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# Quantifying and Predicting the Impacts of Major Roads in Tropical Forest Frontiers

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# Acknowledgements

I would like to start by thanking all my friends and family, for keeping me alive and (relatively) sane throughout this process. It has not been easy and I wouldn't have managed it without trips to the pub with Arun, Kali, Rachael, and Alex; among others. Countless other friends have kept me going by providing conversation and laughs throughout the journey but are too many to name here; if we have shared good conversation, consider yourself a part of this list.

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There are many people who have contributed to my journey as a scientist and must be thanked (or held responsible) for getting me where I am today. Perhaps the first, chronologically, is an elder farmer in a rural village in Madagascar – whose name I have unfortunately forgotten – who shared with me the traditional understanding that motivated him to restore forests around his farm "No forests, no rain; and no rain, no rice." This interaction and my time in Madagascar gave me a renewed appreciation for conservation and restoration that motivated me to return to my studies.

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The fourth person chronologically, but perhaps most responsible, is Prof Susan Laurance. Sue gave me a start in research, put in a good word to get me into Prof Bill Laurance's lab, and has indulged many of my crazy ideas and been a constant source of support and good conversation. Who knows where I'd be today if not for Sue. She is important enough to get her own paragraph.

Fifth is my friend and colleague Dr. Mason Campbell. Mason took me from a GIS technician manually drawing roads in Google Earth, to a lead author on a Nature paper. His trust and support, and well as kindness and friendship, has been a massive help with my career and with surviving my PhD. There are of course so many other people to thank who deserve their own paragraphs, but I am low on space and time so I must summarise more. Dr. Yoko Ishida has been a good friend for many years, a saviour when dealing with paperwork and admin tasks, and an irreplaceable contributor to the road mapping that made all my work possible. Prof Vanessa Adams who was my first employer as a GIS technician on a project which saw me author or co-author three papers and was invaluable for my career progression. The other members of the Laurance lab including Dr. Mohammed Alamgir and Dr. Sean Sloan; Prof Josh Cinner for his support and guidance on our Nature paper. There are many others but I am already filling the page, so I am sorry I can't thank everyone by name.

I would like to thank Dr. Carlos Souza and the whole group at Imazon, and Dr. Fritz Kleinschroth, whose collaborations have made a gigantic improvement to my thesis and to whom I am extremely grateful.

Of course I cannot forget to thank my supervisors, Prof Bill Laurance and Prof Will Edwards for their guidance and support (material and intellectual), and for making everything possible. I would finally like to thank the late great Prof Bob Pressey, who was a source of inspiration for me from my time in undergrad and someone I consider myself truly blessed to have worked with before his passing.

## ETHICS STATEMENT

This PhD research did not involve human or animal subjects, hence no ethics approval was required.

## STATEMENT OF THE CONTRIBUTION OF OTHERS

This PhD project was made possible through the funding provided by JCU in the form of the James Cook University Postgraduate Research Scholarship.

| Chapter | Publications on which chapter is based | Nature and extent of the intellectual input of each author |
|---|---|---|
| **1** | Engert, J.E. & Laurance, W.F. (In press) *Habitat loss and fragmentation due to roads*, in Road Ecology: Synthesis and Perspectives (Eds: D'Amico M., Barrientos R., Ascensão F.). Springer International Publishing AG, (Switzerland). | The authors codeveloped the research question. Engert conducted the research and wrote the first draft. Laurance revised and provided editorial inputs. |
| **2** | Engert, J.E., Campbell, M.J., Cinner, J.E., Ishida, Y., Sloan, S., Supriatna, J., Alamgir, M., Cislowski, J. & Laurance, W. F. (2024). *Ghost roads and the destruction of Asia-Pacific tropical forests*. Nature, 1-6. | Engert, Campbell, and Laurance developed the research question. Engert, Ishida, Sloan, Alamgir, and Cislowski collected the data. Engert performed the analyses and wrote the first draft of the paper with conceptual input from Cinner and Laurance. All other coauthors provided editorial inputs. |
| **3** | Engert, J.E., Souza Jr., C.M., Kleinschroth, F., Juffe-Bignoli, D., Costa, S.P., Botelho Jr., J., Ishida, Y., Nursamsi, I. & Laurance, W.F. (submitted). *Explosive growth of secondary roads is triggering widespread tropical deforestation*. Current Biology. | Engert conceived and developed the research question. Engert, Souza Jr., Kleinschroth, Costa, Botelho Jr, Ishida, and Nursamsi collected the data. Engert performed the analyses. Engert and Laurance wrote the manuscript with conceptual inputs from Souza Jr., Kleinschroth, and Juffe-Bignoli. |
| **4** | Engert, J.E., Souza Jr., C.M., Kleinschroth, F., Costa, S.P., Botelho Jr., J., Ishida, Y. & Laurance, W.F. (submitted). *Road-expansion risk predicts future hotspots of tropical deforestation*. Science. | Engert conceived and developed the research question. Engert, Souza Jr., Kleinschroth, Costa, Botelho Jr, and Ishida collected the data. Engert performed the analyses. Engert and Laurance wrote the manuscript with conceptual inputs from Souza Jr. and Kleinschroth. |

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# Abstract

Roads act as conduits for human movement, and hence enable many of humanity's impacts on nature including natural resource exploitation and land-conversion. By acting as a first access route, new major roads (such as highways) into intact forests – henceforth termed 'first-cut roads' – enable further road building and land colonization with cascading impacts on nature. While this phenomenon is well understood in conservation science – for example the widely documented 'soy corridors' in the Brazilian Amazon – the scale of the impacts have not previously been empirically assessed or quantified. Without this information, the impacts of first-cut roads cannot be modelled for conservation planning and are unlikely to be considered in impact assessment procedures.

The overarching goal of this thesis is, therefore, to generate models to predict the scale and extent of the impacts of first-cut roads in intact forests which may then be applied to assess the numerous proposed highways and developments corridors across the global tropics. I achieve this overarching goal through four steps corresponding to separate thesis data chapters: (1) I demonstrate that roads are key proximate drivers of deforestation in tropical forests, (2) I quantify the scale and extent of first-cut road impacts, (3) I identify biophysical conditions that facilitate or constrain road-building in order to model the risk of secondary road expansion, and finally (4) I combine the information from the previous three steps to build an empirically-verified model of the scale and extent of the impacts of first-cut roads in tropical forests.

Using an extensive spatial dataset including a high-quality manually-digitized road map of the insular Asia-Pacific region, I demonstrate that roads are key proximate drivers of deforestation. I also use annual road maps and spatiotemporal analyses to show that roads are necessary conditions for deforestation – that is, roads almost always precede deforestation. Following this I open collaboration with academics studying roads in the Congo Basin and Brazilian Amazon to conduct pantropical assessments of the scale of secondary roads and their impacts, and the biophysical factors influencing road building. By identifying historical examples of first-cut roads, including well known cases such as Brazil's Cuiabá-Santarém (BR-163) Highway, I am able to use network analyses to delineate secondary roads and their associated forest destruction. With the pantropical road dataset, covering nearly one billion hectares, I use spatial regression methods to identify biophysical correlates of road building while accounting for the influence of socio-economic variables.

I find considerable amounts of secondary roads stemming from first-cut roads across the global tropics, and high variation among regions. The impacts of secondary roads outweigh the impacts

of first-cut roads by orders of magnitude. Additionally, I find that the biophysical correlates of road building – topography, soil condition, waterways, and others – are largely consistent across the tropical forest regions. Using this information, I generate a model to predict the impacts of first-cut roads that performs twice as well as widely-used distance-decay functions, and more than 30 times as well as simple buffer-distance models.

Millions of kilometres of new roads are planned for the coming decades. Many of the proposed projects will penetrate intact forests, conservation priority areas, and the lands of indigenous and forest-dependent peoples. The much-improved, empirically-verified impact model I generated in this thesis will have substantial utility for assessing the environmental and social impacts of these projects, and identifying mitigation methods or alternatives.

# TABLE OF CONTENTS

# List of Tables

# LIST OF FIGURES

# INTRODUCTION

## BACKGROUND

Roads are key enablers and facilitators of a vast array of human impacts on nature, including fires (Nepstad et al., 2001), deforestation and land-clearing (Barber et al., 2014; Busch & Ferretti-Gallon, 2017; Sales et al., 2017), and natural-resource overexploitation (Asner et al., 2013; Benitez-Lopez et al., 2017). The scale of these impacts are amplified for new roads constructed in intact forest landscapes as they often spawn sprawling networks of secondary roads and infrastructure (Fearnside & de Alencastro Graça, 2006; Fearnside, 2007; Perz et al., 2008; Laurance, Goosem & Laurance, 2009; Laurance et al., 2015). While this is a widely recognised phenomenon, the scale and extent of these secondary roads has not been quantified to-date (Laurance & Arrea, 2017). Without empirical assessment of the extent of secondary road networks and their impacts, they cannot be modelled and hence cannot be accurately included in environmental impact assessment or conservation planning. The overarching aim of this thesis is, therefore, to (1) assess the scale of secondary roads and their associated human impacts, (2) identify factors that facilitate or constrain road expansion, and (3) incorporate this information to develop refined, empirically verified, models of the impacts of new roads in intact forests.

Roads enable vehicular movement and are key components of global transport networks. The majority of global resource extraction and resource trade is dependent to some degree on road networks (Redding & Turner, 2015; Curtis et al., 2018). Hence, while road development is the ultimate driver of only a small portion of global deforestation and land-clearing, the major drivers such as agriculture, mining, and urban land-uses are heavily dependent on road networks (Geist & Lambin, 2002; Curtis et al., 2018; Austin et al., 2019). Roads can hence be said to be proximate drivers of land-clearing as they determine where it can occur (Geist & Lambin, 2002), and necessary conditions (Brennan, 2003) of land-clearing as they are required for it to occur even if they are not the motivating factor. In a similar way, as roads are dependent on each other – roads must expand from populated areas through other roads, they cannot be constructed in the middle of nowhere fed by nothing – it can be said that the first road constructed into a non-anthropized landscape is the proximate driver and necessary condition for further road expansion. For this reason, it is reasonable to assert that the impacts of new roads in intact forest landscapes – termed 'first-cut' roads – include also the impacts caused by dependent secondary roads.

Efforts have been made previously to account for the impacts of secondary-road expansion in conservation assessments of major roads. Due to limitations of available data on road networks and human-population densities, and methodological constraints, previous assessments have relied on overly simplistic approaches to quantifying and predicting secondary impacts. The two most widely employed methods to-date are buffer-distance models (i.e Laurance et al., 2015; Spencer et al., 2023) and distance-decay functions (i.e. Sonter et al., 2017; Tulloch et al., 2019; Engert et al., 2021). In buffer-distance models, all impacts within a specified distance of the first-cut road are assumed to be associated with said road, or all areas within a specified distance are said to be at risk because of the roads construction. Distance-decay functions extend this methodology by assigning a probability that impacts are caused by the first-cut road – or that areas are threatened by the road – based on the distance to said road, rather than simply applying a binary filter. However, a wide range of landscape features, such as topographic slope, influence rates of road-building and deforestation (Gaveau et al., 2013; Collier et al., 2015) and hence impacts will not be uniform across the landscape for all areas of equal distance from the first-cut road.

Both road-building and land-clearing are heavily influenced by landscape biophysical characteristics and socio-economic factors. Road construction is more difficult and costly in sloping terrain, and maintenance costs substantially higher (Collier et al., 2015; Alamgir et al., 2019a). Similarly, soil physical and chemical properties (Lim et al., 2014), such as soil pH and clay composition, as well as precipitation intensity (Alamgir et al., 2020), affect the costs of building and maintaining roads. Additionally, as roads are built by people to serve population centres and resource extraction frontiers, they are expected to be associated with population density and other socio-economic factors and mediated by governance and policy (Glover & Simon, 1975; Perz et al., 2007; Meijer et al., 2018). Therefore, with spatially-resolved information on relevant biophysical and socio-economic factors, it should be possible to identify areas more or less prone to road expansion in order to improve the spatial precision of existing model frameworks.

Improved models of the impacts of first-cut roads are urgently needed, as new development corridors and highway megaprojects are rapidly expanding across the developing world (Laurance et al., 2014; Thacker et al., 2019). Millions of kilometers of new roads are proposed or underway as part of continental-scale development agendas such as the Program for Development in Africa (Laurance et al., 2015; Thorn et al., 2022), COSIPLAN in South America (Vilela et al., 2021), Belt and Road Initiative (Ascensão & Laurance, 2019; Kaszta et al., 2020) and national schemes in Indonesia (Alamgir et al., 2019b; Sloan et al., 2019a), Malaysia (Sloan et al., 2019b), and Papua New Guinea (Alamgir et al., 2019a), among others. These road projects will intersect or otherwise impact thousands of protected areas, conservation areas, and intact forests (Laurance et al., 2015; Sloan, Bertzky & Laurance, 2017); potentially threatening thousands of species and releasing millions of tons of carbon dioxide into the atmosphere (Spawn et al., 2020; Noon et al., 2022). While these road projects may deliver socio-economic benefits to some communities (e.g. via improved access to markets and social support infrastructure; Hettige, 2006), they may also cause substantial social impacts. Large road projects such as those outlined here often trigger explosive land colonisation and dispossession, resource theft, and various other social and economic harms to indigenous and rural communities (Porter, 1997; Hecht & Cockburn, 2010; McSweeney et al., 2014; Rodney, 2018; Estrada et al., 2022). However, without empirically verified assessments and predictions of the scale of impacts of these projects, they will be allowed to proceed largely unrestrained.

Environmental and social impact assessments of road projects are overwhelmingly focused on the direct site-level impacts, while secondary and cumulative impacts are often ignored (Karlson, Mörtberg & Balfors, 2014; Jaeger, 2015; Laurance & Arrea, 2017; Johnson et al., 2019; Juffe-Bignoli et al., 2021). This is concerning as the secondary impacts of projects, which are often the most difficult to monitor and regulate (particularly in remote frontier regions; Johnson et al., 2019), are expected to be orders of magnitude larger (Fearnside, 1987; Fearnside, 2015). For example, a coal transport road in Sumatra, Indonesia, was approved under the assumption that it would cause merely 424 ha of deforestation during construction. However, assessments by scientists and conservation groups anticipate that the road will cause between 3,000-6,000 ha of deforestation (Engert et al., 2021). Therefore, empirical assessments of the secondary impacts of first-cut roads are required so that they can be accurately accounted for in development planning and impact assessment procedures.

## AIMS AND GOALS

This thesis aims to advance the state of knowledge in road ecology, conservation planning, and impact assessment in important ways, focusing on the world's major tropical forest regions, and produce outputs with high potential for application in these same sectors. I first (1) demonstrate that roads are spatial predictors of – and necessary conditions for – deforestation, (2) measure the length of secondary roads stemming from first-cut roads in tropical forests and quantify their secondary impacts (forest loss and degradation), (3) identify landscape correlates of road building and create a modelled 'road-expansion risk' surface, and (4) combine the knowledge gained in the first three steps to build a spatially-resolved and empirically-verified model of the impacts of first-cut roads in tropical forests. The model developed in (4) can be used by a variety of scientists and practitioners to assess the potential impacts of major roads and development corridors across the worlds tropical forest biomes.

## THESIS OUTLINE

Following this introduction, my thesis consists of five chapters (Fig. 1), including a literature review and four data chapters, followed by a brief discussion and conclusion. In **Chapter 1** (literature review), I summarise the ways in which roads contribute to habitat loss and fragmentation based on the existing literature, and provide perspectives for future outcomes and research priorities. In **Chapter 2**, I use spatial regression and spatiotemporal analyses to demonstrate the importance of roads as proximate drivers of – and necessary conditions for – deforestation. In **Chapter 3**, I develop a novel methodological framework to identify secondary roads stemming from first-cut roads in tropical forest frontiers. I then delineate forest loss and degradation associated with the first-cut roads and their associated secondary roads in order to generate more realistic estimates of the scale of their impacts. In **Chapter 4**, I use a massive pantropical dataset of road presences and absences to identify correlates of road-building and identify regions with high risk of experiencing further road expansion. I also demonstrate that this novel 'road-expansion risk' index is a reliable predictor of deforestation. In **Chapter 5**, I combine datasets on secondary road impacts generated in *Chapter 3* with the 'road-expansion risk' index generated in *Chapter 4* to create improved models of the scale and extent of the impacts of first-cut roads. This Chapter represents the first empirical developing of such models and demonstrates that including information on suitability for road building substantially improves their performance. The chapters are organised as sequential, independent publications, with each chapter feeding from the previous chapters. Finally, I conclude with a brief discussion in which I summarise the key findings of the five chapters and synthesize the contribution of this thesis to conservation planning and impact assessment globally, and identify avenues for future research.

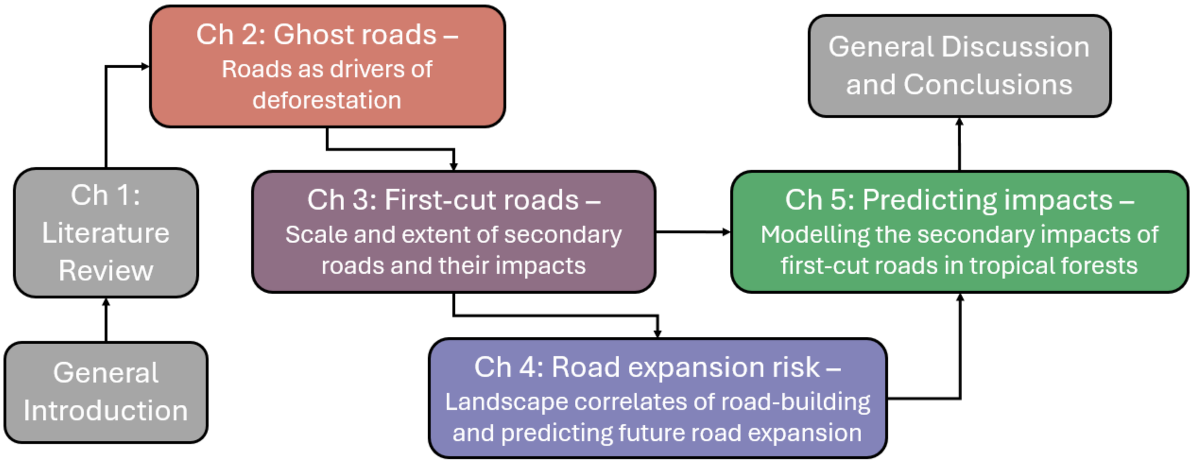


**Figure 1: Thesis structure and links between chapters.**

## RESEARCH PUBLICATIONS

| | |
|---|---|
| Chapter 1: | Engert, J.E. & Laurance, W.F. (In press) *Habitat loss and fragmentation due to roads*, in Road Ecology: Synthesis and Perspectives (Eds: D'Amico M., Barrientos R., Ascensão F.). Springer International Publishing AG, (Switzerland). |
| Chapter 2: | Engert, J.E., Campbell, M.J., Cinner, J.E., Ishida, Y., Sloan, S., Supriatna, J., Alamgir, M., Cislowski, J. & Laurance, W. F. (2024). *Ghost roads and the destruction of Asia-Pacific tropical forests*. Nature, 1-6. |
| Chapter 3: | Engert, J.E., Souza Jr., C.M., Kleinschroth, F., Juffe-Bignoli, D., Costa, S.P., Botelho Jr., J., Ishida, Y., Nursamsi, I. & Laurance, W.F. (accepted with revisions). *Explosive growth of secondary roads is triggering widespread tropical deforestation*. Current Biology. |
| Chapter 4: | Engert, J.E., Souza Jr., C.M., Kleinschroth, F., Costa, S.P., Botelho Jr., J., Ishida, Y. & Laurance, W.F. (in revision). *Road-expansion risk predicts future hotspots of tropical deforestation*. PNAS. |
| Chapter 5: | Engert, J.E., ... Laurance, W.F. (In prep). *Modelling the impacts of tropical development corridors*. |

Over the course of my thesis I have also written, or contributed to, the following **publications** broadly related to my thesis, which have helped to inform my work:

- **Engert, J.E.** (submitted). Current terminology to distinguish rich and poor countries is unfit for environmental science. *Communications Earth and Environment*.
- Parsch, C., Wagner, B., **Engert, J.E.**, et al. (in revision). Deforestation risk in a major biodiversity hotspot: Drivers and patterns of forest loss in New Guinea. *Science of the Total Environment*.
- Sloan, S., Talkhani, R.R., Huang, T., **Engert, J.** & Laurance, W.F. (2024). Mapping remote roads using artificial intelligence and satellite imagery. *Remote Sensing* 16(5), 839.
- Laurance, W.F., Mudhoffir, A.M., Pusparini, W., Meijaard, E. & **Engert, J.E.** (2023). For Indonesia and beyond, nature conservation needs independent science. *Current Biology*, 33, 706-707.
- **Engert, J.E.,** Kartodihardjo, H. & Laurance, W.F. (2022). Major mining road could be death knell for Sumatra's lowland rainforests. *Biological Conservation* 274, 109714.
- Laurance, W.F. & **Engert, J.E.** (2022). Sprawling cities are rapidly encroaching on Earth's biodiversity. *PNAS*, 119, e2202244119.

- **Engert, J.E.,** Ishida, F.Y. & Laurance, W.F. (2021). Rerouting a major Indonesian mining road to spare nature and reduce development costs. Conservation Science and Practice, 3(11), e521

I also wrote, or contributed to, several other academic and non-academic publications which helped to improve my writing, analytical techniques, and scientific skills broadly:

***Other academic publications***

- Middleby, K.B., .. **Engert, J.E.** & Cheesman, A.W. (submitted). Strong site but weak provenance effects for growth and survival of 16 tropical forest restoration species. *Biotropica*.
- **Engert, J.E.** (submitted). Cost-benefit analysis as a form of 'pragmatic injustice' in conservation. *One Earth*.
- **Engert, J.E.** & van Oosterzee, P. (in press). Limits to the ability of carbon farming projects to deliver benefits for threatened species. *Nature Ecology and Evolution*.
- Vogado, NO., Laurance, SL., Liddell, MJ., **Engert, J.E.**, & Cernusak, L.A. (2023). Assessing the effects of a through-fall exclusion experiment on the reproductive phenology and eco-physiology of a wet tropical rainforest community. *Conservation Physiology*, 11, coad064.
- **Engert, J.E.**, Pressey, R.L. & Adams, V.M. (2023). Threatened fauna protections compromised by agricultural interests in Australia. *Conservation Letters*, 16(4), e12975.
- Adams, V.M., ... **Engert, J.E.** & Gallagher, R.V. (2023). Protected, cleared, or at risk: The fate of Australian plant species under continued land use change. *Biological Conservation*, 284, 110201.
- **Engert, J.E.** & Laurance, S.G.W. (2023). Economics and optics influence funding for ecological restoration in a nation-wide Program. *Environmental Research Letters*, 18(5), 054020.
- Adams, V.M. & **Engert, J.E.** (2023). Australian agricultural resources: A national scale land capability map. *Data in Brief*, 46, 108852.
- Potts, E., ... **Engert, J.** & Laurance, S.G.W. (2022). Growth form and functional traits influence the shoot flammability of tropical rainforest species. *Forest Ecology and Manag.*, 522, 120485.
- **Engert, J.E.** (2022). Could environmental and conservation sciences benefit from an anonymized journal?. *Conservation Letters*, 15.
- Vogado, N.O., **Engert, J.E.**, ... Laurance, W.F. & Liddell, M.J. (2022). Climate change increases reproductive phenology in tropical lianas. *Frontiers in Forests and Global Change*, 68.

***Non-academic publications***

- **Engert, J.E.** & Laurance, S.G.W. 2023. Program to plant 20 million trees prioritised cost-saving over gains for nature, research finds. *The Conversation*.
- **Engert, J.E.** & Laurance, W.F. 2021. Alternative routes for a major Indonesian mining road to reduce environmental and financial costs. *TransportEcology*.

Finally, I presented my research work (thesis work and other work) at multiple different scientific **conferences**, allowing me to develop and improve my presentation and speaking skills:

- Identifying gaps between restoration implementation schemes and the species left behind. *Society for Ecological Restoration 10th World Conference*; Darwin, Australia.
- A tool to predict the indirect and induced impacts of new road projects (Workshop). *African Conference on Linear Infrastructure and Ecology*; Nairobi, Kenya.
- Agricultural capability impacts threatened species conservation. *Far North Qld GIS Group Annual Meeting*; Cairns, Australia
- Indirect and induced impacts of first-cut roads. 59$^{th}$ *Annual Meeting of the Association for Tropical Biology and Conservation*; Coimbatore, India.
- Threatened species protections take a back seat to agricultural interests. *James Cook University TESS Seminar*; Cairns, Australia.
- Threatened species protections take a back seat to agricultural interests. *Ecological Society of Australia Conference*; Wollongong, Australia
- Restoration planning: scientific ideals vs real-world limitations. *Society for Conservation Biology Policy Seminar*; Cairns, Australia [online]
- Restoration planning: scientific ideals vs real-world limitations. *James Cook University TESS Seminar*; Cairns, Australia
- A carbon price to save our wildlife. *Climate Force TropRegen Fundraiser*; Cairns, Australia.
- 'Ghost roads' and the future of tropical forests [poster]. *International Congress for Conservation Biology*; Kigali, Rwanda [online].
- 20 Million Trees but few benefits for threatened species. *Ecological Society of Australia Conference*; Darwin, Australia [online].
- Re-routing a major Indonesian mining road to spare nature and reduce development costs. *International Conference on Ecology and Transportation*; Virtual Conference.
- Least-cost path analysis to minimize environmental and construction costs of roads. *African Conference for Linear Infrastructure and Ecology*; Nairobi, Kenya [online]

# Chapter 1: Habitat loss and fragmentation due to roads

Published as: *Habitat loss and fragmentation due to roads* in Road Ecology: Synthesis and Perspectives (Eds: D'Amico M., Barrientos R., Ascensão F.). Springer International Publishing AG, Cham (Switzerland).

## Abstract

Road networks have been expanding at a dramatic pace in recent decades, driven by growing demand for resources, energy, and access to markets. However, roads can also open a Pandora's box of environmental ills, the most significant of which may be habitat loss and fragmentation. The scale of habitat loss driven by roads is dependent on their capacity to promote travel, and hence outcomes differ for paved and unpaved roads and for different habitat types. Where habitat fragments remain intact, spiderweb-like road networks create edge effects and act as barriers to movement for disturbance-sensitive species of plants and animals. This fragmentation means large expanses of remaining habitats are highly degraded and have altered species composition and ecological function. Furthermore, a substantial proportion of all roads today are not recorded in existing roadmaps. With millions of kilometers of new roads expected worldwide in the near future, it will be vital to develop new methods to detect and map roads in order to document the effects of road-related habitat disruption, and develop strategic road plans to minimize these disruptions.

## SYNTHESIS

By acting as a conduit for movement and access to natural environments, roads often open a 'Pandora's Box' of environmental impacts (Laurance et al., 2014). Perhaps the most significant of these road-related impacts, in the contemporary age of exponential population growth and development, are habitat loss and fragmentation. After all, loss and degradation of habitat are the main threat to over 85% of all threatened species listed in the IUCN Red List (Hogue & Breon, 2022). Roads promote habitat loss and fragmentation at two levels. Firstly, the initial road construction, or 'first cut', contributes to habitat loss directly by clearing land for the road footprint, and often areas adjacent to the footprint. This critical 'first cut' may also split intact habitat and create smaller fragments. Secondly, the new road improves access to natural resources that results in further road expansion and land conversion that drives further indirect habitat loss. Road-mediated land use changes often studied include legal and illegal mining, logging, and land colonization and speculation in the vicinity of the new road.

Habitat fragmentation occurs when human modified landscapes, such as road networks, split natural ecosystems into islands of remnant habitat (Murcia, 1995). Anthropogenic landscape modification and road proliferation has resulted in drastic levels of habitat fragmentation and degradation across the globe (Haddad et al., 2015; Ibisch et al., 2016). By creating smaller and more isolated habitat patches, fragmentation reduces the extent of, and quality of, remaining intact habitat (Murcia, 1995; Laurance et al., 2002b; Ewers & Didham, 2006). It also substantially increases the amount of edges between the intact habitat and modified environments, allowing for spill-over of external impacts. It is generally accepted that fragmentation in conjunction with habitat loss can have negative impacts on a wide range of species. However, the effects of fragmentation *per se*, that is the effects of fragmentation excluding the effects of habitat loss, are still heavily debated in the ecological literature (see for example Ewers & Didham, 2006; Fahirg, 2017). Fahrig (2017) for example, point out that the majority of published studies on ecological responses have found a positive effect of fragmentation *per se*. Alternatively, Ewers & Didham (2006) identify numerous confounding factors that may mask potential negative effects of fragmentation in ecological studies, including species-specific responses and time-lags in effects. Despite the apparent prevalence of positive effects of fragmentation *per se*, Fahrig (2017) note that negative effects of fragmentation are more common in studies examining larger landscapes, or considering the degree of spatial isolation of fragments studied. This review also notes that the prevalence of negative impacts of fragmentation vary between taxonomic groups (avifauna are at greater risk than invertebrates or herpetofauna).

The most obvious impact of road fragmentation is the separation of intact habitat patches by modified landscapes. During the process of land colonization and conversion, small remnant areas of natural habitat often remain. While these fragments are able to retain some amount of ecological value, this value is dependent on a variety of factors, including the ecosystem type, degree of modification of the surrounding environment, degree of isolation, and traits of resident species such as ability to traverse modified landscapes (Ewers & Didham, 2006; Fahrig, 2017).

While much of the developed world (in particular countries in Europe and North America) has experienced substantial habitat loss and fragmentation due to roads, the period in which this occurred has somewhat constrained studies in these regions. A great deal of land conversion and road development occurred before satellite imagery was available and large-scale spatial studies were possible, meaning much of the focus of recent influential studies on land conversion has shifted to frontier regions and developing countries (Ferretti-Gallon & Busch, 2014). For example, Sader & Joyce (1988) identified expansion of road networks as an important driver of forest clearing in Costa Rica between the years 1940 and 1983. Similarly, the lack of accurate spatiotemporal road data (for example, annual road maps) has made developing robust causal frameworks and theoretical models extremely challenging. As such, much evidence of the effect of roads on habitat loss and fragmentation comes from studies carried out in developing tropical countries.

*Direct and indirect effects*

Roads contribute to habitat loss directly through clearing of vegetation, filling or bridging waterways, flattening terrain, and removing ‘ecological furniture’ such as fallen trees. The area of direct habitat loss from road construction varies significantly between roads of different sizes and lengths. A four-lane paved highway, for example, results in dramatically more habitat loss than a single-lane dirt road, particularly when considering the additional adjacent clearing that is often required to facilitate road laying. In extensive road networks, the impacts of direct habitat loss from roads can be substantial. In the Congo Basin, for example, Kleinschroth et al. (2019) estimated that 14,000 $km^2$ of forest were cleared for road construction alone. While the direct loss of habitat due to road construction is often substantially less than indirect habitat loss (Austin et al., 2019; Kleinschroth et al., 2019), it can have significant impacts on range-restricted species or species that have already experienced dramatic range reductions. On the other hand, by providing a path of low resistance into the heart of natural landscapes, roads can dramatically reduce the time and cost required for extractive activities. In this way, roads are significant drivers of habitat loss indirectly. In the Brazilian Amazon, for example, Barber et al. (2014) found that around 95% of all deforestation was within 5.5km of a road or navigable river.

Roads provide a method of surpassing barriers to vehicular travel, such as dense vegetation, waterways, or geological barriers. By traversing these barriers, roads allow access for trucks and heavy machinery that facilitate a shift from small-scale and low-impact resource extraction to large-scale and high-impact extraction (Alamgir et al., 2017). Without road access, loggers and miners are severely limited in both the area they can cover and the amount of materials they can remove (Kleinschroth et al., 2019). As such, in the absence of roads, resource extraction operations and agricultural leases are typically small-scale, with landscapes being left to recover following removal of desired resources or a reduction in land productivity. However, with road access, extraction operations are often followed by wholescale clearing and conversion of lands to agricultural or pastoral landscapes (Laurance, Goosem & Laurance, 2009).

Roads also facilitate greater access to markets, and access to industrial fertilizers and machinery that can increase the scale to which resource industries can be maintained (Fearnside, 2015). As roads facilitate land-use change, relationships between road networks and habitat loss may be masked by the subsequent conversion of landscapes to anthropogenic systems. For example, Austin et al. (2019) identified various plantation types as the main drivers of deforestation in Indonesia, however these land-use types are dependent on extensive road networks that would precede the habitat loss.

Paved roads typically have larger impacts than unpaved roads as the influence of roads on habitat loss and conversion is tied to their ability to reduce travel times and costs (Laurance et al., 2002a). Paved roads typically allow for faster travel and can support heavier vehicles. Additionally, paved roads are passable for a wider array of vehicles and can therefore facilitate more illegal or unofficial resource extraction without the need for specialized equipment. By allowing year-round access, paved roads prevent natural systems from having a seasonal respite from human disturbances (Laurance et al., 2002a). In removing this seasonal down-period, even small-scale logging and harvesting operations may become unsustainable as native habitats are unable to regenerate following disturbance.

*Uneven impacts in different habitats*

Roads precipitate habitat loss and fragmentation to varying degrees depending on landscape characteristics, leading to complex land-use dynamics. Direct impacts will likely be higher in sloping terrain or wetlands, as roads must take less direct routes. Conversely, indirect impacts will be greater in topographically simple landscapes with less barriers to movement, as roads may facilitate rapid land conversion. For this reason, indirect habitat loss and fragmentation due to road expansion is typically highest in specific landscapes such as lowland forests or savannahs, while landscapes less conducive to anthropogenic modification remain relatively untouched. In Sumatra, for example, infrastructure development and land-use change has been extensive in the lowlands, while much of the upland forests, which are substantially more difficult to develop, remain intact (see Engert, Ishida & Laurance, 2021). Similarly, within the Wet Tropics bioregion of Australia, a UNESCO World Heritage Area, more than half of the lowland habitats have been cleared while the mountainous forests remain relatively untouched (Metcalfe & Lawson, 2015).

Due to this concentration of road development and habitat disruption in specific landscapes, the threat of habitat loss and fragmentation is significantly more pronounced for species depending on these landscapes. Species dependent on lowland habitats, such as savannah species or lowland forest species in particular, experience higher impact when compared to their upland relatives. In Sabah, Malaysia, for example, central upland forests support the largest orangutan populations, while the degraded lowland forests house substantially smaller populations (Simon, Davies & Ancrenaz, 2019).

*Roads as barriers*

Roads and associated land clearing may additionally represent a barrier that many species will either choose to avoid or are unable to overcome, of will suffer increased mortality when trying to cross. By acting as barriers, roads may contribute to fragmentation of functional connectivity by restricting movement and access to resources. Additionally, by restricting movement or directly causing mortality, roads can fragment the gene pools of many species of flora and fauna, and hence contribute to a reduction in genetic diversity.

While a 4-lane paved highway is a very obvious boundary between areas of natural habitat, even small unpaved tracks may act as dispersal barriers for susceptible species. Many small forest fauna species, such as amphibians and small forest-interior bird species, will not cross a gap of even a few meters (Laurance et al., 2002b). For these species, even logging and hunting trails may create fragmented habitats with diminished ecological value. This phenomenon is not limited to forest-interior birds and water-dependent species. Studies from savanna ecosystems in Brazil found that several savanna bird species avoided a relatively small paved road (da Silva et al., 2017). These reductions in movement and gene flow may negatively impact population persistence by reducing resilience to environmental changes and stochastic events (Ewers & Didham, 2006).

Many fauna species experience population declines in highly fragmented habitats (Schmiegelow, Machtans & Hannon, 1997; Laurance et al., 2002b). Large-bodied species are often at greater risk due to higher resource demands (Woodroffe & Ginsberg, 1998). For example, many species have gone locally extinct from small habitat fragments in both African savannahs and Amazonian rainforest (Woodroffe & Ginsberg, 1998; Laurance et al., 2002b), and numerous bird species experienced declining populations in fragmented Canadian boreal forests (Schmiegelow, Machtans & Hannon, 1997). Alternatively, smaller-bodied species or species that can make use of edge habitat may be resilient to, or even benefit from, reductions in habitat patch size (Fahrig, 2017). Similarly, species that are able to cross roads and human-modified landscapes will likely be resilient to these impacts where roads do not cause increased mortality through roadkill or human-wildlife conflicts.

While barrier effects of roads are often associated with fauna species, they can also have adverse impacts on plant species. A well-travelled, compacted dirt road can be an inhospitable environment for plant seeds, and hence creates a barrier for species with only short dispersal distances. Additionally, plant species that rely on animals for pollination or seed dispersal will experience reduced gene flow when roads act as barriers to the fauna species they depend on. The degree to which a road can act as a barrier is hence dependent on both the size of the road and the susceptibility of the species in question.

*Edge effects*

When separating habitat fragments, roads create distinct edges between the habitat and modified landscapes. Edge effects alter the biotic and abiotic conditions within the habitat fragment through various mechanisms (Murcia, 1995), and characteristics of roads can amplify these impacts. Road-related edge effects are diverse and include changes to microclimate, soil condition, and hydrology flows (Laurance et al., 2002b); as well as acting as permeable surfaces from which invasive species of fauna and flora or diseases may invade.

The degree to which edge effects impact habitat patches is highly dependent on the size of the patch, the road characteristics, and the habitat type (Laurance, Goosem & Laurance, 2009). A road, either paved or unpaved, represents a stark change in ground cover for many natural landscapes, particularly vegetated landscapes. Roads are highly compacted and without vegetation cover they absorb a great deal of thermal energy, thus making them a heat source compared to the surrounding habitat. This results in a change in microclimate adjacent to the road, where temperatures are higher and, due to increased evapotranspiration and reduced water-holding capacities, water availability is lower (Laurance, Goosem & Laurance, 2009). The change in microclimate, leads to higher mortality rates of many plant species along road edges. Increased mortality of specific plant species near edges can contribute to changes in vegetation composition, structure, and function. For example, highly disturbed tropical forests often experience a loss of large old-growth tree species which are replaced by disturbance-adapted pioneer species as well as vines and lianas (Laurance et al., 2002b; Haddad et al., 2015). This loss of large trees can contribute to a reduction in resource availability for herbivorous and frugivorous fauna species, leading to population declines and potentially even local extinction (Bush et al., 2020).

Microclimate impacts at habitat edges may also result in changes to phenological patterns (see Morellato et al., 2016; and references within). These changes can cause mismatches that disrupt relationships with pollinators and seed dispersers that may reduce reproductive capabilities of the plant species and in turn impact habitat regeneration. These impacts also flow on to dependent species and can also result in population declines and even local extinction of their dependent pollinators and frugivores. Therefore, while habitat loss is a clear and ubiquitous impact of roads, fragmentation and its associated impacts also present a significant threat to numerous species and ecosystems.

## Perspectives

*Massive amounts of unmapped roads*

A significant limitation in our ability to predict and plan for future impacts of road developments is the substantial quantity of roads that currently do not appear in existing road maps. Across tropical regions, studies have consistently found that more than half of the roads present were not included in existing maps. Barber et al. (2014) for example, found that for every 1 km of mapped road in the Brazilian Amazon, there were around 3 km of unmapped roads. Similarly, in Sumatra, Engert, Ishida & Laurance (2021) found that for every 1 km of mapped road there were 2-3 km of unmapped roads (Fig. 2). These unmapped roads have important implications for our ability to quantify the extent of road impacts on natural systems, as well as our ability to quantify the relationship between roads and their impacts. The sheer quantity of unmapped roads in many tropical regions suggests that the extent of their impacts, including fragmentation and edge effects are chronically underestimated. Additionally, as road construction typically precedes other land-cover change, incomplete roadmaps diminish our ability to identify future frontiers of habitat loss. Future work on the effects of roads on habitat loss and fragmentation will therefore be dependent on developing high-quality, up-to-date road maps, particularly for developing nations.

*Substantial future road expansion*

As the global population, and associated need for development to reduce poverty and improve living standards continue to grow, it is expected that the planet will see substantial future road construction (Meijer et al, 2018). The vast majority of these roads will be built under massive national- and continental-scale transport infrastructure projects. Development corridor projects in Latin America, Africa, and Southeast Asia in particular are expected to penetrate into previously undisturbed ecosystems and cause significant habitat loss and fragmentation. These development projects, as currently planned, will impact thousands of protected areas and conservation forests and precipitate millions of square kilometers of habitat loss (Vilela et al., 2020; references within Engert, Ishida & Laurance, 2021).

Monitoring this rapid development trajectory in order to minimize adverse impacts will likely be dependent on novel solutions such as automated mapping using artificial intelligence. Current methods of monitoring road impacts rely on manual digitization of roads by humans, and require substantial time investments to map vast expanses of frontier landscapes (Laurance, 2018). These methods will likely be outpaced by the explosive growth of road networks predicted in the coming years. Automated road mapping would also improve our ability to monitor fragmentation, as many roads capable of fragmenting habitat are not large enough to represent a change in land cover for lower-resolution land-use products such as MODIS, or even the Global Forest Change data (Fig. 2).

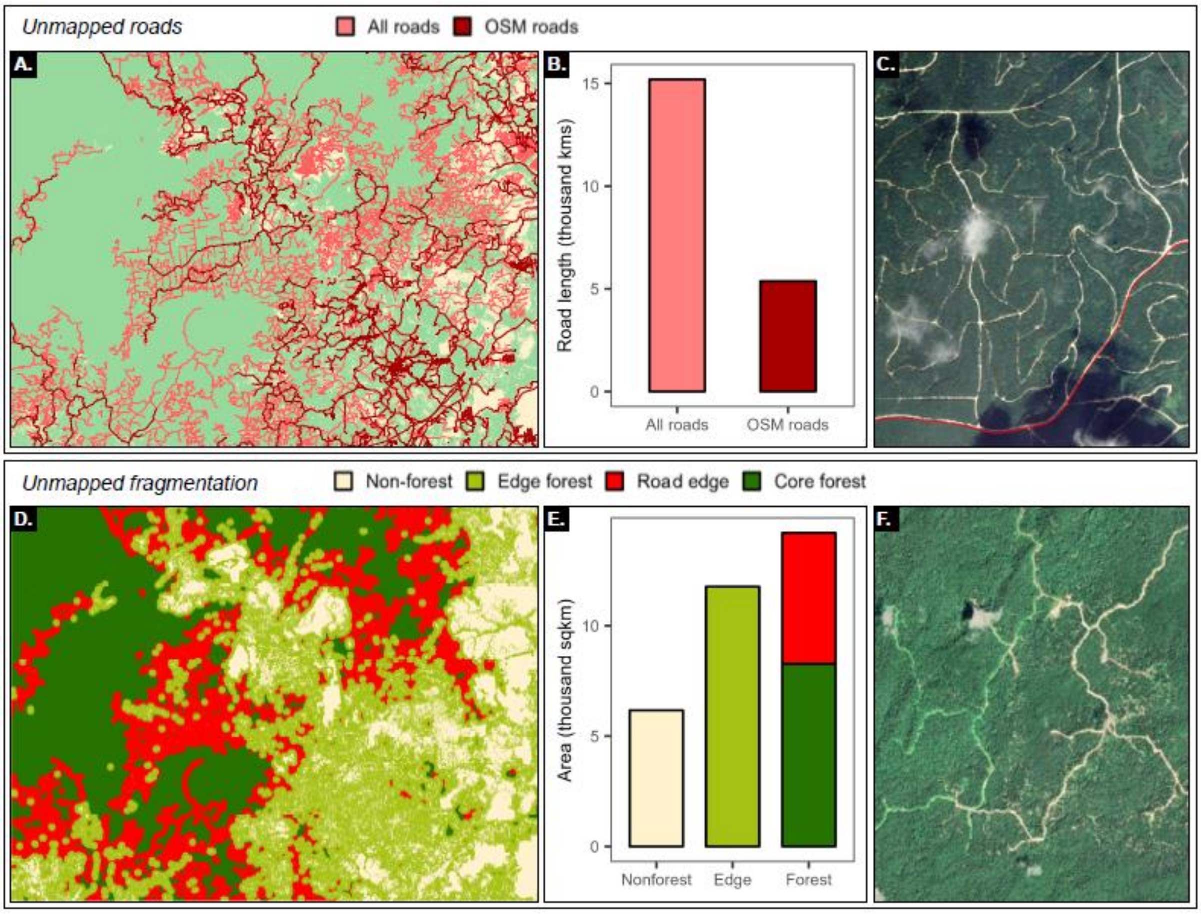


**Figure 2 The scale of unmapped roads in an area of Kalimantan Timur in Indonesian Borneo.** (A - B) Around 65% of all roads in this region were not included in one of the most widely utilized global road datasets, the Open Street Map (OSM). (C) Satellite imagery of unmapped roads in this region, the red line indicates roads that were included in the OSM dataset. (D –E) When these unmapped roads are not included, the area of undisturbed core forest (>1 km from forest edge as per Murcia, 1995) in this region is overestimated by about 170%. (F) satellite imagery of fragmentation of intact forest caused by unmapped roads.

*Mitigating fragmentation*

Efforts to mitigate habitat fragmentation due human impacts to-date have largely depended on restoration of ecological corridors and construction of various forms of road crossings for wildlife. Numerous different road crossing structures have been developed, including overpasses, culverts and tunnels under roads, and canopy bridges for arboreal species. While uptake of these methods has been increasing, there is various evidence as to whether they are effective or not, or even if we have enough information to make a conclusion about their effectiveness. Of greater importance, however, is the scale of human modification of lands. For example, the Netherlands has over 150 wildlife road crossings aimed to reduce habitat fragmentation (Sijtsma et al., 2020), but over 130,000km of roads. Therefore, while methods exist to mitigate impacts of roads on habitat fragmentation, the large magnitude of road networks necessitates alternative approaches.

*Strategic road planning*

In many countries, a substantial proportion of road expansion and land conversion occurs in an absence of regulatory oversight (Barber et al., 2014; Ward et al., 2019). Similarly, road expansion and land conversion are highly contagious and contribute to a positive feedback loop promoting greater habitat loss and human impacts. Because of this, avoiding the 'first cut' from a road, or keeping areas entirely free from roads, is considered the best strategy for maintaining ecosystem integrity (Laurance, Goosem & Laurance, 2009; Laurance et al., 2014; Ibisch et al., 2016). As such, measures to reduce the impacts of roads on habitat loss and fragmentation must incorporate strategic road planning to avoid environmentally sensitive areas (Laurance et al., 2014; Engert, Ishida & Laurance, 2021).

Strategic road-planning methods can be used to proactively designate road routes that will have lowest impacts on land-cover and fragmentation (Laurance et al., 2014). Routing roads through less sensitive landscapes, avoiding protected areas and key biodiversity areas, or improving existing road routes rather than creating new routes, can all substantially improve environmental outcomes (Ibisch et al., 2016; Engert, Ishida & Laurance, 2021). Further, substituting new major roads with alternative forms of transportation, such as railways, may reduce the potential impacts of new transportation corridors. However, strategic road planning also relies on knowledge of existing road locations, and hence underscores the need for comprehensive global roadmaps to mitigate habitat loss and fragmentation from expansion of road networks.

# CHAPTER 2: ROADS AS PROXIMATE DRIVERS OF – AND NECESSARY CONDITIONS FOR – DEFORESTATION

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## ABSTRACT

Roads are expanding at the fastest pace in human history, especially in biodiversity-rich tropical nations where they can promote forest loss and fragmentation, wildfires, illicit land invasions, and negative societal impacts (Dulac, 2013; Laurance et al., 2014; Ibisch et al., 2016; Ascensão et al., 2018; Kleinschroth et al., 2019). Many roads are being constructed illegally or informally and do not appear on any existing roadmap (Laurance et al., 2009; Barber et al., 2014; Fearnside, 2015; Alamgir et al., 2017; Hughes, 2018); the toll of such 'ghost roads' on ecosystems is poorly understood. Here we use ~7,000 hours of effort by trained volunteers to map ghost roads across the tropical Asia-Pacific region, sampling 1.42 million plots, each 1 $km^2$ in area. Our intensive sampling revealed a total of 1.37 million km of roads in our plots—from 3.0 to 6.6 times more roads than leading global-road datasets. Across our study area, road building almost always preceded local forest loss, with road density being by far the strongest correlate (Schrieber-Gregory, 2021) of deforestation out of 38 potential biophysical and socioeconomic covariates. The relationship between road density and forest loss was nonlinear, with deforestation peaking soon after roads penetrate a landscape and then declining as roads multiply and remaining accessible forests largely disappear. Surprisingly, after controlling for lower road density inside protected areas, we found protected areas had only modest additional effects on preventing forest loss, implying their most vital conservation function is limiting roads and road-related environmental disruption. Collectively, our findings suggest that burgeoning, poorly studied ghost roads are among the gravest of all direct threats to tropical forests.

## INTRODUCTION

By mid-century, Earth is expected to have some 25 million km of new paved roads relative to 2010—enough to encircle the planet more than 600 times (Dulac, 2013). Roads serve a number of important societal functions, such as promoting trade and increasing access to natural resources and arable land (Hettige, 2006; Laurance et al., 2009; Alamgir et al., 2017). Without effective planning and law enforcement, however, roads can also unleash a Pandora's box of environmental ills and societal challenges (Laurance et al., 2001; Laurance et al., 2014; van der Ree et al., 2015; Bebbington et al., 2020; Vilela et al., 2020). Unfortunately, many new roads are being constructed informally or illegally, especially in lower-income nations where governance is often hindered by corruption and ineffective law enforcement (Laurance et al., 2009; van der Ree et al., 2015). These 'ghost roads', invisible on official roadmaps, are one of the most vexing direct threats to tropical forests and their wild and human inhabitants (Laurance et al., 2009; Barber et al., 2014).

We define ghost roads operationally as those missing from the two leading global-road datasets, the Global Roads Inventory Project (GRIP; Meijer et al., 2018) and OpenStreetMap (OSM; Ramm et al., 2010). Ghost roads include informally or illicitly constructed roads, bulldozed tracks in logged forests, roads in palm-oil plantation, and other roads missing from existing road datasets for various reasons. Such roads can be either paved or unpaved, although the majority are unpaved. Ghost roads are being constructed by a diversity of actors, including legal or illegal agriculturalists, miners, loggers, landgrabbers, land speculators, and drug traffickers, among others (Laurance et al., 2009; Barber et al., 2014; Fearnside, 2015; Alamgir et al., 2017).

The accuracy and completeness of existing roadmaps vary greatly among nations and regions, and are typically poorest in developing nations with large forest estates (Laurance et al., 2015; Sloan et al., 2018). To assess the extent of ghost roads, we employed an intensive sampling effort (1.42 million plots of 1 $km^2$ each) across a range of human-altered and native-forested regions of Borneo, Sumatra, and New Guinea, three of the world's largest continental islands. We manually mapped and digitized roads on each island using recent (circa 2019), high-resolution satellite imagery in Google Earth. Mapping was conducted by 210 trained volunteers or researchers whose individual mapping accuracy was quality-checked by one or more coauthors of this study, using test datasets (Supplementary Information; Fig. 8). Each mapper was required to attain >90% accuracy on test datasets (including road omissions and commissions) before commencing road-mapping.

After generating high-accuracy road data, we (1) compared the extent of roads from our data directly to those from the two leading global-road datasets (GRIP and OSM); (2) assessed how roads and other key socioeconomic and environmental variables influence forest loss; (3) gauged how protected areas affect the proliferation of roads and associated environmental disruption; and (4) used a novel temporal analysis to assess whether roads tend to precede, or follow, deforestation across our study area.

## METHODS AND RESULTS

We compared our road data to those from the two global road databases, GRIP and OSM, using the same 1.42 million plots for all datasets. Road extent (the percentage of mapped 1-km$^2$ cells containing at least one road) was 13.2% using GRIP and 18.3% using OSM, but a much higher 32.9% when using our road data (Fig 3B). In addition, the total length of mapped roads was 3.0-6.6 times greater when using our dataset (1.37 million km) than the GRIP (0.21 million km) and OSM (0.45 million km) datasets. Compared to GRIP and OSM, our data revealed that 35-45% of unmapped roads were in oil palm or other plantations (23-33% in large plantations, 11-12% in small plantations), 31-39% were in intact forests, and 17-28% were in non-plantation agriculture (see Fig. 9 and Supplementary Information for land-use definitions). Unmapped roads were less prevalent in urban areas, degraded forest, and other land-use types (Fig. 9).

Our findings show that the extent and length of roads, at least in our study area, are severely underestimated in leading road databases and official government statistics (Fig 3, Table 2). Moreover, these badly deficient road data partly underlay popular conservation metrics, such as the 'human-footprint' index (Venter et al., 2016; Williams et al., 2020) and 'roadless' or 'wilderness' areas (Ibisch et al., 2016; Watson et al., 2016), that are widely used in conservation research and management (see below). Further, as a large portion of the mapped 'ghost roads' occurred in plantations and other agricultural lands (where legal or illegal), it may be the case that moderating the demand-side factors – such as improving the sustainability of export commodity supply chains – will be able to limit road construction rates (Pendrill et al., 2019b; Hoang & Kanemoto, 2021).

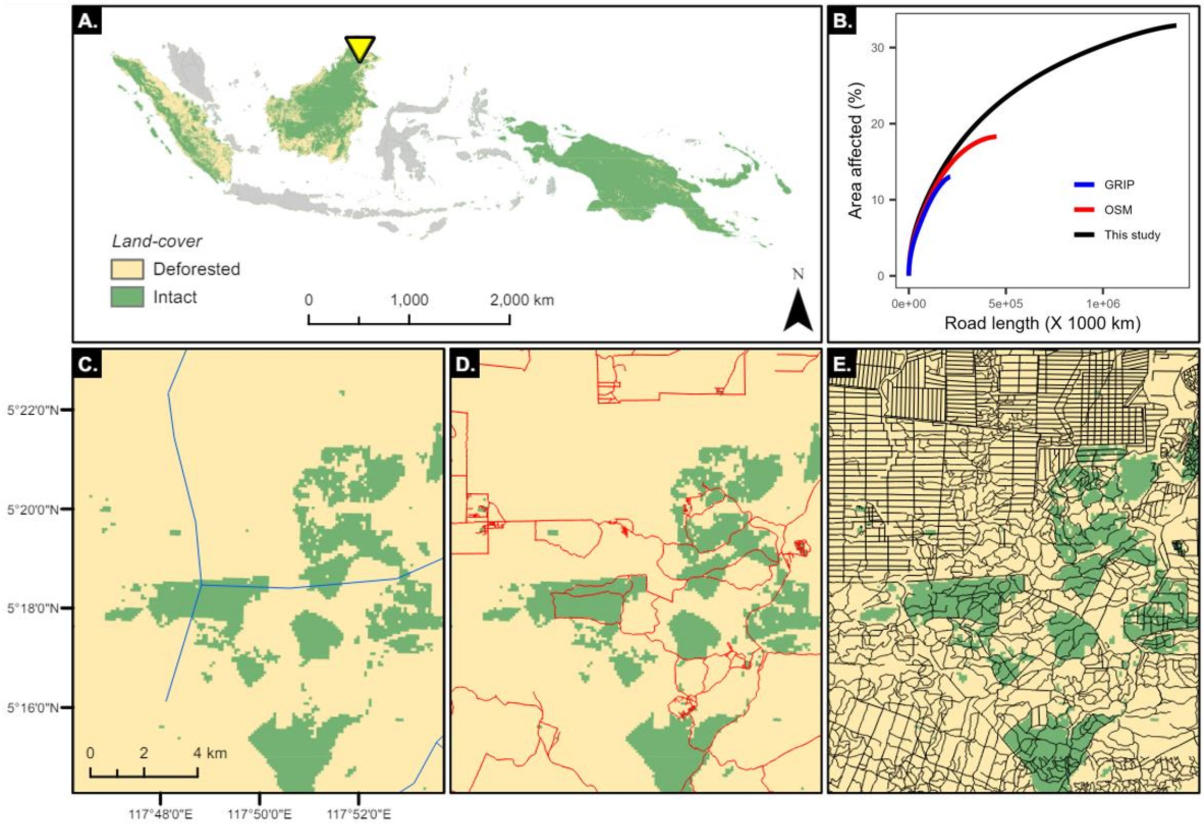


**Figure 3. Road density in the tropical Asia-Pacific region is much higher than indicated by available global datasets.** (A) The study region, comprising part or all of Indonesia, Malaysia, and Papua New Guinea (the yellow triangle shows the location of inset panels C-E). (B) Cumulative plots comparing the total length of roads and proportion of land potentially affected by roads (percentage of 1-km$^2$ cells containing roads) in this study versus data from OpenStreetMap (OSM) and the Global Roads Inventory Project (GRIP). Sites are ordered from highest to lowest road length. (C-E) Mapped roads in a landscape in Sabah, Malaysian Borneo, as shown by GRIP (blue lines; imagery circa 2018), OSM (red lines; circa 2020), and this study (black lines; circa 2019), respectively.

Next, we tested the relative importance of roads and other potential spatial predictors in driving forest loss in our 1.42 million plots. To do this we first created a comprehensive land-cover map for our study region and then quantified the percentage of land cleared per plot (hereafter termed "forest loss") as our response variable. Our map was explicitly designed to accurately detect forest loss while not misclassifying current land covers, such as oil-palm or woodpulp plantations as forested land, or open vegetation, such as wetlands, as deforested land (Supplementary Information). We then identified 38 key environmental, demographic, or socioeconomic variables potentially related to deforestation (Table 4). Included among these were neighborhood road density (total length of roads within a 5-km radius of each plot) and road proximity (linear distance of the plot to the nearest road). Much road building in the tropics is linked to agriculture—the largest ultimate driver of deforestation in the Asia-Pacific region (Curtis et al., 2018; Pendrill et al., 2019; Pendrill et al., 2022) —which itself is influenced by underlying socioeconomic and demographic factors (Thünen, 1966; Geist & Lambin, 2002). Roads also promote deforestation by markedly reducing the costs of transporting timber, bulk minerals, fossil fuels, and poached wildlife to domestic or international markets (Geist & Lambin, 2002; Meyfroidt et al., 2018).

To model forest loss based on our 38 potential predictor variables, we developed a generalized linear model with LASSO regularization (a technique that uses covariate shrinkage to handle multicollinearity and encourage simple, sparse models, with fewer parameters and less model variance and bias) (Schrieber-Gregory, 2021). Out of these 38 potential predictors, 14 had a discernible relationship with forest loss (Supplementary Information), and their effects were then contrasted using road datasets from this study, GRIP, and OSM (Fig. 4). Notably, the marginal relationship between road density and forest loss was distinctly nonlinear (Fig. 4A). This sigmoidal curve suggests a general threshold effect of roads, with deforestation rates being highest when new roads are initially constructed in a landscape, and then gradually decreasing as road density increases. Forests are expected to decline most sharply when roads initially encroach, up to road density of ~4 $km.km^{-2}$, with accessible forests becoming largely depleted if road density exceeds ~7.5 $km.km^{-2}$. Broadly similar dynamics have been observed in rural communities experiencing 'boom-and-bust' development in the Brazilian Amazon (Rodrigues et al., 2009), where initial road building triggers rapid forest loss followed by declines in environmental and human welfare as forest resources are increasingly exhausted.

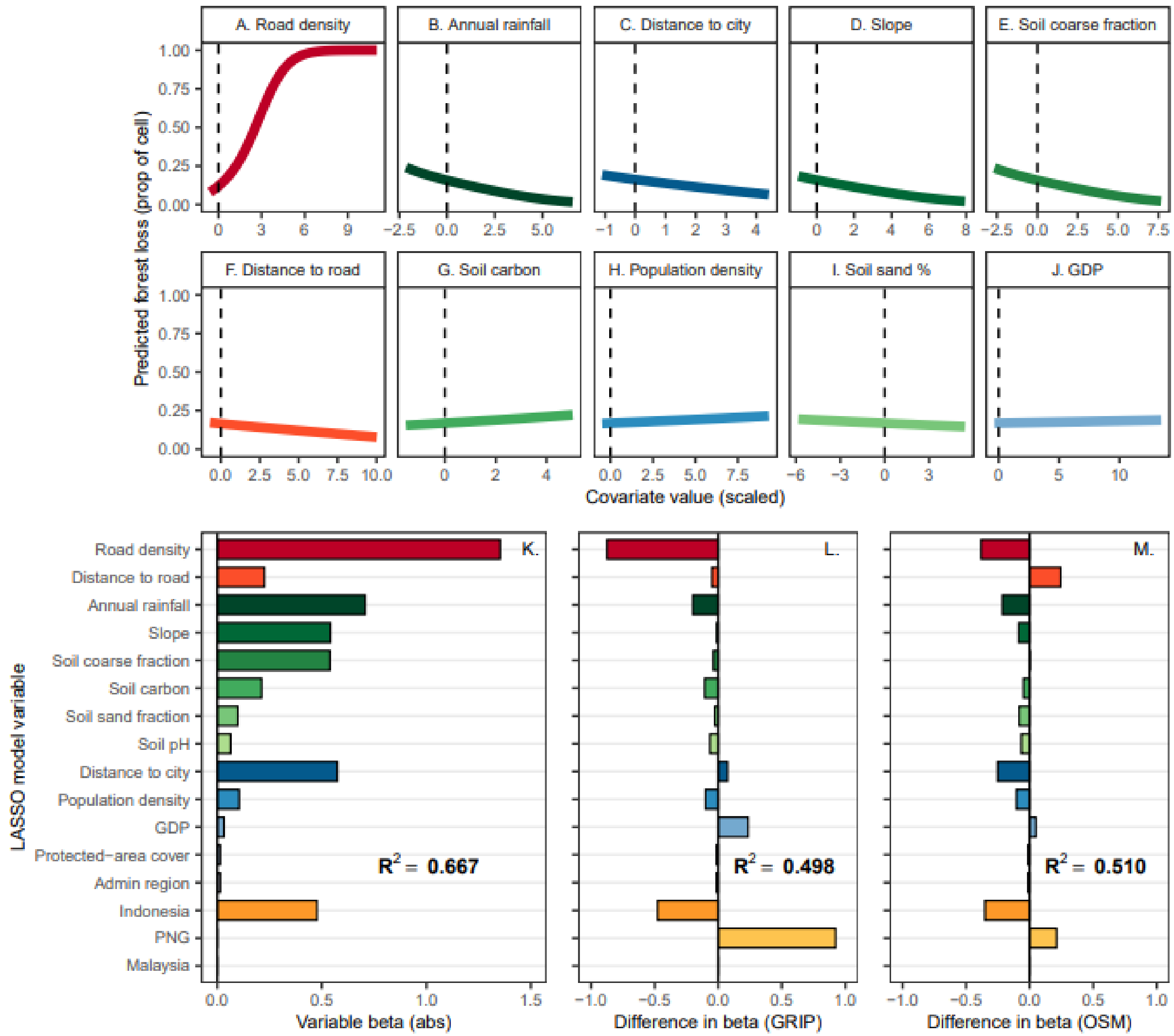


**Figure 4. Environmental and socioeconomic features influencing forest loss across the tropical Asia-Pacific region.** (A-J) Partial differential plots showing relationships between the 10 most influential features and forest cover (X-axis values indicate number of standard deviations from the mean; see Table 5). (K-M) Spatial predictors of deforestation, showing slope (beta) values for model using our road data (K) and the difference in slope values when using alternative road data from the Global Roads Inventory Project (L) and OpenStreetMap (M). “PNG” denotes Papua New Guinea. “Abs” indicates absolute values.

In our final LASSO regression model, several other variables—annual rainfall, distance to nearest city, topographic slope, soil coarse fraction, distance to nearest road, and country—had modest explanatory power, with each having beta (slope) values significantly smaller than that of road density (Fig. 4B-J). Marginal relationships of these variables with forest loss largely followed expected trends (i.e. forest loss was highest near townships or cities, in flatter areas, and in less-rainy locales where forest burning is easier) (Fig. 4B-J). Notably, protected-area coverage (with a beta value of just -0.01) had little influence on model performance. We did not evaluate various other potential drivers of deforestation, especially ultimate factors (e.g. poverty, access to global markets, social norms) (Geist & Lambin, 2002) for which we lacked adequately spatially resolved data. Thus, while road density was the strongest spatial predictor of forest loss in our study, we were unable to consider every conceivable driver of deforestation in our model.

We also ran separate LASSO models for each country and then compared their performance to our region-wide LASSO model, which indicated that Indonesia had a higher marginal rate of forest loss than either Malaysia and Papua New Guinea. Notably, the region-wide model performed better (pseudo $R^2$ = 0.667) than the three country-level models (pseudo $R^2$ = 0.540, using area-weighted averages for each nation) (Fig. 10). In addition, we re-ran our LASSO regression while excluding large-scale oil-palm and pulpwood plantations (Fig. 11), which are associated with considerable deforestation in the Asia-Pacific region (Curtis et al., 2018). This produced only negligible changes in model slope parameters and overall outcome (Supplementary Information), underscoring the robustness of our region-wide model.

The LASSO model based on our road data, which included ghost roads, differed in three important ways from those based on the GRIP and OSM datasets (Fig. 4K-M). First, the model with our improved road data was considerably stronger, explaining more of the total deviance in the response variable (66.7%) than did either the GRIP- or OSM-based models (49.8% and 51.0%, respectively). As a result, our model was better at predicting spatial patterns of forest loss across our study area (Fig. 4). Second, when using our road data, road density was a much stronger correlate of forest loss (with a beta value of 1.35, which is ~1.4 to 2.8 times greater than OSM- and GRIP-based values, respectively). Third, the effect of country on forest-conversion rates differed substantially (particularly for Indonesia and Papua New Guinea) when using GRIP or OSM data, compared to our comprehensive road dataset. Hence, the widely used GRIP and OSM datasets are not just seriously incomplete but also strikingly inconsistent among nations or geographic regions (Table 2)—with developing nations generally having much poorer road data than wealthier nations (Ramm et al., 2010; Ibisch et al., 2016).

Next, we assessed the degree to which IUCN-designated protected areas (Categories I-VI) limit road incursions and forest loss, relative to non-protected areas, using the three road datasets. We first used propensity-score matching (Geldmann et al., 2019) to account for non-random locations of protected areas, such as biases toward steeper or less productive lands

(Supplementary Information). We then used separate propensity-score analyses to assess the capacity of protected areas to reduce both road incursions and forest loss.

When comparing matched sites, we found that average road density was more than twice as high (211.5%) outside protected areas than inside them (Fig. 5A). However, after accounting for lower road densities inside protected areas, the marginal effects of protected-area coverage on forest loss were surprisingly modest: <1% in magnitude when based on the road datasets from this study, and <1.5% in magnitude when based on data from OSM or GRIP (Fig. 5B). This suggests that, on a per-kilometre basis, roads inside protected areas lead to nearly as much forest loss as do roads outside protected areas. We assert that the most critical conservation function of terrestrial protected areas, at least in the Asia-Pacific region, is limiting road incursions and their many associated impacts on forests.

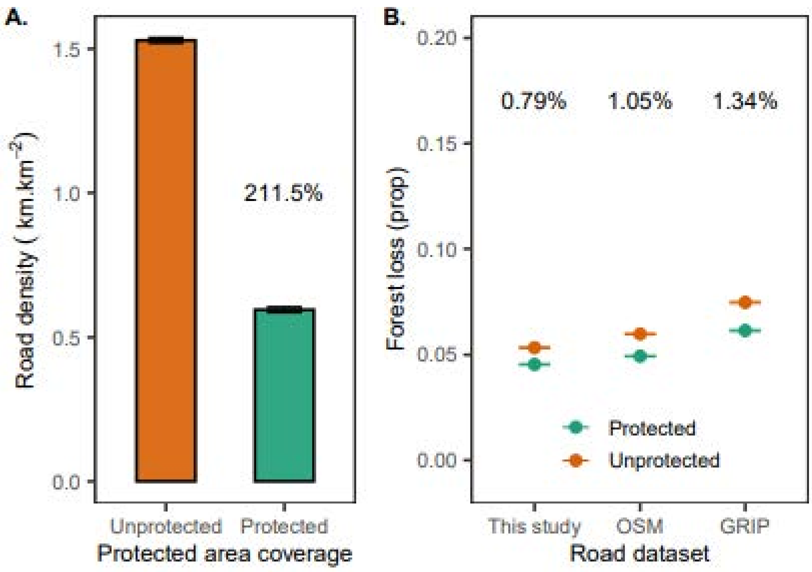


**Figure 5. Effects of protected areas in limiting road construction and forest loss.** (A) Differences in road density between protected and unprotected areas after site-matching analysis. (B) Marginal difference in forest loss between protected and unprotected cells after site matching with the full dataset from this study. For both panels, error bars show 95% confidence limits (in panel B, the error is too small for the gap between bars to be visible).

Finally, to test whether roads tend to precede deforestation, or rather follow it, we evaluated the temporal sequence of land-use change in 12 large land parcels (each ~400 km2 in area) arrayed across Sumatra, Borneo, and New Guinea (Fig. 6A). We created 35 annual roadmaps using annual

Landsat imagery from 1985 to 2020 and then identified the spatio-temporal relationship between road construction and deforestation using published annual deforestation data (Vancutsem et al., 2021) (Supplementary Information). We summarised this relationship by classifying areas within each parcel that were deforested before, during, or after road construction, as well as areas deforested independently of roads (>2 km from the nearest road).

In our 12 study locations, the probability of deforestation was low before road construction, but spiked immediately after nearby roads were created (Fig. 6B). Immediately following proximate road construction, the probability of a cell being deforested increased by approximately 50% (Fig 6B). Our assessment showed that the large majority of deforestation—92.2%, on average—occurred after or concurrently, with the construction of nearby roads (Fig. 6C). Forest loss preceded road construction in just 5.1% of the total area sampled. These trends indicate that forest loss in our study region is overwhelmingly triggered by ongoing road expansion, rather than vice-versa. In the areas in which forest loss occurred prior to road building, it is likely that the deforestation was facilitate by river access, or by local communities that were able to gain access to areas without visible road access. The 12 study locations include some large-scale oil palm and pulpwood plantations, where forest loss also typically followed road construction (Fig. 10).

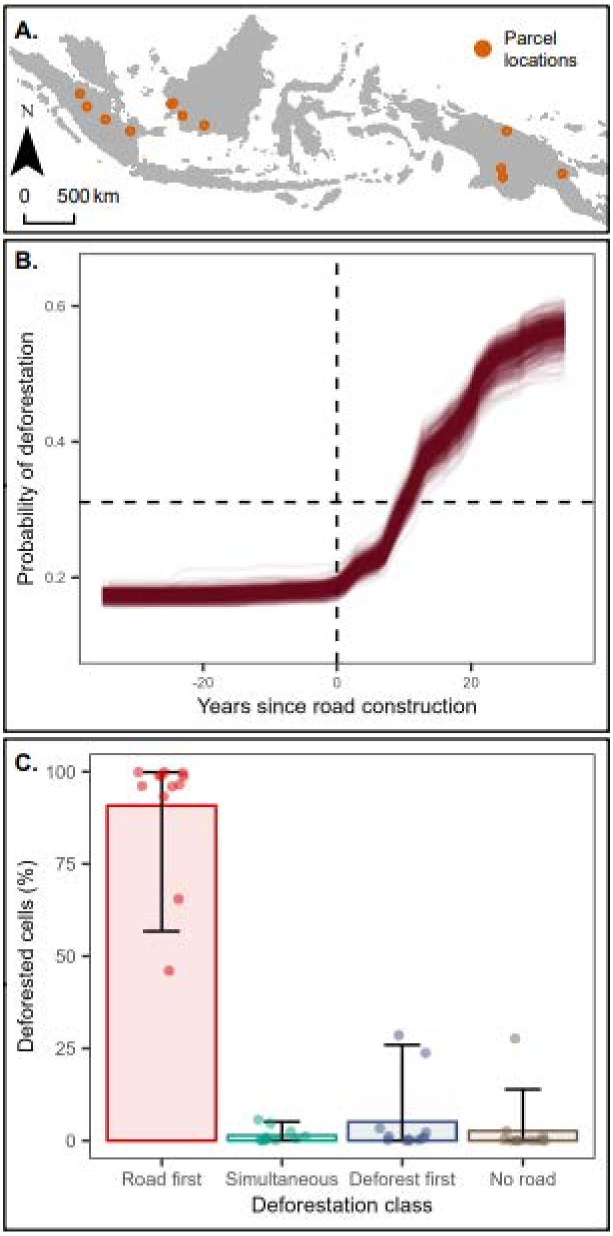


**Figure 6. Roads usually precede deforestation.** Temporal relationships between road construction and deforestation for 12 study sites arrayed across the continental islands of Sumatra, Borneo, and New Guinea. (A) Locations of the 12 study sites. (B) Partial plots for random forest models testing the temporal relationship between nearby road construction and deforestation (negative values for 'Years since road construction' indicate the number of years prior to road building, whereas the horizontal dotted line shows where true positive and true negative rates are maximized—where cells are more likely to be deforested than not). Each red line shows the partial plot from a single model iteration. (C) Median deforestation rates associated with different road-proximity categories. Error bars show the 5% to 95% inter-percentile range for each category.

## SUMMARY AND CONCLUSIONS

Using road data generated by trained volunteers, we recorded from 3.0 to 6.6 times more roads in the Asia-Pacific region than were found in leading global-road datasets, while revealing vast numbers of unmapped 'ghost roads'. These findings have key implications for forest conservation. As a consequence of rapidly proliferating ghost roads, government datasets on roads often have large blind spots and inconsistencies, inhibiting spatial planning, law enforcement, and the collection of government rents and royalties on exploited natural resources (Table 2).

Striking gaps in roadmaps are not at all unusual, especially for developing nations (Laurance et al., 2009; Laurance et al., 2014; Barber et al., 2014; Fearnside, 2015; Ibisch et al., 2016; Alamgir et al., 2017; Hughes, 2018; Kleinschroth et al., 2019). For instance, studies in the Brazilian Amazon, (Barber et al., 2014; das Neves et al., 2021; Botelho et al., 2022), Cameroon (Cameroon Road Network, 2022), and Solomon Islands (Katovai et al., 2016; Hughes, 2018) also detected many unmapped or illegal roads, ranging from 2.8 to 9.9 times those recorded in OSM or government sources—values that broadly overlap and even exceed those observed in our Asia-Pacific study area. Protected areas in this region provided considerable protection against road incursions, bearing just a third as many roads as did comparable unprotected areas (Fig. 5A). On a per-kilometer-basis, however, roads inside protected areas caused nearly as much forest loss as did those in unprotected areas (Fig. 5B). This underscores, in our view, an urgent need to limit unregulated road expansion within protected areas as a general conservation strategy (Laurance et al., 2012; Haddad et al., 2015; Sloan et al., 2017; Qin et al., 2019).

Although global road databases are gradually improving in quality (Herfort et al., 2021), their many gaps and inconsistencies greatly limit their value for comparing different nations, regions, and ecosystem types. Further, popular conservation metrics, such as the 'human footprint' (Venter et al., 2016; Williams et al., 2020) and 'roadless' or 'wilderness' areas (Watson et al., 2016), are being based in part on seriously incomplete road data. For example, the estimated human footprint in the environmentally critical region of east-central Borneo differs markedly when based on a recent OSM roadmap (Fig. 7A) compared to our road data (Fig. 7B). Among these differences, the mapped region in Borneo had twice as much land area with 'very high' disturbance (28.4% vs. 14.5%), and only half as much land with 'low' disturbance (6.6% vs. 13.6%), when based on our updated roadmap and forest-disturbance classifications from the human-footprint study (Williams et al., 2020).

The road-mapping element of this study required ~7,000 hours of effort by more than 200 trained volunteers or study authors. Such an intensive undertaking is justified only because human eyes still outperform AI-based methods for identifying and mapping roads (especially when more-accurate, higher-resolution images are used, as in this study). At larger spatial scales, the required effort is even more daunting. For example, a global-scale analysis using our methods would require ~640,000 hours of effort simply to map all of Earth's current roads just once. For this reason, a viable, AI-based road-mapping system is urgently needed (Laurance, 2018). Such schemes are under development (Wang et al., 2016; de Clerk, 2019; Botelho et al., 2022 Talkhani, 2022) and could potentially be trained using major datasets such as ours, aiming to provide accurate, global-scale road coverage in near real-time. In practical terms, such an automated system is one of the most urgent conservation needs for tropical forests today. Nothing else will keep pace with the contemporary avalanche of proliferating roads.

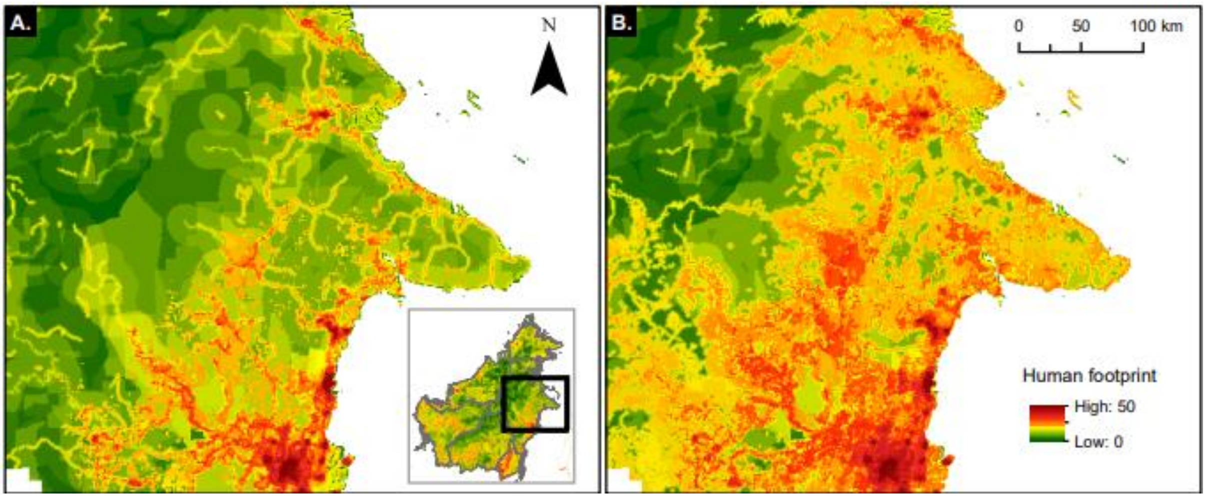


**Figure 7. Two versions of the human footprint[22] for eastern and central Borneo, using data from 2020.** These maps were based on (A) incomplete road data from OpenStreetMap (Williams et al., 2020), and (B) more complete road data from this study.

## SUPPLEMENTARY INFORMATION

### Study region

Our study examined the impacts of road building on forest cover in parts of Indonesia, Malaysia, and Papua New Guinea (Fig. 8). These countries were selected because each contains a substantial area of high-value tropical forest under imminent threat from road expansion, agriculture, and extractive industries, as revealed by our recent work (Alamgir et al., 2019a; Alamgir et al., 2019b; Sloan et al., 2018; Sloan et al., 2019a; Sloan et al., 2019b). Within these three countries, we arrayed our 1-km$^2$ plots to capture the full spectrum of forest conditions—ranging from areas with intact forest cover and sparse human populations, to areas with devastated forests and high human numbers. In terms of land area, our mapping efforts encompassed 51.4% of Sumatra, 65.6% of Borneo, and 100% of New Guinea.

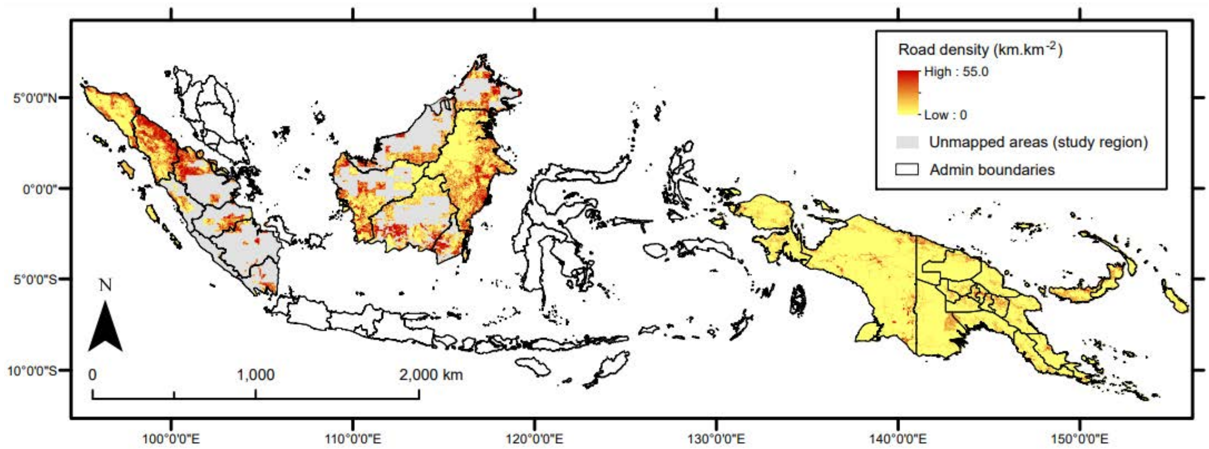


**Figure 8 Road density across mapped areas of the study region.** The study region consisted of Sumatra, Borneo, and New Guinea, three of the world's largest islands.

### Comprehensive roadmap

We gleaned data on existing roads from several sources, including OpenStreetMap and government maps and databases (Table 1). Note that the GRIP dataset was created in 2018 and is not updated. Open Street Map is constantly updated with available datasets and citizen science mapping. We then mapped and digitized all visible roads that were not recorded in these existing road datasets, using Google Earth (circa 2019). Roads were added to new kml files using the New Path tool and by tracing the location of all visible roads in the satellite image, and then exported to shapefiles in Arcmap 10.8. Road-mapping was conducted by 5 coauthors of this study and by 205 trained volunteers, whose individual mapping accuracy was independently quality-checked by one or more study coauthors. Using a standardized protocol that we developed (Sloan et al., 2020), the newly created road files were required to achieve a minimum accuracy of ≥90%, verified using standardized test datasets. Road density was quantified by calculating road lengths at 1-ha grid resolution and then converting this to a raster dataset with 1-km$^2$ resolution by summing the values.

**Table 1. Sources of road data for countries in the study region.**

| Country | Existing road-data source | Reference |
|---|---|---|
| Indonesia | Badan Informasi Geospatial | Badan Informasi Geospatial (2014) |
| Papua New Guinea | OpenStreetMap | Humanitarian Data Exchange (2019) |
| | PNG National Mapping Bureau | Humanitarian Data Exchange (2019) |
| Malaysia | OpenStreetMap | Ramm et al. (2010) |
| | Borneo Logging Roads | Gaveau et al. (2013), Gaveau et al. (2014) |

We compared our final road dataset to the two most widely used and freely available road datasets (Table 2), the Global Roads Inventory Project (GRIP; Meijer et al., 2018) from 2018, and a recent version (2020) of OpenStreetMap (https://www.openstreetmap.org). We coined the term 'ghost roads' to denote roads that were detected in our comprehensive mapping study yet absent from available sources including GRIP, OSM, and official roadmaps. Official road data for Indonesia were government road maps obtained through Badan Informasi Geospatial (Badan Informasi Geospatial, 2014), whereas official road data for Malaysia were government road maps used to produce the GRIP dataset (Meijer et al., 2018).

**Table 2. Estimated length of roads (km) within five broad governance regions in the Asia-Pacific region based on this study and available road datasets.** Numbers in parentheses are the proportions of roads across our study region.

| Region | This study | GRIP (2018) | OSM (2020) | Official data |
|---|---|---|---|---|
| Indonesian Borneo | 521,617 | 84,475 (0.16) | 136,518 (0.26) | 266,591 (0.51) |
| Indonesian Papua | 68,693 | 20,657 (0.30) | 36,643 (0.53) | 46,667 (0.68) |
| Malaysian Borneo | 161,395 | 3,438 (0.02) | 45,107 (0.28) | 3,438 (0.02) |
| Sumatra (Indonesia) | 522,174 | 69,948 (0.13) | 189,230(0.36) | 325,252 (0.62) |
| Papua New Guinea | 97,519 | 29,618 (0.30) | 41,017 (0.42) | ----- |

### Comprehensive land-cover map

Studies on drivers of deforestation often employ simple forest-cover datasets that use remote sensing techniques to classify land based on proportional forest cover. However, these datasets may be limited in their capacity to differentiate between intact forest and tree plantations (such as oil palm or wood-pulp species) or between intact non-forest vegetation types (such as wetlands or grasslands) and cleared land.

To minimize these limitations, we developed a comprehensive land-cover dataset for our Asia-Pacific study area using multiple datasets designed to classify various land-cover types, as well as a general land-cover dataset. These land-cover types were then defined as either 'intact' or 'converted' land to quantify drivers of human land conversion (Table 3). Land-cover was initially classified at 1-ha resolution, then aggregated to 1-km$^2$ resolution for analysis by calculating the proportion of 1-ha cells within each 1-km$^2$ plot that was 'intact'. Because datasets included in this map are from different time periods and with different temporal resolution, our final composite map does not have any temporal dimension. All cells in which the most common land cover class (by proportion of the plot area) was water were excluded from the model routine.

We used multiple sources (Hansen et al., 2013; ESA, 2017; Allen & Pavelsky, 2018; Harris et al., 2019; OpenStreetMap, 2021; Thenkabail et al., 2021; Lang et al., 2022) to estimate the 'original' (pre-clearing) vegetation types within our study region. Overall, forests and forested wetlands (such as peat-swamp forest) were the dominant pre-clearing vegetation types, covering 87.7% of the study area. Other land-cover types, such as non-forested wetlands (8.7%), water bodies (2.8%), and grasslands and other non-forest vegetation (0.8%), were far less abundant (Hansen et al., 2013; ESA, 2017; Allen & Pavelsky, 2018; Harris et al., 2019; Thenkabail et al., 2021; Lang et al., 2022).

**Table 3. Spatial datasets used to create the comprehensive land-cover map.**

| Land-cover type | Data description | Order | Class | Reference |
|---|---|---|---|---|
| Tree plantations | Composite dataset on tree plantations | 1 | Converted | Harris et al. (2019) |
| | Remotely sensed land-cover map 2020 | 2 | Converted | Lang et al. (2022) |
| | Remotely sensed oil palm plantations | 3 | Converted | Descals et al. (2021) |
| | Digitized farms and plantations | 4 | Converted | OpenStreeMap (2021) |

| | | | | |
|---|---|---|---|---|
| Croplands | Remotely sensed cropland extent 2015 | 5 | Converted | Thenkabail et al. (2021) |
| Forest cover | Remotely sensed forest cover 2020 | 6 | Intact | Hansen et al. (2013) |
| Rivers | Remotely sensed inland water and rivers | 7 | Intact | Allen & Pavelsky (2018) |
| Intact non-forest vegetation | Remotely sensed land-cover 2019 | 8 | Intact | ESA (2017) |
| All modified land-cover | Remotely sensed land-cover 2019 | 8 | Converted | ESA (2017) |
| Urban areas | Remotely sensed land-cover 2019 | 8 | Converted | ESA (2017) |
| Water | Remotely sensed land-cover 2019 | 8 | Intact | ESA (2017) |

*Ghost-road landcover classes*

We used our comprehensive landcover dataset to identify whether ghost roads were predominant in specific land use types [e.g. intact forest, large productive landscapes (>$10^4$ ha), or small-scale farms]. We used the Region Group tool in Arcmap 10.8 to measure the area of contiguous patches of different landcover types, using a 4-cell neighborhood with the original 1-ha landcover data. Each 1-ha cell therefore was categorized by its landcover type and the size of the discrete patch in which it was included. Using visual inspection of the spatial data, we identified a size-threshold (>$10^4$ ha) to discriminate large agro-industrial landscapes from other landcover classes. We calculated the length of roads in each 1-ha cell from our dataset for each landcover type, then did the same for the GRIP and OSM datasets separately. To visualise the unmapped roads by each landcover type, we present the difference between our data and the GRIP and OSM as the percentage of total unmapped roads (Fig. 9). Our results show ghost roads tend to occur most commonly in plantations (36% and 45% relative to GRIP and OSM datasets, respectively), but almost as commonly in intact forests (31% and 39% relative to GRIP and OSM datasets, respectively) and to a lesser degree in other agricultural landscapes (28% and 17% relative to GRIP and OSM datasets, respectively).

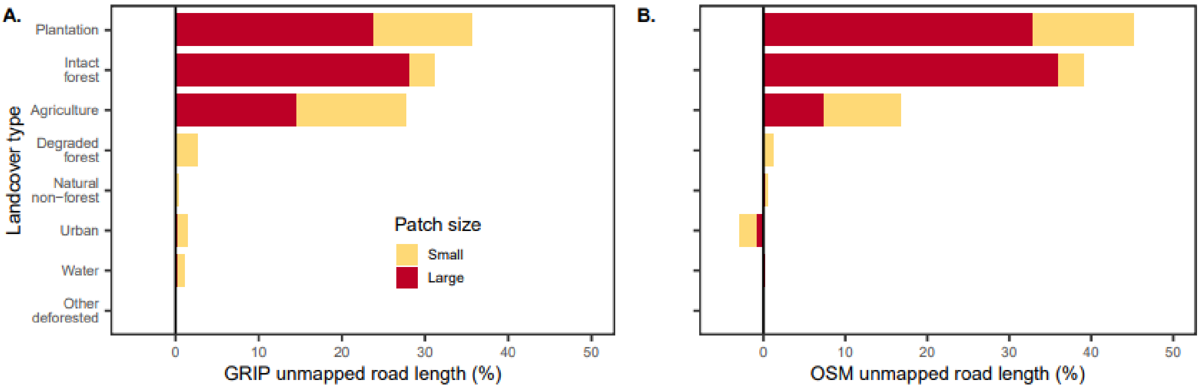


**Figure 9. Percentage of unmapped roads by landcover type in the Asia-Pacific region based on the difference between our data and the GRIP and OSM datasets.** "Plantation" indicates oil palm, pulpwood, or other tree monocultures, whereas "Agricult" includes practices such as swidden farming, rice, and coffee production.

## Landscape correlates of deforestation

*Potential spatial predictor variables*

A large number of potential drivers of forest loss have been identified in earlier studies (Geist & Lambin, 2002; Meyfroidt et al., 2018), sometimes operating at widely varying spatial scales (Cushman et al., 2017). We initially identified 38 socioeconomic and environmental variables (Table 4) that could be related to land conversion and forest loss, particularly via smallholder and industrial agriculture, the largest underlying driver of deforestation in our study region (Curtis et al., 2018; Pendrill et al., 2022).

We classified the 38 potential spatial predictors based on whether they represented proximate, underlying, or environmental drivers (Table 4). Proximate drivers are local-scale human activities that directly influence forest loss (Geist & Lambin, 2002). In our study, proximate drivers include road density, proximity to roads, and conversely, whether a particular forest tract is located in a protected area (Table 4). Underlying drivers in our study are structural traits in the social system (e.g. human population size, market integration, affluence) that can indirectly affect land use by mediating the proximate drivers (Meyfroidt et al., 2018). Such underlying drivers include national and sub-national administrative regions (reflecting national and local-scale policies), population density, distance to the nearest settlement, and distance to the nearest city (market) (Table 4). Environmental drivers include elevation, slope, slope position, topographical roughness, rainfall, and soil characteristics (Table 4). Five of these variables were quantified at varying spatial scales (e.g. population density was recorded for each 1-km$^2$ plot as well as for 5, 10, 20, 50, and 100 km radii around each plot). These data were generated using the Focal Statistics tool, and distance-based variables with the Euclidean Distance tool, in Arcmap 10.8.

Wherever possible, spatial data for the 38 variables were sourced from peer-reviewed global datasets or satellite data with a global extent, to maximize the generality of our models. We strove to use the most accurate spatial data available for our study area, but note that differences in spatial resolution, quality, and precision of different datasets can influence their perceived importance in modelling routines. Most of our variables had minimal modification from the original source material with many were simply transformed to the Asia South Lambert Conformal Conic projection system (https://epsg.io/102012) and resampled to 1-km spatial resolution, during which all layers were snapped to the same extent for ease of analysis. To extract data for these variables, all 1-km resolution cells within the mapped region were converted to points in ArcGIS 10.8, and data from all raster layers were then extracted using the Extract Multi Values to Points tool in ArcGIS.

*Model routine*

Because our initial modelling included many potential predictors ($n$ = 38) and large numbers of observations ($n$ = 1,418,755 plots), we utilized generalized linear modelling with LASSO (L1) regularization. LASSO regression uses covariate shrinkage to create parsimonious models in the presence of numerous covariates while avoiding over-fitting, and is also effective at dealing with multi-collinearity and complex relationships (Schrieber-Gregory, 2021).

We implemented LASSO regression using the cv.glmnet function in the ‘glmnet’ package in the *R* program (Friedman et al., 2010). We initially fitted a LASSO regression using all potential predictors of land conversion (Table 4) and selected variables that were retained for the lambda value at which model deviance was minimized (lambda.min). To further minimize potential collinearity, we removed potential predictors that were quantified at multiple spatial scales, keeping only the most influential (highest absolute beta value). For example, road density was considered influential at both 1-km and 5-km scales, but we retained only the 5-km covariate for further steps as this was more influential. This strategy reduced the number of potential predictors from 38 to 14.

Our response variable, forest loss, was quantified as a proportional value with a relatively high frequency of 0 and 1 values. To accommodate this inflation of 0 and 1 values, we fitted LASSO regressions using a quasi-binomial error distribution. Model fitting was assessed using the plotres function in the ‘plotmo’ package in R (Milborrow, 2021). Influential predictors were chosen using LASSO regression with spatial cross-fold validation. The final model included both spatial cross-fold validation and a spatial autoregressive (SAR) term to account for spatial autocorrelation. Model performance ($R^2$) was calculated while holding the SAR term at its mean value to negate its influence on model performance.

**Table 4. Potential predictors of forest loss used in this study, highlighting our rationale for inclusion, spatial scale, and data sources.** Each variable is categorized as a proximate driver (e.g. a socioeconomic process or condition that directly leads to forest loss), an underlying driver (e.g. a process or condition that indirectly affects forest loss), or an environmental driver (e.g. geographical features such as slope and soil features that can affect agricultural viability).

| Predictor variable | Spatial scale | Rationale | Type of driver | Data source |
|---|---|---|---|---|
| Country | 1 km | Previous work has shown that governance (defined by administrative regions) has direct and indirect effects on agricultural expansion and associated land conversion (Andersson & Gibson, 2006; Duran et al., 2011). | Underlying | GADM (2021) |
| Administrative region (subnational) | 1 km | | Underlying | |
| Population density | 1 km | Previous work has shown that population density is positively associated with both road density (Glover & Simon, 1975) and land conversion (Boserup, 2014; Nzunda & Midtgaard, 2017). | Underlying | Tatem (2017) |
| | 5 km* | | Underlying | |
| | 10 km* | | Underlying | |
| | 20 km* | | Underlying | |
| | 50 km* | | Underlying | |
| | 100 km* | | Underlying | |
| Distance to city (>10 people ha$^{-1}$) | 1 km | Agricultural location theory predicts that agricultural uses vary with distance from cities (Thünen, 1966; Geist & Lambin, 2002; Ahrends et al., 2010). | Underlying | Tatem (2017) |
| Distance to village (>4 people ha$^{-1}$) | 1 km | | Underlying | |
| GDP | 1 km | Gross Domestic Product (GDP) is a measure of affluence. Resource-frontier theory predicts that affluence (in combination with land accessibility and demographic pressures) encourages rapid agricultural expansion (Meyfroidt et al., 2018). It is therefore likely to correlate with road density and land-cover change. | Underlying | Kummu et al. (2018) |
| | 5 km* | | Underlying | |
| | 10 km* | | Underlying | |
| | 20 km* | | Underlying | |
| | 50 km* | | Underlying | |
| | 100 km* | | Underlying | |
| Protected area coverage | 1 km | Previous work has shown that protected areas reduce the amount of land conversion associated with roads (Barber et al., 2014; Nzunda & Midtgaard, 2017). | Proximate | WCMC (2022) |
| Road density | 1 km | Numerous studies have noted the effects of roads on land conversion (Barber et al., 2014; Meyfroidt et al., 2018); hence, we expect that greater | Proximate | Created from data produced by the authors |
| | 3 km* | | Proximate | |
| | 5 km* | | Proximate | |

| | | | | |
|---|---|---|---|---|
| | | amounts of roads in a given area would produce greater rates of land conversion. | | |
| Distance to road | 1 km | Previous work has shown that distance to road has a substantial effect on land conversion rates (Barber et al., 2014; Nzunda & Midtgaard, 2017). | Proximate | Euclidean distance tool in ArcMap 10.8. |
| Distance to river | 1 km | Previous work has shown that distance to navigable rivers can correlate with deforestation rates (Barber et al., 2014). | Proximate | Euclidean distance tool in ArcMap 10.8. |
| Elevation | | Higher elevations often have lower deforestation rates due to inaccessibility (Gaveau et al., 2014). | Environment | Jarvis et al. (2008) |
| Slope | 1 km | Slope has been shown to have a negative effect on land conversion (Gaveau et al., 2014). | Environment | Jarvis et al. (2008) |
| Slope position | 1 km | Slope position is hypothesized to influence land conversion as it affects the accessibility of land. | Environment | Geomorphometry and Gradient Metrics Toolbox (Evans & Oakleaf, 2012). |
| Topographical roughness | 1 km | Topographical roughness is an alternative classification of topography based on neighboring slope values and is hypothesized to influence land conversion in a similar way to slope. | Environment | Created using the Geomorphometry and Gradient Metrics Toolbox (Evans & Oakleaf, 2012). |
| | 5 km* | | Environment | |
| | 10 km* | | Environment | |
| | 20 km* | | Environment | |
| Mean annual rainfall | 1 km | Rainfall is hypothesised to influence road density and land conversion as high rainfall rates are detrimental to road construction and durability in both low-slope and high-slope regions (Sloan et al., 2019a) and impede road use. | Environment | Karger et al. (2021) |
| | 5 km* | | Environment | |
| | 10 km* | | Environment | |
| Soil bulk density | 1 km | Soil characteristics influence land suitability for productive land uses (Barrios, 2007) as well as suitability for road and building construction (Lim et al., 2014). | Environment | Poggio et al. (2021) |
| Soil clay fraction | 1 km | | Environment | |
| Soil sand fraction | 1 km | | Environment | |
| Soil pH | 1 km | | Environment | |
| Soil cation exchange | 1 km | | Environment | |
| Soil carbon content | 1 km | | Environment | |

*Diameter of focal neighborhood across which values were calculated.

*Spatial autocorrelation*

Spatially structured data, such as those in this study, are subject to spatial autocorrelation. Presence of spatial autocorrelation in model residuals violates the assumption of independence and can inflate the Type I error rate (Mets et al., 2017), potentially leading to selection of unimportant explanatory variables and poorly estimated model parameters (Ploton et al., 2020). We opted to manage spatial autocorrelation with an autoregressive approach (Dormann, 2007; Crase et al., 2012), as it is less likely than other methods to bias model-parameter estimates. To create the most parsimonious LASSO model while accounting for spatial structure in our data, we used 18-fold spatial cross-validation.

To determine if we had adequately accounted for spatial autocorrelation in our analysis, we calculated Moran's Index (I), which measures the strength of the correlation between observations dependent on their geographical distance (Valavi et al., 2019). Due to computational limitations, Moran's I was calculated for model residuals at each spatial fold using the moranfast package in R (Cooper, 2020), and the values averaged to estimate the global Moran's I. Moran's I values for our LASSO regressions and ghost-roads dataset, as well as those for the OSM and GRIP data, were all close to 0, indicating a negligible effect of spatial autocorrelation in our models (I values = 0.05±0.02, 0.08±0.04, and 0.08±0.03, respectively).

**Table 5. Mean and standard deviations for selected modelled variables (see Figure 2).**

| Model variable | Mean | SD | Units |
|---|---:|---:|---:|
| Road density (5-km radius) | 1.55 | 2.59 | $km \cdot km^{-2}$ |
| Topographic slope | 8.36 | 8.41 | percent |
| Soil coarse fraction | 81.04 | 30.49 | $cm^{3} \cdot m^{-3}$ |
| Distance to nearest city | 87.14 | 79.56 | km |
| Distance to nearest road | 49.23 | 70.38 | km |
| Soil organic carbon content | 991.1 | 646.5 | $g \cdot kg^{-1}$ |
| Annual rainfall | 3,112.1 | 872.8 | mm |
| Soil pH | 5.07 | 0.44 | pH |
| Population density (100-km radius) | 1,136.8 | 2,308.0 | $\text{People} \cdot km^{-2}$ |
| Soil sand fraction | 297.0 | 50.9 | $g \cdot kg$ |
| GDP (100-km radius) | 593.0 | 1,680.0 | $\text{Million US\$} \cdot km^{-2}$ |

*Country-level deforestation models*

The three countries in this analysis have different road densities and rates of deforestation, and we therefore tested whether country-specific LASSO models outperformed a single region-wide model. Our region-wide model performed better than the country-level models for both Indonesia and Papua New Guinea, and performed better overall for the whole region. Conversely, the country-level model for Malaysia performed better than did the region-wide model for Malaysia (Fig. 10). For all three models, road-related variables had the greatest effect on forest loss.

Although Papua New Guinea had the lowest road density, the beta (slope) terms were similar for both PNG and Indonesia, suggesting that roads had comparable effects on forest loss in both regions. Despite minor differences among countries, the region-wide model still had the best overall performance, and thus we used that model for the subsequent analyses.

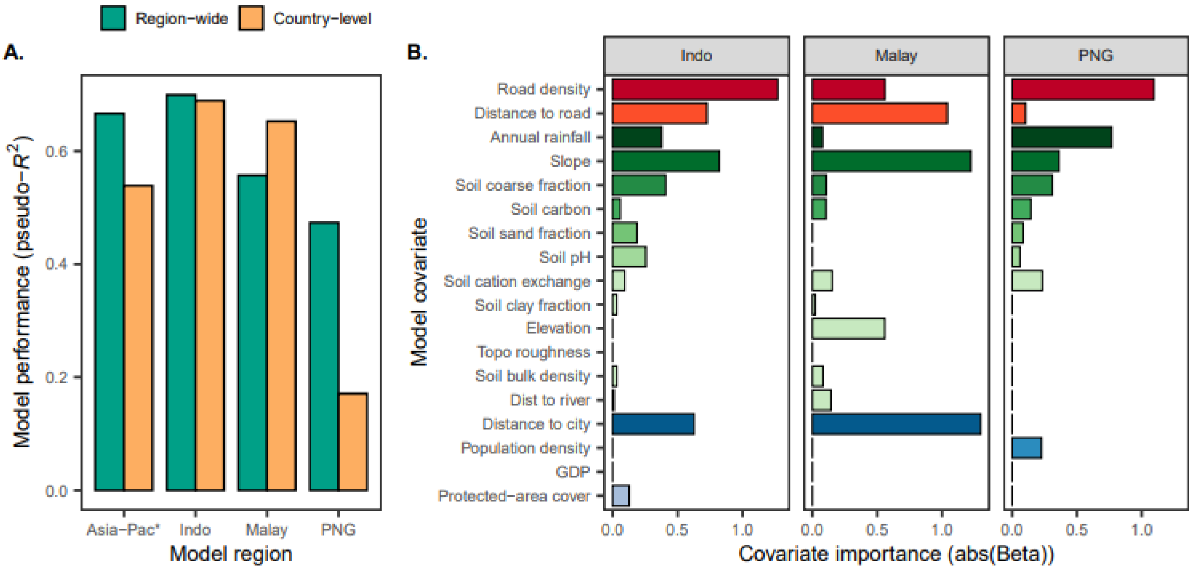


**Figure 10. Model performance and variable importance for a region-wide model and for three country-specific models.** The pseudo-$R^2$ value reported for the Asia-Pacific region is the area-weighted mean of the three country-level models.

*Model sensitivity to large-scale plantation landscapes*

As with the spatio-temporal analysis, we assessed whether large-scale plantation landscapes affected the results of our LASSO regression by re-running the model but excluding large plantations. There was almost no difference in model performance or covariate importance when large plantations (those larger than 10,000 ha, or those larger than 1,000 ha) were each excluded in turn (Fig. 11). Hence, we used the complete dataset, including large plantations, for our deforestation models (Fig. 4).

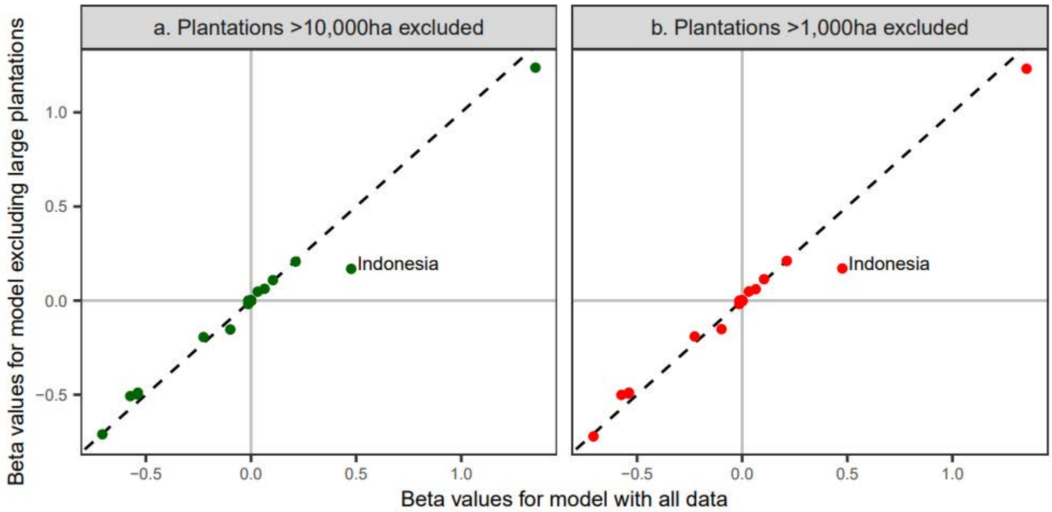


**Figure 11. Beta (slope) values for covariates in a LASSO-regression model based on our entire Asia-Pacific-region dataset, versus the same model excluding large-scale plantation landscapes.** (a) Comparison of beta values when plantation landscapes larger than 10,000 ha were excluded. (b) Comparison of beta values when plantation landscapes larger than 1,000 ha were excluded. Indonesia (labelled) was the only model term in which the beta value was noticeably altered when large plantations excluded.

*Effects of protected areas*

We used propensity-score matching (Geldmann et al., 2019) to determine whether protected areas (WCMC, 2022) limit road incursions relative to non-protected areas, and whether protected areas limit forest disruption when roads are present. This method compensates for potential biases in protected-area location (e.g. the tendency for reserves to be established in steep terrain, where few roads are present; Pressey et al., 2000). Before matching, all of the 1-km$^2$ cells in each plot were removed if the dominant land-cover class was water, or if the 1-km$^2$ cell was partially inside a protected area.

To analyse the effect of protected areas on forest loss, protected and unprotected cells were matched using all influential deforestation drivers identified in our LASSO models (apart from protected-area coverage). Site-matching analysis was conducted without replacement using the MatchIt package in R (Ho et al., 2011), using a 'nearest neighbor' matching method with glm distance and a relatively strict calliper of 0.01 standard deviations. The robustness of site-matching was assessed by comparing the balance of the two datasets (Fig. 12). Following site-matching, we calculated the marginal effect of protected areas on land conversion using a block-bootstrapping method (Abadie & Spiess, 2022).

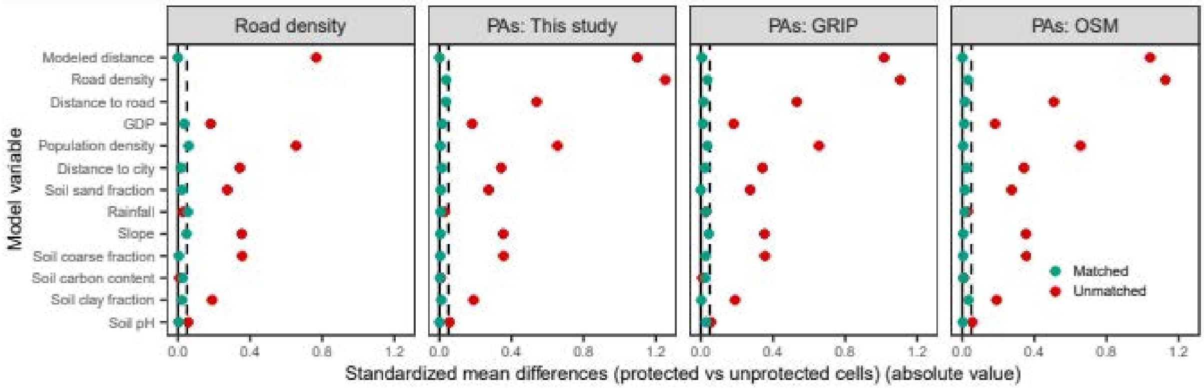


**Figure 12. Standardized mean differences between protected and unprotected cells before (red circles) and after (green circles) propensity-score matching.** Smaller standardized mean difference values indicate greater similarity between values in protected and unprotected sites. Dashed lines indicate a standardized mean difference of 0.05.

Finally, to assess the effect of protected areas on road incursions (Fig. 5), cells for protected and unprotected areas were matched using the influential forest-loss drivers (excepting variables for road density, distance to nearest road, and protected-area coverage). After site-matching, the marginal effect of protected areas on road density was calculated using the coeftest function in package 'lmtest' (Hothorn, 2022).

*Do roads lead to deforestation?*

Our analyses reveal that proliferating roads are strongly associated with forest loss across our study area (Fig. 4). To assess whether roads typically precede (or follow) deforestation, we created spatio-temporal maps of road-network expansion. Using Landsat imagery accessed via Google Earth, we created annual road maps for each year from 1985 to 2020 inclusive by mapping all visible roads every year for 12 large parcels (each ~400 $km^2$ in area) arrayed across our study area. These parcels (Fig. 6) were selected using four criteria: (1) they were arrayed evenly (four plots each) across the three large islands in this study; (2) they occurred in sites that had little if any road construction or forest loss prior to 1990 (because most deforestation in the region has occurred since that date); (3) they broadly sampled prevailing landcover types (small- and large-scale plantations and various agricultural lands) in the region; and (4) each parcel had >50% forest loss by 2020 to ensure it included sizable areas of roads, forests, and deforested lands to evaluate in our analysis. Once mapped, forest roads were retained in the analysis even if no longer detectable, as regeneration of the forest canopy can obscure roads in satellite imagery in just a few years.

For each parcel, we digitized all detectable roads each year between 1985 and 2020, and then used these annual roadmaps to calculate the linear distance to the nearest road for each year at 1-ha raster resolution. We identified the year in which the majority of deforestation occurred for each 1-ha raster cell using the Resample function in Arcmap 10.8 on published deforestation data (Vancutsem et al., 2021). We also assumed that all deforestation located <2 km from a road was associated with that road (in our study area, >80% of all deforestation was <2 km from one or more roads) and conducted a sensitivity analysis to ensure this threshold did not influence results.

We identified the spatio-temporal relationship between road construction and deforestation using random forest models. Random forest models are robust to complex non-linear relationships (Breiman, 2001) and suitable for model averaging techniques that reduce computational burden. For each 1 ha cell that was within 2 km of a road, we calculated the number of years since (or until) road construction by identifying the first year the cell was within 2 km of a road and subtracting this value from the current year, and used this term as a model predictor. The model response was a temporal deforestation term that identified if the cell had been deforested in the current year or some previous year (1), or had not been deforested (0).

To account for temporal pseudo-replication, as each cell had 35 observations (1 observation per year), we used the cell ID as a model predictor. In order to reduce computational burden and quantify model uncertainty, we created groups of 1000 cells and iteratively ran random forest models on each group of cells (circa 411,000 cells that were within 2 km of a road in at least one timestep). We then created partial plots of the relationship between years since road construction and probability of deforestation for visual representation (Fig. 6B) and assessed model performance by predicting from each model and calculating AUC values. Model performance was high with a mean AUC = 0.940. Random forest models were run using the ranger package (Wright & Ziegler, 2017) in R (version 4.1.2), partial plots were created using pdp (Greenwell, 2017), and AUC values calculated using dismo (Hijmans et al., 2022).

Finally, we created a simplified spatio-temporal assessment by classifying each individual 1 ha cell that had been deforested based on the time of deforestation and time of road construction. Cells were classified as either: (1) deforested before road construction (deforest first), (2) deforested concurrent with road construction (simultaneous), (3) deforested after road construction (road first), or (4) >2 km from the nearest road (no road); then we calculated the proportion of each parcel in each of the four deforestation categories. Differences in the frequency of these four categories of landscape change (Fig. 6C) were highly significant ($F_{3,42}$=194.4, $P$<0.0001), with deforestation after road construction being far more prevalent than any other category ($P$<0.0001). No other pairwise comparisons were significant ($P$>0.05). In addition, there were no significant differences in categories among the three large islands in this study ($F_{2,42}$=0.00, $P$=1.00; two-way ANOVA with Tukey's post-hoc tests).

*Sensitivity of spatio-temporal analysis to distance threshold*

To ensure our decision to use a 2 km distance threshold did not influence the results of the spatio-temporal analysis, we also conducted the aforementioned analyses using 1 km and 3 km distance thresholds. While the probability of deforestation occurring before or simultaneous with road construction was slightly higher using a 1 km distance threshold (Fig. 13D, 13E), we found that there was no difference between distance thresholds in the proportion of deforested cells in each deforestation class (Fig. 13E) ($F_{2,139}$ = 0.00, P = 1.00; two-way ANOVA). We therefore reported the results using a 2 km distance threshold as this had a lower proportion of deforested cells not associated with roads than did the 1 km distance threshold.

*Sensitivity of spatio-temporal analysis to large-scale plantation landscapes*

Large-scale plantations are more common in some of our study islands, such as Borneo, than others, such as New Guinea. To ensure that the varying prevalence of large-scale plantation landscapes did not bias our spatio-temporal analysis of roads and deforestation (Fig. 6), we (1) assessed the amount of each landcover class in our study region, and (2) compared the spatio-temporal relationship between roads and deforestation in large-scale plantation landscapes versus all other landscapes (Fig. 13). While the random forest model suggested that deforestation occurred closer to road construction date in large plantation landscapes (Fig. 13B), we found no significant difference in the spatio-temporal relationship of roads and deforestation when comparing areas inside versus outside plantation landscapes ($F_{1,52}$ = 0.45, $P$ = 0.50; two-way ANOVA) (Fig. 13C). Therefore, we conclude that the varying occurrence of large plantation landscapes across our study area did not significantly bias the observed relationship between roads and deforestation.

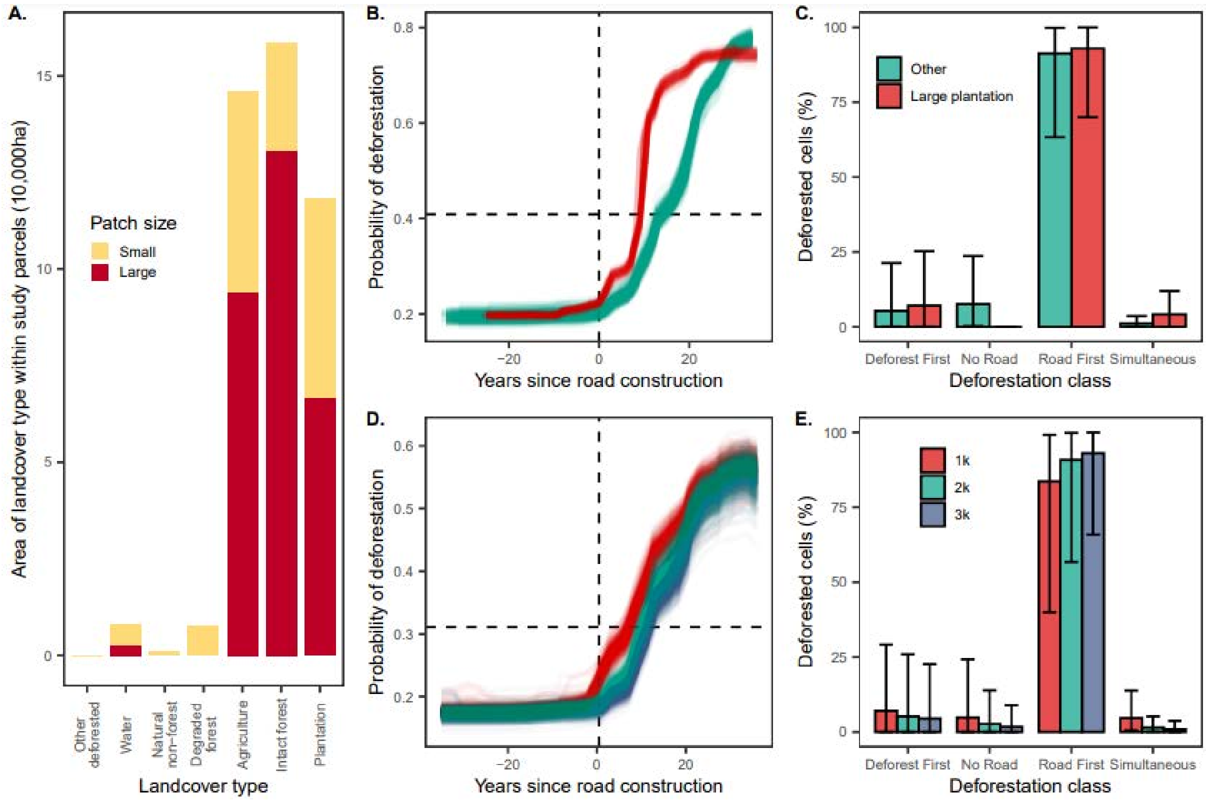


**Figure 13. Relationship between roads and deforestation for large agri-industrial lands versus other land-cover types in the Asia-Pacific region and sensitivity of spatiotemporal analysis to distance threshold.** (A) The area of each landcover type within the spatio-temporal study parcels. (B) Random forest partial plots of the relationship between years since proximate road construction and the probability of deforestation for areas within large plantation landscapes and all other landcover types. (C) Spatio-temporal relationship between roads and deforestation within large plantation landscapes ("Large plantation") and in all other landcover types ("Other"). (D) Random forest partial plots of the relationship between years since proximate road construction and the probability of deforestation for the three distance thresholds (1 km, 2 km, 3 km). (E) Spatio-temporal relationship between roads and deforestation for three distance thresholds (1 km, 2 km, 3 km). In random forest partial plots, negative values for 'Years since road construction' can be considered 'years until road construction'.

# Chapter 3: Classifying and quantifying the impacts of first-cut roads in tropical forest frontiers

Submitted to *Current Biology* as: Engert, J.E., Souza, C.M., Kleinschroth, F., Juffe-Bignoli, D., Costa, S.P., Botelho Jr., J., Ishida, F., Nursamsi, I. & Laurance, W.F. (submitted). Explosive growth of secondary roads is triggering widespread tropical deforestation. *Current Biology*.


## Abstract

In frontier regions, first-cut roads that initially penetrate forests often promote adjoining secondary roads that sharply increase the scale and pace of deforestation. While widely recognised as a conservation concern, the factors that influence such secondary roads and their environmental impacts are poorly understood. Here we disentangle the causes of road-related deforestation in three of the world's major tropical regions. To do this, we identified 92 first-cut roads in the Brazilian Amazon, Congo Basin, and New Guinea for which we quantified the length of adjoining secondary roads and the area of related deforestation. On average, proliferating secondary roads far outstripped first-cut roads in length, being 4.8, 9.8, and 49.1 times longer than first-cut roads in the Congo, Asia-Pacific, and Amazon regions, respectively. Net forest destruction near secondary roads was also remarkably heavy, being 31.5, 22.2, and 305.2 times greater than that directly driven by first-cut roads for the same three regions. We assert that limiting the unbridled spread of secondary roads is a critical priority for conserving tropical forests and their biodiversity.

## INTRODUCTION

In the tropics and beyond, roads are key proximate drivers of environmental impacts, including forest fragmentation (Goosem, 2007; Laurance et al., 2018), fires (Nepstad et al., 2001), mining (Asner et al., 2013; Edwards et al. 2014), and large-scale land-clearing (Busch & Ferretti-Gallon, 2017; Sales et al., 2017; Engert et al., 2024). Such impacts are amplified for the initial roads constructed in intact forests – which we term 'first-cut' roads – and which in turn can promote a rash of associated secondary roads (Fearnside & de Alencastro Graça, 2006; Fearnside, 2007; Perz et al., 2008; Laurance, Goosem & Laurance, 2009; Laurance et al., 2015). These secondary roads, which are often illicit and unmapped (Laurance et al. 2014; Engert et al. 2024), can dramatically elevate forest and biodiversity losses in frontier regions (Barber et al. 2014; Fearnside, 2007; Fearnside, 2015).

First-cut roads provide an important conduit for initial human incursions into natural habitats (Laurance et al., 2014; Laurance & Arrea, 2017). In this way they can promote substantial secondary road expansion and land colonisation, particularly when commodity export facilitation is a motivating factor (Fig. 14) (Frohn, Dale & Jiminez, 1990; Geist & Lambin, 2002; Seibert, 2011; Rodney, 2018). While widely recognized as a conservation concern (Fearnside, 1987; Laurance et al. 2009; Fearnside, 2015; Johnson et al., 2019), the magnitude and effects of secondary road development have not previously been quantified. Without such information, impact assessment procedures for road projects are doomed to misjudge the level of expected environmental destruction and hamper decision-making (Holden, 1987; Fearnside, 1987; Laurance et al., 2001; Engert et al., 2021).

Globally, new investments in roads and extractive industries are creating an unprecedented wave of first-cut roads in forested regions, especially in lower-income nations where development pressures are often intense (Thacker et al., 2019). Vast expanses of new roads are expected by mid-century from major infrastructure schemes such as China's Belt and Road Initiative (Ascensão et al., 2018), the Programme for Infrastructure Development in Africa (Thorn et al., 2022), the Initiative for Integration of Regional Infrastructure in South America (Vilela et al., 2020), and national programs in Indonesia (Alamgir et al., 2019a; Sloan et al., 2019a), Malaysia (Sloan et al., 2019b), and Papua New Guinea (Alamgir et al., 2019b), among others. Many proposed road projects will impact areas with exceptional environmental and societal values, such as protected areas, key biodiversity areas (Laurance et al., 2015; Sloan, Bertzky & Laurance, 2017), and indigenous territories (Estrada et al., 2022).

An urgent priority is understanding whether and how secondary roads increase the environmental impacts of first-cut roads. Here we identify first-cut roads in the Brazilian Amazon, Congo Basin, and New Guinea, and then use network analyses (Cooper, 1963) to identify and determine the lengths of their associated secondary roads (Fig. 14). For each of these three regions, we then contrast forest disruption arising from first-cut versus secondary roads, to evaluate their spatial footprints and overall environmental consequences.

## METHODS

### *Identifying first-cut roads*

To identify first-cut roads and classify and quantify their secondary road and impacts on forest loss and degradation we selected study regions that complied with three key criteria: (1) have high-quality, updated road maps available, (2) have experienced large-scale anthropogenic landscape conversion predominantly within recent decades, and (3) have experienced rapid land colonization and conversion within this period or are expected to in the future. Based on these criteria, we identified the Brazilian Amazon, Congo Basin, and island of New Guinea as important study regions.

We defined “first-cut roads” as major roads (trunk roads, motorways, highways, or primary roads) that were constructed in landscapes that had not yet experienced significant human invasion and modification. Therefore, major roads that were constructed in landscapes that had already experienced notable human modification, for example conversion for perennial agriculture, were not considered first-cut roads. For New Guinea and the Congo Basin, major roads were identified using the aforementioned road classes in the Open Street Map database. For the Brazilian Amazon we considered national highways with BR classification to be major roads, which included some “secondary” roads in frontier regions (i.e. BR-230). We determined which major roads could be considered ‘first-cut roads’ using satellite imagery accessed through Google Earth (Fig. 15) and published information (i.e. Fearnside, 2007), and hence focused on roads constructed in the last 50 – 100 years. These major roads were then separated into discrete “first-cut road” units by splitting at intersections and existing human settlements. To exclude small line segments and small link roads, first-cut roads were excluded from analyses if they were less than 40km long. Our dataset included 13 first-cut roads in New Guinea, 33 in the Congo Basin, and 46 in the Brazilian Amazon.

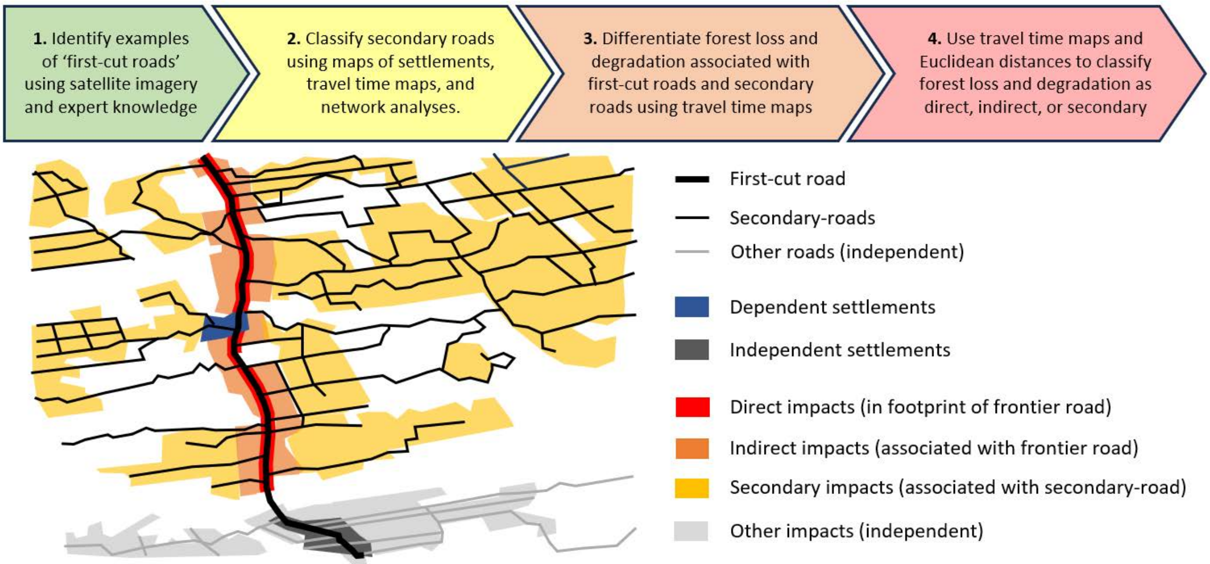


**Figure 14. Conceptual figure demonstrating the classification of secondary roads and impacts.** Direct impacts occur within the road footprint (clearing for road construction), indirect impacts are those within 1 km of the first-cut road (regardless of proximity to secondary roads) or closer to the first-cut road than secondary roads. Secondary impacts are all other impacts associated with secondary roads. By assuming that all impacts within 1 km of the first-cut road would happen without secondary road development, we are being conservative in our estimate of the secondary impacts.

*Network analyses*

We used network analyses, specifically a form of location allocation analysis (Cooper, 1963), to identify both secondary roads and induced deforestation and forest degradation. Location allocation analysis is a modified version of Euclidean allocation that includes a friction surface to identify the nearest source point while accounting for variable travel speeds or travel costs over different surface types. As road expansion and forest loss and degradation are dependent on human populations and enabled by roads, our network analyses required accurate information on road networks and human settlements.

Firstly, we developed high-accuracy road and settlement maps using the best available data for each region. For roads in New Guinea we used the "ghost roads" dataset described in Engert et al. (2024); for the Brazilian Amazon we used the AI-detected road dataset described in Botelho Jr. et al. (2023); and for the Congo Basin we used the road dataset described in Kleinschroth et al. (2019). As both Engert et al. (2024) and Kleinschroth et al. (2019) relied on inconsistent freely-available satellite imagery, they were also supplemented with the most recent Open Street Map data by selecting and appending any OSM roads not included in the aforementioned datasets. All roads that were not classed as major roads as above (BR- designated roads in the Brazilian

Amazon; trunk, motorway, highway, or primary road classes in New Guinea and the Congo Basin) were considered 'minor' roads from which we identified secondary roads. Our human settlement layer was created using both Landscan population density maps (Rose et al., 2021) and Open Street Map building locations (OpenStreetMap contributors, 2022) to account for any gaps in either of these datasets (Supplementary Methods).

We then used the high-accuracy road maps to identify discrete, inter-connected road networks. To do this, we created road presence raster layers at 1 -km resolution and identified discrete networks of connected roads using the Region Group tool with 8-cell neighbourhood in Arcmap 10.8. We chose the 1 -km resolution to account for small gaps in road shapefiles that may occur due to slight inaccuracies in mapping or road detection. The discrete networks were then converted from raster to polygons, and we identified those that were within 2 -km of a first-cut road and considered these to be connected to the first-cut road. This 2 -km distance was selected to account for small gaps in road shapefiles that may be due to mapping inaccuracies or gaps introduced in the data cleaning steps. Secondary roads could henceforth only be identified from those road networks connected to a first-cut road.

As first-cut-road-dependent land-colonisation may result in the development of new human settlements, we then classified human settlements as either dependent on first-cut roads, or independent of first-cut roads. Independent settlements are those that were present before the first-cut road was constructed (based on satellite imagery and expert knowledge) or are not connected to the first-cut road by minor road networks, while dependent settlements are those connected to the first-cut road and established after its construction (Supplementary Information). While existing settlements may increase in size and population due to the increased access provided by a first-cut road (Voss & Chi, 2006), we opted to ignore this effect in order to provide a more conservative estimate of the impacts first-cut roads.

These initial data preparation steps allowed us to develop a robust network analysis workflow to identify secondary roads and induced impacts. For the network analyses, we considered human settlements and major roads to be source points for minor roads; and settlements, roads, and rivers to be source points for forest loss and degradation. To account for differences in travel cost over different surface types, we created a travel time map to use as a friction surface (Supplementary Material, Table 6 – 8). The travel time map was created using a modified version of the methods outlined in Weiss et al. (2018) and Engert et al. (2021) that estimates travel time based on pre-clearing vegetation cover, topography, waterways, and roads. Travel times from source locations were created using the Cost Distance tool in Arcmap 10.8.

*Identifying secondary road*

We used the above outlined network analyses to identify secondary roads stemming from first-cut roads. We considered secondary roads to be those minor roads that were (1) part of a network directly connected to the first-cut road, (2) had a lower travel time (by 20 mins or more) from first-cut roads than from independent settlements, and (3) had a lower travel time from first-cut roads than from other major roads. We therefore created travel time maps using as starting points (1) first-cut roads, (2) other major roads, and (3) independent settlements, and calculated the minimum travel time for each minor road across each of the three travel time maps using the Zonal Statistics tool in Arcmap 10.8. This allowed us to identify minor roads for which the travel time was lower from first-cut roads than from other major roads or independent settlements. We conducted visual inspections across the road networks to ensure these classifications were reasonable. After identifying secondary roads, we determined their first-cut road source using the Cost Allocation tool in Arcmap 10.8, and summed the total length of secondary-road for each first-cut road.

*Classifying human impacts*

We used a similar process to classify impacts as was used to classify secondary road. To identify 'human impacts', we first classified Vancutsem et al. (2021) land-cover change data as 'human impacted' or not at the original raster resolution (Table 9), then aggregated to 1 ha resolution by calculating the proportion of each cell that had experienced human impacts. The Vancutsem et al. (2021) dataset captures a wide range of impacts including complete deforestation, logging, and fires, and we developed a classification scheme that aimed to separate human impacts from natural disturbances, such as river inundation. The Vancutsem et al. (2021) dataset, which assesses Landsat imagery for the period 1982-2021, also includes various classes of 'forest regrowth' which we used to identify forest loss or degradation that occurred before this period. A limitation of the Vancutsem et al. (2021) dataset is a lower ability to detect selective logging, which is a major driver of road network expansion in the Congo Basin (Kleinschroth et al., 2019). Additionally, accuracy in detecting non-forest land cover types was higher for Africa than Latin America or Asia (Vancutsem et al., 2021), hence human incursions may be slightly underestimated for this region.

The new 1-ha cells were considered to be impacted if the proportion of the area with some 'human impact' was >10%. This 10% threshold was set in order to further exclude cells that were more likely to be impacted through some stochastic natural process than through human action.

The use of this threshold and the ~19% omission error rate of the Vancutsem et al. (2021) transition data suggests that our estimates of forest loss and degradation are likely to be an underestimate. While the environmental effects of 'human impacts' differ between impact types (i.e. short term degradation versus persistent deforestation; Nunes et al., 2022), we considered impacts to be equal as the main aim was to assess the extent and scale of area affected. We also recorded the year in which the majority of impacts occurred for each 1 ha cell to assess changes through time.

To disentangle first-cut-road-dependent impacts from other human impacts we identified impacted cells that had a lower travel time to first-cut roads and their secondary roads than (1) independent settlements and their connected roads, (2) other major roads and their dependent roads, (3) all other roads (networks not connected to settlements or major roads), and (4) rivers and other navigable waterways. We also removed all impacts for which the minimum travel time to any mapped source was greater than 420 minutes (Fig. 22), as we assumed these were likely associated with some other unmapped source.

After identifying first-cut-road dependent human impacts, we classified impacts as direct (in the road construction footprint), indirect (associated with the first-cut road itself), or secondary (associated with secondary road). To classify human impacts, we calculated both the Euclidean Distance to the first-cut road, as well as the travel time to the first-cut road and to secondary road. Direct impacts were those that occurred within 100 m of the first-cut road. Indirect impacts were all impacts within 1 km of the first-cut road regardless of proximity to secondary road, or that had a lower travel time to first-cut road than to secondary road; and secondary impacts were those with lower travel time to secondary road than to the first-cut road. A diagrammatic representation of the entire methodology is outlined in Fig. 20.

Using these impact classes, we calculated road effect zones as the distance from the first-cut road in which 95% of impacts occur. We calculated road effect zones separately when considering only the direct and indirect impacts, and when considering all impacts (direct, indirect, and secondary). We also overlaid the identified impacts with a map of deforestation drivers (Curtis et al., 2018) to identify the dominant drivers in each region.

We opted not to assess the governance or legality of secondary roads or their impacts for two key reasons: (1) the governance or legality of roads is often difficult or even impossible to determine as (a) roads may be constructed illegally or informally but subsequently included in official government data or retroactively legalised, (b) some roads may be legal but not included in official data if they are not considered 'roads' for government purposes (i.e. small logging tracks), (c) roads may be constructed by legal landholders but informally and hence not recognised within official data, and (d) official road data may be poor and simply not contain all legal and official roads; and subsequently (2) legality or governance of secondary roads is not within the scope of this paper as we simply aim to quantify the amount of secondary road and their associated impacts.

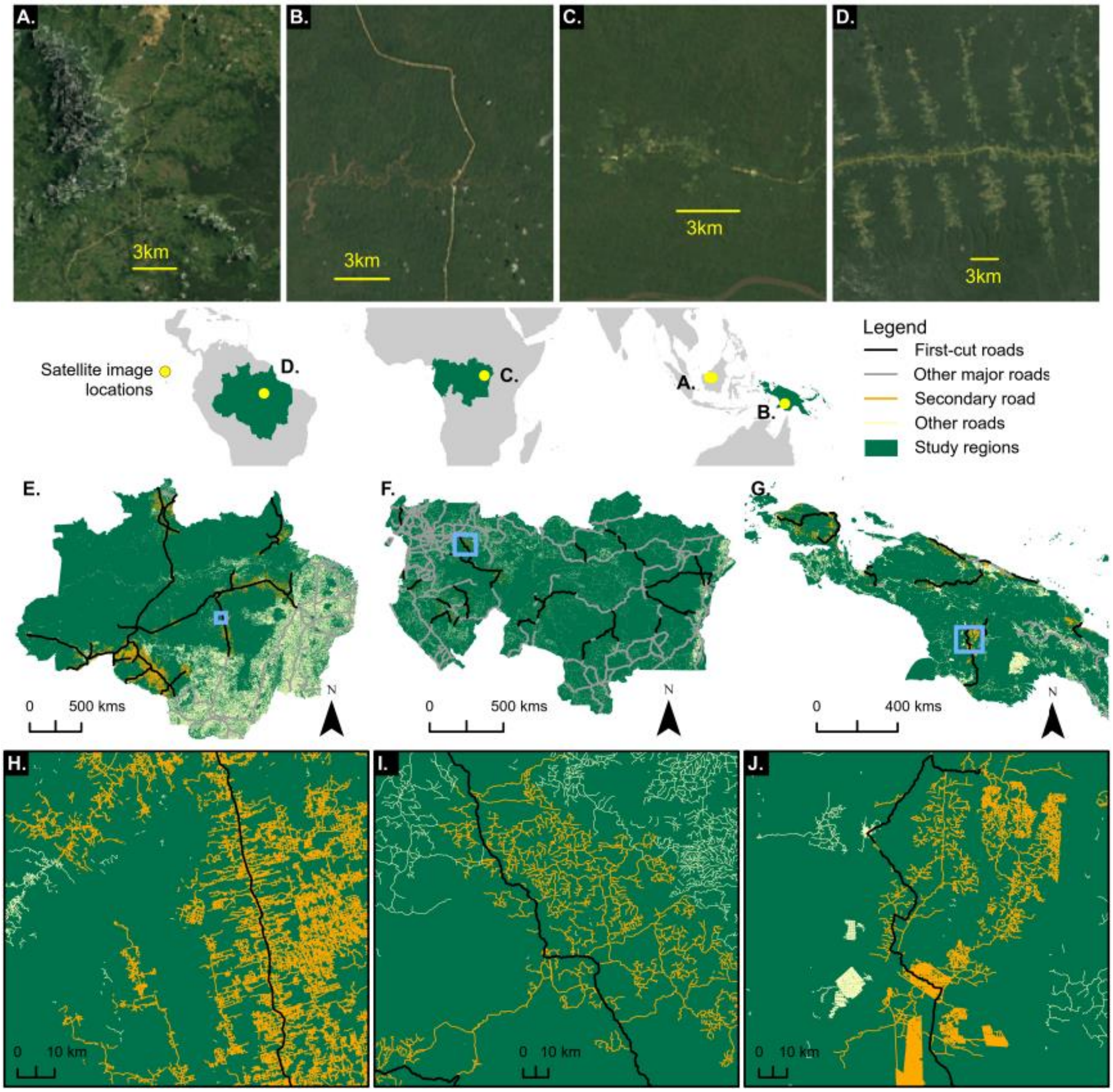


**Figure 15. First-cut roads across the three continental regions assessed in this study: Brazilian Amazon, Congo Basin, and New Guinea.** First row shows satellite images from Google Earth (imagery circa 1984) demonstrating: (A) an example of a major road that was not considered a first-cut road due to existing anthropogenic disturbance, (B) an example of a first-cut road in an area with no existing

anthropogenic disturbance, (C) an example of a first-cut road with minimal anthropogenic disturbance centred around the road, and (D) an example of a first-cut road with some land colonisation extending out from the road. Large maps (E – G) show study region extents and locations of first-cut roads. Focal maps (H – J) show first-cut roads, dependent road, and independent road for example regions.

## Results

### *Secondary roads*

We identified 92 examples of first-cut roads across the Brazilian Amazon, Congo Basin, and island of New Guinea using satellite imagery and existing publications (Fig. 15). We then used network analyses to identify secondary roads stemming from first cut roads by separating out roads that originated from existing human settlements or other major roads (Methods and Supplementary Materials). By using network analyses to identify the source of roads within our study regions, we are able to provide a more realistic assessment of the length of secondary road and area of related forest loss and degradation.

We found a substantial amount of secondary road dependent on first-cut roads, and considerable variation in the length of secondary road both within and among continental regions (Fig. 16). The Congo Basin had the lowest average length of secondary road development, with a mean of 4.8 km of secondary road per 1 km of first-cut road (0.1 km – 16.9 km, 90% confidence range). New Guinea had a higher mean length of 9.8 km (3.7 km – 19.6 km, 90% confidence range); while the Brazilian Amazon had a substantially higher mean length of 49.1 km of dependent secondary road for every 1 km of first-cut road (1.0 km – 139.3 km, 90% confidence range) (Table 10).

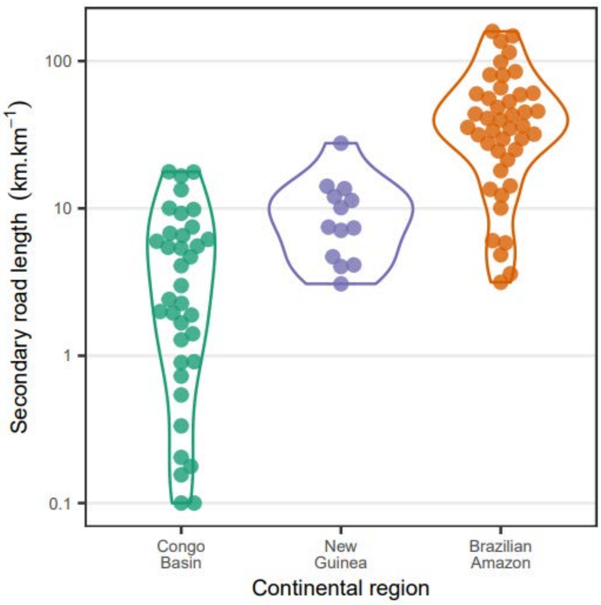


**Figure 16. Length of dependent secondary road constructed from each first-cut road.** (A) length of dependent secondary road for each first-cut road, normalized by first-cut road length (km.km-1), grouped by continental region.

*Secondary road impacts*

After identifying secondary roads stemming from first-cut roads, we were able to quantify their associated forest loss and degradation (Methods). We then separated these associated impacts into those in the construction footprint of the first-cut road (direct impacts), those associated with the first-cut road itself rather than secondary roads (indirect impacts), and those associated with secondary roads (secondary impacts).

For all first-cut roads, the direct impacts were the smallest impact class (Fig. 17). For all three continental regions, indirect impacts were approximately an order of magnitude larger than the direct impacts, and for the Brazilian Amazon and New Guinea, secondary impacts were considerably larger than these indirect impacts also. Indirect impacts were typically between 40 ha and 80 ha for every 1 km of first-cut road (mean of 73.6 ha for the Congo Basin, 59.4 ha for Brazilian Amazon, 43.2 ha for New Guinea). Conversely, the mean secondary impacts were 100.0 ha per 1 km of first-cut road for the Congo Basin, 222.0 ha for New Guinea, and 1857.0 ha for Brazilian Amazon (Table 11).

While secondary impacts were lowest in the Congo Basin, considering these when quantifying total first-cut road impacts resulted in a mean increase of 126.1%. The mean increase in impacts when considering secondary impacts was 398.6% for New Guinea and 2826.5% for the Brazilian Amazon. Compared to the direct impacts alone, the total impacts of first-cut roads were on average 31.5 times higher in the Congo Basin, 22.2 times higher in New Guinea, and 305.2 times higher in the Brazilian Amazon. For the Brazilian Amazon and New Guinea, the total impacts of first-cut roads were correlated with the length of secondary road. However this was not the case for the Congo Basin, where secondary road expansion is often driven by selective logging which results in lower rates of forest loss for the same length of road than conversion for commodity agriculture – a common deforestation driver in New Guinea and Brazil (Fig. 24; Kleinschroth et al. 2019). Conversely, a key driver of deforestation in the Congo Basin is subsistence agriculture, which is typically associated with low road density.

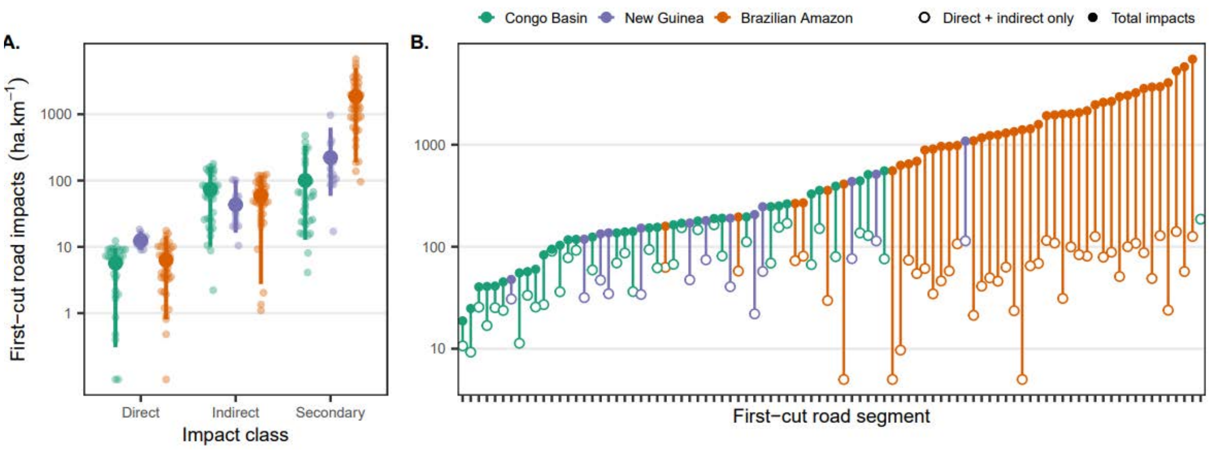


**Figure 17. Human impacts facilitated by first-cut roads. (**A) mean impacted area (ha) for first-cut roads by impact class and continental region. (B) comparison between impact area when considering only direct and indirect impacts and when considering secondary impacts also (total impacts), longer lines indicate greater secondary impacts. In (A), dots represent mean values and lines indicate the 5% - 95% interquartile range.

*Road effect zone*

By classifying secondary roads and their associated impacts, we were able to determine the geographical area affected by first-cut roads and the distance over which their impacts occurred – the road effect zone (Methods). Modelled impact areas of first-cut roads were substantially larger when considering their secondary roads and impacts than when considering only direct and indirect impacts (Fig. 18). Road effect zones – the distance in which 95% of impacts occurred – extended up to 35.9 km, 17.7 km, or 68.0 km from first-cut roads in the Congo Basin, New Guinea, and Brazilian Amazon respectively. Conversely, when the effect of secondary roads was not accounted for, road effect zones were only 3.9 km, 3.8 km, or 1.0 km from first-cut roads in the Congo Basin, New Guinea, and Brazilian Amazon respectively.

New Guinea had the smallest road effect zone when considering all impacts, which is likely due to the concentration of impacts in industrial plantations and logging concessions immediately adjacent to the first-cut roads (i.e. Fig. 15J). Conversely, in the Brazilian Amazon a substantial portion of secondary roads are constructed perpendicular to first-cut roads (i.e. Fig. 15D) and hence the road effect zone is much larger in this region.

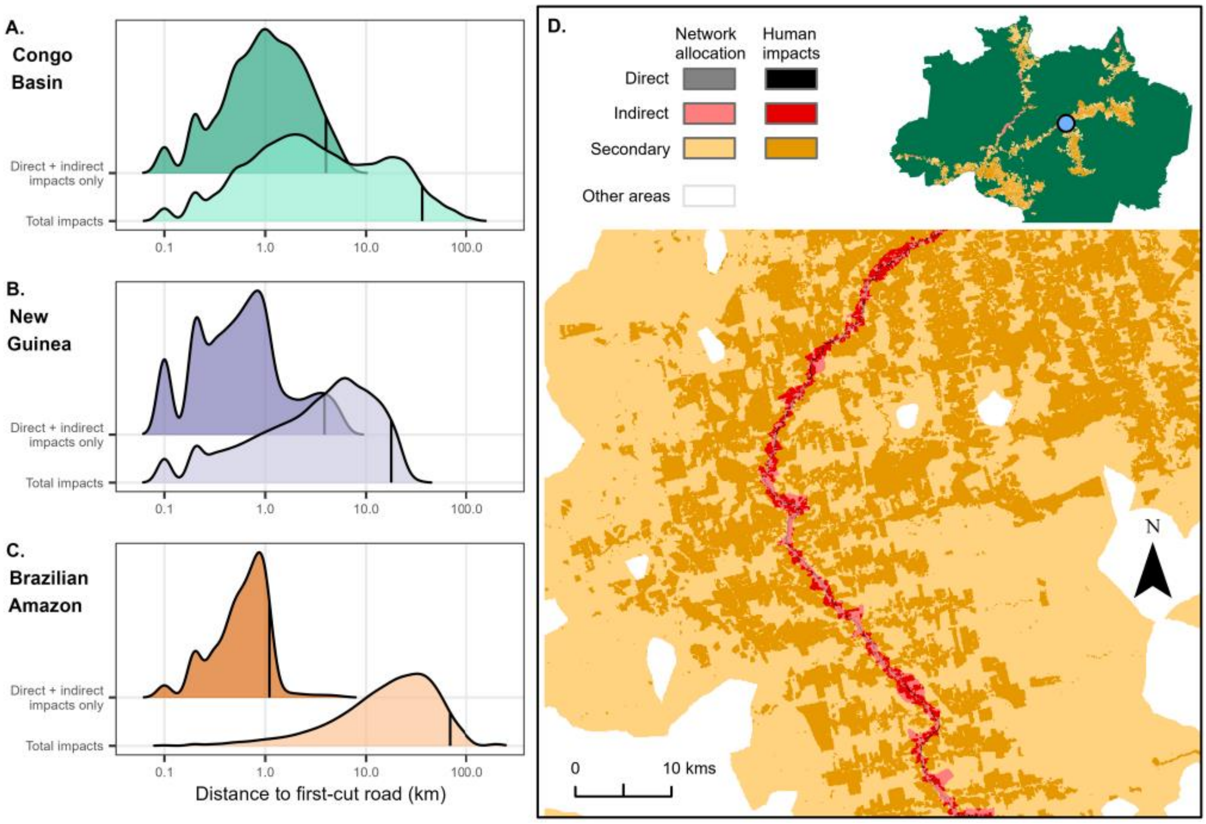


**Figure 18. Relative density distribution of human impacts by distance from first-cut roads for each continental region.** (A) the Congo Basin, (B) New Guinea, (C) Brazilian Amazon, (D) map demonstrating the difference in impacted areas when considering secondary impacts. The 'total impacts' distribution includes direct impacts, indirect impacts, and impacts associated with secondary roads. Impacts are aggregated across all first-cut roads.

*Impacts through time*

When assessing the increase in human impacts through time, first-cut roads in the Brazilian Amazon and New Guinea show similar linear trajectories of increase (the y-axis of Fig. 19 is log-scaled, and hence the linear increase appears as a log-linear curve) (Fig. 19). Conversely, first-cut roads in the Congo Basin had a lower rate of increase in impacts, and the increase followed a stepped progression with periods of low to no increase. However, in more recent years, the rate of increase in impacts has accelerated in the Congo Basin.

These differences in trajectories are likely due to regional differences in resource extraction intensity – Brazil and Indonesia are major exporters of agricultural products – and interannual changes in trajectories likely due to changes in local or global policies. While this plot considers time as the 'years since first impacts', these values are relative to the deforestation dataset from Vancutsem et al. (2021) that starts in 1985, while many of the first-cut roads – particularly in the Brazilian Amazon and the Congo Basin – were constructed many years before this date. Therefore, the general form of the trajectory is more illuminating than the magnitude of the impacts.

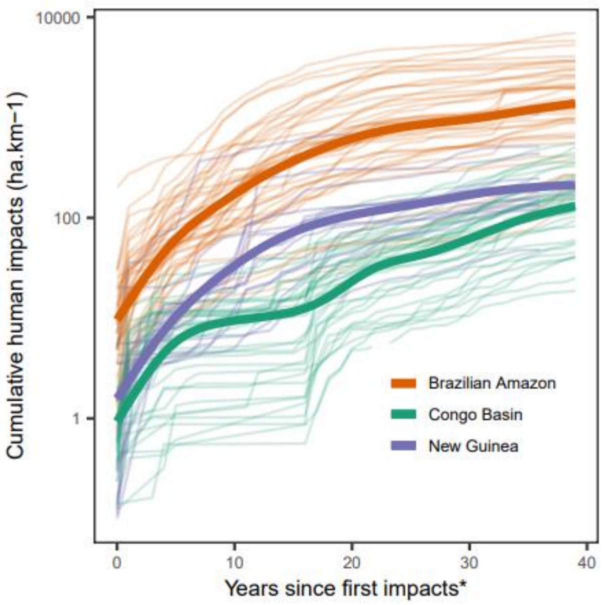


**Figure 19. Accumulating impacts of the first-cut roads in this study.** Shaded lines indicate individual first-cut roads, solid lines are the median values for each continental region. Years since first impact is the number of years since the earliest date of human impact for each individual first-cut road, or the number of years since 1983 for older roads, as the data from Vancutsem et al. (2021) starts in 1984.

## Discussion

Roads that penetrate into frontier regions—so-called first-cut roads—can trigger a surge of secondary roads that can be highly environmentally destructive. Such secondary roads are proliferating across much of the tropics, being on average 29 times greater in length than the first-cut roads from which they have arisen. Of even greater concern, we believe, is that secondary roads are dramatically increasing the scale of environmental degradation, provoking in our study area more than 150 times as much deforestation overall than did first-cut roads.

*Differences among regions*

Secondary roads and their impacts were highly variable among first-cut roads and tropical regions, being most prevalent in the Brazilian Amazon and least prevalent in the Congo. Such differences may reflect local environmental, political, or socioeconomic factors. New Guinea, for example, has steep mountainous regions that limit road construction and land conversion (Alamgir et al., 2019b; Sloan et al., 2019a), and first-cut roads in these areas had lesser impacts than those in the flat lowlands. In the great basins of the Brazilian Amazon and Congo, however, road building is limited in extensive flood-prone areas (Douven & Buurman, 2013) where navigable rivers are often used for transportation (i.e. Reed & Miranda, 2007).

Beyond their environmental differences, our three study regions also have many political, historical, and socioeconomic differences. Brazil, for instance, periodically has the world's highest rates of forest loss, ultimately driven by commodity agriculture and livestock production to supply international markets (Fig. 24) (Curtis et al., 2018; Pendrill et al., 2019a; Pendrill et al., 2019b; Pendrill et al., 2019c; Hoang & Kanemoto, 2021). Notably, many of Brazil's current first-cut roads were built during the military-dictatorship period of the 1960s for the explicit purpose of promoting land colonization and farming (Frohn, Dale & Jiminez, 1990).

Conversely, deforestation from large-scale commodity agriculture is rare in the Congo Basin, which currently produces only modest agricultural exports (Curtis et al., 2018; Pendrill et al., 2022). Much of the productive land in the Congo is being used for industrial selective logging, which can generate dense networks of forest roads but little outright deforestation (Fig. 23) (Laporte et al., 2007; Kleinschroth et al., 2016; 2019). However, the timeframe over which reliable data is available also constrains these analyses. Areas of the Congo Basin were key production regions for oil palm and rubber during the former colonial period but these areas are by now extensively anthropized and can no longer be assessed as 'frontier' regions (Marchal, 2017; Wong et al., 2022).

In New Guinea, road impacts were highly variable but often lower than those in the Brazilian Amazon, as a consequence of the island's low historic levels of development. However, first-cut roads promoted large areas of commodity agriculture (Fig. 24), and new megaprojects – such as massive food-estate and palm-oil projects in Indonesian Papua intended to supply domestic and export markets – are expected to alter these trends in the near future (Alamgir et al., 2019b; Sloan et al., 2019a).

*Impact assessment and policy implications*

Environmental impact assessment (EIA) procedures for road projects often focus on their direct effects (Karlson, Mörtberg & Balfors, 2014; Jaeger, 2015; Laurance & Arrea, 2017; Johnson et al., 2019; Juffe-Bignoli et al., 2021) while ignoring their dangerous secondary impacts, which can be massive in scope. For example, an EIA for a mining road in Sumatra, Indonesia suggested that 424 ha of forest would be lost during road construction — although scientists and activists expect 3,000-6,000 ha of forest loss as a result of the road (Engert, Ishida & Laurance, 2021). While it is currently possible to estimate the impacts of first-cut roads (i.e. Engert, Ishida & Laurance, 2021), as yet there are no spatially-resolved methods for modelling their striking and often-perilous secondary impacts (Laurance et al., 2015; Tulloch et al., 2019).

Our results may be used to establish baseline estimates of the secondary impacts and land colonisation enabled by new road projects to inform future impact assessment procedures. While this study focused on environmental impacts, infrastructure projects such as new roads can improve socio-economic opportunities for rural communities (Hettige, 2006). Conversely, they may also increase the vulnerability of rural and indigenous communities to socio-economic impacts including dispossession of land and resource theft (Davis, 2002; Hecht & Cockburn, 2010; Laltaika & Askew, 2021). Refined extent estimates of the impacts of first-cut roads presented here can be used to identify significant projects that should be avoided (Vilela et al., 2020; Juffe-Bignoli et al., 2021).

The Congo Basin and New Guinea are expected to see rapid increases in industrial oil palm and pulp-wood plantations and logging concessions (Pallares & Ngeunga, 2021; Blaise, 2023; Bokanga, 2024). In the Congo, such concessions will likely be spurred by large-scale development corridors (Laurance et al. 2105; Thorn et al., 2022) that will enable further secondary road expansion and forest loss. Similarly, New Guinea has a number of proposed development corridors, highways, and extractive-industry mega-projects that will dramatically expand secondary roads and forest loss (Alamgir et al., 2019b; Sloan et al., 2019a). Major infrastructure projects in these and other tropical regions (Alamgir et al., 2019a; Kaszta et al., 2020; Vilela et al., 2020) are expected to imperil hundreds of conservation areas, intact-forest tracts, and indigenous territories and cause globally significant carbon emissions (Houghton et al., 2012; Laurance et al., 2015; Sloan, Bertzky & Laurance, 2017; Vilela et al., 2020; Estrada et al., 2022).

In this study we used a novel mapping strategy to assess the source of ~3.85 million km of roads across the world's major tropical rainforest regions. This approach yielded a massive dataset; had we relied on human observers to manually classify these roads, we would have needed a daunting ~18,000 person-hours to collect these same data (Engert et al. 2024). While we did not examine road persistence, road networks are temporally dynamic and can vary markedly in their lifespan and ecological impacts (Ahmed et al., 2013; Kleinschroth et al., 2016; 2019). Further studies of the dynamics of expanding road networks are clearly a top priority given the daunting scale and pace of their environmental impacts.

## SUPPLEMENTARY METHODS

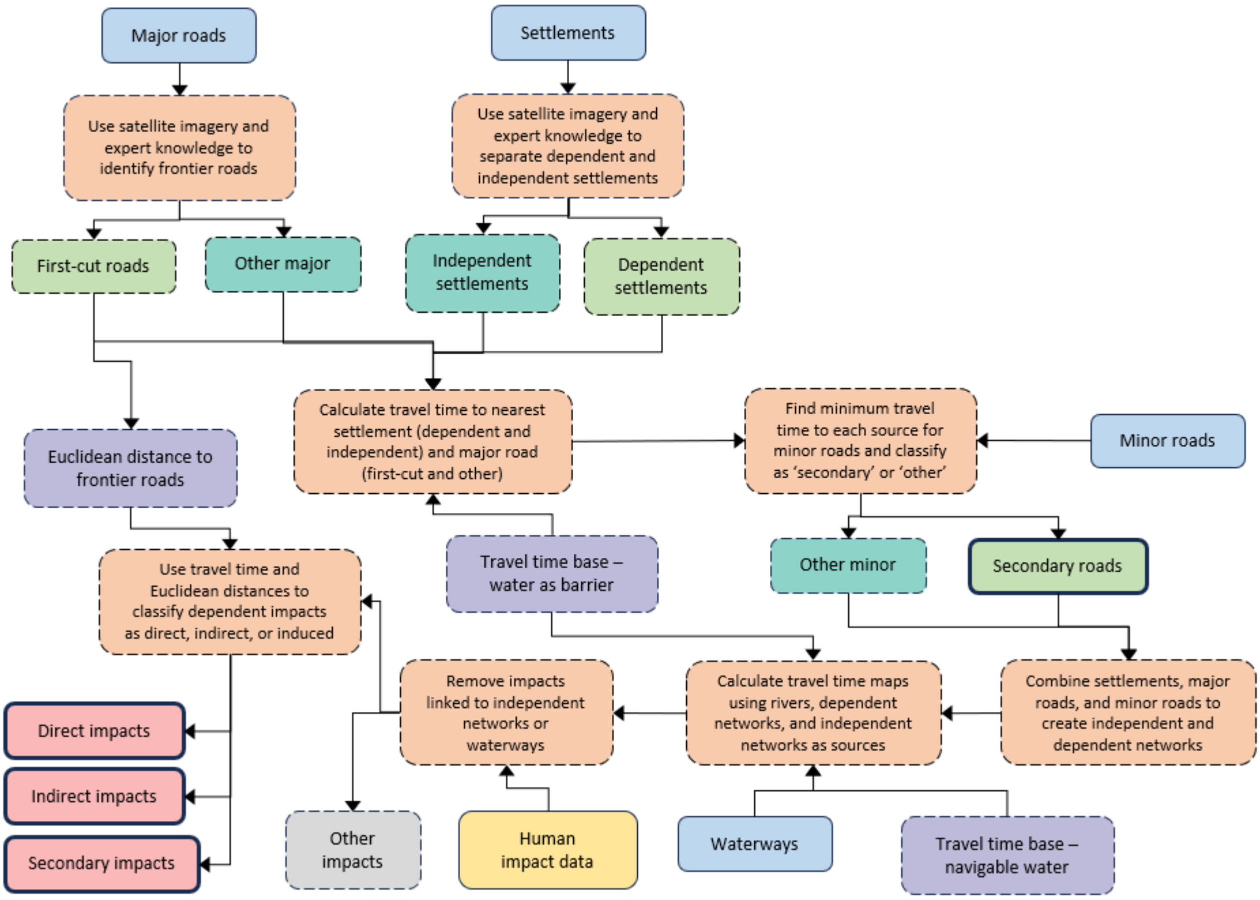


**Figure 20. Methodological flowchart for delineating secondary roads and impacts.** Blue and yellow boxes indicate input files, orange boxes indicate methodological components, boxes with thick borders indicate outputs. Other boxes indicate intermediate files. Specific methodological steps are outlined in the Methods and Supplement sections.

*Travel time*

To estimate travel time for the study regions (New Guinea, Brazilian Amazon, Congo Basin) we used a method developed from an adaption of Weiss et al. (2018) and Engert et al. (2021). Our adapted travel time map used information on vegetation type, slope, road locations, and waterways (Table 6). Contrary to Weiss et al. (2018), we did not use information on current land-cover type or anthropogenic land-cover types, rather we attempted to estimate travel times prior to conversion to anthropogenic land-uses. To accomplish this, we created a map of pre-human-modification vegetation types (Table 8) using a variety of published spatial datasets. Travel times for roads were taken from the reported maximum travel speed in OpenStreetMap when available, and estimated based on road class when maximum speed was not available. All travel speeds and travel times were converted to minutes per meter travel time before creating the maps.

In order to develop network allocation models to identify the sources of both minor roads and human impacts (deforestation and degradation), we developed three separate travel time maps. The first map, used to identify the source of minor roads, was created while excluding major roads in order to identify the travel time to minor roads if the major roads were not present (major roads used as a source, rather than a component of the map). The second and third maps, used to identify the source of human impacts, included all road types (major and minor). The second map was created to identify sources of human impacts associated with land-based travel (roads and settlements as sources) and hence considered waterways to be a barrier to movement. Finally, the third map was created to identify sources of human impacts associated with water-based travel and hence considered waterways to be conduits of movement.

**Table 6. Travel time map component layers.**

| Variable | Component | Travel time | Data source |
|---|---|---|---|
| Major roads | OSM roads with listed max speed | 60km/h – 120km/h | OSM (2023) |
| | OSM roads with fclass (Table S2) | 60km/h – 100km/h | |
| Minor roads | OSM roads with listed max speed | 5km/h – 110km/h | OSM (2023) |
| | OSM roads with fclass (Table S2) | 5km/h – 60km/h | |
| | Roads not in OSM | 40km/h | Engert et al. (2024)<br>Botelho Jr. et al. (2023)<br>Kleinschroth et al. (2019) |
| Waterways | Waterways as barriers | 240 mins/km | Allen & Pavelsky (2018) |
| | Waterways as conduits | 2 mins/km | |
| Slope | Topographic slope | $v = v_0e^{-ks}$ | Jarvis et al. (2008) |
| Pre-cleared vegetation (Table S5) | Closed forest | 60 mins/km | Gumbricht et al. (2017)<br>ESA (2017). [1992 version]<br>Olson et al. (2001) |
| | Open forest | 48 mins/km | |
| | Flooded forest | 120 mins/km | |
| | Grass/shrubland | 36 mins/km | |
| | Flooded grass/shrubland | 48 mins/km | |
| | Montane | 36 mins/km | |
| | Wetlands | 120 mins/km | |

**Table 7 Open Street Map (OSM) road speed by fclass.** Maximum speeds were estimated based on the values for roads of the same fclass that did have reported maximum speeds.

| **Fclass** | **Max speed estimate** |
|---|---|
| Footway, steps, pedestrian | 5 km/h |
| Path, cycleway, bridleway, living street | 20 km/h |
| Residential | 40 km/h |
| Service, unclassified, unknown, track | 40 km/h |
| Tertiary, tertiary link | 60 km/h |
| Secondary, secondary link | 60 km/h |
| Primary, primary link | 80 km/h |
| Trunk, trunk link | 100 km/h |
| Motorway, motorway link | 100 km/h |

**Table 8. Input layers for determining pre-existing vegetation types.**

| Layer | Original class | New class | Data source |
|---|---|---|---|
| Wetlands | Open water | Waterways | Gumbricht et al. (2017) |
| | Mangroves | Wetlands | |
| | Swamps | Wetlands | |
| | Fens | Wetlands | |
| | Riverine and lacustrine | Flooded forest | |
| | Floodouts | Wetlands | |
| | Floodplains | Flooded grass/shrubland | |
| | General Marshes | Wetlands | |
| | Marshes in arid climates | Wetlands | |
| | Marshes wet meadows | Flooded grass/shrubland | |
| Remote-sensed land-cover | Tree cover, broadleaved, evergreen, closed to open (>15%) | Closed forest | ESA (2017) [1992 version] |
| | Tree cover, broadleaved, deciduous, closed to open (>15%) | Open forest | |
| | Tree cover, needleleaved, evergreen, closed to open (>15%) | Closed forest | |
| | Tree cover, needleleaved, deciduous, closed to open (>15%) | Open forest | |
| | Tree cover, mixed leaf type (broadleaved and needleleaved) | Closed forest | |
| | Mosaic tree and shrub (>50%) / herbaceous cover (<50%) | Closed forest | |
| | Mosaic herbaceous cover (>50%) / tree and shrub (<50%) | Grass/shrubland | |
| | Shrubland | Grass/shrubland | |
| | Grassland | Grass/shrubland | |
| | Lichens and mosses | Grass/shrubland | |
| | Sparse vegetation (tree, shrub, herbaceous cover) (<15%) | Grass/shrubland | |
| | Tree cover, flooded, fresh or brackish water | Flooded forest | |
| | Tree cover, flooded, saline water | Flooded forest | |
| | Shrub or herbaceous cover, flooded, fresh/saline water | Flooded grass/shrubland | |
| | Water | Waterways | |
| WWF Ecoregion | Tropical and subtropical moist broadleaf forest | Closed forest | Olson et al. (2001) |
| | Tropical and subtropical dry broadleaf forest | Open forest | |
| | Tropical and subtropical coniferous forest | Open forest | |
| | Tropical and subtropical grasslands/shrublands | Grass/shrubland | |
| | Flooded grasslands and savannas | Flooded grass/shrubland | |
| | Montane grasslands and savannas | Montane | |
| | Mangroves | Wetlands | |

*Classifying human settlements*

We created maps of human settlements by combining Landscan population density maps (Rose et al., 2021) with Open Street Map building locations (OpenStreetMap contributors, 2022). Settled cells were identified from Landscan maps by rescaling the map to 1 ha resolution and reclassifying the population density map as either settled (1) or not settled (0) using a cut-off of 4 people per hectare. We then identified settlements (defined as groups of settled cells) by calculating the proportion of cells within a 1km neighbourhood that were settled and classifying all areas with >20% of the neighbourhood settled as a 'settlement'. Similarly, we converted Open Street Map building locations to a building presence layer at 1 ha resolution, and classified all areas with more than 20% of cells containing buildings within a 1 km neighbourhood as being settlements.

To identify settlements dependent on first-cut roads, we first used the network analyses to identify settlements that were both (1) linked to first-cut roads through the road network, and (2) more accessible by first-cut roads than other major roads. We then used satellite imagery, available information, and expert knowledge, to identify which of these settlements appeared after the construction of the nearest first-cut road and which appeared before. Settlements that were connected to the first-cut road, more accessible via first-cut road than other major roads, and appeared after first-cut road construction were considered dependent on the first-cut road, all other settlements were considered independent (Fig. 21).

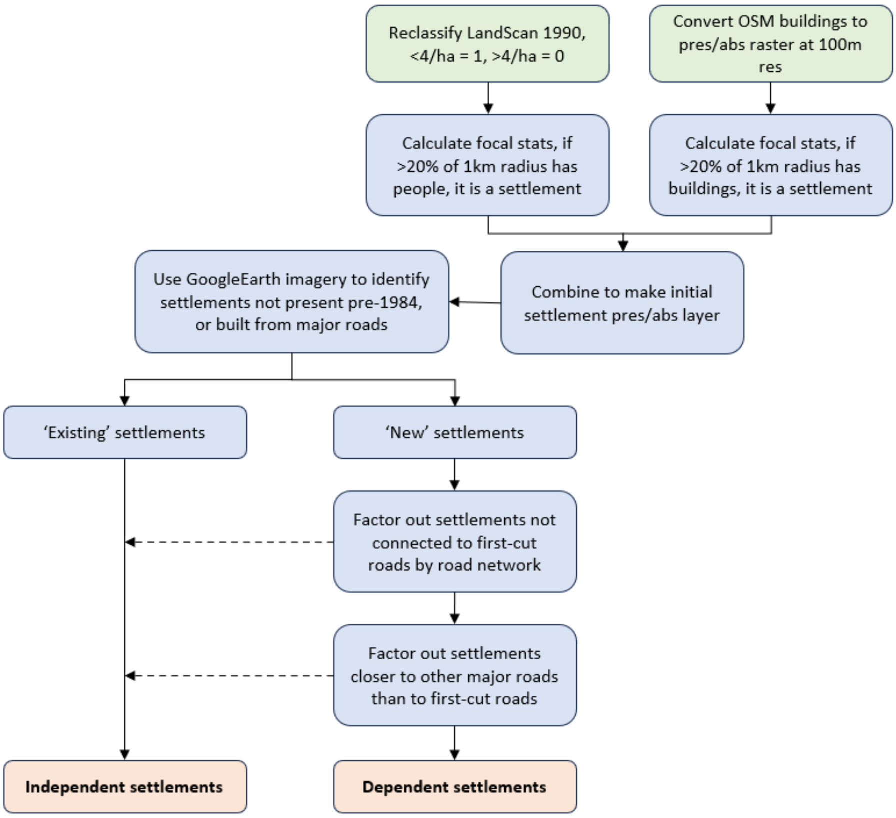


**Figure 21. Method flowchart for the generation and classification of human settlement data.** Green boxes indicate input data, blue boxes indicate intermediate layers, and orange boxes indicate final outputs.

**Table 9. Reclassification of Vancutsem et al. (2021) forest change data into human impact layers.**

| Original land-cover class | New impact class | Human impact presence (1) |
|---|---|---|
| NoData | NA | 0 |
| Undisturbed tropical moist forest | NA | 0 |
| Bamboo-dominated forest | NA | 0 |
| Undisturbed mangrove | NA | 0 |
| Degraded forest short-duration disturbance | Short degradation | 1 |
| Degraded forest long-duration disturbance | Long degradation | 1 |
| Degraded forest 2/3 short degradation periods | Short degradation | 1 |
| Old forest regrowth (disturbed before 2002) | Regrowth | 1 |
| Young forest regrowth (disturbed in 2002-2011) | Regrowth | 1 |
| Very young forest regrowth (disturbed in 2012-2018) | Regrowth | 1 |
| Deforestation (any start date) | Deforestation | 1 |
| Degradation (any start date) | Short degradation | 1 |
| Degraded mangrove (started before 2012) | Long degradation | 1 |
| Mangrove regrowing | Regrowth | 1 |
| Mangrove deforested | Deforestation | 1 |
| Mangrove recently disturbed (started in 2019-2021) | Short degradation | 1 |
| Permanent Water | NA | 0 |
| Seasonal Water | NA | 0 |
| Deforestation to permanent Water | NA | 0 |
| Deforestation to seasonal water | NA | 0 |
| Old plantation | Deforestation | 1 |
| Plantation regrowing | Deforestation | 1 |
| Conversion to tree plantation | Deforestation | 1 |
| Recent conversion to plantation | Deforestation | 1 |
| Other LC without afforestation | Deforestation | 0 |
| Young afforestation (between 3 and 9 years of regrowth) | Regrowth | 1 |
| Old afforestation (between 10 and 20 years of regrowth) | Regrowth | 1 |
| Water converted recently into forest regrowth | Regrowth | 1 |

*value of 1 indicates human impacts, value of 0 indicates areas free from human impacts

SUPPLEMENTARY RESULTS

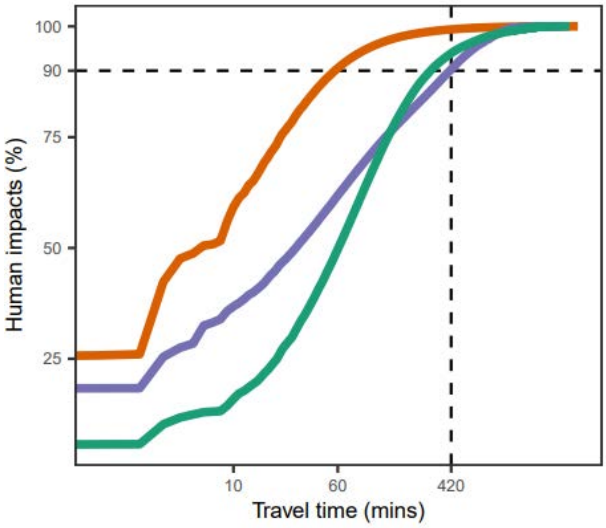


**Figure 22. Cumulative distribution of human impacts by minimum travel time to any mapped source.** Based on distribution of impacts, we used 420 minutes (7 hours) as a cut-off point at which we considered human impacts to no-longer be dependent on a secondary road or first-cut road.

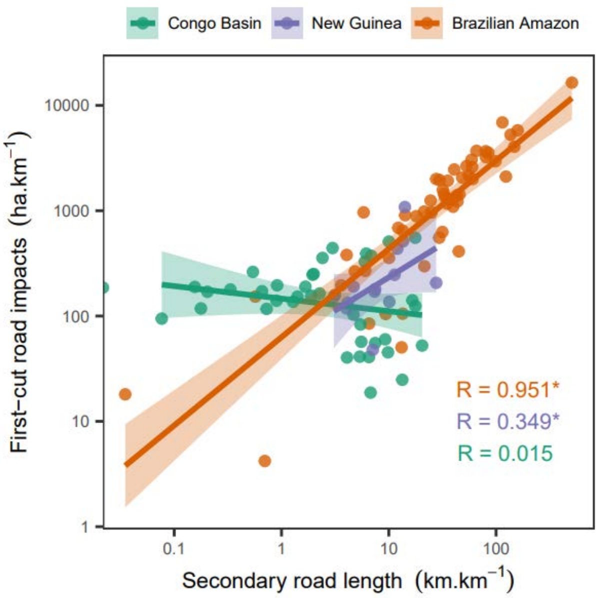


**Figure 23. Relationship between secondary road length and total human impacts of first-cut roads in the three continental regions.** R values indicate Pearson correlation statistics for each region, with asterisks indicating significant results. In New Guinea and the Brazilian Amazon, total first-cut road impacts are correlated with the amount of secondary road, however, in the Congo Basin they are not.

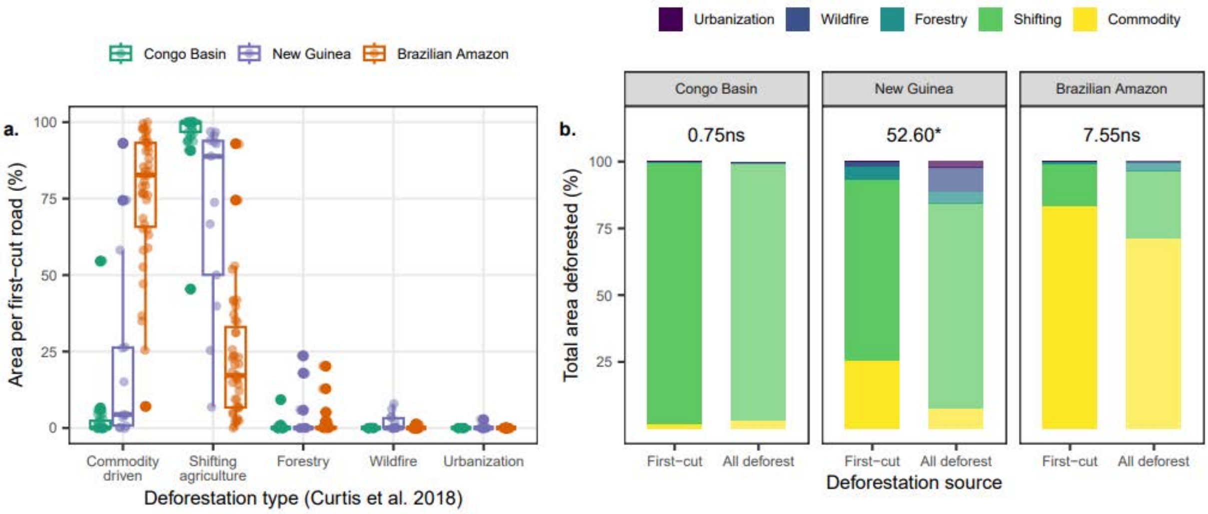


**Figure 24. Deforestation types (as classified in Curtis et al. 2018) by region.** (a) comparison of relative deforested area by class for each region. (b) comparison of deforested area by class for first-cut road impact areas and the total deforested area in each region. Inset text in (b) indicates results of chi-square test of independence, ns = non-significant comparison, * = significant comparison.

**Table 10. Summary of the length of secondary road per kilometre length of first-cut road for each region separately, and all study regions together (Global).**

| Region | Secondary road length by first-cut road length (km.km$^{-1}$) | | | | | |
|---|---|---|---|---|---|---|
| | Mean | Median | 5% Conf | 25% Conf | 75% Conf | 95% Conf |
| Brazilian Amazon | 49.13 | 32.25 | 1.03 | 12.94 | 56.54 | 139.30 |
| Congo Basin | 4.84 | 2.70 | 0.14 | 0.91 | 6.60 | 16.90 |
| New Guinea | 9.75 | 7.46 | 3.65 | 4.70 | 12.00 | 19.60 |
| Global* | 28.52 | 10.08 | 0.25 | 3.92 | 32.83 | 108.98 |

*for all first-cut roads included in this study

**Table 11. Summary of impacts by impact class for each region separately and all study regions together (Global).**

| Region | Impact class | Impact area by first-cut road length (ha.km$^{-1}$) | | | | | |
|---|---|---|---|---|---|---|---|
| | | Mean | Median | 5% Conf | 25% Conf | 75% Conf | 95% Conf |
| Brazilian Amazon | Direct (Footprint) | 6.30 | 5.06 | 0.81 | 3.27 | 9.48 | 14.60 |
| | Indirect | 59.40 | 53.90 | 2.75 | 38.60 | 82.80 | 118.00 |
| | Secondary | 1857.00 | 1364.00 | 188.00 | 849.00 | 2544.00 | 5016.00 |
| Congo Basin | Direct (Footprint) | 5.69 | 6.39 | 0.31 | 3.06 | 8.41 | 9.58 |
| | Indirect | 73.60 | 65.60 | 10.00 | 26.30 | 111.00 | 159.00 |
| | Secondary | 100.00 | 59.20 | 12.80 | 24.30 | 101.00 | 333.00 |
| New Guinea | Direct (Footprint) | 12.50 | 11.50 | 9.02 | 10.50 | 13.40 | 17.20 |
| | Indirect | 43.20 | 34.10 | 16.30 | 20.60 | 57.80 | 101.00 |
| | Secondary | 222.00 | 123.00 | 58.70 | 102.00 | 189.00 | 627.00 |
| Global* | Direct (Footprint) | 6.95 | 7.04 | 0.48 | 3.45 | 9.69 | 14.40 |
| | Indirect | 62.70 | 57.80 | 9.01 | 26.60 | 84.70 | 145.00 |
| | Secondary | 948.00 | 306.00 | 16.00 | 85.30 | 1278.00 | 3597.00 |

*for all first-cut roads included in this study

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# Chapter 4: Identifying correlates of road building to model landscape level road-expansion risk

Submitted to *Science* as: Engert, J.E., Souza Jr., C.M., Kleinschroth, F., Ishida, Y., Costa, S.P., Botelho Jr., J. & Laurance, W.F. (submitted). Road-expansion risk predicts future hotspots of tropical deforestation. Science.

## Abstract

Roads underlie many of humanity's impacts on nature, including deforestation, wildfires, and resource overexploitation. However, existing roadmaps often drastically underestimate the true extent of road networks and future predictions rely on outdated data, undermining development planning and conservation decision-making. Here we develop a novel "road-expansion risk" index to identify areas prone to road building and therefore susceptible to road-related environmental impacts. Using 137 million 1-ha raster cells arrayed across the world's major tropical-forest regions, we identify biophysical correlates of road-building to identify areas likely to contain unmapped roads or experience future road building—including large expanses of the Amazon basin, Congo basin, and island of New Guinea. Notably, our analysis can identify future road-building and deforestation hotspots, even for locales entirely lacking road data.

## INTRODUCTION

In forested regions, new roads can trigger many destructive impacts on nature, including deforestation (Fearnside, 2007; Busch & Ferretti-Gallon, 2017), wildfires (Nepstad et al., 2001), and overexploitation of fauna and flora (Benitez-Lopez et al., 2017), among others (Laurance et al., 2009). Unfortunately, the management of roads is challenging because existing datasets dramatically underestimate road networks in many nations (Hughes, 2018; das Neves et al., 2021; Botelho Jr et al., 2023; Engert et al., 2024a). Such road networks, furthermore, are constantly expanding (Ahmed et al., 2013; Kleinschroth et al., 2019; Nascimento et al., 2021; Che et al., 2023), undermining efforts to conserve ecosystems and biodiversity (Engert et al., 2024a). For these reasons, we devised a novel "road-expansion risk" model that predicts where new roads and deforestation are likely to occur across the world's major tropical forest regions.

In the tropics, road building rates are increasing rapidly (Laurance et al. 2014; Fearnside, 2015; Alamgir et al., 2017; Kleinschroth et al., 2019) and often immediately precedes deforestation, especially in remote frontier areas (Sader & Joyce, 1988; Engert et al., 2024a). However, not all areas are suitable for roads. Road building is strongly influenced by local factors such as topographic slope (Collier et al., 2015) and soil chemical and physical properties (Lim et al., 2014). Climatic variables such as rainfall, and socioeconomic factors such as population density and economic growth, also affect the costs of road construction and maintenance (Glover & Simon, 1975; Perz et al., 2007; Meijer et al., 2018; Alamgir et al., 2020). Given that the ultimate causes of deforestation, such as mining and agriculture, are largely constrained to areas suitable for road building (Geist & Lambin, 2002; Curtis et al., 2018; Austin et al., 2019), identifying the factors that promote road proliferation is a key priority.

We propose the index of road-expansion risk as a powerful tool for predicting and safeguarding future hotspots of deforestation. Here we (1) use road data from the Brazilian Amazon, Congo Basin, and tropical Asia-Pacific region to identify correlates of landscape suitability for road-building and then compare these patterns among different geographic regions; (2) use our road-expansion risk index to predict landscape suitability for road building; and (3) demonstrate that our index can effectively predict patterns of future forest destruction in the absence of actual road data.

## METHODS AND RESULTS

*Correlates of road-building*

We obtained road locations from leading published road datasets (Kleinschroth et al., 2019; Botelho Jr. et al., 2023; Engert et al., 2024a) and used these to create road presence-absence maps at 1-ha resolution. These maps covered the Congo Basin, Brazilian Amazon, and insular Asia-Pacific region respectively – all regions with exceptional environmental and socio-ecological values that are under threat from increased anthropogenic pressures (Curtis et al., 2018; Meijaard et al., 2020; Jung et al., 2021). We then created a model training sample of 137 million 1-ha raster cells, of which 47 million were road presences, and extracted information for 44 different environmental and socio-economic variables expected to influence road building (Methods). We used this data to build region-specific and pantropical random forest models of road suitability, and developed a 'road-expansion risk' index based on environmental suitability alone (Fig. 25).

Our final model included 20 correlates of road presence out of our initial list of 44 potential covariates. The most influential covariates in the pantropical model were distance to river, population density, and topographic features such as slope and topographic roughness (Fig. 26A). Soil characteristics such as silt and clay fraction were also highly important, as was rainfall seasonality (measured as the coefficient of variation among months). Vegetation class alone – of which wetlands were one class – did not have a strong influence on model accuracy, however this may be due to other correlated variables having greater explanatory power (i.e. soil and rainfall characteristics) or due to inconsistent patterns of vegetation management across the study region (i.e. peat-swamp drainage in the Asia-Pacific region).

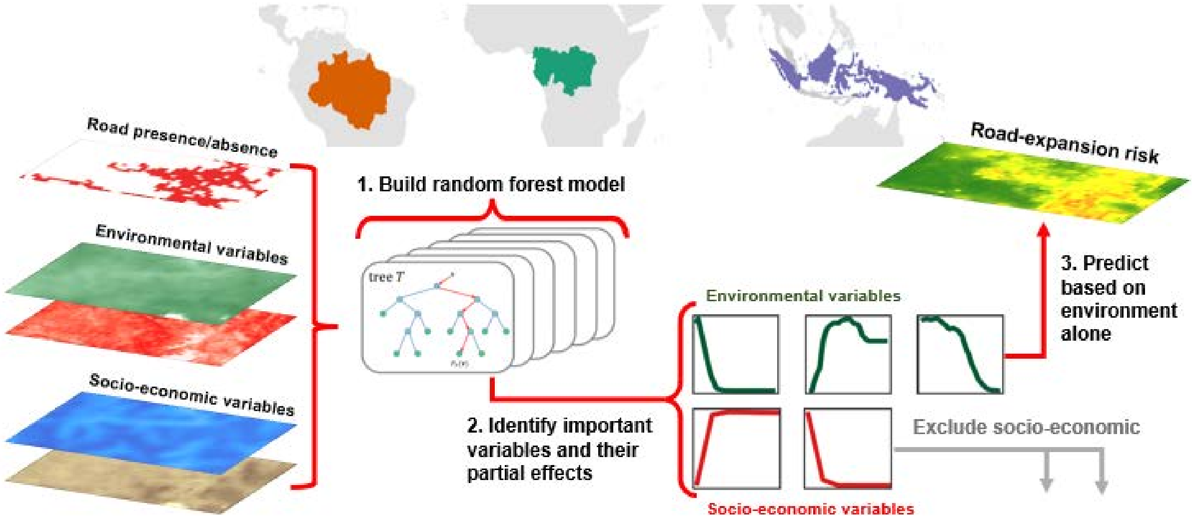


**Figure 25. Conceptual layout of study region and methodology for road-expansion risk modelling.**

The importance of covariates was generally similar among all models (Fig. 26B-D, Fig. 32), apart from population density, which was substantially more influential in the Congo Basin, and topographic variables, which were less influential in the Asia-Pacific region. The Congo Basin region has lower rates of commodity-agriculture-driven deforestation when compared to the Brazilian Amazon and Asia-Pacific regions (Curtis et al., 2018; Engert et al., 2024b), a land-use system which is often associated with extensive road network expansion in the absence of high population densities. Partial relationships between covariates and road presence were also largely consistent across regions and in the pantropical model (Fig. 26E – L, Fig. 33A – L). Relationships followed expected trends, with roads more likely to occur in dry, flat areas, in inorganic soils, close to rivers (which act as an alternative access point for human incursion), or in populated areas. As the key correlates of road-building are primarily topographic and soil conditions, we suggest that patterns may be consistent in areas outside of our study region, including other areas of tropical moist and dry forests, however this would require further study.

Notably, the rank-encoded categorical variables did not have linear monotonic relationships with road presence (Fig. 33). This is particularly relevant in the case of sub-national administrative region as it suggests that while influential, governance did not have substantial power in determining road building when contrasted against landscape factors and population density. Encouragingly, however, protected area coverage notably reduced the probability of road building in all models, supporting conclusions from Engert et al. (2024a) that protected areas are able to reduce environmental and social impacts by minimising road incursions.

Importantly, our pantropical model had reasonably high predictive performance, with a mean Area Under the receiver operator Curve (AUC) = 0.802. The (AUC) is an assessment of the models ability to distinguish between classes (road presence or absence) with a range from 0 – 1; with values of 1 indicating perfect distinction between classes, 0.5 indicating no ability to distinguish between classes, and 0 indicating perfect reciprocation of the classes. While this AUC may not be considered high in other modelling applications, given the complexity of predicting locations of roads (i.e. due to connectivity and topological attributes; Botelho Jr. et al., 2024), we considered this to be a robust model. The performance of the pantropical model also differed between regions, with a mean AUC = 0.746 for the Asia-Pacific region, AUC = 0.850 for the Brazilian Amazon, and AUC = 0.809 for the Congo Basin (Fig. 35 - 37). While the region-specific model for the Asia-Pacific performed better than the pantropical model (AUC = 0.850), we opted to use only the pantropical model for future work as it performed better than the region-specific models for the Brazilian Amazon (AUC = 0.847) and the Congo Basin (AUC = 0.792), and in order to overcome any regional biases that may be present in training data or region-specific land-use practices. For example, topographic variables were less influential in the Asia-Pacific region, where there is substantial deforestation in sloping terrain and at high elevations (Feng et al., 2021).

While many roads may be abandoned post-construction, such as roads within logging concessions (Kleinschroth et al., 2019), we did not consider road persistence in our model development as we were focused on identifying factors effecting road building only. Though it is important to note that road persistence and long-term ecological impacts are also influenced by a range of socio-economic and environmental factors (Kleinschroth et al., 2016; 2019).

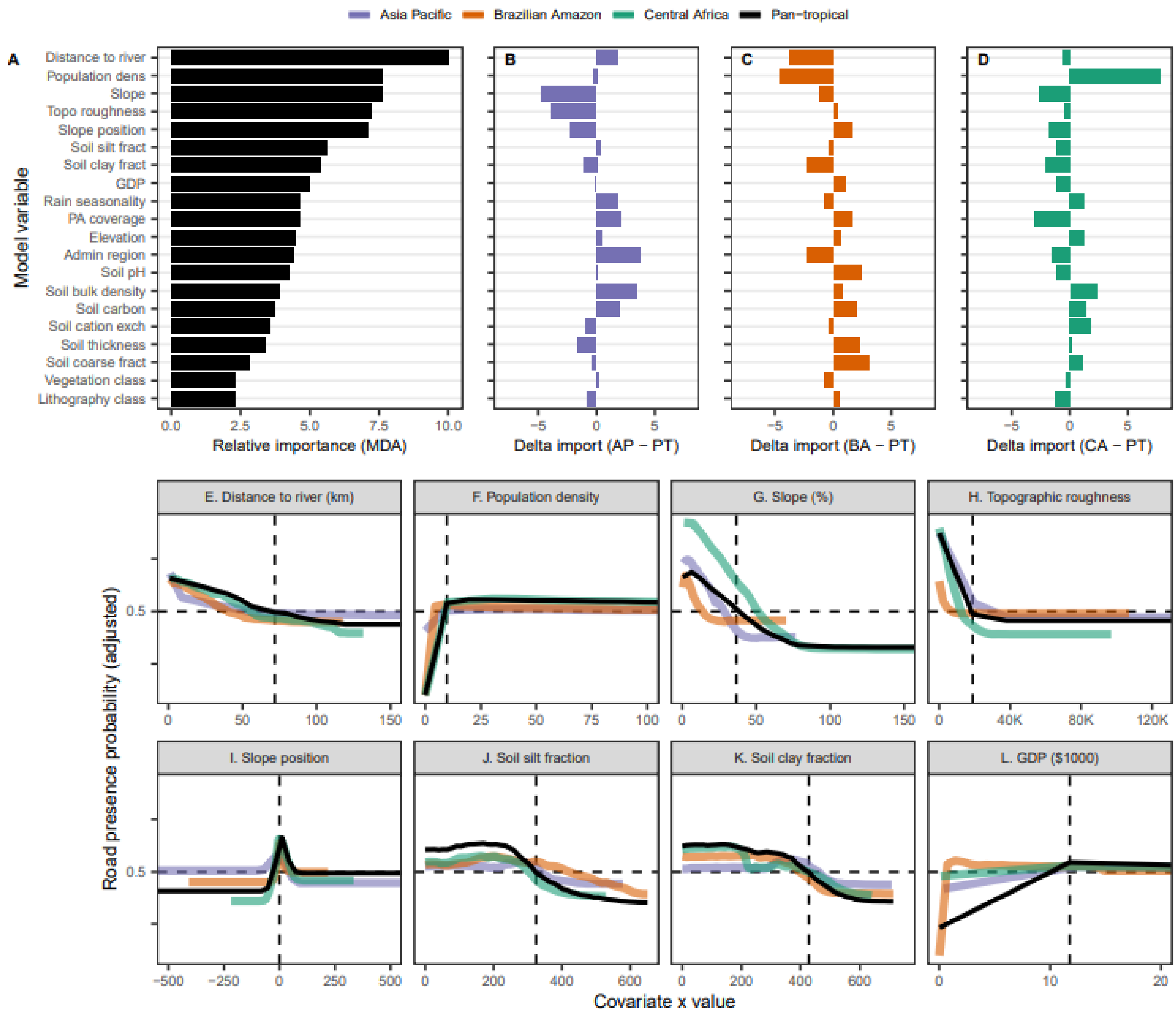


**Figure 26. Spatial predictors of road presence when modelling using a pantropical dataset or modelling continental regions separately.** (A) Relative importance (mean decrease in accuracy when permuting) for model variables in the pantropical model. (B – D) Difference in relative importance for model variables between the pantropical model and (B) the Asia-Pacific model, (C) Brazilian Amazon model, and (D) Central Africa model). (E – L) Partial differential plots for the eight most important model variables, for the pantropical model and all three region-specific models. Horizontal dashed lines indicate the 0.5 threshold value when roads are more likely to be present than absent. Vertical dashed lines indicate the first value for the model term at which the 0.5 threshold is crossed (except for slope position in which it is located at 0).

*Road-expansion risk index*

We developed a novel spatial index of road-expansion risk using the modelled partial relationships between environmental variables and road presence (Fig. 27). This layer categorizes the suitability of land for road-building based on various biophysical features while accounting for the influence of socio-economic factors. Our models suggest that much of the Amazon and Congo regions have high road-expansion risk, with their extensive wetlands being less susceptible. Some areas, such as central Sumatra, can experience substantial roading even when appearing to be low-risk, for example due to high population densities or local land-use practices – such as peat-swamp drainage (Yule, 2010) – that predispose even non-optimal locales to roading and related environmental impacts.

We identified several regions – such as the Guyana Shield in Amazonia, Congo Basin rainforests, and New Guinea – that have high road-expansion risk scores but have not yet experienced substantial land colonisation and conversion (Vancutsem et al., 2021). These areas are of particular conservation concern as they are often the subjects of proposed future developments, including highways, development corridors, and major oil palm and wood-pulp projects (Alamgir et al., 2019a; Meijaard et al., 2020). Similarly, areas of eastern Kalimantan, Indonesia have only low to moderate road development but are vulnerable to further road expansion precipitated by the development of Pan-Borneo highways and the new Indonesian capital city of Nusantara (Alamgir et al., 2019b; Spencer et al., 2023). Our road-expansion risk map can be used to identify and help mitigate environmental degradation in areas prone to future roading and deforestation.

In the Brazilian Amazon, many vulnerable areas are located within protected areas or Indigenous territories. In such locales, strong governance and legal support are essential to help protect forests and their biodiversity (Arima et al., 2014; Silva-Junior et al., 2023). Our modelled road-expansion risk layer can be used to identify areas at risk of future road incursions—so that policy actions and enforcement activities can be appropriately focused and brought to bear against illicit land-invaders.

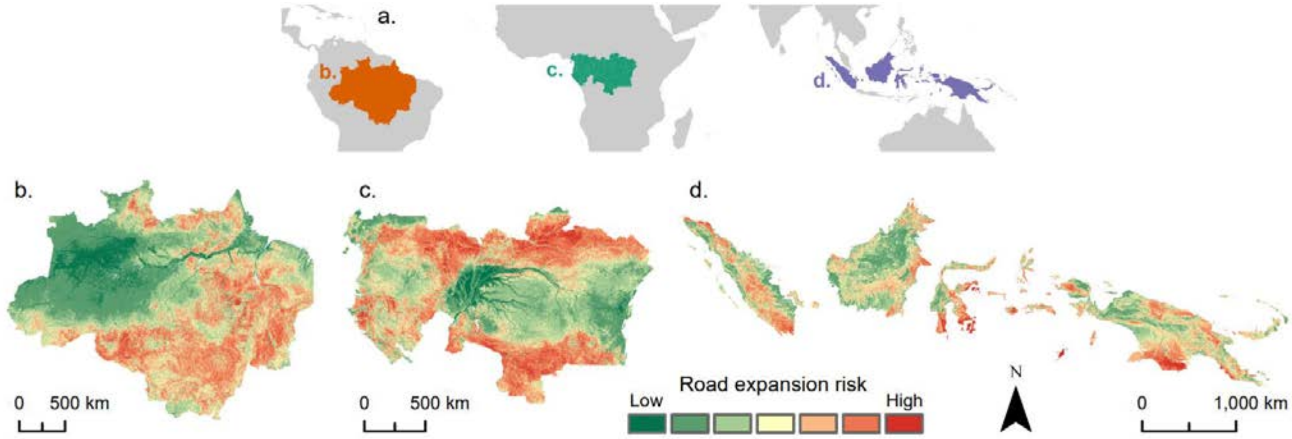


**Figure 27. Predicted road-expansion risk (adjusted road suitability) as calculated using the pantropical model.** (a) study region extent indicating delineated continental regions: Brazilian Amazon (orange), Central Africa (green), and Asia-Pacific (purple). (b – d) model predictions for the aforementioned continental regions.

*Road-expansion risk predicts deforestation*

Roads act as key proximate drivers of tropical deforestation by promoting activities such as commodity agriculture, logging, and mining (Geist & Lambin, 2002; Curtis et al., 2018; Austin et al., 2019). Hence, our index of road-expansion risk should be a reliable predictor of forest destruction. Using a simplified model with only five variables – one of which was road-expansion risk – we were able to predict forest loss and degradation with high performance (AUC = 0.870; Fig. 28). The other four variables were administrative region, population density, GDP, and protected areas (Fig. 34). Our model's predictive performance is comparable to models with many more variables (including high-resolution road locational data, and landscape fragmentation and deforestation metrics; i.e. Cushman et al., 2017; Engert et al., 2024a). Despite having little influence on road-building, administrative region was the strongest predictor of forest loss and degradation in our simplified model, highlighting the role of governance in mediating the effects of roads and development on rates of environmental destruction (Duran et al., 2011; Fischer et al., 2020).

Our road-risk model can be used for many conservation-related activities. For example, it can be used to evaluate the performance of protected areas (Laurance et al. 2012; Engert et al., 2024a; Geldmann et al., 2019), and identify regions likely experiencing de-facto protection due to their unsuitability for development. The road-expansion risk layer can also be used to identify areas at risk from a range of other anthropogenic environmental disturbances including illegal logging and mining (Austin et al., 2019).

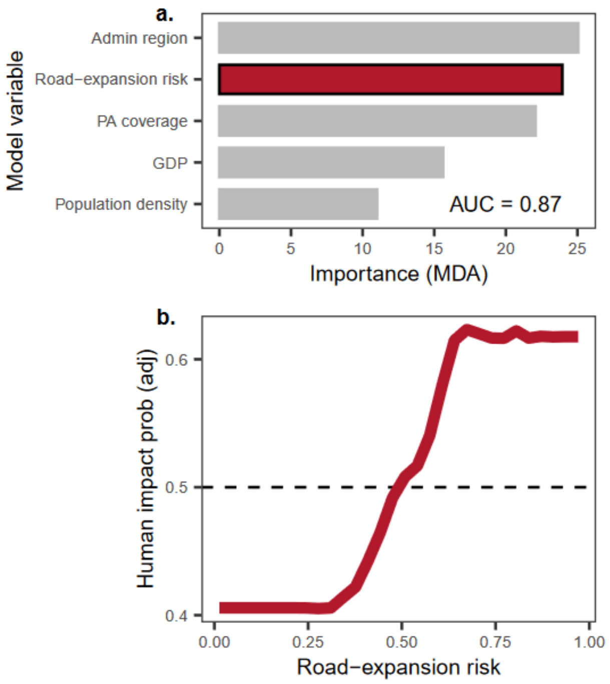


**Figure 28. Road -expansion risk (probability of road presence) as a spatial predictor of human impacts.** (A) Importance of model variables (mean decrease in model accuracy when variable is permuted) for the five variables retained in the final model. (B) Partial differential plot showing the relationship between road-expansion risk and probability of human impact presence. Human impacts were forest loss and forest degradation identified using Vancutsem et al. (2021) dataset.

## Conclusions

Using a massive pantropical dataset, we identified robust correlates of road building in forested regions. After accounting for several relevant socioeconomic variables, road building was influenced most by rainfall patterns, soil conditions, topographic variables, and proximity to rivers. With this information, we created a road-expansion risk index that allowed us to reliably predict the locations of forest loss and degradation, thereby overcoming the badly incomplete road datasets typical of many tropical nations (Laurance et al. 2009; Engert et al. 2024a).

Roads are strong and consistent spatial predictors of deforestation (Busch & Ferretti-Gallon, 2017; Sales et al., 2017; Engert et al., 2024a). As such, they are vital for predicting future deforestation frontiers and hotspots. However, spatio-temporal deforestation models are hampered by static – often seriously outdated – road data (e.g. Estoque et al., 2019), while millions of kilometers of new roads are constructed annually (Ahmed et al., 2013; Kleinschroth et al., 2019; das Neves et al., 2021; Che et al., 2023).We suggest that our road-expansion risk layer can reduce the impact of this major methodological constraint by identifying areas in which future road building, and hence deforestation hotspots, are likely to arise (Singh & Yan, 2021; Baumann et al., 2022; Buchadas et al., 2023). This advancement is particularly relevant given the explosive expansion of road networks and other infrastructure across the global tropics, including dozens of massive development corridors across Africa (Laurance et al., 2015; Thorn et al., 2022), South America (Vilela et al., 2020), and the Asia-Pacific region (Alamgir et al., 2019a; Sloan et al., 2019).

Because roads are almost universal vectors of human encroachment, our road-expansion risk index has many uses outside of land-use-change modelling. For example, roads play a key role in spreading human pathogens (Walsh et al., 1993; Sehgal, 2010; White & Razgour, 2020), and our index can be used to identify high-risk areas for zoonotic-pathogen spillover into human populations (Skinner et al., 2023; Plowright et al., 2024). Similarly, our index can be used to identify likely invasion routes for non-native species, which commonly spread along roads and in human-disturbed ecosystems (Mortensen et al., 2009; Spear et al., 2013). Finally, first-cut roads can be destabilizing socially. They often bring certain benefits, such as improved access to markets and social support systems (Hettige, 2006), but also present major risks—such as when land invaders or land speculators displace forest peoples by violently dispossessing them of their land and natural resources (Porter, 1997; Hecht & Cockburn, 2010; McSweeney et al., 2014). Across the tropics, our road-expansion risk index could be a particularly powerful tool for predicting future hotspots of social and environmental conflict.

## SUPPLEMENTARY METHODS

*Study region*

Our study region encompassed tropical wet forest regions for which high-quality, recent road data was available. This included the rainforests of the Congo Basin covered by Kleinschroth et al. (2019), the Brazilian Amazon covered by Botelho Jr. et al. (2023), and the insular Asia-Pacific region covered by Engert & Campbell et al. (2024). We focused on tropical wet forests as this was the ecosystem type predominantly covered by the above datasets, and because these regions were also covered by the Vancutsem et al. (2021) forest disturbance dataset. While relying on a single forest cover or forest loss dataset has limitations, the Vancutsem et al. (2021) dataset appeared to be the most robust single forest disturbance dataset for our study region at the time of assessment. The regions covered in this study are also characterized by exceptionally high biodiversity, carbon, and socioecological values (Jung et al., 2021; Neugarten et al., 2024), and high current or future rates of economic development and commodity-driven land conversion (Curtis et al., 2018; Meijaard et al., 2020).

*Road data*

We obtained the most recent, highest quality road data available for each of the continental regions covered by the study, including data produced by Kleinschroth et al. (2019), Botelho Jr. et al. (2023), and Engert et al. (2024a). Kleinschroth et al. (2019) and Engert et al. (2024a) road datasets were manually digitised using satellite imagery, while Botelho Jr. et al. (2023) was created using automatic road detection from satellite imagery. As these three road datasets were primarily focused on digitising roads outside of populated areas, we supplemented the datasets with the most recent Open Street Map data (circa 2023). We selected all roads in the Open Street Map data that did not intersect roads in the aforementioned datasets and appended them to the relevant road dataset using Select Layer by Location and Append tools in Arcmap 10.8.

*Model variables*

Our response variables for the two models were (1) road presence or absence, and (2) presence or absence of human impacts. Road presence or absence was quantified by converting the aforementioned road datasets to a raster layer at 1-ha resolution (presence) using the Feature to Raster tool in Arcmap 10.8 and mosaicking onto a map of the study region extent (areas not covered by the presence layer considered absences). Human impact presence or absence was quantified by first reclassifying the Vancutsem et al. (2021) Transition Map – Sub types data as either 'human impact' or not following Engert et al. (2024b) at 25m raster cell resolution. We aggregated this layer to a 1-ha raster resolution by calculating the proportion of each 1-ha cell that had some human impact. This was then converted to a binary presence absence layer using a cut-off threshold of 10% impacted to remove cells where natural disturbances may have been misclassified as human impacts.

We created an extensive list of potential correlates of both road construction suitability and road-related deforestation based on published literature and hypothesised relevance (Table 12). While the aim was to identify environmental drivers of road construction, we included socio-economic variables in the model for multiple reasons. We included national and subnational administrative regions, for example, to account for differences in road construction rates between governance regions. Alternatively, variables such as population density may have a more complex relationship with road construction where roads initially act as a driver by allowing access for colonization of land, but as the population density increases it itself becomes a driver of road construction as more infrastructure is required to support the population. We therefore included such variables to account for their influence on road construction rates relative to underlying environmental constraints. Additionally, previous work has shown that many correlates have neighbourhood effects (Cushman et al. 2017; Engert et al., 2024a), hence for several covariates we calculated mean values over varying focal window sizes. Our initial list included 44 potential correlates (Table 12). All spatial data for model variables was obtained from published or authoritative sources.

As the model sampling and iteration structure we employed is not suitable for handling categorical variables, we converted these from categorical to numeric terms using rank encoding. Rank encoding allows categorical variables to be considered as numeric variables, while reducing the amount of information leakage when compared to target-encoding (Jarapala, 2023). Using the Focal Statistics tool in Arcmap 10.8 we calculated the mean road presence and human impact presence for each class of each categorical variable (country, sub-national administrative region, pre-clearing vegetation class, protected area governance, protected area IUCN class, lithography class) across the study region and ranked the classes using these values. For protected area governance and protected area IUCN class, we created a basic rank encoded value which did not consider differences between countries (a single rank value for each class irrespective of country), and a second rank encoded value that did consider differences between countries (a rank value for each combination of protected area class and country).

**Table 12. Potential correlates of road-expansion and deforestation.** Model covariates were selected based on published studies and hypothesized relevance. Spatial data was sourced from high-quality published datasets and authoritative sources.

| Variable | Type | Scale* | Rationale | Data source |
|---|---|---|---|---|
| Country | Socio-eco | 1ha | Governance has direct and indirect effects on road construction and human impacts (Duran et al., 2011), i.e. through expansionist development policy. | GADM (n.d.) |
| Sub-national admin region | Socio-eco | 1ha | | |
| Population density | Socio-eco | 1km | Population density has been shown to correlate with both road density (Glover et al., 1975) and human impacts (Nzunda & Midtgaard, 2017). | Rose et al. (2021) |
| | | 5km | | |
| | | 10km | | |
| | | 50km | | |
| | | 100km | | |
| Gross Domestic Product | Socio-eco | 1km | As a raw measure of economic output, GDP is expected to be correlated with both infrastructure development and human impacts (Nzunda & Midtgaard, 2017). | Kummu et al. (2018) |
| | | 5km | | |
| | | 10km | | |
| | | 50km | | |
| | | 100km | | |
| Protected area cover (%) | Socio-eco | 1ha | Protected areas can reduce rates of road construction (Engert et al., 2024a) and forest loss (Barber et al., 2014), and this may differ between classes and governance types. | UNEP-WCMC, IUCN (2023) |
| Protected area governance | Socio-eco | 1ha | | |
| Protected area IUCN class | Socio-eco | 1ha | | |
| PA IUCN class by country | Socio-eco | 1ha | Protected area effectiveness has been shown to differ significantly between countries (Graham et al., 2021). | |
| PA governance by country | Socio-eco | 1ha | | |
| Distance to river | Enviro | 1ha | Rivers may effect road planning and influence deforestation by providing access points (Barber et al., 2014). | Created from Allen & Pavelsky (2018) |
| Pre-clearing vegetation | Enviro | 1ha | We expect that different vegetation types may facilitate (i.e. grasslands) or constrain (i.e. wetlands) road construction. | Engert et al. (2024b) |
| Mean annual rainfall | Enviro | 1km | Rainfall can influence road construction and degradation rates (Alamgir et al., 2017). Similarly it has been shown to influence | Karger et al. (2021) |
| | | 5km | | |
| | | 10km | | |
| | Enviro | 1km | | |

| | | | | |
|---|---|---|---|---|
| Rainfall seasonality (Coefficient of Variation) | | 5km | deforestation rates (Engert et al., 2024a). | Created from Karger et al. (2021) |
| | | 10km | | |
| Elevation | Enviro | 1ha | Slope, elevation, and other topographic variables constrain road construction (Collier et al., 2015) and have been shown to reduce deforestation and other human impacts (Gaveau et al., 2013) | Jarvis et al. (2008) |
| Slope | Enviro | 1ha | | Created from Jarvis et al. (2008) |
| | | 1km | | |
| Slope position | Enviro | 1ha | | |
| Slope anomaly** | Enviro | 1ha | | |
| Topographic roughness | Enviro | 1km | | Created from Evans & Oakleaf (2012) |
| | | 5km | | |
| | | 10km | | |
| | | 20km | | |
| Lithography | Enviro | 1ha | Soil properties can influence road construction (Lim et al., 2014) and suitability for anthropogenic land uses (Barrios, 2007), therefore influencing human impacts. | Hartmann & Moosdorf (2012) |
| Soil sand fraction | Enviro | 1ha | | Poggio et al. (2021) |
| Soil clay fraction | Enviro | 1ha | | |
| Soil silt fraction | Enviro | 1ha | | |
| Soil bulk density | Enviro | 1ha | | |
| Soil coarse fraction | Enviro | 1ha | | |
| Soil cation exchange | Enviro | 1ha | | |
| Soil organic carbon | Enviro | 1ha | | |
| Soil pH | Enviro | 1ha | | |
| Soil thickness | Enviro | 1ha | | Pelletier et al. (2016) |

* all values apart from 1-ha indicate the diameter of focal windows over which variables were averaged.

** slope anomaly was calculated as the slope value for a the cell minus the 1km focal mean slope.

*Sampling*

Our study region (model training) included ~866 million 1-ha raster cells, of which ~53 million cells contained roads. Therefore, to reduce computational burden and imbalance in the response variable, we created a model training sample of ~137 million 1-ha raster cells, including ~47 million cells containing roads. Our training sample included 15 million observations for Central Africa (5 million with roads), 32 million for the Asia-Pacific region (12 million with roads), and 90 million for the Brazilian Amazon (30 million with roads). To further reduce computational burden and model training time, we divided each region into subsamples of ~1.5 million points, with 500,000 road presences and 1 million road absences (10 subsamples for Central Africa, 20 for the Asia-Pacific region, and 60 for the Brazilian Amazon) (Fig. 29).

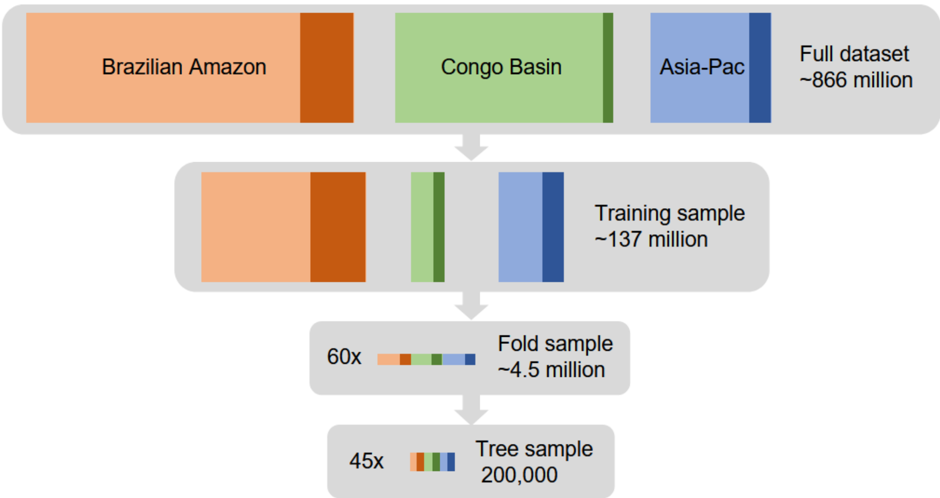


**Figure 29. Data sampling structure for random forest modelling.** Dark coloured bars indicate the proportion of the data that has road presences, and the light coloured bars indicate the proportion with road absences.

*Model routine*

To identify spatial determinants of road construction, we created random forest classification models with road presence or absence as the response variable. Random forest models are built by combining multiple independent classification trees, and as such are robust to complex non-linear and non-monotonic relationships and collinearity (Breiman, 2001). As roads are not constructed everywhere that they could be, we considered this modelling routine to be similar to a presence-background formulation, for which previous work has demonstrated the high performance of down-sampled random forest models (Valavi et al., 2022). We additionally chose to use random forest models because trees can be trained independently on separate data samples and combined into a final forest, which allowed us to develop a complex data subsampling method (Fig. 29) to improve computational efficiency and minimize overfitting.

To ensure that each continental region was equally represented in model training, we built the random forest model by training on one subsample (1.5 million observations) from each region in each iteration (4.5 million observations total per iteration). As road density is highly variable between regions, there were uneven numbers of subsamples. To minimise the impact of the differences in road density, each subsample for the Brazilian Amazon was used once, each from the Asia-Pacific used twice, and each from Central Africa used six times in total. The random forest was therefore built by iterating through 60 'folds' each containing 45 trees, for a total of 2700 trees. To further reduce computational burden and minimise risk of over-fitting, individual trees in each fold were trained on a sample containing 100,000 presences and 100,000 absences, and sampling was conducted with replacement so that each individual tree was trained on a different portion of the subsample (Fig. 29). Random forest models were fit using the randomForest package (Liaw & Weiner, 2002) in R (R Core Team, 2021).

We developed the final road suitability model through three model generations (Fig. 30). In the first generation, we ran the random forest model with all 44 potential correlates and determined the variable importance. We then removed all variables with an importance (mean decrease in accuracy) of 0. Additionally, for variables that were measured in different ways (protected area governance vs protected area IUCN category) or at different spatial scales (population density at different neighbourhood size) we kept only the version with the highest importance value, leaving 20 correlates (Fig. 31). This step was employed to minimise the chance of including colinear variables and has previously been identified as a robust method of optimizing multi-scale models (Cushman et al., 2017), however some information on influential covariates may be lost in the process. We then re-ran the model with this reduced list of covariates to create the second-generation model. This second-generation model was then used to predict road presence across our entire dataset (866 million ha) and create a spatial autoregressive (SAR) term following Crase et al. (2012). Finally, we re-ran the model again including this SAR term to create the third-generation model. We used the spatial autoregressive term to minimize spatial autocorrelation as this method is less likely to bias variable estimates than other methods (Crase et al., 2012).

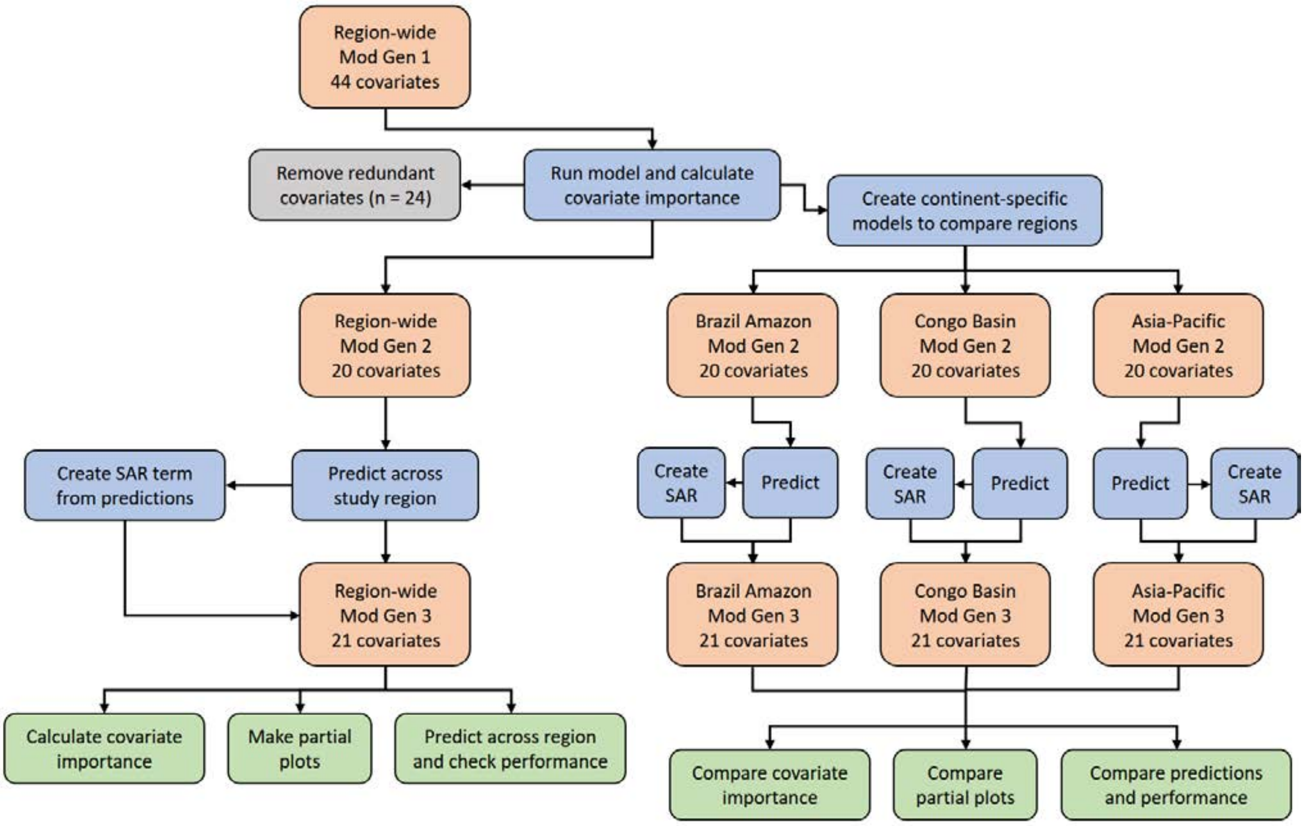


**Figure 30. Model generation structure for the region-wide model and continental-region-specific models.**

This third-generation model was the final model for which variable importance, partial plots, model performance, and model predictions were calculated (Fig. 30). Model performance and model predictions were calculated holding the SAR term at a value of 0 to negate its influence on both performance and prediction. Model performance was calculated through 100 iterations of 100,000 randomly sampled observations for each continental region from the full dataset (30 million total observations) to give mean AUC values and AUC variance. To test for spatial autocorrelation, we calculated Moran's I using the same 100 iterations of 100,000 randomly observations using the moranfast package (Cooper, 2020). Moran's I values were low (mean = 0.07, sd = 0.01) and hence we considered that spatial autocorrelation was adequately accounted for. The model was trained on a subset of the total dataset (~137 million observations) while performance and spatial autocorrelation were assessed over the total dataset (~866 million observations), hence they were assessed on at least some data that was not included in the training sample.

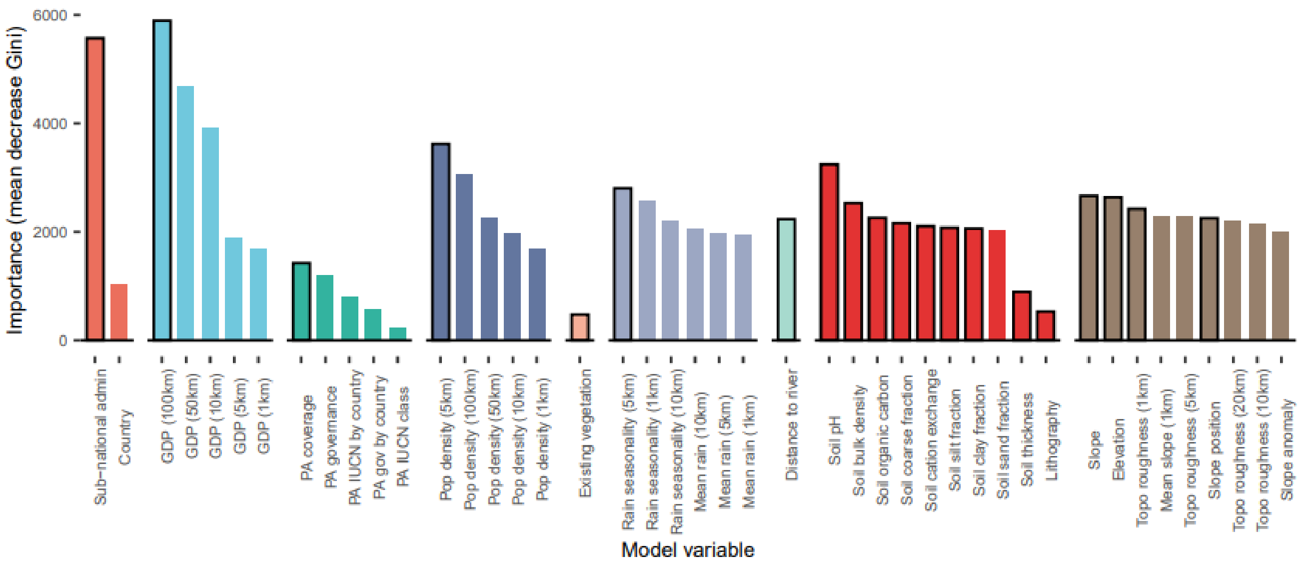


**Figure 31 Potential correlates of road construction and covariates retained in third-generation model.** Columns with black outlines indicate the covariates that were retained in the second- and third-generation model, columns without outlines were not retained.

*Region-specific models*

After the first model generation and removal of redundant covariates, we used the new list of 20 model covariates to create continental-region specific models. These models each followed the same second and third generations as the pantropical model (run second generation and predict to create the SAR term, run third generation including the SAR term). We then used these three continental models (for the Brazilian Amazon, Congo Basin, and Asia-Pacific) to compare (1) the importance of model covariates across regions, (2) the partial effect of covariates on road building across regions, and (3) the predictions and performance of the continental models against the region-wide model.

*Road-expansion risk*

After developing the third-generation model of road suitability, we developed a road-expansion risk layer based on the environmental variables alone. To do this, we predicted the probability of road presence while holding all socio-economic variables (population density, administrative region, etc) at either their mean value or zero. This method allowed us to preserve the partial relationship between environmental variables and road presence accounting for the socio-economic variables, but ignoring the influence of the socio-economic variables in the prediction surface. We then used the dismo package (Hijmans et al., 2022) to identify the value for this prediction surface for which specificity and sensitivity were maximised and rescaled the prediction surface so that this value became 0.5, the minimum value became 0, and the maximum became 1. This final adjusted probability layer was termed the 'road-expansion risk' layer.

*Road-expansion risk drives deforestation*

To examine the effect of road construction suitability as a correlate of human impacts, we developed a similar random forest model routine as used to identify drivers of road presence. We followed the same data sampling and model fitting structure as outlined for road suitability, however for this model we used human impact presence or absence (as classified in Engert et al. 2024b) as the response variable. Model variables included the road-expansion risk layer as well as the socio-economic variables related to population density, GDP, governance regions, and protected area coverage.

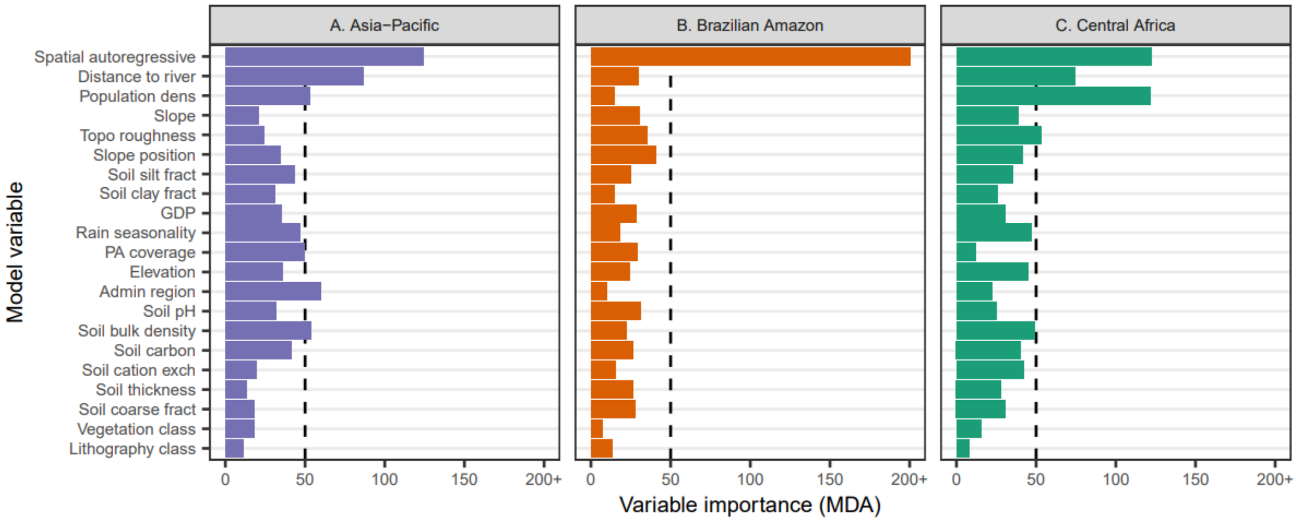


**Figure 32. Actual values of variable importance (mean decrease in model accuracy when permuted) for model variables in each region-specific model.** The spatial autoregressive (SAR) term had substantially higher importance in the Brazilian Amazon than in either Asia-Pacific region or Central Africa.

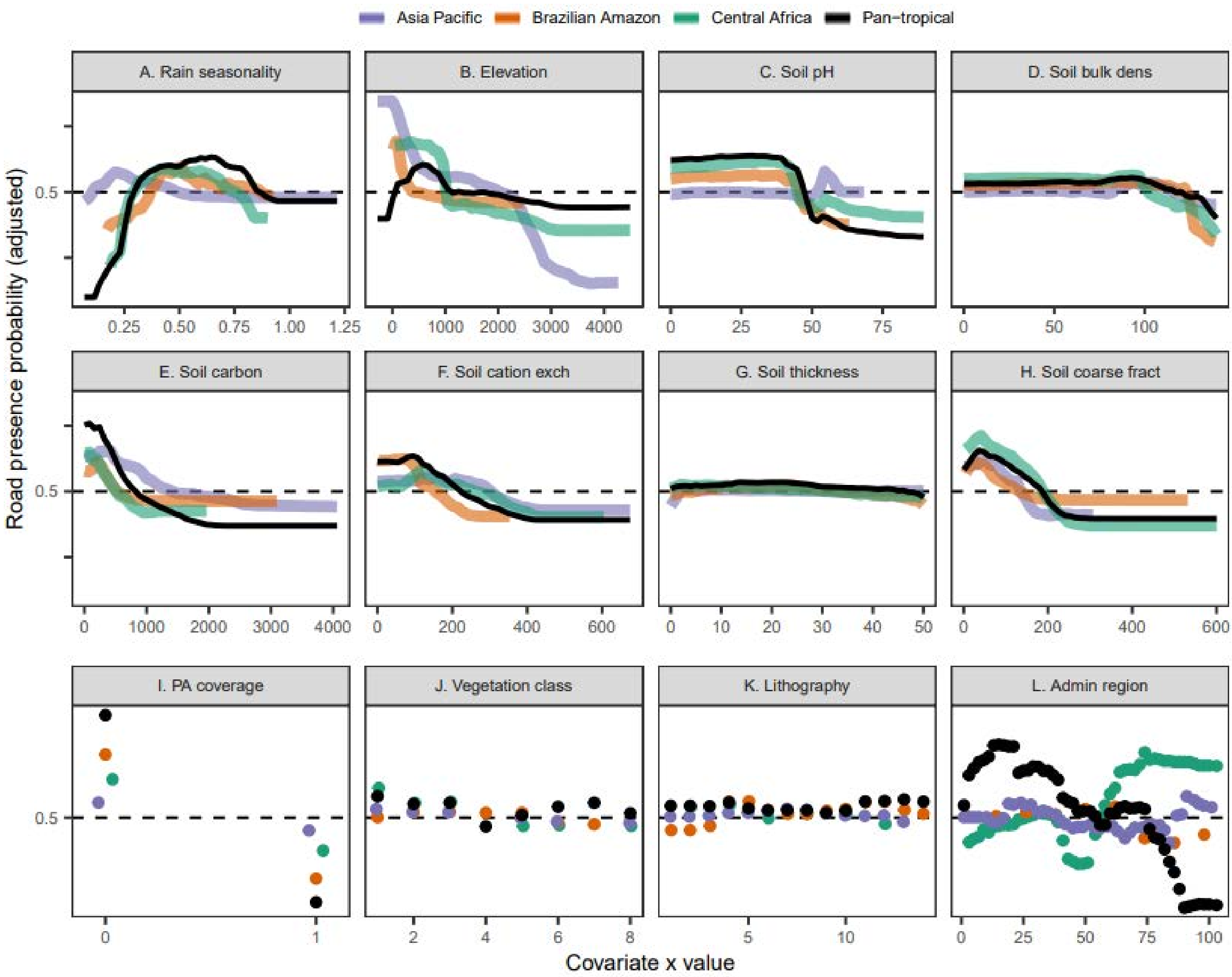


**Figure 33. Partial differential plots for the 12 variables not shown in the main text (less important as determined using mean decrease in accuracy when permuted).**

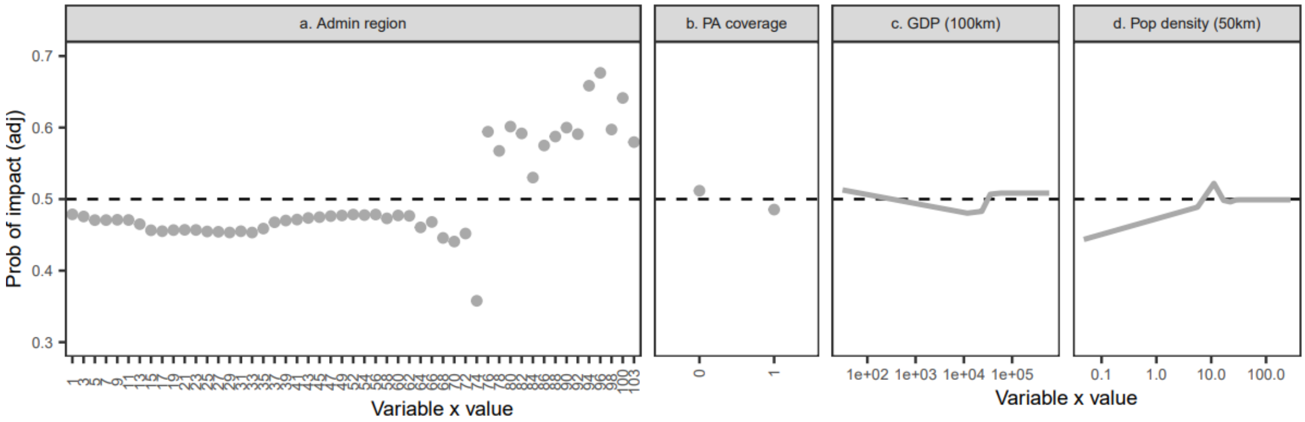


**Figure 34. Partial differential plots from the impact model for variables other than the road-expansion risk index.**

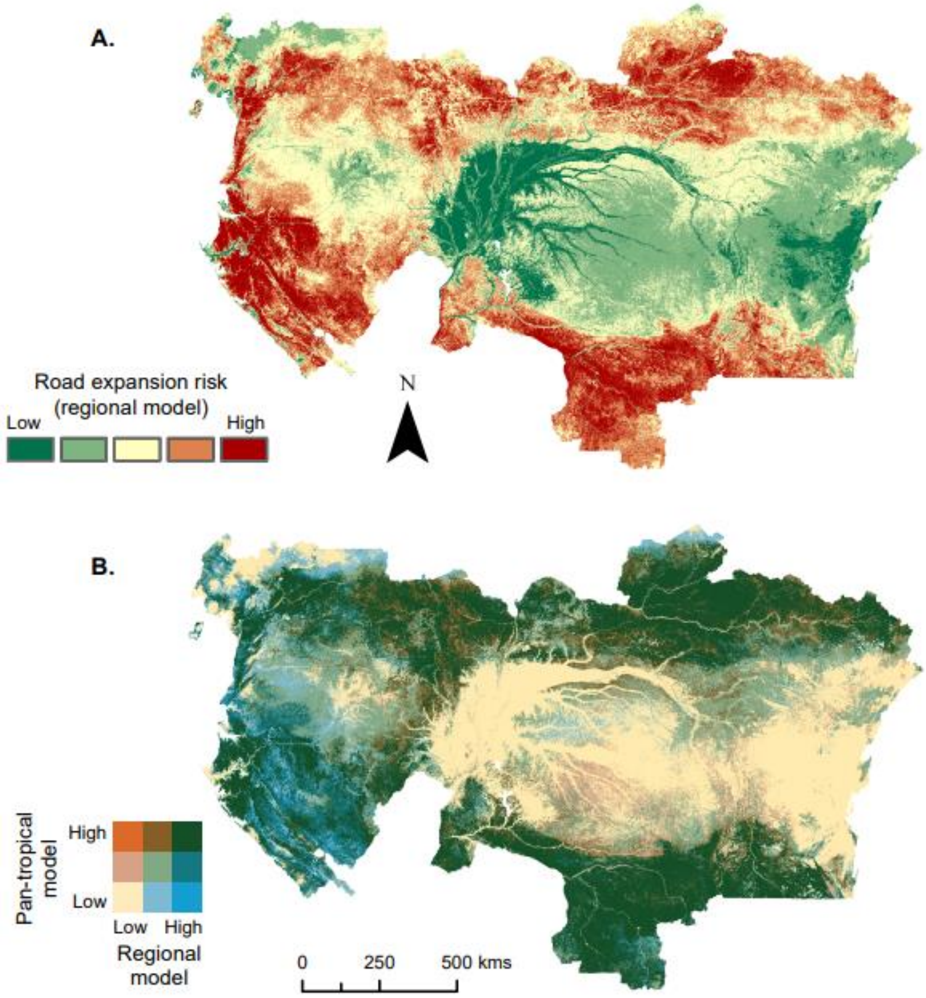


**Figure 35. Road-expansion risk from the region-specific model for the Congo Basin and comparison to predictions from the pantropical model.** For the comparison plot, low-medium-high thresholds are as follows: low = 0 – 0.45, medium = 0.45 – 0.55, high = 0.55 – 1.

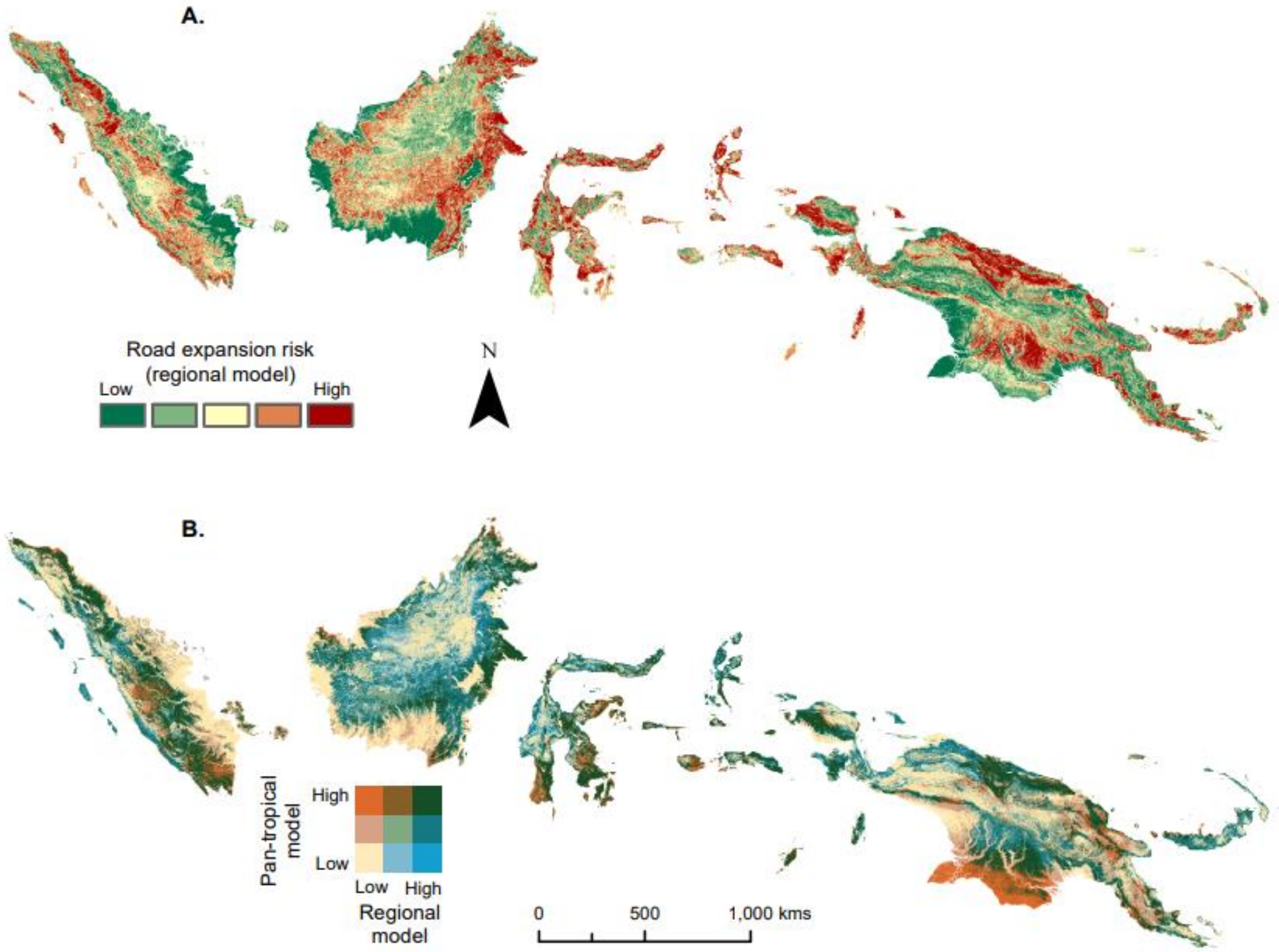


**Figure 36. Road-expansion risk from the region-specific model for the Asia-Pacific region and comparison to predictions from the pantropical model.** For the comparison plot, low-medium-high thresholds are as follows: low = 0 – 0.45, medium = 0.45 – 0.55, high = 0.55 – 1.

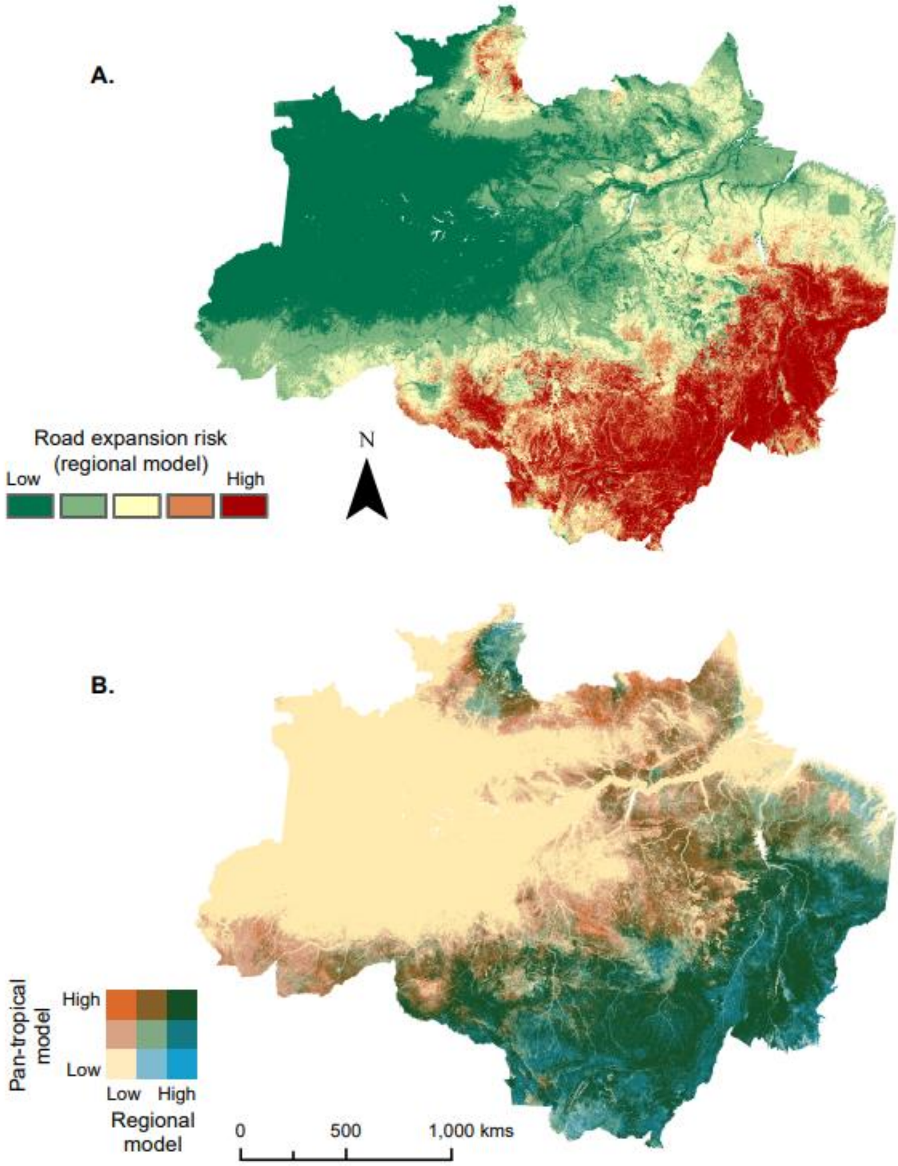


**Figure 37. Road-expansion risk from the region-specific model for the Brazilian Amazon and comparison to predictions from the pantropical model.** For the comparison plot, low-medium-high thresholds are as follows: low = 0 – 0.45, medium = 0.45 – 0.55, high = 0.55 – 1.

# Chapter 5: Building a spatially-resolved model of the impacts of first-cut roads

Submit as: Spatially-resolved models of the impacts of tropical development corridors to *Nature*


## Abstract

New roads penetrating into intact forest regions often enable an avalanche of secondary road development. This expansion of secondary roads and other infrastructure causes amplified rates of land colonisation and deforestation. Conservation assessments of major road projects have attempted to quantify or predict these secondary impacts using relatively simple buffer-distance or distance-decay functions, however these methods are blind to underlying landscape features that may constrain road building. Here we use previously delineated data on secondary impacts and a modelled 'road-expansion risk' surface to develop improved models of the impacts of first-cut roads in intact forest frontiers. Our new model performs twice as well as simple distance-decay functions and over 30 times as well as buffer-distance models. We then develop an application framework for our new model and demonstrate its utility by predicting the impacts of over 200 proposed roads across the tropical Asia-Pacific region.

## Introduction

Millions of kilometers of road developments are expected across the globe in the coming decades (Ascensão et al., 2018; Alamgir et al., 2019a; 2019b; 2020; Sloan et al., 2019a; Thacker et al., 2019; Vilela et al., 2020; Thorn et al., 2022). These roads are expected to facilitate substantial environmental impacts such as mining (Asner et al., 2013), logging (Kleinschroth et al., 2019), and deforestation (Sales et al., 2017; Engert et al., 2024a) through the networks of secondary roads they precipitate (Fearnside & de Alencastro Graça, 2006; Fearnside, 2007; Perz et al., 2008; Fearnside, 2015; Engert et al., 2024b). While only recently quantified (Engert et al., 2024c), the impacts associated with secondary road expansion have not yet been included in spatial models, making them impossible to accurately assess and mitigate.

Current methods to estimate the impacts of large-scale road projects have limited spatial precision and have seldom been empirically verified. Environmental impact assessments of major roads typically focus on the direct impacts of road construction (Karlson et al., 2014; Jaeger, 2015; Laurance & Arrea, 2017; Johnson et al., 2019; Juffe-Bignoli et al., 2021) while the total impacts precipitated are often orders of magnitude larger (Engert et al., 2024b). Conversely, assessments by scientists and conservationists have necessarily drawn on buffer-distance models (i.e. Laurance et al., 2015; Spencer et al., 2023), distance-decay functions (i.e. Sonter et al., 2017; Tulloch et al., 2019; Engert et al., 2021), or models of deforestation (i.e. Gaveau et al., 2021). However, these approaches are largely blind to landscape biophysical factors that constrain or facilitate road-building (Lim et al., 2014; Collier et al., 2015; Engert et al., 2024c) and are not explicitly trained on the impacts of first-cut roads (Engert et al., 2024b).

Developing spatially-resolved models to predict the scale and extent of secondary impacts is an urgent conservation concern. In this study we assess 92 historical examples of first-cut roads across the Brazilian Amazon, Congo basin, and New Guinea (Engert et al., 2024b). We make use of empirically delineated secondary road impacts (Engert et al., 2024b) and a modelled road-expansion risk surface (Engert et al., 2024c) to generate a spatially-resolved model of the impacts of so-called first-cut roads. We then show that our refined model outperforms existing buffer distance and distance-decay functions and detail an implementation framework for use on proposed road development projects. Finally, we demonstrate this utility by predicting the impacts of over 200 proposed national highways and development corridors across the islands of Sumatra, Borneo, and New Guinea.

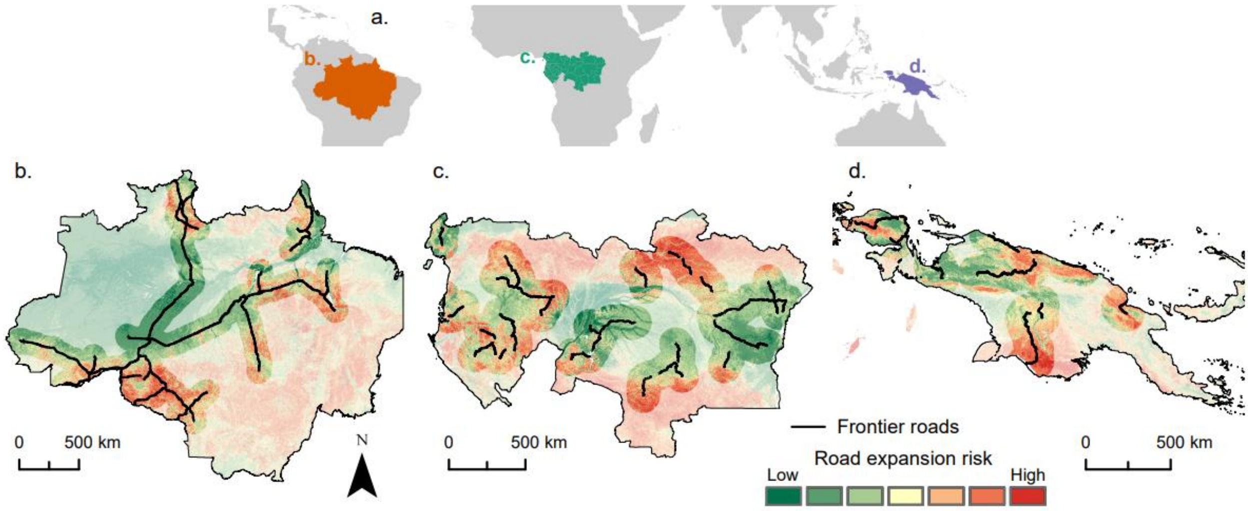


**Figure 38. Study region showing location of first-cut roads identified in Engert et al. (2024a) and road expansion risk from Engert et al. (2024b).** Study region (a) includes (b) the Brazilian Amazon, (c) the Congo Basin, and (d) New Guinea.

## METHODS AND RESULTS

*Spatially-resolved impact model*

We built models of the impacts of 92 'first-cut' roads in the tropical forest regions of New Guinea, the Congo Basin, and the Amazon Basin (Engert et al., 2024b). To ensure that the final model would have high reuse potential, we created generalised linear mixed models (GLMMs) and employed model summarising steps to identify a simple model formula that could be calculated in various software at low computational burden (Methods). A crucial aim of the modelling exercise was to build a model that could predict secondary impacts in areas not yet anthropized, and hence in the absence of information on existing infrastructure and populated areas. Similarly, as country-level and regional socioeconomic and political conditions (i.e. deforestation regulation and export trade) are highly dynamic, we did not include this information in the modelling framework. Models were therefore generated that contained only a few variables, including protected area coverage, the road-expansion index outlined in Engert et al. (2024c), and either Euclidean distance or travel time as a distance metric. We assessed 20 different modelling frameworks that included different combinations of the aforementioned variables and included either random intercepts or random slopes with individual first-cut roads as the random variable (Table 13).

The best-performing model – referred to as TRD – included the road-expansion risk index, used travel time as the distance metric, and included a random intercept that separated low, medium, and high impact roads. This model had an impacted-weighted true skill statistic (TSS) score of 0.32, with the next best performing model having a TSS score of 0.30 (Fig. 38). Conversely, the basic distance-decay function (no random effect to separate roads by impact class) had a TSS score of just 0.16 and all buffer-distance models had negative TSS scores (Fig. 45), indicating very poor performance. These values outline the poor performance of existing model frameworks when empirically verified and demonstrate that our new model represents a substantial improvement when predicting the impacts of major roads.

Partial effects of model variables followed expected patterns, with unprotected areas more accessible from first-cut roads (low travel time) and more suitable for road-building having the highest chance of being impacted (Fig. 39I – K). The total area impacted – as predicted using the best performing model – was significantly correlated with the observed impact area for first-cut roads studied (Fig. 39G), however the accuracy was relatively low ($R^2$ = 0.28) and hence estimation of the impacted area of proposed road projects will benefit from local expertise.

Compared to prediction maps using the distance-decay model, those produced using our new model show that impact areas can vary in their distance from first-cut roads, depending on landscape characteristics. Even areas in close proximity to the first-cut road may not be impacted, for example when they are highly unsuitable for road building or have high travel times due to steep slopes or presence of waterbodies (Fig. 39). Conversely, impacts may occur over very large distances when conditions are suitable for travel and road-building. These results are more likely to represent real-world patterns, as the impacts of first-cut roads are unevenly distributed in space and are influenced by the underlying landscape (Gaveau et al., 2021; Engert et al., 2024c).

This improvement in the spatial precision and accuracy of predicted impacts has important implications for land-use planning and impact mitigation schemes. Imprecise impact predictions may lead to miscalculations of the potential environmental and social impacts of road projects, or allocation of conservation funds to areas unlikely to be impacted (Tulloch et al., 2015).

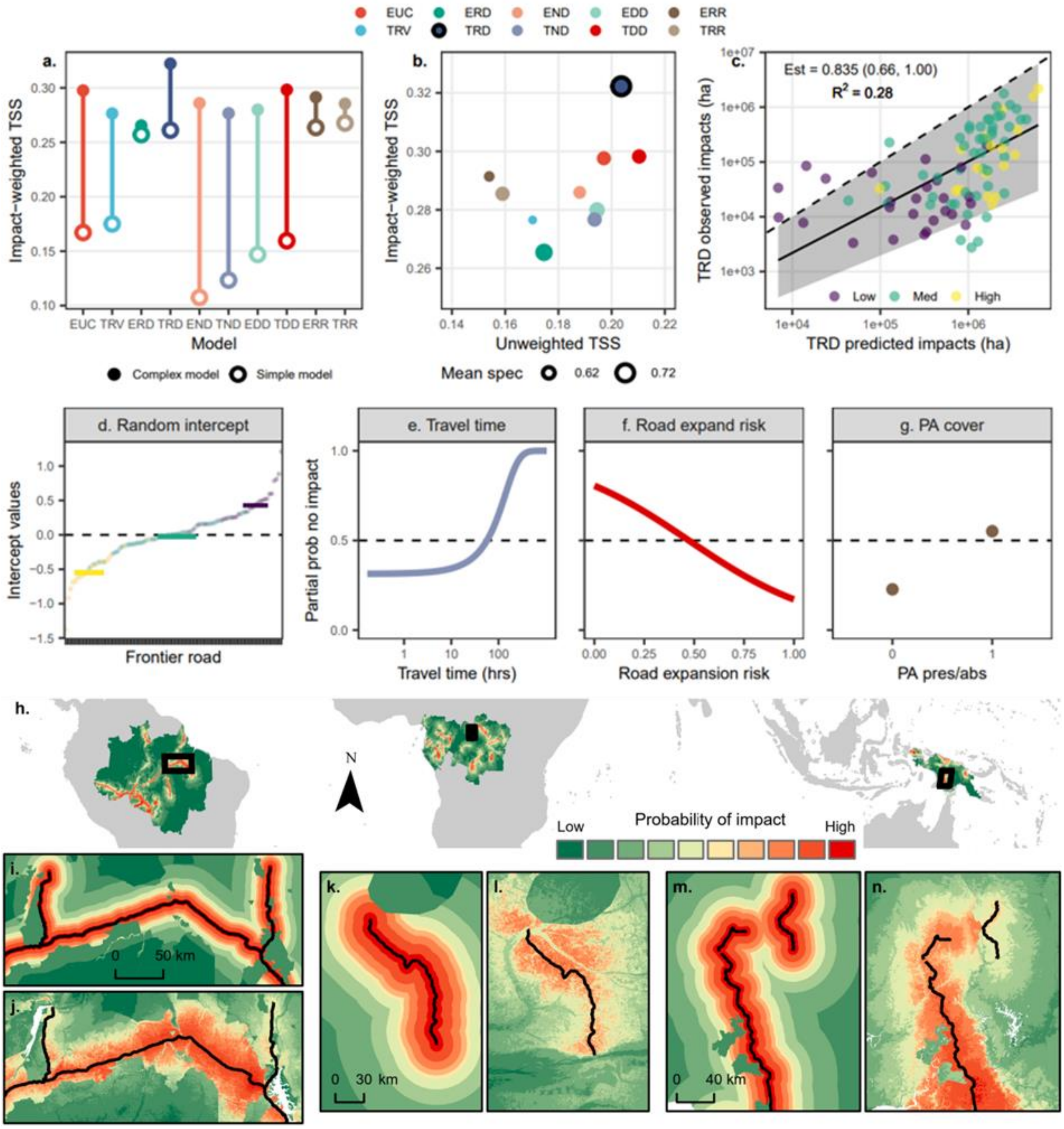

**Figure 39. Selection of the best performing model and covariate partial-dependence plots and example predictions.** (a) comparison between simple models (global mean slope and specificity:sensitivity threshold) and complex models (group mean slopes and high/low impact specificity:sensitivity thresholds) for each model structure. Impact-weighted TSS values for all buffer-distance models (1km, 10km, 25km, 50km) were all negative. (b) the final model was selected using the true-skill statistic (TSS) by comparing the mean TSS across all training roads, and the mean TSS weighted by the total impacts (deforestation and forest degradation) caused by each training road. (c) comparison of the total predicted impacts (true positive plus false positive) against the total observed impacts (true positive plus false negative). (d – g) partial-dependence plots for model covariates in the final TRD model, including random intercept (coloured bars indicate group mean values used in complex model). (h) prediction map for the whole study region using model TRD. (i – n) comparison of predictions between the basic distance-decay model and the new TRD model for (i – j) Brazilian Amazon, (k – l) Congo Basin, and (m – n) New Guinea. Model structures are outlined in Table 13, the final model (TRD) includes travel time, road expansion risk, and a random intercept.

*Implementation framework*

The final model requires only three inputs (Fig. 40) and can be run as an R function or python script through various software, hence it is extremely accessible for scientists and practitioners alike. The road-expansion index is an existing raster layer stored in the webpage, travel time to first-cut road is calculated within the prediction function, and protected area coverage information can be obtained readily from open sources (Protected Planet) or provided by the user. Therefore, to assess the potential impacts of a proposed road project, the user only needs to input the road location and specify a cut-off distance over which to calculate impacts.

Our model did not include a temporal dimension, as forest loss and degradation rates are highly dependent on socio-economic and political conditions (Duran et al., 2011; Reside et al., 2017; Fischer et al., 2020). However, Engert et al. (2024b) show that the cumulative rate of increase in impacts for most first-cut roads was approximately linear. Impact probability output maps can therefore be used to estimate expansion of forest disturbances through time using existing forecast methods such as cellular automata (i.e. Gaveau et al., 2021; Parsch et al. 2024).

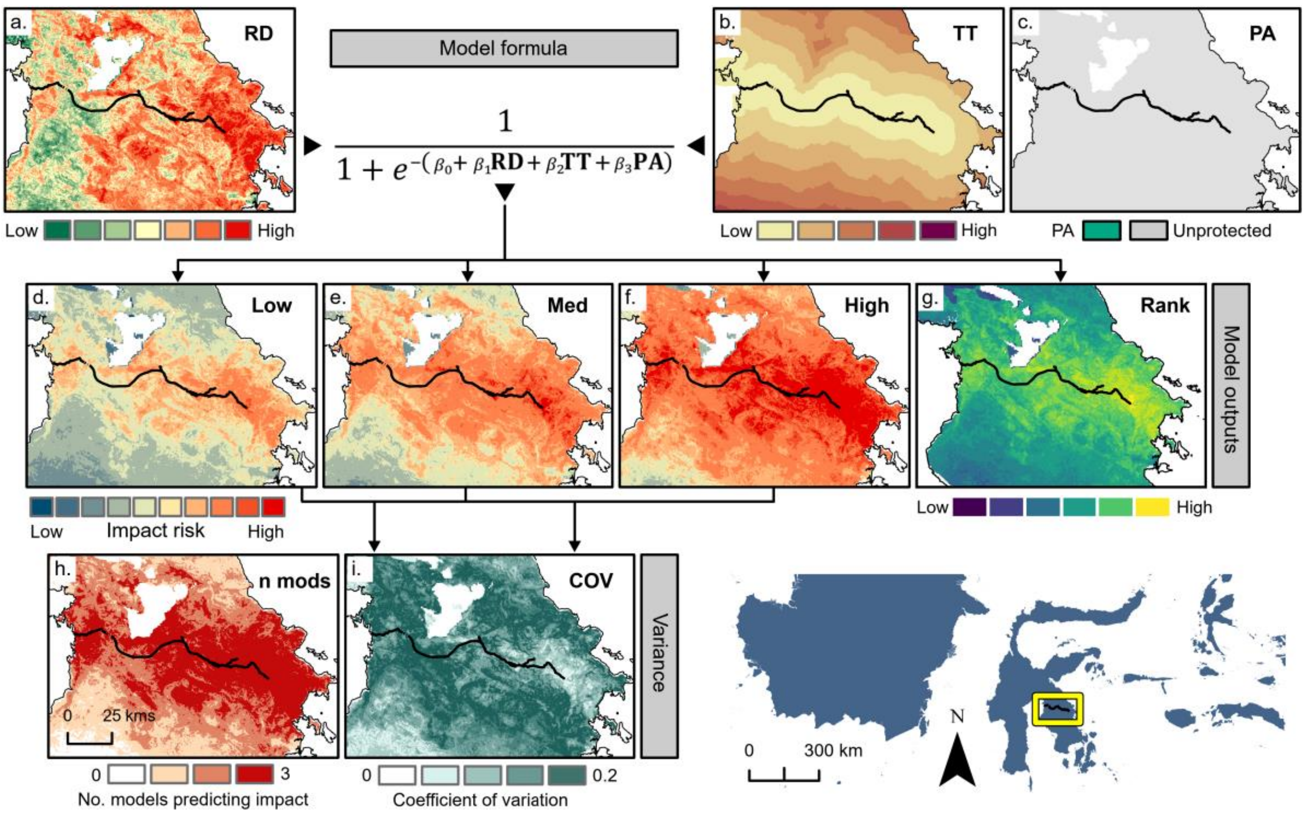


**Figure 40. Visual representation of the model implementation and outputs.** (a – c) model variables used to predict the impacts of first-cut roads following the logistic equation formula. (a) road-expansion risk, (b) travel time, and (c) protected area coverage. (d – g) model outputs: probability of impact from (d) low impact

road, (e) medium impact road, (f) high impact road, and (g) rank-likelihood of impact. (h) number of models for which a binary reclassification of the impact probability is 1. (i) coefficient of variation for the three impact probability outputs (low, med, high). (j) area of extent for road assessed in this model demonstration.

*Model application*

Utilizing our new framework, we assessed the potential impacts of 188 proposed road projects across the insular Asia-Pacific region. Encompassing the countries of Indonesia, Malaysia, and Papua New Guinea, this region has exceptional biodiversity, socio-ecological, and environmental values (Myers et al., 2000; Cámara-Leret et al., 2020; Jung et al., 2021; Estrada et al., 2022) – but is under increasing threat particularly from commodity agricultural expansion (Curtis et al., 2018; Meijaard et al., 2020). Under various national and subnational development schemes, the region is expected to see an explosive growth in large-scale road construction projects (Alamgir et al., 2019a; 2019b; 2020; Sloan et al., 2019a; 2019b; 2019c).

We employed our new model to create impact probability surfaces for all 188 roads and road segments. We then overlaid these surfaces with an integrated land-cover map (Engert et al., 2024a) and a modelled carbon density map (Spawn et al., 2020) to assess potential deforestation extents of road projects and carbon emissions resulting from subsequent land conversion. We also identified areas in which predicted 'impacts' occurred in lands already converted to anthropogenic uses (urban areas and productive lands) that may deliver benefits such as improved access to markets (Hettige, 2006). However this improved access facilitated by large road projects may also contribute to various social and socio-economic impacts to communities such as violent land dispossession and resource theft (Hecht & Cockburn, 2010; Laltaika & Askew, 2021).

Projected impacts of planned road projects in the Asia-Pacific region were highly variable. All proposed roads in New Guinea (Indonesian Papua and Papua New Guinea) had greater predicted 'impact' areas in intact ecosystems than in human modified landscapes (Fig. 41). This is largely due to the low levels of historical development on the island, hence the majority of projects were in areas yet to experience significant land conversion. As such the majority of the proposed roads were also expected to precipitate substantial forest loss and associated carbon emissions (Fig. 42).

Conversely, all proposed road projects in Sumatra were had greater overlap of 'impact' areas with human modified landscapes than in natural systems as little intact lowland forest remains on the island. Many projects however still have the potential to precipitate large amounts of forest loss and carbon emissions due to intensification of productive lands and removal of remaining vegetation patches. Additionally, while it is not assessed here, previous work has shown that these roads will further fragment habitat and reduce dispersal potential for many species (i.e. Kaszta et al., 2024).

Impacts of proposed roads in Borneo were highly variable between those located in already anthropized landscapes and those planned for intact forest frontier regions. Many projects crossing the interior of Borneo or location in East and North Kalimantan, for example, are expected to promote substantial land clearing and associated habitat loss and land-use change carbon emissions. Conversely, some projects, and some sections of larger roads, in the more populated southern portion of the island may deliver socio-economic benefits if they improve access to markets and social support systems (Hettige, 2006) without contributing to the dispossession of small-holder and subsistence producers. If all road projects are realised across the three islands, the region is expected to see over 22.7 million Mg of carbon released (Fig. 42).

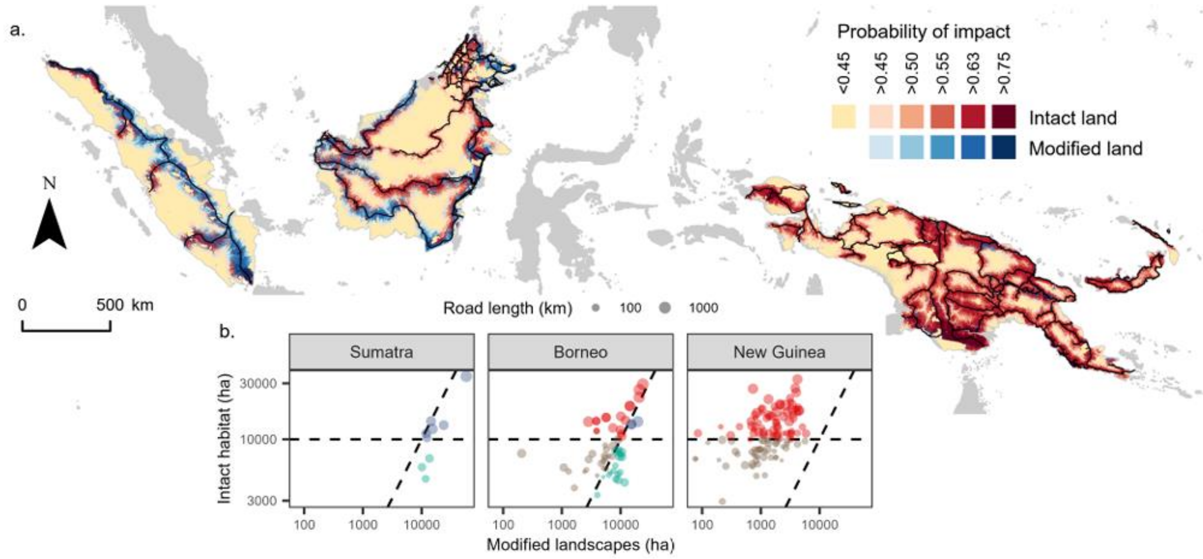


**Figure 41. Application of the impact prediction model to 188 proposed roads (and road sections) across the tropical Asia-Pacific region.** (a) graphical representation of predicted impact extents overlaid with current land-cover to identify potential impacts in intact natural habitats and improved road access in modified landscapes. (b) summarised impact area values by location (in intact habitats or modified landscapes) for each road (or segment) in each of the three islands studied. Values reported for each road in (b) are the low-end predictions (5% confidence interval) for medium-impact roads.

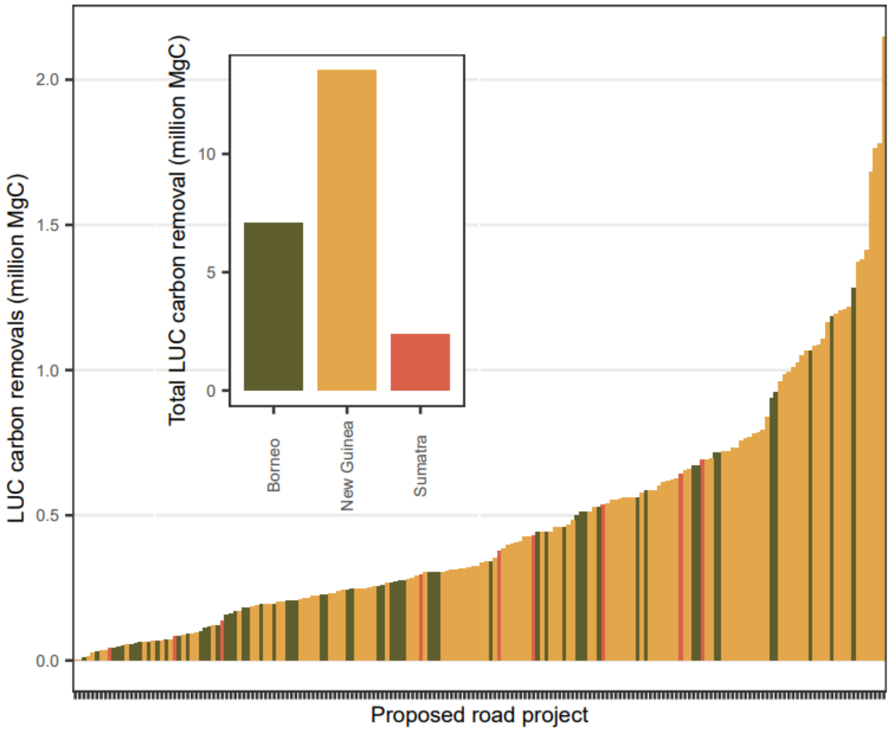


**Figure 42. Project land-use change (LUC) carbon removals for each road (or road segment) assessed, and summarised values for each island.** Values for each road are the low-end estimate (5% confidence interval) for medium-impact model predictions. Values for individual roads do not consider potential overlaps in areas impacted by other roads, but whole-island calculations do account for this overlap.

## Discussion

Using historical data on the impacts of first-cut roads in tropical forest regions, we created an empirically verified and spatially-resolved model of the secondary impacts of major roads. This model substantially outperforms existing methods such as buffer-distance and distance-decay functions. We propose that this new model can be used to inform impact assessment procedures to more accurately account for the scale of impacts of new road projects, as well as conservation planning actions in order to avoid misallocating funding to areas less likely to be impacted.

Existing project impact assessment procedures, such as EIA, overwhelmingly focus on the direct impacts of new road projects (Karlson, Mörtberg & Balfors, 2014; Jaeger, 2015; Laurance & Arrea, 2017; Johnson et al., 2020), while the cumulative and secondary impacts are orders of magnitude larger (Engert et al., 2024b). Our new model can be used to estimate the potential magnitude of the secondary impacts of proposed road projects in a more robust and empirical manner so that they may be included in impact assessment procedures. For example, previous reviews have noted the lack of quantitative assessment of the ecological impacts of roads in EIAs (Karlson et al., 2014), and prior to Engert et al. (2024b) there were no quantitative assessments of the impacts of secondary roads. The model presented here may overcome this limitation in EIA procedures by providing a robust method to predict the secondary impacts of major road projects. Additionally, as climate triggers – assessments of the potential effects of projects on climate change – are gaining traction in impact assessment (Sydes et al., 2022; Mayembe et al., 2023), our model can be used to predict the land-use change carbon emissions of projects under such assessment procedures. As large infrastructure projects such as those assessed here often contribute to a range of socio-economic impacts – such as violent land dispossession and resource theft (Porter, 1997; Davis, 2001; Hecht & Cockburn, 2010; McSweeney et al., 2014) – our model can also be incorporated into social impact assessment (SIA) to identify regions where secondary road expansion and land colonisation is likely to impact indigenous and rural communities. Hence the model is a robust tool for assessing proposed road projects and identifying those for which the potential impacts outweigh the benefits, and hence should not proceed (Juffe-Bignoli et al., 2021; Vilela et al., 2021).

By creating an open and accessible impact model, projects may also be assessed independently by scientists and activists where impact assessment procedures are opaque or insufficient. For example, a mining road in Sumatra, Indonesia, was approved following an EIA suggesting that 424 ha of forest would be lost during road construction while estimates from scientists and activists indicated between 3,000-6,000 ha of forest loss (Engert, Ishida & Laurance, 2021). However, these estimates were based on distance-decay modelling and local knowledge, and the actual impacts may be even higher. Similarly, a proposed superhighway in Nigeria was rerouted following pressure from scientists and environmental organisations who drew attention to the massive potential impacts (Cannon, 2017; Mahmoud et al., 2017) using simple buffer-distance models. We propose that our model can be used by activists and academics to provide assessments of the impacts of proposed roads in a transparent and reproducible manner in order to press developers to engage in best-practice impact mitigation methods, such as strategic route planning.

We have presented here a simple application of our model in the prediction of deforestation extents and land-use change carbon emissions for proposed roads. However, roads and land-use change have a wide range of other impacts which this model may be used to identify areas likely at risk. The model may be used, for example, to quantify loss of habitat or habitat connectivity for threatened and charismatic species, or identify which species are expected to be impacted by specific projects (Alamgir et al., 2019a; Kaszat et al., 2020; Spencer et al., 2023; Kaszta et al., 2024). Similarly, identifying areas in which further road building is likely to occur may be useful in predicting future hotspots of road-kill mortality (Lala et al., 2021). Further, the model may be used to identify areas in which road building and other human activities such as mining will contribute to erosion into rivers or other hydrological impacts (Jones et al., 2000; Kastridis, 2020). We propose that our new model will have broad utility to a wide range of academics, activists, and practitioners in numerous fields of environmental and biological research.

## SUPPLEMENTARY METHODS

*Training data*

We built models of the impacts of major roads in tropical forest frontiers using example roads identified in Engert et al. (2024b). This included 92 first-cut roads across New Guinea, the Congo Basin, and the Amazon Basin. Sampling regions were the areas within the network allocation zones dependent on first-cut roads, as modelled in Engert et al. (2024b). These were areas that were more likely to be spatially dependent on first-cut roads and their secondary roads than other major roads or settlements, and were delineated for each first-cut road separately, leaving 92 distinct sample regions. Our response variable was presence or absence of 'human impacts' identified by classifying and summarising Vancutsem et al. (2021) forest cover data as outlined in Engert et al. (2024b).

As our aim was to build low-complexity models with few variables, we extracted information only on Euclidean distance to first-cut road, travel time to first-cut road (calculated following Engert et al. 2024b), protected area coverage, and road-expansion risk (Engert et al. 2024c). Road-expansion risk is a modelled surface that quantifies the probability of road construction based on landscape features such as topography, soil, and rainfall while accounting for socio-economic variables; and can hence be used to identify areas in which secondary roads and their impacts are likely to spread following first-cut road construction. We created an initial large sample for each sample region which included all human impact presences (up to 1 million presences) and all human impact absences up to twice the number of absences as presences – in order to reduce the imbalance in the response variable in model training.

To minimize computational burden and reduce spatial autocorrelation in model training, we created a smaller subsample dataset for each sample region. For each of the 92 first-cut roads, we took a balanced sample (1:1 presence absence ratio) relative to the number of impacted 1-ha cells (Eqn 1; $N_{pres}$ refers to the number of impact presences). This sampling strategy ensured that the weighting of first-cut roads in the model was influenced by their total impacts, but not to a degree such that low impact roads had no influence on parameter estimation.

$$Eqn\ 1:\ Sample\ N_{pres} = 1000\ \times\ \log_{10}(Total\ N_{pres})$$

To ensure the data sampling did not influence results, we ran 25 iterations of each model – with each iteration taking a random subsample of the overall large sample – and calculated mean values for fixed and random effect terms. Variance in fixed effects was generally very low (Fig. 42), hence we assume that data sampling had little effect on parameter estimation and model performance.

*Model structure*

As we aimed to maximise the re-use potential of our model, we opted to utilise simple modelling techniques and simplify model terms as much as possible. We hence opted to use generalised linear mixed models (GLMMs) with individual first-cut roads acting as random slopes or random intercepts. By using generalised linear mixed models, our final model could be reduced to a formula with defined slope terms – rather than a model function – which can then be reproduced and calculated in a wide range of statistical and geospatial programs with low computational burden.

We tested 10 different model structures, comparing the use of Euclidean distance or travel time as the distance variable, including or excluding the road-vulnerability layer, and using random slopes or random intercepts (Table 13). All models included protected area coverage (binary) as a fixed effect.

**Table 13 Structure of models used to predict the impacts of first-cut roads.** 'Fixed' indicates that the relevant model term was included as a fixed effect, while 'random' indicates it was included as a random effect. Cells with NA indicate that the variable was not included in the relevant model.

| Name | Intercept | PA cover | Euclidean distance | Travel time | Road expansion risk |
|---|---|---|---|---|---|
| **EUC** | Random | Fixed | Fixed | NA | NA |
| **TRV** | Random | Fixed | NA | Fixed | NA |
| **ERD** | Random | Fixed | Fixed | NA | Fixed |
| **TRD** | Random | Fixed | NA | Fixed | Fixed |
| **END** | Fixed | Fixed | Random | NA | NA |
| **TND** | Fixed | Fixed | NA | Random | NA |
| **EDD** | Fixed | Fixed | Random | NA | Fixed |
| **TDD** | Fixed | Fixed | NA | Random | Fixed |
| **ERR** | Fixed | Fixed | Fixed | NA | Random |
| **TRR** | Fixed | Fixed | NA | Fixed | Random |

*Model summarising and comparison*

We ran 25 iterations of each model using different samples from the total dataset. We then calculated the mean values for the fixed effect variables in each model across the 25 iterations (Fig. 42). We summarised the random effect terms in two ways: (1) calculating three group means by grouping roads with similar random effect values, and (2) calculating a global mean for all roads (Fig. 43). We then used these summarised fixed and random effect values to generate predictions across the larger sample dataset for each road, and used the dismo package (Hijmans et al., 2022) to calculate the threshold prediction value for which specificity and sensitivity were maximised (spec_sens threshold). We also summarised the spec_sens threshold in two ways: (1) calculating group means for low- and high-impact roads, and (2) global mean values. These summarisation steps resulted in a total of 20 different model structures: simple (global mean values for all fixed and random effects, and global mean spec_sens thresholds) and complex (group mean values for random effects and group mean spec_sens thresholds) versions of each of the 10 models outlined in Table 13.

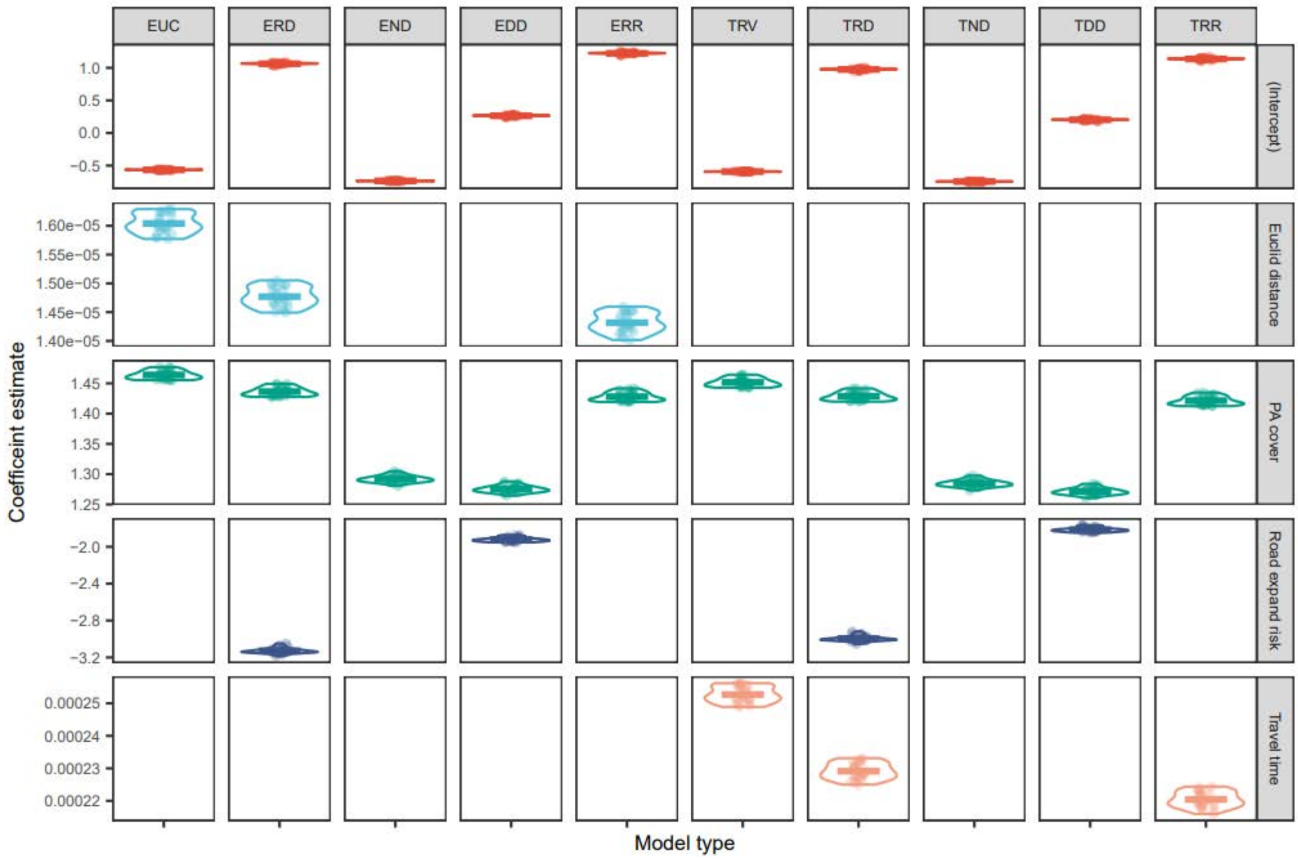


**Figure 43 Fixed effect values for model covariates.** Fixed effect values are grouped by covariate and model form. Each individual point represents the value for an individual model iteration.

To compare the performance of the final summarised models, we used the models to predict impacts across the entire datasets for each major road. Models were trained on a subset of the entire dataset (~92,000 observations) and predictive performance was assessed over the entire dataset (~87 million observations), hence performance was assessed on a large amount of data held-out during model training. We then created confusion matrixes and calculated weighted and unweighted true-skill statistic values. The true-skill statistic (TSS) is calculated using the model sensitivity and specificity and is not influenced by model prevalence and is hence a more reasonable comparison method than overall accuracy or kappa statistic when presences and absences are unbalanced (Allouche et al., 2006). The unweighted TSS was calculated by averaging the TSS values for each first-cut road, while the weighted TSS was calculated by summing the confusion matrix values for all roads and calculating the TSS from this aggregated confusion matrix (hence it is weighted by road size and impacted area). The weighted TSS was included in model comparisons as we considered it more important to be able to accurately predict the impacts of highly destructive roads than roads with low impacts.

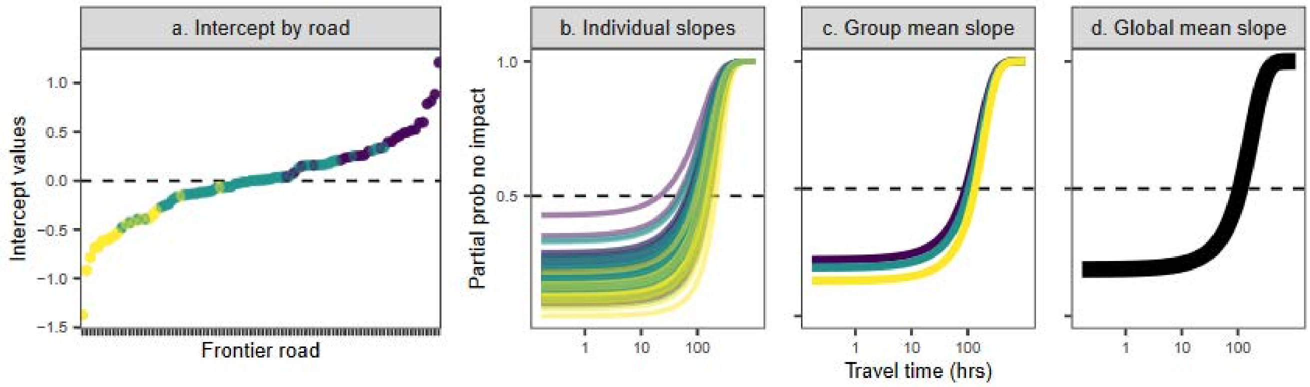


**Figure 44. Example of the steps to summarise random effect values into (c) group mean slopes and (d) a single global mean slope.**

After identifying model TRD (random intercept model with road-expansion risk included and travel time as the distance metric) as the best performer, we compared the predicted impacts (true positive and false positive) and observed impacts (true positive and false negative) to determine the models' ability to estimate total area impacted by roads as well as the spatial configuration of impacts. The low-impact and high-impact spec_sens thresholds for model TRD were very similar (0.277 and 0.291 respectively), and hence we opted to average these values and instead used the group mean random intercepts to define low, medium, and high impact road prediction models. By calculating slope coefficients of the relationship between observed and predicted impacts, we were able to provide scaling factors for each impact prediction model to estimate the total summed impacts of proposed roads. Model summarisation steps are outlined graphically in Fig. 44.

Finally, we used the TRD formula to build an R function that can be used to predict the impacts of proposed major road projects in tropical rainforest regions. The R function (which can be adapted into a python script for use in GIS platforms such as QGIS and ArcGIS) requires a road shapefile as an input and a specified distance cut-off (recommended to use 100km) and provides as outputs (1) the modelled impacts of a low-impact road, (2) the modelled impacts of a medium-impact road, (3) the modelled impacts of a high-impact road, (4) a raster giving the rank-likelihood of each cell within the cut-off distance being impacted, and (5) an estimate of the number of cells impacted (including standard deviations). The rank-likelihood layer can be used to examine the area impacted under different development and policy assumptions (i.e. 5% of cells impacted).

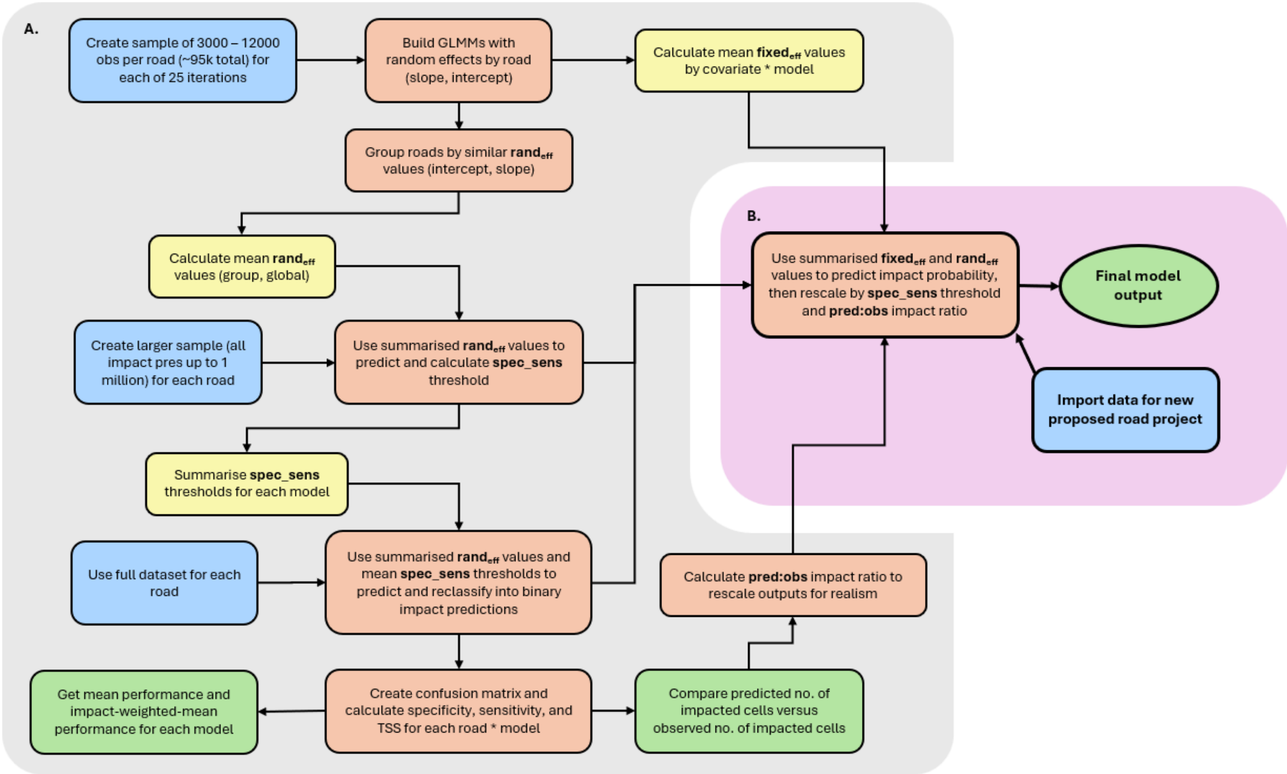


**Figure 45. Model training and refinement process for use in predicting impacts of future roads.** (a) model training and refinement, and (b) use for predicting impacts of future projects.

*Model application*

To demonstrate the utility of our new impact model, we applied it to proposed road projects across the Asia-Pacific region. Specifically, we ran the model to predict the potential impacts of proposed road projects in Sumatra (Sloan et al., 2019b), Borneo (Alamgir et al., 2019a; 2020; Sloan et al., 2019c), and New Guinea (Alamgir et al., 2019b; Sloan et al., 2019a). We selected all roads from the listed studies that >50km long (n = 188) and impact predictions using the R function outlined above. We then reclassified the impact prediction maps to identify the areas likely to be impacted, and overlaid these areas with (1) an integrated landcover map (Engert et al., 2024a) and (2) a modelled carbon density map (Spawn et al., 2020). Using the landcover map, we were able to identify areas where new roads were likely to improve market access for productive lands and use this to conduct a rudimentary cost-benefit analysis for each road under the assumption that improved market access in productive lands and populated areas is a benefit while predicted deforestation is a cost.

# General discussion and conclusions

I began this thesis project with the aim of developing improved models of the impacts of new road developments in intact forest areas that explicitly included the effects of secondary development. To reach this goal, I first had to demonstrate that roads were proximate drivers of, and necessary conditions for, forest destruction. I then had to develop an empirical dataset on the scale and spatial extent of secondary road development and associated impacts, in order to have a response variable around which to build the model. Following this, I needed to understand the ways in which biophysical and socio-economic factors shape road building and road network expansion in order to improve the spatial precision of the impact modelling. Finally, by combining information gained in the first three data chapters, I was able to create an impact model which massively outperformed existing methods. The final impact model is, crucially, a low complexity generalized linear model with only three covariates requiring low computational burden, which can be utilized by a wide range of stakeholders from activists and practitioners to scientists and impact assessment professionals.

***Chapter 2: Roads as proximate drivers of – and necessary conditions for – deforestation***

Roads are well known to be associated with deforestation, with road density and distance to roads often identified as key correlates of deforestation (Barber et al., 2014; Ferretti-Gallon & Busch, 2017; Sales et al., 2017). However, some contend that roads are simply products of development and land-use change that causes deforestation rather than a necessary condition. In Chapter 1, I extend on previous correlational assessments showing the importance of roads in predicting deforestation, by demonstrating that roads are both proximate drivers and necessary conditions for deforestation. By comparing the performance of models with high- and low-quality road data, I show that having accurate information on where roads are is vital for accurately predicting deforestation. Additionally, through annual road maps (1985 – 2020) and high-resolution spatiotemporal analysis I confirm that roads almost always precede deforestation and that infrastructure is hence a necessary condition for most deforestation. These results provide more robust evidence that roads can act as drivers of deforestation (at least spatially), rather than simply being a by-product of other development such as agricultural intensification. The impact of poor-quality road data in deforestation models also clarifies the importance of using high quality road data for future chapters assessing scale and extent of secondary impacts of first-cut roads.

***Chapter 3: Classifying and quantifying the impacts of first-cut roads in tropical forest frontiers***

It is widely recognized that first-cut roads – new roads constructed in intact natural landscapes – often enable sprawling networks of secondary roads (Fearnside & de Alencastro Graça, 2006; Fearnside, 2007; Perz et al., 2008; Laurance, Goosem & Laurance, 2009). It is also expected that the impacts, such as deforestation, mining, and land conversion among others, associated with secondary roads will be substantially larger than those associated with the first-cut road (Fearnside, 2007; Fearnside, 2015). However, this thesis chapter presents the first large-scale analysis and quantification of these two phenomena. Using 92 historical first-cut road cases across the worlds largest rainforest regions – the Amazon and Congo basins and island of New Guinea – I show that there is on average 28.5km of secondary road for every 1km of first-cut road. The impacts of secondary roads were orders of magnitude larger than the direct impacts of first cut roads, being on average 135 times larger. Both secondary road length and impact area were highly variable among roads and regions, and the Congo basin was the only region of the three where the area of secondary impacts was not correlated with the length of secondary road.

Intra-regional variation in the length of secondary road and magnitude of secondary impacts are likely due to landscape biophysical conditions. For example, some first-cut roads are constructed in mountainous terrain where road building is expensive and difficult (Collier et al., 2015), and roads often become unusable after a short period due to high rainfall or landslides and other erosion events (Sloan et al., 2019a). First-cut roads in wetland areas may not spawn as much secondary road due to difficulty of road construction in water-logged soils (Douven & Buurman, 2013) and the possibility of using waterways for transport (i.e. Reed & Miranda, 2007). Conversely, the large inter-regional variation is almost certainly due to differences in socio-economic and political contexts. For example, the Brazilian Amazon is a globally important exporter of commodity agricultural and pastoral products (Hoang & Kanemoto, 2021), as are some areas of New Guinea. Conversely, the Congo basin is not a significant exporter of agricultural commodities and most anthropogenic forest disturbances in the region are related to selective logging and subsistence agriculture (Curtis et al., 2018; Pendrill et al., 2022), neither of which result in extensive land clearing although logging may produce extensive road networks (Kleinschroth et al., 2019). Therefore, models to predict the impacts of proposed future first-cut roads will need to consider the underlying biophysical conditions of the landscape and the socio-economic context.

***Chapter 4: Identifying correlates of road building to model landscape level road-expansion risk***

Existing road datasets often understate the length and extent of road networks, and road networks are constantly expanding, hence the majority of analyses are constrained by poor-quality and often outdated road data. Additionally, not all areas are suitable for road building – such as steep slopes (Collier et al., 2015) and flooded landscapes (Douven & Buurman, 2013) – hence it should be possible to identify areas unlikely to have roads and in which roads are unlikely to expand into. Therefore, to identify areas potentially impacted by proposed first-cut roads, it is important to understand where secondary roads are likely to be built. As the overarching aim of this thesis was to produce a simple, readily deployable model of the impacts of first-cut roads, I decided that developing a single layer representing the risk of road expansion and road-related deforestation would massively simplify the final model.

To build this index, I modelled the correlates of road presence and absence data across the Congo and Amazon basins, and the insular Asia-Pacific region, covering over 137 million 1-ha raster cells. I found that the influence of biophysical and socio-economic conditions on road building were largely consistent across the global tropical rainforest regions assessed. Distance to river, topographic conditions, and soil properties were the most influential biophysical features, and population density was also very important. Population density was substantially more important in the Congo basin where there is limited commodity agricultural production to drive massive road networks in areas with low population densities.

Using information on only the biophysical features (while accounting for the effect of socio-economic variables) I developed a 'road-expansion risk' index to characterize the probability of road building in a given area. This index had a strong ability to predict deforestation, indicating its utility in conservation planning and other assessments of human interaction with nature. I decided to relegate the development of this index to its own chapter and publication as it has wide utility, including predicting routes for the spread of invasive species through anthropogenic dispersal (Mortensen et al., 2009; Spear et al., 2013), and identifying regions potentially at risk of zoonotic pathogen spillover and spread through human contact with vector populations (Sehgal, 2010; Skinner et al., 2023; Plowright et al., 2024).

***Chapter 5: Building a spatially-resolved model of the impacts of first-cut roads***

After creating a dataset of the secondary impacts of first-cut roads and the road-expansion risk index in previous chapters, I was able to create an improved model of the impacts of first-cut roads. Due to a lack of empirically delineated secondary impact data, and various other data and methodological constraints, existing studies of the impacts of major roads have relied on simple correlational analyses such as distance-decay functions (i.e. Sonter et al., 2017; Tulloch et al., 2019; Engert et al., 2021) and buffer-distance models (i.e. Laurance et al., 2015; Spencer et al., 2023). The aim was hence to develop a model that have greater spatial precision and performance than these existing techniques, and was able to predict impacts without considering socio-economic data as this information will be unknown for first-cut roads in intact forest frontiers.

Using the road-expansion risk index and a metric of travel time from the first-cut road, I created a model that performed twice as well as a simple distance-decay function, and over 30 times as well as buffer-distance models. The two crucial improvements represented by this model are (1) more realistic estimates of the area impacted by new roads, and (2) greater spatial precision and consideration of the underlying landscape – i.e. low probability of steep cliffs being deforested even if they are in close proximity to the new road. By providing more realistic estimates of the impact area for first-cut roads, we are less likely to under- or overestimate their impacts (Fearnside, 1987; Laurance et al., 2001), and by empirically verifying the estimates they will hold greater weight in EIA procedures and development planning phases (Jaeger, 2015; Juffe-Bignoli et al., 2021). The greater spatial precision provided will allow conservation funds and impact mitigation strategies to be allocated to the most threatened areas rather than wasted in regions unlikely to be impacted (Tulloch et al., 2015). This model therefore represents a substantial potential benefit to the conservation and development planning communities, as well as conservation and human rights activist groups, as land colonization facilitated by major road projects often also results in violent dispossession of the lands of indigenous and rural communities.

***Future research***

The first chapter of this thesis outlined the extent of unmapped roads across the insular Asia-Pacific region, and the impact of this data deficiency on deforestation models. Similar data gaps have been reported in the Amazon (das Neves et al., 2021; Botelho et al., 2022), Cameroon (Cameroon Road Network, 2022), and the Solomon Islands (Katovai et al., 2016; Hughes, 2018). Additionally, road networks are rapidly expanding, particularly across the tropical forest regions, with hundreds of thousands of kilometers added every year (Ahmed et al., 2013; Kleinschroth et al., 2019; Nascimento et al., 2021; Che et al., 2023). This information underscores the importance of developing remote-sensing methods and road-detection algorithms in order to keep pace with expanding road networks and ensure accurate threat assessments and conservation planning outcomes. This thesis benefitted from such work, incorporating AI-mapped roads across the Brazilian Amazon from leading academics at Imazon (Botelho Jr et al., 2022). Efforts to improve these methods and extend their coverage are vital for nature conservation in many regions.

In Chapter 3 of this thesis I employed a novel network analysis methodology to delineate secondary roads stemming from first-cut roads. However, this method was based on probability assessments rather than direct confirmation of the source point for new roads. To account for this, I included steps to underestimate the total length of secondary road and area impacted, but advances in satellite imagery analysis and road detection algorithms in the future may allow for more precise and in-depth analyses. Analysis of annual Landsat imagery, for example, may be used to more accurately describe the spatiotemporal patterns of road network and settlement expansion in order to improve our understanding of the dynamics of land-colonisation and landscape conversion. Such information may also allow for further future refinements of models to predict the impacts of first-cut roads.

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