Annals of Forest Science (2012) 69:235–243
DOI 10.1007/s13595-011-0155-2

ORIGINAL PAPER

Reconstructing harvesting diameter distribution from aggregate data

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Received: 12 October 2011 / Accepted: 25 October 2011 / Published online: 1 December 2011

Abstract
• ***Context*** Distribution of removed trees among species and diameter classes is usually used to characterize selection harvesting. This information is, however, rarely available when analysing past time series. The challenge is then to determine the minimal level of information required to characterize harvests.
• ***Aims*** We tested in this work whether an algorithm based on the total number of trees and volume to be removed enabled the reconstruction of harvesting diameter distributions, when combined with stand diameter distribution before harvest.
• ***Methods*** We tested the algorithm against empirical data in the case of selection system, comparing distributions by χ^2 tests, and extended its evaluation to more diversified theoretical situations.
• ***Results*** Observed harvesting distributions were well-reconstructed in most empirical cases, with better results when considering mean simulated distributions. The algorithm was also effective for other thinning and harvesting strategies: low thinning, thinning of dominants, and mechanical thinning, whatever the structure of the stand before being cut.
• ***Conclusion*** Total number of trees and volume harvested appeared thus sufficient to reconstruct DBH distribution of removed trees in diverse situations, provided that the distribution before harvest was known. This algorithm, therefore, enables the simulation of complex harvesting operations with minimal information.

Keywords Silviculture · Uneven-aged selection forest · Thinning and harvesting algorithm · Diameter distribution · Forest dynamics modeling

1 Introduction

Greater social expectations in relation to sustainable management and protection of biodiversity require evaluation of forest management practices and development of new silviculture strategies. Simulation experiments using forest dynamics models then have a key role to play, as they do not require long time periods, as field experimentation does (Peng, 2000; Goreaud et al. 2005; Pretzsch et al. 2008). Accurate characterization of thinning and harvesting operations is critical to the analysis and reproduction of silviculture strategies in the context of silviculture evaluation (Söderbergh and Ledermann, 2003), whether it is based on past silviculture analysis, field or simulation experiments, as well as for management guidelines and instructions (Gauquelin and Courbaud, 2006). In uneven-aged selection harvesting, the number of trees to remove per species and their distribution per category of diameter at breast height (DBH) give a rather accurate description of harvesting operations at the stand scale. It may be completed by a description of the spatial pattern of harvests. Many recent thinning and harvesting algorithms use this information to accurately formalise and automate management operations within simulation models

Handling Editor: Daniel Auclair

Contribution of the co-authors V. Lafond carried out the study and wrote this paper, under supervision of T. Cordonnier and B. Courbaud (who is also the coordinator of the BGF project). They contributed to experiment designs, writing, and multiple revisions. F. de Coligny helped to program the algorithm, and implemented it in the Capsis4 simulation platform.

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(Daume and Robertson, 2000; Söderbergh and Ledermann, 2003; Arii et al. 2008). Characterizing cutting operations with such details is nevertheless not always possible or even appropriate in practice. In the context of silviculture guidelines, excessively complex instructions lead to multiple variants which are difficult to adapt to the real nature of the field. Moreover, practical feasibility limits the number of modalities one can test during field or simulation experiments. The challenge is then to characterize uneven-aged selection harvesting simply enough for practical use, but with enough detail to ensure its reproducibility: repeated applications of an instruction should lead to similar harvests, and have similar effects on residual stand structure.

Furthermore, one step of forest dynamics simulation model evaluation relies on confronting model prediction to empirical data (Vanclay and Skovsgaard, 1997; Busing and Mailly, 2004; Mette et al. 2009). One possible way is to simulate the dynamics of a forest, whose initial state and management history are known, and then compare predicted stand structure and composition to field observations. Yet, when reconstructing past management, long-term records are often restricted to aggregate harvesting characteristics, for instance total number of trees and volume harvested per hectare. These two attributes have been recorded at the compartment scale for about 1 century in most forests managed by the French Forest National Office (ONF). These management data are less informative than the detail of the number of trees harvested per DBH class, information generally recorded on permanent observation plots only, but management time series are usually longer than permanent plot data and cover wider ecological and management situations. Management data would then be extremely valuable to analyse past silviculture and test simulation models, provided that they are sufficient to describe unambiguously thinning and harvesting strategies. In the particular context of the evaluation of a mountain forests simulation model developed by Cemagref (Courbaud et al. 2001; Cordonnier et al. 2008), few permanent plots were available for French northern Alps, and using ONF's records to reconstruct past management operations appeared to be a necessary issue.

Our objective in this study was to test whether a very simple description of harvest, given by the total number of trees and volume to be removed, was sufficient to mimic different harvesting operations, especially in an uneven-aged selection harvesting system. We hypothesised that combining a total number of trees to be removed, a corresponding total volume, and a DBH distribution before harvest would lead to a small number of possible DBH distributions of trees to be removed. We formalised the marking process into a silviculture algorithm, and tested its ability to reconstruct DBH distribution of thinning and harvesting operations in both empirical and theoretical cases. We first tested this algorithm against empirical data, using a method based on multiple Pearson χ^2 tests (Pearson 1900) to compare predicted and observed harvesting DBH distributions, and thus to study its adaptability, variability, and performance. We then extended its evaluation to more diversified cases by controlling both stand DBH distribution before cut and thinning and/or harvesting strategy.

2 Materials and methods

2.1 Presentation of the algorithm

We developed a simple algorithm to reconstruct diameter distribution of selection harvesting from an initial ("before cut") diameter distribution and aggregate information on the harvest to be reproduced, namely the number of trees (N, t/ha) and the total volume (V, m^3/ha) to be removed. A list of trees is created from the initial diameter distribution, and contains only trees with DBH larger than a given threshold (10 cm here). The algorithm consist in randomly exchanging the target number of trees (N) from the initial list of trees, then iteratively exchanging random pairs of "selected" vs "unselected" trees to converge towards the target volume (V) to be removed. At each step, the exchange is done only if the new volume gets closer to the target one; otherwise, the algorithm selects another pair. The algorithm stops when the predicted volume equals the target volume, more or less 1 percent.

2.2 Algorithm evaluation against empirical data

2.2.1 Empirical data

We first evaluated the capacity of the algorithm to reconstruct empirical DBH distribution of selection harvesting in an uneven-aged stand. Our validation set of data consisted in individual tree monitoring of a spruce-fir permanent forest plot located in the Rougemont forest in Switzerland, monitored by the Swiss Federal Institute for Forest, Snow and Landscape Research (WSL). This stand of about 2 hectares is managed as uneven-aged selection forest, and belongs to *Aceri-Fagetum rumicetosum* and *–prenanthetosum* and to *Asplenio-Piceetum* (Wehrli et al. 2005). The dataset reports twelve harvests from 1932 to 2003, covering a wide range of characteristics with regard to the number of trees and volume removed (Table 1) or the shape of the harvesting DBH distribution (Fig. 1).

2.2.2 Evaluation method

We based our evaluation on three complementary criteria: first the ability for the algorithm to converge, second the variability among replications, and third the similarity between predicted

Table 1 Global characteristics and DBH distribution of observed and predicted harvests. The observed number of trees (N_o) and total volume (V_o) removed for each of the twelve empirical harvests to be simulated were used as inputs for the algorithm. N_o was rounded because the algorithm only accepts integers as target number of trees. For each harvest, the algorithm removed N_s=N_o trees and V_s=V_o (1± 0.01) for each of the 5,000 runs. Similarity between simulated and observed harvesting DBH distributions was assessed by Pearson's χ² test, through mean χ² and percentage of simulated distributions replications deemed similar to the observed one. Distances between observed and mean predicted distributions were also assessed by χ². Observed and predicted DBH distributions were deemed "identical" for mean χ² below 7.81 and at least 75% of identical distributions

Date	Before cut		Observed cut		Simulated cut		Pearson's χ²		
	N_b (t/ha)	V_b (m^3/ha)	N_o (t/ha)	V_o (m^3/ha)	V_s (m^3/ha)		Mean χ²	% similar distributions	χ² of mean distribution
					Mean	*Sd*			
1932	491	347.73	55	34.16	34.17	0.20	3.64	90.68%	1.70
1937	497	351.45	35	34.28	34.26	0.20	4.63	82.46%	2.38
1942	513	362.78	36	39.11	39.08	0.22	4.91	79.94%	2.56
1947	553	356.53	56	41.06	41.05	0.24	2.62	96.40%	0.66
1952	548	362.96	55	34.02	34.02	0.20	2.52	96.98%	0.60
1957	539	352.76	50	39.25	39.23	0.24	2.18	97.58%	0.09
1963	522	361.96	43	20.41	20.41	0.13	4.93	80.26%	2.17
1969	600	402.19	58	83.49	83.39	0.49	24.57	8.46%	20.73
1978	652	388.17	69	78.52	78.44	0.47	3.25	94.90%	1.04
1987	668	387.28	82	95.66	95.54	0.57	9.28	48.44%	6.74
1995	674	359.48	53	91.71	91.58	0.54	100.10	0.00%	93.25
2003	677	349.5	114	96.56	96.40	0.59	5.78	74.84%	3.37

and observed harvesting DBH distributions. The first criterion was necessary for practical use, whereas the second and third criteria were intended to assess whether the number of trees and volume to remove are sufficient to reconstruct DBH distribution of selection harvests.

For each harvest, mean predicted distributions of removed trees and their 95% confidence interval (Fig. 1) were obtained from 5,000 runs of the algorithm. We then calculated Pearson's χ², which is based on the comparison of predicted and expected (i.e., observed in our case) frequencies for all size classes of a distribution [E1]. Pearson's χ² could be used to test the equality between two distributions, as well as a measure of proximity (Reynolds et al. 1988). To avoid biased χ² estimation for low "expected frequencies" (an inferior limit of 5 is broadly acknowledged), we grouped the initial 5-cm classes into four size classes matching the classical size categories "Poles" (diameters of [7.5;17.5[cm), "Small" trees (diameters of [17.5;27.5[cm), "Medium" trees (diameters of [27.5;42.5[cm) and "Large" trees (diameters≥42.5 cm).

Pearson's chi − square (1900)
For each size class i :
Pi, predicted number of trees
Ei, expected number of trees

$$\chi^2 = \sum_{i=1}^{n} \frac{(Pi - Ei)^2}{Ei} \qquad \text{(E1)}$$

A predicted DBH distribution was judged "identical" to the observed one if the χ² value was less than 7.81. This threshold corresponds, for 3 degrees of freedom (4 size classes − 1), to a risk α=0.05 of rejecting the hypothesis that the simulated distribution represents a random variable following the same law than the observed distribution, when it does.

The test was applied for each predicted distribution and a percentage of "identical distributions" was thus obtained from the 5,000 replications for each selection harvest (Table 1), as well as a mean χ² value. The test was also applied to the mean predicted DBH distribution obtained from the 5,000 replications, as a measure of its proximity to the observed one.

2.3 Extending evaluation to theoretical cases

Though the previous empirical evaluation aimed at giving quantitative assessment of the algorithm in the case of selection harvesting, we extended the evaluation to more diversified cases in theoretical stands. We controlled both the stand DBH distribution before cut and the type of thinning and/or harvesting operation simulated. The choice was made to test the algorithm for low-thinning (or thinning from below), mechanical thinning and selection thinning (or thinning of dominants), in even-aged, two-layer and uneven-aged stands.

2.3.1 DBH distribution of stand before harvest

Three theoretical initial stands were simulated, characterized by the same volume (400 m^3/ha) but different DBH distributions. The even-aged stand was defined by

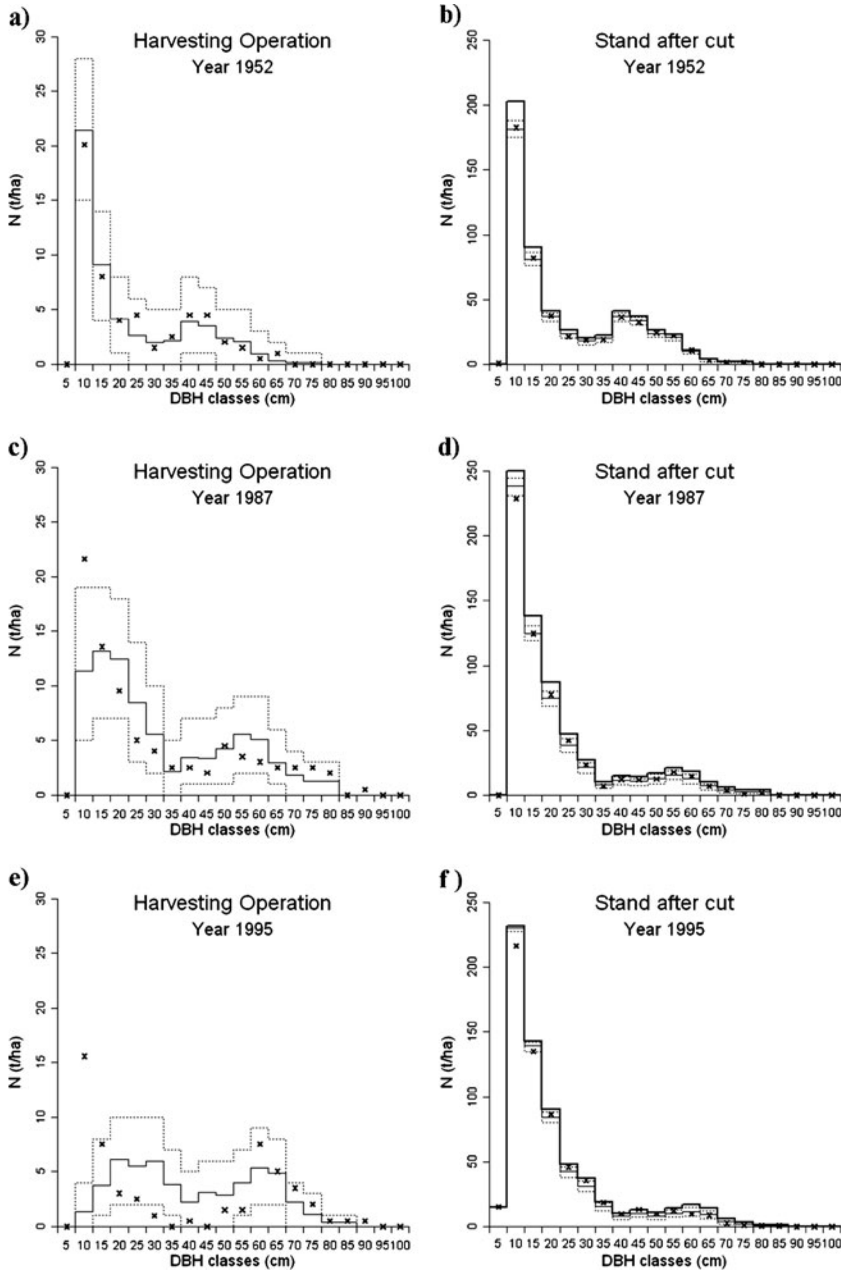

Fig. 1 Graphical comparisons of predicted and observed (x) diameter distributions of removed trees and residual stand for three uneven-aged selection harvests, with DBH distributions of the stand before cut (*bold solid lines*), mean predicted harvesting DBH distributions (*normal solid lines*) and 95% confidence intervals (*dotted lines*) calculated on 5,000 runs

the rounded mean distribution obtained by 10,000 simulations of random truncated normal distributions of 400 individuals (t/ha), with a mean diameter of 35cm and a standard deviation of 10cm. The two-layer stand was obtained the same way, with two normal distributions of 365 and 155 individuals, mean diameters of 15 and 50cm and standard deviations of 7 and 10 cm respectively. The DBH distribution simulated for the uneven-aged stand was an reverse J-shape distribution obtained by Liocourt's law (de Liocourt 1898) [E2], with N1=350 t/ha and K=1,5.

Liocourt's law (1898)
For each DBH class i :
N_1, number of trees of first class
$$Ni = N1 \times K^{1-i} \quad \text{(E2)}$$
Ni, number of trees of the ith class
K, Liocourt's coefficient

2.3.2 Thinning and harvesting strategies

We assessed the algorithm's ability to simulate three different and contrasted strategies for each of the initial stands. Usually called “thinning strategies”, they could imply thinning of small trees and/or harvesting of large ones. We will use “thinning” to designate strategies and “harvesting” for their implementation and results, as in “harvesting DBH distribution”.

Low thinning, or thinning from below, is characterized by the removal of the lower crown classes, i.e., dominated trees. Selection thinning, also called “thinning of dominants”, consists in removing trees amongst the largest. No size selection is made for mechanical thinning, sometimes called geometric thinning, as the systematic selection of trees often follows geometric designs. These three thinning methods might be quantitatively characterized by the ratio $D_{qCut}/D_{qBefore}$, where D_{qCut} is the quadratic mean diameter of removed trees and $D_{qBefore}$ is the quadratic mean diameter of trees before cut. The ratio is then exactly 1 for mechanical thinning, higher than 1 for selection thinning and lower than 1 for low thinning (Smith et al. 1997).

For each of the three initial stands, we simulated these three thinning methods by setting the target volume at 100 m^3/ha (25% of volume before cut) but varying the target number of trees from 5% to 95% of the total number of trees before harvest. We selected the three cases whose D_q ratio was the most consistent with previous definitions, namely 15%, 25% and 45% of the total number of trees for selection, mechanical and low thinnings respectively (Table 2). For each of these nine cases, we studied the shape of the mean DBH distribution of removed trees and its variability, obtained through 5,000 runs of the algorithm (Fig. 2).

3 Results

3.1 Algorithm behaviour

The algorithm showed a good adaptability to different harvest characteristics. It always converged and cut the exact target number of trees and target volume with a 1% precision. For each harvest, variability of removed volume among replications was thus very low (Table 1). More importantly, relative variability of predicted DBH distributions was reasonably low for removed trees and very low for residual stand after harvest, as shown by 95% confidence intervals (Figs. 1 and 2). In the empirical evaluation case, variability of the number of trees removed in each DBH class was usually less than five trees around the mean for small to large trees, and less than ten trees around the mean for poles (Fig. 1).

3.2 Reconstruction of empirical DBH distributions in uneven-aged selection system

Graphical comparisons of predicted and observed distributions showed that most harvesting DBH distributions were well-reconstructed (Fig. 1a,c,e), with mean predicted distributions close to observed ones and 95% simulation confidence intervals including observed values for all diameter classes. Pearson’s χ^2 tests confirmed this result (Table 1), with 9 out of 12 harvests presenting both a mean χ^2 below the 7.81 similarity threshold and at least 75 % of predicted distributions considered as “identical” to observed ones. 5 of them even reached 90% of identical distributions (1932, 1947, 1952, 1957, and 1978). Finally, these results improved when applying the χ^2 test on the mean DBH distribution obtained from 5,000 runs of the algorithm, for each simulated harvest. The χ^2 of each mean predicted distribution was indeed lower than the mean of the 5,000 χ^2 values. Only two mean predicted distributions could not be considered as “identical” to the observed ones (Table 1).

The similarity between predicted and observed DBH distribution was shape-dependent. Predicted DBH distributions were smoother than observed ones (Fig. 1). As a consequence, smooth observed diameter distributions of removed trees (1947, 1952 and 1957) were better simulated than uneven

Table 2 Characteristics of the nine theoretical harvests simulated. This table presents mean value (first line) and standard deviation (second line, in italics) obtained for the total number of trees (t/ha) and volume (m^3/ha) removed by each of the nine theoretical harvests simulated, as well as for D_q ratio ($D_{qCut}/D_{qBefore}$). The three thinning methods are based on the same target volume (100 m^3/ha) but differs in the percentage of total number of trees to be removed (15, 25 or 45% of Ntot)

Thinning method		Selection thinning			Mechanical thinning			Low thinning		
N target (% Ntot)		15% Ntot			25% Ntot			45% Ntot		
Variable		Ncut (t/ha)	Vcut (m^3/ha)	D_q ratio	Ncut (t/ha)	Vcut (m^3/ha)	D_q ratio	Ncut (t/ha)	Vcut (m^3/ha)	D_q ratio
DBH distribution of initial stand	Even-aged	60.00	99.44	1.24	100.00	100.03	1.00	180.00	100.72	0.79
		0.00	*0.42*	*0.00*	*0.00*	*0.62*	*0.00*	*0.00*	*0.28*	*0.00*
	Two-layer	78.00	99.81	1.26	130.00	100.00	1.00	234.00	100.20	0.77
		0.00	*0.57*	*0.00*	*0.00*	*0.60*	*0.00*	*0.00*	*0.58*	*0.00*
	Uneven-aged	158.00	99.71	1.25	262.00	99.99	1.00	472.00	100.35	0.77
		0.00	*0.60*	*0.01*	*0.00*	*0.66*	*0.01*	*0.00*	*0.59*	*0.00*

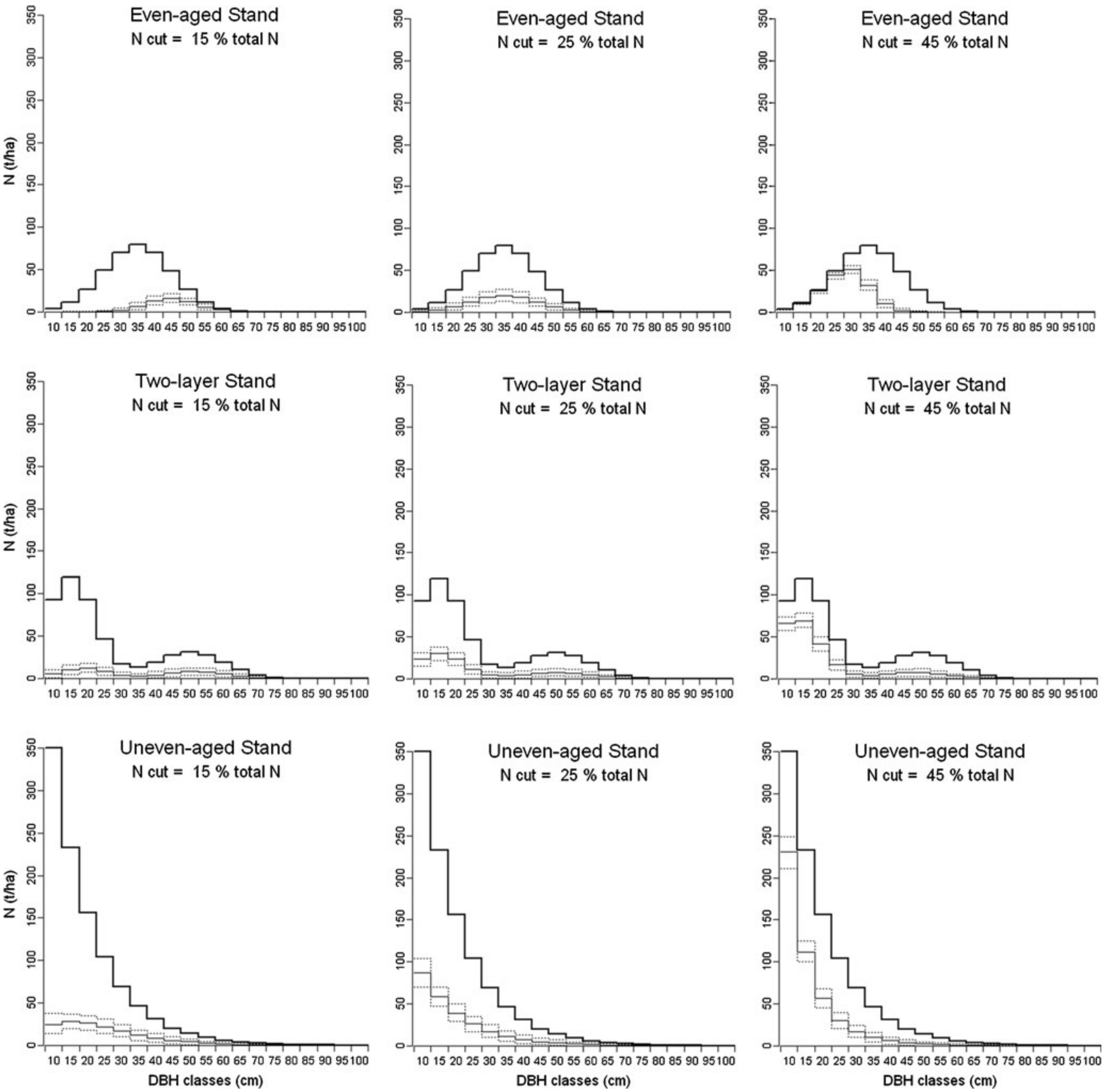

Fig. 2 Contrasted thinning strategies simulated in even-aged, two-layer and uneven-aged stands. Initial stands (*bold solid lines*) had a same volume (400 m^3/ha) but different densities (N=400, 520 and 1,050 trees/ha respectively). Results of the simulation of selection thinning (15% of total N), mechanical thinning (25% of total N) and low thinning (45% of total N) are presented through mean harvesting DBH distributions (*normal solid lines*) and 95% confidence intervals (*dotted lines*)

ones (Fig. 1, Table 1), with the highest discrepancy for bimodal and very uneven DBH distributions (1969 and 1995).

Nevertheless, differences between simulated and observed stands after harvest remained relatively small, and prediction variability remained low (Fig. 1b,d,f), with highest absolute discrepancies and variability obtained for small trees. In the case of 1995 for instance, the algorithm made an underestimate of the number of trees to be removed in the 10cm DBH class of about 14 trees (Fig. 1e), which had however limited consequences on the residual stand, as this discrepancy affected only about 6.5% of residual trees of the class (Fig. 1f).

3.3 Algorithm behaviour in more diversified theoretical cases

The algorithm proved able to reproduce selection, mechanical and low thinnings, whatever the DBH distribution before cut. DBH distribution shapes of removed trees (Fig. 2) and D_q ratios (Table 2) were consistent with the objectives of these different strategies, which were to target either poles, small, medium, or large trees during harvesting operations.

Variability of simulated DBH distributions of removed trees depended both on DBH distribution of initial stand and on thinning strategy. It was low (more or less five trees around the mean) when few possible DBH distributions lead to the target volume, as for selection thinnings, high (more or less 15 trees around the mean) for mechanical thinnings, and variable for low thinnings (Fig. 2). Nevertheless, confidence interval bands always highlighted unambiguously which diameter categories (poles, small, medium and large trees) were targeted by the algorithm.

4 Discussion

4.1 Evaluation method

The method we proposed to evaluate the algorithm against empirical data was based on an original application of Pearson's chi-square test (1900). In most studies, similarity between distributions is assessed only graphically (Arii et al. 2008). Some authors use χ^2 values as measures of distance between distributions but similarity between distributions is rarely evaluated statistically, as this test is very strict (Reynolds et al. 1988). When used, this test is usually performed on a single pair of distributions (Wehrli et al. 2005), thereby leading to a success/failure dichotomy. Here, we applied this test on numerous runs of the algorithm, thereby obtaining a percentage of success for each harvest and a mean χ^2. This strategy enables the algorithm to be evaluated in a more quantitative way in the context of uneven-aged selection forests.

Unfortunately, this method was not applicable to the nine theoretical cases because of lack of reference DBH distributions for the different thinning and harvesting operations simulated. Indeed, thinning strategies are usually defined in a qualitative way, through the type and size of target trees, and occasionally by a general and imprecise distribution shape of trees to be removed. Quantitative characterizations of those methods are then based on ratios like $D_{qCut}/D_{qBefore}$ (Smith et al. 1997; Montero et al. 2001) or D_{qCut}/D_{qAfter} (Schütz, 1990; Karlsson, 2006; Bradford and Palik, 2009), the latter being based on quadratic mean diameters of trees after thinning. These two ratios lead to similar ratio values, around 0.7 and 0.8 for low thinning (Schütz, 1990; Montero et al. 2001) and from 1.0 to 1.2 or more for thinning of dominants (Schütz, 1990; Smith et al. 1997; Bradford and Palik, 2009), which are very close to the values obtained for the theoretical thinning operations simulated by the algorithm.

4.2 Algorithm performance

The algorithm we developed proved simple but effective in this case study. It always converged, and reached the target volume (with a 1% precision) in less than 5 seconds (computer's characteristics: 1.73 GHz, 3.24 GB RAM). It was thus possible to reconstruct harvesting DBH distributions from aggregate data, such as number of trees and total volume, provided that the DBH distribution before cut was known. These three variables restricted the number of potential DBH distributions of removed trees, first by limiting the potential number of trees to be removed per diameter class, then by forcing the choice of trees to be harvested so as to reach the target volume.

In the case of the empirical evaluation, reconstructions of harvesting DBH distribution appeared acceptable in most cases, although discrepancies were sometimes observed between predicted and observed distributions, especially for heterogeneous and bimodal ones. However, consequences of these discrepancies on the structure of residual stands were limited (Fig. 1b-d-f). The highest absolute discrepancies were observed for small trees, but remained relatively low. Indeed, the algorithm removed the right number of poles for two harvests; 60% of discrepancies were due to underestimations of tree removal by the algorithm, and overestimations were related to small differences of three poles maximum. Nevertheless, in the case of simulation studies, the consequences of these discrepancies on stand dynamics might depend on the simulation model used and on its sensitivity to varying number of poles.

With regard to its adaptability, the algorithm performed well in the nine different cases tested through the theoretical evaluation (Table 2). It was able to simulate different thinning strategies, from low thinning to thinning of dominants, whatever the initial stand structure. It was even able to reproduce harvests with bimodal DBH distribution (Fig. 2), combining thinning of small trees and harvesting of large ones. However, the evaluation against empirical data pointed out that the algorithm seemed to reproduce smooth harvesting distributions better than heterogeneous ones. It thus appears effective in balanced selection forests, but might be less appropriate for simulating silvicultural operations that aim at deeply modifying stand structure.

4.3 Algorithm relevance

Several thinning simulation tools have been proposed in the literature (Daume and Robertson, 2000; Söderbergh and Ledermann, 2003; Arii et al. 2008), but they usually require very detailed information on the thinning and/or harvesting strategy. Here, we proposed an original and intermediate approach. The relevance of this algorithm lies in its ability to simulate different operations by removing the required target number of trees and volume while simulating cutting DBH distributions consistent with the relevant strategy. The algorithm thus meets the researchers' needs when no detailed data is available to reconstruct past management of forest, for example in the case of simulation experiments.

Nevertheless, using this algorithm might appear unnecessary in the case of mechanical thinning, or when harvesting DBH distribution strictly follows the stand distribution before harvest, as random selection could hypothetically lead to similar results. Complementary analyses were conducted on that point, and demonstrated that although DBH distributions appeared to be close when comparing algorithm results to random distributions in the cases in question, the algorithm had the advantage of removing the exact target volume and simulating DBH distributions closer to the observed ones. The exchanging trees step is therefore the algorithm's cornerstone, as it makes it possible to reach the target volume almost exactly while forcing the DBH distribution of removed trees.

4.4 Perspectives of applications

When coupled with a simulation model, this algorithm enables past forest dynamics to be simulated. Past management can indeed be characterized from time series of number of trees and volume removed per operation, which are available in many current management documents. If a forest inventory indicates the distribution of diameters at the beginning of a time series, and a model simulates how this distribution evolves between two harvests, then the algorithm is sufficient to simulate tree removal due to management. Our algorithm has been implemented in the simulation platform Capsis4 (de Coligny, 2005; de Coligny, 2007), and is available for retrospective forest dynamics simulation analyses as well as for prospective simulations. It has been used to reconstruct and simulate management from ONF's records in the context of the evaluation of a mountain forest simulation model against empirical data.

As the algorithm leads to some variability in the distribution of removed trees, we can consider two possible ways of applying it in a simulation context. A first option consist in performing the algorithm only once each time we want to simulate a harvest, and applying the result directly. In that case, the variability between replications of forest dynamics simulations will encompass both the variability linked to demographic processes stochasticity and the variability linked to the distribution of removed trees among size classes. A second option is to replicate several times the algorithm as a preliminary task each time we want to simulate a harvest, and apply only the mean predicted distribution. This second option would have the advantage of reducing the variability of forest dynamics simulations by eliminating the part linked to the algorithm. In addition, our results proved that mean predicted DBH distributions were often very close to observed ones. We therefore recommend this way to use the algorithm.

4.5 Possible improvements

The speed of convergence could probably be increased by taking into account diameter ranks when selecting pairs of trees to be tested for potential exchange. For instance, if the harvested volume is lower than the target one, the algorithm could test only exchanges for bigger trees. This would decrease the rate of exchange rejections. However, it would not change the solution, and convergence time did not appear a limiting factor in our simple algorithm, as it never exceeded 5 seconds.

Inclusion of two important additional variables in this algorithm should nevertheless be considered. It might be possible to implement the distribution of removed trees among species in mixed stands by adding priority order, taking diameter and species identity into account (Pierrat, 2004). However, this would have required detailed empirical data and information about management strategies in relation to species, which were not available in our case study.

Adding spatial pattern parameters appears more complicated. Several algorithms have been developed for individual tree models to imitate individual selection of trees by a forest manager. The selection process is usually based on criteria such as distance between trees, (Söderbergh and Ledermann, 2003), identification of elite-trees and competitors (Daume and Robertson, 2000; Söderbergh and Ledermann, 2003) or simulation of harvest as a contagious process from target trees to neighbouring trees (Arii et al. 2008).

However, a trade-off exists between the applicability of the algorithm to numerous situations and the precision of the prescription it provides. In many cases, detailed information on silviculture strategies is not available. Complex algorithms then require default parameter values to be provided, so as to enable simulations to be conducted even when information is lacking.

Acknowledgments We are grateful to Andreas Zingg, from the Swiss Federal Institute for Forest, Snow and Landscape Research (WSL), who supplied us with the dataset used for the empirical evaluation. We also thank two anonymous reviewers for their valuable comments.

Funding This work was financially supported both by the French Forest National Office (ONF), through a Cemagref-ONF contract (2009 contract endorsement of 2007 09 9 058 U), and by the research program Biodiversity, Forest Management and Public Policy (BGF, n°E23/2010).

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