Identifying deforestation and defaunation fronts in Indonesia's tropical forests

Author list

Dave J.I. Seaman[1], Maria Voigt[1,2], Nicolas J. Deere[1], Nurul L Winarni[3], Sonny Mumbunan[3,4], Jatna Supriatna[3], Matthew J. Struebig[1]

Institutional affiliations

1. Durrell Institute of Conservation and Ecology, School of Natural Sciences, University of Kent, Canterbury, UK
2. Global Science, The Nature Conservancy, Berlin, Germany
3. Department of Biology, Faculty of Mathematics and Natural Sciences, Universitas Indonesia, Depok, Indonesia
4. Master of Public Policy in Climate Change, Faculty of Social Sciences, Indonesian International Islamic University, Depok, Indonesia

Contact Information

Dave J. I. Seaman – Durrell Institute of Conservation and Ecology, School of Natural Sciences, University of Kent, Canterbury, Kent, UK. CT2 7NR

Email – d.j.i.seaman@kent.ac.uk

Abstract

Tropical forests are central to global climate regulation and biodiversity conservation, yet continue to face intense pressure from agricultural expansion, resource extraction, and infrastructure development. Indonesia contains some of the world's largest remaining tropical forests and exceptionally high vertebrate diversity, but its islands differ widely in both historic forest loss and emerging development pressures. Here, we develop a spatially explicit, probabilistic modelling framework to map past forest-cover change (1990–2020) and project forecast deforestation risk to 2055 across Indonesia's seven major island groups. We integrated these deforestation projections with species-specific Areas of Habitat for >3,000 terrestrial vertebrates to quantify spatial overlap between future forest loss and three biodiversity variables: species richness, range-size rarity, and extinction vulnerability. Model validation showed high predictive accuracy across all regions (92–98% pixel agreement), with deforestation strongly influenced by past forest loss, fire occurrence, peatland extent, and proximity to roads and plantations. Projections suggest continued but regionally uneven forest loss, with the greatest future declines expected in Sumatra, Java–Bali, and lowland Kalimantan, while Maluku and Papua are likely to retain most of their forest cover. Biodiversity–deforestation overlaps reveal acute defaunation fronts in northern Sumatra and western and central Kalimantan, where high vertebrate richness and extinction vulnerability coincide with intense projected forest loss. In contrast, the eastern archipelago contains large intact areas with high concentrations of range-restricted species but low deforestation risk, identifying proactive conservation priorities. Together, these findings highlight the urgent need for regionally differentiated strategies that curb biodiversity loss in active deforestation frontiers while safeguarding the globally significant intact forests of eastern Indonesia.

1 Introduction

Tropical forests play pivotal roles in regulating climate, sustaining hydrological cycles, and providing essential ecosystem services for human wellbeing (Barlow et al., 2018; Ellison et al., 2017). They store vast amounts of carbon, buffer against extreme weather events, and support livelihoods for hundreds of millions of people, while delivering broader climatic and cultural benefits to many more (Jagger et al., 2022; Mitchard, 2018). While substantial progress has been made through national reforms, international agreements and zero-deforestation pledges, forest loss persists, reflecting persistent pressures from agriculture, resource extraction, and infrastructure expansion (Carr et al., 2023; Giljum et al., 2022; Pendrill et al., 2022).

Tropical forests are also the foundation of global biodiversity, supporting more than half of the world's terrestrial vertebrates and sustaining vital ecological processes (Barlow et al., 2018; Pillay et al., 2022). This biodiversity contributes functional interactions and energy flows that drive ecosystem stability, the disruption of which can cascade through ecological networks and compromise key forest processes (Malhi et al., 2022; Marsh et al., 2025). The continued loss of these forests therefore threatens not only climate stability and livelihoods but also the persistence of species and ecosystem integrity. Recognising these intertwined crises, the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES, 2019) and the Kunming–Montreal Global Biodiversity Framework (Convention on Biological Diversity, 2022) call for urgent action to halt biodiversity loss and restore ecosystem resilience. Achieving these goals requires a better understanding of where deforestation pressures are likely to overlap with concentrations of biodiversity, enabling conservation and policy responses to prioritise the most vulnerable regions.

Southeast Asia exemplifies the intertwined challenges of tropical deforestation and biodiversity loss, with Indonesia, home to the region's largest remaining forests and globally significant species, playing a pivotal role in shaping both regional and global environmental outcomes (Struebig et al., 2025). Spanning three major biogeographic realms and roughly 44% of Southeast Asia's land area, Indonesia's forests range from lowland dipterocarp and peat swamp forests to mangroves and montane rainforests, supporting exceptional levels of endemism and globally important carbon stocks (Koh et al., 2021; Raven et al., 2020; Struebig et al., 2022). Over recent decades, rapid economic growth and global demand for commodities such as timber, palm oil, and minerals have driven forest conversion, habitat fragmentation, and peatland degradation (Austin et al., 2019; Sasmito et al., 2025; Voigt et al., 2021). While these changes have contributed to national development and poverty alleviation in some regions, they have also resulted in substantial ecological impacts and uneven social outcomes (Santika et al., 2021). Recent governance reforms, including moratoria on new concessions in primary forests and peatlands, alongside greater corporate sustainability commitments, have slowed deforestation in certain areas, yet pressures persist due to the scale of agricultural expansion, infrastructure development, and enforcement challenges (Lyons-White et al., 2025). Crucially, much of Indonesia's remaining forest overlaps with concentrations of threatened and range-restricted species, meaning that future forest loss is likely to have disproportionate consequences for global biodiversity and climate regulation. Understanding where and how deforestation is most likely to occur is therefore essential for guiding conservation, policy interventions, and sustainable land-use planning.

Here, we apply a dynamic, probabilistic modelling framework to project future deforestation across Indonesia's major islands, integrating three decades of observed forest change (1990–2020) with environmental, socio-economic, and infrastructural predictors. We then combine these projections with spatial data on terrestrial vertebrate distributions to identify where emerging deforestation fronts are most likely to overlap with areas of high species richness, range-size rarity, and extinction vulnerability. This integrated approach provides a spatially explicit foundation for mapping "defaunation fronts" and guiding conservation and policy strategies to safeguard Indonesia's forests and biodiversity under accelerating global change.

2 Materials and methods

2.1 Study area and spatial extent

Our analysis encompasses all major islands of Indonesia, modelled independently as seven sub-regions: Sumatra, Kalimantan, Papua, Sulawesi, Maluku, Nusa Tenggara, and Java-Bali. With a few exceptions, such as savannahs and grasslands, the Indonesian archipelago was once almost entirely forested, comprising lowland dipterocarp, hill and montane rainforests, as well as peat swamps, mangroves and seasonal dry forests. These ecosystems have experienced deforestation over the past two centuries due to a combination of human and environmental pressures, though the extent and pace of forest loss varied substantially among islands (Gaveau et al., 2019).

We assessed forest-cover dynamics from 1990 to the present and forecast future changes to 2055. This temporal window captures key phases in Indonesia's land-use history: the rapid expansion of industrial forestry from the 1970s to 1990s, large-scale agricultural development during the 1990s and 2000s, and continuing deforestation linked to global commodity demand and infrastructural expansion in recent decades (Gaveau et al., 2016, 2019; Santoro et al., 2025).

2.2 Forest cover data and explanatory variables

We used spatial data on the extent of closed evergreen or semi-evergreen humid tropical forest from the European Commission's Joint Research Centre *Tropical Moist Forest Annual Forest Change* collection from 1990 to 2020 (Vancutsem et al., 2021). In this dataset, a forest is classified as 'undisturbed' if no detectable deforestation or degradation has been detected over three decades of Landsat observations, although this category may include older secondary forests predating the satellite record. Forest is classified as 'degraded' if it has experienced disturbance, for example via logging, fire, or storms, with regrowth within 2.5 years. Deforestation refers to the long-term loss of forest cover where no regrowth is observed for at least three years. We treated deforestation as predominantly anthropogenic, as most fire-related forest loss in Indonesia occurs in already degraded areas. For undisturbed and degraded tropical moist forest, we calculated total forest extent, percentage of land forested, and the deforestation rate at five-year intervals from 1990 to 2020.

To investigate potential drivers of forest loss, we selected covariates known or hypothesised to influence forest-cover change in tropical regions (Table 1; Supporting Information) (Austin et al., 2019). These included biophysical, infrastructural, and socio-economic predictors such as slope, elevation, fire frequency, proximity to roads and settlements, distance to previous deforestation, land-use concessions, and protection status. Most predictors were treated as static because they are either unlikely to change substantially over the study period (e.g. slope, elevation) or due to data limitations. Fire frequency, derived from MODIS fire occurrence data (Giglio et al., 2016), was treated as a dynamic variable representing long-term fire risk and land-use pressure based on an 18-years composite record. Distance to previous deforestation was also dynamic, updated sequentially between training and calibration periods and at each 5-year prediction interval.

All spatial data layers were reprojected to the Asia South Albers Equal Area Conic projection and resampled to a common resolution of 180 × 180 m, ensuring consistency across datasets. Bilinear interpolation was applied to continuous variables, while categorical variables were resampled using nearest-neighbour methods.

Table 1 | Predictors used in the deforestation models, along with their descriptions, data sources, and reference years.

Name	Description	Source	Year
Forest cover and loss	Forest cover and deforestation prior to the calibration period (1991–2015) and during the calibration period (2016–2020).	Vancutsem et al (2021)	1990, 1991-2015, 2016-2020
Slope	Slope in 2000 derived from the SRTM digital elevation model (30 m)	Farr et al., (2007)	2000

Fire activity	The mean annual count of active fires detected by the Moderate Resolution Imaging Spectroradiometer (MODIS), used as a proxy for fire susceptibility and agricultural activity.	MODIS Collection 6 NRT (2020)	2000–2020
Accessibility	Accessibility from settlements, accounting for road networks, terrain slope, and land cover type (Weiss *et al* 2018, Deere *et al* 2020)	Populated places (World Resources Insitute (WRI)), Landcover (Ministry of Environment and Forestry, Republic Indonesia 2013), Roads (WRI), Slope (Farr *et al* 2007)	1990–2011
Human population pressure	Local population pressure	Described in Rose et al (2018)	1990–2017
Main commodity	Distance to an Indonesian village (Desa), representing human settlements and adjacent lands mapped by the Indonesian Bureau of Statistics, that derives income from staple crop farming, plantation agriculture, non-agricultural sectors, or fisheries.	Indonesian Bureau of Statistics (2018)	2014
Transmigrant settlements	Distance to settlements with an ethnic majority from outside of each modelled region	Indonesian Bureau of Statistics (2011), Indonesian Ministry of Environment and Forestry (2013)	2011
Mining	Mining concession status, distinguishing areas designated for exploration or production from those without concessions, which served as the reference category.	WRI	2017

Land-use	Non-forest areas (APL), production forests (HP, HPK), and limited production forests (HPT). Protected forests (CA, HSAW, KSPA, SM, TN, TAHURA, TNL, TWA, TWA/HW, TWAL, TB) as reference areas	Ministry of Forestry (2010)	2010

2.3 Deforestation modelling framework

We applied a dynamic, spatially explicit forest cover change model originally developed by Rosa et al. (2013) and later adapted for Southeast Asia by (Voigt et al., 2022, 2021). The model is data-driven and probabilistic, and unlike deterministic models it explicitly accounts for uncertainty, spatial emergence and contagion effects in deforestation processes. It integrates past deforestation patterns, spatial autocorrelation of deforested areas, and multiple predictor variables to estimate both the rate and spatial distribution of future forest loss based on historical patterns and latent stochastic processes (Rosa et al. 2013).

The modelling was aggregated to the national scale, but conducted separately for each sub-region of the archipelago to allow for regional calibration and computational efficiency. Although this framework has previously been applied to subsets of Indonesia (Voigt et al., 2022, 2021), we re-modelled all regions using a consistent forest-cover dataset and harmonised predictor variables to ensure consistency in spatial resolution and variable selection. Model fitting followed a separate forward stepwise regression for each sub-region, beginning with single-predictor models and progressively adding uncorrelated predictors (Pearson's $r < 0.7$; variance inflation factors < 3.0.). Each model was fitted using the Filzbach MCMC sampler (https://github.com/predictionmachines/Filzbach), with performance evaluated through 50% cross-validation (training on one half of the data, validating against the other). The best-performing model for each sub-region, defined by the lowest log-likelihood, was used to simulate deforestation from the calibration period (2016–2020) through to 2055, in 5-year increments. The number of model runs varied among regions (105-172), depending on the number of predictors retained. Model performance was assessed using log-likelihood values, cross-validation accuracy, and predictive agreement among runs (see Supporting Information for further details).

2.4 Simulation of future forest loss and uncertainty estimation

To propagate parameter uncertainty, we generated 100 Monte Carlo iterations of deforestation projections for each sub-region. For each iteration, predictor coefficients were randomly sampled from Gaussian distributions defined by the MCMC-derived means and standard deviations. Each pixel's probability of forest loss was then converted to a binary outcome using a random uniform draw, producing multiple realisations of possible future outcomes. The ensemble of simulations was then aggregated to calculate pixel-level probabilities of forest loss, representing the expected likelihood of deforestation by a designated year. All simulations and analyses were conducted using Python (Python Software Foundation 2019) and C++ using Microsoft Visual Studio 2022, with subsequent analysis and visualisation in Python, R (R Core Team 2022), and ArcGIS Pro (Esri 2020).

2.5 Areas of habitat for forest-dependent terrestrial vertebrates

We focused on terrestrial vertebrates - amphibians, birds, mammals, and reptiles - for which spatial range data are available. Distribution polygons were obtained from the IUCN Red List (IUCN, 2023) and, for birds, from BirdLife International (BirdLife International, 2022). These datasets represent the maximum known extent of species distributions, which may include areas of unsuitable habitat. To refine these ranges, we derived Areas of Habitat (AOH) using species-specific information on habitat preferences (Brooks et al., 2019), threat status, population trend and elevational limits from the IUCN Red List accessed via the rredlist package in R. Where altitude data were unavailable, we adopted conservative limits from 0 to 9000 metres above sea level.

Data cleaning followed a conservative approach: species listed as possibly extinct, extinct, or of uncertain presence were excluded. For birds, we retained only native or reintroduced species that are resident or breeding in Indonesia. To focus on forest-dependent taxa, we excluded species for which forest was not listed as a suitable habitat. After filtering, the dataset comprised 685 mammal species, 1,571 birds, 218 amphibians, and 635 reptiles. For each species, we masked distributions by both forest cover and elevation limits, yielding AOH maps representing the potential habitat for terrestrial vertebrates within the Indonesian administrative boundary.

From these AOH maps we produced three biodiversity metrics: species richness, range-size rarity, and extinction vulnerability (Strona et al., 2018; Sze et al., 2024; Wang et al., 2020). Species richness was calculated as the count of species present for each pixel after stacking AOH maps. Range-size rarity emphasizes the importance of areas for species with small ranges, and was calculated as the mean inverse AOH for all species present within a pixel:

$$Range - size\ rarity = \frac{\sum_{i=1}^{n} \frac{1}{AOH_i}}{n}$$

where *AOH* represents the total area of habitat for each species occupied by each species *i* and *n* is the count of species. Higher values indicate areas disproportionately important for range-restricted species.

Extinction vulnerability was quantified as the mean threat score of all species present in a pixel, with scores assigned as Least Concern = 2, Near Threatened = 4, Vulnerable= 8, Endangered= 16, and Critically Endangered = 32, following Wang et al., (2020). For data-deficient species, predicted categories were used (Bland et al., 2015; Butchart and Bird, 2010), assigning values of 16 for threatened and 3 for non-threatened species. Where predictions were unavailable, we used the mean threat score for that taxonomic group within Indonesia (mammals=8, birds=4, amphibians=11, reptiles=6) (Sze et al., 2024). Extinction vulnerability is then simply the mean threat score for each pixel:

$$Extinction\ vulnerability = \frac{\sum_{i=1}^{n} T_i}{n}$$

where *n* is the count of species in each pixel and *T* is the threat score.

To evaluate interactions between biodiversity and deforestation risk, we produced bivariate maps combining deforestation probabilities with each biodiversity metric. Using the bivariatemaps and terra packages in R, we classified both variables into four quantiles representing low to high values and applied a 4 × 4 colour matrix using the colmat() function to produce composite bivariate maps that visualise hotspots of overlapping risk and biodiversity importance.

3 Results

3.1 Model accuracy and predictors of deforestation

Model validation showed strong agreement between observed and predicted forest cover during the calibration period (2016-2020). Mean spatial agreement across all regions was 97% with accuracy ranging from 92% to 98% among the sub-regions, demonstrating high predictive capability of the modelling framework. Omission (false positive) and commission (false negative) errors were low, with median error rates of 3% (range = 0–7%) and 3% (range = 1–6%), respectively.

Deforestation drivers varied substantially among regions (Figure 1). Past deforestation was the most consistent and influential predictor, highlighting the spatial contagion and self-reinforcing nature of land-use change. Fire occurrence strongly increased deforestation probability in Sumatra, Kalimantan, and Papua, where burned areas are highly prone to subsequent conversion. Forest loss was also strongly associated with peatlands in Sumatra and Kalimantan, reflecting persistent conversion pressures in peat-dominated provinces such as Riau and Central Kalimantan. Proximity to roads and industrial plantations also showed moderate positive effects, notably in Sumatra and Kalimantan, consistent with accessibility-driven agricultural and logging expansion. In Java and Bali, where natural forest is highly fragmented, deforestation occurred mostly in small patches influenced by diverse local pressures. In contrast, protected areas were typically negatively associated with forest loss, underscoring their role in reducing deforestation risk, especially within large and strictly protected categories (IUCN I–II).

These regional differences were pronounced (Figure 1). In Papua, most drivers exhibited weak or statistically non-significant effects, reflecting lower infrastructure and development pressure compared to other islands; however, protection efforts were particularly strong. In Java-Bali, deforestation outcomes observed elsewhere in the country's protected areas were reversed, with a slight positive association with deforestation. Maluku displayed patterns typical of the eastern islands, with modest overall effects but elevated sensitivity to fire and prior deforestation. Forests under social forestry tenure showed weak but generally negative association with deforestation, suggesting that community-based management can reduce forest loss, although this effect was inconsistent, particularly in Nusa Tenggara and Sulawesi.

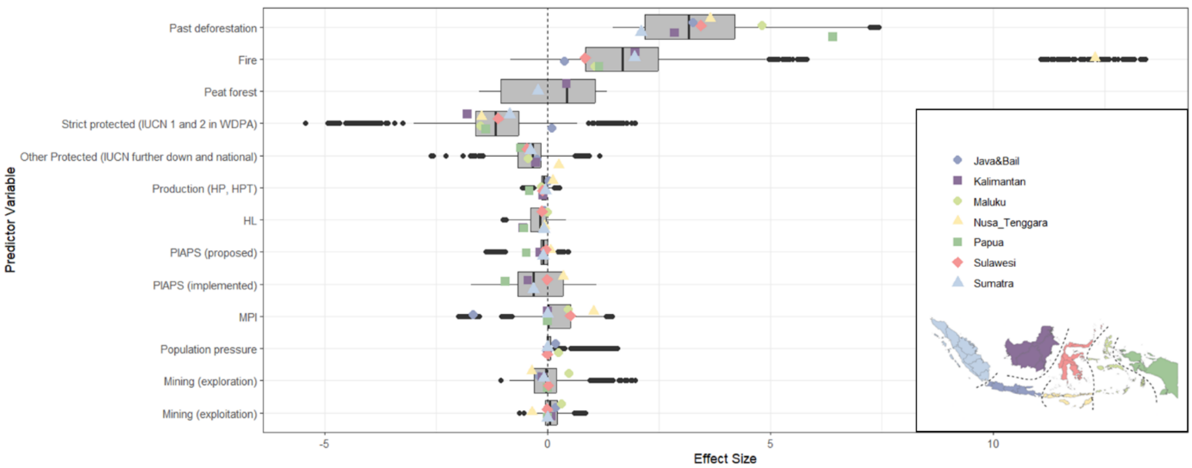

Figure 1 | Predictors of deforestation across Indonesia between 1990 and 2020. Predictor coefficients are summarised across seven island sub-regions as boxplots (median and 25th and 75th quartiles as hinges). Coefficient values lower than 0 (dashed line) increased, while those greater than 0 decreased the probability of forest loss. The effect of mining concessions (exploration and exploitation) is relative to the effect of not having a mining concession. The effect of non-forest, production forest and limited production forest is relative to the effect of protected forests (supporting information S2). Combinations of predictors were tested for each sub-region, and the combination resulting in the highest likelihood selected as the best model. The predictors for each sub-regional model could therefore differ. Predictors for which all sub-regional coefficients were close to zero (mean coefficient smaller than 0.05 and a spread smaller than 0.1) were excluded from the figure (accessibility, plantation, non-agricultural and fisheries commodity production, transmigrant settlements). The 95% confidence intervals derived from the 100 model iterations around points are not shown, as they fall within the points.

3.2 Spatio-temporal deforestation and projections

Over the 30-year period, the most severe forest losses occurred in Sumatra and Java–Bali, where total forest area declined by 55% and 58%, respectively (Figure 2). These reductions reflect the legacy of large-scale agricultural expansion, logging and infrastructure development in western Indonesia (Figure 3). In Kalimantan, forest cover decreased by approximately 20%, with deforestation concentrated in lowland and peatland areas. By contrast, the eastern sub-regions of Sulawesi, Nusa Tenggara, Maluku, and Papua retained much higher forest cover. Between 1990 and 2020 forest loss totalled around 15% in Sulawesi and 24% in Nusa Tenggara, while Maluku and Papua lost only 8% and 4%, respectively. These eastern regions thus remain the country's most extensive intact forest landscapes, although recent increases in deforestation pressure, especially in southern and lowland Papua, are cause for concern (Jamaludin et al., 2022).

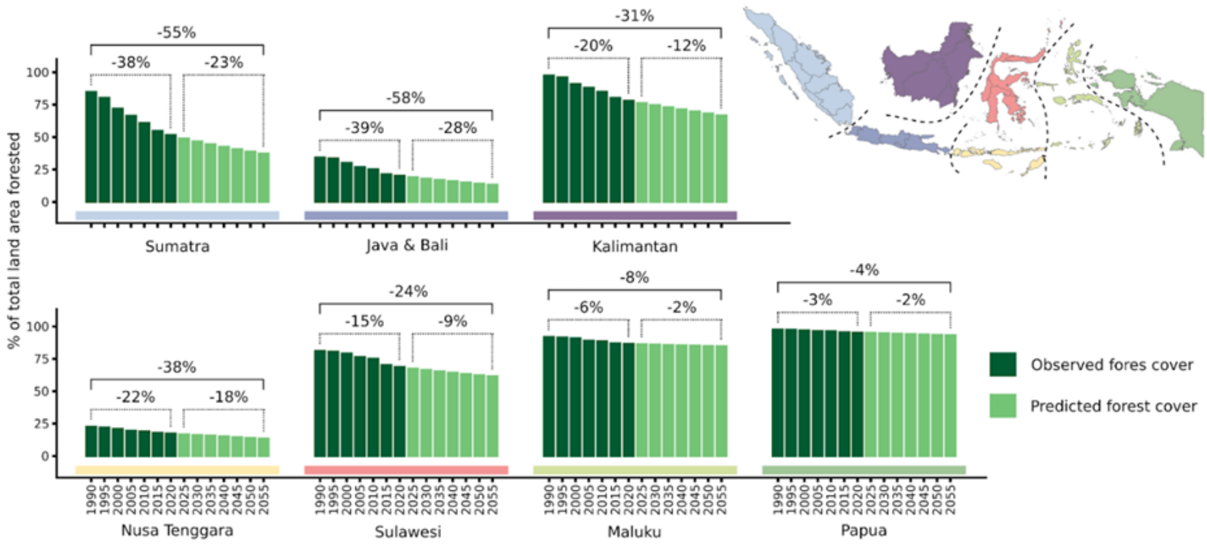

Figure 2 | Percentage in forest loss across Indonesia from 1990 to 2020 and then projected in 5-year increments to 2055. Dark green bars show observed forest loss up until 2020, and light green bars show predicted loss.

Overall, our projections indicate that Indonesia could lose up to 17.0 million ha (14.2%) of its remaining forest by 2055 if recent trends persist. The greatest future losses are expected in lowland and peat-dominated landscapes of western Indonesia: Sumatra and Kalimantan are projected to lose an additional 23% and 12% of forest, respectively, resulting in a cumulative decline of nearly one-third for Kalimantan since 1990. Java–Bali is projected to lose a further 28% from an already low baseline. In contrast, Maluku and Papua are expected to retain most of their forest cover, losing only ~2% each, while Sulawesi is projected to lose around 9%.

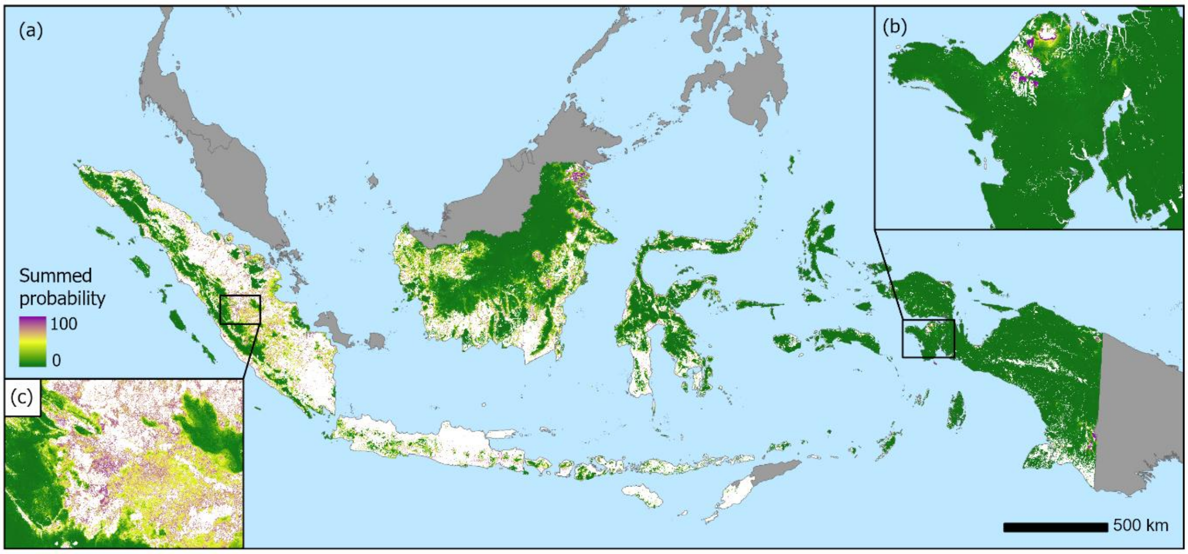

Figure 3 | Summed predicted probability of forest loss by 2055 across Indonesia. This value represents the fraction of simulation runs in which the forest in a pixel was lost; i.e. a pixel selected to be deforested in that time period in 80 out of 100 iterations has an 80% probability of deforestation. Panel (a) shows the summed probability of future deforestation across Indonesia. Panel (b) provides an example of an area with low projected deforestation risk in Papua, while panel (c) illustrates an area of high projected deforestation risk in Sumatra.

3.3 Co-occurrence of biodiversity and deforestation pressures

The spatial overlap between projected deforestation risk and three key biodiversity metrics (species richness, extinction vulnerability, and range-size rarity) reveals strong regional contrasts (Figure 4). High species richness coincides with high deforestation risk across northern and central Sumatra and western and central Kalimantan. These areas represent the core zones of overlap between biodiversity and deforestation risk, where continued forest conversion would threaten assemblages of exceptional diversity. In contrast, the Nusa Tenggara islands exhibit low to moderate values for both biodiversity and deforestation risk, reflecting their more arid and fragmented landscapes. Papua and the Maluku islands retain extensive areas of high species richness but low deforestation risk, identifying them as critical refugia for Indonesia's vertebrate diversity.

Extinction vulnerability, representing the spatial concentration of threatened taxa, shows a broadly similar pattern to species richness, with the highest combined values again in northern Sumatra and across Kalimantan. These overlaps highlight the persistence of risk within remaining lowland forests that support many threatened species. Conversely, Central Kalimantan and Papua contain large areas of high extinction vulnerability but low deforestation risk, suggesting that while these regions currently experience limited conversion, they harbour species inherently at high extinction risk.

Patterns of range-size rarity, which emphasize concentrations of narrow-ranged species, shift markedly eastward compared with richness and vulnerability. The highest values occur in Sulawesi, Maluku, and Papua - regions long recognized as centres of endemism (Struebig et al., 2022). Notably, northern Sulawesi and eastern Borneo contain localized pockets where high range-size rarity coincides with elevated deforestation risk, identifying discrete hotspots of potential future loss. In contrast, the Papuan highlands and much of Maluku maintain high range-size rarity but low deforestation risk, representing irreplaceable reservoirs of endemic biodiversity.

Together, these patterns reveal a pronounced west–east gradient: western islands, especially Sumatra and Kalimantan, exhibit the greatest overlap between biodiversity value and deforestation pressure, demanding urgent mitigation to prevent near-term biodiversity loss. The eastern archipelago, though less affected by immediate deforestation, holds exceptional concentrations of endemic and vulnerable taxa, underscoring its global importance for long-term conservation planning.

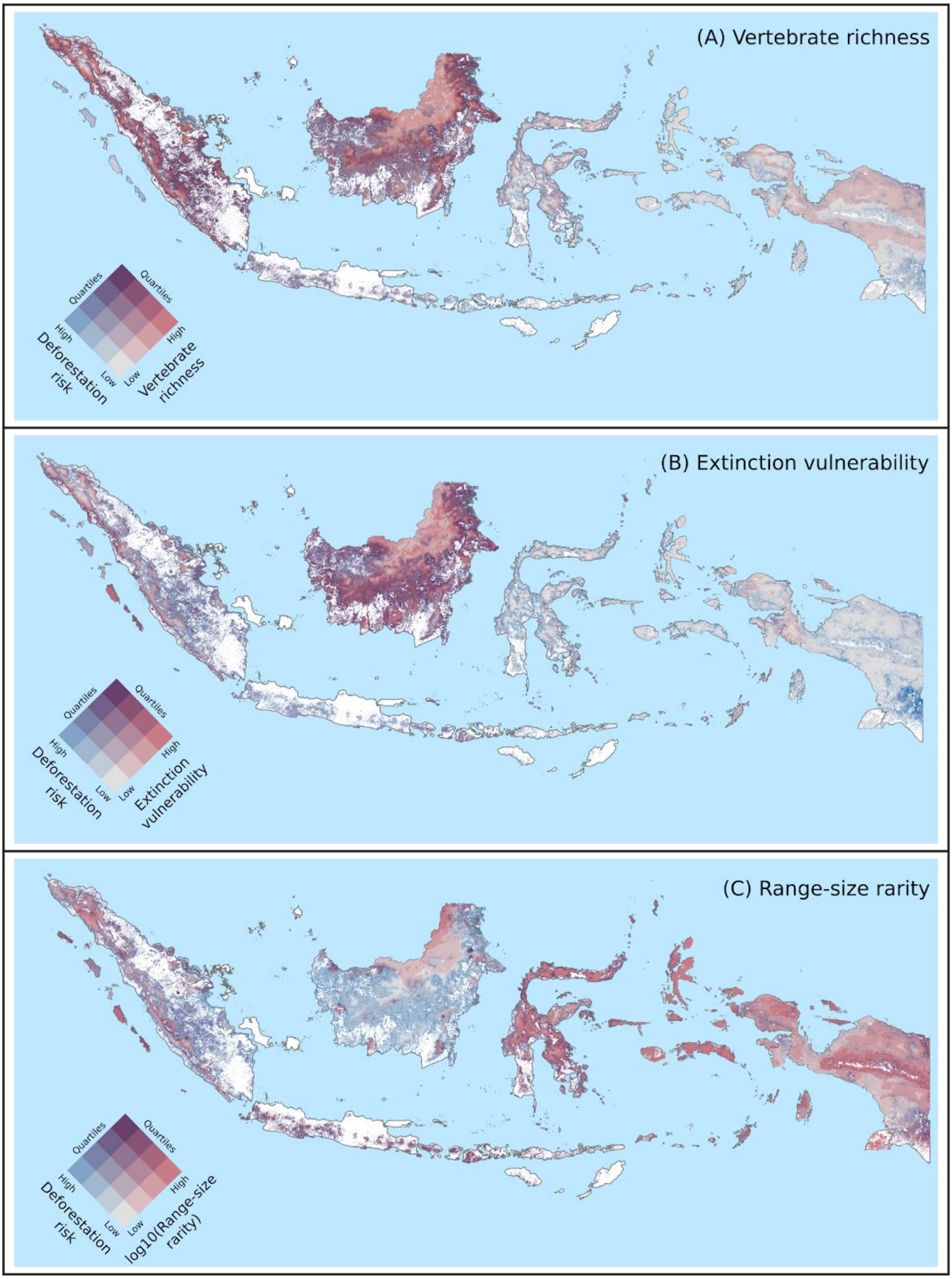

Figure 4 | Bivariate maps showing spatial overlap between deforestation projections and species richness (a), extinction vulnerability (b) and range-size rarity of terrestrial vertebrates in Indonesia. The spatial biodiversity metrics were calculated from International Union for Conservation of Nature (IUCN)-evaluated range maps of 685 mammal species, 1,571 birds, 218 amphibians, and 635 reptiles. Both biodiversity metrics and deforestation risk was reclassified from high to low values based on quartiles of the data.

4 Discussion

4.1 Regional differences in deforestation and trajectories

Our results reveal pronounced spatial heterogeneity in Indonesia's deforestation dynamics, reflecting differences in governance, land tenure, and biophysical context. Western Indonesia (Sumatra, Java–Bali, and Kalimantan) continues to experience the most extensive and persistent forest loss, driven by long-standing plantation expansion, infrastructure-led development, and intensive resource extraction. In contrast, eastern Indonesia, especially Papua and Maluku, retains vast tracts of relatively intact forest but faces growing pressures from mining, agricultural expansion, and infrastructure projects.

These regional contrasts align with prior analyses (Austin et al., 2019; Gaveau et al., 2019; Margono et al., 2014), underscoring that Indonesia's forest transition is uneven and path-dependent. In the west, forest conversion is entrenched within established commodity frontiers, oil palm, pulpwood, and smallholder agriculture, where governance and enforcement capacity are tested by competing economic incentives. In the east, governance institutions are still consolidating, and future deforestation risk will depend critically on proactive spatial planning and safeguards for local tenure and customary land rights.

Lowland and peat forests remain the most vulnerable ecosystems. Their ongoing conversion in Sumatra and Kalimantan threatens globally significant carbon stores and unique biodiversity. Peatland drainage and fires compound these impacts by releasing greenhouse gases and degrading habitat (Hooijer et al., 2010; Posa et al., 2011). Conserving and restoring peat swamp forests and mangroves could mitigate nearly half of land-use carbon emissions in Southeast Asia (Sasmito et al., 2025), highlighting their importance as a national and regional priority. In contrast, montane forests, particularly in Papua and Sulawesi, remain relatively intact, though recent evidence of upslope deforestation (Feng et al., 2021) suggests expanding pressures into previously inaccessible terrain.

4.2 Deforestation drivers and governance context

The dominant predictors of deforestation - past forest loss, fire, and proximity to roads and industrial plantations - reflect both spatial inertia and infrastructural expansion. Past deforestation captures frontier contagion: once land is opened, subsequent conversion becomes more likely. Fires further amplify this process, particularly where peatlands have been drained or degraded.

Accessibility emerged as a key enabling factor. Proximity to formal and informal ("ghost") roads (Engert et al., 2024) was frequently associated with deforestation probability, consistent with the opening of new frontiers even within nominally protected zones, such as in Sumatra's Harapan landscape (Engert et al., 2021). Maintaining up-to-date infrastructure datasets is therefore critical, as national road inventories likely underestimate small-scale and informal routes that facilitate forest conversion.

Protected areas generally exerted a strong deterrent effect, particularly in stricter IUCN categories (I–II), consistent with impact evaluations showing reduced deforestation in Sumatra and Kalimantan (Gaveau et al., 2009; Morgans et al., 2024). However, effectiveness varied, being weakest where little natural forest remained as in Java and Bali. Social forestry and community tenure schemes were weakly but negatively associated with deforestation, echoing prior findings that local management can reduce forest loss under supportive governance and market conditions (Santika et al., 2017). Yet, aggregate analyses across Indonesia has shown no uniform national effect (Kraus et al., 2021), suggesting outcomes are highly context-dependent and contingent on institutional support and economic alternatives.

4.3 Biodiversity patterns and conservation implications

The spatial co-distribution of biodiversity and deforestation pressures reveals a pronounced west–east gradient in conservation priorities. The overlap of high vertebrate richness and extinction vulnerability with active deforestation fronts in Sumatra and Kalimantan indicates acute “defaunation fronts,” where continued habitat loss will directly erode globally-significant biodiversity. These landscapes continue to demand reactive strategies: strengthening protection of remaining lowland forests, restoring degraded peatlands, and mitigating fire and fragmentation.

Conversely, the eastern archipelago (Maluku and Papua, but also parts of Sulawesi) contains the most intact forests, high concentrations of range-restricted taxa, and lower immediate deforestation risk. These regions represent proactive conservation frontiers, where safeguarding intact ecosystems can prevent future biodiversity loss. Their dominance in range-size rarity underscores their irreplaceability; even modest future forest loss could trigger disproportionate species declines. Integrating multiple biodiversity dimensions clarifies that conservation priorities are multidimensional: areas of high richness and vulnerability align with immediate threats, whereas regions of high range-size rarity correspond to long-term evolutionary value.

4.4 Policy pathways and opportunities

Managing the spatial complementarity between deforestation risk and biodiversity requires differentiated strategies - rapid interventions to curb losses in the west, and pre-emptive protection and inclusive governance in the east. These patterns align with recent global analyses of ‘High Forest Low Deforestation’ (HFLD) jurisdictions, which show that even extensive, intact forests are vulnerable to rapid land-use transitions without proactive protection (Teo et al., 2024). Framing Indonesia within this context highlights the urgency of maintaining high-integrity, low-deforestation landscapes before they become new frontiers.

In western Indonesia, conservation should continue to be embedded within production landscapes through nature-based solutions involving fire prevention, peat restoration, and tighter regulation of plantation and infrastructure expansion. Integrating forest conservation into jurisdictional and commodity supply-chain initiatives can enhance accountability and support national emission reduction targets. In eastern Indonesia, maintaining HFLD status should be a central policy objective. HFLD regions like Papua deliver disproportionate global benefits for carbon and biodiversity, yet often receive limited international support. Emerging mechanisms, including results-based payments under REDD+ and biodiversity credits (Struebig et al 2025), as well as “HFLD incentives” that reward avoided deforestation (Maniatis 2024), could sustain forest integrity while supporting local livelihoods. Securing Indigenous and community land rights remains foundational, both for equity and for sustaining low deforestation trajectories and maintaining biodiversity (Sze et al., 2024).

Collectively, these findings emphasise that Indonesia’s forest future depends on balancing reactive interventions in degraded but biodiverse landscapes with proactive protection of intact ecosystems. Ensuring that conservation and development are jointly planned, through spatially explicit, evidence-based strategies, will be essential for meeting Indonesia’s commitments under the Kunming–Montreal Global Biodiversity Framework and the Paris Agreement.

4.5 Future directions

Our modelling framework effectively captured both the magnitude and spatial patterns of deforestation across Indonesia over recent decades, aligning well with observed trends and with comparable probabilistic approaches in tropical systems (Rosa et al., 2013; Voigt et al., 2021, 2022). Model validation indicated strong performance in reproducing the observed spatial distribution of forest loss, reflecting the importance of incorporating spatial autocorrelation and neighbourhood effects in deforestation prediction. Nevertheless, some limitations must be acknowledged. The 180 m spatial resolution constrains the detection of fine-scale degradation or selective logging, while the assumption of static predictor layers (e.g., road networks) does not account for future infrastructure expansion. Although the dynamic component derives from forest loss contagion and stochastic simulation, the model does not yet integrate socio-economic or policy shifts such as commodity price fluctuations, new conservation initiatives, or large-scale infrastructure projects (e.g., the Nusantara capital development). Future work could integrate scenario-based socioeconomic and climate projections, dynamic accessibility networks, and species-level responses to forest loss, thereby enhancing both realism and policy relevance.

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