VNIR spectroscopy for assessment of post-fire impacts on soil properties using linear and non-linear calibration methods

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Introduction

Wildfires

- high temperatures normally have detrimental impacts on soil properties.

- Increase of soil **pH, EC, $CaCO_3$** immediately post-fire is to be expected

(Inbar et al., 2014)

- In low severity wildfires we can expect an increase in **soil C** content

(Pereira et al., 2017)

- In high severity wildfires decrease of soil C content is observed

(Otero et al., 2015)

Introduction

Visible and near infrared (VNIR) spectroscopy

- non-destructive
- enables simultaneous evaluation of soil properties using hyperspectral data

- Studies that investigated how soil spectroscopy could be used in determining:

  Fire severity

  (Veraverbeke et al., 2014)

  Post-fire soil organic matter content

  (Rosero-Vlasova et al., 2016)

  Post-fire changes in N, available P, Mg^{2+} and Ca^{2+} content

  (Vergnoux et al., 2009)

Questions:

- What is the relationship of soil spectral reflectance and soil properties after a wildfire?
- Would a linear or non-linear statistical model be best to estimate the changes after a wildfire?

Objectives:

- 1. Determine the relationship of spectral reflectance and soil properties
- 2. Compare model performance → PLSR vs. ANN

Methodology
Study site

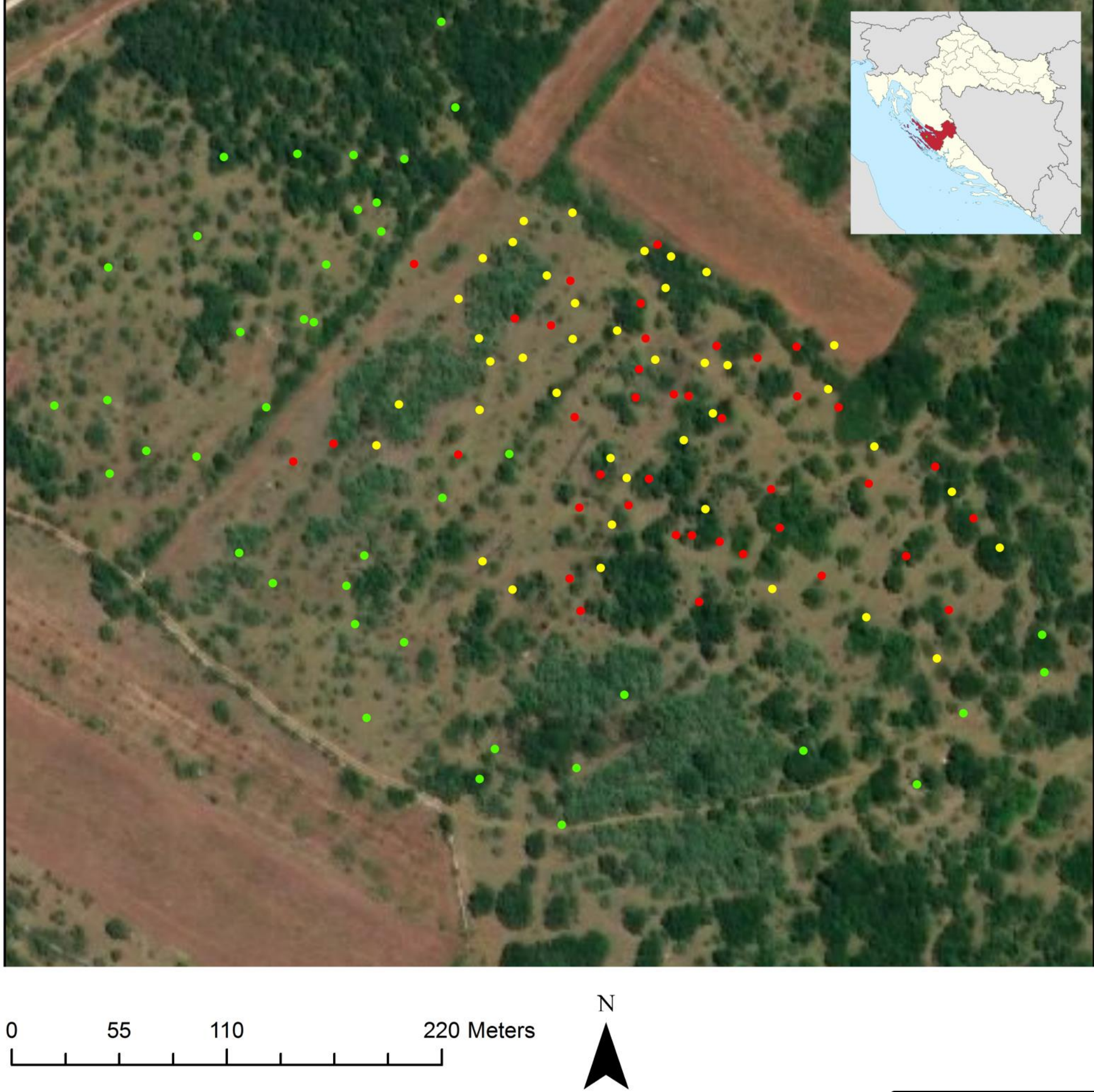
Zadar County, Croatia

Mediterranean climate

mean rainfall → 853.9 mm
mean temp. → 15.3 °C

Legend

- **Control (C)**
- **Medium severity (MS)**
- **High severity (HS)**



Methodology
Study site

Burned area:
~ 13.5 ha

Soil type:
Terra rosa

Vegetation:
Quercus spp. and *Juniperus spp.*

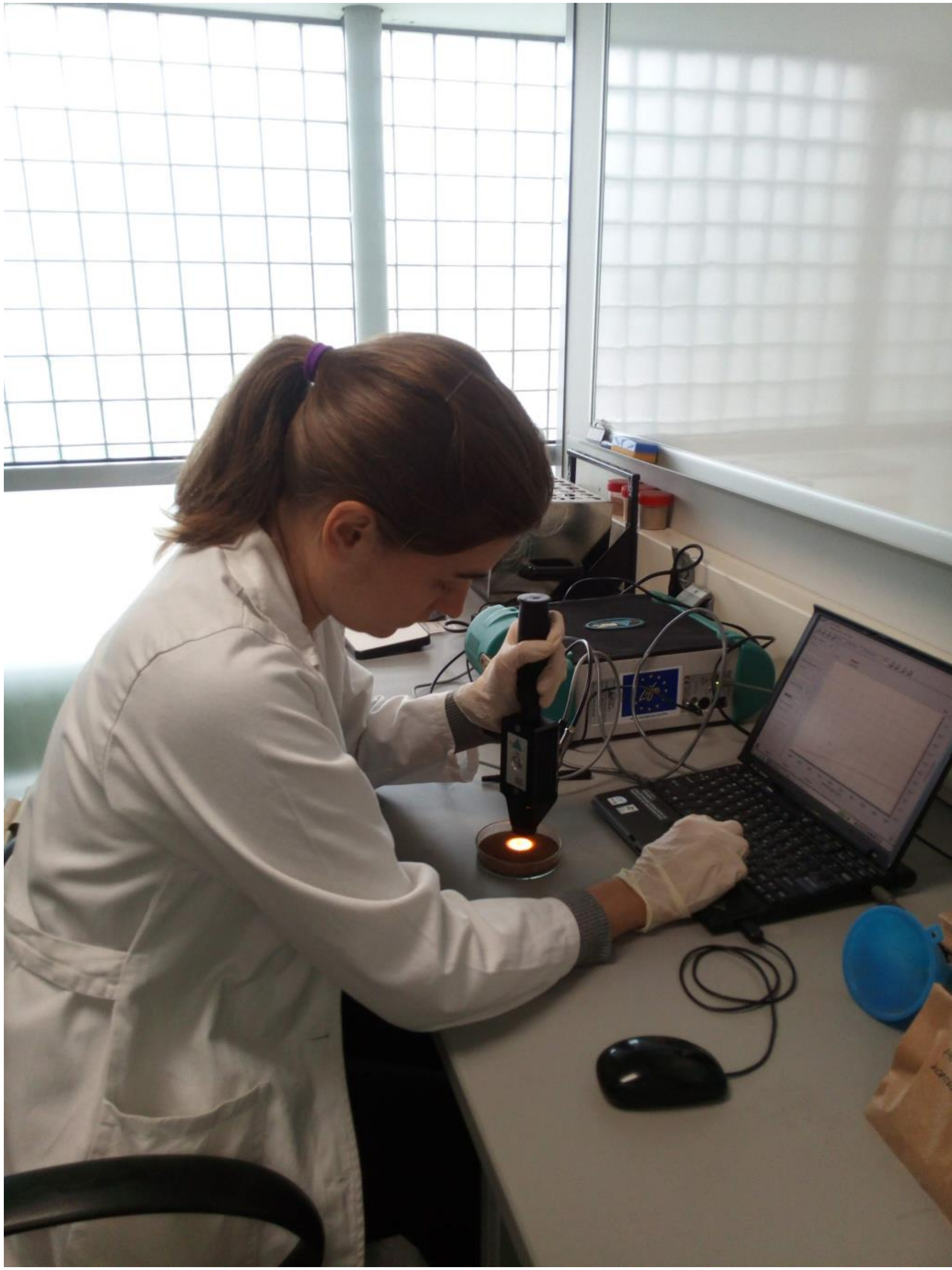
Methodology
Soil sampling

Overall:

- Wildfire occured in **August 2019**
- Samples taken 2 days post-fire
- N = 120 (0-5 cm)

Methodology
Spectral measurements

- **Portable spectroradiometer**
  FieldSpec®3 (ASD Inc., Boulder, USA)
- Manual optical probe
- λ range - 350 to 1050 nm
- simultaneous recording
- Each soil sample is described by 700 reflectance variables
- Soil samples → air-dried and sieved, recorded under artificial light



Methodology
Laboratory analysis

- **pH electrometrically**

pH meter, in H_2O (1:5)

- **EC volumetrically**

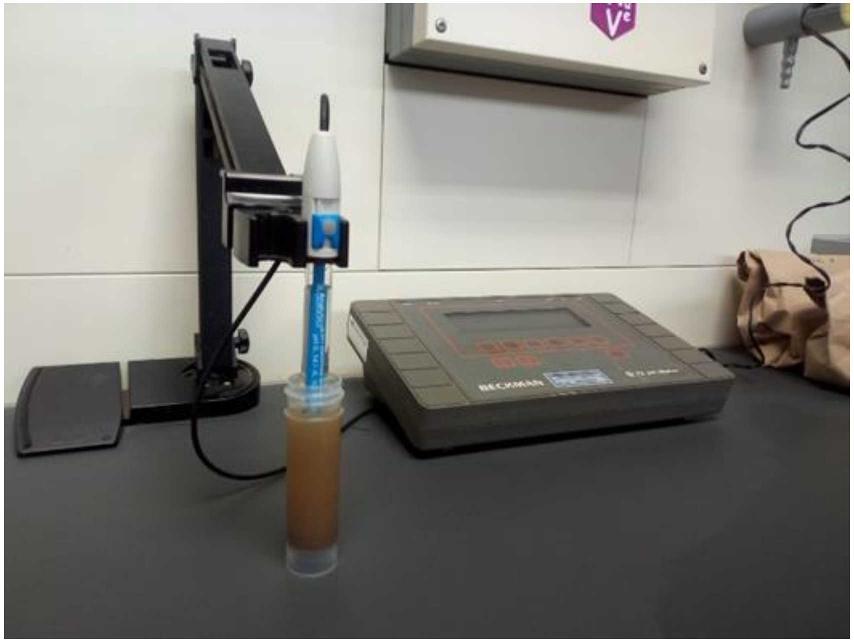
Conductometer (300-1900 µS)

- **$CaCO_3$ volumetrically**

Scheibler calcimeter

- **TC dry combustion**

Vario Macro CHNS analyzer



Methodology
Multivariate analysis

- **PLSR → linear model**

Full spectrum cross-validation

Extracts the relevant information from very large data matrices

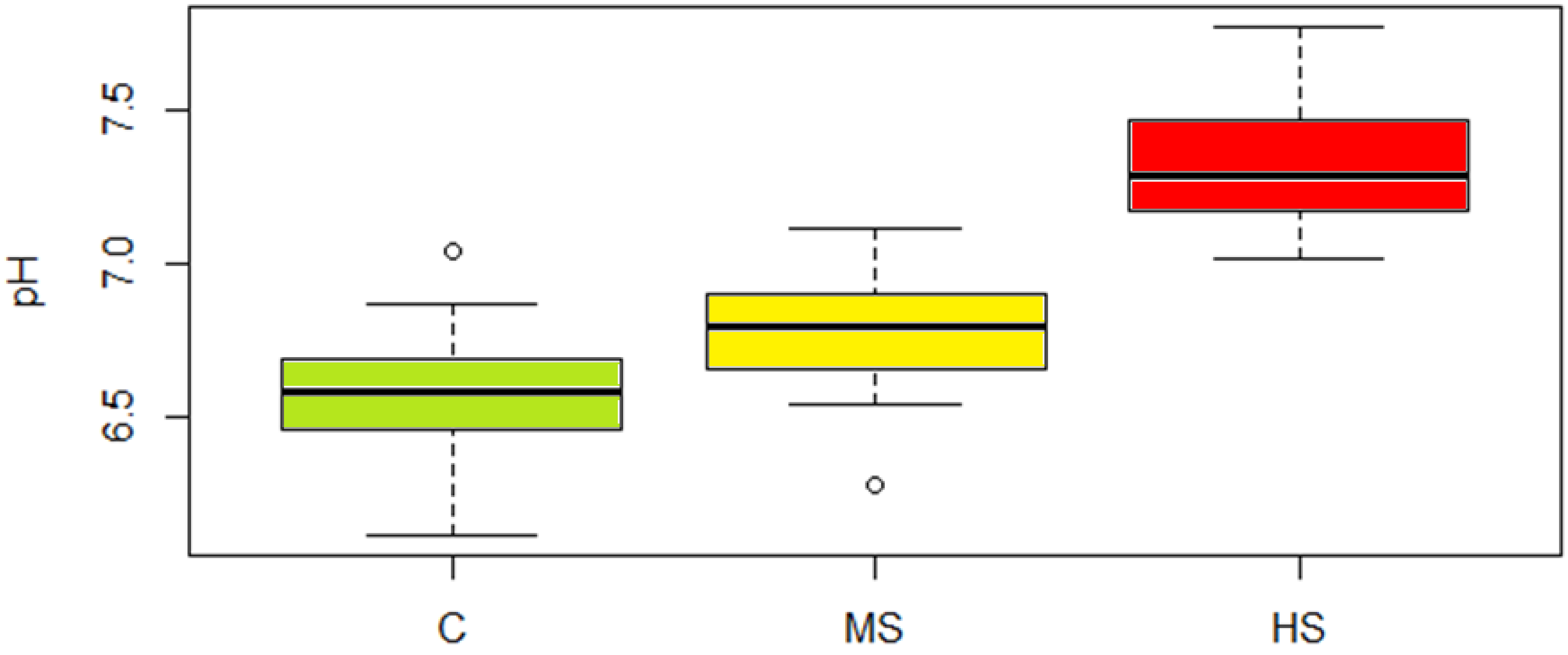
- **ANN → non-linear model**

Training algorithms to automatically learn the structure of the data

Describes non-linear relationships between soil spectral signatures and soil property of interest

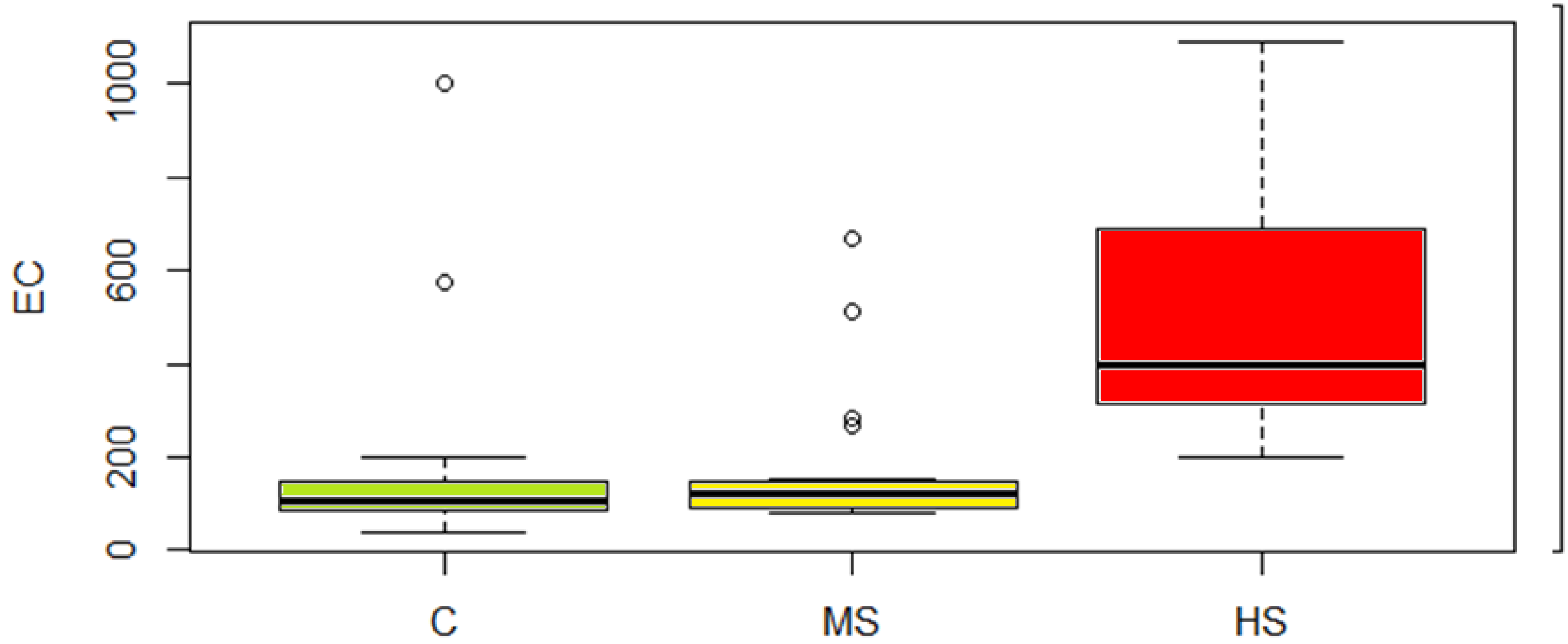
- **Data smoothing:** Savitzky-Golay *(only pH showed improved model performance after smoothing)*
- **Data transformation:** 1st derivative

Results
Chemical analysis



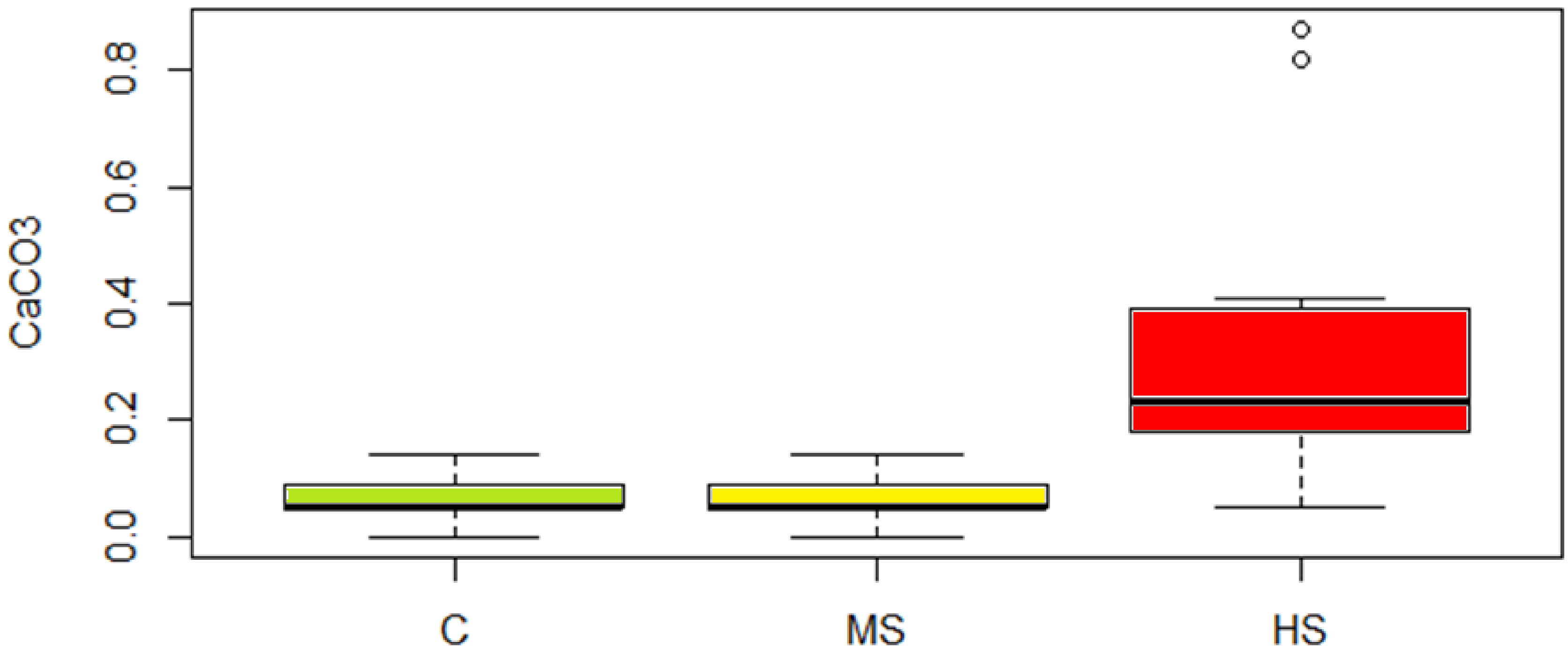
Results

Chemical analysis

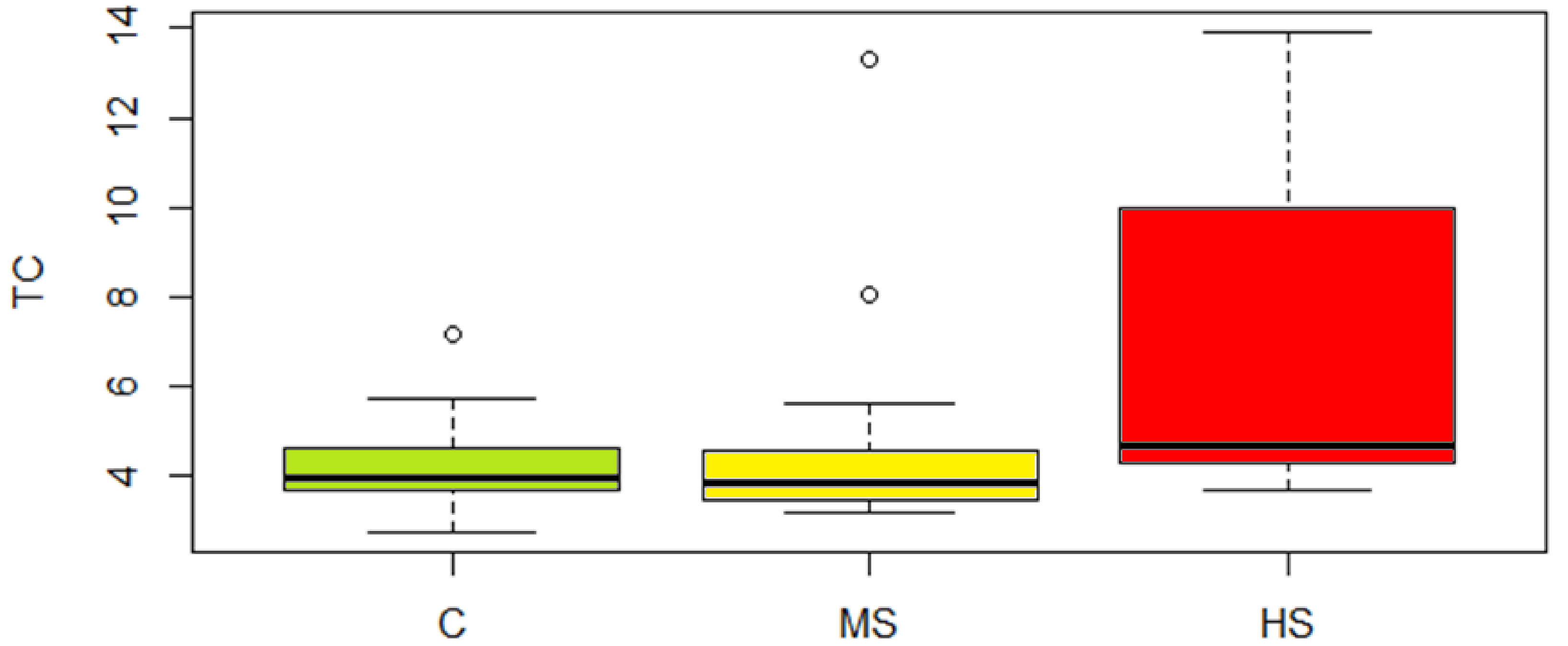


Results

Chemical analysis



Results
Chemical analysis

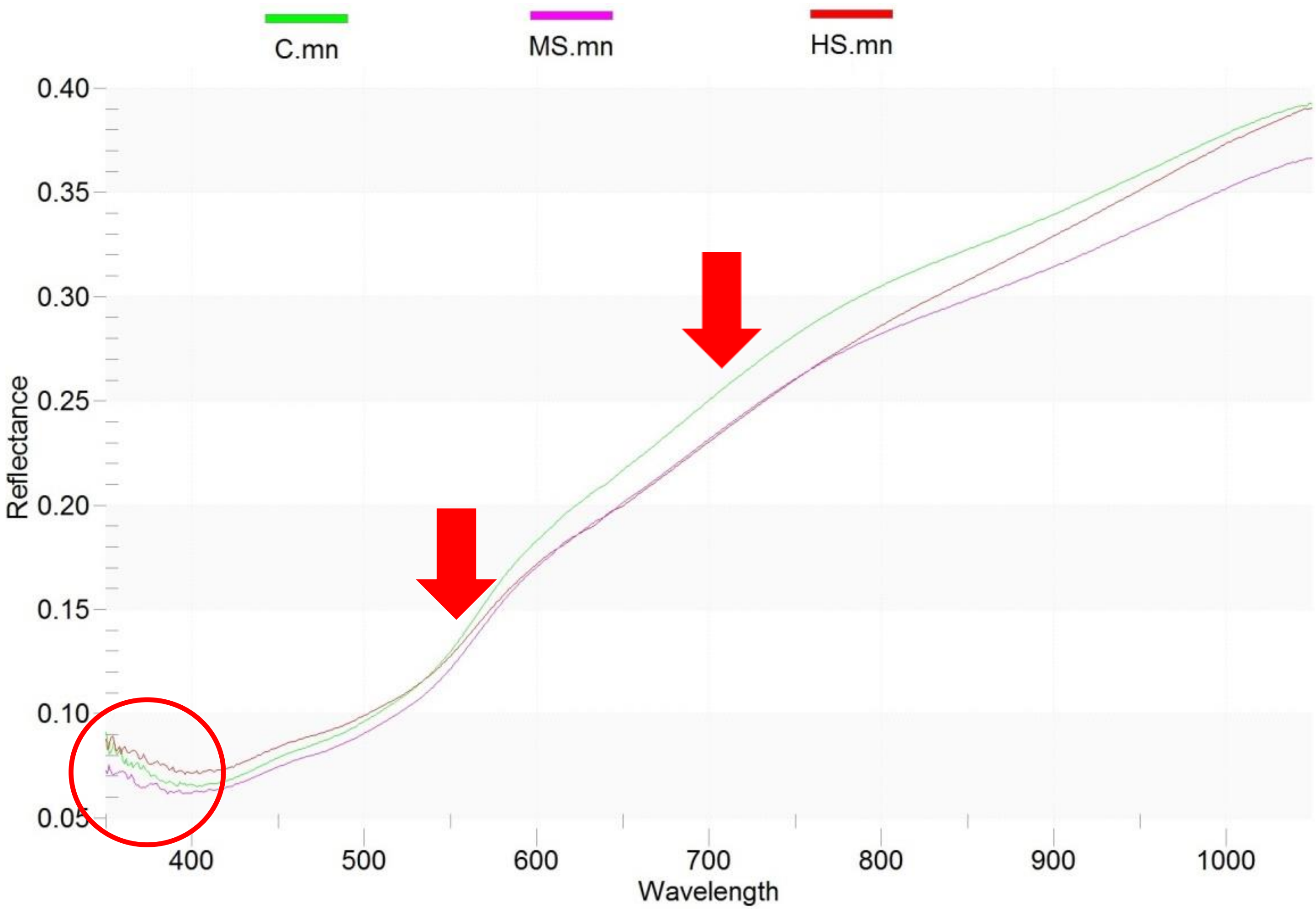


Results

Chemical analysis

Severity	Mean	Stand. Dev.	Minimum	Maximum	Skewness	Kurtosis	CV (%)
			pH				
C	6.59	0.218	6.12	7.04	-0.160	0.445	3.31
MS	6.77	0.185	6.28	7.12	-0.768	1.423	2.73
HS	7.31	0.197	7.02	7.77	0.531	-0.005	2.69
			EC (µS/cm)				
C	174.64	223.85	40.9	1000	3.214	10.589	128.18
MS	174.72	153.96	82.0	668	2.473	5.803	88.12
HS	500.85	252.64	199	1089	0.773	-0.241	50.44
			$CaCO_3$ (%)				
C	0.06	0.03	0.00	0.14	-0.090	-0.371	50.00
MS	0.06	0.03	0.00	0.14	0.156	0.075	50.00
HS	0.33	0.25	0.05	0.87	1.472	1.231	75.76
			TC (%)				
C	4.22	1.05	2.73	7.14	1.237	1.982	24.88
MS	4.58	2.34	3.16	13.31	3.134	10.738	51.09
HS	6.63	3.33	3.67	13.90	0.994	-0.484	50.23

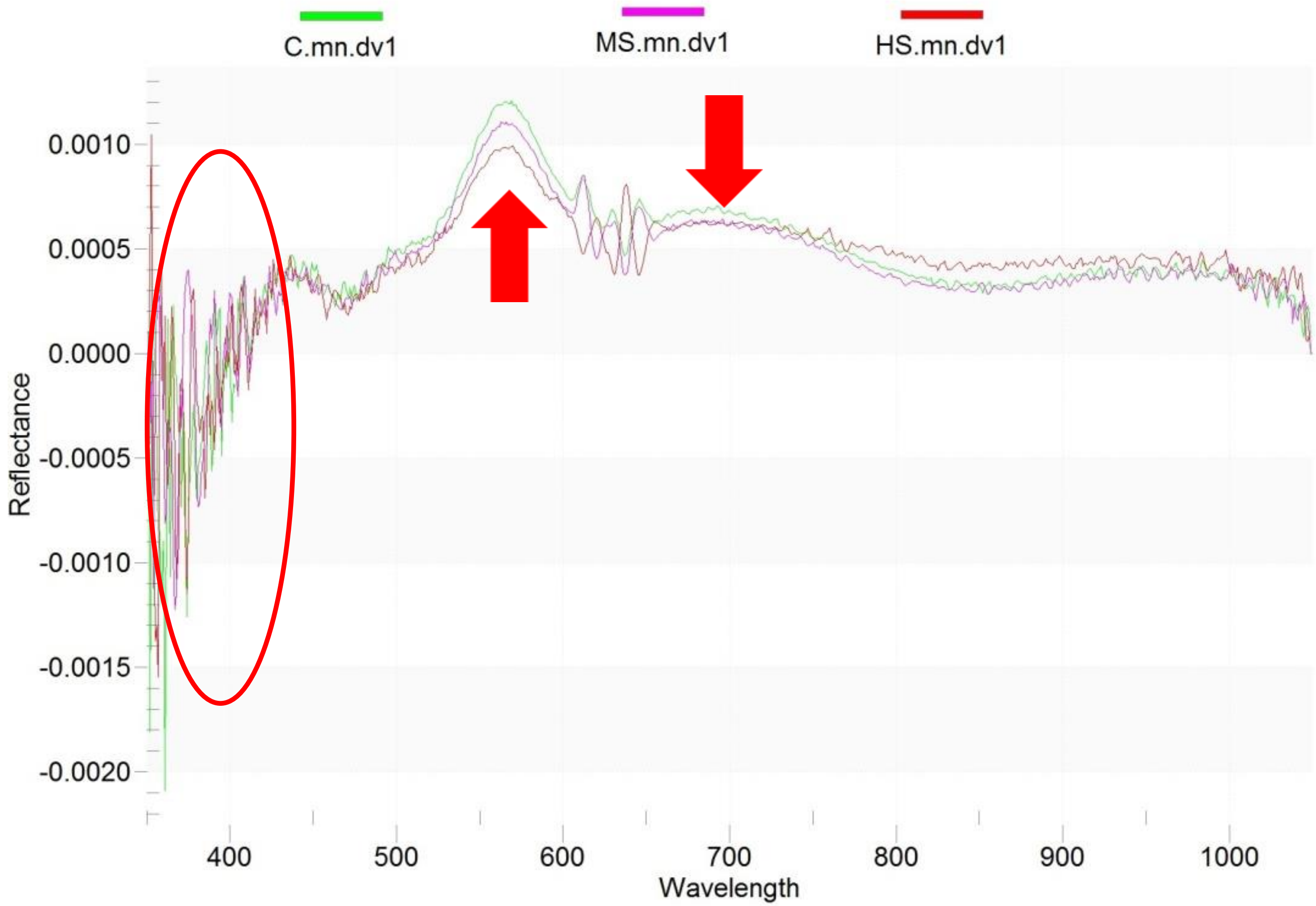
Results
Visual evaluation of soil spectra



Raw spectra

Results

Visual evaluation of soil spectra



Transformed spectra – 1st derivative

Results
Model performance

Soil property	Model	Calibration		Validation	
		R^2	RMSEC	R^2	RMSEP
pH	**PLSR**	0.96	0.07	**0.81**	0.16
	ANN	0.73	0.19	0.69	0.21
EC (µs/cm)	PLSR	0.69	144.97	0.61	163.48
	ANN	0.68	145.82	**0.63**	158.5
$CaCO_3$ (%)	PLSR	0.79	0.09	0.58	0.12
	ANN	0.89	0.07	**0.83**	0.08
TC (%)	PLSR	0.58	1.67	0.55	1.77
	ANN	0.91	0.93	**0.86**	0.98

Conclusion

- In agreement with previous studies: **soil pH increased** after both medium and high severity wildfire. **EC and $CaCO_3$ increased** only where high severity wildfire occured. Unexpectedly, soil **TC** content **increased** after high severity fire.

- **C samples showed higher reflectance than MS and HS.** Possibly explained by lower soil pH and TC content.

- **ANN** model captured the link between EC, $CaCO_3$, and TC soil reflectance spectra more effectively (presumably because of the great variability in the data), while **PLSR** proved to be a more successful model for pH prediction.

Conclusion

Future research:

- Proximal soil sensing is a useful addition to standard laboratory soil analysis, and to satellite and aerial remote sensing methods.

- Next step of the research is to compare super-spectral satellite imagery and existing hyper-spectral data, as well as to monitor the temporal and spatial dynamic of wildfire impact on selected soil properties.

Thank you for your attention!

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This work was supported by Croatian Science Foundation through the project "Soil erosion and degradation in Croatia - SEDCRO"