Retrieving forest moisture content in western USA using a microwave-LiDAR synergy

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1. Goal & Motivation

Goal: Retrieving vegetation moisture in forests using a multi-sensor approach

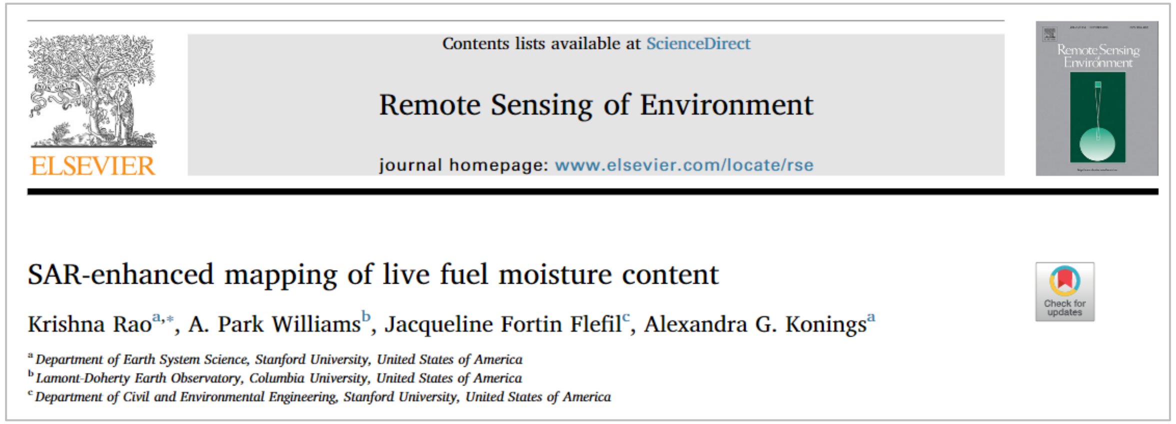
Vegetation optical depth (VOD) → Linked to biomass, water content and structure of plants

$$\boxed{VOD = b \cdot VWC}$$

- Vegetation Water Content (VWC) [kg/m^2] → water per unit area: depends on biomass
- Gravimetric vegetation moisture (m_g) [kg/kg] → water per wet biomass – linked to plant water status

This is important for…

Multi-sensor approaches are promising!



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ELSEVIER

SAR-enhanced mapping of live fuel moisture content

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Rao et al., 2020
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2. Approach

➢ A **multi-sensor approach** (Fink et al., 2018) to retrieve m_g and sense vegetation **water status**:

Lidar-Derived Vegetation Height

VH [m]

Radar-Derived Vegetation Vol. Fraction

δ

① Model VOD from VH and δ

VOD-Model

$$VOD = 4\pi\left(\frac{VH}{\lambda}\right)\cdot Im\left[\sqrt{\varepsilon_{can} = f(\delta, \varepsilon_{veg}, Shapes^{*})}\right]$$

$\varepsilon_{air} = 1$

Radiometer-Derived VOD

② Minimize VOD differences to obtain ε_{veg}

$$min\left(\left|VOD_{Model} - VOD_{Radiometer}\right|\right)$$

$\hookrightarrow \varepsilon_{veg}$

Ulaby & El-Rayes, 1987

m_g [kg/kg]

③ Estimate m_g

*Shapes of inclusions (canopy structure)

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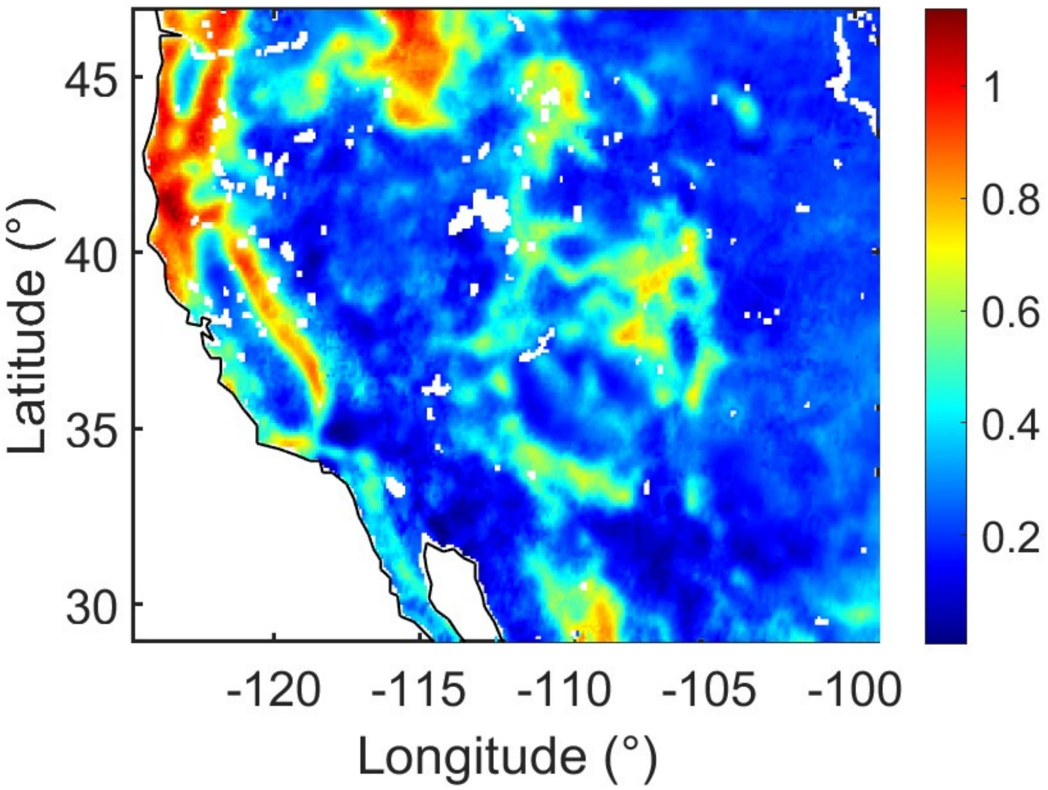
3. Satellite data and algorithm calibration

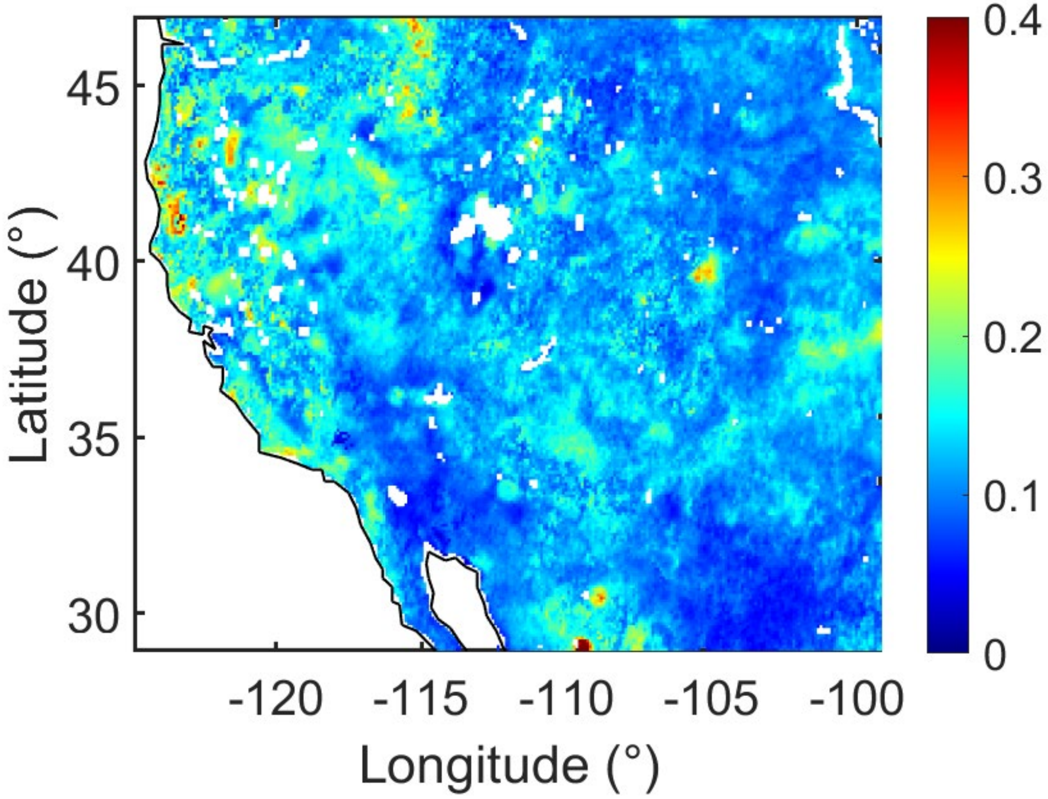
$$m_g = f(\text{VOD}, \text{VH}, \delta, \text{Shapes})$$

- SMAP VOD (Apr. 2016 – Apr. 2018), 9 km gridding
- 61-day moving window
- Filters: snow & frozen ground, outliers (mean ± 1.96·std)

Mean VOD [Np]



Change in VOD [Np]



Change = percentile 95 – percentile 5

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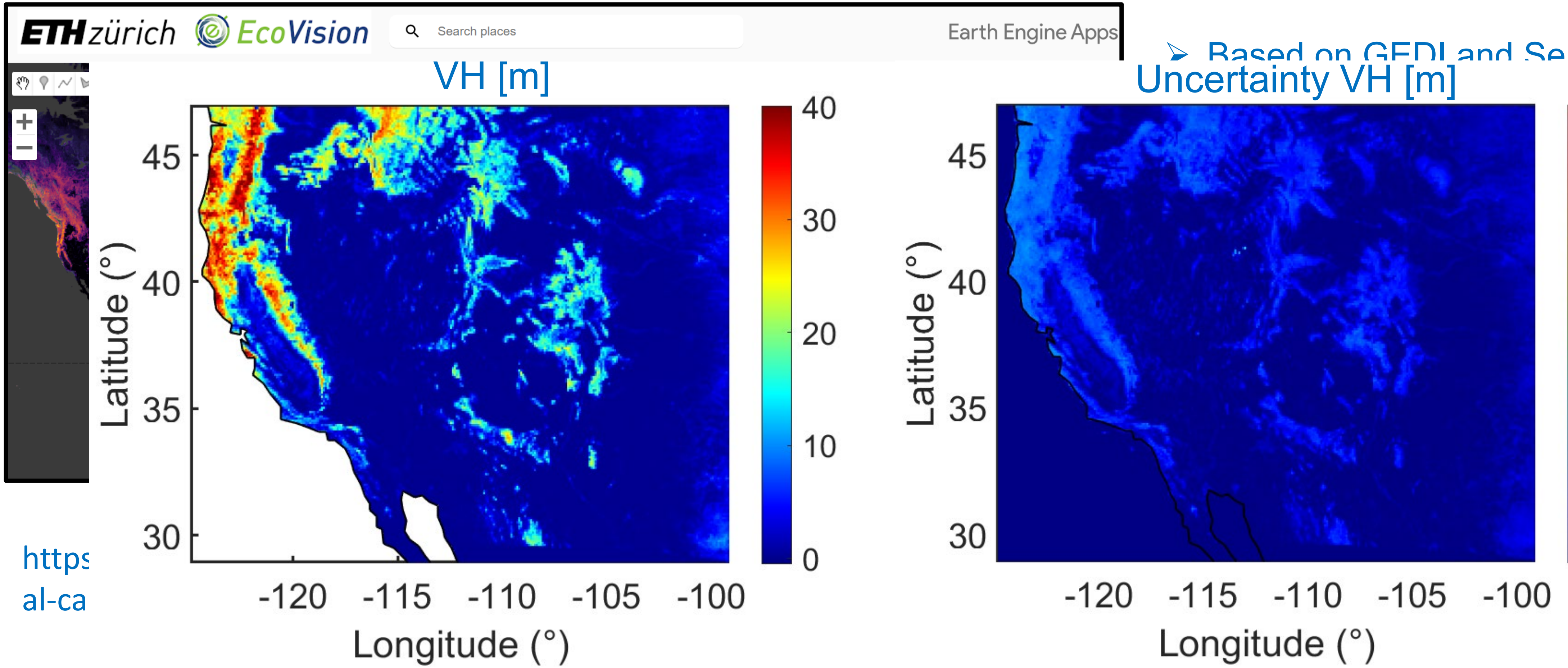
3. Satellite data and algorithm calibration

$$m_g = f(VOD, VH, \delta, Shapes)$$

- Vegetation height: Lang et al., 2022 (preprint)
- Aggregated at 9-km
- Based on GEDI and Sentinel-2



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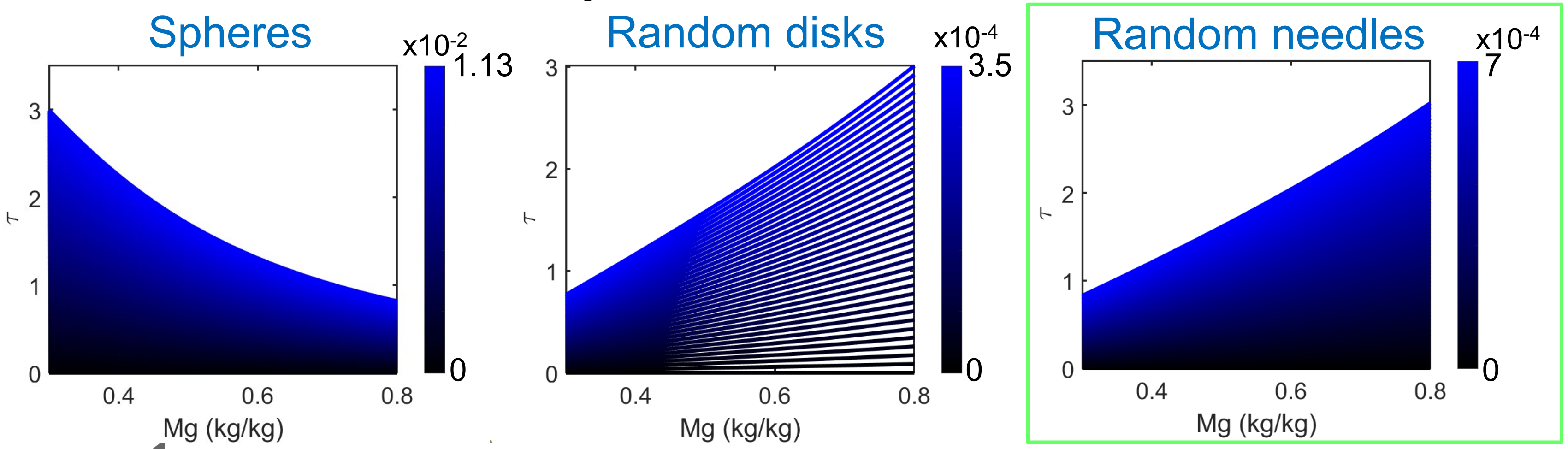
3. Satellite data and algorithm calibration

$$m_g = f(VOD, VH, \delta, Shapes)$$

- Vegetation volume fraction (δ):
  - Previous work: SMAP radar (too short: ~3 mo.) and Aquarius radar (too coarse: ~100 km)
  - Current work: Sentinel-1 backscatter (SMAP-Sentinel L2 SM product; 3 km)
    - ❖ Aggregated at 9 km
    - ❖ Filters: only 30° < α < 50° , snow & frozen ground, outliers (mean ± 1.96·std)

$$\boxed{\delta = k \cdot RVI} \longleftarrow \boxed{RVI = \frac{\sigma_{VH}}{\sigma_{VV} + \sigma_{VH}}}$$

- ***k* calibration and shapes inclusions:**



- *k* calibration to obtain δ range:
  - ❖ Look for "theoric" maximum δ
  - ❖ "Theoric" for a densest forest case
  - ❖ Based on VH_{max}=40m and VOD_{max}=3
- Shape inclusions model selection:
  - ❖ Spheres: +attenuation with $-m_g$
  - ❖ R. needl.: Meyer et al., (2018, RS)

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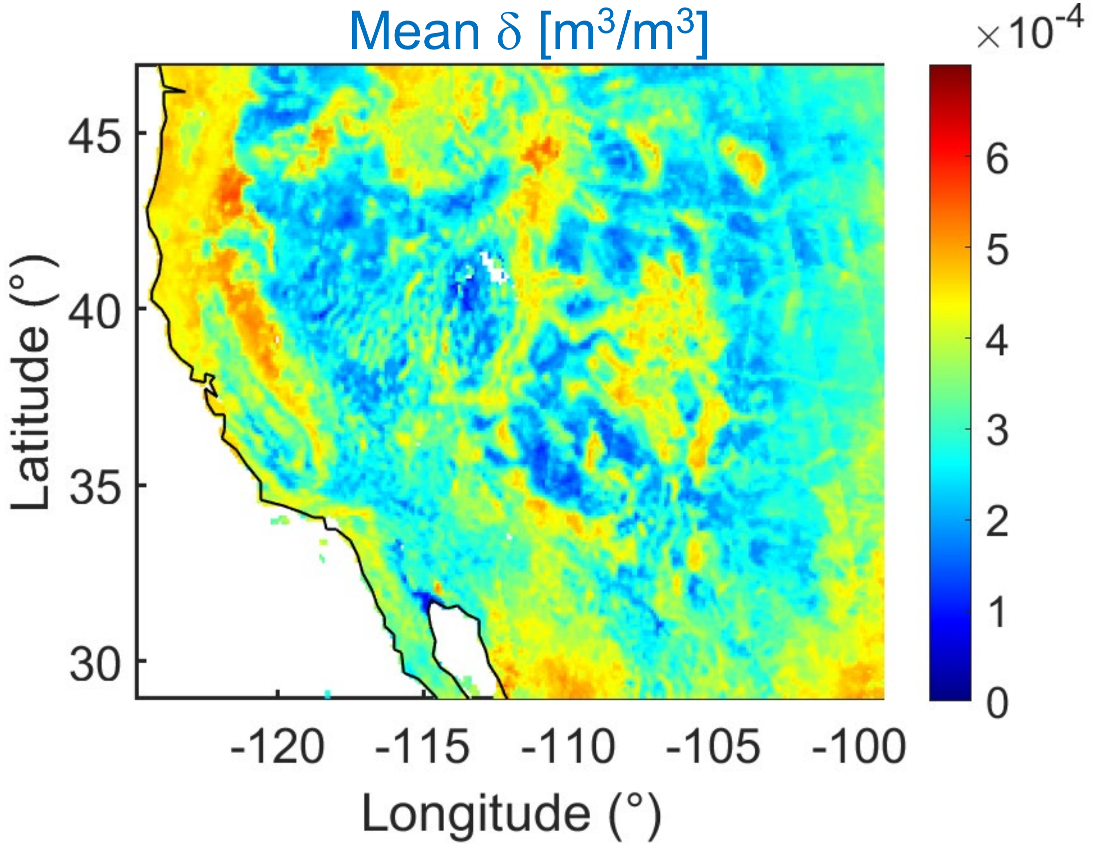
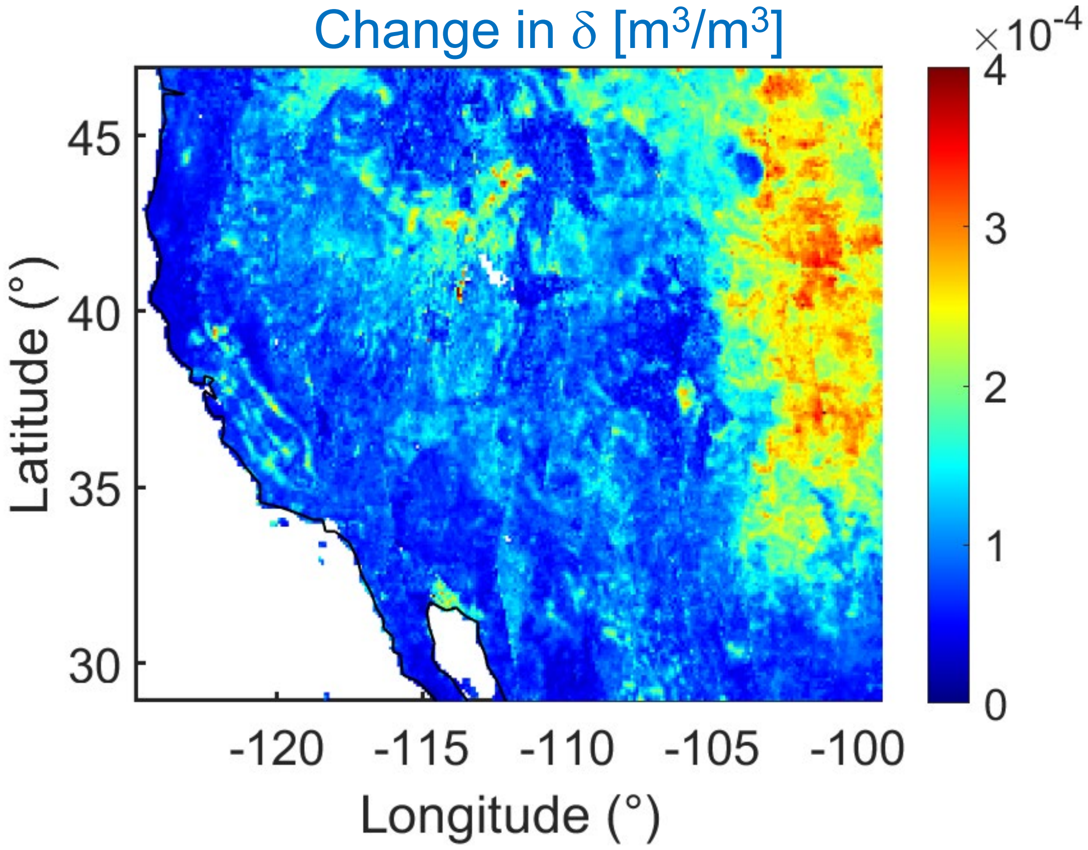
3. Satellite data and algorithm calibration

$$m_g = f(VOD\,,VH\,,\delta\,,Shapes)$$

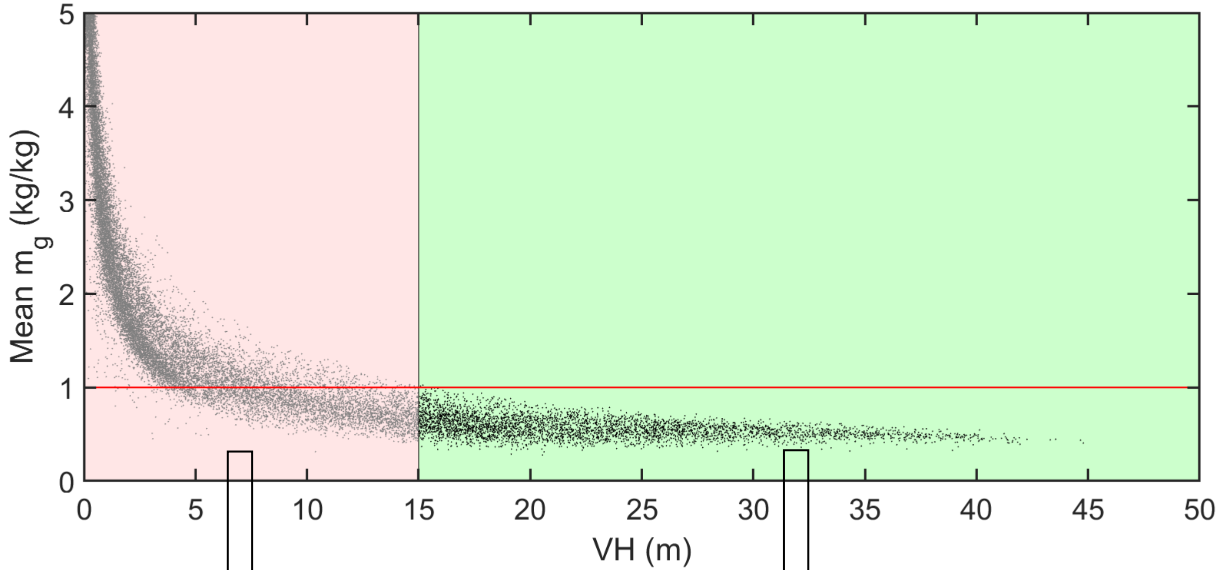
- Vegetation volume fraction (δ):
  - Period 2016-2018





Change = percentile 95 – percentile 5

4. Evaluation of the approach



$$m_g = f(\mathrm{VOD}, \mathrm{VH}, \delta, \mathrm{Shapes})$$

This is a simplification of the water-structure-attenuation relationship

The model is only consistent in forests (VH>15 m)

Ongoing work

ML approach to deal with non-linearities and complex relations

Results

m_g results are presented for forest regions (VH>15 m)

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5. In situ data for validation

- Life Fuel Moisture Content (LFMC) measurements from Yebra et al. (2019)
- Tree species (and only where VH>15 m.)
- Period 2016-2018

SCIENTIFIC DATA

Corrected: Author Correction

OPEN

DATA DESCRIPTOR

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Globe-LFMC, a global plant water status database for vegetation ecophysiology and wildfire applications

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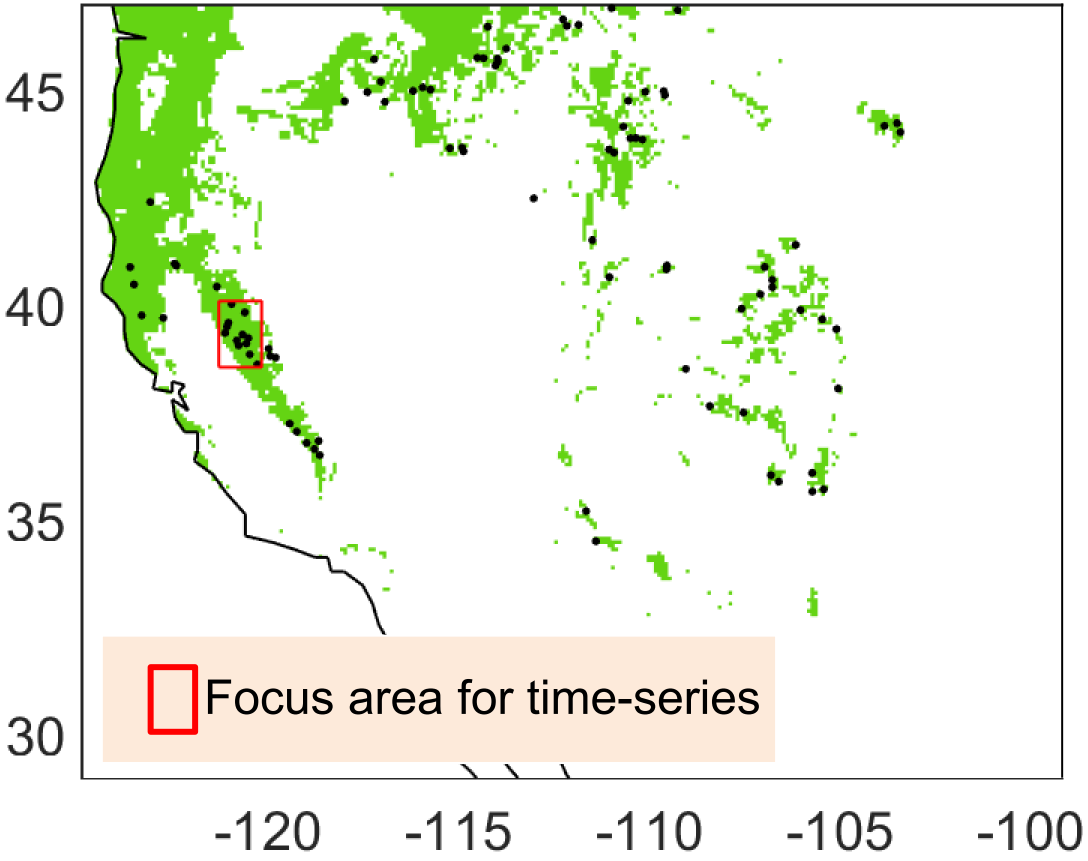
Life Fuel Moisture Content to m_g:

$$m_g = \frac{LFMC/100}{\left(\frac{LFMC}{100}\right) - 1}$$



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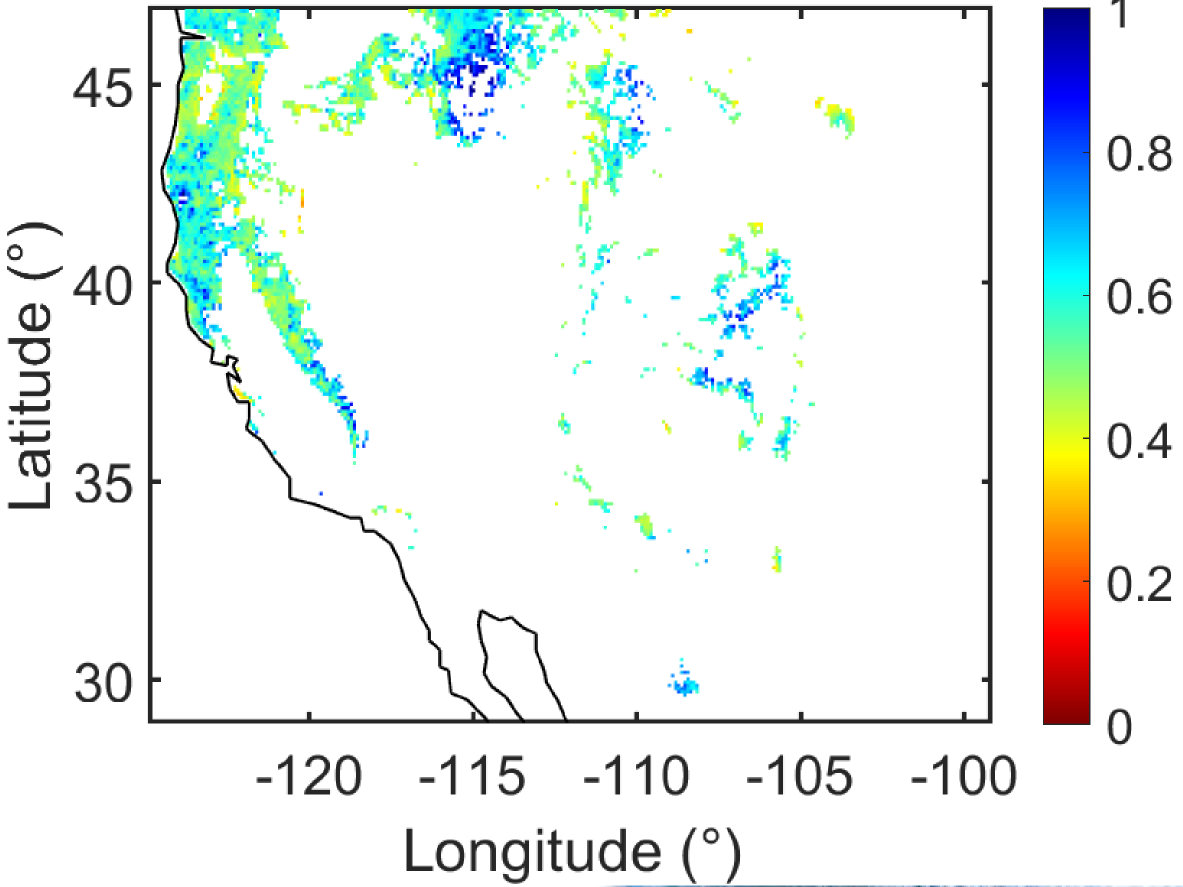
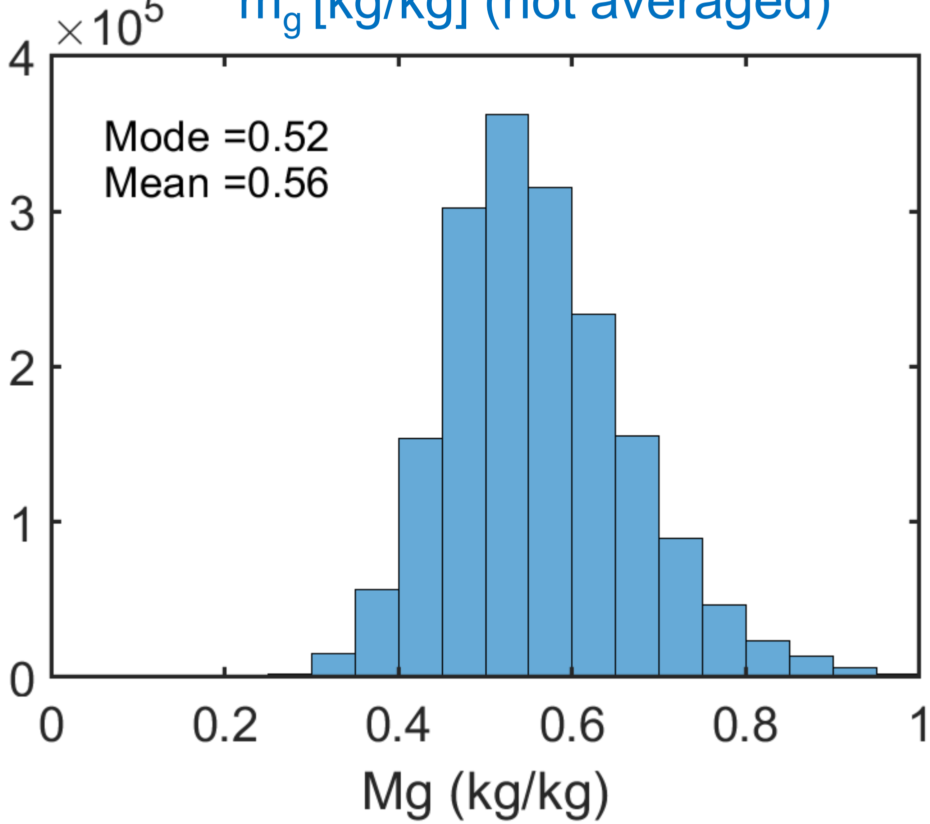
6. Multi-sensor retrieval results of m_g

- m_g results are between 0.3 and 1 kg/kg, showing some overestimation
- Mode and mean are in the expected range (~0.5 kg/kg)
- Overestimation is found especially in low density (lower VH) forests (eastern and northern regions)

Mean m_g [kg/kg]



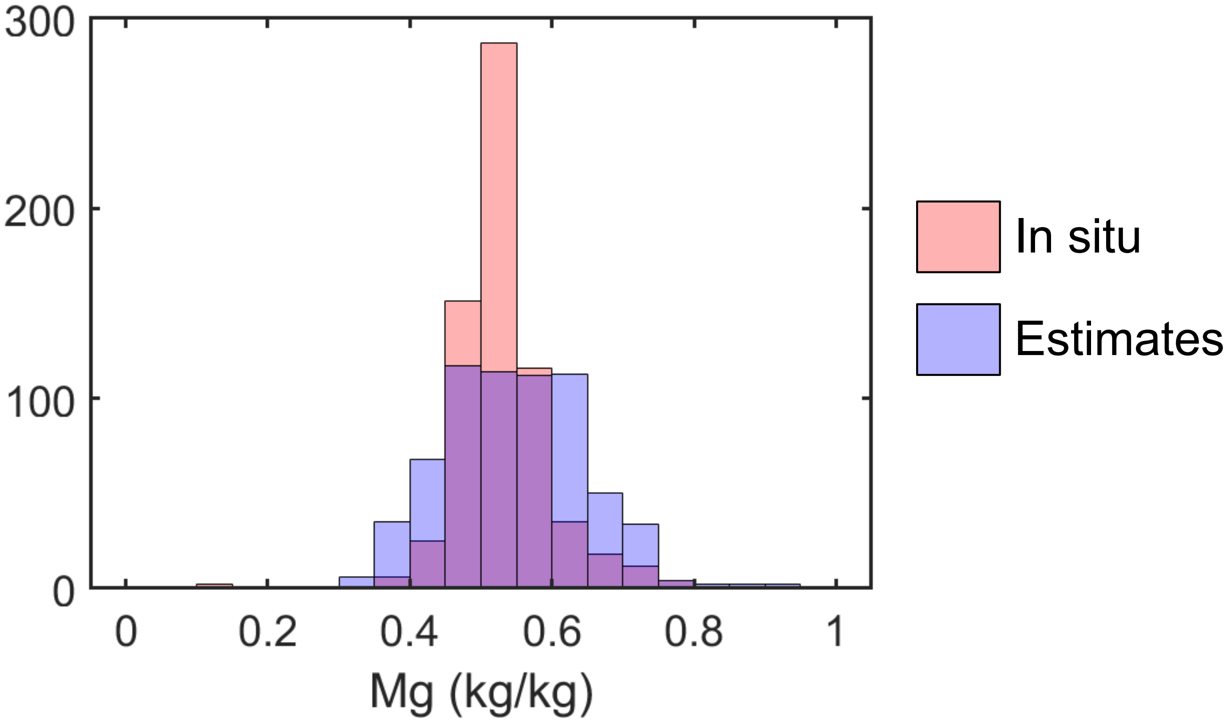
m_g [kg/kg] (not averaged)



6. Multi-sensor retrieval results of m_g

- Comparison between in situ and estimates (per station & day pairs) shows similar results…
  - … with slightly higher spread for the estimates
  - … and average overestimation of 0.02 kg/kg

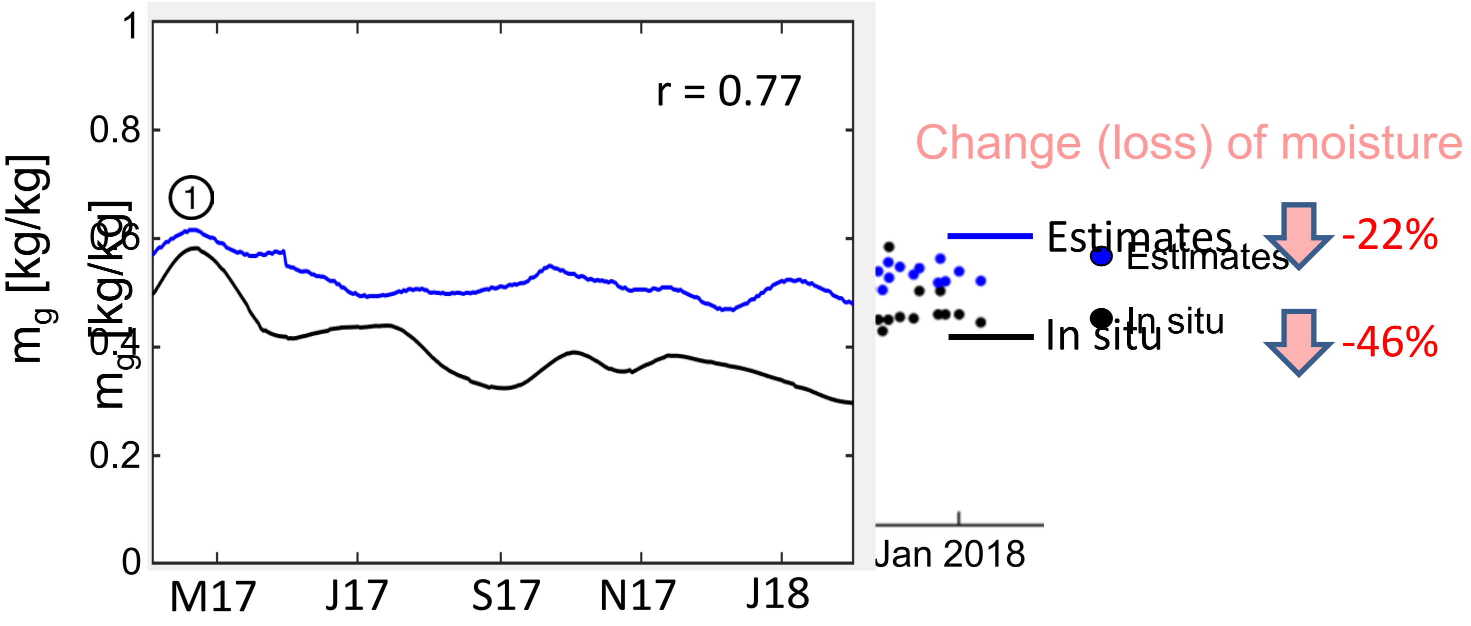
Comparison of station-day m_g pairs

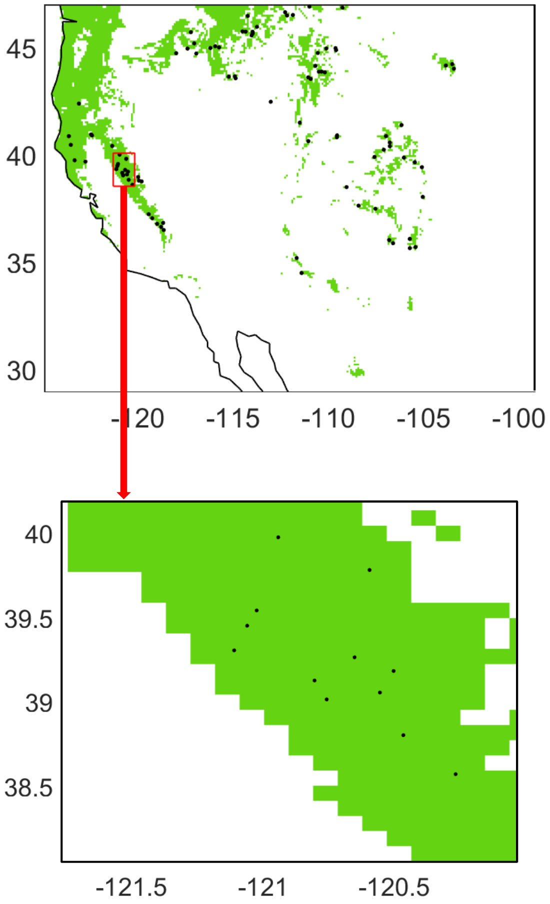


	In situ	Estimates
Mean	0.53	0.55
Mode	0.53	0.61
Std. dev.	0.07	0.09

6. Multi-sensor retrieval results of m_g

- Daily comparisons between in situ and estimates in a focus region:
  - First, daily matches between in situ and estimates show similar trends
  - Regional time-series are well correlated (r = 0.77)
  - Second, we smooth (61-day) the in situ data for the regions:
  - Mg estimates only capture part of the change between mg peak in May 2017 (①) and January 2018
    - ❖ Consistency with remote sensing inputs
    - ❖ Having enough in situ samples → Build a time-series for the region
    - ❖ Focus in Apr. 2017 – Jan. 2018





7. Outline and ongoing work

- A **multi-sensor approach** to retrieve **vegetation moisture in gravimetric units (m_g)** is proposed
  - Synergy among SMAP (radiometer), Sentinel-1 (radar) and GEDI+Sentinel-2 (LiDAR/Optical)

- Non-linear relationship between m_g and VH, with m_g values in the expected range in forests
  - A machine learning approach will be explored to deal with non-linear relationships and more complex links between variables.

- Results show **m_g estimates ranging between 0.3 and 1 kg/kg** → Some overestimation (+0.2 kg/kg) if compared to the expected maximum (~0.8 kg/kg).

- **m_g estimates compare well (similar mean) with in situ values**, but show slightly higher variation and range

- Regional-scale time-series of m_g estimates compare well (r = 0.77) with in situ time-series

- Regional **m_g estimates capture part of the in situ m_g decrease (-22% in front of -46%)** during 9 months in the focus region

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THANKS FOR YOUR ATTENTION!!