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PEATLANDS

Mapping Mountain Peatlands and Wet Meadows Using Multi-Date, Multi-Sensor Remote Sensing in the Cordillera Blanca, Peru

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Abstract
Wetlands (called *bofedales* in the Andes of Peru) are abundant and important components of many mountain ecosystems across the globe. They provide many benefits including water storage, high quality habitat, pasture, nutrient sinks and transformations, and carbon storage. The remote and rugged setting of mountain wetlands creates challenges for mapping, typically leading to misclassification and underestimates of wetland extent. We used multi-date, multi-sensor radar and optical imagery (Landsat TM/PALSAR/RADARSAT-1/SRTM DEM-TPI) combined with ground truthing for mapping wetlands in Huascarán National Park, Peru. We mapped *bofedales* into major wetland types: 1) cushion plant peatlands, 2) cushion plant wet meadows, and 3) graminoid wet meadows with an overall accuracy of 92%. A fourth wetland type was found (graminoid peatlands) but was too rare to map accurately, thus it was combined with cushion peatland to form a single peatland class. Total wetland area mapped in the National Park is 38,444 ha, which is 11% of the park area. Peatlands were the most abundant wetland type occupying 6.3% of the park, followed by graminoid wet meadows (3.5%) and cushion wet meadows (1.3%). These maps will serve as the foundation for improved management, including restoration, and estimates of landscape carbon stocks.

Keywords Bofedales · *Puna* · Peatlands · Tropics · SAR · Wet meadow

Introduction

Mountains function as "water towers" because the high orographic precipitation they capture eventually flows downstream, supplying ecological and human needs at drier low elevations (Viviroli et al. 2007). This water tower effect also supports unique mountain ecosystems, including mountain wetlands (Cooper et al. 2012), which are often an abundant and important component of many mountain ranges (Chimner et al. 2010; Cooper et al. 2012). These mountain wetlands provide many

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benefits, including high quality habitat, nutrient sinks and transformations, carbon and water storage, and pasture.

In Peru, mountain peatlands dominated by cushion plants are often called *bofedales* (Squeo et al. 2006; Maldonado Fonken 2014). In contrast with bryophyte (*Sphagnum*)- and sedge-dominated peatlands, *bofedales* are often dominated by vascular plants with a cushion life form, with a smaller component of mosses and graminoids. Most Andean cushion plants reside in the Juncaceae, Asteraceae, and Plantaginaceae (Cooper et al. 2010; Benavides 2014; Salvador et al. 2014). These cushion plants have dense, low-statured growth forms and long taproots or buried stems. This growth form, which has evolved repeatedly as an adaptation to arctic and alpine conditions (Billings and Mooney 1968), can trap heat, warming plants significantly above the overlying air temperature, and increase vegetation canopy humidity by reducing wind shear and evapotranspiration (Cavieres et al. 2007). Their aerenchymatous roots extend below water tables to acquire deeper soil moisture and nutrients from saturated peat.

Not all Andean mountain wetlands are peat-accumulating or cushion plant dominated. Whereas in the wetter climate of Ecuador the vast majority are peatlands (Hribljan et al. 2017), in the drier climate of Peru, some are wet meadows (Cooper et al. 2010). Furthermore, some Andean mountain wetlands are moss- (Cooper et al. 2010) or graminoid-dominated (Hribljan et al. 2017). However, the relative proportion and combination of these wetland types has not been determined in Peru. To characterize wetland types in the Peruvian Andes it is therefore necessary to examine the relative distribution of peatlands and wet meadows formed under both cushion plants and graminoids.

Tropical Andean land cover and land use have undergone transformations including extensification and intensification (Young 2009) that may have significant consequences for *bofedales* and the many services they provide. *Bofedales* in Peru are important culturally, having been used extensively for pasture over the past millennia; however, grazing intensity has greatly increased recently, and grazers have switched from soft-hooved native camelids to hard-hooved sheep and cattle (Young 2009). Overgrazing is a problem in much of the Andes and current efforts to manage it are hindered by lack of information on both the types and location of *bofedales*.

The remote and rugged setting of mountain wetlands has left them understudied, making them prime candidates for mapping using remote sensing. However, the small wetland size, dense clouds, and complex topography in these landscapes makes mountain wetlands a challenge to map remotely (Weiss and Walsh 2009; Otto et al. 2011; Hribljan et al. 2016). For example, a new global peatland map shows no peatlands in the tropical Andes (The Global Wetlands Map: http://www.cifor.org/global-wetlands/). Or, if wetlands are mapped in the mountains, they are often undifferentiated or misclassified as upland (Eva et al. 2004; Anaya et al. 2015). As a result, wetlands are thought to be sparse in many mountains. For example, wetlands in the *páramo* of Ecuador were estimated to only occupy ~1% of the *páramo* land area (Ecuadorian Ministry of the Environment (http://mapainteractivo.ambiente.gob.ec/)). However, recent mapping using multi-date and multi-sensor remote sensing techniques have overcome many challenges of mapping mountain wetlands, and found that they are much more abundant, estimated to represent ~18% of the Ecuadorian *páramo* (Hribljan et al. 2017).

In addition to providing wetland maps for land management, better Andean wetland maps will improve country level estimates of carbon stocks (Asner et al. 2014). Andean peatlands have thick peat deposits often greater than 5 m with several measured peatlands containing greater than 10 m of peat (Chimner and Karberg 2008; Hribljan et al. 2016). Our mapping and carbon stock estimates for Ecuador found that peatlands likely represent less than 1% of the total land area of Ecuador but could contain as much C as ~23% of the above- and belowground vegetation C stocks in all Ecuadorian forests (Hribljan et al. 2017). However, it is unknown how extensive and diverse *bofedales* are in the *puna* ecoregion of Peru, which has a distinct dry season compared to the *páramo* in Ecuador, so the goal of this project was to test whether we can accurately map wetlands and in particular, differentiate between different wetland types in Huascarán National Park.

Methods

Study Area

We mapped Huascarán National Park and surrounding area, which is in the department of Ancash in the north-central Andes of Peru (Fig. 1). The park was formed to protect the Cordillera Blanca mountain range and has a core area of 340,000 ha with high peaks ranging from 5000 to 6768 masl (including Peru's highest peak, Huascarán Sur). Surrounding the park is a buffer zone of 170,200 ha (SERNANP 2011). As of 2016, the Cordillera Blanca contained approximately 755 glaciers and 830 lakes of glacial origin (Autoridad Nacional del Agua 2016).

Field Data Collection

We collected field data across the study region for training and validation of the wetland map. All field points were sampled in 0.2 ha increments to match the minimum mapping unit of the multi-sensor map product (after Hribljan et al. 2017). For each 0.2 ha location surrounding our field point, we identified dominant plant species, estimated percent cover, and took GPS coordinates, soil samples and photographs. We took field photos in the four cardinal directions to aid the image interpreters in selection of the training polygons, and drew a map

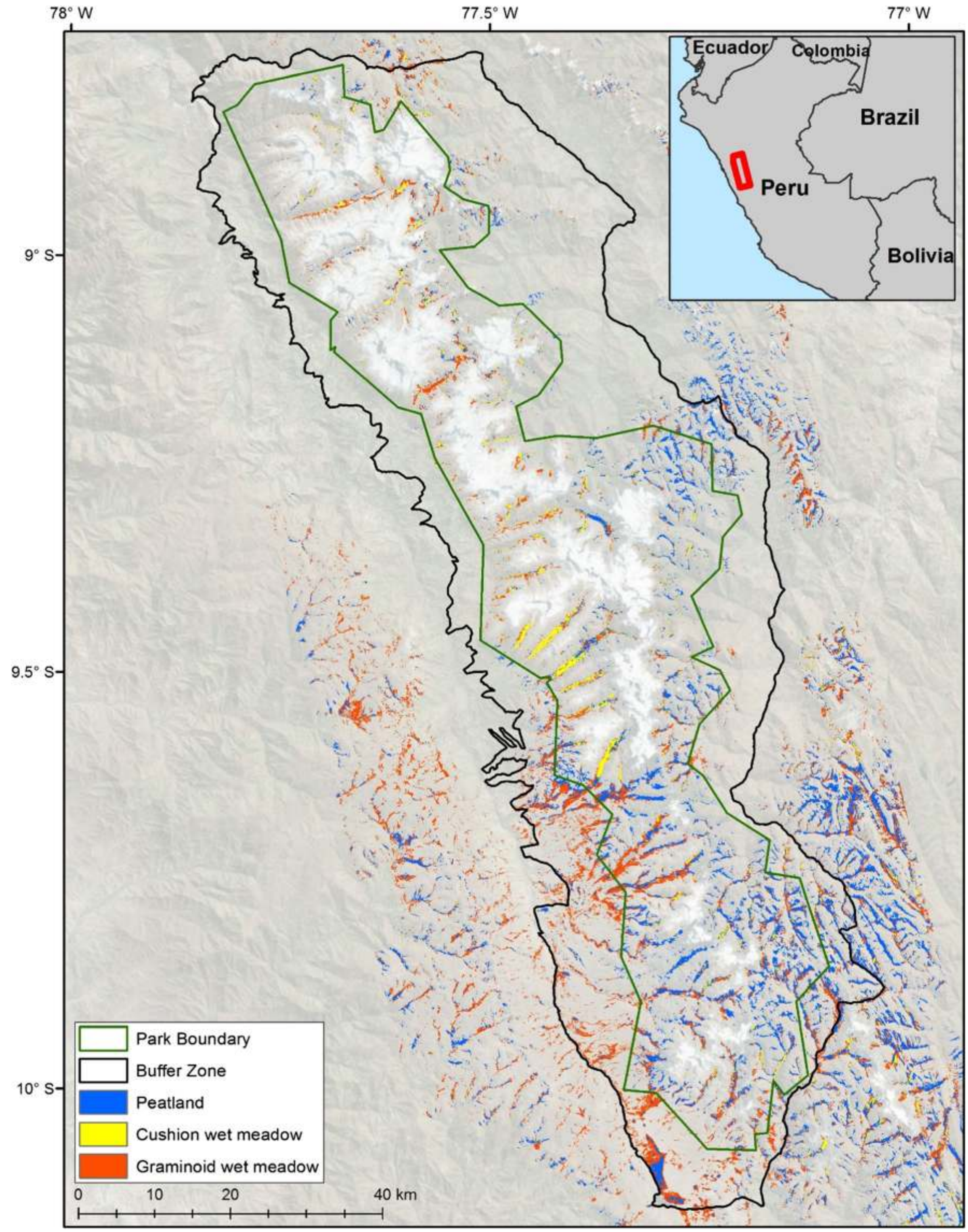

Fig. 1 Wetland map based on multi-date, multi-sensor Landsat, PALSAR, Radarsat-1 and TPI (Overall accuracy 92%) showing distribution of three wetland types. National Park boundary and buffer strip are identified as green and black lines. Upper right inset shows mapping area within the country of Peru

to distinguish vegetation types and species transitions in areas with multiple classes over a small area.

To distinguish between peatlands and wet meadows, at each field point a 40 cm long soil core was collected to quantify soil organic matter content. We defined peatlands as wetlands with organic soils at least 40 cm thick in the top 80 cm and used the USDA Natural Resources Conservation Service's Soil Taxonomy to identify organic soils (Soil Survey Staff 2006). We modified this approach for working in the remote areas by first visually inspecting the core to determine if there was obvious mineral soil and made note of the thickness of organic soil horizon. We then collected soil from 35 to 40 cm depth for analysis, sealed into a whirl-pak bag, and froze upon returning from the field. For a subset of sites with mineral soils at 35–40 cm we also probed to one meter to determine whether there was 40 cm of peat in the top 80 cm. We did not find any sites that had mineral soil at 35–40 cm and had peat below that. All samples were transported to Michigan Technological University Wetland Ecology and Restoration Lab, USA. Soils were dried in a convection oven at 65 °C until a constant mass was obtained. Dry bulk density (g cm^{-3}) was calculated by dividing the oven dried soil mass by the original sample volume. Soil organic matter content was determined for all core sections by loss on ignition (LOI) at 550 °C for 5 h (Chambers et al. 2011). If groundwater was present in the core hole, the pH and specific conductivity of the groundwater that filled the hole was measured using a YSI 63 handheld pH, conductivity, salinity and temperature system (YSI Incorporated, Yellow Springs, Ohio, USA). All data were entered into an iPhone using the EpiCollect (version 5.0) software, and downloaded each day, creating an easily accessible electronic database.

We combined the mapping fieldwork with wetland vegetation sampling that occurred during June and July in 2012, 2013, and 2014. We used a stratified random sampling design by elevation for vegetation quadrats (2 × 2 m, $n = 65$). Pairs were randomly located in a homogeneous wetland vegetation patch. All vascular plants were identified to species and percent cover was visually estimated using the Domin scale (Kent 2012). Unknown plant specimens were collected, dried, and later verified against specimen vouchers at the Museo de Historia Natural, Universidad Nacional Mayor de San Marcos in Lima, Peru. Nonmetric multidimensional scaling (NMS) ordination was conducted in PC-ORD 7.0 to examine the relationship between species composition and wetland type. The ordination was conducted in autopilot mode, which uses Bray-Curtis distance measure, a random starting configuration, 50 runs with real and randomized data, and a Monte Carlo test for selecting dimensionality (McCune and Grace 2002). We conducted an indicator species analysis for each cluster level using Monte Carlo Analysis (McCune and Grace 2002).

Remote Sensing Data Types

Multi-date optical data from Landsat and radar imagery from ALOS PALSAR and Radarsat-1 were used in combination with Digital Elevation Model (DEM) data in the map classification (Table 1), similar to the methods of Hribljan et al. (2017). Multi-sensor data from radar and optical platforms have been shown to provide complementary information that improves accuracy when mapping wetlands (Bourgeau-Chavez et al. 2017; Hribljan et al. 2017). While the spectral information from Landsat allows discernment of vegetation type and wetness to some degree, radar backscatter is indicative of hydrological characteristics of wetlands and vegetation structure. For mountainous regions, topographic position indices (TPI) derived from DEM data are important for identifying low-lying areas suitable for peat development. Multiple dates of imagery were used to capture differences in plant phenology and hydrological differences in wetland types, which were found previously to improve peatland differentiation and classification (Bourgeau-Chavez et al. 2017; Hribljan et al. 2017).

Landsat Data

Landsat 8 imagery was used in mapping Huascarán National Park. Landsat 8 has two sensor instruments, one collecting data in the visible, Near IR and Shortwave Infrared with 30 m resolution (the Operational Land Imager (OLI)); and a Thermal Infrared Sensor (TIRS) collecting data at 100 m resolution. We resampled the TIRS data to 30 m for mapping. Cloud-free Landsat 8 imagery was very limited in the study areas but three dates were available (Table 1). The Landsat 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 et al. 2009). The thermal bands were converted to TOA temperature brightness in degrees C assuming all pixels had an emissivity of water (Rebelo 2010). A Normalized Difference Vegetation Index (NDVI) was calculated using the visible-red and NIR bands after Rouse et al. (1974). NDVI provides an indicator of vegetation greenness/ biomass. All Landsat 8 data and NDVI products were resampled using nearest neighbor to match the SAR pixel size of 12.5 m. Pixel spacing must be consistent across images prior to stacking. Due to the small size of the mountain peatlands and the importance of the SAR data in the mapping we chose to resample the Landsat to the finer resolution of the SAR data.

DEM Data - Topographic Position Index (TPI)

A Digital Elevation Model (DEM) was necessary for accurate terrain correction of the radar imagery and was also used for topographic analysis of this alpine region. DEM data were downloaded from both the United States Geological Survey's (USGS) 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 from which stereographic pairs are used to map surface elevation. The Global ASTER DEM product has 30 m horizontal resolution matching that of SRTM. The absolute vertical accuracy for

Table 1 List of sensors and sensor products used in the random forests classifier

Sensor	Resolution	Bands	Date 1	Date 2	Date 3	Date 4
Landsat 8	30 m OLI, 100 m TIR	Blue, green, red, NIR, SWIR-1, SWIR-2, TIR-1, TIR-2	30 May 2016	15 Jun 2016	20 July 2016	
PALSAR	10 & 20 m	L-HH, HV	1 Sep 2009	20 Oct 2010	17 Jan 2010	7 Mar 2011
Radarsat-1	30 m	C-HH	02 Dec 1996	27 Mar 1998	02 Feb 1999	
SRTM	30 m posting	DEM product				
ASTER	30 m posting	DEM product				

SRTM and ASTER DEM is 16 m, and the relative accuracy is 6 m. Note that the work presented was created prior to the release of the SRTM plus product, which has data gaps filled with ASTER and other sources.

For the topographic analysis, the Topographic Position Index (TPI) was calculated from the merged SRTM-ASTER product. TPI is a measurement of a point's elevation 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 neighborhood. The TPI product represents cells with lower elevation relative to the area surrounding it as negative values and cells with higher relative elevation as positive values. The TPI aids the classifier identification of low-lying areas and depressions, which are more likely to be wet. Note that the 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 (450 m) radius was used.

SAR Data

Synthetic aperture radar (SAR) is an active sensor sending long wavelength signals capable of penetrating vegetation canopies to interact with the ground surface, depending on frequency and path lengths through the vegetation. For example, C-band SAR energy (~5.6 cm wavelength) may penetrate a sparse or low-stature vegetation canopy, while longer L-band wavelengths (~24 cm) may penetrate taller vegetation including forest canopies. The amount of energy returned to the SAR antenna is a function of vegetation biomass/structure and moisture of the vegetation and ground surface. Higher biomass and moisture generally result in stronger SAR returns than low biomass and moisture. Therefore, multi-date SAR data may be used to distinguish wetland from upland and distinguish between wetlands of different vegetation structure and hydropatterns.

For this study, two different SAR sensors were used: L-band data from ALOS PALSAR and C-band data from RADARSAT-1. Both L- and C-band data were downloaded through the Alaska Satellite Facility's (ASF) DAAC and processed through ASF MapReady tool. To accurately process and prevent errors from topographic variation, radiometric terrain correction (RTC) was applied to the SAR imagery. 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 mannual version 3.1," 2013). Next, the geospatial accuracy was further refined to match the Landsat reference images. The root mean square error (RMSE) was used to assess geospatial errors and any misalignment greater than one pixel was further geocorrected in Erdas Imagine. As a final preprocessing step, filtering or multi-looking of SAR data is necessary to reduce speckle prior to applying classification algorithms. Speckle is an artifact of SAR imaging due to the coherent processing of SAR signals from multiple scatterers within a resolution cell. For this reason, a single pixel of SAR data cannot be used to estimate variables on the ground. The SAR data were filtered using a 3×3 median filter to reduce speckle, similar to Hribljan et al. (2017).

Mapping Technique

Due to its proven utility in wetland mapping, the machine learning classifier Random Forests (RF) (Brieman 2001) was used in this study for mapping wetlands. It is a robust method that can be applied to large areas with consistency, and was shown to provide high classification accuracy and time efficiency when used in mapping mountain peatlands in the *páramo* of Ecuador (Hribljan et al. 2017) as well as other wetlands (Whitcomb et al. 2009; Bourgeau-Chavez et al. 2015, 2017; Clewley et al. 2015). RF consists of multiple decision trees generated from a random subset of input training data and bands. The algorithm is able to handle missing attributes, such as a missing image date for part of a scene or cloud-obscured pixels. This is possible because decision trees that are built without the missing attributes can be used to classify the partial data.

Before running RF, training and validation data of the various vegetation ecosystem types must be built from the field sampling and high resolution image interpretation (from Google Earth or Worldview2 data). The high resolution images were used to spatially expand the field-sampled location polygons while avoiding transitions between cover types or land categories. The supervised training data were input to RF with the multi-date Landsat TM/PALSAR/RADARSAT-1/TPI image stacks. The final map was filtered post-classification using the ESRI majority filter to eliminate isolated pixels and reduce the errors introduced by mixed pixels. This 3 × 3 filter replaced each classified pixel's value with the majority class of its eight neighbors. This resulted in the reduction of some errors at the expense of some correctly classified small linear features. Thus, the minimum mapping unit was 37.5 m × 37.5 m or less than 0.2 ha.

Accuracy Assessments

For accuracy assessment, 20% of the input training polygons were reserved for validation (whole polygons and not pixels were reserved). This allows for a more robust and independent accuracy assessment than the "out of bag" accuracy assessment that RF provides, which reuses training data used to generate other trees within RF. Producer's and user's accuracies as well as commission and omission errors are reported. 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. The commission error is equal to 100% minus the user's accuracy and is representative of areas incorrectly included in a mapped class. The Omission Error is calculated as 100% minus the producer's accuracy and represents areas incorrectly left out of a mapped class.

We also used a stratified estimator to calculate land cover area (Olofsson et al. 2013). The mapped area was estimated from a pixel counting approach (counting pixels allocated to a map class and multiplying by the area of the pixel), which might 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).

Results

Wetland Types

Our soil sampling indicated that *bofedales* in the Huascarán National Park and surrounding area are comprised of two major wetland groups, peatlands and wet meadows. Based on NMS, we identified two main vegetation functional groups: short statured cushion plant and taller graminoid dominated wetlands (Fig. 2). We therefore separated *bofedales* into four major wetland types: 1) cushion plant peatlands, 2) cushion plant wet meadows, 3) graminoid peatlands, and 4) graminoid wet meadows (Fig. 3).

Specific conductivity and pH of the groundwater were similar between the four wetland types, averaging 47 μS cm^{-1} and 5.9, respectively (Table 2). The soil carbon content at 35–40 cm depth varied between wetland types. Percent carbon of the peatland types averaged 15.7%, while it averaged 2.9% for the wet meadow types. As a result of the different carbon contents, bulk density also varied between wetland types, with peatland soils having a much lower density (0.15 g cm^{-3}) than wet meadow soils (0.53 g cm^{-3}).

Mapping

Graminoid peatlands were too rare (0.05% of landscape) to map separately, thus, we combined them with cushion peatland, making a single peatland class. The overall map accuracy of all the remaining classes was 92% with individual class producer's accuracies (100-Omission Error) between 74 to 100% (Tables 3; note that Developed had 95% and 99% and Water and Snow had 100% producer's and user's accuracy and were excluded from Table 3). Mapping peatlands had a producer's accuracy of 93% (Table 3). Mapping cushion wet meadows and graminoid wet meadows had a producer's accuracy of 99% and 85% (Table 3). Some peatlands identified in the ground truth were mapped as wet meadows (7%). The user's accuracies (100-commission error) ranged from 79% to 100% (Table 3). Cushion plant peatlands had 93% user's accuracy, with 7% of pixels incorrectly mapped as wet meadows. Cushion wet meadows had a 93% user's accuracy some being mapped as cushion plant peatlands. Graminoid wet meadows had a 79% user's accuracy with some being mapped as either grassland or shrubland.

The total adjusted wetland area (peatland and wet meadow) in the park is 38,444 ha, which is ~11% of the park (Table 4). Total adjusted wetland area of the park and buffer zone is 59,011 ha, which is ~10% of the area (Table 4). In the park, cushion plant peatlands were the most abundant wetland type occupying 6.3% of the park, followed by graminoid wet meadows (3.5%) and cushion wet meadows (1.3%) (Fig. 1, Table 4). In the lower-elevation buffer zone, most of the wetlands were graminoid wet meadows (4.6%), followed by peatlands (2.5%) and cushion wet meadows (1.2%). Wetland type also varied greatly north to south, with cushion wet meadows more abundant in the north, and cushion plant peatlands more abundant in the southern half of the park (Fig. 1).

Within the park and buffer zone, wetlands were most abundant between the elevations of 3950–4650 m, with

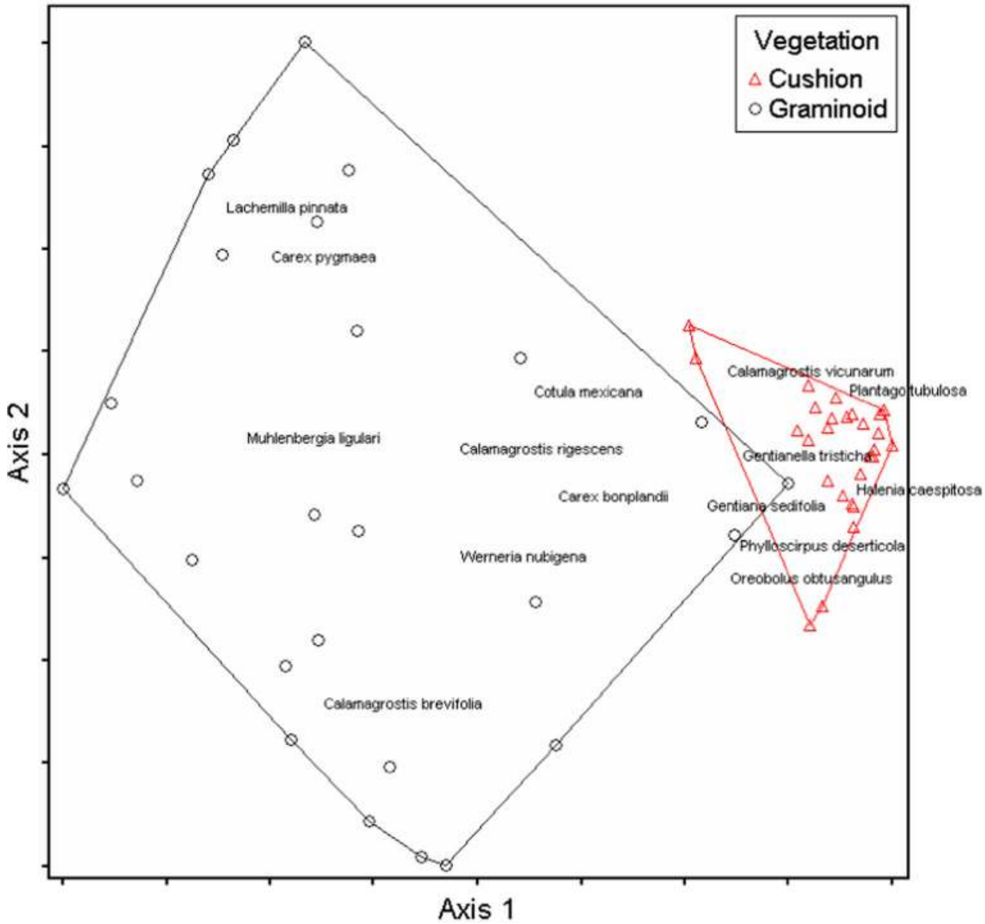

Fig. 2 Two-dimensional plotting of nonmetric multidimensional scaling results using two hierarchical grouping codes along axes 1 and 2 (R^2 of Axis 1 = 0.51, Axis 2 = 0.22, and Axis 3 = 0.13). Red triangles represent the cushion plant dominated communities, and black circles indicate graminoid dominated communities. Species shown are those identified as indicator species with >30% of perfect indication

77% of all mapped wetland area occurring within this elevation zone (Fig. 4). Below 3950 m, wetlands were comprised mostly of graminoid wet meadows and accounted for 11% of all wetland area. Above 4650 m, wetlands were comprised mostly of cushion plant peatlands, which accounted for 12% of all wetland area.

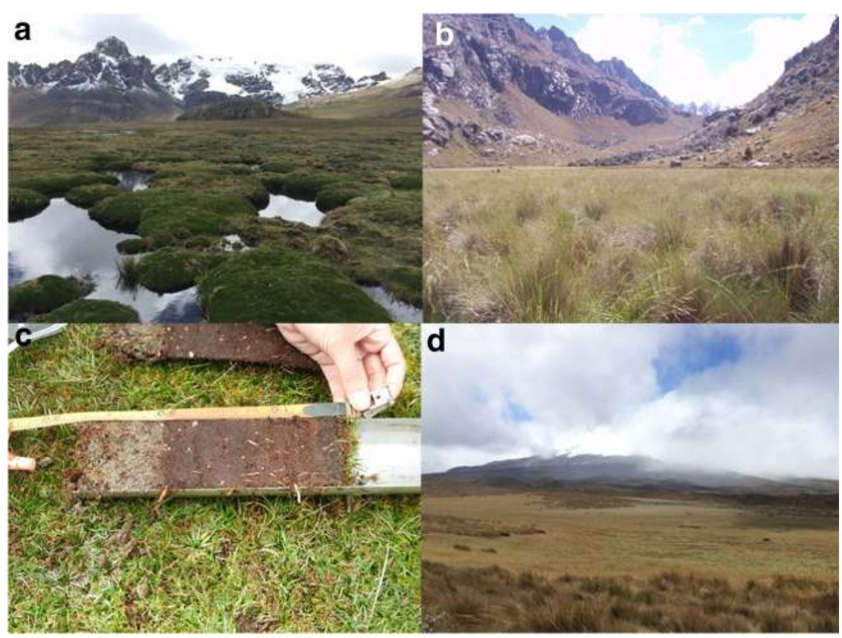

Fig. 3 Representative pictures of the four wetland classes used in this study: **a** cushion plant peatlands, **b** graminoid peatlands, **c** cushion plant wet meadow also showing soil core, and **d** graminoid wet meadows. Due to rare occurrence, graminoid peatlands were not mapped

Table 2 Average (SE) of pH and specific conductivity of ground water, and percent carbon of soil samples at 35–40 cm

Class	pH	Specific conductivity ($\mu S\ cm^{-1}$)	Carbon (%)
Cushion Peatland	5.9 (0.15)	41.9 (6.0)	16.2 (1.2)
Graminoid Peatland	5.7 (0.02)	51.8 (17.8)	15.7 (1.6)
Cushion Wet Meadow	5.8 (0.42)	56.4 (27.8)	2.7 (0.9)
Graminoid Wet Meadow	6.1 (0.42)	37.5 (5.3)	2.9 (0.45)

Discussion

Abundance of Mountain Wetlands

Our mapping indicates that mountain wetlands are extensive in Huascarán National Park and its buffer zone with ~ 10% of the landscape mapped as wetlands. This is a much greater concentration of mountain wetlands than identified in southern Peru (2.5%, Otto and Gibbons 2017) or in the Colorado Rockies, where it was estimated that about 1% of the entire San Juan Mountains of Colorado was mapped as peatland (Chimner et al. 2010). However, it is lower than estimates from the Ecuadorian Andes where 18% of the landscape was mapped as wetlands (Hribljan et al. 2017).

In addition to differences in total wetland area between the Ecuadorian *páramo* and the Peruvian *puna*, there were also differences in proportion of wetland types. In this study, ~50% of the wetlands were classified as peatlands. This contrasts with Ecuador where 100% of the wetlands were identified as peatlands. This difference in the wetland abundance and proportion of wetland types between Ecuador and Peru is likely due to climatic differences. The tropical Andes are divided into a northern (*páramo*) and a central (*puna*) sections (Cleef 1979). The *páramo* ecoregion of Colombia, Venezuela, Ecuador and Northern Peru are in the humid equatorial Andes characterized by cool and wet conditions with no distinct dry season (Balslev and Luteyn 1992; Luteyn 1999). In contrast, the *puna* ecoregion of central Peru, Bolivia, and northern Chile and Argentina (Earle et al. 2003) is characterized by stronger seasonality, with distinct wet and dry season. Most of the *puna*, especially in southern Peru, is xeric, whereas Huascarán National Park is in the humid *puna* (Troll 1968; Young et al. 1997; Josse et al. 2011).

Peatlands form in areas that maintain perennially saturated conditions. Humid areas with high rates of rainfall, such as conditions found in *páramo*, support abundant peatlands (Lottes and Ziegler 1994; Gallego-Sala and Prentice 2013). The seasonal precipitation of the *puna* reduces the area with a stable hydroperiod to areas that receive sufficient groundwater during the dry season. In contrast, wet meadows are also groundwater-supported, but commonly form where soils are only seasonally saturated (Chimner et al. 2011; Cooper et al. 2012). Differences in topography could be another factor that may help explain the greater abundance of wet meadows in Peru. Huascarán National Park has the greatest cover of tropical glaciers in the world, and many of these glaciers have created broad U-shaped valleys with steep side slopes that influence wetlands by slope processes and mineral sediment inputs. The floors of these U-shaped valleys are predominantly dominated by cushion wet meadows.

Table 3 Accuracy assessment of the SAR-optical-TPI random forests classified map mapping four wetland types

Mapped classes	Ground truthed values								
	Agriculture & Pasture	Grassland	Shrubland	Woodland	Peatland	Cushion Wet Meadow	Graminoid Wet Meadow	Sum	User Acc.
Agriculture/Pasture	196	0	8	4	0	0	0	211	93%
Grassland	3	174	8	0	0	0	5	192	91%
Shrubland	1	3	156	12	1	0	0	174	90%
Woodland	0	0	15	204	0	0	0	220	93%
Peatland	1	1	0	0	371	3	24	400	93%
Cushion Wet Meadow	0	0	0	0	14	204	1	219	93%
Graminoid Wet Meadow	10	18	20	0	0	0	176	224	79%
Sum	211	212	212	221	398	207	206	92%	
Prod. Acc.	93%	82%	74%	92%	93%	99%	85%		

Note that areas covered by snow and water had 100% producer's and user's accuracy and were removed from the table for brevity. Values represent number of pixels

Table 4 Mapped areas (based on pixel counting) and adjusted mapped areas (using a stratified estimator) of land classes from Fig. 1

	Total Area		Park		Buffer	
Class	Mapped Area (ha)	Adjusted Area (ha)	Mapped Area (ha)	Adjusted Area (ha)	Mapped Area (ha)	Adjusted Area (ha)
Snow	48,494	48,494(± 0)	46,816	46,816(± 0)	40	40(± 0)
Barren	395,684	343,863(±33,621)	164,553	141,940(±13,475)	37,159	32,628(±3,482)
Developed	23,103	37,989(±18,747)	94	3,735(±5,552)	1,612	3,637(±2,771)
Agriculture	371,923	354,703(±29,099)	2,868	4,199(±2,064)	71,653	68,239(±5,505)
Grassland	333,198	333,116(±36,386)	53,643	59,278(±9,987)	58,688	56,929(±5,545)
Shrubland	251,547	271,174(±38,012)	19,575	25,171(±6,359)	40,900	44,906(±6,516)
Woodland	87,628	107,052(±24,809)	18,714	19,339(±3,008)	20,461	23,284(±4,333)
Water	4,922	4,922(±0)	2,606	2,606(±0)	354.	354(±0)
Peatland	48,375	63,583(±19,617)	15,254	21,516(±7,797)	6,395	7,771(±2,003)
Cushion wet meadow	7,693	7,529(±968)	4,339	4,156(±389)	459	475(±113)
Graminoid wet meadow	52,622	52,961(±16,241)	12,253	11,959(±2,850)	11,460	11,460(±2,940)

Mapping Wetland Types

Mapping different wetland types has been problematic in the Andes. For instance, Otto and Gibbons (2017) mapped only one wetland type in southern Peru. Our methods were very successful for mapping wetlands as we had >93% producer's accuracy when mapping peatlands and > 85% for mapping wet meadows. We attribute this success to the use of multi-date SAR, which can measure the difference in hydroperiod between wet meadows and peatlands to better inform the classification. These accuracies are better than what was found for our *páramo* mapping in Ecuador where the average peatland producer's accuracy was 87% (Hribljan et al. 2017).

The largest difficulty we had was attempting to map graminoid peatlands as a separate category. We only identified a few locations that were dominated by tall rushes (*Juncus arcticus).* These sites were bordering lakes and resembled an emergent marsh, but had deep peat soils. The lack of training and validation points limited our accuracy to the point where it was not feasible to map them separately from cushion peatlands. Although these graminoid peatlands were rare in Huascarán National Park, in other areas they maybe more numerous and extensive and mapping would be possible.

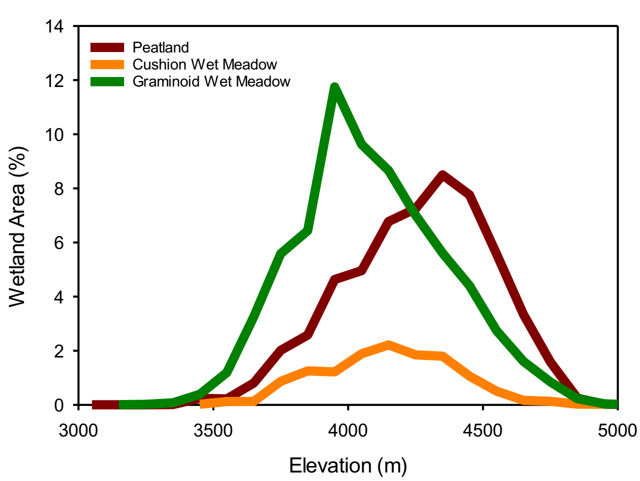

Fig. 4 Percent occurrence of mapped wetland types along elevation gradient (wetland area is summed every 100 m) within park and buffer. Percentages on y axis are of the total area of that elevation band

What Are Bofedales?

Bofedales (singular *bofedal*) is a commonly used term in some areas of the Andes to refer to mountain wetlands. However, there is confusion on what type of wetland *bofedales* are. Many define *bofedales* as high-altitude peat-bogs or peatlands dominated by cushion plants (Bosman et al. 1993; Earle et al. 2003; Squeo et al. 2006; Garcia and Brown 2016). Clearly, peat-bog is not a good term because all studied peatlands in the *puna* are minerotrophic groundwater fed fens, not ombrotrophic bogs as traditionally defined (Cooper et al. 2010; Maldonado Fonken 2014; Salvador et al. 2014; Hribljan et al. 2016).

Defining *bofedales* as cushion plant peatlands is common, and in many areas they do appear to be the dominant wetland type, especially at higher elevations (Cooper et al. 2010; Maldonado Fonken 2014; Salvador et al. 2014). Some of these cushion plant peatlands are very deep (>10 m), accumulate carbon rapidly and contain very high carbon stocks (Earle et al. 2003; Hribljan et al. 2016). However, as we have shown in this study, not all cushion plant dominated wetlands are peatlands, as some have organic soil less than 40 cm thick and are better classified as wet meadows. Our mapping found that about one-quarter of all cushion plant dominated wetlands in Huascarán National Park are wet meadows. It can be very difficult to tell the difference between cushion plant peatlands and wet meadows due to the similar plant communities that grow on both and the fact that they can co-occur in large complexes (Wigmore et al. 2019). Delineating cushion plant wet meadows from peatlands can be important for developing maps, especially when developing carbon stock maps (Hribljan et al. 2017) or if trying to manage wetlands for grazing. In the park, as in most of the Andes, livestock grazing is common (Salvador et al. 2014). Even though they are both wetlands, wet meadows and peatlands have large differences in soils, hydrology, chemistry, and often respond very differently to grazing. Mountain peatlands are often more susceptible to grazing compared to wet meadows due to their thick and soft organic soils, which are easily trampled (Chimner et al. 2010, 2011; Cooper et al. 2012; Enriquez et al. 2015; Sánchez et al. 2017).

Whether peatland or wet meadow, the term *bofedal* usually refers to a wetland dominated by cushion plants. However, other plant functional types can also be dominant in many Andean wetlands. Many grass, sedge and rush species occur, either mixed in with cushion plants, or as dominants. For instance, in Cajamarca, Peru, Cooper et al. (2010) identified 15 wetland vegetation communities dominated by graminoids, compared to only 3 cushion plant communities, and in Ecuador graminoid-dominated peatlands are common in the lower elevations of the páramo (Hribljan et al. 2017). There are also wetlands dominated by *Sphagnum* mosses and other mosses in the Peruvian Andes, but they are rarer (Cooper et al. 2010; Benavides and Vitt 2014).

Given the diversity of wetland types in the *puna*, we support a broader definition of *bofedal*, as also used by Maldonado Fonken (2014). We recommend that *bofedal* be used to refer to any high elevation mountain wetland type in the *puna*, regardless of dominant vegetation type or soil type. Then other more precise terms can be used to refer to wetland types similar to terminology used globally (e.g., peatlands, fens, marshes, and wet meadows).

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