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The role of elections as drivers of tropical deforestation

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ABSTRACT

Tropical forests support immense biodiversity and provide essential ecosystem services for billions of people. Despite this value, tropical deforestation continues at a high rate. Emerging evidence suggests that elections can play an important role in shaping deforestation, for instance by incentivising politicians to allow increased utilisation of forests in return for political support. Nevertheless, the role of elections as driver of deforestation has not yet been comprehensively tested at broad geographic scales. Here, we created an annual database from 2001 to 2018 on political elections and forest loss for 55 tropical nations and modelled the effect of elections on deforestation. In total, 1.5 million km^2 of forest was lost during this time period, especially in the Amazon, the Congo Basin and in Southeast Asia. The annual rate of deforestation increased in 37 (67 %) of the analysed countries. Deforestation was significantly lower in years with uncompetitive lower chamber elections compared to competitive election years (i.e. when the opposition can participate in elections and has a legitimate chance to gain governmental power). Our results show a pervasive loss of tropical forests and suggest that competitive elections can be potential drivers of deforestation. Future analyses at higher resolution (intra-annual deforestation and sub-national governance) and simultaneous collection of data on additional mechanisms (legislative changes, financial investments, and binding term limits) will likely provide additional insights into the impacts of elections. We therefore recommend that organisations monitoring election transparency and fairness should also monitor environmental impacts such as forest loss, habitat destruction and resource exploitation.

1. Introduction

Tropical forests are among the most biodiverse places on Earth and are the last refuges for many imperilled species (Gaston, 2000; Gibson et al., 2011). Tropical forests also provide globally important ecosystem services such as carbon sequestration and clean water provisioning (Foley et al., 2007). As many as 1.6 billion rural people live in close proximity to forests and may depend on forest resources for their livelihoods (Angelsen et al., 2014; Joshi and Joshi, 2019; Rudow et al., 2013). It is therefore concerning that tropical deforestation has reached critically high levels in the last few decades, with as much as 79,000 km^2 (an area similar in size to Austria) being cleared annually (Austin et al., 2017). Understanding what drives tropical deforestation is thus crucial for implementing policy and conservation actions to ensure forest preservation.

The most prevalent direct causes of tropical deforestation include commercial logging (Curtis et al., 2018; Hosonuma et al., 2012), subsistence logging (e.g. for firewood; Heltberg et al., 2000; Hosonuma et al., 2012), conversion of forests to agricultural lands (e.g. for oil palm plantations or cropping; Hosonuma et al., 2012; Koh and Wilcove, 2008; Laurance et al., 2014), and fires (Laurance et al., 2002). Deforestation can also be influenced by seasonality which may be lower in wet seasons, as saturated soils make logging more difficult, and higher in the dry season when flammability increases (Nolan et al., 2016; Putz et al.,

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2000). There is good evidence that deforestation increases when certain enabling factors are at play. For example corruption, where politicians privatize gains through trading away public goods (e.g. land, forest, or policies), has been associated with higher rates of deforestation (Burgess et al., 2012; Smith et al., 2003; Wright et al., 2007). Gross Domestic Product (GDP) of a country may also play a role, with higher deforestation rates in countries with lower GDP. Deforestation is likely rooted to economic development of low GDP countries, whereas the economies of high GDP countries are less likely to depend on logging (Ewers, 2006). Deforestation also tends to be higher in countries with higher human population densities (Sandker et al., 2017). Interestingly, free media is also associated with less deforestation, perhaps countering the effects of corruption by instilling fear of a public scandal for politicians privatizing public goods (Bertot et al., 2010; Kolstad and Wiig, 2009). Other social factors that potentially influence deforestation (e.g. armed conflicts, illegal crop production, or political elections and election cycles) have been less studied, even though there is growing evidence that they could drive deforestation trends in the tropics (Dávalos et al., 2016; Landholm et al., 2019; Negret et al., 2019).

Recent evidence suggests that elections could be key drivers of deforestation (List and Sturm, 2006; Pailler, 2018; Rodrigues-Filho et al., 2015). For example, a study in the Brazilian Amazon found that municipal level deforestation was 8–10 % higher in years when there was a municipal election (Pailler, 2018; Ruggiero et al., 2021). Moreover, a similar increase in deforestation was also found during the national elections in the Atlantic forest biome (Rodrigues-Filho et al., 2015). During gubernatorial elections in the United States of America, governors are also more likely to advance or retract environmental policy based on the preference of their voters. More specifically, in "green" states environmental policy is more likely to advance during the election period, whereas in "brown" states it is more likely to retract (List and Sturm, 2006). Here, the electorate is encouraged to change its voting behaviour during election periods by candidates that propose popular environmental policy (Ruggiero et al., 2021). A recent study investigating the economic and political incentives of deforestation in Indonesia found that deforestation substantially increases before a mayoral election, suggesting that political incentives can reinforce tropical deforestation (Cisneros et al., 2021). This supports the fact that elections can influence deforestation, but generalizations are difficult to make because global studies are mostly lacking and the quality and resolution of deforestation data is often limited.

Elections are power struggles where politicians aim to gain an advantage over opponents. These advantages can be achieved through advancing popular policies and by creating economic opportunities (Akhmedov and Zhuravskaya, 2003; Drazen and Eslava, 2010; Nordhaus, 1975). Politicians might gift or promise forested land for exploitation in order to win favour with powerful potential supporters, or with agricultural or logging businesses. An example of this occurred in Uganda in 2011, where the incumbent government promised forests to win community support (Médard and Golaz, 2013). A similar example is the 2018 Brazilian presidential elections which caused a spike in deforestation due to candidates promising the dismantling of environmental laws (Abessa et al., 2019). During political elections, governments may divert their attention from environmental protection, turning a blind-eye to people utilising forest resources, and allowing them to harvest unsustainably or to settle on protected forested land (Armenteras et al., 2019; Clerici et al., 2020; Negret et al., 2017). Most countries have strong laws against winning political favour through financial means. However, environmental protection laws are usually less rigorously monitored or upheld than financial laws, making winning support by giving away land and forest resources an attractive alternative to money (Ohman, 2013). There are many mechanisms for elections to drive deforestation, but the effect of elections on deforestation remains under-investigated, especially at broad geographic extents.

Here, we analyse the effect of elections as drivers of deforestation at a pantropical scale. We focus on the tropics because the mechanisms and drivers of deforestation are fairly distinct from those of higher latitude forests in the temperate, boreal and taiga zone (Curtis et al., 2018). To assess the drivers of tropical deforestation, we first quantified deforestation (forest loss) within 55 pantropical countries using the annual, remotely-sensed, high-resolution (30 × 30 m) Hansen et al. (2013) global forest product from 2001 to 2018. We then explored the directionality and shape of temporal trends in deforestation per country and created an annual database over this time period covering the year in which national elections took place and which type of election it was (presidential, lower chamber, and upper chamber elections). Additionally, we extracted information on governance (e.g. competitiveness, media integrity, corruption control), seasonality, agricultural contribution to GDP and human population density. Hierarchical Generalized Additive Models (HGAM; Pedersen et al., 2019) were used to assess the effect of elections and the governance variables on the proportional deforestation of countries relative to their forest cover in the year 2000. This HGAM approach allowed us to model non-linear relationships between covariates and proportional deforestation where the shape of the function can vary between countries. This method disaggregated the changes in forest loss in each country over time — which can be driven by various factors — from the election covariates. Specifically, our analyses (1) quantified the effect of presidential, lower chamber, and upper chamber elections on tropical deforestation rates compared to non-election years, and (2) tested whether the competitiveness of an election has an effect on deforestation.

2. Methods

2.1. Data collection

We developed a database (years 2001–2018) for 55 tropical-forest countries (Table A1; Fig. A1) covering national and state-level deforestation, election dates, governance variables, human population density, seasonality, and agricultural contribution to GDP. The governance variables included competitiveness of elections, media integrity of a country, and control of corruption (Table 1), all measured per country and annually. Human population density captured the number of residents per country area and year. Seasonality expressed whether an election was in the wet or dry season, in the majority of a country. Agricultural GDP measured the contribution of agriculture, forestry and fishing to the GDP in a percentage (Table 1).

To quantify deforestation, we extracted annual forest loss data for each country for the years 2001–2018 from the Global Forest Change data, which provides high resolution (30 × 30 m) global maps of forest cover and forest loss (Hansen et al., 2013). Data were extracted and processed in the Google Earth Engine (https://earthengine.google.com), a cloud platform for earth-observation data analysis (Gorelick et al., 2017). We adapted code from Tracewski et al. (2016) to quantify forest loss per year and country, and make our code available in the supplementary material (Table B2). The Global Forest Change data is based on a time-series analysis of Landsat images and defines forest as >50 % crown cover of trees taller than 5 m height. The presence of forest is given for each 30 × 30 m pixel using the year 2000 as a baseline. Forest loss is defined as the disappearance of a forest pixel within a given year (1 = loss, 0 = no loss). A given forest pixel can only be lost once (in years 2001–2018). We used the available data on forest cover (year 2000) and forest loss (years 2001–2018) to calculate the proportional loss (i.e. deforestation) over a given year within national boundaries relative to the forest cover in the year 2000. We accounted for the dynamic changes in national borders through using multiple maps (see methodological example in Fig. A1). We did not include 'gain' in forest area because it was only available until 2013 (Hansen et al., 2013), and because in many cases it is due to plantation forests rather than natural regrowth or restoration (Tropek et al., 2014). The Global Forest Change data is considered the most accurate and consistent global deforestation data currently available. However, we acknowledge limitations such as the

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

Variable	Definition and methods	Reference & source
Elections	Elections is a trinary variable being either a 0) no election year, 1) uncompetitive election year, or 2) competitive election year, where competitiveness is quantified whether elections are sufficiently free for the opposition to gain legislative or executive power. 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 an annual 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 annual, continuous index with a range of -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 in 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, calculated at an annual time scale and ranging from 3.05 to 498.66.	World bank, 2020
Seasonality	Seasonality is a binary variable that quantifies whether elections take place in the wet or dry season. Based on a global gridded dataset of rainy and dry seasons, this variable quantifies the mean onset and demise of the wet season by country (Bombardi et al., 2019). Wet and dry seasons were matched against the REIGN database that contains global monthly election data to check if an election was held in a wet or dry season (Bell et al., 2021).	Bombardi et al., 2019 Bell et al., 2021
Agriculture GDP %	Agriculture GDP % measures the contribution of agriculture to the GDP of a country on an annual scale. This variable includes agriculture, forestry, and fishing. It is a continuous index with a range 2.24–79.04.	World bank, 2020

inability to differentiate between forest and agro-forests, which have been discussed elsewhere (Tropek et al., 2014; Allan et al., 2017).

We gathered data on national level elections dates by examining each country's constitution, and cross-checking this with a number of election databases (see Table B2). We collected information on three types of national elections: (i) *Lower chamber elections* ($n = 199$), where the lower chamber holds the legislative power allowing them to create laws; (ii) *Upper chamber elections* ($n = 86$), where the upper chamber reviews the legislative power; and (iii) *Head-of-state or head-of-government elections* ($n = 141$), hereafter called '*presidential elections*', depending on who holds the executive power to enforce the law and is elected by vote. All analysed countries had a lower chamber and presidential elections. However, many countries did not have upper chamber elections (25 out of 55 countries, i.e. 45 %). Presidential and upper chamber election dates often occur in the same year as lower chamber elections (52 % and 38 % of the time, respectively). We extracted binary data from the Global State of Democracy database for each election year being described as either competitive (= 1) when they are sufficiently free for the opposition to gain legislative or executive power with enough votes, and otherwise as non-competitive (= 0) (see 'Elections' in Table 1). Note that this variable does not capture whether parties have equal funding, media coverage or whether civil liberties are respected. Hence, competitive elections are not equal to free and fair elections (Skaaning et al., 2015). Data on election year and competitiveness were combined to create a new trinary predictor indicating whether there was an election and if this election was competitive or not (0 = no election, 1 = uncompetitive election, 2 = competitive election). A number of countries only had either competitive ($n = 17$) or uncompetitive elections ($n = 15$), while most countries changed between them at least once ($n = 18$). Finally, a lead period was introduced to capture the potential pre-election effects. We modified the 6-month lag method as described in Simmons et al. (2018) to a 3-month period, as previous research suggests that notable election cycle effects are usually between 1 and 3 months (Akhmedov and Zhuravskaya, 2003; Cahan, 2019). This meant that elections in January or February were counted towards the previous year, as most deforestation would have occurred in the previous year.

As co-variates we extracted governance information, human population density, seasonality and agricultural contribution to GDP from various sources (for details see Table 1). We further used an index from the World Bank which captures the control of corruption (temporally varying per country and year), which has been linked to both tropical deforestation and enhancing election cycles (Kaufmann et al., 2011; Pereira et al., 2009; Smith et al., 2003). We also extracted an annually varying variable per country which quantifies to what extent media are diverse and critical ('Media integrity' in Table 1), as this has been shown to counter the effects of election cycles (Akhmedov and Zhuravskaya, 2003; Tufis, 2019). Finally, we also accounted for human population density (annually varying), since higher densities at a national level tend to increase deforestation (World bank, 2020). All predictor variables included in the analysis were dynamically incorporated at a national and annual scale. Five countries lacked data on 'Competitive elections', leading to their exclusion in the Hierarchical Generalized Additive Modelling (Belize, Gabon, Honduras, Suriname, Swaziland; Table A1).

2.2. Statistical analyses

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

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

Second, we used Hierarchical Generalized Additive Models (HGAM)

(Lin and Zhang, 1999; Pedersen et al., 2019; Wood, 2017) to model non-linear trends in deforestation in relation to election type and competitiveness of elections. The flexible nature of HGAMs allows for modelling smooth patterns across space and time, with the amount of smoothing controlled to prevent over-fitting (Wood, 2017). The HGAM approach thus allows the modelling of non-linear functional relationships between covariates and outcomes where the shape of the function itself varies between different grouping levels (e.g. countries). Using country as a grouping variable, this technique allowed us to disaggregate the changes in forest loss in each country over time —which can be driven by various factors — from the election covariates. Our models used a global smoother plus country-level smoothers allowing for differing wiggliness by country (Pedersen et al., 2019).

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

$$g(Deforestation) = Election + f(Pop\,density) + f(Media\,integrity) + f(Corruption) + f\,(Seasonality) + f(Agriculture\,GDP\%) + f_{Country}(Year) + \zeta_{Country} + \in$$

where g(*Deforestation*) is the response variable defined as proportional deforestation of a country relative to the forest cover in the year 2000. The trinary predictor variable *Election* is 1 when an uncompetitive election is being held in a given year, 2 when a competitive election is being held in a given year, and 0 if there is no election in a given year. The *Election* term differs among HGAMs because of the different election data (presidential, lower chamber or upper chamber). The predictors $f(Pop\ density_i)$, $f(Media\ integrity_i)$, $f(Corruption_i)$ *and* $f(Agriculture\ GDP$ %) are all modelled smooths using thin plate regression splines (TPRS) allowing for non-linear relationships (Wood, 2003). With these splines and smooths, the null space is also penalized slightly, and the whole term can therefore be shrunk to zero, effectively acting as a model fitting step (Wood, 2003). During the model fitting, knots are used to act as points where a linear regression is smoothed around. Effectively, this means that zero knots equal to a linear regression, and placing many knots equals to a fluctuating smooth. The advantage of the TPRS approach is that knot amount and place is selected through the data instead of the researcher, eliminating knot placement subjectivity. The binary predictor f (*Seasonality*) is modelled using factor smoothing. Random effects are described by the term $\zeta_{Country}$, which accounts for static country-level mean differences of deforestation at the intercept as suggested by Pedersen et al. (2019). The term $f_{Country}(Year)$ is a separate univariate smooth for each country to account for variability between countries over time. We used a Gaussian process smooth to account for temporal autocorrelation (Wood, 2017). Finally, $\in$ describes the error that is not explained by the other terms. HGAMs were modelled using a beta regression logit link structure to account for the proportional nature of the response variable which is bound between 0 and 1, and overcomes limitations in other more commonly used distributions (Douma and Weedon, 2019). For each term the penalty controlling the degree of smoothing was selected using restricted maximum likelihood (REML; Wood, 2017, p. 185).

Finally, HGAM analysis only tests for mean differences between the reference level (no election) and other levels (competitive elections, uncompetitive elections). Therefore, we did a post-hoc comparison with a single-step correction for each election model (Bretz et al., 2016). This allowed us to test for a difference in means of deforestation between competitive elections and uncompetitive elections.

The autocorrelation function of the residuals, concurvity and model residuals were visually inspected for all models, and no issues of concurvity (i.e. non-linear variant of multicolinearity) or model fit were identified. The supplementary material provides the autocorrelation function of the residuals (Fig. B1), the concurvity (Fig. C1–3), and the model residuals (Fig. D1).

3. Results

3.1. Global deforestation trends from 2001 to 2018

We found that 1.5 million km^2 of tropical forest – an area similar in size to Mongolia – was lost between 2001 and 2018 in the 55 tropical countries analysed (Table 1A). The largest area of forest loss occurred in Brazil (469.839 km^2), followed by Indonesia (227.008 km^2) and the Democratic Republic of Congo (112.626 km^2) (Fig. 1A). On average, 0.52 % of the world's tropical forests was lost each year from 2001 to 2018 (SD = 0.15 %, range = 0.35 %–0.91 %, n = 55 countries). The overall proportion of pantropical deforestation has increased during this time by 182 %, with 37 out of the 55 assessed countries (67 %) showing statistically significant increases (demonstrated by Mann Kendall tests statistically significant positive tau values at $p < 0.05$) (Fig. 1B). Four countries showed a statistically insignificant decrease in their annual rate of deforestation (Argentina, Brazil, Kenya, Swaziland; indicated by negative tau values of the Mann Kendall tests at $p > 0.05$).

3.2. HGAM deforestation trends and typology

The shapes of deforestation trends over 2001–2018 derived from the HGAMs varied considerably among countries (n = 50) (Fig. 2A). In general, they followed five main typologies (Fig. 2B–F): linearly increasing, linearly decreasing, curvilinearly increasing, curvilinearly decreasing and fluctuating. We visually inspected these deforestation trends for each country and found that the shape of the trends supported a deforestation increase in 37 (74 %) of the analysed countries (n = 50). Of those, 24 countries showed a linearly increasing deforestation trend (Fig. 2B) and 13 countries an increasing curvilinear trend (Fig. 2D). Two countries showed a linearly decreasing trend (Fig. 2C) and five countries curvilinearly decreasing trend (Fig. 2E). A total of 6 countries were classified as having fluctuating deforestation trends (Fig. 2F).

3.3. Election types and deforestation

All three HGAMs had high explanatory power ($R^2 > 0.85$, explained deviance >89 %, see Table 2) and showed that tropical deforestation is lower in years when there is an uncompetitive presidential election, compared to years with no election (Fig. 3A). This is demonstrated by the negative and statistically significant logit estimate for *Election* in the presidential HGAM for uncompetitive presidential elections (Table 2). The logit estimate for the lower and the upper chamber HGAMs also showed a negative sign but was statistically not significant (Table 2, Fig. 3B, C).

3.4. Post-hoc comparison on the effect of election competitiveness on deforestation

Deforestation was significantly higher in competitive lower chamber election years compared to uncompetitive election years (Fig. 3B). This is demonstrated in the positive and statistically significant logit estimate in the post-hoc comparison from the lower chamber HGAM ($p = 0.01$, logit estimate = 0.16, SE = 0.06). The post-hoc comparison for the presidential and upper chamber HGAM showed a similar trend, but these were not statistically significant (Fig. 3A, C; $p = 0.06$, logit estimate = 0.16, SE = 0.07 and $p = 0.41$, logit estimate = 0.09, SE = 0.07, respectively).

4. Discussion

Our pantropical analysis of the effect of elections on deforestation in 55 tropical countries over an 18-year time period (2000–2018) shows a pervasive loss of tropical forest. Moreover, it suggests that

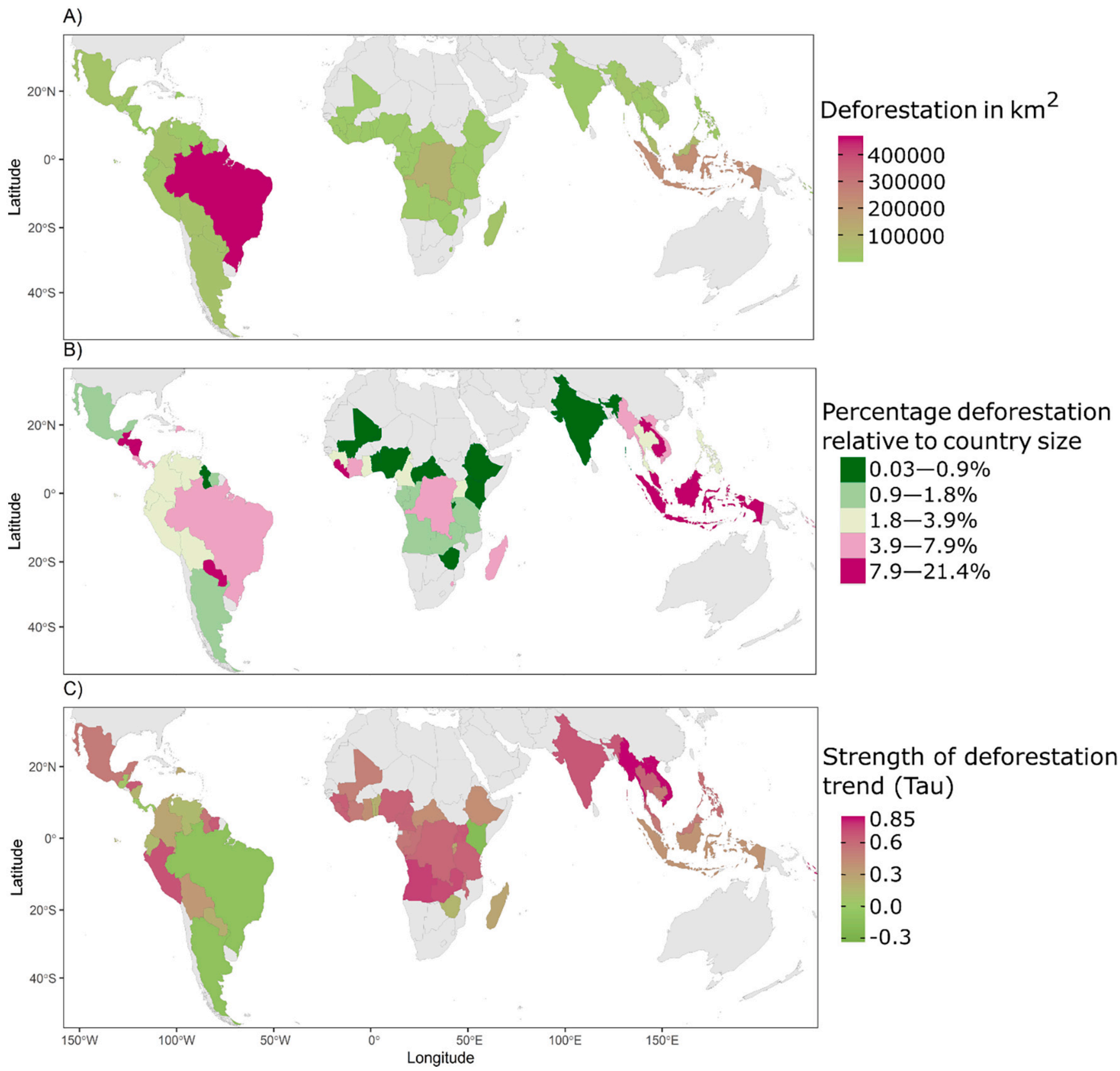

Fig. 1. Deforestation in 55 tropical countries between 2001 and 2018. A) Total amount of deforestation (in km^2) during 2001–2018. B) Accumulative percentage of deforestation between 2001 and 2018 at a national scale relative to country size. C) Directionality and strength of national deforestation trends (from 2001 to 2018) quantified as correlation coefficients (Tau values) from Mann Kendall tests. A total of 51 countries show an increase in the annual rate of deforestation (light green-dark pink: positive Tau values) whereas four countries show a decrease (light green - green: negative Tau values). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

uncompetitive presidential elections years have lower deforestation compared to non-election years, and that uncompetitive lower chamber elections years are associated with a lower deforestation than competitive lower chamber elections years. These results are in line with previous studies on election cycle competitiveness, suggesting that competitive elections can be potential drivers of deforestation.

Deforestation has been dramatic in the tropics over the last two decades (Curtis et al., 2018). Our results confirm that trend by showing that the rate of deforestation has been increasing in more than two-thirds of the studied countries., especially in the Amazon, the Congo Basin and in Southeast Asia. This loss is alarming since deforestation is accelerating while the remaining forest area is becoming smaller and fragmented. While the majority of studied countries (74 %, HGAM) showed a linearly or curvilinearly increasing deforestation trend, there were also a few countries in which deforestation was decreasing (14 %) or fluctuating with sporadic increases and decreases (12 %). These decreases seem to coincide with the implementation of forest protection policies or actions. For example, between 2004 and 2007, the Brazilian environmental enforcement agency (IBAMA), implemented the Action Plan to Prevent and Control Deforestation in the Amazon, which led to a 37 % reduction in deforestation between 2005 and 2007 (Arima et al., 2014; Soares-Filho et al., 2010). Similarly, protected areas and indigenous reservations in the Colombian Guyana Shield reduced deforestation compared to their buffer zones. This protection resulted in a 1 % loss of the natural forest, while the buffer zones suffered losses between 5 and 7 % between 1985 and 2002. Part of the reduced deforestation rates in protected areas may also be linked to a lack infrastructure limiting the accessibility (Armenteras et al., 2009). Indicative of the strength of policy, Australia largely stopped their deforestation through policy reform, only to be increasing after relaxing the regulations (Evans, 2016). These examples are encouraging since they show that effectively implemented policy tools and conservation interventions can limit deforestation, and that governments have means to take the necessary steps to halt ongoing deforestation (Busch et al., 2015; Rudorff et al., 2011; Umemiya et al., 2010; Wehkamp et al., 2018).

In contrast to our expectation, we found that deforestation did not increase during election years. In contrast, we found that deforestation was significantly lower in uncompetitive presidential election years than in non-election years. This result does not support the notion that forests are utilised as a resource during national level electioneering at the pan-

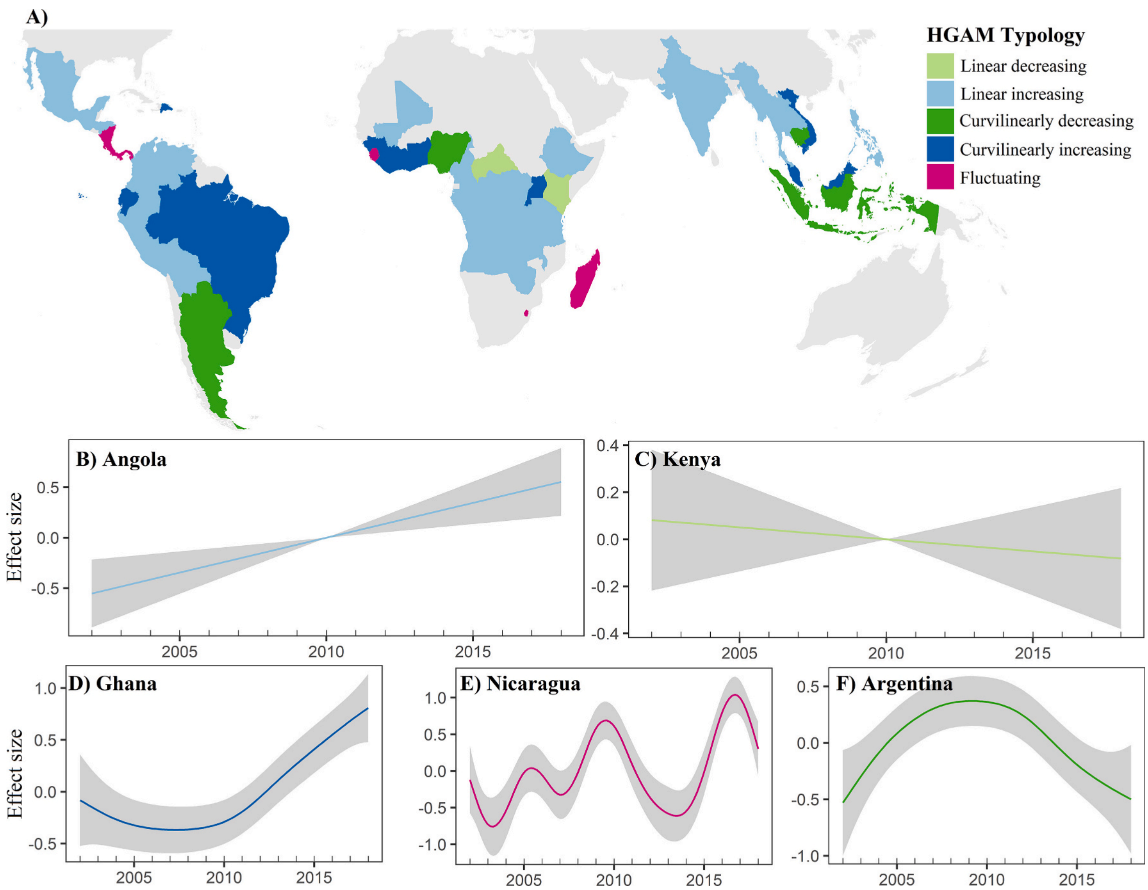

Fig. 2. Shapes of national deforestation trends between 2001 and 2018 across the tropics. A) Pantropical overview of main typologies of deforestation trends (linearly increasing, linearly decreasing, curvilinearly increasing, curvilinearly decreasing and fluctuating) as derived from Hierarchical Generalized Additive Models (HGAMs). Examples of trend typologies: B) linearly increasing (Angola), C) linearly decreasing (Kenya), D) curvilinearly increasing (Ghana), E) fluctuating (Nicaragua), and F) curvilinearly decreasing (Argentina).

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 in the year 2000 (response variable). Three different HGAMs were implemented depending on the specific election type (presidential, lower chamber, or upper chamber election). The election predictor variable is shown with parametric coefficients (logit estimates) whereas covariates are represented with smooth terms. For details of predictor variables see Table 1. Country-level estimates ($n = 50$ 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			
	Estimate	*Std. error*	*Z-value*	*p*	*Estimate*	*Std. error*	*Z-value*	*p*	*Estimate*	*Std. error*	*Z-value*	*p*
Intercept (No Election)	*−5.47*	*0.09*	*−63.39*	***<0.001***	*−5.47*	*0.11*	*−49.04*	***<0.001***	*−5.53*	*0.14*	*−39.65*	***<0.001***
Parametric coefficients												
Uncompetitive election	−0.18	0.06	−2.84	**0.004**	−0.12	0.10	−1.17	0.24	−0.10	0.10	−1.02	0.31
Competitive election	−0.01	0.04	−0.33	0.74	0.04	0.09	0.46	0.64	−0.008	0.08	−0.10	0.92
Smooth term		*edf*	*Chi^2*	*p*		*edf*	*Chi^2*	*p*		*edf*	*Chi^2*	*p*
f (Population density)		<0.001	2072.91	0.14		1.98	2423.07	0.11		<0.001	<0.001	0.45
f (Media integrity)		<0.001	0.001	0.29		0.33	32.59	0.18		5.03	602.35	0.20
f (Control of corruption)		<0.001	<0.001	0.49		<0.001	<0.001	0.49		<0.001	<0.001	0.554
f (Agriculture GDP %)		4.61	717.85	0.22		4.75	776.54	0.17		3.87	888.44	0.14
f (Seasonality)		<0.001	<0.001	0.34		0.78	8.86	**0.03**		0.64	4.37	0.08
Adjusted R^2	0.853				0.855				0.894			
Explained deviance	89.5 %				89.7 %				93.1 %			

tropical scale and is opposite to a study at the national scale of Brazil where municipal-level deforestation increased by 8–10 % in years with a municipal election (Pailler, 2018). Our results suggest that there is currently no statistical support for a globally consistent trend across tropical countries that shows election-driven deforestation as observed at the municipal level in Brazil. Nevertheless, election theory suggests that politicians should utilise all avenues possible to win support and favour in the lead up to an election, which includes giving away or promising forested land for development, or turning a blind eye to forest exploitation (Abessa et al., 2019; Akhmedov and Zhuravskaya, 2003; Burgess et al., 2012; Shi and Svensson, 2006). We suggest that there are several plausible explanations why we did not find increased deforestation in election years compared to non-election years.

First, forested land may already be exploited before an election. We accounted for this by including a 3-month lag period to capture potential effects before the election. However, short term pre-election changes in

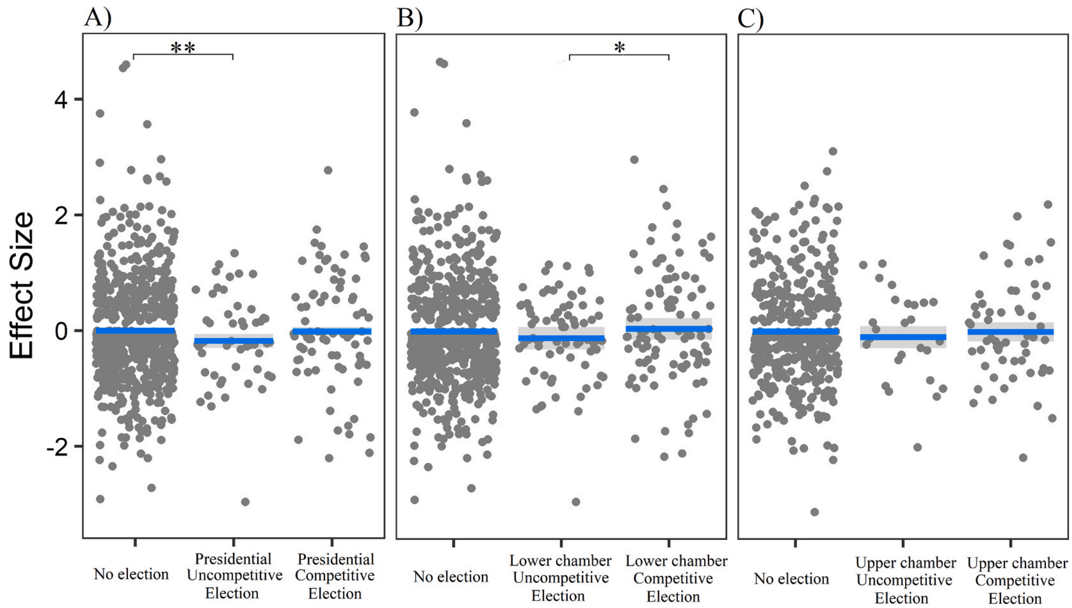

Fig. 3. The effect of elections and their competitiveness on deforestation. Each point represents the amount of logit-transformed deforestation in a given year and country (i.e. effect size). The uncompetitive presidential election (A) show statistically significant lower deforestation compared to non-election years (compare results for Election term in Table 2). Lower chamber and upper chamber elections (B, C) show a similar but statistically not significant trend. Through post-hoc comparisons, competitive lower chamber elections show a statistically significantly higher deforestation compared to uncompetitive election years (B). A similar but statistically not significant trend was found for presidential and upper chamber elections (A, C).

deforestation may vary spatially (e.g. among countries) and temporally (e.g. in length of lag periods) which makes it difficult to analyse them in a consistent way at a global scale. Post-election deforestation may also show different lags. Election cycles are strongly associated with an initial increase in expenditure, followed by a rapid drop after elections (Nordhaus, 1975). Therefore, post-election exploitation of forests is also expected to stop shortly after an election, and may even result in a decrease of deforestation. An example of this phenomenon was recorded in Russia, where the effects of election cycles in social expenditure from local governments generally drop one month after the election (Akhmedov and Zhuravskaya, 2003). Or in the United States of America where employment increases before elections, and drops back to normal levels after elections (Cahan, 2019). However, post-election changes in deforestation may take longer, making it difficult to detect a signal of elections on deforestation rates when analysing deforestation in yearly intervals since the pre-and post-election increase and decrease could cancel each other out. The global forest loss data currently available is in yearly intervals (Hansen et al., 2013) and thus does not account for short term pre/post-election changes in deforestation rates (e.g. within years). Hence, future studies of forest loss at national and global scales could benefit from (ideally near real-time) data that capture intra-annual variation in deforestation rates during election periods. These future studies should also look into unexplored avenues, such as evaluation of deforestation at the subnational level, and investigate countries with different deforestation rates and economical decencies.

Second, another plausible reason for detecting a decrease of national deforestation rates with presidential elections is that forest governance and natural resource management is increasingly decentralised within countries (Ginsburg and Keene, 2020). In principle, such a decentralisation should make it more difficult for national level politicians to exploit locally managed resources (Busch and Amarjargal, 2020). It is currently difficult to account for effects of this decentralisation in global analyses because appropriate data on the degree of local or municipal autonomy in forest management are lacking. Additionally, election data for subnational administrative units which conduct forest management are often missing and currently not available in a globally consistent way. Moreover, there are cases where local governments protect the ecosystems under their jurisdiction from exploitation by higher level politicians (Duarte-Abadía and Boelens, 2016). These protective actions can increase during national election years, as during this time new environmental policies are discussed. Information on election dates within subnational administrative units would help to investigate the effect of elections on deforestation at the spatial scale at which forest management decision are made. For instance, if forests are managed at the state, province, or county level, the effects of state-, province- or county-level elections on deforestation could be analysed. Here, a decentralisation index may also help elucidate the effects of elections on deforestation between the different levels of governance. We therefore recommend to compile a spatially explicit global database that specifies the level and spatial scale of forest governance, together with information on election dates, and decentralisation, within the administrative units.

Third, stakeholders that have invested in logging, or logging-dependent businesses, may change their investing behaviour in response to upcoming elections, which may decrease deforestation. For example, legislative changes are more frequent around elections and could make investment in logging less profitable (List and Sturm, 2006). This could happen through extra protection of land or increasing tax on forest-related goods. As a response, investments may be pulled from the logging-industry and consequently deforestation is slowed down. Such a trend was shown in Africa where private investments dropped by a massive 16 % during election years (Kanyam, 2020). Additional data about legislative changes and logging-related investments would be needed per country or administrative units to analyse such potential drivers in more detail.

Fourth, uncompetitive elections combined with binding term limits could lower deforestation during elections. Both uncompetitive elections and binding term limits are phenomena where politicians experience, more than usual, independence from the electorate. For example, if a politician faces a binding term limit, meaning the politician cannot compete in the next election, it removes the incentive to pursue political support and votes, and has been found to reduce election cycle strength in local governments (Cahan, 2019). Similarly, politicians running in uncompetitive elections, where the elections are largely unconnected to who is in office, may reduce incentives to pursue political support. Both phenomena could remove incentives of land gifting or turning a blind eye to illegal forest utilisation as politicians do not require political favour of the electorate. Such a phenomenon could be observed in the US where independence of the electorate changed the type of policy approved (List and Sturm, 2006). The integration of term-limit data would likely elucidate mechanisms at the core of election cycles, but such data is to our knowledge currently not available at a pantropical scale.

Our analysis revealed that deforestation is significantly higher in competitive election years compared to non-competitive election years. It includes countries (n = 18, 36 %) that alternate between competitive and uncompetitive elections, allowing us to capture partially the actual effect of election competitiveness on deforestation. Our results support our expectation that more competitive elections will increase incentives for politicians to misuse public goods for winning favour (Sanford, 2019; Shi and Svensson, 2006). Additionally, citizens might also pre-emptively clear forests, in fear of new legislation by anti-deforestation regimes (Simmons et al., 2018), or in expectation of impunity (Ferrante and Fearnside, 2019). To improve forest protection, we recommend that integrity and transparency monitoring schemes for elections such as the Global Network of Domestic Election Monitors (GNDEM) extend their mandate to include monitoring natural resources such as forests (Pereira et al., 2009; Shi and Svensson, 2006). Conservation groups should also remain vigilant during the lead up to elections, especially given land gifting practices for forest exploitation is common (Médard and Golaz, 2013).

5. Conclusions

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

CRediT authorship contribution statement

Joeri Morpurgo: Conceptualization, Methodology, Formal analysis, Validation, Investigation, Data Curation, Writing – Original draft, Writing – Review & Editing, Visualization, Project Administration.

Peter Tyrrell: Methodology, Formal analysis, Validation, Writing – Review & Editing.

W. Daniel Kissling: Conceptualization, Methodology, Writing – Review & Editing, Supervision, Funding acquisition.

Pablo Negret: Conceptualization, Writing – Review & Editing.

Peter M. van Bodegom: Conceptualization, Review & Editing, Methodology, Funding acquisition.

James Allan: Conceptualization, Writing – Review & Editing, Visualization, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendices. Supplementary data availability

Supplementary data and code to this article can be found online at http://dx.doi.org/10.17632/5ngc9n3shd.1.

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