NON-PARAMETRIC FOREST ATTRIBUTES ESTIMATION USING LIDAR AND TM DATA

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Abstract:
In a case study in the Waldkirch's forests in the southwestern region of Germany, four non parametric methods of K nearest neighbor (Knn), support vector machine regression (SVR), random forest (RF) and artificial neural network (ANN) algorithms were compared for forest volume and basal area estimation using Lidar and TM data. The volume and basal area per hectare of 411 circular plots were calculated using DBH and height of trees. The one-meter resolution DTM and DSM models were extracted from aerial laser scanner (ALS) data. The plot-based height and intensity statistics images and a canopy cover map were extracted using DTM and DSM models. The TM imagery was georeferenced using an orthorectified CIR image. The proper vegetation indices, tasseled cap transformation and principal component analysis were generated on the TM bands. In Knn, different implementations using different distance measure were performed for both attribute estimations. In SVR, the best parameters were also regularized for different kernel types using v-fold cross validation with a grid search method. The RF was also implemented using regularized the decision tree model and stopping parameters. The ANN with different type of networks of RBF, MLP and GRNN were examined to predict volume and basal area. The validity of performances was examined on 25 percent test samples using absolute and relative RMSe and Bias. Comparison results showed that among four methods, the SVR using RBF kernel could better estimate volume with lower RMSE and Bias. For basal area estimation, the Knn with Euclidean squared distance measure could produce lower percent RMSE and Bias compared to other used algorithms.

1-INTRODUCION:

The optical satellite imagery is often providing two-dimensional spectral information and presenting reflectance responses of canopy cover surface. In other hand, Lidar airborne laser scanner (ALS) data provides three-dimensional vegetation height and cover structure data. Several studies (Naesset, 2002; 2004a; Means et al. 2000; Holmgren 2004; Maltamo et al., 2006a; 2006b; 2007; Dalponte et al., 2009; Breidenbach et al., 2010) have reported that forest characteristics of mean height, basal area and volume can be predicted better using ALS data. However, there are many studies, which show the ALS data were not suitable when ALS data used alone (Packalén, 2009) for forest attributes estimations and classifications. In other hand, in many studies (Gemmell, 1995; Makela & Pekkarinen, 2004; Huiyan et al., 2006; Sivanpillai et al., 2006; Mohammadi et al., 2010) capabilities of optical images were also not acceptable for accurate forest attribute estimations due to they are relatively insensitive to canopy height. Therefore, combining the optical data with lidar data would be more successful in forest attribute estimations (Hudak et al., 2001; Packalén, 2009; Latifi et al, 2010; McInerney et al, 2010).

So far, the parametric algorithms i.e. multiple linear and non linear regressions have been popular methods in estimation of forest attributes using remote sensing data (Sivanpillai et al., 2006; Huiyan et al., 2006; Gebreslasie, et al., 2008; Mohammadi et al., 2010). Recently, the non-parametric algorithms have been explored for forest attribute estimations due to their flexibility and ability to describe nonlinear dependences compared to parametric algorithms (Franco-Lopez et al., 2001; McRoberts et al., 2007). One of the greatest advantages of non-parametric algorithms is that they are free assumption of any given probability distribution (Sironen et al., 2010). The machine learning algorithms are groups of data mining and non-parametric based algorithms that use numerous independent variables in classification and regression applications. The K nearest neighbor (Knn), Support Vector Machine Regression (SVR) and Random Forest (RF), and

artificial neural network (ANN) algorithms are four famous and most used machine-learning algorithms for forest attribute estimations and imputations in few studies. This study will compare these four non-parametric methods for plot-level forest volume and basal area estimation using combing ALS and spectral Landsat-TM data.
The **Knn** method is the simplest among all machine learning and data mining algorithms that use for both classification and regression. For regression, the Knn is simply assigning the property value for the object to be the average of the values of its *k* nearest neighbors. The Knn is widely used for estimation of forest attributes using various remote sensing data (Franco-Lopez et al., 2001; McRoberts et al., 2007; Makela & Pekkarinen, 2004; Tatjana et al., 2007). In Knn implementations, three parameters should be determined including number of k, type of distance measure and weights for nearest neighbors.
The **RF** is an extension of classification and regression tree (CART) methods (Breiman, 2001). The RF can be used for regression-type problems to predict forest continuous dependent variable (Eskelson, et al., 2009; Breidenbach et al., 2010; Yu et al., 2010) and classification problems to predict categorical dependent variable (Watts and Lawrence, 2008; Walton, 2008). In regression problems, the RF is an arbitrary number (ensemble) of simple trees (subset from independent variables) which, are used to vote their responses be combined (averaged) to obtain an estimate of dependent variables. The data and variables can be randomly sampled in an iteratively bagging bootstrap sampling to generate a forest of regression trees.
The **SVM** algorithm is a family of classification and regression techniques based on statistical learning theory developed by Vapnik and coworkers (1963, 1964). Generally, the SVM focus on the boundary between classes and maps the input space created by independent variables using a nonlinear transformation according to the kernel functions including linear, polynomial, radial basis function (RBF), and sigmoid. In SVM regression (hereafter SVR), the algorithm is trying to find a hyperplane that can accurately predict the distribution of information (Wang et al., 2009). Since, the SVR has been used for forest biophysical variables estimations in a few studies including Wang and Brenner (2009) for forest canopy cover; Dalponte et al. (2009) for tree level estimation of biomass and Durbha et al. (2007) for retrieval of leaf area index.
The **ANN** is powerful non-linear modeling technique that is free of the traditional assumptions, well suited for complex non-linear relationships, and perfect for exploratory analyses where the goal is to establish if any relationship exists among a set of variables. It attempts to model nonlinear functions with large numbers of variables. Neural network designers therefore traditionally run training algorithms a number of times with a given "neural network design. In ANN, the type of neural network, the number of input variables and hidden units, and settings of various control parameters in the training algorithms can affect the final performance of the network. Radial basis function (RBF), generalized regression neural networks (GRNN) and multilayer perceptron (MLP) are the most used types of neural networks.

2. MATERIALS AND METHODS
2.1 STUDY AREA
This study was achieved in small area on the municipal and state forest enterprises around the Waldkirch, northeastern of Freiburg, Germany. This managed forest is semi flatted and comprising hardwood and softwood mixed forest with dominant species of European beech (*Fagus sylvatica*), Norway spruce (*Picea abies*), European silver fir (*Abies alba*), Douglas fir (*Pseudotsuga menziesii*) and Sycamore maple (*Acer pseudoplatanus*) (Breidenbach et al., 2010).

2.2 FOREST INVENTORY DATA
In this study, the species–specific volumes of tree species for 411 permanent plots were received from database of Waldkirch forest that took place in 2002 by the Baden-Wurttemberg forest service. The spreadsheet was also containing the species-specific aggregated total basal area and

average of DBH. The all plots were comprised from four concentric circle plots with radii of 2, 3, 6 and 12 m plots and were positioned on the intersection of a 100*200 sample grid. Tree information was recorded within plots consisting of all trees with DBH greater than 7, 10, 15 and 30 cm, within the 4 circle plots, respectively. Singletree volumes and basal area were calculated using DBH and height for volume functions of the Baden-Wurttemberg state forest service and using DBH of trees for basal area. Four radius-specific weighting factors were then applied to the volumes and basal area to scale them to per-hectare values. The plot level attributes were derived by aggregating the weighted singletree volumes and basal areas.

2.3 ALS DATA

The ALS data was acquired in 2002 by the state surveying office of Baden-Wurttemberg using an Optech ALTM 1225 laser scanner. The one meters resolution digital elevation model (DTM) and digital surface models (DSM) were extracted after preprocessing of ALS data in the FELIS department of Freiburg university using the TreesVis software (Weinacker et al. 2004). In Fusion software, by considering two meters height breaks for cover calculation and ignoring height of the shrubs, height and intensity statistics metrics i.e. elevation metrics, elevation percentiles, variance, Skewness and the mean of height data were computed for 30 meters grids equal to plots size. In addition, a canopy cover map was derived by counting the number of return pulses greater than height break (2 meters) divide on total return pulses in 30 meters grid.

2.4 LANDSAT-TM DATA

A small window corresponding to study area was selected from Landsat-TM image acquired on 13 August 2003. The images were co-registered to an orthorectified true color composite of digital aerial photo using tie points and DTM extracted from Lidar data with RMSe of 0.79 pixels. The greenness, brightness and wetness components of tasseled cap transformation (Cohen et al. 1995), the standardized principal components (PCA) and some famous and most used vegetation indices (Table 1) were produced for quantifying the vegetation attributes and enhancing the biophysical characteristics. Spectral values of main and artificial TM bands corresponding to locations of 411 plots were extracted using sample function in ArcGIS.

Table 1: The vegetation indices

Index	Formula
SVI (Simple Ratio Vegetation Index)	NIR/R
TVI (Transformed Vegetation Index)	(NDVI+ 0.5) ½
NDVI (Normalized Difference Vegetation Index)	NIR- Red / NIR+ Red
RVI (Ratio Vegetation Index)	Red / NIR
DVI (Differential vegetation index)	NIR- Red
NRVI (Normalized Ratio Vegetation Index)	(RVI – 1) / (RVI +1)
TTVI (Thiam's Transformed Vegetation Index)	√absolute (NDVI + 0.5)
CTVI (Corrected Transformed Vegetation Index	NDVI+0.5 / absolute(NDVI + 0.5) x √absolute(NDVI + 0.5)
GNDVI	NIR-Green/ NIR+ Green

2-5 ALGORITHM IMPLEMENTATIONS:

In all implementations, first, in a random sampling manner, the 75 percent of plots were selected as prototype samples and the rest 25 percent of plots were selected as test or validation sample set. In Knn implementations, the number of k nearest neighbors, type of distance measure and considering weight for nearest neighbors are three important parameters. Determination of K would be very important in terms consuming of calculation time and producing unbiased results. For finding the optimal k, the leave-one-out (LOO) cross validation selection method with v-fold (dividing samples to two v-fold parts, i.e. v-1 for training and one fold for validation) were used based on a k search range. The LOO is an accepted method to generate unbiased estimates of expected classification or estimation error for the *K*nn estimator (Gong 1986). By applying 10 folds and considering 1 to 64 k search range for nearest neighbors (equal to the number of independent variables) on each distance metrics, the algorithm calculate the RMSE values in validation samples fold for each K value. The best or optimal K will then find based on the lowest produced RMSe and bias. For an efficiency comparison of distance measures, the four distance measures of Euclidean, squared Euclidean, city block (Manhattan) and Chebychev were individually tested as both weighted and non-weighted. In all implementations, the independent variables were standardized through a simple transformation to between 0 to 1.

The good performance of RF is depending on the regularization of decision tree and stopping parameters. The decision tree model parameters are including the maximum number of trees which must be grow in the forest and the number of variables that randomly are selected in each node. The stopping parameters or control parameters are used to stop the algorithm when satisfactory results have been achieved. For determination of optimal trees number, 400 initial trees were used to produce a graph, which is showing the average squared error rates against each number of trees for training and test samples. One of the main parameters, which should be determinate in RF, is k predictor (independent variables) in each node for predicting dependent values (response). The simplest way of determination of k is calculation of root square of total independent variables ($k \leq \sqrt{m}$, m is number of input variables). We also used default rates of stopping splitting parameters and conditions, which stop processes of growing the trees when it reached to given stopping conditions. The used stopping parameters for all estimations were including minimum 1 child node and maximum 200 nodes in each tree to stop growing the trees.

The SVR performance is affected by three parameters, the capacity (C), which presents a trade-off between the model complexity and the amount up to which deviations larger than (C) are tolerated, the epsilon (□) that controls width of the □-insensitive zone used to fit the training data, and gamma (δ) as a kernel function parameter (Cortez and Morais, 2007). The value of epsilon can affect the number of support vectors (SVs) used to construct the regression function. The kernel parameters can be selected by prior knowledge, user experiences or be determined by fixing a parameter and controlling other parameters. In this study, three different based kernels i.e. radial basis function (RBF), polynomial and sigmoid were examined on a fixed value of gamma of 0.016 that calculated based on 1/number of independent variables (Hsu et al., 2010). For selection two other parameters, a specified grid search method using 10-fold cross-validation and 1000 iterations to minimize error function (Schölkopf et al. 1998) was used to determine the best value of capacity and epsilon. The specified grid search was ranged from 1 to 40 for capacity, equal to number of input variables (Mattera & Haykin, 1999) and 0.1 to 0.5 for epsilon.

2.6 VALIDATION AND QUALITY PERFORMANCE ASSESSMENT

The validity of performances examined using regression diagnostics metrics of root mean square error (RMSe), relative RMSe, bias and relative bias using the 25 percent unused samples.

$$RMSe = \sqrt{\sum_{i=1}^{m}(est_i - obs_i)} \Big/ m \qquad RMSe\% = \frac{\sqrt{\sum_{i=1}^{m}(est_i - obs_i)} \Big/ m}{\sum_{i=1}^{m}(obs_i)/m} * 100 \qquad \text{Bias} = \sum_{i=1}^{m}(est_i - obs_i) \Big/ m \qquad \text{Bias\%} = \frac{\sum_{i=1}^{m}(est_i - obs_i) \Big/ m}{\sum_{i=1}^{m}(obs_i)/m} * 100$$

3. RESULTS AND DISCUSSION

Results of Knn implementations in volume estimation showed that lowest relative and absolute RMSe were obtained using weighted squared Euclidian distance measure. An overview on table 2, it can be find that weighted distances could more effective to estimate the target pixels or places, where we would like to estimate volume and basal area for these places. It means that giving the progressively greater weight on references units that are closer or more similar to target unit as squared could be more useful. Second, we can find that squared Euclidean distance could better produces volume and basal area in target units with the lower RMSe and bias compared to other metrics. The result, confirmed outcomes of Kajisa et al. (2008) that reported

Knn using Euclidean distance could consistently produced lower RMSe and relative RMSe. In more studies, the squared Euclidean was the most used distance metric (Franco-Lopez et al. 2001; Reese et al., 2002; Sironen et al., 2010) and could produce better results compared to other metrics (Shataee et al., 2010). In agreement with some studies (Finely et al., 2006, with k between 1-35, and McRobert, 2007, with 1-50 k) that reported the higher k values could better reduced the bias and smaller k often leads to less stable results (Kozma, 2008).

Table 2: Results of Knn implementations for plot-level volume and basal area estimations

KNN	K (optimal K)	Distance measure (* is weighted)	RMSe	RMSe %	Bias	Bias %
Volume	64(64)	Chebychev(*)	174.20	41.16	-14.43	-3.53
	64(14)	Chebychev	169.92	40.15	-0.15	-0.03
	64(38)	Manhattan(*)	168.94	39.91	2.22	0.52
	64(31)	Manhattan	164.89	38.96	-2.04	-0.48
	64(59)	Squared Euclidean (*)	161.48	38.15	-4.03	-0.96
	64(14)	Squared Euclidean	169.27	39.99	3.01	0.70
Basal area	64(59)	Squared Euclidean(*)	11.79	34.80	0.03	0.09
	64(15)	Squared Euclidean	12.38	36.53	0.45	1.31
	64(14)	Chebychev	12.26	36.19	0.5	1.47
	64(48)	Chebychev(*)	12.18	35.97	-0.08	-0.24
	64(38)	Manhattan(*)	12.32	36.36	0.41	1.19
	64(31)	Manhattan	11.97	35.33	0.24	0.71

Results of the SVR implementations with different kernels showed that using RBF kernel could produced lower RMSe and were less biased compared to other kernels (Table 3). It means that RBF kernel with its parameters, obtained by specified grid search method, could prepare and map the best hyperplane or the feature space for SVR model. The suitable kernel parameters for each kernel were come in tables. In volume estimation, although the RMSe of applying polynomial function kernel is close to those obtained by RBF kernel; but results were very biased.

Table 3: Results of SVR implementations for plot-level volume and basal area estimations

SVR	Kernel	Gamma	Capacity	Epsilon	RMSe	RMSe %	Bias	Bias %
Volume	RBF	0.016	6	0.26	156.02	36.86	0.48	0.11
	Polynomial	0.016	19	0.12	156.29	36.92	-19.90	-4.93
	Sigmoid	0.016	20	0.5	165.73	39.16	15.10	3.44
Basal area	RBF	0.016	20	0.1	11.94	35.25	-1.54	-4.79
	Polynomial	0.016	20	0.28	12.05	35.57	-1.03	-3.15
	Sigmoid	0.016	20	0.18	12.05	35.57	-1.28	-3.93

Results of RF showed that using 60 percent subsample portion, 7 predictor (independent variables) in each node and 400 initial trees could better predicted volume with lower RMSe compared to 50 percent subsample portion with 7 predictor, but the predictions were very biased (Table 4). In basal area estimation, the best results come using 50 percent sub sample portion and 2 children in each node with the same 400 initial number of trees and 7 predictor (Table 5).

Table 4: Results of RF implementations for plot-level volume and basal area estimations

RF	K predictor	Number of tree	Subsample portion	Min child in each node	RMSe	RMSe %	Bias	Bias %
Volume	7	400	0.6	5	176.17	40.04	-27.2	-6.59
	7	400	0.5	5	185.20	46.38	-2.5	-0.63
Basal area	7	400	0.6	5	12.87	36.79	-1.99	-6.05
	7	400	0.50	5	12.64	38.54	0.05	0.17

In ANN, the results of volume estimation showed that radial based function network compared to other types of networks could better tested neural networks. However, in basal area, GRNN type of network produced the lower RMSe and bias results (Table 5).

Table 5: Results of ANN implementations for plot-level volume and basal area estimations

Ann	Number of network	Type of network	RMSe	RMSe %	Bias	Bias %
Volume	1000	RBF	185.73	44.64	-3.98	-0.96
Basal area	1000	GRNN	12.06	35.55	-0.6	-1.81

In conclusion (see Table 6), in volume estimation, the best and considerably different results obtained by the SVR algorithm compared to other used algorithms. This result is in agreement with our last study (Shataee, 2010) in a comparison study of SVR, RF and boosting regression tree (BRT) implementation using ASTER data for forest volume in the Hyrcanian forest. However, in basal area estimation, Knn could better produce results with lower RMSe and bias. In both variables, the Knn and SVR were better than RF and ANN algorithms.

Table 6: Comparison results of algorithm implementations for volume and basal area

Variable	Algorithm	RMSe	RMSe %	Bias	Bias %
Volume/ha	Knn	161.48	38.15	-4.03	-0.96
	SVR	156.02	36.86	0.48	0.11
	RF	185.20	46.38	-2.5	-0.63
	ANN	185.73	44.64	-3.98	-0.96
Basal area/ha	Knn	11.79	34.80	0.03	0.09
	SVR	11.94	35.25	-1.54	-4.79
	RF	12.64	38.54	0.05	0.17
	ANN	12.06	35.55	-0.6	-1.81

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