Design-based treatment of missing data in two-phase forest inventories by using canopy heights from laser scanning

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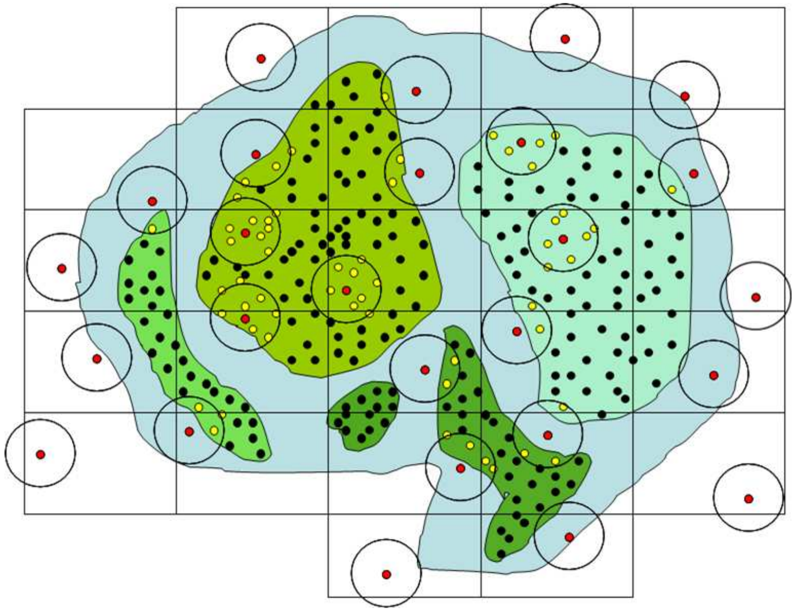
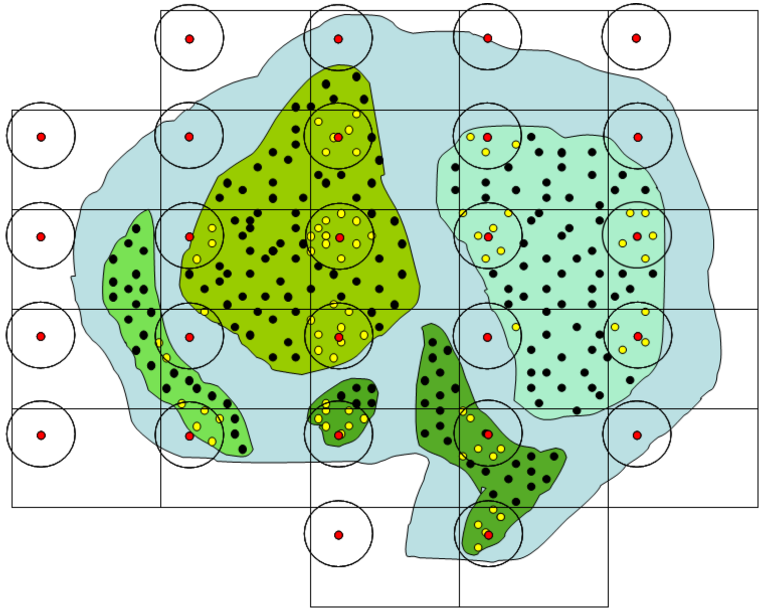
- in the first phase the area is partitioned into regular polygons of the same size and points are randomly or systematically thrown in each polygon.





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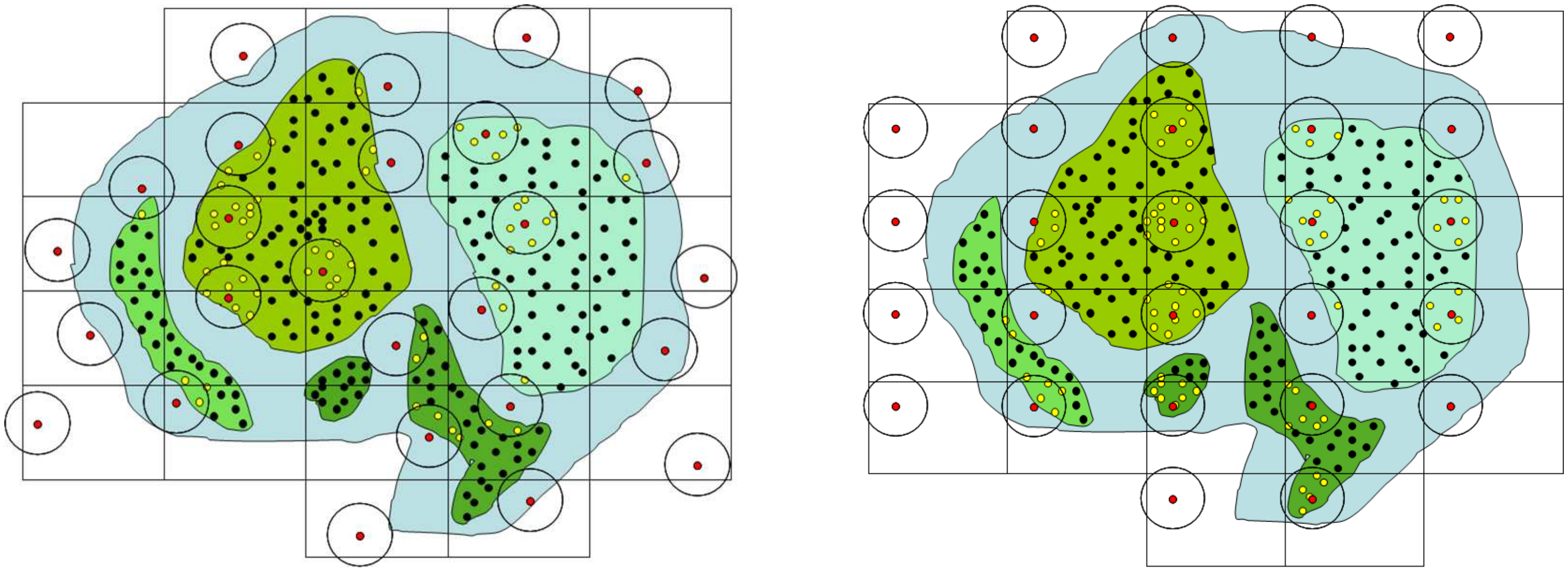
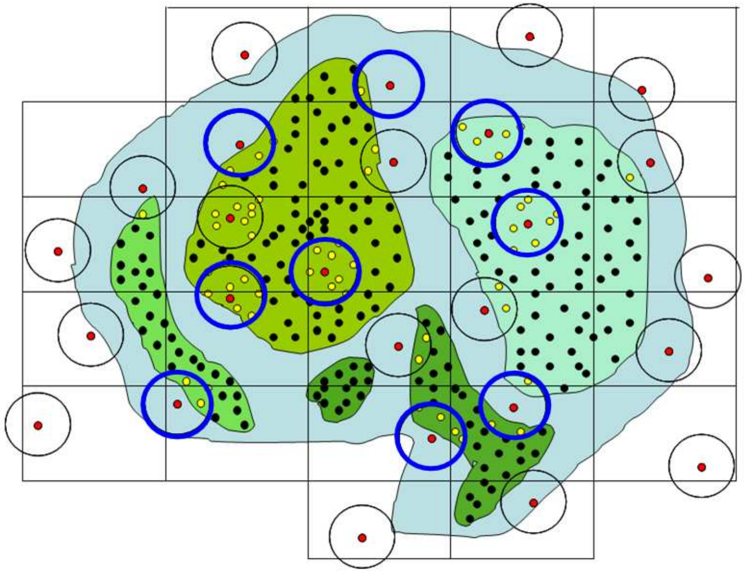


remote sensing information (photo-interpreted land cover class, elevation, thematic mapping spectral bands etc.) is recorded for each first-phase point

- in the second phase, a sample of first-phase points is selected in accordance with a probabilistic sampling scheme



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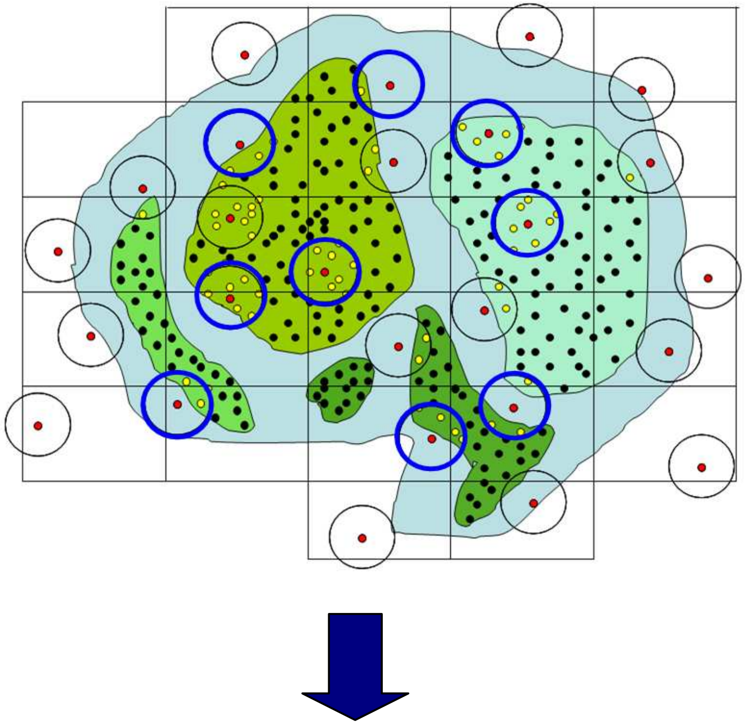

the second-phase points are visited on the ground in order to record several variables (actual land use class, forest category, total wood volume, tree basal area and biomass etc.) within plots of prefixed size centred at these points

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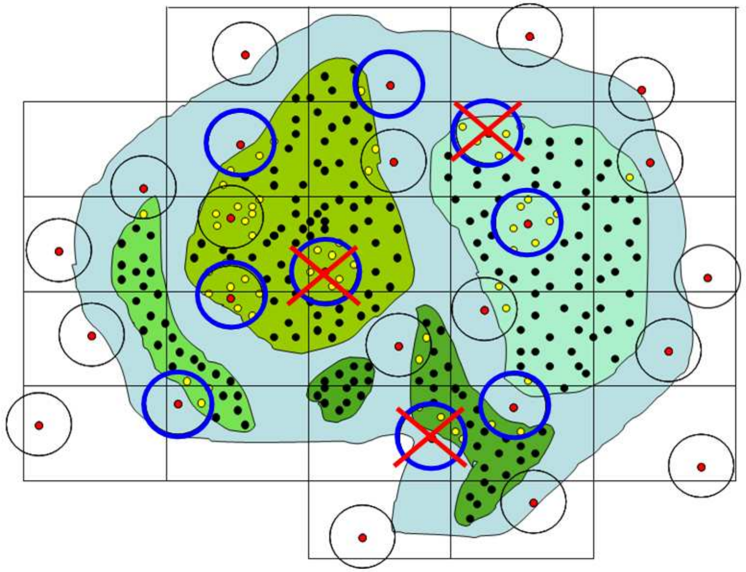

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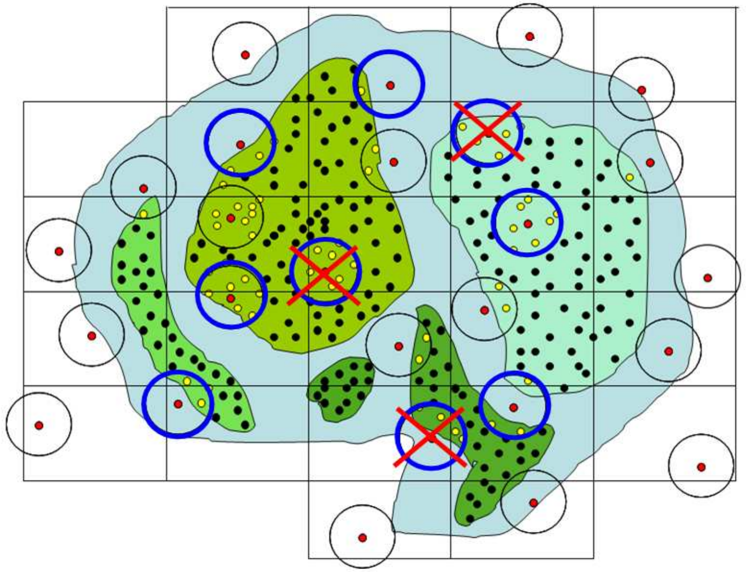

- some attempts for treating nonresponse in forest inventory are proposed by McRoberts (2003) and Scott et al. (2004)

- from a more general point of view, a vast statistical literature deals with the problem of nonresponse

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the use of nonresponse propensity weighting in forest surveys does not seem to be logically defensible

Imputation Techniques (regression imputation, nearest neighbour imputation, hot deck imputation and multiple imputation):

missing values are replaced by substitutes, the imputed values, which are usually obtained by means of a prediction model presuming a relationship among the interest variable and a set of variables and estimation is performed on the completed data

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But prediction models cannot be validated in the set of nonrespondents

it is difficult to scientifically defend any proposed method/model of imputation

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Fattorini et al. (2013) propose the use of a technique recently referred to as *nonresponse calibration weighting* (Haziza et al., 2010).

Nonresponse Calibration Weighting (NCW):

the weights originally attached to each respondent unit are modified into new weights able to estimate the population means of a set of auxiliary variables without error

Rationale if a relationship exists between the interest and the auxiliary variables, the calibration weights should also be suitable for estimating the population mean of the interest variable

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- NCW both reduces nonresponse bias and ensures consistency when the relationships among interest and auxiliary variables are similar in respondents and nonrespondents
- NCW can even increase the accuracy of estimation with respect to the complete-sample estimation when a close linear relationship exists among interest and auxiliary variables

Second-phase calibration estimator

T parameter of interest: total of an attribute (wood volume, basal area, etc.)

R second-phase respondent sample (points allowing recording activities)

$\mathbf{x}_j = \left[x_{j1}, \ldots, x_{jK} \right]^{\mathrm{T}}$ values of K auxiliary variables recorded on the j-th point

$$\hat{\hat{T}}_{2CAL} = \hat{\mathbf{b}}_R^{\mathrm{T}} \overline{\mathbf{X}}$$

where

$\overline{\mathbf{X}}$ is the mean vector of the auxiliary variables in the first-phase sample

$$\hat{\mathbf{b}}_R = \left(\sum_{j \in \mathrm{R}} \frac{\mathbf{x}_j \mathbf{x}_j^{\mathbf{T}}}{\pi_j} \right)^{-1} \sum_{j \in \mathrm{R}} \frac{\hat{T}_j \mathbf{x}_j^{\mathbf{T}}}{\pi_j}$$

π_j first-order inclusion probabilities

$\hat{T}_j$ total estimate in the j-th plot

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In recent years airborn laser scanning is increasingly being applied in forest inventories, providing measurements of the height of upper canopy for the surveyed area:

- canopy height data are often available at low or even no cost

- a close relationship has been proven between the timber volume (or tree biomass) of the inventory plots and the canopy height model (CHM) data obtained from ALS surveys (e.g. Corona and Fattorini, 2008, Gregoire et al., 2011, Corona et al., 2012)

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the exploitation of CHM data as auxiliary variable under the NCW approach seems to be a suitable estimation strategy

Simulation Study

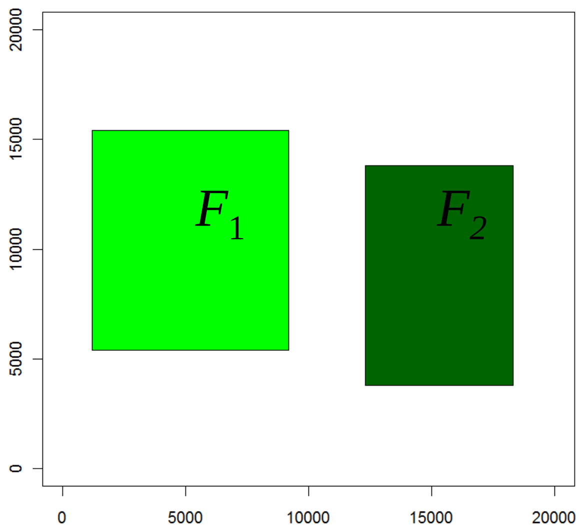
In order to evaluate the use of CHM data as auxiliary variable under the NCW approach a simulation study was performed

The artificial population:

- a quadrat study region of side 20 km was assumed

- the forest portion was : - the 35% of the whole area

  - constituted by two rectangles corresponding to two different forest categories (size 8000ha and 6000ha)



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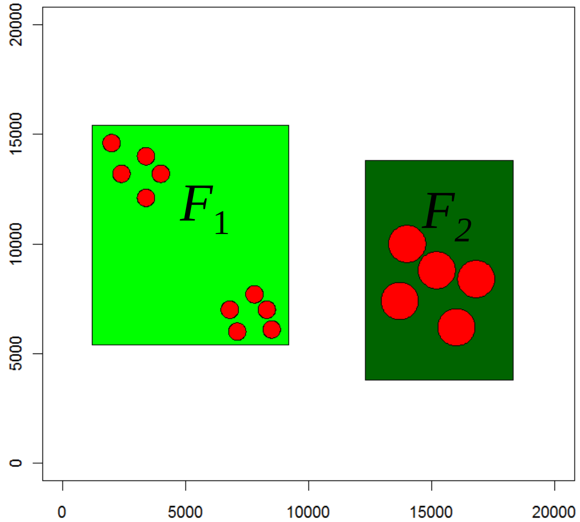

Non respondent pattern:

- F_1 nonresponse area of 5%
- F_2 nonresponse area of 15%

The generation of CHM data and volume values:

- F_1 and F_2 were partitioned into a discrete population of 80 and 60 millions of pixels of size 1 mq labelled by a couple of integers identifying their position in the study region

- for each pixel the canopy height within was obtained from the mixture of 20 bivariate normal probability density functions with different mean vectors and variance-covariance matrices

- in order to represent a forest coverage of about 40% in F_1 and a forest coverage of about 90% in F_2 about 60% and 10% of the heights were respectively set to 0 by means of a mathematical function

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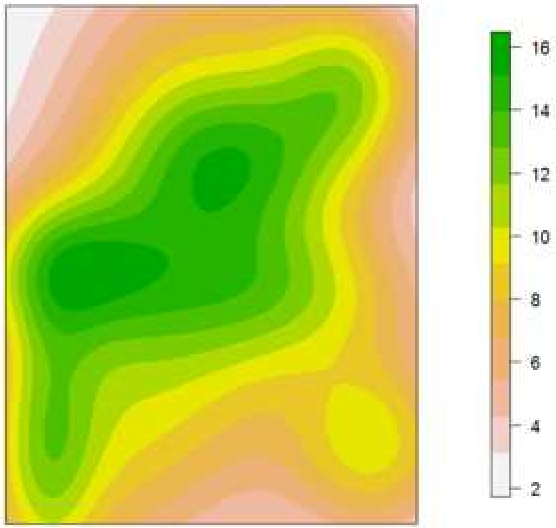
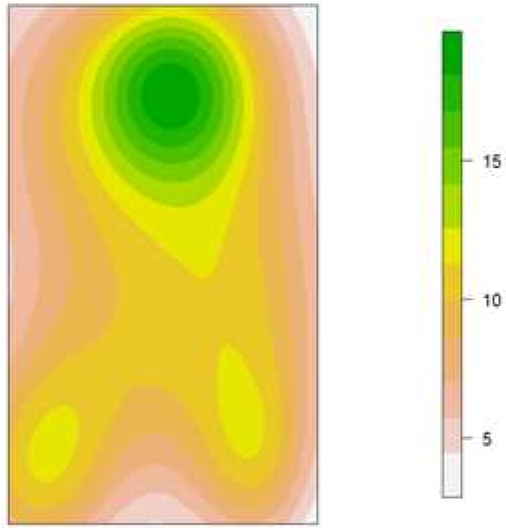
- in accordance with the results of some empirical investigations (Bortolot and Wynne, 2005), for each pixel the tree volume was presumed to be a linear function of the squared canopy height, perturbed by a periodic function



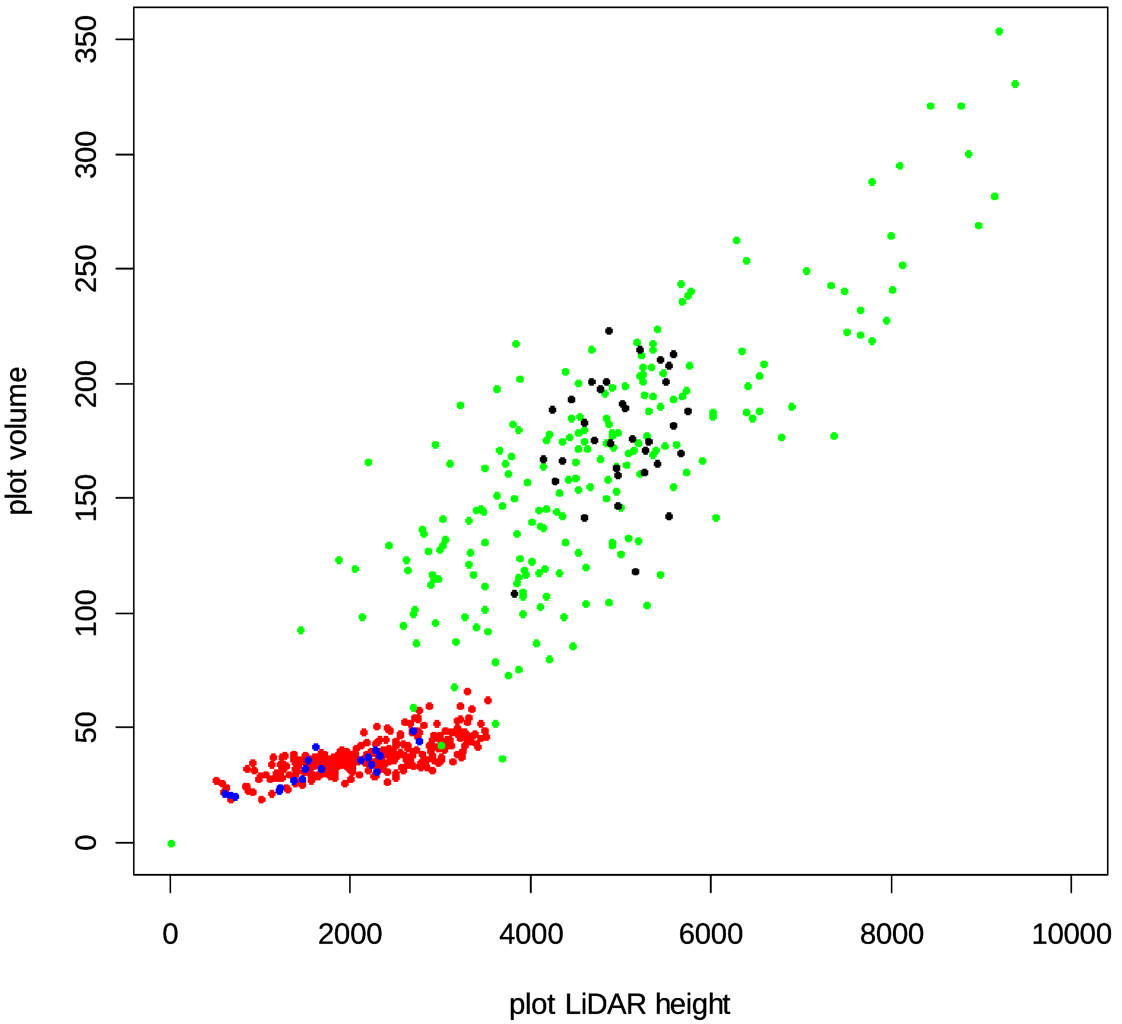
Region F_1



Region F_2

	F_1	F_2
Total canopy height	319 999 999.7 m	540 000 000.0 m
Total Volume	5 639 462.9 m^3	19 042 212.3 m^3
Maximum canopy height at pixel level	16.47 m	19.66 m

Canopy height vs volume at plot level in a sample of first-phase points



Survey simulation:

- 1,000 two-phase inventories were simulated

At each run:

- the study region was partitioned into quadrats of size 25 ha
- the first phase sampling was implemented by randomly (TSS) or systematically (SGS) selecting a point within each quadrat

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- in the second phase, the first-phase points were partitioned on the basis of their position into 3 strata:
  - the stratum of points falling outside the two forest regions
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From each forest stratum a sample of second-phase points was selected by means of SWSROR (sampling fraction equals to 0.25)

Finally, the respondent sample was derived discarding the points falling within the nonresponse areas and for each respondent point a circular plot - centred at the point - of radius 13 mt was considered

Survey simulation – The auxiliary variables

Two alternative choices of the auxiliary variables were considered:

1) Two auxiliary variables: the “intercept” and the total canopy height of the pixels in the selected plot

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2) Four auxiliary variables: the “intercept” and the total canopy height of the pixels in the selected plot taking into account the different forest categories

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$$\hat{\hat{T}}_{2CAL}$$

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$$\hat{\hat{T}}_{2CAL,F_1F_2}$$

Simulation results

As benchmarks, the following two estimators were also computed:

- $\hat{\hat{T}}_{2HT}$ the complete-sample estimator achieved if all the second-phase points were visited

- $\hat{\hat{T}}_{2R}$ the estimator based on the sole sample of respondents

The following performance indicators were considered:

- relative bias (RB)

- relative root mean squared error (RRMSE)

- expectation of the relative standard error estimators (ERSEE)

- coverage of the confidence intervals at the nominal level of 95% (COV95)

Simulation results

	TSS		SGS	
	RB	RRMSE	RB	RRMSE
$\hat{\hat{T}}_{2HT}$	0.1%	2.9%	-0.1%	2.8%
$\hat{\hat{T}}_{2R}$	-12.8%	13.5%	-13.2%	13.7%
$\hat{\hat{T}}_{2CAL}$	-1.3%	3.0%	-1.3%	2.8%
$\hat{\hat{T}}_{2CAL,F_1F_2}$	-0.2%	2.2%	-0.2%	2.0%

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$\hat{\hat{T}}_{2CAL}$	-1.3%	3.0%	-1.3%	2.8%
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✓ the estimator based on the sole respondent sample shows a considerable downward relative bias

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✓ $\hat{\hat{T}}_{2CAL}$ shows a remarkable reduction in the relative bias compared with the sole respondent estimator

✓ the relative bias of the calibration estimator $\hat{\hat{T}}_{2CAL,F_1F_2}$ turns out to be negligible, with a performance comparable with that of the complete sample estimator

Simulation results

TSS first-phase sampling scheme

			ERSEE			COV95		
	RB	RRMSE	SYG	HT	Jack	SYG	HT	Jack
$\hat{\hat{T}}_{2CAL}$	-1.3%	3.0%	5.3%	5.5%	5.4%	1.00	1.00	1.00
$\hat{\hat{T}}_{2CAL,F1F2}$	-0.2%	2.2%	5.1%	5.0%	5.1%	1.00	1.00	1.00

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✓ coverage of the confidence interval were invariably greater than the nominal value

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Survey simulation – The use of the auxiliary variable

Denote by h_j the CHM height within the j-th plot (sum of the heights within the pixels belonging to the plot)

Two alternative choices:

1)

in such a way that $\overline{\mathbf{X}}$ is the mean vector whose components are:

- fraction of first-phase points falling in forest regions
- average CHM height of the first-phase points falling in forest regions

$\hat{\hat{T}}_{2CAL}$

2) $\mathbf{x}_j = \left[I_{F_1}(j), I_{F_2}(j), I_{F_1}(j)h_j, I_{F_2}(j)h_j \right]^{\mathrm{T}}$

in such a way that $\overline{\mathbf{X}}$ is the mean vector whose components are:

- fraction of first-phase points falling in F_1
- fraction of first-phase points falling in F_2
- average CHM height of the first-phase points falling in F_1
- average CHM height of the first-phase points falling in F_2

$\hat{\hat{T}}_{2CAL,F_1F_2}$