

QUANTITATIVE MODELING OF THE CARBON STOCK IN THE FOREST ECOSYSTEMS OF BULGARIA

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Keywords: Landsat 8 satellite data; carbon pools; aboveground biomass; GIS; spatial modelling

Abstract: The forest biomass is considered a major component affecting biosphere-atmosphere interactions and global climate change. Conventional ground-based measurements – a labor-intensive process – has proved insufficient to adequately represent the spatial extent of biomass. Therefore, remote sensing techniques are increasingly used for quantifying aboveground biomass and carbon stock. In this study, a model ND56 Landsat 8 OLI (original: ND45 Landsat ETM+) adapted to the Bulgarian natural conditions was tested in an attempt to quantify the spatial variability of forest carbon stock on a national scale. It was found that in the Bulgarian forests the aboveground biomass varies between 11.6 and 605.5 $m^3 ha^{-1}$, and the carbon stock between 2.7 and 201.3 $t C ha^{-1}$. The total amount of carbon is 336.8 million tons for a total of 35,317 km^2 of forest area. Most of the carbon (71.5%) is stored in deciduous forests, while the remaining 16.8% and 11.7% of carbon are stored in mixed and coniferous forests, respectively.

КОЛИЧЕСТВЕНО МОДЕЛИРАНЕ НА ВЪГЛЕРОДНИЯ ЗАПАС В ГОРСКИТЕ ЕКОСИСТЕМИ НА БЪЛГАРИЯ

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Ключови думи: Сателитни данни на Landsat 8; въглеродни басейни; надземна биомаса; ГИС; пространствено моделиране

Резюме: Горската биомаса се счита за основен компонент, влияещ върху взаимодействието биосфера-атмосфера и глобалното изменение на климата. Конвенционалните наземни измервания (трудоемък процес), се доказваха недостатъчни, за да се представи адекватно пространствения обхват на биомасата. Следователно, техниките за дистанционно наблюдение все по-често се използват за количествено определяне на надземната биомаса и запасите от въглерод. В това изследване е тестван модел ND56 Landsat 8 OLI (оригинал: ND45 Landsat ETM+), адаптиран към българските природни условия, в опит да се определи количествено пространствената променливост на горския въглероден запас в национален мащаб. Беше установено, че в българските гори надземната биомаса варира между 11.6 и 605.5 $m^3 ha^{-1}$, а въглеродният запас между 2.7 и 201.3 $t C ha^{-1}$. Общото количество въглерод е 336.8 милиона тона за общо 35 317 km^2 горска площ. По-голямата част от въглерода (71.5%) е акумулирана в широколистни гори, докато останалите 16.8% и 11.7% въглерод се съхраняват съответно в смесени и иглолистни гори.

Introduction

Being “the chief among the greenhouse gases” in the Earth’s atmosphere the carbon dioxide (CO₂) plays an important role in the global climate changes [25]. According to IPPC [20] the concentration of CO₂ in the atmosphere continues to increase every year. Bulgaria ratified the Kyoto Protocol in July 2002, which came into force on February 16, 2005. Since then efforts have been made to minimize the impact on the climate by reducing greenhouse gas emissions, including carbon dioxide. However, Bulgaria continues to be among the countries with the most polluted air in Europe.

According to Eurostat in 2017 the carbon dioxide emissions in the EU increased by 1.8%, compared with the previous year, with Bulgaria among the top 3 pollutants in EU [28]. A major carbon sink among the terrestrial ecosystems, with considerable proportion of aboveground biomass (AGB), are forests. Therefore, they play a crucial role in the global carbon cycle by sequestering a substantial amount of carbon dioxide from the atmosphere [25]. According to [3] forests store approximately 45% of the terrestrial carbon, contribute approximately 50% of the terrestrial net primary production, and take up approximately 33% of the anthropogenic carbon emission. Deforestation is the second largest source of atmospheric greenhouse gases from terrestrial ecosystems, beside fossil fuel combustion, estimated to account for about 20% of the global anthropogenic CO₂ emissions [24]. While average biomass values have been used in most calculations of carbon flux between terrestrial ecosystems and the atmosphere, knowledge of the spatial distribution of the biomass is important for better understanding the carbon cycle. Although direct measurements of biomass on the ground are still the most accurate method for biomass estimation, they are however implemented on very small areas and have limitations, among which expensiveness, labor- and time consumption [10]. For that reason, during the last two decades remote sensing techniques and GIS-based multilayer modelling have become promising resources to advance the accuracy in carbon stock (C-stock) estimates, especially in remote areas with difficult access. Satellite data allows the carbon stock to be simultaneously quantified and mapped on different spatial scales and the changes in carbon pools to be monitored in different time intervals – advantages that the traditional techniques based on the field measurement cannot provide. Given the good correlation between AGB and remotely sensed data, regression analysis is the most commonly used method for developing suitable models for AGB and C-stock estimations. Coarse spatial-resolution data greater than 100 m pixel size, including NOAA's AVHRR and MODIS, have been used for AGB and C-stock mapping at national, continental, and global scales [2,6,7,17]. Fine spatial-resolution data with pixel size less than 10 m, such as IKONOS or QuickBird, are usually used for applications at local scale on very small areas [22]. Whilst, the Landsat time-series are the most frequently used medium spatial-resolution data (from 10 to 100 m pixel size) for many applications at local, regional or national scales, including forest AGB and C-stock [1,5,8,19,23]. Against the backdrop of increasing use of the remote sensing techniques, their application on the territory of Bulgaria for spatially explicit C-stock quantification is still scarce.

This work aims to further explore the potential of remote sensing technologies in the study of global carbon balance, and to encourage their uses in national forest management. To achieve this purpose, ND56 Landsat 8 OLI model – the original ND45 Landsat ETM+ model by Goodenough et al. [9] – was applied to quantify forest carbon stocks nationally. The ND45 model, originally developed for Canadian boreal forest ecosystems, was chosen because of the several advantages it has. Firstly, the similarity in spectral and spatial resolutions that the two sensors have. Secondly, the Forest Reflectance and Transmittance, which incorporates four other predictive models, has been used for verification of the results of the ND45 model instead of ground-based biomass measurements, thus increasing the transferability of the model. And finally, Partial Least Squares (PLS) regression algorithm has been applied to achieve the best approximation of R²=0.92, avoiding the multi-collinearity between spectral bands [9].

Data and methods

Site description

The Republic of Bulgaria is situated on the eastern part of the Balkan Peninsula, covering 23% of the peninsula's territory. The country, with an area of 110,993.6 km², extends between 41°14' and 44°13' in latitude, and between 22°21' and 28°36' in longitude. The altitude varies from 0 to 2925 m. The climate is temperate, with Mediterranean influence in the southern part. The average annual temperature fluctuates between 10 and 14°C and the vegetation period is about 7 months. Average annual precipitation amounts to approximately 650 mm. According to [30], the forests consist of 69.3% deciduous and 28.7% coniferous species.

Data processing

Images from satellites Landsat 8 were used to quantify C-stock in Bulgarian forest ecosystems. Landsat 8 OLI/TIRS C1 Level-1 data were downloaded on 23 and 24 July 2018 from Landsat 8 collection, freely available through [29]. Nine geometrically correct images, covering the whole territory of Bulgaria, were selected, following two main searching criteria: vegetation period from May to October and cloudiness less than 10%. Satellite data with the best meteorological conditions were found for the years 2015, 2016 and 2017. As a first step the Level 1 data, saved as 16-bit integer values (DN), is converted to TOA reflectance following equations (1) and (2) [27].

$$(1) \quad \rho_{\lambda}' = M_{\rho} * Q_{cal} + A_{\rho}$$

where: ρ_{λ}' is TOA Planetary Spectral Reflectance, without correction for solar angle; M_{ρ} is the reflectance multiplicative scaling factor for the band (from the metadata); A_{ρ} is reflectance additive scaling factor for the band (from the metadata) and Q_{cal} is the L1 pixel value in DN. Then the real TOA Reflectance was calculated, applying correction for the solar elevation angle:

$$(2) \quad \rho_{\lambda} = \rho_{\lambda}' / \sin(\theta)$$

where: ρ_{λ} is the true TOA planetary spectral reflectance and θ is the solar elevation angle (from the metadata).

Quantification and mapping of forest AGB and carbon stock

In this study, the original model ND45 (Landsat 7 ETM+), representing a regression model based on the relationships between forest biomass and ND45 (Normalized Difference 45) vegetation index, is transformed to ND56 (Landsat 8 OLI) in order to quantify forest AGB and C-stock on the territory of Bulgaria, following the procedure of [9]. Firstly, the ND56 (Landsat 8 OLI) vegetation index was calculated for the all 9 satellite scenes using equation (3):

$$(3) \quad ND56_{Landsat8} = 128 * [(b5 - b6) / (b5 + b6)] + 128$$

where $b5$ is the NIR TOA spectral reflectance, and $b6$ is the SWIR TOA spectral reflectance.

Landsat 8 OLI Band-5 (0.851–0.879 μm) and Band-6 (1.566–1.651 μm) were used here, instead of original Landsat ETM+ Band-4 (0.772–0.898 μm) and Band-5 (1.547–1.749 μm). A study, investigating the difference between the Landsat 7 ETM+ and Landsat 8 OLI sensors by pair comparative analysis of several vegetation indices [12], demonstrated that the difference is very slight, especially for indices using NIR and SWIR-1 spectral bands, which show mean difference and standard deviation of less than ± 0.05 . Once the index was calculated, an 11x11 average filter was applied for all satellite scenes to mitigate extreme values caused by atmospheric or environmental disturbance, as suggested in the original model. The filter is expected to strengthen the correlation between AGB and ND56 vegetation index. Then a mosaic process was carried out, averaging the values in the overlapping areas.

As a second step, the forest ecosystems were delineated. To avoid image classification procedures, CLC2012 CIS-data set [30] was used for obtaining forest areas and forest types. Forest land covering classes 311, 312 and 313 from level 3 of the CLC2012 was selected for deciduous, coniferous and mixed forest types, respectively.

As a third step, forest aboveground biomass was calculated only over forested areas using the regression model of [9], adapted to ND56 (Landsat 8) vegetation index:

$$(4) \quad AGB = -478.58 + 4.5041 * ND56_{Landsat8}$$

where AGB is aboveground biomass volume (m^3ha^{-1}) and ND56 is the vegetation index. With the function proposed by [9], the forest C-stock (kg C ha^{-1}) was calculated for each forest type as follows:

$$(5) \quad \begin{aligned} Cstock_{311} &= AGB * 665 * 0.5 \\ Cstock_{312} &= AGB * 460 * 0.5 \\ Cstock_{313} &= AGB * 562.5 * 0.5 \end{aligned}$$

The wood density value (665 kg m^{-3}) for deciduous forests was calculated as an average between basic densities of oven dry wood [11] for *Fagus sylvatica L.* and *Quercus L.*, which are dominant tree species for Bulgarian deciduous forests. The wood density value used for coniferous forests (460 kg m^{-3}) was calculated as an average between basic densities of oven dry wood for species *Pinus sylvestris L.*, *Picea abies L.* and *Abies alba Mill.*, dominant for Bulgarian coniferous forests. The value of 562.5 kg m^{-3} used to calculate the carbon stock in mixed forest is an average value. Biomass to carbon conversion factor 0.5 was applied for all forest types.

Results and discussion

The results obtained in this study were compared to biomass measurements and C-stock mapping of other European countries with species diversity and natural conditions close to the Bulgarian ones. For easier comparison, the C-stock values obtained in kilograms per hectare were transformed in most commonly used units: tons (mega grams) of carbon per hectare (e.g. t C ha⁻¹ or Mg C ha⁻¹). Although the modelled AGB volume fluctuates widely (Fig. 1), in most forest ecosystems it varies from 160 to 400 m³ ha⁻¹ (approx. from 100 to 260 t ha⁻¹). These values are similar to the growing stock of the Bulgarian forests, estimated by [7] in the EU-wide map of growing stock, based on remotely sensed data with a coarser spatial resolution.

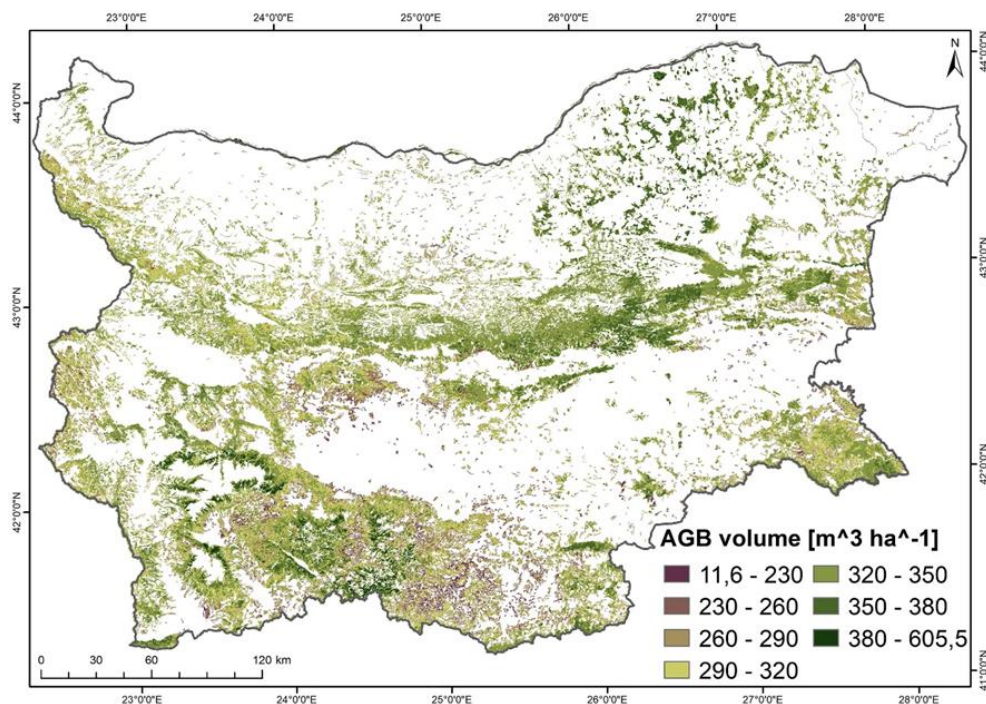


Fig. 1. Aboveground biomass volume of forest ecosystems in Bulgaria (m³ ha⁻¹)

The values of woody biomass derived in this study are also close to the value of 146 t ha⁻¹, for AGB in mixed broad-leaved forests in the Italian Pre-Alps, estimated using low density LiDAR data [16]. Fassnacht et al. [4] estimated a mean of 167 t ha⁻¹ biomass value in Karlsruhe, Germany, using remote sensing (LiDAR) data and ground validating data for 297 inventory plots, obtained by applying species-specific allometric models.

Based on the ND56 model, the total C-stock in Bulgarian forest ecosystems amounts to 336.8 million tons for 35 317 km² forest area (Table 1). Pechanec et al. [18] obtained similar result (206.2 million tons for total area of 24 517 km²) for forest ecosystems of the Czech Republic, using the same method of quantification verified by expert assessment and inventory data. The major part of the total carbon in Bulgarian forest ecosystems is stored in deciduous forests (71.5%). About 16.8% is retained in mixed forests and only 11.7% in coniferous forests.

Table 1. Carbon stock of aboveground biomass in Bulgarian forest ecosystems

Forest type	Forested area [ha]	Total carbon stock [t]	Carbon stock density [t C ha ⁻¹]		
			Minimum	Maximum	Mean
Deciduous forests	2 337 881.5	240 877 800	16.5	201.3	104.9
Coniferous forests	542 771.6	39 146 490	2.7	104.5	72.6
Mixed forests	651 057.9	56 740 950	12.9	127.3	87.5
Forest – total	3 531 711.0	336 765 240	2.7	201.3	96.7

The carbon stored in Bulgarian forests ranges between 2.7 and 201.3 t C ha⁻¹, depending on the forest type (Fig. 2). Comparing the results of Tab.2, it can be seen that [26] obtained similar values of mean carbon density for productive forests in Belgium, based on “biomass expansion factors s.l.” (BEFs s.l.): 85.2 t C ha⁻¹ for forests in Flanders, 105.9 t C ha⁻¹ for forests in Wallonia and 101.0 t C ha⁻¹ on average for all Belgian productive forests. Although the results derived in this work

are comparable to the results of other studies, obtained by different methods, the results' reliability is a complex issue and the accuracy strongly depends on the techniques used. On one hand, the uncertainty of remote sensing measurements is related to the spatial resolution of the data, since a single pixel contains a mixture of information, as well as, to some technical limitations in spectral and radiometric resolutions of the different satellite sensors [14,17,22]. On the other hand, the ground-based measurements, on which the regression models are based, are also prone to errors [5]. Therefore, the accuracy of the estimates may vary significantly, depending on the allometric equation applied, especially in deciduous ecosystems. Seijo et al. [21] reported "a huge variability of results in terms of aboveground carbon storage" of the chestnut forests of Central Spain, applying five different allometric equations: from minimum of 81 to 102 Mg C ha⁻¹ to maximum of 286 to 583 Mg C ha⁻¹. Another aspect that concerns the accuracy of the estimates is transferability of the models between regions. There are factors, such as canopy structure and tree species composition, that can affect AGB estimation results. Many researchers argue that it is difficult to directly transfer a single model to different study areas, but it is generally possible, if the similarity in biophysical parameters and the applicable scale of the original model are taken into account [5,14].

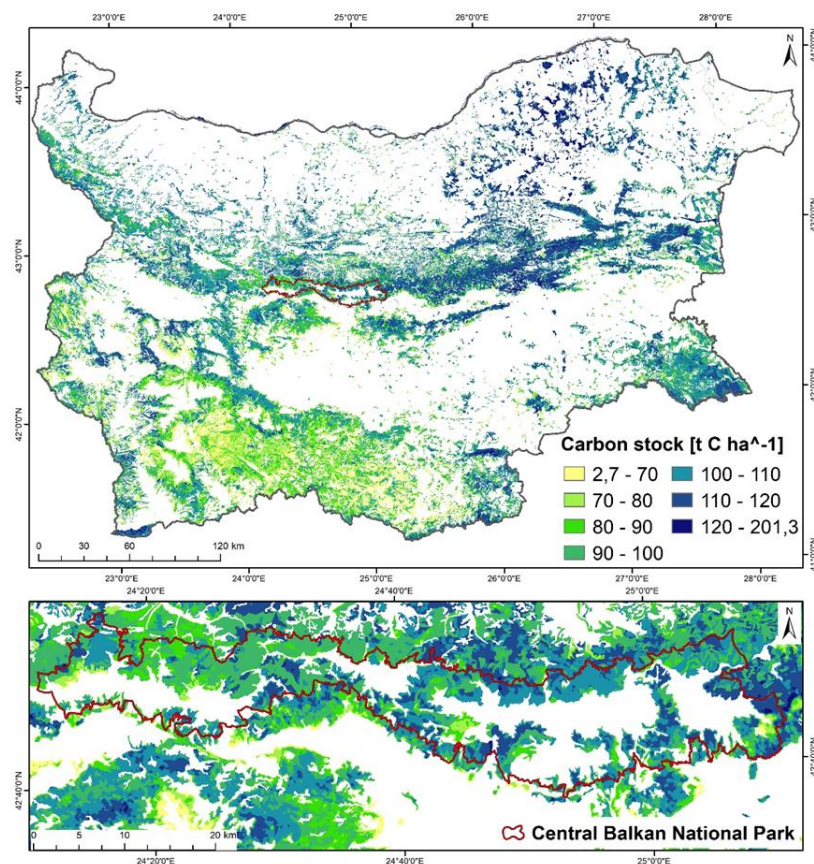


Fig. 3. Carbon content in different forest types:
a) in deciduous forests; b) in coniferous forests; c) in mixed forests

In addition, a small average filter, such as the most often used 3x3 pixels window size [1,6], is not sufficient to establish high correlation between AGB and spectral information, while too large window-size filter can create too much smoothing of the textural variation [13,14]. With this in mind, the results obtained in this study can be used as reference data in future C-stock estimations or model calibrations, as well as in mapping ecosystem services, given that AGB and C-stock are very important indicators for climate regulation ecosystem services, whose role extends beyond the carbon sequestration and also includes "the effect of vegetation on climate via regulation of water vapour and temperature and the provision of shade" [15].

Conclusions

ND56 Landsat 8 OLI model was applied in this study as an adaptation of the original ND45 Landsat ETM+ model in attempt to highlight the potential of remote sensing techniques in forest ecosystem research. As a result, a spatially-explicit quantification of the variability of aboveground

carbon stock and biomass for the entire forested area of Bulgaria was performed at 30x30 meters resolution. The detailed maps show that the AGB volume in the Bulgarian forests ranges from 11.6 to 605.5 m³ ha⁻¹, and the carbon stock from 2.7 to 201.3 t C ha⁻¹, depending on the type and quality of the forests. It was estimated that the total amount of carbon accumulated in the aboveground part of the forests in Bulgaria is 336.8 million tons for a total of 35 317 km² of forest area. These results are comparable to others under similar environmental conditions in Europe. The present study is the first attempt for spatially explicit quantification of carbon stocks in aboveground forest biomass at the national level for the territory of Bulgaria, based on data from remote sensing.

References:

1. Avitabile, V., Baccini A., Friedl M.A., Schmullius C., 2012. Capabilities and limitations of Landsat and land cover data for aboveground woody biomass estimation of Uganda. *Remote Sens. Environ.* 117, 366–380.
2. Baccini, A., Friedl M.A., Woodcock C.E., Warbington R., 2004. Forest biomass estimation over regional scales using multisource data. *Geophys. Res. Lett.* 31, L10501.
3. Bonan, G. B., 2008. Forests and Climate Change: Forcings, Feedbacks, and the Climate Benefits of Forests. *Science* 320 (5882), 1444–1449.
4. Fassnacht, F. E., Hartig F., Latifi H., Berger C., Hernández J., Corvalan P., Koch B., 2014. Importance of sample size, data type and prediction method for remote sensing-based estimations of aboveground forest biomass. *Remote Sens. Environ.* 154, 102–114.
5. Foody, G. M., Boyd D. S., Cutler M. E. J., 2003. Predictive relations of tropical forest biomass from Landsat TM data and their transferability between regions. *Remote Sens. Environ.* 85, 463–474.
6. Fraser, R. H., Li Z., 2002. Estimating fire-related parameters in boreal forest using SPOT VEGETATION. *Remote Sens. Environ.* 82, 95–110.
7. Gallaun, H., Zanchi G., Nabuurs G.J., Hengeveld G., Schardt M., Verkerk P.J., 2010. EU-wide maps of growing stock and above-ground biomass in forests based on remote sensing and field measurements. *For. Ecol. Manage.* 260:3, 252–261.
8. Gizachew, B., Solberg S., Næsset E., Gobakken T., Bollandsas O. M., Breidenbach J., Zahabu E., Mauya E. W., 2016. Mapping and estimating the total living biomass and carbon in low-biomass woodlands using Landsat 8 CDR data. *Carbon Balance Manage.* 11:13.
9. Goodenough, D. G., Chen H., Dyk A., Li J., 2005. Multisensor data fusion for aboveground carbon estimation. *Proc. XXVIIIth General Assembly of the International Union of Radio Science (URSI)*, New Delhi, India, vol. CD 400:1–4.
10. Houghton, R. A., 2005. Aboveground Forest Biomass and the Global Carbon Balance. *Glob. Chang. Biol.* 11, 945–958.
11. Krajnc, N., 2015. *Wood Fuels Handbook*. FAO of the United Nations, Pristina.
12. Li, P., Jiang L., Feng Zh., 2014. Cross-comparison of vegetation indices derived from Landsat-7 Enhanced Thematic Mapper plus (ETM+) and Landsat-8 Operational Land Imager (OLI) sensors. *Remote Sens.* 6:1, 310–329.
13. Lu, D., Batistella M., 2005. Exploring TM image texture and its relationships with biomass estimation in Rondonia, Brazilian Amazon. *Acta Amaz.* 35:2, 249–257.
14. Lu, D., 2006. The potential and challenge of remote sensing-based biomass estimation. *Int. J. Remote Sens.* 27:7, 1297–1328.
15. Maes, J., Paracchini M. L., Zulian G., 2011. *A European Assessment of the Provision of Ecosystem Services: Towards an Atlas of Ecosystem Services*. EUR – Scientific and Technical Research series, EUR 24654 EN – Joint Research Centre – Institute for Environment and Sustainability, Luxembourg.
16. Montagnoli, A., Fusco S., Terzaghi M., Kirschbaum A., Pflugmacher D., Cohen W.B., Scippa G.S., Chiatante D., 2015. Estimating forest aboveground biomass by low density lidar data in mixed broad-leaved forests in the Italian Pre-Alps. *For. Ecosyst.* 2:10.
17. Moreno, A., Neumann M., Hasenauer H., 2016. Optimal resolution for linking remotely sensed and forest inventory data in Europe. *Remote Sens. Environ.* 183, 109–119.
18. Pechanec, V., Strzinek F., Purkyt J., Sterbova L., Cudlin P., 2017. Carbon stock in forest aboveground biomass – comparison based on Landsat data. *Cent. Eur. For. J.* 63, 126–132.
19. Safari, A., Sohrabi H., Powell S., Shataee Sh., 2017. A comparative assessment of multi-temporal Landsat 8 and machine learning algorithms for estimating aboveground carbon stock in coppice oak forests. *Int. J. Remote Sens.* 38:22, 6407–6432.
20. Schimel, D., Grubb M., Joos F., Kaufmann R., Moss R., Ogana W., Richels R., Wigley T., 1997. Stabilization of Atmospheric Greenhouse Gases: Physical, Biological and Socio-economic Implications, in: Houghton J.T., Filho L.G.M., Griggs D.J., Maskell K. (Eds.). *IPCC Technical Paper III*.
21. Seijo, F., Cespedes B., Zavala G., 2018. Traditional fire use impact in the aboveground carbon stock of the chestnut forests of Central Spain and its implications for prescribed burning. *Sci. Total Environ.* 625, 1405–1414.
22. Sousa, A. M. O., Goncalves A. C., Mesquita P., Marques da Silva J.R., 2015. Biomass estimation with high resolution satellite images: A case study of *Quercus rotundifolia*. *ISPRS J. Photogramm. Remote Sens.* 101, 69–79.

23. Suhardiman, A., Tampubolon B.A., Sumaryono M., 2018. Examining spectral properties of Landsat 8 OLI for predicting above-ground carbon of Labanan Forest, Berau. 1st International Conference on Tropical Studies and Its Application (ICTROPS), IOP Conf. Series: Earth and Environmental Science 144, 012064.
24. van der Werf, G. R., Morton D. C., DeFries R. S., Olivier J. G. J., Kasibhatla P. S., Jackson R. B., Collatz G. J., Randerson J. T., 2009. CO₂ emissions from forest loss. *Nat. Geosci.* 2, 737–738.
25. Vashum, K. T., Jayakumar S., 2012. Methods to Estimate Above-Ground Biomass and Carbon Stock in Natural Forests - A Review. *J. Ecosyst. Ecogr.* 2:116.
26. Walle, I. V., Camp N. V., Perrin D., Lemeur R., Verheyen K., Wesemael B.V., Laitat E., 2005. Growing stock-based assessment of the carbon stock in the Belgian forest biomass. *Ann. For. Sci.* 62, 853–864.
27. Zanter, K., 2016. Landsat 8 (L8) Data Users Handbook. USGS, LSDS-1574, Version 2.0.

Websites:

28. Eurostat news release, 4 May 2018. [Online]. Available at: <http://ec.europa.eu/eurostat/web/products-press-releases/-/8-04052018-BP>. (Accessed: 17-Aug-2018)
29. USGS Science for a changing world. Landsat collection 1 Level-1 (Landsat 8 OLI/TIRS C1 Level-1). [Online]. Available at: <https://earthexplorer.usgs.gov/> (Accessed: 23-Jul-2018 and 24-Jul-2018)
30. National Reference Centre, Executive Environmental Agency at the Bulgarian Ministry of Environment and Waters. CLC2012 BG data set. [Online]. Available at: <http://eea.government.bg/bg/projects/korine-14/kzp-danni-clc-data> (Accessed: 04-Dec-2014)