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Optimal Selection of Seed-Trees Using the Multi-Objective NSGA-II Algorithm and a Seed Dispersal Model

Nikos Nanos [1,*], Eduardo Garcia-del-Rey [2] and Luis Gil [3]

[1] Department of Forestry and Natural Environment, Aristotle University of Thessaloniki, 54124 Thessaloniki, Greece
[2] Macaronesian Institute for Field Ornithology, 38001 Santa Cruz de Tenerife, Spain; garciadelreyeduardo@gmail.com
[3] Departamento de Sistemas y Recursos Naturales, Escuela Técnica Superior de Ingenieros de Montes, Forestal y del Medio Natural, Universidad Politécnica de Madrid, 28040 Madrid, Spain; luis.gil@upm.es
* Correspondence: nikosnanos@for.auth.gr; Tel.: +30-231-099-2702

Abstract: Optimal seed-tree selection during natural regeneration of shade-intolerant species requires ensuring an ample and uniform seed supply from residual trees with the smallest possible seed-tree density. Here, we propose a novel approach for seed-tree selection using the genetic algorithm. Data are derived from a 3-hectare even-aged stand of *Pinus canariensis* C.Sm. ex DC, comprising 364 mature trees and 103 seed-traps. Seeds were collected in 2007 and 2008. After constructing a seed-dispersal model for each seed-crop year, we employ the multi-objective non-dominated sorting genetic algorithm to identify the smallest seed-tree set that maximizes post-treatment seed supply and its spatial homogeneity. Optimal solutions range from a maximum of 68.4% to a minimum of 38.1% reduction in stand density, resulting in a 59.5% to 28% reduction in post-felling seed supply. The coefficient of variation of among-site seed-flux varies from 28% to 59.5%. Proposing a treatment involving the removal of 240 trees (65.9% stand-density reduction) and leaving 40 seed-trees per hectare, our findings provide insights into balancing the conflicting objectives of sufficient post-treatment seed supply at a minimum seed-tree density. This approach marks a departure from traditional practices, as the decision about which trees to cut is historically left to the discretion of field managers.

Keywords: forest management planning; optimization; seed-tree

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1. Introduction

Planning final fellings with the double aim to promote natural regeneration and provide revenues to landowners has been a cornerstone of forestry since the inception of the concepts of regulation and even-flow [1]. Indeed, the successful establishment of a new cohort before mature timber is harvested is tied to long-term sustainable yield, a fundamental element in conventional management systems (i.e., those considering sustainability of yield). However, field managers frequently face the challenge of dealing with unsuccessful regeneration after final fellings [2–6]. These challenges not only impose a burden on budgets due to additional planting costs but also prompt transitions to more flexible planning systems that can adjust the duration of the regeneration period in response to delayed establishment of seedlings.

Various factors influence the rate of establishment of a new cohort beneath canopy trees. These factors encompass seed-source and seed-dispersal limitations, seed losses due to predation, availability of safe sites for germination and initial growth, density-dependent mortality, and competitive effects among cohorts [7,8]. Notably, abundant seed supply from mother trees is crucial, as indicated by several studies [9–12].

In even-aged forest management the seed-tree method is frequently used for regeneration of shade-intolerant species. Seed-tree methods are considered when abundant seed supply is needed during the regeneration period while the number of seed-trees is small enough to allow seedlings grow under full sunlight conditions [13]. In these cases operational optimality involves using a strategy to select a small number of seed-trees to achieve sufficient and uniform seed supply over the regeneration area and near-full-light conditions that favor seedling establishment. However, depending on the dispersal ability of the species, seed-supply diminishes as the number of seed-trees is reduced. Therefore, selecting the best seed-tree set may be handled as a problem of optimization with multiple and competitive objectives (sufficient and uniform seed supply vs. minimum number of seed-trees).

Besides being a crucial aspect of planning, the seed-trees selection strategy has often been left to the discretion of field managers that are advised to leave a certain number of seed-trees during marking. Management guidelines usually recommend the selection of a fixed number of seed-trees (see [13] recommending five to seventy seed-trees/ha or [3] recommending leaving more than sixty trees/ha for western larch). Past studies, like [14], have provided numerical solutions for seed-tree problems in specific stands, optimizing various factors such as rotation length, seed-tree number, seed-tree period, and thinnings for maximal land expectation value in a Scandinavian Scots pine stand. Similarly, ref. [15] opted to retain seed trees based on a function of a species' ecological attributes and abundance.

Previous research has predominantly focused on determining the quantity of seed-trees without delving into the considerations of their spatial distribution, although most specialists recognize that the number and distribution of seed-trees should be decided based on the seed dispersal pattern of the focal species [13]. However, the seed-supply from seed-trees can be estimated via seed dispersal models [16,17]. These models are composed of two critical components: one dedicated to assessing the fecundity of mature trees and another focused on predicting random seed dispersal distances [18–20]. Today, in the realm of forest management planning, these models enable professionals to make informed decisions with minimal data, accurately forecasting seed supply in a given area. This knowledge is instrumental in optimizing forest management, and especially, habitat restoration [21], climate-adapted plans of action [22], or the optimal design of natural regeneration treatments [23]. Especially for planning natural regeneration of mature even-aged stands, the use of seed dispersal models may assist field managers to predict seed-supply after regeneration treatments, including seed-tree methods, strip-cutting or shelterwood.

In addition, multiple-criteria decision-making (MCDM, [24]) is now widely used at both the stand- and tree-level to guide decision making in forest management [25]. Previously published experiences on the use of MCDM at tree-level planning include the selection of trees in thinning treatments according to economic [26,27], protective [28], and spatial goals [29], or the optimal allocation of small-area treatment units in group-selections systems [30]. While many methodological approaches to MCDM have been used in tree-level operational planning, the problem with which we are faced calls for a method that can provide multiple candidate solutions to be evaluated by the field-manager at all levels of stand-density reduction (divergence of solutions). Genetic algorithms (GA) introduced in multi-objective optimization in 1993 by [31] are well suited for finding optimal solution-sets that involve several conflicting objectives and accounting, in cases, for integer (including binary) decision variables. The non-dominated sorting genetic algorithm (NSGA-II) [32], combining an effective elitism operator and acceptable divergence of solutions is among the most popular methods [33,34]. This algorithm has been used previously for seeking optimal planning in forest management at all levels of planning [35–37].

In this study we use data from a mature, even-aged, stand of Canary Islands pine in Tenerife (*Pinus canariensis* C.Sm. ex DC). Our objective is threefold: (i) to develop a methodology for identifying the minimum number of seed trees necessary to sustain a sufficient and uniform seed supply across the regeneration area during the regeneration period, (ii) to validate the effectiveness of this methodology through empirical testing and assessment, and (iii) to evaluate the potential of the methodology to provide data-driven assistance to field managers in their decision-making processes, presenting an alternative to traditional empirically-derived cutting schemes. The primary novelty of this article lies in its use of a genetic algorithm to select seed trees based on their predicted capacity to maintain a spatially and temporally homogeneous seed supply.

2. Materials and Methods

2.1. The Data-Set

We utilized an existing dataset obtained from a mature, even-aged stand of Canary Islands pine located on the island of Tenerife (refer to [38,39] for details). The climate in this region is Mediterranean, characterized by an average annual temperature of 12.6 °C and annual precipitation levels ranging from 460 to 930 mm [40]. The stand covers an area of 3 hectares and is situated in the northeastern part of Tenerife. All trees within the stand were identified and mapped using a total station, with their diameter at breast height (DBH) recorded. Additionally, ten percent of the trees were randomly selected for height measurements. To assess seed production and dispersal, we installed 103 circular seed traps measuring 55 cm in diameter beneath canopy trees, which were monitored over the years 2007 and 2008 (refer to Figure 1).

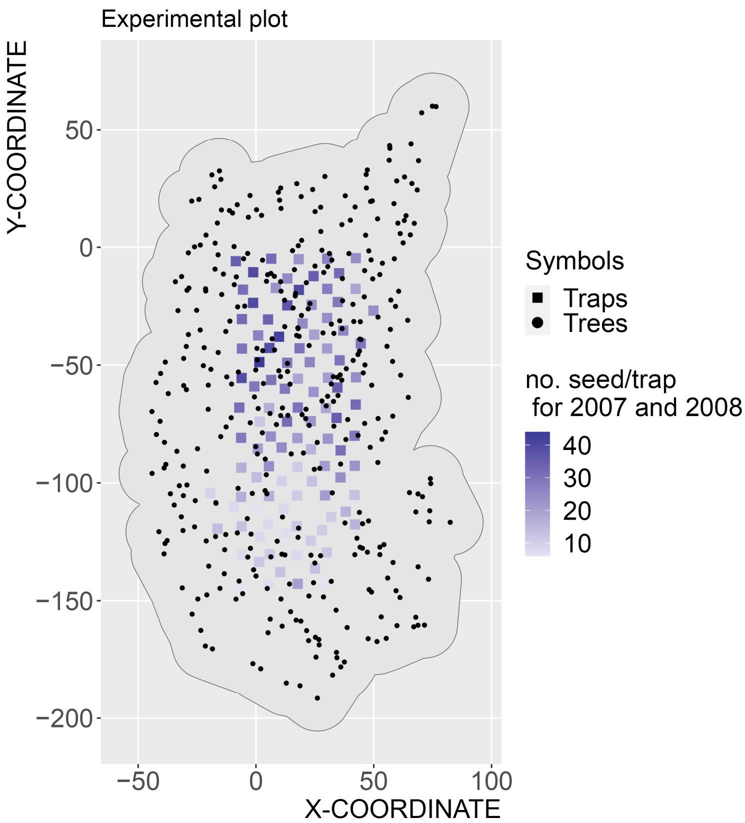


Figure 1. Experimental plot in Tenerife showing the position of 364 adult trees and 103 traps. The color scale for seed traps shows the number of seeds captured during the 2-year seed-collection period (i.e., 2007 and 2008).

2.2. Seed Dispersal Modeling

We used the methods described in [16,18] to model seed dispersal. According to this approach, we assumed that seeds are randomly distributed around parent trees according to a density function $f(r;\ p_1, p_2)$ of the random dispersal distance r, where p_1 is the scale parameter and p_2 is the shape parameter of f. In addition, we assumed that the number of seeds produced by the i-th tree (i = 1, . . ., N) during one year is estimated using the allometric equation $S_i = p_3 BA_i$, where BA_i is the basal area of tree i, S_i is the estimated number of seed produced by tree i during the specific year and p_3 is the unknown fecundity parameter. Note that, using this model formulation, the number of seeds (λ_j) arriving at site j ($j = 1, \ldots, M$) during a specific year is estimated as (see [20] for details):

$$\lambda_j = A\sum\nolimits_{i=1}^{N} \frac{S_i f\left(r_{ij}; p_1, p_2\right)}{2\pi r_{ij}} \tag{1}$$

with A being the surface area of microsite j, and r_{ij} the distance between the i-th tree and the j-th microsite (all other symbols as defined previously).

We used maximum likelihood to estimate the three unknown parameters (p_1, p_2, p_3) of the tested models after assuming a Poisson distribution for the random seed number in traps (see [18] for details). Given that the specific form of f may vary across years, we fitted seven density functions to seed-count data for each year of study. The functions used for this reason were the following: lognormal, Gamma, 2Dt, Weibull, Wald, and geometric (see [41] for the mathematical form of these models). The best out of seven tested density functions was selected using the log likelihood value and the associated Akaike's information criterion (AIC). Goodness-of-fit of the selected models was assessed using the correlation coefficient between real and estimated seed counts in 103 traps as well as several error indices such as the mean square error or the mean absolute error. Parameter estimates were obtained using the 'maxLik' library of R [42].

2.3. Optimization

The selection of seed-trees was formulated as an n-dimensional decision variable vector x_i = {x_1, ..., x_N}, with N being the total number of trees in the stand. Decision variables were binary-coded so that when the i-th tree is marked for cutting then x_i = 1, and x_i = 0 otherwise. The optimization was structured to seek solutions that minimize the following:

1. The relative number of seed-trees (Objective 1),
2. The post-treatment relative seed-crop loss (Objective 2), and
3. The post-treatment coefficient of variation in seed arrival across microsites (Objective 3).

2.3.1. Formulating the First Objective

The first optimization objective, the relative number of seed-trees, is written as:

$$obj.1 = 100\left(1 - \frac{\sum_{i=1}^{N} x_i}{\mathrm{N}}\right), \tag{2}$$

using the notation defined previously.

2.3.2. Formulating the Second Objective

Within the stand, we designated a total of 1933 microsites located at the nodes of a 4 m by 4 m regular grid. Each microsite encompassed an area of 1 square meter. Then we estimated the expected number of seeds landing on each microsite (λ_j), for each year of study, using Equation (1) (i.e., the expected seed arrival rate before the treatment). Note that after removing a mature tree from the stand, the number of seeds arriving at microsite j is reduced at a rate that depends on both the distance separating site j from the removed tree and, also, the fecundity of the marked tree. Thus, after removal of $\sum_{i=1}^{N} x_i$ trees, the number of seeds arriving at site j $\left(\lambda_j^*\right)$ is estimated as $\lambda_j^* = \sum_{i=1}^{N} (1 - x_i)\lambda_j$ and the relative seed-crop loss due to felling for a specific year is estimated as (using the notation defined previously):

$$\frac{1}{M}\sum\nolimits_{j=1}^{M}\left[100\left(1 - \frac{\lambda_j^*}{\lambda_j}\right)\right] \tag{3}$$

If seed counts from multiple years are accessible, Equation (3) needs to be adjusted to incorporate inter-annual variation. By letting t designate the seed-crop year (t = 1, . . ., T) the optimization objective is to minimize the inter-annual average of seed-crop loss over the years. Hence, the second optimization objective is formulated as follows:

$$obj.2 = \frac{1}{T}\frac{1}{M}\sum_{t=1}^{T}\sum_{j=1}^{M}\left[100\left(1-\frac{\lambda_{jt}^{*}}{\lambda_{jt}}\right)\right] \quad (4)$$

with λ_{jt}^{*} and λ_{jt} being the expected number of seeds arriving at site j during year t for the residual and for the uncut stand, respectively, with all other symbols defined as previously.

2.3.3. Formulating the Third Objective

To ensure that seed-tree selection minimizes variations in seed arrival among M sites, we introduced a third objective, aimed at minimizing the coefficient of variation of seed arrival across M sites and T years:

$$obj.3 = \frac{1}{\mathrm{T}}\sum_{t=1}^{T}\frac{s_t}{m_t}. \quad (5)$$

Here, s_t and m_t represent the t-th year's standard deviation of λ_j^* and the mean of λ_j^*, respectively, with all other symbols defined as previously.

2.3.4. NSGA-II Implementation

The pursuit of the optimal solution was guided by the NSGA-II algorithm, employing a population size of 1000 individuals across 100 generations [32]. Mutation and crossover parameters were fine-tuned after a trial and error procedure. We relied in the "nsga2" function of the "rmoo" R-package for the optimization [43].

Selection of the best solution was informed by both empirical evaluation of the stand conditions and a comprehensive examination of the 1000 solutions from the final generation. More specifically, our assessment included the evaluation of the stand's orientation and slope that may increase not only seedling susceptibility to dry conditions but also the risk of post-cutting soil erosion. For evaluating the set of solutions, we compared them against the Pareto-optimal sets for each pair of objectives.

3. Results

The forest stand exhibits a density of ca. 117 stems/ha, a basal area of 25.8 m^2/ha, and a standing volume of 168.7 m^3/ha. Notwithstanding, density conditions varying from 0 to 350 trees/ha (computed using 10 m radius circular support) are far from being considered homogeneous. The average tree DBH was ca. 51 cm and the average tree height was ca. 27 m. Within the stand, the dominant orientations are south and south-east and the slope varies locally from 0% to 110%, lying predominantly in the 40%–45% range. Understory vegetation is scarce but seedlings of *P. canariensis* have been recorded in varying densities (see [38] for details).

3.1. Seed-Dispersal Modeling

Over the two-year seed-collection period, we captured 22.2 seeds/trap on average (range: 6 to 44 seeds). However, the average number of seeds/trap was higher in 2007 (13.11) than in 2008 (9.07).

Among the assessed dispersal kernels, the lognormal and the Weibull kernel outperformed others for years 2007 and 2008, respectively, according to the log likelihood and the AIC criteria (see Table 1). Additionally, these models demonstrated favorable goodness-of-fit statistics, as indicated by the correlation coefficient between observed and estimated seed counts in seed-traps as well as for other error indices (Table 1). Thus, the lognormal kernel (for year 2007) and the Weibull kernel (for year 2008) were used for the following optimization.

Table 1. Goodness-of-fit statistics and parameter estimates for seven seed-dispersal models during years 2007 and 2008. The best fit was decided according to the log likelihood value. The best models for 2007 and 2008 were the lognormal and the Weibull, respectively (in bold).

Year	Model	Lklhd	AIC	r	Maes	Merr	MSerr	p1	p2	p3
2007	**Lognormal**	**−344.035**	**694.070**	**0.484**	**4.462**	**0.00065**	**29.293**	**2.94**	**0.87**	**17,113.3**
	Gamma	−344.129	694.259	0.486	4.460	0.00010	29.261	8.26	2.43	16,079.5
	2Dt	−344.289	694.578	0.486	4.461	−0.00071	29.289	30.35	3.40	16,210.1
	Weibull	−344.421	694.842	0.483	4.466	0.00011	29.317	21.52	1.87	15,952.0
	Wald	−344.480	694.960	0.466	4.481	−0.00091	29.468	39.60	20.97	18,560.5
	Geometric	−344.563	695.126	0.489	4.464	0.00019	29.350	149,690	13,106	16,458.0
2008	**Weibull**	**−329.581**	**665.162**	**0.467**	**3.676**	**0.00036**	**21.666**	**21.84**	**1.56**	**11,150.5**
	Gamma	−329.706	665.412	0.458	3.685	0.00047	21.703	10.55	1.89	11,190.5
	Geometric	−329.748	665.497	0.457	3.689	−0.00054	21.720	60,276	6269	11,125.1
	Lognormal	−330.214	666.427	0.441	3.707	0.00089	21.835	2.82	0.93	11,719.3
	Wald	−330.894	667.788	0.428	3.755	−0.00434	21.997	23.43	23.00	11,482.0
	2Dt	−330.990	667.980	0.485	3.695	0.00090	21.915	1,947.01	6,597	11,147.5

Lklhd: log likelihood at maximum; r: correlation coefficient between observed and predicted counts in seed traps; Maes: mean absolute error; Merr: mean error; MSerr: mean square error; p1 and p2: scale and shape parameter, respectively, of the seed-dispersal density function (see Equation (1)); p3: fecundity parameter of the seed-dispersal model.

The seed dispersal kernels shown in Figure 2a,b for years 2007 and 2008 illustrate the estimated numbers of seeds dispersed from an average-fecundity tree. Highest seed-dispersal rates (more than 4 seeds/m^2) are expected in the proximity of mother trees during year 2008. Noticeably, the maximum estimated number of seeds/m^2 is larger for year 2008, besides being a year of lower total seed-production, due to interannual variation in seed-dispersal. In addition, seed arrival at a rate of 1 seed/m^2-year is expected at distances of ca. 15 m and 13 m from the seed source tree for years 2007 and 2008, respectively.

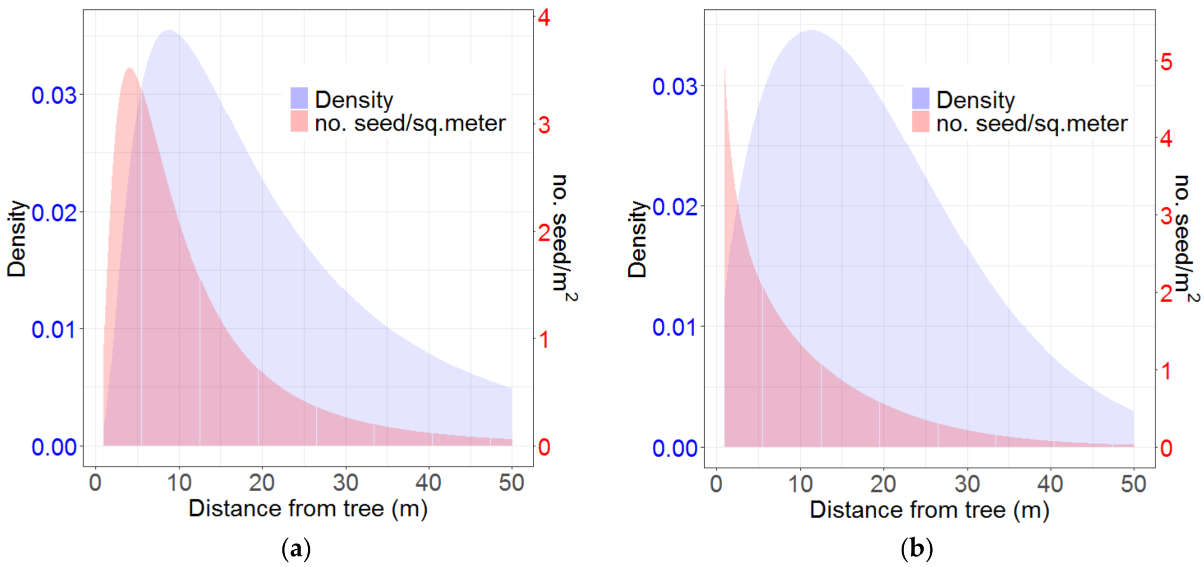


Figure 2. Best seed dispersal kernels (red) and probability densities (blue) for the random dispersal distance. (**a**) Seed crop of 2007; (**b**) Seed-crop of 2008.

3.2. Optimization

In the optimization process, the last generation's population featured 1000 solutions with seed-tree density ranging from 31.6% to 61.8% relative to the pre-treatment density

(Figure 3a). Seed-losses due to density reduction varied from 28% to 59.6% relative to the pre-treatment seed-arrival (Figure 3b) while the post-treatment coefficient of variation in seed supply across microsites ranged from 26.7% to 33.9% (Figure 3c).

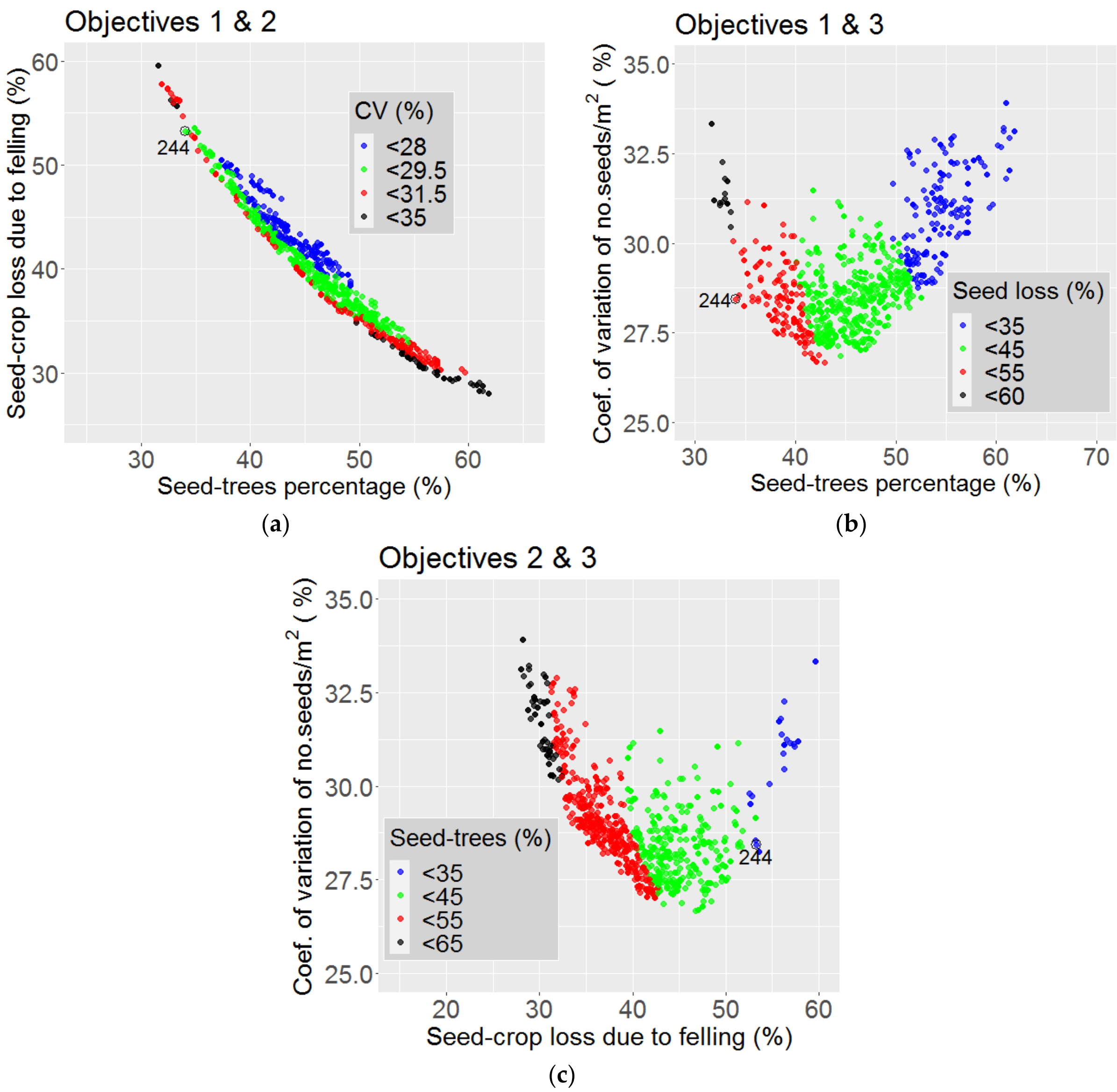


Figure 3. Set of NSGA-II last generation's solutions in the objectives' space. (**a**) Objectives 1–2; (**b**) Objectives 1–3; (**c**) Objectives 2–3. The proposed solution no. 244 is highlighted.

Solutions overlaid on the first- and the second-objective plane were concentrated near the Pareto optimal front (Figure 3a). However, as shown in Figure 3a, solutions near or on the Pareto front are characterized by higher-than-average CVs. Thus, optimal solutions for the first set of objectives are suboptimal for the third-objective. In addition, solutions close to the Pareto front of Figure 3b, which minimize seed-trees and the post-treatment CV are only seen for seed-trees percentage smaller than ca. 45%. Finally, solutions overlaid on the second- and third-objective space that were located close to the Pareto front (Figure 3c), are only seen for seed-tree percentages larger than ca. 55%. In conclusion, trade-offs among the objectives are non-negligible and complicate decision-making.

After manual inspection of trade-offs among the three objectives and in situ knowledge of the stand we decided that the best solution for this stand was a solution with ID 244 (Figures 3–5). The proposed operation is Pareto-optimal for pairs of objectives 1–2 and 1–3, but suboptimal for pair 2–3. Should this operation be adopted, then 240 trees should be marked for cutting (66% reduction of stand density) leaving 124 seed-trees (40 trees/ha). The average DBH of marked trees is 47.7 cm, approximately 10 cm smaller than the average diameter of seed-trees (58.5 cm). The basal area of the stand after this operation is reduced to 11.2 m^2/ha (57% reduction). The spatial distribution of seed trees is shown in Figure 4b (and also in Figure 5b).

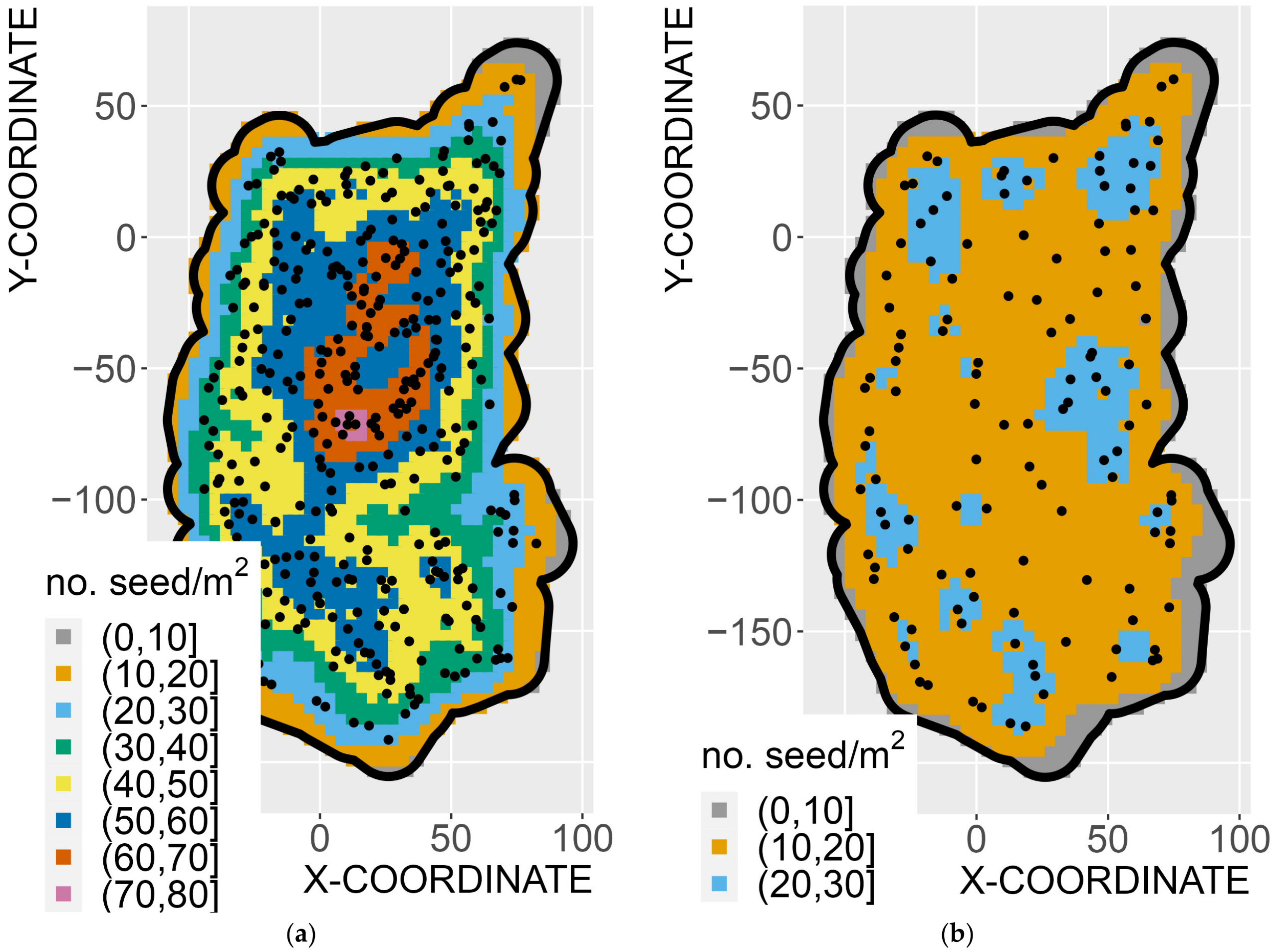
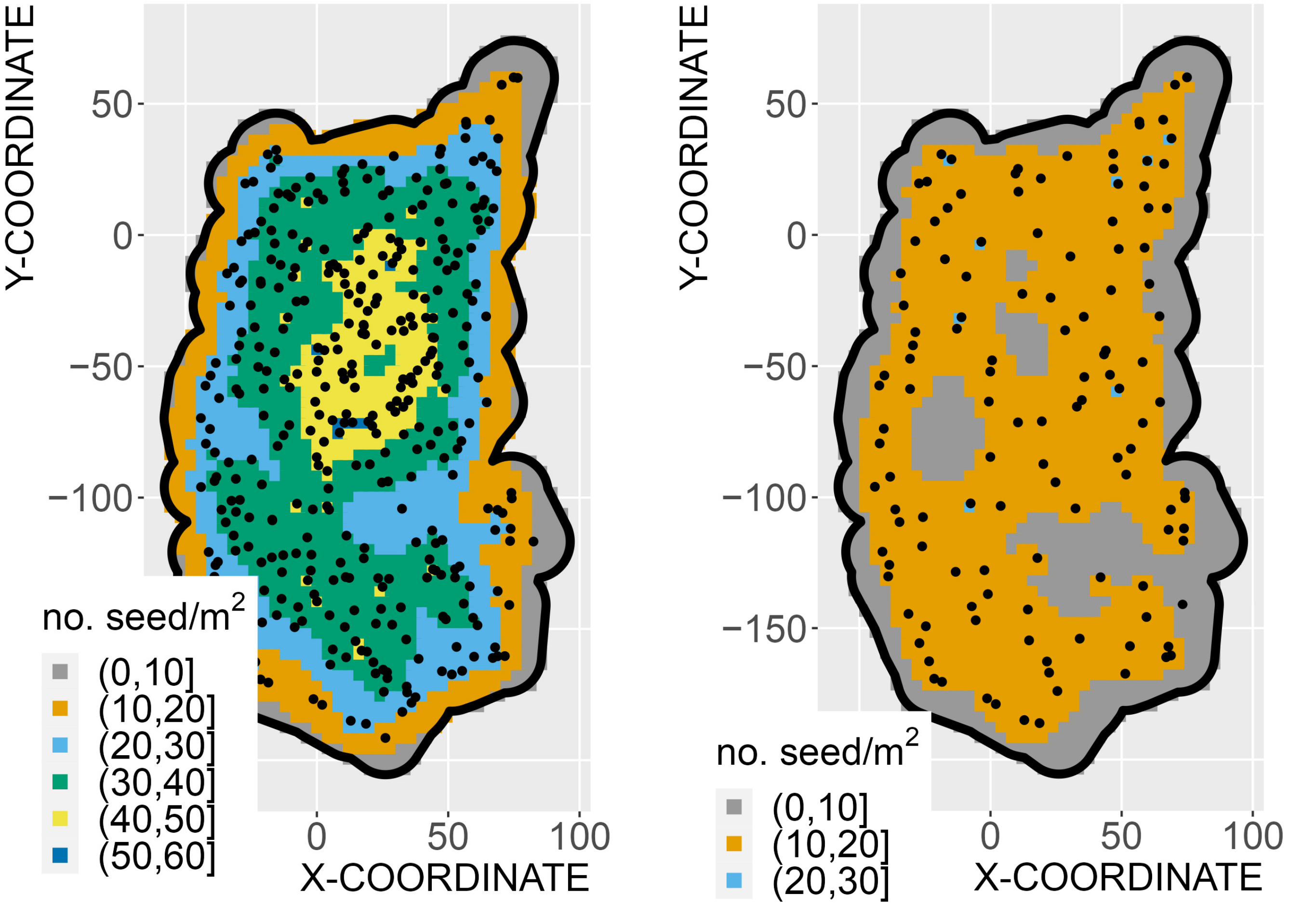


Figure 4. Seed-tree selection in the experimental plot of Tenerife. (**a**) Estimated seed dispersal for year 2007 and trees (black dots); (**b**) Estimated seed dispersal and selected seed-trees (black dots) according to the proposed solution with ID number 244 (see also Figure 3).

The proposed operation will decrease the average seed-supply rate at microsites to approximately 16 seeds/m^2 for 2007, representing a relative reduction to 53.71%, with 88.4% of microsites receiving more than 10 seeds/m^2 (refer to Figure 4). Similarly, for 2008, the operation is expected to lower the average seed-supply rate to around 11 seeds/m^2 or, in relative terms, to 52.83%, with 66.2% of microsites receiving more than 10 seeds/m^2 (refer to Figure 5). Notably, seed supply from seed-trees remains relatively consistent across microsites, with a cross-years average CV of 28.4% (27.5% for year 2007 and 29.4% for year 2008). This CV value corresponds to the 40th percentile of the last generation's population.



(**a**) (**b**)

Figure 5. Seed-tree selection in the experimental plot of Tenerife. (**a**) Estimated seed dispersal for year 2008 and trees (black dots); (**b**) Estimated seed dispersal and selected seed-trees (black dots) according to the proposed solution with ID number 244 (see also Figure 3).

4. Discussion

In the context of natural regeneration planning for even-aged stands, the seed-tree method is often employed to provide an abundant seed supply during the regeneration period while allowing seedlings to grow under conditions that closely resemble those generated after clearcuts [13]. The primary challenge in the seed-tree method lies in the selection of seed-trees, which must be balanced to achieve sufficient and homogeneous post-treatment seed supply over the regeneration area while minimizing seed-tree density [13]. Previous research, however, has neglected to consider post-treatment seed dispersal in the planning process (see, for instance, [44–46]) making this study the first to address this gap in the literature. Contrary to previous practices that rely on un-informed field managers' decisions, in this study, we addressed the seed-tree selection problem as a multi-objective optimization task, utilizing the NSGA-II algorithm [47]. By incorporating multiple objectives such as the total number of seed-trees, seed supply from these trees, and the spatial homogeneity of seed arrival, our approach aimed to pinpoint a range of near-optimal solutions, offering valuable guidance for field managers. Hence this method reduces the burden of responsibility on field managers and mitigates the risks associated with visual assessments of the stand before marking trees for cutting. To accurately predict seed supply from mother trees, we incorporated seed dispersal models into our methodology as suggested by [23]. These models, comprising both fecundity estimation of mature trees and seed dispersal kernels, offered a comprehensive quantification of key ecological processes influencing regeneration of Canary islands pine.

In the studied stand, we observed clear trade-offs among competing objectives, leading us to identify the most favorable alternative considering these trade-offs. Specifically, it became apparent that maximizing all three objectives simultaneously was unattainable, as the Pareto optimal solutions for one pair of objectives were often suboptimal for the third objective. Consequently, based on the optimization results, our decision was to prioritize the most crucial objectives—minimizing seed loss and maximizing the number of trees marked—while accepting a compromise on the third objective, the coefficient of variation (CV) of seed arrival. This approach, led us to propose a solution (ID 244), that entails a reduction of stand density by 66%, resulting in 40 seed-trees per hectare. The proposed treatment is anticipated to significantly decrease seed-tree density while maintaining an average post-treatment seed supply of approximately 16 seeds/m^2 for 2007 and 11 seeds/m^2 for 2008, with suboptimal but satisfactory levels of spatial homogeneity. Consequently, our findings support the utility of this method for forest managers in navigating trade-offs among competing objectives, thereby offering valuable support for the decision-making process.

In our approach to selecting a solution from the pool of 1000 generated by the NSGA-II algorithm, we opted for an empirical method. The decision-making process involved a series of practical considerations. For example, solutions proposing a reduction in stand density lower than 60% were initially rejected, adhering to the core principles of the seed -tree method and the ecology and management guidelines for this species, which requires a decrease of ca. 70% in stand density for effective regeneration [48]. Subsequently, from the subset of solutions, empirical judgment was applied by choosing solutions situated along the Pareto front for the pairs of objectives 1 and 2, as well as 1 and 3. This empirical selection aimed to strike a balance between minimizing seed-tree density and maximizing post-treatment seed supply and spatial homogeneity. While our empirical approach proved effective in this instance, it is acknowledged that alternative methods, including the e-constraint method, can be employed for a more systematic and quantitative decision-making process in future applications [49].

Only a few studies have considered the optimal number of seed-trees to leave and in their vast majority they focused on the economic optimization [14,50]. The study by [14] on Swedish *Pinus sylvestris*, for instance, considers, among others, optimal seed-tree number to maximize profits. However, as the same authors highlight, the estimated number of seedlings produced from seed-trees is highly variable and the net present values of the operation may be underestimated. Additionally, in the dry environment where we are working, operational planning should first consider ecological factors that maximize the probability of operational success rather than maximizing the expected profit of the operation [5].

The proposed methodology offers significant advantages, particularly in the estimation of timber volume to be obtained from regeneration cuttings [1]. Traditionally, in Spain, forest managers have relied on empirical approaches to estimate the timber volume to be cut from a management block during a planning period, typically spanning ten years [51]. This empirical method often introduces uncertainties and potential underestimations. In contrast, using our optimization method, integrated with seed dispersal models, introduces a systematic and data-driven approach to enhance the precision of volume estimation from final fellings. This shift from empirical to model-based estimation not only improves accuracy but also aligns with Spain's management guidelines, ensuring that volume estimations are in harmony with ecological and management goals.

The generalizability of our results, however, warrants consideration within the broader context of even-aged forest management, particularly for shade-intolerant species. While our study focuses on a specific stand of *Pinus canariensis* in Tenerife, the methodology we employed provides a framework applicable to similar forest ecosystems. However, it is crucial to acknowledge the potential effect of other site-specific factors, such as topography, climate, and species traits, on the regeneration success [52–54].

While the proposed methodology offers valuable insights into optimal seed-tree selection, it is crucial to acknowledge inherent limitations and challenges. A significant constraint lies in the uncertainty associated with seed dispersal estimation [16,55]. Notably, [38], conducting research in the same stand, proposed a different dispersal model utilizing genetic markers for mother tree identification, while, even in our study there were other alternative models, such as the Gamma, that could have been used for modeling. Furthermore, despite employing an extensive seed monitoring network with 103 seed traps over two study years, the inherent variability in seed set due to masting events [56] and climate conditions [57] introduces uncertainties into the optimal selection of seed-trees. Additionally, the impact of stand density reduction on adult fecundity and dispersal, a crucial factor influencing post-treatment seed dispersal, remains uncertain and should be studied further [58]. Moreover, our methodology could be further refined by incorporating effective seed dispersal in the planning process (i.e., secondary dispersal and germination, see [59] for instance). Finally, extrapolating our method to other stands within the same forest presents challenges. This process is not straightforward and may be deemed counterproductive, requiring meticulous tree mapping and additional data on seed collection. While tree mapping can be facilitated by light detection and ranging (LIDAR) data acquisition [60,61], obtaining comprehensive seed collection data demands additional investments in research.

5. Conclusions

The proposed method represents a novel data-driven approach aimed at ensuring sufficient and homogeneous seed supply in the years following cuttings, thereby mitigating the risk of regeneration failure. This approach provides an alternative to traditional decision-making practices that rely solely on expert judgment, offering a more objective and evidence-based planning framework. The method can be utilized to identify the trade-offs between maximizing the number of trees marked, while minimizing seed-crop loss and the inhomogeneity of seed arrival over the area to be regenerated, ultimately supporting decision-making processes. However, it is essential to acknowledge the uncertainties inherent in model assumptions and estimation procedures, which may affect the reliability of the method. Moreover, implementing this approach at a whole-forest scale would necessitate significant investment in monitoring seed dispersal over large areas. Despite these challenges, the proposed method represents a promising advancement in regeneration planning efforts for forest management.

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