CIRRELT

Centre interuniversitaire de recherche
sur les réseaux d'entreprise, la logistique et le transport

Interuniversity Research Centre
on Enterprise Networks, Logistics and Transportation

Compiling Disaggregation Coefficients to Link Long- and Short-Term Planning Models

Gregory Paradis
Luc LeBel

July 2017

CIRRELT-2017-43

Bureaux de Montréal :
Université de Montréal
Pavillon André-Aisenstadt
C.P. 6128, succursale Centre-ville
Montréal (Québec)
Canada H3C 3J7
Téléphone : 514 343-7575
Télécopie : 514 343-7121

Bureaux de Québec :
Université Laval
Pavillon Palasis-Prince
2325, de la Terrasse, bureau 2642
Québec (Québec)
Canada G1V 0A6
Téléphone : 418 656-2073
Télécopie : 418 656-2624

www.cirrelt.ca

Compiling Disaggregation Coefficients to Link Long- and Short-Term Planning Models

Gregory Paradis[1,*], Luc Lebel[1,2]

1. Département des sciences du bois et de la forêt, Pavillon Abitibi-Price, 2405, rue de la Terrasse, Local 2121, Université Laval, Québec, Canada G1V 0A6
2. Interuniversity Research Centre on Enterprise Networks, Logistics and Transportation (CIRRELT)

Abstract. It has been shown that credibility of wood supply optimization models can be improved by using a bilevel formulation that anticipates industrial fibre consumption. The upper level model corresponds to the standard long-term wood supply optimization model, and the lower level corresponds to a short-term network flow optimization model. Linking the two levels requires disaggregation of upper-level fibre volume output using a matrix of disaggregation coefficients. These disaggregation coefficients are not typically available, and compiling them involves complex manipulations of large amounts of data. We described a methodology for compiling such a matrix of disaggregation coefficients, using readily-available data.

Keywords: Forest management, hierarchical planning, value-creation potential.

Acknowledgement. This study was supported by funding from the FORAC Research Consortium.

---

* Corresponding author: gregory.paradis.1@ulaval.ca

Dépôt légal – Bibliothèque et Archives nationales du Québec
Bibliothèque et Archives Canada, 2017

1 Introduction

Long-term wood supply optimization models typically use a highly aggregated representation of harvesting activities. A typical wood supply model objective function maximizes the sum of merchantable harvest volume induced by applying one of several possible prescriptions to each forest stratum. Hierarchical forest management (HFM) planning should be implemented with effective linkages between planning levels (Gunn, 2009; Paradis et al., 2013). In practice, these linkages are often ineffective or altogether absent. Lower HFM planning levels will often be modelled on a shorter horizon than wood supply models, using a more detailed representation of reality. Financial performance indicators typically play an important role in short-term planning, whereas financial indicators are generally absent from wood supply models. Linking HFM planning levels, to verify coherence of the overall HFM planning process, requires comparison or decisions expressed at different aggregation levels. In other words, we must be able to *disaggregate* output unit of the upper level model to match the input unit of the lower level model. Paradis et al. (2015) describe a bilevel optimisation model formulation that reduces risk of wood supply failure by anticipating industrial fibre consumption. Although their model is potentially useful, the task of compiling detailed input data for the lower-level model necessarily involves disaggregating upper-level harvest volume into more detailed assortments of logs of different size classes. Data required to build such disaggregation functions is available, however no methodology for compiling disaggregation coefficients from this data has been published. We described a methodology for compiling vectors of disaggregation coefficients using readily-available data.

Our goal is to disaggregate harvest volume output from a wood supply model into discrete 2-centimeter-wide diameter at breast height (DBH) stem size classes. We can use the disaggregated volumes to model value creation potential (VCP) of the wood supply. We start with the volume $u_{cst}(Z)$ of species group s harvested from cover type c with a treatment type t, induced by applying solution Z to the wood supply model for a given management unit. If we have a function $p_{cst}(x)$ defining the proportion of each unit of volume of species s, harvested from cover type c with treatment t, which we can assume will be in stems in size class x, we can define a disaggregated volume function $v_{cst}(z, x)$ by taking the dot product of scalar $u_{cst}(z)$ and vector $p_{cst}(x)$.

$$v_{cst}(z, x) = u_{cst}(z) \cdot p_{cst}(x), \quad \forall c \in C, \forall s \in S, \forall t \in T \tag{1}$$

where C is the set of cover types, S is the set of species groups, and T is the set of treatment types.

$p_{cst}(x)$ is defined as the dot product of three vector components, as follows

$$p_{cst}(x) = f_{cs}(x) \cdot g_{cst}(x) \cdot h_{cs}(x) \tag{2}$$

$f_{cs}(x)$ defines the probability distribution of stem sizes of standing inventory. We compile $f_{cs}(x)$ from permanent sample plot data, using the methodology described in Paradis and LeBel (2017).

$g_{cst}(x)$ defines the probability that a stem of species s and size x will be harvested from cover type c under treatment t. We compile $g_{cst}(x)$ using a statistical model published by Fortin (2014).

$h_{cs}(x)$ defines normalized form factor vectors for each combination of cover type $c \in C$ and species $s \in S$. We compile $h_{cs}(x)$ from regional form factor models published by the Quebec government.

The remainder of this paper is organized as follows. We describe our methodology in §2. Results are presented in §3, followed by discussion in §4 and concluding remarks in §5.

2 Methods

We use the methodology described in Paradis and LeBel (2017) to compile $f_{cs}(x)$. This methodology uses a weighted nonlinear least squares (NLLS) algorithm to find best-fit parameters for a number of candidate distributions, and selects the best distribution based on the small-sample Akaike information criterion (AICc). Our inventory dataset consists of 52 192 stems extracted from a database of PSP data[1]. These stems are filtered from the full PSP dataset to include only live, merchantable stems from the most recent inventory cycle, from mature, undisturbed stands, for which there was valid data in all fields. This dataset was divided into 30 sub-datasets, corresponding to combinations 10 species groups and 3 cover types. We fit generalized gamma (GG), gamma (GA), Weibull (W), and exponential (EXP) distributions to each of these 30 sub-datasets and use the distribution with lowest AICc to compile $f_{cs}(x)$.

Next, we compile $g_{cst}(x)$ using the statistical model published by Fortin (2014) to determine the bin-wise harvest probabilities for selective cutting ($t = 2$) and commercial thinning ($t = 3$) treatment types. All stems in the standing inventory are removed during a final cutting ($t = 1$), so we simply assign a harvest probability of 1 to all bins for this case. Note that we use the post-2004 selection cutting model from Fortin (2014), and that we normalize the vector values, such that $\sum_{x \in X} g_{cst}(x) = 1, \forall c \in C, s \in S, t \in T$.

Fortin (2014) use a species aggregation scheme consisting of 12 species groups. However, we need to compile $g_{cst}(x)$ in terms of our 10 species groups. Using the relative frequency distribution of the 12 Fortin species groups in our permanent sample plot dataset, we generate a set of weight coefficients for each combination of species group s and cover type c. We then use these weight coefficients to compile Fortin model results in terms of our set of species groups S. The Fortin model requires us to provide an estimate of stem density (i.e., stem count per hectare) as one of the input parameters. We use the permanent sample plot data to compile mean stem density estimates for each of the three cover types.

[1] Detailed information on the PSP inventory program under which our test data was collected is available from the MFFP web site (`http://www.mffp.gouv.qc.ca/forets/inventaire/`).

Next, we compile $h_{cs}(x)$. Local form factor models have been compiled by the government authorities for several regions in Quebec[2]. The downloadable package includes documentation (PDF format), species-wise regression parameters and form factors for the LIN3 stem volume model (DBF format), and some spatial data (Shapefile format) delineating the boundaries of the local form factor zones. The form factor model is defined for individual species (i.e., 1-to-1 mapping with the species codes in our permanent sample plot dataset). We compile weighted average form factors, for a given management unit, by cover type c and species group s. We aggregate species into species groups using the relative frequency distribution of species in our permanent sample plot dataset as weight coefficients. Several form factor zones can overlap the boundaries of a given management unit. We use a geographic information system to intersect form factor zones and management unit boundary, to determine a set of zone-wise weights that can be used to blend multiples zone models to derive weighted-average form factors for the management unit of interest.

Finally, we compile $p_{cst}(x)$ from the three vector components.

As an example of the application of the method described here, we compile disaggregation coefficients for management unit UA 064-51 in Quebec, Canada. We show results for management unit UA 064-51, however our methodology can be applied generically to any of the 71 management units in Quebec using the same input data sources. Note that our method could also be applied to other jurisdictions, as long as input data for the three vector components of $p_{cst}(x)$ is available.

A Jupyter Notebook containing Python code implementing our methodology and detailed explanations is available from the corresponding author upon request.

3 Results

Figures 1 and 2 show results of applying our methodology to compile disaggregation coefficients for management unit UA 064-51 in Quebec, Canada. Species group is fixed for a given row of subfigures, and cover type is fixed for a given column of subfigures. Treatment type 1 (solid line) corresponds to clearcut harvesting, treatment type 2 (dashed line) corresponds to selection cut, and treatment type 3 (dotted line) corresponds to commercial thinning.

4 Discussion

Our method outputs distinct disaggregation coefficient vectors for each combination species group, cover type, and treatment type. We tested our method on a real dataset, and confirm that our method outputs 90 distinct probability density functions (PDFs), normalized to sum to 1 across the 26 diameter classes

[2]Detailed information on the form factor model is available from the MFFP web site (`https://www.mffp.gouv.qc.ca/forets/inventaire/fiches/tarif-cubage.jsp`).

(see Figures 1 and 2). The resulting PDFs are relatively smooth, although some combinations of species group, cover types and treatment type yield bimodal distributions (e.g., white birch species group, softwood cover type). These PDFs can be used to convert species-wise volume (from output of wood supply models) into assortments of stems binned by 2-centimeter size class. We plan to use these results to link a long-term wood supply optimization model output with short-term network flow optimization model.

Using only readily-available data, our methodology could easily be applied, as-is, to compile custom disaggregation coefficient vectors for any of the other 70 forest management units in Quebec. Our methodology could also adapted for use in other jurisdictions to compile $p_{cst}(x)$, assuming that input data is available to compile $f_{cs}(x)$, $g_{cst}(x)$, and $h_{cs}(x)$ vector components.

Recall that $f_{cs}(x)$ defines the probability distribution of stem sizes of standing inventory, and that we compile $f_{cs}(x)$ from permanent sample plot data, using the methodology described in Paradis and LeBel (2017). Basically, this part of the method can be applied anywhere, with suitable inventory data.

Recall that $g_{cst}(x)$ defines the probability that a stem of species s and size x will be harvested from cover type c under treatment t, and that we compile $g_{cst}(x)$ using a statistical model published by Fortin (2014). This statistical model was developped using a relatively large dataset from Quebec, Canada. Although clearly suitable for use in Quebec (e.g., our test case), the model may be generalizable to areas with similar forests and harvest prescriptions. Otherwise the method described in Fortin (2014) could be used to derive new models for $g_{cst}(x)$.

Recall that $h_{cs}(x)$ defines normalized form factor vectors for each combination of cover type $c \in C$ and species $s \in S$, and thatwe compile $h_{cs}(x)$ from regional form factor models published by the Quebec government. Form factor models (sometime referred to as *stem taper models*) are fairly common in forest management, as they are commonly used to merchantable volume from forest inventry tally data. Thus, local form factor models will likely be available. Otherwise, there is a large body of literature describing methdologies for deriving stem taper models.

5 Conclusion

Paradis et al. (2015) describe a bilevel wood supply optimization model formulation that can mitigate risk of long-term wood supply failure. Although their bilevel model is potentially advantageous, no methodology has been published to convert volume output from the upper-level model into stem-assortment input for the lower-level model. We developped such a method, which we test on real data from Quebec, Canada.

6 Acknowledgements

This study was supported by funding from the *FORAC Research Consortium*.

References

Fortin, M. (2014). Using a segmented logistic model to predict trees to be harvested in forest growth forecasts. *Forest Systems*, 23(1):139–152.

Gunn, E. (2009). Some Perspectives on Strategic Forest Management Models and the Forest Products Supply Chain. *INFOR: Information Systems and Operational Research*, 47(3):261–272.

Paradis, G., Bouchard, M., LeBel, L., and D'Amours, S. (2015). Extending the classic wood supply model to anticipate industrial fibre consumption. Technical Report CIRRELT-2015-06, CIRRELT.

Paradis, G. and LeBel, L. (2017). Fitting truncated generalized beta distributions to stem density data from permanent sample plots in Quebec, Canada. Technical Report CIRRELT-2017-00, CIRRELT.

Paradis, G., LeBel, L., D'Amours, S., and Bouchard, M. (2013). On the risk of systematic drift under incoherent hierarchical forest management planning. *Canadian Journal of Forest Research*, 43(5):480–492.

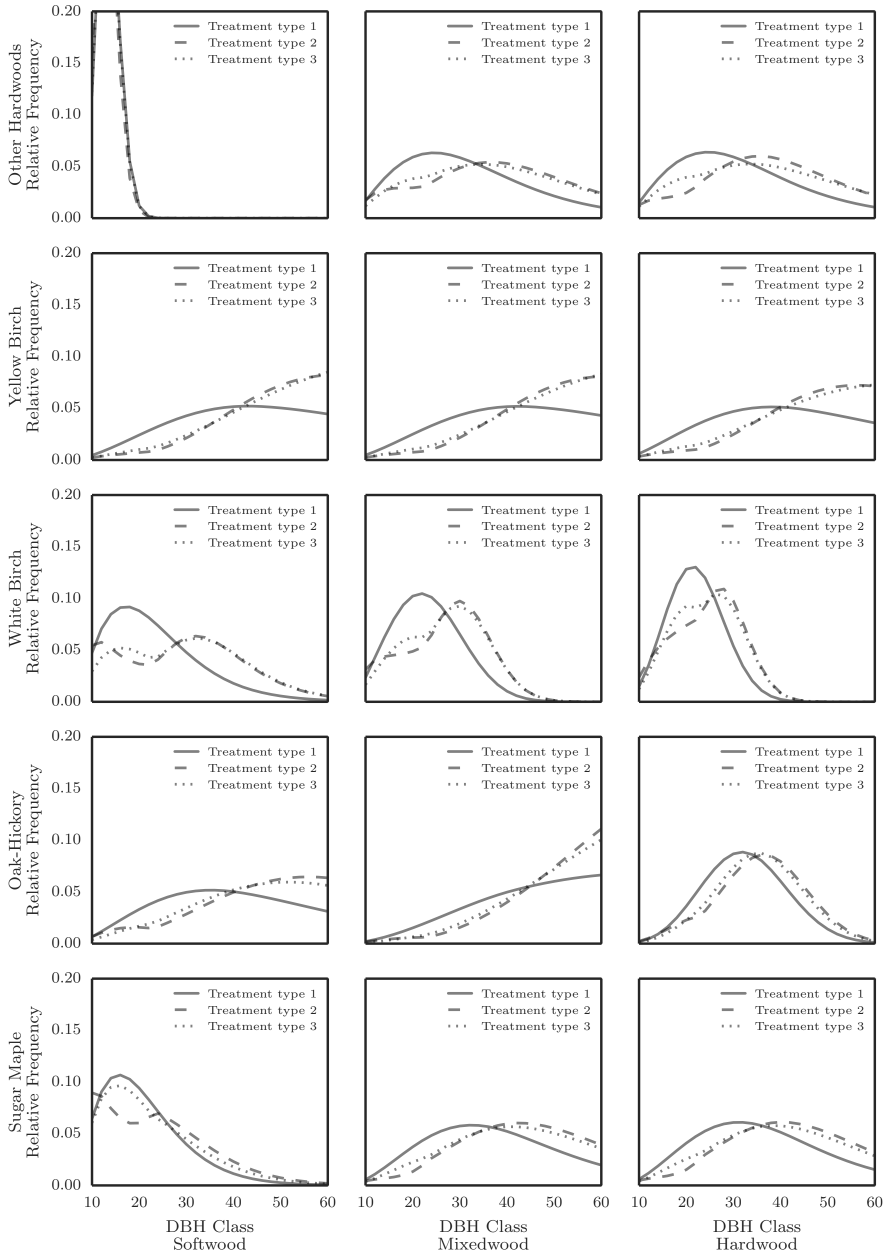

Figure 1: Example of disaggregation functions compiled for management unit UA 064-51 in Quebec, Canada. Species group is fixed for a given row of subfigures, and cover type is fixed forn a given column of subfigures. Treatment type 1 (solid line) corresponds to clearcut harvesting, treatment type 2 (dashed line) corresponds to selection cut, and treatment type 3 (dotted line) corresponds to commercial thinning.

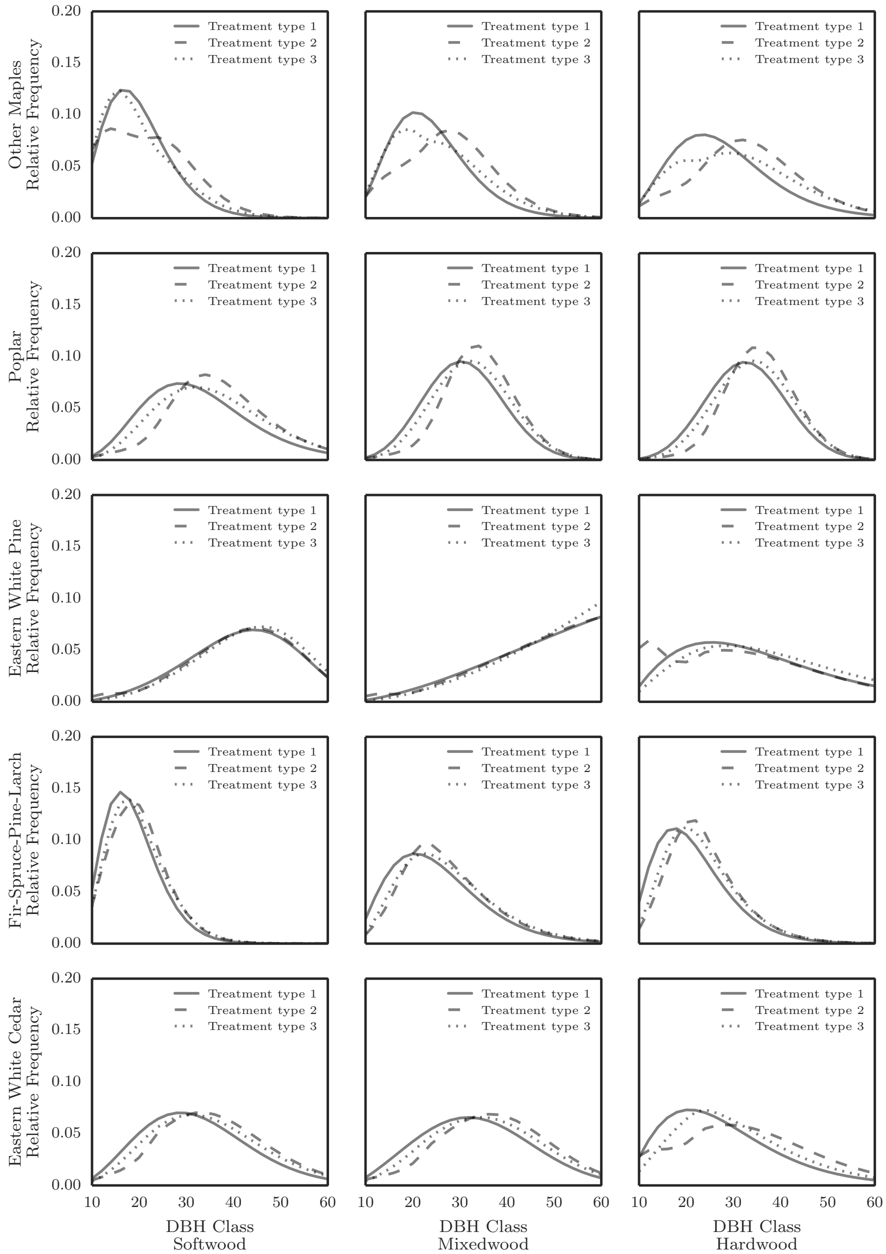

Figure 2: [Continued from Figure 1] Example of disaggregation functions compiled for management unit UA 064-51 in Quebec, Canada. Species group is fixed for a given row of subfigures, and cover type is fixed for a given column of subfigures. Treatment type 1 (solid line) corresponds to clearcut harvesting, treatment type 2 (dashed line) corresponds to selection cut, and treatment type 3 (dotted line) corresponds to commercial thinning.