UNIVERSITÀ DEGLI STUDI FIRENZE

Doctoral research program on sustainable management of agricultural, forestry and food resources

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Cycle XXXII

A model-based assessment of the potential impact of climate change on Italian forest systems

Phd candidate

Dr. Matteo Pecchi

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Florence, 30th October 2019 Pecchi Matteo

Abstract

The future dynamics of forest species and ecosystems depends on the effects of climate change and their resilience and adaptive potential are highly related to forest management strategies. The main expected impacts of climate change are linked to forest growth and productivity. An increase in the length of the growing season and greater productivity are likely as well as shifts in average climatic values and more variable frequency, intensity and duration of extreme events. The purpose of this doctoral thesis is to provide information to support forest management strategies potentially useful to mitigate the effects of climate change to Italian forests. Among all the forest tree species occurring across the Italian peninsula, 19 were considered as the most important for their economic, ecological and aesthetic value. The ecological niche of species was firstly described on the bases of climate requirements and compared with existing scientific literature and expert knowledge in Italy. Then the described niches were projected into the future by means of a species distribution modelling approach to derive insight of the forecasted impact of climate change on Italian forests and to derive implication for future forest management strategies. To model the climatic requirements, interpolated climate data of average annual temperatures and precipitation (1km) were used and 6 different Global Circulation Models (GCMs) were employed to describe future climate condition and in addition to a local Regional Climate Model (RCM). Future climate data were referred to unique emission scenario (the intermediate RCP 4.5) for 2050s. Results showed a substantial shift in knowledge with only 46% of the observations falling within the potential joint temperature and precipitation limits as defined by expert knowledge. Moreover, the similarity between current observed and potential limits differ from species to species with broadleaves in general more frequently distributed within their potential climatic limits than conifers. Paying attention to future climate conditions the analysis showed strong differences between the different climate models; the RCM demonstrated to be a more variable scenario than GCMs. The Apennines strip will probably be affected by strong and important changes as well as the sub-alpine zone. However, no sensible variations in the extension of the forest area have been predicted. The analyses also indicated that forest suitability is going to remain almost unchanged in mountain areas, while in valleys or flood and plains areas is likely to decrease. Moreover, the model establishes a possible strong negative impact of climate change at the level of pure woods compared to mixed woods, characterized by a greater species richness and therefore a higher level of biodiversity. Finally, pure softwood stands (e.g. *Pinus, Abies*) may be more affected by the impacts of global warming than hardwoods (e.g. *Fagus, Quercus*).

According to the provided results and scenarios, specific silvicultural practises should be applied to increase the species richness and favouring hardwoods currently growing as dominates species under conifers canopy. Increased thinning frequency and intensity and a reduced rotation period may contribure to increase the natural regeneration, gene flow and (eventually) support species migration.

Summary

Chapter 1

Introduction

The Earth's climate is rapidly changing as consequence of the "global warming", a biophysical process where temperature and precipitation regimes have been observed to vary more than in the past. The "global warming" is strongly linked with the progressive increasing in atmosphere of the concentration of some gasses called as "greenhouse gasses". This progressive increment can lead to a series of effect at atmosphere level that are known as "climate change". Climate change is expected to have important consequences for tree species because climate represents an important factor that influence both physiology and distribution (Dyderski et al., 2017; van der Maaten et al., 2016). The scientific community agrees in attributing this progressive increment in concentration of this greenhouse gasses in atmosphere to human activity. The principal greenhouse gasses or GHGs are carbon dioxide (CO_2), methane (CH_4) and nitrous oxides (NO_x). There is agreement that human activities are already responsible of the increment of approximately +1°C respect to 1850-1900 reference period. Moreover, it is very likely that the current GHG emission rate will lead to an increment of about 1.5°C in a period comprise among 2030 and 2052 (IPCC, 2018).
There is growing awareness among different forestry stakeholders and scientists about the possible impact of climate change in forest ecosystem and their potential effect on their aesthetic, recreational, ecologic and economic value (van der Maaten et al., 2016). Indeed, today forests are not only producers of timber but also of many more goods and services that are important for human wellbeing. These goods and service are known as "ecosystem service" (Millennium Ecosystem Assessment, 2005). For example, Hanewinkel et al. (2012) have estimated important economic losses in timber production at the end of century without appropriate adaptation strategy. Important economic losses are also expected for certain non-wood products such as mushrooms. This is mainly expected in areas where rainfalls are likely to decrease, as for example Mediterranean area (Martínez de Aragón et al., 2007). While the carbon sequestration seems to be favourite by climate change at least in the short and medium term (Lindner et al., 2010).
Impact of climate change can be both direct and indirect. Direct impact is linked to the effect of temperature and precipitation variability on physiological and reproductive process such as photosynthesis, water use efficiency, flowering. Challenge in these processes can have important consequences for species both under short and long periods. Examples of short period variation may regard the wood density or quality (Daniels et al., 2011; Morin et al., 2018). With

attention to the long period effects, direct impact can lead to variation of the species composition of forests as well as influences on their spatial distribution (Keenan, 2015). Indirect impact is linked to a variation in frequency or intensity of fire or other disturbance agents (windstorm, drought, heat wave, insect or other disease attack). Indirect effects act at stand composition level of forests, on the structure of habitat and finally on the capacity of forests to provide goods and services (Kirilenko and Sedjo, 2007).

However, consequences of climate change are not always predicted to be negative for forest systems. An increasing temperature might enlarge the growing season length where cold is the limiting factor. Also, an increment in carbon dioxide can be positive for species to stimulate the photosynthesis (Lindner et al., 2014, 2010). Messaoud and Chen (2011) for example, demonstrated a positive relationship between height growth and increment in temperature and high carbon dioxide concentration for black spruce and aspen tree in British Columbia (Canada).

In a changing climate condition, forest species can response with changes on ecophysiological processes, adaptive strategies and phenotypic plasticity. The possible strategies that a species can adopt can be summarised in 4 categories according to Bussotti et al. (2015):

a) **acclimatization**: adaptation of an organism to changing conditions in the short period (Alfaro et al., 2014). The response of the different organism is conditionated by a series of species-specific features and functional traits. Functional traits are represented to any morphological, biochemical, physiological, structural, phenological or behavioural characteristic of an organism. A combination between these distinct factors determine the response of the organism that expressed by phenotype, this property is known as "phenotype plasticity" (Alfaro et al., 2014; Salamon-Albert et al., 2017);

b) **adaptation**: an evolution of population following a selection process. The result of adaptation process is represented by a population with individuals that are better fitting to new climate condition;

c) **migration**: vegetation can shift follow latitudinal and altitudinal trend in temperature and precipitation;

d) **extinction**: a considered species or population can not able to persist in new climate condition.

The development of a strategy to reduce risks and impact of climate change towards forest represent today a focal point in many different countries for two main reason:

I) the high longevity of forest tree species respects another organism (Seidl and Lexer, 2013);
II) the high speed of climate change that it is predicted to be higher than the adaptation capacity of many species (Sáenz-Romero et al., 2016).

The adaptation is a possible way to follow. This term is defined by IPCC (Intergovernmental Panel On Climate Change) as any "adjustment in natural or human systems in response to actual or expected climatic changes or their effects, which can be taken to reduce the impact of a particular risk or exploit its beneficial opportunities" (Sousa-Silva et al., 2018).
An adaptative forest management strategy consists into a series of different operation that have the aim to anticipate future possible impact of climate change and increase the resistance anf resilience of ecosystem. A holistic view is so fundamental in order to observe all the possible disequilibrium that a human intervention can introduce in a self-organising system with bot positive effects combined in a unique response (Keenan, 2015; Vilà-Cabrera et al., 2018). The different possible action may be classified into two different group: the autonomous and planned. With the term of automous actions are indicated those action that are reactive action to changing condition while with the term of planned measure those actions that have the aim to anticipate possible impact (Sousa-Silva et al., 2018).
This strategy is based on a particular structure of three different pillars (Yousefpour et al., 2017) that are:

I) **knowledge**: focused on the constant upgrade of the potential effect of climate change on forest ecosystem and on the relate uncertainty;
II) **option**: referred to the analysis of different management option and their effect on the different ecosystem;
III) **decision**: collecting the information coming from the previous pillars, with the aim to identify the most suitable strategy to use.

The different action that constitute an adaptative forest management strategy can be implemented by different subjects (government institutions or research institute or different forest owners) and interesting different spatial scale, from National (i.e. regulation, activation of research or monitoring program) to local (i.e. action at stand level). All the implemented action may allow to respect the natural evolution of forest systems and supporting all the biological processes that would naturally occur over longer period (Williams and Dumroese, 2013).

These different operations can be divided into three categories (Bolte et al., 2009; Coşofreţ and Bouriaud, 2019; Jandl et al., 2019; Kelleher et al., 2015):

I) **Conservation of the forest structure**: a series of practises aimed to maintain the structure of forests avoiding any management strategy. This approach is indicated for old forests located in areas where the expected impacts are very low;

II) **Active adaptation**: a series of measures that have the aim to modify the structure of forest (i.e. thinning or species enrichment) and proposed for forests where the potential impacts are predicted to be severe;

III) **Passive adaptation**: a series of actions where spontaneous adaptative processes are recognized and stimulated (i.e. natural conversion of forest or increase rotation length). These actions are proposed for forests with low ecological and or economic value.

However, despite of an increase of information about vulnerability of forest and adaptation measure a critical gap remains between scientific literature and the application of results into practice (Janowiak et al., 2014). As previously highlighted, information about the possible consequence of climate change and on the response of different species to changing climate conditions are fundamental to an adaptive forest management strategy. Modelling tools represent a very useful technique to reflect about these thematic (Falk and Mellert, 2011; Reyer et al., 2015).
As report in Fontes et al. (2011) these techniques can be divided into three class:

I) Empirical, that are model based on a statistic relation between a response variable and a series of other variables called as predictor;

II) Process-based, a group of techniques that consider a series of process which affect the forest (such as transpiration or photosynthesis;

III) Hybrid, a group of models that use empirical relation to compensate the lack of exhaustive information by process-based model.

In this PhD-Thesis the attention is focused on the group of empirical models. Among the different tools the Species Distribution Model (or SDM) technique is one of the most popular and useful (Pecchi et al., 2019).

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Chapter 2

Background, motivation and aims

Species distribution modelling technique (SDM), sometimes called as ecological niche model (ENM) represents a very promising tool to support adaptative forest management. SDM are defined as statistical algorithms able to connect spatial information about presence/occurrence of a certain species with a series of environmental variables describing the habitat of species. The final aim of this technique is to describe the ecological characteristic of different species (Guisan and Thuiller, 2005; Pecchi et al., 2019a, 2019b). Information about distribution of forest species and the influence of different ecological drivers are today requested by decision makers in order to detect thread and possible refuge areas (Falk and Hempelmann, 2013; Pecchi et al., 2019b).
The growing interest in climate change and the uncertainty in the potential effect on spatial distribution of forest species, have motived the development of this thesis. This thesis would like to give a contribute to fill up the gap in research regarding the assessment of uncertainty level that are related to the use of different climate projections (GCM vs RCM) for species distribution modelling. Moreover, this study would like to give general indications on the possible effect of climate change on Italian forests which can be potentially useful to forest managers.
The specific objectives of each different paper are various and can be summarised as follows:

Paper I: This paper reviews available species occurrence datasets, environmental data, modelling algorithms, evaluation processes and spatial projections, discussing the implications of the findings for forest science, silviculture and forestry. The aim is to describe how ecological modelling of forest tree species has evolved within the framework of spatial ecology to support forest management. A bibliographic search was conducted by analyzing Scopus, Google Scholar and ISI-WoS databases, for the period 2000-2019. The aim of this review is to give a general overview of the techniques and adjustments implemented by researchers in order to improve future applications of SDM in forestry research. The unresolved issues highlighted previously, including the discussion around the definition of real or potential SDM and awareness of the theoretical differences between SDM and ENM, are not discussed further. The term SDM will be used through the text to include all methods intended to link the spatial distribution of target tree species with environmental variables.

Paper II: The main aim of this study is to update knowledge on the climatic drivers related to the most important forest tree species in Italy. We used 7272 field plots from the most recent Italian NFI, INFC2005, for which data are currently available, and the 1 km resolution climatic temperature and precipitation data from downscaled E-OBS gridded data (version 17.0) from the EU-FP6 project ENSEMBLES (Haylock et al., 2008). We compared our findings with ecological niche information available in the literature. This analysis is intended as a starting point for further studies on future spatial distributions of tree species and growth models under climate change scenarios. In fact, adequate and current knowledge of ecological requirements for forest tree species represents the main source of information for future projections and forest ecosystem assessments.

Paper III: The aim of this paper is to evaluate the uncertainties behind a SDM procedure in the Mediterranean environment, where climate change has been predicted to be highly affecting forest tree species distribution. In this work different projections for 19 among the main forest tree species in Italy have been realised, quantifying the discrepancies between and within species when different GCMs and RCMs are used. Wall-to-wall suitability maps have been obtained for Italy to provide indications to forest planners regarding the possible consequence and impact of climate change in Italian forest systems. Then adaptive forest management strategies have been proposed dealing with potential impacts of climate change and uncertainties detected behind the modelling efforts.

Other works

The thesis has also been compiled using two additional papers dealing with the impact of abiotic agents on forests (windstorm) and the use of statistical models to spatialise the data from national forest inventory. Such papers have been added in a separate section (Chapter 4).
During my PhD period my activity and attention of research has addressed towards other themes. These thematics are represented by windstorm events and their consequence and the forest attribute spatialization process. Windstorm represent one of the most important abiotic disturbance events for forest ecosystems. During the last years these events have become more frequent than in the past with important consequences that are linked to the great loss of timber. Here the paper entitled *"A Pan-European spatially-explicit database of windthrows occurred over the 2000-2018 period"* represents a collection of windthrow data coming from 12 different European countries.

Forest attribute spatialization process are used to derive maps of different forest variable (such as biomass or growing stock volume) that are useful for forest management planning. These maps are produced with data collected in the framework of National Forest Inventory (NFI) programs that are designed to provide aggregated estimates of forest parameters. *"A wall to wall spatial prediction of growing stock volume based on Italian National Forest Inventory plots and remotely sensed data"* compare different methods to derive growing stock volume map using as test area in Central Italy.

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Chapter 3

List of papers

Paper I

Pecchi M., Marchi M., Burton V., Giannetti F., Moriondo M., Bernetti I., Bindi M., Chirici G. (2019). ***Species distribution modelling to support forest management. A literature review.***
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Paper II

Pecchi M., Marchi M., Giannetti F., Bernetti I., Bindi M., Moriondo M., Maselli F., Fibbi L., Corona P., Travaglini D., Chirici G. (2019). ***Reviewing climatic traits for the main forest tree species in Italy.***
iForest- Biogeosciences and Forestry 12, pp 173-180.
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Paper III

Pecchi M., Marchi M., Ammoniaci M., Bernetti I., Bindi M., Moriondo M., Chirici G (2020). ***The role of ecological requirements and climate change projections when modelling species distributions for adaptive forest management strategies.***
Manuscript form, under evaluation in Environmental Research Journal

3.1: Species distribution modelling to support forest management. A literature review

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Abstract: Species Distribution Modelling (SDM) techniques were originally developed in the mid-1980s. In this century they are gaining increasing attention in the literature and in practical use as a powerful tool to support forest management strategies especially under climate change. In this review paper we consider species occurrence datasets, climatic and soil predictor variables, modelling algorithms, evaluation methods and widely used software for SDM studies. We describe several important and freely available sources for species occurrence and interpolated climatic data. We outline the use of both presence-only and presence/absence modelling algorithms including distance-based algorithms, machine learning algorithms and regression-based models. We conclude that SDM techniques provide a valuable asset for forest managers. However, it is essential to consider uncertainties behind the use of future climate change scenarios.

Keywords: Forest modeling; ecological mathematics; climate change scenarios; spatial analyses; ecology; ecosystem services from forests

Introduction

The future dynamics and spatial distribution of forest ecosystems is a key issue for biodiversity conservation under the many uncertainties generated by climate change (Rehfeldt et al., 2014; Walentowski et al., 2017). Forest ecosystems deliver a wide range of benefits to human beings and achieving the sustainable use of natural resources is central to research in many disciplines. Knowledge concerning the current spatial occurrence of forest species, the influence of ecological drivers (e.g. climate, soil) and the possible erosion or expansion of their envelopes of suitability is required by decision makers in order to detect both threatened areas and possible refuges (Pecchi et al., 2019; Williams and Dumroese, 2013). The use of better adapted forest tree species (genotypes) and provenance selection (genotyping) has the potential to improve the resilience of forest systems and allow assisted migration strategies (Hanewinkel et al., 2014; Marchi and Ducci, 2018), thus assisting the adaptive processes of forest ecosystems (Ferrarini et al., 2016).

Since the emergence of modelling techniques, spatial data including aerial images, cartographic layers, and national forest inventories have been fundamental resources for statistical mapping (Di Biase et al., 2018; Fleischer et al., 2017; Mura et al., 2016; Spittlehouse and Stewart, 2004). Reliable datasets and statistical models quickly became integral to supporting decisions which aim to support sustainable use of forest resources under a changing climate. Numerous datasets of forest attributes and land suitability surfaces have been developed for many forest tree species in many areas of the world, and these are integral to developing spatial decision support systems (Johnson et al., 2014; Masek et al., 2013). Statistical modelling techniques can be divided into one of three types: 1) empirical, 2) correlative, or 3) mechanistic. Correlative Species Distribution Models (SDM) involve the collation of species occurrence data, relating these occurrences to environmental variables, and generating maps which predict past, present or future species distributions. Their ease of use makes them a popular method, and they represent the vast majority (around 90%) of SDM publications. An alternative approach is to use mechanistic SDMs, which simulate biological processes according to ecological drivers. These mechanistic models rely on huge datasets with long time-series and high-resolution data, which are often not available at national or continental scales. Given that statistical SDMs have emerged as methods by which these limitations can be overcome, mechanistic models are not considered in detail by this review.

Before the mid-1980s SDM attempts were limited by the lack of reliable interpolated climatic data on large spatial scales, i.e. to estimate conditions at species occurrence sites that are often distant from meteorological stations. Modern SDM took off in the late 1990s and early 2000s with the release of global climatic surfaces such as the WorldClim database (Hijmans et al., 2005), which has provided the data used in many SDM studies to date. In 1996 BIOCLIM provided a set of 19 bioclimatic variables which are also still widely used in many SDM studies. The SDM approach was initially based on the ecological niche concept provided by Hutchinson around 1950s and then refined by Booth et al. (1988). This envisaged an 'n-dimensional hypervolume' (which included simple ranges for environmental factors such as precipitation or temperature) describing where the species grows naturally (i.e. its realized niche) or where it can grow and reproduce in the absence of competitors (i.e. its fundamental niche). Appreciating that many tree species can grow under conditions somewhat different from those within their natural distributions is crucial for understanding how they may respond to climate change. It is reasonable to assume that a long-lived tree species already well-established at particular sites may well be able to display some of the climatic adaptability it has shown at trials outside its natural distribution (Booth, 2017). Most SDM studies of forests under climate change ignore this adaptability, thus determining species climatic requirements from their natural distributions only and applying climate change scenarios. This distinction between fundamental (or potential, i.e. Grinellian) and realized (i.e. Hutchinsonian) niche (Pearson and Dawson, 2003; Pulliam, 2000; Vetaas, 2002) has been often discussed. While the fundamental niche represents the entire habitat suitable for a considered species, the realized niche is defined as a smaller part of the expressed fundamental niche as the result of the inter and intra-specific competition for available resources in a specific environment i.e. geographic zone (Booth, 2017). The recognition of this distinction is critical for deciding how an SDM should function (Pearson and Dawson, 2003). The majority of SDM to date make use of ‘realized niches’, often deriving these from the current spatial distributions of forest species. This has limitations, as SDM are not able to consider the relationships between species and other biotic components e.g. pests and diseases (Austin, 2007; Morin and Thuiller, 2009).

SDM is recognized as a powerful method to forecast the most likely impact of a changing climate on the geographic distribution of a target species by means of environmental data and future Global Climate Model (GCM) outputs (Booth, 2018; Guisan et al., 2013; Thuiller et al., 2015). The technique can go by many different names including: habitat model, niche-based model, habitat suitability model, climate envelope, environmental niche model (ENM) and ecological niche model (Elith and Leathwick, 2009; Guisan et al., 2017, 2013; Hamann and Wang, 2006; Jeschke and Strayer, 2008). The use of ENM as synonymous with SDM is contentious given the confusion about the significance of the term "niche" Etienne, 2013; Peterson and Soberón, 2012; Warren, 2012). For some authors, the inability of models based on realized niches to consider biotic interactions means that the 'true' niche of the species cannot be modelled. Consequently, the current spatial distribution of forest species is viewed as inadequate to properly characterize its ecological requirements.

This paper reviews available species occurrence datasets, environmental data, modelling algorithms, evaluation processes and spatial projections, discussing the implications of the findings for forest science, silviculture and forestry. The aim is to describe how ecological modelling of forest tree species has evolved within the framework of spatial ecology to support forest management. A bibliographic search was conducted by analyzing Scopus, Google Scholar and ISI-WoS databases, for the period 2000-2019. The aim of this review is to give a general overview of the techniques and adjustments implemented by researchers in order to improve future applications of SDM in forestry research. The unresolved issues highlighted previously, including the discussion around the definition of real or potential SDM and awareness of the theoretical differences between SDM and ENM, are not discussed further. The term SDM will be used through the text to include all methods intended to link the spatial distribution of target tree species with environmental variables.

Species distribution datasets

The spatial distribution of a target species (species occurrence) as the result of past history, current (long-term) climatic conditions and, above all, forest management strategies, represents the primary basis for any SDM (Falk and Mellert, 2011; Godsoe et al., 2017). There are many possible sources for species distribution records. Selecting the most appropriate dataset is challenging and can influence model performance (Duputié et al., 2014). While many studies have focused their models on the native range only (Gastón et al., 2014; Isaac-Renton et al., 2014), other authors have included the distribution of artificial stands, under the assumption that "if it survives, there it is suitable and worth to be considered" (Duveneck and Scheller, 2015; Marchi et al., 2016). In fact, several studies have demonstrated the ability of many forest tree species to grow well outside their native range and often better than in their origin area (Boiffin et al., 2016; Booth, 2017; Castaldi et al., 2017). Regardless of database source, there are common issues that affect the reliability of datasets. These include: uncertainty in species identification, low or unknown accuracy of sample locations, lack of design sampling, and incomplete spatial coverage of the true distribution of species (Guisan et al., 2017).

Vector format (shapefile) and national forest inventories

Species occurrence data for SDM can be obtained from field surveys (e.g. National Forest Inventories - NFI), compiled on the basis of existing literature (e.g. EUFORGEN maps), or derived from statistical modeling procedures (e.g. EFI maps, Brus et al., 2012). While presence data are easy to obtain, including absences (or pseudo-absences) is a major issue in SDM. The spatial distribution is rarely in a "true" equilibrium with climate/soil due to human pressure on the environment. For this reason, many uncertainties lie behind both presence and absence data. Many additional modelling tools have been proposed to properly simulate absences (Barbet-Massin et al., 2012; Peterson et al., 2011). However only NFI datasets have the advantage of being based on a statistical sampling scheme with additional information on absences (Marchi and Ducci, 2018).

Most of the databases used by authors are open-source and freely available on the web. The EUFORGEN maps (http://www.euforgen.org/species/) are the first example of distribution maps. This database was created by "Forest Genetic Resource Program" and consists of a series of pan- European distribution maps for 45 different species, which are updated continuously. The latest version is available in Caudullo et al. (2017) and was realized in the framework of the European Atlas of Forest species (San-Miguel-Ayanz et al., 2016). The main shortcoming of this database relates to its polygon format, which can affect the quality and reliability of the data given that no information is available within each polygon, considering all locations as potentially suitable at the same level. Such data has been generally used to validate SDM outputs or to constrain the analysis within a native range. For instance, Akosbede-Fazekas and Levente Horvath (2014) used it to investigate the potential distribution of 4 different species of Mediterranean pine. Another study proposed by Falk and Hempelmann (2013) was explored the distribution and shift of beech and spruce in Europe.

ICP-Forest is another freely available European database but, in contrast to EUFORGEN which can be freely downloaded from the website, ICP-forest download requires a formal request. ICP is the result of the "International Cooperative Program on Assessment and Monitoring of Air Pollution Effects on Forests" project. The data are split into two different monitoring intensities and spatial distributions: "Level I" and "Level II". In the first case, almost 6,000 forest monitoring plots are available, regularly distributed on a 16km grid (Hanewinkel et al., 2012). Hanewinkel et al. (2012) use ICP forest to examine the distribution of important forest species in Europe, while Casalegno et al.

(2010) used ICP to realize a map of vulnerability of *Pinus cembra* to present and future climate conditions. Level II is an intensive monitoring network and provides keys insights into factors affecting the condition of forest ecosystems and relative effects of different stress factors. In this case only around 800 plots have been established within the major forest types of Europe. While ICP-Forests might be used as presence-absence dataset, a lack of a spatial sampling scheme a major shortcoming of this dataset. For this reason, an adjustment was proposed by Brus et al (2012) where a mixture of compositional kriging in areas with NFI plot data and a multinomial multiple logistic regression model between ICP-Forests plots was performed.

Although often initially conducted for different purposes e.g. to record management actions or inform economic research, National Forest Inventory (NFI) data are probably the most important and detailed source of biological data for SDM. The main superiority of NFI for SDM relies on the sampling method used which respects statistical rules and can be used for inference. NFI are an unbiased sampling of the forest area in a specific country and can be used to derive estimators of forest attributes. Their repetition at (almost) regular intervals of time enables monitoring and modelling of temporal changes (Teuscher et al., 2013). Hanewinkel et al. (2010) modeled the potential economic consequences of a shift from Norway spruce to European beech in a forest in the south of Germany. Similarly, Rivera and Lòpez-Quilez (2017) worked in Spain to compare several statistical techniques for predicting species distribution of forest species. Iverson et al. (2008) evaluated a potential response of forest species to climate change following two different emission scenarios in eastern of USA using inventory data for 134 different species of forest tree. Recently NFIs have been used to study the possibility for detecting and conserving marginal and peripheral forest populations with several SDM techniques in order to forecast possible adaptation strategies for two Mediterranean species (Abies alba and Fagus sylvatica) sharing a common environment (Marchi and Ducci, 2018). Based on the classic SDM evaluation method (True Skill Statistic – TSS, see below), a higher accuracy of predictions was obtained modeling only a small part of the whole distribution, referred as "provenance" and mainly due to the reduction in the "background noise". Consequently, authors concluded that the "Provenance Species Distribution Modeling" may represent a valuable step forward in spatial analysis, particularly for the detection of marginal peripheral populations.

Global datasets and raster layers

The "Global Biodiversity Information Facility" (GBIF) database is an important source of auxiliary information for SDM. The database gives information on occurrence data outside the native range and therefore an indication of the ability of species to grow under different climate conditions (Booth, 2014; Dyderski et al., 2018). As with ICP-Forests, its main problem is the lack of sample design (Guisan et al., 2017); and thus, it is rarely use as a principal source of data. However, there are several examples of it being utilized. Hernández-Quiroz et al. (2018) related Quercus occurrence data to its current distribution using GBIF data. In Booth (2014) the GBIF is related to the Atlas of Living Australia (ALA) to develop a methodology which describes the climatic requirements of Eucaplyptus nitens. Dyderski et al. (2018) also worked with GBIF as additional information to improve the predicted performance of their SDM. In another study, Zhang et al. (2017) integrated data from the FIA (United States Forest Inventory and Analysis) and PSP (Canadian Permanent Sampling Plots) with GBIF to develop an ensemble SDM which evaluated potential habitat suitability for forest species under different conditions of climate, land use and dispersal constraints.

Local, regional or national datasets such as forest category maps represent valuable strata for regional studies which can enrich national, continental or global datasets. For example, forest ecotypes link plant species to certain zones. Marchi et al. (2016) used ecotypes to model future scenarios for a marginal forest population of Black pine (Pinus nigra spp. nigra var. italica) in the Mediterranean area in order to forecast potential mitigation strategies and propose an assisted migration protocol. Similarly, in Iturbide et al. (2015), 11 different ecotypes of Quercus spp. were used to analyze the effect of different methods for pseudo-absence data generation and generate optimal results. National forest maps have also sometimes been utilized. In Garzòn et al. (2006) a distribution map at a resolution of 1 km was used to assess the potential distribution of Pinus sylvestris in Spain. Similarly, Wang et al. (2016) studied likely climate change effects on the distribution of some common Chinese tree species.

Statistical maps of forest tree species represent an alternative and interesting source for SDM. Brus et al. (2012) recently generated raster maps at 1km resolution for 20 forest tree species in Europe. Input data was sourced from ICP-Forests records and NFI inventory statistics for 18 European countries. For areas covered by National Inventory plots, the proportional area of each of the 20 species was calculated using a kriging interpolation method. A multinomial regression model was then applied to predict species composition for the rest of Europe. The results of the model were then scaled using independent data. These datasets have been widely used. Van der Maaten et al. (2017) investigated the hypothesis that future climate projections are linked to temporal or spatial variation in forest growth (ring width). These datasets were also used by maps were also used by Noce et al. (2017) to study the potential effect of climate change on hot-spot distribution in southern Europe with regards to common group of forest species.

Climate, soil, land cover and variable choice

Many factors need to be taken into account when choosing an appropriate predictor variable: the purpose of the study, the availability of data, and the redundancies between variables. An additional issue in variable selection is 'collinearity' which can occur between predictors. This phenomenon occurs where two or more predictors are related to one another, linearly or not. This can affect the proportion of variance explained by each independent variable. While no impact has been found on final prediction, this characteristic can make it difficult to establish the relative importance of predictors in affecting the distribution of species (Dormann et al., 2013). Where there is high collinearity among predictors, the easiest method is to remove some of the highly correlated variables from the computational steps (Schröder, 2008). A pre-determined threshold which generally ranges between 0.8 and 1.0 (Dormann et al., 2013) can be applied to filter them. To avoid subjective selection, the use of a pre-selective technique such as Principal Component Analysis (PCA) can be used. Variables are then chosen according to the proportion of variance explained by each component (Cruz-Cárdenas et al., 2014; Metzger et al., 2012). Alternatively, PCA components can be used as predictors (Marchi and Ducci, 2018). However, even with a mathematically perfect model (the components are orthogonal for construction) the importance of each ecological predictor is hard to estimate. Another option is the Cluster independent method with two sub-variants: i) to select variables where the correlation values are under 0.7 or ii) residual regression. Finally, latent variable models can be used to infer 'hidden' variables from observed and collinear variables (Dormann et al., 2013).

Worldclim and Worldclim-based raster surfaces

The environmental variables (or predictors) in SDM are used to derive the ecological niche which can then be used to model species distributions according to their drivers (Pearson, 2010). The choice of predictor variables represents a critical step which must be based on the ecoogical tolerance and habitat requirements of the species in question (Jarnevich et al., 2015). Despite its important repercussions on model performance, the "predictors issue" has only recently begun to acquire greater attention (Barbet-Massin and Jetz, 2014). Climate variables (e.g. temperature and precipitation but also derived climatic indexes) are generally the most used variables in SDM (Thuiller, 2013). At current time, many different sources of climate data are freely available on the web (Barbet-Massin and Jetz, 2014) Worldclim (Fick and Hijmans, 2017) being the most common. Worldclim collects monthly climate data at several resolutions ranging from 10 minutes (about 300 square km) to 30 arc-seconds (about 1 square km). After initial release (1960-1990, Version 1.4) where only temperature (maximum, minimum and average), precipitation and 19 bioclimatic indices were available, new indices including solar radiation, vapor pressure and wind speed have been added, and all other indices extended for the period 1970-2000 (Version 2.0) (Fick and Hijmans, 2017). Worldclim implementation in SDM is very common in the scientific literature. For example, Casalegno et al. (2010) build an SDM describing the vulnerability of Pinus cembra to climate change. Märkel and Dolos (2017) used the 19 bioclimatic variables from Worldclim to calculate starting from climate data derived from German climate service. The final aim is to build a methodology to combine them in unique technique to better evaluate the climate change impact in Germany. However, two main shortcomings arise: i) the global extension makes the dataset often unsuitable for local application and ii) the lack of an adequate coverage in some regions of the globe make some climatic variables unreliable, especially precipitation data (Bedia et al., 2013; Marchi et al., 2019),

Given these limitations, an alternative or complementary source to Worldclim is the recently released ENVIREM dataset (Environmental Raster for Ecological Modeling). It combines a set of biological and topographic variables calculated from WorldClim rasters and solar radiation (Title and Bemmels, 2018).

Standalone software for climatic custom queries

The use of standalone software for local downscaling of climatic data is gaining attention in the scientific literature. Among these, ClimateEU, ClimateNA, and ClimateSA software packages are valuable tools (https://sites.ualberta.ca/~ahamann/data.html) with which to generate customized raster maps for Europe, North America and South America respectively, for both historical time slices or future scenarios. These packages provide a method to downscale PRISM data using a combination of bilinear interpolation and "dynamic lapse rate" adjustment. The PRISM (Parameter-elevation Regression on Independent Slopes Model) climate database, available for United States only, provides mean monthly precipitation and minimum and maximum temperature values for the period 1971-2000. These data were interpolated to produce climate variables for the entire United States using a

DEM available at 30 arcsec of spatial resolution (Daly et al., 2008). The software calculates monthly, seasonal and annual climate variables for a specified location on the base of latitude, longitude and elevation (Wang et al., 2012). Hamann et al. (2013) and Van der Maaten (2017) used this database to build an SDM for distribution of European tree forest species inclduing Norway spruce, Scots pine, European beech and Pedunculate oak. Isaac-Renton et al. (2014) also used ClimateNA and ClimateEU to build an SDM for Douglas fir and evaluate species transferability between continents in view of climate change. Concerning Europe, ClimateEU was used by Marchi & Ducci (2018) to generate raster surfaces at 250 m of spatial resolution in combination with NFI data.
Local climate datasets are undoubtably the most accurate source of information for SDM, but they are also the least accessible. Local data is used widely in forest management and especially in forest monitoring due to its higher precision and quality (Ferrara et al., 2017). Bedia et al. (2013) compared the use of national climate data to data from Worldclim in order to verify the differing sensitivity in SDMs using distribution data for Fagus sylvatica in smaller region. Local climate databases were also used in Crimmins et al. (2013). Four predictor variables (minimum and maximum temperature, mean annual actual evapotranspiration and mean annual climatic water deficit) hypothesized to have a direct influence on species distribution were tested in order to evaluate the success of a consensus approach for predicting the distribution of plant species.

Soil and land cover datasets

In addition to climate data, soil and land cover information can be included in SDM approaches. The principal characteristics of interest with regards to soil are PH, texture, fertility and soil moisture. Roces-Diàz et al. (2014) used NFI data for Spain together with 9 different predictors (among them an index of fertility of soils) to realize a distribution model which investigates the relationship between climate and the distribution of 6 different tree species. Coudun et al. (2006) used many different predictor variables to realize a SDM to investigate the importance of climate and other edaphic variables to distribution of Acer campestre. PH was a key variable together with other 6 other variables linked to aspects of soil. Despite soil being a critical predictor variable, its use in SDM is limited as the lack of available datasets in either digital format or suitable resolution makes it hard to find data of comparable quality to climate data (Mod et al., 2016; Thuiller, 2013). The most relevant and up-to-date information with global coverage is SoilGrids250m (Hengl et al., 2017). This dataset provides global predictions for standard numeric soil properties (organic carbon, bulk density, Cation Exchange Capacity (CEC), pH, soil texture fractions and coarse fragments) at seven standard depths (0, 5, 15, 30, 60, 100 and 200 cm), in addition to predictions of depth to bedrock and distribution of soil classes based on the World Reference Base (WRB) and USDA classification systems. The interpolated surfaces were built using more than 150,000 soil profiles and 158 remote sensing-based soil covariates (primarily derived from MODIS land products, SRTM DEM derivatives) used as predictors in a combination random forest model and multinomial logistic regression algorithm. In Manchego et al. (2017) this database was used to evaluate the potential effects of deforestation and climate change on the distribution of 17 characteristic forest tree species of dry forest in Ecuador.

In terms of land cover, land cover change (for example agricultural intensification) can have important effect on the distribution of different organisms. By including land cover data in SDM the explanatory power of the model is often increased, while the predictive performance remains unchanged (Thuiller et al. 2004). Despite this, use of land cover data has not been common in plant distribution studies, except when predicting species abundance (Bradley et al., 2012; Mod et al., 2016). For example, Hill et al. (2017) predicted the future abundance of typical forest trees in UK by means of a land cover change map. In addition to land use and land cover maps, Digital Elevation Models (DEM) or Digital Terrain Models (DTM) and mathematically derived maps (i.e. slope, aspect, topographic position index, etc.) are sometimes included. When choosing an appropriate DEM, spatial resolution and any uncertainties associated with interpolation are principal factors to consider (Franklin, 2010). Garzòn et al. (2006) used aspect and slope as predictors, while Duan et al. (2014) included altitude among several other predictive variables. However, generally the use of terrain models has often been neglected, given that the information they provide is already included in climatic maps and no climate change effects can be added to such predictors.

Modelling algorithms

Many different algorithms are currently implemented in SDM processes (Guisan et al., 2017) and 12 modeling methods have been described and selected according to their use in the analyzed literature (Fig. 1). There is consensus that a single and perfect technique for all possible SDM cases is impossible, and thus the selection of the an appropriate modeling algorithm is fundamental. As demonstrated by many studies (Beale and Lennon, 2012; Buisson et al., 2010; Duan et al., 2014; Jarnevich et al., 2015; Koo et al., 2017) choosing the correct algorithm can reduce the uncertainty within the model. The algorithms involved in SDM computational steps can be divided into different groups and according to various characteristics and grouping criteria. In this review paper the analyzed algorithms were firstly divided according to input data: i) presence only and ii) presence/absence algorithms. Then subgroups were made based on intrinsic characteristics e.g. distance based, linear (or regression model), classification and decision trees, machine learning. A graphical scheme of the proposed structure is shown in Fig. 2.

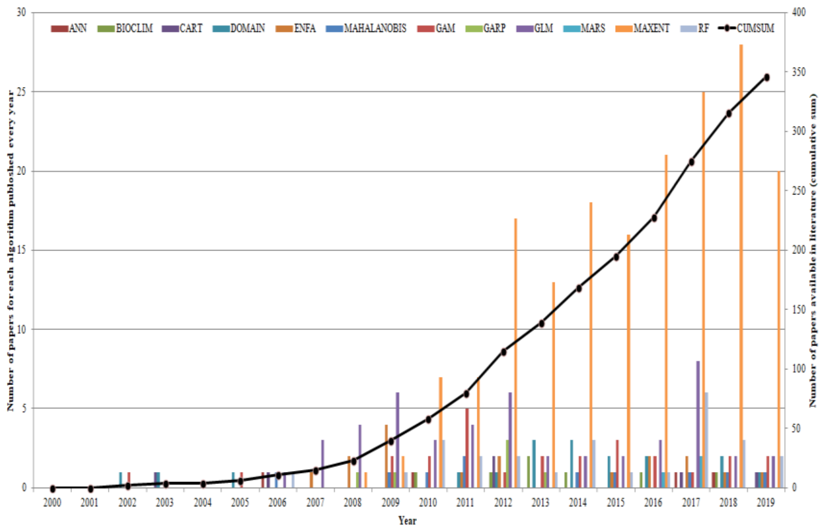

Fig.1. Number of Scopus papers published between 2000 and the present time dealing with the use of SDM in forestry and grouped according to the used modelling algorithm(s)

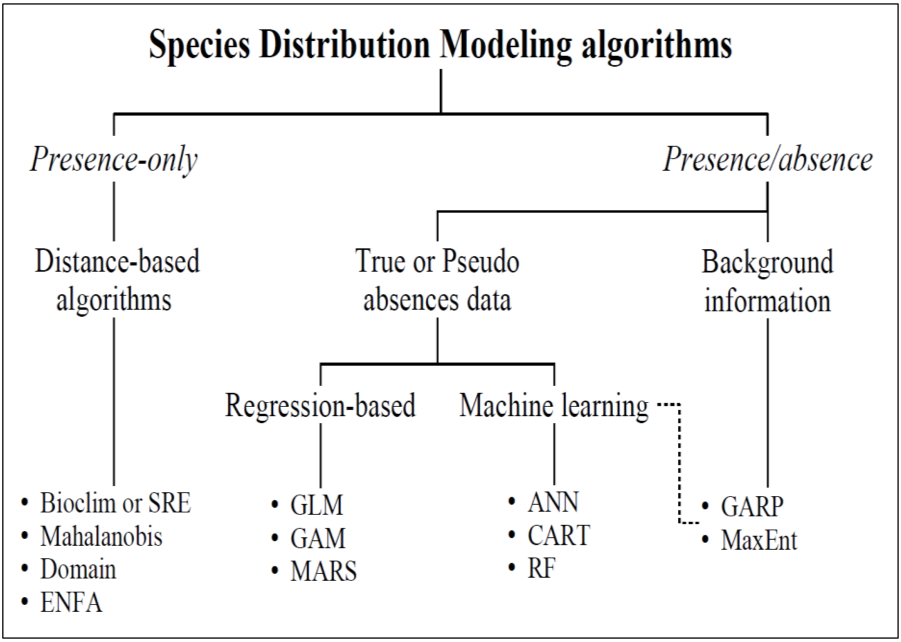

Fig.2. A hierarchical structure of the 12 SDM algorithms used by the literature analysed by this review

Presence-only algorithms

All techniques included within this group are characterized by their ability to model the spatial distribution of a target species simply on the basis of species occurrence (or presence). Very simple and computationally light, these are the oldest technique used in ecological modeling but also acknowledged as being less powerful and often unsuited for predicting the effects of climate change (Guisan et al., 2017; Hijmans and Graham, 2006; Miller, 2010). Algorithms included in this group and reported here are: Bioclim or Surface Range Envelope (SRE), the Mahalanobis Distance, the Domain algorithm and the Environmental Niche Factor Analysis (ENFA).

The Bioclim or Surface Range Envelope (SRE) algorithm has been extensively used for SDM and represents the classic 'climate-envelope-model' (Booth, 2014; Hijmans and Elith, 2011). Although it generally does not perform as well as some other modelling methods (Elith et al., 2006) it is still used as it is easy to understand and thus useful in teaching SDM. This method computes the similarity of a location by comparing the values of environmental variables at any location to a percentile distribution of the values at known locations of occurrence. The closer to the 50th percentile (the median), the more suitable the location is. A key shortcoming is that the tails of the distribution are not distinguished and the 10th percentile is treated as equivalent to the 90th percentile. Bioclim has been used less by recent literature and where it does occur, this is often in comparative papers. For example, Duan et al. (2014) evaluated the predictive capacity and solidity of different techniques for estimating species distribution for many forest tree species (Pinus massoniana, Betula platyphylla, Quercus wutaishanica, Quercus mongolica and Quercus variabilis). An interesting use of such algorithm is as ancillary model to generate pseudo-absences in biomod2 package (Thuiller et al., 2009a). In this package, Bioclim (called SRE) can be used to generate a user-defined number of pseudo absences in a target spatial extent, laying outside the ecological distribution of the species to be modeled and described by the occurrences.

We found the Mahalanobis distance to be the most popular algorithm among the distance-based methods. This method calculates the suitability area as a multivariate and environmental distance between the study area and a vector of optimum climate condition, generally calculated as a mean of all values which occur in a presence dataset (Farber and Kadmon, 2003; Peterson et al., 2011). The predictive power of Mahalanobis is higher than Bioclim (Farber and Kadmon, 2003) but some disadvantages still occur. Franklin (2010) highlighted the inability to weight the relative influence of different predictor variables.

Similarly, to Mahalanobis, the Domain algorithm (Carpenter et al., 1993) computes environmental distance. In this case the 'Gower' distance is used, which calculates the distance between environmental variables at any location and those at any of the known locations of occurrence (training sites). For each variable the minimum distance between a site and any of the training points is taken. To integrate findings across environmental variables, the maximum distance to any one of the variables is used and this distance is subtracted from one. Environmental Niche Factor Analysis (ENFA) is the last algorithm in the family of presence only and distance-based methods. This algorithm is able to estimate the ecological niche through a comparison of presence data and environmental values for the entire area (Guisan et al., 2017; Hirzel et al., 2002). Rupprect et al. (2011) used this method to evaluate the prediction capacity of different type of algorithms for a distribution of Juniperous oxycedrus species.

Presence-absence algorithms

This second group is populated by more complex and time-consuming but also more complete algorithms. This is due to both the higher amount of information they can handle and the inclusion of absences in the modeling steps. Indeed, absence data are often numerically more common than presence data (sometimes even ten times more). For this reason, such models need to handle this problem properly, weighting the sun of presences and absences equally. This statistical method is generally called "prevalence" (Barbet-Massin et al., 2012; Manel et al., 2001; Marchi and Ducci, 2018).

According to the statistical family, two different sub-groups can be defined: regression based and machine learning. The first group includes parametric models such as Generalized Linear Models (GLM), Generalized Additive Models (GAM) and Multivariate Adaptive Regression Splines (MARS). Among the immense literature on machine learning algorithms, Artificial Neural Network (ANN), Classification Trees (CART), Maximum Entropy (MaxEnt), Genetic Algorithm (GARP), and Random Forest (RF) are herewith discussed as the most used nonparametric algorithms.

GLM represent one of the principal algorithms in SDM, as a flexible and relativley simple tool derived from linear model (Guisan et al., 2002). The main characteristic of GLM which distinguishes it from a general linear model is the possibility to include a response variable with a different distribution family from the Gaussian, for example Binomial or Poisson (Guisan et al., 2017). This algorithm is particularly useful for non-normal distribution data (Bolker et al., 2009). Its use in the case of SDM is allowed by means of the specification of a binomial family and a logistic link function. The GLM algorithm is extensively used in the literature. Higa et al. (2013) assessed the importance of non-climatic factors on the provision of the potential habitat for typical Japanese tree species: Fagus crenata, Betula grossa, Carpinus laxiflora, Carpinus tschonoskii, Celtis sinensis, Ulmus laciniate and Zelkova serrata. Thuiller et al. (2006) evaluated the potential change in distribution of 112 tree species following climate change in Europe. In Roces-Diaz et al. (2014) GLM clearly revealed both the difference in habitat suitability among different tree species in Spain and the importance of predictor variables, in particular minimum temperature and soil fertility. Finally, Thuiller et al. (2009b) compared the predictive accuracy of GLM with GAM and CTA using three independent datasets of tree species at different scales and resolution. Results showed that the predictive performance of GLM were superior to other algorithms, especially at finer scales.

An "extension" of GLM is represented by the mixed-effecst Generalized Linear Mixed Model (GLMM). GLMM is currently not commonly used in the forestry sector and has only recently been applied to build a novel SDM approach (Benito Garzón et al., 2019) where forest tree species were modelled according to the performances obtained in common garden experiments. The main novelty of GLMM rely on the use of the common garden as random effect predictor which allows to handle the differences within sites in a model, "cleaning" the prediction from artifacts and unexplained differences. As an example, from another field, GLMM has been used to quantify the effect of imperfect detection on the estimation of niche overlap between two forest dormice (Muscardinus avellanarius and Glis glis) Paniccia et al. (2018).

GAM represents a natural expansion of the GLM algorithm (Guisan et al., 2002) with its principal feature being high flexibility. This aspect allows use of this algorithm to represent situations where there are non-linear combinations

between variables (Elith et al., 2006). GAM adopts a particular smoothing function to fit a non-linear relation between predictive variables and species occurrence. The GAM algorithm is used by Keenan et al. (2011) to compare the future distribution of different forest species with an output from mechanistic processes. Walentoski et al. (2017) used GAM to evaluate the suitability of a Franconian Plateau in the south of Germany for three different species in the context of climate change. Rivera and Lòpez-Quìlez (2017) compared algorithms including GAM, CART, MARS and MaxEnt to predict the potential distribution of 17 species of forest tree from NFI data. No significant differences were found between these techniques, although GAM showed a slightly higher predictive capacity.
Similarly, to GAM, the MARS algorithm is a further development of GLM. It is computationally faster than other algorithms of the regression family and is particularly suitable when a wide range predictive variables are available (Choe et al., 2016; Miller, 2010). This algorithm represents an important alternative to fitting non-linear responses using a piecewise linear fit instead of a smooth function. It has been used by Bedia et al. (2013) in comparison with GLM to evaluate the sensitivity of these algorithms to different climate databases. In Marchi et al. (2016) the algorithm was used to evaluate the potential effect of climate change on the spatial distribution of a marginal and peripheral forest population of European black pine (Pinus nigra spp. nigra var. italica) in comparison with GLM and RF and to generate a consensus map. In Perie and De Blois (2016) MARS is used together with other seven algorithms to evaluate the potential decline in habitat suitability for 5 forest tree species in Canada: Picea mariana (Mill.) Britton, Sterns & Poggenb, Abies balsamea (L.) Mill., Betula papyrifera Marshall, Acer saccharum Marsh. and Betula alleghaniensis Britton.
CART is the first nonparametric algorithm within the machine learning group. The technique is based on a recursive partitioning process, where the dataset is broken into small homogeneous groups. Noce et al. (2017) used this algorithm within a suite of different models to investigate the likelihood of future provision of suitability distributions for important forest tree species in Europe. The predictive performance of CART is compared with several otheralgorithms used by Aertsen et al. (2010) to model three different forest species (Pinus brutia, Pinus nigra, Cedrus libani) in Turkey. CART algorithms were found to be one of the most user-friendly models. McKenney and Pedlar (2003) used a CART algorithm to predict site productivity on the base of climatic and soil characteristics for two forest species in Canada.

ANN (or sometimes simply Neural Networks, NN) is a complex technique inspired by working principles of the brain. A basic ANN procedure consists of a network of simple elements (artificial neurons) representing the brain (Li and Wang, 2013). The use of a set of adaptive weights allow the tuning of the algorithms with a learning process. A non-linear relationship between a response variable and an explanatory variable is allowed and the possibility of use data in every statistical distribution except with Gaussian data are the most relevant features of the algorithm (Li and Wang, 2013; Pearson et al., 2002). ANN algorithm is among the 4 different techniques used by Thuiller (2004) to evaluate the potential distribution of different species of plant under various hypothetic climate change scenarios. Bedia et al. (2011) also use an ANN algorithm as one of 6 different algorithms in assessing and comparing the predictive performance for distributions of herbaceous plant species in a northern region of Spain. In most cases ANN turned out to be the best algorithm for predictive performance.

Often improperly reported as presence-only algorithm (Elith et al., 2011; Merow et al., 2013; Phillips et al., 2006), we include the MaxEnt algorithm in the presence/absence group. This is due to the fact that this algorithm is deeply different from SRE, Domain, Mahalanobis and ENFA. MaxEnt requires additional information about the external environment where the species is located: i.e. the background. This information is generally obtained automatically during computation by means of a spatial random sampling procedure (Guillera-Arroita, 2017). As recognizable from the name, this technique estimates the suitability of an area through a maximum entropy principle. The algorithm calculates the maximum entropy probability of the distribution species and compares it with a maximum entropy probability of the entire object region (Guillera-Arroita et al., 2015). The MaxEnt algorithm has been extensively used in the literature. Lahssini et al. (2015) studied the distribution of Ceratonia siliqua L. across Morocco. Results showed a good predictive performance. Antunez et al. (2018) used the algorithm to predict potential distribution for 13 tree species in three different time periods: the most recent glaciation, the present and the future period using the A2 scenario form the Third Assessment Report of IPCC. Del Rio et al. (2018) implemented MaxEnt to evaluate the principal driving factors shaping the distribution of Spanish beech in current and future climate conditions. Cruz- Cardenas et al. (2014) developed a methodology to reduce or resolve the problem of spatial autocorrelation for predictor variables with MaxEnt, offering a PCA for predictor variables and randomness selection for presence records. Clark et al. (2014) examined the current and future potential distribution of an important invasive species (Ailanthus altissima) in the Appalachian region of the United

States. Finally, Dyderski et al., (2018) modelled the potential distribution of 12 forest species for current and future climate conditions.

GARP (Genetic Algorithm for Rule-set Prediction) works similarly to MaxEnt in that it requires a presence/background method (Barbet-Massin et al., 2012). The 'genetic algorithm' works on the base of a set of mathematical rules, which are randomly selected and interpreted as a different and limited environmental condition or particular relationship between the environment and a species. Each rule is defined as a "gene", and each combination of genes generates a different algorithm (Janet Franklin, 2010; Li and Wang, 2013). Elith et al. (2006) use GARP among 16 different algorithms to predict the potential distribution of 226 different species (both animals and plants) in 6 different regions of the globe. GARP was found to be the most suitable and best- performing algorithm. Vessella and Schirone (2013) used both MaxEnt and GARP to investigate the potential distribution of Quercus suber on the basis of current climate conditions. The GARP algorithm outperformed MaxEnt, with drought and cold stress found to be the main factors influencing the distribution of the species.

RF is one of the most important, most used and high-performing algorithms. It consists of a series of decisional trees, which are randomly generated and used to build a virtual forest. Each single tree is constituted by a random bootstrap sample (Wang et al., 2016). The most important feature of RF is that it is nonparametric and not vulnerable to collinearity. Moreover, it is a robust algorithm and performs well with large datasets (Li and Wang, 2013). Shortcomings of the algorithm include over-fitting which can occur in some cases and the black-box structure which doesn't allow the user to fully understand the calculation process as well as the weights applied to predictors. Morin and Thuiller (2009) used different techniques to assess the potential range shift of 15 different north-eastern American tree species in the context of climate change. This technique (RF) was compared to PHENOFIT which is a process-based model and in addition to all the correlative algorithms contained within the biomod2 package (Thuiller et al., 2009a). The main aim was to compare the final output of a niche-based method with other mechanistic models. A high degree of uncertainty was demonstrated by the results which was similar for both models. Attorre et al. (2011) compared RF, GAM and CART to evaluate the potential effects of climate change on the abundance of 27 species on the Italian peninsula. In Garzòn et al. (2006) FR, ANN and CART are used to study the potential distribution area of Pinus sylvestris RF demonstrated the best predictive performance. RF is also used in Koo et al. (2017) 6 other algorithms were combined to model the geographical distribution of Machilus thunbergi Siebold & Zucc. a typical evergreen broadleaved tree in

Korea Peninsula. Finally, RF was used in Benito Garzón et al. (2008) together with CART and ANN to study the future tree distributions in the Iberian Peninsula. The predictive performance of RF is consistently found to be slightly higher than other models.

All the above-described algorithms are briefly summarized in Table.1 where the main software involved in SDM are reported. For each of them the included algorithms are reported. Concerning R language, the basic packages such as, for instance, stats for GLM, mgcv for GAM, randomForest for RF etc. were dropped.

Tab. 1. List of software currently available for SDM and related characteristics

Software	Reference	Operating System	Implemented Algorithms
Biomod2 (R package)	(Thuiller et al., 2009)	Linux distributions, Mac OS, Windows	SRE, ANN, CART, GAM, GARP, GLM, MARS, MaxEnt, RF
dismo (R package)	(Hijmans et al., 2015)	Linux distributions, Mac OS, Windows	Bioclim, Mahalanobis
SDM (R package)	(Naimi and Araújo, 2016)	Linux distributions, Mac OS, Windows	ANN, GLM, GAM, MARS, CART, RF, ENFA, MaxEnt, Domain, Mahalanobis distance
SDM toolbox (ARCGIS)	(Brown, 2014)	Windows only	MaxEnt
ENiRG (GRASS + R)	(Cánovas et al., 2016)	Linux distributions, Mac OS, Windows	ENFA
Species	(Pearson et al., 2002)	Windows only	ANN
MOPA (R package)	(Iturbide et al., 2015)	Linux distributions, Mac OS, Windows	GLM, SVM, MaxEnt, MARS, RF, CART

Model evaluation

As stressed in section 4, the choice of SDM algorithm can give different predictions for habitat suitability. The causes of these observed difference can be due to the small sample sizes and measurement errors, as well as possible omission of an important predictor variable, and the choice of GCM and climate scenario used (Buisson et al., 2010; Marmion et al., 2009). In the scientific literature many comparisons between differential algorithms have been published in order to quantify and evaluate this variability and uncertainty. This issue can raise further problems, in particular: i) how to compare between different statistical algorithms? ii) which parameters should be used for evaluation? and iii) how to evaluate the compatibility between the statistical model and ecological model? In such a framework two principal solutions to resolve these problems are reported in literature: i) comparison between different models can be made by indicators of goodness of "fit", or ii) a consensus model approach can be used to balance projections obtained from different algorithms (Austin, 2007; Cheaib et al., 2012; Marmion et al., 2009; Thuiller, 2004). Both approaches aim to assess the relative accuracy of different modelling algorithms. Within these solutions, methods can be groups into one of two categories: threshold dependent, or threshold independent (Liu et al., 2011; Watling et al., 2013). A threshold independent method evaluates the performance of algorithm only based on comparison of the resulting probabilities. In contrast, a threshold dependent method requires the conversion of raw probabilities produced by the algorithm into two classes based on a defined cut-off value or threshold (Watling et al., 2013). The choice of threshold is a key source of uncertainty. Three different approaches can be followed: a) fixed threshold, b) data-driven (i.e. linked to species data or predicted probability); c) accuracy based (i.e. the value is selected to produce the best compromise between original and the evaluated data) (Hanewinkel et al., 2014a). In ecology, three main methods are consistently applied: Area Under Curve (AUC) or Receiver Operating Characteristic (ROC), Kappa or Cohen Kappa Statistic and the True Skill Statistic (TSS) (Leroy et al., 2018). While the first technique is generated by means of an analysis of the AUC curve, the last two methods are derived from the 'confusion matrix' classification system, which facilitates visualization of the performance of an algorithm (Márcia Barbosa et al., 2013). The AUC "Area Under Curve" or ROC values represents an independent threshold technique. AUC produces a bi-dimensional analysis with true positive error on the y axis and false positive error on the x axis (Fig.3). The value of AUC can vary between -1 and 1 (Noce et al., 2017; Rivera and López-Quílez, 2017). Much of the literature reports the method to be biased and of limited use. Lobo et al. (2008) report five key disadvantages: i) it ignores the predicted probability values and goodness-of-fit; ii) performances are calculated over regions of the ROC space in which one would rarely operate; iii) omission and commission errors are weighted equally; iv) lack of information concerning spatial distribution of model errors; v) model extent strongly influences the rate

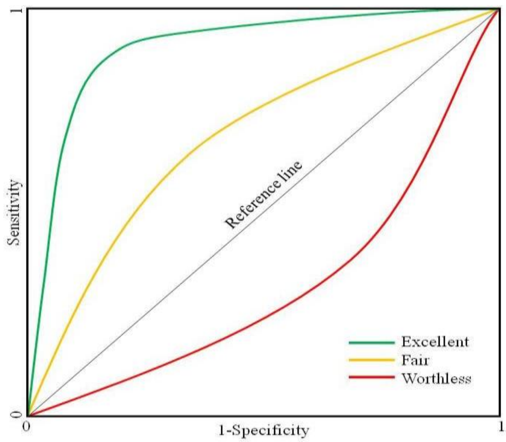

Fig.3. Possible AUC (or ROC) curves in SDM evaluation

of well-predicted absences and AUC scores.
Despite these disadvantages AUC continued to be used, even by recent papers. Alternatively, threshold dependent methods such as the Kappa or Cohen Kappa rates algorithm performance between 0 and 1, with 1 representing good agreement between predicted and observed presence data. The indicator is calculated according to the following equation:

$$Kappa = \frac{(\mathrm{TP}+\mathrm{TN}) - \frac{[(\mathrm{TP}+\mathrm{FN})\cdot(\mathrm{TP}+\mathrm{FP}) + (\mathrm{FP}+\mathrm{TN})\cdot(\mathrm{FN}+\mathrm{TN})]}{N}}{\mathrm{N} - \frac{[(\mathrm{TP}+\mathrm{FN})\cdot(\mathrm{TP}+\mathrm{FP}) + (\mathrm{FP}+\mathrm{TN})\cdot(\mathrm{FN}+\mathrm{TN})]}{N}}$$

where TP is the number of true positives, TN is the number of true negatives, FP is the number of false positives and FN is the number of false negatives detected by the algorithm on the total number of testing samples (N). The method is limited by the fact that it is strongly reliant on linked to species prevalence, as well as uncertainty relating to the application of a threshold (Miller, 2010; Watling et al., 2013, 2012).
TSS "Total Sum of Squares" is also threshold dependent, but it has the advantage of being independent from species prevalence. Values between -1 and 1 correspond to the sum of the value of sensitivity and the value of specificity, which are calculated as a proportion of presence areas and absence areas respectively (Barbet-Massin et al., 2012). TSS is calculated using the following equation:

$$TSS = \mathrm{Sensitivity} + \mathrm{Specificity} - 1$$

where:

$$Sensitivity = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

$$Specificity = \frac{\mathrm{TN}}{\mathrm{FP} + \mathrm{TN}}$$

Both AUC and TSS have been applied by Noce et al. (2017) to evaluate the capacity of different SDM algorithms to predict potential future suitability of hot-spots for many important forest tree species in southern of Europe. Morin and Thuiller (2009) used only AUC to evaluate predictive performance of alternative niche modelling techniques (process based vs. correlative). Similarly, only the Kappa statistic was calculated by Freeman and Moisen (2008) to evaluate predictive performance of SDM for 13 forest tree species in USA. A combination of methods was used by Falk and Hempelmann (2013) to evaluate predictive performance. Zhang et al. (2015) compared all three different methods to evaluate the accuracy of alternative predictive models to study plant distribution in China. AUC and TSS were found to outperform Kappa. Thurm et al. (2018) also adopted TSS to evaluate algorithms used to estimate the present and future potential distribution of 12 forest tree species in Europe.

All the statistics discussed above are among the most used (but not the only) in literature and are often employed to generate consensus or ensemble maps. The interest in ensemble modeling is growing rapidly, not only in ecology but also in other fields such as economy and medicine. Individual algorithms are combined using different techniques: for example, a selective algorithm (PCA) or a mathematical or statistical function such as taking the median, mean or weighted average. Taking the mean remains the most commonly used option in SDM (Kindt, 2017; Marmion et al., 2009). In many papers studying the forestry sector, TSS values are the most common weight applied to each algorithm. Keenan et al. (2011) evaluated the predictive performance of models using the weighted mean of TSS. Engler et al. (2013) used the same technique to present an interesting method to map the distribution of each individual tree belonging to a principal forest species in Switzerland. Zhang et al. (2015) calculated Kappa, AUC and TSS values for each different SDM algorithm, employing an ensemble technique which considered three different functions: the median, the frequency and the simple mean.

Future scenarios: dealing with the uncertainty behind modeling steps

The process of selecting adequate software, presence/absence datasets, environmental predictors, modeling algorithms and weighting procedures is often carried out with the aim of exploring future scenarios in order to derive insight on how climate change might impact forest tree species distributions. The future provision of ecosystem services will be highly influenced by climate change (Albert et al., 2017; Ray et al., 2019) and SDM techniques can support decision makers in developing forest management strategies. The use of better adapted forest tree species (genotypes) and provenance selection (genotyping) will improve the resilience of forest systems and allow assisted migration strategies (Hanewinkel et al., 2014; Marchi and Ducci, 2018) thus enforcing the adaptive processes of forest ecosystems (Ferrarini et al., 2016). Dealing with the uncertainties generated by climate change is a challenging matter. By sampling along latitudinal (north-south or east-west) or altitudinal gradients, research strategies often aim to search for regions where local adaptation is taking place (Becerra, 2016; Boisvert-Marsh et al., 2014; Kozyr, 2014). The selective pressure exerted upon genotypes at higher elevations (colder temperatures) or southern latitudes (warmer temperatures) forces forest species to adapt to local conditions. This kind of adaptive process, if recognized as genetic difference, will be a valuable resource in forest management strategies (Williams and Dumroese, 2013).

Future projections are generally based on a specific emission scenario, which represents a hypothetical image of the possible trend in greenhouse gas emissions. Alternative pathways for environmental, socio-economic, technological and demographic development are also included. Currently, the most commonly used projections have been generated by the IPCC 5th Assessment Report (AR5). Emission scenarios are represented by "Representive Concentration Pathways" (RCPs) with four possibilities trajectories of increasing severity (RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5). These replaced the previous Special Report on Emissions Sscenarios (SRES): A1, A2, B1, B2 (Goberville et al., 2015). In addition to the AR5 RCPs, many Global Circulation Models (GCM) have been developed by research groups around the world, often targeted at specific geographic regions. These regional GCMs rely heavily on statistical probability, which introduces deep degree of uncertainty in SDM efforts using those datasets. For this reason, researchers have tried to tackle the issue by combining multiple GCM and RCP inputs and analyzing the resulting variance. The most common method is to average different outputs (Goberville et al., 2015). For example, Iverson et al. (2008) used three different climate models and data from the SRES emission scenarios A1 and B1. Walentowski et al. (2017) did repeated this method using new AR5 scenarios, thereby providing a comparison. Hanewinkel et al. (2010) used data from emission scenarios A2 and B1 to predict the possible economic consequences of a shift from Picea abies to Fagus sylvatica in Southern Germany. Finally, Benito Garzón et al. (2008) used data from a range of emission scenarios (A1, A2, B1, B2) to simulate the impact on the distribution of the Iberian tree species in three different time slices: 2020s, 2050s, 2080s. The use of Regional Climate Models (RCM) allow higher precision than GCM due to their greater detail at small scale (Franklin et al., 2013; Koca et al., 2006). RCM are derived from GCM models through a process of statistical downscaling. For instance, an interesting comparison was made by Liu et al. (2014) where the use of GCM or RCM was assessed when dealing with climate change impacts and the future scenarios for invasive plants in USA.

A "static" SDM (i.e. no migration included) is based on the assumption that species distribution is in equilibrium with climate and will react locally to a changing climate. The inclusion of the migration capacity of different tree species is a rapidly increasing theme in recent literature and could be used to improve estimations of the ability of a target species to colonize new sites. Two important methods are currently available to evaluate the migration capacity: the MigClim (Engler et al., 2012) and KissMig algorithms (Subba et al., 2018). Both are currently available as R packages and while the first enables the implementation of species specific dispersal constraints into projections of SDM, KissMig offers a simple, raster-based and stochastic migration model (Nobis and Normand, 2014).

Conclusions

This review has found an evident increment in scientific contribution relating to SDM from 2000 to 2019, demonstrating a growing interest for the technique. The primary aim of SDM in forest research and management is to derive insights relating to the future potential distribution of tree species in order to implement effective adaptation strategies (Janowiak et al., 2017). The literature highlights that the correct interpretation and use of presence/absence datasets is central to deriving a correct estimation of the ecological niche for the species in question. Another key finding is the need to reduce the uncertainties associated with modelling steps (e.g. reliability of species distribution data, climate surfaces, GCMs) and further work in this area is highly important to improve estimations of future forest distribution and resulting ecosystem services.

A key downfall of SDM as it stands is the lack of inclusion of biotic interaction into the modeling procedure. Inclusion of these processes would see a shift from SDM to true Ecological Niche Models. However, such models, even if theorized, are yet to be achieved. A promising area of further research are multi-species and multi-level SDM, where many target trees are modeled at the same time. Currently only single tree models are in use, leaving the final merging procedure to a simple overlay process in a GIS environment. Host-disease models offer a similar promising advancement, where both host and disease are modelled according to climate change scenarios to simulate the potential future impact of biotic stresses (e.g. insects, fungi, bacteria) on forest tree species. In this case a co-evolution in modelling techniques is expected and, consequently, a combined SDM offers a promising method to model such interactions.

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3.2: Reviewing climatic traits for the main forest tree species in Italy

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Abstract: The future dynamics of forest species and ecosystems depend on the effects of climate change and are related to forest management strategies. The expected impacts of climate change are linked to forest growth and productivity. An increase in the length of the growing season and greater productivity are likely as well as shifts in average climatic values and more variable frequencies, intensities, durations and timings of extreme events. The main aim of this work is to assess and describe the climatic requirements for Italian forest tree species. We used 7272 field observations from Italian National Forest Inventory plots and average annual temperatures and precipitation as interpolated from raster maps with 1 km spatial resolution. On this basis we evaluated the current observed distributions of the 19 most important tree species in Italy with respect to potential climatic limits based on expert knowledge and the available literature. We found that only 46% of the observations fall within the potential joint temperature and precipitation limits as defined by expert knowledge. For precipitation alone, 70% of observations were within the potential limits, and for temperature alone, 80% of observations were within the potential limits. Similarity between current observed and potential limits differ from species-to-species with broadleaves in general more frequently distributed within the potential climatic limits than conifers. We found that ecological requirements and potential information should be revised for some species, particularly for the *Pinus* genus and more frequently for precipitation.
The results of the study are particularly relevant given the threat of climate change effects for Italian forests which are broadly acknowledged to be a biodiversity hotspot. Further investigations should be aimed at modelling the effects of climate changes on Italian forests as a basis for development of mitigation and adaptation forest management strategies.

Keywords: National Forest Inventory; sustainable forest management; spatial analysis; forest monitoring; climatic drivers

Introduction

The sustainable management of forest resources is acknowledged as one of the main issues for human well-being (Wagner et al. 2014). Forests are fundamental for economic and productive aspects, as indicated by the growing interest in the bioeconomy (Corona, 2015) and strategies for mitigating the effects of future climate. The Intergovernmental Panel on Climate Change (IPCC), characterizes climate change as "any change in climate over time, whether due to natural variability or because of human activity" (IPCC, 2001). For most scenarios, the expected increase in average annual temperature ranges between +2 and +4°C for this century. The precipitation regime is predicted to be more discontinuous with precipitation concentrated in fewer and potentially dangerous extreme events (Ummenhofer and Meehl, 2017). The combined temperature and precipitation interactions may threaten forest ecological processes leading to modifications of growth rates and delivery of ecosystem services (Ray et al. 2017). Moreover, changes in the frequency, intensity, duration and timing of "exogenous disturbances" such as wildfires, pests and diseases are expected.

Climate change effects have already been observed for tree species and ecological systems (Lindner et al. 2010). For example, Boisvert-Marsh et. al. (2014) reported a latitudinal shift of the distribution of forest species in North America; similar studies have been conducted in Europe and specifically in the Mediterranean region (Marchi et al. 2016). Chirici et al. (2017) reported the effects of recent, unprecedented windstorms in Italy, and Allen et al. (2010) conducted a global review of tree mortality following heat waves and water stresses.

Forest planning oriented on implementing strategies that adapt to climate change are central across all of Europe (Petr et al., 2014). The growth rate and resilience of forest systems to disturbances are directly connected to ecological requirements and adaptation capacity (Williams & Dumroese 2013). Changes in species composition, reduction in biodiversity reduction and smaller wood increments with reduced carbon sequestration are just few examples of the possible effects of climate change on forest ecosystems. In this sense, future provisioning of forest ecosystem services will be strongly influenced by the soil type, climatic drivers and forest management (Lindner et al. 2010, Ray et al. 2017).

The worldwide relevance of forests in climate change scenarios is acknowledged in international agreements, particularly by the IPCC (2014), thanks to their ecosystem services such as Volatile Organic Compounds absorption and CO2 sequestration (Canadell and Raupach, 2008). Knowledge of the ecological plasticity of a given species is essential to support selection of suitable forest planning and management choices for mitigating the adverse effects of climate change (Nocentini et al., 2017). As a consequence, adequate and current information on forest tree species auto-ecology can be useful for adaptive forest management and for genetic selection (Williams & Dumroese 2013, Marchetti et al. 2015).

Recently, the Joint Research Centre (JRC) of the European Commission proposed a broad study on all forest tree species found in Europe: the European Atlas of Forest Species (San-Miguel-Ayanz et al., 2016). This publication describes the main forest European tree species and their ecological and genetic characteristics. Predictive models have been applied to construct land suitability maps for each species. The spatial data were obtained starting from the European Forest Data Center - Forest Information Service for Europe (EFDAC-FISE) (http://forest.jrc.ec.europa.eu/) datasets while local bioclimatic variables were retrieved from publicly available datasets at the global scale. Using these data, a series of three bi-dimensional auto-ecology diagrams or climate space diagrams were drawn for each species. These graphs describe the distribution of species relative to pairs of bioclimatic factors: annual average temperature and total annual precipitation which are investigated for this study, potential solar irradiation during spring and summer season with the average temperature of the coldest month and the seasonal variation of the monthly precipitation. However, no numeric values have been publicly shared. Another extensive study regarding forest tree species is represented by the climate change tree Atlas proposed by the USDA Forest Service (L. R. Iverson et al., 2008). This Atlas is based on plot data acquired by the Forest Inventory and Analysis program of the USDA Forest Service and forms a spatial database for the 134 most common forest tree species in the eastern USA. The main aim of this database is to evaluate the current distribution of forest species and to forecast the possible impacts of climate change using regression tree analysis, bagging trees and random forest (RF) as predictive algorithms.

NFIs are the most extensive and comprehensive source of forest information suitable for spatial analysis, ecological modelling and statistical mapping of forest attributes (Johnson et al. 2014, Marchi & Ducci 2018, Di Base et al. 2018). Raw georeferenced data for sampling units obtained in the field are fundamental for many research activities in the forestry field and are becoming publicly available in most countries (Borghetti & Chirici 2016, Mauri et al. 2017). At the same time, several large research projects from the last decade have made spatially interpolated climate variables available at different scales (Maselli et al. 2012, Fick & Hijmans 2017). All the above-mentioned spatial sources of information are now available for the entire Italian territory, although no extensive analysis of the relationships between tree species distributions and current climate conditions have yet been conducted. Despite Italy being one of the most climate change prone countries in Europe and in the Mediterranean region, auto-ecological characterization of vegetation in Italy still relies on expert-based literature (Bernetti, 1995) and empirical observations based on the bioclimatic classification proposed early in the last century by Pavari (1916), and later implemented by De Philippis (1937).

The primary scientific literature consulted to assess auto-ecological characteristics of forest tree species consists of a recent series of textbooks by Del Favero (2004, 2008, 2010) and Pedrotti (2013). However, no additional quantitative information about the auto-ecology of species beyond Bernetti (1995) could be identified.

Climate is acknowledged to be one of the main factors accounting for the spatial distribution of forest tree species and represent one of the most important aspect to be carefully evaluated in forest monitoring efforts (Del Favero 2010, Ferrara et al. 2017). Thus, a detailed and current analysis of the relationship between vegetation and climate is essential for any investigation of the possible climate change effects on forest species distributions. The main aim of this study is to update knowledge on the climatic drivers related to the most important forest tree species in Italy. We used 7272 field plots from the most recent Italian NFI, INFC2005, for which data are currently available, and the 1 km resolution climatic temperature and precipitation data from downscaled E-OBS gridded data (version 17.0) from the EU-FP6 project ENSEMBLES (Haylock et al., 2008). We compared our findings with ecological niche information available in the literature. This analysis is intended as a starting point for further studies on future spatial distributions of tree species and growth models under climate change scenarios. In fact, adequate and current knowledge of ecological requirements for forest tree species represents the main source of information for future projections and forest ecosystem assessments.

Materials and Methods

The spatial distributions of tree species in Italy were determined from the raw INFC2005 data freely available at https://www.inventarioforestale.org/ (Borghetti and Chirici, 2016). INFC2005 was based on a three-phase sampling procedure with 13m-radius plots located at the intersections of a 1-km x 1-km grid. Such scheme gave a statistical robustness to this dataset and can be used for further analysis. Here we used data for all 7272 plots from the INFC2005 third phase that were visited in the field between 2006 and 2007. For each plot,

data for the callipered trees are in the form of 230,874 tree records which served as a key source of information species distribution analysis.
We considered 19 forest tree species selected as the most representative based on economic, ecological and landscape factors: European beech (*Fagus sylvatica L.)*, silver fir (*Abies alba Mill.),* Norway spruce (*Picea abies)*, downy oak (*Quercus pubescens Willd),* Turkey oak *(Quercus cerris L.),* common chestnut *(Castanea sativa Mill),* holm oak *(Quercus ilex L.),* European larch *(Larix decidua),* black pine *(Pinus nigra),* cork oak (*Quercus suber),* sessile oak *(Quercus petraea),* Aleppo pine *(Pinus halepensis),* maritime pine *(Pinus pinaster),* Corsican pine (*Pinus laricio),* stone pine (*Pinus pinea),* pedunculate oak *(Quercus robur),* arolla pine *(Pinus cembra)* , Mediterranean cypress *(Cupressus sempervirens*) and Douglas fir *(Pseudotsuga menziesii Mirb.* Franco). The number of forest inventory plots by species is reported in Tab.1. For this study, Bernetti (1995) was considered the sole reference regarding the climatic limits of Italian forest tree species. Bernetti (1995) describes 81 species with respect to botanical, geographic and ecological factors and includes potential climatic ranges based on mean annual temperature (MAT) and total annual precipitation (TAP, Tab. 1).
Climatic temperature and precipitation data were derived from a 1-km downscaled climatological maps for Italy for the 1981-2010 period developed from the E-OBS database. Specifically, these climatic data were derived using a downscaled procedure via a spatially weighted regression model fully described by Maselli et al. (2012). The significant underestimation of mapped rainfall reported by Maselli et al (2012) was corrected using ground measurements reported by Fibbi et al. (2016).
Because INFC2005 plots may include multiple tree species (Bravo-Oviedo et al., 2014), we omitted species representing less than 15% of the plot basal area (Giannetti et al. 2017). The dataset included a total of 7272 tree species observations. For each georeferenced INFC2005 plot we further extracted the total rainfall and average annual temperatures from the downscaled E-OBS 1 km resolution maps.
All spatial analysis was in the R statistical language (R Core Team, 2018).

Tab. 1 – Studied tree species and observations (i.e. plots Studied tree species and observations (i.e. plots from INFC2005). For each species the basal area share, and standard deviation are reported and including the extreme limits (average annual temperatures and annual total precipitation) reported by Bernetti (1995).

SPcode	**Species**	**Observations**		**MinTmean**	**MaxTmean**	**MinPrec**	**MaxPrec**
		n	**%**				
10	*Abies alba*	210	2.8	6	12	1200	1500
280	*Castanea sativa*	865	11.4	10	14	700	2400
60	*Cupressus sempervirens*	42	0.6	12	17	800	1200
330	*Fagus sylvatica*	1003	13.2	6	12	1200	1500
80	*Larix decidua*	465	6.1	1	5	400	700
20	*Picea abies*	715	9.4	3	7	400	2000
45	*Pinus laricio*	104	1.4	7	12	1400	1800
40	*Pinus cembra*	58	0.8	1	5	400	2000
42	*Pinus halepensis*	155	2.0	15	23	300	400
49	*Pinus nigra*	329	4.3	7	12	1400	2900
47	*Pinus pinaster*	113	1.5	14	30	800	1200
43	*Pinus pinea*	93	1.2	14	18	350	600
90	*Pseudotsuga menziesii*	33	0.4	8	13	700	1500
300	*Quercus cerris*	1078	14.2	10	14	700	2400
311	*Quercus ilex*	494	6.5	12	17	800	1200
307	*Quercus petraea*	155	2.0	10	15	700	2400
308	*Quercus pubescens*	1392	18.4	10	14	700	2400
302	*Quercus robur*	89	1.2	10	15	700	2400
313	*Quercus suber*	179	2.4	14	18	600	800

Results

The distributions of 19 tree species from INFC 2005 plots relative to TAP and MAT are graphically reported in Table 2 and Fig. 1 along with the comparisons to the potential limits for these variables reported by Bernetti (1995).

Tab. 2 – Results from spatial overlay between INFC plots and interpolated climatic data used in this study.

Species	MinTmean	Tmean	MaxTmean	MinPmean	Pmean	MaxPmean
Abies alba	2.10	8.03	15.78	676	1310	2002
Castanea sativa	3.80	11.76	17.20	669	1238	2257
Cupressus sempervirens	10.78	14.00	17.95	487	865	1359
Fagus sylvatica	3.07	9.15	15.78	742	1361	2708
Larix decidua	-0.91	5.40	11.56	589	1067	1914
Picea abies	-0.88	6.32	12.86	570	1170	2446
Pinus laricio	9.46	11.81	15.20	752	1116	1543
Pinus cembra	0.85	3.27	6.86	642	942	1213
Pinus halepensis	11.53	14.92	17.60	447	772	1310
Pinus nigra	5.44	11.31	16.11	663	1172	2441
Pinus pinaster	9.81	13.19	16.38	614	1039	1789
Pinus pinea	11.75	14.99	17.97	480	831	1345
Pseudotsuga menziesii	6.99	11.26	14.80	802	1261	1929
Quercuscerris	7.51	12.54	17.07	607	1011	1847
Quercus ilex	8.60	14.07	17.53	507	883	1529
Quercus petraea	5.78	11.73	16.18	546	1188	1999
Quercus pubescens	5.16	12.82	17.66	527	965	2098
Quercus robur	9.13	13.16	16.87	649	1002	1810
Quercus suber	12.37	15.00	18.01	473	751	1347

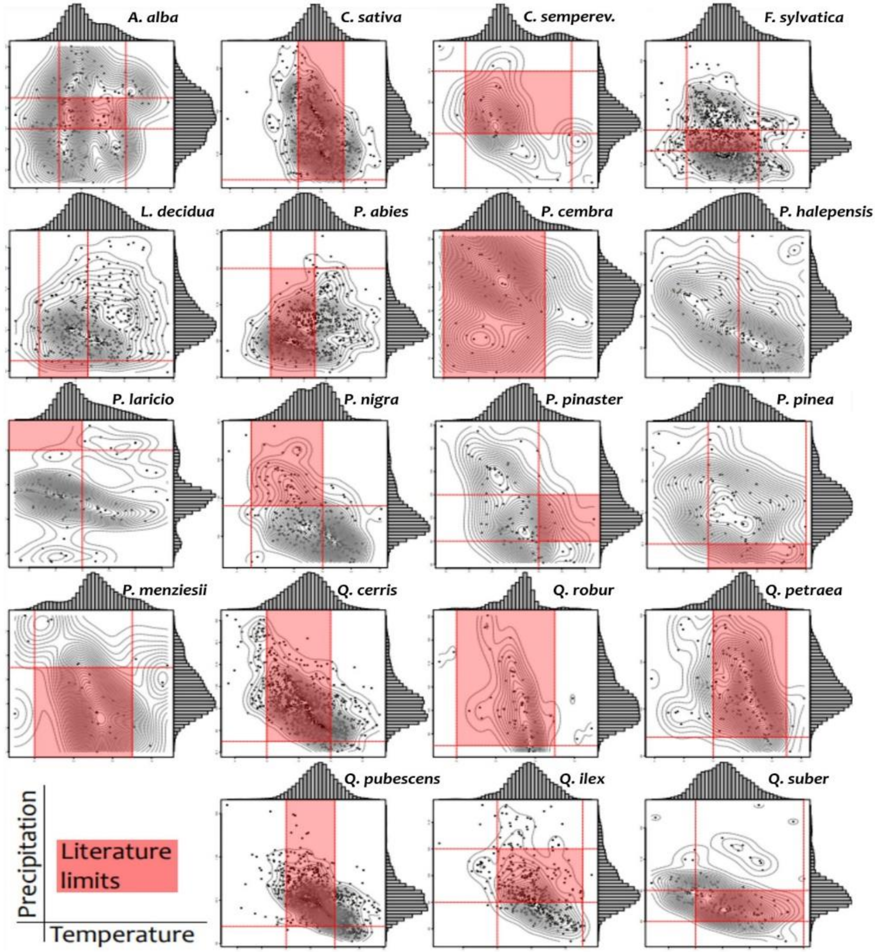

Fig. 1 - Distribution of the 19-tree species in terms of average annual temperature (x axis) and total annual precipitation (y axis). The literature limits are highlighted as a red square. Marginal histograms represent the distribution of records.

In Fig.1 a bi-dimensional graph for each species is presented with MAT values as the x-axis and TAP as the y-axis. On the side opposite the axes, density distribution graphs have been added to characterize the frequency of records across the analyzed ecological ranges. Asymmetric distributions were often observed, mainly for rainfall. This is confirmed by the skewness and smaller ranges for the histograms, i.e., the distribution tails were often outside literature limits or were poorly characterized. The current observed MAT and TAP distribution limits for the 19 Italian forest tree species are reported in Fig. 2.

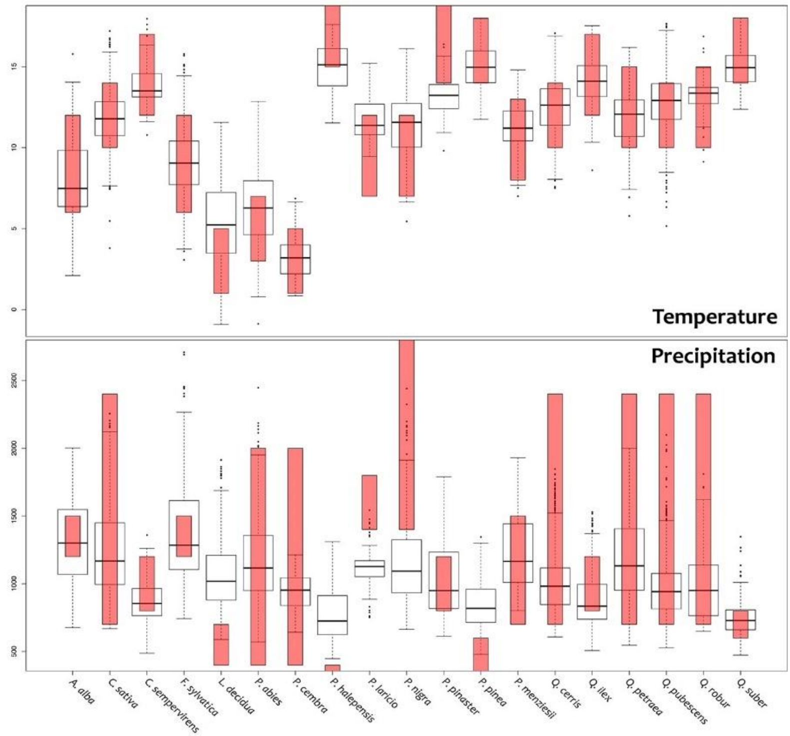

Fig. 2 – Boxplots for precipitation (above) and temperature (below) values retrieved from INFC data for the 19 different forestry species. Literature limits are reported as red rectangles

The spatial analysis shows that the climatic ranges proposed by Bernetti (1995) are generally appropriate. Of the total number of observations for the 19 species, 46% fall within the joint temperature and precipitation ranges, 70% fell within the ranges for TAP alone, and 80% fell within the ranges for MAT alone. Similarities between current observed and Bernetti (1995) potential ranges differed by species (Fig. 3).

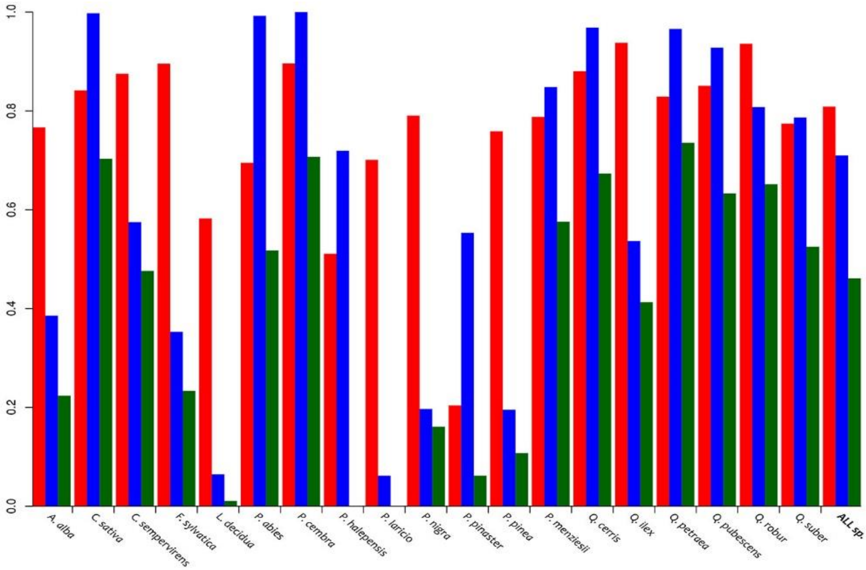

Fig. 3 – Proportion of observations falling within literature limits for each species and the whole dataset concerning temperature (red), precipitation (blue) and both (green).

For the species of the *Fagaceae* family which represent almost the 70% of the observations, the limits of our current observed distributions are similar to the potential limits reported by Bernetti (1995): for all species of this family the current observed limits fell within the Bernetti (1995) limits (Figure 2). For the genus *Quercus*, at least 60% of the observations with the exception of the most Mediterranean species (*Quercus ilex* and *Quercus suber*) were usually within the potential limits for both MAT and TAP. *Q. ilex* tends to grow in drier conditions than those described by Bernetti (1995) with current observed TAP of 883 mm versus a potential minimum of 800 mm, while *Q. suber* tends to be distributed in cooler and more humid areas than the potential limits of Bernetti (1995).
The current observed distribution of *Castanea sativa* is similar to the potential distribution with 70% of the observations within both the temperature and precipitation potential limits. Also, for *Fagus sylvatica* the temperature limits are similar, while for precipitation the observations show that beech forests are also present in extremely rainy sites. From this perspective, the maximum potential TAP limit of 1500 mm reported by Bernetti (1995) is too low.
For the Pinaceae family the situation is different. For the genus Pinus, except for *Pinus cembra* where current observed and potential limits were similar, the investigation demonstrated that these species tend to grow in conditions that differ from the potential limits reported by Bernetti (1995). The limits of the

current observed distribution of *Pinus pinea*, *Pinus nigra* and *Pinus laricio* are similar to the potential limits for temperature but not for precipitation. *Pinus pinea* tends to grow in conditions that are rainier than those predicted by Bernetti (1995) who report a maximum potential of 600 mm versus the current observed average of 831 mm. On the contrary, *Pinus nigra* and *Pinus laricio* are currently distributed in drier conditions than those reported by Bernetti (1995) with current observed TAP of 1172 and 1116 mm respectively for *P. nigra* and *P. laricio* versus a minimum potential of 1400 mm for both species.
The limits of the current observed distributions of *Pinus pinaster* and *Pinus halepensis* are generally similar to the potential precipitation limits but not the potential temperature limits. In fact, both these species tend to grow in warmer conditions than those reported by Bernetti (1995) with 14°C and 15°C as minimum MAT value reported by Bernetti (1995). *Abies alba* tends to be more plastic than reported by Bernetti (1995) in that it is able to grow in conditions that have both more or less rainfall than the potentials. Bernetti (1995) reported a potential minimum TAP value of 1200 mm and a potential maximum of 1500 mm while the observation averages are 1310 mm with minimum of 676 mm and maximum of 2002 mm. The current observed limits of the distributions for *Picea abies* are similar to the potential limits with almost all precipitation observations within the potential limits and almost 70% of the temperature observations within the potential limits. *P. abies* also tends to grow in slightly warmer conditions than the potential with observed MAT of 6.3°C which is very close to the maximum limit of 7°C reported by Bernetti (1995).
Larix decidua tends to grow in warmer and more humid conditions than those reported by Bernetti (1995). For precipitation the current observed average was 1067 mm versus a potential maximum of 700 mm while for temperature the current observed average was 5.4°C versus 5°C as the potential maximum.
Finally, for *Cupressus sempervirens* current observed and potential distributions were generally similar, especially for temperature for which almost 90% of the observations were within the potential limits.

Discussion

Traditional knowledge about potential climatic limits for Italian forest tree species was found to be only partially consistent with the data we derived from the current observed spatial distributions, particularly for some species of the Pinaceae family. Unfortunately, it is difficult to determine if these inconsistencies are due to inadequate characterisations of species potential limits or to the results of forest management and reforestation programmes (Cantiani

& Marchi 2017, Del Perugia et al. 2017). Actually, foresters often distributed forest tree species beyond their geographical limits (i.e., the expected ecological domain), especially after the First and the Second World Wars. In addition, it is important to note that such particular are represented, in our analysis, by a relatively limited number of observations from the NFI database and that some uncertainties may arise from the mappings of the climatic data. In particular, temperature is generally easier to map than rainfall whose distribution is more irregular and has a more complex dependence on altitude (Maselli et al., 2012). This problem was partly addressed for this study using the correction proposed by Fibbi et al. (2016), thereby reducing the inaccuracy of the rainfall estimates where the density of the original E-OBS stations was small.
To frame our results in a European context, a simple graphical comparison has been conducted using graphs provided in the JRC European Atlas of forest tree species. However, as mentioned, no tables neither numerical supplementary data were delivered in addition to the full text file and the comparison was possible for all the species with some exceptions. I this sense just a broad comparison has been performed and in order to include the "Italian forest" in a broader context. Pinus laricio is absent from the European Atlas while Quercus petraea and Quercus robur are grouped as are Pinus halepensis and Pinus brutia. The comparison is, therefore, only indicative and is reported here simply to provide hints about the comparison of Italian population relative to Europe populations. Moreover, sensible differences are possible between different meteorological data used. Italian tree species populations are generally within European Atlas limits, although with some exceptions. Moreover, the climatic ranges that we observed in Italy are narrower than the Europe ranges for some species as is expected given the smaller study area, particularly for temperature. Concerning rainfall, a restricted range is clearly detectable for Italian populations of stone pine, Douglas fir and peduncolate oak for which Italian minima are greater than European minima, while the Italian maxima are less than the European maxima. Italian populations of arolla pine, Mediterranean cypress, cork oak and Norway spruce grow in conditions that are drier than the European areal limit. The Italian populations of common chestnut, European beech, Turkey oak, black pine, maritime pine and Downy oak seem to be slightly shifted to more humid conditions with Italian minima and maxima greater than the European limits. Finally, the observed precipitation ranges for Italian Silver fir were greater population then the ranges reported in the European Atlas. For the other species differences relative to the European Atlas were less relevant.
Regarding temperature, the areal extents of Italian populations of species of the genus Quercus were shifted to slightly warmer conditions relative to European

populations with Italian climatic minima for these species greater than the European minima. Climatic maxima for Italian and European populations were similar except for sessile and pedunculate oaks for which the Italian climatic maxima were greater than the European maxima. A similar situation was observed for species of the genus Pinea (black pine, maritime pine and stone pine), Mediterranean cypress and Douglas Fir.

Regarding European larch, Norway spruce and Arolla pine, European populations are located in slightly colder areas than Italian populations with European climatic minima greater than Italian minima. Finally, Italian populations of common chestnut are shifted to slightly colder conditions relative to European populations with the current observed Italian temperature minimum smaller than the corresponding European minimum.

In recent years, marginal and peripheral forest populations have gained unique importance with respect to information they provide regarding the potential of forest tree species to adapt to ecological stresses (Hampe & Petit 2005). The new quantitative data provided by this study can be used to identify stands that may be adversely affected by the effects of climate change effects earlier than those located in the core of the geographic distribution. This information can be fundamental in Italy and more generally in the Mediterranean region, both of which are considered important European biodiversity hotpots featuring unique species richness (Médail & Quézel 1997, Hampe & Petit 2005, Marchi & Ducci 2018). Moreover, the Mediterranean region is also considered to be seriously threatened by future climate change effects (Resco De Dios et al. 2007, Lelieveld et al. 2012). Mediterranean trees species are classified among many different taxa with a large biodiversity levels that, in part, originated as adaptive responses to previous climate changes (Benito Garzón et al. 2007). Indeed, many recent research efforts have focused on populations living at marginal ecological domains in the Mediterranean region (Hampe and Petit, 2005; Marchi et al., 2016). Both biodiversity conservation and sustainable forest management issues may be supported by the results we report. Besides conservation, inaccurate characterization of environmental conditions characteristic of current growing zones may produce inaccurate future projections of ecosystem services and timber from productive forests and consequently a loss of economic return (Ray et al.2017). In such a framework, the recently released georeferenced raw data from the last Italian NFI (Borghetti and Chirici, 2016) represent a new source of consistent, empirical, big-data in the form of real information regarding climatic and growth conditions for the most important Italian forest trees species that circumvents the traditional reliance on expert opinion and out-dated observations. In addition to climatic conditions, soil attributes, which are also a fundamental for describing forest species distributions, can mitigate or amplify climatic drivers (Bréda et al. 2006, van der Maaten-Theunissen et al. 2016). Future analyses should also consider features such as soils, but a consistent source of quantitative soil information at the national level is still not publicly available in Italy.

Conclusions

For 7272 plots of the Italian National Forest Inventory, we calculated average annual temperatures and precipitation from 1 km resolution climatic data. Using these data, we compared the current observed ecological distribution of the 19 most important tree species in Italy to the expert knowledge potential limits reported by Bernetti (1995). We found that climatic limits and potential information should be probably revised for some of the species, particularly for some conifers and more frequently for precipitation data.
The public availability of georeferenced, national forest inventory (NFI), plot-level data is fundamental for ecological forest studies (Corona et al., 2011). Further evidence concerning growth trends provided by the next inventory cycle, INFC 2015 which is still in progress, will increase the knowledge about existing adaptive traits across Italy and will allow comparison among and within the plots. On the other side, new interpolation techniques and methodological research on climate may increase accuracy and precision with respect to climatic information(Gavin et al., 2014; Hampe and Petit, 2005; Marchi and Ducci, 2018; Médail and Quézel, 1997). Knowledge of the actual distribution of forest species and ecological niches is fundamental for both spatial and process-based simulation models used to deal with future scenarios. Thus, this study should motivate more detailed analyses on species distribution which could be used to identify country-level, future forest management strategies.

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3.3: The role of ecological requirements and climate change projections when modelling species distributions for adaptive forest management strategies

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Abstract: The wide range of ecosystem services delivered by forests will be probably influenced by climate change magnitude and directly connected to applied decisions by policy makers. In a climate change scenario, the resilience and adaptive potential of forest systems represent the key processes to be stimulated by forest managers and are strictly related to each other. The aim of this paper is to report the results a modelling effort where the potential impact of climate change in Italian forests has been evaluated to support the forest management strategies. Among all the forest tree species occurring across the Italian peninsula, 19 were here considered describing their ecological niche by means of a species distribution modelling approach. Six different Global Circulations Models (GCMs) were then employed to describe future climate condition and in addition to a local Regional Climate Model (RCM) using an intermediate scenario (RCP 4.5) for 2050s. While no sensible variation in extension of the forest surfaces have been predicted, results showed wide differences between species and between different climate models, with the RCM as the most affecting the spatial distribution of forests in Italy. The analyses also indicated the land suitability to remain almost unchanged in mountain areas and compared with valleys or flood and plains where a decrease has been predicted to be likely to occur. Pure woods were the most threatened when compared with mixed stands which are characterized by a greater species richness and therefore a higher level of biodiversity. Then pure softwood stands (e.g. *Pinus, Abies*) were evaluated as more sensitive than hardwoods (e.g. *Fagus, Quercus*). According to the provided results, silvicultural practise should be applied to increase the species richness and favouring hardwoods currently growing as dominates species under conifers canopy, stimulating the natural regeneration, gene flow and supporting migration processes.

Keywords: climate change; biomod2; species distribution; forest tree species; Italy; Mediterranean area

Introduction

Climate change represents an important challenge for ecologists, biologists and modellers whose research interest is the prediction/simulation of potential effect of climate change on delivered ecosystem services from forests (Deal et al., 2017; Dyderski et al., 2018; Ray et al., 2017). The use of predictive models and statistical tools has registered an increased interest in scientific literature since 1980s (Broome et al., 2019; Di Biase et al., 2018; Falk and Mellert, 2011) aimed at stimulating the most likely effect of climate change with a spatial movement as one of the main result, both geographic and altitudinal gradient (Lenoir et al., 2008). Species migration across a latitudinal and/or altitudinal direction represents one of the possible responses of forest tree species to climate change impact (Bussotti et al., 2015). Each vegetation shift (i.e. the colonization of a new environment) is dependent to species-specific seed dispersal ability as well as, for example, the nutrient availability in the new environment, the landscape fragmentation and the inter-specific competition (Cudlín et al., 2017). However, there is a scientific evidence that this shift is already underway both in altitude (Chen et al., 2011; Marchi et al., 2016) and in latitude (Boisvert-Marsh et al., 2014; Monleon and Lintz, 2015).

In a climate change framework, forest management and planning efforts must be oriented toward maintaining and improving biodiversity and ecosystem services, assuring the long-term availability of forest resources and their biological functioning (O'Hara, 2016; Puettmann et al., 2015; Williams and Dumroese, 2013). A development of a sustainable forest management strategy (SFM) represents a very urgent topic to forestry sector (Deal et al., 2017; Nocentini et al., 2017; Ruddell et al., 2007). Information about the ecological requirements of different tree species are fundamental data to implement sustainable forest management strategy (Fady et al., 2016; Pecchi et al., 2019b; Roces-Díaz et al., 2014) allowing conservation plans, ecological restoration actions (Olthoff et al., 2016) as well as the detection of threatened areas and also possible refuges (Hampe and Petit, 2005; Marchi and Ducci, 2018; Zhang et al., 2017). The spatial modelling of ecological niche of organism, being animals of plants and generally called Species Distribution Modelling (SDM) or, sometimes, Ecological Niche Modelling (ENM) is currently seen as one of the most interesting technique to support forest management strategies (Pecchi et al., 2019a). SDM are statistical algorithms able to derive and model the ecological requirements of a specific target species or ecological group from its spatial distribution, assuming its equilibrium with climate. As any statistical model, many uncertainties lays behind the final prediction, which can be summarised in

three main sources: i) the parameter uncertainty i.e. imperfect species occurrence data, unavailableness of important predictor variables; ii) the model uncertainty that it is linked to the choice of different SDM algorithms; iii) climate uncertainty, linked with future climate scenarios. However, this last aspect is often underestimated by researches (Beaumont and Hughes, 2002; Buisson et al., 2010; Goberville et al., 2015; Koo et al., 2017) but can heavily impact predictions. To deal with these researchers developed ensemble modelling strategies (Crimmins et al., 2013; Hao et al., 2019; Kindt, 2017), aimed at averaging many replicates of the same procedure (i.e. the simulation processes), deriving confidence intervals and weighted means or using different climate change trajectories for probabilistic results (Douglas and Newton, 2014; Guisan and Zimmermann, 2000). Indeed, future climate scenario represents the result of the action of General Circulation Model or sometimes Global Climate Model (GCM) which are often calculated at global scale and thus describing a plausible future climate condition under a set of hypothetic climate forcing. GCM is a three-dimensional, numerical representation of the climate system based on the physical, chemical and biological properties of the atmosphere, oceans and land surface. Climate forcing is a component of GCMs representing a specific greenhouse gas concentration trajectory and the Recursive Concentration Pathway (RCP) scenarios developed in the Fifth Assessment Report (AR5) from IPCC (IPCC, 2013) are the most common and widely used. Besides GCM, Regional Circulation Model (RCM) have been developed too, to adapt/adjust GCMs at local scale, mainly using downscaling procedures (Flint and Flint, 2012; I. Harris et al., 2014; Moriondo and Bindi, 2006).
According to the provided evidences, many uncertainties are still masked under the predictions generally provided by researchers in their studies, with climate as one of the main issues with the projection i.e. the use of a GCM versus an RCM an vice versa (Thuiller et al., 2019). The aim of this paper is to evaluate the uncertainties behind an SDM procedure in the Mediterranean environment, where climate change has been predicted to be highly affecting forest tree species distribution. In this work different projections for 19 among the main forest tree species in Italy have been realised, quantifying the discrepancies between and within species when different GCMs and RCMs are used. Wall-to-wall suitability maps have been obtained for Italy to provide indications to forest planners regarding the possible consequence and impact of climate change in Italian forest systems. Then adaptive forest management strategies have been proposed dealing with potential impacts of climate change and uncertainties detected behind the modelling efforts.

Materials and Methods

2.1 Spatial data and climatic scenarios

The Italian peninsula is well known as one of the most relevant biodiversity hotspots in the Mediterranean area, where many endemic species have been detected and where some post-glacial recolonization processes have begun (Aitken et al., 2008; Piotti et al., 2017). Among the 263 species detected in the framework of the last available national forest inventory (INFC 2005) this paper has been focused on 19 forest tree species. Such species were recognised as the most interesting and relevant for the country according to Pecchi et al. (2019b) and here reported as supplementary file (Table S1). National forest inventories (NFI) are the main input data form may SDM procedures, given their ability to provide tree-level information which allow a refinement of modelling steps (Marchi and Ducci, 2018). In this paper information about spices occurrence of the 19 forest tree species were derived from the raw data of INFC 2005 which was based on a three-phase sampling procedure for a total of 7,272 sampling plots, spatially distributed according to a probabilistic sampling scheme (Fattorini, 2014) and with associated data for 230,874 callipered trees (Borghetti and Chirici, 2016).

In order to build the climatic niche of target species and to project its spatial distribution into the future conditions, current climate data were firstly retrieved from the downscaled E-OBS climatological map, available for Italy with 1 km of spatial resolution and calculated as average of the 1981-2010 normal period (Maselli et al., 2012; Moreno and Hasenauer, 2016). Then to describe future climate conditions and to allow comparison between GCMs and RCMs as well as within GCMs, the 19 bioclimatic variables available in WorldClim portal were downloaded for 6 GCMs from the WorldClim website (http://worldclim.org/cmip5_30s) and addition to 1 RCMs provided by the Institute of BioEconomy (IBE) of the Italian National Research Council. All climatic scenarios were all referred to RCP4.5 of the AR5 for 2050s and added to the current climatic scenario we used for modelling as anomalies with the same spatial resolution. This was done to avoid artefacts between GCMs and RCMs which might occur due to intrinsic features of each and due to different interpolation method, baseline used etc. (Moreno and Hasenauer, 2016; Ramirez-Villegas and Jarvis, 2010). The selected GCMs where those elaborated by the fourth version of Community Climate System (CCSM) hereafter CC, the Hadley Centre Global Environment Model version 2 family (HADGEM2 2-AO, 2-CC, 2-ES) here after respectively HD, HE and HG, the Max Planck Institute for Meteorology Earth System Model (MPI-ESM-LR) hereafter MP

and the Meteorological Research Institute climate model (MRI-CGCM3) here after MG. The RCM model is here represented by the output of COSMO-CLM climate model hereafter, COSMO, the climate version of operational weather forecast model COSMO-LM, that it developed by German weather service (Bucchignani et al., 2018). The choice of this RCM has been done on the basis of its acknowledged ability to characterise the Italian climate conditions (Fibbi et al., 2019).
To better describe seasonal variation in climate condition and to allow the RCM to be comparable with WorldClim data, the complete set of 19 bioclimatic index of Worldclim have been calculated for both E-OBS and COSMO data using the dismo package (Hijmans et al., 2015) of R statistical language (R Development Core Team, 2019).

2.2 Species distribution modelling

According to the existing literature, the ensemble forecasting model from different SDM techniques is recognised as the most powerful, stable and well-referenced method for climate change scenarios forecasting (Araújo and New, 2007; Crimmins et al., 2013; Pecchi et al., 2019a). In this paper the ensemble technique was used as predictive method for each of the 19 studied species to estimate potential suitability of each considered tree species under present and future climate conditions. An ensemble (or sometimes consensus) modelling is based on the idea that each different modelling output represents a possible state of the real distribution. Each single projection is then combined into a final output using a mathematical technique. In this study the consensus technique was represented by the weighted mean (Hao et al., 2019; Marmion et al., 2009). Nine algorithms were used for modelling, then averaged according to their predictive power, calculated using the True Skill Statistic (TSS) indicator (Leroy et al., 2018) calculated with a cross-validation procedure using 75% and 25% for training and testing (Hao et al., 2019). The random extraction procedure was repeated for 50 times which brought to 450 single-model projections for each tested species. Used algorithms were: General linear model (GLM), Generalized additive model (GAM), Classification tree analysis (CTA), Artificial neural network (ANN), Flexible discriminant analysis (FDA), Multivariate adaptive spline (MARS), Random Forest (RF) and finally Maximum entropy (MAXENT) as available in the biomod2 package (Thuiller et al., 2016) of R statistical language.
To avoid the problem linked to collinearity of predictors (Dormann et al., 2013) a Principal Component Analysis (PCA) was performed on the complete set of variables to obtain uncorrelated (i.e. orthogonal) predictors conserving all the variability of the system (i.e. the ecological variability of the Italian

environment). Then the species occurrence was modelled with biomod2, using all the NFI plots where the target species reached 15% of basal area share at least as presence point. In combination to this, 10 different datasets were also simulated for pseudo-absences (PA) with the Surface Range Envelope method (Barbet-Massin et al., 2012), made by a number of records equal to the presence points of the species to be modelled. Indeed, even if available from the NFI dataset and detectable from tree-level information, the use of all the plots where the species has not been detected as "real absences" can drive the models to biased predictions, even if setting prevalence to 0.5 (Marchi and Ducci, 2018). The main reason behind this issue is that, in a managed environment, while the presence is certain, the absence can be due to both inhospitable environment or human pressure (selective logging, forest management, etc.) and no information is available to confirm any of the above-mentioned possibilities in the NFI data.

2.3 Suitability maps analysis and uncertainties quantification

Once the land suitability (LS) maps for the 7 climate change scenarios (6 GCMs + 1 RCM) were created for all the 19 studied species, the agreement between projections and the standard deviation among all the surfaces was analysed with the aim of evaluating the potential effect of climate change on Italian forest systems. The difference in habitat suitability values between future and current distribution for each species was used as input data for a Principal Component Analysis (PCA) where the connection between the combined used of Species and GCM/RCM has been evaluated. The variability within GCM/RCM was then studied, with the aim of quantifying the climatic uncertainties in our study as well as the most likely effect of climate change in the Italian environment. To achieve this the 133 LS maps (an ensemble model for each of the 7 climatic scenarios times 19 forest tree species) were grouped according to the used climatic scenario containing the same number of layers each (i.e. each modelled species). For each group, the maximum LS value for each pixel was then calculated. A single map for each climatic scenario has been obtained and representing the probability of a specific location (pixel) to be populated in future (2050s) by one of the 19 analysed species at least. These maps were processed using several LS thresholds, ranging between 51% and 90%, used to transform continuous values in binary predictions (1/0). Information on changes in the suitable envelope (i.e. all pixels equal to or higher than the threshold) were then obtained and especially concerning the total number of pixels (i.e. total forested surface in future) and altitudinal information such as average value, standard deviation, minimum and maximum of altitude (i.e. extension of the suitable envelope) to determine whether an altitudinal shift could be recognised. A linear model was used to examine the influence of threshold level and different climate projection in determine the number of pixels and as consequence the most variable scenario.

$$Land\ suitability = intercept + \beta\_1\ GCM + \beta\_2\ threshold + \varepsilon$$

Finally, the most variable scenario (i.e. the most dangerous prediction) was used to study the likely the impacts of climate change on the currently forested areas. The maximum values across the 19 species for the current scenario was firstly added to the dataset and then subtracted from the selected future projection, creating a land suitability variation map. Afterwards all the INFC 2005 inventory plots were superimposed on this raster surface obtaining a dataset where the LS variation could be modelled as a function of forest plot attributes. Among these the spatial coordinates (latitude, longitude) the altitude, the forest type (i.e. beech forests, silver fir forests), the admixture level (i.e. pure, mixed) the admixture type (i.e. conifer and broadleaves or the opposite), the main species and the other components of the forest stand obtained from the INFC 2005 dataset were used as predictors in a model aimed at providing statistical evidences supporting the future forest management strategies.

Results

The spatial prediction for the 19 testes species with the adopted method showed a wide variability between both algorithms and analysed species. Concerning models, better results were obtained with RF (average value of TSS 0.844 ±0.092) while the worst performances were observed for MAXENT (average value 0.752 ±0.121). Concerning the 19 species, TSS values were more variable and ranging between an average value of 0.647 (±0.113) for Pinus pinea and 0.922 (±0.087) for Pinus cembra. The situation is graphically summarised in Figure 1.

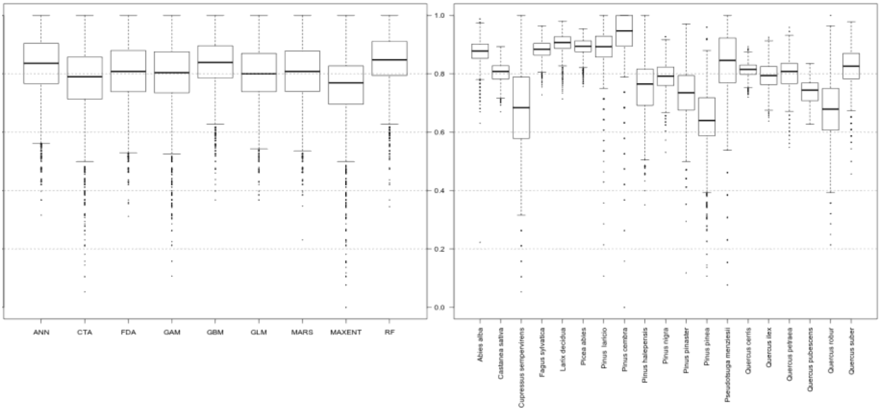

Fig. 1. True Skill Statistic values (TSS) obtained during the SDM procedure for each involved algorithm (left) and for each species (right)

When the standard deviation between projections map was calculated (Figure 2, left) the central part of Italy has been acknowledged as the most variable, with spatial projections poorly in agreement and partially connected to the spatial shape of the Apennines chain between Latium, Tuscany and Emilia-Romagna regions. Conversely, a general agreement was observed in flat areas such as the Po valley, spatially next to the central Apennines chain and currently characterised by farms and cultivated areas. According to the PCA analysis the within-species variability was the most influencing factor than the within-scenarios. Higher eigenvalues were obtained for factors expressing the between-species variability (e.g. COSMO, CC, HE, HD labels in Figure 2) than those obtained between scenarios which stressed the importance of a species-specific SDM approach. Then among climatic scenarios, the COSMO RCM was highlighted as the most independent with all the GCMs (i.e. CC, HE, HD etc. labels in Figure 2) partially overlapping with some species and sharing the proportion of explained variability.

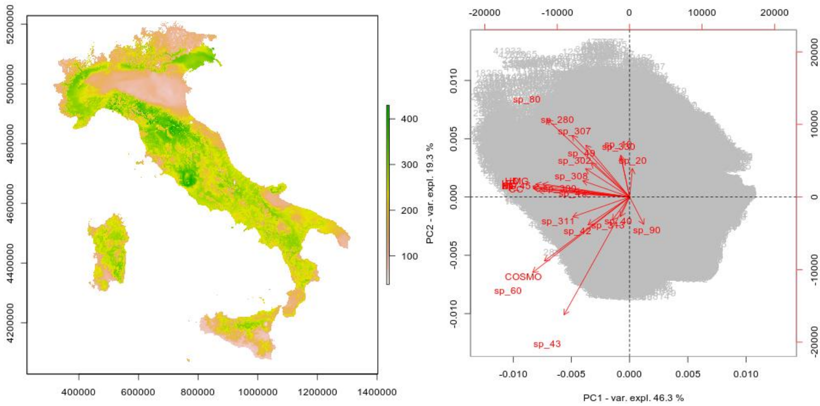

Fig. 2. Raster map (left) of the standard deviation of the future land suitability minus the current value for each species using all the future scenarios (133 layers) and PCA run on the same data.

In agreement with the PCA results, the histogram analyses of "maximum suitability rasters" (Figure 3) reflected the COSMO climate scenario as the most different with respect the other climate projections GCMs. While all the other GCMs used in this study showed a density plot mainly cumulated on the right side of the image (between 900 and 1000), two distinct peaks were found for COSMO, with the most important between 400 and 600, much lower than those observed for the other GCMs as well as the current scenario too. In combination with the histogram analysis, the use of a threshold for evaluating the total suitable forested area in Italy stressed the elevation as important driver (Table 1). According to Table 2 where the results of the statistical model we run on such data are shown, the number of pixels for a specific threshold was substantially similar between GCMs and generally higher than the COSMO model. Then the COSMO was also the most important predictor in the model.

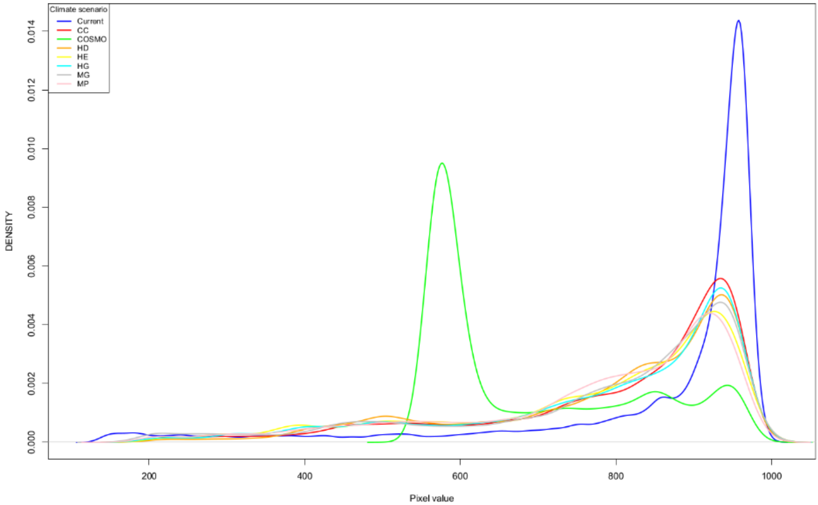

Fig. 3. Density distribution (histogram) of each "maximum GCMs and RCM" obtained in this study when using the maximum land suitability value for each pixel within the 19 analysed species.

Tab.1 Number of pixels of maximum that exceed of different threshold level and values of mean, sd, min, max of altitude.

Scenario	Threshold	nPixel	Mean altitude	Sd altitude	Min altitude	Max altitude
Current	500	277,469	570.2	584.0	0	4322
	600	270,012	565.3	561.8	0	3536
	700	259,095	565.9	544.1	0	3536
	800	241,857	563.5	522.7	0	3154
	900	202,913	580.5	496.9	0	2974
CC	500	272,212	551.0	560.3	0	3786
	600	253,718	551.8	538.2	0	3050
	700	232,846	557.3	524.3	0	3033
	800	191,699	572.0	514.0	0	3033
	900	117,636	580.1	498.2	0	2841
COSMO	500	302,091	535.2	586.3	0	4783
	600	161,849	794.8	622.7	0	4322
	700	117,167	911.1	622.1	0	3840
	800	83,045	1005.3	610.5	0	3536
	900	38,627	1122.9	560.5	2	3536
HD	500	271,421	559.0	571.4	0	4322
	600	249,366	556.8	537.2	0	3478
	700	227,487	562.3	523.2	0	3093
	800	186,541	570.0	498.9	0	3033
	900	107,279	526.5	444.1	0	2921
HE	500	264,667	571.2	575.2	0	4412
	600	243,331	567.0	541.5	0	3346
	700	220,858	574.7	530.2	0	3093
	800	175,290	588.2	511.6	0	3033
	900	97,472	561.2	468.0	0	2921
HG	500	266,667	563.0	575.6	0	4783
	600	248,089	553.3	538.4	0	3478
	700	225,522	557.4	523.1	0	3346
	800	183,055	555.1	504.9	0	3033
	900	111,688	513.8	441.4	0	2921
MG	500	263,520	553.5	562.4	0	3786
	600	245,959	548.4	536.0	0	3213
	700	225,935	541.2	514.4	0	3038
	800	183,215	553.1	503.0	0	2974
	900	103,091	549.1	495.1	0	2810
MP	500	266,133	558.3	561.1	0	3840
	600	245,089	558.2	534.0	0	3478
	700	222,756	563.2	520.9	0	3216
	800	170,854	588.6	516.9	0	2974
	900	90,737	579.7	493.0	0	2680

Tab.2. results of linear model to determine the most important climate scenario between the used.

Predictors	Sum Sq	Prop of Expl. Var	Df	F value	Pr(>F)	Significativity
Climate scenario	3.E+10	0.20	7	6.2045	0.000137	***
Threshold	1.E+11	0.80	1	168.565	4.49E-14	***

Once acknowledged the COSMO model as the most variable and intense scenario, the land use change across altitudinal gradient showed a different pattern across the whole country (Figure 4, left) or on forested areas (i.e. INF2005 inventory plots, Figure 4, right side). A potential gain in term of LS has been predicted by BIOMOD2 especially at high class of altitude but only in the case of the whole Italian country. Conversely, only a decrease in LS was found on the INFC2005 domain (i.e. forested areas). When such changes were modelled as a function of forest stand characteristics, the altitude variable intercepted the higher proportion of explained variance and close to 45%. Then also latitude highly relevant with about 35%. The forest category was the last relevant predictor (11%) while the total basal area of the stand and admixture type were much less important than the other variables with value of explain variance of 0.3% and 0.4% respectively.

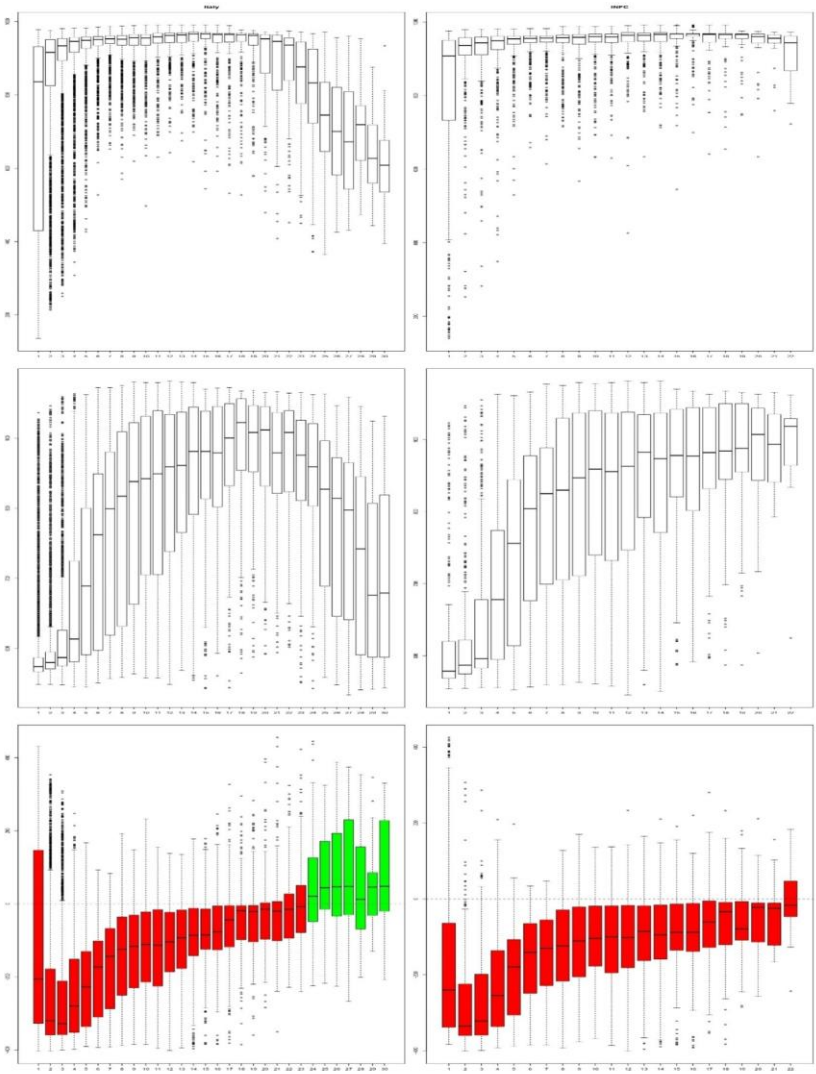

Fig. 4. Maximum suitability values grouped by altitudinal envelopes (100 m) across the whole country (left) and on the 7272 INFC2005 inventory plots only (right)

Tab.3 final linear model result

Predictors	DF	Sum SQ	Proportion explained variance	Mean Sq	F value	Pr(>F)	Significativ ity
altitude	1	1.72E+07	0.45	1.72E+07	1401.5	< 2.2e-16	***
longitude	1	2.96E+06	0.08	2.96E+06	241.161	< 2.2e-16	***
latitude	1	1.33E+07	0.35	1.33E+07	1086.71	< 2.2e-16	***
fortype	18	4.21E+06	0.11	2.34E+05	19.0496	< 2.2e-16	***
Gtot	1	1.15E+05	3.04E-03	1.15E+05	9.4081	0.00217	**
TypeFor	3	1.58E+05	4.15E-03	5.25E+04	4.2801	0.00502	**

Where:
Fortype: Forest type (i.e. beech forest, silver fir forest, etc.)
Gtot: Total basal area in m^2
TypeFor: pure or mixed forest (on the base of basal area of species), coniferous or broadleaves species

Discussion

The species-specific ecological requirements of forest tree species are one of the main drivers for ecological modelling. While similar output can be obtained with species sharing the same climatic envelope (i.e. silver fir and European beech), different projections are instead calculated for species that are highly differentiated (e.g. European beech and holm oak). However, our results stressed how the uncertainty on climate change projections and the use of GCM/RCM for projections greatly impact spatial simulations. The use of rough or not representative data can lead to very different final results in SDM and bias derived decisions (Beaumont et al., 2008; R. M. B. Harris et al., 2014). This aspect is confirmed by our results that showed a sensible difference among COSMO climatic model (regional) and all the Worldclim-based group. These results also highlighted the importance of the use of local data and optimized scenarios at very high resolution especially for Mediterranean area (Giannakopoulos et al., 2009; Lelieveld et al., 2012; Marchi et al., 2019). Unfortunately, the use of local data is not still very common, despite the best results in terms of performance of the model that can be obtained (Liu et al., 2014). While several GCMs are sometimes used and then averaged, the use of a single average layer causes the loss of variability with no information on the range of all the potential predictions made by the same SDM procedure. While some papers have introduced consensus method to assessment the uncertainty in different climate scenario (Wang et al., 2016, 2012) the use of more GCMs, RCMs and RCP projections seems to be necessary. Even if just one RCP scenario has been used

in this paper, strong differences has been detected; this was the main aim of this paper, which is not focused to produce a specific reliable projection.
Concerning the mathematical structure of SDM, the importance of the quality of data sources is confirmed as well as its relationship with the uncertainty in species occurrence data and the different statistical technique used to predict the distribution of species (Beale and Lennon, 2012). Uncertainty in species occurrence data can have negative effect on the accuracy of model and any possible correction might bring to a reduction of the total number of records, removing the uncertain or filtering possible outliers (Marchi and Ducci, 2018). However, this effect is different according to the modelling technique: for example, MAXENT algorithm is acknowledged as able to provide high accuracy despite the use of occurrence data with this type of error (Fourcade et al., 2018). Similarly, the algorithms belonging to the "regression family" (e.g. GLM, GAM) has been often detected as not affected by this error type; for this reason, the tendency is to not consider this type of error unless the error is very significative (Graham et al., 2008). Therefore, a real and powerful SDM should be based on high-quality data, representative of the phenomena and without any prejudice on the modelling algorithm to be used, with the unbiased comparisons as the unique technique to asses their predictive power (Hao et al., 2019). As for instance, while MAXENT is probably the most used algorithm in literature for SDM (Pecchi et al., 2019a), its predictive power was the lowest among all the tested methods. However, the reasons should be found on the low number of absences we used (i.e. the background points for MAXENT), probably too few to allow the model to work properly (Barbet-Massin et al., 2012).
All the above-mentioned uncertainties greatly impact on the use of SDM as decision support system. One of the main outputs of SDM is the possibility to detect better-adapted forest tree species (genotypes) and provenance types (genotyping) which may be more adapted to future climate condition in a specific area. Provenance selection has the potential to improve the resilience of forest system and allow assisted migration strategies (Benito Garzón et al., 2019; Valladares et al., 2014). This operation represents also a valid action to response at quick changes imposed by climate change such as the altitudinal or latitudinal shift of species. In an "assisted migration scenario", the intentional movement of species or population to match climate condition which organisms are already adapted to (best fitting) should be evidence-based (Corona, 2018). This movement must be realized by the human intervention and response to different aims such as preventing species extinction, reduce economic loss and sustaining ecosystem service (Sáenz-Romero et al., 2016; Williams and Dumroese, 2013). Such action is probably the most extreme, potentially dangerous and expensive and must be driven by reliable models and statistical probability. The higher the

uncertainty in the modelling steps are, the more dangerous and biased the efforts could be, with the probability of failure which is proportional to the magnitude of disconnection between what is projected and what is likely to occur.
According to the provided evidences, the altitudinal gradient will play a very important role in determining different pattern of species distribution in future climate condition in Italy. This parameter strongly influences the shape, structure and specific composition of forests worldwide with a direct effect on a series of important process, such as water availability, temperature and soil properties (Lin et al., 2018; Littell et al., 2008; Zhang et al., 2016). The tendency in altitudinal shift of different organism, both animal and plant, is often confirmed by many research papers (Chen et al., 2011; Lenoir et al., 2008; Rumpf et al., 2018; Vacchiano and Motta, 2015) with the altitudinal shift generally occurring at very lower speed than latitudinal (Sáenz-Romero et al., 2016). One of the main issues is if the velocity of colonisation of new areas is too low if compared to expected climate change scenarios. In this case most of the studies are focussed on the upper elevational limit, sometimes also called as leading edge, while the lower elevational limit or rear edges is less investigated even if fundamental to plan adequate conservation scenarios for threatened species (Hampe and Petit, 2005; Rumpf et al., 2019, 2018). According to Lenoir et al. (2008) an average trend shift of 29 meters in upward sense for decade seems to be reliable a value for forest tree species in southern of France considering the variation in optimum climatic of species in two different periods that it 1905-1985 and 1986-2005. A confirm of this process with regarding Italian mountains can be found in Rogora et al. (2018) where a progressive thermophilization process of climate and a progressive natural introduction of typical species of lower altitudinal strip both for Alps and Apennine has been detected. According to our results, the altitudinal movement of the forested areas with the worst scenario (COSMO) seemed to be lower and around 18 meters per decade, demonstrating a possibility of Italian forest tree species to colonize new lands. In this sense the higher sensitivity to climate change of pure broadleaf stands is one of the main results of our modelling efforts. This result confirms the recent literature where a general contraction of broadleaves species, especially those species that are adapted to cold and wet conditions was studied (Hanewinkel et al., 2012; Ruiz-Labourdette et al., 2012).

Conclusions

Climate change will probably affect the spatial distribution of forest tree species worldwide and many research groups are currently working to adapt GCMs to local contexts. Anyway, the uncertainty is still wide with many factors involved in physical and anthropogenic process on one hand and all the possible adaptive processes of forest systems to deal with climate change scenarios on the other, which are only partially known in a long-term period. With this study an initial framework of the possible consequences of climate change phenomenon in Italian forest has been proposed, trying to understand the different dynamics between different variables and not merely describing the potential expected species geographical shift. While any model can build with any data coming from different sources, a real error assessment is fundamental to derive useful and effective management strategies. Dealing with uncertainties and working with self-updating procedures seems to be the main path to address climate change effects properly, mitigating the negative effects and maintaining the delivery of ecosystems services from forests. Anyway, only monitoring networks and site-specific trends will be able to certify or confute this tendency. Such new data will be fundamental to test current SDM and adjust projection properly.

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Chapter 4

4.1: A spatially explicit database of wind disturbances in European forests over the period 2000-2018

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Abstract: Strong winds may uproot and break trees and represent one of the major natural disturbances for European forests. Wind disturbances have intensified over the last decades globally and are expected to further rise in view of the climate change effects. Despite the importance of such natural disturbances, there are currently no spatially explicit databases of wind-related impact at Pan-European scale. Here, we present a new database of wind disturbances in European forests (FORWIND). FORWIND comprises more than 80,000 spatially delineated areas in Europe that were disturbed by wind in the period 2000-2018 and describes them in a harmonized and consistent geographical vector

format. Correlation analyses performed between the areas in FORWIND and land cover changes retrieved from the Landsat-based Global Forest Change dataset and the MODIS Global Disturbance Index corroborate the robustness of FORWIND. Spearman rank coefficients range between 0.27 and 0.48 (p-value<0.05). When recorded forest areas are rescaled based on their damage degree, correlation increases to 0.54. Wind-damaged growing stock volumes reported in national inventories (FORESTORM dataset) are generally higher than analogous metrics provided by FORWIND in combination with satellite-based biomass and country-scale statistics of growing stock volume. Overall, FORWIND represents a valuable and open-access spatial source to improve our understanding of the vulnerability of forests to winds and develop large-scale monitoring/modelling of natural disturbances. Data sharing is encouraged in order to continuously update and improve FORWIND. The dataset is available at https://doi.org/10.6084/m9.figshare.9555008 (Forzieri et al., 2019).

Introduction

Natural forest disturbances represent a serious peril for maintaining productive forests. Studies indicate that their excess can reduce primary production and partially offset carbon sinks or even turn forest ecosystems into carbon sources (Kurz et al., 2008; Yamanoi et al., 2015; Ziemblińska et al., 2018). This is particularly critical for windthrow and tree breakage due to strong winds, which represent one of the major natural disturbance for European forests (Schelhaas et al., 2003; Seidl et al., 2017). Such disturbances are intensifying globally, a trend which is expected to continue with further climate change (Bender et al., 2010; Knutson et al., 2010; Seidl et al., 2014).

European windstorms are associated with areas of low atmospheric pressure that typically occur in the autumn and winter months (Martínez-Alvarado et al., 2012). Deep low-pressure areas frequently track across the North Atlantic Ocean towards Western Europe, pass the north coast of Great Britain and Ireland and into the Norwegian Sea. However, when they track further south, they can potentially hit any country in Europe. In 1999, storm Lothar damaged approximately 165 million m3 of timber, which is equivalent to 43% of the average annual harvest rate, mainly in France, Germany, Switzerland and Scandinavia (Gardiner et al., 2010). In 2005, 75 million m3, equivalent to one year's cuttings, were damaged by storm Gudrun in Sweden. In 2007, the storm Kyrill caused the loss of 49 million m3 of timber in Germany and the Czech Republic. In 2009 and 2010, storms Klaus and Xynthia hit forests in France and Spain and caused timber losses totalling approximately 45 million m3. In 2018, the Vaia storm hits the North-Eastern regions of Italy causing a damaged growing stock volume of about 8.5 million m3.

The socio-economic consequences of wind disturbances can be critical especially for local economies highly dependent on the forest sector. Countries in Northern Europe and Central-Eastern Europe, where the forest sector may cover up to 6% of the national GDP (FOREST EUROPE, 2015), are, therefore, potentially more vulnerable to wind-related impacts.

Despite the risks they pose, spatially explicit databases of wind disturbances across European currently do not exist. Recent assessments of current and future forest damages due to windstorms at European scale are based on catalogues of disturbances collected at country level (Gregow et al., 2017; Schelhaas et al., 2003; Seidl et al., 2014; Senf et al., 2018). Such databases are subject to multiple sources of bias and uncertainty associated to the diversity of the underlying inventories. Furthermore, estimates of forest damage aggregated at national scale may only partially represent the spatial variability of the phenomenon. In fact, the coarse spatial resolution of such data hampers inferential analysis of potential drivers of forest vulnerability and their use in spatially explicit models to monitor or forecast wind-related impacts (Masek et al., 2015; Phiri and Morgenroth, 2017). Despite the lack of systematic mapping of wind disturbances in European forests, a multitude of local, national, and transnational initiatives have accurately mapped forest areas affected by wind over the last decades These data represent highly informative observational records to characterize spatial patterns of forest damages. However, they are collected by different institutes, and are often difficult to retrieve or poorly documented. Since 2012, the Copernicus Emergency Management Service (https://emergency.copernicus.eu/) produces maps of natural disasters throughout the world based on the analysis of satellite images and other geospatial data. While this important initiative can help map wind-affected areas, it only covers recent years and, being an on-demand service, it is not comprehensive as it depends on the interests of individual authorized users of the service to map a given forest disturbance.

In this study, we try to fill the above-mentioned gap. To this aim, we collected and harmonized 89,434 forest areas damaged by wind into a consistent geospatial dataset. The work was carried out through a unique joint effort of 26 research institutes and forestry services across Europe. This collaboration led to the first spatially explicit database of wind disturbances in European forests over the period 2000-2018, hereafter referred to as the FORWIND database. We believe that it provides essential spatial information to improve our understanding of forest damage from wind and can assist in large-scale systematic monitoring and modelling of forest disturbances. In the following sections, we describe the data collection, the harmonization process, and the cross-comparison performed against satellite-retrievals of changes in vegetation cover and data from national inventories of forest disturbances. We conclude the data description with some examples of the possible usage of the FORWIND database.

Methods

We collected wind disturbances events caused by windstorms or tornadoes that occurred in Europe between 2000 and 2018. A wind disturbance event is represented by a georeferenced polygon that delineates the damaged forest stand, regardless of the degree of damage. The data were managed mostly on the Google Earth Engine platform (Gorelick et al., 2017) to efficiently quantify the extent of disturbances over large scales and extract additional informative attributes (e.g., Hansen et al., 2013; McDowell et al., 2015). We structured the data collection process in four main phases, described below.

- **Literature review and data gathering.** We searched PubMed and Scopus for articles published up to January 2019, with no language restrictions, using the search terms "wind disturbance" OR "windthrow" OR "forest damage" OR "wind damage" OR "forest disturbance" AND "Europe" OR single country name in the publication title OR abstract. The identified studies had mainly mapped the effects of wind on forests for single events and/or for a limited areal extent. We then retrieved the spatial delineation of the observed wind damages from the corresponding authors or contact persons responsible for the data acquisition. The collected data were originally recorded by different research institutes and international initiatives across Europe using diverse methodologies. Table 1 lists the data providers and the acquisition methods.

- **Coordinate system transformation**. The wind disturbances were transformed to the same geographical unprojected coordinate system (World Geodetic System 1984, WGS84, EPSG:4326).
- **Spatial segregation.** The spatial segregation of each record was verified. In case multiple features for the same event overlapped, they were merged.
- **Harmonization of the degree of damage.** A damage classification for forest disturbances was originally recorded for windstorms that occurred in France in 2009, in Lithuania in 2010, in Germany in 2017, in Italy in 2015 and –for part of the records - in 2018. In order to make these records comparable in terms of the severity of damage, the original classes were harmonized into a single damage metric following the rationale reported in Table 2.

Table 1: List of institutions responsible of wind disturbance mapping and corresponding number of records collected and acquisition methods employed. Spatial delineation of tornado-related impacts on forests have been based on a semi-automatic algorithm and every record has been singularly validated based on visual inspection of high-resolution of satellite images (Shikhov and Chernokulsky, 2018). Area subject to wind disturbances have been retrieved for FORWIND by intersection of the 2005 registered forest clear-cuts between 2005-01-07 and 2005-12-31 larger than 500 m^2 (http://skogsdataportalen.skogsstyrelsen.se/Skogsdataportalen/) with the spatial delineation of the Gudrun storm (Gardiner et al., 2010). The use of forest clear-cuts as proxy for wind-affected areas is reasonable because the morning after the storm all normal felling activity stopped and moved to storm damaged areas (Swedish Forest Agency, personal communication).

Data provider	**Number of records**	**Event type**	**Acquisition method**
Alto Adige province forest service, Italy	1457	Windstorm	Aerial photointerpretation and field survey
Copernicus Emergency Service	4425	Windstorm	Aerial photointerpretation
Department of Cartography and Geoinformatics, Perm State University, Perm, Russia	3056	Tornado	Satellite data classification [a]

Department of Forest Management, Geomatics and Forest Economics, Institute of Forest ResourcesManagement, Faculty of Forestry, University of Agriculture in Krakow, Poland	321	Windstorm	Aerial photointerpretation
Department of Forest Resource Planning and Informatics, Faculty of Forestry, Technical University in Zvolen, Slovakia	14	Windstorm	Aerial photointerpretation and field survey
Department of Geoinformatics, Faculty of Science, Palacky University, Czech Republic	1175	Windstorm	Aerial photointerpretation
Department of Land Change Science, Swiss Federal Institute for Forest, Snow and Landscape Research WSL, Birmensdorf, Switzerland	64	Windstorm	Aerial photointerpretation
Department of forestry Mecklenburg-Vorpommern state, Germany	2073	Windstorm	Aerial photointerpretation
Forest national service of Sweden, Sweden	19358	Windstorm	Semiautomatic classification [b]
Friuli-Venezia Giulia forest service, Italy	191	Windstorm	Aerial photointerpretation and field survey
Ign-Institut National de information geographique et forestiere	21691	Windstorm	Aerial photointerpretation
Laboratory of Geomatics, Institute of Land Management and Geomatics, Aleksandras Stulginskis University, Lithuania	14571	Windstorm	Aerial photointerpretation

National Forest Centre, Forest Research Institute, Slovakia	555	Windstorm	Aerial photointerpretation
North Rhine-Westphalia forest service, Germany	13642	Windstorm	Aerial photointerpretation
Tesaf Department- Padua University	1532	Windstorm	field survey and aerial photointerpretation
Trento province forest service, Italy	3596	Windstorm	Aerial photointerpretation and field survey
University of Bucharest, Faculty of Geography, Romania	186	Windstorm	Aerial photointerpretation and field survey
University of Lorraine	256	Windstorm	Aerial photointerpretation
geoLAB - Laboratory of Forest Geomatics, Department of Science and Technology in Agriculture, Food, Environment and Forestry, University of Florence, Italy	1271	Windstorm	Field survey

Table 2: Conversion table to pass from class of damage to degree of damage. Records of windstorms occurred in Italy in 2015 are already expressed as damage degree in a consistent range between 0 (no damage) and 1 (full destruction of forest pattern).

	Class of damage	Definition of damage (D)	Degree of damage
France 2009	0	no forest area (not included in FORWIND)	
	1	D ≤ 20%	0.1
	2	20% < D ≤ 40%	0.3
	3	40% < D ≤ 60%	0.5
	4	60% < D ≤ 80%	0.7
	5	80% < D ≤100%	0.9
	6	marginally affected	missing data
	7	missing data	missing data
Lithuania 2010	0	no damage (not included in the FORWIND)	
	1	D ≤ 25%	0.125
	2	25% < D ≤ 50%	0.375
	3	50% < D ≤ 75%	0.625
	4	D > 75%	0.875
Germany 2017	1	D ≤ 50%	0.25
	2	50% < D ≤ 90%	0.7
	3	90% > D	0.95
Italy 2018	1	D ≤ 30%	0.15
	2	30% < D ≤ 50%	0.4
	3	50% < D ≤ 90%	0.7
	4	D > 90%	0.95

Data records

The FORWIND database is the final output of the data collection procedure and it is publicly available at https://doi.org/10.6084/m9.figshare.9555008 (Forzieri et al., 2019). The FORWIND dataset contains records as polygon features in shapefile format (.shp). The geometry of a feature is stored as a shape comprising a set of vector coordinates corresponding to the boundaries of the area of a given wind disturbance. Records are georeferenced in geographical coordinates, i.e. latitude and longitude, following the WGS84 standard (EPSG:4326). Basic attributes of each disturbance (Table 3) are provided in an associated table, stored in a .dbf file.

Table 3: Attribute table of the FORWIND database. Name and description of the attributes associated to each wind disturbance in FORWIND and listed in the .dbf file. Missing data are reported as -999.

Attribute name	**Description**
Id_poly	Identifier code
EventDate	Date of event (MM/DD/YYYY)
StormName	Storm name
EventType	Type of event: windstorm/tornado
Country	Country where the wind disturbance occurred
Area	Area affected by wind disturbance (in hectares)
Perimeter	Perimeter of the forest area affected by wind disturbance (in meters)
Damage_deg	Damage degree (in %)
Methods	Acquisition method
Dataprovid	Data provider responsible of the wind disturbance mapping
Source	Original source of the data

Overall, FORWIND includes 89,434 records, corresponding to ~1 million ha of forest area affected by wind disturbances during the 2000-2018 period. Each record should not be viewed as independent as a single storm may cause multiple, geographically disjunct, disturbances. At European level, the median wind-caused forest disturbance measures 1.08 ha (Table 4).

Table 4: Statistics of wind disturbance records collected in the FORWIND database aggregated at country level and for whole Europe.

Country	**Number of records**	**Accumulated affected area (ha)**	**Median affected area (ha)**	**Standard deviation of affected area (ha)**
AU	646	1222.15	0.78	5.69
CH	64	41.28	0.26	0.79
CZ	1175	540.98	0.14	1.67
DE	18909	34075.95	0.64	5.33
FR	21947	875407.23	8.79	993.80
IR	561	541.03	0.36	1.60
IT	8047	33991.61	1.06	14.18
LT	14571	13378.80	0.53	1.28
PL	345	46065.34	24.03	573.29
RO	186	417.59	0.80	4.92
RU	3056	17188.38	0.85	25.41
SE	19358	24450.73	0.82	1.73
SK	569	9150.24	0.65	118.65
Europe	89434	1056471.32	1.08	494.05

However, there is substantial variability across disturbances and countries likely driven by the high heterogeneity of forest and landscape characteristics. Figure 1 shows the spatial and temporal variations of records in the FORWIND database. In order to better visualize the data, we summed the areas affected by wind disturbances in 0.5-degree cells (Fig. 1a). A similar aggregation was used to show the timing of the disturbances, here expressed as the year in which most area was disturbed within a given cell (Fig. 1b). The current release of FORWIND includes wind disturbances that occurred in Austria, Switzerland, the Czech Republic, France, Germany, Ireland, Italy, Lithuania, Poland, Romania, Russia, Slovakia and Sweden. The major windstorms that occurred in the last two decades are included in FORWIND, particularly Gudrun in 2005 (Sweden), Kyrill (Germany) in 2007, Klaus in 2009 (France), Xhynthia in 2010 (Germany) and Vaia in 2018 (Italy). The high spatial detail of FORWIND is illustrated in Figure 2 for some key windstorms.

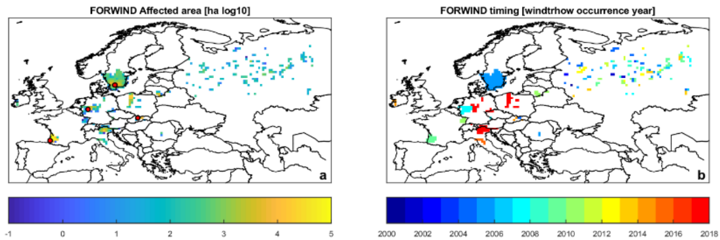

Figure 1: Spatial and temporal distribution of wind disturbances in the FORWIND database. *(a) The total area affected by wind disturbances over the multi-year observational period (2000-2018) in 0.5-degree cells. (b) Wind disturbance occurrence year in the same cells. Red circles in (a) refer to site locations shown in Fig. 2.*

Technical validation

The lack of alternative datasets with the same spatially explicit mapping of wind disturbances as in FORWIND does not allow for a standard validation exercise. Therefore, we evaluated the validity of FORWIND based on the plausibility of the collected spatial delineations of wind disturbances with respect to two satellite-based proxies of forest disturbances and estimates of forest damages reported in national inventories.

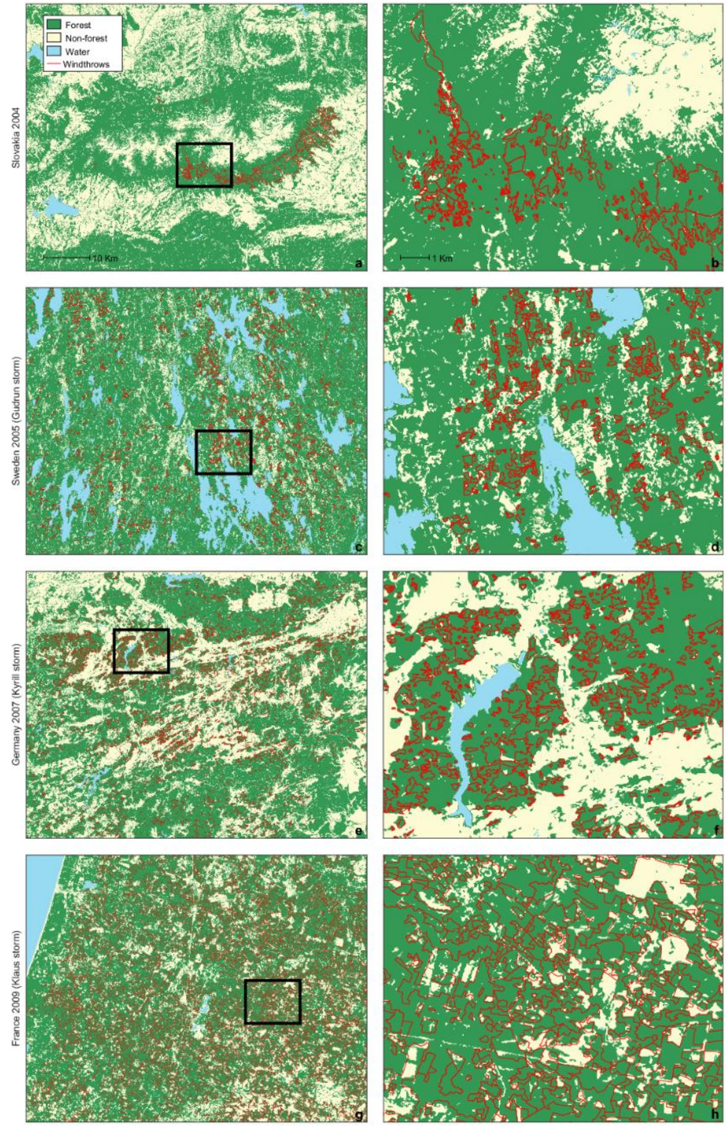

Figure 2: Examples of wind disturbances recorded in the FORWIND database. *(a, b) Tatra Mountains, Slovakia, affected by a windstorm in 2004. (c, d) Southern Sweden affected by the Gudrun storm in 2005. (e, f) Western Germany affected by the Kyrill storm in 2007. (g, h) Western France affected by the Klaus storm in 2009. Wind disturbances recorded in the FORWIND database are shown as red polygons. Background colors show forest and non-forest areas derived from the 25-meter forest cover map of 2000(Pekkarinen et al., 2009) while water bodies are derived from the 25-meter land cover*

type map of 2006(Kempeneers et al., 2011) (https://forest.jrc.ec.europa.eu/en/past-activities/forest-mapping/#Downloadforestmaps). Site locations in (a, c, e, g) are shown in Fig. 1a whereas zoomed plots in (b, d, f, h) refer to black boxes in (a, c, e, g).

4.1 FORWIND versus LANDSAT-based forest cover loss

FORWIND was initially compared with satellite-based estimates of forest cover loss derived from the Global Forest Change maps (Hansen et al., 2013) (GFC, https://earthenginepartners.appspot.com/science-2013-global-forest). GFC maps characterize the annual forest coverage at global scale during the period 2000–2018 at 30-meter spatial resolution based on time-series analysis of Landsat images. Forest cover loss is defined as an area that has changed from a state of forest to non-forest, following a given disturbance event (natural or anthropogenic). The change detection is based on the variation in the spectral properties of the land surface. Windstorm events in Europe often occur in autumn and the beginning of winter, when the availability of cloud-free images is typically much more limited than in summer. Hence, satellite retrievals of forest cover loss may miss the exact timing of the disturbance. Therefore, the GFC-based forest cover loss may only record wind disturbances the year after the event occurred. In addition, fallen trees following a windstorm or tornado often maintain their leaves for months. This may lead to limited or no change in land reflectance properties, even when cloud-free images are available. Therefore, satellite-based products may underestimate forest cover loss in the short-term (interannual scale). In order to account for these effects, we considered the forest cover loss by summing up the forest loss over the year of a given event together with that of the following year (lag-01). The loss estimate was quantified with respect to the pre-event conditions (the forest cover in the year before the event). To reduce potential contamination effects from other disturbances on the resulting total forest cover loss, we removed areas affected by fires the year following a wind event. Information on forest areas affected by fires were retrieved from the European Forest Fire Information System (EFFIS, http://effis.jrc.ec.europa.eu/). Insect outbreaks, which may be triggered by large numbers of dead trees following wind disturbances (Stadelmann et al., 2013), generally lead to a slow change in tree cover, which may only marginally affect the 1-year temporal lag used for our estimates of forest cover loss. Furthermore, forest logging following a wind event can be considered a secondary effect of the strong winds, as it is often employed to reduce the risk of other forest disturbances (specifically insect outbreaks and fires). Therefore, the resulting estimates of forest cover loss for the selected areas should reflect wind disturbances first and foremost. We emphasize that Landsat-derived estimates of forest cover loss are affected by the uncertainty in satellite retrievals and do not represent the true impacts. However, their suitability for detecting forest disturbances over large scale has been widely recognized (Curtis et al., 2018; Hansen et al., 2013) and, therefore, they are here considered a good proxy of forest loss. For each selected FORWIND record we computed the area of affected forest based on the spatial delineation of the polygon and the corresponding Landsat-derived forest cover loss and calculated the correlation between the two sets of estimates. In order to account for the spatial dependence structure of FORWIND data, correlation values were derived for 100 subsets of 1000 records randomly selected from the entire dataset. The final estimate of correlation was then quantified as the average of the correlation values derived from the 100 subsets. Results for the whole dataset are shown in Figure 3a.

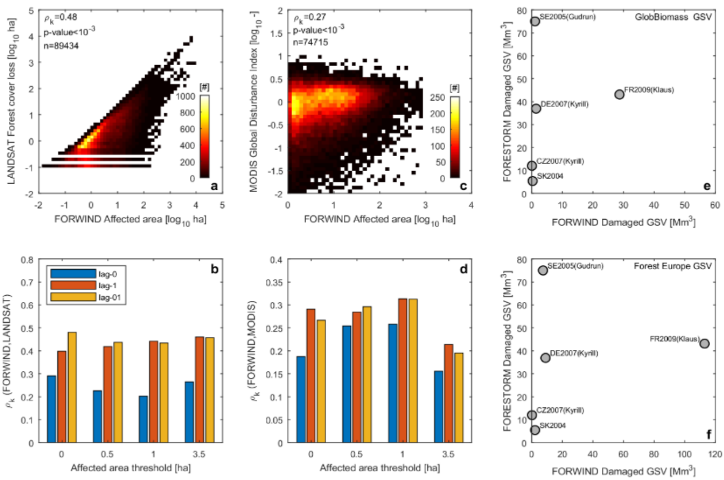

Figure 3: Validation of the FORWIND database. *(a) Density plot of FORWIND affected area versus LANDSAT-derived forest cover loss, both expressed in logarithmic scale and for lag-01 effects. The color reflects the number of records, top left labels report the Spearman rank correlation coefficient (ϱ_k), the significance (p-value) and the sample size (n). (b) Spearman rank correlation coefficients for different affected area thresholds (on the x-axis) and different lagged effects displayed in color bars. Lagged effects considered include the forest cover loss cumulated over the event of a given year together with that of the following year (lag-01), forest cover loss estimated for the year event only (lag-0) and forest cover loss estimated for the following year only (lag-1). (c) and (d) as (a) and (b) but for the MODIS-derived Global Disturbance Index in place of Landsat-derived forest cover loss. (e) Scatter plot of damaged growing stock volume estimated from FORWIND (on the x-axis) and FORESTORM (on the y-axis) for five windstorms: Slovakia in 2004 (SK2004); Sweden*

in 2005 (SE2005 (Gudrun)), Germany in 2007 (GE2007 (Kyrill), the Czech Republic in 2007 (CZ2007 (Kyrill)) and France in 2009 (FR2009 (Klaus)). FORWIND estimates are derived using GlobBiomass-derived estimates of GSVs and reported damage degree information. (f) as (e) but with estimates of GSVs derived from Forest Europe national inventories and assuming a 100% damage degree for all FORWIND records.

Overall, we found a modest but significant Spearman rank correlation coefficient (ϱ_k=0.48, p-value$<10^{-3}$), which supports the validity of FORWIND in mapping areas subject to changes of forest coverage due to wind disturbances. We point out that for this calculation we did not mask the data based on the degree of damage, because such information is available only in some countries. However, a similar correlation analysis performed by rescaling the recorded areas based in their damage degree (for those records that report the information) led to higher correlation values up to 0.54. We further tested the sensitivity of our results to the temporal lag used to quantify the forest cover loss. To this aim, we complemented the previous analysis (lag-01) using Landsat-based forest cover loss estimated for the year of the event only (lag-0) and the following year only (lag-1). In order to investigate possible scaling relations, the correlation analysis was performed accounting for the FORWIND records with a spatial extent above a given threshold derived from the percentiles 0, 0.25, 0.50 and 0.75 of the full dataset (corresponding to about 0, 0.5, 1, and 3.5 ha, respectively). Results show that correlation values between FORWIND affected areas and lag-0 forest cover loss tends to slightly decrease with an increasing size of the wind disturbance (Fig. 3b). The opposite pattern is observed for correlation values with lag-1 forest cover loss. The forest cover loss accumulated over the two years considered (lag-01) appears dominated by the contribution of lag-1 forest cover loss. We argue that such contrasting tendencies may be linked to the scale and climatology of extreme winds. Wind-related forest impacts of limited areal extent originate from local windstorms or tornadoes that may occur throughout the year. For these events, most of the damage is probably well captured by lag-0 effects, as it is more likely that cloud-free images are available after the event. In contrast, the larger and more damaging windstorms, which affect larger forest areas, typically occur in autumn and early winter (decreasing the likelihood of cloud-free images after the storm and before the end of the year). For these events, the inclusion of the lag-1 effect is key to characterize the impact on forest cover.

4.2 FORWIND versus MODIS Global Disturbance Index

FORWIND was also compared with an independent dataset of satellite-based estimates of forest disturbance as expressed by the MODIS-based Global Disturbance Index (Mildrexler et al., 2007, 2009) (MGDI, http://files.ntsg.umt.edu/data/NTSG_Products/MGDI/). MGDI maps quantify the overall annual forest disturbance globally for the period 2004-2012 at 500-meter spatial resolution. The disturbance retrieval is based on the variations in the Enhanced Vegetation Index and land surface temperature following a given sudden change in forest cover. Consistent with the previous Landsat-based analysis - the total change in MGDI potentially related to a given wind disturbance was computed as the accumulated net change in MGDI over the event year and the following year (lag-01). The change was quantified with respect to the pre-event conditions (MGDI in the year before the event). The technique used to disentangle the fire signal, as well as the correlation and sensitivity analyses with respect to the temporal lags and wind disturbance size, were performed analogously to the previous validation exercise.

Overall, we found a low but significant correlation coefficient (ϱ_k=0.27, p-value<10^{-3}) (Fig. 3c). The lower correlation compared to the Landsat-based dataset is presumably due to the coarser spatial resolution of MGDI that probably does not fully capture the changes in land surface properties due to wind disturbances (Mildrexler et al., 2009). This seems to be supported by the generally increasing correlation values up to 0.31 for wind disturbances of 1 ha consistently across the different temporal lags (Fig. 3d).

4.3 FORWIND versus FORESTORM

FORWIND data were finally compared with estimates of damaged growing stock volume (GSV) that are recorded at country level in the FORESTORM database (http://www.iefc.net/storm/) for five windstorm events: Slovakia in 2004; Sweden in 2005 (Gudrun storm), Germany in 2007 (Kyrill storm), the Czech Republic in 2007 (Kyrill storm) and France in 2009 (Klaus storm). We derived the damaged GSV by multiplying the estimated GSV by the percentage damaged, both of which are reported in FORESTORM. An analogous metric was derived from FORWIND data by first calculating for each FORWIND record the amount of GSV lost by multiplying the areal average GSV by the damage level reported for the record. As the damage level was only reported for Klaus, for the other events we assumed a damage level equal to the average level reported for Klaus weighted on the spatial extent of each record. The GSV was retrieved from the GlobBiomass dataset (Santoro et al., 2018) (https://doi.pangaea.de/10.1594/PANGAEA.894711) which is based on multiple remote sensing products and is considered the state-of-the-art global biomass product. This satellite based GSV estimate refers to the year 2010 and has a spatial resolution of 100 meter. The damages to GSV were then summed by event and country. Event-scale FORWIND damaged GSVs were then compared with estimates derived from FORESTORM. Overall, results show that the magnitude of damages estimated from FORWIND and FORESTORM are largely different, except for the 2009 Klaus storm in France for which we found a very good agreement (Fig. 3e). For most of the events, however, FORESTORM tends to systematically give higher forest damage estimates than FORWIND with differences exceeding 90%. We note that such differences persist when we derive FORWIND estimates of damaged GSV assuming a 100% damage degree for all records (not shown). Therefore, the uncertainty in the damage degree in FORWIND does not affect substantially the difference between FORWIND and FORESTORM. We recognize that estimates of forest damages based on FORWIND are fully dependent on the GSV derived from GlobBiomass. Indeed, any deviations of the mapped GSV from the true forest state are inherently translated into our damaged GSV estimates. In particular, the GSV map refers to the year 2010, therefore it is very likely that it largely reflects the biomass conditions following, rather than preceding, the windstorm events (all the five events considered in this validation exercise occurred before 2010).

In order to disentangle such source of bias we derived country-scale estimates of average GSVs for the year 2000 (pre-event conditions) from the State of Europe's Forest (FOREST EUROPE, 2015) (https://www.foresteurope.org/docs/SoeF2015/OUTPUTTABLES.pdf). We then derived the damages GSVs by multiplying Forest Europe-derived GSVs by the total forest area affected for each of the considered wind events by assuming a 100% degree of damage. Similar to the previous results, expect for the Klaus storm, we found higher values of damaged GSVs in FORESTORMS than in our estimates based on the integration of FOREWIND and country values of GSVs (Fig. 3f). We recognize that FORWIND could miss some wind damage occurrences. However, according to the institutions responsible for the data acquisition, the forest areas affected by the windstorm events considered in this validation exercise were exhaustively mapped. Therefore, possible residual omissions are expected to only marginally affect our results. We therefore argue that a possible source of error may be associated to the FORESTORM database. Estimates of forest damages from FORESTORM originate from different sources and are collected by multiple actors. Hence, the loss figures should be viewed in light of their potential biases, including a possible overestimation of the true impacts.

Data usage and conclusions

The FORWIND database is the first Pan-European collection of spatially delineated forest areas affected by wind disturbances and includes all major events that occurred over the 2000-2018 period. FORWIND provides fundamental spatial and temporal information to improve our understanding of the vulnerability of forests to winds and develop large-scale monitoring and modelling of natural disturbances.

For demonstration purposes, we show how FORWIND data can be used to quantify forest vulnerability as a function of the fraction of evergreen needleleaf forest (ENF) and annual maximum wind speed. The fraction of ENF was derived from the annual land cover maps of the European Space Agency's Climate Change Initiative (ESA, 2017) (ESA-CCI, https://www.esa-landcover-cci.org/) aggregated at 0.5 degree spatial resolution. Annual maximum wind speeds were computed from NCEP/NCAR Reanalysis 2 data(Saha et al., 2010) (NCEP2,https://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis2.html). Daily average wind data at 0.5-degree spatial resolution were acquired and the two horizontal components combined to derive the magnitude of the wind vector. For each cell, the fraction of ENF and the annual maximum wind concomitant with a wind disturbance were then selected from the time series and used in our experiment as potential drivers of vulnerability (Fig. 4a, c). The values of fraction of ENF and annual maximum wind speed (predictors) were linked with the corresponding FORWIND affected area (response variable) within each 0.5-degree cell. In order to increase the spatial consistency of the emerging relationships, spatial averages in the response variable were derived using bins that spanned the sampled ranges of the predictors (bin sizes of 10% and 2 m/s for fraction of ENF and annual maximum wind speed, respectively). The resulting datasets were ultimately fitted by linear regression models (Fig. 4b, d).

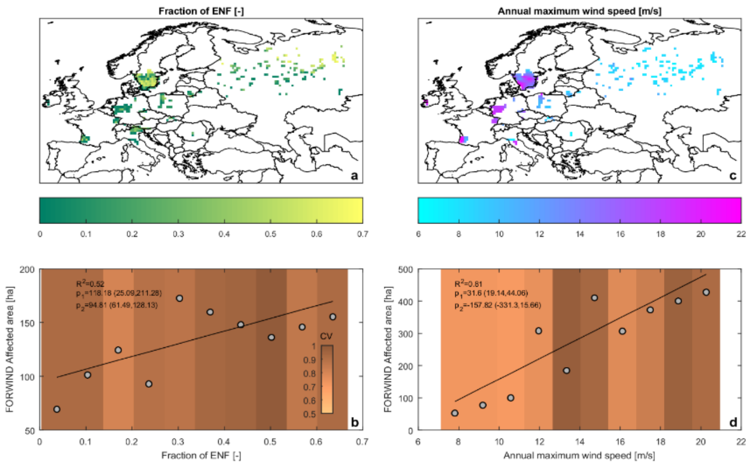

Figure 4: Use of FORWIND to explore susceptibility factors and drivers of forest vulnerability to wind disturbances. *(**a**) Spatial map of the fraction of evergreen needleleaf forest (ENF). (**b**) Relation between the fraction of ENF (on the x-axis) and area affected by wind disturbances (on the y-axis) as derived from the FORWIND database. Averaged values, shown in grey circles, were derived using bins that spanned the sampled range. Colour patterns reflect the coefficient of variation within each bin. The fitted linear regression model is shown in black line with the coefficient of determination (R^2), slope (p_1) and intercept (p_2) reported in the labels. The confidence interval for each of the coefficient is shown in brackets. (**c**) Spatial map of annual maximum wind speed; (**d**) as (**b**) but for annual maximum wind speed in place of the fraction of ENF. The grid cells in (**a**) and (**c**) with no wind disturbances occurred over the 2000-2018 period are masked out.*

Wind disturbance areas manifest a substantial variability, as evident form the generally high values of the coefficient of variation. However, when data are spatially averaged at bin level, simple linear regression models show a reasonably good fit, with R^2 values of 0.52 and 0.81 for the fraction of ENF and annual maximum wind speed, respectively. Emerging patterns are largely consistent with expectations and previous studies. An increasing fraction of ENF leads to an increase in wind disturbance area (growing rate of 12 ha of affected forest per 0.1 increase in ENF fraction). Indeed, this plant functional type is typically characterized by shallower rooting systems compared to other forest types. Combined with the limited flexibility of its branches and trunk this makes ENF more prone to uprooting and breakage by strong winds (Klaus et al., 2011; Ruel, 1995). A similar pattern emerges with respect to annual maximum wind speed (Seidl et al., 2011). Wind disturbance area tends to increase with rising wind speed (growing rate of 32 ha of affected forest per 1 ms^{-1} increase in wind speed). Maximum wind speeds are the primary determinant of wind disturbances. However, we point out that the coarse spatial and temporal resolution on NCEP2 data largely underestimate the speed of wind gusts and may completely miss peak winds originating from tornados. This is clearly evident from the range of values of annual maximum wind speed (6-22 m/s) which are far lower than the wind speeds reported in country-scale inventories of forest disturbance (e.g., 42 m/s for Gudrun, FORESTORM).

We recognize that the above example is an oversimplification of the biomechanical processes that may cause wind disturbances. Multiple variables, susceptibility factors, and drivers (e.g., tree species, tree dimension, management regimes, planting patterns, soil depth, snow cover), contribute concurrently to the vulnerability of trees (Hart et al., 2019; Klaus et al., 2011; Mitchell, 2013) and therefore their contribution should be analysed in a multidimensional space. Therefore, the approach described here should not be considered as a reference methodology to analyse the vulnerability of forests but only as an informative application to explore the usefulness of the FORWIND database.

FORWIND could also be suitable in diverse contexts for large-scale monitoring and modelling of forest ecosystems. For instance, some pioneering studies have begun producing classification maps of various forest disturbance agents based on remote sensing data (Cohen et al., 2016; Hermosilla et al., 2015; Potapov et al., 2015; White et al., 2017). However, the attribution of forest change to windstorms remains challenging. Previous systematic monitoring has been performed only over limited areal extents and showed considerable uncertainty (Baumann et al., 2014; Schroeder et al., 2017) mostly due to the limited number of sampled wind-affected areas available for training/testing classification algorithms (Schroeder et al., 2017). Similar critical issues affect land surface models (LSM) now widely applied to support policy-relevant assessments on the impact of climate change on terrestrial ecosystems. Recently, windstorm effects have been incorporated in LSMs (Bonan and Doney, 2018; Chen et al., 2018). However, these models are hampered by the lack of harmonized spatially explicit information on windstorms required as input for robust model parameterization and large-scale representation of wind disturbance. In such contexts, the FORWIND database represents a valuable source of harmonized wind-affected forest areas for improving model calibration and validation.

Data availability

Data are freely available at https://doi.org/10.6084/m9.figshare.9555008 (Forzieri et al., 2019) and will be periodically updated with new and historical events. To this effect, the authors welcome further data contributions and commit to properly acknowledging them.

Author contributions. G.F. designed the study. M.P. performed the data collection and harmonization. M.G. assisted in data integration tasks, M.M., C.Nikolov., M.R., J.T., D.S., C.Nistor., D.J., F.G., R.C., A.W., F.P., F.M., S.I., W.L-S., K.S., K.Z-K., P.S-J., M.M., F.S., L.K., I.H., M.N., P.W. and G.C. collected forest disturbance data. G.F. analysed the data and wrote the manuscript with contribution from all co-authors.

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4.2: Wall-to-wall spatial prediction of growing stock volume based on Italian National Forest Inventory plots and remotely sensed data

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Abstract: Spatial predictions of forest variables are required for supporting modern national and sub-national forest planning strategies, especially in the framework of a climate change scenario. Nowadays methods for constructing wall-to-wall maps and calculating small area estimates of forest parameters are becoming essential components of most advanced National Forest Inventory (NFI) programs. Such methods are based on the assumption of a relationship between the forest variables and predictor variables that are available for the entire forest area. Many commonly used predictors are based on data obtained from active or passive remote sensing technologies. Italy has almost 40% of its land area covered by forests. Because of the great diversity of Italian forests with respect to composition, structure and management and underlying climatic, morphological and soil conditions, a relevant question is whether methods successfully used in less complex temperate and boreal forests may be applied successfully at country level in Italy.

For a study area of more than 48,657 km^2 in central Italy of which 43% is covered by forest, the study presents the results of a test regarding wall-to-wall, spatially explicit estimation of forest growing stock volume (GSV) based on field measurement of 1350 plots during the last Italian NFI. For the same area, we used potential predictor variables that are available across the whole of Italy: cloud-free mosaics of multispectral optical satellite imagery (Landsat 5 TM), microwave sensor data (JAXA PALSAR), a canopy height model (CHM) from satellite LiDAR, and auxiliary variables from climate, temperature and precipitation maps, soil maps, and a digital terrain model.

Two non-parametric (random forests and k-NN) and two parametric (multiple linear regression model and geographically weighted regression) prediction methods were tested to produce a wall-to-wall map of growing stock volume at 23-m resolution. Pixel level predictions were used to produce small-area, province-level model-assisted estimates. The performances of all the methods were compared in terms of percent root mean-square error using a leave-one-out procedure and an independent dataset was used for validation. Results were comparable to those available for other ecological regions using similar predictors, but random forests produced the most accurate results with a pixel level $R^2 = 0.69$ and $RMSE_{\%} = 37.2\%$ against the independent validation dataset. Model-assisted estimates increased the precision of original design-based estimates provided by the NFI.

Keywords: National Forest Inventory; Spatial estimation; Growing stock; Landsat; Italy; Growing stock volume

INTRODUCTION

Forest data are essential for multiple purposes including international and national forest monitoring programs, reporting and assessing forest resource distribution (e.g. Kyoto protocol) (FAO, 2010), monitoring biodiversity (Chirici et al., 2012; FOREST EUROPE, 2015), improving restoration programs (FAO and UNCCD, 2015; Smith et al., 2016) and managing at local scales to improve decision-making processes, silvicultural measures, harvesting and conservation activities.

Usually, in the context of international and national programs, this type of data is collected using sample-based National Forest Inventories (NFIs) that are designed to provide aggregated estimates of forest parameters such as forest area, growing stock volume, biomass, increments at national and regional levels (Brosofske et al., 2014; Kangas et al., 2018). These aggregated statistics are essential to support decision-making processes and to develop strategies over large areas only, because they just provide limited explicit geographic spatial detail, such as large sub-national regions. In these traditional NFIs, remote sensing is used mainly for the initial stratification of sampling units according to their main land uses, most commonly through the use of fine resolution remotely sensed imagery (McRoberts et al., 2009; McRoberts et al., 2010).

In countries characterized by longer NFI traditions and/or a stronger interests in the operational implementation of sustainable forest management practices such as in Sweden, Finland, Denmark (Næsset et al., 2004; Nord-Larsen and Schumacher, 2012; Tomppo et al., 2008), Canada (Boudreau et al., 2008; Matasci et al., 2018), Austria (Hollaus et al., 2009) and Switzerland (Waser et al., 2017, 2015), traditional inventories are now integrated with a more advanced use of remote sensing technology for mapping forest variables (McRoberts and Tomppo, 2007).

Most frequently these methods are applied to construct wall-to-wall spatial estimates of forest variables such as growing stock volume (Nilsson et al., 2017; Nord-Larsen and Schumacher, 2012), biomass (Nord-Larsen and Schumacher, 2012), forest cover (Waser et al., 2015), or forest changes (Næsset et al., 2013).

Wall-to-wall forest mapping in these modern forest inventories, sometimes characterized as Enhanced Forest Inventories (EFI) (Stinson and White, 2018), is considered an essential component of the forest inventory project aimed at producing forest parameter estimates at multiple spatial scales: traditional aggregated statistics useful for national planning, and at the same time, consistent small-area estimates for sub-national planning or even pixel-level raw data to support local forest management (Matasci et al., 2018; McRoberts et al., 2010; Næsset et al., 2004; Nilsson et al., 2017; Tomppo et al., 2008; Waser et al., 2015).

The EFI approach produces a variety of benefits: it is able to provide detailed information to support decision-making and reduce the costs for a variety of forest activities including silvicultural treatments (frequently in the framework of precision forestry), quantification of forest ecosystem services, wood harvesting, and conservation strategies (Kangas et al., 2018). The costs of the shift from a traditional NFI to an EFI are limited, because the major required investment, the field activity, remains the same or it may be even reduced if remote sensing is used for the optimization of the sampling strategy. Major costs may be related to the acquisition and elaboration of remotely sensed data.

Research activities carried out in the last 20 years demonstrated that 3D pulses from airborne laser scanning (ALS) is the most valuable data source for enhancing of growing stock volume and other forest structural variables estimates (Kangas et al., 2018; McRoberts et al., 2010; Næsset, 2007; Nilsson et al., 2017; Montaghi et al., 2013; Nord-Larsen and Schumacher, 2012). The optimal option for the implementation of an EFI is thus the use of ALS data acquired in the same period as the field survey.

ALS acquisition is still expensive, but ALS data are useful for a vast array of applications in land planning, thus its cost can be shared among multiple stakeholders and agencies. However, wall-to-wall ALS data at country level are not yet available in several regions of Europe such as Italy (Giannetti et al., 2018), Spain (Fernández-Landa et al., 2018), and most developing countries.

Together with ALS, or in case ALS is not available, satellite multispectral data can also be useful, with only small costs because they are nowadays available online for free. Barrett et al. (2016) reported in their review that when NFI data are linked with remotely sensed data, the most frequently used satellite systems are medium-resolution satellites with Landsat the most used. Medium-resolution satellite images (pixel size between 20 and 30 m) permit the prediction of forest variables with spatial detail relevant for forest inventories and sustainable forest management, and also as reported by Nilsson et al. (2017), for forest plans although forest agencies, forest companies, and forest owner associations would prefer as fine resolution as possible (in the range 10 – 30 m).

Several methods produce wall-to-wall maps of forest variables from field observations (Corona et al., 2014). Such methods are based on the assumption that a model of the relationship between the forest variables to be predicted and predictor variables that are available for the entire forest area can be constructed. These methods include both parametric (i.e. multiple linear regression model, geographically weighted regression) and non-parametric (i.e. k-NN, random forests, Artificial Network Analysis) techniques (Barrett et al., 2016; Brosofske et al., 2014; Chirici et al., 2016; Moser et al., 2017) and have already been tested across different forest types and regions (Chirici et al., 2016).

All these methods have been widely applied with remote sensing-based predictors such as 3D data (from ALS data, microwave, or photogrammetry) (e.g. McRoberts et al., 2010; Næsset, 2007; Nilsson et al., 2017; Nord-Larsen and Schumacher, 2012; Persson et al., 2017; Waser et al., 2017, 2015) or multispectral images from aerial, manned or unmanned, or satellite platforms, (e.g. Brosofske et al., 2014; Fernández-Landa et al., 2018; Matasci et al., 2018; Reese et al., 2002). All these approaches have already become operational for boreal forests (Kangas et al., 2018), while in Mediterranean areas experiences are yet limited, most probably because wood production is economically less relevant and forest composition and structure is more complex, and thus more difficult to model.

Maselli et al. (2014) tested moderate resolution imagery from global 1 km resolution forest canopy height data from the Geoscience Laser Altimeter System (GLAS) onboard the ICESat (Ice, Cloud, and land Elevation Satellite) for enhancing of growing stock volume estimates at country-level in Italy. Fernández-Landa et al. (2018) enhanced the estimates of the main forest inventory variables (i.e. stand density, basal area and growing stock volume) acquired in the Spanish NFI with Landsat images and ALS in a small study area in La Rioja (Spain). Condés and McRoberts (2017) developed an accurate method for updating NFI estimates of mean growing stock volume (m3ha-1) using models to predict annual plot-level volume change, and for estimating the associated uncertainties using four monospecific forest types and Landsat images for two study areas in Spain.

Mura et al. (2015) and Bottalico et al., (2017) used ALS for enhancing the estimates of structural diversity in different test areas in Italy (i.e. Molise, Tuscany and Sardinia) using a remote-sensing base estimates, while Mura et al. (2018) used Sentinel-2 imagery to enhancing the estimates of growing stock volume for two test areas in Italy.

To our knowledge country-level experiences in Mediterranean areas have not yet been reported in the literature.

However, in Mediterranean areas there is an increasing need for wall-to-wall forest maps because these forests are considered more vulnerable to climate change scenarios and to natural and anthropogenic disturbances such as forest fires and urban sprawl (Scarascia-Mugnozza et al., 2000).

The current study aims at constructing wall-to-wall estimates of forest growing stock (GSV) for a large test area (i.e. 48,657 km2) in central Italy by combining NFI plot data, remotely sensed and auxiliary variables. In particular, the research evaluated the most accurate imputation approach for mapping GSV at fine spatial resolution (23x23 m) and calculating small area estimates using a model-assisted approach. The results of this experimental test are aimed at identifying the optimal procedure for the operational GSV and biomass estimation at country-level in Italy.

MATERIALS

Study area

To test possible wall-to-wall spatial estimation alternatives at country-level in Italy we selected a large region in central Italy including the whole of Tuscany and most of the Emilia-Romagna and part of the Liguria Regions for a total extent of 48,657 km^2 (Figure 1). The area is characterized by large geographical and topographical variability from flat coastal areas, to gentle hills, to steep

mountains with elevation up to 2,000 m a.s.l. Total precipitation per year ranges between 3,000 mm in Alpi Apuane to 600 mm in the Maremma area (south of Tuscany), while mean temperature ranges between 6° C in Abetone Mountain and Camaldoli to 17° C along the coast.
Broadleaf species such as downy oak (*Quercus pubescens* Willd.), pedunculated oak (*Q. robur* L.), Turkey oak (*Q. cerris* L.) and sessile oak (*Q. petraea* Liebl.) (Pecchi et al., 2019) comprise 88% of the total forest area and are mainly managed as coppice. The coppice management system is applied in 63% of the forests in the study area. Dominant coniferous species, mainly in artificial plantations, are maritime pine (*Pinus pinaster* Ait.) and black pine (*P. nigra* Arnold). Six out of the 14 European Forest Types (Barbati et al., 2014; Giannetti et al., 2018) are represented in the study area.

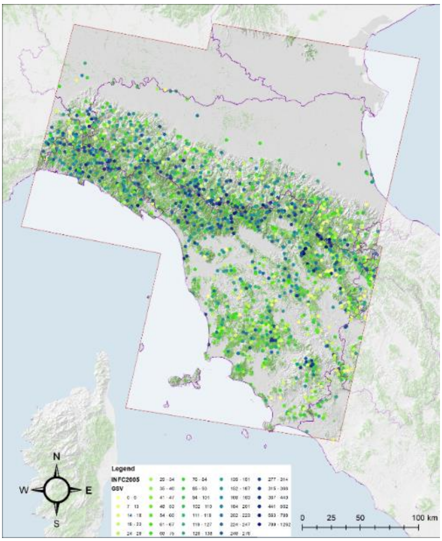

Figure 2 - Study area location (red boundary) and spatial distribution of NFI plots (INFC,2005). Values of GSV in m^3 ha^{-1}.

Italian National Forest Inventory data

The field reference data for the study area were acquired for 1350 plots measured in the framework of the 2nd Italian NFI (INFC, 2005) (Figure 1) which is based on a three-phase, non-aligned, systematic sampling design (Fattorini et al., 2006). Sampling units are located randomly within 1-km x 1-km grid cells, and in the first phase are classified on the basis of land use using aerial photos. For a subsample of the first-phase forest sampling units, qualitative information such as forest type, management, and property is collected during a terrestrial survey. For a subsample of the second-phase units, a quantitative survey is carried out in the field using circular 13 m radius plots (i.e., 530 m^2). The first two phases are aimed at estimating the forest area and classifying it into forest categories, while the third phase is aimed at collecting biophysical variables. The plot data used for this study were acquired in the third phase (INFC, 2005). The plot geolocation available for this study has been the target coordinate of the sampling unit, i.e. the theoretical center of the plot that the field crew should reach. Several studies reported in the literature have

evaluated the impact of inexact plot location for the estimation of forest growing stock volume or biomass. All of them relate to the use of Airborne Laser Scanning (ALS) pulses, which resulted in very sensitive to plot location accuracy (McRoberts et al., 2018). On the other hand, in this study we predict the GSV for pixels of 23 m resolution and we expect that the error of GNSS receivers should be much smaller than the pixel size and for this reason in this study we ignored potential positional inaccuracy of NFI plots.
For each field plot, the predicted GSV per hectare for all callipered trees is freely available online via a spatial database at https://www.inventarioforestale.org/ (Borghetti and Chirici, 2016; Pecchi et al., 2019). The GSV of each tree was predicted using species-specific allometric models developed in the framework of the NFI using tree DBH and tree height as independent variables (Tabacchi et al., 2011). The GSV per hectare of each plot was predicted as the aggregation of volume predictions for all the trees callipered in the plot. The uncertainty of allometric model predictions was considered negligible and ignored following previous results (McRoberts et al., 2016). In Figure 1 we report the spatial distribution of sample plots, while in Figure 2 we report the GSV distribution for the 1350 field plots used in this study.

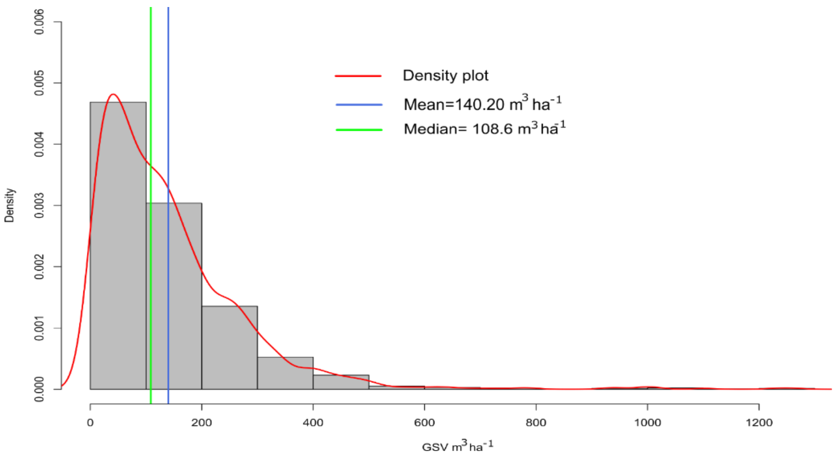

Figure 3 - GSV distribution measured in 1350 INFC plots. The red line is the density distribution, the green line is the median value and the blue line is the mean value.

Validation data

To validate the results of our estimation we used independent field data from 332 circular plots for a different dataset, of which 297 plots of 1256.4 m² were measured between 2004 and 2009 to support forest management in forest areas in Tuscany and 35 are ICP level I circular plots measured in 2005 in the framework of the BioSoil Forest Biodiversity project (Galluzzi et al., 2019). The plots are representative of all forest types in the study area. The plots measured to support forest management activities are located in: Vallombrosa, Cerventosa, Lucignano, Chianti, Muraglione, Rincine and Cecina (Figure 3).

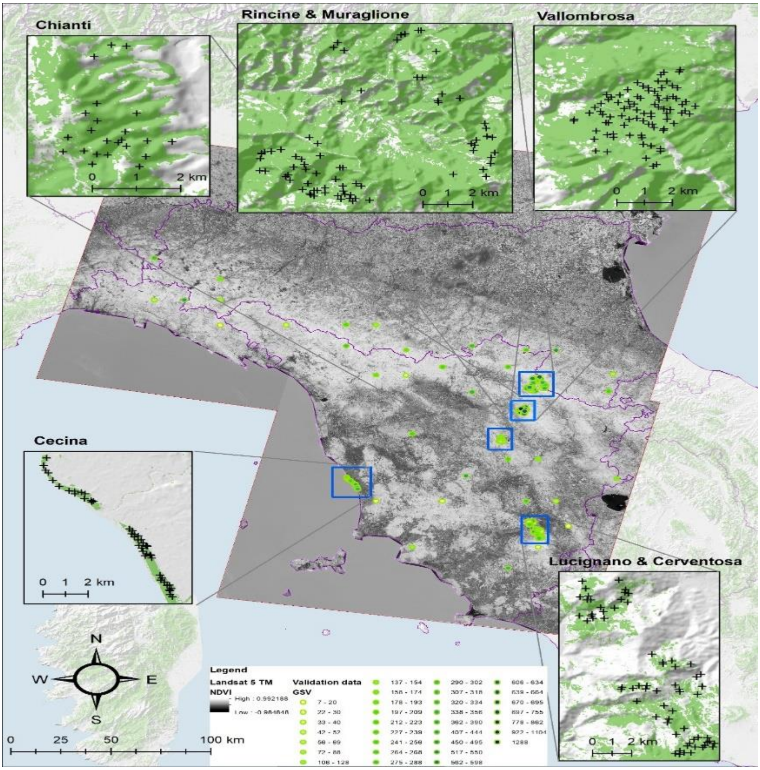

Figure 4 – validation data used in the study on the basis of the Landsat 5 TM NDVI imagery.

The centers of these plots were georeferenced using a Trimble Juno 3B GNSS system and post-processed with sub-meter accuracy with the closest GNSS national base station and for each plot we applied the same field protocol developed for the Italian INFC. The GSV of each tree and the GSV per hectare of the validation plots were predicted using the same approach described in the previous paragraph for INFC plots. The GSVs of ICP BioSoil Forest Biodiversity plots were calculated using international allometric models as reported in Galluzzi et al. (2019).

The mean GSV in the validation dataset is 350.57 m^3ha^{-1}, with a minimum of 6.8, a maximum of 1288.2 m^3ha^{-1} and a standard deviation of 254.79 m^3ha^{-1}. The average GSV in the validation data is therefore consistently greater than the GSV registered in the INFC dataset. This was expected since the validation dataset is related to forests located in productive sites where the main forest management objective is nature and landscape conservation. This means that wood removals are generally less than the increments and the GSV tends to accumulate.

Predictor variables

The rationale for choosing the predictors are based on two elements: *i*) the availability for the whole Italy, since this test is aimed at evaluating different approaches for a country level wall-to-wall GSV spatial estimation, and *ii*) that the predictor can be at least potentially related to GSV from the results of previous investigations or from literature.

Remotely sensed variables

Landsat

After having evaluated other possible imagery (Chirici, in press), to cover the study area we used imagery for three Landsat 5 Thematic Mapper (TM) scenes, 192030 and 192029 acquired the 23rd of June 2005, and an image for scene 193029 acquired the 30th of June 2005. The three images are cloud-free for the forest part of the study area. Level-1 data products in Digital Numbers (DN) where transformed to top of atmosphere (TOA) radiance using radiometric rescaling coefficients provided with the Level-1 products (Figure 3).

Global PALSAR/PALSAR-2

The SAR data used are the global 25 m resolution PALSAR-2/PALSAR mosaic available for the year 2007 as free open spatial dataset at Japanese Aerospace Exploration Agency (JAXA). Images are available as backscattering coefficient for each polarization HH and HV using the L-band Synthetic Aperture Radars (PALSAR and PALSAR-2) on Advanced Land Observing Satellite (ALOS) and Advanced Land Observing Satellite-2 (ALOS-2). The global 25 m resolution PALSAR/PALSAR-2 mosaic is processed for the geometric correction and radiometric correction to reduce topographic effects on image intensity (i.e. slope correction). The observation mode is FBD (HH, HV) and the off-nadir angle is 34.3 degrees.

Auxiliary variables

Digital Elevation Model

We used the 10 m resolution DEM TINITALY which is the finest and most accurate DEM currently available in Italy (Fornaciai et al., 2012; Tarquini et al., 2007; Tarquini and Nannipieri, 2017). TINITALY is available at http://tinitaly.pi.ingv.it/ in grid format.

Climate data

Climate data were derived from 1-km downscaled climatological surfaces released for Italy by Maselli et al. (2012). This dataset was obtained through application of geographically weighted regression to the Pan-European E-OBS data-base, which has a 0.25° spatial resolution (Haylock et al., 2008). The Italian dataset is representative for the period 1981-2010 and includes total annual rainfall and minimum and maximum temperatures, from which mean temperature was currently estimated. The downscaled E-OBS dataset over-estimates minimum temperature and under-estimates maximum temperature and, most importantly, rainfall (Maselli et al. 2012). For this reason, we used a version of the rainfall dataset that was corrected as described in Fibbi et al. (2016).

Soil data

The soil data used were derived from the European Soil Database v2.0 (2004) (Panagos, 2006). This spatial dataset is the only geographically harmonized soil database available for Europe. It contains a soil geographic database (SGDBE) (i.e. polygons) to which a number of essential soil attributes are attached. From this database we used the quantitative information related to: (i) subsoil available water soil capacity; (ii) topsoil available water soil capacity; (iii) volume of stones; (iv) depth to rock; (v) subsoil cation exchange capacity; (vi) topsoil cation exchange capacity; (vii) soil exchange capacity.

World Canopy Height Model

We used the vegetation height available in the wall-to-wall Canopy Height Map (Simard et al., 2011) estimated at 1-km spatial resolution from the ICESat GLAS.

Forest mask

A forest mask was needed to limit the spatial estimation to pixels with forest land cover only. As far as possible the forest mask should mimic the same standard FAO definition used in the Italian NFI (INFC, 2005) and should be dated as close as possible to the reference year 2005 used for the acquisition of the inventory field plot data. After several tests we decided to use local fine resolution land use/land cover maps constructed at a 1:10,000 scale. We used maps from regional geoportals of Liguria, available for the year 2009 (https://geoportal.regione.liguria.it); Toscana, available for the year 2007 (http://dati.toscana.it/dataset/ucs); and Emilia Romagna, available for the year 2008 (http://geoportale.regione.emilia-romagna.it). We rasterized the original fine resolution maps obtaining a 23 m resolution forest mask of approximately 21,327 km^2, 44% of the study area (Figure 3).

Methods

Imputation methods facilitate prediction of a *response variable* Y measured for a sample of size n selected from a finite population of size N. X is used to denote a vector of *auxiliary variables* with observations for all population units.

The terminology developed for remote sensing applications in forest inventory may vary with respect to the estimation method. When regression models are used, the auxiliary variables are designated as *independent variables* and the response variable is the *dependent variable* (Mardia et al., 1979). For k-Nearest Neighbors (k-NN), the auxiliary variables are designated *feature variables* and the space defined by the feature variables is designated the *feature space;* the set of sample population units for which observations of both response and feature variables are available is designated the *reference set*; and the set of population units for which predictions of response variables are desired is designated the *target set* (Chirici et al., 2016). For random forests, Breiman (2001) used the term *predictors* to denote the auxiliary variables.

The test area was tessellated into 23 x 23 m pixels whose size mimicked the area of the field plots measured in the field in the NFI program. All the predictors were resampled using a cubic convolution filter of 3 x 3 pixels to the final pixel of resolution of 23 m.

Thus, the population size of N= 40,317,260 was equal to the number of forest pixels in the study area. For each 23 x 23 m pixel a vector of 24 predictors was available from the remote sensing platforms and other auxiliary sources (Table 1). The response variable was GSV (m^3ha^{-1}) measured in the field for n=1350 INFC plots and an independent validation set of n=332 plots measured for forest management purposes and for the BIOSOIL project.

Table 1 – Predictors based on remotely sensing and auxiliary data used to predict GSV.

Spatial Database	Band/ information	Name of predictors variables	Original spatial resolution
Landsat 5 TM	Band 1	Landsat_B1	30 m
Landsat 5 TM	Band 2	Landsat_B2	30 m
Landsat 5 TM	Band 3	Landsat_B3	30 m
Landsat 5 TM	Band 4	Landsat_B4	30 m
Landsat 5 TM	Band 5	Landsat_B5	30 m
Landsat 5 TM	Band 6	Landsat_B6	60 m
Landsat 5 TM	Band 7	Landsat_B7	30 m
Global PALSAR/PALSAR-2	HH polarization	SAR_HH	25 m
Global PALSAR/PALSAR-2	HV polarization	SAR_HV	25 m
TIN Italy	DTM	DTM	10 m
TIN Italy	SLOPE based on DTM	SLOPE	10 m
Regional land use/land cover map	Forest/non-Forest map	Forest mask	Vector 1:10.000
Climate data	Total annual precipitation	prec	1 km
Climate data	Mean annual temperature	temp_mean	1 km
Climate data	Maximum annual temperature	temp_max	1 km
Climate data	Minimum annual temperature	temp_min	1 km
European Soil Database v2.0	Subsoil available water capacity	AWC_SUB_P	1 km
European Soil Database v2.0	Topsoil available water capacity	AWC_TOP_P	1 km

European Soil Database v2.0	Volume of stones	VS_P	1 km
European Soil Database v2.0	Depth to rock	DR_P	1 km
European Soil Database v2.0	Subsoil cation exchange capacity	CEC_SUB_P	1 km
European Soil Database v2.0	Topsoil cation exchange capacity	CEC_TOP_P	1 km
European Soil Database v2.0	Soil exchange capacity	DIMP_P	1 km
Wall-to-wall Canopy Height Map	Mean Vegetation Height	CHM	1 km

We tested four imputation approaches for predicting GSV. Two are non-parametric, random forests and k-NN, and two are parametric, multiple linear regression model and geographically weighted regression model. We optimized the four methods using a leave-one-out (LOO) procedure based on the 1350 NFI plots, with the most accurate approach used to predict GSV for all 40,317,260 forest pixels, hereafter characterized as estimation of the GSV map. Predictions were compared to data for the 332 plots of the independent validation set and were used for small-scale aggregated estimation with a model-assisted approach.

In the next sections, we present details for:

(i) the different imputation approaches for predicting GSV and how we optimized these methods with a LOO cross validation technique;

(ii) estimation of the GSV map applying the most accurate approach formerly identified and assessment of its accuracy using the independent validation set;

(iii) small-scale GSV estimation at study area, region (NUT-2) and province (NUT-3) levels.

Modelling methods and prediction of growing stock volume

Random forests

Random forests (RF) is a decision tree algorithm and nowadays is among the most popular ensemble methods for classifying and predicting forest variables. The algorithm was introduced by Breiman, (1996), and its application for the spatial prediction of forest variables using remotely sensed data is well-documented (Baccini et al., 2012; Evans and Cushman, 2009; Falkowski et al.,

2009; Houghton, 2007; Stumpf and Kerle, 2011; Yu et al., 2011). RF generates a set of regression trees (n_{tree}) that are aggregated to produce predictions without overfitting the data (Breiman, 2001). To build and grow trees, RF uses a randomly chosen subset of predictors at each splitting node (m_{try}), and trees are grown without the need of pruning. To grow trees, RF uses a procedure called out-of-bag samples (OOB) where each tree is built independently to arrive at the maximum size based on bootstrap samples from the training dataset (i.e., two-thirds of the data), while the remaining one-third of the sample are randomly left out. The OOB allow calculation of an OOB error rate and variable importance measured by calculating the percent increase in the mean square error when the OOB data for each variable are permuted (Breiman, 2001). The predictors that produce the most accurate splits are chosen from a random subset (m_{try}) of the entire predictor set (p).
Following the OOB sample procedure, the prediction error (OBB error) for each of the individual trees can be estimated as,

$$OOB_{error} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2, \qquad (1)$$

where $\hat{y}_i$ is the predicted output of an OOB sample and y_i is the actual output and n is the total number of OOB sample units.
Among the 24 predictors variables (Table 1), RF was optimized for the number of predictors, n_{tree} and m_{try}. We optimized the number of predictor variables (p) to eliminate irrelevant variables. The cross validation error rate (CV_e) was calculated to assess the performance of each value of p adopted in the model with predictors being removed at each step using various m_{try} functions (m_{try}=p, p/2, P/3, P/5, P/6….P/n) using the same procedure described by LI et al., (2017).
RF was optimized by searching for the combination of n_{tree} and m_{try} that minimized the OOB error. More details on RF imputation can be found in the review of Belgiu and Drăgu, (2016) and in the research article of LI et al., (2017).
All analyses in this study were performed using the *randomForest* package within the statistical software package R 3.2.0 (Liaw and Wiener, 2002) (https://www.r-project.org).

k-Nearest Neighbors

With the k-Nearest Neighbors (k-NN) technique, predictions are calculated as linear combinations of observations for sample units that are nearest to population units for which predictions are desired with respect to a selected distance metric in a space of feature (auxiliary) variables. Chirici et al. (2016) provided a detailed description of the k-NN method and documented more than 250 k-NN forestry applications based on remote sensing for more than 25 countries on six continents. Optimization included consideration of all possible combination of feature variables and selection of the subset that minimized RMSE. For the selected feature variables, we adopted an equal weighting approach. Simultaneously with the selection of feature variables, we searched for *i)* the optimal number of nearest neighbors, *k*, used for prediction between a minimum of *k*=1 and a maximum of *k*=40; and *ii)* the optimal distance metric among unweighted Euclidean, weighted Euclidean, and Canonical Correlation analysis (CCA) (McRoberts et al., 2016).

Multiple Linear regression

Multiple linear regression (MLR) techniques entail the use of models of the form:

$$y_i = \beta_0 + \beta_1 \cdot x_{1i} + \cdots + \beta_p \cdot x_{pi} + \varepsilon_i, \tag{2}$$

where i indexes sample units, y_i denotes the single response variable, p≥1 denotes the number of predictor variables, j=1, …, p indexes the predictor variables, β_j is the respective regression coefficient, and ε_i denotes a random residual term assumed to be distributed $N(0, \sigma_i^2)$. The model was optimized by comparing all possible combinations of all numbers of predictors with coefficients estimated using ordinary least square. Negative GSV predictions were set to 0, and the cross-validation accuracy assessment was performed after this transformation.

Geographically weighted regression

Geographically weighted regression (GWR) is a variant of locally weighted regression, which was originally developed by Cleveland and Devlin, (1988), proposed for geographical applications by Brunsdon et al. (1996), and introduced into the remote sensing community by Maselli (2002). Mathematically, GWR entails constructing a linear regression model for each target unit by weighting the values of the reference units according to the Euclidean (geographic) distance between the target unit and the reference units used for prediction. GWR can, therefore, be easily used for forest inventory applications where reference units (pixels) are regularly distributed in geographical space (Maselli, 2002).

Using the same notation as for multiple linear regression, the GWR model can be written in the form:

$$y_i = \beta_0^* + \beta_1^* \cdot x_{1i} + \cdots + \beta_p^* \cdot x_{pi} + \varepsilon_i, \tag{3}$$

where β^* are the geographically weighted regression coefficients, which are estimated for each target unit from relevant statistics (mean vectors and variance-covariance matrices) computed by giving different weights to the N reference units.

A fundamental step for the application of GWR is therefore the definition of a suitable function to compute these weights. An efficient option is given by a negative exponential function of the spatial Euclidean distance (ED), i.e. $\exp^{(-ED/EDR)}$, which is regulated by the distance range (EDR). The model was optimized as in 3.1.3 using a LOO cross validation strategy, which also served to identify the optimum EDR (see Maselli, 2002, for details).

Model optimization

During the optimization phase the performance of the different configurations of the four imputation methods was evaluated using the LOO cross validation technique. Each reference set unit is deleted in sequence and predicted using the remaining reference set units (McRoberts et al., 2015).

For each method, we calculated the coefficient of determination (R^2) between the measured and predicted values, the root main square error (RMSE), and the relative RMSE ($RMSE_{\%}$). The RMSE was calculated as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{n}} \tag{4}$$

where n is equal to 1350 (the number of field plots), y_i is the value of the GSV observed in the field, and $\hat{y}_i$ is the predicted value of the GSV. $RMSE_{\%}$ was calculated as the percent of RMSE against the mean value of the GSV observations in the 1350 NFI plots. The optimization was finalized by selecting the most accurate method based on RMSE for the estimation phase.

Mapping and small-scale estimation

The most accurate imputation approach was used to construct a regular 23 m resolution GSV map.

We assessed the accuracy of the GSV map by comparing map unit estimates and field observations for the independent validation set of 332 plots. Again, following the same approach used in the optimization phase described in § 3.2, we estimated the coefficient of determination (R^2), the root mean square error (RMSE) and the relative RMSE ($RMSE_{\%}$). RMSE was calculated as reported in equation 4, where n this time is equal to 332.

To construct an inference for the mean value of the GSV for the whole study area, the model-assisted, generalized regression estimators were used (Särndal et al., 1992; Breidt and Opsomer, 2009; McRoberts et al., 2016). Before doing so

we deleted from the GSV map all the non-forest pixels on the basis of the forest mask (§ 2.4.3).
The map-based estimate of the mean GSV in the forest area was:

$$\hat{\mu}_{map} = \frac{1}{N} \sum_{j=1}^{N} \hat{y}_i \qquad (5)$$

where N was the number of 23 m x 23 m forested population units in the study area and $\hat{y}_i$ is the model prediction for the *i-th* population or map unit. However, the map-based estimate must be adjusted for systematic prediction errors using a bias estimate calculated as:

$$B\hat{i}as(\hat{\mu}_{map}) = \frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i) \qquad (6)$$

where n is the sample size of INFC (i.e. 1350 plots), $\hat{y}_i$ is the model prediction for the *i-th* sample INFC plot and y_i is the observed value for the *i-th* INFC plot. The model-assisted estimate is the map estimate with the estimated bias subtracted:

$$\hat{\mu}_{model-assisted} = \hat{\mu}_{map} - B\hat{i}as(\hat{\mu}_{map}) \qquad (7)$$

while the standard error (SE) of $\hat{\mu}_{model-assisted}$ is:

$$SE\ (\hat{\mu}_{model-assisted}) = \sqrt{V\hat{a}r(\hat{\mu}_{model-assisted})} = \sqrt{\frac{1}{n(n-1)} \sum_{i=1}^{n} (e_i - \bar{e})^2} \qquad (8)$$

where $e_i = (\hat{y}_i - y_i)$ and $\bar{e} = \frac{1}{n} \sum_{i=1}^{n} e_i$
In addition, to assess the efficiency of the model-assisted estimator we compared it with the original design-based estimates produced by the INFC and its relative efficiency coefficient (RE) calculated as:

$$\text{RE} = \frac{V\hat{a}r(\hat{\mu}_{NFI})}{V\hat{a}r(\hat{\mu}_{model-assisted})} \qquad (9)$$

Because RE coefficient is the ratio between the variances of $V\hat{a}r(\hat{\mu}_{NFI})$ and $V\hat{a}r(\hat{\mu}_{model-assisted})$, values greater than 1 are evidence of greater precision in the model-assisted estimates (Moser et al., 2017). RE coefficient can be interpreted as the factor by which the original sample size would have to be increased to achieve the same precision as that achieved using the remotely sensed auxiliary data.

RESULTS

Optimization

All the four imputation methods produced comparable results with only limited differences. Independently of the parameter used for evaluating the results, RF always achieved the greatest accuracy and MLR the least accuracy. R^2 ranged between 0.35 and 0.47; RMSE between 96.3 m^3ha^{-1} and 108.42 m^3ha^{-1}; and $RMSE_{\%}$ between 68.70% and 77.3 % (Figure 3).

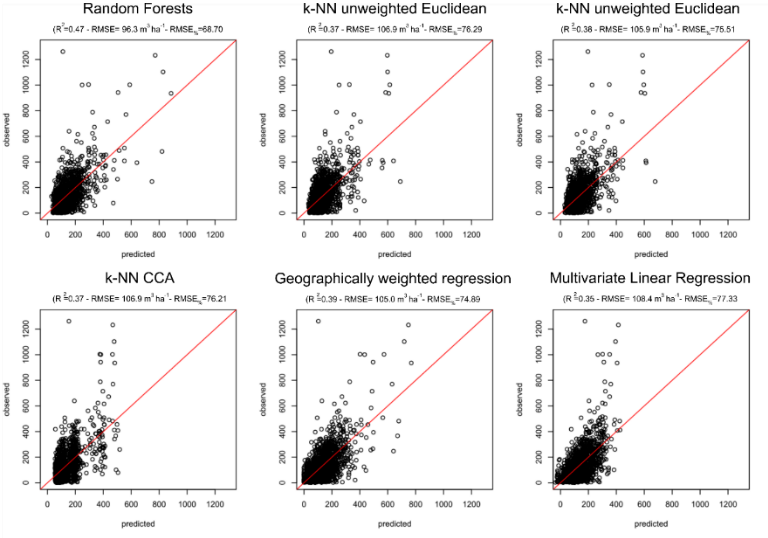

Figure 3 - Scatterplots of GSV observations versus predictions for all the imputation approaches. R^2, RMSE and $RMSE_{\%}$ are based on LOO cross-validation during the optimization phase.

The three different k-NN configurations achieved very similar results with R^2 ranging between 0.369 and 0.382, RMSE ranging between 105.86 m^3ha^{-1} and 106.96 m^3ha^{-1}, and $RMSE_{\%}$ ranging between 75.51% and 76.29% with k=21 for the Euclidean methods and k=54 for the CCA approach.
For the GWR approach we found an optimal EDR of 0.107° with performances very similar to those achieved for k-NN with R^2 of 0.396, RMSE of 105.0 m^3ha^{-1} and $RMSE_{\%}$ of 74.89, and always more accurate than MLR.
Of the 24 available predictors considered during the optimization phase, only 15 variables were ever selected with nine predictors never selected. In terms of usefulness of the predictors, the variables derived from Landsat images were the most frequently selected; band 5 was the only one selected by all six models, followed by band 3 selected by five models. The HV polarization of radar backscattering was selected by four models, the rest of the Landsat bands were selected by three models except for band 4 that was selected for two models; similar results were found for HH polarization of radar, precipitation and AWC of topsoil. The other variables that were selected at least once were the average annual temperature, the maximum annual temperature, vegetation height, and

the volume of rocks in the soil. In terms of number of predictors, k-NN with weighted Euclidean distance metric, k-NN with the unweighted Euclidean distance metric, and GWR all selected five; RF selected six; k-NN with the CCA distance metric selected seven, and MLR selected 10 (Table2). The full list of the optimization results is reported in Table 2.

Considering these results RF based on six predictors and 300 regression trees was selected for the following estimation phase.

Estimation

The RF model was used to predict GSV for each of the 4,031,726 23 m resolution forest target units in the study area (Figure 5). GSV predictions ranged between 0 and 1021.54 m^3ha^{-1} with a standard deviation of 70.32 m^3ha^{-1}. For each of the 332 plots in the independent validation set, we predicted GSV using RF and compared it with field observations. We found R^2 = 0.68 and RMSE%= 38.2% (Figure 5) demonstrating a performance that was greater than achieved using LOO cross-validation at INFC plot level during the optimization phase.

Table 2 – Parameters used for the different imputation approaches and results reported in terms of R^2, *RMSE, RMSE*

Imputation	Type of imputation	Selected predictors	Optimization parameters	R^2	RMSE m^3ha^{-1}	$RMSE_{\%}$
Random Forests	Non-Parametric	LANDSAT_B1 LANDSAT_B3 LANDSAT_B5 LANDSAT_B7 prec SAR_HV CHM	n_{tree}=300	0.47	96.3	68.70
k-NN unweighted based on Euclidean distance	Non-Parametric	LANDSAT_B1 LANDSAT_B3 LANDSAT_B5 LANDSAT_B6 AWC_TOP_P	k=21	0.369	106.96	76.29
k-NN weighted Euclidean based on Euclidean distance	Non-Parametric	LANDSAT_B1 LANDSAT_B3 LANDSAT_B5 LANDSAT_B6 AWC_TOP_P	k=21	0.382	105.86	75.51
k-NN CCA	Non-Parametric	LANDSAT_B2 LANDSAT_B4 LANDSAT_B5 LANDSAT_B7 SAR_HV SAR_HH temp_mean	k=54	0.370	106.88	76.23
Geographically weighted regression	Parametric	LANDSAT_B2 LANDSAT_B3 LANDSAT_B5 SAR_HV prec	Euclidean distance range (EDR) 0.107°	0.396	105.0	74.89
Multiple Linear Regression	Parametric	LANDSAT_B2 LANDSAT_B3 LANDSAT_B4 LANDSAT_B5 LANDSAT_B6 LANDSAT_B7 SAR_HV SAR_HH temp_mean VS_P		0.352	108.42	77.33

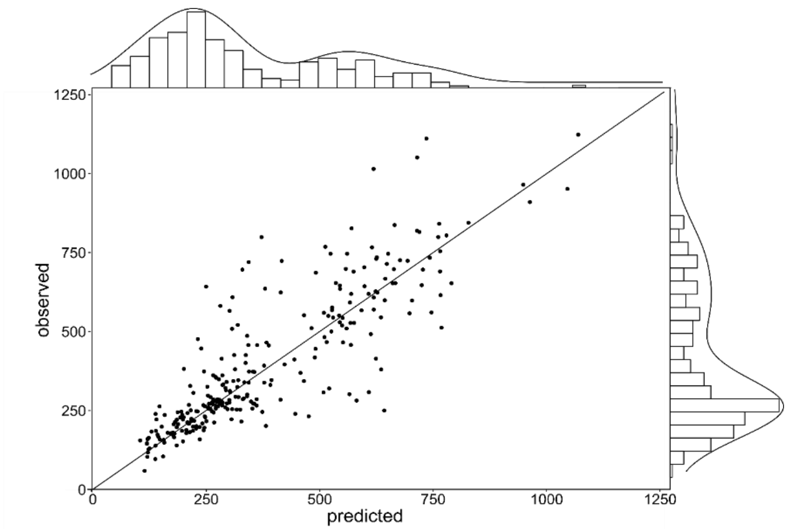

Figure 5 - Scatterplot of GSV observations versus predictions for the 332 units of the independent dataset.

On the basis of RF estimation for the entire study area, $\hat{\mu}_{model-assisted}$=126.17 m^3ha^{-1} with $SE(\hat{\mu}_{model-assisted})$=2.78 m^3ha^{-1}, while at regional level $\hat{\mu}_{model-assisted}$= 131.58 m^3ha^{-1} with $SE(\hat{\mu}_{model-assisted})$= 4.19 m^3ha^{-1} for Tuscany, and $\hat{\mu}_{model-assisted}$135.42 m^3ha^{-1} with $SE(\hat{\mu}_{GREG})$= 5.55 m^3ha^{-1} for Emilia Romagna. These regional model-assisted estimates are in line with the official design-based estimates from INFC plots (Gasparini and Tabacchi, 2011) which are 128.8 m^3ha^{-1} with SE= 4.6 m^3ha^{-1} for Tuscany and 128.4 with SE= 7.12 m^3ha^{-1} for Emilia-Romagna. These results revealed a RE of 1.09 for Tuscany Region and a RE of 1.28 for Emilia-Romagna Region.

Moreover, the model-assisted estimate of GSV was calculated at province administrative level (Annex 1). Such estimates are not provided by official NFI aggregated statistics.

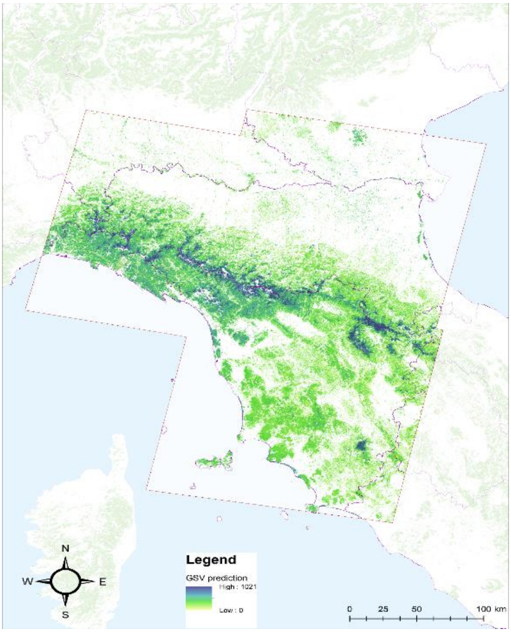

Figure 6 - Growing stock map of the study area generated with Random Forest Imputation. GSV in m^3 ha^{-1}.

DISCUSSION

The aim of this study focused on three objectives: *(i)* to demonstrate that even in large complex Mediterranean landscapes, without the availability of ALS, it is possible to produce spatial wall-to-wall estimates of GSV measured in the field in the National Forest Inventory (INFC, 2005) on the basis of predictors from remotely sensed images and other auxiliary variables, (*ii*) to understand the relative importance of possible predictors available wall-to-wall in Italy and the performance of the different estimation approaches, and *(iii)* to suggest a methodology that can be applied at country level in Italy to produce wall-to-wall predictions of forest variables to support forest planning and management.
To achieve these results for a large study area of 45,438 km² in central Italy, we acquired 24 potential predictors which are available wall-to-wall in Italy and that may directly or indirectly be related to forest biomass and GSV. We compared six different prediction techniques, all of which comparable accuracies but with random forests producing the greatest accuracy.
Among the other imputation approaches, GWR yielded the greatest accuracy, in particular outperforming conventional multiple regression. This can be explained considering that the relationships between GSV and virtually all predictors currently considered are affected by several factors which can vary spatially (Lu, 2006). GWR can account for this spatial variability by allowing the per-pixel computation of different regression models. This is particularly relevant in heterogeneous Mediterranean environments, where GWR has already been proficiently applied to Landsat TM/ETM+ imagery for forest GSV prediction (Maselli and Chiesi, 2005; Maselli et al., 2014a; Maselli et al., 2014b).

Landsat bands of which B5 acquired in short-wave infrared between 1.55 and 1.75 μm was most important, and climate variables of which precipitation was most important, emerged as the most influential predictors. The resulting 23 m resolution GSV map, when compared against an independent set of field measures, demonstrated a good relationship between observed and predicted values ($R^2 = 0.69$ and $RMSE_{\%} = 37.2\%$). However our results are less accurate than those obtained in boreal forests using ALS in Sweden by Nilsson et al., (2017) and in the review of Næsset et al., (2004) for which RMSE usually ranged between 15% and 25% of the average real value measured in the field.
The relatively larger $RMSE_{\%}$ we obtained can be due to several reasons.
Firstly, we did not use metrics from ALS data which are usually the best candidate predictors for GSV estimation. This is confirmed if we compare our results with results reported for studies where ALS was not used. For example Reese et al., (2002), using Landsat data in Sweden, reported pixel-level $RMSE_{\%}$ in the range of 59% and 80%, and Immitzer et al., (2016) in Germany using WorldView-2 imagery report a $RMSE_{\%}$ between 46% and 37% using only spectral variables.
Secondly, GSV is relatively small for our forests, we observed a field GSV average of 139 m^3ha^{-1}, less than half of the 287 m^3ha^{-1} reported by Nilsson et al. (2017) in Sweden.
Thirdly, Italy has a heterogeneous landscape, and Mediterranean forests are characterized by considerable complexity in tree species composition and structure relative to temperate and boreal forests.
Moreover, we found that the accuracy of the pixel-level estimation evaluated with the independent dataset was greater than those we found with the LOO procedure in the optimization phase. The result was not expected but it is probably due to the fact that the GSV measured in the independent validation dataset has a more normal distribution around the mean values (Figure 5) than those from the INFC (Figure 2) and that the average GSV in the independent validation dataset is also greater (351 m^3ha^{-1}) than those measured in INFC plots (140 m^3ha^{-1}).
In line with previous results from the literature, we observed an underestimation for large GSV observations, independently of the prediction approach. This effect has anyhow a limited impact when the comparison was done with LOO against the INFC plots because a just a few of them have very large GSV observations (Figure 4). This saturation effect with under-predictions for plots with GSV greater than 600 m^3ha^{-1} was well-known because spectral reflectance values are not sensitive, for example, to multilayer canopy forest or dense forest (Zhao et al., 2016). Moreover, some authors have reported that areas

characterized by very complex topographic features (i.e. from flat terrain to mountains up to 2000 m a.s.l.) affect the spectral signature and the data saturation values of forest above ground biomass and growing stock volume (Lu et al., 2012; Lu et al., 2016; Foody et al., 2001; Nichol et al., 2011). However, the saturation effect was reported in the literature even when ALS data were used (Nilsson et al., 2017; Giannetti et al., 2018; Lefsky et al., 2005).

Even if RF was found to be the most accurate method, only small differences in prediction accuracies were found across the different non-parametric and parametric methods. Nilsson et al. (2017) reported similar conclusions for Sweden using ALS data.

Regarding the model-assisted estimates calculated on the basis of the GSV map, with the use of our approach it was possible to increase the precision of INFC predictions at regional level (RE=1.09 in Tuscany and RE=1.28 in Emilia Romagna) and to provide for the first time growing stock estimates at Province level.

It is important to remember that the use of pixel level estimates of map products like those we presented in Figure 6 is discouraged since GSV predictions in a single pixel may be affected by a consistent bias (McRoberts and Tomppo, 2007). We therefore suggest aggregation of predictions from several pixels (Areas of Interests – AOI), since in case the pixel prediction errors are independent and distributed with zero mean, then when the AOI increases, then averaged value of the pixels tend to equal the real value (McRoberts and Tomppo, 2007). Users could aggregate GSV pixel level estimates to create estimates for different AOIs, for example related to ecological regions, municipality boundaries, or forest management units.

CONCLUSIONS

Forest tree monitoring and assessment are rapidly evolving as new information needs arise and new techniques and tools become available. However, the exploitation of the latter, as well as their implementation within operative management processes, should be evidence-based (Corona, 2018).

Under this prospective, several conclusions can be drawn from the study. Firstly, Landsat data are confirmed as a reliable and efficient source of information for modeling GSV, even in large and complex Mediterranean forest areas. Secondly, we found that in the Mediterranean area, predictors derived from climate data are a valid spatial data source for modeling GSV most probably because they can describe different growing season conditions. Thirdly, all the tested modelling approaches have the capability to predict GSV with comparable results. Fourthly, the GSV map is confirmed as a valid tool for model-assisted inference at regional and province levels.

We can affirm that the 23 m resolution GSV map we produced can be useful and practical to support the requirements of national and regional forest bodies, forest companies and forest owners. This map could be the basis for decision support systems as proposed by Puletti et al. (2017) for a test area in south Italy, as a tool to assess wood production and harvesting activities in forest proprieties, thereby contributing to improving the Mediterranean forest economy and, if used at forest management scale, reducing the cost for data acquisition needed for the implementation of management plans.

Moreover, the GSV map can be used to produce model-based estimates at province level (NUT-3), augmenting the spatial resolution of traditional NFI design-based estimates which are currently available only for administrative Regions (NUT-2) and thus adding value to the INFC. Under this point of view, the proposed methodology is now ready for a wall-to-wall application in Italy to move the traditional NFI program to a more modern EFI, in line with achievements in other countries.

Under this point of view, it is also strongly recommended that in the future the Italian NFI could evolve in a permanent monitoring system, where a sample of the total number of field plots is visited in the field every year in order to complete the revisit of all the plots in 5-10 years.

In the future we hope that ALS will be finally available wall-to-wall in Italy to facilitate prediction of forest variables estimates with even greater accuracy. In such a context satellite LiDAR data from the Global Ecosystem Dynamics Investigations (GEDI space laser data) and from the ICESAT-2 (Geoscience Laser Altimeter System - GLAS) are potentially extremely important in Italy if ALS will not be available sooner.

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Annex 1: Small-scale estimates of mean GSV (m^3 ha^{-1}) obtained with RF model at Province (NUT-3) level. For each Province we also report the forest area estimation from the second Italian National Forest Inventory **(**INFC**,** Gasparini and Tabacchi, 2011**).**

Region	Province	Province Area (km^2)	Total Forest Area (km^2) (INFC)	SE Total Forest Area (%) (INFC)	n_i	GSV $\hat{\mu}_{GREG}$ (m^3ha^{-1})	GSV $SE(\hat{\mu}_{GREG})$ (%)
Tuscany	Arezzo	323300	1792,19	4.2	127	111.13	8.5
	Firenze	351369	1785,00	4.2	117	151.89	12.3
	Grosseto	450312	1979,61	4.0	116	98.35	8.6
	Livorno	121371	473,64	8.6	23	108.88	16.7
	Lucca	177322	1210,44	5.2	64	198.86	13.1
	Massa Carrara	115468	867,13	6.2	30	148.69	14.69
	Pisa	244472	950,53	6.0	54	98.82	11.28
	Pistoia	96412	506,40	8.3	32	214.30	43.91
	Prato	36572	233,34	12.3	13	186.87	24.1
	Siena	38298	1717,10	4.3	115	85.81	6.09
Emilia-Romagna	Bologna	370232	1007,61	5.6	56	112.60	11.12
	Forlì-Cesena	237840	1066,21	5.5	70	86.08	15.24
	Modena	268802	686,95	7.0	49	123.97	14.97
	Parma	344748	1525,42	4.4	85	170.81	9.94
	Piacenza	258586	848,37	6.2	51	111.66	13.07
	Ravenna	185944	213,32	13.0	19	80.55	12.39
	Reggio Emilia	229126	635,18	7.3	58	126.75	11.26
Liguria	La Spezia	88135	542,29	7.6	46	144.55	16.34

Chapter 5

Conclusions

This PhD-thesis (paper I-III) proposed a method for an initial assessment of the possible consequences of climate change on Italian forest ecosystem. Climate change represents an important challenge for the future of forest. The possible (and sometimes already observed) increment of temperature and decrease of precipitation amounts will lead to a various effect both direct and indirect. One of the main important consequences regarding the progressive displacement of distribution area of different species, both in altitudinal and latitudinal direction. The proposed methodology is based on the use of Species Distribution Modelling technique (or SDM) to trying to understand the different dynamics and relation that are currently underway between the different involved variables.

An important aspect of SDM is linked to uncertainty assessment because this characteristic negatively impacts the predictive performance of different technique and finally the possibility to use these tools in support decision making process. If the possibility to select the best suited individuals/populations for nursery activities and reforestation projects under climate change condition is probably one of the most important use of such models, a model heavily affected by uncertainty can lead to incorrect intervention and to the useless waste of resources.

An important source of uncertainty in SDM is called as "climate uncertainty". This source is linked to the use of future climate data and so with the choice between GCM/RCM climate model and in the end with the climate scenario or RCP. The results of the study highlight the importance of the use of RCM climate model respect than GCM. RCM is based on the use of local climate data and this aspect allows the possibility to create optimized scenarios for different areas that realize more accurate future prediction. However, the use of local climate data is in practice more difficult given the huge efforts that researchers must put in place to merge outputs from different sources (i.e. national, regional, etc.). The analysis showed also a significant rule of altitudinal gradient in determine future pattern of species distribution, different functional or physiological traits will play in the future a great influence. However, a shift in altitudinal range is already observed for many organisms both animal and plant and it is well documented into scientific literature. Climate change has only increased the speedily of this process that it is often greater than the movement capacity of considered species. This aspect represents a great problem for forest species which lived in condition that they are not adapted.

An assisted migration strategy represents an interesting option to preserve endangered species or local genotypes and mitigate potential effect of climate change. In this scenario the shift of species is mediated by human interventions.

Finally, the carried-out analysis confirms that in optic of climate change pure stand forest result more susceptible versus climate change than mixed stand forest.

The methodology describes in the previous paper (I-III) can also have possible other uses when referred to abiotic destructive events (windstorm, paper IV) and spatial information of forest attributes (paper V). In this situation as example modelling techniques might be helpful to predict potential damages and plan restoration strategies. The possible final uses are manifold, with regarding versus extreme climate events such as wildfires or windstorms, the use of SDM is relate with: I) the possibility to identify those areas that can be most affected (i.e. risk maps) and II) the possibility to select the most suitable species or provenance according to the future (local) climate conditions of planting site for restoration processes. Instead in the second case, spatialize data of forest attribute (i.e. growing stock, volume increment) can be useful to provide general indication of the wood productivity of forest attribute and to balance forest management strategies to preserve the minimum standing volume to support precision forestry activities and to design novel thinning applications. Modelling techniques might be helpful to predict potential damages and plan restoration strategies.

Finally, these data can be correlate with climatic (both present and future) characteristics of the site using transfer or response function. In this sense the general objective of research is to investigate the effect of climate on the different growth capacity of considered species and to planning a more sustainable use of forest resources for human wellbeing.


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