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AgriLAC Resiliente: Sistemas de Innovación Agroalimentaria Resilientes en América Latina y el Caribe

Remote Sensing and Artificial Intelligence for Soil Organic Carbon Geospatial Modeling

Background

High plateau grasslands and peatlands are great carbon sequesters but highly vulnerable

Most of the efforts have been mostly addressed soil organic carbon; however, recalcitrant carbon and their isopic compositions are also key variables to pay attention when taking about climate change.

In Junin, from 1987 to 2015, Maca areas increased from 60 ha to 1543 ha, which meant a 55% loss of pastures (Fig 1).

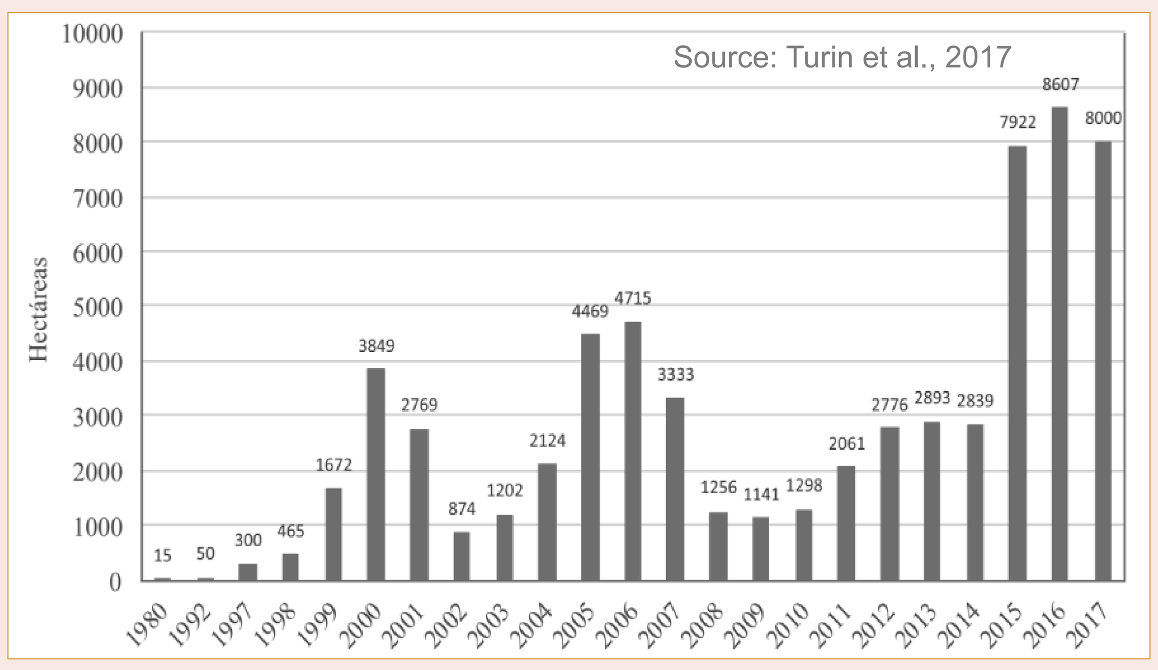

Fig. 1: Evolution of the area planted with maca in Peru.

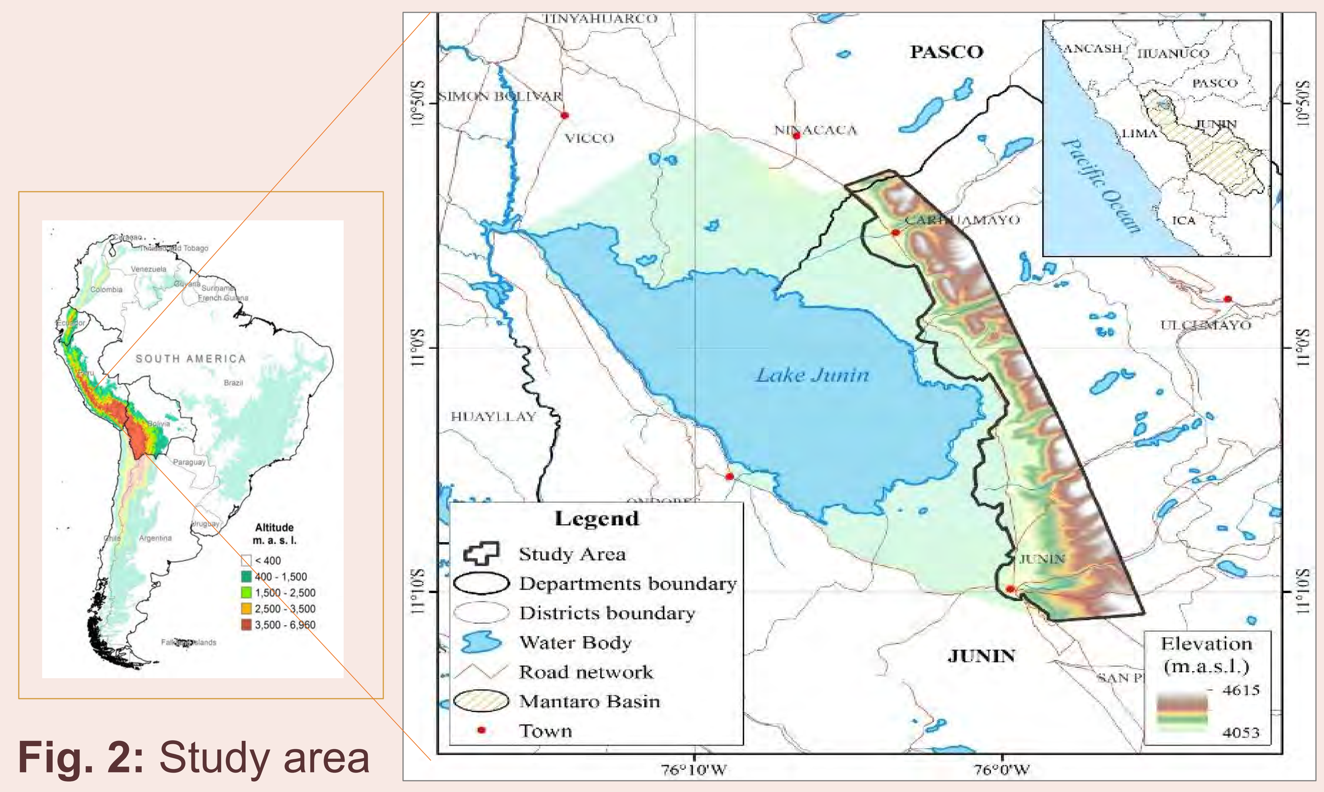

Fig. 2: Study area

Land use change has a significant impact on carbon sequestration/emissions, soil fertility, livestock, sustainability, among others.

Grasslands **Peatland** **Cultivated pasture** **Fallow** **Maca**

Soil sampling and analysis

Fig. 3: Soil sampling approach

Soil sampling:
- Sampling sites were defined with the Latin hypercube method.
- Soil samples were collected as shown in Fig. 3.

Soil analysis:
- Soil carbon analysis were performed at University of Tennessee, USA.
- Texture and pH at UNALM-Lima, Peru

Carbon variables of interest for this study and their abbreviations:
- Soil organic carbon (SOC)
- Isotopic composition of soil organic carbon (δ13C SOC)
- Recalcitrant carbon (Recalc. C)
- Isotropic composition of recalcitrant carbon (δ13C Recalc. C)

Table 1: Pearson correlation among the carbon variables.

	SOC	δ13C SOC	Recal. C	δ13C Recal. C
SOC	1			
δ13C SOC	-0.514	1		
Recal. C	0.796	-0.276	1	
δ13C Recal. C	0.179	-0.001	0.196	1

Machine learning modeling approach

- Due to the complexity of the carbon dynamics, machine learning algorithms was tested and compared.
- Complementary to the sampling data environmental data from remote sensing were considered as potential drivers of the carbon variables.

Machine learning models used for comparison:
- Random Forest
- Neural Networks
- Support vector Machine

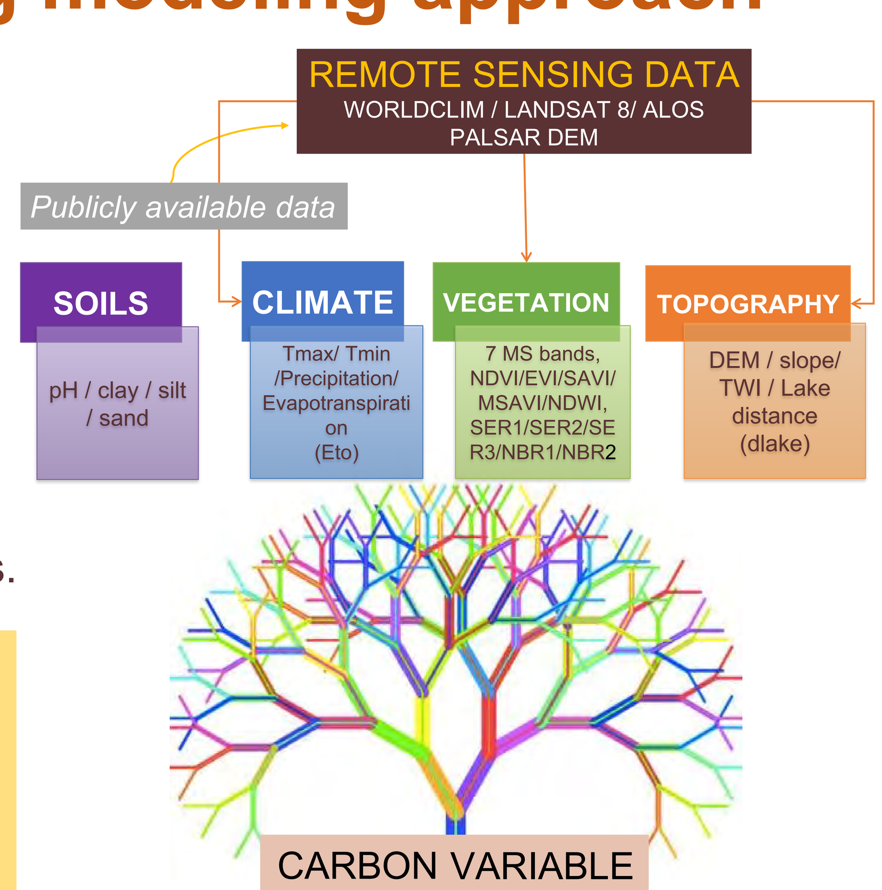

Fig. 4: Machine learning model components.

Preliminary Results

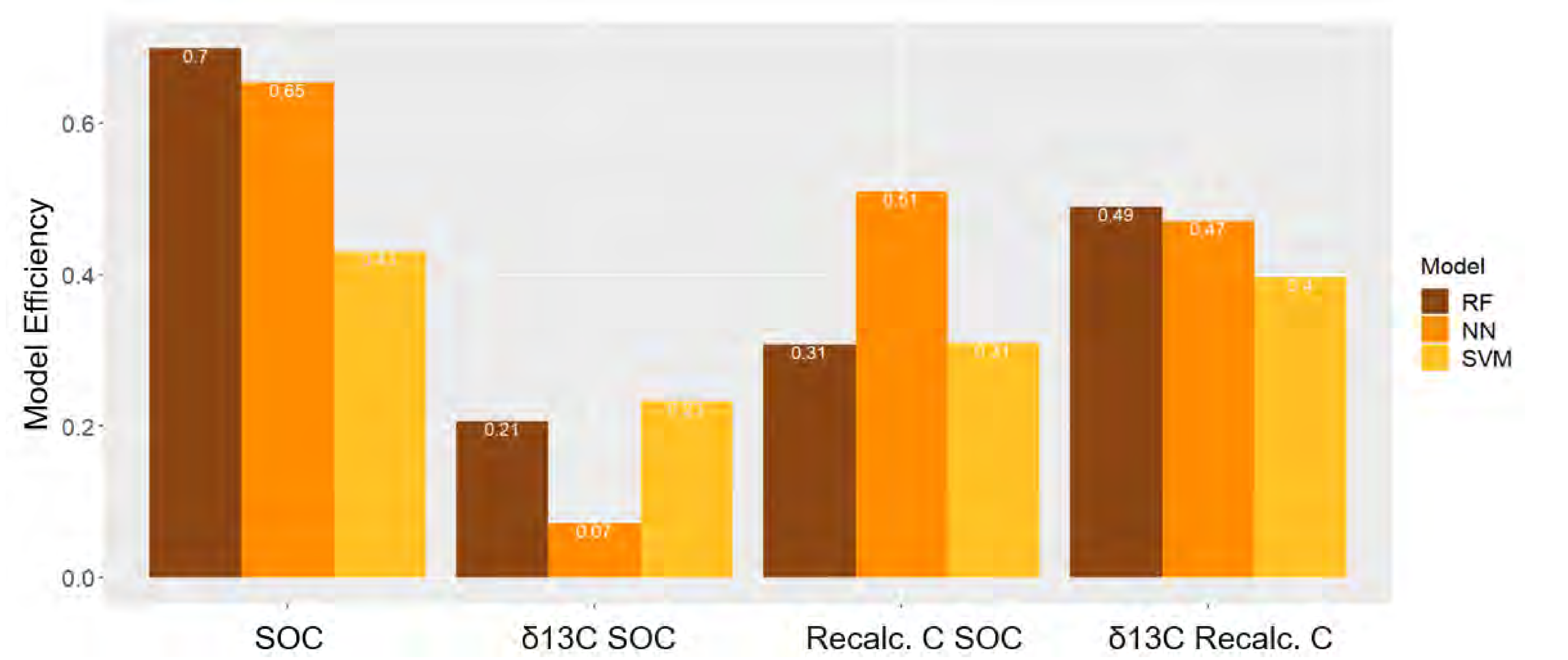

Fig. 5: Model efficiencies for total soil organic carbon, recalcitrant carbon and their isotopic compositions. RF = random forest, NN = neural networks, and SVM = support vector machine.

Table 2: Most important variables found by the models for all the carbon variables.

SOC	Land-use, NBR, SWIR2, NDMI
δ13C SOC	Land-use, NDMI
Recal. C	Land-use, pH, Eto
δ13C Recal. C	pH, dlake, Tmin, NDMI

- Land-use was the most important variable for almost all carbon variables (except δ13C Recal. C), followed by pH for both recalcitrant C variables. NDMI was also in the top-5 for almost all of the carbon variables.
- δ13C Recal. C had very different top-3 most important variables from the others; which is consistent with its lack of correlation with the other carbon variables.
- Both model performance and most important variables agree with other similar studies [2,3]

Main Takeaways

- The RF and NN models captured non-linear interaction with an acceptable performance (except for δ13C SOC), considering that majority of land-uses were a kind of pasture in the end.
- Different carbon variables seems to have somewhat different drivers. Further research is needed.
- The high spatial heterogeneity of the Andes as well as the small plots could not be well represented by remote sensing data.

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CIP thanks all donors and organizations that globally support its work through their contributions to the CGIAR Trust Fund: www.cgiar.org/funders