

**GEOSTATISTICAL TECHNIQUE FOR GROWING STOCK ESTIMATES ON
SMALL FOREST STANDS USING INVENTORY, ENVIRONMENTAL AND
LANDSAT 8 DATA**

**Geostatistička tehnika procjene drvnih zaliha u šumskim sastojinama male površine na
bazi inventurnih, okolišnih i spektralnih podataka Landsat 8**

Azra Čabaravdić¹, Merisa Osmanović², Galib Mahmutović³, Sanela Mulić⁴

Abstract

Regular forest inventory on state owned forest delivers plenty of data and information enabling detailed insight in forest structure and quantities. Current methodology for forest assessment on private properties considers time-consuming, low-intensive terrestrial measurement and observation on scattered small forest stands distributed on hilly and plane position around complex of state owned forests.

Here are evaluated two modeling techniques: ordinary least square (OLS) regression and geographically weighted regression (GWR) estimating growing stock quantities of point sample inside the smallest state owned forest stands (area less than 10 ha). Used material contained forest attributes local estimates from regular inventory distributed in unique management class: beech and fir mixed forest on deep silicate soil, environmental and transformed spectral Landsat 8 data.

Obtained results pointed out statistical significance of normalized standardized spectral radiance of NIR and SWIR Landsat bands in regression models. The GWR estimates achieve up to almost 30% higher variability explanation than OLS models. Also, GWR showed wider range than OLS estimates with smaller prediction errors. Evaluation on sample stand level resulted in reliable estimates of particular species or groups and total mean growing stock for all small stands. Further research about potential of GWR and other geo-statistical techniques for forest attribute estimates on more intensive point sample inside small spatial unit and/or whole spatial unit is recommended.

Key words: *growing stock, geographically weighted regression, forest inventory, environmental data, Landsat 8*

¹ University of Sarajevo, Faculty of Forestry

² University of Sarajevo, Institute of forestry and urban greenery

³ Public enterprise „Šume TK“ d.d. Kladanj

⁴ Private enterprise „Wald-projekt“ d.o.o Bosanska Krupa

INTRODUCTION - Uvod

Recent studies about forest characteristics on large area integrate all available information compiled with multivariate analysis and geographic information system tools.

Lately forest terrain observations and measurements, environmental and remote sensing data are used as for land use classification so for prediction of forest end environmental management related variables (BARHOSA *ET AL.*,2013; GÜNLÜ *ET AL.*,2014; MATTIOLI *ET AL.*,2012; MCROBERTS *ET AL.*,2010; OSMANOVIĆ *ET AL.*,2016; VAN DER LAAN *ET AL.*,2014).

Periodical intensive forest inventory on state owned management unit level deliver plenty of data and information for statistical characterization of forest resources. Knowing that spatial variation of forest characteristics over space could be modeled it is interesting to examine if regression based estimation of the most important forest attributes on small stands outside of forest complex are efficient enough to use such approach for private forest characterization.

Usually private forest properties are distributed on hilly sides around state forests and/or randomly scattered around with small area. Current forest resource characterization on private properties is based on limited measurement and ocular classification and estimation mainly without possibility to determine statistical estimation error. So compilation of terrestrial, environmental and spectral data could be examined in order to estimate forest characteristics on scattered small areas. Such possibility opens alternative solution for current time-consuming and mainly non-reliable forest production estimates as the most important management information of private forest.

In this paper are developed and compared OLS and GWR regression models for the growing stock using forest inventory sample divided on the sub sample covering stands with more than 10 ha size and the sub sample with smaller stands (less than 10 ha) compiled with environmental and Landsat 8 spectral data. Estimates are developed using the first sub sample and evaluated on known ground data on the second sub sample.

MATERIAL AND METHODS OF RESEARCH - Materijal i metode istraživanja

Study area includes part of the state owned forest stands in Management unit Oskova. Study area, also as a part of the Forest Management area "Sprečko" is located in the north east part of Bosnia situated between Longitudes 18° 29' - 18° 37' and Latitudes 44° 23' - 44° 17' (Figure 1).

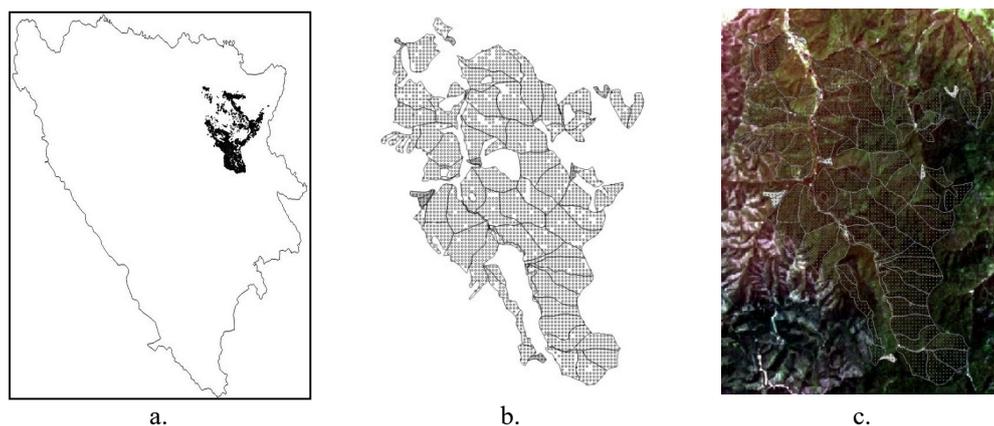


Figure 1. Forest management area (a.) study area with stands and sampling plan (b.) (small stands – grey) and study area Landsat 8 segment (c.)

Slika 1. Šumsko-gospodarsko područje (a.), područje istraživanja sa uređajnom podjelom i planom uzorka (b.) (male sastojine – sivo) i dio Landsat 8 snimka

The terrestrial measurement for the research was conducted in the summer 2012 and was part of regular forest inventory. Terrestrial sample in this study consists of 3034 sample plots distributed on square grid of 200 meter distance covering unique management class (code 1203). Each sample plot was consisted of system of concentric circles with one centre and different range radius. Forests species, diameter at the breast height and height are recorded as geo-position of circle centre and local estimates of forest attributes (growing stock total, per groups and the main species) are produced following standard inventory procedure. According to management classes classification chosen management class is named as beech and fir mixed forest on deep silicate soils.

Ground sample is divided in two sub samples: the first one consisting sample points in stands with more then 10 ha size (n=2993) and the second sub sample with smaller stands (less then 10 ha) (n=41).

Table 1. Growing stock (m³/ha) descriptive statistic of sample in stands larger then 10 ha (n=2993)

Tabela 1. Deskriptivna statistika uzorka drvne zalihe (m³/ha) odjeljenja većih od 10 ha (n=2993)

	Mean	Std. Dev.	Min	Max	CI (95.0%)
Fir	95.33	128.12	0	828	4.62
Beech	237.45	187.27	0	990	6.75
Conifers	98.95	130.11	0	900	4.69
Broadleaves	263.88	186.85	0	1028	6.74
Total	362.81	177.44	2	1051	6.40

Information about forest stands with area less then 10 ha are given in table 2.
Table 2. Information about forest stands less then 10 ha (small stands)

Tabela 2. Informacije o šumskim sastojinama manjim od 10 ha (male sastojine)

Small stand	Compartment	Stand	Area (ha)	Sample size (n)
1	066	03	6.62	6
2	085	01	9.78	9
3	107	01	3.51	3
4	048	02	5.77	5
5	028	03	3.85	2
6	086	01	7.90	6
7	005	05	7.68	5
8	038	03	4.97	4

Table 3. Descriptive statistic of sample growing stock in stands smaller then 10 ha

Tabela 3. Deskriptivna statistika drvne zalihe uzorka u odjeljenjima manjim od 10 ha

Stand	Statistic	Fir	Beech	Conifers	Broadl.	Total
1	Mean	49.8	81.8	126.3	105.7	232
	Std. Dev.	53.6	69.4	76.6	63.3	131
2	Mean	162	233.7	169.7	245.9	415
	Std. Dev.	183	163.3	180.7	153.3	229
3	Mean	0	73.7	0	155.7	156
	Std. Dev.	0	68	0	67.9	67.9
4	Mean	27.8	163	62.8	253.2	316
	Std. Dev.	39	142.8	73.4	113.8	138
5	Mean	175	78.5	174.5	148.5	323
	Std. Dev.	19.1	0.7	19.1	98.3	79.2
6	Mean	118	299.2	117.5	299.2	417
	Std. Dev.	72	160.6	72	160.6	150
7	Mean	84.6	95	84.6	106.6	191
	Std. Dev.	84.1	50.5	84.1	50.6	81.3
8	Mean	25.5	227.3	25.5	241.8	268
	Std. Dev.	43.4	84.4	43.4	102	65.3

As additional information here are used environmental data obtained using digital elevation model: slope, aspect, hill shade and altitude. Hill shade is calculated using information about elevation and azimuth of Landsat 8 satellite image compiled in this study.

Table 4. Descriptive statistic of environmental data sample in stands larger then 10 ha (n=2993)

Tabela 4.. Deskriptivna statistika okolišnih podataka uzorka u odjeljenjima većim od 10 ha (n=2993)

	Mean	Std. Dev.	Min	Max	CI (95.0%)
Slope	19.79	8.11	0	49	0.29
Aspect	203.18	108.69	0	360	3.92
Hill shade	113.95	56.66	0	240	2.04
Altitude	698.63	172.53	350	1143	6.22

A Landsat 8 imagery (Path 188/Row 29) covered the study area and was acquired on 21 July 2015. The pre-processing of the image included merging bands in one image, assigning projection that fits Bosnia (E=3908), changing image resolution to 20 m and extraction the study area from satellite image. Then digital values transformation was completed calculation top of reflection values. Not all bands were included in the research. It was used reflectance of six spectral bands [Blue_{RT}, Red_{RT}, Green_{RT}, Near infrared (NIR_{RT}) and two short wave infrared (SWIR1_{RT} and SWIR2_{RT} bands). The pre-processing is performed using QGIS Open Source.

In this study two statistical approaches were used: parametrical ordinary least-squares regression (OLS) and geo-statistical technique: geographically weighted regression (GWR). For OLS regression is used Statgraphics Plus 5.0 and GWR regression analysis is applied using Windows Application for Geographically Weighted Regression Modeling GWR4 (NAKAYA 2014).

The OLS regression is the most commonly statistical technique used for estimating forest attributes, where the depended variable is estimated by producing unbiased minimum sum of squared residuals depending of the predictors (MONTGOMERY *ET AL.*, 2001). The equation used to perform OLS is given below:

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_1 + \dots + \hat{\beta}_n X_n + \varepsilon_i$$

where \hat{Y}_i is the dependent variable (in this case represents the growing stock estimated), $X_1 \dots X_n$ are the independent or predictors (in this case environmental and spectral data), $\hat{\beta}_0$ is the intercept parameter, $\hat{\beta}_1 \dots \hat{\beta}_n$ are the regression coefficients, and ε_i are the regression residuals. Regression models, based on correlation analysis, are determined using stepwise regression and normalised standardized predictors. The same statistically significant predictors are used in GWR models. Geographically weighted regression considers geographically varying parameters. Conventional (Gaussian) GWR model is described by the equation:

$$\hat{Y}_i = \sum_k \beta_k(u_i, v_i) x_{k,i} + \varepsilon_i$$

where \hat{Y}_i , $x_{k,i}$, and ε_i are, respectively, dependent variable, k th independent variable, and the Gaussian error at location i , (u_i, v_i) is the x, y coordinate of the k th location, and coefficients $\beta_i(u_i, v_i)$ are varying conditions on the location (NAKAYA 2014). To fit a Gaussian GWR model it is necessary to specify several inputs behind dependent variable and predictors: (1) location variables as (x, y) coordinates, (2) character of independent variable (local, global) and (3) the kernel function for geographical weighting to estimate local coefficients, its bandwidth size, and model selection criteria that are necessary for finding the best bandwidth and for comparing it with other modeling results using the same data. Here are used terrain geo-location of sample plots (x, y) , local character independent variables, fixed Gaussian distance, golden section search for optimal bandwidth size and AICc criterion. Detailed method and procedure description are given in NAKAYA (2014) and CHARLTON *ET AL.* (2006).

For OLS and GWR models determinations and correlation coefficients are obtained and compared. Growing stock estimates on known sample-based geo-location in small forest stand (less than 10 ha) are determined as prediction on non-sampled points. Samples based on OLS and GWR estimates are then compared with terrestrial determined samples using t-test for each small stand.

Also, growing stock distribution for broadleaves and conifers are compared in order to analyze differences in ranges of OLS and GWR estimates.

RESULTS - Rezultati istraživanja

In order to perform OLS and GWR regressions modelling, correlation between target variables (growing stock for the main species, groups: conifers and broadleaves and total) and spectral and environmental predictors are calculated (Table 5).

Table5. Correlation matrix between growing stock and predictors (environmental and spectral data)

Tabela 5. Korelaciona matrica drvne zalihe i prediktora (okolišni i spektralni podaci)

	Fir	Beech	Conifers	Broadleaves	Total
Blue _{RT}	-0.20	-0.05	-0.20	0.02	-0.13
Green _{RT}	-0.22	0.02	-0.22	0.08	-0.08
Red _{RT}	-0.19	-0.02	-0.18	0.04	-0.10
NIR _{RT}	-0.33	0.28	-0.34	0.31	0.07
SWIR1 _{RT}	-0.38	0.27	-0.40	0.32	0.04
SWIR2 _{RT}	-0.37	0.23	-0.38	0.27	0.00
Slope	-0.11	0.03	-0.11	0.06	-0.02
Aspect	0.03	0.05	0.03	0.03	0.06
Hill shade	-0.09	-0.08	-0.09	-0.08	-0.15
Altitude	0.04	0.12	0.05	0.08	0.12

The highest correlations are obtained between species and groups of target variables with spectral NIR_{RT}, SWIR1_{RT} and SWIR2_{RT} predictors. It is visible that correlations with environmental data are very low and insignificant mainly. Applying stepwise regression significant predictors are identified and models are determined. Parameter of OLS regression models are given in following equations:

$$\hat{y}_{fir_i}^{OLS} = 306.11 + 0.16NIR_{z_i} - 1.42SWIR1_{z_i} + \varepsilon_i$$

$$\hat{y}_{beech_i}^{OLS} = 78.45 + 0.54NIR_{z_i} + 1.76SWIR1_{z_i} + \varepsilon_i$$

$$\hat{y}_{conifers_i}^{OLS} = 317.12 + 0.27NIR_{z_i} - 1.61SWIR1_{z_i} + \varepsilon_i$$

$$\hat{y}_{broadleaves_i}^{OLS} = 198.12 + 5.53SWIR1_{z_i} - 5.54SWIR2_{z_i} + \varepsilon_i$$

$$\hat{y}_{total_i}^{OLS} = 374.29 + 0.96NIR_{z_i} - 1.31SWIR2_{z_i} + \varepsilon_i$$

It is obtained that significant predictors for regression modeling are combination of NIR_{RT} and SWIR_{RT} bands.

The same predictors are used for GWR modeling and following models are determined:

$$\hat{y}_{fir_i}^{GWR} = 299.19(X_i, Y_i) - 0.05(X_i, Y_i)NIR_{z_i} - 1.14(X_i, Y_i)SWIR1_{z_i} + \varepsilon_i$$

$$\hat{y}_{beech_i}^{GWR} = 122.17(X_i, Y_i) + 0.12(X_i, Y_i)NIR_{z_i} + 0.95(X_i, Y_i)SWIR1_{z_i} + \varepsilon_i$$

$$\hat{y}_{conifers_i}^{GWR} = 306.71(X_i, Y_i) - 0.04(X_i, Y_i)NIR_{z_i} - 1.20(X_i, Y_i)SWIR1_{z_i} + \varepsilon_i$$

$$\hat{y}_{broadleaves_i}^{GWR} = 190.401(X_i, Y_i) + 3.07(X_i, Y_i)SWIR1_{z_i} - 2.67(X_i, Y_i)SWIR2_{z_i} + \varepsilon_i$$

$$\hat{y}_{total_i}^{GWR} = 350.411(X_i, Y_i) + 0.21(X_i, Y_i)NIR_z - 0.147(X_i, Y_i)SWIR2_z + \varepsilon_i$$

Geographically weighted regression considers local character of predictors with estimates of coefficient means in equations above. So, prediction values are connected with varying geo-position of circle centre in relation with predictors.

Following figures present observed versus predicted growing stock quantities of two regression types for broadleaves and conifers that are similar as the main species: beech and fir too.

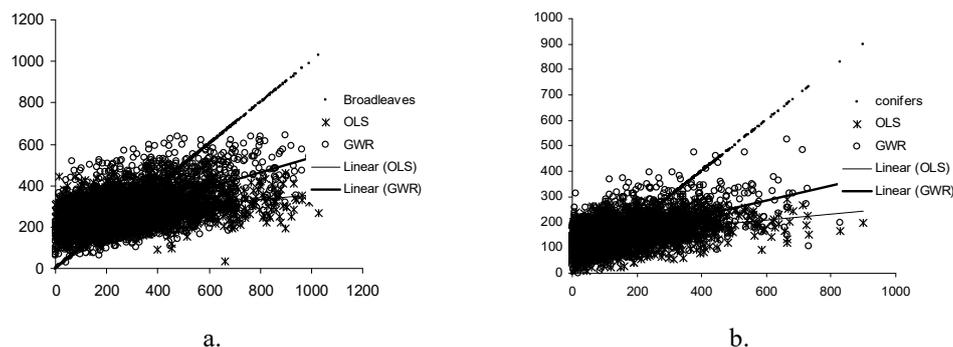


Figure 1. Observed versus OLS and GWR predicted growing stock for broadleaves (a.) and conifers (b.)

Slika 1. Observirane prema OLS i GWR procjenjenim vrijednostima drvene zalihe za lišćare (a.) i četinare (b.)

Both regression methods show in average overestimated quantities less then ground observations and underestimate quantities above ground average. But it is visible that GWR slopes for both broadleaves and conifers are closer to ground observation then OLS slopes.

Determination and correlation of OLS and GWR models are given in table 6. The GWR models deliver higher determinations then OLS models. Determination improvement is achieved for all models and ranges from 18% to 30%.

Table 6. Determination and correlation of OLS and GWR models

Tabela 6. Determinacije i koeficijenti korelacija OLS i GWR modela

	OLS		GWR		ΔR^2
	R^2	R	R^2	R	
Fir	0.11	0.33	0.29	0.54	0.18
Beech	0.07	0.27	0.32	0.57	0.25
Conifers	0.12	0.35	0.32	0.57	0.20
Broadleaves	0.11	0.33	0.40	0.63	0.29
Total	0.02	0.13	0.24	0.49	0.22

Finally, evaluation of OLS and GWR growing stock estimates using corresponding sample on stand level using t-test was performed for stands with less then 10 ha area (Table 7.):

Table 7. Evaluation of OLS and GWR growing stock estimates on stand level using t-test (p-value)

Tabela 7. Evaluacija OLS i GWR procjena drvne zalihe na nivou sastojine pomoću t-testa (p-vrijednost)

Stand	Fir		Beech		Conifers		Broadleaves		Total	
	OLS	GWR	OLS	GWR	OLS	GWR	OLS	GWR	OLS	GWR
1	0.09	0.26	0.10	0.06	0.72	0.82	0.02	0.01	0.19	0.06
2	0.24	0.21	0.36	0.67	0.73	0.20	0.35	0.50	0.81	0.71
3	-	-	0.67	0.40	-	-	0.06	0.08	0.02	0.03
4	0.00	0.73	0.38	0.89	0.06	0.50	0.79	0.43	0.80	0.47
5	0.47	0.66	0.06	0.10	0.49	0.65	0.48	0.73	0.80	0.70
6	0.56	0.75	0.74	0.15	0.58	0.81	0.89	0.16	0.54	0.10
7	0.79	0.40	0.12	0.06	0.76	0.34	0.00	0.05	0.01	0.04
8	0.76	0.47	0.86	0.67	0.75	0.53	0.39	0.64	0.08	0.09

(Statistically significant at $p < 0.05$)

Obtained results related to significance of mean differences between ground and estimated sample values show non-significant differences for species or/and groups/total for both methods mainly.

Then, we found that important information about possible estimates is related to sampling distribution of target variables. So here are graphically presented growing stock distributions for sample and predictions based on OLS and GWR models. Following figures present comparative growing stock distribution of sample and predictions for broadleaves (Figure 2.) and conifers (Figure 3.).

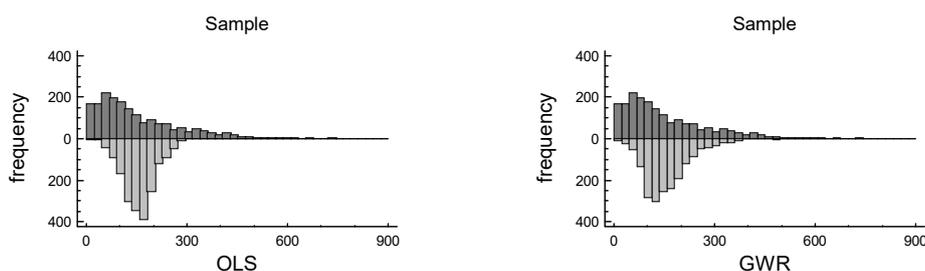


Figure 2. Distribution of OLS and GWR growing stock predictions for conifers

Slika 2. Raspodjela OLS i GWR procjena drvne zalihe četinarara

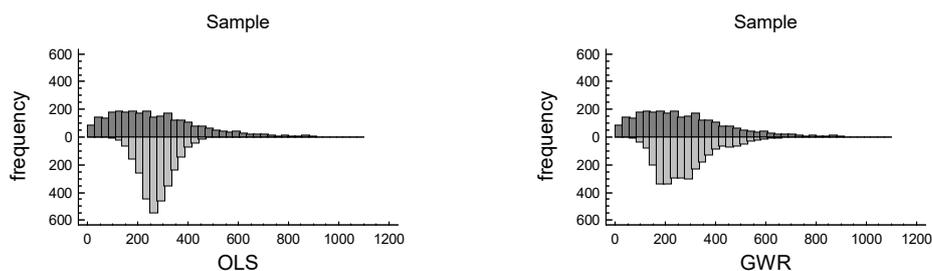


Figure 3. Distribution of OLS and GWR growing stock predictions for broadleaves
Slika 3. Raspodjela OLS i GWR procjena drvne zalihe lišćara

It is visible that GWR growing stock distributions have wider range and closer shape to ground distributions than OLS distributions for both groups (broadleaves, conifers).

DISCUSSION - *Diskusija*

Potentials of compilation of all available terrestrial and remote sensing data about forest resources and recent technological achievements in GIS intensified research about application of geo-statistical techniques which are more advanced than standard regression based estimates of forest attributes (AKHAVAN ET AL., 2015; PROPASTIN 2008; PROPASTIN ET AL., 2012; ZHANG ET AL., 2008). Geo-statistically weighted regression has been recognized and examined in different forest and environmental conditions delivering more reliable estimates than ordinary least-squares regression (BENÍTEZ ET AL., 2016; CHEN ET AL., 2012; SHRIESTA 2006; TIRYANA ET AL., 2010).

Significant correlations between spectral data and forest attributes are found and presented in this paper confirmed their role as in quoted researches where particular spectral bands or their transformations also become significant predictors. Also, GWR estimates deliver higher determinations up to 30% for all forest attributes than OLS estimates in all environmental conditions.

Related to sample means differences the OLS estimates give better results than GWR for some small stands. ZHANG ET AL., (2008) found that OLS estimates are appropriate in homogenous forest stands without spatial autocorrelation (regularly distributed over space). Authors reported that GWR gave more accurate precision in case of clustered or randomly distributed trees over space. These points out the role of spatial patterns of plot (tree) locations. So detailed spatial pattern analysis should contribute to regression method selection too.

Analyzing whole ground sample and its estimates, the GWR preserves variability better what is influential for point based estimations (Figure 3.).

Obtained results show potentials of OLS and GWR to integrate in small stand estimations to calculate not only forest attribute mean estimates then error assessment as on stand so for management class level.

CONCLUSIONS - *Zaključci*

Here are applied OLS and GWR regression estimates of forest attributes on geo-located points distributed on regular sampling scheme in order to connect with current standard inventory methodology.

The results of this study indicate that the geographically weighted regression method was more accurate in representing the variability of growing stock, providing up to 30% higher R^2 than ordinary least square regression. Then comparing observed and estimated values it is visible that, in average, GWR estimates are more close to observed than OLS estimates. Also, GWR growing stock estimates distributions cover larger range of values so it could be expected that this method preserve attributes variability more realistic on dispersed small forest stands with clustered or randomly distributed trees mainly situated on hilly position around state owned forests. In this case only transformed spectral Landsat 8 bands data were found as significant so further research could analyze other transformation as vegetation indexes, Tassel Cap and/or PCA components.

Obtained results indicate possibility to apply GWR on more intensive geo-located points sample inside small stand. Also, GWR has potential to determine estimates and statistics for whole spatial units what could be analyzed in further research as other geo-statistical techniques compiling inventory, environmental and spectral data (MENG 2014).

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SAŽETAK

U okviru regularnih periodičnih inventura državnih šuma prikuplja se veliki broj podataka i informacija koje omogućavaju detaljniji uvid u strukturne i proizvodne karakteristike šuma. Kada su u pitanju privatni šumski posjedi kod kojih dominiraju male površine šume, inventure su manje intenzivne uz veći utrošak vremena prelaza od posjeda do posjeda s obzirom da su šumoposjedi locirani većinom raspršeno na brdskim, padinskim ili u ravničarskim predjelima.

U ovom radu su analizirane dvije regresione tehnike procjene krupne drvene mase po ha sa ciljem da se utvrdi mogu li regresijske procjene zasnovane na uzorku regularne inventure šuma biti dovoljno precizne za procjenu drvene zalihe u sastojinama manjih površina lociranim na rubnim područjima velikih kompleksa državnih šuma. Primjenjene su višestruka linearna regresija po metodu najmanjih kvadarata (OLS) i geografski ponderisana regresija (GWR) koja uvažava lokacijski varijabilitet procjenjivane varijable. Kao prediktori su analizirani okolišni (nadmorska visina, nagib, ekspozicija, pozicijska lokacija) i radiometrijski transformisani spektralni podaci Landsat 8 satelitskog snimka.

Regresionim analizama su određeni OLS i GWR regresioni modeli i ustanovljeno da GWR modeli bolje objašnjavaju varijabilitet krupne drvene mase. Za osam rubnih sastojina površine manje od 10 ha procjenjene su veličine krupne drvene mase i ustanovljeno da nema statistički značajnih razlika između prosječnih veličina određenih terenskim uzorkom za dominirajuće vrste ili grupe (četinari, lišćari, total) stabala. Ustanovljeno je da GWR procjene bolje prate raspodjelu krupne drvene mase iz terenskog uzorka nego OLS procjene. Zapaženo je da u nekim slučajevima OLS procjene daju manje razlike u odnosu na terenske prosjeke odabranih sastojina nego GWR što se može tumačiti odsustvom lokacijskog uticaja (homogene stanišne i sastojinske prilike).

Dobijeni rezultati ukazuju na potencijal regresionih tehnika u procjeni drvene produkcije u malim prostornim jedinicama pri čemu se GWR može označiti kao tehnika sa boljim performansama. Dalje mogućnosti geografski ponderisane regresije, zasnovane na korištenju terenskih, okolišnih i spektralnih podataka, kao i drugih geostatističkih analiza treba provjeriti u našim specifičnim prirodnim i uređajnim okolnostima u narednim istraživanjima.

Corresponding author: Azra Čabaravdić; Faculty of Forestry University of Sarajevo, Zagrebačka 20, 71000 Sarajevo, Bosnia & Herzegovina; e-mail: a.cabaravdic@sfsa.unsa.ba