

Multitask Observation using Satellite Imagery and Kitchen Sinks (MOSAIKS)

Togo Data Lab Training – UCSB, CEGA, & emLab
January, 2025

Tamma Carleton (UC Berkeley & emLab)

in collaboration with: Jonathan Proctor, Trinetta Chong, Taryn Fransen, Simon Greenhill, Jessica Katz, Hikari Murayama, Luke Sherman, Jeanette Tseng, Hannah Druckenmiller, Solomon Hsiang

A growing set of measurements from space

Science

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0 | REVIEW

Using satellite imagery to understand and promote sustainable development

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SCIENCE • 19 Mar 2021 • Vol 371, Issue 6535 • DOI: 10.1126/science.abb524

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Coastal Engineering

Volume 174, June 2022, 104102



Open Access Review

Forest Biodiversity Monitoring Based on Remotely Sensed Spectral Diversity—A Review

by Patrick Kacic ^{1,*}  and Claudia Kuenzer ^{1,2}

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Remote Sens. **2022**, *14*(21), 5363; <https://doi.org/10.3390/rs14215363>

Multispectral satellite imagery and machine learning for the extraction of shoreline indicators

Emma McAllister     , Andres Payo ^b, Alessandro Novellino ^b, Tony Dolphin ^c, Encarni Medina-Lopez ^a



Computers and Electronics in Agriculture

Volume 175, August 2020, 105584

High-resolution satellite imagery applications in crop phenotyping: An overview

Chongyuan Zhang, Afef Marzougui, Sindhuja Sankaran  

A growing set of measurements from space

Each measurement or monitoring system is costly to implement in practice.

A growing set of measurements from space

Each measurement or monitoring system is costly to implement in practice.



Source: Farmonaut

For what **outcomes**, in what **places**, and for which **populations** should we invest in satellite-based monitoring?

Evaluating satellite-based predictions for over 100 variables

What can we see from space?

- Existing satellite imagery and machine learning (SIML) predictions are customized and heterogeneous
- This limits our ability to assess what can and cannot be feasibly monitored using this new technology

Evaluating satellite-based predictions for over 100 variables

What can we see from space?

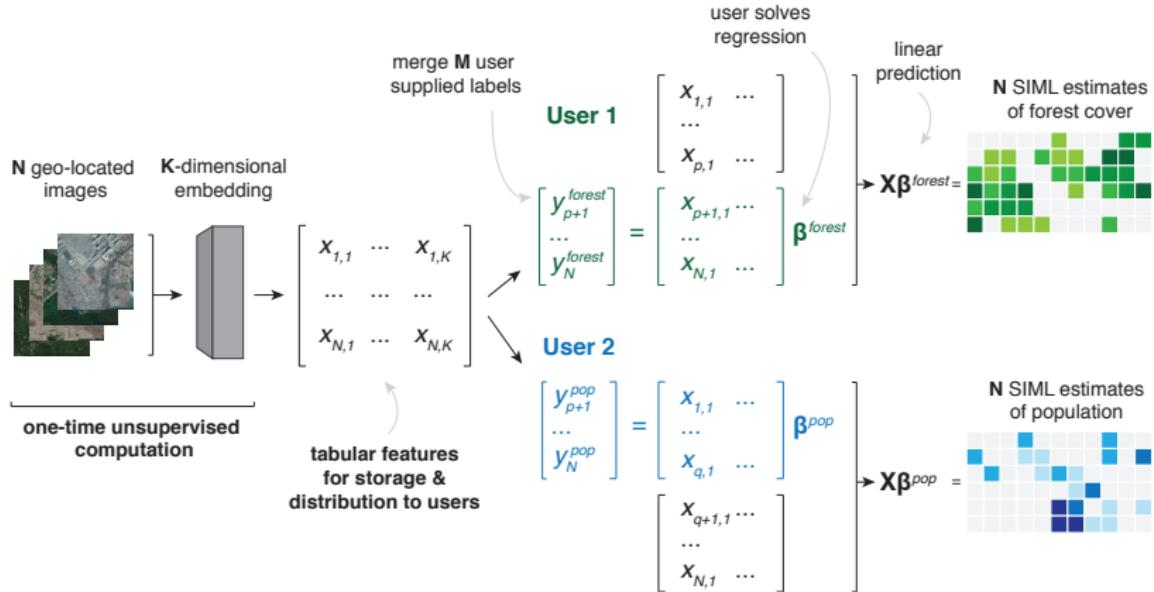
- Existing satellite imagery and machine learning (SIML) predictions are customized and heterogeneous
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In this paper, we:

- Assemble ground truth data for 115 outcomes at national to global scales
- Build a flexible pipeline to **mass produce** MOSAIKS maps/predictions
- **Systematically examine** which categories of variables, geographic locations, and populations are most amenable to SIML-based monitoring
- **Distribute 115 maps** and associated data quality layers

Recall: MOSAIKS pipeline

Multi-task Observation using Satellite Imagery and Kitchen Sinks



Rolf, Proctor, Carleton, Bolliger, Shankar, Ishihara, Recht, & Hsiang (2021)

Pipeline extensions

Original MOSAIKS pipeline

7 tasks

Sparse sampling

By-hand label customization

Posted replication code

Pipeline extensions

Original MOSAIKS pipeline		This work
7 tasks	→	115 tasks
Sparse sampling	→	Dense sampling
By-hand label customization	→	Automated variable handling
Posted replication code	→	Interactive pipeline and resources

What are the limits of a planetary mapping pipeline?

For what types of variables does it work for?
What can we learn about the promise of satellite imagery?

Outline

Methods

Results

Summary

Outline

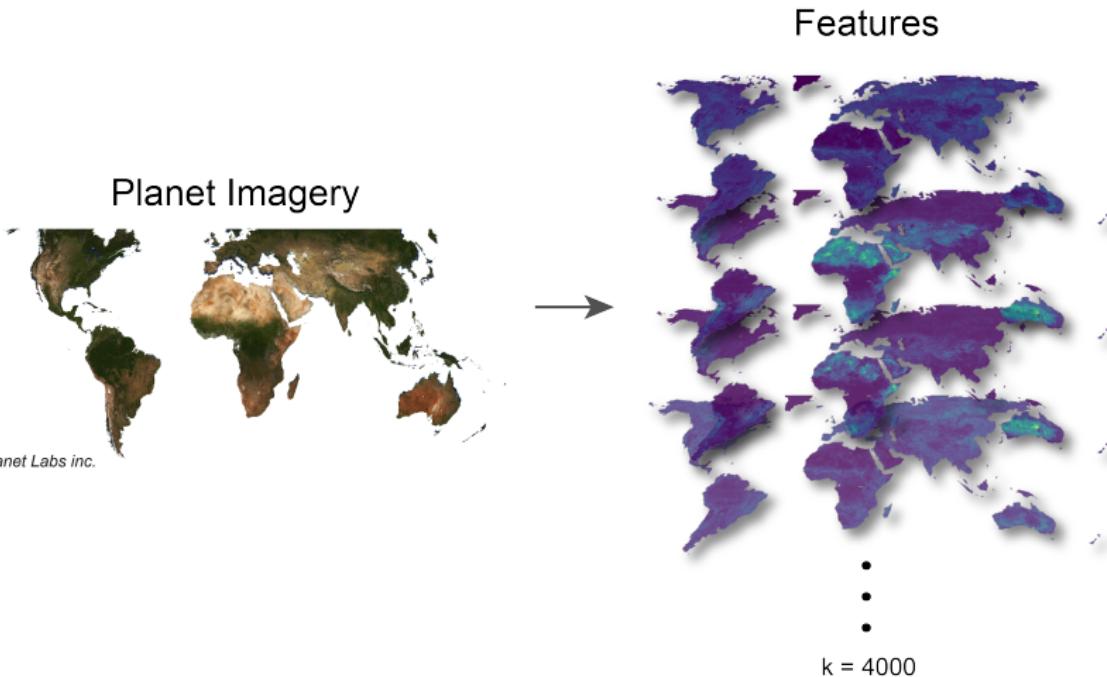
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One-time feature extraction

Random Convolutional Features (Rahimi & Recht (2007, 2008a,b))



details

Automated model specification

$$y_l = X\beta_l + \epsilon_l$$

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$$y_l = X\beta_l + \epsilon_l$$



We automatically test variations of the ridge regression to find the optimal specification

Transformation: log or levels?

Intercept in regression: yes or no?

Use regional model: yes or no?

If polygon use weighting: area or population weighted?

Data gathering

We gather publicly available data with a diversity in spatial structures and categories.

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Category	Number of Labels	Example Label
Agricultural Assets	5	Agricultural land ownership

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Agriculture	16	Maize yield
Built Infrastructure	9	Buildings

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Category	Number of Labels	Example Label
Agricultural Assets	5	Agricultural land ownership
Agriculture	16	Maize yield
Built Infrastructure	9	Buildings
Demographics	5	Median age
Education	10	Expected years of schooling
Health	15	Malaria in children
Household Assets	21	Mobile phones
Income	9	Human development index
Natural Systems	8	Tree cover
Occupation	17	Unemployment

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Pipeline performance

Labels that...	have been remote sensed before	56
	have been remote sensed before with covariates	11
	have <u>not</u> been remote sensed before	48
Total Labels		115

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Training time for one label

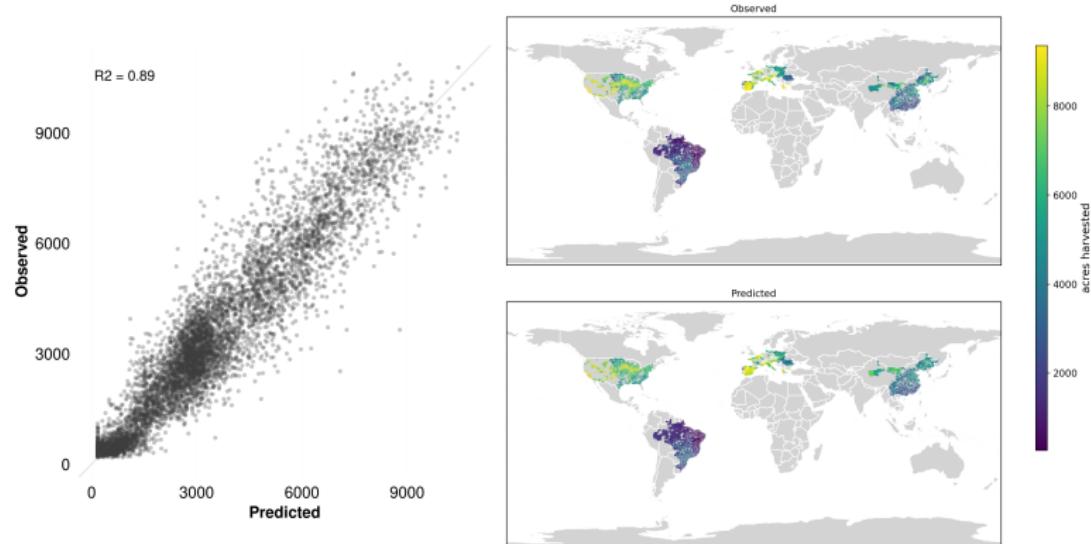
Run with autotuning: 20 CPU Hours

Run final model: 2 minutes on laptop

Maize yield

Source: Proctor (2021)

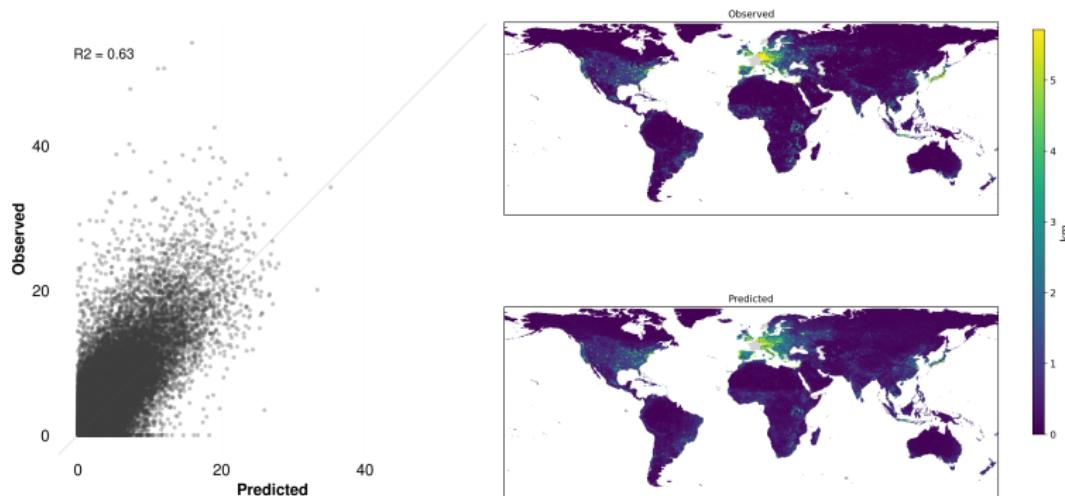
Description: Amount of maize harvested in acres



Road length

Source: Open Street Maps

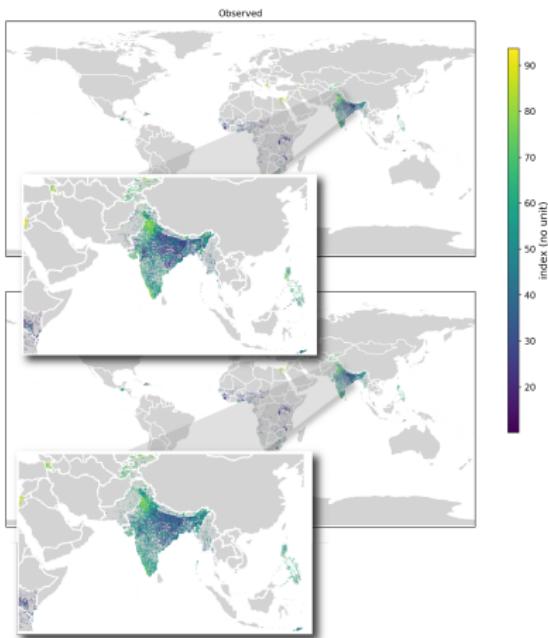
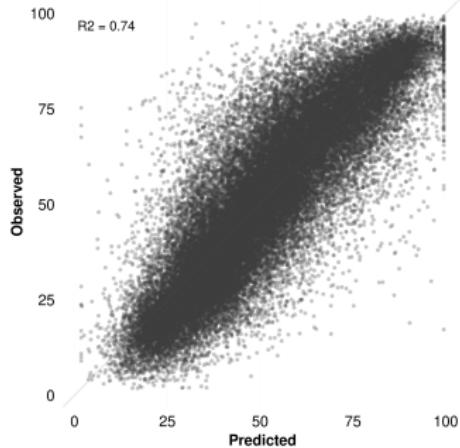
Description: Length of roads in kilometers



International wealth Index

Source: Demographic and Health Surveys

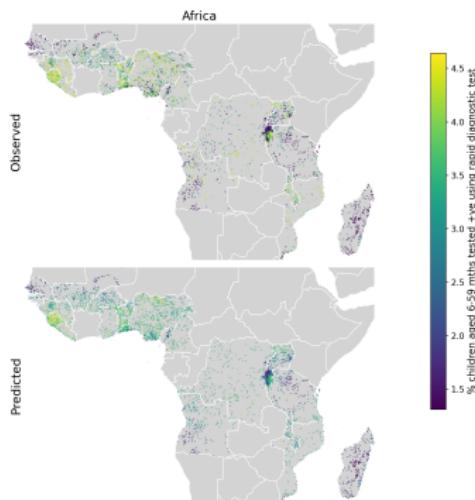
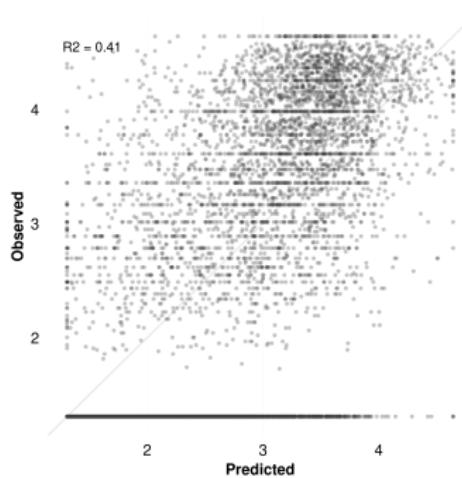
Description: Mean international wealth index (IWI) for each DHS cluster



Malaria cases among children

Source: Demographic and Health Surveys

Description: Percentage of children age 6-59 months tested using a rapid diagnostic test (RDT) who are positive for malaria



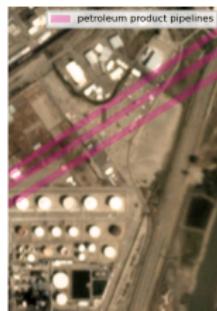
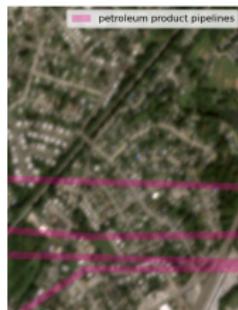
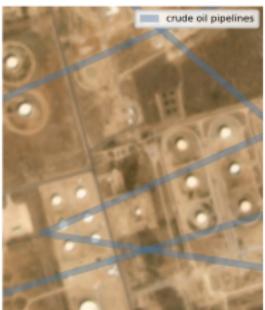
Petroleum pipelines

Source: Energy Information Administration

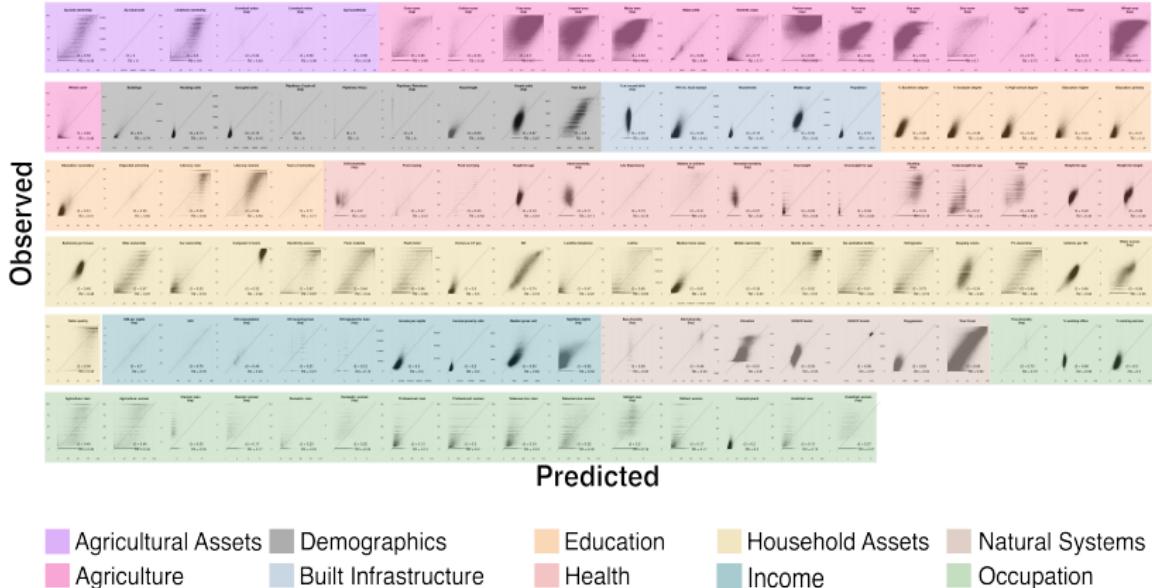
Description: Length of major petroleum product pipelines in kilometers



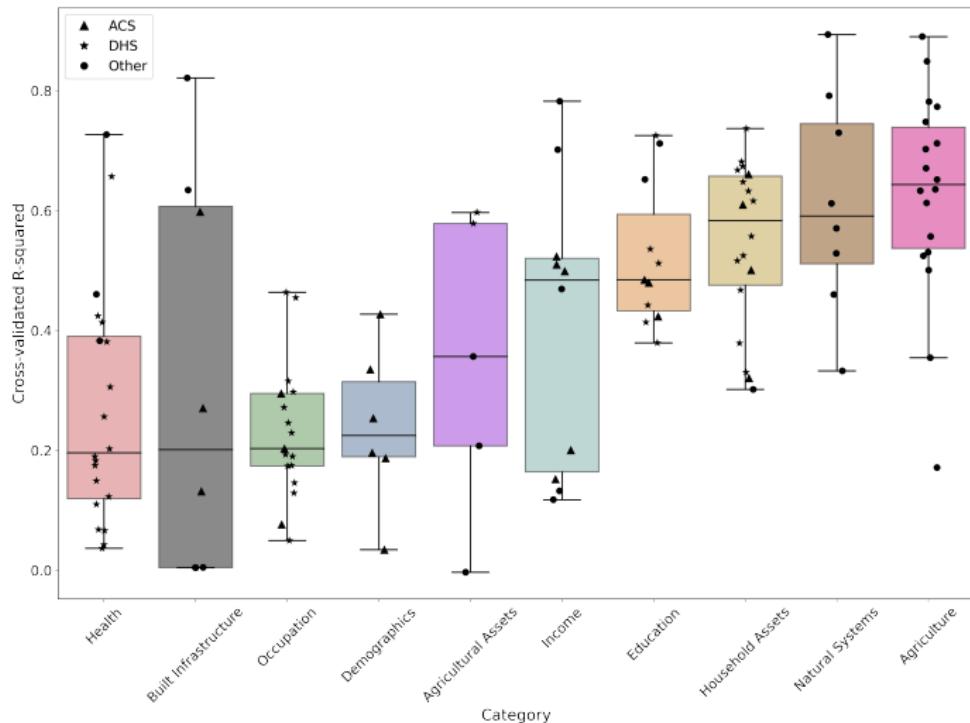
Pipelines not visible in imagery



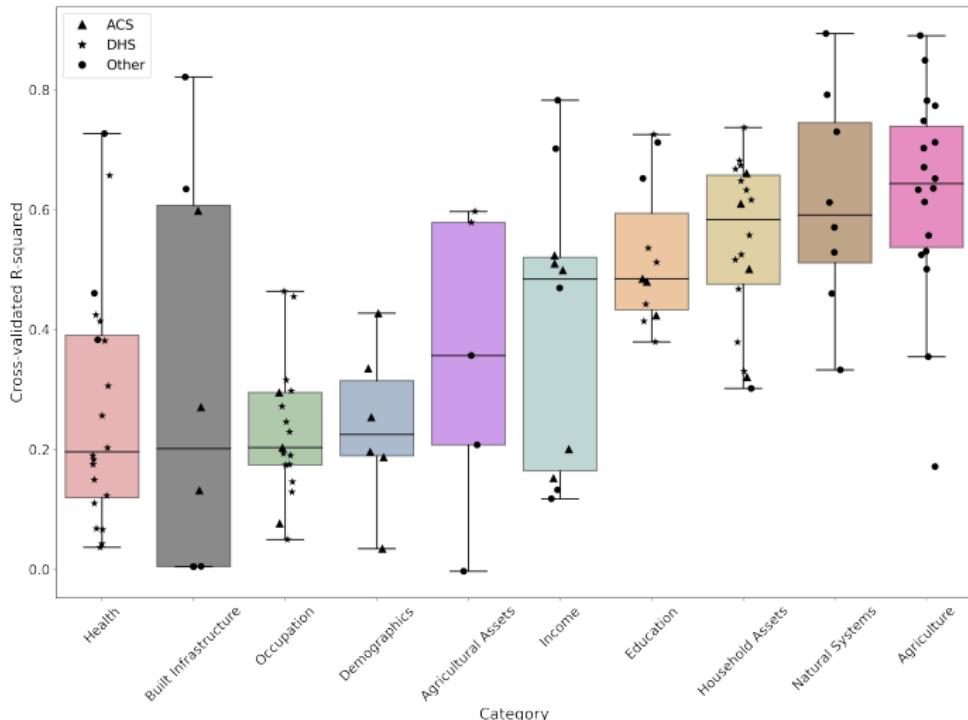
Performance across labels



Which label categories are amenable to SIML?

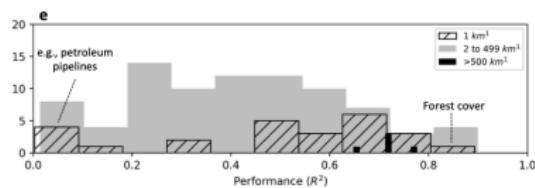
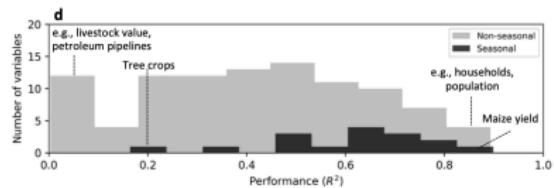
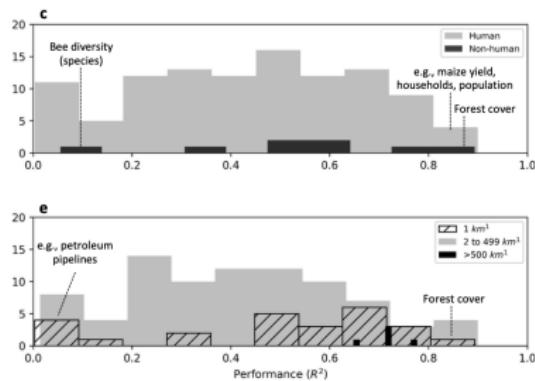
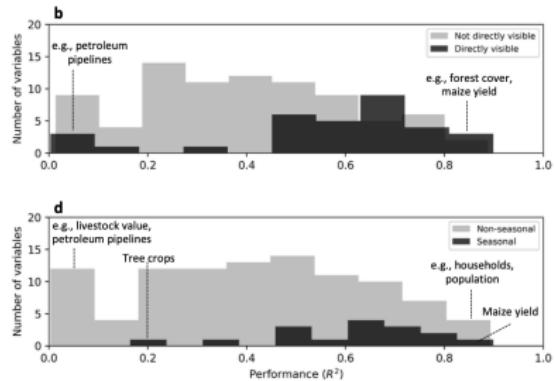


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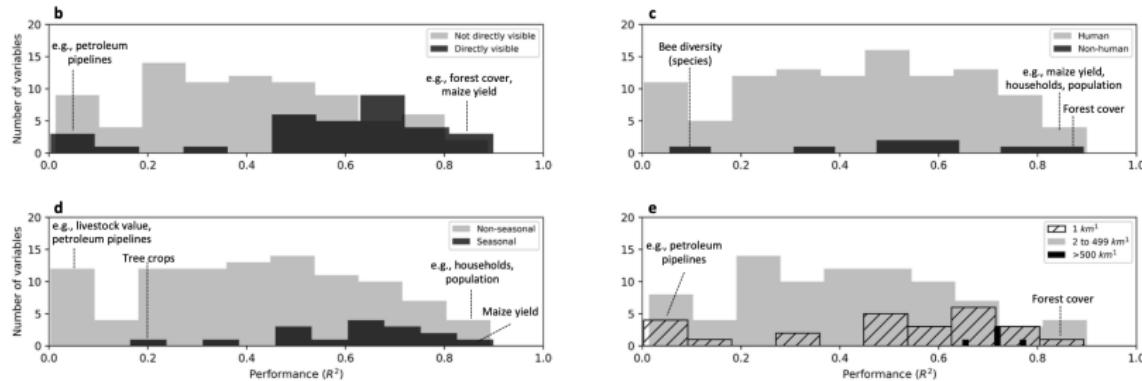


- Large variation in performance across, but especially within categories: $\sigma_{\text{within}} = 0.19$ and $\sigma_{\text{across}} = 0.12$

Which label categories are amenable to SIML?



Which label categories are amenable to SIML?



- Directly visible versus emergent: difference in mean $R^2 = 0.18$ ($p < 0.001$)
- Clear seasonal cycle versus without: difference in mean $R^2 = 0.19$ ($p < 0.05$)
- Human versus natural systems: difference in mean $R^2 = 0.1$ ($p = 0.23$)
- Spatial resolution of ground-truth data: all differences in mean $p > 0.1$.

Where are SIML measurements reliable?

Mean Absolute Normalized Error

$$\text{MANE}_i = \frac{1}{|L_i|} \sum_{l \in L_i} \left| \frac{\hat{\varepsilon}_{li} - \bar{\hat{\varepsilon}}_l}{\sigma(\hat{\varepsilon}_{li})} \right|$$

- $\hat{\varepsilon}_{li}$: residual of pixel i of label l
- $\bar{\hat{\varepsilon}}_l$: mean of residuals for label l
- $\sigma(\hat{\varepsilon}_{li})$: standard deviation for residuals label l in pixel i
- L_i : the set of labels we have in pixel i

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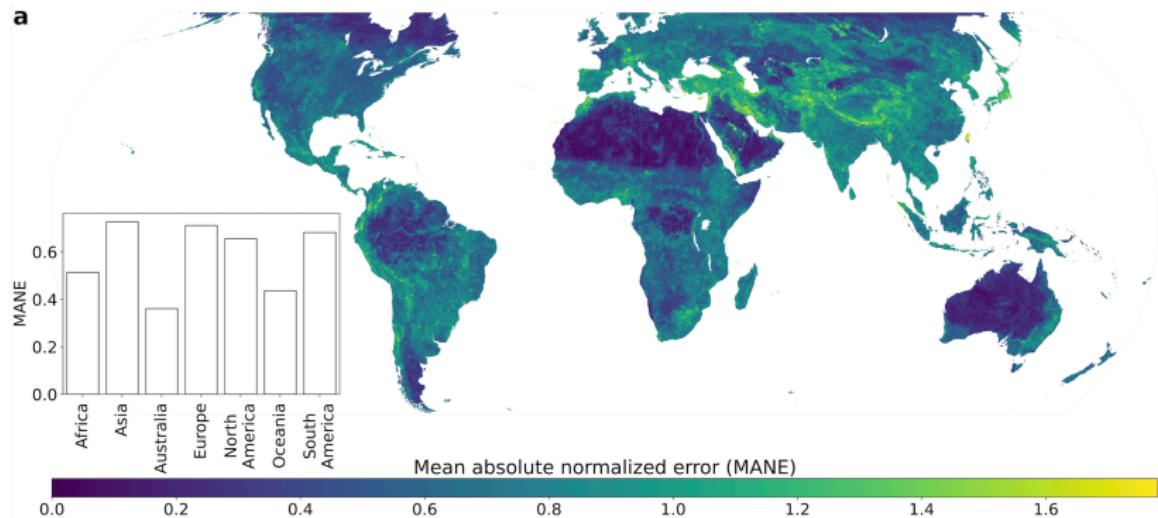
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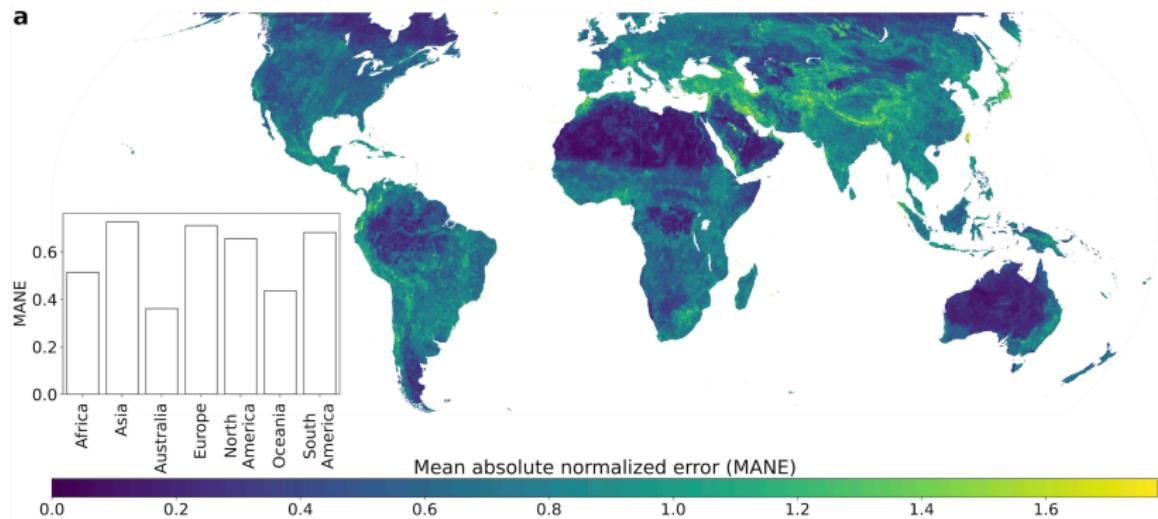
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$\text{MANE} \approx \text{z-score}$

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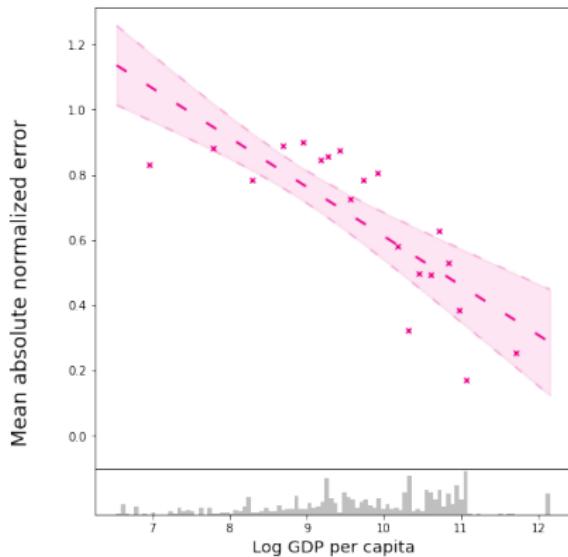
Where are SIML measurements reliable?



- MANE differs significantly across continents: $p < 0.01$
- Lowest errors in Australia and Africa (deserts) and highest errors in North America and Asia (urban areas and high elevation)
- High errors in extreme locations → mean-reverting measurement error (common in ML)

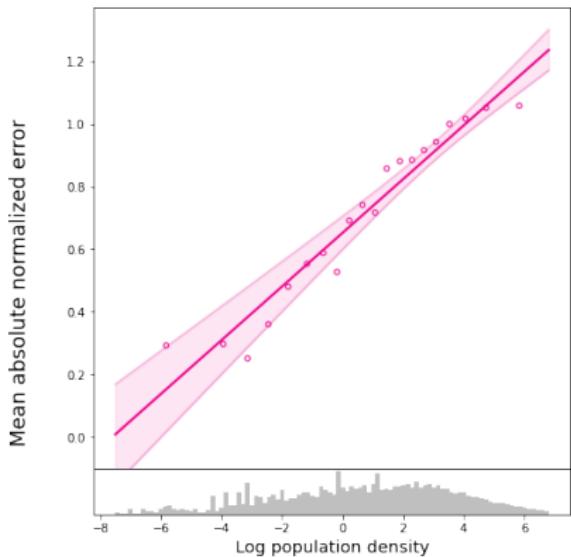
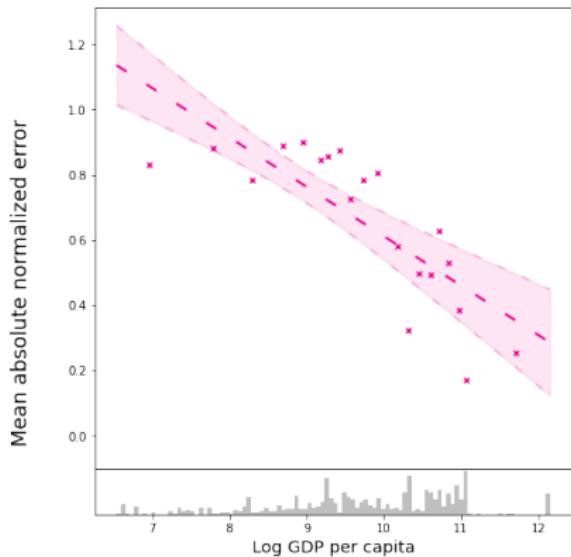
Where are SIML measurements reliable?

Example: Agriculture



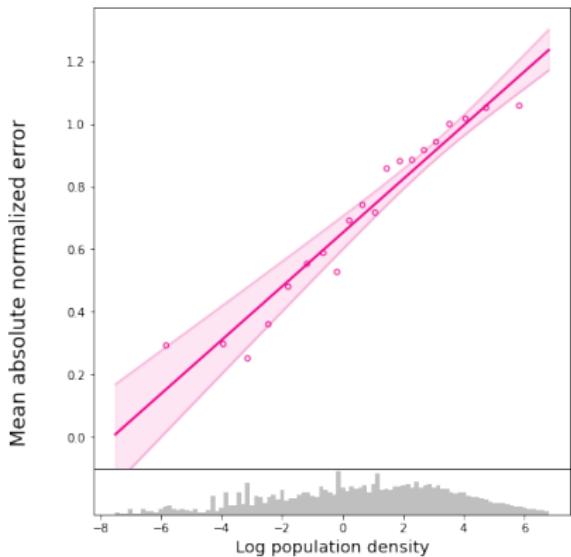
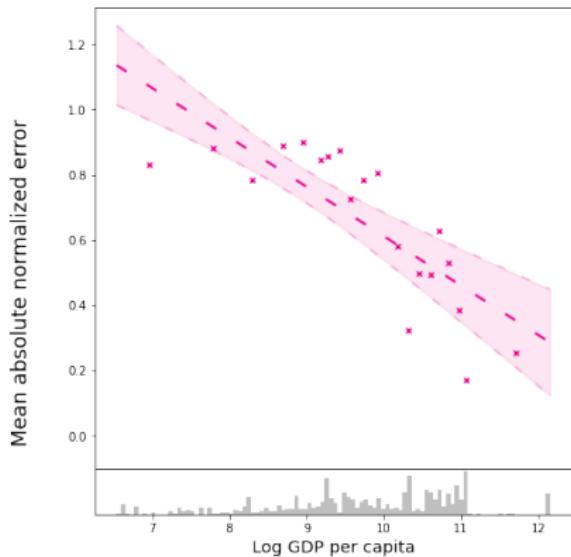
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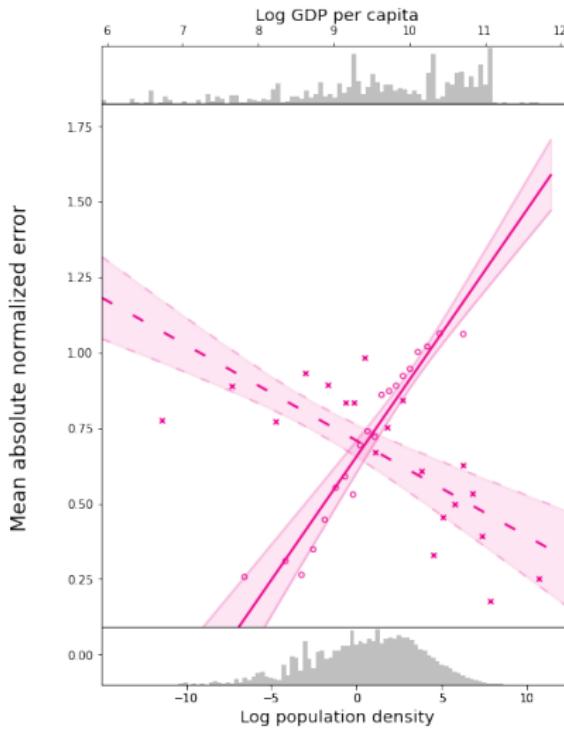
Example: Agriculture



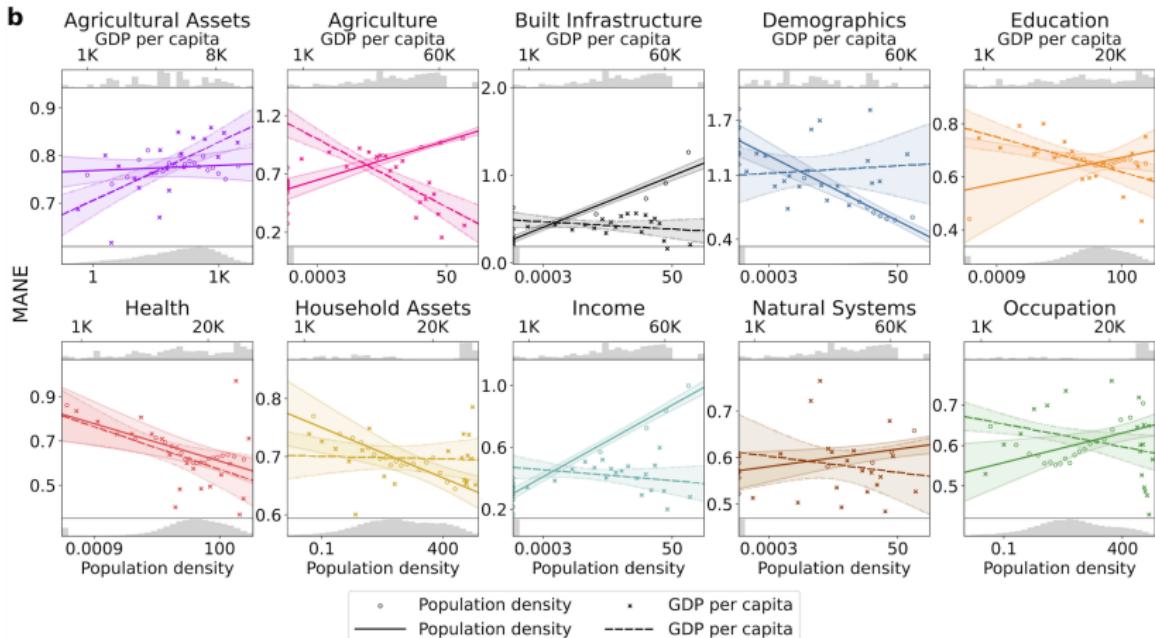
Put it together...

Where are SIML measurements reliable?

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Where are SIML measurements reliable?

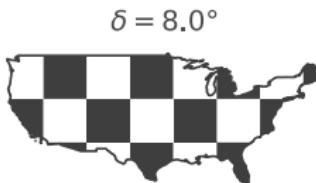


How far from training data can we extrapolate?

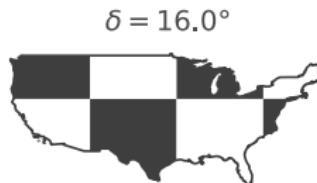
1. Partition sample in checkerboard
2. Train on white squares
3. Test on black squares
4. Jitter checkerboard location & repeat
5. Compare to spatial interpolation of ground-truth



$$\delta = 0.5^\circ$$



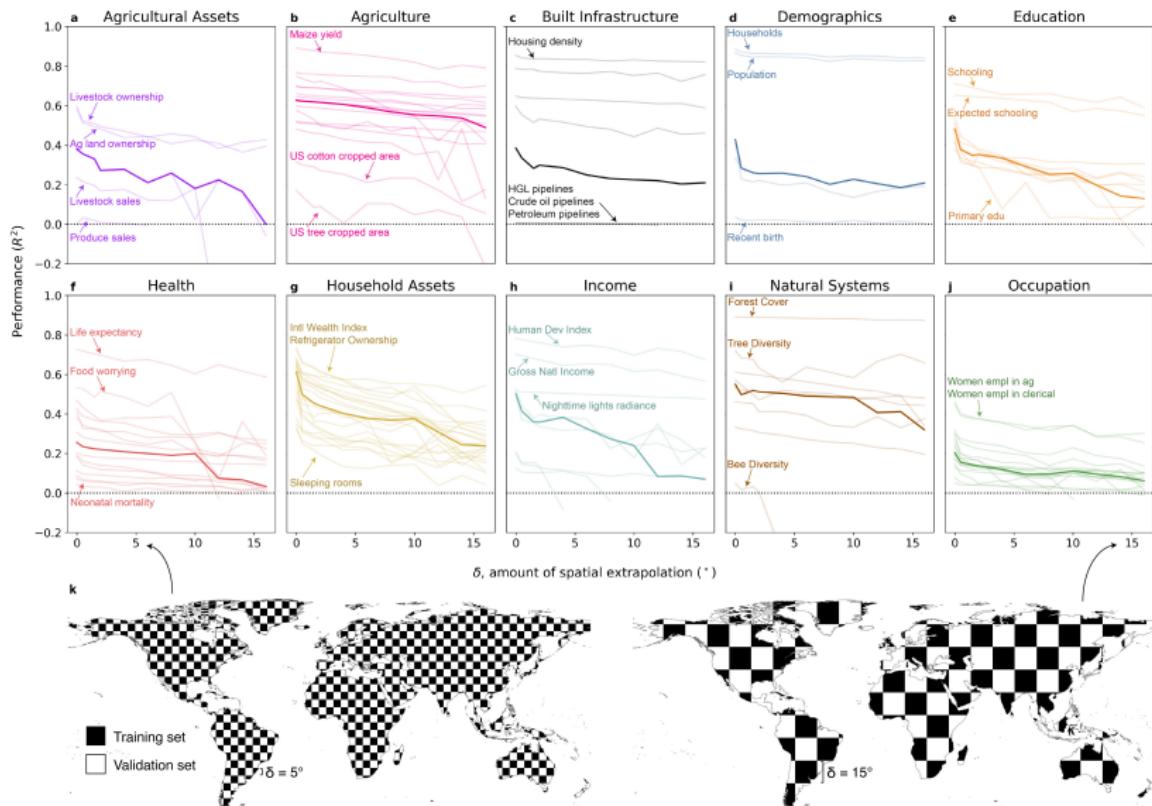
$$\delta = 8.0^\circ$$



$$\delta = 16.0^\circ$$

(Reference: $8^\circ \times 8^\circ = 888 \text{ km} \times 682 \text{ km}$ (552 mi \times 424 mi) at centroid)

How far from training data can we extrapolate?



Assessing and communicating uncertainty

We use the results from spatial cross-validation to report estimated data quality alongside release of global predictions

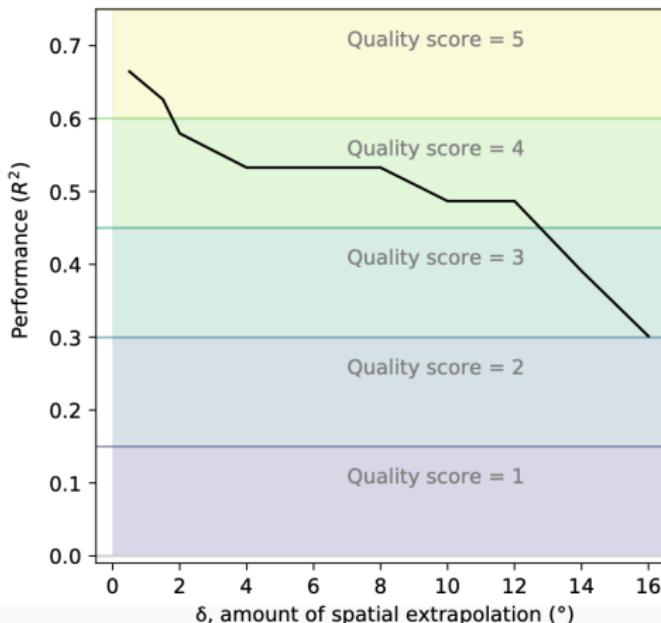
For each of 115 outcomes:

1. Conduct spatial cross-validation (i.e., “checkerboard” experiment detailed above)
2. Determine estimated R^2 for all locations outside training set based on distance to nearest ground truth observation
3. Assign all locations a quality score based on estimated R^2 :
 $0 (R^2 < 0) \rightarrow 5 (R^2 \geq 0.6)$
4. For socioeconomic outcomes, mask populated areas

Assessing and communicating uncertainty

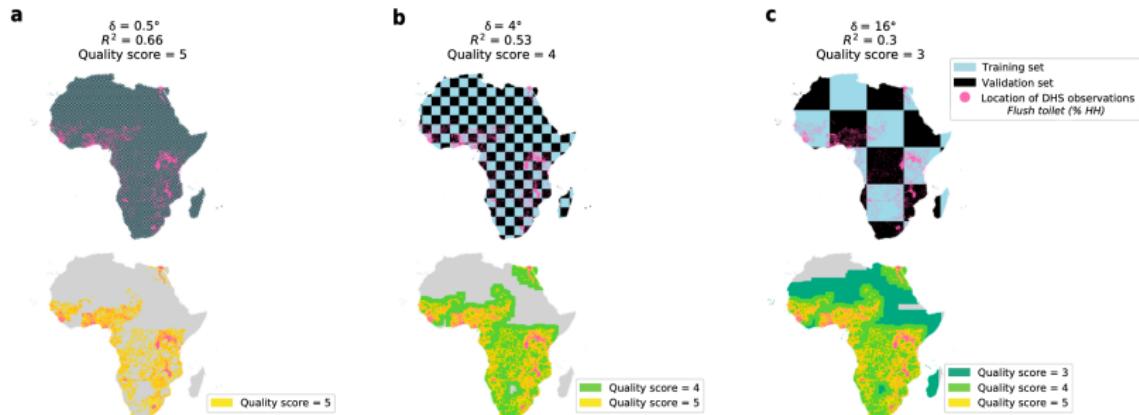
1. Conduct spatial cross-validation (i.e., “checkerboard”) experiment detailed above

E.g., access to flush toilets:



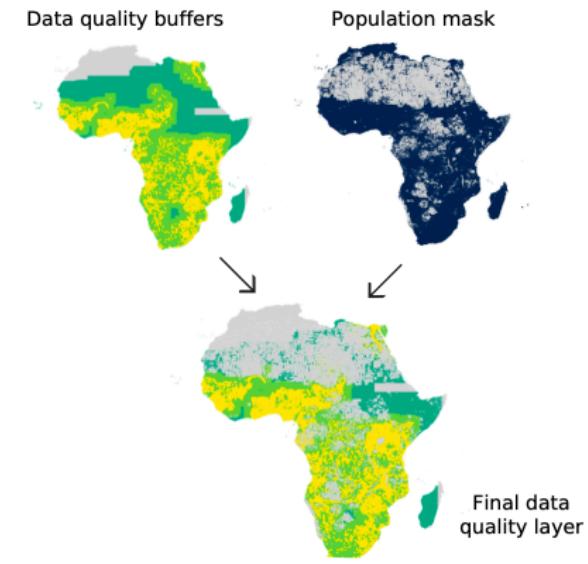
Assessing and communicating uncertainty

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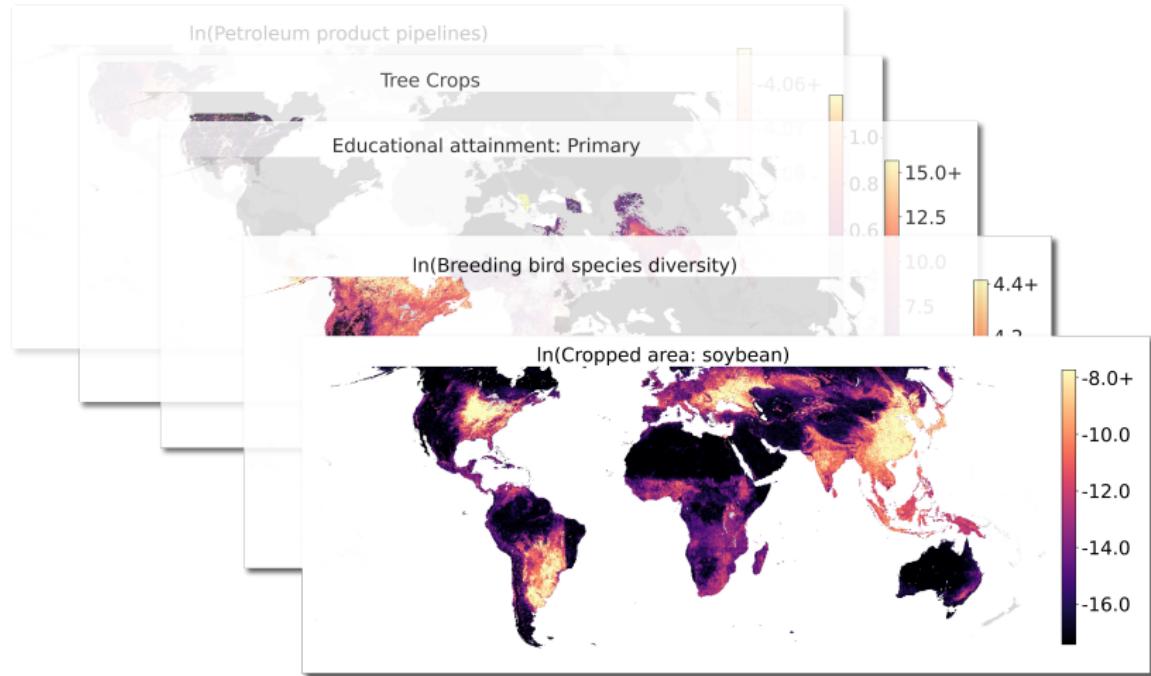
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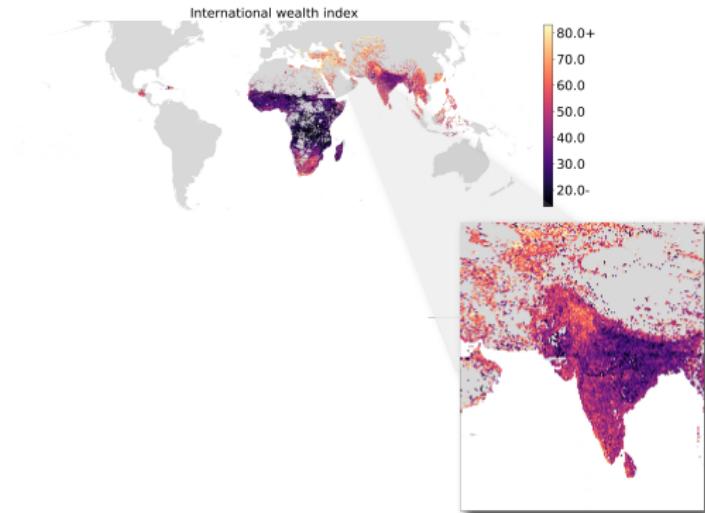


Distribute predictions and data quality layers

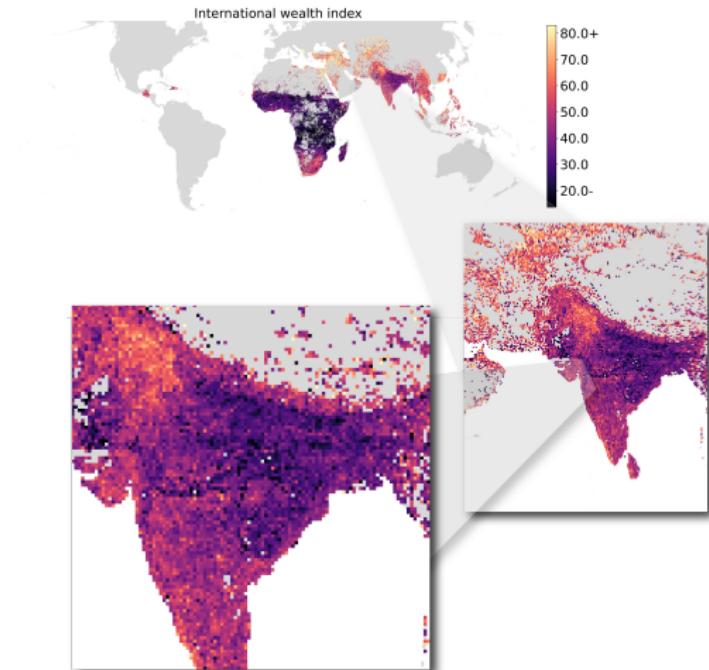
115 Maps



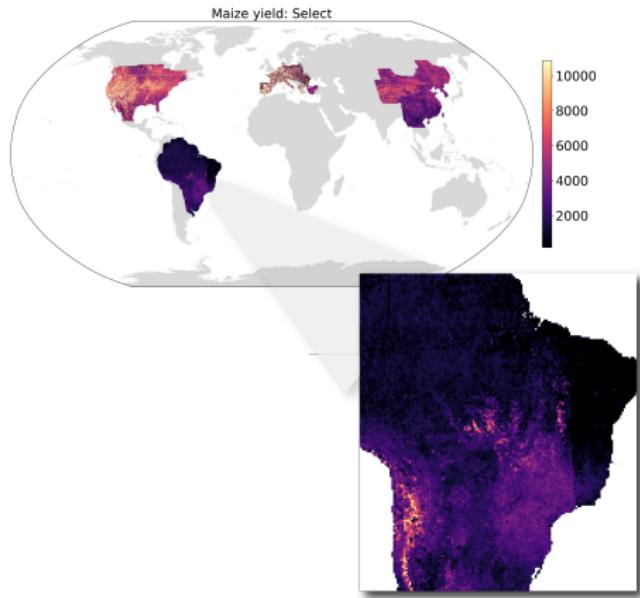
Example map layers



Example map layers

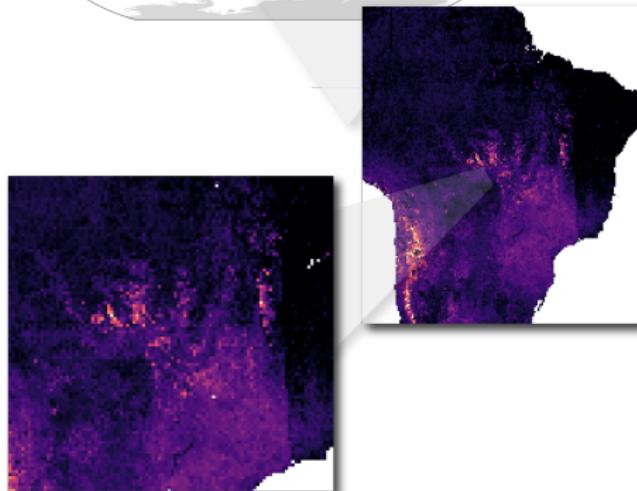
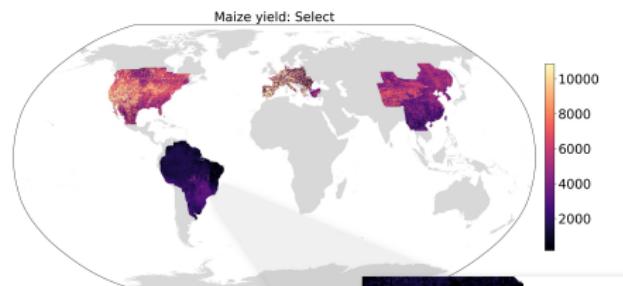


Example map layers



details

Example map layers



MOSAIKS API - www.mosaiks.org

The image displays the MOSAIKS API interface, which includes a main dashboard and a detailed observation tool.

Main Dashboard: The top section shows a map of a coastal area with various geographical features and administrative boundaries. A sidebar on the left lists tasks: Monitoring forests, Observing rivers using the Rule Game, Monitoring green resources using Mosaiks features, and Climate response.

Multi-Task Observation Tool: This is a modal window titled "MULTI-TASK OBSERVATION USING SATELLITE IMAGERY & KITCHEN SINKS (MOSAIKS)". It includes a "Beta version" notice, a note about the beta status of the platform, and a "Get started" button. The "Introduction" section provides a brief overview of the tool's purpose: "Combining satellite imagery with machine learning (ML) to automatically detect and monitor environmental problems in one place, right now". It also mentions the goal of MOSAIKS: "to make SMEs more accountable by making predictions of areas of interest in one step".

Observation Form: The "Input task coordinates" form contains fields for "Latitude" (40.7128), "Longitude" (-74.0060), "Start time in seconds", and "End time in seconds". Below the form is a "Submit" button.

Image Preview: An aerial satellite image of a coastal area with a winding river and dense green vegetation. A white rectangular overlay on the image contains the title "MULTI-TASK OBSERVATION USING SATELLITE IMAGERY & KITCHEN SINKS" and a small note: "Please sign up at [mosaiks.org](#) to access features".

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1. We demonstrate that mass production of global maps from satellite imagery is possible
 - >100 maps predicted using a single featurization of imagery, at low computational cost
 - Automated tuning pipeline makes imagery-based predictions “plug-and-play”

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 - Observe high (agriculture, household assets, natural systems) and low (health, demographics) performers
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1. We demonstrate that mass production of global maps from satellite imagery is possible
 - >100 maps predicted using a single featurization of imagery, at low computational cost
 - Automated tuning pipeline makes imagery-based predictions “plug-and-play”
2. We uncover patterns that characterize the promise of satellite imagery for global mapping
 - Observe high (agriculture, household assets, natural systems) and low (health, demographics) performers
 - Show how prediction error correlates with location, income, population
3. We publicly release inputs, outputs, and training resources
 - API: 4,000 features from Planet Labs, Inc., extensive tutorial resources
 - Data quality layer provided alongside predicted maps
 - All code and input data public



Acknowledgements

Team

Benjamin Recht, Esther Rolf,
Eugenio Noda, Hikari Murayama,
Hannah Druckenmiller, Ian
Bolliger, Jeanette Tseng, Jessica
Katz, Jonathan Proctor, Luke
Sherman, Miyabi Ishihara, Simon
Greenhill, Solomon Hsiang,
Tamma Carleton, Taryn Fransen,
Trinetta Chong, Vaishaal Shankar

MOSAIKS API



Partners and Funding

USAID, UNDP, CEGA, UCSB Bren
School: Data Science students

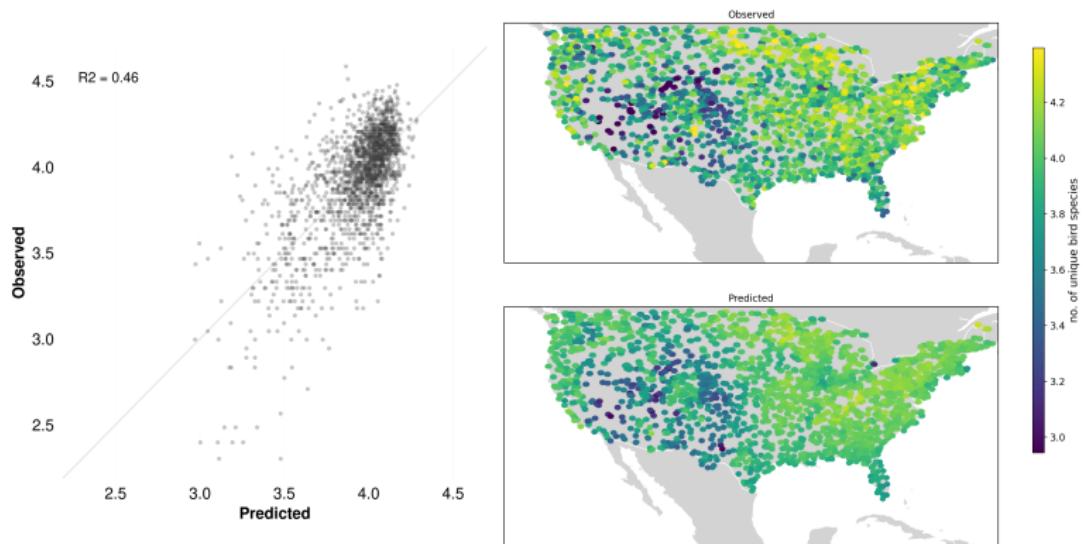
www.mosaiks.org

Appendix

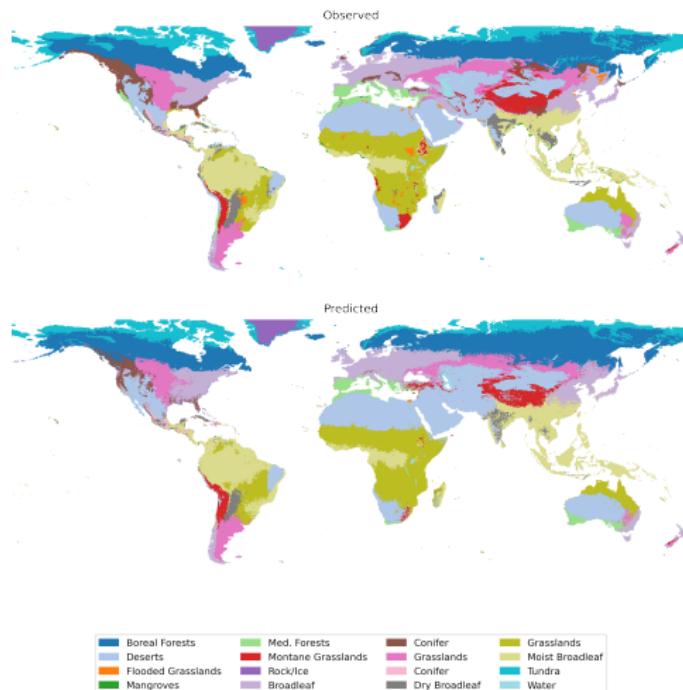
Breeding bird species diversity

Source: U.S. Geological Survey

Description: Count of the unique species documented by all road segments



Classifier Example



Test and cross-validated performance

