Accounting for Climate Change in a Forest Planning Stochastic Optimization Model

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Abstract:

An approach is proposed for incorporating into the forest harvesting decision process the variations in timber growth and yield due to climate change uncertainty. A range of possible climate scenarios are transformed by a forest growth and yield model into tree growth scenarios, which in turn are integrated into a multistage stochastic model that determines the timber cut in each future period so as to maximize net present value over the planning horizon. For comparison purposes a deterministic model using a single average climate scenario is also developed. The performance of the deterministic and stochastic formulations are tested in a case study of a medium term forest planning problem for a Eucalyptus forest in Portugal where climate change is expected to severely impact production in the coming years. Experiments conducted using 32 climate scenarios demonstrate the stochastic model's superior results in terms of present value, particularly in cases of relatively high minimum timber demand. The model should therefore be useful in supporting forest planners' decisions under climate uncertainty.

Keywords: Forestry, Stochastic Decision models, Forest Planning, Climate Change, Uncertainty.

1. Introduction

Uncertainty and risk play an important role in the development of forest management planning (Pasalodos et al. 2013; Yousepfour et al. 2012). Typical examples of these phenomena are market uncertainties, usually expressed as fluctuations in the prices of timber products but sometimes also as bounds on their demand. Another type of uncertainty takes the form of variations in future growth and yields. These variations are caused in part by fires and pests, but an additional factor with a significant influence on future yields is climate change. In the Mediterranean region, for instance, especially large productivity losses are expected in the years ahead as water becomes increasingly scarce due to projected increases in the frequency and severity of droughts (Christensen et al. 2007; Spathelf et al. 2013). In the particular case of Portugal, existing scenarios predict a decline in annual precipitation of about 15%, with increases in winter seasons more than offset by decreases over the rest of the year, especially in spring and autumn for which the projections indicate a fall of up to 30% and 50%, respectively (Duarte Santos et al. 2001). These reductions will impact the growth and survival of plants, and therefore also of the timber supply.

Dealing with climate change is thus a major challenge for forest managers, especially when it comes to addressing harvest scheduling problems. Failure to correctly anticipate the impact of climate change on timber availability may leave forestry operators unable to satisfy industry demand for timber or fulfil supply commitments, leading in turn to financial penalties for breach of contract or other difficulties. If climate change is to be successfully integrated into forest planning, new tools and methods are needed.

The first step in the creation of such tools and methods is the development/use of growth and yield models sensitive to climate factors that can project forest growth over time under climate change. Generally speaking, regression and simulation models can produce reasonable predictions of future harvest volumes. The inherent variability of growth in these formulations is usually considered unbiased. Often referred to as empirical growth models, they are based on inventory data and are not suitable for estimating growth under conditions different from those observed during the period for which the data were collected (Landsberg and Waring 1997). In other words, they assume that the growing conditions in the future will be similar to those of the past and therefore cannot be used to predict growth when climate conditions are changing. Thus, regression and simulation models have historically been considered inadequate as projection tools for supporting decision-making under climate change.

By contrast, process-based growth and yield models are grounded not on historical growth measurements but rather on physiological processes controlled by climatic and edaphic factors (see, for example, Kellomäki et al. 1997, Kellomäki and Väisänen 1997). These models predict growth through the calculation of physiological processes (e.g., radiation interception, canopy photosynthesis, estimation of respiratory losses, allocation of the resultant carbohydrates to component parts of the trees) and use environmental data such as climate information as input. Thus, they overcome the shortcomings of empirical models and can be employed for decision-making under changing climatic conditions.

Another option is the use of transfer functions (Pukkala and Kellomaki 2012). This methodology consists in calculating the relative impact of climate change on growth with a process-based model and then using the resulting correction factors to adjust the predictions of an empirical model. Another method is the creation of additive site index models that are able to predict productivity changes in a changing climate (Albert and Schmidt 2010; Trasobares et al. 2016). Recently, Garcia-Gonzalo et al. (2014) developed a decision support system (DSS) known as SADfLOR v ecc 1.0 that boosts the efficiency and effectiveness of forest management under changing environmental conditions. This system incorporates a process-based model (Tomé et al. 2004) that is sensitive to environmental changes and has been shown to be valid for predicting forest growth under climate change.

The effects of climate change on future timber supply are raising concerns in Portugal regarding the local pulp and paper industry, one of the country's leading export sectors whose main source of raw material is eucalyptus trees. According to the Portuguese Forest Inventory they occupy 739 x 10^3 ha, or about 23% of Portugal's forest cover. Most of the eucalyptus are found in evenly aged stands that are intensively managed under a coppicing system with 11-12 year rotations. The concerns are therefore focussed on the effects of climate change on medium term productivity and how to incorporate climate change uncertainty into the industry's forest management planning.

The present paper reports on a case study of a medium-term harvest planning problem for a forest area in Portugal. The main decisions to be made relate to which stands (units) should be harvested in each period of the planning horizon. Although this is a well-known problem (e.g. Clutter 1968; Bettinger et al. 2009; Dykstra 1976; Eriksson 2006; Weintraub 2007), it has not heretofore been addressed in the context of climate change uncertainty. Previous works have used stochastic programming to integrate uncertainty through scenarios with a given probability of occurrence (e.g., Hoganson and Rose, 1987; Eriksson, 2006; Gassmann, 1989; Boychuck and Martell, 1996; Alonso-Ayuso et al. 2011). In Alonso-Ayuso the authors incorporated uncertainty in markets (i.e., timber price variations and bounded demand) via 16 scenarios, each of which defined price and demand bounds for each period considered. In Badilla et al. 2014, uncertainty in forest growth was also included, with up to 324 scenarios. Both of these studies found that using multiple stochastic scenarios proved superior to just one scenario with average values. Unlike the approach to be presented here, however, in the two just-cited papers the timber growth scenarios were generated as variations in historical data.

The uncertainty in tree growth due to climate change is represented in our case study through 32 climate scenarios. They are inputted to a process-based growth and yield model that then generates 32 corresponding tree growth scenarios. This information is incorporated into a multistage stochastic optimization model developed for our study, whose objective is to maximize the expected net present value of harvesting operations over the time horizon while satisfying even-flow harvest constraints and demand bounds for each period.

Following Badilla et al. (2014), the harvest planning problem is also solved by a simpler deterministic version of our model using a single average climate scenario, thus mimicking the behaviour of a forest manager attempting to incorporate climate change without a stochastic analysis. For comparison purposes the results of this model are contrasted with those obtained from the stochastic formulation.

The remainder of this paper is divided into five sections. Section 2 develops the deterministic forest model; Section 3 extends the deterministic harvest scheduling planning problem to include uncertainty of forest growth due to climate change, setting out the climate scenarios, the resulting tree growth scenarios and the stochastic model; Section 4 presents our case study; Section 5 discusses the case study results; and finally, Section 6 concludes.

2. The Deterministic Harvest Scheduling Planning Model

In what follows we present a deterministic tactical planning model in which the planner must decide which stands of trees in a forest area will be cut in each time period of the planning horizon. The entire forest area is considered suitable for harvesting and by the end of the horizon will be totally harvested. To reduce the size of the model, the area is divided into several spatially separated stands that are classified as separate homogeneous strata. This way, spatial information is not needed and the planning decisions thus reduce to how many hectares of each stratum will be harvested in each period.

Typically, harvest scheduling problems include timber flow constraints to ensure a sustainable flow of timber to the pulp mill customers. Since this planning problem is one of deterministic optimization, the parameters are known or are assumed to be known. Thus, just one scenario reflecting expected values is used.

The formal specification of the deterministic linear programming model is as follows:

Sets

$T = Periods\ in\ Planning\ Horizon, \{t\}.$

$H = Harvest\ units\ (strata), \{h\}.$

Parameters

$A_h = \ Area\ of\ stratum\ h\ (Ha)$

$a_h^t = \ Productivity\ of stratum\ h\ if\ \ harvested\ in\ period\ t\ \left(\frac{m^3}{Ha}\right)$

$npv_h^{t,r} = $ Discounted net revenue per $ha\ given\ an\ interest\ rate\ r$ if stratum i is harvested in period t $(€/Ha)$

$r \quad = $ Interest rate used for discounting revenues(%)

$D^t = Lower\ bound\ on\ demand\ in\ period\ t\ (m^3)$

$\beta\ = \ Maximum\ fluctuation\ of\ \ timber\ harvested\ allowed\ (\%)\ between\ two\ consecutive\ periods.$

Decision variables:

$x_h^t = $ Proportion of stratum h harvested in period t

Accounting variables:

$w^t \ = Timber\ harvested\ in\ period\ t$

Objective Function

$$\max \quad \sum_{t\,\epsilon\,T} \sum_{h\,\epsilon\,H} npv_h^{t,r} A_h x_h^t \qquad (1)$$

Constraints

1. Timber harvested

$$\sum_{h\,\epsilon\,H} a_h^t A_h x_h^t = w^t \quad \forall\, t\,\epsilon\, T \qquad (2)$$

2. *Each stratum is totally harvested over the planning horizon*

$$\sum_{t\,\epsilon\,T} x_h^t = 1\ \forall\, h\,\epsilon\, H \qquad (3)$$

3. *Even − flow of harvest constraint*

$$w^{t+1} - (1+\beta)w^t \leq 0 \quad \forall\, t \in \{1, \ldots T-1\} \qquad (4)$$

$$w^{t+1} - (1-\beta)w^t \geq 0 \quad \forall \quad t \in \{1, \ldots T-1\} \qquad (5)$$

4. *Minimum demand constraints*

$$w^t \geq D^t \qquad (6)$$

Bounds on variables x_h^t

$$0 \leq x_h^t \leq 1 \quad \forall t \in T, h \in H \qquad (7)$$

Equation (1) defines the objective function, which maximizes the net present value of timber sales. Equation (2) calculates the total timber harvested per period. Equation (3) ensures that each stratum is completely harvested over the planning horizon. Equations (4) and (5) impose the maximum fluctuation in timber harvested between two consecutive periods. The value of the maximum fluctuation parameter used in both of these constraints is 15%. Equation (6) ensures that minimum demand for each period is satisfied. Typically, these constraints reflect timber supply contracts or market demand. Equation (7) ensures that the decision variables take a value between 0 and 1, representing the percentage of area harvested.

3. The Harvest Scheduling Planning Problem under Uncertainty of Forest Growth due to Climate Change

3.1. A climate change case study

As already explained, our case study considers the uncertainty in future timber growth and yield (the latter defined as the volume in m^3 per hectare harvested in each unit) due to climate change. One way of incorporating this factor is to define scenarios that reflect alternative possible realizations of the future. Thus, a given scenario is a particular realization of uncertain parameters for each period through the end of the planning horizon. Here, we consider different climate change scenarios that are then transformed into scenarios for timber growth and yield based on transformation models (i.e., process-based growth and yield models) as described in section 3.2 below. For this purpose, we use the DSS developed by Garcia-Gonzalo et al. (2014).

A total of 32 possible climate scenarios were developed, each of which is a series of weather data over the planning horizon. Thus, the climate uncertainties are expressed as scenarios with specific values of the uncertain parameters for each period. This approach to expressing future uncertainty is well known. How these climate change scenarios are transformed into growth scenarios is explained in more detail in section 3.2.

The 32 scenarios are based on information from the ENSEMBLES project 2009 (www.ensembles.eu.org), which provides climate datasets constructed by the (Hadley Centre) using emission scenarios developed by the Intergovernmental Panel on Climate Change (Nakicenovic and Swart 2000). These datasets are considered the most appropriate for Portuguese conditions (Soares et al. 2012). According to a study conducted in Portugal (the SIAM project), climate change take the form of a shift in weather patterns by up to 150 km from the southwest of Portugal to the northeast.

To obtain more complete coverage for the climate scenarios of our study area, we combined them with scenarios for a series of points located within 100 km of the area's perimeter. The resulting scenarios cover a wide range of possible climates for the area, including black swans that are represented by extreme scenarios. Thus, our set of scenarios range from very dry and hot to unusually cool with heavy rain. The weather indicators for each scenario are daily total solar radiation, monthly rainfall, mean air temperature, daytime atmospheric vapour pressure deficit (VPD) and frost days per month. An average climate scenario was also calculated (Table 1).

Table 1.

3.2. Generating the growth scenarios

To predict forest growth and timber yields per period for the 32 climate scenarios over the planning horizon (fifteen 1-year periods), we used the SADfLOR v ecc 1.0 decision support system (on which see Garcia-Gonzalo et al. 2014). This DSS supports eucalyptus forest management planning under climate change scenarios. It contains four modules, of which the projection module and the management model module are the two main components. The projection module simulates the growth of trees based on climate scenarios and consists of a set of routines and growth and yield functions to generate the outcomes of different management alternatives (i.e., cutting rules) for each land unit and climate scenario. It includes the process-based model Glob3PG, first developed by (Tomé et al. 2004) and recently updated by (Oliveira 2015). Glob3PG is a hybridization of the empirical model Globolus 3.0 (Tomé et al. 2006) and the process-based model 3PG calibrated for Portuguese conditions by (Fontes et al. 2006; Landsberg and Waring 1997). It takes advantage of 3PG's flexibility and ability to predict the effects of changes in growing conditions (e.g., climate change, fertilization) and GLOBULUS 3.0's prediction capacity under current conditions (Barreiro, 2011).

Glob3PG generates monthly predictions of the development of eucalyptus globulus stands based on values for the following input variables: i) stand data, which includes site information (latitude, maximum available soil water, available soil water, soil class and fertility rating) and biometric information (initial stem number, stand age, foliage biomass, stem biomass and roots); ii) the cutting rules (possible cutting ages that define in which period each stand can be harvested), and iii) the monthly weather data included in the climate scenarios (daily total solar radiation, monthly rainfall, mean air temperature, daytime atmospheric vapour pressure deficit (VPD) and frost days per month).

More specifically, the Glob3PG growth and yield model uses these variable data with a series of equations developed from experimental observations (see Fontes et al. 2006; Landsberg and Waring 1997) to compute the amount of photosynthesis produced and therefore the growth of the different components of the trees. The model also includes the water balance in the calculation and uses allometric ratios (which vary widely from specie to specie) to determine how much biomass is allocated to the different parts of the trees. Thus, these equations transform the climate scenarios (a sequence of weather data for the entire 15-year planning horizon) into growth scenarios that can then be used for decision-making under changing climatic conditions. For a given forest unit the projection module growth and yield simulator computes the monthly growth of the trees and the potential harvested timber. These values are then converted into annual values for use in the optimization model.

Note finally that Glob3PG has recently been validated by comparing its predictions to measured permanent plots and by contrasting its performance with predictions of the empirical growth and yield model Globulus 3.0, which had already been validated against permanent inventory plots. These comparisons analyzed modelling efficiency, bias and estimate accuracy, concluding that the estimates produced by Glob3PG were indeed accurate (Barreiro, 2011).

3.3. The stochastic optimization model

The stochastic optimization model is a version of the deterministic model introduced in Section 2 that has been modified to incorporate uncertainty in tree growth due to climate change as expressed in the 32 tree growth scenarios discussed above. The problem is thus one of multistage stochastic optimization in which the scenarios have been pre-defined. We assume that each scenario is equiprobable but we concentrate a larger number of scenarios around average values.

The scenarios may be visualized as a tree diagram (Figure 1) in which each scenario takes the form of a path from the root node (node 1) through the leaves that represents the growth of the stand over the planning horizon. Each stage in the tree is a time period (in this case, one year) in which the stochastic parameters take a given value. The set of scenarios in each stage constitutes a scenario group in which growth up to that point has been realized identically.

The example in Figure 1 has 4 periods and 5 scenarios. The decision on whether or not to harvest a stand is represented by the variables x^1, x^2, x^3, x^4 for the respective periods 1, 2, 3 and 4. Thus, $x_h^{t,1}$ is the decision variable *x* in growth scenario 1 for period t and stand *h*.

The constraints in the stochastic model reflect the well-known non-anticipativity principle (Wets 1975), which states that given two scenarios S_i and S_k, if their representations are identical up to a given period *t* in the planning horizon, then the decision variables in these scenarios must also be identical up to period *t*, (for more details, see Birge and Louveaux 2011 and Rockafellar and Wets 1991). This ensures that the solution (i.e., the decisions) obtained up to a given period will not depend on information that is not yet available. In an extended formulation of this problem, these non-anticipativity constraints are defined explicitly in the model; in an implicit formulation, they are expressed by introducing shared decision variables at each node in the scenario tree (Alonso-Ayuso et al. 2011).

Returning to the Figure 1 example, in period 1 all scenarios share identical decisions while up to period 2 scenarios 1 and 2 are equal. Scenarios 3, 4 and 5 form another scenario group. Thus, considering a single stand *h*, the non-anticipativity constraints are as follows: First stage, $\mathrm{x}_{\mathrm{h}}^{\mathrm{t},1} = \cdots \ldots = \mathrm{x}_{\mathrm{h}}^{\mathrm{t},5}$; second stage, $\mathrm{x}_{\mathrm{h}}^{\mathrm{t},1} = \mathrm{x}_{\mathrm{h}}^{\mathrm{t},2}$; third stage, $\mathrm{x}_{\mathrm{h}}^{\mathrm{t},3} = \mathrm{x}_{\mathrm{h}}^{\mathrm{t},4} = \mathrm{x}_{\mathrm{h}}^{\mathrm{t},5}$; etc.

Figure 1.

We now formally present the stochastic model. Since various of its sets and parameters have already been defined above in the presentation of the deterministic model, only those not in that formulation are given here.

Sets

S = Scenarios {s}.

Parameters

$\delta = \text{Penalty coeficient used to penalize the violation of minimum demand constraints}$

Parameters that vary by scenario:

$npv_h^{t,s,r} = \text{ discounted net revenue per } ha\ given\ an\ interest\ rate\ r \text{ if stratum } h \text{ is harvested in period } t\ under\ scenario\ s\ (\text{Euro}/Ha)$

$a_h^{t,s} = Productivity\ of\ stratum\ h\ if\ harvested\ in\ period\ t\ under\ scenario\ s\ (m^3/Ha)$

$\Pr(s) = Probability\ of\ the\ occurrence\ of\ scenario\ s$

Decision variables:

$\mathrm{x}_{\mathrm{h}}^{\mathrm{t,s}}$ proportion of stratum h harvested in period t under scenario s

Accounting variables:

$w^{t,s} = Timber\ harvested\ in\ period\ t\ under\ scenario\ s$

$Dslack^{\,t,s} = Timber\ demand\ not\ satisfied\ in\ period\ t\ under\ scenario\ s$

$NPV^{\,s} = Total\ discounted\ net\ revenues\ under\ scenario\ s$

Objective Function

$$\max \sum_{s\,\epsilon\,S} \Pr(s)\ NPV^{s} - \delta \sum_{t\,\epsilon\,T} Dslack^{t,s} \quad \forall\, s\,\epsilon\,S \qquad (8)$$

Constraints

1. $Discounted\ net\ revenues$

$$\sum_{t\,\epsilon\,T}\sum_{h\,\epsilon\,H} npv_h^{t,r,s} A_h x_h^{t,s} = NPV^{s} \quad \forall\, s\,\epsilon\,S \qquad (9)$$

1. $Timber\ harvested$

$$\sum_{h\,\epsilon\,H_0} a_h^{t,s} A_h x_h^{t,s} = \ w^{t,s} \ \ \forall\, t\,\epsilon\,T, s\,\epsilon\,S \qquad (10)$$

2. $Each\ stratum\ is\ totally\ harvested\ over\ the\ planning\ horizon$

$$\sum_{t\,\epsilon\,T} x_h^{t,s} = 1\ \forall h\,\epsilon\,H, \forall s\,\epsilon\,S \qquad (11)$$

3. $Even - flow\ of\ harvest\ constraint$

$$w^{(t+1),s} - (1+\beta) w^{t,s} \leq\ 0 \quad \forall\, s,t \quad s\,\epsilon\,S, \qquad t\ \in \{1,\ldots,T-1\} \qquad (12)$$

$$w^{(t+1),s} - (1-\beta) w^{t,s} \geq\ 0 \quad \forall\, s,t\ \ s\,\epsilon\,S, t\ \in \{1,\ldots,T-1\} \qquad (13)$$

4. $Minimum\ demand\ constraints$

$$w^{t,s} + Dslack^{t,s} \geq D^{t}\ \forall\, t\,\epsilon\,T, s\,\epsilon\,S \qquad (14)$$

5. $Non - anticipativity\ constraints$

$$x_h^{t,s} = x_h^{t,s\prime} \quad \forall\, t\,\epsilon\,T-, \forall s, s \neq s', \forall s\,\epsilon\,S, \forall h, \forall s \qquad (15)$$

Bounds on variables $x_h^{t,s}$

$$0 \leq x_h^{t,s} \leq 1 \; \forall \; t \in T, s \in S, h \in H \tag{16}$$

Equation (8) defines the objective function, which maximizes the expected net present value of timber sales penalized by the penalty term (δ) representing the sum of the shortfalls in relation to the minimum demand constraint per period. Equation (9) calculates the total net present value of timber sales under each scenario. Equation (10) calculates the total harvested timber per period in each scenario. Equation (11) ensures that each stratum is completely harvested over the planning horizon for each scenario. Equations (12) and (13) set the maximum fluctuation of timber harvested between two consecutive periods under each scenario. Equation (14) defines the minimum demand at each period in each scenario. The slack variables for the minimum demand constraints can correspond to either of two situations: (i) the shortfall can be purchased in the market, in which case the penalty on the slack variables (δ) is the cost of the timber purchase in the market; or (ii) the constraints are hard. However, since we do not want the model simply to conclude that there is no feasible solution, we add heavily penalized slack variables (see equation 8) so that a feasible solution will always be delivered. Since the algorithm will always try to drive the penalized slack variables to 0, if the slack variable of a solution for a specific scenario is positive then the original problem for that scenario was unable to satisfy all the minimum demand requirements. Therefore, if the slack variable is positive we will define the solution as infeasible even though technically speaking it is feasible.

The even flow requirements +- 15% (equations 12 and 13) could also have been considered as "soft" constraints, but this would complicate the analysis of the solution since there is a connection between the demand and the even-flow constraints. If both sets of constraints are soft then those not satisfied can be in either set. For example, consider a simple case of 3 periods with minimum demand levels in periods 1, 2 and 3 of 100, 70 and 100, respectively. To simplify, assume there is no growth. Total timber availability for the 3 periods is then 270. If we add the maximum flow variation constraints of +- 15%, there is no feasible solution. This is so because, since the period 1 harvest is 100, in period 2 it must be 85 (it cannot decrease more than 15%), leaving only 85 of the original 270 to satisfy the minimum demand of 100 in period 3. So either the minimum demand constraint or the maximum flow variation constraint can be satisfied, but not both. The program can choose which of the constraints to satisfy depending on which one has the higher penalty. For this reason we chose to model only one of the constraint sets as soft (i.e., the minimum demand). Formulated in this manner, the model will generate all possible solutions to the problem, which will fall into either of the following three classes: (i) the problem is solved and the slack variables are not positive so that the demand and even-flow constraints are met and the solution is feasible; (ii) the problem is solved and the slack variables are positive, in which case, although the solution is technically feasible, we define it as infeasible because it does not satisfy demand; or (iii) the problem is infeasible since even if we include slack variables in the minimum demand constraints, the even-flow constraints cannot be satisfied. Finally, equation (15) defines the non-anticipativity constraints while equation (16) ensures that the decision variables take a value between 0 and 1 (representing the percentage of area harvested).

The stochastic model seeks to maximize the expected incomes across all scenarios. It is then formulated with one block of constraints per scenario plus the non-anticipativity constraints that link the blocks. In cases where the number of scenarios is very large, a direct solution using a commercial solver package may not be attainable. For such situations, decomposition approaches have been proposed (Alonso-Ayuso et al 2011 and Badilla et al 2014). In our case, however, since the problem under consideration is not too large (i.e., neither the number of harvest units nor the number of scenarios is particularly high), decomposition techniques were not needed.

4. The Case Study

The management problem for decision-making in the forest area covered by our case study was described during interviews with the area's forest industry stakeholders conducted in the framework of the consultation process reported by Marques et al. (2013). The interviewees highlighted the importance of taking climate change into account in their decisions and defined their objectives as the maximization of economic returns and regulation of harvest flows while satisfying demand. For purposes of this study, different minimum demand levels per period ranging from low to high were used. High demand was taken to mean levels similar to the forest's maximum sustainable harvest volumes while the lower demand levels encompassed a range significantly below these maxima.

The forest in the case study area is dominated by eucalyptus stands located in central Portugal. Mean annual rainfall in the area is 826 mm, of which less than 20% (130mm) occurs between May and September. The soils are of low fertility, with low organic carbon content (0.23-0.28%) and a water holding capacity averaging 395 mm and ranging between 242 and 737 mm. For the most part they are sandy and may be classified as Arenosols (FAO/UNESCO) (Madeira and Ribeiro 1995). Environmental and biometric data from the study area were stored in a relational database.

The problem facing the planner in this case study is to decide which areas of the forest to cut in each time period. We assume the entire forest is suitable for harvesting. The 15-year planning horizon consists of 15 one-year periods over which the forest will be totally harvested. The forest contains 1000 spatially separated stands, so to reduce the size of the planning model we aggregated them into 24 strata having the same rotation cycle, tree age and soil quality. These criteria were used given that for stands with the same rotation/age, density did not vary significantly. Regeneration is carried out after harvesting each unit but has no influence on the results of the model.

As noted earlier, the 32 climate scenarios defined for the study cover a wide range of possible climates from very dry and hot to cool and rainy, thus including some whose probability for the study area is extremely low. These scenarios may therefore be considered to cover the whole range of growth possibilities. Since the available information for calculating the exact probabilities of the individual scenarios is incomplete, we assume they are all equiprobable. However, expert knowledge does exist indicating that extreme scenarios are less likely to occur than those concentrated around the average. To capture this pattern, we used a higher number of scenarios around the average expected climate. Thus, 50% of the scenarios represent average weather while 12.5% represent extreme weather and the remaining 37.5% are somewhere in between.

The heart of our case study is a series of simulation/optimization experiments to compare and contrast the results of the deterministic and the stochastic models. The steps in these experiments are as follows (see Figure 2):

1. Introduction of biometric data for the 24 forest strata.
2. Introduction of the climate change scenario(s) for use in the simulations.
3. Generation of harvesting prescriptions. In this study, trees can only be harvested if they are more than 9 years old at the time of cutting. Therefore, while harvesting of some strata can begin right from the 1st period, in others it cannot start until anywhere from the 2nd to the 9th period (recall that the periods are one year long).
4. Computation of timber yields associated with each harvesting prescription in all of the strata over the planning horizon (i.e., 15 years).
5. Calculation of economic indicators such as net present value at average eucalyptus pulpwood prices and operating costs, using data provided by the Portuguese Forest Service. We used an average stumpage of 36 € per m^3 and three different interest rates (3%, 6% and 9%).
6. Generation of the management model. The coefficients for the linear programming models (stochastic and/or deterministic) are obtained from projections and economic indicators based on steps 4 and 5.
7. Running an external application (CPLEX) to solve the models.

Figure 2.

We begin with our deterministic model, using a single climate scenario with the average values for all the parameters of the 32 climate scenarios (precipitation, temperature, etc. Then, the stochastic model using the whole set of scenarios is solved. To compare the deterministic and stochastic approaches we input the harvest scheduling plan solution generated by the deterministic model (a single vector of decisions) into each of the 32 scenarios (as is done in Alonso-Ayuso et al. 2011 and in Badilla et al. 2014) to determine how much timber would be obtained in each period for each scenario using that specific plan. Once we have that information, we check for each scenario whether the minimum demand and/or even-flow constraints are satisfied. This procedure provides what we denote the average-scenario-based solutions. These are then compared with the solutions of the stochastic approach for different minimum levels of timber demand per period up to 90,000 m^3 (see Tables 2, 3 and 4). More specifically, for each scenario total net present value of the average scenario approach (NPVd) (simulating what happens in a given scenario when applying the harvest scheduling plan obtained in the deterministic model), the total net present value of the stochastic approach (NPVs) and the percentage difference between them is computed as follows: (NPVd –NPVs) 100 / NPVd, are presented in Table 3 using a 3% discount rate and Table 4 using a 9% discount rate.

5. Results

Total timber production for the average climate scenario is 1.86 million m^3. Using the stochastic model, production in the average scenario is similar to the average production of the 32 scenarios. The maximum timber yield difference among the various scenarios was recorded between Scenario 24 (the "best" scenario) and Scenario 1 (the "worst"), the latter characterized by high average and maximum temperatures and the lowest precipitation. Their respective yields were 2.24 million m^3 and 1.36 million m^3, the "worst" thus producing about 60% of the "best."

As regards the NPV results, at the lowest interest rate (3%) and with no minimum timber demand, the deterministic (average scenario) approach in most cases produces worse results than the stochastic approach, although for scenarios where demand is satisfied the difference in total NPV is not great (Table 3). In 25 cases, the average scenario solution violates the even-flow harvest constraints (Table 2). These violations occur in the upper bound constraints, which means that the average scenario solution overcuts in these periods. In the worst case, the average scenario cuts 38% more than the limit allowed by the even-flow constraint.

At the same 3% interest rate but with a minimum demand per period of 60,000 m^3, the deterministic approach falls short of the minimum demand level in at least one period in half of the scenarios (1 to 16). By contrast, the stochastic solutions always satisfy the assumed minimum demand (Table 2). In the 11 scenarios where the minimum is satisfied by both approaches, the stochastic solution is better in 8 of the cases, or 72%, though the differences are not very substantial.

When a minimum demand level of 70,000 m^3 is assumed, the deterministic approach does not satisfy it in 18 scenarios. In 7 of the other 10 cases, its solution is inferior to the stochastic approach result.
At higher minimum demand levels, more of the solutions fail to reach them and are therefore infeasible, and the deterministic solutions are always worse than the stochastic ones. This is so because the deterministic approach, since it uses an average expected climate scenario, does not take into account the worst scenarios, that is, scenarios producing less timber than the average scenario. For some periods in the worst scenarios the timber available for cutting in the stands selected by the deterministic model's harvest plan is considerably less than the expected timber for the average scenario, thus violating the timber demand constraint. In these scenarios the deterministic model tends to overcut in the initial periods of the planning horizon, reducing timber stock to a level insufficient to satisfy demand in the later periods. With very high timber demand levels (e.g., 90,000 m^3) the deterministic approach fails to reach the minimum demand levels in almost all scenarios while the

stochastic approach satisfies them in 22 scenarios, though this implies that in 10 scenarios it, too, does not fulfil the minimum. The stochastic solutions are considerably better in the cases where both approaches satisfy demand and even-flow constraints (Tables 2, 3 and 4).

Table 2.

With the higher discount rates (6% and 9%), the deterministic approach results are worse than those obtained at 3%. The difference is greater for the relatively inferior scenarios (Table 4) given that at higher interest the model becomes greedier, that is, the deterministic approach harvests even more timber in the early periods, leaving low timber stocks for the later ones. In the worst scenarios, the decline in timber harvested in the later periods is considerable.

Tables 3 and Table 4.

6. Conclusions

An approach was developed for incorporating into the forest harvesting decision process the variations in timber growth and yield attributable to the uncertainties of climate change. The basis for the approach is the transformation of a range of different possible climate scenarios into an equal number of tree growth scenarios using a process-based forest growth and yield model. These tree growth scenarios are integrated into a proposed stochastic optimization model that determines the amount of timber to be cut in each future period so as to maximize the net present value of the harvesting operations over the entire planning horizon. For comparison purposes we also specified a deterministic model to represent the traditional methodology of a decision maker who accommodates uncertainty only partially using a single average climate scenario.

A case study of a forest area in Portugal was conducted using various sets of relevant data in order to contrast the results of the two models, and in particular to determine the direction and magnitude of the impact of including climate change uncertainty using the proposed methodology on the net present value of harvesting the study area. A total of 32 scenarios based on these data were constructed for use in the stochastic model while the deterministic model used the average values of these scenarios. The planning horizon for the case study consisted of 15 annual periods, and solutions were generated using discount rates of 3%, 6% and 9%. The stochastic model was subject to non-anticipativity constraints and a range of different minimum timber demand levels.

The results of the case study indicated that the proposed stochastic approach performed better than the traditional deterministic approach. With the lowest discount rate (3%), the deterministic model's net present values were only slightly below those of the stochastic model, but the difference widened at higher minimum demand levels where the stochastic model's performance was clearly superior. At the highest discount rate (9%), meanwhile, the stochastic model always generated considerably better results. Furthermore, as minimum demand rises the deterministic model displayed growing difficulty in satisfying it, with a significant proportion of its solutions falling short of the demand constraint. This suggests that while at relatively low timber demand levels the benefits of the rather complex stochastic model are relatively minor, as demand levels grow its advantages become ever more evident.

The proposed methodology thus demonstrates the value of explicitly introducing climate change uncertainty in forestry harvest management using a stochastic approach. The superiority of its results in terms of objective values and feasibility of the solutions is especially apparent at high timber demand levels where the feasible region is smaller and the forest is less flexible. The stochastic model developed for this study should thus provide valuable support for forest managers in making more robust harvesting decisions and better adapt forest management plans to climate dynamics. A possible extension of this work would be to consider uncertainty in future timber markets expressed in terms of future prices and demand levels.

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Tables.

Table 1. Summary of the meteorological data averages over the 15-year planning horizon for the 32 scenarios.

Scenario	Taverage (^{0} C)	Tmax (^{0} C)	Tmin (^{0} C)	Annual Rain (mm)	Annual Rad (MJ m^2)	RainDays (nr Days)	FrostDays (nr Days)
1	18.2	35.5	5.6	277.6	191.8	48.9	6.5
2	18.2	32.0	7.6	310.3	200.2	50.2	6.1
3	18.0	36.6	5.1	386.9	185.8	61.6	8.3
4	17.8	35.4	5.5	409.0	185.4	61.9	6.5
5	17.0	36.6	4.0	515.0	180.0	71.7	9.3
6	17.2	36.4	4.7	524.8	179.8	71.3	6.8
7	16.9	34.7	4.9	610.7	174.3	81.7	6.9
8	17.0	34.4	5.2	621.1	176.3	78.9	5.3
9	16.3	34.7	4.1	689.2	171.6	87.7	10.8
10	15.0	33.4	3.1	729.9	168.7	96.9	21.2
11	15.9	35.4	3.6	700.2	174.5	86.8	14.5
12	15.0	34.8	2.6	708.6	173.6	90.3	23.3
13	16.0	34.7	3.9	756.7	176.2	91.0	14.1
14	15.8	33.1	4.4	762.0	174.0	91.6	12.8
15	16.0	32.0	5.3	766.2	172.0	90.5	9.9
16	15.7	33.9	3.9	811.6	174.6	90.6	13.5
17	16.8	33.2	5.3	718.9	174.5	82.0	2.9
18	15.9	34.2	3.6	757.8	174.4	86.5	14.1
19	16.1	34.8	4.2	869.4	171.5	94.7	6.0
20	14.9	33.6	3.2	890.9	170.0	98.7	16.7
21	15.7	34.2	4.1	877.2	169.8	98.1	9.7
22	15.6	34.8	3.5	913.7	171.1	98.3	11.1

23	14.9	32.4	3.8	933.3	167.8	108.3	17.0
24	15.1	32.6	4.1	935.2	167.6	108.3	13.0
25	15.7	34.9	3.8	950.1	170.7	99.4	11.3
26	15.1	34.2	3.2	977.6	171.5	97.1	13.3
27	15.3	34.3	3.6	1004.6	169.3	103.9	12.0
28	15.2	31.9	4.4	1100.0	161.9	114.3	10.8
29	15.7	31.0	5.4	1111.3	161.4	110.9	4.6
30	15.6	31.8	5.1	1183.3	161.2	113.4	5.3
31	15.0	33.5	3.7	1269.2	165.6	112.7	10.7
32	15.3	33.7	3.9	1224.5	165.2	109.5	9.5
Average	16.1	34.0	4.3	790.5	173.5	90.2	10.7

Taverage is the average annual temperature, Tmax is the average annual maximum temperature, Tmin is the average annual minimum temperature, Annual Rad is the average annual incoming radiation, RainDays is the average annual number of days with precipitation, FrostDays is the average annual number of days with frost.

Table 2. Solutions obtained with the deterministic approach for 32 scenarios, various minimum demand levels (0 to 90,000 m^3) and two interest rates (3% and 9%). The Inf Demand columns indicate the number of scenarios where the deterministic solution (i.e., using the average obtained for an average scenario) falls short of the minimum demand level while the Inf. Even-flow columns indicate, for cases satisfying minimum demand, the number of scenarios where the even-flow constraints are violated.

	3%		9%	
Demand	Inf Demand	Inf. Even-flow	Inf Demand	Inf. Even-flow
0 m^3	0	25	0	28
60000 m^3	16	5	16	16
70000 m^3	18	4	20	5
80000 m^3	22	3	26	5
90000 m^3	26	3	26	4

Table 3. Comparison of net present value (NPV) obtained under stochastic approach (NPVs) with NPV obtained under deterministic-average scenario approach (NPVd) in each scenario, for different levels of minimum timber demand when maximizing expected NPV using a 3% interest rate.

	Minimum demand per period														
	0 m^3			60,000 m^3			70,000 m^3			80,000 m^3			90,000 m^3		
Scenario	NPVs	NPVd	Gap	NPVs	NPVd	Gap	NPVs	NPVd	Gap	NPVs	NPVd	Gap	NPVs	NPVd	Gap
1	36659654	36477956*	-0.50	35687429	-	-	35099590	-	-	34257132	-	-	-	-	-
2	41555003	41877631*	0.78	40015766	-	-	38939524	-	-	37270232	-	-	-	-	-
3	40254726	39801216*	-1.13	38954245	-	-	38090234	-	-	36913916	-	-	-	-	-
4	41161227	40690648*	-1.14	39760446	-	-	38806278	-	-	37515136	-	-	-	-	-
5	42961770	42395503	-1.32	41397227	-	-	40317811	-	-	38912775	-	-	-	-	-
6	43521507	42945723	-1.32	41897978	-	-	40770292	-	-	39301255	-	-	-	-	-
7	47921935	47333611*	-1.23	45899543	-	-	44624997	-	-	42963869	-	-	-	-	-
8	48217379	47628671*	-1.22	46166079	-	-	44869791	-	-	43175084	-	-	-	-	-
9	48730788	47991545*	-1.52	46718926	-	-	45519427	-	-	43953091	-	-	42414157.28	-	-
10	48418687	47678689*	-1.53	46429313	-	-	45252472	-	-	43713198	-	-	42216116.62	-	-
11	44270999	43619958	-1.47	42702527	-	-	41646183	-	-	40237262	-	-	-	-	-
12	43596000	42953541	-1.47	42096096	-	-	41095080	-	-	39771114	-	-	-	-	-
13	52775794	52041054*	-1.39	50799144	-	-	49802645	-	-	48609813	-	-	47602925.24	-	-
14	53935409	53198604*	-1.37	51859984	-	-	50810968	-	-	49545480	-	-	48453212.94	-	-
15	56000062	55238137	-1.36	53680364	-	-	52569839	-	-	51201414	-	-	50048480.74	-	-
16	53762273	53001524*	-1.42	51653349	-	-	50636779	-	-	49406456	-	-	48398043.89	-	-
17	49987803	49097151*	-1.78	48235936	48055441	-0.37	47335131	47135090*	-0.42	46208863	-	-	45137263.15	-	-
18	46792186	46020085*	-1.65	45367646	45132052	-0.52	44630949	44375107	-0.57	43735451	-	-	42942229.05	-	-
19	51826008	50975409*	-1.64	50089318	49843469	-0.49	49129268	48823021	-0.62	47912417	47499749	-0.86	46833474.22	45810498	-2.18
20	50587451	49779668*	-1.60	48957927	48711046	-0.50	48059488	47754182	-0.64	46925402	46524207	-0.85	45947049.79	44991674	-2.08
21	50514482	49652584*	-1.71	48706800	48570726	-0.28	47848976	47588968	-0.54	46619303	46303585*	-0.68	45496976.7	-	-
22	50017684	49152229*	-1.73	48246743	48090481	-0.32	47409375	47132460	-0.58	46212581	45882184	-0.71	45131466.84	-	-
23	58907406	57717498*	-2.02	56441971	56256474*	-0.33	55405680	54942886*	-0.84	54119230	53335356*	-1.45	53069012.14	51434482*	-3.08
24	59195813	57987664*	-2.04	56697809	56508511*	-0.33	55649318	55178416*	-0.85	54347244	53546743*	-1.47	53280259.35	51605404*	-3.14
25	48302346	47526600	-1.61	46557979	46483656	-0.16	45595464	-	-	44303232	-	-	43030436.55	-	-
26	48248913	47475016*	-1.60	46519122	46440946	-0.17	45563880	-	-	44283332	-	-	43020710.28	-	-
27	49155092	48362553	-1.61	47148506	47285552	0.29	46179294	46279053	0.22	44931254	-	-	43729806.49	-	-
28	52434271	51627296*	-1.54	50036433	50380867*	0.69	48903377	49196820*	0.60	47403386	-	-	45911920.61	-	-
29	57921884	56949096*	-1.68	55019351	55463262*	0.81	53861545	54062813	0.37	52217713	52183088	-0.07	50740012.03	49791309*	-1.87
30	57432733	56443381*	-1.72	54579972	54980020*	0.73	53440572	53604325	0.31	51826504	51763354	-0.12	50381519.58	49439804	-1.87
31	51751619	50811996*	-1.82	49488495	49618699	0.26	48562644	48522832	-0.08	47165482	47063068	-0.22	45841852.8	-	-
32	51974831	51025434*	-1.83	49686919	49820814	0.27	48750837	48712181	-0.08	47336970	47234042	-0.22	45992578.02	-	-
AVGSC	36659654	-	-	35687429		-.	35099590		-	34257132		-	30461665.49	-	

- Indicates that the demand constraints slack variables are positive, meaning that the scenario would be infeasible since a very high penalty term (δ)is used. *Indicates that minimum demand constraints are satisfied but even-flow constraints (α = 15%) are not.

NPVs = total net present value of the stochastic approach for each scenario; NPVd = total net present value of the average scenario approach for each scenario; GAP = the percentage difference between the results of the two approaches, i.e., (NPVd – NPVs)x100/NPVd. AVGSC =average scenario.

Table 4. Comparison of net present value (NPV) obtained under stochastic approach (NPVs) with NPV obtained under deterministic-average scenario approach (NPVd) in each scenario, for different levels of minimum timber demand when maximizing expected NPV using a 9% interest rate.

	Minimum demand per period														
	0 m^3			60,000 m^3			70,000 m^3			80,000 m^3			90,000 m^3		
Scenario	NPVs	NPVd	Gap	NPVs	NPVd	Gap	NPVs	NPVd	Gap	NPVs	NPVd	Gap	NPVs	NPVd	Gap
1	23405037	22840019*	-2.41	23471195	-	-1.67	23385386	-	-1.10	23141059	-		-	-	
2	24536549	24161271*	-1.53	24590717	-	-1.72	24608596	-	-1.74	24515687	-		-	-	
3	24685992	24281675*	-1.64	24703692	-	-1.12	24655999	-	-0.87	24511314	-		-	-	
4	24852138	24551413*	-1.21	24877595	-	-0.90	24850371	-	-0.77	24730660	-		-	-	
5	25539860	25457136	-0.32	25514761	-	0.01	25506358	-	-0.06	25436245	-		-	-	
6	25662802	25625977	-0.14	25638825	-	0.07	25630199	-	-0.02	25564164	-		-	-	
7	27705256	27846613*	0.51	27652240	-	0.50	27619954	-	0.30	27454908	-		-	-	
8	27783679	27945735*	0.58	27731111	-	0.51	27696394	-	0.31	27527669	-		-	-	
9	28226209	28308094*	0.29	28212920	-	0.16	28116581	-	0.20	27972948	-		27698277	-	
10	28141989	28207020*	0.23	28128183	-	0.18	28040857	-	0.21	27900945	-		27630849	-	
11	26049466	26019786	-0.11	26043542	-	-0.02	26023788	-	-0.06	25976074	-		-	-	
12	25909509	25828683	-0.31	25903468	-	-0.06	25886924	-	-0.09	25829460	-		-	-	
13	30860627	30897217*	0.12	30836126	-	0.24	30815016	-	-0.16	30677595	-		30488163	-	
14	31150432	31245488*	0.31	31124576	-	0.25	31054605	-	-0.03	30913759	-		30726288	-	
15	31942770	32111072*	0.53	31913204	-	0.26	31765525	-	0.14	31612370	-		31362890	-	
16	31355362	31427247*	0.23	31328297	-	0.32	31277080	-	-0.04	31120581	-		30910265	-	
17	29088751	29016567*	-0.25	29086462	29008930*	-0.27	29048541	28946838	-0.35	29035581	-		28952623	-	
18	28268816	28040808*	-0.81	28384198	28193623*	-0.67	28381315	28161164	-0.78	28351680	-		28195537	-	
19	30195588	30193731*	-0.01	30161616	30171935*	0.03	30096359	30082383	-0.05	29977622	-		29860882	29831751	-0.10
20	29894783	29812510*	-0.28	29898117	29862441*	-0.12	29841060	29783085	-0.19	29709671	-		29581197	29560168	-0.07
21	29406475	29381770*	-0.08	29381615	29365972*	-0.05	29326979	29291208	-0.12	29235648	-		29132282	-	
22	29300733	29242921*	-0.20	29288464	29251235*	-0.13	29234406	29181115	-0.18	29137070	-		29024238	-	
23	33951778	34162675*	0.62	33986304	34163782*	0.52	33905126	33976941*	0.21	33762128	33751492*	-0.03	33518454	33361784*	-0.47
24	34023216	34233256*	0.62	34043643	34218248*	0.51	33959081	34029232*	0.21	33809048	33798331*	-0.03	33563781	33409596*	-0.46
25	28159739	28184554*	0.09	28155821	28172330*	0.06	28120237	-	-0.05	28037298	-		27919083	-	
26	28177113	28205075*	0.10	28176610	28197470*	0.07	28142440	-	-0.04	28056776	-		27932854	-	
27	28538777	28577294*	0.13	28514255	28547343*	0.12	28413926	-	0.20	28329855	-		28231058	-	
28	29773498	29660576*	-0.38	29712802	29461717*	-0.85	29608317	29350399	-0.87	29473649	29157225	-1.07	29218815	-	
29	32577397	32577917*	0.00	32475306	32347247*	-0.39	32276792	32166900*	-0.34	31997371	31859857*	-0.43	31606567	31533882*	-0.23
30	32388540	32437400*	0.15	32307528	32236012*	-0.22	32117615	32060360*	-0.18	31841176	31764215*	-0.24	31477730	31434619*	-0.14
31	29785302	29826636*	0.14	29754178	29754658*	0.00	29641852	-	0.00	29494481	-		29291376	-	
32	29856137	29886689*	0.10	29815432	29804054*	-0.04	29700001	29689867*	-0.03	29547703	29515320*	-0.11	29340669	-	
AVGSC	29454410	-	-	29411921		-	29318377		-	29191757		-	29017524.93		-

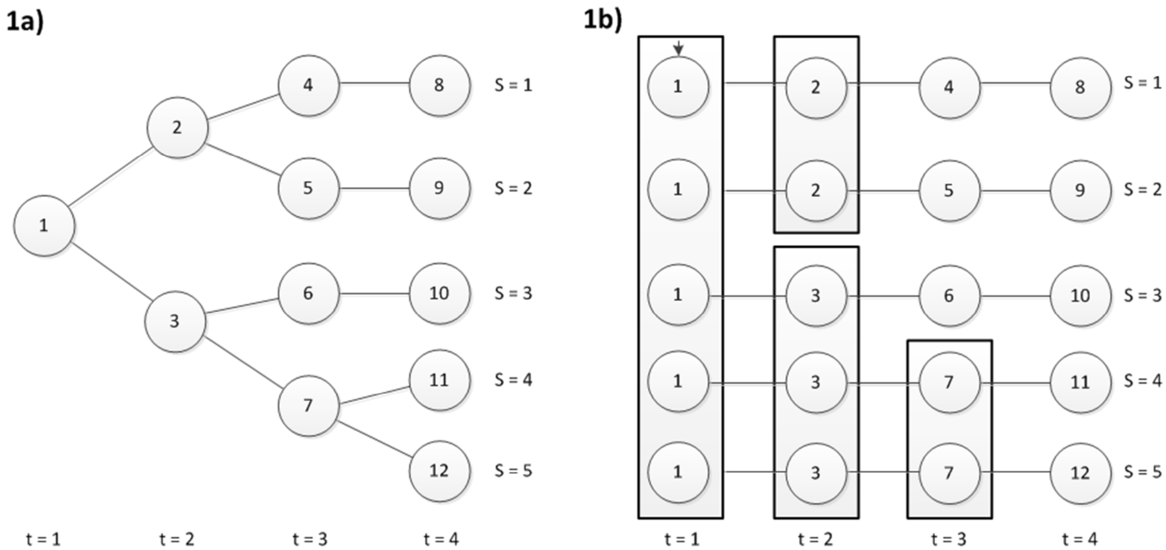
- Indicates that the demand constraints slack variables are positive, meaning that the scenario would be infeasible since a very high penalty term (δ)is used. *Indicates that minimum demand constraints are satisfied but even-flow constraints (α = 15%) are not.

NPVs = total net present value of the stochastic approach for each scenario; NPVd = total net present value of the average scenario approach for each scenario; GAP = the percentage difference between the results of the two approaches, i.e., (NPVd – NPVs)x100/NPVd. AVGSC =average scenario.

Figure captions

Figure 1a is an example of a scenario tree covering 4 stages (time periods). In all, 12 nodes are represented. Figure 1b presents the 5 growth scenarios in disaggregated form; the non-anticipativity constraints are represented by the nodes within rectangles. In period 1, all scenarios share identical decisions (to harvest or not harvest the stand) since no knowledge of future uncertainty has yet been acquired. By contrast, in period 2 (t = 2), node 2 represents scenarios 1, 2 while node 3 shares scenarios 3, 4 and 5.

Figure 2. Steps followed and flow of information for solving the case study management problem.



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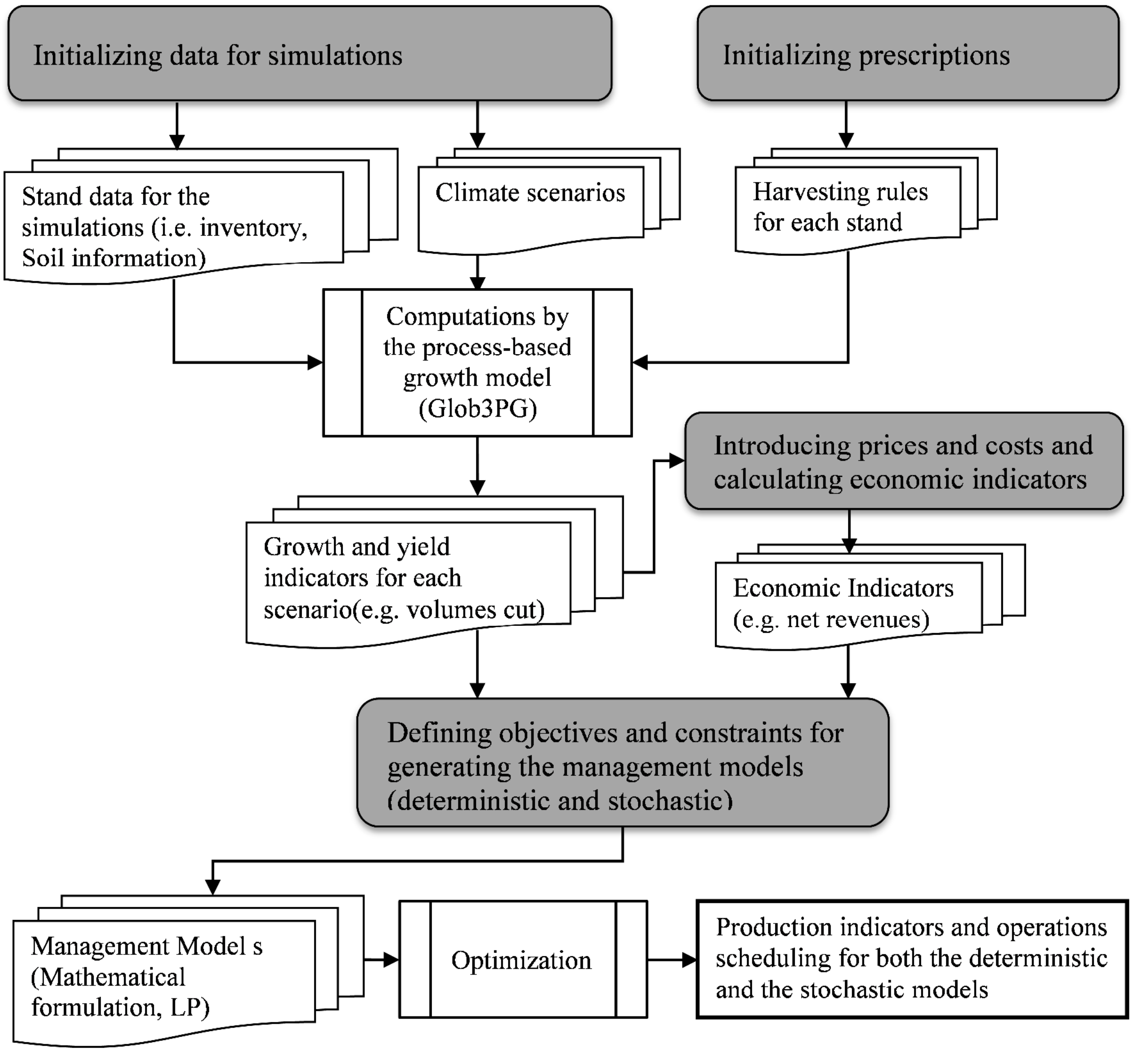

Figure 2. Steps followed and flow of information to address the case study management problem.

Highlights

- We present a stochastic model to account for climate change in forest planning
- The climate change scenarios are transformed into tree growth scenarios
- The stochastic model is solved subject to non-anticipativity constraints
- The stochastic approach performs considerably better than the deterministic
- The deterministic approach provides infeasible solutions in most of the scenarios