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Multi-objective forest harvesting under sustainable and economic principles

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Abstract Selective logging is well-recognized as an effective practice in sustainable forest management. However, the ecological efficiency or resilience of the residual stand is often in doubt. Recovery time depends on operational variables, diversity, and forest structure. Selective logging is excellent but is open to changes. This may be resolved by mathematical programming and this study integrates the economic-ecological aspects in multi-objective function by applying two evolutionary algorithms. The function maximizes remaining stand diversity, merchantable logs, and the inverse of distance between trees for harvesting and log landings points. The Brazilian rainforest database (566 trees) was used to simulate our 216-ha model. The log landing

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design has a maximum volume limit of 500 m³. The nondominated sorting genetic algorithm was applied to solve the main optimization problem. In parallel, a sub-problem (*p*-facility allocation) was solved for landing allocation by a genetic algorithm. Pareto frontier analysis was applied to distinguish the gradients α -economic, β -ecological, and γ -equilibrium. As expected, the solutions have high diameter changes in the residual stand (average removal of approximately 16 m^3 ha⁻¹). All solutions showed a grouping of trees selected for harvesting, although there was no formation of large clearings (percentage of canopy removal < 7%, with an average of 2.5 ind ha^{-1}). There were no differences in floristic composition by preferentially selecting species with greater frequency in the initial stand for harvesting. This implies a lower impact on the demographic rates of the remaining stand. The methodology should support projects of reduced impact logging by using spatial-diversity information to guide better practices in tropical forests.

Keywords Amazon rainforest management · Computational intelligence · Multi-objective functions · Evolutionary computing

Introduction

Tropical forests are the world's most biodiverse land ecosystems (Betts et al. 2008), with the largest store of carbon and biomass productivity (Esquivel-Muelbert et al. 2019). Specifically, Amazonian species are key in assimilating and storing more carbon compared to other ecosystems (Fauset et al. 2015). In spite of the Amazon forests' relevance to the provision of ecosystem services, severe pressures have threatened its conservation (Amaral et al. 2019) through forest degradation and deforestation (Matricardi et al. 2020).



Poorly planned selective logging practices are one of these pressures leading to forest degradation by harvesting a few high value species (Dionisio et al. 2018; Amaral et al. 2019). The conventional use of this practice is attributed to the high species diversity of the Amazon forests and limited markets for timber from less desirable species (Otani et al. 2018). Although selective logging targets a small proportion of trees, it significantly impacts stand structure (Pinagé et al. 2019), composition (Bezerra et al. 2021), and aboveground biomass (D'Oliveira et al. 2021). Gaui et al. (2019) suggested that it would take approximately 25 years to recover to a pre-logged status of floristic composition. Facing modifications in forest dynamics caused by selective logging, a major challenge is in implementing sustainable forest management (SFM) for commercial species across felling cycles (Avila et al. 2017). In fact, policies and rigorous control by environmental agencies are crucial to develop viable SFM practices and contribute to forest maintenance (Conde et al. 2022).

Reduced impact logging (RIL) has been shown to be a promising method to minimize the impacts of harvesting operations in tropical forests (Putz et al. 2008; Schwartz et al. 2017). The procedure includes a detailed map for skidding and yarding operations, tree felling directions, and the optimum density of roads and landings to minimize soil disturbance. Under these conditions, RIL has been widely applied for a range of global forests to reduce impacts of forest harvesting. In contrast, selective logging often has negative effects on stand structure, dynamics, biodiversity, and ecosystem services (Gatti 2018). The loss of dominant canopy trees affects forest composition and resources for animal communities (Sheil and Van Heist 2000; Morgan et al. 2019), birds and small mammals (Hall et al. 2003), and genetic structure of natural populations (Soliani et al. 2016).

Ecological evidence is shows that selective logging practices helps to guide canopy gaps and minimize soil disturbance (Carvalho et al. 2017), maintain fauna composition (Azevedo-Ramos et al. 2006), limits the degree of damage to trees (Shenkin et al. 2015), and minimizes loss of carbon stocks (Yguel et al. 2019). Many studies have focused on the impacts of selective logging on the remaining trees (Amaral et al. 2019), buffers of the damage area (Gatti 2018), or forest biomass exported (Martin et al. 2015). Selective logging should be designed within a multifactorial perception of ecology and management to balance trade-offs between these factors. The new frontier of forest science is at the inter-tree neighborhood species connections into selective logging, and how these trees are linked ecologically. A multi-objective view may support decision-making with high benefits. This is essential to develop forest management plans with environmental, economic, and operational components (Capanema et al. 2022). The result is biased solutions favoring only a single condition (Konak et al. 2006). In fact, the ideal solution to drive all management aspects is impractical and a range of technical criteria must be applied for sustainable practices. An illustrative framework, for example, is the individualbased forest model (FORMIND) which evaluates forest management regimes with a high degree of detail about forest recovery (Hiltner et al. 2018).

Sustainable forest management has multi-functional objectives in an economic-ecological balanced approach (Poudyal et al. 2018). Early efforts to identify this degree of conciliation represented a challenge for decision-makers (Contreras and Chung 2007; Durbach and Stewart 2012). Currently, multi-objective functions have been progressively applied in many science fields (Steuer and Schuler 1979; Tecle et al. 1998). Packalen et al. (2020) proposed a multi-objective forest planning system that considered spatial tree optimization selection. Additionally, forest planning has had historically many integer variables, resulting in a complex problem to solve (Bettinger and Zhu 2006; McNaughton and Ryan 2008; França et al. 2022). The problem complexity usually affects the processing time and internal computational memory when the solving methods are exact (Crowe et al. 2003). Bettinger and Boston (2017) promoted advances in heuristics implementation to delineate forest plans, highlighting their flexibility for addressing large, nonlinear conditions. The nondominated sorting genetic algorithm II (NSGA II) is a customized, meta-heuristic model for addressing multiobjective problems with reliable and robust results (Deb et al. 2002) and is recommended over other evolutionary algorithms (Deb and Jain 2014; Zhou et al. 2019). The advantage of this algorithm is its operation based on the ranking of each individual in its population in dominance (nondominated sorting) and distribution (crowding distance) along the Pareto frontier.

Mutual thinking between economists and ecologists is the critical point of how forests should be simultaneously managed and preserved (Koch et al. 2009). Although there are some positive insights and research initiatives exploring this gap between economists and ecologists, few consider harvest simulation. It defines a new frontier of forest management science to support tropical forest projects applying RIL principles and provides an opportunity to weigh each factor under forest harvest simulation. Under reduced impact logging, the remaining stand may recover after harvesting for additional cycles of wood production. This research addresses questions after our simulations: (1) Does the solution meet economic and ecological goals? and (2) what is the diameter distribution, floristic composition, and spatial distribution of the residual stand? The outline solution of economic (α), ecological (β), and balanced (γ) gradients support our analysis from Pareto frontier.

Materials and methods

Forest site and data

A selective tree removal simulation was carried out in the Brazilian Amazon rainforest (Fig. 1B). The residual primary forest covers the municipality of Bujari in Acre state (Fig. 1C). Soils are predominantly Podzolic Red-Yellow dystrophic/alic (Amaral 2000). Annual average temperature is 25.6 °C with annual average precipitation of 1,952 mm designating this as an Am climate (Köppen) (Fig. 1A). Due to the property dimensions and modeling complexity, a portion of the annual harvested area (1,579.8 ha) was considered. The study site was 254.1 hectares, with 37.7 ha (14.8%)established as permanent (Fig. 1D and E). In 2016, an inventory was carried out and trees with diameter at breast height (DBH) > 50 cm were identified, tagged, mapped (X, Y coordinates), and measured. The floristic composition is typical of Acre forests with 37 commercial species and 1,131 harvestable trees, with a density of 5.2 trees ha^{-1} and a basal area of $2.6 \text{ m}^2 \text{ ha}^{-1}$

Selective logging

Trees are highly connected within a small-world network in primary forests (Schmid et al. 2020). As expected, selective impact logging will interrupt their ecological functions from undesirable selections. This is only one technical solution from a wide range of harvesting combinations. Therefore, the problem has multi-objective gradients without trivial answers. The non-linearity of variables suggests the use of meta-heuristic algorithms instead of an integer linear programming model. The timber harvesting simulation was performed applying a selective logging of 556 trees from 1,131 available ones and is a binary vector $\{0, 1\}$ set for those trees assigned for felling under a range of constraints, rules, and algorithms. It was assumed that all harvested trees were skidded to a log landing (500 m³). Overall impacts of skid trails, haul roads, and landings were not available for our simulations. The optimization problem considered the maximization of three sub-functions: (1) gross profit of log sales, (2) the minimum log skidding distance, and (3) diversity of remaining trees. In addition, the Rao and Waghmare (2014) standardized function (0-1) was applied to equalize these coefficients.

Initially, the log landing location and the issue of tree selection were resolved, with the inverse of Euclidean distance between trees and log landings applied. In spite of the optimum distance, market log prices also affect gross profits as a second economic factor. The correct selection is required for financial reasons. The economic value of each harvested tree was derived from log size (volume) and the species market price (USD $$41-93 \text{ m}^{-3}$) according to the Permanent Development Forum of Acre (2018). Under these circumstances, these factors have been identified as the economic goal. The ecological goal included species diversity and the remaining diameter structure under S-index (Pastorella and Paletto 2013) to guide the stochastic search.

This index analyzes the structural and functional behavior of a forest stand resulting from the combination of three sub-indices (Pastorella and Paletto 2013). The second gradient of the main function express the sum of three sub-indexes (Eqs. 1-4), whereby: TM-horizontal structure of the forest (Füldner 1995); M—species diversity analysis (Von Gadow 1993); W—spatial distribution of trees (Von Gadow et al. 1998); p_n —weights associated with each sub-indexes $\{0.2, 0.5, 0.3\}$; k—the number of tree neighbors; *dij*—the ratio between the smallest/ largest DBHs within the k neighborhood; vij—a species dichotomous variable (1, whether i and j are different species; 0, otherwise); wij-a binary variable (1, whether the angle between the two nearest neighbors of the object tree *i* is smaller than 360/k; 0, otherwise). The S-index requires a high radius rate to overlay the neighboring trees (k) in quantification analysis. Once a set of tree distribution has been established by geographical location, we assumed 300 m of neighbors radius for our simulations. Hence, the candidate tree for selective logging may express the partial contribution of the S-index (TM + M + W), and the final harvest simulation assesses the overall influences in the remaining stand. Finally, these numerical values $\{0-1\}$ are classified within three levels of diversity: (a) lower (< 0.3), (b) medium (0.3-0.4), (c) higher (≥ 0.4). The TM index reflects the diameter distribution of the forest, also classified into three levels: (a) lower (< 0.3), (b) medium (0.3–0.5), (c) higher (≥ 0.5). The species diversity (M index) considers categories of species dissimilarity: (a) lower (< 0.3), (b) medium (0.3–0.5), (c) higher (≥ 0.5). The last sub-index (W) evaluates the spatial combination of trees: (a) regular (<0.3), (b) random (≥ 0.3 and <0.4), or (c) clustered $(\geq 0.4).$

$$S_i = p_1 T M_i + p_2 M_i + p_3 W_i$$
(1)

$$TM_{i} = \frac{\sum_{j=1}^{k} (1 - d_{ij})}{k}$$
(2)

$$M_i = \frac{\sum_{j=1}^k \mathcal{V}_{ij}}{k} \tag{3}$$



Geodesic and Cartographic Parameters: Geographic Coordinate System | Ellipsoid and Datum - WGS 1984



Fig. 1 A Amazon climate classification; B location of the study area within the Amazon forest biome; C residual primary forest in the municipality of Bujari in Acre state; D forest management unit, available trees and permanent preservation areas; and, E topographic gradient

$$W_i = \frac{\sum_{j=1}^k W_{ij}}{k} \tag{4}$$

Problem solving method

The multi-objective optimization problem was solved applying a NSGA II (non-dominated sorting genetic algorithm II) with genetic algorithm (GA) as a sub-function (Fig. 2). The economic and ecological goals were separated for better processing performance and to bypass the problem complexity. The log skidding distance (D) was obtained by a singleobjective genetic algorithm (GA) with Euclidean distance (trees-log landing) function and steady-state strategy. A 100 m buffer zone restriction was assumed for preservation around water bodies, and 500 m³ of log landing stock. The chromosome has fixed size and number (10) with binary variables {0, 1} selecting log yard locations according to

volume and harvested trees, and was randomized at the first iteration cycle. The k-means clustering technique was applied to accelerate the final solution considering the centroid of the cluster as the location. This strategy improved the final distribution of the log landings into better convergence. GA tuning was performed to seek the best parameter set and we reached tournament selection for crossover, mutation rate (30%), and stopping criteria (40 iterations). The main algorithm integrates the best GA solution within the ecological goal stage. The NSGA II has binary chromosome encoding $\{0,1\}$ chosen harvestable trees over the forest, which later accesses the GA solution. The NSGA II configuration was adopted: tournament selection, mutation (1%), population size (10), and stopping criteria (40)iterations). Population selection assumed a Pareto frontier strategy to guide the dominant solution and the distribution of the chromosomes. Regardless of multiple solutions, the function value within ranking scores of non-dominated sets and the distance of chromosomes within each frontier was



Fig. 2 Problem-solving flowchart applying evolutionary algorithms with multi-objective function for selective logging simulation

verified. Hence, the selection for chromosome preference was driven into not dominated solutions with better distributions over the borderline (Deb et al. 2002; Pasandideh et al. 2015). The algorithms and analysis structures were encoded in R programming language. Due to the high complexity and high computational cost, we applied 4-cores parallel processing with the Parallel package (Weston and Calaway 2019) in R software, version 3.6.2 (R Core Team 2019) and Intel (R) Core (TM) i7-3632QM.

Assessing the remaining stand

There are several advantages to using stochastic algorithms for optimization. Overall, it is extremely difficult to find the optimal solution, and a set of only feasible solutions were chosen for our analysis. These methods may explore a deep searching into the space solution mapping the Pareto frontier. In addition, three classes of solutions have been proposed according to their trends with maximum gradients at the multi-objective function: (α) economic, (β) ecological (S-index), and (γ) balanced gradient. The equilibrium solution has graphically identified the shortest Euclidean distance from the utopia point represented by the position in the search space that has optimal values for all criteria (Lu et al. 2012). A detailed analysis of our simulations was assessed with a, b, and y solutions to check the diameter structure and floristic composition of the remaining forest, the spatial distribution of harvested trees and the economic ratio for each solution separately.

Diameter structure

The diameter structure used the *TM* index to evaluate the horizontal distribution of the remaining forest. These *TM* values were compared by the non-parametric Wilcoxon test ($\alpha = 5\%$) to check for significant differences. In a complementary way, basal area was adopted as a second analysis item of the remaining diameter distribution. In this case, the unbiased Gini coefficient (Eq. 5) was applied (Glasser 1962). One of its uses is to compare structural heterogeneity between management strategies (Erfanifard et al. 2019) with the most advisable index for this type of comparison (Valbuena et al. 2012).

$$GC = \frac{n}{n-1} \frac{\sum_{i=j}^{n} \sum_{j=1}^{n} \left| g_i - g_j \right|}{2n^2 \overline{g}}$$
(5)

where: g is the sectional area referring to each measured tree i or j; \bar{g} is the average sectional area; n is the total number of trees.

Spatial distribution of harvested trees

Spatial analysis refers to the geographic location of individual trees and their relationship in the study area. Thus, spaces occupied by trees selected for cutting generate the opening of clearings, which are differentiated according to the greater or lesser grouping. The W index was used in this evaluation to assess the degree of clustering of trees selected for harvesting. The non-parametric Wilcoxon test ($\alpha = 5\%$) was also applied to verify equality between the solutions evaluated. The selected trees were evaluated by the univariate paired correlation function g(r), being widely spread as in Getzin et al. (2006), Wiegand et al. (2016) and Erfanifard et al. (2019). The function aims to analyze the spatial behavior of identified trees along a given radius (r), with the distribution being classified as regular g(r) < 1, random g(r) = 1 or clustered g(r) > 1of neighboring trees of each individual in the stand (Illian et al. 2008). The *spatstat* package was adopted to analyze spatial data (Baddeley and Turner 2005). The distribution maps of the selected trees were also generated, grouping them by log landing. These maps illustrate the aggregation behavior of each solution and how the occupancy density behaved for each allocated landing subdivided into grids of 22.5×10^3 m². In addition, Eq. 6 (Pereira Júnior et al. 2002) was used to predict the harvesting impacts of canopy damage (y) according to the volume harvested (v_{log}) .

$$y = -0,013 + 0,0048v_{\log} \tag{6}$$

Floristic composition

The methodology to evaluate floristic composition was the M index, which assesses the species diversity of the remaining stand. The Wilcoxon test ($\alpha = 5\%$) checked for statistical equality between the M-indices of the generated solutions. In order to analyze floristic similarity, the individual abundance of selected species for harvest was generated and a cluster analysis employing Ward's method was performed. In addition, the community weighted mean (CWM) index was used to compare changes in stand dynamics (Lin et al. 2015) resulting from the impact of harvesting. This index (CWM) consists of the average of a functional stand characteristic weighted by a factor representing the abundance of the taxa. The functional characteristic used was average wood density, since it makes it possible to quantify the resistance of wood to biotic and abiotic effects, as well as the volume increment of the stem (Chave et al. 2009), being efficient in capturing the variation of biomass under an environmental disturbance (Lin et al. 2015). Basic density was obtained by the BIOMASS package (Réjou-Méchain et al. 2017) and the CWM index by the FD package (Laliberté et al. 2014) in R software, version 3.6.2 (R Core Team 2019). The weighting factor was the total volume obtained from the forest inventory.

Economic ratio

This ratio consisted of the revenue from the harvest and the hauling distance between the trees and their respective log landings. Therefore, the species were classified into high, medium, and low unit price per cubic meter in order to analyze the percentage of harvested trees, DBH and the revenue of the solutions in the classes, in addition to detailing tree frequency, basal area, and revenue of the species. For the D (hauling distance), the drag for each log landing of the solutions was analyzed.

Results

Multi-objective solutions in tree selection

The stochastic method generated 47 local optimum solutions at the end of processing, with a total time of 2.9×10^5 s. This

time includes both processing phases since the duration of the first phase was 1.5×10^5 s and the second, 1.3×10^5 s. The average processing time of the genetic algorithm for log landing allocation was 150 s per evaluation and is directly influenced by the number of chromosomes. The coefficient of variations decomposed objective functions were reduced to below 3.5%, except for the inverse of D (hauling distance) (10.9%). The objective functions from the local optimum solutions were USD $$214.77 \times 10^3 (\pm $7.44 \times 10^3)$ for revenue; USD \$ 121.87×10^3 m (\pm \$13.26 $\times 10^3$ m) for total D; and USD 0.68 (\pm \$0.01) for the S-index. The multiple solutions were graphically represented in two half-planes, allowing an inversely proportional behavior between the revenue and the S-index to be analyzed. The correlation between these two parts of the objective function was -0.93, a significant value (Fig. 3 a-c). This was not observed between the D with the others. When analyzing the solutions that made up the Pareto frontier, pairing the S-index and the economic ratio (revenue/dragging distance), there is a reduction in the economic ratio as the S-index increases, as expected. From the Pareto frontier, α , β and γ for comparative criteria were identified. These solutions were highly correlated between



Fig. 3 Decomposition of the objective function involving the non-dominated solutions establishing the Pareto frontier

the cost functions, allowing the analysis of the inversely proportional behavior between the D and the revenue (-0.87), similar to the revenue and *S*-index (-0.99). This behavior differed between the distance of drag and the S-index, being increasingly influenced (0.81).

The multi-objective function was broken down into economic-ecological values for the analysis (Table 1). It is important to note that the number of trees harvested was constant between the solutions and therefore comparable. Solution α produced the highest harvest volume (3.615.7 m^3) and shortest D (106.5 m), negatively impacting the S index (0.682). The β solution favored the ecological aspects, reducing the harvest by 198.0 m³ compared to the α solution. Due to the selected species/tree changes, revenue was 7.6% lower, further increasing the D by 30.9%. However, there was an improvement in the S-index of 1.6%. The γ solution, being closer to the ideal solution, gave intermediate results from the other solutions. When analyzing the economic bias, there was a reduction in R of 4.1% and an increase in distance of only 2.8%, compared to solution α . As for the ecological bias, there was a reduction of 0.6% of the index obtained in solution β .

Ecological components of the selective logging simulation

Selective impact logging is an effective operation on the forest, depending on the basal area or number of individuals removed. The TM indices, which evaluate the diameter distribution structure of the remaining stand, were statistically different between the α and β solutions by the Wilcoxon test ($\alpha = 5\%$), with γ statistically equal to the other solutions. Thus, there is an expectation that the remaining stand will exhibit a distinct behavior between α and β , with γ being the equilibrium point between the two. Analyzing the values of the Gini coefficients for the solutions, $\alpha = 0.267$, $\beta = 0.280$ and $\gamma = 0.273$. This coefficient evaluates the structural heterogeneity of the remaining forest and is used to verify the post-harvest effect on the stand (Fig. 4). Therefore, β was more heterogeneous than the other values, as it distributed the cut better across diameter classes. One point that stands out is the elimination of the α class above 175 cm, which is not observed in the other solutions.

The spatialization of logging in the area can reflect a number of assumptions. The first is the opening of clearings if there is a point concentration, but still facilitating the

Table 1	Descriptive analysis of the best stochastic solutions	
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Solution	Revenue $(\times 10^3 \text{\$})$	Log skidding dis- tance (×10 ³ m)	Economic ratio	Harvested trees			Sub-indexes*			S-index
				Volume		N	TM	W	M	
				(m ³)	$(m^3 ha^{-1})$					
α	219.1	106.5	2.06	3,615.7	14.2	566	0.202	0.553	0.952	0.682
β	203.4	139.5	1.46	3,417.7	13.4	566	0.211	0.571	0.958	0.693
γ	210.2	109.5	1.92	3,523.9	13.8	566	0.208	0.567	0.955	0.689

*TM: horizontal structure of the forest; W: species diversity analysis; M: spatial distribution of trees



Fig. 4 Diameter distribution of the remaining population (dbh \geq 50 cm) resulting from α , β and γ , represented by **a** boxplot and **b** frequency histogram

allocation of the log landing but damaging the forest. Thus, the values obtained by the W index were $\alpha = 0.438$, $\beta = 0.424$ and $\gamma = 0.423$. Solution α had the highest value, indicating that there was a selection of trees closer to the log landing which enhanced economic aspects. Among the solutions, there was statistical difference only between α and γ in the spatial distribution of harvested trees by the Wilcoxon's test ($\alpha = 5\%$).

There was the possibility to evaluate the pattern (clustered, random, and uniform) in each stand at the tree level. The g(r) test showed that the solutions produced a clustered pattern with a random distribution at small distances, up to 10 m (α), 13 m (β) and 14 m (γ). This behavior was also analyzed in the maps, showing regions with higher harvest intensity, with an average harvest per grid of 51% for all solutions. These distributions were closely related to the W index values, which were greater than 0.4, and classified as a clustered behavior. This behavior can lead to the formation of clearings and consequently ecological disturbances, thus the need to measure this impact. The percentages of canopy damage using reduced impact logging were 6.3% (α), 6.0% (β) , and 6.0% (γ). The percentages of canopy openings of the solutions were close, since the volume harvested per hectare did not show great differences, i.e., 15.9 m³ ha⁻¹ (α), 15.2 $m^{3} ha^{-1} (\beta)$ and 15.2 $m^{3} ha^{-1} (\gamma)$ (Fig. 5).

The diversity of species in the area was represented by the *M* index, which showed a heterogeneous behavior in the floristic aspects of the remaining trees. There was a statistical difference only between α and β by the Wilcoxon test ($\alpha = 5\%$), with γ being equal to the others. However, despite this similarity, γ is closer to β by Ward's dendrogram. This high floristic post-harvest relationship is associated with dominant species and their abundance (Table 2).

These dominant species are almost 45% of the entire forest community. Mean wood density also indicates decreasing values between our simulations ($\beta = 0.609 \text{ g cm}^{-3}$, $\gamma = 0.604 \text{ g cm}^{-3}$, and $\alpha = 0.597 \text{ g cm}^{-3}$). There was a slight superiority of β compared with the unharvested stand (0.607 g cm⁻³). This simulation has focused on smaller trees and more species diversification.

Economic components of the selective logging simulation

Diameters and unit price of the harvested tree directly impacted the final revenue. As a result, it was necessary to analyze the selection of trees generated by the solutions. The solutions showed a similarity of 46.3% of trees selected for harvesting, although there were no trends in prioritizing the harvest in a given price class. The α solution, by producing higher revenue, had a larger percentage of the harvest in the high economic class, as well as higher average DBH in all

price classes. This resulted in the highest economic return. For the β solution, there was less revenue for all classes, which is related to the lower average DBH, and the lower number of trees harvested with the high economic value. Solution γ had greater similarity in frequency of individuals with solution β , differing in the average DBH of the harvested trees with larger diameters. This resulted in revenues to be higher, especially for the medium price class (Table 3).

As shown in Fig. 6, the species with the highest harvest frequency were *Eschweilera odora* (Poepp. ex O. Berg) Miers. ($\alpha = 9.4\%$; $\beta = 8.5\%$; $\gamma = 8.8\%$), Hura crepitans L. $(\alpha = 7.9\%; \beta = 8.8\%; \gamma = 9.9\%)$, Dipteryx odorata (Aubl.) Willd. ($\alpha = 7.8\%$; $\beta = 6.9\%$; $\gamma = 7.4\%$), Apuleia leiocarpa (Vogel) J.F. Macbr. ($\alpha = 6.9\%$; $\beta = 6.9\%$; $\gamma = 5.8\%$), Parkia *nítida* Miq. ($\alpha = 6.5\%$; $\beta = 6.9\%$; $\gamma = 6.7\%$). The species with the highest harvest in area was Hura crepitans L., 44.4 m², 49.0 m² and 50.6 m², representing 14.0%, 17.0% and 17.0% of the total basal area of the α , β and γ solutions, respectively. Dipteryx odorata (Aubl.) Willd. produced higher revenue than the other species, representing 17.0% (solution α), 16.0% (solution β) and 17.0% (solution γ) of the total revenue. The species not harvested by the solutions were Tetragastris altíssima (Aubl.) Swart and Cassia fas*tuosa* Willd. ex Benth., for solutions α and γ , respectively (Fig. 6). Another economic component that influenced the final revenue was the number of log landings and the average skidding distance of each solution. Due to the larger diameters selected by solutions α and γ , it was necessary to create eight log landings, resulting in shorter skidding distances. Solution γ allocated the log landings closest to the trees to be harvested, presenting an average skidding distance of 15.7×10^3 m ($\pm 5.01 \times 10^3$ m). Solution α had an average skidding distance close to solution γ , being 17.8×10^3 m $(\pm 4.08 \times 10^3 \text{ m})$. For solution β , due to the fewer log landings, skidding distances were longer at 25.93×10^3 m $(\pm 12.48 \times 10^3 \text{ m}).$

Discussion

Harvesting in tropical forests is a complex operation and will always result in some damage to the residual stand. The process, if not carefully planned, will enhance these impacts. In addition, the harvesting of rare tree species can endanger their survival and that of fauna that depend on them. In addition, the rational use of this renewable resource allows the local economy to grow, generating income and important taxes. Currently, there are guidelines for reduced impact logging which brings benefits to the remaining stand compared to conventional logging. According to Asner et al. (2004), in a short period of time there are significant differences in canopy closure between the two procedures. Sustainable use of the resource is not the same as with other raw materials



Fig. 5 Spatial harvest analysis of selective logging simulation based on α , β and γ solutions;(— univariate paired correlation g(r), upper and lower confidence limit ($\alpha = 5\%$); ---random behavior

g(r)=1; log landings limit; harvested tree intensity: 0-1 2 trees; 2 -1 4 trees; 4 -1 6 trees; 6 -1 8 trees; 8 -1 10 trees)

objectives by means of specific algorithms (Fotakis et al.

such as metals and petroleum. Timber is renewable as long as it is managed correctly.

A balance between the effects of harvesting and damage to the remaining stand should be the goal of future studies to consider trade-offs between ecological, economic, and climatic aspects (Hiltner et al. 2018). However, management issues with ecological and economic objectives are complex in addressing constraints, often generating inferior solutions when compared to single objectives. Therefore, the use of multi-objective solutions is more advisable in these situations since they aim to meet all conflicting 2012). Numerically, a small positive variation of 0.01 in the S-index was found to cause a decrease in revenue of USD \$ 9,272.40. The α solution selected the largest and most valuable trees, following a clustered pattern. Solution β had a reverse behavior and a smaller number of patios. For solution γ , there was an economic tend towards α due to the selection of larger trees, and an ecological one towards β , corroborated by the similarity of frequency of the harvested species.

 Table 2
 The floristic post-harvest relationship associated with dominant species and their abundance

Scientific name		Abundance				
	<i>α</i> (%)	β (%)	γ(%)			
Hura crepitans Linnaeus	9.9	9.0	7.9			
Eschweilera odora (Poepp. ex O. Berg) Miers	8.3	9.2	8.8			
Castilla ulei Warb	7.1	6.2	6.7			
Parkia nítida Miquel	5.5	5.1	5.3			
Clarisia racemosa Ruiz & Pav	5.5	5.1	5.8			
Brosimum alicastrum Sw	5.1	4.9	4.6			
Apuleia leiocarpa (Vogel) J.F. Macbr	4.9	4.9	6.0			

Due to the combined nature of the problem and the method of solving, numerous solutions can be generated, which also impacts the answers obtained. However, the algorithms implemented in this study are robust and the effects of these differences are associated with the type of solution (α , β or γ). Removing some trees increases solar radiation on the forest floor, as well as water and nutrients. As a result of the increase in these factors, a result of less competition between species, there is a reduction in species diversity (Decocq et al. 2004). They found that aspects of forest management modify the availability of several types of resources simultaneously, and the effect on forest biodiversity is unpredictable.

It is inferred that the natural spatial distribution of trees and species was the main factor influencing the distinct patterns obtained, as well as their biomass. Because of this, an optimizer that allows interaction between ecological and economic aspects, as in the present study, generates a selection of trees in a basic, conscious way, and assists decisionmaking, enabling a scenario analysis, as shown by Kiker et al. (2005) and Santibañez-Aguilar et al. (2011). Selective impact logging does not reduce regeneration but causes an increase in seedling recruitment (Duah-Gyamfi et al. 2014). The concern with not creating major impacts on the remaining stand is still the biggest challenge in the wood processing chain to guarantee future productions.

Among the relevant factors for maximizing harvest profitability is the horizontal structure of the forest since it impacts profitability (Pukkala et al. 2015) and the number of log landings. This can be seen in solution β which had fewer log landings resulting in greater skidding distances. Generally, skid trails in high intensity logging may result in 30%–40% disturbance or damage to remaining trees in tropical forests (Pinard and Putz 1996). This can be attributed to the selection of smaller-sized individuals in order to maximize the S-index.

Another element that must be considered when harvesting is the spatial distribution of the selected trees, as this contributes significantly to the costs, the degree of impact on the environment, creation of clearings, and damage to the remaining trees. Selective impact logging may affect the forest recovery pattern as it modifies the interaction between species, such as competition, composition, and the location of trees (Qi et al. 2016). One such effect is the creation of canopy openings, which several studies have reported its positive effect on the remnant forest (Naaf and Wulf 2007; Torras and Saura 2008; Wang and Liu 2011), increasing richness when compared to a homogeneous understory. This is due to the increased light entering these stands, creating a favorable environment for the development of seedlings from different species. Hall et al. (2003) showed that increased canopy disturbance, if well- planned, can lead to faster stand recovery and enrich the number of high-quality woody species. In the present study, the solutions presented a grouped cutting selection with an average removal of approximately 16 m³ ha⁻¹ and did not report the formation of large clearings since the percentage of canopy removal was less than 7%, with an average of 2.5 tree ha^{-1} . The maximum removal intensity legally allowed is $30 \text{ m}^3 \text{ ha}^{-1}$ (CONAMA 2009).

Variables	Solution	log price classes				
		Low (\leq \$ 50.0 m ⁻³)	Medium (\$ 51.0 m ⁻³ -\$ 75.0 m ⁻³)	High (> $$75.0 \text{ m}^{-3}$)		
Frequency (%)	α	41.3	32.2	26.5		
	β	42.6	32.7	24.7		
	γ	42.7	32.7	24.5		
$\overline{DBH}(cm)^*$	α	85.7 (±27.3)	71.2 (±13.9)	83.29 (±18.7)		
	β	84.3 (±26.8)	69.3 (±12.1)	80.70 (±17.5)		
	γ	84.2 (±27.4)	71.2 (±13.7)	82.16 (±17.8)		
Gross profit ($\$ \times 10^3$)	α	72.3	54.3	92.3		
	β	70.7	52.7	79.9		
	γ	72.0	55.1	83.0		

Table 3 Economic effects of log price classes in α , β and γ solutions



Fig. 6 Set of assigned trees for selective logging considering three solutions (α , β , and γ) and forest attributes (Frequency–absolute number of trees or density, G–basal area per t area, Price–merchantable logs)

The damage caused by falling trees affects the canopy constitutional time, with reduced impact logging resulting in a shorter time for canopy closure when compared to conventional logging (Asner et al. 2004). There is, therefore,

a need to reconcile the techniques used in this study with the methods recommended by reduced impact logging. D'Oliveira and Ribas (2011) recommended a canopy opening percentage of 27% for the Brazilian Amazon, considered ideal in terms of recruitment, species richness, mortality, and density of pioneer species, with an interval of 12 years of regeneration. However, it should be noted that the size of the clearings may result in a monodominance of species (Decocq et al. 2004), impeding pollination between fragile species (Niggemann et al. 2012). In the Amazon rainforest, the blowdown associated with clearings is common and further damages the stand. The creation of large clearings impacts the seed bank and leaves these areas susceptible to other trees falling (Bordon et al. 2019), reducing the living biomass and adding uncertainty to the magnitude if the carbon sink of the Amazon forest (Rifai et al. 2016). In addition, gap formation influences the vegetation arrangement, composition, and diversity within the forest (Marra et al. 2014). The impacts on fauna may be as high as a 50% reduction of mammals and amphibians when logging rates in tropical forests are 38 m³ ha⁻¹ and 63 m³ ha⁻¹, respectively (Burivalova et al. 2014).

The impact analysis focused only on the size of the trees harvested is simplistic, since stands generally show high diversity. When there is no specificity of species, there may be imbalance in the harvest criteria for certain species (Freitas and Pinard 2008). In the solutions obtained in this study, this type of analysis was identified, since the most harvested species were those that had the highest frequency in the initial stand, these being *Eschweilera odora* and *Hura* crepitans. When analyzing the number of individuals within each species with higher harvest, Dipteryx odorata showed a higher cutting rate, 72% (α), 64% (β), and 69% (γ) due to its high economic value. This can also be associated with the grouped behavior of the solutions since they can provide the selection of individuals of higher economic value (Packalen et al. 2020). The trees belonging to the unselected species were low volume and economically unattractive for the α and γ solutions. This situation was not present in β since it harvested at least one individual per species in order to maximize the M index.

In addition to the analysis of the harvested species, it is necessary to evaluate the dynamics of the remaining stand by means of functional characteristics (Hogan et al. 2018). One of these is the basic stand density (Santiago et al. 2004; Chave et al. 2006, 2009; Marin-Spiotta et al. 2007) because it correlates with morphological, mechanical, and ecological properties. This variable has an intrinsic relationship with environmental disturbances, showing a reduction in density as anthropic activities increase (Lin et al. 2015). There is a greater predominance of pioneer species (low density), decreasing regeneration of secondary species (high density) (Hogan et al. 2018). The impact of harvesting on CWM_{WD} (community weighted mean) is shown in the study by Lin et al. (2015), who quantified this variable in a subtropical forest with sites that were unharvested and highly harvested, having a variation of 5.2% (harvested 50 years ago) and 7.8%

(two harvest cycles 30 years ago). This indicates the lengthy period that the forest needs to return to near its natural dynamics. The advantage of using ecological factors in the harvesting plan, such as the one presented in the solutions generated in this study, show that the maximum variation of CWM_{WD} between the three solutions and the initial population was 1.7%, indicating low impact on the dynamics of the remaining stand.

The concepts presented in this study are intrinsically related to reduced impact logging to minimize damage to the remaining stand. Low intensity reduced impact logging is the best way to reduce damage to biodiversity and the carbon cycle (Senior et al. 2018). They also noted that when reducing the harvesting intensity, it is necessary to look for other solutions to supply the high demand for wood without affecting the yields and with low impact on the ecosystem. Thus, an important question arises: to concentrate the cut and open clearings or to spread out the harvesting as much as possible and increase the final cost of the operation? Although this study did not answer this question, it directs indications capable of incorporating ecological conditions in the management of tropical forests, and the solutions presented here met these demands, especially the γ -solution with a balance between economic and ecological characteristics. This point is important as it reflects on the growth of post-harvest remnants (Hogan et al. 2018), the resilience and recoverability of exported biomass (Lin et al. 2015; Prado-Junior et al. 2016), the level of impact on the soil (Asner et al. 2004) and the canopy (Pereira Júnior et al. 2002). Another advantage of this proposed methodology is the flexibility of the algorithm, since the weight associated with this index can be increased or spatial constraints may be used which limit the number of trees extracted in a predefined area (Silva et al. 2018).

Conclusions

The solutions obtained in this study were influenced by the species spatial distribution, with a positive point being the reduction of large clearings since the equilibrium solution presented an ecological aspect close to the solution with the best *S*-index, and an economic aspect close to the solution with the best economic ratio. The *S*-index was efficient as an objective function for selecting trees for harvesting, allowing scenarios to be generated to facilitate decision- making. Thus, this index is recommended as an indicator of anthropogenetic effects on the diversity of forest stands, taking into consideration horizontal and spatial distribution and species richness. Through this study, there is a possibility for future research using simulations of *S*-index weights to evaluate their on tropical forest diversity. Given the methodology presented in this study, the ecological objective provided

complexity in the model; in contrast, the ecological bias solution (β) showed a lighter harvest, reducing the impact on the stand. Our results provide indications of incorporating ecological conditions in the management of tropical forests, and the solutions presented met these demands, especially the γ -solution with a balance between economic and ecological characteristics. In addition, different variables, and methodologies for optimizing forest management challenges can be applied to distinct levels of planning to avoid environmental impacts and make harvesting operations viable.

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