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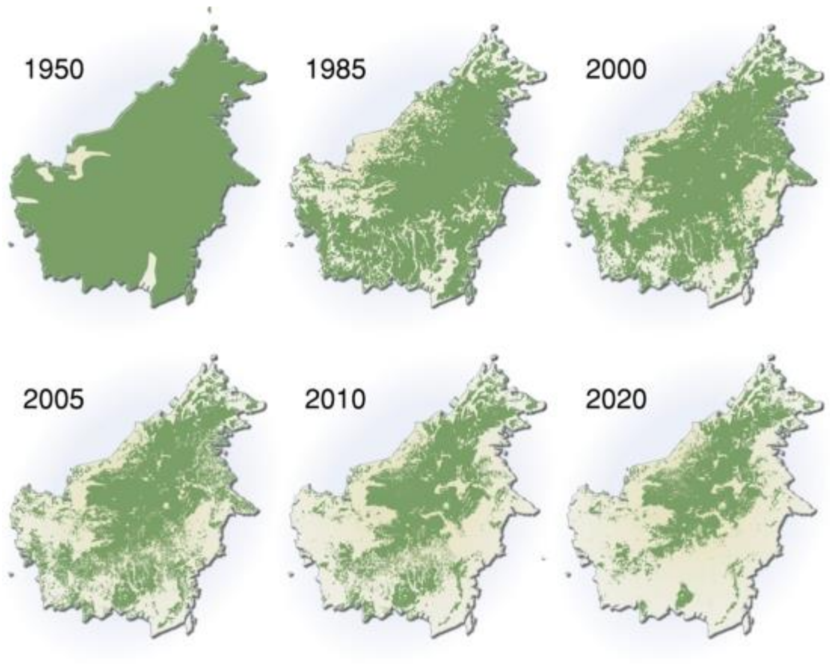
Spatial Analysis of Causes of Deforestation in Indonesia

Tombayu Amadeo Hidayat

3 April 2019



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Spatial Analysis of Causes of Deforestation in Indonesia

Tombayu Amadeo Hidayat

Registration number 94 04 03 838 010

Supervisor:

dr. Veronique De Sy

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It seems to me, that when it's time to die,
-and that will come to all of us-,
there will be a certain pleasure in thinking that
you had utilized your life well,
that you had learn as much as you could,
gathered in as much as possible of the universe,
and enjoyed it.

—Isaac Asimov

Abstract

As one of the countries with the largest forest cover in the world, Indonesia is facing a severe problem of deforestation. The enormous land use change in the country has serious impact in the global greenhouse emission, making REDD+ a significant initiative for Indonesia. To ensure effective REDD+ intervention measures, identifying and analysing drivers of deforestation in the country are of a great importance. In this study, we conduct spatial analysis of drivers of deforestation to assess the link between the direct and indirect drivers of deforestation. Random forest algorithm was employed to identify the major indirect drivers of deforestation in the country. Utilizing a number of direct and potential indirect driver data in 139 sample units, we found that the majority of the deforestation in the country is related to palm oil and is greatly influenced by their distance to palm oil mills and roads. Smallholder agriculture-driven deforestations tend to occur near roads and rivers. While biophysical properties of the area can influence the deforestation pattern to a certain extent, it is deemed as insignificant determinant of deforestation, alongside the socioeconomic variables. We conclude that different direct driver has specific underlying driver linked to it. Its effect can be studied by firstly distinguishing the proximate cause of the deforestation rather than analysing the deforestation as a whole. This implies the need of comprehensive direct driver data as a prequisite. This study demonstrated a way to link the direct and indirect drivers, and can possibly be extended to greater scale and detail to produce detailed information regarding drivers of deforestation. This knowledge can further contribute to countries in setting up effective and accurate REDD+ strategies.

Keywords: deforestation, direct driver, indirect driver, palm oil, REDD+, random forest, Indonesia

Acknowledgement

Alhamdulillah. This thesis –or I might say journey– has been a fruitful one. I am thankful that I have chosen this topic from the very beginning, and most importantly, that I have enjoyed every single phase of this journey. 6 months felt so fast! I want to thank my supervisor Niki De Sy, who has been very dedicated and patient in supervising me during this thesis journey. I feel like this is the first time I did a *real* collaborative research, where you don't feel alone because you always have someone to discuss and consult with. I will truly remember your guidance and dedication. Thank you! Mama and Papa, my main source of inspiration. *Alasanku untuk selalu berjuang*. Distance can be painful at times, but I am thankful that the world has allow us to always connect. I love you both. Ajeng, you may say that you don't want to be included here, but here you are. How can I not mention you here? Cheers!

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1. Introduction

1.1 Forest and deforestation

It is well known that forests play significant roles in the ecosystem. Currently, forests cover around 30.6% of the Earth's surface and contain 80% of the planet's biomass (FAO, 2015; Pan et al., 2013). In the tropics, the tropical rainforests host over 80% of the world's biodiversity whilst covering just over 7% of the world's land (Malhi and Wright, 2004). Forests also act as major carbon sinks, absorbing billions of tons of greenhouse gases (GHG) each year (Canadell and Raupach, 2008). As such, forests hold important role in the global climate due to its role in the global carbon cycle.

Despite the significant roles, forests are now widely regarded as the most endangered habitat on the Earth. More and more forests are being cleared to make way for agricultural lands and settlements (FAO, 2015). This practice is called deforestation, i.e., clearing forest lands into non-forest. It is estimated that deforestation accounts for 18% of global GHG emission (Angelsen et al., 2009). Therefore, deforestation is a prominent on-going problem, particularly in regard to the climate change (Achard et al., 2014a; Hansen et al., 2013b).

Deforestation historically occurred in temperate forests of Europe, North America, and Asia up until the 20th century (FAO, 2012). Nowadays, deforestations are shifting into the tropical countries. Currently, among the countries with the highest deforestation rate is Indonesia, alongside with Brazil (FAO, 2015). Forests hold an essential role in the development in these countries. In Indonesia alone, forest is a major source of livelihood for around 6 to 30 million of people (Sunderlin et al., 2000). As a consequence, forests have continually been exploited, leading to the loss of 21 MHa of forests area between 1990-2005 (Hansen et al., 2009). Inevitably, this enormous area loss has significant implications in the climate change issue (Margono et al., 2014).

1.2 REDD+

To tackle deforestation and therefore mitigating climate change, the parties of United Nations Framework Convention on Climate Change (UNFCCC) has developed REDD+: reduce emissions from deforestation and forest degradation, and foster conservation, sustainable management of forests, and enhancement of forest carbon stocks (UNFCCC, 2007). The ultimate objective of REDD+ aligns with the Paris Agreement, which central aim is to keep the rising global temperature below 2°C. REDD+ is a set of guidelines to set up efforts to ultimately mitigate climate change. These guidelines are aimed to a group of developing countries located in subtropical or tropical area, where land use change is a prominent source of GHG emissions. REDD+ is thus considered as a significant initiative for Indonesia.

The early phase of REDD+ focuses on the participating countries to formulate their national strategy, action plan, policies, measures, and capacity building activities (Minang et al., 2014). This phase is called as the readiness phase, where the countries are prepared before the actual REDD+ activities, national strategies and policies are implemented. Currently, most of the participating countries are within this phase (UNFCCC, 2018).

The UNFCCC calls for the participating countries to address drivers of deforestation and forest degradation in the formulation of their national strategies (UNFCCC, 2009). This is because the drivers are "unique to countries' national circumstances, capacities and capabilities" (UNFCCC, 2014). Moreover, drivers of deforestation also hold an important role in monitoring, reporting, and verification (MRV) of the REDD+ activities (Grassi et al., 2008). Ultimately, the MRV system needs to be driver-specific as different drivers would need different monitoring and evaluation method (Achard et al., 2014b; Salvini et al., 2014). Specifically addressing these drivers is an important component of a good MRV system, ensuring effective and accurate REDD+ activities (UNFCCC, 2009).

Indonesia has already submitted their national strategy back in 2012 (Indonesian REDD+ Task Force, 2012), and is currently on the readiness phase leading up to the implementation phase. It is then becoming a major importance to specify the drivers of deforestation in the country. A good system of monitoring is crucial so that the REDD+ intervention measures would be effective (Salvini et al., 2014).

1.3 Drivers of deforestation

In addressing deforestation drivers, there are two critical aspects to underline. The first is the distinction of the direct and indirect drivers of deforestation, and the second is that deforestation drivers can vary regionally.

Deforestation is not merely caused by the proximate (direct) drivers, but also by the underlying (indirect) drivers (Geist and Lambin, 2001; Kissinger et al., 2012; Rautner et al., 2013). Proximate drivers are those circumstances that affect the occurrence of deforestation directly (Geist and Lambin, 2001). This is commonly related to human activities that directly affect the loss of forest, such as the opening of new agricultural lands or establishment of roads/infrastructures.

In contrast, the underlying drivers push the occurrence of deforestation indirectly. Such drivers are formed by multiple factors and processes, such as economic, demographic and governance (Rademaekers et al., 2010; Salvini et al., 2014). For example, population growth is widely deemed as the primary underlying cause of deforestation (Geist and Lambin, 2001). The increasing population size may increase the need of agricultural land to be cultivated, thus putting the forests into deforestation risk (Kaimowitz and Angelsen, 1998).

Regional variation of deforestation drivers is primarily influenced by different local circumstances. Geist and Lambin (2002) identified clear regional pattern of causes of deforestation influenced by economic factors and national policies. Currently, small-holder farmers still constitute as the main direct driver of deforestation in Africa, while in Latin America, cattle ranching and soybean farming are more prominent (Rudel et al., 2009). The increasing demand of these commodities pushes the countries to increase their production, thus there are needs to open new lands (Rautner et al., 2013).

1.4 Drivers of deforestation in Indonesia

In Indonesia (and Southeast Asia in general), agricultural expansion is the most important driver of deforestation, followed by infrastructure expansion (Rademaekers et al., 2010). In the island of Sumatra, approximately 70% of the forests have been lost due to the establishment of palm oil plantations (Rautner et al., 2013). Borneo has also seen high deforestation rate due to timber extraction and the establishment of rubber and palm oil fields. Currently, only half of its original forest remain, a third of these were lost in just the last three decades (Gaveau, 2017).

Some of the main direct and indirect drivers of deforestation in Indonesia are highlighted by Indrarto et al. (2012) in CIFOR's Indonesia country profile. According to the report, agriculture establishment constitutes the main direct driver of deforestation in Indonesia. The increasing price and the rising global demand of palm oil stimulates the expansion of the agriculture. Indonesia is the world's largest producer of palm oil (Indrarto et al., 2012). According to Sawit Watch (2009), the area of palm oil estates increased for about five-fold in the span of merely ten years (1989-1998).

The future demand for palm oil is not expected to slow down, because it has the lowest production cost, highest yield per area and is very versatile (Corley, 2009). Furthermore, the current trend of biofuel would need palm oil as the raw material. Corley (2009) estimated that around 12 Mha of palm oil plantations would need to be established worldwide, to meet the world's demand. Various plans have been established for this, and in Indonesia, the island of Papua is likely to be the next target (AFP, 2008; Indrarto et al., 2012). Klute (2008) described Papua as the 'last forest frontier' of Indonesia, so it is of great importance to protect Papua's forest.

On the other hand, mining, although not as significant as estate crops, also acts among the major driver because many small-scale mining are operating illegally (Indrarto et al., 2012). Illegal logging is also among the most significant deforestation causes (Indrarto et al., 2012). Loggings cause tree density to decrease. Such sparse and degraded lands are easy to clear, thus leading to land conversion into farm or agricultural lands, for example. Forest fire is also a common cause of deforestation. Some occurred naturally, but many others are intentionally burned mostly for swidden agriculture (Applegate et al., 2001).

Among the highlighted indirect drivers of deforestation in Indonesia are economic development and population growth (Indrarto et al., 2012). The fast-growing economy of Indonesia sees the increasing population of the middle-class, which in turn escalates the development (Rademaekers et al., 2010). A study shows that a 1% increase in population is followed by 0.3% shrinkage of forest cover (Sunderlin and Resosudarmo, 1997). Increasing population densities also constitutes as the main indirect driver of deforestation and has a similar effect to economic growth (Laurance, 2007).

Other indirect stimulating factors include the demand for various commodities (e.g., timber, palm oil, and pulp). Huge demand for timber pushes Indonesia to export around 33 million m^3 of timber annually to the USA, Europe, Japan and China combined (Indrarto et al., 2012). Pulp and paper industry is also among the prominent forest-related industries (Palmer, 2001).

2. Problem definition and objectives

Some prior studies have identified the major direct drivers of deforestation. However, most of them are more focused on the global and regional scale (Geist and Lambin, 2002; Kissinger et al., 2012; Rademaekers et al., 2010). De Sy (2016) addressed the importance of incorporating national circumstances in studying deforestation drivers because spatial dynamics play a significant role in determining the drivers of deforestation in a different area. For example, each island in Indonesia has its own specific circumstances. Thus, deforestation in different regions of the country can be driven by varying drivers (Indrarto et al., 2012).

Kissinger et al. (2012) emphasized the need to also address the underlying deforestation driver by "looking beyond the forest sector". Solely focusing on the proximate driver would be less effective in reducing deforestation and forest degradation because direct and indirect drivers are interrelated. Effective intervention measures thus can be achieved by identifying the link between the direct and indirect deforestation drivers. While this is important, quantitative assessment on this issue is still uncommon (De Sy, 2016). Researchers also experienced difficulties in identifying the clear links between the direct and indirect drivers due to the complex and multifaceted trait of the indirect drivers (Angelsen, 2008; Kissinger et al., 2012).

All in all, this research aims to explore the relationship between the direct and indirect deforestation drivers using spatial analysis. The area scope would be constrained to Indonesia. The objectives of this research are outlined as follows:

- Assess the link between the direct and indirect driver of deforestation in Indonesia in a spatially explicit manner.
- Identify the indirect drivers of deforestation in Indonesia for deforestation in general and for specific direct drivers.

3. Methodology

3.1 Data sources

To explore the spatial relationship between the drivers of deforestation, it is important that the data covering both types of drivers are available. Among the initial steps of this research is to gather such data from various sources. As this research aims to explore the spatial dimension of the drivers, those data need to have location attributes so spatial analysis can be made.

The data used in this research are classified into two main categories, i.e., direct drivers and indirect drivers. The indirect drivers would be further divided into several sub-categories.

3.1.1 Direct drivers

A previously conducted research by De Sy et al. (2015) has identified the main direct drivers of deforestation. The study makes use of the forest land use change data from the 2010 Global Remote Sensing Survey (RSS) of the United Nations Food and Agricultural Organisation (FAO & JRC, 2012). The data is a systematic 10 km x 10 km sample units, which are then segmented into polygons. Each polygon–if there is any deforestation–is assigned with a follow-up land use (Table 3.1) as a proxy of the direct driver of deforestation. This follow-up land use was determined by visual interpretation of high-resolution imagery (De Sy et al., 2015). The dataset provides information for two periods of time: 1990-2000 and 2000-2005. A total of 139 sample units were used to sample the entire area of Indonesia (Figure 3.1).

Table 3.1 lists the categorization of the follow-up land use classes used in this study (De Sy et al., 2015; Hosonuma et al., 2012). Several land use classes were not considered, such as mixed agriculture, pasture, and mining because these follow-up land uses were either not present or making a very small presence in the current study area. Out of the whole dataset, the deforested area was mainly followed by agriculture (53%) and other land use (42%). Built-up lands take a portion of about 4% of the follow-up land use, while water takes about 1%.

It is important to note that some sample units do not have land use information for the 2000-2005 period due to either cloud obscuration, poor satellite coverage or low-quality images (FAO & JRC, 2012). To ensure consistency in the analysis, such sample units are omitted. Only regions with complete information for the whole period are kept, resulting in 110 sample units throughout the country. From those, a total of 100 sample units have a portion of its region deforested, and only 62 sample units have a portion of its area classified as forest region.

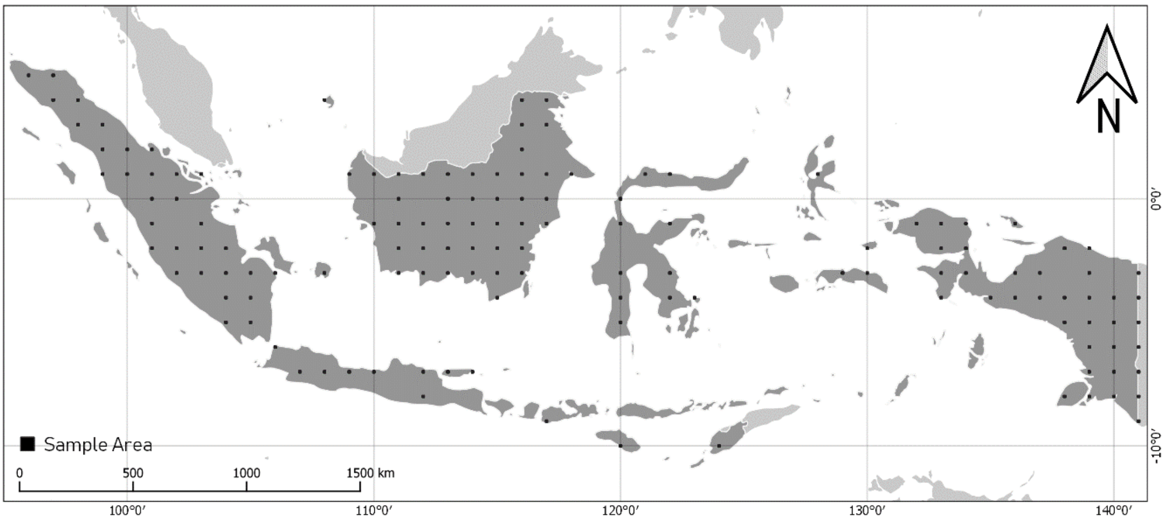

Figure 3.1 The distribution of the sample units, with each black square indicates a sample unit of 10 x 10 km.

Table 3.1 Direct driver categories, modified from De Sy et al. (2015). Note that not all of the land uses listed here are present in the study area.

Category	**Follow-up land use**	**Description**
Agriculture	Commercial crop	Land under cultivation for crops, characterised by medium (2-20 ha) to large (>20 ha) field sizes.
	Small-holder crop	Land under cultivation for crops, characterised by very small (<0.5 ha) to small field sizes (0.5-2 ha).
	Tree crop	Miscellaneous tree crops (e.g., coffee, palm trees), orchards and groves.
Built-up	Urban & settlements	Urban, settlements and other residential areas.
	Roads and built-up	Roads, built-up areas and other transport, industrial and commercial infrastructures.
Other	Bare land	Barren land (exposed soil, sand, or rocks).
	Other wooded land	Land not classified as forest, spanning more than 0.5 ha; with trees higher than 5 m and canopy cover of 5-10%, or trees able to reach these thresholds *in situ*, or with a combined cover of shrubs, bushes, and trees above 10%. It does not include land that is predominantly under agricultural or urban land use.
	Grass and herbaceous	Land covered with (natural) herbaceous vegetation or grasses.
	Wetlands	Areas of natural vegetation growing in shallow water or seasonally flooded environments. This category includes Marshes, swamps and bogs.
Water	Natural	Natural water source (river, lake, etc.).
	Artificial	Man-made water bodies (e.g. reservoirs).
Unknown land use		All land that cannot be classified (e.g., due to low-resolution imagery).

3.1.2 Indirect drivers

This research incorporates different indirect drivers as outlined in Table 3.2. These were chosen based on its significance in the reviewed studies, mainly as outlined in Geist and Lambin (2002) and Kaimowitz et al. (2002).

Table 3.2 List of the considered indirect drivers.

Category	Data	Source	Format/ Resolution	Year
Zonation	Oil palm concession zones	GFW	Vector	2018
	Wood fibre concession zones	GFW	Vector	2018
	Logging concession zones	GFW	Vector	2018
	Plantation	GFW	Vector	2018
Distance/ proximity	Road networks	Meijer et al. (2018)	Vector	2018
	Piers	BIG	Vector	
	Ports	BIG	Vector	
	Oil palm concession zones	GFW	Vector	
	Wood fibre concession zones	GFW	Vector	
	Logging concession zones	GFW	Vector	
	River	BIG	Vector	
	Oil palm mills	GFW	Vector	
Biophysical	Elevation	SRTM	Raster/90 m	2000
	Slope	SRTM	Raster/90 m	
	Temperature	WorldClim	Raster/900 m	
	Precipitation	WorldClim	Raster/900 m	
Socioeconomi c	Population, GDP, HDI, Employment	World Bank	Table	1990-2013

Zonation

Concession zones refer to areas allocated by the government or other official bodies in cultivating a particular commodity. Including such factors is an attempt to incorporate policy factors, because several studies have linked concession zones with higher deforestation rate (Abood et al., 2015; Busch et al., 2015). Concession zones for oil palm (Global Forest Watch, 2018b), wood fibre (Global Forest Watch, 2018d) and loggings (Global Forest Watch, 2018a) are gathered from Global Forest Watch's open data portal (GFW), which were initially compiled from government agencies, non-governmental organization (NGOs) and other bodies. Oil palm concession refers to industrial-scale oil palm plantations, wood fibre concession area concerns the area where fast-growing tree plantations for the production of timber and wood pulp are established, and logging concession zones refer to the area where forest exploitation is permitted through selective logging.

Tree plantation data by Transparent World and published by GFW is also considered (Global Forest Watch, 2018c). Seen from above, it is difficult to distinguish between natural forest and plantation forest. Assisted by high-resolution imagery, the dataset was made by discriminating the two types of forest through visual interpretation.

Distance/proximity factors

Distance to certain features have proved to be a determinant factor in the occurrence of deforestation (Barber et al., 2014; Kaimowitz et al., 2002; Zhang et al., 2016). Proximity factors relate to the distance of forest to a certain feature that may drive deforestation. This involves features such as infrastructures, transportation hubs, river, or concession areas as listed in Table 3.2.

Special attention is paid into transportation networks due to its significant effect in pushing deforestation (Barber et al., 2014; Miyamoto, 2006). A study by Barber et al. (2014) revealed that in the Amazon, around 95% of deforestation happened within 5.5 km from roads or 1 km from navigable rivers. Considering the importance, road networks and rivers are thus included among the factors considered. This also includes other related transportation hubs such as piers and ports. The main source of the road network data is gathered from the Global Road Inventory Project (GRIP) by Meijer et al. (2018). This data covers the road network for most parts of the country.

The oil palm mills dataset are also gathered from GFW (FoodReg and WRI, 2018). Distances from palm oil, wood fibre and logging concession zones were also calculated because deforestation tends to occur near a previously deforested area (Bray et al., 2008).

Biophysical parameters

Findings of Nakakaawa et al. (2011) and Zhang et al. (2016) found that deforestation can be correlated with specific biophysical specifications. Biophysical parameters usually determine the land suitability for a plantation or agricultural field to be established (Zhang et al., 2016). Flatlands located in lower altitude are usually considered in plantation establishment. Thus, deforestation is more likely to occur in the same land characteristics. Biophysical parameters considered in this study concerns topographic and climatic variables.

The Shuttle Radar Topography Mission (SRTM) is used as the primary source of elevation data (Jarvis et al., 2008). Using the same dataset, the slope is also calculated. The climatic variables are sourced from the WorldClim, consisting of annual mean temperature and annual precipitation (Fick and Hijmans, 2017).

Socioeconomic variables

Romijn et al. (2013) observed higher deforestation probability linked with developed socioeconomic conditions such as higher GDP and population. They are the main underlying factors that drive the landscape change in a particular area by putting pressure into land use change. The increasing population in a certain region, for example, cause the demand for food to increase thus stimulating more forest to be converted into farms because more land is needed.

In this study, an attempt to take these parameters into account is made through the Indonesia Database for Policy and Economic Research (INDO-DAPOER) (World Bank Group, 2018). INDO-DAPOER is a dataset that covers a number of economic and social indicator, compiled from various sources such as governmental institutions, and statistical bureau. A total of 220 parameters are provided, spanning across four main categories: fiscal, economic, social and demographic. From the range of variables, only four parameters are considered in this study: population, GDP (Gross Domestic Product), HDI (Human Development Index) and employment. These variables are picked by considering its completeness and relevance of the data.

3.2 Methods

3.2.1 Theoretical framework

Several researches have previously studied the spatial link between deforestation and its drivers. Literature reviews were conducted to study different methods for assessing this relationship. Most studies used either regression or classification method to explore the link of such issues.

Logistic regression was used by Kaimowitz et al. (2002) to study the deforestation in Santa Cruz, Bolivia. The study used factors such as access to roads and markets, biophysical conditions and area classification (e.g., indigenous, concession, protected). This research uses the polygon approach: by dividing the study area into predetermined classifications based on those factors. These polygons are selected carefully so that the resulting areas are not overly large since the incorporated variables are regarded homogeneous in the polygons. Thus, for each polygon, the potential explanatory variable is computed. It is then fitted to a model as a logistic model weighted by the polygon area. The result of the regression is assessed from its coefficient, t-value and significance, revealing different factors that have the most influence on the deforestation of the area.

Another study by Apan et al. (2017) employed correlation and logistic regression analysis to explore the relationship between forest cover and its predictor variables in the Philippines. Similar to Kaimowitz et al. (2002), they utilized binary logistic regression approach to estimate whether deforestation would occur or not. Factors considered include topographic, land use, land cover, population and proximity to several features (i.e., roads, river, forest canopy, and cropping areas). In contrast to Kaimowitz et al. (2002), pixel-based sampling was used rather than polygon-based.

However, they found out that their spatial predictor was not effective in predicting forest loss. A suggestion was to use as many spatial predictors as possible as outlined by Geist and Lambin (2002), also incorporating demographic, policy and cultural factors. The nation-wide analysis was also considered inefficient; reducing the spatial extent was suggested to come up with better results, so the considered factors can be site-specific.

Zhang et al. (2016) utilized a machine learning technique, i.e., random forest, to determine the factors influencing tree cover gain/loss in Li River Basin, China. They incorporate factors similar to previous researches, such as initial landscape, biophysical and proximity. Tree cover loss was then modeled for each county covering the basin and for each period. Special attention was given to the variable importance feature. This feature of random forest enables significance assessment of the incorporated factors to the model; thus, the most influential factor can be determined. Using the partial dependence plot, individual assessment of the factors in relation to the model result can also be assessed.

Considering the advantages/disadvantages of the reviewed methods, as well as the objectives aimed at this research, random forest is deemed as the most suitable method. Different factors and data can be easily incorporated using this method. Besides, the factor importance and the partial dependent plot would provide a way to answer the second research question. The overview of the data processing steps is illustrated in Figure 3.2.

3.2.2 Pre-processing

During the pre-processing step, each of the data is initially transformed/assigned the same projection system, i.e., WGS 84/World Equidistant Cylindrical (EPSG: 4087).

Zonation

Incorporating zonation into model-ready variable was done through rasterizing the data. The initial format of data is mostly vector. While converting the data into a raster format, the values assigned are binary. For example, a pixel is assigned value one if it fell inside a logging concession zone and assigned 0 otherwise.

Distance/proximity

Proximity variable was gathered from the distance raster. The values of each cell in such raster represent the closest distance of a particular pixel into a certain feature. The calculated distance is Euclidean distance: the distance from the centre of a cell into the centre of the nearest source feature cell. A total of eight distance raster were calculated, each representing different features as listed in Table 3.2.

Socioeconomic

The initial format of the socioeconomic variable was a table, thus it needs to be converted into geo-data, i.e., data with location information. Because the data was presented in district level, with the name of the corresponding region presented, georeferencing can be made. District boundary vector was gathered from the Indonesian Ministry of Home Affair. The link between the boundary vector and the table was then made through the district name, so the district boundary files are now attached with the socioeconomic data from INDO-DAPOER. Finally, the data was converted into raster format.

Biophysical

Every biophysical data was presented in a raster format. Except for the slope, every data was already ready to use. The slope was calculated from the digital elevation model, i.e. SRTM. Here, the slope was presented in degrees and was calculated considering its eight neighbouring cells using the basic algorithm of Burrough and McDonnel (1998).

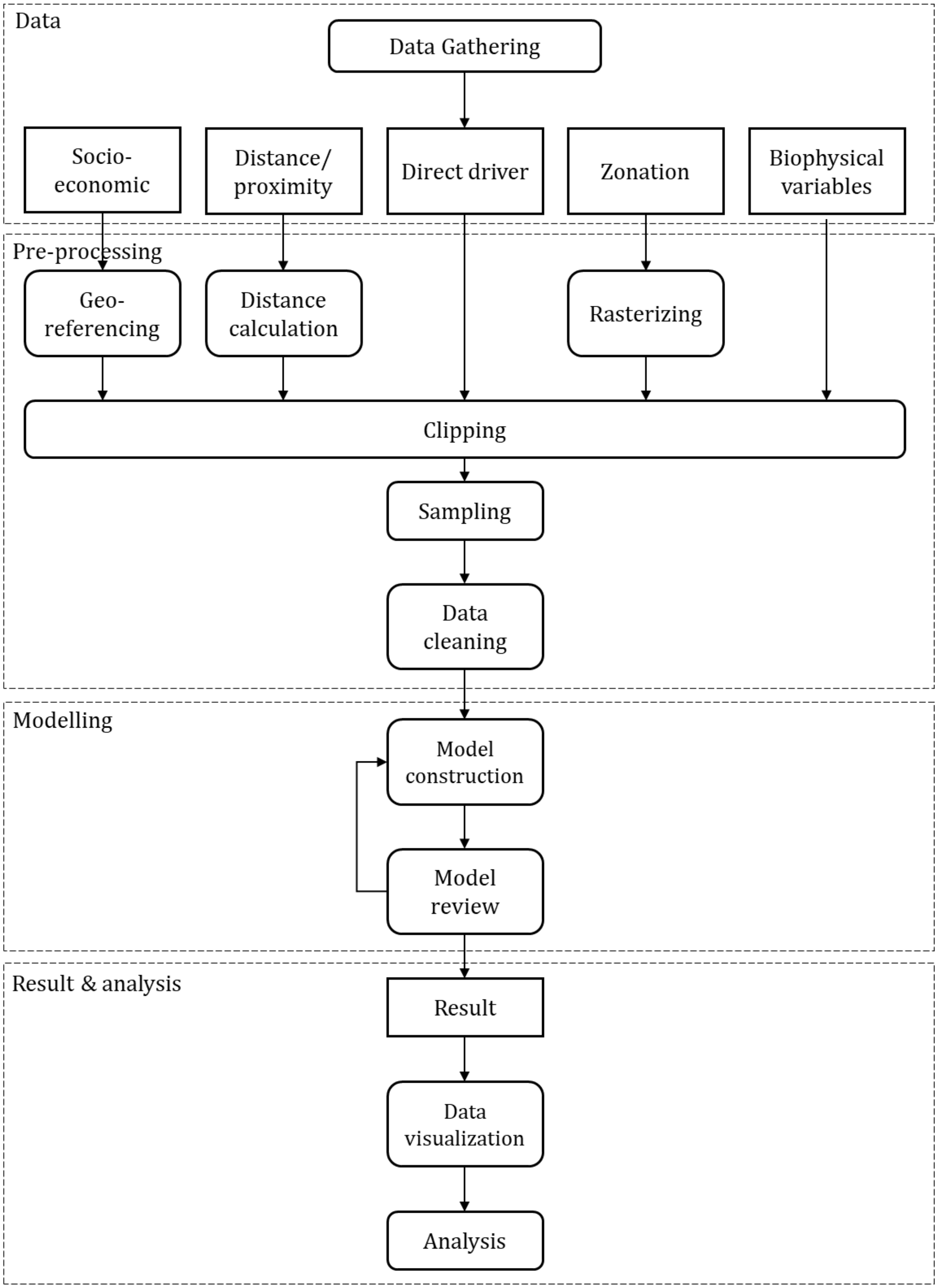

Figure 3.2 Flowchart illustrating the pipeline of the research. The research starts with gathering the data, pre-processing them, modelling, and analysis.

3.2.3 Sampling

Implementation of random forest requires the input to be presented in a data frame. With each data is now assembled in geo-data, a mechanism to sample the values from the sample units was developed, similar to Zhang et al. (2016).

Systematic, regular sampling was the method used to sample the data due to its trait in reducing spatial autocorrelation (Zhang et al., 2016). A regular grid of points with 500 m interval was distributed among the sample units (Figure 3.3). This resulted in the sample size of 44,037 records. A huge portion of the data, however, consists of NA values because not all of the data cover the whole sample areas. Any sample points containing NA values was omitted. Thus, the number of sampled data inputted into the model was much less.

Following Kaimowitz et al. (2002) polygon-based sampling was also used. Polygons representing deforestation/forest occurrence from De Sy et al. (2015) and FAO & JRC (2012) were used as the sampling polygons. The values of all pixels falling within the polygon were averaged and taken as the sampled variable.

The point-based and polygon-based sampling resulted in slightly different number of records, as shown in Table 3.3. For the point-based sampling, the proportion of the deforested and forest sample are quite balanced, while less balance is achieved in the polygon-based sampling. Almost all of the major islands in the country have its sample area consisting of deforested polygon, particularly in Sumatra, Kalimantan, Sulawesi, and Papua. However, only a small portion of the sample units in Java show deforested polygons.

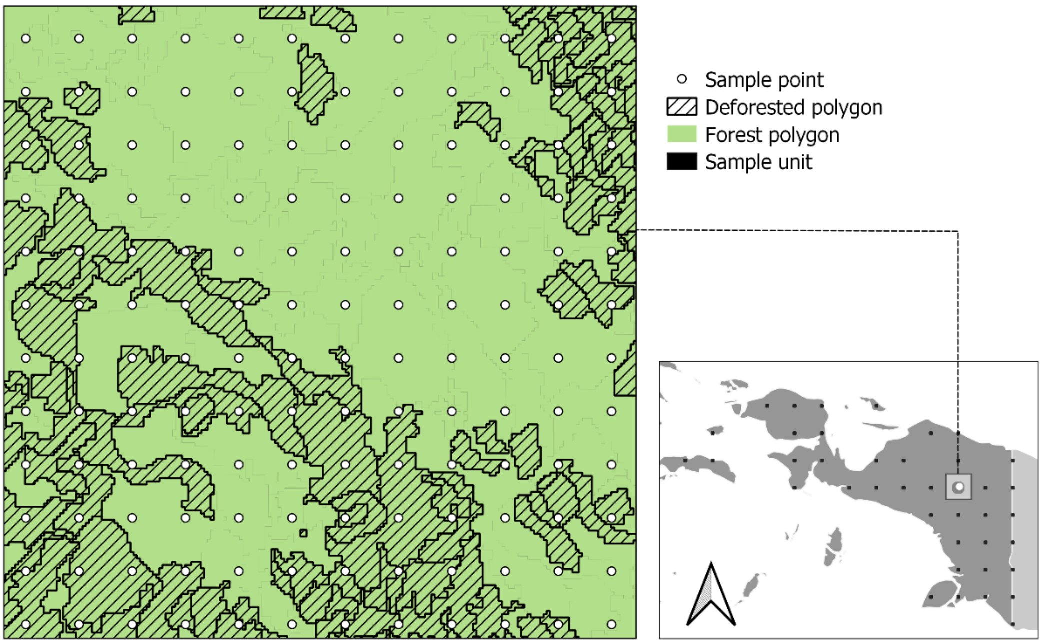

Figure 3.3 Illustration of the sampling mechanism in the existing sampling unit. The white dots indicate the sample points with the interval of 500 m. The deforested polygon is the base of the polygon-based sampling method.

Table 3.3 Overview of the sampling result. Different sampling methods return different number of records. In agriculture direct driver, only smallholders and tree crops were dominant; there was not enough sample of commercial agriculture to be considered in the models.

Category	# of features	
	Point	Polygon
All	**4621**	**4199**
Deforested	2361	2482
Non-deforested	2260	1717
Agriculture	**1311**	**1360**
Smallholder	358	409
Tree crops	955	950
Other	**1085**	**1079**
Built-up	**56**	**100**
Water	**11**	**26**

3.2.4 Random forest model

Random forest model was developed by Breiman (2001). It is a machine learning technique that constructs an ensemble of decision trees to conduct classification or prediction (regression). Random forest employs the bagging method. This algorithm is sensitive to the number of variables chosen to split the nodes (m_{try}) and the number of decision trees constructed in the model (n_{tree}).

In the first step, the algorithm constructs multiple decision trees n_{tree} (Liaw and Wiener, 2002). At the nodes of each decision tree, the algorithm use a portion of the predictors (m_{try}) by randomly sampling them. The result of every tree is then averaged, and the prediction is inferred from them.

In this research, the models would be constructed with the main aim to predict whether deforestation happened or not. Thus, the dependent variable is the deforestation occurrence. It is categorical and binary; there is only two possible value on the dependent variable, i.e., whether deforestation occurs or do not occur. The model will be constructed such that the binary value is determined by the value of other independent variables, which corresponds mostly to the indirect driver data. The number of the trees (n_{tree}) is 500 by default, and the number of randomized variables is equal to the square root of the number of available variables.

The models were constructed multiple times to accommodate 1) different sampling method (i.e., regular vs. polygon-based); 2) different variable combination and 3) detailed assessment of different direct drivers. To reach the latter, a base model needed to be constructed. Such models would built from the most effective indirect driver combination. Some measures were conducted to come up with this base model, such as variable reduction, detection of false predictor and accuracy analysis. Because not all of the considered indirect drivers might be useful, measures to detect the significance of all of the indirect drivers were also conducted so the ineffective indirect drivers can be omitted. It is also important to detect potential false predictors. Finally, the models were judged from its accuracy so that the most accurate model can be picked out.

Due to the randomization trait of random forest, each of the constructed model would produce a slightly different classification result and accuracy. To achieve a more consistent and reliable result, the averaged outcome of 50 runs of the model is used.

3.2.5 Result assessment

Assessment of the model can be made through the accuracy, and the out-of-bag (OOB) estimate error rate. During the construction of the model, the initial dataset is partitioned into 70:30 proportion of training and testing data. Accuracy shows the percentage of the validation dataset that was correctly predicted.

Each constructed tree in random forest also only utilizes around two-thirds of the observations. The remaining data is not used to fit the tree; thus, it is called *out-of-bag*. The result of the model is compared to the OOB, such that the test error can be estimated (Breiman and Cutler, 2003; James et al., 2013).

2.2.6 Variable Importance

This feature of random forest is useful to assess which variables (i.e., indirect drivers) have the most significant role in classification. During the randomized selection of variables in constructing the nodes, some variables are left out. The tree is constructed without considering the left-out variables. After running the model, the trees are rerun by also considering the left-out variable to produce another classification result. The result are then compared with the original classification results, typically resulting in a margin: the proportion of votes for its true class minus the maximum of the proportion of votes for each of the other classes (Breiman and Cutler, 2003). The importance was measured by averaging the lowering of the margin across all cases when a particular variable is permuted. The larger the margin means, the more important a variable is. If that particular variable is left out, the classification accuracy will greatly decrease.

Feature importance can also be measured through the Gini index, i.e. the measure of the purity of a node. A smaller value indicates that a node is pure; the result of a single dominant observation (James et al., 2013). Therefore, a split on the classification tree will decrease the gini. Averaging all of the decreases in the forest caused by a particular variable thus produce the Gini measure. Although it is known to be not as reliable as the former measure, this feature may still be useful in assessing the importance of a variable (Breiman and Cutler, 2003).

2.2.7 Partial Dependence

Partial dependence plot is method to show the effect of a feature into the outcome of a machine learning model (Friedman, 2001). In this research, this plot can show the effect of a particular indirect driver in predicting deforestation occurrence. Partial dependence plot is visualized in a 2-axes graph. The x-axis depicts the independent variable of interest. In the case of classification, the y-axis shows the marginal effect of a variable on the class probability (Breiman et al., 2011). A positive value suggests that the particular value of the independent variable is more likely to corresponds with the positive class of the dependent variable, and vice versa.

3.3 Software

Most of the data processing and analysis were conducted within R (R Core Team, 2018). R is a programming language which provides an environment for statistical computing and graphics. Pre-processing, spatial data handling, and data visualization were implemented in R using relevant packages. Implementation of random forest was done through the ‘randomForest’ and ‘caret’ package (Kuhn, 2008; Liaw and Wiener, 2002). In addition to model implementation, those packages were also utilised to review the model, such as getting the model accuracy as well as assessing the variables in detail. These assessments were visualised using package ‘ggplot’ (Wickham, 2016).

4. Results

4.1 Statistical properties of the indirect drivers

Table 4.1 presents the statistical overview of the indirect drivers. These statistics are only computed for continuous indirect drivers (i.e., proximity, socioeconomic and biophysical); categorical indirect drivers (i.e., zonation) is left out. In general, no significant difference is observed between different sampling methods. Notable differences are only observed in indirect drivers with high standard deviation, such as distance to palm oil mills and GDP.

The average distance to both roads and rivers suggests that most of the deforestation happened within 3-5 km proximity from these features. A similar pattern is also observed in distance to concession zones: deforestation is more common in forests closer to concession zones (Table 4.1). However, different observation is noticed in the distance to palm oil mills and piers. For the point-based sample, the average distance to those variables suggests that deforestation is more common in forests further away from palm oil mills and piers, although the standard deviation themselves are relatively high.

As suggested by its high standard deviation, the socioeconomic variables tend to have high variations. The histograms (Figure 4.1) show that the value tend to spread out, thus confirming this finding. Notable gaps and patches are evident particularly in GDP and HDI. The only socioeconomic variable with low standard deviation is the HDI. Different sampling methods show the same average HDI of 70, either for forest or deforested area. Different observations for different sampling methods were also observed. For GDP, polygon-based sample shows deforested area is correlated with higher GDP (2642 bil. compared to 2884 bil. on the forested area), while the point-based sample shows the opposite (2515 bil. compared to 2450 bil. on the forested area).

Average precipitation suggests that deforestations are commonly occurring in areas where the precipitation rate is higher (around 2700 mm/year compared to 2550-2600 mm/year for forested area). The standard deviation of this variable is also relatively low (around 370-400 mm/year), suggesting that there is less variation. Looking at the elevation, point-based sample suggests that deforestation tend to occur in higher altitudes (121 m for forest, 160 m for deforested), while polygon-based sampling shows the opposite (204 m for forest, 188 m for deforested). There is no significant difference noted between forest/deforested region in temperature and slope. The average temperature for both forest and deforested area is circa 26°C, and the slope is around 3-5° steep.

Table 4.1 Statistical properties of the (a) point-based sampled and (b) polygon-based sampled indirect drivers. These overviews seem to agree with the initial assumption, except for some (greyed-out) variables. The deforested region was initially assumed to be associated with higher socioeconomical properties and closer to the human-made structures.

(a)

Category	Variable	Mean		Standard Deviation	
		Forest	Deforested	Forest	Deforested
Distance	Concession logging (km)	81.2	66.8	77.7	55.7
	Concession palm oil (km)	36.1	16.3	50.3	30.1
	Concession wood fibre (km)	83.4	39.1	204.2	74.3
	Palm oil mills (km)	89.4	97.5	165.6	211.7
	Piers (km)	53.6	65.7	45.9	61.0
	Ports (km)	79.4	62.5	47.9	43.8
	River (km)	7.6	5.3	5.3	3.8
	Roads (km)	7.7	3.1	8.3	4.9
Socioeconomic	GDP (IDR billion)	2884.5	2642.2	2398.5	2929.6
	Population	423,737	319,552	276,052	220,539
	HDI	70	70	3	4
	People employed	168,308	135,398	98,571	85,964
Biophysical	Precipitation (mm/year)	2,569	2,703	373	390
	Temperature (°C)	26.3	26.1	15	19
	Elevation (m)	121	160	279	389
	Slope (°)	3	3	5	6

(b)

Category	Variable	Mean		Standard Deviation	
		Forest	Deforested	Forest	Deforested
Distance	Concession logging (km)	74.0	63.4	78.3	56.6
	Concession palm oil (km)	36.8	17.9	47.6	33.9
	Concession wood fibre (km)	82.1	42.4	183.6	89.9
	Palm oil mills (km)	123.1	104.5	243.5	230.1
	Piers (km)	60.8	65.0	54.5	56.6
	Ports (km)	79.7	64.1	49.1	47.2
	River (km)	7.1	5.0	4.8	3.9
	Roads (km)	8.5	3.3	8.5	5.3
Socioeconomic	GDP (IDR billion)	2450.6	2515.2	2099.3	2624.8
	Population	367,692	324,067	266,800	218,305
	HDI	70	70	3	5
	People employed	148,700	138,314	96,265	86,465
Biophysical	Precipitation (mm/year)	2,631	2,725	451	402
	Temperature (°C)	25.9	26	21	21
	Elevation (m)	204	188	386	416
	Slope (°)	5	4	7	6

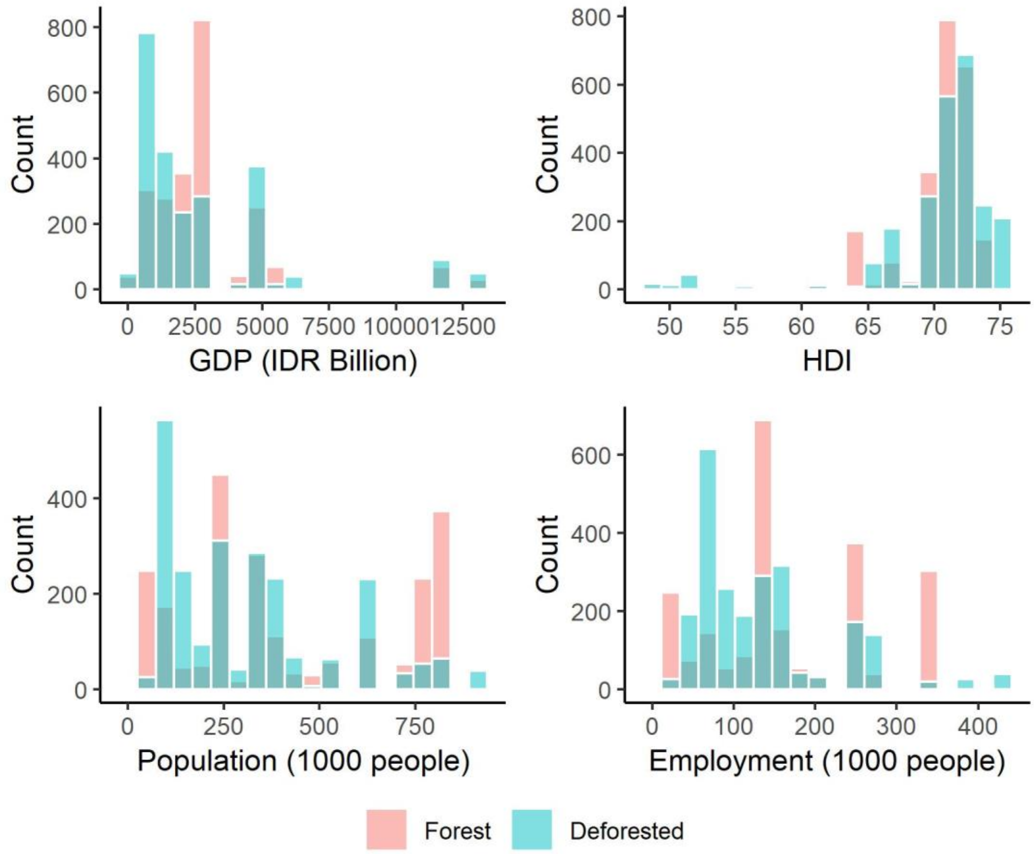

Figure 4.1 Histogram of the point-sampled socioeconomic variables. Discrete distributions are observed, especially in GDP and population.

4.2 Model construction

The base model was determined by trying out different combination of indirect drivers (Table 4.2). In total, three different combinations were tested to come up with the base model. These combinations were determined according to the significance of each indirect driver. Potential false predictor was also left out.

The model was initially constructed by incorporating all of the indirect drivers listed in Table 3.2. Using these 20 indirect drivers, the significance of each considered indirect driver is assessed from its average decrease of accuracy when the particular indirect driver is removed from the model. As can be seen in Figure 4.2, both sampling methods agree that the zonation indirect drivers are among the least significant predictors in the model. This is followed by the socioeconomic indirect drivers, putting both categories among the candidate of the removed indirect drivers.

A detailed assessment of precipitation suggests its role as a potential false predictor, as identified from Figure 4.3. This partial dependence plot suggests that deforestation seem to happen within a specific precipitation rate of 2700 mm. Downward spike around 2500 mm precipitation rate also suggest another specific value for forest area. While these values coincide with the average precipitation rate indicated in Table 4.1, the overall shape of the curve shows no variation; indicating strong evidence of false predictor.

The base model is thus constructed by removing these categories of indirect drivers: zonation, socioeconomic and precipitation (Table 4.2). Each combination is tested on both point-based and the polygon-based sample. Accuracy is used to judge the model rather than the OOB error estimate, because between different models, there are only minor differences on the OOB error estimate.

Overall, the models return good results with low error rate and high accuracy. As depicted in Table 4.3, point-based models always return higher accuracy and lower OOB error estimate. Around 2% difference of error estimate is observed between the two different sampling methods, while the accuracy returns about 3% discrepancy. Excluding zonation and precipitation saw an increase of accuracy by 0.08% in the point-based model but a decrease of 0.33% for the polygon-based model. Further removal of the socioeconomic variable was able to recover the accuracy by 0.14% in the polygon-based model. A slight increase of 0.02% is also observed in the point-based model. All things considered, Model 3 is thus selected as the base model. Although accuracy-wise the polygon-based model does not return the best accuracy, including false predictor is deemed to produce biased result.

Using model 3 as the base model, four different direct driver-specific models were constructed: 1) agriculture, 2) other drivers, 3) smallholder agriculture and 4) tree crop agriculture. The last two models are constructed to assess the indirect drivers of agricultural-driven deforestation in detail. The accuracy of these models is listed in Table 4.3. In all cases, the models are able to reach relatively high accuracy. It appears that the effect of different sampling method is reduced here with both sampling method returning similar accuracy; even the polygon-based model is more accurate than its counterpart. In contrast to its base models, notable differences can be observed on the OOB error estimate between the different direct driver models.

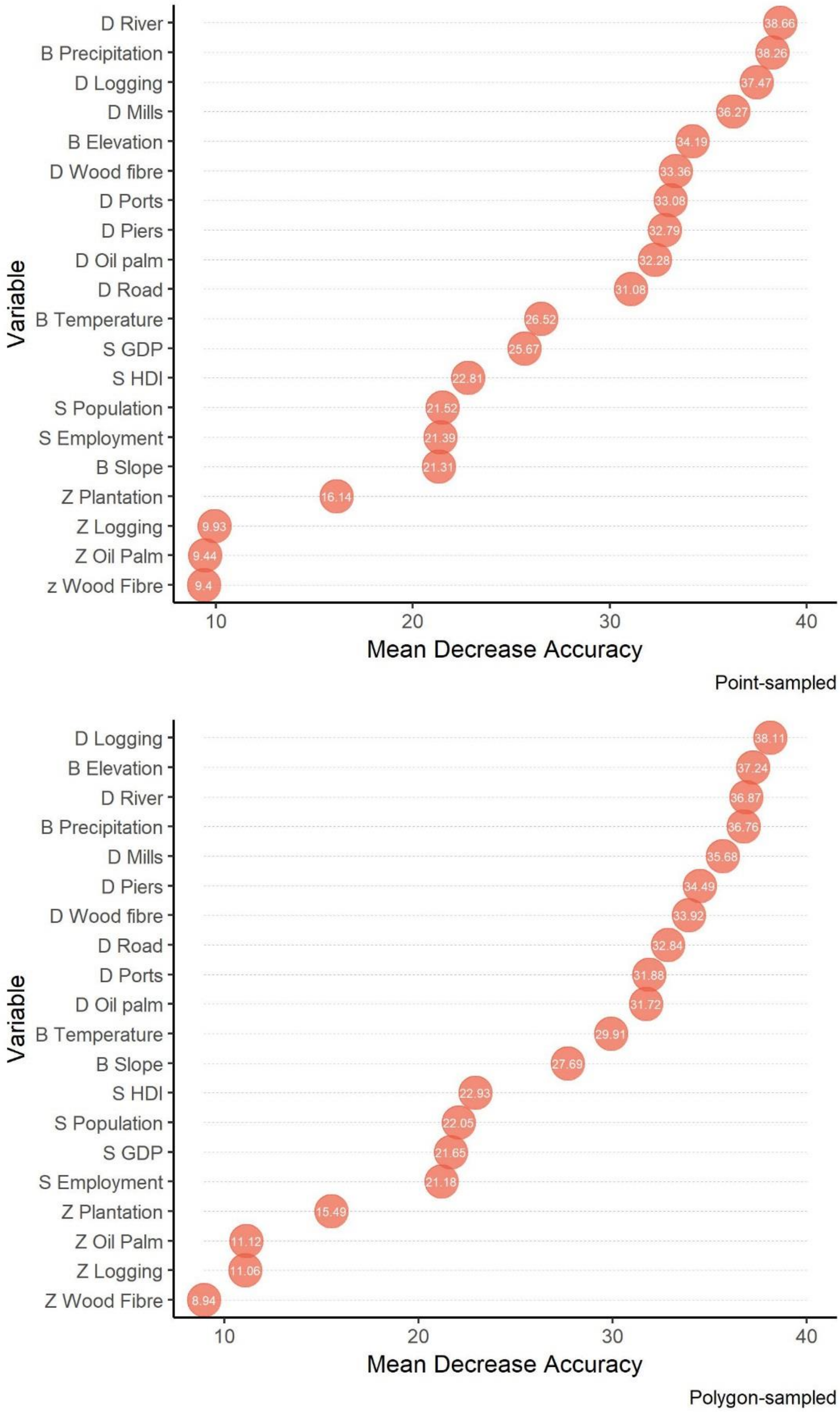

Figure 4.2 Variable importance plot for model 1 applied to (a) point-based sample and (b) polygon-based sample.

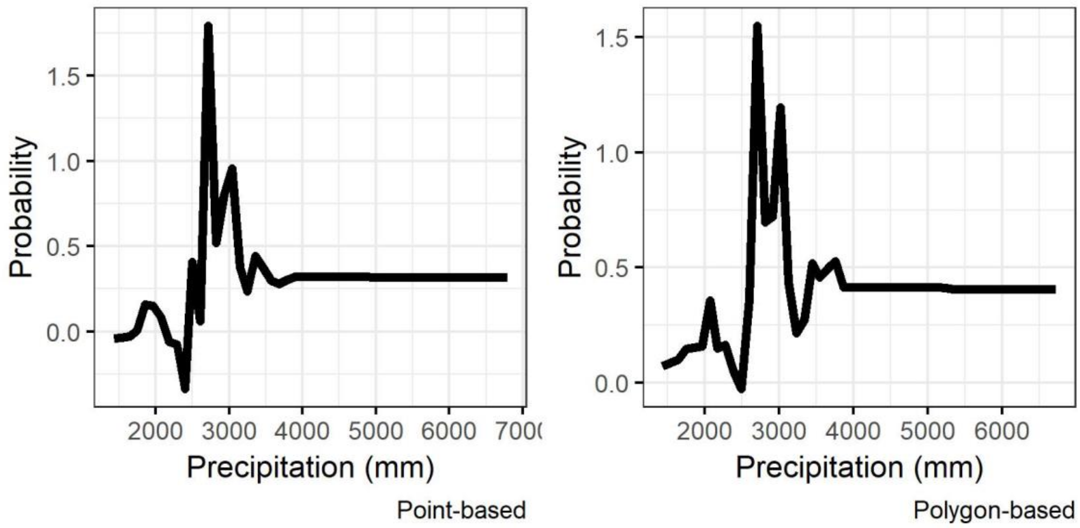

Figure 4.3 Partial dependence plot of precipitation.

Table 4.2 Variable combinations of each random forest model.

Variables			Model 1	2	3 (Base)	Agri	Small	Treecrop	Other
Driver	Agriculture	Smallholder	✓	✓	✓	✓	✓	×	×
		Tree crop					×	✓	×
	Other					×	×	×	✓
Zonation	Concession logging		✓	×	×	×	×	×	×
	Concession palm oil								
	Concession wood fibre								
	Plantation								
Distance	Roads		✓	✓	✓	✓	✓	✓	✓
	River								
	Ports								
	Piers								
	Palm oil mills								
	Concession logging								
	Concession palm oil								
	Concession wood fibre								
Socioeconomic	Population		✓	✓	×	×	×	×	×
	GDP								
	HDI								
	Employment								
Biophysical	Elevation		✓	✓	✓	✓	✓	✓	✓
	Slope			✓	✓	✓	✓	✓	✓
	Precipitation			×	×	×	×	×	×
	Temperature			✓	✓	✓	✓	✓	✓

Table 4.3 Overview of model accuracy. Because there are not many variations on the OOB error estimate between the model, the accuracy is used as the main judgement of the model.

Model	OOB		Accuracy (%)	
	Point	Polygon	Point	Polygon
1	5.92%	7.66%	95.12%	92.56%
2	5.94%	7.64%	95.20%	92.23%
3 (Base)	5.96%	7.64%	95.22%	92.37%
Agriculture	3.72%	4.39%	96.21%	95.18%
Smallholder	5.37%	5.30%	93.57%	96.41%
Tree Crop	2.99%	4.11%	97.91%	97.33%
Others	6.23%	6.75%	94.59%	92.78%

4.3 Direct driver models

4.3.1 Variable importance

The overview of variable importance for the direct driver-specific models is visualised in the heatmap in Figure 4.4. A detailed depiction of these are also visualised in variable importance plot in Annex A. Between different direct drivers, variations of the order of the most significant indirect drivers are spotted, indicating that specific circumstances are only revealed when analysing the direct drivers in detail. In general, all of the models agree that distance to palm oil mills is always among the most important, and slope is always the least important. Other important variables include distance to roads and elevation. It can be seen that in the base model, the mean decrease accuracy tends to be in a higher value, while splitting the direct drivers into specific categories result in lower mean decrease accuracy.

In agriculture-driven deforestation, different magnitude of mean decrease accuracy is identified between different sampling methods, but the composition of the top-5 indirect driver stays the same. It includes elevation, distance to piers, palm oil mills, river, and roads. Looking into specific agricultural direct drivers, smallholder agricultures seem to be related to the presence of roads and river. On the other hand, tree crop agriculture is most prominently related to the distance to palm oil mills, followed by distance to roads and logging concession zones.

Both sampling methods agree that other direct drivers are associated with the distance to palm oil mills. Compared to other models, biophysical parameters (i.e., elevation and temperature) seem to take more importance in this model. Other significant indirect drivers include distance to logging concession zones and distance to ports.

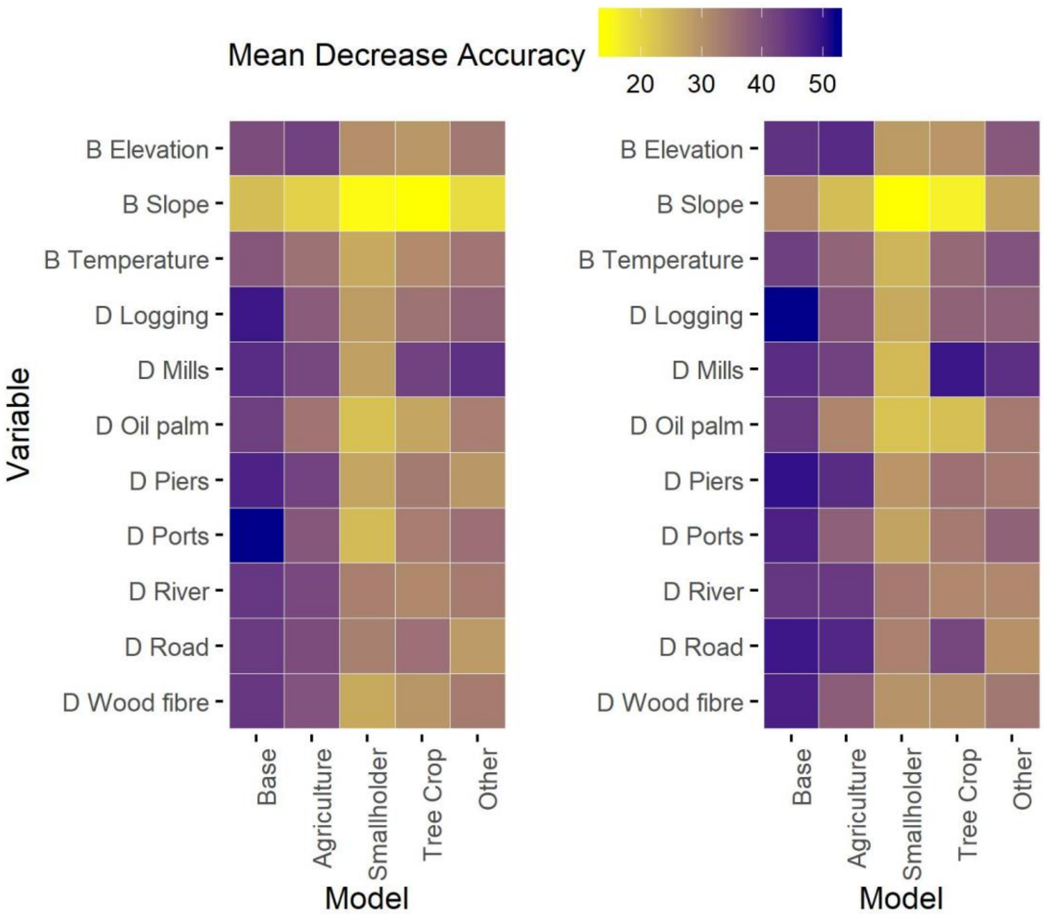

Figure 4.4 Heat map of variable importance of (a) point-based model and (b) polygon-based model. The heatmap is coloured based on the mean decrease on accuracy when a particular variable is removed. A higher value corresponds to a more important variable.

4.3.2 Partial dependence

The partial dependence plots (PDP) of the most significant indirect drivers are presented in Annex B. When interpreting the PDP, we are interested mainly with the trend of the graph and the value of the x- and y-axis (Friedman, 2001; Sharma, 2017). In this research, the y-axis shows how the likelihood of deforestation is changing with the change in the given indirect driver (shown in the x-axis). Positive y-axis value means for that particular value on the x-axis, the model is likely to predict deforestation. Negative value indicates the opposite. If the y-axis value is zero, that particular indirect driver has no effect in the prediction outcome.

Clear trends are observed in the PDP of distance to road and distance to river. These PDPs suggest that deforestation is more likely to occur nearby roads or rivers. The farther a forest is from roads or river, the less likely deforestation to occur. Breaking up the data into specific direct driver revealed that distance to roads and rivers have the strongest effect in predicting deforestation in the tree crop and other direct driver.

Different breakpoints (i.e. where the line crosses the x-axis) are observed between different direct driver models, suggesting different effect of roads and rivers to specific direct drivers. This might indicate the distance where the presence of a certain feature loses its effect in constituting deforestation. For roads, it is observed that smallholder agriculture and tree crop agriculture have lower breakpoint (< 5000 m) compared to other direct driver. Higher breakpoints are observed in the distance to river, ranging from 5000-7500 m, with smallholder agriculture has the lowest breakpoint (around 5000 m). For both roads and rivers, it is also noted that the peak probability is achieved circa 1000-1500 m. This might suggest that deforestation does not necessarily occur right beside the road/river, but at a certain distance from it.

Although analysis of the variable importance plots previously signified the importance of distance to palm oil mills, the pattern indicated in its PDP is not as obvious as expected. Relative to the base, agriculture and smallholder model, distance to palm oil mills is only apparent in deforestation driven by tree crop agriculture (in 0-30 km) and other driver (> 25 km).

The PDP of both distance to ports and distance to piers suggest that they have a mixing effect on the deforestation occurrence. The effect of distance to port in predicting deforestation is apparent within 0-25 km distance, while the effect of piers is notable within 50-60 km distance. For both indirect drivers, the effect is strongest in the tree crop and other driver model. Smallholder-driven deforestation is only slightly affected by the distance to pier.

In the biophysical variables, specific pattern is again only revealed in the direct driver-specific models. The base, agriculture and other direct driver model initially show no significant pattern; the pattern is only revealed when looking into specific categories of agriculture. Smallholder-driven deforestation is more likely to occur in higher elevation (> 500 m) and in temperature range of 20-24°C. Tree crop-driven deforestation is more likely to happen in lower altitudes (100-250 m) and warmer temperature (25-26°C).

5. Discussions

5.1 Overview

This research assessed the link between the direct and indirect drivers of deforestation. Models were initially constructed using two different sampling methods, i.e., point and polygon-based sample. These two methods result in different accuracy and in general, the point-based sample was able to deliver the higher accuracy. This might be addressed to the trait of the sampling methods. In handling large areas, polygon-based sampling would average the value of the whole area, thus generalizing the variables. In contrast, point-based sampling is able to sample the extremes: higher/lower value would not be dissolved. Despite this, similar trend and pattern are still observed in the variable importance and partial dependence plot. Between the two different sampling methods, the composition of the most important variable, as well as its marginal effect are still comparable.

All in all, initial assessment at the direct driver data suggests that most deforestation in Indonesia is directly driven by agricultural and other direct drivers. Contrasting order of importance of the indirect drivers are apparent when comparing the variable importance plot of different models, suggesting that general deforestation model (i.e. base model) do not always reflect the pattern shown in the driver-specific model. Apparently, these hidden patterns are only revealed by constructing the model based on the specific direct driver. Some of the most important findings are described below.

5.2 Palm oil as a driver of deforestation

Though it does not always rank as the most important variable, the consistent significance of distance to palm oil mill in each of the constructed model signifies the role of palm oil in constituting deforestation. This finding seems to confirm the long-growing perception of palm oil as a cause of deforestation in Indonesia. Koh and Wilcove (2008) estimated that at least 56% of palm oil expansion in Indonesia is established in a formerly natural forests-lands. A regional analysis in Southeast Asia found that at least 45% of the palm oil plantations in the region were originally forests (Vijay et al., 2016). This role is also underlined by Indrarto et al. (2012) in CIFOR's Indonesia country report, where a five-fold increase of palm oil estate area in the 90s was observed: from 1,652,301 ha in 1989 to 8,204,524 ha in 1998 (Sawit Watch, 2009).

The significance of distance to palm oil mills is particularly apparent in the tree crop and other driver model. In both models, this variable ranks as the most important variable with a clear gap of mean decrease accuracy value with the other variables. This provides a compelling evidence that the tree crops in Indonesia is dominated by palm oil. While in the data the scale of plantation is not distinguished, this palm oil-related deforestation is most likely be dominated by large scale plantations. In their study, Lee et al. (2014), found that in Indonesia, deforestation leading to palm oil establishment are mostly driven by large-scale palm oil industry (89.2%), in contrast to smallholder (10.7%).

Distance to palm oil mills also acts as an important variable in the other driver models. Looking at the data into detail, most of the other direct drivers here refer to other wooded lands, mainly consisting of degraded forest and shrubs. The strong presence of distance to palm oil mills in the other driver model suggests that these abandoned lands are eventually turned into palm oil plantations in the following years.

Several explanations can be attributed to this. First, it might be related to the establishment of new moratoriums. While the demand for palm oil keeps on increasing, the establishment of new moratoriums in 2010 prohibits local governments for granting new concession licenses (Busch et al., 2015). This makes it harder for farmers to clear new forests. However, this moratorium was often criticised, one of them for not covering the secondary (degraded) forest (Murdiyarso et al., 2011). Exploiting existing degraded forest or cleared land might be seen as the most reasonable option; thus providing a strong explanation of this finding (Sheil et al., 2009).

Second, it is possible that this other land use is merely a step in the land use change process. Boucher et al. (2011) outlined that forest logging is often followed by the establishment of palm oil plantations. This is further confirmed by Romijn et al. (2013) whose study found out that around 25% of open and degraded lands are eventually converted into commercial agriculture. This is related to the third explanation, the result of misused concession licenses for establishing plantations (Romijn et al., 2013). Many companies used this license merely to clear the forest, sell the timbers, and then abandon the lands. These wastelands, as referred by WWF Indonesia (2008), are then abandoned, covered by shrubs before eventually converted into palm oil plantations.

It is interesting to note the biophysical pattern found on the tree crop driver. The peaks shown on the PDP of temperature and elevation correspond with some biophysical suitability of palm oil. During their study in mapping palm oil suitability across Indonesia, Pirker et al. (2016) used similar parameters, such as by setting the optimum temperatures between 24-28 °C. Gingold et al. (2012) described altitudes below 500 m as 'highly suitable' for palm oil plantations. While such biophysical variables are not the most determinant variable in characterising palm oil plantations (thus relating it to deforestation), it can be useful to a certain extent (Vijay et al., 2016).

Vijay et al. (2016) emphasised the need to "not relying solely on biophysical requirements" to characterise palm oil expansion. They suggested to include proximity to infrastructures to come up with better characterisation. These transportation infrastructures (i.e., roads) rank amongst the important variables in the tree crop model, thus confirming Vijay's hypothesis.

5.3 Role of smallholder agriculture

The composition of the variable importance in smallholder model suggests that the circumstances are more complex than in the tree crop agriculture, where palm oil is the lone dominant direct driver. Here, distance to roads and rivers, as well as elevation play a much greater role than palm oil mills. This is expected, as the categorization of smallholder agriculture on the data does not include palm oil plantation. Hence, other circumstances play a greater role here.

Lee et al. (2014) outlined that expansion of smallholder agricultures in Indonesia cover various commodities such as rubber plantation, rice fields or rattan garden. The biophysical variables attributed to smallholder agriculture tend to spread out and does not specifically point out on a specific value, unlike the ones observed in the tree crops model. The temperature ranges from 16-24 °C, and it tends to present in higher elevation (500-2000 m). This suggests that the variety of commodities can be very diverse. Rice might be preferred in the lowlands, while in the highlands cash crops (e.g., coffee and tea) is also common (FAO, 2005). Perennial crops such as rubber tree are quite versatile, and it has been associated with shifting agriculture practice, i.e., slash and burn system especially in the highlands (FAO, 2005).

5.4 Direct and indirect drivers of deforestation in Indonesia

Constructing specific direct driver models produced different level of importance of indirect drivers. For each direct driver, different indirect driver tends to also have different marginal effect. These variations suggest that there are some links that are specifically related between each direct and indirect driver.

The first link is notable from the transportation networks. In general, Miyamoto (2006) outlined the strong role of road networks in determining deforestation is because roads provide accessibility, thus reducing transportation cost and time of logistics. The role of roads as a driver of deforestation is not new, and numerous studies have previously emphasised the role (Barber et al., 2014; Miyamoto, 2006; Zhang et al., 2016). However, it is interesting to note that in this research, the marginal effect of distance to roads is only most apparent in the palm oil-related direct drivers (i.e., tree crops and other direct drivers), and not in the smallholder direct driver. A possible explanation of this might be related to the ability of large-scale palm oil industry to establish their own 'unofficial' road networks.

In their study, Barber et al. (2014) outlined that in addition to major roads, the presence of 'unofficial' road networks can amplify the risk of deforestation. These roads were built without official supervision and incentives from the government (Arima et al., 2005; Brandão and Souza, 2006). In Indonesia, these roads are frequently established near areas with vulnerable forests and agriculture activities (Sloan et al., 2018). In contrast to smallholder agricultures that utilize existing 'official' road networks, large-scale plantations might possibly establish their own road network, thus explaining the significant marginal effect of distance to roads in tree crop and other direct driver.

Another link can be found in the role of distance to river. The role of river as a predictor of deforestation has been underestimated in previous studies (Barber et al., 2014; Laurance et al., 2002). However, this finding suggests that distance to rivers is particularly important in predicting deforestations driven by smallholder agricultures. This might be attributed to the farming system in Indonesia. Most of the farm system in Indonesia is rain-fed agricultures, i.e., they rely on rain to irrigate the field. Additionally, a relatively big portion (31.5%) of them uses irrigation system; utilizing natural freshwater sources such as rivers and lakes to irrigate the crops (Devendra, 2016).

According to the CIA's World Factbook, Indonesia has over 67 km^2 of irrigated farmlands, the 6th highest in the world (Central Intelligence Agency, 2009).

There is not enough evidence on the common use of navigable river as a mean of transportation and logistics of agricultures, especially in Indonesia. In Indonesia, rivers are only a common means of transporting extracted woods after deforestation (Bauch et al., 2007; McCarthy, 2002).

5.5 Implications for REDD+

Detailed information regarding drivers of deforestation is vital for REDD+ activities to succeed. While addressing these drivers are beyond the scope of this study, the methods presented in this research have demonstrated an approach to analyse the link between direct and indirect drivers of deforestation in Indonesia. Merely analysing deforestation as a general model is deemed inadequate, because our results show that specific link to indirect drivers are only revealed in the direct driver-specific models. This implies the need of detailed direct driver data as a prerequisite.

Prior studies have utilized land uses following deforestation as a proxy of direct driver data (De Sy et al., 2015; Hosonuma et al., 2012). The present study has demonstrated the usability of such proximate direct driver in linking them with indirect driver data. This opens up a way to potentially analyse the link between direct and indirect drivers in greater scale and greater detail. To achieve this, one may use detailed forest cover change (Hansen et al., 2013a) or temporal land cover data (Bontemps et al., 2013; Jun et al., 2014). The advances in earth observation system has also open up ways to detect forest disturbance in near real-time, thus providing even more detailed data (Popkin, 2016; Verbesselt et al., 2010). Detailed information on the link between direct and indirect drivers can therefore help the countries in setting up their national strategies to effectively address the drivers of deforestation.

5.6 Limitations and recommendations

5.6.1 Potential bias in variable importance and partial dependence plot

Random forest has been popularly used in geospatial domain. However, one should consider some limitations in the method, especially during the interpretation of the variable importance (Okun and Priisalu, 2007). Strobl et al. (2007) pointed out that the algorithm's variable importance measures can be unreliable when "potential predictor variables vary in their scale of measurement or their number of categories". Gislason et al. (2006) also outlined the insensitivity of this method when dealing with noise and overtraining. The false predictor role of precipitation in this research demonstrated this potential bias.

This research attempted to overcome this issue by making comparisons of the results to preceding studies. While some of our results produce sensible outcomes, this might explain the insignificant role of several variables throughout different models. Critical assessment is thus a necessity in interpreting the results. Several studies have developed improved random forest algorithm to tackle this issue, therefore future studies might be directed into implementing such improved algorithms (Strobl et al., 2007; Zhang and Lu, 2012).

Molnar (2018) outlined several disadvantages of Partial Dependence Plot (PDP) to be considered when interpreting such plots. First, PDPs do not show distribution. For example, there might be some regions of the graph with actually no data that is represented as straight line in the plot. This might lead to false conclusions. Second, PDPs assume the independence of the assessed variable (i.e., indirect driver). This plot assumes that one indirect driver is not correlated with another indirect driver. In reality, this is mostly not the case. For example, population and economic growth often have positive correlation (Geist and Lambin, 2001).

5.6.2 Socioeconomic variables

Prior studies have indicated the importance of socioeconomic variables in modelling deforestation, such as by incorporating GDP, population and employment rate (Kissinger et al., 2012; Romijn et al., 2013; Vijay et al., 2016). An attempt to incorporate these variables was made by using data from World Bank Group (2018). However, the socioeconomic variables always rank low in the variable importance plot. There are several possible explanations.

First, it is possible that the socioeconomic variables are simply not of importance in the model. The effect of these variables in influencing deforestation might be too complex for random forest to model, as the effect of socioeconomic variables in deforestation is not very straightforward.

Second, this might be attributed to the quality of the data. Presenting the data in district level means assuming that every area of a district is homogeneous, having the same value. In reality, this is not always the case; the different neighbourhood of a city, for instance, would always have different population densities. The same case applies to other socioeconomic variables such as HDI or GDP. In spatial analysis, one way to present continuous data is through raster. With each pixel representing a snippet of an area, a specific value can be attributed to them. Currently, such gridded socioeconomic data is rare; even if there is any, they are often presented in poor resolution, and the range of the available socioeconomic variable is limited such as the population estimate grid produced by NASA SEDAC (Socioeconomic Data and Application Center).

5.6.3 Categorical variables and other potential drivers

Seen from the variable importance across the models, in general, categorical (i.e., binary) variables are not good predictors of deforestation. Initially, these variables were expected to be able to represent the concession zones, as one of the policy factors governing deforestation. The considered concession zones in this research are the main industrial causes of deforestation in Indonesia, i.e. palm oil, wood fibre and logging (Abood et al., 2015). In fact, between these three industries, palm oil is actually the direct driver with the least impact in terms of forest loss between 2000-2010. Fibre plantation and logging have greater disturbance, responsible for 1.9 Mha and 1.8 Mha of forest loss, respectively.

Excluding these variables means that they are not represented well in the model. As a result, detailed assessment of the drivers was only able to be conducted on palm oil, because the distance to palm oil mills seems to be very decisive in constructing the model. In future studies, it is suggested to include also variables related to the other drivers. Continuous, rather than categorical variable would be recommended. Potential features may include, for example, distance to pulp factories or logging mills.

6. Conclusions

The present study was conducted to assess the link between direct and indirect drivers of deforestation in Indonesia. Random forest-based spatial analysis of deforestation drivers revealed that factors affecting different direct drivers could vary. In general, tree crop driven deforestation is dominated by palm oil; particularly in large scale tree plantations and is linked with the presence of palm oil mills and roads. In contrast to the tree crop direct driver, the smallholder direct driver does not point out to a specific crop type; it is rather a complex driver and may be associated with different categories of agriculture, such as cash crops, perennial plants or swidden agriculture. In addition to roads, smallholder agriculture is linked with the distance to river as its underlying driver of deforestation.

Although some results have indicated specific biophysical characteristics for specific direct drivers of deforestation, biophysical variables are less determinant compared to the distance variables. The significance of socioeconomic variables as underlying driver of deforestation was also not observed in this study.

The method proposed in this study can possibly be extended to greater level of detail, such as to be implemented in nation-wide monitoring. This implies the need of detailed direct driver data, so that the deforestation can be distinguished. Future studies might be directed into producing and including continuous socioeconomic variables. Including more factors concerning other potential indirect drivers (i.e., logging and wood fibre) would also be useful. Due to the lack of data, this study has not been able to analyse in detail regarding smallholder agricultures. Given its dominant role, one can conduct detailed spatial analysis specifically in this type of agriculture to reveal the hidden circumstances, e.g., the specific types of crops that cause deforestation.

Nevertheless, this study demonstrated the utilization of spatial analysis in analysing deforestation. Proximity and spatial distribution are among the spatial properties of forest clearing, and spatial analysis can be a useful instrument in studying deforestation. The findings made in this study can contribute to countries in setting up effective and efficient REDD+ strategies.

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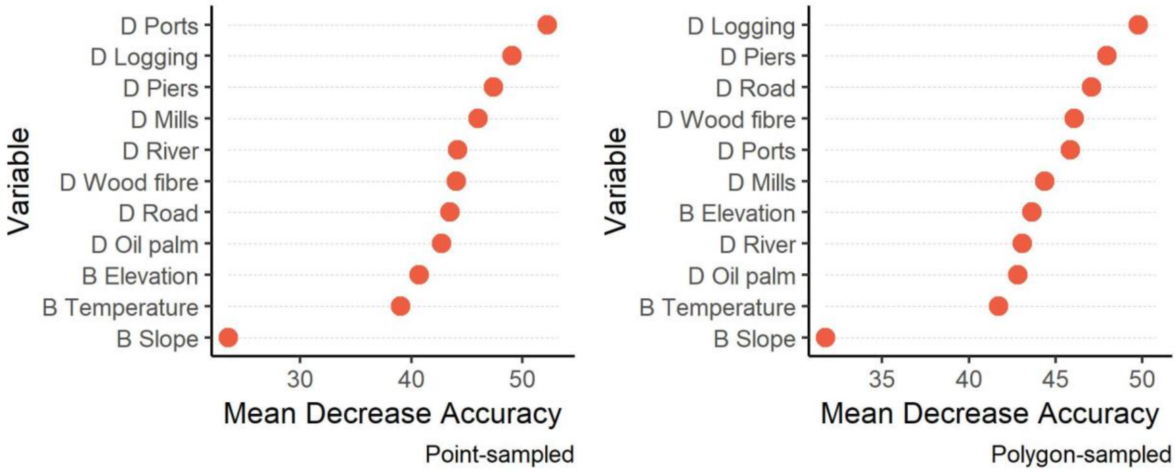
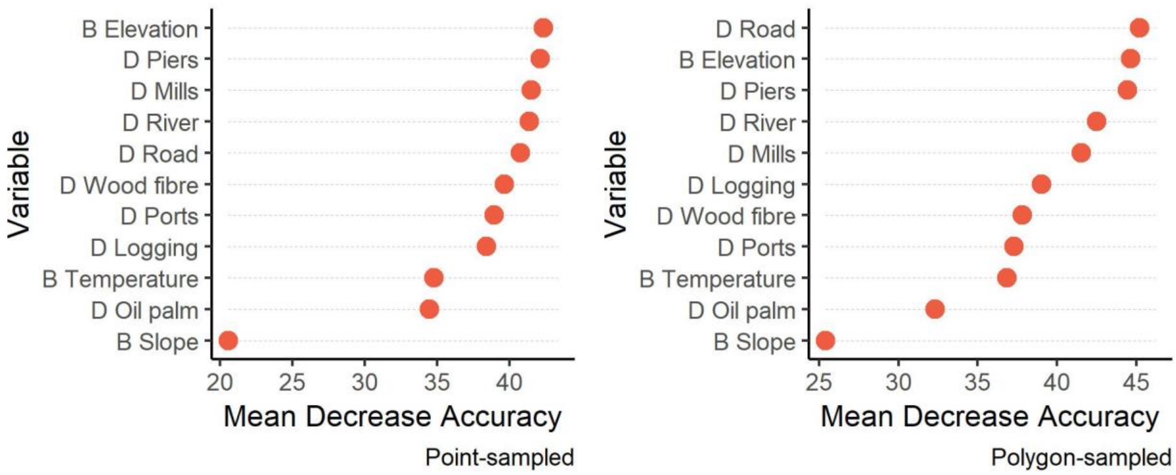
Annex A: Variable importance plot

The variable importance plots of each of the constructed model is presented here. It can be noted that different direct drivers have different order of importance of indirect drivers. For example, in the general (base) model, distance to roads does not seem to have high importance value. The importance is only revealed in the direct driver specific model, that roads are of high importance in the agriculture (i.e. smallholder and tree crops) but not in the other direct driver.

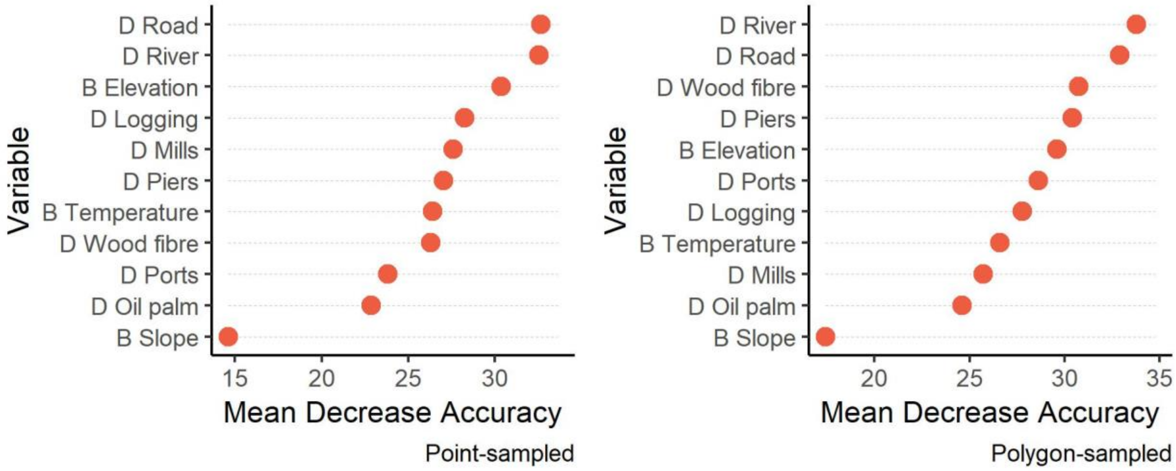
Base model



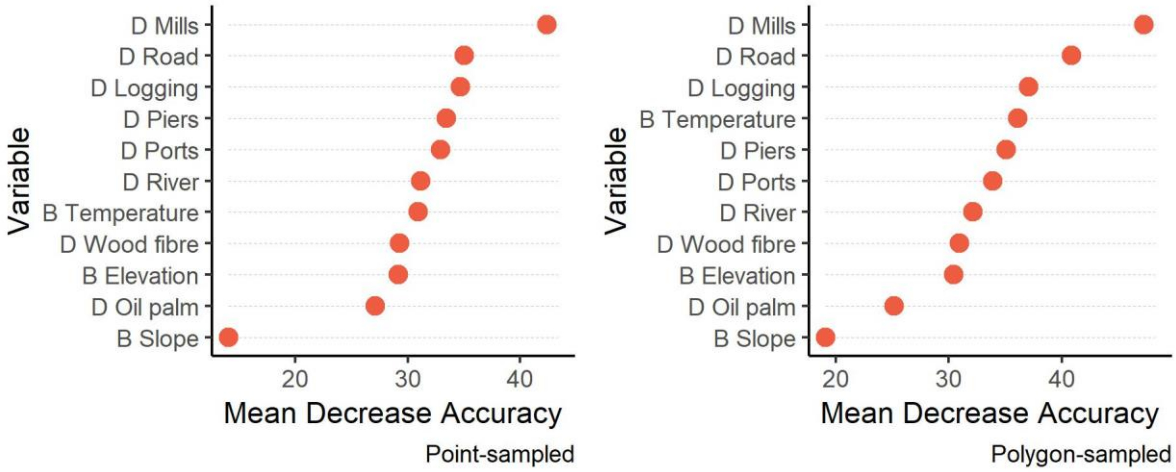
Agriculture



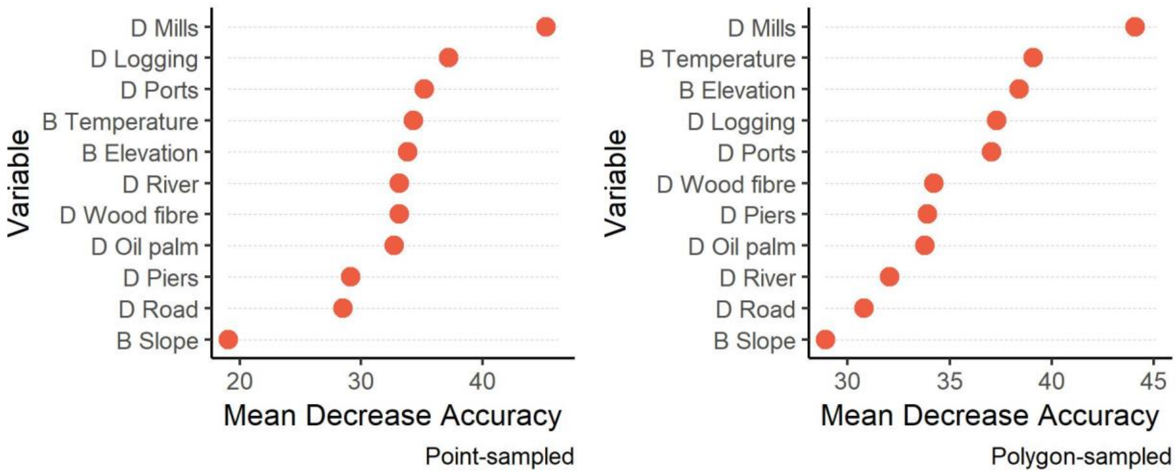
Smallholder agriculture



Tree crop

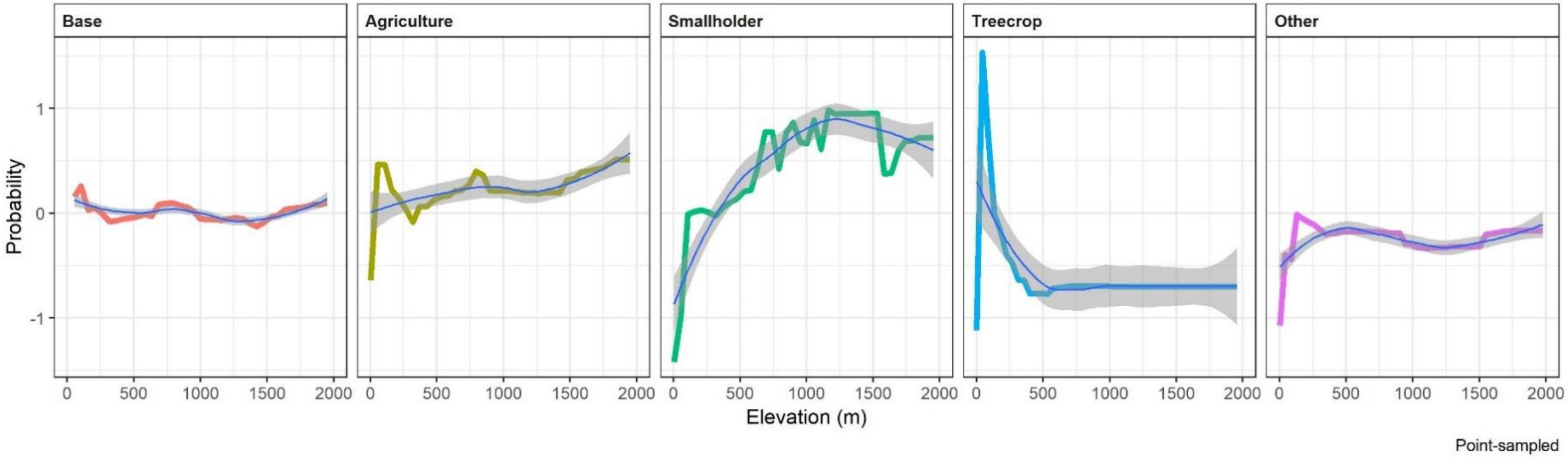


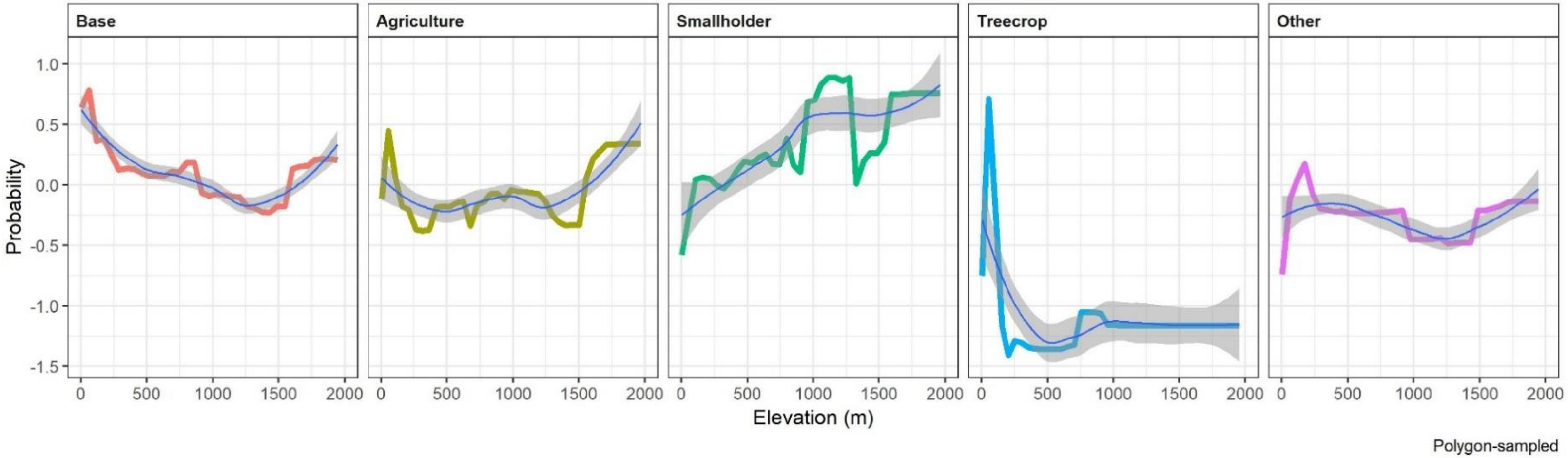
Other drivers



Annex B: Partial dependence plot

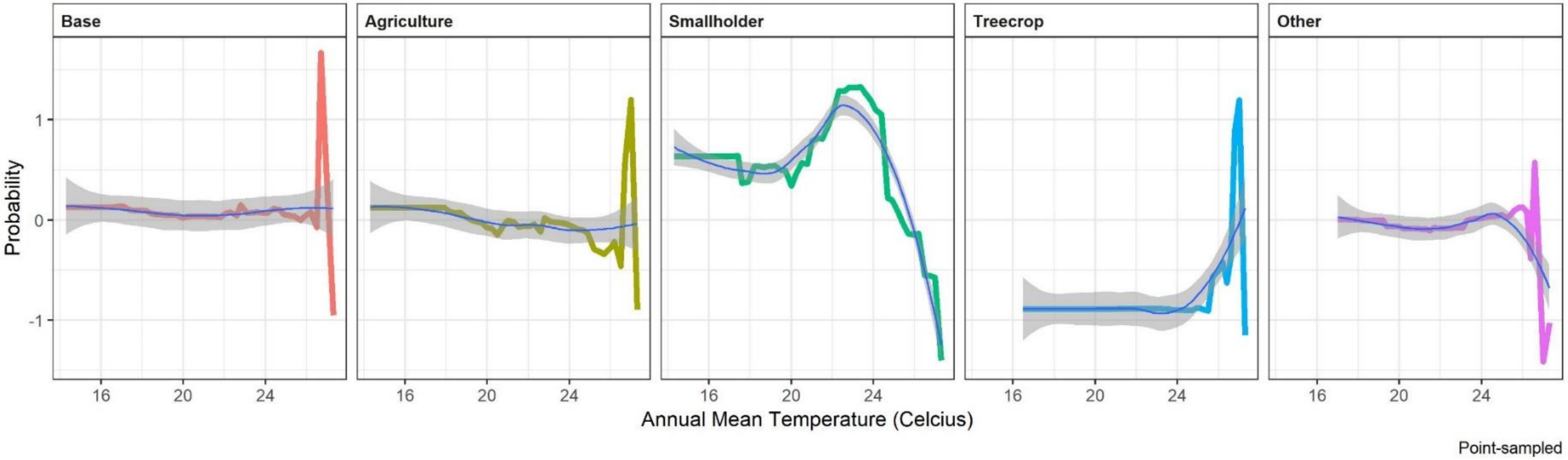
Elevation

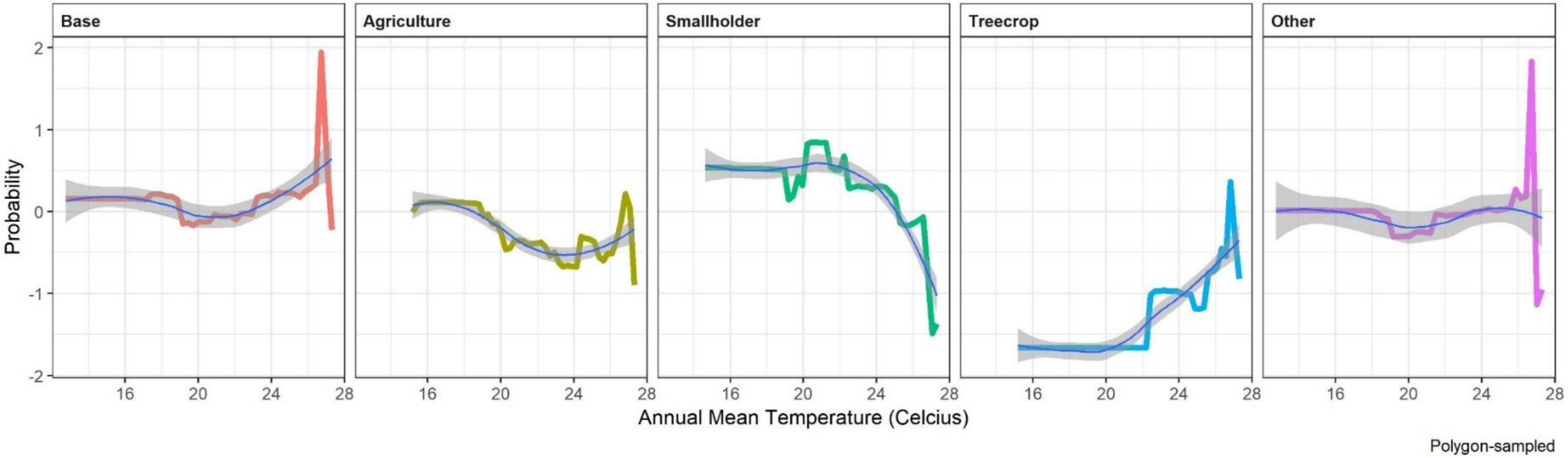




The influence of elevation as indirect driver in constituting deforestation is almost zero in the base, agriculture and other direct driver model. The effect is only apparent in specific direct drivers: smallholder agriculture and tree crops agriculture. Smallholder-driven deforestation tend to occur in higher altitudes (500-2000 m) and tree crops-driven deforestation is only apparent in lower altitudes (~150 m).

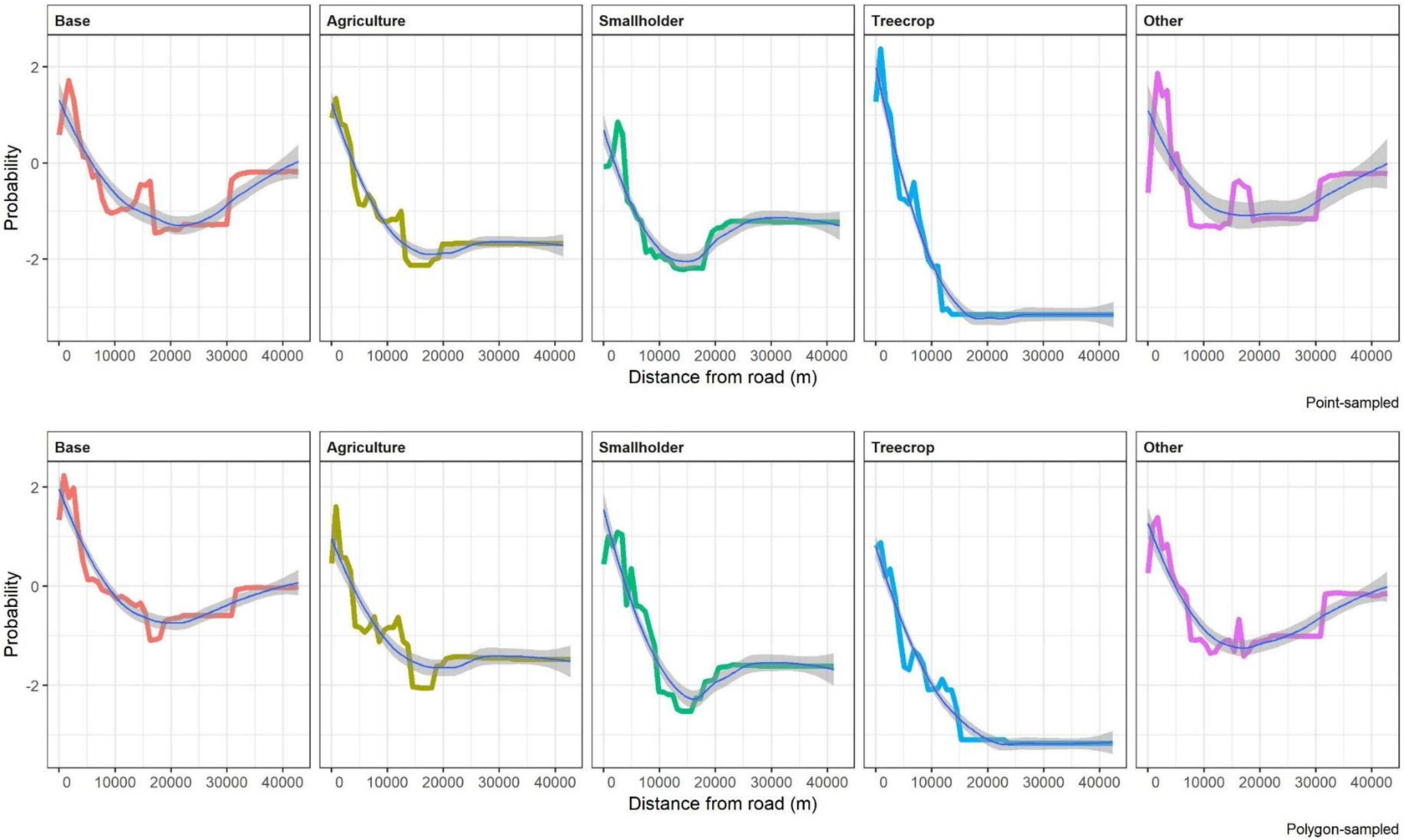
Temperature





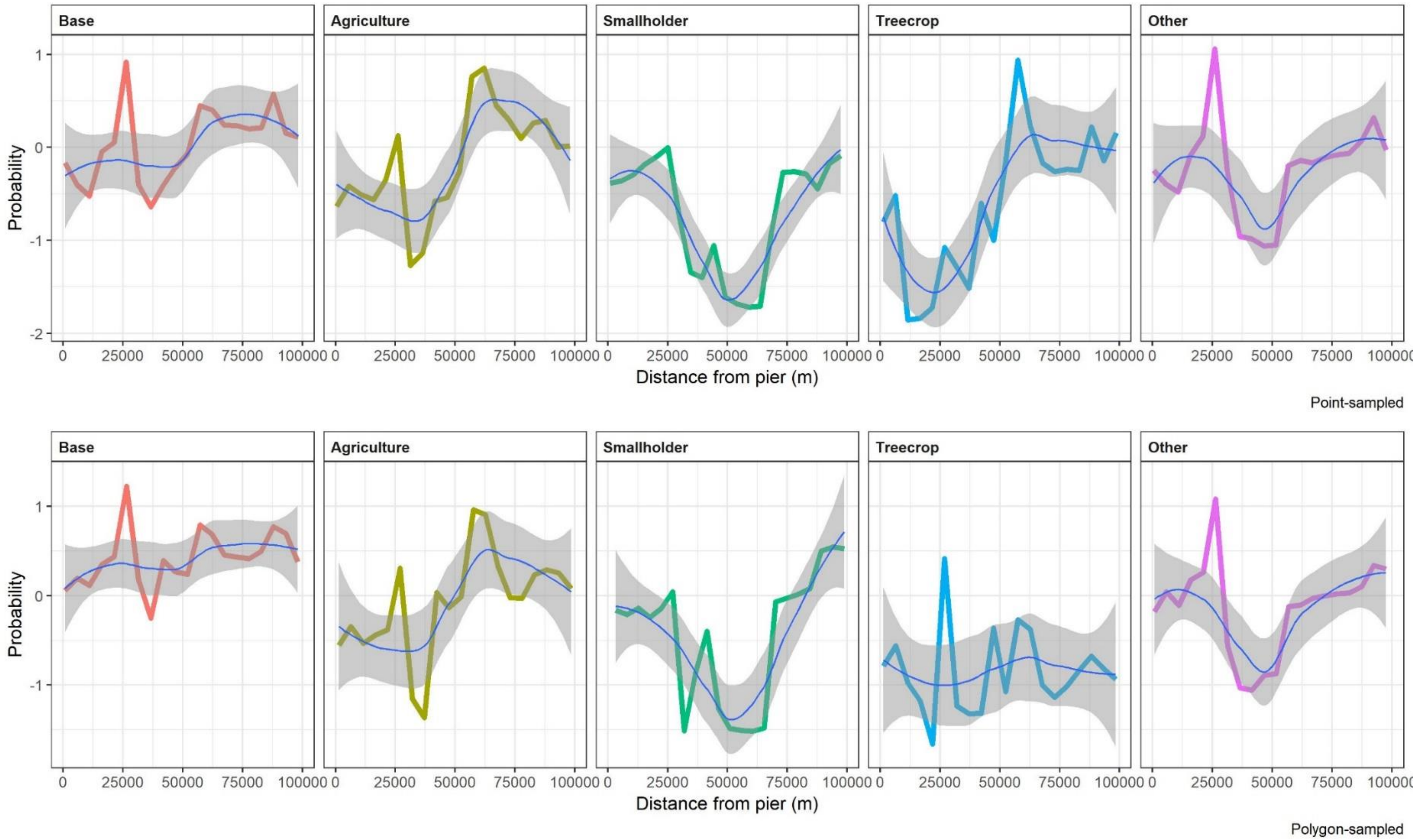
Temperature seem to constitute deforestation in all direct drivers. Only the range between different direct drivers is different: in almost all direct drivers, 26.5°C is the most common temperature where deforestation occur. Only in smallholder agriculture-driven deforestation the range of temperature tend to spread out, between 16-26°C.

Distance to Roads



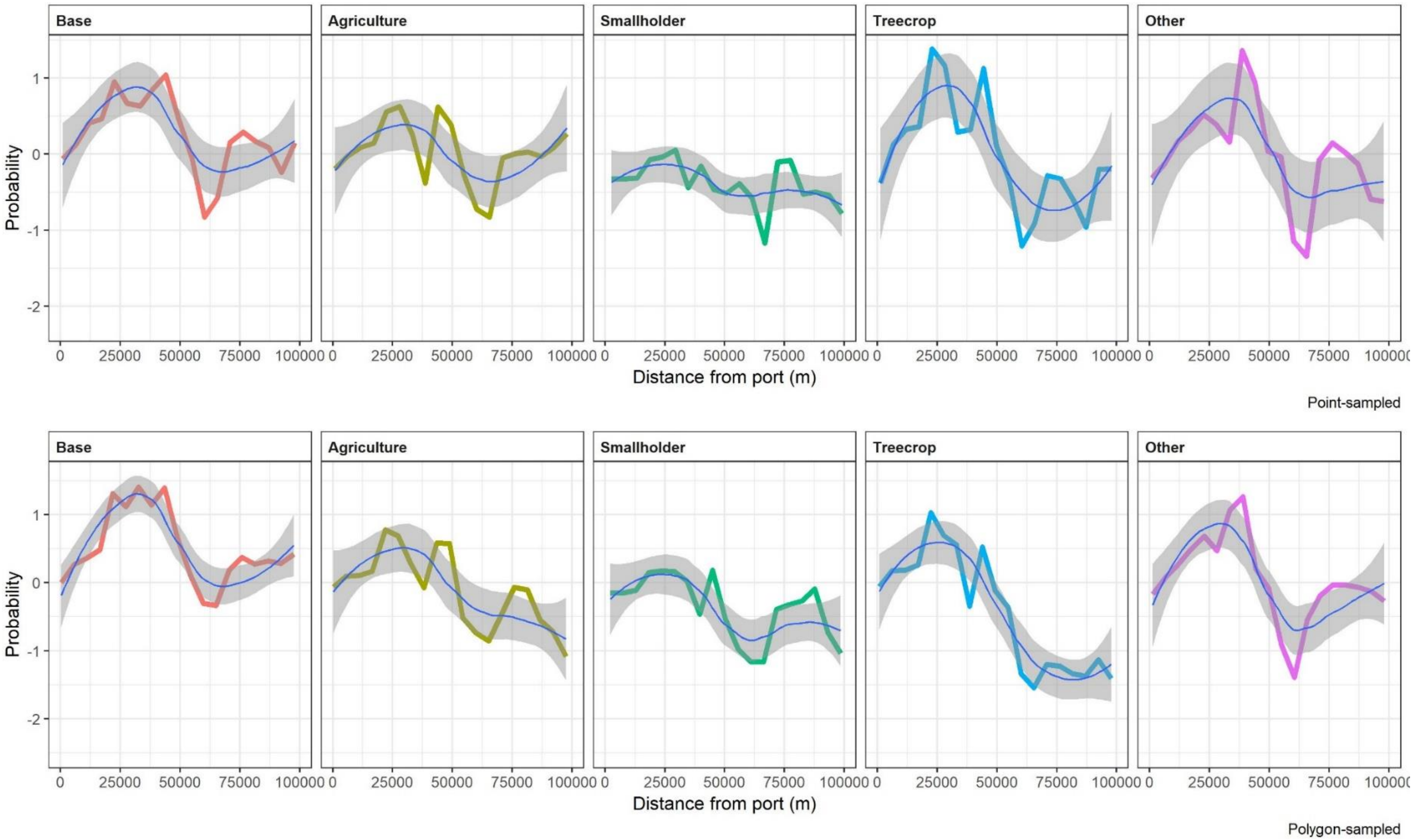
The effect of distance to roads as indirect driver of deforestation shows almost a negative linear relationship in all direct drivers. The probability of deforestation decreases the further a forest is from roads. This effect is most apparent in the tree crop driven deforestation. The breakpoints suggest that this underlying driver has effect around 0-5 km.

Distance to Piers



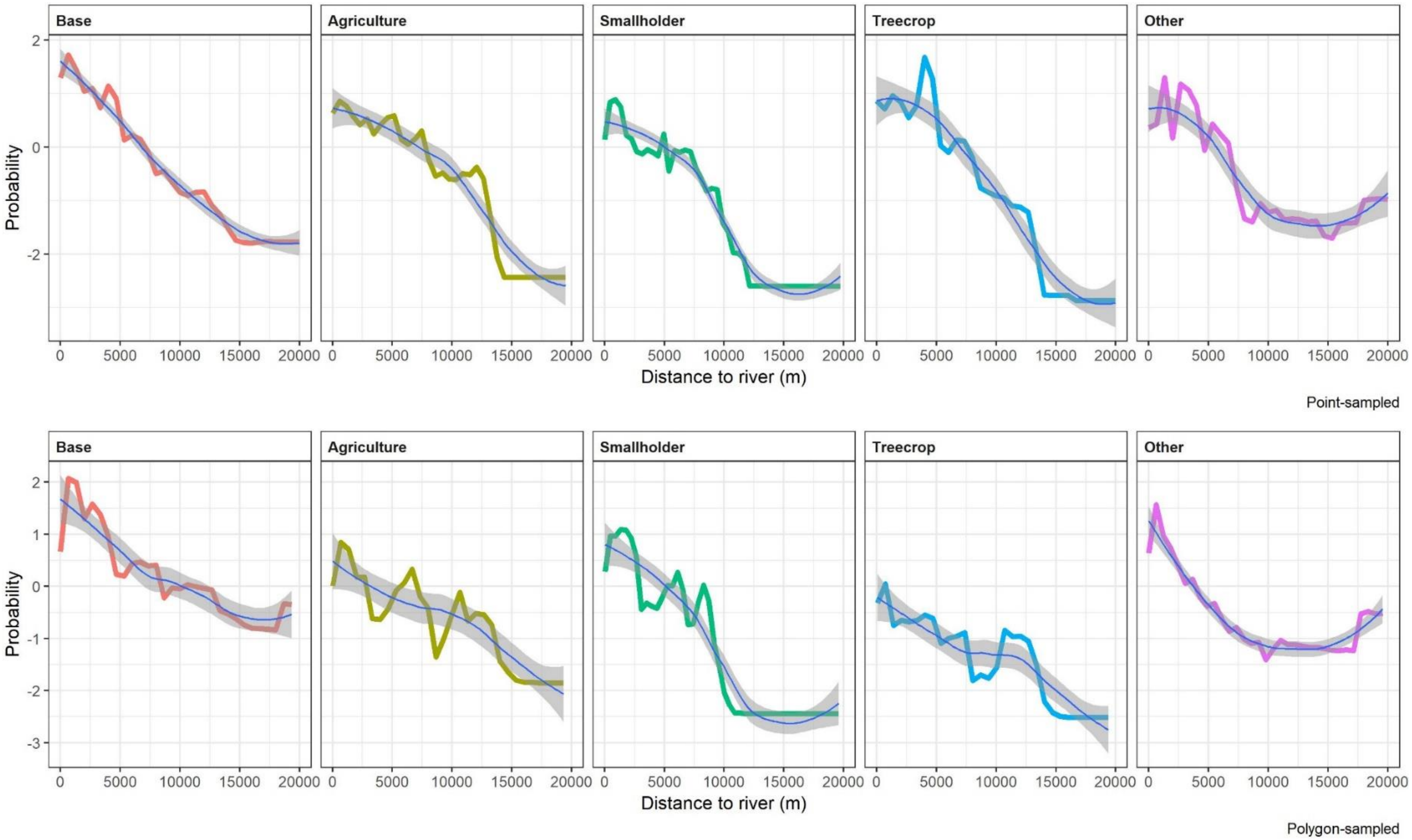
Distance to piers have mixing effects in different direct drivers. This indirect driver is most apparent in tree crop and other direct driver-related deforestation. The model is more likely to predict deforestation in the farther distances (> 50 km), except for the other direct driver, where the peak is observed in the distance around 25 km.

Distance to Ports



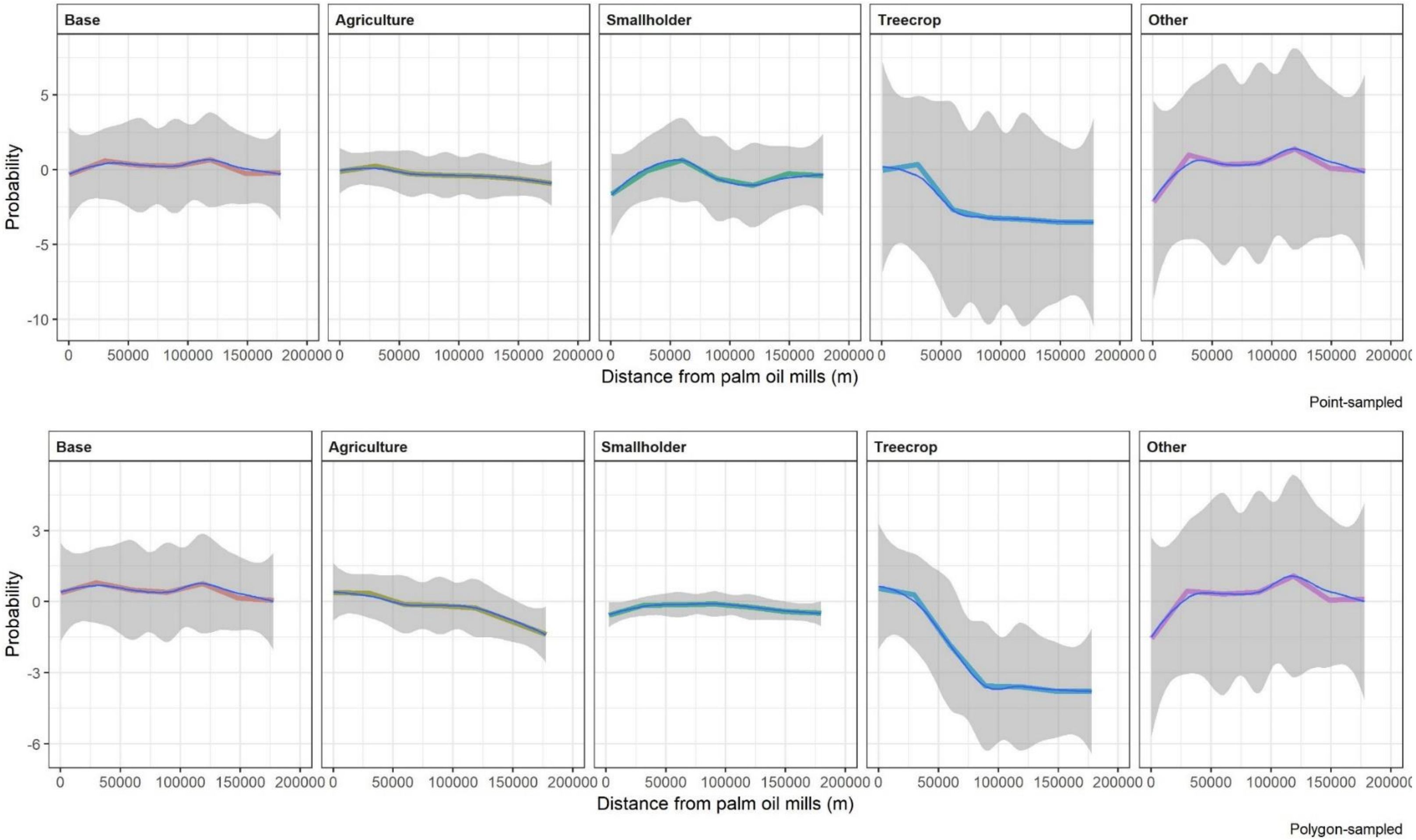
Distance to ports have similar effect to distance to piers. While it seems to have no effect in constituting smallholder driven-deforestation, its influence is very apparent in the tree crop and other direct drivers (between 0-50 km).

Distance to River



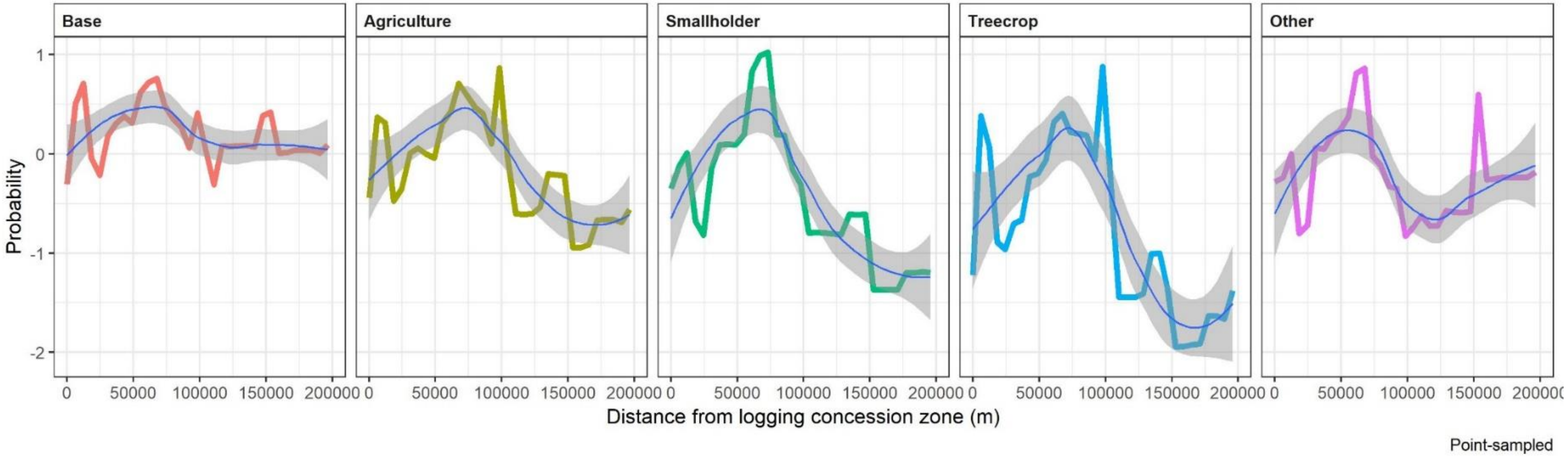
Similar to distance to roads, distance to river also have negative linear relationship with the probability of deforestation. The effect is more or less of the same magnitude for every direct driver. The effect of this indirect driver is apparent within 5-7.5 km radius from river.

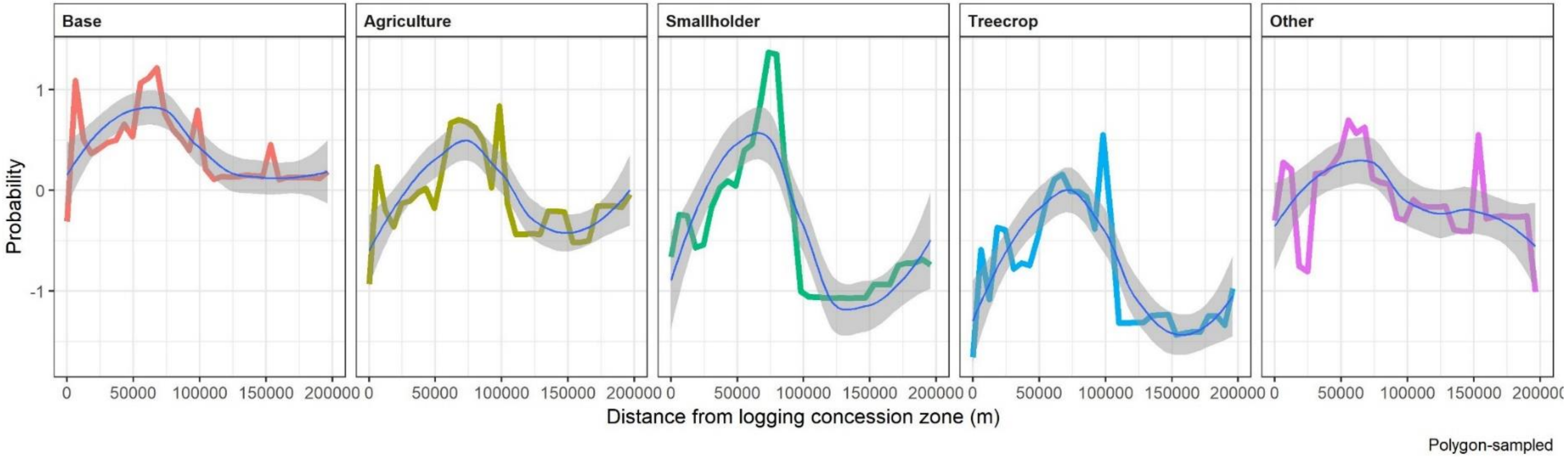
Distance to Palm Oil Mills



While the variable importance plot for different direct driver signified the high importance of distance to palm oil mills, the PDPs of this indirect driver are not showing striking pattern. However, these plots agree that the effect of distance to palm oil mills is only apparent in the tree crop agriculture and other direct drivers.

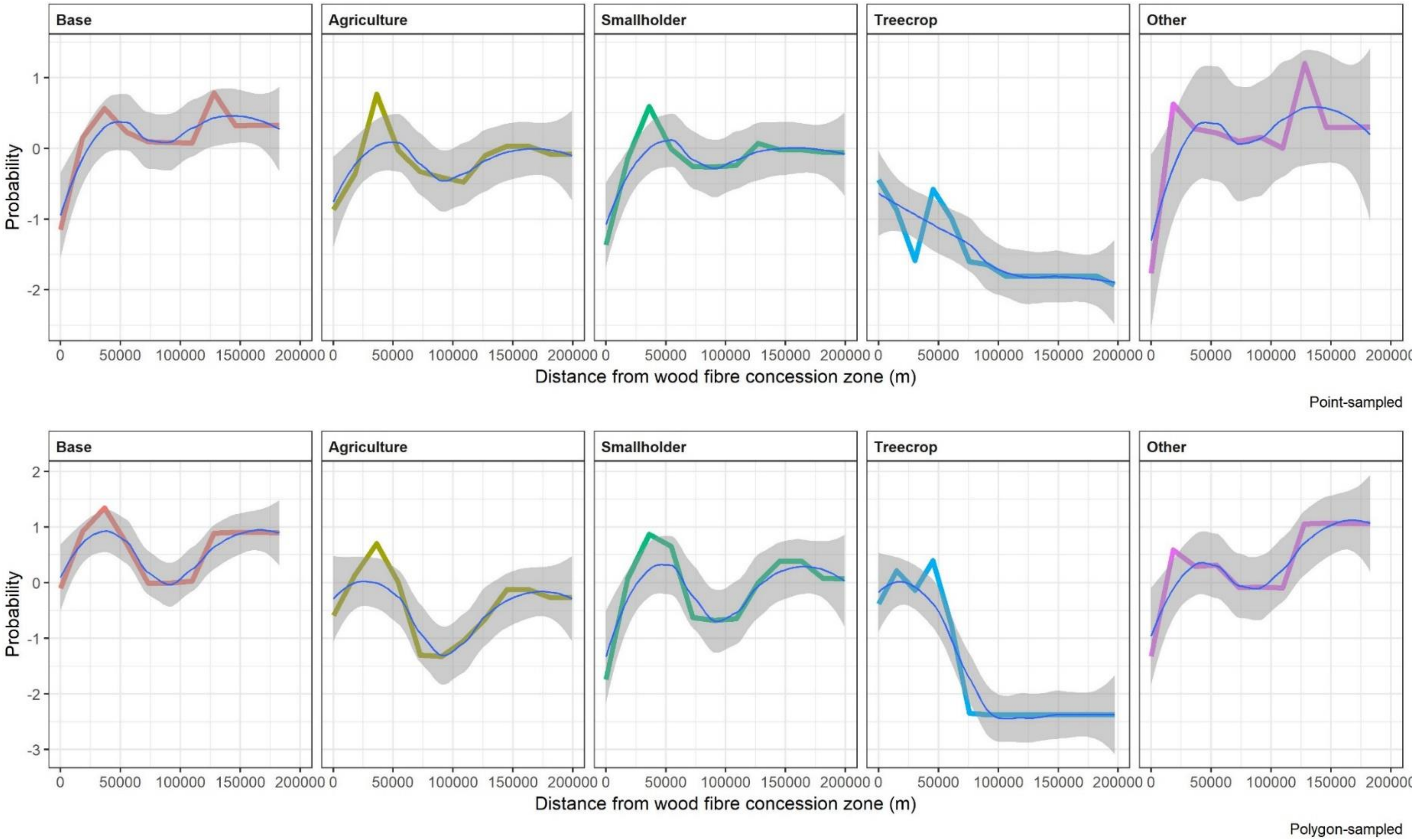
Distance to Logging Concession Zones





As suggested by the peak, these plots suggest that deforestation is more likely to happen in forests nearby the logging concession zone (between 0-75 km). There is less probability of deforestation in farther distance. Every direct driver shows similar pattern, suggesting that the effect is almost identical for different direct drivers.

Distance to Wood Fibre Concession Zones



Distance wood fibre concession zones have minor influence in constituting deforestation agriculture and smallholder-driven deforestation, and seem to have the strongest effect in the other driver model. In contrast, it has no effect in constituting deforestation in tree crop-driven deforestation.