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Geoprocessing Applied to the Assessment of Carbon Storage and Sequestration in a Brazilian Medium-Sized City

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Abstract: The emission of greenhouse gases (GHG) is a cause for concern when seeking sustainable development in view of global warming. The multiple ecosystem services associated with land use and land cover are at the center of the global climate agenda, both as a mitigation and adaptation strategy to climate change and growing urbanization. Among these services is carbon storage and sequestration (CSS). It can remove GHG carbon from the atmosphere and store it in the form of organic matter, a natural carbon stock. Thus, to design projects that guarantee sustainable development, it is necessary to use metrics that can quantify the impact of sequestration on natural carbon stocks. We aimed to implement the InVEST CSS methodology in the region of Itaperuna-RJ (Brazil) to quantify the net change in carbon storage over time (sequestration and loss) between 2015 and 2020. The obtained total difference in carbon stocks between the analyzed maps was \(-39,103.56 \times 10^3\) kg C, which has an equivalent social cost of carbon of USD 16,559,187.69. This social value represents the social damage caused by releasing that amount of carbon into the atmosphere. This main result brings an important application for validating the InVEST CSS methodology in Brazil. Furthermore, it points out parameters that can help elaborate sustainable development policies.

Keywords: land use and land cover change; GIS; remote sensing; ecosystem service; carbon storage

1. Introduction

There have been debates in the scientific community in the previous decades concerning the concept of Sustainable Development. However, in the Brundtland Report [1], this concept was established as one of the strongest guidelines on which human society would seek to build its future. The World Commission prepared this report on Environment and Development (WCDE) of the United Nations (UN). The document was one of the main ones presented at the United Nations Conference on Environment and Development in 1992 in Rio de Janeiro, Rio-92. The term ceased to be a scientific concept and became part of political and social debates [2]. In its pages, the Brundtland Report defines “sustainable development” as development which “meets the needs of the present without compromising the ability of future generations to meet their own needs” [3].

The United Nations (UN) estimated that in 2018 the urban population was 86.6% of the Brazilian population and that in 2050, this percentage would be 92.4% [4]. This highlights not only a change in the Brazilian consumption pattern but also the way that population distribution interferes with the environment. The situation is accentuated when looking at medium-sized Brazilian cities (between 100 thousand and 1 million inhabitants). Average annual growth of more than 1% is observed in their population, whereas this growth is lower than 1% in cities with more than 1 million inhabitants [5]. Such changes in the way the land is occupied trigger worrying effects when thinking about sustainable development.

According to data from the Intergovernmental Panel on Climate Change (IPCC), changing the characteristics and properties of the Earth’s surface is a factor that contributes to the accumulation of greenhouse gases (GHG), and this process alters the energy balance of the
climate system. Conversions from native ecosystems to agrosystems currently contribute to approximately 24% of global CO₂ emissions, 55% of CH₄ emissions, and 85% of total N₂O emissions to the atmosphere [6]. In Brazil, the scenario is even more worrying since the GHG emissions due to changes in land use and agriculture were estimated in 2015 by the System for Estimating Greenhouse Gas Emissions (SEEG), representing about 68% of the national GHG annual emissions [7]. Land use and land cover (LULC) changes are continuously occurring, mainly due to natural causes or anthropogenic activities, with the latter recently being a dominant force [8–11]. The main drivers of these changes are location- and time-specific, varying by region and time [9,12]. In developing countries, the fast increase in population has been often leading to LULC changes by deforestation caused by agricultural production and the production of other materials for consumption [13–15].

Observing such trends, it is necessary to adopt metrics capable of supporting decision making while meeting the ideal of sustainable development and urban population growth. Among the widely discussed quantifiable concepts, there is carbon storage and sequestration, which removes carbon from the atmosphere and its subsequent incorporation or storage in the form of biomass. This concept was established after the Conference of the Parties held in 1997 in Kyoto, Japan, ratified by the Kyoto Protocol. This document reinforces the importance of studying and quantifying carbon sequestration as an indispensable parameter for sustainable planning [16]. Carbon storage and sequestration generate larger and more qualified amounts of organic matter. Thus, if well balanced, this process of fixing carbon to the soil is one of the main ecosystem services acting on the environment. Therefore, understanding and modeling the process allows the control and instrumentalization of the biological absorption of carbon by the soil and, consequently, the reduction in the amount of GHG in the atmosphere [17].

Daily [18] defined Ecosystem Services as the set of conditions and processes through which natural ecosystems, and the species that constitute them, sustain and satisfy human life. The author also claimed that they are responsible for maintaining biodiversity and the production of ecosystem goods, such as food, wood, fuels, natural fibers, raw material for pharmaceutical products, and others. Thus, the preservation of these services is fundamental to achieving sustainability. With the increasing GHG emissions caused by human activities, it is already possible to notice the increase in global average temperatures, representing a threat to the environment [19]. According to the IPCC [20], the gases with the greatest capacity to reflect solar radiation and thus sustain the greenhouse effect are carbon dioxide (CO₂), nitrous oxide (N₂O), and methane (CH₄). Furthermore, the IPCC Press Release 2021/17/PR states that carbon dioxide (CO₂) is the main driver of climate change [21].

An essential ecosystem service for regulating the concentration of greenhouse gases (GHG) is carbon storage and sequestration. Lal [22] defined carbon sequestration as the process by which CO₂ is removed from the atmosphere, and it is stored (carbon storage) in ways that make it difficult to return to the atmosphere. One of the most natural ways to carry out this removal is through plants, which, through the photosynthesis process, can fix carbon to the soil in the form of organic matter, also called biomass. Hinge et al. [23] explain this fixation process by stating that during the life cycle of plants, photosynthesizing cells are able, through chemical processes, to use the carbon present in atmospheric carbon dioxide to synthesize organic molecules that will serve as input not only for energy production but also for the physical and structural composition of the plant. Thus, during its life, the vegetable entity removes carbon from the atmosphere and stores it in its leaves, branches, trunks, roots, etc. Once the plant or some of its parts die, the organic matter that composes it is decomposed, returning some of the CO₂ to the atmosphere, while most of the carbon remains stored in the soil itself. According to Batjes [24], organic compounds are called primary production from inorganic substances. Carbon, in turn, is the main component of organic matter present both in plant biomass and organic substances found in soil and water bodies. The distribution of material resulting from primary production depends on three main things: the production of plant entities through photosynthesis, how the entity
distributes it, and how it will be gradually decomposed. Thus, it is possible to conclude that a given area will have its quantity of carbon fixed in it due to the variability of vegetation and soil types. This quantity, which empirical methods can estimate, is called carbon stock.

To understand and model the complex processes related to ecosystem services, InVEST (Integrated Valuation of Ecosystem Services and Tradeoffs) models were developed. Among these models, we used the InVEST Carbon Storage and Sequestration (InVEST CSS) methodology [25], which focuses on carbon storage and sequestration dynamics. Therefore, it is necessary to know three fundamental information about the case study: the LULC, the amount of carbon in each of the occupations (LULC classes), and the social cost of carbon (SCC), which estimates the value of possible socioeconomic damage caused by climate change for each kg of carbon released into the atmosphere [26]. Thus, the methodology forecasts the amount of carbon stored in an area, calculates the variations that have occurred, and predicts the amount that will be stored in a future scenario for that same area through the analysis of land use, also estimating the variation in carbon sequestration between the two dates and their monetization [27].

In this study, we applied the InVEST CSS methodology to the region of the municipality of Itaperuna, located in the northwest of the state of Rio de Janeiro (RJ), Brazil, by comparing its 2015 and 2020 LULC maps. From this analysis, it will be possible to better understand the dynamics of the modification of the land use in a medium-sized city in this region of the country. In addition to estimating the variation in carbon stocks and sequestration in the region due to changes in land use, the monetary values for this transformation will be estimated using the SCC. The results of this study contribute to a better understanding of the dynamics of LULC changes and their drivers at regional and national levels, and the consequent impacts on carbon stocks. This allows decision makers to better manage the environmental planning and ensure the maintenance of ecosystem services while dealing with sustainable development in Brazilian projects concerning LULC changes. It is an original and innovative study for bringing to Brazil the application of a worldwide applied methodology, and in particular, supporting the sustainable management of small and medium-sized cities. Furthermore, this study is intended to encourage the method’s application in other regions of the country, especially in the areas which are most affected by LULC changes.

2. Materials and Methods
2.1. Case Study

The municipality of Itaperuna, located in the northwest region of Rio de Janeiro, 320 km from Rio de Janeiro city, has a semi-urbanized territory of 1106.694 km² and an estimated population for 2021 of 104,354 inhabitants (in the last census of 2010, the estimated population was 95,841, which highlights a significant population increase in the past decade) [5]. Therefore, it is considered a medium-sized city in urban growth. Its territory is located inside the Muriaé River basin, whose main river flows through the urbanized city center. Figure 1 presents the locations of the municipality of Itaperuna and the case study area (which is a selected rectangle over the urbanized area of the municipality).

Itaperuna presents an essential role in the north/northwest region of the State of Rio de Janeiro, especially in the domains of logistics, health, and education. The national highway (BR-356), which crosses the city center, helps in the flow of trade in the region linking the capital of the state of Minas Gerais (Belo Horizonte/MG) to the Açú Port (São João da Barra/RJ), and the São José do Avaí Hospital (located at Itaperuna) is a reference hospital in the region and one of the best and most important hospitals in the entire state of Rio de Janeiro.
The predominant climate type of the region is Aw (tropical dry, according to Köppen–Geiger), with average annual rainfall between 1100 and 1200 mm, characterized by two very distinct seasons: rainy summer–spring, with December being the month with the highest rainfall, and dry autumn–winter, with August being the driest month [28,29]. The average annual temperature in the municipality is 23.6 °C, the lowest average for the coldest month (July) is 15.2 °C, and the highest average for the warmest month (February) is 33.1 °C [29].

The vegetation of the municipality region is classified as seasonal semideciduous forest (subdeciduous tropical forest) with an alluvial aspect, containing secondary vegetation and agricultural activities [30] (Figure 2a). Furthermore, the most common soil types in the study area are red-yellow argisol and red oxisol [31] (Figure 2b), which are typical of areas between the tropics, being commonly named “tropical soils” [32,33].

Figure 1. Municipality of Itaperuna in the state of Rio de Janeiro and the study area.

Figure 2. (a) Vegetation [30] and (b) soil [31] maps of the study area.
Besides the historical irregular occupation of the margins of the Muriaé River, the Muriaé River basin has been subject to a deforestation process since the 19th century [34,35]. The changes in local landscapes are linked not only to urban areas but also to agricultural activities. These LULC changes, especially in the urbanized area of Itaperuna-RJ, have also affected the population with recurrent floods [36,37].

2.2. Remote Sensing in Image Classification

The process of classifying remote sensing images consists of extracting information from these images to recognize homogeneous patterns and objects, in which targets are analyzed and classified for each class of interest. In this sense, three main image classification approaches have been used in remote sensing: Unsupervised Image Classification, Supervised Image Classification, and Object-Based Image Analysis. Table 1 presents some common image software or algorithms based on each image classification technique, followed by the associated references.

**Table 1.** Image classification approaches used in remote sensing.

| Image Classification Technique       | Software/Algorithm     | Reference    |
|-------------------------------------|------------------------|--------------|
| Unsupervised Classification         | K-means                | [38,39]      |
|                                     | ISODATA                | [40,41]      |
|                                     | Maximum Likelihood     | [42]         |
|                                     | Gaussian Mixture Model (GMM) | [43]   |
| Supervised Classification           | Minimum Distance       | [44]         |
|                                     | Support Vector Machine (SVM) | [45,46] |
|                                     | Fisher Kernel (FK)      | [47,48]      |
|                                     | Mahalanobis Distance    | [49,50]      |
| Object-Based Image                  | Object-Based Image     | [51,52]      |

We focused on the Supervised Image Classification process to provide the LULC maps from high-spatial resolution satellite imagery (HRSI) (<30 m). The Supervised Classification technique called the Support Vector Machine method was used to classify the image used in this study. SVM consists of a computational learning technique for pattern recognition issues. Introduced through the statistical theory of learning by Vapnik [45] and Cortes and Vapnik [46], this classification is based on the principle of optimal separation between classes, such that if the classes are separable, the solution is chosen to separate the maximum classes. The process is based on three main steps:

1. Selecting training areas: Selection of pixels representing the classes of interest in the image and construction of decision-making rules. Each LULC class must have a collection of representative samples (pixels) given “D” training samples \( [x_i, y_i] \), with \( i = 1, 2, \ldots, D \), where \( x_i \in \mathbb{R}^M \) is a vector representation of a set and \( y_i \in \{-1, 1\} \) is its associated class to generate a signature file with all spectral training information.
2. Generating signature file: These “training sites” are taken as the Real Map (composed of the selected samples of each LULC class) to enable the algorithm applied to classify the entire image, creating a Predicted Map.
3. Classifying: Finally, the entire image is classified by the selected algorithm.

In this study, two remotely sensed images of the China–Brazil Earth Resources Satellite (CBERS 04A) were used, covering the area of the municipality of Itaperuna-RJ in 2015 and 2020. These satellite images were obtained from the National Institute for Space Research (INPE) [53], following the technical specifications detailed in Table 2.
Table 2. Technical specifications of the remotely sensed images of the China–Brazil Earth Resources Satellite (CBERS 04A) provided by the National Institute for Space Research (INPE).

| Specification | 2015                  | 2020                  |
|--------------|-----------------------|-----------------------|
| Date         | 27 December 2015      | 6 October 2020        |
| Satellite    | CBERS 04A             | CBERS 04A             |
| Sensor       | MUX                   | MUX                   |
|              | B05: 0.45–0.52 µm     | B05: 0.45–0.52 µm     |
|              | B06: 0.52–0.59 µm     | B06: 0.52–0.59 µm     |
|              | B07: 0.63–0.69 µm     | B07: 0.63–0.69 µm     |
|              | B08: 0.77–0.89 µm     | B08: 0.77–0.89 µm     |
| Spatial Resolution (Nadir) | 16 m                  | 16 m                  |

The geometric correction was performed, using as reference an orthorectified scene provided by the Global Land Cover Facility, and the satellite images were georeferenced with QGIS (Quantum Geographic Information System GIS) software, QGIS 3.26.

The following step consisted of selecting and validating training areas. The classification process was based on five LULC classes: forest, grass, urban area, water surface, and exposed soil. At least 200 samples were selected for each LULC class, of which 70% were used to train the algorithm and 30% were used to validate the process. Regarding the acquired samples, 2015 and 2020 satellite images were analyzed by the land use/land cover classification algorithm called the Support Vector Machine method. Lately, the LULC maps were validated using a confusion matrix. In this study, the classification accuracy was estimated with the help of the F1-score, overall accuracy, kappa coefficient, producer’s accuracy, and user’s accuracy [54–56].

2.3. InVEST CSS Methodology

Lal [57] proposed that terrestrial ecosystems can store more carbon (the main constituent element of GHG) than the amount contained in the atmosphere itself, where for each LULC class, there will be a different carbon storage capacity. Thus, to quantify the mass of carbon stored in a specific area, it is necessary to understand where the organic matter is, how it is distributed, and in what quantity it is found.

To better analyze the carbon storage distribution in each of the LULC classes, the InVEST CSS methodology [25], adopted in this work, suggests the division of stored carbon into four carbon pools: aboveground biomass, soil biomass, soil organic matter, and dead organic matter.

Aboveground biomass comprises all living organic matter above the ground line. Soil biomass consists of all organic matter from the roots of the plants considered. Soil organic matter refers to all that is present in the organic components of the ground itself. Finally, dead organic matter contains organic mass related to dead leaves, branches, and trunks [25].

In possession of the LULC raster maps, the total area for each LULC class is calculated, and knowing the amount of carbon stored in each type of LULC class, the total amounts of carbon stored on each map are obtained by:

\[
C_{storage} = \sum_{k=1}^{5} C_k . A_k
\]

(1)

where \( C_{storage} \) is the total amount of carbon stored on the map, \( C_k \) is the total carbon stored on the LULC class \( k \), being the sum of the four carbon pools, and \( A_k \) is the total area of each LULC class \( k \). Thus, to obtain the change in carbon storage over time (sequestration and loss), the difference in storage is calculated:

\[
Carbon_{seq} = C_{storage_{Year\ final}} - C_{storage_{Year\ initial}}
\]

(2)
where \( \text{Carbon}_{\text{seq}} \) is the total carbon sequestration, \( \text{Year}_{\text{final}} \) is the final year of the analysis (2020), and \( \text{Year}_{\text{initial}} \) is the initial year (2015).

### 2.4. Social Cost of Carbon

The social cost of carbon (SCC) is a concept that aims to represent the monetary value of the socio-economic–environmental damage caused by the emission of \( 10^3 \text{ kg of carbon} \), either in the form of carbon dioxide or its equivalence to other GHGs [58]. This concept is still being validated and is discussed mainly in media related to environmental public policies, ranging from USD 32 to USD 326, quoted in 2010 [25]. Thus, unlike countries that already have a value defined by government agencies, Brazil is still discussing the possibility of adopting this type of policy, as shown in the technical note of the Energy Research Company [39] of the Ministry of Mines and Energy, entitled “Carbon Pricing: Risks and Opportunities for Brazil”, which assesses the conditions for the adoption of an SCC policy in the country.

Thus, in this study, we used the SCC value calculated by Kotchen [58], estimating that the social cost of carbon in Brazil in 2015 was USD 45 per \( 10^3 \text{ kg of CO}_2 \) or equivalent gases. This value corresponds to USD 165.00 per \( 10^3 \text{ kg of carbon} \), quoted in US dollars in 2015.

The InVEST methodology [25] proposes a way to carry out the temporal update of this value using the market discount \( (r) \) and the annual variation in the carbon price \( (c) \). The market discount reflects the variation in society’s interest in investing in more immediate benefits at the expense of long-term ones. This study adopts an annual market discount of 7\%, which the InVEST manual accepts for environmental projects as a base value if there is no specific study on the subject.

The annual variation in carbon price is an integer percentage value representing the year-to-year adjustment of the impacts of carbon sequestration in the expected reduction in damage related to climate change. For this indicator, a negative value represents the increased impact of carbon sequestration in combating climate change, while positive values indicate the opposite. In the absence of more objective data for Brazil, this work will adopt \( -35\% \) for the annual variation in the carbon price, a value that was estimated for the variation in SCC from 2015 to 2020 by the French government and adopted in the study carried out by Borges et al. [60].

After assessing the LULC raster maps for the final and initial years of analysis, and estimating the total carbon sequestration, as explained in the previous section, the total monetary value of carbon sequestration can be obtained as presented below:

\[
\text{Value}_{\text{seq}} = \frac{V \cdot \text{Carbon}_{\text{seq}}}{\text{Year}_{\text{final}} - \text{Year}_{\text{initial}}} \sum_{t=0}^{\text{Year}_{\text{final}} - \text{Year}_{\text{initial}} - 1} \frac{1}{(1 + r)^t \cdot (1 + c)^t}
\]

where \( \text{Value}_{\text{seq}} \) is the monetary total of the change and \( V \) is the reference SCC.

### 3. Results

#### 3.1. LULC Maps Classification

Firstly, the SVM method was applied to classify the CBERS 04A satellite images and generate the 2015 and 2020 LULC maps of the study area. Following the classification steps described in Section 2.2, the confusion matrix (Table 3) was determined to analyze both maps’ accuracy. The classification results indices estimated an overall accuracy of 97.33% for 2015 and 96.17% for 2020, and a kappa coefficient of 96.66% for 2015 and 93.33% for 2020. These classification indices presented an acceptable threshold (>90%), achieving the requirements of the LULC classification. In addition, the F1-score and the user’s and producer’s accuracies were estimated for each class.
Table 3. Confusion matrix of 2015 and 2020 LULC maps.

| LULC Classes  | 2015                        | 2020                        |
|---------------|-----------------------------|-----------------------------|
|               | User’s Accuracy (%)         | Producer’s Accuracy (%)     | F1-Score (%) | User’s Accuracy (%) | Producer’s Accuracy (%) | F1-Score (%) |
| Forest        | 100.00                      | 100.00                      | 100.00       | 96.03               | 97.58                   | 96.80        |
| Grass         | 96.15                       | 98.04                       | 97.09        | 98.29               | 95.83                   | 97.05        |
| Urban Area    | 95.16                       | 96.72                       | 95.93        | 94.26               | 93.50                   | 93.88        |
| Water Surface | 100.00                      | 100.00                      | 100.00       | 99.13               | 100.00                  | 99.56        |
| Exposed Soil  | 95.52                       | 92.75                       | 94.12        | 93.33               | 94.12                   | 93.72        |
| Overall       |                             |                             |              |                     |                         |              |
| Accuracy (%)  | 97.33                       |                             |              |                     |                         | 96.17        |
| Kappa         |                             |                             |              |                     |                         | 96.66        |

From the GIS-based analysis of the maps for 2015 and 2020, the total areas for each of the LULC were obtained, as presented in Table 4.

Table 4. Areas of the municipality of Itaperuna/RJ for 2015 and 2020, and their differences, distributed per each LULC class.

| Year          | Area (10^4 × m^2) |     |     |     |     |     |
|---------------|------------------|-----|-----|-----|-----|-----|
|               | Forest           | Grass | Urban Area | Water Surface | Exposed Soil | Total |
| 2015          | 2436.92          | 13,106.64 | 1017.12 | 294.16 | 533.96 | 17,388.80 |
| 2020          | 1908.40          | 13,337.28 | 1547.08 | 360.16 | 235.88 | 17,388.80 |
| 2020–2015     | −528.52          | 230.64   | 529.96  | 66.00  | −298.08 | 0.00   |

Table 4 shows that the forest and exposed soil LULC classes were reduced by −21.69% and −55.82%, respectively, while the grass, urban area, and water surface LULC classes were increased by +1.76%, +52.10%, and +22.44%, respectively. The greatest total LULC augmentation occurs for the urban area class, with a positive balance of 529.96 ha, whereas the greatest total LULC reduction occurs for the forest class, with a negative balance of 528.26 ha. It is also possible to note, from both Figure 3 (by performing a visual analysis of the 2015 and 2020 LULC maps) and Table 4, that this forest conversion occurs mainly in the grass and urban area. Furthermore, part of the exposed soil area present in the 2015 map was transformed into an urban area in 2020. Therefore, the grass LULC class area increase from 2015 to 2020 can lead to a misinterpretation of the global situation if analyzed separately.

The resolution of the LULC raster maps (Figure 3) obtained from this process was 20 m × 20 m, with an occupation code for each pixel referring to its LULC class.

3.2. Carbon Pools

For this study, the municipality territory map was classified into five main types of LULC classes: forest (LULC code 1), grass (LULC code 2), urban area (LULC code 3), water surface (LULC code 4), and exposed soil (LULC code 5). Table 5 presents the amounts of carbon storage (kg/m²) per carbon pool of the municipality of Itaperuna/RJ.
Figure 3. Land cover classes of the municipality of Itaperuna-RJ: 2015 and 2020 maps.
Table 5. Carbon pools of the municipality of Itaperuna/RJ.

| LULC Class    | LULC Code | Carbon Storage (kg/m²) |  |
|---------------|-----------|-----------------------|---|
|               |           | Aboveground Biomass    | Soil Biomass | Soil Organic Matter (0–40 cm) | Dead Organic Matter | Total  |
| Forest        | 1         | 3.748 [61]            | 0.695 [61]   | 6.376 [62]                    | 0.427 [61]         | 11.246 |
| Grass         | 2         | 0.291 [6]             | 0.466 [6]    | 3.988 [62]                    | 0                  | 4.745  |
| Urban Area    | 3         | 0                     | 0            | 3.988 [62]                    | 0                  | 3.988  |
| Water Surface | 4         | 0                     | 0            | 0.216 [64]                    | 0                  | 0.216  |
| Exposed Soil  | 5         | 0                     | 0            | 3.988 [62,63]                 | 0                  | 3.988  |

Due to the lack of specific data for the municipality of Itaperuna-RJ, data from similar regions were used, e.g., carbon storage data related to the forest were obtained from the region of Viçosa, located about 115 km from Itaperuna-RJ, in the state of Minas Gerais (MG). This municipality, similarly to Itaperuna-RJ, has a natural flora considered as seasonal semideciduous forest (subdeciduous tropical forest) of alluvial aspect, containing secondary vegetation and agricultural activities [30]. Furthermore, both municipalities also have similar soils: oxisols and argisols, eutrophic and dystrophic [31]. Thus, for soil organic matter, the carbon storage estimated for the forest (6.376 kg/m²) and the grass (3.988 kg/m²) were also obtained from Viçosa-MG, adding the carbon storage amounts of the layers from 0 to 20 cm and 20 to 40 cm in depth [62].

In the forest LULC class, the carbon storage estimate for the aboveground biomass (3.748 kg/m²) comes from the sum of the contributions, calculated by the IPCC method, of the tree species (3.422 kg/m²), the *Attalea dubia* (Indaiá palm tree) (0.086 kg/m²), and the understory (0.240 kg/m²). The soil biomass for the forest, also estimated by IPCC, was obtained by adding the carbon masses present in the roots of tree species (0.682 kg/m²) and *Attalea dubia* (0.013 kg/m²). For dead organic matter (understory) (0.427 kg/m²), the value once again obtained by the IPCC method was adopted [61].

In the grass LULC class, the carbon storage estimates for the aboveground biomass (0.291 kg/m²) and the soil biomass (0.466 kg/m²) were obtained using tables 4.3, 6.4, and 6.1 of the Guidelines for National Greenhouse Gas Inventories [6]. The same report states that the amount of carbon present in dead organic matter in non-forest bodies can be admitted as zero.

In the urban areas LULC class (considered as soil covered by buildings, roads, or sidewalks), and in exposed soil LULC class, the amount of carbon storage estimates for the aboveground biomass, the soil biomass, and the dead organic matter are considered to be close to zero. On the other hand, for the soil organic matter, due to the traditional development of urban occupation (it starts with the deforestation of native forest, land use as a rural area, which later becomes uncovered soil and then built-up urban area), it is considered that the amount of carbon storage is the same as that found in the grass LULC class [63].

In the water surface LULC class, the carbon storage estimate (0.216 kg/m²) is obtained from the sum of 3 years of annual deposition accumulations [64]. In this study, it was considered the carbon stored in water bodies to be soil organic matter in the soil since it is below the soil surface level.

3.3. InVEST CSS

After preparing and analyzing the LULC raster maps for 2015 and 2020, the carbon storage raster maps were generated (Figure 4) with the help of the carbon pools developed for this case study (see Table 5). These maps present the amounts of carbon storage per area of the case study in 2015 and 2020. They are displayed at the same resolution (20 m × 20 m) as the LULC raster maps.
The observed LULC transformation happens following the conventional trend of the LULC evolution in the urbanization process, which occurs, sequentially, through the deforestation of native forests, land use and occupation for rural activities, “soil cleaning”
(removal of the undergrowth layer, exposing the soil) and its consequent use as a built-up urban area. From Tables 4 and 5, one may note that the LULC change from forest to grass is one of the protagonists of the degradation of carbon stocks, with the transformation that generates the greatest negative impact during the entire urbanization process. For example, in this change, there is a drop in carbon stocks from 11.246 kg/m$^2$ to 4.745 kg/m$^2$, representing 89.57% of all the loss that occurred if we consider a final state of an urban area with 3.988 kg/m$^2$. In Itaperuna-RJ, the main drivers of the observed LULC changes from 2015 to 2020 were population growth and the lack of awareness of the importance of natural resource conservation for sustainable livelihoods.

Then, from the analysis of the carbon storage raster maps for 2015 and 2020 (Figure 4), the total values of the carbon mass stored in 2015 and 2020 were estimated, as presented in Table 6.

Table 6. Carbon storage amounts (kg) of the municipality of Itaperuna/RJ for 2015 and 2020, and their differences, distributed per each LULC class.

| Year    | Forest       | Grass        | Urban Area  | Water Surface | Exposed Soil | Total       |
|---------|--------------|--------------|-------------|---------------|--------------|-------------|
| 2015    | 274,056.02   | 621,910.07   | 40,562.75   | 635.39        | 21,294.32    | 958,458.55  |
| 2020    | 214,618.66   | 632,853.94   | 61,697.55   | 777.95        | 9406.89      | 919,354.99  |
| 2020–2015 | −59,437.36 | 10,943.87    | 21,134.80   | 142.56        | −11,887.43   | −39,103.56  |

The total difference in carbon stocks between the analyzed maps is $−39,103.56 \times 10^3$ kg, representing negative carbon sequestration or even a carbon emission related to changes in the LULC in the region. The SCC for Brazil updated by Equation (3) results in a value of USD 387.90 (per $10^3 \times$ kg of C) in 2015 dollars, or even USD 423.59 (per $10^3 \times$ kg of C) in 2020 dollars, considering accumulated inflation of 9.2% [65]. Thus, applying the updated carbon pricing, an estimate of USD 16,559,187.69 is obtained for the total monetary value of carbon sequestration from 2015 up to 2020, quoted in 2020.

4. Discussion

Political and social debates worldwide are increasingly concerned with the development of public policies and sustainable enterprises [66–68]. In this scenario, the environmental aspect and the subsequent understanding of ecosystem services are more and more prominent. In Brazil, it is necessary to apply methodologies capable of accurately and efficiently measuring how its projects and actions impact the environment.

The continuous urbanization process in Brazil reflects the growth of urban populations and the consequent growth of urban areas to the detriment mainly of areas occupied by agriculture or native forest. Although Brazil has continental dimensions, it can be seen, with the study of carbon stock variations, that the key factor when seeking sustainable development is not the territorial extension, but how the land is occupied and used. Thus, the GIS-based analysis of the LULC changes in the region of the municipality of Itaperuna-RJ due to urban development between 2015 and 2020 is important for understanding how this process impacts the carbon stocks of a medium-sized city in this region of the country.

In this study, an expressive increase and reduction in the total areas of the urban area and forest LULC classes, respectively, can be observed between 2015 and 2020. In the same period, the total areas of the LULC classes of grass and water surface increased, while the total area of the exposed soil LULC class decreased. However, it can be seen that the reduction in the area of exposed soil was due to the increase in the urban area and the increase in the area of grass was due to the reduction in part of the area of forest, which could give the false impression that the increase in the grass area was something positive. Another part of the reduction in the forest area was also due to the increase in the urban area.
In a case study with a much smaller area than the one analyzed in this work, Borges et al. [60] addressed the carbon storage and sequestration processes due to the LULC changes in the region of La Bonde inside the Massy catchment, in the south of Paris region (France). Although the urbanization process addressed by the authors from the past map of 2015 to the estimated future map of 2025 has also generated negative impacts on carbon stocks, with an estimated SCC of approximately EUR 450,000, there was in this case a concern with minimizing the effects of that process. While the total areas occupied by the LULC classes of roads and houses increased and the total area of the grass LULC class decreased from 2015 to 2025, the total area occupied by the forest LULC class increased in the same period.

This demonstrates the influence of the different territorial characteristics between both studies, where the territorial limitation of La Bonde is opposed to the territorial amplitude of Itaperuna-RJ, as well as the impacts of urban planning on carbon socks, providing greater conditions for the mitigation and minimization of environmental impacts in contrast to the disordered urbanization consequences.

Besides the limitations and simplifications of the model (InVEST, 2021) (e.g., dependency on the precision and variability of LULC maps; linearity of carbon sequestration path over time; assumption of fixed amounts of carbon storage levels within the same LULC class over time), it enables decision makers to better deal with sustainable development in urban areas.

The importance of this methodology is correlated with municipal policies and the proposition of mitigating measures to urbanization impacts, such as the creation (or revision) and implementation of the Municipal Master Plan, reforestation, and preservation of green areas. Thus, this study allows local government agents to analyze the critical areas and then allocate resources and efforts in the short, medium, or long term. Finally, it serves as a reference for the use of the same methodology in other areas, helping to mitigate the impacts of urban growth in medium-sized cities of Brazil and around the world.

5. Conclusions

The InVEST CSS methodology adopted in this study brought significant results to understanding the evolution of carbon stocks by comparing different LULC maps. Thus, it is considered that InVEST CSS can be a valuable tool to be integrated into the development of sustainable projects in Brazil that involve changing the distribution of LULC in a region of interest.

Furthermore, this research can be easily replicated in other parts of the country. In this context, future work could be developed to present a carbon pools table for all LULC classes in Brazil, especially in the regions most affected by LULC changes, such as the Amazon.

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References
1. UN. Secretary-General. World Commission on Environment and Development. Report of the World Commission on Environment and Development: Note by the Secretary-General; United Nations: New York, NY, USA, 1987.
2. Prado, A.L. Desenvolvimento urbano sustentável: De paradigma a mito. Oculum Ens. 2015, 12, 83–97. [CrossRef]
3. Simon, D. Our Common Future: Report of the World Commission on Environment and Development (Book Review). Third World Plann. Rev. 1987, 9, 285. [CrossRef]
4. United Nations. World Urbanization Prospects: The 2018 Revision; United Nations: New York, NY, USA, 2018.
5. IBGE Instituto Brasileiro de Geografia e Estatística Cidades e Estados, Itaperuna (RJ). Available online: https://www.ibge.gov.br/cidades-e-estados/ri/itaperuna.html (accessed on 25 June 2022).
6. Intergovernmental Panel on Climate Change. 2006 IPCC Guidelines for National Greenhouse Gas Inventories, Volume 1: General Guidance and Reporting Annex 8a.2 Reporting Tables; Institute for Global Environmental Strategies (IGES): Hayama, Japan, 2006.
7. de Azevedo, T.R.; Costa Junior, C.; Brandão Junior, A.; Cremer, M.D.S.; Piatto, M.; Tsai, D.S.; Barreto, P.; Martins, H.; Sales, M.; Galuchi, T.; et al. SEEG initiative estimates of Brazilian greenhouse gas emissions from 1970 to 2015. Sci. Data 2018, 5, 180045. [CrossRef]
8. Bennett, A.F.; Saunders, D.A. Habitat fragmentation and landscape change. In Conservation Biology for All; Oxford University Press: Oxford, UK, 2010; pp. 88–106.
9. Munthali, M.G.; Davis, N.; Adeola, A.M.; Botai, J.O.; Kamwi, J.M.; Chisale, H.L.W.; Orimoogunje, O.O.I. Local Perception of Drivers of Land-Use and Land-Cover Change Dynamics across Dedza District, Central Malawi Region. Sustainability 2019, 11, 832. [CrossRef]
10. Hailu, A.; Mammo, S.; Kidane, M. Dynamics of land use, land cover change trend and its drivers in Jimma Geneti District, Western Ethiopia. Land Use Policy 2020, 99, 105011. [CrossRef]
11. Ahmed, R.; Ahmad, S.T.; Wani, G.F.; Ahmed, P.; Mir, A.A.; Singh, A. Analysis of landuse and landcover changes in Kashmir valley, India—A review. Geojournal 2021. [CrossRef]
12. Weng, S.-S.; Chen, K.-Y.; Li, C.-Y. Application of the Analytic Hierarchy Process and Grey Relational Analysis for Vendor Selection of Spare Parts Planning Software. Symmetry 2019, 11, 1182. [CrossRef]
13. Ramankutty, N.; Foley, J.A. Estimating historical changes in global land cover: Croplands from 1700 to 1992. Glob. Biogeochim. Cycles 1999, 13, 997–1027. [CrossRef]
14. Maitima, J.M.; Mugatha, S.M.; Reid, R.S.; Gachimbi, L.N.; Majule, A.; Lyaruu, H.; Pomery, D.; Mathai, S.; Mugisha, S. The linkages between land use change, land degradation and biodiversity across East Africa. Afr. J. Environ. Sci. Technol. 2009, 3, 310–325. [CrossRef]
15. Berihun, M.L.; Tsunekawa, A.; Haregeweyn, N.; Meshesha, D.T.; Adgo, E.; Tsubo, M.; Masunaga, T.; Fenta, A.A.; Sultan, D.; Yibeltal, M. Exploring land use/land cover changes, drivers and their implications in contrasting agro-ecological environments of Ethiopia. Land Use Policy 2019, 87, 104052. [CrossRef]
16. United Nations. Kyoto Protocol to the United Nations Framework Convention on Climate Change; United Nations: New York, NY, USA, 1998.
17. Amaral, R.; Costa, S.D.A.P.; Muzzi, M.R.S. O sequestro de carbono em trechos da floresta urbana de Belo Horizonte: Por um sistema de espaços livres mais eficiente no provimento de serviços ecosistêmicos urbanos. Paisag. Ambient. 2017, 39, 163–179. [CrossRef]
18. Gretchen, C. Daily Nature’s Services: Societal dependence on Natural Ecosystems; Island Press: Washington, DC, USA, 1997.
19. Kweku, D.; Bismark, O.; Maxwell, A.; Desmond, K.; Danso, K.; Oti-Mensah, E.; Quachie, A.; Adormaa, B. Greenhouse Effect: Estimating historical changes in global land cover: Croplands from 1700 to 1992. Energy Environ. Sci. 2018, 11, 86–100. [CrossRef]
20. Lal, R. Sequestration of atmospheric CO2 in global carbon pools. Energy Environ. Sci. 2008, 1, 86–100. [CrossRef]
21. Hinge, A.; He, J.; Bartram, J.; Javier, J.; Xu, J.; Fjellman, E.; Sesaki, H.; Li, T.; Yu, J.; Wunderlich, M.; et al. Asymmetrically Segregated Mitochondria Provide Cellular Memory of Hematopoietic Stem Cell Replicative History and Drive HSC Attrition. Cell Stem Cell 2020, 26, 420–430.e6. [CrossRef] [PubMed]
22. Batjes, N.H. Total carbon and nitrogen in the soils of the world. Eur. J. Soil Sci. 2014, 65, 10–21. [CrossRef]
23. InVEST. InVEST Carbon Storage and Sequestration User Guide. Available online: https://storage.googleapis.com/releases.naturalcapitalproject.org/invest-userguide/latest/carbonstorage.html (accessed on 4 May 2021).
24. Blufstone, R.; Coulston, J.; Haight, R.G.; Kline, J.; Polasky, S.; Wear, D.N.; Zook, K. Estimated Values of Carbon Sequestration Resulting from Management Scenarios Chapter 1: Assessing Pollinator Habitat Services to Optimize Conservation Programs Chapter 2: Ecosystem Service Benefits Generated by Improved Water Quality from Conservat. In The Valuation of Ecosystem Services from Farms and Forests: Informing a Systematic Approach to Quantifying Benefits of Conservation Programs. Report No. 0114-301; Council on Food, Agricultural and Resource Economics (C-FARE): Washington, DC, USA, 2017; pp. 7–24.
27. Sharp, R.; Tallis, H.; Ricketts, T.; Guerry, A.; Wood, S.; Chaplin-Kramer, R.; Nelson, E. The Natural Capital Project. The Nature Conservancy and World Wildlife Fund. In VEST Version 3.2. 0 User's Guide; Stanford University: Stanford, CA, USA; University of Minnesota: Minneapolis, MN, USA, 2015.

28. Embrapa. Sistema Brasileiro de Classificação de Solos; Embrapa: Brasília, Brazil, 2018; ISBN 978-85-7035-198-2.

29. Martorano, L.G.; Rossiello, R.O.P.; Menegueli, N.A.; Lumberais, J.F.; Valle, L.S.S.; Motta, P.E.F.; Rebelo, E.R.G.; Said, U.P.; Martins, G.S. Aspectos Climáticos do Noroeste Fluminense. RJ.—Portal Embrapa; Embrapa Solos: Rio de Janeiro, Brazil, 2003.

30. IBGE Instituto Brasileiro de Geografia e Estatística Mapa de Vegetação do Brasil. Available online: https://geoftp.ibge.gov.br/informacoes_ambientais/vegetacao/mapas/brasil/vegetacao.pdf (accessed on 20 August 2021).

31. IBGE Instituto Brasileiro de Geografia e Estatística Mapa de Solos do Brasil. Available online: https://geoftp.ibge.gov.br/informacoes_ambientais/pedologia/mapas/brasil/solos.pdf (accessed on 20 August 2021).

32. Campos, P.C.O. Avaliação do Efeito da Variação da Umidade no Comportamento Mecanístico de um Trecho da Estrada de Ferro Carajás; Instituto Militar de Engenharia: Rio de Janeiro, Brazil, 2019.

33. Campos, P.C.D.O.; Silva, B.-H.D.A.E.; Marques, M.E.S. Caracterização geotécnica dos solos de subleito ferroviário: Investigação de campo e laboratorial. Rev. Ibero-Am. Ciências Ambient. 2019, 10, 178–193. [CrossRef]

34. CPRM—Companhia de Pesquisa Recursos Minerais Bacia do Rio Muriaé. Available online: https://www.cprm.gov.br/sace/index_bacias_monitoradas.php?getbacia=bmuriae# (accessed on 24 April 2020).

35. CEIVAP—Comité de Integração da Bacia Hidrográfica do Rio Paraíba do Sul Plano de recursos hídricos da Bacia Paraíba do Sul—Resumo. Available online: https://www.ceivap.org.br/downloads/cadernos/Caderno6-Muriae.pdf (accessed on 24 November 2021).

36. Campos, P.C.D.O.; Paz, T.D.S.R.; Lenz, L.; Qiu, Y.; Alves, C.N.; Simoni, A.P.R.; Amorim, J.C.C.; Lima, G.B.A.; Rangel, M.P.; Paz, I. Multi-Criteria Decision Method for Sustainable Watercourse Management in Urban Areas. Sustainability 2020, 12, 6493. [CrossRef]

37. Campos, P.C.D.O.; Paz, I. Spatial Diagnosis of Rain Gauges’ Distribution and Flood Impacts: Case Study in Itaperuna, Rio de Janeiro—Brazil. Water 2020, 12, 1120. [CrossRef]

38. Jain, A.K. Data clustering: 50 years beyond K-means. Pattern Recognit. Lett. 2010, 31, 651–666. [CrossRef]

39. Steinhaus, H. Sur la division des corps matériels en parties. Bull. L’academie Pol. des Sci. 1956, IV, 801–804.

40. Ball, G.H.; Hall, D.J. ISODATA, a Novel Method of Data Analysis and Pattern Classification; Stanford Research Institute: Stanford, CA, USA, 1965.

41. Forgy, E. Cluster Analysis of Multivariate Data: Efficiency versus Interpretability of Classifications. Biometrics 1965, 21, 768–780.

42. Dempster, A.P.; Laird, N.M.; Rubin, D.B. Maximum Likelihood from Incomplete Data Via the EM Algorithm. Biometrics 1977, 39, 1–22. [CrossRef]

43. Ari, C.; Aksoy, S. Unsupervised classification of remotely sensed images using Gaussian mixture models and particle swarm optimization. In Proceedings of the 2010 IEEE International Geoscience and Remote Sensing Symposium, Honolulu, HI, USA, 25–30 July 2010; pp. 1859–1862.

44. Mather, P.; Tso, B. Classification Methods for Remotely Sensed Data, 2nd ed.; CRC Press: Boca Raton, FL, USA, 2009; ISBN 9780429192029.

45. Vapnik, V. The Nature of Statistical Learning Theory, 2nd ed.; Springer Science & Business Media: New York, NY, USA, 1999.

46. Cortes, C.; Vapnik, V. Support-vector networks. Mach. Learn. 1995, 20, 273–297. [CrossRef]

47. Zhao, B.; Zhong, Y.; Zhang, L.; Huang, B. The Fisher Kernel Coding Framework for High Spatial Resolution Scene Classification. Remote Sens. 2016, 8, 157. [CrossRef]

48. Fisher, J.R.B.; Acosta, E.A.; Dennedy-Frank, P.J.; Kroeger, T.; Boucher, T.M. Impact of satellite imagery spatial resolution on land use classification accuracy and modeled water quality. Remote Sens. Ecol. Conserv. 2018, 4, 137–149. [CrossRef]

49. Khan, U.; Minallah, N.; Junaid, A.; Gul, K.; Ahmad, N. Parallelized and Mahalanobis Distance based Classification for forestry identification in Pakistan. In Proceedings of the 2015 International Conference on Emerging Technologies (ICET), Peshawar, Pakistan, 19–20 December 2015; pp. 1–6.

50. Raiyani, K.; Gonçalves, T.; Rato, L.; Barão, M. Mahalanobis distance based accuracy prediction models for Sentinel-2 Image Scene Classification. Int. J. Remote Sens. 2020, 1–26. [CrossRef]

51. Ma, L.; Li, M.; Ma, X.; Cheng, L.; Du, P.; Liu, Y. A review of supervised object-based land-cover image classification. ISPRS J. Photogramm. Remote Sens. 2017, 130, 277–293. [CrossRef]

52. Blaschke, T. Object based image analysis for remote sensing. ISPRS J. Photogramm. Remote Sens. 2010, 65, 2–16. [CrossRef]

53. Instituto Nacional de Pesquisas Espaciais Catálogo de Imagens. Available online: http://www.dgi.inpe.br/CDSR/ (accessed on 11 May 2021).

54. Solôrzano, J.V.; Mas, J.F.; Gao, Y.; Gallardo-Cruz, J.A. Land Use Land Cover Classification with U-Net: Advantages of Combining Sentinel-1 and Sentinel-2 Imagery. Remote Sens. 2021, 13, 3600. [CrossRef]

55. Damte, W.; Kim, D.; Im, S. Spatiotemporal Analysis of Land Cover Changes in the Chemoga Basin, Ethiopia, Using Landsat and Google Earth Images. Sustainability 2020, 12, 3607. [CrossRef]

56. Liu, C.; Li, W.; Zhu, G.; Zhou, H.; Yan, H.; Xue, P. Land Use/Land Cover Changes and Their Driving Factors in the Northeastern Tibetan Plateau Based on Geographical Detectors and Google Earth Engine: A Case Study in Gannan Prefecture. Remote Sens. 2020, 12, 3139. [CrossRef]
57. Lal, R. Soil Carbon Sequestration Impacts on Global Climate Change and Food Security. *Science* **2004**, *304*, 1623–1627. [CrossRef] [PubMed]

58. Kotchen, M. *Which Social Cost of Carbon? A Theoretical Perspective*; National Bureau of Economic Research: Cambridge, MA, USA, 2016.

59. Energy Research Company Carbon Pricing: Risks and Opportunities for Brazil. Available online: https://www.epe.gov.br/sites-pt/publicacoes-dados-abertos/publicacoes/PublicacoesArquivos/publicacao-549/NT%20EPE-DEA-GAB-014-2020-20-%20Pre%20C_final_05012021.pdf (accessed on 20 August 2021).

60. Borges, E.C.; Paz, I.; Leite Neto, A.D.; Willinger, B.; Ichiba, A.; Gires, A.; Campos, P.C.D.O.; Monier, L.; Cardinal, H.; Amorim, J.C.C., et al. Evaluation of the spatial variability of ecosystem services and natural capital: The urban land cover change impacts on carbon stocks. *Int. J. Sustain. Dev. World Ecol.* **2021**, *28*, 339–349. [CrossRef]

61. Torres, C.M.M.E.; Jacovine, L.A.G.; Soares, C.P.B.; Oliveira Neto, S.N.; Santos, R.D.; Castro Neto, F. Quantificação de biomassa e estocagem de carbono em uma floresta estacional semidecidual, no Parque Tecnológico de Viçosa, MG. *Rev. Árvore* **2013**, *37*, 647–655. [CrossRef]

62. Baldotto, M.A.; Vieira, E.M.; Souza, D.D.O.; Baldotto, L.E.B. Estoque e frações de carbono orgânico e fertilidade de solo sob floresta, agricultura e pecuária. *Rev. Ceres* **2015**, *62*, 301–309. [CrossRef]

63. Pouyat, R.V.; Yesilonis, I.D.; Nowak, D.J. Carbon Storage by Urban Soils in the United States. *J. Environ. Qual.* **2006**, *35*, 1566–1575. [CrossRef]

64. Adhikari, S.; Lal, R.; Sahu, B.C. Carbon sequestration in the bottom sediments of aquaculture ponds of Orissa, India. *Ecol. Eng.* **2012**, *47*, 198–202. [CrossRef]

65. U.S. Bureau of Labor Statistics CPI Inflation Calculator. Available online: https://www.bls.gov/data/inflation_calculator.htm (accessed on 25 August 2021).

66. Paz, T.D.S.R.; da Rocha Junior, V.G.; de Oliveira Campos, P.C.; Paz, I.; Caiado, R.G.G.; de Aragão Rocha, A.; Lima, G.B.A. Hybrid method to guide sustainable initiatives in higher education: A critical analysis of Brazilian municipalities. *Int. J. Sustain. High. Educ.* **2022**, [CrossRef]

67. Galán-Valdivieso, F.; Sarraite-Sariene, L.; Alonso-Cañadas, J.; Caba-Pérez, M. Do Corporate Carbon Policies Enhance Legitimacy? A Social Media Perspective. *Sustainability* **2019**, *11*, 1161. [CrossRef]

68. Nikologianni, A.; Moore, K.; Larkham, P. Making Sustainable Regional Design Strategies Successful. *Sustainability* **2019**, *11*, 1024. [CrossRef]