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Down-scaling MODIS operational vegetation products with machine learning and fused gap-free high resolution reflectance data in Google Earth Engine

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Cloud contamination in optical remote sensing.

- Clouds and vegetation biophysical parameters retrieval don't get along very well (gaps+noise).
- High spatial resolution sensors (low revisit cycle) present lots of missing data.

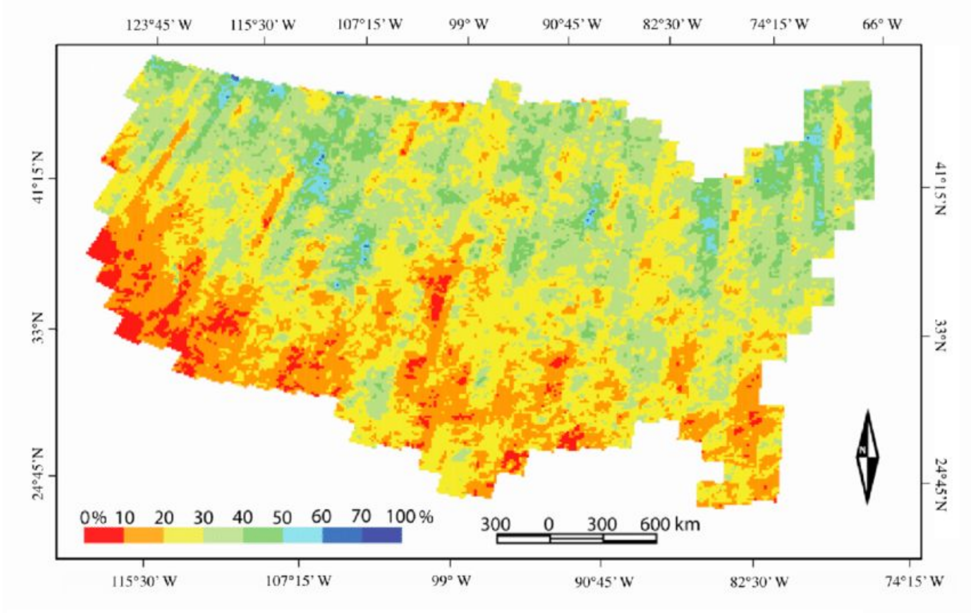

Figure 1. Percentage of high confidence cloud detections over 53 weeks of Landsat 8 observations derived at each 30 m conterminous US [1]

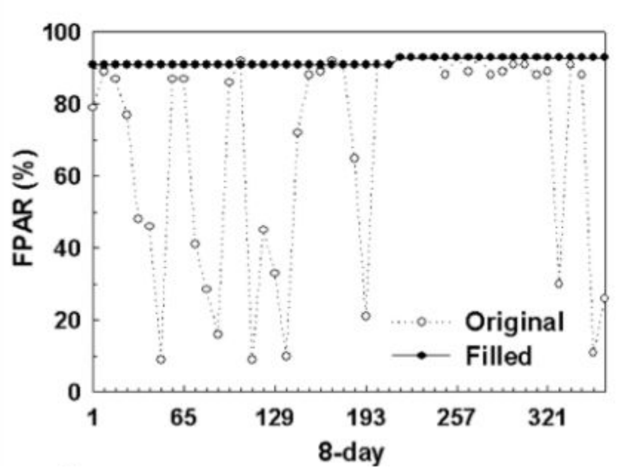

Figure 2. Example of a MODIS FPAR (MOD15) time series over a cloudy area [2]

Gap filling and noise removal in optical remote sensing data

Complexity

- Gap filling methods usually rely on temporal, spatial interpolation or both:
  - Replacement of missing data with climatologies.
  - Maximum Value Composites
  - Linear/polynomial interpolation (lowess, SG,...)
  - Model fits such as polynomial, Double Logistic (DLOG),...
- Multi-sensor data fusion approaches such as STARFM like approaches combine different sensors, but they don’t scale well....
- We created HISTARFM to produce gap free reflectance data at continental scales with high spatial resolution sensors in mind.

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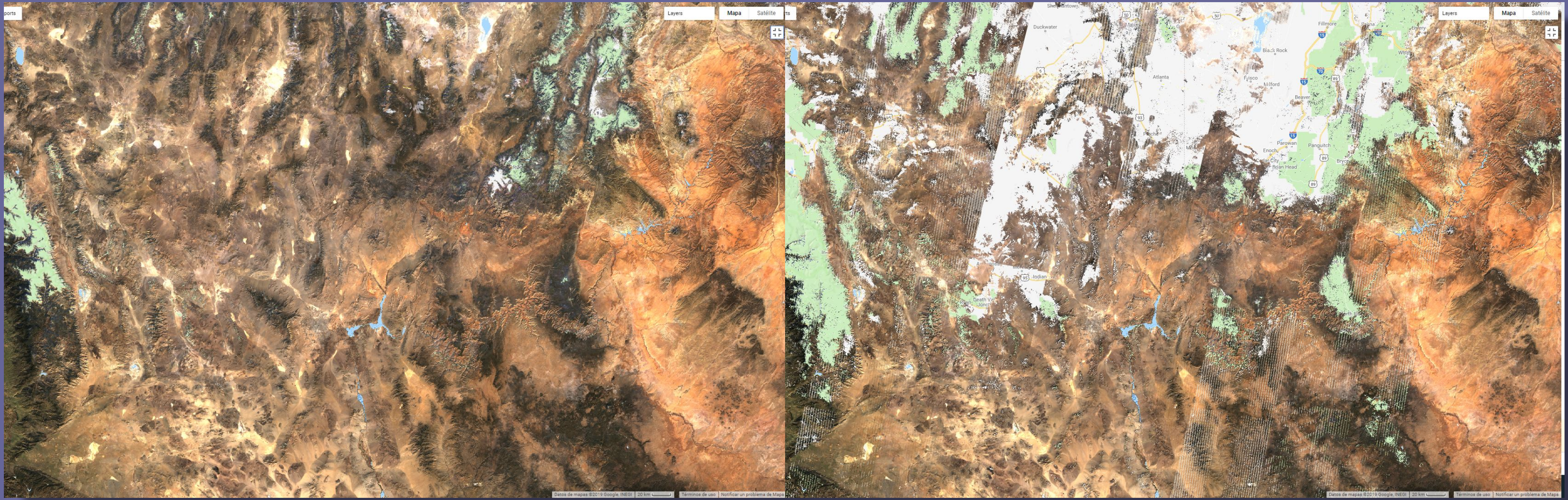
Why have we implemented our data fusion method in GEE?

- Google Earth Engine advantages:

  - ❑ Remote Sensing Archive with petabytes of data in one location
    - ✓ MODIS
    - ✓ Landsats
    - ✓ Sentinels
    - ✓ NOAA NCEP
  - ❑ A very powerful cloud-based geospatial processing platform (analyses are automatically parallelized on many CPUs).

Google Earth Engine

HIghly Scalable Temporal Adaptive Reflectance Fusion Model (HISTARFM)



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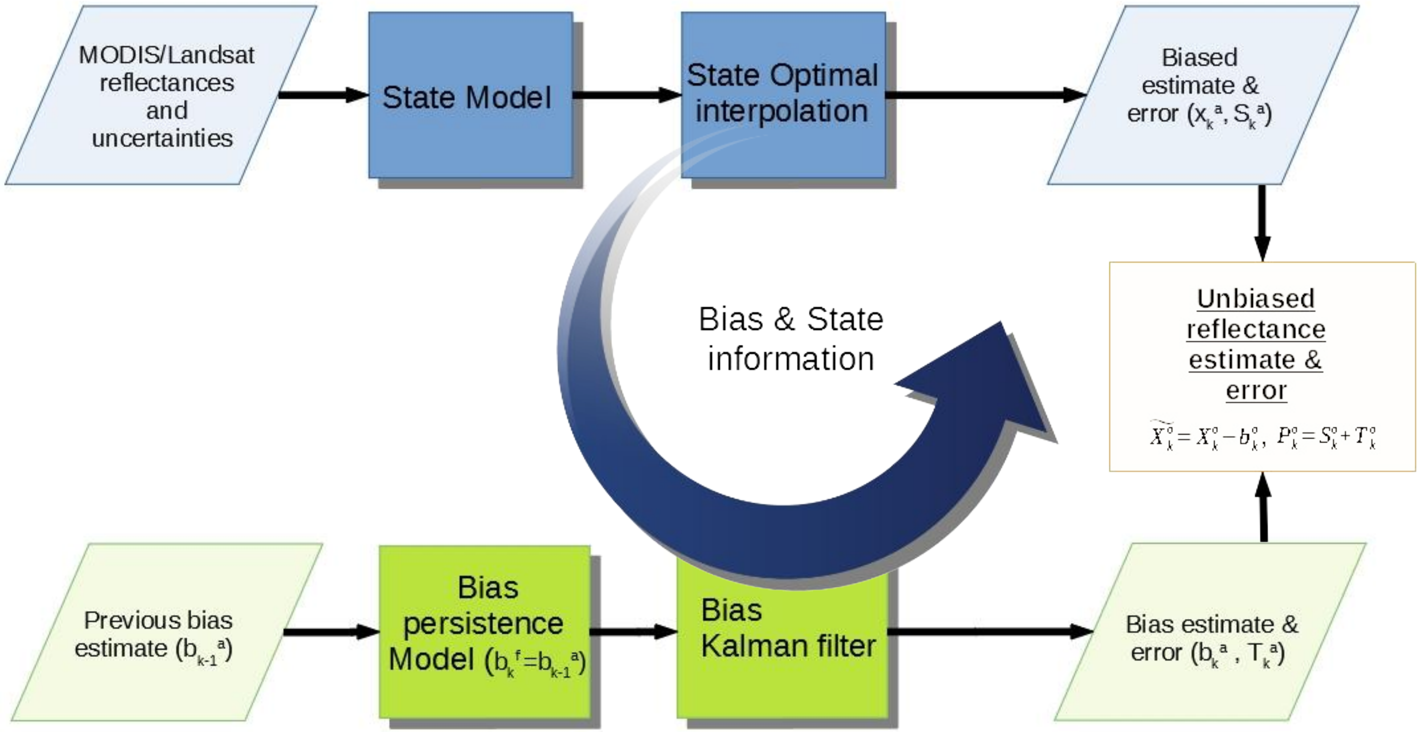
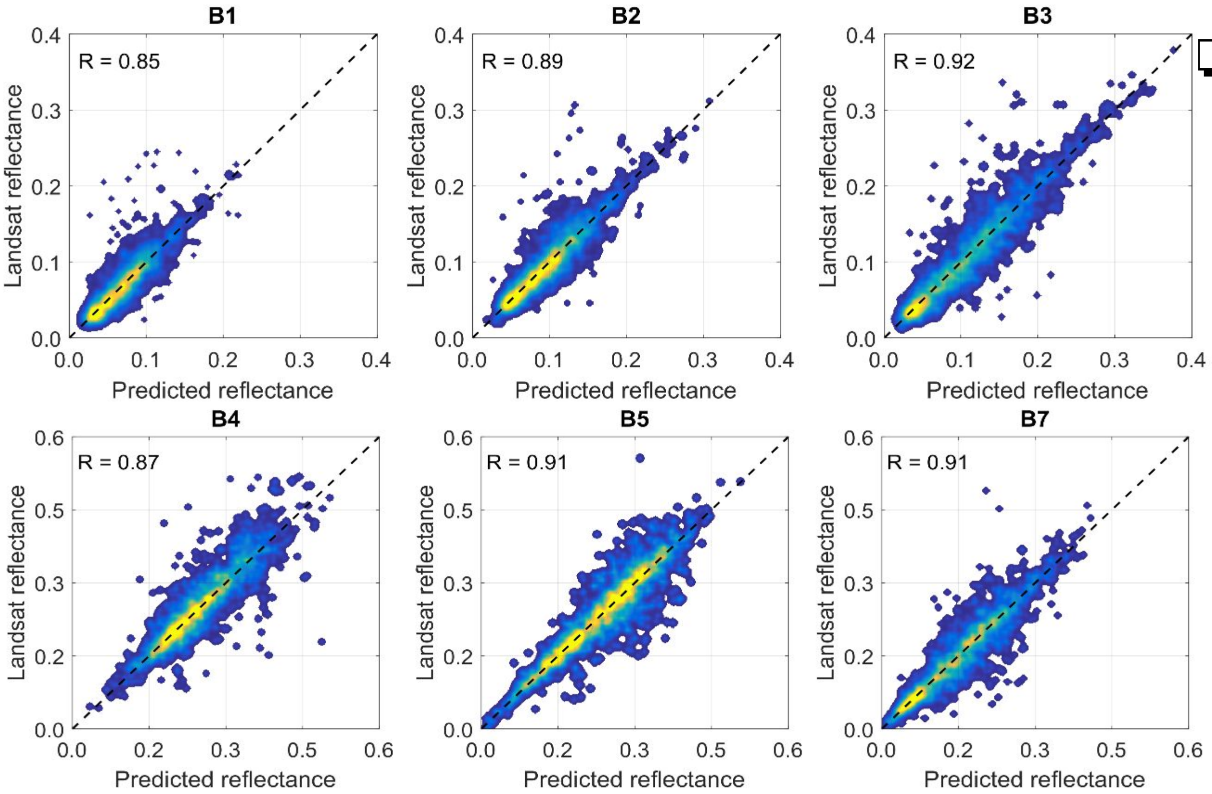
HISTARFM is a bias aware Kalman filter algorithm [3]



Validation of HISTARFM over thousands of sites [4].



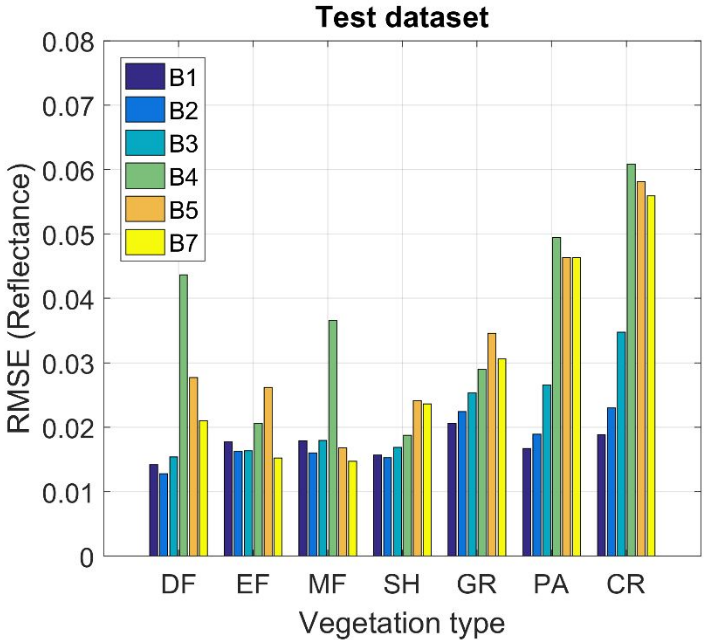
- Validation results (artificial gaps over CONUS)

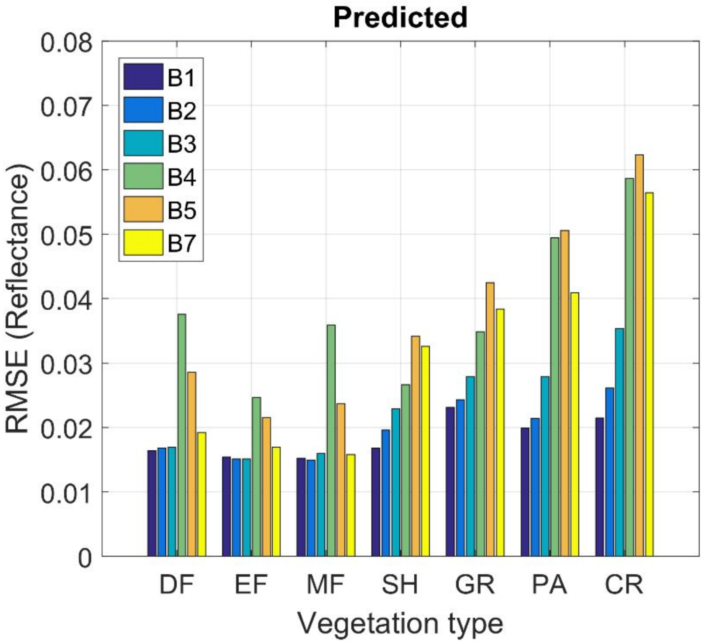
Table 1: Results over a validation data set

Band	ME	MAE	RMSE
B1	0.0009	0.011	0.017
B2	0.0003	0.011	0.018
B3	0.0002	0.015	0.023
B4	0.0028	0.026	0.039
B5	-0.0004	0.024	0.037
B7	-0.0006	0.022	0.035

Predicted band uncertainties by HISTARFM are realistic.

❑ Actual errors vs Predicted uncertainties [4]





Down-scaling MODIS FAPAR/LAI products in GEE

Porting MODIS LAI/FAPAR to 30m resolution

- ❑ Artificial neural networks (ANN) [6] were trained to learn MODIS LAI/FAPAR algorithm [5] from data using Landsat reflectance.
- ❑ 4000 locations over the CONUS were used for training/validation (2016).
- ❑ We propagate HISTARFM uncertainties thru the ANN model.

General expression of an ANN:

$$y = g\left(\sum_{j=1}^{m} v_j\, f\left(\sum_{i=1}^{n} w_{ij} x_i + b_j\right) + c\right).$$

where x_i is the input feature i, n is the number of inputs, w_{ij} are the weights, b_i is the bias term of the ith node, and m is the number of nodes in the hidden layer.

Error propagation (Taylor's expansion):

$$f(\mathrm{x} + \Delta\mathrm{x}) \approx f(\mathrm{x}) + \sum_{i=1}^{n} \frac{\partial f(\mathrm{x})}{\partial x_i} x_i,$$

$$J_i := \frac{\partial y}{\partial x_i} = \sum_{j=1}^{m} v_{jk}(1 - f^2(a_j)) w_{ij},$$

J is the Jacobian matrix, $a_j = \sum_i^n w_{ij} x_i + b_j$, and we used a linear output layer.

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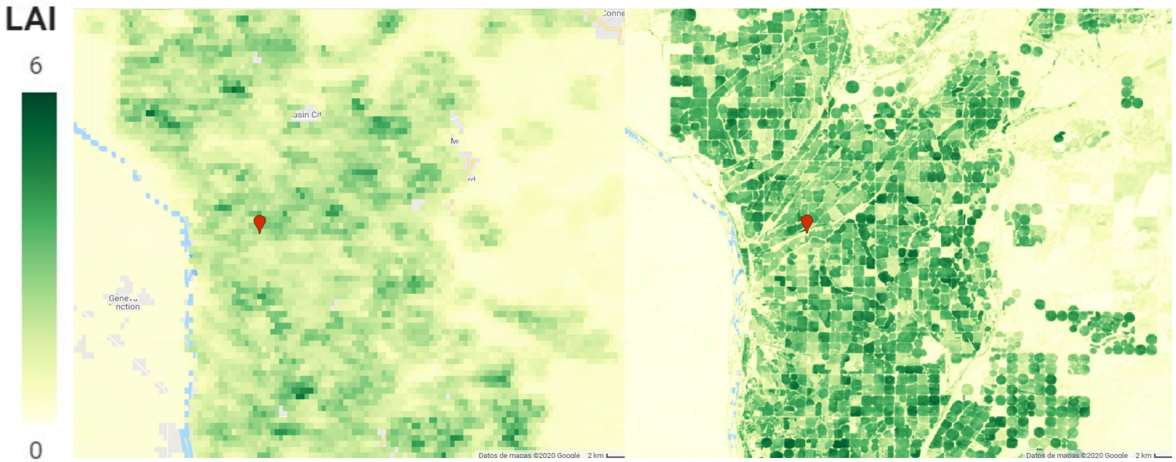
Porting MODIS LAI/FAPAR to 30m resolution



- Calculated high spatial (30 m) resolution LAI (right) versus the original NASA MOD15 (500 m) product (left) in a cropland area.

- Validation over test datasets.

Product	MBE	RMSE	R
FAPAR	0.0042	0.08	0.95
LAI ($m^2\ m^{-2}$)	0.0017	0.58	0.90

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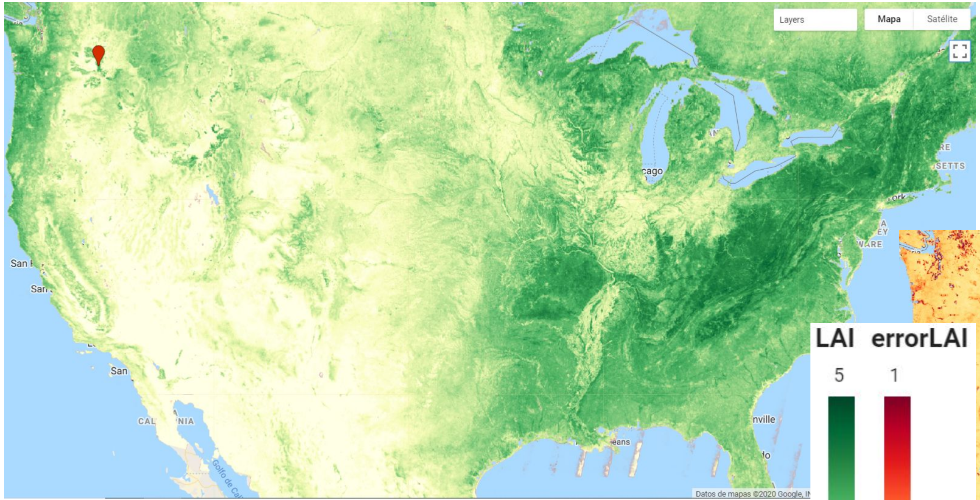
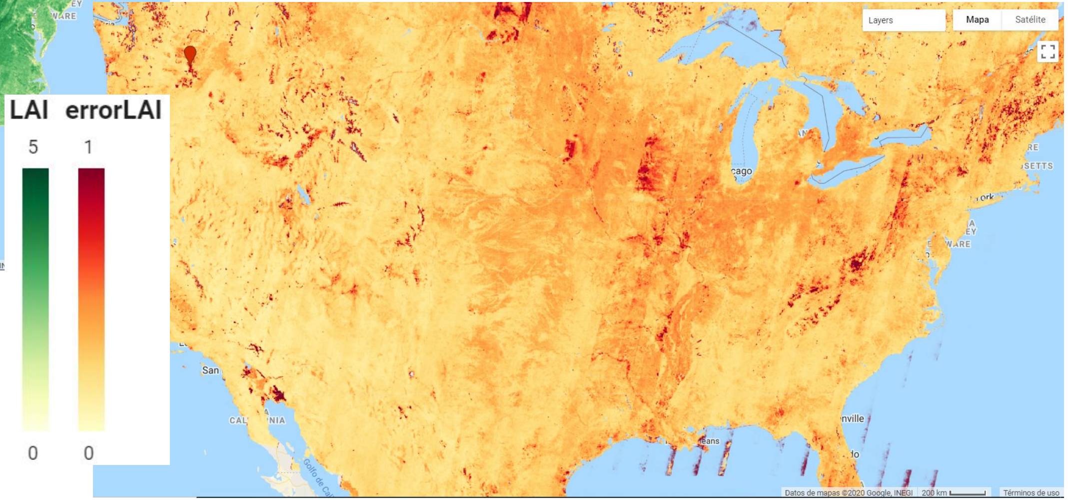
MODIS LAI/FAPAR at 30m resolution in GEE (let’s go continental)

- <u>Predicted LAI (30m) and its uncertainties (June, 2016)</u>



- ANN produce almost instantly their estimates and predicted uncertainties.



- Higher uncertainties are observed in croplands and gap filled data (as expected).

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Take-home messages

- HISTARFM allows to obtain gap-free reflectance observations over large areas.
- The validation of HISTARFM presented low errors for all Landsat bands.
- ANN allowed to port easily, efficiently, and accurately standard MODIS products to Landsat native resolution.
- Error propagation methods and the HISTARFM predicted uncertainties allowed to provide realistic error maps of LAI/FAPAR.
- Many applications: crop monitoring, high resolution phenology, GPP, and ET could take advantage of our gap free FAPAR/LAI estimates at broad scales.

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Thanks!

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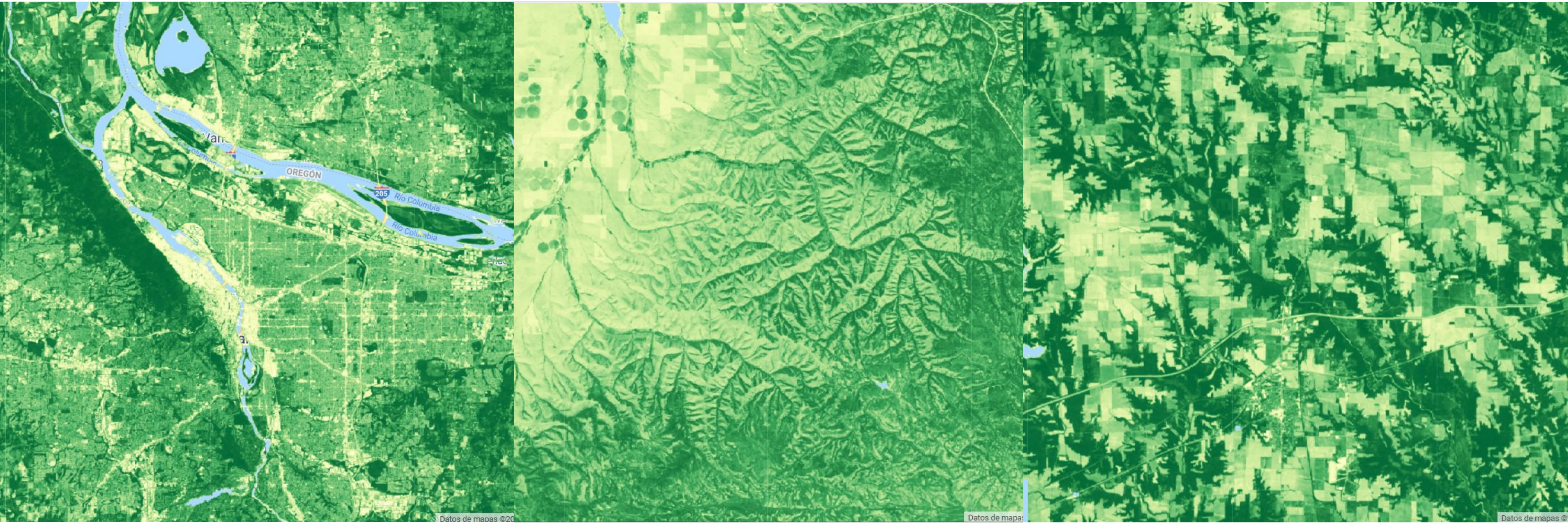

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