Multi-temporal and multi-frequency analysis to assess forest degradation

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1. Abstract

We Investigated the potential of integrating multi -frequency Synthetic Aperture Radar (SAR) data: ALOS PalSAR-2, Sentinel-1B and TanDEM-X, in combination with field data to identify and classify different levels of forest disturbance in a secondary forest in Colombia, that has been under pressure from gold mining and selective logging at different intensities. Hereafter, we assessed the capabilities of Sentinel-1 to discriminate between the classes already identified.

2. Introduction

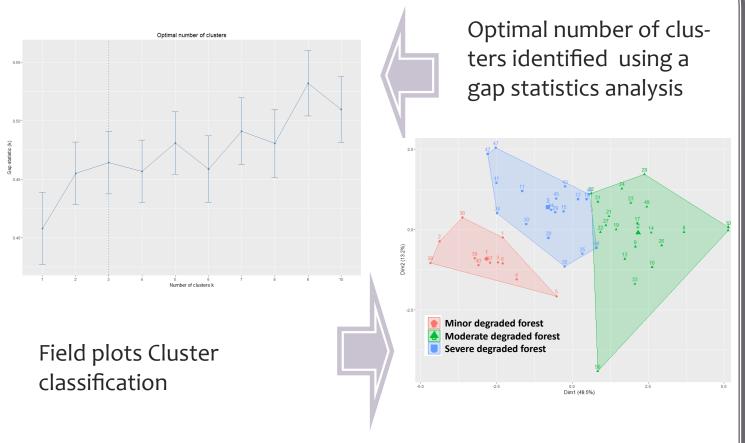
Forest disturbances (i.e. deforestation and degradation) are a serious problem significantly contributing to greenhouse emissions and biodiversity loss [1].

Quantifying the impact of forest degradation on the carbon budget is challenging because of the diversity of definitions, varying scale of the changes, and many drivers that are applying pressure on the forests. As a result, the measuring and mapping of forest degradation is still a technical challenge [1-3].

Radar (SAR) data is very promising for detecting and monitoring forest degradation considering its sensitivity to above ground biomass and forest structure [4]. There is also evidence that the integration of sensors in combination with field data can provide more precise results when monitoring changes in forest [5].

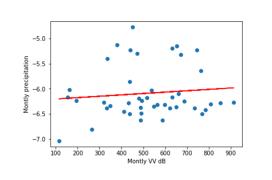
Methods Field data **Multi-frequency SAR Data** campaign. SENTINEL-1B ALOS-2 TanDEM-X Geo-referenced inventory data observations X-Band C-Band L-Band Interferometric - Backscatter Backscatter DBH > 10 cm Coherence and Species Forest in different decompositions disturbance degree - Polarimetric Selection of the most raining data representative variables for using very high Tree height / identifying differences in resolution forest structure DBH per plot images from Species per plot Sentinel 2 and Google Earth Super Vector Machine (SVM) Classification Training data K-means unsupervised set for machine learning calibration cluster algorithm Calibration and validation Multi-temporal **Validation** observations Classification of the Validation inventory field plot dataset according to its similarity to SENTINEL-1 identify different levels of 2014 - 2018

6. Results 6.1 Field data classification



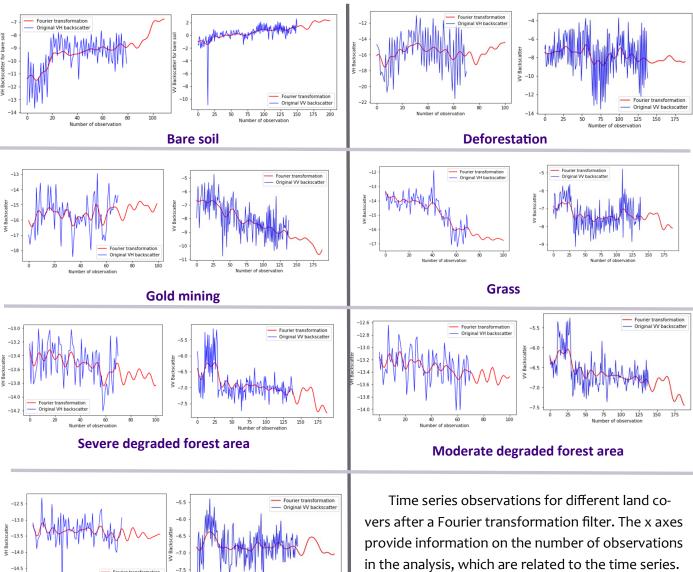
	Minor	Moderate	Severe	
Parameters	disturbed	disturbed	disturbed	
Plot tree density	615.64	381.33	212.76	
Species/ha	39.18	34.11	27.10	
Biomass Mg/ha	82.84	60.29	18.93	
Mean height	10.33	12.06	8.62	
Mean DBH	18.21	17.46	17.04	
Basal area/ha	350.70	208.69	104.46	

Correlation analysis between rainfall and backscatter observations:



The forest in the study area is aseasonal, and here it can be seen the no correlation between the precipitation and the ranges in backscatter for a forest area.

6.3 Multi-temporal analysis Sentinel -1



in the analysis, which are related to the time series. For VV polarization the analysis started from October 2014, and for VH polarization in December 2015. Minor degraded forest area This because of the data availability.

7. Conclusions

Most definitions from the literature agree that forest degradation is related to the detriment of forest structure. We investigated whether it was possible to assess significant differences in forest structure and link them to different levels of disturbance. A key aim of our research was to gain a better understanding of the state of the forest in our study area from the field data in order to investigate the capabilities of multi-frequency SAR data in discriminating variances in structure. Results from the SVM show a good approximation to categorize these forests by degrees of deterioration. And results from the multi-temporal observations from Sentinel-1 Show the variation in the backscatter related to changes. It is particularly important for this area, as it has been subject to intense selective logging and gold mining for decades. This study is the first insight into the structural variability of this forest from a remote sensing perspective.

4. Field site

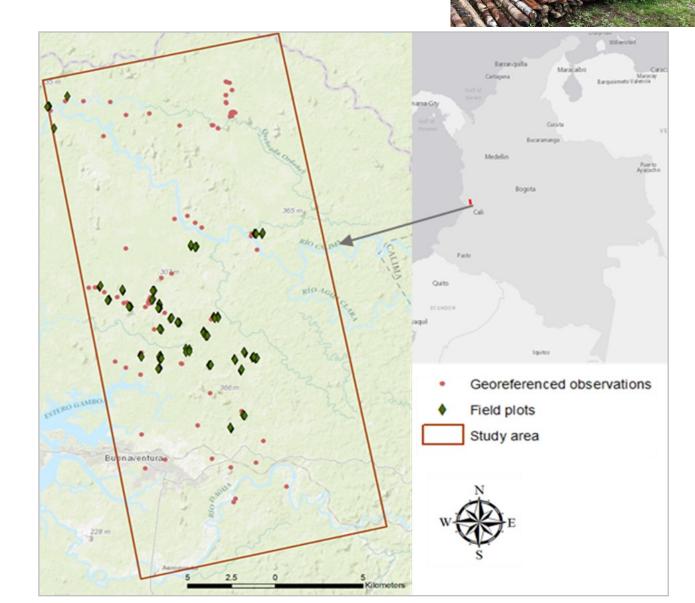
Location: Located in the Bajo Calima municipality – in the Pacific costal region at the Department of Valle del Cauca in Colombia. The area belongs to the Chocó-Darién bioregion: a national and international important area in terms of biodiversity and ecosystem services [6-7].

Ecosystem: Very-moist tropical forest. Precipitation oscillates between 4000 and 8000 mm, therefore it is permanently cloud cover. Its altitude varies between o and 700.

Forest conditions: Very degraded forest due to historical illegal logging and gold mining.

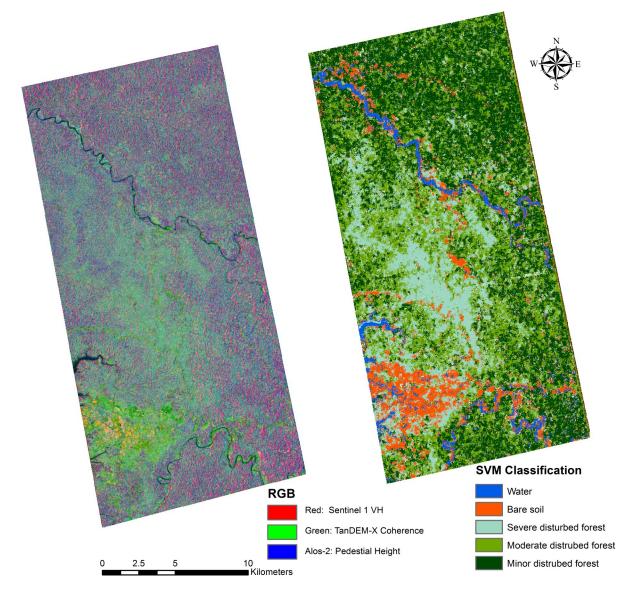






6.2 SVM Classification results

Multi-sensor classification of the three levels of forest disturbance observed.



The accuracy assessment showed a Kappa coefficient of 0.72 and an overall accuracy of 66.2%

		Bare	Severe	Moderate	Minor		User
CLASS	Water		disturbed	disturbed	disturbed	Total	accuracy
		soil	forest	forest	forest		(%)
Water	137	24	5	10	28	211	64.93
Bare soil	25	163	24	41	80	357	45.66
Severe disturbed forest	16	11	427	129	34	635	67.24
Moderate degraded forest	1	8	91	473	139	735	64.35
Minor degraded forest	6	4	9	129	572	736	77.72
Total	185	210	556	782	853	2674	Overall
Producer accuracy (%)	74.1	77.6	76.8	60.5	67.1		accuracy 66.2 %

7. Further work

This methodology can be applied and tested in other study areas and hence contributes to the scarce knowledge of how to assess forest disturbances and degradation. Further research will explore the temporal dynamics of Alos Pal-SAR and Alos-2

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