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Forecasting deforestation and carbon loss across New Guinea using machine learning and cellular automata

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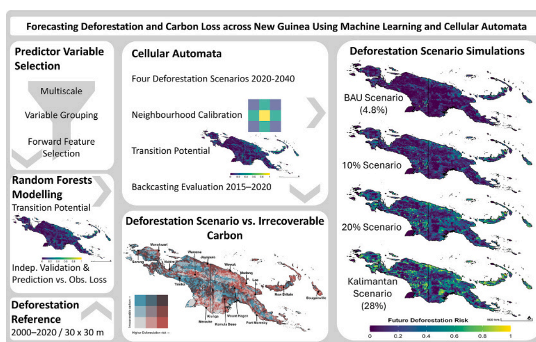
HIGHLIGHTS

- New Guinea may emerge as a new deforestation frontier, especially in lowland regions.
- Our models revealed deforestation patterns and linked emissions.
- High deforestation rates affect ecosystem services, carbon emissions, and biodiversity.
- Proactive planning could address threats to design landscapes for people and nature.

GRAPHICAL ABSTRACT



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ABSTRACT

The island of New Guinea harbors some of the world's most biologically diverse and highly endemic tropical ecosystems. Nevertheless, progressing land-use change in the region threatens their integrity, which will adversely affect their biodiversity as well as carbon stocks and fluxes. Our objectives were to (1) compare deforestation drivers between Indonesian New Guinea and Papua New Guinea, (2) identify areas with a high risk of future deforestation under different development scenarios, and (3) evaluate the effects of potential deforestation scenarios on carbon pools. We integrated machine learning and cellular automata to model and forecast deforestation across New Guinea. We assessed the potential loss of irrecoverable carbon stocks for deforestation scenarios ranging from 4.8 % (business-as-usual) to 28 % (high development scenario) forest loss between 2020 and 2040. Areas of high deforestation risk were consistently forecasted in lowland regions across the

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four deforestation scenarios. In Indonesian New Guinea, 75 % of deforestation was forecasted below ~380 m a.s.l., but ranged higher in Papua New Guinea (<750 m a.s.l.). Land change-induced carbon loss varied largely across the four scenarios and ranged between 156 and 918 Mt in Indonesian New Guinea and between 223 and 1082 Mt in Papua New Guinea, respectively. Our analysis reveals promising potential for integrating random forests and cellular automata models to forecast high-resolution deforestation over large spatial extents. Our models reveal the vulnerability of New Guinea's lowlands to future deforestation, emphasizing the need to protect key areas where deforestation conflicts with the conservation of carbon stocks, ecosystem functions, and biodiversity.

Abstract in Bahasa Indonesia: Pulau New Guinea merupakan rumah bagi beberapa ekosistem tropis yang paling beragam secara biologis dan sangat endemik di dunia. Namun demikian, perubahan penggunaan lahan yang terus terjadi di kawasan ini mengancam integritas kawasan tersebut, yang akan berdampak buruk terhadap keanekaragaman hayati serta persdiaan dan fluks karbon. Tujuan penelitian ini adalah (1) membandingkan penyebab deforestasi antara New Guinea dan Papua Nugini, (2) mengidentifikasi kawasan dengan risiko tinggi deforestasi di masa depan berdasarkan skenario pembangunan yang berbeda, dan (3) mengevaluasi dampak skenario deforestasi potensial terhadap sumber karbon. . Kami mengintegrasikan pembelajaran mesin dan automata seluler untuk memodelkan dan memperkirakan deforestasi di seluruh New Guinea. Kami menilai potensi hilangnya cadangan karbon yang tidak dapat dipulihkan untuk empat skenario deforestasi yang berkisar antara 4,8 % (skenario pembangunan biasa) hingga 28 % (skenario pembangunan tinggi) antara tahun 2020 dan 2040. Wilayah dengan risiko deforestasi tinggi secara konsisten diperkirakan berada di wilayah dataran rendah dalam empat skenario deforestasi. Di Papua Nugini, 75 % deforestasi diperkirakan berada di bawah ~380 m dpl, namun berkisar lebih tinggi di Papua Nugini (<750 m dpl). Hilangnya karbon yang disebabkan oleh perubahan lahan sangat bervariasi di keempat skenario dan berkisar antara 156 dan 918 Mt di Nugini, dan masing-masing antara 223 dan 1.082 Mt di Papua Nugini. Analisis kami mengungkapkan potensi yang menjanjikan untuk mengintegrasikan hutan acak dan model automata seluler untuk memperkirakan deforestasi resolusi tinggi pada wilayah spasial yang luas. Model kami mengungkap bahwa kerentanan dataran rendah New Guinea terhadap deforestasi di masa depan, menekankan perlunya melindungi wilayah-wilayah utama di mana deforestasi bertentangan dengan konservasi persediaan karbon, fungsi ekosistem, dan keanekaragaman hayati.

1. Introduction

Deforestation and forest degradation pose significant threats to global biodiversity, ecosystem services, and climate change mitigation (Hansen et al., 2013). Anthropogenic disturbances have become the most important factor shaping regional structural variations and the second most influential factor, after climate, in shaping global patterns of forest structure (Li et al., 2023). Tropical forests, particularly in Southeast Asia, continue to exhibit the highest deforestation rates globally, although regions of largely undisturbed rainforest still exist, such as the island of New Guinea (Hansen et al., 2020). While New Guinea's forests are already experiencing progressing deforestation and degradation, these changes occur at a much smaller scale compared to other tropical regions (Hansen et al., 2020).

Indonesian New Guinea (ING) features extensive old-growth forest tracts covering an area of 34.29 million hectares (Mha), which constitutes 83 % of the land area (Gaveau et al., 2021). Although historically not defined as biodiversity hotspot due to low levels of environmental degradation (Myers et al., 2000), New Guinea's high-biodiversity wilderness areas, are gaining increasing recognition as a global priority for conserving biodiversity and addressing climate challenges (Brooks et al., 2006; Jung et al., 2021). The region has recently emerged as a new development frontier in Indonesia, with increasing rates of primary forest conversion (Austin et al., 2017; Gaveau et al., 2021; Sloan et al., 2019). Between 2001 and 2022, ING lost ~1.04 Mha (~ 2.8 %) of its tree cover, which has resulted in ~ 0.8 Gt of CO_2-equivalent emissions (Hansen et al., 2013; Harris et al., 2021). The key drivers of this recent deforestation are forest logging, expansion of oil palm (*Elaeis guineensis*), plantations for pulp and paper, aquaculture, road construction, mining, and forest fires (Austin et al., 2019; Gaveau et al., 2021; Sloan et al., 2019). As developments are still recent and forest loss limited in spatial extent, ING has now reached a crossroads between severe environmental degradation and implementing sustainable development policies (Parsch et al., 2022), such as landscape-scale conservation targets, as outlined in the 2018 Manokwari Declaration (Cámara-Leret et al., 2019; Parsch et al., 2022).

In Papua New Guinea (PNG), the scale of forest conversion to agriculture is considerably higher than in ING (Alamgir et al., 2019; Gamoga et al., 2021; Shearman and Bryan, 2015). Between 2001 and 2022, PNG lost ~1.79 Mha of tree cover, equivalent to a 4.2 % decrease in tree cover since 2000, and released 1.34 Gt of CO_2 equivalents in emissions (Hansen et al., 2013; Harris et al., 2021). In 2015, 35.96 Mha (~78 %) of the country was forested, of which >23 % was degraded through anthropogenic activities (Gamoga et al., 2021). The expansion of subsistence agriculture, oil palm plantations, and commercial logging operations were identified as the main drivers of deforestation by Gamoga et al. (2021). Additionally, infrastructure expansion and mining are emerging drivers of more recent deforestation (Alamgir et al., 2019).

While Southeast Asia's forests have become a net source of carbon emissions due to deforestation, forest fires, and drainage of peat soils, the forests of New Guinea remain a net carbon sink, aiding in the mitigation of climate change (Harris et al., 2021). Still, their integrity is at risk due to ongoing deforestation and forest degradation, driven by the increasing pressure on forests to support economic development and meet global demands for commodities (Austin et al., 2017; Lewis et al., 2015). Given these imminent environmental threats and past lessons from rapid and extensive forest clearing in other parts of the region such as Sumatra and Indonesian Borneo (Kalimantan), it is important to assess how an analogous development could affect New Guinea's forests, including their biodiversity and carbon stocks. In contrast to carbon emissions and fluxes, as assessed by Harris et al. (2021), irrecoverable carbon describes ecosystem carbon stocks, which are manageable, vulnerable to disturbance and cannot be recovered within 30 years (Noon et al., 2022). Irrecoverable carbon thus exemplifies that despite carbon sequestration and management of deforested areas recoverability of carbon stocks, following loss may still leave a deficit in the carbon budget. Therefore, it represents an important measure to advise and evaluate climate change policies to reach net-zero emissions by the middle of this century (Noon et al., 2022). Monitoring deforestation at a global scale in near-real-time is available in the form of remotely sensed forest loss data (Hansen et al., 2016; Hansen et al., 2013; Harris et al., 2017). Spatial analyses based on these remote sensing platforms enable the systematic identification of priority areas such as emerging hotspots of forest loss in need of management interventions and policy enforcement (Harris et al., 2017), as seen in Indonesia's forestry law enforcement efforts (Finer et al., 2018). In addition to monitoring, land-use change models are a powerful approach to advance our understanding of current and future deforestation, changes in land use, and their potential effects on climate and biodiversity.

In this study, we employ an integrated approach combining random forest machine learning with cellular automata forecasting to (1) elucidate and compare the patterns and drivers of deforestation between ING and PNG, (2) delineate areas with a high future deforestation risk under different development scenarios; and (3) evaluate the effects of four deforestation scenarios on potential loss in forest-stored carbon within the study region.

2. Methods

2.1. Study area

New Guinea, the world's largest tropical island (786,000 km^2), is politically divided along the 141°E meridian. The western half belongs to Indonesia, referred to locally as "Tanah Papua," and encompasses approximately 411,000 km^2, including adjacent islands. This region was recently subdivided into six provinces, but for consistency and clarity, we use the term "Indonesian New Guinea" (ING) to refer cohesively to this area throughout the study. The eastern part consists of the country of PNG and covers about 468,000 km^2. New Guinea's extensive tracts of tropical rainforests harbor outstanding biodiversity and endemism, with high structural forest integrity (Cámara-Leret et al., 2020; Orme et al., 2005; Schrader et al., 2024). To compare deforestation drivers and patterns, our analysis looked at ING and PNG separately.

2.2. Machine learning

We derived machine learning models (Fig. S1), which were utilized to compile the transition potentials for cellular automata forecasting. These analyses were conducted using the CAST package version 1.0.0 in R version 4.3.3 (Meyer et al., 2024; R Core Team, 2024). To model forest loss across ING and PNG, we utilized a Landsat derived dataset, which provides annual forest cover loss information at a 30 m × 30 m spatial resolution from 2001 to 2020, within the boundaries of existing tree cover as of the year 2000 (Hansen et al., 2013). The dataset has been validated globally with high accuracy (~90 %) and is well-suited for detecting large-scale deforestation events, which are the focus of this study, though accuracy may vary regionally. While the dataset is well-suited for detecting large-scale deforestation events, which are the focus of this study, more fine scale regional studies should be validated by comparison with independent reference data interpreted from high resolution imagery (e.g. see Egorov et al., 2023). We selected random forests for our predictive model due to the non-linear relationships and spatial autocorrelation often inherent in spatial data. Decision-tree-based models such as random forests are non-parametric and capture complex, non-linear relationships with the response variable and interactions between the predictor variables that are often associated with high-resolution remote sensing data (Belgiu and Drăguţ, 2016; Pal, 2005). The ensemble nature of random forest models allowed us to effectively address these data characteristics as opposed to less complex approaches such as linear regression. The autonomy of each decision tree and the stochastic nature of creating subsets from the input data render random forests robust against outliers, noise, and overfitting while capable of handling large datasets (Chan and Paelinckx, 2008; Gounaridis et al., 2019). Integrating machine learning with cellular automata, as applied here, enhances the ability to capture both spatial heterogeneity and spatiotemporal neighborhood features, leading to significantly improved accuracy in land-use change simulations (Gounaridis et al., 2019; Qian et al., 2020).

2.3. Predictor variable selection and model validation

To select suitable predictors of deforestation, we compiled 19 candidate variables, categorized into five variable groups (Table 1). We implemented a three-stage selection process to identify the best combination of predictors of deforestation separately for ING and PNG. In the first stage, we selected the most important spatial scale for landscape metrics by testing different radii: 100 m, 500 m, 1000 m, 2000 m, and 5000 m. We considered the proportion of deforested neighbors, edge density, and aggregation index using random forests.

In the second stage, we employed forward feature selection (FFS) using random forests to identify the most important predictor variable in each group. The FFS algorithm trains all possible two-variable combinations, then selects the best combination before iteratively increasing the number of variables. The process stops when adding further variables does not improve model performance (Meyer et al., 2018). This variable grouping approach reduced the number of combinations in the subsequent modeling process and thus computation time and resources, while simultaneously accounting for variable correlations and interactions, as similar variables were grouped. In the third stage, we constructed machine learning models with all previously selected variables and applied FFS as implemented by Meyer and Ludwig (2022) to identify the variable combination achieving the highest model performance.

Within each of the two regions, we initially sampled 20 % of all raster cells and balanced the sample ratio of forest and forest loss (1:1; Papua ~3 M cells / PNG ~6.3 M cells) to create a calibration dataset for the random forest models. From this dataset, 70 % of the cells were used for model training, while 30 % were reserved for testing, ensuring that the balanced ratio of forest and forest loss was maintained. Model performance was evaluated using the True Skill Statistic (TSS = Sensitivity + Specificity −1), as this indicator is not dependent on prevalence affecting predictive accuracy, such as the kappa statistic (Table 2) (Allouche et al., 2006). TSS and Kappa values <0 indicate no agreement, values between 0.01 and 0.20 indicate slight agreement, values between 0.21 and 0.40 indicate fair agreement, values between 0.41 and 0.60 indicate moderate agreement, values between 0.61 and 0.80 indicate substantial agreement, and values above 0.80 indicate almost perfect agreement (Allouche et al., 2006; Cohen, 1960). Variable importance for the final model was assessed by measuring the mean decrease in model accuracy if a variable was removed from the model. Besides an independent validation of the machine learning models, we compared the predictions of the resulting machine learning models to observed deforestation. Therefore, we used Cohen's Kappa to determine the probability of occurrence threshold (De'Ath, 2007; Elith et al., 2008; Elith et al., 2006) for predicted deforestation 2020 in ING and PNG to derive binary deforestation prediction maps (i.e., presence or absence of deforestation) and compared these with the observed deforestation map for the year 2020 by Hansen et al. (2013) using confusion matrices (Table 2, Fig. S3). The following cellular automata approach incorporates the predictions of our deforestation models, which are utilized to create transition potential maps.

2.4. Cellular automata

To forecast patterns of deforestation, we built on the SIMLANDER modeling framework (Hewitt et al., 2013; Roodposhti et al., 2019) to develop cellular automata deforestation scenarios. Cellular automata are discrete dynamic process models that uses space, state, time step, neighborhood, and transition rules as key components. The spatial representation involves raster cells that evolve over discrete time steps. These cells change based on a set of transition rules that determine their state and influence the states of neighboring cells (Wolfram, 1983). Therefore, the suitable determination of transition and neighborhood rules is crucial for accurate simulations of dynamic land-use processes in a bottom-up fashion. Cellular Automata (CA) explicitly model spatial dependencies by updating the state of each cell based on the states of its neighbors. This characteristic allows CA to better complement our RF model than other forecasting options, as it incorporates neighborhood

Table 1
Predictor variables used in the analysis.

Variable Group	Variable Name	Rationale	Source
Topography	Digital elevation model	Deforestation risks decrease with elevation	Farr et al. (2007)
	Slope	Deforestation risk decreases with increased slope	Farr et al. (2007)
	Roughness	Deforestation risk decreases with increased roughness	Farr et al. (2007)
	Hierarchical slope position	Deforestation risk decreases with increased slope	Farr et al. (2007)
	Distance to rivers	Deforestation risk is higher near rivers	Pickens et al. (2020)
Governance, People, and Tenure	Protected areas	Deforestation risk is lower in protected areas	UNEP-WCMC (2024)
	Land-use concessions*	Deforestation risk is higher in land-use concessions	Global Forest Watch (2019)
	Population density	Deforestation risk positively correlates with population density	Florczyk et al. (2019)
	Subnational Administrative Boundaries (Districts)	Deforestation risk varies between districts	GADM (2022)
Proximity to Infrastructure	Distance to roads, the planned Trans-Papua highway, and in- and excluding “ghost roads” **	Deforestation risk is higher near roads	Engert et al. (2024), Meijer et al. (2018), Sloan et al. (2019)
	Travel time to ports (in- and excluding “ghost roads”) **	Deforestation risk is higher near ports	Engert et al. (2024), Nelson et al. (2019)
	Travel time to cities	Deforestation risk is higher near cities	Engert et al. (2024), Nelson et al. (2019)
Landscape Structure (Multiscale)	Proportion of deforested neighbors	Deforestation risk is higher near previous loss	Hansen et al. (2013); Hesselbarth et al. (2019)
	Edge density	Deforestation risk is higher in more fragmented areas	Hansen et al. (2013); Hesselbarth et al. (2019)
	Aggregation Index	Deforestation risk is higher in more fragmented areas	Hansen et al. (2013), Hesselbarth et al. (2019)
	Distance to forest edges	Deforestation risk is higher near forest edges	Hansen et al. (2013)
	Distance to recent forest loss	Deforestation risk is higher near recently lost forest	Hansen et al. (2013)
Soil & Environmental Conditions	Aboveground biomass carbon	Deforestation risk correlates positively with aboveground biomass carbon	Spawn et al. (2020)
	Precipitation	Deforestation risk correlates with precipitation	Karger et al. (2017)

[*] Not available for PNG.
[**] We compared model performance with and without including ghost roads to the predictor dataset.

Table 2
Model performance metrics based on independent model validation (based on 30 % of the dataset) and comparison of predicted deforestation 2020 with observed deforestation 2020 maps (Hansen et al., 2013) for Indonesian New Guinea (ING) and Papua New Guinea (PNG).

Evaluation Metric	Independent Validation		Comparison to Observed Deforestation	
Region	ING	PNG	ING	PNG
Kappa threshold	0.49	0.50	0.49	0.52
Accuracy	0.98	0.96	0.99	0.98
Kappa	0.96	0.93	0.49	0.41
Sensitivity	0.97	0.94	0.99	0.98
Specificity	0.99	0.98	0.88	0.95
Balanced Accuracy	0.98	0.96	0.93	0.96
True Skill Statistic	0.96	0.93	0.87	0.93

effects that simulate the spatial contagion of deforestation, as well as dynamic feedback mechanisms, such as changes in accessibility and suitability over time (Liang et al., 2017; Pérez et al., 2015; Rosa et al., 2013). Alternative forecasting methods, such as greedy algorithms, often produce dispersed allocations that may not reflect the contiguous nature of deforestation and therefore tend to overlook the dynamic interactions that drive land use changes, leading to predictions that do not accurately capture the spatial processes involved (da Silva et al., 2021; Rosa et al., 2015).

In our cellular automata model, a predetermined number of cells was designated to be deforested during each time step, strategically allocated to cells exhibiting the highest transition potential based on the derived machine learning model predictions (Fig. S1). The transition potential layers were compiled by incorporating neighborhood rules, accessibility, suitability, and randomness. The neighborhood rules included a weighted matrix of deforested neighboring cells for each focal cell, where weights can be altered for calibration. Accessibility was calculated using a sigmoid function for distance decay from road networks, with a threshold marking the limit of viable timber extraction activities. We incorporated our deforestation risk prediction maps for ING and PNG as the model suitability component, while an element of randomness was introduced through a Weibull distribution function following Roodposhti et al. (2019). We calibrated the cellular automata model for the period 2015–2020, as we assumed that this time frame best represented recent dynamics of deforestation across New Guinea. Neighborhood rules are recognized as the most influential parameters for cellular automata calibration (Roodposhti et al., 2019). Following the automatic rule detection procedure proposed by Roodposhti et al. (2019), we compared 50 neighborhood rules based on 10 different matrices and 5 radii. The best-performing neighborhood rule, when compared to observed deforestation within the same time frame, was selected for forecasting purposes (Table S1 & Table S2). Other parameters for calibration included an accessibility distance decay function, a threshold, and the compilation of the transition potential maps. We evaluated our calibration approaches by comparing deforestation simulations for 2020 against the 2020 reference deforestation layers (Hansen et al., 2013). The True Skill Statistic (TSS) was used to assess model accuracy. With the calibrated cellular automata, we forecasted four scenarios of future deforestation for ING and PNG, respectively (2020–2040). Each scenario incorporated a particular rate of change which represents the level of forest loss we defined over the simulation period.

2.5. Deforestation forecasting

For the development scenarios, we used deforestation rates from the five-year period (2015–2020) to establish a business-as-usual (BAU) scenario. This scenario entailed a linear extrapolation of the observed rates, projecting a deforestation rate of 4.8 % over a span of 20 years. Two intermediate scenarios assumed accelerated forest loss of 10 % and 20 % over the same period. We also formulated a high development scenario that forecasted ~28 % deforestation over 20 years, mirroring the deforestation trends observed in Kalimantan between 2001 and 2020 (Fig. 2). The scenario was based on the raised concerns that New Guinea could follow the deforestation pathways analogous to other major deforestation hotspots in Indonesia (Austin et al., 2017).

2.6. Effect of topography on deforestation

We intersected the forecasted forest loss for the year 2040 with topographical characteristics such as elevation and slope derived from Farr et al. (2007) to characterize the topographic effects on simulated deforestation per region and scenario (Fig. 3, Table 3). We compared the topographical characteristics of forecasted forest loss scenarios with observed losses in Kalimantan from 2001 to 2020 to evaluate the plausibility of forecasted deforestation in New Guinea. To compare the distributions of elevation and predicted deforestation in ING and PNG, as well as past deforestation in Kalimantan, we applied the Kolmogorov–Smirnov test to assess whether the elevation and deforestation profiles were significantly different between the two parts. To account for differences in sample size between the elevation and deforestation datasets, we downsampled the larger dataset (PNG) to match the smaller one (ING) before conducting these tests.

2.7. Carbon loss from deforestation

To assess potential carbon emissions from forest cover loss associated with the respective development scenarios, we assessed irrecoverable carbon content (Noon et al., 2022) for which future forest loss was simulated by our models. Irrecoverable carbon refers to carbon stocks in ecosystems such as forests, peatlands, and wetlands that are vulnerable to be released into the atmosphere upon land conversion. Once lost, these stocks cannot be recovered within timescales relevant to avoiding severe climate impacts (Noon et al., 2022). We considered the carbon content of a given cell as lost once a respective cell was completely deforested in a scenario and calculated its share of the total irrecoverable carbon loss per scenario and region (Table 4).

3. Results

3.1. Predictor selection

The three-step selection process of predictor variables using random forest models revealed that, in the multiscale analysis of landscape metrics, all variables performed best at the scale of a 100-m buffer around the focal cell. The proportion of deforested neighboring cells emerged as the most important variable and represents the impact of fine-scale deforestation within a 100 m buffer radius. The variable grouping stage selected for ING the proportion of deforested neighbors, elevation, travel time to cities, population density, and precipitation. For PNG, the proportion of deforested neighbors, elevation, population density and travel time to ports were selected in the grouping process. These variables were utilized to compile the final machine-learning models during another round of forward feature selection.

Our final models revealed that the variables associated with the drivers of deforestation were comparable across both regions (Fig. 1). The importance of each variable is indicated by the mean decrease in model accuracy if the respective variable was removed. In both regions, the proportion of deforested neighbors emerged as the most significant predictor of future deforestation (Fig. S2). For both regions, deforestation increased with the proportion of deforested neighbors (Fig. 1), while nonlinear responses to the other environmental and socioeconomic factors, such as elevation, population density, travel time to cities or ports, and precipitation, highlighted complex interactions influencing deforestation (Fig. 1). For ING, elevation was the second most important variable.

Deforestation was predicted to predominantly occur at lower elevations. Areas with higher rainfall, higher human population densities, and better accessibility were found to be at increased risk of deforestation in ING. In PNG, population density and elevation both reduced model accuracy by an average of 8 %, highlighting their equal importance in predicting deforestation. Areas with more human activity were more susceptible to forest conversion. Deforestation also predominantly occurred at lower altitudes in PNG, while deforestation risk was higher in areas closer to ports.

3.2. Model performance

Overall, we observed similar patterns and performance in likelihood of deforestation from independent validation and when comparing with observed deforestation. Model power and accuracy were high (all TSS $\geq$ 0.6, Kappa >0.4 Table 2) for both ING and PNG. The models exhibited high sensitivity, specificity, and balanced accuracy, both in independent validation and when compared to observed deforestation between 2001 and 2020. Incorporating ghost roads in the analysis improved TSS in the independent validation from 0.94 to 0.96 for ING and from 0.89 to 0.93 for PNG. Compared to observed deforestation, TSS improved from 0.82 to 0.87 for ING and from 0.71 to 0.93 for PNG when ghost roads were included in the analysis.

3.3. Cellular automata calibration and forecasting

The high importance of deforested neighboring cells further supported the use of cellular automata for deforestation forecasting (Roodposhti et al., 2019). Compared to standard parameters utilized by SIMLANDER, TSS values were improved by calibrating the neighborhood influence in our cellular automata models following an automatic rule detection approach (Roodposhti et al., 2019). Out of 50 trials per region, the best calibration of neighborhood dynamics according to the highest TSS was selected (matrix 1; radius 1). The calibration results demonstrate substantial agreement with the observed deforestation

Table 3
Comparative analysis of elevation (m a.s.l.) and slope statistics for forecasted deforestation scenarios. ING = Indonesian New Guinea, PNG = Papua New Guinea.

Region	Scenario	Q1	Q3	Median	Mean	SD	CV	Prop. [%] <500 m	Prop. [%] <10°
	4.8 % (BAU scenario)	36	356	78	387	630	163	79	69
	10 %	31	383	75	437	734	168	79	69
ING	20 %	31	368	77	436	751	172	79	69
	28 % (Kalimantan scenario)	32	368	78	431	745	173	79	68
	Topography of ING	27	494	96	468	781	167	90	64
PNG	4.8 % (BAU scenario)	51	482	148	394	532	135	75	61
	10 %	47	603	154	443	591	133	72	59
	20 %	49	700	167	509	686	135	70	58
	28 % (Kalimantan scenario)	51	751	176	534	711	133	69	57
	Topography of PNG	45	979	214	621	791	127	63	60
Kalimantan	Deforestation in Kalimantan 2001–2020	20	170	82	170	282	167	63	99.9
	Topography of Kalimantan	55	285	109	228	288	127	85	98.7

Table 4
Loss of irrecoverable carbon (IC) for Indonesian New Guinea (ING) and Papua New Guinea (PNG) under the four deforestation scenarios from 2020 to 2040. IC Lost refers to the total stock of IC lost due to deforestation. Net IC loss refers to the proportion of total IC stock lost. Forest loss is the forest area lost due to deforestation.

Scenario	ING			PNG		
	IC Lost [Mt]	Net IC Loss [%]	Forest Loss [Mha]	IC Lost [Mt]	Net IC Loss [%]	Forest Loss [Mha]
4.8 % (BAU)	156	4.03	2.62	223	5.76	3.90
10 %	318	8.20	4.57	382	9.57	6.29
20 %	648	16.74	8.34	762	19.06	10.88
28 % (Kalimantan)	918	23.68	11.35	1082	27.07	14.55

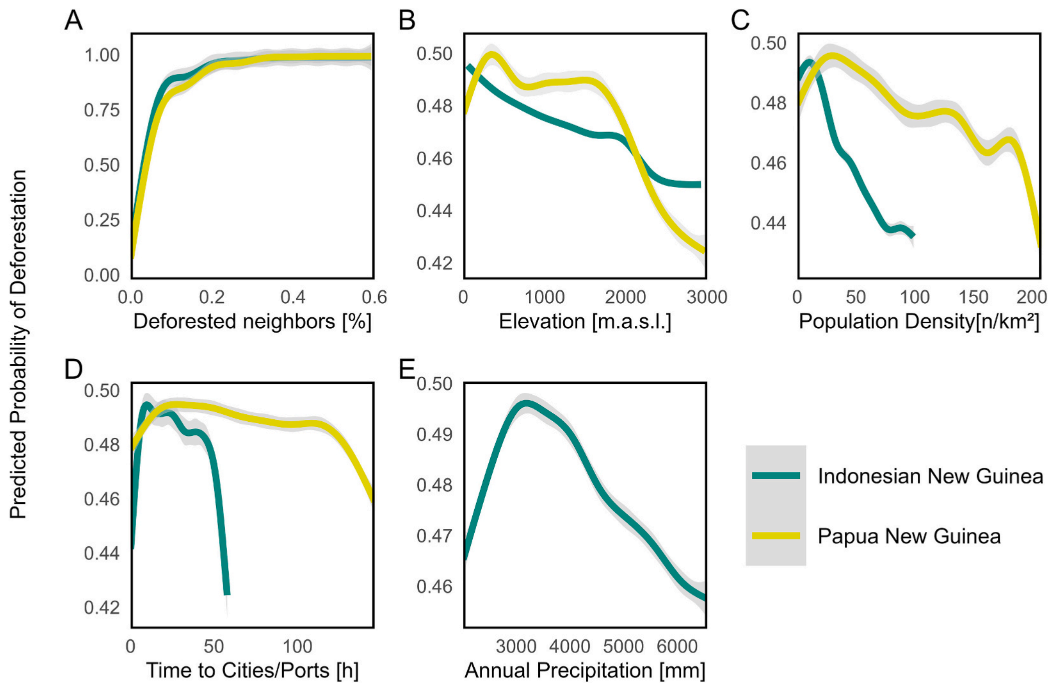

Fig. 1. Partial dependence plots for the selected variables of the final machine-learning models for Indonesian New Guinea (green) and Papua New Guinea (yellow).

between 2015 and 2020 (max. TSS 0.64 for ING, 0.65 for PNG, Table S1 & Table S2).

3.4. Scenario results forecasting deforestation 2020–2040

The area converted in each deforestation scenario ranged from ~26,158 km^2 for ING with a forest conversion rate of 4.8 % over 20 years ("BAU scenario") to 113,570 km^2 under the pessimistic "Kalimantan scenario" (Fig. 2). In PNG, the BAU scenario resulted in the clearance of ~39,004 km^2 of forest, while the Kalimantan scenario resulted in 145,444 km^2 of forest loss. Our deforestation scenarios identified potential future deforestation hotspots, encompassing regions such as Manokwari, Sorong, the southern Vogelkop lowlands, the Bomberay Peninsula, Nabire, Wamena, and Jayapura. Also, the Boven Digoel and Merauke Regencies in ING had a high deforestation risk across scenarios. In PNG, forecasting highlighted the Western and East Sepik Provinces, Madang, the Gulf Province, and the Kamula Doso rainforest in the Western Province as well as East New Britain and West New Britain as susceptible to future deforestation (Fig. 2, Fig. 4).

3.5. Changes in forecasted deforestation risk with elevation

Patterns of deforestation across all scenarios exhibited a marked tendency for deforestation to occur in lowland areas (Fig. 3, Table 3). In ING, 79 % of modeled deforestation occurred below 500 m a.s.l. above sea level, while in PNG 68 % of deforested raster cells were located below 500 m a.s.l. (Table 3). Higher forecasted deforestation risk was evident in the lowlands of ING, where the median of deforested cells ranged from 28 to 78 m a.s.l. across the four scenarios in comparison with a median elevation of 96 m a.s.l. A similar pattern was observed in PNG; however, PNG has relatively less lowland area below 500 m a.s.l. (63 %) compared to ING (90 %), which is also reflected in the higher median and mean elevation values of forecasted deforestation (Table 3). Although most forecasted deforestation is predicted to occur in lowlands, it is notable that lowlands experienced lower-than-expected deforestation, while mid-elevations (500–1500 m) showed relatively higher levels in predicted or observed deforestation across all scenarios and regions (Table 4a). In PNG, scenarios with higher deforestation rates resulted in the expansion of forecasted deforestation to higher elevations from a median of 148 m a.s.l. Higher forecasted deforestation risk was evident in the lowlands of ING, where the median of deforested cells ranged from 28 to 78 m a.s.l. across the four scenarios in comparison with a median elevation of 96 to 214 m a.s.l. in the BAU scenario. Higher forecasted deforestation risk was evident in the lowlands of ING, where the median of deforested cells ranged from 28 to 78 m a.s.l. across the four scenarios in comparison with a median elevation of 96 m a.s.l. in the Kalimantan scenario. This relationship was not evident in ING, where the median elevation of forecasted deforestation remained constant throughout the scenarios. Historic forest loss between 2001 and 2020 in Kalimantan exhibited similar elevation patterns to ING, with 63 % of deforested cells occurring below 500 m a.s.l., with a median of 82 m a.s.l. Higher forecasted deforestation risk was evident in the lowlands

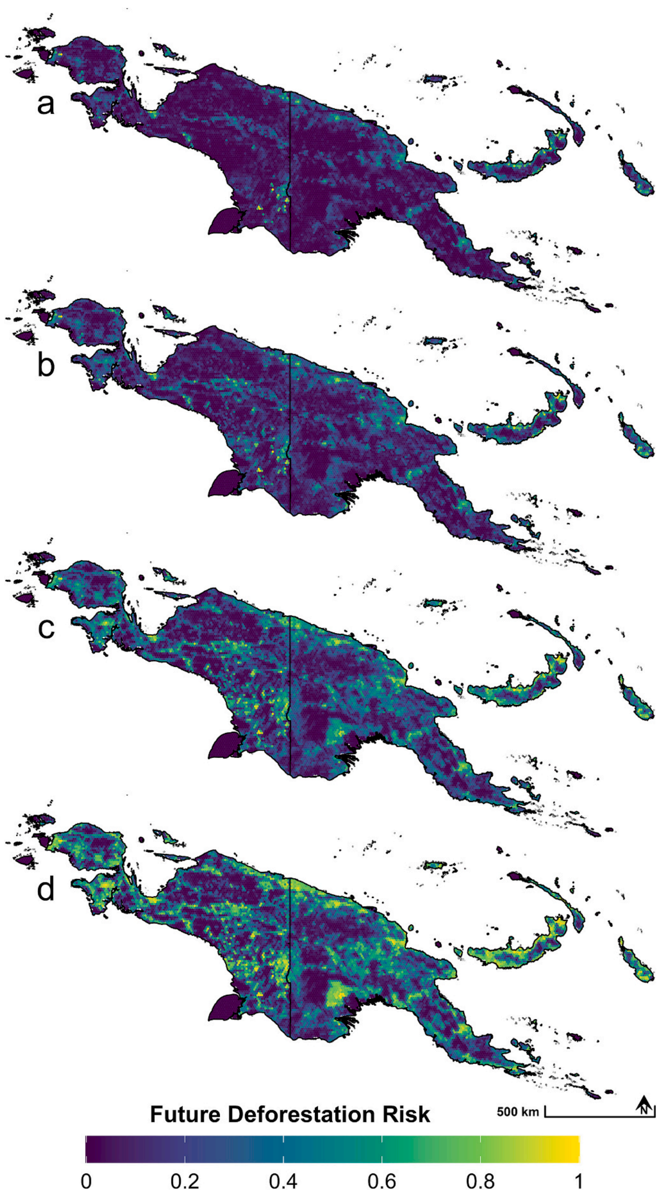

Fig. 2. Cellular automata forecasting for four future deforestation scenarios (a) 4.8 % (BAU), (b) 10 %, (c) 20 %, and (d) 28 % (Kalimantan scenario) for New Guinea between 2020 and 2040. Cell values show the proportion of deforested 30 m × 30 m raster cells per 10 km × 10 km hexagonal grid cell.

of ING, where the median of deforested cells ranged from 28 to 78 m a.s.l. across the four scenarios in comparison with a median elevation of 96 m a.s.l. (Fig. 3). When comparing slope characteristics, historical forest loss in Kalimantan had 99 % deforestation in slopes below 10°, while the forecasted deforestation on flat slopes in ING and PNG was approximately 69 % and 60 %, respectively (Fig. 3).

Kolmogorov–Smirnov tests revealed statistically significant differences between the distributions of elevation and deforestation across all three regions. In ING ($D = 0.0519$, $p < 0.0001$) and PNG ($D = 0.0646$, $p < 0.0001$), the differences between elevation and deforestation distributions were moderate. In contrast, Kalimantan exhibited a larger difference ($D = 0.2462$, $p < 0.0001$), indicating a more pronounced divergence between elevation and deforestation patterns in this region.

3.6. Deforestation effects on carbon emissions

For ING, the loss of carbon associated with forecasted deforestation ranged between 156 and 918 Mt, depending on the scenario (Table 4). For PNG, the range extended from 223 to 1082 Mt of carbon lost. In all four ING scenarios, the forest carbon loss was proportional to the rate of forest conversion.

Fig. 4 highlights key regions where irrecoverable carbon and forecasted deforestation under the Kalimantan scenario (Fig. 2d) coincide. Areas of high congruence in ING include the southern lowlands north of Merauke, the lowlands of the Bird's Head Peninsula east of Sorong, and the Bomberai Peninsula. In PNG, areas with high irrecoverable carbon and future deforestation risk, inter alia, extend along the northern coast, the southern highlands, and on New Britain.

4. Discussion

4.1. Overview of deforestation scenarios

In this study, we simulated a spectrum of deforestation scenarios to assess future deforestation and identify potential deforestation hotspots across New Guinea. Our primary objectives were to identify patterns and predictors of deforestation, highlight areas at high risk under different land-use scenarios, and estimate potential carbon losses linked to these scenarios. While emerging deforestation hotspots have previously been described for ING (Gaveau et al., 2021) and PNG (Alamgir et al., 2019; Shearman and Bryan, 2015), this study represents the first application of a consistent methodological framework to model current and future deforestation scenarios across the island of New Guinea based on high-resolution remote sensing data. Our modeling approach enables the comparison of patterns, deforestation hotspots, and their attributes while accounting for region-specific drivers of deforestation. The delineation of geographical context in deforestation modeling is essential, as regions may have distinct drivers and conditions affecting deforestation patterns (Brown et al., 2013). Our spatially confined models here resulted in more accurate spatial predictions and enabled a more tailored assessment of policy implications. In contrast, studies encompassing broader scales (e.g., the entire Indonesian archipelago) often lack the granularity necessary to accurately model land-use change within specific subregions of a study area (e.g. see Brun et al., 2015; Lim et al., 2019).

4.2. Model performance and drivers of deforestation

The integration of machine learning and cellular automata offer a robust methodological approach for predicting future deforestation over large geographical scales, such as the entire island of New Guinea, combining the strengths of both approaches. All models performed well, with model evaluation indicating strong agreement in independent validation and when compared to observed deforestation according to Hansen et al. (2013). The most important predictors of forest loss across New Guinea were associated with measures of past forest conversion and human modification (i.e., land-use change, population density, roads), highlighting that forest loss is spatially clustered and expands over time into areas subject to anthropogenic pressures and development. Globally, increasing human populations, road density, and agricultural land use are positively correlated with greater human modification, which in turn is associated with the loss of wilderness areas, higher degradation of forest structure, and biodiversity loss (Kennedy et al., 2019; Li et al., 2023; Venter et al., 2016).

Across New Guinea, the proportion of deforested neighboring cells, elevation, and accessibility were the most important predictors of forest loss, shaping deforestation and thus highlighting the importance of these factors in constraining human modification. These findings align with Cushman et al. (2017), who reported that patterns of forest loss risk in Kalimantan were primarily driven by elevation and distance to the edge of previous forest loss. Similarly, Li et al. (2023) observed that forest height, density, and structural complexity in Borneo were positively influenced by slope and elevation, indicating that such areas are less

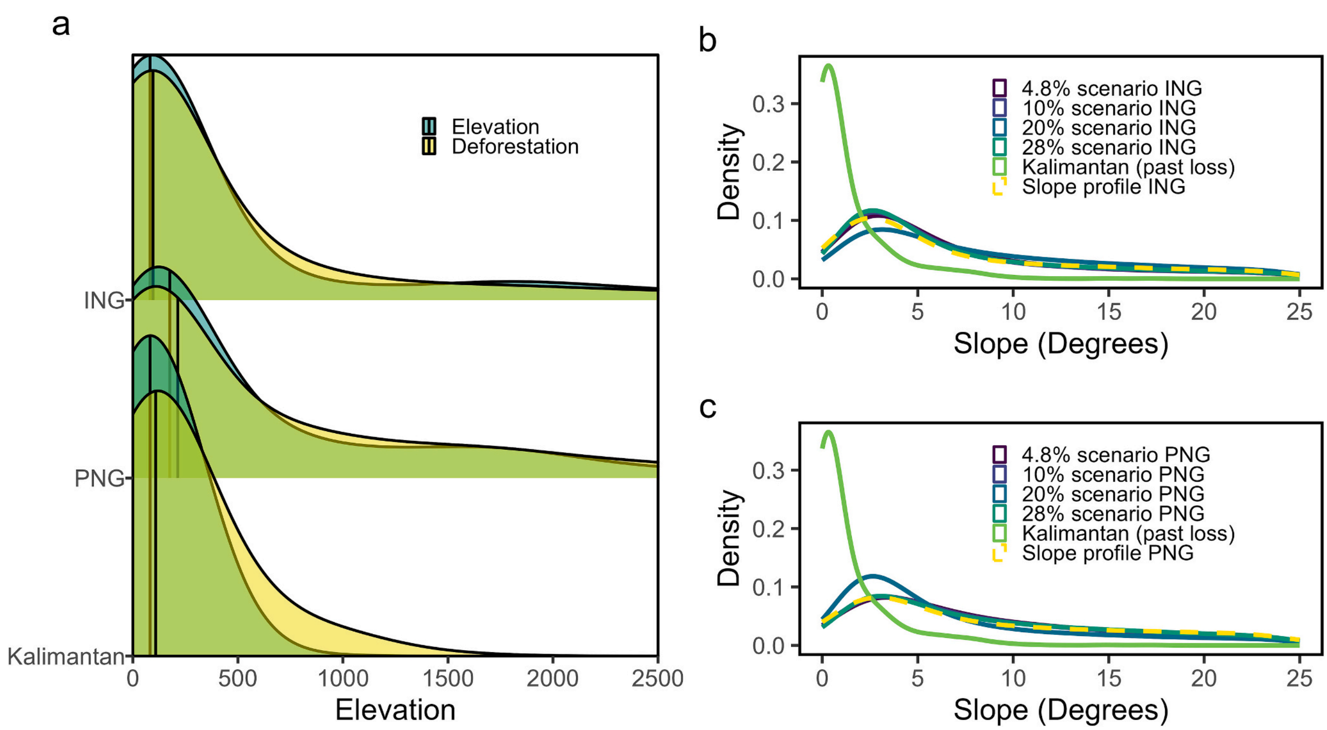

Fig. 3. (a) Elevation profiles and elevation of projected forest loss for Indonesian New Guinea (ING) and Papua New Guinea (PNG) under the 28 % deforestation scenario 2020–2040 and historical deforestation in Kalimantan, Indonesia 2000–2020 (<2500 m a.s.l.). (b–c) Slope profiles of historical deforestation in Kalimantan (2001−2020) and Simlander forecast scenarios for Indonesian New Guinea and Papua New Guinea capped at 25°.

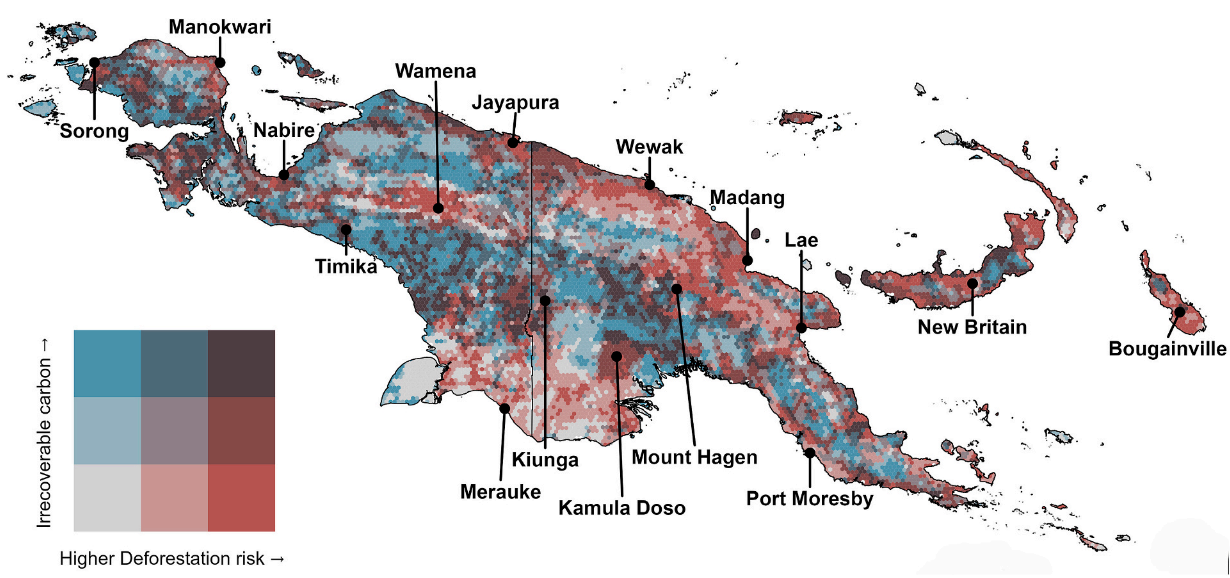

Fig. 4. Bivariate map of irrecoverable carbon content and deforestation risk across New Guinea (Kalimantan scenario) per 10 km x10 km hexagonal grid cell. Class breaks were calculated using Fisher breaks.

likely to experience forest loss and degradation. We identified that accessibility plays a key role as a predictor for deforestation across New Guinea. In tropical forests, accessibility is a major driver of deforestation, as roads provide access to forested regions for exploitation (Laurance et al., 2009). Besides mapped road networks, we utilized a novel dataset of previously unmapped "ghost roads" (Engert et al., 2024), which significantly improved model performance and the accuracy of our predictions. This result is important as ghost roads are often constructed and utilized for logging, mining, and agricultural development. Most previous studies used incomplete road data, and hence likely underestimate the importance of roads as a driver of deforestation (Engert et al., 2024).

While machine-learning models are conceptually robust to predict land-use change, predictive accuracy depends on the availability of spatially explicit information about drivers of these changes for model calibration. Land change trends and their driving factors may be subject to change over time and under varying socioeconomic and political environments (Brown et al., 2013). To account for dynamic predictors, we considered concepts such as area partitioning and spatiotemporal convolution for dynamic land-use change simulation (Qian et al., 2020).

However, these approaches were not feasible given the large spatial scale and grid size of this analysis. To address an uncertainty in conversion rates, we assessed a range of development scenarios. While our models aim to predict future deforestation, we were constrained by static socioeconomic data such as current road locations and population density. As development and land conversion potentially increase under national goals aimed at economic development in New Guinea, the extent of road networks and accessibility of previously remote regions may expand rapidly (Alamgir et al., 2017). Therefore, our model results likely present conservative estimates, particularly considering recent large-scale agricultural forest conversions, termed the "World's biggest deforestation project" (Jong, 2024) in the southern New Guinea. Future research should further advance considerations of economic and infrastructure development, potentially indicating increased deforestation in lowland areas not yet connected by existing roads.

4.3. Hotspots of deforestation

Our identified deforestation hotspots show considerable overlap with previous studies on forest loss in ING (Gaveau et al., 2021; Sloan et al., 2019) and PNG (Alamgir et al., 2019), indicating that these are at high risk of forest loss (Fig. 4). Lowland regions were identified as particularly vulnerable to future forest loss, with concentrations of deforestation forecasted around populated areas. Major deforestation hotspots are likely to develop in the southern Vogelkop lowlands, the southeast of Papua in the Merauke Regency and around Jayapura in ING. Interestingly, the probability of forest loss mapped by (Gaveau et al., 2021) was more clustered around these areas where current development has already progressed, while our compiled deforestation scenarios predicted more scattered patterns of deforestation along major planned and existing ghost roads, which are not explicitly limited to the proximity to major cities. For PNG, no nationwide deforestation modeling approach is currently available, but a descriptive analysis focused on new road development projects and resulted in coarse-scale deforestation frontiers (Alamgir et al., 2019). These frontiers align with and thus support our identified deforestation hotspots. Here, we present the first comprehensive deforestation risk mapping across PNG, identifying major forecasted deforestation hotspots in the lowlands of the Western and East Sepik Provinces, Madang and the Gulf Province. The Kamula Doso rainforest in the Western Province, however, is likely the most prominent identified area of high deforestation risk in PNG (Fig. 2), where indeed a complex conflict between logging companies and ambitions for forest carbon projects persists (Filer et al., 2023).

4.4. Elevation

The elevation and slope profiles of our modeled deforestation scenarios (Fig. 3) illustrate how a significant portion of land in ING and PNG consists of higher elevations and steeper, i.e., more rugged terrain compared to Kalimantan. Despite these challenging topographies, concentrated clearings in New Guinea's lowland forests continue, leading to habitat fragmentation that poses significant risks to biodiversity, landscape connectivity, and ecosystem services. These impacts contribute to increased soil erosion and higher carbon emissions (Fahrig et al., 2019; Metzger et al., 2021). While the majority of deforestation was forecasted below 500 m, the cellular automata model also selected considerably steeper slopes in ING and PNG compared to historical deforestation in Kalimantan. This was likely driven by the absence of otherwise "suitable" areas, with high transition potential for expanding deforestation in flat or lowland regions once most nearby areas were classified as deforested, and was especially apparent in the high deforestation scenarios (see Figure 3, Table 4). As the aim of the cellular automata model is to meet the rate of deforestation set by the user, it can simulate deforestation in areas that may be unlikely to experience deforestation. Thus, it is questionable whether ING and PNG may experience deforestation dynamics, as seen in Kalimantan, given the contrasting topographies. Overall, the more challenging terrain in New Guinea will likely constrain the accessibility for large-scale deforestation.

4.5. Carbon

We identified areas with a high deforestation risk and their overlap with high irrecoverable carbon stocks, which are relevant for climate change mitigation (Fig. 4). Our deforestation scenarios suggest that ING could lose 156–918 Mt. and PNG 223–1082 Mt of irrecoverable carbon between 2020 and 2040. These potential losses represent a substantial portion of Indonesia's and PNG's annual greenhouse gas emissions, with Indonesia emitting approximately 1200 Mt and PNG around 10 Mt in 2023 (European Commission: Joint Research Centre et al., 2024). Future forest loss bears implications for both countries in light of their net-zero carbon commitments under the Paris Agreement. However, it is important to note that our estimates only reflect the loss of irreplaceable carbon (Noon et al., 2022), while total greenhouse gas emissions (Harris et al., 2021) from the respective scenarios would be significantly higher.

4.6. Policy implications

Our findings are highly relevant for regional planning, identifying the region's most susceptible to deforestation across New Guinea. Areas with a high risk of future deforestation across scenarios should be in the focus of regional planning, especially in the light of regional sustainability and conservation targets. The 2018 Manokwari Declaration pledged to safeguard 70 % of ING's land area, underscoring a regional commitment to fostering sustainable development (Cámara-Leret et al., 2019; Parsch et al., 2022).

However, land formalization of customary land for large scale agricultural developments is a shared pressing topic (Hambloch, 2022; Sopaheluwakan et al., 2023) and national development agendas, including infrastructural and agricultural expansion projects, seem to diverge from this path in both ING and PNG (Alamgir et al., 2019; Sloan et al., 2019). Development projects such as the Merauke Integrated Food and Energy Estate (MIFEE), referred to as the "World's biggest deforestation project", pose devastating social and ecological impacts (Ito et al., 2014; Jong, 2024). The recent subdivision of ING from two into six provinces may further complicate coordinated efforts for sustainable development in the region and should be subject of future research. The highest forecasted deforestation risk was evident in the lowland forests of ING (Fig. 3), where only 10 % of land below 500 m a.s.l. falls currently within protected areas (Parsch et al., 2022). Given the constraints imposed by limited resources for the management of protected areas (Sheil et al., 2015), governance should focus on limiting the ongoing large-scale conversion of lowland rainforests while including customary land rights and development opportunities of Indigenous communities. Planned road developments should be reevaluated for their impacts on landscape connectivity, as our findings reinforce previously documented environmental concerns regarding road infrastructure projects in the region (Alamgir et al., 2019; Gaveau et al., 2021; Sloan et al., 2019). In early 2024, PNG passed the Protected Areas Act to safeguard 30 % of its territories by 2030, reflecting the countries' commitment to biodiversity conservation. While the act has been praised for establishing a legal framework to preserve PNG's ecosystems, concerns persist about its implementation, particularly regarding collaboration with customary landowners and securing sustainable funding (Raman, 2024). As vast areas of New Guinea's forests are still in a pristine state, the region provides a unique window of opportunity for proactive conservation prioritization that designs human-modified landscapes for the benefit of humans and nature.

4.7. Conclusion

The future trajectory of deforestation across New Guinea remains uncertain. However, numerous indicators suggest that ongoing deforestation and environmental degradation occur and may potentially accelerate. Our models consistently identified lowland areas as particularly vulnerable across all development scenarios. These prospects highlight the need for systematic, proactive conservation planning to mitigate the effects of land-use change. Such an approach should promote sustainable development, preserve biodiversity, and safeguard New Guinea's unique ecosystems in line with global climate commitments.

CRediT authorship contribution statement

Christoph Parsch: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Benjamin Wagner:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Jayden E. Engert:** Writing – review & editing, Data curation. **Rawati Panjaitan:** Writing – review & editing, Writing – original draft. **William F. Laurance:** Writing – review & editing, Data curation. **Craig R. Nitschke:** Writing – review & editing, Methodology, Conceptualization. **Holger Kreft:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization.

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.

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Supplementary material

Supplementary material to this article can be found online at https://doi.org/10.1016/j.scitotenv.2025.178864.

Data availability

Spatial layers presented in this study are available for download from the repository [doi:10.25625/BELHTK].

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