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Supplementary Information

Frontier metrics for a process-based understanding of deforestation dynamics

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5 Text S1: Reconstructing annual land-cover change time series 1985-2020

6 Our first step was to reconstruct year-to-year land-cover change for the time period 1985-2020 7 at 30m resolution based on all Landsat images recorded during that time period. Specifically, we 8 derived time series of spectral-temporal metrics (STM) based on all available Landsat TM4, 9 TM5, ETM+, and OLI imagery across the Chaco (81,233 images total). STM are composites 10 that summarize the spectral properties of all available imagery at a given location, for a given 11 time window (Azzari et al, 2019; Oeser et al, 2020; Pflugmacher et al, 2019), and describe land-12 cover characteristics, such as the amount of photosynthetic active vegetation, albedo or soil 13 moisture (Crist & Cicone, 1984). We used the Collection 1 Tier 1 Surface Reflectance data and 14 subdivided the image collection for each year of our analysis (i.e., 1985-2020) into a wet season 15 (April-September) and a dry season (October-March of the following year). We then calculated the seasonal (i.e., for both dry and wet season) mean, standard deviation, 10th and 90th 16 17 percentile of the six multispectral bands as well as seven spectral indices (i.e., the Normalized 18 Burn Ratio (NBR. (Key & Benson, 1999)), the Normalized Difference Moisture Index (NDMI. 19 (Gao, 1996)), the Enhanced Vegetation Index (EVI, (Justice et al, 1998)), the Modified Soil 20 Adjusted Vegetation Index (MSAVI, (Qi et al, 1994)) and the three Tasseled Cap (TC) 21 components brightness, greenness and wetness (Kauth & Thomas, 1976)), resulting in a total of 22 104 STM per year and pixel (2 seasons x 4 metrics x (6 bands + 7 indices). All pre-processing 23 was done in Google Earth Engine (Gorelick et al, 2017). 24 The STM served as input for our annual land-cover classification to map the following

25 classes: (1) woodlands, (2) all other types of (semi-)natural vegetation (hereafter: other 26 vegetation, e.g., natural grasslands, palm savannas), (3) croplands, (4) pastures, and (5) other 27 land covers (i.e., water, bare soil, wetlands, urban areas). As training data, we used data from 28 our own previous research (Baumann et al, 2017a; Baumann et al, 2017b), complemented with 29 additional training polygons through on-screen digitization. Once our training dataset was 30 complete, we randomly sampled 5,000 points per land-cover class within training polygons and 31 used a random forest classifier (Breiman, 2001) to predict class-wise land-cover probabilities for 32 our five land-cover classes for each pixel and year. We then implemented several steps to

33 ensure temporal consistency. First, we derived baseline land cover based on the land-cover 34 probabilities from 1985-1987 (we used three years to account for noise in the data). We 35 hierarchically assigned each pixel to one land-cover category in the order (1) woodlands, (2) 36 other vegetation, (3) pastures, (4) croplands, and (5) other if the maximum probability of the 37 respective land cover during the period 1985-1987 exceeded 50% (e.g., a pixel was assigned to 38 other (semi-) natural vegetation if the maximum probability of that class in 1985-1987 was >50% 39 and the pixel had not already been assigned to *woodlands*). Remaining areas, which did not 40 show land cover probabilities larger than 50% were assigned to the class with the highest 41 probability.

42 Once our baseline map was available, we mapped six land-cover transitions in the 43 Chaco (Table SI-1): (1) woodlands to pasture, (2) woodlands to cropland, (3) woodlands to 44 other vegetation, (4) other vegetation to pasture, (5) other vegetation to cropland, and (6) 45 pasture to cropland. We assigned a transition only if it had occurred consistently over a period of three years. For example, a former woodland pixel would have to have a cropland probability 46 47 >50% during three consecutive years to qualify as a woodland to cropland transition. Areas not 48 undergoing any transitions, were labeled as unchanged and had the same land cover in 1985 49 and 2020. Importantly, this avoids labelling ephemeral change (e.g., pixels flipping back and 50 forth between classes) and illogical or unlikely change (e.g., cropland to woodlands) as land-use 51 transitions. Finally, we applied a minimum mapping unit of six pixels (0.56 ha). 52 We validated our annual land-use transition maps with a stratified random sample of 25 53 points per year and land-cover class (4,500 validation points in total), and labelled each point 54 based on high-resolution imagery from Google Earth or Planet Labs and the Landsat time 55 series. We calculated annual confusion matrices, overall and class-wise accuracies, as well as

56 class-wise area estimates with confidence intervals (Pflugmacher et al, 2019; Stehman, 2014).

57 Using these data, we summarized land-use transitions (a) for the entire Chaco, (b) for each

58 country (i.e., Argentina, Bolivia and Paraguay), and (c) for the dry and wet Chaco.

- 60 Table SI 1: Transition rules for consistently reconstructing year-to-year land-cover change 1985-
- 61 2020 based on yearly land-cover probabilities.

#	Transition	Transition rule
1	Woodland to Pasture	1. Class WL in 1985
	$(WL \rightarrow P)$	2. 3 consecutive years $P_{WL} < 50\%$
		3. At least 2 consecutive years with $P_P > 50\%$
2	Woodland to cropland	1. Class WL in 1985
	$(WL \rightarrow C)$	2. 3 consecutive years $P_{WL} < 50\%$
		3. At least 3 consecutive years with $P_C > 50\%$
3	Woodland to Other Vegetation	1. Class WL in 1985
	$(WL \rightarrow ONV)$	2. 3 consecutive years $P_{WL} < 50\%$
		3. Not belonging to #1 and #2
4	Other Vegetation to Pasture	1. Class ONV in previous year (i.e., in LC 1985 or
	$(ONV \rightarrow P)$	resulting from transition #3)
		2. At least 2 consecutive years with $P_P > 50\%$
5	Other Vegetation to Cropland	1. Class ONV in previous year (i.e., in LC 1985 or
	$(ONV \rightarrow C)$	resulting from transition #3)
		2. At least 3 consecutive years with $C_P > 50\%$
6	Pasture to Cropland	1. Class P in previous year (i.e., in LC 1985 or resulting
	$(P \rightarrow C)$	from transitions #1 or #4)
		2. At least 3 consecutive years with $C_P > 50\%$

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63 Text S2: Deriving frontier metrics

Our second main step was the quantitative description of frontier development using a novel set of frontier metrics. We identified frontier areas as those areas with at least 0.5% woodland loss during three consecutive years, following Rodrigues et al (2009) and Buchadas et al (2022). The latter rule helps to separate permanent change in land cover from short-term disturbances (e.g., fire, drought impact) and management signals (e.g. logging). To calculate metrics, we aggregated our 30m time series to a resolution of 1.5x1.5 km² (i.e., 50x50 pixels), yielding time series of fractional *woodland* cover as well as the dominant agricultural land cover in each

1.5x1.5 km² grid cell (i.e., *pasture* or *cropland*). Then, we fitted a sigmoid function through the

time series of fractional woodland cover for each grid cell to describe woodland dynamics

73 (Figure 1, main manuscript) according to:

74

$$W(fit)_t = \frac{W_{1985}}{1 + e^{-k*(t-t_0)}} + W_{2020}$$

75 where $W(fit)_t$ represents the fitted woodland cover in year t, W_{1985} the woodland cover in 1985 76 (i.e., at the beginning of our time series), W_{2020} the woodland cover in 2020 (i.e., at the end of 77 the time series), and k a parameter that controls the slope of the curve. We extracted W_{1985} and 78 W_{2020} from our time series and estimated k by least-squares curve fitting (Baumann et al, 79 2017c). We also calculated the first and second derivative of the sigmoid function to extract two 80 parameters of the fitted curve: (a) the year of the onset of woodland decline, identified as the 81 point of the local minimum of the second derivative in the fitted time series, and (b) the year of 82 the strongest woodland decline (Figure 1, main manuscript).

83 Based on these data, we derived six metrics (Table SI 1) for our *frontier areas*. As a first 84 metric, we derived *frontier timing* that describes woodland change during the last five years 85 (2016-2020) relative to background change (period 1985-2015), differentiating between 86 suspended frontiers (i.e., >0.5% annual woodland loss during any three-year period 1985-2015, 87 but not after 2016), active frontiers (i.e., >0.5% annual woodland loss before and after 2015), 88 and emerging frontiers (i.e., >0.5% annual woodland loss only after 2016). Second, we derived frontier speed by calculating the strongest annual woodland loss, measured by the maximum 89 90 slope of our fitted woodland time series (and corresponding to the minimum value of the first 91 derivative), and categorized speed into slow (i.e., maximum annual woodland loss <25%), medium (i.e., 25%-50%), and fast (i.e., >50%). Third, we calculated the metric *remaining* 92 93 woodlands in 2020, that represented woodlands left after deforestation relative to baseline 94 woodlands (high= 66% of baseline woodlands left; medium= 33%-66% baseline woodlands; 95 low= 33% or less baseline woodland). Fourth, we calculated the metric *frontier diffusion* by 96 subdividing our frontiers into gradual frontiers (i.e., characterized by gradually progressing 97 deforestation) and *leap-frogging* frontiers (i.e., emerging new frontiers at least 45 km (i.e., 30 arid cells) away from other frontier cells or baseline agriculture in 1985). Fifth, we calculated the 98 99 frontier onset, describing the point in time when frontier development started, defined as the 100 location of the local minimum of the second derivative. Sixth, we characterized frontier land use 101 based on the dominant agricultural land use that followed woodland conversion. We 102 distinguished three frontier types: cropland frontiers, pasture frontiers, and transition frontiers 103 (i.e., frontiers, where initially pasture or natural vegetation followed deforestation, but was later 104 replaced by cropland). We created spatial layers for each of the five metrics, applying a 105 minimum mapping unit of four cells (i.e., 9 km²).

107 Text S3: Analyzing frontier patterns and dynamics

108 To assess frontier dynamics in the Chaco, we carried out two analyses. First, we 109 identified the temporal patterns of frontier processes across the Chaco for the period 1985-110 2020. To assess the emergence of different frontier types over time, we related our metric 111 frontier onset (i.e., that describes the year of emergence of a frontier pixel) to the five other 112 frontier metrics (i.e., frontier timing, frontier speed, frontier naturalness, frontier progress and 113 frontier land use), to understand temporal patterns of the dominance of individual frontier types. 114 We did this for the Chaco as a whole, and separately for the three countries as well as the dry 115 and the wet Chaco.

116 Second, we identified high-level, typical combinations of our five thematic frontier 117 metrics, and we did this for the Chaco as a whole as well as for the three countries and the dry 118 and wet Chaco by calculating the area share of each metric combination relative to all frontier 119 areas. In addition, we related our frontier metrics to a set of frontier regions derived in our own 120 previous work (le Polain de Waroux et al, 2018). Specifically, we assessed for each region the 121 five most common combinations of metrics (i.e., archetypical combinations) based on their area, 122 and identified across these archetypical combinations for each metric the dominant category. 123 For example, if within a region the five most common archetypical combinations showed *pasture* 124 as the dominant frontier land use, the entire region was characterized as pasture. Likewise, if 125 the five most common archetypical combinations suggested that frontier speed was *fast*, the 126 entire region was labeled as such. We only considered frontier diffusion in a different way, as in 127 leapfrogging frontiers per definition only the first grid cells would receive the label leapfrogging 128 whereas neighboring, during subsequent years as frontier identified, grid cells would receive the 129 label progressing. Here, we considered a region being a leapfrogging region when leapfrogging 130 appeared at least once within the ten most common metric combinations. Where a region could 131 not be uniquely characterized (e.g., when frontier speed in the five most common metric 132 combinations was 2x fast, 2x slow, and 1x medium), we subdivided the region into two separate 133 regions (e.g., Anta into Anta I and Anta II).



135 Figure SI 1: Overall classification accuracy [%] for the annual land-cover maps 1985-2020. The

136 red bars represent the error bars resulting from the accuracy assessment.

137



139 Figure SI 2: Class-wise user's and producer's accuracies for the land-cover time series 1985-

140 2020



142 Figure SI 3: Class-wise area estimates for the five land-cover class in the Chaco 1985-2020143

- 144 Table SI 1-1: Combinations of metric classes and their respective area proportion across frontier
- 145 areas in the entire Chaco. The table represents a detailed and extended version of figure 6 in
- 146 the main manuscript. Presented are all combinations with at least 1% share of all frontier
- 147 regions.

Entire Chaco	Frontier metric					
% of all frontier areas	Diffusion	Naturalness	Timing	LandUse	Speed	
17.8	Progressing	Medium	Active	Pasture	Slow	
14.2	Progressing	Low	Suspended	Pasture	Fast	
13.5	Progressing	High	Active	Pasture	Slow	
8.5	Progressing	Low	Active	Pasture	Slow	
5.8	Progressing	Low	Suspended	Transition	Fast	
4.5	Progressing	Medium	Suspended	Pasture	Slow	
4.4	Progressing	High	Suspended	Pasture	Slow	
3.9	Progressing	Low	Suspended	Pasture	Slow	
2.6	Progressing	Low	Active	Pasture	Fast	
2.3	Progressing	Medium	Suspended	Pasture	Medium	
2.3	Progressing	Low	Active	Transition	Slow	
2.1	Progressing	Medium	Active	Transition	Slow	
2.1	Progressing	Medium	Suspended	Pasture	Fast	
2.0	Progressing	Low	Suspended	Transition	Slow	
1.6	Progressing	Low	Suspended	Pasture	Medium	
1.4	Progressing	Medium	Suspended	Transition	Slow	
1.1	Progressing	Low	Active	Pasture	Medium	

- 149 Table SI 1-2: Combinations of metric classes and their respective area proportion across frontier
- 150 areas for Argentina. The table represents a detailed and extended version of figure 6 in the
- 151 main manuscript. Presented are all combinations with at least 1% share of all frontier regions.

Argentina	Frontier metric				152
% of all frontier areas	Diffusion	Naturalness	Timing	LandUse	Speed
18.1	Progressing	Medium	Active	Pasture	Slow
13.4	Progressing	High	Active	Pasture	Slow
10.2	Progressing	Low	Suspended	Transition	Fast
8.0	Progressing	Low	Suspended	Pasture	Fast
7.0	Progressing	Low	Active	Pasture	Slow
4.6	Progressing	High	Suspended	Pasture	Slow
4.0	Progressing	Low	Active	Transition	Slow
3.9	Progressing	Medium	Suspended	Pasture	Slow
3.7	Progressing	Medium	Active	Transition	Slow
3.6	Progressing	Low	Suspended	Transition	Slow
2.4	Progressing	Medium	Suspended	Transition	Slow
2.2	Progressing	Low	Suspended	Pasture	Slow
1.7	Progressing	Medium	Suspended	Pasture	Medium
1.7	Progressing	Low	Suspended	Transition	Medium
1.5	Progressing	Low	Suspended	Cropland	Fast
1.3	Progressing	High	Active	Transition	Slow
1.3	Progressing	High	Suspended	Transition	Slow
1.2	Progressing	Medium	Suspended	Pasture	Fast
1.1	Progressing	Low	Suspended	Pasture	Medium

- 153 Table SI 1-3: Combinations of metric classes and their respective area proportion across frontier
- areas for Bolivia. The table represents a detailed and extended version of figure 6 in the main
- 155 manuscript. Presented are all combinations with at least 1% share of all frontier regions.

Bolivia	Frontier metr	Frontier metric				
% of all frontier areas	Diffusion	Naturalness	Timing	LandUse	Speed	
22.8	Progressing	High	Active	Pasture	Slow	
20.9	Progressing	Medium	Active	Pasture	Slow	
12.9	Progressing	Low	Active	Pasture	Slow	
7.3	Progressing	High	Suspended	Pasture	Slow	
6.6	Progressing	Low	Suspended	Pasture	Fast	
5.2	Progressing	Medium	Suspended	Pasture	Slow	
4.4	Progressing	Low	Active	Pasture	Fast	
3.4	Progressing	Low	Suspended	Pasture	Slow	
2.3	Progressing	Medium	Suspended	Pasture	Medium	
2.2	Progressing	Low	Active	Pasture	Medium	
1.6	Progressing	Low	Suspended	Pasture	Medium	
1.4	Progressing	Medium	Suspended	Pasture	Fast	
1.3	Progressing	High	Suspended	Pasture	Medium	

- 157 Table SI 1-4: Combinations of metric classes and their respective area proportion across frontier
- 158 areas for Paraguay. The table represents a detailed and extended version of figure 6 in the
- 159 main manuscript. Presented are all combinations with at least 1% share of all frontier regions.

Paraguay	Frontier metric				
% of all frontier areas	Diffusion	Naturalness	Timing	LandUse	Speed
24.3	Progressing	Low	Suspended	Pasture	Fast
16.9	Progressing	Medium	Active	Pasture	Slow
12.2	Progressing	High	Active	Pasture	Slow
10.2	Progressing	Low	Active	Pasture	Slow
6.4	Progressing	Low	Suspended	Pasture	Slow
5.1	Progressing	Medium	Suspended	Pasture	Slow
4.8	Progressing	Low	Active	Pasture	Fast
3.6	Progressing	High	Suspended	Pasture	Slow
3.5	Progressing	Medium	Suspended	Pasture	Fast
3.1	Progressing	Medium	Suspended	Pasture	Medium
2.4	Progressing	Low	Suspended	Pasture	Medium
1.5	Progressing	Low	Active	Pasture	Medium
1.2	Progressing	Low	Emerging	Pasture	Fast

- 161 Table SI 1-5: Combinations of metric classes and their respective area proportion across frontier
- areas for the dry Chaco. The table represents a detailed and extended version of figure 6 in the
- 163 main manuscript. Presented are all combinations with at least 1% share of all frontier regions.

Dry Chaco	Frontier metric				164
% of all frontier areas	Diffusion	Naturalness	Timing	LandUse	Speed
18.4	Progressing	Low	Suspended	Pasture	Fast
11.0	Progressing	Medium	Active	Pasture	Slow
8.4	Progressing	Low	Active	Pasture	Slow
8.2	Progressing	Low	Suspended	Transition	Fast
7.1	Progressing	High	Active	Pasture	Slow
4.5	Progressing	Low	Suspended	Pasture	Slow
3.8	Progressing	Medium	Suspended	Pasture	Slow
3.4	Progressing	Low	Active	Pasture	Fast
3.2	Progressing	Low	Active	Transition	Slow
3.0	Progressing	Medium	Active	Transition	Slow
2.9	Progressing	Low	Suspended	Transition	Slow
2.7	Progressing	High	Suspended	Pasture	Slow
2.5	Progressing	Medium	Suspended	Pasture	Fast
2.5	Progressing	Medium	Suspended	Pasture	Medium
1.9	Progressing	Low	Suspended	Pasture	Medium
1.9	Progressing	Medium	Suspended	Transition	Slow
1.4	Progressing	Low	Suspended	Transition	Medium
1.3	Progressing	Low	Active	Pasture	Medium
1.3	Progressing	Low	Suspended	Cropland	Fast
1.1	Progressing	High	Suspended	Transition	Slow
1.1	Progressing	High	Active	Transition	Slow

- 165 Table SI 1-5: Combinations of metric classes and their respective area proportion across frontier
- areas for the wet Chaco. The table represents a detailed and extended version of figure 6 in the
- 167 main manuscript. Presented are all combinations with at least 1% share of all frontier regions.

Wet Chaco	Frontier metric					
% of all frontier areas	Diffusion	Naturalness	Timing	LandUse	Speed	
31.8	Progressing	Medium	Active	Pasture	Slow	
26.4	Progressing	High	Active	Pasture	Slow	
8.8	Progressing	Low	Active	Pasture	Slow	
7.8	Progressing	High	Suspended	Pasture	Slow	
5.8	Progressing	Medium	Suspended	Pasture	Slow	
5.7	Progressing	Low	Suspended	Pasture	Fast	
2.7	Progressing	Low	Suspended	Pasture	Slow	
1.9	Progressing	Medium	Suspended	Pasture	Medium	
1.3	Progressing	Medium	Suspended	Pasture	Fast	

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