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Original Article

Estimating Stand Top Height Using Freely Distributed ICESat-2 LiDAR Data: A Case Study from Multi-species Forests in Artvin

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ABSTRACT

Forest inventories require up-to-date data on dominant tree height and stand top height from forest sample plots. These data are used to characterize the vertical structure of forests, providing a baseline for volume and yield tables as well as many other biomass studies. Obtaining height information through ground measurement is laborious, costly, and time-consuming. The aim of this study is to estimate stand top heights of the Artvin-Hatila Valley's forests using freely available laser scanning (LiDAR) data from the ICESat-2 satellite for the first time in Turkey. For this purpose, the dominant tree heights, traditionally measured by digital hypsometer in 52 sample plots, were evaluated by stand types and compared with the ICESat-2 canopy data. Then, two data sets were modeled using the Convolutional Neural Network (CNN) and simple regression methods. The model accuracies were evaluated with correlation (Pearson's *R*), coefficient of determination (R^2), and root mean squared error (RMSE) using ground-based data. The results showed that the CNN-based model performed better than the linear regression model in height estimation. Its *R*, R^2, and RMSE values were .82, .68, and 4.2 m, respectively. As for stand types, broadleaves-dominated, mature, and fully covered stands seem more appropriate for top height modeling with spaceborne LiDAR data. Degraded, coniferous, and young stands, as well as non-forest areas, barely allow accurate top height estimations due to their complex canopy surfaces and small openings among trees. Given the promising results, we conclude that satellite-based LiDAR systems provide opportunities to forest professionals as a free auxiliary data source for operational forest management in Turkey.

Keywords: Artvin, canopy height model, forest management and planning, ICESat-2, light detection and ranging, the Hatila Valley National Park, remote sensing

*The preliminary findings from this study were presented at the *"IV. Ulusal Karadeniz Ormancılık Kongresi (KAROK2021)"* and it was published in the abstract book. Nevertheless, further analyses have been employed and the work has been significantly improved in the present manuscript.

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Introduction

Forest ecosystems cover a large number of carbon pools (aboveground, belowground, deadwood, litter, and soil organic carbon) considering the global carbon cycle. Structural parameters of forests play a significant role in determining biomass and carbon storage estimation (Dorado-Roda et al., 2021). Forest canopy and its height, in this sense, have a high relationship with the level of aboveground biomass (AGB) in forest ecosystems (Fayad et al., 2021; Tolunay, 2019).

Forests cover about 31% of the world's terrestrial land. It is one of the indicators for the sustainable development goals (SDG) under *15 – Life on Land* which focuses on the protection and sustainable management of forests biodiversity (FAO and UNEP, 2020). Monitoring of forest dynamics contributes to early recognition problems that forest professionals and decision-makers can solve. Remote sensing (RS) satellites have been widely used for large-scale monitoring of forest fires, delineating burned areas (Polat & Kaya, 2021; Sabuncu & Ozener, 2019), estimating carbon stocks in forest ecosystems (Vatandaslar & Abdikan, 2021), and modeling forest stand height (Ozdemir, 2013). To model the stand height, several RS tools exist including interferometric SAR (InSAR) (Balzter et al., 2007), airborne LiDAR (Gülçin, 2021; Patenaude et al., 2005), and unmanned aerial systems (UAV) (Lisein et al., 2013).

Ice, Cloud, and land Elevation Satellite (ICESat), as the first spaceborne laser altimeter (Geoscience Laser Altimeter System GLAS), provided canopy height data globally. It operated from 2003 to 2009 and was used for canopy height and AGB estimations. Lefsky et al. (2005) studied over coniferous and deciduous forest types of USA and Brazil. They estimated RMSE values between 4.85 and 12.66 m over the USA. The coefficient of determination (R^2) was 73% and RMSE for forest biomass was about 58 Mg/ha between the field-based measurements and ICESat-derived canopy heights. The ICESat-2 that has been launched in 2018 extends the spaceborne LiDAR observations worldwide. ICESat-2 mission produces timely information on various surface types, and among them, land/vegetation elevation (ATL08) is used for characterizing the vertical structure of forests and other landscapes. For example, Dandabathula et al. (2021) estimated building heights from ICESat-2 and calculated accuracy levels ranged from 8 cm to 17 cm. In another study, Yu et al. (2021) estimated the canopy height of mangroves over Australia. They used terrestrial LiDAR data for validation and calculated 2.5 m RMSE with an R^2 value of 66%. In these studies, it is also noticed that weak beams provided less accurate results than strong beams. Both ICESat-1 and ICESat-2 can provide spatiotemporal changes of forest height. Sun et al. (2020), for example, extracted the changes in forest height from 2005 and 2019 over China and determined a significant increase in forest canopy height. Nandy et al. (2021) combined ICESat-2 and Sentinel-1 data to predict deciduous forest canopy in a subtropical region characterized by the humid climate. They applied a random forest approach and predicted canopy height values with an RMSE of 1.15 m and R^2 of 84%. These studies show that spaceborne LiDAR data provide important opportunities to model and monitor forests' biophysical structure which is strongly correlated with many forest-related parameters such as aboveground biomass, stand top height, and growing stock.

The aim of this study is to analyze the performance of the ATL08 product of the ICESat-2 satellite for forest canopy height estimation in a multi-species forest composed of coniferous and deciduous trees in NE, Turkey. This is the first study using satellite-based LiDAR data for forestry purposes in Turkey. Therefore, the outputs of the present study are thought to be useful for national forestry studies including forest inventories, aboveground biomass calculations, as well as forest yield and increment estimations.

Material and Methods

Study Area

The Hatila Valley National Park is a protected area located in Artvin, NE Turkey (Figure 1). The area coverage of the National Park is 17,000 ha, which is about 80% forested. The main tree species in the forest are spruce (*Picea orientalis*), fir (*Abies nordmanniana* ssp. *nordmanniana*), Scots pine (*Pinus sylvestris*), hornbeam (*Carpinus sp.*), European hophornbeam (*Ostrya carpinifolia*), and oak (*Quercus petraea*). Biodiversity is very rich in the study area. The Hatila Valley National Park has a mountainous landscape. The mean terrain slope rate is more than 60%. That is why field surveys are hard to conduct on the ground. In general, the climate is a transition-type between the Black Sea and terrestrial climate characteristics. However, many Mediterranean trees and shrub elements can grow in the area due to favorable microclimate along the bottom of the V-shape valleys. For example, Greek strawberry trees (*Arbutus andrachne*) and Stone pine (*Pinus pinea*) are frequent on lowlands. It makes the Hatila Valley special in terms of biodiversity conservation value. The Hatila Valley's forests have been strictly protected under the National Park statute since 1994.

Data Source

In the present study, we used both strong and weak beams from the ATL08 dataset of ICESat-2. The ICESat-2 satellite was developed by NASA for the purposes of determining and monitoring water survey, ice thickness, vegetation height, and land elevation. It started collecting data on September 15, 2018. Moving 500 km above the ground and in a polar orbit, the ICESat-2 satellite carries the Advanced Topographic Laser Altimeter System (ATLAS) Lidar measuring system (ICEsat-2, 2021). The ICESat-2 uses a micropulse, that is, a multibeam approach. Each beam has strong and weak beam modes. The ATLAS system emits three pairs of beams 3.3 km apart. The distance between the rays in each pair is 90 m (Markus et al., 2017). Each beam has a footprint of 17 m in diameter and the distance between both footprints is 70 cm.

Methodology

The relationship between tree height and ICESat-2 ATL08 data was investigated (Neuenschwander et al., 2020). ICESat-2 canopy data (LiDAR points) dated August 30, 2020, and October 29, 2020, were downloaded via openaltimetry.org (Khalsa et al., 2020; Openaltimetry, 2021). Their coordinate system was converted to UTM with WGS84 datum. Thus, they handled in Geographic Information System environment in accordance with the stand-types map which was in vector data type with polygon feature. Afterward, the polygon layer was intersected

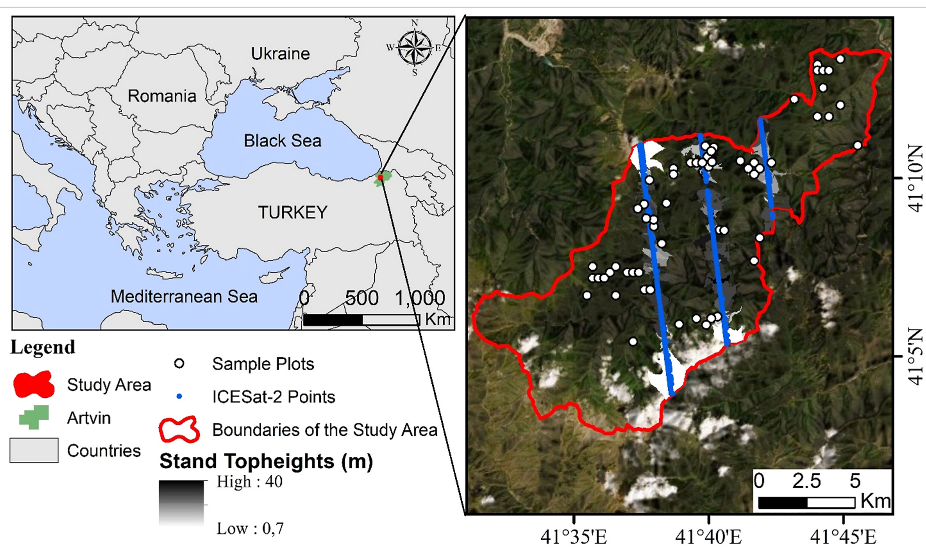

Figure 1.
Location of the Study Area with ICESat-2 Data Points.

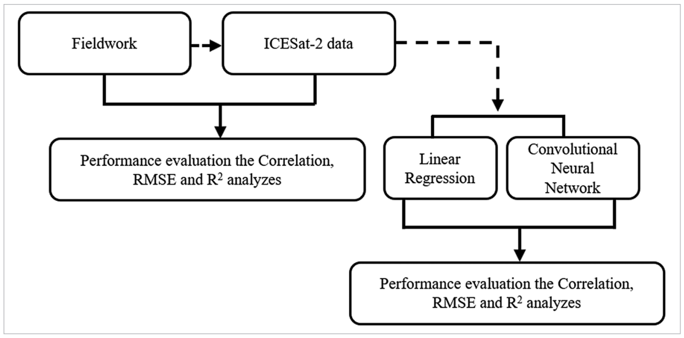

Figure 2.
The Workflow of the Methodology Followed in the Study.

with canopy height (LiDAR) points to eliminate the stands without LiDAR points. In the next step, polygon and point layers were joined to merge their attribute tables in one place. Finally, the stand-types column was summarized based on the LiDAR height values using the average function found in ArcGIS. In this way, each stand's top height was derived based on the ICESat-2 data.

Then, we analyzed the relationship between ICESat-2 data and field-measured stand top heights. Additionally, we tried to make the regression models better by using the Convolutional Neural Network (CNN) method (Figure 2). The cross-validation (four-fold) technique was used for the top height values from 52 forest stands (39 for training and 13 for testing). Lastly, two data sets (i.e., field-based heights VS. LiDAR-based heights) were subjected to correlation analysis. Correlation (Eq. 1), root mean square error (RMSE) (Eq. 2), and R^2 (Eq. 3) were calculated to compare linear regression (section 2.3) and CNN (section 2.4) results:

$$Correlation(P,V) = \frac{\sum(p-\bar{p})(v-\bar{v})}{\sqrt{\sum(p-\bar{p})^2 \sum(v-\bar{v})^2}} \tag{1}$$

p is the ICESat-2 value, v is the top height. $\bar{p}, \bar{v}$ are the average value of 52 data.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i^{act} - y_i^{cal}\right)} \tag{2}$$

where n the number of parcels is, y_i^{act} is the known value, and y_i^{cal} is the value produced by the linear regression and CNN.

$$R^2 = \frac{\sum\left(y_i^{act} - \overline{y_i^{act}}\right)\left(y_i^{cal} - \overline{y_i^{cal}}\right)}{\sqrt{\sum\left(y_i^{act} - \overline{y_i^{act}}\right)^2\left(y_i^{cal} - \overline{y_i^{cal}}\right)^2}} \tag{3}$$

where y_i^{act} is the measured top height and y_i^{cal} is estimated top height, $\overline{y_i^{act}}$ and $\overline{y_i^{cal}}$ the average measured and estimated top height.

Linear Regression

In order to model, firstly, linear regression functions were created between the top heights and ICESat-2 data. Linear regression establishes a linear relationship between two variables. Equation 4 is used to express this relationship:

$$y = a + bx + \varepsilon \tag{4}$$

where y is the dependent and x is the independent variable, a is the slope, b is the intercept, and ε is the error term.

Convolutional Neural Network (CNN)

Convolutional Neural Network is a multi-layer artificial neural network model and is in the category of deep learning. Convolutional Neural Network can process 1D (signal, etc.), 2D (image, etc.), and 3D (video, etc.) data. There are four different layers in the CNN architecture. These are the input layer, convolutions layers, pooling layers, and fully connected layers (Li et al., 2018). R software was used for CNN analysis (CNN, 2021). Convolutional Neural Network was structured as one-dimensional and Keras sequential model was used. Concerning the model variables, the activation function was Relu, the optimization algorithm was Adam, filters and units were 256 and 1024, and the number of the epochs was 50.

Fieldwork

Ground measurements were performed during an official forest inventory survey conducted between June and July 2021. Sample plots were distributed over the entire forested area in a systematic manner with 300 × 300 m intervals. The plots were circular and their sizes ranged from 400 m² to 800 m² according to canopy closure classes. Among many other parameters, the heights of three dominant trees were measured in each plot using a digital hypsometer, i.e. Vertex-IV. Then, they were averaged and recorded as the "top height" of each forest plot. Finally, top height values from 56 forest sample plots were aggregated based on the stand-types map (aka forest cover map) of the study area. For example, if three plots fall into a given stand (aka sub-compartment) and their top heights are 15 m, 20 m, 25 m, then the stand's top height is calculated as 20 m. In this way, all stands' top heights were entered into the attribute table of the map in ArcGIS 10.3.

Results

The field-based measurements of stand top heights ranged from 10 m (stand type: BL) to 40 m (LKncd1). Lower height values below 10 m also existed in non-forest surfaces, such as grassland and bareland. When all data were modeled using linear regression with ICESat-2 data, their correlation coefficient, R^2, and RMSE values were found as 0.78, 0.61, and 8.1 m, respectively. The model results showed that most of the stands'

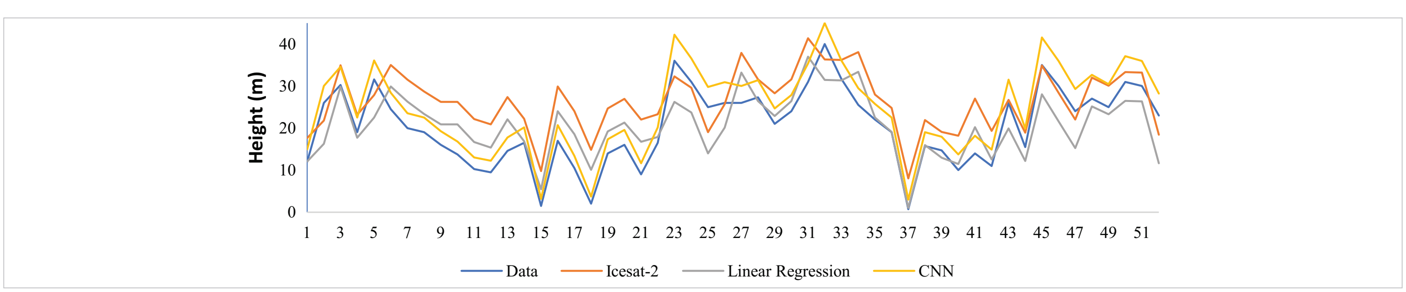

Figure 3.
The Comparison of the ICESat-2, Field-Measured, and Modeled Data.

Table 1.
The Comparison of the Models Based on Three Statistics

	ICESat-2	Linear Regression	CNN
Correlation	.782	.758	.824
R^2	.612	.575	.679
RMSE (m)	8.105	5.853	4.209

Note: RMSE = root mean squared error; CNN = Convolutional Neural Network.

top heights were better estimated by the CNN model (Figure 3). In order to assess the models' accuracies, two evaluation statistics (R^2 and RMSE) were used (Table 1). In the table, high R^2 values show the model better fits reference data measured on the ground. In this case, the CNN model provided the highest R^2 value as 0.68. The linear regression had a lower R^2 value (0.58) compared to the CNN model. The RMSE presents the error rate of the models. The results indicated that the CNN method had smaller estimation errors than the linear regression method. The CNN model estimated it with an RMSE value of 4.2 m, whereas the linear regression model resulted in an RMSE value of 5.9 m.

Disccusion

In a recent study, in Finland, Neuenschwander and Magruder (2019) derived canopy heights with an RMSE of 3.7 m. They used 854 canopy height values from terrestrial LiDAR and ICESat-2 data. In another study from India, Nandy et al. (2021) reported an R^2 value of 0.89 with RMSE of 1.1 m between field measurements and ICESat-2 data. They could predict canopy heights with an R^2 of 0.84 and their RMSE value was only 1.15 m from 130 samples over a deciduous forest in the Himalayan. Yu et al. (2021), on the other hand, reported an R^2 value of 0.66 with 2.5 m RMSE in the mangrove forests of Australia. They used ICESat-2 and terrestrial LiDAR data for modeling and validation, respectively.

In the present study, we modeled stand top heights in a heterogeneous and mixed forest complex. The landscape was very harsh, with a mean slope rate of >60%. In this sense, topographic variations could be one of the reasons for higher RMSE values compared to the studies mentioned above. Another reason could be tree species and species mix in the forest. The Hatila Valley's forests are dominated by spruce, Scots pine, and fir species whose canopy forms are conical. Therefore, thin tree tops may cause higher height differences between the field- and satellite-based top height values.

In a study by Neuenschwander and Magruder (2019), the usage of strong beam is recommended for characterizing vegetation structure but they state that the weak beam also provides useful data. In the present study, ICESat-2 data were collected from weak and strong beams to increase the sample size. However, using only the strong beam data for high forest stands might reduce the RMSE value. Researchers should test different data combinations for distinct forest types to maximize LiDAR satellites' efficiency in the future.

Figure 4 presents the differences between the field-based measurements and the data acquired with ICESat-2 and the estimated height values. The differences range between −13.5 m and 4.2 m and compared to estimated data using the linear regression model, the CNN model performs better. The maximum and minimum differences vary between 12 m and −6.5 m with CNN, whereas it is higher and ranges between 14.5 m and −8 m with the linear regression model. The best estimated stands were KnLcd2 (beech-spruce mixed), GnLbc3 (hornbeam-spruce mixed), KnLcd3 (beech-spruce mixed), LGbc3 (spruce-fir mixed), Kzbc2 (pure alder), LKncd1 (spruce-beech mixed). The estimation errors were less than 10% in these stand types. In contrast, the worst height estimations were in grasslands, small forest openings (OT), barelands, degraded stands (BMz, BLG, BL), and MzGnbc2 (oak-hornbeam mixed). The field-measured heights of those stands were generally less than 10 m but ICESat-2 overestimated them with unacceptable error rates.

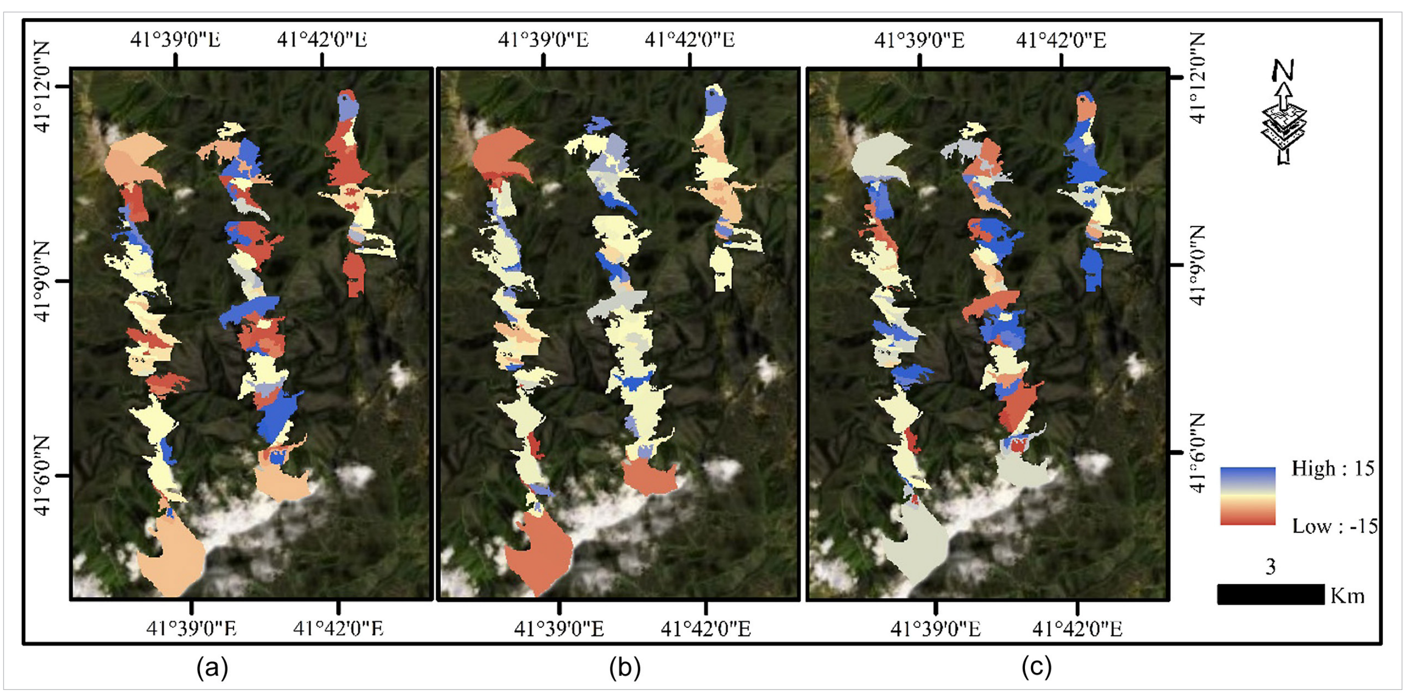

Figure 4.
Height Differences Among Field-Measured Data and (a) Raw ICESat-2 Data, (b) CNN Model, and (c) Linear Regression Model.

The results from this study suggest that spaceborne LiDAR data are useful, particularly in broadleaves-dominated, dense, and mature forests. Since their canopies are smoother and tally, ICESat-2 canopy height values better fit the observed heights on the ground. The coniferous forests, on the other hand, have generally conic or pyramidal canopies resulting in higher error rates in ICESat-2 data. Similarly, sparsely-covered weak forest stands have a lot of openings among tree tops, resulting in the rugged surface over the forest canopy. In these cases, ICESat-2 cannot derive accurate canopy height data. Degraded forest stands, which have a canopy closure of <10%, are another stand type we fail in accurate topheight estimation. Non-forest areas, that is, grassland, pasture, treeless forest soil (OT), rocky areas, and bareland, other land use land cover classes that ICESat-2 does not work. Thus, it can be said that the spaceborne LiDAR data may help modelers to derive height information from fully covered productive forests in an efficient way.

Conclusion and Recommendations

The new spaceborne laser altimetry mission of ICESat-2 provides significant opportunities to forest professionals in modeling the vertical structure of forests. Former studies present the first outlook on canopy height estimation using ICESat-2 in different forest types such as tropical, boreal, and mangroves. In the present study, we derived stand top height information from the same satellite system for the first time in Turkey. The results showed ICESat-2-derived height estimations have acceptable accuracy levels even in mixed temperate forests located on harsh topography. In particular, top heights of the broadleaved, fully covered, and tally forest stands can be better modeled by ICESat-2 data. It is also observed that the model accuracies can be improved by using the CNN regression method. In all forest stands, CNN models performed better than the linear regression model as well as the raw ICESat-2 data. The CNN model increased the Pearson's R, and R^2 values by 6.6% and 10% compared with the linear regression model. It also decreased the RMSE by about 1.6 m in the Hatila Valley National Park. Thus, we conclude that satellite-based free LiDAR data, which has not been widely used in Turkey yet, can be utilized as an auxiliary data source in various forestry applications and the models may be significantly improved using the CNN method. Nevertheless, further analyses are needed for different forest types with higher amount of sample sizes. The weak and strong beams should also be analyzed separately to identify their performances in model accuracies.

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References

- Balzter, H., Rowland, C. S., & Saich, P. (2007). Forest canopy height and carbon estimation at Monks Wood National Nature Reserve, UK, using dual-wavelength SAR interferometry. *Remote Sensing of Environment*, *108*(3), 224–239. [CrossRef]
- CNN. (2021). CNN code R implementation. Retrieved from https://www.datatechnotes.com/2020/01/how-to-fit-regression-data-with-cnn.html
- Dandabathula, G., Sitiraju, S. R., & Jha, C. S. (2021). Retrieval of building heights from ICESat-2 photon data and evaluation with field measurements. *Environmental Research*, *1*(1). [CrossRef]
- Dorado-Roda, I., Pascual, A., Godinho, S., Silva, C. A., Botequim, B., Rodríguez-Gonzálvez, P., González-Ferreiro, E., & Guerra-Hernández, J. (2021). Assessing the accuracy of GEDI data for canopy height and aboveground biomass estimates in Mediterranean forests. *Remote Sensing*, *13*(12), 2279. [CrossRef]
- Fayad, I., Ienco, D., Baghdadi, N., Gaetano, R., Alvares, C. A., Stape, J. L., Ferraço Scolforo, H., & Le Maire, G. (2021). A CNN-based approach for the estimation of canopy heights and wood volume from GEDI waveforms. *Remote Sensing of Environment*, *265*, 1–16. [CrossRef]
- FAO and UNEP. (2020). *The state of the World's Forests 2020. Forests, biodiversity and people*. Rome: FAO and UNEP. [CrossRef]
- Gülçin, D. (2021). Spatial distribution of urban vegetation: A case study of a Canadian University Campus using LiDAR-based metrics. *Forestist*, *71*(3), 196–209. [CrossRef]
- ICESat-2. (2021). *ICESat-2 data information*. Retrieved from https://icesat-2.gsfc.nasa.gov/
- Khalsa,S. J. S., Borsa, A., Nandigam, V., Phan, M., Lin, K., Crosby, C., Fricker, H., Baru, C., & Lopez, L., Baru, C., & Lopez, L. (2020). OpenAltimetry-rapid analysis and visualization of Spaceborne altimeter data. *Earth Science Informatics*, 1–10. [CrossRef]
- Lefsky, M. A., Harding, D. J., Keller, M., Cohen, W. B., Carabajal, C. C., Del Bom Espirito-Santo, F., Hunter, M. O., de Oliveira Jr., R., & de Oliveira, R. (2005). Estimates of forest canopy height and aboveground biomass using ICESat. *Geophysical Research Letters*, *32*(22), n/a–n/a. [CrossRef]
- Li, Y., Zhang, H., Xue, X., Jiang, Y., & Shen, Q. (2018). Deep learning for remote sensing image classification: A survey. *WIREs Data Mining and Knowledge Discovery*, *8*(6), e1264. [CrossRef]
- Lisein, J., Pierrot-Deseilligny, M., Bonnet, S., & Lejeune, P. (2013). A photogrammetric workflow for the creation of a forest canopy height model from small unmanned aerial system imagery. *Forests*, *4*(4), 922–944. [CrossRef]
- Markus, T., Neumann, T., Martino, A., Abdalati, W., Brunt, K., Csatho, B., Farrell, S., Fricker, H., Gardner, A., Harding, D., Jasinski, M., Kwok, R., Magruder, L., Lubin, D., Luthcke, S., Morison, J., Nelson, R., Neuenschwander, A., Palm, S., ... (2017). The Ice, Cloud, and land Elevation Satellite-2 (ICESat-2): Science requirements, concept, and implementation. *Remote Sensing of Environment*, *190*, 260–273. [CrossRef]
- Nandy, S., Srinet, R., & Padalia, H. (2021). Mapping forest height and aboveground biomass by integrating ICESat-2, Sentinel-1 and Sentinel-2 data using Random Forest algorithm in northwest Himalayan foothills of India. *Geophysical Research Letters*, *48*(14), e2021. [CrossRef]
- Neuenschwander, A. L., & Magruder, L. A. (2019). Canopy and terrain height retrievals with ICESat-2: A first look. *Remote Sensing*, *11*(14), 1721. [CrossRef]
- Neuenschwander, A. L., K. L. Pitts, B. P. Jelley, J. Robbins, B. Klotz, S. C. Popescu, R. F. Nelson, D. Harding, D. Pederson, and R. Sheridan. 2020. ATLAS/ICESat-2 L3A Land and Vegetation Height, Version 3. [41°15'N, 41°30'E; 41°N, 41°50'E.]. Boulder, Colorado USA. NASA National Snow and Ice Data Center Distributed Active Archive Center. [CrossRef]
- Openaltimetry. (2021). ICESat-2 data download page. Retrieved from https://openaltimetry.org/about.html
- Ozdemir, I. (2013). Estimation of forest stand parameters using airborne LIDAR data. *SDU Faculty of Forestry Journal*, *14*(1), 31–39
- Patenaude, G., Milne, R., & Dawson, T. P. (2005). Synthesis of remote sensing approaches for forest carbon estimation: Reporting to the Kyoto Protocol. *Environmental Science and Policy*, *8*(2), 161–178. [CrossRef]
- Polat, N., & Kaya, Y. (2019). Damage detection in forest fires with multi-band satellite images. *Journal of Bartin Faculty of Forestry*, *23*(1), 172–181. [CrossRef]
- Sabuncu, A., & Ozener, H. (2019). Detection of burned areas by remote sensing techniques: İzmir Seferihisar Forest fire case study. *Journal of Natural Hazards and Environment*, *5*(2), 317–326. [CrossRef]
- Sun, T., Qi, J., & Huang, H. (2020). Discovering forest height changes based on spaceborne lidar data of ICESat-1 in 2005 and ICESat-2 in 2019: A case study in the Beijing-Tianjin-Hebei region of China. *Forest Ecosystems*, *7*(1), 1–12. [CrossRef]
- Tolunay, D. (2019). Biomass factors used to calculate carbon storage of Turkish forests. *Forestist*, *69*(2), 144–155. [CrossRef]
- Vatandaşlar, C., & Abdikan, S. (2021). Carbon stock estimation by dual-polarized Synthetic Aperture Radar (SAR) and forest inventory data in a Mediterranean forest landscape. *Journal of Forestry Research*. [CrossRef]
- Yu, J., Nie, S., Liu, W., Zhu, X., Lu, D., Wu, W., & Sun, Y. (2021). Accuracy assessment of ICESat-2 ground elevation and canopy height estimates in mangroves. *IEEE Geoscience and Remote Sensing Letters*, *19*, 1–5. [CrossRef]