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Predicting the loss of forests, carbon stocks and biodiversity driven by a neotropical 'gold rush'

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ABSTRACT

The loss of tropical forests represents a major threat to biodiversity. With accelerating deforestation in large parts of the Amazon, the Guiana Shield region, with its large expanse of closed forest cover, has the potential to play a crucial role in both climate change mitigation and biodiversity conservation. However, the region is now facing increasing deforestation pressures, primarily from artisanal gold mining activities concentrated in the nation of Guyana. To identify areas of Guyana at the highest risk of deforestation over the next 25 years, we employed a spatio-temporal modelling approach that accounted for the stochastic and contagious nature of deforestation. Our model predicted a 9 % net decrease in total forest cover by 2043. While the primary drivers of deforestation were mining and human settlements, protected areas were shown to reduce the probability of deforestation. Therefore, we assessed the potential impact of a proposed expansion of the protected area network in Guyana, on forest loss, carbon stocks and habitat loss for the country's most threatened forest vertebrates. Establishing the proposed protected areas would reduce forest loss by 17 %, predicted habitat losses by an average of 1.9 % per vertebrate group, and aboveground carbon emissions by 466,968 t over the next 25 years. These findings highlight the utility of using predictive models to identify areas at risk of future deforestation, which can contribute to the development of effective strategies against tropical forest loss, biodiversity loss and climate change.

1. Introduction

Tropical deforestation poses one of the greatest threats to biodiversity loss and ecosystem degradation (Lawrence and Vandecar, 2015; Pimm and Jenkins, 2010), while also acting as a key driver of climate change due to its substantial impact on global emissions (Le Quéré et al., 2015; Van der Werf et al., 2010). Recent estimates, derived from data on carbon stock and forest area loss, indicate that tropical deforestation accounts for 2 % - 9 % of total global greenhouse gas emissions (Achard et al., 2014; Baccini et al., 2012; Harris et al., 2012; Liu et al., 2022; Pan et al., 2011; Pendrill et al., 2019; Tyukavina et al., 2015). Consequently, effective strategies to mitigate the adverse effects of tropical deforestation requires prioritising conservation efforts in regions with high biomass, forest cover, and historically low rates of deforestation (Bovolo et al., 2018; Schweikart et al., 2022; Soares-Filho et al., 2010). The Guiana Shield, a prominent region on the northern coast of South America, presents a compelling case for such conservation efforts (Hosonuma et al., 2012; Saatchi et al., 2007, 2011), in lieu of recent large-scale deforestation in the southern Amazon Basin (Maeda et al., 2021; Macedo et al., 2012; Zemp et al., 2017). Covering a substantial area of 1.3 million km^2 and accounting for 26 % of the Amazon's major tropical wilderness, the forests of the Guiana Shield have emerged as a crucial focal point for carbon storage and biodiversity conservation, storing more carbon per unit than the rest of Amazonia (Saatchi et al., 2011). They represent a greater share of closed forest cover in the wider region, underscoring their significance in maintaining ecological integrity and functioning (Saatchi et al., 2011).

In recent decades, the Guiana Shield has experienced a significant

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surge in forest loss (Dezécache et al., 2017; Fearnside, 2005; Kalamandeen et al., 2018; McAlpine et al., 2009; Pasha et al., 2017; Roopnarine, 2002). Unlike the large-scale deforestation primarily driven by cattle grazing and soy elsewhere in the Amazon (Geist and Lambin, 2002; Kuschnig et al., 2019), in the Guiana Shield, small-scale, but widespread gold mining is the primary cause of deforestation (Bholanath and Cort, 2015; Dezécache et al., 2017; Hammond et al., 2007; Kalamandeen et al., 2018; Lowe, 2014; Rahm et al., 2015). The transition towards intensified gold mining can be attributed to a mining ban imposed in Brazil in 2007, which resulted in a notable rise in annual forest loss in the Shield (Kalamandeen et al., 2018). Interestingly, this shift in the spatial dynamics of deforestation across the Amazon, from large-scale clearance to more small-scale loss, corresponds with the region's "gold rush" period, characterised by consistently high gold prices (Kalamandeen et al., 2018). Indeed, deforestation and forest degradation from gold mining expanded by 621 %, encompassing 160,850 ha, during the period 2001–2014 (De Salazar et al., 2021; Rahm et al., 2015). This trend is concerning at both the global and regional levels due to the potential ramifications predicted by climate modelling for the region. It is anticipated that deforestation resulting from the sharp increase in mining activities could trigger mass die-back in the wider Amazon due to perturbed hydrological processes that transport atmospheric moisture from the Guiana Shield across the South American continent (Bovolo et al., 2018). Such outcomes emphasise the urgent need to address the environmental impacts of small-scale gold mining in the Guiana Shield to prevent ecological disruptions on both a local and global scale.

While the Guiana Shield forests are home to high levels of terrestrial biodiversity in the world (Cincotta et al., 2000; Hammond et al., 2007; Hollowell and Reynolds, 2005; Saatchi et al., 2007), including 5 % of all known vascular plant species, and at least 1850 terrestrial vertebrate species, comprising 269 amphibians (54 % endemic), 295 reptiles (29 % endemic), 282 mammals (11 % endemics) and 1004 birds (7.7 % endemic) (Gond et al., 2011; Hollowell and Reynolds, 2005), regional deforestation predictions have predominantly focused on the Amazon River Basin, overlooking the Guiana Shield (Jaffé et al., 2021; Júnior et al., 2015; Ochoa-Quintero et al., 2015; Rosa et al., 2013; Soares-Filho et al., 2010). This knowledge gap limits the reliability and efficacy of land use and conservation planning, particularly in light of recent upsurges in deforestation linked to mining activities.

Guyana, as the largest country in the Guiana Shield, plays an important role in the region's gold mining activities (Rahm et al., 2015). Here, we apply a spatio-temporally explicit modelling approach (Rosa et al., 2013) to address four key objectives: (1) predicting the spatial and temporal patterns of future deforestation in Guyana; (2) estimating the potential losses in carbon stocks; (3) assessing the impact of deforestation on biodiversity, with a focus on threatened species; and (4) informing the design of conservation interventions to protect the ecosystem integrity of Guyana's forests. By achieving these objectives, our study enhances our understanding of the scale and patterns of future deforestation in Guyana and could therefore guide strategic interventions aimed at mitigating the impacts of forest loss in this highly biodiverse and carbon-rich country (Bholanath and Cort, 2015; Lowe, 2014; Rahm et al., 2015).

2. Methods

2.1. Study system

Guyana boasts some of the most intact and biodiverse tropical rainforests on the planet. Currently classified as a High Forest Low Deforestation (HFLD) country (Dezécache et al., 2018), Guyana has made significant commitments in 2009 to transition to a green economy based on climate resilience, low carbon emissions and low rates of deforestation through its Low Carbon Development Strategy (LCDS) (Megwai et al., 2016). Covering an area of 215,000 km^2, Guyana comprises 87.5 % primary rainforests (Fig. 1) and is home to >100 indigenous communities whose subsistence and livelihoods depend on these forest (Hilson and Laing, 2017). However, recently increases in mining activities pose a threat to the country's biodiversity and undermine its green economy goals (Lowe, 2014; Rijal et al., 2019). Kalamandeen et al. (2020) reported a loss of approximately 57,000 ha of forest between 2010 and 2017 due to small-scale gold mining activities. This rate is comparable to that caused by gold mining in Peru, a country six times larger than Guyana, where over 60,000 ha were lost during the same period (Kalamandeen et al., 2020).

In this study, we identified potential predictors of deforestation based on existing literature focused on the neotropics and specifically on Guyana (Table 1). The majority of mining activity in Guyana is concentrated in areas characterised by geological features associated with gold deposits, known as greenstone belts (Rahm et al., 2015). We currently lack the ability to differentiate between illegal and legal mining activities when analysing previous forest loss. However, the model takes into account the broader context of historical forest loss, which includes various factors such as mining activities. Although the model does not explicitly incorporate illegal mining as a distinct spatial variable, it encompasses the cumulative impact of all mining activities. Furthermore, our mining variable is derived from reliable mining permits data provided by the GGMC (Guyana Geology and Mines Commission). Access for small-scale miners is typically facilitated through existing roadways or the construction of new ones, as well as along waterways, and the rate of forest loss is often influenced by the proximity to these features (Barber et al., 2014; Newman et al., 2014; Southworth et al., 2011). Furthermore, the size of waterways play a crucial role as predictor of deforestation, enabling human activities such as transportation and human settlement along larger rivers, as well as alluvial gold mining along the smaller streams (Dezécache et al., 2017). The presence and expansion of human settlements, often connected by roads and waterways, significantly contributes to deforestation across the tropics, with highest deforestation occurring on the peripheries of urban and peri-urban areas (Ochoa-Gaona and González-Espinosa, 2000; Yanai et al., 2020). In Guyana, approximately 15 % of forest is located in titled indigenous lands, where farming systems, mining, logging and community infrastructure have been identified as contributors of forest change. Forestry concessions for timber have also been associated with high deforestation rates (Brandt et al., 2016). Conversely, protected areas have demonstrated effectiveness in curbing deforestation in some of the Earth's most biodiverse regions due to legal restrictions on human activities and their enforcement within protected boundaries (Bebber and Butt, 2017; Gomes et al., 2019; Poor et al., 2019). We selected candidate predictors for the deforestation model based on the aforementioned potential drivers (see Table 1). All predictor layers were clipped to our forest cover extent map, and reprojected to WGS 1984 UTM Zone 21 N coordinates as well as resampled to 180 m spatial resolution (bilinear for continuous predictors, and nearest-neighbour resampling for categorical predictors).

In order to analyse spatio-temporal patterns of past forest loss in Guyana, we used the Global Forest Change (GFC) dataset developed by Hansen et al. (2013). The GFC data provided annual information on tree cover losses based on Landsat satellites, with a resolution of 30 m. We extracted the forest cover data specifically for the years 2000 to 2018 from this dataset. To ensure compatibility and feasibility for our predictive model, which requires significant computational requirements, we resampled the data to a resolution of 180 m. This resampling allowed us to effectively cover the entire country and facilitate the execution of our model. Consistent with the approach outlined by Voigt et al. (2021), we defined forest as pixels with over 70 % cover from the year 2000, while areas below this threshold were classified as non-forest (Fig. 1). This method enabled us to establish a consistent and reliable representation of forest and non-forest areas for our analysis.

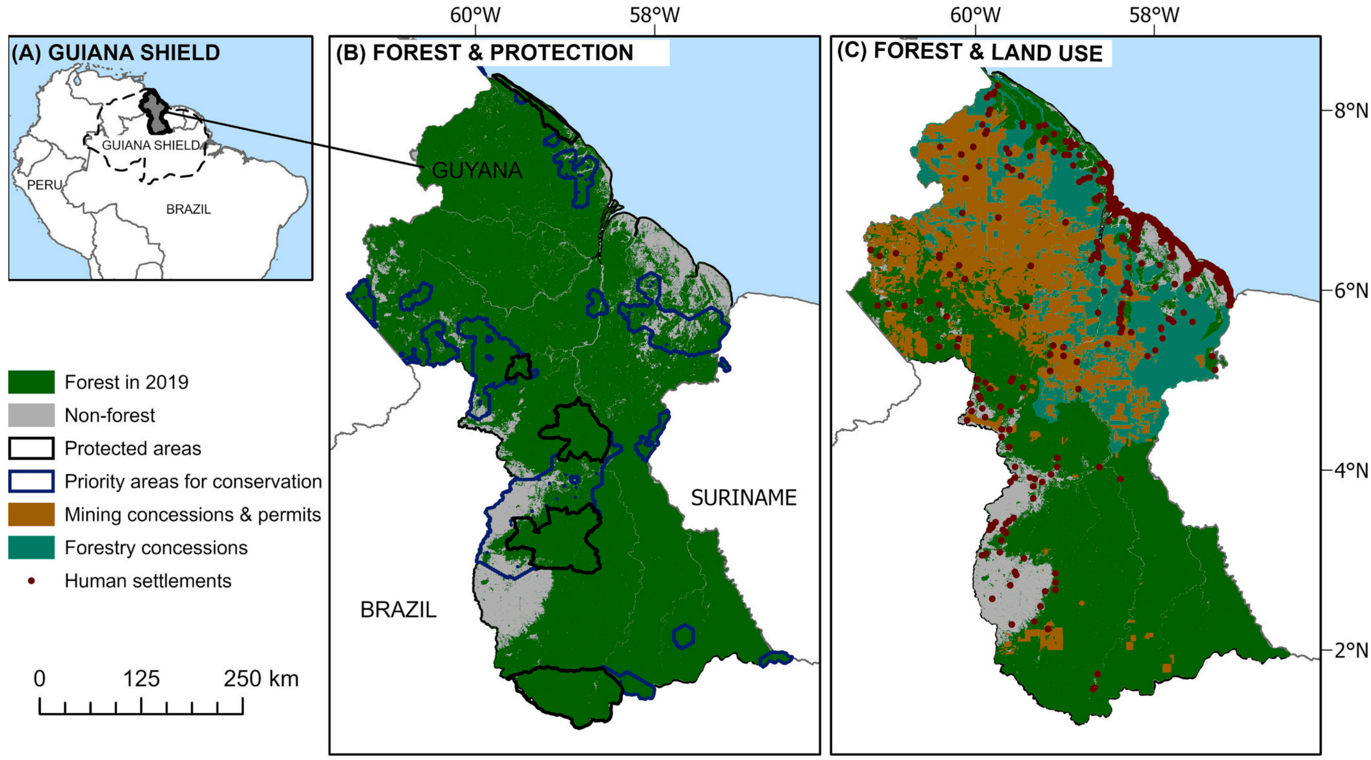

Fig. 1. (A) South America with the boundaries of the Guiana Shield indicated by dashed line. (B) shows forest cover (2019) in Guyana (data from Hansen et al., 2013) with existing protected areas outlined in black and priority areas for conservation from Bicknell et al. (2017) in blue. (C) shows forest cover in (2019) with forestry concessions, mining permits and areas of no forest cover. Where mining permits and forestry concessions occupy the same space, mining permits are shown on top. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Details of the input data and sources used to calibrate a deforestation model for Guyana for the study period, 2014–2018. The deforestation model uses past deforestation data, a spatial autocorrelation effect of the neighbourhood of deforested pixels and spatial layers of potential drivers of deforestation, such as those listed below as inputs.

Name	Description	Source layer	Year	Data type
Forest cover	Forest cover and loss previous to the calibration period (2001–2013) and in the calibration period (2014–2018)	Hansen et al. (2013)	2000, 2001–2013, 2014–2018	Raster
Elevation	Slope in 2000 derived from the digital elevation model (30 m)	–	–	Raster
Waterways	Proximity to large (rivers) and small (streams) waterways based on Strahler stream order classifications.	This study	2018	Polygon
Roads	Proximity to all roads (official and unofficial)	Guyana Government Agency	2016	Polygon
Settlements	Proximity to all settlements including cities, towns, villages and smaller settlements	Guyana Government Agency	2018	Points
Mining permits	All small, medium and large mining permits granted until 2013	Guyana Government Agency	2013	Polygon
Forestry concessions	All forestry concessions granted until 2013	Guyana Government Agency	2013	Polygon
Protected areas	State reserves	Guyana Government Agency	2018	Polygon
Greenstone belt	Underlying geological feature associated with gold deposits	Guyana Government Agency	–	Polygon
Indigenous lands	All titled Indigenous territories	Guyana Government Agency	2018	Polygon

2.2. Future deforestation predictions

To project future deforestation, we employed a dynamic and spatially-explicit probabilistic deforestation model developed by Rosa et al. (2013) that accounts for the stochastic and contagious nature of deforestation (see Supplementary Material S1). While the model has been previously applied in tropical regions with relatively high levels of deforestation (Bradley et al., 2017; Guerra et al., 2020; Voigt et al., 2021), it has not yet been used in predominately intact forests of the Guiana Shield. These forests, facing an increasing threat from mining activity across the region (Kalamandeen et al., 2018), present a unique application for the model.

The deforestation model uses past deforestation data, a spatial autocorrelation effect of the neighbourhood of deforested pixels and spatial layers representing potential drivers of deforestation, such as elevation, infrastructure, and land use as inputs (see Table 1). The model dynamically updates past deforestation patterns in the neighbourhood of each pixel for each projected time-period, building on the results of the previous time-period (Fig. S1). The remaining predictors were assumed to be static, as predictors such as the presence of greenstone and location of waterways were unlikely to change over the calibration or projected time-period. Similarly, predictors that involved uncertain future events, such as locations of mining permits yet to be granted or roads to be developed, could not be reliably forecasted into the future.

Waterways in Guyana were categorised based on their size using the Strahler stream order classification method (Strahler, 1952), which orders streams based on their bank to bank width (Supplementary Material S1). The classification resulted in eight distinct stream orders for Guyana, (Strahler stream orders 1,2,3,4,5,6,7,8). In our analysis, we considered each stream order individually. Additionally, a sensitivity analysis was conducted by grouping the waterways into two categories: small rivers (stream orders 1–4) and large rivers (stream orders 5–7), while excluding stream order 8 due to its low representation.

This classification aligns with utilisation patterns observed in the region. Smaller streams typically contain stream-bed gold deposits, which are the main target of small-scale gold mining activities (Miller et al., 2003). On the other hand, larger rivers serve as access routes for miners to reach these otherwise remote forests. Consequently, deforestation patterns are expected to differ depending on whether the streams are small or large. In our sensitivity analyses, the deforestation model that considered grouped rivers demonstrated the highest predictive power, indicating its effectiveness in capturing the variations in deforestation patterns associated with different stream sizes.

Prior to running the deforestation model, all candidate predictors were tested for multicollinearity. Any predictors that exhibited high correlation (Pearson's correlation coefficient > 0.7) were excluded from the model. As a result, the forestry concessions variable was removed due to its strong correlation with mining permits. We employed a forward stepwise model selection approach to incrementally incorporate candidate predictors into the deforestation model. The models were fitted using the Monte Carlo Markov Chains (MCMC) sampling method, implemented in the 'Filzbach' library (https://github.com/predictionmachines/Filzbach). This approach yielded a posterior probability distribution for individual parameters associated with each predictor variable, allowing use to extract a range of credible intervals and posterior means.

To evaluate the predictive capability of each predictor in the deforestation model, we employed a cross-validation technique. This involved parameterising the model using a randomly selected training subset of 50 % of the data. We then compared the model's performances on the remaining data that was not used to train calculating the test likelihood. The predictors were added to the model in the order they provided the greatest increased likelihood. From the final set of deforestation probability models ($n = 45$), we selected the model with the highest test likelihood, indicating the best performing model. The selected model was then employed to simulate future deforestation for a five-year calibration period spanning from 2014 to 2018 as well as for subsequent five-year periods: 2019–2023, 2024–2028, 2029–2033, 2034–2038, and 2039–2043.

Following Rosa et al. (2013), we considered uncertainty in the deforestation model at two steps. First, we drew predictor values for the simulation from a Gaussian distribution, using their estimated mean and standard deviation. With these values we calculated the probability of deforestation in each pixel, time period and iteration. Second, we assessed whether a deforestation event had taken place, by comparing the probability with a random number drawn from a uniform distribution ranging between 0 and 1. If the generated number was smaller than the probability of deforestation, the pixel was classified as deforested. This step allows us to realise the probability value into a binary map with that probability. The simulation was repeated 100 times to generate as a set of binary forest maps allowing us to represent uncertainty and incorporate observed stochasticity in deforestation events in the model projections.

The binary forest maps were used to estimate overall projected deforestation by the year 2043, assess potential declines in carbon stock, and evaluate the potential impact of deforestation on the habitat of multiple threatened vertebrate species. For the carbon stock and threatened species analyses, the binary maps were overlaid with relevant data on carbon stock and species range maps, as detailed below. Additionally, to characterise the overall deforestation risk across Guyana, the 100 binary maps were aggregated to calculate a summed probability of deforestation. This calculation involved summing the number of times each pixel was predicted to be deforested across the simulation iterations and dividing it by the total number of iterations ($n = 100$).

The model's projections of deforestation for the period from 2014 to 2018, which were simulated using deforestation data from 2000 to 2013 (Table 1), were validated against observed data for the calibration period (2014–2018). Validation was performed by calculating the Area Under the Curve (AUC) value for the 100 iterations. Additionally, the proportion of match, omission and commission between observed forest cover and loss were assessed, along with the agreement between the projected and observed deforestation within specified distances (0, 1, 5 and 10 pixel neighbourhood) surrounding each deforested pixel (see Voigt et al., 2021).

2.3. Deforestation predictions: protected areas, carbon, biodiversity

2.3.1. Effects of deforestation predictions on aboveground carbon stocks

Our model projections of deforestation were used to evaluate the potential decline in aboveground carbon stocks (Gg C) in Guyana in the future. We estimated remaining carbon stocks by overlaying the aboveground biomass carbon density maps for the year 2010 obtained from Spawn et al. (2020) with our binary forest loss projections ($n = 100$) for the year 2043. This was done by excluding any pixels predicted to be deforested from the carbon density maps and recalculated the total carbon remaining (Gg C). This approach allowed us to evaluate how carbon stocks may declinate in the absence of additional protective measures such as new protected areas.

2.3.2. Effects of deforestation predictions on threatened species

To predict the potential impact of forest loss on biodiversity in Guyana, we overlayed species distributions with our final binary forest loss projection maps for the year 2043. Specifically, we focused on 38 vulnerable, endangered, or critically endangered species of forest-dwelling terrestrial vertebrates such as the endemic Roraima mouse (*Podoxymys roraimae)* and critically endangered Rio Branco antbird (*Cercomacra carbonaria)* (IUCN, 2021; Supplementary Material Table S1). We obtained species range data from the IUCN database, and in cases where the available IUCN maps were inadequate (e.g., covering vast and nonspecific areas of South and Central America), we generated species distribution models (SDMs). The SDMs were created using the SSDM (Stacked Species Distribution Models) package in R software (Schmitt et al., 2017), which uses multiple modelling algorithms to achieve the best possible outcomes (Supplementary Material S2). To ensure consistency, all species range maps were projected to WGS 1984 UTM Zone 21 N coordinates and resampled to match the resolution and extent of the binary maps predicting deforestation.

We quantified the mean losses in area of occupancy for each species by 2043 using a spatial overlay of species range maps and the binary maps projecting deforestation without and with protected areas to determine the extent of habitat loss caused by deforestation. Our estimates of species range loss were based on the assumption that the removal of forest habitat leads to a reduction in the occupied area by species (Brook et al., 2003; Miranda et al., 2021; Ortega-Huerta and Peterson, 2004; Peterson et al., 2000; Symes et al., 2018).

2.3.3. Effects of new protected areas on deforestation predictions

Recognising the global significance of protected areas (PAs, defined herein as areas under legal protection by legislation and managed either by the government, co-managed with communities or indigenous-managed/led conservation areas) in combating deforestation and safeguard biodiversity (Anderson and Mammides, 2020; Naughton-Treves et al., 2005), Guyana has committed to expanding its conservation area. Under the Convention on Biological Diversity, the initial target was to achieve 17 % coverage, with further expansion to 30 % by 2030 (Low Carbon Development Strategy LCDS 2030 - Government of Guyana, 2022). Therefore, we assessed the potential impact of establishing PAs in locations previously identified as high conservation priorities(Bicknell et al., 2017). In their study, Bicknell et al. (2017) employed systematic conservation planning to determine the optimal spatial expansion of Guyana's protected area network. This process was co-developed with local stakeholders, ensuring inclusive decision-making. The findings revealed the identification of 3 million hectares (ha) of new priority areas for conservation, effectively increasing the country's existing terrestrial protected area network from 8.5 % to 22.5 % (Fig. 1). Our analysis focused on assessing the influence of PAs on deforestation, aboveground carbon stocks, and biodiversity. We assumed that the establishment of new terrestrial protected areas would prevent forest loss within its boundaries. This assumption was based on two factors: (1) the historically low rate of deforestation of 0.008 % between 2001 and 2018 in Guyana's existing PAs (calculated from Hansen et al. (2013) data); and (2) the low predicted rate of future deforestation (0.03 % by 2043) within protected areas as projected by our deforestation model (see Results).

3. Results

3.1. Model accuracy and predictors of deforestation

The deforestation model that exhibited the highest test likelihood included several predictor variables: previous forest loss, mining permits, indigenous lands, greenstone belt, proximity to small and large rivers, proximity to settlements and protected areas (Table 2). Among these variables, previous deforestation emerged as the most important predictor, showing a substantial increase in test likelihood, followed by proximity to human settlements and mining, respectively. Previous deforestation exhibited the largest impact on deforestation probability, with a median coefficient of 13.98. While predictors such as mining, indigenous land and greenstone belt also contributed to deforestation probabilities in Guyana, their predictive power was comparatively lower. Notably, protected areas were associated with very low deforestation probabilities in the model.

Our deforestation model for Guyana demonstrated a strong predictive power, as indicated by a mean AUC value of 0.92. During the calibration period (2014–2018), the agreement between projected and observed forest cover was exceptionally high, with a median of 99 % of pixels accurately matched (false positives = 0 % and false negatives = 1 %,Table S2). Using the approach proposed by Rosa et al. (2013), we also evaluated the consistency between observed and projected loss, which represented a more conservative measure of model fit. We found that, across the iterations, a median of 88 % of projected deforestation events occurred in close proximity (within 1800 m) of an observed deforestation event (Table 3). This analysis demonstrated that our model effectively approximates the actual deforestation that occurred during the calibration period.

Table 2
Mean coefficients and 95 % confidence intervals of the final set of predictor variables used in the final deforestation simulations. Coefficient values <0 decreased, while values >0 increased the probability of deforestation. The variables are arranged in order based on their inclusion into the model during the stepwise procedure, with the first variables representing the ones that contributed the most significant increase in the model's test likelihood.

Variable	Mean coefficient	Lower-limit	Upper-limit
Previous deforestation	13.98	13.92	14.06
Protected areas	−1.56	−1.58	−1.54
Proximity to settlements	−0.000131	−0.000133	−0.000128
Mining leases/permits	0.43	0.42	0.46
Indigenous lands	0.33	0.32	0.34
Greenstone belt	0.26	0.25	0.26
Proximity to small rivers	−0.000048	−0.000049	−0.000047
Proximity to large rivers	−0.000082	−0.000083	−0.000071

3.2. Future deforestation predictions without intervention

Based on our projections, Guyana is expected to experience a significant loss of forest during the period 2018 to 2043, with a total accumulated loss of 19,488 km^2. This corresponds to a net decrease of 9 % in forest coverage, reducing the proportion of forested areas from 86.7 % in 2018 to 77.6 % by 2043. The rate of deforestation is projected to escalate from 0.03 % in 2018 to 0.32 % by 2043, representing a tenfold increase (Table S3). The regions most susceptible to forest loss are predominantly locations in the northern and western parts of the country(Fig. 2a), which coincides with areas characterised by a high concentration of mining permits and settlements (Fig. 1).

3.3. Deforestation predictions: protected areas, carbon, biodiversity

3.3.1. Effects of new protected areas on deforestation predictions

Our analysis revealed that implementing new protected areas in identified conservation priority zones could have a significant impact on reducing predicted net deforestation by approximately 3276 km^2 by 2043. This reduction corresponds to a 17 % decrease compared to scenarios where new protected areas are not implemented (Fig. 2b; Supplementary Material Fig. S6; Table S3), highlighting the potential effectiveness of protected areas in mitigating deforestation. This translates to an annual rate of 0.27 %, which is lower than the projected rate of 0.32 % in absence of new protected areas.

3.3.2. Effects of deforestation predictions on aboveground carbon stocks

In our study, we found that deforestation in Guyana would result in a loss of approximately 2746.8 Gg C of aboveground carbon stock, corresponding to an 11.1 % decline in the country's total stock (Fig. 2c). However, if additional protected areas are implemented, this loss is estimated to be reduced by 2279.8 Gg C, resulting in a total loss of aboveground carbon stocks of 9.2 % by 2043. By implementing these protected areas, it is projected that 466.9 Gg C could be saved over the 25-year period of assessment.

3.3.3. Effects of deforestation predictions on threatened species

Projected forest loss had a significant impact on the suitable habitat area for all various taxonomic groups examined in this study. Birds experienced the highest range loss, with an estimated average reduction of 12.6 % due to deforestation (Fig. 2d). Reptiles followed closely with a predicted range loss of 10 %, while mammals and amphibians had

Table 3
Percentage of observed deforestation events matched by projected deforestation (0 m = perfect match) and near matches within the neighbourhood of the pixel (180 m = 1 pixel, 360 m = 2 pixels, 1800 m = 10 pixels) for Guyana. Median, 95 % lower confidence interval (CI) and upper CI were calculated across binary projected deforestation maps (n = 100).

	Deforestation location match (% observed vs projected)			
	0 m	≤ 180 m	≤ 360 m	≤ 1800 m
Median	3	14	27	86
Lower CI	3	13	26	85
Upper CI	4	15	27	88

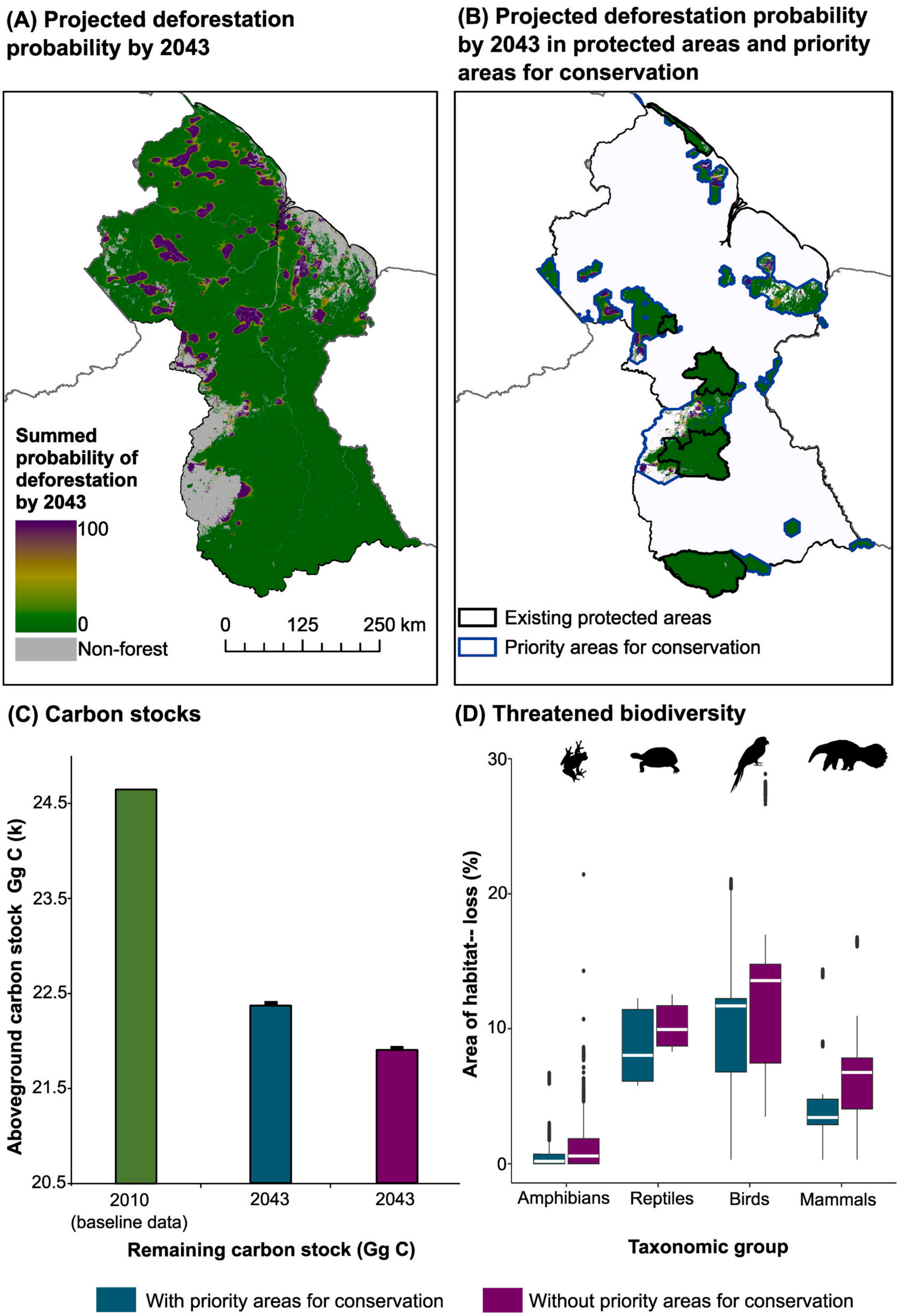

Fig. 2. (a) Projected summed probability of deforestation in Guyana in 2043. Areas in purple represent forest with a high probability of deforestation by 2043, (b) The projected summed probability of deforestation in existing protected areas and in potential new protected areas based on priority for conservation from Bicknell et al. (2017), (c) estimated aboveground carbon stock (Gg C) remaining in Guyana's forests before our projected deforestation period (in green), after projected 2043 deforestation (in purple) and after 2043 deforestation, but with additional protected areas, based on priority areas for conservation from Bicknell et al. (2017, implemented (in teal). Standard error bars are included for projected periods, and (d) estimated mean sum of area of habitat lost (%) from deforestation during the period 2018–2043 for threatened terrestrial species ($n = 38$) in Guyana with a proposed protected area network (in teal) based on priority areas of conservation from Bicknell et al. (2017) and without (in purple). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

projected range losses of 6.3 % and 1.8 %, respectively. Among the 38 species analysed individually, it was projected that 32 species would face a decrease in their suitable habitat area. The extent of area loss varied, with the most affected species experiencing a mean reduction of 27.4 % and the least affected species experiencing no loss. Notably, the sun parakeet (*Aratinga solstitialis*), Venezuelan fish-eating rat (*Neusticomys venezuelae*) and white-throated toucan (*Ramphastos tucanus*) were projected to suffer the largest mean area losses at 27.4 %, 16.1 % and 15.1 % respectively (Table S4). Overall, nine out of the twelve assessed amphibian species were estimated to have little or no range loss.

Further analysis revealed that implementing new protected areas in the identified priority conservation areas would lead to reduced predicted habitat losses for the majority of species assessed in this study (Fig. 2d; Table S4). On average, birds would experience 2.7 % decrease in habitat loss, followed by mammals (2.2 %), reptiles (1.5 %) and amphibians (1.0 %) (Table 4). The expansion of PAs would provide significant protection to numerous species, with some species, including *Stefania ackawaio*, *Stefania ayangannae,* Rio Branco antbird and Reig's opossum *(Monodelphis reigi),* projected to experience almost no loss in habitat area. With the exception of four amphibian species that were estimated to have no habitat loss due to deforestation, 32 of the remaining 34 species assessed would have parts of their ranges safeguarded from deforestation through the expansion of the protected area network (Figs. S2 – S5). Only the grey tinamou (*Tinamus tao)* and two-lined caecilian (*Rhinatrema shiv*) would not receive additional benefit from establishing the proposed protected areas (Table S4).

4. Discussion

4.1. Emerging drivers for predicting future forest loss

Despite the crucial role of the Guiana Shield in global forest cover, it has received considerably less attention in terms of forest loss compared to other parts of Amazonia, as highlighted by previous studies (De Salazar et al., 2021; Fearnside, 2017; Junior et al., 2021; Rahm et al., 2015; Sonter et al., 2020). Recognising this disparity, our research aimed to address this gap by using a spatio-temporally explicit deforestation model to project future forest loss in Guyana.

Our analysis indicated that mining, particularly concentrated in Guyana's vast greenstone belt located in the northern and western regions, is a major contributor to deforestation. This finding aligns with previous research showing increasing deforestation associated with mining activities throughout the country (Kalamandeen et al., 2018; Rahm et al., 2015). The extraction of mineral resources in these areas leads to the transformation of complex and biologically diverse ecosystems into bare ground and standing water bodies, which have limited potential for forest recovery (Peterson and Heemskerk, 2001; Kalamandeen et al., 2020). Our deforestation projections indicate that this trend is likely to continue in the future.

Our study further supports the pattern observed in other regions of South America (Chadid et al., 2015; Dávalos et al., 2016) by highlighting the considerable influence of forest proximity to human settlements as a key driver of forest loss. In our model, this variable ranked second during the stepwise procedure, resulting in a substantial increase in the likelihood, indicating that forests located close to human settlements face a higher risk of deforestation. In Guyana, the forested interior is predominantly inhabited by indigenous people and mining settlements, with many mining residents being migrants from the urbanised coastal region (Colchester, 1997). With the profitability of mining activities driven by global gold prices (Hammond et al., 2007; Mei-Se et al., 2018) it is likely that the expansion of existing mining towns and the emergence of new settlements will continue. However, such expansion, accompanied by infrastructure development and logging, poses severe threats to Guyana's forest ecosystems and undermines livelihoods that depend on forests, often leading to conflicts between miners and surrounding communities (Ellis et al., 2010; Hilson, 2002; Hook, 2019; Mackenzie et al., 2012). Furthermore, some of Guyana's indigenous communities, who reside primarily on indigenous lands, are also actively involved in mining and agriculture, both of which contribute to deforestation (Colchester et al., 2002). This further highlights the complex dynamics of deforestation drivers in Guyana and the need for tailored interventions to address the specific challenges faced by different stakeholder groups.

Proximity to roads did not demonstrate a strong influence on probability of deforestation, contrary to its documented significance in the literature (Barber et al., 2014; Bax et al., 2016; Etter et al., 2006). This is noteworthy because roads have been recognised as facilitators of human settlement, logging and mining throughout the Amazon (Laurance, 2015). It is important to note that our analysis considered only official roads and tracks. However, there is anecdotal evidence suggesting the existence of an undocumented network of unofficial access roads and tracks for logging and mining operations in certain parts of the country, which were not accounted for in our model (Pierre et al., 2020). Furthermore, although waterways are likely to serve as main access routes for miners and transportation routes for timber, similar to roads, our analysis indicate that the proximity to waterways (both large and small) had little influence on deforestation probability at the national level, where our analyses were conducted (Barber et al., 2014; Bos et al., 2020). It is worth noting that the projected forest loss is concentrated in the northern and western regions of the country, which are intersected by a network of large and small rivers. These findings highlight the complexities and nuances associated with the drivers of deforestation in Guyana. While roads and waterways have been recognised as key factors in deforestation processes in other regions, their influence in the specific context of Guyana may be different. The presence of undocumented access roads and tracks for logging and mining activities suggests the need for enhanced monitoring and regulation to address these informal practices that contribute to deforestation. Furthermore, while not explicitly accounted for in our model, climate change may enhance forest loss in the region. Anadón et al. (2014) suggest that climate change could lead to increased savannization of the tropical and subtropical Americas, potentially resulting in the expansion of savannas at the cost of forests. Thus, future modelling could gain insights by integrating climatic variables, which might influence the outcomes of the model.

Table 4
Average predicted area of suitable habitat loss for Guyana's most threatened terrestrial vertebrate species (n = 38) by 2043, with and without the priority areas for conservation becoming protected areas (PA; Bicknell et al., 2017). Mean, median, and interquartile ranges were calculated across binary maps of predicted deforestation (n = 100). Species are grouped into their respective taxonomic groups (birds, mammals, amphibians, reptiles). Average mean percent of area of habitat that would be protected from deforestation under proposed protected area implementation in bold.

	Area of habitat loss without PA (%)			Area of habitat loss with PA (%)			
Taxa	Mean	Median	IQR	Mean	Median	IQR	Mean protected (%)
Birds	12.58	13.25	7.32	9.85	11.43	5.44	2.73
Mammals	6.33	6.46	3.83	4.14	3.13	1.88	2.19
Amphibians	1.84	0.49	1.85	0.81	0	0.70	1.03
Reptiles	10.01	9.86	2.99	8.51	7.9	5.30	1.50

4.2. Increasing habitat loss and increasing species at risk due to deforestation

Our study presents concerning projections regarding the impact of deforestation on forest-dependent species in Guyana, with nearly all assessed species (84 % out of 38 species) facing the risk of habitat loss. While amphibians are projected to experience relatively lower losses in habitat area due to their limited range sizes, mainly occurring in isolated areas such as tabletop mountains known as tepuis, birds, reptiles, and mammals are estimated to face significant habitat reductions over the next 25 years. This is particularly alarming considering that these species are already classified as threatened. Among the taxonomic groups analysed, larger species such as the white-lipped peccary (*Tayassu pecari*), Amazonian tapir (*Tapirus terrestris*), and black currasow (*Crax alector*) may be more vulnerable to predicted habitat losses. Previous studies have reported similar findings, highlighting the negative impact of habitat loss on the abundance of larger species (Ewers and Didham, 2006; Gaston and Blackburn, 1996; Lino et al., 2019). Our assessment of Guyana's threatened vertebrates that depend on forest habitats shows the importance of considering deforestation predictions in proactive conservation efforts. By identifying potential habitat losses in terms of scale and location, we can gain valuable insights to inform targeted conservation actions.

At a regional scale, the majority of forest loss will occur in the northern and western forests of Guyana. This pattern is particularly evident in the projected reductions in habitat areas for species distributed in these regions, such as the sun parakeet (*Aratinga solstitialis),* Venezuelan fish-eating rat *(Neusticomys venezuelae),* white-lipped peccary (*Tayassu pecari)* and white-throated toucan (*Ramphastos tucanus)*. These results underscore the importance of implementing conservation strategies aimed at reducing deforestation in these specific areas. Accordingly, the prioritised conservation areas identified by Bicknell et al. (2017) align with our findings, highlighting the importance of their implementation as potential protected areas in the northern and western regions of Guyana. By designating these areas as new protected or conservation areas, not only would deforestation be mitigated, but the estimated loss of habitat area for species across all taxonomic groups would also be reduced.

4.3. Policy implications due to increasing deforestation

The findings of our study indicate a concerning trend if no intervention occurs, with approximately 2 million ha of forest in Guyana is projected to be lost over the next quarter century. This translates to a significant 9 % reduction in the country's total forest cover. While this percentage might appear relatively small on a global scale, it poses a significant challenge for Guyana, especially considering its current status as a High Forest Low Deforestation (HFLD) country (Dezécache et al., 2018) and its commitment to a Low Carbon Development Strategy (LCDS) (Megwai et al., 2016; Government of Guyana, 2022). The LCDS sets the goal for Guyana to maintain deforestation rates 90 % below the global average. However, if the projected 9 % forest loss by 2043 becomes a reality, it would likely undermine Guyana's objectives of achieving low deforestation rates. Furthermore, our projected trajectories indicate that Guyana's deforestation rate by 2043 (0.32 %) is expected to surpass the inclusion criteria for High Forest Low Deforestation (HFLD) status, which is set at 0.22 % (Grafton et al., 2012; Roopsind et al., 2017). This has significant implications for Guyana's eligibility in forest carbon accreditation programs such as the Architecture for REDD+ Transactions (ART), which recognises carbon stored within HFLD countries (Government of Guyana, 2022). Meeting the criteria for HFLD status is crucial for Guyana to participate in and benefit from initiatives like ART, which provide financial incentives for reducing deforestation and preserving carbon stocks.

Effective policy measures aimed at reducing deforestation requires a thorough understanding of the specific drivers that contribute to forest loss (Rudel et al., 2009). In our analysis, we identified mining activities, proximity to human settlements, and the extent of prior forest loss as the key factors with the highest probabilities of deforestation in Guyana. These findings highlight the potential effectiveness of implementing initiatives such as active restoration and protecting forest systems near human activity. Similar approaches have proven successful in mitigating deforestation risks in other regions (Gaveau et al., 2009; López-Barrera et al., 2014; Orsi et al., 2013; Vettorazzi and Valente, 2016). Tailoring policies to address these specific drivers can target the underlying causes of deforestation. Active restoration projects can be implemented to regenerate degraded areas and facilitate the recovery of forest cover (Erbaugh et al., 2020; Vettorazzi and Valente, 2016). Additionally, establishing protected areas around human settlements can act as buffer zones, reducing encroachment and alleviating pressures on the forests (McDonald et al., 2008; Small and Sousa, 2016; Watson et al., 2014). Other strategies may include sustainable land-use planning, effective environmental regulations and effective governance mechanisms to manage forest resources, particularly along supply chains. However, it is essential to adopt a comprehensive approach that considers the socio-economic, cultural and political dimensions contributing to deforestation. Collaborative efforts involving government agencies, local and indigenous communities, and various stakeholders are crucial for the success of these policy measures. Our findings underscore the effectiveness of the current protected area network in Guyana in combating deforestation and habitat loss. However, the implementation of additional protected areas based on priority areas for conservation is crucial. Effectively implementing new protected areas in forested regions facing immediate anthropogenic threats, we can achieve significant payoffs in reducing carbon emissions (Soares-Filho et al., 2010). Based on our results, without the implementation of additional protected areas, aboveground carbon stocks are projected to decrease by 11.1 % by 2043. However, this reduction could be mitigated to 9.2 % if the priority areas of conservation were designated as PAs.

In light of the ongoing climate and ecological crisis, any efforts aimed at reducing greenhouse gas emissions through avoiding deforestation are vital. Therefore, areas that are most susceptible to deforestation should be prioritised for conservation action. Our study strongly supports the effectiveness of protected areas in Guyana, as we observed very low probabilities of forest loss within the existing PAs, which currently cover 8.5 % of country's land area. This aligns with previous studies emphasising the reduced deforestation rates within protected areas (Amin et al., 2019; Bebber and Butt, 2017; Yang et al., 2019).

Therefore, to counteract the increasing deforestation events, the implementation of additional protected areas specifically focused on conserving primary forests, could serve as a robust buffer against future forest clearance, prevent declines in aboveground carbon stocks, and mitigate biodiversity loss (Kalamandeen et al., 2018). Our analysis predicts that by designating priority areas for conservation with protected area status, the deforestation rate could be reduced to 0.27 % by 2043. However, this rate still exceeds the HFLD threshold of 0.22 %. Therefore, the country will need to consider a greater investment in the conservation estate beyond the 22.5 % of the country identified as priority areas for conservation. To meet its commitments, Guyana as a signatory of the Leaders Pledge for Nature, which aims for 30 % protection by 2030, will need to establish new PAs and Other Effective Area-based Conservation Measures (OECMs) strategically in biodiverse regions. This ensures optimal utilisation, addressing the past issue of limited effectiveness in PAs (Joppa & Pfaff, 2009). In some parts of the tropics, PAs have shown residual protection, often due to their establishment in cost-effective, peripheral zones to avoid conflicts with extractive industries. This approach neglected critical biodiversity conservation areas (Vieira et al., 2019). These actions can help the country achieve its goals and ensure that the forest loss predictions presented in our study do not become a reality. By adopting these conservation measures, Guyana can make significant progress in preserving its natural resources, reducing deforestation, and fulfilling its environmental commitments.

5. Conclusion

Our study, the first of its kind in the Guiana Shield, highlights the need to address the drivers of forest loss in this region, particularly the impacts of mining and related activities. As such, it is vital to improve the monitoring of legal and illegal small-scale mining activities in this region. We show that the projected future forest loss poses significant risks to carbon stocks, and forest-dependent threatened species, underscoring the importance of implementing proactive conservation strategies, such as the establishment of protected areas among others, tailored to address specific drivers. The evidence from this research supports the potential for policies that align with Guyana's aspirations for balanced economic growth, environmental preservation and community well-bein (Government of Guyana, 2022; Lowe, 2014). Overall, our study demonstrates the utility of deforestation models in providing an early warning system to help direct action to parts of the planet that could play a pivotal role in mitigating the effects of global environmental change.

CRediT authorship contribution statement

Will Hayes: Conceptualization, Formal analysis, Investigation, Methodology, Visualization, Writing - original draft. **Maria Voigt:** Conceptualization, Formal analysis, Visualization, Methodology, Writing- Reviewing and Editing. **Isabel Rosa**: Conceptualization, Methodology. **KerryAnne Cort**: Conceptualization, Investigation. **Nic Kotlinski:** Methodology. **Michelle Kalamandeen**: Methodology, Writing- Reviewing and Editing. **Zoe Georgina Davies:** Methodology, Writing- Reviewing and Editing Methodology. **Jake Bicknell:** Conceptualization, Formal analysis, Visualization, Methodology, Writing-Reviewing and Editing.

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.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

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