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Continuous Degradation Detection (CODED) in support of national forest emissions reporting in Fiji

Methodology and results

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Background

Fiji is developing capabilities for monitoring, reporting, and verification (MRV) of emissions in the forest sector. With support from The Forest Carbon Partnership Facility (FCPF), Fiji has recently developed a forest reference level (FRL), field inventory, and initial design of a National Forest Monitoring System (NFMS). As part of their REDD+ readiness program, the FRL covers the three largest islands of Viti Levu, Vanua Levu, and Taveuni and includes carbon loss from deforestation and degradation and gain from forest growth.

A primary area for improvement identified in the readiness program is monitoring degradation, which for the FRL was performed using census data reported from logging companies. The disadvantage of this approach is the possibility of underestimated emissions due to unreported degradation occurring outside of commercially logged areas. The objective of this research is to pilot a remote sensing approach to monitoring degradation that is 1) wall-to-wall and inclusive of all anthropogenic activities; 2) methodologically consistent with the approach to monitoring deforestation; and 3) adoptable by Fiji.

Fiji has not formally defined forest degradation, but it can generally be defined as an anthropogenic disturbance resulting in a partial reduction in tree cover that does not result in a land use change. Fiji's REDD+ readiness phase underwent an extensive analysis of the drivers of deforestation and degradation. The analysis of drivers found six prominent drivers of deforestation and degradation: forest conversion to agriculture, infrastructure, logging, natural disasters, invasive species, and mining. The primary driver affecting forest degradation is logging for timber in support of infrastructure development, which is often "poorly planned" and in support of tourism ("ERPD", 2019). The types of logging identified as prominent drivers of degradation are selective logging in Viti Levu and conventional logging in Vanua Levu.

Other factors causing forest degradation include mining in Vanua Levu, Kava harvesting (Vanua Levu and Taveuni), and fires in sugarcane plantations (Vanua Levu and Viti Levu). All the islands are also susceptible to damage from cyclones, including the 2016 Category 5 Cyclone Winston which caused extensive damage across the country. Emissions due to natural disturbances such as cyclones are not included in the FRL or other GHG reporting as they are considered natural disturbances.

Despite its name, degradation is often excluded in REDD+ reporting in participating countries. As of January 2021, 25 of 58 countries that have submitted a FRL to the United Nations Framework Convention on Climate Change (UNFCCC) included emissions from degradation (FAO, 2020). While the original reference level for Fiji included degradation, it was limited to self-reported areas of logging in natural forests according to the Ministry of Forestry. This area therefore neglects degradation due to logging outside the areas reported (i.e. illegal logging) in addition to degradation from other causes such as kava cultivation or mining. For example, Figure 1 shows an area of logging that occurred during the 2006-2016 reference period outside of a designated logging parcel. Degradation from these logging events would be omitted from the reference level if they were not reported by the company operating nearby. A national monitoring program that uses spatially explicit data to identify degradation, rather than relying on reported data, can better capture the entirety of forest change.

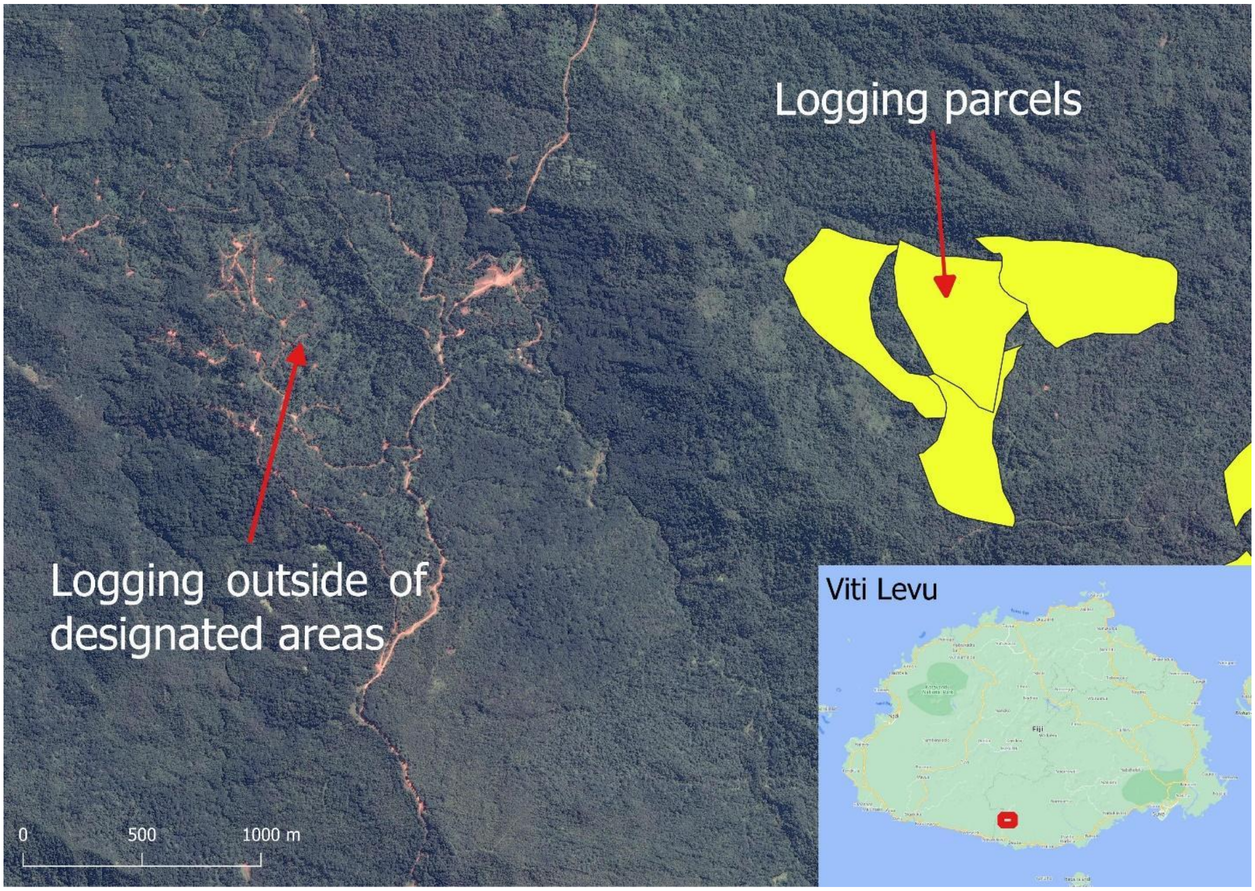


Figure 1. Logging outside of designated logging parcels during reference period of 2006 to 2016.

Monitoring forest degradation at the national scale is inherently challenging. Forest degradation often occurs over small areas and causes canopy damage that is partial and ephemeral. Approaches to monitoring degradation include field inventory, proxy methods (such as the approach used in Fiji's FRL), direct mapping, and sample-based estimation.

Recent evidence suggests that time series analysis of remote sensing data offers a potential to overcome the challenges to effective monitoring of degradation. Dense time series data can be used to track forests continuously through time and identify subtle and temporary changes to forest canopy from degradation. One approach that uses time series analysis of Landsat data is Continuous Degradation Detection (CODED), which has proven capable of estimating activity data at the national scale that is consistent with international reporting standards.

This research evaluates the use of CODED for calculating activity data for deforestation and degradation in Fiji. CODED is applied for the three islands used in the FRL and is compared to previous estimates.

Methodology

Overview

The methodology presented here for calculating activity data for forest degradation is based on three general pillars (Table 1):

1. Forest type mapping into strata representing the different forest types.
2. Forest disturbance mapping using Continuous Degradation Detection (CODED).
3. Area estimation using a reference sample.

Table 1. The three primary components to calculating activity data from degradation.

Component	Platform	Methodology	Inputs	Outputs
Forest type mapping	Google Earth Engine	Random Forest	NFI, PSP, ALOS-PALSAR, Landsat	Land cover and forest type map circa 2006
Forest disturbance mapping	Google Earth Engine	Continuous Degradation Detection	Landsat	Deforestation and degradation maps
Sample interpretation	Collect Earth Online	Stratified estimation	Planet, Landsat	Activity data

The three-pillared approach was designed to match Fiji's existing emission factor (EF) data that was calculated using a national forest inventory. The EFs were calculated according to two natural forest strata: open forests (10-40% canopy cover) and closed forests (>40% canopy cover). An EF for degradation could therefore be applied based on the difference between the two forest types. It was therefore necessary to classify the country into open and closed forests prior to change detection using CODED.

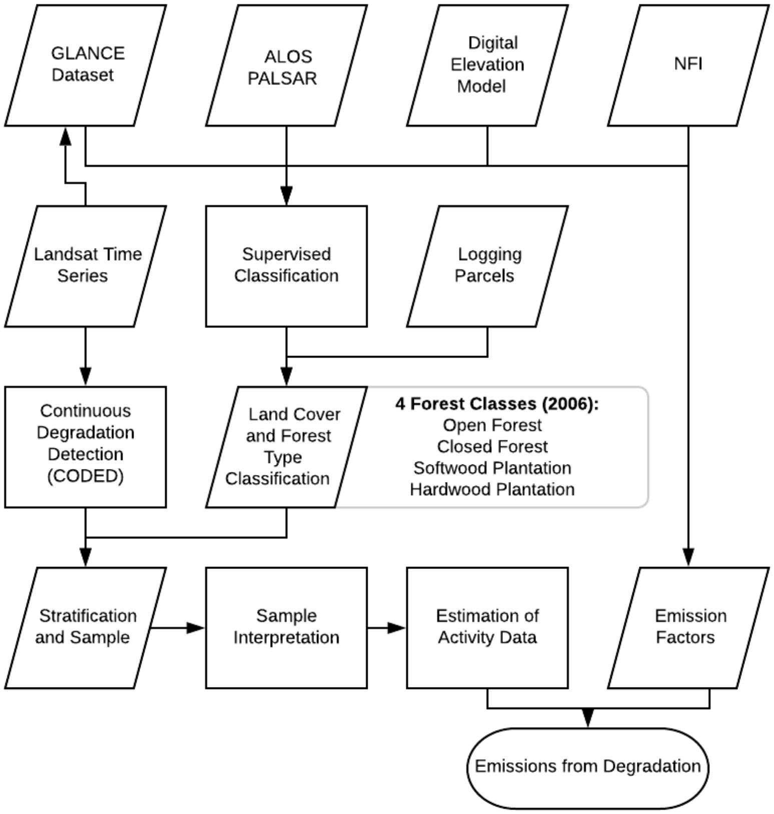


Figure 2. A schematic diagram of the proposed methodology for estimating emissions from forest degradation in Fiji.

Forest Type Classification

Forest type classification was performed using a Random Forest classifier on Google Earth Engine (GEE). In GEE, the smileRandomForest function was used with default parameters except for 200 decision trees (numberOfTrees=200). A total of 611 training points were extracted from Fiji's NFI or through interpretation of high-resolution imagery (Figure 2). Classification was performed using multi-sensor satellite imagery. First, backscatter statistics from data from the L-band ALOS-PALSAR was calculated for the year 2005, which corresponded to the year prior to the beginning of the reference period. The 'Global PALSAR-2/PALSAR Yearly Mosaic' GEE collection was used for this purpose. The yearly mean and variance for the VV-and-VH polarization backscatter bands, in addition to the ratio of the two, were calculated and used as predictor data.

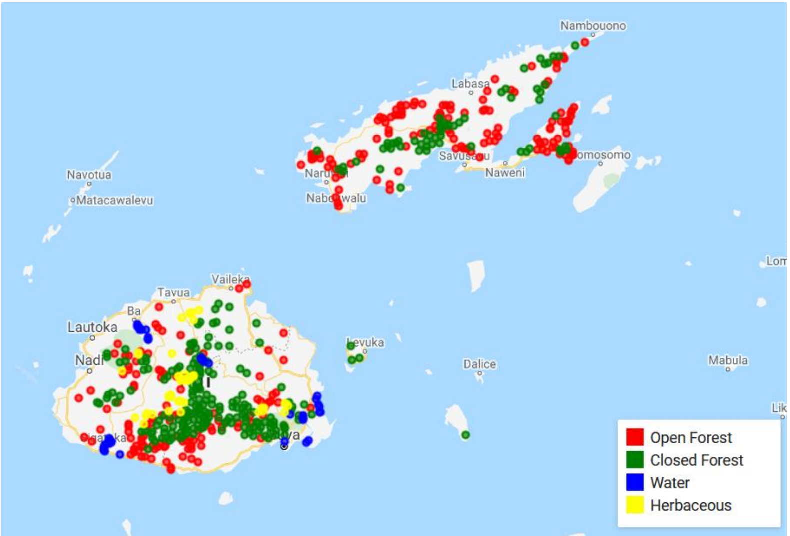


Figure 3. Distribution of training samples for land cover and forest type classification.

Multi-temporal Landsat metrics were extracted from the global Continuous Change Detection and Classification (CCDC) multi-temporal spectral change model (Arévalo et al., 2020). Each spectral band is modeled using harmonic regression, and the dataset consists of model parameters for every band. For example, the intercept parameter of the blue band is the regression model intercept fit to the blue reflectance as a function of time. This data is temporally consistent and free from cloud contamination. Furthermore, the model parameters have previously been shown to relate to seasonal landscape variability from causes such as phenology (Pasquarella et al., 2018, 2017; Zhu and Woodcock, 2014). It therefore serves as a useful dataset that summarizes spectral-temporal space in the absence of clouds. A total of six spectral bands and five model coefficients were used for classification. Finally, elevation data from the Shuttle Radar Topography Mission (SRTM) from the GEE collection 'NASA SRTM Digital Elevation 30m' was used as well (Jarvis et al., 2008).

Table 2. Input data characteristics used for land cover and forest type classification.

Data source	GEE Collection	Date	Data type	Layers	Derived metrics
ALOS PALSAR/PALSAR 2	"Global PALSAR-2/PALSAR Yearly Mosaic"	2005	Backscatter	VV, VH, ratio	Mean, Variance
NASA Shuttle Radar Topography Mission	"NASA SRTM Digital Elevation 30m"	2000	Elevation		
Landsat	"LANDSAT/L[4-8]/C01/T1_SR"	2005	Reflectance	Blue, Red, Green, NIR, SWIR1, SWIR2	Intercept, RMSE, Slope, Cosine, Sine

The input data are summarized in Table 2. The Landsat, PALSAR, and elevation data were combined to a single data stack for classification. The training data was used to train and Random Forest classifier. After experimenting with feature selection, no feature trimming was ultimately performed. The full code for data pre-processing and classification can be found in (Appendix 1).

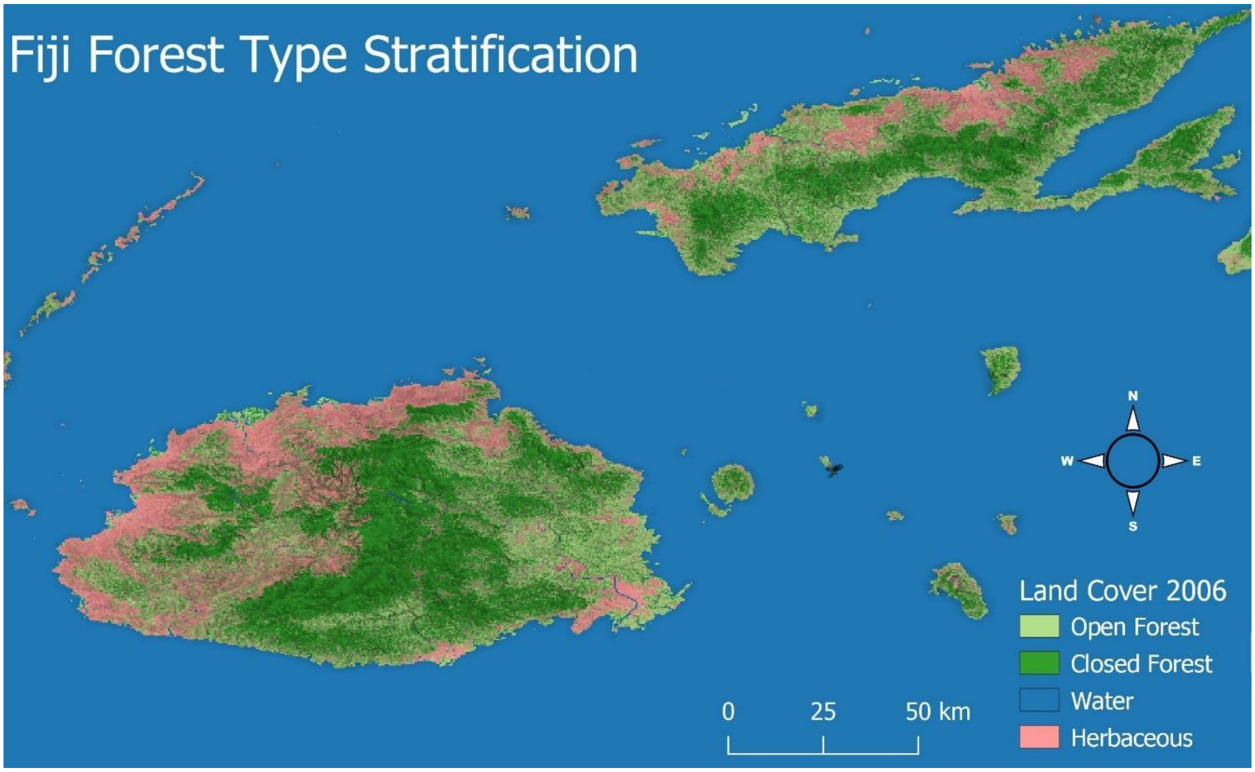


Figure 4. Landcover and forest type classification for the year 2006.

The landcover and forest type classification can be seen in Figure 4. CODED was run for all pixels classified as Open or Closed Forests in 2006 (Table 3).

Table 3. Map areas of forest types for the three largest islands.

Island	Open Forest	Closed Forest	Total
Vanua Levu	207,152	194,965	402,117
Viti Levu	249,595	372,269	621,864
Taveuni	11,948	21,986	33,934
Total	468,695	589,220	1,057,915

Continuous Degradation Detection (CODED)

Change detection and attribution was performed using the Continuous Degradation Detection (CODED) algorithm on GEE. CODED is a forest change monitoring algorithm that uses Landsat data and was introduced in the state of Rondônia, Brazil in Bullock et al. (2020). CODED has previously been applied to map and estimate degradation and deforestation in the Amazon ecoregion and Guatemala (E.L. Bullock et al., 2020; Eric L. Bullock et al., 2020b). CODED has also been used in exploratory case studies for REDD+ monitoring, including in Cameroon, Cambodia, Paraguay, Uruguay, and Republic of the Congo.

CODED has three primary components: pixel decomposition using spectral unmixing, temporal modeling using harmonic regression, and change detection using structural break detection. The first step is the transformation of Landsat reflectance data into spectral endmember fraction images. An endmember is a spectrally "pure" spectral signature. The endmembers used in Fiji were green vegetation (GV), non-photosynthetic vegetation (NPV), soil, shade, and clouds. For simplicity, the endmembers derived for the Amazon in Souza et al. (2005) were used in Fiji (Table 4). While it was originally assumed that Fiji-specific endmembers would be required to calibrate the unmixing model, it was revealed through trial and error that the Amazon model would suffice.

Table 4. The five endmembers used to calculate fractional images and NDFI. The units are reflectance and the band names correspond to Landsat 4-7 surface reflectance bands 1-7 and Landsat 8 surface reflectance bands 2-8.

Endmember	Blue	Green	Red	NIR	SWIR1	SWIR2
GV	0.05	0.09	0.04	0.61	0.30	0.10
NPV	0.14	0.17	0.22	0.30	0.55	0.30
Soil	0.20	0.30	0.34	0.58	0.60	0.58
Shade	0.00	0.00	0.00	0.00	0.00	0.00
Cloud	0.90	0.96	0.80	0.78	0.72	0.65

Each pixel of each image in Fiji was transformed into fractions of the five endmembers described above. As described in Souza et al. (2005) and Bullock et al. (2020), the endmember fraction images were used to calculate the Normalized Difference Fraction Index (NDFI). NDFI is defined as:

$$NDFI = \frac{GV_{Shade} - (NPV + Soil)}{GV_{Shade} + (NPV + Soil)}$$

where,

$$GV_{Shade} = \frac{GV}{1 - Shade}$$

The parameters GV, Shade, NPV, and Soil, are the fractional estimates of each endmember. NDFI ranges from -1 to 1 and is weakly correlated with tree cover.

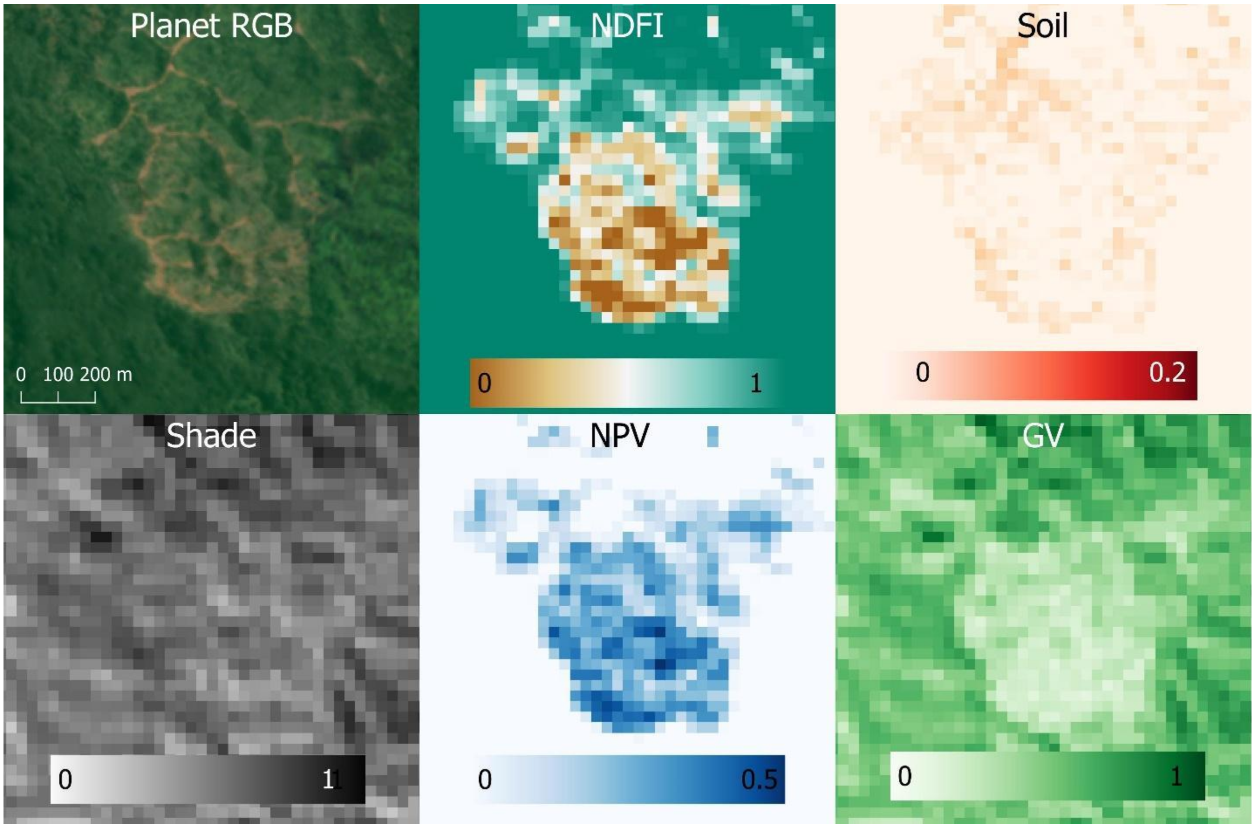


Figure 5. A Landsat 8 image on June 13, 2016 in Vanua Levu, Fiji (longitude, latitude: 178.475, -17.936).

NDFI is a spectral index that has been shown to be sensitive to subpixel forest disturbance due to degradation (Eric L. Bullock et al., 2020a; Schultz et al., 2016; Souza et al., 2005). In essence, the unmixing process is used to reveal subpixel change in forest structure or composition, and NDFI is used to highlight these changes (Figure 5). The CODED methodology essentially extends the unmixing model to the temporal domain, enabling the tracking of subpixel change through time.

CODED monitors for change using time series of NDFI and endmember fraction images. For each fraction or NDFI, an Ordinary Least Squares (OLS) harmonic regression model is fit to the pixel-level trajectories during a training period. The regression model is defined as:

$$y_{(i,x)} = \beta_0 + \beta_1 x + \beta_2 \cos \cos \left(\frac{2\pi}{365.25}x\right) + \beta_3 \sin \left(\frac{2\pi}{365.25}x\right)$$

where,

x = day of year

$y_{(I,x)}$ = predicted endmember of NDFI *i* at time *x*

β_0 = coefficient for overall magnitude or intercept

β_1 = coefficient for inter-annual variability or slope

$\beta_{2,3}$ = coefficient for intra-annual variability or seasonality

The regression parameters are used to predict observations during a monitoring period. A statistical test is applied to the regression residuals within the monitoring period, and if they exceed a statistical boundary then a change is flagged. A detailed explanation of the CODED methodology can be found in (Eric L. Bullock et al., 2020a).

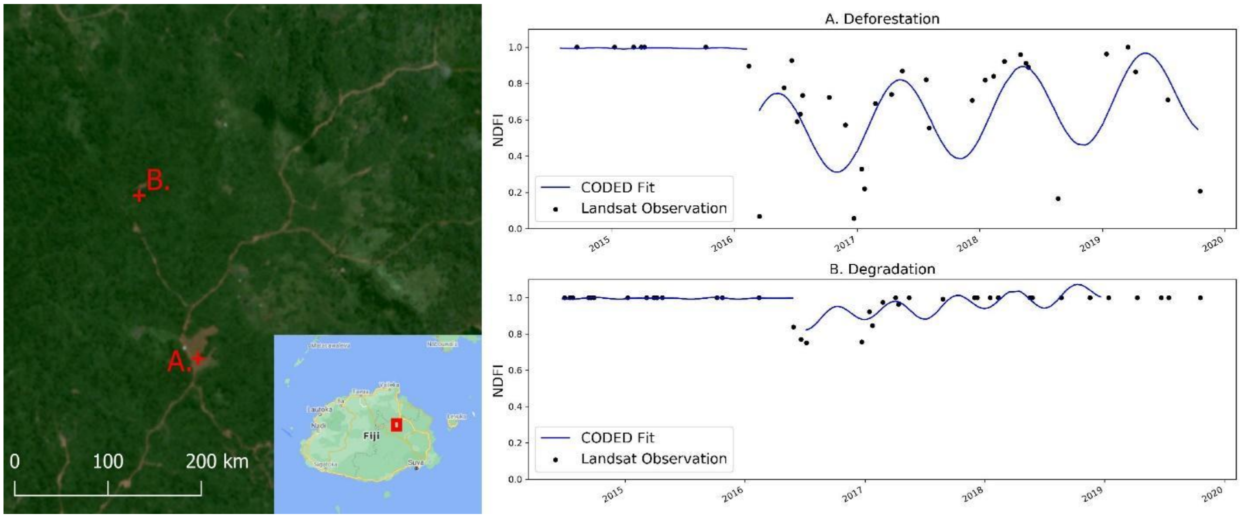


Figure 6. Example NDFI trajectories for deforestation (A.) and degradation (B.). NDFI is loosely correlated with tree canopy cover, and therefore a disturbance that results in a total canopy clearing (e.g. deforestation) will cause a larger reduction in NDFI than one that results in partial clearing (e.g. degradation).

CODED is used to attribute change as deforestation or degradation using forest and non-forest training data. For this exercise, the same training data used in the forest type classification was used for change attribution. The coefficients for the endmember fraction regression models in addition to NDFI were used to classify each independent regression segment (e.g. the blue lines in Figure 6) as either forest or non-forest. All changes with the sequence of forest to non-forest are applied a label of deforestation, while a change in forest remaining forest is labeled degradation (Figure 6). CODED was run for the three largest islands (Viti Levu, Vanua Levu, and Taveuni) for the period 2006 to 2016.

Storm Damage

Tropical cyclones are frequent in Fiji and cause structural damage that is natural but appears similar to degradation. A few approaches to mitigating false degradation labels in forests affected by storms were tried. First, we attempted to use storm track GIS data to model the potential extent of storm damage to create a mask of pixels that should not be classified as degradation. However, we found the use of storm track data alone infeasible due to the diversity in Fiji’s terrain, forests, and tropical cyclone intensity. Next, we tried omitting Landsat imagery immediately after major storms. We tested different intervals of one, two, three, and six months after a major (Category three, four, or five) tropical cyclone to remove data from analysis. Initial assessment found that most low-intensity tropical cyclone damage was no longer visible after two months. Therefore, we decided to remove two months of data after every major storm.

However, severe storms such as Cyclone Winston caused widespread forest damage that persisted beyond two months. To further reduce misclassification of storm damage as degradation we used a conservative *Minimum Observations* threshold in CODED. This threshold determines the number of consecutive observations that are beyond a statistical threshold (they look like change) for a change to be detected. A parameter setting of six was chosen which means six consecutive observations are needed to flag a change. In Fiji it generally takes between three and six months to obtain six consecutive observations. The assumption here is that degradation will be more persistent than storm damage due to the removal of trees that generally occurs from logging.

In the end, it is inevitable that the change maps contain errors. The process of mapping degradation is inherently challenging, with the most common errors being due to:

- misclassification of natural disturbance as degradation.
- false change alerts due to persistent clouds.
- omitted change due to the subtle nature of degradation.

Therefore, it is imperative that comprehensive national-scale estimation of forest degradation use a reference sample and unbiased statistical estimator. For this purpose, the CODED map was used to derive a stratified random sample.

Area Matching

CODED is tested here as an improvement to the mapping approach used in the FRL, which did not include disturbance due to degradation. CODED should therefore be able to replicate the area of deforestation estimated for the FRL with the added class of degradation. An "area matching" approach was designed to ensure consistency between estimates of deforestation calculated from the two models. The objective was to tune CODED so that it created estimates of deforestation similar to the FRL, and then identify degradation in the remaining forest. CODED has parameters that are used to control the sensitivity of the change detection. First, CODED flags a change if n consecutive observations exceed a statistical boundary (the "Minimum Observation" parameter), the size of which is controlled by m (the "Chi-Squared Probability" parameter). Both n and m are parameters controlled by the user. Changes are kept or removed in the final change maps depending on their change magnitude p, defined as the shift in NDFI during the monitoring period (the "Minimum Change Magnitude" parameter). Values of n, m, and p were calibrated so that the areas of deforestation closely resembled the yearly areas in the FRL. As noted above, however, the *Minimum Observations* threshold was ultimately set to 6 to reduce the influence of clouds, so the area matching was primarily performed using the other two parameters.

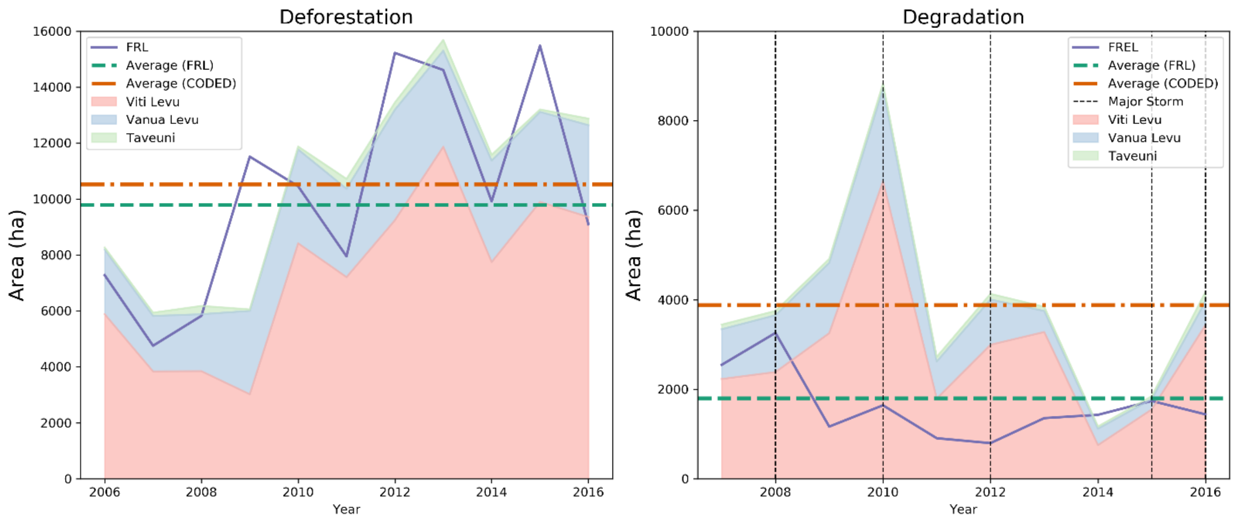


Figure 7. Areas of deforestation and degradation estimated using CODED and the mapping approach from the FRL. Despite efforts to reduce erroneous detection of storm damage, there is still evidence of storm damage in the estimates of degradation.

Accuracy Assessment

All large area maps created using automated classification of satellite imagery will inevitably contain errors. These errors can be quite large when targeting subtle change processes such as forest degradation. Errors in a map will introduce a bias to estimates of area obtained through "pixel counting", or summing the area mapped as a particular land cover or change class. The International Panel on Climate Change (IPCC) stipulates that areas reported for international treaties related to greenhouse gas inventories be "neither over- nor underestimates so far as can be judged, and [with] uncertainties [that] are reduced as far as practicable" (Penman et al., 2003, preface). Sample-based estimates of area present a method for meeting this IPCC requirement and can be calculated by applying reference data in an unbiased statistical estimator (GFOI, 2020). A sample-based design for area estimation can accommodate map errors and provide both an estimate of a sample mean (e.g., area of degradation in Fiji) and variance (e.g., uncertainty in the estimate of degradation), thus meeting the IPCC "Good Practice" recommendations.

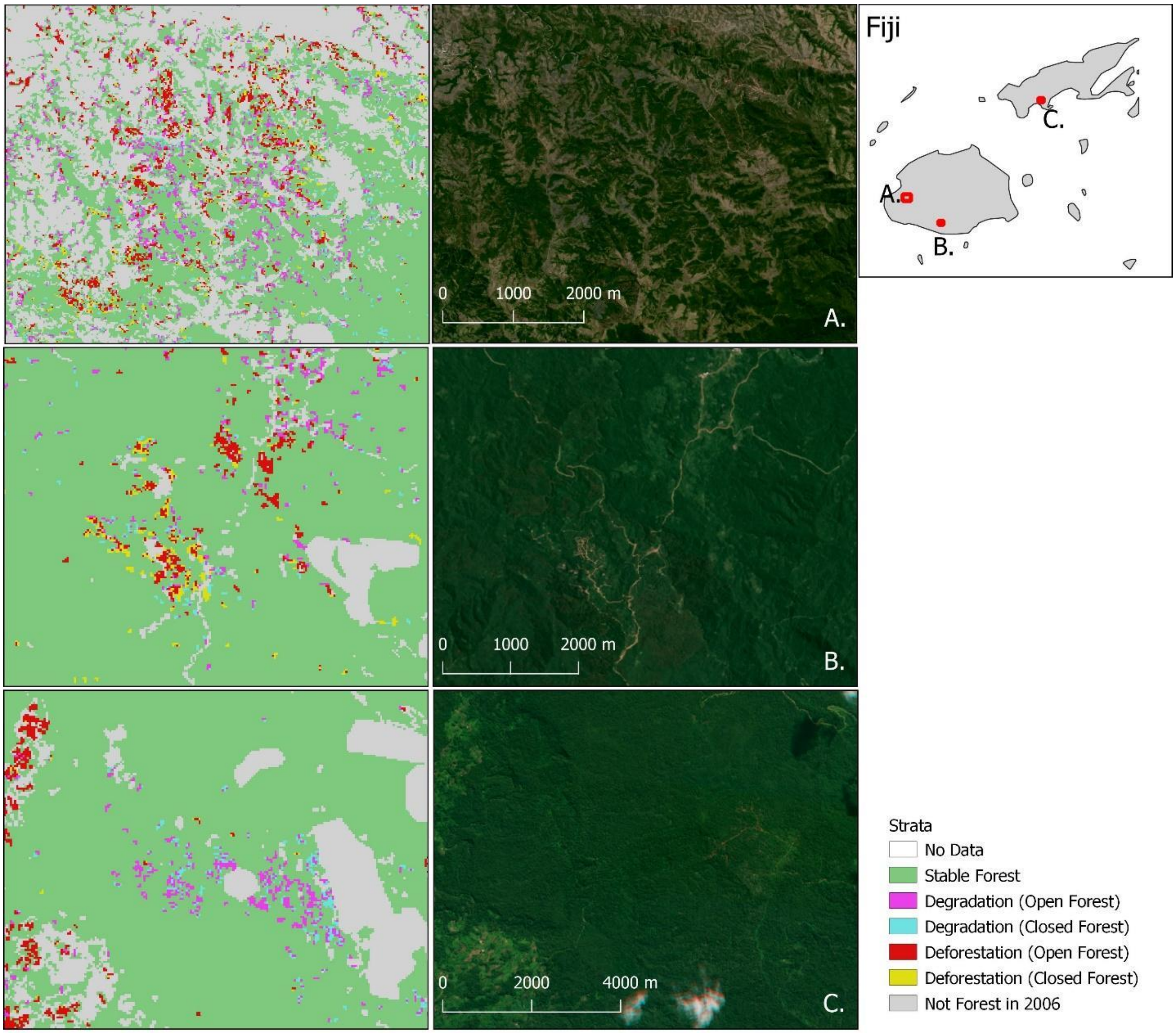


Figure 8. Stratification of degradation and deforestation in open and closed forests for three locations in Fiji.

After calibration of CODED, a reference sample was derived under stratified design for estimating area and accuracy. The results from CODED were stratified into 5 strata: Non-Forest Change (Stable) (1), Deforestation in Open Forest (2), Deforestation in Closed Forest (3), Degradation in Open Forest (4), and Degradation in Closed Forest (5). Importantly, this sample was not designed for the ultimate calculation of area estimation. Instead, the focus was to evaluate the accuracy of the change classes. Therefore, fewer samples were allocated to the stable class than would be recommended for the creation of activity data. A total of 40 sample units were allocated to the stable class, 25 to each of the deforestation classes, and 40 to each of the degradation classes, resulting in 140 total sample units. Reference interpretation was performed by two interpreters using the Collect Earth Online platform (Saah et al., 2019).

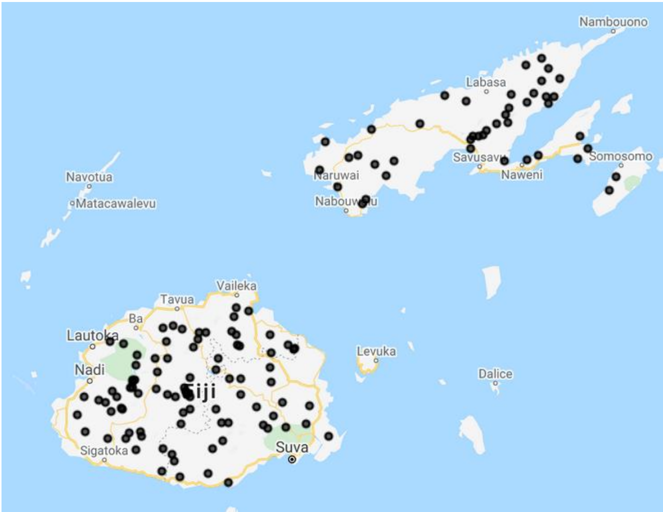


Figure 9. Distribution of samples for accuracy assessment.

Cross-tabulation of the reference samples and CODED stratification can be seen in Table 5. There are two important findings of this assessment. First, only 5% of the samples from the stable class (or 2 out of 40) contained degradation, showing that omission of degradation was relatively low. While Producer's Accuracy for Degradation is low, this is mostly due to these 2 errors of omission from the large Stable stratum. The effect of omission errors can be mitigated in the future through stratification that better captures potential change pixels (Olofsson et al., 2020). Regardless, it is encouraging that the User's Accuracy of degradation was relatively high, and only 2 omission samples were found in the Stable stratum. This suggests that national estimation of degradation using CODED is feasible. Even with only 50 samples from Degradation classes, the estimate of area was statistically significant at the 95% confidence level. Since precision improves with sample size, the precision in the estimate of area of degradation will improve with a sample size that reflects usual national assessments (approximately 500-2000 sample units).

Second, CODED largely overestimated Deforestation. Only 3 sample units were deforestation in the reference data, despite 50 samples being selected from the Deforestation strata. This resulted in a very low User's Accuracy and proved problematic for calculation of activity data. The high commission errors resulted in low precision in the estimate of area, as evident in the 95% confidence interval (0.01), which is larger than the area estimate (0.008).

While the total sample count was low, it was clear from the results that the accuracies of the individual change classes were poor. Notably, there was substantial overestimation of deforestation. The accuracies substantially improved when collapsing change classes, due largely to confusion between Open and Closed forests. One way of interpreting this is that the change detection performed with 56% Producer's and 57% User's Accuracy, but the attribution by forest and change type was much lower. For comparison, the deforestation/clearings class used to calculate activity data for the FRL had a 38% and 20% Producer's Accuracy for Lowland and Upland forests, respectively, and a User's Accuracy of 59% and 56%. For degradation, CODED had a Producer's Accuracy of 65% and a User's Accuracy of 24%, and for deforestation it was 62% and <1%, respectively.

In summary, CODED proved capable of estimating degradation but not deforestation at the national level. In the past, CODED has achieved better levels of accuracy and precision for deforestation than degradation. For example, in three previous studies, CODED-based maps of deforestation had User's Accuracies of 93%, 84%, and 57%, Producer's Accuracies of 82%, 85%, and 84%, and margins of error for the area estimate of 5%, 9%, and 19% (E.L. Bullock et al., 2020; Eric L. Bullock et al., 2020a, 2020b). One difference here is the small sample size, which would directly affect the size of the confidence interval for the area estimate. Another important difference was the approach to model calibration. In previous studies, CODED was calibrated to the study region using visual inspection of change maps in addition to calibration data. Here, however, the area matching approach was used instead.

Table 5. Error matrix for map evaluation.

			Reference				
				Degradation		Deforestation	
			Stable	Open	Closed	Open	Closed
Map		Stable	38	0	2	0	0
	Degradation	Open	2	4	3	1	0
		Closed	23	12	5	0	0
	Deforestation	Open	13	7	3	1	1
		Closed	14	5	6	0	0

Table 6. Summary statistics from accuracy assessment.

	Area Proportion	Standard Error	User's Accuracy	Producer's Accuracy
Stable	0.896	0.033	0.950	0.947
Degradation (Open)	0.033	0.007	0.400	0.353
Degradation (Closed)	0.064	0.032	0.125	0.014
Deforestation (Open)	0.005	0.004	0.040	0.449
Deforestation (Closed)	0.002	0.002	0.000	0.000
Degradation (Combined)	0.097	0.039	0.644	0.240
Deforestation (Combined)	0.008	0.006	0.001	0.620
Disturbance (Combined	0.104	Not calculated	0.572	0.558

Degradation + Deforestation)				

Comparison to FREL and Recalibration

The area matching approach was designed to ensure continuity from the FRL to CODED. However, the assessment revealed this to be a poor strategy. To understand why the area matching approach resulted in widespread overestimation of deforestation a comparison of CODED to the FRL was conducted. Activity data for the FRL was created from a sample that was derived from a change map created using the 'CSIRO approach' which applies an algorithm referred to as CPN. The area matching approach matched the areas mapped from CODED to those produced with CPN. It is important to note that the reference interpretation procedure is designed to adjust for uncertainties in the map, so perfect maps are not necessary. Nevertheless, it is preferable to have a good quality map, so understanding sources of uncertainty is beneficial to long term monitoring objectives.

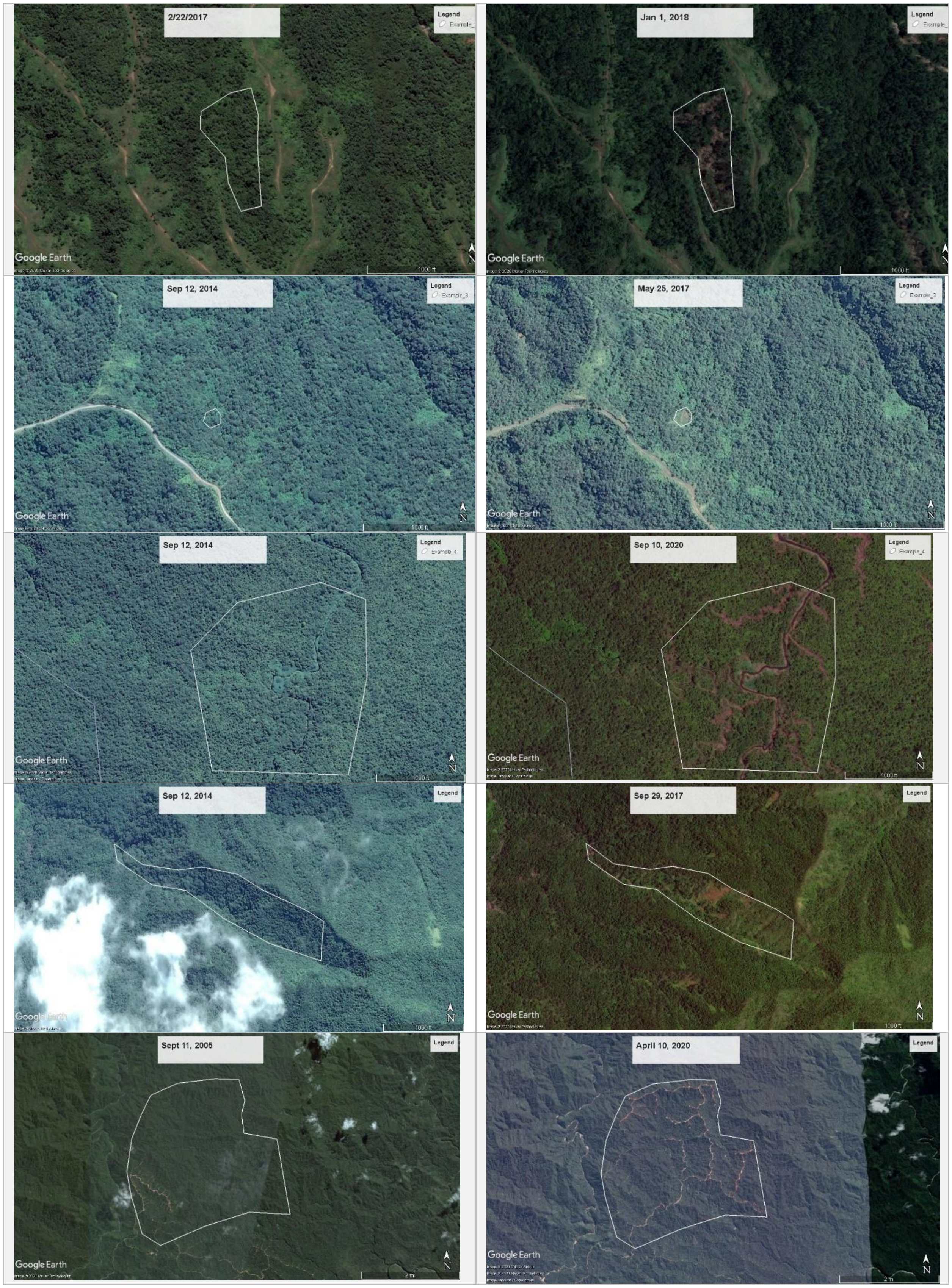
To summarize the comparison, evidence was found to suggest pervasive overestimation of deforestation in the CPN results. The assessment for the FRL revealed a commission of clearings/deforestation of 41% and 44% 59%, respectively, suggesting that overprediction was common. Furthermore, a sample of 20 locations identified as change in the 2006-2016 CPN map but stable in CODED was randomly selected, and only 2 were identified as correct attribution of change. Visual inspection of the CPN output map shows widespread commission error as well, such as the erroneous attribution of change in 2015 that, according to the map, resulted in the deforestation over 4% of the island of Taveuni, despite it occurring in remote and mountainous terrain (Figure 10).

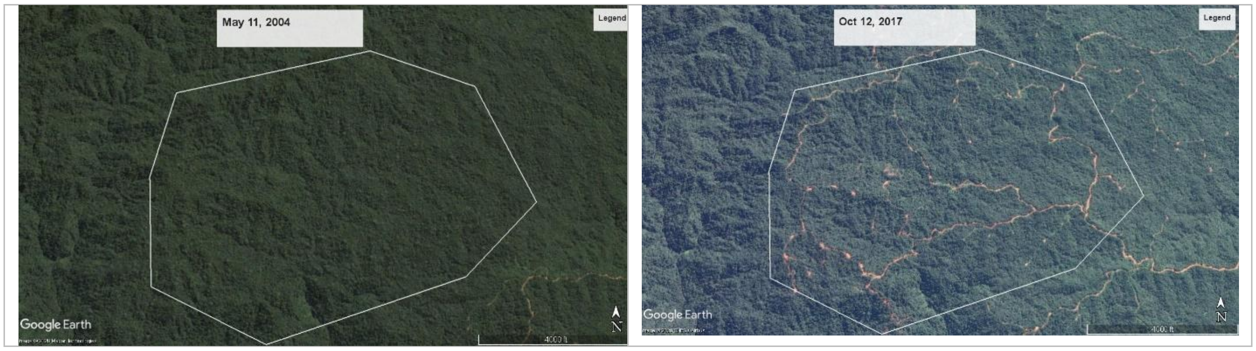
Figure 10. Deforestation in the FRL map for the year 2015 in Taveuni (red). The majority of the change is at high altitude and in remote regions, and is likely commission due to clouds.

For future application of CODED in Fiji, including for the National Forest Reference Emission Level, the parameters were recalibrated independently. A few strategies were deployed for recalibration. First, a coordinated field campaign was conducted in December 2020 across the three major islands to verify areas mapped as degraded or deforested. A total of 256 field plots were visited and analyzed for signs of deforestation and degradation and the forest type (open or closed) was recorded. Second, a calibration dataset of confirmed change events was created by comparing CODED maps to Google Earth (GE), in addition to consultation with the Fiji REDD+ team (Table 7). The field and GE calibration dataset was used to iteratively adjust model parameters, resulting in more conservative change detection than the version using the area matching approach.

Table 7. Examples of degradation and deforestation calibration polygons (white). High resolution imagery from Google Earth is shown before and after the disturbance events.

Before Change	After Change


2/22/2017
Legend
Google Earth
Jan 1, 2018
Legend
Google Earth
Sep 12, 2014
Legend
Example_3
Google Earth
May 25, 2017
Legend
Example_3
Google Earth
Sep 12, 2014
Legend
Example_4
Google Earth
Sep 10, 2020
Legend
Example_4
Google Earth
Sep 12, 2014
Legend
Sep 29, 2017
Legend
Google Earth
Sept 11, 2005
Legend
Google Earth
April 10, 2020
Legend
Google Earth



After recalibration, CODED was used to create a map of degradation and deforestation for 2010-2020. The analysis was extended to all islands in Fiji (Figure 11). The time period was chosen as a possible reference period for the National Reference Level. As of June 2021, no accuracy assessment has been performed on these results, but it is planned to be conducted in the summer of 2021.

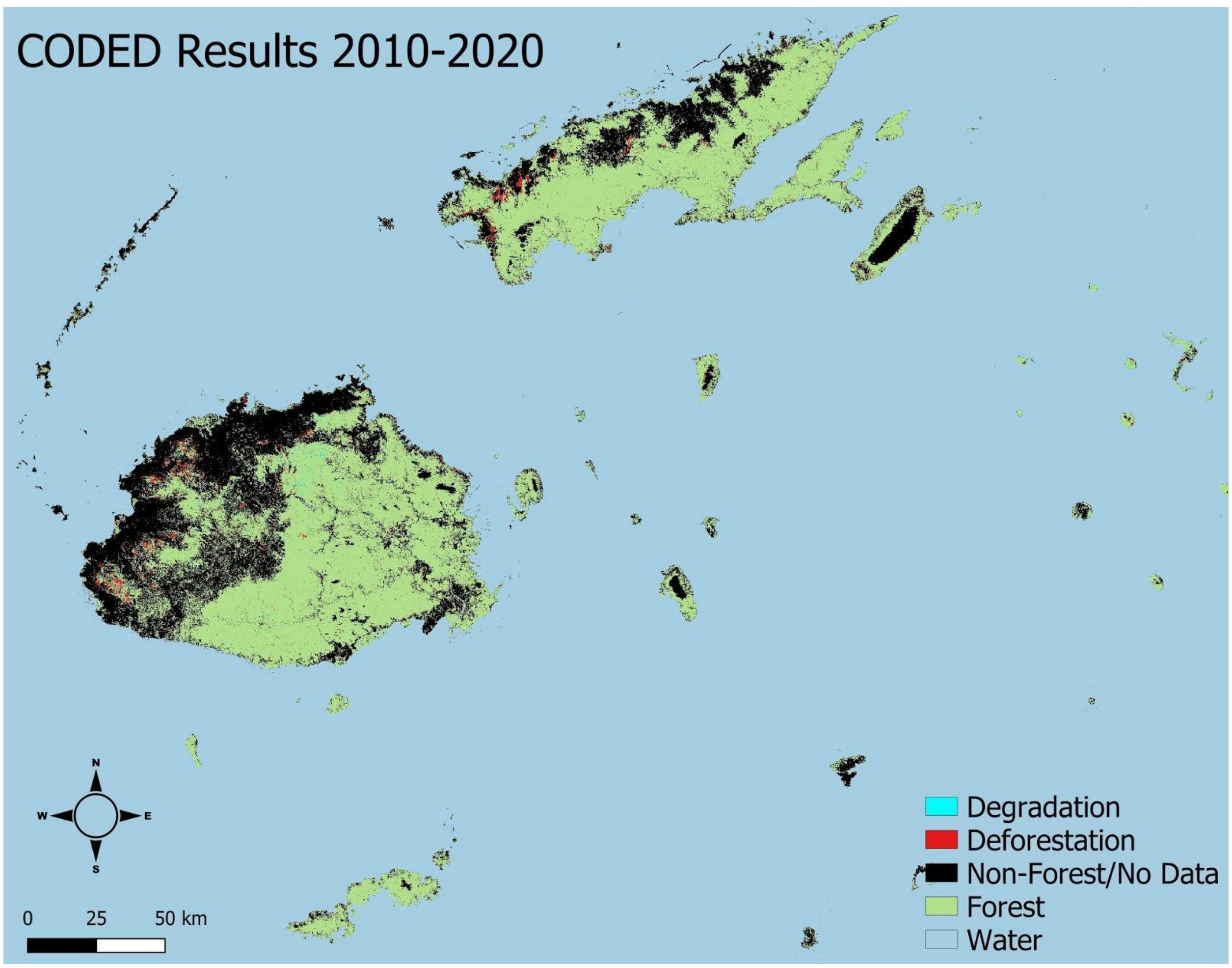


Figure 11. Recalibrated CODED results for 2010-2020.

Conclusion and Next Steps

National monitoring of forest degradation using CODED is achievable, but challenges remain. We were able to estimate wall-to-wall areas of degradation at the 95% confidence level. However, our accuracy assessment revealed that an "area matching" approach to model calibration was not appropriate in the context of mapping deforestation. The development of a calibration dataset using field campaigns and high-resolution imagery would provide an independent source of model calibration, which can be used to create more accurate maps of deforestation in the future. These improvements will soon be tested with an evaluation of the 2010-2020 dataset for the National Reference Level. To reach the objectives of the national monitoring program the following steps are recommended:

1. Activity classes should be aligned with the results of the most recent forest inventory. The areas mapped with CODED, and estimated using a reference sample, must correspond to unique emission factors.
2. A comprehensive accuracy assessment should be performed for CODED results that correspond to the time of the national reference level using a stratified sample and Collect Earth Online.
3. Fiji's REDD+ team should be trained in all components of the creation of activity data, including the forest type classification, running CODED, designing and selecting a sample, and interpreting the sample using reference imagery.

References

Arévalo, P., Bullock, E.L., Woodcock, C.E., Olofsson, P., 2020. A Suite of Tools for Continuous Land Change Monitoring in Google Earth Engine. Front. Clim. https://doi.org/10.3389/fclim.2020.576740

Bullock, E.L., Nolte, C., Segovia, A.R., Woodcock, C.E., 2020. Ongoing forest disturbance in Guatemala's protected areas. Remote Sens. Ecol. Conserv. 6. https://doi.org/10.1002/rse2.130

Bullock, Eric L., Woodcock, C.E., Olofsson, P., 2020a. Monitoring tropical forest degradation using spectral unmixing and Landsat time series analysis. Remote Sens. Environ. 238. https://doi.org/10.1016/j.rse.2018.11.011

Bullock, Eric L., Woodcock, C.E., Souza, C., Olofsson, P., 2020b. Satellite-based estimates reveal widespread forest degradation in the Amazon. Glob. Chang. Biol. 26, 2956–2969. https://doi.org/10.1111/gcb.15029

FAO, 2020. From reference levels to results reporting: REDD+ under the United Nations Framework Convention on Climate Change, From reference levels to results reporting: REDD+ under the United Nations Framework Convention on Climate Change. https://doi.org/10.4060/cb1635en

Forestry, R. of F.M. of, 2019. Emission Reductions Program Document (ER-PD).

GFOI, 2020. Integration of Remote-Sensing and Ground-Based Observations for Estimation of Emissions and Removals of Greenhouse Gases in Forests. Methods Guid. from Glob. For. Obs. Initiat. 3.

Jarvis, A., Reuter, H.I., Nelson, A., Guevara, E., 2008. Hole-filled SRTM for the Globe. Version 4. Available from the CGIAR-CSI SRTM 90m Database (http://srtm.csi.cgiar.org).

Olofsson, P., Arévalo, P., Espejo, A.B., Green, C., Lindquist, E., McRoberts, R.E., Sanz, M.J., 2020. Mitigating the effects of omission errors on area and area change estimates. Remote Sens. Environ. 236, 111492. https://doi.org/10.1016/j.rse.2019.111492

Pasquarella, V.J., Bradley, B.A., Woodcock, C.E., 2017. Near-real-time monitoring of insect defoliation using Landsat time series. Forests 8. https://doi.org/10.3390/f8080275

Pasquarella, V.J., Fickas, K.C., Holden, C.E., Sulla-Menashe, D., Bullock, E.L., Arevalo, P., Olofsson, P., Cohen, W.B., Woodcock, C.E., 2018. The benefits of time: Characterizing the Landsat spectral-temporal domain. Remote Sens. Environ.

Penman, J., Gytarsky, M., Hiraishi, T., Krug, T., Kruger, D., Pipatti, R., Buendia, L., Miwa, K., Ngara, T., Tanabe, K., Wagner, F., 2003. Good Practice Guidance for Land Use, Land-Use Change and Forestry, Intergovernmental Panel on Climate Change, Good Practice Guidelines on Land Use, Land Use Change and Forestry.

Saah, D., Johnson, G., Ashmall, B., Tondapu, G., Tenneson, K., Patterson, M., Poortinga, A., Markert, K., Quyen, N.H., San Aung, K., Schlichting, L., Matin, M., Uddin, K., Aryal, R.R., Dilger, J., Lee Ellenburg, W., Flores-Anderson, A.I., Wiell, D., Lindquist, E., Goldstein, J., Clinton, N., Chishtie, F., 2019. Collect Earth: An online tool for systematic reference data collection in land cover and use applications. Environ. Model. Softw. 118, 166–171. https://doi.org/10.1016/j.envsoft.2019.05.004

Schultz, M., Clevers, J.G.P.W., Carter, S., Verbesselt, J., Avitabile, V., Quang, H.V., Herold, M.,

2016. Performance of vegetation indices from Landsat time series in deforestation monitoring. Int. J. Appl. Earth Obs. Geoinf. 52, 318–327. https://doi.org/10.1016/j.jag.2016.06.020

Souza, C.M., Roberts, D.A., Cochrane, M.A., 2005. Combining spectral and spatial information to map canopy damage from selective logging and forest fires. Remote Sens. Environ. 98, 329–343. https://doi.org/10.1016/j.rse.2005.07.013

Zhu, Z., Woodcock, C.E., 2014. Continuous change detection and classification of land cover using all available Landsat data. Remote Sens. Environ. 144, 152–171. https://doi.org/10.1016/j.rse.2014.01.011

Appendix 1: Code

The code for performing the analysis can be permanently found in the links below.

Land cover and forest type classification:

https://code.earthengine.google.com/c200b54b8c1ef336bdca05f272d4ce88

CODED:

https://code.earthengine.google.com/5dbd353f9075aeb076cf0efa61dc96a9