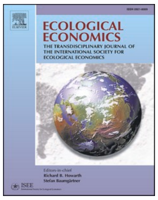
Ecological Economics 225 (2024) 108322

Contents lists available at ScienceDirect

Ecological Economics

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



Optimal forest management under climate change variability

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ARTICLE INFO

Keywords:
Climate change
Climate variability
Forest management
Climate change adaptation
Bioeconomic modeling

ABSTRACT

Ecosystems are likely to be severely affected by climate change. While the literature on this subject focuses primarily on climate variable means, increasing evidence has been gathered on the importance of changes in climate variability in determining ecosystem impacts. In this context, forests play a significant role. While, on the one hand, forests have often been identified to be a key element in mitigating greenhouse gas emissions, on the other, forests are also affected by changes in climate. However, the number of studies on optimal forest management under climate change remains limited and has overlooked the role of climate variability. This paper adds to that literature by developing a coupled ecological-economic forest stand model in which forest dynamics are a function of monthly climate variables. We show that accounting for changes in climate variability substantially changes earlier findings. In particular, ignoring climate variability may fail to adequately account for changes in optimal harvest age and lead to erroneous conclusions regarding the effects of climate change on forested land value.

1. Introduction

Climate change is expected to drastically impact the Earth's ecosystems, affecting essential services supporting human well-being (Walther et al., 2002). Understanding the magnitude of such effects is thus crucial and has been the research subject of a vast literature primarily focused on changes in climate variable means. However, an increasing number of studies support the hypothesis that changes in climate variability are likely to be more relevant in determining climate-driven ecosystem impacts (Seddon et al., 2016; Thornton et al., 2014; Holmgren et al., 2013). Also, changes in climate variability have been predicted to be greater in regions that are particularly vulnerable ecologically and economically (Bathiany et al., 2018). Limiting the study on ecosystem impacts to changes in mean climate may thus underestimate effects on both human and non-human populations (Thornton et al., 2014).

Given their relevance in the global carbon cycle, forests play a particularly relevant role in that context. As with other ecosystems, forests are expected to be substantially affected by climate change, namely through changes in induced tree mortality, productivity, and/or tree species distribution (see, e.g., Bergh et al., 2003; Jump et al., 2006; Kurz et al., 2008; Allen et al., 2010; Lindner et al., 2014). Again, while forests may respond to linear trends in climate variables, changes in climate variability have a greater effect in driving forest dynamics (e.g., Stephenson, 1990; Reyer et al., 2013; Lindner et al., 2014). In a scenario of increased variability, efficient resource use thus demands the study of adaptive forest management.

The applied study of forest management resorts to forest growth models, which can be grouped under two broad categories: mensuration-based growth models (or empirical growth models) and process-based models. The former builds upon statistical functions describing stand development assuming constant site conditions. As a result, they are appropriate to predict growth only within the calibration data range or under current environmental conditions. In contrast, process-based models rely upon modeling fundamental physiological and ecological mechanisms that determine forest productivity (Fontes et al., 2010) and are thus particularly suitable for studying forest growth under a changing environment/climate (Johnsen et al., 2001). Compared to empirical growth models, process-based models are considerably more complex, thus hampering forest management' study

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https://doi.org/10.1016/j.ecolecon.2024.108322
Received 26 January 2024; Received in revised form 16 May 2024; Accepted 24 July 2024

through optimization methods. One notable difficulty is that in process-based models, volume is time-dependent, stand development cannot be reduced to a simple one-state variable growth function and thus demands the use of derivative-free optimization algorithms.

As a result, most literature using process-based models to investigate the impacts of climate change on forest productivity and profitability resort to simulations assuming exogenous, pre-specified management regimes. Such studies typically analyze the effects of alternative management regimes under different climate scenarios, computing various silvicultural and economic metrics. In this context, the number of studies is already substantial, varying in both complexity and breadth on the number of simulated management regimes, climate scenarios and considered regional scale (e.g., Bryars et al., 2013; Meason and Mason, 2014; Waring et al., 2014; Perdue et al., 2017; Susaeta et al., 2017; Bourke et al., 2023). Augustynczik et al., 2017 provides a particularly good example of that literature, studying robust management under uncertainty considering a total of 20 management regimes under 12 climate trajectories. As with other studies, however, the management regimes considered in that analysis are assumed not to change over the entire simulation period. By using process-based models, those studies are thus able to capture changes in forest productivity induced by climate variability. However, their assumption regarding silvicultural regimes hinders the study of adaptive forest management. In fact, under climate transition and increasing climate variability, optimal management is expected to respond to changes in forest productivity occurring within the time horizon of a given climate scenario.

In contrast to the literature using simulation, the number of studies applying optimization techniques to study forest management under climate change is still relatively scarce. Also, these have primarily relied on extending empirical growth models to capture climate impacts on forest dynamics, resulting in analyses that overlook climate change variability. Sohngen and Mendelsohn (1998) pioneered this line of research by developing a U.S. timber market model in which mortality rate from dieback and annual tree growth rate are functions of a linear climate forcing factor. Comparing their results against studies focusing on steady-state climate change, the authors show that accounting for both climate and market dynamics is critical in valuing large-scale ecological changes. Given the national scale of the study, the paper focuses its analyses on the aggregate level welfare impacts of different climate scenarios; changes in optimal management are discussed only briefly. In contrast, Goetz et al. (2013) studies that issue by developing an applied stand-level forest growth model for *Pinus sylvestris* in Catalonia, in which diameter growth depends linearly on CO_2 concentration. When considering changes in optimal forest management, the study concludes that carbon sequestration costs per ton and hectare increase under climate change. Finally, Guo and Costello (2013) extend the work of Sohngen and Mendelsohn (1998), focusing their discussion on management adaptation to climate change on both the intensive (i.e., forest management) and extensive margins (i.e., changes in land use). In this case, forest dynamics is given by a set of stand biomass growth functions in which the effects of climate change on stand productivity are captured through a plantation year parameter. After plantation occurs, forest productivity is not time-dependent, i.e., climate does not affect it. Interestingly, the authors conclude that the value of adaptation in the extensive margin is large but that the same is not valid in the intensive margin. This finding is in remarkable contrast with recent studies on forestry literature discussing the challenges caused by climate variability to adaptive forest management (Jandl et al., 2019; Vilà-Cabrera et al., 2018; Linder et al., 2008).

The two strands of literature discussed above offer relative advantages and disadvantages. On the one hand, the studies using process-based models adequately account for the effects of climate on forest productivity but are less successful in studying adjustments to forest management. On the other hand, precisely the opposite is true for the literature applying optimization techniques. Note, in fact, that as forest dynamics are more sensitive to changes in climate variation than to changes in climate trends, the choice of extending empirical growth models to account for climate may have strong implications for management, and therefore, for reported findings. This paper thus adds to previous literature by developing a coupled ecological-economic forest stand model merging the merits of the two approaches discussed above. In particular, we develop an optimization strategy maximizing stand NPV in which forest dynamics are represented by a process-based model and optimal harvest ages are endogenously computed under alternative climate scenarios.[1]

To that end, we develop a case study resorting to a process-based model calibrated to *Eucalyptus globulus*, one of the most widely planted hardwood species in temperate regions of the world (Potts et al., 2004). Due to its rapid growth and wood properties, *E. globulus* is a highly productive species. In Europe, this species supports an important pulp and paper industry and is acknowledged as one of the most valuable in that continent (Tomé et al., 2021). Also, while today it is cultivated mainly in the Iberian Peninsula, where it covers an area of more than 1.5 million ha (ICNF, 2019; MAPA, 2019), climate change may expand this species to other regions of Europe (Tomé et al., 2021). We argue that the results obtained using the optimization strategy developed in this paper have significant implications for established findings in previous literature. First, adaptive forest management requires substantial adjustments in harvest ages during climate transition, an issue overlooked in simulation studies. Second, we show that studies investigating optimal forest management assuming linear climate trends, i.e., ignoring changes in variability, are likely to lead to inaccurate conclusions concerning the effects of climate change on forested land value and management adaptation. Ultimately, the findings presented in this paper thus reinforce the idea that accounting for variability is critical for accurately assessing the impacts of climate change on forest ecosystems.

The rest of the paper is organized as follows. Section 2 introduces the model, data, and the optimization strategy; Section 3 presents the results. Finally, Section 4 provides concluding remarks on the paper's main findings.

2. Methods and data

2.1. *The 3-PG Forest growth model*

Initially developed by Landsberg and Waring (1997), the 3-PG (Physiological Principles in Predicting Growth) model is a simple monthly-step process-based, stand-level growth model requiring minimal parametrization and readily available site and climate input data. As a result of its flexibility, the model is particularly appropriate for studying forest management of a given tree species across different regions and climate scenarios. In fact, the model has been successfully applied to several species in various regions of the globe (Gupta and Sharma, 2019). In addition, and in contrast to other more complex process-based models, the 3-PG model has also been used as a practical forest management tool (Fontes et al., 2010).

The 3-PG model combines empirical relationships with the modeling of physiological processes (Fontes et al., 2006; Gupta and Sharma, 2019). Light use efficiency depends on environmental factors, including climate variables. Consequently, this model can be used to analyze the impact of climate change on the productivity of forestry systems or to assess forest management practices across diverse regions and climate scenarios. Required input includes data on locally specific stand, soil, and monthly climate conditions. Climate variables used as inputs by the model consist of monthly mean temperature, precipitation, vapor

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[1] Applied forestry economics literature is still primarily based on empirical forest growth models; a few exceptions include Niinimäki et al. (2012), Niinimäki et al. (2013), and Pihlainen et al. (2015). These studies have also studied optimal forest management but have not explicitly investigated the role of climate variability.

pressure deficit, number of frost days and radiation.

In the rest of this section, we briefly present the model closely following Almeida et al. (2004) and focusing on the role of climate variables in simulating forest growth. The 3-PG model resorts to a radiation absorption model to compute the absorbed photosynthetically active radiation intercepted by a stand (ϕ_{pa}). The forest production submodel then estimates gross primary production (P_G) based on the monthly absorbed ϕ_{pa} multiplied by canopy quantum efficiency (α_C). The latter is obtained based on a theoretical maximum canopy quantum efficiency (α_{Cx}) constrained by physiological (stand age *Age*, vapor pressure deficit *VPD* or available soil water *SW*) and environmental modifiers (mean temperature *T*, soil fertility *N*, and days of frost *F*) (Landsberg and Waring, 1997; Almeida et al., 2004; Stape et al., 2004). Assuming values between 0 and 1, these modifier functions (f_T, f_N, f_F) are the primary model drivers constraining growth and productivity (see Supplementary Information). Under optimal conditions, all modifiers have the value 1 (Landsberg and Waring, 1997; Sands and Landsberg, 2002). Canopy quantum efficiency (α_C) is given by:

$$\alpha_C = f_T f_N f_F \varphi \alpha_{Cx} \tag{1}$$

in which φ is a physiological modifier defined by the most restrictive value of the vapor pressure deficit (f_{VPD}) and soil water modifiers (f_{SW}) multiplied by an age-dependent modifier (f_{age}):

$$\varphi = f_{age} min\{f_{VPD} f_{SW}\} \tag{2}$$

The model includes a monthly soil water balance that includes precipitation and simulates precipitation interception and transpiration, with the Penman-Monteith equation. The physiological modifier φ affects, among other things, the biomass partitioning to roots.

Finally, gross primary production (P_G) is thus given by:

$$P_G = \alpha_C \phi_{pa} \tag{3}$$

The ratio of net primary production (P_N) to P_G is taken to be constant (Waring et al., 1998). The total biomass is then allocated to leaves, stems, and roots through a set of dynamic equations. The model runs monthly, providing key management output variables, such as stand basal area, stand volume, net primary production, standing biomass in foliage, stem, and roots, available soil water, and transpiration. Various publications providing a detailed presentation of the model are available (e.g., Landsberg and Waring, 1997; Sands and Landsberg, 2002; Almeida et al., 2004; Gupta and Sharma, 2019). Also, detailed documentation on the model is accessible online.[2] For a complete description of the model, we thus refer the reader to that literature.

2.1.1. Model calibration

One of the first 3-PG model calibration studies was developed by Sands and Landsberg (2002) for *Eucalyptus globulus*. This species is native to Australia but has been introduced in several countries. Today it is one of the most widespread eucalyptus species and the leading planted pulpwood species in temperate regions of the world (Tomé et al., 2021). In Europe this species represents one of the most important forest plantations, supporting an economically important pulp and paper industry, occupying in the Iberian Peninsula alone a total of 1.5 million ha of forested area (Tomé et al., 2021). In Portugal, where the species enjoys especially favorable growth conditions, *E. globulus* forests represent the number-one national forest area (approximately 845,000 ha – ICNF, 2019). Given its economic significance, considerable research has been devoted to modeling eucalyptus growth in the country. Fontes et al. (2006) successfully calibrated and tested the 3-PG model for *E. globulus* plantations across different locations in Portugal. This paper uses the parameters provided in that study (see Table 1 in the Supplementary Information).

Table 1
Management costs by year and rotation.

Year	First rotation (€/ha)	Second and third coppice rotations (€/ha)
0	2479	6
1	114	6
2	137	141
3	126	320
4	6	6
5	6	345
6 et seq.	6	6

Silvicultural Operations by year:
First Rotation: Site preparation and plantation (Stump destruction and remotion, Opening roads and firebreaks, Harrowing, Subsoiling, Ripping, Planting, Fertilization, Beating up, Mechanical weed control around seedlings); First Year (Maintenance of roads and firebreaks, Weed control – harrowing); Second Year (Fertilization, Maintenance of roads and firebreaks); Third Year (Weed control -chemical, Maintenance of roads and firebreaks); Fourth and following years (Maintenance of roads and firebreaks).
Second and third rotations: First Year (Maintenance of roads and firebreaks); Second Year (Maintenance of roads and firebreaks 1st shoot selection); Third Year (Weed control - 90% harrowing + 10% brushcutter, Fertilization, Maintenance of roads and firebreaks); Fourth Year (Maintenance of roads and firebreaks); Fifth Year (Weed control - 30% harrowing + 50% chemical + 20% brushcutter, 2nd shoot selection, Maintenance of roads and firebreaks), Sixth and following years (Maintenance of roads and firebreaks).

2.2. The optimization problem

Tree species such as *Eucalyptus globulus* can generate new shoots from their stools after felling, allowing for stand regeneration without replanting. However, ceteris paribus, stand productivity under this regime tends to decrease after the first harvest, and replanting may become optimal. *E. globulus* plantations are thus typically managed as a silvicultural even-aged coppice management system. The calibrated forest growth model used in this study, though, assumes no stand productivity loss between plantations cycles directly resulting from stand natural regeneration. As a result, the number of rotations within a plantation cycle is assumed to be constant and equal to 3, corresponding to silvicultural practices for the areas considered in this study. In what follows, we thus focus on optimizing harvest ages.

The optimization problem's objective function is given by the Net Present Value (NPV) of an infinitely replanted forest stand under even-aged coppice management and changing climate. Note that climate scenarios inevitably provide projections for a limited number of years. Formalizing an infinite time optimization problem thus requires defining the climatic conditions for the period after which projections are unavailable. We thus assume that the changing climate occurs until T^{clim}, the year after which an average future constant climate is considered.[3] Accounting for changing climate implies that optimal harvest ages may differ during that period, which greatly increases the complexity of the optimization problem (Pihlainen et al., 2015). The objective function thus comprises two parts. In the first, timber volume is time-dependent and harvest ages are allowed to differ. The second part, corresponding to the future constant climate period, is given by the NPV formula of an infinitely replanted forest stand in repeated plantation cycles of three rotations. Note, though, that the second part formula used in the objective function, i.e., the one corresponding to the forest stand value under future constant climate (V_i), depends on the number of rotations occurring until or immediately after T^{clim}. In particular, this formula can take three different values depending on whether the first

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[2] A dedicated manual and other modeling documentation is available at the following website: https://3pg.forestry.ubc.ca/

[3] Assuming a constant future climate necessarily is a simplifying assumption. Note, however, that it affects timber revenues occurring only far in the future, and as a result have a negligible impact on the model's optimal solution.

harvest under future constant climate coincides with the first (V_1), second (V_2), or third (V_3) rotation within a plantation cycle. Given that management costs differ between rotations, it is impossible to formulate a general analytical formula for the objective function considering an endogenous number of plantation cycles until T^{clim}. Nevertheless, computing the objective function value for any given optimal solution candidate is straightforward. As a result, in the numerical optimization developed in this paper the number of plantation cycles during changing climate is endogenously computed – more details are provided in Section 2.4. As an example, in what follows, we present the optimization problem for an objective function, assuming a complete plantation cycle of 3 rotations during changing climate. In that case, the stand NPV is given by:

$$Pv_T(T_1 - T_0)b^{T_1} + Pv_T(T_2 - T_1)b^{T_2} + Pv_T(T_3 - T_2)b^{T_3} - C_1 - C_2b^{T_1} - C_3b^{T_2} + V_1b^{T_3} \tag{4}$$

in which T_1, T_2, and T_3 are the harvesting years measured in calendar time with $T_0 = 0$ and $T_3 \geq T^{clim} > T_2$. P denotes stumpage price (€/m^3), $b = \frac{1}{1+r}$ is the discount factor associated with the discount rate r, and $v_T(.)$ is the time-dependent timber volume measured in cubic meters. C_1, C_2, and C_3 denote the present value of all costs incurred during the first, second, and third rotations discounted to the corresponding rotation starting date. Finally, V_1 corresponds to the NPV of an infinitely replanted forest under coppice management and constant climate, and is given by:

$$V_1 = \frac{Pv(t_1)b^{t_1} - C_1 + Pv(t_2)b^{(t_1+t_2)} - C_2b^{t_1} + Pv(t_3)b^{(t_1+t_2+t_3)} - C_3b^{(t_1+t_2)}}{1 - b^{(t_1+t_2+t_3)}} \tag{5}$$

in which, t_1, t_2, and t_3 are the corresponding harvest ages for the first, second and third rotations under constant climate. The optimization problem in this case consists in finding the vector $[T_1, T_2, T_3, t_1, t_2, t_3]$ maximizing (4) + (5) subject to the stand dynamics given by the forest growth model, stand initial condition, and usual non-negativity conditions for the control and state variables.

2.3. Climate and economic data

We consider three regions in Portugal that are representative of the diversity of both site and climatic growth conditions for *Eucalyptus globulus* in the country – *Figueira da Foz* (Central Coast), *Odemira* (South), and *Braga* (North). Specific site climate data for these three locations from 2006 to 2100 were obtained through the online tool *CliPick* (Palma, 2017). Two contrasting climate scenarios from the IPCC Assessment Report 5 are considered to investigate the effects of climate variability on optimal forest management: RCP4.5 and RCP8.5. The first represents an intermediate scenario in which global mean surface temperature by the end of the 21st century is likely to increase by 1.1 °C–2.6 °C relative to 1986–2005. In contrast, RCP8.5 is a high emissions scenario in which the global mean surface temperature by the end of the 21st century is likely to increase by 2.6 °C to 4.8 °C. In addition to climate data, regional differences in the model are captured by different parameterizations of site conditions related to soil water, soil class, and latitude (see Table 2 in the Supplementary Information). Finally, economic data on silvicultural operational costs (Table 1) were obtained from the annual report of the Portuguese Monitoring Committee for Forestry Operations. No information on stumpage price value is available publicly, and was therefore obtained through expert opinion, and equals 32€/m^3.

2.4. Optimization strategy

The optimization problem is divided into two steps. First we optimize forest stand value under future constant climate (V_i) considering the three possible cases discussed in Section 2.2. The climate change projection scenarios used in this study cover the period 2006–2100; we thus assume $T^{clim} = 95$. After that period all climate variables are computed assuming their monthly averages between 2091 and 2100. Note that in this case stand growth is no longer time-dependent and volume functions can be obtained using the 3-PG model. As a result, the optimization process for determining the harvest ages maximizing V_i is straightforward. Table 2 presents the corresponding optimal harvest ages and NPV assuming a discount rate of 5%.

The harvest ages during changing climate are optimized using the genetic algorithm from Matlab's optimization toolbox. The optimization algorithm initially defines a random set of possible solution candidates (population), i.e., each individual in that population is a vector of candidate harvest ages solving the problem described in section 2.2. The harvest volumes for each candidate (individual) are obtained using 3-PG. Once the volumes were obtained, the NPV for each individual candidate is computed considering the corresponding number of rotations occurring during changing climate and the corresponding V_i presented in Table 2. The next population generation is obtained at each iteration by applying a set of operators (scaling, selection, crossover, and mutation) to the individuals with the highest NPV (fitness function). At the end of each generation the procedure described above to obtain timber volume and NPV is repeated. The optimization process ends when the termination criterion is met, i.e., NPV can no longer be improved. Given the existence of nonconvexities, the optimal solution may depend on the initial population. Accounting for that, two strategies were adopted. In the first the problem was solved for several

Table 2
Optimal harvest ages and NPV under future constant climate.

Climate Scenario: RCP 4.5

	North		Central Coast		South	
	Rotation Ages	Function Value (€/ha)	Rotation Ages	Function Value (€/ha)	Rotation Ages	Function Value (€/ha)
$V_1(t_1^*, t_2^*, t_3^*)$	16,17,18	5399	15,15,17	7993	16,17,19	3921
$V_2(t_2^*, t_3^*, t_1^*)$	17,18,16	7283	15,17,15	9852	17,19,16	5810
$V_3(t_3^*, t_1^*, t_2^*)$	18,16,17	6718	17,15,15	9268	19,16,17	5252

Climate Scenario: RCP 8.5

	North		Central Coast		South	
	Rotation Ages	Function Value (€/ha)	Rotation Ages	Function Value (€/ha)	Rotation Ages	Function Value (€/ha)
$V_1(t_1^*, t_2^*, t_3^*)$	18,18,20	4199	15,16,17	5821	17,18,20	3177
$V_2(t_2^*, t_3^*, t_1^*)$	18,20,18	6116	16,17,15	7686	18,20,17	5079
$V_3(t_3^*, t_1^*, t_2^*)$	20,18,18	5578	17,15,16	7107	20,17,18	4532

random initial populations. In the second the problem was solved iteratively. Each iteration consisted of a new initialization of the problem, but, in this case, the solution of the previous iteration was introduced as an individual of the next problem's initial population.

3. Results

The methodology developed above allows for studying optimal forest management while explicitly accounting for the impacts of climate variability on forest productivity. In what follows, we thus start by characterizing optimal harvesting and the corresponding NPVs under different climate scenarios. To better identify the effects of climate variability, those are compared with optimal forest management under past and future constant climate scenarios. Computing the NPV and optimal harvest ages under past constant climate follows the same procedure used for future constant climate discussed in the previous section. In this case, timber volumes were computed using the 3-PG model considering a monthly average of the climate variables between 2006 and 2015.

As will be shown below, climate variability implies substantial changes in optimal harvest ages during climate transition. The ensuing discussion thus moves to identifying the climate drivers explaining adaptive forest management. To that end we take advantage of one of the features of the 3-PG model, namely its use of modifier functions to model the effects of stand and climate variables on forest productivity.

Finally, subsection 3.2 presents one last exercise allowing us to better place our findings in the context of previous literature using optimization to study forest management. As mentioned earlier, those studies have examined the impacts of climate change on management considering that forest productivity is a function of linear trends in climate. We thus consider an additional climate scenario. In particular, one in which the climate inputs used in 3-PG are given by the linear monthly trends of the original climate variables in RCP 45. By doing so, it is thus our goal to more clearly identify the insights resulting from a framework in which climate variability is taken into account, and, ultimately, as these may inform previous findings that ignored it.

3.1. *Changing climate – climate variability*

3.1.1. *Optimal harvest ages and Net Present Value*

In a constant climate scenario, optimal forest management is characterized by replicating plantation cycles. Also, given that timber volume is not time-dependent and management costs are higher for the first rotation, optimal harvest ages within a plantation cycle are non-decreasing (see Tables 3 and 4, second column). None of these results holds when changing climate conditions are considered (see Tables 3 and 4, third column). Reflecting changes in stand productivity, optimal harvest ages differ across plantation cycles and may optimally decrease within one. Finally, optimal rotation ages under changing climate conditions may substantially differ from their optimal values under past constant climate. For the North region, for instance, this difference may amount to five years, corresponding to a change of approximately 30%.

When compared to constant past climate, NPV is lower under climate change across all regions and for both climate scenarios (see Tables 3 and 4, columns 2 and 3), i.e., climate change negatively affects *Eucalyptus globulus* plantations. The largest reductions in NPV occur under a more severe climate change scenario; in both cases, the South is the most negatively affected region (Tables 3 and 4). At first sight, one could expect those reductions in NPV to correspond to forest productivity continuously decreasing during the period under investigation. That, however, is not the case. Figs. 1–3 show, for all regions and climate scenarios, timber volumes assuming a harvest age of 10 years. Note that when the intermediate climate scenario is considered (RCP 4.5), timber production falls during transition before increasing again by the end of the century. In those cases, timber volume recovers and eventually surpasses its initial levels. In fact, if a future constant climate is considered, NPV is higher for the North and Central Coast regions under RCP 4.5 (see Table 3, columns 2 and 4). An analysis considering static or steady-state changes in climate would, therefore, lead to misleading conclusions on the impact of climate change for this species and, as a result, to erroneous predictions concerning optimal land use change. This result highlights the limitations of considering the static impacts of climate change on forestry, an issue that will be explored in greater detail in Section 3.2.

3.1.2. *Climate variables, stand growth, and forest management*

Process-based models allow for studying how climate affects timber production by capturing the effects of climate variables on stand productivity. In the 3-PG model, those effects are captured by a set of modifier functions based on available soil water, mean air temperature, atmospheric vapor deficit, site nutrition, frost days per month, and stand age (see Section 2.1). The modifiers corresponding to site nutrition (f_n) and stand age (f_{age}) equal approximately 1 for all regions under the two climate scenarios, implying that those variables do not affect stand productivity (see Section 2.1). In contrast, the modifiers associated with climate variables are not only relevant in restricting stand growth, but their effects are also different across regions (Figs. 1–3). For the North (Fig. 1), the lowest modifier value is the one associated with mean air temperature (f_{temp}), while for the Central Coast and South (Figs. 2 and 3, respectively), variables related to trees' water use, namely atmospheric vapor deficit (f_{vpd}) and available soil water (f_{sw}), are the ones with the highest negative impact on forest productivity.

The impact of climate variability on timber production can thus be investigated by examining the evolution of the modifiers' function values during transition *vis-à-vis* their respective values under constant climate. Fig. 1–3 presents those values under past constant climate (dashed lines) and their 10-year average value under changing climate (solid lines). In this context, first consider the North and Central Coast regions under RCP 4.5 (Figs. 1 and 2 - upper panels). In those cases, the reduction in the number of frost days per month (f_{frost}) and changes in temperature (f_{temp}) positively affect stand productivity, i.e., the modifier function values for those variables are higher under changing climate when compared to constant past climate. On the other hand, the modifier function values corresponding to available soil water and VPD fall during transition before increasing again by the end of the century. The combined outcome of these counteracting effects on stand productivity results in lower yields during the middle of the period, which then recover and eventually surpass their initial levels only by the end of the century. The South region follows a similar pattern (Fig. 3- upper panel), except that the available soil water modifier remains below its initial levels.[4] The non-linear combined effects of climate variables thus impose adaptive forest management, i.e., harvest ages optimally change in time. Consider the Central Coast region as an example. In this case, the more favorable conditions on temperature and the number of frost days, but the lower availability of water resources during transition, requires reducing harvest ages in the second plantation cycle (see Table 3, third column). By the end of the century, though, when water abundance increases, optimal harvesting increases to levels above past constant climate.

3.2. *Linear climate transition*

The findings reported in the section above disclosed some limitations of considering the effects of climate change on stand growth using 1) a single climate variable (the effects on stand productivity depend on the combined effect of several variables) or 2) assuming that such effects may be reasonably approximated through static/steady-state changes in

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[4] When a more pessimistic scenario is considered, the modifier values follow a similar trend, except that under RCP 85 the modifiers associated with VPD and available soil water tend to decrease during transition.

Table 3

Optimal harvest ages and NPVs under past/future constant climate and changing climate scenarios. Harvest ages under constant climate and the three last harvest ages under changing climate consist of an infinitely replanted plantation cycle.

Climate Scenario: RCP 4.5	North				
		Past Constant Climate (2006–2015)	Changing Climate (2006–2100)	Future Constant Climate (2091–2100)	Linear Changing Climate (2006–2100)
	Harvest ages	17,17,19	17,18,20 | 18,22,18 | 16,17,18	16,17,18	16,17,18 | 15,14,14 | 16,17,18
	NPV (€/ha)	4920	4780	5399	5023
	Central Coast				
		Past Constant Climate (2006–2015)	Changing Climate (2006–2100)	Future Constant Climate (2091–2100)	Linear Changing Climate (2006–2100)
	Harvest ages	14,15,16	14,15,16 | 11,15,15 | 15, 15, 17	15,15,17	15,15,16 | 15,15,17 | 15,15,17
	NPV (€/ha)	7641	6973	7993	7871
	South				
		Past Constant Climate (2006–2015)	Changing Climate (2006–2100)	Future Constant Climate (2091–2100)	Linear Changing Climate’(2006–2100)
	Harvest ages	16,16,18	17,16,17 | 15,13,16 | 16,17,19	16,17,19	16,17,18 | 15,14,14 | 16,17,19
	NPV (€/ha)	4022	3421	3921	4079

Table 4

Optimal harvest ages and NPVs under past/future constant climate and changing climate scenarios. Harvest ages under constant climate and the three last harvest ages under changing climate consist of an infinitely replanted plantation cycle.

Climate Scenario: RCP 8.5	North			
		Past Constant Climate (2006–2015)	Changing Climate (2006–2100)	Future Constant Climate (2091–2100)
	Harvest ages	16,17,18	18,17,20 | 18,22,18 | 18,18,20	18,18,20
	NPV (€/ha)	5634	4419	4199
	Central Coast			
		Past Constant Climate (2006–2015)	Changing Climate (2006–2100)	Future Constant Climate (2091–2100)
	Harvest ages	15,16,17	12,16,16 | 13,13,15 | 15,16,17	15,16,17
	NPV (€/ha)	8054	6610	5821
	South			
		Past Constant Climate (2006–2015)	Changing Climate (2006–2100)	Future Constant Climate (2091–2100)
	Harvest ages	15,16,18	13,16,16 | 13,15,20 | 17,18,20	17,18,20
	NPV (€/ha)	3987	3071	3177

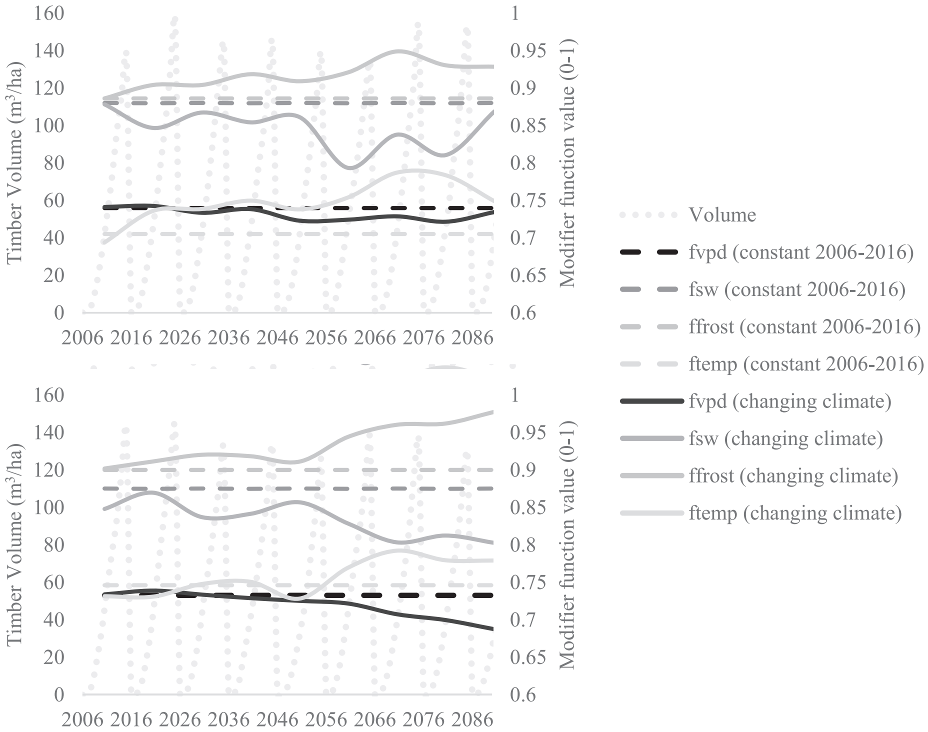

Fig. 1. North Region. Timber volumes for a 10-year harvest age. Growth modifier functions values for constant and changing climate – 10-year average. Upper panel: climate scenario RCP 45. Lower panel: climate scenario: RCP85.

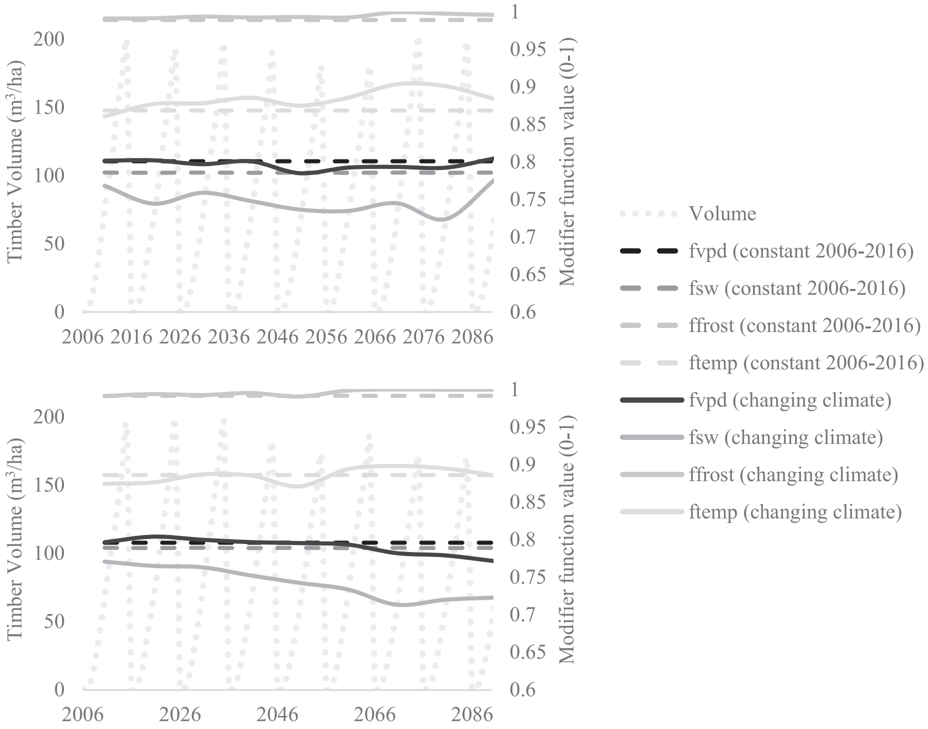

Fig. 2. Central Coast. Timber volumes for a 10-year harvest age. Growth modifier functions values for constant and changing climate – 10-year average. Upper panel: climate scenario RCP 45. Lower panel: climate scenario: RCP85.

climate (stand productivity may both decrease and increase in the course of a climate scenario). This section explores that issue further. To that end, the methodology described in Section 2 is applied considering a scenario in which climate variables follow a linear trend. In particular, the climate scenario here considered is given by the linear monthly trend of all climate variables in the original RCP 45 scenario (Table 3, column 5).

Optimal harvest ages under a linear climate scenario substantially differ from those obtained under full climate variability (see Table 3, columns 3 and 5). Consider, for example, optimal rotation ages for the

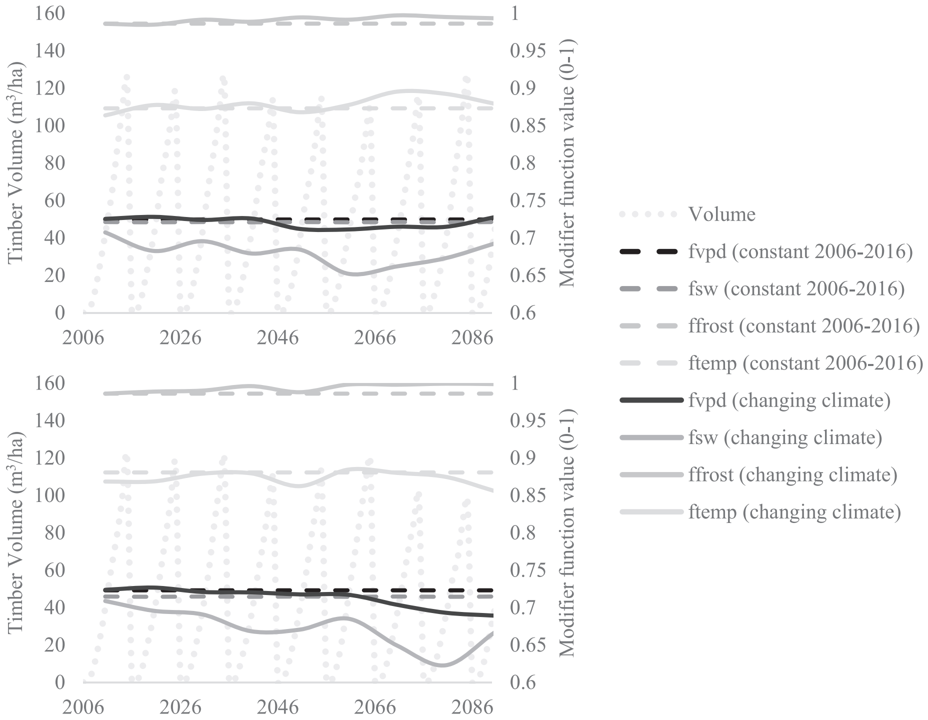

Fig. 3. South. Timber volumes for a 10-year harvest age. Growth modifier functions values for constant and changing climate – 10-year average. Upper panel: climate scenario RCP 45. Lower panel: climate scenario: RCP85.

North region during the second plantation cycle. In that case, differences in optimal harvest age may amount to an 8-year difference. More important, however, is to note that the changes in optimal harvest age also differ in sign. For the North region, and when variability is accounted for, optimally adjusting forest management during the second plantation cycle requires increasing optimal harvest ages with respect to past constant climate (see Table 3, columns 2 and 3). In contrast, under linear climate transition, optimal harvest age decreases (see Table 3, columns 2 and 5). Approximating the effects of climate change by considering a linear transition thus fails to adequately capture changes in optimal forest management. However, the consequences of neglecting climate variability are more significant in NPV terms. Not only are NPVs higher under linear climate than those obtained under climate variability (see Table 3, columns 3 and 5), but they are also above their values under past constant climate (see Table 3, columns 2 and 5). Considering linear trends in climate variables thus leads to the erroneous conclusion that *Eucalyptus globulus* plantations benefit from moderate climate change. In section 3.1, we showed that considering static changes in climate led to flawed conclusions on future land use allocation. The results obtained here are relevant as they reveal that using linear trends in climate remains unsatisfactory to adequately evaluate the effects of climate change in forestry.

4. Discussion and concluding remarks

In this paper we study optimal forest management under climate change using a process-based forest model.[5] The analysis presented here is relevant to three strands in the literature. First, we show that the assumption of constant management regimes applied in simulation studies using process-based models is inappropriate under changing climate variability (Bryars et al., 2013; Meason and Mason, 2014; Waring et al., 2014; Augustynczik et al., 2017; Perdue et al., 2017; Susaeta et al., 2017; Bourke et al., 2023). Optimal resource use requires implementing adaptive forest management, i.e., forest practices alter within the time horizon of the considered climate scenario. In particular, we show that optimal harvest ages must decrease/increase as a function of the time-varying combined effect of multiple climate variables affecting forest productivity. As a result, assuming constant management regimes may result in inaccurate predictions of the impacts of climate change on timber production and, consequently, on forest profitability.

Second, our results add to previous studies using optimization techniques in which forest dynamics are affected by linear trends in one or more climate variables. In this context, we argue that such an assumption remains limited to model the effects of a changing climate on forest ecosystems. As discussed above, considering one variable is insufficient to adequately model changes in forest productivity; the latter depends on the combined effect of multiple variables changing in time. Also, we show that while timber productivity may progressively increase under a linear climate scenario, the same may not be observed when climate variability is considered. Variability during transition thus implies complex adjustments in optimal management in ways that a linear approximation cannot capture, i.e., optimal forest management is qualitatively different when variability is accounted for. Note that, when comparing the results obtained under full climate variability against those assuming a linear trend in section 3.2, the observed changes did not resume to differences in rotation length; it was actually the direction of the adjustment that differed. Finally, fluctuations in timber production due to climate variability may have significant implications on forested land value. Consequently, linear climate scenarios may overestimate the effects of climate on forest profitability, leading to erroneous conclusions regarding future land use change. Note that, for the case studies areas considered in this paper, a linear intermediate climate scenario resulted in NPVs above past climate. However, the opposite was true when variability was taken into account. Interestingly, previous studies ignoring climate variability argued that management adaptation

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[5] While other studies have also optimized forest management using a process-based model (see Niinimäki et al., 2012; Niinimäki et al., 2013; and Pihlainen et al., 2015), to the best of our knowledge, this is the first to investigate the role of climate variability.

to climate primarily requires adjustments in land use and minor changes in forest management (Guo and Costello, 2013), which precisely correspond to the limitations we found in this study when a simplifying linear climate trend impact was assumed.

Finally, the findings reported in this paper are also relevant to the literature examining the use of forests in the overall emissions' mitigation portfolio (Sohngen and Mendelsohn, 2003; Tavoni et al., 2007; Michetti and Rosa, 2012; Bosello et al., 2015). Those studies have typically disregarded the effects of climate on stand growth. Our results show, however, that the costs of forest-based carbon sequestration are likely to strongly depend on climate-induced changes in forest productivity.

At this stage, some final remarks are in order. While changes in the economic parameters used in this paper may change the corresponding optimal harvesting ages and NPV, the effects of larger/lower discount rates, costs or timber prices on rotation length are already well documented in the literature. As a result, if, on the one hand, those may quantitatively change our findings, on the other, the main insights resulting from our analyses are expected to remain valid. In fact, by considering the same economic parameters across different climate scenarios allowed us to better isolate the effects of climate change on optimal management. One more considerable limitation, however, consists in the fact that silvicultural practices considered in this study resume to harvesting. While this is adequate for the case study considered here, the same is not true for other species. As Patto and Rosa, 2022 showed, increasing the analysis to consider forest practices other than harvesting, namely commercial thinnings, may substantially change adjustments in rotation length. Also, the framework considered in this paper assumes perfect foresight regarding future climate development. In the context of increased climate variability, however, uncertainty is critical. Extending the analysis to include those issues thus presents itself as a particularly valuable research agenda.

CRediT authorship contribution statement

Renato Rosa: Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Constança Simas:** Software, Methodology, Investigation, Formal analysis, Data curation. **Rodrigo Ataíde:** Validation, Formal analysis. **Paula Soares:** Writing – review & editing, Validation, Methodology, Investigation, Data curation. **Margarida Tomé:** Writing – review & editing, Validation, Supervision, Methodology, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

CeBER's research is funded by national funds through FCT – Fundação para a Ciência e a Tecnologia, I·P., Project UIDB/05037/2020 with DOI 10.54499/UIDB/05037/2020.

This work was funded by Fundação para a Ciência e Tecnologia (UID/ECO/00124/2019, UIDB/00124/2020 and Social Sciences DataLab, PINFRA/22209/2016), POR Lisboa and POR Norte (Social Sciences DataLab, PINFRA/22209/2016).

CENSE is financed by Fundação para a Ciência e Tecnologia, I.P., Portugal (UIDB/04085/2020).

This work was supported by FCT – Fundação para a Ciência e Tecnologia, I.P. by project reference UIDB/00239/2020 of the Forest Research Centre and DOI identifier 10.54499/UIDB/00239/2020

Renato Rosa acknowledges funding from FCT under the Scientific Employment Stimulus (CEECIND/02230/2017) and the The FCT Investigator Programme (IF/01106/2012/CP0153/CT0003).

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