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Integrating Strategic and Tactical Forest-Management Models within a Multicriteria Context

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Forest-management planning could be addressed at various temporal scales, namely strategic and tactical scales. The former are associated with extended temporal horizons, whereas the latter focus on shorter periods of time and typically encompass further spatial requirements. On the other hand, in most forestry scenarios, the existence of multiple criteria of different nature is the rule rather than the exception. It seems sensible to think that forest-management models would significantly increase their practicality in many cases, if the strategic and tactic models were to be integrated within a multicriteria context. This paper presents an integrated framework for dealing with this type of situation. Thus, two approaches called "*top down*" and "*integrated*" have been formulated. To undertake this task, the well-known tool called extended goal programming has been resorted to. The functioning and the strengths of the integrated framework are illustrated with a case study corresponding to fast-growing plantations in Brazil. This framework includes the decisionmaker's preferences in a more compact model that allows the inclusion of different spatial issues.

Keywords: goal programming, harvest scheduling, multiple criteria

Conventionally, forest managers have been using hierarchical planning models to solve timber-harvest scheduling problems. This hierarchy is established from strategic planning to tactical planning, and from the latter to operational planning (Weintraub and Bare 1996). However, in the past few years, forest-planning models have become increasingly sophisticated thanks to technological advances and the inclusion of spatial components. Also, it is already habitual to integrate other criteria, not related to timber supply, and to interact with decisionmakers using multicriteria methods merged with group decisionmaking tools (Diaz-Balteiro and Romero 2008). Nevertheless, there have not been any significant advances in these methods related to the connection between strategic and tactical planning, which has been generally dealt with by a top-down hierarchical approach (Kangas et al. 2014) within a single criterion context. This hierarchical approach is chosen either because it is easier to link different time horizons (Church et al. 2000), or because strategic and tactical planning are nested in a decision-support system, with a hierarchical structure (Seely et al. 2004). However, some authors find open problems when it comes to developing sound optimization models in a top-down approach (Rönnqvist et al. 2015). In short, it may create some discrepancies between planning levels, e.g., the inconsistencies of long-term timber supply (Paradis et al. 2013), and the effects of different spatial and temporal aggregation (Andersson and Eriksson 2007).

On the other hand, some authors have suggested alternative approaches to link strategic and tactical planning, given that the hierarchical approach presents discrepancies and suboptimal or even unfeasible solutions (Beaudoin et al. 2008). Thus, two of the pioneers following this line were Weintraub and Navon (1976), who proposed a monolithic approach, called "integrated," as opposed to a hierarchical approach, called "sequential," in order to address the strategic and tactical planning link. Later, Weintraub and Cholaky (1991) defined an interactive hierarchical approach, called "top-down-bottom-up," from the inclusion of harvesting targets between planning levels. Thereafter, Cea and Jofré (2000) proposed a clustering technique, "k-means," to link the strategic

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and tactical planning. Recently, Troncoso et al. (2015) compared a monolithic "integrated" approach and a hierarchical "decoupled" one for the analysis of strategic and tactical problems; their results demonstrated that the integrated approach produces better outcomes. Additionally, some models have been formulated that also link tactical and operational planning (Beaudoin et al. 2008). Finally, Eyvindson et al. (2018) compared different models: hierarchical, monolithic, and integrated in a regional planning problem in Finland using a goal-programming (GP) methodology.

GP is one of the optimization techniques most used in the field of forest management (Diaz-Balteiro et al. 2013), including works oriented toward plantations (Belavenutti et al. 2018). It makes sense that in industrial forest-plantation management problems, where planning horizons are short, and where there is no unanimity when defining the duration of the tactical planning horizon, the versatility of some GP models such as extended goal programming (EGP) (Romero 2001) can be very helpful. On the other hand, the large number of decision variables (prescriptions) and the significant number of criteria involved in this type of problem make applying other multicriteria methods problematic. Besides, these GP models can provide the manager with diverse attractive solutions, which enables decisionmakers (DMs) to choose which one they consider to be the most suitable (Diaz-Balteiro et al. 2013). EGP has been used in the management of industrial plantations, but not in addressing these types of problems embracing jointly the strategic and the tactical perspectives (Giménez et al. 2013, Diaz-Balteiro et al. 2016, Broz et al. 2017).

This article aims to compare two approaches, by linking strategic and tactical multicriteria models obtained from an interactive process with the decisionmaker (Diaz-Balteiro et al. 2013, Diaz-Balteiro et al. 2014). In the first approach, the strategic problem is carried out sequentially with the tactical problem, whereas in the second approach, both problems are solved simultaneously. The case study was a typical industrial pine plantation located in the south of Brazil.

A Generalized Framework for the Integration of Strategic and Tactical Models

Forest management requires strategic and tactical models. In what follows, these two types of models will be jointly formulated within a multiple-criteria context with the help of a GP approach.

It is widely accepted nowadays that a strategic forest-planning model must consider not only economic (e.g., net present value) but also environmental criteria (e.g., carbon uptake), plus the criteria leading to the classic normal forest like the even flow and the regulated forest. Unfortunately, within this new context, there is usually a significant degree of conflict among the criteria previously introduced, which implies the need to seek good compromises among them. In short, it seems necessary to resort to multicriteria optimization methods. For a comprehensive overview of these methods, see Miettinen (1998). Regarding these approaches, the EGP approach (see Romero 2001, 2004) seems to be especially suitable for dealing with the problem posed in this paper, because it can deal efficiently with complex problems involving many criteria and many decision variables as is usual in realistic forest-management problems. In addition, with this type of approach, it is possible to obtain the solution providing the best average achievement among all the criteria (efficiency), the solution with a more balanced achievement among solutions (equity) as well as compromises between these two types of solutions; for the application and assessment of the EGP approach in forest-management issues, see Diaz-Balteiro et al. (2013).

On the other hand, as is well known, the tactical forest planning models usually incorporate spatial criteria, with the purpose of increasing connectivity and reducing the environmental impact as well as the cost associated with the harvest. In some situations, the model also incorporates the design of the road network (Öhman and Eriksson 2010). In short, within a tactical orientation, the decisionmaking problem involves establishing harvest schedules that take into account not only the management prescriptions but also the tactical spatial criteria considered.

We proposed a generalized framework able to show two different approaches to link strategic and tactical forest-management models. The starting-point involves the formulation of the classic Model I (Johnson and Scheurman 1977) within the context of an EGP framework. The first approach to implement the linking is called "top down" and embraces two steps. In the first step of the "top-down" approach, the strategic model is solved (with the parameters $\mu = 1$ and $\delta = 0$), and in the second step the results from the first step are transferred to the tactical model and solved (with the parameters $\mu = 0$ and $\delta = 1$). Following the literature (i.e., Weintraub and Navon 1976), we have called the second approach "integrated," because this approach aims to solve jointly strategic and tactical models. In the following paragraphs, we will show the formulation of this generalized framework to continue with the explanation of the two linking approaches in the next subsections.

General Achievement Function

$$\gamma_1\left\{\text{Min}\,(1-\lambda)\,D_1+\lambda\left[\sum_{i=1}^{I}\left(\alpha_i n_i+\beta_i p_i\right)+\delta\sum_{j=1}^{J}\left(\alpha_j n_j+\beta_j p_j\right)\right]\right\}+$$
$$\gamma_2\left\{\text{Min}\,(1-\lambda)\,D_2+\lambda\sum_{q=1}^{Q}\left(\alpha_q n_q+\beta_q p_q\right)\right\} \tag{1}$$

Goals and constraints for the top-down approach ($\gamma_1 = 1$ and $\gamma_2 = 0$):

$$\left(\alpha_i n_i+\beta_i p_i\right)-D_1\le 0 \qquad \forall i \tag{2}$$

Management and Policy Implications

In the literature, as well as in the forest-management practice, the strategic and tactical planning models are usually formulated in a rather disconnected way. However, it seems rational to accept that there is, in general, a certain degree of linkage between these two types of planning levels. This paper proposes a generalized framework encompassing two alternative approaches for dealing in a connected way with both planning orientations. The two proposed approaches resort to goal-programming formulations covering several classes of decision criteria of a different nature. The exercise has a clear interactive orientation, involving the decisionmaker in several phases of the work to provide basic information for feeding the respective models. In short, these models can be applied in the management of industrial forest plantations, and the managers can include other spatial constraints or even a third operational level (monthly/weekly period) to consider different operational capacities, relating the spatial consequences of dispatching harvest crews to certain distances.

$$\delta\left[\left(\alpha_j n_j + \beta_j p_j\right) - D_1\right] \le 0 \qquad \forall j \tag{3}$$

$$\mu\left(\sum_{s=1}^{S}\sum_{m=1}^{M} c_{smi} x_{sm} + n_i - p_i = t_i\right) \qquad \forall i \tag{4}$$

$$\delta\left(\sum_{s=1}^{S}\sum_{m=1}^{M} c_{smi} y_{sm} + n_i - p_i = t_i\right) \qquad \forall i \tag{5}$$

$$\delta\left(\sum_{s=1}^{S}\sum_{k=1}^{TH} c_{sk} r_{sk} + \sum_{s=1}^{S}\sum_{k=1}^{TH} c_{vk} z_{vk} + n_j - p_j = t_j\right) \tag{6}$$

$$\delta\left(\sum_{s,l\in g(L)}\sum_{k=1}^{TH} e_{slk} + n_j - p_j = t_j\right) \tag{7}$$

Goals and constraints for the integrated approach ($\gamma_1 = 0$ and $\gamma_2 = 1$):

$$\left(\alpha_q n_q + \beta_q p_q\right) - D_2 \le 0 \qquad \forall q \tag{8}$$

$$\sum_{s=1}^{S}\sum_{m=1}^{M} c_{smq} x_{sm} + n_q - p_q = t_q \qquad \forall q \in E \tag{9}$$

$$\sum_{s=1}^{S}\sum_{k=1}^{TH} c_{sk} r_{sk} + \sum_{s=1}^{S}\sum_{k=1}^{TH} c_{vk} z_{vk} + n_q - p_q = t_q \qquad \forall q \in T \tag{10}$$

$$\sum_{s,l\in g(L)}\sum_{k=1}^{TH} e_{slk} + n_q - p_q = t_q \qquad \forall q \in T \tag{11}$$

$$A_s y_{sm} - x_{sm} \le 0 \qquad \forall s, m \tag{12}$$

$$\sum_{s=1}^{S}\sum_{m\in g(\sigma)} (vol_{smk} x_{sm}) - \sum_{s=1}^{S}\sum_{m\in g(\sigma)} (vol_{smk} A_s y_{sm}) \ge 0 \qquad k = 1, \ldots, TH \tag{13}$$

Endogenous constraints (both approaches):

$$\sum_{m=1}^{M} x_{sm} \le A_s \qquad \forall s \tag{14}$$

$$\sum_{m=1}^{M} y_{sm} = 1 \qquad \forall s \tag{15}$$

$$\sum_{m\in g(\sigma)} (y_{sm} - r_{sk}) = 0 \qquad \forall s, k = 1, \ldots, TH \tag{16}$$

Spatial constraints (both approaches):

$$N_\eta r_{sk} - \sum_{v\in g(\eta)} z_{vk} \le 0 \qquad \forall s \in g(\sigma), k = 1, \ldots, TH \tag{17}$$

$$r_{sk} \ge e_{slk}; r_{lk} \ge e_{slk} \qquad \forall (s,l) \in g(\theta,\sigma), k = 1, \ldots, TH \tag{18}$$

Sign and logic restraints:

$$\gamma_1, \gamma_2, \mu, \delta, y_{sm}, r_{sk}, r_{lk}, z_{rk}, e_{slk} \in \{0,1\}$$
$$n_i, n_j, n_q, p_i, p_j, p_q \ge 0 \qquad 0 \le \lambda \le 1$$

Starting from the general achievement function shown in Equation 1, the auxiliary parameters γ_1 and γ_2 take on a value 1 when considering *top-down* or *integrated* approaches, respectively. Otherwise they take on a value of 0. In this way, this formulation embraces two general achievement functions within an EGP context. The first one corresponds to the top-down approach (γ_1=1; γ_2=0), and the second one corresponds to the integrated approach (γ_1=0; γ_2=1). In both approaches, λ is a control parameter that weights the importance attached to the minimization of the weighted sum of unwanted deviation variables with respect to the minimization of the maximum deviation. Additionally, auxiliary parameters μ and δtake on a value 1 when considering strategic or tactical criteria, respectively; otherwise it takes 0.

Equations 2–11 define the necessary goals and constraints. It should be noted that the negative and positive deviation variables of the respective goals are represented by "*n*" and "*p*," respectively, whereas the target values are represented by "*t*" (see Equations 4–7 and 9–11). To be more precise, t_i is the target value for the strategic goal i of the *top-down* approach. Thus, p_i and $n_i$are the positive and negative deviations from target values of the goal i, measuring their over-achievement and under-achievement, respectively (Equation 4). $\alpha_i = w_i / k_i$ if n_i is unwanted; otherwise, $\alpha_i = 0$, $\beta_i = w_i / k_i$ if p_i is unwanted; otherwise, $\beta_i = 0$. The parameters w_i and k_i are the weights reflecting the preferential and normalizing purposes attached to the achievement of the goal i, respectively. Besides, t_j is the target level for the tactical goal *j* of the *top-down* approach (Equation 6). Regarding the *integrated* approach, t_q is the target value for the strategic or tactical goal *q*. Also, E embeds the different strategic goals, and T embeds the tactical goals (Equations 9–11).

We move on now to the meaning of the variables and parameters of a technical nature. Thus, *S* measures the total number of stands considered, whereas M refers to the total number of possible management prescriptions established according to Model I. x_{sm} denotes the decision variables of the model measuring the total area of stand *s* under management prescription m , and A_s represents the area of stand *s*. c_{smi} embeds the unitary contribution of stand *s* under prescription m for the generic strategic goal i. $y_{sm}$is a binary variable taking a value of 1 when the management prescription *m* is applied on stand *s*; otherwise it is 0. In the same direction, r_{sk} is another binary variable taking a value of 1 only when the stand *s* is managed during the period of time *k*, whereas TH represents the planning horizon for the tactical exercise. $g(\sigma)$ includes the set of productive management prescriptions during the period k. Regarding different costs included in this framework, c_{sk} measures the cost of production corresponding to stand s in the period k, whereas c_{vk} measures the cost of road section *v* conditioned in the period *k*. On the other hand, e_{slk} denotes binary variables that represent the edge connecting harvesting intervention between r_{sk} and r_{lk}. vol_{smk} measures the total timber volume per hectare of stand *s* when it is managed according to the prescription m in the period k. Besides, N_η denotes the total number of road sections in the rout path η, $g(\eta)$ is the set of road sections contained in the optimal rout path η, and z_{vk} is a binary variable that represents the road section *v* conditioned in the period *k*. Finally, $g(\theta)$ represents a pair of adjacent harvesting interventions.

On the other hand, it is appropriate to explain the meaning of the endogenous and spatial constraints that are required in both models. Thus, Equation 14 needs the sum of management prescriptions to be less than, or equal to, the corresponding stand area, whereas Equation 15 requires each stand to receive only one management prescription. The sets of stand-management prescriptions with their respective intervention period are included in Equation 16. In addition, it is important to consider that the variable y_{sm} plays an important role in the model because the stand-management prescriptions could have different production levels when considering the same period of time. Furthermore, the variable r_{sk} simplifies the model formulation by decreasing the number of spatial constraints. In this way, only the spatial constraints regarding the harvesting intervention are considered. These spatial constraints will consider the spatial distribution and promote the clustering of harvesting activities. Equation 17 is a spatial constraint that connects the set of road sections between each harvesting intervention and the production destination, each set composing the optimal route path η. Finally, the spatial harvesting connectivity constraints (Equation 18) activate variables representing two harvesting interventions in adjacent stands and in the same period (see Augustynczik et al. 2016).

Finally, it is worth mentioning some of the properties embedded in the EGP framework mentioned earlier (Equation 1). Thus, for λ =0, we have a Chebyshev achievement function minimizing the maximum deviation and thus obtaining the "most balanced" solution; similarly, for λ = 1, we have a weighted achievement function minimizing the sum of deviations and thus obtaining the "best average" solution. For other values of control parameter λ belonging to the open interval (0,1), intermediate solutions, if they exist, can be obtained. That is, to some extent control parameter λ trades off the "optimum average" versus "optimum balance." We will see throughout the presentation how this type of device is extremely useful for deriving efficient harvest schedules compromising the efficiency (optimum average) with the equity (optimum balance).

1)Top-down approach

As we noted earlier, the *top-down* approach implies a particularization of the generalized model for $\gamma_1 = 1$ and $\gamma_2 = 0$, for different values of control parameter λ, and including the preference weights provided by the DM. Thus, if we considered $\mu = 1$ and $\delta = 0$, we activate Equation 4 and deactivate Equations 3 and 5–7 obtaining the strategic solutions to be applied in the tactical planning horizon considered. Thus, the respective strategic prescriptions x_{sm} are transferred to the tactical planning by the management prescriptions y_{sm}, which implies a re-formulation now considering $\mu = 0$ and $\delta = 1$. This new achievement function involves deviation variables corresponding to the tactical and strategic criteria. Consequently, we now activate Equations 3 and 5–7, whereas Equation 4 is deactivated. In this process, Equation 5 allows us to transfer the results obtained from the strategic to the tactical level. Thus, I embeds the strategic goals transferred to a tactical level, and consequently, c_{smi} measures the contribution of the stand s when it is managed according to the prescription m within the strategic goal i at a tactical level. The tactical goal included in Equation 6 indicates the operation cost of harvesting interventions and road network maintenance. The tactical goal of Equation 7 was related to the connectivity of harvesting interventions. Regarding the common constraints valid for the two approaches, the strategic model only required the merging of Equation 14 and the tactical model required the merging of Equations 15–18.

2)Integrated approach

Within the *integrated* approach, the EGP model has been particularized for $\gamma_1 = 0$ and $\gamma_2 = 1$, including several values of control parameter λ, and considering jointly strategic and tactical criteria by the general achievement function in Equation 1. This approach needs the inclusion of Equations 8–13 in order to obtain the strategic and tactical solutions. Thus, the strategic goals are shown in Equation 9, whereas Equations 10–11 represent the tactical goals associated with the cost of harvesting interventions and road network maintenance, and the connectivity of harvesting interventions, respectively. To understand the integrated model, it is important to note that Equation 12 links the results corresponding to the strategic prescriptions x_{sm} to those corresponding to the tactical ones y_{sm}. Coherently, Equation 13 prevents differences between timber flows obtained by strategic and tactical prescriptions, along the tactical planning horizon. Equations 12–13 allow the possibility of a continuous linkage between the tactical and strategic results. Within this approach, it is convenient to merge Equations 14–18.

Proposed Methodology

The sequential procedure consists of three interactions with the decisionmaker. The first interaction is to select the strategic and tactical criteria (e.g., Diaz-Balteiro and Romero 1998). Then, the respective programming models are formulated to obtain the Payoff Matrix. Thus, in this matrix, the DM is provided with univariate optimized criteria, which allows the degree of conflict between criteria to be quantified and targets of reference to be obtained (e.g., Diaz-Balteiro and Romero 1998). The second interaction is to elicit the preferential weights attached to each criterion, as well as the respective target values, and the third interaction is to select the best solutions in each model according to the values of control parameter λ. Thus, the EGP models are formulated and solved following the "*top-down*" and "*integrated*" approaches. These stages are explained in more detail in the following subsections with the help of a case study. Figure 1 summarizes the method proposed.

Case Study

The case study (Figure 2) was an industrial forest plantation owned by the company Florestal Gateados LTDA [1], located in Santa Catarina State, Brazil. The area covers 6,865 hectares, composed of 2,501 stands of loblolly pine (*Pinus taeda* L.) and slash pine (*Pinus elliottii* Engelm.).

Figure 3 presents the age-class distribution of the forest plantation. It is clear that the current age-class distribution is very uneven and thus two different management systems need to be applied: standard and exception. Each management system allows several options of precommercial thinnings and clear-cut interventions,

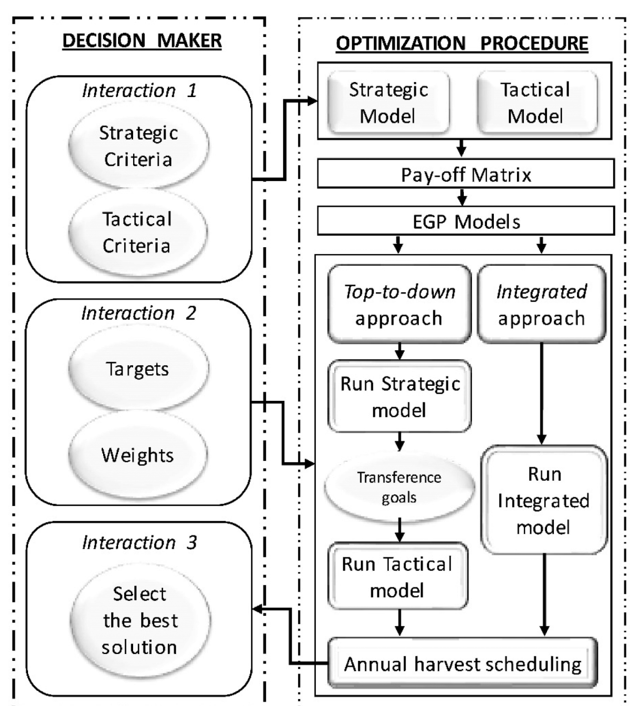

Figure 1. Scheme of the methodology used.

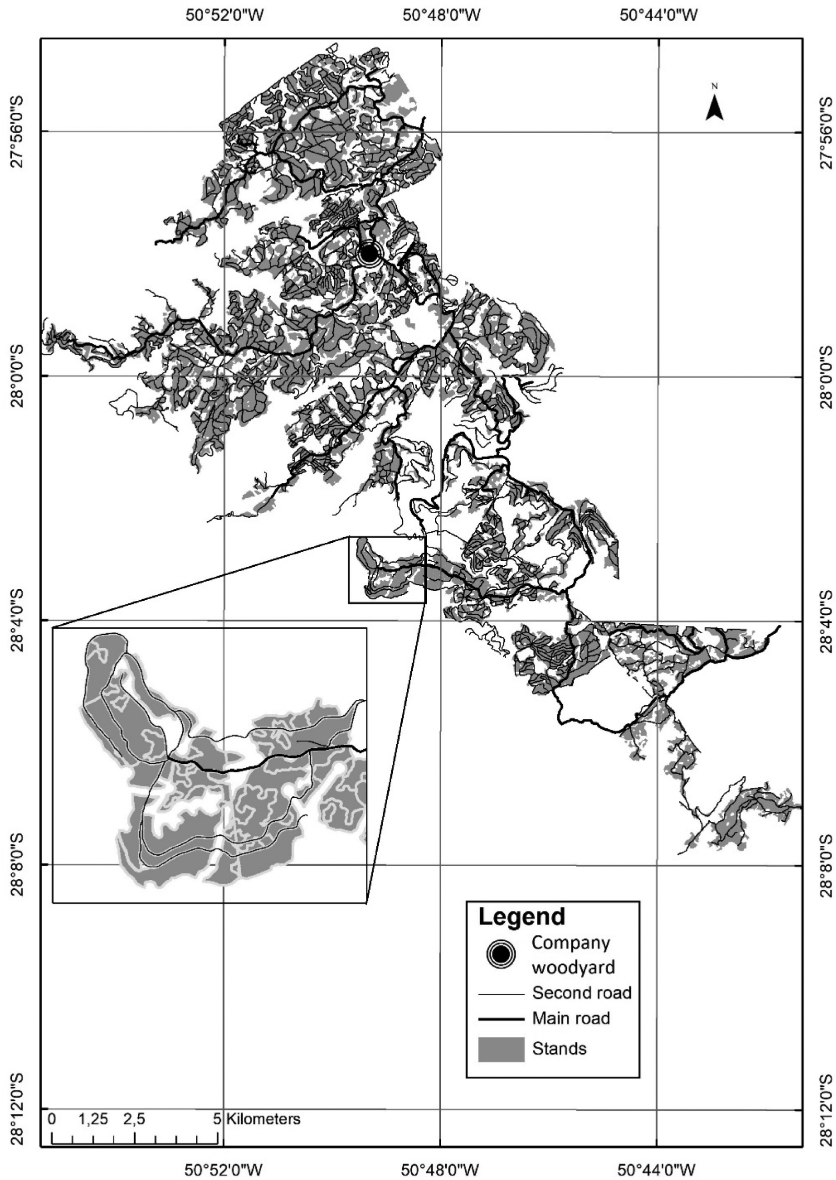

Figure 2. Case study area.

which are performed on different ranges of ages groups (see Fiorentin et al. 2017). The standard system corresponds to two or three precommercial thinnings occurring in the age ranges 8–12, 13–17, and 18–22 years, followed by a clear cut with stand age ranges of 26–27 years. The exception system integrates stands with ages over 27 years and includes a clear cut between 27 and 31 years or a thinning in the same range of ages followed by a clear cut between 31 and 40 years. The management alternatives, considering the replanting in the same year of the clear cut, were implemented using the SisPinus® growth and yield simulator (EMBRAPA 2011).

We used average values of costs (in US dollars) involved in the establishment and maintenance of the forest stands, precommercial thinnings, and clear cuts provided by the forest company. Thus, in the operational cost, we included the log loading expenditures ($1.6/m^3), and annual road maintenance cost considering main road sections ($5,000/km) and secondary road sections ($10,000/km). A minimum spanning tree algorithm optimized the sequence of road sections minimizing the maintenance cost between harvesting interventions and the production destination (the Company woodyard).

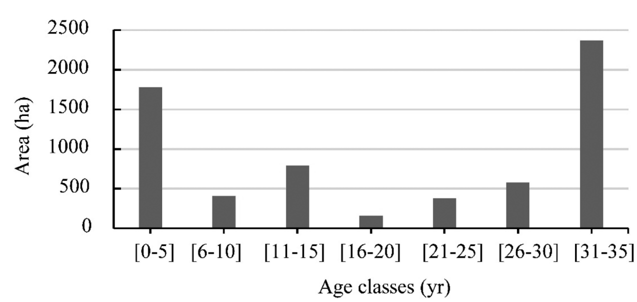

Figure 3. Age class distribution of *Pinus* spp.

The economic profit criterion is the net present value (NPV) that was quantified for each management alternative as being the net sale revenue of the timber assortments: pulpwood, saw, and veneer, minus the silvicultural and harvesting costs, and applying a discounting rate of 8%, a high but realistic one given the state of the Brazilian economy. The carbon sequestration criterion has been calculated as the estimation of annual gains and losses of carbon because of the growth of trees and their removal, computed in physical units (Pasalodos-Tato et al. 2017). In order to compute the carbon sequestration, we considered a timber density of 0.57 t/m^3 and carbon content of 0.41% (EMBRAPA 2011).

Problem Formulation

In the first interaction, the decisionmaker selected six strategic criteria: NPV, total volume, carbon sequestration, even flow of commercial volume, even flow of veneer log volume, and an equal area in each of the five year age classes at the end of the planning horizon. On the other hand, two criteria were selected for tactical purposes: operational cost and harvesting connectivity of each period. These tactical criteria consider the spatial distribution and promote the clustering of harvesting activities.

In the second interaction, the decisionmaker decides on the preferential weight of each criterion and indicates the target for each strategic and tactical goal. Also, the strategic planning horizon (*PH*) of 30 annual periods and the tactical planning horizon (*TH*) of 3-yearly periods were established. The strategic and tactical prescriptions for each stand consider the management alternatives previously defined.

The mathematical formulation of the generalized framework for the integration of strategic and tactical models is presented in the Appendix. Starting from the "*top-down*" approach, the achievement function Equation A1 includes the normalized and weighted deviation variables of each strategic criterion. Besides, Equations A1d–A7 show the strategic goals in this approach. Thus, Equation A2 corresponds to the *NPV* criterion, Equation A3 corresponds to the *total volume*, and Equation A4 embraces the *carbon sequestration* objective, whereas the rest of the goals, regarding technical issues (*Age class regulation*, *Even flow commercial volume*, and *Even flow veneer log volume*), are represented by Equations A5–A7. The mathematical formulation of the tactical achievement function is described in Equation B1, including the normalized and weighted parameter of each tactical criterion and the corresponding constraints Equation B1d. Equations B2–B7 show the transference of strategic results, whereas Equations B8–B9 include the tactical goals: *Operational cost* and *Harvesting connectivity*. Finally, the integrated approach begins with the achievement function and EGP constraints shown in Equations C1–C1d, whereas the goals are presented in Equations C2–C9.

Problem Resolution

Once the strategic and tactical models had been formulated, the problem was solved using the two approaches defined earlier. In the "*top-down*" approach, the first step was to optimize the strategic forest-management model (Equations A1–A8). The second step was to formulate the tactical "*top-down*" model replacing the achievement function in Equation A1 by Equation B1, and the deviations included in Equation A1d by Equation B1d. In addition, the goals regarding the transfer of strategic results have been added in Equations B2–B7 as well as the tactical goals (Equations B8–B9). Finally, considering the EGP formulations, we simulated three scenarios modifying the λ value (λ = 0, λ = 0.5 and λ = 1). In the "*integrated*" approach, the model was formulated to include the achievement function Equation C1 and the deviations Equation C1d, as well as the strategic Equations A2–A8 replicated now as Equations C2–C7 and incorporating the tactical constraints (Equations C8–C9).

As in the previous approach, we simulated three scenarios modifying the λ value (λ = 0, λ = 0.5, and λ = 1), and the third interaction with the decisionmaker involved selecting the most attractive solutions according to the results obtained, using the two approaches and possible alternatives according to the values of λ previously mentioned. As in the second interaction, the procedure was developed through a "pairwise" comparison format, following Saaty's verbal scale (Saaty 1977).Finally, the optimization models were solved using CPLEX 12.7 on an Intel® Core™ i7-7700U 3.60 GHz processor with 16 GB of RAM. The stopping conditions of the optimization were 2 h of processing time and a gap between the current solution and the relaxed solution of below 2%.

Results

Table 1 shows the pay-off matrix obtained by means of the individual optimization of each criterion, either strategic or tactical. The elements of this matrix measure the deviations in relation to the respective ideal values. It should be noted that these ideal values are shown

Table 1. Pay-off matrix for the strategic and tactical criteria.

Criteria	Strategic						Tactical	
	NPV	*Vol*	*Carb*	*ACR*	*FVol*	*FLog*	*Cost*	*HCon*
NPV (MM$)	**0**	15.3	*74.6*	17.1	25.7	36.9	–	–
Vol (MMm^3)	1.8	**0**	*3.9*	1.8	1.3	3.0	–	–
Carb (Mt)	*646*	544	**0**	535	355	497	–	–
ACR (ha)	1,300	*3,048*	2,967	**0**	741	2,439	–	–
FVol (Mm^3)	3,676	*5,881*	3,461	2,088	**0**	1,904	–	–
FLog (Mm^3)	1,053	*1,161*	582	578	633	**0**	–	–
Cost (MM$)	–	–	–	–	–	–	**0**	*4.6*
HCon	–	–	–	–	–	–	*3,421*	**0**
Aditional information: values (not deviations) of the three criteria more habitually used in strategic planning models								
NPV (MM$)	**114.5**	99.2	*39.9*	97.4	88.8	77.6	–	–
Vol (MMm^3)	6.7	**8.5**	*4.6*	6.7	7.2	5.5	–	–
Carb (Mt)	*–377*	–275	**269**	–266	–86	–228	–	–

Note: Matrix values represent deviations in relation to the ideal or optimal values. Bold figures denote ideal deviations, and italic figures denote anti-ideal deviations.
NPV: net present value; *Vol*: total volume; *Carb*: carbon sequestration; *ACR*: age class regulation; *FVol*: even flow commercial volume; *FLog*: even flow veneer log; *Cost*: operational cost; *HCon*: harvesting connectivity (total of adjacent stands interventions).

in bold type, whereas the worst possible values or anti-ideal ones are in italics. For information purposes, at the bottom of this matrix the values of the three criteria are shown (*NPV*, *total volume*, and *carbon sequestration*), which can be usually associated with the maximization of a strategic objective. In that table, an important conflict is observed between the criteria, especially with regard to *carbon sequestration* and to *Even flow veneer log volume*. It should be emphasized that the value of the criterion associated with carbon sequestration is negative when any one of the five remaining criteria is optimized.

Table 2 displays the preferential weights attached by the decisionmaker to the different goals, as well as the results obtained in the criteria space according to the approach considered, and the value of control parameter λ. In relation to the responses resulting from the third iteration with the decisionmaker for the "*top-down*" models, the scenario of λ = 1 was the one selected (shown in bold in Table 2). Again, according to the decisionmaker, for the "*integrated*" models, the scenario of λ = 0.5 presents the preferred solution (also shown in bold in Table 2). Finally, the decisionmaker prefers the results of the "*integrated*" scenarios to the "*top-down*" ones, if the two scenarios are compared with each other.

However, the evaluation of the two scenarios previously selected ("*Top Down*" λ = 1and "*integrated*" λ = 0.5) requires a higher level of details in some of the criteria that are of great importance to the decisionmaker. It should be pointed out that, for the even flow criteria, related to the *commercial volume*, and to the *veneer log volume*, the two scenarios selected by the decisionmaker obtained, on average, a result of over 92% in their respective targets (Figure 4). However, some periods can be identified in which those ideal values were not reached or, on the contrary, had been surpassed.

It is interesting to note that the criterion *connectivity of harvesting interventions* is of paramount importance at a tactical level for

Table 2. Preference values and results, in the criteria space, for the different values of control parameter λ.

Criteria	Weights	"*Top to down*"			"*Integrated*"		
		$\lambda = 1$	$\lambda = 0.5$	$\lambda = 0$	$\lambda = 1$	$\lambda = 0.5$	$\lambda = 0$
NPV (MM$)	13	**96.3**	89.3	86.0	94.6	**97.0**	95.4
Vol (MMm^3)	04	**6.8**	6.5	6.2	6.9	**6.9**	6.5
Carb (Mt)	07	**–117**	1	15	–92	**–74**	–220
ACR (ha)	07	**6,521**	6,384	5,697	6,453	**6,521**	5,354
FVol (Mm^3)	11	**556**	1051	1904	614	**599**	2064
FLog (Mm^3)	33	**122**	147	137	129	**163**	316
UnitCost ($/m^3)	06	**4.8**	5.1	6.3	5.2	**6.7**	8.3
ConHInt	19	**1.4**	1.3	1.3	1.7	**1.8**	1.8

Note: UnitCost: operational unit cost; *ConnectHInt*: connectivity of harvesting interventions. In order to permit a better comparison between the scenarios, the tactical criteria used were: the *Operational unit cost*, obtained from dividing the result of the criterion *Operational cost* by the commercial volume produced in the tactical periods, and the *Connectivity of harvesting interventions*, obtained from dividing the result of the criterion *Harvesting connectivity* by the total of the tactical harvesting interventions.

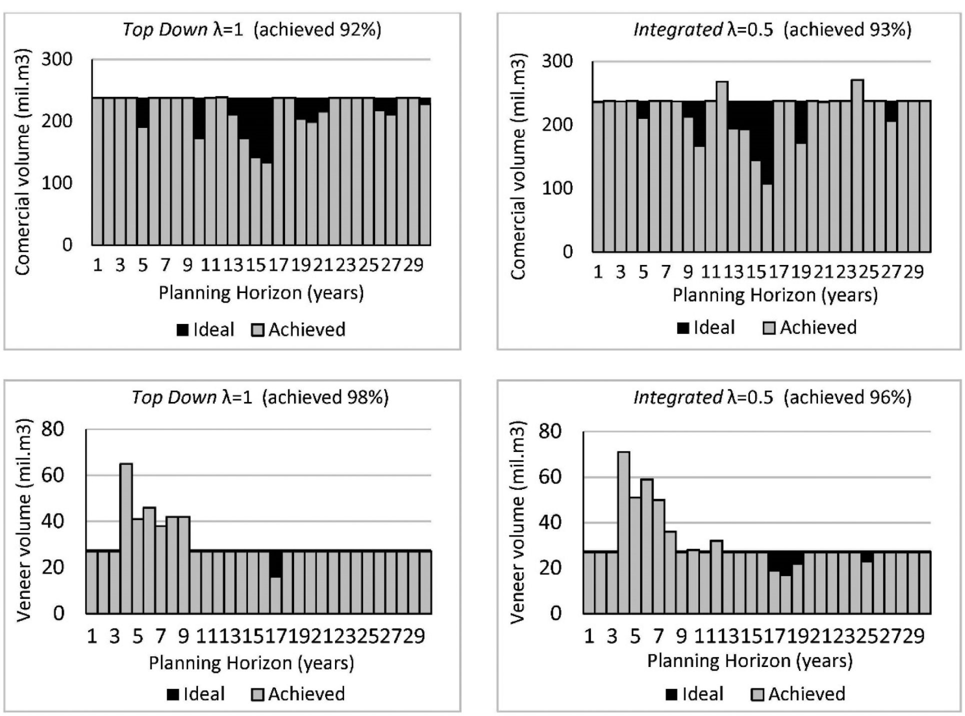

Figure 4. Results of the flows of commercial volume production and veneer log of the "*top down*" λ = 1 and "*Integrated*" λ = 0.5 scenarios. The values in brackets refer to the result (%) reached in relation to the value of the target considered.

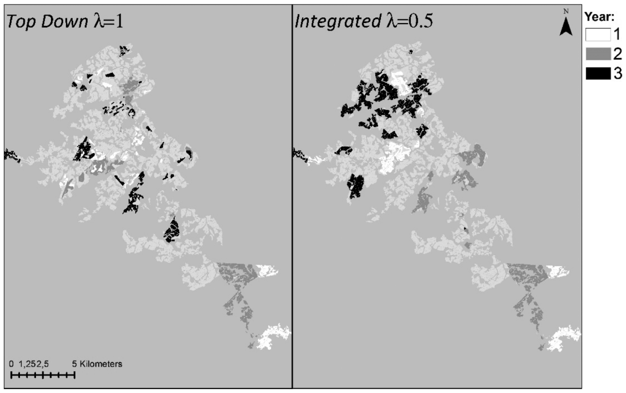

Figure 5. Annual result of the harvesting schedule for the "*top down*" λ = 1 and "*Integrated*" λ= 0.5. Harvesting interventions in each year of the tactical planning horizon are also shown.

being an indicator of the spatial result of the annual harvesting schedule. In this sense, it should be taken into account that the "*integrated*" approach for $\lambda = 0.5$ gives the best result in comparison with the "*top-down*" approach for $\lambda = 1$. The image of the annual result of the harvesting schedule (Figure 5) reaffirms that the "*integrated approach*" for $\lambda = 0.5$ performs better in the aggregation of harvesting interventions (forming harvesting blocks along the TH) compared with the "*top-down*" approach.

Discussion and Conclusions

The multicriteria models presented in this paper represent two different approaches for embedding strategic and tactical planning, taking into account the decisionmaker's preferences, and addressing economic, technical, and environmental criteria. Further, for each approach, several solutions have been calculated according to different values of the control parameter λ, which trades off the "optimum average" with the "optimum balance" (i.e., trading-off efficiency versus equity).

If the two approaches employed are compared in the light of the results obtained in Table 2, it can be seen that the results are reasonably alike, although, for some criteria, better results are procured by the "*top-down*" approach (even flow deviations and operational unit cost), whereas for other criteria, the one selected would be, everything else being equal, the "*integrated*" approach (*connectivity of harvesting interventions*). In the end, taking into account the results shown in Table 2, none of the solutions dominate, although the decisionmaker has chosen the "*integrated*" approach and a value of $\lambda = 0.5$. Also, it is surprising that, for each approach, the decisionmaker has selected a different scenario, which, logically, means a different preferential interpretation (Diaz-Balteiro et al. 2013).

Analyzing other works on these lines, it seems that there is no unanimity on which approach should be selected. Starting from the basis that the case studies are different, Beaudoin et al. (2008) show that the "*top-down*" approach holds some advantages when measuring the impact of the results of the upper level on the lower one, in anticipation of future problems. However, Troncoso et al. (2015) and Bouchard et al. (2017) give evidence of the superiority of the results of integrated monolithic approaches in improving the "forest profitability" of the respective companies. Also, it is worth noting that GP has already been used in tactical planning problems including spatial issues. Thus, Silva et al. (2010) raise some environmental objectives (soil erosion, contamination of water resources, and visual impact of harvesting). However, Gómez et al. (2011) show a model that hybridizes a nonlinear GP model with a metaheuristic one called "SSPMO" (Scatter Search Procedure for Multiobjective Optimization; Molina et al. 2007), incorporating spatial constraints (ARM). Finally, also in Augustynczik et al. (2016), GP models are formulated to integrate spatial objectives, in this case linked to adjacency constraints. The spatial issues shown in these papers could be incorporated into the generalized framework explained above.

However, it has also been proven that the complexity of the problem could have a notable influence when selecting one approach or another. To be specific, the tactical criteria considered in this work (harvesting connectivity and operational cost) are not extended along the whole strategic PH, because of the computational complexity of the formulated models. This makes it impossible for them to be resolved unless other techniques such as metaheuristics are used (Bachmatiuk et al. 2015, Dong et al. 2015, Augustynczik et al. 2016). In this regard, Eyvindson et al. (2018) recommend selecting the approach in terms of the complexity of the case study analyzed.

The results obtained for the criteria of strategic nature are similar to the ideal values shown in the Table 1, except for the criterion associated with carbon capture. This result is explained by the initial structure of the forest age classes that is somewhat unbalanced, as shown in Figure 2. This situation has already been noted in other works that have used similar multicriteria techniques (Diaz-Balteiro and Romero 2003). Also, given the initial unbalanced structure of this forest plantation, modifications of this criterion could have been entered in the EGP models, with the aim of tempering this situation. Some examples in this respect can be consulted in Bertomeu et al. (2009), Diaz-Balteiro et al. (2009a) and Hernández et al. (2014).

In another direction, it is of interest to note the interactive challenge offered by this methodology. Indeed, the decisionmaker not only selects the criteria, the weights associated with them, and the targets related to each goal, but also chooses the optimal solution of each approach, selecting a posteriori the value of λ in each case. Therefore, it would seem to be relatively simple to extend this methodology to a set of stakeholders, which constitutes an open problem nowadays in the field of operations research in forestry (Rönnqvist 2015). Concretely, the proposal would be to hybridize this technique (EGP) with a group decision model to integrate the preferences of different stakeholders on the lines shown in Diaz-Balteiro et al. (2009b) or Aldea et al. (2014). One possible future line of research for this type of forest system would be to introduce other ecosystem services and incorporate them into these hybrid models. One example can be found in Borges et al. (2017). On the other hand, it also seems interesting to extend these types of models to nondeterministic scenarios, either introducing risk as an additional component of a GP model (Diaz-Balteiro et al. 2014) or merging GP models with stochastic elements, as proposed by some authors (Eyvindson and Kangas 2014, Álvarez-Miranda et al. 2017). This direction as stated by Eyvindson and Kangas (2018) will require not only changes in the models but also probably changes in the formulation of the criteria considered in the exercise.

Because of its modular structure, the proposed framework might be the embryo of a general decision-support system for dealing with many forest-management problems of different nature just by activating and deactivating their different modules by different particularizations of the auxiliary parameter values of the generalized model according to the characteristics of the particular problem analyzed.

Endnote

1. http://www.gateados.com.br/novo/index.php

Appendix

Top-Down Approach

Strategic achievement function [$\gamma_1 = 1, \gamma_2 = 0, \mu = 1$, and $\delta = 0$]:

$$\text{Min}(1-\lambda)D_1 + \lambda(2.3n_1 + 14n_2 + 149p_3 + 28(n_4 + p_4) + 25(n_5 + p_5) + 380(n_6 + p_6)) \tag{A1}$$

Strategic goals [$\mu = 1$ and $\delta = 0$]:

$$\begin{aligned} &2.3n_1 \le D_1 \\ &14n_2 \le D_1 \\ &149p_3 \le D_1 \\ &28(n_4 + p_4) \le D_1 \\ &25(n_5 + p_5) \le D_1 \\ &380(n_6 + p_6) \le D_1 \end{aligned} \tag{A1d}$$

$$\sum_{s=1}^{2551}\sum_{m=1}^{M} NPV_{sm}x_{sm} + n_1 - p_1 = 103{,}305{,}019 \tag{A2}$$

$$\sum_{s=1}^{2551}\sum_{m=1}^{M} VOL_{sm}x_{sm} + n_2 - p_2 = 7{,}650{,}016 \tag{A3}$$

$$\sum_{s=1}^{2551}\sum_{m=1}^{M} (CS_{sm} - CE_{sm})x_{sm} + n_3 - p_3 = 242{,}106 \tag{A4}$$

$$\sum_{s=1}^{2551}\sum_{m=1}^{M} x_{sma} + n_4 - p_4 = 1{,}235 \quad a = 1,\ldots,5 \tag{A5}$$

$$\sum_{s=1}^{2551}\sum_{m=1}^{M} Vc_{smk}x_{sm} + n_5 - p_5 = 238{,}309 \quad k = 1,\ldots,30 \tag{A6}$$

$$\sum_{s=1}^{2551}\sum_{m=1}^{M} Vl_{smk}x_{sm} + n_6 - p_6 = 27{,}841 \quad k = 1,\ldots,30 \tag{A7}$$

subject to Equation 14.

Tactical achievement function [$\gamma_1 = 1, \gamma_2 = 0, \mu = 0$, and $\delta = 1$]:

$$\text{Min}(1-\lambda)D_1 + \lambda(1.7n_1 + 10n_2 + 112p_3 + 22(n_4 + p_4) + 19(n_5 + p_5) + 285(n_6 + p_6) + 54n_7 + 13p_8) \tag{B1}$$

$$\begin{aligned} &1.7(n_1) \le D_1 \\ &10(n_2 + p_2) \le D_1 \\ &112(n_3 + p_3) \le D_1 \\ &22(n_4 + p_4) \le D_1 \\ &19(n_5 + p_5) \le D_1 \\ &285(n_6 + p_6) \le D_1 \\ &54(n_7) \le D_1 \\ &13(p_8) \le D_1 \end{aligned} \tag{B1d}$$

Transference of strategic results $\delta = 1$:

$$\sum_{s=1}^{2551}\sum_{m=1}^{Mt} NPV_{sm}x_{sm} + n_1 - p_1 = npv^* \tag{B2}$$

$$\sum_{s=1}^{2551}\sum_{m=1}^{Mt} VOL_{sm}x_{sm} + n_2 - p_2 = vol^* \tag{B3}$$

$$\sum_{s=1}^{2551}\sum_{m=1}^{Mt} (CS_{sm} - CE_{sm})x_{sm} + n_3 - p_3 = carb^* \tag{B4}$$

$$\sum_{s=1}^{2551}\sum_{m=1}^{Mt} x_{sma} + n_4 - p_4 = acr^* \tag{B5}$$

$$\sum_{s=1}^{2551}\sum_{m=1}^{Mt} Vc_{smk}x_{sm} + n_5 - p_5 = fvol^* \quad k = 1,\ldots,30 \tag{B6}$$

$$\sum_{s=1}^{2551}\sum_{m=1}^{Mt} Vl_{smk}x_{sm} + n_6 - p_6 = FLog^* \quad k = 1,\ldots,30 \tag{B7}$$

It should be noted that the right-hand terms of equations B2–B7 are transference targets. Thus, in each strategic scenario for several values of λ, a different strategic result is obtained, implying different target values. The values of the tactical targets, which transfer strategical results, differ according to the formulated scenario following the respective value.

Tactical goals [$\delta = 1$]:

$$\sum_{s,l \in g(L)}\sum_{k=1}^{3} e_{slk} + n_7 - p_7 = 8{,}562 \tag{B8}$$

$$\sum_{s=1}^{2551}\sum_{k=1}^{3} c_{sk}r_{sk} + \sum_{s=1}^{S}\sum_{k=1}^{3} c_{vk}z_{vk} + n_8 - p_8 = 3{,}501{,}652 \tag{B9}$$

subject to Equations 15–18.

Integrated Approach

Integrated achievement function [$\gamma_1 = 0$ and $\gamma_2 = 1$]:

$$\text{Min}(1-\lambda)D_2 + \lambda(1.7n_1 + 10n_2 + 112p_3 + 22(n_4 + p_4) + 19(n_5 + p_5) + 285(n_6 + p_6) + 54n_7 + 13p_8) \tag{C1}$$

$$\begin{aligned} &1.7(n_1) \le D_2 \\ &10(n_2 + p_2) \le D_2 \\ &112(n_3 + p_3) \le D_2 \\ &22(n_4 + p_4) \le D_2 \\ &19(n_5 + p_5) \le D_2 \\ &285(n_6 + p_6) \le D_2 \\ &54(n_7) \le D_2 \\ &13(p_8) \le D_2 \end{aligned} \tag{C1d}$$

Goals:

$$\sum_{s=1}^{2551}\sum_{m=1}^{M} NPV_{sm}x_{sm} + n_1 - p_1 = 103,305,019 \quad (C2)$$

$$\sum_{s=1}^{2551}\sum_{m=1}^{M} VOL_{sm}x_{sm} + n_2 - p_2 = 7,650,016 \quad (C3)$$

$$\sum_{s=1}^{2551}\sum_{m=1}^{M} (CS_{sm} - CE_{sm})x_{sm} + n_3 - p_3 = 242,106 \quad (C4)$$

$$\sum_{s=1}^{2551}\sum_{m=1}^{M} x_{sma} + n_4 - p_4 = 1,235 \quad a = 1,\ldots,5 \quad (C5)$$

$$\sum_{s=1}^{2551}\sum_{m=1}^{M} Vc_{smk}x_{sm} + n_5 - p_5 = 238,309 \quad k = 1,\ldots,30 \quad (C6)$$

$$\sum_{s=1}^{2551}\sum_{m=1}^{M} Vl_{smk}x_{sm} + n_6 - p_6 = 27,841 \quad k = 1,\ldots,30 \quad (C7)$$

$$\sum_{s,l\in g(L)}\sum_{k=1}^{3} e_{slk} + n_7 - p_7 = 8,562 \quad (C8)$$

$$\sum_{s=1}^{2551}\sum_{k=1}^{3} c_{sk}r_{sk} + \sum_{s=1}^{2551}\sum_{k=1}^{3} c_{vk}z_{vk} + n_8 - p_8 = 3,501,652 \quad (C9)$$

subject to Equations 12–18.

Literature Cited

Aldea, J., F. Martínez-Peña, C. Romero, and L. Diaz-Balteiro. 2014. Participatory goal programming in forest management: An application integrating several ecosystem services. *Forests.* 5(12):3352–3371.

Álvarez-Miranda, E., J. Garcia-Gonzalo, F. Ulloa-Fierro, A. Weintraub, and S. Barreiro. 2017. A multicriteria optimization model for sustainable forest management under climate change uncertainty: An application in Portugal. *Eur. J. Oper. Res.* 269(1):79–98.

Andersson, D., and L.O. Eriksson. 2007. Effects of temporal aggregation in integrated strategic/tactical and strategic forest planning. *Forest Policy Econ.* 9(8):965–981.

Augustynczik, A.L.D., J. Arce, and A.C.L. Silva. 2016. Aggregating forest harvesting activities in forest plantations through integer linear programming and goal programming. *J. Forest Econ.* 24(C):72–81.

Bachmatiuk, J., J. Garcia-Gonzalo, and J.G. Borges. 2015. Analysis of the performance of different implementations of a heuristic method to optimize forest harvest scheduling. *Silva Fenn.* 49(4):1–18.

Beaudoin, D., J.M. Frayret, and L. LeBel. 2008. Hierarchical forest management with anticipation: An application to tactical-operational planning integration. *Can. J. Forest Res.* 38(8):2198–2211.

Belavenutti, P., C. Romero, and L. Diaz-Balteiro. 2018. A critical survey of optimization methods in industrial forest plantations management. *Sci. Agric.* 75(3):239–245.

Bertomeu, M., L. Diaz-Balteiro, and J.C. Gimenez. 2009. Forest management optimization in Eucalyptus plantations: A multicriteria approach. *Can. J. Forest Res.* 39(2):356–366

Borges J.G., S. Marques, J. Garcia-Gonzalo, A. Ur Rahman, V. Bushenkov, M. Sottomayor, P. O. Carvalho, and E. V. Nordström. 2017. A multiple criteria approach for negotiating ecosystem services supply targets and forest owners' programs. *Forest Sci.* 63(1):2017.

Bouchard, M., S. D'Amours, M. Rönnqvist, R. Azouzi, and E. Gunn. 2017. Integrated optimization of strategic and tactical planning decisions in forestry. *Eur. J. Oper. Res.* 259(3):1132–1143.

Broz, D., G. Durand, D. Rossit, F. Tohmé, and M. Frutos. 2017. Strategic planning in a forest supply chain: A multigoal and multiproduct approach. *Can. J. For. Res.* 47(3):297–307.

Cea, C., and A. Jofré. 2000. Linking strategic and tactical forestry planning decisions. *Ann. Oper. Res.* 95(1):131–140.

Church, R.L., A.T. Murray, M.A. Figueroa, and K.H. Barber. 2000. Support system development for forest ecosystem management. *Eur. J. Oper. Res.* 121(2):247–258.

Diaz-Balteiro, L., M. Bertomeu, and M. Bertomeu. 2009a. Optimal harvest scheduling in *Eucalyptus* plantations. A case study in Galicia (Spain). *Forest Policy Econ.* 11(8):548–554.

Diaz-Balteiro L., J. Gonzalez-Pachon, and C. Romero. 2009b. Forest management with multiple criteria and multiple stakeholders: An application to two public forests in Spain. *Scand. J. Forest Res.* 24(1):87–93.

Diaz-Balteiro, L., and C. Romero. 1998. Modelling timber harvest scheduling problems with multiple criteria by multigoal programming: An application in Segovia, Spain. *Forest Sci.* 44(1):47–57.

Diaz-Balteiro, L., and C. Romero. 2003. Forest management optimization models when carbon captured is considered: A goal programming approach. *Forest Ecol. Manag.* 174(1–3):447–457.

Diaz-Balteiro, L., González-Pachón, J., and C. Romero. 2013. Goal programming in forest management: Customizing models for the decision-maker's preferences. *Scand. J. Forest Res.* 28(2): 166–173.

Diaz-Balteiro, L., D. Martell, C. Romero, and A. Weintraub. 2014. The optimal rotation of a flammable forest stand when both carbon sequestration and timber are valued: A multi-criteria approach. *Nat. Hazards.* 72(2):375–387.

Diaz-Balteiro, L., O. Alfranca, M. Bertomeu, M. Ezquerro, J. C. Giménez, J. González-Pachón, and C. Romero. 2016. Using quantitative techniques to evaluate and explain the sustainability of forest plantations. *Can. J. For. Res.* 46(9):1157–1166.

Diaz-Balteiro, L., and C. Romero 2008. Making forestry decisions with multiple criteria: A review and an assessment. *Forest Ecol. Manag.* 255(8–9):3222–3241.

Dong, L., P. Bettinger, Z. Liu, and H. Qin. 2015. Spatial forest harvest scheduling for areas involving carbon and timber management goals. *Forests.* 6(4):1362–1379.

EMBRAPA - Brazilian Agricultural Resource Corporation. 2011. Software for management and economic analysis of forest plantations. Available online at www.embrapa.br/documents.html; last accessed Feb. 12, 2018.

Eyvindson K., and A. Kangas. 2014. Stochastic goal programming in forest planning. *Can. J. Forest Res.* 44(10):1274–1280.

Eyvindson K., and A. Kangas. 2018. Guidelines for risk management in forest planning – what is risk and when is risk management useful? *Can. J. Forest Res.* 48(4):309–316

Eyvindson, K., J. Rasinmäki, and A. Kangas. 2018. Evaluating a hierarchical approach to landscape level harvest scheduling. *Can. J. Forest Res.* 48(2):208–125.

Fiorentin L.D., J.E. Arce, A.L. Pelissari, H.C. David, P.H.B.M. Silva, M.B. Stang, and A.F. Filho. 2017. Strategies for regulating timber volume in forest stands. *Sci. For.* 45(116):717–726.

Giménez, J.C., M. Bertomeu, L. Diaz-Balteiro, and C. Romero. 2013. Optimal harvest scheduling in *Eucalyptus* plantations under a sustainability perspective. *Forest Ecol. Manag.* 291:367–376.

Gómez Núñez, T., M. Hernández Huelín, J. Molina, M.A. León, E. Aldana, and R. Caballero. 2011. A multiobjective model for forest planning with adjacency constraints. *Ann. Oper. Res.* 190(1):75–92.

Hernandez M., T. Gómez, J. Molina, M.A. León, and R. Caballero. 2014. Efficiency in forest management: A multiobjective harvest scheduling model. *J. Forest Econ.* 20(3):236–251

Johnson, K.N., and H.L. Scheurman. 1977. Techniques for prescribing optimal timber harvest and investment under different objectives—discussion and synthesis. *For. Sci. Monogr.* 18. 31 p.

Kangas, A., M. Nurmi, and J. Rasinmäki. 2014. From a strategic to a tactical forest management plan using a hierarchic optimization approach. *Scand. J. Forest Res.* 29(1):154–165.

Miettinen, K. 1998. *Nonlinear Multiobjective Optimization.* Kluwer Academic Publishers, Dordrecht.

Molina, J., M. Laguna, R. Marti, and R. Caballero. 2007. SSPMO: A scatter tabu search procedure for non-linear multiobjective optimization. *Informs J. Comput.* 19(1):91–100.

Öhman, K., and L.O. Eriksson. 2010. Aggregating harvest activities in long term forest planning by minimizing harvest area perimeters. *Silva Fenn.* 44(1):77–89.

Paradis G., L. LeBel, S. D'Amours, and M. Bouchard. 2013. On the risk of systematic drift under incoherent hierarchical forest management planning. *Can. J. Forest Res.* 43(5):480–492.

Pasalodos-Tato, M., E. Almazán, G. Montero, and L. Diaz-Balteiro. 2017. Evaluation of tree biomass carbon stock changes in Andalusian forests: Comparison of two methodologies. *Carbon Manag.* 8(2):125–134.

Romero, C. 2001. Extended lexicographic goal programming: A unifying approach. *Omega-Int J. Manage S.* 29(1):63–71.

Romero, C. 2004. A general structure of achievement function for a goal programming model. *Eur. J. Oper. Res.* 153(1):675–686.

Rönnqvist, M., S. D'Amours, A. Weintraub, A. Jofre, E. Gunn, R. Haight, D. Martell, A. Murray, and C. Romero. 2015. Operations research challenges in forestry: 33 open problems. *Ann. Oper. Res.* 232(1):11–40.

Saaty, T.L. 1977. A scaling method for priorities in hierarchical structure. *J. Math. Psychol.* 15(3):317–332.

Seely, B., J. Nelson, R. Wells, B. Peter, M. Meitner, A. Anderson, H. Harshaw, S. Sheppard, F.L. Bunnell, H. Kimmins, and D. Harrison. 2004. The application of a hierarchical, decision-support system to evaluate multi-objective forest management strategies: A case study in northeastern British Columbia, Canada. *Forest Ecol. Manag.* 199(2–3):283–305.

Silva, M., A. Weintraub, C. Romero, and C. de la Maza. 2010. Forest harvesting and environmental protection based on the goal programming approach. *Forest Sci.* 56(5):460–472.

Troncoso J., S. D'Amours, P. Flisberg, M. Rönnqvist, and A. Weintraub. 2015. A mixed integer programming model to evaluate integrating strategies in the forest value chain—a case study in the Chilean forest industry. *Can. J. Forest Res.* 45(7):937–949.

Weintraub, A.P., and D. Navon. 1976. A forest management planning model integrating silvicultural and transportation activities. *Manage. Sci.* 22(12):1299–1309.

Weintraub, A., and B. Bare. 1996. New issues in forest land management from an operations research perspective. *Interfaces.* 26(5): 9–25.

Weintraub, A., and A. Cholaky. 1991. A hierarchical approach to forest planning. *Forest Sci.* 27(2):439–460.