





Universidad de Oviedo

# Large scales monitoring of sort-term topsoil organic carbon variations using sensor MODIS

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#### Summary

The current study aimed perform a valid method to monitor the spatial and temporal variability of Soil Organic Carbon (SOC) at large scale using conventional sampling and laboratory methodologies, mixing soil spectroscopy and MODIS images. Combining laboratory and spectroscopic soil analysis, MODIS remote sensing data and statistical methods SOC were mapped for the south west of the Cantabrian Range, North of Spain. The results indicate a strong relationship between predicted and measured values.



### Introduction and Objetives

At regional scales and long-term periods, SOC is highly variable due to the land-use and land cover changes, crop

productivity increase, etc. But also SOC shows sort-term variability associated mainly to seasonal storage variations and wildfires. In the context of highly changing terrestrial biosphere is essential to establish robust methodologies by which SOC can be monitored via diary measured. MODIS images can provide estimates of the spatial and temporal distribution of SOC stock at large terrestrial scales.

#### Methods

Hyperspectral VIS-NIR-SWIR satellite imaging was related to laboratory diffuse reflectance spectrum in topsoil organic carbon mapping by Fernandez et al. (2015).

	TOC (%)	OC (%)	Eighty-nine so
Number of samples (n)	89	89	collected from
Minimum	4.3	2.7	5 cm of the so
Maximum	63.2	37.9	in random po
Mean	29.4	19.5	the heathery
Median	28.3	17.4	
Standard deviation	14.9	10.3	training plot

Eighty-nine samples were
collected from the topmost
5 cm of the soil were taken
in random points placed in
the heathery slopes of the
training plot .

These methodology was used over MODIS images. TOC and OC were modelled using PLSR under leave-one-out cross-validation. Akaike Information Criterion (AIC) was used to determine the optimal number of factors to be included in each model (Akaike, 1969; Li et al., 2002).





Spectral resampling of the ASD reflectance spectrum of a soil sample for the different imaging spectrometers (a). Note that, for sake of clarity, the resampled spectra plots have been given an offset. HYP: Hyperion; MOD: MODIS; L5TM: Landsat 5 TM. Band spectral responses of the imaging spectrometers.

#### Preliminary results and discussion

Summary statistics of the PLSR models for soil organic C prediction based on laboratory spectra Accurate prediction models were obtained for MODIS in the VIS, with RPD = 2.00 for TOC and RPD = 2.68 for OC. The performance of these models was very similar to that obtained with ASD (Table 3). The models based on NIR bands of MODIS had a limited predictive power, both in TOC (RPD = 1.43) and OC (RPD = 1.77). A limited performance was also obtained for the models based on MODIS SWIR bands. The significant drop of accuracy observed when the entire lab-spectra was resampled to the MODIS bands in the NIR and SWIR was attributed to the low number of bands in these regions: 7 in the NIR and only 3 in the SWIR. This drop of performance may also be attributed to the location of the bands and its bandwidth, which could be too wide to successfully detect some important absorption features for the estimation of SOC. Some significant regions for SOC prediction, such as 2041-2154 nm and 2287-2315 nm are not entirely covered by MODIS bands.

			Lab	Resampled MOD	– Region	Parameter	Lab ASD	Resampled MOD
	Region	Parameter	ASD					
		NF	6	6		NF	5	7
		AIC	186.6	190.7		AIC	133.3	134.0
TOC (%) V	VIS	R <sup>2</sup> <sub>cv</sub>	0.77	0.75	OC (%) VIS	R <sup>2</sup> <sub>cv</sub>	0.85	0.86
		RMSE <sub>cv</sub> (%)	7.11	7.44		RMSE <sub>cv</sub> (%)	4.00	3.85
		RPD	2.10	2.00		RPD	2.58	2.68
		NF	6	6		NF	11	6
N		AIC	196.6	220.7		AIC	153.6	168.9
	NIR	R <sup>2</sup> <sub>cv</sub>	0.72	0.51	NIR	R <sup>2</sup> <sub>cv</sub>	0.82	0.68
		RMSE <sub>cv</sub> (%)	7.96	10.44		RMSE <sub>cv</sub> (%)	4.39	5.83
		RPD	1.87	1.43		RPD	2.35	1.77
		NF	4	3		NF	4	3
		AIC	181.5	211.3		AIC	133.5	169.4
	SWIR	R <sup>2</sup> <sub>cv</sub>	0.78	0.55	SWIR	R <sup>2</sup> <sub>cv</sub>	0.84	0.63





## References

- Akaike, H., 1969. Fitting autoregressive models for prediction. Ann. Inst. Stat. Math. 21, 243-247

500 700 900 1100 1300 1500 1700 1900 2100 2300 2500

Wavelength (nm)

- Fernández, S., Peón, J., Recondo, C., Calleja, J.F., Guerrero, C., 2015. Spatial modelling of organic carbon in burned mountain soils using hyperspectral images, field datasets, and NIR spectroscopy (Cantabrian Range; NW Spain). Land Degrad. Dev. DOI: 10.1002/ldr.2452.

1100 1300 1500 1700 1900 2100 2300 2500

- Li, B., Morris, J., Martin, E.B., 2002. Model selection for partial least squares regression. Chemometr. Intell. Lab. 64, 79-89.

900

Wavelength (nm)

300