ANNEX C – SENSITIVITY ANALYSIS PROCESS AND PRESENTATION OF THE MORRIS' SCREENING METHOD

This annexe aims at describing the different steps of this analysis and highlight key questions and decisions.

OBJECTIVES AND GLOBAL FRAME

Sensitivity and uncertainty analysis techniques (SA and UA) consist in studying the impact of variations of input parameters on output variables (Saltelli et al. 2008). There are commonly used to deal with complementary objectives and the related questions:

- Detect influent parameters
  Question: Which parameters are really influent on model outputs? Which are not influent and could be fixed to their default value? Is the model over-parameterized (numerous non-influent parameters) and could some process be simplified?
- Assess the effect of uncertainties regarding input parameters values on model predictions
  Question: For which parameters do the uncertainty regarding the mean value has important – and potentially problematic – effects on model predictions? On which parameters should we focus a future recalibration effort?
- Check the consistency of model's behaviour
  Question: Are the results consistent with theoretical knowledge regarding key demographic processes? Are model predictions influenced by the expected parameters?
- Detect potential interactions between parameters
  Question: Do the different parameters - and related processes - interact and in a consistent and expected way?

Besides the variety of questions that these techniques can answer, there also exist numerous possible ways to conduct these analyses, depending on the objectives, the integration of such analyses within a global approach, and knowledge and questions about the variation range of each input parameters. In our case, we had the possibility to conduct this analysis on the short (50 years, like for the quantitative evaluation simulations) or long run (500 years, like for the qualitative evaluation simulations), using no-management, prospective management or historical management scenarios, and varying input parameters within their "natural range" or using an empirical 10 or 20% variation. Among all these possibilities, we decided to apply this approach on the retrospective/historical simulations used for the quantitative evaluation step, as it enabled to control simulated management, to assess the effect of uncertainties regarding demographic parameters on model predictions and detect priority parameters for the future recalibration process – also based on these historical simulations.

INPUT FACTORS AND VARIATION RANGE

We analysed conjointly the sensitivity of output variables to 42 demographic parameters (21 per species), combined with the effect of two “initial state” factors. As regard demographic processes, we decided to vary parameters within their expected natural variation, approached by the 95% confidence interval of calibration data, i.e. +/- 1.96 standard deviations around the mean value. We only tested two options for individual effects in allometric and growth equations: with/without individual effects, so as to assess the impact of the consideration of individual variability on model predictions. The input parameters related to stand structure and topography were not varied separately, but conjointly through an “initial state” factor encompassing several stand characteristics. Indeed, the structure and composition of the initial stand appeared to us as an important component of this analysis, as we hypothesised that the influence of demographic processes on stand development dynamics would depend on its maturation state. A Principal Component Analysis (PCA) of initial stand characteristics showed that Queige’s stands highly differed regarding their initial density and their “heterogeneity”, which encompassed both diameter diversity and composition. Apart from pure stands, we indeed observed a group of well mixed and uneven-aged stands on the one hand, and a group of spruce-dominant stands with a more even-aged structure on the other hand. Pure or quasi-pure spruce were set apart to ensure a minimum proportion of 20% of fir (over total basal area), to be sure to have enough firs to detect the effect of fir demographic parameters on model predictions at the stand scale. We then selected four stands to represent this diversity, combining two levels of heterogeneity (P36 and P39 for mixed and uneven-aged stands, P26 and P28 for spruce-dominant even-aged stands) and two levels of density (P26 and P36 for low density ~30 m^2/ha, P28 and P39 for high density ~40 m^2/ha) . These two axes were synthesised as two factors in the sensitivity analysis, respectively IS_F1 and IS_F2. In the experiment design, each of the four selected stands was associated with the management history that had effectively been applied on that stand, so as to control management and detect only demographic parameters’ effects.

CHOICE OF THE SENSITIVITY ANALYSIS TECHNIQUE : THE MORRIS’ SCREENING METHOD

Numerous sensitivity/uncertainty analysis techniques exist (Saltelli), differing from the way the input parameters are varied, the necessity – or not – of repetitions, the sensitivity indices calculated etc. The choice of a given technique depends on several criteria, one of the most important being the maximum number of simulations conceivable – i.e. the size of the experiment design – considering simulation constraints, which highly depend on several factors: the type of model (stochastic or determinist), the number of parameters tested, the model’s computing speed and the length of simulations (ref Saltelli, Mexico). In our case, this choice was highly constrained by the computation speed, with was very low due to the light interception model, which is time consuming. This, added to a non-negligible number of input parameters and the presence of stochastic processes, led us to select the Morris ‘method (Figure C-1).

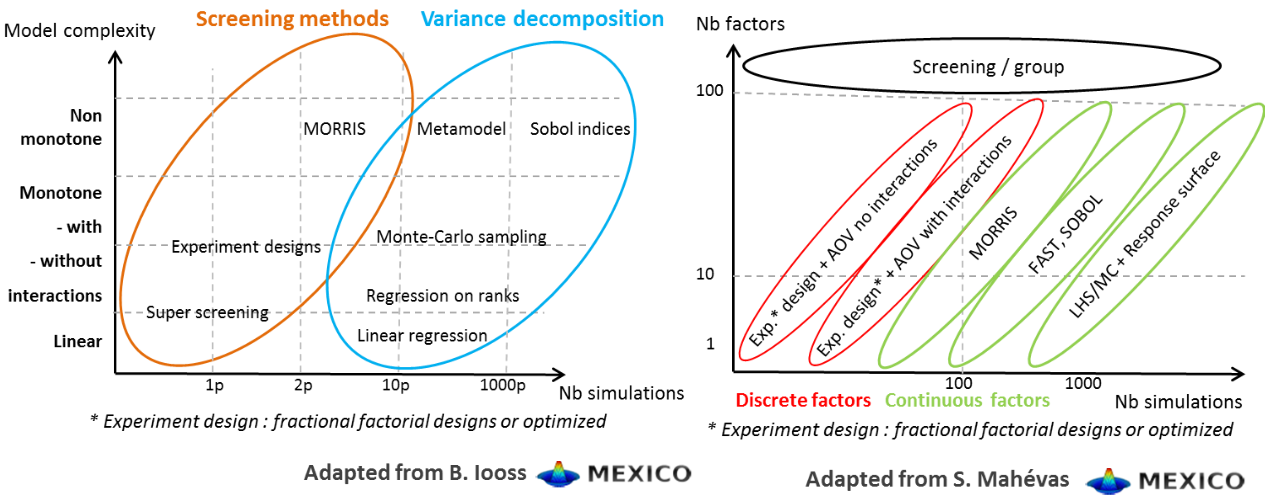

Figure C-1: Grids for sensitivity analysis techniques selection, depending on several criterion. These two grids are adapted from those presented by Stéphanie Mahévas and Bertrand Iooss at the Mexico sensitivity analysis summer-school 2012 (http://reseau-mexico.fr).

The Morris' method is a screening technique designed to sample large factorial spaces in an efficient way, following several trajectories based on one-at-a-time (OAT) discrete jumps within parameter levels (Figure C-2). The method ensures that, provided a sufficient number of trajectories, the set of simulations made at the different points in the parameter space detect efficiently influent and non-influent parameters at a low simulation cost – i.e. with a lower required number of simulations than other methods. The size of a Morris' experiment design is indeed defined by r*(p+1), for r trajectories and p parameters, whereas a complete plan would involve n^p combinations of p parameters with n levels. No rules exist regarding the definition of the "sufficient" number of trajectories. However, so as to ensure sufficient screening intensity of factorial space, the total number of trajectories (r) should be chosen while considering the numbers of tested parameters (p), the number of levels per parameters, model's stochasticity and computation speed, therefore involving a trade-off between computation cost and accuracy of the sensitivity indices. The number of levels (modalities) tested per factor should be pair (C. Bruchou, personal communication) but depends on the variation range of each parameter and on the maximum number of simulations conceivable. A higher number of levels per factor would require a higher number of trajectories – and thus a larger simulation design – to ensure sufficient and balanced sampling of all levels of a given factor.

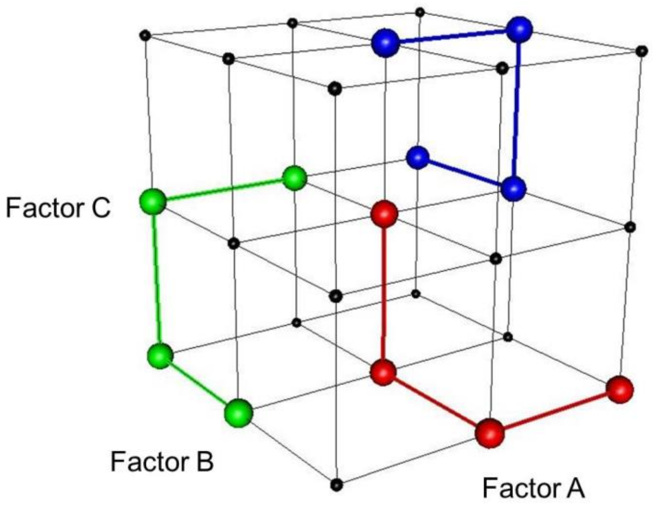

Figure C-2: Illustration of Morris' screening method of factorial space.
This figure illustrates the sampling strategy used by the Morris’ screening method. It is based on the definition of r trajectories (here r = 3) screening the factorial space, defined by p factors (here p= 3) with several modalities per factor (here 3). Each trajectory starts at a random coordinate of the factorial space, defined by a combination of modalities of all factors (points). The trajectory is then determined step by step by a One At a Time (OAT) process, involving successive variations of factors’ modalities. Each trajectory is thus defined by p+1 different combinations of factors modalities (here 4). This plots have been realized with the R function *plot3d()* of the *“rgl”* R package (Adler and Murdoch, 2012; R Core Team, 2012).

EXPERIMENT DESIGN DEFINITION

In this study, given the high computation cost (2-3 minutes per simulation) but the possibility to run simulations on a cluster (~10 hours per bloc of 250 simulations), we estimated that we could run up to a few thousands simulations. With p=44 factors, we could thus use from 20 to 200 trajectories. We finally used r=100 trajectories, which appeared as a good compromise, but decided to limit the number of levels to 4 in the case of demographic parameters, while the number of levels had already been set to 2 for other factors (individual variability parameters and initial state). We thus obtained an experiment design, of r*(p+1) = 4500 different combinations of parameter values. We used the *morris()* R function from package “*sentivity*” (Pujol *et al.*, 2012; R Core Team, 2012) to generate the experiment design. An adaptation of this method by Campolongo *et al.* (2007) select the r best trajectories among m tested trajectories, so as to optimize the exploration of factorial space. The experiment design was run externally on the cluster and the simulation outputs were then uploaded and transferred to the *morris()* R function to conduct the sensitivity analysis.

SENSITIVITY INDICES AND RELATIVE FACTORS' INFLUENCE

The Morris' method is based on the calculation of the elementary effect (EE) –for a given output variable – associated with each single variation (jump) of each input parameter. Then, for each input factor, the mean of absolute values of all EE (μ*) is considered as a good proxy of its elementary effect on the selected output variable, whereas the standard deviation of all EE (σ) assess the variability of its effect, indicating either a non-linear effect or potential interactions with other parameters. Morris' results are often presented graphically by $\sigma = f(\mu^*)$ (Figure C-3), and both indices are used to interpret factor's absolute and relative influence.

However, besides analysing both indices separately, we chose to use the index proposed by Ciric *et al.* (2012), which combines both Morris' indices into a unique sensitivity index (SI), also interpreted as the Euclidian distance between the "sensitivity coordinates" (μ*, σ) of the factor and the origin (0,0) of the Morris' plot (Figure C-3):

$$SI = \sqrt{\mu *^2 + \sigma^2}$$

By taking both main and second order effects – interactions or nonlinear effects – into account, this index gives an estimation of the total effect of each input factor on a given output variable (Figure C-4). It therefore enabled the relative influence of input factors to be assessed and factors' rank to be established for each output variable (Table C-2). It also enabled groups of different degree of influence to be detected (Figure C-5), so as to put factors' ranks into perspective (Table C-2). The analysis was performed for seven response variables, i.e. final stand structure characteristics (density, basal area, quadratic mean dbh, basal area Gini index, pole quantity, species mixture, and pole tree species mixture). A global rank was then obtained for each factor, based on the sum of the ranks obtained for all output variables (Table C-2). This step allowed us to detect non-influent and influent factors, as well as to assess the impact of uncertainties regarding input parameters on model's predictions.

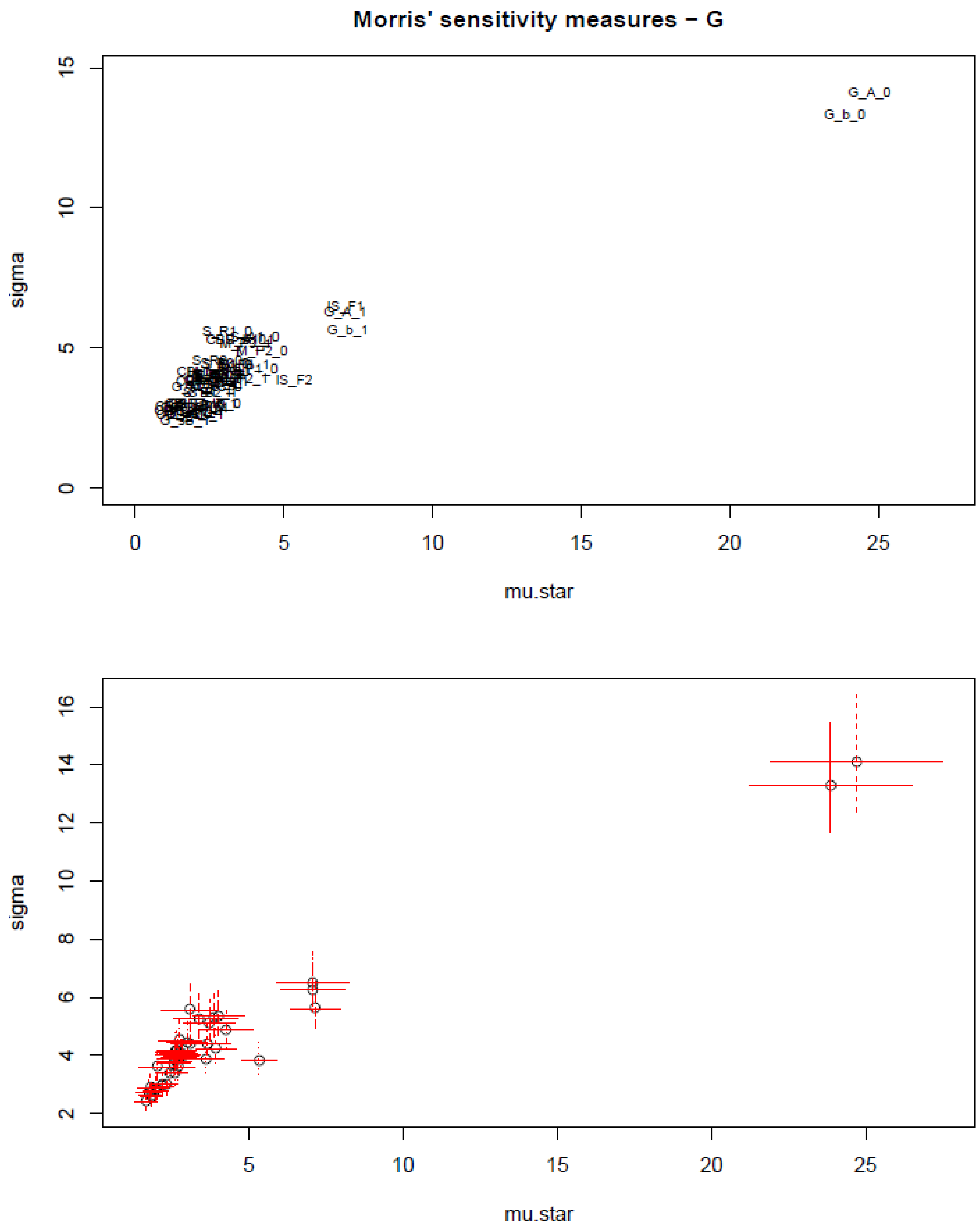

Figure C-3: Graphical representation of Morris' sensitivity results.

The first plot (above) is the classical representation of Morris' sensitivity indices results and has been obtained with the *morris()* function of the R package "sensitivity" (Pujol *et al.*, 2012; R Core Team, 2012). It enables the conjoint analysis of both Morris' indices values for each input factor, i.e. their main effect (μ* = mu.star) and the variability of this effect (σ = sigma) on a given outpout variable (here G= stand basal area, m^2/ha). The values obtained for each factor are referred to by the factor code name (cf. Table for the entire factor name and signification). A high *μ value indicates that the output variable is highly sensitive to this input factor, while a high σ value indicates that the effect of this factor is either nonlinear or act in interaction with other parameters (NB : the method does not allow to separate both sources of variability). The second plot comes from a package diffused by the MEXICO scientific network (http://reseau-mexico.fr) during summer schools on sensitivity analysis. It enables the computation of 95% confidence intervals associated with each index (based on bootstrap selection among individual effects of each factor). The sensitivity indices are in the same unit as the considered output variable (here m^2/ha).

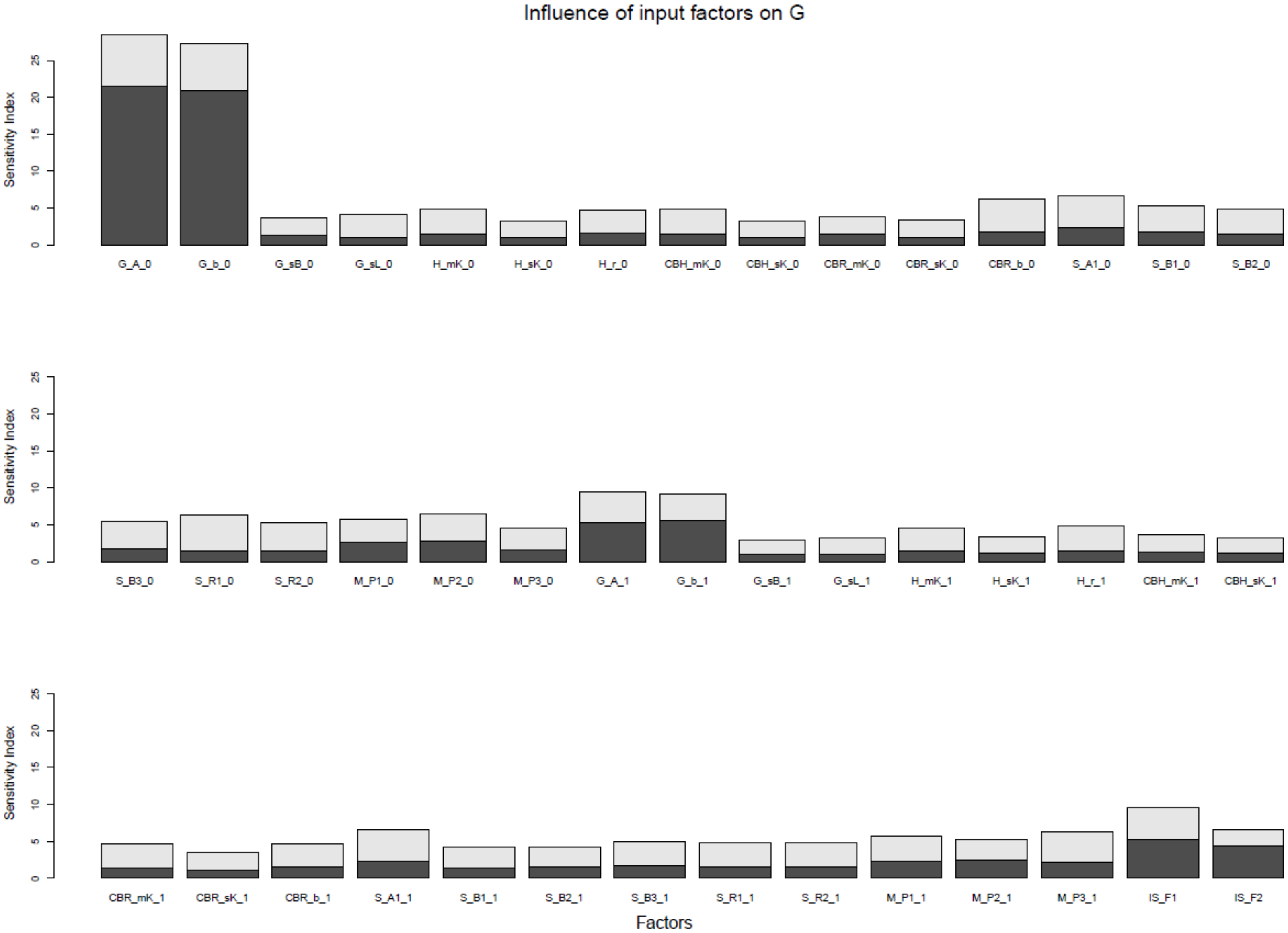

Figure C-4 : Representation of Morris' results using the combined sensitivity index.

This graphic is a personnal and alternative representation of Morris' results based on the sensitivity index proposed by Ciric *et al.* (2012) and combining both Morris indices. Each bar thus represents the value of this combined index for an input factor and a given ouput variable (here G, stand basal area, m^2/ha), with the dark grey part corresponding to the main effect of the factor (Morris' μ*) and the light grey part corresponding to the variability component (Morris'σ). The sensitivity index is in the same unit as the considered output variable (here m^2/ha)

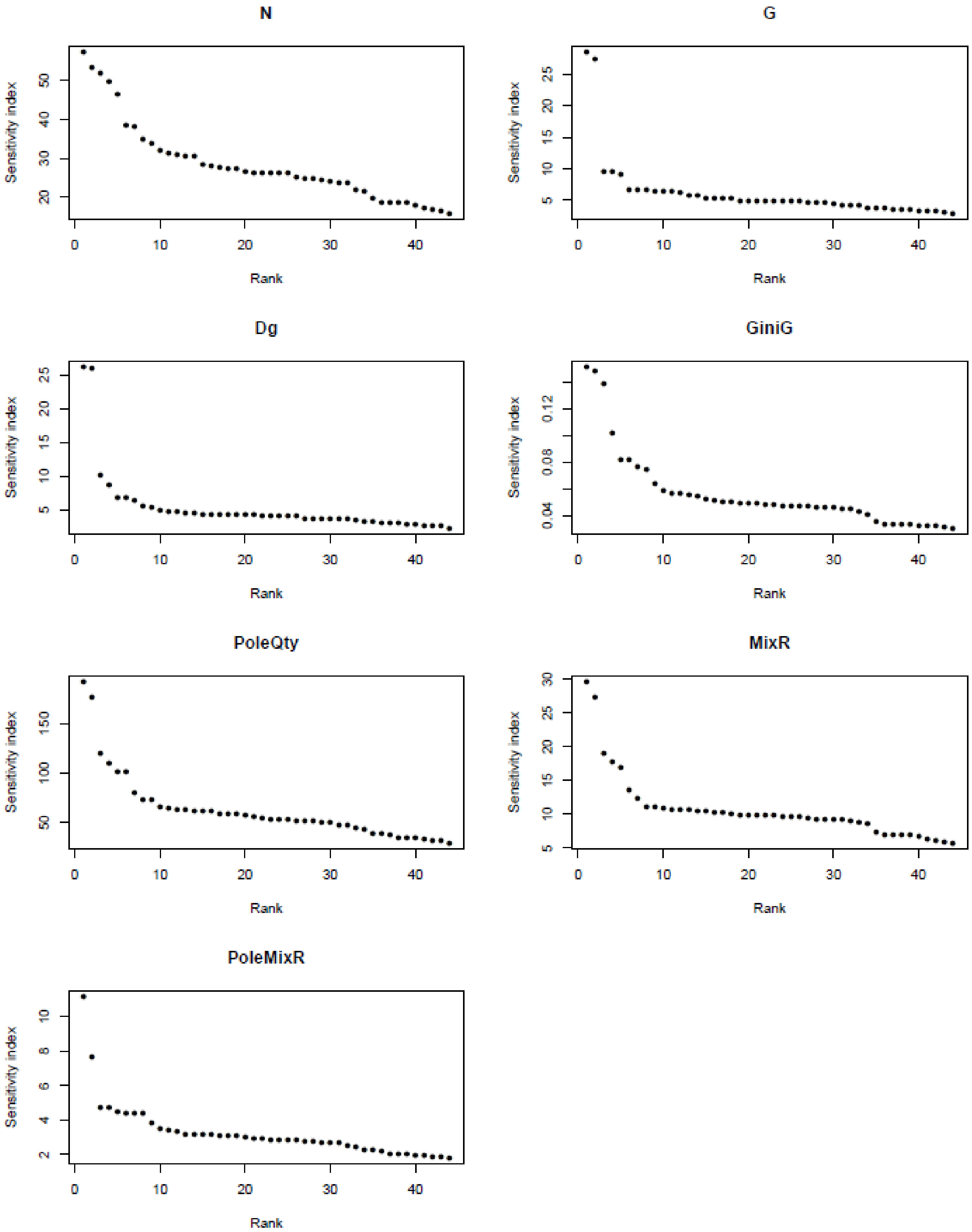

Figure C-5 : Detection on influence group for each output variable, based on the combined sensitivity index. Each of this plots represent the sensitivity index (SI) values obtained by each input factor (sorted by decreasing SI value) for a given output variable. This enabled groups of very influent, influent, moderately influent and few or low influent factors to be graphically detected. Factors' names are not indicated, for a better readability, but were given by crossed analysis with table of factors' ranks. The sensitivity index is in the same unit as the considered output variable: t/ha for the total stem density (N), m²/ha for stand basal area (G), cm for the quadrtaic mean diameter (Dg), no unit for the Gini index based on individual basal areas (GiniG), t/ha for pole density (PoleQty), % of spruce basal area over total basal area for the mixong ratio (MixR), % of spruce pole number over the total pole numer for the pole mixing ratio (PoleMixR).

SENSITIVITY OF SA RESULTS TO INPUT FACTORS' VARIATION RANGE

The original sensitivity analysis have been conducted by variying demographic parameters within their uncertainty range, approached by +/- 1.96 standard deviation around their mean (Table C-1). This choice was driven by the idea that this would approach the "natural variation range" of demographic parameters, and thus avoid extreme parameters values, possibly leading to unrealistic situations. This asumptions however led to very uneven variation ranges between parameters, corresponding to variations from ~0.6% to ~80% around the mean.

Yet, it is acknowledged that the range explored for a given parameter might affect the results of sensitivity/uncertainty analysis techniques: a narrow variation range might reduce the ability of the SA technique to detect the influence of a "very influent" parameter, whereas a large variation range might artificially increase the influence of a "moderately influent" one. This might explain some of our results, but not all of them. Indeed, although the high influence of the regeneration parameter might be partly explained by its wide variation range (+/- 1.96 SE corresponded to a variation of +/- 66.9 and 81.8% of the mean value, for spruce and fir respectively), the variation range of the two growth parameters (approximately +/- 20% for growth alpha and +/- 10% for growth beta) was close to the mean variation range calculated on all parameters (+/- 18%), whereas parameters with the same order of variations were not detected as influent (ex. CHR_mK, CBH_mK). Moreover, we also detected the non-negligible influence of "low uncertainty parameters", despite their reduced variation range (+/- 0.64% for S_R1_0, +/-1.24% for H_mK_0, +/- 4.48% for CBR_b0).

Considering the possible high sensitivity of SA results to the size of input factors' variation range, we decided to conduct another sensitivity analysis to check the sensitivity of SA results to parameters' variation range. This second SA was based on a fixed +/-20% variation range for all demographic parameters (corresponding to the mean % of variation for the first SA),whereas other parameters we varied as in the previous SA.

Equation	Parameter	Code	Calibration: mean	Calibration: SE	Variation range - 1st SA: mean +1.96 SE	Variation range - 1st SA: mean - 1.96 SE	Variation range - 1st SA: % variation	Variation range 2nd SA: mean + 20%	Variation range 2nd SA: mean - 20%
Growth	Alpha	G_A_0	-3.97E+00	4.25E-01	-3.13E+00	-4.80E+00	2.10E+01	-3.17E+00	-4.76E+00
		G_A_1	-2.02E+00	2.02E-01	-1.62E+00	-2.41E+00	1.96E+01	-1.61E+00	-2.42E+00
	Beta	G_b_0	5.88E-01	3.80E-02	6.62E-01	5.14E-01	1.27E+01	7.06E-01	4.70E-01
		G_b_1	4.16E-01	1.90E-02	4.53E-01	3.79E-01	8.95E+00	4.99E-01	3.33E-01
	sigmaBeta*	G_sB_0	6.00E-01	2.40E-03	na	na	na	na	na
		G_sB_1	6.02E-01	2.91E-03	na	na	na	na	na
	sigmaLambda*	G_sL_0	1.05E-01	4.00E-04	na	na	na	na	na
		G_sL_1	1.84E-01	8.90E-04	na	na	na	na	na
Crown Base Height	muK	CBH_mK_0	4.88E-01	8.45E-02	6.54E-01	3.22E-01	3.39E+01	5.86E-01	3.90E-01
		CBH_mK_1	7.14E-01	6.16E-02	8.35E-01	5.93E-01	1.69E+01	8.57E-01	5.71E-01
	sigmaK*	CBH_sK_0	6.16E-01	0.00E+00	na	na	na	na	na
		CBH_sK_1	4.62E-01	0.00E+00	na	na	na	na	na
Crown Base Radius	Beta	CBR_b_0	5.25E-01	1.20E-02	5.49E-01	5.01E-01	4.48E+00	6.30E-01	4.20E-01
		CBR_b_1	4.54E-01	1.33E-02	4.80E-01	4.28E-01	5.74E+00	5.45E-01	3.63E-01
	muK	CBR_mK_0	-7.74E-01	4.48E-02	-6.86E-01	-8.62E-01	1.13E+01	-6.19E-01	-9.29E-01
		CBR_mK_1	-3.54E-01	4.30E-02	-2.70E-01	-4.38E-01	2.38E+01	-2.83E-01	-4.25E-01
	sigmaK*	CBR_sK_0	1.58E-01	1.00E-04	na	na	na	na	na
		CBR_sK_1	1.22E-01	2.15E-04	na	na	na	na	na
Height	muK	H_mK_0	3.53E+00	2.24E-02	3.57E+00	3.49E+00	1.24E+00	4.24E+00	2.82E+00
		H_mK_1	3.28E+00	3.59E-02	3.35E+00	3.21E+00	2.15E+00	3.94E+00	2.62E+00
	r	H_r_0	7.67E-02	1.50E-03	7.96E-02	7.38E-02	3.83E+00	9.20E-02	6.14E-02
		H_r_1	8.46E-02	1.55E-03	8.76E-02	8.16E-02	3.59E+00	1.02E-01	6.77E-02
	sigmaK*	H_sK_0	1.04E-01	1.00E-04	na	na	na	na	na
		H_sK_1	1.77E-01	8.94E-05	na	na	na	na	na
Regeneration (Saplings)	Alpha1	S_A1_0	7.68E+01	2.62E+01	1.28E+02	2.54E+01	6.69E+01	9.22E+01	6.14E+01
		S_A1_1	8.91E+00	3.72E+00	1.62E+01	1.62E+00	8.18E+01	1.07E+01	7.13E+00
	Beta1	S_B1_0	-9.28E+00	3.15E-02	-9.22E+00	-9.34E+00	6.65E-01	-7.42E+00	-1.11E+01
		S_B1_1	-6.11E+00	2.67E-02	-6.06E+00	-6.16E+00	8.55E-01	-4.89E+00	-7.33E+00
	Beta2	S_B2_0	2.40E-01	1.40E-03	2.43E-01	2.37E-01	1.14E+00	2.88E-01	1.92E-01
		S_B2_1	1.88E-01	1.26E-03	1.90E-01	1.85E-01	1.31E+00	2.25E-01	1.50E-01
	Beta3	S_B3_0	-1.90E-03	1.23E-05	-1.88E-03	-1.92E-03	1.27E+00	-1.52E-03	-2.28E-03
		S_B3_1	-1.50E-03	1.15E-05	-1.48E-03	-1.52E-03	1.50E+00	-1.20E-03	-1.80E-03
	Rhg1	S_R1_0	4.65E+00	1.51E-02	4.68E+00	4.62E+00	6.36E-01	5.59E+00	3.72E+00
		S_R1_1	4.55E+00	1.32E-02	4.57E+00	4.52E+00	5.70E-01	5.46E+00	3.64E+00
	Rhg2	S_R2_0	-4.92E-02	4.50E-03	-4.04E-02	-5.80E-02	1.79E+01	-3.94E-02	-5.90E-02
		S_R2_1	-2.70E-02	3.71E-03	-1.97E-02	-3.42E-02	2.70E+01	-2.16E-02	-3.24E-02
Mortality	P1	M_P1_0	-3.60E+00	1.35E-01	-3.33E+00	-3.86E+00	7.34E+00	-2.88E+00	-4.32E+00
		M_P1_1	-3.21E+00	2.54E-01	-2.71E+00	-3.71E+00	1.55E+01	-2.57E+00	-3.85E+00
	P2	M_P2_0	-1.25E-02	4.00E-03	-4.66E-03	-2.03E-02	6.27E+01	-1.00E-02	-1.50E-02
		M_P2_1	-3.01E-02	7.80E-03	-1.48E-02	-4.54E-02	5.08E+01	-2.41E-02	-3.61E-02
	P3	M_P3_0	2.20E-02	2.70E-03	2.73E-02	1.67E-02	2.41E+01	2.64E-02	1.76E-02
		M_P3_1	2.28E-02	5.40E-03	3.34E-02	1.22E-02	4.64E+01	2.74E-02	1.82E-02

Table C-1 : Description of parameters' values and variation ranges for the two sensitivity analysis.

This table indicates, for demographic and allometrics parameters, the mean values and variations ranges for the two successive sensitivity analysis (SA), respectively +/- 1.96 SE and +/-20% around mean value, except for the individual variability parameters (in grey *), which had two modalities (mean value or null).

The comparison of SA results revealed several differences regarding parameters' influence and relative order (Table C-2). Although we also detected the influence of the two initial state factors, their impact was less important than for the first SA and many demographic parameters had similar or higher influence, with sometimes very high sensitivity indices values, due to larger variations of model predictions. We even reached unrealistically high densities for adult trees (N up to 600-800 t/ha and G up to 100-150 m²/ha; Figure C-7a-b) and poles (up to 2000-4000 t/ha depending on initial stands; Figure C-7e), as well as for tree sizes (Dg up to 150 cm; Figure C-7c), leading to stands with very large trees (which affected GiniG index with values up to 0.8; Figure C-7d). These values question the realism of the variation ranges tested, which led to unrealistic situations.

The two growth parameters were still among those parameters, but their relative influence changed, with a higher influence of growth beta than growth alpha, probably due to the increase of its variation range (~20% against ~10% previously for growth beta; ~20% for growth alpha in both SA). In the same way, a smaller variation range strongly reduced the influence of the two seed production parameters (SA_1), while the increased variation range revealed the potentially high influence of other regeneration parameters like light survival parameters (especially S_B1 and S_B2) or sapling height growth, with SR_1 being among the most influent parameters (n° 1 and 4 for spruce and fir). Higher sapling/seed survival would explain the very high pole densities obtained for these simulations (Figure C-7e).

Contrary to the first SA, we detected here the influence of allometric parameters affecting tree height (H_mK and H_r) and crown radius (CBR_b), as well as the associated individual effect (CBR_sK and H_sK). These parameters highly influenced tree diameter growth (Dg) due to their effect on crown dimensions and thus potential light interception. Crown radius also influenced regeneration and stem number, through competition for light with saplings and smaller trees. These parameters are also potentially responsible for the unrealistically high tree sizes and density values obtained for these simulations (Figure C-7).

Finally, we also detected a high influence of mortality parameters linked to dbh-related mortality for fir (M_P2_1) and competition-related mortality for spruce (M_P3_0), though their variation range was lower than for the first SA (50.79% and 24.05% respectively). This reveal the regulation role of the mortality process when density is high and not regulated by management (harvesting quantities were fixed to the historical recorded values and thus not adapted to higher simulated productivity).

This SA results comparison revealed the high sensitivity of SA results to parameters' variation range, as well as the risks associated with variation range disconnected from realistic variation ranges and possibly leading to unrealistic situations. This thus confirmed our initial assumption regarding the choice of the variation range, which should be as realistic as possible, and the fact that variation within +/- 1.96 SE enabled us to limit these risks compared to a fixed +/- 20% range, as we had no information about the "natural variation range". We hope that future recalibration results conducted on different ecological conditions would help us define this "natural variation range" and thus refine the SA process.

		Variation of demographic parameters within +/- 1.96 SE around the mean									Variation of demographic parameters within +/- 20% around the mean								
	Factors	**N**	**G**	**Dg**	**GiniG**	**Pole Qty**	**MixR**	**Pole MixR**	**Rank Sum**	**Global Rank**	**N**	**G**	**Dg**	**GiniG**	**Pole Qty**	**MixR**	**Pole MixR**	**Rank Sum**	**Global Rank**
Growth	**G_A_0**	2	1	1	3	4	1	5	17	**1**	2	2	5	14	5	4	25	57	**7**
	G_A_1	7	4	7	6	8	5	7	44	**6**	11	6	9	24	14	7	27	98	**11**
	G_b_0	3	2	2	1	6	2	9	25	**2**	4	1	1	1	7	1	8	23	**2**
	G_b_1	8	5	5	5	11	4	27	65	**8**	6	4	8	10	10	2	10	50	**5**
	G_sB_0	38	36	35	35	43	36	42	265	**37**	31	33	41	41	34	42	29	251	**40**
	G_sB_1	39	44	36	39	39	40	40	277	**40**	38	44	18	13	43	23	37	216	**32**
	G_sL_0	43	33	38	36	36	39	39	264	**36**	44	36	21	40	44	26	39	250	**39**
	G_sL_1	41	42	41	40	38	38	30	270	**38**	36	39	39	12	40	39	36	241	**38**
Crown B. Height	**CBH_mK_0**	30	21	33	34	14	31	24	187	**32**	26	24	37	37	26	34	38	222	**35**
	CBH_mK_1	31	35	32	24	21	25	26	194	**34**	29	31	31	39	37	36	35	238	**37**
	CBH_sK_0	37	40	37	43	40	37	37	271	**39**	42	41	42	43	30	43	12	253	**41**
	CBH_sK_1	35	43	43	42	44	44	36	287	**42**	41	38	43	42	42	44	34	284	**44**
Crown B. Radius	**CBR_b_0**	17	12	20	29	9	22	31	140	**20**	3	8	2	19	2	6	15	55	**6**
	CBR_b_1	18	27	26	17	15	12	35	150	**21**	10	18	13	7	6	17	6	77	**9**
	CBR_mK_0	24	34	17	13	12	33	28	161	**23**	17	25	34	33	12	29	22	172	**25**
	CBR_mK_1	22	28	15	9	33	17	15	139	**19**	22	20	33	16	25	27	20	163	**21**
	CBR_sK_0	36	39	40	38	35	35	38	261	**35**	43	42	40	44	36	38	33	276	**43**
	CBR_sK_1	44	37	39	37	42	42	41	282	**41**	40	40	19	9	41	40	43	232	**36**
Height	**H_mK_0**	23	20	21	22	13	7	21	127	**13**	20	15	17	31	19	16	28	146	**19**
	H_mK_1	26	29	22	15	27	26	23	168	**25**	24	34	38	34	23	37	21	211	**31**
	H_r_0	33	25	23	27	32	8	29	177	**29**	19	16	11	38	16	13	17	130	**17**
	H_r_1	32	26	13	21	24	15	33	164	**24**	30	12	7	26	38	10	44	167	**24**
	H_sK_0	42	41	44	41	41	41	44	294	**44**	39	37	20	18	33	20	41	208	**30**
	H_sK_1	40	38	42	44	37	43	43	287	**42**	37	43	44	22	35	41	42	264	**42**
Regeneration (Saplings)	**S_A1_0**	4	6	8	7	2	9	2	38	**5**	32	23	28	35	18	30	31	197	**29**
	S_A1_1	1	8	6	8	5	6	1	35	**4**	18	21	29	36	28	28	23	183	**27**
	S_B1_0	29	15	25	31	29	28	32	189	**33**	5	5	12	5	3	11	3	44	**3**
	S_B1_1	21	32	18	19	16	11	34	151	**22**	13	14	27	27	15	24	5	125	**14**
	S_B2_0	34	22	34	25	19	32	12	178	**31**	9	11	25	21	4	18	4	92	**10**
	S_B2_1	28	31	29	20	25	19	19	171	**27**	15	29	14	2	17	14	7	98	**11**
	S_B3_0	25	16	30	28	30	27	18	174	**28**	21	27	30	17	13	32	26	166	**23**
	S_B3_1	20	19	16	18	20	16	22	131	**15**	28	35	22	20	29	22	9	165	**22**
	S_R1_0	11	10	12	32	7	20	4	96	**10**	1	3	3	4	1	5	1	18	**1**
	S_R1_1	27	24	31	33	17	23	14	169	**26**	7	9	4	11	8	3	2	44	**3**
	S_R2_0	10	18	9	10	10	18	3	78	**9**	35	30	35	15	39	25	40	219	**33**
	S_R2_1	15	23	10	11	18	30	20	127	**13**	34	28	36	32	31	35	24	220	**34**
Mortality	**M_P1_0**	9	13	24	23	31	24	11	135	**17**	12	10	26	25	21	19	16	129	**16**
	M_P1_1	12	14	19	14	22	13	17	111	**11**	16	19	23	29	22	21	19	149	**20**
	M_P2_0	13	9	28	16	23	21	25	135	**17**	25	22	32	30	24	33	30	196	**28**
	M_P2_1	14	17	11	12	34	29	16	133	**16**	27	26	6	8	20	8	32	127	**15**
	M_P3_0	19	30	27	26	28	34	13	177	**29**	23	32	16	6	27	15	18	137	**18**
	M_P3_1	16	11	14	30	26	10	10	117	**12**	33	17	24	28	32	31	11	176	**26**
Ini. State	**IS_F1**	5	3	3	2	1	3	8	25	**2**	8	7	10	3	9	9	14	60	**8**
	IS_F2	6	7	4	4	3	14	6	44	**6**	14	13	15	23	11	12	13	101	**13**

Table C-2: Comparison of sensitivity analysis results depending on factors' variation ranges.

This table compares the results obtained for the first (+/- 1.96 SE, left) and second (+/- 20%, right) sensitivity analysis (SA). Each sub-table indicates, for each output variables (in columns), the rank obtained by each input factor (in lines), based on the comparison of the sensitivity indices proposed by Ciric *et al.* (2012) and considering both Morris' indices (μ* and σ). The last column indicates the global order, based on the sum of the ranks obtained by each factor. Besides factors' rank, groups of factors have been identified depending on their relative degree of influence (determined graphically based on Morris' indices): very high (dark grey), high (grey), medium (light grey) and low (white). Tested factors encompass demographic and allometric parameters for each species (0 for spruce and 1 for fir), as well as the two "initial state" factors (IS_F1 and IS_F2). Studied output variables included stand density (N, t/ha) and basal area (G, m²/ha), tree mean quadratic diameter (Dg, cm), stand diameter diversity (GiniG, no unit) and composition (MixR, % of spruce basal area), total pole density (PoleQty, t/ha) and pole mixing ratio (PoleMixR, % of spruce poles).

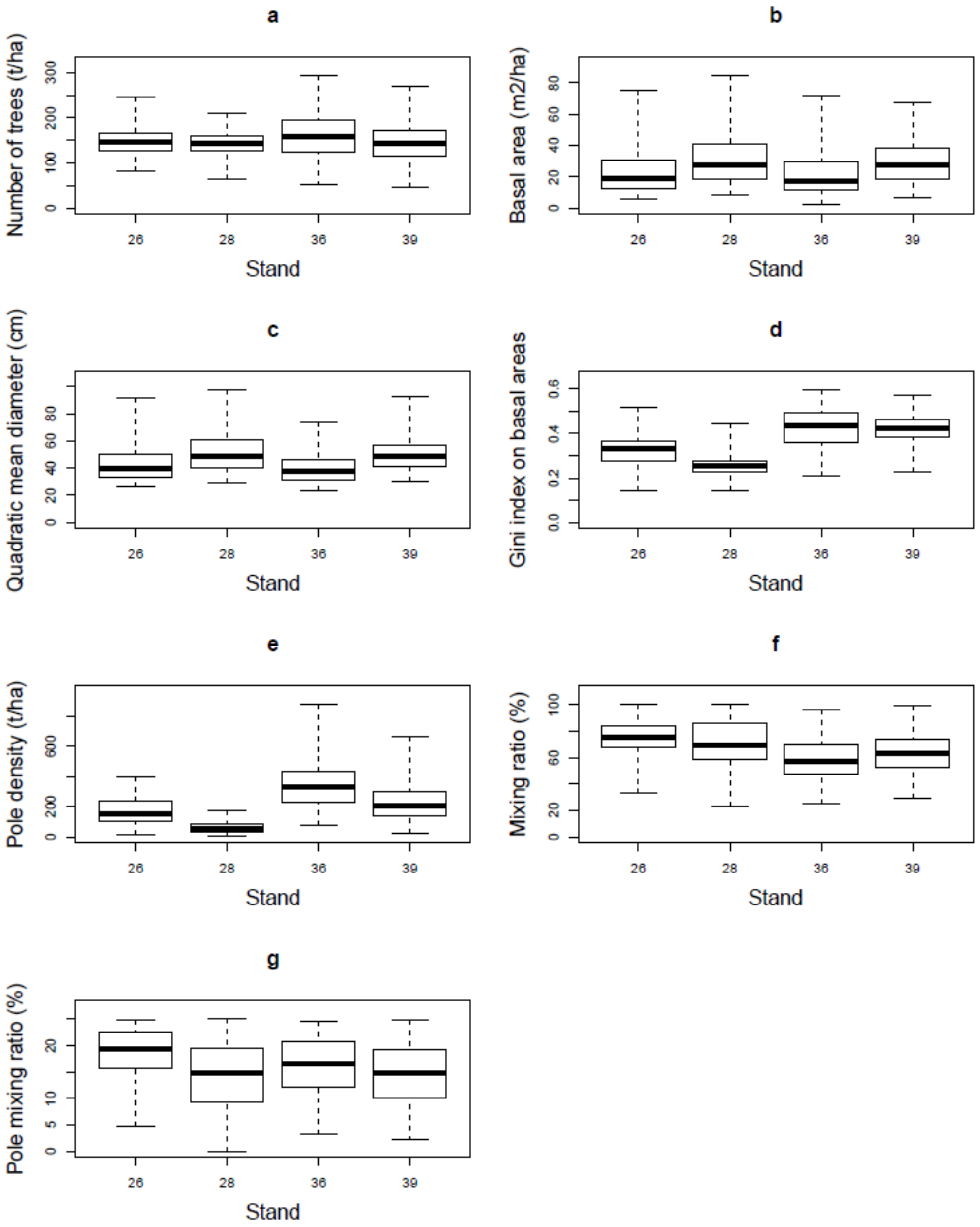

Figure C-6 : Values and variability of final stand characteristics, for the first SA.

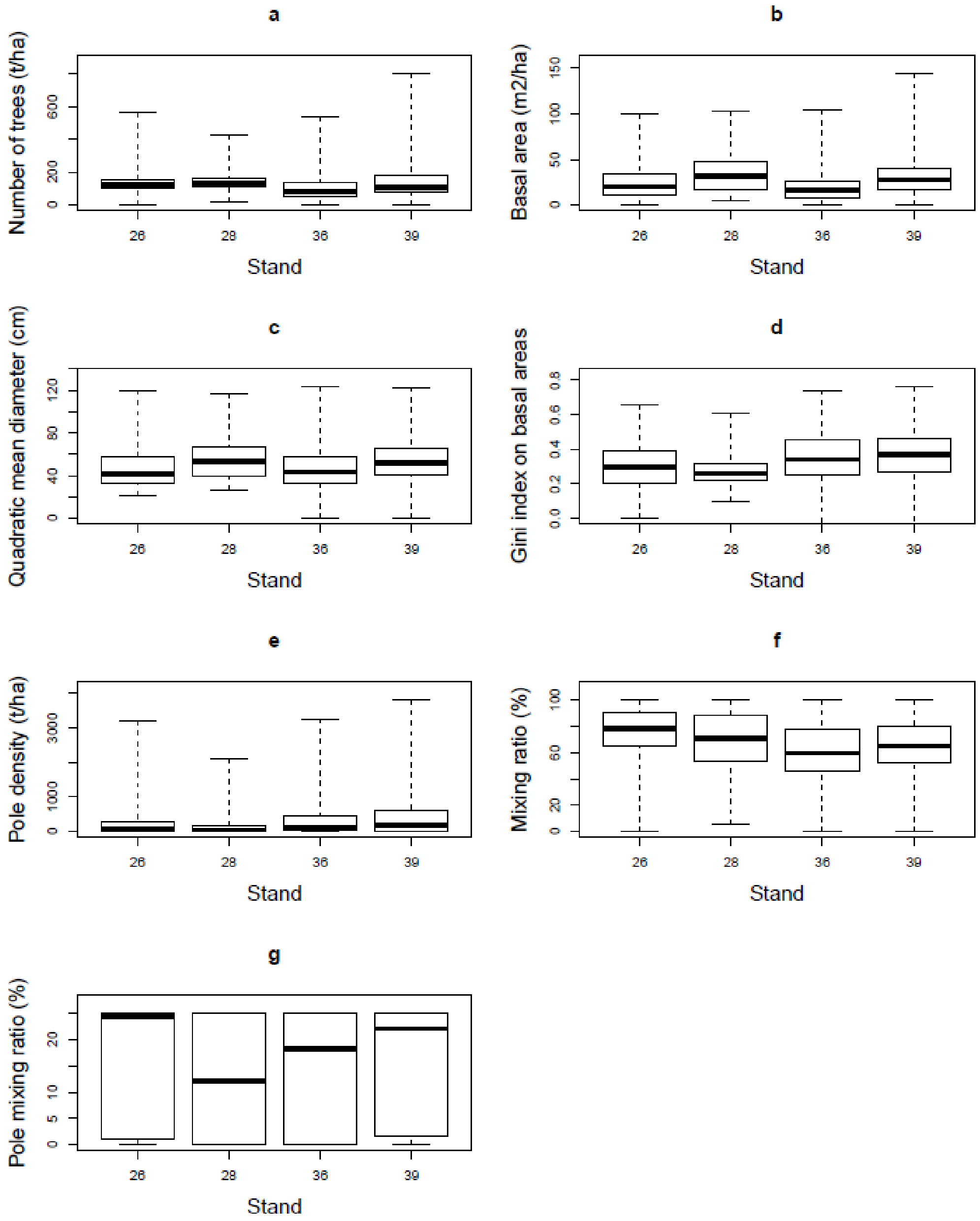

Figure C-7 : Values and variability of final stand characteristics, for the second SA.
NB: scales are different from Figure C-6.

TRADE-OFF NUMBER OF TRAJECTORIES/ ACCURACY OF SENSITIVITY MEASURES

Successive SA test showed that SA results were sensitive to the number of trajectories. Previous analysis with r = 30 trajectories led to very high uncertainties regarding sensitivity indices(large confidence intervals) and we expected important variations between replications of the same experiment design and thus non-robustness of the SA results. These uncertainties were reduced with r=100 trajectories, but the confidence intervals of some factors were still overlapping, thus questioning the confidence given to factor ranks. The comparison between two realisations of the same experiment design enabled us to detect small differences regarding factors' ranks, especially among the moderately influent parameters, although the affiliation to the groups of very influent and influent factors and general conclusions were identical. We however detected higher variations regarding factors affiliation to the group of "moderately influent parameters", first because this third group did not always appeared clearly when analysing eDist values, second because we observed more differences between different run for this group. It was also very difficult to set a limit between low and non-influent parameters based on the graphical visualization of different groups.

These results underlined the necessity to keep the confidence intervals in mind while analysing eDist values and factors ranks. As regard the limit between low and non-influent factors, we finally concluded that using a threshold on the sensitivity index values would probably facilitate the analysis, with however high uncertainty regarding the value to use for such thresholds.

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