Two decades of land cover changes in the Colombian Andes

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Abstract

The Colombian Andes faces severe anthropogenic pressures from deforestation, agricultural expansion, mining, and urban development. Given its status as one of the world's biodiversity hotspot, land cover monitoring for effective conservation strategies and sustainable development planning is essential. While early research relied on coarse or medium-resolution satellite imagery for limited temporal coverage, recent initiatives like MapBiomas Colombia have improved national-scale mapping capabilities. However, mapping the complex spectral-temporal patterns of heterogeneous tropical mountain environments benefits from advanced methods that can track long-term surface trends. This study presents comprehensive annual land cover maps for the Colombian Andes and Sierra Nevada of Santa Marta spanning 1997-2024, representing the longest and most detailed temporal analysis of this critical region to date. We employed the Continuous Change Detection and Classification (CCDC) algorithm applied to Landsat data, coupled with machine learning models trained on a custom dataset designed to address existing limitations in temporal depth and spatial detail. Our time series approach leverages spectral-temporal signatures to distinguish land cover types with similar spectral characteristics but distinct temporal behaviors, providing a unique method for monitoring forest dynamics, habitat changes, and anthropogenic impacts across the Colombian Andes.

Introduction

The tropical Andes constitute one of the world's biodiversity hotspots in terms of species richness and endemism (Myers et al., 2000). Forests in this region are important for habitat provision, carbon sequestration, water regulation, landslide prevention, and climate change adaptation. The Colombian Andes are home to approximately 78% of Colombia's population and to the largest percentage of endemic species in the country (González et al., 2018). However, the Colombian Andes have been substantially transformed due to anthropogenic pressures from deforestation, agricultural expansion, mining, and urban development. Many threatened species are confined to substantially reduced forest habitats and small ranges that will likely shift and contract with climate change (Báez et al., 2016; Velásquez-Tibatá et al., 2013). Accurate land cover monitoring is therefore essential for evidence-based conservation strategies, sustainable development planning, and compliance with international environmental agreements, including the Convention on Biological Diversity and REDD+ mechanisms.

Early research efforts in the area focused on forest cover assessment using coarse-resolution satellite imagery (Etter et al., 2006; Sánchez-Cuervo et al., 2012), or medium-resolution for one or a few anniversary epochs (González-González et al., 2022; Rodríguez Eraso et al., 2012). Recent advances include the MapBiomas Colombia initiative, which generates annual land cover maps for the entire country from 1985 to present using cloud processing and automated classifiers (MapBiomas Colombia, 2024).

Time series algorithms offer substantial advantages over traditional mapping methods for complex landscapes. The spectral-temporal patterns captured by them aid in the separation of land cover types that exhibit similar spectral characteristics but distinct temporal behaviors. Time series algorithms such as the Continuous Change Detection and Classification algorithm (CCDC) (Zhu and Woodcock, 2014), or BFAST (Verbesselt et al., 2010) can model the complex temporal signatures that can arise in heterogeneous tropical mountain environments, where vegetation varies significantly across elevation gradients and microclimatic conditions.

This study presents high-quality annual land cover maps for the Colombian Andes and the Sierra Nevada of Santa Marta, covering the temporal range between 1997-2024. The maps have been generated using the outputs of the CCDC algorithm applied to Landsat data, and a machine learning model training using a custom dataset compiled to address existing limitations and provide great temporal depth and spatial detail.

Methods

Study area

The study area encompasses the natural Andean region of Colombia, plus the municipalities connecting it to the Sierra Nevada of Santa Marta (Fig 1). The Andean region has the highest population density in the country, resulting in extensive historical conversion of original forest cover to human-dominated landscapes such as agricultural fields, grazing lands, planted forests, and built infrastructure (Armenteras et al., 2011; Etter et al., 2008, 2006). The Andean region is rich in threatened and endemic species (CITE) , while the Sierra Nevada is considered the most irreplaceable protected area in the world for threatened species(Le Saout et al., 2013). Forest fragmentation is widespread throughout the study area region, but substantial intact forest blocks remain, particularly in the Pacific coast and in the eastern slopes of the eastern mountain range (Hansen et al., 2013).

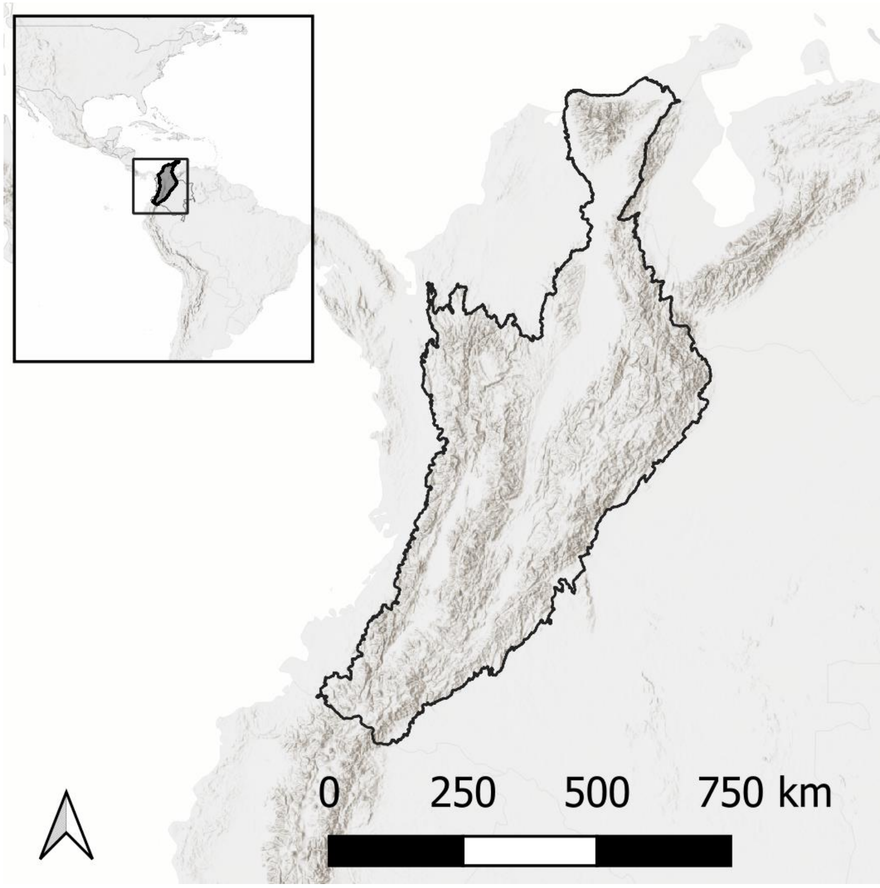

Figure 1. Study area, which includes the Andean region of Colombia and Sierra Nevada of Santa Marta municipalities. Basemap attribution: Esri, Maxar, Airbus DS, USGS, NGA, NASA, CGIAR, N Robinson, NCEAS, NLS, OS, NMA, Geodatastyrelsen, Rijkswaterstaat, GSA, Geoland, FEMA, Intermap, and the GIS user community.

Training dataset

We generated a training dataset containing labels for the following classes: natural forest, planted forest, developed, pasture/agriculture, water, barren, and oil palm. Training data for all classes except plantations and oil palm was generated through a mix of opportunistic collection and a sample generated from a vector land cover map available for the Andes generated by visual interpretation by the multiple official research institutes in Colombia for the year 2009-2010 (IDEAM, 2010). Additional data was also supplemented from (Stanimirova et al., 2023). Training data for oil palm and forest plantations was collected manually, using high resolution imagery from Google Earth, ESRI Wayback and Planet basemaps, as well as the time series of Landsat-derived indices and bands (when required).The training dataset distribution is shown in Figure 2.

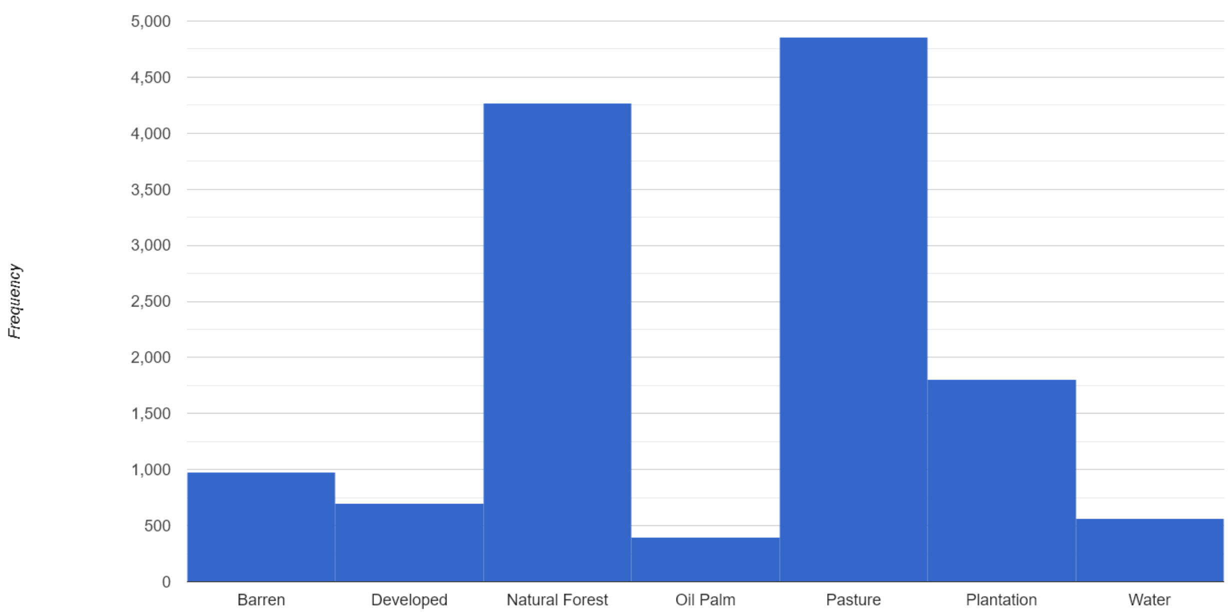

Figure 2. Training data histogram.

Land cover classification

We trained a random forest model with the training dataset described above to predict annual land cover classes in probability mode using predictor variables derived from the

Continuous Change Detection and Classification (CCDC) algorithm (Zhu and Woodcock, 2014). We ran CCDC on a 25-year (1997-2022) time-series stack of Landsat Collection 2-derived data including: surface reflectance and unmixed spectral components. We filtered surface reflectance data to remove low-quality pixels, including pixels with radiometric saturation, clouds or cloud shadows, and high atmospheric opacity. We then derived the unmixed spectral components from the filtered images. The use of spectral unmixing (Souza et al., 2005) allowed us to obtain fractional abundances of green vegetation (GV), non-photosynthetic vegetation (NPV), soil and shade per pixel, and with those, the Normalized Difference Fraction Index, which can be useful to detect subtle forest disturbances. In addition to the intercept (INTP) and slope (SLP) of the time segments, we used the first two harmonics, transformed to phases and amplitudes, as well as the segment Root-Mean-Square-Error (RMSE) and synthetic (SYNT) reflectance computed for the first of July of each year. The final predictors used, including additional ancillary data, are shown in (Table 1).

Table 1. Predictors used for the random forest model

<table>
<tr><th>BAND TYPE</th><th>BAND NAME</th><th>CCDC COEFFICIENTS AND DERIVATIVES (Generated for every single band)</th></tr>
<tr><td>Surface reflectance</td><td>GREEN, RED, NIR, SWIR1, SWIR2</td><td rowspan="3">INTP, SLP, PHASE, PHASE2

AMPLITUDE, AMPLITUDE2

RMSE, SYNT</td></tr>
<tr><td>Index or transform</td><td>NDFI</td></tr>
<tr><td>Unmixed spectral components</td><td>Shade</td></tr>
<tr><td>Other variables</td><td>ELEVATION, ASPECT, DEM_SLOPE, WATER OCCURRENCE, WORLD SETTLEMENT FOOTPRINT</td><td>-</td></tr>
</table>

Post-processing

Given the complexity of the landscape in our study area and the spectral-temporal similarity between some vegetation classes, we implemented steps to improve the separation between classes and their temporal stability and to address topographic and environmental corrections, as well as conduct final map adjustments.

We applied a temporal consistency enhancement similar to that implemented by the Land Change Monitoring, Assessment, and Projection (LCMAP) initiative (Brown et al., 2020; Xian et al., 2022), in which class probabilities are averaged across all years for each stable CCDC segment, and the class with highest average probability is assigned to represent the dominant land cover for that segment. In turn, CDCDC segments that show signs of being in a transitional state (e.g. conversion from one vegetation class to another) are identified and processed to improve the label assignment in the first and second halves of the segments. Missing values between CCDC segments are filled using temporal interpolation of the labels, resulting in continuous labels for the entire study period.

A post-processing step to identify omission of forest loss mapping was also used, in which we identified pixels where CCDC detected a break, but the land cover sequence did not show evidence of it. For those pixels, we inspected the magnitude of change, as well as the change in class probabilities before and after the break: if either of them crossed a threshold (> 0.4 for the difference between forest class probability before and after the break; or a CCDC break magnitude >= 0.080), the labels from the break until the middle of the segments were changed to pasture/agriculture.

Finally, a set of post-processing steps were applied to address specific issues, such as: 1) pixels with repeated alternation between shrubs and pastures, and barren and pastures, for which we replaced the label with the temporal mode, and 2) improbable labels (e.g. water in high slopes, barren in areas that green up regularly, or in areas with permanent water cover), for which we applied the most likely label based on environmental conditions. In addition, we removed patches equal to or less than 1 ha, replacing the class labels as follows: for oil palm, second most likely vegetation class; for developed, the second most likely class among all possible classes; and for tree plantation classes, the second most likely class of either the natural forest or pasture classes. Finally, we removed pixels with less than 29 clear observations (as reported by the CCDC algorithm), which is equivalent to approximately only one observation per year, because those were considered low quality.

Stratification and extra post-processing

A final post-processing step was applied after deriving the final stratification used to assess the dataset accuracy. The strata layer was generated for the period 2012 - 2024 (Table 2), coinciding with the era of the best high-resolution imagery availability on Google Earth and ESRI Wayback. A preliminary accuracy assessment conducted on a previous iteration of the land cover datasets had revealed excessive change from pasture/ag into other classes, and overprediction of planted forest. We used the transition probabilities from that map to derive the transition matrix to parameterize a Hidden Markov Model (HMM) but modified it to address those issues by increasing the probability of pasture/ag remaining stable, and increasing the change probabilities from planted forest. After implementing those changes, we applied the HMM only over the strata pixels labelled as planted forest, forest loss 2, and forest gain, replacing the entire sequence of labels for the entire study period with those indicated by HMM. With those modified labels, we re-generated the final stratification used for the accuracy assessment, with the class proportions shown in Table 2.

A stratified design and estimation approach was implemented (Cochran, 1977; Olofsson et al., 2014), with the stratified random sample (n=1960) targeting stable and change classes. The sampling assessment unit was a 30 m × 30 m Landsat pixel, which was chosen to coincide with the minimum mapping unit. A buffer class was included to minimize the negative effects of forest loss omission (Arévalo et al., 2019; Olofsson et al., 2020).

Table 2. Stratification for 2012 - 2024. Any changes not described below were assigned the class “Other changes”, class number 13.

Stratum name	**Description**	**Class number**	**Wh**	**nh**
Stable Natural forest		1	0.323	560
Stable Planted forest		2	0.002	40
Stable Developed		3	0.006	40
Stable Pasture / Ag		5	0.418	730
Stable Water		6	0.007	40
Stable Barren		7	0.008	40
Stable Oil Palm		8	0.003	40
Forest loss 1	Natural forest to Pasture/Ag	9	0.025	60
Forest loss 2	Natural forest to Oil palm | plantation	10	0.001	40
Forest gain	Pasture/Ag to Natural or planted forest	11	0.016	40
Buffer class	1 pixel from other classes into Natural Forest	12	0.182	300
Other	Other changes not described above	13	0.008	30

Reference observations for the range 2012 - 2024 were provided by each sample unit by examining high resolution imagery (Google Earth, ESRI Wayback, Planet-NICFI basemaps), as well as time series of Landsat Collection 2 surface reflectance observations, NDFI and NDVI time series for the range between 2010 and 2024. All the points mapped or referenced as change classes were cross-checked.

Results

Preliminary accuracies (prior to complete cross-checking) for the final stratification layer are shown in Table 2. Overall accuracy is 0.68.

Stratum name	Class number	User's accuracy	Producer's accuracy
Stable Natural forest	1	0.927	0.618
Stable Planted forest	2	0.700	0.078
Stable Developed	3	0.775	0.625
Stable Pasture / Ag	5	0.808	0.818
Stable Water	6	0.900	0.537
Stable Barren	7	0.575	0.386
Stable Oil Palm	8	0.925	0.347
Forest loss 1	9	0.600	0.770
Forest loss 2	10	0.073	0.175
Forest gain	11	0.225	0.244
Buffer class	12	0.000	-
Other	13	0.200	0.165

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