 2007; Eilmann et al. 2009). Dendroclimatology is a recognized and acknowledged method to understand how trees react to climate variations (Fritts 1976). All these methods are correlative in nature, inferring biological response from climate (or vice versa).

While historical records of biological response to climate *in situ* are perhaps the most dependable data we have to predict future climate change impacts and develop realistic adaptation strategies, correlative approaches share some common weaknesses with respect to predictions. First, correlations observed over one time period may not hold under substantially different climate regimes of the past or future. For example, Briffa et al. (1998) reported a significant reduction of correlation between climate and tree rings over the 20th century for the northern hemisphere. This implies possible overestimates of temperature in tree ring based reconstructions of past climate, as well as overestimates of future climate change impacts on tree growth. Similar observations of a change of tree ring sensitivity to limiting climate factors were made in several regional studies (Biondi, 2000; Carrer & Urbinati, 2006; Carrer et al., 2007; Di Filippo et al., 2007).

Secondly, correlative models make the assumption that the same species (or forest types) in different geographic locations would respond similarly to the same climate drivers (Chen et al., 2010; Case & Peterson, 2005). This implies that populations at the southern or low elevation margins would be most affected by climate warming. However, if
populations have adapted to local environmental conditions, climate change may cause different response by species throughout their range (Hampe & Petit 2005; Borghetti et al. 2012). Hence, more time-sensitive and locally explicit information is needed to ascertain how species respond to climate variability and projected climatic conditions (Schar et al. 2004).

Introduction of Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco) has been indicated as an important adaptive management strategy in Europe (Spiecker 2010). Under favorable climatic conditions, Douglas-fir growth exceeds that of all native softwood species, showing a clear advantage over species such as Scots pine (*Pinus sylvestris* L.) and European larch (*Larix decidua* Miller) (Eilmann and Rigling 2012).

In Italy, 98 experimental stands of Douglas fir were planted between 1922 and 1938 (Pavari & De Philippis, 1941) to test the productive potential of this species. These trials have demonstrated that a variety of sites are suitable for Douglas fir along the Apennine range (Pavari, 1958). In this research we describe and discuss the relationship between climate variables and individual tree ring chronologies of Douglas-fir from two contrasting sites, representing, respectively, the northernmost and southernmost stands where Douglas fir has been planted along the Apennine range, in order to highlight which climate variable controls the diameter growth to a greater extent.
III.2 MATERIALS AND METHODS

III. 2.1 FIELD SAMPLING

The two study areas were “Acquerino” (ACQ), located in the northern Apennines (44.01 °N, 11.01 °E), and “Mercurella” (MRC) in the southern Apennines (39.34 °N, 16.08 °E) (Figure 10).

![Study areas](image)

*Figure 10: Study areas.*

The sites are at a similar elevation (900 and 835 m a.s.l, respectively), but the southernmost site has a warmer and drier yearly climate (mean annual temperature: 10 °C and 13°, annual precipitation: 1430 mm and 930 mm, respectively) and a proper summer dry period (Figure 11).
Due to the different area covered by the two stands, a different measurement design was used at each location, i.e., calliper in all the trees within three circular plots with a 20-m-radius in ACQ and total calliper in MRC. The total height of a representative sample of trees was also measured (n= 15 per site).

The sites have similar elevation, but differed in fertility and distance from the sea; on the other hand, the two stands have similar tree density and mean diameter at breast height (Table 6).

Two cores from 20 dominant Douglas-fir tree stems were extracted from the cross-slope sides at 130 cm height at each stand. Ring widths were measured to 1/100 mm precision using a LINTAB® measuring table and TSAP-WIN software (Rinntech) and cross-dated to correct for missing rings or human error. Each tree-ring series was standardized separately with a double detrending procedure, using a negative exponential curve to remove age trends and then a spline function (Cook and Peters, 1981) with a 50% frequency response (cut-off) of 10 years to emphasize higher inter-annual frequency climatic variance (Biondi and Visani 1993, Amodei et al. 2012). Standardized individual chronologies (ring-width index, RWI) were averaged to build two mean site chronologies. For each chronology we calculated mean sensitivity, i.e. the mean percentage change from each measured yearly ring value to the next (Douglass 1936, in Fritts 1976), the expressed population signal (EPS), i.e. a measure of how well the sampled chronology represents a theoretical population with a finite number of trees, and average first-order...
autocorrelation (AC), which indicates the influence of the previous year on the current year’s growth.

Table 6. Main stand (mean value ± standard deviation) and sampled tree characteristics at the two investigated sites.

<table>
<thead>
<tr>
<th></th>
<th>Acquerino</th>
<th>Mercurella</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elevation (m)</td>
<td>900</td>
<td>835</td>
</tr>
<tr>
<td>Sea distance (km)</td>
<td>63.8</td>
<td>3.4</td>
</tr>
<tr>
<td>Trees (n/ha)</td>
<td>247</td>
<td>294</td>
</tr>
<tr>
<td>Basal area (m²)</td>
<td>111.7</td>
<td>90.4</td>
</tr>
<tr>
<td>Quadratic mean of tree diameter at</td>
<td>75.9</td>
<td>62.5</td>
</tr>
<tr>
<td>Age (years)</td>
<td>min 56</td>
<td>60</td>
</tr>
<tr>
<td></td>
<td>mean 68</td>
<td>70</td>
</tr>
<tr>
<td></td>
<td>max 78</td>
<td>76</td>
</tr>
<tr>
<td>Tree height (m)</td>
<td>48.7±5.4</td>
<td>37.5±1.7</td>
</tr>
<tr>
<td>Tree diameter at breast height (cm)</td>
<td>69.4±14.8</td>
<td>73.1±8.6</td>
</tr>
</tbody>
</table>
III.2.2 CLIMATIC DATA

Climatic data were initially obtained from the Italian meteorological network: however the available data from the stations nearest to the two study areas are non continuous, with too many missing values that severely influenced the whole data structure. To overcome this problem, monthly precipitations and temperatures (maximum and minimum) from 1901 to 2009 were generated by ClimateEU v4.63 software package, available at [http://tinyurl.com/ClimateEU](http://tinyurl.com/ClimateEU) (Table 7), based on methodology described by Hamann et al. (2013). In addition to temperature and precipitation, the Standardized Precipitation Index (SPI) was calculated by the “spi” package (Neves 2012) from the R statistical framework (R Core Team 2015). Mann-Kendall nonparametric test was applied to assess the presence of climatic trends which could influence further analysis (Brunetti et al. 2006).

Table 7. Climatic data at the two investigated sites.

<table>
<thead>
<tr>
<th></th>
<th>Acquerino</th>
<th>Mercurella</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean annual temperature (°C)</td>
<td>9.8</td>
<td>13.1</td>
</tr>
<tr>
<td>Mean warmest month temperature (°C)</td>
<td>19.6</td>
<td>21.7</td>
</tr>
<tr>
<td>Mean coldest month temperature (°C)</td>
<td>1.2</td>
<td>5.6</td>
</tr>
<tr>
<td>Mean annual precipitation (mm)</td>
<td>1438</td>
<td>936</td>
</tr>
<tr>
<td>Mean summer (May to Sept.) precipitation</td>
<td>450</td>
<td>186</td>
</tr>
</tbody>
</table>
III.2.3 CLIMATE GROWTH RELATIONSHIPS

The influence of climate on tree-ring growth was investigated using mean correlation function (CF) and moving correlation functions (MCF), computed on a 30-years-window to retain the influence of mid-frequency climate variations (Fritts, 1976). This base length satisfied the conditions (< 80% of all available years; ≥ twice the number of predictors) suggested by Biondi and Waikul (2004).

Climate variables were calculated at monthly intervals from October of the previous year (t-1) to September of the year of growth (t). Pearson’s correlations were tested for significance using the 95% percentile range method after a bootstrap resampling with 1000 replications. The dplR package (Bunn 2008) and the treeclim package (Zang and Biondi 2015) from R were used for tree ring series management and analysis of climate-growth relationships.
### RESULTS

*Figure 12: On the left, raw (above) and detrended (below) chronologies of Acquerino stand; on the right, raw (above) and detrended (below) chronologies of Mercurella stand.*

In both site chronologies (Figure 12), mean sensitivity was around 12% (table 3) and EPS was high, indicating that the sampled chronology represents very well the analyzed populations. After standardization, autocorrelation from carryover effects by previous year’s growth was mostly canceled out (Table 8).

<table>
<thead>
<tr>
<th></th>
<th>Acquerino</th>
<th>Mercurella</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean sensitivity</td>
<td>0.121</td>
<td>0.127</td>
</tr>
<tr>
<td>EPS</td>
<td>0.926</td>
<td>0.913</td>
</tr>
<tr>
<td>Autocorrelation (before)</td>
<td>0.822</td>
<td>0.918</td>
</tr>
<tr>
<td>Autocorrelation (after)</td>
<td>-0.22</td>
<td>0.218</td>
</tr>
</tbody>
</table>

The Mann-Kendall test ascertained the absence of significant trends in the climate data, even if a growing linear trend in annual minimum and maximum temperatures was
observed for both stands, in particular after 1970 (Figure 13, above). Annual precipitation decreased in ACQ after 1970, but remained stable in MRC (Figure 4, below).

---

**Figure 13:** Climate variables at Acquerino (left) and Mercurella (right) from 1900 to 2015 (thin line: annual data, think line: locally-weighted polynomial regression fit).

Annual SPI did not change in the observation period (1901-2009); both sites exhibited SPI <0 (i.e., less than median precipitation: McKee et al., 1993) between May-June and September, and positive winter SPI. ACQ displayed also a spring drought, with increased frequencies in the last two decades (Figure 14).

---

**Figure 14:** Standardized Precipitation Index (SPI) at Acquerino (left) and Mercurella (right) sites.

At ACQ, a significant and positive correlation was found between growth and minimum and maximum February temperature, whilst a negative correlation was found with minimum temperature of August-September of the current year and maximum temperature of July to September of the current year (Figure 15). Precipitation and SPI were negatively correlated to ring width in October and November of the previous year,
and positively correlated in May and July (SPI: May-July-August) of the current year (Figure 15).

Figure 15: Acquerino stand: above - correlation functions (CF) between ring width and maximum (left) and minimum (right) temperature; below - CF for precipitation (left) and SPI (right).

At MRC, ring width showed a significant and positive correlation with minimum and maximum temperatures of February and March, and a negative correlation with maximum temperatures of October (t-1) and July (Figure 16). Precipitation and SPI showed a negative correlation with ring width in the months of December (t-1) (Figure 16).
Figure 16: *Mercurella* stand: correlation functions (CF) between ring width and maximum (left) and minimum (right) temperature above; CF for precipitation (left) and SPI (right) below.

MCF highlighted several periods with significant Pearson’s correlations between ring width and climate. While some of them were approximately stable over time, others appeared unstable throughout the observation period. At ACQ, significant correlations between ring width and minimum temperatures were generally confirmed across the whole time-series, even if a significant correlation was also detected for the month of March in the period 1945-1985 (Figure 17).
Growth and maximum temperatures were positively correlated only in September, in particular during the last period (1975-2009). Weak and fragmented correlations were detected with rainfall and SPI (Figure 8), especially in the last period (1973-2009), for the months of May, July and August of the growing season (t). At MRC, MCF evidenced a more or less fragmented positive correlation with minimum and maximum temperatures of February and March (Figure 18) and a negative correlation with maximum temperature in October (t-1) and July, as well as with minimum temperature in July, even if not visible in CF.
Figure 18: Mercurella stand: moving correlation functions (MCF) between ring width and maximum (left) and minimum (right) temperature above; MCF for precipitation (left) and SPI (right) below.
Minimum temperatures, in particular those of February, are positively correlated with ring width at both sites; this outlines the preference of this species for the mild climates and, furthermore, Douglas fir is sensitive to winter frost (Burns and Honkala 1990; Timmis et al. 1994).

Minimum temperatures of August and September in ACQ are negatively correlated with growth: the species needs cold temperatures in late summer in order to close the growing season (sensitivity to early and late frosts). Instead in MRC this correlation was not significant, because early frosts do not occur due to the greater proximity to the sea.

July temperatures are negatively correlated with growth in MRC (and also in ACQ, although not significantly), underlying the importance of summer evaporative stress (Chen et al. 2010). However, summer precipitation (and, more strongly, SPI) were positively correlated to growth only in ACQ, and not in MRC whose climodiagram displayed a true summer dry period (Figure 2). This difference can be due either to the higher continentality of the northern Appennine site, or to differences in physiological activities of the southernmost population, that may stop growth earlier in the season in order to adapt to the summer dry period.

Autumn precipitations of the previous year are negatively correlated with growth in both sites. Similarly, Douglas fire trees on xeric sites on the Alps were previously found to be sensitive to soil water recharge in the preceding autumn and early spring. Trees on more mesic sites were more vulnerable to water deficits of shorter duration than on xeric sites (Lévesque et al. 2013).

The strength and significance of most correlations against temperature, precipitation, and SPI increased at both sites in the last decades. A shift in the most sensitive month for summer precipitation and temperature was also observed in ACQ. This may be attributed to the effect of climate warming; however, as long as winter and spring precipitation remains sufficient to refill the soil water reservoir, summer growth reductions should not be too strong even if summers will become drier (Christensen et al., 2007; CH2011, 2011).

Stand and site characteristics may have an influence on the occurrence of water stress (Bauwe et al. 2012). Carnwath et al. (2012) showed that basal area of Douglas fir was more sensitive to water availability on xeric sites. There is still much debate as to how stand density or individual competitive conditions, regulated by initial spacing and
thinnings, modify the growth reaction patterns of trees in dry years (e.g., Aussenac and Granier 1988; Castagneri et al. 2015). On the other hand, more studies are needed to ascertain the role of soil and stand variables on the climate sensitivity of Douglas fir planted under Mediterranean mountain environments. This is also a broader key issue for forest ecosystem monitoring and assessment programs as means of contingently identifying and assessing mechanisms that influence global changes (Corona 2016).
CONCLUSION

Under climate change expectations, Douglas fir is considered to have a great potential to supplement timber supply in Southern Europe, given its tolerance to summer drought. Ultimately, this study stresses that growth of Douglas fir in the Italian Apennines is positively influenced by winter-spring temperature, suggesting a low tolerance of winter extremes and a need for spring soil water recharge. Summer water stress has a negative influence only at the site that does not suffer from regular climatic summer drought, suggesting a possible physiological adaptation of the species.

From a general standpoint, the obtained results highlight the potential of dendrochronology, and, distinctively, of dendroclimatology, to identify local climatic adaptations of populations that can normally only be revealed by long-term provenance trials or genetic analyses (Chen et al. 2010). These results could be extrapolated to the average environmental conditions of the Mediterranean area, albeit carefulness may be advised because local populations may be adapted to additional factors other than climate, such as soils, mycorrhiza, or the pressures of pests and pathogens (Montwè et al. 2015).

This work has calibrated an age-independent, individual-tree, distance-independent growth and yield simulator for Douglas fir for Central Italy. A tree level simulator is an effective tool for planning forest management. Calibrating this model to other areas and for other species in Italian forests may be a useful management support instead of traditional yield tables.

Other FVS submodels and extensions can be calibrated besides those here considered (Russell et al. 2015): regeneration, climate-FVS and especially mortality, which is an important growth submodel to be considered in future evaluations because it is one of the most sensitive features to changes in future climate regimes, such as increase in drought severity and duration (Crookston et al. 2010). Simple modifications to the tree mortality model within PN-FVS could result in improved precision for estimating future number of trees (e.g., Radtke et al. 2012).

The self-calibration feature of FVS extends the geographic range over which the model can be exploited, assuming that the factors affecting growth in a given area also affect growth in the same way elsewhere. If this assumption cannot be accepted, the only other option is to refit the relationships using data from the geographic area of interest. If this procedure can be accepted, then the model equations can be calibrated rather easily.
Here, we have proved a relevant improvement for the application of FVS in Italy over the original model. The results also highlight the importance of using long-term historical growth data for the calibration and validation of the model. Permanent plots are generally well suited for tracking long-term model reliability and for evaluating model performance relative to specific treatments. Maintaining existing local networks of permanent plots, especially those with long histories of measurement, to predict forest growth in the climate change, is suggested (Crookston et al. 2010).

In conclusion, FVS has been proven to be a suitable type of yield modeling for Douglas fir forest growth in Italy: (i) it suitably represents current understanding of the dynamic forest ecosystem and how it responds over time to management interventions; (ii) it provides a monitoring target to test our assumptions with (for example, stand yield following different silvicultural treatments and successional pathways when no treatments are applied); (iii) it provides a modeling framework to integrate existing modeling components such as crown equations, site index curves and ecological land classification; (iv) it provides tools to develop and compare various silvicultural treatments; (v) simulation stand development may be effectively used to inform and instruct forest managers; (vi) it can be effectively adopted to update inventory data.
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