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COLOMBIA´S NATIONAL MOUNTAIN PEATLAND MAP: PEATLAND DISTRIBUTION, CONDITION AND CARBON STOCKS

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By

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Author Contribution Statement

This manuscript is planned for submission in the near future. Project design, data collection and analysis, map creation, pictures, figures, tables, and the written document were all conducted by Patrick Nicolás Skillings. Significant insights into the project design and essential editing assistance were provided by Rod Chimner, Erik Lilleskov, Michael Battaglia, and Laura Bourgeau-Chavez. Additionally, Michael Battaglia offered crucial map classification training and scripts. Juan Carlos Benavidez contributed to field data collection, provided invaluable assistance and resources for fieldwork and lab analysis, and offered feedback throughout the mapping process.

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Abstract

In this research, I explore the distribution, condition, and carbon stocks of peatlands in the Colombian Andes. High mountain peatlands in Colombia, usually found within the páramos, face significant ecological challenges. Although Law 1930 (2018) mandates sustainable páramo management, it does not prohibit peatland disturbance. Undisturbed peatlands act as long-term carbon sinks, but their degradation can convert them into greenhouse gas sources. The lack of comprehensive national peatland mapping hampers effective environmental management and policy formulation. I aim to create a national-scale peatland map, assess peatland distribution, quantify degraded pasture peatlands, and report preliminary soil carbon stocks. Additionally, I compared classification results at subregional, regional, and national scales to determine the optimal approach for mapping peatlands across Colombia. Using a combination of extensive ground truthing and remote sensing products, I mapped approximately 4.7 million ha. These products are obtained from Sentinel-2 multispectral imagery, Sentinel-1 and ALOS PALSAR Synthetic Aperture Radar data, and Shuttle Radar Topography Mission data. These were used as inputs to a Random Forest machine learning classification algorithm to classify land use and land cover into 17 distinct classes, including five peatland classes. Results indicate that peatlands occupy 224,848 ha (± 19,244) to 250,306 ha (± 19,100), representing 5.2-5.73% of the mapped area. Among these, 13-15% are classified as pasture peatlands, highlighting significant human disturbance. Despite 51% being within protected areas, they often lack adequate protection, leading to substantial greenhouse gas emissions and water storage disruption. Scaling up carbon analysis, I estimate that peatlands above 2750 m may store 366 to 407 Tg of soil carbon. Comparing our three national maps, created by combining classification results at different scales, allowed us to identify areas needing further ground truthing to improve future national peatland maps. Discrepancies among our three maps are primarily located in shallow peat areas or transitional zones between peatlands and other land classes. These findings underscore the critical role of peatlands and mountain ecosystems in regional carbon storage and emphasize the importance of integrating peatlands into conservation and management practices to prevent further degradation and mitigate climate change impacts.

1 Introduction

Peatlands cover only 3-4% of the world's land surface but store one-third of global soil carbon, estimated at 450,000 to 650,000 million tons (Mt) (UNEP, 2022). Undisturbed peatlands act as long-term net carbon sinks, but degradation can convert them into net sources of greenhouse gases (GHG) estimated at over four percent of human-caused emissions (UNEP, 2022). However, this estimate is still uncertain since many areas have not been mapped for peatlands. Mapping not only reveals the distribution of peatlands, but also helps estimate soil carbon stocks and allows evaluation of their potential risk of degradation (Chimner et al., 2023; Gutiérrez-Díaz et al., 2020; Hribljan et al., 2015; Hribljan et al., 2016). This has led to worldwide initiatives to map peatland (Gumbricht et al., 2017; Melton et al., 2022; UNEP, 2022; Xu et al., 2018) reflecting their importance for climate change mitigation and conservation efforts of these ecosystems. While global peatland mapping efforts have made significant progress, gaps persist due to a range of challenges in accurately mapping peatlands.

The Global Peatland Assessment 2.0 (GPA2) offers the most updated overview of the distribution and status of peatlands globally, providing the most comprehensive global peatland map to date, the Global Peatland Map 2.0 (GPM2)) (Greifswald Mire Centre, 2022; UNEP, 2022). This map has identified 500 million ha of peatlands worldwide, predominantly distributed in Asia (33%), North America (32%), Latin America and the Caribbean (13%), Europe (12%), and Africa (8%). The Global Peatland Assessment highlights that 88% of existing peatlands are conserved. However, if GHG emissions from drained and degraded peatlands persist at the current rate until 2100, their impact on the global emissions budget will constitute 41% of the emissions needed to keep global warming below 1.5°C (UNEP, 2022). This highlights the importance of addressing the significant data gaps and challenges in peatland conservation as new peatland mapping methods arise.

The GPM2 along with other global peatland mapping efforts (Gumbricht et al., 2017; Melton et al., 2022; UNEP, 2022; Xu et al., 2018) still has numerous data gaps. In many countries, peatland areas are underestimated. This is often due to the small size of peatlands, incomplete national-scale data, or ineffective classification models in regions with unique climate and topographic conditions.

Specifically, in Latin America and the Caribbean (LAC), mapping effort predominantly focuses on larger and lower elevation peatlands. This focus leads to a systemic underrepresentation of mountain peatlands, particularly in the northern Andes. For instance, the GPM2 estimates that only 2% of peatlands mapped in LAC are located over tropical mountain systems (Greifswald Mire Centre, 2022). Other global studies have failed to map any peatlands in the Andes due to model limitations in capturing mountain peatlands (Gumbricht et al., 2017; Melton et al., 2022; Xu et al., 2018). However, recent regional studies in the northern Andes, covering areas between 250,000-400,000 ha, reveal that peatlands might constitute 6.3%-18% of these regions (Battaglia et al., 2024; Chimner et al., 2019; Hribljan et al., 2017). This suggests a substantial underestimation of

Andean peatland coverage in global assessments, emphasizing the need for more dedicated and accurate mapping efforts.

These peatlands, play a crucial role in the regional carbon budget due to their significant peat deposits (Chimner et al., 2023; Cooper et al., 2015; Hribljan et al., 2015; Hribljan et al., 2024; Hribljan et al., 2016). The humid climate and unique topography of these areas promote peat accumulation, typically occurring within poorly drained valleys and geomorphological depressions rather than on mountain slopes (Cooper et al., 2019). These peatlands are characterized by dense soils, composed of a mix of mineral sediments and organic matter from geologically active basins (Cooper et al., 2019; UNEP, 2022). In some cases, they produce more organic carbon than peatlands at higher latitudes and can reach depths of up to 11 m (Cooper et al., 2015; Hribljan et al., 2016). Additionally, the high-water retention capacity of Andean peatlands is vital for water regulation. They maintain water flow and regulate runoff, adapting to varying rainfall intensities and environmental changes (Hofstede et al., 2023; Lazo et al., 2019; Mosquera et al., 2015). This function is particularly important for ensuring a consistent water supply during both dry and wet periods, safeguarding lower elevation communities from climate hazards like El Niño (Galvis et al., 2021; Hofstede et al., 2023).

Mapping peatlands in the northern Andes presents significant challenges. Accurate mapping is difficult because of small size of individual peatlands, high diversity of wetland types, and high similarity of vegetation in peatland and non-peatland areas (Battaglia et al., 2024; Bourgeau-Chavez et al., 2018; Hribljan et al., 2017). Persistent cloud cover and a lack of comprehensive field data also hinder large-scale mapping (Bourgeau-Chavez et al., 2018; Hribljan et al., 2017; UNEP, 2022; Xu et al., 2018).

Despite these challenges, regional efforts in páramos of Ecuador, Colombia (Battaglia et al., 2024; Hribljan et al., 2017), as well as the puna of Peru (Chimner et al., 2019) have advanced mountain peatland mapping. These mapping efforts used a combination of field ground truthing, topographic information, multispectral imaging, and Synthetic Aperture Radar (SAR) for their classification. Multispectral imagery is crucial for classifying vegetation types, but it faces challenges in distinguishing between wetland and upland areas within páramos due to similar vegetation composition. SAR data has been effective in mapping wetlands, with both L and C band sensors playing a key role in detecting soil moisture and differences in vegetation structure (Bourgeau-Chavez et al., 2015; Bourgeau-Chavez et al., 2018). Temporal analysis of SAR imagery allows for comparing conditions across wet and dry seasons, distinguishing between peatlands, which have stable water tables in both wet and dry seasons, and mineral wetlands or other upland areas, which do not (Battaglia et al., 2024). Additionally, a digital elevation model (DEM) is employed to obtain topographic data. While elevation data is not used directly for classification, it proves useful in generating topographic indexes and slope layers. These are particularly valuable in peatland detection, allowing for the differentiation between flat terrains, valleys and depressions, and convex surfaces, which is instrumental in classifying peatlands.

High mountain peatlands in Colombia, located within the páramos—a biome between the Andean treeline and the periglacial zone—face significant ecological challenges. Although Colombia's Law 1930, enacted in 2018, mandates the sustainable management and protection of páramos by restricting activities to low-impact agriculture, it does not specifically prohibit peatland disturbance. This oversight leads to substantial greenhouse gas emissions and disrupts water storage and supply (Benavides, 2014; Krause et al., 2021; Planas Clarke et al., 2018; Roucoux et al., 2017). Despite 51% of páramo regions being under a category of protection, 15% have undergone significant transformation of its natural landscape due to the economic activities of about 80,000 páramo inhabitants who rely primarily on grazing, and potato and onion farming (DANE, 2020; Galvis Hernández & Ungar Ronderos, 2021; Galvis et al., 2021). These activities often involve draining peatlands to simplify water access or utilize organic-rich soils in flatter areas, which in turn reduces the agricultural labor required in mountainous terrains. Quantifying the extent and degradation of peatlands converted to pasture is crucial for identifying priority areas for conservation and restoration. Since these areas can rapidly release carbon into the atmosphere, detailed assessments of their size and condition are necessary.

The absence of comprehensive peatland mapping at a national level in Colombia hampers effective environmental management and policy formulation. This gap significantly affects land use planning, conservation efforts, and climate change mitigation strategies. Addressing this need, the main objective of this research is to create a national map to evaluate the abundance and distribution of peatlands across the Colombian páramos. With this map our goal is to provide insights into the state of peatlands, allowing us to estimate the carbon stocks stored in these ecosystems in the Andes and identify which peatlands are degraded or at potential risk of degradation.

In addition to these goals, this study addresses a technical question regarding our mapping approach: What differences emerge in peatland classification results and distribution when using different spatial extents classification results for our study area, and is there a most effective spatial extent for mapping peatlands in Colombia? The spatial extent refers to the size of the geographic areas used in combination with the corresponding training data when running our classifier. To address this question, we generated three maps: National, Regional, and Subregional. The Subregional map combines the classification results from independent runs on four subregions of the study area. The Regional map merges the results from independent runs on two regions, each formed by combining two of the initial subregions. The National map represents the classification result from an independent run on the entire study area.

By addressing these goals, we aim to provide a comprehensive tool that will serve policymakers, local authorities, community leaders, land managers, and environmental organizations. This tool will facilitate informed decision-making in land management, conservation, and restoration efforts in the páramo peatlands, ensuring their protection and sustainable management.

2 Methodology

2.1 Study Area

Colombia's high mountain peatlands are found across the páramos, covering the isolated Sierra Nevada de Santa Marta and the Eastern, Central, and Western Andean Mountain ranges, also known as cordilleras (**Figure 1**). These cordilleras, branching off from the southern Andes near the Ecuador border, are shaped by the subduction of the Nazca Plate beneath the South American Plate, a process that, along with volcanic activity, glacier movement, and erosion, has created the current landscape. These geological features, combined with the páramos' cold, humid climate, create optimal conditions for peatland formation. Humid air currents from the oceans and the Amazon, shaped by the Intertropical Convergence Zone, deliver abundant rainfall, particularly to windward slopes (Hofstede et al., 2003). This results in a gradient of páramo environments, ranging from dry to superhumid, with annual precipitation varying from 600 mm to over 4000 mm (Rangel-Ch, 2000). Such climatic variability, alongside significant daily temperature fluctuations, supports the biodiversity and the structure of páramo ecosystems.

This research was conducted on approximately 4.7 million ha in the northern Andes, above an elevation of 2750 masl and extending 30 km beyond Colombia's national borders (**Figure 1**). This geographical selection criteria serves multiple research purposes. It includes continuous páramo ecosystems that Colombia shares with Venezuela (Páramo de Tamá and La Serranía del Perijá) and Ecuador (Páramo de Chiles and the Reserva Ecológica El Ángel), contains all known páramo areas extending down to an elevation of 2750, and covers disturbed peatlands which, despite agricultural conversion into pastures and croplands, can still be found at elevations above 2 750 m. A few isolated small polygons equal to or less than 200 ha were removed from the study area, as they predominantly consisted of small ridges or mountain tops, mostly characterized by forested or disturbed land cover with no peatlands. Moreover, a portion of the Southeastern cordillera (57,400 ha, or 1.2 % of the area above 2750 m) was omitted from the analysis owing to the scarcity of cloud-free images and the logistic challenges to obtaining field data (**Figure 1**).

Building on the delineated study area, this research undertakes a multi-level spatial extend classification assessment. Three classification maps are produced at different spatial extends levels: Subregional, Regional, and National. The Subregional extent divides the area into four specific subregions: the Northeastern Cordillera (NEC), the Southeastern Cordillera (SEC), Nariño-Putumayo (NAR), and the combined Central and Western Cordilleras (CC_WC) (**Figure 1**). Intentional overlaps between NEC and SEC, as well as NAR and CC_WC, are designed to enhance models by reusing training and validation data in these overlapping areas. The Regional extent merges these pairs of subregions into two broader areas: NEC_SEC and NAR_CC_WC. Meanwhile, the National extent covers the entire study area, including the Sierra Nevada of Santa Marta (SNS), where field data collection was precluded by logistical challenges.

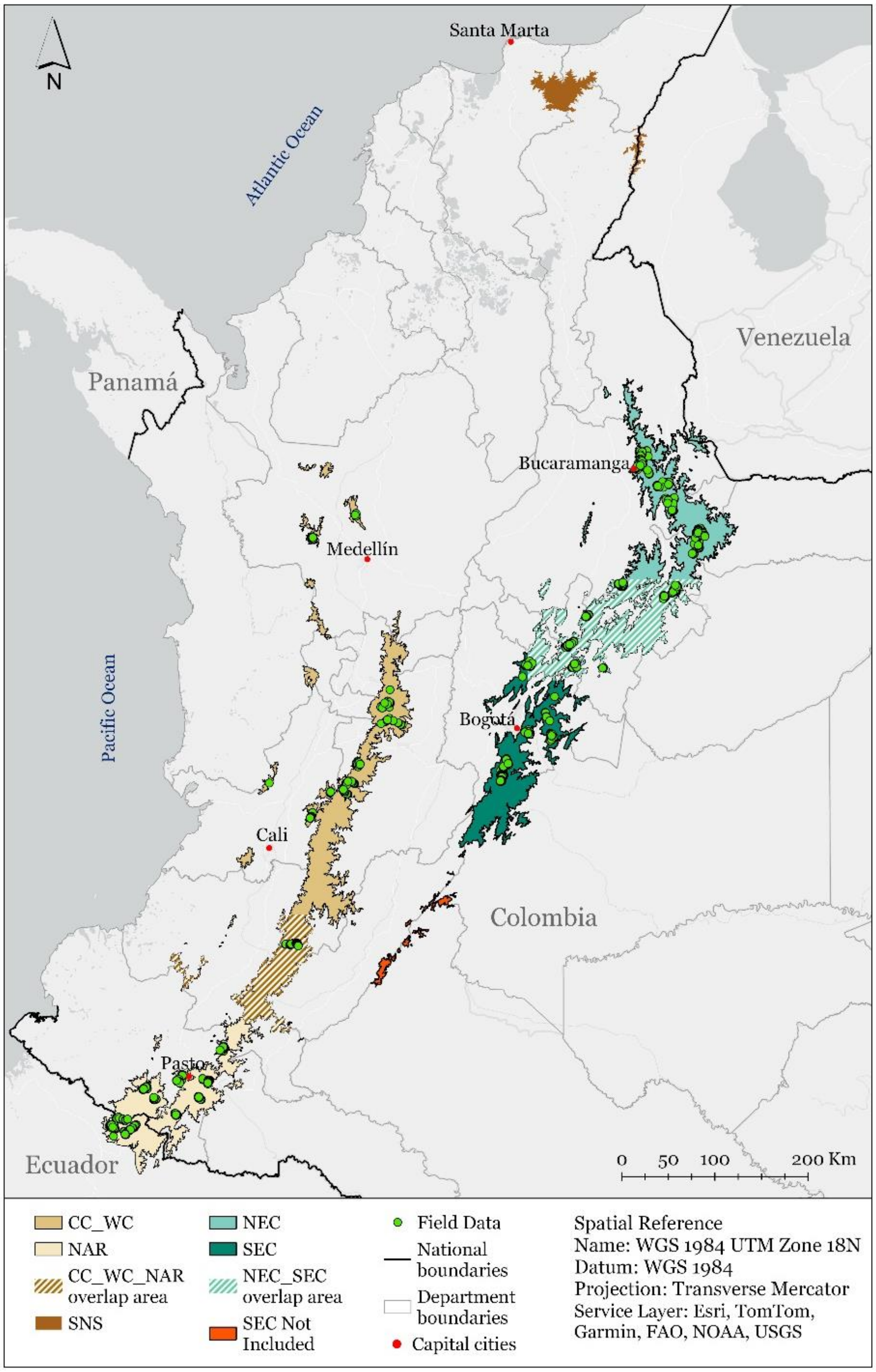

Figure 1. Study area map. Subregional extents: Northeastern Cordillera (NEC), Southeastern Cordillera (SEC), Nariño-Putumayo (NAR), and Central and Western Cordilleras (CC_WC). Striped areas show overlaps. Blue colors represents the Eastern Cordillera region; beige colors represents the Nariño and Central/Western Cordilleras region. The Sierra Nevada de Santa Marta and Perijá regions in the north were included in the National extent but had limited analysis due to insufficient ground truth data. Green points mark ground truth data collection sites.

2.2 Data Collection

To create the classification maps, it was necessary to have two types of data sources: the training and validation polygons for the model, and our predictive variables, which consist of a set of images we processed from various remote sensors (**Figure 2**).

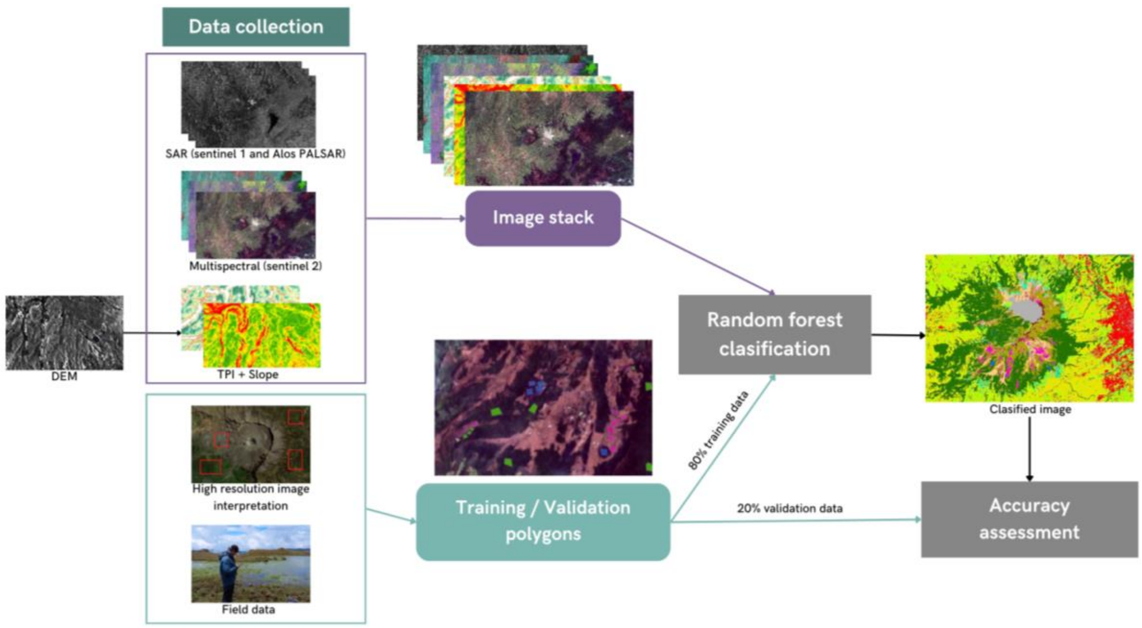

Figure 2. Peatland mapping methods diagram. Integrated mapping methodology, utilizing field data, multiple remote sensor images, and the Random Forest Algorithm for accurate image classification.

2.2.1 Training and Validation Polygons

For the creation of classification maps, a shapefile containing polygons for training and validation was produced. These polygons, delineated on the input image stack, were used to select pixels that represent sites with accurately known land use and land cover (LULC) classes. The dataset comprises 4242 polygons covering the entire study area, drawn from diverse sources of georeferenced information that provided specifics on location and land cover. Of these, 2240 polygons were drawn using image interpretation of high-resolution imagery from Google Earth, Google Street View, or a selected combination of Sentinel 2 bands within our image stack, enhancing the interpretation of LULC classes. This approach facilitated the identification of various LULC classes as shown in **Figure 3**. However, the reliance on satellite imagery for initial classification had limitations, especially in accurately distinguishing mineral wetlands and peatland types and refining other LULC classes, which led to the necessity of field verification.

A total of 2002 polygons were delineated with field verification data obtained from multiple sources. Our primary source of field verification consisted of extensive field visits conducted from April 2019 to March 2023. Secondary sources included interpretation of drone images taken during these field visits, a review of peatland literature offering georeferenced site descriptions, a field database from Ecuadorian colleagues involved in peatland mapping (specifically from the *Reserva el Angel*, which borders the páramo of Chiles in Colombia), and personal communications with experts possessing firsthand knowledge of peatlands within the study area.

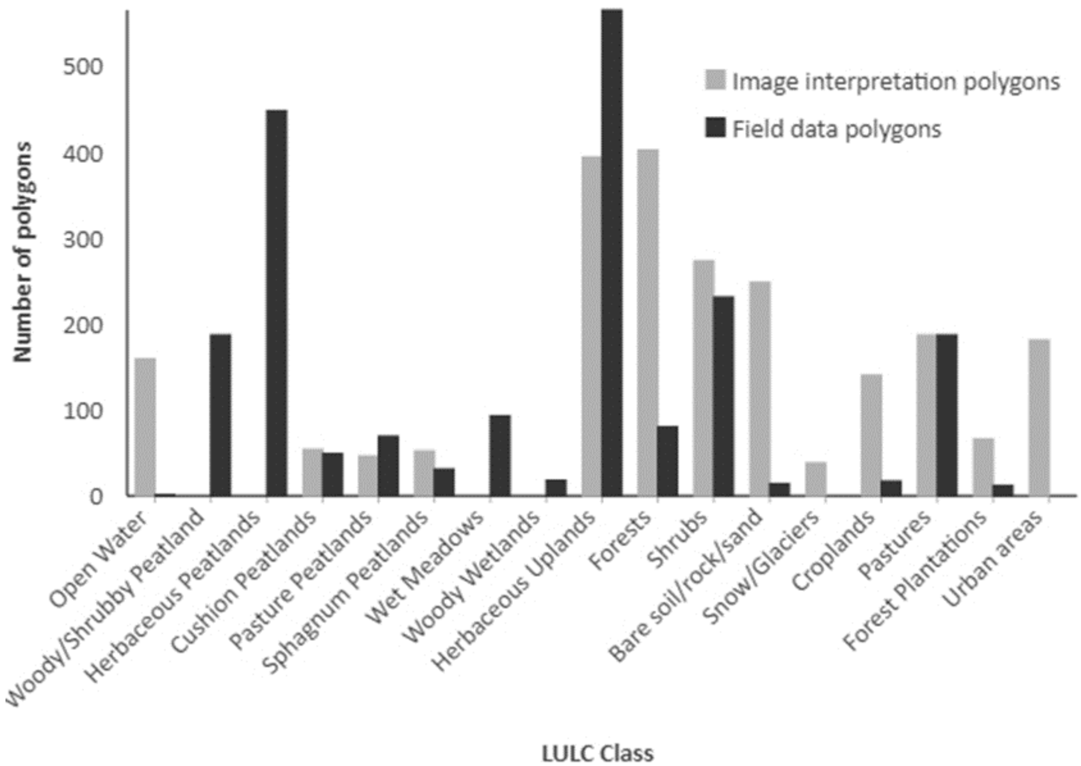

Figure 3. Field data polygons vs high resolution interpretation Polygons.

2.2.1.1 Primary Field verification methods

Over the course of three years, our field visits necessitated an adaptable and evolving approach to site selection, driven by the unique logistical requirements essential for maintaining safe working conditions for our field crew. This study used the approach of (Battaglia et al., 2024) where we created a preliminary weakly supervised classification in which potential wetland and upland areas were classified using visual analysis of aerial and satellite imagery from Google Earth, identifying likely peatland and upland points. These points were buffered by 20 m to form training polygons for a Random Forest classifier (Breiman, 2001), incorporating remote sensing data and imagery from Landsat 8 and Sentinel-1 C-band SAR via Google Earth Engine (GEE) to create classified maps containing two classes: Potential wetlands and Uplands. Subsequently, potential field sites were determined through a random sampling strategy constrained by accessibility from roads using an Open Street Maps layer. This approach, designed to overcome terrain challenges, prioritized potential wetland areas to ensure a representative sample. Additionally, we avoided areas deemed unsafe by local authorities because of political unrest or crime.

After the first round of sampling described above, for each subregion visited, we planned field trips to include not only protected areas (National Parks) but also disturbed páramos outside of protected areas. We collaborated with park rangers and local guides to identify accessible and safe areas that contain diversity of wetlands and could be covered in a day's work, regardless of road proximity. We still generated random points as described above, but permitted minor field adjustments if the original points were unreachable or excessively time consuming to reach, opting for sites with similar apparent LULC classes. To ensure a diverse dataset, we conducted a targeted search for disturbed peatlands and wetlands outside protected areas. This involved utilizing our preliminary classification maps, aerial drone surveys, and consultations with local guides to identify potential sites. For navigation and data collection in the field, we utilized the Avenza Maps mobile application, which enabled us to use georeferenced maps (created using the Imagery Basemap in ArcGIS Pro) to locate these random points accurately.

At each site, we identified the dominant vegetation and designated a preliminary LULC class. We extracted a 40 cm soil core using a side cutting peat corer, segmented it into 10 cm intervals, and stored them in Zip-lock bags. In peatlands, we recorded additional measurements like peat depth, pH, and specific conductivity. We logged all data into the Epicollect 5 mobile application.

We analyzed the soil samples at The Pontificia Universidad Javeriana's Ecosystems and Climate Change Lab. First, we dried them at 65 °C for 24 hours to ascertain their dry bulk density. We then determined the organic matter (OM) and carbon percentage (C%) through loss on ignition (LOI) at 550 °C for 5 hours (Soil Survey Staff, 2014). We calculated the proportion of organic matter using the formula: OM = (DW - IW) / DW, where DW is the oven-dry weight (g) before ignition, and IW is the weight (g) after ignition. Assuming the carbon content of dry mass to be 48% of the incinerated organic matter (Benavides, 2014), we estimated the carbon percentage as %C = 0.48 × OM. We determined the Bulk Density (g cm^{-3}) (BD) by dividing the total dry weight (TW) (g) of each soil sample by the corer's volume (cm^3). We determine soil carbon content in Mg per hectare for every 10 cm segment with the formula: Carbon content (Mg ha-1) = BD (g cm^{-3}) × %C × 10. To obtain the total carbon content for the full 40 cm depth of the soil samples, we summed the carbon content results for each 10 cm segments.

We performed a reclassification of LULC classes based on the carbon content of each soil sample, adhering to the specified definition of peatlands. For this study, peatlands are defined as organic soils that are saturated and contain more than 12% carbon within the first 40 cm of depth. It is essential that the carbon content in the 30-40 cm layer consistently exceeds 12% (Soil Survey Staff, 2015). When primary or secondary field data sources lacked soil carbon information, we utilized all available resources—including photographs, vegetation composition, saturation levels, and expert consultations—to accurately align each field point with one of our predefined LULC classes, as outlined in **Table 1**.

Table 1. Land use and Land cover classes.

Class level 1	Class level 2	Class level 3	Class description
Open Water	**Open Water**	Open Water	Permanently flooded water bodies with no dominant emergent or floating vegetation.
Natural Wetland Areas	**Peatlands**	Woody/Shrubby Peatlands	Poorly drained areas with organic soils >40 cm depth and C >12% in Histosols or 25% in Andisols, where woody species dominate (e.g., *Hypericum spp., Diplostephium spp., Pentacalia spp.*) and or shrubs (*e.g., Chusquea spp.*)
		Herbaceous Peatlands	Poorly drained areas with organic soils (>40 cm depth and C >12% in Histosols or 25% in Andisols), characterized by a matrix dominated by herbaceous species. This includes grasses (e.g., *Calamagrostis* spp., *Agrostis spp., Chusquea* spp., *Cortaderia* spp.), sedges (e.g., *Carex* spp., *Richosphera* spp.), rushes (e.g., *Juncus* spp., *Luzula* spp.), ferns (e.g.,*Blechnum* spp.), and herbs (e.g., *Geranium* spp., *Pernettya* spp., *Puya* spp.). While shrubs (e.g. *Diplostephium* spp. *and Hypericum* spp.) may be present, they are not the dominant vegetation.
		Cushion Peatlands	Poorly drained areas with organic soils (>40 cm depth and C >12% in Histosols or 25% in Andisols), dominated by cushion-forming vegetation such as *Distichia muscoides* and *Plantago rigida*.
		Pasture Peatlands	Poorly drained areas with organic soils (>40 cm depth and C >12% in Histosols or 25% in Andisols), characterized by a dominance of naturalized herbaceous species (e.g. *Cenchrus clandestinum*, *Lolium perenne*, *Anthoxanthum odoratum, and Trifolium* spp.) These areas may also present native species of grasses, sedges, ferns, and herbs. Typically, these areas exhibit evidence of ditches.
		Sphagnum Peatlands	Poorly drained areas with organic soils (>40 cm depth and C >12% in Histosols or 25% in Andisols), dominated by Sphagnum spp. mosses.
	Mineral Wetlands	Wet Meadows	Areas with evidence of saturation and variable water table which contain mineral soils (C <12%) with less than 40 cm in depth, and may be over bedrock. Dominated by herbaceous vegetation and/or mosses.
		Woody Wetlands	Areas with evidence of saturation and variable water table which contain mineral soils (C <12%) with less than 40 cm in depth. Dominated by woody species like *Escallonia myrtilloides*.

Seminatural and Natural Upland Areas	**Natural Vegetated Upland Areas**	Herbaceous Uplands	Areas with non-saturated soils predominantly featuring herbaceous species, including grasses (e.g., *Calamagrostis* spp., *Agrostis* spp., *Festuca* spp.), ferns (e.g., *Jamesonia* spp.), and herbs (e.g., *Geranium* spp., *Pernettya* spp., *Lupinus* spp.). Shrubs such as *Diplostephium* spp. and *Hypericum* spp. may occur but do not dominate the landscape. *Espeletia* spp., when prevalent, are classified within this group.
		Forests	Native Andean and high Andean woody vegetation exceeding 6 m in height (e.g. *Miconia* spp., *Cedrela* spp. *Polylepis* spp. *Quercus* spp.)
		Shrublands	Dominated by native páramo woody vegetation shorter than 6 m (e.g., *Pentacalia* spp., *Hypericum* spp., *Diplostephium* spp., *and Aragoa* spp.)
	Natural Non-Vegetated Surfaces	Bare soil/rock/sand	Areas with minimal or no vegetation, predominantly characterized by rocks, sand, gravel pits, or quarries. Gravel roads may appear in this category.
		Snow/Glaciers	Areas covered with ice or snow.
Anthropo-genic Land Uses	**Productive Territories**	Croplands	Agricultural lands where crops are cultivated; in the páramo regions, potatoes and onions are the most common crops.
		Pastures	Lands dedicated to grazing or cultivating grasses for livestock feed
		Forest Plantations	Areas designated for timber production. Homogeneous tree plantings of non-native species such as *Pinus* spp. and Eucalyptus spp.
	Urban areas	Urban Areas	Areas with any man-made infrastructure (e.g. buildings, roads) that is recognizable from satellite images with a spatial resolution of 10m

2.2.2 Remote sensing data

In our classification strategy, we combined multidate, multi-sensor radar and optical imagery with topographic information from a DEM (**Table 3**), a method proven effective for accurately identifying peatlands in the Andes (Battaglia et al., 2024; Bourgeau-Chavez et al., 2018; Chimner et al., 2019; Hribljan et al., 2017). This approach aims to identify variables such as hydrologic regimes, landforms, soil moisture, and vegetation composition and structure, enabling us to distinguish between peatland types and other wetland or upland classes (Bourgeau-Chavez et al., 2018). We use Sentinel-2 multispectral imagery to provide the classifier with information on vegetation types. However, distinguishing between some upland and wetland LULC classes can be challenging due to their similar spectral signatures. To address this, we integrate SAR imagery from Sentinel-1 and PALSAR, which supplied additional insights into the hydrology and vegetation structure of all LULC classes. Additionally, TPI and slope data, extracted from the SRTM DEM, are crucial for distinguishing between flat terrain, valleys, and mountain peaks, playing a key role in the accurate classification of peatlands.

Table 2. Summary of Remote Sensing Data Sources, Spatial Resolutions, Bands, and Availability Periods Used in the Study.

Remote Sensor	Spatial Resolution	Bands	Date ranges
Sentinel-1 SAR GRD: C- band	10 m	Mean and standard deviation of VH and VV polarizations, for wet and dry seasons.	2015-2022; Dry (D) and Wet (W) seasons vary by subregion: **NEC:** D->Dec-Feb; W-> Mar-May **SEC:** D->Dec-Jan; W-> Apr-May **CC_WC:** D->Jan – Feb; W-> Oct - Nov **NAR:** D->Dec-Jan; W-> Apr-May **SNS:** D->Aug; W-> Apr - May
Sentinel 2- Multispectral Instrument	10 m (visible/NIR), 20 m (Red Edge/SWIR)	Blue, Green, Red, Red Edge 1-4, NIR, SWIR 1-2, NDVI	Jan 2020-Dec 2022 for all subregions
PALSAR L-band	20 m	Mean, coefficient of variance, and standard deviation of HH and HV polarizations.	May-Oct, 2006-2011
Shuttle Radar Topography Mission (SRTM)	30 m	Topographic Position Index (TPI) for neighborhoods of 20 and 50 pixels, and Slope. Bands derived from a DEM	Data from the mission flown Feb 11-22, 2000 (Farr et al., 2007).

2.2.2.1 Optical Imagery – Sentinel 2 Multispectral Imagery

We utilized Sentinel-2 surface reflectance data, pre-processed for atmospheric corrections, to capture multispectral imagery across the páramo. Sentinel-2's twin satellites provide wide coverage at high resolutions, capturing data in 13 spectral bands to offer detailed insights with a global revisit frequency of five days. This capability is particularly crucial given the challenge of persistent cloud cover in these regions. To mitigate cloud interference, a two-step cloud filtering process was executed through GEE. We initially filtered images to select those with less than 80% cloud cover, followed by the application of a cloud probability mask to further exclude pixels with a greater than 10% likelihood of clouds. Additionally, an edge masking function was used to eliminate pixels potentially affected by cloud shadows.

Following cloud masking, we calculated the Normalized Difference Vegetation Index (NDVI) from filtered images using the Red and Near-Infrared (NIR) bands. The formula NDVI = (NIR - RED) / (NIR + RED) was applied to all filtered and cloud-masked images. For each pixel, the median value across the selected period was used for the final image composite. This selection was refined through visual assessments to optimize the dataset, particularly in cloud-prone areas, by adjusting the date ranges from 2019 to 2023 for each subregion. However, it is important to note that not all clouds were eliminated from the final composite (estimated 0.2% residual cloud cover), introducing some noise into the classification process for each subregion. We generated a total of 11 bands, shown in **Table 2**.

2.2.2.2 Synthetic Aperture Radar – Sentinel 1 (C-band) and ALOS PALSAR (L-band)

Synthetic Aperture Radar (SAR) imagery, generated by active sensors, can penetrate clouds, hence offering detailed imagery under all weather conditions, both day and night. In our study, we utilize SAR imagery from Sentinel-1's C-band and ALOS PALSAR's L-band to accurately map wetlands in páramos. The capability of SAR to penetrate vegetation canopies and interact with the ground surface is essential for detecting wetlands. These include variations in vegetation, structure, and moisture within both the canopy and ground layers. Our methodology allows for the clear differentiation between wetland and upland areas, as well as the identification of distinct wetland types, distinguished by their unique vegetation structures and hydrological patterns.

Given the predominance of short vegetation in páramos, the C-band's ability to penetrate a sparse or low-stature vegetation canopy and detecting soil moisture offers significant advantages. The Sentinel-1 mission, equipped with a dual-polarization C-band SAR instrument operating at a wavelength of approximately 5.6 cm, corresponding to a frequency of about 5.4 GHz, offers Ground Range Detected (GRD) scenes that are processed to yield calibrated and ortho-corrected products. In Google Earth Engine, the Sentinel-1 data undergoes preprocessing steps including thermal noise removal, radiometric calibration, and terrain correction, to ensure the data accurately reflect surface backscatter while accounting for topographical variations. All available Sentinel-1 images from 2015-2022 were converted from decibels (how GEE stores the images) to linear scale allowing for image compositing by obtaining the mean and standard deviation for all VV and VH polarization during the driest and wettest months. Although the images are not speckle filtered, image compositing effectively serves as temporal multi-looking, thus eliminating the need for additional spatial filtering (Battaglia et al., 2024). Driest and wettest months selection was informed by a decade of precipitation data from IDEAM's meteorological stations, all located above 2750 m, to accurately reflect the climatic conditions of each subregion (**Table 2**). As a result, we were able to process 8 bands for our classification analysis (**Table 2**).

In parallel to the C-band analysis, we utilized L-band SAR imagery from the ALOS PALSAR, operating at a longer wavelength of 24 cm. This characteristic enhances its ability to penetrate denser biomass, such as shrubby or woody vegetation found in páramos and sub-páramos, allowing for more effective discrimination of denser vegetation cover types that could also be considered wetlands. High resolution Radiometrically Terrain Corrected (RTC) data were downloaded from the NASA Alaska Satellite Facility. We selected Fine Beam Dual (FBD) polarization data, focusing on HH and HV polarizations. Given the limited availability of images, we were only able to obtain images between the months of May to October (2006 – 2011) which mostly correspond to dry season. To mitigate speckle effects, we applied a 5x5 median filter before temporal averaging, using Python scripts for preprocessing and analysis. Mean, standard deviation and coefficient of variance was calculated for each polarization over all available images, resulting in a total of 6 bands (**Table 2**).

2.2.2.3 . Topographic Data – Slope and Topographic Position Index

The Shuttle Radar Topography Mission (SRTM) Version 3 product provides a digital elevation model (DEM) at a 1 arc-second (~30 m) resolution, enhanced by void-filling with data from ASTER GDEM2, GMTED2010, and NED for improved global coverage. Our topographic analysis involved calculating the Slope and the Topographic Position Index (TPI) from the SRTM DEM using Google Earth Engine. The Slope layer, which indicates the terrain's steepness in degrees, is crucial for identifying potential hydrological dynamics. For the TPI, calculated at neighborhoods of 20 and 50 pixels, approximately 600 m and 1500 m respectively, we evaluated each cell's elevation relative to the average elevation of its surrounding cells. This method assigns positive values to cells that are higher than their average surroundings and negative values to those that are lower, providing a detailed representation of the landscape. It helps in identifying potential wetland areas by delineating elevated and depressed terrains. We ultimately obtain three topographic bands from this process.

2.3 Classification Approach, Accuracy, and Congruency assessments

For the classification approach and accuracy assessment, we integrated multispectral and radar data from Sentinel-1, Sentinel-2, and PALSAR, with SRTMGL1-derived topographic information into a unified image stack dataset, resampled to a spatial resolution of 10 m/pixel. This image stack served as the input for the Random Forest (RF) model, leveraging a comprehensive mix of variables to optimize model accuracy. Before running any classification, we calculated mean pixel values within our training and validation polygons of all the 28 bands of the image stack, carefully excluding outliers to minimize classification noise. Excluded outliers predominantly consisted of polygons that were drawn over areas affected by optical imagery disturbances, such as clouds, shadows, and fog.

To train the classifier, we used polygons representing approximately 80% of the total training polygon area for each class, reserving the remaining 20% for validation purposes. This division into training and validation sets was conducted randomly for each subregion. However, we retained the same validation and training polygons for both Regional and National spatial extent classifications. For these classifications, we merged the training and validation polygons of subregions within the same region, and subsequently combined all for the National spatial extent classification. This strategy allowed for a more robust comparison of outputs across our final three maps.

The RF algorithm, selected for its proven effectiveness in wetland mapping (Bourgeau-Chavez et al., 2017), processes the data through a series of decision trees based on random data subsets and training bands, with the final classification based on majority voting among the trees (Breiman, 2001). This approach is in line with established methodologies that ensure high accuracy in peatland ecosystem classification by utilizing RF with a combination of field-verified data and high-resolution imagery (Battaglia et al., 2024; Bourgeau-Chavez et al., 2015; Bourgeau-Chavez et al., 2018; Bourgeau-Chavez et al., 2017; Bourgeau-Chavez et al., 2021; Chimner et al., 2019; Hribljan et al., 2017). We included all input variables in our peatland mapping, as past research indicates that variable importance rankings for the entire model may not reflect their significance for specific classes. Excluding variables deemed of low overall importance could remove crucial predictors for particular classes (Bourgeau-Chavez et al., 2021).

Following the classification with the RF algorithm, we employed ESRI's 'Mosaic to New Raster' tool to combined corresponding classified sections of the Subregional and Regional maps . At the Subregional level, where overlaps occurred between NEC-SEC and CC_WC-NAR, we prioritized classifications from NEC and NAR due to their higher accuracy. Three maps for each spatial extent level were then our final product: Sub-regional (SREG), Regional (REG) and National (NAT), including in the latter an area outside the ground-truth subregions from which we had no field data, the Sierra Nevada of Santa Marta and Perijá.

We post-processed these three classification maps to improve their quality and accuracy. Using the ESRI’s majority filter, we refined our maps by adjusting each pixel's value to reflect the majority class among its eight neighbors, which improved accuracy but occasionally removed smaller features. To address misclassifications caused by noise in Sentinel-2 imagery, such as clouds, shadows, and spectral distortions, we made several targeted corrections: For areas classified as cushion peatlands below 3700 masl, we reclassified them by assigning values based on the majority within a 10x10 cell neighborhood. Although it is known that cushion peatlands in the country are typically found above 4000 masl (Benavides et al., 2023), we selected the 3700 masl limit due to field findings of dominant *Plantago spp.* peatlands around this elevation. We follow a similar approach for misclassified Glacier/snow pixels due to cloud pixels, replacing all glacier/snow pixels below 4500 (no glaciers found below this elevation in Colombia) and reassigned values based on the majority within a 20x20 cell neighborhood. Bare rock and urban areas are sometimes misclassified due to spectral similarities rock has with cement. Given the unlikelihood of significant human settlements over 4000 masl and the abundant bare rocks in periglacial zones, we corrected misclassifications as urban areas at these elevations by reclassifying them to bare rock class. Additionally, using the OpenStreetMap Road layer for Colombia, we buffered main roads by 3 m and rasterized this to 10-meter pixels, replacing these pixels into the map.

For the validation phase, we specifically chose polygons that had been field-verified to ensure the robustness of our assessment process. Both producer's and user's accuracies were calculated to evaluate the model's performance (Congalton & Green, 2019). Producer's accuracy measures the proportion of correctly identified validation pixels for a given class relative to the actual number of pixels belonging to that class, thereby determining the model's efficacy in accurately classifying pixel data. User's accuracy, on the other hand, assesses the proportion of correctly classified pixels for a class against the total classified as that class, including misclassifications, offering insight into the reliability of the model's classification accuracy for identified classes.

We conducted a peatland congruency analysis to better understand the differences among our three final maps. We began by reclassifying peatland types into a single class with unique pixel values on each map. This reclassification allowed us to combine the three maps and assess overlaps in peatland areas. Using this method, we could easily identify areas of congruence across each pair or all three maps, as well as regions where no shared peatland classification exists. Following this, we separated areas where peatland classification coincided in all three maps. We generated three buffer areas of 1, 3, and 5 cells, which we used as masks to extract peatland classifications from our original congruency map that fall within these buffered zones. This analysis helps us quantify if peatland areas classified by only one or two maps are adjacent to peatland areas where all three maps coincide. It also allows us to identify specific sectors where there is no adjacency, highlighting areas that may require further investigation and ground truthing to improve map accuracy.

2.4 Adjusting Peatland Areas and Scaling Up Peatland C stocks

To estimate the total carbon stocks in peatland classes, we utilized a stratified estimator for calculating cover area, following the methodology proposed by Olofsson et al. (2013). The area of peatlands determined by pixel counting may significantly differ from the actual area due to errors of omission and commission (Hribljan et al., 2017). Although it is not feasible to pinpoint the exact locations of these errors, the actual or adjusted area of each land cover class can be estimated using the error matrix and the proportion of each class in the map (Olofsson et al., 2013). This approach assumes a random, systematic, or stratified random sample of ground truth points. Our ground truth samples were collected through extensive field visits, primarily from our main field sites, using a stratified random sampling method. Additionally, targeted sampling was employed to ensure a comprehensive representation of various peatland types and conditions. To estimate total peatland carbon stocks, we used the páramos peatland average carbon content per hectare, as reported by Hribljan (2024), which includes the total depth of 16 cores obtained in the páramos of Ecuador and Colombia. This average carbon content was then multiplied by the total adjusted mapped area of each peatland class.

3 Results

3.1 Mapping

We mapped 17 LULC classes, including five peatland-specific classes— one of which identifies disturbed peatlands (pasture peatlands). Other classes include an open water class, two mineral wetland types, five semi-natural and natural upland areas, and four anthropogenic land use classes.

To compare differences in spatial extent classification results, we generated three national maps: subregional (SREG), regional (REG), and national (NAT). The peatland areas (based on pixel counting) for the entire study area on these maps measured 221,825 ha (SREG), 215,023 ha (REG), and 187,280 ha (NAT), accounting for 4.8%, 4.7%, and 4.1% of the total mapped area, respectively (Supplementary material, **Table 8**). Total areas for all classes within the Colombia national border are presented in **Table 3**. The results are presented as ranges representing the minimum and maximum values among our three maps. Herbaceous and woody/shrubby peatlands proved to be the most extensive peatland classes, representing 40-43% and 39-43% of all peatlands, respectively. Pasture peatland areas ranged from 13- 15% of the total peatland area. Sphagnum peatlands covered 2-3% of all peatland area. Cushion peatlands represented the least extensive peatland class, representing 1% of the total peatland area for all three maps. For the areas of all LULC classes, refer to **Table 3**.

Pooled peatland producer's, peatland user's, and overall accuracies were consistently high across all three maps, with values between 92-94%, 87-88%, and 90-93%, respectively (**Table 4**). Notably, the Wet Meadow and Woody Wetlands classes exhibited lower accuracy, with producer's accuracy for Wet Meadows at 43-57% and user's accuracy at 43-50%. Woody Wetlands' producer's accuracy varied between 17-54% and user's accuracy between 12-38%. Although some peatland type producer’s and user’s accuracies appear to be low, they mostly are confused with other peatland classes, hence the high overall peatland producer’s and user’s accuracies (see confusion matrices in Section A in the supplementary material).

Table 3. Mapped areas within Colombia national borders (based on pixel counting) and adjusted areas (using a stratified estimator) with its respective margin error (95% CI) of LULC classes. Small differences in the total area of the maps are due to pixel variation at the edges, primarily resulting from resampling pixels (nearest neighbor) when generating the mosaics. We included the areas estimated in the Sierra Nevada de Santa Marta (SNS), however we did not calculate the adjusted area because we did not had any ground truthing in this region of the country.

	SREG				REG				NAT				SNS	
LULC Classes	**Area (ha)**	**Area %**	**Adjuste Area (ha)**	**Adjusted Area (%)**	**Area (ha)**	**Area %**	**Adjuste Area (ha)**	**Adjusted Area (%)**	**Area (ha)**	**Area %**	**Adjuste Area (ha)**	**Adjusted Area (%)**	**Area (ha)**	**Area %**
Open Water	19134	0.44%	19337 ± 254	0.44%	19230	0.44%	19823 ± 936	0.45%	18989	0.44%	19216 ± 260	0.44%	1708	0.92%
Woody/Shruby Peatlands	90932	2.08%	99134 ± 7685	2.27%	83877	1.92%	84955 ± 6451	1.95%	79939	1.83%	76952 ± 6547	1.76%	82	0.04%
Herbaceous Peatlands	78491	1.80%	89661 ± 4191	2.05%	85382	1.96%	116800 ± 6615	2.67%	68430	1.57%	103432 ± 5955	2.37%	391	0.21%
Cushion Peatlands	2802	0.06%	5804 ± 1007	0.13%	2623	0.06%	5981 ± 1177	0.14%	2096	0.05%	6080 ± 1568	0.14%	3	0.00%
Wet Meadows	9596	0.22%	9219 ± 1531	0.21%	16486	0.38%	16336 ± 2421	0.37%	12058	0.28%	11215 ± 1663	0.26%	208	0.11%
Pasture Peatlands	30853	0.71%	33080 ± 2232	0.76%	27669	0.63%	33858 ± 2908	0.78%	22520	0.52%	29380 ± 2940	0.67%	99	0.05%
Sphagnum Peatlands	6364	0.15%	9585 ± 1142	0.22%	3898	0.09%	8712 ± 1950	0.20%	4200	0.10%	9005 ± 2233	0.21%	1	0.00%
Woody Wetlands	10662	0.24%	4663 ± 1479	0.11%	13761	0.32%	5168 ± 2334	0.12%	7759	0.18%	4670 ± 2206	0.11%	39	0.02%
Forests	1636449	37.47%	1804309 ± 15412	41.31%	1730408	39.63%	1960164 ± 16885	44.89%	1644405	37.68%	1878286 ± 16859	43.03%	20573	11.12%
Herbaceous Uplands	629659	14.42%	645747 ± 13472	14.79%	639773	14.65%	599672 ± 13842	13.73%	758606	17.38%	690871 ± 16664	15.83%	47493	25.68%
Bare soil/rock/sand	97886	2.24%	115962 ± 3244	2.66%	91863	2.10%	107222 ± 2781	2.46%	95629	2.19%	113020 ± 3131	2.59%	84102	45.47%
Shrublands	847267	19.40%	652175 ± 19410	14.93%	749780	17.17%	547567 ± 18520	12.54%	808723	18.53%	563173 ± 20468	12.90%	26634	14.40%
Snow/glaciers	2964	0.07%	2964 ± 0	0.07%	2967	0.07%	2967 ± 0	0.07%	3068	0.07%	3068 ± 0	0.07%	889	0.48%
Croplands	115516	2.64%	204690 ± 8881	4.69%	143284	3.28%	288294 ± 9925	6.60%	145391	3.33%	317810 ± 11839	7.28%	229	0.12%
Pastures	766519	17.55%	566768 ± 10994	12.98%	732419	16.77%	498178 ± 10808	11.41%	664583	15.23%	444997 ± 9775	10.20%	2356	1.27%
Forest Plantations	12305	0.28%	90781 ± 10217	2.08%	12215	0.28%	57149 ± 6359	1.31%	18035	0.41%	79812 ± 8911	1.83%	125	0.07%
Urban Areas	10124	0.23%	13643 ± 1762	0.31%	11209	0.26%	13998 ± 1823	0.32%	10277	0.24%	13720 ± 1704	0.31%	19	0.01%
Total Peatlands	**209442**		**237264 ± 16258**		**203449**		**250306 ± 19100**		**177185**		**224848 ± 19244**		**576**	
Percentage of peatlands	**4.80%**		**5.43%**		**4.66%**		**5.73%**		**4.06%**		**5.15%**		**0.31%**	
Total Area	**4367522**				**4366844**				**4364707**				**184951**	

Table 4. Summarizes the producer's accuracy (PA) and user's accuracy (UA) for LULC classes across the three national maps.

	SREG		REG		NAT	
Class	**PA**	**UA**	**PA**	**UA**	**PA**	**UA**
Open Water	100%	100%	100%	100%	100%	100%
Woody/Shrubby Peatlands	83%	73%	68%	62%	66%	58%
Herbaceous Peatlands	86%	75%	79%	75%	78%	74%
Cushion Peatlands	89%	98%	92%	99%	90%	100%
Wet Meadows	54%	48%	48%	43%	57%	50%
Pasture Peatlands	93%	86%	91%	83%	89%	80%
Sphagnum Peatlands	87%	94%	86%	89%	85%	90%
Woody Wetlands	54%	38%	17%	12%	26%	30%
Forests	92%	97%	90%	97%	89%	97%
Herbaceous Uplands	88%	87%	88%	78%	89%	74%
Bare soil/rock/sand	98%	99%	95%	99%	96%	98%
Shrublands	72%	71%	64%	64%	59%	60%
Snow/glaciers	100%	100%	100%	100%	100%	100%
Pastures	93%	98%	86%	96%	83%	93%
Croplands	95%	73%	90%	66%	86%	65%
Forest plantations	75%	81%	81%	90%	79%	85%
Urban areas	95%	96%	96%	89%	95%	92%
Overall Peatland's Accuracy	**94%**	**87%**	**92%**	**88%**	**92%**	**88%**
Overall Accuracy	**93%**		**90%**		**90%**	

The peatland extent varied significantly with elevation (**Figure 4**). All peatland classes, except for cushions, are found between 2750 and 4500 m, with most peatlands occurring between 3250 – 3750 m (62%). Herbaceous and woody/shrubby peatlands are present at all elevations, but herbaceous peatlands are more abundant above 3500 m, while woody/shrubby peatlands dominate below 3500 m. Cushion peatlands were found above 3700 m, with *Plantago rigida* being the most dominant below 4000 m and *Distichia muscoides* above 4000 m. Overall, cushion peatlands are more abundant between 4000 and 4500 m. Conversely, *Sphagnum* peatlands are more abundant at lower elevations (2750-3000 m) and gradually decrease as elevation increases.

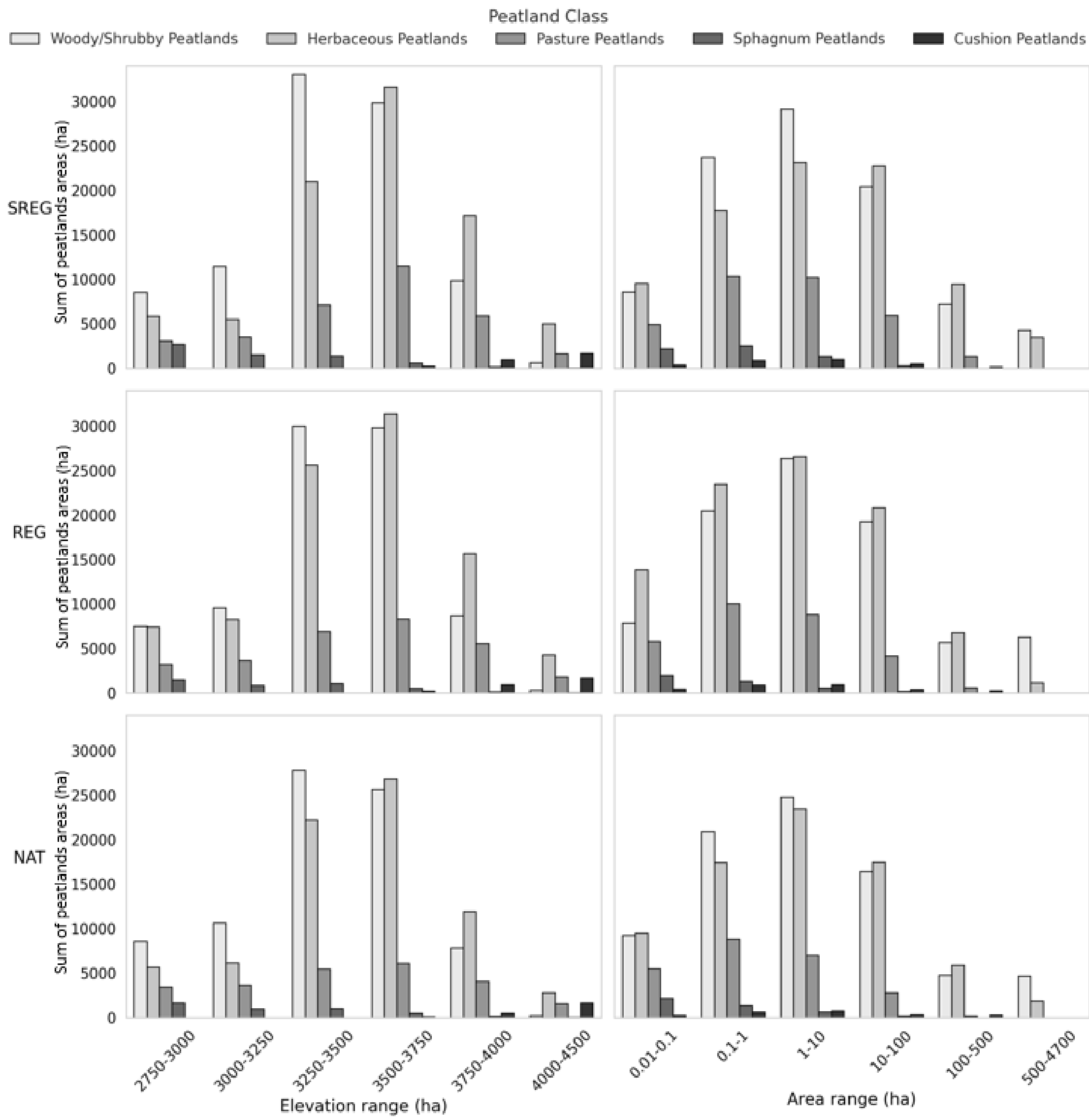

Figure 4. Distribution of peatland areas by elevation and area ranges across our three national maps. Each bar represents the sum of peatland areas (ha) within specific elevation and area ranges (shown in the two columns), categorized by peatland class. Our three national maps (SREG, REG, and NAT) are labeled in the rows.

The combined peatland areas, i.e., locations mapped as peatlands in at least one of the three maps, totaled 294,165 ha. Of these, 132,098 ha (45%) were consistently classified as peatland by all maps. Nonetheless, when examining the areas adjacent to this 45% congruent region, we observed distinct patterns. Specifically, 21%, 36%, and 42% of the peatland areas classified by only one or two maps were near the regions where all three maps coincided, within distances of 1, 3, and 5 cells respectively (each cell representing 10 m). This suggests that the discrepancies between the maps are predominantly at the edges of the peatlands, indicating a high likelihood of agreement in the location of these areas. In other words, 42% of the total peatland areas in the three maps are within 50 m of the regions where all maps are congruent. Many of these zones are likely gradual ecotones where transition to shallower peat makes distinguishing peat from other classes difficult. The remaining 13% of discrepancies can be attributed to isolated pixels classified by each map and the larger areas of pasture peatlands in the NEC subregion identified only in the SREG map (**Figure 7**).

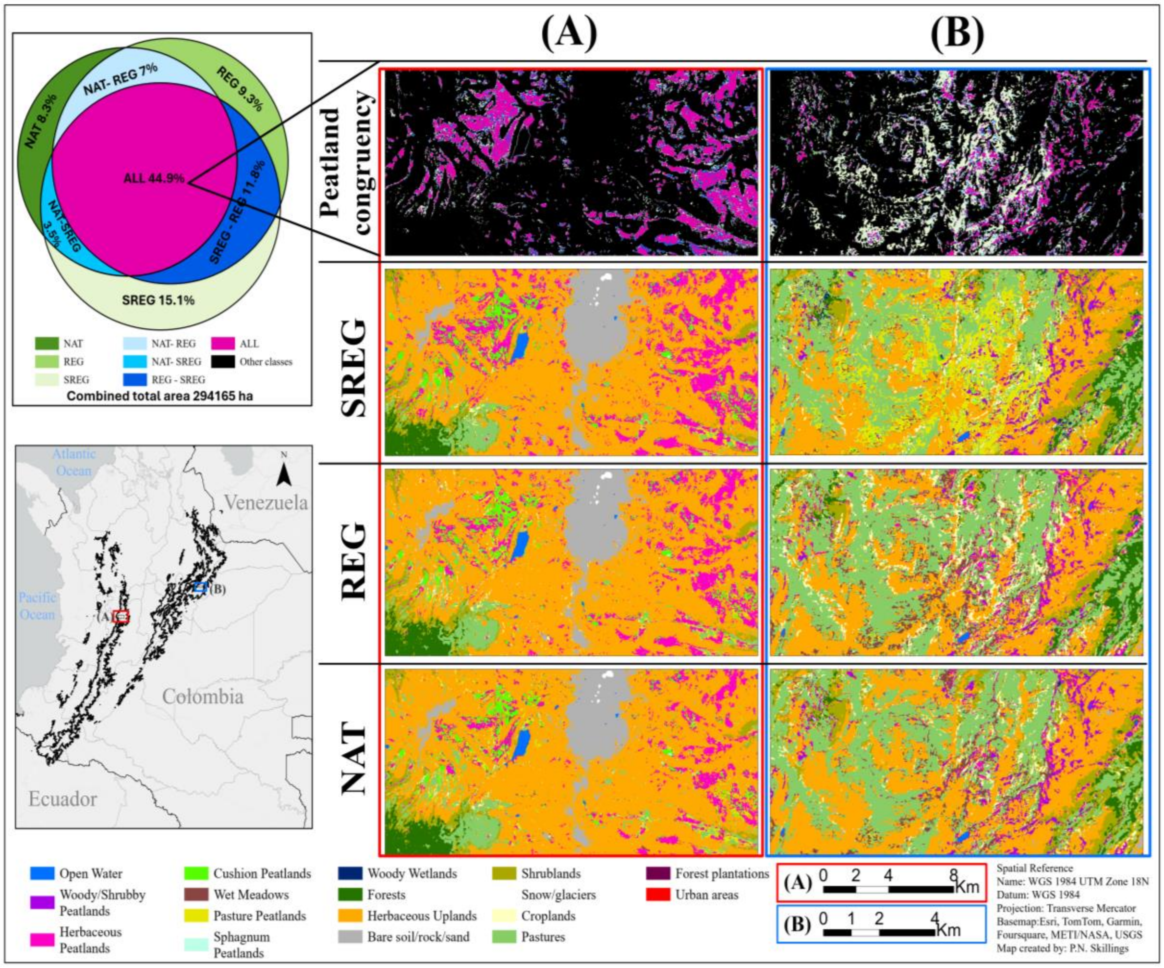

Figure 5. Comparison of peatland distribution across three classification maps: SREG, REG, and NAT. Maps in column (A) show an area in Nevados National Park, highlighting significant peatland congruency, with SREG regions appearing larger than NAT regions upon close inspection. Site (B), located in the department of Boyacá, demonstrates discrepancies in peatland classification: the SREG map shows a large area of pasture peatlands, while the REG and NAT maps classify the same area as either pastures or wet meadows. The maps at the top of both columns show the combined peatland area for the three maps, with a Venn diagram on the left illustrating the total area percentages of congruency between the three maps.

3.2 Soil Carbon Analysis

Distinct trends in carbon percentage (C%) and bulk density (g/cm³) at depths of 0-40 cm are evident across various land cover types (**Figure 6**). Herbaceous and S*phagnum* peatlands are combined due to limited primary field data for *Sphagnum* peatlands. This combination is logical as sphagnum peatlands are typically integrated within herbaceous peatlands. For all classes, C% generally decreases with depth, with non-peatland classes showing a more abrupt decline. Peatlands consistently exhibit the highest C% at all depths (e.g., Cushion peatlands: 33% at 0-10 cm to 29.5% at 30-40 cm; Herbaceous peatlands: 30.5% at 0-10 cm to 25.1% at 30-40 cm). Additionally, peatlands have low bulk densities that increase slightly with depth (e.g., Cushion peatlands: 0.09 g/cm³ at 0-10 cm to 0.14 g/cm³ at 30-40 cm; Herbaceous peatlands: 0.11 g/cm³ at 0-10 cm to 0.19 g/cm³ at 30-40 cm). However, within the peatland categories pasture peatlands exhibit lower C% and higher BD. This is expected, because drainage leads to mechanical settling and exposes peat to oxygen, facilitating microbial decomposition of organic matter. As the water table drops in drained peatlands, the peat structure becomes more compact, leading to higher BD. This oxidation reduces the carbon storage of these peatlands, highlighting the detrimental effects of land-use changes on peatland ecosystems. Other classes like mineral wetlands and productive territories display lower C% and higher bulk densities.

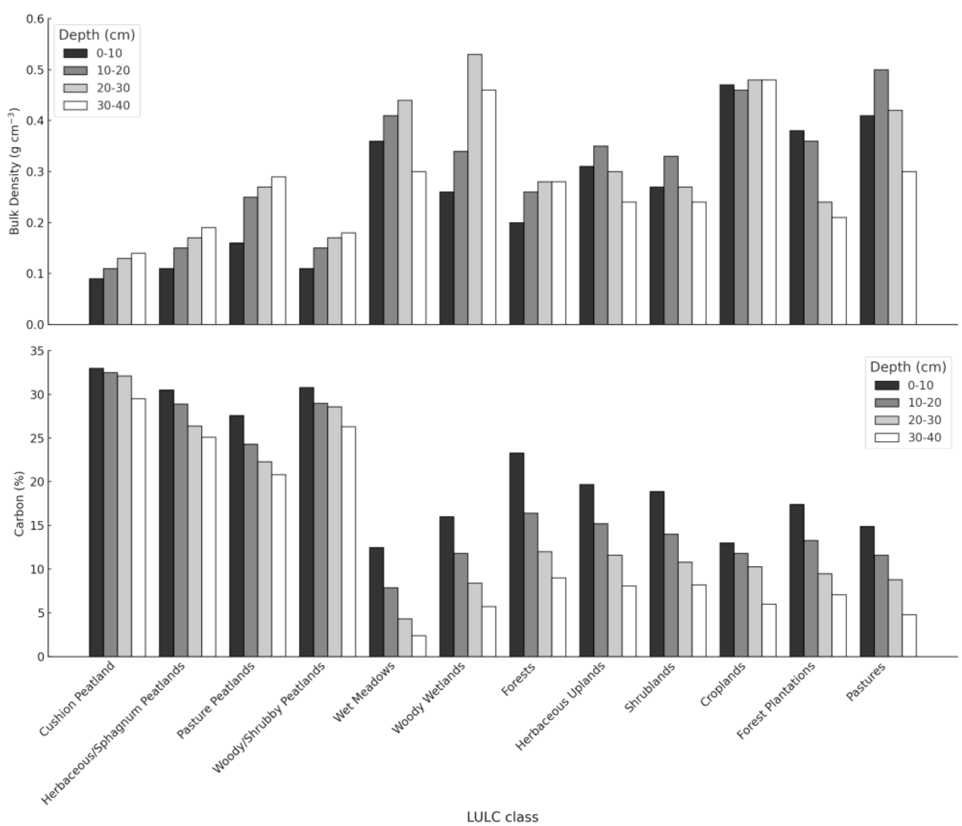

Figure 6. Bulk density and carbon percentage across different LULC classes at various soil depths.

4 Discussion

4.1 Mountain Peatlands of Colombia

We present the first comprehensive national-scale maps of peatland distribution in Colombia's mountain ecosystems (above 2750 m), estimating a total peatland adjusted area between 224,848 ha (± 19,244) and 250,306 ha (± 19,100) (**Table 3**), representing 5.2-5.73% of the total mapped area within the country (**Figure 5**). These maps will serve as a crucial tool for the research, management, conservation, and restoration of mountain peatlands in the country.

Our maps reveal that 13-15% of all peatland areas have been transformed into pasture peatlands, which has significant implications for greenhouse gas emissions and water supply for the country. Although 51% of the peatlands from all three maps are located within protected areas as defined by the National System of Protected Areas (SINAP), peatland disturbances were commonly observed during our field visits within these protected areas (Figure 6). We also estimated that 7-8% of all peatlands located in protected areas are classified as pasture peatlands. This finding underscores the critical need to integrate peatlands into comprehensive management practices. Despite their location within protected areas, peatlands are not adequately protected due to a widespread lack of knowledge among the public and, more importantly, among land managers and decision-makers about the vital ecosystem services peatlands provide, such as water storage and carbon stock.

4.1.1 National Peatland Maps Comparison

Advantages and disadvantages for each of the three maps created using different spatial extents were observed. Smaller spatial extents classifications, benefit from similar environmental conditions and vegetation composition. This is because we expect more uniformity within these localized areas, which reduces variability in the data. Additionally, the overall computing time for classification is faster than processing larger regions of our study area. However, in the case of the SREG level approach, merging adjacent subregions into a cohesive map is challenging, as differences from independent classifications are much more notable at adjacent borders of these subregions. Furthermore, limited training and validation data in smaller extents may fail to represent some classes, especially those hard to find in the field or interpret with high-resolution techniques. Conversely, larger spatial extents cover broader areas, leveraging a more extensive range of training data to address gaps but potentially lacking the detail needed for capturing local variations and requiring more computational time.

Discrepancies between the peatland areas of our three maps are predominantly found at the edges of the peatlands, indicating that major differences are located within shallow peat areas or transitional ecozones between peatlands and other classes. We did not find significant differences between the accuracies of the three maps to choose a better map, highlighting the individual benefits of using each map for different occasions. While a comprehensive and complete database at the subregional extent would be beneficial, our approach using different spatial extents allows us to fill gaps and use important information from each map to improve future versions of the national peatland map. For example, the SREG map will allow us to locate areas of pasture peatlands not classified as such in the other maps, while the NAT map will serve as a tool to identify mineral wetlands, considering the lack of mineral wetland field data in our study. For peatland assessment in the field, we recommend using the combined peatland area from the three maps since there is a better chance of finding peatlands where all three maps are congruent without discarding areas that might contain shallow peatland areas or that were not classified in one or two of the maps. By comparing these three maps, we can better plan further field ground truthing to improve future versions of the national peatland map.

It is also important to note that the SREG and REG maps will not represent all LULC classes due to the lack of field data for some classes in certain subregions. For instance, the SREG map lacks classified wet meadows in the CC_WC subregion, woody wetlands in the NAR and CC_WC subregions, and cushion peatlands in the SEC subregion because no field data for these classes were collected in those subregions. Consequently, for the REG map, we won't find any classified woody wetlands in the CC_WC_NAR region. The NAT map, however, included classified areas for all LULC classes across all subregions because it combined training data from all subregions. Ideally, each subregion should have significant amounts of training data for each class, but this is often difficult to achieve in fieldwork.

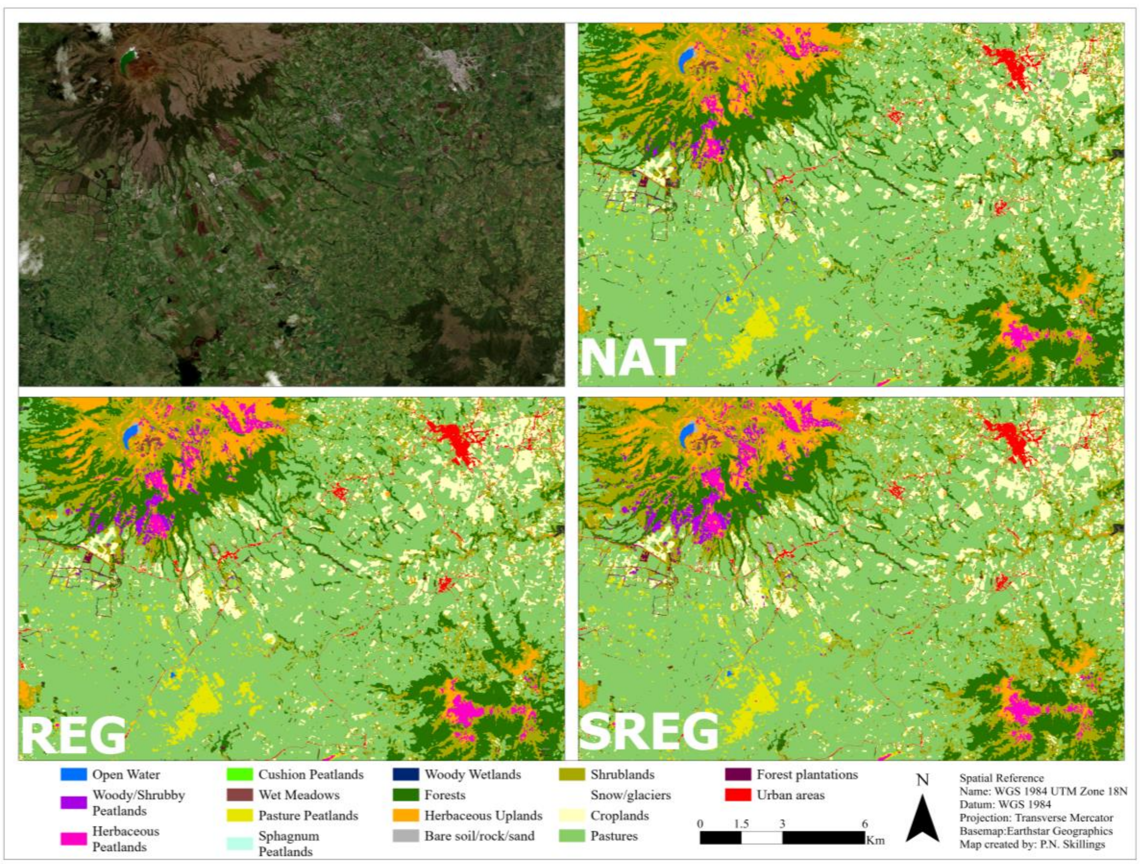

Figure 7. Comparison of peatland classification maps using different spatial extent at national (NAT), regional (REG), and subregional (SREG) levels for an area in Nariño. These maps zoom in on a developed landscape with a matrix of pastures and croplands, revealing a relatively large pasture peatland area in the southwest. The maps also highlight the urban area of Puerres in the northeast, the Azufral volcano páramo in the northwest, and the Páramo de Paja Blanca in the southeast.

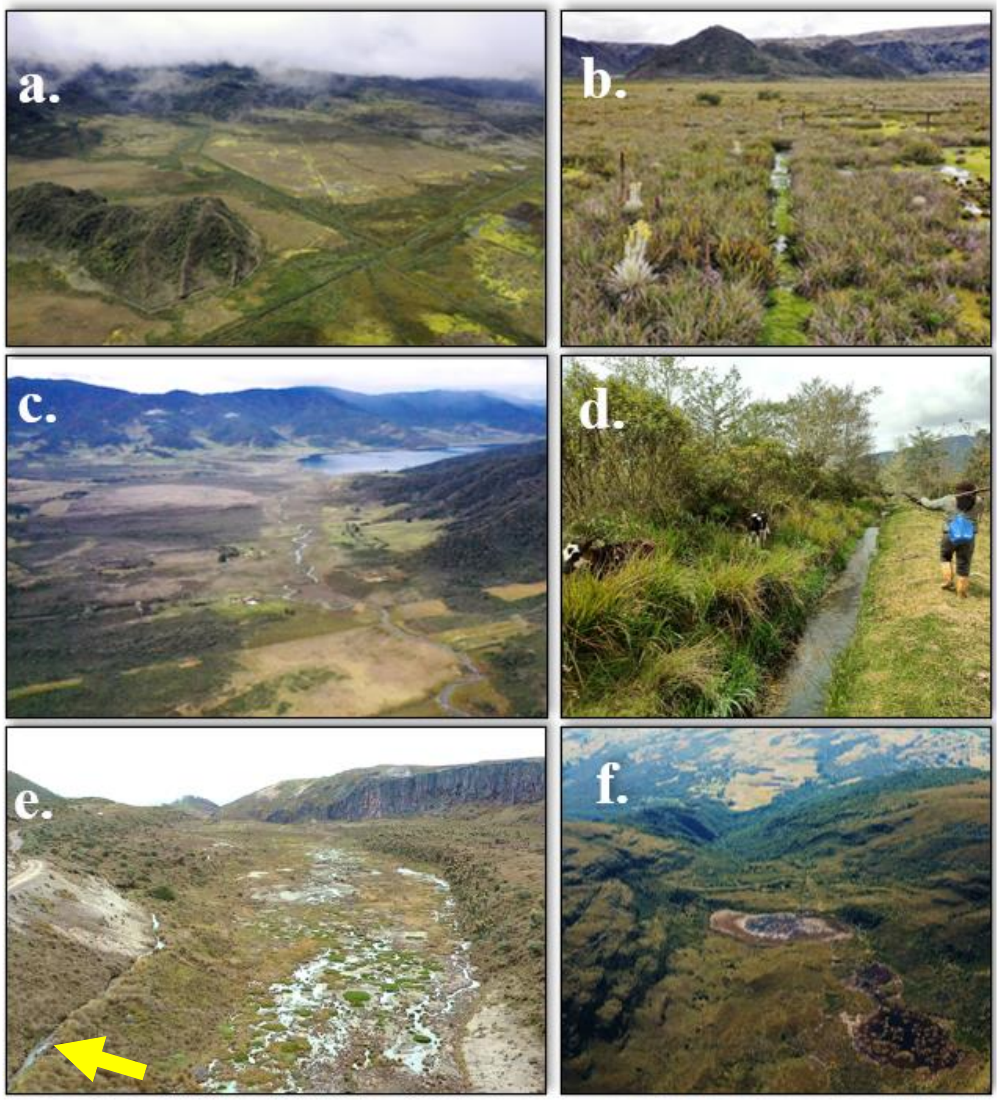

Figure 8. Disturbed peatland landscapes, all within protected areas in Colombia. (a) and (b) show the Vista Hermosa de Moquentiva Regional Park in Cundinamarca. (a) An aerial image of a peatland complex (sphagnum, herbaceous, and shrubby peatlands) with unsuccessful drainage ditches, now a research site for monitoring peatland's greenhouse gas emissions and conducting peatland restoration. (b) A closer view of a small ditch within the peatland complex. (c) and (d) show the Protected Forest Reserve in Laguna La Cocha and Cerro Patascoy. From 1997 to 2001, this area was a military base for the armed rebel group FARC. Since their departure, rapid population growth has led to

increased interest in draining peatland areas. (c) An aerial image of a disturbed section of the largest peatland complex in Colombia. (d) A close-up of peatland areas affected by drainage efforts. (e) Shows the Alfombrales area in Los Nevados National Park, where a ditch (pointed with the yellow arrow) diverts glacial water, causing severe damage to cushion peatlands. (f) Displays the "Ojo de Agua" in Iguaque National Park, where peatlands are drained using buried hoses, where water is used mainly for irrigation. Since the 1950s, increased population and high-density potato farming have led to extensive peatland drainage.

4.1.2 Comparisons With Existing Maps

Our mapping effort provides valuable insights when compared with global, national, and regional peatland maps.

4.1.2.1 Global Peatland Map 2.0

High-resolution mapping is crucial for informing global peatland maps, which often lack detailed data on mountain peatlands in the tropics(Gumbricht et al., 2017; Melton et al., 2022; UNEP, 2022; Xu et al., 2018). The Global Peatland Map 2.0 (GPM2) estimates approximately 3.3 million ha of peatlands in Colombia, with 37,500 ha within our study area (Greifswald Mire Centre, 2022). By comparing the combined peatland areas from our maps with those from the GPM2 map within our study area, we found that only 27% of the peatland areas identified by GPM2 align with our mapped peatland areas. This discrepancy is primarily due to the significantly larger spatial resolution of the GPM2 map. The 1 km^2 pixel area from the GPM2 is 10,000 times larger than our maps´100 m^2 pixel (**Figure 9**) reducing their ability to detect smaller peatlands. Although the GPM2 estimates that only 1% of all peatlands in the country occur above 2750 m, our study suggests that 5-6% of the country's peatlands are found above this elevation. Additionally, 75-80% of the total area of mapped peatlands have individual sizes under 100 ha, highlighting the importance of high-resolution mapping for accurately identifying mountain peatlands (**Figure 4**).

4.1.2.2 National Maps of Colombia

The 2015 National Wetland Map of Colombia (NWMC) combines geomorphological, soil, land cover, hydrographic, and flood frequency data to identify wetlands at a 25-meter spatial resolution (Flórez-Ayala et al., 2016; Jaramillo Villa et al., 2016). It categorizes wetlands based on water presence and environmental traits into the following classes: Permanent Open, with visible and continuous water; Permanent Under Canopy, where water is ever-present beneath forest cover; Temporal, with fluctuating water levels; and Medium and Low Potential, suggesting probable but uncertain wetland conditions. Comparing the combined peatland areas from our maps with this map, we found that only 34.7% of the peatland area falls within its wetland classes, mainly as Low Potential wetlands (32.1%) and Temporary Wetlands (2.6%). Additionally, the National Wetland Map classifies about 850,000 ha of wetlands in our study area, including open water and glaciers as Permanent Open wetlands (**Figure 9**). In contrast, we estimated (using adjusted areas) 240,734 - 271,810 ha of combined mineral wetlands and peatlands, with combined areas of open water and glacier/snow classes accounting for 22,284 - 22,790 ha. While the NWMC provides a broad estimate of wetland areas, its general classifications do not capture the specific types and extents of wetlands needed for detailed ecological studies and management of peatlands (**Figure 9**). The broad categories and the integration of various mapping products, with differences in resolution and classification criteria, may introduce errors and overestimate wetland areas.

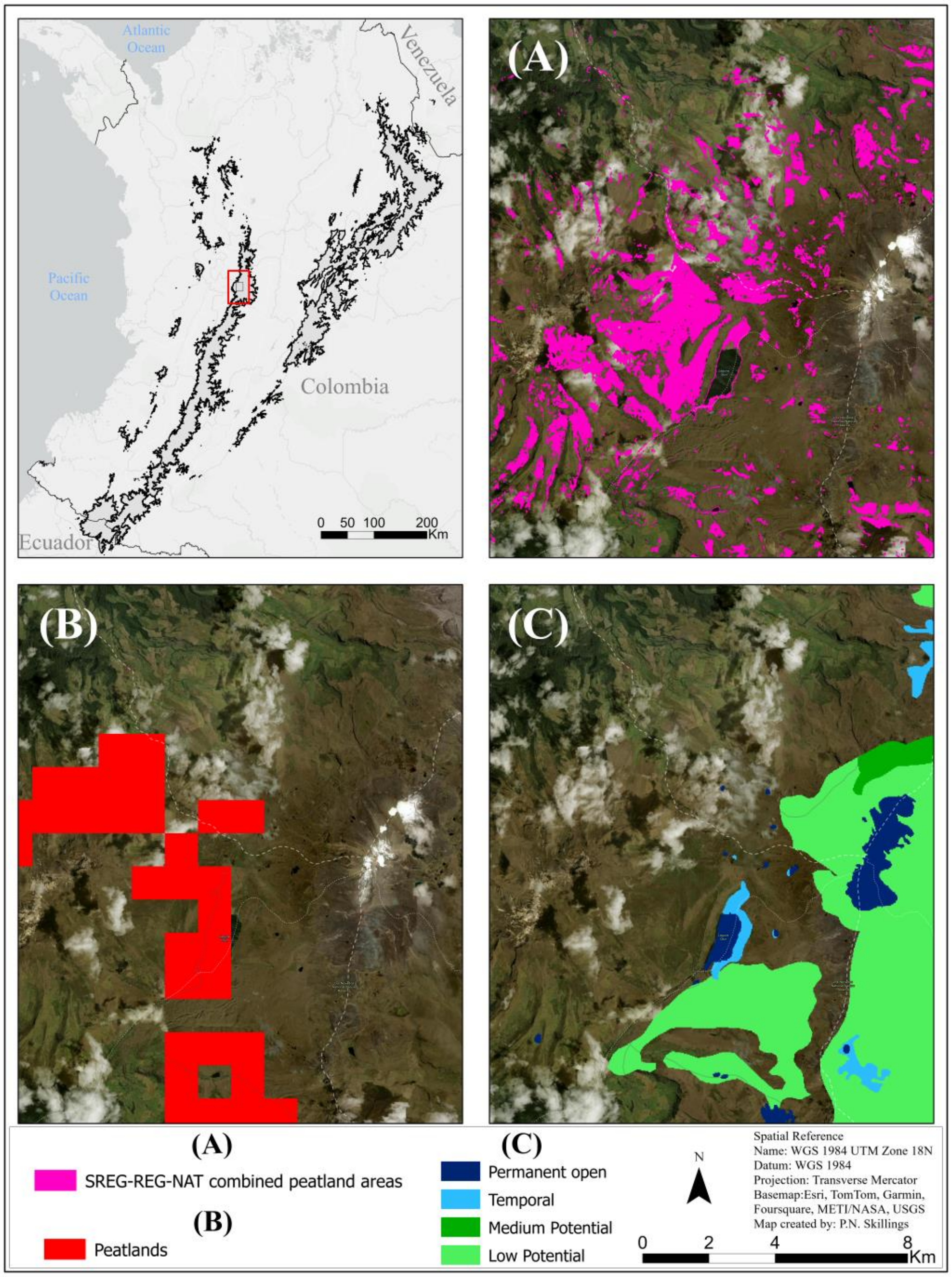

Figure 9. This study's (A) combined peatland area map compared with the (B) Global Peatland Map 2 and the (C) National Wetlands Map of Colombia

In contrast, the 2018 National Land Cover Map of Colombia (NLCMC), developed at a 1:100,000 scale using the Corine Land Cover methodology, employs Landsat satellite images for visual interpretation and reports a 91% overall accuracy across 54 land cover classes, including a peatland class (Castellanos et al., 2021). The classification was performed using the Photo-Interprétation Assistée par Ordinateur (PIAO) technique, which involves visual interpretation of satellite images on a screen. Although it claims 100% user's and producer's accuracies for the peatland class, the map only reports 11 peatland polygons totaling 793.3 ha within our study area. Comparing our map to this official land cover map, we found that 70% of peatlands are classified as Herbaceous uplands, 16% as Pastures, 10% as Shrublands, and 3% as Forests, with the remaining 1% in other classes.

Although this NLCMC map is widely used, it lacks thorough wetland data, mainly because Landsat-only imagery is insufficient for mapping wetlands and because of inadequate ground truthing to resolve peatland classes. The accuracy assessment for the NLCMC involved assigning reference labels to sampling points based on visual interpretation, without extensive ground truthing specifically for peatlands. In contrast, peatland mapping studies have shown improved results using a multi-date, multi-sensor SAR and optical approach, combined with extensive field data (Bourgeau-Chavez et al., 2018). For example, Hribljan et al. (2017) compared classification accuracies using several remote sensor data for mapping alpine peatlands in northern Ecuador. Using Landsat-only optical imagery, they achieved an overall accuracy of 86% but had moderate errors in distinguishing between peatland classes. When combined with Radarsat, PALSAR, and TPI data, the overall accuracy increased to 90%, with most individual peatland class accuracies also improving or remaining the same. This comparison underscores the limitations of the NLCMC in accurately representing peatland areas. Relying solely on visual interpretation and Landsat imagery without extensive ground truth data leads to inaccuracies specially for mapping wetlands.

4.1.2.3 Regional Maps from the Andes

When comparing our findings with other studies in the Andes, notable differences emerge regarding proportions of peatland area with total mapped area. The Ecuadorian Andes páramo peatland map estimates peatland coverage at 18% of the total mapped area of 271,492 ha above 3,500 m (Hribljan et al., 2017). Similarly, in Peru, the Huascaran National Park and its buffer areas in the puna region, covering a total area of 510,200 ha, estimate peatlands to cover approximately 6.3%, primarily consisting of cushion peatlands at elevations between 3,950 and 4,650 m (Chimner et al., 2019). In Colombia, regional peatland maps for the Las Hermosas, Chili-Barragán, and Guanacas-Purace-Coconucos páramo complexes reported peatland coverage of 40,337 ha, representing 9.4% of the total mapped area of 429,530 ha (Battaglia et al., 2024).

Although our study shows that within the entire study area peatlands only cover 4-4.8%, we used a lower elevation boundary of 2,750 m compared to other mapping efforts. This lower boundary allows us to detect peatlands in azonal páramos (páramos that occur in areas influenced by specific local conditions rather than the typical high-altitude environments) and in transformed areas where peatlands might still exist. This approach includes large proportions of areas of Andean forests, pastures, and croplands that are not considered in other maps. When estimating the total peatland areas from an elevation greater than 3,500 m, the peatland percentage increased to 7.7-10.2% of the total area. Moreover, pasture peatlands over 3,500 m were account for 14-17% of all peatland categories.

4.1.3 Peatland Mapping Challenges

Mapping peatlands in the Andes presents several challenges. First, constant cloud cover in these mountainous ecosystems makes the acquisition of cloud-free optical images from Sentinel-2 difficult. Although we used Google Earth Engine (GEE) to automate the selection of the best pixels possible through cloud masking techniques, we still encountered several defects in our images, especially in cloud forests and steep valleys. Shadows, fog, and clouds introduced noise, affecting classification results. Visual inspections of the map suggest that many areas where we detected noise in the optical imagery have misclassified forests or shrublands as pastures and some herbaceous uplands as croplands. While our focus in these maps is on peatlands, and we consider these classes to be accurate, there may be some errors in upland classification classes due to these defects in the optical images.

Regarding SAR imagery, emerging technologies will likely improve classification results for dense vegetation classes. Our woody wetlands and shrublands classes, which currently show lower accuracy, might achieve better results with upcoming freely available high-resolution SAR data. The NASA/ISRO NISAR sensor, expected to provide global L-band SAR coverage with a twelve-day repeat cycle, and the ALOS PALSAR 2, which will soon offer recent and high-resolution data, are promising advancements. These sensors will enhance our ability to accurately classify dense vegetation and improve overall peatland mapping in the Andes.

4.2 Peatland soil Carbon storage

The first 40 cm of carbon percentage (C%) and bulk density (BD) data may not accurately reflect the averaged conditions of peatland soils throughout their entire depth. Although our study only analyzed soil data up to 40 cm deep, full core analyses of mountain peatlands have provided a broader perspective. According to Hribljan (2024), high BD (0.2-0.4 g cm-3) and low C% (15.4 – 31.6%) in páramo peatland soils are due to their high mineral content, a common characteristic of mountain peatlands. These peatlands are often found on mountainsides or valley bottoms, where steep eroding slopes can contribute significant alluvial, colluvial, or aeolian sediment, lowering % C and increasing BD (Hribljan et al., 2024). Additionally, mountain peatlands in volcanic regions receive considerable ash, further increasing the mineral content.

Peatlands have greater soil depths than any other land cover in the mountains (Chimner et al., 2023; Hribljan et al., 2024; Hribljan et al., 2016). The average depth of peatlands in the páramos of Colombia and Ecuador is estimated to be 442 cm, with an average total peatland carbon of 1628 Mg ha^{-1} (Hribljan et al., 2024). Scaling up these carbon estimates to the adjusted peatland areas from our national maps (**Table 3**), we estimated that peatland stocks in the mountains of Colombia contain between 366 and 407 Tg of carbon, playing a significant role for the total carbon storage in the country. In comparison to the total carbon stored in forest biomass across the country, which is estimated to be 7145 Tg over 59 million ha (Phillips et al., 2011), mountain peatlands can store 16 to 17 times more carbon per hectare in their soils. This translates to peat C equivalent to about 5% of national forest biomass C on 0.2% of the land area. This highlights the critical implications of draining or transforming peatlands and underscores the necessity of developing strategies to mitigate disturbances in these ecosystems.

It is worth noting that, although peatlands store the most soil C per unit area when considering the entire soil column to the base of the peatland, the soil C density of all ecosystems that we measured was quite substantial and roughly equivalent when only considering the top 40 cm of the soil. According to the Colombia National Report on Soil Organic Carbon Sequestration Potential (Araujo-Carrillo, 2021), the Andean region is identified as the area with the highest potential to sequester CO2, especially through improved management of croplands and grazing lands. Although this study does not mention peatlands, it highlights the importance of other Andean land covers, for carbon stock and carbon sequestration. They estimate that the Andean region possesses high contents of soil organic carbon stocks, often exceeding 100 Mg C ha^{-1} for soil depth up to 30 cm. This aligns with our soil carbon stocks result, which for all classes ranged from approximately 100 to 200 Mg ha^{-1} for the first 40 cm of soil depth. These results show how valuable mountain ecosystems are for storing and sequestrating carbon and underscore the need to adopt management practices, such as water table management, peatland restoration, better agricultural practices, and upland reforestation, which can enhance the carbon sequestration potential of these vital ecosystems.

5 Conclusion

This map serves as a critical resource for understanding the extent and distribution of peatlands, informing conservation and management practices, and facilitating climate change mitigation efforts. Our national peatland map provides essential data for policymakers, land managers, and environmental organizations, supporting efforts to conserve and restore these critical ecosystems.

Future work should focus on ground-truthing in identified areas of discrepancy and integrating new remote sensing technologies to further refine and improve peatland mapping in Colombia. As the climate warms, there is an increasing likelihood that locals will seek new water sources from peatlands at higher elevations, further threatening these ecosystems. This is particularly concerning given that tropical Andes peatlands contain substantial soil carbon deposits that are highly sensitive to temperature changes (Hribljan et al., 2024), making them vulnerable to both warming and drainage.

The national-scale mountain peatland map presented in this study is the first step toward understanding peatland distribution. Mapping of peatland extent and condition is a critical step in determining the potential for peatland protection and sustainable management in Colombia as natural climate solutions that can contribute to climate adaptation and mitigation efforts. However, much more needs to be done to comprehend the full scope of peatland dynamics and to develop effective management and conservation strategies. To inform science-based effective climate policy, it is essential to conduct scientific research to determine the potential for adaptation and mitigation strategies that can enhance the resilience of these carbon-rich ecosystems to climate change.

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A Supplementary Material

A.1 Confusion Matrixes

Table 5. National level confusion matrix.

	Open waters	Woody - Shrubby Peatlands	Herbaceous Peatlands	Cushion Peatlands	Wet Meadows	Pasture Peatlands	Sphagnum Peatlands	Woody Wetlands	Forests	Herbaceous Uplands	Bare soil - Rocks	Shrublands	Snow - Glaciers	Croplands	Pastures	Forest Plantations	Urban Areas	Users Acc.	Commission Error
Open waters	5002	0	0	0	0	0	0	0	1	0	0	4	0	0	0	0	0	100%	0%
Woody - Shrubby Peatlands	0	551	195	0	6	0	4	2	10	48	2	116	0	0	9	1	0	58%	42%
Herbaceous Peatlands	2	153	1523	32	18	48	54	16	0	112	0	19	0	67	1	0	0	74%	26%
Cushion Peatlands	0	0	0	488	0	0	0	0	0	0	0	0	0	0	0	0	0	100%	0%
Wet Meadows	0	13	10	0	113	26	0	0	0	38	0	21	0	3	0	0	0	50%	50%
Pasture Peatlands	0	40	12	4	17	991	0	5	8	16	0	20	0	52	69	0	0	80%	20%
Sphagnum Peatlands	0	0	21	0	0	0	398	0	2	0	0	0	0	3	17	0	0	90%	10%
Woody Wetlands	0	5	4	0	0	5	0	9	1	0	0	6	0	0	0	0	0	30%	70%
Forests	1	0	0	0	0	0	0	0	13086	0	0	187	0	5	0	245	0	97%	3%
Herbaceous Uplands	0	45	186	14	9	11	7	0	0	3917	116	240	0	711	14	0	5	74%	26%
Bare soil - Rocks	7	0	0	0	0	0	0	0	0	0	11395	0	0	101	0	0	163	98%	2%
Shrublands	0	31	14	1	0	4	4	3	204	219	0	948	0	69	3	67	2	60%	40%
Snow - Glaciers	0	0	0	0	0	0	0	0	0	0	0	0	3982	0	0	0	0	100%	0%
Croplands	0	0	0	0	25	11	0	0	0	1	48	5	0	6134	333	0	23	93%	7%
Pastures	0	0	0	2	12	20	0	0	1146	29	6	23	0	255	2778	0	4	65%	35%
Forest Plantations	0	0	0	0	0	0	0	0	198	0	0	6	0	0	0	1191	0	85%	15%
Urban Areas	0	0	0	0	0	0	0	0	0	0	283	0	0	0	0	2	3503	92%	8%
Prod. Acc.	100%	66%	78%	90%	57%	89%	85%	26%	89%	89%	96%	59%	100%	83%	86%	79%	95%		
Omission Error	0%	34%	22%	10%	44%	11%	15%	74%	11%	11%	4%	41%	0%	17%	14%	21%	5%		

	Overall Peatlands
Producers Accuracy	92%
Users Accuracy	88%
Overall accuracy	90%

Table 6. Regional level confusion matrix.

	Open waters	Woody - Shrubby Peatlands	Herbaceous Peatlands	Cushion Peatlands	Wet Meadows	Pasture Peatlands	Sphagnum Peatlands	Woody Wetlands	Forests
Open waters	5002	0	0	0	0	0	0	0	1
Woody - Shrubby Peatlands	0	569	169	0	6	6	5	1	3
Herbaceous Peatlands	2	127	1551	25	23	36	43	9	2
Cushion Peatlands	0	0	0	497	2	3	0	0	1
Wet Meadows	0	13	5	0	95	28	0	7	0
Pasture Peatlands	0	36	20	2	29	1011	1	3	6
Sphagnum Peatlands	0	1	23	0	0	0	403	0	9
Woody Wetlands	0	23	0	0	0	0	0	6	0
Forests	0	4	0	0	0	0	0	5	13228
Herbaceous Uplands	0	30	163	14	11	0	12	0	0
Bare soil - Rocks	7	0	0	0	0	0	0	0	0
Shrublands	1	33	31	0	0	5	3	4	238
Snow - Glaciers	0	0	0	0	0	0	0	0	0
Croplands	0	2	0	0	0	0	0	0	0
Pastures	0	0	3	3	34	27	0	0	1029
Forest plantations	0	0	0	0	0	0	0	0	139
Urban areas	0	0	0	0	0	0	0	0	0
Prod. Acc.	100%	68%	79%	92%	48%	91%	86%	17%	90%
Omission Error	0%	32%	21%	8%	53%	9%	14%	83%	10%

	Herbaceous Uplands	Bare soil - Rocks	Shrublands	Snow - Glaciers	Croplands	Pastures	Forest plantations	Urban areas	Users Acc.	Commission Error
Open waters	0	0	4	0	0	0	0	0	100%	0%
Woody - Shrubby Peatlands	61	0	97	0	0	5	0	0	62%	38%
Herbaceous Peatlands	195	0	26	0	21	5	0	0	75%	25%
Cushion Peatlands	0	0	0	0	0	0	0	0	99%	1%
Wet Meadows	40	0	33	0	0	0	0	0	43%	57%
Pasture Peatlands	18	0	26	0	32	39	1	0	83%	17%
Sphagnum Peatlands	0	0	0	0	0	15	0	0	89%	11%
Woody Wetlands	0	0	13	0	0	0	10	0	12%	88%
Forests	0	0	169	0	27	0	239	0	97%	3%
Herbaceous Uplands	3845	103	194	0	564	2	0	7	78%	22%
Bare soil - Rocks	0	11281	0	0	40	0	0	115	99%	1%
Shrublands	168	0	1019	0	37	13	28	3	64%	36%
Snow - Glaciers	0	0	0	3982	0	0	0	0	100%	0%
Croplands	22	12	1	0	6346	233	0	21	96%	4%
Pastures	31	11	12	0	333	2912	0	2	66%	34%
Forest plantations	0	0	1	0	0	0	1226	0	90%	10%
Urban areas	0	443	0	0	0	0	2	3552	89%	11%
Prod. Acc.	88%	95%	64%	100%	86%	90%	81%	96%		
Omission Error	12%	5%	36%	0%	14%	10%	19%	4%		

	Overall Peatlands
Producers Accuracy	**92%**
Users Accuracy	**88%**
Overall accuracy	**90%**

Table 7. Subregional level confusion matrix.

	Open waters	Woody - Shrubby Peatlands	Herbaceous Peatlands	Cushion Peatlands	Wet Meadows	Pasture Peatlands	Sphagnum Peatlands	Woody Wetlands	Forests	Herbaceous Uplands	Bare soil - Rocks	Shrublands	Snow - Glaciers	Croplands	Pastures	Forest Plantations	Urban Areas	Users Acc.	Commission Error
Open waters	5004	0	0	0	0	0	0	0	4	0	3	0	0	0	0	0	0	100%	0%
Woody - Shrubby Peatlands	0	692	113	1	0	8	4	0	1	54	0	63	0	0	4	8	0	73%	27%
Herbaceous Peatlands	2	56	1683	35	25	32	42	9	2	252	0	47	0	69	5	0	0	75%	25%
Cushion Peatlands	0	0	0	483	0	9	0	0	0	0	0	0	0	0	0	0	0	98%	2%
Wet Meadows	0	2	6	0	107	13	0	7	0	49	0	23	0	18	0	0	0	48%	52%
Pasture Peatlands	0	8	18	12	27	1034	2	0	8	16	0	18	0	0	56	1	0	86%	14%
Sphagnum Peatlands	0	0	15	0	0	1	406	0	0	0	0	0	0	0	10	0	2	94%	6%
Woody Wetlands	0	14	0	0	0	0	0	19	9	0	0	8	0	0	0	0	0	38%	62%
Forests	1	0	0	0	0	0	0	0	13438	0	0	119	0	1	0	284	0	97%	3%
Herbaceous Uplands	0	19	128	10	6	4	12	0	0	3837	113	166	0	92	0	0	5	87%	13%
Bare soil - Rocks	5	0	0	0	0	0	0	0	0	0	11581	0	0	0	0	0	139	99%	1%
Shrublands	0	47	2	0	0	2	0	0	139	139	0	1141	0	32	13	88	2	71%	29%
Snow - Glaciers	0	0	0	0	0	0	0	0	0	0	0	0	3982	0	0	0	0	100%	0%
Croplands	0	0	0	0	25	0	1	0	0	1	10	4	0	6869	79	0	17	98%	2%
Pastures	0	0	0	0	10	13	0	0	756	32	14	6	0	319	3057	0	4	73%	27%
Forest Plantations	0	0	0	0	0	0	0	0	265	0	0	0	0	0	0	1123	0	81%	19%
Urban Areas	0	0	0	0	0	0	0	0	34	0	129	0	0	0	0	2	3531	96%	4%
Prod. Acc.	100%	83%	86%	89%	54%	93%	87%	54%	92%	88%	98%	72%	100%	93%	95%	75%	95%		
Omission Error	0%	17%	14%	11%	47%	7%	13%	46%	8%	12%	2%	28%	0%	7%	5%	25%	5%		

	Overall Peatlands
Producers Accuracy	94%
Users Accuracy	87%
Overall accuracy	93%

A.2 LULC areas in Colombia, protected areas and above 3500 m of elevation.

Table 8. LULC areas (based in pixel counting) for the entire study area including 30km buffer area from Colombia national borders.

	SREG		REG		NAT		SNS	
Class	**Area (ha)**	**Area %**	**Area (ha)**	**Area %**	**Area (ha)**	**Area %**	**Area (ha)**	**Area %**
Open Water	19426	0.42%	19545	0.43%	19252	0.42%	1718	0.84%
Woody/Shrubby Peatlands	93433	2.04%	86014	1.88%	80839	1.77%	100	0.05%
Herbaceous Peatlands	86227	1.88%	92716	2.02%	75628	1.65%	1068	0.52%
Cushion Peatlands	2924	0.06%	2810	0.06%	2245	0.05%	3	0.00%
Wet Meadows	10004	0.22%	16922	0.37%	12559	0.27%	324	0.16%
Pasture Peatlands	32786	0.72%	29488	0.64%	24283	0.53%	101	0.05%
Sphagnum Peatlands	6455	0.14%	3995	0.09%	4285	0.09%	1	0.00%
Woody Wetlands	10737	0.23%	14078	0.31%	8146	0.18%	41	0.02%
Forests	1694605	36.98%	1800057	39.29%	1714276	37.43%	26232	12.90%
Herbaceous Uplands	662427	14.46%	671414	14.65%	791756	17.29%	52708	25.91%
Bare_soil/rock/sands	99513	2.17%	92818	2.03%	96735	2.11%	84714	41.65%
Shrublands	892680	19.48%	786066	17.16%	842811	18.40%	32624	16.04%
Snow/glaciers	2964	0.06%	2967	0.06%	3068	0.07%	889	0.44%
Croplands	128619	2.81%	155754	3.40%	158005	3.45%	272	0.13%
Pastures	815453	17.80%	781723	17.06%	715366	15.62%	2386	1.17%
Forest plantations	12684	0.28%	12551	0.27%	18879	0.41%	209	0.10%
Urban Areas	11453	0.25%	12796	0.28%	11430	0.25%	20	0.01%
Total Peatlands	**221825**		**215023**		**187280**		**1272**	
Percentage of peatlands	**4.84%**		**4.69%**		**4.09%**		**0.63%**	
Total Area	**4582388**		**4581712**		**4579563**		**203409**	

Table 9. LULC areas (based in pixel counting) within protected areas in Colombia.

	SREG		REG		NAT		SNS	
Class	**Area (ha)**	**Area %**	**Area (ha)**	**Area %**	**Area (ha)**	**Area %**	**Area (ha)**	**Area %**
Open Water	10251	0.61%	10270	0.61%	10294	0.61%	1703	0.93%
Woody/Shrubby Peatlands	52161	3.11%	50758	3.02%	48589	2.89%	80	0.04%
Herbaceous Peatlands	42138	2.51%	43134	2.57%	32648	1.94%	356	0.17%
Cushion Peatlands	2084	0.12%	1964	0.12%	1719	0.10%	3	0.00%
Wet Meadows	3860	0.23%	6231	0.37%	5187	0.31%	197	0.10%
Pasture Peatlands	8471	0.50%	6874	0.41%	5864	0.35%	99	0.05%
Sphagnum Peatlands	1725	0.10%	1114	0.07%	1175	0.07%	1	0.00%
Woody Wetlands	2842	0.17%	3164	0.19%	1900	0.11%	39	0.02%
Forests	694103	41.32%	714351	42.53%	689792	41.09%	20221	9.94%
Herbaceous Uplands	323762	19.27%	329843	19.64%	374156	22.29%	46585	22.90%
Bare soil/rock/sand	73847	4.40%	72414	4.31%	72308	4.31%	84009	41.30%
Shrublands	339248	20.19%	314074	18.70%	319738	19.04%	25852	12.71%
Snow/glaciers	2964	0.18%	2967	0.18%	3068	0.18%	889	0.44%
Croplands	18302	1.09%	23092	1.37%	19857	1.18%	227	0.11%
Pastures	97073	5.78%	92920	5.53%	83008	4.94%	2326	1.14%
Forest plantations	6047	0.36%	5691	0.34%	8567	0.51%	119	0.06%
Urban areas	985	0.06%	885	0.05%	997	0.06%	18	0.01%
Total Peatlands	**106578**		**103843**		**89996**		**538**	
Percentage of peatlands	**6.34%**		**6.18%**		**5.36%**		**0.29%**	
Total Area	**1679862**		**1679746**		**1678868**		**182721**	

Table 10. LULC areas (based in pixel counting) above 3500 m of elevation in Colombia.

	SREG		REG		NAT	
Class	**Area (ha)**	**Area %**	**Area (ha)**	**Area %**	**Area (ha)**	**Area %**
Open Waters	4081	0.24%	4058	0.24%	4071	0.24%
Woody/Shrubby Peatlands	38276	2.28%	35967	2.14%	31475	1.87%
Herbaceous Peatlands	49248	2.93%	46796	2.79%	37109	2.21%
Cushion Peatlands	2802	0.17%	2623	0.16%	2096	0.12%
Wet Meadows	5700	0.34%	10110	0.60%	7319	0.44%
Pasture Peatlands	18612	1.11%	15320	0.91%	11335	0.68%
Sphagnum Peatlands	735	0.04%	599	0.04%	635	0.04%
Woody Wetlands	1048	0.06%	1960	0.12%	870	0.05%
Forests	76205	4.54%	73922	4.40%	70930	4.22%
Herbaceous Uplands	472648	28.14%	480860	28.63%	530985	31.63%
Bare soil/rock/sand	82149	4.89%	80567	4.80%	80440	4.79%
Shrublands	240176	14.30%	238159	14.18%	225535	13.43%
Snow/glaciers	2963	0.18%	2967	0.18%	3068	0.18%
Croplands	10707	0.64%	8612	0.51%	7038	0.42%
Pastures	65622	3.91%	68377	4.07%	56705	3.38%
Forest Plantations	613	0.04%	728	0.04%	2006	0.12%
Urban Areas	451	0.03%	412	0.02%	418	0.02%
Total Peatlands	**109673**		**101304**		**82650**	
Percentage of peatlands	**10.23%**		**9.45%**		**7.71%**	
Total Area	**1072036**		**1072036**		**1072036**	

A.3 Soil Carbon lab analysis results

Table 11. Avereged C% and bulk density per 10 cm subsamples segments.

LULC class	C% 0-10cm	BD 0-10cm	C% 10-20cm	BD 10-20cm	C% 20-30cm	BD 20-30cm	C% 30-40cm	BD 30-40cm
Cushion Peatlands	33.0	0.09	32.5	0.11	32.1	0.13	29.5	0.14
Herbaceous/Sphagnum Peatlands	30.5	0.11	28.9	0.15	26.4	0.17	25.1	0.19
Pasture Peatlands	27.6	0.16	24.3	0.25	22.3	0.27	20.8	0.29
Woody/Shrubby Peatlands	30.8	0.11	29.0	0.15	28.6	0.17	26.3	0.18
Wet Meadows	12.5	0.36	7.9	0.41	4.3	0.44	2.4	0.30
Woody Wetlands	16.0	0.26	11.8	0.34	8.4	0.53	5.7	0.46
Forests	23.3	0.20	16.4	0.26	12.0	0.28	9.0	0.28
Herbaceous Uplands	19.7	0.31	15.2	0.35	11.6	0.30	8.1	0.24
Shrublands	18.9	0.27	14.0	0.33	10.8	0.27	8.2	0.24
Croplands	13.0	0.47	11.8	0.46	10.3	0.48	6.0	0.48
Forest Plantations	17.4	0.38	13.3	0.36	9.5	0.24	7.1	0.21
Pastures	14.9	0.41	11.6	0.50	8.8	0.42	4.8	0.30

Table 12. Summary of total carbon for the top 40 cm stocks and adjusted areas.

	SREG		REG		NAT	
LULC class	**Adjusted Area (ha)**	**Total Carbon Stock (Tg) (40cm soil depth)**	**Adjusted Area (ha)**	**Total Carbon Stock (Tg) (40cm soil depth)**	**Adjusted Area (ha)**	**Total Carbon Stock (Tg) (40cm soil depth)**
Woody/Shrubby Peatlands	99134 ± 7685	14.91	84955 ± 6451	12.78	76952 ± 6547	11.57
Herbaceous/Sphagnum Peatlands	99246 ± 5333	13.86	125512 ± 8565	17.53	112437 ± 8188	15.71
Cushion Peatlands	5804 ± 1007	0.68	5981 ± 1177	0.70	6080 ± 1568	0.71
Wet Meadows	9219 ± 1531	0.98	16336 ± 2421	1.74	11215 ± 1663	1.20
Pasture Peatlands	33080 ± 2232	5.95	33858 ± 2908	6.09	29380 ± 2940	5.29
Woody Wetlands	4663 ± 1479	0.64	5168 ± 2334	0.71	4670 ± 2206	0.65
Forests	1804309 ± 15412	262.88	1960164 ± 16885	285.59	1878286 ± 16859	273.66
Herbaceous Uplands	645747 ± 13472	108.40	599672 ± 13842	100.66	690871 ± 16664	115.97
Shrublands	652175 ± 19410	95.59	547567 ± 18520	80.26	563173 ± 20468	82.55
Pastures	566768 ± 10994	97.28	498178 ± 10808	85.51	444997 ± 9775	76.38
Croplands	115516 ± 8881	40.81	288294 ± 9925	57.48	317810 ± 11839	63.36
Forest Plantations	90781 ± 10217	14.64	57149 ± 6359	9.22	79812 ± 8911	12.87
Total soil C stock for 40cm depth		**656.64**		**658.28**		**659.92**

Table 13. Averaged Carbon stocks (Mg ha^{-1}) for the 40 cm soil depth.

LULC class	Averaged Carbon stocks (Mg ha^{-1}) for 40 cm soil depth
Woody/Shrubby Peatlands	150.4 ± 5.5
Herbaceous/Sphagnum Peatlands	139.7 ± 4.7
Cushion Peatlands	117 ± 11.1
Wet Meadows	106.7 ± 7.3
Pasture Peatlands	180 ± 12.1
Woody Wetlands	138.1 ± 11.8
Forests	145.7 ± 8
Herbaceous Uplands	167.9 ± 4.4
Shrublands	146.6 ± 6
Pastures	171.6 ± 8.2
Croplands	199.4 ± 28.5
Forest Plantations	161.3 ± 28.9