December 2025

Phase 1 Project Report

Consolidating 'prototype modelling' outputs

(task 2 of our workplan)

The Impact of Agricultural Land Use Change on Forestry, Carbon Storage, Biodiversity and Climate Resilience in Indonesia, 2000-2020

RG2-009569

LEAF Indonesia Team Report

Lead author Jeremy Reffin

Executive Summary

The LEAF Indonesia project is examining the environmental and social impacts, trade-offs and synergies that are associated with efforts to increase food production in Indonesia, both through area expansion (major plantation or cropland projects, mixed smallholder mosaics) and intensification (raising output density through seeds, fertiliser, mechanisation, water control etc.). The aim is to support integrated decision making for sustainable land-use planning, and the ongoing monitoring, evaluation and management of interventions aimed at increasing food production.

This report provides a historical baseline, focussing on the extensification of agricultural land use in Indonesia over the first two decades of this century. Over this period, we have seen a combination of strong demographic and political pressure to raise local food production, particularly of rice, maize, and horticulture, intersecting with highly uneven agricultural land availability across the nation. To reflect this, we look at agricultural land expansion at a national level and in three case-study provinces: East Kalimantan, Gorontalo, and West Papua, each of which represent agricultural land use frontiers in varying stages of development and exploitation.

Data visualisation and analysis was carried out with the Landscape Integrative Mapping and Modelling for Multifunctional Analysis platform (LIMMMA) (University of Sussex, 2025), which was designed by the LEAF team and is being further developed over the course of the project. The report describes preliminary development of a system for modelling (with LIMMMA) the trade-offs with carbon storage, biodiversity and climate resilience that will arise from specific agricultural land use change interventions across scales. The illustrations are based on secondary data and do not deal with other impacts and trade-offs of interest to the LEAF project -such as those related to multiple dimensions of food security and multiple dimensions of poverty - or with distributional or intersectional analysis. However, the system is being designed with the capacity to integrate these issues; evolving with empirical work and available data, stakeholder demand and user engagement.

Typology of interventions

Agricultural land use expansion in Indonesia can usefully be examined through the lens of progressive exploitation of its established forest, leading to resultant impacts on forest coverage, carbon storage capacity, biodiversity, and the frequency of natural adverse events. We distinguish two sources of agricultural extensification:

1. Established forest extensification: primarily through the direct clearance of established forest (but also peat and mangrove exploitation) and immediate conversion to new agricultural land uses, usually accomplished through large-scale projects.

2. Natural vegetation extensification: indirect forest exploitation through gradual encroachment on established forest. The edge regions of established forest are gradually thinned, reducing canopy density and height to the point at which the land is no longer considered forest - rather "natural vegetation" of woodland, scrub, grassland, or similar - at which time it is seen as open to conversion to new land uses through many small-scale projects. The land is often in this intermediate stage for a considerable period e.g. as alang-alang grasslands, scrub, or ex-mining land, before agricultural conversion takes place.

The key observation is that, in both cases, the primary objective of this exploitation is agricultural, with the land generally being converted to agricultural uses, either in their broader sense (oil palm, pulpwood, timber) or, more narrowly, for food production (rice, maize, coconut, horticulture).

This analytical lens is dependent on a definition of "established forest"; the concept of established forest reflects the notion of forest largely untouched by human intervention but, in reality, often undergoing exploitation through logging or other practices. We define "established forest" for the purposes of this work in section 1 of the report.

Modelling impact

Changes in agricultural land use, involving either "established forest extensification" or "natural vegetation extensification", as defined and examined in this report, have an impact on forest coverage, carbon storage, biodiversity, and climate resilience.

This report explores some preliminary methods for measuring these four categories of impact. For each impact category, we suggest an appropriate direct measurement that can act as a proxy for impact, a metric derived from that measurement that is quantifiable and scales appropriately, and an estimated relationship between the measurement and the metric. This process provides a quantifiable figure for impact, opening up the possibility of modelling directly the trade-offs arising from any specific agricultural land use change intervention.

In this report, we examine the impact of agricultural extensification on forestry, carbon storage, biodiversity, and natural adverse events, covering broadly the first two decades of the century (2000-2020).

1. Impact on Forests

The two patterns of exploitation have clear effects on forest coverage and forest quality in Indonesia. Established forest is gradually dwindling, converted either directly to agricultural uses or, more commonly, initially degraded to woodland (lower density trees with a more open canopy) or natural vegetation, which is subsequently converted to other land uses, again primarily agricultural in purpose. Section 1 of the report provides data and analysis to illustrate these observations across Indonesia as a whole and in our three case-study provinces: East Kalimantan, Gorontalo, and West Papua.

For measuring impact, we propose using established forest canopy volume as our measurement, derived directly from remote observation studies, and as our metric. "Canopy volume" is the average woodland canopy height per unit area summed over the area under consideration. "Established forest" is defined, just for the purposes of this assessment, as woodland where the average canopy height per unit area is greater than 10 metres. For any small patch of land, this measure therefore decreases linearly as the average canopy height decreases towards 10 metres and then drops to zero as the canopy height falls below 10 metres. A comparable impact estimate is derived by multiplying a change in value from an intervention by a fixed constant to allow direct integration with other impact measures.

2. Impact on Carbon Storage

These patterns of exploitation also have an impact on the Indonesian land mass's vegetative carbon storage capacity. Carbon storage capacity is, to a first order of approximation, proportional to average canopy height; both forms of forest exploitation for agricultural exploitation therefore lead to a reduction in carbon storage. This negative impact has, in part, been mitigated by intact established forest growing naturally – an established forest carbon sink effect (Qie et al., 2017; Pan et al., 2024): in regions where established forest has been left relatively undisturbed, vegetative carbon storage has actually increased. This carbon-sink effect has been widely reported in the literature and, in the case of Indonesia, points towards the preservation of extensive areas of established forest as a valuable step to conserve net carbon storage capacity going forwards (Williams, 2024). Section 2 of the report identifies areas of vegetative carbon loss and preservation across Indonesia and the case-study provinces, highlighting the impact of different forms of agricultural exploitation.

For measuring impact, we propose using canopy volume as our measurement, and estimated vegetative carbon storage as our metric. Estimated vegetative carbon storage is a modelled estimate of the amount of carbon being stored that is attributable to the vegetation in each patch of land. Based on previous work (University of Sussex, 2023), we currently model this as a linear relationship between carbon storage and canopy volume. A comparable impact estimate for an intervention is derived by multiplying a change in this carbon storage value by a fixed constant to allow direct integration with other impact measures.

3. Impact on Biodiversity

Although systematic biodiversity data are generally not consistently available over a historic time series, the limited available data and modelling, from the Commonwealth Scientific and Industrial Research Organisation (CSIRO), suggest that biodiversity has continued to decline between 2000 and 2020, across Indonesia as a whole and within our case-study provinces. Not surprisingly. the biodiversity loss has been less severe in areas where established forest has been left relatively undisturbed. There is also some indication that the index may be an early-warning indicator for further environmental degradation: as an example, the indices for West Papua show significant loss at a time when other measures of environmental impact show minor impact. These observations are discussed in more detail in section 3 of the report.

For measuring impact, we propose using the CSIRO biodiversity habitat index (Harwood et al., 2022) directly as both measurement and metric. The CSIRO Biodiversity Habitat Index (BHI) estimates how much of the original terrestrial species diversity in a patch is likely to be retained based on the size, condition, and connectivity of remaining natural ecosystems. It assigns each patch, a 1 km grid cell, a score between 0 and 1, representing the “effective proportion of habitat” remaining across all ecologically similar cells.

A comparable impact estimate for an intervention is derived by multiplying a change in this BHI value by a fixed constant to allow direct integration with other impact measures.

4. Impact on Climate Resilience (using Natural Adverse Events as a proxy)

Climate resilience is estimated by looking at natural adverse event data as a proxy for the broader concept. The available data on natural adverse events points to a large increase in reports of flooding, fires, and landslides in our three case-study provinces over the past decade. This might, in part, reflect increases in reporting, but the data are consistent with a thesis of greater environmental instability associated with the regions where both direct and indirect agriculture-driven forest exploitation is taking place.

Using a more fine-grained analysis of the data, we identify a set of locations where high levels of flooding have occurred, and where high numbers of landslides have occurred. Previous reports and studies have identified common themes, some of which appear to be traceable to deforestation and associated changes in agricultural practices (e.g. Patuti et al., 2017). More analysis is required to explore the underlying patterns. The available data are discussed in section 4 of this report.

Flooding and landslide events have substantial negative impacts on Indonesia’s economy and people. Causative relationships have been proposed between changes in agricultural land use, particularly deforestation, and increases in flooding and landslides, but it is challenging to develop a robust model for the relationship. This remains a work in progress.

5. The pattern of agricultural land use change

Much of the direct and indirect forest exploitation is attributable to agricultural development, but the pattern of development has differed along these two axes of forest exploitation. Section 5 examines these patterns in more detail.

i. Direct exploitation of established forest

To date, direct exploitation of established forest has mostly been attributable to three forms of agricultural land use: oil palm plantations, pulpwood plantations, and logging. The former show up clearly on land use maps as this large-scale land use re-designation is clear. The latter leads to accumulated degeneration of established forest to the point where it is no longer considered forest.

ii. Direct exploitation of established forest in this fashion is generally attributable to large-scale coordinated projects.

Although most projects in the historic period have been non-food agricultural projects, large-scale direct forest exploitation for crop production has been observed and has the potential to be utilised more impactfully if avenues for indirect exploitation are exhausted (see below).

iii. Indirect exploitation of forest

Across Indonesia as a whole, there has been an increase in crop production over the period studied. Although different data sources attribute differing land areas to this crop production, the sources are mostly consistent in this respect. There is some evidence that this increase in food production has been seen predominantly in the second half of the period.

Over this period, very little of this increase in crop production was achieved through direct exploitation of established forest. Rather, it was accomplished through the repurposing of land that had previously been degraded from established forest to the point where it no longer met our definition of established forest, a pattern of exploitation that we term here "encroachment". The case-study province of Gorontalo provides a clear example of this pattern of exploitation.

Other indirect exploitation of forest for agricultural purposes includes large-scale conversion of areas of natural vegetation to pulpwood plantations and oil palm plantations. These developments are seen, in particular, in our case-study province of East Kalimantan.

6. Next Steps

i. More sophisticated land-use mapping

The work to date has improved our understanding of the recent historic patterns of land-use change. We will continue to develop and refine our land-use models in LIMMMA, combining aspects of existing third-party mapping exercises and creating revised composite views. Our primary focus is to capture in a land-use map the dynamic change in forest canopy height and density over time and to provide more detailed maps of changes in crop distribution and type over time, to the limited extent that this is possible from the available historic data. This revised mapping can be used to examine in more detail, and to extend the findings reported here.

ii. Building out the impact analysis

A direct next-step goal is to create a "what if" system that allows users directly and simultaneously to compare the impact on forest coverage, carbon storage, biodiversity, and climate resilience of future possible landscape changes. Our ongoing work involves building out the capability in software, improving the impact metrics proposed in this report, and potentially incorporating additional impact estimates derived from agricultural landscape changes. The contribution of these what-if scenarios to knowledge and for practical application for agricultural land use change planning will be greatly enhanced as we are able to make further progress in addressing key data gaps such as:

a. Remote-sensing identification of cropping systems

More work is required to identify cropping systems remotely to increase the ability to distinguish more precisely both crops and cropping systems e.g agroforestry, mixed cropping or monocrops. This data is not currently available consistently or reliably from secondary sources.

b. Socio-economic indicators at district level and below

We will explore alternatives for these critical factors. We aim to be able to work towards being able to assess the synergies and trade-offs associated with alternative agricultural land use options - not only in terms of carbon and biodiversity and climate resilience - but also in terms of multiple dimensions of food security, livelihoods and poverty indices.

The work to date highlights the importance of a specific subset of habitats within Indonesia. Here, we highlight appropriate next steps.

i. Established forest carbon sinks and biodiversity reserves

There is evidence to suggest that large tracts of minimally disturbed established forest can continue to act as valuable carbon sinks and biodiversity reserves. We map out the areas that appear to meet these criteria within our three case-study provinces.

ii. Future direct exploitation of established forest

Direct exploitation of established forest through large-scale projects has a rapid, quantifiable negative impact on forestry cover, vegetative carbon storage, and biodiversity. It may also be a contributor towards the observed increase in natural adverse events. It is possible to undertake "what-if" modelling based on the research to date to estimate the impact of future direct exploitation of specific tracts of established forest.

iii. Critical transition zones

The available evidence points tentatively towards the particular vulnerability, in Indonesia, of degraded forest land on the edge of existing established forest.We term these habitats "critical transition zones", due to the major potential negative impacts of their further degradation, and conversely their priority in terms of conservation or regeneration. Exploitation of non-established forest natural vegetation habitats has continued to the point that pressure is likely increasing to exploit these critical transition zones. We recommend a particular focus, therefore, on monitoring these zones and implementing suitable and sustainable strategies for development.

iv. Understanding and analysing the idea of 'suitable land'

We believe that we can usefully open the debate around the concept of 'land suitability' and what determines it, beyond broad FAO classifications (Food and Agriculture Organization of the United Nations (FAO), 1976). Here we would hope to be able to make visible the evidence gaps, uncertainties and assumptions that are associated with current decision making about what land is suitable for agricultural expansion and what land is suitable for particular types of cropping system - extending our scenario analysis to examine the social and ecological winners and losers associated with particular land use suitability approaches and choices, and exploring context appropriate alternatives. We aim to work towards this being a headline focus for our stakeholder engagement activities, alongside critical transition zones.

1 IMPACT ON FORESTS

Summary

Indonesia's rich natural environment is dominated by its natural forest landscape. Depending on the definition of the term, "forest" covered between 48% and 82% of Indonesian land area in 2000. (Figures based on Global Forest Watch canopy height data, set as a minimum of 20 metres, and 4 metres, respectively). Changes in forest land use therefore potentially has a dominant impact on Indonesian food security, carbon storage, and environmental climate resilience.

The agricultural development of Indonesia can usefully be examined through the lens of the gradual, progressive, exploitation of its established forest, leading to resultant impacts on forest coverage, carbon storage capacity, biodiversity, and carbon resilience. We distinguish two sources of agricultural extensification through land use change: established forest extensification and natural vegetation extensification.

These two patterns of exploitation have clear effects on forest coverage and forest quality in Indonesia. Established forest is gradually dwindling, converted either directly to agricultural uses or, more commonly, initially degraded to woodland or natural vegetation, which is subsequently converted to other land uses, again primarily agricultural in purpose. This section of the report provides data and analysis to illustrate these observations across Indonesia as a whole and in our three case-study provinces: East Kalimantan, Gorontalo, and West Papua.

In the Indonesian context, therefore, agricultural land use change through the practice of extensification has been closely tied to direct and indirect established forest degradation and deforestation. Loss of established forest is therefore a direct, quantifiable impact arising from agricultural land use change through the current policy of extensification.

For measuring impact, we propose using established forest canopy volume both as our measurement, derived directly from remote observation studies, and as our metric.

In this section, we address five questions: How do we define "forest"? How much forest has been lost to agricultural land use and where? How does this forest loss relate to land use change in areas adjacent to forest? Can we define a standard measurement and metric for quantifying forest loss?

How do we define "established forest"?

A definition of "forest" in these circumstances is not a politically neutral act. Different types of land that might have a claim on the term "forest" have been exploited in a quite markedly different manner in Indonesia over this period. To develop a robust definition for our own purposes, we have chosen to develop a hybrid land use map that combines the work from two organisations: Global Forest Watch (GFW) (Hansen et al., 2013) and MapBiomas (MB) (MapBiomas Project, 2023).

i. Global Forest Watch Data

GFW provides annual landscape maps showing forest coverage as a Boolean (true/false) value for every patch of land across Indonesia, and annual maps showing average canopy height for every patch of land. GFW takes an inclusive definition of "forest", incorporating all land areas with significant tree coverage. Based on GFW available documentation, this appears to be vegetation with a canopy height above 4m i.e. vegetation with a canopy less than 4m is excluded from their definition of "forest".

ii. MapBiomas Data

MapBiomas produces annual land-use maps that assign one category from a fixed list for each patch of land across Indonesia. MapBiomas has the following land-use categories:

- Forest Formation
- Non-forest Natural Vegetation
- River, Lake, Ocean
- Mangrove
- Aquaculture (agricultural use)
- Oil Palm Plantation (agricultural use)
- Pulpwood Plantation (agricultural use)
- Rice Paddy (agricultural use)
- Other Agricultural Crop (agricultural use)
- Mining Pit (other use)
- Other non-vegetation (urban etc.) (other use)

For our definition of established forest we want to start with the GFW canopy data, of which we can make extensive use. Under our definition, at any point in time, "established forest" is GFW canopy, with an average canopy height of 10m or more, but which is not otherwise identified by the MB land use maps having been exploited for agricultural or other uses.

For example, an area with average canopy height of 15m but identified by MapBiomas as oil palm plantation will not be categorised as established forest, but as oil palm plantation.

Our revised land-use map, incorporating our definition of established forest, therefore has the following land-use categories:

- Established Forest
- Natural Vegetation (Sub 10m Forest & Non-forest Natural Vegetation)
- River, Lake, Ocean
- Mangrove
- Aquaculture (agricultural use)
- Oil Palm Plantation (agricultural use)
- Pulpwood Plantation (agricultural use)
- Rice Paddy (agricultural use)
- Other Agricultural Crops (agricultural use)
- Mining Pit (other use)
- Other non-vegetation (urban etc.) (other use)

Our “Established forest” definition therefore supersedes the MapBioMas forest definition, with the balance one way or another being assigned to or taken from the “natural vegetation” category. In practice these adjustments are relatively minor, in that the MapBiomas “Forest Formation” analyses are broadly comparable, in that GFW’s “forest” areas approximately coincide with the union of the MapBiomas preserved “forest” and “non-forest natural vegetation” areas. As an example, for the Gorontalo province in 2000, the GFW forest extent was 10,517 km2 while MB forest plus natural vegetation was 10,483 km2, with 94% overlap in coverage (see figure 1.1, below).

Differences are primarily attributable to further detailed categorisation of land in MapBiomas, on the one hand or, on the other, the canopy falling below a minimum height for GFW to define the patch of vegetation as “forest”.

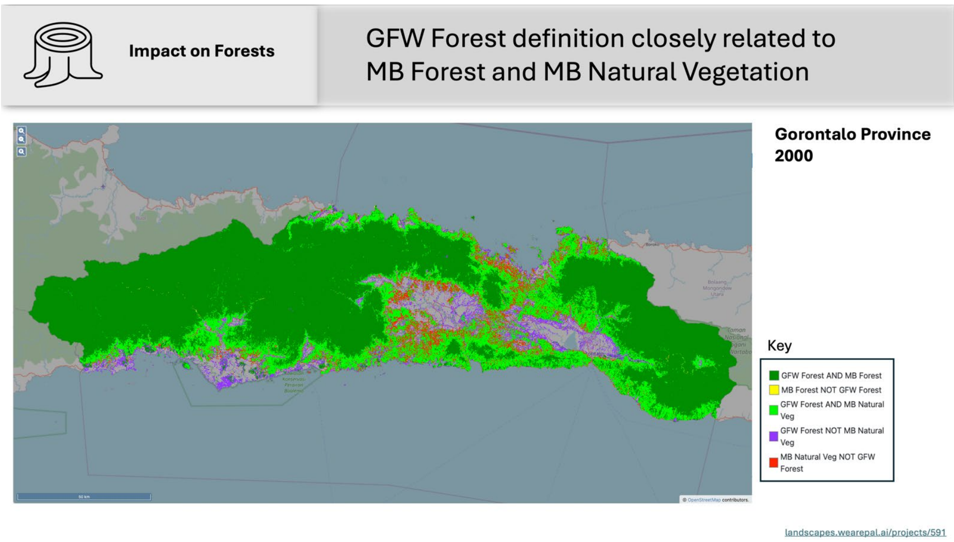

Figure 1.1 GFW Forest definition closely related to MB Forest and

MB Natural Vegetation (Gorontalo province case study)

How much forest has been lost to agricultural land use and where?

To address this question, we make use of the hybrid land use maps developed above. We compare the maps for 2020 and, for patches where the use has changed, we examine what the land use change was. We focus in particular on the following: (i) changes in land use of established forest. This is generally either degradation of established forest into natural vegetation, or a shift in land use reflecting some category of primary exploitation.

i. Indonesia

Our land use maps for Indonesia in 2000 and 2020, based on a combination of GFW and MapBiomas data, are shown in figure 1.2, below.

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LAND-USE; ECOSYSTEMS; AGRICULTURE; FOOD SECURITY

Impact on Forests | Land Use Maps for Indonesia, 2000 and 2020

Indonesia, 2000 | Indonesia, 2020

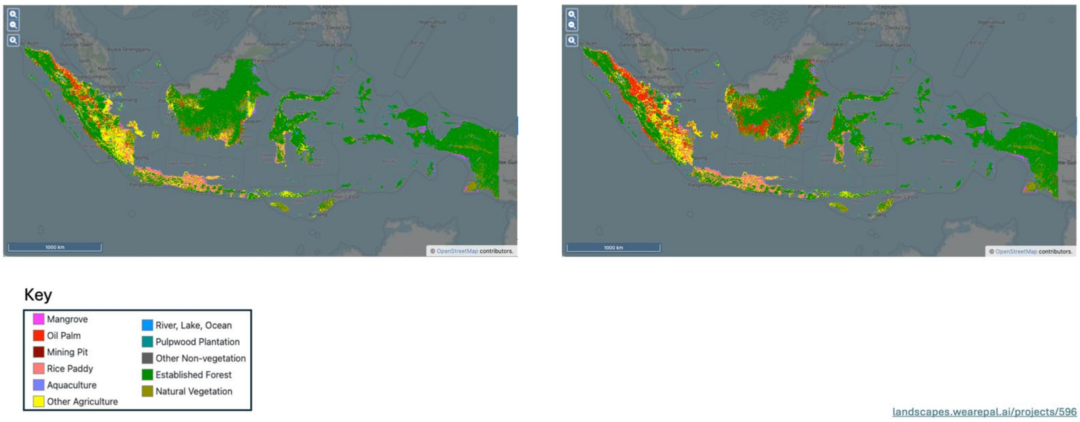

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Figure 1.2 Land Use Maps for Indonesia, 2000 and 2020

As the figure illustrates, in 2000 Indonesia was richly endowed with established forest.

Between 2000 and 2020, we observe significant loss of the established forest category and an increase of the natural vegetation category across the country. In 2000, established forest covered 61% of Indonesia's land mass, this figure falling by 5% to 56% over the period from 2000 and 2020. A total of 97,000 km2 of established forest was lost between 2000 and 2020, 8.1% of the total established forest stock in 2000. The natural vegetation category increased by a net 2.5%, 27,700 km2; this was a result of an increase in area from degradation of established forest, partially offset by a loss of habitat to other land uses.

a. Loss of Established Forest

Figure 1.3 provides an outline analysis of how much established forest has been lost in Indonesia and where. The 97,000 km2 decline in established forest stock is broadly attributable to direct conversion of established forest into oil palm plantations (39%), forest degradation into natural vegetation (29%), a direct change in land use into non-rice crop production (20%), pulpwood plantations (9%), urban development (1.7%), and rice paddies (1.3%). Note that MapBiomas underestimates urban coverage, placing some urban land into other agricultural crops, so this latter 20% figure may be an overestimate.

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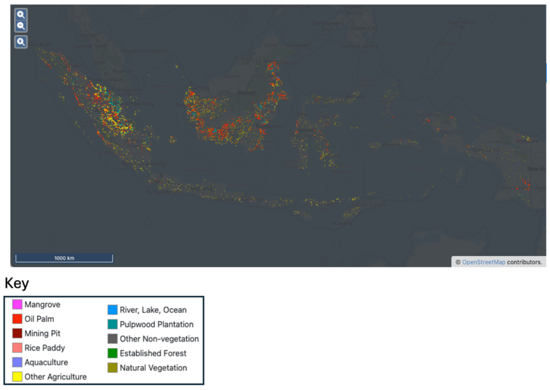
Impact on Forests — Loss of Established Forest in Indonesia, 2000 - 2020



Established Forest, 2000	1,192,483 km^2
Established Forest Change	- 96,812 km^2 (-8.1%)
- Oil Palm	39 %
- forest degradation*	29 %
- Other Agriculture	20 %
- Pulpwood Plantation	9 %
- Urban	1.7 %
- Rice Paddy	1.3 %

*forest degradation included as a loss

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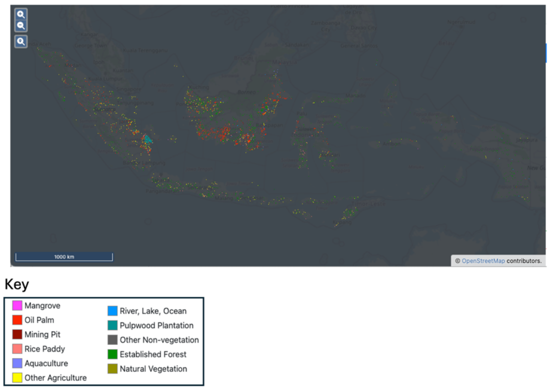
Figure 1.3 Loss of established forest in Indonesia, 2000 - 2020

b. Change in Natural Vegetation

In addition to direct exploitation of established forest, natural vegetation, typically created by deforestation through logging, is also subject to land use change. Figure 1.4 provides a broad overview of the evolution of the natural vegetation landscape across Indonesia between 2000 and 2020. Approximately 8.9% of the area of natural vegetation in 2000 had been converted to different land uses by 2020. This land was primarily converted to oil palm plantations (50%), other agricultural crops (28%), pulpwood plantations (11%), rice paddies (7%), and urban expansion (5%). An additional 28,000 km2 of established forest was degraded during this period, however, so the net stock of natural vegetation increased by 2.5%.

Impact on Forests — Change in Natural Vegetation in Indonesia, 2000 - 2020



Natural Vegetation, 2000	242,195 km^2
Loss before degraded forest	- 21,614 km^2 (-8.9%)
- Oil Palm	50 %
- Other Agriculture	28 %
- Pulpwood Plantation	11 %
- Rice Paddy	7 %
- Urban	5 %
Degraded forest contribution	+ 27,717 km^2
Natural Vegetation, 2020	248,268 km^2 (+2.5%)

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Figure 1.4, Change in natural vegetation in Indonesia, 2000-2020

Summarising, we observe large-scale direct exploitation of the stock of established forest between 2000 and 2020, impacting on 8% of the forest area, with agricultural practices dominating. Changes in land use to foster estate products (oil palm, pulpwood, logging products) was responsible for 50% of the land use shift - and degraded a further 30% of the affected forest out of established forest status into natural vegetation. Crop production was largely responsible for the remaining 20% of the exploitation of established forest.

For land that was already degraded to natural vegetation status in 2000, exploitation of 9% of that stock was split roughly 60:35:5 between estate crops (oil palm, pulpwood): crop production: and urban expansion. This overall picture varied somewhat across provinces, however, as illustrated for our three case-study provinces.

ii. East Kalimantan

Land use maps for East Kalimantan are presented in figure 1.5.

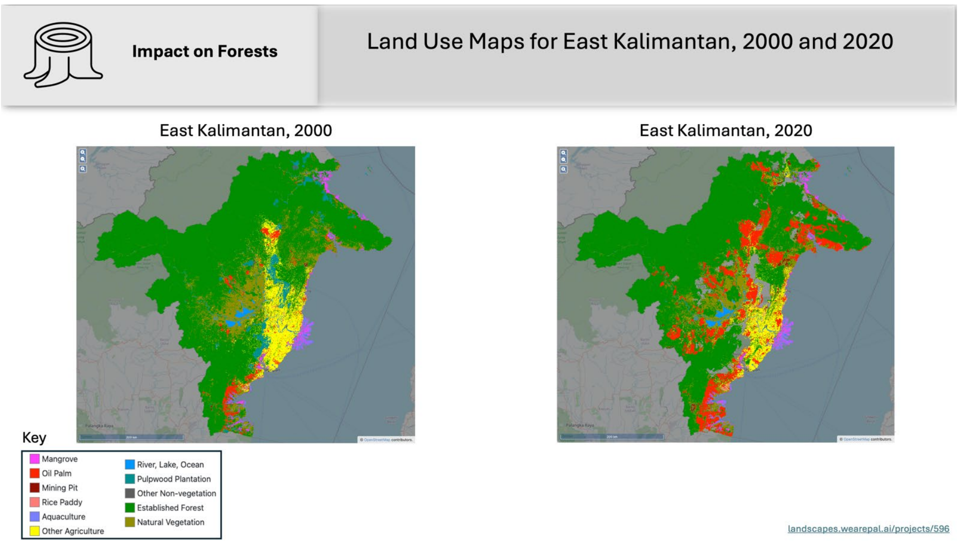

Figure 1.5, Land use maps for East Kalimantan province, 2000 and 2020

East Kalimantan is a large province and experienced significant forest loss in established forest (-13%) and a small net loss in natural vegetation. For established forest, 11,600 km2 were lost (figure 1.6): oil palm plantations was the dominant cause of deforestation (57%) but there was a significant loss to pulpwood plantations (11%), and food crops (5.3%), of which rice was a very small proportion. Mining was the largest non-agricultural contributor to established forest loss (1.4%).

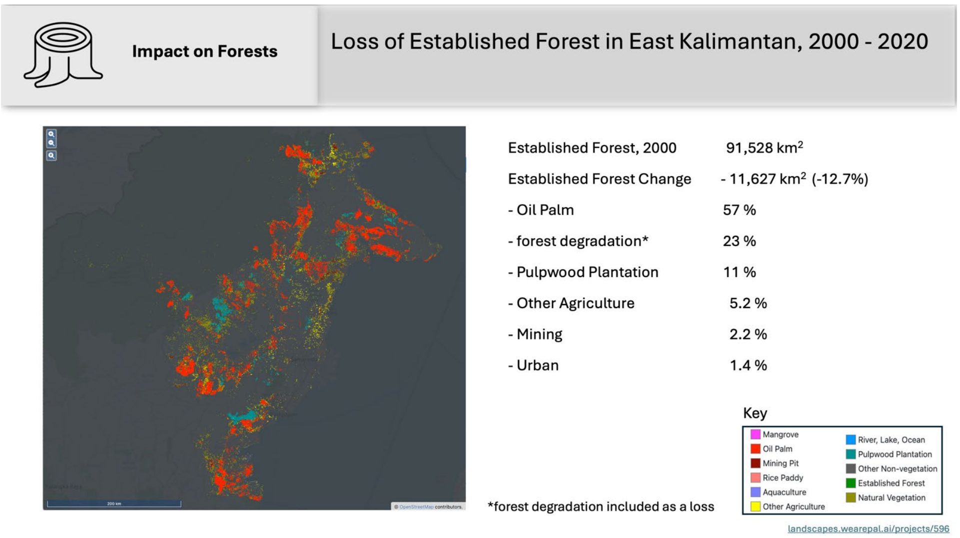

Figure 1.6, Loss of established forest in East Kalimantan province, 2000-2020

East Kalimantan also experienced a high level of exploitation of pre-existing natural vegetation (figure 1.7). Of the stock in 2000, 20% was subjected to land use change. Oil palm plantations again dominated (72%), with crop production (15%), pulpwood plantations (8%), mining (3%) and urban expansion (3%) also contributing. Degrading of established forest into natural vegetation over the period, however, ensured that the net area of natural vegetation only decreased by 1.8% in the time period.

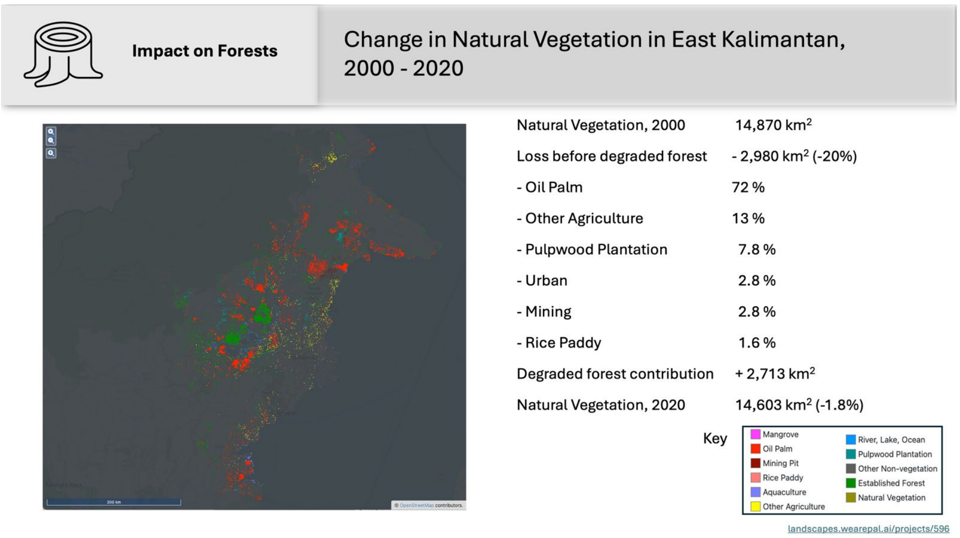

Figure 1.7, Change in natural vegetation in East Kalimantan province, 2000-2020

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iii. Gorontalo

Land use maps for Gorontalo are presented in figure 1.8.

Impact on Forests | Land Use Maps for Gorontalo, 2000 and 2020

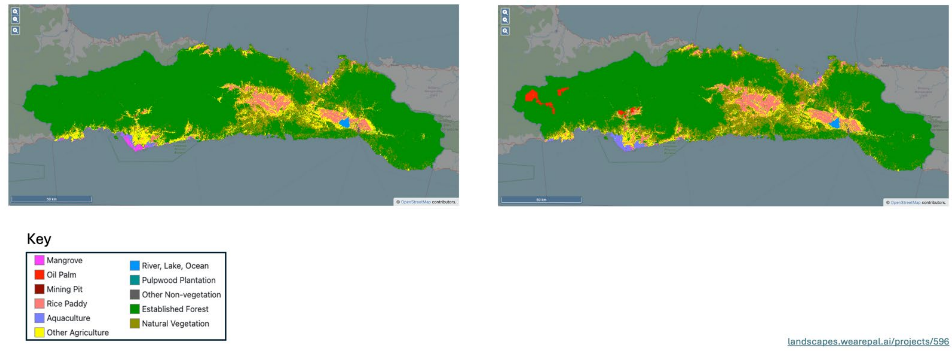
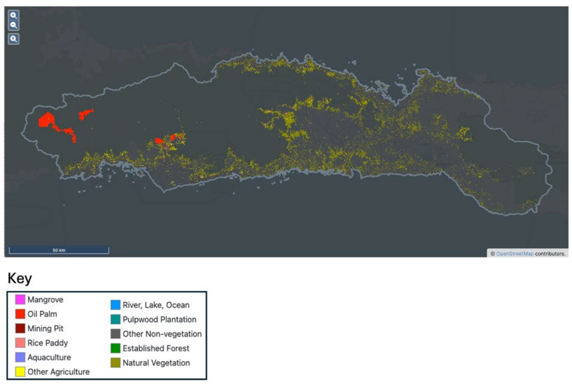


Figure 1.8, Land use maps for Gorontalo province, 2000 and 2020

In the much smaller province of Gorontalo, by contrast, established forest was primarily lost to forest degradation (81%), with additional contributions from oil palm plantations (12%), and agricultural crops (7%) – but the absolute figures here are far lower (figure 1.9).

Impact on Forests | Loss of Established Forest in Gorontalo, 2000 - 2020



Established Forest, 2000	9,114 km^2
Established Forest Change	- 600 km^2 (-6.6%)
- forest degradation*	81 %
- Oil Palm	12 %
- Other Agriculture	4.3 %
- Rice	2.9 %

*forest degradation included as a loss
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Figure 1.9, Loss of established forest in Gorontalo province, 2000 - 2020

Gorontalo province saw a large 35% increase in the area of land designated as natural vegetation. This was largely attributable to degradation of established forest over the period. Some of the available natural vegetation was pressed into expanding crop

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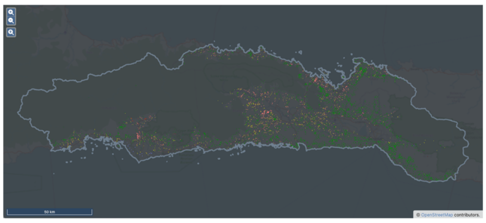
production, split roughly 60:40 between rice paddies and other crop production (see figure 1.10, below).

Impact on Forests | Change in Natural Vegetation in Gorontalo, 2000 - 2020



Natural Vegetation, 2000	1,356 km^2
Loss before degraded forest	- 19 km^2 (-1.4%)
- Other Agriculture	40 %
- Rice Paddy	60 %
Degraded forest contribution	+ 488 km^2
Natural Vegetation, 2020	1,825 km^2 (+35%)

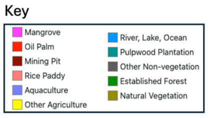


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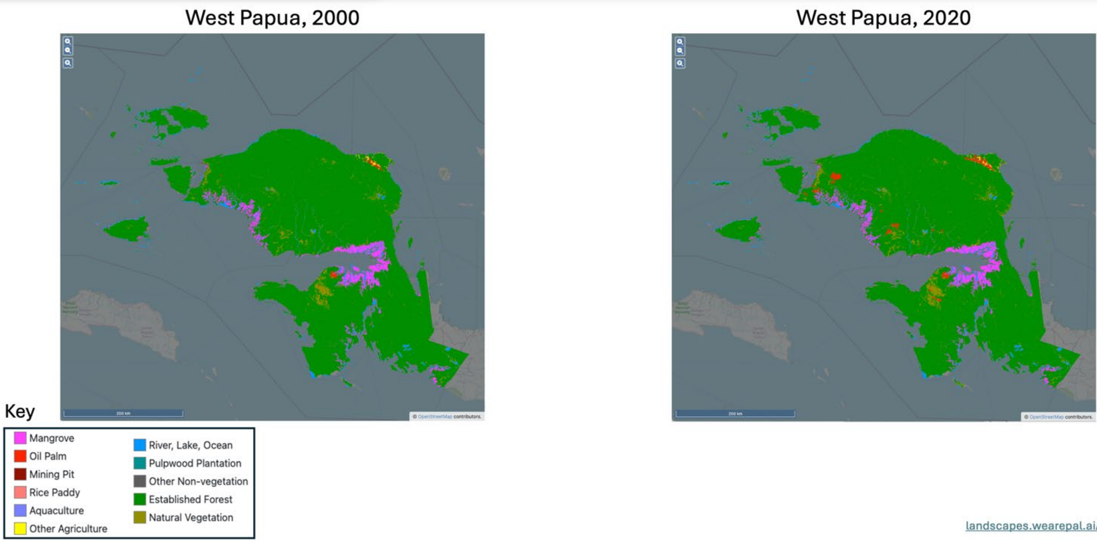
Figure 1.10, Change in natural vegetation in Gorontalo province, 2000 - 2020

iv. West Papua

West Papua, a large province, we see a high-forest resource province that has been subject to light exploitation over this period. Figure 1.11 provides our land use maps for the province in 2000 and 2020, adapted from the GFW and MapBiomas studies, as outlined above.

Impact on Forests | Land Use Maps for West Papua, 2000 and 2020

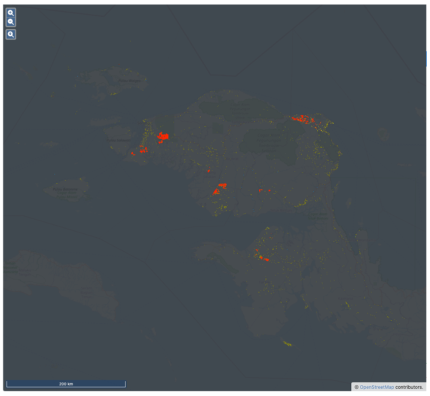


landscapes.wearepal.ai/projects/596

Figure 1.11, Land use maps for West Papua province, 2000 and 2020

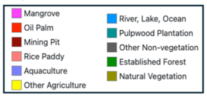
Exploitation of established forest was limited. 1.1% of the area was affected directly, with equal split between forest degradation and oil palm plantation development with a small balance to settlement expansion and increased crop production (figure 1.12).

Impact on Forests | Loss of Established Forest in West Papua, 2000 - 2020



Established Forest, 2000	88,226 km^2
Established Forest Change	- 960 km^2 (1.1%)
- forest degradation*	46 %
- Oil Palm	48 %
- Settlement	3.6%
- Other Agriculture	1.6 %
- Rice	0.3 %

Key



*forest degradation included as a loss

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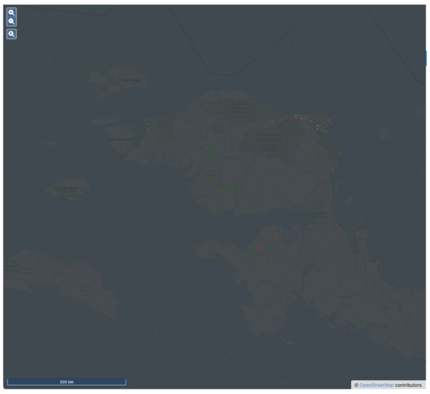
Figure 1.12, Loss of established forest in West Papua province, 2000 – 2020

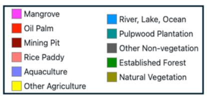
The amount of vegetation, degraded forest, increased by 12% from a very low base. The contribution of newly degraded forestry was slightly offset by increases in settlement area (42%) and oil palm plantations (38%), with the 20% balance attributable to crop production expansion. See figure 1.13, below.

Impact on Forests | Change in Natural Vegetation in West Papua, 2000 - 2020



Natural Vegetation, 2000	3,207 km^2
Loss before degraded forest	- 58 km^2 (-1.8%)
- Settlement	42 %
- Oil Palm	38 %
- Other Agriculture	10 %
- Rice Paddy	10 %
Degraded forest contribution	+ 442 km^2
Natural Vegetation, 2020	3,591 km^2 (+12%)

Key



landscapes.wearepal.ai/projects/596

Figure 1.13, Change in natural vegetation in West Papua province, 2000 – 2020

How does forest loss relate to land use change in areas adjacent to forest?

We have seen that the answer to this question depends on one's definition of "forest"; the narrower the definition, the smaller the apparent forest loss and the more focused that loss becomes on particular land uses (e.g. oil palm, pulpwood), but the more significant the land use changes are in adjacent areas. The analysis above suggests that the optimal approach is to consider land-use change across the broadest possible definitions of forest and non-forest natural vegetation and then layer on to this the changes in land use seen beyond this broad scope.

It is also useful to view this process through two perspectives – an integrative approach which emphasizes commonalities in patterns of exploitation across Indonesia, and a more granular approach, which focuses on the specificities of each province's circumstances.

i. Integrative approach

From an integrative perspective, we can infer an overarching pattern. Forest closest to human habitation is gradually degraded over time, losing density and canopy average height (e.g. 10m forest transitioning to sub-10m forest) until a point is reached at which it is no longer recognised as forest (e.g. non-forest natural vegetation); subsequently, exploitation is pursued more aggressively on this marginal land. This pattern of development and exploitation is characterised by a gradual encroachment on the forest landscape and resulting shrinkage of the forest estate.

In parallel with this process, often undertaken by large numbers of independent actors, we see more focused direct exploitation of previously well-preserved forest, often through the agency of a small number of large-scale projects. Oil palm plantations, pulpwood plantations, and mining concessions are all observed, leading directly to changes in land use of previously well-preserved forest.

Under this integrative perspective, these two parallel processes alter the pattern of land use over time, with differences between provinces primarily reflecting differing absolute and relative weightings applied to these two approaches. Under this view, East Kalimantan can be characterised as showing a high absolute weighting for both approaches between 2000 and 2020, affecting 11.3% of the land mass with a roughly even balance between direct and indirect exploitation. Gorontalo, by contrast, has much lower levels of exploitation (2.0% of land) and with a much greater relative weight towards gradual encroachment. West Papua shows a low weighting for development overall over this timeframe (0.7%) but much greater emphasis on direct exploitation. Indonesia as a whole is broadly similar to East Kalimantan. See figure 1.14.

Impact on Forests

Relative balance of direct and indirect exploitation varies between provinces

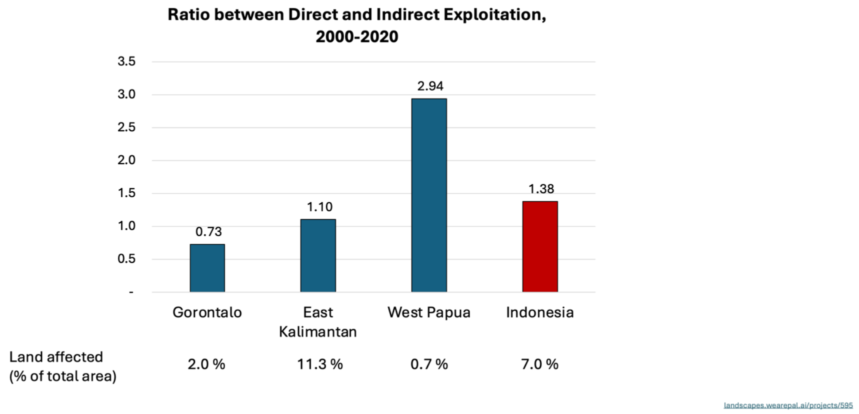


Figure 1.14. Balance between direct and indirect exploitation varies between provinces

Our earlier analysis highlights a picture of a degradation over time of established forest into natural vegetation, woodland, shrubs, grassland or similar habitats, which subsequently lie adjacent to the surviving established forest. These areas of vegetation are then subsequently exploited for agricultural development in turn.

Looking beyond the forest defined in its broadest possible sense - established forest and degraded forest in the form of natural vegetation, we observe shifts to new land use that are dictated by the outcome in land use for the natural vegetation, and/or explicable as part of a coordinated (or market-led) shift in agricultural practices. This becomes clearer when we look at a more granular level.

ii. Granular approach

In contrast to the integrative perspective, a granular, bottom-up approach highlights the contingencies and idiosyncratic aspects of each province that leads to differing patterns of land use change.

a. Gorontalo

Gorontalo specifically has seen a combination of a relatively low level of direct exploitation of preserved established forest but a relatively high impact from the gradual encroachment process, leading to significant transition from forest to natural vegetation habitats along the forest edges, and significant shifts in crop-based practices, those shifts being observed most clearly on land that in 2000 was either already agricultural or which was already natural vegetation.

It appears, therefore, that there have been weak drivers for established forest exploitation but strong drivers for conversion of marginal forest land to crop production accompanied by shifts in the pattern of crop production. The former weak direct exploitation may reflect the fact that the area of established forest is already quite small, in a small province, and part of it is a designated natural reserve. The latter, stronger indirect exploitation, may reflect on-the-ground responses to specific food security and food estate policies requested by the central Indonesian government, coupled with the decisions of local landowners and entrepreneurs.

b. East Kalimantan

The much larger province of East Kalimantan, by contrast, is characterised by more proactive direct exploitation of established forest. This is evidenced by, relatively, greater land-use change (see figures 1.5, 1.6 and 1.7, above) and by evidence of more direct reduction in canopy height across the established forest estate (see section 2 Carbon, below).

In further contrast to Gorontalo, indirect exploitation is more directed towards non-food agricultural production (palm oil, pulpwood) with crop production playing, relatively, a more minor role. Nevertheless, crop production remains comparable to Gorontalo both in absolute terms and on a per capita basis.

c. West Papua

Throughout this period (2000-2020), West Papua has remained relatively lightly exploited. Marginal forest land (our natural vegetation category) forms a small proportion of land relative to established forest (see figures 1.11, 1.12 and 1.13, above), likely reflecting a history of limited exploitation. As a result, direct exploitation of established forest predominates, and indirect exploitation is small-scale and local in nature, focused around existing areas of habitation, and/or prior exploitation.

Can we define a standard measurement and metric for quantifying forest loss?

For measuring impact, we propose using established forest canopy volume both as our measurement, derived directly from remote observation studies, and as our metric.

"Canopy volume" is the average woodland canopy height per unit area summed over the area under consideration. "Established forest" is woodland where the average canopy height per unit area is greater than 10 metres.

For any small patch of land, this measure therefore decreases linearly as the average canopy height decreases towards 10 metres and then drops to zero as the canopy height falls below 10 metres. A comparable impact estimate is derived by multiplying a change in value from an intervention by a fixed constant to allow direct integration with other impact measures

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2 IMPACT ON CARBON

Summary

The two patterns of exploitation also have an impact on the Indonesian land mass's vegetative carbon storage capacity.

Indonesia's capacity to store carbon above ground in the environment is dominated by its forests. Estimates of absolute amounts and trends in this forest-based carbon storage provide a first order-of-magnitude estimate of Indonesia's overall carbon storage. Vegetative Carbon storage capacity is, to a first order of approximation, proportional to average canopy height; both forms of forest exploitation for agricultural exploitation therefore lead to a reduction in carbon storage.

This negative impact has, in part, been mitigated by intact established forest growing naturally – an established forest carbon sink effect: in regions where established forest has been left relatively undisturbed, vegetative carbon storage has in fact increased. This carbon-sink effect has been widely reported in the literature and, in the case of Indonesia, points towards the preservation of extensive areas of established forest as a valuable step to conserve net carbon storage capacity going forwards.

The loss of carbon storage capacity is therefore a quantifiable impact from direct or indirect established forest exploitation for agricultural land use.

For measuring impact, we propose using canopy volume as our measurement, and estimated vegetative carbon storage as our metric. A comparable impact estimate for an intervention is derived by multiplying a change in this carbon storage value by a fixed constant to allow direct integration with other impact measures.

This section identifies areas of vegetative carbon loss and preservation across Indonesia and the case-study provinces, highlighting the impact of different forms of agricultural exploitation. We address three questions: How does forest coverage change, outlined in section 1, relate to changes in vegetative carbon storage? How does this pattern of carbon storage change reflect changes in agricultural practice over the period? How can we measure impact, using a standard measurement and metric, in a manner that can be combined with other types of impact?

How does forest coverage change relate to changes in vegetative carbon storage?

In Indonesia, forestry is the dominant contributor to vegetative (above-ground) carbon storage in the environment. Forest loss therefore leads directly to losses in vegetative carbon storage.

It is known that, in woodland and forest habitats, there is a close relationship between the amount of vegetative carbon stored in the landscape and the height of the forest canopy;

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this relationship can be approximated well as a linear relationship between the canopy height for a particular area and the amount of carbon stored in that area. This canopy volume, the average woodland canopy height per unit area summed over the area under consideration, is approximately linearly proportional to the vegetative carbon storage in a given piece of land.

Changes in canopy height across the landscape over time therefore provides an opportunity to estimate vegetative carbon storage change. We establish the patterns of change in Indonesia by combining canopy height data from GFW with land use data by year from MapBiomas.

i. Global Forest Watch Data

GFW provides canopy height data estimates at high resolution by year between 2000 and 2020. We combine this with an estimator of the relationship between carbon storage and canopy height developed by the current team in a previous research project (University of Sussex, 2023).

ii. MapBiomas Data

We use MapBiomas high-resolution land usage categorisation mapping to link the carbon lost through canopy reduction to changes in land use. For this work, we use the MapBiomas classification of forestry into preserved forest (MB forest) and non-forest natural vegetation (i.e. woodland, scrub) (MB natural vegetation).

Our work estimates that Indonesia stored approximately 24 Billion tonnes of Carbon (Bn tC) in its forests and woodland in 2000, falling by 1.24 Bn tC (5.2%) to 22.8 Bn tC in 2024 (figures 2.1 and 2.2, respectively).

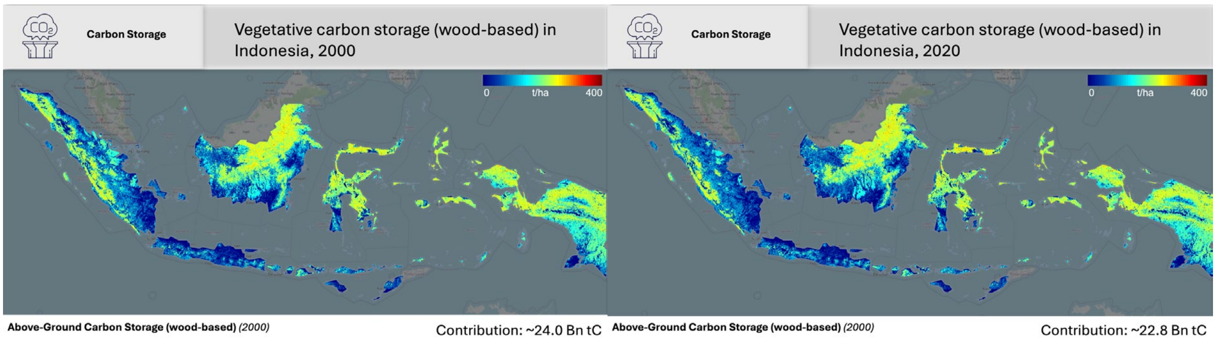


Figure 2.1, 2.2 Estimated vegetative carbon storage (wood-based) in Indonesia

The pattern of change across the environment is not uniform (figure 2.3). Areas in red show where the losses are greatest, areas in blue show where more carbon has been stored between 2000 and 2020 i.e. where the environment has served as a carbon sink.

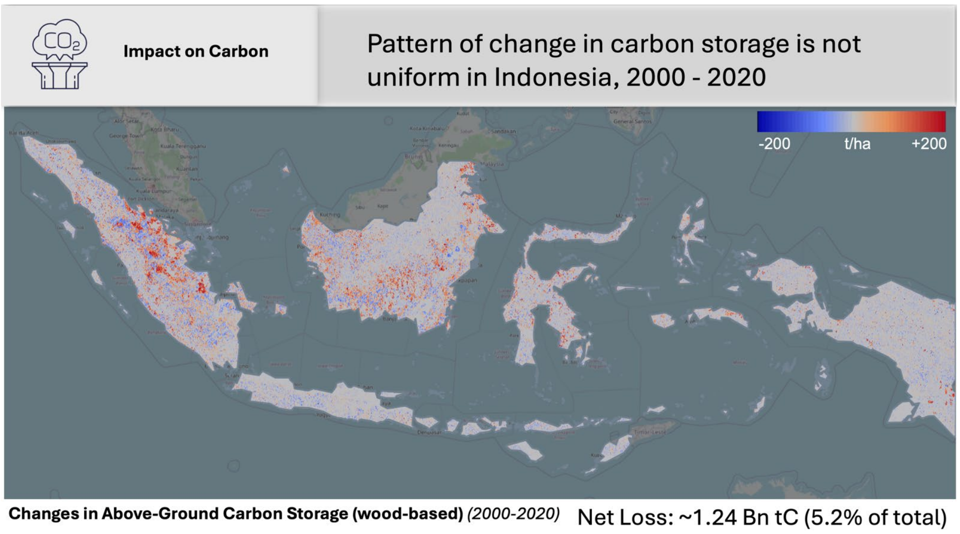


Figure 2.3 Pattern of change across the environment is not uniform

i. Carbon sink effects

Carbon sink effects were observed diffusely across preserved forest between 2000 and 2020, a well-recognised phenomenon found across the globe.

The observation that preserved forests across the globe are not in equilibrium, and continue to grow, is generally attributed to climate change, although in some instances it may point to forest re-growth following prior degradation arising from human intervention or other factors.

Specific carbon sink effects were also observed in isolated cases, principally reflecting the establishment of pulpwood plantations in areas previously denuded of forest canopy (see discussion of case-study provinces, below).

ii. Carbon losses effects

Losses in carbon storage observed in the landscape are generally more focused and arise from specific human exploitation of the environment and associated changes in land use.

How does this pattern of carbon storage change reflect changes in agricultural practice over the period?

To study the relationship between changes in vegetative carbon storage and land use, we combine the GFW forest height data with MapBiomas land use maps. We examine changes in land use (or preservation of land use) between 2000 and 2020 identified by the MapBiomas land use maps for those years, and then measure the size of change in vegetative carbon storage associated with those land use changes (or preservation).

For Indonesia as a whole, we observed that patterns of vegetative carbon storage loss were primarily associated with five land-use effects: forest canopy reduction; replacement of natural forest with oil palm cultivation for the production of palm oil; changes in crop-based practices; natural vegetation canopy reduction, and development of pulpwood plantations (see figure 2.4, below). All of these primary impacts are likely related to changes in agricultural practice in its broader sense, incorporating logging, oil palm cultivation, and pulpwood plantation cultivation in addition to crop-based practices.

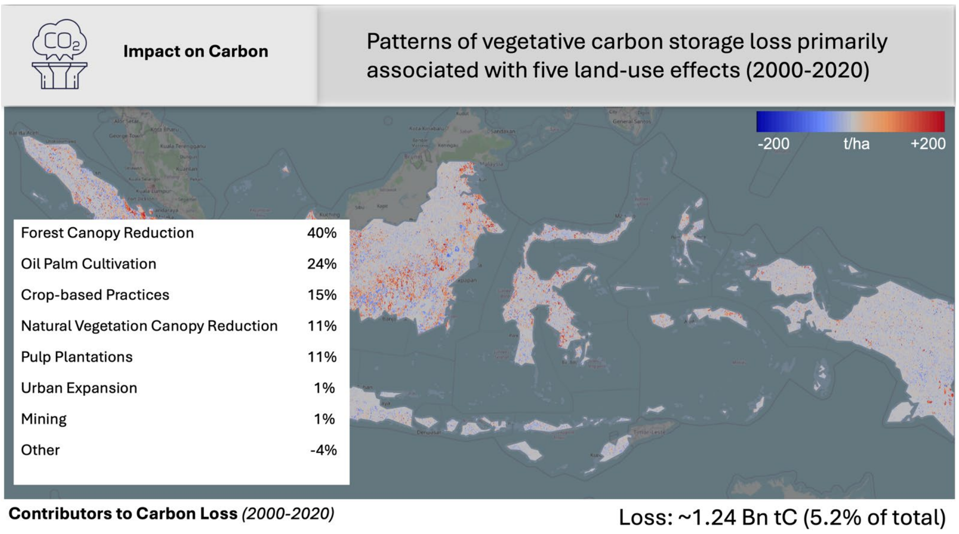


Figure 2.4 Vegetative carbon storage loss and land use, Indonesia 2000-2020

i. Forest canopy reduction

We found that 40% of the net lost carbon storage was attributable to natural forest canopy reduction, net loss of canopy height, in environments which remain forest,as of 2020 (figure 2.4). A reasonable hypothesis might be that this reflects logging activities and other activities (toad building, limited clearance) that reduces canopy height and forest density without formally changing land use. These "silent" effects, in terms of land use, were the single largest source of loss of vegetative carbon.

ii. Replacement of natural forest with oil palm cultivation for the production of palm oil

A further 24% of the net lost carbon storage was associated with a switch in land use from forestry to oil palm cultivation, largely from established forest (MB forest, 21%) but also from non-forest natural vegetation (MB natural vegetation, 3%). Possible logging aside, oil palm cropping was therefore by a large factor the single largest agricultural land-use change leading to loss of carbon storage in Indonesia.

iii. Changes in crop-based practices

15% of the estimated lost carbon was found to be associated with crop practices, specifically switching from established forest (MB forest) to crop production (8%), from MB non-forest natural vegetation to crop production (2%), and from changes in carbon storage within areas already attributed to crop production in 2000 (5%).

iv. Natural vegetation canopy reduction

Degradation of the marginal land (MB non-forest natural vegetation) contributed 11% to net carbon loss.

v. Development of pulpwood plantations

The growth in pulp plantations, switching land use from MB forest and MB non-forest natural vegetation to pulp plantation, was associated with a further 11% net loss in carbon storage.

Balancing contributors were negligible by comparison. In particular, neither mining (1%) nor urban expansion (1%) were major contributors to carbon storage loss relative to these other effects. The impact of urban expansion, however, is probably underestimated as the MapBiomas land use maps are poor at recording urban extent.

We have observed somewhat different patterns of forest exploitation across our three case-study provinces, so it is not unexpected to observe variations in carbon storage loss across the three provinces.

i. East Kalimantan

The pattern of carbon loss in East Kalimantan, the largest of the three case-study provinces, quite closely reflects that of the nation as a whole: net established forest degradation, presumably from logging and other “silent” land-use exploitation, accounted for 35% of the carbon loss, matched by oil palm cultivation (35%).

In line with national figures, natural vegetation degradation and pulp plantations each accounted for 10-11% of net carbon storage loss over the period, with mining and urban expansion accounting for 3% and 2%, respectively.

Overall, we estimate that East Kalimantan lost 7.9% of its vegetative carbon storage capacity between 2000 and 2024, a greater fall than nationally, resulting in the province’s contribution to Indonesia’s total carbon storage capacity falling from 7.5% to 7.3%. See figure 2.5, below.

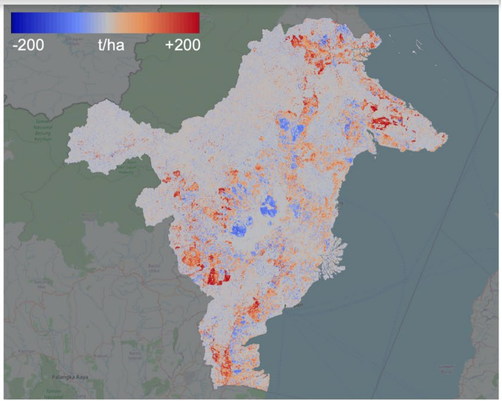
Impact on Carbon	Patterns of vegetative carbon storage loss primarily associated with five land-use effects (2000-2020)

East Kalimantan

Contribution (2000): ~1.81 Bn tC (7.5% of Indonesia)
Contribution (2020): ~1.67 Bn tC (7.3% of Indonesia)

Forest Canopy Reduction	~~40~~ 35%
Oil Palm Cultivation	~~24~~ 35%
Crop-based Practices	~~15~~ 7%
Natural Vegetation Canopy Reduction	~~11~~ 11%
Pulp Plantations	~~11~~ 10%
Urban Expansion	~~1~~ 2%
Mining	~~1~~ 3%
Other	~~-3~~ -1%

Contributors to Carbon Loss *(2000-2020)*



Loss: ~143 m tC (7.9% of 2000)

Figure 2.5 Vegetative carbon storage loss and land use, East Kalimantan 2000-2020

ii. Gorontalo

In sharp contrast, Gorontalo province shows evidence of much better preservation of the bulk of its remaining established forest, the net effect of which is that MB forest actually showed a gain of 20% of the net carbon loss, offsetting losses elsewhere (figure 2.6, below).

Gorontalo's forests provide the strongest signal of the carbon sink effect. Partly as a result, the province suffered a relatively modest 3.4% estimated loss in vegetative carbon storage over the 2000 to 2020 period, and accounted for 0.8%, increasing to 0.9% by 2020, of the total vegetative carbon storage capacity in Indonesia.

Natural vegetation degradation, exploiting marginal forest land, was responsible for a dominating 86% of the net carbon loss; Gorontalo shows the clearest pattern of gradual encroachment, outlined above, particularly evident on the eastern and southern edges of the largest area of established forest in the province, in the west of the province (figure 2.6, below).

Oil palm cultivation was the largest direct exploitation of established forest and accounted for 17% of the observed net loss, with changes in crop practices accounting for an additional 16%.

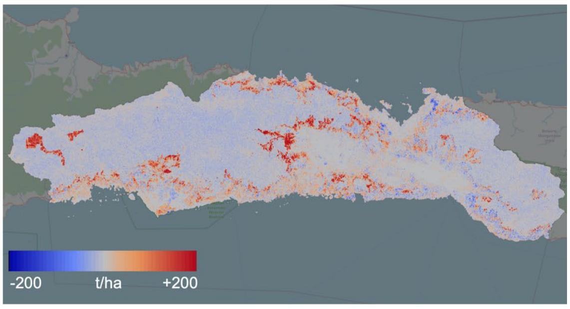
There was no pulpwood plantation cultivation in the province, while mining and urban expansion were each responsible for less than 1% of the net vegetative carbon loss. (Figure 2.6).

Impact on Carbon	Carbon sink effects observed arising from forest growth. Natural vegetation canopy reduction dominates vegetative carbon storage loss (2000-2020)

Gorontalo

Contribution (2000): ~203 m tC (0.8% of Indonesia)
Contribution (2020): ~196 m tC (0.9% of Indonesia)

Forest Canopy ~~Reduction~~ Growth	~~40~~ -20%
Oil Palm Cultivation	~~24~~ 17%
Crop-based Practices	~~15~~ 16%
Natural Vegetation Canopy Reduction	~~11~~ 86%
Pulp Plantations	~~11~~ 0%
Urban Expansion	~~1~~ <1%
Mining	~~1~~ <1%
Other	~~-3~~ <-1%



Contributors to Carbon Loss *(2000-2020)*

Loss: ~7 m tC (3.4% of 2000)

Figure 2.6 Vegetative carbon storage loss and land use, Gorontalo 2000-2020

iii. West Papua

As a result of a low level of exploitation in West Papua throughout this period, the province contributed an estimated 8% of Indonesia's vegetative carbon storage, rising to 8.4% by 2020; it also lost only an estimated 1% (20m tC) of its vegetative carbon storage capacity over the period.

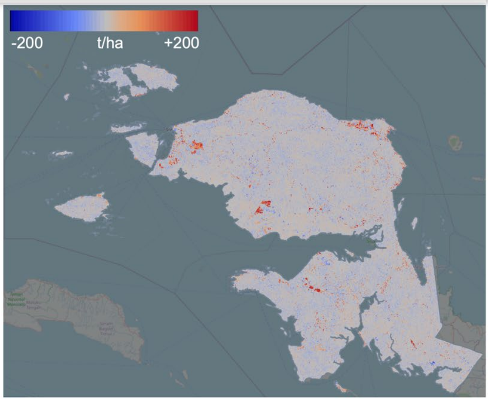
These small losses were attributable to established forest degradation (51%) (notwithstanding a diffuse carbon sink effect), oil palm cultivation (27%), and natural vegetation degradation (16%). There were no pulp plantations, while urban expansion and mining were responsible for 2% and less than 1% of this net loss, respectively.

Impact on Carbon	Patterns of vegetative carbon storage loss primarily associated with three land-use effects (2000-2020)

West Papua

Contribution (2000): ~1.93 Bn tC (8.0% of Indonesia)
Contribution (2020): ~1.91 Bn tC (8.4% of Indonesia)

Forest Canopy Reduction	~~40~~ 51%
Oil Palm Cultivation	~~24~~ 27%
Crop-based Practices	~~15~~ 1%
Natural Vegetation Canopy Reduction	~~11~~ 16%
Pulp Plantations	~~11~~ 0%
Urban Expansion	~~1~~ 2%
Mining	~~1~~ <1%
Other	~~-3~~ 3%



Contributors to Carbon Loss *(2000-2020)*

Loss: ~20.1 m tC (1.0% of 2000)

Figure 2.7 Vegetative carbon storage loss and land use, West Papua 2000-2020

In summary, the carbon storage analysis serves to highlight and reinforce the findings from the forest loss analysis as well as providing additional insights:

1. The greatest gains in vegetative carbon storage come from undisturbed established forest. This effect is particularly noticeable in Gorontalo province, but evidence of a carbon sink effect is also seen in East Kalimantan and West Papua.

2. Nevertheless, the greatest net losses in vegetative carbon storage in Indonesia have come from established forest degradation – the reduction in canopy across established forest, assumed to be as a result of logging and other human activity – counteracting the carbon sink effect such that it is responsible for 40% of Indonesia's estimated net loss of 1.24 Bn tC between 2000 and 2020.

3. After (presumed) logging, the development of new oil palm plantations is the single largest agricultural practice leading to loss of vegetative carbon storage (24% of net loss).

4. Development of large-scale pulp plantations show a similar exploitation pattern to oil palm and is responsible for 11% of carbon loss nationally.

5. Changes in crop production practice are responsible for 15% of net vegetative carbon storage loss. The underlying mechanism is unclear from this analysis, but it might be attributable to a reduction in tree coverage in agricultural areas, reflecting greater intensification of agricultural practices.

6. The balance of vegetative carbon storage loss is primarily attributable to degradation of non-forest natural vegetation, per the MapBiomas definition, which is typically classified by GFW as (marginal) forest. Again, the underlying mechanism for this loss is unclear but may reflect clearance activities related to agricultural exploitation.

7. Other non-agricultural activities, principally urban expansion and mining, account for a very small proportion of vegetative carbon losses (<2%).

Overall, if we exclude logging and other established forest and natural vegetation degradation from our definition of agricultural practices, agricultural practices account for approximately 50% of net loss (600 million tC) in Indonesia's carbon vegetative storage capacity between 2000 and 2020. Almost four-fifths of this is attributable to the establishment of large-scale oil palm and pulpwood plantations.

If we assume that logging and other crop-based practices was primarily responsible for canopy reduction in forests and non-forest natural vegetation, then over 95% of the net loss in Indonesia's vegetative carbon storage capacity over that period was attributable to agricultural changes in land use.

How can we measure impact, using a standard measurement and metric, in a manner that can be combined with other types of impact?

For measuring impact, we propose using canopy volume as our measurement, and estimated vegetative carbon storage as our metric.

For Indonesia, GFW provides suitable annual estimates of carbon canopy height at relatively high resolution and fidelity. We recommend using this measure, potentially cross-checked against other available resources.

Estimated vegetative carbon storage is a modelled estimate of the amount of carbon being stored that is attributable to the vegetation in each patch of land. Based on previous work, we currently model this as a linear relationship between carbon storage and canopy volume.

A comparable impact estimate for an intervention is derived by multiplying a change in this carbon storage value by a fixed constant to allow direct integration with other impact measures.

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3 IMPACT ON BIODIVERSITY

Summary

Although systematic biodiversity data are generally not consistently available over a historic time series, the limited available data and modelling, from CSIRO, suggest that biodiversity has continued to decline between 2000 and 2020, across Indonesia as a whole and within our case-study provinces.

There is some suggestion, however, that proportional biodiversity loss has been less severe in areas where established forest has been left relatively undisturbed. There is also some indication that the index may be an early-warning indicator for further environmental degradation: as an example, the indices for West Papua show significant loss at a time when other measures of environmental impact show minor impact.

If one accepts the validity of the CSIRO analysis, then, in Indonesia, there is an apparent relationship between established forest extent and high biodiversity, and between established forest loss and biodiversity loss. Given the direct link between vegetative carbon storage capacity and forest canopy height, in Indonesia there is therefore also suggested a strong relationship between carbon storage loss and biodiversity loss.

All Indonesia's provinces appear to be losing established forest cover over time and losing biodiversity over time. Although correlation isn't proof of causation, and other factors appear to be influencing such widespread biodiversity loss, it seems likely that further loss of established forest will reduce biodiversity and, more contestably, that preserving established forest will slow the loss of biodiversity.

Biodiversity loss can therefore be considered as a quantifiable impact arising from established forest exploitation for agricultural land use.

The questions we address are: What biodiversity data sets are available? What are the trends in biodiversity in Indonesia between 2000 and 2020? Can biodiversity trends be tied to granular changes in forestry and carbon storage? What are the relationships between the environment and agricultural practice? How can we estimate the impact on biodiversity of losses in forestry and other land-use changes?

What biodiversity data sets are available?

Deforestation and vegetative carbon storage loss can be estimated directly and at high spatial resolution using remote sensing. No such facility is available for biodiversity, however, which is hard to pin down conceptually and extremely difficult to measure empirically at a reasonable spatial resolution. Geospatial measures of biodiversity rely, therefore, on extensive modelling, are subject to unconscious bias in their formulation, and lack transparency.

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We examine here two biodiversity data sets and explore whether useful trends can be seen over the period from 2000 to 2020, whether they tie to the granular changes seen in forest coverage and vegetative carbon storage, and whether they tell us more about the relationship between the environment and agricultural practice.

We have to date engaged with data sets produced by the Commonwealth Scientific and Industrial Research Organisation (CSIRO) and by the International Union for Conservation of Nature and Natural Resources (IUCN).

i. CSIRO Biodiversity Habitat Index

For historical work over this timeframe, CSIRO produce a high spatial resolution landscape Biodiversity Habitat Index, which we have made use of here to explore the possible relationship between biodiversity and land use. We need to recognise, however, that the CSIRO Biodiversity Habitat Index is a modelled output, and observed associations may reflect, in part or in whole, modelling assumptions. This is a topic for further exploration.

The CSIRO Biodiversity Habitat Index (BHI) (Harwood et al., 2022) estimates how much of the original terrestrial species diversity in a patch is likely to be retained based on the size, condition, and connectivity of remaining natural ecosystems. It assigns each patch, a 1 km grid cell, a score between 0 and 1, representing the "effective proportion of habitat" remaining across all ecologically similar cells. This can be converted via a species–area assumption into the proportion of species expected to persist in the long term.

The modelling combines: a time-series map of habitat condition derived from land-use data and analysis of local biodiversity responses, models of ecological similarity between locations built from species occurrence records and environmental variables (climate, water balance, soils, topography), and measures of habitat connectivity that account for dispersal through landscapes of varying permeability over multiple distance scales.

ii. IUCN Red List

It would be extremely useful to have access to primary data that illustrates directly the decline or retreat of certain species that are either critical to ecosystem health, and/or sensitive to small changes in ecosystem health. Such data would help to highlight areas of the landscape that were suffering critical losses.

The IUCN Red List is a "checklist of taxa that have undergone an extinction risk assessment using the IUCN Red List Categories and Criteria (IUCN, 2025).

The majority of assessments appearing on The IUCN Red List are carried out by members of the IUCN Species Survival Commission (SSC), appointed Red List Authorities (RLAs), Red List Partners, or specialists working on IUCN-led assessment projects" (see https://www.iucnredlist.org/assessment/process).

Of the Red List Threatened Species, the spatial distribution of 152,300 species has been estimated, providing a potential dataset from which species retreat or loss might be assessed.

We have identified a small set of "keystone" species for each of the three case-study provinces that could potentially be used to track ecosystem health (see table 3.1).

Unfortunately, our findings are that the available data for these species are not adequate for our goals: in all cases, there are not enough observations, they are collected unsystematically, and they are scattered randomly. Systematic observation over time of select "keystone" species may, however, going forwards offer a viable approach for monitoring ecosystem health in critical zones of interest.

Table 3.1: Indicator Species List

Province - Species Type	**Ecological Role (What they indicate)**	**Information from IUCN Redlist website**
Gorontalo - Knobbed Hornbill - *Rhyticeros cassidix* **Animal (Keystone)**	**Forest Regeneration:** The primary disperser for large rainforest fruits. Their flock density directly correlates with fruit availability and canopy health.	R. cassidix occupies evergreen forest up to 1,800 m elevation, but primarily occupies lowland forests below 1,100 m (Kemp and Boesman 2020). The species also will travel locally during the non-breeding season and extend into patches of secondary forest, woodlands, and plantations, moving in flocks of up to 50 birds and covering up to 30-50 km2 (Kemp and Boesman 2020). **Intact mature forest is of particular importance to the species, as the majority of its diet constitutes figs** (Ficus spp.), and they will congregate in larger numbers and spend more time feeding in stands with a higher density of feed trees (Suryadi et al. 1994, Kinnaird and O'Brien 2007). The species **nests in naturally forming tree cavities that occur in larger mature/emergent trees** (Cahill 2003).
Gorontalo - Common Birdwing - *Troides helena* **Animal (Indicator)**	**Microclimate Stability:** A large butterfly sensitive to temperature changes and host plant availability. Absence suggests understory degradation.	Both sexes of birdwing are often observed flying around flowering trees to drink nectar. These host plants include Spathodea campanulata, Alstonia scholaris, Hibiscus rosa-sinensis, Ixora paludosa, Callistephus chinensis, Lantana spp. and Mussaenda spp. (Bashar 2008). The butterflies are dependent on the nectar of the host plants, and the host plants are dependent on the butterflies for gene flow. In some parts of its range, the abundance of both this species and of their host plants has decreased. For a spatial unit to be considered Functional, the abundance of the species would need to be restored to pre-decline levels.

Gorontalo **- Sugar Palm** *-Arenga pinnata* **Plant (Keystone)**	**Soil/Water Integrity:** Grows in mixed forests and edges; its deep roots stabilize riverbanks. Used for "green curtains" and erosion control.	This solitary palm can grow to 20 m tall and 60 cm in diameter. It inhabits lowland rain forest or deciduous forest up to 700 m elevation, or rarely up to 1,200 m asl. This species only reproduces once during its lifetime (Henderson 2009). In Java, its seeds are eaten and dispersed by civet cats (Dransfield et al. 2008).
Gorontalo **- Fig** *-Ficus minahassae AND recomosa* **Plant (keystone)**		Continuing decline in area, extent and/or quality of habitat
Gorontalo **- Scaly Tree Fern** *-Sphaeropteris glauca* **Plant (Indicator)**	**Humidity/Old Growth:** Requires high, constant humidity and shade. A decline indicates canopy thinning and "drying out" of the forest floor.	This tree fern has a tall trunk, 15–20 m tall with fronds reaching to 3–4 m long (Large and Braggins 2004). It occurs in open places in forests, often near streams (Holttum 1963). It has also been collected from secondary forest and disturbed areas of forest.
Gorontalo **- Makassar Ebony** *-Diospyros celebica* **Plant (Indicator)**	Possible alternative to Scaly Tree Fern which isn't really on the IUCN Red List formally.	Continuing decline in area, extent and/or quality of habitat.
East Kalimantan **-Long-tailed Macaque** *-Macaca fascicularis* **Animal (Keystone)**	**Edge Effect Proxy:** Highly adaptable. An *increase* in human dominated landscapes often indicates forest fragmentation and higher human-wildlife conflict at forest edges.	The species is a generalist and opportunist and has adapted to living in a wide range of habitats, including forests, coasts, hills, and mountains (Fooden 1995). They occur in mangroves and swamp forests, particularly in riverine habitats; in lowland forests and in human-altered habitats, which include temples, roadsides, agricultural areas, and rural/urban settlements (Gumert 2011). Anthropogenic ecologies are an important aspect of their natural ecology (Fuentes et al. 2005, Gumert et al. 2011, Marty et al. 2020) and should be considered as such when considering their habitat types.
East Kalimantan **-Asian Fairy-bluebird** *-Irena puella* **Animal (Indicator)**	**Fruit Diversity:** A specialist frugivore requiring a diverse array of ripening fruits year-round. Indicates a complex, non-monoculture forest.	Continuing decline in area, extent and/or quality of habitat

East Kalimantan **-Ironwood (Ulin)** *-Eusideroxylon zwageri* **Plant (Keystone)**	**Forest Structure:** Slow-growing canopy giant. Even stumps/regrowth are key indicators of historical logging intensity and recovery potential.	The species is a canopy, late successional tree. It can grow in clusters and be dominant in the canopy where it occurs (Slik 2009). It is often associated with species of Dipterocarps, in mixed dipterocarp forest. The fruit of the seed is thought to be dispersed by some megafauna species which may no longer exist, or by the rare Bornean Rhino or porcupines. The seeds are too heavy for other forms of dispersal. This tree is a keystone species, used for nesting of hornbills, eagles and other large birds. The flower buds are consumed by mammals and primates, and fruit are eaten by mammals (Franco et al. 2014).
East Kalimantan **-Rotan Sega** *-Calamus caesius* **Plant (Indicator)**	**Disturbance History:** Thrives in light gaps. A high density of young rattan often indicates recovering secondary forest after logging.	This rattan is a spiny, evergreen climbing palm, forming a cluster of stems that can reach lengths of 100 m or more (Dransfield and Manokaran (Eds) 1993). It tolerates a wide range of soil conditions, including seasonally flooded alluvial clay soils, peat-swamp soils, and well-drained steep slopes, but is commonest on lowland alluvial flats beside rivers (Dransfield 1977). In Sarawak, it occurs at relatively high elevations on steep ridges up to 800 m (Dransfield 1992). Although it benefits from mild and seasonal flooding, the seedlings can be killed by prolonged and severe floods ((Dransfield and Manokaran (Eds) 1993)).
West Papua **-Blyth's Hornbill** **-***Rhyticeros plicatus* **Animal (Keystone)**	**Canopy Connectivity:** Flies long distances across the canopy. Presence in high numbers confirms contiguous, unfragmented forest tracts.	The species is found in primary and secondary forests along with riverine woodland and swamp forests. It can feed on both plant and animal matter. Besides figs, food plants include Arenga pinnata, A. saccarifera, Canarium indica, C. commune, Horsfieldia sylvestris, Myristica fatua, Chisocheton sp.
West Papua **-Papuan Pitta** **-***Erythropitta macklotii* **Animal (Indicator)**	**Floor Health:** Ground-dweller sensitive to leaf-litter depth and soil moisture. Disappears quickly when forests are cleared or dried.	Continuing decline in area, extent and/or quality of habitat
West Papua **-Sago Palm** **-***Metroxylon sagu* **Plant (Keystone)**	**Wetland Health:** Dominates swamp forests. Its abundance supports a massive food web (insects to humans) and indicates hydrological stability.	This palm species occurs in lowland swamp forest with permanent or intermittent flooding during the year (Flach 1997). Continuing decline in area, extent and/or quality of habitat

West Papua **-Gaharu** -*Aquilaria filaria* **Plant (Indicator)**		Aquilaria filaria is a small or large tree which occurs in lowland tropical forest, it was also once collected in an open swamp forest (Hou 1960, Soehartono 1999, Rojo 1999). Aquilaria spp. have been observed to have a low natural regeneration and to be slow growing (CITES 2015).

What are the trends in biodiversity in Indonesia between 2000 and 2020?

The CSIRO Biodiversity Habitat Index (BHI) varies from 0 to 1 (or 0% to 100%), where 0 represents total loss of proportion of habitat, relative to a natural baseline, and 1 represents no loss of habitat.

As figure 3.1 (below) demonstrates, in 2000, the estimated degree of habitat loss varies widely across Indonesia. Across the whole of Indonesia, the simple mean BHI was 0.582, the median 0.544. For 2020 (figure 3.2), the equivalent mean and median BHI were 0.528 and 0.489, respectively, a decline of 5.4 percentage points (ppt) and 5.5 ppt, respectively.

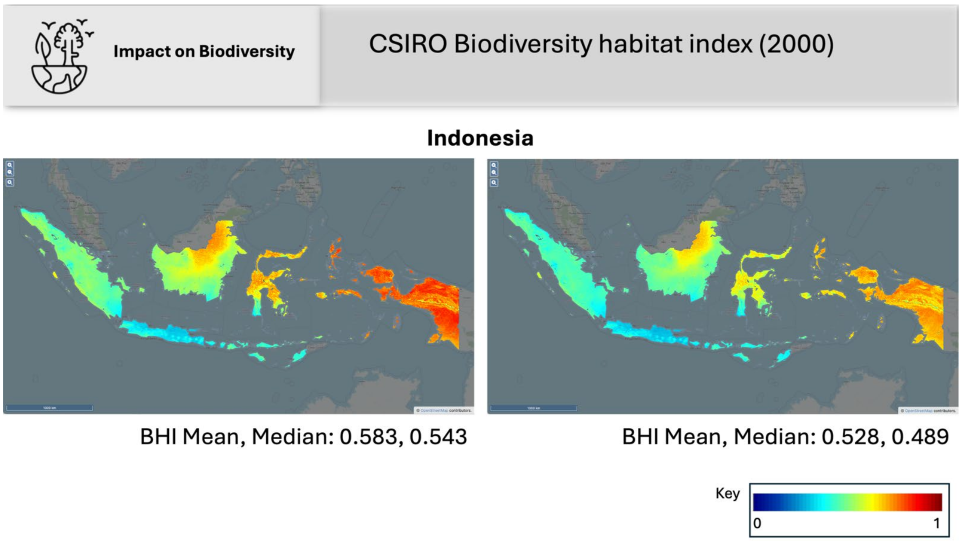

Figure 3.1, 3.2 CSIRO Biodiversity Habitat Index across Indonesia (2000, 2020)

Absolute declines in habitat preservation broadly increased as one looks across the nation from west to east and, to a lesser extent, north to south (figure 3.3), while proportional declines showed a similar but smaller effect (figure 3.4). There was no evidence of habitat improvement in any part of the province.

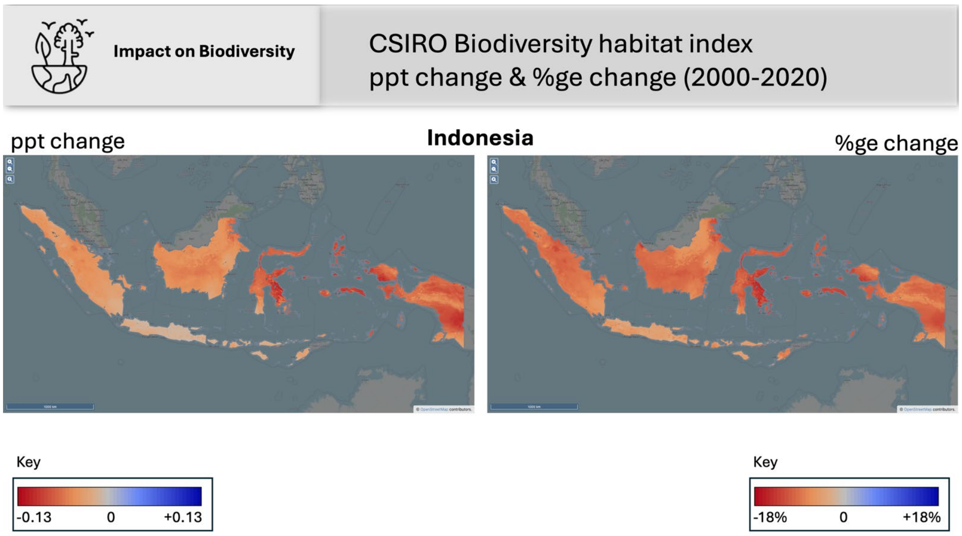

Figure 3.3, 3.4 Absolute and proportional change in BHI across Indonesia

The three case-study provinces show contrasting levels of preserved habitat in 2000 and subsequent habitat loss between 2000 and 2020, as estimated by the CSIRO BHI.

i. East Kalimantan

East Kalimantan enjoyed higher than average habitat preservation for Indonesia in 2000 (mean, median = 0.578, 0.562) with the western part of the province particularly well preserved (figure 3.5). By 2020 the BHI had fallen (mean, median = 0.527, 0.506) by 5.1 ppt and 5.6 ppt, respectively (figure 3.6).

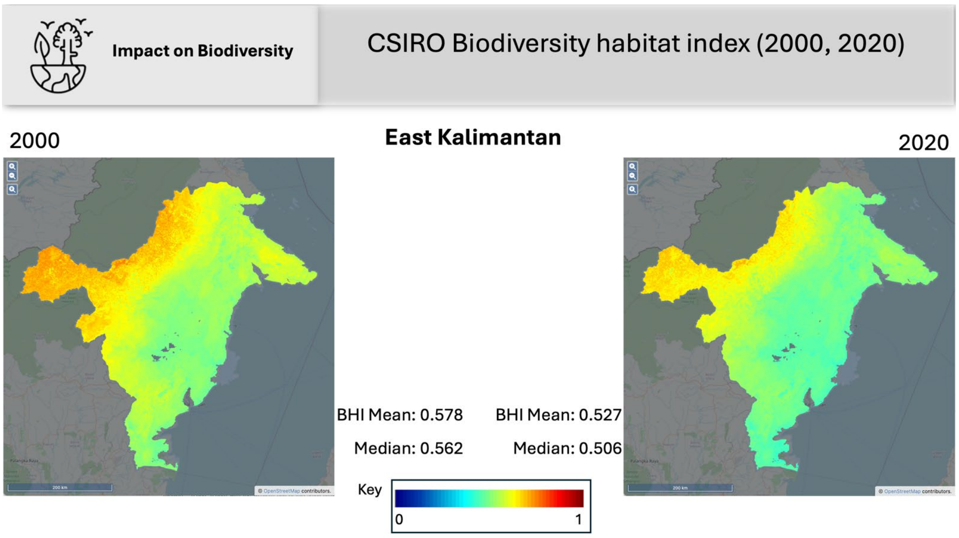

Figure 3.5, 3.6 CSIRO Biodiversity Habitat Index in East Kalimantan (2000, 2020)

Absolute declines in habitat preservation were largest in the north and west (figure 3.7), while proportional declines were particularly evident in the north of the province (figure 3.8). There was no evidence of habitat improvement in any part of the province.

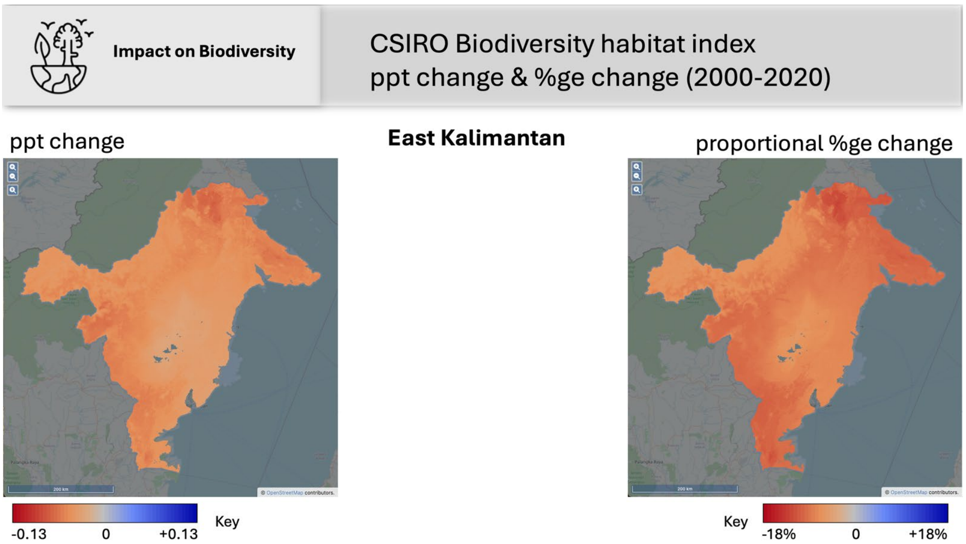

Figure 3.7, 3.8 Absolute and proportional change in BHI in East Kalimantan

ii. Gorontalo

In 2000, Gorontalo showed even better habitat preservation than East Kalimantan (mean, median = 0.650, 0.658) with the west half of this small province showing strong habitat preservation, according to the BHI (figures 3.9, 3.10). In the period to 2020, the index fell (mean, median = 0.578, 0.582), with large declines of 7.2 ppt and 7.6 ppt, respectively.

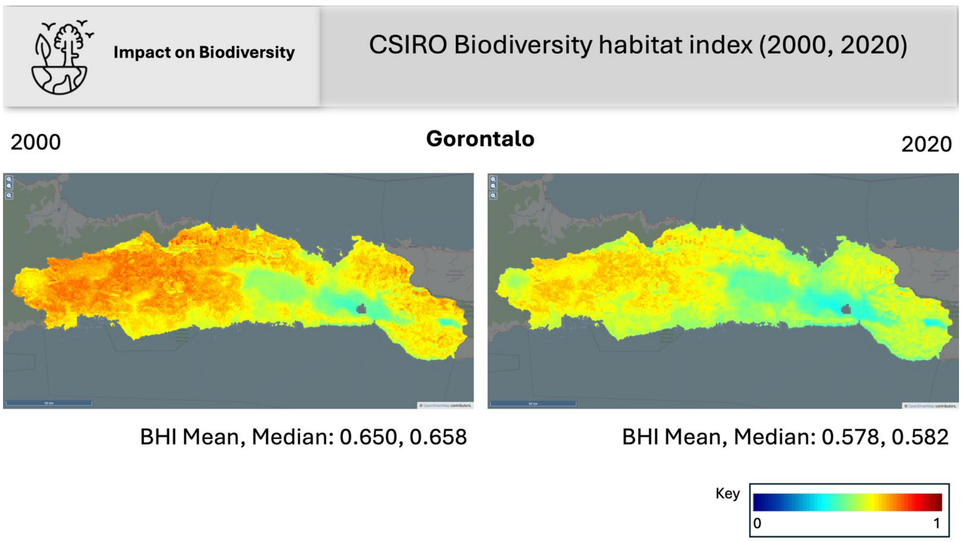

Figure 3.9, 3.10 CSIRO Biodiversity Habitat Index in Gorontalo (2000, 2020)

Absolute declines were largest in the previously best-preserved areas, while relative declines were most marked in the north of the province and the far west, where palm oil cultivation was aggressively pursued (see figures 3.11 and 3.12, below). The index showed no areas where the habitat had improved.

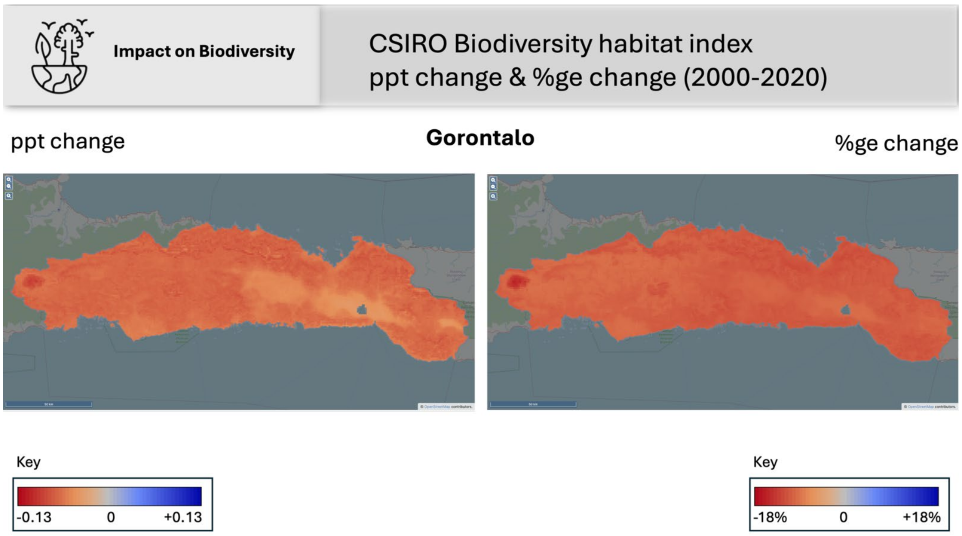

Figure 3.11, 3.12 Absolute and proportional change in BHI in Gorontalo

iii. West Papua

West Papua, in 2000, was an ecosystem with excellent habitat preservation, enjoying a high Biodiversity Habitat Index across all the province (mean, median = 0.774, 0.778). By 2020, the BHI has fallen (mean, median = 0.692, 0.693) by 8.2 ppt and 8.5 ppt, respectively (figures 3.13, 3.14).

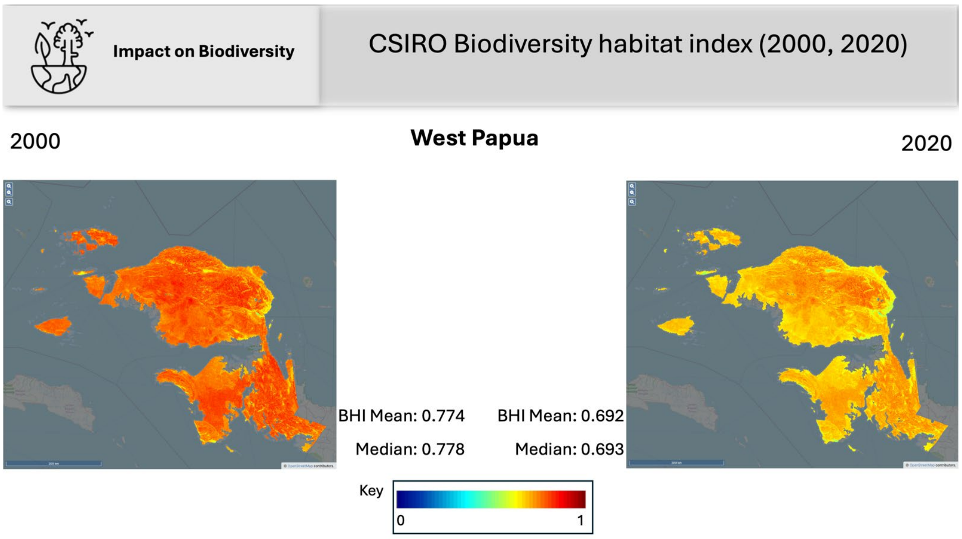

Figure 3.13, 3.14 CSIRO Biodiversity Habitat Index in West Papua (2000, 2020)

Patterns of absolute and relative decline suggest the greatest losses of habitat diversity in the western parts of the province. There were no areas where the habitat index improved (figures 3.15, 3.16).

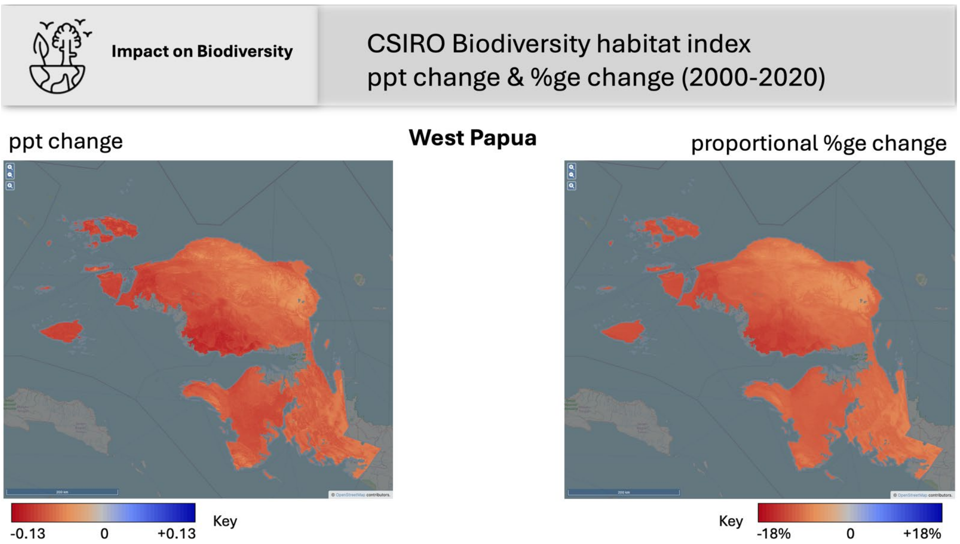

Figure 3.15, 3.16 Absolute and proportional change in BHI in Gorontalo

The pattern of large habitat loss, as estimated by the CSIRO BHI Index, stands in contrast to the prior plots of forest and carbon loss which proposed a pattern of relatively mild forest and carbon storage losses in West Papua.

One speculative idea is that large absolute and proportional losses, from a high level, of the index are leading indicators of environmental loss, attributable to the model design or, more interestingly, reflecting the high fragility and sensitivity of habitat and biodiversity to even low levels of human intervention.

Can biodiversity trends be tied to changes in forestry and carbon storage?

Taking the above analysis and expanding across all provinces, we can see a clear relationship between established forest coverage and biodiversity habitat index, and an association between biodiversity loss and loss of established forest coverage.

Figure 3.17 shows, for each province in Indonesia, how established forest coverage (x-axis, established forest as a percentage of total land mass) and CSIRO mean biodiversity habitat index (BHI) for the province (y-axis) evolved between 2000 and 2020. Each pair of points connected by an arrow show the evolution between 2000 and 2020 of BHI and established forest coverage.

This relationship between overall average BHI and forest coverage seems to be driven by a decrease in the average biodiversity habitat index for the established forest itself within the province. As the established forest coverage decreases, the average biodiversity habitat index of the surviving established forest itself decreases. Fragmentation of forestry appears to reduce the CSIRO modelled biodiversity habitat index for that forest.

Impact on Biodiversity

Evolution of forest coverage and BHI index (overall, left panel; primary forest, right panel) for Indonesia's provinces, 2000-2020

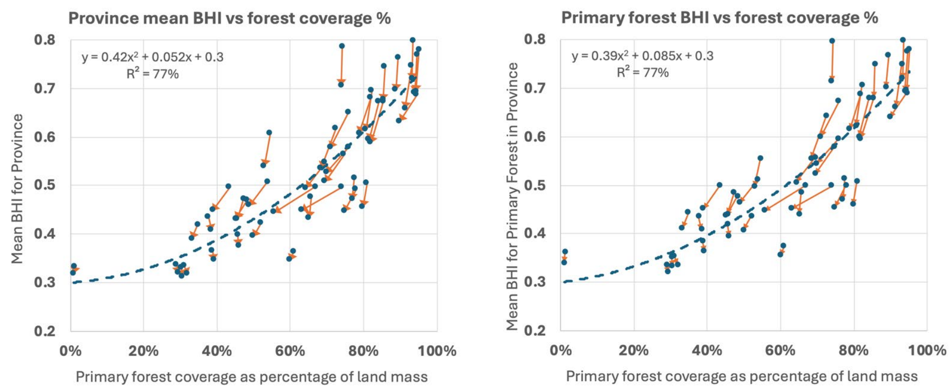

Figure 3.17,3.18 CSIRO BHI and forest coverage for Indonesia's provinces, 2000-2020

We see that, both from the viewpoint of decreasing established forest cover and of biodiversity richness, that provinces in Indonesia therefore appear broadly to be following one another down the same path over time of decreasing established forest coverage and decreasing biodiversity habitat index.

Furthermore, for the two moments in time, 2000 and 2020, we see on both occasions a simple broad linear relationship for both (a) the overall CSIRO mean biodiversity habitat index for each province and province forestry coverage (figures 3.19, 3.20), and (b) the established forest CSIRO average BHI in the province and province forestry coverage (figures 3.21, 3.22).

Impact on Biodiversity

Relationship between Province mean BHI and forest coverage percentage, 2000 (left panel) and 2020 (right panel)

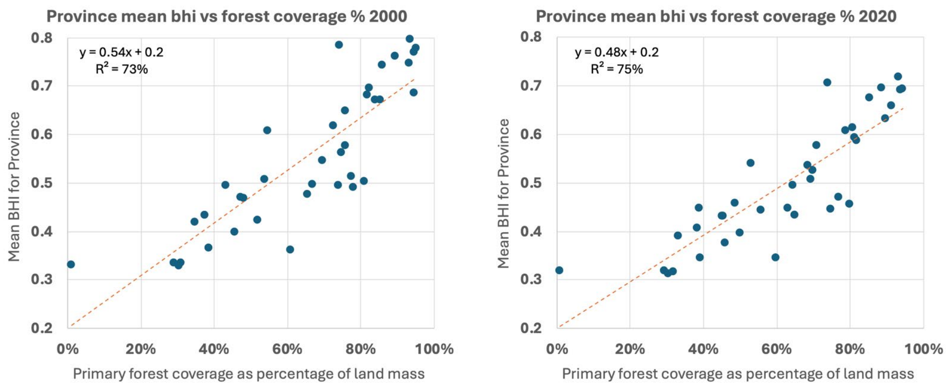

Figure 3.19,3.20 Province mean BHI vs forest coverage percentage, 2000 & 2020

Impact on Biodiversity

Relationship between Primary forest mean BHI and forest coverage percentage, 2000 (left panel) and 2020 (right panel)

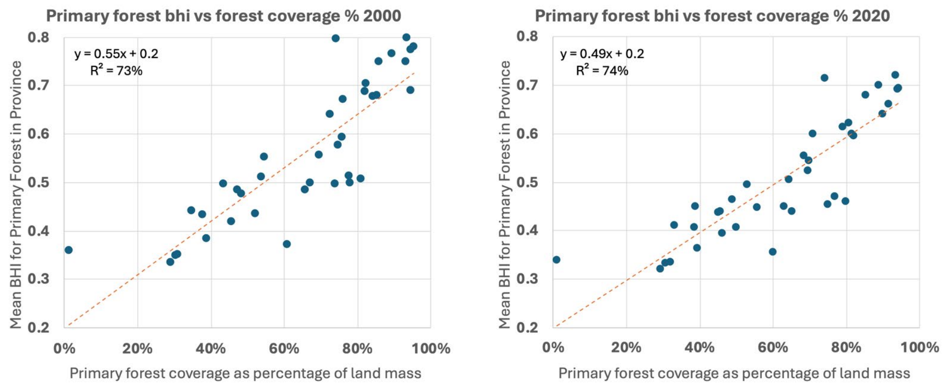

Figure 3.21,3.22 Established forest mean BHI vs forest coverage percentage, 2000 & 2020

These observations reinforce the linking association between established forest loss and biodiversity habitat index loss. These associations may, in part, be revealing of model assumptions within the index itself but, to the extent the BHI is a valid index of biodiversity health, the relationship holds.

Our carbon storage estimates are directly and linearly linked to forest canopy height, so, for the Indonesian environment illustrated by these provinces, the above associations hold also for vegetative carbon storage.

If we accept the validity of the CSIRO analysis then, in the context of Indonesia, preservation of habitat diversity appears to be closely correlated to the preservation of established forest cover, and to the intimately related preservation of vegetative carbon storage in the environment.

What are the relationships between environment and agricultural practice?

We examine this question simply, by looking at the relationship between land use type and biodiversity habitat index (BHI) across the three provinces and at the two dates of interest (2000, 2020).

For this analysis, we employ the MapBiomas land use maps for 2000 and 2020, and examine the average CSIRO biodiversity habitat index (BHI) associated with different MapBiomas land use categories. We look separately at our three case study provinces and then combine the province data together for an overall estimate.

The overall pattern is clear. In every province, and for both dates (2000, 2020), established forest (natural forest with average canopy greater than 10m in height) always has the highest CSIRO BHI, and, of the agricultural land uses, crop production areas (MapBiomas categories "rice paddy" and "other agriculture") always have the lowest BHI. Oil Palm and Pulpwood plantations (where observed) always have a calculated BHI that is intermediate between established forest and crop production areas, as do mining areas, which are typically surrounded by established forest.

These observations are illustrated in figure 3.23, which averages across the three provinces and both points in time, giving each time point and each province equal weight, and summarises the average percentage difference between established forest habitat BHI and the BHI for these other land uses.

Impact on Biodiversity	Crop production areas associated with lowest CSIRO BHI relative to primary forest

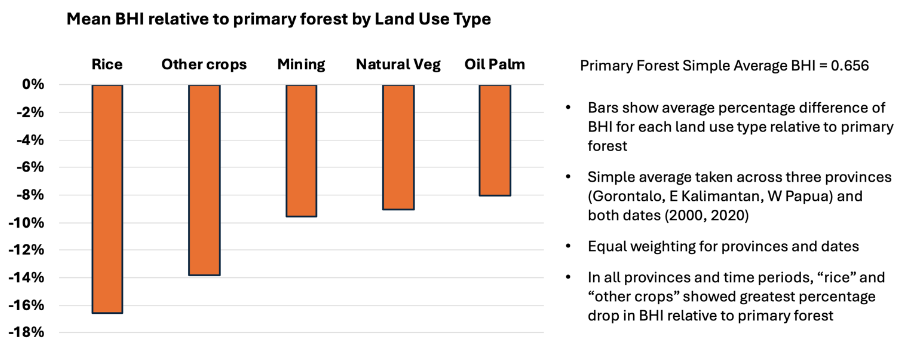

Figure 3.23 Crop production associated with lowest BHI relative to established forest

The individual provinces show some differing detailed characteristics, reflecting the specific environmental circumstances in each province.

i. East Kalimantan

East Kalimantan is the most exploited environment of the three case-study provinces, albeit enjoying higher habitat preservation than Indonesia as a whole, with long-standing exploitation from oil palm and pulpwood plantations, mining, degradation of established forest, and, to a lesser degree, crop production. All types of land use show double digit percentage reductions in biodiversity habitat index relative to established forest in both time periods, albeit crop production areas are the most impacted. See figure 3.24.

ii. Gorontalo

The small province of Gorontalo has been primarily exploited for crop production, and these land-use areas show the most dramatic decrease in biodiversity habitat index relative to established forest in both 2000 and 2020, followed by areas of natural vegetation. See figure 3.25.

iii. West Papua

This large province has been least exploited and shows the highest biodiversity habitat index of the three case-study provinces in both 2000 and 2020. The areas of exploitation are small relative to surviving established forest, but the observed effect is also seen here of lowest BHI associated with areas under crop production.

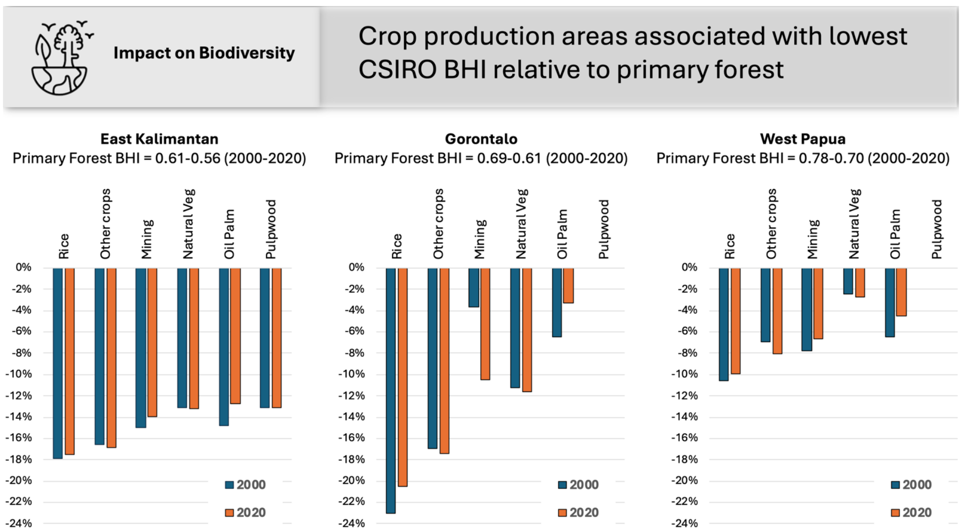

Figure 3.24, 3.25, 3.26 Crop production associated with lowest BHI relative to forest

Again, the observed associations may, in part, reflect the underlying model assumptions in the BHI itself but, to the extent the BHI is a valid indicator of biodiversity loss, the observations are of use.

Biodiversity habitat index is, therefore, strongly linked to established forestry, and all agricultural practices, whether estate crops (oil palm plantations) or food crops (rice, other crops), are associated with lower BHI estimates.

How can we estimate the impact on biodiversity of losses in forestry and other land-use changes?

For measuring impact, we propose using the CSIRO biodiversity habitat index (Harwood et al., 2022) directly as both measurement and metric. The CSIRO Biodiversity Habitat Index (BHI) estimates how much of the original terrestrial species diversity in a patch is likely to be retained based on the size, condition, and connectivity of remaining natural ecosystems. It assigns each patch, a 1 km grid cell, a score between 0 and 1, representing the “effective proportion of habitat” remaining across all ecologically similar cells.

A comparable impact estimate for an intervention is derived by multiplying a change in this BHI value by a fixed constant to allow direct integration with other impact measures.

4 IMPACT ON CLIMATE RESILIENCE

Summary

Changes in land use can have an impact on climate resilience, the capacity to anticipate, absorb, adapt to and recover from climate-related shocks and stresses. We have examined trends, in the three case-study provinces, in natural adverse events between 2010 and 2020, in order to understand whether exposure to climate-driven adverse events is increasing, and to gain insight as to whether land-use change has affected resilience.

The available data on natural adverse events points to a large increase in reports of flooding, fires, and landslides throughout Indonesia over the past decade. This might, in part, reflect increases in reporting, but the data are consistent with a thesis of greater environmental instability associated with the regions where both direct and indirect agriculture-driven forest exploitation is taking place.

Using a more fine-grained analysis of the data, we identify a set of locations where high levels of flooding have occurred, and where high numbers of landslides have occurred. Previous reports and studies have identified common themes, some of which appear to be traceable to deforestation and associated changes in agricultural practices. More analysis is required to explore the underlying patterns.

Human interventions in the environment can alter the frequency and pattern of natural adverse events. These interventions might be globally mediated, for example through actions that change the climate, or locally enacted, for example by actions that lead to a higher frequency of local flooding events.

It is challenging to disentangle these different effects from acts of chance; coupled with these problems, data are difficult to collect objectively and comprehensively, and to localise.

On balance, it seems reasonable to conclude that an increase in flooding and landslide events are linked not only to broader trends in climate change, but also, quantifiably, to agricultural land use change lowering the ability of the landscape to absorb climate-driven flooding, through a policy of extensification from direct and indirect established forest exploitation.

We are processing available data for Indonesia and addressing the following questions: Can any broad-scale trends in natural adverse events can be observed? Can local changes in natural disasters be credibly linked to land-use changes? Can measurements and metrics be developed to model the likely impact on these aspects of climate resilience?

Can any broad-scale trends in natural adverse events be observed?

We have data available (Badan Nasional Penanggulangan Bencana, n.d.) covering forest fires, landslides, and floods and for longer term data have geolocated reported natural adverse events by regency by year between 2010 and 2024. (Earlier data are available but deemed unreliable). There are three fundamental challenges to interpreting the data. First, the number of natural adverse events fluctuate year-by -year through the operations of chance; we have attempted to reduce this effect by summing across 5-year periods at the beginning (2010-2014, inclusive) and the end (2020-2024, inclusive) of our survey period. Second, the vigilance in reporting may have increased over time, or otherwise fluctuated. Third, the reporting of an event is more likely in more heavily populated areas.

With these caveats in mind, we report large increases in the number of reported fires, floods, and landslides across our case-study provinces when we compare the two periods 2010-2014 to 2020-2024. The table below summarises the number of floods, fires, and landslides across the provinces in these two time periods – providing a stark picture of increased (reported) natural adverse events everywhere.

	Landslides 2010-14	Landslides 2020-24	Floods 2010-14	Floods 2020-24	Fires 2010-14	Fires 2020-24
Gorontalo	4	13	74	158	0	6
E. Kalimantan	37	105	107	193	30	320
West Papua	2	4	6	49	0	6

Given our previous caveats, these differences are too large to accept uncritically, and we are conducting further work to understand the reliability of earlier data. It is clear, however, that the prominence of natural adverse events has grown substantially over the historic study period.

Can local changes in natural disasters be linked to land-use changes?

Natural adverse event data reflects a mosaic of events across a wide geographical area, the proximal and longer-term causes of which can only be estimated through detailed location-by-location analysis.

Gorontalo

i. Gorontalo: flood data, 2020-2024

The map on figure 4.1 shows the number of floods by district in Gorontalo province across the 4-year period of 2020-2024, highlighting those districts that saw 6, 7, 8 or 9+ major flooding events.

Impact on Climate Resilience | Number of floods by district, 2020-2024

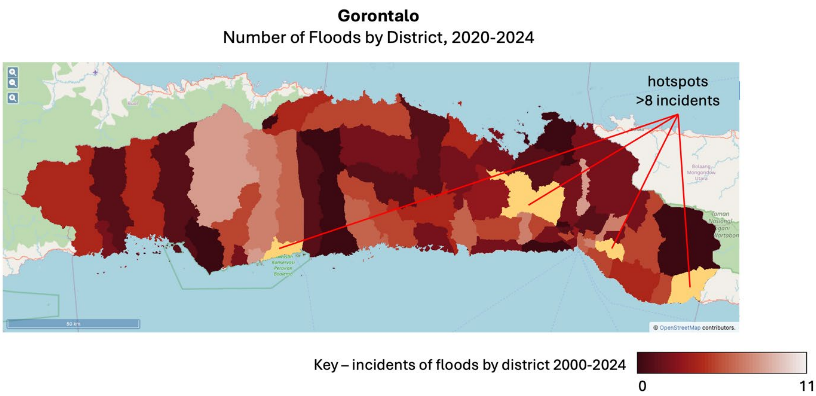

Figure 4.1 Number of floods by district 2020-2024

We highlight four hotspots.

Hotspot #1: Bone river watershed, east of Gorontalo city

Severe flooding of villages east of Gorontalo city and in the city itself along the basin of the Bone river are reported to be proximally attributable to urbanisation and associated conversion of agricultural land to dwellings in the peri-urban zone as the city expands to the east.

The panel on the right of figure 4.2 shows flooding report volumes by district, apparently localising the problem along the floor of the river (red oval), along which we see peri-urban development.

We use grey shading in the left panel to highlight headwaters to the north and south that feed the Bone river; agricultural development in these areas may be impacting downstream flood resilience.

It has been speculated that climate change provides the larger driving force of increased flooding in the area. There is an opportunity to explore further the impact of peri-urban expansion on agriculture, flooding, and flood control.

Impact on Climate Resilience

Reported flooding in Bone river watershed, east of Gorontalo City, 2020-2024

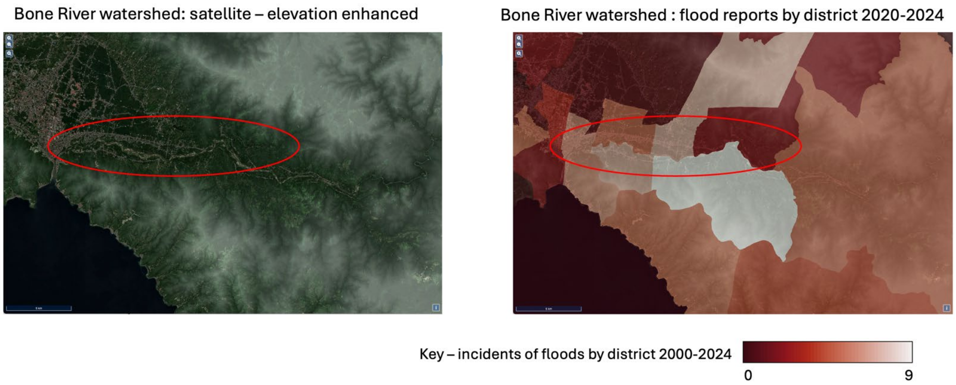

Figure 4.2 Bone river watershed flooding 2020-2024

Hotspot #2: Alo-Pohu watershed system west of Limboto

See figure 4.3, below. Extensive flooding throughout this area is associated with heavy rain overtopping the rivers feeding into Limboto lake.

Some studies have tied the flooding to reduced water storage capacity in the lake itself, potentially attributable to increased sediment carriage into the lake by the feeding rivers.

These issues may reflect upstream landscape uses e.g. logging, cropping, leading to reduced capacity to retain soil and greater river sedimentation. Detailed analysis of upstream land-use patterns may provide further insight.

The right hand panel identifies the districts with the highest flood reports, with the red ovals indicating likely river valleys and low-lying regions approaching the lake (lower right) that flood. The grey shading in the left panel highlights local higher land and headwaters, although agricultural-mediated upstream landscape uses impacting flooding may also be further to the north.

Impact on Climate Resilience

Reported flooding in Alo-Pohu watershed system, west of Limboto, 2020-2024

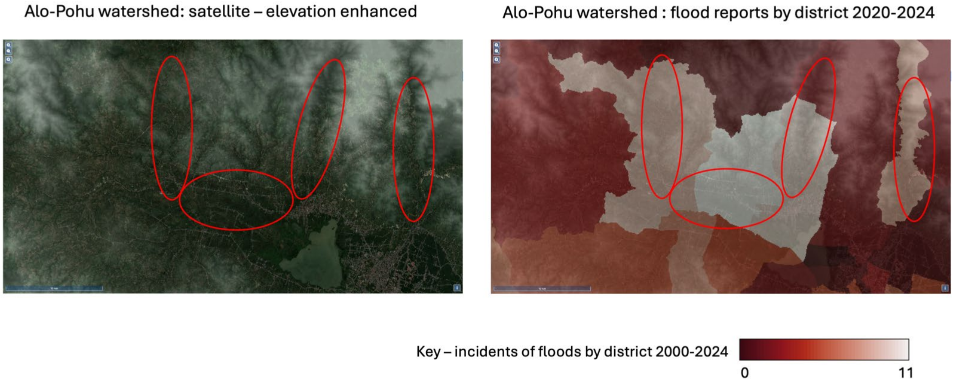

Figure 4.3 Alo-Pohu system watershed flooding 2020-2024

Hotspot #3: River Taludaa coastal area and watershed in south east Gorontalo.

This flooding hotspot is most frequently attributed to the Taludaa river overflowing, often compounded by damage or failures of levees and embankments. Proximal causes most often stated are intense and/or long-duration rainfall events, 14 hours or more, with additional runoff from uplands and mountains in the watershed, highlighted using grey shading in the left panel of figure 4.4, leading to breaches of existing inadequate flood defences of embankments and levees.

For candidate ultimate causes, it has been suggested that upstream changes in land use, particularly logging, deforestation, and cropping on steeper upland terrain has increased erosion, debris and sediment flow – leading to landslide and flooding events. This hotspot provides a potential case study for studying the impact of deforestation and cropping in steeper watershed terrain on downstream communities, and infrastructure.

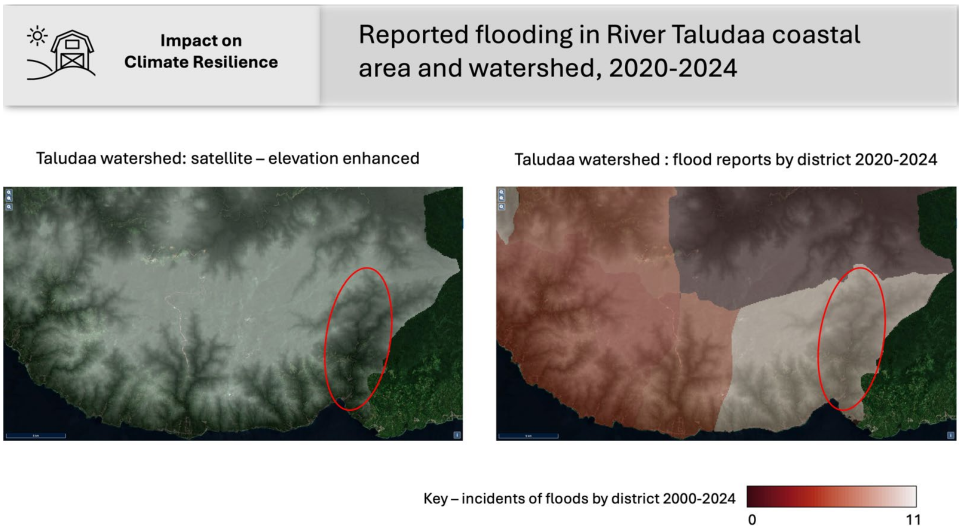

Figure 4.4 River Taludaa watershed flooding 2020-2024

Hotspot #4: Marisa – watershed along Marisa river and in coastal area to the east.

The coastal area east of Marisa form the fourth hotspot. Causes reflect aspects of other hotspots – heavy rainfall, inadequate flood prevention measures, and upstream erosion from human activity supporting a mechanism of sediment loads and resulting reduced channel capacity.

This hotspot may be useful for exploring the impact of upstream land use change on downstream communities where flood prevention measures are inadequate. Climate change is increasing the frequency of sustained rainfall events. See figure 4.5.

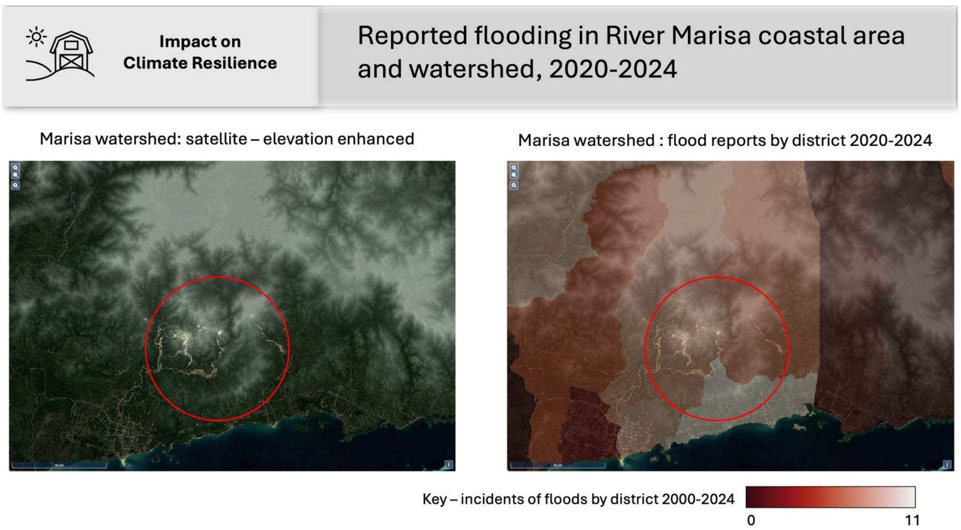

Figure 4.5 River Marisa coastal area flooding 2020-2024

ii. Gorontalo: landslides and forest fire data, 2020-2024

The total number of landslides (13) and forest fires (6) reported in the data are too low to provide reliable indicators, but landslide data suggests four hotspots centred around (i) the river watershed to the north of Limboto, (ii) Gorontalo city and immediate surrounds, (iii) the upper watershed of the Bone river to the east of Gorontalo, and (iv) the upper watershed near the coast to the west of Gorontalo city. Each potential hotspot has seen land use changes in the recent past. Further investigation will be required to substantiate this.

Impact on Climate Resilience

Number of landslides by district, 2020-2024

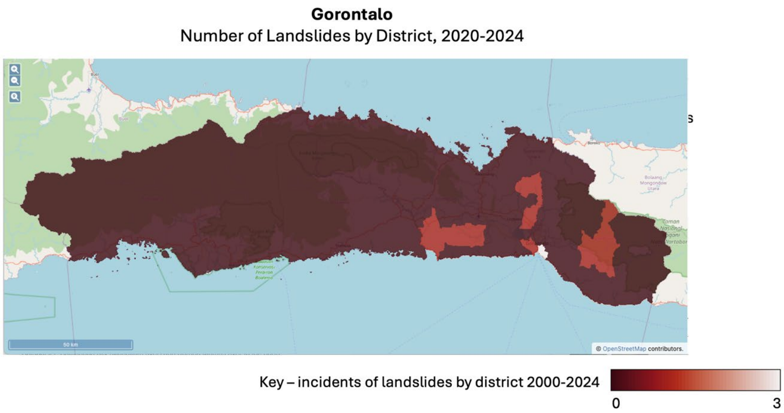

Figure 4.6 Number of landslides by district, 2020-2024

East Kalimantan

i. East Kalimantan: floods data, 2020-2024

For the much larger province of East Kalimantan, three hotspots (figure 4.7) can be identified from the available floods data (193 events):

Impact on Climate Resilience

Number of floods in East Kalimantan by district, 2020-2024

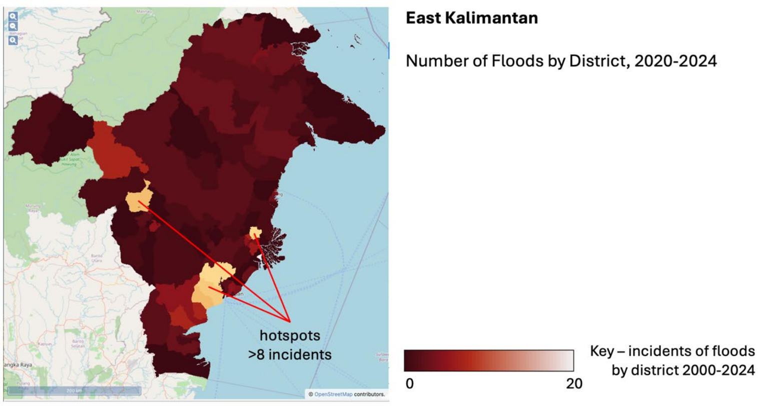

Figure 4.7 Number of floods in East Kalimantan by district, 2020-2024

Hotspot #1: Samarinda city (Mahakam river) and Karang Mumus river to the north

Flooding in Samarinda city along the Mahakam river is generally attributed proximally to a combination of flood waves from upstream heavy rainfall runoff, combined with tidal and backwater effects, impacting on densely populated urban areas with minimal flood protection. Figure 4.8 shows the local area is low lying (left panel) with specific flooding in specific districts of north Smarinda (right panel).

Far upstream land-use change (deforestation, mining) and in-situ urbanisation are believed to be leading to increased runoff, erosion, and sedimentation. In the north of Samarinda, extensive flooding in the Karang Mumus river basin is attributed to heavy extended rainfall (climate-derived), urbanisation constraining channel capacity, and upstream flow control operations exacerbating natural flooding.

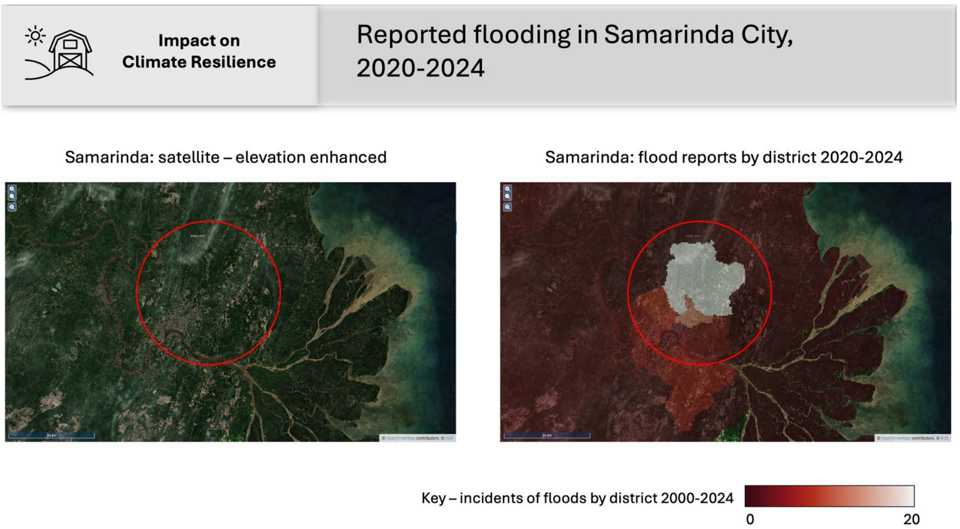

Figure 4.8 Samarinda City, East Kalimantan flooding, 2020-2024

Hotspot #2: Sepaku river basin west of Balikpapan

Flooding in the low-lying regions of the Sepaku river towards the coast is proximally attributed generally to high levels of extended rainfall and inadequate channel and drainage facilities, culverts, and bridges, leading to runoff chokepoints. Sedimentation from upstream is leading to channel blockage and erosion of banks. The creation of new housing on the flood plain is deemed to be increasing flood hazards and leaving more people exposed. See figure 4.9.

Impact on Climate Resilience

Reported flooding in Sepaku river basin, 2020-2024

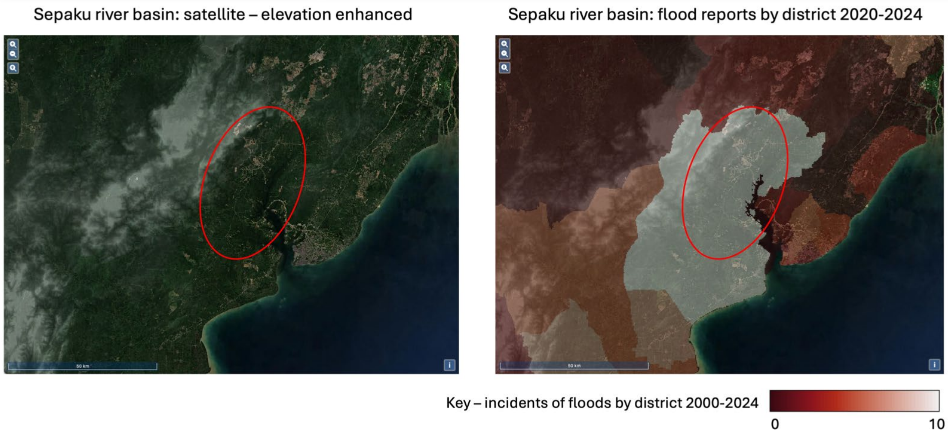

Figure 4.9 Sepaku river basin, East Kalimantan flooding, 2020-2024

Hotpot #3: Mahakam river basin north of Sendawar

The upper Mahakam river basin is a hotspot for heavy flooding, the proximal causes of which are increased incidence of multi-day heavy rain leading to overtopping in low-lying riverside settlements, with flood waves subsequently propagating downstream.

Increased incidence of rainfall is usually framed as attributable to climate change. However, in addition, reduced catchment storage is attributed to forest degradation and land use conversion upstream, leading to higher runoff volumes faster during storms. The proximity of settlements to the river, on the floodplain, increases the impact of floods.

In figure 4.10 (below), we use grey highlighting in the left panel to highlight the location of upstream headwaters feeding the basin, over 100 km distant. The right panel localises the reported flooding (red circle) based on the displayed district reports of volume of floods. The hotspot provides an opportunity to study the potential impact of agricultural changes in land use in highland areas on flooding far downstream.

Impact on Climate Resilience	Reported flooding in upper Mahakam river basin, 2020-2024

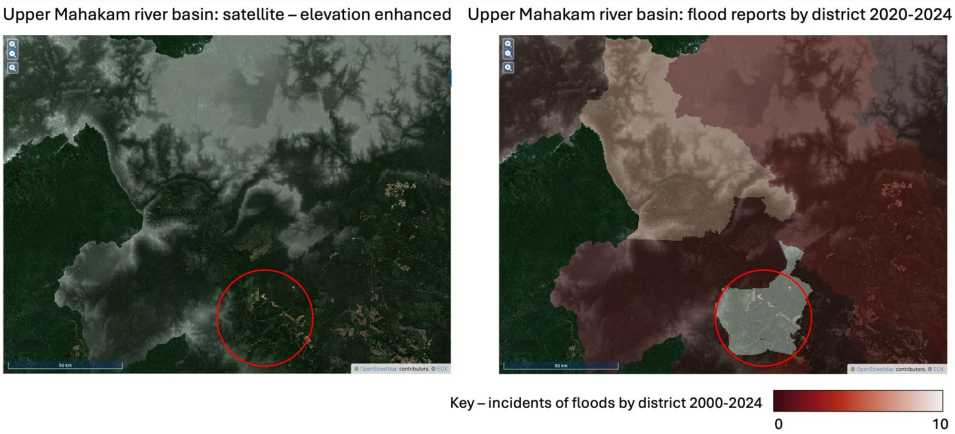

Figure 4.10 Upper Mahakam basin, East Kalimantan flooding, 2020-2024

ii. East Kalimantan: landslides data, 2020-2024

The data set for East Kalimantan contains records of 105 landslides over the period (figure 4.11), but these can be isolated to just two major hotspots, both of which may be related to two of the flooding hotspots:

Impact on Climate Resilience	Number of landslides in East Kalimantan by district, 2020-2024

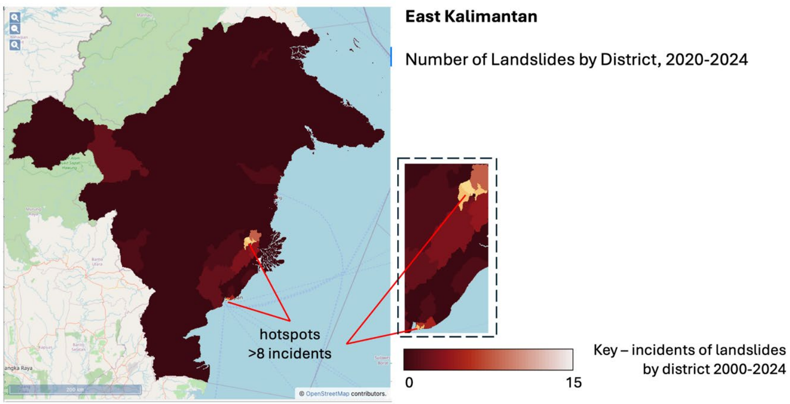

Figure 4.11 East Kalimantan landslide hotspots, 2020-2024

Hotspot #1: Samarinda city

The proximal causes of landslide events align with flood risk – heavy rain – but the landslides in Samarinda are generally attributed ultimately to unstable steep slopes, either proximal to or built on with new settlements, a product of peri-urban city expansion, often informal in fashion.

The topography of steep slopes with unstable clay layers, on the edge of an expanding city, coupled with increasing long-duration heavy rainfall, make Samarinda extremely exposed to the phenomenon. Elevation data has been superimposed with false colouration to highlight the presence, position, and orientation of the bluffs in Samarinda city.

In figure 4.12, the right panel shows the number of landslide reports by district in Smarinda city. In the left panel, we have highlighted the location of bluffs, roughly 150 metres above the near sea-level river valley, using false colouration. Using this information we identify likely places where building on steep slopes may be leading to landslides.

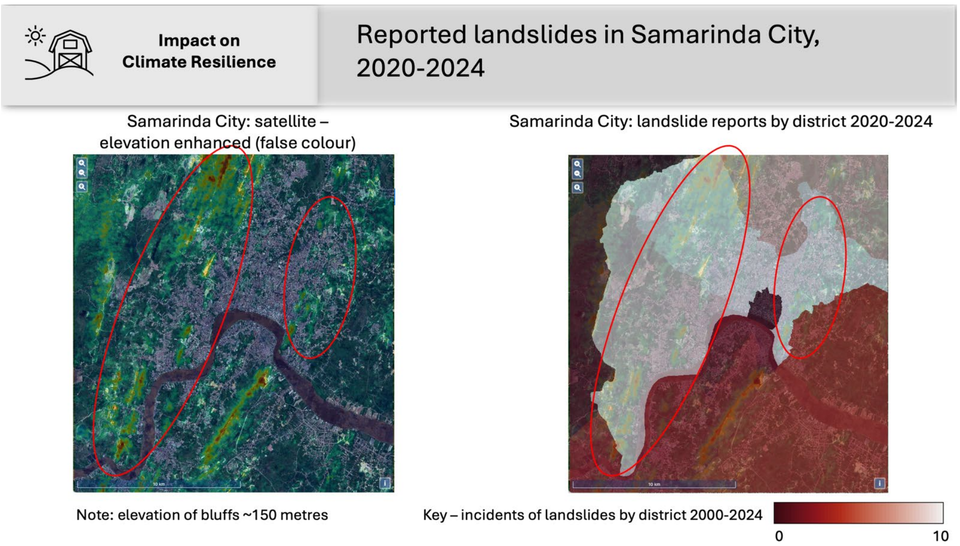

Figure 4.12 Samarinda City landslides, 2020-2024

Hotspot #2: Balikpapan Bay shoreline

A second hotspot on the shoreline of Balikapan Bay appears attributable to a combination of heavy rain, with intensive coastal development altering coastal form and currents, raising abrasion potential and undermining coastal edges over time. This landslide hotspot therefore seems also to be primarily attributable to the pressures of urban development, here in a coastal setting. We use false colouration to identify the position of 100 metre high bluffs (figure 4.13, left panel) that may be the landslide locus.

Impact on Climate Resilience	Reported landslides in Balikpapan Bay, 2020-2024

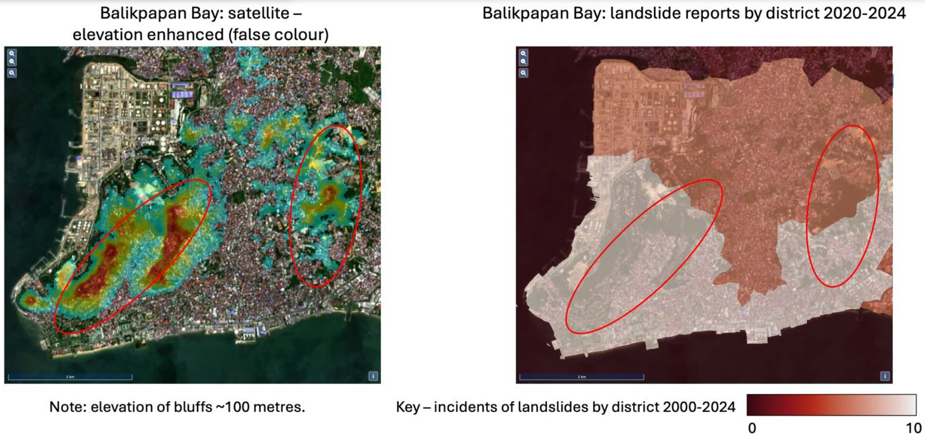

Figure 4.13 Balikpapan Bay landslides, 2020-2024

West Papua

i. West Papua: floods data, 2020-2024

Over the historic period studied, West Papua has been, by a considerable margin, the province subjected to the least development pressure. Nevertheless, at the province level, a large increase in the number of reported floods was seen, from 6 to 49, in the periods from 2010-14 to 2020-24. A brief analysis at district level suggests one principal hot spot:

Hotspot #1: River systems in the Manokwari area

Figure 4.14 highlights the region in the north west of West Papua that has seen the main flooding hotspot. In the right panel, we identify the districts reporting higher flooding volumes, and we outline likely river valleys and basins that are experiencing the flooding. We use grey highlighting to identify the highland headwater regions for these downstream valleys (left panel).

Proximal causes of this hotspot have been identified by others as high rainfall leading to river overflow, influenced by low river gradients and limited drainage density. Illegal mining in upstream areas, conversion of forestry to plantations, and other forms of environmental degradation have, however, been linked as possible ultimate causes.

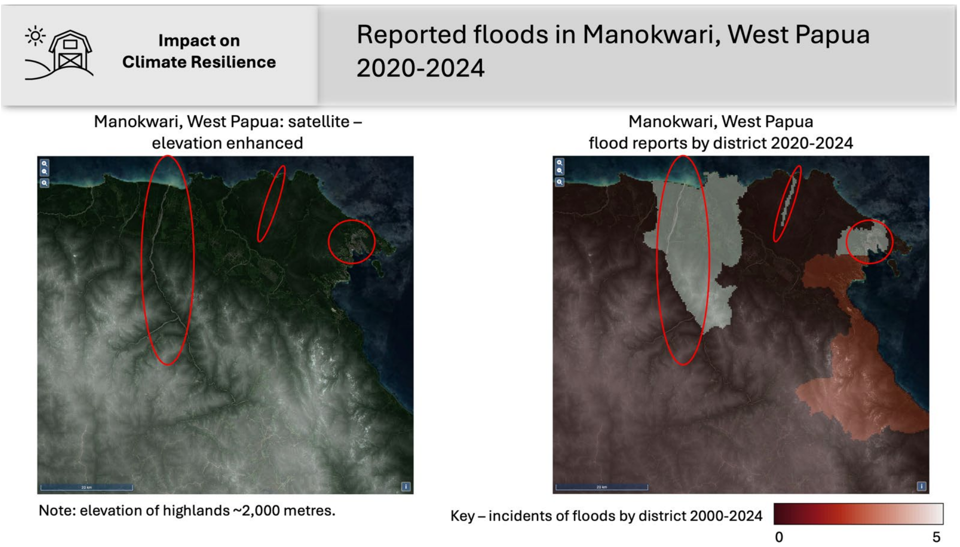

Figure 4.14 Manokwari, West Papua floods, 2020-2024

Can measurements and metrics be developed to model the likely impact on these aspects of climate resilience?

Flooding and landslide events have substantial negative impacts on Indonesia's economy and people. Causative relationships have been proposed between changes in agricultural land use, particularly deforestation, and increases in flooding and landslides, but it is challenging to develop a robust model for the relationship. This remains a work in progress.

5 THE PATTERN OF AGRICULTURAL LAND USE CHANGE: CROP PRODUCTION

Summary

Much of the direct and indirect forest exploitation is attributable to agricultural development, but the pattern of development has differed along these two axes of forest exploitation. This section examines these patterns in more detail.

i. Direct exploitation of established forest

To date, direct exploitation of established forest has mostly been attributable to three forms of agricultural land use: oil palm plantations, pulpwood plantations, and logging. The former show up clearly on land use maps as this large-scale land use re-designation is clear. The latter leads to accumulated degeneration of established forest to the point where it is no longer considered forest.

Direct exploitation of established forest in this fashion is generally attributable to large-scale coordinated projects.

Although most projects in the historic period have been non-food agricultural projects, large-scale direct forest exploitation for crop production has been observed and has the potential to be utilised more impactfully if avenues for indirect exploitation are exhausted.

ii. Indirect exploitation of forest

Across Indonesia as a whole, there has been an increase in crop production over the period studied. Although different data sources attribute differing land areas to this crop production, the sources are mostly consistent in this respect. There is some evidence that this increase in food production has been seen predominantly in the second half of the period.

Over this period, very little of this increase in crop production was achieved through direct exploitation of established forest. Rather, it was accomplished through the repurposing of land that had previously been degraded from established forest to the point where it no longer met our definition of established forest, a pattern of exploitation that we term here "encroachment". The case-study province of Gorontalo provides a clear example of this pattern of exploitation.

Other indirect exploitation of forest for agricultural purposes includes large-scale conversion of areas of natural vegetation to pulpwood plantations and oil palm plantations. These developments are seen, in particular, in our case-study province of East Kalimantan.

Detailed plot-by-plot maps for crop production are not available for Indonesia, and it is extremely challenging to reconcile the limited available spatial location data, which

identifies where on the ground crops are grown, with the available government regency-by-regency crop area production statistics. For the purposes of this project, we have developed hybrid maps that provide our best view of the spatial distribution of crops being grown in Indonesia.

Availability of Crop Production Data

There are two broad types of crop production data currently: spatial location data and area production data.

i. Spatial location data

This type identifies where on the ground crops are being grown and harvested; this is estimated using remote sensing data, typically from satellites. At the current state of technology, maps attempt to delineate where crops are being grown but generally do not specify what type of crop is being grown. These approaches link cleanly with our geospatially driven research methodology. This provides only an estimate of harvested area, so crop production can only be estimated if we assume an average yield.

We are currently working with two sources of geospatial crop production estimates: MapBiomas and GLAD (Potapov et al., 2022).

a. MapBiomas

MapBiomas has developed annual landscape maps from 2000 to 2024, identifying for each year land devoted to rice paddies, and land devoted to all other agricultural crops grouped as a single category. This is part of a broader land use classification of every patch of land into one of a set of 12 possible classes (table section 1, above). The MapBiomas data is our best available single resource for estimating land use and we are currently relying heavily on it for land use analysis.

With respect to crop production, however, our investigation, summarised below, suggests that it has tended historically to overstate the area of land devoted to crop production, primarily by failing to exclude smaller patches of either natural vegetation or non-vegetation - specifically settlements, buildings, ND roads within crop production areas. The attempt to differentiate rice paddies from other crop production areas is valuable, however.

b. GLAD

The GLAD data set provides more detailed geospatial maps of crop production for the years 2003, 2007, 2011, 2015 and 2019. The apparent higher spatial fidelity is a strong advantage, offset by (i) the lack of annual coverage or more recent data than 2019, (ii) the lack of differentiation between any crop types, and (iii) the lack of land-use classification for all other terrain. It has proven challenging, however, to reconcile the harvested areas claimed under the GLAD analysis with the harvested areas claimed by the government's area production data (see below).

c. LGRIP

The Landsat-Derived Global Rainfed and Irrigated Cropland Product LGRIP data set (Teluguntla et al., 2023) provides a map for crop production, covering all crops, for a single year, 2015.

For this initial analysis, we present the absolute values and trends indicated by the MapBiomas, GLAD, and LGRIP data sets, and we propose a possible hybrid approach to create maps that attempt to combine the best features of both approaches.

ii. Area production data

This more traditional type collects data on the ground to specify crop production, harvested areas, and yield for some specific, usually administrative, area. We have accessed two data sources: Indonesian Government data (BPS) (Ministry of Agriculture, Republic of Indonesia, 2016) and a modelled dataset Spatial Production Allocation Model SPAM produced by International Food Policy Research Institute (IFPRI), (2024).

a. BPS data

The Indonesian government collects data at a local level annually and collates this data to form estimates of production, harvestable area, and yield for administrative areas. The advantages of this data are that its collection is supported by the government. Disadvantages include: (i) it is harder to integrate administrative area level data into geospatial representations; (ii) data collection is ostensibly annual but not always conducted for all crops, everywhere; (iii) data accuracy may be affected by transcription errors and, on some occasions, there can be instances of subconscious observation bias and/or changes in methodology.

The Indonesian government produces tables for each province, showing estimated production, harvested area, and yield at regency level of detail. Our review of data tables reveals evidence of transcription errors, missing observations for some crops and some years, and changes in methodology which may have been introduced to reduce errors, for example subconscious bias, in previous years. We have corrected errors and interpolated some data points for missing years for particular crops to try to provide a clearer picture of the underlying trends. As with all other data sources, the resulting figures are indicative rather than definitive.

For our initial work, the available government data for Gorontalo province have been accessed and analysed, with transcription errors corrected and estimations provided for missing data using interpolation and averaging. These data are used to address the following question: What trends in crop production do the available government data suggest?

b. SPAM data

SPAM data source provides a modelled crop-by-crop analysis that produces estimated production, harvested area and yield across the landscape on a 10km-by-10km grid. It is a third-party analysis that effectively attempts to combine the geospatial view with the administrative region statistics to provide geospatial estimates, albeit at a relatively low spatial resolution.

This data set provides an additional viewpoint on the evolution across the landscape over time of crop production. SPAM data are already processed and available for each of the case-study provinces for a very wide range of individual crops. Unfortunately, in our analysis to date, we have been unable to confirm that the SPAM data provides an accurate or realistic assessment of the geographical distribution of specific crops. The data appear to be comprehensive but inaccurate.

What trends in crop production do the available data suggest?

i. Spatial location data

Comparison of the different available sources of spatial location data reveal the challenges associated with an apparently straightforward remote-sensing methodology, with wide disagreements between different data sets.

a. Indonesia

Table 5.1 compares estimated crop harvested areas across the whole of Indonesia between 2003 and 2019 for GLAD, MapBiomas, and (for 2015 only) LGRIP. The three sources offer widely different estimates of the amount of land under cultivation.

	GLAD Crop	MapBiomas Crop	LGRIP Crop	MB/GLAD x	LG/GLAD x	LG/MB x
2003	66,715	280,831		4.2x		
2007	68,873	274,439		4.0x		
2011	70,802	264,106		3.7x		
2015	77,036	264,318	350,417	3.4x	4.9x	1.3x
2019	83,939	266,369		3.2x		

Table 5.1 Widely differing estimates of crop production areas across Indonesia

The GLAD data is most conservative, across Indonesia estimating a steady increase in total crop production area over the period, rising from 66,700 square kilometres (km2) in 2003 to 84,000 km2 in 2019, a compound annual growth rate (CAGR) of 1.4% per year over 16 years.

MapBiomas (MB), by contrast, estimates a much larger area given over to crop production. The total estimated crop area in the MB data therefore shows a slight decrease from 281,000 in 2003 to 266,000 in 2019, an average of -0.3% per annum. Comparing like-with-like, MB estimates 4.2x total land area for crops in 2003 versus GLAD, declining to 3.2x in 2019.

MapBimoas offers an assessment of crop production areas for "rice paddies" and "other agriculture". Table 5.2, below, offers these assessments for the same years as Table 5.1.

km2	MapBiomas Rice	MapBiomas Other Agriculture
2003	90,194	190,637
2007	91,092	183,347
2011	92,226	171,879
2015	96,945	167,373
2019	97,275	169,094

Table 5.2 MapBiomas rice paddy & other agriculture areas across Indonesia

MB estimates an average annual increase in rice paddy crop production area of 0.5% CAGR, rising from 90,000 km2 in 2003 to 97,000 km2 in 2019. The "other agriculture crop" classification in MB is much higher, suggesting 191,000 km2 in 2003, decreasing by a CAGR of -0.7% per annum to 169,000 km2 in 2019.

One way to reconcile these figures is to suggest that the MB Other Agriculture figure is a large source of error; visual inspection suggests that a lot of the built-up environment is mistakenly labelled by MB as "Other Ag" rather than buildings. Supporting this, the MB estimates for rice paddy, whilst more generous than GLAD total crop areas, do show similar trends of a gradual annual increase.

LGRP estimates are available for one year only, 2015, but add a strong cautionary note to this explanation. The LGRIP total crop area estimate across Indonesia of 350,000 km2 in 2015 is even greater than that for MB (264,000 km2), and 4.5x that for GLAD (77,000 km2). Crop production area estimates from government data for Gorontalo province, below, also strongly suggest that the GLAD estimates are far too low.

b. East Kalimantan

The discrepancies in the available spatial location data are even more stark in the province of East Kalimantan. These figures are summarised for these chosen comparison years in table 5.3.

Notwithstanding the large size of East Kalimantan (125,000 km2), GLAD estimates a small crop area in the province, 103 km2 in 2003, rising to 306 km2, at a 7% CAGR, by 2019.

MapBiomas (MB) suggests paddy fields at a similar scale, 266 km2 in 2003, rising to 385 km2 in 2019, a 2.3% CAGR. MB proposes "other agriculture", however, at 8,700 km2 falling to 4,900 km2 in 2011 and then recovering to 6,100 km2 by 2019.

The 2015 LGRIP estimate dwarfs this – 31,000 km2 in 2015, mainly rainfed agriculture.

The discrepancies are very great. Total MB crop estimate is moving from 87x to 21x that of GLAD over the time period, with the LGRIP estimate 163x that of GLAD.

km2	GLAD Crop	MapBiomas Crop	LGRIP Crop		MapBiomas Rice Paddy	MapBiomas Other Ag
2003	103	8,992			266	8,726
2007	99	7,652			284	7,367
2011	107	5,181			296	4,885
2015	190	5,525	31,049		364	5,161
2019	306	6,525			385	6,140

Table 5.3 Widely differing estimates of crop production areas in East Kalimantan

c. Gorontalo

Gorontalo (table 5.3) shows the closest overlap between the different datasets.

GLAD describes 454 km2 of cropland in 2003, flat then growing strongly at 12% per annum from 2011 onwards, for a net growth rate from 2003-2019 of 5.8%, to 1,124 km2 of crops.

MB suggests 497 km2 of rice paddies in 2003, growing steadily at 1.7% per annum to 654 km2 by 2019. MB "other agriculture" reverses the trend, 842 km2 in 2003 to 723 km2 in 2019. The total cropland identified by MB over the time period is constant across the time period at approximately 1,360 km2.

Once again LGRIP is higher, suggesting a total of 2,374 km2 crop land in 2015 – 1.7x the MB total crop figure.

km2	GLAD Crop	MapBiomas Crop	LGRIP Crop	MapBiomas Rice Paddy	MapBiomas Other Ag
2003	454	1,339		497	842
2007	445	1,356		527	829
2011	453	1,361		579	782
2015	707	1,370	2,374	614	755
2019	1,124	1,377		654	723

Table 5.4 More comparable data for Gorontalo province

d. West Papua

The estimated crop area figures for West Papua (table 5.4) are very small relative to the size of the province (96,000 km2).

GLAD suggests 9.3 km2 in 2003 growing at 7.1% to 28 km2 in 2019 – with the fastest growth in the latter half (11%).

MB rice shows a roughly similar pattern – 20 km2 in 2003, doubling to 40 km2 in 2019, a 4.4% CAGR.

MB “other agriculture” compensates such that the total MB crop area is roughly constant between 2003 and 2019 – going from 100 to 115 km2.

LGRIP suggests a total crop area of 420 km2 in 2015 – 5x the GLAD estimate.

km2	GLAD Crop	MapBiomas Crop	LGRIP Crop	MapBiomas Rice Paddy	MapBiomas Other Ag
2003	9	100		20	80
2007	10	82		17	65
2011	12	86		28	58
2015	19	98	421	31	66
2019	28	115		40	75

Table 5.5 Limited crop production in West Papua

Extrapolating from the details above, we suggest the following tentative conclusions:

1. Differing methodologies make comparisons between data sets hard to reconcile. Trends over time within data sets, however, seem more useful.

2. GLAD offers the most conservative estimate but points to clear development patterns of accelerating growth in crop areas. We see growth in crop area between 2003 and 2019 in all case-study provinces – East Kalimantan (7% per annum), Gorontalo (6%), and West Papua (7%) – all growing faster than Indonesia as a whole (1.4% per annum). In each province, growth was very limited between 2003 and 2011, but much faster after that time (11% - 14% per annum 2011-2019).

3. MapBiomas's (MB) land use designation "Other Agriculture" appears not to be reliable, as it includes much urban land and is hard to interpret. MB rice paddy estimates do, however, show consistent growth trends in all provinces - East Kalimantan (2.3% per annum), Gorontalo (1.7%), and West Papua (4.4%) – with the first and last showing faster growth in the second half of the time period. The MB "total crop" area is flat over the period.

4. LGRIP only provides estimates for 2015. It is the most generous in area estimation, exceeding MB total crop area by 30% (1.3x) for Indonesia as a whole, and for each province (East Kalimantan 5.6x, Gorontalo 1.7x, West Papua 4.3x).

ii. Area production data

Two sources are analysed here: BPS government data and SPAM data. As discussed above, BPS data are complex, bottom-up estimates: to date, we have analysed available data for our case-study Gorontalo province alone. This provides an important source of primary data to cross-check the other third-party estimates and help us come to some conclusions. But problems outlined earlier in this section make interpretation of the available data challenging both in understanding change over the time and the current pattern of crop production.

The SPAM data, at this time, would on the face of it be the most useful for examining trends in agricultural practice over time, both at large (nation, province) and medium (regency, district) scale. The data have been prepared independently and offer an objective analysis. SPAM data have been produced on 10km x 10km grids across Indonesia so provide a comprehensive third-party source of harvested area estimates. We focus on harvested area as our key metric as this ties directly to the strategies of agricultural extensification that we are studying. Unfortunately, we have not yet been able to confirm a reliable relationship between the observed distribution of production over the ground and the claimed pattern in SPAM data, making its interpretation also problematic. Work on this is ongoing and SPAM results are presented here without modification.

a. Indonesia

Figures 5.1, 5.2 and 5.3 summarise trends in harvested area across Indonesia for key exemplar food crops (rice, maize) and key exemplar estate crops (coconut, oil palm, rubber, cocoa).

In figure 5.1, we note the domination of Java as a producer of rice throughout and the overall lack of growth in cultivated land for rice and maize production at a national scale. This stands in contrast to our case-study provinces, see below, which show significant shifts in patterns of food production.

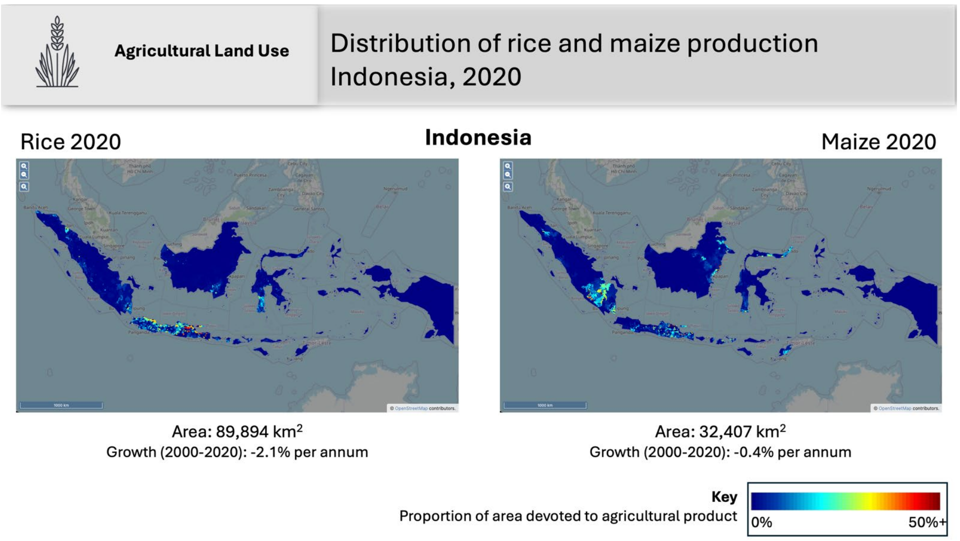

Figure 5.1 Areas devoted to Rice and Maize cultivation across Indonesia, 2020

Similarly, the distribution of coconut, rubber and cocoa production across Indonesia varies significantly by crop type (figure 5.2) but, according to the SPAM data source, the area devoted to the crops for which data are available (coconut, cocoa) actually shrank between 2010 and 2020.

LEAF INDONESIA
LAND-USE; ECOSYSTEMS; AGRICULTURE; FOOD SECURITY

Agricultural Land Use	Distribution of coconut, rubber and cocoa production in Indonesia in 2020

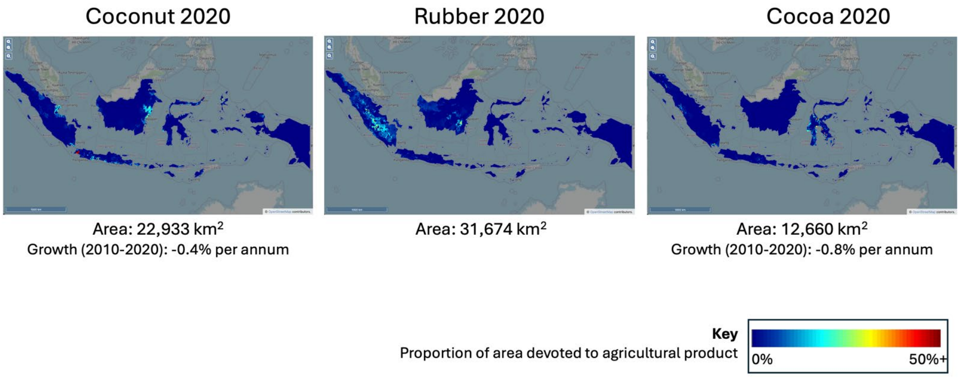

Figure 5.2 Areas devoted to Coconut Rubber and Cocoa cultivation

In contrast, across Indonesia as a whole, most striking has been the strong increase in land dedicated to oil palm plantations (figure 5.3), such that oil palm now constitutes the largest consumer of land for any single agricultural product – 125,000 km2 against 90,000 km2 for rice production.

Agricultural Land Use	Transformation of oil palm plantation areas 2010 - 2020

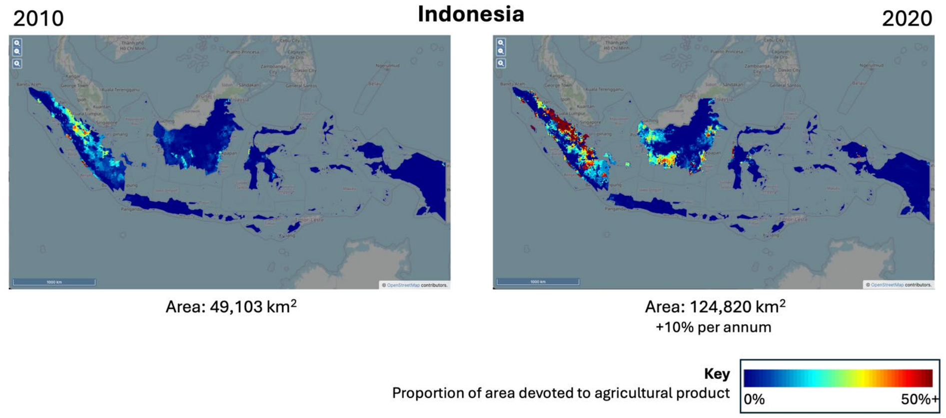

Figure 5.3 Transformation of oil palm plantation areas, 2010 - 2020

b. East Kalimantan

For East Kalimantan, we see significant shifts in the pattern of land dedicated to different key agricultural outputs. The SPAM outputs at within-province level need further work to reconcile with government data and to validate against findings on the ground, so work here is in progress.

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Rice remains a relatively small contributor relative to the size of the province with some suggestion of, if anything, a reduction in rice cultivation between 2000 and 2020 (987 km2 falling to 500 km2) (figure 5.4, left panel).

Likewise, East Kalimantan is not a major maize producer according to government BPS statistics, although between 2010 and 2020 there was a significant increase between 2010 (30 km2) and 2020, when official data suggest that harvested area had expanded to around 150 km2 – still only of the order of 0.5% of Indonesian total maize production. By contrast the SPAM data (figure 5.4, right panel) suggests an area of 5,212 km2. This seems unlikely and a significant discrepancy with available government data - resolution of this data conflict is open.

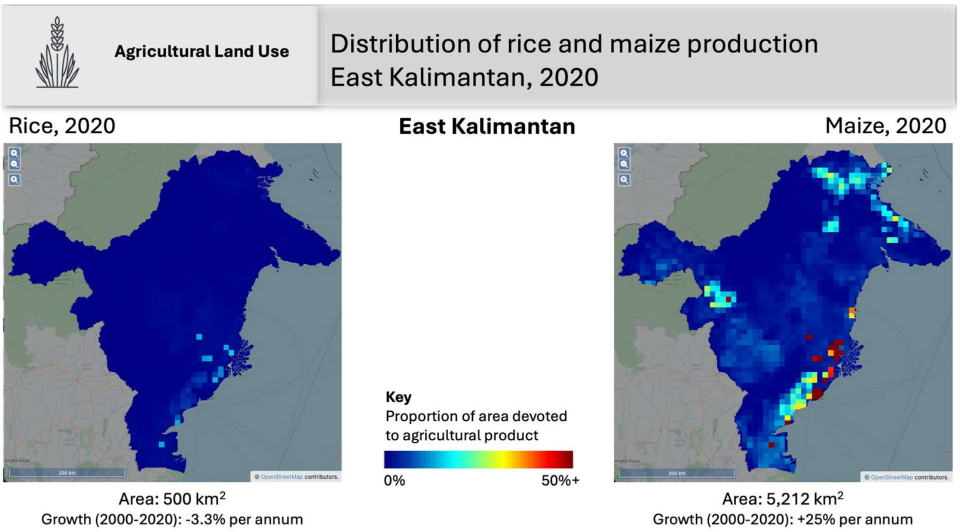

Figure 5.4 Rice and Maize production areas, 2020

In the SPAM data we see a strong increase in land dedicated to Oil Palm plantations between 2010 and 2020, rising from 2,400 km2 in 2010 to 8,900 km2 in 2020 (figure 5.5). As a result, East Kalimantan's share of Indonesia's harvested area for Oil Palm increased from an estimated 5.0% to 7.3%. East Kalimantan contributed just under 9% of the total increase in Indonesia's Oil Palm harvested land between 2010 and 2020.

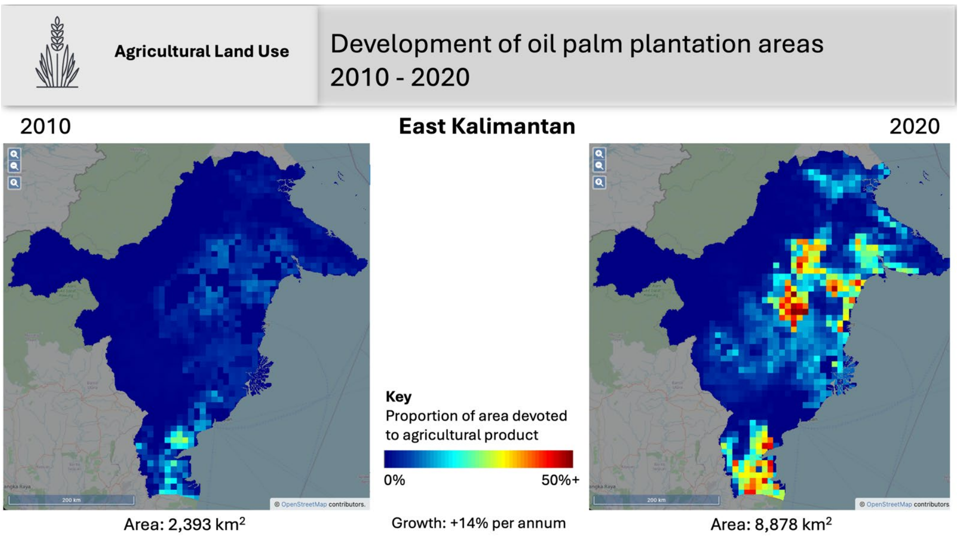

Figure 5.5 Transformation of oil palm plantation areas, 2010 - 2020

Similarly, there was a strong increase in the other estate crop examined here, coconut, with an increase from 180 km2 in 2010 to 4,602 km2. According to these figures, which need validating, East Kalimantan rose from contributing a negligible proportion to Indonesia's total land dedicated to coconut production in 2010 to accounting for an estimated 22% of the nation's total (see figure 5.6).

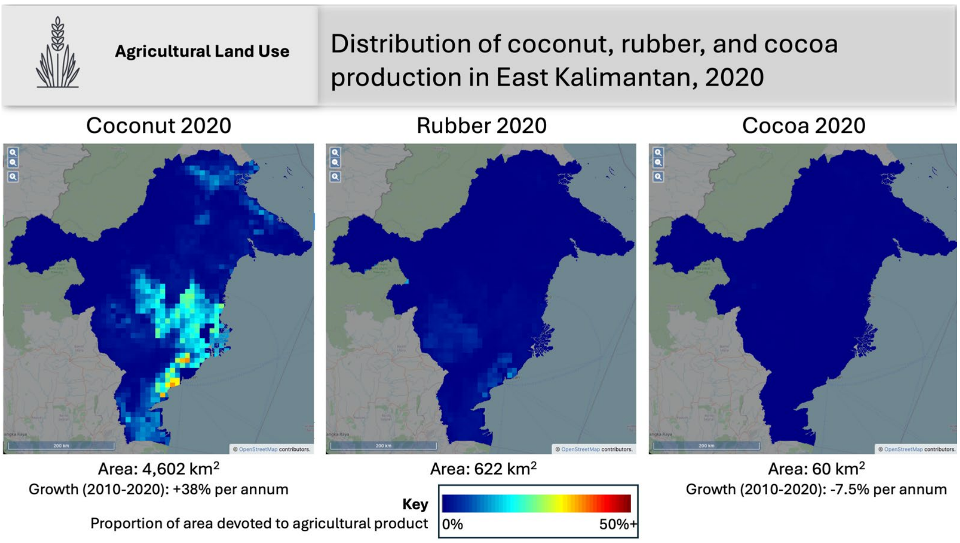

Figure 5.6 Coconut, rubber and cocoa harvested areas, 2020, in East Kalimantan

These indicators point to a strong expansion of food and estate crop production in East Kalimantan between 2000 and 2020, with a focus on creating a major national food crop and estate crop resource. This conclusion remains subject to further investigation, however, given uncertainties over the available data.

c. Gorontalo

For Gorontalo, according to available SPAM data, the area devoted to rice harvesting has changed little between 2000 and 2020, at around 400 km2, while Maize harvesting has seen a rise from around 500 km2 to 900 km2 in 2020 (figure 5.7), an overall increase in area of 2.3% per year over the 20-year period. These figures are awaiting confirmation on the ground.

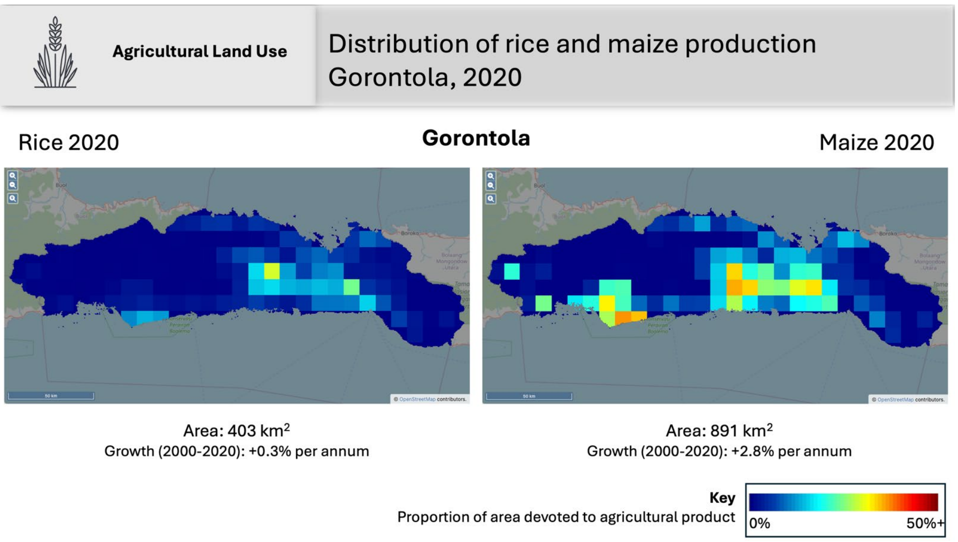

Figure 5.7 Rice and Maize production areas, 2020

Data for coconut and cocoa suggest stagnation, with little change in the area devoted to these estate crops between 2010 and 2020 (figure 5.8). There is no rubber cultivation in Gorontalo province.

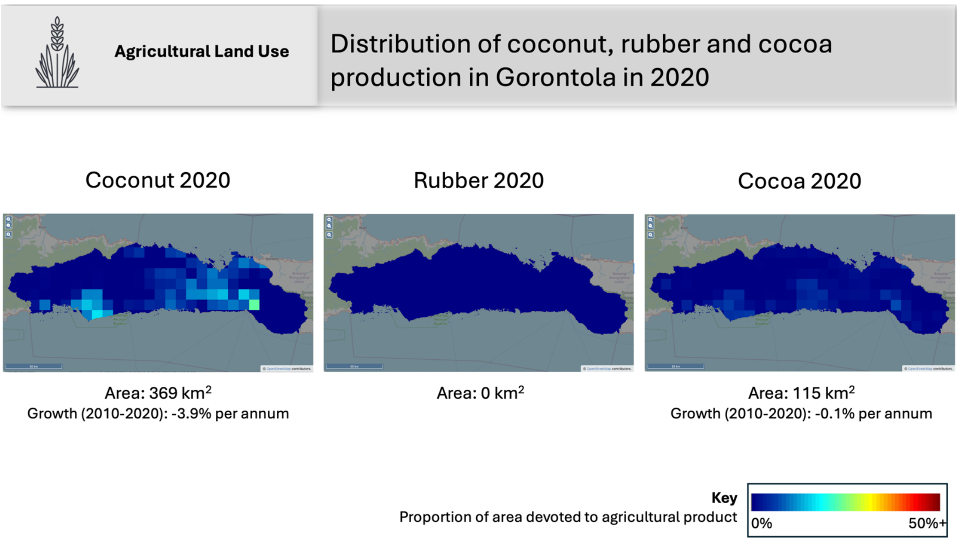

Figure 5.8 Coconut, rubber and cocoa harvested areas, 2020, in Gorontalo

Oil palm cultivation has seen strong growth in Gorontalo province, increasing from a negligible 2 km2 in 2010 to a reported 108 km2 in 2020, according to SPAM data, an increase of 49% per annum compounded over a decade. This reflects the observations in West Papua (below), East Kalimantan, and across Indonesia as a whole.

d. West Papua

The landscape of West Papua remains dominated by natural forestry and relatively inaccessible highland landscapes. The available SPAM data, table 5.5, suggests that increases over the past decade have been primarily in the production of estate crops, starting from a very low base. As elsewhere in our case study areas, oil palm cultivation leads the way, with significant increases also seen in coconut production. In the historical record, rice and maize production have remained relatively constant.

km2	SPAM Rice	SPAM Maize	SPAM Oil Palm	SPAM Coconut	SPAM Cocoa
2000	41	2			
2010	72	9	142	102	100
2020	48	4	621	373	113
Growth 00-20	+0.8% p.a.	+3.5% p.a.			66
Growth 10-20			+16% p.a	+14% p.a	+1.2% p.a

Table 5.6 Limited crop production in West Papua - SPAM data

LEAF INDONESIA
LAND-USE; ECOSYSTEMS; AGRICULTURE; FOOD SECURITY

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