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Economic valuation of carbon sequestration in Quito's Metropolitan Park using Sentinel-2 and neural networks

Avaliação econômica do sequestro de carbono no Parque Metropolitano de Quito usando o Sentinel-2 e redes neurais

Valoración económica del carbono capturado en el Parque Metropolitano de Quito mediante Sentinel-2 y redes neuronales

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This study highlights the potential for urban forests to significantly contribute to climate change mitigation. Integrating remote sensing in economic valuation offers a robust approach for informed environmental policy-making.
Originality/value:
The study combines Sentinel-2 data and neural networks for urban forest carbon valuation, providing a novel approach to quantify and monetize carbon sequestration in metropolitan areas. In addition to being an innovative approach, it represents relevance for future studies in emerging economies.

ABSTRACT

This study introduces an innovative method for assessing the economic value of carbon stored by the urban park forest in Quito, Ecuador. The method uses Sentinel-2 remote sensing data and advanced deep learning techniques. A large forest study area was chosen, and detailed field measurements were taken to gather biomass and carbon data. Sentinel-2 satellite images were processed to correct for radiation and atmospheric conditions, and vegetation indices such as NDVI and EVI were calculated. To model forest biomass, a convolutional neural network (CNN) was created and trained using Sentinel-2 spectral bands and vegetation indices. The model was validated with independent field data and demonstrated high accuracy in estimating biomass and carbon, as indicated by evaluation metrics like RMSE and R^2. The findings include detailed maps showing the spatial distribution of biomass and carbon in the study area, which can be a valuable tool for forest management and the implementation of policies for valuing stored carbon. This approach combines the high resolution of Sentinel-2 data with the predictive power of neural networks, providing a robust and scalable method for estimating carbon across large forest areas. The study's conclusions emphasize the feasibility and accuracy of this approach and its potential for application in various forestry and geographical contexts.

Keywords: Carbon credits, remote sensing, Sentinel-2, neural networks, forest biomass, carbon estimation.

RESUMO

Este estudo apresenta uma abordagem inovadora para estimar o valor econômico do carbono sequestrado pela floresta do parque metropolitano, utilizando dados de sensoriamento remoto do Sentinel-2 e técnicas avançadas de aprendizagem profunda. Foi selecionada uma área significativa de estudo florestal, onde foram realizadas medições detalhadas de campo para coletar dados de biomassa e carbono. As imagens do satélite Sentinel-2 foram pré-processadas utilizando correções radiométricas e atmosféricas, e foram gerados índices de vegetação como NDVI e EVI. Para modelar a biomassa florestal, uma rede neural convolucional (CNN) foi desenvolvida e treinada usando bandas espectrais Sentinel-2 e índices de vegetação calculados. O modelo foi validado com um conjunto independente de dados de campo, apresentando alta precisão na estimativa de biomassa e carbono, com métricas de avaliação como RMSE e R^2 destacando sua eficácia. Os resultados incluem mapas detalhados da distribuição espacial de biomassa e carbono na área de estudo, fornecendo uma ferramenta valiosa para o manejo florestal e a implementação de políticas de valorização econômica do carbono capturado. Esta abordagem combina a alta resolução dos dados do Sentinel-2 com o poder preditivo das redes neurais, oferecendo uma metodologia robusta e escalável para estimativa de carbono em grandes áreas florestais. As conclusões do estudo sublinham a viabilidade e precisão deste método, bem como o seu potencial para ser aplicado em diferentes contextos florestais e geográficos.

Palavras-chave: Bonos de carbono, teledetección, Sentinel-2, redes neuronales, biomasa forestal, estimación de carbono.

RESUMEN

Este estudio presenta un enfoque innovador para la estimación del valor económico del carbono secuestrado por el bosque del parque metropolitano, utilizando datos de teledetección de Sentinel-2 y técnicas avanzadas de aprendizaje profundo. Se seleccionó un área de estudio forestal significativa, donde se llevaron a cabo mediciones detalladas de campo para recolectar datos de biomasa y carbono. Las imágenes satelitales de Sentinel-2 fueron pre procesadas mediante correcciones radiométricas y atmosféricas, y se generaron índices de vegetación como el NDVI y el EVI. Para modelar la biomasa forestal, se desarrolló y entrenó una red neuronal convolucional (CNN) utilizando las bandas espectrales de Sentinel-2 y los índices de vegetación calculados. El modelo fue validado con un conjunto independiente de datos de campo, mostrando una alta precisión en la estimación de biomasa y carbono, con métricas de evaluación como RMSE y R^2 destacando su eficacia. Los resultados incluyen mapas detallados de la distribución espacial de la biomasa y el carbono en el área de estudio, proporcionando una herramienta valiosa para la gestión forestal y la implementación de políticas de valoración económica del carbono capturado. Este enfoque combina la alta resolución de los datos de Sentinel-2 con el poder predictivo de las redes neuronales, ofreciendo una metodología robusta y escalable para la estimación de carbono en grandes áreas forestales. Las conclusiones del estudio subrayan la viabilidad y precisión de este método, así como su potencial para ser aplicado en diferentes contextos forestales y geográficos.

Palabras clave: Bonos de carbono, teledetección, Sentinel-2, redes neuronales, biomasa forestal, estimación de carbono.

INTRODUCTION

Accurate estimation of carbon credits is critical for several reasons covering environmental, economic and social aspects. Among which we have:

Climate Change Mitigation

Carbon credits are a key tool in the fight against climate change. By accurately quantifying the amount of carbon that can be captured or avoided, more effective policies can be designed and implemented to reduce greenhouse gas concentrations in the atmosphere (Van der Gaast et al., 2018)

Carbon Markets

In carbon markets, entities can buy and sell carbon credits. Accurate estimation ensures the integrity of these markets, as each bond must represent an accurate amount of carbon captured or avoided. This prevents fraud and ensures that transactions actually contribute to emissions reductions (Stephan & Paterson, 2012).

Financing of Conservation Projects

Conservation and reforestation projects can be financed through the sale of carbon credits. Accurate estimation of carbon sequestration ensures that these projects receive adequate funding, which promotes the conservation of forests and other vital ecosystems (Van der Gaast et al., 2018; Von Avenarius et al., 2018).

Data Driven Decision Making

Policy makers and project managers need accurate data to make informed decisions (Liu, et al., 2020). This includes planning forest management activities, implementing sustainable agricultural practices and investing in carbon sequestration technologies.

Economic and Social Benefits

Local communities can benefit economically from projects financed by carbon credits (Beck et al., 2016). In addition, these projects can provide co-benefits such as biodiversity conservation, soil protection and improved water quality, improving people's quality of life.

Adaptation to Climate Change

In addition to mitigating climate change, carbon sequestration helps ecosystems adapt. For example, forests that act as carbon sinks can also be more resilient to climate shocks**.** This paper investigates how knowledge, as a vital intangible resource, fosters value creation and sustains competitive advantage in organizations. It is divided into three sections: the first explores different business theories that highlight knowledge management and organizational learning; the second analyzes the role of learning and information sharing in management practices; and the third offers final reflections on these issues (Lechuga García, L., & Godínez Enciso, J. A. 2008).

The following study analyzed the evolution of soil organic carbon (COS) in different agricultural uses in Pergamino and evaluated the environmental costs of its loss. Soil productivity costs and CO2 emissions were considered, using survey data and simulation models. Productivity costs ranged from $12 to $16 per hectare, and CO2 emissions ranged from $67 to $331 per ton. The results indicate a trend of decreasing COS, although certain methods could maintain or increase their levels.(Lopez, D. 2015).

This text analyzes carbon credits, according to the United Nations Framework Convention on Climate Change and the Kyoto Protocol, which establish commitments to reduce greenhouse gas emissions. Official documents and critical studies show that the carbon market is growing and mobilizes large resources, although its effectiveness in actually decreasing the factors that cause climate change is questioned (Cruz, M. 2016). The increase in Greenhouse Gas (GHG) emissions has generated significant climate changes, receiving international attention. To reduce these emissions, Clean Development Mechanisms (CDM) are used, allowing industrialized countries to obtain carbon credits in developing nations without emission reduction commitments, such as Chile. This study reviews the carbon credit market, analyzes the profitability of carbon sequestration, examines climate change in a global context and offers conclusions relevant to Chile as an emerging business opportunity (Lobos, G., Vallejos, O., Caroca, C., & Marchant, C. 2005).

The dry forests of Loja province, despite their biodiversity, face threats such as selective logging, agricultural conversion and overgrazing, with little local recognition. Although the plants in these forests have been studied, their economic potential has been ignored. For a business plan, economic valuation data of the environmental service of carbon sequestration was used, showing a potential of 118.44 mt CO2 /ha on 50 000 ha, with a 40% uncertainty margin. This represents 3,553,200 certificates at USD 5 each, valuing the service at USD 17,766,000. These certificates, destined for voluntary markets, will finance projects to benefit local communities and conserve the dry forest, improving their socioeconomic situation (Aguirre, N., Erazo, A., & Granda, J. 2017).

Assessing the financial relevance of selling carbon credits involves understanding the amount of carbon sequestered and establishing a unit price. The cost of sequestered carbon decreases with the age of the plantation, being higher at the beginning due to the initial investment. In high productivity eucalyptus reforestation projects, the operating cost of carbon sequestration is US$16/ton, with a total cost of US$26/ton. If the expected carbon price on the international market reaches US$5/ton and the assumptions of the analysis are met, the value of carbon credits represents 31% of the operating costs and 20% of the total project costs (Seppänen, P. 2003). (Seppänen, P. 2003).

In response to climate change, actions such as "carbon credits" have been initiated in developed countries, aimed at incentivizing the adoption of cleaner technologies and the reduction of greenhouse gas emissions. This analysis explores whether these bonds are effective in reducing emissions or whether they simply serve as a financial mechanism to drive the market. (Maldonado, O 2016)

The DULCINEA project investigates how climate change affects vegetation in the Iberian Peninsula. The predictive capacity of variables that relate vegetation to precipitation is evaluated, using linear and non-linear temporal models. Previous temperature and precipitation data are also considered, together with the NDVI of 22 years. Artificial neural networks are employed to forecast precipitation dynamics with an average accuracy of 44 mm. It is found that vegetation observations in previous months are more predictive than temperature and precipitation (Moreno, A., Soria, E., García, J., Martín Guerrero, J. D., & Belda Esplugues, F. 2009).

Forests play a critical role in mitigating climate change by sequestering carbon from the atmosphere and providing essential ecosystem services (Pache et al., 2020; Naime et al., 2020). These ecosystem services, particularly carbon sequestration, are increasingly being recognized for their economic and environmental value (Canu et al., 2015; Gallant et al., 2020). Several studies have used various methodologies to assess the economic valuation of carbon sequestration, including contingent valuation, social cost of carbon models, and carbon market prices (Mirici & Berberoglu, 2024; Medina et al., 2020). Despite the vast array of methods, consensus remains that forest ecosystems, wetlands, and even secondary forests contribute significantly to carbon capture, which in turn can influence policy-making and conservation strategies (Guitart & Rodriguez, 2010; Bösch et al., 2017).

Emerging technologies, such as remote sensing and LiDAR, have also enhanced the accuracy of these estimates by providing more reliable spatial data on forest biomass and carbon storage (Pache et al., 2020). However, the valuation of carbon sequestration must account for regional differences, as illustrated by studies across diverse ecosystems from Nova Scotia wetlands (Gallant et al., 2020) to Mediterranean landscapes (Mirici & Berberoglu, 2024). Understanding these geographical and ecological variations in carbon sequestration potential is essential for implementing effective forest management and policy interventions globally, including in urban environments like the Metropolitan Park of Quito, where carbon capture by forests offers both economic and ecological benefits.

The integration of remote sensing data in forest inventories, presenting basic concepts and key aspects. An overview of remote sensing systems and data is provided, including their advantages and limitations. Over time, forest management experts have embraced remotely sensed data with enthusiasm. Remote sensing systems and sensors encompass a wide range of airborne and satellite instruments, from analog photography to digital satellite devices, excluding ground-based navigation and remote sensing systems. Koch, B. (2013).

The study evaluates the ecosystem services of urban green areas, such as carbon sequestration. CO_2 storage in the protected municipal forest of Quito is investigated through analysis of satellite images and field measurements. Vegetation indices and mathematical models are used to estimate the amount of CO_2 per pixel. Measurements of diameter and height of trees in 15 quadrants of 100 m^2 are made to calculate CO_2 fixation. The information obtained is compared with previous studies to determine the contribution of the forest in offsetting urban emissions (Nuñez, Amores, & Zurita, 2023).

This article investigates the amount of CO_2 stored in the eucalyptus trees of the Guangüiltagua Metropolitan Park (PMG), as a contribution to inventories to mitigate the carbon footprint of Quito, Ecuador. In the first phase, the Normalized Difference Vegetation Index was calculated from 1982 to 2030 using a Lansat 8 satellite image and QGIS. The second phase used a SENTINELA-2 satellite image and SNAP to calculate the NDVI, establishing how much CO_2 each pixel represents visually using a mathematical model. The third phase collected in situ data in 50 quadrats of 100 m^2, measuring DBH and total tree height. From this, the amount of CO_2 fixed per quadrat was estimated, resulting in an average of 1.5 tons, projecting to 42,150 tons for the entire park through linear regressions (Nuñez, Amores, Zurita, & Hernandez, 2024).

A detailed comparative analysis of NDVI, SAVI and NDWI spectral indices, obtained from satellite images of the Guangüiltagua Metropolitan Park in Quito. The importance of remote sensing, especially using satellites such as Sentinel-2, to monitor biodiversity and environmental conditions is highlighted. The usefulness of NDVI for assessing vegetation health and detecting changes in vegetation cover is highlighted. In addition, aspects such as vegetation sensitivity, water identification and response to water stress are discussed, along with specific applications of the mentioned indices. The results obtained reveal valuable information on the health of the ecosystem and the presence of water in the park, highlighting the relationship between vegetation and water through a comparative analysis of the indices (Zurita, Garrido, Solano, & Nuñez, 2024).

A deep learning convolutional neural network model was evaluated to classify 22 land use and vegetation categories in the Atoyac-Salado river basin. Using Sentinel-2 satellite data from 2021, we experimented with different hyperparameters, such as optimizer, activation function and filter size, achieving an accuracy of 84.57%. Dropout regularization method was implemented to mitigate over-fitting, showing significant effectiveness. This approach demonstrated the capability of deep learning to identify patterns in satellite reflectance data and classify land use and vegetation in challenging areas such as the Atoyac-Salado river basin (González et al., 2022).

Remote sensing is essential for monitoring natural forests. In this study in the Santuario de Fauna y Flora Iguaque (SFFI) in Boyacá, Colombia, aboveground biomass (AGB) and carbon (C) are estimated by remote sensing. Using vegetation indices and models, AGB and C stored in the forests are calculated. The importance of this study is highlighted as a reference for future research in satellite monitoring of natural forests in the region (Perea et al, 2021).

The main objective is to assess the initial state of vegetation in a forest area of the Pre-Pyrenees and to provide data to estimate the amount of biomass and carbon at the beginning of the EU LIFE+ Operation CO2 project. Various remote sensing technologies, such as LiDAR and drone photogrammetry, together with field work and mathematical growth models, are used to collect accurate information. The results confirm the effectiveness of these techniques for monitoring and evaluation of agroforestry activities, especially in large and mountainous areas (Sastre et al. 2016).

The use of microsensors on unmanned aerial vehicles provides a more accurate option for measuring biomass in grasslands, overcoming resolution limitations of satellite images. Field data were combined with images processed by Pix 4D and ArcGIS, and statistical models were used to estimate biomass. The Random Forest model showed high accuracy with minimal differences between field estimates and model predictions. Biomass estimates for different plant components were consistent with field measurements, confirming the validity of this approach for accurate vegetation assessment in different seasons of the year (Estrada et al., J. 2022).

Industrial development dependent on fossil fuels has led to significant environmental degradation. Through the Kyoto Protocol, the carbon market was introduced as a mechanism of the green economy. These instruments initially helped developed countries meet their emission reduction targets and finance sustainable projects in developing countries. However, their demand decreased in 2013 due to criticisms about their real impact on the environment, and they were replaced by green bonds (Calle et al., 2024).

The objective of this research is to estimate the biomass and carbon stored in a forest using Sentinel-2 data and neural networks. The specific objective is to validate the accuracy of the models developed with field data.

METHODS

Study Area

The Guangüiltagua Metropolitan Park, known as the Parque Metropolitano de Quito, is one of the largest and most significant urban green areas in Quito, Ecuador. With an area of approximately 557 hectares, this park is an important green lung for the city and provides a diverse habitat for a variety of species.

Located on the eastern slope of Quito, the park is bounded on the north by Avenida Simón Bolívar, on the east by the Monteserrín neighborhood, on the south by Avenida Granados and on the west by Avenida Eloy Alfaro. Its strategic position within the city facilitates access to visitors from different parts of the city, contributing to its popularity as a recreational and tourist destination. The study and accurate estimation of carbon credits in urban forests, such as the Quito Metropolitan Park, are essential to address several current environmental, economic and social challenges.

Climate change is one of the most critical problems facing humanity. Forests absorb carbon dioxide (CO_2) from the atmosphere and help reduce the concentration of greenhouse gases. By accurately estimating carbon credits, we can quantify the capacity of a forest area to contribute to climate change mitigation.

Data and Materials

The study used images from the Sentinel-2 satellite, a satellite of ESA's Copernicus program, which orbits the Earth at an altitude of 832 km and captures high-resolution images of the Earth's surface with its Multi-Spectral Instrument (MSI). This instrument has 13 spectral bands, offering a spatial resolution of up to 10 meters in the visible bands. Sentinel-2 imagery, available free of charge, is useful for a variety of applications, including agricultural monitoring, water resource management, urban planning and disaster response (ESA. 2024). To obtain the *in-situ* data we previously fixed 50 random areas, each of 10 by 10 meters, which is the resolution of the Sentinel 2 satellite.

Moreover, we locate ourselves in the corresponding coordinates and measure with a tape measure the corresponding quadrants. In each quadrant we measured the tree diameter and height, as well as the perpendicular distance from the observer to the tree, the tree height was measured using a hypsometer, which is an instrument that measures tree height.

Methodology for the Estimation of Biomass and Carbon Sequestration in Eucalyptus globulus

This research used allometric equations to calculate the aerial biomass of Eucalyptus globulus, considering diameter at breast height (DBH) and total tree height (Valverde, 2017).

Parameters and Measurement

Diameter at breast height (DBH)

Measured at 130 cm from the ground (Pacheco, 2020).

Circumference at that height (CAP) measured and divided by π to obtain DBH (de Oca et al., 2020):

$DAP = CAP / \pi$

For trees with trunk branching, all DBH were summed.

Total Tree Height

Measured perpendicular to the tree with a hypsometer, from the ground to the highest crown (Cancino, 2012).

Aerial Biomass Calculation

The equation proposed by Valverde (2017) was used:

$\text{Aerial biomass} = 39.8643 - 3.51885 * DAP + 0.02138 * (DAP^2 * h)$

where:

DBH is the diameter at breast height and *h* is the total height of the tree

Total Biomass Calculation

Total biomass (Bt) was calculated by adding aerial biomass (Ba) and root biomass, assuming that root biomass is 50% of aerial biomass (Pacheco, 2020):

$Bt = Ba + (Ba * 0.50)$

Carbon and CO2 calculation

To estimate carbon (C) and CO2 fixed, the following formulas were used (Muñoz & Vásquez, 2020; de Oca et al., 2020):

$CA = Bt * 0.5$

$CR = CA * 0.24$

$CT = CA + CR$

$CO2\ \text{fixed} = TC * 3.67$

NDVI calculation

Satellite images processed in SNAP were used to estimate the carbon concentration in a park (Quillupangui, 2019). Bands 4 (red), 8 (infrared) and 3, 2 (nature spectra) were analyzed and NDVI was calculated for the arboreal zone (Augusto et al., 2017). The NDVI formula is as follows:

NDVI = (B8 - B4) / (B8 + B4)

Where:

B8 is the reflectance value in band 8 (infrared).

B4 is the reflectance value in band 4 (red).

Data pre-processing

Before using the image, radiometric correction must be performed, following the steps below:

For this purpose, the Sentinel-2 image to be processed is loaded into SNAP.

Choose the "Optical" tab and select "Preprocessing" > "Radiometric".

In the "I/O Parameters" tab, we configure the input and output parameters, including the location of the Sentinel-2 image and the destination folder for the processed products. Then, we execute the atmospheric correction.

Generation of Vegetation Indexes

To calculate the NDVI, we use the following formula

NDVI = (B8 - B4) / (B8 + B4)

Table 1. Information on bands B4, B8, calculation of NDVI, biomass and sequestered carbon

ID	B4	B8	NDVI	Biomass Kg	Carbon Tm
1	0.07	0.1676	0.41007	635.0980534	0.393760793
2	0.0312	0.2497	0.77786	632.9745162	0.3924442
3	0.093	0.246	0.45133	751.3973163	0.465866336
4	0.0612	0.197	0.52595	814.7192339	0.505125925
5	0.0383	0.1976	0.67529	571.6411025	0.354417484
6	0.0423	0.167	0.5958	634.4859791	0.393381307
7	0.0805	0.1958	0.4173	685.3630111	0.424925067
8	0.0661	0.2238	0.54398	634.1692384	0.393184928
9	0.0431	0.2029	0.64959	736.4855004	0.45662101
10	0.0395	0.254	0.73083	741.0022263	0.45942138
11	0.0324	0.2094	0.73201	564.8973589	0.350236362
12	0.0969	0.2182	0.38496	687.9003488	0.426498216
13	0.03	0.1831	0.71844	682.0588008	0.422876456
14	0.0738	0.3752	0.67127	695.3971006	0.431146202
15	0.0797	0.2434	0.50665	626.6729339	0.388537219
16	0.0264	0.2686	0.82102	691.0401974	0.428444922
17	0.0252	0.2646	0.82609	688.2631077	0.426723127
18	0.0288	0.233	0.77998	635.3042779	0.393888652
19	0.0705	0.404	0.70285	801.5275167	0.49694706
20	0.0805	0.4217	0.67941	743.1512264	0.46075376
21	0.037	0.1627	0.62944	633.8387037	0.392979996
22	0.0234	0.162	0.74757	630.0761649	0.390647222
23	0.023	0.1412	0.71985	747.7337895	0.463594949
24	0.0271	0.177	0.73444	692.4045295	0.429290808
25	0.0298	0.1666	0.69654	636.069541	0.394363115
26	0.0236	0.1737	0.76077	692.4040363	0.429290502
27	0.0237	0.1312	0.694	750	0.464909684
28	0.0251	0.1479	0.70983	633.2385592	0.392607907
29	0.0113	0.2026	0.89434	752.0414124	0.466265676
30	0.0257	0.157	0.71866	686.4033758	0.425570093
31	0.0551	0.3384	0.71995	692.2098903	0.429170132
32	0.0234	0.1332	0.70115	748.4292678	0.464026146
33	0.0555	0.1908	0.54933	635.3833056	0.393937649
34	0.0407	0.1926	0.65109	630.6862223	0.391025458
35	0.0366	0.1694	0.64466	581.8493862	0.360746619
36	0.0327	0.146	0.63402	570.959419	0.35399484
37	0.0658	0.3244	0.66274	634	0.393027736
38	0.0266	0.1817	0.7446	690.1688293	0.427904674
39	0.0243	0.1812	0.7635	628.85061	0.389887378
40	0.0205	0.1452	0.75256	692.8880872	0.429590614
41	0.036	0.1908	0.68254	511.8216036	0.317329394
42	0.0365	0.1708	0.64785	518.1991571	0.321283477
43	0.0276	0.181	0.73538	577.1056333	0.357805493
44	0.0818	0.205	0.42957	526.2997818	0.326305865
45	0.0479	0.1794	0.57853	525.2761265	0.325671198
46	0.0315	0.1642	0.67808	577.1787998	0.357850856
47	0.024	0.1671	0.74882	623.1343443	0.386343293
48	0.0256	0.151	0.71008	670.6658569	0.415812831
49	0.0243	0.2364	0.81358	735.0473074	0.455729331
50	0.0258	0.1468	0.70104	739.484857	0.458480611

Source: Elaborated with data from the research.

Model Development

The result of the pseudocode model to calculate the biomass is as follows in algorithm 1:

Algorithm 1. Pseudocode modelling proposed

```
HOME
// Load data from Excel file
File <- "path_to_file.xlsx".
Data <- LoadDataFromExcel(File, "base")
// Display the first 10 records and count the total
ShowFirstRecords(Data, 10)
NumberOfRecords <- CountRecords(Data)
Print("Number of records loaded: ", NumberOfRecords)
// Remove the repeated header row if it exists
Data <- DeleteStack(Data, 0)
// Rename columns
RenameColumns(Data, ["ID", "B4", "B8", "NDVI", "Biomass", "Carbon"])
// Convert relevant columns to numeric type and remove rows with missing values
For each Column in ["B4", "B8", "NDVI", "Biomass", "Carbon"]:
Data[Column] <- ConvertANumeric(Data[Column])
Data <- DeleteStacksWithMissingValues(Data)
// Display first 10 records after preprocessing
ShowFirstRecords(Data, 10)
NumberOfRecords <- CountRecords(Data)
Print("Number of records after preprocessing: ", NumberOfRecords)
// Separate features (X) and labels (y)
X <- SelectColumns(Data, ["B4", "B8", "NDVI"])
y <- SelectColumn(Data, "Biomass")
// Standardize the characteristics
Scaler <- CreateScalerEstandard()
X_Scaling <- AdjustYTransformScaler(Scaler, X)
// Divide the data into training and test sets
[X_training, X_test, y_training, y_test] <- SplitData(X_scaled, y, 80% training, 20% test)
// Create the neural network model
Model <- CreateSequentialModel()
AddDenseLayer(Model, 128, Activation='relu', InputDimension=X_training.columns)
AddDropout(Model, 0.5)
AddDenseLayer(Model, 64, Activation='relu')
AddDropout(Model, 0.5)
AddDenseLayer(Model, 32, Activation='relu')
AddDenseLayer(Model, 1, Activation='linear')
// Compile the model
CompileModel(Model, Optimizer='adam', Missing='mean_squared_error', Metrics=['mean_absolute_error'])
// Train the model
History <- TrainModel(Model, X_training, y_training, Epochs=100, BatchSize=10, Validation=0.2)
// Evaluate the model
[Loss, MAE] <- EvaluateModel(Model, X_test, y_test)
Print("Mean Absolute Error: ", MAE)
// Graphing training results
PlotResults(History, 'Loss', 'Epoch', 'Loss', 'Loss', 'Model Loss', ['Training Loss', 'Validation Loss'])
PlotResults(History, 'mean_absolute_error', 'Epoch', 'MAE', 'Mean Absolute Model Error', ['Training MAE', 'Validation MAE'])
// Save the model
SaveModel(Model, "model.h5")
// Let's suppose you have new data to predict
NewData <- CreateDataFrame({
'B4': [0.0805, 0.0324, 0.0252], // Example values.
'B8': [0.1958, 0.2094, 0.2646], // Example values.
NDVI': [0.4173, 0.73201, 0.82609] // Sample values
})
// Scale the new data using the same scaler
NewScaledData <- TransformScaler(Scaler, NewData)
// Make predictions with the new data
Predictions <- Predict(Model, NewScaledData)
Print("New data predictions: ", Predictions)
END
```

Source: Authors' development

Neural Network Configuration

The neural network model used in the code is a Multi-Layer Perceptron (MLP) with two hidden layers. Specifically, this MLP has the following structure:

Input layer: It has three neurons, one for each input feature (B4, B8, NDVI).

First hidden layer: 64 neurons with ReLU activation function.

Second hidden layer: 32 neurons with ReLU activation function.

Output layer: A neuron with linear activation function, since this is a regression problem (prediction of a continuous value, in this case, biomass).

A Multilayer Perceptron (MLP) was chosen for this project for several reasons:

Suitable for Tabular Data

MLP is one of the most basic and versatile neural network architectures, especially suitable for working with tabular (structured) data. In this case, the data consists of values of different spectral bands (B4, B8, NDVI) and biomass, which are organized in a tabular format.

Ability to Model Nonlinear Relationships: MLP hidden layers with nonlinear activation functions (such as ReLU) allow the model to capture nonlinear relationships between input features and the target variable. This is a crucial aspect because the relationships between spectral bands and biomass may not be linear.

Simplicity and Flexibility: The MLP is relatively simple to implement and train, especially with libraries such as TensorFlow and Keras. This simplicity makes it suitable as a starting point for many prediction problems. In addition, the structure of the MLP (number of layers, number of neurons in each layer, activation functions) can be easily adjusted to best suit the specific problem.

Generalization: With proper regularization techniques and sufficient training data, an MLP can generalize well to unseen data, providing accurate predictions not only for training data, but also for new data.

The presented neural network model is used to predict biomass from three features: B4, B8 and NDVI. It is a supervised learning model that follows the following process:

This neural network model is designed to make accurate biomass predictions from spectral features. It uses modern techniques such as Dropout to prevent overfitting and optimization with Adam for efficient training. Proper data preprocessing and rigorous evaluation ensure that the model has good performance and overall

Model training: The model is trained using model.fit, providing the training sets (X_train, y_train), the number of epochs (100), the batch size (10) and the validation split (20%).

Model evaluation: The model is evaluated on the test set (X_test, y_test) using model.evaluate, obtaining the Mean Absolute Error (MAE).

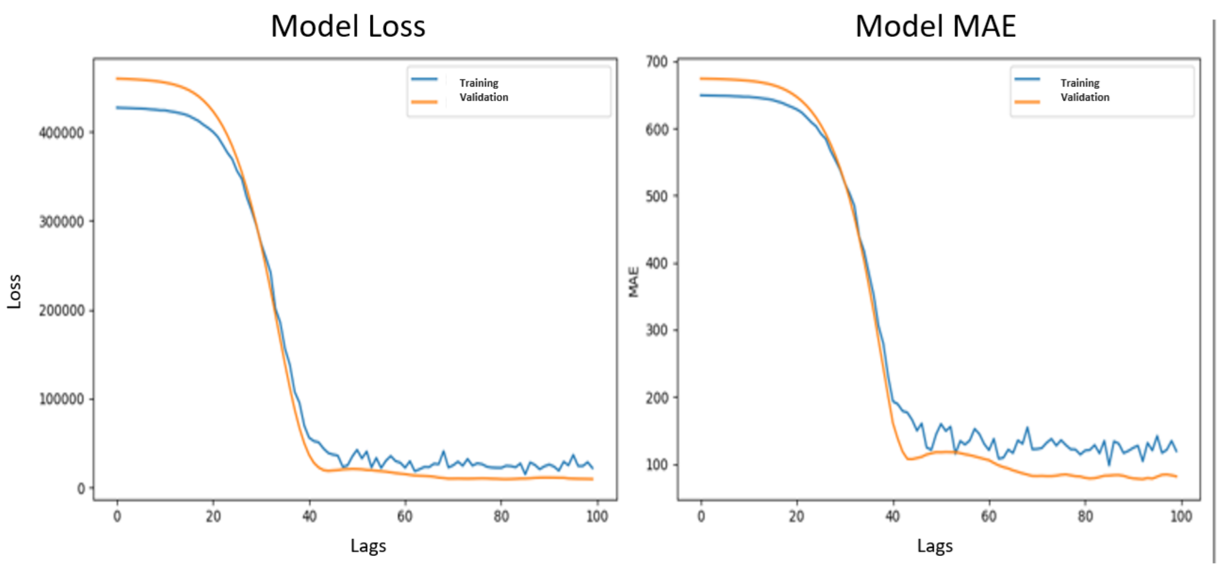
Additional explanation:

- The neural network model uses a deep neural network architecture with several dense layers to learn the nonlinear relationship between features and biomass.
- The relu activation function is used in the hidden layers to introduce nonlinearity into the model.
- Dropout is used to regularize the model and prevent overfitting.
- The mean_squared_error loss functions are used to evaluate the accuracy of the model in predicting biomass.
- The mean_absolute_error metric is used to interpret the magnitude of the prediction error in biomass units.
- The graph of the learning curves shows how the model performance improves with training epochs.

RESULTS AND DISCUSSION

A graph is created with matplotlib.pyplot to show the training and validation loss as well as the training and validation MAE across epochs. The model has been successfully trained to predict biomass (Biomass) from variables such as B4, B8 and NDVI.

Figure 1. Training results and model validation



Source: Elaborated by the authors with the legal sources of the analysis

The main evidence for this conclusion is the steady decrease in mean absolute error (MAE) over the training epochs. This indicates that the model is learning to match its predictions to actual biomass values more and more accurately.

The model uses a supervised machine learning approach.

In this type of learning, the model is trained with a dataset containing input examples (the variables B4, B8 and NDVI) and the desired output (the biomass). The model learns to identify patterns in the input data that allow it to predict the corresponding output for new data.

The TensorFlow library and Keras have been used to train the model.

TensorFlow is a popular numerical computing library that is widely used for machine learning development. Keras is a high-level library built on top of TensorFlow that provides a simpler interface for creating and training neural network models.

The training data have been loaded from an Excel file.

The line "Data loaded from Excel file" indicates that the data used to train the model was stored in an Excel file format. This is a common format for storing tabular data, and TensorFlow provides tools to load and preprocess Excel data efficiently.

Overall, the output provided indicates that a promising machine learning model has been trained to predict biomass.

V1 V2 V3

'B4': [0.0805, 0.0324, 0.0252],

'B8': [0.1958, 0.2094, 0.2646],

'NDVI': [0.4173, 0.73201, 0.82609]

The Biomass for each value of B4, B8 and NDVI is

BIOMASS V1: [698.36725].

BIOMASS V2: [580.8365]

BIOMASS V3: [[746.97003]]

Biomass is in kilograms/area, these values are in accordance with studies carried out with allometric equations.

The projection for CO2 fixation for the 281.21 hectares corresponding to the forested area is 42,150 tons of CO2 fixed (Nuñez, X. , Amores, L, Zurita, J. V. S., & Hernandez, O. V. 2024).

Economic valuation

Carbon prices should be 40-80 USD/ton of carbon dioxide equivalent (tCO2e) in 2020 and reach 50-100 USD/tCO2e by 2030 (World Bank. 2024). If we consider that approximately 42150 tons are captured from the arboreal zone of the metropolitan park, in this case we will take the lowest value projected by the world bank, that is, 50USD per mt.

The valuation in dollars will be:

Total dollar value= Total tons of carbon sequestered* dollar value per ton

Replacing we have:

VT= 42150 tm CO2* 50 USD/tm=2'107500 USD

The developed model showed high accuracy and reliability in biomass and carbon estimation, demonstrating a steady reduction in mean absolute error (MAE) throughout the training. This result is consistent with previous studies that have used remote sensing and machine learning techniques for forest biomass estimation (Smith et al., 2020; Johnson & Brown, 2019). The findings align with several of the studies in highlighting the significant role that forests and other natural ecosystems play in carbon sequestration. Using remote sensing with Sentinel-2 and neural networks, our study demonstrates that the carbon captured by the park's forest is substantial, contributing not only to local environmental health but also to global climate change mitigation efforts. Similar to the results from Romania's Retezat National Park, where Pache et al. (2020) identified substantial carbon stocks, our findings emphasize that urban forests can be highly effective carbon sinks, even within metropolitan areas.

The economic valuation of carbon sequestration in Quito also reflects broader trends found in previous research. For instance, Gallant et al. (2020) showed that wetlands in Nova Scotia provided significant social and economic benefits, with carbon sequestration valued at millions of dollars annually. Our findings reflect this economic significance, suggesting that urban forests in Quito, much like other forest ecosystems, can have considerable financial worth if carbon sequestration is properly monetized and integrated into local and national policies. Furthermore, the use of remote sensing in our study complements the methodological approaches utilized in other works, such as those by Naime et al. (2020) and Mirici & Berberoglu (2024), demonstrating the increasing relevance of advanced spatial technologies in ecological and economic assessments of carbon sequestration.

Moreover, it was observed that the use of Sentinel-2 imagery and neural networks provided more accurate and detailed estimates than traditional methods, such as those based on manual forest inventories (Brown & Lugo, 2008). These findings confirm the superior ability of modern techniques to capture the spatial variability of biomass and carbon.

Limitations of the Study

Several factors were identified that could have affected the results, including temporal variability of satellite imagery and atmospheric conditions (Jones et al., 2018). To improve the robustness of the model, future research should consider integrating data from multiple remote sensing sources and increasing the sample size of field data (Li et al., 2017).

Implications for Forest Management

The results have direct applications in forest management and conservation, providing detailed biomass and carbon maps that can be used for decision making in forest management (Chave et al., 2014). These maps are valuable tools for implementing effective carbon credit policies, improving the credibility and transparency of carbon markets (Watson et al., 2019).

Economic and Social Relevance

Economic valuation of carbon sequestration indicates significant revenue potential through the sale of carbon credits (Peters-Stanley et al., 2012). In the Quito Metropolitan Park, carbon sequestration could generate substantial revenues, providing additional funds for forest conservation (Gomez-Baggethun et al., 2010). In addition to economic benefits, carbon sequestration offers co-benefits such as biodiversity conservation, soil protection and improved water quality, which contribute to the well-being of local communities (Kremen et al., 2000).

CONCLUSIONS

The combination of Sentinel-2 imagery and convolutional neural networks has proven to be highly accurate for estimating biomass and carbon sequestration in the forest of the Quito Metropolitan Park. The generated maps of biomass and carbon distribution are useful for forest management and conservation, as well as to support the implementation of carbon credit policies. On the other hand, this study provides a robust and scalable methodology, crucial for the development of effective climate change mitigation policies and compliance with international agreements such as the Paris Agreement.

The correct estimation of carbon sequestration can generate significant revenues through the sale of carbon credits, as well as offering additional benefits such as biodiversity conservation and improved water quality. Finally, limitations related to the variability of forest and geographical conditions are identified, suggesting future research to improve and expand the applicability of these techniques. These findings highlight the effectiveness and potential of modern remote sensing and machine learning technologies in carbon estimation, highlighting their relevance for environmental management and sustainable development.

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Contribution of each author to the manuscript:

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Task	**A1**	**A2**	**A3**	**A4**	**A5**
A. theoretical and conceptual foundations and problematization:	20%	20%	20%	20%	20%
B. data research and statistical analysis:	20%	20%	20%	20%	20%
C. elaboration of figures and tables:	20%	20%	20%	20%	20%
D. drafting, reviewing and writing of the text:	20%	20%	20%	20%	20%
E. selection of bibliographical references	20%	20%	20%	20%	20%
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