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Conversion from Forest to Agriculture in the Brazilian Amazon from 1985 to 2021

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Abstract: Land-use and land-cover (LULC) changes in the Amazon biome are key processes that influence the environment and societies at local, national, and global scales. Numerous studies have already relied on land-cover and land-use maps to analyze change processes. This study presents a new dataset created by calculating the time required for deforested areas to transition to agriculture (annual and permanent crops) in the Brazilian Amazon biome. The calculations were performed over MapBiomas land-cover data (version 7), which range from 1985 to 2021, at a spatial resolution of 30 m. The method consists of basic algebraic operation and recursion to identify every conversion from forest to agriculture between 1985 and 2021. The results show a correlation between environmental policies and the time required for the conversion to be completed, such as the adoption of the soy moratorium and the New Forest Code, that were followed by a search for old cleared areas for the establishment of new agricultural sites. The new data can be useful in interdisciplinary studies focused on land-use and land-cover change analysis in Brazil, such as planning of forest restoration initiatives, and the evaluation of carbon stocks according to conversion length. Our accuracy assessment shows an opportunity to improve conversion length calculations by reducing errors in the classification of agriculture establishment. The major innovation of this study is the establishment of explicit links between the deforestation year of a given pixel and its respective year of agriculture establishment, which can provide new insights into understanding long-term land-use conversion processes in tropical ecosystems.

Keywords: amazon; agriculture expansion; deforestation; land cover change

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1. Introduction

Brazilian policies since the 1960s were focused on the expansion of the agricultural frontier in the Amazon, especially focused on fostering the economic growth and national security of the territory [1–3]. Such a development model led to the construction of thousands of kilometers of roads, and the establishment of large-scale crop and livestock farms [1–3]. This period was marked by high rates of deforestation of mature forests [4]. At the same time, cattle and soybean production started to move from Southern Brazil into the Midwest and Northern parts of the country [5], in which soybean cultivation areas followed cattle expansion (i.e., pastureland expansion) over the Amazon forest [6–8]. The pattern of extensive livestock production after deforestation, followed by the establishment of annual crops after a given period, is typical of the Amazon biome [7], and persists at present. This process can take several decades to be accomplished, but sometimes it takes less than a year. In this last case, the land change process can be considered as a direct conversion [9] (i.e., from forest to agriculture).

Land-use and land-cover (LULC) changes are known to cause impacts on different scales. Deforestation and LULC changes can affect hydrological processes in large basins [10] and reduce the forest's resilience to extreme events (e.g., drought) and other sources of perturbation [11]; deforestation and farming practices can reduce convective rainfall and increase surface temperature [12], increase carbon emissions [13], have an important impact on fauna and flora diversity, soil properties, and carbon stocks [14,15], and even negatively impact public health [16].

Data on LULC classification have been evolving rapidly in the past decade. Initiatives such as MapBiomas [17], launched in 2015, provide high-resolution annual classifications for the Brazilian territory. Such types of data are essential to analyze LULC change processes [18], make causal inferences [19–22], and understand what drives and what are the impacts of the transformation of the landscape in Brazil [14]. In this context, this study aims to quantify and characterize the length (time span) of the conversions from forest formations to agriculture in the Amazon over the past 36 years.

The calculations of conversion length were performed by algebraic operation and recursion to identify every conversion from forest to agriculture, in the Amazon biome, between 1985 and 2021, at a spatial resolution of 30 meters. The final results show the year of deforestation of primary and secondary forests, the year of agriculture establishment on areas previously occupied by forests, and the amount of years for the conversion to be completed.

These data can be useful to the development of interdisciplinary research, since they can provide useful insights into the environmental, economic, and social impacts of land conversion. The conversion length calculations provide an innovative perspective over deforestation and agriculture expansion in the Amazon biome by creating an explicit link between these two processes. These data can provide insights into the planning of forests restoration, the fluctuations of soil carbon stocks, the economic costs and benefits associated with land conversion, the effects of land conversion on local ecosystems, and the impact of land conversion on livelihoods and social dynamics.

2. Methods

2.1. Conversion Length Calculation

The estimations of conversion from forest to agriculture were performed for the Amazon biome (biome limits defined by the Brazilian Institute of Geography and Statistics (IBGE) in 2019). Conversions were calculated using LULC classification data from MapBiomas [17], collection 7, which range from 1985 to 2021, at a spatial resolution of approximately 30 m and a global accuracy of 91.3%. The calculation considers forests as the "Forest Formation" (class code 3) class from MapBiomas, and does not include other types of natural vegetation. The agriculture is composed of eight classes from MapBiomas: "Soybean", "Sugar Cane", "Rice", "Cotton", "Other Temporary Crops", "Coffee", "Citrus", and "Other Perennial Crops" (class code 39, 20, 40, 62, 41, 46, 47, and 48, respectively). The conversion length (time span) was considered to be the number of years between the deforestation and the establishment of agriculture in the same area.

The MapBiomas data were downloaded from the Google Earth Engine platform [23]. The pixels within the Amazon biome were filtered to contain only those that were occupied by forest and agriculture in the period under and that were not considered as water, according to the Global Surface Water product provided by Copernicus [24]. For the download, the data were divided into 2732 tiles to allow the local processing of a large quantity of pixels. Two sets of data were downloaded with the same spatial dimensions, one with the LULC classifications for each year, and another with binary values, indicating whether the pixels were valid for processing or not (according to the filter conditions mentioned above).

The first part of the processing was to create a table (mask_cells) from the binary data, and set a unique identification for each pixel, along with their coordinates, area (square meters), and the respective municipality of each pixel. In this part, an additional metadata table (tiles_metadata) was generated with the spatial information of each tile, so that it was possible to convert the generated tables back to raster format.

The second part of the processing was to load each raster tile separately, convert it to a new table (lulc_table), and calculate every possible conversion from forest to agriculture (Figure 1). The calculation of the conversion length (time span) was simple. It consisted of the year of the agriculture establishment subtracted by the last year classified as forest formation. Then, we added one year to the latter, so that it represented the year of deforestation (since it was more meaningful for analysis). For example, let us consider a conversion where the last forest year was 1986, and then the area was turned to agriculture in 1989. In this case, we would add one year to the last forest year (1986 + 1 = 1987) and then subtract it from the agriculture establishment year (1989), which returns a conversion length of 2 years (Figure 1). More details about the calculation progress are provided in the Supplementary Figure (Figure S1).

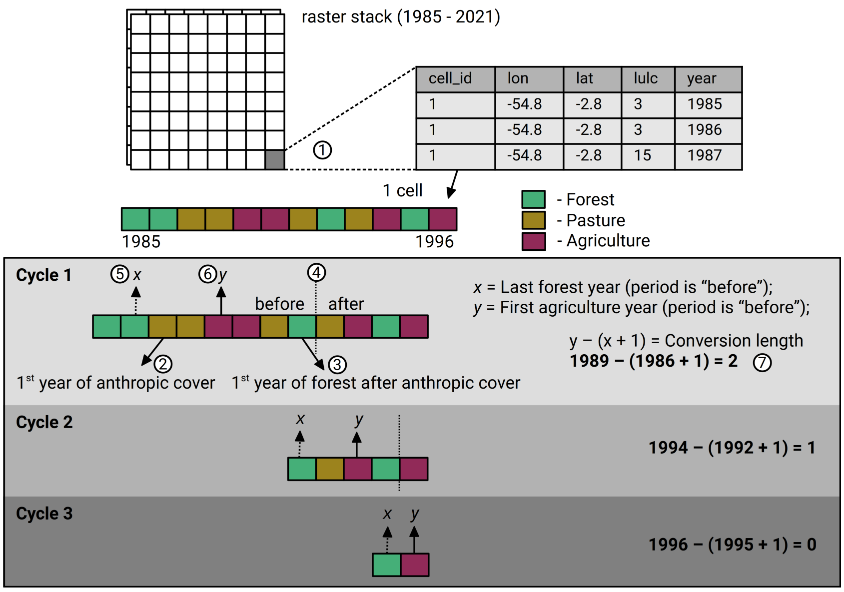

Figure 1. Representation of the process to calculate the conversion length from forests to agriculture. Numbers inside circles represent the step of the process to calculate the conversion length (1 to 7). All values presented are hypothetical and serve only as an illustration of the method.

The process of calculation of the conversion length (Figure 1) can be divided into seven steps of processing:

1. Load raster and extract valid values into a table.
2. Calculate the year of first occurrence of any anthropic class for each pixel.
3. Calculate the first year of "Forest Formation" LULC class after the year calculated in step 2. This step identifies the occurrence of more than one conversion in a given pixel.

4. Classify rows as "before" or "after" the occurrence of the year calculated in step 3. This is the identification of periods before and after a return of forest after a first conversion to agriculture.
5. Calculate the last year of "Forest Formation" within the rows classified as "before", and add 1 year to represent the deforestation year.
6. Calculate the first year of any agriculture type class within the rows classified as "before" for each pixel.
7. Calculate the difference between years from items 5 and 6 to get the LULC conversion length in years for each pixel.

Steps 2 to 7 were performed recursively to identify multiple cycles of conversions (e.g., forest → agriculture → forest → agriculture), in case they were present. In addition to the conversion length values and the years of the conversion, they were also qualified by the agriculture class that was established after deforestation, if the conversion occurred from primary or secondary forests, and the number of cycles of conversions at the pixel. The LULC classes between the deforestation and the agriculture establishment, and 5 years after the conversion, were also stored.

The conversion results were stored in a dataset of tabular files, where data can be queried for further analysis. After the calculations, data were also converted back to raster format, with the aim of expanding the accessibility of the dataset.

2.2. Description of Data Collection

After the calculation of conversions, the results were stored in three different types of tables (Figure 2), organized in a folder structure and stored as Apache Parquet files.

b

cell_id	agri_code	forest_year	agri_year	c_length	f_cycle	forest_type	tile_id	c_cycle
36869	20	1986	1989	3	1	1	1174	1
36870	41	2002	2004	2	2	2	1174	1
36871	39	1987	2017	30	1	1	1174	1

a

cell_id	tile_cell_id	area	code_muni	coords	tile_id
36869	89	875.	5104526	POINT ()	1174
36870	90	875.	5104526	POINT ()	1174
36871	91	875.	5104526	POINT ()	1174

c

cell_id	year	class_code	tile_id	c_cycle
36869	1987	15	1174	1
36869	1988	15	1174	1
36869	1989	20	1174	1

Figure 2. Representation of the tables generated by the conversion length calculation. Table **a** stores spatial information of the data, table **b** stores convertion length values and table **c** contains the classes observed between the conversion period. All values presented are hypothetical and serve only as an illustration of the method.

The first type of table (Figure 2a) contains the spatial information (longitude, latitude, and area) of each pixel, its unique identification, and the code of the municipality which contains the pixel. The "cell_id" column contains a unique identification for the whole data, while the "tile_cell_id" holds a unique value of each pixel for a single tile. Each tile is also uniquely identified in the column "tile_id". This table is named "mask_cells".

A second type of table (Figure 2b) stores conversion length values, the first and last year of the conversion, the resulting agriculture type, and the number of the conversion cycle. It also contains the unique id of each pixel and tile (same as the table above). The "agri_code" column holds information about the type of agriculture that was established after deforestation. The "forest_year" column has values that represent the year of deforestation, "agri_year" is the year when the agriculture establishment happened, and the subtraction of the former from the latter (the conversion length) is stored in the "c_length" column. Since it is possible that one pixel contains more than one conversion from forest to agriculture, we store the number of the conversion in the column "c_cycle" (1 is the first conversion cycle). However, conversion from forest to other LULC is also possible, so the column "f_cycle" holds information about the number of the conversion from forest to any LULC except agriculture. If the forest has suffered any conversion, it starts being considered as a secondary forest, as indicated in the column "forest_type". This table is named "c_length".

The third type of table (Figure 2c) contains the LULC classes of all years between the deforestation and the agriculture establishment, and also the first 5 years after the conversion. The column "year" holds the year of the MapBiomas classification, and the "class_code" variable stores the LULC classification (according to MapBiomas) for the respective year. This table is named "c_classes".

The three tables are related to each other and can be used altogether, and are separated by tiles. Another table containing the metadata of each tile is also created, and holds the spatial characteristics of the tiles. With this spatial information, it is possible to convert the tabular data back to a spatial raster, with identical spatial properties as the original MapBiomas classification data.

The tabular data were organized in a system of folders and sub-folders in a hive format partitioning (Figure 3). This structure allows us to easily access parts of the dataset and also to filter it without the necessity to read the tables. In the case of this dataset, it was partitioned by the "tile_id" and "agri_cycle" variables. This dataset also has a metadata file with the spatial characteristics of each file, which stores the identification of the tile, the maximum and minimum latitude and longitude, the coordinate reference system, and the number of columns, rows, and cells of each tile.

Figure 3. Representation of the dataset, structured in folders and sub-folders.

2.3. Accuracy Assessment

Accuracy assessment was performed by visual inspection of annual composites of Landsat images from MapBiomas. We selected 100 random points to be analyzed. An area of approximately 4 square kilometers around the sample point was used in the visual inspection of satellite images.

The visual inspection used several variables derived from the Landsat historical collection. The median of Red, Green, Blue, Near-Infrared (NIR), and Short-Wave Infrared (SWIR1) from dry and wet seasons were used, and also the annual amplitude of the Normalized Difference Vegetation Index (NDVI). The process of accuracy assessment was performed in a Shiny app and was conducted without any consultation of the conversion length results. In the validation app, we estimated, by visual inspection, the year of deforestation and the year of agricultural establishment. The observed conversion length was obtained by subtracting one date from the other.

To evaluate the accuracy, we calculated the Mean Absolute Error (MAE), the Bias (BIAS), and the Percent Bias (PBIAS). We also analyzed the results by plotting the errors as frequency bars and scatter plots between observed and estimated values. After the completion of the analysis of the 100 sample points, we also conducted a qualitative assessment, where we compared our results with satellite image composites.

3. Results

The conversion calculations show that in the Brazilian Amazon biome, 64,874 square kilometers of forests were converted to agriculture between 1985 and 2021. The length of the conversions can go from 0 to 35 years (time span), in which conversions closer to 0 years are considered fast conversions, and conversions closer to 35 years are considered slow conversions. Conversions of 0 years are considered "direct" conversions, where there was no presence of pasture before the establishment of agriculture. Our estimations show that around 9.2% of the conversions were "direct".

Our results found pixels that presented up to six conversions (i.e., six cycles) from forest to agriculture since 1985. However, since these cycles were unlikely to happen (they were distributed as sparse pixels and did not show patterns of real conversions, being common at borders), we proceeded with the analysis considering only the first conversions found in each of these pixels (these pixels with multiple conversions represented 0.5% of the total converted areas in our study).

Although we named the year of change from forest to anthropic land uses as deforestation, we acknowledge that it is not a direct measurement of deforestation (such as PRODES); however, it represents a proxy to deforestation.

3.1. Conversion Spatial Patterns

Conversions from forest to agriculture can be found in almost every region in the Amazon, but are mostly concentrated in clusters, specially in the south and east of the biome, in the states of Mato Grosso, Pará, and Maranhão (Figure 4).

Well-defined clusters can be observed in the map created with aggregated conversion length data (Figure 4a). Slow conversion areas tend to concentrate in specific regions of the biome, while fast conversions seem to have a wider distribution, but also tend to form spatial clusters. However, this pattern does not hold completely when observing the data at their original scale (Figure 4b), where areas with different conversion lengths are mixed with each other. When observing at the original scale, we could not identify any well-defined patterns or directions of the occurrence of faster to slower conversions (Figure 4).

Faster conversions were more common than slower ones, as can be observed in the spatial distribution (Figure 4a) and the histogram (Figure 4c). The conversions that occurred in under 5 years represented 38% of the total, while conversions in under 10 years represented 55% (Figure 4c). A higher concentration of fast conversions was observed in the states of Mato Grosso and Pará, in which 58% and 55% of conversions happened in under ten years, respectively. Slower conversions were more present in the states of

Rondônia and Tocantins, where only 12% and 18% of conversions occurred in under 10 years, respectively.

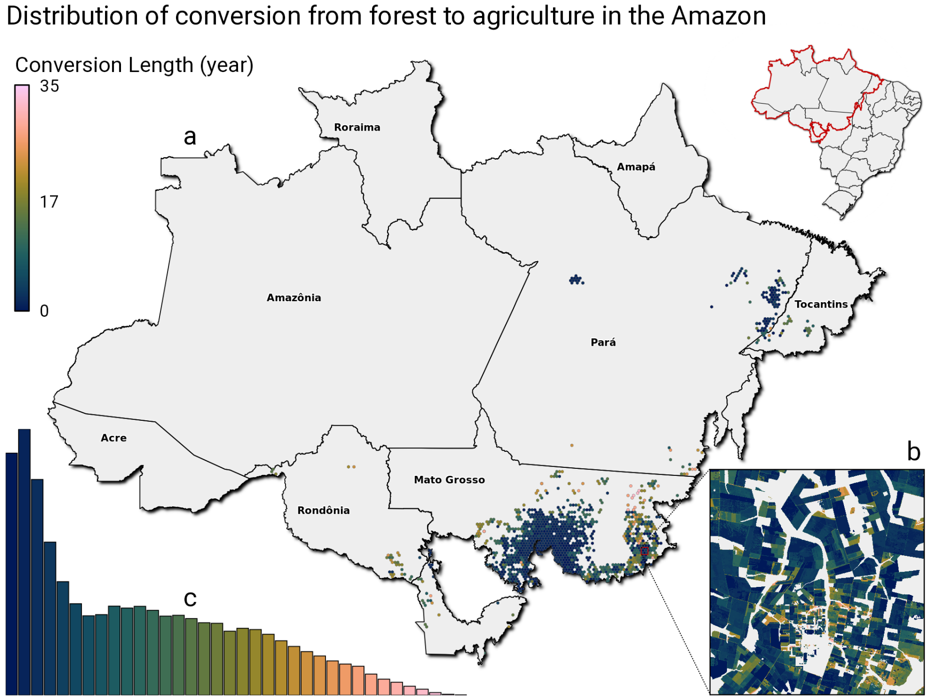

Figure 4. Map of distribution of conversion from forest to agriculture in the Brazilian Amazon biome. (**a**) The hexagonal cells represent the most common conversion length and do not reflect the amount of area of conversions inside a cell. Conversions are concentrated in the south (Mato Grosso state) and the east (Pará and Maranhão states). The conversion length ranges from 0 (dark blue) to 35 years (light pink), and clusters of fast conversions (conversions closer to 0 year) can be distinguished from clusters of slow conversions (conversions closer to 35 years). (**b**) The zoomed map in the bottom right shows the results in finer resolution, where it is possible to observe different conversion lengths between properties. The red square shows the extent of the zoomed map. (**c**) The histogram located in the bottom left shows that fast conversions are more common than slower conversions.

3.2. Conversion Temporal Patterns

The data can be analyzed year by year and they can also be separated by primary and secondary forests being converted to agriculture (Figure 5).

The results of forest conversion show that the deforestation area of primary forests increased largely from 1986 to 2003 (Figure 5a). Areas deforested in this period were mainly followed by pasture, which remained for a long time before being converted to agriculture (Figure 5a). From 1986 to 1995, most deforested areas had a slow conversion to agriculture, mostly longer than 10 years (76%). After this period (1986–1995), fast conversions started to become more common (Figure 5a), especially from 2002 to 2004, where 70% of the conversions occurred in under 10 years. Our results show that in 2003 (the peak of deforestation), 12.7% of the conversions were a direct conversion from forest to agriculture. If we include fast conversions (from 0 to 2 years), the proportion jumps to 48.1% of all conversions in 2003.

After the peak of deforestation in 2003, there was a steep decrease until 2009, when the deforested areas reached a stable rate (Figure 5a). Most of these areas suffered a rapid conversion to agriculture (Figure 5a). It is important to note that during this period, important policies were employed to curb deforestation. In 2004, the Brazilian Government launched the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm). In 2006, the Brazilian Association of Vegetable Oil Industries (BIOVE) and the National Association of Cereal Exporters (ANEC) committed to avoid the commercialization of soybean grains harvested from areas deforested after 2008, known as the soy moratorium.

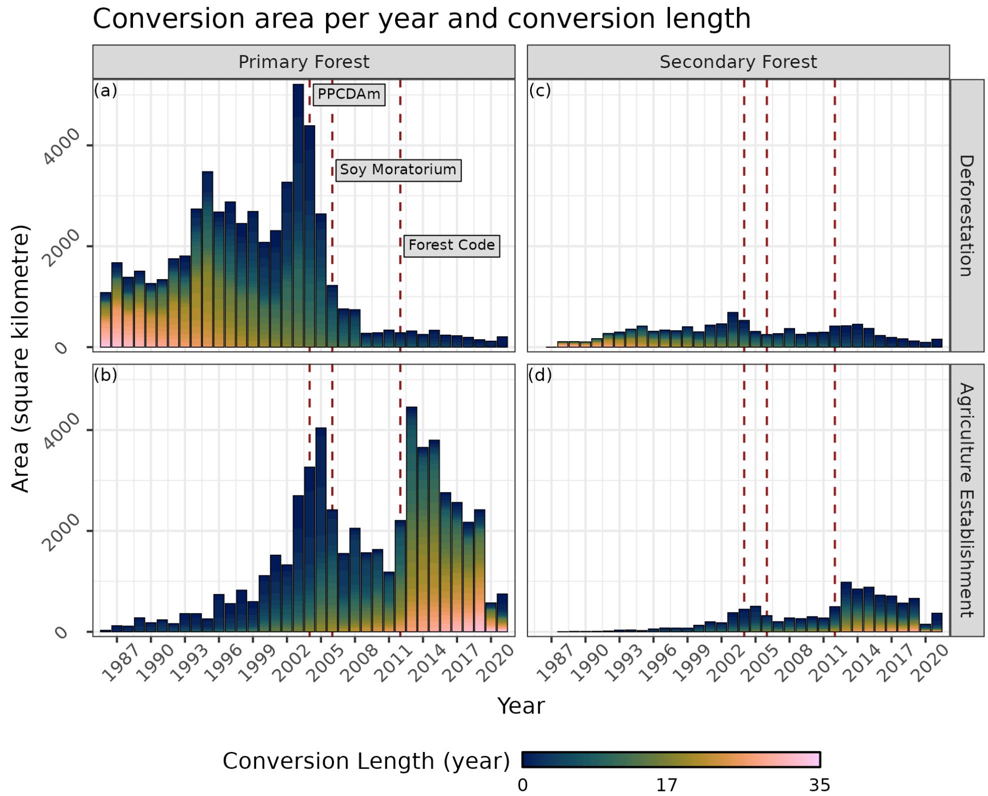

Figure 5. Conversion area from forest to agriculture per year and conversion length. The bars represent the total amount of area at some stage of the conversion for each year. The color gradient in each bar represents the conversion length related to a deforestation or an agriculture establishment event. Blue tones represent fast conversions (closer to 0 years) and pink tones represent slow conversions (closer to 35 years). Conversion events are separated by the deforestation of primary forests (**a**) and secondary forests (**c**), and the subsequent agriculture establishment of primary forests (**b**) and secondary forests (**d**).

The deforestation of secondary forests showed similar temporal patterns in relation to primary forests (Figure 5c), but in a smaller scale. However, in 2012, an increase in the deforestation of secondary forests can be observed (Figure 5c). This is the same year of the approval of the new Forest Code in Brazil.

By analyzing the year of agricultural establishment over areas of primary forests, it is possible to observe different patterns (Figure 5b). Between 1986 and 1996, there was just a small amount of agriculture being established over deforested areas (deforested after 1985). After this period, there was a steep rise in the areas being converted to agriculture (1996–2005), mostly of them being fast conversions (Figure 5b). The peak of 2005 was followed by a steep decline in agriculture establishment over deforested areas, which remained relatively stable until 2012. In 2013, there was a significant rise in conversions, which were mostly slow conversions (Figure 5b). From 2013 to 2019, the new primary forest areas being occupied by agriculture were mainly areas that were cleared before 2008 (Figure 5b), which is the last year of deforestation tolerated by the soy moratorium. After 2019, a sudden drop of agriculture establishment rate occurred (Figure 5b).

Agricultural establishment peaked in 2005 and 2013 (Figure 5b). Despite similar agricultural establishment areas in both years, their conversion lengths differ greatly (Figure 5b). In 2005, most of the conversions occurred in under 10 years (78%), while in

2013, the majority of conversions took more than 10 years (66%). In 2010, a shift in the conversion length from forest until the establishment of agricultural areas was observed. From this year onward, 68% of the conversions happened in areas deforested at least 10 years before (Figure 5b). Even after the decrease in deforestation after 2002, areas under agriculture expanded over lands where deforestation had happened before 2002 (mostly over pastureland).

The expansion of agricultural areas over cleared areas of secondary forests (Figure 5d) showed similar patterns as with primary forests (Figure 5b), but there was a higher occurrence of faster conversions, especially after 2012 (Figure 5d).

Even though it is possible to analyze the results in the Amazon as a whole, the conversion length patterns across years can change significantly between different states (Figure 6).

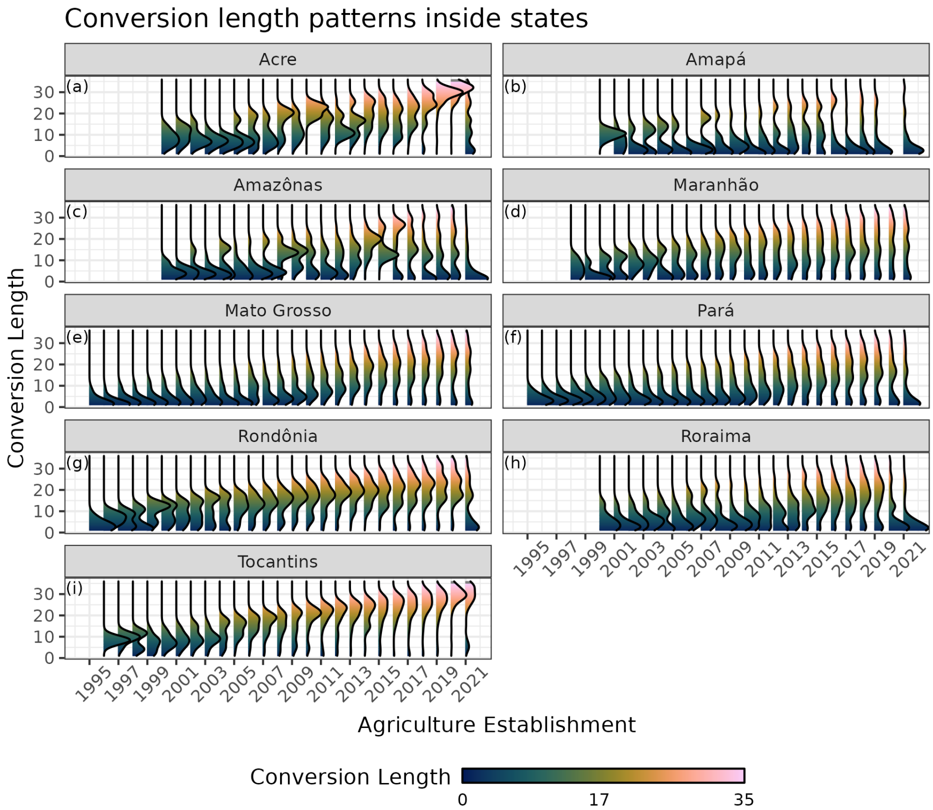

Figure 6. Conversion length patterns inside states in the Amazon biome (**a**–**i**). Each year has a density estimate of the conversion lengths, represented by the colored curves. The peak of the curves represents conversion length values with more frequency in one year of one state. Blue tones represent fast conversions (conversions closer to 0 years) and pink tones represent slow conversions (conversions closer to 35 years).

The state of Amapá presented fast conversions throughout the time series, without any significant period of slow conversion. In contrast, conversions in Acre were majorly slow, and only 2021 showed faster conversions. There are two states where the pattern of conversion length are alike, Mato Grosso (MT) and Pará (PA). Both states underwent fast conversions from 1995 to 2005, and after this period, slow conversions became predominant until the end of the time series. Rondônia (RO) and Tocantins (TO) presented a similar pattern to MT and PA, in which conversions decelerated, but for RO and TO, they did so since the beginning of 2000s, which was earlier than for MA and PA.

The great majority of conversions were from forests to soybean and "Other Temporary Crops", which represented 95% of the conversions in the Amazon biome (14% of soybean and 81% of “Other Temporary Crops”). When analyzing what happened after 5 years following the conversion, the soybean area persistence rate was at 79% (i.e., areas that remained as soybean), 14% was converted to “Other Temporary Crops”, and 7% was converted to pasture. “Other Temporary Crops” were less persistent. Hence, 27% of these areas remained in the same class, 56% were converted to soybean, and 15% to pasture. Conversions from soybean and “Other Temporary Crops” to other LULC classes (apart from the ones already cited) are negligible. Sugar cane, cotton, and perennial crops also appeared, but in a negligible proportion.

3.3. Validation

Of the 100 random sample points used in the validation of the results, 1 point (sample 21) was not considered a conversion in our estimations; however, the visual inspection pointed to a likely event of conversion from forest to agriculture. Also, there were six points (samples 6, 7, 55, 56, 78, and 97) in which the visual inspection did not find a conversion from forest to pasture, although our estimations pointed them out as conversions. Therefore, 7% of the sample points were completely misclassified by our estimates, and the rest of the accuracy assessment was performed over the remaining 93 sample points.

When analyzing the errors from the conversion length estimates, we observed that the year of deforestation showed the smallest number of errors (Figure 7). The MAE of the deforestation year was 1.42 years, and the error showed a bias towards underestimation. The year of the agriculture establishment and the conversion length estimates showed larger errors when compared with visual inspection.

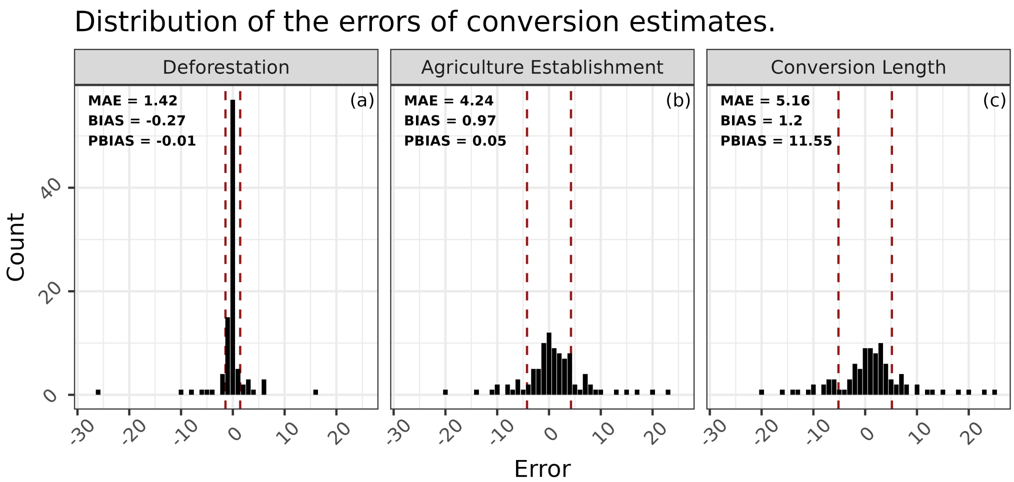

Figure 7. Bars with the count of error values (difference between observed and estimated values) for year of deforestation (**a**), year of agriculture establishment (**b**) and conversion length (**c**). Positive values indicate an underestimation of the variable (estimations were lower than observations) and negative values indicate an overestimation (estimations were higher than observations). Error metrics (Mean Absolute Error, Bias, and Percent Bias) are displayed in the top right position of each box. The red dashed lines represent the MAE values of each variable.

The dispersion of observed and estimated values showed no clear pattern of errors (Figure 8). Deforestation errors (Figure 8a) are smaller in comparison to agriculture establishment erros (Figure 8b). Conversion length values were more concentrated in smaller values, which also showed higher errors (Figure 8c). However, this was expected since faster conversions were more common (Figure 4).

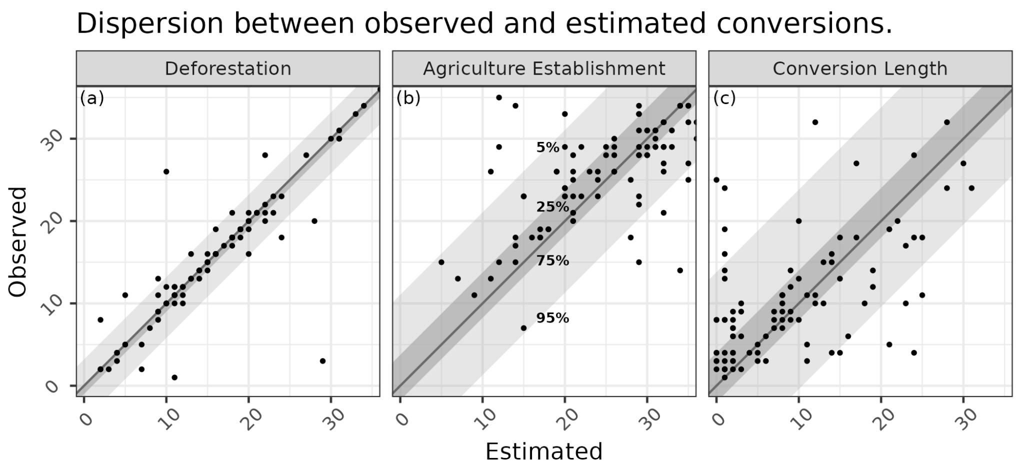

Figure 8. Scatter plot between paired values of estimated and observed deforestation (**a**) and agriculture establishment years (**b**), and their respective conversion lengths (**c**). The gray line represents values where there would be no errors of the estimated values in comparison with the observed values. Translucid gray areas represent the quantile ranges (5%, 25%, 75%, and 95%) of the errors. The area between the 5% and 95% quantile includes 90% of the points. The area between the 25% and 75% quantile includes 50% of the points.

According to accuracy assessment from MapBiomas, collection 7 presents a global accuracy of 96.6% for the Amazon biome, which is the proportion of pixels that are classified correctly. For the Forest class, MapBiomas showed small errors of inclusion (a proportion of pixels were misclassified as other classes, but the real class was Forest), which fluctuated around 1%. The omission errors for Forest were also small (a proportion of pixels were misclassified as Forest, but the real class was not Forest), which fluctuated around 2%. The Agriculture class presented more errors; the inclusion errors ranged from 22% to 5%, and were mostly composed of Forest pixels (Forest pixels misclassified as Agriculture). The omission errors of Agriculture ranged from 22% to 8%, and were also mostly composed of Forest pixels (Agriculture pixels misclassified as Forest).

3.4. Qualitative Assessment

A qualitative assessment of the 100 samples was performed to analyze the results in conjunction with the error calculations and metrics. It allowed the interpretation of results with more context, since the results were compared visually with reference satellite image composites, in an area of 4 square kilometers for each sample.

We found high heterogeneity inside agriculture plots (sample 56), caused by both the year of deforestation and the year of agriculture establishment. This heterogeneity may be caused by smaller uncertainties within properties, where a higher homogeneity of conversion length values would be expected. In a few samples, roads were considered to be agriculture (sample 2), so there was in fact no conversion to agriculture. Other inclusion errors were detected, where areas that clearly showed no agriculture were considered to be conversions (sample 10, 98). There were also omission errors, especially agriculture plots not being considered to be conversions as a whole, where parts of a plot that were clearly a conversion to agriculture were not considered to be one (samples 16, 30, and 75). A significant amount of uncertainty was identified at borders of agricultural areas (samples 25, 56, 84, and 92), which is a very common issue in the classification of satellite imagery, due to the presence of mixed pixels, where different objects share the space of the same pixel [25]. We also observed that areas with sparse forest vegetation presented a large error of deforestation year (sample 33).

We also observed that in many samples, the agricultural areas were generally well represented (sample 25, 43, 56, and 84), the shapes of agricultural plots were clear, and it was possible to distinguish different agricultural areas. Some locations presented a higher homogeneity of conversions inside agriculture plots (sample 84), which may be related to areas with smaller uncertainties.

4. Discussion

4.1. Conversion Patterns

The causes of deforestation and agricultural establishment in the Brazilian Amazon are complex and diverse. Political context, public policies, market prices, and law enforcement can influence how these processes evolve over time. In Brazil, the end of the 1980s and the 1990s were marked by the development of policies for the protection of the environment, with the creation of the National Environmental Policy, the establishment of the Brazilian Institute of Environment and Natural Resources (IBAMA), and the Ministry of Environment [3]. However, this new policy environment was not immediately translated into a significant deforestation decrease in the Amazon, which remained at high levels until the beginning of the 2000s.

Apart from protectionist policies created in the 1990s, development programs kept pressuring forests in the Amazon. In the late 1990s, the development policies "Brasil em Ação" and "Avança Brasil" (1995–2003) accelerated the national infrastructure expansion, which caused a substantial increase in deforestation in the Amazon biome [1,26]. According to our estimates, the period between 1986 and 2004 was characterized by a rise in deforestation, in which most of it would give place to pasture, that would only be converted to agriculture after 2012 (Figure 5a). However, this was a period when there was also a rapid conversion of forests to agriculture, specially from 2003 to 2005 (Figure 5b). Our results show that from 2003 to 2005, 13% of the conversions were direct conversions from forest to agriculture (Figure 5b). Previous studies estimated a proportion of 23% in the Mato Grosso state in 2003 [9], our estimates from MapBiomas show a proportion of 25% of direct conversions for Mato Grosso in the same year (Figure 5b). If we include conversions from 0 to 2 years, the proportion jumps to 55% of all conversions in 2003. These patterns correlate with the development policies that were being adopted in that period.

In 2004, the Brazilian Government launched the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm), which was composed of many initiatives to curb deforestation [27]. The PPCDAm was considered as a successful policy to slow deforestation rates in Brazil, with international recognition. Our calculations from MapBiomas data reinforce the correlation of the PPCDAm with the reduction in deforestation after 2004 [27,28] (Figure 5a) and the reduction in agriculture establishment after 2005 (Figure 5b).

After 2004, other policies were adopted in order to curb deforestation. In 2006, the Brazilian Association of Vegetable Oil Industries (BIOVE) and the National Association of Cereal Exporters (ANEC) committed to avoid the commercialization of soybean grains harvested from areas deforested after 2008, known as the soy moratorium. The soy moratorium is considered to have contributed to the decline in deforestation directly related to soybean expansion [29–32]. The period between 2006 and 2010 is also considered as a turnover point, known as the decoupling of deforestation and soybean production, where the total production (total weight of grains) was not as dependent on agriculture expansion as before [33]. However, the observed increase in soybean establishment after 2012 shows that soybean expansion did not halt after the soy moratorium nor after periods of high soybean productivity. Instead of a halt in expansion, producers started to expand over areas cleared many years previously (70% of the conversions took more than 10 years), which may still have indirect impacts on deforestation increase over distant areas [8,34,35].

There were also policies that are considered to be drivers of increased deforestation, such as the approval of a new Forest Code in 2012, which is considered to have undermined the environmental protection of forests [36,37], since it opened up the possibility of amnesty for illegally deforested areas [38–40], and the possible reduction in legal reserve area [41]. Our results reinforce the affirmation that this policy is related to negative environmental impact. It is possible to observe that after 2012, that was a substantial increase in the establishment of agriculture over areas previously occupied by primary forests (Figure 5b) and secondary forests (Figure 5d), and an increase in the deforestation of secondary forests after the approval of the new Forest Code (Figure 5c).

After 2019, a sudden drop of agriculture establishment rate occurred (Figure 5b). This behavior could be related to economic causes [9,42,43] or even the scarcity of suitable areas for agricultural expansion, which seems unlikely, since the past years have been marked by an increase in deforestation rates and the advance of pastureland over the forest.

Our calculations provide results that reinforce the evidence showing the impact of public policies on deforestation and agriculture expansion in the Amazon. However, our greatest contribution is that by analyzing the length of the conversion from forest to agriculture, it is possible to analyze deforestation and agriculture establishment as an integrated process. This can be useful in providing new information for investigations on the impact of the conversion length on environmental and social dimensions in the Brazilian Amazon.

Conversion length data can be used to define priority areas for restoration initiatives, since areas where agriculture is already established are less prone to forest restoration [44], and given that old pasture areas are being prospected for agriculture expansion, it may be possible to curb this expansion by prioritizing old pasture areas for restoration projects.

The new data can also provide information for estimating the impact of conversion length on soil carbon stocks. Studies have shown that conversion to agriculture is mostly followed by carbon stock losses [45–48], and that the establishment of pastureland is associated with the maintainance or accumulation of carbon stocks over time [47–49]. If the conversion of old pastures to agriculture results in more carbon losses, avoiding the establishment of new agriculture areas is reinforced by taking into account the carbon stocks. However, it is also important to note that livestock is also a major emission source of greenhouse gases. Our calculations provide an opportunity for simulating the impact of these land-cover transformations for the whole biome, taking into account the conversion length from forest to agriculture.

4.2. Accuracy

Uncertainties are inherent in satellite image classification (such as the one performed by MapBiomas). These errors can arise due to artifacts present in satellite images, to imperfections of ground reference observations, and also to the transformation of a continuous landscape into categorical representations [50,51].

Tha land-cover classification from MapBiomas is in continuous improvement, which ranges from developing better ground references to the adoption of post-classification processing techniques and the expansion of classification labels [17]. However, there are limitations that are difficult to overcome. To be able to provide land-cover classification throughout the period from 1985 to 2021, it is necessary to use the Landsat mission time series, which provides satellite imagery at a spatial resolution of 30 m and a revisit period of 16 days. Therefore, it is not possible to use other data, such as imagery from radar missions or from Copernicus Sentinel missions, which could help reduce uncertainty in borders and in the classification of smaller objects, such as small roads. Possible ways to further improve the land-cover classification from MapBiomas are exploring the possibility of using object-based classification [52] and using different classification algorithms such as neural networks [53] or sub-pixel mapping models, such as Markov random field, which can improve errors in mixed pixels [54,55].

According to our results, reducing the number of errors in the classification of agricultural areas would be most beneficial for a more precise calculation of conversion length (Figure 7).

5. Conclusions

Our research explores new aspects of the MapBiomas classification data, which were not yet analyzed, by explicitly linking deforestation with agricultural establishment. The conversion from forest to agriculture estimates can be a valuable source of information to support research in different disciplines related to LULC changes. We showed that our data relate to many historical events in Brazil, which shaped the landscape of the Brazilian Amazon biome, covering public policies and economic and environmental aspects. Usually, analyses focus on the impact of public policies on deforestation or agriculture expansion, whereas our results show that these policies also relate to the length of the conversion from forest to agriculture.

The conversion length from forest to agriculture can provide a new perspective to be applied in forest restoration planning and the quantification of carbon fluxes in different spatial and temporal patterns of conversion in the Amazon biome.

For further investigations into the conversion length in the Amazon biome, we provide the data in a ready-to-analyze format, which is very convenient to be analyzed in conjunction with economic and demographic data.

The accuracy assessment creates new opportunities for future improvements in LULC data, especially concerning conversions from forest to agriculture. We show that there are opportunities for improvement in the classification of agriculture establishment, which would increase the accuracy of conversion length calculations.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/land14020300/s1, Figure S1: Diagram representing the process of conversion length calculation.

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Data Availability Statement: The data presented in this study are publicly available at https://zenodo.org/records/7484163 (accessed on 24 October 2024). The code of the data processing and analysis is available at https://github.com/hugotseixas/forest-agri-conversion/tree/main (accessed on 24 October 2024).

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