



Intensity Analysis to Study the Dynamics of Reforestation in the Rio Doce Water Basin, Brazil

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Conservationists routinely require methods to analyze the effects of conservation interventions such as reforestation. Although methods to measure the effects of reforestation abound, these methods often fail to track and communicate the complexities of reforestation interventions. This paper uses intensity analysis to analyze the effects of reforestation intervention in Brazil's Rio Doce water basin. In particular, this paper uses intensity analysis to study the effects of reforestation on three land cover categories in Brazil's Rio Doce water basin. The illustrative approach analyzes the temporal difference of forest in three land cover maps at time points 1998, 2008, and 2015 from the Rio Doce water basin, Brazil, where each map has four land cover categories: forest formation, pasture, mosaic of agriculture and pasture, and urban infrastructure. Interval level intensity indicates that change is faster during the second time interval (1998–2008). The results from the categorical level intensity show that the forest formation and the mosaic of agriculture and pasture are active gainers during both time intervals, while pasture is an active loser. Forest formation targets the mosaic of agriculture and pasture more intensively at the interval level during the first time interval. Forest formation gains the most from a mosaic of agriculture and pasture while at the same time targeting the mosaic of agriculture and pasture during the second time interval. The mosaic of agriculture and pasture gains the most from both forest formation and pasture during both time intervals but targets pasture. The results for the second time interval show that the reforestation process in the Rio Doce water basin, Brazil, only forced the farmers to move to other forest covers in the vicinity. This process constitutes exchange, which accounts for more than half of the change during the second time interval, and thus contributes 0 to the net change of forest.

Keywords: reforestation, agriculture, land change, intensity analysis, Brazil

1 INTRODUCTION

Forest covers only 31% of the Earth's land surface but provides a haven for most of Earth's species (Marx, McFarlane and Alzahrani, 2017). However, anthropogenic activities such as urbanization (Faulkner, 2004) and mechanized agriculture (Hobson, Bayne and Van Wilgenburg, 2002) coupled with natural disasters such as wildfires have resulted in deforestation worldwide (Bradshaw et al., 2007; Marlon et al., 2012). Consequentially, the world is experiencing a rise in the above-ground carbon stock and biodiversity loss (Costa and Foley, 2000; Caplow et al., 2011), leading to increased reforestation interventions from various organizations.

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Latin America and the Caribbean are home to most of Earth's tropical forests and thus receive most reforestation interventions. Five out of ten of the literature works concerning deforestation and reforestation on Google scholar are in Latin America, specifically Brazil or Amazon (Scullion et al., 2019). Although these papers report on reforestation, they often fail to provide any insight concerning the complexities involved in the relationship between the reforestation process and other land use such as agriculture (Wei, Liu and Zhou, 2013; Cortés-Capano et al., 2020).

Remotely sensed imagery, specifically satellite imagery, has played a critical role in studying forest changes at varying scales (Gopal and Woodcock, 1996; Huete, 2012; Lechner, Foody and Boyd, 2020). Advancements in remote sensing platforms such as Landsat, Sentinel, the Moderate Resolution Imaging Spectroradiometer, and Unmanned Aerial Vehicles during the past decade have resulted in an influx of categorical land cover data, which are more detailed spatiotemporally and in the number of categories (Lu et al., 2004; Masek et al., 2015). *MapBiomass*, *The Global Forest Watch*, and ICIMOD are examples of institutions that have benefited tremendously from the advancements in remotely sensed imagery and the creation of land cover maps. These institutions have leveraged land cover maps and existing methods to create online platforms which quantify forest change in North America and the rest of the world. Although some strides have been achieved in the creation and availability of data concerning forest change, there is still a gap in methods that can help quantify and characterize the complex changes in forests. The next three paragraphs describe some of the existing methods concerning the quantification of forest change from remotely sensed data.

The reducing emissions from deforestation and forest degradation (REDD+) project is perhaps the most popular method concerning the quantification of reforestation (Alexander et al., 2011; Groom and Palmer, 2012; Ingalls et al., 2018). Although the REDD + project has benefits that promote reforestation to reduce above-ground carbon, scientists who use the REDD + project to tell the success stories of reforestation often fail to track and communicate clearly the relationship between reforestation and other land uses such as agriculture (Schneider et al., 2015; Skutsch and Turnhout, 2020).

Other studies quantify the success of reforestation intervention by comparing the area of deforestation that has undergone reforestation. Gerlein-safdi et al. (2020) computed the area (in hectares) of reforestation in China's drylands for six time points: 2004, 2006, 2008, 2010, 2012, and 2014. They compared the reforestation areas from a manual, airplane, and natural methods. Although their study provided information concerning the area of reforestation, it failed to offer any insight into the transition patterns of forests. Philippe, Astrid and Catherine (2013) used an object-based automatic and national expert validation to analyze the patterns of forest cover change between 2000 and 2005 in the Congo Basin. The study used a transitional table to compare maps from two time points: 2000 and 2005, and reported three types of forest cover change: degradation, regeneration, and reforestation. However, their study reported the types of change as fractions of tree cover

and failed to provide any insight beyond the fractions of change. Tasser et al. (2007) measured the rate of reforestation from 1908 to 2000 in four regions of the Eastern Central Alps. In particular, they used a zero-inflated binomial model to measure the rate of reforestation in the Eastern Central Alps. Although the model included variables such as altitude, slope, drainage, and pasture land, their study failed to account for any transition pattern that resulted in the rates of reforestation they observed.

Pontius and Santacruz (2014) showed that the complexities involved in the transition patterns of land cover categories could result from quantity, exchange, and shift. Quantity refers to the absolute value of net change. Exchange refers to the situation where, in a part of the landscape, one category transitions to another while the two categories experience a reversal of transitioning in other parts of the landscape. Exchange, therefore, contributes a zero net change for both categories (Quan, Pontius and Song, 2020). Shift refers to a situation in which a category loses to another category while the losing categories gains from a third category. Aldwaik and Pontius (2012) provided a framework called intensity analysis to show that a category's quantity, exchange, and shift could be expressed at three levels of intensities: interval, category, and transition levels.

The preceding discourse shows that the relation between a land category of interest and other land cover categories is so complex that reforestation programs often fail to realize that farmers only shift to nearby forest covers to sustain their lives. As a result, it is common to read the success stories of reforestation intervention, which are solely based on evidence that an area that experienced deforestation has undergone reforestation (Honey-Rosés et al., 2018). However, failing to track the activities of other land categories, such as agriculture which often require deforestation in places like the Amazon may only result in short-lived reforestation.

This paper therefore, examines the complexities associated with reforestation on three land cover categories: forest formation, pasture, and a mosaic of agriculture and pasture in Brazil's Rio Doce water basin.

2 METHODS

2.1 Study Area

The study area is the Rio Doce water basin, located in the Aimorés (in Minas Gerais state) of Brazil, measuring 1787.2 acres (**Figure 1**). Its land cover comprises mainly forest, agriculture, and pasture. In the 1980s, severe deforestation destroyed the tree cover and ecological system of the Rio Doce water basin. Coincidentally, deforestation was spreading like wildfire across the Amazon of Brazil, and the world watched, via satellite imagery, with awe at the rate of the deforestation (Fernandes et al., 2020; West and Fearnside, 2021). The major turning point in the Rio Doce water basin occurred when two Brazilian couples, Sebastião Salgado and Lélia Deluiz Wanick Salgado, decided to champion the course of reforestation. Sebastião Salgado, a photographer, had been in Rwanda to take the photographic coverage of the Rwandan genocide but decided to return to

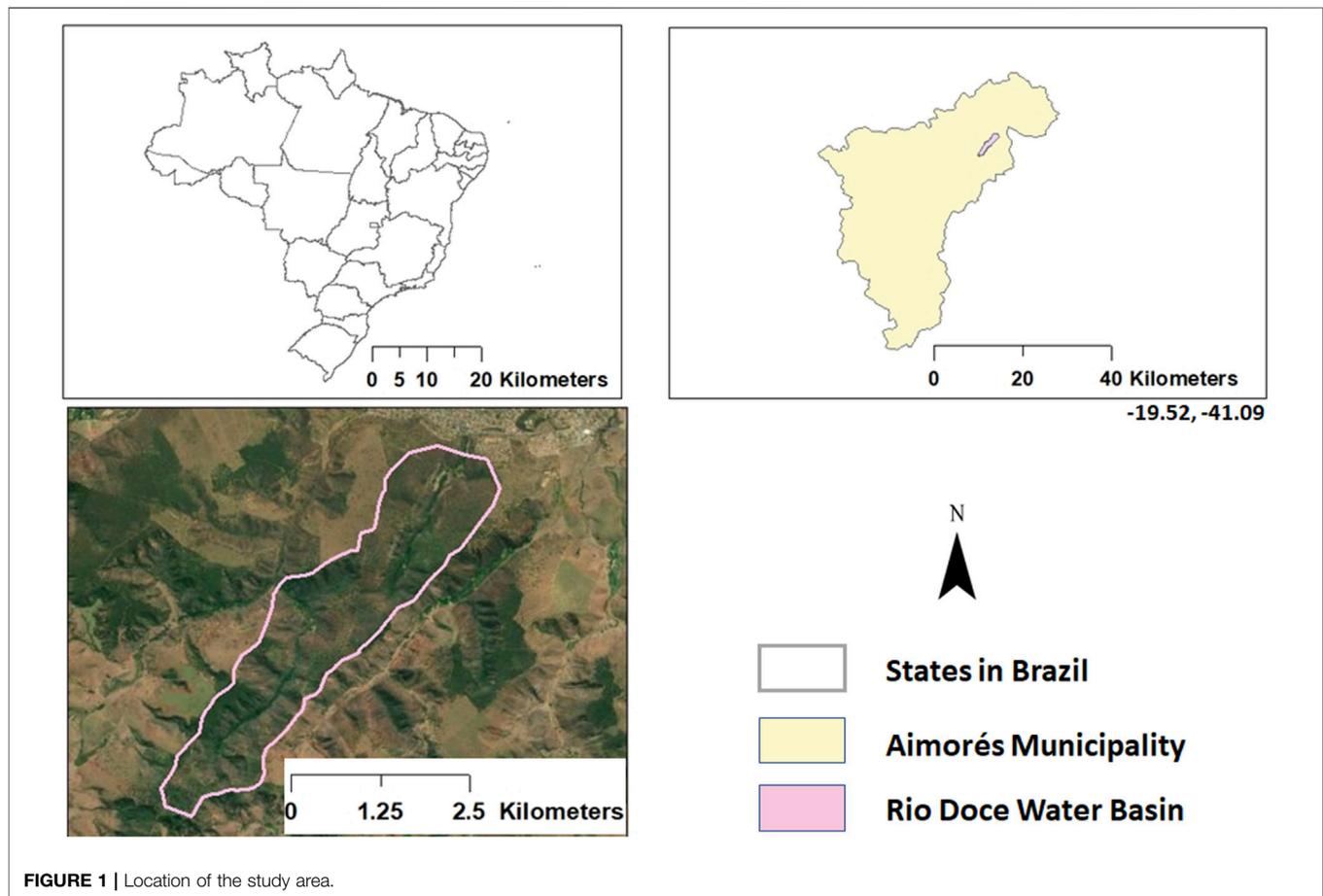


FIGURE 1 | Location of the study area.

Aimorés (his home) in 1994. Upon returning, he discovered that the beautiful scenery of the lush forest, which he enjoyed during his childhood, had been converted to pasture lands. Lélia Deluiz Wanick Salgado, his wife, encouraged him to team up with her to recover the lost forest. They commenced a reforestation intervention in 1999 and have since planted more than 4.5 million seedlings, encompassing about 293 of the tree species native to the Atlantic Forest (INSTITUTOTERRA, 2019). After 20 years, the world celebrates their success story of reforestation in the Rio Doce water basin. This paper will provide insights into the complex relationship between the reforestation intervention and other land cover categories such as pasture and agriculture.

2.2 Data

Figure 2A shows three land cover maps of the study area at time points 1998, 2008, and 2015. These time points were selected to reflect pre, mid, and post-reforestation efforts. The land cover maps are subsets of collection 3.1 of MapBiomias' land cover maps for the Minas Gerais state. The Landsat sensors Thematic Mapper™, Enhanced Thematic Mapper Plus (ETM+), and the Operational Land Imager and Thermal Infrared Sensor (OLI-TIRS) onboard Landsat 5, Landsat 7, and Landsat 8, respectively, serve as input data for creating MapBiomias' land cover maps with an overall accuracy of 85%. MapBiomias relies on Python and

JavaScript codes to classify the mosaic of Landsat images in a Google Earth Engine environment. Souza and Azevedo (2017) also provide detailed information concerning the methodology used to create the land cover maps. Readers can access all the JavaScript and Python codes at MapBiomias' public GitHub repository: <https://github.com/mapbiomas-brazil>. In addition, the land cover maps can be downloaded for free from https://mapbiomas.org/en/termosdeuso?cama_set_language=en. Each map shows four land cover categories: forest, pasture, agriculture and pasture, and infrastructure. Each land cover's spatial resolution is 30 m * 30 m, and **Table 1** provides definitions for each land cover category. **Figures 2B,C** show maps of losses and gains during 1998–2008 and 2008–2015.

Figure 3 shows the transition matrices for 1998–2008 and 2008–2015. **Figure 3** departs from the traditional, transitional table prominently features in most land change papers. This departure is useful because it does not bombard the reader with a wall of numbers, which often characterizes the traditional, transitional table. The squares in **Figure 3** clearly show the sizes of the trajectories associated with each category and offer a direct and easy way to gain insights into the sizes of loss, gain, and persistence associated with each category. The two transition figures in **Figure 3** serve as a data input for the intensity analysis.

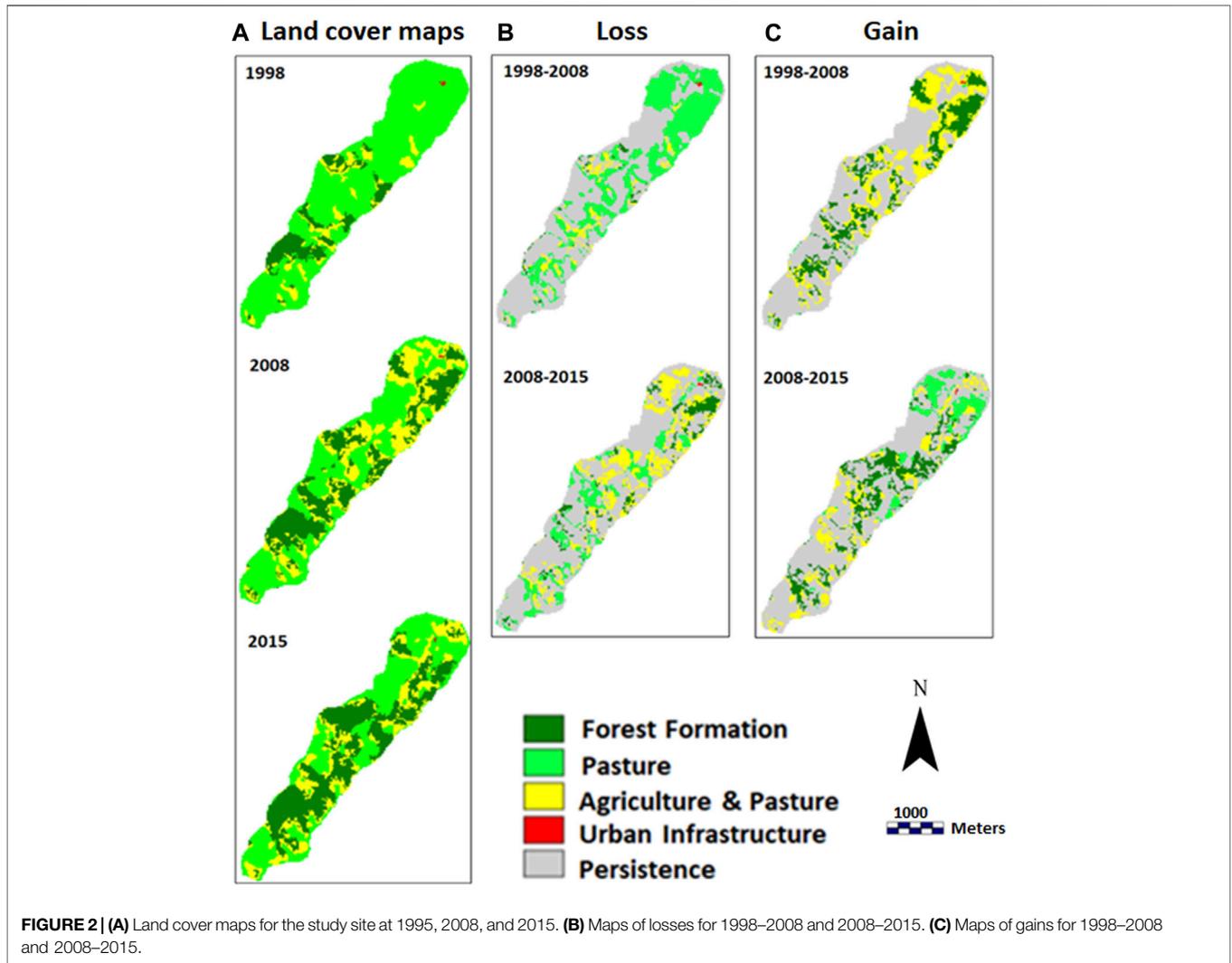


TABLE 1 | Definition of land cover categories (source: Souza et al., 2020).

Land cover	Definition
Forest formation	Vegetation types with a predominance of tree species with high-density continuous canopy, areas that were disturbed by fires and/or logging, and forest resulting from natural regrowth
Pasture	Pasture areas, natural or planted, related with farming activity. In particular, in the Pampa and Pantanal biomes, part of the area classified as grassland formation also includes pasture areas
Agriculture and pasture	Farming areas where it was not possible to distinguish between pasture and agriculture
Infrastructure	Urban areas with a predominance of non-vegetated surfaces, including roads highways, and constructions

2.3 Intensity Analysis

Intensity analysis is a quantitative framework developed by Aldwaik and Pontius (2012) to characterize change patterns in categorical data at varying temporal resolutions. The original framework of intensity analysis revolved around three levels of intensities: interval, categorical, and transitional, which shows

different levels in detail. **Table 2** provides information concerning the mathematical notations to analyze transition matrices.

2.3.1 Interval Level and Components

Interval level intensities measure variations in size and the annual rate of gross change during a given time interval (see **Eq. 1**). A time

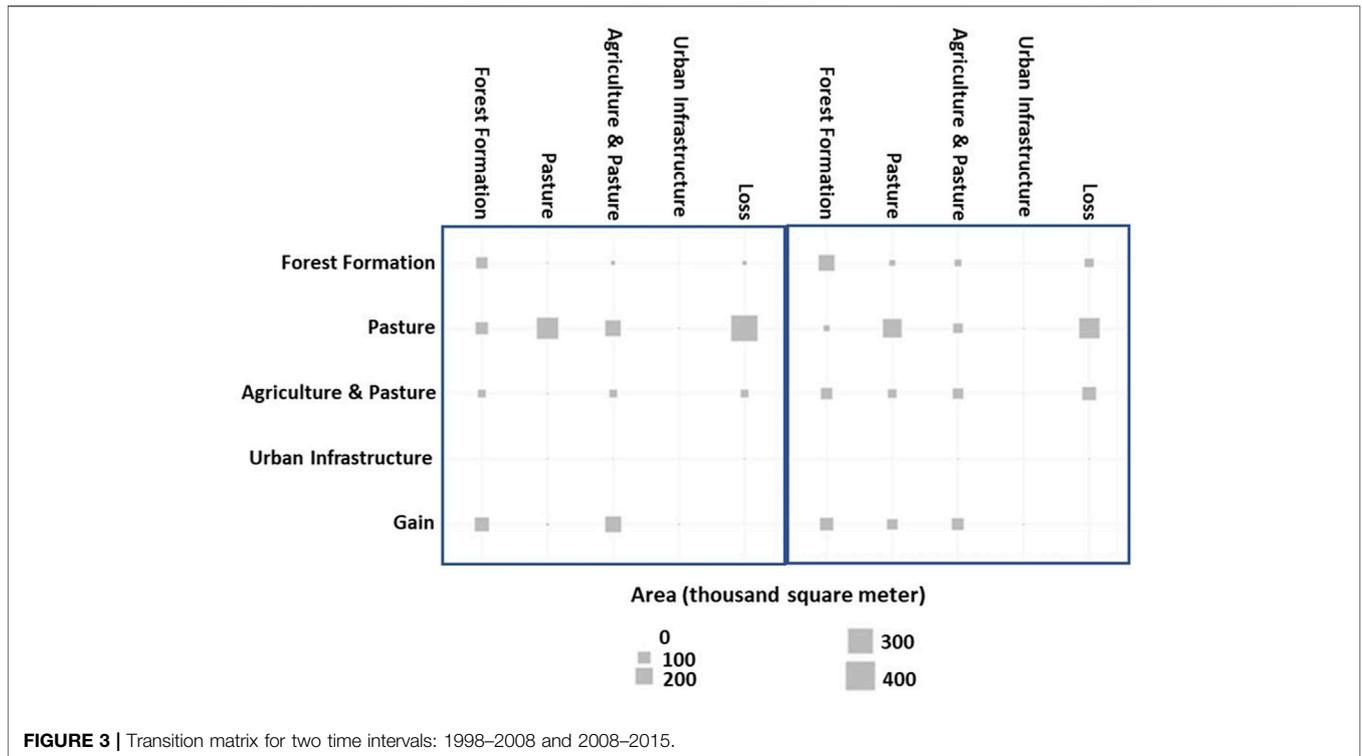


FIGURE 3 | Transition matrix for two time intervals: 1998–2008 and 2008–2015.

TABLE 2 | Mathematical notation.

Symbol	Meaning
I	Index for a category where $i = 1, 2, \dots, J$
J	Index for a category where $j = 1, 2, \dots, J$
J	Number of categories
T	Index for a time interval where $t = 1, 2, 3 \dots t$
C_{tii}	Size spatial extent that persists during interval t as a category i
C_{tj}	Size of the spatial extent that transitions during interval t from category i to category j
C_{tji}	Size of the spatial extent that transitions during interval t from category j to category i
C_{tjj}	Size of the spatial extent that persists during interval t as category j
D_t	Change intensity during interval t
Q_t	Quantity component of change intensity as a percentage of spatial extent during interval t
S_t	Shift component of change intensity as a percentage of spatial extent during interval t
E_t	Annual exchange component overall during the interval t intensity
L_{tj}	Loss intensity in the spatial extent during interval t for category i relative to the size of category i at the start of interval t
R_{tij}	Intensity of annual transition from category i to category j during time interval $[Y_t, Y_{t+1}]$ relative to the size of category i at time point t annual
W_{tj}	Uniform intensity of annual transition from all non- j categories to category j during time interval $[Y_t, Y_{t+1}]$ relative to the size of all non- j categories at time point t year
Y_t	Year at the start of time interval t
Y_{t+1}	Year at the end of time interval t

interval is duration between two time points. Thus, the interval level intensity offers insight into which site’s annual rate of gross change is slow or fast (Huang et al., 2012). **Equation 1** shows how to compute gross change; while **Equations 2, 3, and 4** show how to compute the three components of change: quantity, exchange, and shift from the gross change. **Eq. (2)** is divided by 2 because each change involves a losing and gaining category (Quan et al., 2018). As a result, the numerator of **Eq. 2** is double the absolute net (Chen and Pontius,

2011). **Equations 5–8** compute intensities for gross change and the three components of change.

$$Change_t = \sum_{i=1}^J \left[\left(\sum_{j=1}^J C_{tij} \right) - C_{tii} \right], \tag{1}$$

$$Quantity_t = \left[\sum_i^J \left| \sum_{j=1}^J (C_{tij} - C_{tji}) \right| \right] / 2, \tag{2}$$

$$Exchange_t = \sum_{i=1}^J \left\{ \left[\sum_{j=1}^J MINIMUM(C_{tij}, C_{tji}) \right] \right\}, \quad (3)$$

$$Shift_t = Change_t - Quantit y_t - Exchange_t, \quad (4)$$

$$D_t = \frac{Change_t 100\%}{size\ of\ region} = \frac{Change_t 100\%}{\sum_{i=1}^J (\sum_{j=1}^J C_{tij})}, \quad (5)$$

$$Q_t = \frac{Quantit y_t 100\%}{size\ of\ region} = \frac{Quantit y_t 100\%}{\sum_{i=1}^J (\sum_{j=1}^J C_{tij})}, \quad (6)$$

$$E_t = \frac{Exchange_t 100\%}{size\ of\ region} = \frac{Exchange_t 100\%}{\sum_{i=1}^J (\sum_{j=1}^J C_{tij})}, \quad (7)$$

$$S_t = \frac{Shift_t 100\%}{size\ of\ region} = \frac{Shift_t 100\%}{\sum_{i=1}^J (\sum_{j=1}^J C_{tij})}. \quad (8)$$

2.3.2 Categorical Level

The categorical level intensity measures sizes and intensities of each category’s gross gains and gross losses. It provides insights concerning which categories are dormant or active during a given time interval. As a result, the categorical level intensity shows which patterns of change are stable across given time intervals (Pontius et al., 2013). L_{ti} in Equation 9 defines the size of the loss intensity of category i as the percentage of the start size of category i that loses during the time interval $Y_{t+1} - Y_t$. Equation 10 computes the gain intensity (G_{tj}) and thus defines G_{tj} as the size of the gain intensity of category j as the percentage of the end size of category j that loses during the time interval $Y_{t+1} - Y_t$. The uniform intensity is D_t . Thus, if $L_{ti} < D_{ti}$ or $G_{tj} < D_{ti}$ then the loss and gain of categories i and j are dormant. If $L_{ti} > D_{ti}$ or $G_{tj} > D_{ti}$ then the loss and gain of categories i and j are active. Finally, if $L_{ti} = D_{ti}$ or $G_{tj} = D_{ti}$, then the loss and gain of categories i and j are uniform.

$$L_{ti} = \frac{annual\ loss\ of\ i\ during\ [Y_t, Y_{t+1}]}{size\ of\ i\ at\ Y_{t+1}} 100\% = \frac{[(\sum_{j=1}^J C_{tij}) - C_{tji}]/(Y_{t+1} - Y_t)}{\sum_j C_{tij}} 100\%, \quad (9)$$

$$G_{tj} = \frac{annual\ gain\ of\ j\ during\ [Y_t, Y_{t+1}]}{size\ of\ j\ at\ Y_{t+1}} 100\% = \frac{[(\sum_{i=1}^J C_{tij}) - C_{tji}]/(Y_{t+1} - Y_t)}{\sum_i C_{tij}} 100\%. \quad (10)$$

2.3.3 Transitional Level

The transitional level intensity shows which category’s transitions are intensively avoided or targeted during a given time interval. Equation 11 defines R_{tij} as the transition intensity from category i to category j (for $i \neq j$). Equation 12 defines W_{tj} as the uniform transition intensity to category j. Therefore, if $R_{tij} < W_{tj}$ then the gain of j avoids i during interval t. Conversely, if $R_{tij} > W_{tj}$ then the gain of j targets i during interval t. Finally, if $R_{tij} = W_{tj}$ then the gain of j is uniform to the gain of i during interval t. Aldwaik and

Pontius (2012), Quan, Pontius and Song (2020), and Pontius (2019) provided extensive mathematical expressions for each level of intensity analysis. In addition, readers can visit: <https://ww2.clarku/faculty/pontius/to> to download computer programs that facilitate the intensity analysis. Alternatively, readers can use the differR package in R to compute the intensity analysis. Figure 4 describes the workflow of this paper.

$$R_{tij} = \frac{annual\ transition\ from\ i\ to\ j\ during\ [Y_t, Y_{t+1}]}{size\ of\ i\ at\ Y_t} 100 = \frac{C_{tin}/(Y_{t+1} - Y_t)}{\sum_{j=1}^J C_{tij}} 100\%, \quad (11)$$

$$W_{tj} = \frac{annual\ gain\ of\ n\ during\ [Y_t, Y_{t+1}]}{size\ of\ non - j\ at\ Y_t} 100\% = \frac{[(\sum_{i=1}^J C_{tij}) - C_{tjj}]/(Y_{t+1} - Y_t)}{\sum_{j=1}^J [(\sum_i C_{tij}) - C_{tji}]} 100\%. \quad (12)$$

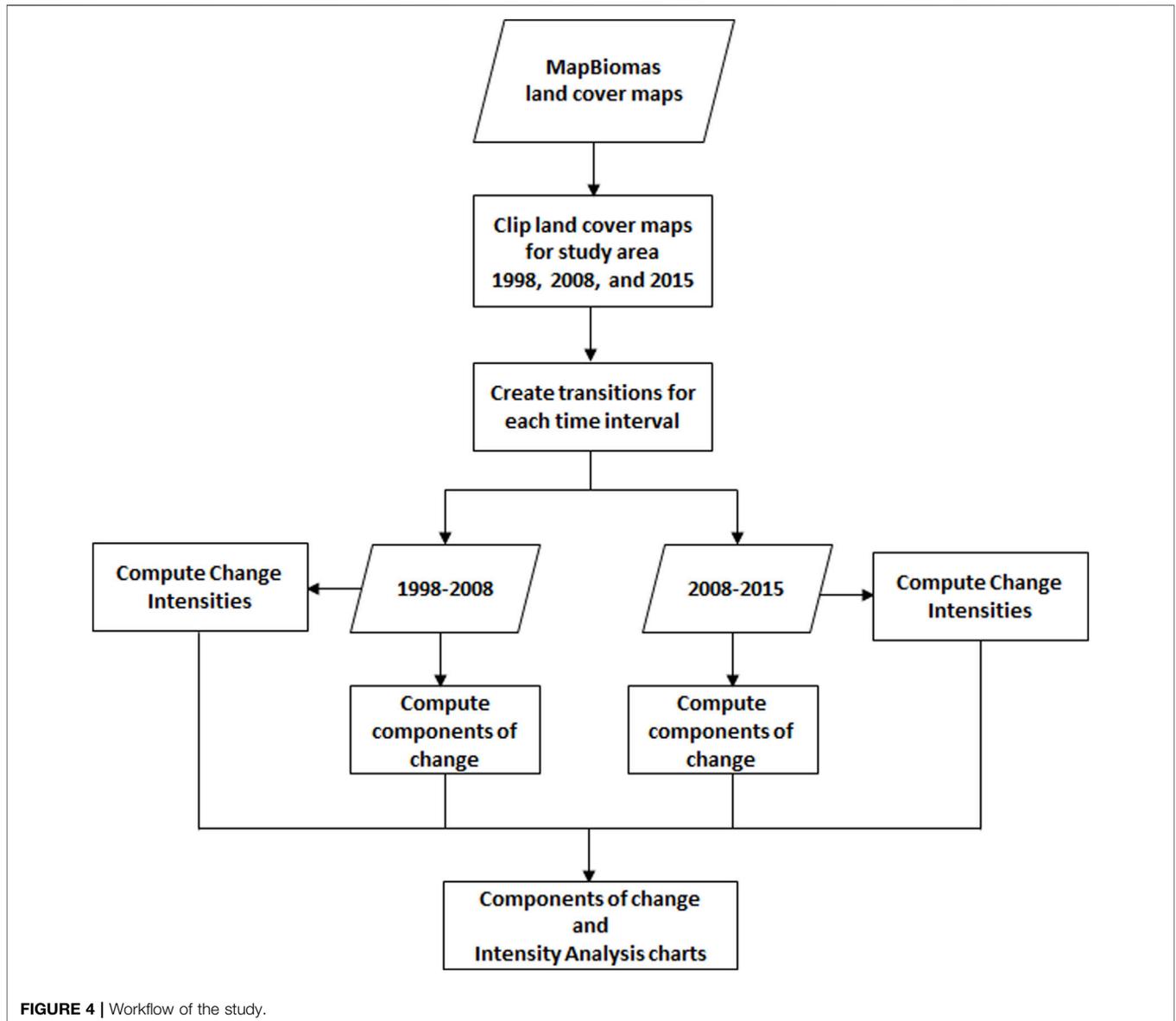
3 RESULTS

3.1 Interval Level

Figure 3 shows that the transitions involving infrastructure are almost zero during both time intervals. Thus, this paper focuses on analyzing the other categories’ intensities that have relatively larger transitions. Figure 5A shows that the percentage of the study area experiencing change during the first time interval (1998–2008) is larger than the percentage of the study area experiencing change during the second time interval (2008–2015). However, Figure 5B, which shows the interval and size for the two time intervals, shows that the annual change during the first time interval is slower than the annual change during the second time interval. This is because the short-dashed black line shown in Figure 5B is the uniform annual change. Thus, if a time interval’s bar falls short of the line, the time interval corresponding to that bar experiences a slow annual change. Conversely, if a time interval’s bar extends beyond the short-dashed black line, the time interval experiences a faster annual change.

3.2 Categorical Level

Figures 6A,B show quantity and allocation disagreement for the first and second time intervals. Pontius and Millones (2011) provide a detailed description of quantity and allocation disagreement. Figure 6A shows that quantity accounts for most of the change in forest formation, pasture, and the mosaic of agriculture and pasture during the first time interval. Figure 6A also indicates that the mosaic of agriculture and pasture experiences both exchange and shift during the first time interval. However, in Figure 6B, forest formation, pasture, and the mosaic of agriculture and pasture’s change are primarily exchange during the second time interval. Figures 7A,B show information concerning the categorical intensities for the two time intervals. In particular, Figures 7A,B show how uniform intensity compares with each

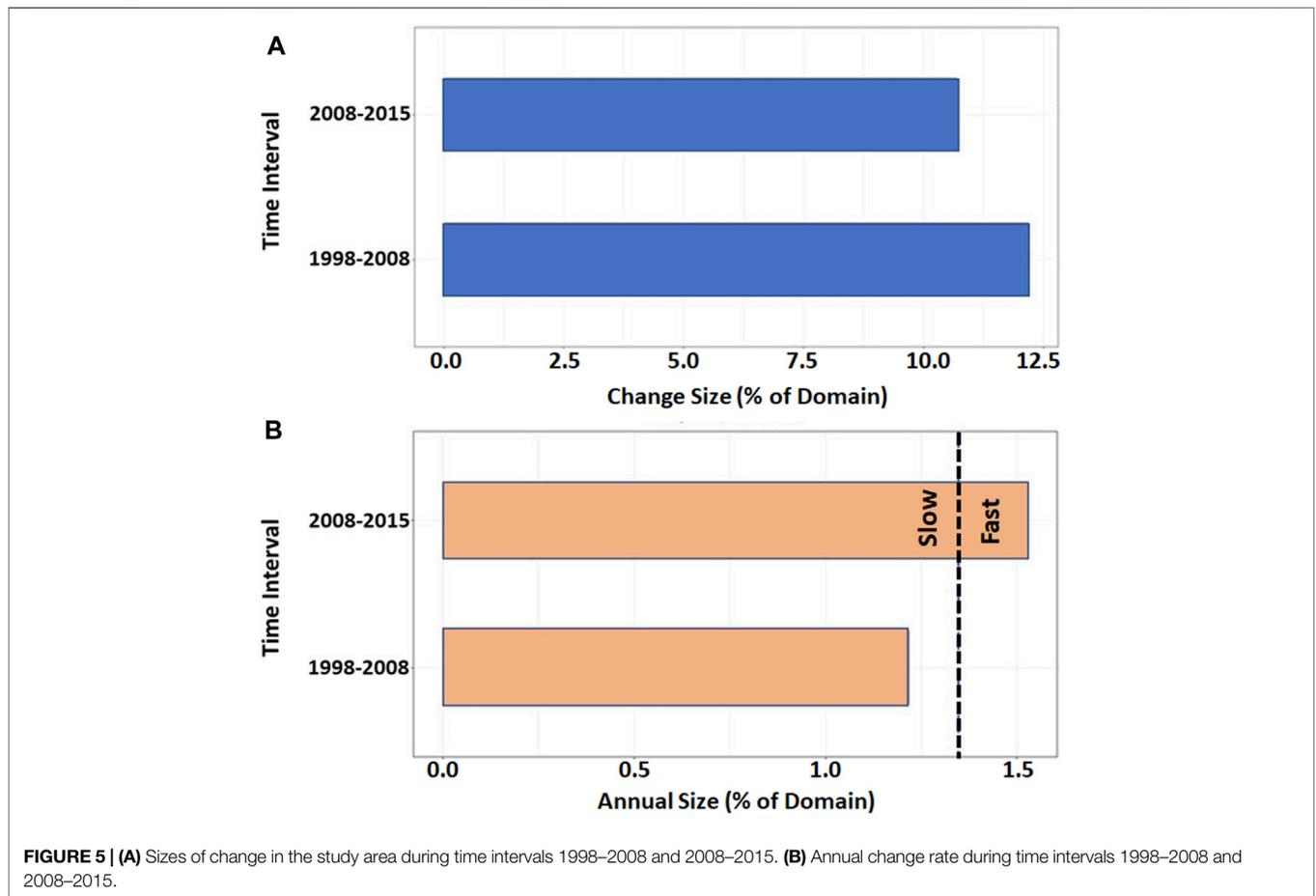


category’s intensity. If a category’s intensity falls short of the uniform intensity bar then the category’s change is dormant. If a category’s intensity bar extends beyond the uniform intensity bar then the category’s change is active. Finally, if the length of a category’s intensity bar equals the uniform intensity bar then the category’s intensity is uniform. Figures 1) and 2) show that forest formation and the mosaic of agriculture and pasture are active gainers during both time intervals; while pasture is an active loser.

3.3 Transitional Level

Loss or gain precedes the name of each category in **Figures 8A,B**. If loss precedes the name of a category, then that category is the losing category, and the categories in the stacked bar are the gaining categories. Conversely, if gain precedes the name of a category, then that category is the gaining category, and the categories in the stacked bar are the losing categories. For

instance, the first staked bar in **Figure 8A** is loss forest formation, which shows the intensities of two categories: pasture and the mosaic of agriculture and pasture. This indicates that the forest formation loses to both Ppasture and the mosaic of agriculture and pasture. **Figures 8A,B** show that forest formation gains more from pastures than the mosaic of agriculture during the first time interval. This is because pasture’s intensity is larger than the mosaic of pasture and agriculture’s intensity size in the gain forest formation stacked bar. Conversely, the forest formation gains more from the mosaic of agriculture and pastures than pasture during the second time interval. A > indicates that a gaining category targets the losing category, an = symbol indicates that a category’s transition intensity equals the gaining category’s uniform intensity, and an intensity bar without a > or = symbol indicates that a category’s transition intensity avoids the gaining category’s uniform intensity. Thus, forest



formation and pasture’s gains target forest formation more intensively than the mosaic of agriculture and pasture during both time intervals.

4 DISCUSSION

4.1 Time Interval Level

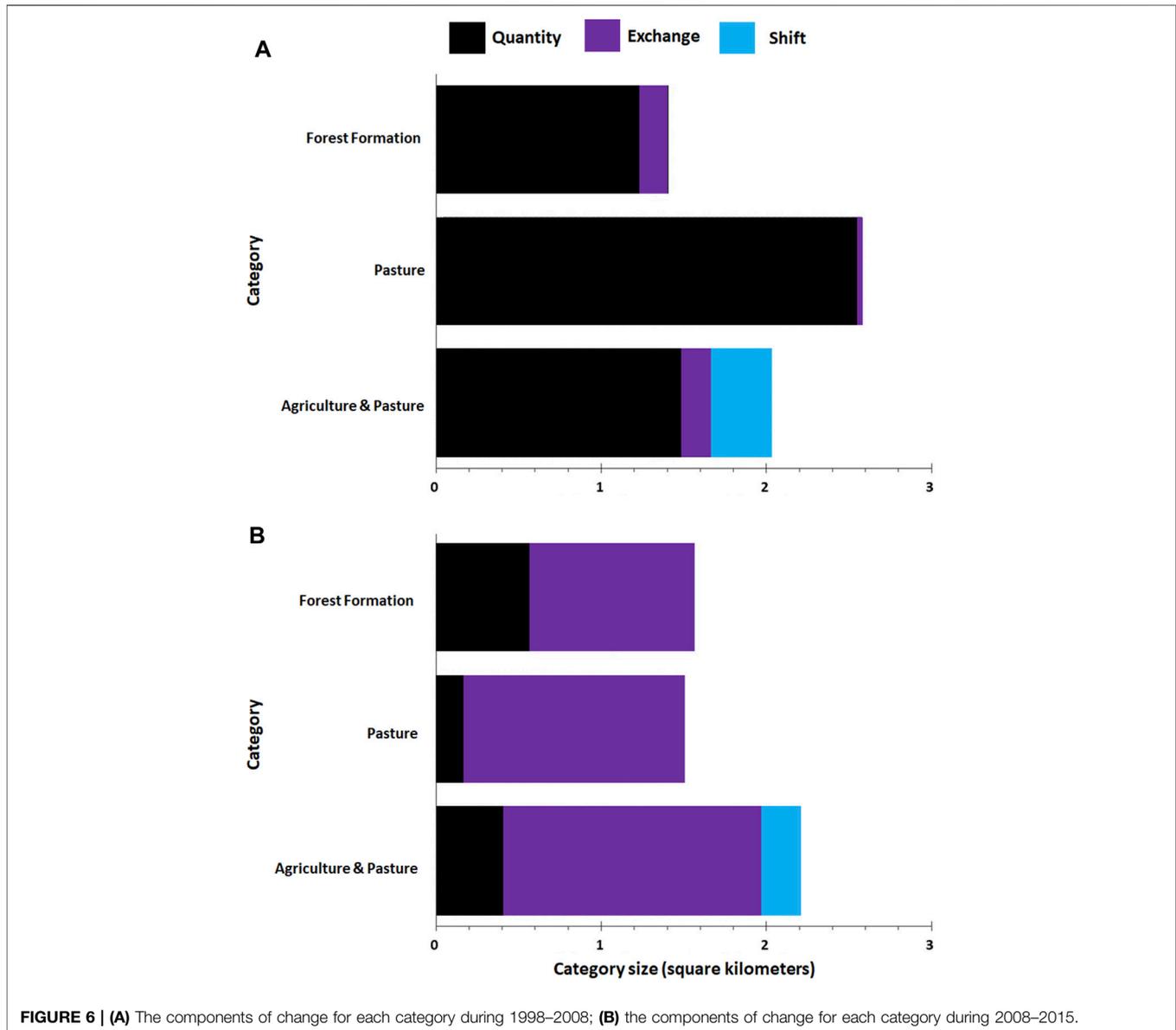
Land change in the Rio Doce water basin was faster during the second time interval (2008–2015) as compared to the first time interval (1998–2008). An increase in reforestation efforts, global demand for coffee, sugar, beef, and milk during the 20th century could have accounted for this observation (Rezende et al., 2009; Salter, 2017; Lyra and Rigo, 2019).

4.2 Category Level

Forest formation is an active gainer during both time intervals. This aligns with the goal of the reforestation program in the Rio Doce’s water basin (INSTITUTOTERRA, 2019). However, forest formation’s gain characteristics during the first time interval are different from the second time interval. During the first time interval, gain quantity is the largest component of change for the forest formation category with a small exchange component. On the other hand, forest formation’s gain quantity is almost the size of exchange during the second time interval.

Figure 6B and **Figure 7B** show that exchange accounts for most of the change in pasture and the mosaic of agriculture and pasture during the second time interval. This observation is consistent with findings from Lyra and Rigo (2019), which reported that an increase in the global demand for coffee and sugarcane (cash crops cultivated in the study area) influenced the decision of farmers in and around the Rio Doce water basin to convert forest into agriculture lands. Similarly, Silva, Batistella and Moran (2017) showed that between 1985 and 2010 farmers in the Atlantic Forest region of Brazil and, by extension, the Rio Doce water basin converted the large parcels of forest into pastures to sustain their livestock (primarily cattle). This action was again influenced by the high demand for milk and beef across the globe (Salter, 2017).

The decision to welcome change that affects the source of livelihood is not a simple one, especially for farmers living and practicing farming within a geographical region. Beymer-Farris and Bassett (2012), Nielsen et al. (2018), and Bauer (2005) showed that farmers’ decision to embrace a reforestation process might be influenced by a myriad of factors such as direct financial incentives, a guaranteed alternative source of livelihood, and the sustainability of the alternative source of livelihood. Thus, it is possible that the farmers in the Rio Doce basin saw the global demand for coffee, sugar, milk, and beef as an opportunity to profit from their pasture and



agricultural lands. This decision could have bolstered their resolve to continuously convert other land covers such as forest in the study area to pasture and agricultural lands.

4.3 Transitional Level

During the first time interval, forest formation gains more from pasture than it gains from a mosaic of agriculture and pasture. However, the > sign on the bar for the mosaic of agriculture and pasture shows that forest formation targets the mosaic of agriculture and pasture more intensively. This observation is perhaps due to prioritizing reforesting locations closer to forest or areas previously populated by forest formation (Valente, Petean and Vettorazzi, 2017). Another possibility is that it was more convenient to access seeds nearer to areas already forested (Ukrainetz, O'Neill and Jaquish, 2011). Janzen (1970)

and Wright (1983) demonstrated that the mortality of a seed increased with proximity to a reproductive adult tree and the density of seeds. Inferably, it is easier to find nursing seedlings of a specific tree species closer to an area currently or previously inhabited by the same tree species. It is, therefore, logical that the conservationists in the study area scouted for seeds from areas relatively closer to the exiting forest to 1) acquire seedlings having the same species of the trees in the study area and 2) save the cost of having to traverse to other regions to collections or purchase new seedling for the reforestation project. Conversely, **Figure 8B** shows that forest formation gains the most from a mosaic of agriculture and pasture while at the same time targeting the mosaic of agriculture and pasture during the second time interval. During both time intervals, the mosaic of agriculture and

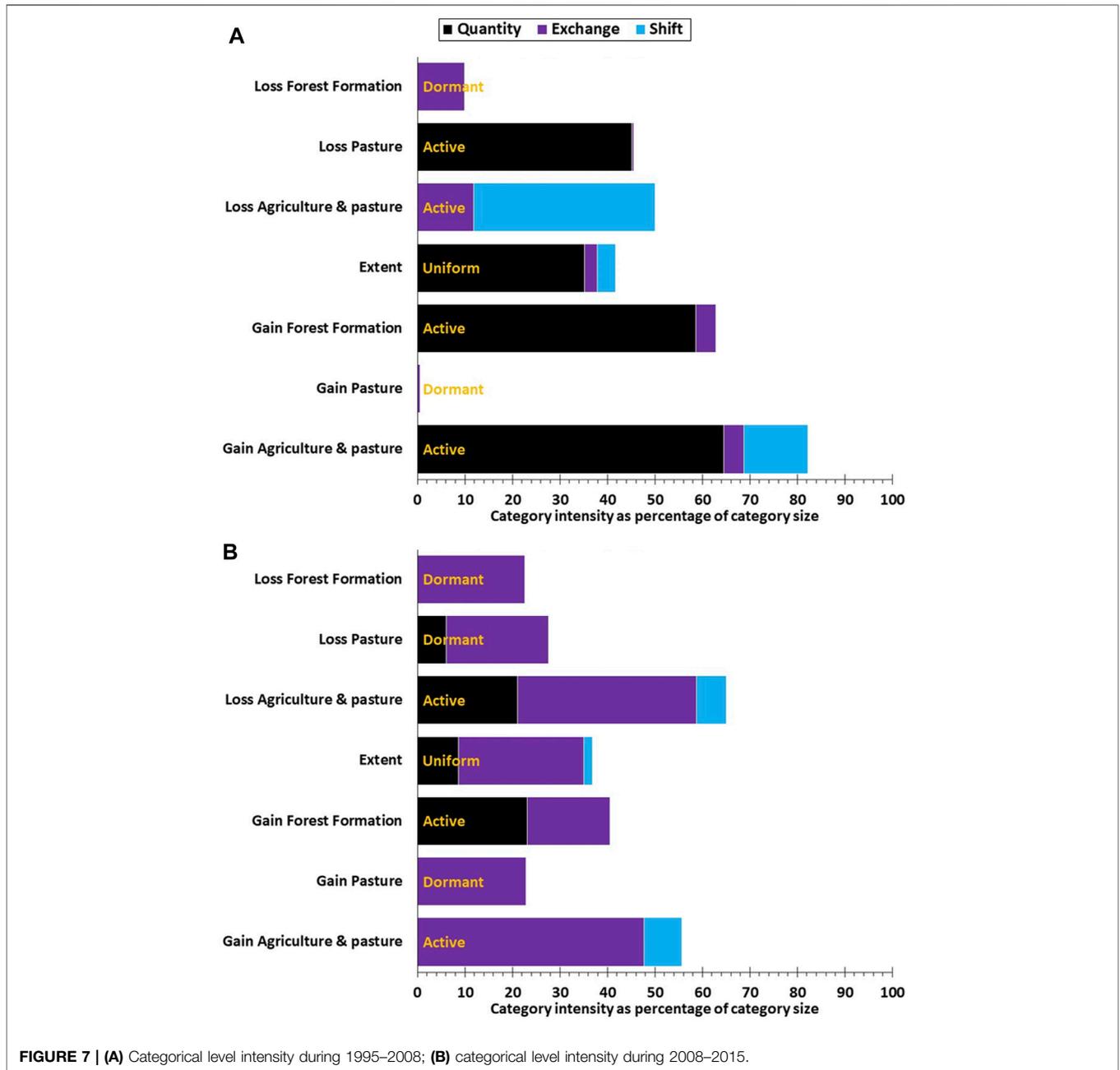


FIGURE 7 | (A) Categorical level intensity during 1995–2008; (B) categorical level intensity during 2008–2015.

pasture gains the most from both forest formation and pasture but targets pasture. This observation is attributable to the fact that the size of pasture in 1998 and 2008 is larger than the relative sizes of the other land cover categories. Furthermore, it is easier for farmers to convert pasture to a mosaic of agriculture and pasture because pasture consists of grassland, which is relatively easier to plow. Rashford, Walker and Bastian (2011) allude to a similar observation concerning farmers’ decision to convert grassland to agriculture land in the Prairie Pothole Region (north-central United States). They used a statistical model to show that farmers’ decision to convert

grassland to cropland increased on the average by 1.3% (from 1979 to 1997) and 1.5% from (2006–20011).

4.4 Next Steps

The results from intensity analysis show the intensity at which forest gains or losses during a specific time interval. However, it may be important also to gain insight into the relative distance at which forest gains or losses. Therefore, the author plans to develop or rely on existing methods to quantify the relationship between the loss and gain of reforestation in relation to distance to existing forests and other variables such as elevation.

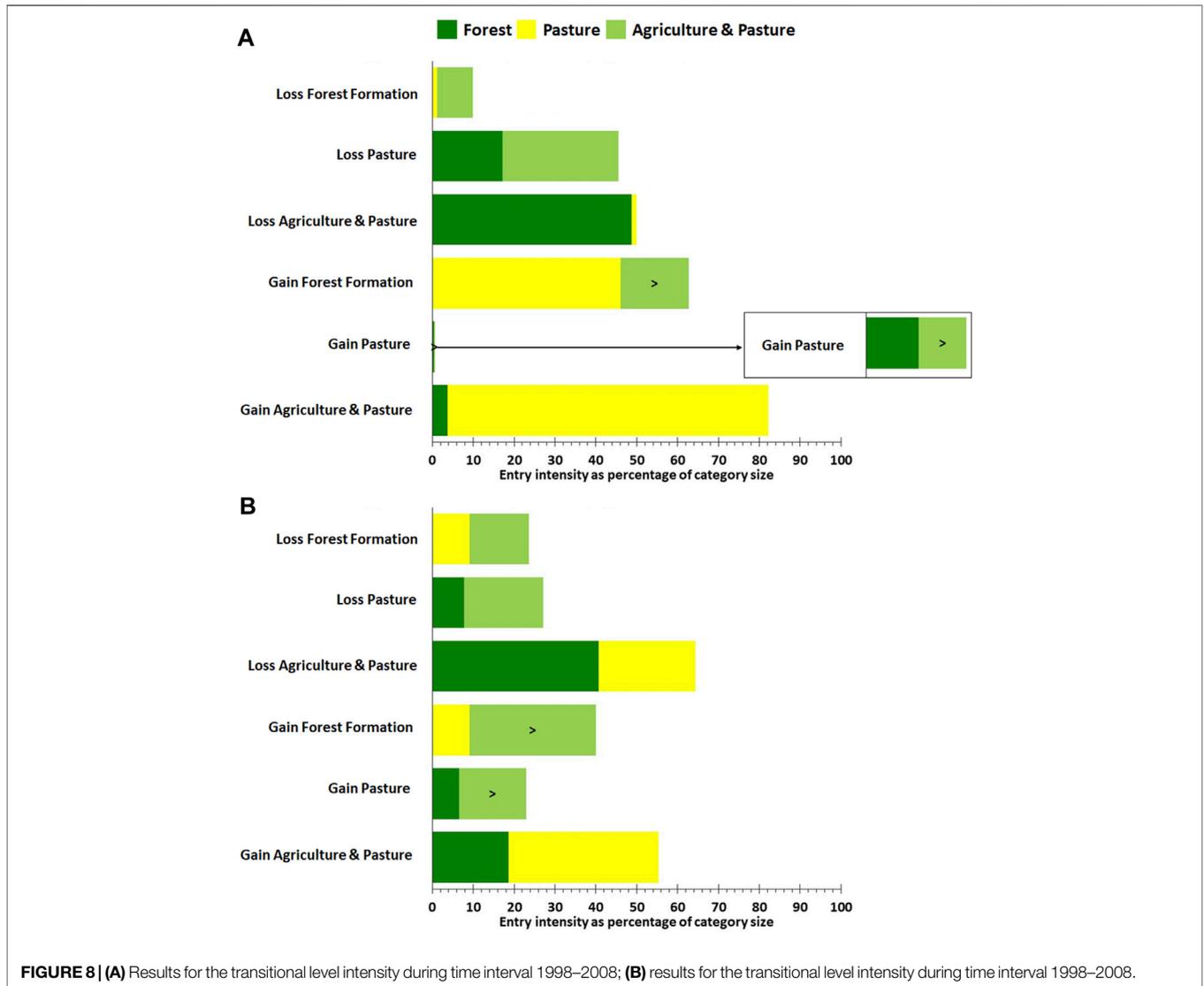


FIGURE 8 | (A) Results for the transitional level intensity during time interval 1998–2008; **(B)** results for the transitional level intensity during time interval 1998–2008.

5 CONCLUSION

This paper shows how a combination of land cover maps (derived from satellite imagery) and intensity analysis can reveal the complex dynamics between forest and other land cover categories during a reforestation process. It is clear from this paper that the reforestation process in the study site might be affected by an exchange between land cover categories, which contribute 0 to net change. Thus, the author recommends that the Terra institute, policymakers, and conservationists employ the methods described in this paper to review the progress of their reforestation programs. This will provide an insightful approach to measuring the success rate of the reforestation

process in the Rio Doce water basin and reforestation programs worldwide.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. These data can be found at: https://drive.google.com/file/d/1AGClGyg_8IRWhyz51NgeINs1Edhdf71/view?usp=sharing.

AUTHOR CONTRIBUTIONS

The author confirms being the sole contributor of this work and has approved it for publication.

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