Article

ReUse: REgressive Unet for carbon Storage and above ground biomass Estimation

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Abstract: United Nations Framework Convention on Climate Change (UNFCCC) has recently established the Reducing Emissions from Deforestation and forest Degradation (REDD+) program that requires countries to report their carbon emissions and sink estimates through national greenhouse gas inventories (NGHGI). Thus, developing automatic systems capable of estimating the carbon absorbed by forests without in-situ observation becomes essential. To support this important need, in this work we introduce ReUse, a simple but effective deep-learning approach to estimate the carbon absorbed by forest areas based on remote sensing. The novelty of the proposed method is in the use of the public above-ground biomass (AGB) data from the European Space Agency's Climate Change Initiative Biomass project as ground truth to estimate the carbon sequestration capacity of any portion of land on Earth using Sentinel-2 images and a pixel-wise Regressive UNet. The approach has been compared to two literature proposals, using a private dataset and human-engineered features. The results show a greater generalization ability of the proposed approach, with a decrease in Mean Absolute Error and Root Mean Squared Error, respectively, of 16.9 and 14.3 in the area of Vietnam and 4.7 and 5.1 in the area of Myanmar over the runner-up. Finally, as a case study, we reported an analysis made for the Astroni area, a nature reserve located near the metropolitan area of Naples in southern Italy, struck by a large fire, producing predictions consistent with values found by experts in the field. These results further support the use of such an approach for the early detection of AGB variations, both in urban and rural areas.

Keywords: U-Net; Carbon Storage; Above-Ground Biomass; Remote Sensing; Deep Learning; CNN; Sentinel-2; ESA CCI Biomass Project.

1. Introduction

Accurate assessment of forest above-ground biomass (AGB), which in this work is defined as the mass expressed as oven-dry weight of the woody parts (stem, bark, branches, and twigs) of all living trees excluding stump and roots, and related carbon stock is essential for the sustainable management of forests. Recently, the United Nations Framework Convention for Climate Change (UNFCCC) established the Reducing Emissions from Deforestation and forest Degradation (REDD+) that requires countries to report their carbon emissions and sink estimates through national greenhouse gas inventories (NGHGI) [1][2]. Furthermore, Sustainable Development Goal 15 aims to "protect, restore and promote the sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, halt and reverse land degradation and halt biodiversity loss"[3]. Subsequently, it is paramount to conduct an explicit investigation into the methods and procedures for quantifying carbon sinks. Generally, the above-ground dry biomass holds about 50% of carbon; as such, a friction factor of 0.5 is commonly used for converting AGB into carbon concentration [4][5].

There are two basic approaches to obtaining biomass estimation: traditional field-based and remote sensing (RS) methods. There is no doubt that traditional methods are more accurate [6], but they are also time-consuming, laborious, challenging to implement in inaccessible areas, and destructive in nature[7]. Sentinel-2 (equipped with a multi-spectral instrument, MSI) sensor, launched on 23 June 2015 by the European Space Agency (ESA), presents a high potential for applications in land management, agricultural industry (food security), forestry (AGB) disaster control, and humanitarian relief operations [8]. Sentinel-2 is a polar-orbiting sensor comprised of two satellites, each carrying an MSI characterized by a 290-km swath width, offering a multi-purpose design of 13 spectral bands traversing from visible and near-infrared (NIR) wavelengths to shortwave infra-red wavelengths at refined (10, 20 m) and coarse (60 m) spatial resolution. Furthermore, the presence of four bands within the red-edge region, centred at 705 (band 5), 740 (band 6), 783 (band 7), and 865 nm (band 8a), gives the sensor the potential for mapping various vegetation characteristics [9].

Typically in the literature, to estimate above-ground biomass (AGB) and the related carbon stock, field surveys are carried out, and a classical machine learning model is trained on sentinel-2, and its extracted features as input and AGB's collected field measurements as output [10] [11] [12] [13] [14]. Instead, continuing without field measurements might be an optimal solution to monitor AGB and carbon storage globally and on time, even downstream of natural disasters such as large fires, which cause deforestation. To the best of our knowledge, this is the first time that a study has been done using both Sentinel-2 images and open data released by the ESA CCI BIOMASS project as ground truth for AGB and not field surveys and using a deep learning approach rather than classical machine learning which requires feature extraction from the images. Concerning the model, a U-Net network [15] was used and trained for pixel-wise regression so that the network itself can extract features related both to the different bands' information content and spatial correlations that then enable AGB prediction. Finally, a case study is reported for the Astroni nature reserve in Southern Italy that shows how the network recognizes the decrease in carbon storage due to deforestation caused by fires and brings the output into the ranges expected for areas where the ground truth is known from the literature.

2. Related Works

Literature on remote sensing for vegetation detection is wide. However, Above Ground Biomass (AGB) detection is a different and more crucial task, especially when needed for detailed estimation of other indicators, such as the carbon sequestration ability of a portion of land. Thus, in this section we focus only on works aimed at estimating above-ground biomass and carbon storage from Sentinel-2.

In [13], the authors attempted to examine the prospects of Sentinel-2 spectral data for quantifying the carbon stock in a reforested urban landscape, using Random Forest and, as predictors, 10 Sentinel bands plus 15 spectral indices that summarise the spectral content without taking into account in any way the spatial correlations typical of an image. Similarly, in [10] the authors applied Sentinel-2 satellite images combined with field-measured biomass using Random Forest (RF) to estimate above-ground biomass (AGB) in Yok Don National Park, Vietnam. A total of 132 spectral and texture variables were extracted from the Sentinel-2 images; the grey level co-occurrence matrix (GLCM) method [16] was used to compute the texture variables.

In [12], Sentinel-2 performance was evaluated for a buffer zone community forest in Parsa National Park, Nepal, using field-based AGB as a dependent variable, as well as spectral band values and spectral-derived vegetation indices as independent variables in the Random Forest (RF) algorithm; in this study, no features were extracted from the spatial dimensions, but indicators were only extracted from the spectral dimension of the input tensor. In [14] spectral bands, vegetation indices (VIs) and texture variables derived from processed S-2 data and topographic parameters were utilized to statistically link with field-based AGB by implementing random forest (RF) and stochastic gradient boosting (SGB) algorithms. The grey level co-occurrence matrix (GLCM) method[16] and wavelet decomposition were applied using the first principal component of the Sentinel-2 multispectral tensor.

These works use machine learning techniques combined with intensive feature extraction that sometimes focuses only on the spectral dimension and sometimes involves both spatial and spectral dimensions. To the best of our knowledge, no deep-learning approach with convolutional networks has been found in the literature to predict AGB and carbon storage that incorporates feature extraction within the network. In addition, the cited works use Sentinel-2 multispectral images as input and AGB field measurements as output. In the following work, on the other hand, ESA public data for AGB are used. The combined use of a Regressive UNet network with public data shows that it can help monitor carbon content in forest areas. It should be noted that there is i-Tree Eco in the literature, which provides an in-depth analysis of forests and individual trees, including carbon storage estimation; however, this model requires input data for which field surveys are necessary [17].

3. Materials and Methods

In this paper, we introduce a Regressive UNet trained on the public above-ground biomass (AGB) data from the European Space Agency's Climate Change Initiative Biomass project as ground truth to estimate the carbon sequestration capacity of any portion of land on Earth using Sentinel-2 images, comparing its performance against two literature proposals [10,14] on their respective study areas. Section 3.1 introduces the proposed approach, describing ideas and motivations. Section 3.2 details the experimental setup as well as the considered competitors. Finally, section 3.3 describes the considered dataset, focusing on data acquisition and pre-processing.

3.1. Regressive UNet

In the following study, we introduce ReUse, a UNet network trained to carry out a pixel-wise regression task to map Sentinel-2 images into AGB rasters. The UNet was developed by [15] for BioMedical Image Segmentation. The architecture contains two paths. The first path is the contraction path (also called the encoder) which is used to capture the context in the image. The encoder is just a traditional stack of convolutional and max pooling layers. The second path is the symmetric expanding path (also called the decoder), which enables precise localization using transposed convolutions. In order to localize, high-resolution features from the contracting path are combined with the upsampled output. A successive convolution layer can then learn to assemble a more precise output based on this information. The main difference to the [15] introduced in this work is that the network was trained not for semantic segmentation but for a pixel-wise regression, omitting the softmax in the last layer. To the best of our knowledge, this is the first time such an approach has been used to estimate AGB. The advantage of this approach over classical approaches, such as [10] and [14], is that the extraction of both spatial and spectral features is incorporated into the same network in an end-to-end paradigm. A patch-wise approach was followed as in [18] so that each Sentinel-2 input and AGB-raster output were divided into many non-overlapping patches of 16*16. Fig. 1 shows the architecture: the input of ReUse is the Sentinel-2 image with dimensions (patch size, patch size, number of bands equal to 10); the output is the AGB image with dimensions (patch size, patch size, 1). The patch size, as specified above, is equal to 16.

3.2. Competitors and Experimental Setup

ReUse was compared with Random Forest [19] by taking the feature extracted as in [10] and in [14] as a reference, in which indicators are extracted not only considering the spectral component but also taking spatial information into account. Note that [14] also uses topographical parameters such as altitude as a variable; however, in this work, only Sentinel-2 data were used as input for the model comparison. Comparisons between ReUse and the [10] and [14] approaches were made on study areas containing those of [10] and [14] in the Yok Don National Park, located in the Central Highlands of Vietnam, and the Yinmar Forest (YM) located in the northern and central-eastern part of Myanmar, respectively. In [10], a total of 132 spectral and texture variables were extracted from the

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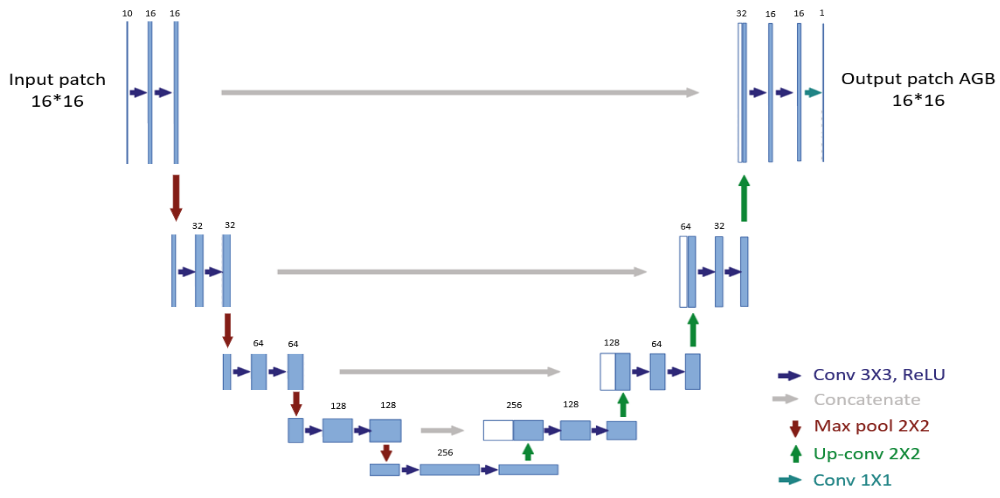

Figure 1. ReUse architecture for pixel-wise regression; the numbers above the layers describe the number of channels. The input is the Sentinel-2 image with dimensions (patch size, patch size, number of bands equal to 10); the output is the AGB image with dimensions (patch size, patch size, 1).

Sentinel-2 images; the grey level co-occurrence matrix (GLCM) method [16] was used to compute mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment and correlation. In [14], principal component analysis (PCA) [20] was used to eliminate correlated information in satellite images and simultaneously reduce their dimensionality. The first principal component (PC1) was used for texture extraction. When extracting textural features, the grey level co-occurrence matrix (GLCM) method [16] was used to compute mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment and correlation, and wavelet decomposition was also applied considering their usefulness for the representation of relevant features [21]. The wavelet analysis produces four essential components: the approximation image, horizontal detail, vertical detail, and diagonal detail images. The latter three are regarded as helpful textural measures. In [14], the Coiflect discrete wavelet function was chosen. Thus, based on the first principal component (PC1), a three-level decomposition strategy was implemented to generate nine detailed images as independent textural variables for AGB modeling. Finally, two types of textures derived from GLCM-based and wavelet analysis were included in the AGB modeling in combination with 11 spectral indices [14]. In this work, a 5*5 kernel was used to construct the GLCM-based features; consider that training was conducted at a spatial resolution of 100 meters because this is the spatial resolution of ESA's AGB data, so a 5*5 kernel involves an area of 500 meters by 500 meters.

The images were all reported at a spatial resolution of 100 meters during training because this is the resolution of the ESA CCI Biomass Project data for AGB. Each study area was reorganized, obtaining the tensors (num. of patches constituting the study area, patch size, patch size, number of bands equal to 10) and (num. of patches constituting the study area, patch size, patch size, 1) for the Sentinel-2 and AGB rasters respectively. As already specified in the previous section, the patch size in this work is equal to 16. For the two machine learning (ML) pipelines, the array sizes were rearranged: (num. of patches constituting the study area, patch size * patch size, number of features extracted) and (num. of patches constituting the study area, patch size* patch size, 1). In this way, it was possible to divide the dataset into eight folds where each fold results in having the dimensions (number of patches constituting the fold, patch size, patch size, number of bands equal to 10) and (number of patches constituting the fold, patch size, patch size, 1) for input and output of ReUse and (number of patches constituting the fold, patch size * patch size, number of extracted features) and (number of patches constituting the fold, patch size * patch size, 1) for input and output of ML. Launching the experiments using an eight-fold cross-validation for the error estimation was now possible. For each iteration, 6 of the eight folds were used for training, 1 for validation, and 1 for testing. For ReUse, the patches were concatenated along the zero axis to create the training, while for machine learning, the size of the training was rearranged: (number of patches making up the training* patch size* patch size, number of features extracted).

The validation set was used to optimize the number of epochs for ReUse with an early stopping procedure [22] and the number of trees for the two Random Forest approaches using two possible values: 250 or 500. In this study, concerning the early stopping procedure, training is stopped when the monitored validation loss has stopped improving after 35 epochs; the maximum number of epochs is set at 500. The optimizer used is Adam [23] with the default parameters. For the learning rate, the [24] was implemented in which if no improvement in validation loss is seen for 25 epochs, the learning rate is reduced by a factor of 0.2. The Mean Absolute Error is used as a loss function for ReUse. The trees in the Random Forest are maximally grown, and the number of variables that each tree can choose at each split is equal to the square root of the number of features as suggested by [25]. The source code is released at https://github.com/priamus-lab/ReUse.

3.3. Image Acquisition and Pre-Processing

AGB file name	Area of interest represented in WKT
N60E00	Polygon ((6.41116296045328227 50.733179027500789, 7.47810311940281469 50.733179027500789, 7.47810311940281469 51.57252282701965385, 6.41116296045328227 51.57252282701965385, 6.41116296045328227 50.733179027500789))
N20E100	Polygon ((107.10766723771612874 12.51511413035953346, 107.83207927588165376 12.51511413035953346, 107.83207927588165376 13.26250192346686596, 107.10766723771612874 13.26250192346686596, 107.10766723771612874 12.51511413035953346))
N30E90	Polygon ((96.00143548690360262 22.97297258442770485, 96.49905818628494103 22.97297258442770485, 96.49905818628494103 23.42872411816529876, 96.00143548690360262 23.42872411816529876, 96.00143548690360262 22.97297258442770485))

Table 1. The file names downloaded from the ESA Biomass Climate Change Initiative of the Global above-ground forest biomass for 2018, v3 in Geotiff format containing AGB rasters are reported. In each GeoTiff file, a study area was cut out and reported in WKT format.

Starting from the Global Dataset of above-ground biomass of the year 2018 version 3 of the ESA CCI BIOMASS Project, three study areas were downloaded, two of which were used separately to compare ReUse with the competitors [10], and [14] on their respective study areas. One was used for the Astroni case study detailed in section 4.1. The file "N20E100" contains the AGB of the study area of [10] in Vietnam, while the file "N30E90" contains the AGB of the study area of Yinmar (YM) forest of [14] in Myanmar. It is again emphasized that [10] and [14] use field AGB data, while in this work, public AGB data provided by ESA are used. The third study area cut from file "N60E00" in central Europe was used for the Astroni use case (section 4.1). Table 1 shows the names of the downloaded AGB files in Geotiff format and the clipped areas of interest in WKT, a text markup language for representing vector geometry objects. From the WKTs, it was possible to download the corresponding Sentinel-2 L2A satellite multispectral images acquired during available cloud-free days. The dates of the downloaded Sentinel-2 images of Vietnam, Myanmar, and Europe are three April, seven March, and twenty-seven July 2018, respectively.

The Sentinel-2 sensor acquires images with 13 spectral channels (e.g., coastal-b1, blue-b2, green-b3, red-b4, red-edge-b5, red-edge-b6, red-edge-b7, near-infrared-b8, red-edge-b8A, water vapor-b9, clouds-b10, short-wave infrared-b11 and short-wave infrared-b12) at variable spatial resolutions of 10, 20 and 60 meters. This sensor covers the red-edge region (i.e., b5, 6, 7, and 8A), strategically positioned in the electromagnetic spectrum with unique band settings critical for vegetation modeling [26]. Bands 1, 9, and 10 were eliminated because they have a coarse spatial resolution; therefore, the work was carried out with 10-band images. The values in the retrieved rasters are digital numbers (DN) that must be transformed into reflectance by dividing them by the quantification value. The quantification value in the Sentinel-2 product metadata is equal to 10000 [27]. The infrastructure provided by the company Latitudo 40 was used to download and prepare the Sentinel-2 data described above.

Concerning the AGB data, the dataset [28] comprises estimates of forest above-ground biomass for 2010 [29], 2017, and 2018. They are derived from a combination of Earth observation data, depending on the year, from the Copernicus Sentinel-1 mission, Envisat's ASAR instrument, and JAXA's Advanced Land Observing Satellite (ALOS-1 and ALOS-2), along with additional information from Earth observation sources. The data has been produced as part of the European Space Agency's (ESA's) Climate Change Initiative (CCI) program by the Biomass CCI team. The mapping is at 100 m grid spacing with a target relative error of less than 20 percent where AGB exceeds 50 Mg/ha.

4. Results

As described in the previous section, the proposed ReUse approach has been compared against two machine learning approaches using Random Forest on the same feature extracted as in [10] and in [14]. The study areas used are the area of Vietnam and the area of Myanmar, containing the areas of the articles mentioned above, respectively, to compare ReUse with competitors in the areas in which these methodologies were originally designed. An eight-fold cross-validation was used to estimate the error of the models. Table 2 presents the experiments for Vietnam and Myanmar. All the experiments conducted show that ReUse performs better than its two competitors in terms of MAE and RMSE, as well as having the advantage of not needing any feature engineering.

area	model	MAE	RMSE
	ReUse	42.0 ±6.6	57.7 ±7.3
Vietnam	Random Forest with feature extraction as [10]	60.1 ±8.3	73.0 ±9.4
	Random Forest with feature extraction as [14]	58.9 ±8.6	72.0 ±9.7
	ReUse	10.8 ±2.0	15.0 ±2.4
Myanmar	Random Forest with feature extraction as [10]	15.7 ±1.9	20.2 ±2.3
	Random Forest with feature extraction as [14]	15.5 ±1.5	20.1 ±1.8

Table 2. The results of the experiments performed on the Vietnam and Myanmar study areas of [10] and [14]. At each iteration of the eight-fold cross-validation, six folds are used for training, one for validation, and one for testing. The averages and standard deviations of the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) metrics are calculated on the test set.

4.1. Case Study: Astroni Nature Reserve

A case study for the Astroni nature reserve in southern Italy was reported to show how ReUse, Sentinel-2, and ESA's AGB public data can help estimate CO2 in forest areas and monitor deforestation downstream of events such as fires. The area of central Europe contained in the file 'N60E00' was chosen to monitor the Astroni reserve to train ReUse because it is certainly an area with characteristics closer to those of southern Italy than the other two datasets containing the areas of Vietnam and Myanmar. In [30], research was conducted within the Astroni Crater World Wildlife Fund (WWF) Reserve in the volcanic area of the Campi Flegrei in the urban area of Naples, Italy. The Reserve (247 hectares) lies within the caldera of an extinct volcano with a maximum altitude of 255 m above sea level and an elliptical shape (2 × 1.6 km). The inner part of the crater has a deep depression containing a lake, where a minimum altitude of 9 m above sea level is reached. In the central part of the crater, near the largest lake, two other small lakes and three hills rise to the bottom at 45, 74, and 82 m above sea level, respectively. Throughout the crater, [30] focused on the area of holm oak forest (127 ha) and the area of mixed forest (104 ha) to define the two main ecosystems and found that the total C stocks of the phytomass of these two ecosystems were 22173 ± 7054 tonnes using sampling from April to October 2016.

In order to make inferences, the Sentinel-2 images downloaded on 31 May 2017 were upscaled to a spatial resolution of 20 meters, assuming that the spatial correlations learned from the network at 100 meters are also reproducible at 20 meters; this improves the resolution of the predictions compared to the resolution of the AGB raster of the ESA CCI Biomass project which is at 100 meters. The predictions of Carbon stocks were made by creating the predicted raster of AGB 5 by five non-overlapping patches, corresponding to one hectare each; then, for each patch, the average AGB value expressed in tonnes per hectare was taken, which, when multiplied by 1 hectare, which is the extent of the patch, yields a value in tonnes; these values were summed over all patches, and the final result multiplied by 0.5 [4][5] to obtain the value of absorbed carbon in tonnes. From this procedure, the estimate of the Carbon stock for Astroni on 31 May 2017 was 18840 tons, in line with the forecast of [30], which is 22173 ± 7054 tons for phytomass in the year 2016, also considering that the latter includes the roots of the plants, which is not included in our estimate, but which can be considered around 30% of above-ground biomass for temperate oak forest [31]; so if you consider 0.3*18840 + 18840 you get 24492 tons which are within the ranges of Astroni's estimate of 22173 ± 7054 tons. In order to confirm the fact that the trained network recognizes a decrease in AGB downstream of a fire, the AGB raster of Astroni on 24 August 2017 downstream of the fire on July 2017 is shown in Fig. 2 compared with the AGB raster of the same area before the fire. The estimated carbon stock on 24 August 2017 for the nature reserve downstream of the fire on July 2017 is 9967 tonnes, confirming the above.

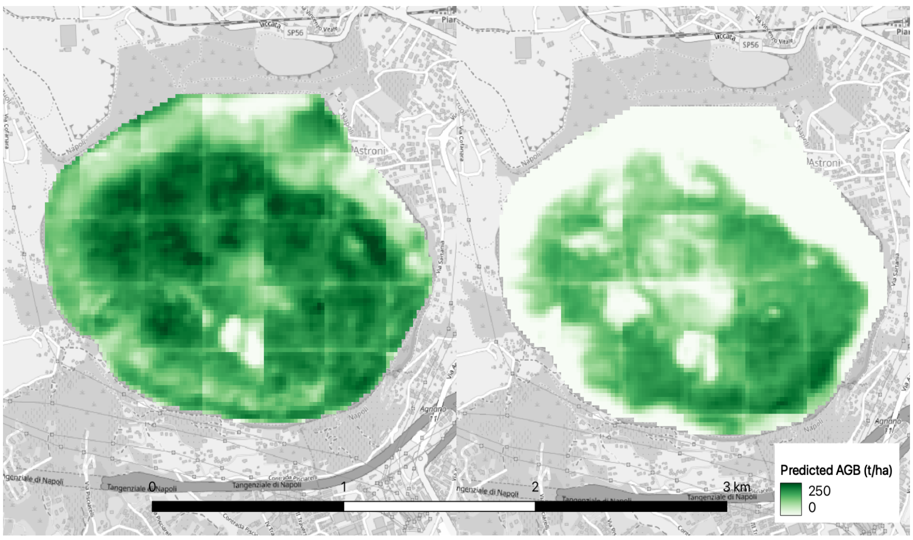

Figure 2. On the left is the predicted above-ground biomass raster of the Astroni nature reserve before the July 2017 fire; on the right is the predicted above-ground biomass raster after the fire for the same area.

It is stressed that the work done is based entirely on open data, and the fact that a prediction based on public data is in agreement with ranges given by a ground truth gives worth to a tool that can be obtained without field measurements and that could be useful for monitoring carbon stocks in forest areas. The prediction after the fire cannot be verified in any way; however, the fact that the prediction before the fire is in line with the ground truth and that the forecast after this event shows a decrease due to the fire is encouraging.

5. Discussion with Conclusions

Sustainable Development Goal 15 aims to 'protect, restore and promote the sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, halt and reverse land degradation and halt biodiversity loss' [3]. Furthermore, REDD+ projects aim to reduce GHG concentrations in the atmosphere and contribute to climate change mitigation through various activities, including carbon stock enhancement [32]. It is essential to develop systems that can estimate the carbon absorbed by forests globally and monitor losses associated with deforestation phenomena such as fires in a timely manner. As explained in chapter 1 of the introduction, systems that rely on field measurements are the most reliable; however, this work aimed to show how it is possible to estimate the carbon absorbed by forests and nature reserves such as Astroni using open AGB data from the ESA CCI Biomass Project in conjunction with Sentinel-2 images. It is the first time that such a study has been done with open data and not with field measurements, to the best of our knowledge. Obtaining carbon storage predictions for the Astroni nature reserve as the literature values is encouraging for monitoring forests and estimating carbon stocks quickly and on a global scale.

The experiments were conducted for the first time on this task to the best of our knowledge using a pixel-wise ReUse, unlike classical machine learning algorithms that require feature extraction work to derive indices that capture both spectral and spatial information content as [10] and [14]; with the UNet this phase is instead incorporated into the network. The ReUse showed better performance in estimated MAE and RMSE using cross-validation than the Random Forest with the same feature extraction of [10] and [14] on study areas corresponding to those of the articles just mentioned. The neural network exhibited a MAE of 42.0 ± 6.6 and RMSE of 57.7 ± 7.3 in the Vietnam area and a MAE of 10.8 ± 2.0 and RMSE of 15.0 ± 2.4 on the Myanmar area. Note that the errors, particularly for the Vietnam area, are higher than for [10] because the data used are public and not field measurements. When trained on the central European zone, the network's predictions were validated on Astroni, a nature reserve located close to the metropolitan area of Naples in southern Italy. The predicted Carbon storage of above-ground biomass of Astroni, prior to the July 2017 fire, is 18840 tonnes in line with the estimates reported in [30]. In addition, an estimate of carbon storage of above-ground biomass of Astroni was also made on 24 August 2017 after the fire, resulting in 9967 tonnes. This last forecast cannot be verified in any way; however, the fact that the first prediction is in line with the ground truth and the second forecast shows a decrease due to the fire is encouraging.

In conclusion, the combined use of Sentinel-2 data and ESA's AGB data with a deep learning approach could be suitable for estimating the carbon absorbed both in urban and rural areas and could help monitor deforestation events without field measurements. To this end, we have released the code available as a monitoring tool for deforestation. Future research directions could concern the use of multi-temporal Sentinel-2 data in which the spectral image of several dates are examined, the joint use of Sentinel-2 raw and feature engineering as input for ReUse, and the search for other case studies to further verify how well the AGB data of ESA's Climate Change Initiative Biomass project is suitable for forest monitoring.

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A.E.P., G.G., S.M. and C.S.; visualization, A.E.P., G.G. and S.M.; supervision, S.M. and C.S.; project administration, S.M. and C.S. . All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: Sentinel-2 L2A data are available at https://scihub.copernicus.eu/ and ESA's AGB data are available at https://climate.esa.int/en/projects/biomass/.

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