

1 **For *Biological Conservation***

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3 **The role of elections as drivers of tropical deforestation**

4

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21

22 *Abstract*

23 Tropical forests support immense biodiversity and provide essential ecosystem services for billions of
24 people. Despite this value, tropical deforestation continues at a high rate. Emerging evidence
25 suggests that elections can play an important role in shaping deforestation, for instance by
26 incentivising politicians to allow increased utilisation of tropical forests in return for political support
27 and votes. Nevertheless, the role of elections as a driver of deforestation has not been
28 comprehensively tested at broad geographic scales. Here, we created an annual database from 2001
29 to 2018 on political elections and forest loss for 55 tropical nations and modelled the effect of
30 elections on deforestation. In total, 1.5 million km² of forest was lost during this time period, and the
31 rate of deforestation increased in 37 (67%) of the analysed countries. Deforestation was significantly
32 lower in years with presidential or lower chamber elections compared to non-election years, which is
33 in contrast to previous local-scale studies. Moreover, deforestation was significantly higher in
34 presidential or lower chamber elections that are competitive (i.e. when the opposition can
35 participate in elections and has a legitimate chance to gain governmental power) compared to
36 uncompetitive elections. Our results document a pervasive loss of tropical forests and suggest that
37 competitive elections are potential drivers of deforestation. We recommend that organisations
38 monitoring election transparency and fairness should also monitor environmental impacts such as
39 forest loss, habitat destruction and resource exploitation. This would benefit the tracking of potential
40 illegal vote buying with natural resources.

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42 **Keywords:** biodiversity threat, forest loss, governance, habitat loss, policy, democracy

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53 1. Introduction

54 Tropical forests contain Earth's richest biota and are the last refuges for many imperilled species
55 (Gaston, 2000; Gibson et al., 2011). Tropical forests also provide globally important ecosystem
56 services such as carbon sequestration and clean water provisioning (Foley et al., 2007). As many as
57 1.6 billion rural people live in close proximity to forests and may depend on forest resources for their
58 livelihoods (Angelsen et al., 2014; Joshi and Joshi, 2019; Rudow et al., 2013). It is therefore
59 concerning that tropical deforestation has reached critically high levels in the last few decades, with
60 as much as 79,000 km² – an area similar in size to Austria – being cleared every year (Austin et al.,
61 2017). Understanding what drives tropical deforestation is thus crucial for implementing policy and
62 conservation actions to ensure forest preservation.

63 The most prevalent direct causes of tropical deforestation include commercial logging (Curtis
64 et al., 2018; Hosonuma et al., 2012), subsistence logging (e.g. for firewood; Heltberg et al., 2000;
65 Hosonuma et al., 2012), conversion of forests to agricultural lands (e.g. for oil palm plantations or
66 cropping; Hosonuma et al., 2012; Koh and Wilcove, 2008; Laurance et al., 2014), and wildfires which
67 are often started by subsistence slash and burn agriculture (Laurance et al., 2002). There is good
68 evidence that these drivers of deforestation increase when certain enabling factors are at play. One
69 of these factors is corruption, which has been associated with higher rates of deforestation (Burgess
70 et al., 2012; Smith et al., 2003; Wright et al., 2007). Another factor is the Gross Domestic Product
71 (GDP) of a country, with higher deforestation occurring in countries with lower GDP (Ewers, 2006).
72 Deforestation also tends to be higher in countries with higher human population densities (Sandker
73 et al., 2017). Interestingly, factors such as a free media are associated with less deforestation,
74 perhaps countering the effects of corruption (Bertot et al., 2010; Kolstad and Wiig, 2009). Other
75 factors that potentially influence deforestation (e.g. armed conflicts, illegal crop production, or
76 political elections and election cycles) have been less studied, even though there is growing evidence
77 that they could drive deforestation trends in the tropics (Dávalos et al., 2016; Landholm et al., 2019;
78 Negret et al., 2019).

79 Recent evidence suggests that elections could be key drivers of deforestation (List and Sturm,
80 2006; Pailler, 2018; Rodrigues-Filho et al., 2015). For example, a local scale study in Brazil found that
81 municipal level deforestation was 8–10% higher in years when there was a municipal election
82 (Pailler, 2018). Moreover, a similar increase in deforestation was also found during the national
83 elections in Brazil (Rodrigues-Filho et al., 2015). During gubernational elections, in the United States
84 of America, governors are more likely to advance or retract environmental policy based on the
85 preference of the voters of their state. For instance, in “green” states environmental policy is more

86 likely to advance during the election period, whereas in “brown” states it is more likely to retract
87 (List and Sturm, 2006). A recent study investigating the economic and political incentives of
88 deforestation in Indonesia found that deforestation substantially increases before a mayoral
89 election, suggesting that political incentives reinforce tropical deforestation (Cisneros et al., 2021).
90 This suggests that elections can influence deforestation, but broad generalizations should be made
91 cautiously given the limited geographical scope, or the limited quality and resolution of deforestation
92 data used in these studies so far.

93 Elections could increase deforestation via multiple mechanisms. Elections are power
94 struggles where politicians aim to gain an advantage over opponents. These advantages can be
95 achieved through popular policies and by creating economic opportunities (Akhmedov and
96 Zhuravskaya, 2003; Drazen and Eslava, 2010; Nordhaus, 1975). For example, politicians might gift or
97 promise forested land for exploitation to win favour with powerful potential supporters, or with
98 businesses such as developers and loggers. A real world example occurred in Uganda in 2011, where
99 the incumbent government promised forests to win community support (Médard and Golaz, 2013). A
100 similar example is the 2018 Brazilian presidential elections which caused a spike in deforestation due
101 to candidates promising the dismantling of environmental laws (Abessa et al., 2019). Leading up to
102 elections, governments may be so focussed on electioneering that diverts their attention from
103 environmental protection and turn a blind-eye to people utilising forest resources, allowing them to
104 harvest unsustainably or to settle on protected forested land (Negret et al., 2017). Most countries
105 have strong laws against winning political favour through financial bribery. However, environmental
106 protection laws are usually less rigorously monitored or upheld than financial laws, making winning
107 support by giving away land and forest resources an attractive alternative to money (Ohman, 2013).
108 There are many mechanisms for elections to drive deforestation but the effect of elections on
109 deforestation remains under-investigated, especially at broad geographic extents.

110 Here, we analyse the effect of elections as drivers of deforestation at a pantropical scale. We
111 focus on the tropics because the mechanisms and drivers of deforestation are fairly distinct from the
112 higher latitude forests in the temperate, boreal and taiga zone (Curtis et al., 2018). To assess the
113 drivers of tropical deforestation, we first explored the directionality and shape of temporal trends in
114 deforestation within 55 pantropical countries from 2001 to 2018 using remotely-sensed global forest
115 loss data (Hansen et al., 2013). High-resolution (30 × 30 metre) year-by-year global forest loss data is
116 now available from 2000 to 2018 (Hansen et al., 2013), providing new opportunities to study the
117 effect of elections on deforestation more accurately and at unprecedented spatial extents.

118 We created an annual database over this time period covering the year in which national
119 elections took place and which type of election it was (presidential, lower chamber, and upper
120 chamber elections). We further extracted additional information on governance (e.g.
121 competitiveness, media integrity, corruption control) and human population density. We used a
122 Hierarchical generalized additive model (HGAM; Pedersen 2019) to assess the effect of election and
123 the governance variables on the proportional deforestation of countries relative to their forest cover
124 in the year 2000. This HGAM approach allows the modelling of non-linear functional relationships
125 between covariates and outcomes where the shape of the function itself varies between different
126 grouping levels (e.g. countries). This technique allowed us to disaggregate the changes in forest loss
127 in each country over time - which can be driven by various factors - from the election covariates.
128 These analyses allowed us to (1) quantify the effect of presidential, lower chamber, and upper
129 chamber elections on tropical deforestation rates compared to non-election years, and (2) to test
130 whether the competitiveness of an election has an effect on deforestation.

131

132 **2. Methods**

133 *2.1 Data collection*

134 We developed an annual 2001–2018 database for 55 tropical-forest countries (Table A1; Figure A1)
135 covering national and state-level deforestation, election dates, governance variables and human
136 population density. The governance variables included competitiveness of elections, media integrity
137 of a country, and control of corruption (Table 1). Human population density captured the number of
138 residents per country area (Table 1).

139 We extracted annual forest loss data for each country for the years 2001–2018 using high
140 resolution (30 × 30 metre) global maps of forest cover and forest loss (Hansen et al., 2013). Data
141 were extracted and processed in the Google Earth Engine (<https://earthengine.google.com>), a cloud
142 platform for earth-observation data analysis (Gorelick et al., 2017). We adapted code from Tracewski
143 et al. (2016) to quantify forest loss per year and country, and make our code available via GitHub
144 (<https://github.com/JoeriMorpurgo/Elections2020>). The Global Forest Change database defines
145 forest as >50% crown cover of trees taller than 5 m height. The presence of forest is given for each 30
146 × 30 metre pixel using the year 2000 as a baseline. Forest loss is defined as the disappearance of a
147 forest pixel in a given year (1 = loss, 0 = no loss). A given forest pixel can only be lost once (in years
148 2001–2018). We used the available data on forest cover (year 2000) and forest loss (years 2001–
149 2018) to calculate the proportional loss (i.e. deforestation) over a given year within (sub)national
150 boundaries relative to the forest cover in the year 2000 (see methodological example in Figure A1).
151 We did not include ‘gain’ in forest area because it is only provided as a total over the whole time

152 period (Hansen et al., 2013) and because it is often due to plantation forests rather than natural
153 regrowth or restoration (Tropek et al., 2014). The Global Forest Change data is considered the most
154 accurate global deforestation data available. However, we acknowledge limitations such as the
155 inability to differentiate between forest and agro-forests, which have been discussed elsewhere
156 (Tropek et al., 2014, Allan et al. 2017).

157 We gathered data on when national level elections took place by examining each country's
158 constitution, and cross-checking this with a number of election databases (see Table B2). In the few
159 cases where we could not find a formal source we utilised Wikipedia ($n = 4$, 0.9%), which is regarded
160 as a credible source for election data (Brown, 2011). We collected information on three types of
161 national elections: (i) *Lower chamber elections*, where the lower chamber holds the legislative power
162 allowing them to create laws; (ii) *Upper chamber elections*, where the upper chamber reviews the
163 legislative power; and (iii) *Head-of-state or head-of-government elections* (hereafter called
164 '*presidential elections*') depending on who holds the executive power to enforce the law and is
165 elected. All countries analysed had a lower chamber and presidential elections. However, many
166 countries did not have upper chamber elections (25 out of 55 countries, i.e. 45%). Presidential and
167 upper chamber election dates often occur in the same year as lower chamber elections (52% and
168 38% of the time, respectively). All election types were treated as a binary predictor variable (1 = year
169 with election, 0 = no election), i.e. either occurring in a given year or not.

170 We extracted governance information and human population density from various sources
171 (for details see Table 1). Elections were scored as competitive (= 1) when they are sufficiently free for
172 the opposition to gain legislative or executive power with enough votes, and otherwise as non-
173 competitive (= 0) (see 'Competitive elections' in Table 1). Note that this variable does not capture
174 whether parties have equal funding, media coverage or whether civil liberties are respected. Hence,
175 competitive elections are not equal to free and fair elections (Skaaning et al., 2015). We further used
176 an index from the World Bank which captures the control of corruption, which has been linked to
177 both tropical deforestation and enhancing election cycles (Kaufmann et al., 2011; Pereira et al., 2009;
178 Smith et al., 2003). We also extracted a variable which quantifies to what extent media are diverse
179 and critical ('Media integrity' in Table 1), as this has been shown to counter the effects of election
180 cycles (Akhmedov and Zhuravskaya, 2003; Tufis, 2019). Finally, we also accounted for human
181 population density, since higher densities at a national level tend to increase deforestation (World
182 bank, 2020). All predictor variables, included in the analysis, were compiled at national and annual
183 scale. Four countries lacked data on 'Competitive elections', leading to exclusion in the Hierarchical
184 Generalized Additive Modelling (Table A1).

185 **Table 1. Summary of predictor variables which were included in Hierarchical Generalized Additive Models to**
186 **explain proportional deforestation of a country relative to the forest cover in the year 2000 (response**
187 **variable).** The predictor variables capture governance aspects (competitive elections, media integrity and
188 control of corruption) and human population density.

Variable	Definition and methods	Reference & source
Competitive elections	Competitive elections (referred to as 'Competitive' in our analysis) is a binary variable that quantifies whether elections are sufficiently free for the opposition to gain legislative or executive power (1) or not (0). This reflects whether the seats of the executive and legislative body are filled by elections that are characterized by uncertainty in terms of the final outcome. This includes that (1) the legislature is only constitutionally dissolved, (2) members of the executive or legislative are only constitutionally removed, (3) elections are held at a time consistent with constitutional requirements, (4) non-extremist parties are not banned, and (5) voters experience little systematic coercion in their electoral vote.	Tufis, 2019
Media integrity	Media integrity measures to what extent media are diverse and critical on governmental issues. It is a continuous composite variable with a range 0.00–0.83, based on five indicators: (1) How often media are critical of the government, (2) how wide the range of media perspectives is, (3) if there is media bias against government opposition, (4) whether media accepts bribes to alter news coverage, and (5) to what extent criticism of the government is common and normal in the mediated public sphere.	Tufis, 2019
Control of corruption	Control of corruption measures the perception of corruption by public power for private gain. It is an continuous index with a range -1.68–0.76, created by modelling 50 variables on corruption. It intends to capture the extent to which public power is exercised for private gain. This includes both petty and grand forms of corruption, and the 'capture' of state assets by elite and private interests.	Kaufmann et al., 2011
Human population density	Population density is defined as all residents of a given political unit divided by its area (i.e. individuals per km ² of terrestrial land of a country). Refugees who are not permanently settled are excluded. The variable is continuous and ranges 3.05–498.66.	World bank, 2020

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191 2.2 Statistical analyses

192 The statistical analysis aimed to assess (1) the directionality and shape of temporal trends in
193 deforestation, (2) the effect of presidential, lower chamber, and upper chamber elections on
194 deforestation, and (3) the effect of competitiveness of elections on deforestation trends.

195

196 First, we used a non-parametric Mann-Kendall test (Kendall, 1938; Mann, 1945) to test for
197 monotonic trends (i.e. directionality) of deforestation over time for each country. This test is more
198 robust to outliers, non-normality and temporally autocorrelated data than simple linear models and
199 is widely used in time-series analysis (Yue et al., 2002).

200

201 Second, we used Hierarchical Generalized Additive Models (HGAM) (Lin and Zhang, 1999; Pedersen
202 et al., 2019; Wood, 2017) to model non-linear trends in deforestation in relation to election type and
203 competitiveness of elections. The flexible nature of HGAMs allows for modelling smooth patterns
204 across space and over time, with the amount of smoothing controlled to prevent over-fitting (Wood
205 2017). The HGAM approach thus allows the modelling of non-linear functional relationships between
206 covariates and outcomes where the shape of the function itself varies between different grouping
207 levels. In our case, this grouping variable was the country level. This technique allowed us to
208 disaggregate the changes in forest loss in each country over time - which can be driven by various
209 factors - from the election covariates. Our models used a global smoother plus country-level
210 smoothers with differing wiggleness (Pedersen et al., 2019).

211

212 We used three separate HGAMs to model each election type independently: a presidential model, a
213 lower chamber model and an upper chamber model. The general mathematical formulation of the
214 HGAMs was:

215

$$\begin{aligned} g(\text{Deforestation}) &= \text{Election} + (\text{Election} \times \text{Competitive}) + f(\text{Pop density}) + f(\text{Media integrity}) \\ &+ f(\text{Corruption}) + f_{\text{Country}}(\text{Year}) + \zeta_{\text{Country}} + \epsilon \end{aligned}$$

216 Where $g(\text{Deforestation})$ is the response variable defined as proportional deforestation of a country
217 relative to the forest cover in the year 2000. The binary predictor variable Election is 1 when an
218 election is being held in a given year, and 0 if not. The Election term differs among HGAMs because
219 of the different election data (presidential, lower chamber or upper chamber). The binary predictor
220 variable Competitive is 1 if the election setting is competitive, and 0 if it is not, and modelled as an
221 interaction with the Election term (i.e. $\text{Election} \times \text{Competitive}$). The predictors $f(\text{Pop density}_i)$,
222 $f(\text{Media integrity}_i)$ and $f(\text{Corruption}_i)$ are all modelled smooths allowing for non-linear
223 relationships. All smooths used penalized thin plate regression splines (TPRS) (Wood, 2003). With
224 these splines, the null space is also penalized slightly, and the whole term can therefore be shrunk to
225 zero, effectively acting as a model fitting step (Wood, 2003). The additional advantage of the TPRS
226 approach is that knot positions were selected automatically from the data, eliminating knot
227 placement subjectivity. Random effects are described by ζ_{Country} , which accounts for country-level
228 mean differences of deforestation at the intercept as suggested by Pedersen et al. (2019). The term
229 $f_{\text{Country}}(\text{Year})$ is a separate univariate smooth for each country to account for intergroup
230 variability. We used a Gaussian process smooth to account for temporal autocorrelation (Wood,
231 2017). Finally, ϵ describes the error that is not explained by the other terms. HGAMs were modelled

232 using a beta regression logit link structure to account for the proportional nature of the response
233 variable which is bound between 0 and 1, and overcomes limitations in other more commonly used
234 distributions (Douma and Weedon, 2019). For each term the penalty controlling the degree of
235 smoothing was selected using restricted maximum likelihood (REML; Wood 2017, p. 185)

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237 The autocorrelation function of the residuals, concurvity and model residuals were visually inspected
238 for all models, and no issues were identified. The supplementary material provides the
239 autocorrelation function of the residuals (Figure B1), the concurvity (Figure C 1–3), and the model
240 residuals (Figure D1).

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242 **3. Results**

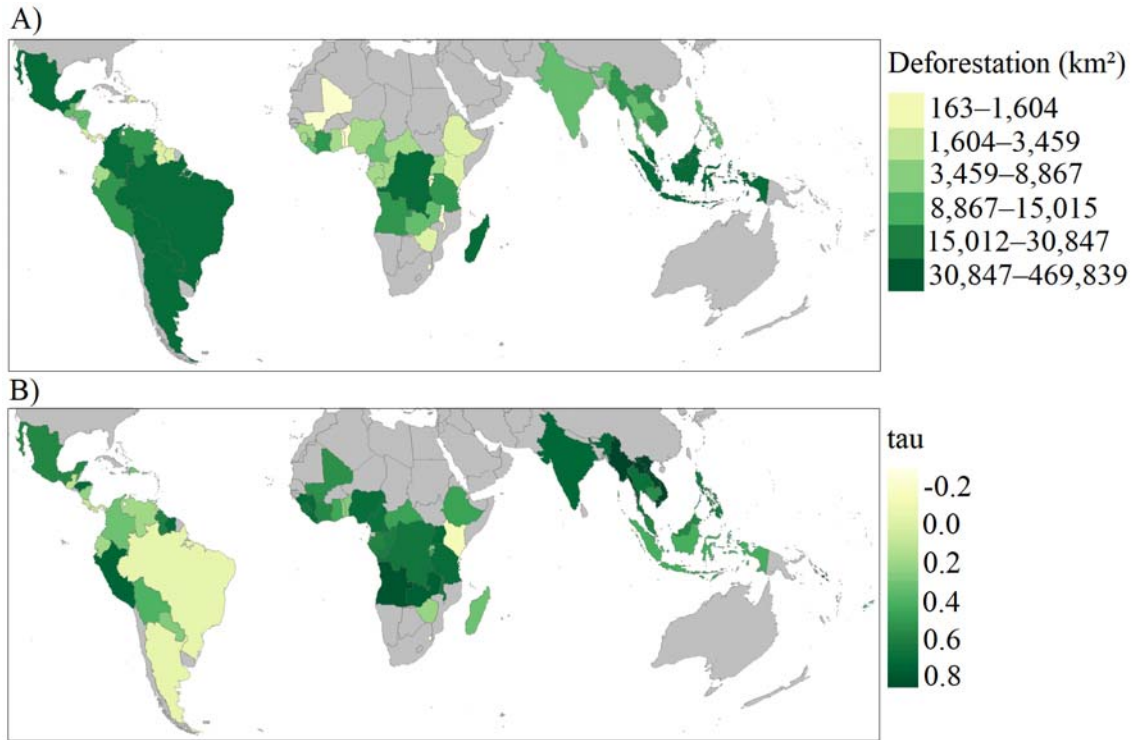
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244 *3.1 Global deforestation trends from 2001 to 2018*

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246 We found that 1.5 million km² of tropical forest – an area similar in size to Mongolia – was lost
247 between 2001 and 2018 in the 55 tropical countries analysed (Table 1A). The largest area of forest
248 loss occurred in Brazil (469.839 km²), followed by Indonesia (227.008 km²) and the Democratic
249 Republic of Congo (112.626 km²) (Figure 1A). On average, 0.52% of the world’s tropical forests were
250 lost each year from 2001 to 2018 (SD = 0.15%, range = 0.35%–0.91%, $n = 55$ countries). The overall
251 proportion of pantropical deforestation has increased during this time by 182%, with 37 out of the 55
252 assessed countries (67%) showing statistically significant increases (demonstrated by Mann Kendall
253 tests showing statistically significant positive tau values at $p < 0.05$) (Figure 1B). Only four countries
254 decreased in their annual rate of deforestation (indicated by negative tau values of the Mann Kendall
255 tests), but these were statistically not significant (at $p > 0.05$).

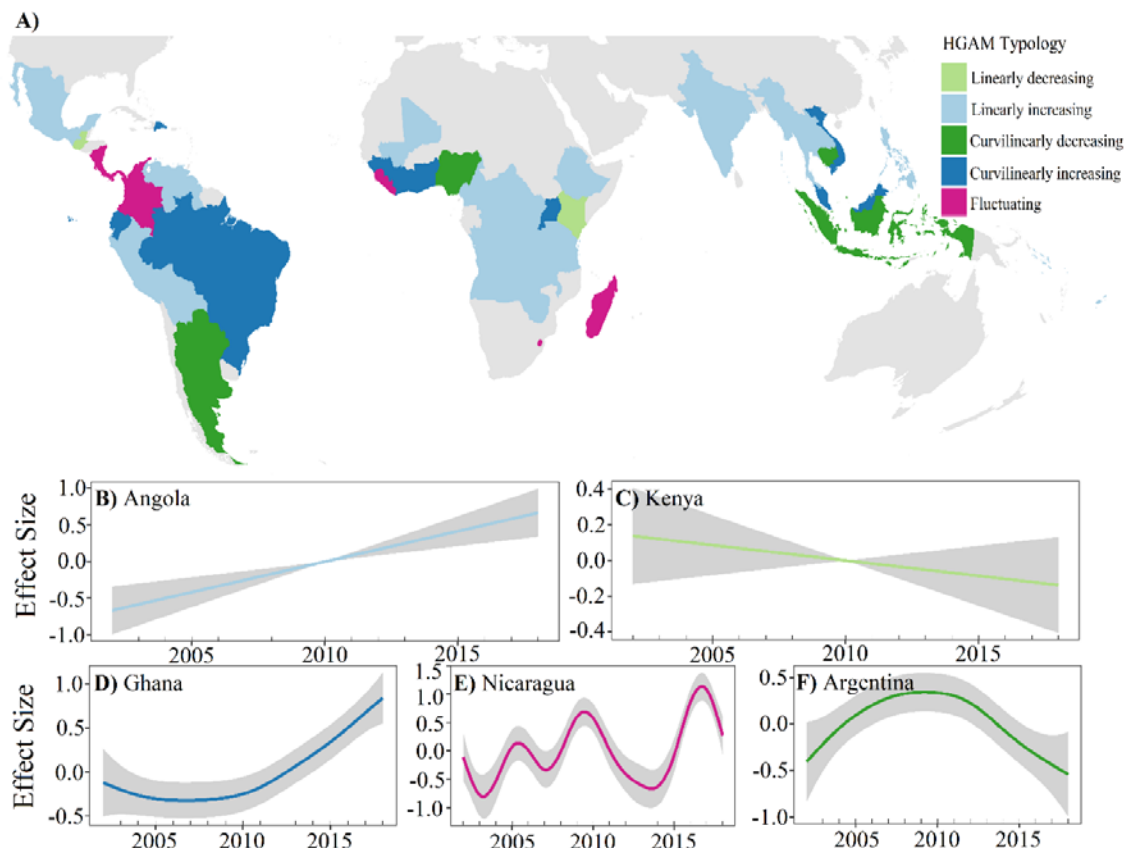
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258 **Figure 1. Deforestation in 55 tropical countries between 2001–2018.** A) Total amount of deforestation (in km²)
259 at a national scale from 2001–2018. B) Directionality and strength of national deforestation trends quantified
260 as correlation coefficients (Tau values) from Mann Kendall tests. A total of 51 countries show an increase in the
261 annual rate of deforestation (light green-green: positive Tau values) whereas four countries show a decrease
262 (light yellow: negative Tau values). Annual forest loss data for each country were derived from high resolution
263 (30 × 30 metre) global maps of forest cover and forest loss (Hansen et al., 2013).
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265 The shapes of deforestation trends derived from the HGAMs varied considerably among
266 countries ($n = 51$) (Figure 2A). In general, they followed five main typologies (Figure 2B–F): linearly
267 increasing, linearly decreasing, curvilinearly increasing, curvilinearly decreasing and fluctuating. We
268 visually inspected these deforestation trends for each country and found that the rate of
269 deforestation increased in 36 (71%) of the analysed countries ($n = 51$). Of those, 24 countries showed
270 a linearly increasing deforestation trend (Figure 2B) and 12 countries an increasing curvilinear trend
271 (Figure 2D). Two countries showed a linearly decreasing trend (Figure 2C) and five countries
272 curvilinearly decreasing trend (Figure 2E). A total of 8 countries were classified as having fluctuating
273 deforestation trends (Figure 2F).
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277 **Figure 2. National deforestation trends between 2001–2018 across the tropics.** A) Pantropical overview of
278 main typologies of deforestation trends (linearly increasing, linearly decreasing, curvilinearly increasing,
279 curvilinearly decreasing and fluctuating) as derived from Hierarchical Generalized Additive Models (HGAMs).
280 Examples of trend typologies: B) linearly increasing (Angola), C) linearly decreasing (Kenya), D) curvilinearly
281 increasing (Ghana), E) fluctuating (Nicaragua), and F) curvilinearly decreasing (Argentina).

282 3.2 Election types and deforestation

283 All three HGAMs had high explanatory power ($R^2 > 0.87$, explained deviance $> 90\%$, see Table 2) and
284 show that tropical deforestation is lower in years when there is a presidential or lower chamber
285 election, compared to years with no election (Figure 3A, B). This is demonstrated by the negative and
286 statistically significant logit estimate for in the two HGAMs for presidential and lower
287 chamber elections (Table 2). The logit estimate for the upper chamber HGAM also showed a negative
288 sign but was statistically not significant (Table 2, Figure 3C).

289

290 *3.3 Effect of competitiveness on deforestation*

291 Deforestation was significantly higher in competitive presidential and lower chamber election years,
292 compared to non-competitive election years (Figure 4A, B). This is demonstrated in the positive and
293 statistically significant interaction term *Election* × *Competitive* in the presidential and lower
294 chamber HGAMs (Table 2). The upper chamber HGAM showed a negative interaction term
295 *Election* × *Competitive* but this was not statistically significant (Table 2, Figure 4C). None of the
296 other predictors (human population density, media integrity, and control of corruption) showed a
297 statistically significant effect on deforestation trends (Table 2).

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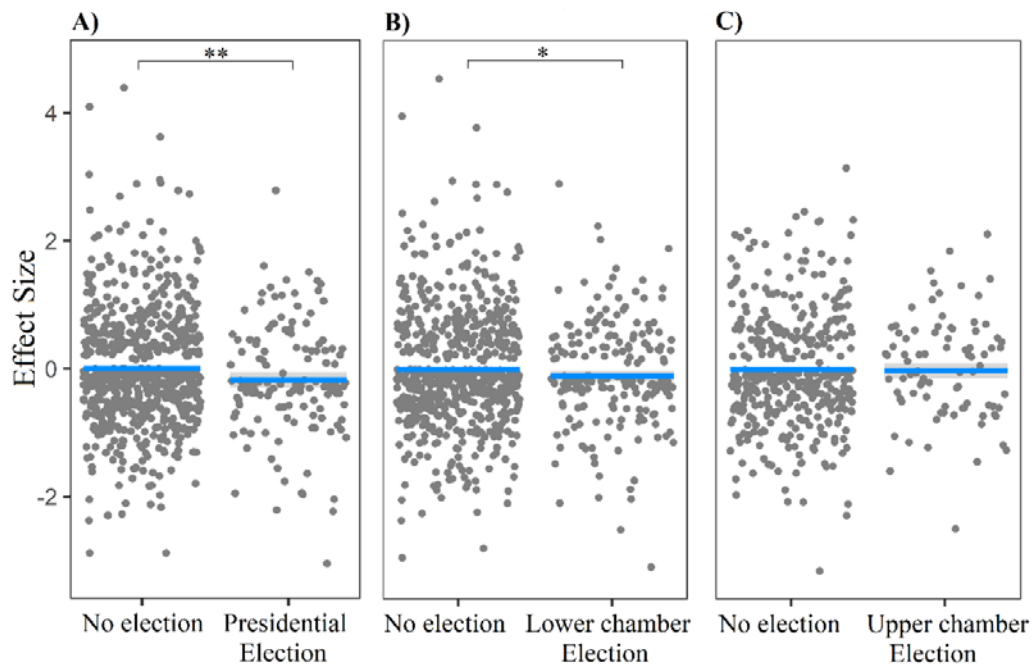
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321 **Table 2. Results of Hierarchical Generalized Additive Models (HGAMs) with a logit-link to explain the proportional deforestation of a country relative to the forest cover**
 322 **in the year 2000 (response variable). Three different HGAMs were implemented depending on the specific election type (presidential, lower chamber, or upper chamber**
 323 **election).** Binary predictor variables are shown with parametric coefficients (logit estimates) whereas continuous variables are represented with smooth terms. For details
 324 of predictor variables see Table 1. Country-level estimates ($n = 51$ countries) were excluded from this table. Statistically significant p -values ($p < 0.05$) are indicated in bold.

Predictor	Presidential model				Lower chamber model				Upper chamber model			
	<i>Estimate</i>	<i>Std. error</i>	<i>Z-value</i>	<i>p</i>	<i>Estimate</i>	<i>Std. error</i>	<i>Z-value</i>	<i>p</i>	<i>Estimate</i>	<i>Std. error</i>	<i>Z-value</i>	<i>p</i>
<i>Intercept</i>	-5.47	0.10	-57.10	<0.001	-5.47	0.10	-56.90	<0.001	-5.52	0.14	-40.34	<0.001
Parametric coefficients												
<i>Election</i>	-0.19	0.06	-3.07	0.002	-0.10	0.04	-2.33	0.02	-0.02	0.06	-0.35	0.73
<i>Election × Competitive</i>	0.16	0.07	2.30	0.02	0.13	0.06	2.26	0.02	-0.01	0.07	0.09	0.93
Smooth term		<i>edf</i>	<i>Chi²</i>	<i>p</i>		<i>edf</i>	<i>Chi²</i>	<i>p</i>		<i>edf</i>	<i>Chi²</i>	<i>p</i>
<i>f (Population density)</i>		<0.001	<0.001	0.79		<0.001	<0.001	0.82		<0.001	<0.001	0.36
<i>f (Media integrity)</i>		<0.001	<0.001	0.41		<0.001	<0.001	0.37		4.70	454.09	0.39
<i>f (Control of corruption)</i>		<0.001	<0.001	0.70		<0.001	<0.001	0.67		<0.001	<0.001	0.70
Adjusted R ²	0.87				0.87				0.91			
Explained deviance	90.2%				90.1%				93.2%			

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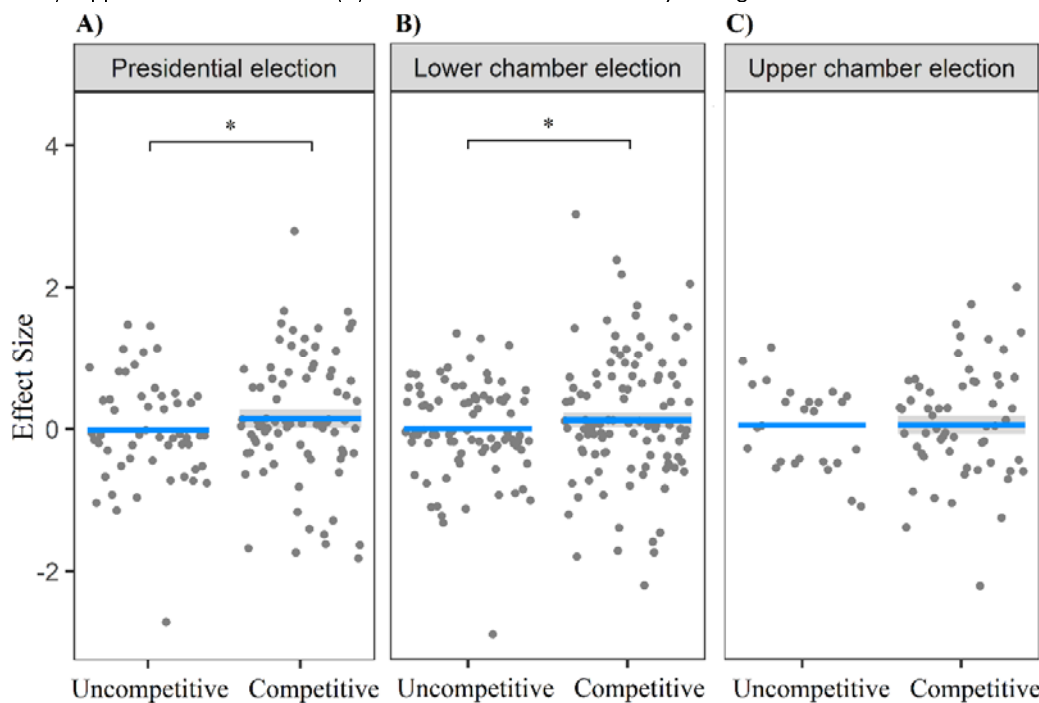
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Figure 3. The effect of elections on deforestation. Each point represents the amount of logit-transformed deforestation in a given year and country. The presidential election and lower chamber election (A and B) show statistically significant lower deforestation compared to non-election years (compare results for term in Table 2). Upper chamber elections (C) show a similar but statistically not significant trend.



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Figure 4. The effect of competitive elections on deforestation. Each point represents the amount of logit-transformed deforestation in an election year by country. Competitive presidential and lower chamber elections (A, B) show statistically significant higher deforestation compared to uncompetitive elections (compare results for interaction term in Table 2). Upper chamber elections (C) show an opposite but statistically not significant trend.

341 **4. Discussion**

342 We analysed the effect of elections on deforestation in 55 tropical countries over an 18-year time
343 period and found that competitive elections are potential drivers of pantropical deforestation,
344 whereas a general effect of election years on deforestation was not confirmed. We focused on
345 tropical forests because they are predominantly lost due to agriculture and commodities exploitation
346 rather than changes caused by forestry management and wildfires, as for instance in boreal and taiga
347 forests (Curtis et al., 2018). Our results document a massive tropical forest loss from 2000 to 2018,
348 with the rate of deforestation increasing in more than two-thirds of the studied countries. To our
349 knowledge, this represents the most comprehensive and most up-to-date study of its kind covering a
350 pantropical extent.

351 Our results confirm the well-known trend that deforestation rates are increasing across the
352 tropics (Curtis et al., 2018). This is alarming since deforestation is accelerating while the remaining
353 forest area is becoming smaller. While the majority of studied countries (70.5%, HGAM) show linearly
354 or curvilinearly increasing deforestation trends, there are a few countries in which deforestation is
355 decreasing (13.7%) or fluctuating with sporadic increases and decreases (15.6%). The decreases
356 observed in our results seem to coincide with the implementation of forest protection policies or
357 actions. For example, in 2004, The Brazilian Government founded the country's environmental
358 enforcement agency (IBAMA) which led to a 37% reduction in deforestation between 2005 and 2007,
359 by using in field enforcement using real time deforestation detection (Arima et al., 2014; Soares-Filho
360 et al., 2010). Similarly, conservation in the Colombian Guyana Shield reduced deforestation in
361 protected area's compared to their buffer zone, with only 1% of the natural forest in protected areas
362 lost, while the buffer zones lost between 5–7% between 1985 and 2002. In particular, the reduced
363 deforestation in protected areas was linked with lower infrastructure, accessibility and reduction in
364 illicit agriculture (Armenteras et al., 2009). These examples are encouraging since they show that
365 policy tools and conservation intervention can effectively limit deforestation and that governments
366 have the means to take the necessary steps to halt ongoing deforestation (Busch et al., 2015; Rudorff
367 et al., 2011; Umemiya et al., 2010; Wehkamp et al., 2018).

368 In contrast to our expectation, we found that deforestation was significantly lower in
369 election years than in non-election years. This is, for instance, opposite to a study at the national
370 scale of Brazil where municipal-level deforestation increased by 8–10% in years with a municipal
371 election (Pailler 2018). In general, election theory suggests that politicians should utilise all avenues
372 possible to win support and favour in the lead up to an election, which includes giving away or
373 promising forested land for development, or turning a blind eye to forest exploitation (Abessa et al.,

374 2019; Akhmedov and Zhuravskaya, 2003; Burgess et al., 2012; Shi and Svensson, 2006). We suggest
375 that there are several plausible explanations why our analysis did not show such an expected effect.

376 First, forested land might be exploited before an election, causing an increase in
377 deforestation above baseline levels. This exploitation may then stop shortly after an election, and
378 result in a decrease of deforestation. This has been observed in some countries, for example in
379 Russia, where election cycles in social expenditure from local governments generally drop one month
380 after the election (Akhmedov and Zhuravskaya, 2003). This makes it difficult to detect a signal of
381 elections on deforestation rates when analysing deforestation in yearly intervals since the pre-and
382 post-election increase and decrease could cancel each other out. The global forest loss data that we
383 used is currently only available in yearly intervals (Hansen et al., 2013) and thus does not account for
384 short term pre/post-election changes in deforestation rates (e.g. within years). More detailed data
385 (e.g. capturing intra-annual variation in deforestation rates during election periods) could benefit
386 future studies of forest loss at national and global scales.

387 A second plausible reason for not detecting an increase of deforestation with presidential,
388 lower and upper chamber elections is that forest governance and natural resource management is
389 increasingly becoming decentralised within countries (Ginsburg and Keene, 2020). In principle,
390 decentralisation should make it more difficult for national level politicians to exploit locally managed
391 resources (Busch and Amarjargal, 2020). It is difficult to account for this decentralisation in global
392 analyses because appropriate data to quantify the degree of local or municipal autonomy in forest
393 management are lacking. Additionally, election data on the subnational administrative units that
394 manage the forests are often missing. Hence, it is possible that local governments protect their
395 forests from exploitation by higher level politicians during national election years. An alternative way
396 to study this could be to investigate the effect of elections on deforestation at the spatial scale at
397 which forest management decision are made. For instance, if forests are managed at the state or
398 county level, the effects of state or county-level elections on deforestation could be analysed. To our
399 knowledge, there are currently no global databases available that specify the level and spatial scale
400 of forest governance.

401 Besides the general effect of presidential, lower and upper chamber elections on
402 deforestation, our analysis revealed that deforestation is significantly higher in competitive election
403 years compared to non-competitive election years. This supports our expectation that more
404 competitive elections will increase incentives for politicians to misuse public goods for winning
405 favour (Sanford, 2019; Shi and Svensson, 2006). To improve forest protection, we recommend that
406 integrity and transparency monitoring schemes for elections such as the Global Network of Domestic

407 Election Monitors (GNDEM) extend their mandate to include monitoring natural resources such as
408 forests (Pereira et al., 2009; Shi and Svensson, 2006). Conservation groups should also remain vigilant
409 during the lead up to elections, especially given land gifting practices for forest exploitation during
410 the elections of Uganda in 2011 (Médard and Golaz, 2013).

411 **5. Conclusions**

412 Protecting biodiversity in tropical forests and their ecosystem services is crucial for meeting
413 international policy targets such as the United Nations Sustainable Development Goals (SDGs) and
414 the post-2020 targets of the Convention on Biological Diversity (CBD). Our analysis shows that
415 tropical forests continue to decline and that elections can at least partly play a role in driving
416 deforestation trends. However, more detailed data on intra-annual variation of deforestation and the
417 spatial scale of forest governance are needed to improve our global (pan-tropical and cross-national)
418 understanding of how elections influence forest loss driven. We urge electoral management bodies
419 and conservation groups to be vigilant during competitive elections, because forests and other
420 natural resources could be traded for votes. Further elucidating the role of elections on deforestation
421 should be a focus of forest conservation efforts.

422

423 **6. Data accessibility**

424 Data and code used for this study have been made permanently and publicly available on the
425 Mendeley Data repository at <http://dx.doi.org/10.17632/5ngc9n3shd.1>.

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432 **7. Literature**

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