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The effect of natural and anthropogenic disturbances on the uncertainty of large-area forest growth forecasts

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This study aimed to estimate the contribution of disturbances to the uncertainty of forest growth forecasts in the Bas-Saint-Laurent region in Quebec, Canada. We focused on two major disturbances affecting that region: spruce budworm (SBW) outbreaks and harvest activities. Growth forecasts were carried out for a period of 100 years (2003–2103) using ARTEMIS-2009, a stochastic individual-based model. Using the Monte Carlo technique, we simulated four scenarios: a baseline; a harvest scenario; a SBW scenario; and a scenario including both harvest and SBW. Uncertainty estimation was performed using a bootstrap variance estimator that applies to the context of hybrid inference. The results revealed that the total variances increased over time. For the scenarios including SBW, the variances were three to six times greater than those in the scenarios without outbreaks. Harvesting did not greatly contribute to the total variance. We conclude that to reduce the uncertainty of large-area growth forecasts in the Bas-Saint-Laurent, considering SBW dynamics is a crucial issue.

Introduction

The influence of disturbances on forest ecosystems has been given special attention over the last decades due to anticipated environment changes (Turner, 2010). The disturbance regime plays a dominant role in shaping forest dynamics, such as influencing structure and composition (Bouchard and Pothier, 2011), as well as determining temporal and spatial patterns (Didion *et al.*, 2007). This important role has triggered efforts to include disturbances in forest management plans (Daniel *et al.*, 2017) and in growth forecasts (Turner, 2010).

Natural disturbances along with anthropogenic activities are one of the major agents that shape the landscape. In European forests, the most common large-scale disturbances are storms, followed by fires and insect outbreaks (Schelhaas *et al.*, 2003). In the Canadian boreal forests, the natural disturbances are mainly fires and insect outbreaks such as forest tent caterpillar (*Malacosoma disstria*), jack pine budworm (*Choristoneura pinus*) and spruce budworm (*Choristoneura fumiferana* (Clem.); SBW) (Brandt *et al.*, 2013). They are known to affect up to millions of hectares (Gauthier *et al.*, 2015). Among other anthropogenic disturbances such as agriculture and roads, harvest activities have become a key driver of forest dynamics (Venier *et al.*, 2014). Approximately 40 per cent of the boreal forest is under management and these managed areas are more disturbed by harvesting than by natural disturbances (Venier *et al.*, 2014).

Including disturbances in growth models is necessary to properly simulate forest dynamics over large areas (Seidl *et al.*, 2011). It generates more realistic growth forecasts, which are of great interest in practical forestry, ecology and climate change mitigation activities (Ståhl *et al.*, 2016). Nevertheless, the process of simulating forest growth over large areas implies propagating errors. Such uncertainties arise from the model and the sampling. Model errors are a result of parameter estimation and the structure of the model, among others factors (Walker *et al.*, 2003; Refsgaard *et al.*, 2007). Sampling errors are due to the upscaling of forest variables to a higher level (Breidenbach *et al.*, 2014).

Because large-area growth forecasts are based on both the model and the sampling design (Ståhl *et al.*, 2016), they represent a typical case of what is known as hybrid inference (Corona *et al.*, 2014). This context of hybrid inference arises when: (1) the variable of interest, such as growth, is not observed but predicted using a model; and (2) the explanatory variables of the model are observed in the sample only and not throughout the entire population (McRoberts and Westfall, 2014; Fortin *et al.*, 2016). This requires special estimators that account for both sources of uncertainty (McRoberts and Westfall, 2016). Hybrid estimators applied with forest growth models propagate errors from the plot to the regional or national level and they represent an implementation of an upscaling method known as the direct extrapolation method (Wu *et al.*, 2006).

Uncertainty assessment of forest growth forecasts has been studied by many authors (Kangas, 1999; Xu and Gertner, 2008; Horemans *et al.*, 2016). In some cases, natural and anthropogenic disturbances were taken into account. However, to the best of our knowledge, the uncertainty they induce in large-area growth forecasts has not been fully addressed. In the very few cases where the uncertainty due to the disturbances was addressed, it was either for anthropogenic or natural disturbances, but not for both. Moreover, the uncertainty that stemmed from the sampling was overlooked (Bergeron *et al.*, 2017). This conjecture motivated this study.

The impact of a particular type of disturbance on growth forecast uncertainty can be assumed to be closely related to its spatial and temporal patterns. Some authors who studied these patterns with regard to population dynamics found that different populations from the same species present a synchronicity (Williams and Liebhold, 2000), i.e. one population is likely to occur simultaneously with other populations. This correlated population fluctuation has been detected in various taxa and over many spatial scales (Liebhold *et al.*, 2004). For insects acting as a disturbance in forests, the synchronicity of outbreaks can impact growth forecasts due to the coincident changes in forest attributes. At the landscape level, the extent of these changes can lead to variability.

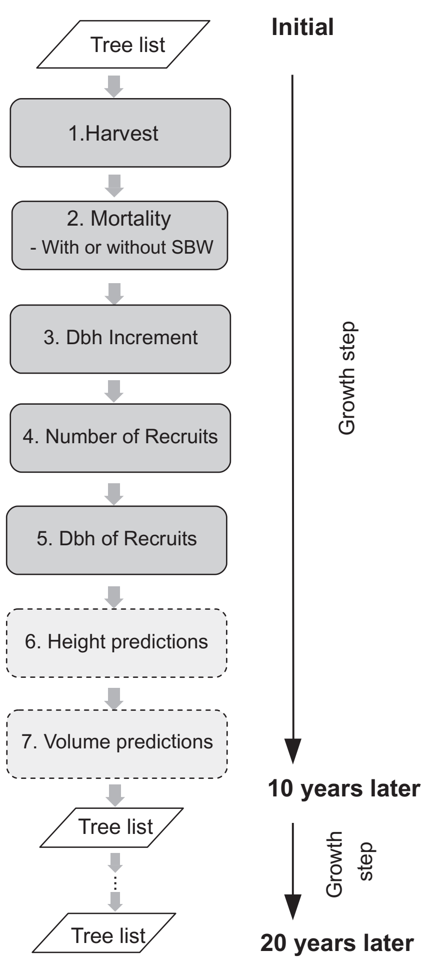

Figure 1 Flowchart of ARTEMIS-2009 considering its iterative process. Dark gray boxes represent the dynamic sub-models. Dotted light gray boxes are the static sub-models.

Given the influence of disturbances on forests, our main objective was to take them into consideration in large-area growth forecasts and to estimate their contribution in terms of uncertainty. To do this, we worked on a real-world case study: the administrative region of Bas-Saint-Laurent, Quebec, Canada. More specifically, we focused on spruce budworm outbreaks and harvesting, which are the two major disturbances in that region. As a natural component, spruce budworm outbreak is of concern since it occurs on a large scale with return intervals of a few decades, and has a great impact on forest productivity (Boulanger *et al.*, 2012). The region is presently facing a SBW outbreak.

Motivated by the spatial synchrony theory, we first hypothesized that spruce budworm outbreaks have a greater impact than harvesting on the uncertainty of large-area growth forecasts. In the context of hybrid inference, the uncertainty related to the predicted occurrence of natural and anthropogenic disturbances belongs to the model part and not to the sampling. In a previous study on large-area growth forecasts, Melo *et al.* (2018) found that the model-related variance increased along the projection length and could match that of the sampling in the absence of disturbances. Given that the occurrence of natural disturbances is highly stochastic, our second hypothesis was that disturbances induced more uncertainty than the sampling in these large-area growth forecasts. Data from the provincial network of permanent plots in Quebec, Canada, and the ARTEMIS growth model (Fortin and Langevin, 2012) were used to generate those large-area growth forecasts for the Bas-Saint-Laurent region.

Material and methods

ARTEMIS growth model

We worked with the distance-independent individual-based growth model, ARTEMIS (Fortin and Langevin, 2010, 2012). The first version of the model was designed in 2009. Since then, it has been regularly updated. The model was fitted using the network of permanent plots of the Quebec provincial forest inventory (MFFP, 2009, 2015). Briefly, ARTEMIS is composed of seven sub-models, with five of them being dynamic and the other two static (Figure 1). The dynamic sub-models predict the harvest probability, the mortality probability, the diameter increment, the number of recruits and the diameter of these recruits, respectively. The two static sub-models make it possible to predict tree height and commercial volume based on other characteristics of the trees and the plot. All these sub-models were fitted using mixed-effects models or covariance structures in order to account for serial and spatial dependence at the plot, interval and tree levels. More details are available in Fortin and Langevin (2010, 2012).

The model uses 10-year growth steps. The output of a given step is re-inserted in the model in order to obtain forecasts over longer time periods. Users may run growth simulations in a deterministic or stochastic fashion. The stochastic mode relies on the Monte Carlo technique (Rubinstein and Kroese, 2007). In such a mode, three types of errors are simulated: the errors in the parameter estimates, the plot or interval random effects and the residual errors. The model provides tree-level predictions. Plot-level predictions are obtained through the aggregation of the predictions at the tree level.

ARTEMIS relies on a large array of explanatory variables. At the plot and tree levels, the model considers the tree species, harvest occurrence (yes/no), stem density (tree ha^{-1}) and basal area (m^2 ha^{-1}), which is the sum of the cross-section areas at 1.3 m in height. These aforementioned variables are considered as endogenous variables, i.e. influenced by factors within the system (Rao and Toutenburg, 1995). ARTEMIS also considers the potential vegetation. The potential vegetation refers to the composition at a late successional stage (Grondin *et al.*, 2009). Thirty-two potential types of vegetation exist in the province of Quebec (Saucier *et al.*, 2015) and ARTEMIS was designed to work with the 25 most frequent ones. Each potential vegetation type was modelled individually, thus resulting in 25 versions of the model (Fortin and Langevin, 2010).

Finally, mean annual precipitation (mm) and temperature (°C) are predictors in ARTEMIS. They are both entries in the mortality and recruitment sub-models. The diameter increment sub-model considers only precipitation, whereas the sub-models predicting recruit diameter and tree height consider only the mean temperature. These variables are estimated using BioSIM, a software program that predicts climate variables for a particular geographical location based on the data of the nearest climate stations (Régnière *et al.*, 2010).

Considering that disturbances are the focus of this study, the way they are taken into account in ARTEMIS is further described in the next lines. The harvest module works in two steps. It first yields a 10-year harvest occurrence prediction for a particular plot considering some plot-level variables (e.g. slope inclination) and the annual allowable cut volume (AAC) (MFFP, 2003). This AAC volume is estimated by a governmental agency for a particular territory and it represents the maximum volume that can be sustainably harvested. In our simulations, we assumed that this AAC volume remained constant over time, even though it is re-estimated every 5 years in practice. Whenever a plot is harvested, the second part of the sub-model predicts a harvest probability for each tree of this plot given a management regime (Fortin, 2014). Readers are referred to Melo *et al.* (2017) and to Fortin (2014) for additional details about the harvest sub-model.

ARTEMIS also takes the impact of spruce budworm defoliation into account. A recurrence of outbreaks must be specified by the user. An outbreak is here defined as at least 4 consecutive years of moderate to severe defoliation on all the host species at the regional level. According to Pothier *et al.* (2005), this 4-year period can be considered as a threshold beyond which the mortality rates of the host species significantly increase. For the recurrence R, the annual probability of occurrence can be derived as the inverse of the recurrence, i.e. $1/R$. The probability that no outbreak occurs during a 10-year growth step is based on the balance of probability: $(1-1/R)^{10}$. The probability that at least one outbreak occurs is then $1-(1-1/R)^{10}$. We assumed that all the plots were affected by the outbreak when it occurred.

The impact of SBW outbreaks was statistically tested in the mortality sub-model and it was included as a dummy variable (Fortin and Langevin, 2010, 2012). This variable takes the value of 1 whenever an outbreak occurs during a particular 10-year growth step. This induces an increase in the predicted probabilities of mortality for spruce (*Picea* spp.) and balsam fir (*Abies balsamea* (L.) Mill.).

Uncertainty estimation

A key step in our study is to estimate uncertainty in the predicted volumes in the context of hybrid inference, that is, inference relying on both the model and the sampling design (Corona *et al.*, 2014). To do this, we used a hybrid variance estimator based on the bootstrap method (Fortin *et al.*, 2018). The mathematical developments behind the estimator are presented in the Supplementary Material 1.

If we consider a design of simple random sampling without replacement with even inclusion probabilities, an unbiased estimator of the population mean is the sample mean:

$$\hat{\mu} = \frac{1}{n}\sum_{i \in s} y_i \tag{1}$$

where s is the sample, y_i is the variable of interest in plot i and n is the sample size.

The variance of this estimator is, in turn, estimated as follows:

$$\hat{\mathbb{V}}(\hat{\mu}) = \left(1 - \frac{n}{N}\right)\frac{\sum_{i \in s}(y_i - \hat{\mu})^2}{n(n-1)} \tag{2}$$

where N is the number of units in the population.

When y_i is not available, a model can be used to obtain a prediction that is denoted as $\hat{y}_i$. Substituting $\hat{y}_i$ for y_i in Eq. (1) still yields an unbiased estimator of the mean provided that the model has no lack of fit. However, the adaptation of the variance estimator requires further developments, namely propagating errors from different sources within the model. This error propagation can be carried out using the Monte Carlo technique (Rubinstein and Kroese, 2007). The technique consists of drawing random deviates to account for the errors in the parameter estimates, the random effects and the residual errors. A single simulation based on a particular set of deviates provides a realization of the estimated mean and the estimated variance shown in Eqs. (1) and (2). After a great number of realizations, the bootstrap estimator of the mean is as follows:

$$\hat{\mu}_{\mathrm{BS}} = \frac{1}{B}\sum_{b=1}^{B}\hat{\mu}_b \tag{3}$$

where $\hat{\mu}_b$ is the sample mean obtained from realization b, and B is the total number of realizations.

Consistent with Fortin *et al.* (2018), an unbiased bootstrap variance estimator is as follows:

$$\hat{\mathbb{V}}(\hat{\mu}_{\mathrm{BS}}) = \frac{\sum_{b=1}^{B}(\hat{\mu}_b - \hat{\mu}_{\mathrm{BS}})^2}{B} + 2\hat{\mathbb{V}}(\hat{\mu}_{\bar{y}}) - \frac{\sum_{b=1}^{B}\hat{\mathbb{V}}(\hat{\mu}_b)}{B} \tag{4}$$

where $\hat{\mathbb{V}}(\hat{\mu}_{\bar{y}})$ can be obtained by substituting $\bar{y}_i = \sum_{b=1}^{B}\frac{y_{i,b}}{B}$ and $\hat{\mu}_{\mathrm{BS}}$ for y_i and $\hat{\mu}$, respectively, in the variance estimator found in Eq. (2). The sampling contribution to the total variance is obtained through $\hat{\mathbb{V}}(\hat{\mu}_{\bar{y}})$, while the model contribution is calculated as $\hat{\mathbb{V}}(\hat{\mu}_{\mathrm{BS}}) - \hat{\mathbb{V}}(\hat{\mu}_{\bar{y}})$.

Study area and dataset

The inventory data were a subset of the provincial network of permanent plots of Quebec's Ministry of Forests, Wildlife and Parks (MFWP). We limited our analysis to the regional level. Thus, our dataset included only the plot measurements from the Bas-Saint-Laurent administrative region. Covering a surface of 22 185 km^2, the forest composition is representative of broadleaved, mixed and coniferous vegetation. The dominant species in this region are sugar maple (*Acer saccharum* Marsh.), yellow birch (*Betula alleghaniensis* Britton), balsam fir, white spruce (*Picea glauca* Voss) and black spruce (*Picea mariana* Britton). The plots are located in five different ecological regions, the result of a classification established by the MFWP to characterize the composition and dynamics of the vegetation (MFFP, 2016). The plot distribution in the different ecological regions is shown in Figure 2.

Historically, the Bas-Saint-Laurent region has been subject to anthropogenic and natural disturbances. The region was affected by severe SBW outbreaks during the last century, which, as a consequence, triggered salvage cutting (Boulanger and Arseneault, 2004). Moreover, silvicultural practices have deeply transformed forest composition (Boucher *et al.*, 2009). The current regional forest planning guidelines prescribe silvicultural practices adapted to the different forest types (Gagnon *et al.*, 2015): selection cutting in shade-tolerant broadleaved forests; irregular and regular shelterwood cutting in mixed stands; and

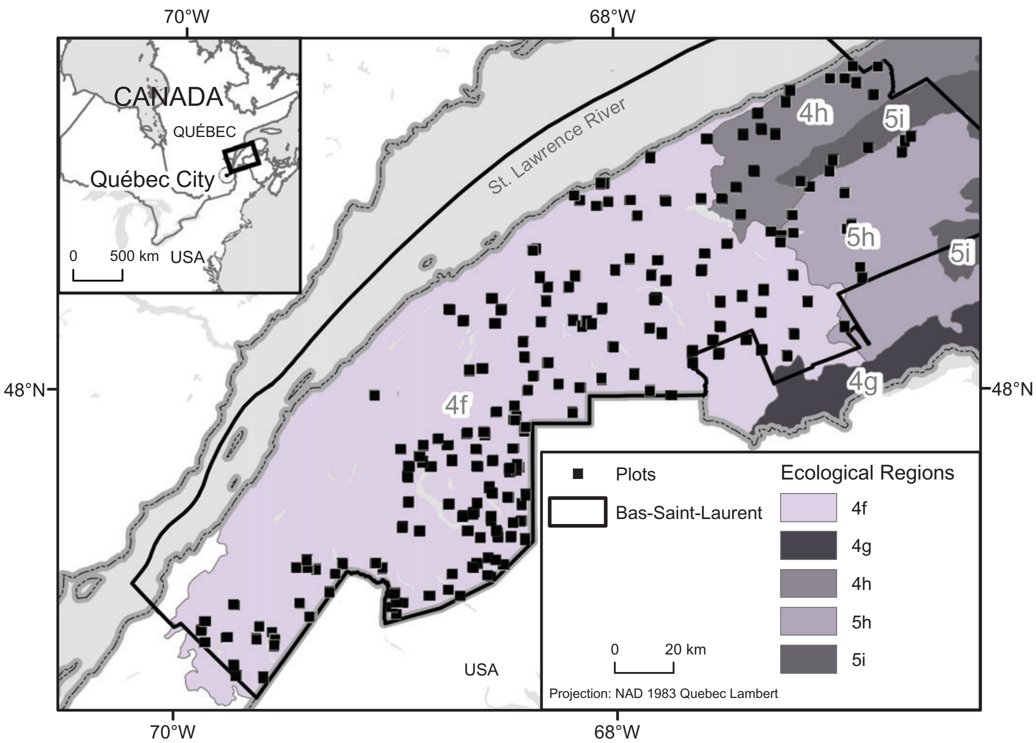

Figure 2 Distribution of the 393 permanent plots in Bas-Saint-Laurent. The plots are located in the ecological regions classified according to the MFWP: Appalachian Hills (4f); Baie des Chaleurs Coastline (4g); Gaspé Coastline (4h); Mountains of Gaspé Peninsula (5h); Highlands of Gaspé Peninsula (5i).

Table 1 Summary of 393 plots in the dataset. Attributes were broken down for the most abundant species. The minimum and maximum values are shown in parentheses. *n*, number of trees.

Plot-level	Basal area (m^2 ha^{-1})	Stem density (trees ha^{-1})	Volume (m^3 ha^{-1})
Sugar Maple	2.5 (0–29.7)	68 (0-–1266)	73.3 (0.48–226.94)
Red Maple	1.2 (0–13.7)	57 (0–900)	19.55 (0.40–120.81)
Balsam fir	5.1 (0–42.6)	256 (0–2350)	42.01 (0.25–162.73)
White spruce	1.5 (0–28.2)	61 (0–1850)	22.38 (0.19–143.39)
Black spruce	0.7 (0–21.5)	48 (0–1800)	17.24 (0.27–111.12)
White birch	1.6 (0–18.5)	95 (0–875)	23.92 (0.26–156.76)
All species	17.8 (0–61.2)	778 (25–2550)	53.7 (0.06–221.04)
Tree-level	***n***	**DBH (cm)**	**Height (m)**
Sugar Maple	1 124	20.4 (9.1–78.3)	17.5 (7.2–27.1)
Red Maple	901	14.9 (9.1–68.3)	14.6 (9.2–24.1)
Balsam fir	4 072	15.1 (9.1–49.3)	13.3 (3.8–24.5)
White spruce	983	17.0 (9.1–54.5)	13.0 (5.0–24.5)
Black spruce	762	13.3 (9.1–32.5)	10.7 (5.2–21.0)
White birch	1 492	14.2 (9.1–42.8)	13.2 (6.5–19.8)
All species	12 451	16.2 (9.1–98.8)	14.5 (3.8–27.7)

harvest with protection of regeneration and soils for most coniferous forests and some mixed stands.

Our dataset consisted of 393 permanent plots located in the Bas-Saint-Laurent region, each one with an area of 400 m^2. In these plots measured in 2003, all trees with diameter at breast height (DBH, 1.3 m in height) equal to or greater than 9.1 cm were tagged for individual monitoring. A summary of the dataset is provided in Table 1.

Forecasting

We built a framework to predict forest growth for the Bas-Saint-Laurent region, taking harvest and SBW outbreak effects into account. These projections were carried out for a period of 100 years (2003–2103), considering a 2°C temperature increase and a 5 per cent precipitation increase over the 21st century, which roughly corresponds to the representative concentration pathway (RCP) 4.5 provided by the IPCC (2013, p. 1335). Since the initial year of our forecasts was 2003, the observed disturbance history up to 2018 is known. We first configured the forecasts to update the plot status, i.e. to take the management of the first two decades (2003–2023) and the SBW outbreak initiated in 2013 into account. Once this initial condition was established, we then tested four scenarios: (i) a baseline scenario with no disturbances; (ii) a harvest scenario, in which plots were harvested according to the current level of annual cut volume allowance and the prescribed treatments for each forest type; (iii) a SBW scenario, in which we considered an average outbreak recurrence of once every 35 years, according to Boulanger and Arseneault (2004); and (iv) a scenario including both harvest and SBW outbreaks, structured as in the second and third scenarios but acting simultaneously here. The simulations were run on the CAPSIS platform (Dufour-Kowalski *et al.*, 2012). We ran a total of 10 000 Monte Carlo realizations to account for the variability induced by disturbances for each scenario. It is worth mentioning that the forecasts include stochasticity from disturbances, as well as from the parameter estimates, the random effects and the residual errors.

ARTEMIS provides tree-level predictions. The individual predicted volumes were aggregated at the plot level. The hybrid bootstrap estimators shown in Eqs. (3) and (4) were then used to perform the upscaling to the regional level, as proposed in the direct extrapolation method (Wu *et al.*, 2006).

Results

Long-term volume forecasts for the Bas-Saint-Laurent region are shown with their confidence intervals in Figure 3. The baseline scenario, in which no disturbance was considered, resulted in an increasing volume that reached 220 $m^3\,ha^{-1}$ in 2103 (Figure 3a). When the disturbances were taken into account, similar growth patterns were observed but predicted volumes were smaller. More precisely, when SBW outbreaks were included in the forecasts, the volume in 2103 was 20 $m^3\,ha^{-1}$ lower than that of the baseline (Figure 3b). When considering harvest occurrence only, volume for the same period was 45 $m^3\,ha^{-1}$ lower compared to the baseline (Figure 3a). For the scenario in which harvest and spruce budworm outbreaks occurred simultaneously, predicted volumes for 2103 were 60 $m^3\,ha^{-1}$ smaller than the baseline (Figure 3b).

The confidence intervals provide an assessment as to how future growth can vary in the Bas-Saint-Laurent region under disturbances. Considering the predicted lower limit of the interval for the scenario considering both SBW outbreaks and harvesting (Figure 3b), it is very unlikely that the mean volume per hectare at the end of the 21st century will be smaller than what it was in 2003.

Growth forecasts were characterized by a total variance that increased over time (Figure 4). The magnitude of the increase was dependent on the scenario. The increase was steep for these scenarios including SBW (Figure 4c and d). At the end of the time horizon, the variances of these two scenarios were >100 $m^6\,ha^{-2}$, whereas the variances of the scenarios without SBW were smaller than 50 $m^6\,ha^{-2}$.

The scenarios including harvesting were characterized by smaller total variances. The total variance in the scenario considering harvesting only reached 30 $m^6\,ha^{-2}$ in 2103, whereas it was estimated at 43 $m^6\,ha^{-2}$ for the baseline scenario (Figure 4a,b). Likewise, in the scenario including simultaneously harvest and SBW, total variance was estimated at 138 $m^6\,ha^{-2}$, compared with 199 $m^6\,ha^{-2}$ in the scenario with SBW only (Figure 4c,d).

The sampling-related variances showed the same pattern across the scenarios. The variance slightly decreased in the first two decades and then remained stable or slowly increased over time. Model-related variances increased over time. Our results revealed two main trends. In the first case, for the baseline and harvest scenarios, the model-related variances increased steadily

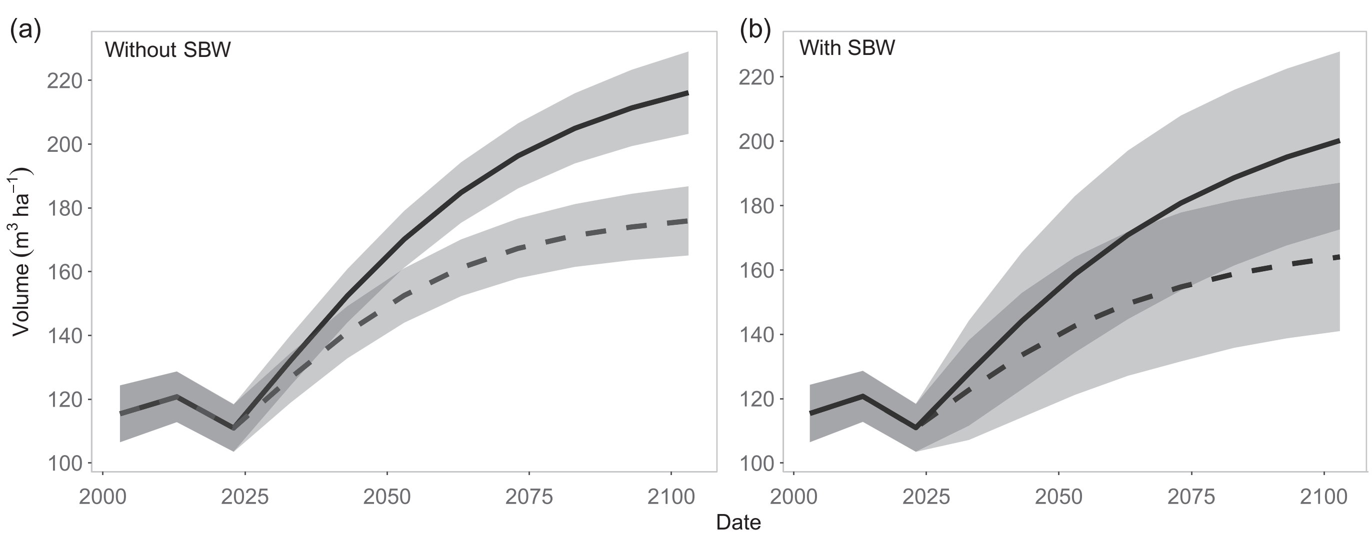

Figure 3 Mean predicted volumes ($m^3\,ha^{-1}$) and their 0.95 confidence intervals for the Bas-Saint-Laurent region. The confidence intervals rely on the assumption of a normal distribution. The solid line represents the scenarios without harvesting, while the dashed line represents the scenario including harvesting.

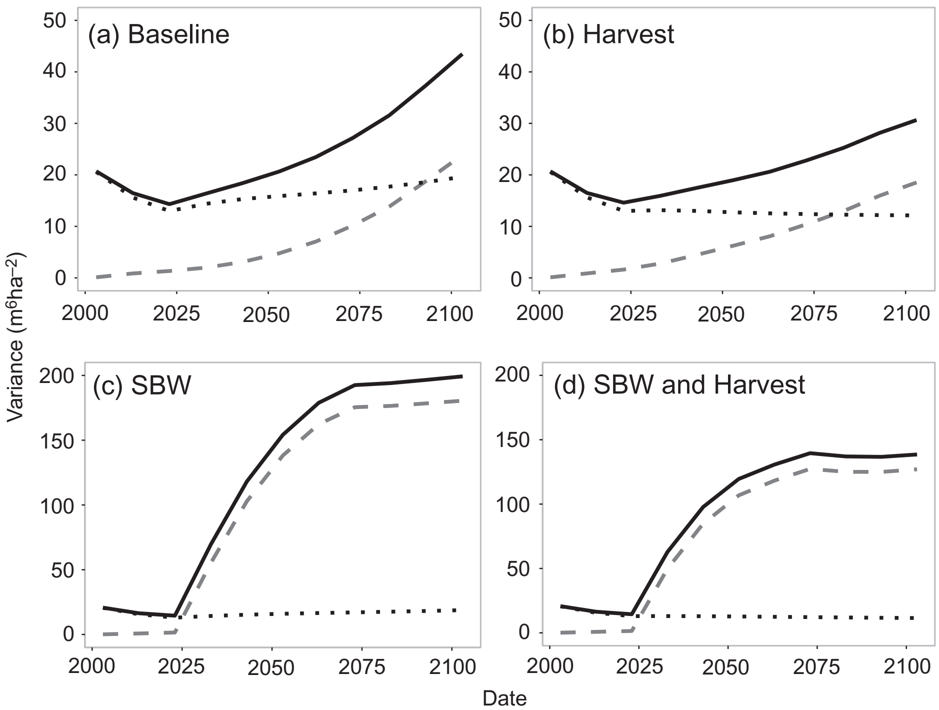

Figure 4 Model, sampling and total variances illustrated per growth scenario. Model contribution: gray dashed line; Sampling contribution: dark gray dotted line; Total variance: black solid line.

(Figure 4a,b). The second case was related to the inclusion of SBW outbreaks, which already greatly inflated the model-related variance on the short-term (Figure 4c,d). In both cases, the model-related variance mainly explained the patterns observed in the total variance. The absolute and relative variances related to all four scenarios are presented in Table 2.

Discussion

This study focused on the uncertainty of large-area volume forecasts under the effect of harvesting and SBW outbreaks. It turns out that both disturbance types affect the volume yield in predictions and their variances. It is obvious that omitting disturbances leads to overestimating growth (Valle *et al.*, 2006). In our study, we managed to estimate this bias. Harvesting is accounted for in most simulations, while natural disturbances are often omitted due to their stochastic nature. In the Bas-Saint-Laurent region, omitting SBW outbreaks caused an overestimation of 7.4 per cent in volume at the end of the 21st century (Figure 3).

Uncertainty estimation was performed in the context of hybrid inference at the regional scale. This was possible because: (1) a hybrid bootstrap variance estimator was available and (2) the model benefited from a full stochastic implementation, which is a requirement for the use of the estimator (Fortin *et al.*, 2018). Using this framework, we reproduced the variance patterns arising from the model and the sampling, and checked how they were affected by SBW outbreaks and harvest activities. Such a comprehensive consideration for the different sources of uncertainty in growth forecasts contributes to the originality of our study compared to past efforts.

Our first hypothesis was that SBW outbreaks induced more uncertainty in volume forecasts than harvesting. The scenarios including SBW outbreaks led to a variance that was three to six times greater than those in the scenarios without outbreaks (Figure 4). In our forecasts, enabling the occurrence of SBW outbreaks generated some realizations where all plots that contained host species were suddenly affected by greater mortality rates, whereas the other realizations were only subject to regular mortality. In contrast, harvesting affected all realizations, and in each of them, only a few plots were harvested while the others were left untouched. The clear consequence is a greater variability from the model in the scenarios including SBW outbreaks.

A surprising result was that the scenario including harvest was slightly less uncertain than the baseline scenario. Although unexpected, it can be reasonably assumed that the endogenous nature of the harvest sub-model implies less variability. In ARTEMIS, harvest probabilities are based on some plot-level variables that are predicted by the model. For instance, the larger the basal area is, the greater the probability of harvest will be (Melo *et al.*, 2017). Regardless of the realizations, plots with greater basal areas are then more prone to be harvested. As a consequence, there are fewer plots with large basal areas, and the population tends to be more homogeneous than in the baseline scenario. As outlined in Kneeshaw *et al.* (2011), harvest activities are likely to produce similar structural forests when compared with others natural disturbances such as spruce budworm outbreaks. Given this homogenizing effect of the harvesting, we cannot entirely validate our second hypothesis, which was that disturbances were expected to induce a greater deal of uncertainty in the forecasts than the

Table 2 Model and sampling-related variance contribution ($m^6\ ha^{-2}$), as well as the total variance estimated for each one of the four scenarios. The percentage contribution appears in parentheses.

Scenarios	Year	Model-related	Sampling-related	Total variance
Baseline	2003	0.12 (0.6%)	20.59 (99.4%)	20.70
	2013	0.86 (5.3%)	15.61 (94.7%)	16.47
	2023	1.34 (9.3%)	12.98 (90.7%)	14.32
	2033	1.99 (12.1%)	14.39 (87.9%)	16.38
	2043	3.09 (16.8%)	15.31 (83.2%)	18.40
	2053	4.77 (23.1%)	15.89 (76.9%)	20.66
	2063	7.05 (30.1%)	16.41 (69.9%)	23.46
	2073	10.14 (37.4%)	17.00 (62.6%)	27.14
	2083	13.82 (43.8%)	17.72 (56.2%)	31.54
	2093	18.76 (50.2%)	18.59 (49.8%)	37.35
	2103	23.86 (54.8%)	19.62 (45.2%)	43.48
Harvest	2003	0.11 (0.5%)	20.58 (99.5%)	20.70
	2013	0.87 (5.3%)	15.63 (94.7%)	16.50
	2023	1.61 (11.0%)	12.99 (89.0%)	14.61
	2033	2.78 (17.5%)	13.15 (82.5%)	15.93
	2043	4.47 (25.6%)	13.00 (74.4%)	17.48
	2053	6.26 (32.9%)	12.73 (67.1%)	18.99
	2063	8.10 (39.3%)	12.53 (60.7%)	20.63
	2073	10.43 (45.7%)	12.39 (54.3%)	22.82
	2083	12.96 (51.4%)	12.28 (48.6%)	25.24
	2093	15.98 (56.7%)	12.19 (43.3%)	28.17
	2103	18.53 (60.4%)	12.13 (39.6%)	30.66
Harvest and SBW	2003	0.13 (0.6%)	20.59 (99.4%)	20.72
	2013	0.80 (4.8%)	15.61 (95.2%)	16.41
	2023	1.47 (10.1%)	12.98 (89.9%)	14.45
	2033	49.77 (79.2%)	13.04 (20.8%)	62.81
	2043	84.78 (86.8%)	12.94 (13.2%)	97.71
	2053	106.72(89.3%)	12.72 (10.7%)	119.54
	2063	118.23 (90.5%)	12.46 (9.5%)	130.70
	2073	127.34 (91.3%)	12.21 (8.7%)	139.54
	2083	125.08 (91.3%)	11.94 (8.7%)	137.02
	2093	125.00 (91.4%)	11.69 (8.6%)	136.70
	2103	127.03 (91.7%)	11.51 (8.3%)	138.54
SBW	2003	0.13 (0.6%)	20.58 (99.4%)	20.71
	2013	0.77 (4.7%)	15.61 (95.3%)	16.38
	2023	1.53 (10.5%)	12.99 (89.5%)	14.52
	2033	55.24 (79.4%)	14.28 (20.6%)	69.52
	2043	102.84 (87.1%)	15.27 (12.9%)	118.11
	2053	138.14 (89.6%)	15.99 (10.4%)	154.13
	2063	162.35 (90.7%)	16.56 (9.3%)	178.91
	2073	175.46 (91.1%)	17.07 (8.9%)	192.53
	2083	176.47 (90.9%)	15.59 (9.1%)	194.06
	2093	178.45 (90.8%)	18.14 (9.2%)	196.59
	2103	180.48 (90.6%)	18.80 (9.4%)	199.28

sampling. This was true for SBW outbreaks, but not for harvesting activities.

The sampling-related variance did not show a decreasing trend in long-term predictions as it did in the study of Melo *et al.* (2018). It must be stressed that the sampling-related variance as estimated through the hybrid estimator of Fortin *et al.* (2018) is actually the variance of the mean plot-level predicted values. As the projection length increases, these plot-level predicted values tend to be similar due to model convergence. As reported in Melo *et al.* (2018), the population variance cannot be estimated from this sampling variance because it overlooks the increasing contribution of the residual errors. In other words, the flat trends we observed for the sampling-related variances cannot be interpreted as a constant degree of heterogeneity between the plots all along the projection. This plot-to-plot heterogeneity actually increases because of the model residual errors.

In the study of Melo *et al.* (2018), model- and sampling-related variances of basal area predictions were reported per ecotype for the Bas-Saint-Laurent region. To check if the different patterns in the sampling-related variances were a matter of ecotype, we also estimated model- and sampling-related variances of volume predictions per ecotype. We obtained trends similar to those observed by Melo *et al.* (2018), even if we were working with volumes, which allowed us to rule out any variable representation effect. This led us to consider the implications of an ecotype stratification on the sampling variance. The differences observed in the behaviour of sampling uncertainty herein and in Melo *et al.* (2018) could probably be due to inter-ecotype variance. Further details about these additional results can be found in the Supplementary Material 2.

Melo *et al.* (2018) also outlined the impact of sample size in sampling variance. Despite the greater sample size in this study, the estimated sampling variances were still large. Again, the inter-ecotype variance could be an explanation for this trend that we observed in our simulations.

It is known that a stratified sampling design can decrease the variance of the estimates. The decrease in the variance is linked to the homogeneity within the strata (Gregoire and Valentine, 2008, p. 127). In forestry, McRoberts *et al.* (2012) demonstrated that a stratification based on LiDAR data reduced the variance of mean volume estimates of growing stock. McRoberts and Westfall (2016) also obtained smaller variance estimates when using a stratified estimator in the context of individual tree volume. Building on this, we can reasonably assume that our sampling variance would decrease if we used a stratification based on the ecotypes, for example. The original version of the bootstrap estimator developed by Fortin *et al.* (2018) relies on the Horvitz–Thompson estimator (Horvitz and Thompson, 1952) which easily adapts to stratified sampling designs (Gregoire and Valentine, 2008, p. 135). However, the gain in precision under a stratified sampling design remains to be tested.

Finally, in our simulations, we observed that there is uncertainty related to sampling, but more importantly, there is greater uncertainty in modelling growth when SBW outbreaks are included. Previous studies (Breidenbach *et al.*, 2014; Ståhl *et al.*, 2014) concluded that the efforts to reduce sampling uncertainty were justified because it was the greatest source of uncertainty. In our study, priority should be given to reducing the uncertainties that stemmed from SBW outbreaks when forecasting growth. We do not advocate that sampling uncertainty should not be considered at all, but it clearly is smaller than the uncertainty from SBW outbreaks.

Existing research in growth forecast uncertainties under SBW is limited. The recent studies that are available support our findings. Boulanger *et al.* (2016) argued that model-specification uncertainty should be the focus of research assessing future pest outbreak dynamics. Gray (2017) suggested that future outbreak forecasts could be improved by building models with more precise data.

In this respect, an obvious question arises as to whether or not other exogenous disturbances such as fire and wind have the same effect on growth forecasts as those we observed for SBW. Introducing exogenous disturbances is subject to high levels of uncertainty (Artés *et al.*, 2013; Cencerrado *et al.*, 2015). Relying on the spatial synchrony theory (Williams and Liebhold, 2000), it is reasonable to assume that large forest fires and severe windstorms would greatly impact some realizations, while others would remain untouched. In the study of Bergeron *et al.* (2017), in which forest age classes were assessed in relation to fire and harvest activities, the scenarios with the greatest variability were those that considered fire occurrence. In addition, Pichancourt *et al.* (2018) also reported an increase in the variance of carbon predictions when considering windstorms.

However, the comparison between the three types of disturbances – fire, storms and insect outbreaks – in terms of uncertainty contribution is not so simple and remains to be tested. The vulnerability of forest stands is dependent on the type of disturbances. For example, forest fires are more likely to occur in old boreal stands (Bernier *et al.*, 2016). When windstorms occur, the tallest trees are more prone to damage than the smaller ones (Schmidt *et al.*, 2010). For insect outbreaks, the number of host species is often limited and, for this reason, the damage is highly dependent on the species composition. In the case of SBW outbreaks, the host-tree species are: balsam fir, black spruce, white spruce and red spruce (Gray, 2017).

The variance of large-area forecasts is closely related to the severity of the damage when the disturbance occurs. In our case study, the damage of SBW was severe because the host species were abundant at the regional level. The three host species represented 30 per cent of the basal area of Bas-Saint-Laurent forests, with balsam fir alone representing 20.5 per cent of the basal area at the regional level (Table 1).

Bergeron *et al.* (2017) assumed that all stands had an equal probability to be burned, regardless of their age or changes in vegetation composition. Likewise, in our study, we assumed that SBW outbreaks had equal probabilities of occurrence over time. In other words, the probability that a SBW outbreak occurs is not impacted by previous outbreaks. This can have an effect on the estimated variance. As a matter of fact, the probabilities of SBW outbreak occurrence are probably not independent of previous outbreaks. Candau and Fleming (2005) modelled SBW outbreak occurrences, and reported that the frequency and defoliations exhibited a spatial pattern that is influenced by climate and forest composition. This is a more complete approach in modelling, and using it would probably reduce the estimated variances we obtained in our study.

Estimating uncertainty arising from disturbances can provide important insights. In past studies, the focus was generally on model development or model uncertainty, while the perspective of hybrid inference was missing. In terms of approach, we chose to run the model at the plot level and to then scale the predictions up to a greater spatial level. This approach is known as the direct extrapolation method and is recommended to reduce errors arising from nonlinearity, such as Jensen's inequality (Wu *et al.*, 2006). Furthermore, variance estimates based on the Monte Carlo technique, like those in this study, are preferred to analytical methods since they apply to complex and nonlinear models (Wilson and Smith, 2013), such as ARTEMIS.

The scenario in which harvest and SBW outbreaks could occur simultaneously resulted in smaller volume forecasts. In reality, the estimates in this particular scenario can be underestimated. In the event of an outbreak, salvage cuttings normally take place (Boulanger and Arseneault, 2004). However, ARTEMIS does not consider this possibility, which means that some plots that are harvested by the model are actually spared. Moreover, a major driver of the harvest model is the AAC volume, that is estimated by a government agency. In our simulation, this AAC volume is constant, whereas in practice, it is re-estimated every 5 years.

Even if harvest activities did not have the greatest contribution to the forecast variance, some authors reported the impacts of uncertainties related to harvest in forest planning. For example, Pasalodos-Tato *et al.* (2013) observed economic losses on harvest scheduling due to errors in forest inventory. Makinen *et al.* (2012) also found that errors on growth predictions and forest inventory had a critical impact on harvest scheduling planning problems. As recommended by Robinson *et al.* (2016) and Daniel *et al.* (2017), efforts to assess uncertainties in harvest activity should be done with respect to management planning. Recent developments integrated uncertainties into forest management planning. Non probabilistic methods, such as programming analysis, were developed in Eyvindson and Kangas (2016) and Eyvindson and Kangas (2017). This issue of management planning is beyond the scope of this paper, but our framework may serve as a basis to facilitate the implementation of these methods.

Conclusions

Estimating uncertainties in forest growth forecasts under disturbances can provide insights to decision-makers. Volume forecasts for the Bas-Saint-Laurent region are more uncertain when including SBW outbreaks. This natural disturbance proved to be the most important source of uncertainty against harvest and sampling variance. We therefore suggest that forest management would be more realistic if it accounted for the uncertainties that stem from natural disturbances.

In order to reduce the uncertainty of large-area growth forecasts in the Bas-Saint-Laurent region, the understanding and prediction of SBW dynamics is a crucial issue. An essential step would be to take the relationships between the variables that explain the occurrence of disturbance events into account. Along with what was proposed by Gray (2017), we also suggest that efforts should be made to gather reliable datasets that could be used to create or improve existing models of SBW dynamics.

Supplementary data

Supplementary data are available at *Forestry* online.

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Conflict of interest statement

None declared.

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