ECOSPHERE

Evaluation of impacts of management in an anthropogenic peatland using field and remote sensing data

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Abstract.   Peatlands are a type of wetland characterized by the accumulation of organic matter, called peat, and are important carbon reservoirs. In areas with poor drainage, human-induced forest fires and logging can produce flooded conditions and organic matter accumulation, which generates an ecosystem called anthropogenic peatland. Productive management activities such as *Sphagnum* moss harvesting and livestock grazing take place there. Our hypothesis was that productive management has a strong impact on the aboveground C reservoir and increases the presence of exotic species. We established 44 sampling points in a 16-ha anthropogenic peatland on Chiloé Island, Chile, comparing productive and conservation types of managements. Carbon stocks, vegetation structure and composition variables were quantified. These variables were used to classify the ecosystem into microsites to analyze the different locations in the peatland. In addition, predictive models of aboveground carbon were created using Landsat 8 OLI and Pleiades images. The results revealed a carbon stock of 11.99 ± 0.77 kg C m^{-2}, which is smaller than in natural peatlands, and showed a wide variability of conditions within the peatland itself. This variability, mainly expressed in aboveground carbon, produces microsites dominated by either shrubs, species of the genus *Juncus* or grasses. Productive management reduced accumulated carbon in the aboveground stock and in the woody debris. However, the strongest impact was found on the vegetation variables, with a decrease in total cover, cover of shrubs and herbaceous plants, and in vegetation height. There was also an increase in the richness and presence of exotic species. The spatial prediction of aboveground carbon yielded significant results using only spectral indices, showing also that the impact of productive management is not homogenous, being less intense in waterlogged areas. This study is the first to quantify carbon reservoirs in this type of ecosystem and to propose variables that can be used as indicators of the impact of human activities.

Key words: carbon stocks; carbon reservoirs; effects of management; grazing; harvesting; moss; *Sphagnum*; vegetation.

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INTRODUCTION

Wetlands are ecosystems generated in areas where the water presence produces soils subject-ed to anaerobic processes, and are thus dominated by a biota adapted to flooding (Keddy 2010). These ecosystems offer numerous ecosystem services, including fresh water purification

and storage (Bullock and Acreman 2003) and being important carbon (C) reservoirs (Zedler and Kercher 2005). Peatlands are wetlands where organic matter is produced and deposited more quickly than it can decompose, leading to the formation of peat (Gore 1983). The peat thickness needed to classify an ecosystem as peatland differs between authors, but the most common value is between 30 and 40 cm.

Peatlands fulfill an important role in regulating climate on a global scale, being one of the world's most important land reservoirs (Parish et al. 2008). Peatlands may retain approximately one third of C from soils (Moore 2002, Roig and Roig 2004, Asada and Warner 2005), although they occupy only 3% of the world's surface (Joosten and Clarke 2002). Nevertheless, when these ecosystems are degraded or disturbed, particularly for uses that include draining the land to harvest peat or for farming with a plow, they can become significant sources of CO_2 (Parish et al. 2008). The greenhouse gas emissions produced by the degradation and burning of peatlands have increased considerably in recent years, and it is estimated that it could surpass the current 2 $\times 10^9$ Mg C yr^{-1} (Joosten 2010). As a result, the most recent report from the Intergovernmental Panel on Climate Change (Settele et al. 2014) stated that the conservation, restoration and rewetting of degraded peatlands is an effective measure to mitigate C losses. Therefore, proposals have been made to implement clean development mechanisms related to activities that reduce degradation in peatlands (Strack 2008), which requires an adequate quantification of C stocks and flows associated with the different classes of peatlands (Oliván et al. 2010).

Joosten and Clarke (2002) estimated the surface of peatlands in Chile to be an area of 10,470 km^2, concentrated in the regions of Aysén and Magallanes in southern Chile, and corresponding to 1.4% of the national territory (Schlatter and Schlatter 2004). On Chiloé Island (Los Lagos Region), as a consequence of accelerated human colonization, vast expanses of forest areas were burned or cleared for timber or to prepare the land for agriculture or livestock. According to Nahuelhual et al. (2013), the northern part of the island (Ancud municipality) suffered a loss of 38% of old-growth forest area from 1976 to 2007 (equivalent to 39,013 ha). As a result, areas of poor drainage were colonized by *Sphagnum* mosses (mainly *S. magellanicum*) or by successional shrublands (Díaz and Armesto 2007, Díaz et al. 2007). These areas have many names, including "secondary peatlands" (Díaz and Silva 2012) and the local term *pomponales*. For the purposes of this study, the term "anthropogenic peatlands" will be used, as in previous studies (Díaz et al. 2008, 2012, León and Oliván 2014). A similar situation has occurred in New Zealand, where logged or burned areas have been colonized by *Sphagnum* species (Whinam et al. 2003), forming an ecosystem that can be called "induced Pakihi," due to the similarity with a local ecosystem; unfortunately, most of the work in these ecosystems is in unpublished reports (R. Buxton, *personal communication*).

Given the recent nature of their formation, these peatlands do not have large accumulations of peat and their plant composition differs considerably from natural peatlands (Díaz et al. 2008). These ecosystems have recorded recent C accumulation rates higher than those of peatlands of glacial origin because anthropogenic peatlands, being newer ecosystems, are more active (León and Oliván 2014). Also, these types of peatlands have a great capacity to retain water (Iturraspe and Roig 2000), which makes them important water reservoirs.

Chiloé Island has a long history of using peat as fuel; however, since around 1996, exploitation of the moss from the uppermost layer of the peat began due to the demands of such activities as horticulture and floriculture. From then until 2010, exports increased 29-fold due to a high external demand, valued at approximately 13 million dollars in 2012, equivalent to 3,900 tons of dry moss (Agüero 2013). Unrestricted harvesting of this resource has had irreversible environmental effects that go beyond exhaustion of the moss and impoverishment of the producers, affecting the C cycle and local hydrology, causing landscape erosion and loss of biodiversity (Zegers et al. 2006, Díaz and Delano 2012). *Sphagnum* moss extraction is performed mainly in anthropogenic peatlands (Valenzuela-Rojas and Schlatter 2004, Zegers et al. 2006).

In New Zealand and Australia, two of the world's main moss producers, studies have evaluated the impact of harvesting this resource, showing a reduction in the moss growth rate, a

smaller total biomass and a decrease in the regeneration of the woody plants that grow in the peatland (Buxton et al. 1996, Whinam and Buxton 1997, Whinam et al. 2003). Moss harvesting, which limits the establishment of other species, has contributed to preserving the dominance of *Sphagnum* sp. (Whinam et al. 2003). In New Zealand, most *Sphagnum* harvesting is performed in induced Pakihis (R. Buxton, *personal communication*).

These ecosystems are also used for livestock. It has been demonstrated that the introduction of sheep in peatlands in the Northern Hemisphere alters the C balance, increasing greenhouse gas emissions (Worrall and Clay 2012, Clay and Worrall 2013). Van der Knaap et al. (2011) suggested that another possible impact of grazing is a change in the type of dominant vegetation, promoting the establishment of shorter monocotyledons over the formation of *Sphagnum* sp. Other studies such as those by Bardgett et al. (1995) and Critchley et al. (2008) indicate that overgrazing may cause the shrubby vegetation to be replaced by herbaceous vegetation. This herbaceous vegetation is dominated by competitive grasses, because livestock tend to facilitate the dispersion of exotic grasses and because many invading plants are not very palatable, which aids in their survival (Vavra et al. 2007).

Different market mechanisms have been proposed to regulate the potential adverse impacts on these anthropogenic peatlands, such as payment for environmental services (Oliván et al. 2010). To make this possible, however, a knowledge base about these ecosystems is required, and studies about them are scarce (León 2012).

The C contained in peatlands is often studied using spatial analysis tools, in which predictor variables and interpolations are used to model the peat depth. This approach has shown that peatland C content is strongly influenced by local topography (Parry et al. 2012). Several studies have obtained good results by modeling peat depth, density and C content (Parry et al. 2012, Parry and Charman 2013). The application of interpolation tools such as kriging is also common to calculate the C content in large areas of land, as Djurhuus et al. (2005) did in peatlands of Denmark.

The use of remote sensing for mapping these types of ecosystems, particularly the use of multispectral images like SPOT or Landsat for their identification and monitoring is very frequent (Adam et al. 2009). In addition, it is possible to classify biotypes and identify changes in biodiversity on a large scale due to anthropic disturbances or other causes (Middleton et al. 2012). Thus, supervised classification techniques are used to create an initial boundary of the peatlands in order to then calculate the total C content in the ecosystem, extrapolating precise measurements of C content by area (Weissert and Disney 2013). Similarly, Akumu and McLaughlin (2014) used SPOT 5 images to delimit and classify the different types of peatlands in a portion of the Nayshkootayaow river basin in Ontario, Canada, obtaining classifications that allowed them to calculate the C content by type of peatland.

One of the most important applications of remote sensing is the quantification of biomass in green vegetation, detecting changes and patterns for better analysis and decision-making, particularly considering that in cases of changes in soil use or degradation, this biomass can become an important source of greenhouse gas (Lu 2006, Barbosa et al. 2015). In this respect, biomass or aboveground C in peatlands is not frequently taken into consideration, since the underground reservoir is more important (Gore 1983). In the case of anthropogenic peatlands in particular, a significant growth of vascular vegetation on the substrate is seen, which may act as an indicator of succession (Díaz and Armesto 2007), and thus be considered an important component of the ecosystem. In order to construct models that can predict aboveground biomass, the use of indices derived from high-resolution multispectral satellite information has been successful in other types of wetlands dominated by herbaceous or shrub vegetation (Mutanga et al. 2012, Ling et al. 2014).

Our hypothesis was that peatland productive management has a strong impact on the aboveground C reservoir and in the increased presence of exotic species. We also suggest that the spatial distribution of C reservoirs can be modeled from spectral information in an anthropogenic peatland. To ascertain this, we evaluated the effects of a mixed productive management of grazing and

Sphagnum moss harvesting on the carbon stocks and vegetation of an anthropogenic peatland on Chiloé Island (Los Lagos Region, Chile). Our aims were (1) to analyze the changes on vegetation composition and structure created by productive management of the peatland, (2) to analyze the distribution of C in the different ecosystem reservoirs, and (3) to model the spatial patterns of the aboveground C reservoir in the peatland using variables measured in the field and taken from remote sensing.

METHODS

Study area

The study area is in the north of Chiloé Island, in the Los Lagos Region in Chile (Fig. 1). Specifically, it is an anthropogenic peatland located in the Senda Darwin Biological Station (SDBS; 41°52′ S, 73°40′ W) and the neighboring site. This ecosystem has its origins in the cutting and burning of the tepú forest (*Tepualia stipularis*) located in the area, which left a poorly drained soil colonized by species of *Sphagnum* sp. (Díaz et al. 2007, 2008). It is estimated that the accumulation of organic matter began in 1900 (León 2012).

The study area is located in a temperate climate with strong ocean influence and has a dry period during the summer (Di Castri and Hajek 1976). According to nine years' worth of data from the SDBS weather station, the average temperature is 10°C and there is 2,110 mm of precipitation annually (Carmona et al. 2010).

The anthropogenic peatland has an approximate area of 16 ha and has two types of management. The conservation management site has an area of 5.5 ha and is located in the SDBS (Fig. 1). This research station was created 20 years ago (Carmona et al. 2010), although the division of the peatland with the neighboring site with a fence only occurred eight years ago (J. Armesto, *personal communication*). The productive management site covers the rest of the peatland (10.5 ha), and belongs to the neighboring property, where artisanal *Sphagnum* moss harvesting is performed for commercial purposes (approximately 10 kg of dry moss per month). The productive site is also used for grazing for four oxen, which according to the conversion factor of 1.35 indicated by the National Resources

Conservation Service (1997) corresponds to 0.51 AU ha^{-1}. These two productive activities are mainly undertaken in summer.

Vegetation sampling

Given that peatland vegetation has a high spatial heterogeneity (Bridgham et al. 1996, Ulanowski and Branfireun 2013), a systematic sampling was used to adequately represent this ecosystem. A grid with 60 m intervals was created to match with the lower resolution image (Landsat 8, 30 m pixels), and 44 sampling points were determined based on the size of the peatland (Fig. 1). To characterize the vegetation, 2×2 m quadrants were created at each sampling point (Wassen et al. 1990, Díaz et al. 2008, Ulanowski and Branfireun 2013). These quadrants were sampled, identifying the existing species and visually estimating the cover of each one, also calculating the total cover and cover of shrubs and herbaceous plants. Only vascular plants were studied because these are the main contributors in terms of aboveground C in these types of ecosystems (as the *Sphagnum* layer was treated as a belowground reservoir). Additionally, the height of the vegetation was measured at nine points in each quadrant (vertices, midpoints of each side and the central point; Fig. 2). The average of the cover found was calculated to determine the most abundant species in the ecosystem, as well as that of greatest frequency. The richness of species in each quadrant and the percentage of exotic species were calculated. The Shannon-Wiener index was calculated as a diversity estimator (Shannon 1949).

Measurement of biomass and carbon stocks

The biomass and C reservoirs were divided into two: the aboveground stock, which corresponds to the vascular flora growing on the substrate, and the underground stock, which corresponds to the peat, live moss, debris (fine and coarse) and buried trunks (remnants from burning the forest). Sampling from the vascular plant stock, trunks buried in the peat and coarse debris (trunks or branches >5 mm in diameter) was done by harvesting all the biomass on 0.25 m^2 in the center of the quadrants (Moore et al. 2002, Bubier et al. 2006), separating the herbaceous plants shrubs and trees, which were dried at 70°C for 72 h. The presence of trunks was
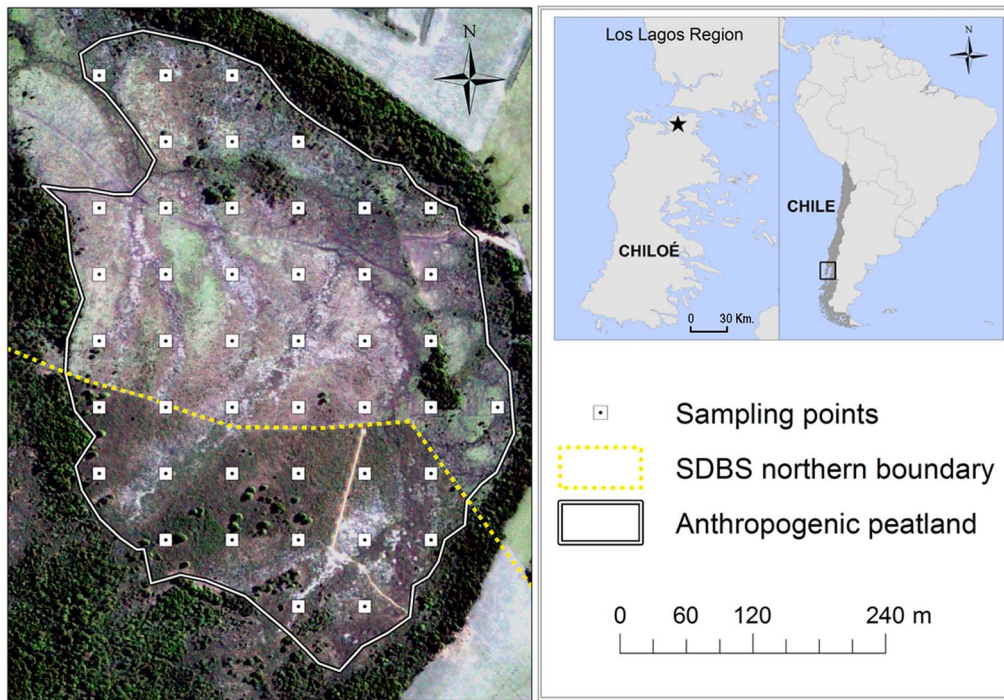
Fig. 1. Location of the anthropogenic peatland in the north of Chiloé Island. The points represent the location of the sampling points. The land belonging to the Senda Darwin Biological Station (SDBS) is on the southern side of the peatland.

verified with a rod and these were extracted when necessary. In order to harvest the tree biomass, the 0.25 m^2 quadrant was projected vertically and the material in that projection was harvested.

To sample the underground C stocks, cylindrical samples 52 mm in diameter were extracted at the central point of the quadrants using a peat profile sampler (Eijkelkamp, Giesbeek, Netherlands). To separate the components of this reservoir, a methodology based on the classification proposed by Von Post (1924) was used, which has a scale of 10 degrees of humification (H1 to H10): H1 is for moss with live components and H10 for completely decomposed live components. This original scale was reduced to three classes (Domenico and Delicato 1996, Raviv et al. 2002) and one layer corresponding to the live moss found on the surface, as shown in Table 1. Since in many cases it was mixed with moss, fine woody debris (<5 mm in diameter) was considered a separate layer where it existed and was clearly identifiable. The thickness of each layer

was measured in the field and a sub-sample of each material was obtained, which was weighed on site. The sub-samples were dried to calculate their weight and the density of the material in order to estimate the stock in kg m^{-2}. The aboveground biomass and vegetation measurements were taken in January 2014 and those belowground in April of the same year.

In order to obtain the C fraction from the stocks, five composite samples for each stock were generated, using material from random sampling points. From these composite samples, a sub-sample of 10 g was extracted, ground, mixed and processed in an elemental analyzer (model NA2500, Carlo Erba, Milan, Italy).

Analysis of vegetation and carbon data

To analyze the high heterogeneity of abiotic and biotic conditions found in the field, as well as of the composition of the vegetation and the magnitude of the C stocks, the ecosystem was classified in microsites that reflected differences in the vegetation. A cluster analysis algorithm
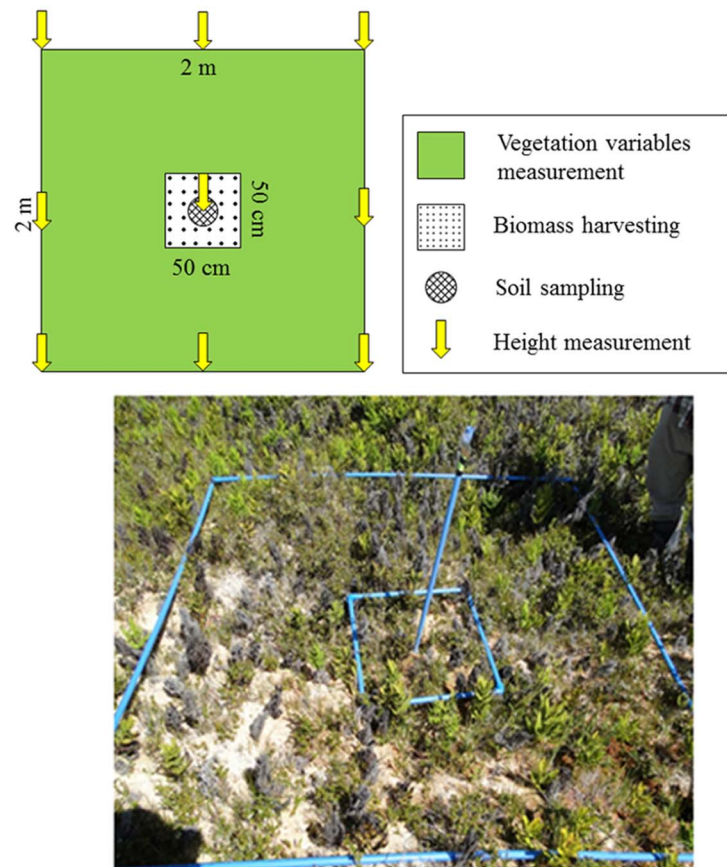
Fig. 2. Diagram and picture of the sampling plot.

based on the k-means method (Hartigan and Wong 1979) was used, classifying the 44 sampling points using the C stocks from shrubs and herbaceous plants. First, the variables were standardized using the z-scores method (Mohamad and Usman 2013), then the analysis was performed considering a cluster number (k) that minimized the sum of squares within the groups and that permitted their adequate analysis, for

which the graph of the internal sum of squares vs. the cluster number was interpreted.

To verify the differences between means of the vegetation and C stocks variables of the microsites, parametric tests were used. To verify the assumptions, the Shapiro-Wilk (normality; Shapiro and Wilk 1965) and Bartlett's (homoscedasticity; Bartlett 1937) tests were used. Since in many cases the assumptions of the analysis of

Table 1. Classification and characteristics of the components of the underground carbon reservoir.

Component	Characteristics of runoff	Plant parts	Von Post	Peat characteristics
Live moss	colorless, almost transparent	plants are full recognized (live)		
R1	slightly cloudy	plant parts are easily recognized	H1–H3	slightly decomposed or light peat
R2	brown or cloudy	difficult to recognize plant parts, mainly roots are recognized	H4–H6	moderately decomposed or dark peat
R3	no water released or only a small amount of cloudy water	plant parts are not recognized	H7–H10	completely decomposed or black peat

Note: Modified based on Von Post (1924).

variance were not fulfilled, the Kruskal-Wallis non-parametric test (Kruskal and Wallis 1952) and Dunn's test (Dunn 1964) were used to perform the multiple comparisons, with Bonferroni's correction as described by Dunn (1961) to reduce type I error (Rice 1989).

To make the comparison between management types (conservation and productive), all the previously described variables were taken and the Wilcoxon non-parametric test was used (Wilcoxon 1945). The C stocks corresponding to the tree biomass and buried trunks were not included in the analysis since their appearance in the sampling points was very limited.

Modeling of carbon stocks

Predictive models of the aboveground and underground C were generated to model the stocks. The underground C was modeled through ordinary kriging (Stahlhut and Rieley 2007), using the variables underground C (kg m^{-2}) and soil depth (cm) as an indirect indicator. To verify spatial autocorrelation between variables, a condition necessary for this method, the Moran index (Moran 1950) was used.

The aboveground C was modeled using predictors derived from remote sensing. These predictive variables were obtained using an image from the Operational Land Imager (OLI) sensor on board the Landsat 8 satellite taken on 24 December 2013 and an image from Pleiades 1B from 28 January 28 2014. Four different spatial resolutions were used, 30 and 15 m for the OLI sensor and with 2 m and 50 cm in the case of Pleiades. To improve the image resolution, in both cases a merger was used with the Gram-Schmidt method (Laben and Brower 2000). The images were corrected radiometrically using the coefficients given in the metadata of each of the images and atmospherically with the FLAASH algorithm (Fast Line-of-sight Atmospheric Adjustment of Spectral Hypercubes; Matthew et al. 2000). It was not necessary to use a topographical correction since the relief is flat. All the image pre-processing was carried out using the Envi 5.1 software (Exelis Visual Information Solutions, Boulder, Colorado, USA).

Given the high spatial heterogeneity of this ecosystem, the best spectral variables for aboveground C prediction were not known, so in order to obtain the most relevant predictors, we compiled an exhaustive bibliography of different indexes used in similar studies, obtaining a list of several predictive spectral variables (SV; Table 2). We classified these indexes into three groups: "spectral information," variables that were extracted from a part of the spectrum alone (e.g., the reflectance of a single band); "photosynthetic indexes," spectral indexes including the difference between the near infrared (NIR) and the red bands; and "feature extraction," variables that represented different properties of the surface (e.g., wetness). The value of the pixel for each of these predictors was extracted using a bilinear interpolation. Additionally, for each of these variables the local standard deviation of the pixel was calculated with respect to its neighbors in a 3 × 3 quadrant; this variable was considered a textural variable, as in Kelsey and Neff (2014). The four spatial resolutions analyzed obtained 223 spectral variables in total. In addition, eight vegetation and distance variables, described in Table 2, were included. All the indices were calculated using the ArcGis 10.1 software (ESRI, Redlands, California, USA).

Given the different conditions of management, models were created including three subsets of observations: the total data (TD, $n = 44$), only the data in the conservation management area (CM, $n = 15$), and only the data in the productive management area (PM, $n = 29$), looking for the best fit and the best predictors for each use. Different subsets of predictors were also used, generating models with only the SV or all the variables (AV: SV, distance and land variables).

Descriptive statistics were calculated in order to analyze the results of the aboveground C predictive models. Given the large number of predictors to consider, an exploratory analysis was done first through the classification algorithm based on Random Forest (RF) decision trees (Breiman 2001) so as to select a subset of predictors (Ceballos et al. 2015). Thus, a total of 1000 bootstrap iterations were run, in which a RF model was evaluated with different subsets of the observations, from two-thirds of the sample up to the whole sample. On each iteration, the importance of each variable was calculated in terms of the percent increase in mean square error when the predictor is removed from the regression tree (%IncMSE). To obtain a subset of predictors, the 15 variables with the highest

Table 2. Variables used to model the carbon reservoirs.

Index or variable (abbreviation)	Formula or description	Reference	OLI	Pleiades
Spectral information				
Coastal aerosol (CA)	reflectance in the coastal aerosol band		x	
Blue (B)	reflectance in the blue band		x	x
Green (G)	reflectance in the green band		x	x
Red (R)	reflectance in the red band		x	x
NIR (NIR)	reflectance in the near infrared band		x	x
SWIR 1 (SWIR1)	reflectance in the short-wave infrared band		x	
SWIR 2 (SWIR2)	reflectance in the short-wave infrared band		x	
Photosynthetic indexes				
Normalized difference vegetation index (NDVI)	$\frac{NIR-R}{NIR+R}$	Silleos et al. 2006	x	x
Green normalized difference vegetation index (GNDVI)	$\frac{NIR-G}{NIR+G}$	Gitelson et al. 1996	x	x
Transformed vegetation Index (TVI)	$\sqrt{\frac{NIR-R}{NIR+R}} + 0.5$	Silleos et al. 2006	x	x
Modified soil adjusted vegetation index 2 (MSAVI2)	$\frac{2 \cdot NIR + 1 - \sqrt{(2 \cdot NIR + 1)^2 - 8 \cdot (NIR - R)}}{2}$	Qi et al. 1994	x	x
Difference vegetation index (DVI)	$NIR - R$	Ling et al. 2014	x	x
Simple ratio (SR)	$\frac{NIR}{R}$	Ling et al. 2014	x	x
Modified simple ratio (MSE)	$\left(\frac{NIR}{R} - 1\right)/\sqrt{1 + \frac{NIR}{R}}$	Haboudane et al. 2004	x	x
Renormalized difference vegetation index (RDVI)	$\frac{NIR-R}{\sqrt{NIR+R}}$	Haboudane et al. 2004	x	x
Triangular vegetation index (TriVI)	area of the triangle formed by the G-R-NIR reflectances	Broge and Leblanc 2000	x	
Enhanced vegetation index (EVI)	$2.5 \cdot \frac{NIR-R}{NIR + 6 \cdot R - 7.5 \cdot B + 1}$	Huete et al. 2002	x	x
Soil adjusted vegetation index (SAVI)	$1 + L \cdot \frac{NIR-R}{NIR+R+L}; L = 0.5$	Huete et al. 1997	x	x
Feature extraction				
All normalized difference vegetation index (BandX-BandY-ND)	$\frac{BandX - BandY}{BandX + BandY}$	Mutanga et al. 2012	x	x
Shortwave angle slope index (SASI)	$\beta_{SWIR1} \cdot SWIR \cdot NIR$; β_{SWIR1} is the angle formed on the SWIR1 vertex by the NIR-SWIR1-SWIR2 reflectances (in radians)	Khanna et al. 2007	x	
Angle at NIR (ANIR)	angle formed on the NIR vertex by the R-NIR-SWIR1 reflectances (in radians)	Khanna et al. 2007	x	
Tasseled cap transformation: greenness (TCT-G)	$-0.29 \cdot B - 0.24 \cdot G - 0.54 \cdot R + 0.73 \cdot NIR + 0.07 \cdot SWIR1 + 0.16 \cdot SWIR2$	Baig et al. 2014	x	
Tasseled cap transformation: brightness (TCT-B)	$0.30 \cdot B + 0.28 \cdot G + 0.47 \cdot R + 0.56 \cdot NIR + 0.51 \cdot SWIR1 + 0.19 \cdot SWIR2$	Baig et al. 2014	x	
Tasseled cap transformation: wetness (TCT-W)	$0.15 \cdot B + 0.2 \cdot G + 0.33 \cdot R + 0.34 \cdot NIR - 0.71 \cdot SWIR1 - 0.46 \cdot SWIR2$	Baig et al. 2014	x	
Vegetation				
Height of the vegetation at the central point of the quadrant (Height_Veg_C)				
Average height of the vegetation at nine points of the quadrant (Height_Veg)				
Shrub cover (Cov_Shr)				
Herbaceous plant cover (Cov_Her)				
Distance				
Distance to the fence (Dis_Fen)				
Distance to the road (Dis_Rod)				
Distance to the main patch of forest to the west of the peatland (Dis_P_For)				
Distance to the forest including the small patches on the border of the peatland (Dis_For)				

average %IncMSE were chosen among these 1000 iterations.

Once this subset was obtained, a best subset regression (BSR) model was applied (Goodenough et al. 2012), transforming the response variable to its natural logarithm to fulfill the linear model assumptions. Thus, all the possible regressions were evaluated, choosing through the adjusted coefficient of determination (R^2 adj) the best fit with the lowest number of predictors. To obtain robust models and avoid the over-fitting caused by collinear predictors, multicollinearity was evaluated using the variance inflation factor (VIF), ensuring that no predictor had a VIF >10 and that the average of these values was not significantly > 1 (Chatterjee et al. 2000). To verify the assumptions of the method, the Shapiro-Wilk test was used (Shapiro and Wilk 1965) on the residuals of the regression and a Moran test was used to verify there was no spatial autocorrelation from these residuals (Cliff and Ord 1972). In the cases where the model did not fulfill some of the assumptions (particularly the multicollinearity), a model with a smaller number of variables was selected, always being fit to the alternatives suggested by the BSR method.

Once the final model was obtained, the variable was retransformed using the Smearing estimator (Duan 1983) to avoid retransformation bias. With the values predicted on the original scale, the R^2 was calculated, the root mean square error (RMSE) and relative root mean square error (RRMSE), dividing the RMSE by the mean of the observations. Additionally, a leave-one-out cross-validation (LOOCV) procedure was performed to obtain R^2 and RMSE values and evaluate the models.

To choose the best models to predict the C reservoirs, the Akaike's information criterion (AIC) and the Bayesian information criterion (BIC) were calculated (Posada and Buckley 2004); but both indices gave similar results, which is why only the AIC appears. All the statistical analyses were carried out with the R 3.1.2 software (R Core Team 2014), with a level of significance of 0.05.
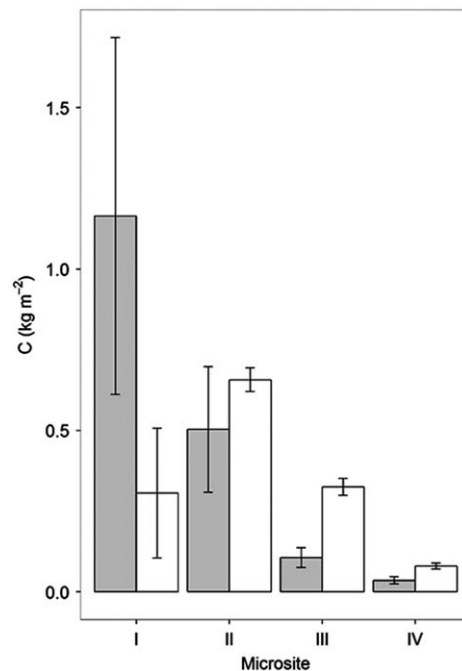

Fig. 3. Characteristics of the four microsites in terms of the carbon content of shrubs (gray) and herbaceous plants (white).

RESULTS

Characteristics and distribution of microsites

The results of multiple iterations of data grouping indicated that the appropriate number of microsite groups was four, since from this point the sum of squares tends to stabilize. The procedure using a number of clusters equal to five left a sampling unit separate from the rest due to its high shrub and herbaceous biomass, which is why it was considered an outlier. To perform the proposed statistical analyses and reduce the number of microsites, this sampling unit (fifth microsite) was included in the cluster of higher similarity, which in this case were microsites of cluster I, characterized as having a high C stock in shrubs compared to the C in herbaceous plants (Fig. 3). Microsites grouped in cluster II have a high C content from shrubs and herbaceous plants, whereas microsites in cluster III have a lower total C content, with a large proportion from herbaceous biomass. Microsites in cluster IV have a low amount of C in both shrub and herbaceous plants components (Fig. 3).
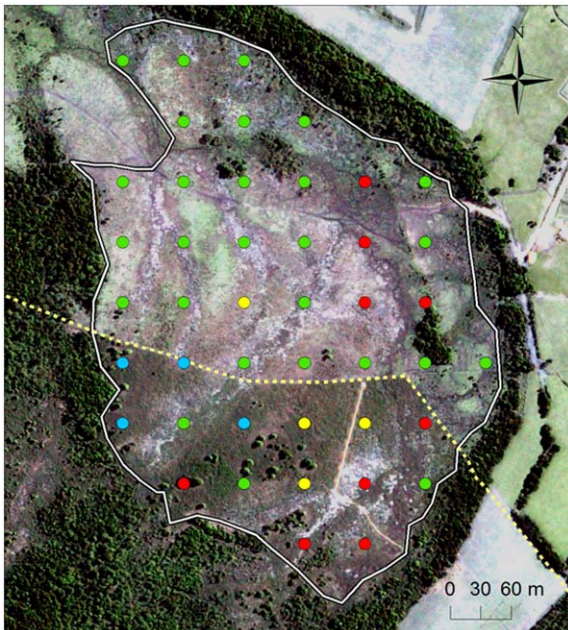
Fig. 4. Spatial location of the four clusters of microsites, defined on the basis of carbon in shrubs and herbaceous plants. Microsites of cluster I are represented in yellow, II in blue, III in red and IV in green.

As illustrated in Fig. 4, the distribution of the microsites is spatially continuous in most cases. Microsites of clusters I and II have a high shrub biomass and are located mainly in the conservation area (within the SDBS). Microsites of cluster III are cross-sectional to the peatland use and are located mainly on the permanently waterlogged areas. Finally microsites of cluster IV, with low shrub and herbaceous biomass, are located mainly on the productive management site (Fig. 5).

Flora and vegetation structure

A total of 46 vascular plants were identified at species level and two at genus level (they were not used in the analysis of exotic species and had a very low abundance). The complete listing of species appears in Appendix: Table A1, including growth habits, families and origin. Of all the species identified at species level (46), 34 (73.91%) are native species, of which only two (4.35%), *Juncus acuminatus* and *Polypogon linearis* are endemic to Chilean territory, whereas 12 (26.09%) are exotic species. Considering all the

species found (48), the analysis of the growth habits shows that 32 (66.67%) are herbaceous, 10 are shrub (20.83%) and six are tree species (12.5%). The latter grow isolated in the peatland.

The most frequent families within the peatland are the *Cyperaceae* family (seven species), *Asteraceae* (six species), *Juncaceae* (four species) and *Poaceae* (four species). The herbaceous species with the greatest cover is the fern *Sticherus cryptocarpus* with 15.64% of mean cover, even considering that this species was recorded in only 64% of the quadrants, followed by *Juncus procerus* with 7.68% of cover and frequency of 39%. This indicates a localized presence of these two species that generates the highest mean covers. In addition, the most frequent species were *Myrteola nummularia* and *Gaultheria mucronata,* with 91% and 89%, respectively.

The most remarkable dominances were observed on microsites of clusters I and II, characterized by a high cover of *S. cryptocarpus* and *Baccharis patagonica* (Table 3) on both microsites. Microsites of cluster III, permanently waterlogged, are dominated by *J. procerus,* a species found in wet environments. Microsites of cluster IV, are mainly found on the productive management site and have a high cover of low-statured herbaceous species with no marked dominance, creating an ecosystem similar to a pasture.

With respect to the vegetation variables (Table 4), significant differences were noted in the height ($P < 0.0001$), which is considerably lower at cluster IV microsites, since it is dominated by low-growing herbaceous plants. The plant richness ($P = 0.0453$) and percentage of exotic plants were the greatest at cluster IV, however, the results were not significant in the latter case ($P = 0.0689$). This condition produces a higher Shannon index at this microsite ($P = 0.0238$) due to the greater richness and evenness in the cover.

With respect to the species that dominate each type of land management (Table 4), it is worth noting that peatland conservation has fostered the establishment of the herbaceous (fern) species *S. cryptocarpus* and shrub species *B. patagonica,* which is consistent with what is observed at microsites of clusters I and II. However, the managed area has no clear dominance, with *J. procerus* being the species with the greatest cover, which is in line with the presence and cross-
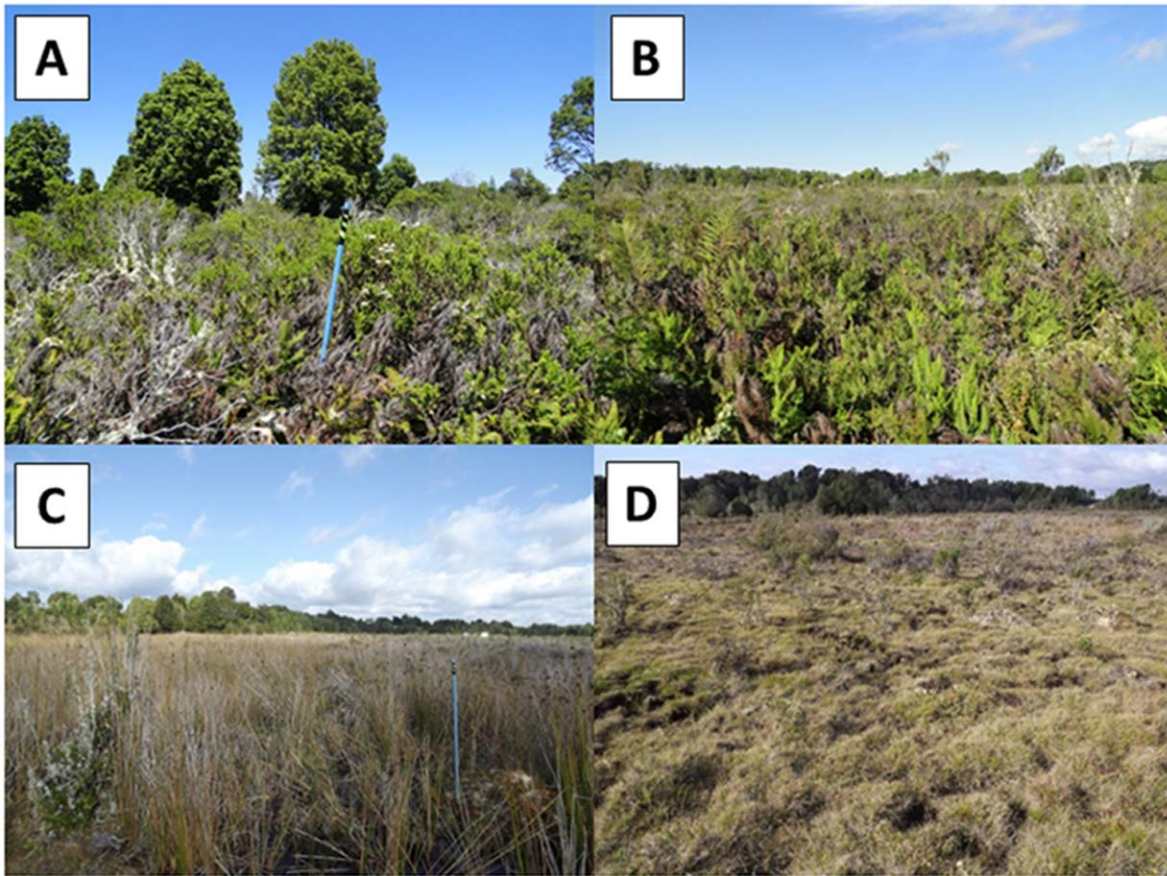
Fig. 5. Photos of the microsites defined on the basis of carbon in shrubs and herbaceous plants. Microsites I (A) and II (B) show high dominance of *S. Cryptocarpus* and *B. patagonica*. Microsite III (C) is dominated by *J. procerus* in response to waterlogging. Microsite IV (D) is dominated by low-growing herbaceous plants. Table 4 provides the percentage of cover of the dominant species in each microsite.

Table 3. Dominant species and vegetation variables by microsite (mean $\pm$ SE).

	Microsite				Kruskal-Wallis	
Dominant species	I	II	III	IV	χ^2	P
Species 1	*S. cryptocarpus* (37.5)	*S. cryptocarpus* (60)	*J. procerus* (27.8)	*Juncus stipulates* (7.3)		
Species 2	*B. patagonica* (21.3)	*B. patagonica* (20)	*S. cryptocarpus* (13.4)	*G. mucronata* (7.4)		
Species 3	*G. mucronata* (10.3)	*Schoenus rhynchosporoides* (13.8)	*Blechnum cordatum* (8.7)	*Danthonia chilensis* (6.6)		
Variables						
Total cover (%)	80.00 $\pm$ 9.79[ab]	96.25 $\pm$ 3.75[a]	77.22 $\pm$ 5.53[ab]	63.52 $\pm$ 4.11[b]	11.45	0.0095
Shrub cover (%)	31.25 $\pm$ 4.27[a]	22.50 $\pm$ 5.20[ab]	12.22 $\pm$ 5.41[ab]	10.37 $\pm$ 2.01[b]	9.81	0.0203
Herbaceous cover (%)	48.75 $\pm$ 13.29	73.75 $\pm$ 5.91	65.00 $\pm$ 8.70	52.96 $\pm$ 3.79	6.78	0.0794
Height of vegetation (cm)	45.83 $\pm$ 18.39[ab]	73.82 $\pm$ 15.04[a]	59.51 $\pm$ 14.38[a]	11.82 $\pm$ 1.66[b]	22.76	<0.0001
Plant richness	8.00 $\pm$ 1.08[ab]	6.25 $\pm$ 0.48[a]	8.88 $\pm$ 0.79[ab]	10.44 $\pm$ 0.64[b]	8.04	0.0453
Percentage of exotic plants	2.27 $\pm$ 2.27	0	1.00 $\pm$ 0.44	13.53 $\pm$ 2.59	7.1	0.0689
Exotic plant cover (%)	0	0	9.42 $\pm$ 3.83	2.96 $\pm$ 1.37	2.32	0.5081
Shannon index	1.48 $\pm$ 0.19[ab]	1.16 $\pm$ 0.13[a]	1.67 $\pm$ 1.67[ab]	1.65 $\pm$ 0.05[b]	9.46	0.0238

Notes: Average cover of dominant species in parentheses. Same superscripted letters indicate no significant differences.

Table 4. Dominant species and vegetation variables by management type (mean ± SE).

Dominant species	Management		Wilcoxon	
	Conservation	Productive	W	P
Species 1	*S. cryptocarpus* (40.63)	*J. procerus* (7.79)		
Species 2	*B. patagonica* (11.94)	*Uncinia tenuis* (7.18)		
Species 3	*J. procerus* (7.50)	*G. mucronata* (6.82)		
Variable				
Total cover (%)	87.00 ± 3.30	62.41 ± 3.82	368	0.0002
Shrub cover (%)	19.00 ± 3.39	11.03 ± 2.31	303.5	0.0315
Herbaceous cover (%)	67.67 ± 4.19	51.38 ± 4.17	313.5	0.0175
Height of vegetation (cm)	64.68 ± 9.65	12.52 ± 1.78	418	<0.0001
Richness (number of species)	6.93 ± 0.33	10.86 ± 0.56	59.5	0.0001
Richness exotic plants	0.07 ± 0.07	1.93 ± 0.32	59.5	<0.0001
Percentage exotic plants	0.67 ± 0.67	15.49 ± 2.37	60.5	<0.0001
Cover of exotic plants (%)	1.00 ± 1.00	2.76 ± 1.28	188	0.2594
Shannon index	1.33 ± 0.07	1.67 ± 0.05	62	<0.0001

Note: Average cover of dominant species in parentheses.

sectional location of microsites of cluster III, dominated by this species, which has similar cover (approximately 7%) in the conservation area.

More differences were observed between land management than between microsites, with the height of the vegetation being significantly lower in the productive management zone ($P < 0.0001$). Also, the total richness in the productive management area was higher ($P = 0.0001$), which coincided with a higher number and proportion of exotic species ($P < 0.0001$). Furthermore, the difference between land management on the Shannon index was significant, with the greatest value being in the productive management area, which indicates there was no remarkable domi-

nance by any one species in this area (Table 4).

Carbon stocks

In terms of belowground C, the R3 layer was the densest (0.11 ± 0.01 g cm^{-3}) and the thickest (28.95 ± 1.25 cm; Fig. 6). The C fractions from vegetation showed values around 50%, whereas the layers of peat varied between 35% and 47% (Table 5). The largest amount of C was in the R3 layer (9.83 ± 0.95 kg C m^{-2}), which represents 82% of the total content at ecosystem level (Table 5). This important reservoir is followed by the other less humified components from the soil (R1, R2; Table 5).

As shown in Table 6, the greatest difference between microsite clusters is noted in the C
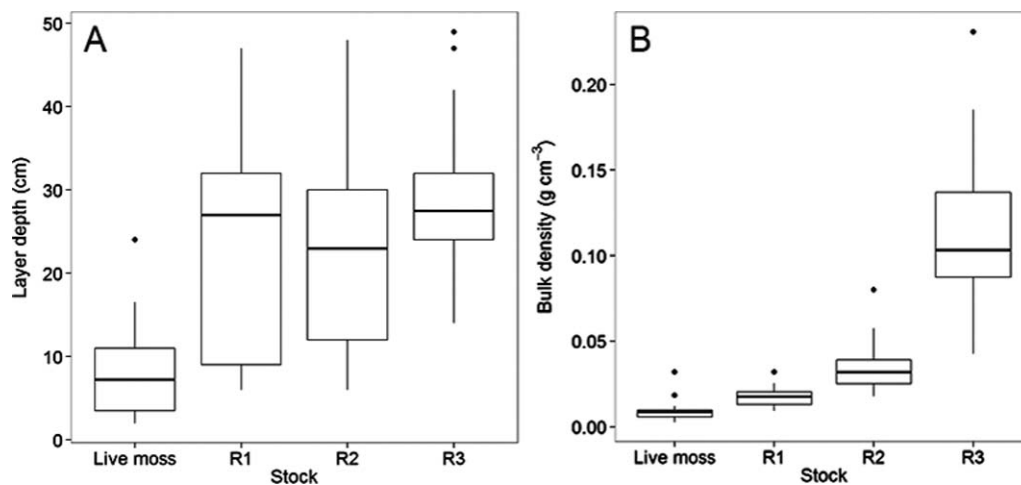

Fig. 6. Thickness of the belowground layers (A) and density (B) by carbon stock.

Table 5. Percentage of carbon by component (mean ± SE), carbon content by component (mean ± SE) and percentage of the total.

Component	Carbon fraction (%)	Reservoir (kg C m^{-2})	Contribution (%)
Shrub	51.22 ± 0.32	0.20 ± 0.07	1.63
Herbaceous	48.87 ± 0.27	0.20 ± 0.03	1.69
Fine debris	49.04 ± 1.07	0.12 ± 0.04	0.96
Coarse woody debris	52.24 ± 0.24	0.04 ± 0.04	0.37
Moss	50.85 ± 2.52	0.11 ± 0.03	0.91
R1	47.50 ± 0.55	0.41 ± 0.16	3.41
R2	41.30 ± 1.83	0.93 ± 0.27	7.75
R3	35.28 ± 2.00	9.83 ± 0.95	82.03
Tree	52.99 ± 0.43	0.03 ± 0.03	0.28
Trunks	51.98 ± 0.40	0.12 ± 0.08	0.96
Total		11.99 ± 0.77	100.0

content stored in the herbaceous vascular plants and shrubs, which is explained by their composition (i.e., microsites of clusters I and II were the sectors with the tallest vegetation and with the presence of shrub species of greatest biomass such as *B. patagonica*). The total C also showed significant differences ($P = 0.0309$), with microsites of clusters I and II having the highest C content. The soil-related reservoirs showed no significant differences between clusters, except in the fine woody debris, which was not found on microsites of cluster IV, and the coarse woody debris which was found only at microsites of cluster II.

Table 7 shows no significant difference in total C between land management which is caused by the similarity of the R1, R2, and R3 stocks. Yet the stocks from herbaceous plants and shrubs were significantly greater in the conservation management area.

Modeling of carbon stocks

Given that no spatial autocorrelation was found in the underground C (Moran I $= -0.05$; $P = 0.6818$) nor in the variable soil depth (Moran I $= 0.004$; $P = 0.3311$), an interpolation of the underground C could not be employed using ordinary kriging.

The aboveground C showed a non-normal distribution, with the data concentrated on values near zero due to the managed surface (less biomass); therefore, the mean was low (0.40 kg C m^{-2}). The variable also had a high variability (coefficient of variation [CV] = 157%) that responds to samplings in the shrubland area (microsites I and II) in contrast to the data in the productive management area. This variability is increased by a piece of data that could be considered anomalous (3.65 kg C m^{-2}), which corresponds to a sampling point where the biomass of a shrub was harvested almost in its entirety. There is less variability when the data set is divided between management (CV = 94%)

Table 6. Carbon reservoirs (kg C m^{-2}; mean ± SE) by microsite.

| Reservoir | Microsite | | | | Kruskal-Wallis | |
	I	II	III	IV	χ^2	P
Total	14.65 ± 0.74[a]	16.50 ± 3.21[ab]	9.29 ± 1.07[b]	11.75 ± 1.02[ab]	8.88	0.0309
Total aboveground	1.47 ± 0.74[a]	1.16 ± 0.22[a]	0.43 ± 0.05[a]	0.12 ± 0.02[b]	30.83	<0.0001
Shrubs	1.64 ± 0.55[a]	0.50 ± 0.19[a]	0.11 ± 0.03[ab]	0.04 ± 0.01[b]	22.1	0.0001
Herbaceous	0.31 ± 0.20[ab]	0.66 ± 0.04[a]	0.32 ± 0.03[a]	0.08 ± 0.01[b]	27.64	<0.0001
Total underground	13.18 ± 1.18	15.34 ± 3.23	8.71 ± 1.01	11.44 ± 1.02	6.68	0.0827
Moss	0.13 ± 0.13	0	0.06 ± 0.04	0.14 ± 0.05	2.17	0.5369
R1	0.12 ± 0.12	0	0.04 ± 0.04	0.63 ± 0.24	2.38	0.4970
R2	0.40 ± 0.40	0	1.78 ± 0.96	0.86 ± 0.29	2.19	0.5339
R3	12.46 ± 0.96	14.99 ± 6.46	6.45 ± 5.13	9.81 ± 6.53	7.18	0.0665
Fine debris	0.07 ± 0.07[ab]	0.35 ± 0.12[a]	0.37 ± 0.18[a]	0[b]	18.37	0.0004
Coarse debris	0[a]	0.49 ± 0.37[b]	0.00 ± 0.00[a]	0[a]	20.47	0.0001

Note: Same superscripted letters indicate no significant differences.

Table 7. Carbon reservoirs (kg C m^{-2}; mean ± SE) by management.

| | Management | | Wilcoxon | |
Reservoir	Conservation	Productive	W	P
Total	13.00 ± 1.38	11.46 ± 0.93	261	0.2907
Total aboveground	0.86 ± 0.23	0.16 ± 0.03	397	<0.0001
Shrubs	0.47 ± 0.18	0.05 ± 0.02	374	<0.0001
Herbaceous	0.39 ± 0.07	0.11 ± 0.02	386	<0.0001
Total underground	11.92 ± 1.34	11.12 ± 0.93	245	0.5082
Moss	0.14 ± 0.06	0.09 ± 0.04	234	0.6317
R1	0.26 ± 0.15	0.49 ± 0.22	230	0.6734
R2	0.86 ± 0.41	0.97 ± 0.36	223	0.8780
R3	10.39 ± 1.66	9.55 ± 1.17	240	0.5852
Fine debris	0.27 ± 0.10	0.03 ± 0.03	310	0.0007
Coarse debris	0.13 ± 0.10	0.00 ± 0.00	247	0.0506

and conservation (CV = 104%), but it continues to be high nevertheless.

The selection of predictors to model the aboveground C resulted in many cases in an optimal number of variables of eight and nine. However, in these cases the predictors were highly correlated (high values of VIF). Therefore, the final models were obtained with a maximum of four variables, fulfilling the assumptions mentioned in the Methods section in every case. Table 8 shows the final prediction models using all the subsets of data and predictor variables.

In the case of the SV-TD model, which is the best fit model of those constructed using only spectral variables (Table 8), what stands out is the appearance of normalized differences that do not correspond to traditional indices, such as the difference between the red and blue bands (R-B-ND), the enhanced vegetation index (EVI) and the normalized difference between the red band and the short-wave infrared band (SWIR1-R-ND). When the land variables were added as predictors, the R^2 value increased from 0.51 to 0.62 for the model that includes the entire peatland.

Table 8. Statistical parameters of the aboveground carbon models.

| | | | | | | | | LOOCV | |
Model and equation	P	RMSE	RRMSE (%)	R^2	R^2 adj	AIC	RMSE	R^2
SV-TD								
17.19 − 28.02 R-B-ND (30m) − 17.4 EVI (15m) − 14.36 SWIR1-R-ND (30m)	0.0001	0.43	109	0.51	0.47	125.83	0.50	0.35
SV-PM								
2.8 + 3.83 MSR (SD; 15m) − 68.96 NIR-B-ND (SD; 15m) − 64.48 NIR (SD) (30m) − 8.43 R-B-ND (2m)	0.0214	0.11	72	0.40	0.30	71.90	0.13	0.24
SV-CM								
15.02 − 23.17 NIR-B-ND (15m) + 7.65 SWIR2-R-ND (15m)	0.0215	0.74	86	0.28	0.15	36.23	0.87	0.00
AV-TD								
5.32 + 0.016 Height_Veg_C − 12.67 R-B-ND (30m) − 5.63 TCT-G (15m) − 5.31 SWIR1-R-ND (30m)	<0.0001	0.38	95	0.62	0.61	106.30	0.50	0.34
AV-PM								
−2.91 + 0.026 Height_Veg_C + 0.029 Cob_Shr	0.0004	0.09	59	0.60	0.57	63.62	0.10	0.52
AV-CM								
−1.35 + 0.012 Height_Veg_C	0.0015	0.57	66	0.57	0.54	31.72	0.76	0.23

Notes: SV, spectral variables; AV, all the variables; TD, the entire peatland ($n = 44$ plots); PM, productive management area ($n = 29$ plots); CM, conservation management area ($n = 15$ plots). The equations represent the modeling of Ln (aboveground carbon). The meaning of the variables included in the models are in Table 2.

Table 9. Total carbon stock (mean ± SE) in peatlands.

Study	Location	Total stock (kg C m^{-2})
Loisel and Yu (2013)	Patagonia. Chile and Argentina	168 †
Weishampel et al. (2009)	Minnesota, USA	151.8 ± 9.8
Weishampel et al. (2009)	Minnesota, USA	122.1 ± 1.3
Beilman et al. (2008)	Mackenzie River Basin, Canada	118 ± 0.23
Buffam et al. (2010)	Wisconsin, USA	104 ± 19
Weishampel et al. (2009)	Minnesota, USA	71.8 †
Valdés (2012)	Magallanes, Chile	24.7 ± 1.3
Weissert and Disney (2013)	Isle of Man, UK	22.4 ± 1.32‡
Weissert and Disney (2013)	Isle of Man, UK	14.7 ± 1.18‡
Weissert and Disney (2013)	Isle of Man, UK	13.4 ± 1.06‡
This study	Chiloé, Chile	11.99 ± 0.77
Weissert and Disney (2013)	Isle of Man, UK	7.8 ± 0.54‡

   † Neither SE nor SD was reported.
   ‡ Mean ± SD where SE could not be calculated.

DISCUSSION

Effects of management on vegetation

The high number of plant species found (46) contrasts to the report by Díaz et al. (2008), who identified a total of 18 vascular species in the SDBS peatland. This difference may be because we sampled over a greater area, including also the neighboring site, which has a productive use.

The high frequency of species from the families *Cyperaceae* and *Juncaceae* is consistent with their habit of growing in humid environments (Ulrich and Freiburg 2005). At species level, the high frequency of *M. nummularia* is in line with what was reported by Díaz et al. (2008), who indicated that it may be the most prolific species in the peatlands on Chiloé Island. The dominance and height of *S. cryptocarpus* and *B. patagonica* at microsites I and II (within the conservation area) could indicate a more advanced successional state (Díaz and Armesto 2007). Nevertheless, according to what was described by Díaz et al. (2007) and Díaz and Armesto (2007) in the conservation management area (SDBS), the establishment of dense shrub covers could be restraining succession, when there is an almost null regeneration of tree species on these surfaces. This may occur due to shrubland intercepting less precipitation than the forest, which causes a shallower water table than the forest, limiting the establishment of trees. However, microsite II is unique in that it contains coarse woody debris, a detail that may be important because the presence of woody debris facilitates the regeneration of tree species (Papic 2000). It may be inferred that microsites of cluster IV have more successional constraints mainly due to the reduced interception of precipitation (lower-growing vegetation) and the absence of woody debris.

The lower-growing vegetation in the managed sector is consistent with what was observed by Bardgett et al. (1995) on the moorlands in the United Kingdom, where continuous overgrazing transformed a landscape dominated by shrubs and short herbaceous plants. In our case, this situation is accompanied by an increased presence of exotic plants, which despite not showing significant differences in terms of their cover, show clear differences in terms of the percentage of total richness. This suggests that productive management activities are increasing the number of exotic species, which could increase in cover in the future, since grazing not only aids in the establishment of these plants, but also in their propagation (Vavra et al. 2007).

Carbon stocks and effects of management

Our results confirm that the most important C stock in this type of ecosystem is the soil (Gore 1983). The total reservoirs from vascular plants did not exceed 4%; nevertheless, they were found in 100% of the sampled points. This ecosystem has a low total C stock (12 kg m^{-2}), comparable only with the case studies by Weissert and Disney (2013) in the United Kingdom, where the study ecosystem was a natural peatland, but with low depth, intensive use and high degradation (Table 9). Valdés (2012) studied a natural peatland of *S. magellanicum* in the Magallanes region in Chile, obtaining results that duplicate the C stock found in this anthropogenic peatland.

On the other hand, the Patagonian peatlands studied by Loisel and Yu (2013) have an average of 168 kg C m^{-2}, an amount that widely exceeds the values obtained here. Likewise, C stocks from peatlands in the Northern Hemisphere widely exceed (in some cases more than 10-fold) the amount found in the anthropogenic peatland in this study (Table 9).

The soil profile densities observed are lower than those found in the literature referring to natural peatlands (Domenico and Delicato 1996, Raviv et al. 2002). The values found in this investigation (0.01–0.11 g cm^{-3}), however, agree with those of León and Oliván (2014), who reported densities between 0.01 and 0.065 g cm^{-3} in the same study area. These low values may be due to the recent formation of the ecosystem. It should be noted that certain components, like the moss and the R1 layer, were only found at some sampling points. With respect to the C fraction of each component, the percentage obtained in the components associated with the vegetation is consistent with the 50% indicated by the IPCC (1996). In the case of the components from the peat, it occurred that as the wetness increased, the C percentage decreased, falling to an average of 35.2% of C in the R3 layer, which contrasts with 52% of C used by Gorham (1991) in peatlands in the Northern Hemisphere. Our result is similar to that reported by León and Oliván (39.6% ± 7.23%; 2014). The authors explained this difference in the C content by saying that minerotrophic peatlands have a lower C content than ombrotrophic ones and the peatland studied here had transitional characteristics between the two states, unlike other peatlands on Chiloé Island, which are clearly ombrotrophic and with a C content in the order of 50%.

When comparing the C content at the different microsite clusters, the greatest differences were found in the vegetation components. The only microsites revealing differences in the total C stock between groups were clusters I and III, which is explained by a lower C content in the R3 layer of microsites of cluster III, which showed marginally significant differences. This may be due to flooding, which encourages dissolved C transport (Mulholland 2003).

The lower C accumulation in herbaceous plants and shrubs in the productive management area is consistent with other studies that show a reduction in shrub vegetation due to the introduction of livestock (Bardgett et al. 1995, Critchley et al. 2008) and that moss harvesting could halt the establishment of shrub species (Whinam et al. 2003). Other important variables were the fine woody debris, which showed significant differences, and the coarse woody debris, which showed marginally significant differences, implying that these two reservoirs are possibly being accumulated at a lower rate in the productive management area. The process being carried out in this ecosystem is similar to that described by Shang et al. (2013), in which alpine wetlands are being turned into pastures due to anthropic disturbances, changing their vegetation and thus their capacity to store C, and even causing significant losses of other elements in the soil such as nitrogen and phosphorus.

According to on-site observations, the livestock avoid grazing in wet areas like microsite III or lands dominated by *Sphagnum* moss. Yet when the water table is deep due to the absence of precipitation, the livestock tend to advance towards dry lands, increasing the area of degradation. If we project a scenario of lower precipitation in this area, this could have a strong negative impact on these ecosystems.

The stocks most directly related to *Sphagnum* moss (moss and R1) showed no significant differences, which is why the direct impact of the harvest is not clear. This may be due to *Sphagnum* not covering the entire peatland, with dominant moss cover on only 20% of the sampling points. Moreover, moss harvesting in the study area is not very abundant; therefore, it can be inferred that a large part of the impact is due to grazing.

Spatial prediction of the aboveground carbon stock

Kriging interpolation visually reproduced the C distribution in the peatland, but with a very low level of adjustment. This may be due to this method generally being used for natural peatlands (Djurhuus et al. 2005), where the depth variation and topographic factors are highly relevant when modeling the C or the peat thickness (Parry et al. 2012). In the case of this anthropogenic peatland, the land on which it is formed is relatively flat and the peat depth does not exceed 1 m; therefore, the microtopography

could play a very important role in this reservoir.

The selected spectral variables in the models generally corresponded to feature extraction indexes instead of classic vegetational (photosynthetic) indices like the normalized difference vegetation index (NDVI), which saturates in dense covers, as is the case with this type of ecosystem (Huete et al. 2002). The spectral variables selected to model the aboveground C throughout the peatland (SV-TD model) corresponded to uncommon indices like the normalized difference between the red and blue band (R-B-ND), which could be explained by several reasons. The study by Hansen and Schjoerring (2003) reported good correlations of this index with the chlorophyll concentration in wheat plants. For their part, Shimada et al. (2012) found that a similar index (normalized difference between the blue region and the yellow-red region) was related to water stress in *Hibiscus rosa-sinensis* in controlled conditions, which in our case could be related to the different water conditions of the different microsites. Another index selected in this model of greater application for vegetation monitoring is the EVI, which is related to photosynthetic activity (Huete et al. 2002), which includes factors to correct the influences of aerosols and soil. The third index in the equation was the normalized difference between the red band (R) and band 1 of the short-wave infrared (SWIR1), which can represent higher *Sphagnum* sp. moss covers. These have lower reflectance in the short-wave infrared due to their increased water content, which may be absorbing much of the energy from the sun, particularly in those wavelengths (Bubier et al. 1997). The presence of this genus of plants in the peatland generally coincides with a smaller biomass of vascular plants.

By contrast, the SV-PM model includes three variables of pixel standard deviation (Table 8), which may be due to the high variability of the productive management area, since livestock tend to avoid the flooded areas that are related to patches of vegetation with a high biomass (like microsite III), surrounded by a degraded pasture with a low biomass (microsite IV). These results are consistent with those of Lu (2005) and Kelsey and Neff (2014) in wooded ecosystems, who report that the texture of the pixels is closely related to the aboveground biomass, or in this case to the C stock.

Another characteristic of the variables selected by the algorithm is the almost complete absence of variables derived from the Pleiades 1B satellite (only the R-B-ND variable in the SV-CM model). One of the possible causes is the lower spectral resolution of the satellite (four bands vs. eight bands of OLI), especially considering that the biomass estimation often uses variables derived from the SWIR (Lu 2006), which the Pleiades satellite does not have. Another possible reason is the problem of the high spatial variation, saturation and shadows produced by the objects present in the ecosystem (Lu 2006), which in the Landsat case is attenuated by larger pixels (15–30 m), because of the mixing effect. The different methods associated with remote sensing are conditioned by the cost of implementation given the effects in the processing times, storage, imaging costs, among others, which limits or encourages their use (Lewis et al. 2013). The results indicate that for the estimation of aboveground C in these anthropogenic peatlands, the use of high-resolution spatial images is not necessary, as these are generally associated with higher costs and prevent their use on larger scales (Lu 2006). Nevertheless, before ruling out the use of higher resolution spatial sensors, some with greater spectral resolution should be tried, such as Worldview-2 (Mutanga et al. 2012) or hyperspectral sensors.

The models that included all the predictor variables showed a slight improvement in their fit (R^2), comparing them to those that only used spectral variables. In addition, a decrease in these parameters is noted when compared to the AIC of the models constructed with the same observations (Table 8). Since the land variables were measured as points, their spatialization requires interpolations that may increase the error. However, it should be emphasized that the land variable that repeats the most, the height of the vegetation in the center of the quadrant, is easy to measure, and thus it is easier to make observations on a denser grid without higher implementation costs. In the AV-PM model the variable cover of shrubs also appears (Table 8), since in this area the greatest biomass is the sporadic presence of specimens of *B. patagonica* and *G. mucronata*.

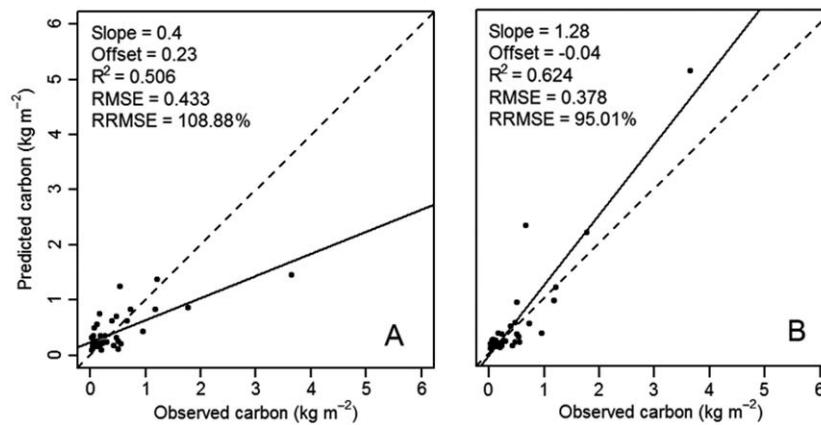Even so, the results indicate that the SV-TD

Fig. 7. Values of aboveground carbon predicted vs. observed for the models SV-TD (A) and AV-TD (B).

model has a significant fit comparable to what has been reported by other studies based on remote sensing ($R^2 = 0.51$). Fig. 7 shows that the C is overestimated in low values and underestimated in high values, a problem improved in the AV-TD model, which also has a better fit and a lower RMSE.

The adjustments reported in this study (Table 8) are generally lower than those obtained by Mutanga et al. (2012), who created predictive models of the aboveground biomass of a wetland in the eastern part of South Africa using Random Forest (RF) model with fits between $R^2 = 0.39$ and 0.79. Also, Güneralp et al. (2014) reported fits that varied between $R^2 = 0.66$–0.96 using Landsat and SPOT images and a model using multivariate adaptive regression splines (MARS), stochastic gradient boosting (SGB) and Cubist to estimate biomass on the flood plains of the Lower Trinity River (Texas, USA). The results of the present study are comparable to those obtained by Byrd et al. (2014) in the marshes of the delta of the Sacramento and San Joaquin rivers (California, USA), where fits were obtained between $R^2 = 0.56$ using Landsat 7 multi-temporal images and $R^2 = 0.45$ using World-view-2 images (in both cases using partial least square regression [PLS] to perform the modeling).

These studies generally used non-parametric regression methods (like RF or MARS) or those of medium complexity like PLS, which can guarantee a better fit but increase the difficulty in the model construction and application (Sohl

and Claggett 2013). In our case RF was used for an exploratory analysis of the variables and then predictive models were generated through a widely known and easily applied technique like linear regression, which facilitates its use by decision-makers. In addition, the interpretation of the linear regression models is simpler and more intuitive as it is based on widely known statistical assumptions.

As can be seen in the prediction of aboveground C using the SV-TD model (Fig. 8), the higher value is observed in the conservation area due to greater shrub cover, which corresponds to microsites I and II. On the other hand, the prediction for microsite IV clearly shows that the aboveground C in this microsite is low. Finally, a mean level of aboveground C can be seen in the area corresponding to microsite III on the eastern side of the peatland, an area that does not appear to be as affected by waterlogging as areas in microsite IV. The image indicates that the impact of livestock is not evenly distributed throughout the managed area, generating a drastic decrease in aboveground C and cover in some sectors, which could in turn affect productivity (Fig. 8).

The C prediction shows us that even though management is an important factor to consider, there are different conditions in the ecosystem that explain the variability of the C content. This model also shows that the classic spectral indices are not generally the most useful for characterizing this highly heterogeneous ecosystem. Despite it generally being recognized that the
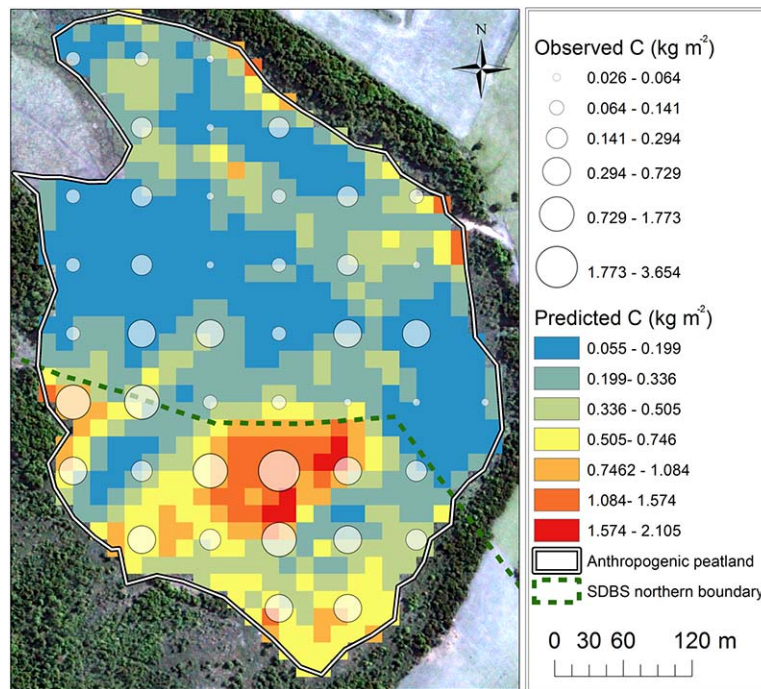
Fig. 8. Aboveground carbon content (kg m^{-2}) and its prediction using model SV-TD, reported in Table 8.

models constructed in an area or region cannot be applied elsewhere without discretion due to the many errors that can occur (Foody et al. 2003), information about the possible spectral indices to use is valuable for creating larger-scale models of C reservoirs for these new ecosystems of anthropogenic peatlands.

CONCLUSIONS

This is the first study to quantify C stocks in an anthropogenic peatland and the first in Chile to evaluate the effects of productive management. Significant differences were found between the structure and composition components, demonstrating that productive management changes the vegetation from one dominated by shrubs and moss to a low-growing pasture with the presence of exotic species. The impacts on C stocks are evident and significant only in the aboveground reservoirs. However, given that the larger C stocks (R3, R2 and R1) show no differences, the total C in the ecosystem was not significantly affected by 8 years of productive management.

The spatial modeling of the aboveground C revealed that it is possible to generate predictive models with a good fit using spectral variables. The spectral indices used in this study, together with the variables of vegetation and C stocks, constitute a proposal of indicators that could be applied when analyzing the scope of the impacts of management on other similar ecosystems.

Questions requiring further long-term study include characterization of the successional dynamics of this type of peatland, and investigations that approach the effects of *Sphagnum* moss extraction continuously in time and space. Also needed are studies that compare different animal loads and more intensive moss harvesting regimens (like those observed in nearby peatlands), specifically to determine the impact of each activity. Thus the foundations will be laid to establish future more sustainable regulations regarding this type of little known ecosystem.

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SUPPLEMENTAL MATERIAL

ECOLOGICAL ARCHIVES

The Appendix is available online: http://dx.doi.org/10.1890/ES15-00232.1.sm