Food and Agriculture Organization of the United Nations

LATSOLAN
LATIN AMERICAN SOIL LABORATORY NETWORK

Pathways to precision in soil analysis: advancing soil laboratories in Latin America and the Caribbean

Caminos hacia la Precisión en el Análisis de Suelos: avance de los Laboratorios de Suelos en América Latina y el Caribe

Desarrollo de una Biblioteca Nacional de Espectros de Suelos: EL CASO DE CHILE

WORKSHOP
SANTIAGO - CHILLÁN | CHILE
8-11 APRIL 2024

Erick Zagal, María de los Ángeles Sepúlveda, Marcela Hidalgo, David Contreras, Katherine Rebolledo.

Estudiantes Elizabeth Godoy (pregrado), Jean Iván Intriago (Posgrado MSc), Omar Orellana (Posgrado PhD)

GLOBAL SOIL PARTNERSHIP

Algunos ejemplos recientes de uso de Espectroscopía de suelos en Chile

Chilean J. Agric. Anim. Sci., ex Agro-Ciencia (2021) 37(1): 32-42.

https://doi.org/10.29393/CHJAAS37-4CCIL40004

CHEMICAL CHARACTERIZATION OF VOLCANIC SOILS USING NEAR INFRARED SPECTROSCOPY (NIRS)

CARACTERIZACIÓN QUIMICA DE SUELOS VOLCANICOS UTILIZANDO ESPECTROSCOPIA DE INFRARROJO CERCANO (NIRS)

Iris Lobos Ortega[1*], Marta Alfaro Valenzuela[1], Josué Martínez Lagos[1] and Paula Pavez Andrades[1]

[1] Instituto de Investigaciones Agropecuarias, INIA Remehue, Ruta 5 Norte, Km 8, Osorno, Chile.

*** Corresponding author E-mail: iris.lobos@inia.cl**

Algunos ejemplos recientes de uso de Espectroscopía de suelos en Chile

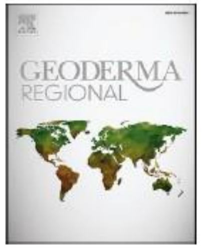
Geoderma Regional 34 (2023) e00675

ELSEVIER

Contents lists available at ScienceDirect

Geoderma Regional

journal homepage: www.elsevier.com/locate/geodrs



Check for updates

Evaluation of a miniaturized portable NIR spectrometer for the prediction of soil properties in Mediterranean central Chile

Osvaldo Salazar[a,*], Angelo Benvenuto[b], Mario Fajardo[c], Juan Pablo Fuentes[d], Francisco Nájera[e], Ayleen Celedón[a], Marco Pfeiffer[a], Leah L.R. Renwick[a], Oscar Seguel[a], Yasna Tapia[a], Manuel Casanova[a]

[a] *Departamento de Ingeniería y Suelos, Facultad de Ciencias Agronómicas, Universidad de Chile, Santiago, Chile*
[b] *Programa de Magíster Manejo de Suelos y Aguas, Facultad de Ciencias Agronómicas, Universidad de Chile, Santiago, Chile*
[c] *Sydney Institute of Agriculture & School of Life and Environmental Sciences, The University of Sydney, Australia*
[d] *Departamento de Silvicultura y Conservación de la Naturaleza, Facultad de Ciencias Forestales y de la Conservación de la Naturaleza, Universidad de Chile, Chile*
[e] *Laboratorio de Conservación y Dinámica de Suelos Volcánicos, Departamento de Ciencias Químicas y Recursos Naturales, Universidad de la Frontera, Chile*

Algunos ejemplos recientes de uso de Espectroscopía de suelos en Chile

Geoderma Regional 25 (2021) e00397

Contents lists available at ScienceDirect

Geoderma Regional

journal homepage: www.elsevier.com/locate/geodrs

ELSEVIER

GEODERMA REGIONAL

Near-infrared spectroscopy: Alternative method for assessment of stable carbon isotopes in various soil profiles in Chile

Check for updates

María de los Ángeles Sepúlveda [a], Marcela Hidalgo [a], Juan Araya [b], Manuel Casanova [c], Cristina Muñoz [a], Sebastian Doetterl [d], Daniel Wasner [d], Ben Colpaert [e], Samuel Bodé [e], Pascal Boeckx [e], Erick Zagal [a,*]

[a] *Department of Soil and Natural Resources, Faculty of Agronomy, University of Concepción, Chile*
[b] *Department of Instrumental Analysis, Faculty of Pharmacy, University of Concepción, Chile*
[c] *Department of Engineering and Soil, Faculty of Agronomics Science, University of Chile, Santiago, Chile*
[d] *ETH-Zürich, Department of Environmental Systems Science, Zürich, Switzerland*
[e] *Department of Green Chemistry and Technology, Isotope Bioscience Laboratory (ISOFYS), Ghent University, Gent, Belgium*

Algunos ejemplos recientes de uso de Espectroscopía de suelos en Chile

Journal of Soil Science and Plant Nutrition (2022) 22:2105–2117
https://doi.org/10.1007/s42729-022-00797-w

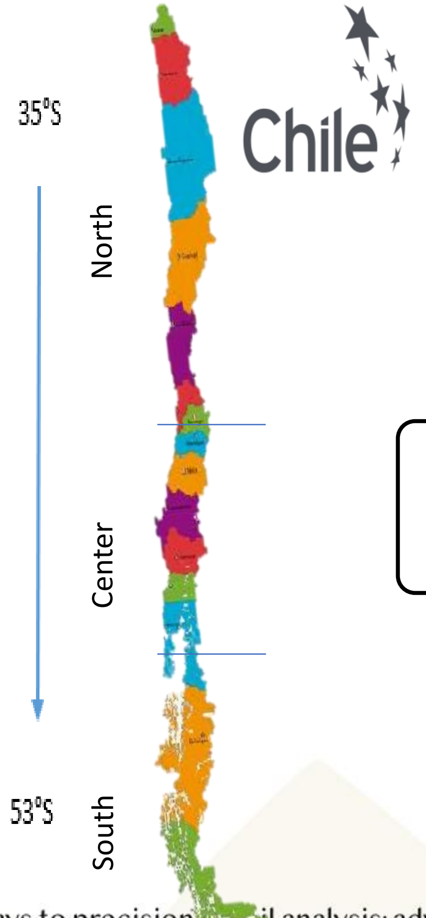
ORIGINAL PAPER

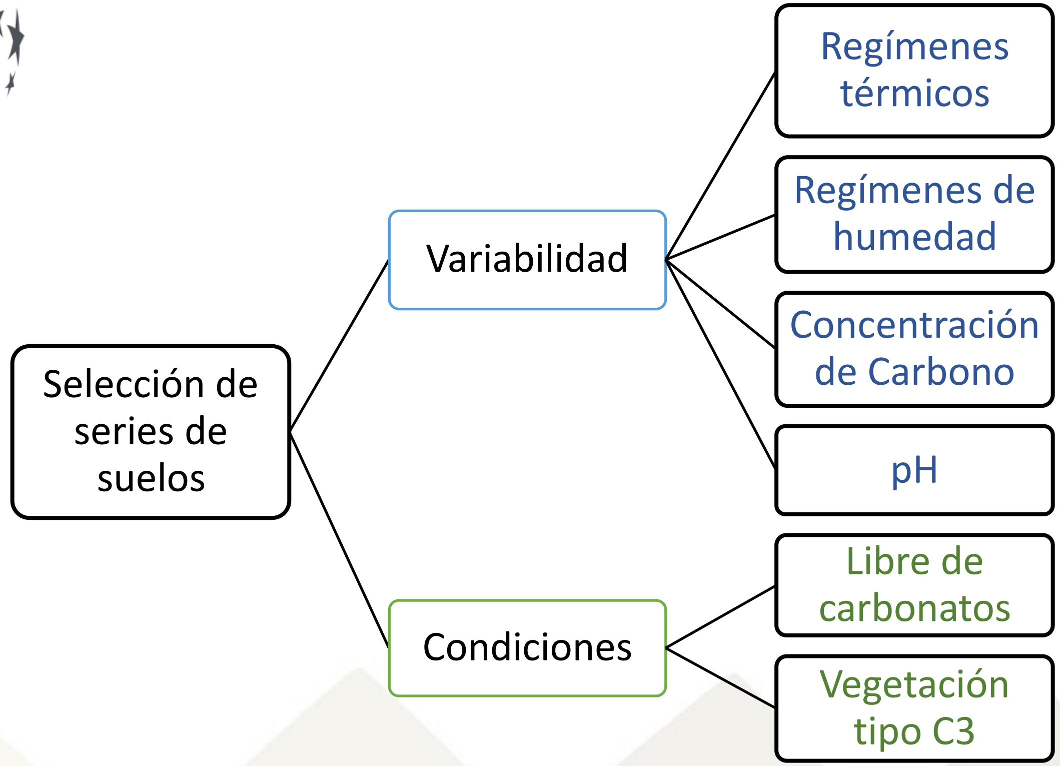
Check for updates

Predicting Soil Organic Carbon Mineralization Rates Using $\delta^{13}C$, Assessed by Near-Infrared Spectroscopy, in Depth Profiles Under Permanent Grassland Along a Latitudinal Transect in Chile

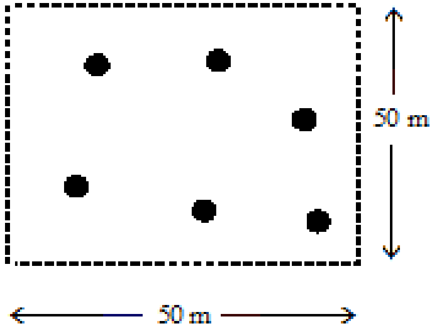
Hidalgo Marcela[1,2] · María de los Ángeles Sepulveda[2] · Cristina Muñoz[2] · Manuel Casanova[3] · Daniel Wasner[4] · Samuel Bodé[5] · Sebastian Doetterl[4] · Pascal Boeckx[5] · Erick Zagal[2]

Metodología: Muestreo de Suelos.



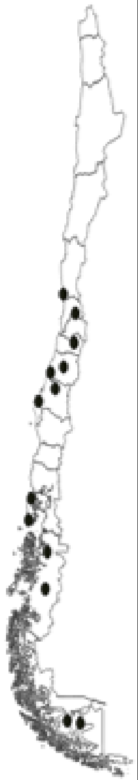


Un total de 11 sitios fueron seleccionados
Profundidad entre 30-60 cm
Estos análisis se trabajaron en triplicado



Parcela de muestreo

Table1. Description of the geographical and climatic zones, location and soil orders of the sample sites.

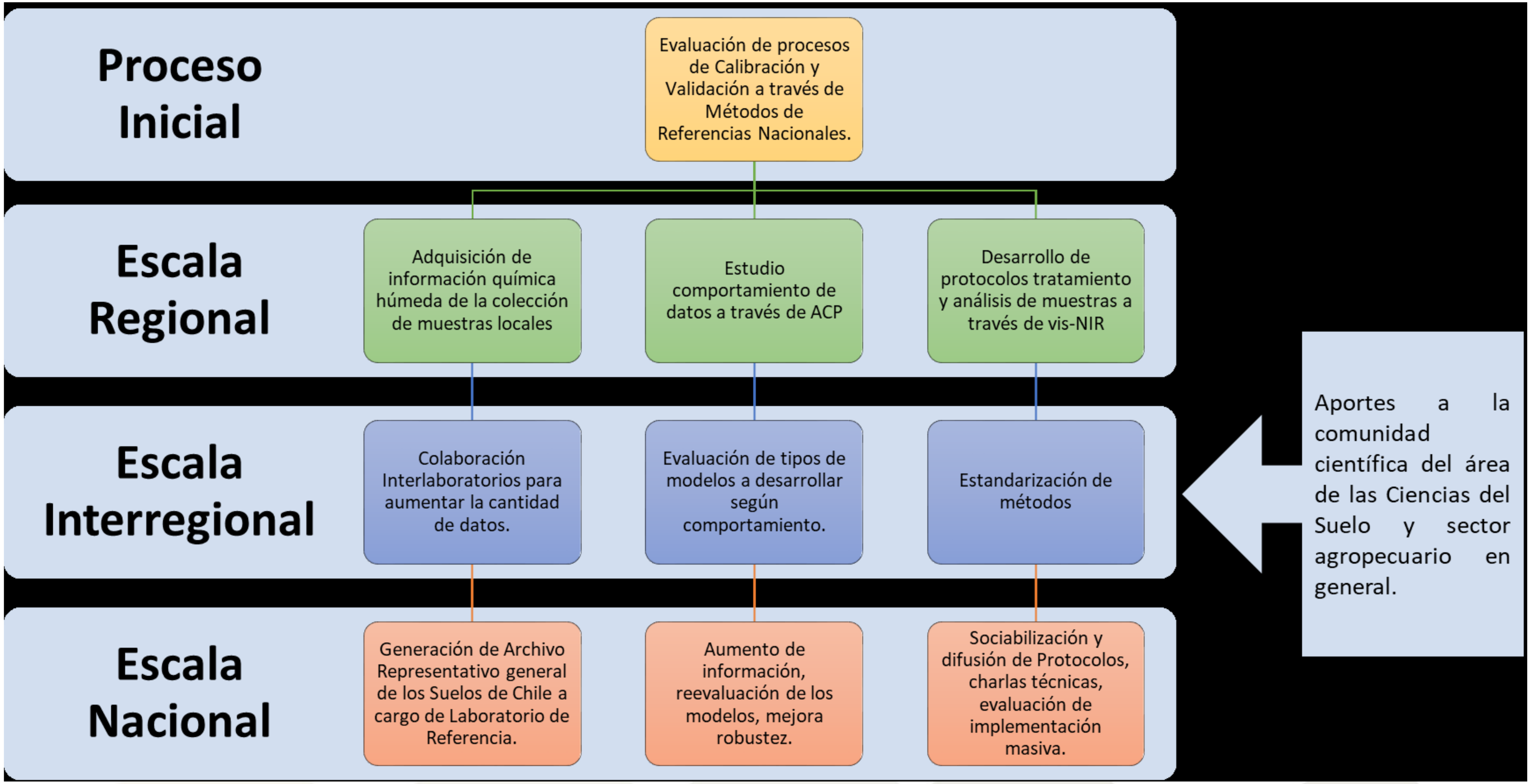
Geographical zone	Soil series		E-UTM m	N-UTM m	Soil taxonomy	Climatic zone
North	Los Vilos		263342	6477586	Torric Psamment	Mediterranean semiarid (MSA)
	Calle larga		357651	6361423	Typic Argixeroll	
	Pimpinela		340864	6200578	Mollic Haploxeralf	
	Matanza		234301	6237593	Oxic Haplustoll	
South-central	Bramadero		290355	6056474	Humic Haploxerand	Template semi-oceanic (TSO)
	Santa Bárbara		258294	5961851	Typic Haploxerand	
	Carampangue		653701	5875605	Fluvaquentic Dystrudept	
South	Pachabrám		596724	5302714	Histic Duraquand	Template oceanic (TO)
	Aitiú		612611	5302714	Hydric Fulvudand	
	Puerto Cisne		688801	5041291	Acrudoxic Fulvudand	Sub-polar semi-oceanic (SPSO)
Extreme south	B. Exploradores		643673	4849209	Oxyaquic Hapludand	
	Agua Fresca		368000	4080000	Inceptisol	Sub-polar dry (SPD)
	Santa Olga		409570	4091863	Inceptisol	

Proyecto Actual

- **Desarrollo y Validación en análisis de suelos de un proceso costo efectivo, rápido y ambientalmente amigable a nivel local y global: la alternativa de espectroscopia de suelos**
- Concurso IDeAI+D 2021

Problema/Oportunidad

Solución Propuesta



Hipótesis

- ***La Espectroscopía Infrarroja Visible y Cercana (vis-NIRS) constituye una alternativa, rápida, robusta, costo efectiva y amigable al ambiente, a las técnicas convencionales de análisis de suelos (química húmeda) en la determinación de propiedades básicas y/o fundamentales del suelo, relevantes en la condición de salud de los suelos y su manejo sustentable.***

Objetivo general

- **Desarrollar y validar un conjunto de herramientas para el análisis de suelos, la Espectroscopía Infrarroja Visible y Cercana (vis-NIRS), como alternativa a los análisis convencionales de rutina (química húmeda), y para propiedades básicas y/o fundamentales en la condición de salud de los suelos y su manejo sustentable; generando en una primera etapa una biblioteca de referencias de patrones espectrales visibles e infrarrojos a nivel regional.**

Objetivos específicos

- ***Desarrollar y generar un protocolo de la toma y preparación de muestras para Espectroscopía visible e Infrarroja Cercana (vis-NIRS).***
- ***Desarrollar y generar un protocolo de análisis en el espectrómetro para reducir interferencias y mejorar la capacidad predictiva de los modelos, para propiedades del suelo como pH, C orgánico, Nitrógeno, textura (% de arena y arcilla), bases de intercambio***.

Objetivos Específicos

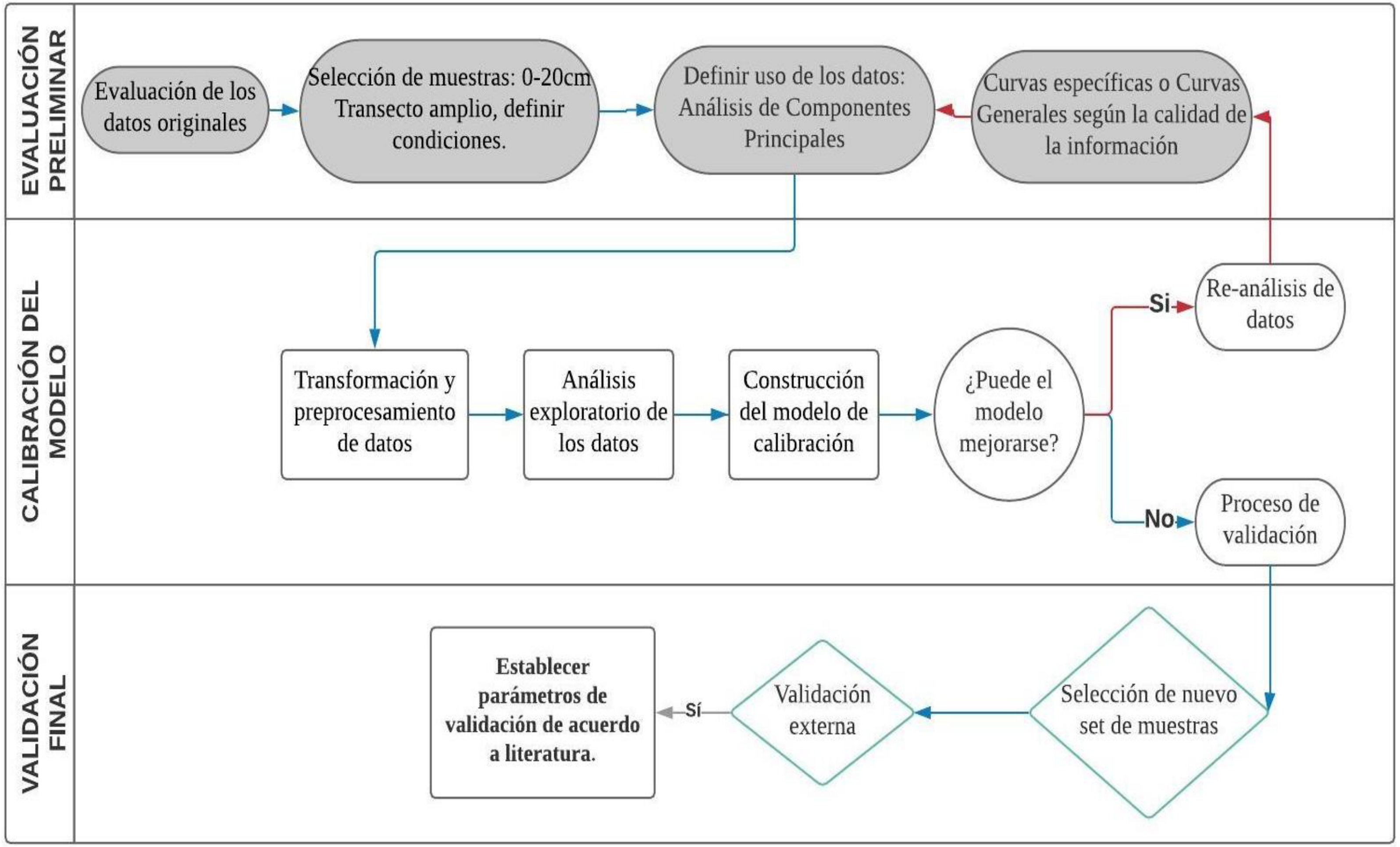
- ***Desarrollar y generar un protocolo de visualización de los datos y su predicción (generación de modelos), es decir, de calibración y validación para la estimación de las propiedades del suelo mencionadas anteriormente, usando valores de referencia (métodos de química húmeda).***
- ***Construir una biblioteca de referencias de patrones espectrales visibles e infrarrojos a nivel regional con muestras de las regiones del Maule, Ñuble y la Araucanía***.

Metodología Investigación y desarrollo

- 1. Descripción de la recolección de muestras y regiones (trabajo en terreno), que responde a la caracterización fisico-química tradicional inicial con la que se debe contar.
- 2. Archivo de espectros y análisis por espectroscopia vis-NIR, esta etapa responde al ordenamiento de las muestras para la obtención de una adecuada lectura espectral.

Metodología Investigación y desarrollo

- 3. La tercera etapa general corresponde específicamente al desarrollo del modelamiento de datos. Ver flujo.


EVALUACIÓN PRELIMINAR
Evaluación de los datos originales
Selección de muestras: 0-20cm Transecto amplio, definir condiciones.
Definir uso de los datos: Análisis de Componentes Principales
Curvas específicas o Curvas Generales según la calidad de la información
CALIBRACIÓN DEL MODELO
Transformación y preprocesamiento de datos
Análisis exploratorio de los datos
Construcción del modelo de calibración
¿Puede el modelo mejorarse?
Si
Re-análisis de datos
No
Proceso de validación
VALIDACIÓN FINAL
Selección de nuevo set de muestras
Validación externa
Sí
Establecer parámetros de validación de acuerdo a literatura.

Producto, proceso o servicio a desarrollar

- **Servicio y Productos finales :**

1. Protocolo y estandarización de la colección, preparación y procesamiento de muestras de suelo para la obtención de datos espectrales bajo Espectroscopia Visible e Infrarrojo Cercano.

2. Protocolo y técnicas de calibración, validación y evaluación de los modelos.

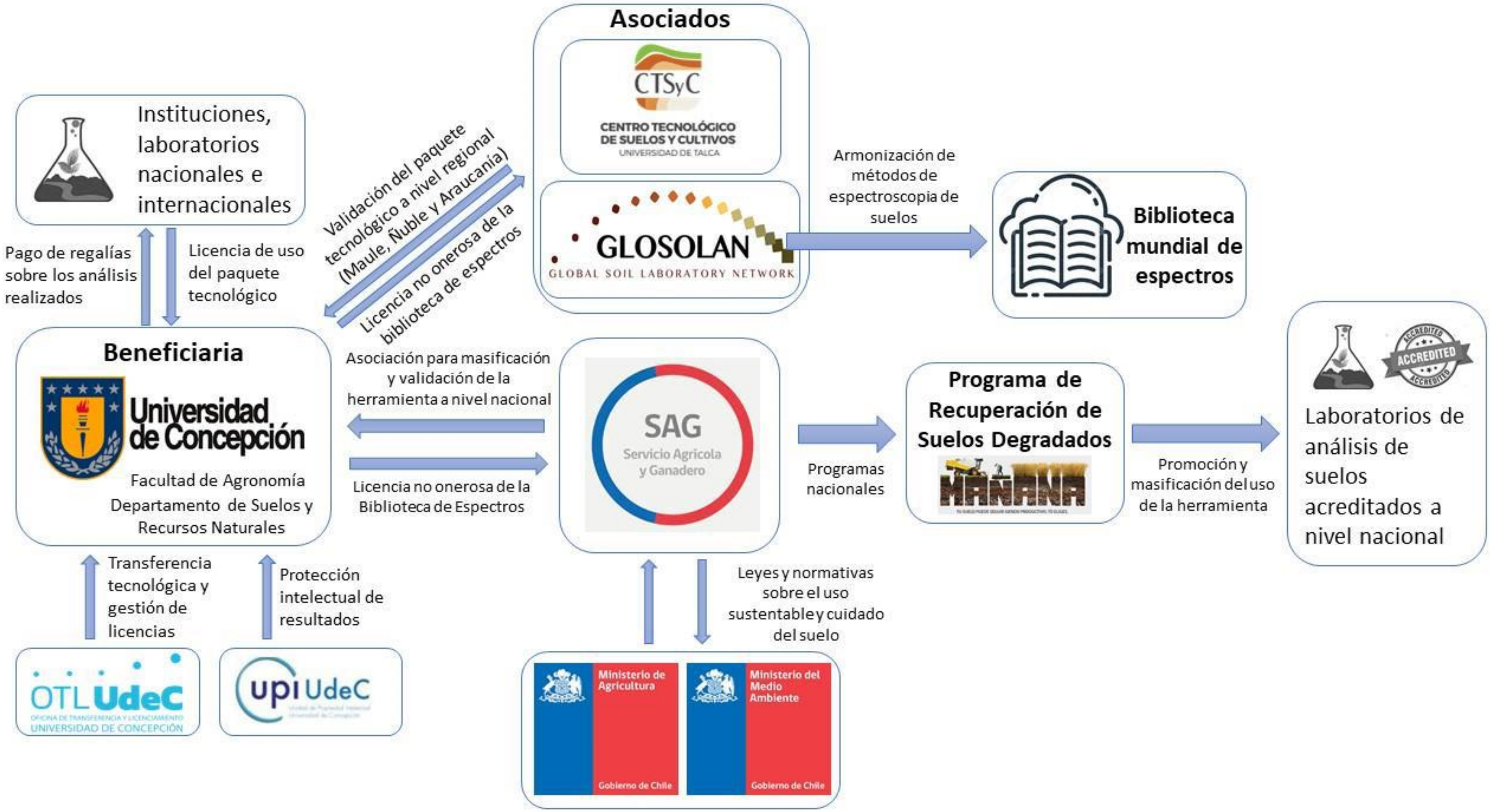
3. Protocolo de construcción de librería espectral.

Producto, proceso o servicio a desarrollar

- **Otros productos**

- Protección "Derecho de autor" del paquete tecnológico.
- Transferencia y Negocios a través del "Licenciamiento y Transferencia tecnológica.
- Producción Científica "Artículo científico en revista WoS; tesis de pre y posgrado (Magister).
- Inicio de Centro de referencia en espectroscopia de Suelos

Estrategia de desarrollo y negocio o masificación



Resultados preliminares

A Good example of the performance of VNIR spectroscopy as an alternative to wet chemistry and potential for soil monitoring at large scales can be found in the following results.

1. *Soil spectral soil modelling*

a.1 Methodology

The analysis and processing of obtained spectra was carried out using Partial Least Squares (PLS) regression models, employed to analyze soil properties. Two main treatments of the spectral data were applied: (1) PLS models without treatment, where the raw spectral data were directly used for model training, and (2) PLS models with additional data treatments, including PLS-OSC (Orthogonal Signal Correction) to remove orthogonal variations, PLS-Smoth(35) involving spectral smoothing with a Savitzky-Golay filter, and PLS-1st derv(5)+Smoth(25) combining first derivative transformation followed by spectral smoothing. Finally, the validity of the models was evaluated using the coefficient of determination (R^2), and the rVal and rCal of each variable (Amin et al., 2020). Besides, for soil spectral soil mapping a Random Forest algorithm was tested and applied (see below, section Soil spectral soil mapping). In Figure 1, the flowchart of the methodology for soil spectroscopy analysis is depicted.

Flowchart of the soil spectroscopy methodology.

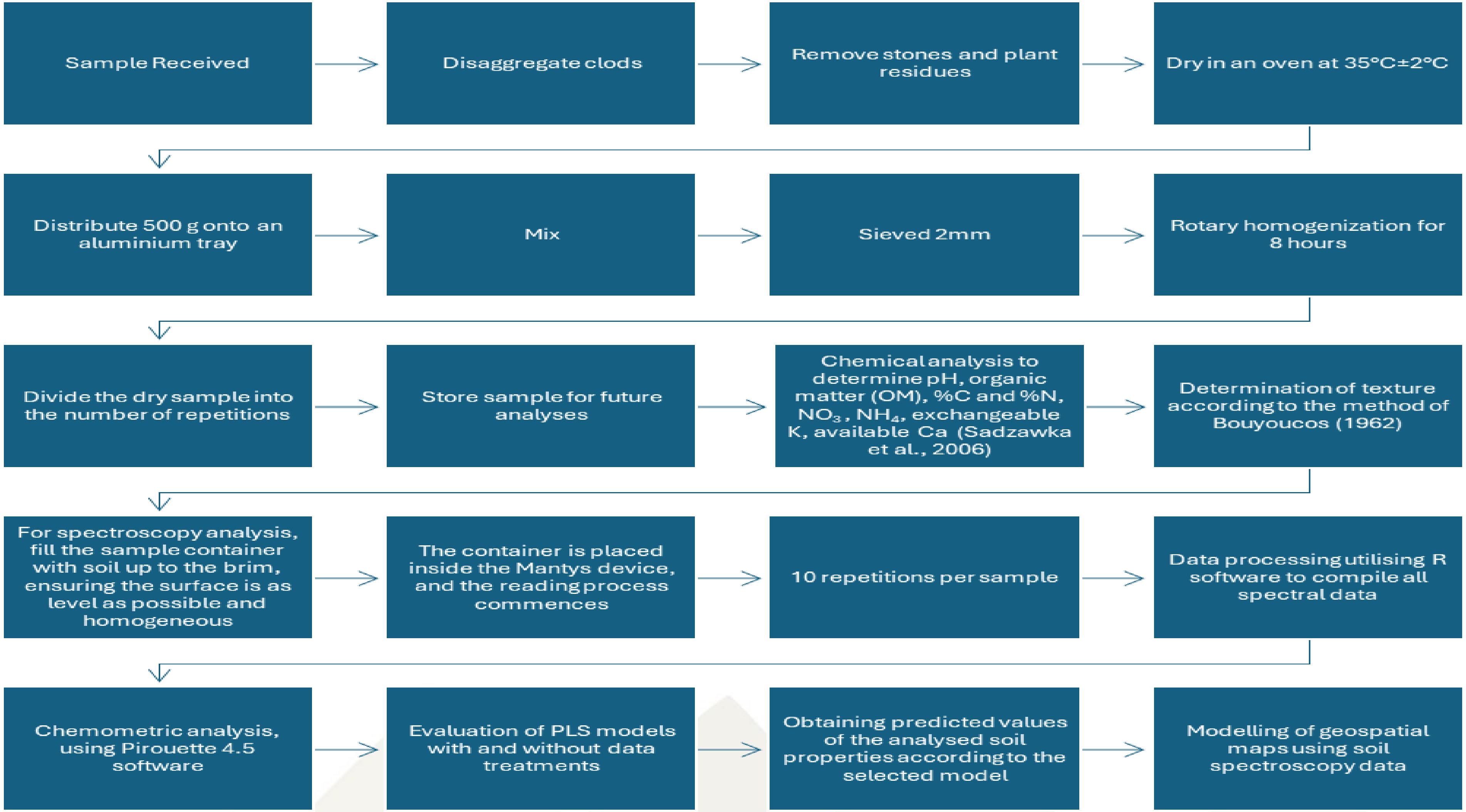


Table 1. Comparison Table of Models Used for Soil Variable Prediction and Their Statistical Data

Variable	Model	Data treatment	Cumulative of variance	r Val	r Cal
pH	PLS	none	0.999	0.40	0.43
%C	PLS	none	0.999	0.78	0.79
%N	PLS	none	0.999	0.78	0.79
MO	PLS	none	0.999	0.79	0.80
NO3	PLS	none	0.999	0.38	0.41
NH4	PLS	none	0.999	0.22	0.26
N-available	PLS	none	0.999	0.39	0.42
P-Olsén	PLS	none	0.999	0.40	0.43
K-available	PLS	none	0.999	0.40	0.44
K-exchangeable	PLS	none	0.999	0.40	0.44
Ca-available	PLS	none	0.999	0.48	0.51
%Arena	PLS	none	0.999	0.44	0.47
%Limo	PLS	none	0.999	0.43	0.46
%Arcilla	PLS	none	0.999	0.67	0.68
pH	PLS	OSC	0.998	0.43	0.46
%C	PLS	OSC	0.986	0.77	0.77
%N	PLS	OSC	0.983	0.82	0.83
MO	PLS	OSC	0.984	0.82	0.82
NO3	PLS	OSC	0.998	0.41	0.44
NH4	PLS	OSC	0.944	0.52	0.53
N-available	PLS	OSC	0.998	0.41	0.44
P-Olsén	PLS	OSC	0.998	0.41	0.44
K-available	PLS	OSC	0.997	0.43	0.45
K-exchangeable	PLS	OSC	0.991	0.43	0.45
Ca-available	PLS	OSC	0.995	0.53	0.54
%Arena	PLS	OSC	0.999	0.33	0.38
%Limo	PLS	OSC	0.999	0.41	0.45
%Arcilla	PLS	OSC	0.998	0.53	0.55
pH	PLS	MSC	0.995	0.04	0.10
%C	PLS	MSC	0.997	0.08	0.26
%N	PLS	MSC	0.997	0.06	0.27
MO	PLS	MSC	0.996	0.05	0.26
NO3	PLS	MSC	0.995	0.02	0.12
NH4	PLS	MSC	0.993	-0.01	0.04
N-available	PLS	MSC	0.995	0.02	0.12
P-Olsén	PLS	MSC	0.993	0.00	0.09

K-available	PLS	MSC	0.997	-0.02	0.12
K-exchangeable	PLS	MSC	0.997	-0.02	0.12
Ca-available	PLS	MSC	0.997	0.00	0.16
%Arena	PLS	MSC	0.994	0.05	0.14
%Limo	PLS	MSC	0.997	0.04	0.17
%Arcilla	PLS	MSC	0.995	0.08	0.15
pH	PLS	Smoth	0.647	0.52	0.60
%C	PLS	Smoth	0.649	0.82	0.85
%N	PLS	Smoth	0.649	0.86	0.88
MO	PLS	Smoth	0.649	0.86	0.88
NO3	PLS	Smoth	0.644	0.48	0.57
NH4	PLS	Smoth	0.641	0.42	0.53
N-available	PLS	Smoth	0.643	0.49	0.57
P-Olsén	PLS	Smoth	0.642	0.45	0.55
K-available	PLS	Smoth	0.639	0.39	0.52
K-exchangeable	PLS	Smoth	0.640	0.39	0.52
Ca-available	PLS	Smoth	0.645	0.35	0.49
%Arena	PLS	Smoth	0.646	0.53	0.61
%Limo	PLS	Smoth	0.629	0.49	0.58
%Arcilla	PLS	Smoth	0.650	0.64	0.70
pH	PLS	1°Derv+Smoth	0.388	0.55	0.70
%C	PLS	1°Derv+Smoth	0.386	0.74	0.83
%N	PLS	1°Derv+Smoth	0.387	0.78	0.85
MO	PLS	1°Derv+Smoth	0.387	0.78	0.85
NO3	PLS	1°Derv+Smoth	0.378	0.60	0.74
NH4	PLS	1°Derv+Smoth	0.387	0.53	0.68
N-available	PLS	1°Derv+Smoth	0.376	0.59	0.73
P-Olsén	PLS	1°Derv+Smoth	0.385	0.43	0.63
K-available	PLS	1°Derv+Smoth	0.387	0.45	0.65
K-exchangeable	PLS	1°Derv+Smoth	0.387	0.45	0.65
Ca-available	PLS	1°Derv+Smoth	0.384	0.45	0.64
%Arena	PLS	1°Derv+Smoth	0.386	0.60	0.73
%Limo	PLS	1°Derv+Smoth	0.379	0.55	0.70
%Arcilla	PLS	1°Derv+Smoth	0.384	0.57	0.73

Resultados Preliminares

b. Soil spectral soil mapping

b.1 Study Area Location and Field Samples

To assess advancements in digital soil mapping using spectroscopy data, georeferenced records from the actual FONDEF project were utilized. The database includes 78 sites distributed across four regions in the central-south of Chile (Maule, Ñuble, Bio Bio, La Araucanía; Between latitude -35° to -39.5°) containing laboratory values for Organic Matter (OM), total Carbon (C), and total Nitrogen (N), as well as estimations of these parameters through vis-NIR spectroscopy models. Soil samples do not contain inorganic C; therefore, total C is synonymous of soil organic C (SOC). The study area was delineated, excluding the Andean Mountain regions (see Figure 2).

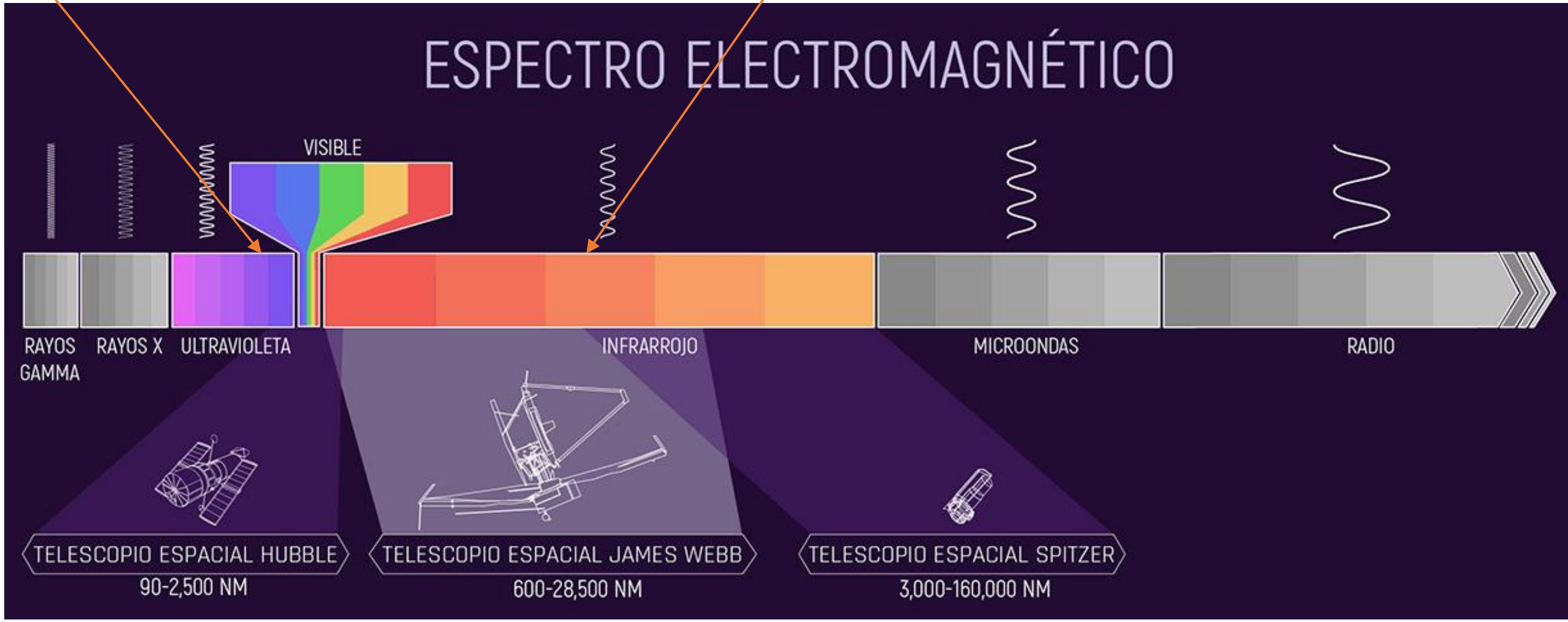
Column1	Column2
Convert to Abs("M9.1.1"):M9.1.1	
Wavelength (nm)	Abs
3300	0.1462681592
3299	-0.007602510508
3298	1.52526772
3297	9.999899864
3296	9.999899864
3295	-0.13049528
3294	9.999899864
3293	9.999899864
3292	9.999899864
3291	9.999899864
3290	9.999899864
3289	9.999899864
3288	9.999899864
3287	9.999899864
3286	9.999899864
3285	0.1166308969
3284	0.3891232908
3283	0.4728216231
3282	0.1551831067
3281	0.2582832575
3280	9.999899864
3279	0.1484932303
3278	-0.4201975167
3277	-0.6592809558
3276	0.8201592565
3275	9.999899864
3274	9.999899864
3273	0.2615779042
3272	9.999899864
3271	9.999899864
3270	0.8094537258
3269	2.826517344
3268	0.7455255985

10 Repeticiones por muestra

175 nm

3126 valores de absorbancia

3300 nm



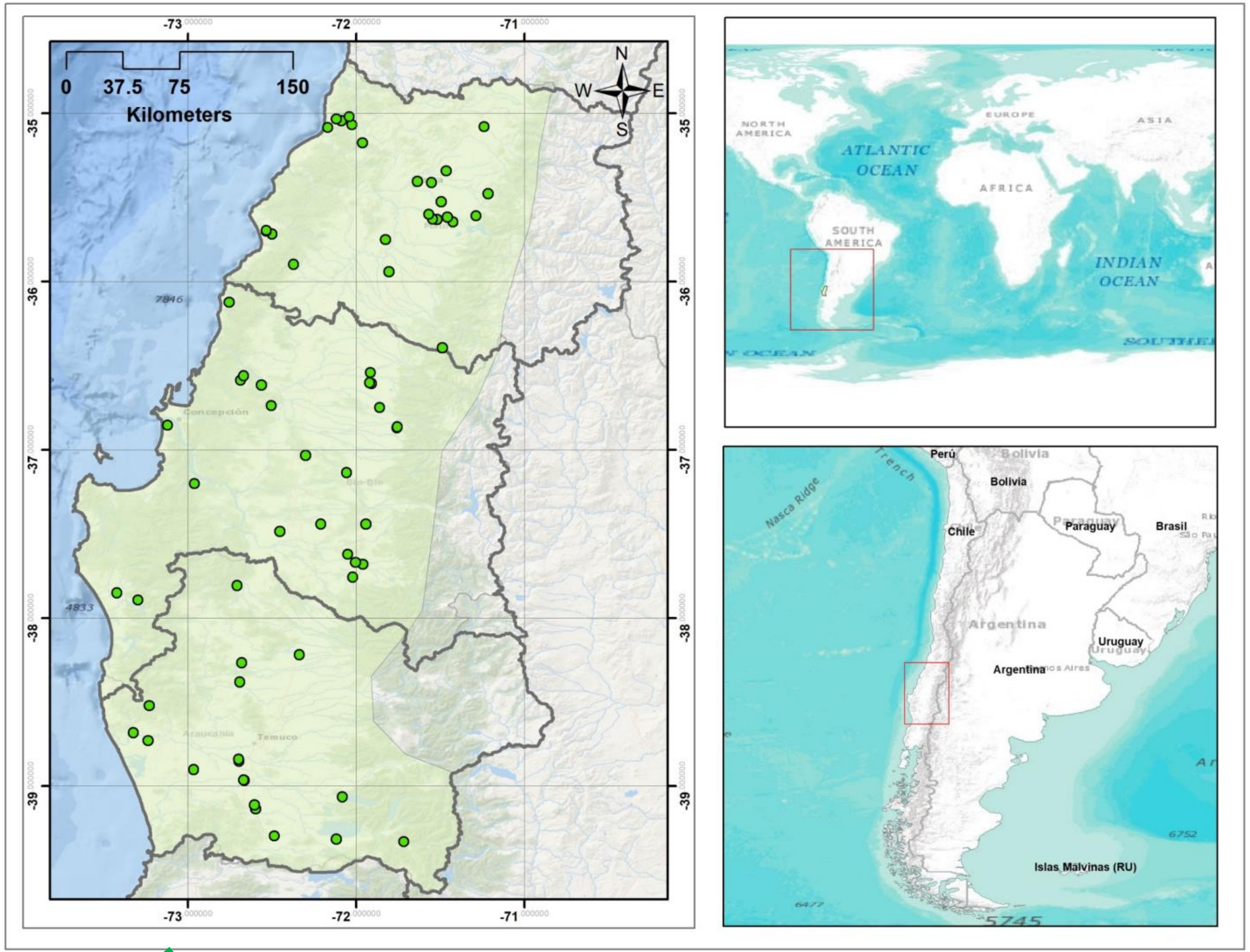
Base de datos unificada de absorbancia en espectroscopía

Abs	M911A	M914A	M915A	M916A	M917A	M918A	M919A	M9110A	M921A	M922A	M923A	M924A	M925A	M926A	M927A	M928A
3300	1.52526772	0.062548056	-0.07079047	-0.578032732	-0.565190435	-0.534629285	0.027399687	-0.506799221	9.999899864	0.562325656	0.40518105	9.999899864	9.999899864	9.999899864	9.999899864	1.136674762
3299	9.999899864	9.999899864	9.999899864	9.999899864	9.999899864	9.999899864	9.999899864	9.999899864	1.16827476	9.999899864	9.999899864	0.699321389	9.999899864	0.623961508	9.999899864	0.777874231
3298	9.999899864	9.999899864	9.999899864	0.843537629	1.982522249	9.999899864	9.999899864	9.999899864	-0.172613308	9.999899864	0.210995346	0.175947338	9.999899864	0.195853114	0.502056897	9.999899864
3297	-0.13049528	-0.456974089	-0.016970595	9.999899864	9.999899864	-0.345394045	-0.22989212	-0.054549113	9.999899864	0.341782451	0.868814468	9.999899864	0.693437576	0.656131566	0.677576721	0.266310215
3296	9.999899864	-0.134642273	-0.093449831	9.999899864	0.822807431	9.999899864	0.575261712	0.421854883	9.999899864	0.133327842	0.073708385	0.297375292	1.026394844	0.129878178	1.124043226	9.999899864
3295	9.999899864	9.999899864	0.515292049	9.999899864	1.424329877	9.999899864	9.999899864	0.200446412	9.999899864	9.999899864	-0.201058209	9.999899864	9.999899864	9.999899864	9.999899864	9.999899864
3294	9.999899864	9.999899864	0.250909537	0.111634858	9.999899864	9.999899864	9.999899864	0.217611268	-1.156601548	9.999899864	9.999899864	9.999899864	9.999899864	9.999899864	9.999899864	9.999899864
3293	9.999899864	9.999899864	9.999899864	-0.238677681	1.033714533	0.213575915	9.999899864	9.999899864	1.210540175	0.75621444	9.999899864	9.999899864	0.604164004	0.130627915	0.636934578	0.308053076
3292	9.999899864	9.999899864	9.999899864	1.588230133	9.999899864	9.999899864	9.999899864	0.077153191	0.66326046	-0.203415096	0.011444429	9.999899864	0.25006339	0.015848918	0.213987216	0.232893139
3291	9.999899864	0.007711699	0.577157259	1.307451725	0.199714869	0.381624341	0.229608581	0.409063965	0.667285025	0.107093222	0.37327072	0.128655881	9.999899864	0.549952507	0.124812156	0.098376296
3290	9.999899864	9.999899864	9.999899864	9.999899864	0.995311558	0.119520575	0.347692072	-0.127443239	-0.773466349	9.999899864	-1.582687259	9.999899864	9.999899864	9.999899864	9.999899864	-1.500427723
3289	9.999899864	9.999899864	9.999899864	9.999899864	-0.676714659	9.999899864	9.999899864	9.999899864	0.675680399	0.244451568	0.712762296	0.327498347	9.999899864	1.137235522	0.387918413	0.185517266
3288	9.999899864	0.137736097	-0.194064692	9.999899864	0.438843399	0.147985727	-0.00018106	0.809152305	0.33925876	0.297890693	9.999899864	9.999899864	9.999899864	9.999899864	9.999899864	9.999899864
3287	0.116630897	-0.0197968	0.256088942	0.240304485	0.180525243	0.429406136	0.5968647	0.216367468	9.999899864	0.353592604	9.999899864	1.372083068	9.999899864	0.410447478	0.556745648	9.999899864
3286	0.389123291	0.883147001	0.084807612	0.108415172	0.940017164	9.999899864	0.342810005	1.078848243	0.421523064	0.242676318	0.308403403	0.838680148	0.275483042	0.261784256	0.223660767	0.257618785
3285	0.472821623	0.395526767	0.622518003	9.999899864	0.850210726	0.094615042	0.800657511	0.674212873	0.809813142	0.394693226	0.18645446	0.76143688	0.489655405	0.263473451	0.295744181	9.999899864
3284	0.155183107	0.375744969	0.152068868	0.266741395	9.999899864	0.738030493	0.214838609	0.085396305	-0.551975489	0.055765729	0.001574232	-0.276984304	0.078170151	-0.163344801	9.999899864	-0.080505379
3283	0.258283258	0.324951112	0.083718255	0.532839954	0.069868349	9.999899864	9.999899864	0.557698846	0.544226766	0.438754559	0.701468885	0.899635196	0.731818974	0.303978384	0.267255992	0.307406724
3282	9.999899864	0.916365445	0.940388382	0.452430189	0.364684135	0.40560618	0.226280987	0.382600039	0.744921684	9.999899864	0.001420717	0.019914541	9.999899864	0.013971282	0.585432291	0.684849441
3281	0.14849323	0.48837775	0.163703144	0.339377463	0.530366242	9.999899864	0.252035022	0.26555559	0.513971448	0.264708638	0.283834159	0.231377766	0.410661787	0.839262903	0.696045935	0.162556201
3280	-0.420197517	-0.514180899	0.024720332	-0.770427108	0.050897751	-0.80029732	9.999899864	-0.667148113	1.343679667	9.999899864	1.178824067	0.451930851	0.276499033	0.145391226	0.246082351	0.211324737
3279	-0.659280956	-0.774217367	9.999899864	-0.437572867	-0.675580859	9.999899864	0.062585458	-0.448096842	0.324050218	0.591604292	0.161815301	0.069081843	0.290276349	0.09885662	0.136663154	0.164715931
3278	0.820159257	0.544852853	9.999899864	0.469666094	9.999899864	9.999899864	0.662297368	9.999899864	0.085155822	0.083728619	0.037947793	0.631842732	0.188711464	-0.017418107	-0.025156116	0.40648815
3277	9.999899864	9.999899864	-1.707074165	9.999899864	9.999899864	9.999899864	9.999899864	9.999899864	0.840007186	-0.089097522	9.999899864	0.049014606	9.999899864	0.212076128	0.259140253	-0.008224858
3276	9.999899864	9.999899864	9.999899864	9.999899864	9.999899864	9.999899864	0.116666451	9.999899864	9.999899864	9.999899864	1.881353617	0.695011079	0.363985926	9.999899864	0.350772679	0.300553739
3275	0.261577904	0.299992442	0.312521994	0.420307159	0.380008906	0.150380045	0.285677433	0.450265437	9.999899864	-0.089232571	9.999899864	9.999899864	0.340087563	0.440461844	0.341246873	9.999899864
3274	9.999899864	9.999899864	9.999899864	9.999899864	9.999899864	9.999899864	9.999899864	9.999899864	0.55360204	0.214672238	0.6809659	0.824803054	0.247893006	0.237618715	1.082883239	0.7115888

F_C	F_N	MO	Pred__C	Pred___N	Pred_MO
0.335	3.98	6.643333	0.215383	3.600237	5.814894
0.553	7.12	12.286667	0.470139	6.708299	11.12058
0.558	7.16	10.646667	0.489638	7.097118	11.664417
0.646	8.79	14.683333	0.341652	5.648154	9.088079
0.469	6.48	10.663333	0.339511	5.50693	8.801746
0.547	7.95	12.543333	0.427458	6.78387	11.019023
0.733	10.1	16.106667	0.417223	6.986044	11.397782
0.738	8.99	14.966667	0.573969	8.03007	13.169327
0.803	9.75	15.57	0.612163	7.646284	12.447233
0.286	3.53	6.113333	0.290073	4.012815	6.548345
0.604	7.59	12.573333	0.718576	8.232682	13.365678
0.548	6.8	12.243333	0.38703	6.129509	9.923331
0.286	3.29	5.42	0.300498	3.352098	5.493976
0.334	5.91	10.67	0.492588	6.250134	10.243531
0.266	3.4	5.276667	0.246323	2.866899	4.56487
0.147	1.72	2.483333	0.246419	2.963087	4.469393
0.276	4.16	6.56	0.293259	3.639543	5.812781
0.327	4.51	7.863333	0.286607	2.782166	4.430563
0.142	2.03	3.256667	0.063976	1.520794	2.887681

Datos convencionales de laboratorio

Datos de predicciones con espectroscopía

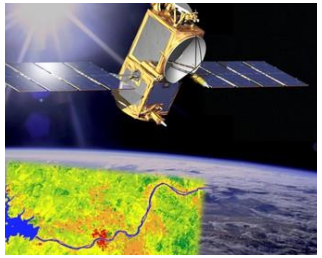


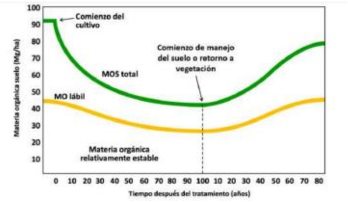
Ubicación de las muestras

Covariables predictivas para el Mapeo Digital de Suelos

S C O R P A N

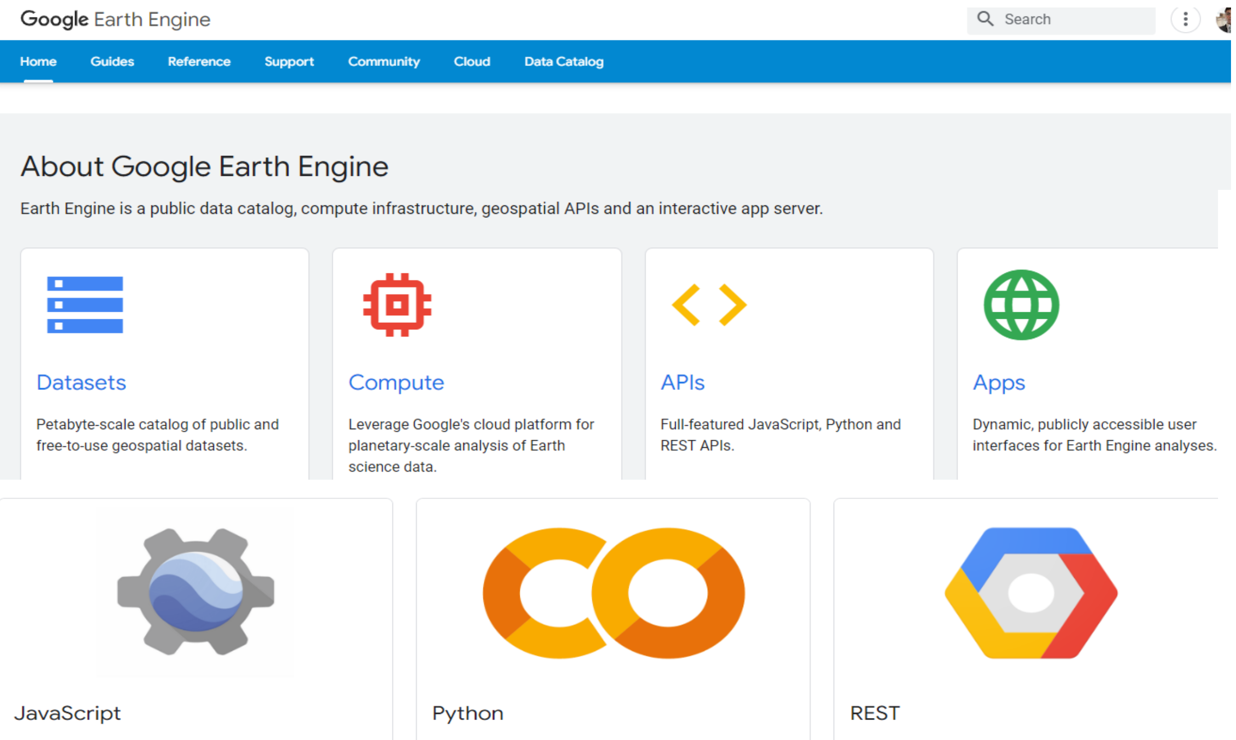
Suelo	Clima	Organismos	Relieve	Parental	Años	Posición

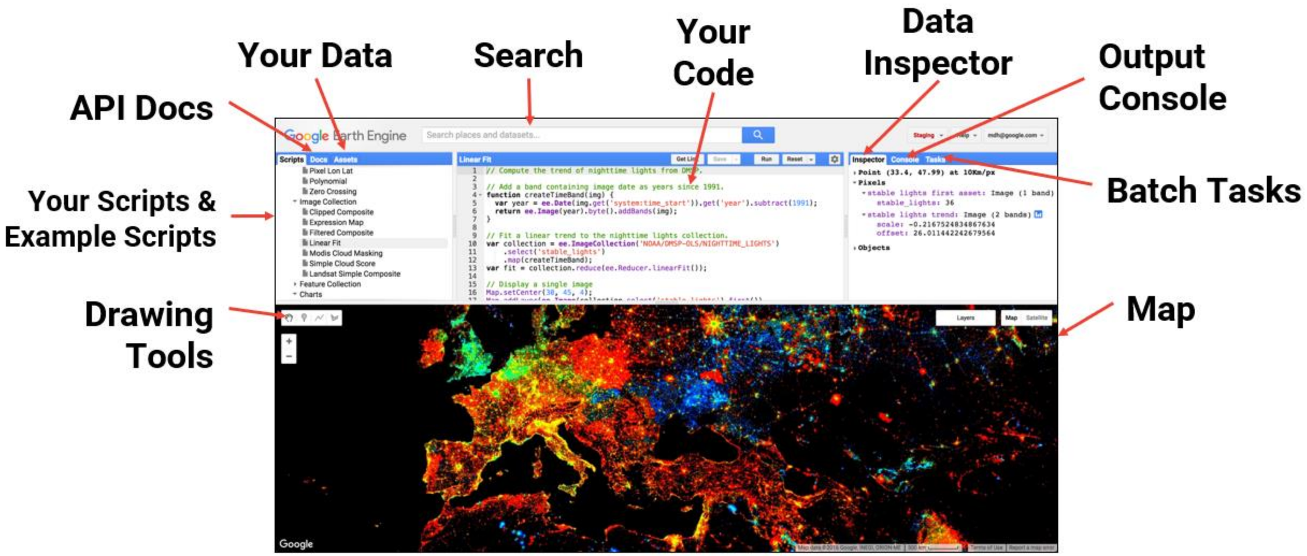



(Jenny, 1994)

…Covariables ambientales, los sensores remotos y Plataformas de procesamiento



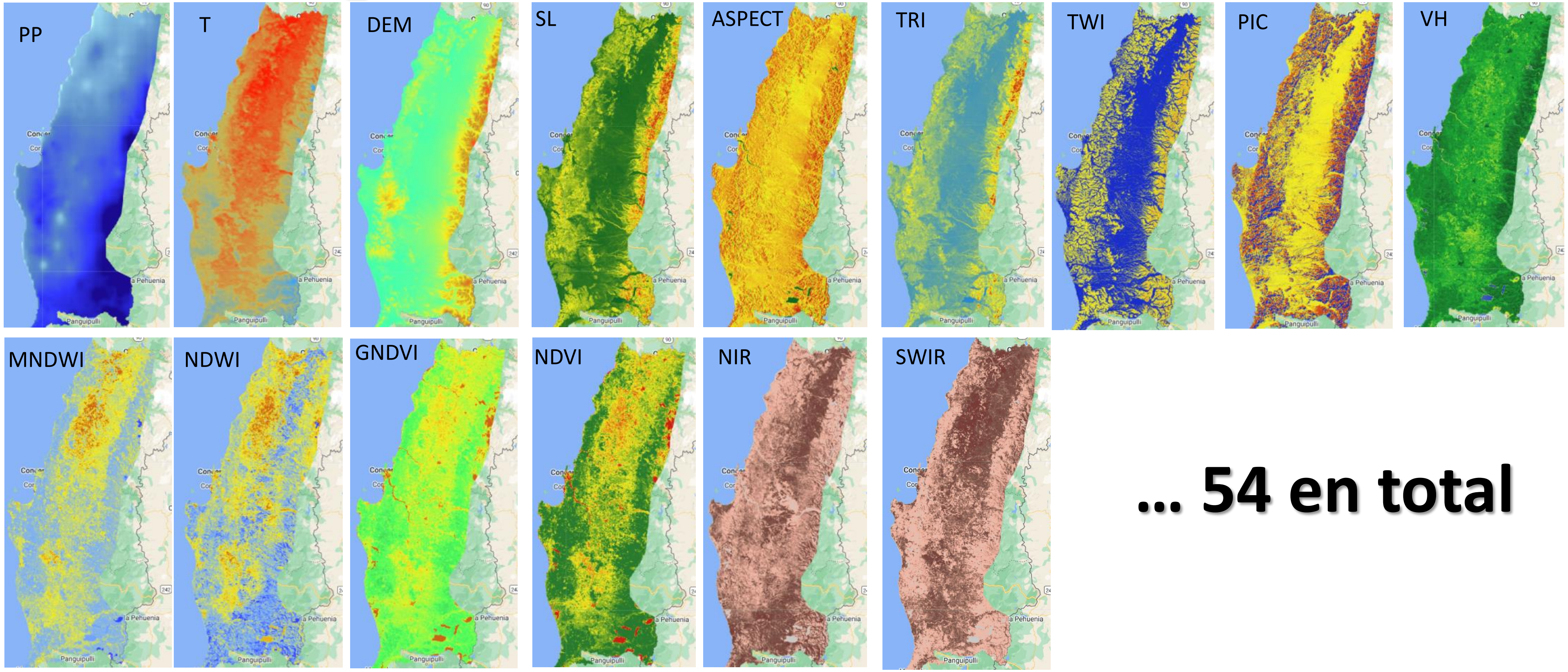
The Earth Engine Code Editor



code.earthengine.google.com

Herramientas de procesamiento

Covariables generadas en GEE



… 54 en total

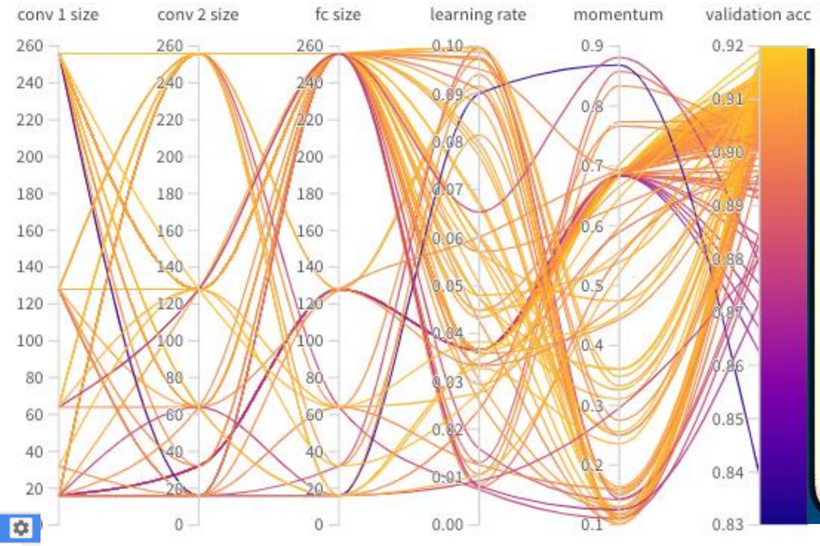
Selección de covariables

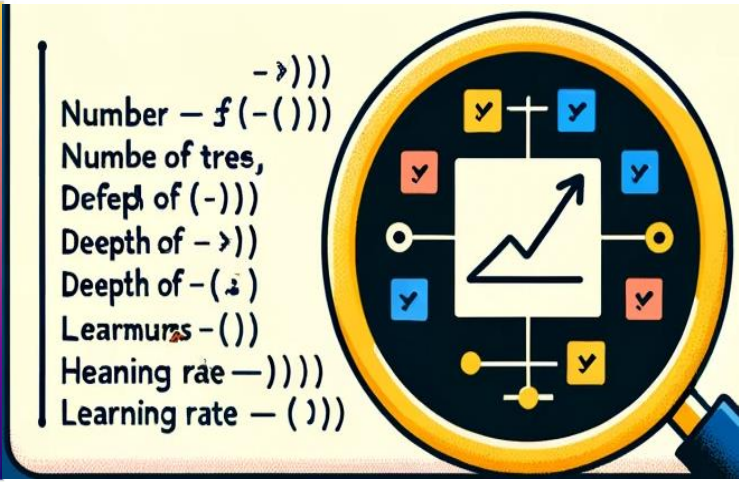
Reducción de la dimensionalidad de variables utilizando regularización estadística con Elastic Net

```python
import numpy as np
from sklearn.linear_model import ElasticNet
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import StandardScaler

# Definir Independientes y dependiente
X = data [['P_ANUAL', 'T_Anual', 'T_Elluvia', 'T_Eseca', 'blue', 'green', 'red', 'nir',
    'swir1', 'swir2', 'VARI', 'SAVI', 'CMR', 'EVI', 'NDVI', 'FMR', 'RGRI',
    'MTVI', 'RDVI', 'NBR', 'GARI', 'OSAVI', 'TDVI', 'NLI', 'DVI', 'IPVI', 'IOR',
    'GEMI', 'ARVI', 'GDVI', 'GRVI', 'GNDVI', 'GCI', 'GVI', 'MSAVI2', 'NDWI',
    'TNDVI', 'RVI', 'NDWI2', 'MNDWI', 'NDTI', 'CI', 'BI', 'VV', 'VH', 'elevation',
    'slope', 'aspect', 'TRI', 'TWI', 'PIC', 'PRC', 'longitude', 'latitude']]

y = data['MO']
```

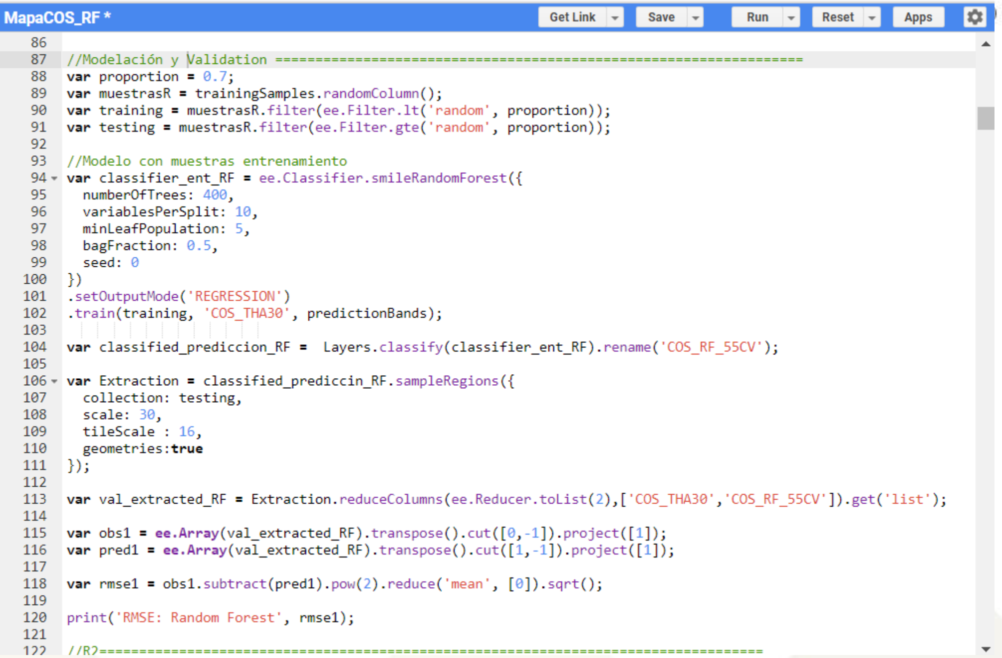
NO	COVARIATES	COEFFICIENT
1	ANNUAL_P	1.166409
2	LATITUDE	-1.074451
3	VV	0.545786
4	DRY_S_T°	-0.409429
5	CI	-0.40423
6	IOR	-0.35525
7	ELEVATION	0.328928
8	TRI	-0.237836
9	NDWI2	0.234883
10	CMR	0.198836
11	TWI	-0.162475
12	ANNUAL_T°	-0.11673
13	MNDWI	0.096377
14	SLOPE	-0.086951
15	VARI	0.032133
16	NIR	-0.018373
17	GEMI	0.014893

Selección de Hiperparámetros





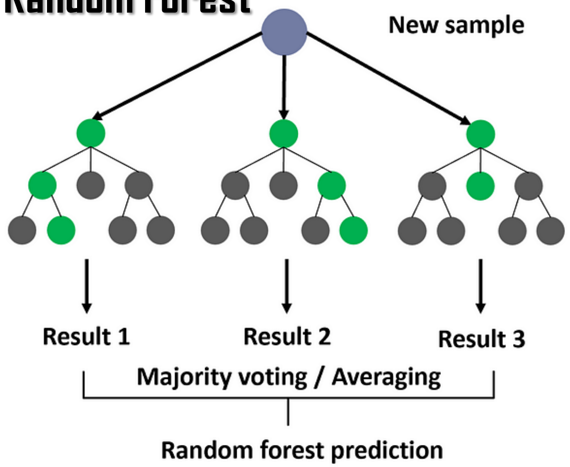
Modelaciones



MapaCOS_RF * Get Link Save Run Reset Apps

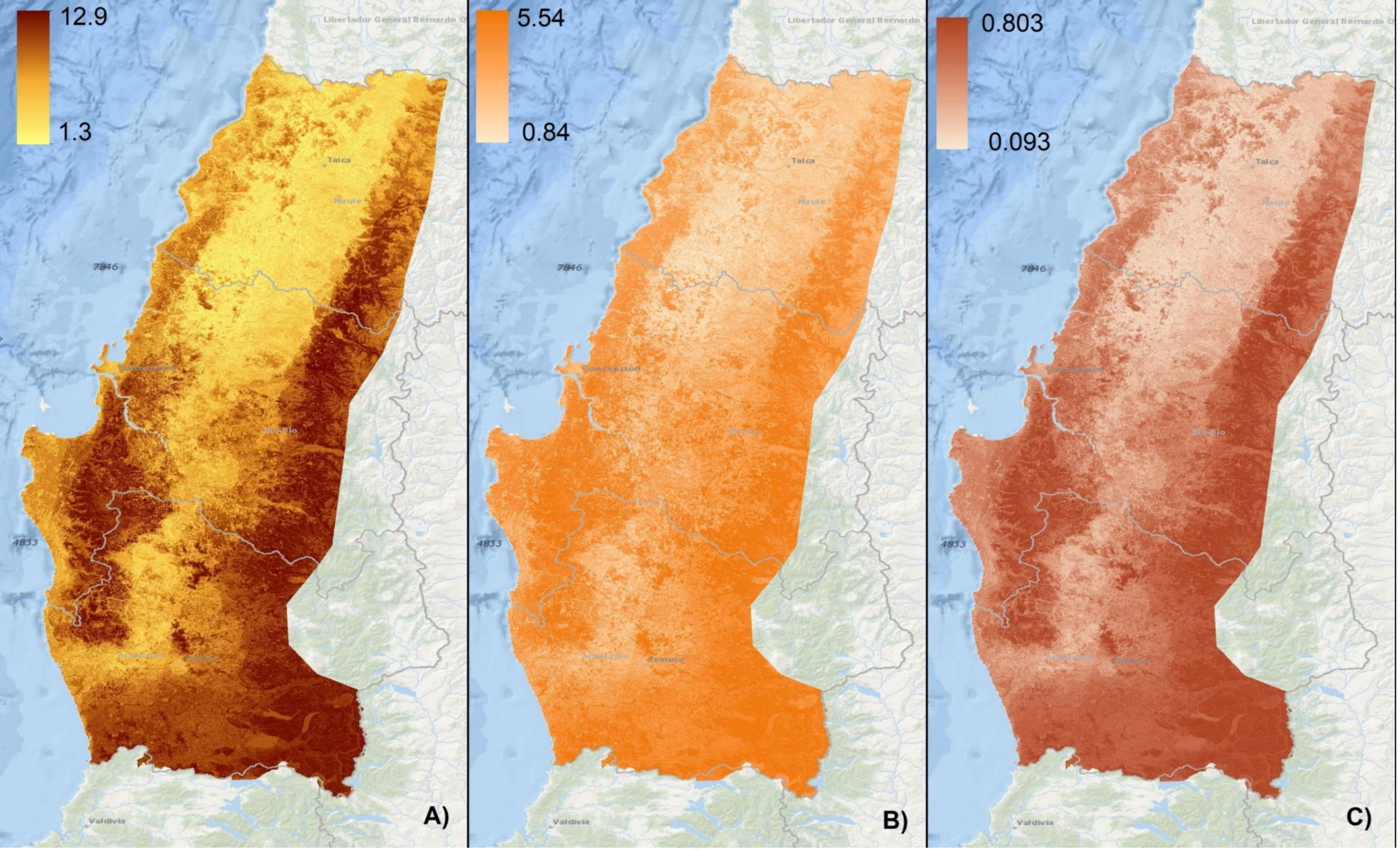
```
//Modelación y Validation ===================================================================
var proportion = 0.7;
var muestrasR = trainingSamples.randomColumn();
var training = muestrasR.filter(ee.Filter.lt('random', proportion));
var testing = muestrasR.filter(ee.Filter.gte('random', proportion));

//Modelo con muestras entrenamiento
var classifier_ent_RF = ee.Classifier.smileRandomForest({
  numberOfTrees: 400,
  variablesPerSplit: 10,
  minLeafPopulation: 5,
  bagFraction: 0.5,
  seed: 0
})
.setOutputMode('REGRESSION')
.train(training, 'COS_THA30', predictionBands);

var classified_prediccion_RF =  Layers.classify(classifier_ent_RF).rename('COS_RF_55CV');

var Extraction = classified_prediccin_RF.sampleRegions({
  collection: testing,
  scale: 30,
  tileScale : 16,
  geometries:true
});

var val_extracted_RF = Extraction.reduceColumns(ee.Reducer.toList(2),['COS_THA30','COS_RF_55CV']).get('list');

var obs1 = ee.Array(val_extracted_RF).transpose().cut([0,-1]).project([1]);
var pred1 = ee.Array(val_extracted_RF).transpose().cut([1,-1]).project([1]);

var rmse1 = obs1.subtract(pred1).pow(2).reduce('mean', [0]).sqrt();

print('RMSE: Random Forest', rmse1);

//R2=========================================================================
```

Random Forest



Muestras

80% Entrenamiento (Espectroscopía)
20% validación (Convencional)



A) OM

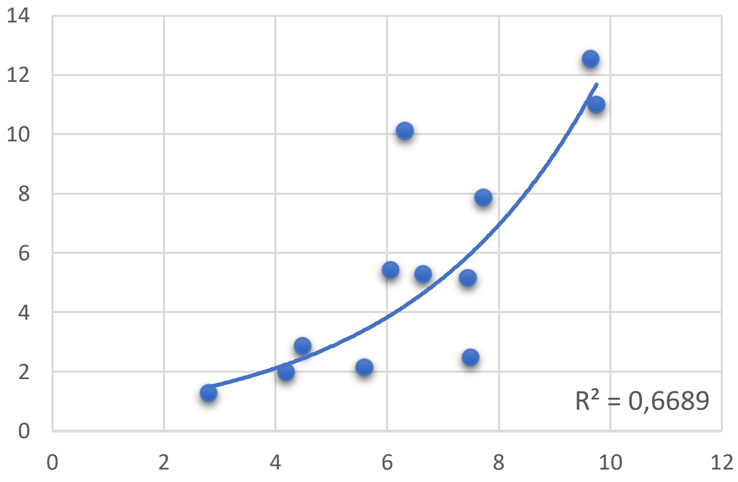
B) C,

C) N

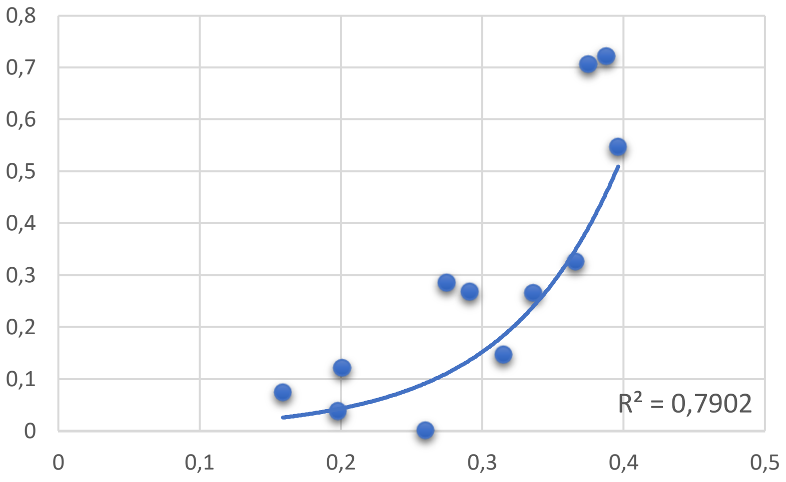
Maps of geospatial modeling
Using predicted soil
Spectroscopy Data

Precisión de las modelaciones espaciales de espectroscopía

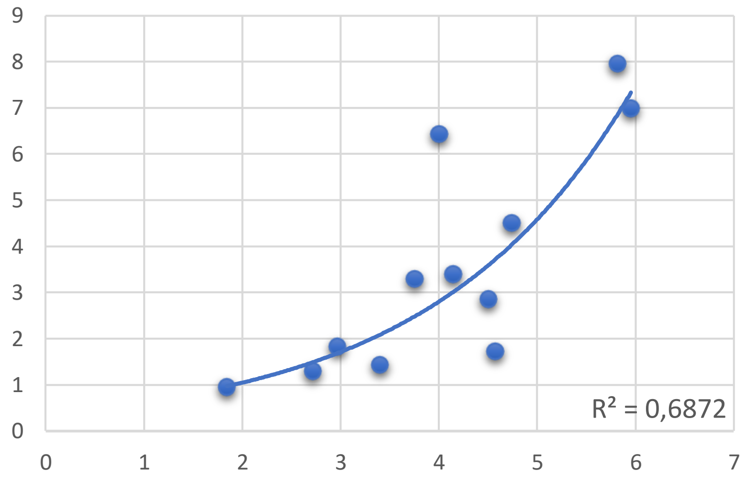
Organic Matter (OM real vs Modeled)



Total Carbon (C real vs modeled)

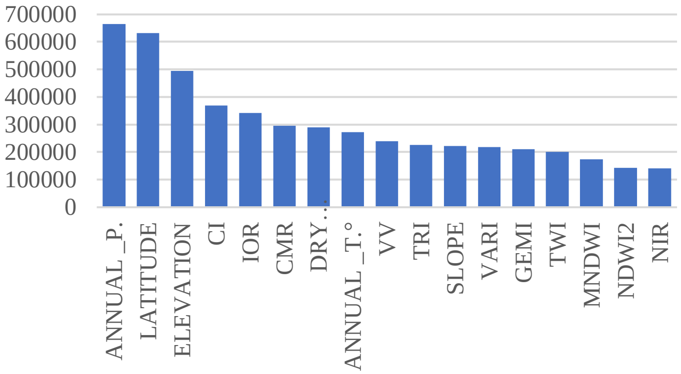


Total Nitrogen (N real vs modeled)

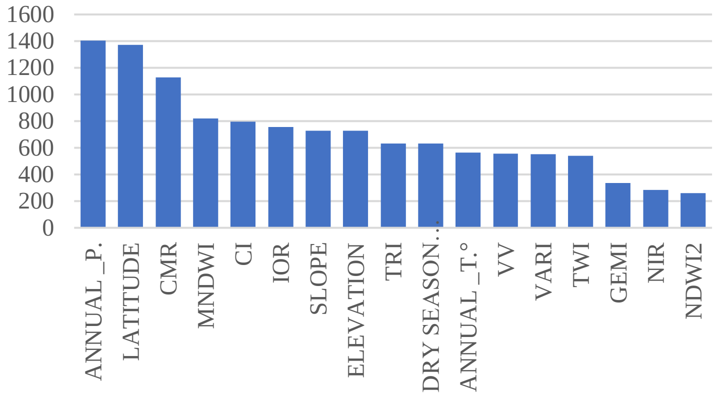


Importancia de las covariables en las modelaciones

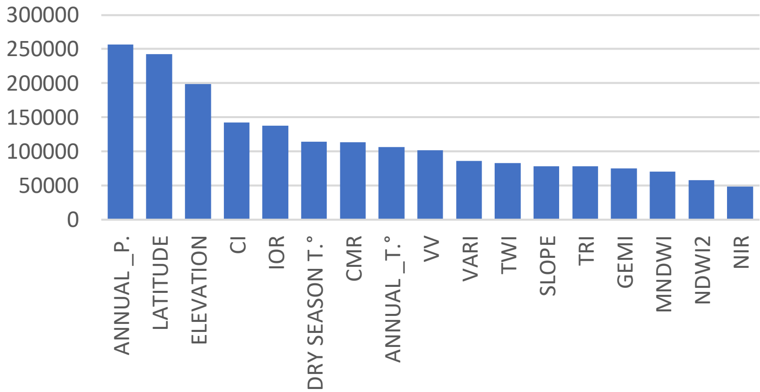
A) Importance for OM



B) Importance for C

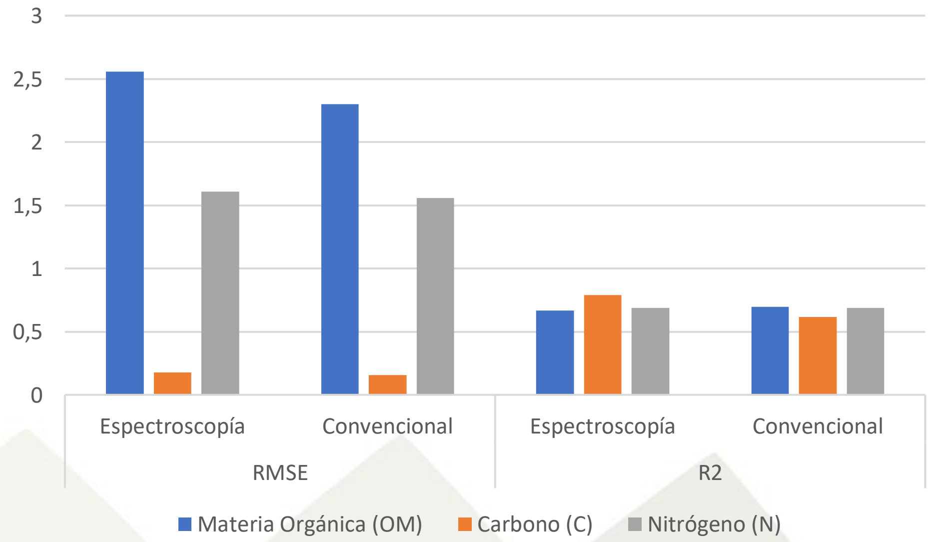


C) Importance for N



Comparación de la precisión entre modelación con espectroscopía y datos convencionales

Parámetro	RMSE		R2	
	Espectroscopía	Convencional	Espectroscopía	Convencional
Materia Orgánica (OM)	2.56	2.3	0.67	0.7
Carbono (C)	0.18	0.16	0.79	0.62
Nitrógeno (N)	1.61	1.56	0.69	0.69



Conclusiones

In conclusion, the findings from this study in our actual project underscore the effectiveness of Vis-NIR spectroscopy in soil analysis, particularly with the PLS model without treatment yielding the most accurate predictions for various soil properties such as %C, %N, OM, and %Clay. The high coefficients of determination and calibration correlations demonstrate strong relationships between the spectral data and these soil properties. While the PLS-OSC models also performed well, models such as PLS-Smoth(35) and PLS-1st derv(5)+Smoth(25) showed more moderate to weak predictive capabilities. These results emphasize the importance of selecting appropriate data pre-processing techniques to enhance the accuracy of soil spectroscopy models. Moving forward, further research should aim to refine predictive models and address challenges associated with indirect estimations, ultimately advancing the utility of Vis-NIR spectroscopy in soil analysis across diverse soil types and environmental conditions.

Conclusiones

The comparison of accuracy between spectroscopy-based modelling and laboratory data reveals minimal differences. In the modelling of Organic Matter (OM), where laboratory data show a Root Mean Square Error (RMSE) of 2.30 and a determination coefficient (R^2) of 0.70, it is slightly superior to the R^2 of 0.67 obtained with spectroscopy. In contrast, for Carbon (C), laboratory data register an RMSE of 0.16 and an R^2 of 0.62, below the R^2 of 0.79 from spectroscopic modelling. Similarly, Nitrogen (N) presents an RMSE of 1.56 and an R^2 of 0.69 with laboratory data, marginally inferior to the R^2 of 0.64 from spectroscopy. These results indicate a notable consistency between the modelling methodologies for OM, C, and N, underlining the competence of spectroscopy as an estimation method. However, it is crucial to continue expanding and deepening these comparative analyses at a national level to consolidate and enrich the findings, emphasizing the importance of cross-validation in soil property mapping.

Food and Agriculture Organization of the United Nations

LATSOLAN

LATIN AMERICAN SOIL LABORATORY NETWORK

Thank you

GLOBAL SOIL PARTNERSHIP