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Chapter

Estimating Aboveground Biomass Loss from Deforestation in the Savanna and Semi-arid Biomes of Brazil between 2007 and 2017

Eduarda Martiniano de Oliveira Silveira, Marcela Castro Nunes Santos Terra, Fausto Weimar Acerbi-Júnior and José Roberto Soares Scolforo

Abstract

Brazilian Savannas and Semi-arid woodlands biomes exhibit high levels of aboveground biomass (AGB) associated with high rates of deforestation. The state of Minas Gerais (MG), southeast of Brazil, encompasses landscape variations ranging from Savanna and Atlantic Forest to Semiarid woodlands. The understanding of land-cover changes in these biomes is limited due to the fact that most of the efforts for estimating forest cover changes has been focused on the tropical rain forests. Hence, the question is: What is the total amount of AGB loss across Savanna and Semi-arid woodland biomes in MG state, during the period 2007–2017? We first used a total of 1914 field plots from a forest inventory to model the AGB using a combination of remote sensing and spatio-environmental predictor variables to produce a spatial-explicit AGB map. Second, from a global map of forest cover change (GFC), we obtained deforestation patches. As a result, from 2007 to 2017, the Savanna and the Semiarid woodland biomes lost together 508,042 ha of native vegetation in MG state, leading to 21,182,150 Mg of AGB loss (4.65% of total AGB). In Savannas and Semi-arid woodland biomes in MG state, conservation initiatives must be implemented to increase the forests protection and expand AGB.

Keywords: aboveground biomass, land-cover changes, remote sensing, spatial analysis

1. Introduction

The high levels of biomass found in Brazil's forest biomes associated with land-cover changes, such as deforestation and fires, make Brazil one of the five biggest carbon dioxide-emitting nations globally [1]. Brazil has a total area of about 8,514,877 km², from which 7% occurs in Minas Gerais (MG) state, southeast region (586,528 km²). This large area encompasses landscape variations and vegetation types ranging from Savanna and Atlantic Forest to Semi-arid woodland (**Figure 1**) [2]. The current

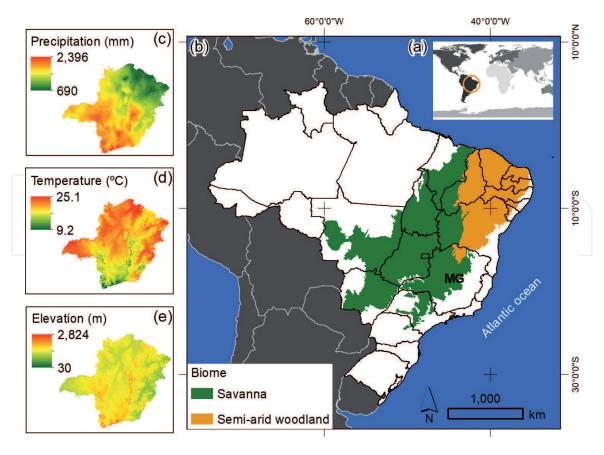


Figure 1.

(a) Geographic location of Brazil; (b) the Savannas and Semi-arid woodland biome in Minas Gerais (MG) state, Brazil; (c) average annual precipitation in MG state; (d) average annual temperature in MG state; and (e) elevation of MG state.

understanding of land-cover changes in the so called "forgotten ecosystems"—Savanna and Semi-arid woodland biomes—is still limited [3, 4] due to most of the efforts for estimating forest cover changes have been focused on the tropical rain forests, with far less attention dedicated to the less humid seasonal region [5].

The Brazilian Savanna (also known as Cerrado) is a heterogeneous biome [6], dominated by grasslands, shrublands, and woodlands [7, 8]. Savannas are mixed tree-grass systems characterized by a discontinuous tree canopy in a continuous grass layer [9]. Tree cover is highly variable such that they range from sparsely "treed" grasslands to heavily "treed" woodlands, often along a gradient of increasing precipitation, but also modified by edaphic factors and fire regimes [10, 11]. Semi-arid woodland (also known as Caatinga) is an ecosystem occupied by seasonally dry tropical forests, which is characterized by leaf deciduousness during the prolonged dry season. Semi-arid woodland biome is located in areas with high temperatures and low amount of rain, being characterized as the region with the greatest meteorological limitations and water-stress in MG [12].

These biomes exhibit high levels of terrestrial carbon stocks and biomass [13, 14], estimated mainly from remotely sensed data [15, 16]. In general, these data are empirically linked to AGB measurements of field plots, ranging from simple linear regression to complex machine learning algorithms (MLA) [17, 18], and regression Kriging technique [19, 20]. Landsat images are the most medium-resolution data commonly used due the longest data record along with a spatial resolution of 30 m. However, Savannas and Semi-arid woodland biomes are the Brazilian biomes that have most suffered human-induced disturbances [5, 21, 22], and are among the most fragmented and threatened ecosystems in the world [23].

The expectations regarding their future are not very optimistic. For instance, based on recent trends in deforestation [24], the Savannas may effectively no longer exist in 25 years' time [25, 26]. Estimates indicate between 39 and 55% of the Brazilian Savannas have already been modified [27]. Tropical dry forests are among the most threatened and overlooked biomes, where conversion to pasture and agriculture are major threats [24].

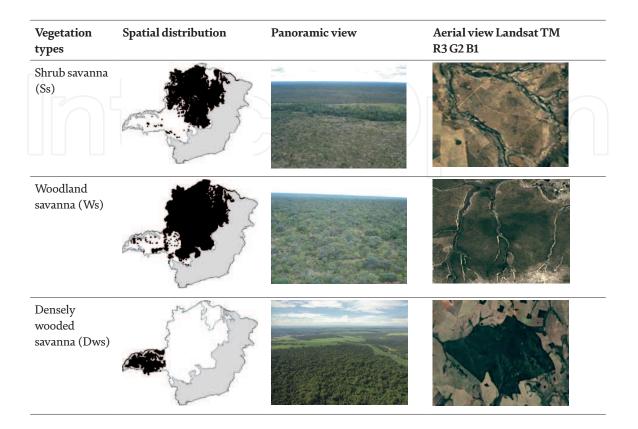
Hence, the question is: What is the total amount of aboveground biomass (AGB) loss across Savanna and Semi-arid woodland biomes in MG state, during 2007–2017?

In order to answer this question, we assessed the reduction of AGB due to deforestation. We produced a spatial-explicit AGB map from forest inventory measures linked with remote sensing and spatio-environmental predictor variables and we also used a reliable global map of forest cover change [28] to measure the AGB loss.

2. Savanna and Semi-arid woodland biomes in MG state

The Minas Gerais (MG) state is located in the southeast Brazil (**Figure 1a**), encompassing the Savanna (57%) and Semi-arid woodland (2%) biomes (**Figure 1b**). The Brazilian Savannas comprise vegetation types of shrub savanna (shrub type of savanna, encompassing both herbaceous vegetation, and scattered small trees), woodland savanna (savanna formation with twisted trees and shrubs up to 8–10 m high and with a grass understory), and densely wooded savanna (forest formation with trees up to a height of 20 m) [7]. Semi-arid woodland represents the vegetation type of deciduous forest. Semideciduous forests are present in both biomes (**Table 1**).

The climate variability of MG state indicates a negative precipitation and a positive temperature gradient from south to north (**Figure 1c, d**). This variability helps to explain the predominance of these biomes. The elevation ranges from 30 to 2824 m and the greatest altitude variation is found in the eastern region (**Figure 1e**).



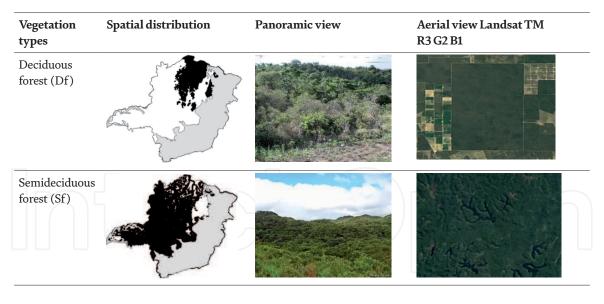


 Table 1.

 Vegetation types comprised on Savannas and Semi-arid woodlands biomes of the Minas Gerais (MG) state.

3. Aboveground biomass modeling

In order to model and map the AGB within Savannas and Semi-arid woodland biomes in MG state, we used a total of 1914 field plots (10 × 100 m), spatially well distributed (**Figure 2**), established from 2006 to 2008 during the implementation of the Project "Forest Inventory of Minas Gerais," conducted by the Federal University of Lavras (UFLA), MG, Brazil. The plots comprised five vegetation types: Shrub savanna—Ss, Woodland savanna—Ws, Densely wooded savanna— Dws, Deciduous forest—Df, and Semideciduous forest—Sf. The trees used to determine the AGB (2060 trees) were all from destructive sampling campaigns, scaled and divided into categories according to diameter and height, proportioned by the relative density of species. The methodology is described in Ref. [29].

The plots presented high AGB variability due to different degrees of anthropization, different site conditions, different successional stages, and presence of trees with different diameters and heights. The descriptive statistics for each vegetation type (**Table 2**) highlight the structural variability among them. High biomass and standard deviation values were observed in semideciduous and deciduous forest. The lowest biomass value in shrub savanna occurs because this vegetation type is characterized by herbaceous vegetation with scattered bushes and small trees. To model the AGB, we used two groups of predictive variables to train the

random forest (RF) [30] regression algorithm:

1. Remote sensing:

- Six reflective spectral bands from Landsat TM: B1 (blue), B2 (green), B3 (red), B4 (NIR), B5 (SWIR 1), and B7 (SWIR 2);
- Three vegetation indices from Landsat TM: Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Vegetation Index Soil-Adjusted (SAVI);
- Seventeen monthly data of six Moderate Resolution Imaging Spectroradiometer (MODIS) product composites: MOD9Q1—Surface reflectance; MOD13Q1—Vegetation index; MOD44B—Vegetation Continuous Cover/Fields; MOD17A2H—Gross primary productivity; MOD15A2H—LAI/ FPAR; and M11A2—Land Surface Temperature and Emissivity.

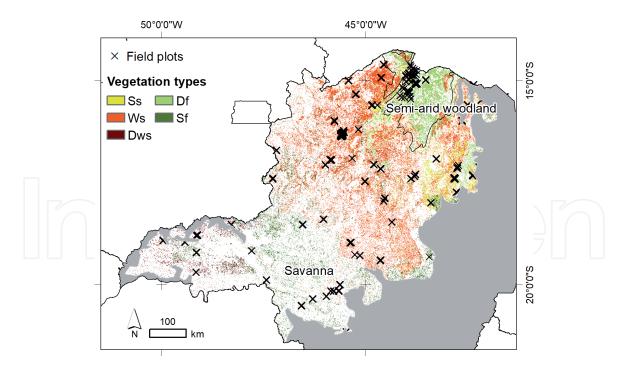


Figure 2.

Plots spatially distributed in Savanna and Semi-arid woodland biomes of MG state. Ss = shrub savanna; Ws = woodland savanna; Dws = densely wooded savanna; Df = deciduous forest; and Sf = semideciduous forest.

Vt	Savanna				Semi-arid woodland			
_	Min	Mean	Max	SD	Min	Mean	Max	SD
Ss	1.08	13.83	49.67	10.72	_	_	_	_
Ws	10.81	57.12	177.97	30.67	_	_	_	_
Dws	10.02	36.10	170.23	22.86	16.59	22.84	33.08	6.15
Df	38.26	119.88	279.41	51.03	10.61	74.68	295.45	55.63
Sf	10.34	97.74	398.16	63.58		_		_

Vt = vegetation types; Min = minimum; Max = maximum and SD = standard deviation; Ss = shrub savanna; Ws = woodland savanna; Dws = densely wooded savanna; Df = deciduous forest; and Sf = semideciduous forest.

Table 2.

Descriptive statistics of the aboveground biomass (AGB, Mg/ha) estimated for each vegetation type.

2. Spatio-environmental data:

- Nineteen climatic variables of 1 km² of spatial resolution from WorldClim dataset [31].
- Digital elevation model (DEM) with 30 m of spatial resolution developed from the Shuttle Radar Topography Mission (SRTM).
- Geographical coordinates (latitude and longitude).

From Landsat TM, we acquired 35 images to cover the study area (one image date by scene completely cloud-free). Four MODIS tiles were necessary to cover MG state, namely, h13v10, h13v11, h14v10, and h14v11. We selected one image per month to explore the temporal resolution of these products.

Vegetation types	Stratified model		
	RMSE (Mg/ha)	MAE (%)	
Shrub savanna (Ss)	7.72	54.73	
Woodland savanna (Ws)	14.53	31.51	
Densely wooded savanna (Dws)	16.47	23.62	
Deciduous forest (Df)	42.76	34.74	
Semideciduous forest (Sf)	51.25	37.84	

Table 3.

Random forest models analysis by root mean squared error (RMSE, in t/ha) and mean absolute error (MAE, in %).

The RF regression algorithm was adopted due to its capability to select and rank important variables for AGB prediction. We adopted a stratified random forest approach based on the five native vegetation types of our study area, so we created five individual RF models. The accuracy of the models was analyzed based on the statistical precision: mean absolute error (MAE, in %) and root mean squared error (RMSE, in Mg/ha) (**Table 3**). Many factors, such as saturation of remotely sensed data, complex forest stand structures, quality and quantity of sample plots, selection of suitable variables, and the modeling algorithms, can affect the accuracy of AGB estimation [15]. In our study, the challenge affecting AGB estimation is related to the complex forest stand structures of tropical forests, which increase the data heterogeneity, impairing the performance of the modeling algorithm.

To derive the AGB maps, we created continuous cells with dimensions of 1 ha (100 × 100 m) covering all vegetated areas in MG state. In each cell containing the selected variables values, we applied the RF regression model to predict the AGB. We thus merged the AGB maps of each individual vegetation type to generate the final AGB map.

The total AGB estimate for Savanna and Semi-arid woodland biome is 363,290,145 and 92,200,203 Mg, respectively, ranging from 3.66 to 214.40 Mg/ha (**Figure 3**). At a broad scale, it has long been recognized that the distributions of these biomes are mainly governed by precipitation and its seasonality [12]. The high values of Savannas and Semi-arid woodland's AGB are concentered in the west and south part of the state, where densely wooded savannas and semideciduous forests are more representative, followed by the north region, where deciduous forests and woodland savannas are predominant. Moreover, these forests have experienced anthropogenic disturbances, such as exploitation of vegetation for charcoal production, cattle grazing, and conversion for agricultural practices, and are also in an advanced degradation stage.

The low AGB values obtained for the middle region of the state occurred due to climatic effects related to a geographical barrier (Espinhaço Range), which generates an unfavorable situation for vegetation growth, and also due to the predominance of shrub savannas. The lower overall humidity and the stronger climate seasonality certainly have a negative impact on plant growth [32]. The edaphic component also plays an important role in vegetation structure. Therefore, despite the presence of "enclaves" of highly fertile soils, where dry forests predominate [33], there is a general trend towards sandier soils, like the Cambisol and Lythollic Neossol. These soils generally have low fertility that, together with the physical characteristics, low precipitation and high temperatures, create conditions that are unfavorable for plant growth.

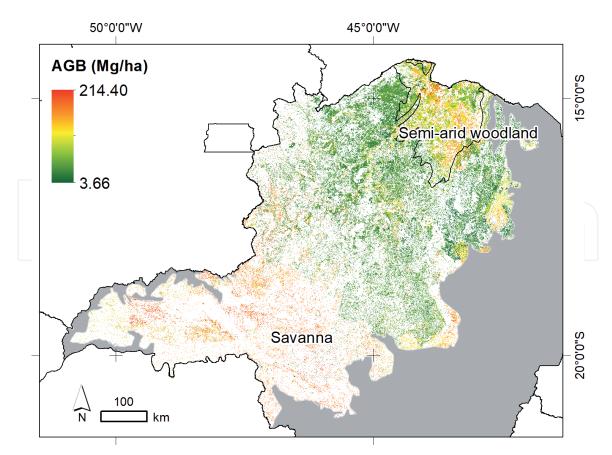


Figure 3.

The spatial distribution of aboveground biomass (AGB) in Savanna and Semiarid woodland biomes in Minas Gerais state.

Similarly, aboveground carbon (AGC) maps were produced by Refs. [13] and [29]. Both mapped the spatial distribution of AGC stocks of the arboreal vegetation in Brazilian biomes of Savanna, Atlantic Forest, and Semi-arid woodland in MG state. They found the lowest weighted average of carbon stock per hectare in the Savanna Biome, particularly in the central, northern, and northwestern regions of MG state.

4. Deforestation analysis

To analyze the deforestation across the Minas Gerais state from 2007 to 2017, we used the Global Forest Change (GFC) map [28]. These authors mapped global annual loss at a spatial resolution of 30 m, based on Landsat time series. Forest loss was defined as a stand-replacement disturbance or the complete removal of tree cover canopy at the Landsat pixel scale. Forest was defined as canopy closure for all vegetation taller than 5 m in height. From these maps, we calculated the deforestation density (N/ha) within Savanna (**Figure 4**) and Semi-arid woodland (**Figure 5**) biomes in MG state, as well as deforestation areas from 2007 to 2017. We masked the deforestation polygons into our five vegetation types (Shrub savanna—Ss, Woodland savanna—Ws, Densely wooded savanna—Dws, Deciduous forest—Df, and Semideciduous forest—Sf).

For the Savanna biome, the spatial analysis showed deforested areas concentrated on the northeast region of the biome, with exception in the year 2008 with high density in the south region. The vegetation loss between 2007 and 2017 was 423,798 ha. From this total, 11.97% of the deforested areas were in 2007, while

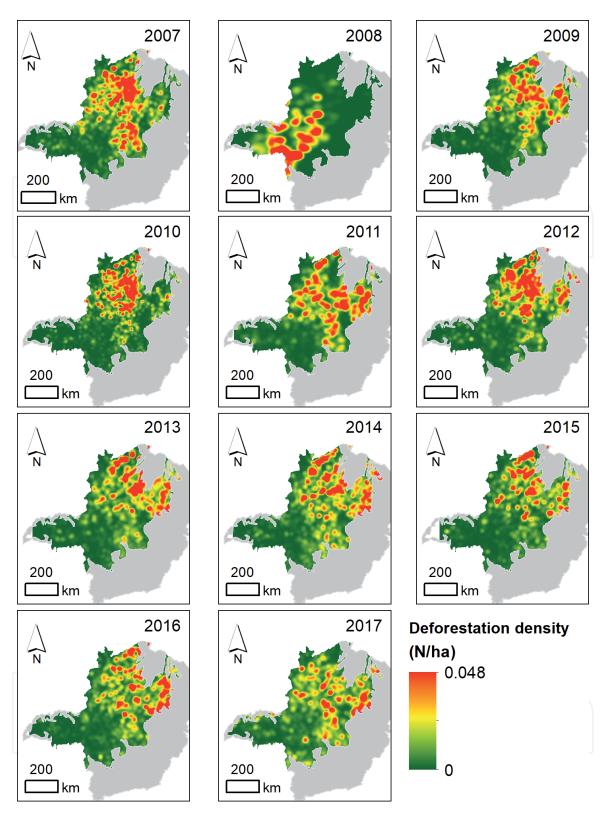


Figure 4.

Annual deforestation density (N/ha) across Savanna biome in MG state from 2007 to 2017.

3.76% was in 2011. Analyzing the Semi-arid woodland biome, the spatial analysis did not indicate a clear pattern, with deforestations areas scattered along the biome. The vegetation loss between 2007 and 2017 was 84,244 ha. From this total, 16.44% of the deforested areas were in 2013, while 3.57% was in 2008.

Overall, from 2007 to 2017, the Savanna and the Semi-arid woodland biomes lost together 508,042 ha of native vegetation (**Figure 6**). We identify a continued loss of natural vegetation types for both biomes during the analyzed period.

Reference [5] provided consistent information on historical and recent vegetation cover changes in the Brazilian Savannas and Semi-arid woodland biomes from

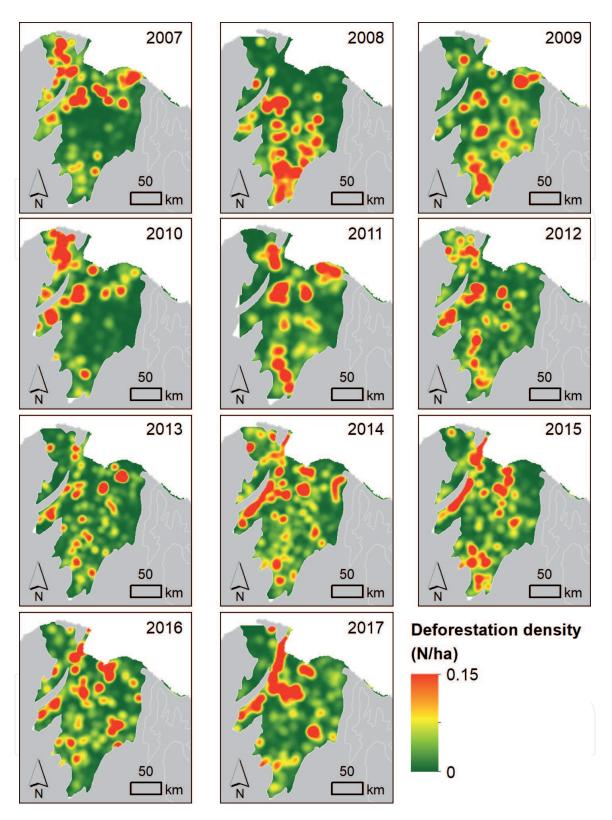


Figure 5. Annual deforestation density (N/ha) across Semi-arid woodland biome in MG state from 2007 to 2017.

1990 to 2010, based on the analysis of Landsat imagery acquired over a systematic sample of 10 × 10 km size units. Although their analysis was not "wall to wall," their study covered the whole area of these biomes in Brazil. They estimated that the Savanna lost approximately 11,787,000 ha of tree cover between 1990 and 2010. For the Semi-arid woodland biomes, their results showed that the tree cover loss was 2,533,500 ha. For Savannas, the annual rates of change were -0.79 from 1990 to 2010, -0.44 from 2000 to 2010, and -0.61 from 1990 to 2010. Considering the Semi-arid woodland biome, the annual rates of change for 1990–2000, 2000–2010 and 1990–2010 were -0.19, -0.44, and -0.32, respectively

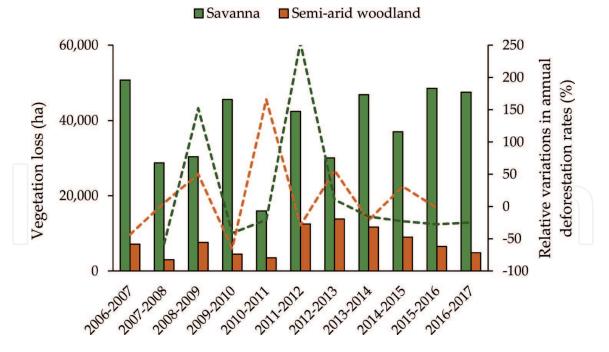


Figure 6.

Annual deforestation area (ha) and relative variations in annual deforestation rates (%) across Savannas and Semi-arid woodland biome in MG state from 2007 to 2017.

Annual rates of change	Savanna	Semi-arid woodland
2006–2007	_	_
2007–2008	-43.33	-58.08
2008–2009	5.64	152.33
2009–2010	50.19	-41.21
2010–2011	-65.02	-20.65
2011–2012	165.75	253.73
2012–2013	-29.06	10.68
2013–2014	55.83	-15.62
2014–2015	-21.00	-22.99
2015–2016	31.13	-27.43
2016–2017	-2.09	-25.03
Average	14.80	20.57

Table 4.

Relative variations (%) in annual rates of natural vegetation loss.

According to their results, the average annual rate of change is higher in the Savanna than in the Semi-arid woodland biome. On the contrary, our analysis showed contrasted results, where Semi-arid woodland biome presented higher annual rate of change than the Savanna biome (**Table 4**). The discrepancies can be explained by the different land-cover maps used as basis for analysis, the area of analysis (Brazil versus Minas Gerais state), and the analyzed period. Another important point is that GFC only include vegetation taller than 5 m in height in their analysis, thus not always capturing deforestation under shrub savannas vegetation types.

According to the results obtained from the GFC, the tropical dry forests of South America had the highest rate of tropical forest loss due to deforestation dynamics in Argentina (Chaco woodlands), Paraguai, and Bolivia. Brazil presented the largest

decline in annual forest loss, with a high of over 40,000 km²/year in 2003 to 2004 and a low of under 10,000 km²/year from 2000 through 2003 and a high of over 20,000 km²/year in 2011 to 2012 [28]. Although the decline of Brazilian deforestation is well documented, recent studies are reporting high deforestation rates. For example, between 2001 and 2012, according to the GFC data set, more than 8,300,000 ha of forest were lost in Mato Grosso, a Brazilian state inserted in the Amazon biome [34].

In the period from 2000 to 2015, tropical dry forests in the north of MG state undergone a considerable change in land cover, expressed as 982,000 ha [35]. From 2002 to 2008, the GFC data estimated 2,000,000 ha of forests were lost per year in the Amazon biome. From 2006 to 2008 rates then felt to 1,000,000 ha. Significant deforestation occurred in 2010 and 2012, when loss rates increased to approximately 1,500,000 ha per year [36]. Ref. [37] analyzed forest loss patterns across Amazon biome over a 14-year period (2001–2014). Their results showed that Amazonian forest losses are moving away from the southern Brazilian Amazon to Peru and Bolivia and the number of deforestation patches less than 1 ha increased over time. This last result presents a significant challenge on remote sensing change detection, highlighting the use of high resolution images to capture small scale deforestation.

5. Estimating aboveground biomass loss from deforestation

The deforestation across Savanna biome in MG state (423,798 ha) generated an AGB loss of 16,549,138 Mg from year 2007 to 2017 (**Figure 7**). This amount represents about 4.56% of the total AGB in 2007 (363,290,145 Mg). The higher AGB loss occurred in the year 2017 (2,231,755 Mg), followed by the year 2007 (2,050,366 Mg). The lower AGB loss occurred in the year 2011 (586,282 Mg). The high rates of deforestation were found during 2007, 2016, and 2017, indicating that along 10 years, Brazil is not avoiding deforestation across Savannas biome in MG state, with a decrease from 2007 to 2011 and an increase from 2011 to 2017. Compared to other Brazilian states and even to studies in Savannas and Semi-arid woodland in MG state, our deforestation rates are underestimated. This fact is because we analyzed deforestation patches within our five vegetation types, not considering all vegetation

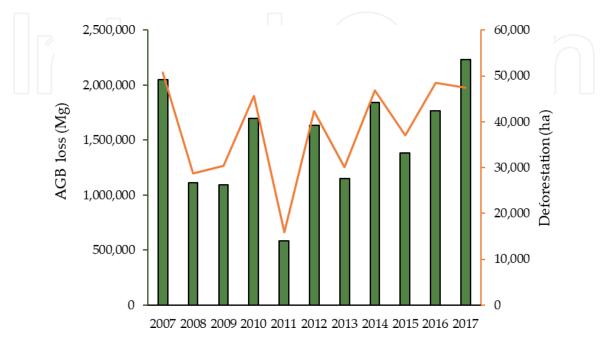


Figure 7. Savanna's aboveground biomass loss (AGB/Mg) and deforested areas from 2007 to 2017.

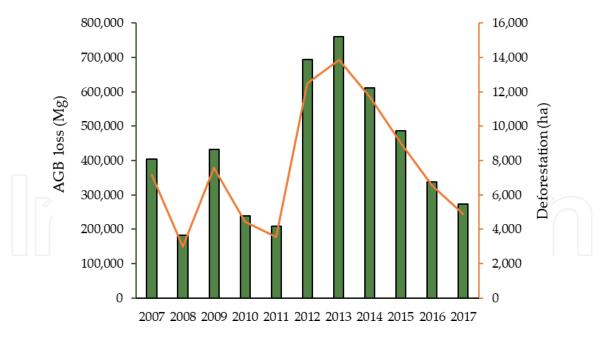


Figure 8.

Semiarid woodland's aboveground biomass loss (AGB/Mg) and deforested areas from 2007 to 2017.

types which occur in MG state. Another point is the problems associated with the use of the GFC map. This product does not capture herbaceous plant, may leading to an underestimate of deforestation into shrub savannas.

The deforestation across Semi-arid woodland biome in the MG state (84,244 ha) generated an AGB loss of 4,633,011 Mg from year 2007 to 2017 (**Figure 8**). This amount represents about 5.02% of the total AGB in 2007 (92,200,203 Mg). The higher AGB loss occurred in the year 2013 (761,271 Mg), followed by the year 2012 (694,546 Mg). The lower AGB loss occurred in the years 2008 (183,203 Mg), 2010 (238,628 Mg), and 2011 (209,485 Mg). These results indicate an increase in deforestation from years 2012 and 2013 and a decrease towards 2017.

In summary, the total AGB loss from 2007 to 2017 of Savannas and Semiarid woodland biomes in MG state was 21,182,150 Mg (4.65% of total AGB) due to 508,042 ha of deforestation. The remaining AGB of Savanna and Semi-arid woodland biomes is 346,741,007 Mg and 87,567,192 Mg, totaling 434,308,198 Mg.

The absolute values of AGB loss are expressive. The implications of such AGB loss are vast. Biomass loss usually leads to impacts on carbon and nutrients cycles [38, 39] and possibly on regional and global climate [40]. Biomass density (the quantity of biomass per unit area—Mg dry weight per ha) determines the amount of carbon emitted to the atmosphere (such as CO₂, CO, and CH₄ through burning and decay) when ecosystems are disturbed. Although biomass density over biomes may change little over time, the biomass density of individual stands and plots is continuously changing and the sum of these changes is largely responsible for the net sources and sinks of terrestrial carbon [39].

Furthermore, biomass loss is intrinsically linked with biodiversity loss. Both biomass and biodiversity are important drivers of ecosystem functions and services and may represent key elements in climate change mitigation. The potential for forest regeneration in these areas is often limited by continuous disturbances and climate change effects [41] worsening this issue. Previous studies have suggested a positive relationship between forest productivity and biodiversity at global scales [42], as well as at the regional level in tropical biomes [43]. Biodiversity is needed for maintaining primary productivity and nutrient uptake and can also improve water quality by removing nitrates through niche partitioning [44].

6. Conclusion

We analyzed the aboveground biomass loss from deforestation in the Savanna and Semi-arid biomes of Brazil between 2007 and 2017. In summary, from 2007 to 2017, the Savanna and the Semi-arid woodland biomes lost together 508,042 ha of native vegetation, leading to 21,182,150 Mg of AGB loss (4.65% of total AGB). The remaining AGB in 2017 is 434,308,198 Mg.

Our study provides a contribution to the knowledge of the deforestation impact on aboveground biomass on Brazilian Savanna and Semi-arid woodland biomes. Our results indicate that land-cover changes continue to reduce the AGB/carbon storage of the Savanna and Semi-arid woodland biomes in MG state. Due to the expressive absolute values of AGB loss, conservation initiatives in Savannas, and Semi-arid woodland biomes in MG state, such as law protection, creation of new protected areas (parks), payments for ecosystem services must be implemented to increase the forests protection and expand AGB.

As major challenge, we highlight the problems associated with the use of the global forest cover map to realize deforestation analysis under Savannas and Semiarid woodland biomes. This product does not distinguish forests from plantations and even herbaceous plant, leading to an underestimate of deforestation patches. In this sense, a more accurate global forest cover map would significantly improve our estimates.

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Conflict of interest

No potential conflict of interest.



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