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Developing a long-term live-fuel moisture content dataset based on passive microwave vegetation optical depth

LFMC - Live-Fuel Moisture Content

Vegetation water content (VWC) influences ecosystem processes

Key variable for investigations of fire behavior, spread and danger

$$FMC(\%) = \frac{mass_{fresh} - mass_{dry}}{mass_{dry}} * 100 \text{ (Yebara et al., 2013)}$$

- in-situ measurements or
- Derived from remote sensing observations of visible and infrared wavelengths

Hypothesis

Usage of link between vegetation water content and vegetation optical depth leads to reliable LFMC predictions on a daily and global basis.

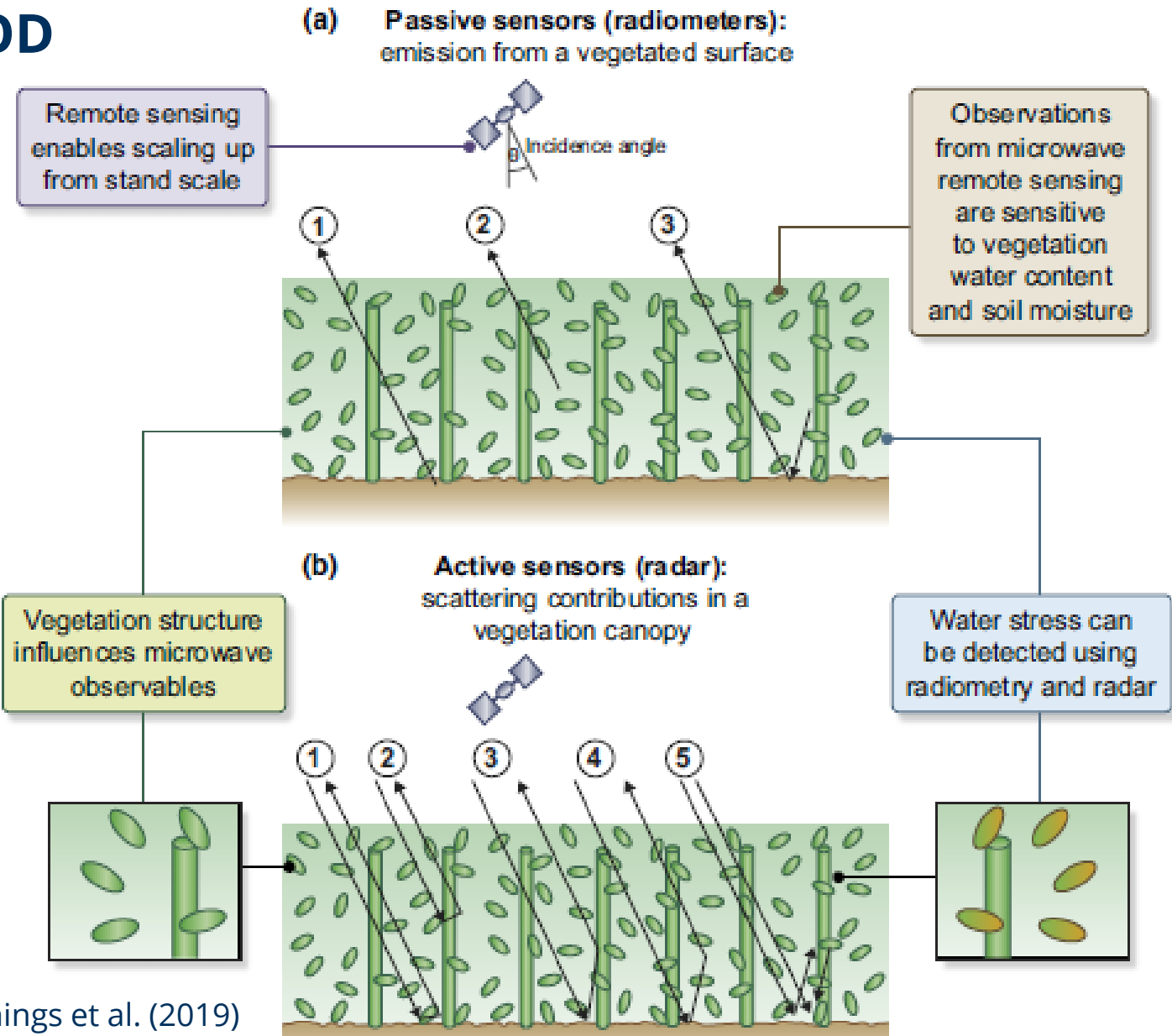
Vegetation Optical Depth - VOD

Jackson and Schmugge (1991)

$$VOD = b * VWC$$

Konings et al. (2019)

$$= b * mass_{dry} * LFMC$$



Data

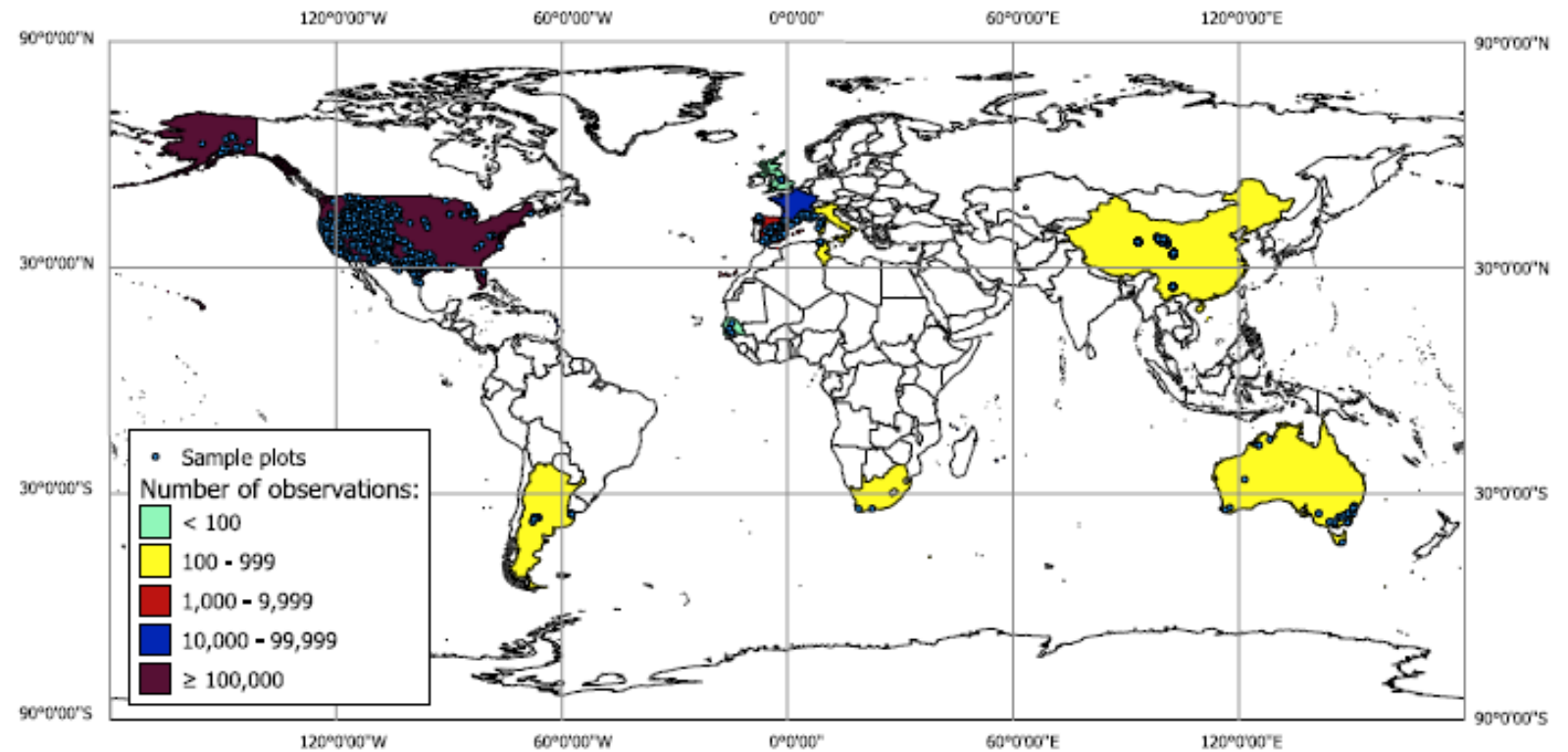
VOD – VODCA v1.0.0 → long-term time series for Ku-, X- and C-band

LAI – MODIS MOD15A2H v006 → as proxy for total leaf biomass

GlobeLFMC database

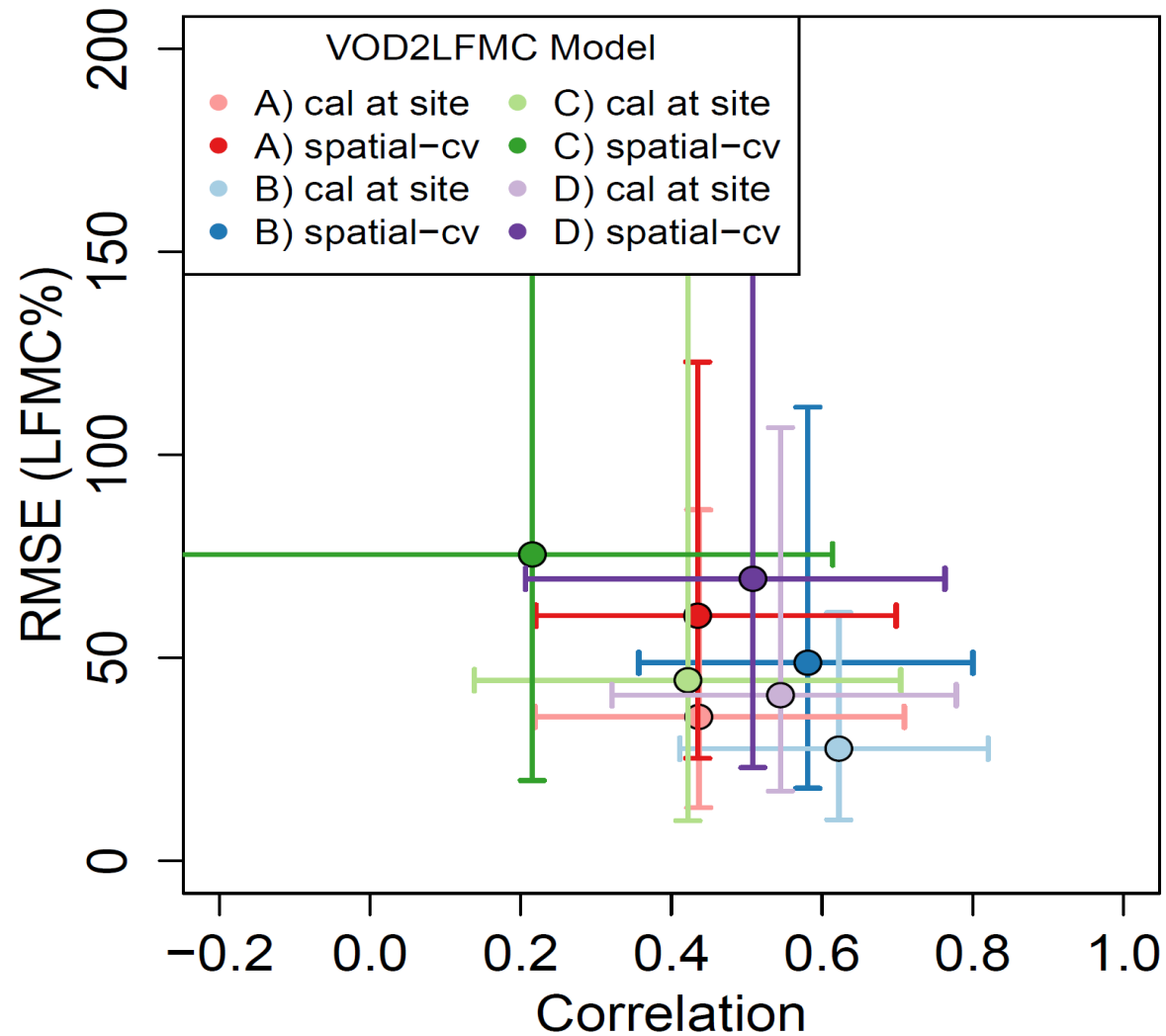
- In-situ measurements
- > 161,717 data samples
- Since 1977

Yebara et al. (2019)



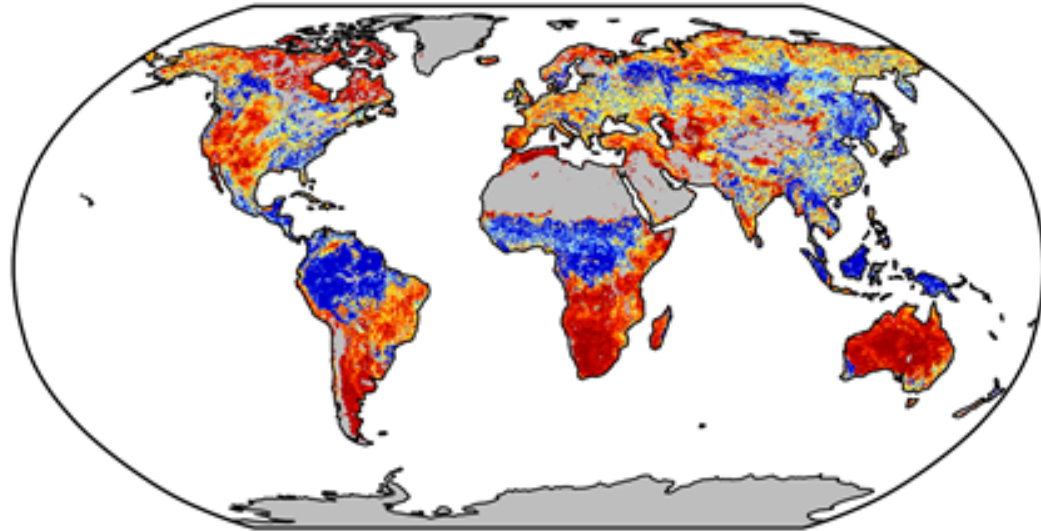
Model approaches

Model	LFMC=
● A)	$f(VOD)$
● B)	$f(VOD + LAI)$
● C)	$\frac{VWC}{mass_{dry}} = \frac{VOD}{b * f(LAI)}$
● D)	$\frac{VWC}{mass_{dry}} = \frac{f(LAI)}{g(VOD)}$

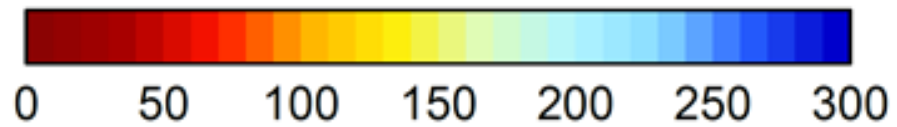


Results

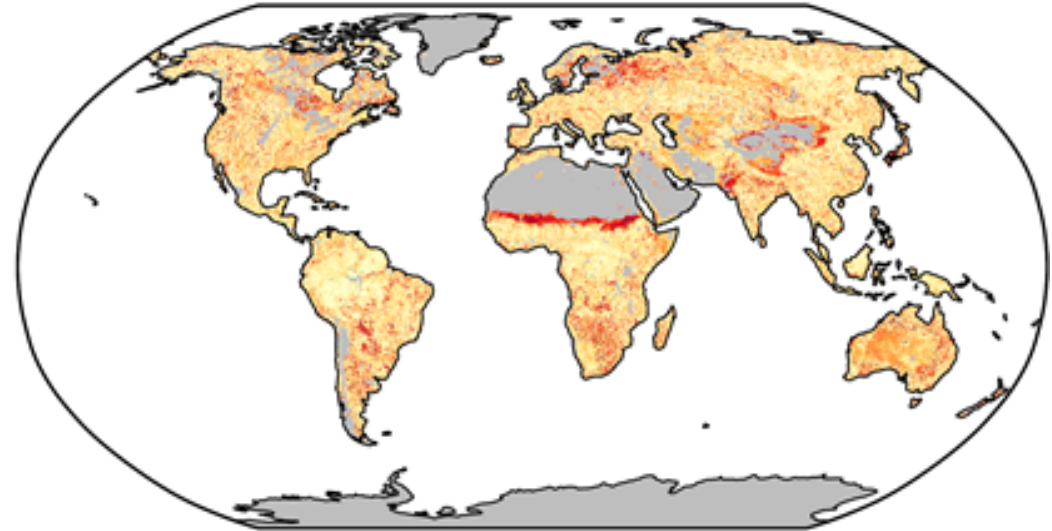
LFMC 2003-08-01



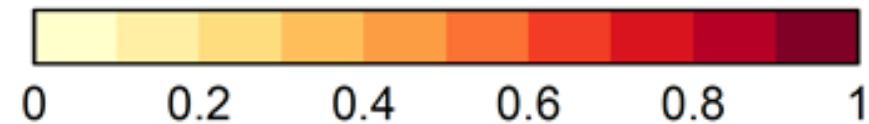
Live-fuel moisture content (%)



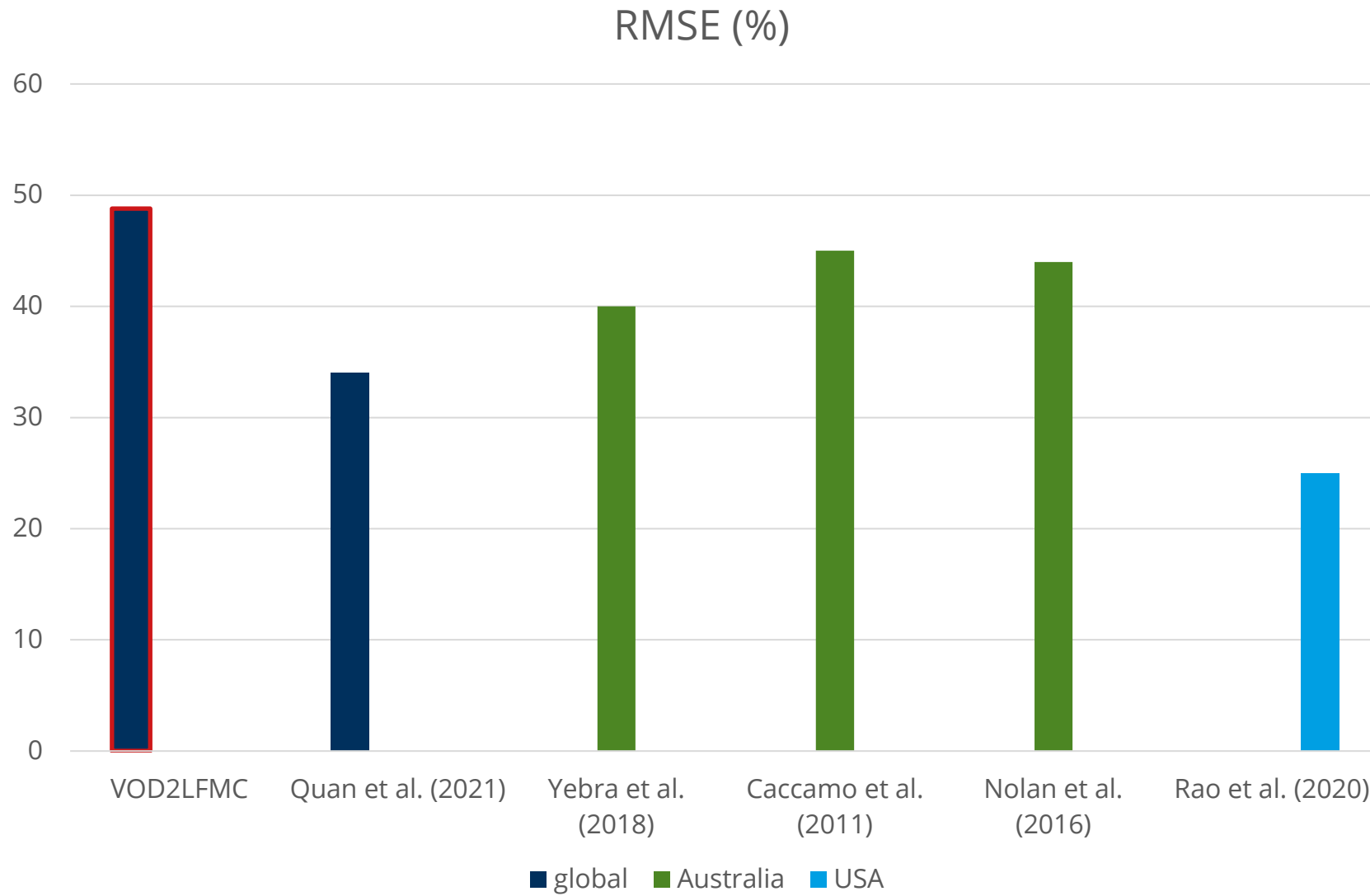
Uncertainty 2003-08-01



Relative uncertainty



Comparison with other data sets



Summary

Long-term LFMC data set with daily temporal resolution on global scale

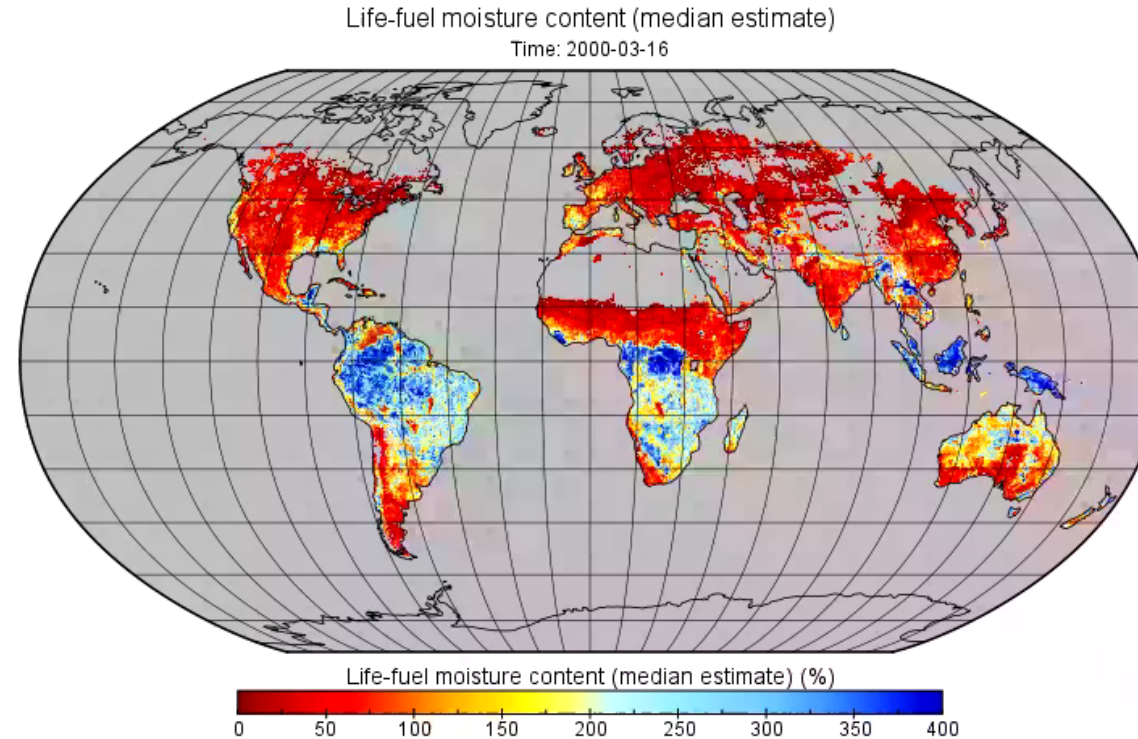
- For large-scale investigations
- As complement, e.g. for analyses with SIF, LAI, GPP
- Effects of drought and long-term climate trends on fuel moisture and fire risk

Outlook

For extending LFMC data set: testing of different LAI data sets like

- GLOBMAP (1981-2020)
- PROBAV/SPOT/Sentinel3 (1999-2020)
- GIMMS (1981-2018)

VOD2LFMC v01 <https://doi.org/10.5281/zenodo.6545571>



Forkel, M., Schmidt, L., Zotta, R.-M., Dorigo, W., and Yebra, M.: Estimating leaf moisture content at global scale from passive microwave satellite observations of vegetation optical depth, *Hydrol. Earth Syst. Sci. Discuss.* [preprint], <https://doi.org/10.5194/hess-2022-121>, in review, 2022.

Thank you for your attention!

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Methods

Best model

$$LFMC = \frac{LFMC_{max}}{1 + e^{-sl*(x-x_0)}}$$

$$x = f * VOD + (1 - f) * LAI$$

LFMC_{max}... maximum value of LFMC (400%)

sl... slope of logistic curve

x₀... inflection point of logistic curve

f... weighting fraction (0-1)

Random forest: *sl*, *x₀* and *f*