

Calibration and variogram analysis in a small forest area

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ABSTRACT

The combined use of field measurements, statistical analysis and remote sensing measurements allows understanding the complexity of ecological forest landscapes. In this work we analyzed data from a small forest landscape to estimate forest tree diameter, a variable often used in ecological research literature. Based on 40 forest inventory plots field measured in one Alpine watershed, we compared a calibration model with remote sensing auxiliary data to a spatial dependence regression kriging model which use only field measured interdependence. The use of the comparison of statistical techniques proposed is innovative for the study of small forests.

Keywords: point pattern analysis, field measurements, remote sensing, forest estimation.

Mathematics Subject Classification: 62D05

Journal of Economic Literature (JEL) Classification Number: Q23

1 Introduction

The statistical analysis of spatial data supports the predictions of natural landscapes both with remote sensing instruments and data collected only on the ground. In the first case, a sampling phase of detection can be followed by a calibration phase based on analysis of remotely sensed images. In the second case, the data collected on the ground can be studied for an evaluation of the interdependence of the measurements based on the theory of regionalised variables. The two approaches have been used for the analysis of the landscape and for the prediction of structural variables such as the tree diameters of a forest. Remote sensing instruments demonstrate particular effectiveness in prediction analysis studies of wooded areas, for example Lidar is a laser-based aerial or terrestrial system that allows remote measurements of natural landscapes. A field sampling phase can be followed by a calibration on remotely sensed data by building model-assisted predictions. This detection and prediction structure has considerable advantages in terms of economics and time spent on the analysis. The calibration is based on the knowledge of the totals of the remotely sensed variables by incorporating in the model a function constrained to the knowledge of these totals. The calibration can be considered a particular generalized linear model and can be useful in natural landscape studies. The integration of Lidar data or aerial photos proves useful in improving the precision of forest area

estimates, particularly in the construction of forest inventories. The prediction method based only on ground data can be based on the theory of regionalized variables according to which nearby objects have similar characteristics. The study of the spatial interdependence of characteristics of the natural landscape can be done with the analysis of the variogram tool which collects on the Cartesian axes the semivariance and the distance between measured objects. The characteristic variogram curve has three parameters called nugget, sill and range. The spatial interdependence analysis allows the construction of a prediction model called regression kriging that incorporates the parameters of the theoretical variogram model that best fits the experimental curve.

The scales suitable for managing information on the landscape were studied with image segmentation and variogram analysis (Karl and Maurer, 2008), and the same approach on images analysis and related segmentations made it possible to analyze the influence of topographic gradients (Garbarino, Lingua, Weisberg, Bottero, Meloni and Motta, 2013) on the landscape and the effects of the interaction of the physical environment and anthropic disturbances on a forest landscape (Garbarino, Weisberg and Motta, 2009). Landscape use changes based on climate change and natural disturbance suppression in forests were also considered (Kulakowski, Bebi and Rixen, 2011) and image analysis was used for biodiversity studies (Remteng, Adepoju and Akinyede, 2015), and to construct forest attribute maps (McRoberts, Cohen, Næsset, Stehman and Tomppo, 2010). Human disturbance in forest ecosystems has been studied (Gimmi, Burgi and Stuber, 2008), (Majumdar, Polyakov, Teeter and Butler, 2009) and statistical models has been evaluated for natural resources surveys (Breidt, Opsomer, Johnson and Ranalli, 2007). Lidar and Insar systems were used to produce images that provide ancillary data for the assessment of boreal forests (Naesset, Gobakken, Solberg, Gregoire, Nelson, Ståhl and Weydahl, 2011) as an analysis of change and reforestation in the Alps (Tasser, Walde, Tappeiner, Teutsch and W., 2007). A review describes remote sensing technologies used to improve forest inventories (White, Coops, Wulder, Vastaranta, Hilker and Tompalski, 2016).

From the point of view of statistical methods, in our previous work we considered the comparison of model-assisted estimators in surveys of forest areas (Sciascia, Garbarino, Vacchiano and Motta, 2012) and the estimation of natural resources is performed with additive generalized models (Opsomer, Breidt, Moisen and Kauermann, 2007), (Breidt et al., 2007). The theoretical models refer to the calibration estimators (Deville and Sarndal, 1992), (Sarndal, 2007) and to the fundamentals of sample inference (Cassel, Sarndal and Wretman, 1977) and to applicative studies on non-parametric estimation with a calibration model (Montanari and Ranalli, 2005). Calibration as an estimation model can consider constraints on the information of spatial data (Sciascia, 2013).

The study of variation in the analysis of spatial data is based on the theory of regionalized variables (Matheron, 1971) and many applications have been considered for example in the study of space-time scenarios on air quality (Cameletti, Ignaccolo and Sylvan, 2013).

In this work we present a comparison of two prediction models, calibration and variogram with regression kriging, for the estimation of tree diameter in a small forest area in the Italian Alps. Chapter 2 deals with the description of the study landscape, chapter 3 deals with point pattern

analysis, calibration and regression kriging analysis and chapter 4 describes the results of the comparison between the predictions of the two methods. Chapter 5 summarizes the advantages of the two methods considered.

2 Study site: Alps Ventina

Field data were collected in a watershed (Ventina) in Lombardy region (Italy). Total land area is 1124 ha. Forests are dominated by European larch (*Larix decidua* Mill.) with Norway spruce (*Picea abies* (L.) H. Karst) as a co-dominant species at lower elevations. Mountain pine (*Pinus uncinata* Mill.) and Swiss stone pine (*Pinus cembra* L.) are abundant (Garbarino et al., 2009). In Table 1 are shown field measured (diameter and height) and remote sensed (elevation, slope, proximity to buildings, proximity to roads) variables of the site and in Figure 1 are represented the Digital Elevation Model and the spatial sampling for the Ventina site.

Variable	Unit	Mean (SE)	Range
Diameter	cm	17.76 (0.56)	5 - 105
Height	m	7.97 (0.20)	1.3 - 30.5
Elevation	m a.s.l.	2030.12 (23.34)	1676.4 - 2288.6
Slope	°	31.24 (1.06)	18.49 - 45.2
Proximity to buildings	m	24.02 (1.42)	11.31 - 34.22
Proximity to roads	m	108.92 (14.37)	2.5 - 370

Table 1: Mean values, standard errors (SE) and range of variables collected at the study site.

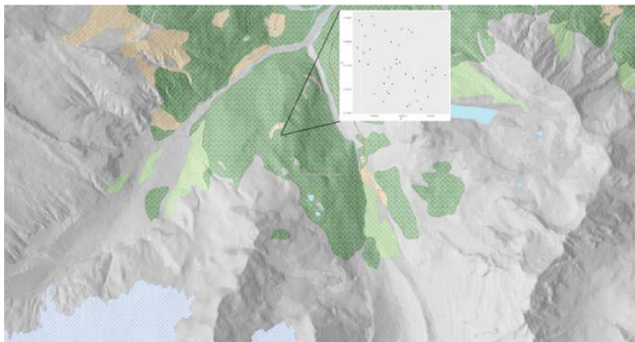


Figure 1: Digital Elevation model and plots in Ventina.

3 Statistical models and comparing predictions

From a finite population $U=1,2,...N$ of 40 circular sampling plots (N) (radius = 12m) in a watersheds (Ventina: 46°18 N, 9°46 E) in northern Italy, we extracted a probability sample of n plots. In each plot, tree size and species, forest structure, topographic variables (Table 1) were collected. Details of the field protocol are provided in a previous study (Garbarino et al., 2009). The study variable was the tree diameter (DBH), and the population parameter under estimation was the mean diameter (Sciascia et al., 2012). All statistical analyzes were performed with R, packages ggplot2, gstat, survey, sampling and SPSS ver. 28. We analysed the point spatial distribution observing eventual difference from casual spatial distribution using the Clarks and Evans index. To evaluate the spatial dependence of the measurement of the diameters we constructed a variogram between all the pairs of observations of the plots. We adapted a spherical model using gstat. Characteristics of the semivariogram are the nugget, sill and range parameters and the nugget to sill ratio (NSR). We use regression kriging (RK) and calibration as regression prediction models.

We used the calibrated model CAL in comparison with the regression kriging RK to predict the mean diameter per plot as a function of remotely sensed variables available at the plot level. The model calibrated on the totals of the explanatory variables is used to establish the relationship between the measurements in the field and the remotely sensed variables and then proceed with predictions of total diameter per plot. The regression kriging method was developed to use autocorrelation in the dataset to increase the accuracy of predictions. The RK uses generalized least squares GLS regression to predict a response variable and then uses the geostatistical technique and simple kriging to predict the value of GLS residuals at unsampled positions or to evaluate residuals. The predictor RK for an unsampled position variable, or model validation plots, is the sum of the GLS regression and the predicted residuals. In the calibration model CAL the procedures adjust sampling weights by multipliers calibration factors that make the estimates agree with known totals. These calibration weights will generally result in estimates that are design consistent, and that have a smaller variance than the Horvitz Thompson estimator.

3.1 Point pattern analysis

Clarks and Evans index

The average distance between a tree and its nearest neighbor (r_a) is related to the average of the distance expected if the points were randomly distributed, (r_e). Where r_i is the distance between the three i and its nearest neighbor (in m), N is the total number of trees in the image, A is the area of the image in m^2 and P is the perimeter of the image in m.

$$A = 452.16m^2 \quad P = 75.36m$$

$$CE = \frac{r_a}{r_e} = \frac{\frac{1}{N} \sum_{i=1}^N r_i}{0.5(A/N)^{1/2} + 0.0514 \frac{P}{N} + 0.041 \frac{P}{N^{3/2}}}$$

We thought it useful to start an ecological statistical analysis from the distribution of the points represented by the positions of the trees in each plot. Point pattern analysis is considered to

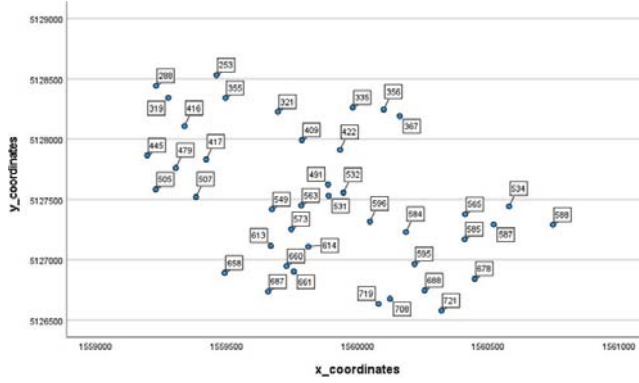


Figure 2: Coordinates of the 40 plots of Ventina in Italian Alps.

measure whether the point patterns are randomly distributed. We used the Clarks and Evans index which evaluates the intensity of the points to obtain an index of the spatial regularity. In a Poisson process of intensity λ the expected distance to the nearest neighbor is

$$\mathbb{E}[D] = \frac{1}{2\sqrt{\lambda}}$$

Index $C=1$ is for completely random pattern, $CE > 1$ suggests regularity, and $CE < 1$ suggests clustering.

$$CE = \frac{\bar{d}}{\mathbb{E}[D]} = \frac{2\sqrt{\lambda}}{t} \sum_{i=1}^t d_i$$

where t is the number of sampled points (trees), and

$$\bar{\lambda} = \frac{n}{P}$$

is the estimated point pattern intensity of n points in a plot P .

The CE hypothesis test of spatial randomness of CE index comparing a normal distribution of mean 1 and variance $s^2 = (1/\pi - 1/4)/t\lambda$ for a two tailed test for $(CE - 1)/s$ statistics.

3.2 Kriging

We considered a statistical technique based on the variogram analysis. Semivariance is a function of distance between pairs of objects and the plot of the experimental function is called variogram:

$$\gamma_h = \frac{1}{2Nh} \sum_{(p_i, p_{i+h}) \in S} [y_{p_i} - y_{p_{i+h}}]$$

where $\gamma(h)$ is the semivariance in function of the distance h for a pairs of trees, $N(h)$ are the trees pairs at distance h , S is the plot sample y_{p_i} is the diameter in m at the coordinates p_i and $y_{p_{i+h}}$ is the diameter m at the coordinates p_{i+h} .

	N	$\sum d_i$	$\bar{D}$	$\bar{H}$	CE
288	52	391.30	14.45	8.83	5.046
319	25	196.7	28.36	11.73	3.643
417	14	98.9	34.18	12.67	2.428
507	16	139.7	17.18	7.08	3.216
491	9	71	35.4	10.77	2.151
563	15	113.4	15.8	6.85	2.693
596	11	80.6	18.9	4.86	2.221
584	7	53.3	37.4	10.86	1.815
534	16	139.3	17.2	6.41	3.206
588	11	83.1	14	5.35	2.289

Table 2: Survey plots, descriptive statistics and CE index

The point cloud of the variogram and the theoretical estimation function of the variogram are then drawn according to one of the estimation models. Distance from plot points from an arbitrary point implies the variogram analysis considers the mean values at plot level for comparisons between two distant plots and evaluation of both study and explanatory variables. We studied how the autocorrelation changes as a function of the distance between observations through the analysis of the semivariance and we have fitted a theoretical spherical model for diameter using the OLS ordinary least squares of the regression method using the gstat package of R [23]. The parameters characteristics of the variogram are nugget as variability between point at a shorter distance, sill, the variation of the study variable, range, distance for two observations independence.

We calculated the regression kriging model (RK) with ordinary kriging:

$$\hat{Y}_{s_0} = \sum_{i=1}^N \lambda_i y_{s_i}$$

where y_{s_i} is the measured diameter value at location i , λ_i is the weight for the measure depending on the variogram, N the number of threes.

The Regression kriging is:

$$\hat{Q}_{s_0} = \beta Y(s^*) + w(s^*)$$

Where $\beta Y(s^*)$ depends on the grid position of the point and $w(s^*)$ is a function of the second order stationary process described by the theoretical spherical model that we have visually adapted to the experimental variogram and which is described by the spherical model as a function of the distance h between points of the grid:

$$\gamma_h = c_h + \sigma^2 \left(\frac{3}{2} \frac{h}{r} \right) - \frac{1}{2} \left(\frac{h}{r} \right)^3$$

Then we calculated the spherical model as in equation where σ^2 is the sill, c_h is the nugget and r is the range. These parameters of the spherical variogram are estimated by weighted least squares for all grid point in the n plots. All RK predictions on validation plots were performed

with R gstat package. The goal of implementing regression kriging in addition to calibrated regression modeling was to determine if the additional predictive capability could be achieved through the explicit insertion of spatial dependence in the predictors. At each validation plot we used the calibrated regression and the developed residual variogram model to construct RK predictions of the mean or total diameter. We evaluated the RK predictions using cross validation to derive a correlation between predicted and observed mean diameter.

3.3 Calibration

Calibration

The variable field measured y_i is calibrated according to the knowing total of the variable remote sensed x_i .

$$\hat{Y}_c = \sum_{i=1}^n c_i y_i$$

where c_i is the calibrated weight of i th observation according to constrained optimization:

$$\begin{aligned} c_i : \min \sum_{i=1}^n G_i(c_i, w_i) \\ \text{subject to } \sum_{i=1}^n c_i x_i = X \end{aligned}$$

where X is the variable total and $G_i(c_i, w_i)$ is the generic distance function among c_i and w_i ; considering the Euclidean distance among c_i and w_i :

$$G_i(c_i, w_i) = (c_i - w_i)^2 / w_i$$

We used for predictions the calibrated model (CAL) which is composed by linear regression with constraints equations on populations known totals of the four remote sensing predictors: elevation, slope, proximity to buildings, proximity to tracks.

4 Results

The point pattern analysis from which we started to estimate the forest area considering 10 validation sites out of the 40 available demonstrated in all sites a CE index significantly different from 1 ($p < 0.05$) and therefore a condition of regularity of the distribution of observations. The estimates with Regression kriging (RK) model is obtained with coordinates x , y as predictors. The variogram of the pairs of observations of the $n=728$ trees in the forty sampling plots are shown in Figure 3b.

The empirical variogram and the variogram model allow to visually evaluate the characteristic values: nugget=150, sill=320, range=180m indicating that at a distance of 180 meters the observations can be considered independent. In the study of the spatial dependence between observations in the validation plots 3a we note a slight variation in the NSR between neighboring sites with distances less than 100 meters between them (NSR (A) = 0.4; NSR (B) = 0.452

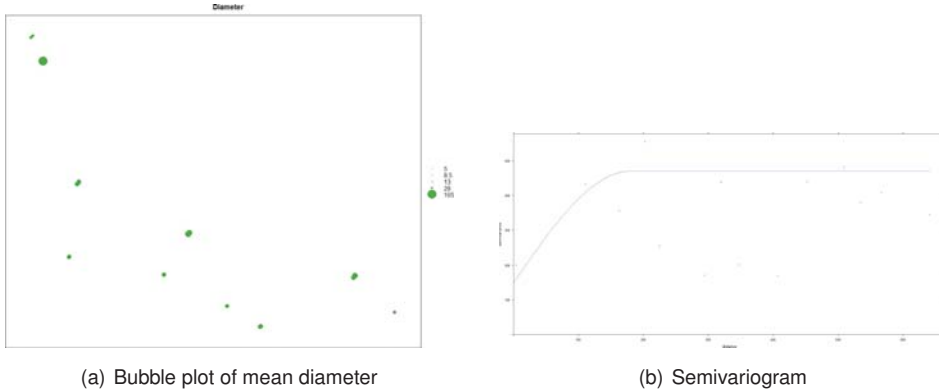


Figure 3: Spatial interdependence between diameters in 10 circular plots. Sampling sites A 288-319, B 417-507, C 491-563, D 596-584, E 534-588

and an increase in the distances between sites greater of 200m (NSR (C) = 0.46; NSR (D) = 0.47). The calibrated estimation and regression kriging models are built on thirty two plots and the verification of their performance is carried out on four validation sites, each consisting of two plots. For each validation plot we compared the predicted vs observed correlation for the calibrated regression and kriging regression predictions. The empirical variogram constructed for the mean diameter variable showed that most of the variability observed in field measurements can not be explained by the distance between observations. The variogram that we have adapted have spatial dependence on the diameter cannot extend over a range of 600m. The nugget and the sill are 150 and 320 m with a NSR of 0.468 which means that quite half of the variation in diameter can be considered short range or within the plot variability and cannot be explained by the dependence model space. We calculated cross correlations between calibrated and regression kriging predictions and field measurements through r correlation coefficient in validation sites. Regression kriging (RK) correlations are more large depending on the evaluation sites, and they vary highly 5b. There is evidence that the calibration estimation (CAL) grow slightly in correlation with the measurements in the field at the various validation sites. The RK estimations instead do not show high correlation increases at the validation sites. The ranges of variogram models at different plot sites are from 100 to 600 meters for predicted values and 100 to 400 meters for predicted residuals. The ranges for the variogram models of the residuals are always shorter than those of the predicted values and tend to decrease or to be different according to the different spatial interdependence in the validation sites. The sites whose residual variograms have the longest ranges also tend to have the largest difference between the CAL and RK predictions. Calculation of the R^2 is lower in this case, where the two estimates are not correlated. At the different validation sites, with different levels of spatial dependence, the shape of the spatial dependence of the calibration residues is closer to the variogram of the data collected in the field than does the spatial dependence of the calibrated predictions. At a different site the variograms for the predicted values become more similar in form to the variograms obtained from the field measurements and the spatial dependence of the regression residuals decreases as the range decreases. On the different site the variogram

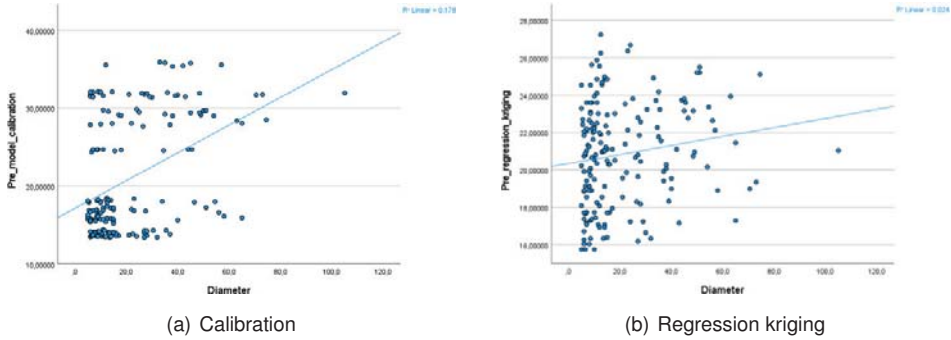


Figure 4: Fit of linear models

range of the calibrated predictions are increased to the different site where the variograms of the predicted values respect the variograms derived from the field. When measured from the predicted values range of the variogram and NSR, the site that most closely matches the field derived variogram diameter corresponds to the maximum correlation for the calibrated predictions. This also applies to the RK results with the exception of one site which has the strongest observed predicted correlation but whose spatial dependence of the predicted values is very different from the field derived variograms. When the correlation between predicted and observed diameters is plotted against the difference in range between the variograms of predicted and measured values in the field, for the calibrated regression there is evidence of a general decrease in the strength of the correlation as the difference in range increases. For the RK, however, there is no trend in correlation with changes in difference between the ranges of the variogram. These results are consistent with the results in those sites that produce predictions with spatial dependence approaching those observed in the field that achieve the best predictions when geostatistical statistical techniques are not used. The use of geostatistical techniques, however, could achieve similar results regardless of the site as they take into account the spatial dependence not detected by the regression predictions. In Table 2 we described the descriptive statistics and point pattern analysis results for the CE index. In figure 4 we described the CAL and RK linear fitting and in Figure 5 are shown the changes in correlation with validation sites between diameter predictions with calibrated model and regression kriging an we can note the greatest variance in model calibration. In Figure 6 are shown the linear fitting. In Table 3 are described the estimator performance..

5 Discussion

In this article, models with complementary prediction variables are CAL and RK. They are both generalized linear models. Complementary variable models CAL and RK use information from various sources as remote sensing and field measurements variograms. An important role of prediction models is to help in the analysis and management choices of the evolution of ecological forest landscapes considering the use of digital elevation models, orthophotos and topographic databases. Digital elevation models coupled with topographic databases are useful for building landscape models and complementary variable models integrate the

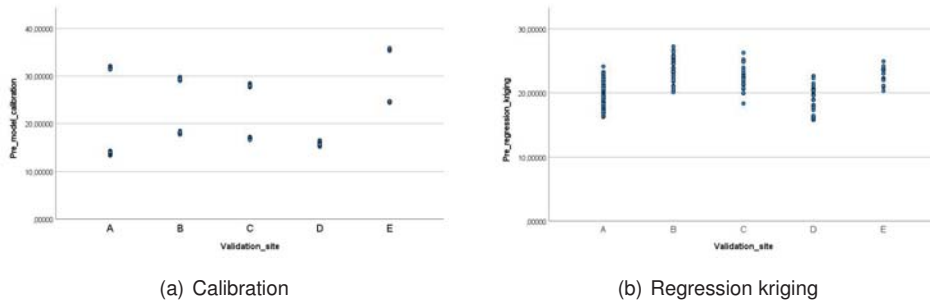


Figure 5: Changes in correlation in CAL and RK models

description of landscapes and their patterns, and plot predictions for study variables. Complementary models allow to evaluate the spatial dependence of the measured variables. For the regression kriging technique the degree of spatial autocorrelation between observations can be interpreted as a confirmatory value of the analyses performed with calibration models. Comparison of regression and residual models versus calculated semivariance in soil samples at different evaluation sites have been evaluated in different wooded area sites. Since forest structure in the study area is significantly influenced by previous anthropogenic activities (Garbarino et al., 2009), we were particularly interested in the effect of anthropogenic auxiliary variables (Sciascia et al., 2012) where elevation consistently produced the most efficient estimates, and distance to roads the least efficient. Abiotic environmental gradients, described by simple topographic variables including elevation, slope, and aspect, are often the best predictors of forest structure (Sciascia et al., 2012), even in forests that are still recovering from recent, intensive human influence (Garbarino et al., 2013). On the other hand, measuring anthropogenic impact is not straightforward. Relevant variables, including those chosen in this study, are often indirect indicators of human disturbance on forests, and may hide complex relationships with forest structural variables. However, distance from buildings was already found to be a stronger predictor of stand structure than distance from roads in a comparable forest ecosystem (Garbarino et al., 2009). The presence of shepherd huts is probably more directly related to grazing activity, and thus to human pressure on forest structure. Generalization of our results is somewhat limited by the fact that, differently from studies on national forest inventories (White et al., 2016), our sampling design was built upon a previously available dataset (Garbarino et al., 2013), (Sciascia et al., 2012), the variance of which was unknown because no knowledge of the wider population characteristics was available. Moreover, the choice of trees as elementary sampling units is not optimal for large forest inventories, but can be reasonable in small area forest inventories of test sites. Further developments will be possible by building either non-linear or multivariate model-assisted estimators, and by developing methods to take into account measurement errors in both field and remotely sensed data.

The robustness of the ecological analysis of the landscape is obtained with models that integrate different sources of information. We used publicly available geographic databases with digital elevation models, color aerial photos and topographic database (Province of Sondrio) and a previous research to test the predictions performance of two statistical techniques ap-

plied previously in different study fields. The semivariogram between each pair of observations for characteristic plots to evaluate the spatial dependence of the measurements in the field of mean trees diameter at different validation sites affect correlations and predictions of study variables, to look at the changes in spatial dependence of regression predictions and residuals for four different validation sites. The calibration model as a particular type of linear regression model performed for best mean squared error using remote sensed variables. In this study we combined data from a probability sample of field plots with full-coverage thematic layers, in order to achieve better estimates of relevant forest attributes in the area of interest.

Estimator	R^2
CAL	0,178
RK	0,024

Table 3: Estimators performance

In this work we use the analysis of the distribution of points of trees located in a plot with the point pattern analysis to verify their random or aggregate distribution through the Clarks and Evans index, then we studied the variogram of tree size disposition then we make predictions with ordinary kriging model (that uses data measured on the ground) and predictions with calibration that uses data measured on the ground with the support of remote sensing data through aerial photographs. We analyze the correlation relationships between diameters and distances within the 40 plots by building the variogram of the analysis site to evaluate the spatial autocorrelations and then estimate with ordinary kriging values.

We construct the graph of the empirical semivariogram for the 40 plots and superimpose a theoretical spherical model of interpolation. This analysis approach is based on the theory of regionalised variables. The calibrated estimator is constructed with the constraints on the totals of the remotely sensed variables. We evaluate the accuracy of the estimates with the R^2 index.

Our study is relevant in forest management, carbon and habitat inventories at the watershed scale, where knowledge of the local anthropogenic disturbance regime is necessary. Complementary variable models have proven to be the most efficient in predicting study variables and the confirmatory analysis of semivariance has shown that at long distances the values are less correlated both for the variables measured in the field and for the remotely sensed variables. This exploratory research on a small wooded area of study allows the use of multiscale monitoring of forest ecosystems based on the integration of remote sensing techniques with georeferenced databases using satellite monitoring systems of disturbances to forest ecosystems with use of spatial statistical analysis applications. The combined use of remote sensing technologies and field measurements with statistical estimation models allows the development of estimation strategies useful in evaluating the structure and processes of ecological landscapes.

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