

REGULATION OF EVEN-AGED FORESTS WITH INCLUSION OF ENVIRONMENTAL CONSTRAINTS

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ABSTRACT: This study aimed to propose alternative methods of inclusion of environmental constraints in forest regulation models. Models were constructed for an experimental rural estate with a total planted area of 3.491 ha which was divided into 135 management units. The formulation of the regulation models included integer constraints for all management units. Genetic algorithm metaheuristic was used for solving the models. For comparison purposes, the classical model of forest regulation (model I) was used, and the model with adjacency constraints. The proposed formulations proved to be environmentally more effective than the imposition of adjacency constraints.

Key words: Genetic algorithms, adjacency constraints, eucalypt.

REGULAÇÃO DE FLORESTAS EQUIÂNEAS COM INCLUSÃO DE RESTRIÇÕES AMBIENTAIS

RESUMO: Neste estudo, objetivou-se propor formas alternativas de inclusão de restrições ambientais nos modelos de regulação florestal. Os modelos foram construídos para uma fazenda modelo, com uma área de efetivo plantio de 3.491 ha, divididos em 135 unidades de manejo. Os modelos de regulação foram formulados, incluindo restrições de inteireza para todas as unidades de manejo. Utilizou-se meta-heurística algoritmo genético para a resolução dos modelos. Para efeito de comparação, foi empregado o modelo clássico de regulação florestal (modelo I), e o modelo com restrições de adjacência. As formulações propostas demonstraram ser ambientalmente mais eficientes do que a imposição de restrições de adjacência.

Palavras-chave: Algoritmos genéticos, restrições de adjacência, eucalipto.

1 INTRODUCTION

Forest management involves an integrated combination of silvicultural practices and economic concepts aimed at ensuring the objectives of producers are met (BETTINGER et al., 2009). The main challenge of forest management plans today is that they have to continually adapt to environmental changes and social circumstances. This is not trivial since forest growth is a slow process and, therefore, making rapid changes to species and clone composition or to diameter structure and many other traits that affect both the quality and the quantity of services, is usually impossible to achieve (GADOW; PUKKALA, 2008).

In order to adapt regulation models to the social and environmental needs of populations neighboring a forest enterprise, it is important to consider spatial traits (BASKENT; KELES, 2005). A mathematical formulation of social and environmental constraints requires use of integer variables in the representation of management units (MURRAY; CHURCH, 1995).

When establishing a management plan, the selection of silvicultural activities in each management unit will be dependent on the characteristics of neighboring units. For this reason, silvicultural and harvest activities should be oriented both temporally and spatially (BETTINGER et al., 2009). Such orientation is achieved by applying green-up, adjacency or connectivity constraints.

Adjacency constraints seek to minimize environmental impacts brought about by the destruction of natural habitats, thereby preventing harvest in adjacent or extensive contiguous areas while providing shelter and food to animal populations living in the managed forest and also mitigating the visual impacts caused by harvest-related activities (CASTRO, 2007; MOREIRA, 2008). Such constraints assume that the management unit will regenerate in less than one year. Imposition of green-up constraints occurs whenever the management unit is incapable of regenerating in less than one year (BOSTON; BETTINGER, 2000). And the need for the fauna to shift between different fragments of native forest is met by connectivity constraints (MOREIRA, 2008).

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Adjacency constraints were originally proposed by Thompson et al. (1973), whereby for each pair of adjacent plots in each year of the planning horizon a restriction was formulated (MURRAY; CHURCH, 1996; TORRES-ROJO; BRODIE, 1990; YOSHIMOTO et al., 1990). Several formulation alternatives were proposed aimed at reducing the number of constraints required to represent the various existing adjacency relationships (MCDILL; BRAZE, 2000).

Implementation of adjacency constraints will result in models that consider a landscape with several management units which in turn differ in their characteristics and are dispersed in space (BASKENT; JORDAN, 1995; GADOW; PUKKALA, 2008).

There are several ways to determine the spatial relationships between different management units, including the extent of common borders between them and the distance between them (BAILEY; GATRELL, 1995; CHEN; GADOW, 2002; KURTTILLA et al., 2002). Where management units have different conformations as to shape and size, the distance between them could be used as a condition for determining the adjacencies (HURME et al., 2007) or else any other trait indicating that such units have mutual influence.

Due to the interdependent nature and complexity of the correlations between the variables, regulation models with integer variables are potentially impossible to solve using classic mathematical programming methods (MCDILL; BRAZE, 2000). As a result, many research studies have been suggesting use of heuristic techniques to solve such problems (BORGES et al., 1999; BOSTON; BETTINGER, 1999; HOGANSON; BORGES, 1998; MURRAY; CHURCH, 1995; NELSON; BRODIE, 1990; WEINTRAUB et al., 1994).

Metaheuristics used for solving adjacency constraint problems include simulated annealing, tabu search and genetic algorithms (BASKENT; JORDAN, 2002; BETTINGER et al., 2002, 2003, 2009; BOSTON; BETTINGER, 1999; BRUMELLE et al., 1998; CARO et al., 2003; CHEN; GADOW, 2002; CROWE; NELSON, 2003; DEUSEN, 2001; MULLEN; BUTLER, 1997; MURRAY; CHURCH, 1995; OHMAN; ERIKSSON, 2002). Some findings suggest that genetic algorithms are more effective than other search heuristics in solving problems with complex spatial objectives.

On account of the complexity of regulation models with spatial constraints, this study was designed to assess and solve a mathematical regulation model ultimately

looking to reduce the negative environmental impacts of a forest enterprise.

2 MATERIAL AND METHODS

Mathematical models were formulated in order to:

1. minimize the harvest area index (IAC);
2. maximize the total net present value (VPL) by applying penalties as a function of the IAC.

Assessment of the best modeling alternatives was done as a function of VPL and IAC.

2.1 Data

Data were obtained from an experimental rural estate where a case study was implemented to represent a situation found in a forest company of central-eastern Minas Gerais state. The total area of the rural estate is around 9.750 ha, of which 35% (3.412 ha) is effectively cultivated while the remaining part consists of a legal reserve and permanent preservation areas. The site was divided into 135 management units according to administrative, soil, climate and physiographic traits. The distribution of the management units and respective age classes are illustrated in Figure 1.

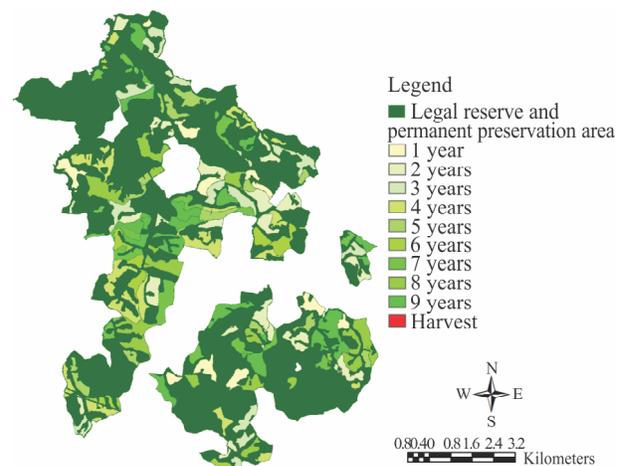


Figure 1 – Spatial distribution of age classes across the experimental rural estate.

Figura 1 – Distribuição espacial de classes de idade das áreas da Fazenda modelo utilizada.

2.2 Mathematical models

The model was formulated using the optimized forest planning system *SifPlan* (www.treesoftware.com.br).

The approach adopted for generating management units was that of model I, according to Johnson and Scheurman (1977), using binary variables for the decision variables, as is illustrated next.

Objective Function:

$$MAXZ = \sum_{i=1}^m \sum_{j=1}^n c_{ij} x_{ij} \quad (1)$$

Subject to:

$$\sum_{i=1}^m \sum_{j=1}^n x_{ij} = 1 \quad (2)$$

$$\sum_{i=1}^m \sum_{j=1}^n V_{ij} x_{ij} \geq Dmin_k \{k = 0, 1, \dots, H-1\} \quad (3)$$

$$\sum_{i=1}^m \sum_{j=1}^n V_{ij} x_{ij} \leq Dmax_k \{k = 0, 1, \dots, H-1\} \quad (4)$$

$$\sum_{l=1}^{IR} A_{lk} = \left(\frac{totalarea}{R} \right) \{k = H-1\} \quad (5)$$

$$x_{ij} \in \{0, 1\} \quad (6)$$

where Z = total net present value (R\$); x_{ij} = decision variables, representing the j -th management alternative adopted in the i -th management unit; c_{ij} = net present value of each management unit i , as managed according to management alternative j ; m = total number of management units; n = total number of management alternatives in the i -th management unit; V_{ijk} = volume (m^3) produced by the i -th management unit when the j -th management alternative is adopted, for period k ; $Dmin_k$ and $Dmax_k$ = minimum and maximum volume requirement (m^3), respectively, in each period of the planning horizon; A_{lk} represents the area of the stand at age l and period k ; and R is the regulating age.

According to this integer programming model, maximization of Z (1) is subject to singularity constraints (2) and (6) and to minimum (3) and maximum (4) outputs in each period of the planning horizon. Constraint (5) ensures establishment of the forest regulation. The planning horizon was defined as with 1.5 cycle, as suggested by Leuschener (1984), adopting a rotation of 6 years and a cycle of 2 rotations, the planning horizon thus being 18 years. The maximum and minimum imposed annual volume requirements were 150,000 and 200,000 m^3 respectively.

Interventions in stands included harvest, immediately followed by replanting, or harvest with replanting in the next period, meaning that only one management regime was evaluated (high forest). Harvest age was made possible to vary between 5-9 years within the planning horizon, with a regulatory rotation length of

6 years. For purposes of comparison, the same model was obtained without inclusion of adjacency constraints and age class constraints restrictions per cell.

The optimization procedure was performed using genetic algorithm metaheuristic (GA), with a computational routine developed in the programming environment *Visual Basic for Applications* combined with *Software Microsoft Excel*. The solutions (individuals) generated for the problem in question had the following vector format $V(x) = \{X_{1j}, X_{12}, \dots, X_{ij}\}$, in which the decision variable X_{ij} ($X_{ij} \in \{0, 1\}$) symbolizes management alternative j ($j = 1, 2, \dots, n$) assigned to management unit i ($i = 1, 2, \dots, m$) (RODRIGUES et al., 2004).

The initial population of the GA consisted of 30 randomly generated individuals, considering the viability of each solution by the singularity constraint. The evolution of the genetic algorithm depends on mechanisms known as genetic operators which are responsible for changes in the population, generating improved populations over time. Multiple-point crossover and a mutation rate of 0.6% were used for each individual of the population, with selection of individuals being based on elitism. The algorithm run was terminated when, with fitness stabilized, the GA produced 20 new generations.

2.3 Assessment of dispersion of interventions in management units

Among the various metrics described in literature for assessing landscape management (BASKENT; JORDAN, 1995), the choice in this study was to assess the effect of adjacency constraint by the weighted average of the square of the inverse of the smallest distance between the management units harvested in the same period, subject to the square areas of the management units under intervention. The index used was:

$$IAC = \frac{\sum_{k=0}^{H-1} \sum_{i=1}^m A_i^2 \left(\frac{1}{d_i} \right)^2}{\sum_{i=1}^m A_i}$$

where IAC = harvest area index, A_i = area of management unit i under intervention, in m^2 , d_i = distance to the nearest management unit under intervention, in meters.

2.4 Adjacency constraint

A model was developed for comparison in which classic adjacency restrictions were applied. Due to the very rugged relief of the study site, the management units

were considered to be adjacent when the distance between their boundaries (edges) was 50 m or less. The adjacency constraint to avoid harvest in adjacent management units was:

$$n_i x_{ij} + \sum_{i \in N_i} x_{ij} \leq n_i \forall i, k \quad (6)$$

where n_i refers to the number of adjacent management units with harvest in period k (MCDILL; BRAZE, 2000).

2.5 IAC minimization

IAC minimization was used as objective function. Optimization was done using genetic logarithm metaheuristic, the fitness function being as follows:

$$MaxZ = \frac{\sum_{k=0}^{H-1} \sum_{i=1}^m A_i^2 \left(\frac{1}{d_i}\right)^2}{\sum_{i=1}^m A_i} - \alpha \left(H_k - \sum_{i=1}^m \sum_{j=1}^n V_{ij} x_{ij} \right) - \gamma \left(A_i - \sum_{i=1}^m A_i x_i \right)^2$$

where Z = value of the fitness function; x_{ij} = decision variables, representing the j -th management alternative adopted in the i -th management unit; c_{ij} = net present value of each management unit i , as managed according to management alternative j ; m = total number of management units; n = total number of management alternatives in the i -th management unit; V_{ijk} = volume (m^3) produced by the i -th management unit when the j -th management alternative is adopted for period k ; H_k = volume requirement (m^3) in each period of the planning horizon; α , β and γ are penalty coefficients associated with each constraint; A_{ikq} refers to areas of cell q harvested in period k ; A_i = regulatory area and A_i = area of management unit i .

2.6 VPL maximization with penalties as a function of the IAC

The fitness function of the genetic algorithm used in this model was based on application of penalties to the objective function, consisting of maximizing the total net present value. Penalties were imposed as a function of percentages (μ) of VPL and IAC. Percentages ranged at a 5% rate with an initial value of 5% and a maximum value of 100%. The fitness function used for this model was:

2.7 Output, Revenue and Cost

$$Max = \sum_{i=1}^m \sum_{j=1}^n c_{ij} x_{ij} - \alpha \left(H_k - \sum_{i=1}^m \sum_{j=1}^n V_{ij} x_{ij} \right) - \mu \left(\sum_{i=1}^m \sum_{j=1}^n c_{ij} x_{ij} \right) \left(\frac{\sum_{k=0}^{H-1} \sum_{i=1}^m A_i^2 \left(\frac{1}{d_i}\right)^2}{\sum_{i=1}^m A_i} \right) - \gamma \left(A_i - \sum_{i=1}^m A_i x_i \right)^2$$

One hybrid clone (*Eucalyptus urophylla* x *Eucalyptus grandis*) was considered as being the sole source of timber used. The output curve obtained from plot data of a forest inventory was:

$$Volume = \frac{197.833}{1 + 75.674e^{-1.315Age}}$$

The costs table used in the analyses was obtained from Binoti 2010. The interest rate used was 8.75% a year and the timber sale value was R\$ 80.00/ m^3 .

3 RESULTS

Formulation of the regulation model generated a problem with 8,755 decision variables. In all forest regulation problems, satisfactory results were obtained for the regulation constraints and annual volume variation.

Imposition of adjacency constraints reduced the total VPL by around 8%. The value of the objective function for the models with and without inclusion of adjacency constraints were R\$ 17,143,857.17 and R\$ 18,599,169.37 respectively.

IAC minimization resulted in a VPL of R\$ 17,322,217.40. Variations in VPL and IAC corresponding to the models with VPL maximization with penalties imposed as a function of IAC and distance between harvested units, are provided in Figure 2.

The IAC value for the model, with and without inclusion of the adjacency constraint, was 0.246436 and 0.615032 respectively. Using models with IAC minimization resulted in an index of 0.176432. The influence of applying IAC penalties is illustrated in Figure 3, noting that penalties above 20% resulted in better models environmentally and landscape wise (lower IAC), with improved economic returns (higher VPL).

4 DISCUSSION

The description of the forest management model was rapidly expanded from traditional timber production to sustainable production of multiple services (BASKENT; JORDAN, 1995). Such changes added characteristics even more complex and difficult to solve to forest regulation models.

Preference for scenically beautiful landscapes is a value inherent in people and such values vary from one socioeconomic group to another. With that in mind, it is important to consider the scenic beauties of a forest

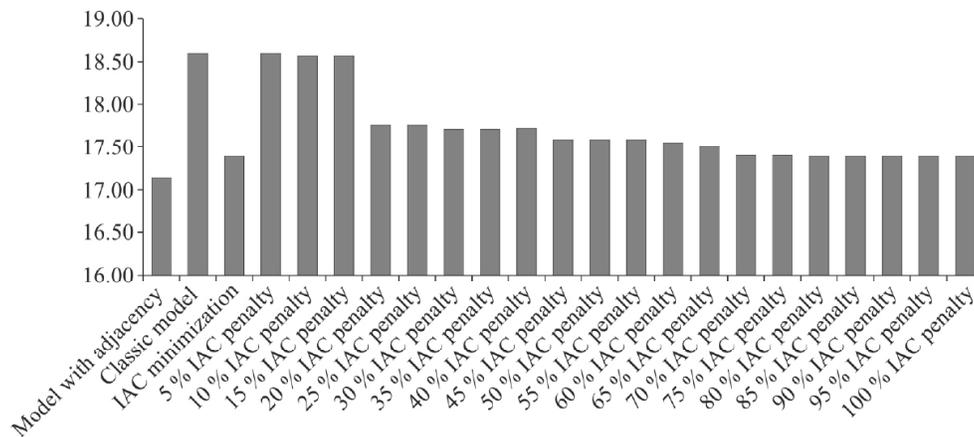


Figure 2 – VPL (in millions of Brazilian reais) for each regulation model as derived from various modeling methods (adjacency, classic, IAC minimization, VPL maximization with penalties as a function of IAC).

Figura 2 – VPL (em milhões de Reais) para cada modelo de regulação gerado nas diversas formas de modelagem (adjacência, clássico, minimização do IAC, maximização do VPL com penalidades em função do IAC).

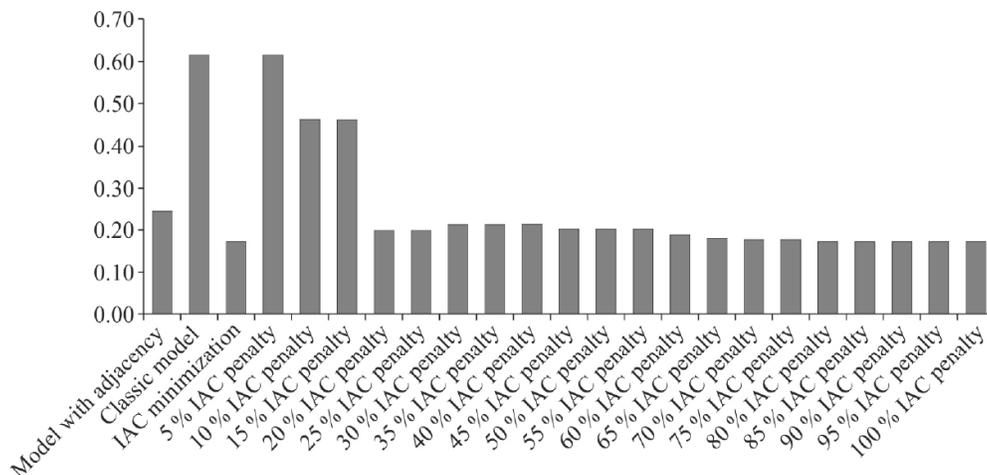


Figure 3 – IAC for each regulation model as derived from various modeling methods (adjacency, classic, IAC minimization, VPL maximization with penalties as a function of the IAC).

Figura 3 – IAC para cada modelo de regulação gerado nas diversas formas de modelagem (adjacência, clássico, minimização do IAC, maximização do VPL com penalidades em função do IAC).

when developing forest management plans (BETTINGER et al., 2009).

Inclusion of environmental and landscape restrictions is mainly done by imposing adjacency constraints. Constraints consist of controlling interactions between management units within a forest in such way that harvest activities in one management unit will restrict harvest actions in neighboring or adjacent units (MURRAY; CHURCH, 1995). They also

prevent formation of large contiguous harvested areas. Imposition of constraints entails a considerably increased computational effort, requiring long hours, if not days, to solve problems with relatively few management units using classic integer programming algorithms (MCDILL; BRAZE, 2000). For this reason, many research studies have been conducted to try and reduce the processing time involved in solving such problems.

Adjacency constraints were originally formulated by Thompson et al. (1973), with one constraint formulated for each pair of adjacent plots. Subsequent studies based on this type of formulation resulted in significant reductions in the processing time (MCDILL; BRAZE, 2000). Besides the considerable dimension a regulation model acquires with imposition of this type of constraint, obtaining a feasible solution to the problem while meeting all constraints is many a time unenforceable.

The index used for models comparison is extremely simple and easy to obtain with application of Geographic Information Systems (GIS) or mapping techniques. The index was found to be consistent with assumptions adopted for management of even-aged plantation landscapes. The index is directly proportional to the area under intervention and inversely proportional to the distance between management units under intervention, weighted by the annual harvest area. In practical terms, the closer it is to zero, the better the environmental and socioeconomic influences will be on neighboring communities and ecosystems.

The purpose of this study was to introduce alternative methods for solving regulation problems with inclusion of environmental and landscape constraints. The proposal of IAC minimization resulted in an IAC value lower by 17% than the result found by the model with adjacency constraint and in a VPL value higher by around 2%. IAC minimization revealed economic and environmental superiority in relation to the model with adjacency constraints. Application of IAC penalties above 20% on VPL maximization resulted in better IAC values than the adjacency model and higher VPL values, being thus preferred to models with adjacency constraints. The reduction in the magnitude of the regulation model, the ease of modeling and the increased environmental benefits did favor IAC minimization as an alternative for forest regulation models.

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