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The final publication is available at:

<https://doi.org/10.1139/cjfr-2015-0329>

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Canadian Journal of Forest Research
Revue canadienne de recherche forestière

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Journal:	<i>Canadian Journal of Forest Research</i>
Manuscript ID	cjfr-2015-0329.R3
Manuscript Type:	Article
Date Submitted by the Author:	09-May-2016
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Keyword:	dynamic programming, coppice systems, climate change, eucalypt, uncertainty

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A climate change adaptive dynamic programming approach to optimize eucalypt stand management scheduling. A Portuguese application.

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May 9, 2016

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Abstract

The aim of this paper is to present approaches to optimize stand-level short rotation coppice management planning taking into account uncertainty in stand growth due to climate change. The focus is on addressing growth uncertainty through a range of climate scenarios so that an adaptive capacity may be possible and the vulnerability of the stand to climate change may be reduced. The optimization encompasses finding both the harvest age in each cycle and the number of coppice cycles within a full rotation that maximize net present revenue. The innovation lies in the combination of the process-based model (Glob-3PG), with two dynamic programming (DP) approaches. The former is able to project growth of eucalypt stands under climate change scenarios. The innovative approaches are thus influential to define the management policy (e.g. stool thinning, number of coppice cycles and cycle length) that maximizes net present revenue taking into account uncertainty in forest growth due to climate change. In both approaches, the state of the system is defined by the number of years since plantation while DP stages are defined by the cumulative number of harvests. The first approach proposes the optimal policy under each climate change scenario at each state. The second approach addresses further situations when the climate scenario is unknown at the beginning of the planning horizon. Both help address uncertainty in an adaptive framework as a set of readily available options is proposed for each scenario. Results of an application to a typical *Eucalyptus globulus* Labill stand in Central Portugal are discussed.

Keywords: dynamic programming, coppice systems, climate change, eucalypt, uncertainty

19 **1 Introduction**

20 Climate has been changing and there is a warming trend. Foresters must be aware of that change as the biological
21 processes involved in forest dynamics are strongly impacted by environmental changes. In Mediterranean
22 environments, climate change will have a negative impact on forest growth. For example, in Portugal, all climate
23 change scenarios predict less precipitation all over the country and a reduction of forest growth (Christensen
24 et al. 2007). This is different from the North of Europe where the increase of temperature may expand the
25 growing season in very cold areas resulting in more growth. This introduces uncertainty in the forecast of timber
26 production. Nevertheless, the industry has to schedule forest operations to meet timber demand. Typically, the
27 estimate of future timber yields is made with empirical growth and yield (G&Y) models. However, they are based
28 on the assumption that future climatic conditions will be similar to those in the past (Landsberg and Wearing
29 1977). This makes them inadequate to support decision making under climate change (Garcia-Gonzalo et al.
30 2014). On the contrary process-based G&Y models are based on physiological processes controlled by climatic
31 and edaphic factors (e.g. Kellomäki et al. 1997). Thus, they are suitable to forest planning when addressing
32 climate change impacts and when developing adaptive management options. Spittlehouse and Stewart (2003)
33 presented a review of adaptive actions in forest management and discussed how to increase forestry adaptive
34 capacity to climate change. Jacobsen and Thorsen (2003) analysed the potential advantages in a mixed species
35 stand when encompassing growth uncertainty caused by climate change. Lindner et al. (2010) presented the
36 climate change trend in Europe and projected impacts of climate change in European forests. Seidl and Lexer
37 (2013) addressed climatic and social uncertainty in a multi-criteria forest management model and analyzed
38 trade offs between the options of reducing adverse climate change impacts and of favoring adaptive capacity.
39 Johnston and Hesseln (2012) characterized the results of several discussions about the ability of Canadian forest
40 systems to face a successful adaptation to climate change. Garcia-Gonzalo et al. (2014) suggested a decision
41 support system to help forest managers address the challenge of climate change in long term forest management
42 planning. This tool assessed the impacts of climate change on the selection of prescriptions for stands in forest-
43 wide management plans. Rammer et al. (2014) developed a DSS toolbox that includes a vulnerability assessment
44 tool as well as an optimization tool to generate optimized management plans at forest-wide level. Nevertheless,
45 these approaches to address climate change impacts on forest management planning were deterministic. Each
46 climate change scenario was assumed to occur with certainty and its stochasticity was not addressed. Dynamic
47 programming (DP) models have been previously used by several authors to find optimal forest management
48 prescriptions (e.g., Amidon and Akin 1968, Kao and Brodie 1979, Hoganson and Rose 1984, Buongiorno and
49 Gilless 1987, Arthaud and Pelkki 1996). When optimizing stand-level management, DP may be very valuable
50 as it overcomes the problem of evaluating and enumerating every management option (Hoganson et al. 2008).

Addressing risk and uncertainty in forest management has also been object of numerous previous studies (e.g., Spring et al. 2008, Zhou and Buongiorno 2011, Couture and Reynaud 2011; Ferreira et al. 2012; Buongiorno and Zhou 2015). Segura et al. (2014) highlighted the use of DP models to optimize forest management planning. DP may help develop an adaptive management framework as it allows recognizing the stochastic nature of the problem and decisions are taken considering the state of the system. (e.g., Gunn 2005, Díaz-Balteiro and Rodriguez 2008). The forestry literature discussed two DP solution approaches (e.g. Hoganson et al. 2008). In the context of stand-level management planning, the forward solving method provides the optimal management path up to a stand state while the backward solving method provides the optimal management path out of a stand state. Therefore, only the latter is suited for solving stochastic problems, since a decision at stage $n - 1$ will lead to more than one possible state at stage n due to uncertainty (Kennedy 1986). The backward solving method allows the forest manager to choose the policy that fits better to the new situation if a change occurs due to a random event such as wildfire (e.g., Hoganson et al. 2008, Ferreira et al. 2011, Ferreira et al. 2012). In this context, DP may be a useful method to develop policies to adapt management to climate change as it provides the best management policy at each stand state under each scenario.

The model presented in this paper has similarities with the dynamic programming model developed by Ferreira et al. (2012). Both models incorporate uncertainty through a stochastic endogenous factor. Ferreira et al. (2012) aimed at incorporating fire risk in coppice stand management planning while the objective of this research is to consider uncertainty in forest growth due to climate change when designing coppice stand management plans. Climate change scenarios are “translated” to growth scenarios by the Glob3PG process-based model. The process-based model Glob3PG, was first developed by Tomé et al. 2004 and has been recently updated by Oliveira and Tomé, submitted and validated by (Barreiro et al. 2014). Glob3PG is a hybridization of the empirical model Globolus 3.0 (Tomé et al. 2006) and of the process-based model 3PG calibrated for Portuguese conditions (Fontes et al. 2006; Landsberg and Waring 1997). Glob3PG takes advantage of the flexibility and ability of 3PG to predict the effects of changes in growing conditions (e.g. climate change, fertilization) and the prediction capacity under current conditions of GLOBULUS 3.0 (Barreiro, 2011). The model is based on physiological processes (e.g. photosynthesis) that are controlled by climatic and edaphic factors which allow predicting growth under changing environmental conditions. This is influential to help develop effective adaptive management policies.

In this paper we propose a stochastic approach to mitigate adverse climate change impacts and to increase the adaptive capacity of forest stands. This approach is further innovative as it fully integrates a stochastic dynamic approach with a process-based model that is sensitive to climate parameters. This is influential to help address climate change uncertainty in forest management planning.

A typical *Eucalyptus globulus* Labill stand in Central Portugal is used for testing purposes. In the case

84 study three climate change scenarios, wich differ in the values of parameters such as temperature, number of
85 rain days, number of frost days and solar radiation, are considered to define different climate scenarios (more
86 humid or drier).

87 2 The dynamic programming approach

88 2.1 Model building

89 Kennedy (1986) and Hoganson et al. (2008) provide an excellent introduction and review of dynamic
90 programming (DP) concepts and applications to forest management scheduling. DP has been used further to
91 address eucalypt stand-level management planning. Diaz-Balteiro and Rodriguez (2006) presented a DP model
92 to optimize eucalypt rotations targeting both pulpwood supply and carbon sequestration while Ferreira et al.
93 (2012) presented a stochastic DP approach to address wildfire risk in eucalypt stands management planning.

94 In this paper two DP approaches are developed to provide optimal management policies for a Eucalyptus
95 globulus coppice stand. These encompass proposals of stool thinning options as well as of cycle lengths according
96 to the stand state and the climate change scenario. Additionally, this approach provides insights about the
97 optimal number of cycles within a full rotation of a coppice system. This information is influential for decision-
98 makers to address uncertainty resulting from a random event such as climate change. It further helps develop
99 an adaptive framework for stand-level management planning. The DP approach formulation decomposes the
100 management problem into stages, corresponding to the cumulative number of harvests since the plantation of
101 the coppice stand. Thus, the maximum number of harvests within a full coppice rotation determines the possible
102 number of stages.

103 DP model building considered climate change scenarios. Each scenario corresponds to a time series of
104 monthly climate data that includes values for temperature, precipitation, solar radiation, frost days, among
105 others. Scenarios allow to anticipate realizations of the stochastic event and to determine optimal policies from
106 each stand state on.

107 **Figure 1**

108 For each climate scenario there is one network. DP network nodes correspond to feasible stand states in
109 each stage. A stand state is characterized by the number of years since the stand was planted (Figure 1). Thus,
110 each stand state depends on the range of cycle lengths. The arcs of the DP network correspond to management
111 policies that may be implemented from each state (e.g. options for cycle length and stool thinning). Therefore,

each arc includes a harvest decision. Deterministic networks associated to specific climate change scenario may be solved by the backward recursion process. To start the solution process, for each climate scenario problem, an estimate of the soil expectation value (SEV) is necessary. This estimate provides the “bare land nodes” values, i.e. the net present value of an infinite series of rotations after the first. All DP network nodes are linked to a “bare land node” as a new rotation may be started after all coppice harvests (Figure 1). The solution process of these deterministic problems will find the optimal stand-level management planning strategy to adopt in each climate scenario.

At the beginning of each stage, for each climate scenario j , the stand state is described by T_n , the number of years in the period ranging from coppice stand planting up to the harvest at the end of the $(n - 1)^{th}$ stage. The set of management policies that may be implemented at the beginning of the n^{th} stage is given by a vector (I_n, NS_n) , associated to a DP arc. I_n corresponds to the number of years of the n^{th} cycle, with $I_n \in \Psi_n$; Ψ_n is the set of feasible cycle lengths. NS_n stands for the average number of sprouts per stool after a stool thinning in the n^{th} cycle, with $NS_n \in \Theta_n$; Θ_n is the set of feasible average numbers of sprouts per stool (Figure 2).

Figure 2

To provide information useful for developing an adaptive forest management framework, the DP problem is solved through backward recursive equations. As mentioned before, to start the backward recursion process an estimate of the bare land value is assigned to all potential harvest ages at the end of the rotation. This is done for all climate scenarios. The discounted net return of all management policies that may be implemented over a full cycle is computed by the DP return function. The recursive function $F_n^j(T_n)$ selects the optimal path out of a node T_n , at the beginning of the n^{th} stage, which includes the sum of net returns of management policies that may be implemented at that state with the net return associated to the optimal management policy to be implemented at either the state T_{n+1} , or with the estimate of the bare land value associated with the age when the clearcut occurs. $F_n^j(T_n)$ thus identifies the optimal management policy, for each scenario j , when the stand is in state T_n . This policy encompasses a decision regarding whether to clearcut or to consider one further coppice cycle. In the case of the latter, the decision includes further cycle length and stool thinning options for the new cycle.

2.2 Mathematical description of the model

Two different approaches are presented to address climate change scenarios. The first one is a deterministic approach. It assumes that all climate change scenarios are known beforehand. Thus, the approach proposes the

optimal management policy for each scenario. At the beginning of the planning horizon, the forest manager takes into account the possible scenarios and makes a decision according to his attitude toward risk. For instance, if the forest manager is averse to risk he will probably choose the optimal policy corresponding to a more pessimist scenario. A second approach is proposed to take fully into account the stochasticity of the climate change scenarios. This approach takes into account the climate change scenarios occurrence probabilities. The main difference with the previous approach is that in this case it is assumed that at the first stage the decision maker does not know which climate change scenario will occur. In this approach, the model does not propose the optimal policy to be adopted at the beginning of the planning horizon for each scenario. At the first stage a decision is proposed without knowing the climate change scenario that will occur. Thus, the first cycle length chosen is the one that maximizes the expected net present value according to climate change scenarios probabilities. From the second stage on, the model is again deterministic, and it proposes a management policy for each scenario. Both approaches incorporate the impact of climate change scenarios on forest growth. In both approaches, the forest manager may change his forward decisions in an adaptive reaction to some changes that might occur in the stand state or in the climate. This is the most important advantage of using a backward dynamic programming solution method in forest management to address risk.

2.2.1 Deterministic problem for each scenario

This decomposition approach may be illustrated by the set of networks corresponding to a deterministic problem for each scenario. In this approach, the model was defined as follows:

$$\text{Determine } Z^j = F_1^j(0) - CP, \quad j = 1, \dots, J \quad (1)$$

$$F_1^j(T_1) = \max_{I_1 \in \Psi_1} \left\{ R_1^j(T_1, I_1) + F_2^j(T_1 + I_1) \right\}, \quad j = 1, \dots, J \text{ and } T_1 = 0 \quad (2)$$

$$F_n^j(T_n) = \max_{\substack{I_n \in \Psi_n \\ NS_n \in \Theta_n}} \left\{ R_n^j(T_n, I_n, NS_n) - C NS_n^j(T_n, I_n, NS_n) + F_{n+1}^j(T_n + I_n), \frac{F_1^j(0) - CR}{(1+i)^{T_n}} \right\}, \quad n = 2, \dots, N, \quad j = 1, \dots, J \quad (3)$$

$$F_{N+1}^j(T_{N+1}) = \frac{F_1^j(0) - CR}{(1+i)^{T_{N+1}}}, \quad j = 1, \dots, J \quad (4)$$

where,

160 N = maximum number of harvests over a coppicing system rotation;
 161 $n = 1, \dots, N$ identifies the stage, defined by the number of harvests completed; the first harvest occurs at the
 162 end of stage 1; $N + 1$ identifies the end of stage N ;
 163 T_n = number of years since the stand was planted at the beginning of stage n ; it corresponds to the value
 164 of state variables defining a DP network node, at the beginning of the n^{th} stage; T_{N+1} identifies the number of
 165 years since the stand was planted at the end of stage N , when the stand is harvested the N^{th} time; $T_1 = 0$;
 166 I_n = decision regarding cycle length with $n = 1, \dots, N$;
 167 NS_n = average number of sprouts per stool after a stool thinning;
 168 Z^j = soil expectation value associated to the optimal management planning strategy under
 169 climate change scenario j ;
 170 $F_n^j(T_n)$ = optimal discounted value of network node T_n , at the beginning of the n^{th} stage;
 171 $R_n^j(T_n, I_n, NS_n)$ = discounted financial return associated to the sale of wood after an harvest, at the end
 172 of n^{th} stage, under the j^{th} climate change scenario; If $n = 1$ we have $R_1^j(T_1, I_1)$ as there is no stool thinning in
 173 the first stage;
 174 $CNS_n^j(T_n, I_n, NS_n)$ = discounted cost of a stool thinning option at the n^{th} stage, under the j^{th} climate
 175 change scenario; $CV_1^j(T_1) = 0$;
 176 CR = conversion cost at the end of each rotation;
 177 CP = plantation cost at the beginning of the first rotation.

178 Equation (1) presents the objective of maximizing the soil expectation value of the coppice stand ($SEV^j =$
 179 Z^j), for each climate change scenario. The maximum value of SEV^j is calculated using the backward solving
 180 method. SEV is computed as the difference between the optimal value $F_1^j(0)$ of the initial network node and the
 181 plantation costs. To initiate the solution process is necessary to provide an estimate of the SEV^j as the value of
 182 $F_1^j(0)$ is still unknown. This estimate is also needed to satisfy the boundary condition that will allow stopping
 183 the iterative process. This estimate assigns a value for all bare land nodes. In the first iteration of the solution
 184 process $F_1^j(0)$ is replaced by an estimate, in equations (4). The net present value of the subtraction between
 185 $F_1^j(0)$ and the conversion cost is computed discounting the number of years since the plantation. At the end of
 186 the solution process, a comparison between the optimal value $F_1^j(0)$ and the estimate used is made. If these two
 187 values differ, the iterative process continues and the process considers the optimal value $F_1^j(0)$ to re-estimate the
 188 bare land nodes' value (Hoganson et al., 2008). Thus, this method uses successive approximations to find the

189 true SEV^j value. The method has been proven to converge (Ferreira, 2011). DP recursive relations are defined
 190 by equations (2) and (3). Equation (2) computes the value of the function F at the first stage, when a clearcut
 191 is not allowed, while equations (3) defines the value for each stand state (each node T_n), at the beginning of the
 192 n^{th} stage, under climate change scenario j , i.e., $F_n^j(T_n)$. Equations (4), as mentioned above, calculate the values
 193 of the F function at the end of the N^{th} stage. The return function of DP provides the discounted return from
 194 the sale of timber, when the harvest scheduling policy I_n is implemented, at the n^{th} stage, if the j^{th} scenario
 195 occurs.

$$R_n^j(T_n, I_n, NS_n) = \frac{P}{(1+i)^{T_n+I_n}} Vol^j(n, I_n, NS_n) \quad (5)$$

196 In equations (5), P is discounted $T_n + I_n$ years and corresponds to the timber stumpage price (€/m³); NS_n
 197 is the thinning option over a coppice cycle and corresponds to the average number of sprouts selected per stool
 198 as described in section 2.1, with $n = 2, \dots, N$; the volume harvested ($Vol^j(n, I_n, NS_n)$) is estimated by a growth
 199 and yield model.

200 The cost of stool thinning in coppice cycles over the rotation is also included in the DP return function
 201 component. This cost occurs after coppice harvests, i.e., for $n > 1$. Typically, stools are thinned only once over
 202 a coppice cycle. This cost is computed as the product of sprout selection cost (CS) by the number of sprouts
 203 NNS_n^j (equations (6)). This value is discounted $T_n + x$ years, being x the year in the cycle when the stool
 204 thinning takes place.

$$CNS_n^j(T_n, I_n, NS_n) = \frac{CS}{(1+i)^{T_n+x}} NNS_n^j(T_n, I_n, NS_n) \quad (6)$$

205 2.2.2 Integrated formulation for all scenarios

206 A second approach to address the climate change scenarios with dynamic programming was developed. This
 207 approach considers further situations when the decision-maker needs to make a decision in the first stage while
 208 still ignoring which climate change scenario will occur.

209 In this approach, the model is thus defined as follows:

$$\text{Determine } Z = F_1(0) - CP, \quad j = 1, \dots, J \quad (7)$$

$$F_1(T_1) = \max_{I_1 \in \Psi_1} \sum_{j=1}^J p^j \left[R_1^j(T_1, I_1) + F_2^j(T_1 + I_1) \right], \quad T_1 = 0 \quad (8)$$

$$F_n^j(T_n) = \max_{\substack{I_n \in \Psi_n \\ NS_n \in \Theta_n}} \left\{ R_n^j(T_n, I_n, NS_n) - CNS_n^j(T_n, I_n, NS_n) + F_{n+1}^j(T_n + I_n), \frac{F_1(0) - CR}{(1+i)^{T_n}} \right\}, \quad n = 2, \dots, N, \quad j = 1, \dots, J \quad (9)$$

$$F_{N+1}^j(T_{N+1}) = \frac{F_1(0) - CR}{(1+i)^{T_{N+1}}}, \quad j = 1, \dots, J \quad (10)$$

210 p^j = corresponds to the occurrence probability of the j^{th} climate change scenario.

211

212 The remain indexes, parameters and variables were defined in the previous subsection.

213 As it is assumed that in the first stage the climate change scenario is unknown the management decision
 214 regarding the first cycle length is the one that maximizes the expected values according to climate change
 215 scenarios probabilities. Therefore, in the first stage, $F_1(T_1)$ is computed considering the same I_1 for all scenarios.
 216 From the second stage on, the model is deterministic, as it is assumed that the decision-maker knows the climate
 217 change scenario. In each stage, a choice is made between allowing the stand to keep growing after a coppice
 218 harvest or implementing a clearcut and a conversion of the stand.

219 3 Case Study

220 Eucalypt is one of the main forest species in Portugal. It covers around 21% of the total Portuguese forest
 221 area (AFN 2010). Eucalypt globulus stands are managed as a coppice system and supply key raw material for
 222 the Portuguese pulp and paper industry. A typical eucalypt rotation may include up to 2 or 3 coppice cuts, each
 223 harvest being followed by a stool thinning in year 3 of the coppice cycle that may leave an average number of
 224 sprouts per stool ranging from 1.4 to 1.6. Harvest ages range from 9 to 16. Several costs have to be considered
 225 in the eucalypt stand management problem. The regeneration cost includes a fixed and a variable component
 226 and occurs only once in the beginning of the planning horizon. The former includes the soil preparation and the
 227 removal of shrubs. The latter depends on the number of plants. For testing purposes, this research considered
 228 a plantation with 1500 trees per hectare. At the end of a full rotation, the stand is converted, i.e., the stools are
 229 replaced by new plants in order to regenerate the stand. This involves a conversion cost. Three years after the
 230 beginning of the coppice cycle a stool thinning is performed with a cost that depends on the existing number of
 231 sprouts. Model solving considered average eucalypt pulpwood prices and operations costs in Portugal (Tables
 232 1 and 2). A real rate of 4% was used to discount costs and revenues.

Model solving considered average eucalypt pulpwood prices and operations costs in Portugal (Tables 1 and 2). In order to check further the validity of the results of our approach, the solutions proposed by the stochastic dynamic model were compared to a prescription that is often applied in Portugal. For this purpose we considered a typical prescription where 1500 trees per hectare are planted, followed by two coppice cuts at harvest age of 13 years, each coppice harvest being followed by a stool thinning in year 3 of the coppice cycle that may leave an average number of sprouts per stool of 1.4. The final harvest age is 13 years. This typical prescription was applied in each climate scenario and the results were compared to the results of the optimal stochastic solution.

Table 1

Table 2

3.1 Growth forecast

Climate change impacts substantially the growth of the forest and, consequently, the management schedule and both its revenues and its costs. Eucalypt growth was estimated using the decision support system - DSS SADfLOR vecc 1.0 (Garcia-Gonzalo et al., 2014). The DSS is a web-based platform with a modular structure that encompasses a management information module, a growth simulation module, a prescriptions' generator module, a decision module and a solution report module. This tool was used to generate the eucalypt prescriptions, i.e., the DP network paths and to further estimate the volume harvested at each age in each coppice cycle. The latter was completed with the process-based model thus considering the impacts of climate change scenarios on growth and yield. Specifically, the eucalypt stand growth was projected for a planning horizon of 65 years using the stand-level growth and yield process-based model *Globulus 3.0* that enables to predict tree growth considering climate scenarios (Tomé et al., 2004).

3.2 The dynamic programming model

Stages are described by the number of harvests over a whole coppice rotation. In this case study, the maximum number of harvests is four ($N = 4$). Thus, the DP network includes four stages that correspond to four cycles. In any stage, the states characterize the number of years since the plantation of the stand. The fourth harvest may occur at the end of the 4th stage, which is denoted by $N + 1 = 5$. In order to design the DP network all feasible management options over a cycle were taken into account, i.e., harvest age, length of the n^{th} cycle and number of sprouts per stool left after stool thinning, (Table 3).

Table 3

The values of state variable T_n will extend, under each climate change scenario, from 0 at the beginning of stage 1 to 64 at the end of stage 4 (Table 4).

Table 4

Three different climate change scenarios were considered with equal probability of occurrence. Each scenario is characterized by parameters such as temperature (mean, maximum, minimum), raining days, frost days and solar radiation. Among the three climate scenarios, scenario 2 is the driest one as it is associated with higher temperatures and a number of raining days lower than the others. Precipitation is 43% and 35% lower than in the case of scenarios 1 and 3, respectively. Scenario 1 is the coolest and more humid. It presents the highest precipitations and the lowest monthly mean temperature (Table 5). It is thus the scenario associated with higher eucalypt growth rates.

Table 5

3.3 Results

The software C++ and a desktop computer (CPU Duo P8400 with 3GB of RAM) were used to program the DP algorithm and to test the problem presented with the case study. A *SEV* estimate of 4000€/ha was used to trigger the backward solution process. A boundary condition must be satisfied as a stopping criteria for the iterative solution process. The process was stopped when the difference between the optimal *SEV* and the estimate of $F_1(0)$ was lower or equal than 0.01. The problem was solved using both dynamic programming approaches. The first approach provides the optimal management planning strategy under each climate change scenario while the second provides the optimal management strategies at each state at the end of the first stage when the climate change scenario becomes known.

The solution by the first approach includes four cycles within the full rotation, for all scenarios (Table 6). The scenario that most constrains economic returns is scenario 2 (Table 7). In this case *SEV* is equal to 4029.72€/ha. The solution by this approach provided further the optimal management planning strategy at each state in subsequent stages under each climate change scenario (Table 6). For example, under scenario 1, the optimal strategy at state 13 in the second stage included the decision to conduct a stool thinning leaving an average of 1.4 sprouts per stool and to have a coppice harvest 11 years later (Table 6). The strategy to be followed at the resulting state $T_3 = 24$ is provided by the recursive solution of this DP approach and may be read in a similar way (Table 6). If for some reason, in one given scenario, the state of the system changes, the solution approach provides the optimal strategy (network path) at the new state (network node) under that

climate change scenario. The rotation ranged from 51 to 55 years in the case of, respectively, scenarios 3 and 1. For all the scenarios the convergence was achieved after 7 iterations.

Table 6

Table 7

The solution by the second approach includes a single optimal decision regarding the first coppice cycle rather than three optimal decisions one for each scenario. This decision is associated to the value I_n that maximizes the expected economic returns values, considering the probabilities of the three scenarios. As expected, the soil expectation value for the second approach is a little lower than the expected value computed with the optimal values obtained in the first approach for the three scenarios. The first approach provided the optimal stand-level management plan under each climate change scenario, while the second selected the best policy at the beginning of stage 1, for the set of 3 scenarios, thus constraining further the options to be made in later stages under each scenario (Table 8). The solution by the second approach for all scenarios also includes four coppice cycles in all three scenarios. The rotation ranged from 51 to 53 years in the case of, respectively, scenario 2 and scenarios 1 and 3.

Table 8

Here, the convergence was also achieved after 7 iterations (Table 9).

Table 9

The SEV associated to the typical prescription was 4537€/ha euros in scenario 1, 3417€/ha in scenario 2 and 4221€/ha in scenario 3. This is clearly less than the SEV obtained by the optimal stochastic solution.

4 Discussion and Conclusions

This research considered climate change as an endogenous component of the forest management planning method. The introduction of this uncertainty influences the growth of the stand and, consequently, the timber production forecasts. Therefore, it impacts the returns from management policies.

Addressing climate change is a challenge to forest managers. Process-based models are based on biophysical processes (e.g. photosynthesis) and this makes them very useful to predict growth under alternative climatic

conditions. To some extent, they have already been used in decision making. For example, Garcia-Gonzalo et al. 2014 discussed the integration of a process-based model in a decision support system to address eucalypt forest management planning under climate change scenarios at landscape level. Vacik et al. (2010) developed ClimChAlp, a system with multicriteria-decision analysis tools to help forest owners design adaptive strategies at stand level. Nevertheless, there is no experience in combining a process-based model with dynamic programming techniques to optimize eucalypt management at stand level.

The comparison of the results by the SDP method with the outcomes from the implementation of the typical prescription for all climate scenarios (i.e. without any adaptation to climate change) suggests further that the stochastic solutions compare favorably to business-as-usual management. This demonstrates further the validity of the method presented in this article.

One of the most valuable characteristics of dynamic programming to optimize stand management planning is that it does not need to evaluate and enumerate all management options. This reduces considerably the solution time (Hoganson et al. 2008). Some previous studies have used this optimization technique to determine not only the optimal length of each coppice cycle but also the optimal number of cycles within a full coppice system rotation (e.g., Tait 1986, Diaz-Balteiro and Rodriguez, 2006). Nonetheless, none of these studies has addressed the impact of climate change in management planning. The use of a process-based growth and yield model to project forest growth under different climate scenarios combined with the proposed stochastic DP solution approaches did contribute to address climate change in short rotation coppice systems management scheduling. Dynamic programming proved to be an efficient optimization technique to solve the problem and to provide helpful information regarding the impact of climate change on coppice systems management scheduling at stand level. It further provided information about management options to be selected at any state of the stand under each scenario. The climate scenario 2 encompasses higher temperatures and lower precipitation. This limits the growth of the trees and explains why this scenario constrains economic returns. Rotation lengths are longer namely in cycles 1 and 2. Later cycles (3 and 4) are longer for scenario 1 which represents a very humid scenario. This is probably due to the fact that trees have a growth rate higher than in the other two scenarios.

The convergence of the model is usually achieved after a moderate number of iterations and a short running time. For instance, in the case study used for testing this research, the convergence was always reached after seven iterations and in less than one minute of running time. Thus, the convergence of these DP approaches is quite good. Even if the initial *SEV* estimate is far from the correct value, the convergence process is straightforward and efficient.

The DP approaches presented in this paper provide information useful to address risk and uncertainty in an adaptive framework. Instead of optimizing management for each climate scenario separately and proposing a management plan for the whole rotation, as in *anticipatory optimization* (Pukkala and Kellomaki, 2012), our

approaches provide rules to adapt management based on the actual growth and stand development. As such they may be classified as adaptive management approaches as defined by Lohmander (2007). The approaches presented propose coppice stand optimal management policies such as stool thinning and cycle lengths according to the stand state and to climate scenario. Furthermore, they offer insight about the optimal harvest's number within a whole coppice system rotation. A huge advantage of the approach is that it provides information on which are the best management options based on the actual state of the stand and climate scenario. Thus, at any time it is possible to check the state of the system and look for the optimal policy from that state on. For this reason this research model may be seen as an adaptive coppice system management model.

In this study we applied an innovative approach (i.e. the combination of SDP with a process-based model) to address climate change uncertainty when planning the management of a typical eucalypt stand growing in Central Portugal. However, the proposed approach may also be used to integrate climate uncertainty in other short rotation coppice systems.

Future research may focus on the development of DP functions that may encapsulate other management planning objectives as well as different clones' growth models. Of interest is the research of the potential of the DP network structure for analysis of trade-offs between several objectives (e.g. Borges et al. 2014) under climate change scenarios. The sensitivity of the solutions to parameters of these functions (e.g. interest rate, prices, costs) may further be researched. It may further focus on the conjugation of two stochastic elements as fire risk and climate change. These could be considered as endogenous and would be incorporated into the coppice stand management model through a set of scenarios combining and integrating wildfire risk and climate change.

Acknowledgments: This study was partially supported by the projects UID/MAT/04561/2013, funded by the Portuguese Foundation for Science and Technology (FCT - Fundação para a Ciência e a Tecnologia). Furthermore, this research has received funding from the European Union's Seventh Programme for research, technological development and demonstration under grant agreements: i) Nr 282887 INTEGRAL "Future-Oriented Integrated Management of European Forest Landscape" and Nr PIRSES-GA-2010-269257 (ForEAdapt, FP7-PEOPLE-2010-IRSES). It was also partially supported by Project PTDC/AGR-FOR/4526/2012 Models and Decision Support Systems for Addressing Risk and Uncertainty in Forest Planning (SADRI).

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Table 1 - Timber stumpage price used for eucalypt stand management scheduling.

Source: Personal communication by forest managers at the Portuguese forest industry

	Price (€/m ³)
Eucalypt pulpwood stumpage price	36

Table 2 - Operational costs.

Source: CAOOF 2010.

	Fixed cost (€/ha)	Variable Cost
Plantation cost	725	0.14€×number of plants
Stool thinning cost	–	0, 15€×number of sprouts
Conversion cost	1204	0.14€×number of plants

Table 3 - Possible values for management decisions. In each coppice cycle, the harvest age might range from 9 to 16 years. The set Ψ_n encompasses possible values for variable I_n , the length of the n^{th} cycle in the n^{th} stage. In the third year of each coppice cycle a stool thinning takes place and may leave in average 1.4 or 1.6 sprouts per stool (NS_n values in set Θ_n).

Silviculture parameters	Set of feasible values
Harvest age	$\Psi_n = \{9, 10, \dots, 16\}$
Average number of sprouts per stool	$\Theta_n = \{1.4; 1.6\}$

Table 4 - Possible states under climate change scenario. T_n is the number of years since the stand was planted until the beginning of the n^{th} stage.

Stage	States
1	$T = \{0\}$
2	$T = \{9, 10, 11, \dots, 16\}$
3	$T = \{18, 19, \dots, 32\}$
4	$T = \{27, 28, \dots, 48\}$
5	$T = \{36, 37, \dots, 64\}$

Table 5 - Monthly mean values for parameters, under each scenario, over all years of the planning horizon.

Tmean: mean monthly temperature; Tmax: mean monthly maximum temperature; Tmin: mean monthly minimum temperature; Rain: mean of monthly rain in mm; Rain_days: mean of monthly rainy days; Frost_days: mean of monthly frost days; Solar_rad: mean of monthly solar radiation in MJ m^2 ;

		Tmean	Tmax	Tmin	Rain	Rain_days	Frost_days	Solar_rad
<i>j</i> = 1	1	11.08	15.41	6.74	97.73	9.77	1.30	6.1
	2	11.73	16.76	6.70	47.22	7.20	0.52	9.3
	3	13.50	19.01	8.00	52.14	7.72	0.28	13.5
	4	15.42	21.50	9.34	45.68	7.81	0.02	17.9
	5	19.58	26.67	12.49	26.29	4.94	0.00	22
	6	24.51	32.72	16.28	10.68	2.19	0.00	24.3
	7	27.08	35.87	18.28	2.74	0.52	0.00	24.1
	8	26.94	35.71	18.16	2.62	0.47	0.00	21.5
	9	24.83	32.86	16.81	17.69	2.80	0.00	16.7
	10	19.41	25.67	13.15	48.97	6.67	0.00	11.1
	11	14.46	19.29	9.64	100.5	9.83	0.03	6.9
	12	11.83	16.02	7.64	104.4	9.84	0.69	5.3
<i>j</i> = 2	1	12.63	17.17	8.08	53.08	6.14	0.31	7.4
	2	13.35	18.51	8.21	26.03	4.19	0.13	10.8
	3	15.03	20.66	9.40	29.88	5.06	0.09	14.9
	4	17.32	23.57	11.05	31.73	5.78	0.00	19.3
	5	21.68	28.84	14.53	14.99	3.00	0.00	23
	6	26.68	34.50	18.86	5.46	1.16	0.00	24.5
	7	29.59	37.87	21.32	1.75	0.30	0.00	24.3
	8	29.21	37.18	21.23	0.63	0.16	0.00	22
	9	26.12	32.91	19.33	12.48	1.98	0.00	17.4
	10	20.76	26.40	15.12	36.01	4.94	0.00	12.2
	11	16.09	20.88	11.29	56.77	6.23	0.02	8.2
	12	13.38	17.88	8.88	50.91	5.64	0.22	6.7
<i>j</i> = 3	1	11.65	16.05	7.25	93.31	9.08	0.56	6.5
	2	12.28	17.40	7.15	42.09	6.59	0.23	9.8
	3	13.92	19.57	8.28	48.15	7.64	0.17	13.8
	4	16.03	22.36	9.70	44.52	8.02	0.00	18.3
	5	20.46	27.96	12.96	22.26	4.48	0.00	22.3
	6	25.70	34.44	16.97	10.07	2.16	0.00	24.2
	7	27.98	37.40	18.57	2.42	0.38	0.00	24.2
	8	27.63	36.85	18.40	1.98	0.48	0.00	21.5
	9	25.40	33.42	17.38	16.92	3.03	0.00	16.9
	10	19.82	26.03	13.61	45.31	6.42	0.00	11.5
	11	14.98	19.83	10.13	80.91	8.75	0.02	7.4
	12	12.37	16.72	8.02	82.21	8.53	0.39	5.9

Table 6 - Results by the deterministic problem for each scenario (first approach). T_n is the number of years since the stand was planted until the beginning of the n^{th} stage; I_n is the decision regarding cycle length; NS_n corresponds to the average number of sprouts per stool after a stool thinning; F_n^j is the optimal value of network node T_n , at the beginning of the n^{th} stage.

1 st cycle	$j = 1$	$T_1 = 0$	F_1^1	5010.73	I_1	13
	$j = 2$	$T_1 = 0$	F_1^2	4029.72	I_1	16
	$j = 3$	$T_1 = 0$	F_1^3	4752.74	I_1	16
2 nd cycle	$j = 1$	$T_2 = 13$	F_2^1	3932.85		
			V_2	1.4	I_2	11
	$j = 2$	$T_2 = 16$	F_2^2	2664.01		
			V_2	1.4	I_2	14
	$j = 3$	$T_2 = 16$	F_2^3	3192.89		
			V_2	1.6	I_2	14
3 rd cycle	$j = 1$	$T_3 = 24$	F_3^1	2330.38		
			V_3	1.6	I_3	16
	$j = 2$	$T_3 = 30$	F_3^2	1531.86		
			V_3	1.6	I_3	13
	$j = 3$	$T_3 = 30$	F_3^3	1804.35		
			V_3	1.6	I_3	12
4 th cycle	$j = 1$	$T_4 = 40$	F_4^1	1108.75		
			V_4	1.6	I_4	15
	$j = 2$	$T_4 = 43$	F_4^2	789.26		
			V_4	1.6	I_4	10
	$j = 3$	$T_4 = 42$	F_4^3	975.89		
			V_4	1.6	I_4	9

Table 7 - Convergence process for the deterministic problem for each scenario (first approach).

Scenario	Iterations	SEV
1	1	4785.700
1	2	4984.709
1	3	5007.725
1	4	5010.387
1	5	5010.695
1	6	5010.731
1	7	5010.735
2	1	3909.044
2	2	4014.628
2	3	4027.836
2	4	4029.488
2	5	4029.694
2	6	4029.720
2	7	4029.723
3	1	4546.881
3	2	4546.880
3	3	4749.147
3	4	4752.257
3	5	4752.675
3	6	4752.732
3	7	4752.740

Table 8 - Results by the integrated formulation for all scenarios (second approach). T_n is the number of years since the stand was planted until the beginning of the n^{th} stage; I_n is the decision regarding cycle length; NS_n corresponds to the average number of sprouts per stool after a stool thinning; F_n^j is the optimal value of network node T_n , at the beginning of the n^{th} stage.

<i>1st cycle</i>		<i>SEV</i>		4590.67	
		I_1		16	
<i>2nd cycle</i>	$j = 1$	$T_2 = 16$	F_2^1	3355.43	
			V_2	1.6	I_2 14
	$j = 2$	$T_2 = 16$	F_2^2	2738.20	
			V_2	1.4	I_2 14
	$j = 3$	$T_2 = 16$	F_2^3	3171.81	
			V_2	1.6	I_2 14
<i>3rd cycle</i>	$j = 1$	$T_3 = 30$	F_3^1	1834.80	
			V_3	1.6	I_3 13
	$j = 2$	$T_3 = 30$	F_3^2	1606.05	
			V_3	1.6	I_3 12
	$j = 3$	$T_3 = 30$	F_3^3	1783.27	
			V_3	1.6	I_3 13
<i>4th cycle</i>	$j = 1$	$T_4 = 43$	F_4^1	917.885	
			V_4	1.6	I_4 10
	$j = 2$	$T_4 = 42$	F_4^2	898.92	
			V_4	1.6	I_4 9
	$j = 3$	$T_4 = 43$	F_4^3	907.35	
			V_4	1.6	I_4 10

Table 9 - Convergence process for the integrated formulation for all scenarios (second approach).

Iterations	SEV
1	4408.393
2	4567.245
3	4587.657
4	4590.279
5	4590.617
6	4590.660
7	4590.665

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Figure 1 - DP networks considering different climate change scenarios.

Figure 2 - Recursive function of the DP model. Function F takes the value of the optimal option, i.e., the clearcut of the stand or else a new coppice cycle'

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