SUPPORTING INFORMATION

S1 Spatial layers of deforestation drivers and processing

Table S1: Predictors used in deforestation modelling, including their description, source and year. While forest was aggregated for the calibration period (2013-2017) and the years preceding the interval (2001-2012), fire occurrence was aggregated over the available time. For the remaining predictors the available time point closest to the calibration interval was chosen.

Name	Description	Source	Year
Forest loss	Forest loss before calibration period (2001-2012) and in calibration period (2013-2017)	Gaveau et al. (2019)	2001-2012, 2013-2017
Elevation	Elevation in meters derived from digital elevation model	Jarvis et al. (2008)	2000
Distance to roads	Distance to primary and logging roads	Center for International Earth Science Information Network - CIESIN - Columbia University (2013), Gaveau et al. (2014)	2010, 2013
Distance to rivers	Distance to major rivers with a minimum of 200 km^2 drainage area	Abram et al. (2015)	2010
Active fire incidence	Aggregated number of active fires (MODIS and VIIRS)	MODIS Collection 6 NRT (2018), VIIRS 375 m NRT (2018)	2000/2002-2017
Human population density	Number of humans within 1 km^2	Bright et al. (2012)	2012
Land-use and management	Protected areas, logging concessions, industrial timber plantation concessions, industrial oil palm plantation concessions, unprotected areas outside concessions (as reference areas)	IUCN & UNEP-WCMC (2017) Santika et al. (2015)	2012, 2017

In the deforestation model, forest loss was parameterized by using a forest cover layer from Gaveau et al, (2019) at a resolution of 30 m, incorporating changes based on global forest loss estimates by Hansen et al., (2013) (Figure 2c in main text). Annual forest loss represents the area of old-growth ("primary") natural forest that has been cleared each calendar year from 2001 until 2017 and includes intact and selectively harvested old-growth forests. Old-growth forests usually have closed canopies (>80% cover) and high carbon stock (above ground carbon: 150 – 310 Mg C/ha). They typically consist of tall evergreen dipterocarps growing on drylands or in swamps (including peat-swamps). There is considerable variation within and among these forest types. For example, on peat domes, forests may naturally be thinner, low carbon stock pole forests. In coastal regions, forests include mangroves as well as natural stands of Sago palm (*Metroxylon sagu* Rottb.). Intact forests have either escaped significant recent cutting or modification by people, or such modifications were too minor to be detected. Selectively harvested forests have been subjected to industrial scale mechanized selective timber cutting and extraction but are recovering.

The forest layer limits the inclusion of natural mortality and non-permanent loss within agricultural areas (industrial plantations and small-holder agriculture) by excluding the loss of tree cover within plantations, agro-forests, mixed gardens, regrowth or scrubland. We used yearly measures of forest loss and aggregated forest cover and loss at a 1 km resolution using nearest-neighbour resampling, to minimize inclusion of short-term and small-scale degradation and to facilitate data processing and modelling. All predictors where clipped with the forest cover in 2000, since the model does not calculate probability of forest loss for pixels deforested before.

To account for the varying probability of deforestation between areas designated for different land-use types, we included a layer of land-use as a predictor of forest loss (Figure 2b in main text). Borneo is governed by multiple countries, each with their own land-use system. We used a land-use map by Santika et al., (2015) that harmonizes these systems into the following land-use types: protected areas, logging concessions, industrial timber and oil palm plantations, and areas not allocated to protection or concessions (i.e. areas without any formal management, as well as urban or infrastructure development areas). We only considered protected areas from the WDPA database (IUCN and UNEP-WCMC, 2017) present in the layer by Santika et al. (2015), as these were derived from national data, assumed to be more representative of the situation on the ground. All areas included in both sources and ranked as category 1-3 in the WDPA database were combined in one class (‘strict conservation’), which represents the highest protection and areas with little to no active human intervention (Dudley, 2013). Classes 4-6, where sustainable use can be practiced (Dudley, 2013) and areas included as ‘not applicable’ and ‘not reported’ (but still included in national land-use planning as protected area) were categorized into a ‘sustainable use’ class. All areas that were included in Santika et al. (2015), but missing in the WDPA database were classified as ‘national’ protected areas. They constitute, for example, protection forest (*Hutan lindung*) and wildlife and ‘nature reserves’ (*cagar alam)* in Indonesia; ‘protection forest reserves’ and ‘wildlife reserves‘ in Sabah, and protected forests in Sarawak (Santika et al., 2015). Land-use classes describe the designation and not the land-cover, hence concessions can include forests that have not yet been converted or logged.

Forest loss on Borneo was analyzed within geopolitical units. Province (for Indonesia), state (for Malaysia) and country borders (for Brunei) were downloaded from the Global Administrative Areas database (Global Administrative Areas, 2012) and combined within the extent of the island. Analysis excluded Brunei, as important predictors were missing for the country, and it does not harbor orangutans.

Initial models suggested that the inclusion of a predictor representing the type of soil (mineral or peat), did not significantly improve model predictions. Hence soil types were not included. All predictor variables, except for forest loss, were static, i.e., only one time-step was considered, while forest loss in the neighborhood of a cell was dynamically updated by the model in each time-step.

All spatial manipulations were performed in Python (Python, 2016), using gdal (GDAL/OGR Contributors, 2017) and numpy (Oliphant, 2016) packages, and aggregated, analyzed and visualized in Python, R (R Core Team, 2017) and ArcGIS (Esri Inc., 2014).

S2 Deforestation model and calibration

The model of forest loss for each province and state was adapted from Rosa et al. (2013) and is based on $P_{trloss,x,t}$, the probability that trees in a cell x are lost in a time interval t. The probability of loss is defined as a logistic function:

$$Ptrloss_{x,t} = \frac{1}{1 + exp^{-k_{x,t}}} \quad (1)$$

in which $k_{x,t}$ can range from minus to plus infinity and $P_{trloss,x,t}$ from 0 to 1. We then used linear models to describe $k_{x,t}$ as a function of the predictor variables that affect forest loss at location x and time t.

Using a forward stepwise regression, a total of 31 models were fitted to the observed forest loss data (2013 – 2017). Each model differed in the combination of predictor variables that define $k_{x,t}$. The models were fitted using ‘Filzbach’, a freely available library (https://github.com/predictionmachines/Filzbach), which uses a Markov Chain Monte Carlo (MCMC) sampling method to return a posterior probability distribution for each parameter. From this distribution, given a specific parameter combination Θ, the posterior mean and credible interval was extracted. To estimate the parameters, the log-likelihood, a measure of the goodness of fit between the observations and the model predictions, is defined for a particular combination of variables:

$$L(X \vee s, \theta) = \sum log\left(Z_{x,t}Ptrloss_{x,t} + (1 - Z_{x,t})(1 - Ptrloss_{x,t})\right) \quad (2)$$

in which $Z_{x,t}$ is the observed forest loss at location *x* and time *t,* and *s* one of the 31 models considered.

To assess the predictive power gained by adding variables to the model, a cross-validation technique was used. This technique allowed to check how accurately the model predictions compared to a randomly selected subset of 50% of the data that was not used to train the model. This cross-validation is necessary to find models that only comprise predictors with evident predictive ability. After successively adding the variable that resulted in the highest likelihood model, the overall best model (i.e. the one with the maximum test likelihood) was selected from the whole set of models for each province.

The simulations were based on recalculating equation (1) for each time-step, while using a slightly different set of parameter values at each iteration, thereby incorporating parameter uncertainty. These values were drawn from a Gaussian distribution resulting from the MCMC fitting, using the estimated mean and standard deviation for each parameter. As a result we received an updated $P_{trloss,x,t}$ for each individual cell (*x*) in each individual time period (*t*). We subsequently evaluated whether or not the respective pixel was lost, by drawing a random number from a uniform distribution between 0 and 1. We then classified the pixel as lost, if the number was less than the probability of deforestation $P_{trloss,x,t}$. This procedure was repeated for all four time-steps and run multiple times (n = 100 iterations) to assess the uncertainty in model predictions over time. The different iterations were aggregated into the summed probability of deforestation and represent the fraction of simulation runs in which the forest in a pixel in location *x* was lost.

Supplementary references

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Table S2: Overview over best models and predictor effect sizes for each province. Models were ranked according to their test likelihood and the model with the maximum test likelihood per province is show.

Province	Sabah	Sarawak	West Kalimantan	South Kalimantan	Central Kalimantan	East Kalimantan	North Kalimantan
Test Likelihood	-3,003.5606	-7,252.6683	-5,678.1869	-777.9408	-7,806.2213	-4,022.0491	-2,494.173
Intercept	-2.5678	-2.5542	-2.0578	-2.1246	-1.644	-2.2285	-2.3206
Previous deforestation	4.2044	3.2768	3.5371	2.6688	3.8692	4.4006	3.4051
Distance to road	-0.0002	-0.0002	0	0	0	-0.0002	-0.0001
Distance to river	0	0	0	0	0	0	-
Fire incidence	0	0	0	-	0.0001	0	-
Elevation	-	-0.0007	-0.0062	-0.0031	-0.0097	-0.0015	-0.0033
Population density	0.0001	-	0.0002	-	-	0	0.0002
Strict protected area	-1.9465	-1.6718	-1.5418	-1.6142	-0.2912	1.2358	-1.1241
Sustainable use protected area	-1.1166	-0.5832	-0.0575	-0.0001	-0.2958	-0.1787	-0.0488
National protected area	-0.7207	-0.6811	-0.2723	-0.2916	0.0541	-0.6829	-0.5877
Logging concession	-0.2545	-0.0838	-0.2339	0.1031	-0.1263	-0.2025	-0.1585
Timber plantation concession	-0.0757	-0.0225	0.0083	0.0124	-0.1796	0.0916	0.1565
Oil palm plantation concession	-0.1256	-0.0346	0.0953	-0.0358	0.0338	0.0753	0.0554

Table S3: Validation (perfect match, omission and commission errors) of observed against projected forest maps in the calibration period (2013-2017) for Borneo and provinces. Percentage perfect match and omission were calculated in comparison to all observed forest pixels, while commission errors were calculated in comparison to all projected forest pixels. Median, 95% lower confidence interval (CI) and upper CI were calculated across binary projected forest maps (n = 100).

	Match (% observed)			Omission error (% of observed)			Comission error (% of projected)		
	Median	Lower CI	Upper CI	Median	Lower CI	Upper CI	Median	Lower CI	Upper CI
Borneo	94	92.66	97.51	6	2.49	7.34	5	2.13	6.11
Sabah	96	95.37	95.81	4	4.19	4.63	4	3.89	3.99
Sarawak	93	93.08	93.52	7	6.48	6.92	6	6.02	6.15
West Kalimantan	93	92.86	93.26	7	6.74	7.14	5	4.96	5.17
South Kalimantan	94	93.67	94.75	6	5.25	6.33	5	5.11	5.46
Central Kalimantan	93	92.57	92.99	7	7.01	7.43	6	5.45	5.6
East Kalimantan	96	95.73	96.1	4	3.9	4.27	3	3.3	3.41
North Kalimantan	97	97.33	97.56	3	2.44	2.67	2	2.11	2.21

Table S4: Province area, forest area and forest cover in the past (2000 and 2017), projected into the future (2032) and percentage annual deforestation rate.

		Forest in 2000		Forest in 2017		Forest area in 2032 in km^2			Forest loss 2018 to 2032 in %		
Province	Area in km^2	Area in km^2	%	Area in km^2	%	Median	Lower Confidence Interval	Upper Confidence Interval	Median	Lower Confidence Interval	Upper Confidence Interval
Sabah	73,541	43,495	59	37,605	51	30,747	30,571	30,861	18	18	19
Sarawak	123,797	78,996	64	61,900	50	46,912	46,666	47,153	24	24	25
West Kalimantan	146,981	69,927	48	58,841	40	44,883	44,680	45,114	24	23	24
South Kalimantan	36,620	8,841	24	7,556	21	5,901	5,815	5,969	22	21	23
Central Kalimantan	153,568	90,471	59	75,833	49	53,969	53,654	54,192	29	29	29
East Kalimantan	126,783	64,781	51	59,207	47	49,390	49,179	49,629	17	16	17
North Kalimantan	69,840	63,145	90	58,774	84	53,164	53,046	53,340	10	9	10

Table S5: Difference between observed and projected annual deforestation rates for the calibration period 2013-2017 (in comparison to 2000). Annual deforestation rates were averaged over five years, with the exception of maximum observed rate, which is for one year.

	Annual deforestation rate					Difference between observed and projected		
Province	Observed	Maximum Observed	Median projected	Lower Confidence Interval	Upper Confidence Interval	Median	Lower Confidence Interval	Upper Confidence Interval
Sabah	0.76	1.01	0.84	0.8	0.88	0.08	0.04	0.12
Sarawak	1.12	1.6	1.22	1.18	1.25	0.1	0.06	0.14
West Kalimantan	1.18	1.58	1.51	1.47	1.55	0.33	0.29	0.37
South Kalimantan	1.07	1.59	1.14	1.04	1.25	0.07	-0.03	0.18
Central Kalimantan	1.21	3.3	1.51	1.47	1.56	0.3	0.26	0.35
East Kalimantan	0.74	0.95	0.88	0.84	0.92	0.14	0.1	0.17
North Kalimantan	0.48	0.68	0.55	0.53	0.58	0.07	0.05	0.1

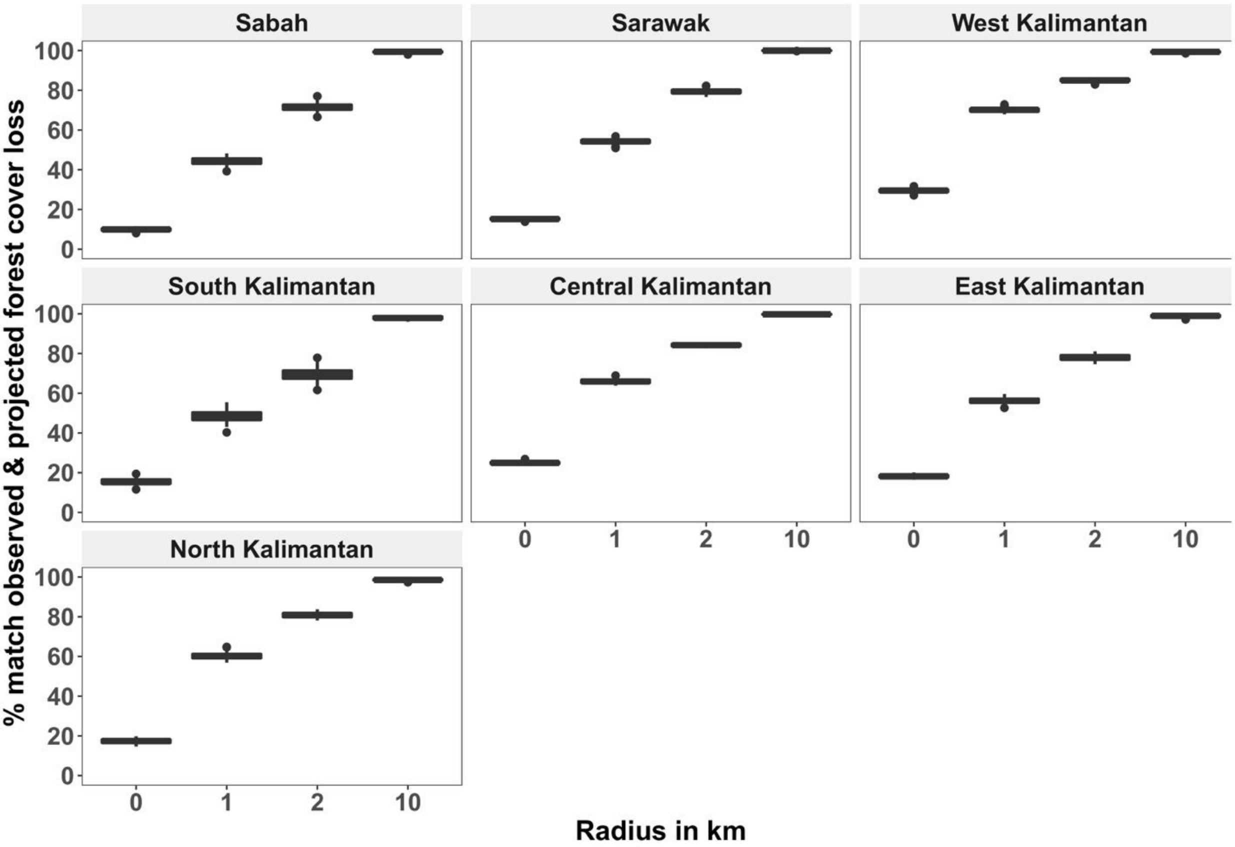

Figure S1 Percentage observed deforestation matched by projected deforestation in the pixel (0 m, perfect match) and near-misses where the pixel is matched in its neighbourhood (1 pixel, 1 km; 2 pixels, 2 km; 10 pixels, 10 km) for the provinces of Borneo. Boxplots show the median across simulations (n = 100) and 25th and 75th quartiles.

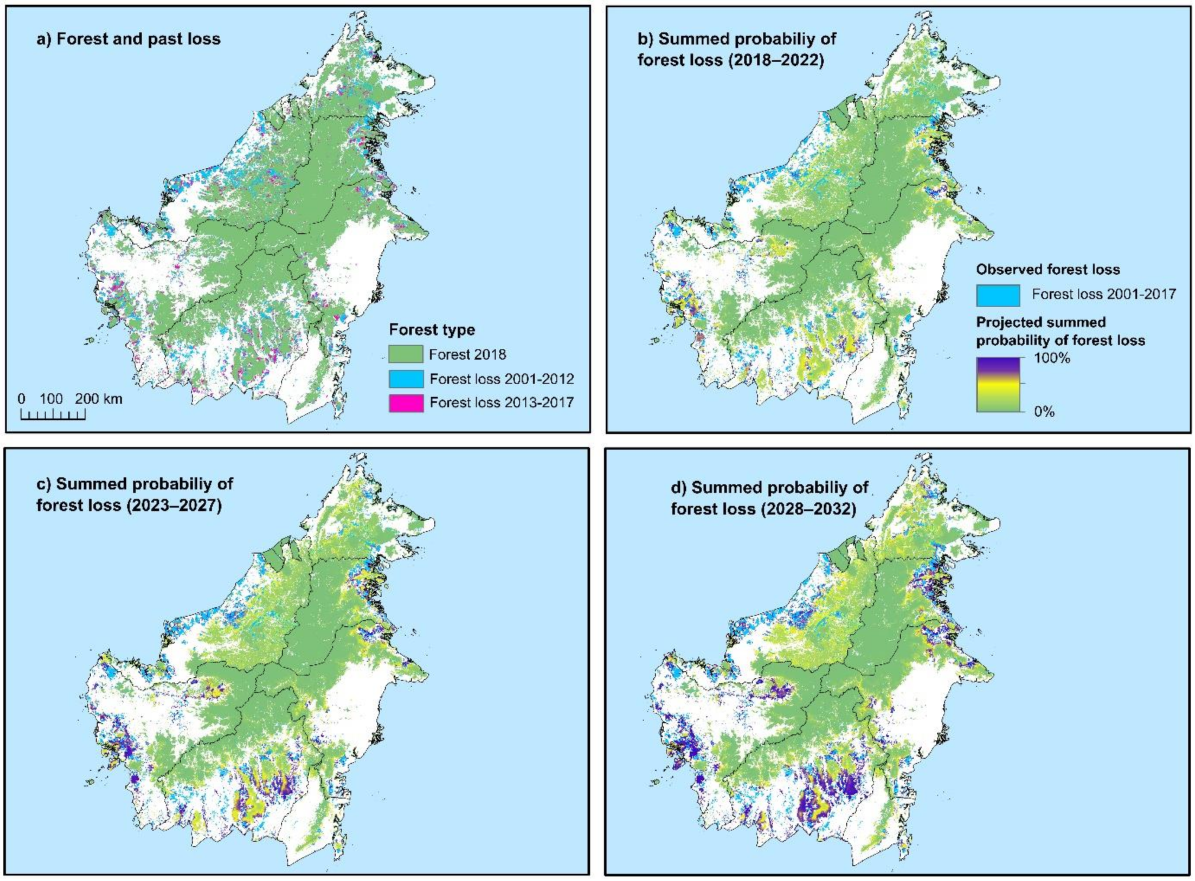

Figure S2: Observed deforestation and projected probability of forest loss across Borneo (2001–2032). a) Remaining forest in 2018, past forest loss (2001-2012) and loss in calibration period (2013-2017). b-d) Summed probability of projected forest loss in five-year time steps from 2018 to 2032.

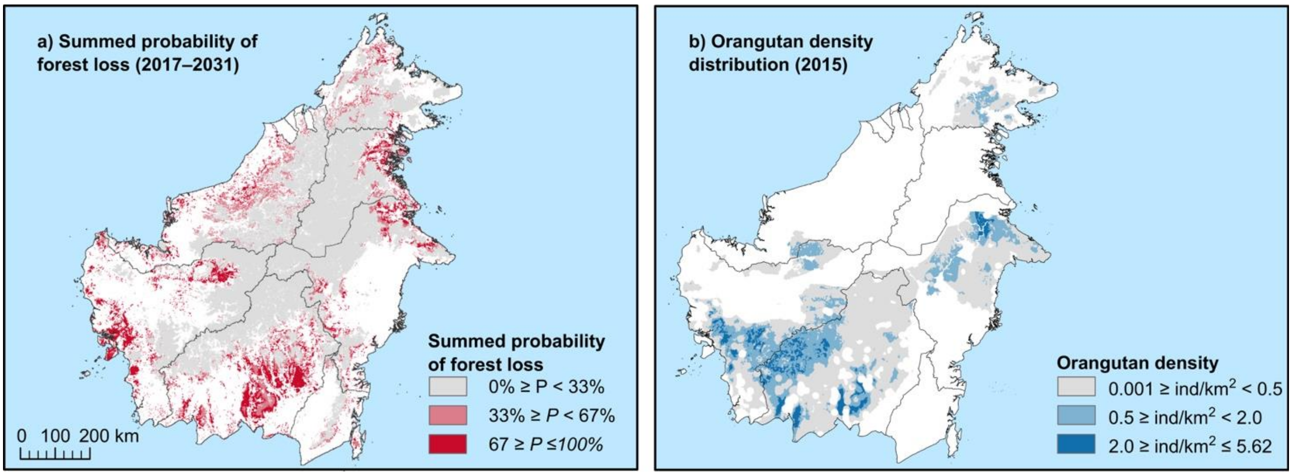

Figure S3: Summed probability of forest loss and orangutan density across Borneo. a) The distribution of projected probability of forest loss in three classes for all pixels forested in 2000. b) Orangutan density distribution in three classes for all pixels with a density higher than 0.001 ind/km^2.

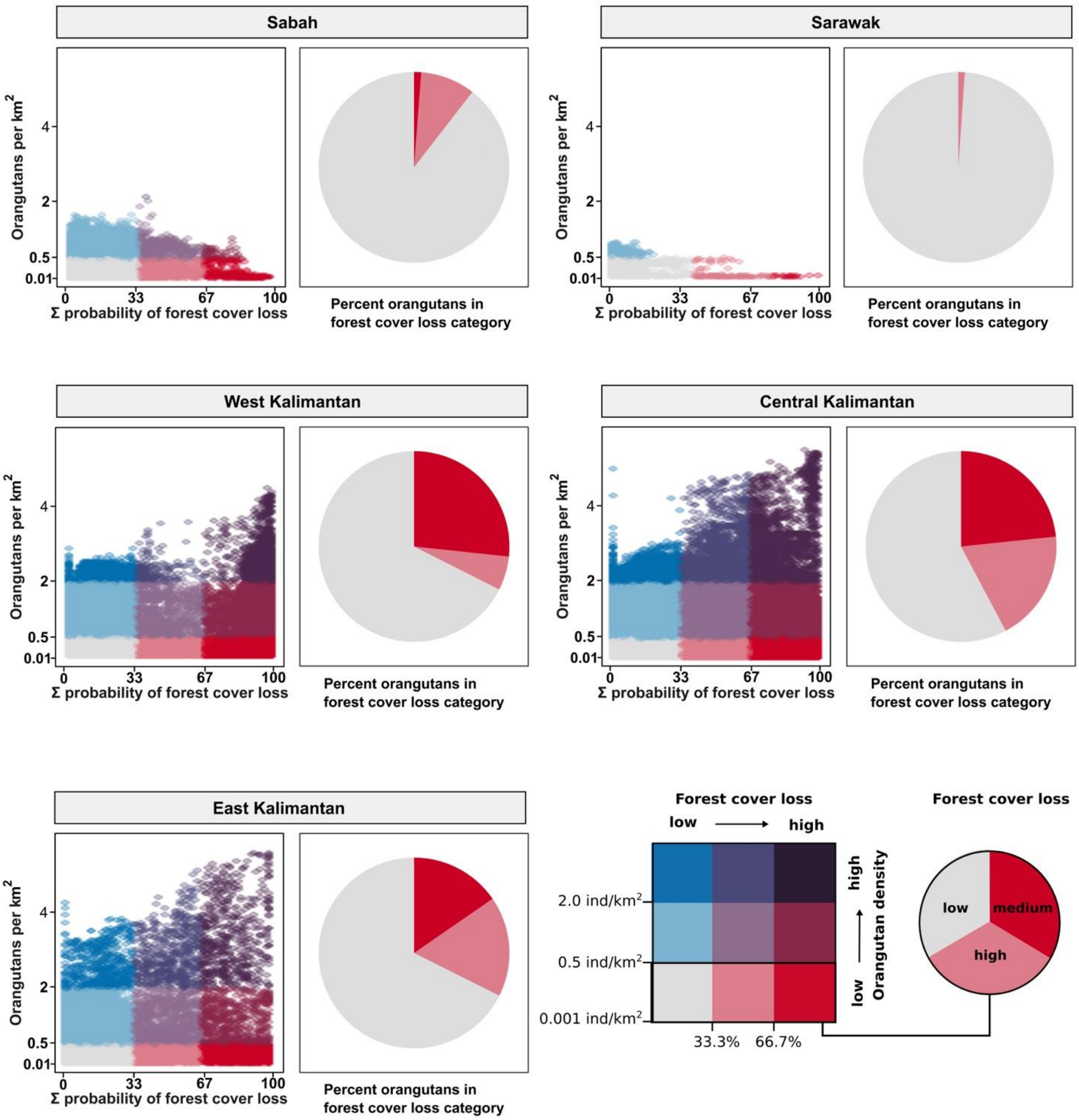

Figure S4: Density of orangutans and summed probability of forest loss in provinces. Density of orangutans shown in blue and summed probability of forest loss in red. The color intensity corresponds to values, purple hues represent a mix of elevated levels (in maps and scatterplot). The distribution of pixels with respect to the orangutan density per square-kilometer and the summed (Σ) probability of forest loss is represented in the scatterplot. The proportion of orangutans in areas with low, medium or high levels of forest loss is shown in the pie charts (red shades only). North and South Kalimantan are not shown, as low number of orangutans (<100 individuals) occurred there.

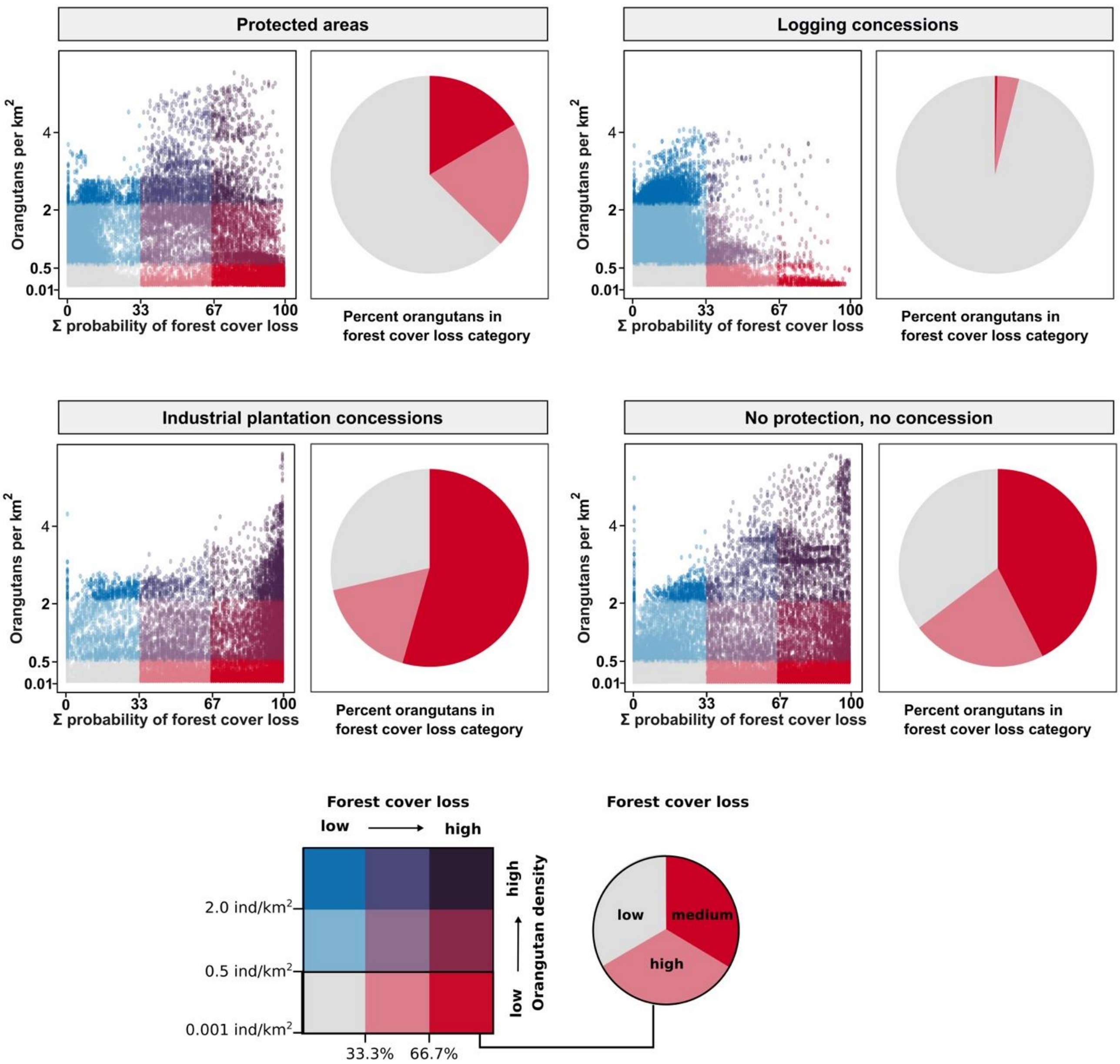

Figure S5: Density of orangutans and summed probability of forest loss in land-use areas. Density of orangutans (blue) and summed probability of forest loss (red). Blue and red shades indicate either factor, intensity corresponding to values, purple hues represent a mix of elevated levels (in maps and scatterplot). The distribution of pixels with respect to the orangutan density per square-kilometer and the summed (Σ) probability of forest loss in scatterplot. The proportion of orangutans in areas with low, medium or high levels of forest loss in pie charts, red shades only.

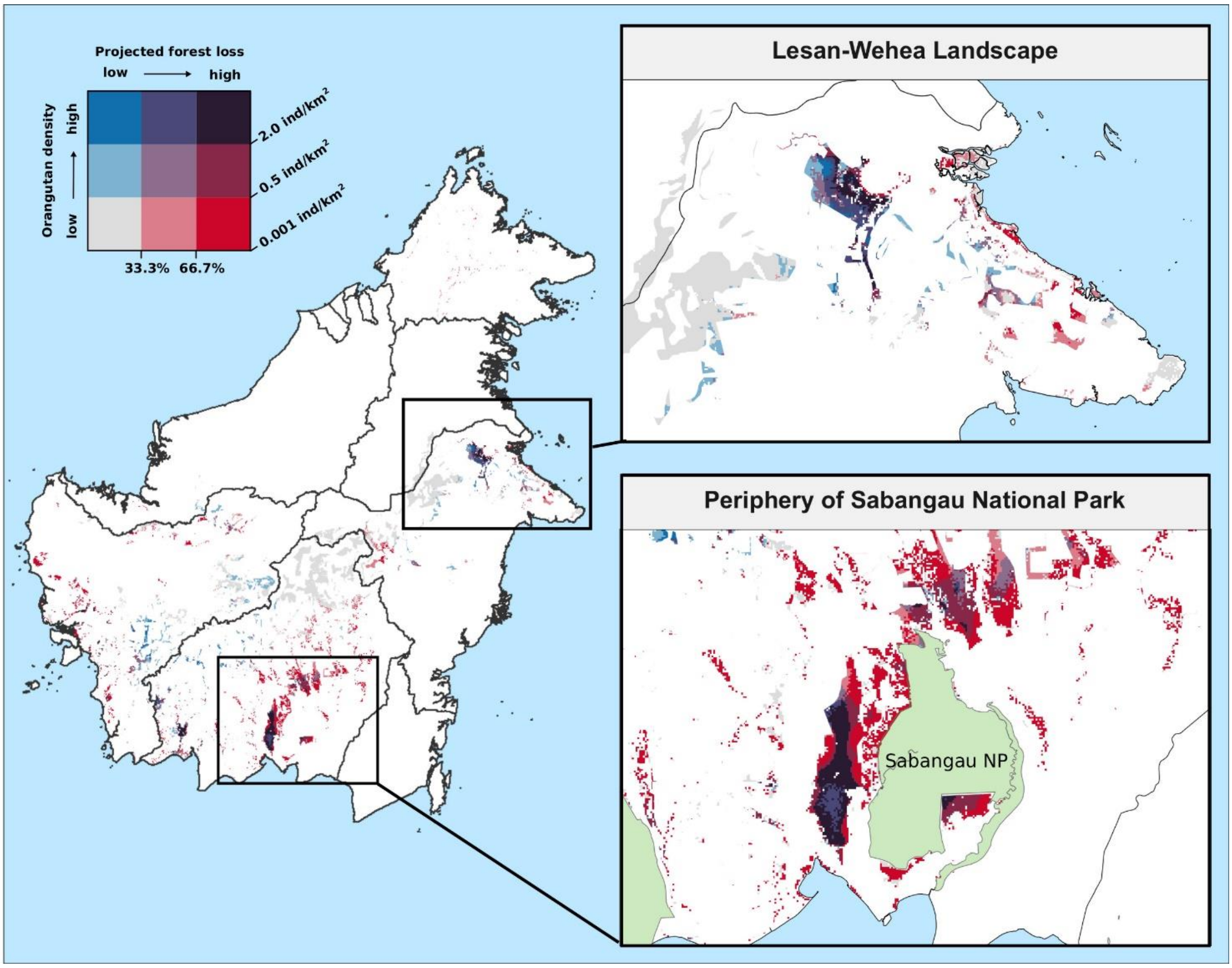

Figure S6: Density distribution of orangutans and summed probability of projected forest loss in unprotected areas outside of concessions until 2032. Two areas with especially high orangutan densities at high risk of projected deforestation are highlighted in insert maps: Lesan-Wehea Landscape and an area in the periphery of Sabangau National Park (NP), especially in the west of the park. This area is now the Katingan Peatland Restoration and Conservation Project, thus decreasing the likelihood of losing its forest and orangutan population (Indriatmoko et al., 2014).