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# Nitrogenous and Phosphorus Soil Contents in Tierra del Fuego Forests: Relationships with Soil Organic Carbon, Climate, Vegetation and Landscape Metrics

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**Abstract:** Soil nitrogen (SN) and soil phosphorus (SP) contents support several ecosystem services and define the forest type distribution at local scale in Southern Patagonia. The quantification of nutrients during forest surveys requires soil samplings and estimations that are costly and difficult to measure. For this, predictive models of soil nutrients are needed. The objective of this study was to quantify SN and SP contents (30 cm depth) using different modelling approaches based on climatic, topographic and vegetation variables. We used data from 728 stands of different forest types for linear regression models to map SN and SP. The fitted models captured the variability of forest types well ($R^2$-adj. 92–98% for SN and 70–87% for SP). The means were 9.3 ton ha$^{-1}$ for SN and 124.3 kg ha$^{-1}$ for SP. Overall, SN values were higher in the deciduous forests than those in the mixed evergreen, while SP was the highest in the *Nothofagus pumilio* forests. SN and SP are relevant metrics for many applications, connecting major issues, such as forest management and conservation. With these models, the quantification of SN and SP stocks across forests of different protection status (National Law 26,331/07) and national/provincial reserve networks is possible, contributing to the determination of nutrient contents at landscape level.

**Keywords:** soil nutrient contents; native forests; land use planning; vegetation productivity; forest structure; linear regression

## 1. Introduction

Soil functions (e.g., production of biomass, acting as a sink/source) are key for food production, climate regulation and adaptation, nutrient sequestration, water filtering and biodiversity conservation [1]. Consequently, soils are directly linked to some of the United Nations Sustainable Development Goals [2,3]. In this context, accurate and detailed spatial soil information at landscape level is essential for monitoring, land use planning and environmental modelling [4], which can be influenced by parent material, topography, climate, vegetation, time and anthropogenic activities [5]. The knowledge of spatial soil variation is necessary to define management and conservation proposals in the context of sustainable land use and climate change [6,7].

Soil organic carbon (SOC), soil nitrogen (SN) and soil phosphorus (SP) are essential nutrients for plant growth and play a major role in the nutrient cycle of forest ecosystems [3,8–10]. Nitrogen also contributes to greenhouse gases and global climate change in combination with carbon emissions [11]. Organic and inorganic soil phosphorus are important for plant growth [12], where a small portion of the phosphorus is soluble and available for plants [13]. Therefore, SP deficiency is one of the main limitations in many natural forests [14], being scarce in many agricultural and forest soils [12,15,16].

Soil mapping techniques mostly depend on ground-based surveys and rarely provide information about the spatial distribution at adequate resolution over the landscape [17]. Besides, mapping soil spatial variations by traditional field surveys is expensive and time-consuming at large scales [3,4]. The simplest approach to predict the spatial distribution of nutrient stocks is to allocate the average sampling values to each map unit of soil types [10,18,19]. However, this approach results in constant values within each map unit, reducing the spatial heterogeneity and increasing the error of estimations [20,21]. Therefore, it is necessary to have other robust methods to predict soil properties at different scales [22], such as digital soil mapping [7,17] or maps of spatial variations of nutrient stocks using environmental variables [4,20,23,24]. This last method can be useful in areas with low data availability, as in Patagonia [25,26]. These methods were designed to overcome the limitations of the conventional soil mapping approach and to estimate soil properties based on relationships between soils and environmental variables obtained from terrain attributes (e.g., digital elevation models) and satellite imagery [7,17,27]. Recent advances in the mapping of forest structure and functionality for large areas combine field-based measurements with data from passive and active satellite sensors, including radar [28–30], at a much lower cost than traditional field inventories [31–33]. Many of the described methods are largely used in estimating SN and SP [4,5,7,10,34–36]. In contrast to the advances in biomass and C stock estimations in the above-ground components of forests, soil components of other nutrients have largely been ignored. While SN and SP content has been characterized in local studies of Patagonian native forests [37–44], modelling of SN and SP at regional scale has rarely been attempted, e.g., in Santa Cruz province [42,45,46]. However, the current methods are unable to represent the land forest cover characteristics at a high accuracy. One alternative is to sort the landscape in more homogeneous units (e.g., different forest types) and then combine the different models into one (e.g., Martínez Pastur et al. [47] modelling the forest biodiversity for different forest types and then combining the outputs to obtain the regional map).

Soil fertility is a key factor for provisioning ecosystem service [42,48,49] and for supporting biodiversity in native forests [47]. Soil fertility influences the capacity of forests to produce timber and forage for both wild and domestic animals [50,51]. Forest management affects soil respiration, carbon mineralization, nitrogen cycling and the microbial community [52,53]. In this context, soil properties, including nutrient stocks, can be greatly affected by silviculture practices [54,55], depending on forest cover, past disturbances, climatic conditions and harvesting [56,57]. For this, the use of vegetation variables improves the estimation of nutrient stocks in impacted forests [42,45]. SN and SP are closely related to soil microbial communities and biomass, and their activity is related to the microenvironments (e.g., differences in soil moisture and temperature at a microscale) as well as to the quantity and quality of forest substrates [14,58,59].

Soil mineralization rates are primarily controlled by climate and soil properties [8], increasing with temperature [60] and rainfall [61,62]. However, soil microbial communities directly contribute to nutrient mineralization and availability [63]. A comprehensive understanding of the relative importance of these factors and their impacting pathways on nutrient changes is lacking in the context of climate change [62]. The latest research on soil nutrient dynamics suggest that changes in soil microbial biomass under global change would result in profound consequences on the main ecosystem processes [62,64]. Understanding these soil patterns at landscape level under global change is important for modelling the biogeochemical cycle and its feedback to climate [65]. Besides, SN and SP are not considered in the design of the protection networks. Argentina has a strong protected area network that covers nearly 12% of the land area but does not equally protect all the native forest ecosystem types [66]. Most native forests are privately owned, and regulations are needed to assure forest conservation [67]. Zoning is one of the instruments used by the Argentinian government to regulate human activities in native forests, and the provinces are obligated to define land use zones every five years, e.g., Ordenamiento Territorial de los Bosques Nativos/Land Use Planning of Native Forests (OTBN) defined by the National Law 26,331/07 [68,69].

In this context, the accurate quantification of SN and SP stocks is important for assessing the source/sink capacity of soils and to quantify the change rate of soils [21]. Spatially explicit information of soil nutrients thus plays a crucial role in global cycling studies and climate change effects [10,18,24,62,64]. In addition, nutrient mapping is of great significance for identifying the spatial characteristics and influencing factors to provide a reference for agricultural management and ecological conservation [36]. Additionally, continuous distributions of soil nutrient contents are important for understanding the role of the different nutrients (e.g., SOC, SN and SP) in the nutrient cycles at landscape level [3,10,20,70]. The objective of this study was to model SN and SP contents (0–30 cm depth) in Tierra del Fuego forests (Argentina) using two modelling approaches (global forest cover vs. individual forest types) based on climatic, topographic and vegetation variables. We hypothesized that (i) SN and SP estimations at landscape scale based on forests vary with climate, topography and vegetation, and therefore, it is possible to model them as a function of the variability of these characteristics; and (ii) the obtained models are more accurate when they are developed for individual forest types than when they are developed without considering the dominant forest species cover. We specifically aim to (i) compare the different model approaches performance for each forest type; (ii) quantify the SN and SP contents by forest type, protection status (National Law 26,331/07) and national and provincial reserve networks and compare them with the SOC; and (iii) determine potential relationships among the nutrient contents with topography and regional climate variables.

## 2. Materials and Methods

We analyzed the native forests (7292.4 $km^2$) of Tierra del Fuego province (21,263 $km^2$) located between 52.6° and 55.1° SL and 63.8° and 68.6° WL (Figure 1). The forest area of the province was estimated using the National Forest Inventory [71] and data of the Global Forest Change [72]. The native forests are dominated by temperate *Nothofagus* species, mostly pure stands or mixed with 1–3 species, and include different assemblages of deciduous and evergreen trees [73]. For the analyses, we considered three categories where *Nothofagus* are the dominant genus, growing in pure or mixed stands, based on Martínez Pastur et al. [26]: (i) NA: *N. antarctica* forests with >70% basal area (BA) and the remaining 30% or less composed of other associated native tree species; (ii) NP: *N. pumilio* forests with >70% BA and the remaining 30% or less composed of other associated native tree species; and (iii) MIX: Pure evergreen *N. betuloides* forests or mixed forests associated in different proportions with other native tree species (*N. pumilio*, *Drimys winteri*, *Maytenus magellanica*).

The climate in the study area is influenced by the oceans, Antarctica and the insularity that determine a uniform climate regime with a low range of annual temperature (7–10 °C) and rainfalls associated to the orography (500 to 700 mm $yr^{-1}$) with abundant snowfall during the winter season [29,30,47]. The parent materials of the soils are metamorphic rocks modulated by glacial processes. In general, the *Nothofagus* forest soils are classified as podzols with loamy texture, massive granular structures, low usable water capacity and moderate-to-slow internal and external drainage. These soils are characterized by an organic uppermost layer up to 2 cm thick (O horizon) followed by a mineral layer of less than 40 cm where most roots develop (mostly A horizon) with a variable proportion of stony material [26,73].

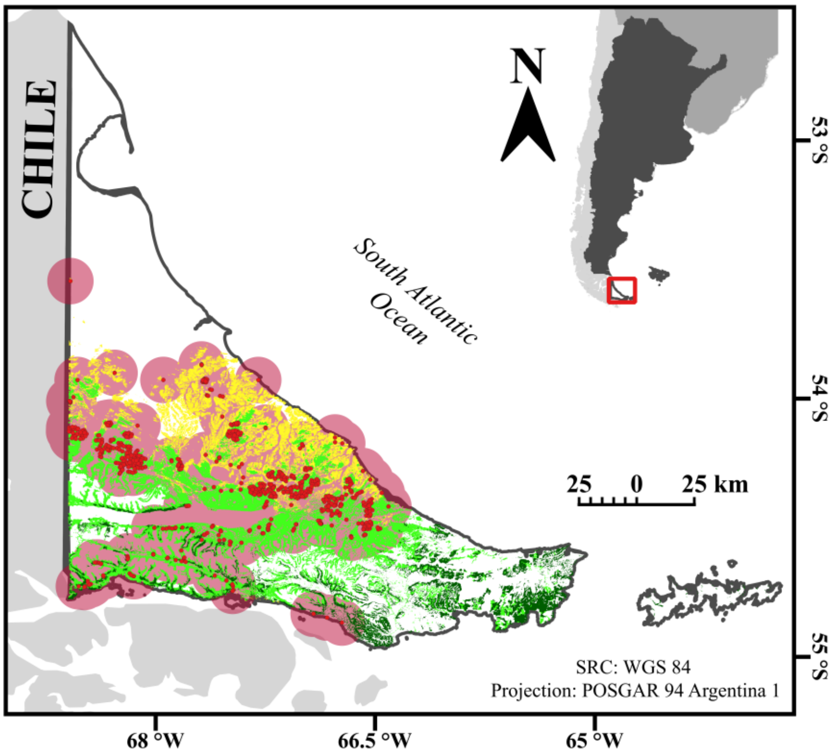


**Figure 1.** Location of the study area indicating the sampled stands (red dots), a 10 km buffer (pink area) and the main forest types of Tierra del Fuego (yellow: *Nothofagus antarctica*, light green: *N. pumilio*, dark green: mixed evergreen).

We selected stands (>2 ha) from different forest types for soil sampling (Figure 1) based on their conservation status (e.g., we discarded stands with BA <30–40 $m^2$ $ha^{-1}$ or with recent forest harvesting), covering most of the accessible forests of the Grande Island in the Tierra del Fuego archipelago. In total, we sampled 728 stands (1 stand every 1001 ha of forest) (Table 1). The sampling effort was not equally distributed among the different forest type covers (Table 1) given that the timber forests (*N. pumilio*) were over-sampled (+29%, 614 stands) and the other forest types were under-sampled (−14%, 95 stands of *N. antarctica* and 19 stands of mixed evergreen forests). Some areas were under-sampled (Figure 1) due to their inaccessibility in the western (mountain areas) and eastern (peatland areas) areas of the Archipelago.

**Table 1.** Sampling effort for the modelling, showing the area ($km^2$) of the different forest types (NA: *Nothofagus antarctica*, NP: *N. pumilio*, MIX: mixed evergreen) and number of sampled stands. Sampling effort compares the percentage of forest area and the percentage of stands at each category, where (+) indicates over-sampling relative to the extension of each forest type, and (−) indicates under-sampling.

| Forest Type | Area ($km^2$) | | Plots (n) | | Sampling Effort (%) |
|---|---|---|---|---|---|
| NA | 2014.7 | 27.6% | 95 | 13.0% | −14.6% |
| NP | 4045.1 | 55.5% | 614 | 84.3% | +28.9% |
| MIX | 1232.6 | 16.9% | 19 | 2.6% | −14.3% |
| *Total* | *7292.4* | | *728* | | |

In each stand, soil samples (n = 4 covering > 200 $cm^2$ at each stand) were taken at 0–30 cm depth using a hand soil sampler of known volume (200–300 $cm^3$). From this, we estimated the soil bulk density (SBD). The calculations were conducted with samples that were air-dried after removing >2 mm particles (roots, stones, woody debris) following the Carter and Gregorich [74] methodology. We performed the chemical analyses using pooled individual soil samples, maintaining the identity of the soil depth layers, including (i) soil total nitrogen (SN) by a semi-micro Kjeldahl method [74] and (ii) soil extractable phosphorus (SP) according to the method of Bray and Kurtz [75]. The nutrient data were presented as contents for the first 30 cm soil layer (ton $ha^{-1}$ for SN and kg $ha^{-1}$ for SP) using the SBD of each stand.

We used a combination of climate (n = 21), topography (n = 4) and vegetation productivity measures (n = 4) as predictors for our SN and SP models, which were rasterized at a 90 × 90 m resolution grid using the nearest neighbor resampling technique on ArcMap 10.0 software [76]. The climatic variables [77] included temperature and precipitation, characterized as annual, monthly and seasonal, as well as global potential evapotranspiration and global aridity indexes obtained from WorldClim [78]. The topography variables were defined using the shuttle radar topography mission [79], which produced a high-resolution digital elevation model. With these images, we defined altitude and aspect and slope; in addition, we used the soil organic carbon content (SOC, ton $ha^{-1}$) developed for Patagonian forests [26]. Finally, we included forest landscape metrics derived from the normalized difference vegetation index (NDVI) [80], net primary productivity (NPP) [81] and forest structure variables (dominant height and BA) [30].

Before modelling, the final variables were chosen according to their correlation and adjustment. We based the selection on the lower Pearson's correlation index obtained through paired analyses of each variable. We only included a single independent variable if the Pearson correlation coefficient was free from collinearity and with a $p$-value < 0.05. For prediction of SN and SP stocks, we developed models based on stepwise multiple regressions. The final selection of the models, including the most powerful independent variables free from collinearity, was performed after one hundred steps. The robustness of the regression models of SN and SP stocks was assessed considering (i) the coefficient of adjustment ($R^2$-adj.); (ii) the standard error of estimation (SEE), which is the average of the difference between the predicted and observed values; and (iii) the mean absolute error (MAE), defined as the average difference between the predicted and observed absolute values (Statgraphics Centurion, Statpoint Technologies, Warrenton, VA, USA). The adjustment of the models was conducted individually; however, the final performance of the models was tested together. There is one difference between the SN and SP modelling, due to us modelling the SN first, and then this variable was also used to model the SP together with the SOC values.

We tested two different approaches for modelling: (i) GLOBAL: where modelling was conducted for all the forest area in Tierra del Fuego, and (ii) INDIVIDUAL: where modelling was conducted for each forest type separately. The approaches were then integrated into one final map. SEE and MAE were used to test the robustness of the GLOBAL or INDIVIDUAL approaches based on auto-validation analyses. Finally, we extrapolated the obtained models to obtain the SN and SP maps across Tierra del Fuego province (Argentina), integrating the variables into a geographical information system (GIS) using ArcMap 10.0 software [76], where a mask was applied using the forest cover previously described.

Based on our final SN and SP maps, we characterized the Tierra del Fuego forests according to defined categories, which was used as a mask. We calculated SN (million ton) and SP (thousand ton) stocks as well as the SOC contents (million ton) previously determined [26], and then we related this to (i) previously defined forest types; (ii) status protection according to the province land use planning (Law 26,331/07): red (high conservation value forests for ancestral uses, gathering of non-timber forest products, scientific research, conservation plans, ecological restoration), yellow (medium conservation value forests for sustainable productive activities and tourism under the guidelines of management and conservation plans), green (low conservation value forest where land-use change is allowed) and unclassified forests [68]; and the existing reserve network according to the Administración de Parques Nacionales (APN) of Argentina (www.argentina.gob.ar/

parquesnacionales accessed on 12 December 2022) (national parks, provincial reserves, unprotected). For each category and combinations, we calculated the mean SN and SP values and the standard deviation (SD). Finally, SOC, SN and SP were graphically analyzed (mean ± SD) based on the comparisons with average mean annual temperature (°C, TEMP), mean annual rainfall (mm $yr^{-1}$, RAINFALL) and elevation (m a.s.l.).

## 3. Results

The SN adjusted models were robust ($R^2$-adj. > 92%) with acceptable statistics and errors (Table 2). The SN-GLOBAL model used SOC, precipitation seasonality (BIO15) and NPP as predictor variables. The INDIVIDUAL models presented higher coefficient of adjustments (93% to 98%) with lower SEE and MAE. The predictor variables changed with the forest types: (i) NA presented better adjustment when the annual mean temperature (BIO1) was combined with SOC and BIO15; (ii) NP showed better adjustment when some forest structure variables (DH: dominant height and BA) were combined with SOC, annual precipitation (BIO12) and NDVI; and (iii) MIX displayed better adjustment when forest variables (DH) were combined with SOC. All the employed variables were significant ($p$ < 0.05).

**Table 2.** Linear regression models of soil nitrogen content (SN, ton $ha^{-1}$) for all the forest cover (GLOBAL) or for each forest type (NA: *Nothofagus antarctica*, NP: *N. pumilio*, MIX: mixed evergreen). $R^2$-adj. = coefficient of adjustment, F: Fisher test, T: statistic of adjustment of each variable, p: probability, SEE: standard error of estimation, MAE: mean absolute error (acronyms of the variables are listed in the text).

| | | | | |
|---|---|---|---|---|
| SN-GLOBAL | $0.0354235 \times SOC + 0.224559 \times BIO15 - 0.00281924 \times NPP$ | | | |
| | $R^2$-adj. = 92.1% | F(p) = 2824.9 (<0.01) | | |
| | SEE = 2.8 | T(p) | SOC = 22.2 (<0.01) | BIO15 = 9.7 (<0.01) |
| | MAE = 2.1 | | NPP = −4.6 (<0.01) | |
| SN-NA | $0.0610033 \times SOC + 3.3065 \times BIO1 - 0.939747 \times BIO15$ | | | |
| | $R^2$-adj. = 98.0% | F(p) = 1579.0 (<0.01) | | |
| | SEE = 1.4 | T(p) | SOC = 15.0 (<0.01) | BIO1 = 7.4 (<0.01) |
| | MAE = 1.1 | | BIO15 = −8.0 (<0.01) | |
| SN-NP | $0.106466 \times DH + 0.0312037 \times BA + 0.0376064 \times SOC - 0.00890734 \times BIO12 + 2.40688 \times NDVI$ | | | |
| | $R^2$-adj. = 92.9% | F(p) = 1609.8 (<0.01) | | |
| | SEE = 2.6 | T(p) | DH = 3.9 (<0.01) | BA = 4.2 (<0.01) |
| | MAE = 1.9 | | SOC = 23.1 (<0.01) | BIO12 = −6.3 (<0.01) |
| | | | NDVI = 3.7 (<0.01) | |
| SN-MIX | $0.0682924 \times DH + 0.0174538 \times SOC$ | | | |
| | $R^2$-adj. = 95.8% | F(p) = 208.9 (<0.01) | | |
| | SEE = 1.9 | T(p) | DH = 2.2 (0.04) | SOC = 7.1 (<0.01) |
| | MAE = 0.9 | | | |

The SP models were less robust than the SN models ($R^2$-adj. > 70%). However, the statistics and errors were acceptable for these model types (Table 3). The SP-GLOBAL model used DH, SN and the precipitation of the wettest quarter (BIO16) as predictor variables. The INDIVIDUAL models showed higher coefficient of adjustments (71% to 87%) with similar or lower SEE and MAE. The predictor variables changed with the forest types: (i) NA displayed better adjustment when SN was combined with the temperature seasonality (BIO4); (ii) NP showed better adjustment when SN was combined with BIO4 and BIO12; and (iii) MIX exposed better adjustment when DH and SOC were combined with the SLOPE. All the employed variables were significant ($p$ < 0.05).

**Table 3.** Linear regression models of soil phosphorus content (SP, ton ha$^{-1}$) for all the forest cover (GLOBAL) or for each forest type (NA: *Nothofagus antarctica*, NP: *N. pumilio*, MIX: mixed evergreen). $R^2$-adj. = coefficient of adjustment, F: Fisher test, T: statistic of adjustment of each variable, p: probability, SEE: standard error of estimation, MAE: mean absolute error (acronyms of the variables are listed in the text).

| | | | | |
|---|---|---|---|---|
| **SP-GLOBAL** | 0.00812562 × *DH* + 0.00833205 × *SN* − 0.000885286 × *BIO16* | | | |
| | $R^2$-adj. = 70.3% | F(p) = 574.58 (<0.01) | | |
| | SEE = 0.08 | T(p) | DH = 12.8 (<0.01) | SN = 10.1 (<0.01) |
| | MAE = 0.06 | | BIO16 = −8.4 (<0.01) | |
| **SP-NA** | 0.0026018 × *SN* + 0.00692245 × *BIO4* | | | |
| | $R^2$-adj. = 83.5% | F(p) = 238.6 (<0.01) | | |
| | SEE = 0.02 | T(p) | SN = 3.5 (<0.01) | BIO4 = 2.8 (<0.01) |
| | MAE = 0.01 | | | |
| **SP-NP** | 0.00840194 × *SN* + 0.094582 × *BIO4* − 0.000500307 × *BIO12* | | | |
| | $R^2$-adj. = 71.4% | F(p) = 512.9 (<0.01) | | |
| | SEE = 0.09 | T(p) | SN = 8.2 (<0.01) | BIO4 = 8.9 (<0.01) |
| | MAE = 0.06 | | BIO12 = −7.8 (<0.01) | |
| **SP-MIX** | −0.0014144 × *DH* + 0.000239921 × *SOC* + 0.000873535 × *SLOPE* | | | |
| | $R^2$-adj. = 86.7% | F(p) = 39.9 (<0.01) | | |
| | SEE = 0.02 | T(p) | DH = −2.4 (0.02) | SOC = 5.3 (<0.01) |
| | MAE = 0.01 | | SLOPE = 2.1 (0.04) | |

The *Nothofagus antarctica* forests showed the highest SN average contents (10.25 ton ha$^{-1}$) followed by the *N. pumilio* forests (9.27 ton ha$^{-1}$), while the mixed evergreen forests grew in SN-poor soils (5.45 ton ha$^{-1}$) (Table 4). SP demonstrated a completely different pattern, where *N. pumilio* showed a significantly higher content (138.44 kg ha$^{-1}$) than the other forest types (46.58–48.84 kg ha$^{-1}$). Concerning SOC values, based on the modelling proposed by Martínez Pastur et al. [26], the highest content was in the mixed evergreen forests followed by the *N. pumilio* and *N. antarctica* forests (Table 5), evidencing that the three considered nutrients (C, N, P) are not totally correlated in the soils of the Tierra del Fuego forests. Auto-validation of the sampling plots compared with the outputs of the linear regression models showed lower SEE and MAE values for the INDIVIDUAL modelling approach than those of the GLOBAL modelling approach (Table 4) both for all the forest cover area and for each forest type (*Nothofagus antarctica*, *N. pumilio* or mixed evergreen). These auto-validations suggest that the combination of the individual models into one map is better than one single GLOBAL modelling, highlighting that each forest type has particular soil properties. For this, the integration of the INDIVIDUAL models was used for the following analyses.

**Table 4.** Auto-validation of sampling plots (n = 728) and the outputs of the linear regression models of soil nitrogen (SN, ton ha$^{-1}$) and soil phosphorus (SP, kg ha$^{-1}$) contents for all the forest cover (GLOBAL) or the combination of the models (INDIVIDUAL) for each forest type (NA: *Nothofagus antarctica*, NP: *N. pumilio*, MIX: mixed evergreen). SEE: standard error of estimation, MAE: mean absolute error.

| **Model** | **SN** | **Global** | | **Individual** | | **SP** | **Global** | | **Individual** | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **(ton ha$^{-1}$)** | **SEE** | **MAE** | **SEE** | **MAE** | **(kg ha$^{-1}$)** | **SEE** | **MAE** | **SEE** | **MAE** |
| NA | 10.25 | 0.72 | 1.97 | 0.01 | 1.14 | 48.84 | −13.14 | 27.19 | −0.04 | 16.53 |
| NP | 9.27 | 0.01 | 2.08 | <0.01 | 1.96 | 138.44 | 3.99 | 66.70 | −0.06 | 65.34 |
| MIX | 5.45 | −4.72 | 4.72 | −0.03 | 0.91 | 46.58 | −22.97 | 58.25 | −0.28 | 16.15 |
| *Total* | *9.30* | *−0.02* | *2.14* | *<0.01* | *1.82* | *124.35* | *1.05* | *61.32* | *−0.07* | *59.38* |

**Table 5.** Forest cover area, soil organic carbon (SOC), soil nitrogen (SN) and soil phosphorus (SP) contents based on the combination of the individual models, discriminated according to (A) forest types (NA: *Nothofagus antarctica*, NP: *N. pumilio*, MIX: mixed evergreen), (B) land use planning (Law 26,331/07, red: maximum, yellow: medium, green: minimum forest values) and (C) formal protection network (national parks, provincial reserves, unprotected). Standard deviation is included between brackets for each category.

| Type | Class | Area ($km^2$) | SOC (ton $ha^{-1}$) | Total SOC (mill ton) | SN (ton $ha^{-1}$) | Total SN (mill ton) | SP (kg $ha^{-1}$) | Total SP (thousand ton) |
|---|---|---|---|---|---|---|---|---|
| (A) | NA | 2014.7 | 141.3 (±22.3) | 28.5 | 7.7 (±1.7) | 1.56 | 45.0 (±20.6) | 9.1 |
| | NP | 4045.1 | 158.7 (±22.8) | 64.2 | 6.9 (±2.1) | 2.81 | 129.8 (±41.6) | 52.5 |
| | MIX | 1232.6 | 184.5 (±30.6) | 22.7 | 4.9 (±1.1) | 0.60 | 77.2 (±25.0) | 9.5 |
| (B) | Red | 2926.7 | 165.5 (±28.0) | 48.4 | 5.7 (±1.9) | 1.67 | 97.5 (±39.8) | 28.5 |
| | Yellow | 3845.4 | 154.7 (±26.6) | 59.5 | 7.7 (±1.7) | 2.95 | 98.9 (±57.8) | 38.0 |
| | Green | 192.8 | 133.0 (±20.7) | 2.6 | 6.6 (±1.9) | 0.13 | 87.2 (±57.1) | 1.7 |
| | Unclassified | 327.5 | 151.6 (±27.2) | 5.0 | 6.5 (±2.1) | 0.21 | 86.6 (±46.5) | 2.8 |
| (C) | National | 262.1 | 143.1 (±15.5) | 387 | 4.8 (±1.3) | 0.12 | 86.6 (±19.2) | 2.3 |
| | Provincial | 643.7 | 153.4 (±19.9) | 9.9 | 7.3 (±1.8) | 0.47 | 126.7 (±43.3) | 8.2 |
| | Unprotected | 6386.6 | 159.4 (±28.7) | 101.8 | 6.8 (±2.1) | 4.37 | 94.9 (±51.5) | 60.6 |
| | *Total* | *7292.4* | *158.3(±27.9)* | *115.4* | *6.8 (±2.1)* | *4.97* | *97.4 (±50.9)* | *71.1* |

The final maps showed similar trends, but extreme predicted values of SN and SP were less evident for the INDIVIDUAL modelling approach than the GLOBAL modelling approach (Figure 2). However, both approaches showed the patterns of the SN and SP average contents previously described. The total nutrient contents for the Tierra del Fuego forests totaled 115.4 million tons of carbon, 4.97 million tons of nitrogen and 71.1 thousand tons of phosphorus (Table 5), where the *N. pumilio* forests presented the greatest reservoirs. The most valuable forests (red) according to the land use planning of the province (Law 26,331/07) have greater SOC but the lowest SN values. The yellow category, where forest management is allowed, showed higher SN and SP values, mostly due to those forests having a higher offer of provisioning ecosystem services. Regarding the formal protection network, the unprotected areas displayed the highest SOC contents in the forests and are the main sinks of the three studied nutrients due to most of the forest area being outside the protected areas. Despite this, Provincial Reserves house the forests with the greatest SN and SP contents, highlighting the importance of this conservation strategy that complements the national initiatives (e.g., national parks).

The soil nutrient contents were affected by forest type, regional climate (e.g., annual mean temperature and rainfall) and topography (e.g., altitude) (Figure 3). NA grows at lower altitudes close to the ecotone with the steppe (higher temperatures and lower rainfall), MIX forests occupy the intermediate altitude landscapes (e.g., middle hillsides and shores of lakes with intermediate temperatures and higher rainfall), and NP can grow from sea level to the upper tree-line boundaries (lower temperatures and intermediate rainfall). In general, SOC was greater at high altitudes (NP-MIX > NA) and SN at low altitudes (NA > NP-MIX). SP increased with the altitude (NP > MIX > NA). Temperature also influenced SOC, where higher temperatures resulted in lower SOC (NP-MIX > NA) and higher SN (NA > NP-MIX) values. The SP content increased when the temperature decreased (NP > MIX > NA). Finally, rainfall also influenced SOC and SP, which increased with rainfall values (MIX-NP > NA); however, SN decreased with rainfall (NA > NP > MIX). These different patterns and behaviors showed that climate and topography also modulate the nutrient contents, defining the forest types that developed across the landscape.

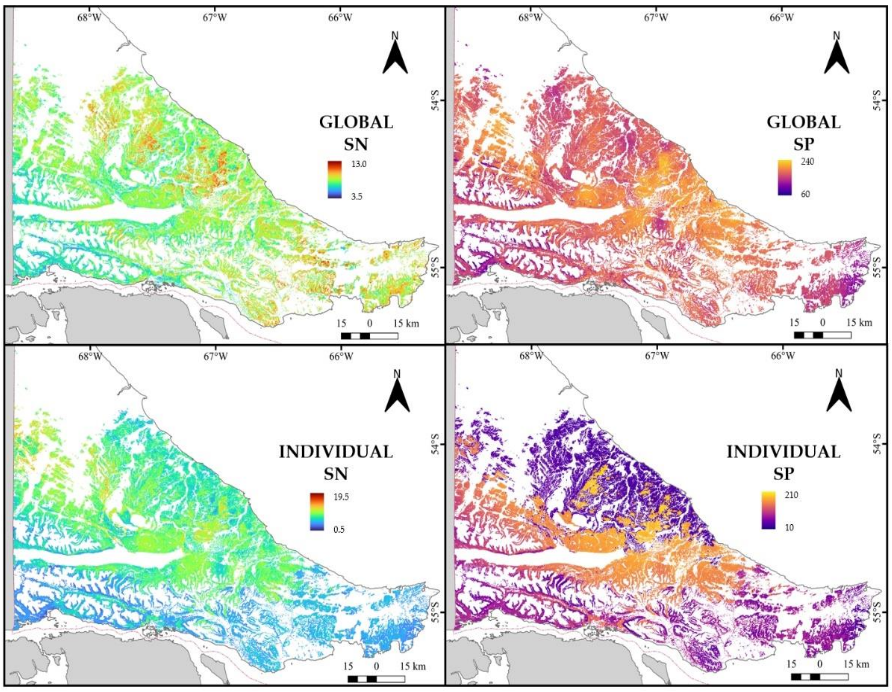


**Figure 2.** Final maps of soil nitrogen content on the left (SN, ton ha$^{-1}$) and soil phosphorus content on the right (SP, kg ha$^{-1}$) for all the forest cover (GLOBAL) or the combination of the models (INDIVIDUAL) for each forest type.

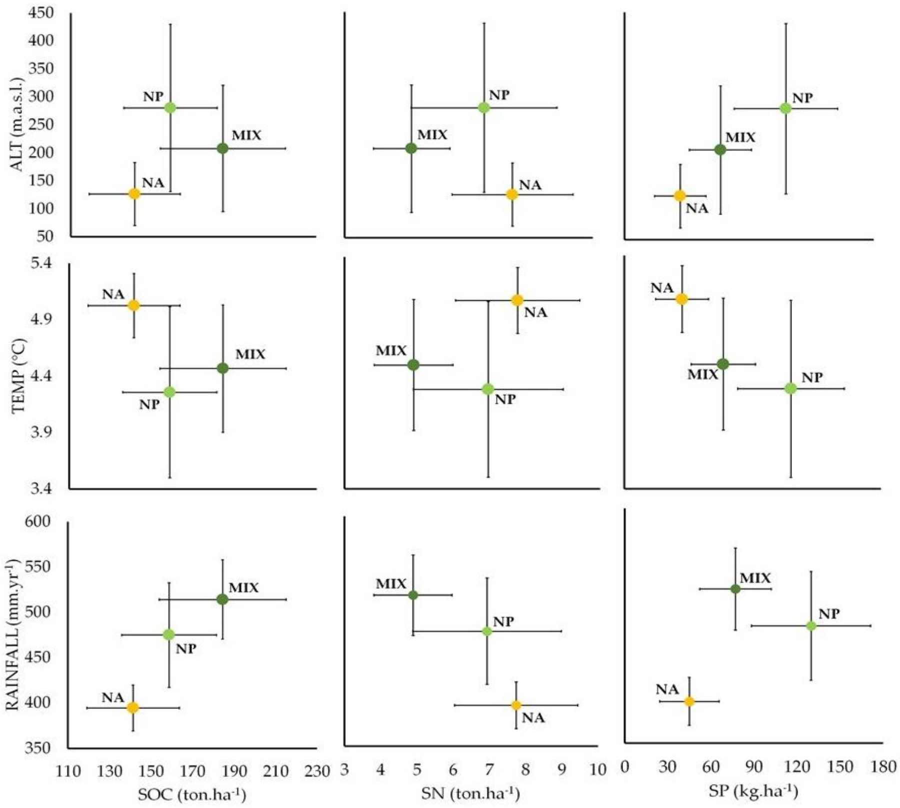


**Figure 3.** Soil organic carbon (SOC, ton ha$^{-1}$), soil nitrogen (SN, ton ha$^{-1}$) and soil phosphorus (SP, kg ha$^{-1}$) contents based on the combination of the individual models of each forest type (NA: *Nothofagus antarctica*, NP: *N. pumilio*, MIX: mixed evergreen) related to climate (TEMP: mean annual temperature, °C, and RAINFALL: mean annual rainfall, mm yr$^{-1}$) and elevation (m a.s.l.). Bars indicate the standard deviation of each axis.

## 4. Discussion

The sampling effort was higher than other soil modelling in the region [25,26,45,46,82]. However, it was not equally distributed among the different forest type covers, mainly due to accessibility, which was identified as the main trade-off for field surveys in other studies in Patagonia [83]. The under-sampled areas were located in the mountain (west) and peatland (east) areas, where no economic activities were conducted [84], and included the less profitable species in terms of monetary values (e.g., timber or silvopastoral) [50,68,73]. These limitations must be considered when the models are used and must be tested in future research to improve the proposed models.

Remote sensing data provide a direct representation of the Earth's surface, and most of the time, these variables are closely related to soil properties [7,35], increasing the feasibility to develop models based on direct linear regressions. For example, it was possible to predict the soil nutrient contents directly with remote sensing data, e.g., it was informed that SN was closely related to the natural vegetation and the above-ground biomass [36,82], while SP was more related to the parent material [85]. Different techniques have been used in the literature to predict soil distribution, e.g., multiple linear regression [10,25,45,46,82,86], regression kriging [87–89], random forest models [26,35,89], geographically weighted regression [88], cubist models [90,91] and principal component regressions [92]. These strategies were successfully implemented in different natural and managed environments and according to different research objectives, but none showed to be the best one for all the stated forests and landscapes.

In several studies, vegetation units were not considered as a source of variation. Here, we tested the influence of forest types as the main variable responsible for soil property variability. Other studies considered soil types to homogenize the landscape modelling [10,18,19], but vegetation unit was not usually taken into account. Here, the individual modelling approach for each forest type was more accurate than considering globally all the forest types together. This strategy was followed in other studies where vegetation type had influence over the modelled variables, e.g., potential biodiversity [47] or phenoclusters [29] in Patagonia. Other studies also suggest improving the prediction accuracy by introducing new environmental covariates and more stratified sampling in homogeneous sub-areas [7,93]. Our models showed higher coefficient of adjustments ($R^2$-adj.) and errors (SEE and MAE) than other local soil modelling variables [25,26,45,46,82] or than those stated in the literature, e.g., Razakamanarivo et al. [94], Adhikari et al. [20], Martin et al. [23] and Wang et al. [10].

The SN models (global and individuals for all forest types) were closely related to SOC as a source of both nutrients in forest soils. The second explanatory variable groups were related to climate (e.g., BIO1, BIO15, BIO12) followed by vegetation proxies (e.g., NPP and NDVI) and forest structure variables (DH and BA). The SP models (global and individuals for deciduous forest types) were closely related to SN, while the mixed evergreen forests were related with SOC. Both variables (SN and SOC) were also related to the biomass input in the forest ecosystems as was previously stated. The second explanatory variable groups were related to climate (e.g., BIO16, BIO4, BIO12) followed by one topography variable (e.g., SLOPE) and some forest structure variables (DH).

Some of these variables, such as vegetation indexes, NPP and climate, are mainly derived from remote-sensing products. Because of substantial advances, satellites can now provide products with a high spatiotemporal resolution [3]. Vegetation proxies (NDVI and NPP) were identified as the main factors associated to SOC and SN [7,10,21,95] due to the relationship with vegetation productivity and biomass [8,88,96]. Vegetation is one of the major covariates related to soil nutrients in digital soil mapping [35], especially in areas with good natural vegetation coverage [21]. A significant positive correlation has been reported between the topsoil nutrient content and vegetation [97], which was confirmed with our research. Those findings imply that there was a potential application of remote-sensing techniques to mapping nutrient distribution in large regions.

Associated variables, such as temperature and rainfall, are the key climatic factors that affect the spatial distribution of soil nutrients (SN and SP) [10,98]. These variables are widely used in the spatial prediction of soil nutrient content [10,99]. In mountain ecosystems, climatic variables affected the hydrological system and ecological function, which indirectly exerted an influence on the spatial distribution of SN [10,35]. On the micro-scale level, an improvement in forest productivity results in more input from organic matter in the soil leading to an increase in the nutrients in soils (e.g., SOC and SN) [35]. However, low temperatures and rainfall reduce decomposition rates and, therefore, decrease the availability of nutrients in the soils [40,41,100]. Climate data and their variance within periods are a useful covariate to characterize soil properties [101] because this information provides insights into key soil processes (e.g., dynamics of soil moisture) [3].

Topographic variables are usually good predictive factors in areas with complex changes in topography for modelling soil nutrient contents [87]. Relief is the main factor involved in soil formation and soil moisture distribution across the landscape [35]. In our model, the relief derivative variable (e.g., SLOPE) was important for the SN and SP estimations, as it was also reported for soil depth modelling and other development dynamic processes [3]. The influence of this variable was also cited by Wang et al. [10] and Yang et al. [21], which also can be related to land uses (e.g., agriculture lands) and microclimate regulation in local areas [102]. For SP, broad-scale studies of parent material derived from geological maps are reported to be a useful variable [43,103]. In our modelling, the soils with more phosphorus content were related to geological areas with parent material containing more phosphate sedimentary rocks [85].

Forest structure variables were useful to predict the soil nutrient contents. The main variables were dominant height (as a proxy of site quality) and basal area (as a proxy of tree density) [30,38,44,104]. Both variables can be related to tree biomass, which results in the main organic source material for soil nutrients [40,41,100].

In this context, our study showed that multiscale interactions among environmental covariates and soil properties may be considered. Other authors emphasize the importance of considering different source drivers in the modelling of soil characteristic influence from micro to global scales, e.g., [3,105]. Finally, validation criteria should be interpreted carefully because it could be concluded that the best model is not necessarily able to make the most accurate estimation. Moreover, further studies may still be required to investigate and suggest new environmental covariates to capture soil variability and distribution at landscape level [7].

The Tierra del Fuego forests grow in a wide topography, climate and soil conditions [106], where SN and SP are limited for forest development [37]. Nutrient content was identified as one of the key factors for site quality and stand recovery after impacts (e.g., beavers) [107,108]. In addition, soil nutrients were proposed as the main factor that influences the natural dynamic and overstory cover composition (e.g., deciduous and evergreen) [104]. Canopy tree composition can influence forest soil properties [109], being greater in the upper soil layers near the roots [110], and can be correlated with site quality and stand density [108,111]. Mineralization rates under different species also can change [112], where mixing species can result in increased soil mineralization rates compared with pure species stands [104]. In our study, we found similar average nutrient contents as those found in other studies [50,82,108,113–116], where deciduous forests presented more SN (*Nothofagus antarctica* > *N. pumilio*) than mixed evergreen forests, and where SP is greater in *N. pumilio* stands than the other forest types. Toro-Manríquez et al. [104] found the same trends, where SP is the main nutrient associated with *N. pumilio* occurrence.

The distribution maps of SOC and SN showed similar spatial distribution patterns as those cited by Wang et al. [10]. However, the spatial distribution of SP was related to the parent rock material as described by Olivero et al. [85]. The spatial distribution patterns of SN and SP also have a strong relationship with the topographic variables, where mountainous areas showed lower values and discontinuity, as was cited in other studies [117]. Different topography gradients affected the input and loss of soil nutrients through indirect factors, such as temperature and rainfall [104,118].

For a non-soil scientist, soil maps are difficult to interpret and use for decision-making in land management [119] because they are mostly based on taxonomic classification rather than quantifying soil properties. The digital soil mapping developed here facilitates soil property predictions by integrating soil survey data, geographic information systems, geostatistics, topography, remote sensing and high-performance computing [3,17,24]. Because of the need for better planning strategies and adaptation to climate change, the potential of soil to store or sequester additional nutrients has received considerable attention during the last few years [3,24,78,120]. Accurate, broad-extent, fine-resolution information on forest resources is needed for sustainable management and conservation planning [121–124] and for scientific researchers [125]. In Argentina, national and provincial governments are lacking accurate information to quantify emissions (e.g., SOC) and nutrient stocks (e.g., SP and SN), which is required for both policy formulation and meeting reporting requirements by international agencies [126,127]. Without detailed information on forest nutrient dynamics, it is impossible to gauge the effectiveness of both proposed and implemented policies [25,42,128]. Digital soil mapping can be an efficient decision-making platform (e.g., GIS or web platforms) for implementing proper, sustainable management practices and identifying areas with high potential for sequestering atmospheric gases or for protecting soils to avoid nutrient release into the atmosphere [3,23,24,27] or, due to erosion, non-desirable processes or desertification in Patagonia [129–131].

## 5. Conclusions

This study showed that easily obtainable remote-sensing data can provide spatially detailed and reasonably accurate maps of SN and SP in topsoil in naturally forested areas. We successfully modelled and mapped soil nitrogen (SN) and soil phosphorus (SP) stocks in the top 30 cm in native forests of Tierra del Fuego (Argentina) at 30 m resolution. The most important variables predicting SN and SP were vegetation productivity and forest structure, climate (temperature and rainfall) and slope. The SN and SP distribution was well explained by vegetation-related variables directly related to forested environments. The modelling of forest types individually improved the accuracy compared with the global models, and our final SN and SP maps integrated these subsets and greatly improved the information about nutrient stocks, which can support (i) the use of nutrient stocks as predictors for assessment design and modelling at landscape level; (ii) evaluation of the habitat quality and identification of priority conservation areas; (iii) monitoring to achieve sustainable forest management; and (iv) zoning of native forests in multiple uses according to management and conservation criteria. These models can strengthen the national forest monitoring system, support compliance with national and provincial regulation and provide information to achieve the international agreements signed by Argentina. In addition, we developed an approach to obtain accurate SN and SP maps across the entire province with different forest types, allowing us to characterize the nutrient stocks in the land use areas (e.g., OTBN, National Law 26,331/07) and protected area network.

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## References

1. Adhikari, K.; Hartemink, A. Linking soils to ecosystem services: A global review. *Geoderma* **2016**, *262*, 101–111. [CrossRef]
2. Bouma, J. Soil science contributions towards sustainable development goals and their implementation: Linking soil functions with ecosystem services. *J. Plant Nutr. Soil Sci.* **2014**, *177*, 111–120. [CrossRef]
3. Chen, S.; Arrouays, D.; Mulder, V.; Poggio, L.; Minasny, B.; Roudier, P.; Libohova, Z.; Lagacherie, P.; Shi, Z.; Hannam, J.; et al. Digital mapping of GlobalSoilMap soil properties at a broad scale: A review. *Geoderma* **2022**, *409*, e115567. [CrossRef]
4. Forkuor, G.; Hounkpatin, O.; Welp, G.; Thiel, M. High resolution mapping of soil properties using remote sensing variables in South-Western Burkina Faso: A comparison of machine learning and multiple linear regression models. *PLoS ONE* **2017**, *12*, e0170478. [CrossRef] [PubMed]
5. Lin, Y.; Prentice, S.; Tran, T.; Bingham, N.; King, J.; Chadwick, O. Modeling deep soil properties on California grassland hillslopes using LiDAR digital elevation models. *Geoderma Reg.* **2016**, *7*, 67–75. [CrossRef]
6. Rodrigo-Comino, J.; Senciales, J.; Cerdà, A.; Brevik, E. The multidisciplinary origin of soil geography: A review. *Earth Sci. Rev.* **2018**, *177*, 114–123. [CrossRef]
7. Zeraatpisheh, M.; Ayoubi, S.; Jafari, A.; Tajik, S.; Finke, P. Digital mapping of soil properties using multiple machine learning in a semiarid region, central Iran. *Geoderma* **2019**, *338*, 445–452. [CrossRef]
8. Liu, Y.; Wang, C.; He, N.; Wen, X.; Gao, Y.; Li, S.; Niu, S.; Butterbach-Bahl, K.; Luo, Y.; Yu, G. A global synthesis of the rate and temperature sensitivity of soil nitrogen mineralization: Latitudinal patterns and mechanisms. *Glob. Chang. Biol.* **2017**, *23*, 455–464. [CrossRef]
9. Wang, S.; Wang, Q.; Adhikari, K.; Jia, S.; Jin, X.; Liu, H. Spatial-temporal changes of soil organic carbon content in Wafangdian, China. *Sustainability* **2016**, *8*, 1154. [CrossRef]
10. Wang, S.; Zhuang, Q.; Wang, Q.; Jin, X.; Han, C. Mapping stocks of soil organic carbon and soil total nitrogen in Liaoning Province of China. *Geoderma* **2017**, *305*, 250–263. [CrossRef]
11. Lehmann, J.; Kleber, M. The contentious nature of soil organic matter. *Nature* **2015**, *528*, 60–68. [CrossRef] [PubMed]
12. Vincent, A.; Schleucher, J.; Gröbner, G.; Vestergren, J.; Persson, P.; Jansson, M.; Giesler, R. Changes in organic phosphorus composition in boreal forest humus soils: The role of iron and aluminium. *Biogeochemistry* **2012**, *108*, 485–499. [CrossRef]
13. Hinsinger, P. Bioavailability of soil inorganic P in the rhizosphere as affected by root induced chemical changes: A review. *Plant Soil* **2001**, *237*, 173–195. [CrossRef]
14. Hu, B.; Yang, B.; Pang, X.; Bao, W.; Tian, G. Responses of soil phosphorus fractions to gap size in a reforested spruce forest. *Geoderma* **2016**, *279*, 61–69. [CrossRef]
15. McDowell, R.; Stewart, I. The phosphorus composition of contrasting soils in pastoral, native and forest management in Otago, New Zealand: Sequential extraction and 31P NMR. *Geoderma* **2006**, *130*, 176–189. [CrossRef]
16. Hu, B.; Jia, Y.; Zhao, Z.; Li, F.; Siddique, H. Soil P availability, inorganic P fractions and yield effect in a calcareous soil with plastic-film-mulched spring wheat. *Field Crop Res.* **2012**, *137*, 221–229. [CrossRef]
17. McBratney, A.; Santos, M.; Minasny, B. On digital soil mapping. *Geoderma* **2003**, *117*, 3–52. [CrossRef]
18. Batjes, N. Total carbon and nitrogen in the soils of the world. *Eur. J. Soil Sci.* **1996**, *47*, 151–163. [CrossRef]
19. Arrouays, D.; Deslais, W.; Badeau, V. The carbon content of topsoil and its geographical distribution in France. *Soil Use Manag.* **2001**, *17*, 7–11. [CrossRef]
20. Adhikari, K.; Hartemink, A.; Minasny, B.; Kheir, R.; Greve, M.; Greve, M. Digital mapping of soil organic carbon contents and stocks in Denmark. *PLoS ONE* **2014**, *9*, e105519. [CrossRef]
21. Yang, R.; Zhang, G.; Yang, F.; Zhi, J.; Yang, F.; Liu, F.; Zhao, Y.; Li, D. Precise estimation of soil organic carbon stocks in the northeast Tibetan Plateau. *Sci. Rep.* **2016**, *6*, e21842. [CrossRef]
22. Khaledian, Y.; Brevik, E.; Pereira, P.; Cerdà, A.; Fattah, M.; Tazikeh, H. Modeling soil cation exchange capacity in multiple countries. *Catena* **2017**, *158*, 194–200. [CrossRef]
23. Martin, M.; Orton, T.; Lacarce, E.; Meersmans, J.; Saby, N.; Paroissien, J.; Joliveta, C.; Boulonnea, L.; Arrouays, D. Evaluation of modelling approaches for predicting the spatial distribution of soil organic carbon stocks at the national scale. *Geoderma* **2014**, *223*, 97–107. [CrossRef]

24. Minasny, B.; Malone, B.; McBratney, A.; Angers, D.; Arrouays, D.; Chambers, A.; Chaplot, V.; Chen, Z.; Cheng, K.; Das, B.; et al. Soil carbon 4 per mille. *Geoderma* **2017**, *292*, 59–86. [CrossRef]
25. Peri, P.L.; Rosas, Y.M.; Ladd, B.; Toledo, S.; Lasagno, R.; Martínez Pastur, G. Modelling soil carbon content in South Patagonia and evaluating changes according to climate, vegetation, desertification and grazing. *Sustainability* **2018**, *10*, 438. [CrossRef]
26. Martínez Pastur, G.; Aravena Acuña, M.C.; Silveira, E.; von Müller, A.; La Manna, L.; González-Polo, M.; Chaves, J.; Cellini, J.M.; Lencinas, M.V.; Radeloff, V.; et al. Mapping soil organic carbon in Patagonian forests based on climate, topography and vegetation metrics from satellite imagery. *Remote Sens.* **2022**, *14*, 5702. [CrossRef]
27. Minasny, B.; Hartemink, A. Predicting soil properties in the tropics. *Earth Sci. Rev.* **2011**, *106*, 52–62. [CrossRef]
28. Gonzalez Musso, R.; Oddi, F.; Goldenberg, M.; Garibaldi, L. Applying unmanned aerial vehicles (UAVs) to map shrubland structural attributes in northern Patagonia, Argentina. *Can. J. For. Res.* **2020**, *50*, 615–623. [CrossRef]
29. Silveira, E.; Radeloff, V.; Martínez Pastur, G.; Martinuzzi, S.; Politi, N.; Lizarraga, L.; Rivera, L.; Gavier Pizarro, G.; Yin, H.; Rosas, Y.M.; et al. Forest phenoclusters for Argentina based on vegetation phenology and climate. *Ecol. Appl.* **2022**, *32*, e2526. [CrossRef]
30. Silveira, E.; Radeloff, V.; Martinuzzi, S.; Martínez Pastur, G.; Bono, J.; Politi, N.; Lizarraga, L.; Rivera, L.; Ciuffoli, L.; Rosas, Y.M.; et al. Nationwide native forest structure maps for Argentina based on forest inventory data, SAR Sentinel-1 and vegetation metrics from Sentinel-2 imagery. *Remote Sens. Environ.* **2023**, *285*, e113391. [CrossRef]
31. Gasparri, I.; Parmuchi, M.; Bono, J.; Karszenbaum, H.; Montenegro, C. Assessing multi-temporal Landsat 7 ETM + images for estimating above-ground biomass in subtropical dry forests of Argentina. *J. Arid Environ.* **2010**, *74*, 1262–1270. [CrossRef]
32. Gasparri, I.; Baldi, G. Regional patterns and controls of biomass in semiarid woodlands: Lessons from the Northern Argentina Dry Chaco. *Reg. Environ. Chang.* **2013**, *13*, 1131–1144. [CrossRef]
33. Bouvier, M.; Durrieu, S.; Fournier, R.; Renaud, J. Generalizing predictive models of forest inventory attributes using an area-based approach with airborne LiDAR data. *Remote Sens. Environ.* **2015**, *156*, 322–334. [CrossRef]
34. Wang, Y.; Zhang, X.; Huang, C. Spatial variability of soil total nitrogen and soil total phosphorus under different land uses in a small watershed on the Loess Plateau, China. *Geoderma* **2009**, *150*, 141–149. [CrossRef]
35. Wang, S.; Jin, X.; Adhikari, K.; Li, W.; Yu, M.; Bian, Z.; Wang, Q. Mapping total soil nitrogen from a site in northeastern China. *Catena* **2018**, *166*, 134–146. [CrossRef]
36. Chi, Y.; Zhao, M.; Sun, J.; Xie, Z.; Wang, E. Mapping soil total nitrogen in an estuarine area with high landscape fragmentation using a multiple-scale approach. *Geoderma* **2019**, *339*, 70–84. [CrossRef]
37. Diehl, P.; Mazzarino, M.; Funes, F.; Fontenla, S.; Gobbi, M.; Ferrari, J. Nutrient conservation strategies in native Andean-Patagonian forests. *J. Veg. Sci.* **2003**, *14*, 63–70. [CrossRef]
38. Peri, P.L.; Gargaglione, V.; Martínez Pastur, G. Above and belowground nutrients storage and biomass accumulation in marginal *Nothofagus antarctica* forests in Southern Patagonia. *For. Ecol. Manag.* **2008**, *255*, 2502–2511. [CrossRef]
39. Bahamonde, H.; Peri, P.L.; Alvarez, R.; Barneix, A.; Moretto, A.; Martínez Pastur, G. Litter decomposition and nutrients dynamics in *Nothofagus antarctica* forests under silvopastoral use in Southern Patagonia. *Agrofor. Syst.* **2012**, *84*, 345–360. [CrossRef]
40. Bahamonde, H.; Peri, P.L.; Alvarez, R.; Barneix, A.; Moretto, A.; Martínez Pastur, G. Silvopastoral use of *Nothofagus antarctica* in Southern Patagonian forests, influence over net nitrogen soil mineralization. *Agrofor. Syst.* **2013**, *87*, 259–271. [CrossRef]
41. Bahamonde, H.; Peri, P.L.; Martínez Pastur, G.; Monelos, L. Litterfall and nutrients return in *Nothofagus antarctica* forests growing in a site quality gradient with different management uses in Southern Patagonia. *Eur. J. For. Res.* **2015**, *134*, 113–124. [CrossRef]
42. Peri, P.L.; Lasagno, R.; Martínez Pastur, G.; Atkinson, R.; Thomas, E.; Ladd, B. Soil carbon is a useful surrogate for conservation planning in developing nations. *Sci. Rep.* **2019**, *9*, e3905. [CrossRef]
43. Besteiro, S.; Descalzo, A. Contenidos de nitrógeno y fósforo del suelo ante un cambio de cobertura y condición topográfica. *Rev. Inv. Agrop.* **2021**, *47*, 285–292.
44. Chaves, J.; Lencinas, M.V.; Cellini, J.M.; Peri, P.L.; Martínez Pastur, G. Changes in nutrients and fibre tissue contents in *Nothofagus pumilio* trees growing at site quality and crown class gradients. *For. Ecol. Manag.* **2022**, *505*, e119910. [CrossRef]
45. Rosas, Y.M.; Peri, P.L.; Martínez Pastur, G. Assessment of provisioning ecosystem services in terrestrial ecosystems of Santa Cruz province, Argentina. In *Ecosystem Services in Patagonia: A Multi-Criteria Approach for an Integrated Assessment*; Peri, P.L., Nahuelhual, L., Martínez Pastur, G., Eds.; Natural and Social Sciences of Patagonia; Springer Nature: Cham, Switzerland, 2021; pp. 19–46.
46. Rosas, Y.M.; Martínez Pastur, G.; Peri, P.L. *Servicios Ecosistémicos y Biodiversidad de los Recursos Naturales de Santa Cruz*; INTA: Buenos Aires, Argentina, 2022; 60p.
47. Martínez Pastur, G.; Peri, P.L.; Soler, R.; Schindler, S.; Lencinas, M.V. Biodiversity potential of *Nothofagus* forests in Tierra del Fuego (Argentina): Tool proposal for regional conservation planning. *Biodiv. Conserv.* **2016**, *25*, 1843–1862. [CrossRef]
48. Gutsch, M.; Lasch-Born, P.; Kollas, C.; Suckow, F.; Reyer, C. Balancing trade-offs between ecosystem services in Germany's forests under climate change. *Environ. Res. Let.* **2018**, *13*, e045012. [CrossRef]
49. Orsi, F.; Ciolli, M.; Primmer, E.; Varumo, L.; Geneletti, D. Mapping hotspots and bundles of forest ecosystem services across the European Union. *Land Use Pol.* **2020**, *99*, e104840. [CrossRef]
50. Peri, P.L.; Ladd, B.; Lasagno, R.; Martínez Pastur, G. The effects of land management (grazing intensity) vs. the effects of topography, soil properties, vegetation type, and climate on soil carbon concentration in Southern Patagonia. *J. Arid Environ.* **2016**, *134*, 73–78. [CrossRef]

51. Köhl, M.; Lasco, R.; Cifuentes, M.; Jonsson, O.; Korhonen, K.; Mundhenk, P.; de Jesus Navar, J.; Stinson, G. Changes in forest production, biomass and carbon: Results from the 2015 UN FAO Global Forest Resource Assessment. *For. Ecol. Manage.* **2015**, *352*, 21–34. [CrossRef]
52. Moghaddas, E.; Stephens, S. Thinning, burning, and thin-burn fuel treatment effects on soil properties in a Sierra Nevada mixed-conifer forest. *For. Ecol. Manag.* **2007**, *250*, 156–166. [CrossRef]
53. Nilsen, P.; Strand, L. Thinning intensity effects on carbon and nitrogen stores and fluxes in a Norway spruce (*Picea abies* (L.) Karst.) stand after 33 years. *For. Ecol. Manag.* **2008**, *256*, 201–208. [CrossRef]
54. Nunery, J.; Keeton, W. Forest carbon storage in the north-eastern United States: Net effects of harvesting frequency, post-harvest retention, and wood products. *For. Ecol. Manag.* **2010**, *259*, 1363–1375. [CrossRef]
55. Ontl, T.; Janowiak, M.; Swanston, C.; Daley, J.; Handler, S.; Cornett, M.; Hagenbuch, S.; Handrick, C.; Mccarthy, L.; Patch, N. Forest management for carbon sequestration and climate adaptation. *J. For.* **2019**, *118*, 86–101. [CrossRef]
56. La Manna, L.; Tarabini, M.; Gomez, F.; Rostagno, C. Changes in soil organic matter associated with afforestation affect erosion processes: The case of erodible volcanic soils from Patagonia. *Geoderma* **2021**, *403*, e115265. [CrossRef]
57. Gómez, F.; von Müller, A.; Tarabini, M.; La Manna, L. Resilient Andisols under silvopastoral systems. *Geoderma* **2022**, *418*, e115843. [CrossRef]
58. Pang, X.; Bao, W.; Zhu, B.; Cheng, W. Response of soil respiration and its temperature sensitivity to thinning in a pine plantation. *Agric. For. Meteorol.* **2013**, *171*, 57–64. [CrossRef]
59. Bolat, I. The effect of thinning on microbial biomass C, N and basal respiration in black pine forest soils in Mudurnu, Turkey. *Eur. J. For. Res.* **2014**, *133*, 131–139. [CrossRef]
60. Dawes, M.; Schleppi, P.; Hattenschwiler, S.; Rixen, C.; Hagedorn, F. Soil warming opens the nitrogen cycle at the alpine treeline. *Glob. Chang. Biol.* **2017**, *23*, 421–434. [CrossRef]
61. Burke, I.; Lauenroth, W.; Parton, W. Regional and temporal variation in net primary production and nitrogen mineralization in grasslands. *Ecology* **1997**, *78*, 1330–1340. [CrossRef]
62. Li, Z.; Tian, D.; Wang, B.; Wang, J.; Wang, S.; Chen, H.; Xu, X.; Wang, C.; He, N.; Niu, S. Microbes drive global soil nitrogen mineralization and availability. *Glob. Chang. Biol.* **2019**, *25*, 107–1088. [CrossRef]
63. Verhoef, H.; Brussaard, L. Decomposition and nitrogen mineralization in natural and agroecosystems: The contribution of soil animals. *Biogeochemistry* **1990**, *11*, 175–211. [CrossRef]
64. Maaroufi, N.; De Long, J. Global change impacts on forest soils: Linkage between soil biota and carbon-nitrogen-phosphorus stoichiometry. *Front. For. Glob. Chang.* **2020**, *3*, e16. [CrossRef]
65. Thornton, P.; Lamarque, J.; Rosenbloom, N.; Mahowald, N. Influence of carbon-nitrogen cycle coupling on land model response to $CO_2$ fertilization and climate variability. *Glob. Biogeochem. Cycles* **2007**, *21*, GB4018. [CrossRef]
66. Luque, S.; Martínez Pastur, G.; Echeverría, C.; Pacha, M. Overview of biodiversity loss in South America: A landscape perspective for sustainable forest management and conservation in temperate forests. In *Landscape Ecology and Forest Management: Challenges and Solutions in a Changing Globe*; Li, C., Lafortezza, R., Chen, J., Eds.; HEP-Springer: Amsterdam, The Netherlands, 2010; pp. 352–379.
67. Angelstam, P.; Albulescu, C.; Andrianambinina, O.; Aszalós, R.; Borovichev, E.; Cano Cardona, W.; Dobrynin, D.; Fedoriak, M.; Firm, D.; Hunter, M.; et al. Frontiers of protected areas versus forest exploitation: Assessing habitat network functionality in 16 case study regions globally. *AMBIO* **2021**, *50*, 2286–2310. [CrossRef]
68. Martínez Pastur, G.; Schlichter, T.; Matteucci, S.; Gowda, J.; Huertas Herrera, A.; Toro Manríquez, M.; Lencinas, M.V.; Cellini, J.M.; Peri, P.L. Synergies and trade-offs of national conservation policy and agro-Forestry management over forest loss in Argentina during the last decade. In *Latin AMERICA in Times of Global Environmental Change*; Lorenzo, C., Ed.; The Latin American Studies Book Series; Springer: Cham, Switzerland, 2020; pp. 135–155.
69. Ministerio de Ambiente y Desarrollo Sustentable (MAyDS). *Informe de Estado de Implementación 2010–2016 de la Ley N°26.331 de Presupuestos Mínimos de Protección Ambiental de los Bosques Nativos*; Ministerio de Ambiente y Desarrollo Sostenible de la Nación: Buenos Aires, Argentina, 2017; 80p.
70. Wang, S.; Huang, M.; Shao, X.; Mickler, R.; Li, K.; Ji, J. Vertical distribution of soil organic carbon in China. *Environ. Manag.* **2004**, *33*, 200–209. [CrossRef]
71. Dirección Nacional de Bosques. *Datos del Segundo Inventario Nacional de Bosques Nativos de la República Argentina*; Ministerio de Ambiente y Desarrollo Sostenible de la Nación: Buenos Aires, Argentina, 2021; 67p.
72. Hansen, M.; Potapov, P.; Moore, R.; Hancher, M.; Turubanova, S.; Tyukavina, A.; Thau, D.; Stehmans, S.; Goetzt, S.; Loveland, T.; et al. High-resolution global maps of 21st-Century forest cover change. *Science* **2013**, *80*, 850–853. [CrossRef]
73. Peri, P.L.; Martínez Pastur, G.; Schlichter, T. *Uso Sustentable del Bosque: Aportes Desde la Silvicultura Argentina*; Ministerio de Ambiente y Desarrollo Sostenible de la Nación Argentina: Buenos Aires, Argentina, 2021; 888p.
74. Carter, M.; Gregorich, E. *Soil Sampling and Methods of Analysis*, 2nd ed.; Canadian Society of Soil Science; Taylor and Francis: Boca Ratón, FL, USA, 2007; 1261p.
75. Bray, R.; Kurtz, L. Determination of total, organic, and available forms of phosphorus in soils. *Soil Sci.* **1945**, *59*, 39–45. [CrossRef]
76. ESRI. *ArcGIS Desktop: Release 10*; Environmental Systems Research Institute Inc.: Redlands, California, USA, 2011.

77. Hijmans, R.; Cameron, S.; Parra, J.; Jones, P.; Jarvis, A. Very high-resolution interpolated climate surfaces for global land areas. *Int. J. Climat.* **2005**, *25*, 1965–1978. [CrossRef]
78. Zomer, R.; Trabucco, A.; Bossio, D.; Van Straaten, O.; Verchot, L. Climate change mitigation: A spatial analysis of global land suitability for clean development mechanism afforestation and reforestation. *Agric. Ecosyst. Environ.* **2008**, *126*, 67–80. [CrossRef]
79. Farr, T.; Rosen, P.; Caro, E.; Crippen, R.; Duren, R.; Hensley, S.; Kobrick, M.; Paller, M.; Rodriguez, E.; Roth, L.; et al. The shuttle radar topography mission. *Rev. Geophys.* **2007**, *45*, RG2004. [CrossRef]
80. ORNL DAAC. *MODIS Collection 5 Land Products Global Sub-Setting and Visualization Tool*; ORNL DAAC: Oak Ridge, TN, USA, 2008.
81. Zhao, M.; Running, S. Drought-induced reduction in global terrestrial net primary production from 2000 through 2009. *Science* **2010**, *329*, 940–943. [CrossRef] [PubMed]
82. Peri, P.L.; Rosas, Y.M.; Ladd, B.; Toledo, S.; Lasagno, R.; Martínez Pastur, G. Modelling soil nitrogen content in South Patagonia across a climate gradient, vegetation type, and grazing. *Sustainability* **2019**, *11*, 2707. [CrossRef]
83. Rosas, Y.M.; Peri, P.L.; Lencinas, M.V.; Lizarraga, L.; Martínez Pastur, G. Multi-taxon biodiversity assessment of Southern Patagonia: Supporting conservation strategies at different landscapes. *J. Environ. Manag.* **2022**, *307*, e114578. [CrossRef] [PubMed]
84. Carrasco, J.; Rosas, Y.M.; Lencinas, M.V.; Bortoluzzi, A.; Peri, P.L.; Martínez Pastur, G. Synergies and trade-offs among ecosystem services and biodiversity in different forest types inside and off-reserve in Tierra del Fuego, Argentina. In *Ecosystem Services in Patagonia: A Multi-Criteria Approach for an Integrated Assessment*; Peri, P.L., Nahuelhual, L., Martínez Pastur, G., Eds.; Natural and Social Sciences of Patagonia; Springer Nature: Cham, Switzerland, 2021; Chapter 4; pp. 75–97.
85. Olivero, E.; Castro, L.; Scasso, R.; Fazio, A.; Miretzky, P. Fosfatos marinos del Paleógeno de la Isla Grande de Tierra del Fuego. *Rev. Asoc. Geol. Argent.* **1998**, *53*, 239–246.
86. Selige, T.; Böhner, J.; Schmidhalter, U. High resolution topsoil mapping using hyperspectral image and field data in multivariate regression modeling procedures. *Geoderma* **2006**, *136*, 235–244. [CrossRef]
87. Sumfleth, K.; Duttmann, R. Prediction of soil property distribution in paddy soil landscapes using terrain data and satellite information as indicators. *Ecol. Indic.* **2008**, *8*, 485–501. [CrossRef]
88. Wang, K.; Zhang, C.; Li, W. Predictive mapping of soil total nitrogen at a regional scale: A comparison between geographically weighted regression and cokriging. *Appl. Geogr.* **2013**, *42*, 73–85. [CrossRef]
89. Hengl, T.; Heuvelink, G.; Kempen, B.; Leenaars, J.; Walsh, M.; Shepherd, K.; Tondoh, J. Mapping soil properties of Africa at 250m resolution: Random forests significantly improve current predictions. *PLoS ONE* **2015**, *10*, e0125814. [CrossRef]
90. Bui, E.; Henderson, B.; Viergever, K. Knowledge discovery from models of soil properties developed through data mining. *Ecol. Model.* **2006**, *191*, 431–446. [CrossRef]
91. Adhikari, K.; Kheir, R.; Greve, M.; Bøcher, P.; Malone, B.; Minasny, B.; Greve, M. High-resolution 3-D mapping of soil texture in Denmark. *Soil Sci. Soc. Am. J.* **2013**, *77*, 860–876. [CrossRef]
92. Chang, C.; Laird, D.; Mausbach, M.; Hurburgh, C. Near infrared reflectance spectroscopy: Principal components regression analysis of soil properties. *Soil Sci. Soc. Am. J.* **2001**, *65*, 480–490. [CrossRef]
93. Mosleh, Z.; Salehi, M.; Jafari, A.; Borujeni, I.; Mehnatkesh, A. The effectiveness of digital soil mapping to predict soil properties over low-relief areas. *Environ. Monit. Assess.* **2016**, *188*, e195. [CrossRef]
94. Razakamanarivo, R.; Grinand, C.; Razafindrakoto, M.; Bernoux, M.; Albrecht, A. Mapping organic carbon stocks in eucalyptus plantations of the central highlands of Madagascar: A multiple regression approach. *Geoderma* **2011**, *162*, 335–346. [CrossRef]
95. Jobbágy, E.; Jackson, R. The vertical distribution of soil organic carbon and its relation to climate and vegetation. *Ecol. Appl.* **2000**, *10*, 423–436. [CrossRef]
96. Bronson, K.; Zobeck, T.; Chua, T.; Acosta-Martínez, V.; van Pelt, R.; Booker, J. Carbon and nitrogen pools of southern high plains cropland and grassland soils. *Soil Sci. Soc. Am. J.* **2004**, *68*, 1695–1704. [CrossRef]
97. Bardgett, R.; Streeter, T.; Bol, R. Soil microbes compete effectively with plants for organic-nitrogen inputs to temperate grasslands. *Ecology* **2003**, *84*, 1277–1287. [CrossRef]
98. Follett, R.; Stewart, C.; Pruessner, E.; Kimble, J. Effects of climate change on soil carbon and nitrogen storage in the US Great Plains. *J. Soil Water Conserv.* **2012**, *67*, 331–342. [CrossRef]
99. Thornton, P.; Doney, S.; Lindsay, K.; Moore, J.; Mahowald, N.; Randerson, J.; Fung, I.; Lamarque, J.; Feddema, J.; Lee, Y. Carbon-nitrogen interactions regulate climate-carbon cycle feedbacks: Results from an atmosphere-ocean general circulation model. *Biogeosciences* **2009**, *6*, 2099–2120. [CrossRef]
100. Bahamonde, H.; Gargaglione, V.; Peri, P.L. Sheep feces decomposition and nutrient release across an environmental gradient in Southern Patagonia. *Ecol. Austral* **2017**, *27*, 18–28. [CrossRef]
101. Liu, J.; Zhu, A.; Rossiter, D.; Du, F.; Burt, J. Trustworthiness indicator to select sample points for the individual predictive soil mapping method (iPSM). *Geoderma* **2020**, *373*, e114440. [CrossRef]
102. Baxter, S.; Oliver, M. The spatial prediction of soil mineral N and potentially available N using elevation. *Geoderma* **2005**, *128*, 325–339. [CrossRef]
103. Viscarra Rossel, R.; Adamchuk, V.; Sudduth, K.; McKenzie, N.; Lobsey, C. Proximal soil sensing: An effective approach for soil measurements in space and time. *Adv. Agron.* **2011**, *113*, 243–291.
104. Toro-Manríquez, M.; Soler, R.; Lencinas, M.V.; Promis, A. Canopy composition and site are indicative of mineral soil conditions in Patagonian mixed *Nothofagus* forests. *Ann. For. Sci.* **2019**, *76*, e117. [CrossRef]

105. Adhikari, K.; Mishra, U.; Owens, P.; Libohova, Z.; Wills, S.; Riley, W.; Hoffman, F.; Smith, D. Importance and strength of environmental controllers of soil organic carbon changes with scale. *Geoderma* **2020**, *375*, e114472. [CrossRef]
106. Dreiss, L.; Volin, J. Influence of leaf phenology and site nitrogen on invasive species establishment in temperate deciduous forest understories. *For. Ecol. Manag.* **2013**, *296*, 1–8. [CrossRef]
107. Henn, J.; Anderson, C.; Kreps, G.; Lencinas, M.V.; Soler, R.; Martínez Pastur, G. Determining abiotic and biotic drivers that limit active riparian forest restoration in abandoned beaver meadows in Tierra del Fuego. *Ecol. Rest.* **2014**, *32*, 369–378. [CrossRef]
108. Bahamonde, H.; Martínez Pastur, G.; Lencinas, M.V.; Soler, R.; Rosas, Y.M.; Ladd, B.; Duarte Guardia, S.; Peri, P.L. The relative importance of soil properties and regional climate as drivers of productivity in southern Patagonia's *Nothofagus antarctica* forests. *Ann. For. Sci.* **2018**, *75*, e45. [CrossRef]
109. Augusto, L.; Ranger, J.; Binkley, D.; Rothe, A. Impact of several common tree species of European temperate forests on soil fertility. *Ann. For. Sci.* **2002**, *59*, 233–253. [CrossRef]
110. Binkley, D.; Valentine, D. Fifty-year biogeochemical effects of green ash, white pine and Norway spruce in a replicated experiment. *For. Ecol. Manag.* **1991**, *40*, 13–25. [CrossRef]
111. Rothe, A.; Binkley, D. Nutritional interactions in mixed species forests: A synthesis. *Can. J. For. Res.* **2001**, *31*, 1855–1870. [CrossRef]
112. Binkley, D.; Giardina, C. Why do tree species affect soils? The warp and woof of tree-soil interactions. *Biogeochemistry* **1998**, *42*, 89–106. [CrossRef]
113. Gerding, V.; Thiers, O. Caracterización de suelos bajo bosques de *Nothofagus betuloides* (Mirb) Blume, en Tierra del Fuego, Chile. *Rev. Chilena Hist. Nat.* **2002**, *75*, 819–833. [CrossRef]
114. Romanya, J.; Fons, J.; Sauras-Yera, T.; Gutiérrez, E.; Vallejo, R. Soil-plant relationships and tree distribution in old growth *Nothofagus betuloides* and *N. pumilio* forests of Tierra del Fuego. *Geoderma* **2005**, *124*, 169–180. [CrossRef]
115. Huygens, D.; Rütting, T.; Boeckx, P.; Van Cleemput, O.; Godoy, R.; Müller, C. Soil nitrogen conservation mechanisms in a pristine south Chilean *Nothofagus* forest ecosystem. *Soil Biol. Biochem.* **2007**, *39*, 2448–2458. [CrossRef]
116. Gargaglione, V.; Gonzalez Polo, M.; Birgi, J.; Toledo, S.; Peri, P.L. Silvopastoral use of *Nothofagus antarctica* forests in Patagonia: Impact on soil microorganisms. *Agrofor. Syst.* **2022**, *96*, 957–968. [CrossRef]
117. Podwojewski, P.; Poulenard, J.; Nguyet, M.; de Rouw, A.; Nguyen, V.; Pham, Q.; Tran, D. Climate and vegetation determine soil organic matter status in an alpine inner-tropical soil catena in the Fan Si Pan Mountain, Vietnam. *Catena* **2011**, *87*, 226–239. [CrossRef]
118. Garten, C.; Hanson, P. Measured forest soil C stocks and estimated turnover times along an elevation gradient. *Geoderma* **2006**, *136*, 342–352. [CrossRef]
119. Sánchez, P.; Ahamed, S.; Carre, F.; Hartemink, A.; Hempel, J.; Huising, J.; Lagacherie, P.; McBratney, A.; McKenzie, N.; Mendonça-Santos, M.; et al. Digital soil map of the world. *Science* **2009**, *325*, 680–681. [CrossRef]
120. Chenu, C.; Angers, D.; Barre, P.; Derrien, D.; Arrouays, D.; Balesdent, J. Increasing organic stocks in agricultural soils: Knowledge gaps and potential innovations. *Soil Tillage Res.* **2019**, *188*, 41–52. [CrossRef]
121. Moreno, A.; Neumann, M.; Hasenauer, H. Optimal resolution for linking remotely sensed and forest inventory data in Europe. *Remote Sens. Environ.* **2016**, *183*, 109–119. [CrossRef]
122. Zald, H.; Wulder, M.A.; White, J.C.; Hilker, T.; Hermosilla, T.; Hobart, G.W.; Coops, N.C. Integrating Landsat pixel composites and change metrics with lidar plots to predictively map forest structure and aboveground biomass in Saskatchewan, Canada. *Remote Sens. Environ.* **2016**, *176*, 188–201. [CrossRef]
123. Silveira, E.M.O.; Terra, M.; ter Steege, H.; Maeda, E.; Acerbi Júnior, F.; Scolforo, J. Carbon-diversity hotspots and their owners in Brazilian southeastern savanna, Atlantic forest and semi-arid woodland domains. *For. Ecol. Manag.* **2019**, *452*, e117575. [CrossRef]
124. Silveira, E.M.O.; Espírito Santo, F.; Wulder, M.A.; Acerbi Júnior, F.; Carvalho, M.C.; Mello, C.R.; Mello, J.M.; Shimabukuro, Y.E.; Terra, M.; Carvalho, L.; et al. Pre-stratified modelling plus residuals kriging reduces the uncertainty of aboveground biomass estimation and spatial distribution in heterogeneous savannas and forest environments. *For. Ecol. Manag.* **2019**, *445*, 96–109. [CrossRef]
125. White, J.; Wulder, M.; Hobart, G.; Luther, J.; Hermosilla, T.; Griffiths, P.; Coops, N.; Hall, R.; Hostert, P.; Dyk, A.; et al. Pixel-based image compositing for large area dense time series applications and science. *Can. J. Remote Sens.* **2014**, *40*, 192–212. [CrossRef]
126. Yuping, L.; Ramzan, M.; Xincheng, L.; Murshed, M.; Awosusi, A.; Ibrahim, S.; Adebayo, T. Determinants of carbon emissions in Argentina: The roles of renewable energy consumption and globalization. *Energy Rep.* **2021**, *7*, 4747–4760. [CrossRef]
127. Murshed, M.; Rashid, S.; Ulucak, R.; Dagar, V.; Rehman, A.; Alvarado, R.; Nathaniel, S. Mitigating energy production-based carbon dioxide emissions in Argentina: The roles of renewable energy and economic globalization. *Environ. Sci. Pollut. Res.* **2022**, *29*, 16939–16958. [CrossRef]
128. Baldassini, P.; Bagnato, C.; Paruelo, J. How may deforestation rates and political instruments affect land use patterns and carbon emissions in the semi-arid Chaco, Argentina? *Land Use Policy* **2020**, *99*, e104985. [CrossRef]
129. Aagesen, D. Crisis and conservation at the end of the world: Sheep ranching in Argentine Patagonia. *Environ. Conserv.* **2000**, *27*, 208–215. [CrossRef]

130. Mazzonia, E.; Vazquez, M. Desertification in Patagonia. *Dev. Earth Surface Proc.* **2009**, *13*, 351–377.
131. Peri, P.L.; Lasagno, R.; Chartier, M.; Roig, F.; Rosas, Y.M.; Martínez Pastur, G. Soil erosion rates and nutrient loss in rangelands of Southern Patagonia. In *Imperiled: The Encyclopedia of Conservation*; Della Sala, D., Goldstein, M., Eds.; Elsevier: Amsterdam, The Netherlands, 2022; Volume 1–3, Chapter 9; pp. 102–110.