

# What do satellite-based burn severity indices tell us? - Explaining Sentinel-2 dNBR variability using very high resolution pre- and postfire UAV imagery

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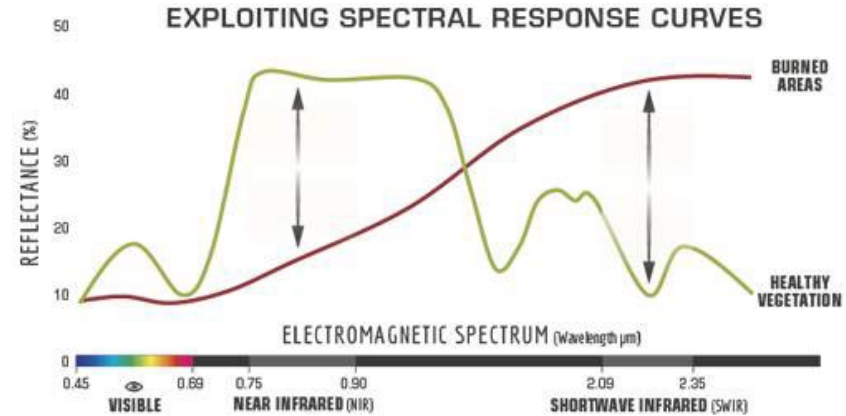
- **Burn severity** is an ambiguous term mostly referred to as *long-term ecological changes introduced to a landscape via fire* (Cansler & McKenzie, 2012<sup>1</sup>)
- Knowing the **burn severity patterns** of a burned area is helpful to understand ecological and economic consequences of wildfires and to coordinate post-fire management
- **Vegetation indices** derived from **satellite images** were suggested as a tool to characterize burn severity patterns across large areas

<sup>1</sup>Cansler, C. A., & McKenzie, D. (2012). How robust are burn severity indices when applied in a new region? Evaluation of alternate field-based and remote-sensing methods. *Remote sensing*, 4(2), 456-483.

- The difference normalized burn ratio **dNBR** has become a standard tool to quickly characterize burn severity after wildfires

$$NBR = \frac{NIR - SWIR}{NIR + SWIR}$$

$$dNBR = NBR_{pre-fire} - NBR_{post-fire}$$

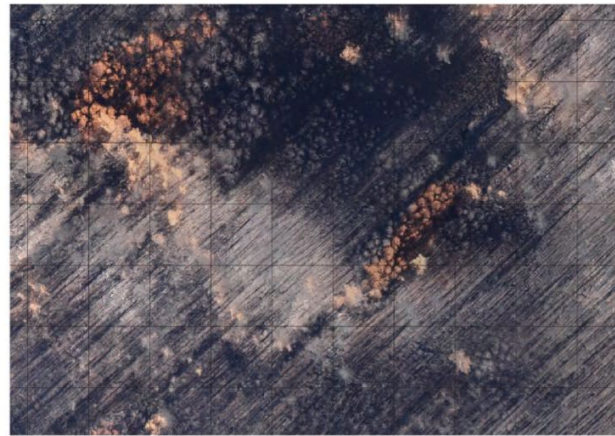


[https://un-spider.org/sites/default/files/Spectral\\_responses.jpg](https://un-spider.org/sites/default/files/Spectral_responses.jpg)

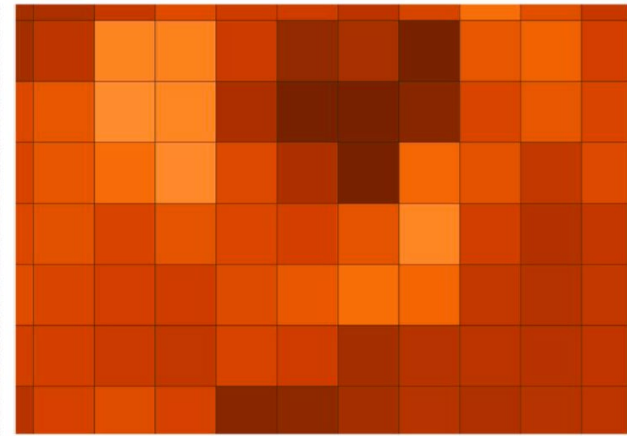
- Example of a burned area with situation before and after the fire as seen from an unmanned aerial vehicle and a dNBR product derived from Sentinel-2 data



Pre-fire



Post-fire



0 **dNBR** 1.5



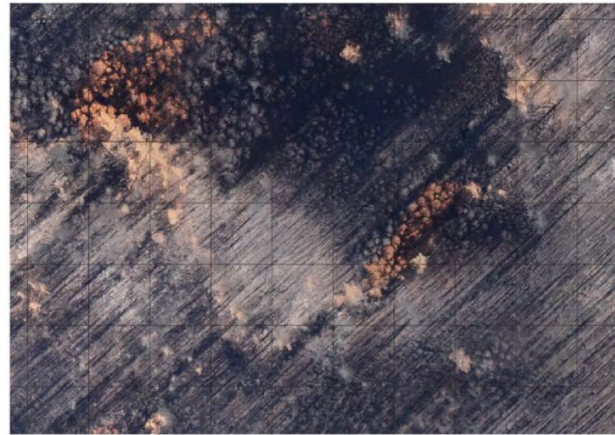
# Introduction

- RdNBR has been suggested as a refinement of dNBR to account for pre-fire vegetation composition

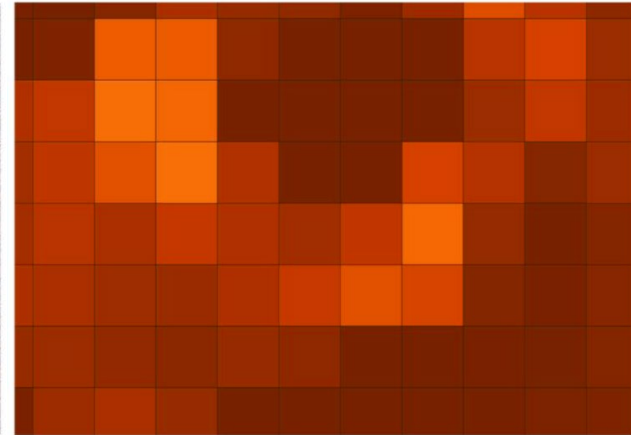
$$RdNBR = \frac{dNBR}{abs(NBR_{prefire})^{0.5}}$$



Pre-fire



Post-fire



0 **RdNBR** 1.5

# Challenges / research gaps

- **dNBR** and **RdNBR** have been related to field-plot measured indicators of burn severity but identified relationships vary with geographic location and timing
- **Pre-fire vegetation composition** is often unknown (no spatially continuous data available)

- Better understand what drives the Sentinel-2 based dNBR and RdNBR signal
- Exploit the availability of very high resolution UAV imagery acquired shortly before and after the 2016/2017 mega-fires of central Chile
- Particularly understand the role of cast-shadows of dead standing trees and trunks

# Study area

a) overview

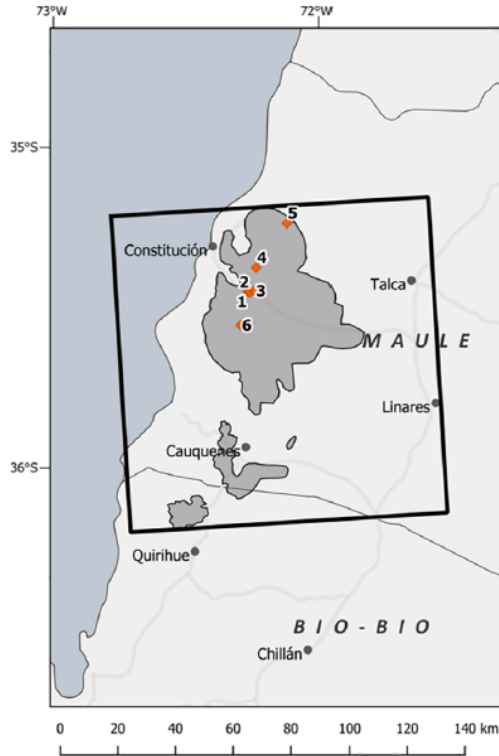


EPSG 32719

This map was created using data from NaturalEarth Project (naturalearthdata.com), from Divagis (diva-gis.org), from CONAF (sit.conaf.cl) and products of data processed in this study in QGIS-2.18 Las Palmas de G.C.

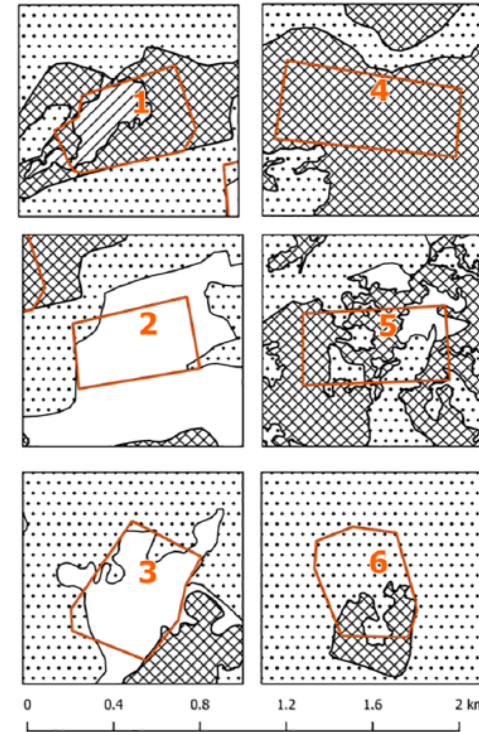


b) study region



- ♦ study sites
- cities
- roads
- satellite footprint
- burned area

c) study sites



- tree plantation
- mixed forest
- ▨ native forest
- ▨ meadows and shrubs
- study sites













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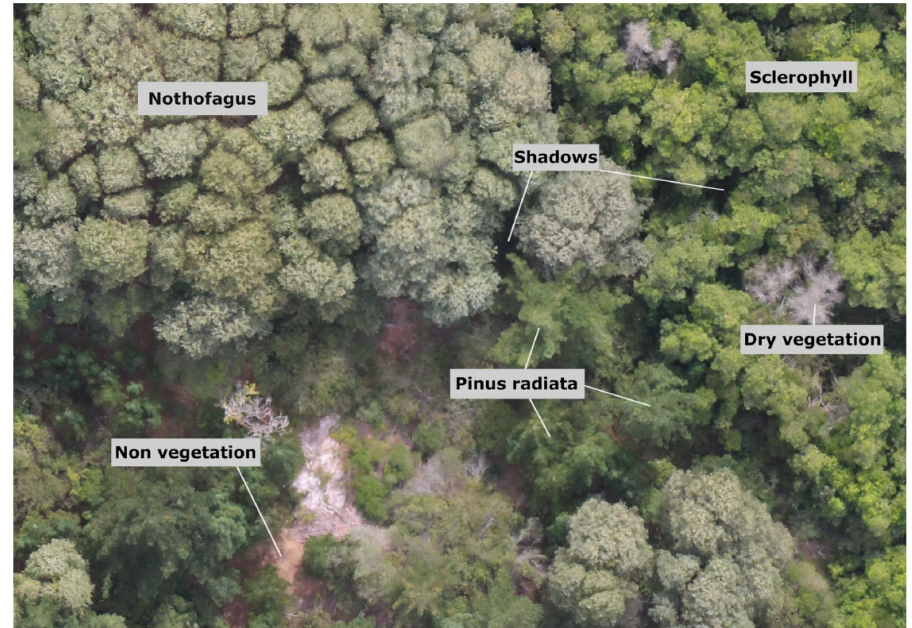
<b>Dataset</b>	<b>Acquisition date</b>
Prefire UAS survey	11th-21st of March 2016
Prefire Sentinel-2 image	5th of March 2016
Postfire UAS survey	10th and 13th of April 2017
Postfire Sentinel-2 image	29th of April 2017

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- Supervised classification of UAV images into 6 (pre-fire) and 4 (post-fire) classes

Number of sample plots per class and flight. Prefire and Postfire classifications were conducted separately.

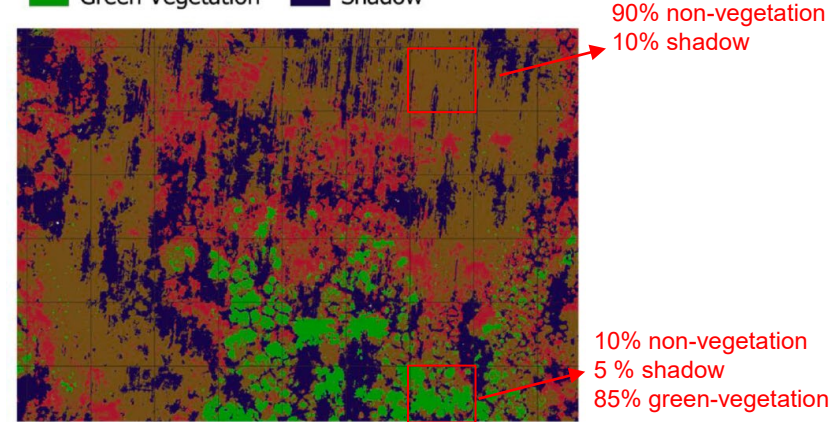
Class	Site 1	Site 2	Site 3	Site 4	Site 5	Site 6
Prefire non vegetation	382	153	200	33	361	120
Prefire Sclerophyll	128	57	116	193	100	16
Prefire Pinus radiata	310	164	325	190	193	176
Prefire Nothofagus	406	134	426	696	306	172
Prefire dry vegetation	130	58	22	98	17	21
Prefire shadow	76	114	85	73	53	50
Postfire non vegetation	170	729	359	209	1058	145
Postfire green vegetation	26	134	100	20	233	92
Postfire singed vegetation	46	201	207	79	252	54
Postfire shadow	30	268	37	126	178	27





- For each Sentinel-2 pixel the **fractional cover** of each land-cover class in the UAV-classification maps was determined (see example →)
- Additionally mean and variance of height was derived per Sentinel-2 pixel from the canopy height model

■ Non vegetation ■ Singed vegetation  
■ Green Vegetation ■ Shadow





## Predictors (after dropping highly correlated predictors)

%cov prefire non vegetation

%cov prefire Sclerophyll

%cov prefire Pinus radiata

%cov prefire Nothofagus

%cov prefire dry vegetation

prefire mean canopy height

prefire variance canopy height

%cov postfire non vegetation

%cov postfire shadow

%cov postfire singed vegetation

%cov postfire green vegetation

Generalized  
Additive Models  
(GAM)

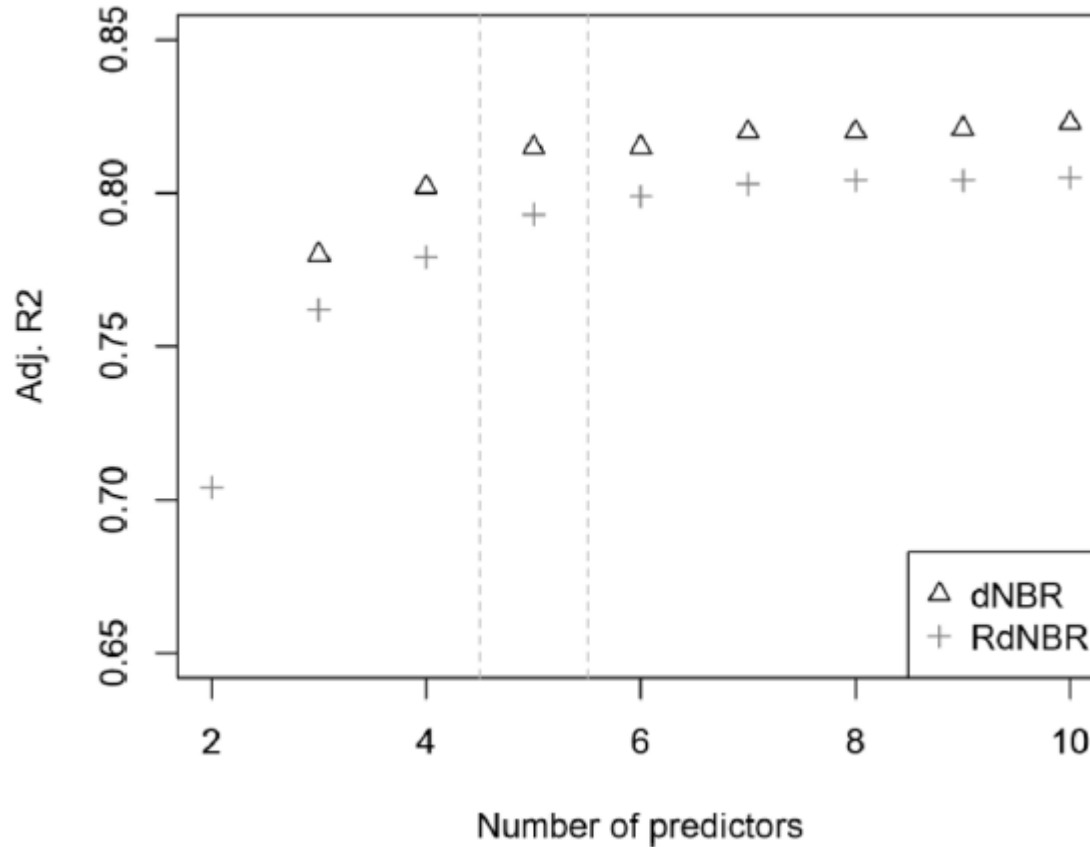
*Iterative search – all  
predictor combination for  
models with 2-10 predictors  
Best model via AIC*

Response

dNBR

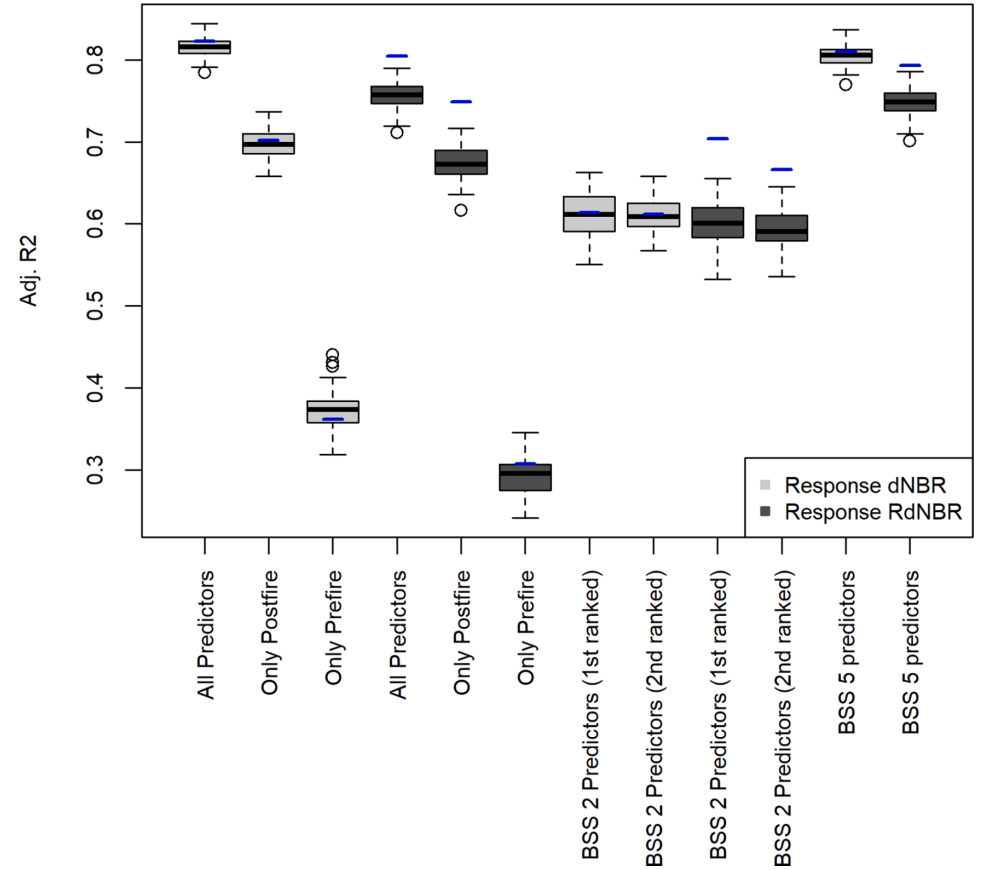
RdNBR

# Results



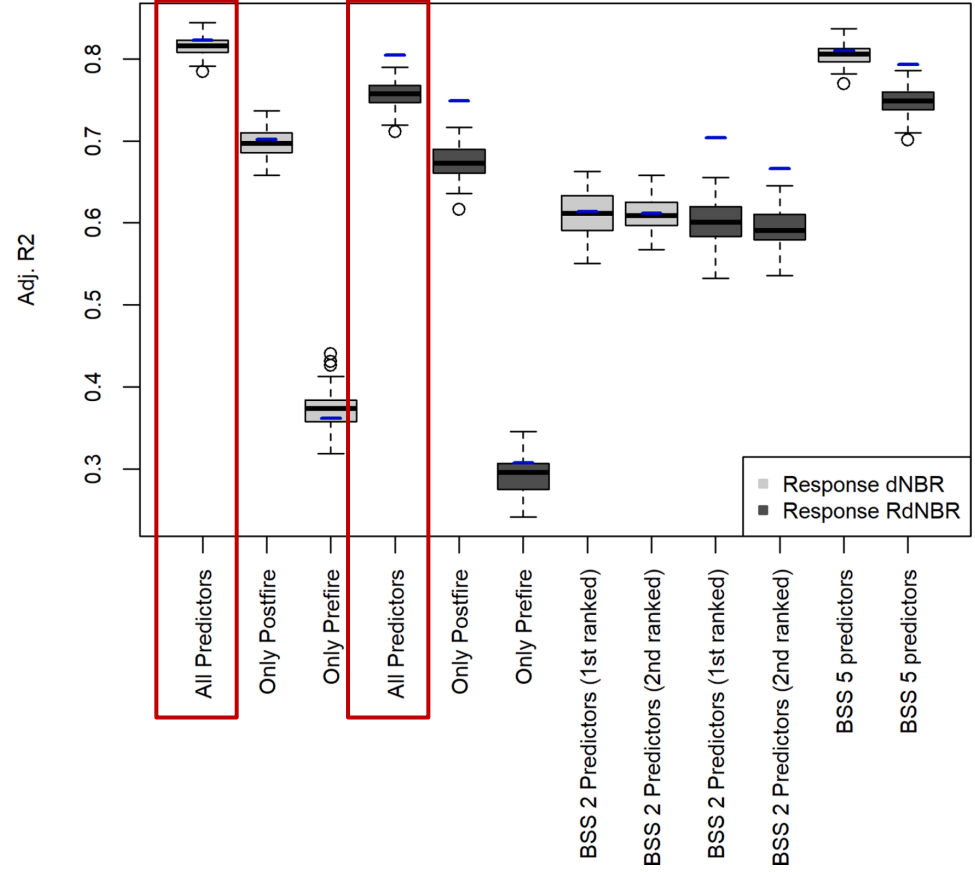
# Results

Blue = results without independent validation



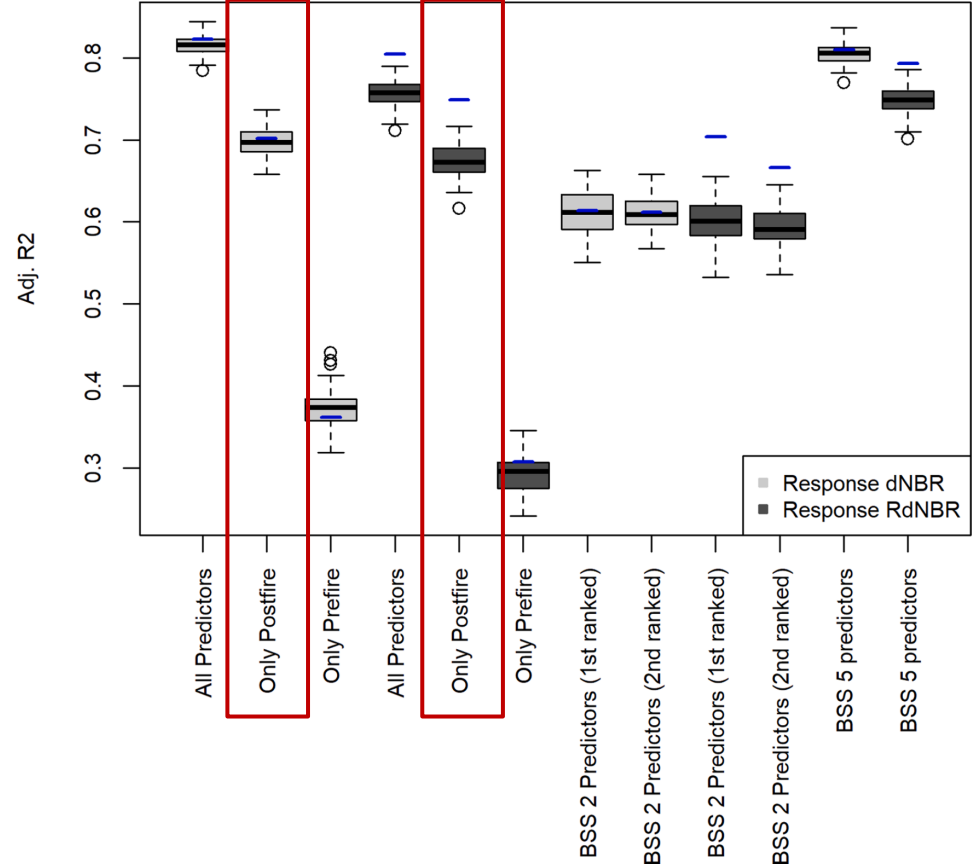
# Results

Blue = results without independent validation



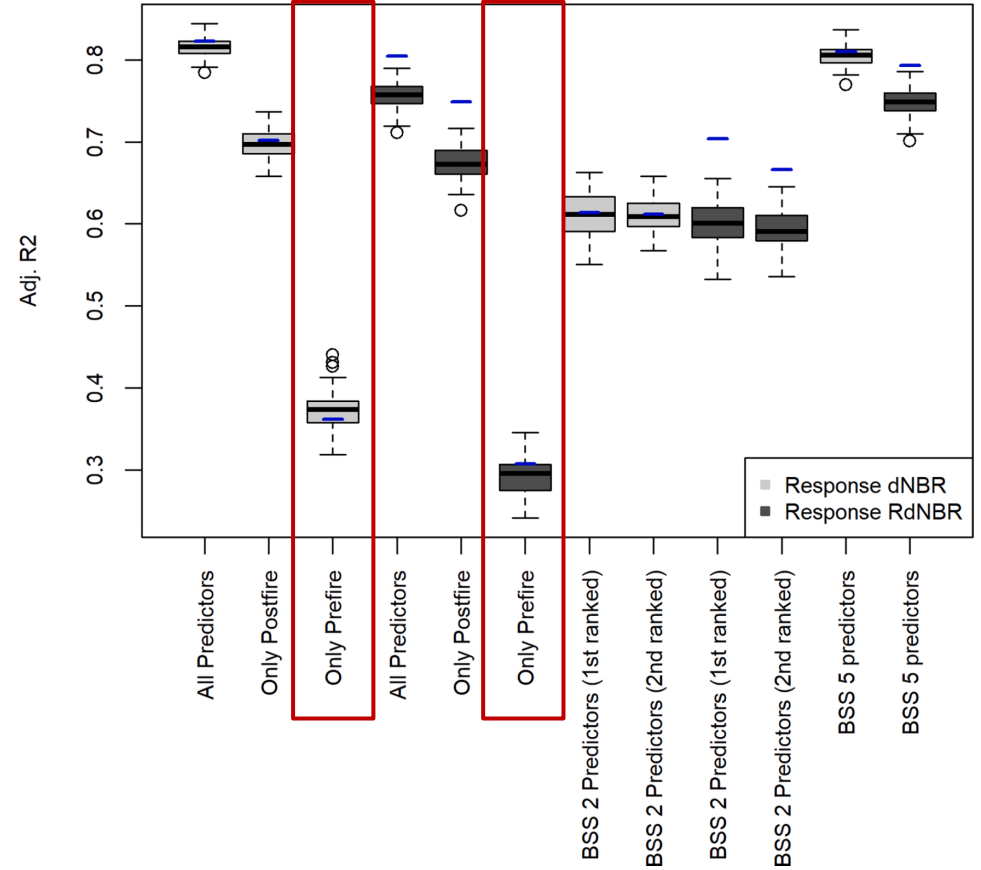
# Results

Blue = results without independent validation



# Results

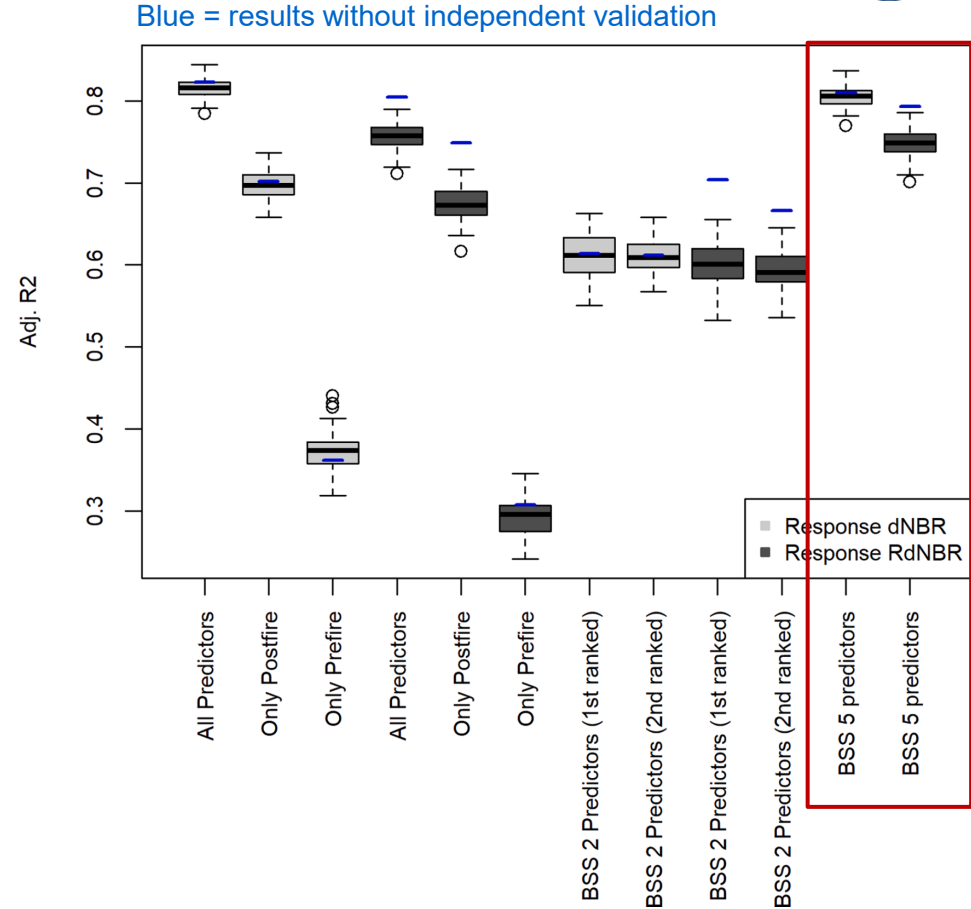
Blue = results without independent validation





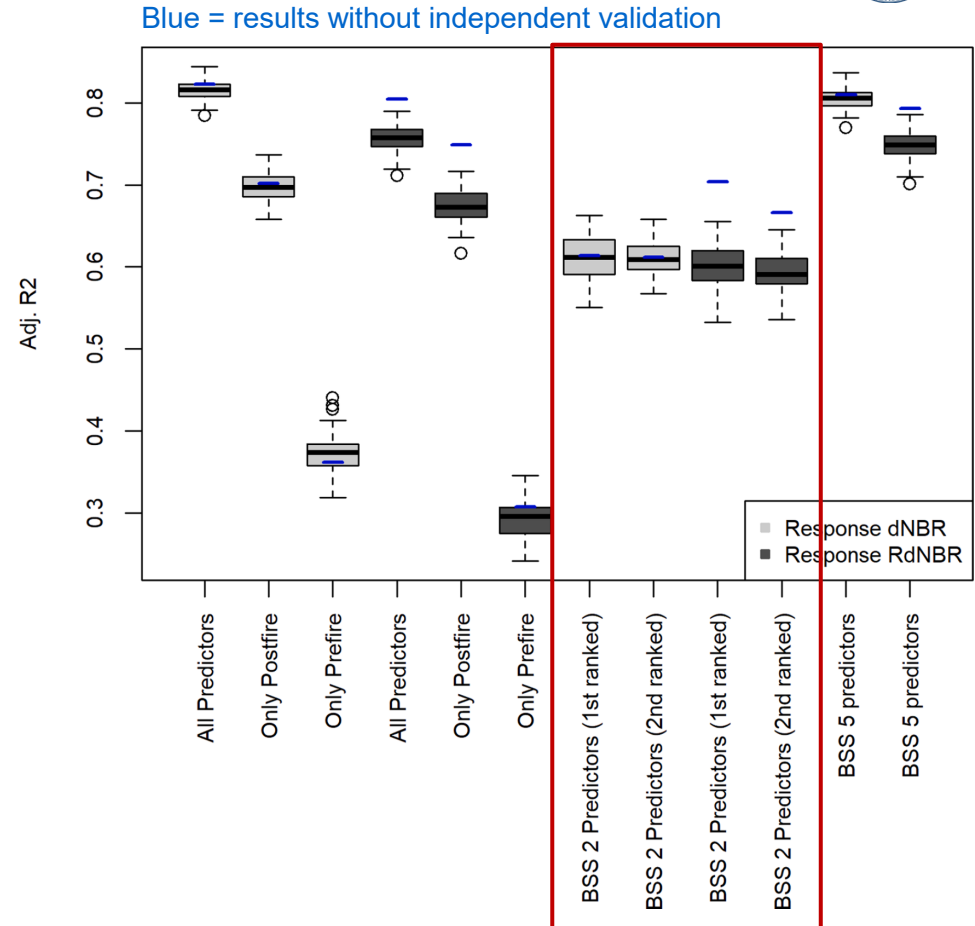
# Results

- Models with 5 predictors explain more than 70% of dNBR and RdNBR variability

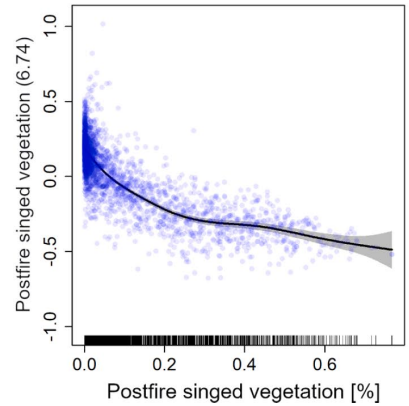
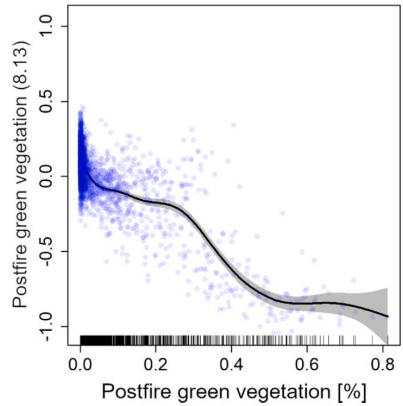
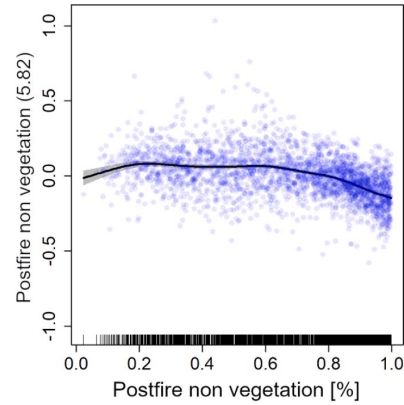
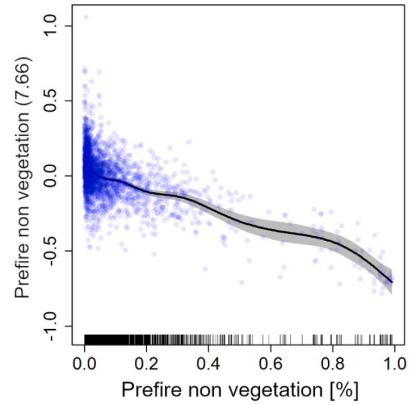
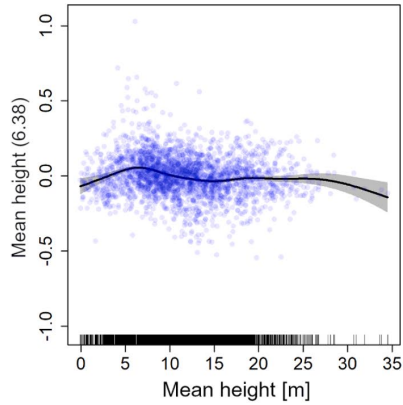


# Results

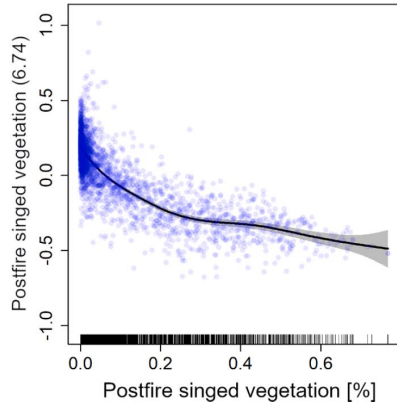
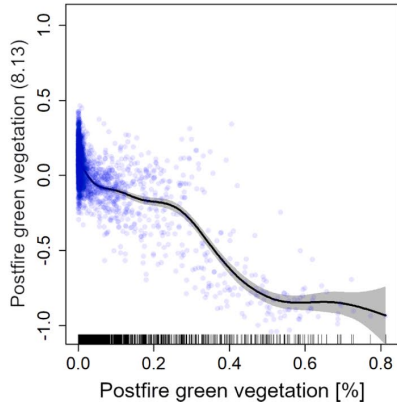
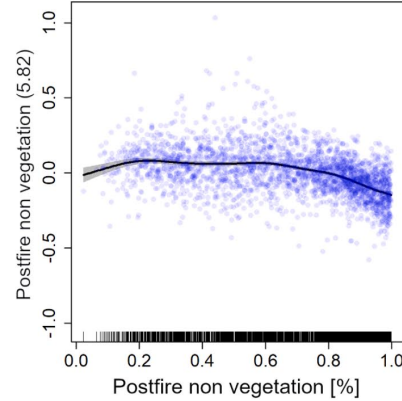
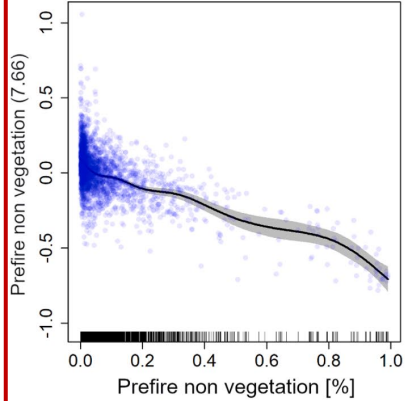
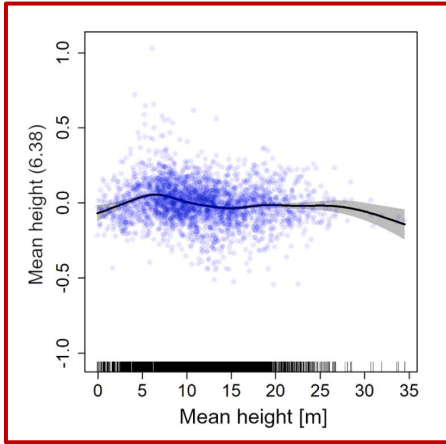
- Models with 5 predictors explain more than 70% of dNBR and RdNBR variability
- Models with only 2 predictors explain approximately 60% of variability



# Results

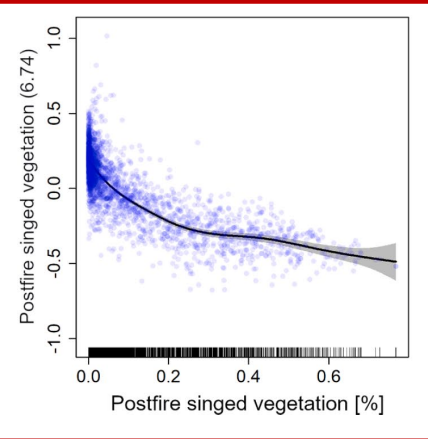
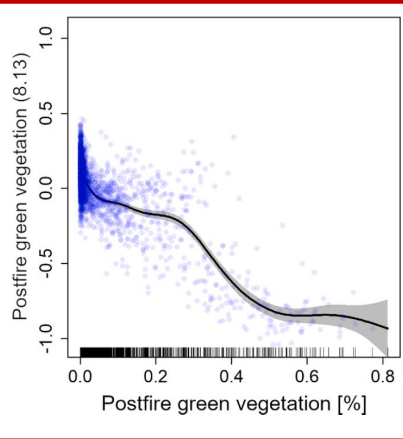
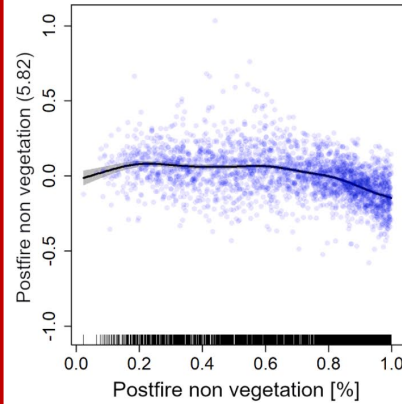
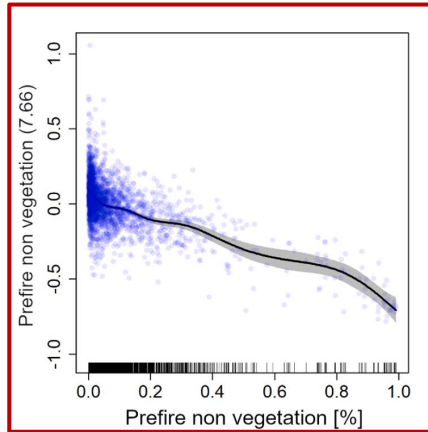
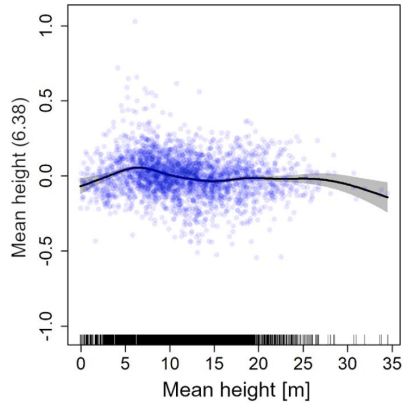


# Results



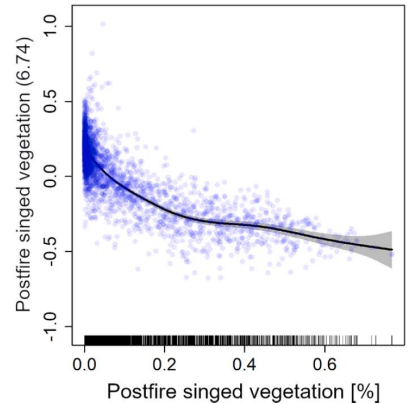
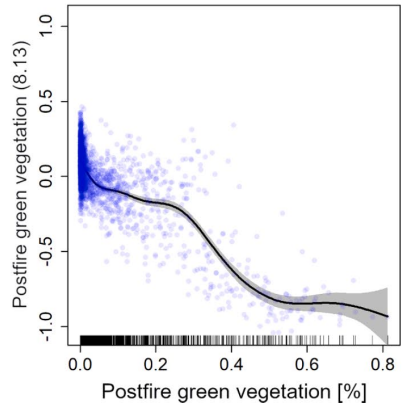
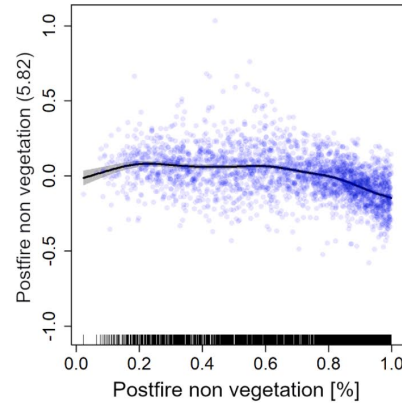
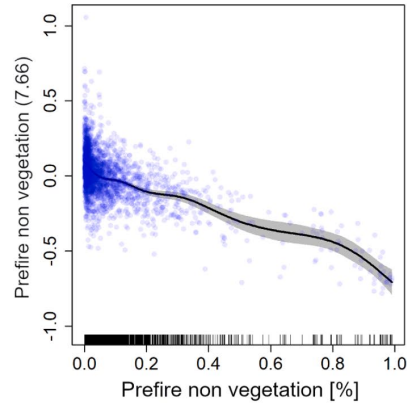
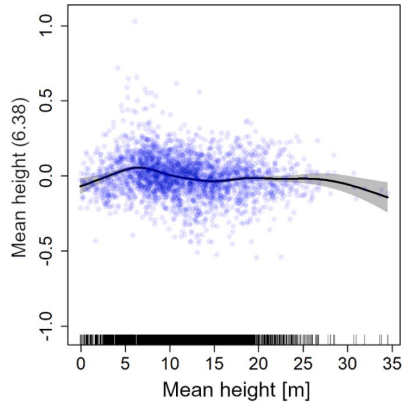
- Unclear signal with mean height →  
dNBR does not capture burned biomass?

# Results



- Unclear signal with mean height → dNBR does not capture burned biomass?
- Vegetation related predictors show plausible, nearly linear trends

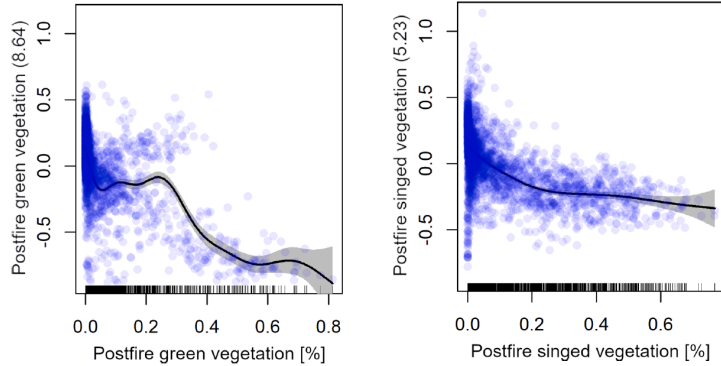
# Results



- Unclear signal with mean height → dNBR does not capture burned biomass?
- Vegetation related predictors show plausible, nearly linear trends
- Mostly post-fire predictors / no species related predictor selected

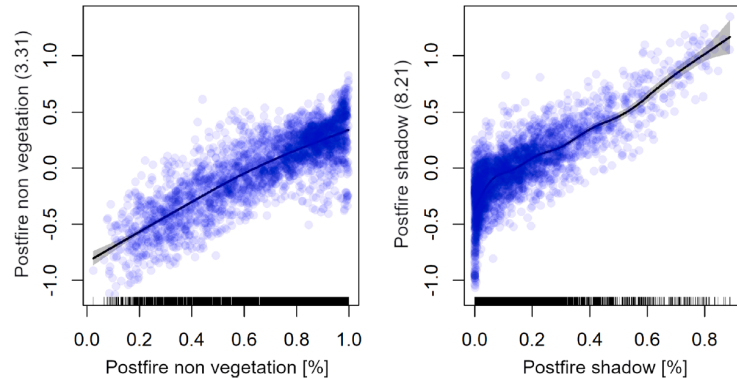


## Best model with 2 predictors



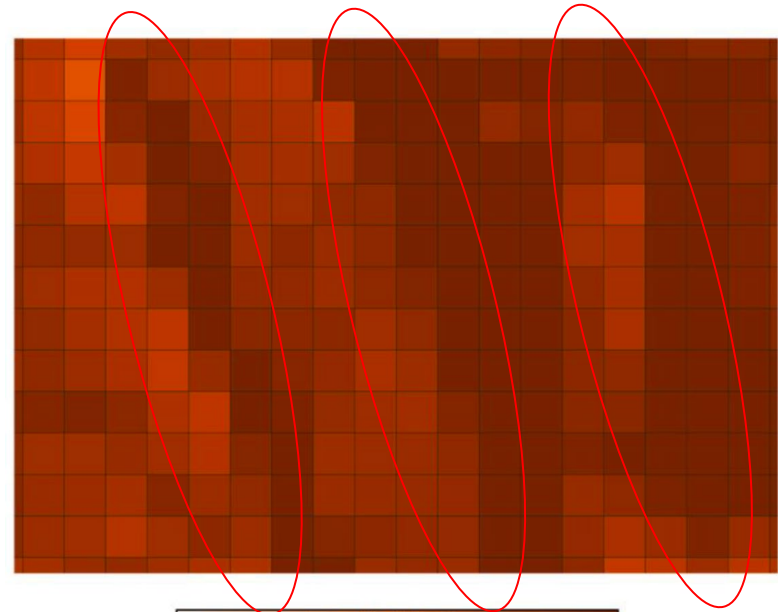
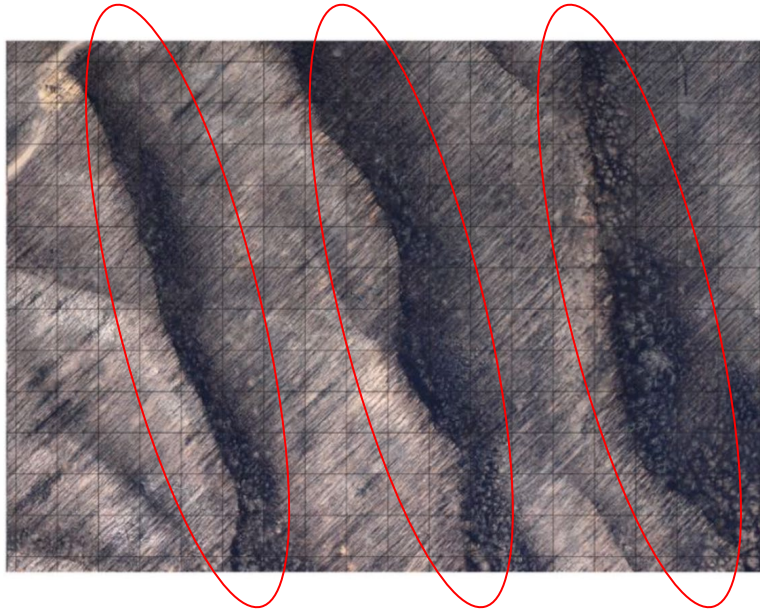
- Vegetation-related predictors show plausible trends
- More green/singed vegetation → lower dNBR

## 2nd best model with 2 predictors



- Postfire shadow and non-vegetation shows strong positive linear trend with dNBR

# Results



0 **RdNBR** 1.5

- Largest fraction of variability in dNBR and RdNBR can be explained by canopy cover consumed (green vegetation / singed vegetation)
- Pre-fire Vegetation composition and height showed hardly any effect in our study area
- Cast and terrain shadows may influence the observed dNBR signal quite notably

# Thank you for your attention!

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## Explaining Sentinel 2-based dNBR and RdNBR variability with reference data from the bird's eye (UAS) perspective

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Wildfire  
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RdNBR  
Shadows

### ABSTRACT

Characterizing the spatial variability of the severity of wildfires is important to assess ecological and economic consequences and to coordinate mitigation strategies. Vegetation indices such as the differenced Normalized Burn Ratio (dNBR) have become a standard tool to assess burn or fire severity across larger areas and are being used operationally. Despite the frequent application of dNBR-like vegetation indices, it is not yet fully understood which variables exactly drive the variability in dNBR observed by multispectral satellites. One reason for this is the lack of high quality prefire information about vegetation structure and composition. Consequently, the influence of prefire vegetation composition and other potentially influential variables such as cast shadows has hardly been examined. Here, we use very high resolution Unmanned Aerial System (UAS) orthoimages collected briefly before and after the large wildfires in Central Chile in the fire season 2016/2017 to derive variables related to the pre- and postfire landscape composition and structure. The variables are used as predictors in Generalized Additive Models (GAM) to explain the spatial variability in dNBR and RdNBR pixel values as observed by Sentinel-2. Our models explain more than 80% and 75% of the variability in dNBR and RdNBR values, respectively, using a sparse set of five predictors. The results suggest that in our study area the largest fraction of variability in Sentinel-2 based dNBR and RdNBR values can be explained by variables related to the fraction of consumed canopy cover while the vegetation composition before the fire does not have a large influence on dNBR and RdNBR.

Our results further suggest that cast-shadows of snags and standing dead trees with remaining crown structure have a notable influence on the dNBR signal which may have been underestimated so far. We conclude that spatially continuous, very high spatial resolution data from UAS can be a valuable data source for an improved understanding of the exact meaning of common vegetation index products, operationally used for monitoring the environment.