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LETTER

Forest loss is significantly higher near clustered small dams than single large dams per megawatt of hydroelectricity installed in the Brazilian Amazon

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Abstract

Hydropower in the Brazilian Amazon is a prevalent form of development, but dams have widespread and long-term environmental impacts that include deforestation in the areas surrounding the dams. Small hydropower plants (SHPs) are often perceived as having reduced environmental impacts compared to the large ones. In Brazil, SHPs are licensed by state governments, which have less strict requirements than the federal environmental agency. Brazil's definition of 'small' dams has grown with successive increases in the maximum installed capacity from 10 to 30 to 50 megawatts (MW). This expanding loophole has increased the attractiveness of investing in multiple small dams rather than a single large dam, with resulting proliferation of SHPs. Forest dynamics surrounding the clustered SHPs when compared to single large dams are not well documented. In this study, we capitalized on a dense time series of satellite images to quantify and compare forest loss in the regions (over 110 000 km^2 in area) surrounding 15 SHPs and 7 large dams at multiple watershed and buffer scales in the Brazilian Amazon for nearly two decades (2000–2018). The landscapes containing SHP clusters had lower cumulative forest loss as compared to those with large dams. However, when deforestation and hydroelectric generating capacity were jointly considered (i.e. forest loss per megawatt installed), we discovered an opposite trend. The regions surrounding the SHP clusters exhibited significant impacts ranging from 1.9 to 2.5 times that of the regions surrounding large dams across 5 km to sub-basin scales. Due to the considerable consequences of SHPs on deforestation, we argue that the rapid expansion of small hydropower should be approached with caution and requires more stringent environmental assessments.

1. Introduction

Tropical forests are widely known for having the greatest amount of biodiversity on Earth, sequestering carbon, and providing numerous valuable ecosystem services (Gentry 1992, Di Corato *et al* 2016). The Amazon rainforest is the largest tropical forest in the world, with 70% of it being located within the nation of Brazil (Kirby *et al* 2006). Anthropogenic forest loss is currently threatening the Brazilian Amazon, with one driver being hydroelectric dams. Dams drive forest loss directly by inundating upstream landscapes, altering river flow regimes, and by their associated access roads, quarries, and transmission lines, while indirectly promoting forest loss through the facilitation of urban development, human resettlement, agriculture, and additional downstream and upstream hydropower projects (Rosenberg *et al* 1995, Ledec and Quintero 2003, Fearnside 2014). The Brazilian Amazon contained operational hydroelectric dams with installed capacity totaling 23 246 megawatts (MW) in 2018, with 38 537 MW inventoried, 997 MW proposed, and 783 MW under construction (Brazil, Eletrobras 2018). Brazil aspires to add over 31 gigawatts (GW) in hydropower capacity to its part of the Amazon region over the next two decades (Westin *et al* 2014).

Brazil's announced plans for Amazonian dams have varied dramatically over the years depending on the perception of the country's electrical authorities regarding restrictions on impacts on indigenous peoples. Changes in policy have caused small hydropower plants (SHPs) in Brazil to increase by approximately five times since circa 2000 (Couto and Olden 2018, Athayde *et al* 2019). Worldwide, definitions of SHPs vary widely depending on the region or country in question; however, they are typically located on smaller rivers and generate less electricity than large dams (Kelly-Richards *et al* 2017, Couto and Olden 2018). In Brazil, the definition of a SHP has progressively become more inclusive: in 2004 the limit defining 'small' dams increased from 10 to 30 MW, and in 2016 the limit increased to 50 MW (Ferreira *et al* 2016, Couto and Olden 2018). Due to their small size and widespread adoption of run-of-the-river technology that causes minimal flooding and impoundment, SHPs are commonly classified as having low ecological impacts without proper evidence to substantiate these claims (Abbasi and Abbasi 2011, Okot 2013). Since existing policies, regulations, and public perceptions of SHPs often view them as highly sustainable, SHPs receive less attention than large hydroelectric projects and consequently require less stringent Integrated Environmental Assessments (Kelly-Richards *et al* 2017, Athayde *et al* 2019).

Although SHPs are assumed to have less environmental impacts than larger projects, critics have argued that the environmental and social impacts per MW may be comparable to those of large dams (Abbasi and Abbasi 2011, Couto and Olden 2018, Kelly 2019). In fact, SHPs often perform worse on a variety of environmental criteria when compared to larger hydro projects (Kibler and Tullos 2013, Bakken *et al* 2014, Premalatha *et al* 2014). For example, assessments of SHPs and large dams in Norway found that, while the large dams and their reservoirs occupied a greater amount of land and greatly impacted water temperature, SHPs had a more severe impact on red-listed species, wilderness-area reduction, local climate, erosion, recreation, and fish populations (Bakken *et al* 2012, 2014). In China, an evaluation of both small and large dams found that SHPs had greater negative impacts per MW on habitat diversity and sub-basin connectivity, and also had direct and indirect impacts on conservation land and on water quality (Kibler and Tullos 2013). Since multiple SHPs are often developed along the same portion of a river, an assessment and management at the watershed scale is needed to successfully mitigate the cumulative impacts of multiple small dams (Couto and Olden 2018). In Brazil, there is a growing concern about small and large dams within other biomes as well, and a number of studies have recently evaluated their impacts on aquatic and terrestrial fauna (Arantes *et al* 2019, Ruocco *et al* 2019, Alho 2020, Campos *et al* 2020), on bird communities (Abreu *et al* 2020, Alho 2020), and on human populations (Sgarbi *et al* 2019, Moran 2020, Santos *et al* 2020).

Regional landscape changes and forest loss surrounding hydroelectric dams have largely been studied using remote-sensing-based approaches, with research linking deforestation and fragmentation to inundation, changing settlement patterns, and increases in agriculture (Indrabudi *et al* 1998, Tefera and Sterk 2008, Zhao *et al* 2013, Chen *et al* 2015, Jiang *et al* 2018). These studies have primarily focused on landscape change and forest loss surrounding a single large dam, and at only one scale (Indrabudi *et al* 1998, Tefera and Sterk 2008, Chen *et al* 2015, Jiang *et al* 2018). However, drivers of forest loss occur at a variety of scales. Changes in flow regimes driven by hydropower dams also cause environmental impacts across scales, with increasing riparian species mortality observed as far away as 40 km downstream, and decreases in flow altering the seasonal hydrologic cycle, sometimes all the way to the ocean (Neu 1982, Rood *et al* 1995). Zhao *et al* (2013) tested landscape change for multiple buffer zones extending up to 10 km from the Manwan Dam in China and found that distance decay was clear, with stabilization occurring beyond a distance of approximately 3 km from the dam. Although a substantial increase of SHPs in Brazil has occurred, how these dams directly and indirectly influence long-term, multi-scale forest loss and fragmentation is not well understood.

To better understand the implications of SHP expansion on forest dynamics in the Brazilian Amazon, an assessment and comparison of small and large dams across spatial scales is essential. In this study, we took advantage of a dense time series of satellite images spanning nearly two decades (one to two image scenes per day from 2000 to 2018) to capture and compare forest loss surrounding both clustered SHPs and large dams at multiple buffer and watershed scales in the Brazilian Amazon. This study aims to address the question: Are forest-loss rates in the Brazilian Amazon greater surrounding large dams when compared to the cumulative impact of SHP clusters? This study aspires to guide policy makers by facilitating a greater understanding of the impact SHPs and large dams on post-construction forest dynamics.

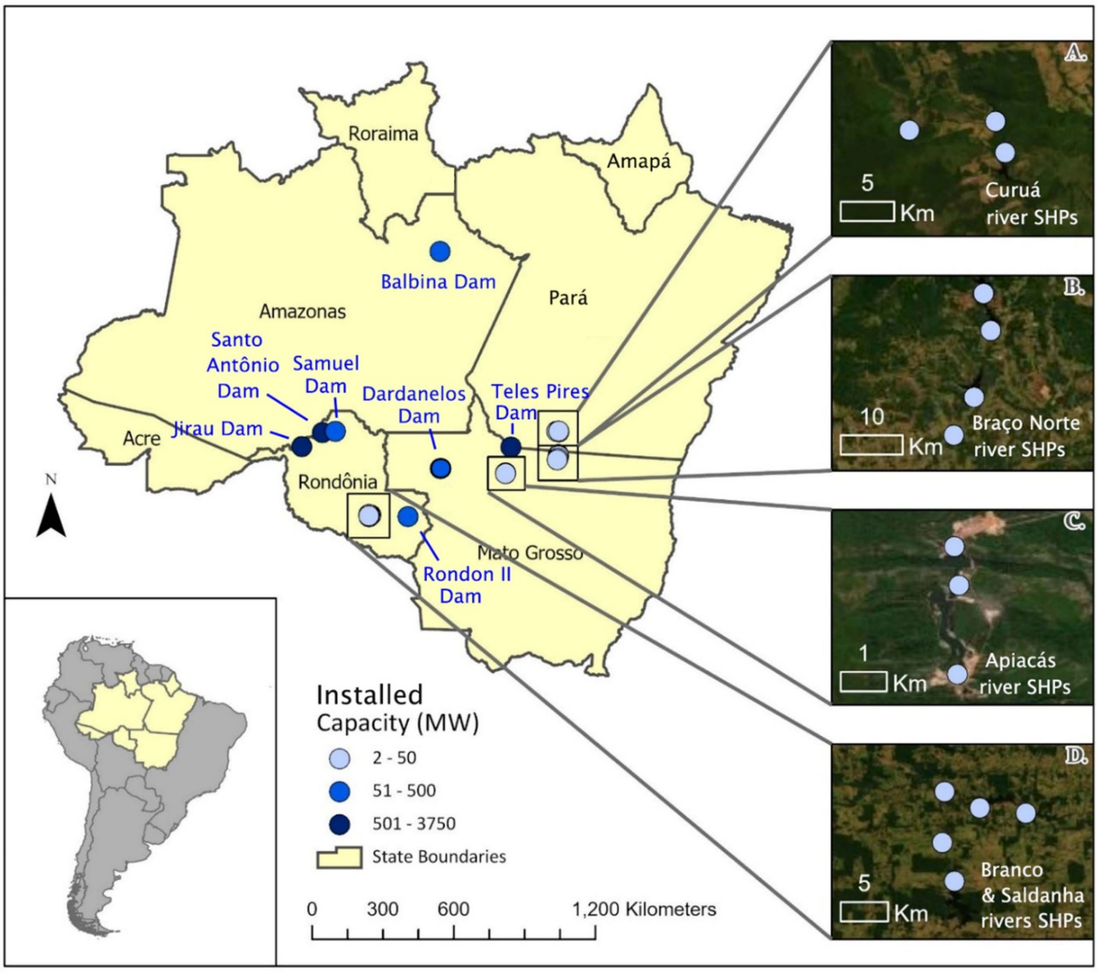

Figure 1. The geospatial locations and installed-capacity ranges of the selected hydroelectric dams in Brazil, with high-resolution imagery provided for the SHPs (see detailed dam capacities in table 1).

2. Methods

2.1. Study areas

Our study areas consist of the landscapes surrounding 22 hydroelectric dams within the Legal Amazon, known as 'Amazônia Legal' in Portuguese. The Legal Amazon has more than five million square kilometers comprising the Brazilian states of Acre, Amapá, Amazonas, Mato Grosso, Pará, Rondônia, Roraima, Tocantins and part of Maranhão. The selected hydropower dams were based on information acquired from the Amazon Dams Network, and Dams in Amazonia (Amazon Dam Network 2019, International Rivers, Fundación Proteger and ECOA 2020). These dams were primarily surrounded by a forested landscape. Each dam was classified based on installed capacity in MW, as this was the most readily available metric and has been used previously to classify dams (Fearnside 2014). For each dam, Table 1 presents the dam name, impacted river, state, installed capacity, construction beginning year, and operation beginning year for a total of seven large dams (>50 MW) and 15 SHPs ($\leqslant$50 MW, all of which were $\leqslant$30 MW). The locations and installed capacities are presented in figure 1. To understand the cumulative forest loss near multiple SHPs along the same river, four clusters of three or more SHPs were analyzed collectively (table 1). For each cluster, the SHPs were built in close proximity to one another (figure 1). Most of the dams chosen are located in the southern Amazon region due to the large amount of hydroelectric development that has occurred there, primarily over the past two decades.

The landscape-level analysis surrounding these dams was performed using nested buffers at 5, 15, 30 and 50 km from the dam and two watershed scales. These four buffer scales and two watershed scales were used to understand forest loss in both the dam neighborhood and the greater surrounding region. Watershed scales were derived from the Amazon GIS-based river basin framework developed by Venticinque *et al* (2016). Level 5 and 6 minor sub-basin data were utilized with approximate areas ranging from 5000 to 10 000 and 1000 to 5000 km^2, respectively to determine watershed boundaries (Venticinque *et al* 2016). The database developed by Venticinque *et al* (2016) was also used to obtain river locations. Since hydropower's impacts on landscape change occurs

Table 1. Name, river, state, installed capacity, and construction and operation years for the 22 selected dams, with SHPs in the same cluster highlighted in the same color.

	Name	River	State[a]	Installed capacity (MW)	Year of beginning construction	Year of beginning operation
SHPs	Cabeça de Boi	Apiacás	MT	30	2013	2016
	Da Fazenda	Apiacás	MT	20	2013	2016
	Salto Apiacás	Apiacás	MT	30	2013	2016
	Braço Norte I	Braço Norte	MT	6	2005	2008
	Braço Norte II	Braço Norte	MT	10	1992	1998
	Braço Norte III	Braço Norte	MT	15	2000	2003
	Braço Norte IV	Braço Norte	MT	14	2000	2003
	Salto Buriti	Curuá	PA	10	2004	2008
	Salto Curuá	Curuá	PA	30	2005	2009
	Salto Três de Maio	Curuá	PA	20	2007	2010
	Alta Floresta	Saldanha	RO	5	2008	2011
	Cachoeira Cachimbo Alto	Branco	RO	10	2013	2017
	Rio Branco	Branco	RO	7	2001	2005
	Saldanha	Saldanha	RO	5	2002	2008
	Monte Belo	Branco	RO	5	2003	2005
Large Dams	Dardanelos	Aripuanã	MT	256	2007	2011
	Rondon II	Comemoração	RO	74	2006	2011
	Samuel	Jamari	RO	216	1982	1988
	Jirau	Madeira	RO	3750	2010	2012
	Santo Antônio	Madeira	RO	3568	2008	2011
	Balbina	Uatumã	AM	250	1977	1989
	Teles Pires	Teles Pires	MT	1820	2011	2015

[a] States: AM = Amazonas, MT = Mato Grosso, PA = Pará, RO = Rondônia.

at a variety of scales, and since both buffer and watershed scales have been previously utilized (Rood *et al* 1995, Indrabudi *et al* 1998, Zhao *et al* 2013), the aforementioned scales were included to facilitate a robust assessment of forest loss surrounding hydroelectric dams. Hence, our study covers a total of over 110 000 km^2 of forested regions in the vicinities of 22 dams.

2.2. Data acquisition and pre-processing

All available satellite Moderate Resolution Imaging Spectroradiometer (MODIS) Terra enhanced vegetation index (EVI) and pixel reliability images (MOD13Q1) from 2000 to 2018 were acquired using NASA's Application for Extracting and Exploring Analysis-Ready Samples (AρρEEARS) (Didan 2015). MOD13Q1 is a level-3 product that provides 16 days image composites of vegetation indices (including EVI) at a spatial resolution of 250 m. Although the MODIS system has a temporal resolution of 1–2 days, MOD13Q1 compiles the highest quality pixels, low clouds, and low view angles over a 16 days temporal period (Didan 2015). A forest mask was used to remove all non-forested pixels from the images at the beginning of the study period. The mask was created using MODIS continuous vegetation fields (MOD44B) data from 2000 with a percent tree-cover threshold of 50% to distinguish forest from non-forest (DeVries *et al* 2015, Dutrieux *et al* 2015). Once pre-processing was complete, a total of 411 MODIS EVI images for each neighborhood region of SHP clusters or large dams were compiled into a dense image stack for subsequent processing.

2.3. Detection of forest loss

Studies using remote-sensing-based methods to monitor vegetation changes have conventionally employed bi-temporal change detection methods (Chen *et al* 2012, Morrison *et al* 2018). However, these methods often lead to high temporal uncertainties, especially in the tropics where heavy cloud contamination limits the amount of annual cloud-free images (Ju and Roy 2008, DeVries *et al* 2015). To address this challenge, time-series decomposition algorithms are becoming increasingly popular to study forest dynamics because they can accurately monitor forest dynamics by detecting the temporal location of changes while simultaneously isolating errors (Verbesselt *et al* 2012, Zhao *et al* 2019). In this study, a recently developed time-series decomposition method known as a Bayesian Estimator of Abrupt change, Seasonality, and Trend (BEAST, Zhao *et al* 2019) was used to detect forest loss. BEAST decomposes time series into seasonality, trend, abrupt changes, and noise through Bayesian model averaging, which considers numerous candidate models to formulate one average model. It incorporates model uncertainty by providing information on the probability of abrupt changes in a time series. Time series are decomposed by BEAST using the formula (Zhao *et al* 2019):

$$Y_i = S\left(t_j;\theta_s\right) + T\left(t_i;\theta_t\right) + \varepsilon_i$$

where ε_i is the noise component that is assumed to have a Gaussian distribution. Abrupt changes in the seasonal and trend components are represented as θ_s and θ_t respectively. Both parameters include information on the probability, confidence intervals and number of estimated abrupt changes. The locations of abrupt changes are represented by t_j in the seasonal component and t_i in the trend component. For the sake of brevity, technical details of BEAST are not be included here, but can be found in Zhao *et al* (2019).

While other time-series decomposition algorithms define abrupt changes as sudden changes in vegetation index values, BEAST broadly defines abrupt changes as any point where the trend or seasonal signal begins to diverge from the previously defined trajectory (Zhao *et al* 2019). The abrupt changes detected by BEAST that represented decreases in EVI trends were used to track forest loss in our study areas. Using the mean number of changes at the most-likely locations in the time series, forest loss was quantified over time for each study area.

Once forest loss was detected using BEAST, maps were created showing the time of forest loss from 2000 to 2018 in each region. An accuracy assessment was performed in the neighborhood of each dam. For the SHPs on the same river, their buffer zones were merged to create single zones due to the close spatial proximity among these SHPs. Here, we chose the largest level-5 sub-basin scale for accuracy evaluation. We applied a stratified random sampling approach using 500 points to select reference points from the strata for 'change detected' and 'no change detected.' To determine the true land cover at each point, we used high-resolution imagery from Google Earth Pro© (Google Inc., Mountain View, California, USA). We applied the classic confusion matrix (Congalton 1991) to calculate overall accuracies, user's accuracies (100%—commission errors) due to falsely detected changes and producer's accuracies (100%—omission errors) due to true changes not being detected.

2.4. Statistical analysis of forest-loss patterns near dams

Statistical analyses of forest-loss patterns were conducted within the neighborhoods (four buffer zones and two sub-basins; section 2.1) of each large dam or cluster of SHPs. For each year, the number of pixels that experienced abrupt changes was divided by the total number of forested pixels based on the year 2000 forest mask to yield the percent change on an annual basis. Since the study areas contained varying numbers of forested pixels, normalizing the data in this way was crucial to compare different regions.

The Wilcoxon signed-rank test was used to determine whether the rate of forest loss changed after dam construction (Hollander and Wolfe 1999). Because not every dam analyzed in this study was built after 2000, only study areas that had a dam introduced post 2000 were considered in the Wilcoxon test. As a result, five large dams (Dardanelos, Rondon II, Jirau, Santo Antônio and Teles Pires) and six SHPs in two clusters (along rivers Apiacás and Curuá) were used to compare average forest-loss rates before and after the beginning of construction. To compare forest loss in the two time periods (i.e. pre- and post-period), the percent of forest loss per year was averaged for each time period, thereby creating percent forest-loss rates pre and post dam construction. Based on this rate, the Wilcoxon signed rank test was used to compare the two groups. A null hypothesis of no difference between the two groups, with an alternative of forest loss being greater post dam construction, was used as the alternative. A p value <0.05 was used to determine statistical significance.

To understand if forest loss surrounding SHPs and large dams differed significantly, the non-parametric Mann–Whitney U test was chosen. The annual percent forest loss was averaged from 2000 to 2018 for dams built prior to 2000, or from the time of construction to 2018 for dams that were built post 2000. This average rate was then used to compare forest loss surrounding SHPs to forest loss surrounding large dams. A p value of <0.05 was used to assess significance. We used a null hypothesis of no difference between SHPs and large dams with an alternative of forest loss being greater surrounding large dams. This test allowed us to statistically compare forest loss surrounding SHPs and large dams. While the typical sinusoidal deforestation rate pattern in the 2000s could conceivably introduce a bias in the analysis by including dams built prior to 2000, only three (out of 22) studied dams were built before 2000, and they include both small and large dams.

2.5. Separating the effect of dams from regional deforestation trends

The wide variation in deforestation rates in Brazilian Amazonia over the past decades, with a high of 27 772 km^2 in 2004 and a low of 4571 km^2 in 2012 (Brazil, INPE, 2021), has been due to macroeconomic factors such as international prices of beef and soy and the exchange rate of Brazilian real against the US dollar, and, especially from 2008 onwards, due to government controls on deforestation (Fearnside 2017b, 2017c, Pereira *et al* 2019, West *et al* 2019, West and Fearnside 2021). This means that the deforestation rate in the post-dam period may be substantially higher or lower than in the pre-dam period for reasons unrelated to the effect of the dam. In the present study, we calculated two types of correction factor to adjust for these region-wide trends. Specifically, the temporal correction factor is the ratio of state-level

Table 2. Temporal correction factors for SHPs and large dams.

Dam	Year of beginning construction	State annual deforestation in pre-construction period (10^3 km^2)	State annual deforestation in post-construction period (10^3 km^2)	Temporal correction factor
Apiacás river SHP cluster:				
Cabeça de Boi	2013	5.000	1.393	0.278
Da Fazenda	2013	5.000	1.393	0.278
Salto Apiacás	2013	5.000	1.393	0.278
Curuá river SHP cluster:				
Salto Buriti	2004	6.035	3.857	0.639
Salto Curuá	2005	6.532	3.524	0.540
Salto Três de Maio	2007	6.688	3.175	0.475
Large dams:				
Dardanelos	2007	7.925	1.491	0.188
Rondon II	2006	3.083	1.056	0.342
Jirau	2010	2.357	0.962	0.408
Santo Antônio	2008	2.753	0.927	0.337
Teles Pires	2011	5.739	1.279	0.223

Table 3. Spatial correction factors for SHPs and large dams.

Dam	State-level average annual forest loss post dam construction (10^3 km^2)	Spatial correction factor
Apiacás river SHP cluster	1.393	1.898
Braço Norte river SHP cluster	3.280	4.469
Curuá river SHP cluster	3.519	4.794
Branco & Saldanha rivers SHP cluster	1.359	1.851
Balbina	0.734	1.000
Dardanelos	1.491	2.031
Samuel	1.696	2.310
Rondon II	1.056	1.439
Jirau	0.962	1.311
Santo Antônio	0.927	1.263
Teles Pires	1.279	1.743

deforestation rates in pre-construction period and deforestation in post-construction period within our study window (table 2). They were derived from the average annual deforestation in the state where each dam is located (Brazil, INPE 2021). State-level deforestation was used for this rather than the rate for the nine-state Legal Amazon region because the annual change often differs between states. Table 2 shows a notable statewide decrease of deforestation in the post-construction period for all the dams, with correction factors ranging from 0.223 to 0.639. We then multiplied the correction factors by the corresponding pre dam construction average forest loss derived from section 2.4. We further applied the Wilcoxon signed-rank test to evaluate the difference in forest loss between the pre and the post construction period following the procedure in section 2.4.

The second type of factor is the spatial correction factor, which is the ratio of post dam construction forest loss between two states. Here, forest loss in the state of Amazonas was chosen as the denominator in all the ratio calculations due to its having the lowest forest loss among all the states. The spatial correction factors, ranging from 1.000 to 4.794 (table 3), account for the variation in regional deforestation trends, allowing a more accurate assessment of dam size effect (SHPs versus large dams across various states) on forest loss. The corrected annual forest loss for each large dam or small-dam cluster was calculated through dividing its post-construction average forest loss value (see section 2.4) by the corresponding spatial correction factor. The Mann–Whitney U test was then applied following the procedure in section 2.4.

3. Results

3.1. Accuracy assessment of forest loss estimation

The total accuracy across all the dam neighborhoods ranged from 82.8% to 98.8%, with most study areas being consistently around 90% accuracy (figure 2). Producer and user accuracies for the forest class were primarily clustered above 90% and did not demonstrate any apparent patterns of bias towards small or large dams. The accuracies of estimating forest dynamics in the neighborhoods of SHPs were comparable to those in the large-dam study areas with no significant difference ($p < 0.05$).

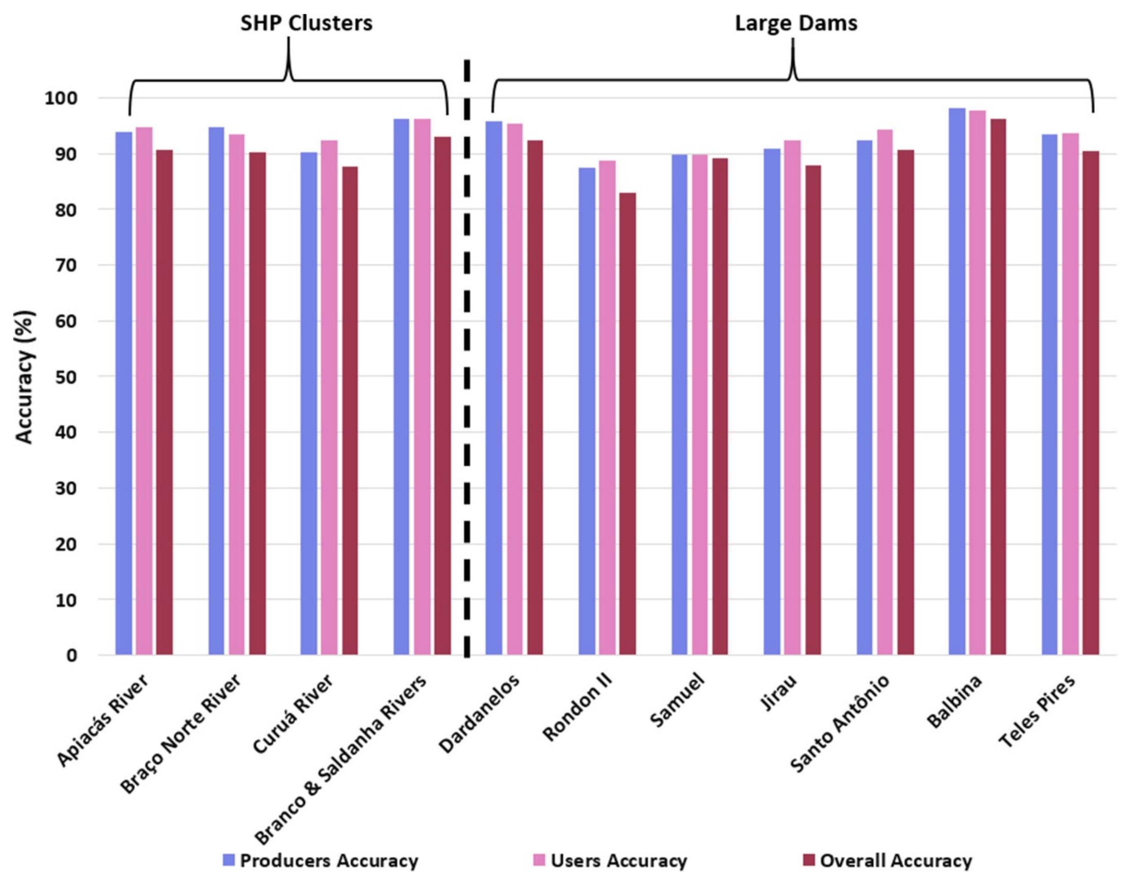

Figure 2. Accuracies of forest-loss detection near SHP clusters and large dams at the largest scale—level-5 sub-basin scale—with x-axis representing the names of the large dams or of the rivers for SHP clusters.

3.2. Statistical analyses

Use of the Wilcoxon signed-rank test to compare the average percent of forest loss pre and post dam construction provided evidence that forest loss was greater after the hydropower plants were introduced into the regions. With $p < 0.05$, the null hypothesis of no difference between pre and post average forest loss was rejected at all scales except at the large level-5 sub-basin scale when there was no adjustment for regional trends using the temporal correction factor (figure 3). The introduction of the temporal correction factor led to a widening difference in annual forest loss pre and post dam construction. The post-construction forest loss was significantly greater across all scales (figure 4).

Generally, the large dams showed a considerable increase in forest loss at the 5 km scale primarily due to inundation of upstream forests. While the large dams in this comparison (those built after 2000: Jirau, Rondon II, Santo Antônio and Teles Pires) had low to moderate forest loss prior to dam construction at the 5 km scale, the annual average forest loss rose to as a high as 3.8% per year for the Teles Pires Dam once the dams were introduced. As the scale increased, the change in forest loss post dam construction became less dramatic. Although the region surrounding the Salto Buriti, Salto Curuá, and Salto Três de Maio SHPs showed a minor increase in forest loss post dam construction at the 5 km scale, at all the larger scales these dams showed double or triple the expected forest loss in their neighborhoods.

The results of the Mann–Whitney U test showed that there was no significant difference between the SHPs and large dams with regards to average annual percent of forest loss when there was no correction for regional trends (figure 5). While most SHPs had lower annual forest-loss totals than large dams, the pattern was not powerful enough to reject the null hypothesis of no difference between the groups. However, introduction of the spatial correction factor led to significantly lower forest losses in the neighborhoods near SHPs across all scales (figure 6). We note that the cumulative forest losses surrounding the dams on the Curuá River were high across all scales and were often greater than those of most large dams (figure 5). This reflects the fact that this SHP cluster is located almost adjacent to Highway BR-163 (Santarém-Cuiabá), which was a major hotspot of deforestation during the 2000–2018 period due to the presence of the road (Fearnside 2007). The spatial correction factor was able to reduce the effect of the regional deforestation trend in the analysis (figure 6).

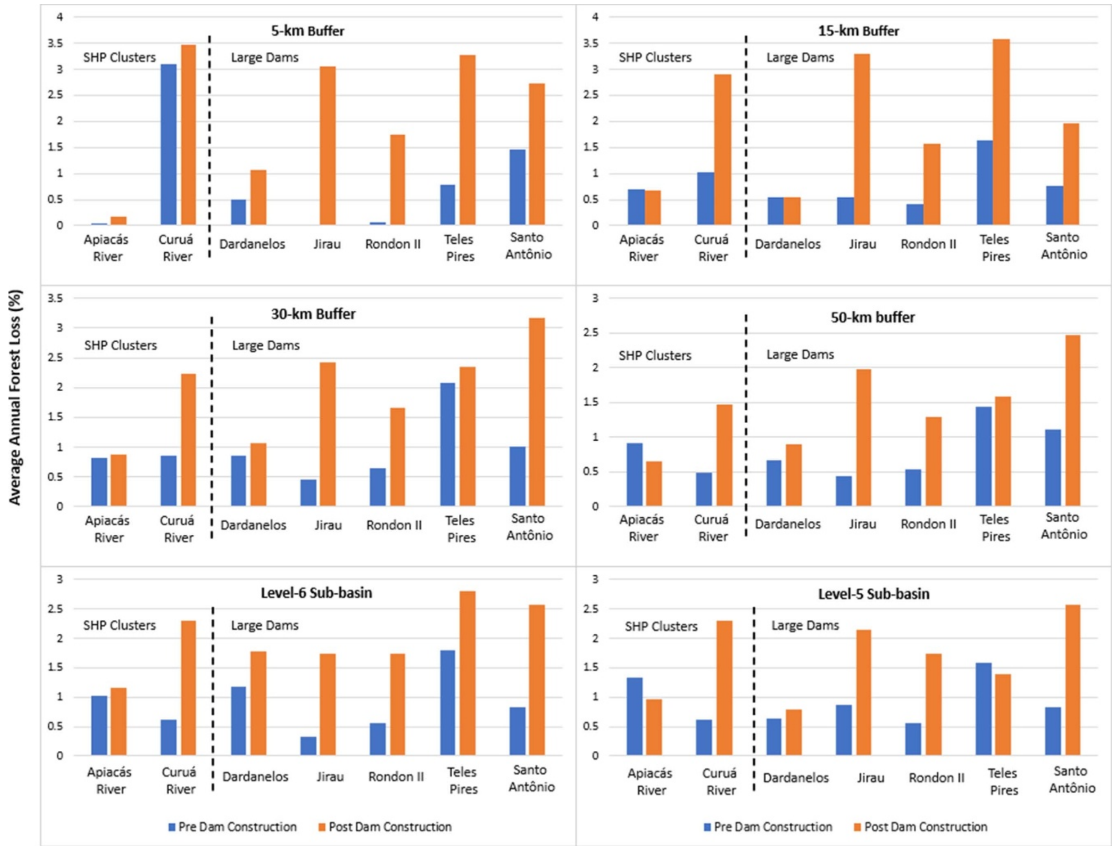

Figure 3. Pre and post dam construction average annual forest loss percentage at various buffer and sub-basin scales before applying the temporal correction factors.

4. Discussion

4.1. Remote sensing analysis

In this study a MODIS image time series of nearly two decades was analyzed using the BEAST algorithm, which allowed the time and location of forest loss in our study regions to be detected. Although remote-sensing studies in the tropics have been challenged by heavy cloud cover, the high temporal resolution of MODIS (one to two image scenes per day) provided enough cloud-free data to monitor forest disturbances in the Brazilian Amazon. This remote-sensing analysis yielded high overall accuracy (>90%) for most of the study areas. Commission errors due to falsely detected breaks were primarily higher than the omission errors, which is consistent with the findings of Zhao *et al* (2019). The accuracy level is comparable to or even higher than that of several large-scale satellite mapping efforts for understanding forest disturbances (e.g. Hansen *et al* 2013, Pelletier *et al* 2016, Wang *et al* 2019). The BEAST algorithm is sensitive to changes in EVI values, and decreases in EVI due to disturbances (such as drought, agriculture, logging, and the construction of infrastructure) have been reported to occur in the neighborhoods of dams (Stickler *et al* 2013, Chen *et al* 2015). It is also crucial to note that the medium-low spatial resolution of 250 m used by MODIS may have marginally decreased the accuracy; however, without the high temporal resolution provided by these data, heavy cloud contamination would have prevented the change detection analysis from producing any meaningful results.

4.2. Forest dynamics surrounding large dams and SHPs

Forest loss surrounding the dams was influenced by many factors, some of which were directly and indirectly related to the dams themselves; however, location and policy plays a crucial role in determining the level of forest loss (Fearnside 2014, Athayde *et al* 2019). Use of the spatial-correction factors to account for the spatial variation in state-level deforestation trends suggests reduced effects of SHPs on forest loss (figures 5 and 6). This is particularly noticeable for regions surrounding the Curuá River dams, and Braço Norte River dams. However, such effects were less significant in the neighborhoods of large dams, making the cumulative effects of large dams significantly higher than those of SHPs.

Figure 7 compares the time at which the first abrupt change was recorded in the 50 km buffer region surrounding the Jirau Dam and SHPs along the Curuá and Três de Maio Rivers. Both study areas are contained in the southern Amazon, as are all but one (Balbina) of the landscapes analyzed

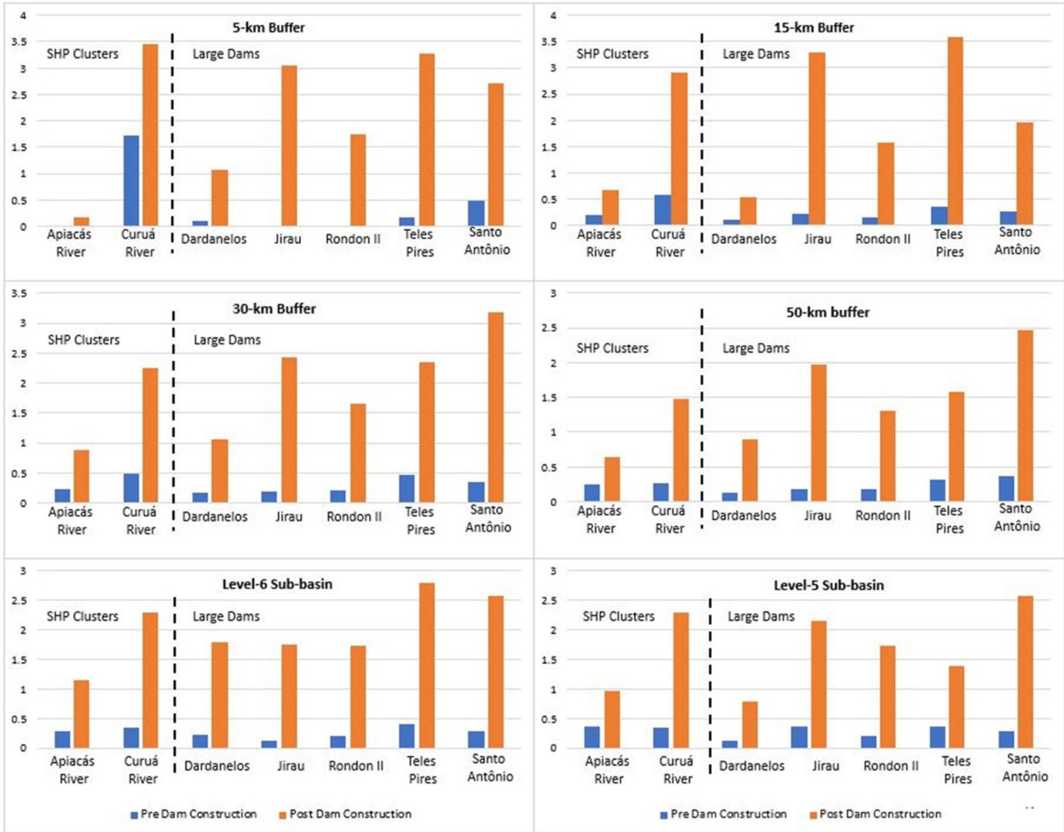

Figure 4. Pre and post dam construction average annual forest loss percentage at various buffer and sub-basin scales after applying the temporal correction factors.

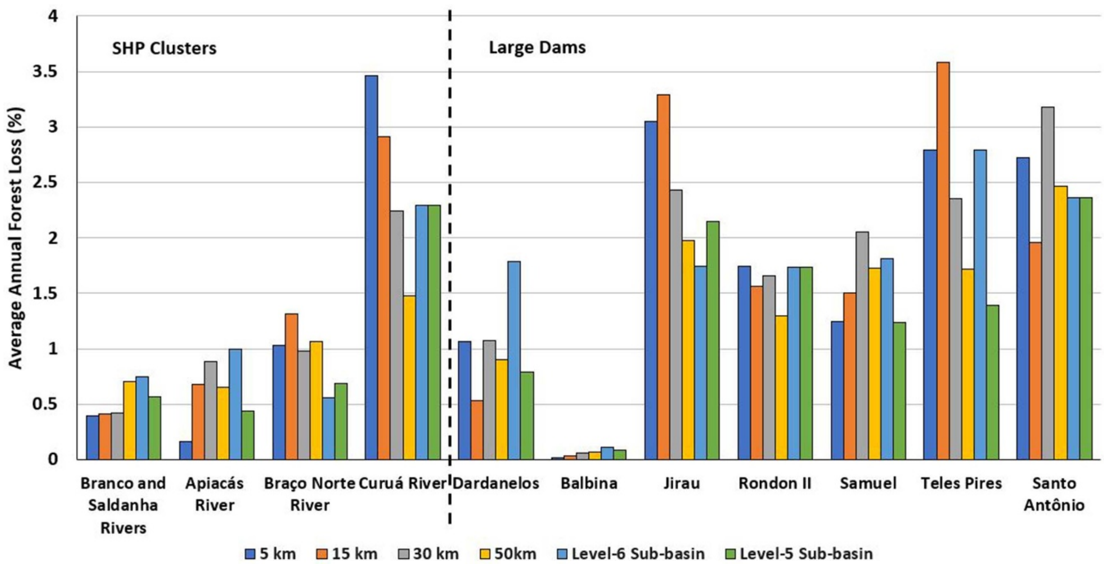

Figure 5. Average annual forest loss percentage (2000–2008) for SHPs (left) and large dams (right) at the scales of 5, 15, 30, 50 km, and level-6 and level-5 sub-basins before applying the spatial correction factors.

in this research. Due to its high accessibility, the region that stretches around the southern periphery of the Amazon is known as the 'arc of deforestation' (Schroth *et al* 2016). Deforestation in this region is concentrated near roads and is driven by logging, cattle ranching and agriculture for crops such as soybeans (Fearnside 2001, Schroth *et al* 2016).

At this large scale, abrupt changes in the vicinity of the Jirau Dam can be found up to a distance of 50 km based on visual inspection of high-resolution

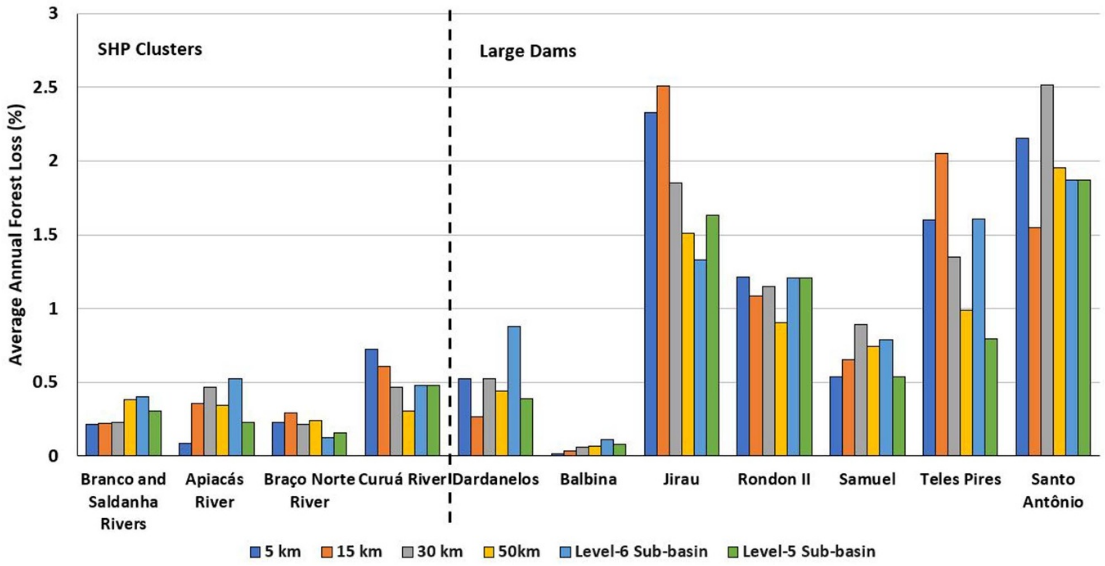

Figure 6. Average annual forest loss percentage (2000–2008) for SHPs (left) and large dams (right) at the scales of 5, 15, 30, 50 km, and level-6 and level-5 sub-basins after applying the spatial correction factors.

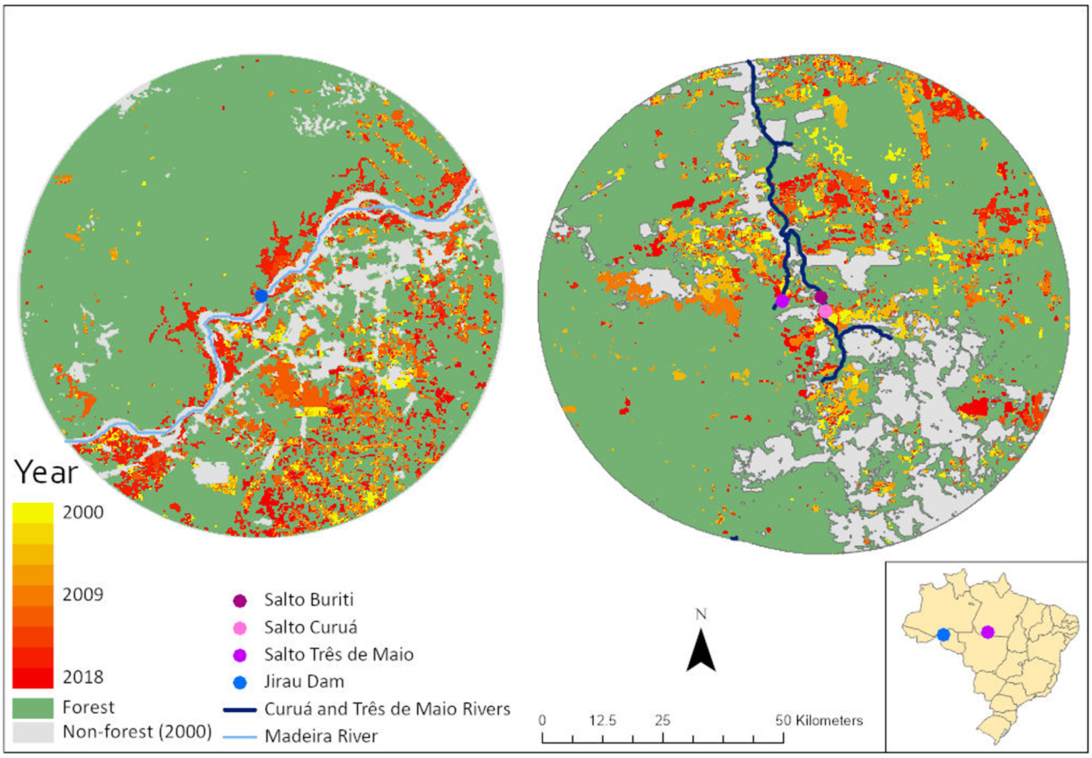

Figure 7. Time of the first abrupt change in the 50 km buffer surrounding the Jirau Dam (left) and the Salto Curuá, Salto Buriti, and Salto Três de Maio SHPs (right).

data. This flooding of the Madeira River is primarily due to the operation of the Jirau hydropower plant and the Santo Antônio plant to the north. In this case, flooding from the Madeira River dams is widespread and reaches as far back as Bolivia (Fearnside 2014). The amount of flooding is unrelated to some of the major causes of deforestation. The effect of the dam-construction projects in attracting migrants is independent of reservoir area. In addition, the local population is normally concentrated along the edges of Amazonian rivers and is therefore proportional to the length of the reservoir rather than directly to the area. This riverside population will be displaced and contribute to clearing at their new locations. Run-of-river dams flood less area than storage dams (Burrier 2016), but this does not imply a proportionally smaller impact on deforestation.

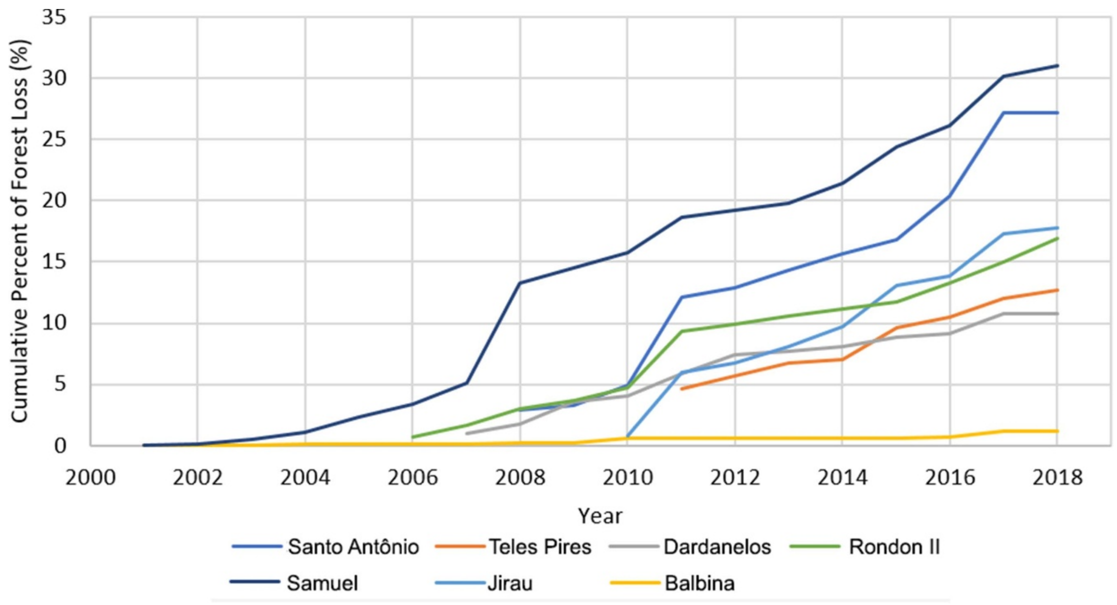

Figure 8. Cumulative forest loss for large dams from 2000 to 2018 at the 50 km buffer scale.

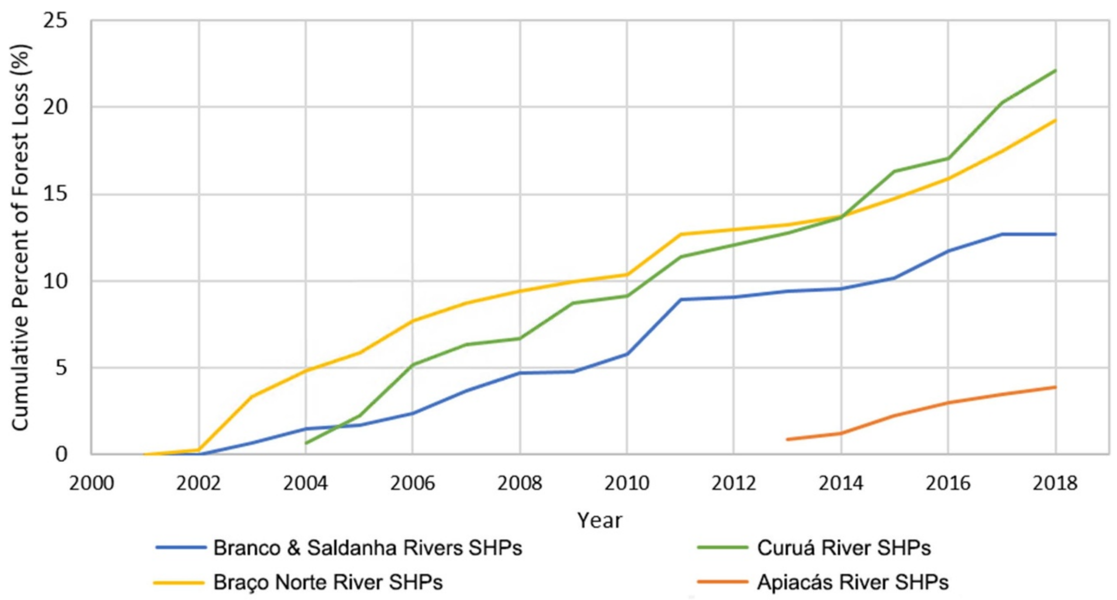

Figure 9. Cumulative forest loss for SHPs from 2010 to 2018 at the 50 km buffer scale.

Although the dams along the Curuá River are SHPs and do not inundate a large amount of upstream habitat, considerable forest loss is still prevalent in the surrounding region. These three SHPs contain a cumulative capacity of 60 MW but experienced more than double the increase in average forest loss following dam construction at the 50 km scale due to their location in a region already prone to higher deforestation rates. However, drivers of forest loss such as agriculture, logging and urban development indirectly linked to hydropower development are more likely to occur here due to the high accessibility and likely proximal distance to market (Malhi *et al* 2008). Because of the greater accessibility of this area and the greater demand for electricity, the motivation for expanding hydropower is greater in this region.

Differing temporal forest-loss patterns were exhibited by both SHPs and large dams. The cumulative percent of forest loss surrounding the 50 km buffers for large dams and SHPs are shown by figures 8 and 9, respectively. While buffers around both dam types experienced somewhat constant forest loss, large dams were associated with greater sudden increases in cumulative forest loss. Here we define 'sudden' as occurring over the temporal period of one

Table 4. Average annual forest loss from 2000 to 2018: comparison per MW for SHPs and large dams across scales.

	5 km	15 km	30 km	50 km	Level-6 sub-basin	Level-5 sub-basin
Average % of forest loss per MW for SHPs	0.0062	0.0070	0.0064	0.0067	0.0075	0.0060
Average % of forest loss per MW for large dams	0.0033	0.0030	0.0034	0.0027	0.0037	0.0032
Times greater for SHPs	1.9	2.3	1.9	2.5	2.0	1.9

year. From 2007 to 2008, 8.05% of the forested land surrounding the Samuel hydropower plant experienced forest loss, this being due to a spontaneous road being built and occupied to the north of the reservoir (see Fearnside *et al* 2009). In the vicinity of the Santo Antônio plant, 7.1% of the forested land was lost from 2010 to 2011 and 6.7% from 2016 to 2017. The Jirau Dam also experienced one sudden forest loss event of 3.3% loss in 2015 (which was a year with extreme drought due to El Niño). The regions surrounding SHPs experienced a more linear increase in forest loss (figure 8).

While large dams tend to cause greater cumulative forest loss than SHPs, forest dynamics surrounding SHPs are of particular concern when accounting is done on the basis of forest loss per MW of installed capacity. For example, Bakken *et al* (2012) assessed the environmental effects of hydropower in Norway and found that small-scale projects produced electricity at a higher environmental cost due to lax monitoring by the authorities and the general public. Analyzing deforestation per MW can inform the effectiveness of forest conservation around the dams. Table 4 shows the annual forest loss per MW, averaged for all large dams and SHPs in the present study. Although the landscapes in the vicinity of SHPs contained lower forest-loss rates than large dams, when considering forest loss per MW, SHPs performed as much as 2.5 times worse than large dams at the 50 km buffer scale. At the scales of 5, 15, and 30 km, SHPs exhibited 1.9, 2.3, and 1.9 times the forest loss per MW when compared to large dams. At the level-5 and level-6 sub-basin scales, SHPs displayed 2.0 and 1.9 times the average forest loss per MW, respectively. Although judging SHPs by MW may mask significant impacts (Kelly 2019), the significant difference ($p < 0.05$) found in the present study between SHPs and large dams in regard to per-MW forest loss reveals the need for careful consideration when planning SHP development projects. We are aware that deforestation rates could vary across regions, scales, or time windows, and that these rates are associated with a variety of regional factors (Biggs *et al* 2008, Rosa *et al* 2013). However, our study was intentionally designed to feature a large area (over 110 000 km^2 in the Brazilian Amazon), a long period (dense time series observations for nearly two decades), multiscale analyses (from small buffers to large watershed scales), and spatial/temporal correction factors (to adjust for region-wide trends), which can effectively mitigate the impact of regional factors causing artifacts.

5. Conclusion

Anthropogenic forest disturbance in the Brazilian Amazon has many drivers, one of which is hydroelectric dams. SHPs are often perceived as having reduced environmental impacts as compared to larger hydroelectric projects, and consequently require less rigorous environmental-impact assessments; however, the cumulative impacts of SHPs are often greater per MW than those of large dams. This study capitalized on a dense time series spanning nearly two decades (2000–2018) of satellite remote sensing to estimate forest dynamics surrounding 22 SHPs and large dams in the Brazilian Amazon. Cumulative forest loss over the 2000–2018 period was significantly lower in the vicinity of SHPs than in the vicinity of large dams. However, when considering impacts per MW of installed capacity, SHPs consistently led to a significantly higher level of forest loss from the small 5 km buffer scale to the large sub-basin scales (1.9–2.5 times). Particularly at the 50 km buffer scale, SHPs caused an average of 2.5 times more forest loss per MW installed than large dams. Our findings indicate that massive SHP expansion should be treated with caution and requires more stringent environmental assessments that consider the cumulative impacts of SHPs per MW installed.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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References

Abbasi T and Abbasi S A 2011 Small hydro and the environmental implications of its extensive utilization *Renew. Sustain. Energy Rev.* **15** 2134–43

Abreu T L S, Berg S B, Faria I P, Gomes L P, Marinho-Filho J S and Colli G R 2020 River dams and the stability of bird communities: a hierarchical Bayesian analysis in a tropical hydroelectric power plant *J. Appl. Ecol.* **57** 1124–36

Alho C 2020 Hydropower dams and reservoirs and their impacts on Brazil's biodiversity and natural habitats: a review *World J. Adv. Res. Rev.* **06** 205–15

Amazon Dam Network 2019 Hydroelectric dams database (available at: http://amazondamsnetwork.org/amazon-databases/) (Accessed 18 December 2019)

Arantes C C, Fitzgerald D B, Hoeinghaus D J and Winemiller K O 2019 Impacts of hydroelectric dams on fishes and fisheries in tropical rivers through the lens of functional traits *Curr. Opin. Environ. Sustain.* **37** 28–40

Athayde S, Duarte C G, Gallardo A L, Moretto E M, Sangoi L A, Dibo A P A, Siqueira-Gay J and Sánchez L E 2019 Improving policies and instruments to address cumulative impacts of small hydropower in the Amazon *Energy Policy* **132** 265–71

Bakken T H, Aase A G, Hagen D, Sundt H, Barton D N and Lujala P 2014 Demonstrating a new framework for the comparison of environmental impacts from small-and large-scale hydropower and wind power projects *J. Environ. Manage.* **140** 93–101

Bakken T H, Sundt H, Ruud A and Harby A 2012 Development of small versus large hydropower in Norway—comparison of environmental impacts *Energy Proc.* **20** 185–99

Benchimol M and Peres C A 2015 Widespread forest vertebrate extinctions induced by a mega hydroelectric dam in lowland Amazonia *PLoS One* **10** e0129818

Biggs T W, Dunne T, Roberts D A and Matricardi E 2008 The rate and extent of deforestation in watersheds of the southwestern Amazon basin *Ecol. Appl.* **18** 31–48

Brazil, Eletrobras 2018 Brazilian hydroelectric potential in each stage for the hydrographic basin (in Portuguese) (available at: https://bityl.co/4x3J)

Brazil, INPE (Instituto Nacional de Pesquisas Espaciais) 2021 PRODES: monitoramento do desmatamento da floresta amazônica brasileira por satélite (São José dos Campos, São Paulo: INPE) (available at: www.obt.inpe.br/OBT/assuntos/programas/amazonia/prodes)

Burrier G 2016 The developmental state, civil society, and hydroelectric politics in Brazil *J. Environ. Dev.* **25** 332–58

Campos M M, Tritico H M, Girard P, Zeilhofer P, Hamilton S K and Fantin-Cruz I 2020 Predicted impacts of proposed hydroelectric facilities on fish migration routes upstream from the Pantanal wetland (Brazil) *River Res. Appl.* **36** 452–64

Chen G, Hay G J, Carvalho L M T and Wulder M A 2012 Object-based change detection *Int. J. Remote Sens.* **33** 4434–57

Chen G, Powers R P, de Carvalho L M and Mora B 2015 Spatiotemporal patterns of tropical deforestation and forest degradation in response to the operation of the Tucuruí hydroelectric dam in the Amazon basin *Appl. Geogr.* **63** 1–8

Congalton R G 1991 A review of assessing the accuracy of classifications of remotely sensed data *Remote Sens. Environ.* **37** 35–46

Couto T B and Olden J D 2018 Global proliferation of small hydropower plants—science and policy *Front. Ecol. Environ.* **16** 91–100

DeVries B, Verbesselt J, Kooistra L and Herold M 2015 Robust monitoring of small-scale forest disturbances in a tropical montane forest using Landsat time series *Remote Sens. Environ.* **161** 107–21

Di Corato L, Moretto M and Vergalli S 2016 Deforestation rate in the long-run: the case of Brazil. EIA: climate change: economic impacts and adaptation 244528 Fondazione Eni Enrico Mattei (FEEM) (https://doi.org/10.22004/ag.econ.244528)

Didan K 2015 MOD13Q1 MODIS/Terra vegetation indices 16-Day L3 global 250m SIN grid V006 [EVI] NASA EOSDIS Land Processes DAAC (https://doi.org/10.5067/MODIS/MOD13Q1.006)

Dutrieux L P, Verbesselt J, Kooistra L and Herold M 2015 Monitoring forest cover loss using multiple data streams, a case study of a tropical dry forest in Bolivia *ISPRS J. Photogramm. Remote Sens.* **107** 112–25

Fearnside P M 2001 Soybean cultivation as a threat to the environment in Brazil *Environ. Conserv.* **28** 23–38

Fearnside P M 2007 Brazil's Cuiabá-Santarém (BR-163) Highway: the environmental cost of paving a soybean corridor through the Amazon *Environ. Manage.* **39** 601–14

Fearnside P M 2014 Impacts of Brazil's Madeira River dams: unlearned lessons for hydroelectric development in Amazonia *Environ. Sci. Policy* **38** 164–72

Fearnside P M 2017c Business as usual: a resurgence of deforestation in the Brazilian Amazon *Yale Environment 360* (available at: https://bityl.co/4x3t) (Accessed 18 April 2017)

Fearnside P M, Graça P M L A, Keizer E W H, Maldonado F D, Barbosa R I and Nogueira E M 2009 Modelagem de desmatamento e emissões de gases de efeito estufa na região sob influência da Rodovia Manaus-Porto Velho (BR-319) *Rev. Bras. Meteorol.* **24** 208–33

Fearnside P M 2017b Deforestation of the Brazilian Amazon *Oxford Research Encyclopedia of Environmental Science* ed H Shugart (New York: Oxford University Press) (https://doi.org/10.1093/acrefore/9780199389414.013.102)

Ferreira J H I, Camacho J R, Malagoli J A and Guimarães Júnior S C 2016 Assessment of the potential of small hydropower development in Brazil *Renew. Sustain. Energy Rev.* **56** 380–7

Gentry A H 1992 Tropical forest biodiversity: distributional patterns and their conservational significance *Oikos* **63** 19–28

Hansen M C *et al* 2013 High-resolution global maps of 21st-century forest cover change *Science* **342** 850–3

Hollander M and Wolfe D A 1999 *Nonparametric Statistical Methods* (Hoboken, NJ: Willey)

Indrabudi H, De Gier A and Fresco L O 1998 Deforestation and its driving forces: a case study of Riam Kanan watershed, Indonesia *Land Degrad. Dev.* **9** 311–22

International Rivers, Fundación Proteger, & ECOA 2020 Dams in Amazonia (available at: www.dams-info.org/)

Jiang X, Lu D, Moran E, Calvi M F, Dutra L V and Li G 2018 Examining impacts of the Belo Monte hydroelectric dam construction on land-cover changes using multitemporal Landsat imagery *Appl. Geogr.* **97** 35–47

Ju J and Roy D P 2008 The availability of cloud-free Landsat ETM+ data over the conterminous United States and globally *Remote Sens. Environ.* **112** 1196–211

Kelly S 2019 Megawatts mask impacts: small hydropower and knowledge politics in the Puelwillimapu, Southern Chile *Energy Res. Soc. Sci.* **54** 224–35

Kelly-Richards S, Silber-Coats N, Crootof A, Tecklin D and Bauera C 2017 Governing the transition to renewable energy: a review of impacts and policy issues in the small hydropower boom *Energy Policy* **101** 251–64

Kibler K M and Tullos D D 2013 Cumulative biophysical impact of small and large hydropower development in Nu River, China *Water Resour. Res.* **49** 3104–18

Kirby K R, Laurance W F, Albernaz A K, Schroth G, Fearnside P M, Bergen S and da Costa C 2006 The future of deforestation in the Brazilian Amazon *Futures* **38** 432–53

Ledec G and Quintero J D 2003 Good dams and bad dams: environmental criteria for site selection of hydroelectric projects Latin America and Caribbean Region Sustainable Development Working Paper No. 16 (Washington, DC: The World Bank, Latin America and Caribbean Region, Environmentally and Socially Sustainable Development Department)

Malhi Y, Roberts J T, Betts R A, Killeen T J, Li W and Nobre C A 2008 Climate change, deforestation, and the fate of the Amazon *Science* **319** 169–72

Moran E F 2020 Changing how we build hydropower infrastructure for the common good: lessons from the Brazilian Amazon *Civitas* **20** 5–15

Morrison J, Higginbottom T P, Symeonakis E, Jones M J, Omengo F, Walker S L and Cain B 2018 Detecting vegetation change in response to confining elephants in forests using MODIS time-series and BFAST *Remote Sens.* **10** 1075

Neu H J 1982 Man-made storage of water resources—a liability to the ocean environment? Part I *Mar. Pollut. Bull.* **13** 7–12

Okot D K 2013 Review of small hydropower technology *Renew. Sustain. Energy Rev.* **26** 515–20

Pelletier C, Valero S, Inglada J, Champion N and Dedieu G 2016 Assessing the robustness of random forests to map land cover with high resolution satellite image time series over large areas *Remote Sens. Environ.* **187** 156–68

Pereira E J D A L, Ferreira P J S, de Santana Ribeiro L C, Carvalho T S and de Barros Pereira H B 2019 Policy in Brazil (2016–2019) threaten conservation of the Amazon rainforest *Environ. Sci. Policy* **100** 8–12

Premalatha M, Abbasi T and Abbasi S A 2014 A critical view on the eco-friendliness of small hydroelectric installations *Sci. Total Environ.* **481** 638–43

Rood S B, Mahoney J M, Reid D E and Zilm L 1995 Instream flows and the decline of riparian cottonwoods along the St. Mary River, Alberta *Can. J. Bot.* **73** 1250–60

Rosa I M D, Purves D, Souza C and Ewers R M 2013 Predictive modelling of contagious deforestation in the Brazilian Amazon *PLoS One* **8** e77231

Rosenberg D M, Bodaly R A and Usher P J 1995 Environmental and social impacts of large scale hydroelectric development: who is listening? *Glob. Environ. Change* **5** 127–48

Ruocco A M C, Portinho J L and Nogueira M G 2019 Potential impact of small hydroelectric power plants on river biota: a case study on macroinvertebrates associated to basaltic knickzones *Braz. J. Biol.* **79** 722–34

Santos R E, Pinto-Coelho R M, Drumond M A, Fonseca R and Zanchi F B 2020 Damming Amazon Rivers: environmental impacts of hydroelectric dams on Brazil's Madeira River according to local fishers' perception *Ambio* **49** 1612–28

Schroth G, Garcia E, Griscom B W, Teixeira W G and Barros L P 2016 Commodity production as restoration driver in the Brazilian Amazon? Pasture re-agro-forestation with cocoa (Theobroma cacao) in southern Para *Sustain. Sci.* **11** 277–93

Sgarbi F A, Uhlig A, Simões A F and Goldemberg J 2019 An assessment of the socioeconomic externalities of hydropower plants in Brazil *Energy Policy* **129** 868–79

Stickler C M, Coe M T, Costa M H, Nepstad D C, McGrath D G, Dias L C P, Rodrigues H O and Soares-Filho B S 2013 Dependence of hydropower energy generation on forests in the Amazon Basin at local and regional scales *Proc. Natl Acad. Sci. USA* **110** 9601–6

Tefera B and Sterk G 2008 Hydropower-induced land use change in Fincha'a watershed, western Ethiopia: analysis and impacts *Mt. Res. Dev.* **28** 72–81

Venticinque E, Forsberg B, Barthem R, Petry P, Hess L, Mercado A, Cañas C, Montoya M, Durigan C and Goulding M 2016 An explicit GIS-based river basin framework for aquatic ecosystem conservation in the Amazon *Earth Syst. Sci. Data* **8** 651

Verbesselt J, Zeileis A and Herold M 2012 Near real-time disturbance detection using satellite image time series *Remote Sens. Environ.* **123** 98–108

Wang Y *et al* 2019 Mapping tropical disturbed forests using multi-decadal 30 m optical satellite imagery *Remote Sens. Environ.* **221** 474–88

West T A P, Börner J and Fearnside P M 2019 Climatic benefits from the 2006–2017 avoided deforestation in Amazonian Brazil *Front. For. Glob. Change* **2** 52

West T A P and Fearnside P M 2021 Brazil's conservation reform and the reduction of deforestation in Amazonia *Land Use Policy* **100** 105072

Westin F F, Dos Santos M A and Martins I D 2014 Hydropower expansion and analysis of the use of strategic and integrated environmental assessment tools in Brazil *Renew. Sustain. Energy Rev.* **37** 750–61

Zhao K *et al* 2019 Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: a Bayesian ensemble algorithm *Remote Sens. Environ.* **232** 111181

Zhao Q, Liu S, Deng L, Dong S, Yang Z and Liu Q 2013 Determining the influencing distance of dam construction and reservoir impoundment on land use: a case study of Manwan Dam, Lancang River *Ecol. Eng.* **53** 235–42