

Supplementary Material

The input data set

Sentinel-2 (S2) imagery (Drusch et al. 2012) was used to map logging activities in the study area (Table S1). S2 mission was conceived to have a temporal resolution (revisit time) of five days at the equator (Drusch et al. 2012). S2 images (MSI Level-1C), tile 20MPS, were obtained from the European Space Agency (ESA) Copernicus portal (<https://scihub.copernicus.eu>). With a spatial coverage of 100 × 100 km per image tile, they provide a good representation of the town of Santo Antônio do Matupi and its surrounding areas (Fig. 1). For the binary map, representing disturbed/undisturbed forests, all images with less than 10% cloud cover, available for a 4-month time period from 1 June to 30 September for the years 2016 and 2017, were analyzed (Table S1). Clouds and cloud shadows were masked out using the fmask algorithm (Zhu et al. 2015), with a 20 m spatial resolution. To accommodate the cloud detection algorithm for the 10 m resolution of Sentinel-2 data, the fmask product was resampled to 10 m using the nearest neighbor method. To improve the detection of small clouds, the cloud probability threshold was modified to 0.1 from the original value of 0.2.

Non-forested areas were masked out using PRODES forest cover mapping for the year 2017 (INPE 2020). PRODES data was chosen for building the forest mask because it applies an object-based image analysis, with a minimum mapping unit (MMU) of 6.5 ha. This ensures that logging infrastructure can be kept inside the forest mask and mapped as part of the forest disturbance process. Contiguous disturbances great than 6.5 ha are classified as deforestation in the PRODES's methodology. Water bodies were masked out using the Global Surface Water data set (Pekel et al. 2016). Both data sets were resampled to 10 m resolution using the nearest neighbor resampling method.

Forest disturbance maps were produced using an adaptation of the difference of a self-referenced normalized burn ratio, the $\Delta rNBR$ approach (Langner et al. 2018), for the years 2016 and 2017. It was adapted because the method was developed for Landsat and here S2 data are used. This method was already tested for S2 data in the same region (Lima et al. 2019). The $\Delta rNBR$ was used to build a binary map of disturbed/undisturbed forests, by considering as disturbed all pixels with values greater than 0.065. The overall accuracy of this binary map is 96.7%, according to the accuracy assessment done for 7 of the 10 FMUs (Lima et al. 2019).

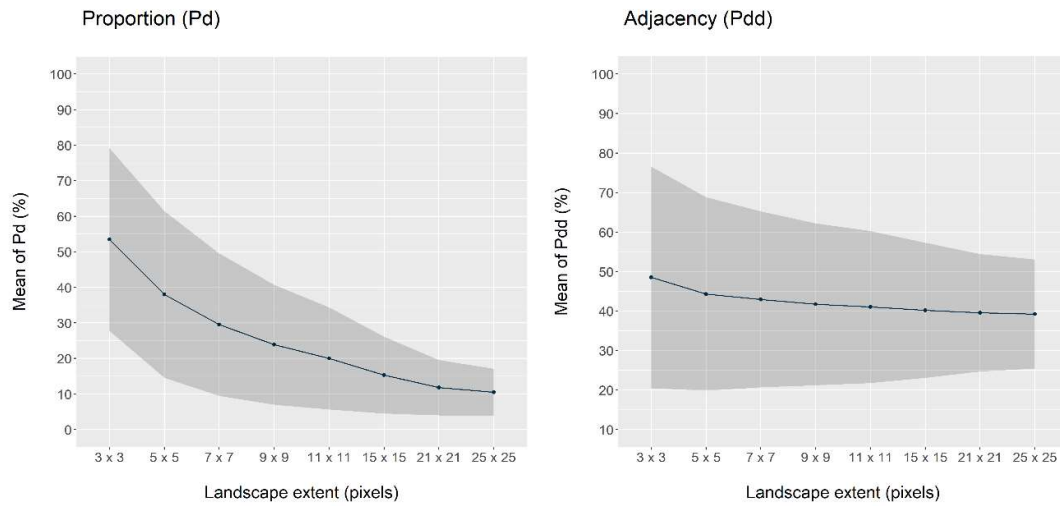
All remote sensing analyses were done in R (R Core Team 2019), using raster (Hijmans 2017) and rgdal (Bivand et al. 2018) packages.

32 Table S1. Sentinel-2 images used in this study. AOI = Area of Interest. Components of the Sentinel-2
 33 filename: MMM: is the mission ID (S2A/S2B), MSIL1C: denotes the Level-1C product level,
 34 YYYYMMDDHHMMSS: the data take sensing start time, Nxyy: the processing baseline number (e.g.
 35 N0204), ROOO: Relative Orbit number (R001 - R143), Txxxxx: Tile Number field.

Year	Sentinel-2 image
	MMM_MSIL1C_YYYYMMDDHHMMSS_Nxyy_ROOO_Txxxxx
2015	S2A_MSIL1C_20150825T143316_N0204_R053_T20MPS
2016	S2A_MSIL1C_20160620T142752_N0204_R053_T20MPS
2016	S2A_MSIL1C_20160710T142802_N0204_R053_T20MPS
2016	S2A_MSIL1C_20160730T142802_N0204_R053_T20MPS
2016	S2A_MSIL1C_20160819T142752_N0204_R053_T20MPS
2017	S2A_MSIL1C_20170615T142751_N0205_R053_T20MPS
2017	S2A_MSIL1C_20170705T142751_N0205_R053_T20MPS
2017	S2B_MSIL1C_20170720T142749_N0205_R053_T20MPS
2017	S2A_MSIL1C_20170725T142751_N0205_R053_T20MPS
2017	S2A_MSIL1C_20170903T142851_N0205_R053_T20MPS
2018	S2B_MSIL1C_20180625T142749_N0206_R053_T20MPS
2018	S2B_MSIL1C_20180725T142849_N0206_R053_T20MPS
2018	S2B_MSIL1C_20180903T142849_N0206_R053_T20MPS
2019	S2A_MSIL1C_20190625T142801_N0207_R053_T20MPS
2019	S2A_MSIL1C_20190725T142801_N0208_R053_T20MPS
2019	S2B_MSIL1C_20190630T142759_N0207_R053_T20MPS
2019	S2B_MSIL2A_20190908T142759_N0213_R053_T20MPS

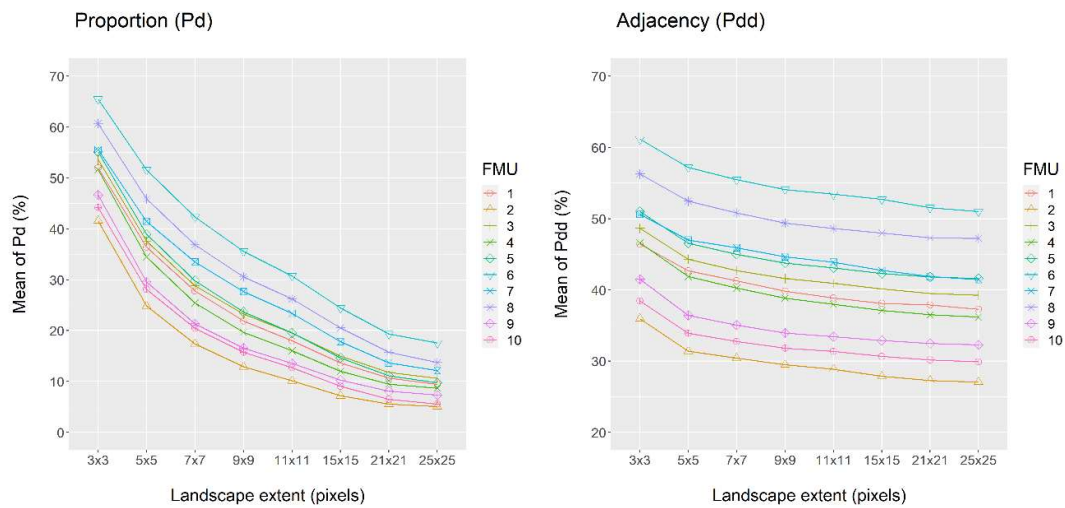
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37 Figure S1. Mean proportion (Pd) and adjacency (Pdd) across different window sizes (grey ribbons
 38 represents mean $\pm$ standard deviation)



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40 Figure S2. Proportion (Pd) and adjacency (Pdd) mean values among different forest management units
 41 (FMU, values from 1 to 10) and across a range of scales.



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Figure S3. Means of Proportion (Pd) and adjacency (Pdd) for five disturbance classes across eight different landscape sizes.

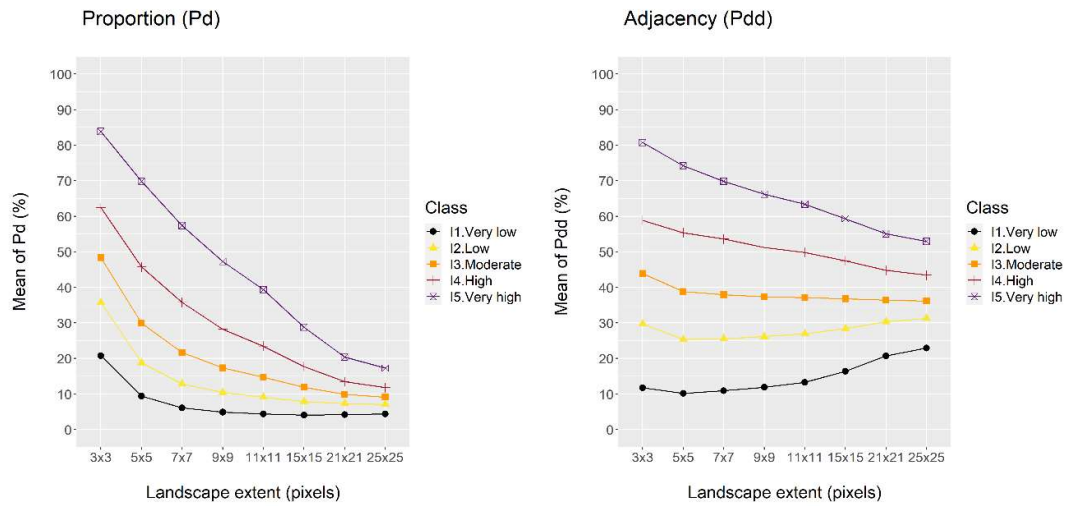


Figure S4. Classes of disturbance (disturbance profiles) in the pattern space (Pdd $\times$ Pd) for eight landscape extents (moving window sizes).

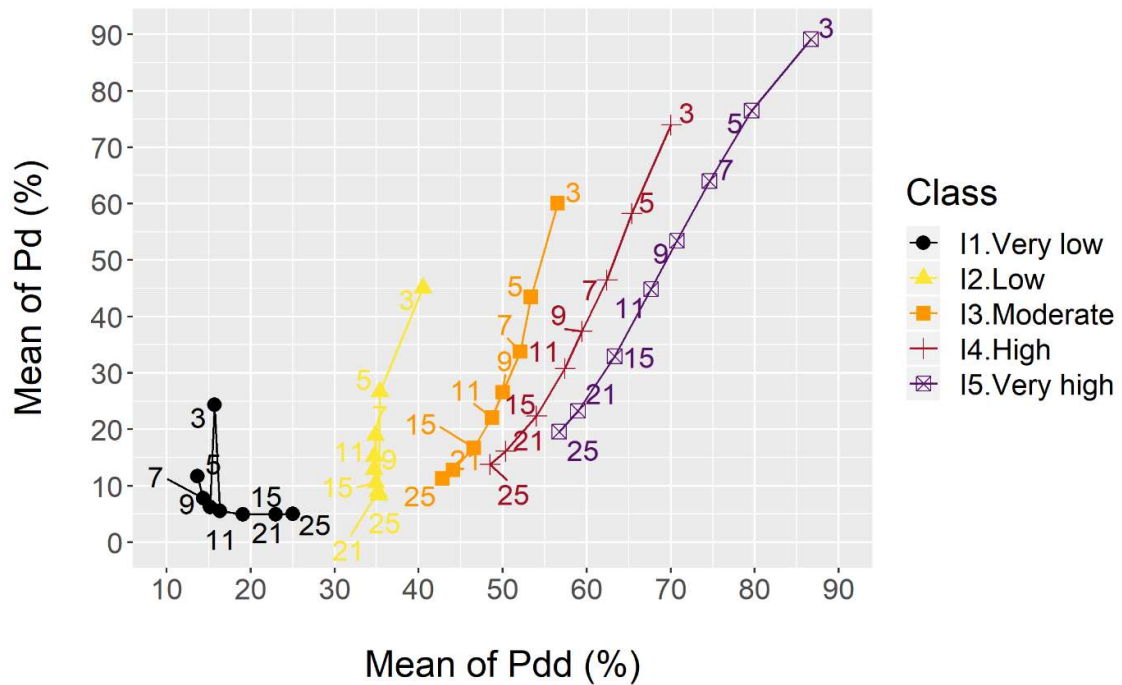


Figure S5. Distribution of disturbance intensity classes (proportionally, in relation to the total disturbed pixels) amongst the 10 FMU under analysis. For the location and size of each FMU see Figure 1.

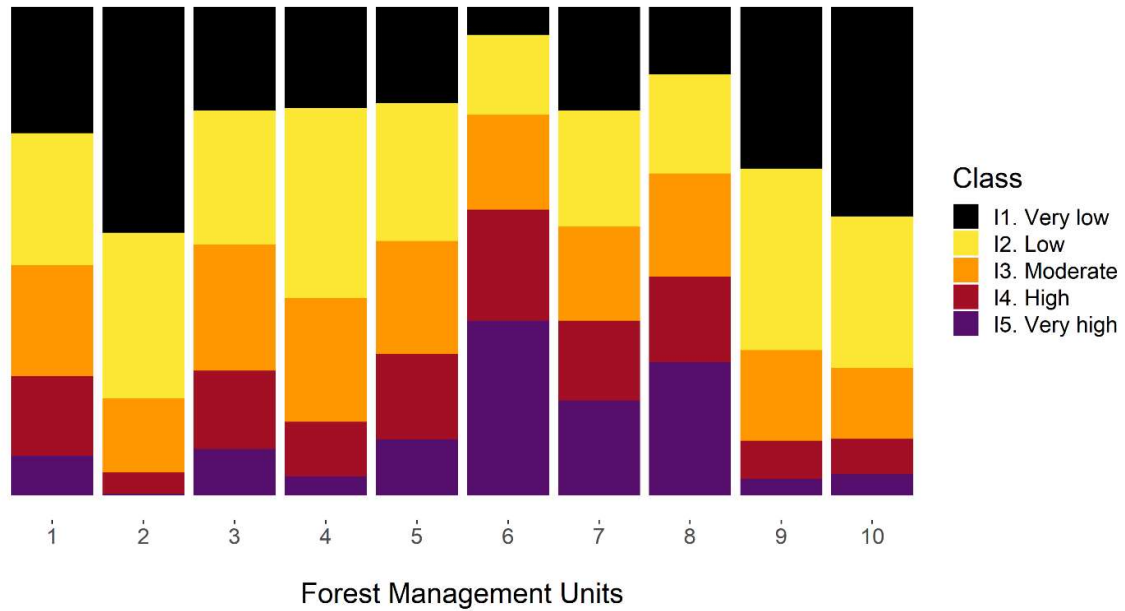


Table S2. Information about the sustainable forest management (SFM) plans implemented in the 10 forest management units (FMU) analyzed in this study. These data were disclosed by the Brazilian Government, represented by the Institute of Environmental Protection of Amazonas State (IPAAM), under the Administrative Process No.1946/2017.

FMU	Geographic Coordinates*	License No.	License validity (mm/dd/yyyy)		Volume authorized for logging (m ³) **	Total area of the SFM (ha)***	Proportion of logged area (%)
			From	To			
1	-61.5939, -8.0544	211/16	09/15/2016	09/15/2018	5,029.36	266.34	4.95
2	-61.7057, -7.9186	060/16	04/28/2016	04/28/2018	6,882.85	373.62	1.95
3	-61.6694, -8.0262	186/17	07/07/2017	07/07/2019	11,398.69	512.00	5.10
4	-61.5880, -7.7731	190/16	8/05/2016	08/05/2018	6,438.60	390.65	4.46
5	-61.3897, -7.6849	020/17	01/27/2017	01/27/2019	14,106.49	680.85	3.07
6	-61.5948, -7.9522	253/16	11/18/2016	11/18/2018	2,335.79	124.78	13.14
7	-61.1899, -8.1221	063/16	05/06/2016	05/06/2018	19,653.36	1,009.51	6.72
8	-61.7871, -8.0518	248/16	11/11/2016	11/11/2018	9,103.11	557.45	5.53
9	-61.1528, -8.0878	235/16	11/01/2016	11/01/2018	23,112.18	1086.71	3.35
10	-61.4342, -8.0860	082/16	05/13/2016	05/13/2018	15,021.94	904.09	2.58

*Centroid of the FMU's polygon (EPSG:4326, WGS 84). **Volume authorized for logging present in the License/Authorization, according to the data provided by IPAAM. It does not necessarily represent the actual volume of logged trees in the moment the mapping was done.

***Area of the polygon representing the SFM test sites.

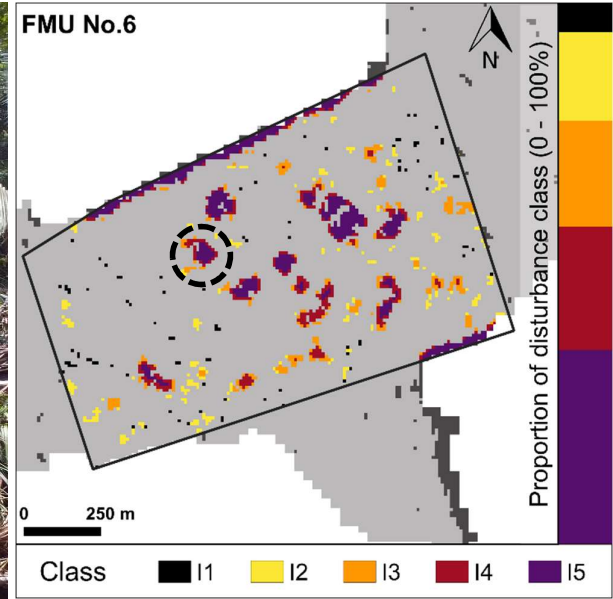


Figure S6. Photograph of a large felling gap in FMU No. 6 (dashed circle in the map) and disturbance intensity map for the same management unit. Vertical bars represent the percentage of each one of the disturbance classes in relation to the total area of disturbance. Codes for each one of the disturbance classes are: I1 (very low), I2 (low), I3 (moderate), I4 (high) and I5 (very high). FMU: Forest Management Unit.

68 **References**

- 69 Bivand R, Keitt T, Rowlingson B, Pebesma E, Sumner M, Hijmans R, Rouault E, Warmerdam F,
70 Ooms J, Rundel C (2018) rgdal: Bindings for the “Geospatial” Data Abstraction Library
71 Drusch M, Bello U Del, Carlier S, Colin O, Fernandez V, Gascon F, Hoersch B, Isola C, Laberinti P,
72 Martimort P, Meygret A, Spoto F, Sy O, Marchese F, Bargellini P (2012) Sentinel-2: ESA’s
73 Optical High-Resolution Mission for GMES Operational Services. *Remote Sens Environ*
74 120:25–36. <https://doi.org/10.1016/j.rse.2011.11.026>
75 Hijmans RJ (2017) raster: Geographic Data Analysis and Modeling
76 INPE (2020) Projeto PRODES: Monitoramento da Floresta Amazônica Brasileira por Satélite.
77 <http://www.obt.inpe.br/OBT/assuntos/programas/amazonia/prodes>. Accessed 25 Jan 2020
78 Langner A, Miettinen J, Kukkonen M, Vancutsem C, Simonetti D, Vieilledent G, Verhegghen A,
79 Gallego J, Stibig H-J (2018) Towards Operational Monitoring of Forest Canopy Disturbance in
80 Evergreen Rain Forests: A Test Case in Continental Southeast Asia. *Remote Sens* 10:544.
81 <https://doi.org/10.3390/rs10040544>
82 Lima TA, Beuchle R, Langner A, Grecchi RC, Griess VC, Achard F (2019) Comparing Sentinel-2
83 MSI and Landsat 8 OLI imagery for monitoring selective logging in the Brazilian Amazon.
84 *Remote Sens* 11:961. <https://doi.org/10.3390/rs11080961>
85 Pekel J-F, Cottam A, Gorelick N, Belward AS (2016) High-resolution mapping of global surface
86 water and its long-term changes. *Nature* 540:418. <https://doi.org/10.1038/nature20584>
87 R Core Team (2019) R: A language and environment for statistical computing. [https://www.r-](https://www.r-project.org/)
88 [project.org/](https://www.r-project.org/). Accessed 1 Oct 2019
89 Zhu Z, Wang S, Woodcock CE (2015) Improvement and expansion of the Fmask algorithm: cloud,
90 cloud shadow, and snow detection for Landsats 4–7, 8, and Sentinel 2 images. *Remote Sens*
91 *Environ* 159:269–277. <https://doi.org/10.1016/j.rse.2014.12.014>

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