Updating Canada's National Forest Inventory with multiple imputations of missing contemporary data

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ABSTRACT

Canada's National Forest Inventory (NFI) is facing an issue of spatial imbalance in photo interpreted data from 400 ha photo-plots available for estimation of state and change. Multiple imputations (MI) of missing data is therefore considered as a means to mitigate a potential bias arising from spatial imbalance, and—to a lesser degree— improve the precision relative to what can be achieved with the subset of plots having current data. In this study we explored MI with data from three study sites located in the provinces of Quebec, Ontario, and Saskatchewan. Specifically, we looked at state at time T_2 and change between T_1 and T_2 in cover-type area proportions and in per unit area stem volume. At each location we found significant T_1 differences in these attributes between plots with and without T_2 data. A MI procedure with 20 replications of stochastic model-based imputations of missing data was therefore effective as a way to mitigate a bias that would arise if T_2 inference was based exclusively on plots with T_2 data. Possible differences between the T_2 and T_1 photo-interpretation, paired with no efficient stratification of disturbed and undisturbed plots, largely eliminated expected gains in precision from the MI boosting of the effective T_2 sample size. Despite recognized limitations, we recommend MI as an effective tool to counteract an emerging spatial imbalance in the NFI.

Key words: forest cover-types, area proportions, stem volume, disturbance rates, ratio estimators.

RÉSUMÉ

L'inventaire forestier national du Canada (NFI) est confronté à une problématique de déséquilibre dans les données de placettes photographiques de 400 ha disponibles pour évaluer l'état de la forêt et son changement. On envisage donc d'utiliser l'imputation multiple (MI) des données manquantes afin d'amoindrir le biais occasionné par le déséquilibre spatial et, dans une moindre mesure, améliorer la précision par rapport à ce qu'il est possible d'atteindre avec le sous-ensemble de placettes pour lesquelles nous disposons de données à jour. Dans cette étude, nous avons exploré les possibilités de MI avec les données provenant de trois sites d'étude situés dans les provinces de Québec, de l'Ontario et de la Saskatchewan. De façon plus particulière, nous nous sommes intéressés à l'état à temps T_2 et au changement survenu entre T_1 et T_2 dans les proportions des surfaces par type de couvert et le volume par tige par unité de surface. À chaque endroit nous avons observé des différences significatives pour ces paramètres à T_1 selon qu'on utilisait ou non les données de T_2 . Une procédure MI avec 20 répétitions d'imputations des données manquantes basées sur un modèle stochastique s'est avérée efficace pour atténuer le biais qui résulterait si l'inférence à T_2 reposait uniquement sur les placettes disposant des données à T_2 . Toutefois, les différences dans la technique de photo-interprétation à T_1 et à T_2 combinées à l'absence de stratification des placettes perturbées et intactes a masqué la majeure partie du gain en précision qu'on aurait pu espérer avec une bonification de la taille des échantillons à T_2 . Malgré ces limitations, nous recommandons l'utilisation de MI pour amoindrir les effets d'un déséquilibre anticipé dans l'inventaire forestier national.

Mots-clés: types de couverts forestiers, proportion des surfaces, volume par tige, taux de perturbation, estimateurs par quotients.

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Introduction

National and regional forest inventories commonly employ a regular spatial network of permanent sample plots to furnish estimates of state and change between successive measurements (Pelz and Cunia 1985, Reams and Van Deusen 1999, Tomppo 2006, Haywood *et al.* 2016). A small proportion of the sample plots may not deliver data when access is denied by the forest owner, or when plot measurements are deemed too dangerous to carry out (McRoberts 2003, Patterson *et al.* 2012, Corona *et al.* 2014). Unplanned events and lack of funding may also create data imbalance. A point may be reached when estimates derived from available data may be lacking in both accuracy and precision. Bias may be introduced when data are not missing at random (Little and Rubin 1987, Glynn *et al.* 1993, Domke *et al.* 2014). This situation can arise when the probability of missing plot data from a specific plot is related in some fashion to the variable of interest (e.g., per unit area stem volume). Evidently, precision suffers from any reduction in sample size due to missing data.

Forest inventories have a long history of successfully exploring and implementing mitigating options under the generic labels of modeling, imputation, and reweighting (Dixon and Howitt 1979, Matis *et al.* 1984, Cunia and Kyaw 1985, Kangas 1991, Bokalo *et al.* 1996, Van Deusen 1996, Crookston and Finley 2008). Canada's National Forest Inventory (NFI) (Gillis *et al.* 2005, Stinson *et al.* 2016) is facing an issue of data imbalance. Options to address the imbalance in photo-interpreted data are needed. The core NFI's systematic sampling framework was established during the period 2000–2006 (T_1) with 2×2 km photo-interpreted plots on a nominal 20×20 km grid. The current measurement cycle (2008–2017) is designed to provide time T_2 estimates of state and time $T_2 - T_1$ estimates of change. The completion of this cycle will present the first opportunity to produce estimates of change. For reasons related to logistics and funding, only a subset of sample units will have been updated to their state at T_2 . It appears that units with T_2 information will not be spatially balanced which raises the possibility of bias.

This study explores multiple imputations (MI) (Rubin 1987, Van Deusen 1997, McRoberts 2003, Carpenter and Kenward 2013) as an option to mitigate the possible bias due to a spatial imbalance in the NFI data. MI is conceptually simple (Carpenter and Kenward 2013). A missing datum is replaced by the sum of a model-dependent expectation plus a random (stochastic) error. A data set with imputed values is then analysed as if it was complete. Due to the random component of an imputation, repeating the imputations will generate different results. As well, all estimates of uncertainty will be downward biased as the uncertainty in an imputation is ignored. To account for the uncertainty in an imputation, the process of imputation is repeated M times and the final mean (total) is estimated as the mean across the M imputations, and the variance of this mean is the average estimate of the variance within an imputation plus the variance among the M estimates of a mean (total).

Our objectives were to: *i*) determine if MI could be used to produce reliable estimates of forest state at T_2 and change between T_1 and T_2 using incomplete T_2 survey data; and *ii*) more broadly illustrate MI with data from very large sample units containing multiple cover-types.

Material and Methods

Estimation objectives and sample data

Design-based estimators of the mean of multiple inventory variables Y at time T_2 and the change in the mean of these variables since time T_1 is required for a population of interest. Estimates of sampling variance are also required. Specifically we focus on the state and change in five cover-type area-proportions and per unit area stem volume. The cover-types are NA (non-forest land), NT (non-treed forest land), TB (treed, broadleaves), TM (treed, mixed-wood), and TC (treed, conifers). The sum of cover-type proportions in NT, TB, TM, and TC is labelled as FO for the proportion of total forest land cover (MacDicken 2015). The area of a sample unit is the sum of the areas in the five cover-types (NA, NT, TB, TM, and TC).

Photo-interpreted data for these estimators come from n permanent 400 ha sample units located on a 20×20 km grid (Gillis *et al.* 2005). There is a full complement of n sample units with T_1 data but T_2 data is limited to a smaller subset of $n_{\text{obs}} < n$ units. The number of sample units without T_2 information is $n - n_{\text{obs}}$. Note that the timing of data collection in Canada's NFI is largely determined by Provincial and Territorial jurisdictions (Stinson *et al.* 2016). Data in support of an estimate of state at T_1 will have been collected during a multi-year period. An estimate of change between nominal years T_1 and T_2 will therefore cover change during both shorter and longer periods.

If the missing T_2 data were missing completely at random with respect to the T_1 data we could obtain unbiased estimates of state at T_2 and change since T_1 and MI would only serve to increase precision. If there are differences between plots having T_2 data and those where T_2 data are missing, then MI could prove helpful for reducing bias and improving precision. To determine if T_1 values in plots with and without T_2 information were exchangeable, we tested for equality in area proportions in units with and without T_2 data (Miller 1981). We found significant differences at each study site. Tests (t -test) of equal per unit area stem volume also indicated a significant difference in at least one of the cover types TB, TM, and TC. Permutation tests (Good 1993) of complete spatial randomness in the assignment of sample units to either category (with or without T_2 data) suggested a non-random spatial pattern in the units with missing T_2 information.

Data

We have three study locations for the demonstration and assessment of MI in the context of photo-interpreted NFI data (Fig. 1–3) from 2×2 km sampling units (photo-plots). Two regions, labelled as QC6 and ON6, are located in the terrestrial ecozone 6 (Boreal shield) of Québec and Ontario, respectively. The third (SK9) is located in terrestrial ecozone 9 (Boreal plains) of Saskatchewan. Data from a photo-plot is provided by expert photo-interpreters who delineate forest stands (forest cover polygons) and measure or interpret stand-level forest attributes following the NFI data dictionary (https://nfi.nfis.org/en/photo_plot). Lookup tables, yield tables, and models are used to calculate volumes for each forest stand layer. For each 2×2 km unit we use T_1 and T_2 data on the area in each of the cover-types NA, NT, TB, TC, TM, and FO (= NT + TB + TC + TM) and the total stem volume associated with these areas.

Fig. 1. Location map of NFI units in study region QC6 in Québec. Black: locations have T_1 and T_2 data. Red: locations have T_1 data only.

Currently the NFI contains a large number of units with T_1 information sourced from the Earth Observation of Sustainable Development land-cover mapping project (Wulder and Nelson 2003, Wulder *et al.* 2008). These plots were excluded from our analyses.

QC6: All 2×2 km plots are located between longitudes 62° and 80° W and between latitudes 45° and 52° N (Fig. 1). The total sample size in the QC6 location is 1272 of which 662 (52%) have T_1 and T_2 and 610 (48%) only have T_1 data. The median T_1 year is 1998 for the plots without T_2 data (interquartile range (IQR): 1995–2001). For plots with both T_1 and T_2 data, the median T_1 year is 1996 (IQR = 1991–1998). The median T_2 year was 2011 (IQR: 2008–2012). The forests are boreal with a predominance of black spruce (*Picea mariana*), paper birch (*Betula papyrifera*), and balsam fir (*Abies balsamea*). Other important species are sugar maple and trembling aspen. The area contains non-boreal forests in the southernmost sections.

ON6: All plots are located between longitudes 76° and 95°

W and between latitudes 44° and 52° N (Fig. 2). The total sample size in the ON6 location is 1210 of which 459 (38%) have T_1 and T_2 and 751 (62%) only have T_1 data. The median T_1 year for plots with no T_2 data is 1997 (IQR: 1995–2005), and 1996 (IQR: 1995–2004) for the plots with both T_1 and T_2 data. The median T_2 year is 2008 (IQR: 2008–2010). The forests are boreal with a predominance of black spruce, trembling aspen (*Populus tremuloides*), and jack pine (*Pinus banksiana*). Other important species are paper birch and sugar maple (*Acer saccharum*). The area transitions to non-boreal forests in the south.

SK9: All plots are located between longitudes 102° and 110° W and between latitudes 52° and 58° N (Fig. 3). The total sample size in the SK9 location is 380 of which 242 (64%) have T_1 and T_2 and 138 (36%) have T_1 data. The median T_1 year is 2003 (IQR: 2001–2006), while the median T_2 year is 2010 (IQR: 2009–2012). The forests are boreal with a predominance of black spruce, jack pine and trembling aspen. Other minor species present are tamarack and white spruce.

Fig. 2. Location map of NFI units in study region ON6 in Ontario. Black: locations have T_1 and T_2 data. Red: locations have T_1 data only.

Multiple imputations

The desired estimators for T_2 and the period $T_2 - T_1$ are the means, $\bar{y}_1$ and $\bar{y}_2$ the variances $\hat{V}(\bar{y}_1)$ and $\hat{V}(\bar{y}_2)$ and the covariance $\hat{COV}(\bar{y}_1, \bar{y}_2)$. They can all be derived from the available data from the n_{obs} sample units with T_1 and T_2 data. But for reasons outlined, it was decided to explore MI (Carpenter and Kenward 2013) for estimation with the full complement of n sample units. MI works by replacing a missing T_2 datum in the $n_{obs} + k$ th sample unit by $\tilde{y}_{2, n_{obs}+k}$, $k = n_{obs} + 1, \dots, n$ viz. the sum of a model-based expectation and a stochastic error. The imputations are thus model-based, with models derived from the sample units with both T_1 and T_2 data. To reduce the stochastic influence on the estimators, an average is taken over M replications of the imputation and estimation steps (Table 1). From the n_{obs} units with actual T_1 and T_2 data, and imputations of T_2 data in $n - n_{obs} - 1$ units, all required design-consistent estimators can be obtained using the estimators applied to a set of n complete observations. With stochastic imputations, the mean and variance of $n - n_{obs} - 1$ imputed values varies among replications of the imputation process (Van Deusen 1997, McRoberts 2001). This is illustrated in Table 1 where we have M replications of the imputation process and therefore M estimates of the mean, and vari-

ance. We also obtain M estimates of covariance and correlation between the T_1 and T_2 means which we need for estimating the variance of an estimated change. In our MI scheme the stochastic errors are exclusively generated from an estimate of the 'lack-of-fit' residuals in the underlying model(s). In other words, we ignore that estimates from a photo-interpretation are subject to errors. The impact of these errors comes from errors in T_1 estimates as they attenuate the estimates of slope in a regression model (Fuller 1987).

The final MI estimators of mean and variance at time T_2 are given in [1] (Little and Rubin 1987, Rubin 1987, Carpenter and Kenward 2013).

$$[1] \bar{y}_2^{MI} = M^{-1} \sum_{j=1}^M \bar{y}_2^{(j)}, \tilde{V}_{MI}(\bar{y}_2^{MI}) = M^{-1} \sum_{j=1}^M \hat{V}(\bar{y}_2^{(j)}) + \frac{(1+M^{-1})}{(M-1)} \sum_{j=1}^M (\bar{y}_2^{(j)} - \bar{y}_2^{MI})^2$$

The MI mean is the mean across the M imputation, and the variance is the mean of the estimated variances plus the variance of the estimated means.

The number M of replications was determined by considering the Monte Carlo error (Koehler *et al.* 2009) and the fraction of missing information (FMI) (Carpenter and Ken-

Fig. 3. Location map of NFI units in study region SK9 in Saskatchewan. Black: locations have T_1 and T_2 data. Red: locations have T_1 data only.

ward 2013). We decided on $M = 20$ because the Monte Carlo error was then an order of magnitude smaller than the estimate of sampling error, and estimates of FMI had stabilized to within 3%.

Our MI procedures rely on the assumption that the models for the imputations apply without modification to units without T_2 data so that we can regard the missing data (values) as missing at random given the information available at T_1 (Carpenter and Kenward 2013). We did not have means to test this assumption, but the large degree of spatial overlap between the units with and without T_2 data (cf. Fig. 1–3) lends support to the use of models derived from units with T_2 data.

MI estimation of state and change in area proportions

Estimation of area proportions at T_2 followed the schemata in Table 1. In each of the M replications of a stochastic imputation, a missing T_2 value of an area proportion was imputed as $\tilde{y}_{2,j}^{(M)} = \hat{y}_{2,j}^{(M)} + \tilde{e}_{2,j}^{(M)}$, $j = n_{obs} + 1, \dots, n$ where $\hat{y}_{2,j}^{(M)}$ is a model-based replication-specific prediction from a truncated regression (Greene 2012) of the expected area proportion at time T_2 given the area proportion at time T_1 and $\tilde{e}_{2,j}^{(M)}$ is a replication-

specific stochastic error. No other T_1 variable qualified as a significant predictor. Model-based replication-specific predictions of the expected proportion (i.e. $\tilde{y}_{2,j}^{(M)}$) were generated via: 1) a random draw ($\hat{\sigma}_e^2$) from the assumed chi-squared distribution of the residual variance in the regression of T_2 area proportions on T_1 area proportions; and 2) a random draw of regression coefficients (intercept and slope) from the assumed distribution of the regression coefficients given $\hat{\sigma}_e^2$. Finally $\tilde{e}_{2,j}^{(M)}$ was obtained via a random draw from a normal distribution with mean zero and a variance $\hat{\sigma}_e^2$ (Carpenter and Kenward 2013). While we have ignored errors in photo-interpreted estimates, it should be emphasized that our imputations are consistent as predictions of the data (with interpretation errors) that one can expect given the established relationship between T_1 and T_2 data and the assumption of temporally constancy in the photo-interpretation (Carroll *et al.* 1995).

As implemented in the statistical software STATA® (Stata-Corp 2016), all imputed values $\tilde{y}_{2,j}^{(M)}$ were restricted to the allowed interval from 0 to 1 for a proportion. The truncated regression failed to converge to a solution for NA in ON6 and SK9 and for NT in ON6. For these cases we resorted to predictive mean matching with the mean of the 5 nearest neighbours (Carpenter and Kenward 2013). Following the imputa-

Table 1. Generic overview of the MI procedure with M replications of stochastic imputations of missing T_2 data in y . Subscripts refer to time (1 or 2) and sample unit ($1, \dots, n_{obs}, n_{obs}+1, \dots, n$). Superscripts refer to the MI replication ($1, \dots, M$). Imputed values are identified by a tilde ($\sim$) and a mean by an overbar. Estimated variances are denoted by $\hat{V}$. Direct estimates based on n_{obs} sample units with T_2 data are in square brackets.

T_1	T_2	$T_2^{(1)}$	$\dots$	$T_2^{(M)}$
$Y_{1,1}$	$Y_{2,1}$	$Y_{2,1}$	$\dots$	$Y_{2,1}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$Y_{1,n_{obs}}$	$Y_{2,n_{obs}}$	$Y_{2,n_{obs}}$	$\dots$	$Y_{2,n_{obs}}$
$Y_{1,n_{obs}+1}$	miss	$\tilde{Y}_{2,n_{obs}+1}^{(1)}$	$\dots$	$\tilde{Y}_{2,n_{obs}+1}^{(M)}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$Y_{1,n}$	miss	$\tilde{Y}_{2,n}^{(1)}$	$\dots$	$\tilde{Y}_{2,n}^{(M)}$
$\bar{Y}_1$	$[\bar{Y}_2]$	$\bar{\tilde{Y}}_2^{(1)}$	$\dots$	$\bar{\tilde{Y}}_2^{(M)}$
$\hat{V}(\bar{Y}_1)$	$[\hat{V}(\bar{Y}_2)]$	$\hat{V}(\bar{\tilde{Y}}_2^{(1)})$	$\dots$	$\hat{V}(\bar{\tilde{Y}}_2^{(M)})$

tions of cover-type area proportions, a post-calibration was done to ensure that the five proportions would add to 1.0. Year of interpretation for T_1 and T_2 data had no practically relevant influence on the results. A more complex MI approach with a multinomial logistic regression model was tried but we found no advantage in terms of implementation or estimates of precision.

Changes in area-proportions were estimated as the difference between estimates of T_2 and T_1 area proportions for each of the M replications and n sample units. Estimation of means and variances of these changes followed the principles laid out in [1].

MI estimation of state and change in unit area stem volume

In an NFI sample unit, the area in a given cover-type (CT) varies among plots ($j, j = 1, \dots, n$) and there is a positive correlation between area and total stem volume ($tvol$). For that reason we employed ratio estimators (Cochran 1977) for per unit area stem volume (VOL). For a full complement of n sample units the estimators of the mean VOL $m^3 ha^{-1}$ at T_t ($t = 1, 2$) and the change T_2-T_1 in a cover-type were

$$[2] \hat{VOL}_{CT,t} = \frac{\sum_{j=1}^n tvol_{CT,t,j}}{\sum_{j=1}^n area_{CT,t,j}}, \Delta \hat{VOL}_{CT,2-1} = \hat{VOL}_{CT,2} - \hat{VOL}_{CT,1}$$

with variance (Cochran 1977)

$$[3] \hat{V}(\hat{VOL}_{CT,t}) = \frac{1}{n \bar{a}_{CT,t}^2} \left(\sum_{j=1}^n tvol_{CT,t,j}^2 - 2 \hat{VOL}_{CT,t} \sum_{j=1}^n area_{CT,t,j} tvol_{CT,t,j} + \hat{VOL}_{CT,t}^2 \sum_{j=1}^n area_{CT,t,j}^2 \right)$$

Where $\bar{a}_{CT,t}$ is the mean of $area_{CT,t,j}$. The variance of a change estimate was computed as:

$$[4] \hat{V}(\Delta \hat{VOL}_{CT,2-1}) = \hat{V}(\hat{VOL}_{CT,2}) + \hat{V}(\hat{VOL}_{CT,1}) - 2 \hat{COV}(\hat{VOL}_{CT,2}, \hat{VOL}_{CT,1})$$

Where the last term on the right-hand-side is the covariance between the volume (ratio) at T_1 and T_2 . We obtained a first-order approximation to this covariance from an estimate of the temporal correlation of volume per ha estimates at time T_1 and T_2 and the squared root of the product of the two variances $\hat{V}(\hat{VOL}_{CT,t}), t = 1, 2$ of a volume ratio estimate. The alternative would be a jackknife estimator (Wolter 2007). The estimators in [3] and [4] make it clear that the MI procedure requires an imputation of both $area_{CT,2,j}$ and $tvol_{CT,2,j}, j = n_{obs} + 1, \dots, n$. Imputed values of $area_{CT,2,j}, j = n_{obs} + 1, \dots, n$ were obtained by multiplying the above imputed area proportions with the fixed and known area of a sample unit. Values of $tvol_{CT,2,j}, j = n_{obs} + 1, \dots, n$ were, with the exception of NA in QC6, imputed in a two-step process: in step one, a stochastic prediction of $VOL_{CT,2}$ was derived from a zero-truncated regression with $VOL_{CT,1}$ as the sole (significant) predictor; and in step two, the predicted volume per unit area was multiplied by the prediction $\bar{a}_{CT,2}$. These models explained between 51 and 72% of the variation in VOL at T_2 in the remeasured plots.

For NA in QC6, the first step was to predict the T_2-T_1 increment ($\delta_{t_2-t_1}$) in per unit area volume $\delta_{t_2-t_1} (VOL_{CT,1,j}) \geq 0$; and in a second step equate $tvol_{CT,2,j}$ to the product of $(VOL_{CT,1,j} + \delta_{t_2-t_1} (VOL_{CT,1,j})) \bar{a}_{CT,2,j}$. The volume increment $\delta_{t_2-t_1} (VOL_{CT,1,j})$ was predicted from the n_{obs} units with positive T_1 and T_2 values of $area$ and $tvol$, and depended on both the initial per unit area volume, and the number of years ($\Delta_{t_2-t_1}$) between the first and second photo-interpretation. To complete a QC6 NA imputation a separate imputation of $\Delta_{t_2-t_1}$ was needed due to the lack of a singular and fixed value for this variable. To this end we drew, for each of the $n-(n_{obs}+1)$ units without T_2 data, a random integer from a Poisson distribution with an intensity parameter expressed as a linear model with an intercept and T_1 fitted to the re-interpreted observations. Random draws were subsequently truncated to comply with both the observed range of $\Delta_{t_2-t_1}$ year and the maximum observed T_2 value. An imputed value of $\Delta_{t_2-t_1}$ was held fixed across the M replications. Finally, we forced the regression through the origin to ensure a positive prediction of volume increment. The forcing increased the regression residual errors by approximately 10% and lowered the coefficient of determination by 0.02.

We explored improvements of these regression models by including rates of plot-level stand-replacing disturbances from the National Terrestrial Ecosystem Monitoring System (NTEMS) (White *et al.* 2014, Hermosilla *et al.* 2015). However, regression models with these rates (discretized to 11 intervals and separated to fire and harvest) were not materially better at explaining change in volume than models without these rates. With a predominance of small fractions of a 400 ha NFI unit size disturbed by fire or harvest, this result was no surprise.

Results

QC6: A summary of T_2 and change (T_2-T_1) estimates of cover type proportions and cubic metre stem volume per ha is given

Table 2. Direct (DI) and MI-based (MI) estimates of mean and sampling error (s.e.) of time T_2 and T_2-T_1 change in cover type (CT) area proportions (P_{CT}) and stem volume per unit area (VOL_{CT} m^3 ha^{-1}) in the QC6 study region. Sample size for DI is 662 and 1272 for MI.

	T_2 (MI) mean	T_2 (MI) s.e.	T_2 (DI) mean	T_2 (DI) s.e.	$T_2 - T_1$ (MI) mean	$T_2 - T_1$ (MI) s.e.	$T_2 - T_1$ (DI) mean	$T_2 - T_1$ (DI) s.e.
P_{NA}	0.22	0.01	0.20	0.01	-0.04	0.01	-0.04	0.01
P_{NT}	0.09	0.00	0.08	0.01	0.03	0.01	0.01	0.01
P_{TB}	0.13	0.01	0.15	0.01	0.03	0.01	0.02	0.01
P_{TC}	0.37	0.01	0.33	0.02	-0.01	0.01	0.04	0.01
P_{TM}	0.19	0.01	0.24	0.01	-0.01	0.01	-0.04	0.01
P_{FO}	0.78	0.01	0.80	0.01	0.04	0.01	0.04	0.01
VOL_{NA}	1.3	0.1	0.4	0.3	-4.1	0.4	-5.1	0.6
VOL_{TB}	145.0	4.4	150.4	4.8	-1.5	3.2	7.8	2.7
VOL_{TC}	118.0	2.4	113.7	2.5	2.4	1.6	2.5	1.2
VOL_{TM}	113.6	2.8	120.0	3.2	-0.6	2.0	7.9	2.1
VOL_{FO}	107.5	1.9	111.1	2.8	-5.0	1.8	-2.7	2.5

Fig. 4. Examples from study region QC6 of imputations of T_2 TC area proportions with a truncated regression model. Imputations are from a randomly selected replication (here 9). Note the scatter plot of observed area proportions is based on the 610 plots with both T_2 and T_1 interpretations.

in Table 2. For TC and TM proportions at T_2 the MI and direct (DI) estimates differed by 4–5%. Large and significant T_1 differences between re-interpreted and non-re-interpreted plots in TB and TM proportions were the main contributor to these apparent differences. All remaining MI and DI area proportions were within 2% of each other. Given the estimates of error, this difference could arise by chance. MI-based estimates of errors were not lower than corresponding errors in the direct estimates, despite having a fairly strong temporal correlation of 0.4–0.8 (mean = 0.7) and a larger sample size. An example of imputations of T_2 TC area proportions in a randomly selected replication is in Fig. 4. There is a wide scat-

ter in imputed T_2 proportions for a given T_1 proportion, but the overall pattern is comparable to the observed pattern in the 610 plots with a T_2 interpretation. The observed scatter is a mix of actual changes and spurious changes resulting from differences in photo-interpretation (Magnussen and Russo 2012).

MI and DI estimates of change in cover type area proportions were generally in agreement in terms of direction and magnitude considering the estimates of errors of approximately 1%. Exceptions are TM and TC but given the large T_1 differences in areas, we do not consider these disagreements to be artefacts of MI. A large replication variance of area proportions (necessitating more than the usually recommended four to five MI replications) and differences in T_1 area proportions are the main explanation as to why the MI estimates of error do not suggest any reduction over the DI estimates despite a near doubling of the sample size used in the MIs.

Statistics from the compiled Landsat time series of stand-replacing harvest and fires in the study region (Hermosilla *et al.* 2015) suggest that plots with T_2 interpreted data experienced a higher rate of harvest and a lower rate of fires during the years 1994–2011 than represented by plots with only a T_1 interpretation. We could,

however, not isolate an impact of these differences on the area proportions.

Time T_2 MI and DI estimates of VOL m^3 ha^{-1} do not suggest any important differences, at least when considering the associated estimates of error. Overall, the MI estimates have slightly lower (approximately 10%) errors, but still far from the maximal possible reduction of 44%.

A scatterplot in Fig. 5 gives an example of imputations in a randomly selected replication. An observation falling on the x-axis means that the per unit area stem volume of a cover-type went to zero either due to a reclassification or a stand-replacing disturbance. A point on the y-axis is also most likely

due to a reclassification to a cover type that was not recognized at T_1 . As in the case of area proportions, the pattern of imputed values was similar to the pattern in the actual data. We again emphasize that an observed change in volume may reflect not only actual changes but also subject- and method-specific changes in interpretation and yield tables.

Estimates of change in volume per hectare for TB, TC, TM, and FO estimated via MI and DI were distinctly different in case of TB and TM as anticipated from the T_2 results in terms of direction and magnitude. We attribute these dif-

ferences to the aforementioned differences in T_1 area proportions. The relatively large estimates of errors associated with these change estimates calls for a cautionary interpretation. The MI estimates of errors of change were again not materially different from parallel DI estimates. There is a lack of additivity in the volume estimates in Table 2. This is, unfortunately, a characteristic of the ratio-estimators we used. Additivity could have been superimposed by the technique of iterative proportional fitting (Jirousek and Preucil 1995, Fuller 2009).

ON6: A summary of T_2 and change (T_2-T_1) estimates of cover type proportions and cubic metre stem volume per ha is given in Table 3. Cover type proportions at T_2 for TB, TC, and TM, estimated via MI and DI, were within 0–4% of each other. The differences largely reflect differences in T_1 proportions between plots with or without a T_2 re-interpretation. As was the case in QC6, there is no apparent reduction in the MI estimates of error in area proportions that customary would be expected from the substantial increase in the number of plots used in MI. An example of imputations of T_2 TC area proportions in a randomly selected replication is given in Fig. 6. The scatterplot suggests that imputations were slightly closer to the one-to-one line (of no change) but also that the number of imputations with ‘no-change’ is slightly lower than in the actual data.

Apart from time T_2 estimates of $\text{VOL m}^3\text{ha}^{-1}$ in classes TB and TM, the MI and DI estimates were in close agreement. For TB and TM the differences were approximately 5% but related to differences in T_1 estimates. The MI estimates of standard errors were slightly lower (10%) in TB, TM, and FO than the corresponding DI estimates. The scatterplot in Fig. 7 gives an example of volume imputations in a randomly selected replication. There is no apparent

Fig. 5. Examples from study region QC6 of imputations of T_2 TC stem volume with a linear regression model. Imputations are from a randomly selected replication (here 9). Note the scatter plot of observed volumes is based on the 610 plots with both T_2 and T_1 interpretations.

Table 3. Direct (DI) and MI-based (MI) estimates of mean and sampling error (s.e.) of time T_2 and T_2-T_1 change in cover type (CT) area proportions (P_{CT}) and stem volume per unit area ($\text{VOL}_{CT} \text{ m}^3 \text{ ha}^{-1}$) in the ON6 study region. Sample size for DI is 459 and 1210 for MI.

	T_2 (MI) mean	T_2 (MI) s.e.	T_2 (DI) mean	T_2 (DI) s.e.	T_2-T_1 (MI) mean	T_2-T_1 (MI) s.e.	T_2-T_1 (DI) mean	T_2-T_1 (DI) s.e.
P_{NA}	0.23	0.01	0.20	0.01	-0.02	0.01	-0.00	0.00
P_{NT}	0.02	0.00	0.02	0.00	-0.01	0.00	-0.01	0.00
P_{TB}	0.16	0.00	0.16	0.01	0.04	0.01	0.04	0.00
P_{TC}	0.39	0.01	0.43	0.01	-0.01	0.01	-0.01	0.01
P_{TM}	0.20	0.01	0.20	0.01	-0.01	0.01	-0.01	0.01
P_{FO}	0.77	0.01	0.80	0.01	0.02	0.00	0.00	0.00
VOL_{NA}	0.1	0.0	0.1	0.1	-0.2	0.1	-0.1	0.3
VOL_{TB}	142.6	4.1	149.9	4.3	-41.3	4.5	-36.2	5.3
VOL_{TC}	115.4	2.2	113.0	2.2	-11.4	2.6	-11.3	3.1
VOL_{TM}	126.6	3.0	133.5	3.3	-29.1	3.2	-22.2	4.0
VOL_{FO}	121.1	1.8	122.3	2.2	-18.3	2.2	-15.5	2.9

Fig. 6. Examples from study region ON6 of imputations of T_2 TC area proportions with a truncated regression model. Imputations are from a randomly selected replication (here 11). Note the scatter plot of observed area proportions is based on the 459 plots with both T_2 and T_1 interpretations.

Fig. 7. Examples from study region ON6 of imputations of T_2 TC stem volume with a linear regression model. Imputations are from a randomly selected replication (here 11). Note the scatter plot of observed volumes is based on the 459 plots with both T_2 and T_1 interpretations.

important difference between the imputed and observed point scatter. Imputed and direct estimates of change in VOL m³ha⁻¹ were similar in terms of direction and magnitude. Given relatively large standard errors on these change estimates, there is no reason to draw attention to specific differences. For the major cover types in the forest category, the MI standard errors of a change in volume were approximately 30% lower than parallel DI estimates, still far from the maximum possible of 62%.

SK9. A summary of T_2 and change ($T_2 - T_1$) estimates of cover type proportions and cubic metre stem volume per ha is given in Table 4. Cover type proportions at T_2 for TB, TC, and TM, estimated by MI and DI were within 0%–3% of each other, and judged by the estimates of error, they may well be due to chance. However, estimates of the proportion of area in NA differed by 5% which is mirrored in the derived proportions of FO. A comparison of T_1 area proportions in NA confirmed that the apparent difference between MI and DI should be seen as direct consequence of differences in the T_1 estimates. MI estimates of standard errors were generally lower than parallel DI estimates and close to a theoretical maximum reduction of 25%. An example of imputations of T_2 TC area proportions in a randomly selected replication is provided in Fig. 8. There are some important differences in the pattern of observed and imputed T_2 proportions. There is a deficit of imputed proportions along the 1:1 line and a surplus of imputations in the T_1 range of 0.9 to 1.0 with a marked decrease in area. An observed pattern of a change from a proportion below 0.4 to a proportion above 0.8 was not apparent in the imputations. Similar issues were seen in other cover types and across replications.

MI and DI estimates of change in TB, TC, and TM cover type area proportions were basically identical. The same holds for associated estimates of error. The only important discrepancy is in the estimate of change of the NA land proportion and a concomitant change of the FO proportion. In light of the T_2 discrepancy in estimates of NA proportions, we should also expect estimates of change to diverge. Estimates of disturbance rates from NTEMS data (Hermosilla *et al.* 2015) suggested equal rates of fire and harvest in the two sets of plots during the period of observation. All differences in annualized rates were less than 0.03% (non-significant with bootstrap *t*-test).

Time T_2 MI and DI estimates of VOL m³ha⁻¹ indicate a difference of approximately 5% in TB (Table 3); however, the estimates of errors suggest that this difference is likely due to chance. We do not see a consistent (across cover types)

Table 4. Direct (DI) and MI-based (MI) estimates of mean and sampling error (s.e.) of time T_2 and T_2-T_1 change in cover type (CT) area proportions (PCT) and stem volume per unit area (VOL_{CT} m³ ha⁻¹) in the SK9 study region. Sample size for DI is 242 and 380 for MI.

	T_2 (MI) mean	T_2 (MI) s.e.	T_2 (DI) mean	T_2 (DI) s.e.	$T_2 - T_1$ (MI) mean	$T_2 - T_1$ (MI) s.e.	$T_2 - T_1$ (DI) mean	$T_2 - T_1$ (DI) s.e.
P_{NA}	0.41	0.02	0.46	0.03	-0.04	0.01	-0.02	0.01
P_{NT}	0.02	0.00	0.02	0.01	0.02	0.00	0.01	0.01
P_{TB}	0.15	0.01	0.15	0.01	0.00	0.01	0.01	0.01
P_{TC}	0.34	0.02	0.31	0.02	0.00	0.01	-0.00	0.01
P_{TM}	0.07	0.02	0.06	0.01	0.01	0.02	-0.00	0.01
P_{FO}	0.59	0.02	0.54	0.03	0.04	0.01	0.02	0.01
VOL_{NA}	13.9	2.2	13.6	2.4	0.5	1.6	-1.3	1.1
VOL_{NT}	5.4	2.2	2.4	1.1	11.5	2.8	4.0	1.5
VOL_{TB}	132.7	5.7	140.2	5.9	-19.9	5.3	-24.4	4.9
VOL_{TC}	69.3	3.5	66.7	3.1	-14.3	5.4	-14.1	3.6
VOL_{TM}	126.8	10.3	129.1	11.0	-32.0	9.2	-30.4	11.1
VOL_{FO}	90.0	3.8	91.8	4.4	-4.7	3.2	-21.3	4.3

Fig. 8. Examples from study region SK9 of imputations of T_2 TC area proportions with a truncated regression model. Imputations are from a randomly selected replication (here 2). Note the scatter plot of observed area proportions is based on the 242 plots with both T_2 and T_1 interpretations.

reduction in MI errors from boosting the sample size from 242 to 380 (57%), a reflection of cover-type specific differences in the strength of the temporal correlation of per unit area volume estimates. The scatterplot in Fig. 9 gives an example of volume imputations in a randomly selected replication. We again observe a deficit of imputations on the 1:1 line of no change in volume, but otherwise the two patterns of scatter appear to concur.

MI and DI estimates of change in unit area stem volume for TB, TC, and TM agreed to within an allowance for error.

A significant disagreement was seen in the NT estimate of change and consequently also in the FO estimate. We could not identify an explanation for this discrepancy. MI estimates of errors were in four cases larger than parallel DI errors and in two cases (TM and FO) smaller.

Discussion

Multiple imputations can be a powerful statistical procedure to reduce bias and improve precision of forest inventories with non-trivial issues of missing items and unit-level responses (McRoberts 2003, Patterson *et al.* 2012). Bias reduction and improvements in precision are contingent on the data being missing at random (MAR), conditional on the covariates and information used to generate an imputation (Scott 1984, Cunia and Kyaw 1985, Brown 1990, Tang *et al.* 2003). In our case studies, we have not been able to prove or disprove the correctness of the MAR assumption. If the models we have used are correct for units with- and without T_2 information, our MAR assumption would be satisfied. A retrospective assessment will be possible at a later time when data are obtained for units currently without T_2 data. It also appears that the combination of T_1 differences and relatively weak contemporaneous and temporal correlations in the data prevented

us from achieving practically important improvement in precision. In forest inventories, the MI approach works best for undisturbed plots where the temporal correlation between the state at two points in time is generally strong for shorter periods (years) between observations, declining as the number of years between observations increases (Massey *et al.* 2014, McRoberts *et al.* 2016). In this regard, a stand-replacing disturbance event acts as a 'correlation-breaker'. Our scatterplots provided illustrative examples of this issue. Imputations could have been improved considerably with information

Fig. 9. Examples from study region SK9 of imputations of T_2 TC stem volume with a linear regression model. Imputations are from a randomly selected replication (here 2). Note the scatter plot of observed volumes is based on the 242 plots with both T_2 and T_1 interpretations.

from covariates on the presence/absence of disturbances. In an inventory based on 400 ha photo-interpreted plots, a second kind of ‘correlation-breaker’ appears in the form of interpreter-specific factors or through changes in the media or guidelines governing an interpretation (Holmström *et al.* 2001, Holmström 2002, Ståhl *et al.* 2011, Magnussen and Russo 2012).

The best strategy to minimize the impact of ‘correlation-breakers’ is to form strata of disturbed plots and use a logic-model for the anticipated consequence of a stand-replacing disturbance (Reams and McCollum 2000, Massey *et al.* 2014). The Canadian NFI is actively in pursuit of this option but an operational system will not be in place for some years to come. Stand-replacing disturbance data from NTEMS (Hermosilla *et al.* 2015) would form a natural basis for identifying a stratum of disturbed land. The full use of this information requires a spatially explicit linkage to stand-polygons within the NFI data base system. Ideally we would have external (to NFI) models for updating data from disturbed stands that could be used in connection with mixed estimators of state and change (Dixon and Howitt 1979, Kangas 1991, Van Deusen 1996).

In our study, the inventory plots with missing T_2 information did not constitute a spatially random subsample of the T_1 plots. Despite a large degree of spatial overlap there were several compact sub-regions with missing T_2 data. However, the degree of overlap was such that it seems reasonable to assume that the identified models capturing the association between T_1 and T_2 attribute values holds irrespective of whether T_2 data is missing or not. When this assumption holds, our MI procedures preserve the effect of T_1 differences in the predictions for T_2 . For the Canadian NFI with photo-interpreted

data, the strongest impetus to use MI on a routine basis may therefore come from a general anticipation of T_1 differences between units with and without current information at time T_2 . In this scenario, our MI estimators of state and change are likely less biased than estimators based exclusively on units having T_2 data. Addition of explicit spatial linkages to disturbance events should make MI even more attractive.

The duality of direct and MI T_2 estimates and estimates of change ($T_2 - T_1$) naturally raises the question of which set of estimates is more correct or ‘believable’. Acceptance of unverified assumptions may meet with resistance. A compromise in the form of composite estimators (Gregoire and Walters 1988, Fuller 2009) may offer a more palatable alternative as it formulates a combination of the direct and MI estimators based on a weighting of the provided information in support of either.

For national forest inventories with a spatial balance in the number of plots measured in different years (Van Deusen 1997, McRoberts 2001), an important rationale for using MI is to boost the variance effective sample size and the associated improvement in precision. In a Canadian NFI context with photo-interpreted data, however, this generally attractive aspect of MI may not materialize to its full potential. An

expectation of T_1 differences in area-proportions and per unit area stem-volume, predicates a relatively large Monte-Carlo error (Koehler *et al.* 2009), all else equal, which translates to a recommendation of a relatively large number of MI replications (20 in this study) and modest gains in precision. Far fewer replicates are needed for data with small T_1 differences and stronger temporal and contemporaneous correlations, (Kangas 1991, McRoberts 2003). A fully efficient fractional imputation (Fuller 2009) may be a theoretically attractive alternative to our MI, but computationally more demanding and lacks readily accessible software.

The large sampling units in the Canadian NFI with multiple cover-types and trees of different ages impose limitations on available MI options. The popular nearest neighbour technique (*viz.* ‘hot deck’; Chen and Shao 2001, Kim and Fuller 2004, Carpenter and Kenward 2013) for multivariate imputations (McRoberts 2001, Eskelson *et al.* 2009a, 2009b) was considered but we failed to construct a meaningful definition of similarity (distance) due to the curse of dimensionality (Marimont and Shapiro 1979). Also, our pool of plots used as ‘donors’ for high-dimensional imputations was too small.

Although readily available software for MI and implementation may at first look straight-forward, it is not trivial and requires expertise in both forestry and statistics. The multivariate nature of forest inventories, restrictions of value ranges, and functional relationships among attributes of interests are challenges to consider.

Our MI approach was hierarchical but not multivariate: we began by imputing missing area proportions that were then used to complete imputations of volume. Multivariate (simultaneous) imputations would be an alternative (Carpenter and Kenward 2013). However, as opposed to *tvol*, we

found no significant correlation between area proportions and per unit area stem volume. That and the fact that we employ ratio estimators for stem volume justify our univariate approach. Our presentation of MI results and discussion has centered on MI as a tool in support of inference. It is equally clear that one might consider imputed data as a replacement for missing values in a NFI data base (Eskelson *et al.* 2009b, Traub *et al.* 2017). However, this may generate bias in estimates of change over time when, with the privilege of hindsight, an imputation turns out to be an outlier.

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