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Data Descriptor

A New Multi-Temporal Forest Cover Classification for the Xingu River Basin, Brazil

Margaret Kalacska [1,*], Oliver Lucanus [1], Leandro Sousa [2] and J. Pablo Arroyo-Mora [3]

1 Applied Remote Sensing Laboratory, Department of Geography, McGill University, Montreal, QC H3A 0B9, Canada
2 Flight Research Lab, National Research Council of Canada, Ottawa ON K1A 0R6, Canada
3 Laboratório de Ictiologia de Altamira, Universidade Federal do Pará, Altamira PA 68372040, Brazil
* Correspondence: margaret.kalacska@mcgill.ca

Received: 26 June 2019; Accepted: 30 July 2019; Published: 1 August 2019

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Abstract: We describe a new multi-temporal classification for forest/non-forest classes for a 1.3 million square kilometer area encompassing the Xingu River basin, Brazil. This region is well known for its exceptionally high biodiversity, especially in terms of the ichthyofauna, with approximately 600 known species, 10% of which are endemic to the river basin. Global and regional scale datasets do not adequately capture the rapidly changing land cover in this region. Accurate forest cover and forest cover change data are important for understanding the anthropogenic pressures on the aquatic ecosystems. We developed the new classifications with a minimum mapping unit of 0.8 ha from cloud free mosaics of Landsat TM5 and OLI 8 imagery in Google Earth Engine using a classification and regression tree (CART) aided by field photographs for the selection of training and validation points.

Keywords: Landsat imagery; land cover change; deforestation; biodiversity; conservation; Xingu river basin

1. Summary

Ongoing deforestation in the tropics is a well-known threat to biodiversity [1–3]. Species with restricted ranges are particularly at risk of extinction from habitat loss [4]. Global- and regional-scale maps developed to analyze large-scale trends (e.g., [5–8]) do not necessarily capture the small-scale changes experienced by restricted range species. Therefore, these areas require the development of detailed land cover datasets that allow for a better understanding of historical and current environmental threats (e.g., deforestation, mining, etc.).

In addition to their high biodiversity, Amazonian forests are also important contributors to drivers of global atmospheric circulation [9] and climate change mitigation [10]. The Xingu River basin encompasses the fourth largest catchment area of the Amazon. It is known for its high fish biodiversity, with an estimated 600 species, 10% of them endemic to this river basin with many remaining to be described [11–14]. Several ethnic groups inhabit a mosaic of indigenous lands in a large part of the basin, contributing greatly to a slower rate of deforestation than is seen in unprotected Xingu basin headwaters [15–17]. The health of the riparian ecosystems is linked to changes in the overall forest cover and has a direct impact the unique fish biota [18]. In order to assess the rapid changes that the Xingu River basin has experienced over the last four decades, we developed a forest/non-forest classification system for four time periods from 1989 to 2018 as a case study applicable elsewhere in the tropics. These datasets were produced from cloud free surface reflectance mosaics of Landsat TM5 and Landsat 8-OLI images, classified with a classification and regression tree (CART) in Google Earth Engine.

2. Data Description

The four classifications are available for download in Geotiff format (30 m pixel size) (Figure 1). Each classification is in a geographic projection (latitude/longitude) with WGS84 datum. Pixels represent one of three classes: forest (1), water (2), or non-forest (3). Our definition of forest is "areas with approximately greater than 30% tree canopy cover", which is consistent with the Brazilian definition [19]. The implementation of this definition was based on approximately 3000 field photographs (see Section 3). The non-forest class encompasses all land covers and land uses that are not considered forest or open water. The water class represents exposed surface water.

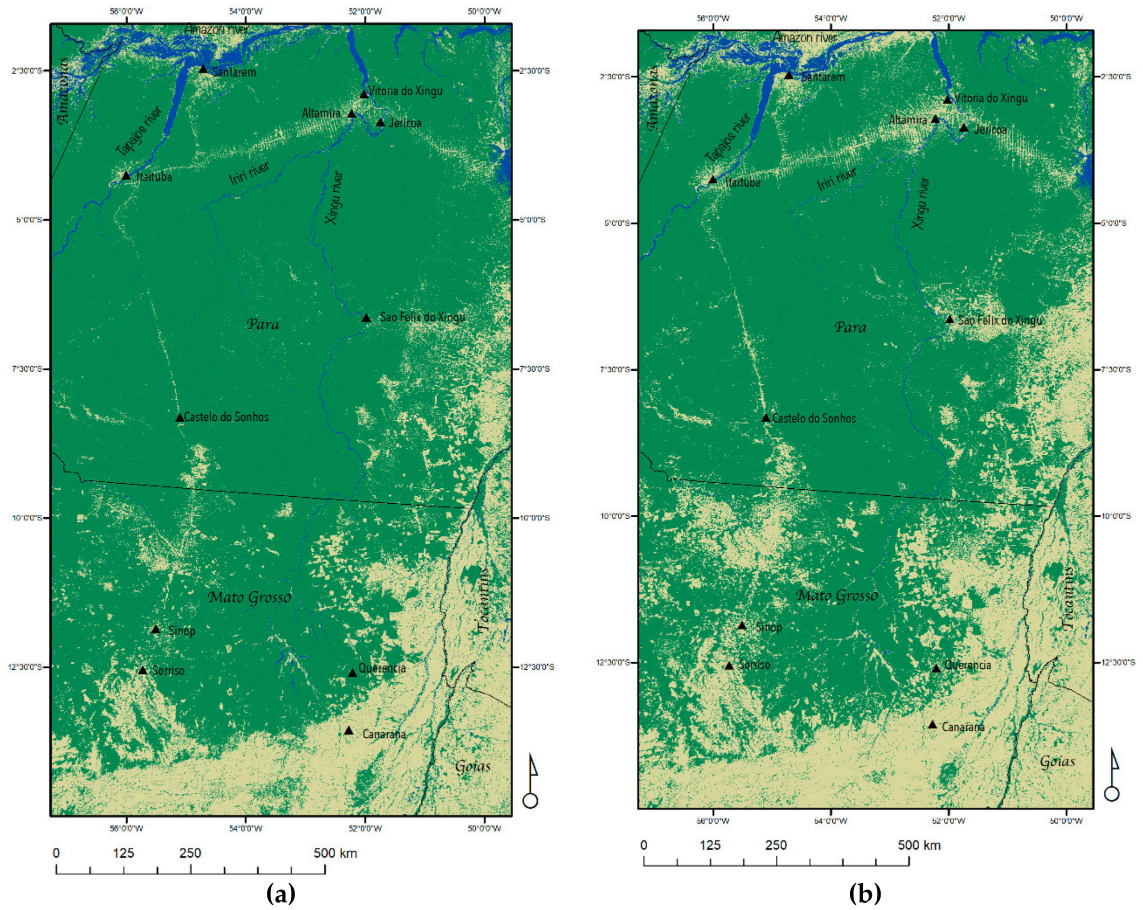
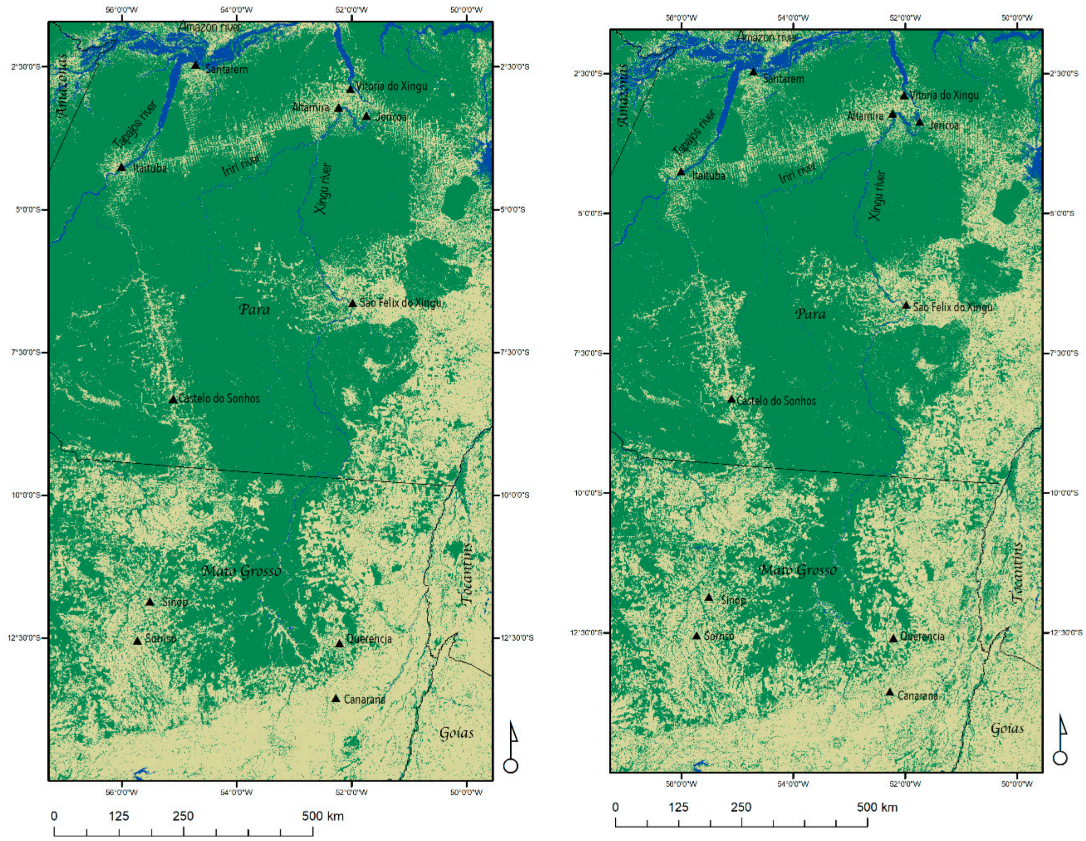


Figure 1. *Cont.*



(c) **(d)**

Figure 1. Four classifications of forest cover for the Xingu river basin for (**a**) circa 1989, (**b**) circa 2000, (**c**) circa 2010, and (**d**) circa 2018 from Landsat TM5 and OLI 8 imagery. Boundaries of states, larger rivers, and landmarks including cities and the Jericoá rapids are shown for reference.

3. Methods

The forest cover classifications were created for a 1.3M km^2 area encompassing the Xingu River basin, Brazil, representing circa 1989, 2000, 2010, and 2018 from Landsat imagery (TM5 and OLI 8) (Table 1). The area crosses the borders of five states: Pará, Mato Grosso, Amazonas, Tocantins, and Goiás (Figure 1). The USGS Landsat Surface Reflectance Tier 1 imagery collection was queried through Google Earth Engine (Table 1). Clouds and cloud shadows were masked using the pixel QA bands to create a cloud free composite of the median surface reflectance for each reference period. In order to achieve cloud free composites for such a large area in the tropics which is prone to persistent cloud cover, the composites represent periods spanning 1985–1989, 1995–2000, 2005–2010, and 2017–2018. A classification and regression tree (CART) [20] was trained in Google Earth Engine for each mosaic, based on user-generated points split 70/30 for training and validation.

For the most recent mosaic, the training and validations points were selected based on photographs taken during four field expeditions in 2015–2018. The photographs were taken along the Xingu River (by boat) from Vitória do Xingu, north of São Félix do Xingu (400 km straight line distance to the south) (Figure 2). Additional photographs were taken along the PA-415 road between Altamira and Vitória do Xingu and along the BR 230 (Transamazônica) highway between Altamira and an unnamed settlement near the river's natural diversion to the west, above the entrance to the Volta Grande, where the river drains from the Brazilian shield to the Amazonian lowlands. In the south, photographs were taken along primary roads and rivers (Culuene, Suiá Missu, Darro, Curuá) in an area bounded by Canarana (SE), Sorriso (SW), Castelo do Sonhos (NW), and halfway downstream the Suiá Missu towards its confluence with the Xingu River (NE). The photographs allowed for an understanding of the landscape from the satellite imagery in order to improve differentiation between the forest and non-forest classes. Based on the landscape in the most recent imagery, these photographs were also used to visualize interpretations of the previous years' mosaics for the manual selection of training points and validation points.

Table 1. Landsat image collections used for the classifications through Google Earth Engine.

Period	Image Collection
1985–1989	LANDSAT/LT05/C01/T1_SR
1995–2000	LANDSAT/LT05/C01/T1_SR
2005–2010	LANDSAT/LT05/C01/T1_SR
2017–2018	LANDSAT/LC08/C01/T1_SR

After classification, a minimum mapping unit (MMU) of 90 m × 90 m (0.8 ha) was applied. Based on the field expeditions, this MMU is reasonable for capturing the majority of the forest fragments in the region. First, a standard sieve routine was applied in ENVI 5.2 to remove isolated pixels. Only pixel groupings of six or more were retained, followed by a clump routine to improve the spatial coherence (e.g., fill in the holes left by the sieve operation). With a kernel of 3 × 3 pixels, the routine first performs a dilation, followed by an erosion. The end result is a clumping of adjacent similarly classified pixels.

Confusion matrices for the four datasets (Tables 2–5) indicate a high accuracy for all three classes. The ground truth data allowed for selecting training points that represent the expected variability of the classes (Figure 2). Nevertheless, these confusion matrices represent the maximum accuracy, and with additional ground truth data, classification errors may be found in areas with rapid land cover change (e.g., secondary growth in abandoned clearings).

Table 2. Confusion matrix for the forest cover classification (around 1989). Sample size for training = 413.

Classification \ Reference	Forest	Non-forest	Water
Forest	56	2	0
Non-forest	0	66	0
Water	0	1	52

Table 3. Confusion matrix for the forest cover classification (around 2000). Sample size for training = 390.

Classification \ Reference	Forest	Non-forest	Water
Forest	53	0	0
Non-forest	2	60	0
Water	0	0	52

Table 4. Confusion matrix for the forest cover classification (around 2010). Sample size for training = 415.

Classification \ Reference	Forest	Non-forest	Water
Forest	57	1	0
Non-forest	4	63	0
Water	0	1	52

Table 5. Confusion matrix for the forest cover classification (around 2018). Sample size for training = 583.

Classification \ Reference	Forest	Non-forest	Water
Forest	62	5	0
Non-forest	0	81	0
Water	0	0	58

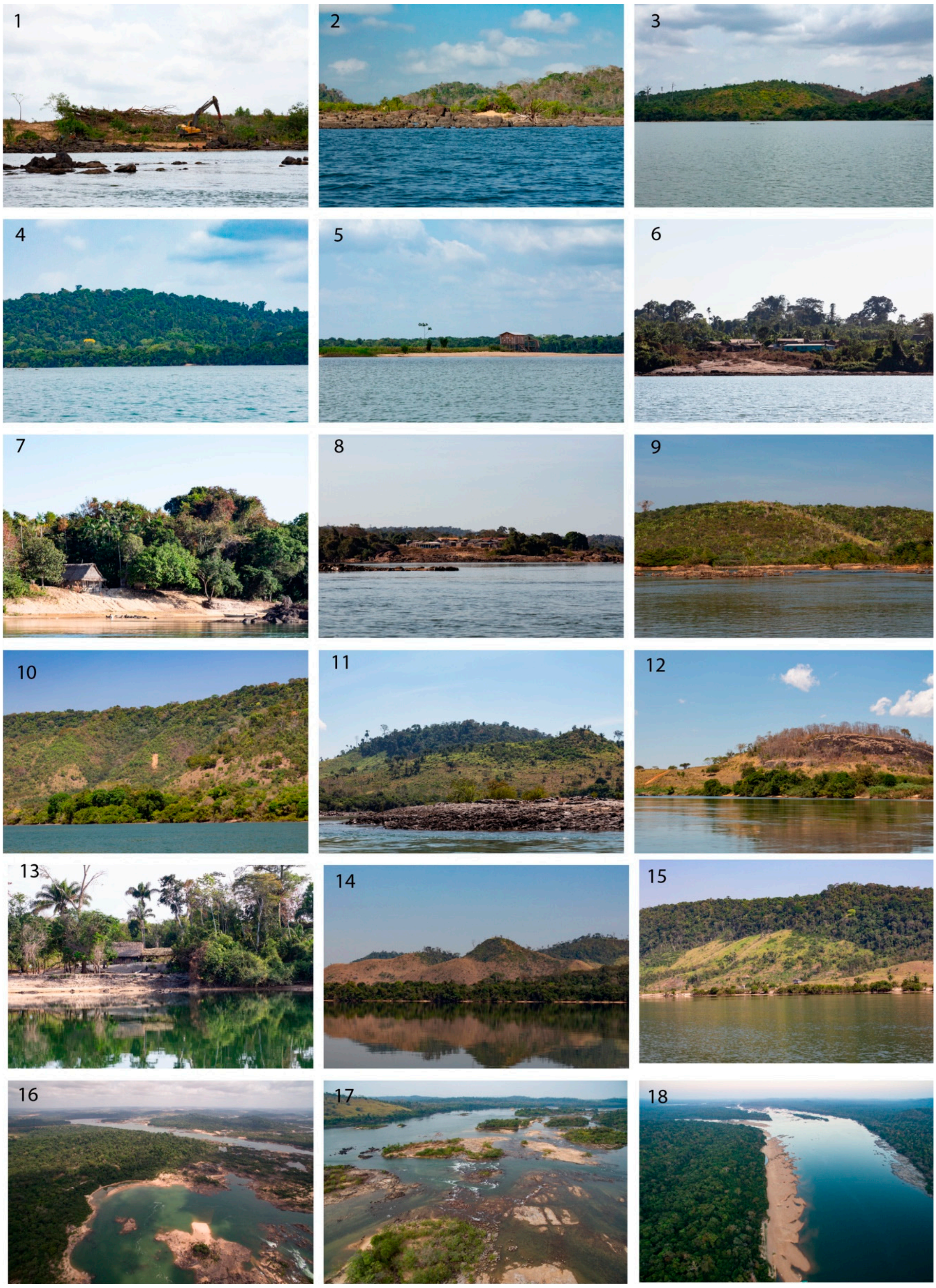


Figure 2. *Cont.*

Figure 2. Examples of field photographs used to train the visual interpretation of the imagery for selecting classification and regression tree (CART) classification training and validation points. * indicates the Northern zone between Vitória do Xingu and Sao Felix do Xingu, ** indicates the Southern sector (south of Castelo do Sonhos). 1: clearing of Arapujá Island across from Altamira*, 2: partially deciduous forest, sandy beach, and rocks*, 3: large patch of cleared forest*, 4: intact forest*, 5: homestead in Amazonia lowlands*, 6: small settlement*, 7: small household*, 8: larger settlement*, 9: large-scale deforestation*, 10: deforestation with secondary growth*, 11: large-scale deforestation*, 12: burned land prior to deforestation*, 13: homestead*, 14: large-scale deforestation*, 15: large-scale deforestation*, 16: aerial view north from the Jericoá rapids*, 17: aerial view from the Xadá rapids with deforestation on the unprotected side*, 18: aerial view of intact forest in protected area*, 19: aerial view of intact forest at the Iriri rapids*, 20: small-scale clearing at the Jericoá rapids*, 21: intact forest along the Culuene river**, 22: exposed soil for agriculture**, 23: cattle herd**, 24: Belo Monte dam*, 25: isolated forest patch in corn field**, 26: large corn field**, 27: plantation**, 28: extensive pasture land**, 29: extensive cotton field**, 30: recently cut forest**, 31: pasture with forest patch **, 32: pasture with isolated trees**, 33: cornfield with forest patch**.

4. Limitations

Users must be aware that due to the pixel size of the satellite imagery, smaller bodies of water and narrow rivers/streams could not be classified (Figure 3). The smaller tributaries where the water is often narrower than a single pixel and may have extensive vegetation covering the banks are not included in the classifications. The MMU of ~1 ha also means that very small forest and non-forest patches will have been sieved out of the classifications. Furthermore, because each classification is representative of the median reflectance for the time period, small temporal scale changes in land cover may not be represented.

Figure 3. Open rivers wider than a single pixel (i.e., >30 m) such as in the photograph on the left are included in the classifications. Users are cautioned, however, in examining the surface water class for narrow rivers/streams (<30 m), especially those with dense overgrowth, such as in the photograph on the right. The classifications underestimate the area for these smaller rivers/streams.

5. Conclusions

We describe a new multi-temporal classification for the Xingu River basin, Brazil. This dataset was created through the classification of Landsat TM5 and OLI 8 imagery in Google Earth Engine. The Landsat archive allowed for consistency in the classifications over the four periods. The purpose of creating these localized classifications is to address the need for accurate forest cover change data in a region with high biodiversity as well as rapid land cover change due to anthropogenic factors including deforestation, hydro-electric dam impoundment, mega-scale agriculture, extensive cattle ranching, and population growth. The inclusion of field photographs in the training of the CART models allowed for the local variability of the classes to be taken into account, an aspect difficult to do on a global scale. This classification does not rely on other reference datasets, and as such, potential errors in other data sets are not propagated further. For future studies, and to address the limitations of the spatial resolution of these data (e.g., underestimation of small water bodies), other global optical satellite image collections (e.g., Sentinel-2) or radar data from archived (e.g., RADARSAT-2) or new data (e.g., RADARSAT Constellation Mission) should be investigated.

Author Contributions: O.L., L.S., M.K. and J.P.A.-M. collected the field data. M.K. carried out the analysis. All authors contributed to the writing and editing of the manuscript.

Funding: Natural Sciences and Engineering Research Council of Canada, and Discovery Grant Program to Kalacska and CNPq Universal Project #486376/2013-3 to Sousa.

Acknowledgments: We thank Márcio Vieira, Damilton Rodrigues de Costa (Dani) and Antônio Silva de Oliveira (Toninho) for their help in the field. We also thank two anonymous reviewers for their comments to improve our manuscript.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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