Technical report for the NERC-Ristekdikti Wallacea Project - Projected deforestation for the Wallacea bioregion

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METHODS

Deforestation and boundaries of analysis

We defined deforestation as the annual loss of primary forest (Margono et al. 2014), including mangrove forest as delineated in by (Giri et al. 2011). Primary forest was defined as mature natural forest with an extent >5 ha, with a natural composition and structure that had not been cleared in recent history. This definition includes both intact and degraded types of primary forest in the year 2000. Yearly forest loss between 2001 and 2018 was downloaded from the Global Forest Change repository of University of Maryland (Hansen et al. 2013) and cover for each year calculated by subtracting loss from primary forest in 2000, including mangroves.

Forest loss for Wallacea was analyzed in nine regions, based on provincial and subregional boundaries during and prior to the study period. We thus divided Wallacea in North Sulawesi and Gorontalo (formerly North Sulawesi; split in 2000), West and South Sulawesi (formerly South Sulawesi, split since 2004), Central Sulawesi, Southeast Sulawesi, East Nusa Tenggara, and West Nusa Tenggara. Although the Mollucan archipelago were formally administered as a single region, and are now two, the dispersed nature of the islands means they can geographically be considered as three regions: North (including Halmahera, Sula and Obi island groups) South (including Tanimbar, Aru and Kai) and Central (Seram, Ambon, and Buru). Borders were downloaded from the Global Administrative Areas database (Global Administrative Areas 2012). All islands below a size of 5 km^2 where excluded.

Identifying deforestation drivers

Deforestation in tropical forests is influenced by multiple drivers, such as physical feature, accessibility characteristics, anthropogenic pressures, and land-use (Gaveau et al. 2014, 2018; Austin et al. 2019(Rosa et al. 2013; Struebig et al. 2015; Austin et al. 2019)). Our selection of potential deforestation covariates was based on those known to be important in driving deforestation in Indonesia (Table S1): slope, yearly average of fire incidence, potential accessibility from a human population centre, human population pressure (including human population density), transmigration, primary livelihood sector (subsistence farming, plantation, non-agriculture occupations or fisheries, as defined in the national census), as well as presence of mining concessions (those under exploration and exploitation) and the official land-use designation from Government of Indonesia (Table S1). Here, land is categorized for production (can be converted into timber plantations), limited production (in which forests can be used for logging), protection (as national parks, wildlife reserves or watershed protection forest), or non-forest (i.e. land converted or allocated for conversion into non-timber plantations such as oil palm, or for other uses). Land-use classes and mining concessions describe the official designation and not the cover, and thus can include forests that were not yet converted or logged. The predictors were selected based on literature describing important drivers of deforestation in the tropics (Rosa et al. 2013; Struebig et al. 2015; Austin et al. 2019), as well as the availability of such data across the archipelago for the relevant time period (Table S1).

All layers were converted to the Asia South Albers Equal Area Conic projection and resampled to the same extent and origin at 180 x 180 m cell size using bilinear for continuous and nearest neighbor resampling for categorical predictors. All spatial manipulations were performed in Python (Python 2016), and aggregated, analyzed and visualized in Python, R (R Core Team 2017) and ArcGIS (ESRI 2014) (Supporting Information for processing details).

Deforestation model framework

We used a dynamic and spatially-explicit model developed by Rosa et al. (2013) to project the probability of deforestation for nine administrative regions within Wallacea. We produced multiple localised models to better capture regional deforestation patterns within the archipelago (i.e. among islands with a shared geopolitical history), and to allow projections at a higher resolution.
The model accounts for stochasticity of deforestation events, and region-wide forest loss rates emerge as the sum of local scale deforestation, resulting from the influence of drivers operating in each particular region. Inherently in the model, deforestation events are more likely to occur in the vicinity of patches surrounding a location of recent forest loss. The model is based on the probability that trees in a cell are lost in a certain time interval. For each region, we checked predictors for collinearity and excluded predictors with a Pearson correlation coefficient > 0.7 and variance inflation factor >3. Combinations of the remaining predictors were fitted to the observed forest loss data from 2014–2018 as a calibration period, with each model defined by the best predictors specific to the region (Appendix Table S2). To find the best candidate performing models (i.e. comprise predictors with evident predictive ability), we used cross-validation. After successively adding the variables that resulted in the highest likelihood model, the overall best model was selected for each region (Appendix Table S2).

Simulations

We used the model with the maximum test likelihood to project the probability of deforestation for the five-year calibration period (2014–2018) and the following seven 5-year periods until 2053 for each region. We selected a calibration interval of five years by considering the trade-off between short intervals, potentially reflecting exceptional years, or long intervals, potentially including outdated trends. The calibration interval also defines the time-steps in which projections can be done into the future. After estimating probability, we evaluated whether or not the respective pixel was lost by drawing a random number from a uniform distribution between 0 and 1. The pixel was then classified as deforested if the number was less than the probability of deforestation. This procedure was performed for all eight time-steps and run 100 times to gauge the uncertainty in model predictions. The different iterations were aggregated into the summed probability of deforestation and represented as the fraction of simulation runs in which the forest in a pixel was lost; i.e. if a pixel was selected to be deforested in 50 of 100 iterations in a given time period then it had a 50% probability of deforestation.

Validation and analysis

We validated the models against observed data for the calibration time-period, by calculating the area under the Receiver Operating Characteristic (ROC) curve (AUC value) for the 100 iterations. We also calculated the proportion of match between observed and cumulative forest loss within certain distances (0, 1, 2 and 10 pixels) surrounding the pixel following Rosa et al. (2013).

RESULTS

Deforestation model for Wallacea

After testing the predictor combinations for each region, the model with the highest test likelihood was used to simulate forest loss for the calibration period and then in 5-year increments from 2019 to 2053. In all nine regions the best performing models included past deforestation, slope, distance to villages with subsistence and non-agricultural livelihoods, and the land-use designation as important predictors (Table S2).

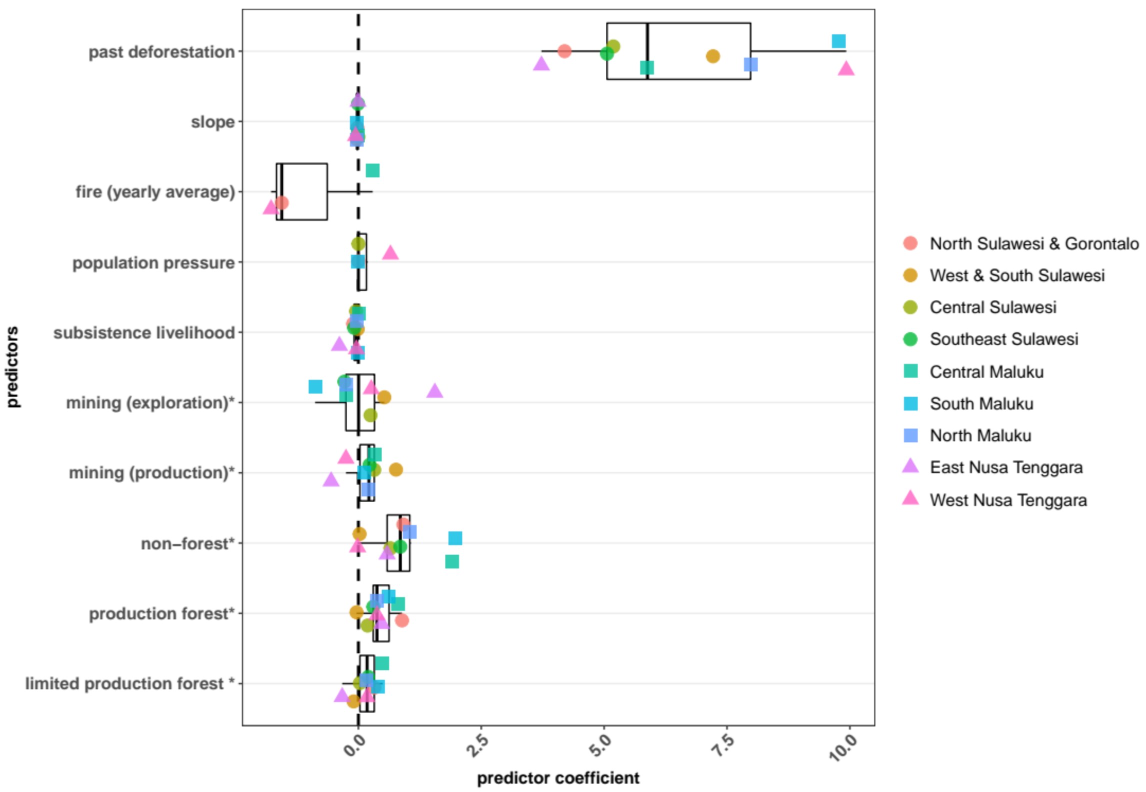

Figure 1: Influence of predictors on deforestation between 2000 and 2019 in nine regions of Wallacea. Predictor values were drawn from a Gaussian distribution, using the estimated mean and standard deviation for each. Values across regions are summarized in a boxplot showing the median and the 25th and 75th quartiles as hinges. Predictors with an effect size smaller than zero (dashed line) were related to lower forest loss, while predictors with an effect size larger than zero to higher forest loss. The effect of mining concessions (exploration and production) is relative to the effect of no mining concessions and the effect of non-forest, production forest and limited production forest is relative to the effect of protected forest (*). Predictors in best model differ across regions (Table S2). Predictors with coefficients close to zero (mean coefficient smaller than 0.05 and a spread smaller than 0.05) and the intercept were excluded from the figure. The 95% confidence intervals around points are not shown, as they fall within the points. Values are standardized.

Mining and distance to villages with fisheries livelihood were in the best model in eight regions; distance to villages with plantation livelihood was include in six regions, while population pressure was included in four, occurrence of fire and distance to transmigrant settlement in three regions, and accessibility in two. Probability of deforestation was highest in the vicinity of past forest loss (Figs. 1 and 2) across all regions, with the effect being strongest in South Maluku and West Nusa Tenggara, and weakest in East Nusa Tenggara as well as North Sulawesi and Gorontalo.

Fire was associated with higher deforestation in Central Maluku, but lower deforestation in West Nusa Tenggara and North Sulawesi and Gorontalo. Although for most regions population pressure had a weak relationship with deforestation, it was associated with increased probability of deforestation in West Nusa Tenggara. Low distance to a village with subsistence livelihood decreased deforestation in the regions, with the exception of Central Maluku. Both types of mining concessions (exploration and production) had varying influence on deforestation (relative to the reference class of ‘no mining’): while the presence of exploration concessions was associated with low deforestation in Southeast Sulawesi and the Malukan regions, the reverse was true in West Sulawesi, Central Sulawesi and both East and West Nusa Tenggara. Forest areas gazetted for mining production (in comparison to no concession), were related to higher probability of deforestation in most regions, with the exception of East and West Nusa Tenggara, where mining production was associated with a small reduction in deforestation.

In general, the production, limited production and conversion land-use categories were linked to higher deforestation probabilities compared to the protected forest reference class. Non-forest areas that still had forest but could be converted into non-forest uses such as oil palm plantations were related to highest levels of probability of deforestation, with the exception of West Nusa Tengarra, with low, negative effects. Production forest, i.e. areas in which forest can be converted into timber plantations, were also related to increased deforestation (with the exception of West South Sulawesi, which had a low negative relationship). Limited production forests, which cannot be converted but are used for logging, were related to lower levels of probability of deforestation in West-South Sulawesi and East Nusa Tenggara, and higher levels in all other regions.

Accessibility, distance to villages with plantation, non-agriculture and fisheries livelihood and distance to transmigrant settlements had estimated model effect sizes close to zero.

Validation

The model selection process in which parameter combinations were screened for each region, yielded models with good discriminatory power via a mean AUC value ranging from 0.97 (Central Sulawesi) to 1 (South Maluku). When comparing the spatial match in the calibration period, across Wallacea a median of 12% of all pixels that were projected to be lost were in the exact location of pixels with observed loss (Interquartile range (IQR)=6%, Fig S1). However, 46% (IQR=26%) of the pixels were in the direct neighborhood (within 180 m), 70% within 360 m (IQR= 30%), and 99% within 1.8 km (IQR=7%) of a pixel with observed forest loss, indicating strong spatial concordance.

Spatio-temporal deforestation projections

Throughout Wallacea 32,566.99 km^2 (95% confidence interval [CI] 32,452.63 – 32,680.41 km^2) of forest was projected to be lost between 2018 and 2033 and 37,356.26 km^2 (CI: 37,186.64-37,492.46 km^2) until 2053. This amounted to 48.0 % (CI: 47.9-48.1%) loss of forest relative to forest cover in 2018. The projections reflected a spread of deforestation in the vicinity of past deforestation (Fig 2).

By 2053 large, continuous areas were projected to be deforested in North Maluku, Central Maluku, in the eastern part of Central Sulawesi and the border region between Central, West and South and Southeast Sulawesi. Forest within protected areas mostly had lower levels of projected deforestation (e.g. in Halmahera or Nusa Tenggara, where the majority of remaining forest was protected). However, protected status was also related to high projected levels of deforestation probability, most notably in the border region between Central, West and South and Southeast Sulawesi, where mining concessions were concentrated. Forests gazetted for conversion were related to higher levels of deforestation (Fig 1 and 2), especially in North Maluku. Across Wallacea, the center of islands were projected to be less threatened than outlying margins of forest.

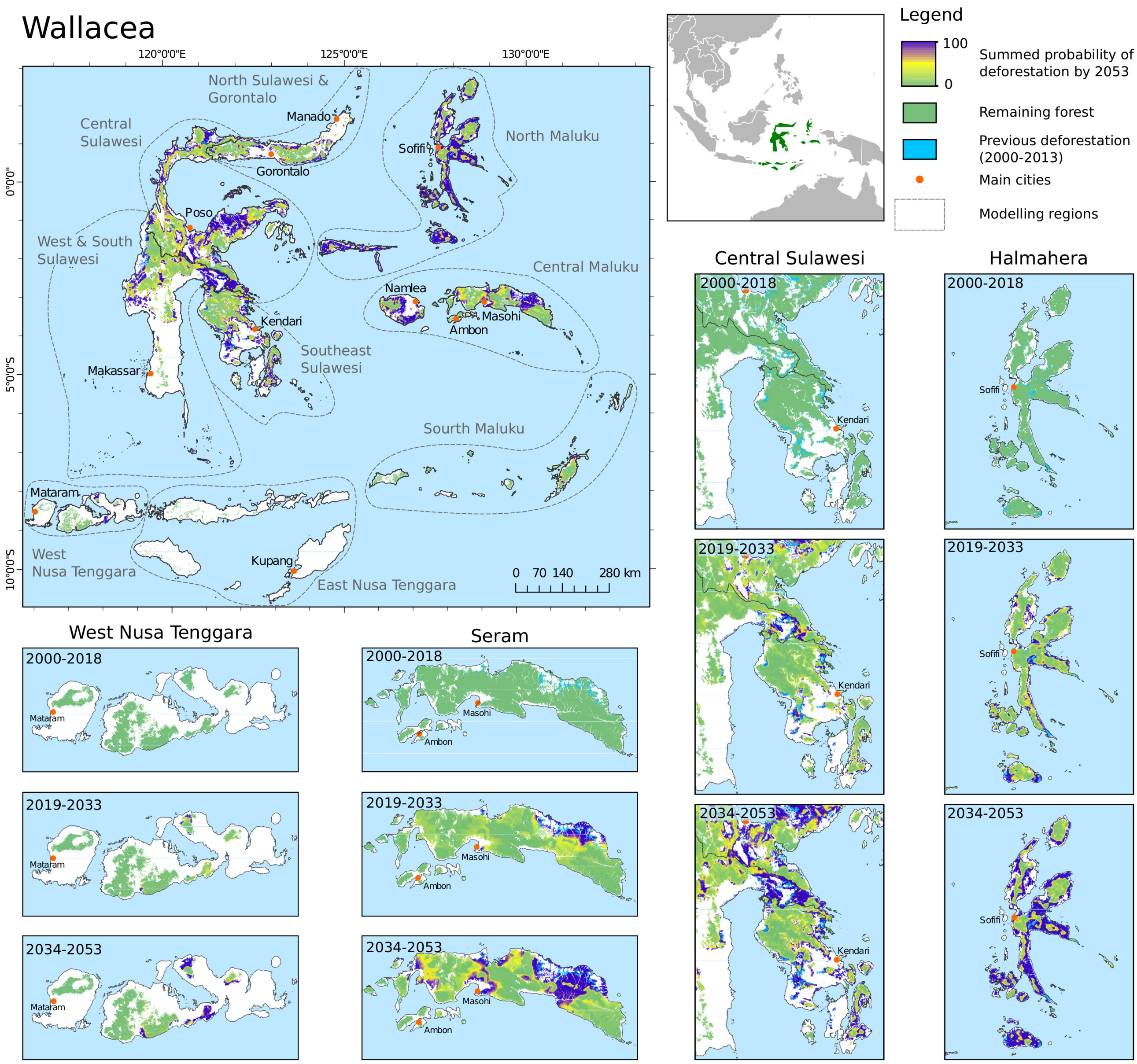

Figure 2: Projected probability of deforestation across Wallacea by 2053
Probability of deforestation was projected for each region using predictors describing slope, accessibility, human pressure and land-use. Probability of deforestation is summed over 100 iteration and accumulated from 2019 until 2053. Modeling regions in overview map as dashed lines and grey name. Location of Wallacea in Southeast Asia (green) in upper right hand corner. Observed deforestation (2000-2018) and projected deforestation probability (2019-33, 2034-53) for West Nusa Tenggara, Seram, Central Sulawesi and Halmahera shown in panels for each time period.

Total forest area at the end of the observation period (2018) varied across regions (Fig. 3 and Table S3) with Central Sulawesi having the largest forest area (37,523.41 km2) in 2018, representing 61.36% of the total area of the region, and East Nusa Tenggara having the smallest forest area

(1,734.40 km2, 3.73% of the islands' area). In all regions natural forest decreased in extent between the start of the observation period in 2000 and 2018, and was projected to decrease further until 2033 and 2053. Forest loss from 2018 ranged from 1.49% (CI: 1.38-1.63%) in 2033 and 3.33% in 2053 in East Nusa Tenggara, to 28.53% in 2033 (CI: 28.25-28.84%) and 67.89% (CI: 67.61-68.26 %) in North Maluku, as the lowest and highest increase respectively.

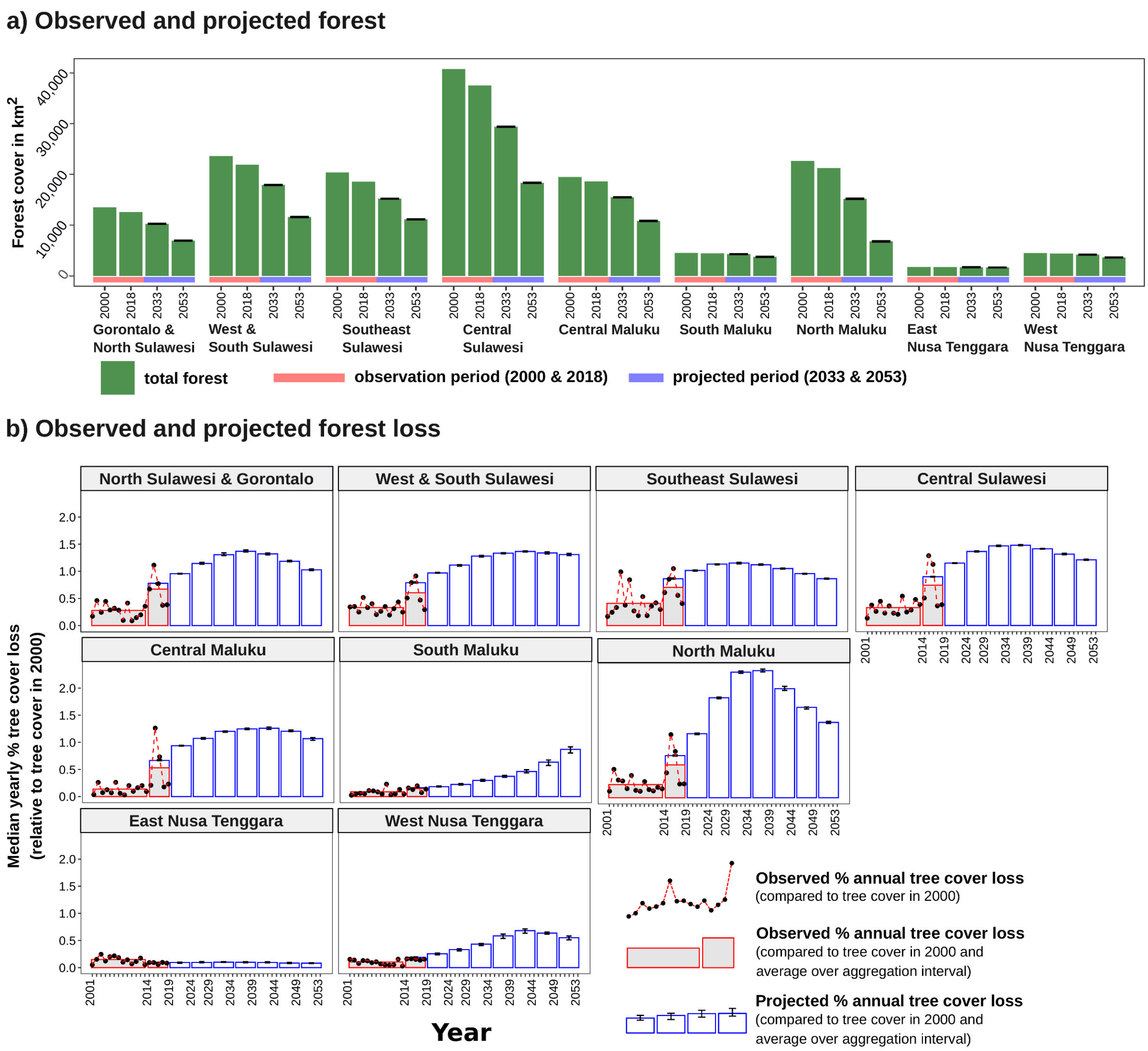

Figure 3: Observed and projected forest area and loss over Wallacea from 2000 to 2053.
a) Total forest in the first and last year of the observation period (2000–2018) and the median forest in the projected five-year periods 2029–2033 and 2049–2053 for each region [95% CI as error bars]. b) Aggregated average percent forest loss before simulation (2001–2013) and in the calibration period (2014–2018) was used for model fitting. The annual observed deforestation

shows inter-annual variability of forest loss in the regions. Deforestation was simulated for 7 five-year periods from 2014–2053 (n = 100, error bars represent CI). The calibration period from 2014–2018 can be compared to the projection of forest loss in the same time interval. All values in b) given in annual percent deforestation in comparison to forest area in 2000, by aggregating over the time-period over which the bar extends and dividing by number of years in interval.

Observed annual deforestation (2000-2018) ranged between 0.03% (South Maluku) and 1.3% (Central Sulawesi), relative to the forest at the beginning of the observation period (2000), with high inter-annual fluctuations (Fig. 3b). On average, the rate increased from the first (i.e., deforestation before the calibration period) 12 years to the 5-year calibration period in all regions, with the exception of East Nusa Tenggara where the deforestation rates were relatively low and decreased slightly (1.00 km^2 or 0.06 percent point difference).

Over the projection period, the increase in projected median forest loss increased and then decreased in all regions with the exception of South Maluku And East Nusa Tenggara. Future projected median annual deforestation rates for regions ranged between 0.08% in East Nusa Tenggara and 2.34% in North Maluku (lowest and highest). In South Maluku the deforestation rate was at a low level in the beginning of the observation period but then continued to increase until the last step. In East Nusa Tenggara projected deforestation rates stayed low over the entire projection period (median percent change over projected years 0.08%). The increase was steepest in North Maluku, with highest levels in the period 2034 to 2039.

In the calibration interval the projected loss over 5 years was slightly larger than the observed rate, with a deviation between 0% (East Nusa Tenggara) to 0.19% (West and South Sulawesi). However, in all regions the projected deforestation rate was within the range of the observed rates, indicating a good fit of projections.

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Supplementary information:

Table S1: Predictor layers used to calibrate the model

Name	Description	Source	Year
Forest loss	Forest loss previous to calibration period (2001-2013) and in calibration period (2014-2018)[1]	Giri et al. (2011), Hansen et al. (2013), Margono et al. (2014)	2001-2013, 2014-2018
Slope	Slope in 2000 derived from digital elevation model (30m)	Farr et al. (2007)	2000
Average fire per year	Average number of active fires per year (MODIS and VIIRS)	MODIS Collection 6 NRT (2018), VIIRS 375m NRT (2018)	2000/2012-2018
Accessibility	Accessibility from settlements, considering roads, slope and landcover	(Weiss et al. 2018; Deere et al. 2020) https://landscan.ornl.gov/downloads/2017	1990-2017
Human population pressure	Local population pressure (Σ = 1) (Deere et al. 2020)	Accessibility, Bright et al. (2012)	2017 (population density)
Livelihood	Distance to a village (*desa*) which derives their primary livelihood from subsistence, plantation, fisheries or non-agriculture occupation	• https://mikrodata.bps.go.id/mikrodata/index.php/catalog/PODES	2014/2018
Transmigrant settlements	Distance to transmigrant settlements	• https://mikrodata.bps.go.id/mikrodata/index.php/catalog/PODES • http://webgis.menlhk.go.id:8080/pl/pl.htm	1990 - 2013 2008/2011 (PODES)
Mining	Exploration and production mining concessions (no mining concessions as reference).[2]	WRI	-
Land-use	Including non-forest areas (*APL*), production forest (*HP*, *HPK*), limited production forest (*HPT*) and protected forests (*CA*, *HSAW*, *KSPA*, *SM*, *TN*, *TAHURA*, *TNL*, *TWA*, *TWA/HW*, *TWAL*, *TB*) as reference areas.[3]	http://data.globalforestwatch.org/datasets/indonesia-legal-classification	2020

[1]Forest loss previous to calibration period was used to inform the projection for the calibration period, while forest loss in the calibration period was used to inform projections in the future.

[2] Mining was extracted from a layer from the World Resources Insititute. We classified the shapes according to activities, which fall either into being under a form of pre-mining concession, either exploration (Exploration (Eksplorasi), during feasibility study (*Studi Kelayakan*), Country Reserves area (*Wilayah Pencadangan Negara*, WPN), Special Mining Efforts Area License (*Wilayah Izin Usaha Pertambangan Khusus*, WIUPK), or are an operating mine (*konstruksi, eksploitasi, operasi produksi*)

[3]Indonesian landuse classification distinguishes between non-forestland (APL), which comprises areas designated for other uses (such as agriculture or settlements), and forest-land. Forest-land can be further classified as conservation (HK), protection (HL) and production forest. Conservation and protection forests were designed to preserve biodiversity and protect ecosystem services respectively and were lumped into a protection category for the deforestation model. Production

forest can be differentiated into limited production forest (HPT), in which low intensity logging is allowed, but no stand replacement. In regular (HP) selective logging is allowed but also clear cutting for silvicultural plantations. In convertible production forest (HPK) logging is also allowed, but so is the conversion to agriculture estates and others uses. HPT was kept as “limited production forest”, while HP and HPK were lumped into one “production forest” category. Protected forests were used as a reference category and coded as 0.

Table S2: Model coefficients for regions in Wallacea

Region name[1]/ Predictor name	N SLW Gorontalo	WS SLW	C SLW	SE SLW	C MLK	S MLK	N MLK	E NT	W NT	in model	in best model
intercept	-0.7995	-3.1626	-3.6868	-2.6923	-2.3736	-5.3676	-4.0426	-5.6488	-5.1037	9	9
past deforestation	4.1161	7.217	5.1835	5.0109	5.9212	9.7533	7.9787	4.0345	9.8418	9	9
slope	-0.0202	-0.0334	-0.0006	-0.0086	-0.0206	-0.0385	-0.0295	-0.0126	-0.0615	9	9
fire (yearly average)	-1.9734	nb	nb	nb	-1.9834	nb	nb	nb	-1.6947	9	3
access (hrs)	nb[2]	nb	nb	-0.0001	nb	nb	nb	0.0273	nb	9	2
population pressure	0.0001	nb	0	nb	nb	-0.0001	nb	nb	0.6592	9	4
subsistence livelihood	-0.1093	-0.0127	-0.0472	-0.0882	0.0101	-0.0102	-0.043	-0.2578	-0.0403	9	9
plantation livelihood	0.0003	0.0015	nb	-0.0017	0.0011	nm	0.0004	nm[3]	0.0028	7	6
non-agricultural livelihood	-0.0044	0.0014	-0.0045	-0.0007	0.0029	0.0004	-0.0002	-0.005	0.0021	9	9
fisheries livelihood	-0.002	-0.0014	0.0043	-0.0023	-0.003	-0.0013	-0.0015	0.0039	nb	9	8
transmigrant population	nb	-0.0009	0.0004	nm	-0.0066	nb	nb	nm	nm	6	3
mining (exploration)*	nb	0.5075	0.2451	-0.2679	-0.1616	-0.8436	-0.1454	1.4684	0.2272	9	8
mining (production)*	nb	0.7879	0.3181	0.2307	0.2708	0.1504	0.2557	-0.4747	-0.2956	9	8
non-forest*	0.8962	0.0322	0.6567	0.8415	1.8143	1.9437	1.0179	0.6083	-0.0299	9	9
production forest*	0.869	-0.0322	0.1912	0.2964	0.7573	0.6139	0.3798	0.5048	0.3686	9	9
limited production forest *	0.3131	-0.0902	0.0296	0.1993	0.4617	0.3748	0.1407	-0.2759	0.168	9	9

[1]N SLW Gorontalo – North Sulawesi & Gorontalo; WS SLW – West and South Sulawesi; SE SLW – Southeast Sulawesi; C MLK – Central Maluku; S MLK – South Maluku; N MLK – North Maluku; E NT – East Nusa Tenggara; W NT – West Nusa Tenggara.

[2]Predictor not included in the best model and thus not used for projection.

[3]Predictor not included in model selection, as correlated with other predictors (Pearson correlation coefficient > 0.7)

Table S3: Region area, forest area and projected proportion of forest loss.

Year	Region name/ Predictor name		N SLW Gorontalo	WS SLW	C SLW	SE SLW	C MLK	S MLK	N MLK	E NT	W NT
-	Region area[1]		26,549	62,045	36,633	61,154	28,010	10,203	31,510	46,445	19,669
2000	Forest area		13,521	23,637	20,381	40,785	19,500	4,534	22,661	1,777	4,517
	Forest cover (%)		50.93	38.1	55.64	66.69	69.62	44.43	71.92	3.83	22.97
2018	Forest area		12,579	21,904	18,582	37,523	18,632	4,448	21,258	1,734	4,420
	Forest cover (%)		47.38	35.3	50.73	61.36	66.52	43.6	67.46	3.73	22.47
2033	Forest area[2]	area	10,275	17,929	15,220	29,399	15,496	4,289	15,193	1,708	4,193
		lower CI	10,252	17,891	15,187	29,364	15,466	4,281	15,127	1,706	4,183
		upper CI	10,299	17,971	15,241	29,439	15,525	4,297	15,252	1,710	4,205
	Forest loss (%)	%	18.31	18.15	18.09	21.65	16.83	3.58	28.53	1.49	5.13
		lower CI	18.12	17.95	17.98	21.54	16.68	3.4	28.25	1.38	4.87
		upper CI	18.5	18.32	18.27	21.74	16.99	3.77	28.84	1.63	5.36
2053	Forest area	%	6,956	11,609	11,149	18,352	10,836	3,766	6,826	1,677	3,644
		lower CI	6,930	11,538	11,116	18,288	10,783	3,732	6,748	1,674	3,627
		upper CI	6,982	11,672	11,189	18,415	10,883	3,796	6,885	1,679	3,659
	Forest loss (%)	%	44.7	47	40	51.09	41.84	15.34	67.89	3.33	17.55
		lower CI	44.49	46.71	39.78	50.92	41.59	14.66	67.61	3.21	17.21
		upper CI	44.91	47.33	40.18	51.27	42.13	16.1	68.26	3.5	17.94

[1]Area estimates in km^2

[2]Median of projected estimates (n=100) given

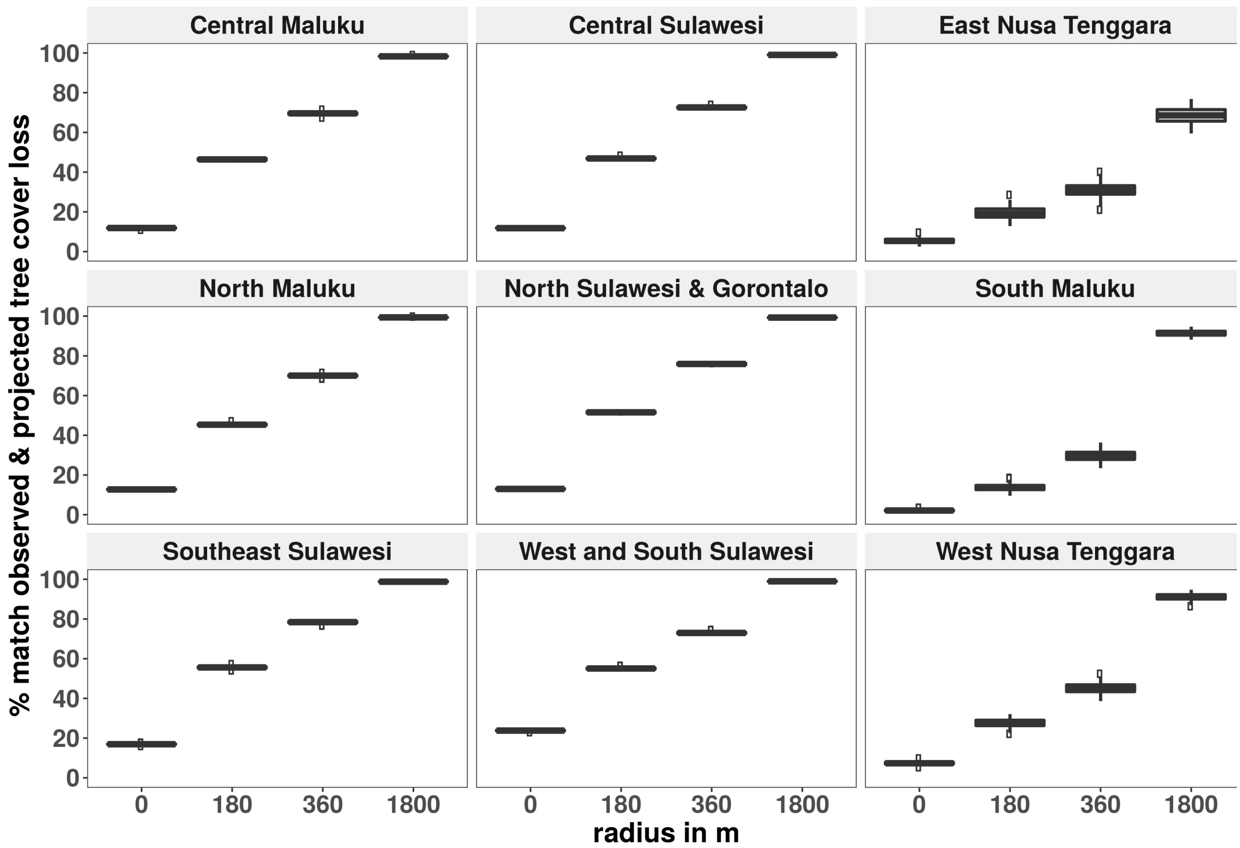

Figure S1: Proportion of match between observed and cumulative forest loss within the neighborhood of a pixel for regions in Wallacea. Boxplots show the median across simulations (n=100).