

Multidate, multisensor remote sensing reveals high density of carbon-rich mountain peatlands in the páramo of Ecuador

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Abstract

Tropical peatlands store a significant portion of the global soil carbon (C) pool. However, tropical mountain peatlands contain extensive peat soils that have yet to be mapped or included in global C estimates. This lack of data hinders our ability to inform policy and apply sustainable management practices to these peatlands that are experiencing unprecedented high rates of land use and land cover change. Rapid large-scale mapping activities are urgently needed to quantify tropical wetland extent and rate of degradation. We tested a combination of multidate, multisensor radar and optical imagery (Landsat TM/PALSAR/RADARSAT-1/TPI image stack) for detecting peatlands in a 2715 km² area in the high elevation mountains of the Ecuadorian páramo. The map was combined with an extensive soil coring data set to produce the first estimate of regional peatland soil C storage in the páramo. Our map displayed a high coverage of peatlands (614 km²) containing an estimated 128.2 ± 9.1 Tg of peatland belowground soil C within the mapping area. Scaling-up to the country level, páramo peatlands likely represent less than 1% of the total land area of Ecuador but could contain as much as ~23% of the above- and belowground vegetation C stocks in Ecuadorian forests. These mapping approaches provide an essential methodological improvement applicable to mountain peatlands across the globe, facilitating mapping efforts in support of effective policy and sustainable management, including national and global C accounting and C management efforts.

KEYWORDS

carbon, mountain, multidate SAR, páramo, peatland, tropics

1 | INTRODUCTION

Worldwide concerns about the consequences of human-induced changes to the global carbon (C) cycle have generated many international initiatives to quantify peatland C stocks. This is particularly important in tropical peatlands that are currently estimated to store 18–25% of global peat C stocks (Page, Rieley, & Banks, 2011). However, our understanding of the extent and C stocks of many of these areas is imperfect because mapping techniques either cannot

detect peat from nonpeat ecosystems, operate at coarse spatial resolution, or have yet to be discovered (Dargie et al., 2017). Developing mapping techniques that provide rapid and accurate tropical wetland area and C stock determinations will enhance estimates of peatland C stocks and turnover.

Recent advances have been made in mapping tropical lowland wetland (e.g., peat swamps and mangroves) spatial extent and C stocks at a global scale (Gumbricht, 2012); however, mountains are not included in these wetland mapping efforts. This creates a large knowledge gap

on the contribution of mountain peatlands to global wetland distribution and C storage. Having effective mapping methods for these ecosystems is important both for quantifying the contribution of mountain peatlands to global C stocks, and also because mountain ecosystems are experiencing high rates of land-use change including drainage, agriculture, mining, peat extraction, and water diversion (Garavito et al., 2012). In addition, the tropics are forecast to experience significant climate change over the next century (Cuesta et al., 2012; Urrutia & Vuille, 2009; Li et al., 2007) with the greatest temperature increases predicted for high elevation ecosystems (Bradley, Vuille, Diaz, & Vergara, 2006). Therefore, land-use conversion and climate change could have synergistic and widespread consequences for tropical mountain peatland sustainability (Mantyka-pringle, Martin, & Rhodes, 2012) and their many ecosystem services (e.g., C sequestration, water source/storage, grazing habitat, plant and animal diversity, and agriculture) (Buytaert et al., 2006; Buytaert & De Bièvre, 2012); Di Pasquale et al., 2008; Mosquera, Lazo, Céleri, Wilcox, & Crespo, 2015).

Mountain peatlands can be challenging to map because they are commonly small and, as a result, when mapped they are often combined with other wetland types into a single class or mapped as upland (Anaya, Colditz, & Valencia, 2015; Eva et al., 2004). Furthermore, mapping with optical imagery alone has disadvantages because: (1) some mountain ranges have persistent cloud cover making it difficult to obtain cloud-free images (Anaya et al., 2015); and (2) the nonpeatland areas can be floristically similar to the peatlands and are hence difficult to differentiate when only using optical sensors (e.g., Landsat).

Successful mapping techniques for delineating low elevation, high latitude peatlands have been developed using multitemporal, multisensor radar and optical imagery (Bourgeau-Chavez et al., 2016; Bourgeau-Chavez, Endres, et al., 2015a; Bourgeau-Chavez, Laubach, et al., 2015b; Bourgeau-Chavez, Riordan, Powell, Miller, & Nowels, 2009) and show promise for detecting mountain peatlands. Using a combination of different sensor frequencies from multiple platforms and multiple seasons improves mapping capability and accuracy, particularly for wetlands which are temporally dynamic not only in floristic characteristics but also in hydrology (Augustenijn & Warrender, 1998; Bourgeau-Chavez, Endres, et al., 2015a; Bourgeau-Chavez, Laubach, et al., 2015b; Grenier et al., 2007; Lozano-Garcia & Hoffer, 1993; Wang, Wang, Hu, & Gao, 2010). Traditional optical imagery is complemented with the capabilities of radar data to detect moisture and biomass variations, improving distinction of wetland types. Furthermore, differences in hydrology between peatland and nonpeatland areas can be detected and monitored with radar data which is sensitive to changes in intra-annual water table and soil moisture dynamics (Bourgeau-Chavez et al., 2009, 2016; Kasischke et al., 2009). Synthetic aperture radar (SAR) systems are active sensors that emit microwave energy to the earth and record the backscattered energy received by the sensor's antenna. The long wavelengths of SAR systems can penetrate cloud cover and vegetation. However, these methods have yet to be applied to mountain peatlands, in part because the complex topography of most alpine landscapes can cause excessive distortions of the SAR signals which must be corrected (Atwood, Andersen, Matthiass, & Holec, 2014).

The objective of this study was to test the accuracy of a multitemporal, multisensor SAR and optical approach (Bourgeau-Chavez et al., 2016) complemented by field surveys in estimating mountain peatland spatial extent, applying these methods in a challenging environment—the Andes of northeastern Ecuador. We then sought to combine the mapping product with an extensive soil coring data set to estimate belowground C storage in the peatlands across the mapping area. This region is part of the Andean páramo ecozone that extends from northern Peru through Ecuador and Colombia and into Venezuela and portions of southern Central America (Luteyn, 1992). The Andean páramo provides an ideal environment to test the strengths and limitations of using a multiplatform mapping approach because of the complex topography, perennially wet soils, similar vegetation structure across many ecosystem types, and an exceptionally cloudy climate. Moreover, no mapping products exist to tease apart peatland from nonpeatland areas in this area or to calculate regional peatland C storage. This is a significant data gap, because peatland soils in the páramo are commonly over 5 m thick with C stocks greater than 1500 Mg ha⁻¹. Therefore, these peatlands are some of the most C dense peatlands in the world (Chimner & Karberg, 2008; Comas et al., 2017; Hribljan, Suárez, Heckman, Lilleskov, & Chimner, 2016) underscoring the importance of including them in global C accounting initiatives. In the research presented, we asked the following questions: (1) are these remote sensing technologies able to accurately detect and delineate peatlands and in particular, differentiate between different peatland types under these challenging conditions; if so, (2) what is the contribution of each peatland vegetation type to total peatland abundance within our mapping area; and (3) what is the total belowground C storage in these peatlands and the contribution of the different peatland vegetation types to these C stocks?

2 | MATERIALS AND METHODS

2.1 | Study area

This study was focused on a 5500 km² area in the Andes of northeastern Ecuador that contained 2715 km² defined as páramo above an elevation of 3500 masl (Figure 1). The páramo is typically characterized by a cool and wet climate that can receive significant rainfall (>3000 mm/year in some localities) with additional moisture inputs from cloud and mist interception by the páramo vegetation (Sklenar, Kucerova, Mackova, & Macek, 2015). The wettest regions of the páramo are in northern Ecuador (including our study area) and Colombia due to the continuous delivery of moisture and rain by Andean orographic effects (Sklenár & Lægaard, 2003). The páramo contains a diverse range of ecosystem types including extensive well-drained grasslands, scrubland, high Andean forests, and peatlands (Hofstede, Segarra, & Mena, 2003). The peatlands, locally known as turberas or bofedales, form in areas with perennial anoxic soil conditions limiting decomposition and promoting the accumulation of thick organic soils. Across our study area, we sampled peatlands that appeared to be pristine with no apparent human disturbance and others that were heavily grazed and trampled by livestock. Therefore, our mapping and carbon

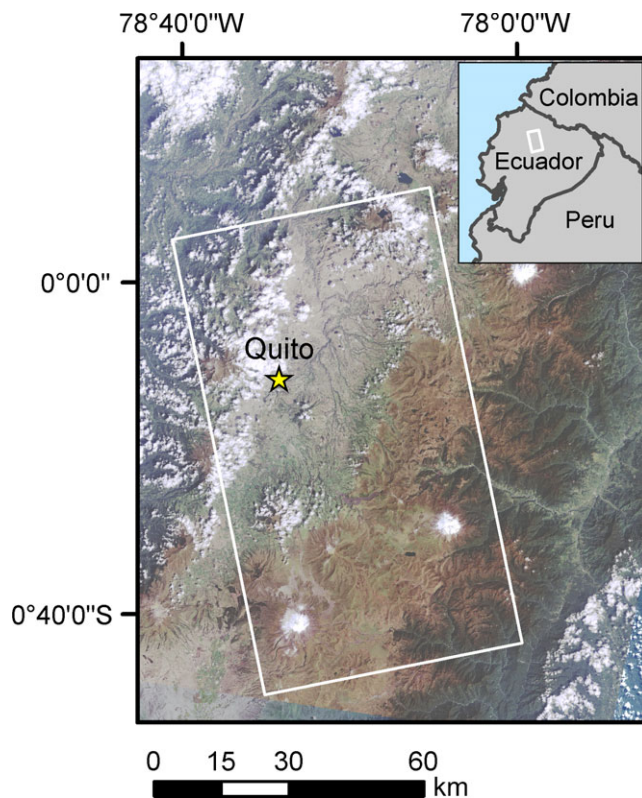


FIGURE 1 Outline of mapping area that covers a 5500 km² region in the Ecuadorian Andes. Upper right inset shows location of mapping area within northeastern Ecuador [Colour figure can be viewed at wileyonlinelibrary.com]

measurements captured a wide range of peatland conditions across the mapping region that is common across the Andes.

2.2 | Field data collection

Field sites were sampled for training and validation of the map. The locations were systematically selected across the study region. Sites were selected by road accessibility with a maximum walking distance of approximately 4 km. Field sites were sought to be distributed across peatland classes and the entire study area. Peatlands were classified by dominant vegetation cover and included cushion, grass, and sedge peatlands (Figure 2).

In the field, site characteristics were recorded for each 0.2 ha location including ecosystem type, dominant plant species, and peat depth. A global positioning system (GPS) point was collected at the plot center and the latitude, longitude, and elevation data were recorded. Field photos in four cardinal directions were also collected to aid the image interpreters in selection of the training polygons. A hand-drawn map was used to distinguish vegetation types and species transitions in areas with multiple classes over a small area.

2.3 | Soil sampling and C analyses

To estimate peatland C storage, soil cores were extracted from 20 peatlands across the mapping area (Chimner & Karberg, 2008;

Hribljan et al., 2015; Suarez et al., unpublished data). In ten of the peatlands, we attempted to core the entire thickness of the peat deposit and successfully confirmed the base of the peatland in eight of these cores. For the remaining ten cores, only the upper section of the peatland was sampled (core depth varied from 90 to 200 cm) and the total peat thickness was estimated by using an extendable steel tile probe (Chimner, Ott, Perry, & Kolka, 2014). The entire length of the peat cores for all sites was cut into ~5–10 cm sections (thickness varied based on visual evidence of mineral-rich layers that were sampled separately) in the field.

Soils were dried in an oven at 65°C to a constant mass. Dry bulk density (g cm⁻³) was calculated by dividing the oven dried soil mass by the original sample volume. Soil organic matter content for each section was determined by loss on ignition (LOI) at 550°C for four hours (Chambers, Beilman, & Yu, 2011) using ~1 g homogenized subsamples of the ground soil. A subset of 400 soil samples selected from all the samples collected were analyzed for C concentration with an elemental analyzer (Costech 4010, Valencia, CA, USA and Fisons NA 1500, Lakewood, NJ, USA). The line equation $C (\%) = (0.5324 \times LOI (\%)) - 0.9986$ ($R^2 = 0.989$; $p < .001$) was developed on the relationship between LOI and C content to calculate C concentration in the remaining samples analyzed only by LOI (Hribljan et al., 2015).

For the full-length cores, soil C density (kg m⁻³) by core section was calculated as the product of dry bulk density (g cm⁻³), sample length (cm), and sample% C. Peatland C stock per unit area (Mg ha⁻¹) was estimated for each peatland by summing C content of all individual soil samples in the entire core. The C stocks of peatlands with only the upper section cored were calculated from the mean C density (mg cm⁻²) of the partial core multiplied by the total peatland thickness determined by probing (Chimner et al., 2014). This approach was validated by comparing the estimates of C storage calculated from a partial core to the total core C calculation for the ten full-length cores (partial core validations were 83.6 ± 8.0 [SE]% of the full-length cores). All cores contained layers with less than 12% C content falling below the general definition of peat (>12% C content) for nonclay soils (Soil Survey Staff, 2014). The total peatland C stock estimates combined the C content of these interbedded mineral layers and peat soil horizons.

2.4 | Remote sensing data types

We used a combination of multisensor radar and optical imagery combined with Digital Elevation Model (DEM) data in our classification (Table 1). Whereas Landsat data provide information on vegetation type and wetness to some degree, SAR provides additional information on hydrological characteristics of wetlands and vegetation structure. In addition, topographic position indices (TPI) can be derived from DEM data to inform the classifier about landform and slope position, identifying low-lying conditions suitable for peat development. Using multiple dates of imagery allows the capture of phenological differences between plant species and differences in



FIGURE 2 Representative pictures of the three peatland classes (cushion, grass, and sedge) used in creating the map that is based on dominant vegetation cover. The tussock grassland (predominant upland area surrounding the peatlands in the páramo) photos are included to show how the peatlands and upland can look similar, making it challenging to separate these classes with remote sensing technologies [Colour figure can be viewed at wileyonlinelibrary.com]

hydrology among seasons, further improving peatland differentiation and classification.

2.5 | Landsat data

Landsat Thematic Mapper (TM) is an optical sensor that collected data from July 1982 to May 2012. Landsat TM data consist of seven spectral bands with a resolution of 30 m (thermal infrared was collected at 120 m and then resampled to 30 m). Cloud free Landsat TM was very limited in the study areas but two dates were downloaded from the United States Geological Survey's (USGS) Earth

Explorer. The data were converted to radiance values, then to top-of-atmosphere (TOA) reflectance to normalize differences in illumination due to temporal changes in sun angle and earth-sun distance (Chander, Markham, & Helder, 2009). The thermal bands were converted to TOA temperature brightness in degrees C assuming all pixels had an emissivity of water (Rebelo, 2010). Normalized Difference Vegetation Index (NDVI) was also produced using the visible-red and near infrared (NIR) bands (Rouse, Hass, Schell, & Deering, 1974). NDVI is useful for vegetation mapping as the red band is low due to the absorption by chlorophyll and near infrared is high due to chlorophyll reflectance (Rouse et al., 1974). All Landsat TM data and

TABLE 1 List of multisensor radar, optical imagery, and Digital Elevation Model (DEM) data and dates used in mapping Ecuadorian alpine peatlands within the study area

Data	Dates
Landsat TM	10/15/1991, 12/21/1998
PALSAR	6/9/2013, 9/16/2010, 4/25/2008, 12/11/2008
RADARSAT	9/20/2000, 10/14/2000
SRTM/ASTER DEM	2000 (SRTM), 2011 (ASTER)

NDVI products were resampled using nearest neighbor to match the SAR pixel size of 12.5 m.

2.6 | Digital Elevation Model data

Due to the large topographic variation in the study area, it was important to include DEM data for accurate terrain correction of the imagery and for topographic analysis. DEM data were downloaded from both the Earth Explorer (ASTER Global Digital Elevation Model [GDEM]) and the USGS Shuttle Radar Topography Mission (SRTM) DEM Directory. The 30 m SRTM DEM is based on interferometric SAR and was preferred but contained several data gaps which were filled with the ASTER GDEM. ASTER is an optical sensor and stereoscopic imaging was used to measure elevations and create the Global ASTER DEM product at 30 m horizontal resolution. Note that the work presented was created prior to the release of the SRTM plus product that also has data gaps filled with ASTER and other sources.

2.7 | SAR data

SAR wavelengths can penetrate vegetation canopies and interact with the ground surface depending on frequency and pathlengths through the vegetation. For example, C-band SAR energy (~5.6 cm in wavelength) will penetrate a sparse or low-stature vegetation canopy, while longer L-band wavelengths (~24 cm) will penetrate forest canopies. The amount of energy returned to the antenna is a function of vegetation biomass/structure and moisture of the vegetation and ground surface. Therefore, SAR data can be used to distinguish wetland from upland and distinguish between wetlands of different vegetation structure and hydro patterns.

For this study, two different wavelengths of SAR data were used: L-band from Advanced Land Observing Satellite Phased Array type L-band Synthetic Aperture Radar and C-band from RADARSAT-1. The data were downloaded through the Alaska Satellite Facility's (ASF) Distributed Active Archive Centers and processed through ASF MapReady. The considerable topographical variation in the study region can make accurate processing of SAR data difficult. Topography skews backscatter, creating issues with foreshortening, layover, and shadow (Atwood et al., 2014). To accurately process and prevent errors from topographic variation, radiometric terrain correction (RTC) was used. RTC uses a DEM to adjust pixel brightness in reference to the geometry of the landscape, allowing for

geolocation to more accurately tie the SAR data to its projection (ASF MapsReady user manual version 3.1, 2013). The geospatial accuracy was compared to Landsat TM images using the root mean square error (RMSE) and any misalignment greater than one pixel was further geocorrected in Erdas Imagine using the Landsat as a reference. Filtering or multilooking of SAR data is necessary to reduce speckle prior to applying classification algorithms. Speckle manifests itself as bright and dark pixels in a SAR image due to the coherent processing of SAR signals from multiple scatterers within a resolution cell. The geocorrected data were, therefore, filtered using a 3×3 median filter to reduce speckle.

2.8 | Topographic position index (TPI)

TPI is a measurement of a point's elevational position relative to the area immediately surrounding it (Weiss, 2001). To calculate TPI, each cell in the DEM was compared to the average value of cells in its surrounding neighborhood. In the resulting data set, negative values indicate a cell is relatively lower in elevation than the area around it, while positive values indicate the cell is relatively higher in elevation. This allows for improved identification of low-lying areas and depressions that are more likely to be wet. TPI is highly dependent on input parameters such as the shape and size of the neighborhood. For this project, a circular neighborhood with a 15 cell radius was used.

2.9 | Mapping technique

The Random Forests (RF) classifier (Brieman, 2001) was chosen for mapping peatlands because it has been shown to provide high classification accuracy and time efficiency when used in previous wetland mapping research (Bourgeau-Chavez et al., 2016; Bourgeau-Chavez, Endres, et al., 2015a; Bourgeau-Chavez, Laubach, et al., 2015b; Bourgeau-Chavez, Leblon, Charbonneau, & Buckley, 2013; Clewley, Whitcomb, Moghaddam, & McDonald, 2015; Whitcomb, Moghaddam, McDonald, Kelndorfer, & Podest, 2009). It is a robust method that can be applied to large areas with consistency.

Random Forests is a machine learning classifier consisting of multiple decision trees generated from a random subset of input training data and bands. Once the forest of decision trees is created, an individual pixel's classification is determined by which class receives the most "votes" across all decision trees. One advantage of the algorithm is that it can easily handle missing attributes, such as cloud obscured pixels, as decision trees built without the missing attributes can be used to classify the compromised data.

The mapping process involved first identifying wetland vegetation types using field data and high resolution image interpretation (from Google Earth or Worldview2 data) (Table 2). The field data collection resulted in 91 field sites including 22 cushion peatlands, 41 grass peatlands, 10 sedge peatlands, and 28 upland sites. Using high resolution images, polygons were drawn to spatially expand the field sampled locations and avoid edges of transitions between cover types or land categories. These polygons were used as training or validation data.

TABLE 2 Descriptions for landscape cover classes across the mapping area

Class	Description
Agriculture/ pasture	Land used for production of food or fiber (corn, potatoes, or other cropland); land use distinguishes agricultural land from similar natural ecosystem types (i.e., wetlands).
Barren	Land with limited ability to support life. Contains less than 33% vegetation cover. May include thinly dispersed scrubby vegetation. Includes bare rock, quarries, gravel pits, and transitional areas.
Developed	Areas where the manmade structures (buildings, towns, etc.) have >75% coverage. Primarily residential areas where manmade structures (i.e., buildings and farm equipment) are present, with less than or equal to 25% vegetation (trees, shrubs, and grass) interspersed.
Peatland - cushion	Poorly drained areas clearly dominated by conspicuous cushion and matt-forming species (<i>Distichia</i> spp., <i>Plantago rigida</i> , <i>Disterigma empetrifolium</i> , and <i>Oreobolus ecuadoriensis</i>). Cushion plants usually <50 cm tall.
Peatland - grass	Poorly drained areas structurally dominated by a matrix of grasses (<i>Cortaderia sericantha</i> , <i>Cortaderia nitida</i> , and <i>Festuca</i> spp.). A sparse layer of shrubs (e.g., <i>Loricaria</i> sp. and <i>Hypericum lancoides</i>) and a rich herb layer (e.g., <i>Niphogeton</i> sp., <i>Huperzia</i> spp., <i>Gunnera maguellanica</i> , and <i>Hypochaeris</i> spp.) might be present.
Peatland - sedge	Poorly drained areas dominated by a dense matrix of several species of Cyperaceae (e.g., <i>Carex</i> spp., <i>Uncinia</i> spp., and <i>Eleocharis</i> spp.). A sparse layer of herbs and mosses might be present (e.g., <i>Niphogeton</i> sp. and <i>Gunnera maguellanica</i> .)
Shrub	Nonwetland vegetation dominated by true shrubs, immature trees, or stunted growth trees/shrubs (e.g., <i>Polylepis</i> spp., <i>Gynoxys</i> spp., <i>Buddleja</i> spp., and <i>Baccharis</i> spp.). Characterized by woody vegetation with a height <6 m.
Tussock grassland	Nonwetland vegetation (woody or herbaceous) under 2 m in height. A dense matrix of tussock grasses (e.g., <i>Calamagrostis</i> spp. and <i>Festuca</i> spp.), enclosing a rich layer of shrubs (e.g., <i>Pentacalia</i> spp., <i>Diplostephium</i> spp., <i>Hypericum</i> spp., and <i>Gynoxis</i> spp.) and herbs (<i>Gentianella</i> spp., <i>Senecio</i> spp., <i>Huperzia</i> spp., and <i>Ortiphium peruvianum</i>).
Water	Streams, canals, rivers, lakes, reservoirs, and impoundments. Areas persistently inundated by water that do not typically show annual drying out or vegetation growth at or above the water's surface. Depth of water column is >2 m, such that light attenuation increases significantly and surface and subsurface aquatic vegetation persistence declines or is less detectable.
Snow	Land covered by snow

The supervised data were input to RF with the multirate Landsat TM/PALSAR/RADARSAT-1/TPI image stacks. To assess the importance of the different input data sources, the RF classifier was run with various combinations of optical, radar, and TPI. In all cases, the multirate data were used, but the data sources were varied. The band combinations tested included: 1) Landsat; 2) Landsat and TPI; 3) Landsat and Radarsat; 4) Landsat, Radarsat and TPI; 5) Landsat/PALSAR/Radarsat and TPI; and 6) PALSAR Radarsat, and TPI. This allows for comparing radar only, in this often cloud-covered environment, and Landsat-only, which is often used in map applications, as well as combinations of the data sources. All resulting classified maps were filtered to eliminate isolated pixels and reduce the errors introduced by mixed pixels. Each classified pixel's value was replaced by the majority class of its eight neighbors using the Environmental Systems Research Institute majority filter. This resulted in the reduction of some errors at the expense of some correctly classified small linear features.

2.10 | Accuracy assessments

To ensure a robust set of validation data (polygons) for the alpine peatland maps, 20% of the input training polygons were randomly selected and reserved for validation. Whole polygons and not pixels were reserved. Using these validation polygons, both producer's and user's accuracies were calculated. The producer's accuracy represents how well the reference pixels are classified, whereas the user's accuracy represents the probability that a classified pixel actually represents that class on the ground. Note that the standard "out of bag" accuracy assessment that is produced by RF was not used since

it is not an independent assessment (i.e., it uses training data that were used to generate other trees within RF).

2.11 | Scaling-up of C stocks

In order to better estimate the mean carbon stocks in the peatlands, we used a stratified estimator to calculate peatland cover area (Olofsson, Foody, Stehman, & Woodcock, 2013). The mapped area of peatlands estimated from a pixel counting approach (counting pixels allocated to a map class and multiplying by the area of the pixel) may be quite different from the actual area on the ground due to weighted errors of omission and commission. While it is not possible to map where these errors are located, the actual area or adjusted area of each land cover class can be estimated using the error matrix and the percentage of area of each land cover class in the map (Olofsson et al., 2013). The assumptions for calculating adjusted area include having a random, systematic, or stratified random sample of ground truth points (Olofsson et al., 2013). Our ground truth samples were randomly selected from our training sites, which were sampled systematically from accessible sites within approximately 4 km of a road (a necessary constraint due to remoteness of our field sites and high transportation costs).

Peatland C storage across the mapping area was determined by summing the products of the mean C stock per area for each peatland vegetation type (cushion, grass, and sedge) by the total adjusted mapped peatland area for each peatland vegetation classification. We also report the contribution of each peatland vegetation type to total peatland C storage.

3 | RESULTS

3.1 | Peatland map

The wet and cool climate in this region of Ecuador supported hydrologic conditions that favored peat accumulation. All the wetlands delineated during the field validation campaigns were determined to be peatlands. Nonpeat accumulating wetlands (e.g., wet meadows or marshes) were not apparent in this area (Figure 3).

Based on the mapping and field campaigns, we were able to identify three main types of peatlands: cushion, grass, and sedge peatlands. Cushion plant peatlands are mostly characterized by open, low stature vegetation (<50 cm) clearly dominated by cushion forming species (e.g., *Plantago rigida*, *Distichia* spp., and *Oreobolus ecuadoriensis*), growing amid a diverse matrix of mosses. Grass peatlands usually exhibit a more complex vegetation which is structurally dominated by several species of grasses (e.g., *Cortaderia sericantha*,

Cortaderia nitida, and *Festuca* spp.), but also contain some cushion plants, mosses, and shrubs. Although this category is very heterogeneous, it seems to follow an altitudinal gradient in which lower elevation sites tend to exhibit larger and more abundant tussock-forming grasses and a higher abundance of shrubs, while higher elevation sites have smaller grasses and higher abundance of cushion forming species. Sedge peatlands are clearly dominated by species of Cyperaceae (e.g., *Carex* spp. and *Uncinia* spp.) that form a dense matrix where herbs, mosses, and a few shrub species are present.

A statistical comparison of the different data sources (i.e., Radar-sat, PALSAR, Landsat, and TPI) used in the RF classifier showed that using PALSAR/Radarsat/TPI without optical data (Table 3) had less than desirable results, with only 61% overall accuracy and low peatland class accuracies ranging from 48% to 81%. When Landsat was used alone to produce the alpine peatland map, it did a fairly good job at mapping the different classes with 86% overall accuracy; however, there was moderate error in distinguishing between the

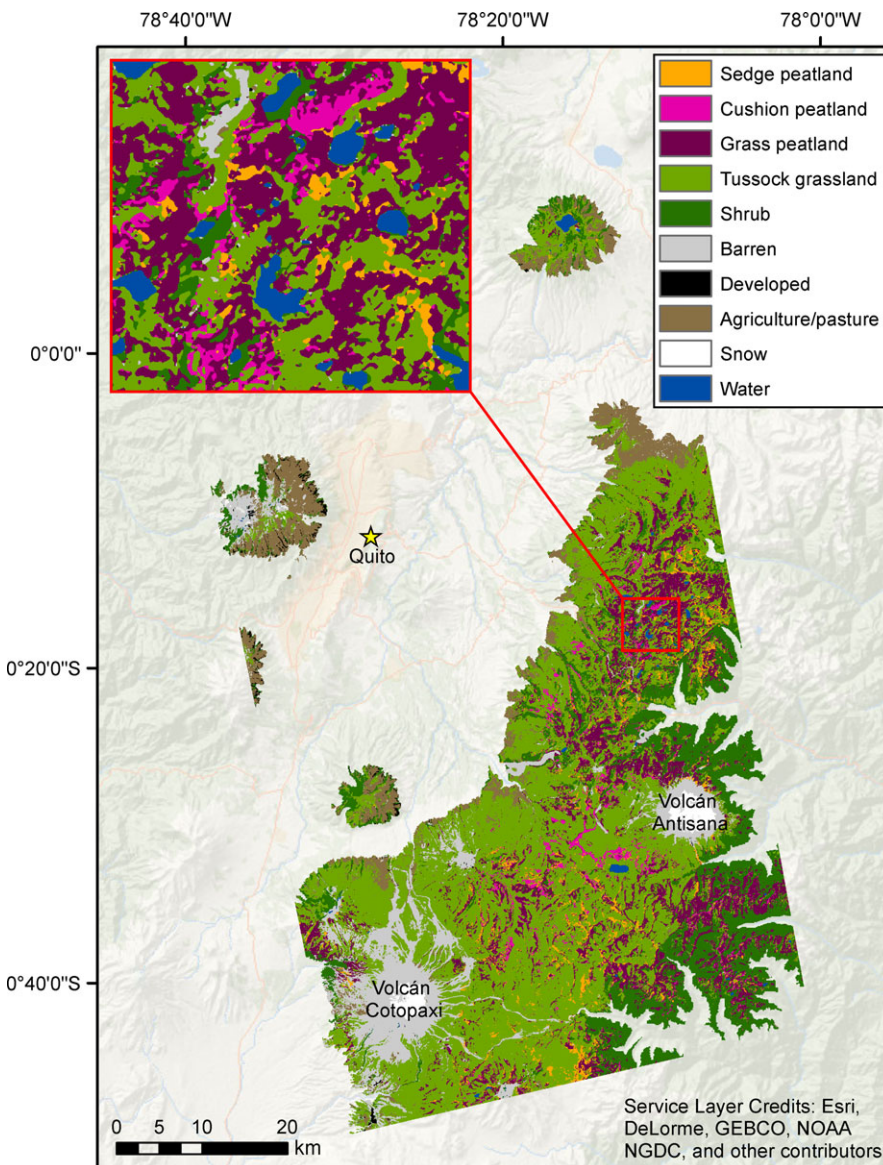


FIGURE 3 Tropical mountain peatland map based on multidecade, multisensor Landsat, PALSAR, Radarsat-1, and TPI (Overall accuracy 90%) showing distribution of three peatland types (cushion, grass, and sedge) within the 5500 km² study region. Mapping area below 3500 masl is grayed out. Upper left inset is a high resolution image of a 56 km² section of the mapping area displaying the ability of the multiple sensor approach to delineate individual small peatlands [Colour figure can be viewed at wileyonlinelibrary.com]

peatland classes (Table 3). Adding multirate Radarsat into the classifier (Table 3) slightly improved the overall accuracy (87%), especially grass peatland accuracy. There was, however, a slight drop in cushion peatland accuracy. When TPI was also used in the mapping (Table 3), overall accuracy remained the same, but there was a further improvement in the user's accuracy for all peatland classes, as well as an increase in producer's accuracy for grass peatland. The producer's accuracy for sedge and cushion peatland dropped slightly. When Landsat/Radarsat/PALSAR/TPI (Table 3) were used together, the overall accuracy was the greatest at 90%, and the individual peatland class accuracies increased or stayed the same for all classes except the producer's accuracy for cushion peatland, which decreased to 80%.

In comparing the different input data sources for mapping (Table 3), it is important to also look at the maps themselves and not just review the statistics on accuracy. Figure 4 shows a comparison of the map from Landsat alone, Landsat and Radarsat, SAR and TPI (Radarsat, PALSAR, and TPI) and the multirate, multisensor Landsat, Radarsat, PALSAR, and TPI. While the overall accuracy of all but the SAR-TPI (Table 3) classification had 86%–90% accuracy, the map products vary considerably. It appears from Figure 4 that the Landsat-only map was greatly overestimating the amount of peatlands, especially the sedge peatland class, probably due to the fact that the vegetation in the nonpeatland shrubby and open areas was quite similar to the peatland vegetation. In contrast, the SAR-TPI map was underestimating the area of peatland in much of the map, likely because the hydrology of the nonpeatlands is also sometimes wet and thus difficult to distinguish with SAR alone, while in other areas the SAR-TPI was overestimating the peatland area (e.g., in the steepest terrain). It is the synergy of the SAR (which is sensing backscatter differences due to hydrology) and Landsat (that is sensing the vegetation types) that allows for an improved distinction of peatland types. The C-band Radarsat-1 HH polarization imagery was of higher importance than PALSAR for distinguishing the peatland

types, but adding the L-band PALSAR data (HH and HV) into the classification refined the accuracy of nearly all of the map classes (Table 3).

The multirate Landsat/TPI/Radarsat-1/PALSAR map (overall accuracy 90%) was determined to be the best peatland map (lowest errors and best distinction of peatland types). This map shows 48,218 ha of peatland, which represents 17.8% of our páramo study area (Table 4). Overall, the accuracy of this method for distinguishing peatlands from nonpeatlands was very high: the combined peatland classes in this map had user's and producer's accuracy of 95%. This was so high because many of the classification errors were among peatland vegetation classes (Table 5). For the three distinct peatland classes, the user's accuracy was 94%, 95%, and 77% for sedge peatland, cushion peatland, and grass peatland, respectively; whereas the producer's accuracy for these peatland types was 86%, 80%, and 96% (Table 5).

The lowest user's accuracy was for the grass peatland: in 23% of the validation pixels the mapped grass peatland was actually either cushion peatland (10%), sedge peatland (6%), or tussock grassland (8%) on the ground. Thus, even in this worst case ~92% of pixels were mapped correctly as peatlands.

3.2 | C stocks

Despite the fact that these peatlands have a fairly high mineral content which puts them at the low end of % C for peatlands, they store large amounts of C per unit soil volume. The mean soil % C (including interbedded ash and other mineral layers) was below 32% for all the peatlands sampled with mean soil C content of 14%, 16%, and 16% for the cushion, grass, and sedge peatlands, respectively. Overall, the soils had a moderate percent C ($15 \pm 1\%$ [± 1 SE]), but their high bulk density ($0.39 \pm 0.01 \text{ g cm}^{-3}$) resulted in a high C density (mean, $32.5 \pm 0.5 \text{ kg m}^{-3}$) of the soil across all the coring sites.

TABLE 3 Comparison of user's accuracy (UA) and producer's accuracy (PA) for peatland and nonpeatland classes of six different RF classifications using: Landsat; Landsat and TPI, Landsat and Radarsat; Landsat, Radarsat, and TPI; Landsat, Radarsat, PALSAR, and TPI; and PALSAR, Radarsat, and TPI

Class	Landsat Only		Landsat-TPI		Landsat-Radarsat		Landsat-Radarsat-TPI		Landsat-Radarsat-PALSAR-TPI		PALSAR-Radarsat-TPI	
	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA
Sedge peatland	89%	81%	87%	78%	92%	86%	94%	83%	94%	86%	70%	54%
Cushion peatland	93%	85%	95%	81%	92%	83%	93%	81%	95%	80%	81%	55%
Grass peatland	68%	87%	72%	92%	72%	90%	74%	93%	77%	96%	54%	48%
Tussock grassland	81%	76%	78%	78%	81%	76%	78%	80%	81%	82%	43%	64%
Shrub	93%	81%	95%	78%	95%	79%	94%	82%	95%	80%	65%	67%
Barren	96%	96%	94%	96%	94%	96%	94%	97%	93%	99%	68%	63%
Developed	83%	79%	82%	80%	82%	80%	83%	77%	95%	90%	63%	79%
Agriculture/pasture	72%	82%	73%	81%	72%	82%	73%	84%	80%	89%	44%	59%
Overall accuracy	86%		86%		87%		87%		90%		61%	

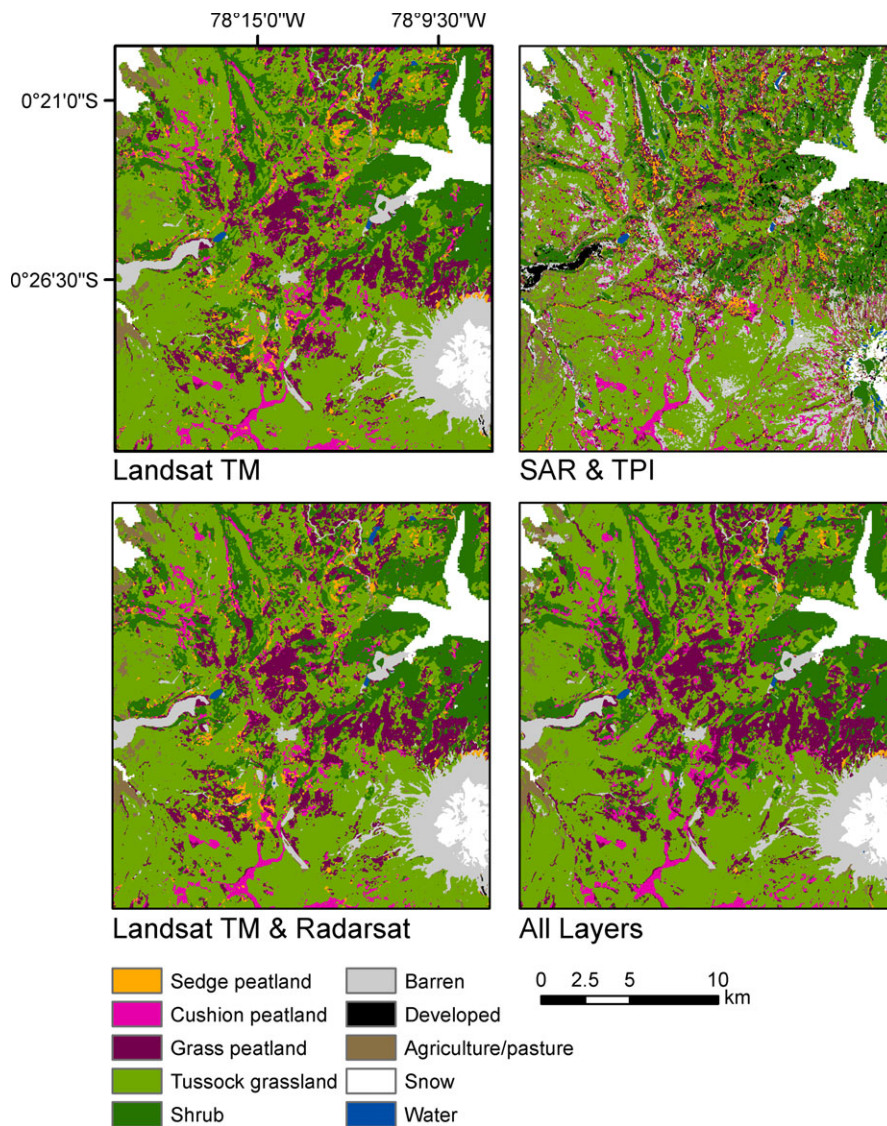


FIGURE 4 Comparison of Random Forests classified maps using Landsat (top left); SAR (PALSAR and Radarsat-1) and TPI (top right); Landsat and Radarsat-1 (bottom left); and all layers (Landsat, Radarsat, PALSAR, and TPI; bottom right). The four maps were created using multivariate data [Colour figure can be viewed at wileyonlinelibrary.com]

The peatland types and peat thickness both varied with elevation. The deepest peatlands were located at the lower elevations of the páramo in the grass (3807–3974 masl) and sedge (3703–4136 masl) peatlands (mean depth 7.7 ± 0.8 m [mean $\pm$ SE, $n = 9$] and 9.4 ± 0.2 m [$n = 2$], respectively). The cushion peatlands occurred at the highest elevations (3904–4881 masl) and contained the thinnest peats (mean depth 3.5 ± 0.5 m, $n = 11$). The three peatland types (cushion, grass, and sedge) differed in their mean C storage and total C stocks. The cushion peatlands contained the most C dense soils (mean, 34.2 ± 1.4 kg m $^{-3}$) due predominately to the high soil dry bulk density (0.43 ± 0.04 g cm $^{-3}$); whereas, the grass peatlands had the lowest soil C density (mean, 28.2 ± 1.6 kg m $^{-3}$) (Table S1).

The mapped area of peatlands is 48,218 ha based on pixel counting but if we take into account weighted errors of commission and omission our adjusted area is $61,356 \pm 5,506$ ha with a 95% confidence interval (Table 6). The tussock grassland class is frequently confused with peatlands (Table 5) and this class dominates the landscape (47% of the mapped area is tussock grassland,

Table 4); therefore, the area of peatland pixels that are misclassified as tussock grassland is greater than the area of tussock grassland pixels misclassified as peatlands (18% of the mapped area is

TABLE 4 Percent of mapped area (based on pixel counting) for each map class above an elevation of 3500 masl

Class	Hectares	Percent area
Agriculture/pasture	21327	7.9%
Barren	25208	9.3%
Developed	1212	0.4%
Peatland - cushion	5704	2.1%
Peatland - grass	34960	12.9%
Peatland - sedge	7554	2.8%
Shrub	44071	16.2%
Snow	2759	1.0%
Tussock grassland	127478	47.0%
Water	1219	0.4%

peatlands). Overall, the total C storage of peatlands based on the adjusted mapped areas, weighted by the relative % cover over the mapping area, of the different peatland vegetation types, was 128.2 ± 9.1 Tg ($\pm$ SE) (Table 6).

4 | DISCUSSION

4.1 | Peatland coverage in the Ecuadorian páramo

Our multidade, multisensor map provides the first estimate of regional peatland coverage that allows the estimate of C storage in the Andean páramo. Other sources of map products for the páramo do not classify peatlands as a separate class, but instead report wetlands as a single category (e.g., Estupinan-Suarez, Florez-Ayala, Quinones, Pacheco, & Santos, 2015). We detected 614 km² of peatlands across our mapping region, an increase of ~4- and 30-fold over the previous mapping efforts of Beltrán et al. (2009) and the Ecuadorian Ministry of the Environment (MAE) (<http://mapainteractivo.ambiente.gob.ec/>), respectively. Our results highlight peatlands as an important feature of the high-elevation páramo environment. Moreover, the current mapping products are the only products available in Ecuador to inform management and conservation of páramo peatlands. High resolution remote sensing products are a vitally important conservation tool because they provide a synoptic view of land cover and land use, which is essential for estimating land use and climatic impacts on ecosystems. This is a critical concern for Ecuadorian land managers that are in need of high quality baseline mapping data to define sustainable land-use practices and prioritize restoration activities in the rapidly changing páramo landscape.

Improved mapping of high elevation regions is also needed to inform global wetland maps that are almost completely lacking information on mountain wetland distribution, especially across the tropics (cf. The Global Wetlands Map: <http://www.cifor.org/global-wetlands/>; Yu, Loisel, Brosseau, Beilman, & Hunt, 2010). Mountain wetlands provide many critically important ecosystem services (e.g., water resources, habitat, and C storage) and are experiencing tremendous environmental impacts from land use and climate change (Benavides, 2014; Urrutia & Vuille, 2009). However, although numerous, these wetlands are typically small, providing a challenge to large-scale global wetland mapping initiatives that can have a coarser resolution than the spatial extent of these wetlands (e.g., The Global Wetlands Map resolution limit of a 250 m $\times$ 250 m pixel size [$\sim$ 6 ha]). Wetland inventories in other mountain systems have shown that when smaller wetlands are quantified at a regional scale they can contribute significantly to regional ecosystem types (Chimner, Lemly, & Cooper, 2010). Furthermore, global mapping products are often parameterized specifically for lowland wetland ecosystems that are larger in size and do not have the complex mountain topography that requires mapping techniques tailored to the alpine environment. Therefore, our remote mapping methods with algorithms to accommodate mountain slopes and signal distortion from backscatter provide a valuable tool to improve the quantification of high elevation wetland extent at the local, regional, and global scale.

We attribute the large increase in wetland detection to the use of a combination of high resolution multidade remote sensing imagery. In particular, the addition of multidade SAR, with its ability to penetrate through vegetation cover and characterize soil moisture dynamics, provides a powerful and valuable method to accurately

TABLE 5 Accuracy matrix for field truthed pixels vs. remotely classified pixels using PALSAR, RADARSAT, DEM, and Landsat. Peatland classes (cushion, grass, and sedge) are mapped individually. Overall accuracy is 90%

Mapped class	Field truthed values												User acc.
	Peatland sedge	Peatland cushion	Peatland grass	Tussock grassland	Shrub	Barren	Developed	Agriculture/pasture	Snow	Water	Sum	Comm-ission	
Peatland - sedge	176	0	7	5	0	0	0	0	0	0	188	6%	94%
Peatland - cushion	0	164	0	8	0	0	0	0	0	0	172	5%	95%
Peatland - grass	15	25	202	20	1	0	0	0	0	0	263	23%	77%
Tussock grassland	14	10	2	187	10	2	0	6	0	0	231	19%	81%
Shrub	0	6	0	0	176	0	1	3	0	0	186	5%	95%
Barren	0	0	0	1	8	209	1	5	0	0	224	7%	93%
Developed	0	0	0	0	0	1	190	10	0	0	201	6%	95%
Agriculture/pasture	0	0	0	6	25	0	19	202	0	1	253	20%	80%
Snow	0	0	0	0	0	0	0	0	202	0	202	0%	100%
Water	0	0	0	0	0	0	0	0	0	200	200	0%	100%
Sum	205	205	211	227	220	212	211	226	202	201	—	—	—
Omission	14%	20%	4%	18%	20%	1%	10%	11%	0%	0%	—	—	—
Prod. acc.	86%	80%	96%	82%	80%	99%	90%	89%	100%	100%	—	—	90%

TABLE 6 Peatland soil metrics (mean $\pm$ SE), mapped areas (based on pixel counting), adjusted mapped areas (using a stratified estimator), and total belowground C stocks (Tg) ($\pm$ SE) for the peatland mapping classes (cushion, grass, and sedge) across the study area

Peatland classes	Thickness (m)	Bulk density (g cm^{-3})	Carbon (%)	Carbon density (kg m^{-3})	Carbon stocks (Mg ha^{-1})	Mapped Area (ha)	Adjusted Area (ha)	Total Carbon stocks (Tg)
Cushion	3.5 ± 0.5	0.43 ± 0.04	14 ± 2	34.2 ± 1.4	1358 ± 268	5704	15702 ± 1914	21.3 ± 4.9
Grass	7.7 ± 0.8	0.29 ± 0.04	16 ± 2	28.2 ± 1.6	2085 ± 148	34960	28237 ± 1203	58.9 ± 4.9
Sedge	9.4 ± 0.2	0.28 ± 0.01	16 ± 1	30.6 ± 0.2	2858 ± 17	7554	16791 ± 2072	48.0 ± 6.0
Total	5.6 ± 0.6	0.37 ± 0.03	15 ± 1	31.8 ± 1.1	2123 ± 308	48218	61356 ± 2753	128.2 ± 9.1

tease apart peatlands from seasonally drier, nonpeat accumulating wetlands or organic matter rich uplands, leading to an increase in accuracy. This agrees with SAR research conducted by others in mapping peatlands on flatter terrain (e.g., Bourgeau-Chavez et al., 2016; Grenier et al., 2007; Touzi, Deschamps, & Rother, 2007). Distinction of peatlands and peatland types is especially challenging in the Andes and other mountain regions of the world that are dominated by a landscape cover type comparable to the blanket bog systems that develop in parts of Europe (Wheeler & Proctor, 2000) and the southern extreme of the Andes in Patagonia (Kleinebecker, Hoelzel, & Vogel, 2010). These environments receive high yearly precipitation and typically display a continuous homogenous vegetation cover over a thick layer of organic rich soil.

Furthermore, high resolution landscape maps with strong predictive power that separate wetlands by vegetation type have been lacking for the tropical Andes. The multitemporal Landsat TM/PALSAR/RADARSAT-1/TPI image stack provided a novel remote sensing approach not only to distinguish peatlands from uplands, but also to tease apart the peatlands based on the dominant vegetation cover. The peatland vegetation classes of cushion, grass, and sedge used in the development of this map were independently confirmed with a multivariate ordination analysis of vegetation structure of twenty peatlands selected from across our mapping area (Suarez et al., in prep). Detailed mapping of wetland vegetation types is critical data because vegetation exerts a strong influence on many ecological processes (e.g., C sequestration, ecosystem productivity, soil decomposition, nutrient cycling, soil density, and hydrological processes). Therefore, accurate land cover maps are needed to monitor impacts of land use and climate change across the Andes that can contribute to shifts in vegetation communities and structure. In addition, maps that are able to distinguish wetland vegetation classes will help to constrain C stock inventories for different peatland types. Moreover, fine-scale vegetation mapping products will be an invaluable resource for informing scientific research, land management, policy development, and restoration efforts for the Andes.

4.2 | Peatland C storage

Our paper is the first attempt to quantify total regional C storage for peatlands in the Ecuadorian páramo. Our calculation for mean peatland C storage in our mapping area (2123 Mg ha^{-1}) is over 50% larger than previously reported by us for the same region (1282 Mg ha^{-1} ; Hribljan et al., 2016). The increase in the peatland C storage estimate for this region is due to a larger representative core

data set from across the entire mapping region, especially the addition of lower elevation grass and sedge peatlands with peat soils that were over 10 m deep at some sites (Table 5). Overall, peatlands in the Andes of northeastern Ecuador have accumulated a large belowground C pool and, surprisingly store 42% more C belowground on a per unit area basis than the current estimates for total ecosystem storage (aboveground and belowground) of lowland tropical Amazonian peat swamp forests reported to contain 892 Mg ha^{-1} (Draper et al., 2014).

Scaling-up our C estimates to the study region produces a total estimated C storage of 128.2 Tg for 614 km^2 of peatlands within 2715 km^2 of the páramo ($>3500 \text{ m}$) across the 5500 km^2 mapping area. The ability to tease apart the different peatland types based on dominant vegetation cover provides a valuable resource for peatland management and restoration strategies. Combining the peatland vegetation classes and applying an overall mean C storage to the adjusted total peatland area overestimates C storage by only 1% or 1.8 Tg.

The large C stocks contained in peat soils across our mapping area have important implications for C accounting initiatives for the Andes, especially when extrapolated to a national scale. Our mapping approach allowed us to estimate that approximately 22% of the páramo landscape within our mapping area is covered by peatlands. If we scale up using the ratio of mapped peatlands in our mapped area to those mapped over the entire country from the Beltrán et al. (2009) map, this would give the entire country approximately 1697 km^2 ($169,700 \text{ ha}$) of páramo peatlands, which represents about 10% of the total Ecuadorian páramo. Scaling-up our C storage of 128.2 Tg for our mapping area to our estimate of total peatland coverage for the Ecuadorian páramo results in a total C storage of 354 Tg for high elevation Ecuadorian peatlands. From this perspective, even though peatlands within the páramo cover less than 1% of the entire country, this ecosystem type stores as much as approximately 23% of the total estimated above- and belowground vegetation C stocks in all the forests throughout Ecuador (1533 Tg ; MAE, 2015). However, the calculated peatland C stocks for the Ecuadorian Andes underestimate the magnitude of C storage in the páramo, because we have not accounted for a potentially greater C pool in upland páramo ecosystems that contain folist (a well-drained histosol) soils with an estimated C storage of 450 Mg ha^{-1} in the upper one meter (Hribljan, unpublished data). Therefore, our results suggest that extending these mapping efforts to include upland ecosystem types at a national scale will be crucial as tropical Andean countries move toward accounting their contribution to global C cycling and their

efforts at reducing C emission. Whereas, under improper management, the Andes could be a significant source of greenhouse gasses, if managed to conserve C, the large C storage in the páramo has the potential to be leveraged as part of regional and global conservation strategies. Carbon trade agreements such as the United Nations REDD+ program are currently developing momentum in South American low elevation tropical rainforest ecosystems (Asner et al., 2010; Wertz-Kanounnikoff, Kongphan-Apirak, & Wunder, 2016). Our results reveal that these mountain ecosystems could be at least as important to consider in international efforts to regulate greenhouse gas emissions.

4.3 | Sources of scaling-up errors and future refinements to C stock estimates

Wetland distribution and C pool estimates can be characterized by many sources of uncertainty (Keith, Mackey, Berry, Lindenmayer, & Gibbons, 2010). The main factors contributing to peatland ecosystem C stock scaling-up errors include inadequate regional soil bulk density and peat thickness measurements for different peatland vegetation types, uncertainty about basin morphology, and spatial uncertainty from mapping products.

Calculating peatland total C stocks without considering differences in soil characteristics could introduce a large scaling-up error in ecosystem C stock calculations. The mean soil dry bulk density across our vegetation types was greater in the cushion peatlands than the grass and sedge peatlands; however, the mean soil % C content did not vary considerably across the peatland vegetation types. Thus, the variation in soil mean dry bulk density was the main driver of the greater soil mean C density measured in the cushion than the grass and sedge peatlands. Furthermore, future research needs to address the successional pathways of páramo peatlands because of potential shifts in vegetation types through time that have the potential to alter soil density and C content. This highlights the importance of considering different peatland types and obtaining reliable determinations of peatland soil properties when conducting C stock inventories.

The estimation of peatland depth and basin morphology is challenging (Comas et al., 2017). For the peatlands that were sampled by only obtaining a shallow core (1–2 m deep), the remaining peat thickness was estimated by probing. Determining the bottom of a peatland with a probe is difficult, especially in mountain environments, because the peatland substratum interface can be difficult to discern due to multiple interbedded mineral rich soil horizons commonly found throughout the peatlands and underlying lake sediments (Hribljan et al., 2016). Ground penetrating radar (GPR) has shown promise in distinguishing the peat/substratum transition and additionally providing a means to calculate peatland volume from basin morphology determinations (Comas et al., 2017). Applying a basin morphology correction factor based on GPR surveys could reduce C stock estimates due to the bowl shaped formation of mountain valleys where peatlands typically form (Hribljan et al., 2015; Comas et al., 2017).

Although adding the SAR layers increases the cost and effort of map production, their inclusion provided the highest accuracy maps. Given their proven accuracy, these mapping methods would be a sound approach to provide national-scale maps for Ecuador and other mountainous regions around the world. Furthermore, when used in combination with coring and C analysis, these approaches revealed the surprisingly high and nationally significant C storage in these mountain ecosystems. Our regional-scale analysis of Ecuadorian peatland distribution and C stocks provided accurate delineation of peatland area that was much higher than discovered in previous efforts, providing a valuable foundation for examining the current and future effects of land use and climate change on C cycling and other wetland functions across the Andean landscape. Improved estimates of peatland distribution and C stocks in the Andes and other mountain ranges is an essential first step toward ensuring long-term sustainability of the many services provided by mountain peatland ecosystems.

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