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Accounting for alternation in temporal quality analysis in MapBiomas Brazil

Ana Paula Matos [a], Maria Hunter [a], Robert Gilmore Pontius Jr. [b], Luis Rodrigo Baumann [c], Leandro Leal Parente [a,d] and Laerte Guimarães Ferreira Jr. [a]

[a]Remote Sensing and GIS Lab (Lapig), Federal University of Goiás (UFG), Goiânia, Brazil; [b]School of Geography, Clark University, Worcester, MA, USA; [c]Institute of Mathematics and Statistics (IME), Federal University of Goiás (UFG), Goiânia, Brazil; [d]OpenGeoHub Foundation, Doorwerth, Netherlands

ABSTRACT

Land use and land cover maps are an important resource for understanding interactions between humans and their environment across space and time with current mapping efforts often spanning upwards of 20 years. We present here a new method for a robust assessment of land cover transitions over time and apply this methodology to the yearly MapBiomas land use land cover maps of Brazil spanning 1985–2022. Based on a reference sample of 85,152 points, we find MapBiomas to have limited accuracy as an indicator of yearly land use change, but consistent over the full mapping period. Alternation, a newly defined error component, captures the number of land use transitions a location experiences throughout time. It is the primary reason for differences in estimates of annual change and is 4.6 times more frequent in the MapBiomas product than reference data. Differences in alternations are particularly prevalent in transitions from pasture to savanna and forest classes. The total land use changes detected over the 37 year study period are consistent between the reference data and the MapBiomas classification with 232 million hectares and 252 million hectares, or 27% and 29% of the Brazilian territory respectively.

HIGHLIGHTS

1. We present a new method, Alternation, to measure quality in land cover transitions over time.
2. The methodology is applied to MapBiomas land cover maps of Brazil from 1985 to 2022.
3. Land cover change is consistent across the full time series, but inconsistent at the annual scale.
4. MapBiomas has 4.6 times more annual transitions than the reference data.

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CONTACT Maria Hunter maria.hunter@ufg.br Remote Sensing and GIS Lab (Lapig), Federal University of Goiás (UFG), Campus Samambaia, Almeida Palmeiras, s/n - Chácaras Califórnia, Goiânia, GO 74001-970, Brazil

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1. Introduction

MapBiomas, a project conceived by the Climate Observatory (Observatório do Clima, OC), represents an innovative initiative co-created and developed by a multi-institutional network that includes universities, non-governmental organizations (NGOs), and private companies to generate land use and land cover maps. The main goal of the project is to map land cover and land use annually in Brazil, aiming to comprehensively monitor change over time (Souza, Shimbo, and Rosa 2020). Maps are based on Landsat image classification and incorporate reference data based on visual interpretation.

Given that the official MapBiomas (Souza, Shimbo, and Rosa 2020) data are cited in over 600 research articles and over 8000 articles are returned by a Google Scholar search on 'MapBiomas', understanding the strengths and weaknesses of this data is of paramount importance to the scientific community. These studies have explored a range of applications such as illegal deforestation (Coelho-Junior et al. 2022), agriculture and pasture expansion (Caballero et al. 2023), ecosystem services (Pereira, Fernandes, and Vieira 2024), surface water loss (Souza et al. 2024), illegal mining in the Brazilian Amazon (Ferreira Neto et al. 2024), social impacts of land cover change(Cruz et al. 2024), restoration of native vegetation (Rosa et al. 2021), and scenarios for future land cover in Brazil (Fendrich et al. 2020).

However, various studies have also pointed out limitations in the dataset's accuracy, particularly in heterogeneous and transitional biomes. For example, classification challenges in the drylands caatinga (Ganem et al. 2020; Rocha et al. 2024). The water surface product in MapBiomas Collection 7 presented user accuracy below 50% in the Pantanal biome across the time series, despite generally exceeding 75% in other regions (MapBiomas 2025a).

Temporal analysis of MapBiomas Brazil is impacted strongly by the difficulties regarding the precision and consistency of annual maps. Data quality is frequently compromised by variability in image quality, changes in sensors, and changes in classification methods, making direct comparisons between years difficult. Additionally, temporal gaps in data and the temporal and spatial resolution of the images can also hinder the detection of rapid changes in land use.

The large extent and diversity of landscapes within Brazil increase the analytic complexity, further complicating the identification of land use change uniformly across different ecosystems. Multifaceted issues such as public policy, effects of climate change and natural phenomena, also lead to further difficulties in identifying patterns in land use change and identifying causes (Turner, Lambin, and Reenberg 2007). Moreover, changes in classification algorithms over time – intended to improve the accuracy of each version – can introduce inconsistencies in temporal analyses (MapBiomas 2019).

Accuracy analyses are essential for validating results of classification using satellite imagery. This can be done through comparison with reference data such as high resolution imagery or field data (Congalton and Green 2019). These analyses allow calculation of indicators of quantity error and allocation error to measure the differences between the classification and reference data (Pontius and Millones 2011). Accuracy analyses also help evaluate and improve classification algorithms, identifying consistent sources of error, identifying more accurate models and making adjustments possible that reduce classification errors.

Land cover map accuracy is traditionally measured by the extent to which the map represents the true ground conditions (Congalton and Green 2008). This is evaluated through comparison of map classes with those of reference data. This reference data can be in the form of ground measurements or inspection of imagery of individual locations (Foody 2002; Olofsson et al. 2014). At global scales and when dealing with extensive temporal series, it becomes impractical to obtain a sufficient quantity of field samples for spatial and temporal validation as field locations are not well-distributed globally and rarely have repeat sampling over multiple decades. Additionally, previous research has indicated that accuracy rates at specific points in time are lower than accuracy rates for changes over time intervals (Stehman et al. 2021).

Many authors recognize the importance of multi-temporal training data when building models for land use land cover classification (Franklin et al. 2015; Gómez, White, and Wulder 2016; Stanimirova et al. 2022). The random distribution of samples at moments in time can capture seasonal variability as well as specific events that occur in one year versus another. However, a random distribution of samples that are inspected through time provides additional insights on the types of changes present in the landscape (Hermosilla et al. 2015).

Although methods are available to evaluate change accuracy compared to stability in a single time interval, our analysis requires the introduction of new methods capable of assessing multiple classes over sequential time intervals. This article, therefore, introduces and details the proposed new methods, offering an important contribution for other researchers to employ in their comparative analyses of two time series of class maps. The objective of this study is to apply comparative analysis of annual reference data to land cover maps from 1985 to 2022 and present suggestions on the use of the MapBiomas product by users.

2. Methods

Two primary datasets are compared in this study, annual maps of land cover in Brazil produced by MapBiomas and a series of reference points with independent land cover classification (Figure 1). We provide a brief overview of the development of both datasets

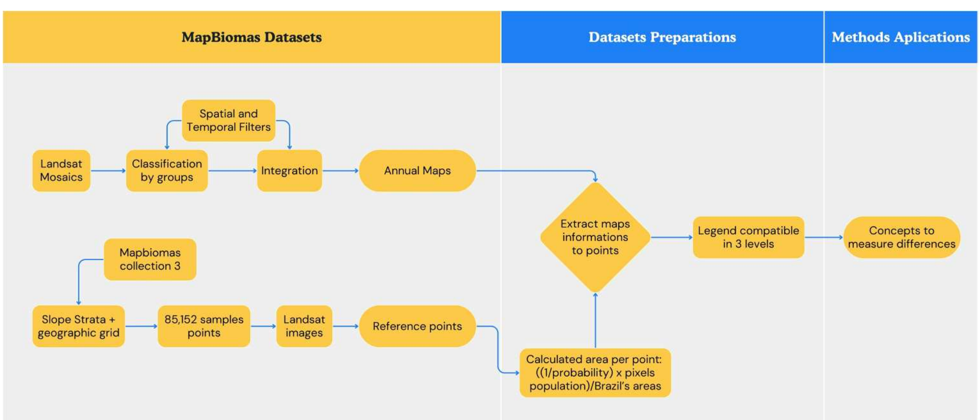

Figure 1. Flow chart of dataset development and comparison.

in the flowchart below as well as their preparation and comparison. In order to compare across the three levels of the MapBiomas legend, the highest level of specificity was used for initial identification, and reclassifications were performed at all levels for both data sets. These datasets were then used to determine differences, allowing for quality analysis and validation at each level of the MapBiomas classification.

2.1. Annual maps

MapBiomas is an initiative led by OC with the objective of comprehensive annual maps of land use for Brazil. The process of temporal analysis of MapBiomas begins with annual mosaics of Landsat imagery, classified for each thematic group and individual classes refined using spatial and temporal filters. Given the diverse ecosystems within the country, this project is split into regions and transversal topics to best align the different necessities of each area. Initial classifications are then integrated using a system of hierarchical overlays and spatial and temporal filters are reapplied to generate the annual classification maps. This creates a unique system wherein experts in differing land cover types come together to build scientific consensus on a yearly basis.

As these classifications are built upon yearly composite Landsat data, pixel-level data are filtered to remove clouds and smoke and then summarized for a given year based on statistics of each of the seven spectral bands, their fractions, and calculated indices (MapBiomas 2023). In the case of areas lacking imagery or where pixels were removed due to clouds or smoke, data is preferentially filled by future observations. In the case that a valid future observation is not found, a valid observation up to three years prior may be used (Diniz et al. 2019). Both spatial and temporal filters are applied to remove isolated classes and 'non-permitted' transitions.

2.2. Reference points

All analyses are based on the reference data collection (version 2.1) available via the MapBiomas website (https://brasil.mapbiomas.org/en/pontos-de-validacao/) and documented in the Analysis Theoretical Basis Document (ATBD) for Accuracy Assessment (MapBiomas 2024). This dataset includes 85,152 sample locations within the Brazilian territory that are distributed taking into account slope and land cover variability within a 2×3 degree geographic grid. Within the preparation of the reference data set, the area that each point represents is calculated based on the probability of inclusion, the sample population and the area of Brazil. Each sample aligns with one 30×30 m landsat pixel and was inspected and labeled by three independent interpreters, based on two landsat images from different periods per year. In cases of disagreement among interpreters, a final decision on the LULC class of the sample was made by a supervising interpreter.

The total interpreter team consisted of 15 analysts who received specific training. The training criteria generated within this project for each Brazilian biome and available at the Lapig website (Silva et al. 2020, march). All evaluations were made using the open source Temporal Visual Inspection (TVI) (Figure 2) tool developed by the Image Processing and GIS Lab and the Federal University of Goiás (LAPIG/UFG) (Nogueira, Parente, and Ferreira 2017; Parente et al. 2021) and follow the classes presented in Table 1. These

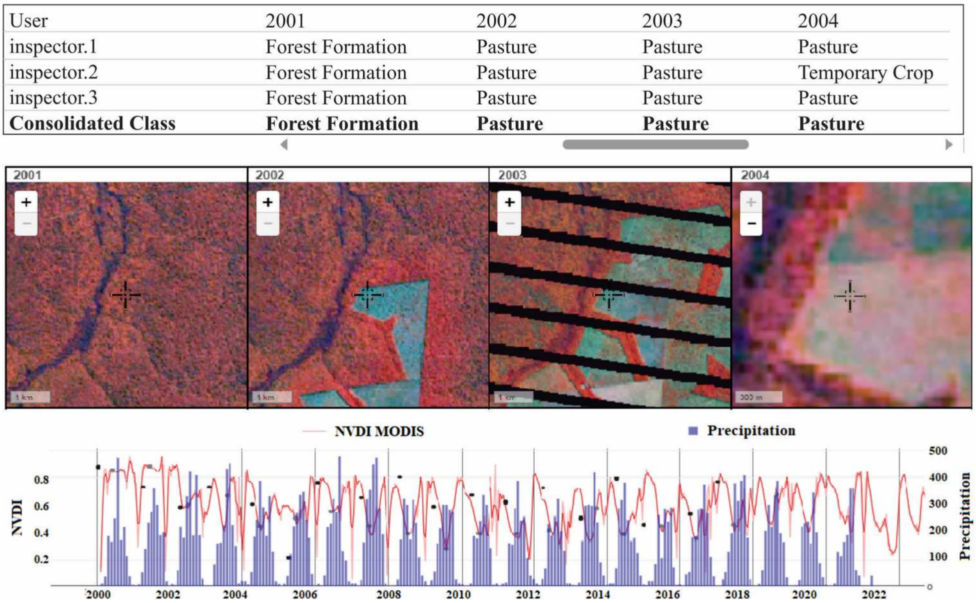

Figure 2. Example of the TVI interface used during the interpretation process. The TVI Interface provides point information regarding the biome, municipality, and coordinates. It offers images for two periods, typically dry and wet seasons, along with links for more detailed inspection in Google Earth. Additionally, there is an NDVI time series derived from MODIS images, accompanied by precipitation data. Interpreters are tasked with classifying the transitional years and LULC classes.

Table 1. Comparison of land cover classes of MapBiomas Collection 9 and reference data.

MapBiomas Collection 9 Legend[a]			
Level 1	Level 2	Level 3	Reference Data Legend
Forest	Forest Formation	Forest Formation	Forest Formation
	Savanna Formation	Savanna Formation	Savanna Formation
	Mangrove	Mangrove	Mangrove
	Floodable Forest (beta)	Floodable Forest (beta)	Floodable Forest (beta)
	Wooded Sandbank Veg	Wooded Sandbank Veg	–
Non Forest Natural Formation	Wetland	Wetland	Wetland
	Grassland	Grassland	Grassland
	Hypersaline Tidal Flat	Hypersaline Tidal Flat	Hypersaline Tidal Flat
	Rocky Outcrop	Rocky Outcrop	Rocky Outcrop
	Herbaceous Sandbank Veg	Herbaceous Sandbank Veg	Herbaceous Sandbank Veg
Farming	Pasture	Pasture	Pasture
	Agriculture	Temporary Crop	Temporary Crop
		Sugar Cane	Sugar Cane
		Perennial Crop	Perennial Crop
	Forest Plantation	Forest Plantation	Forest Plantation
	Mosaic of Uses	Mosaic of Uses	–
Non Vegetated Area	Beach	Beach	Beach
	Urban Area	Urban Area	Urban Area
	Mining	Mining	Mining
	Other Non Vegetated Areas	Other Non Vegetated Areas	Other Non Vegetated Areas
Water	River, Lake and Ocean	River, Lake and Ocean	River, Lake and Ocean
	Aquaculture	Aquaculture	Aquaculture
Not observed	Not observed	Not observed	Not observed

[a]Source: Adapted from Mapbiomas (2024).

classes closely align with the Level 3 MapBiomas classes, except in two cases: Wooded Sandbank Vegetation and Mosaic of Uses. Wooded Sandbank Vegetation is not included in the reference dataset as it is not visibly separable from Forest vegetation. Mosaic of Uses was also not identified in the reference dataset as it applies to mixed use in highly fragmented landscapes. As visual interpretation was conducted for individual pixels, the dominant use was identified and specific classes were applied. When imagery was not available for a given year, but previous and future classifications were of the same class, it was assumed that the class did not change in the year for which imagery was missing. In the case of a change in class that potentially occurred in the year for which imagery was missing, this year is classified as 'Not Observed'. This classification was also used in the case of points with missing imagery at the beginning or end of the time series.

2.3. Concepts to measure differences

In this study we apply and build upon the map quality metrics presented in Pontius (2022). Two complementary frameworks are used to describe accuracy of maps with regard to specific land use classes and overall. The first framework is that of the Error matrix concerning transitions. Within the reference data and maps, and for each class, a separation is made between areas that do not change classes (are stable) and those that transition between classes over a yearly time step. Generally, there are 6 cases for the comparison of land use land cover classes between reference data and maps (Figure 3).

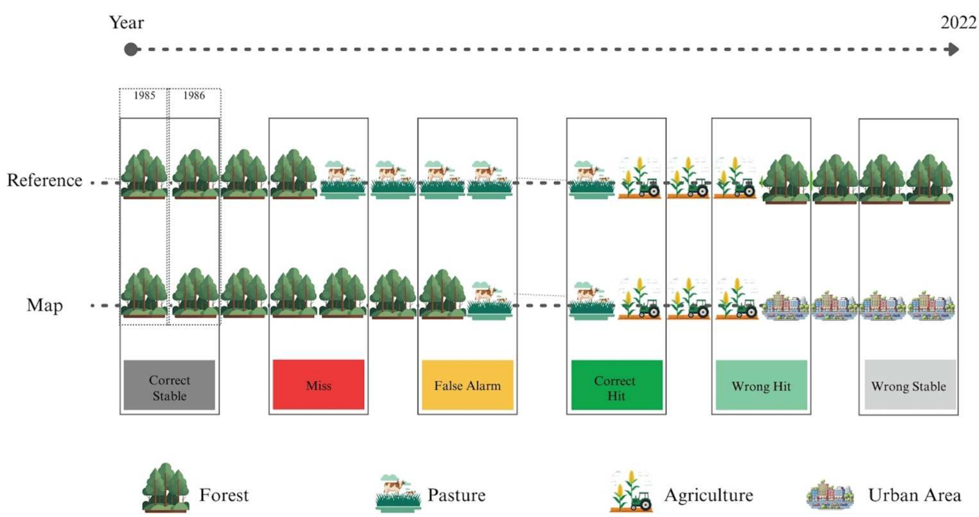

Figure 3. Illustration of example evaluation of temporal accuracy in land cover maps wherein the yearly land cover class (forest, pasture, agriculture or urban area) is represented for the reference data in the top line and the mapped classification in the second line. Outlined blocks represent different types of agreement and disagreement: Correct Stable (dark grey), Miss (red), False Alarm (yellow), Correct Hit (green), Wrong Hit (light green) and Wrong Stable (light grey). This separation allows for the evaluation of consistency of transitions between classes through time, a fundamental aspect of the dynamics in land cover in long-term time series.

These transitions are illustrated for a single pixel in Figure 3 where reference data are compared to mapped land use classes (displayed as 'Map') and consistency and accuracy are assessed through time. Each class change is evaluated and attributed to a specific Error Matrix category for the full time period of 1985–2023. Within the figure four land use classes are considered: forest, pasture, agriculture and urban areas, and are organized into two layers: **Reference**, with the classes considered to be correct based on inspection of high resolution imagery, and **Map**, showing the classes based on mapping or modeling. Comparisons between these two layers are grouped by category and are summed to evaluate the map quality overall.

Where maps and reference data agree on stability and the class of stability this is Correct Stable. Where maps and reference data agree on change and the classes involved in the change this is a Correct Hit. Disagreements between the reference data and the map data are divided into four components within the Error Matrix. In the case of disagreement of stable classes, this is labeled as Wrong Stable, and disagreement of transitional classes is labeled Wrong Hit. Where the reference data does not show a change in class and the map does is noted as a False Alarm, and the opposite case is referred to as a Miss.

However, in the case of maps with many classes it is important to reference these transitions to specific classes. In doing so, each transition between classes is considered as a Loss or Gain. This additional layer of complexity is shown in Figure 4. Agreements on stability and class, identified as Correct Stable are further divided into the Stable Presence of a class or the Stable Absence. Correct Hits may also be divided into whether they represent the gain or loss of a given class.

These cases can be most easily visualized in two formats, a Venn diagram and a bar chart (Figure 5) and applied to either an individual class (following Figure 4) or all classes (following Figure 3). It should be noted that classifying a correct hit is more stringent when all classes are considered as both the initial and final classes identified must match between the map and reference data. In the Venn diagram, the rectangle

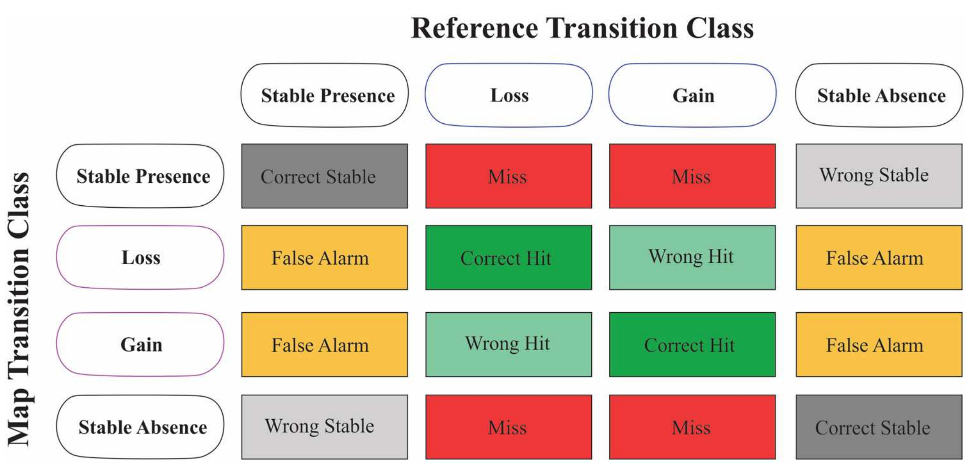

Figure 4. Error matrix concerning transitions for a given land cover category: Terminology used for the comparison of the map with reference data between years for a given class.

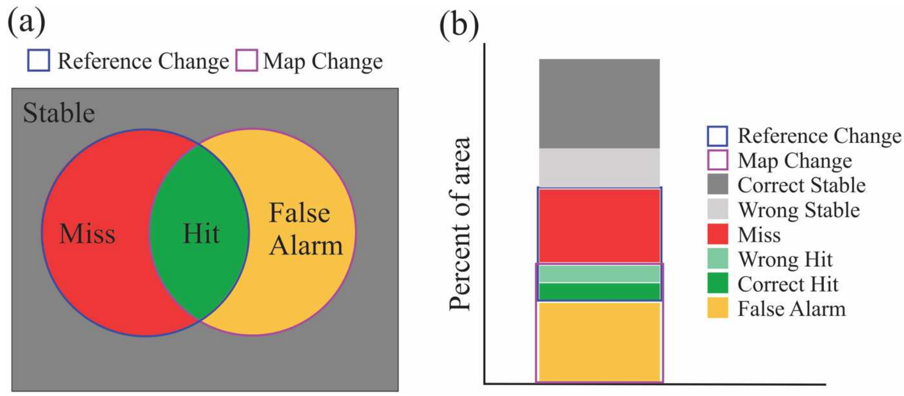

Figure 5. Examples of visualization of the Error Matrix. The (a) Venn diagram combines Correct Stable and Wrong Stable into a single 'Stable' class and Correct Hit and Wrong Hit into a single 'Hit' class. The (b) bar chart visualization maintains all six classes detailed in the text. Both visualizations allow for the comparison of change in the reference (blue outline) and map (purple outline).

represents the universe of pixels evaluated and the red circle represents the change in the reference data whereas a green circle represents the change in the map. Where these two circles overlap are the Hits, both correct and wrong. Where they do not overlap are misses and false alarms on the two sides respectively. This visualization technique is helpful to visualize the size of map and reference changes but does not include an easy-to-view comparative scale axis. For this reason, in this article, we use a secondary visualization technique wherein the six classes are compiled in a stacked bar chart. In this format agreement in terms of stability and transition (Hits) are further divided into those that are Correct and Wrong. Components are ordered such that reference changes (blue box including Miss, Wrong Hit and Correct Hit) and map changes (purple box including Wrong Hit, Correct Hit and False Alarm) are easily comparable by size and component composition.

The second framework separates mapping errors into conceptual groups that separate the error in total area from errors in location, and those that derive from temporal variability. Quantity, Allocation and Alternation are the terms used here to describe the accuracy and quality of classifications in space and time. Quantity discrepancy refers to the difference in class areas whereas allocation divergence is the spatial divergence of that area, and represents less-than-perfect correspondence in terms of the spatial distribution of classes (Pontius 2022). A third component is newly presented here and is specific to the consistency of measurements over time; Alternation represents the frequency of class change that occurs at locations with multiple class changes. The calculation of Alternation is demonstrated in Figure 6.

Figure 6 illustrates changes in land use between 1985 and 2022 and the number of transitions between classes found in the reference data as compared to the maps. In this case the reference data shows transitions from Forest to Pasture, then to Agriculture before transitioning back to Forest. The maps follow the same transitions except for the final transition, which is to Urban Use as opposed to Forest. Both data sets show three transitions between land use classes in the intermediary years, whereas the Map data also shows a Gain to Urban Use and a Loss from Forest. Thereby, following the equation,

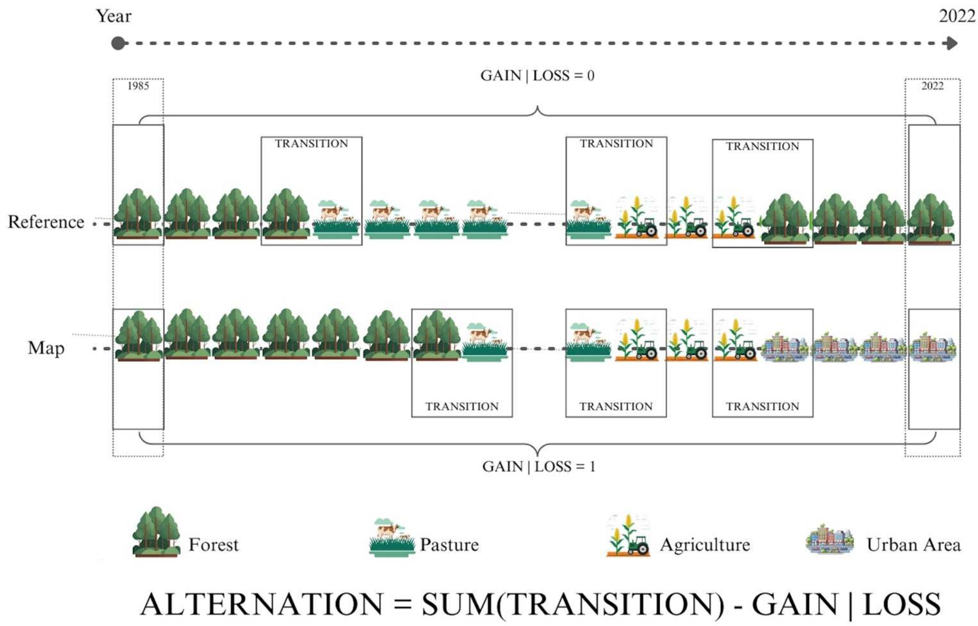

Figure 6. Illustration of how to calculate the newly presented concept of Alternation as applied to temporal series of land use and land cover maps. This figure shows the comparison between Reference Data (top line) and Mapped Land Use (second line) over the analyzed time period between four land uses: forest, pasture, agriculture and urban area. Alternation is calculated independently for each data set as the sum of the number of transitions discounting the overall gain or loss to a land use class. In this example, the Reference data show Alteration = 3 (3 transitions and no change from the initial to the final class) and Map data show Alternation = 2 (3 transitions minus the change from the initial to the final class). Similar values show consistency between reference data and maps, whereas discrepancies highlight increased instability of classes or classification errors through time.

the Alternation of the reference data is 3, and the Alternation of the Map data is 2. This difference is due to discounting the final transition that is accounted for in Quantity or Allocation, following Pontius (2022).

The six concepts previously presented describe the dynamics of quantity, allocation and alternation by affecting the gains and losses in each class and their respective accuracy. Misses contribute to errors in the quantity of a given class by maintaining stable areas in the map that in fact changed classes. False Alarms result from the opposite situation, areas that did not change class in the reference but did on the map. In the case where misses and false alarms are balanced, this is the allocation error of a given class, whereas an imbalance between these classes contributes to quantity errors.

The mathematical formulations used to describe each of the concepts above are included in Appendix A, some of which are referenced in the steps used to apply this methodology to the MapBiomas data set.

2.4. Step by step

1. Calculate pixel weight (Ws) based on initial sampling design.
2. Calculate 'Not Alternation' at the pixel level following Eq.A9

3. Assign Gain and Loss by Class.
4. Calculate Quantity Component following Eq. A10
5. Calculate Allocation Component following Eq. A11.
6. From Year 2 forward, build the Error Matrix by class following Figure 3.
7. Sum False Alarm, Wrong Hit and Correct Hit to total Map Class Transitions per Pixel.
8. Sum Miss, Wrong Hit and Correct Hit to total Reference Data Class Transitions per Pixel.
9. Finalize calculation of Alternations in Reference Data and Maps discounting Gain or Loss from the sums calculated in steps 5 and 6 by class.
10. Apply area weight per pixel to yield area estimate within the Error Matrix.
11. Build matrix of map and reference land use classes, summing areas.

3. Results

When considering all years the most dominant components of the results of the comparison between maps and reference data are Correct Stable and Wrong Stable. The percentage of Brazil that has annual correct stable land cover is 76.26% agreement for level 3 classifications, 76.44% at level 2 and 86.77% at level 1. An additional 10.76% (level 1), 19.68% (level 2), and 19.82% (level 3) agreed on stability but showed disagreement regarding the class, characterized as 'Wrong Stable'.

The non-stable components of change (Wrong Hit, Correct Hit, False Alarm and Miss) showed an increase when the level of classification increased in detail (Figure 7(a)). At Level 1, the average annual change observed in the reference data was approximately 0.63% of the national territory, while map-derived changes reached around 1.57%, indicating an overestimation of mapped changes. Of the changes detected by the maps, 0.15% of area was correctly matched with the reference data in both location and class (Correct Hit), whereas 0.27% was correct in location but incorrect in class (Wrong Hit). False Alarms – changes mapped but not present in the reference – accounted for nearly 1.15% of the territorial area, while 0.21% of areas showed actual changes (Misses) were not captured by the map. At Level 3, the proportion of Correct Hits dropped to 0.12% and Misses to 0.19%, with Wrong Hits increasing and False Alarms more than double compared to Level 1.

In all cases, the most common type of transition is the False Alarm wherein the map classification changes but the reference classification remains stable. In fact, for level three of the legend, the disagreement in change classes (False Alarms, Misses and Wrong Hits) is over 24 times higher compared to Correct Hits, wherein a change in class was consistently measured in both reference and map data. It is important to note the frequency of Wrong Hits compared to Correct Hits, indicating limitations in thematic accuracy even when spatial agreement on change was achieved. Furthermore, the map indicates 12 times more inconsistent changes in mapped class (False Alarm) than in the reference data (Misses), indicating that these differences cannot be attributed solely to a delay in the change detection.

This pattern was consistent across the 1985–2022 time series (Figure 7(b)), with minimal changes in all components, highlighting the challenge of accurately detecting and classifying small-scale transitions using annual map products. Over the full time

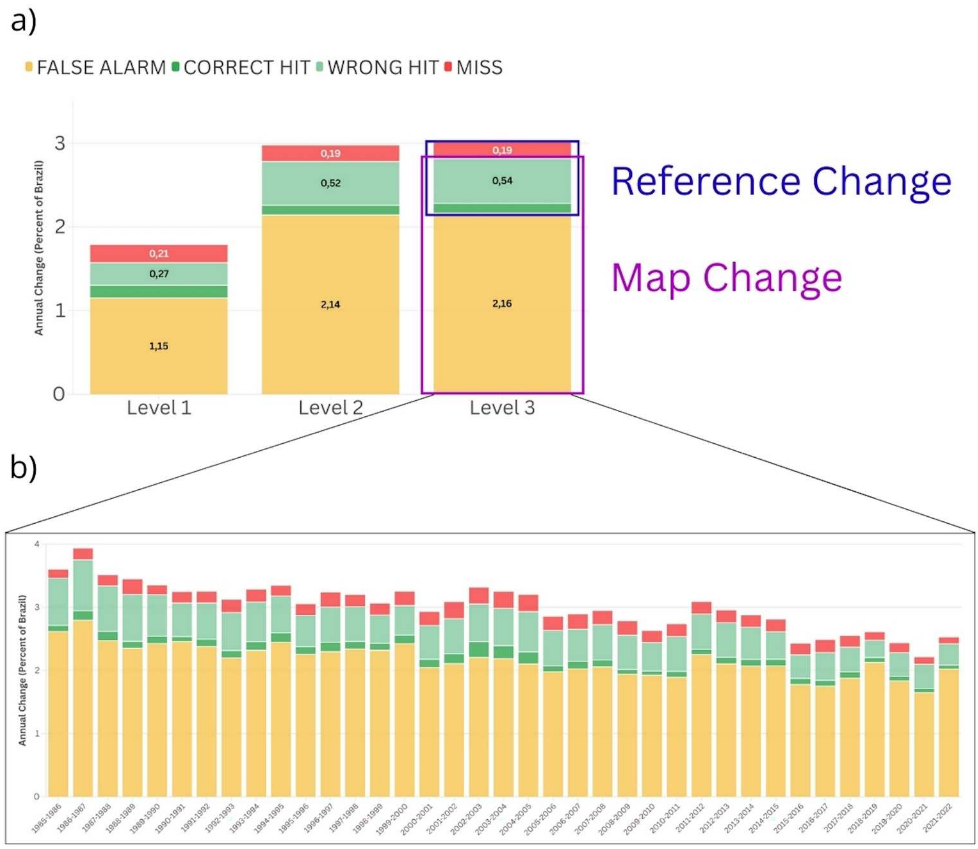

Figure 7. Comparison of annual land cover change rates (% of Brazil's territory) derived from map products and reference data. (a) Average annual change across three hierarchical classification levels, distinguishing changes detected in the map (correct hit, wrong hit, false alarm) and changes present only in the reference data (correct hit, wrong hit, miss). (b) Time series of annual change at Level 3 (most detailed level), from 1985 to 2022. Green shades represent correctly mapped changes (dark green: correct class hit; light green: incorrect class hit), yellow indicates mapped changes not confirmed by reference data (false alarms), and red represents real changes missed in the map (misses). A predominance of false alarms is observed over time, suggesting an overestimation of change by map products compared to reference data.

span studied, the relationship between transitional classes remains steady. The number of misses remains below 0.3% by area (2.5 Mha), supporting the rarity of class change in the reference dataset that shows no change in the map. However, false alarms decrease proportionally to the land use change, suggesting that the decrease across the time series is not related to an increase in accuracy, but rather a decrease in the total amount of land use transitioning per year over time. Throughout the time series, false alarms are substantially higher than all other transition components.

When comparing the changes observed between the first (1985) and the last year (2022) in both the map and the reference data, the differences were decomposed into two main components: Quantity, which represents discrepancies in the total area of each class, and Allocation, which reflects spatial differences in the distribution of classes. Additionally, a third analytical aspect, Alternation, was considered, which evaluates the consistency of year-to-year transitions throughout the time series. The Quantity component remained relatively stable across hierarchical levels of class detail (Level 1 and Level 3), varying between 105 and 122 Mha, 12% and 14% of the country (Figure 8), indicating a general agreement in the territorial dynamics and proportions of land use and land cover classes.

The presence of 'No Data' pixels in the reference data, especially in 1985 and 2022, had an impact on the assessment, resulting in two distinct effects. The first is 'No Data Allocation', when the absence occurs in the first or last year, and prevents confirmation of a class change. Summing the Quantity, Allocation and NA Allocation components, we estimate the total accumulated change in land cover between 1985 and 2022. At Level 1, we find 186 Mha of the Brazilian territory changed class in the reference data, whereas 173 Mha changed class in the MapBiomas product. At Level 3, we find 222 Mha of the territory changed class according to the reference data, and 248 Mha according to the maps. These results indicate that approximately one quarter of land in Brazil was subject to a direct land use or land cover change after 1985.

'No Data Alternation' is the second and occurs when there is missing data in intermediate years creating artificial transitions into and out of the 'No Data' class. These represent uncertainty in the year of a transition and are only present in the reference data. Independent of the affected pixels, the map exhibits far more alternations than the reference. Reference data present a summed area of transition between 65 and 96 Mha of the Brazilian territory (less than 0.3% per year), whereas maps show between 245 and 517 Mha depending on the classification level considered (up to 1.6% per year).

Alternations increase with the level of thematic detail: in the reference data, the average increase was less than 3% of area, while in the map data it reached 32%. This suggests that most alternations occur between classes within the same general category (e.g. savanna and forest, pasture and cropland). Moreover, when compared to the reference, the map data shows three times more alternations at Level 1 and up to 4.5 times more at Level 3. This difference may be related to increased sensitivity to interannual

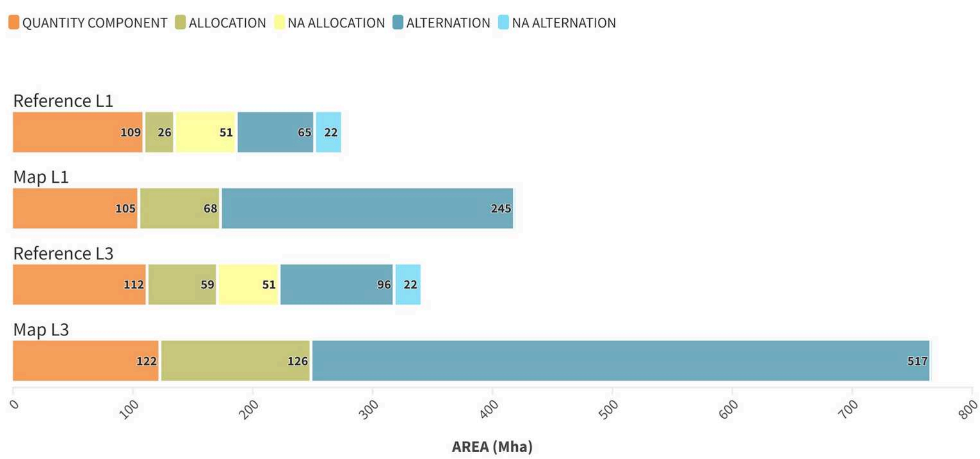

Figure 8. Components of Quantity, Allocation, and Alternation for reference data and maps at level 1 (L1) and level 3 (L3) of class detail.

change, with or without true change in land use. While filters are currently used to reduce single year periods of land use change, the number of map alternations indicate temporal instability that should be considered during longitudinal analyses.

To better understand the gains and losses by classes, and given the primary differentiation between reference data and the MapBiomas product is in terms of Alternation, we investigated the specific class transitions that were most common in the reference data and maps. Some of the most common can be attributed to methodological differences. The mosaic of uses class accounts for 46% of alternations, 24% involve wetland dynamics, and 3% transitions between natural cover classes. The full table of alternations is provided in Supplemental Material as there are over 550 potential transitions between classes.

Principal transitions of land use and land cover in Brazil between 1985 and 2022 are presented in Figure 9, though it is important to remember that these are likely non-permanent and in many cases may be later reversed. The most common transition is from forest to pasture, representing 24 Mha on the map and 19 Mha in the reference data and highlights the ability of detecting forest clearing followed by pasture use. The inverse transition, from pasture to forest, shows a larger difference: 19 Mha mapped and 11 Mha in the reference data, suggesting that maps overestimate temporary regeneration or reforestation.

The same dynamic is present in Savannas in both directions, though to a greater extent. While the transition from savanna to pasture is similar between maps and reference data, representing 14 and 12 Mha respectively, there is a much larger discrepancy in the transition from pasture to savanna. There are a sum of 19 Mha that transition from pasture to savanna over all years according to map data, almost 2.5 times the 8 Mha recorded in the reference data. This may be related to the similarity of spectral signatures and sensitivity of median images to strong seasonality.

Both the reference data and maps show that the transition from pasture to temporary agriculture is more dominant than the inverse. The reference data, in this case, detects more areas of conversion from pasture than the maps (18 versus 14 Mha), which may be related to inspectors having access to more than one yearly image. The inverse transition is more common in the map than the reference data (9 and 7 Mha, respectively).

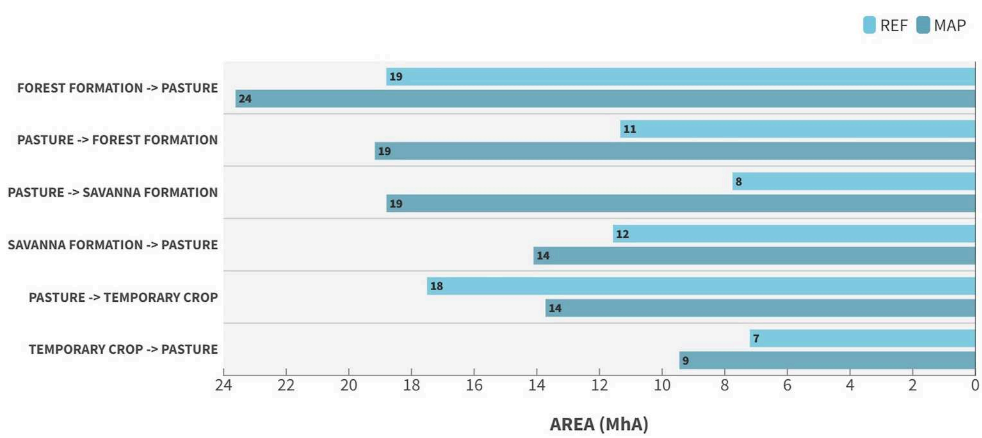

Figure 9. Selected alternations within MapBiomas and Reference data.

Agricultural dynamics, such as pasture usage during fallow periods, may also be a contributing factor.

In general, similar transitions are present in maps and reference data, reflecting large scale changes in land use and land cover. However, maps capture temporary or reversing changes with greater frequency. This is consistent with the higher number of alternations observed in the maps. Pasture is a component of all major alternations, suggesting its transitory nature in the dynamics of land use in Brazil.

4. Discussion

Time is a confounding characteristic in land use and land cover classification due to a variety of factors, such as seasonal variation and human activity. While the majority of reference samples do not change class through the entirety of the time series, the reference data set is sufficient to allow for a robust analysis of the frequency of class transitions and their accuracy. The complexity of these transitions supports the usage of samples that are randomly distributed in space and inspected for all years.

Within the MapBiomas land use maps, there are known limitations, both within component maps of individual land uses and the final maps. The methodology of MapBiomas, which is based on analysis of yearly median images, identifies land use changes with small temporal uncertainty, resulting in an imbalance between 'False Alarm' and 'Miss' (one data set is stable while the other changes). However, these errors tend to balance over longer time scales. This is supported by our analysis of Quantity and Allocation of change that consider the full time series. However, for interannual change, the base maps show spurious transitions. These may be improved using specific change products, such as 'Deforestation' or 'Secondary Vegetation' (MapBiomas 2025b), though these products were not analyzed in the present work.

The summarization of pixel information at the yearly time scale can create issues in the year that change occurs and mask other transitions. In some cases, a single year may include three land cover classes. During times of transition, the spectral signatures of multiple classes are present in a single year and contribute to spectral mixing that becomes indeterminable as an individual class. In the case of an area that transitioned from forest to bare soil, before becoming pasture, this spectrally mixed area would likely be classified as 'mosaic of uses' for the MapBiomas map. In the case of temporary crop areas that are planted with pasture between crop cycles, yearly averaging of signal properties may lead to discrepancies with reference data.

Regarding the Mosaic of Uses class, it only appears on the map and not in the reference data set. Within the documentation, Mosaic of Uses is defined as 'Farming areas where it was not possible to distinguish between pasture and agriculture' (MapBiomas 2023). This is consistent with the case above wherein multiple uses over the course of a growing cycle. However, many cases were observed where an area stayed in this class for multiple years, suggesting that it is capturing other land uses. This is also suggested by the frequent alternations of this class in the MapBiomas maps, which alone accounts for 42% of map alternations. However, when the Mosaic of Uses class is removed, the summed alternations remain 2.7 times higher for the MapBiomas product compared to the reference data suggesting that current methodologies are overly sensitive to spectral changes.

The identification of severely degraded areas (Louzada et al. 2023), and separation of farming and pasture areas (Baeza et al. 2022), especially in regions with heterogeneous coverage, may be additional examples of this sensitivity to spectral change and likely contribute to the large number of alternations shown in pasture to temporary crop classes. It is also important to consider that land use and cover classes have varying levels of complexity for both visual interpretation and spectral signatures used for mapping.

Problems in map accuracy at class edges occur in both point samples and final map products. At the point scale this may occur due to spectral mixing within an individual pixel where two or more classes are present, or due to slight offsets between image geolocation. For point samples, an effort is made to define the majority class through high resolution imagery, maintaining consistency with the full time series. However, this may not be possible when final map products are produced. To minimize this effect, spatial and temporal filters are applied to check for consistency between adjacent pixels through space and time (Souza, Shimbo, and Rosa 2020). However, they are not 100% efficient.

This can be seen within the other transitions between natural classes that are frequent in the maps analyzed and rare in the reference data. One method that could minimize the effect of these alternations is through identifying an improved time window (Stehman et al. 2021). This could then be used to improve filtering in the creation of the MapBiomas product. This is especially important to correct given the potential for future land cover change of natural areas driven by climate change (Oliveira et al. 2021). This time window could also be used in combination with techniques to identify degradation events and thereby minimize mis-classification (Alencar et al. 2022; Pacheco et al. 2023).

It is important to recognize that reference data is also an imperfect source for comparison due to potential issues in interpretation, as individual classes show variable accuracy (Coppin et al. 2004; Gómez, White, and Wulder 2016; Stehman et al. 2021). These difficulties can occur at the individual or regional level. At the individual level, this can be due to a specific interpreter or a specific class. At the regional level, this may be due to terrain characteristics or mixtures of easily confused classes, as in arid regions (Ali and Johnson 2022; Stolz, Braun, and Probeck 2005). In the current data set, an important observation regarding reference data is the presence of information gaps due to the absence of images, mainly in the year 1985, and the presence of clouds. This problem is masked in the MapBiomas final product through efforts to acquire images from subsequent years to compensate for the absence in the specific year, and should also be applied to the reference.

Consistent with patterns observed in both reference data and maps, a wide variety of studies have shown the significant changes in land use in Brazil. There is strong evidence for the advance of agriculture and livestock over native vegetation (Lapola et al. 2014) and the substitution of pasture for agriculture in the south-central region (Macedo et al. 2012; Spera et al. 2016). Economic policy and development have pushed ever increasing agricultural area (Picoli et al. 2020) while the use of pastures as land reserves for speculation has led to deforestation followed by abandonment (Feltran-Barbieri and Féres 2021; Parente et al. 2019; Picoli et al. 2020). These processes help to explain the patterns of land use change identified in both datasets, and some of the fluctuations found.

The analysis of the Alternation component reveals crucial aspects regarding the temporal consistency of land use and land cover, and highlights the stability (or instability) of annual transitions at the pixel scale. High levels of alternations may indicate classification instability, especially in regions where there is ambiguity between similar classes (such as agriculture and pasture), or where seasonal variations or intensive or highly fragmented land use occur. Based on comparison with reference data, the majority of alternations present in the maps do not reflect true land use changes, but noise in the time series. This suggests the need for more effective temporal filters. The Alternation component of error is critical not only for quantifying confidence in land use transitions through the temporal domain, but also to adjust methodologies and to interpret land cover change dynamics.

Overall, we find that discrepancies between reference data and MapBiomas products do not invalidate the maps, but suggest paths to improve their accuracy and temporal consistency. The adoption of additional metrics that capture seasonal variation, longer temporal windows, and refined definitions of transitional land use classes are promising strategies to improve the interpretation of changes in land use and land cover in Brazil, especially given the complexity of ongoing anthropogenic and natural processes.

5. Conclusions

In Brazil, the MapBiomas project is the primary source of nationwide land cover data, provided freely and updated annually. These data are essential for a variety of research purposes and serve as a critical tool for decision-making. In addition to fostering open science, conducting detailed analyses of these data is essential to ensure transparency with users and enable future enhancements.

Our analysis, focused on the discrepancy between maps and reference data, presents a new method for measuring error specific to time series, Alternation, and highlights that this is the predominant component of disagreement. This indicates that the MapBiomas products show much more interannual class change compared to what is recorded in the reference data. This disparity is concentrated at woodland (savanna and forest) to pasture boundaries and temporary crops. Despite this disparity, the overall area in classes was broadly supported by our analysis, as well as the change from the beginning to the end of the time series.

The existence of differences between reference data and maps regarding land use and land cover changes in the territory suggests that map users should take care when considering land use changes at the yearly time scale. Future work is underway to assess at what time scale transitions become more reliable.

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CRediT authorship contribution statement

Ana Paula Matos: Formal Analysis, Supervision, Validation, Visualization, Writing – original draft, Writing – review and editing. **Maria Hunter:** Formal Analysis, Validation, Visualization, Writing – original draft, Writing – review and editing. **Robert Gilmore Pontius Jr:** Conceptualization, Methodology, Supervision. **Luis Rodrigo Baumann:** Methodology, Supervision, Writing – original draft. **Leandro Parente:** Conceptualization, Methodology, Supervision. **Laerte Guimarães Ferreira Jr:** Conceptualization, Methodology, Funding Acquisition, Resources, Supervision, Writing – review and editing.

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Data availability statement

The final sampling dataset with all the classes, sampling probability, and weights is publicly available at Mapbiomas Website (https://brasil.mapbiomas.org/en/pontos-de-validacao/). The TVI source code and the area estimator implementation are available at https://github.com/lapig-ufg/tvi and https://github.com/lapig-ufg/tvi-analysis, respectively, both under the MIT license.

ORCID

Ana Paula Matos http://orcid.org/0000-0002-8000-3046
Maria Hunter http://orcid.org/0000-0001-6449-9718
Robert Gilmore Pontius Jr. http://orcid.org/0000-0001-7287-5875
Luis Rodrigo Baumann http://orcid.org/0000-0001-5308-9721
Leandro Leal Parente http://orcid.org/0000-0003-1589-0467
Laerte Guimarães Ferreira http://orcid.org/0000-0002-0489-1141

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