ESCUELA POLITÉCNICA NACIONAL

FACULTAD DE INGENIERÍA CIVIL Y AMBIENTAL

Probabilistic analysis of the spatiotemporal variability of the Pugllohuma wetland using Synthetic Aperture Radar images of the Sentinel-1 Mission

Keywords:

SENTINEL 1 – RANDOM FOREST – WETLAND – GOOGLE EARTH ENGINE

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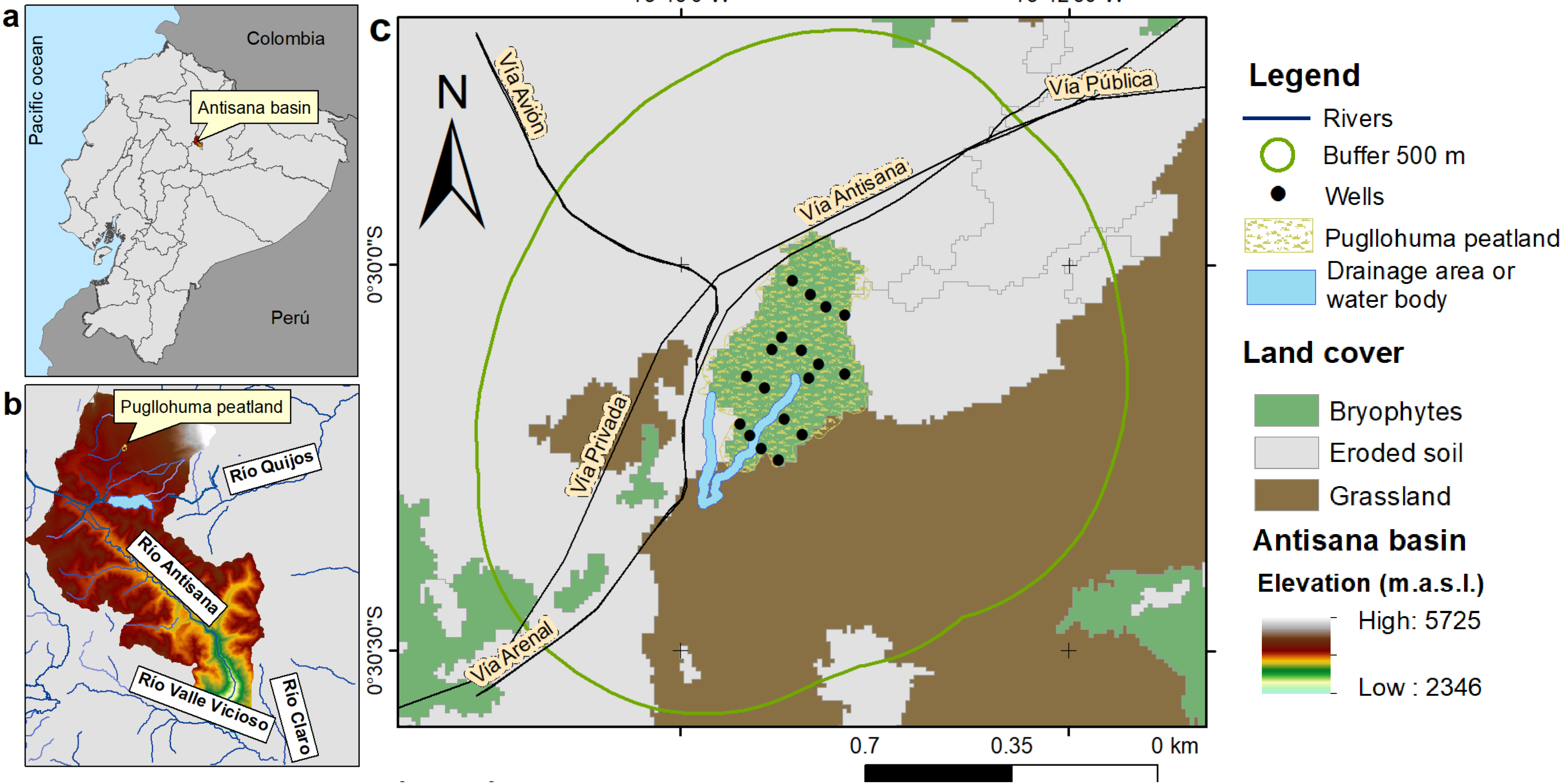
1. Background
2. Methodology
    1. Generation of temporal supervised classification using R Studio
    2. Imagery selection and pre-processing using Google Earth Engine
    3. Generation of spatial supervised classification using Google Earth Engine
3. Results
4. Conclusions and recommendations

1. Background: Research relevance

The Pugllohuma peatland is at the north of La Mica system, whose monitoring of vegetation cover, soil analysis, and water dynamics are carried out by FONAG.

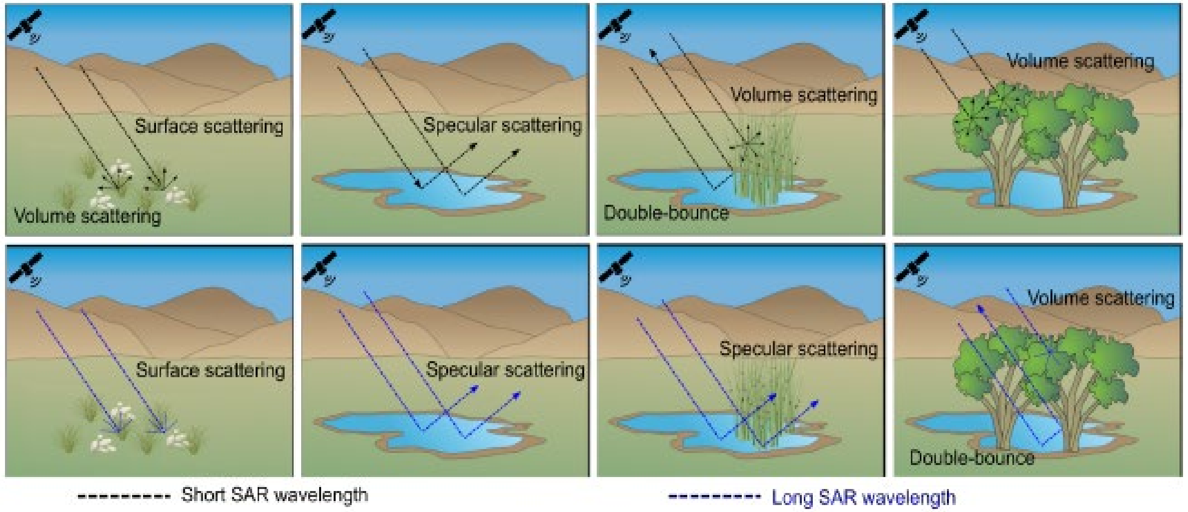
The current research may help to develop strategies and concrete actions for the protection of important water conservation areas for the Metropolitan District of Quito.


a
Pacific ocean
Colombia
Antisana basin
Perú
b
Pugllohuma peatland
Río Quijos
Río Antisana
Río Valle Vicioso
Río Claro
c
78°13'0"W
78°12'30"W
0°30'0"S
0°30'30"S
N
Vía Avión
Vía Pública
Vía Antisana
Vía Privada
Vía Arenal
0.7
0.35
0 km
Legend
Rivers
Buffer 500 m
Wells
Pugllohuma peatland
Drainage area or water body
Land cover
Bryophytes
Eroded soil
Grassland
Antisana basin
Elevation (m.a.s.l.)
High: 5725
Low : 2346

1. Background: SAR relevance

Synthetic aperture radar

Radars are useful in detecting wetland areas with a high level of cloud cover because they are capable of penetrating clouds. Additionally, radar backscatter is sensitive to dielectric properties, including flood level, soil moisture, or salinity, which are common characteristics of wetland ecosystems.



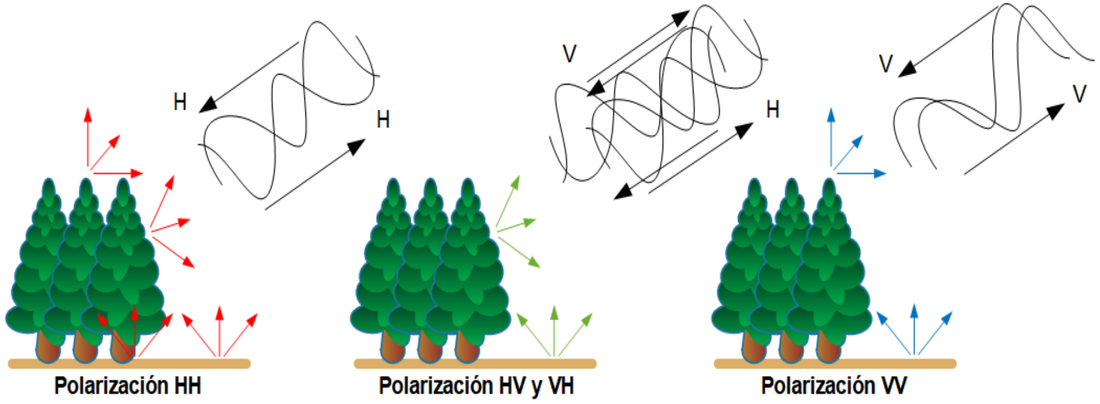
Other investigations

- Bourgeau, et al. (2015). Development of a bi-national Great Lakes coastal wetland and land use map using three-season PALSAR and Landsat imagery.
- Gabrielsen, et al. (2016). Using a multiscale, probabilistic approach to identify spatial-temporal wetland gradients.
- Behnamian, et al. (2017). Semi-automated surfacewater detection with synthetic aperture radar data: A wetland case study.
- Jensen, et al. (2018). Assessing L-Band GNSS-reflectometry and imaging radar for detecting sub-canopy inundation dynamics in a tropicalwetlands complex.
- Armani, et al. (2019). Canadian wetland inventory using Google Earth Engine: The first map and preliminary results.
- El Hajj, et al. (2019). Penetration analysis of SAR signals in the C and L bands for wheat, maize, and grasslands.

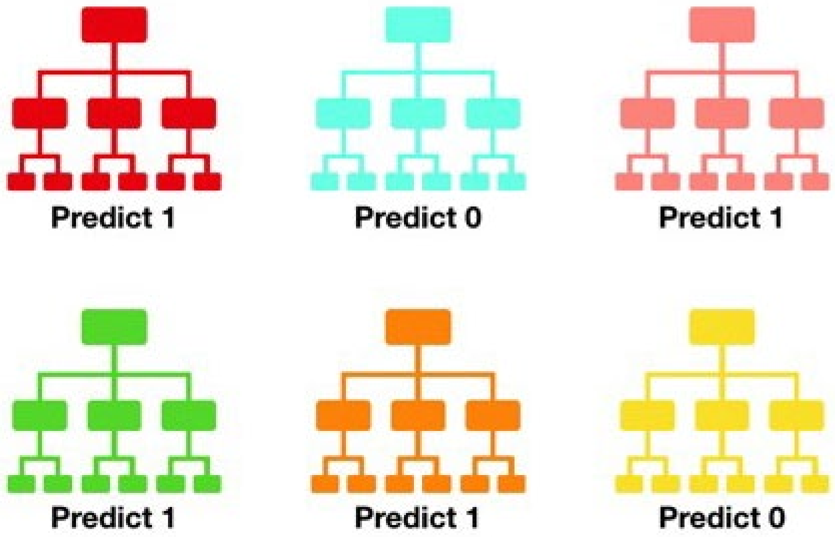
1. Background: Machine learning

Temporal assessments include many information from each image, some of there are:

- Incidence angle
- Terrain
- Day of the year
- Flying trajectory
- Backscattering



Supervised classification is based on the idea that a user can select sample pixels in an image that are representative of specific classes and then direct the image processing software to use these training sites as references for the classification of all other pixels in the image.



2. Methodology

TEMPORAL CLASSIFICATION

Sample
- Water table(2016-2019)
- Dry and wet weather extreme events

Construc. And training
- Use relative humidity, rain, atmospheric pressure, temperature and wind registers to identify saturation extreme events.
- Correlation matrix
- Decision tree number
- Variable importance

Aplicación
- Dry and wet extreme events (2017-2019)

Evaluación
- Adjusting results

SPATIAL CLASSSIFCATION

Sample
- DEM, slope, radar images
- Polarimetric scattering indexes

Construc. And training
- Reducing overtraining
- Correlation matrix
- Variable importance

Aplicación
- Time series

Evaluación
- Results verification: k-means (Sentinel-2) vs random forest (Sentinel-1)

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Class 0: wet extreme event
Class 1: dry extreme event

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Temporal sample

Relative humidity (%)	Atmospheric pressure (mbar)	Rain (mm)	Temperature (ºC)	Wind direction (º)	Wind speed (m s-1)	Day of the year	Class
94.41	623.67	2.32	3.33	259.99	3.58	100	1
94.32	623.77	1.56	3.71	272.18	3.70	101	0

HR: Relative humidity
PA: Atmospheric pressure
Precip: Rain
T: Atmospheric temperature

WD: Wind direction
WS: Wind speed
DOY: Day of the year

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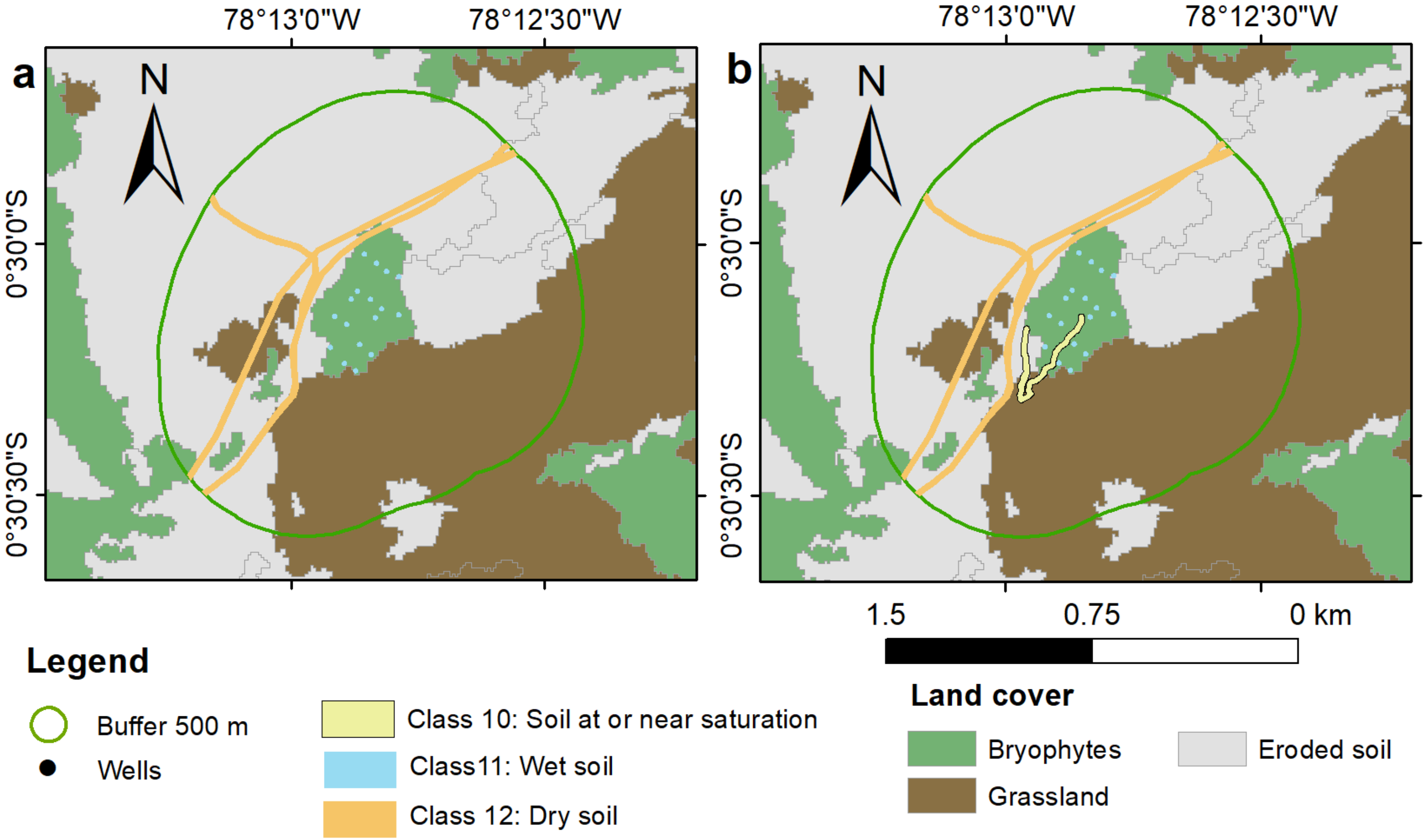


Eva

Class 0: wet extreme event
Drainage area, wet soil and roads
Class 1: dry extreme event
Wet soil and roads

Spatial sample

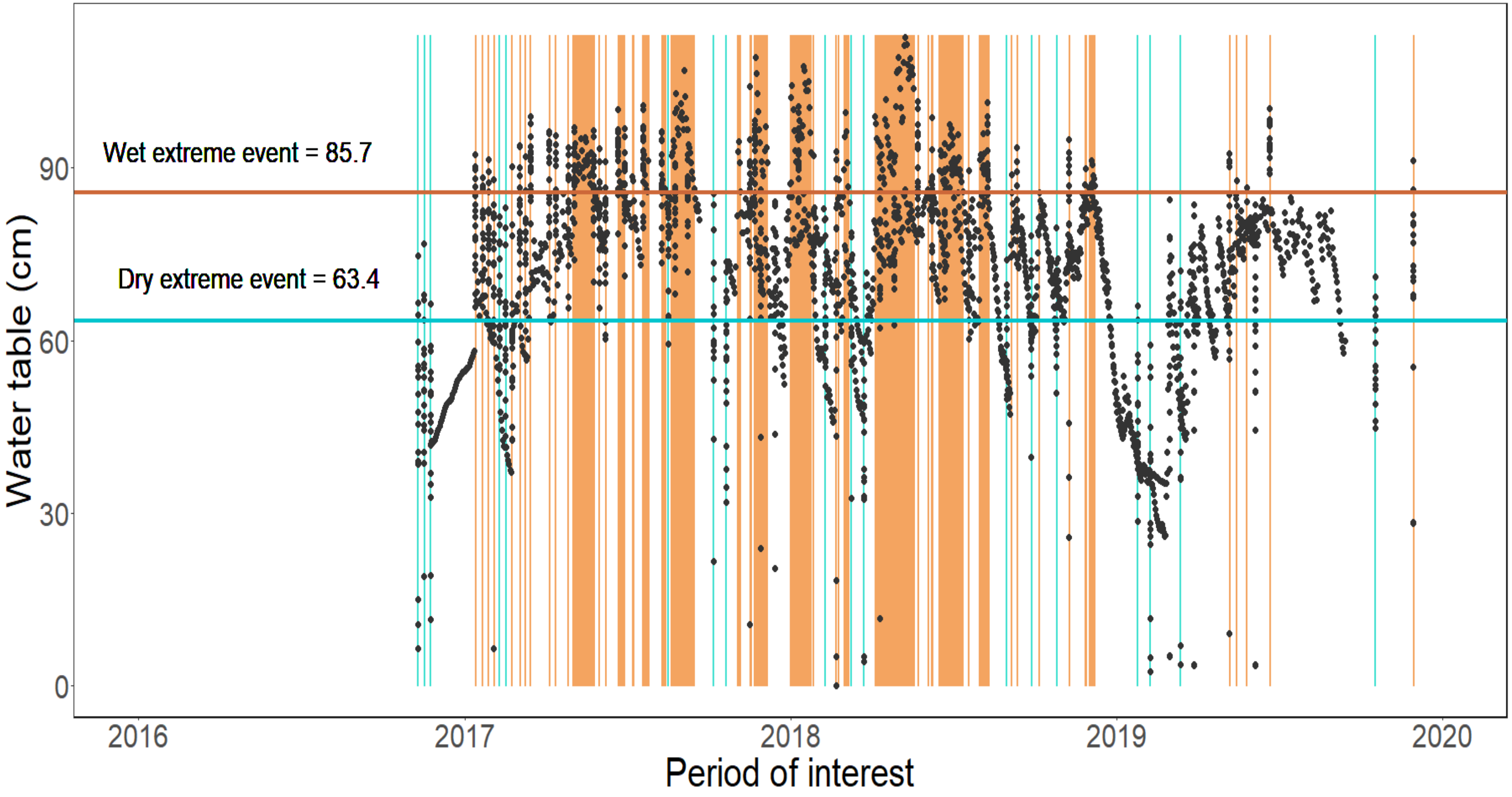
Terrain elevation (m.a.s.l.)	Day of the year	NDPI	NVHI	NVVI	VH (db)	VHrVV	VV (db)	Capture angle (º)	Slope (º)	Class
4132	37	0.19	0.59	0.41	23.00	1.46	15.80	43.06	3.10	11.00
4143	321	0.26	0.63	0.37	25.90	1.71	15.20	43.01	14.00	12.00
4119	138	0.41	0.70	0.30	24.30	2.38	10.20	33.88	3.10	10.00

DEM: Terrain elevation
DOY: Day of the year
NDPI: Normalized polarized difference index
NVHI: Normalized VH index
NVVI: Normalized VV index

VHrVV: Polarized ratio(VH - VV)
VH: Cross-polarization
VV: Co-polarization
Angle: Backscattering incidence angle
Slp: Terrain slope

3. Results

Temporal classification: Sample

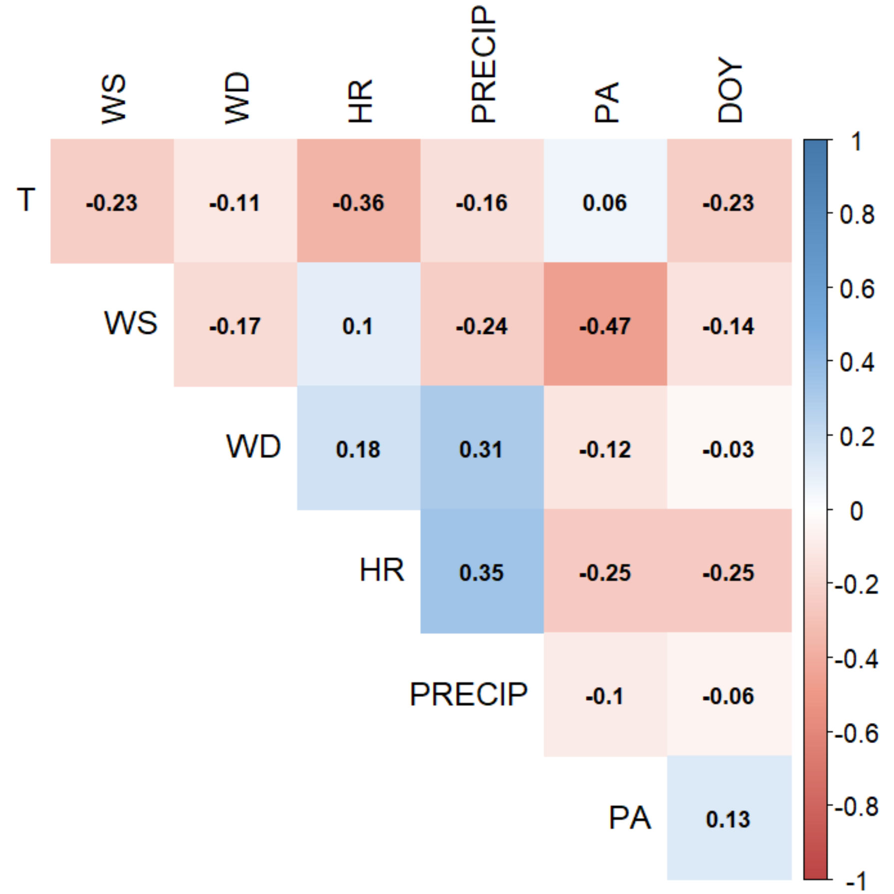


Automatic and manual measurements

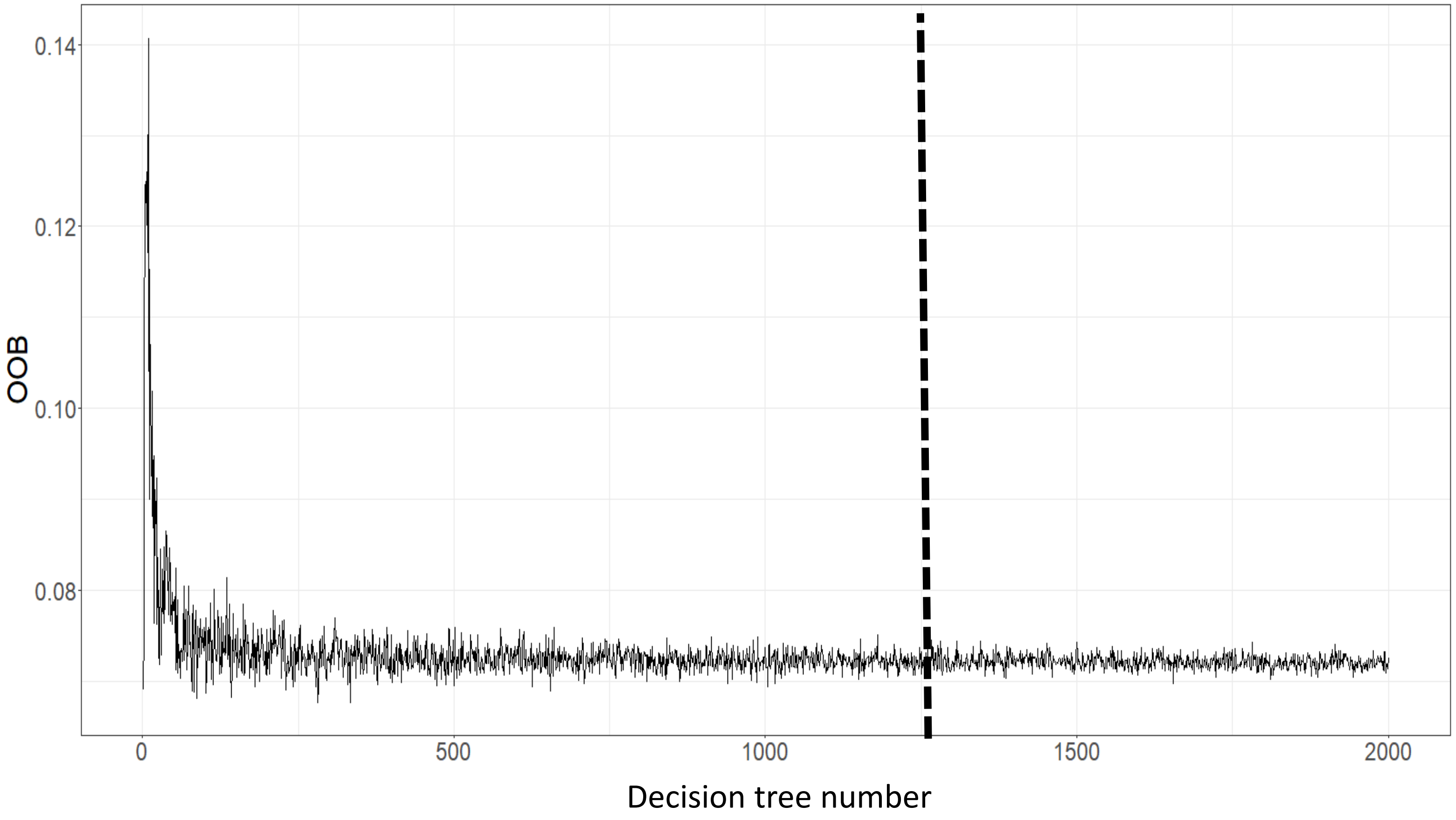
- Data distribution to define thresholds
- 243 wet extreme events from January 2017 to November 2019
- 285 dry extreme events from November 2016 to November 2019

Temporal classification: Construction and training

Variable correlation

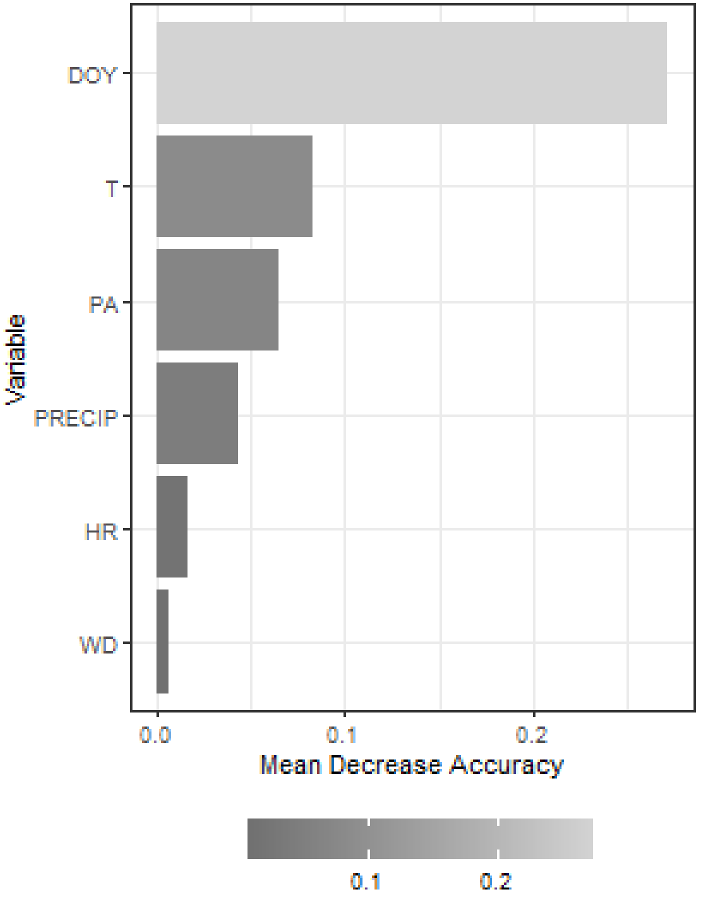


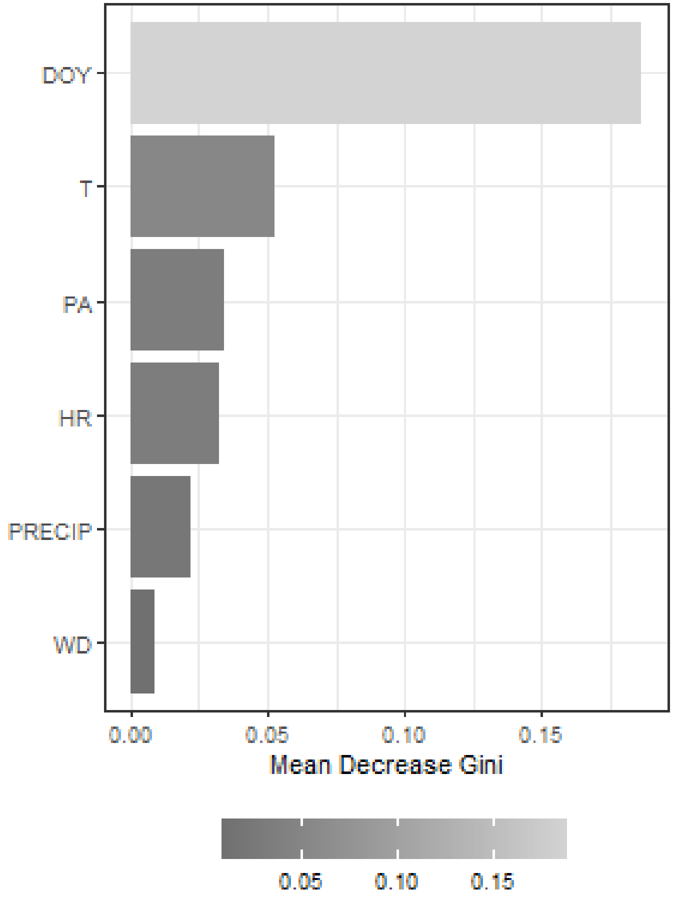
OOB error vs decision tree number



Temporal classification: Construction and training

Variable importance

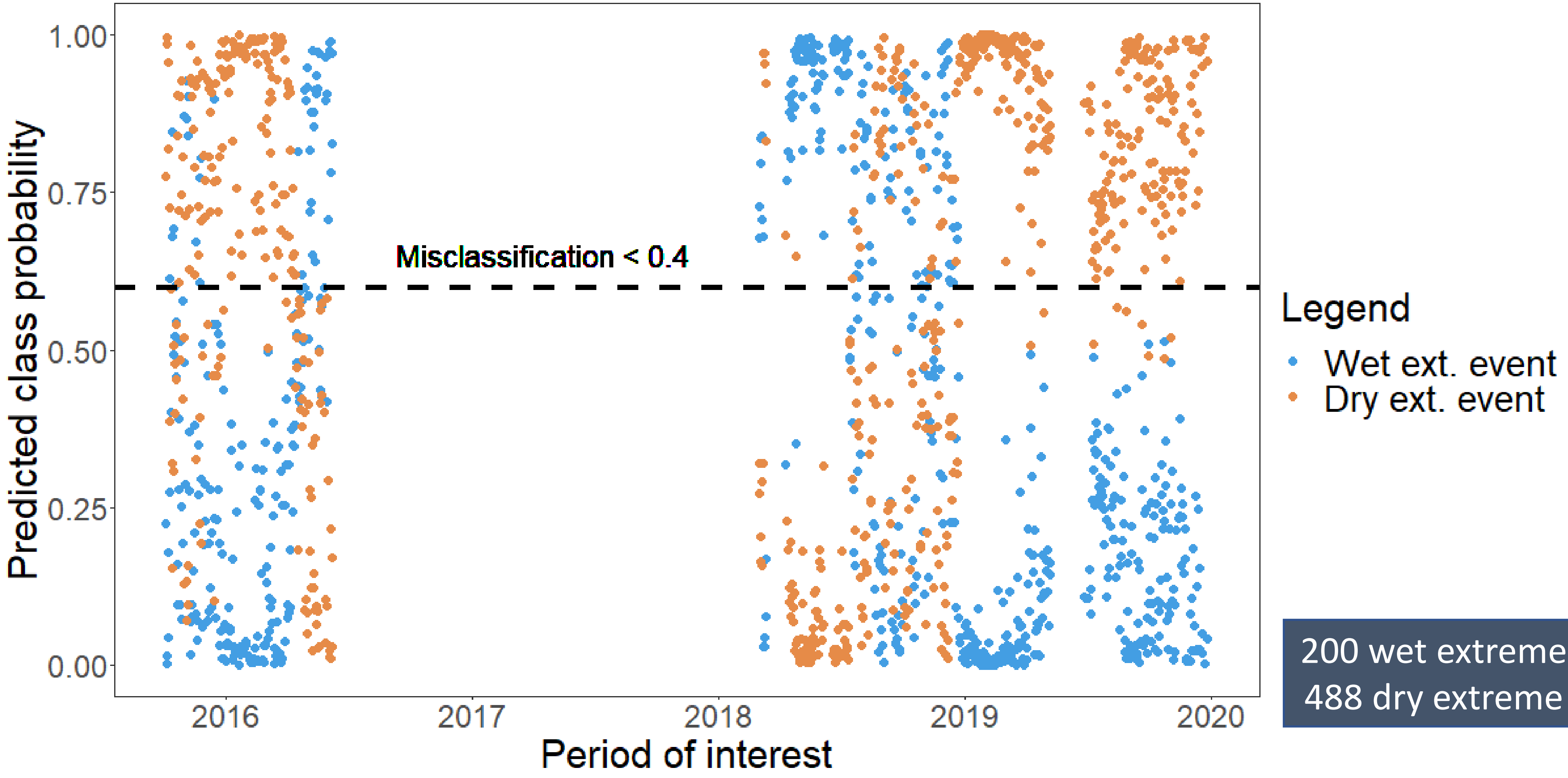




Outputs

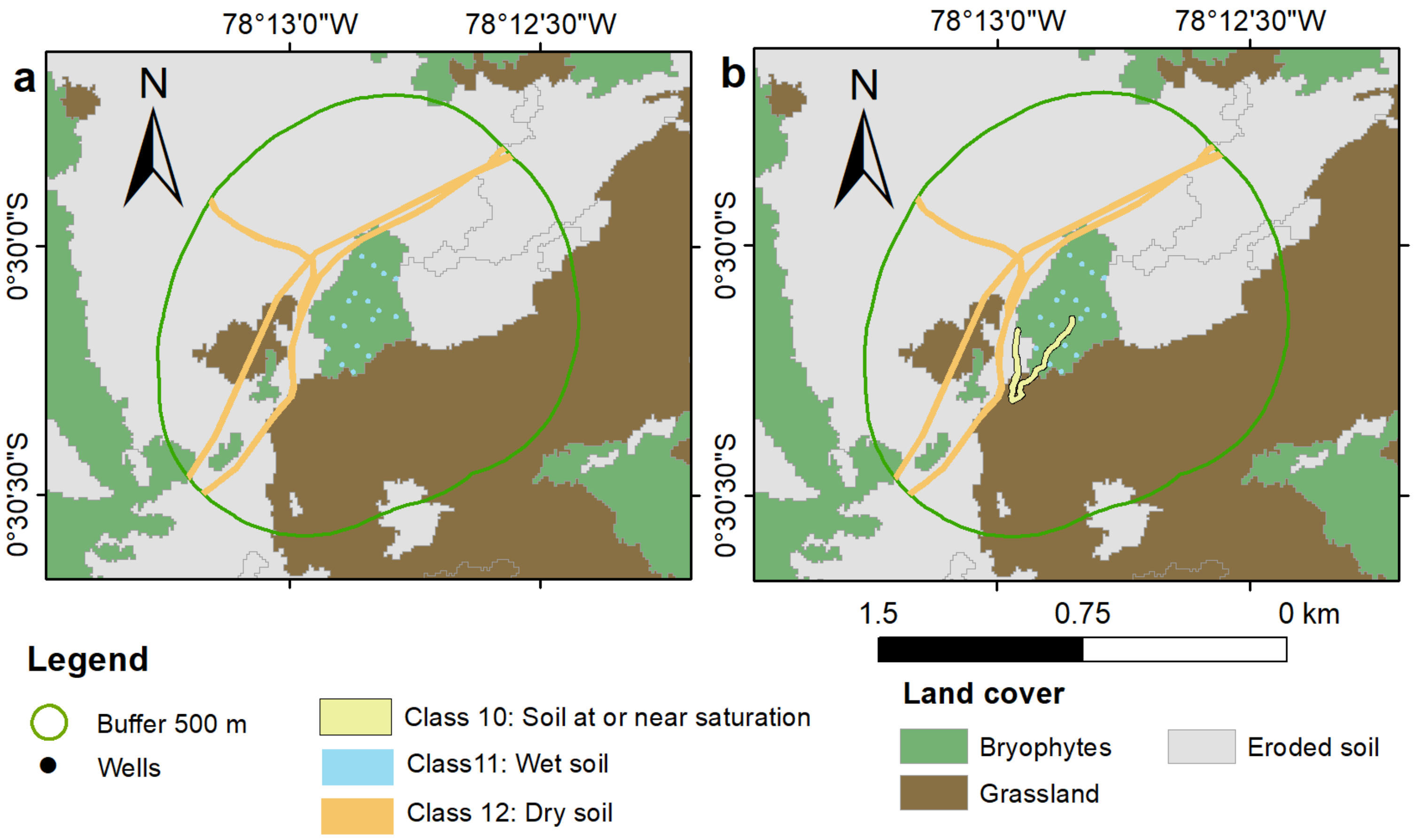
- Data distribution to define thresholds
- 237 wet extreme events from October 2015 to October 2019
- 524 dry extreme events from October 2015 to December 2019

Temporal classification: Adjusting results



200 wet extreme events
488 dry extreme events

Spatial classification: Sample

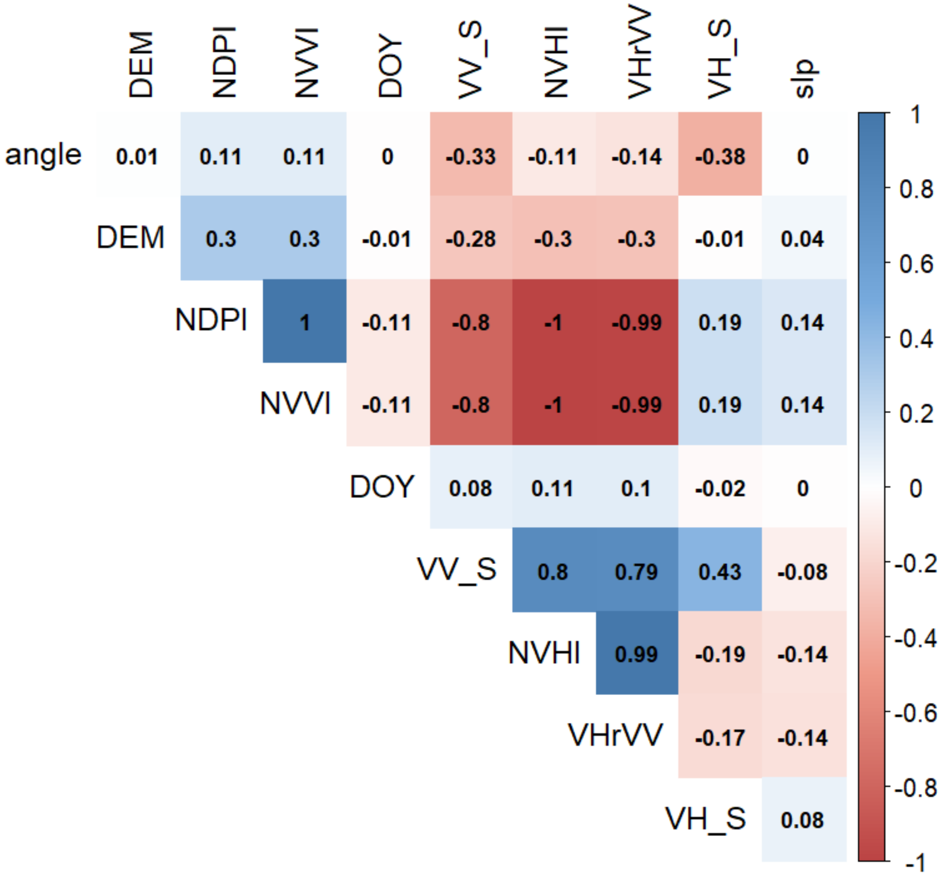


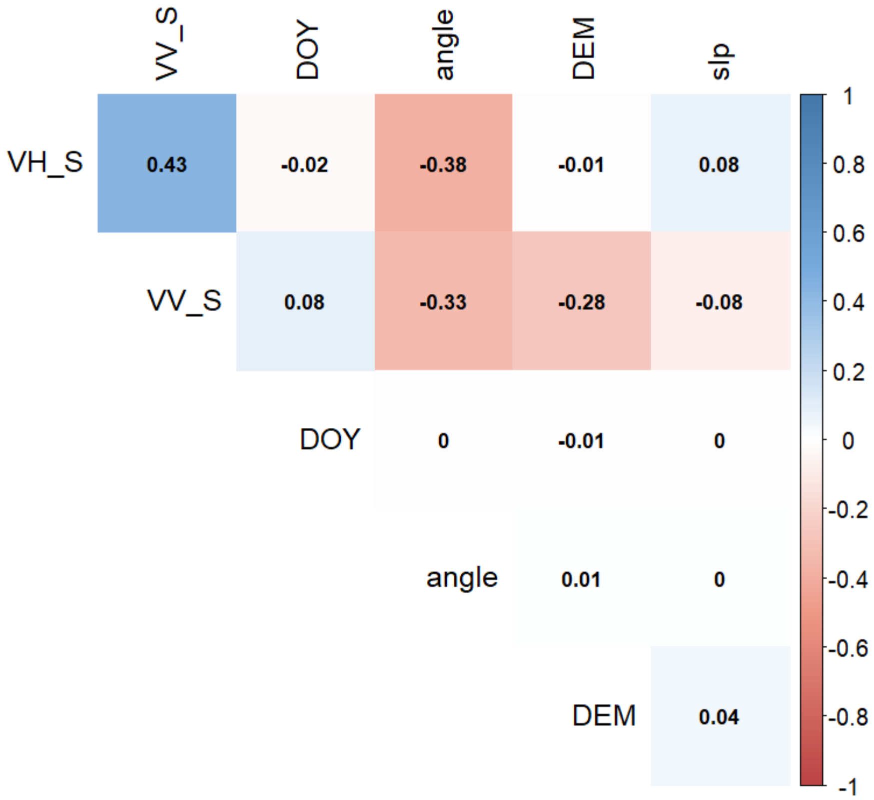
27 images for wet extreme events

86 images for dry extreme events

Spatial classification: Construction and training

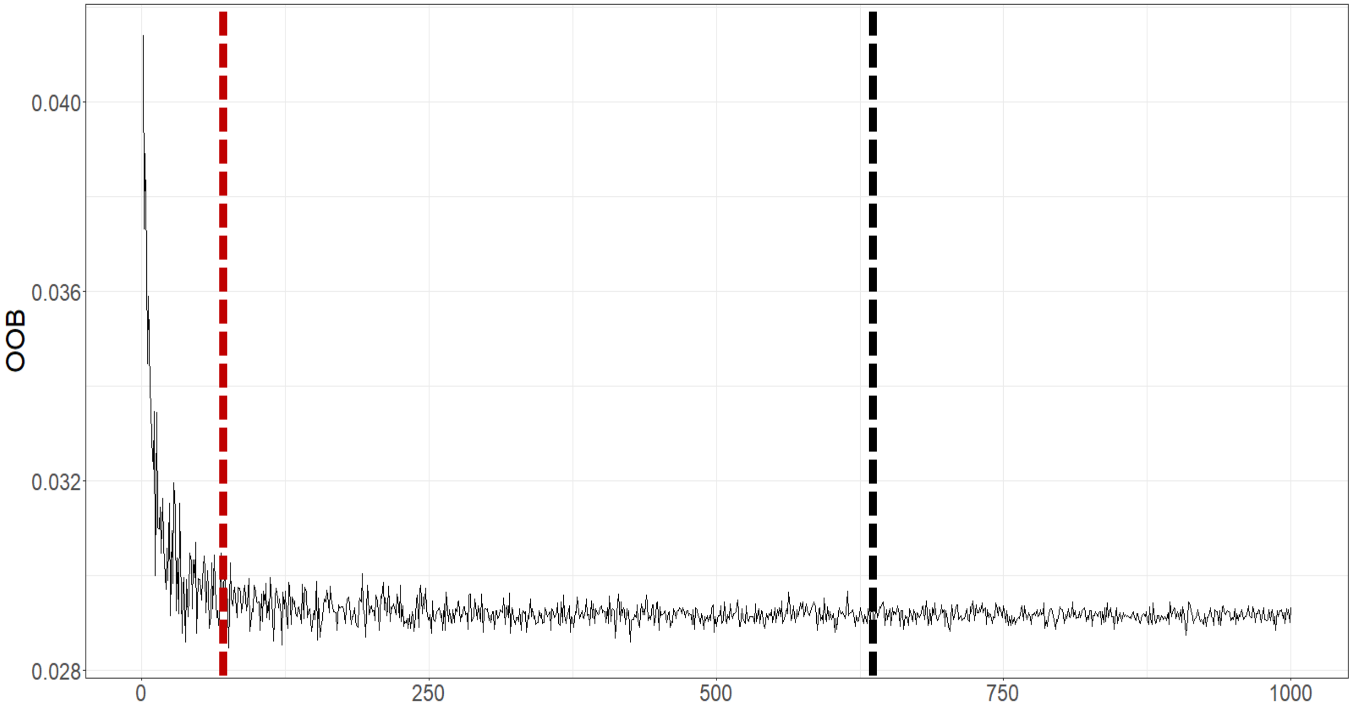
Variable correlation



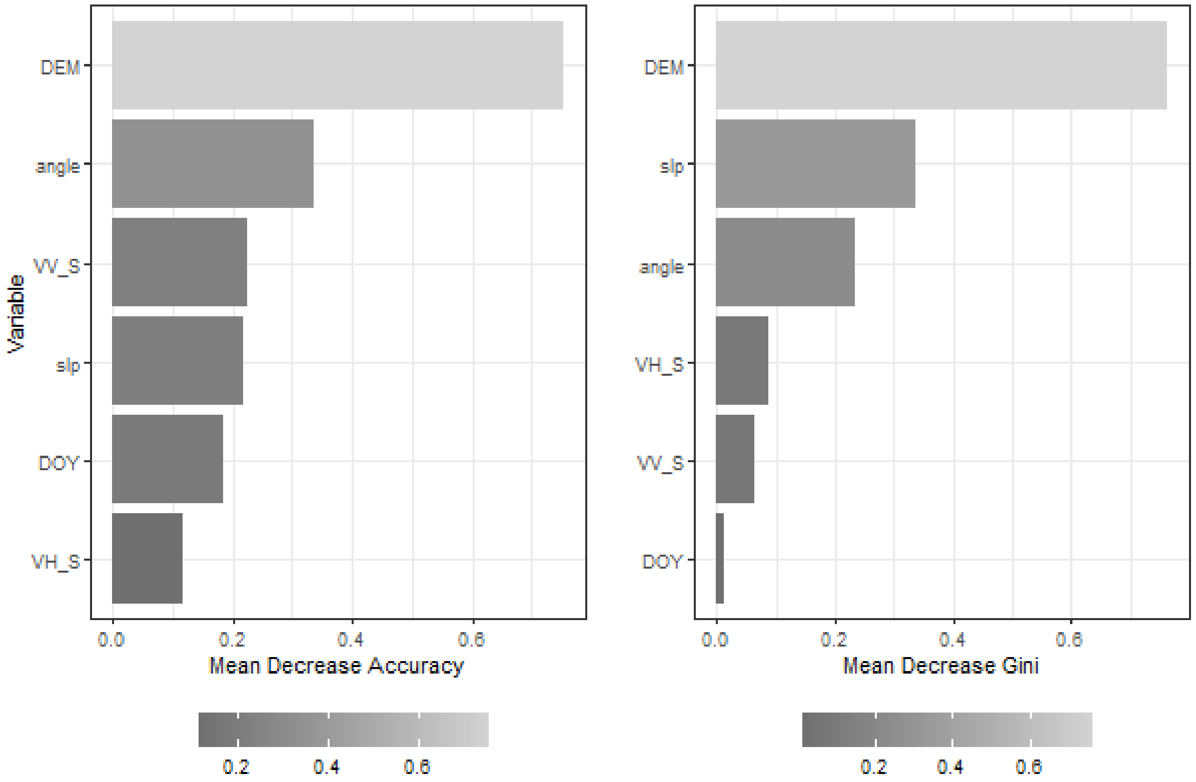


Spatial classification: Construction and training

OOB error vs decision tree number



Variable importance

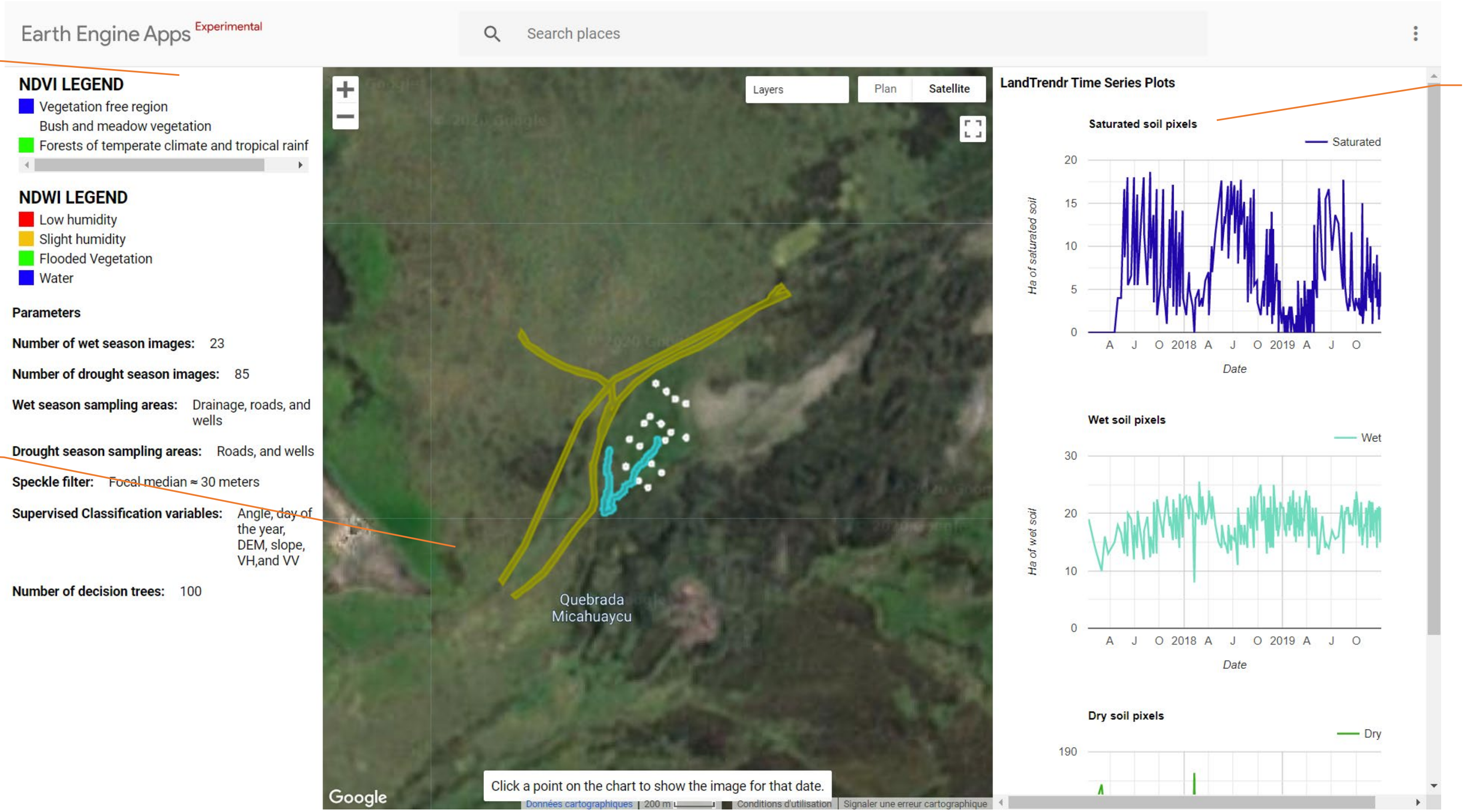


Spatial classification: Result verification

		Supervised classification				
Unsupervised classification		Soil at or near saturation	Wet soil	Dry soil	Total	Coincidence
	Soil at or near saturation	216.9	0.0	434.3	651.2	0.3
	Wet soil	0.0	66.8	201	267.8	1.0
	Dry soil	0.0	0.0	1213.8	1213.8	0.3
	Total	216.9	66.8	1849.1	2132.8	
	Coincidence	1.0	1.0	0.7		0.7

GUI: Pugllohuma peatland classification

Model description



Time series

Layers

Conclutions and recommendations

Conclutions

Temporal classification

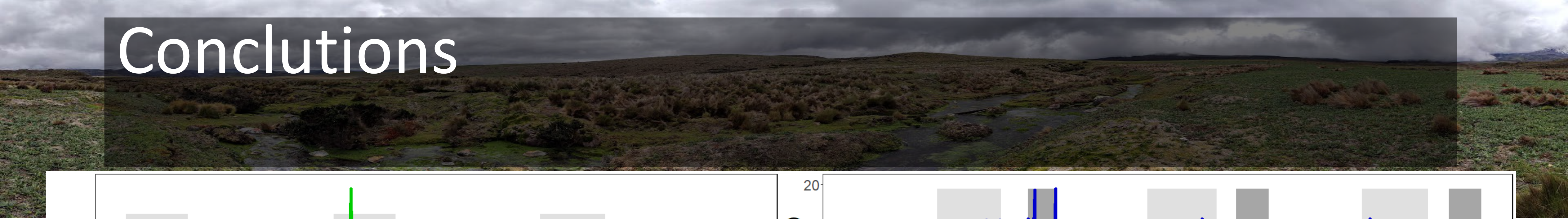
- Day of the year,
- Atmospheric temperature,
- And rain.

Wind direction, relative humidity, and atmospheric pressure

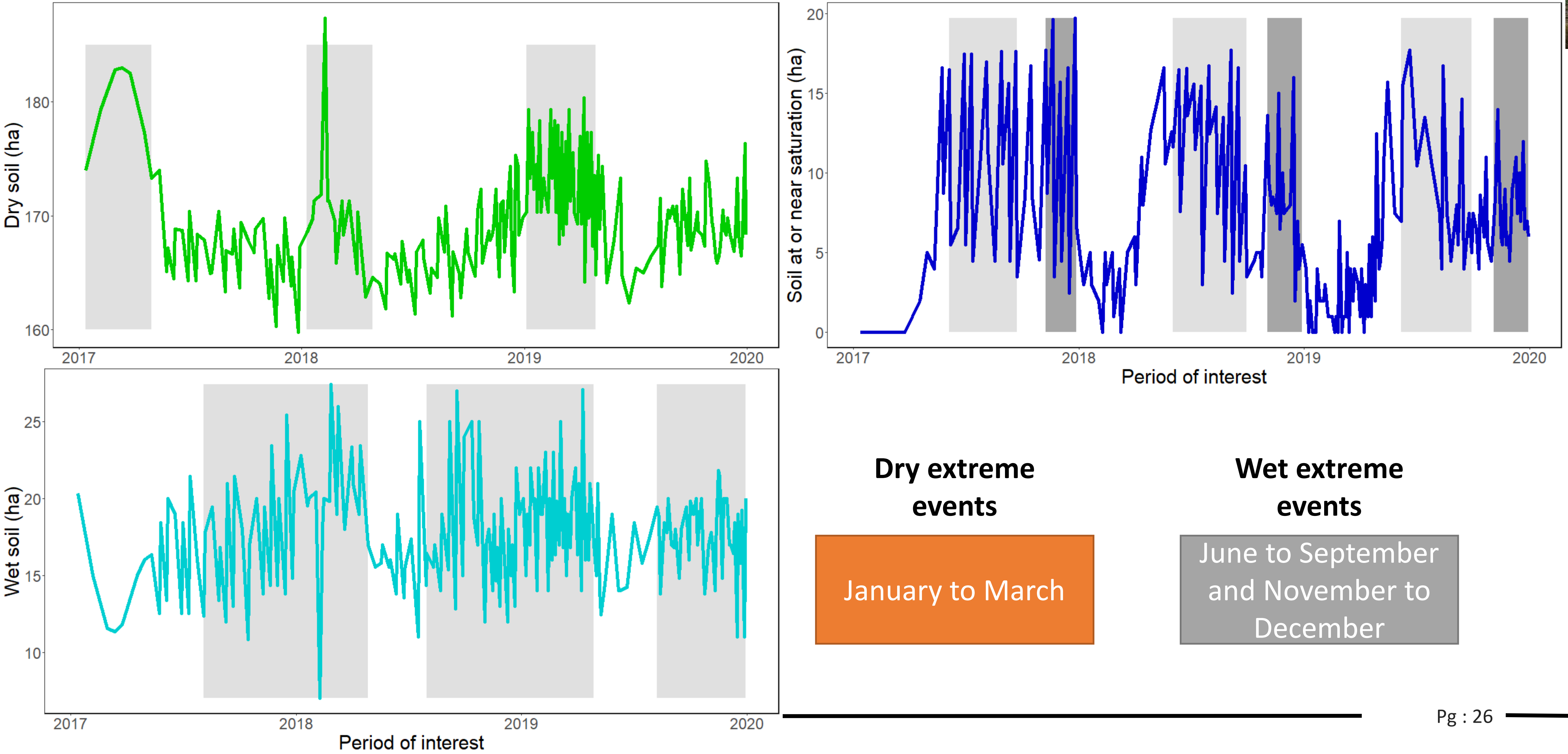
Spatial classification

- Terrain elevation

Incidence angle and day of the year of the image, terrain slope, and backscattering



Conclutions



Dry extreme events

January to March

Wet extreme events

June to September and November to December

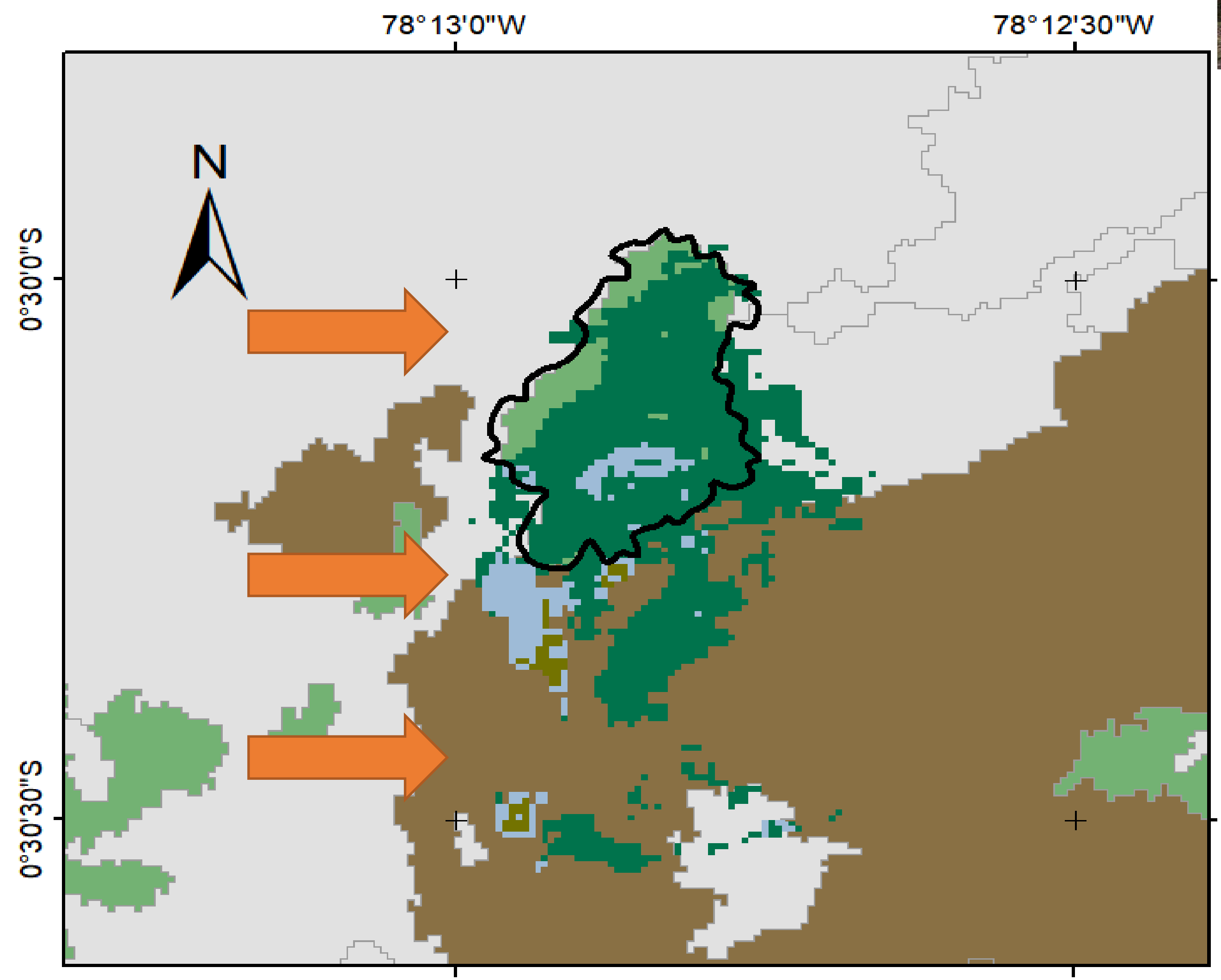
Conclutions

Water accumulation

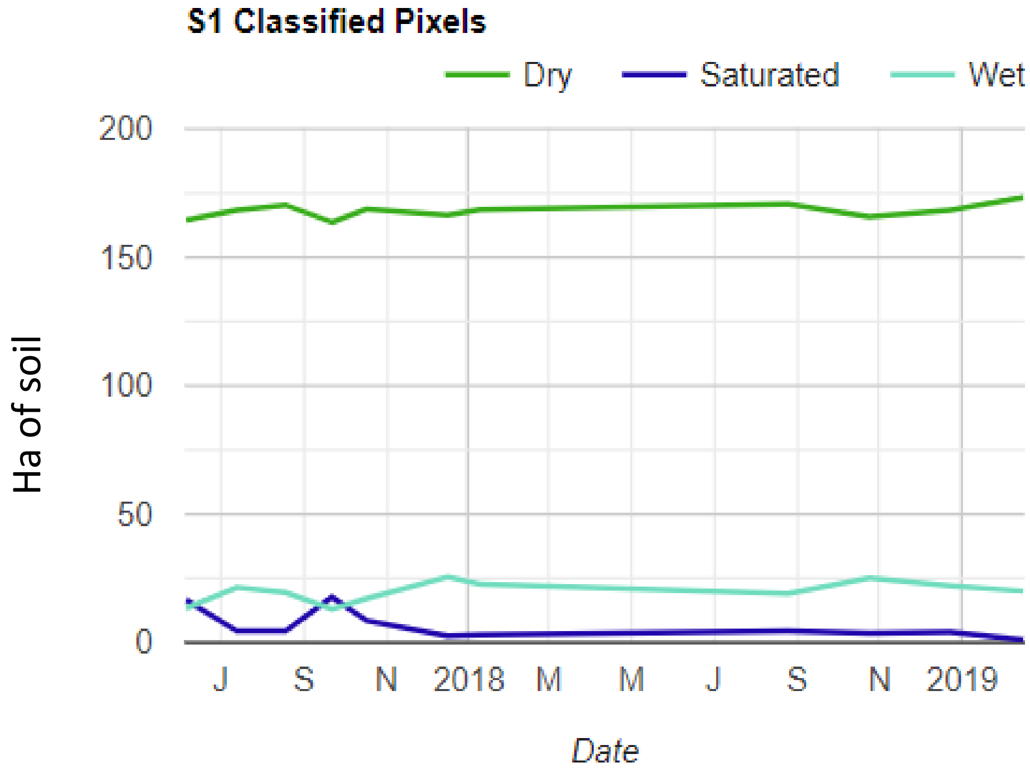
Permanent

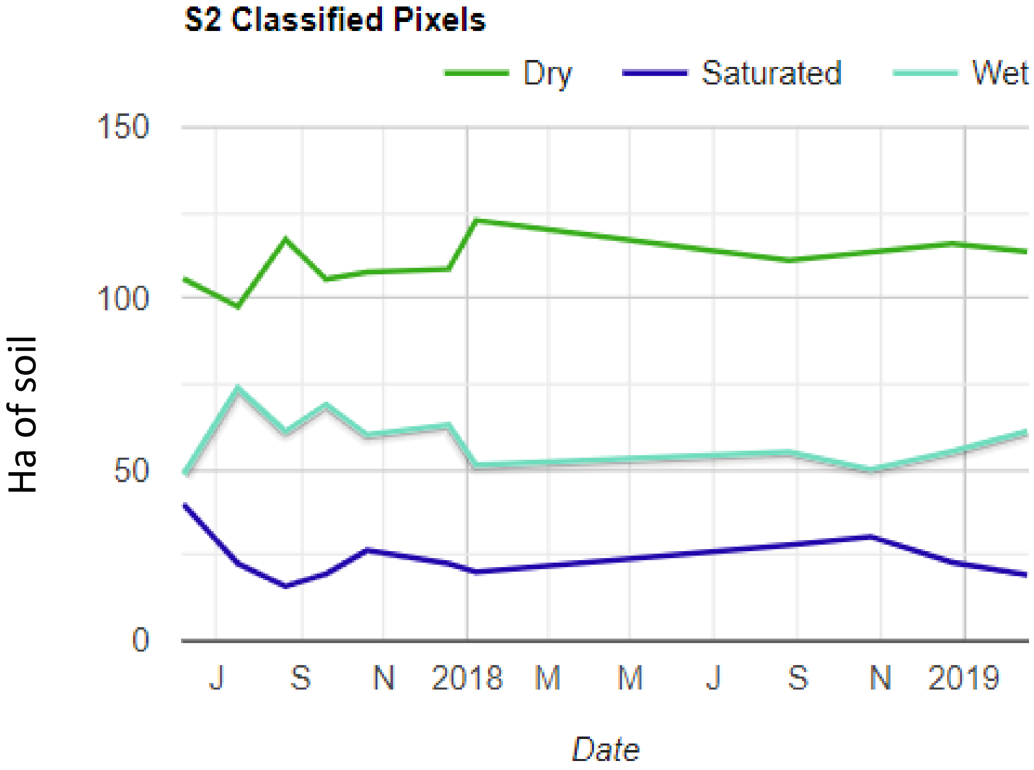
Seasonal

Eventual



Conclutions





Recommendations

Include new climate databases

Work with more satellite missions that are "unaffected" by weather conditions

Include controls of spatio-temporal changes in field visits

Combine information generated by active and passive satellites

Work with different wavelengths and polarizations

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