Imperial College London

LEMONTREE Land Ecosystem Models based On New Theory, obseRvations and ExperimEnts

LEVERHULME Centre for Wildfires, Environment and Society

Fire rate-of-spread model inversion: what can be inferred from remote sensing observations of fire behaviour?

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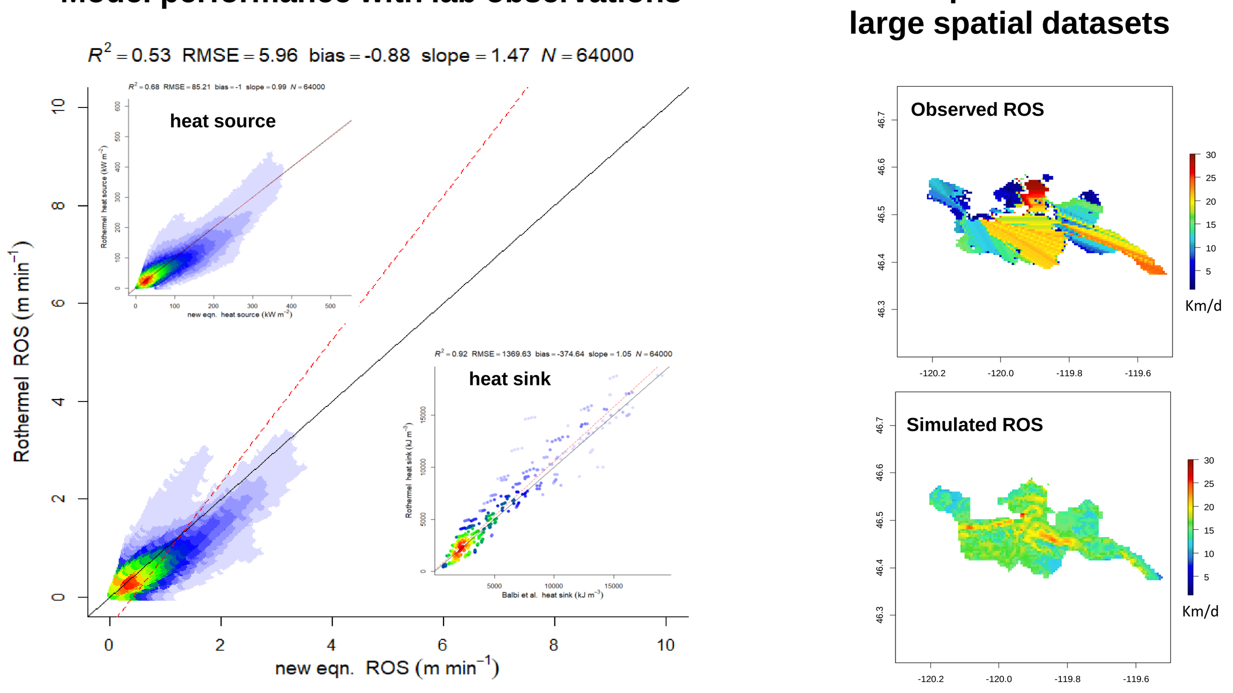
Understanding the drivers of wildfires is crucial to evaluating fire's impact on natural processes and their feedback on human systems. Due to the difficulty of directly observing fires in the wild, our current knowledge of wildfire behaviour heavily relies on lab experiments and open-controlled fires, which are the main source for our models and assumptions. Thus, there are still several gaps on how spot samples upscale to ecosystems, how different fuel types with different moisture contents should be represented in the models or how fire responds to the intrinsic structural complexity of ecosystems. Some of this information is currently encoded in fuel models, which are based on vegetation types and used as prescribed inputs in our models. However, they are a documented source of uncertainties and inaccuracies when applied beyond the spatial domain from which they were originally formulated. Fire behaviour observed from remote sensing could provide more general insights on the emergent response of fire to this complexity. In this work, by inverting Rothermel's model for fire rate of spread (ROS), we show how field observations of fuel load, fuel moisture and environmental variables relate to the remotely sensed ROS and fire radiative power (FRP). We used fuel moisture from 1234 sites provided by the National Fuel Moisture Database, fuel load measurements from 9000 sites provided by the Public LANDFIRE Reference Database, fire ROS from the Fire Atlas and FRP from the MCD14ML product, covering a timespan from 2003 to 2016 over the US. Preliminary results show only partial agreement between the components of the ROS equations calculated from observations and estimated by model inversion.

1. Introduction

- Our current approach to model wildfire behaviour heavily relies on complex semi-empirical models from lab experiments and open-controlled fires.

Model performance with lab observations — **Model performance with large spatial datasets**

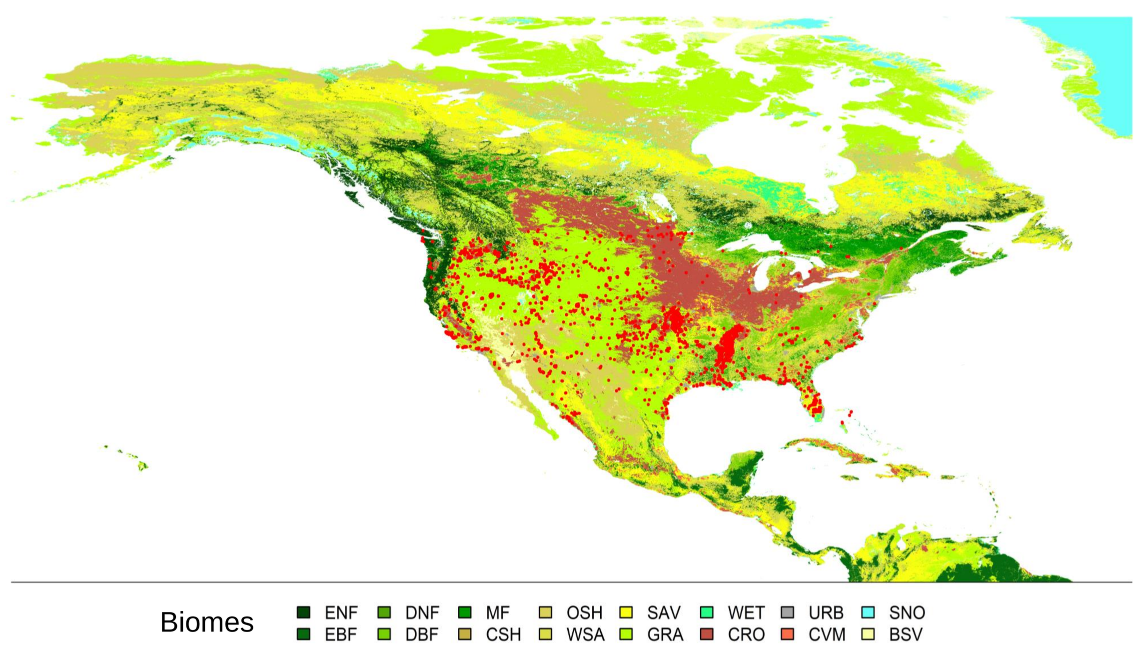


- How do experiments/spot observations upscale to ecosystems?
- How does fire respond to the intrinsic structural complexity of ecosystems in nature?
- Are current fuel models properly representing the diversity of fuel type/moisture-content complexes?
- Is an emergent and simpler empirical parametrization more robust and reliable than a complex semi-empirical formulations of ROS?

2. Methods

Sampling:

Burned areas over N. America (in red) for pre and active-fire retrievals.



Datasets:

Fire behaviour: Fire Atlas (Andela et al., 2019)

Fire radiative power (FRP): MODIS MCD14ML Giglio 2016 (Giglio et al., 2016)

Daily reflectance: MODIS MCD43A4 Schaaf 2002 (Schaaf et al., 2002)

Vegetation C-band backscattering: Sentinel 1 (Copernicus Sentinel data 2023)

Daily high res Environmental data from GRIDMET (Abatzoglou, 2013)

Field observations of fuel load and fuel moisture: National Fuel Moisture Database and Public LANDFIRE database

Metrics:

Vegetation signal NIRv (Badgley *et al.*, 2017): $NIR_v = \frac{NIR-RED}{NIR-RED} * NIR$

Water content signal MSI (Hunt & Rock, 1989): $MSI = \frac{\rho_{1600}}{\rho_{820}}$

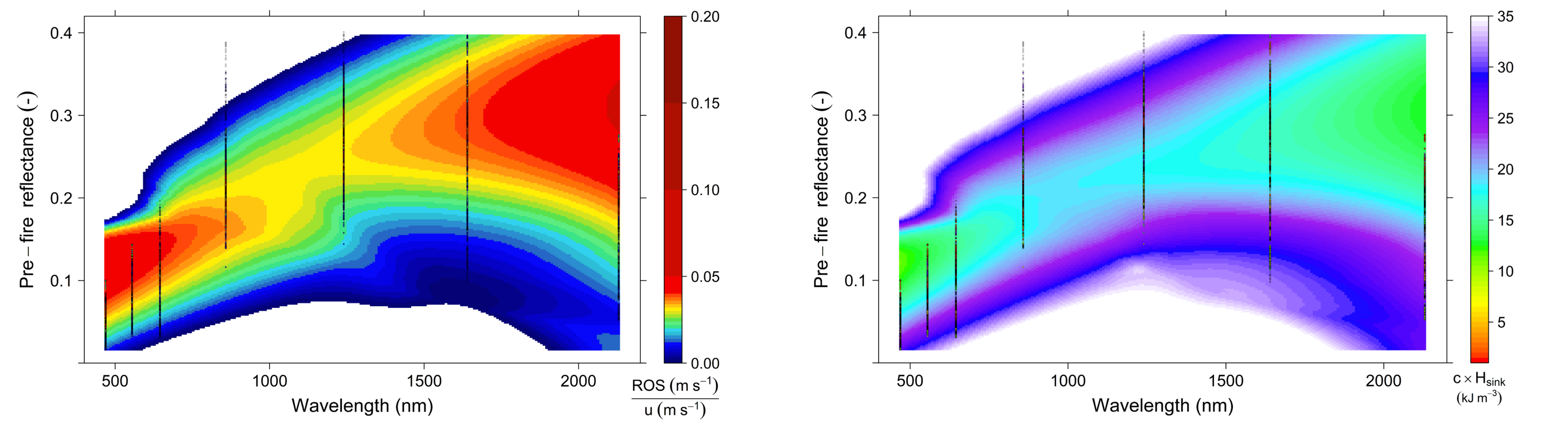
Heath source H_{src} (Peterson *et al.*, 2013): $H_{src} = \frac{FRP}{A_p(\theta, sample)}$

Heat sink H_{snk} (Andrews, 2018): $H_{snk} = \frac{H_{src}}{ROS}$

3. Results and Discussion

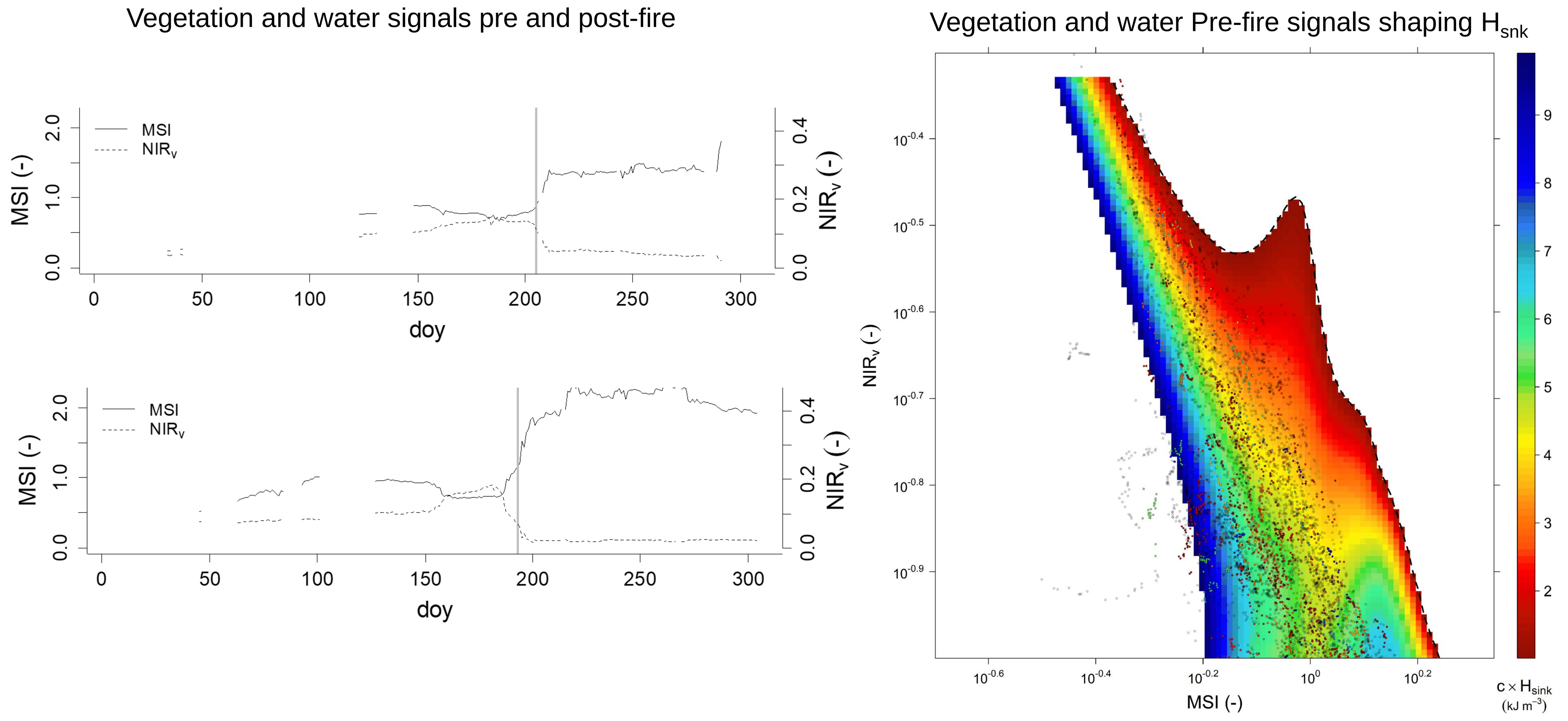
3.1. Potential ROS: Emergent spectral patterns

Pre-fire reflectance vs. potential ROS — Pre-fire reflectance vs. vegetation heat sink

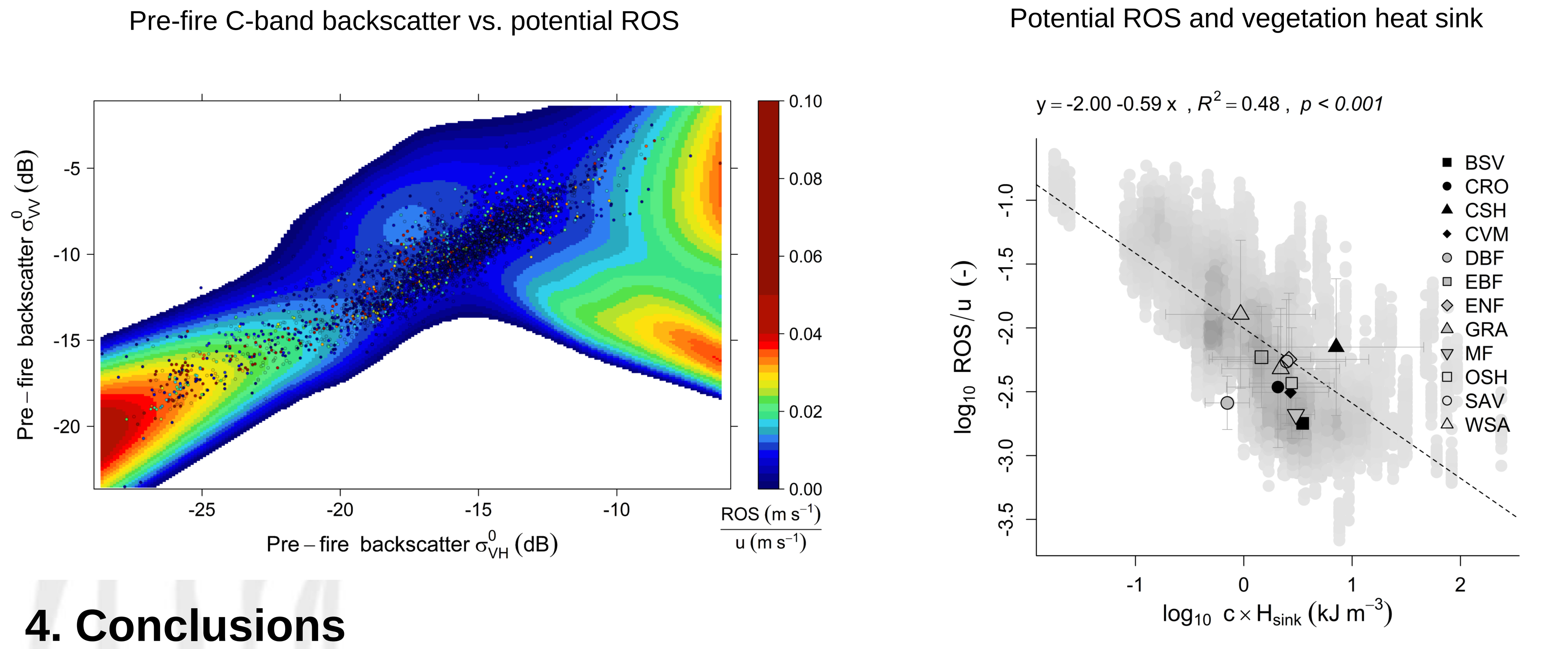


3.2. Signals from fuel load and fuel moisture shape the potential ROS

Vegetation and water signals pre and post-fire — Vegetation and water Pre-fire signals shaping H_{snk}



Pre-fire C-band backscatter vs. potential ROS — Potential ROS and vegetation heat sink



4. Conclusions

- It is possible to bypass the empirical estimations of fuel load and fuel moisture which use RS and directly use these signals to calculate a potential ROS as a fraction of windspeed.
- The pre-fire spectral patterns suggest that ROS up to 20% of u happens only in very narrow regions of the wavelength-reflectance space.
- The patterns of ROS/u responded strongly to H_{snk}.
- The vegetation-water content space shaped a predictable gradient of H_{snk}.
- The signals from the radar suggest that at a similar low level of fuel moisture (backscatter from VV polarization) high ROS/u could happen at either of both extremes of the fuel load scale (backscatter from VH polarization), creating an "island" of low ROS/u in the middle regions of the backscattering.

5. References

Prenticelab

Abatzoglou JT. **2013**. Development of gridded surface meteorological data for ecological applications and modelling. *International Journal of Climatology* **33**: 121–131.

Andela N, Morton DC, Giglio L, Paugam R, Chen Y, Hantson S, Van Der Werf GR, Anderson JT. **2019**. The Global Fire Atlas of individual fire size, duration, speed and direction. *Earth System Science Data* **11**: 529–552.

Andrews PL. **2018**. The rothermel surface fire spread model and associated developments: A comprehensive explanation. *USDA Forest Service - General Technical Report RMRS-GTR*: 1–121.

Badgley G, Field CB, Berry JA. **2017**. Canopy near-infrared reflectance and terrestrial photosynthesis. *Science Advances* **3**: 1–6.

Giglio L, Schroeder W, Justice CO. **2016**. The collection 6 MODIS active fire detection algorithm and fire products. *Remote Sensing of Environment* **178**: 31–41.

Hunt ER, Rock BN. **1989**. Detection of changes in leaf water content using Near- and Middle-Infrared reflectances. *Remote Sensing of Environment* **30**: 43–54.

Peterson D, Wang J, Ichoku C, Hyer E, Ambrosia V. **2013**. A sub-pixel-based calculation of fire radiative power from MODIS observations: 1 Algorithm development and initial assessment. *Remote Sensing of Environment* **129**: 262–279.

Schaaf CB, Gao F, Strahler AH, Lucht W, Li X, Tsang T, Strugnell NC, Zhang X, Jin Y, Muller J, *et al.* 2002. First operational BRDF, albedo nadir reflectance products from MODIS. *Remote Sensing of Environment* **83**: 135–148.