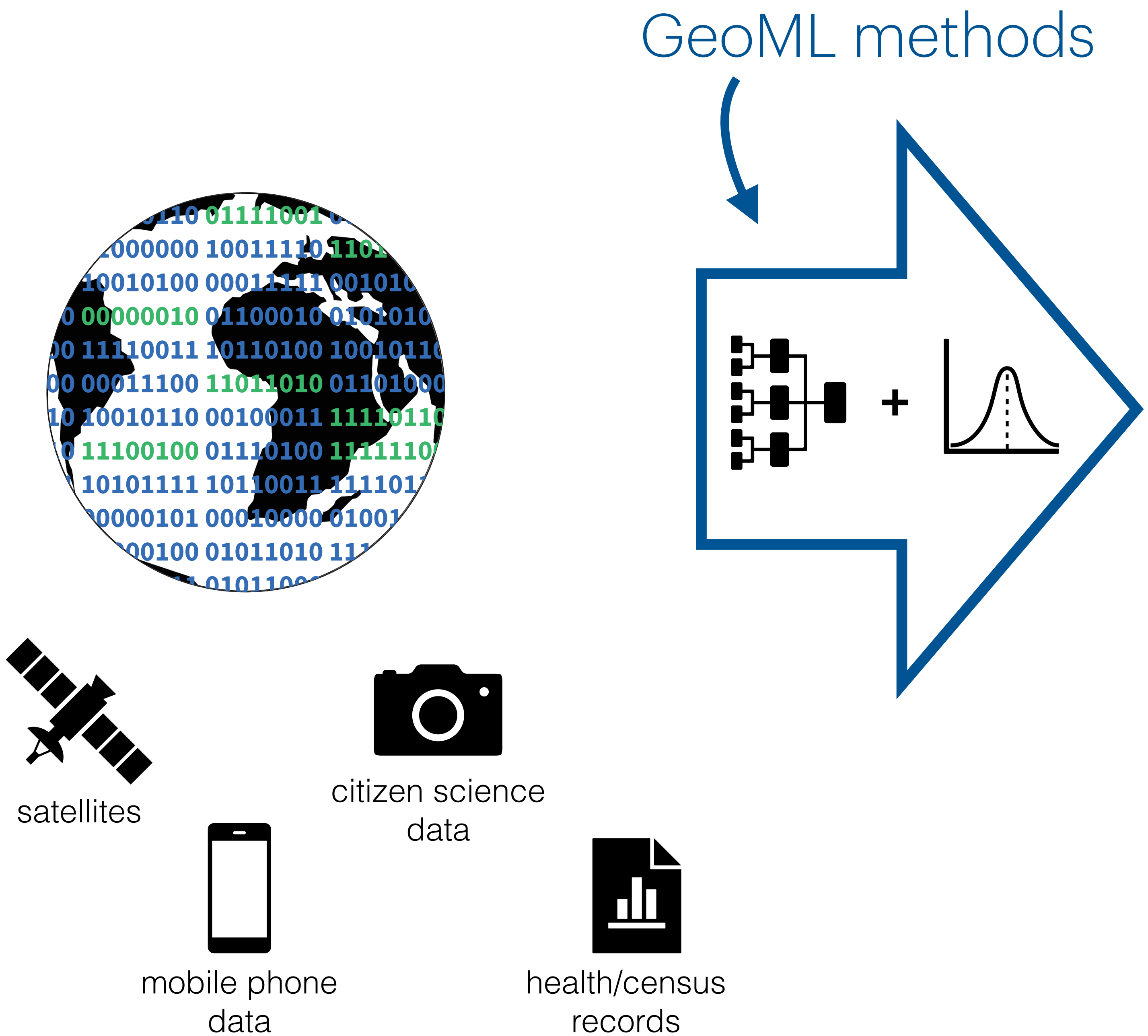
We need to talk (more) about uncertainty in geospatial machine learning

Esther Rolf
Assistant Professor,
University of Colorado Boulder Computer Science

UCSB MOSAIKS Training, January 21, 2025

ML can transform environmental monitoring by extracting crucial information from geospatial data



Mapping tree canopy height and its connection to biodiversity.

Detecting artisanal mining and its connection to health outcomes.

1000+ earth observation satellites collect over **90TB** data / day.

Combining satellite imagery and machine learning (**SatML**) can help researchers and policymakers monitor our world and act in it.

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Environmental monitoring

- tracking species populations
- mapping built infrastructure
- biodiversity mapping

Article

Change Detection of Deforestation in the Brazilian Amazon Using Landsat Data and Convolutional Neural Networks

Pablo Pozzobon de Bem, Osmar Abílio de Carvalho Junior *, Renato Fontes Guimarães and Roberto Arnaldo Trancoso Gomes

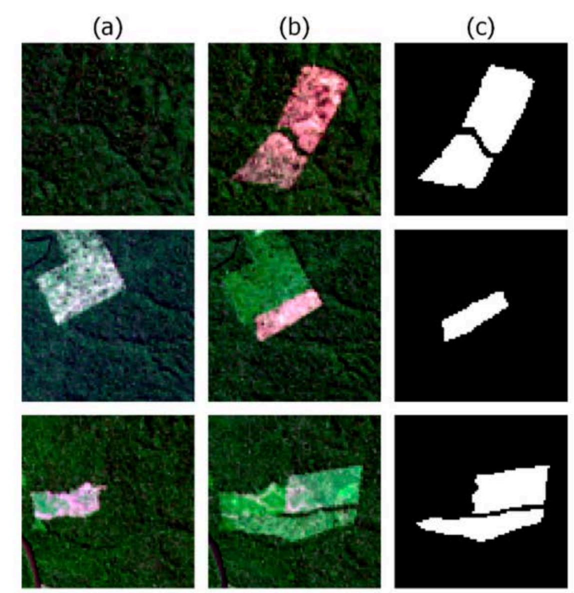

Figure 4. Example of the change mapping in three locations between (**a**) 2017 and (**b**) 2018 and the respective (**c**) rasterized deforestation mask.

Figure from de Bem et al., Remote Sensing 2020.

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Disaster response

- estimating damages from natural disasters with building detection
- finding and prioritizing the most vulnerable or affected areas

MIT Technology Review

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How AI can actually be helpful in disaster response

Humanitarian teams in Turkey and Syria are using machine learning to quickly scope out earthquake damage and strategize rescue efforts

By Tate Ryan-Mosley

February 20, 2023

Islahiye, Turkey - Satellite imagery (left) and the output from xView2 (right)

MAXAR TECHNOLOGIES (LEFT); UC BERKELEY/DEFENSE INNOVATION UNIT/MICROSOFT (RIGHT)

Article: https://www.technologyreview.com/2023/02/20/1068824/ai-actually-helpful-disaster-response-turkey-syria-earthquake/

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Global policy

- food security / yield prediction
- fine grained poverty estimates

Microestimates of wealth for all low- and middle-income countries

Guanghua Chi[a,1,2], Han Fang[b], Sourav Chatterjee[b], and Joshua E. Blumenstock[a,1,3]

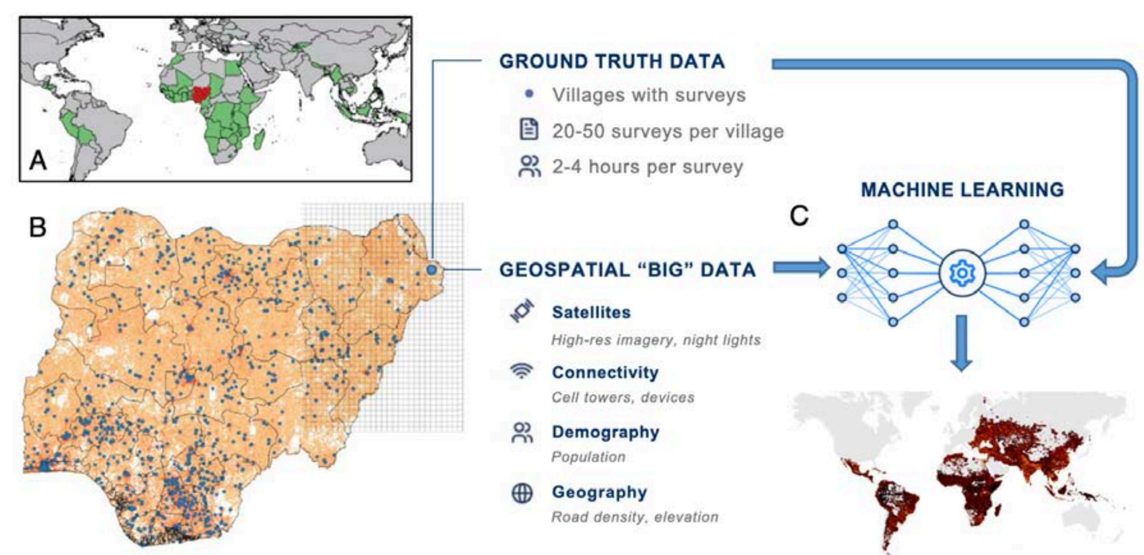
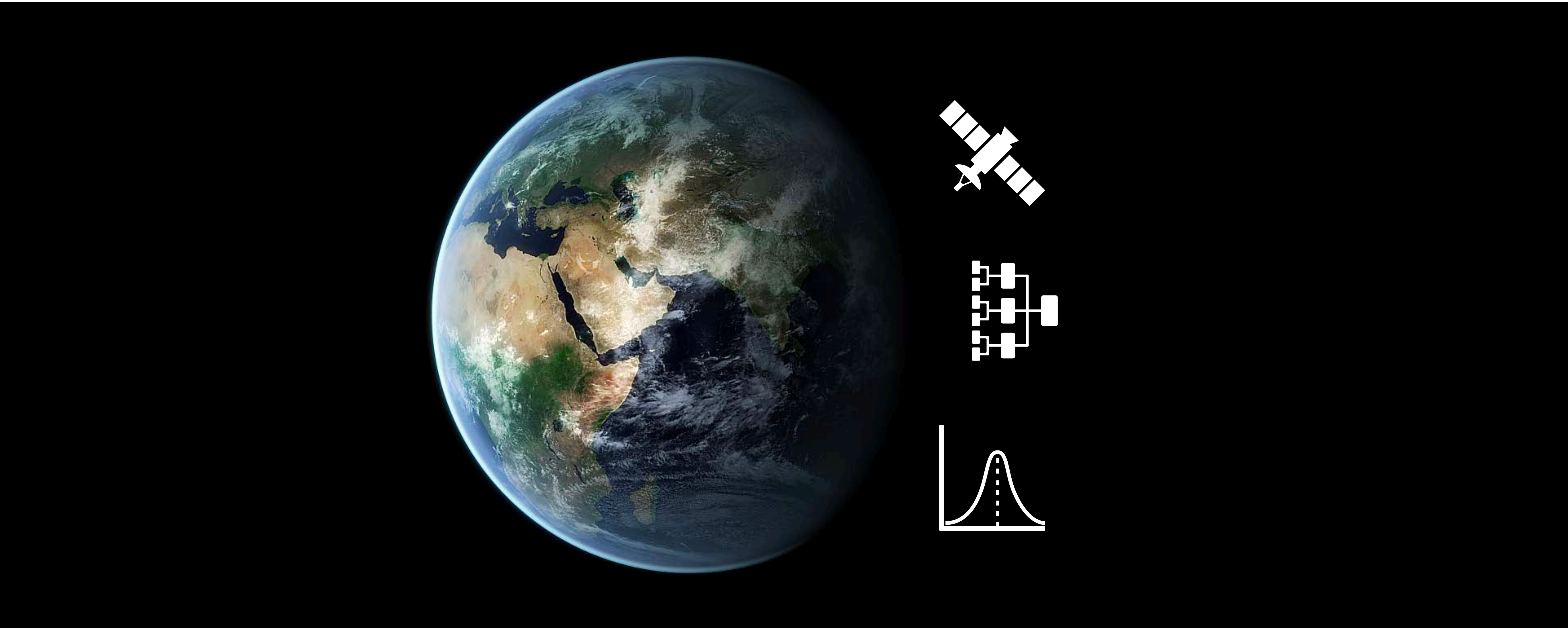


Fig. 2. Overview of approach. (A) Nationally representative household survey data are obtained from 56 different countries around the world. (B) In Nigeria, for example, there are 40,680 households surveyed in 899 unique survey locations ("villages"). Geospatial "big" data from satellites and other existing sensors are also sourced from each location. (C) These data are used to train a machine-learning algorithm that predicts microregional poverty from nontraditional data, even in regions where no ground-truth data exists.

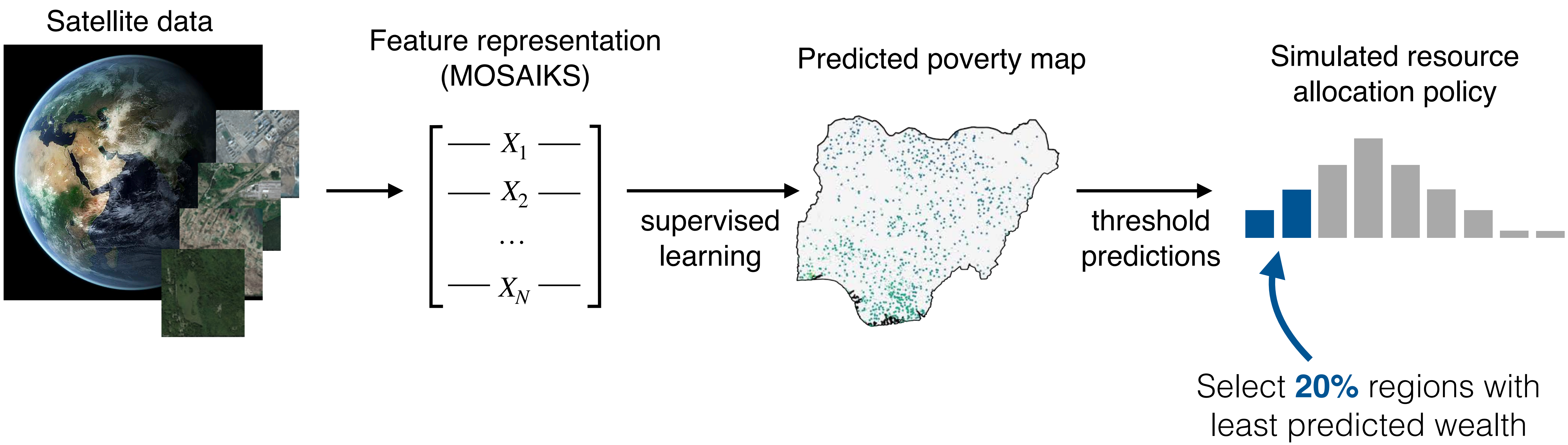
Figure from Chi et al., PNAS 2022

It is easier than ever to make maps with satellite imagery and machine learning...

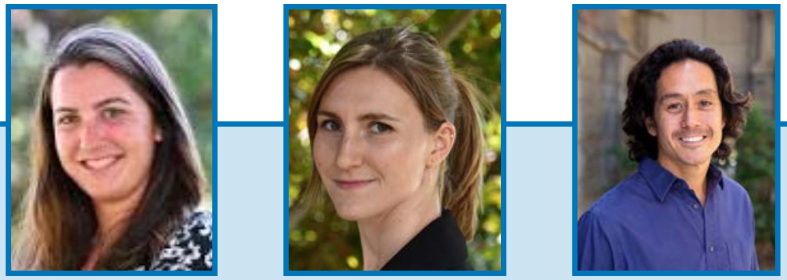


... it is crucial that we understand and convey the limitations and uncertainty of mapped predictions.

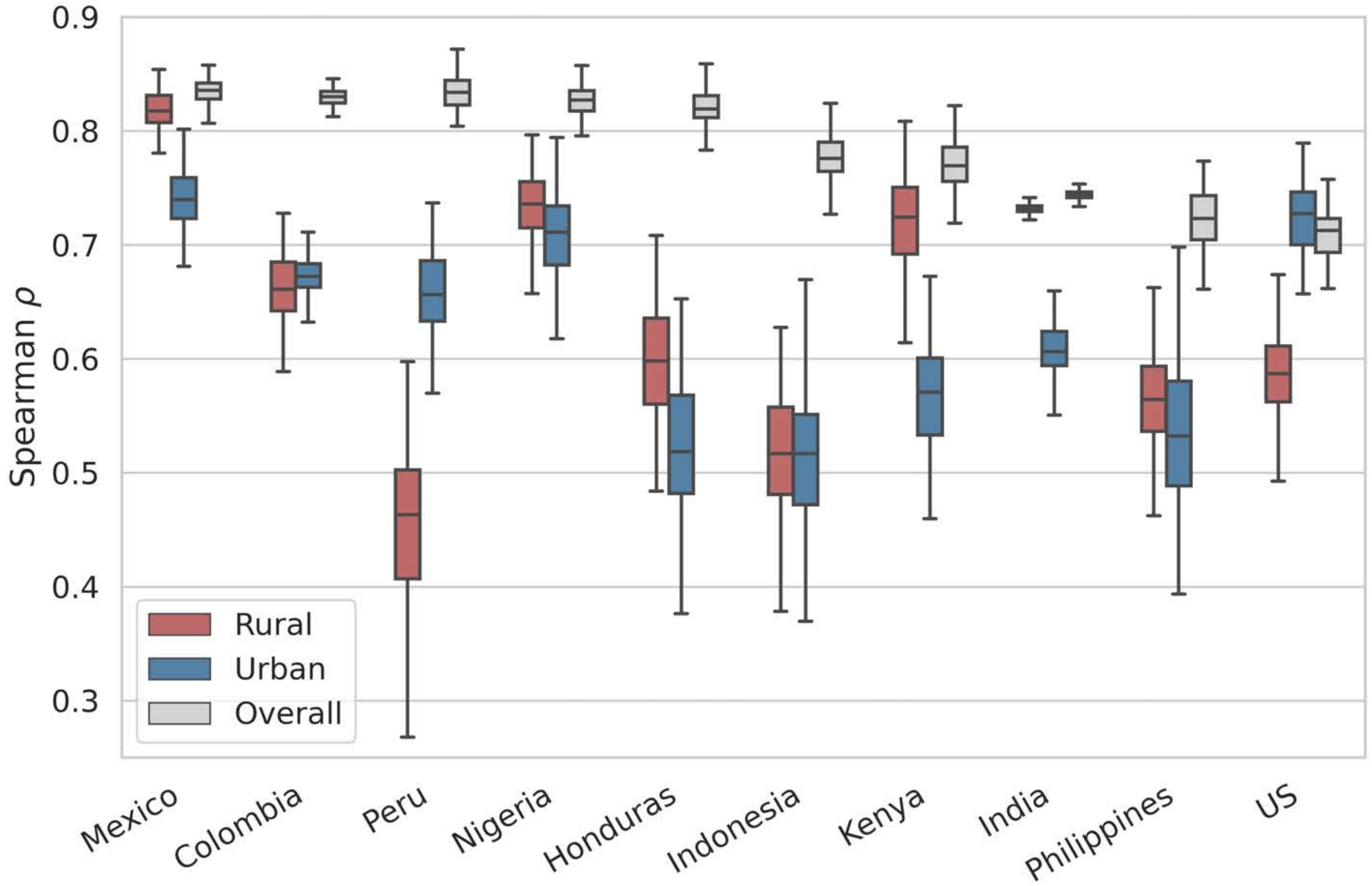
Example: (simplified) poverty prediction with SatML



Aiken*, Rolf*, Blumenstock. *Fairness and representation in satellite-based poverty maps: Evidence of urban-rural disparities and their impacts on downstream policy.* IJCAI 2023.



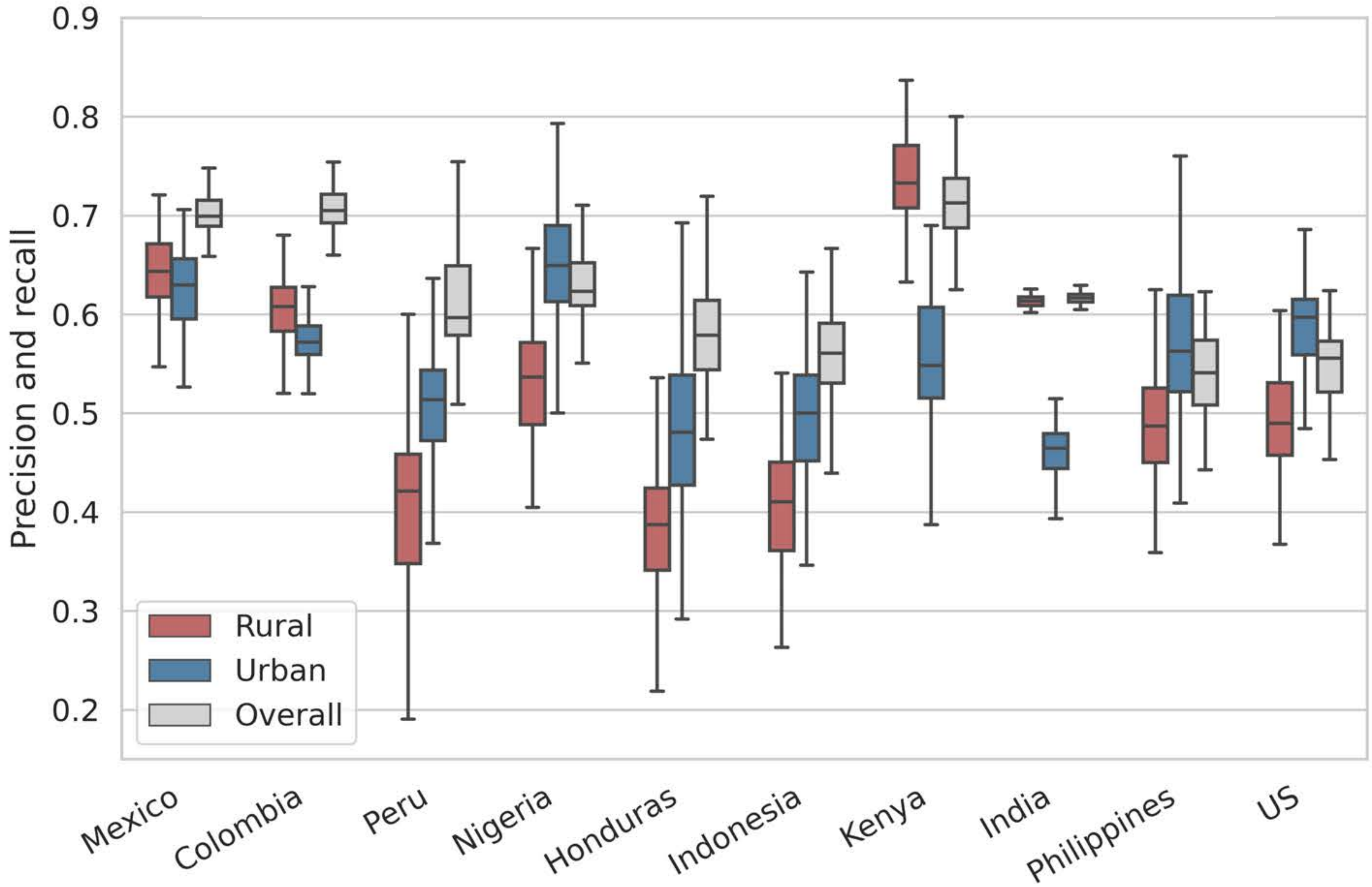
Prediction performance is lower if evaluate only within rural or urban regions vs. in each country as a whole.



**This systematically replicates analysis in [1] for ten countries across the globe.*

[1] Christopher Yeh, Anthony Perez, Anne Driscoll, George Azzari, Zhongyi Tang, David Lobell, Stefano Ermon, and Marshall Burke. Using publicly available satellite imagery and deep learning to understand economic well-being in Africa. Nature communications, 2020.

Targeting effectiveness is lower if aid program allocates resources just within rural or urban areas.



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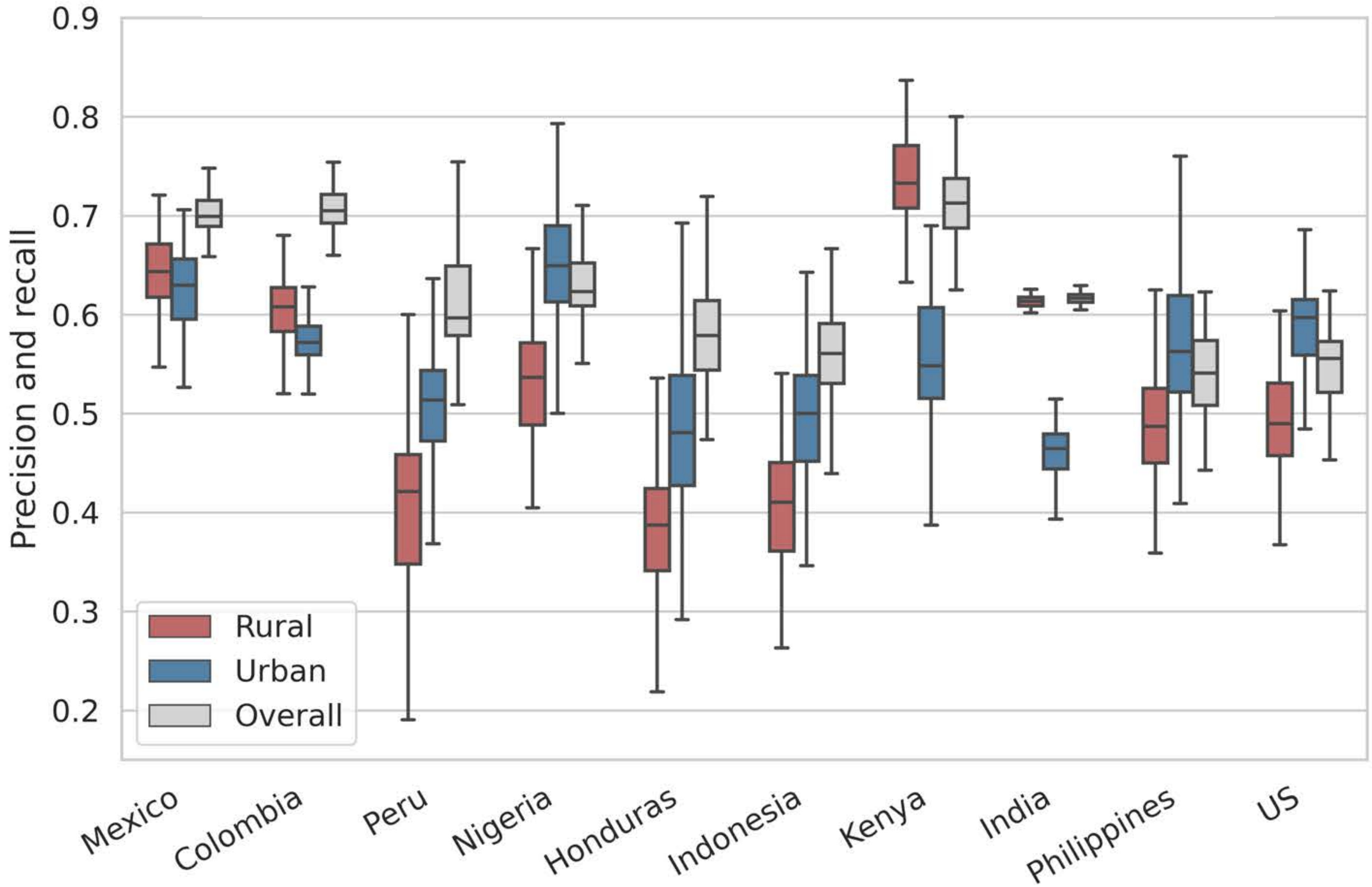
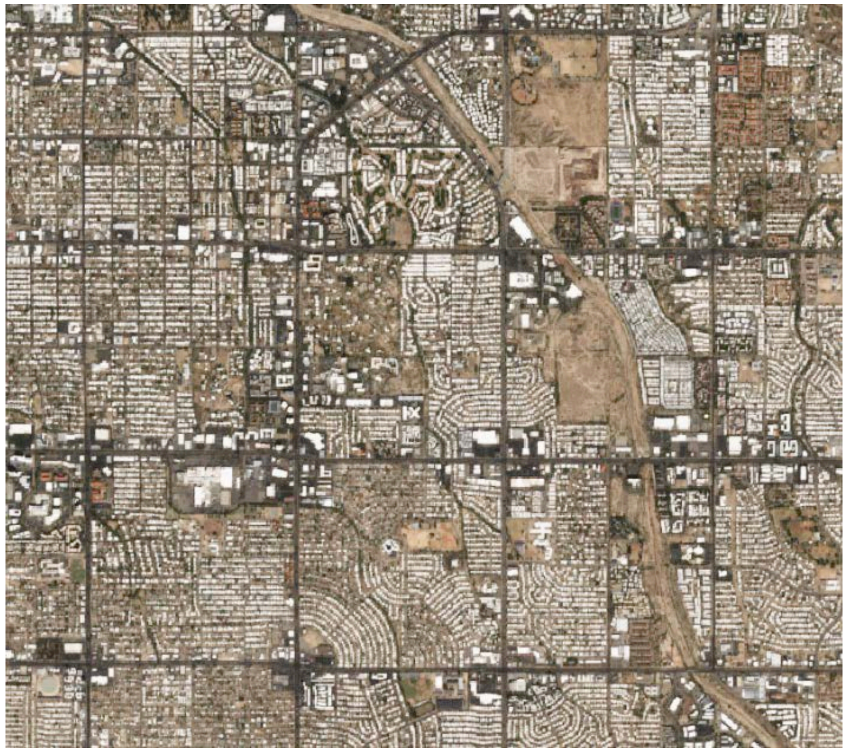


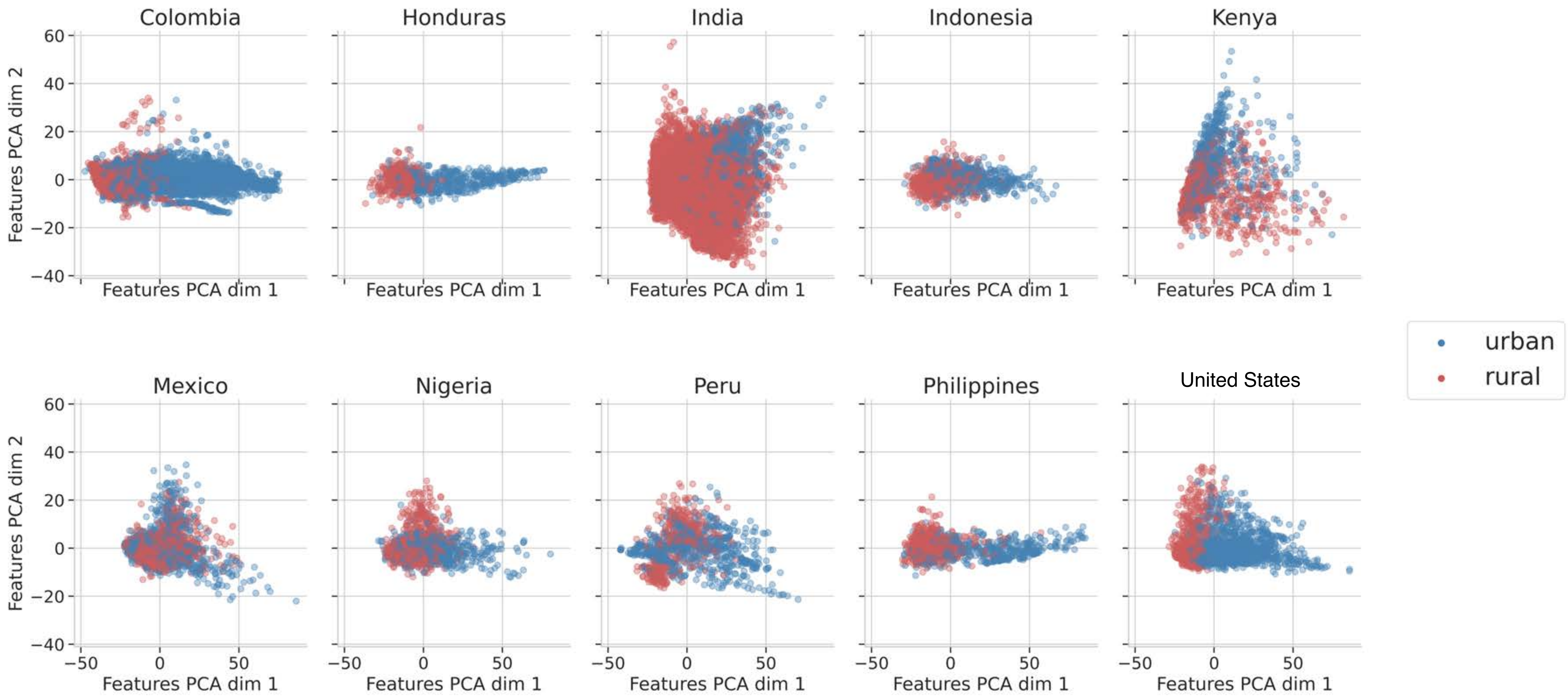
➡ policy implication: sub-population targeting likely less effective than population performance would imply

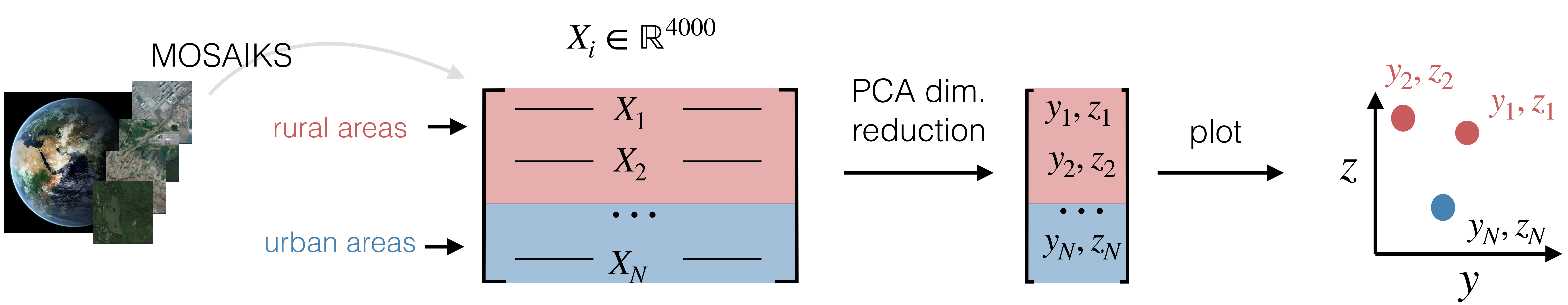
What information does satellite imagery convey about relative wealth across regions?



Sentinel 2 satellite imagery accessed via Microsoft Planetary Computer

Image embedding distributions: urban and rural

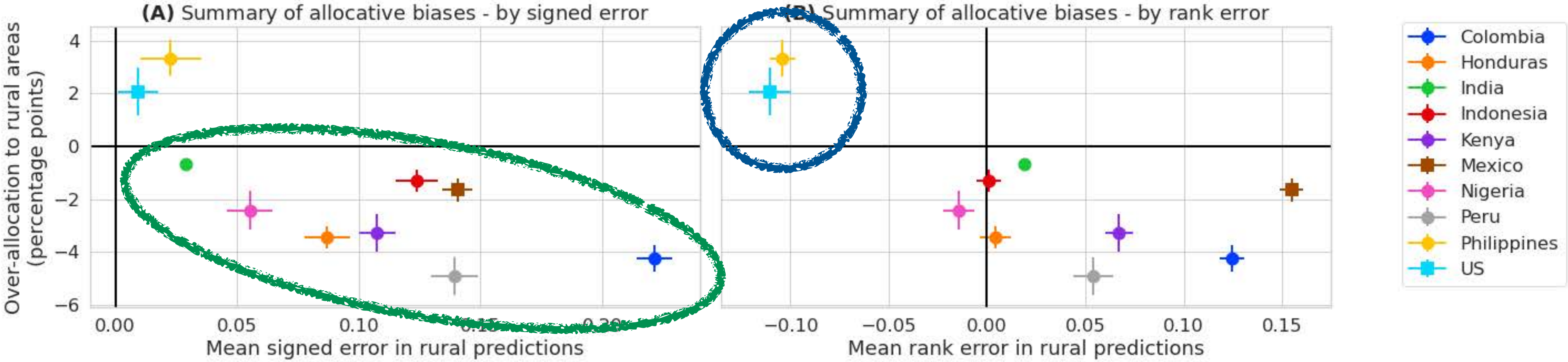




Two (competing) phenomena contribute to allocational disparities:

1) (Over)reliance on correlation between wealth and urbanization

2) Reversion of predictions to the population means



Satellite data only gives a partial representation of many ground phenomena we wish to map

➡ Systematic errors in predictions

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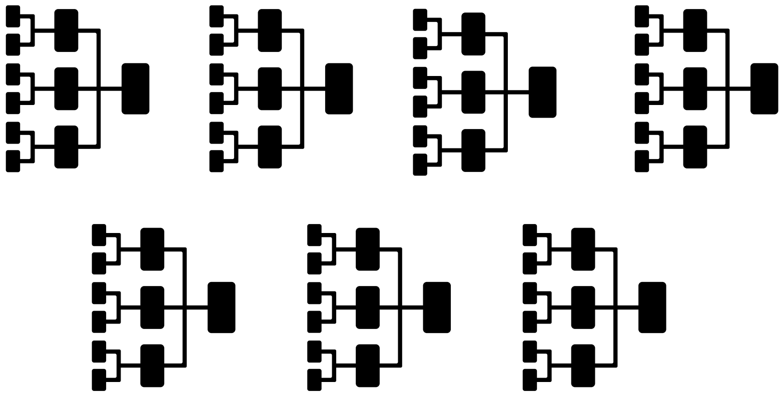
➡ Systematic errors in predictions

We need to convey the uncertainty and errors in GeoML predictions!

Conveying Uncertainty: (1) ensemble-based approaches

1. Train an ensemble of different models (e.g., with different random seeds, or training data)



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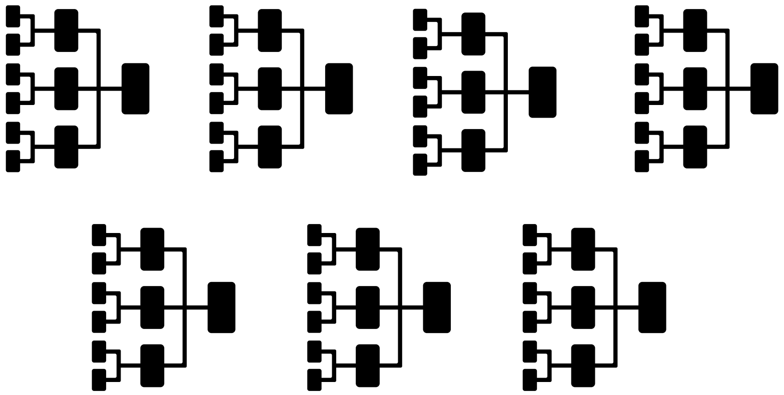

2. For each test point, use all models in the ensemble to predict:

- Final prediction: mean
- Spread: standard deviation of predictions from the models

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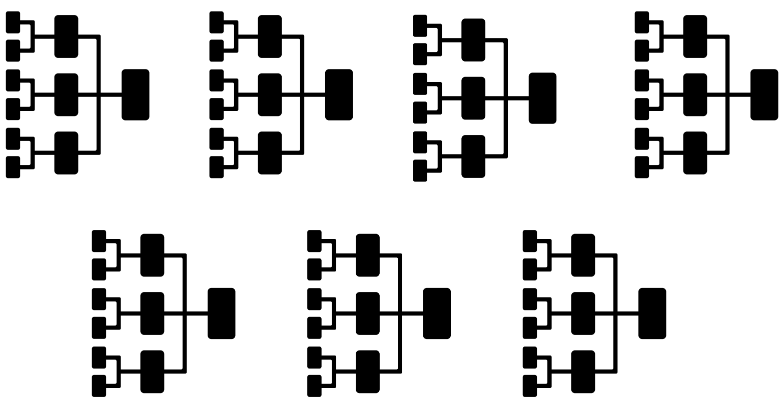

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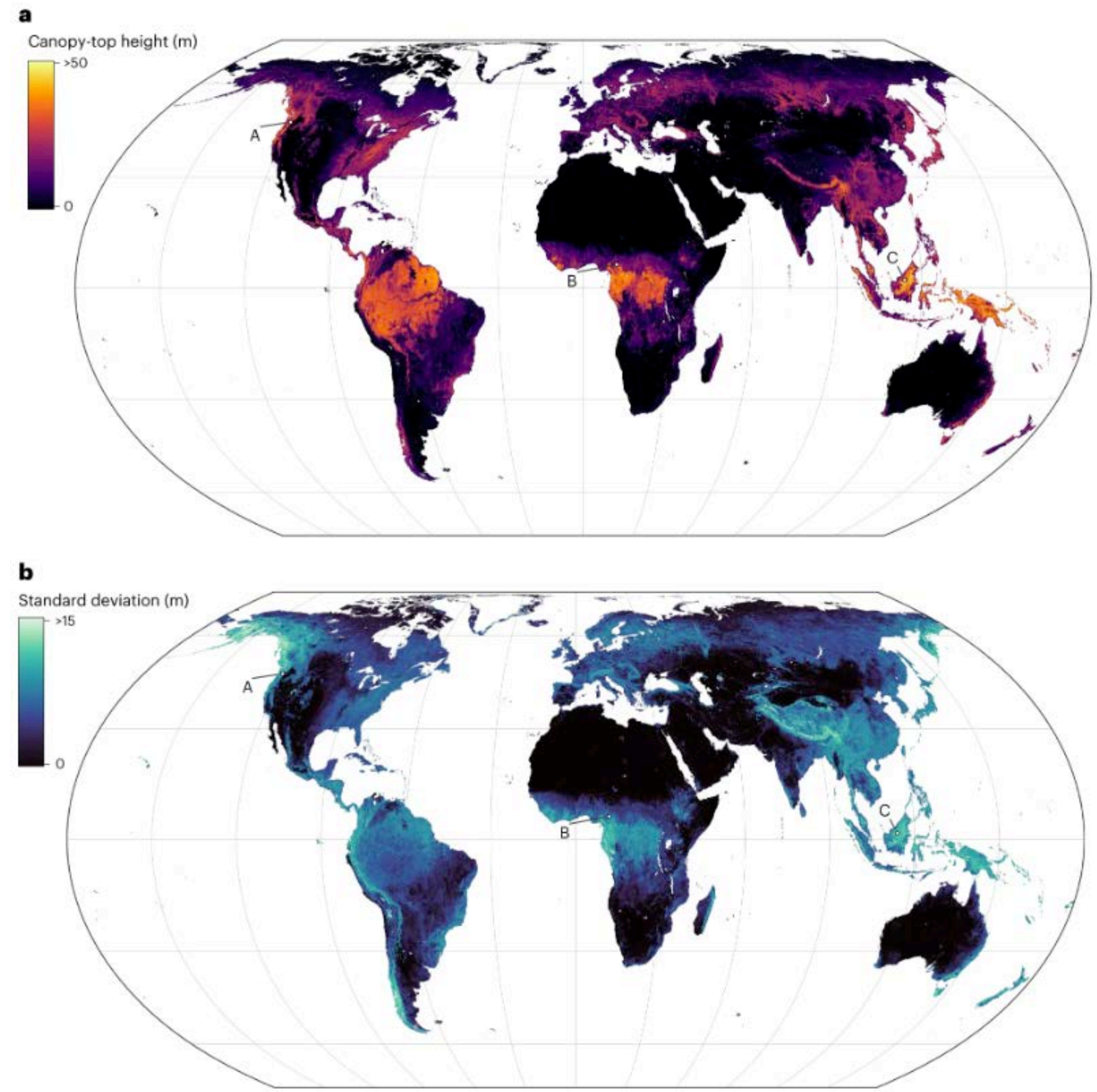
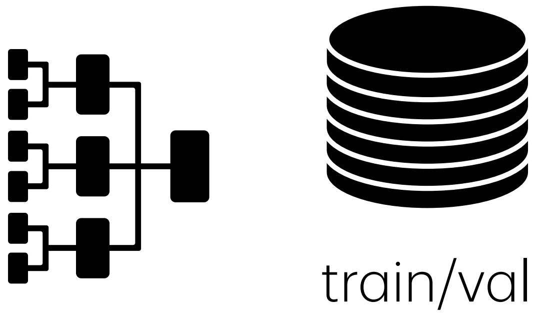


A high-resolution canopy height model of the Earth
Lang et al. 2023

Conveying Uncertainty: (2) calibration-based approaches

1. Train model on train/val set



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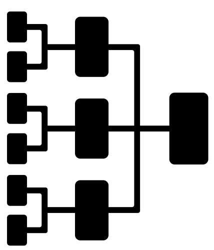
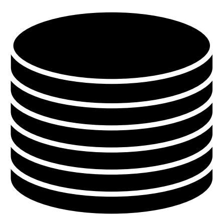
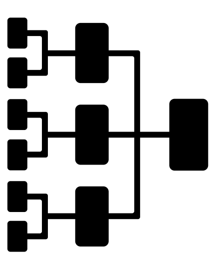
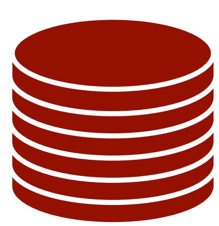




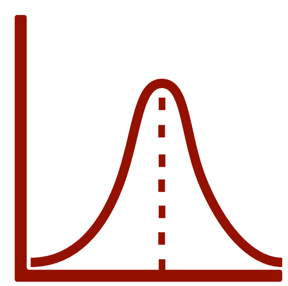
train/val

2. Predict on **new** calibration set;
observe errors





Calibration data



Errors

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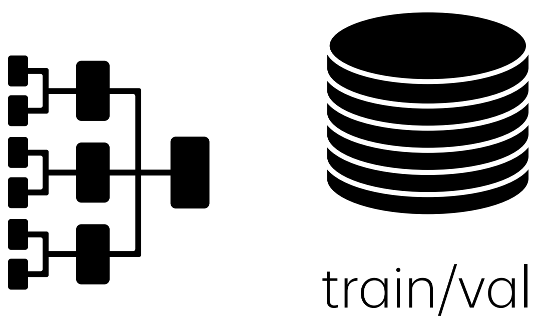

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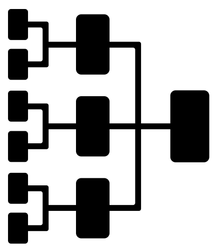

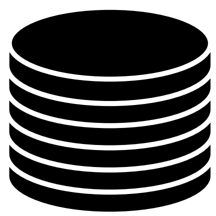

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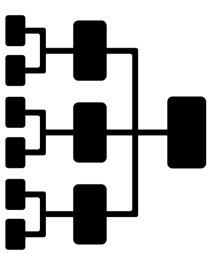

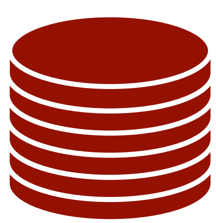

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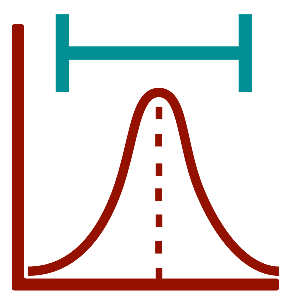

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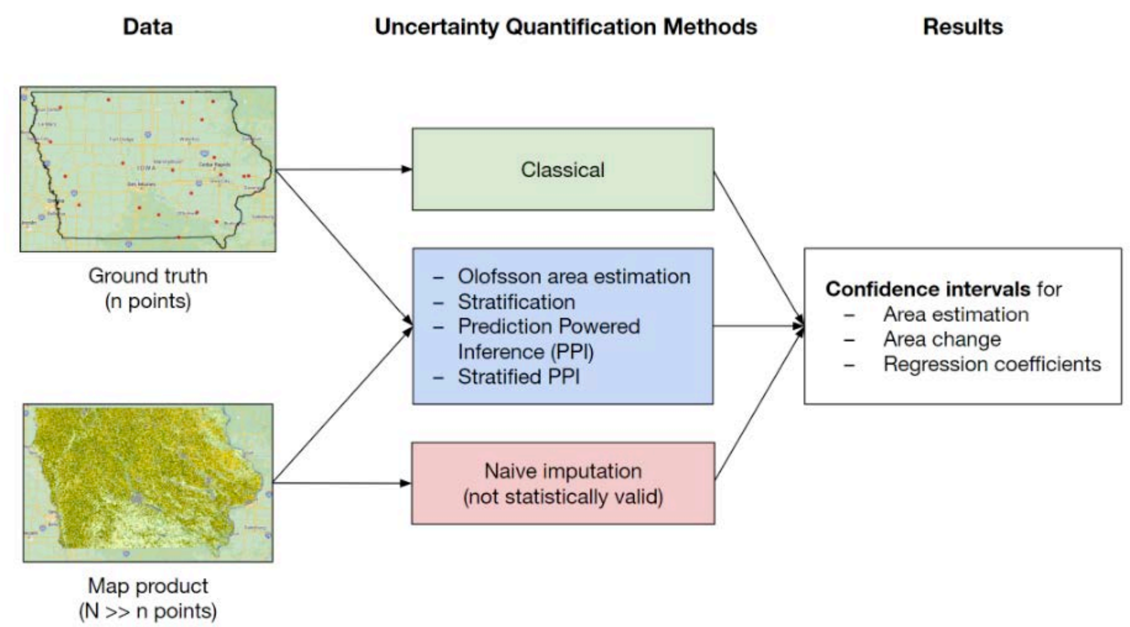

Quantifying uncertainty in area and regression coefficient estimation from remote sensing maps
Lu et al. 2024

Estimating Prediction Performance: spatially-aware evaluation

Challenge 1: multifaceted goals

Map accuracy vs. model performance

How well does the predicted map reflect ground truth conditions?

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Answering this requires a careful (probability) sample of reference ground truth values (coverage)

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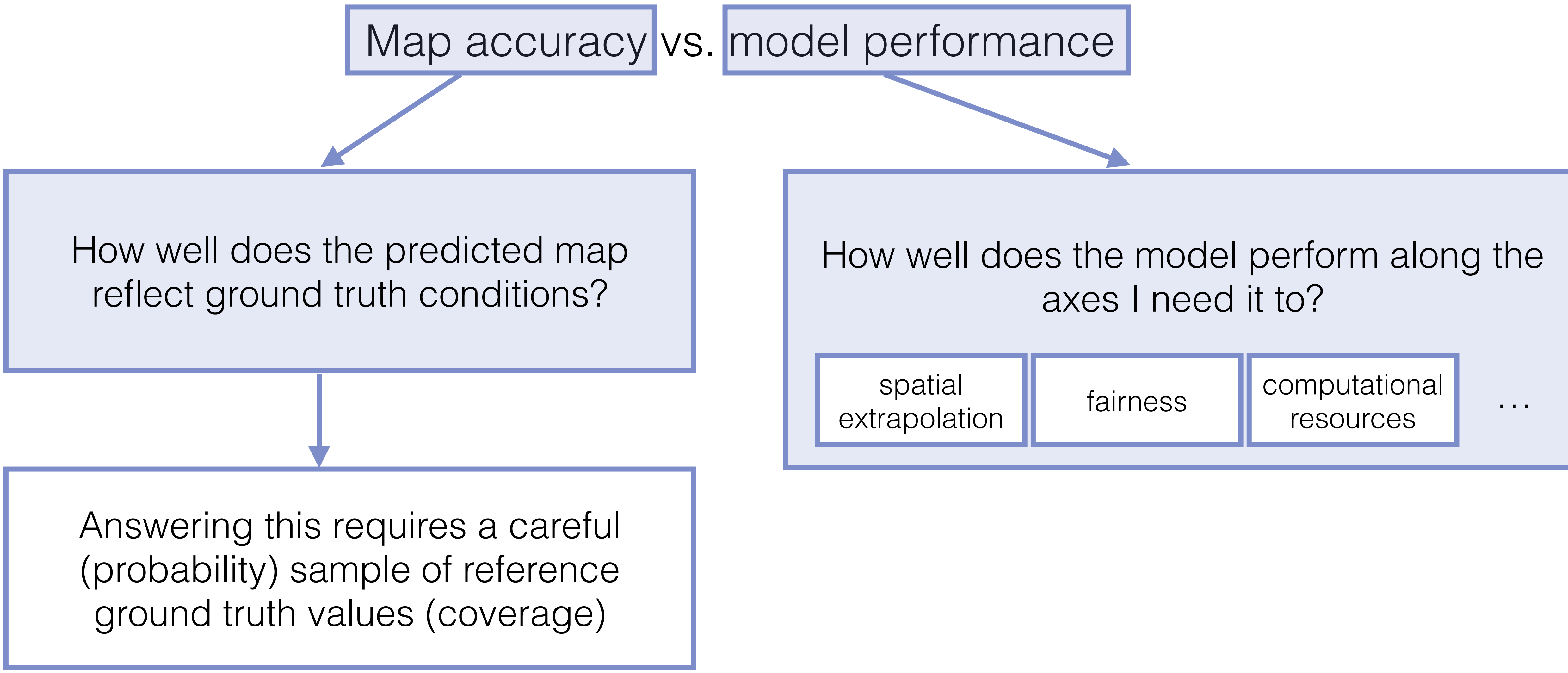

Challenge 1: multifaceted goals

Map accuracy vs. model performance

How well does the predicted map reflect ground truth conditions?

Answering this requires a careful (probability) sample of reference ground truth values (coverage)

How well does the model perform along the axes I need it to?

spatial extrapolation | fairness | computational resources | . . .

Answering this requires acknowledging the main axes of performance, evaluation strategies to asses them

Geospatial ML often most valuable when filling in **substantial coverage or quality gaps in available label data.**

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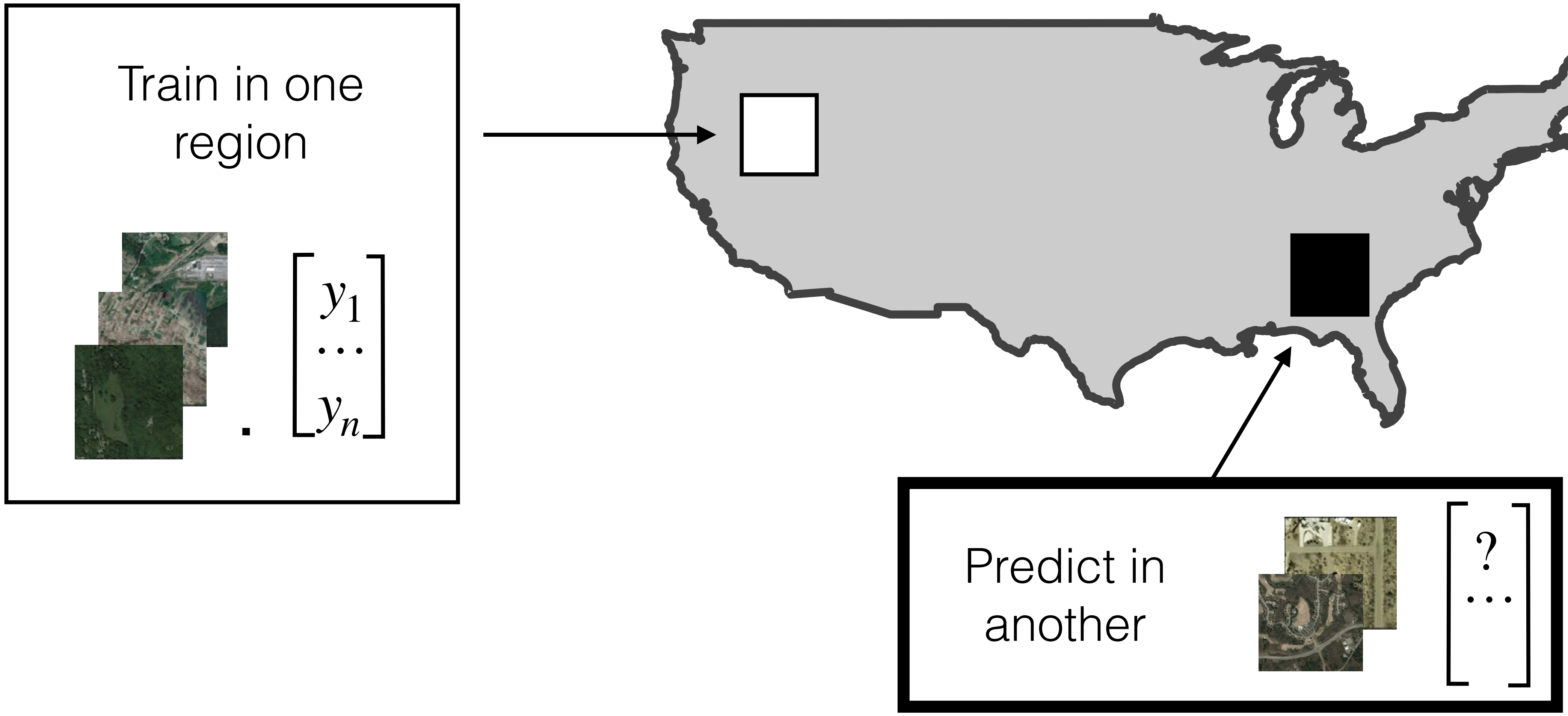
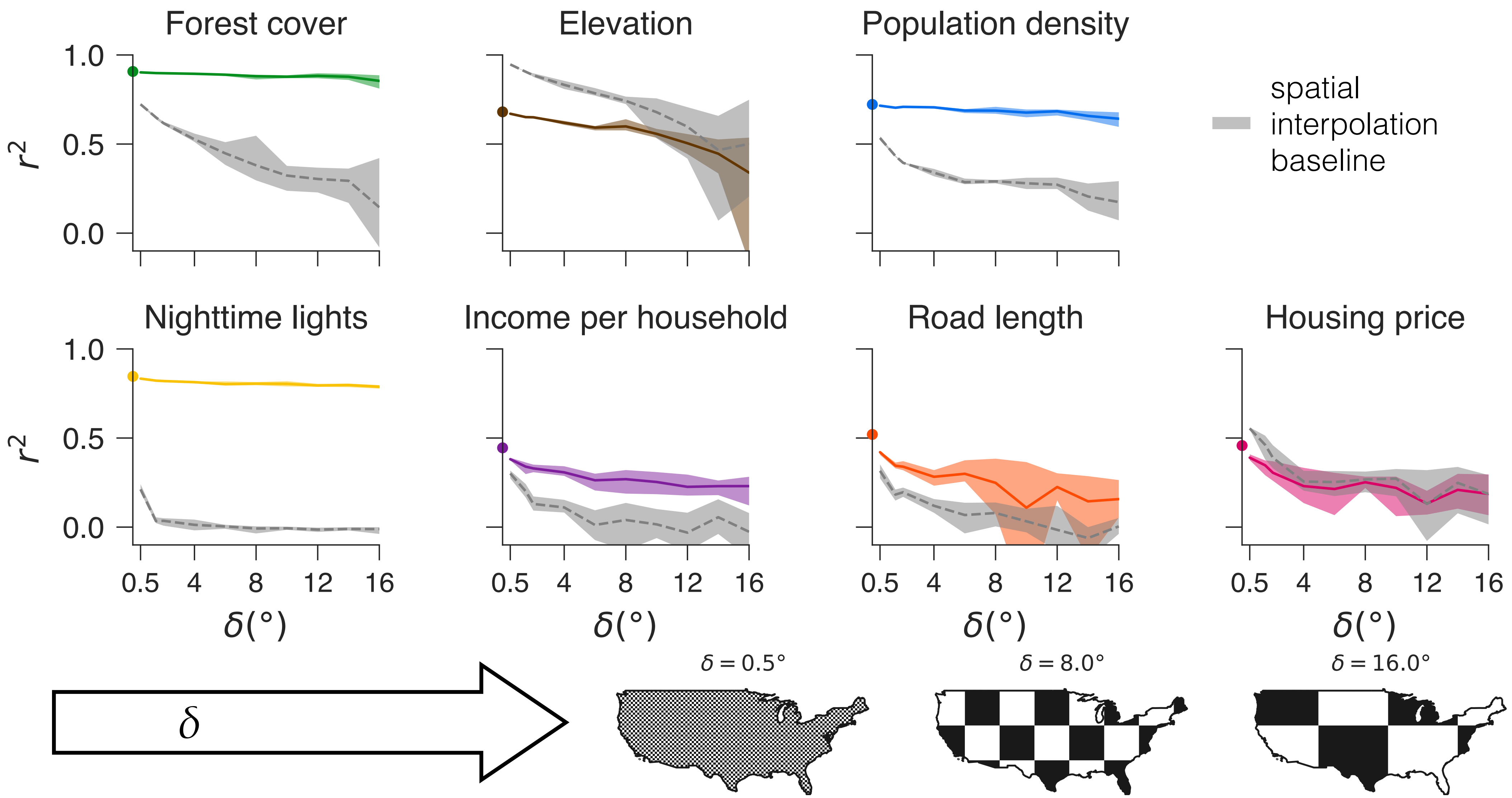


Models perform differently for spatial extrapolation at different scales

e.g.



Spatiotemporal (auto)correlations

Tobler's first law of geography:

"everything is related to everything else, but
***near things are more related than distant things**."*

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Example: "neighborhood" effects, e.g. in housing prices

Spatiotemporal (auto)correlations

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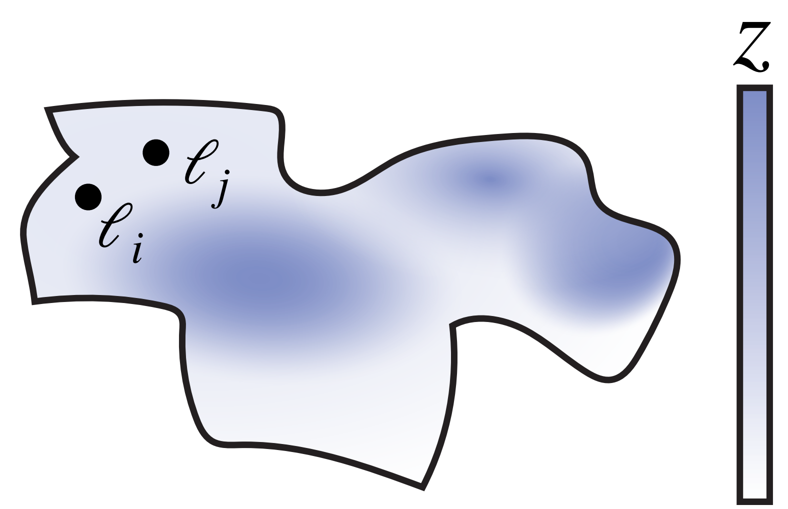
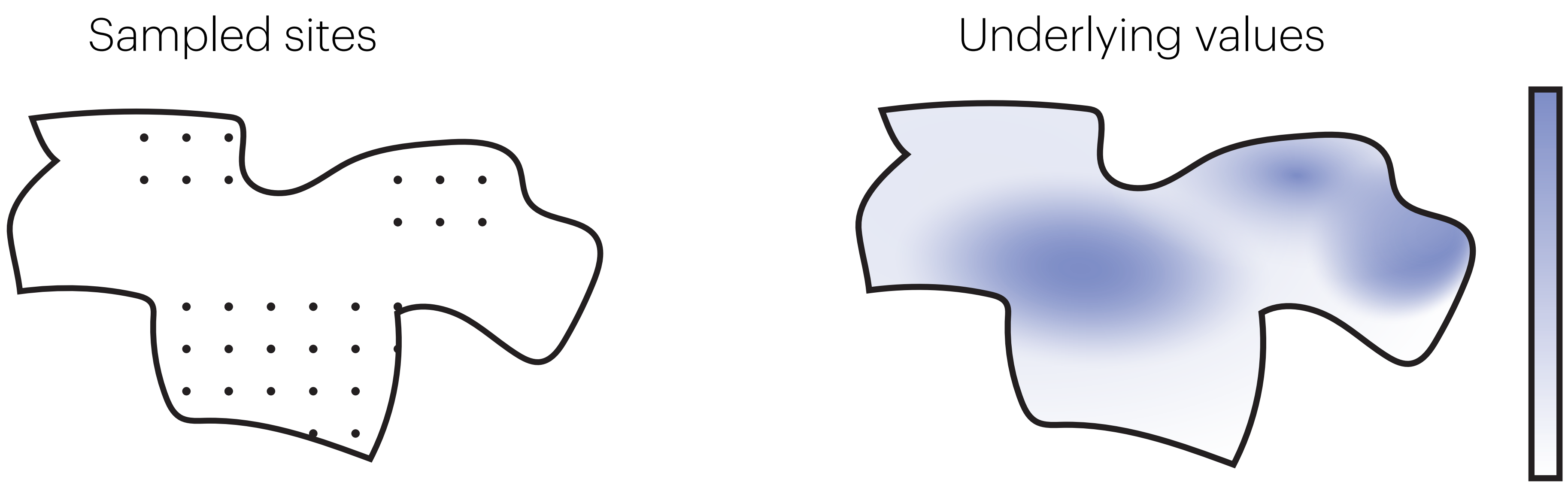
Spatial auto-correlation of random process Z:

$$R_{ZZ}(\ell_i, \ell_j) = \frac{\mathbb{E}\left[Z(\ell_i)Z(\ell_j)\right]}{\sigma_i \sigma_j}$$



For **spatial variables**, we generally expect $R_{ZZ}(\ell_i, \ell_j) > 0$ when are ℓ_i and ℓ_j are close.

Spatiotemporal autocorrelations in data and predictions make it difficult to evaluate real-world model performance in the presence of data-gaps



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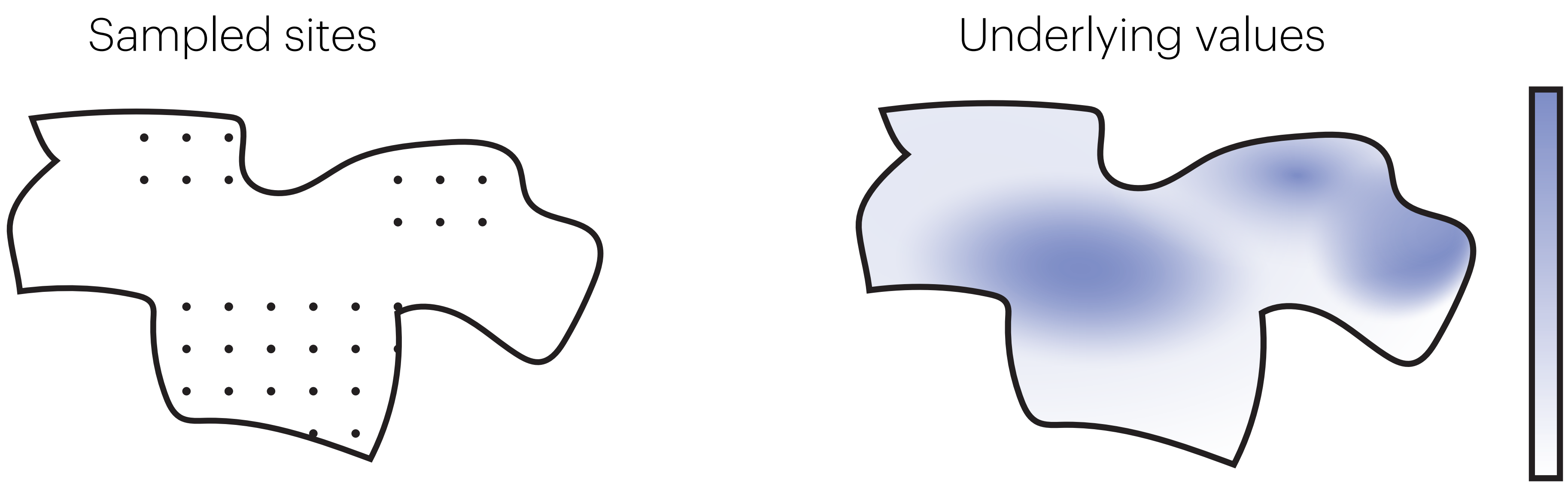
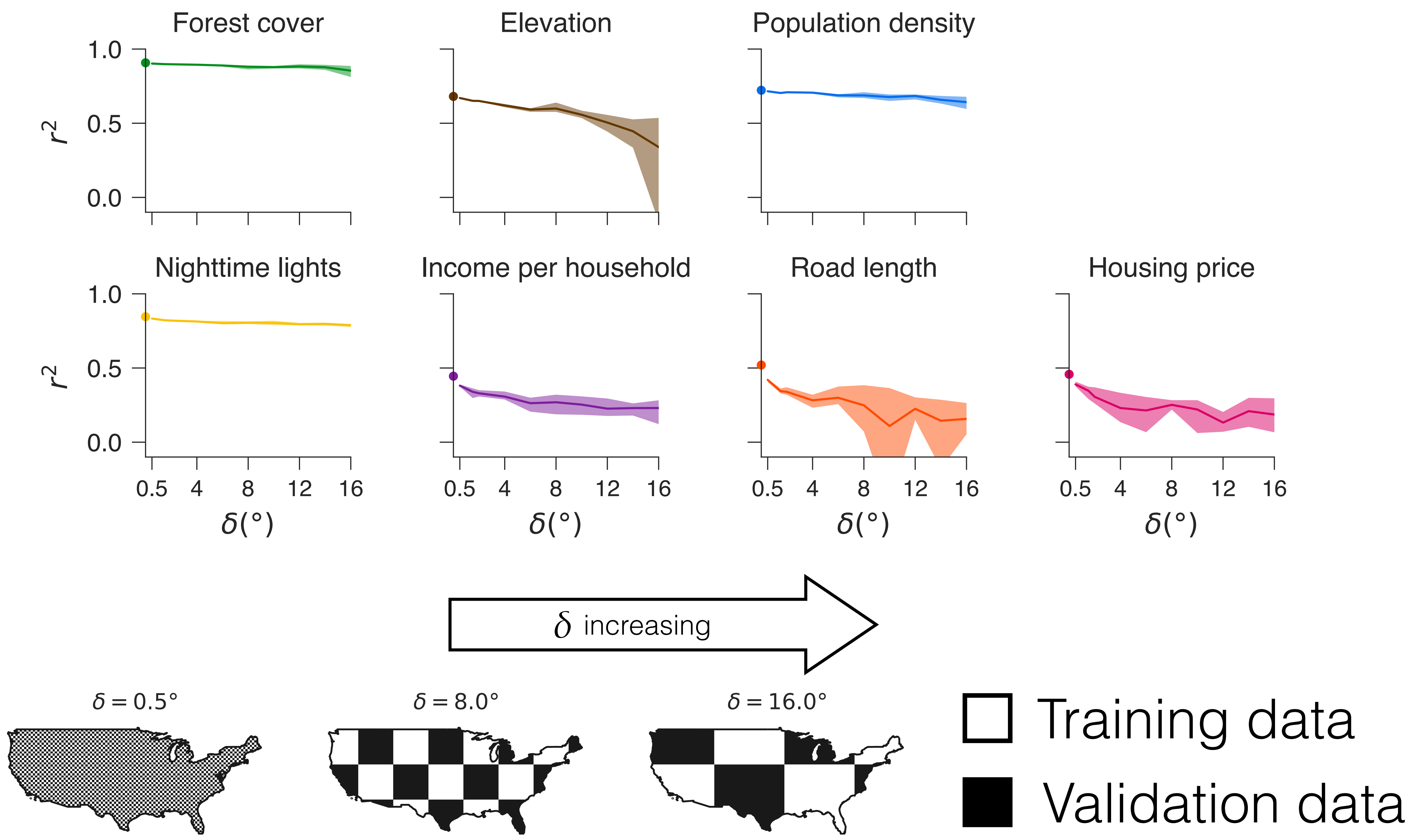
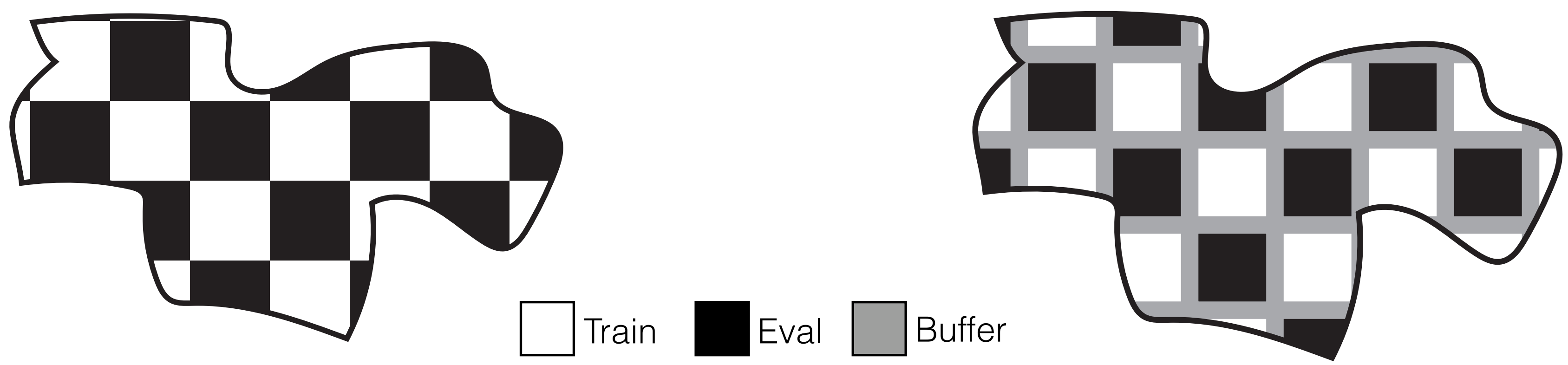


When label data are spatially (auto)correlated, **evaluating with an I.I.D. test split from a fixed (spatially biased) dataset can overestimate model accuracy.**

As degree of spatial extrapolation (δ) increases, performance degrades.



Spatially aware cross-validation can assess model suitability in out-of-domain prediction.



<u>Spatial block cross-validation</u>

- By blocks, admin boundaries, automatically generated clusters

<u>Buffered cross-validation</u>

- Spatial leave-one-out CV
- Buffered train/test blocks

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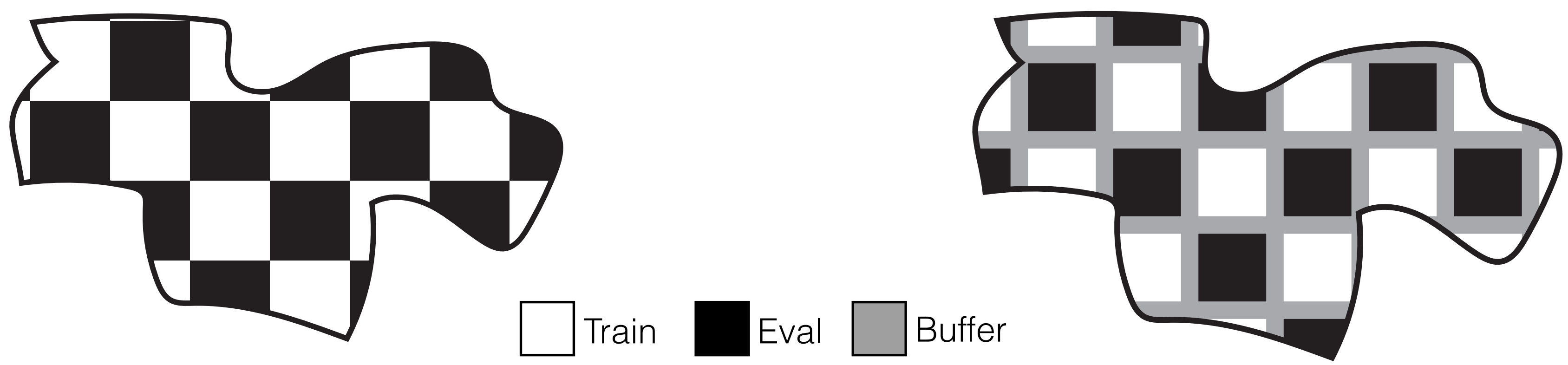

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But, spatial cross-val does not assess map *accuracy* (as a population parameter) [1,2].

[1] Wadoux, Heuvelink, De Bruin, Brus. Spatial cross-validation is not the right way to evaluate map accuracy, Ecological Modelling 2021.
[2] **Rolf**. Workshop on Machine Learning for Remote Sensing @ the International Conference on Learning Representations (ICLR), 2023.

Spatiotemporal autocorrelations in data and predictions make it difficult to choose the best model for spatial generalization

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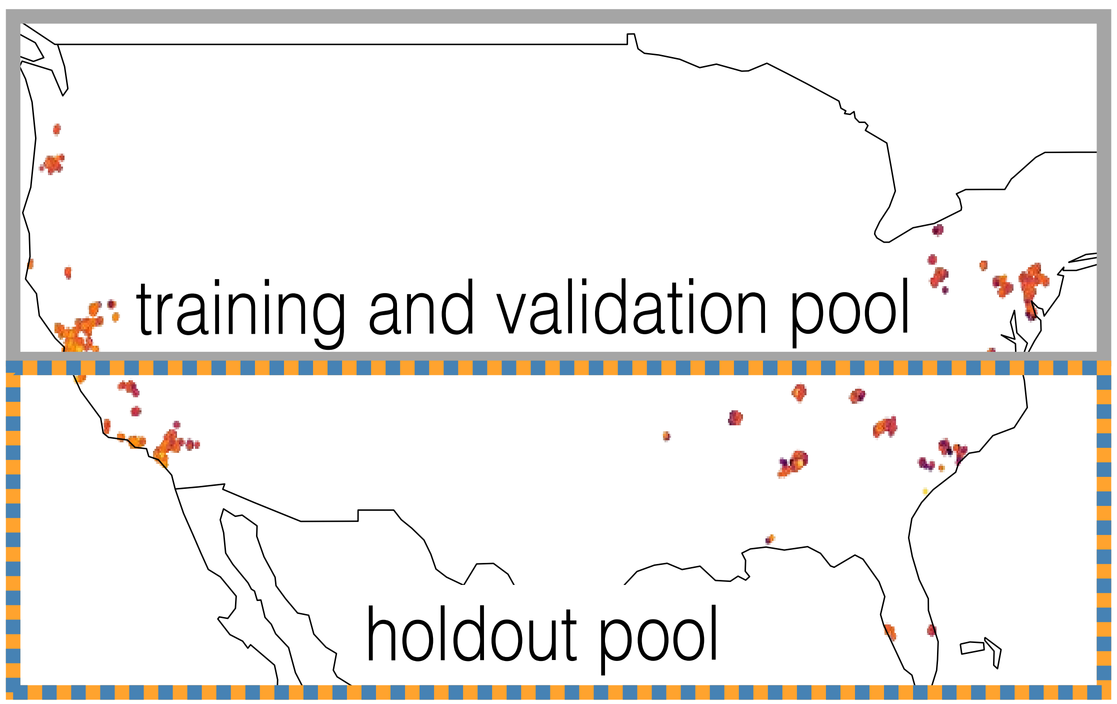
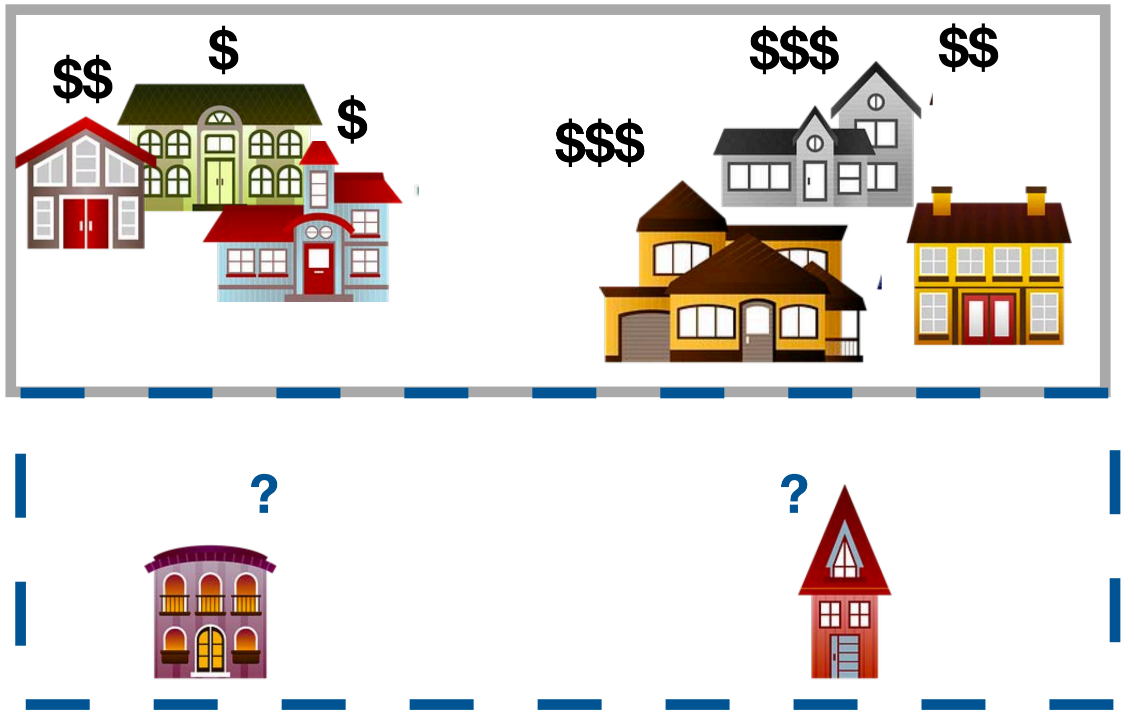
Should we use location as an input feature?





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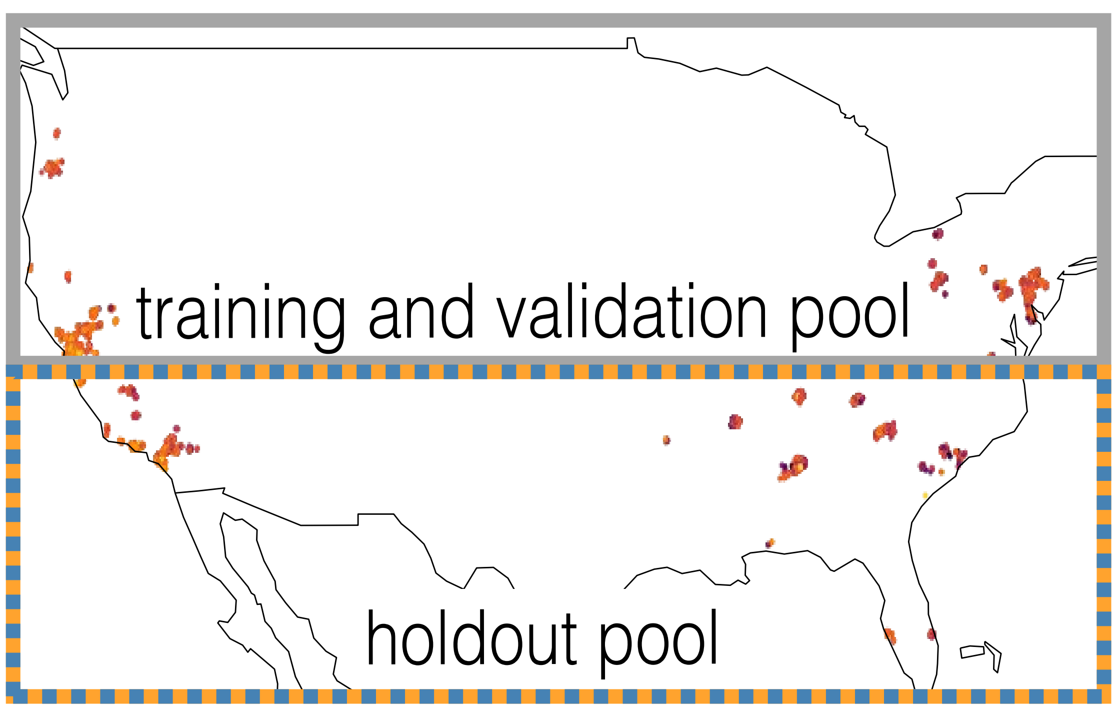
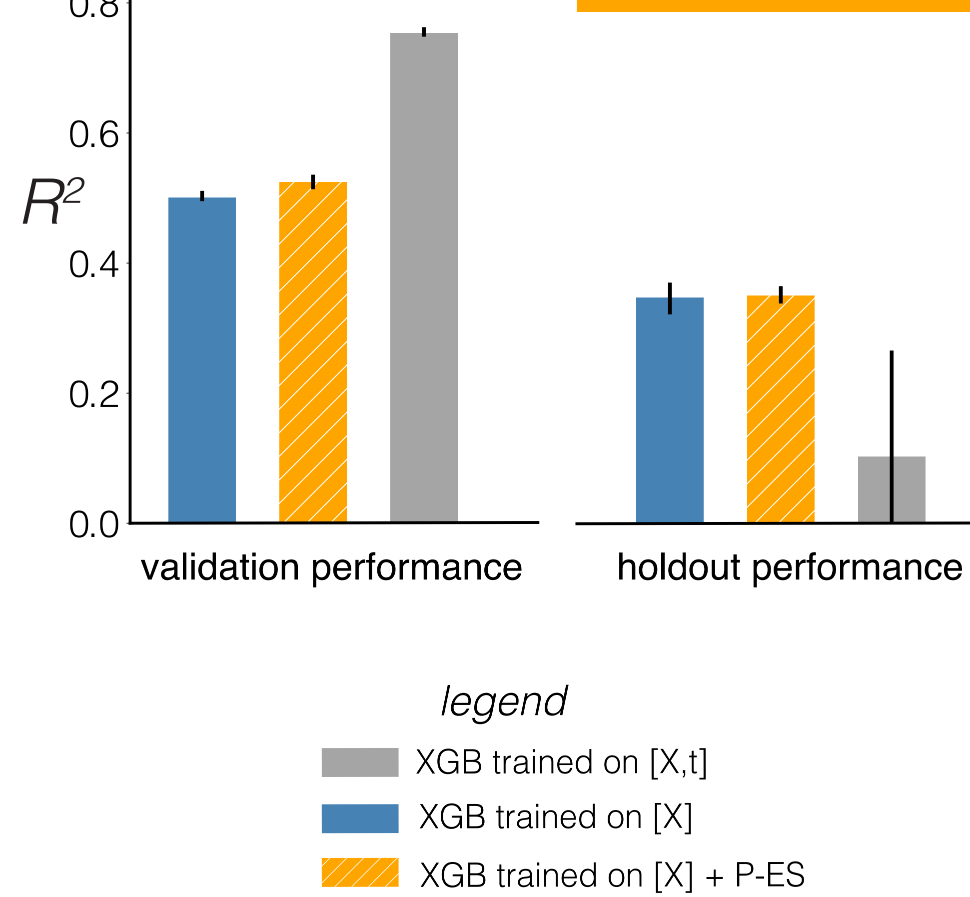
Should we use location as an input feature?

Yes

No

Use, but not as input





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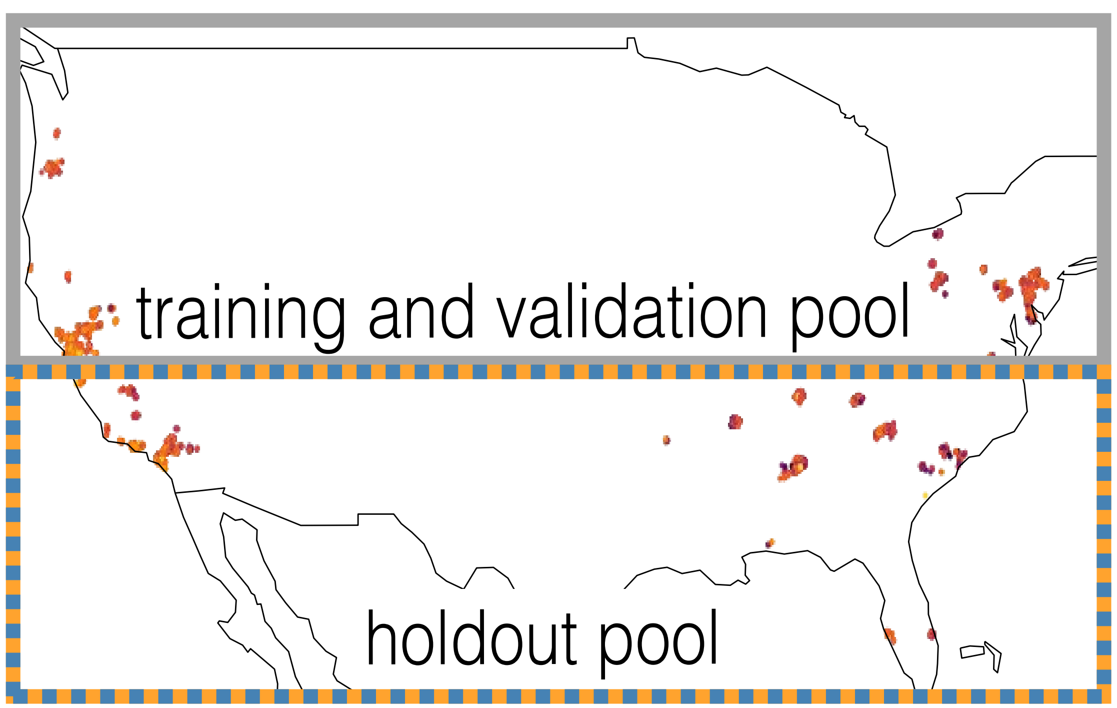

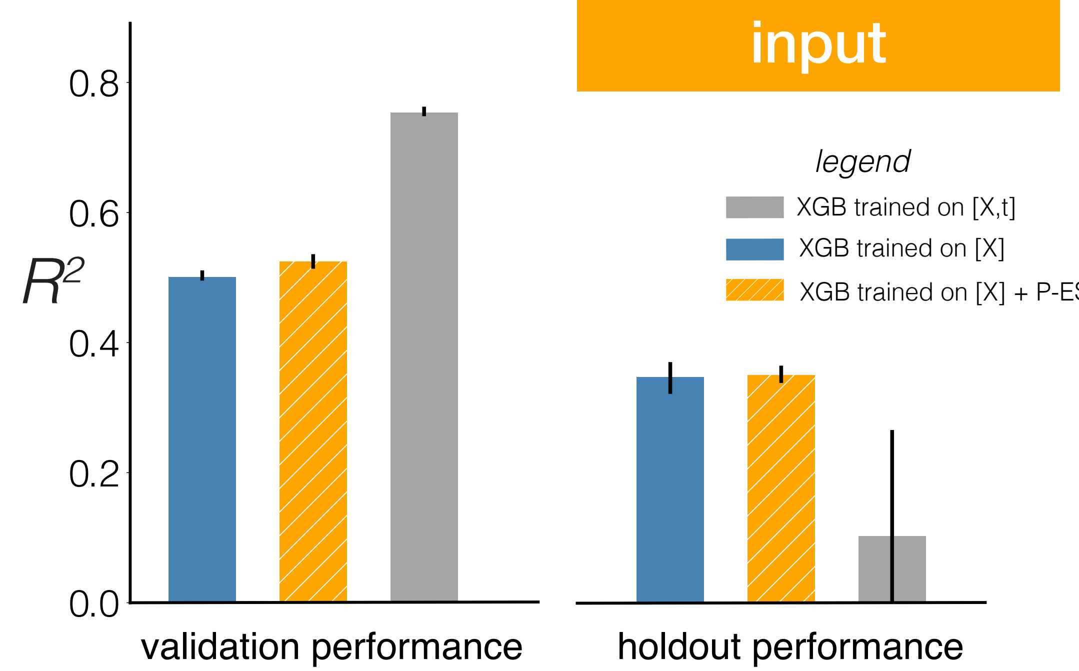

Rolf, Jordan, Recht. International Conference on Artificial Intelligence and Statistics (AISTATS) 2020.

Satellite data only gives a partial representation of many ground phenomena we wish to map

➡ Systematic errors in predictions

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➡ Systematic errors in predictions

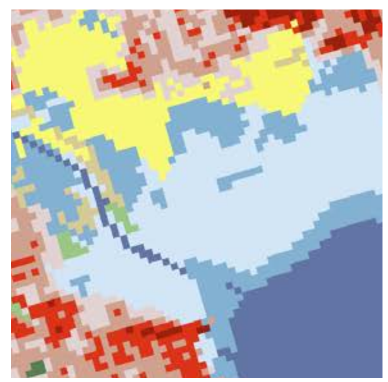
What if we had a more structured, uncertainty based approach for learning with geospatial data?

➡ Ideally, multiple modalities of geospatial data

Often in GeoML, data do not provide appropriate "ground truth," but indirect guidance on label values.

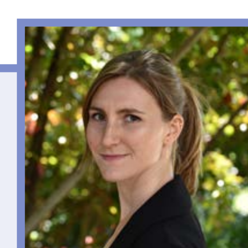
Coarse/incomplete
landcover observations

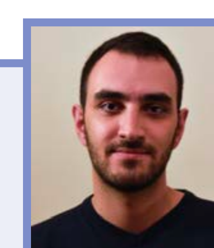
Coarse (30m)
landcover data
(USGS) →

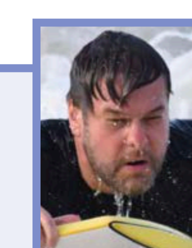


High-res. data for
some classes
(OpenStreetMaps) →

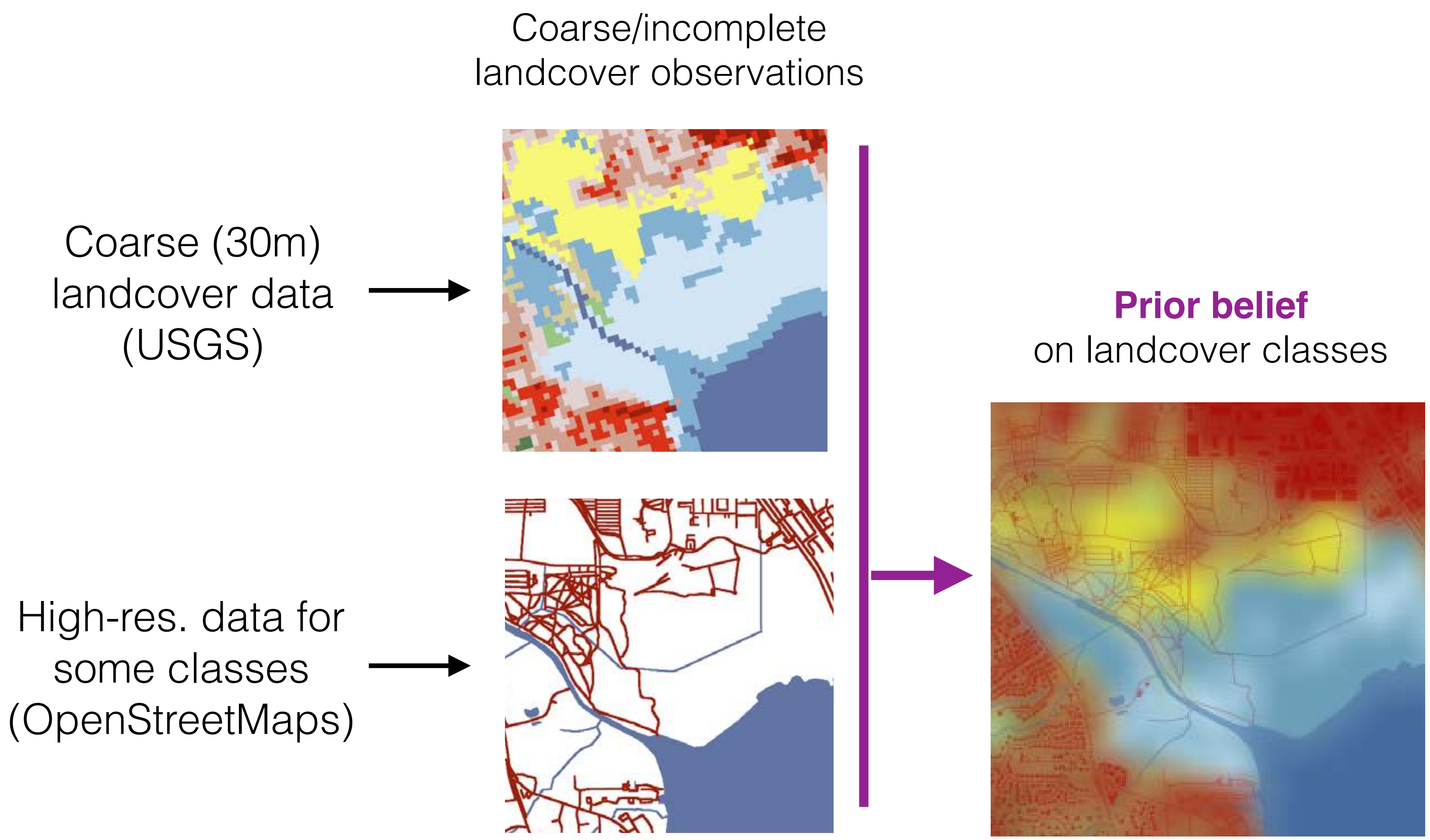
Rolf*, Malkin*, Graikos, Jojic, Robinson, Jojic. *Resolving label uncertainty with implicit posterior models,* UAI 2022.



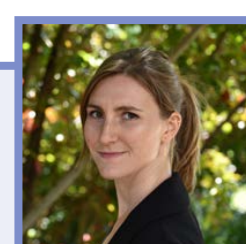


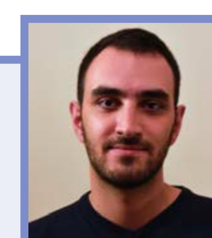
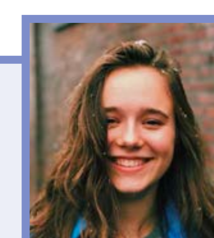



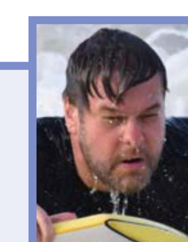
Often in GeoML, data do not provide appropriate "ground truth," but indirect guidance on label values (→ **a prior belief**).



Rolf*, Malkin*, Graikos, Jojic, Robinson, Jojic. *Resolving label uncertainty with implicit posterior models,* UAI 2022.





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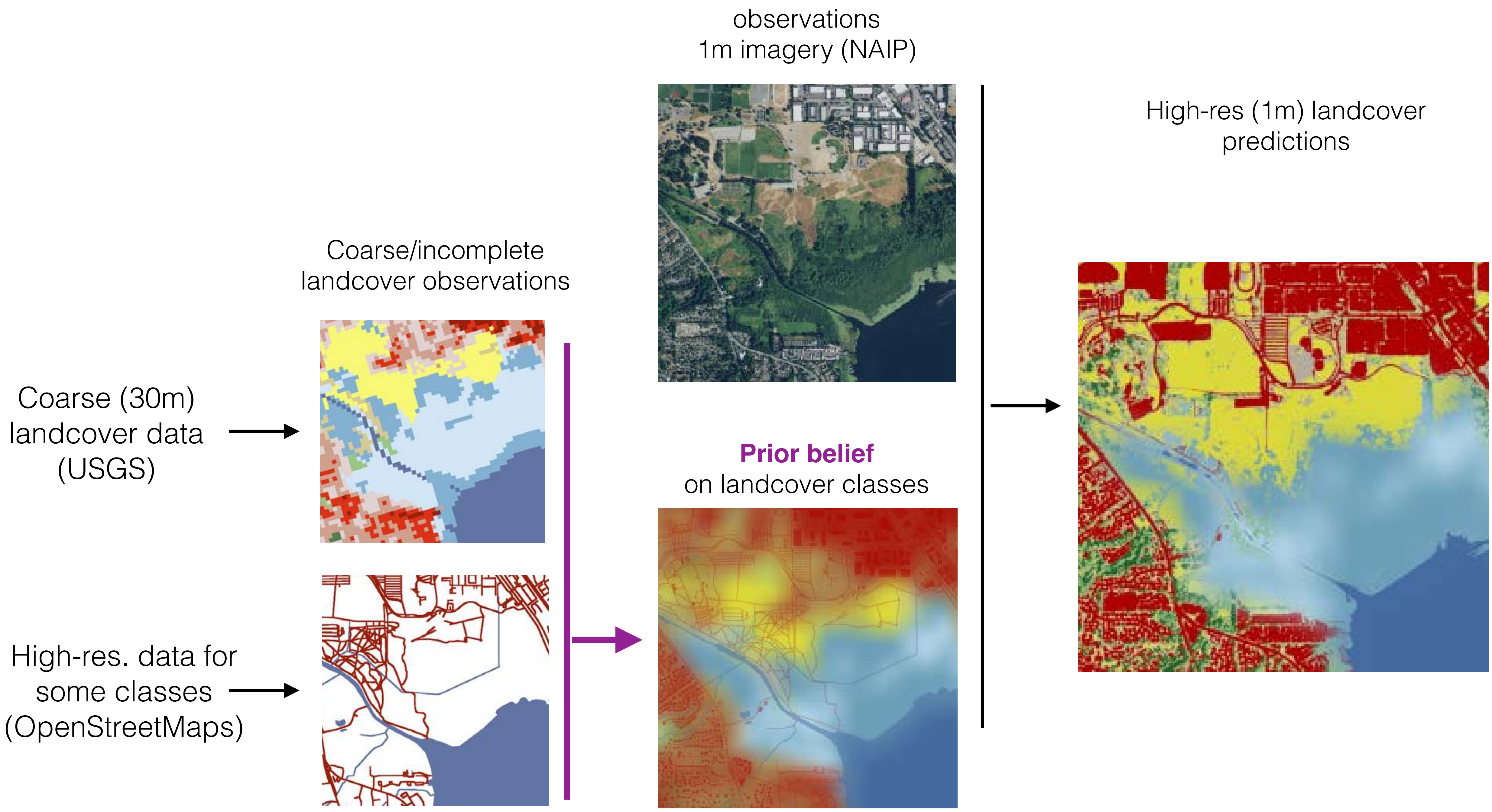
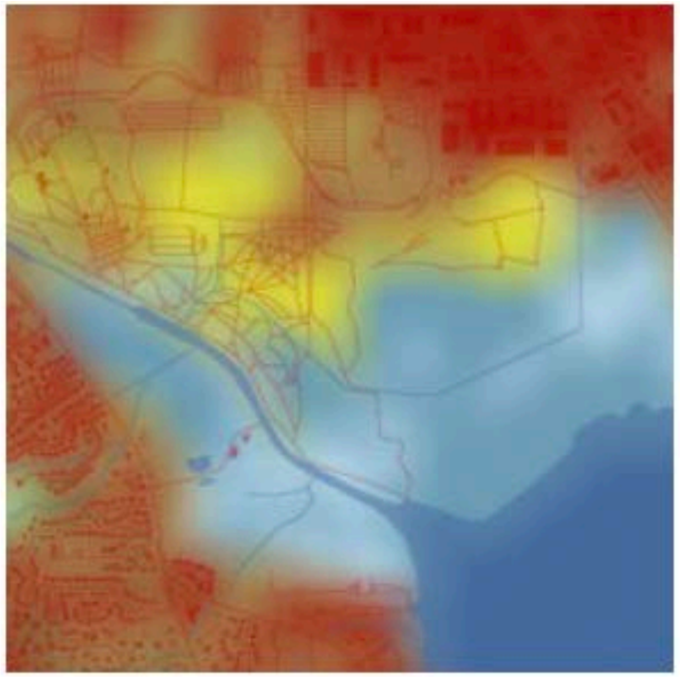


Learning from uncertain labels is hard:

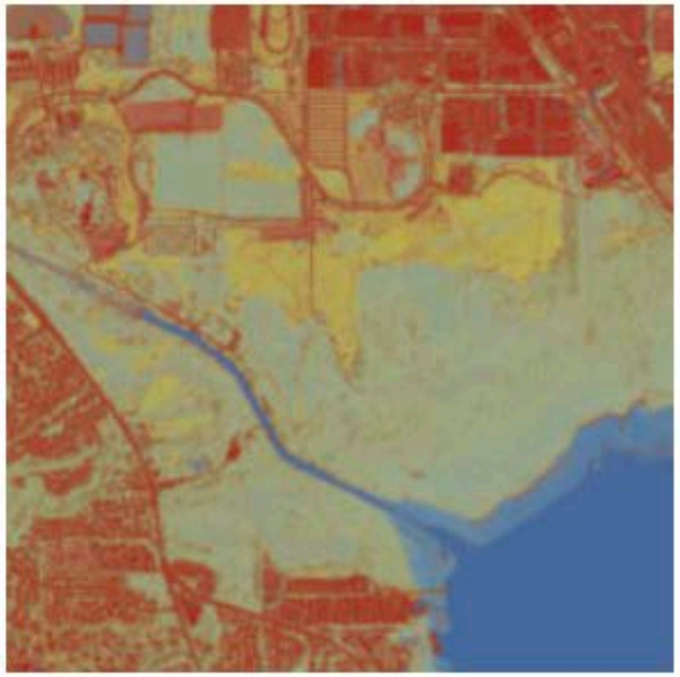
Supervised learning:

- uncertain labels → uncertain predictions
- ✓ amenable to rich model classes
- ✓ simple training w/ standard loss fxns

Prior belief
on landcover classes



Predictions from model
trained with CE loss on prior



Learning from uncertain labels is hard:

Supervised learning:

- uncertain labels → uncertain predictions
- ✓ amenable to rich model classes
- ✓ simple training w/ standard loss fxns

Generative modeling:

- ✓ high certainty in posterior w/ soft priors
- ✓ opportunities to model rich structure in the prior beliefs
- typically more expensive to train (requires sampling, 2x parameters)

Learning from uncertain labels is hard:

Supervised learning:

✓ amenable to rich model classes

✓ simple training w/ standard loss fxns

Generative modeling:

✓ high certainty in posterior w/ soft priors

✓ opportunities to model rich structure in the prior beliefs

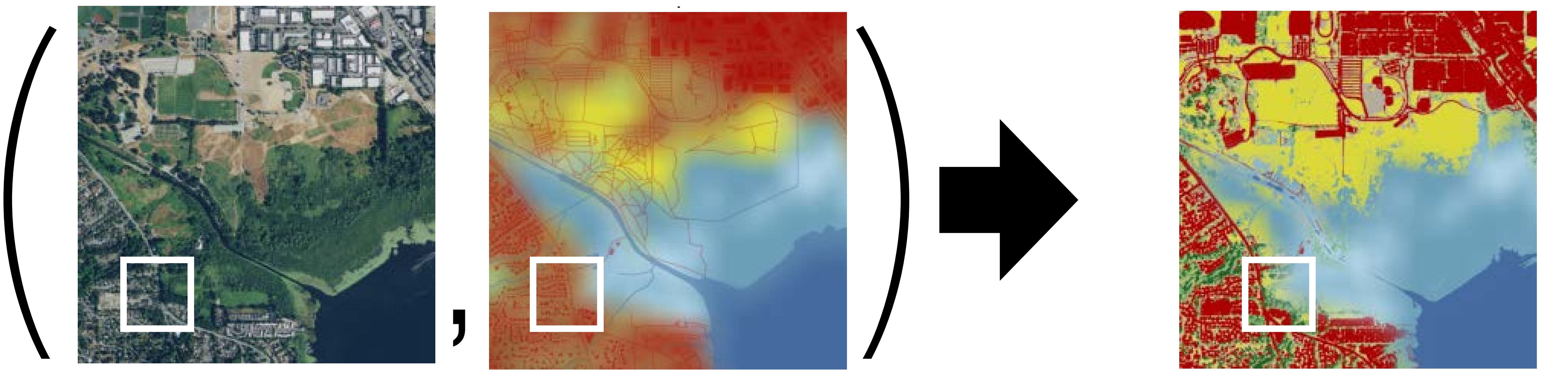
Our approach: match output of supervised learning model with a generative model involving provided prior belief

➡ merges flexibility of generative modeling with ease of supervised learning

Setting: learning from a prior belief

Goal: use observations of $(x_i,\ p_i)$ pairs to disambiguate uncertainty in prior!

$\{x_i\}_{i \in \text{ pixels}}$ $\{p_i\}_{i \in \text{ pixels}}$ $p(\ell \mid x_i) \propto p(x_i \mid \ell) p_i(\ell)$



classes ℓ :

- Open Water
- Developed Open Space
- Developed Low Intensity
- Developed Med. Intensity
- Developed High Intensity
- Barren Land
- Pasture/Hay
- Evergreen Forest
- Mixed Forest
- Woody Wetlands
- Emergent Herbaceous Wetlands

Optimizing implicit posterior models

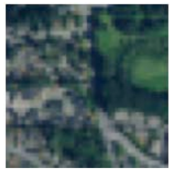
Assume generative model $p(x \mid \ell)$ exists, but **unknown,** then posterior is

$$p(\ell \mid x_i) = c_i \cdot p(x_i \mid \ell) p_i(\ell)$$

Notation

ℓ : classes

x_i : observations



p_i : priors over ℓ

c_i : normalizing constant

Optimizing implicit posterior models

Assume generative model $p(x \mid \ell)$ exists, but **unknown,** then posterior is

$$p(\ell \mid x_i) = c_i \cdot p(x_i \mid \ell) p_i(\ell)$$

Estimate posterior distribution with a parametrized model $q(\ell \mid x_i; \theta)$, then we can minimize:

$$\boxed{\sum_i \mathrm{KL}\left(q(\ell \mid x_i; \theta) \| c_i \cdot p(x_i \mid \ell) p_i(\ell)\right) \quad (\star)}$$

??

Notation

ℓ : classes

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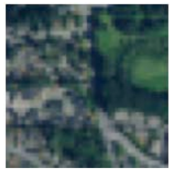

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Optimizing implicit posterior models

Assume generative model $p(x\,|\,\ell)$ exists, but **unknown,** then posterior is

$$p(\ell\,|\,x_i) = c_i \cdot p(x_i\,|\,\ell)p_i(\ell)$$

Estimate posterior distribution with a parametrized model $q(\ell\,|\,x_i;\theta)$, then we can minimize:

$$\boxed{\sum_i \mathrm{KL}\left(q(\ell\,|\,x_i;\theta) \| c_i \cdot p(x_i\,|\,\ell)p_i(\ell)\right) \quad (\star)}$$

Fix $q(\ell\,|\,x_i;\theta) \longrightarrow \underset{p(x_i|\ell)}{\arg\min}\,(\star)$ $= \dfrac{q(\ell\,|\,x_i;\theta)}{\sum_j q(\ell\,|\,x_j;\theta)}$

s.t. $\sum_i p(x_i\,|\,\ell) \leq 1$

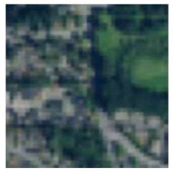
Let direct model **imply** $p(x_i\,|\,\ell)$

approximates all existing data with $i \in$ batch

Notation

ℓ : classes

x_i : observations



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$q_i : q(\ell\,|\,x_i;\theta)$

(e.g., neural net)

Optimizing implicit posterior models

$$\arg\min_{\theta} \sum_{i} \mathrm{KL}\left(q(\ell \mid x_i; \theta) \,\middle\|\, c_i \frac{q(\ell \mid x_i; \theta)}{\sum_j q(\ell \mid x_j; \theta)} p_i(\ell) \right)$$

Notation

ℓ : classes

x_i : observations

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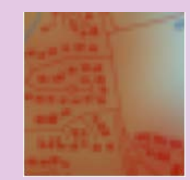

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Optimizing implicit posterior models

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Loss function in 2 lines (PyTorch):

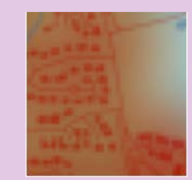
```python
def qr_loss(log_q, prior):
    log_r = (log_q.log_softmax(0) + prior.log()).log_softmax(1)
    return (log_q * log_q.exp()).sum(1) - (log_r * log_q.exp()).sum(1)
```

Notation

ℓ : classes

x_i : observations

p_i : priors over ℓ



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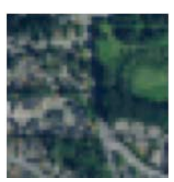
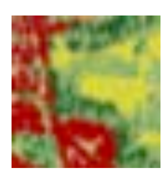
Optimizing implicit posterior models

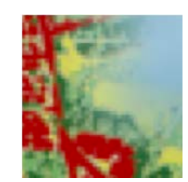
$$\arg\min_{\theta} \sum_i \mathrm{KL}\left(q(\ell \mid x_i; \theta) \,\middle\|\, c_i \frac{q(\ell \mid x_i; \theta)}{\sum_j q(\ell \mid x_j; \theta)} p_i(\ell) \right)$$

Two outputs:

q_i : direct model output of the variational posterior

$q($  $; \theta) =$ 

r_i : implied posterior of q_i and p_i

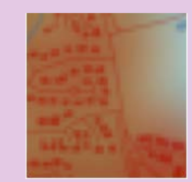
$z(q_i) \times$  $=$ 

Notation

ℓ : classes

x_i : observations

p_i : priors over ℓ



c_i : normalizing constant

$q_i : q(\ell \mid x_i; \theta)$ (e.g., neural net)

r_i : implied posterior

Optimizing implicit posterior models

$$\arg\min_{\theta} \sum_i \mathrm{KL}\left(q(\ell \mid x_i; \theta) \,\middle\|\, c_i \frac{q(\ell \mid x_i; \theta)}{\sum_j q(\ell \mid x_j; \theta)} p_i(\ell) \right)$$

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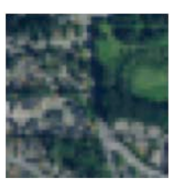
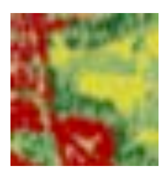
$q($  $;\theta) =$ 

r_i : implied posterior of q_i and p_i

$z(q_i) \times$  $=$ 

At model convergence, r_i and q_i should agree to the amount possible given data and model class

Notation

ℓ : classes

x_i : observations

p_i : priors over ℓ

c_i : normalizing constant

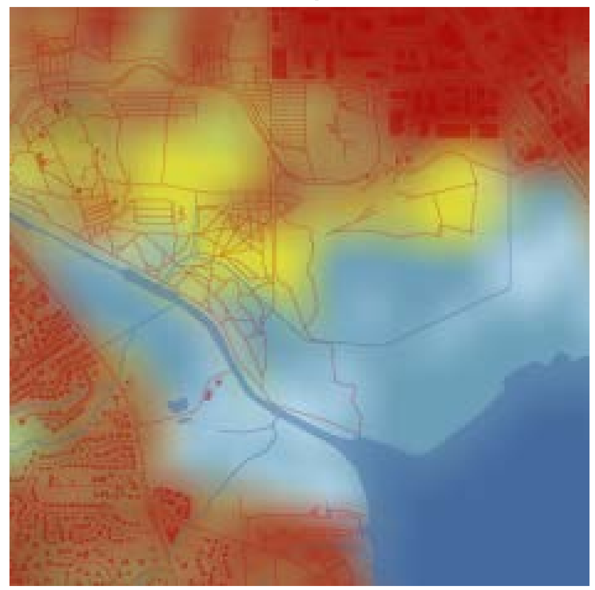
$q_i : q(\ell \mid x_i; \theta)$ (e.g., neural net)

r_i : implied posterior

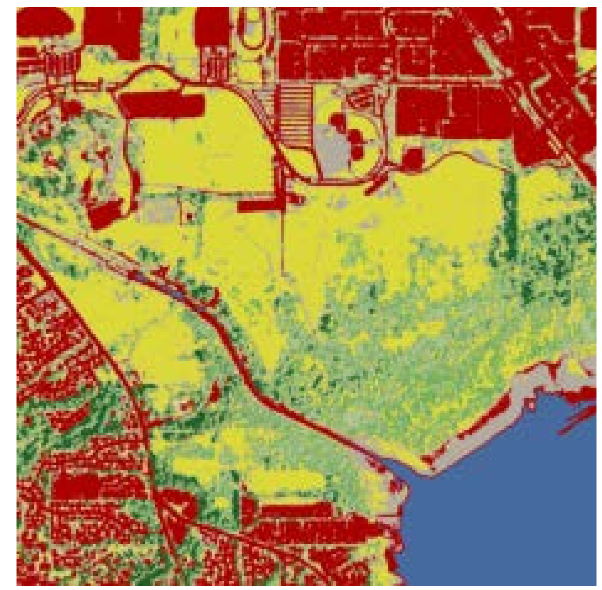
Example: land-cover super-resolution

Observations (x_i) : 1m-resolution

Prior beliefs (p_i) :



Direct model output (q_i) :



Implied posterior (r_i) :

NLCD Legend

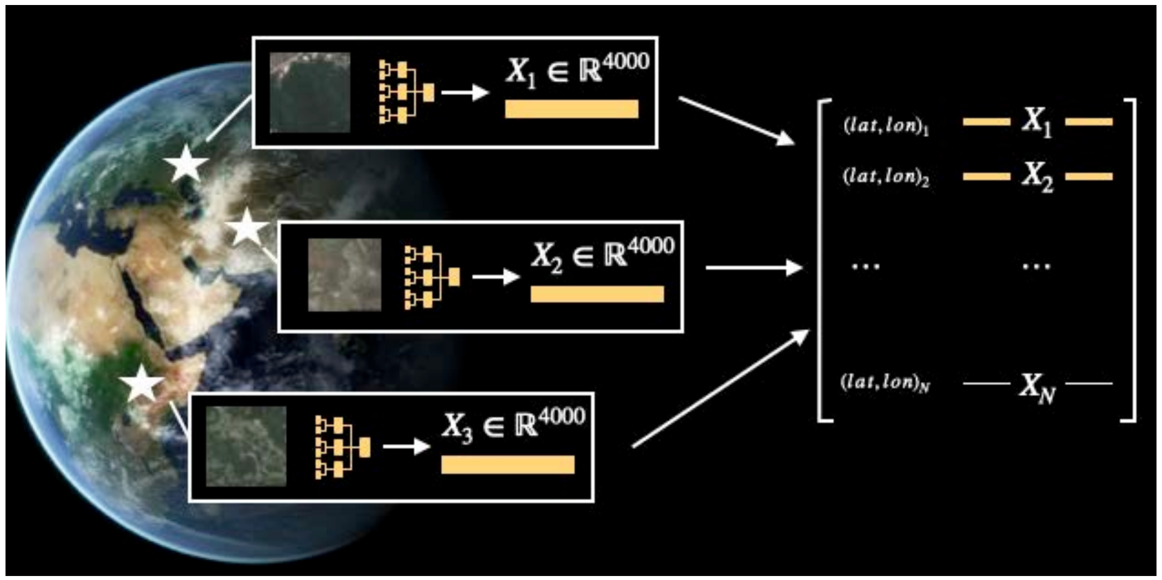
- Open Water
- Developed Open Space
- Developed Low Intensity
- Developed Med. Intensity
- Developed High Intensity
- Barren Land
- Pasture/Hay
- Evergreen Forest
- Mixed Forest
- Woody Wetlands
- Emergent Herbaceous Wetlands

Highlighted results:

- On benchmark land cover super-resolution dataset, QR achieves **72.1% IoU** vs. 59.7% by treating low-resolution labels as ground truth (also higher than previous best at 69.7%)
- on a cross-geography domain adaptation problem, QR/RQ allows for **in-sample predictions from weak sources** (NLCD/ OpenStreetmaps), better than applying models trained on **high-resolution** labels in another region

How do you get a good (global) prior?

Global location embeddings: a “latent space” of geospatial data



MOSAIKS
precomputed image embeddings on a 0.01° grid

mosaiks.org > access

SatCLIP
pretrained location encoder

https://github.com/microsoft/satclip

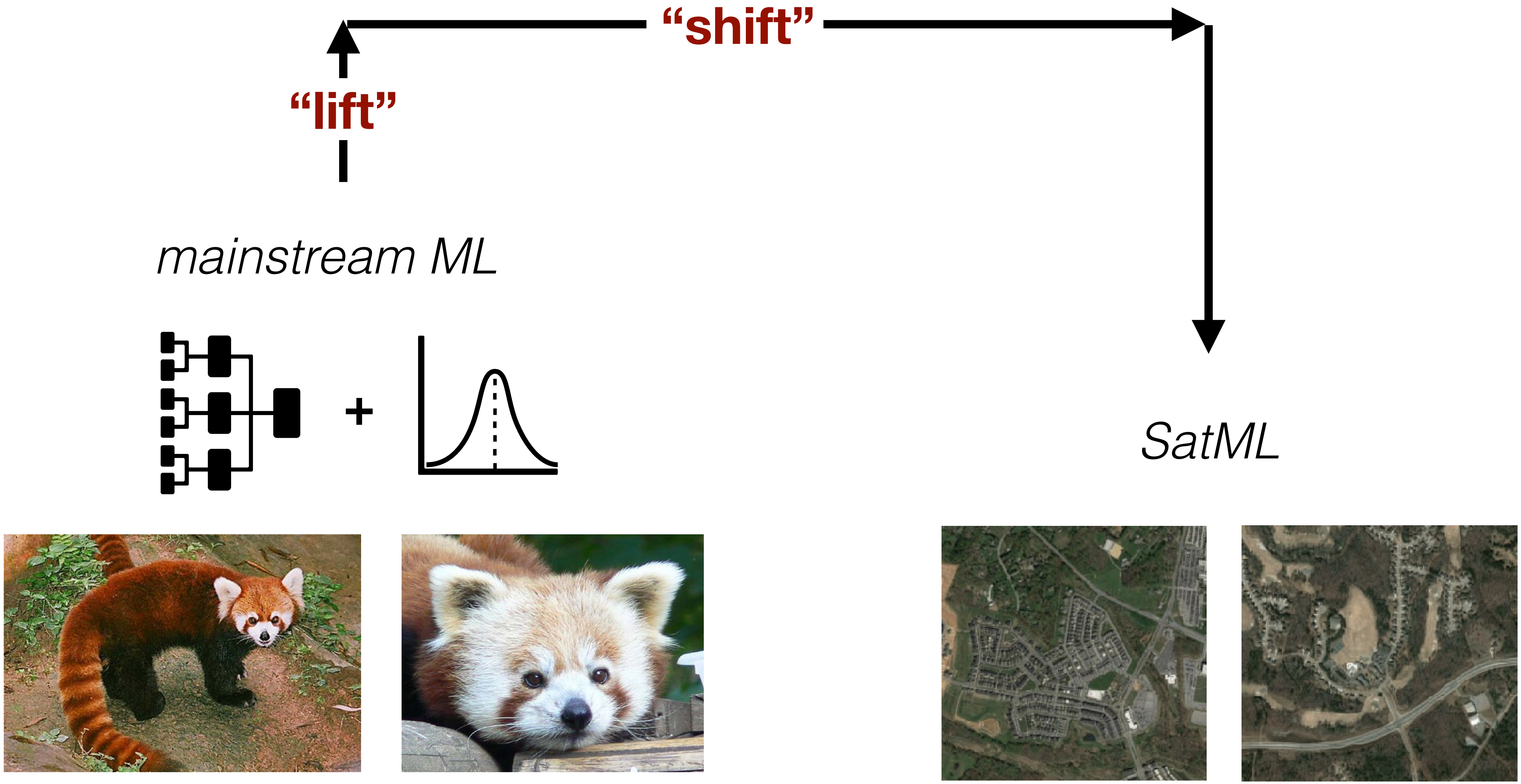
A Generalizable and Accessible Approach to Machine Learning with Global Satellite Imagery.
Rolf, Proctor, Carleton, Bolliger, Shankar, Ishihara, Recht, Hsiang. Nature Communications 2021.

SatCLIP: Global, General-Purpose Location Embeddings with Satellite Imagery.
Klemmer, Rolf, Rußwurm, Robinson, Mackey. AAAI 2025

🤔

Why aren't we talking (enough) about uncertainty in GeoML?

The approach of “**lifting and shifting**” methods from other data modalities leaves a lot on the table for satellite machine learning (SatML).



We can do so much better!

Mission Critical – Satellite Data is a Distinct Modality in Machine Learning

Esther Rolf [*,1,2] Konstantin Klemmer [3] Caleb Robinson [4] Hannah Kerner [*,5]

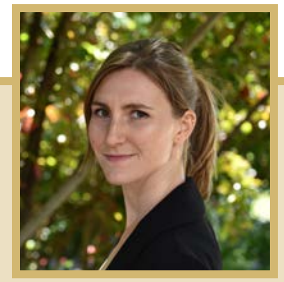
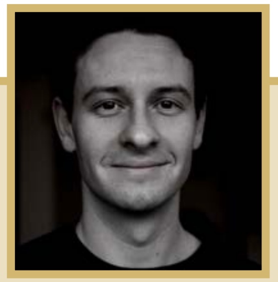
Abstract

Satellite data has the potential to inspire a seismic shift for machine learning—one in which we rethink existing practices designed for traditional data modalities. As machine learning for satellite data (SatML) gains traction for its real-world impact, our field is at a crossroads. We can either continue applying ill-suited approaches, or we can initiate a new research agenda that centers around the unique characteristics and challenges of satellite data. This position paper argues that satellite data constitutes a distinct modality for machine learning research and that we must recognize it as such to advance the quality and impact of SatML research across theory, methods, and deployment.

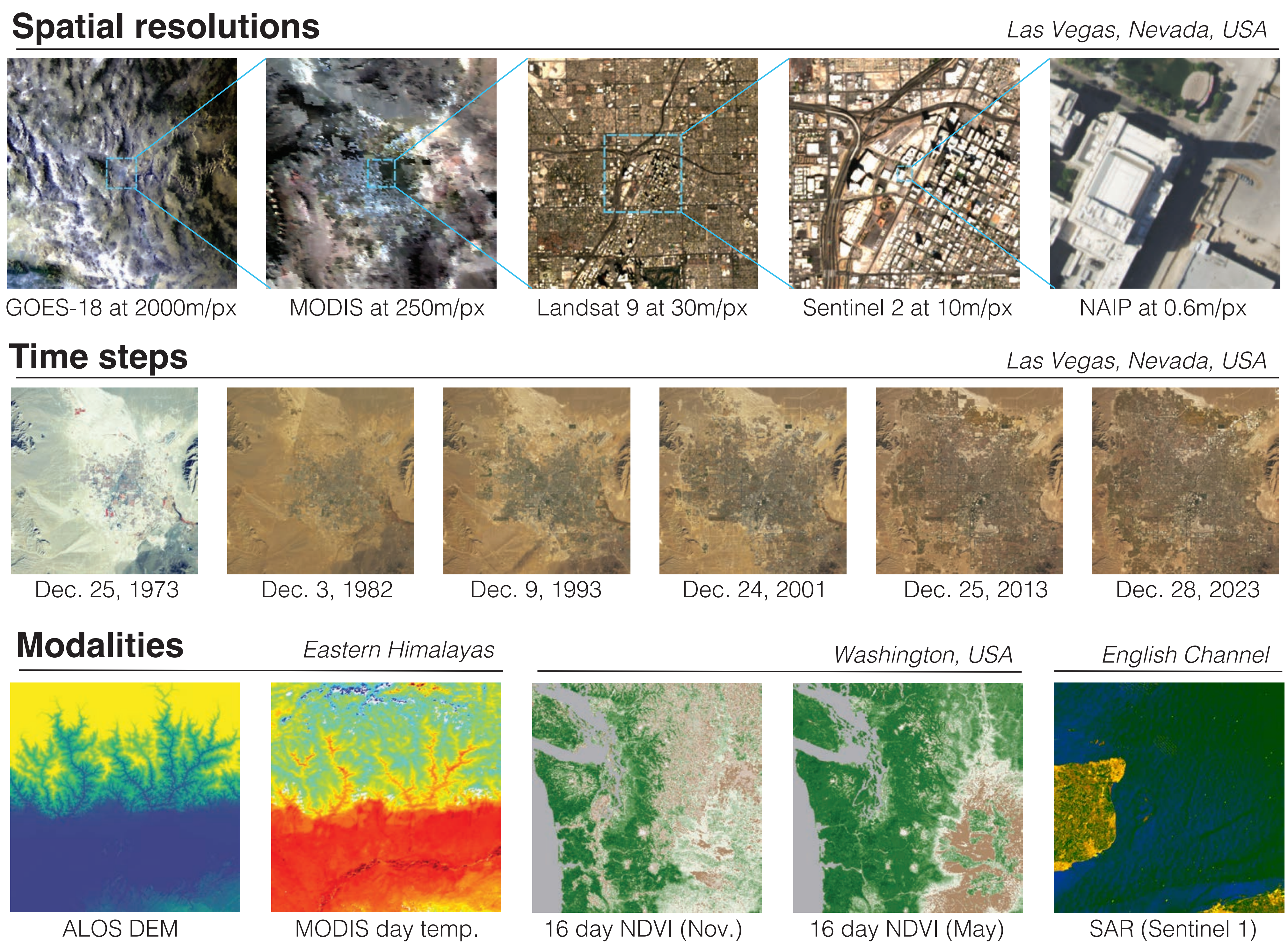
Satellite data presents challenges and opportunities distinct from other data modalities (Figure 1). Unlike natural images, the size of targets in satellite images span a logarithmic scale from $<$ 1m (e.g., trees) to $>$ 1km (e.g., forests). Temporal patterns in satellite time series also span logarithmic scales, from hours or days (e.g., floods) to years or decades (e.g., sea level rise). Data are acquired using a variety of sensors that capture diverse spectral channels (beyond 3-channel RGB) and precise measurements (beyond 8 bits). Satellites collect data over the entire surface of the Earth at fixed time intervals and spatial resolutions. Observations are acquired from an overhead perspective from fixed altitudes and lack a "natural" orientation, unlike natural images.

While there has been increasing interest in ML for satellite data (SatML) (Zhu et al., 2017; Table A1), SatML research

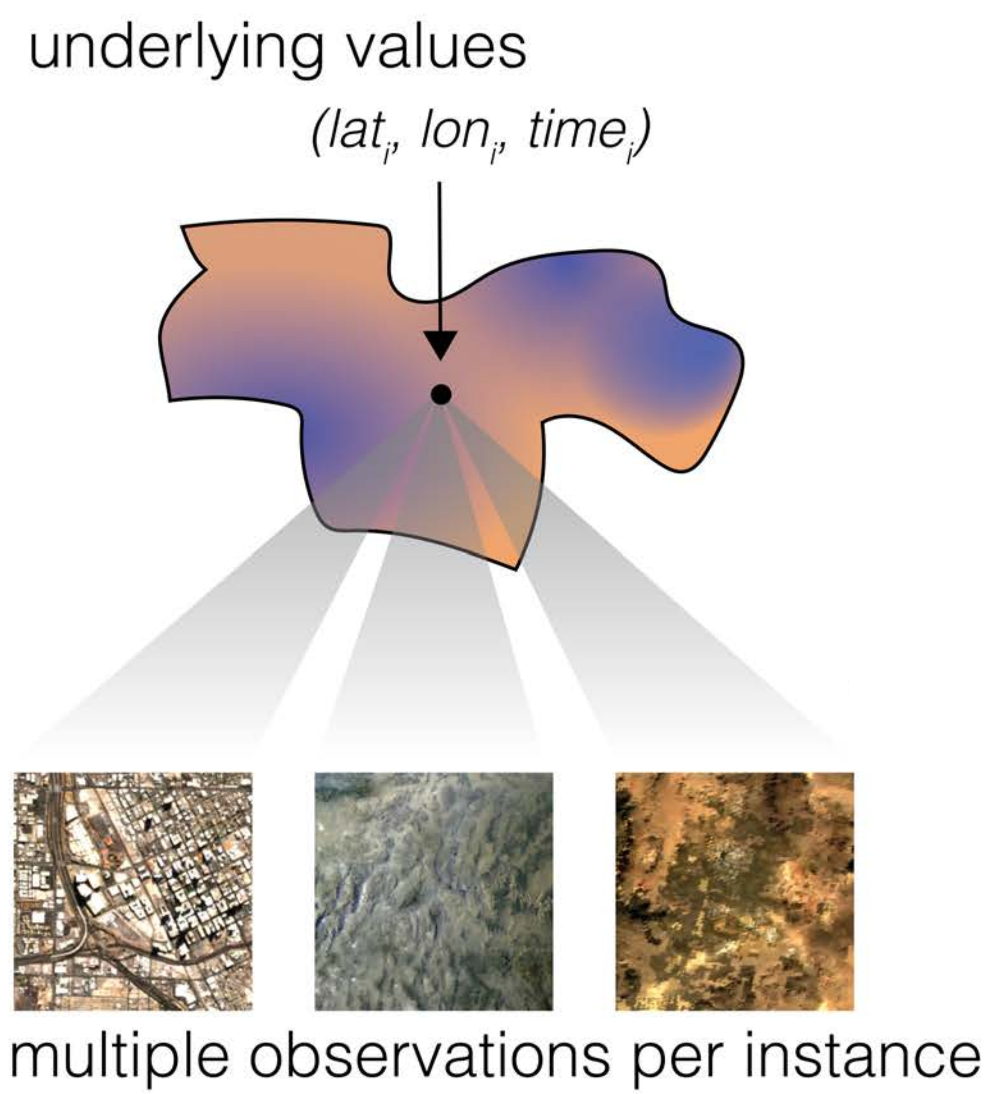
Rolf*, Klemmer, Robinson, Kerner*. *Position: Mission critical — Satellite data is a distinct modality in ML,* ICML 2024.

Satellite data is a **distinct modality** for ML.



GeoML warrants specialized **methods.**



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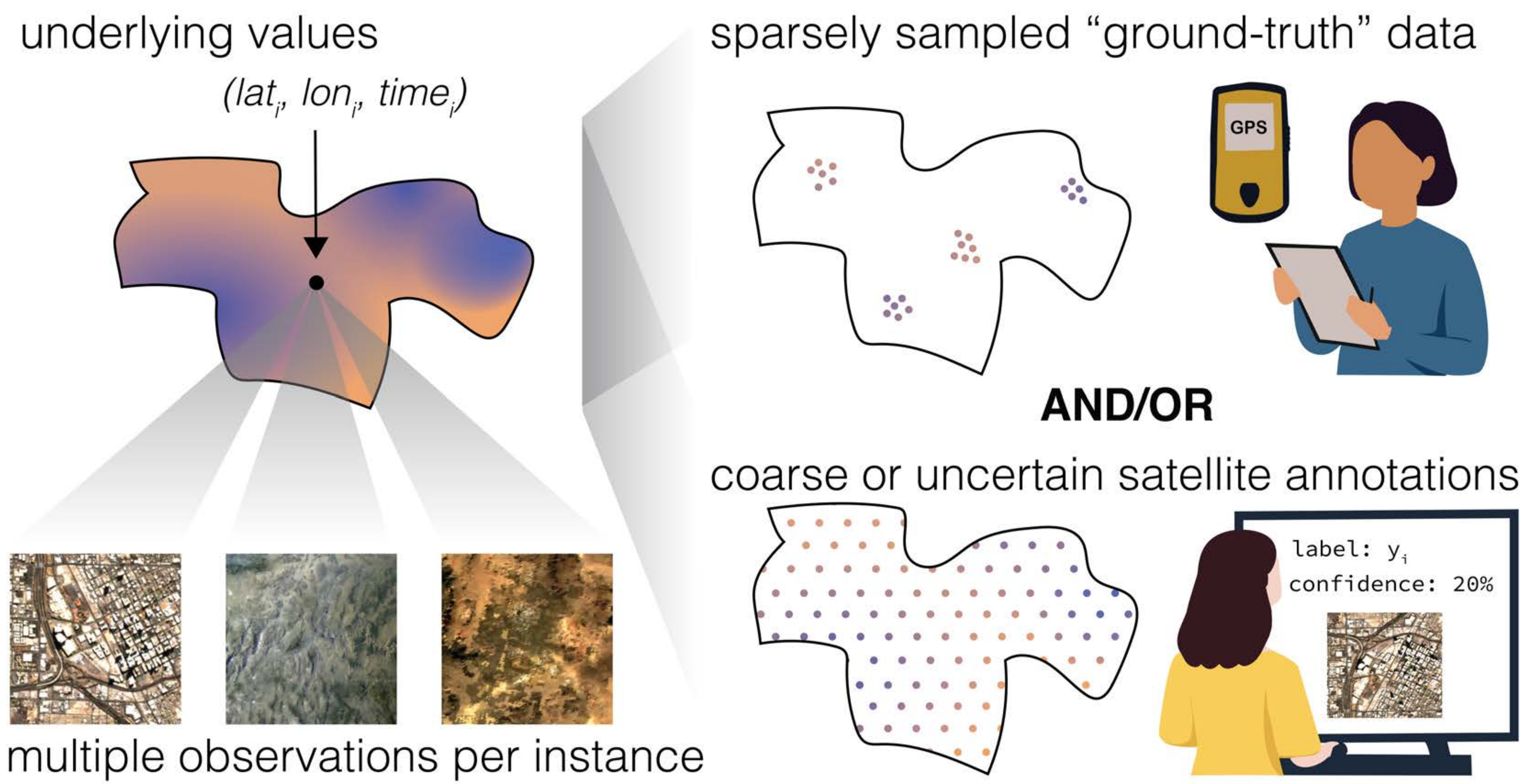
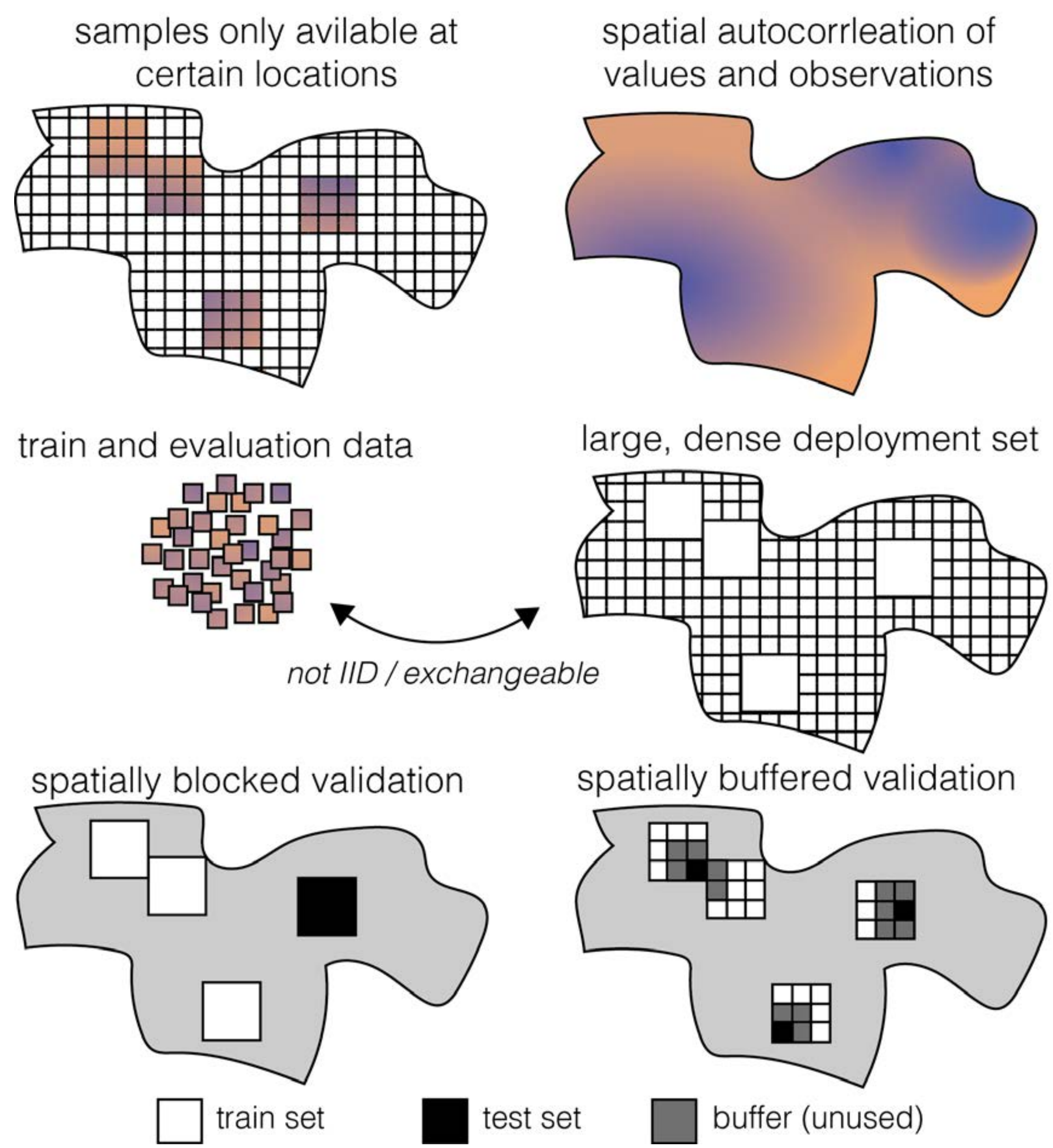


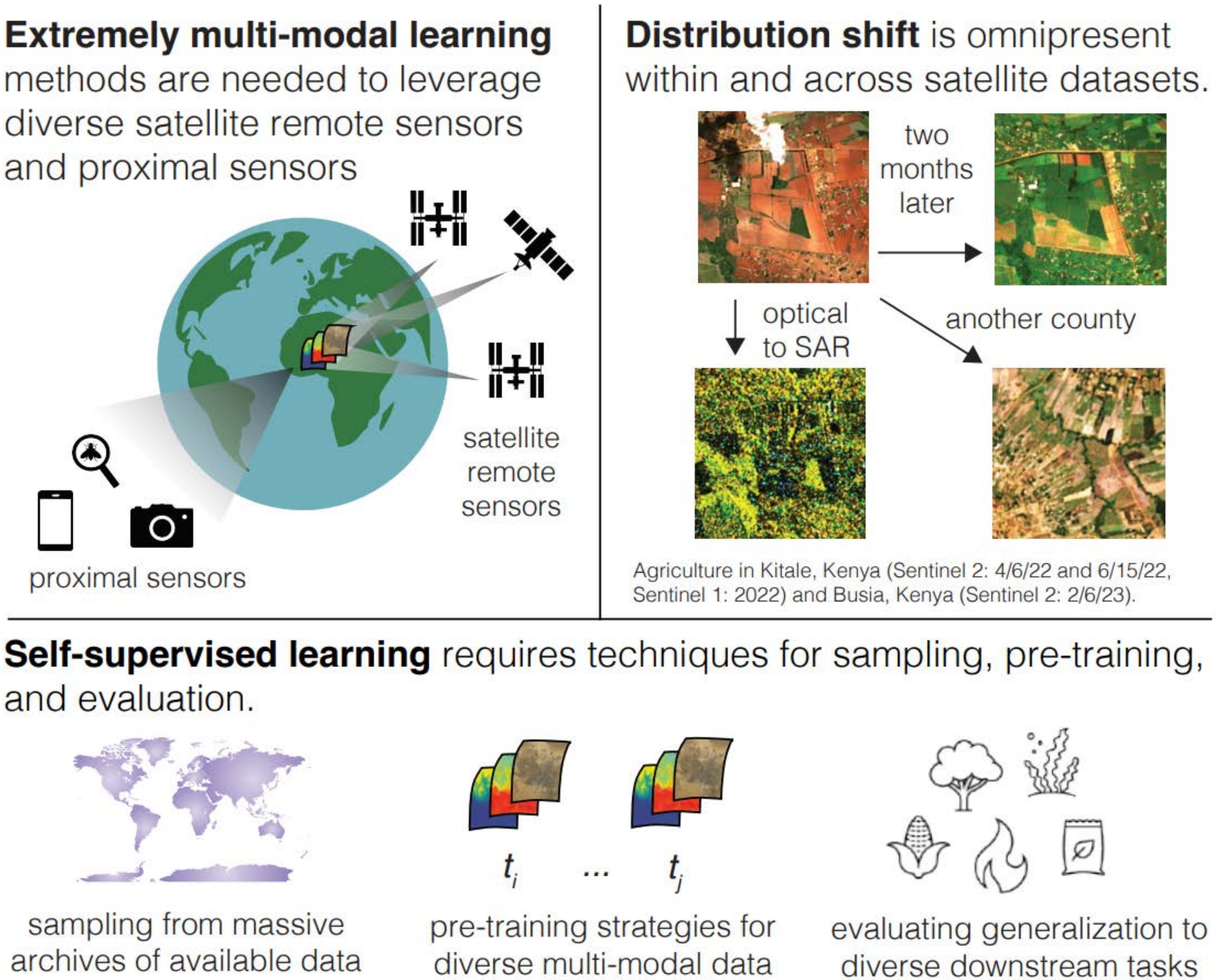
GeoML warrants specialized **evaluation.**



Evaluation challenges for geospatial ML
Rolf, Workshop on ML for Remote Sensing at ICLR 2023.

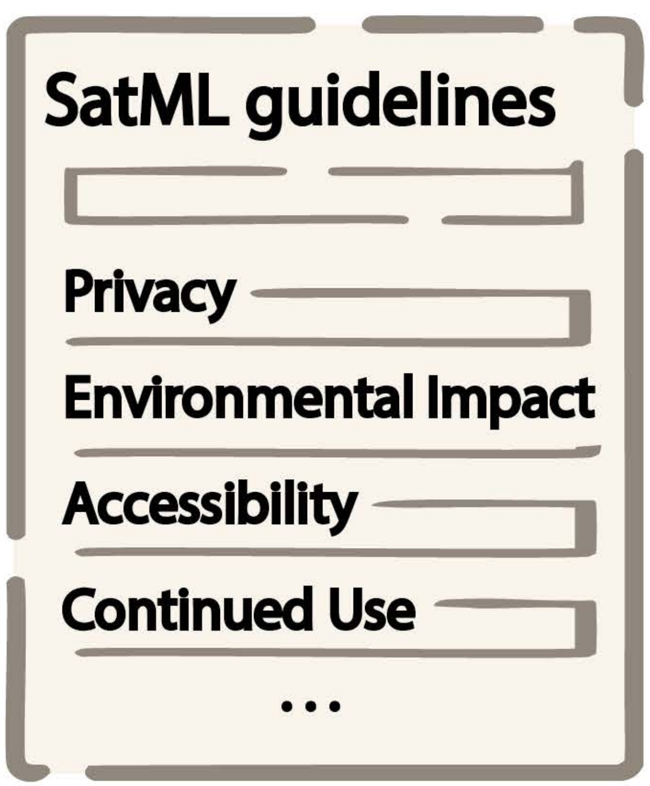
Position: Mission critical — Satellite data is a distinct modality in Machine Learning.
Rolf, Klemmer, Robinson, Kerner. ICML 2024.

Satellite data **enriches ML research.**



As a research discipline, SatML **needs**:

Clearly communicated guidelines and guardrails



Perspectives from multiple stake-holders, nations, and disciplines

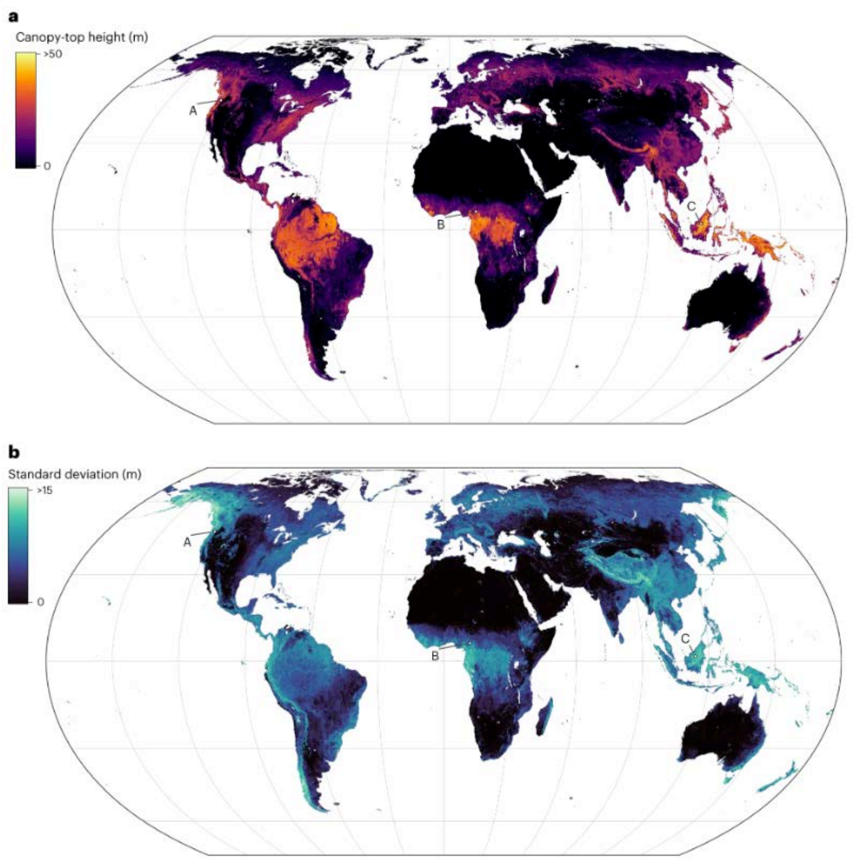
Continuous revision of published models and best practices

We need to talk (more) about uncertainty in geospatial machine learning

We need to talk (more) about uncertainty in geospatial machine learning

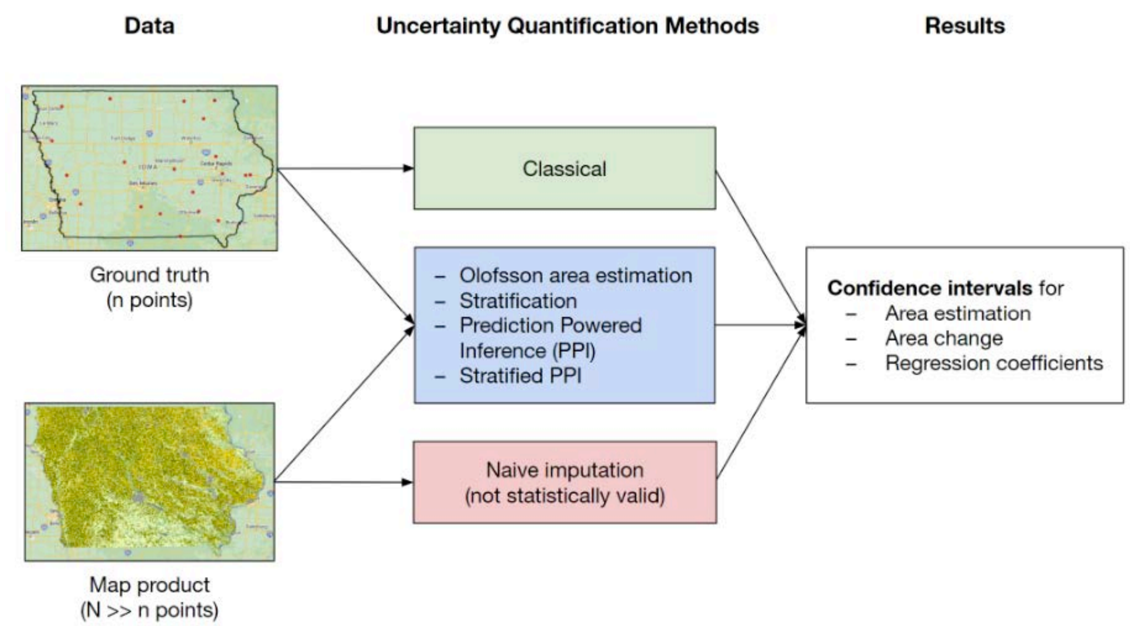
There are some excellent integrations of uncertainty in GeoML predictions!

ensemble-based uncertainty



A high-resolution canopy height model of the Earth
Lang et al. 2023

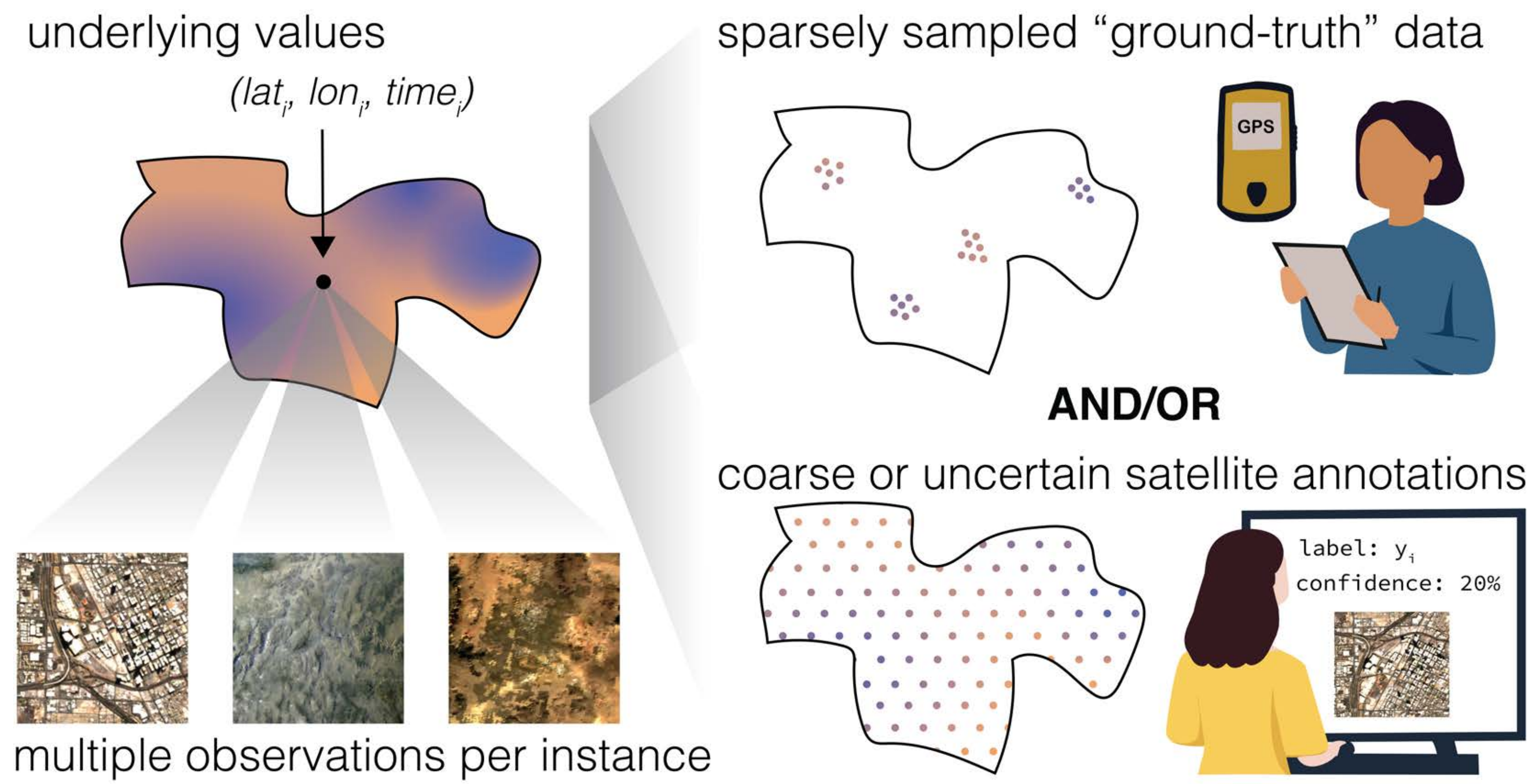
calibration-based intervals



Quantifying uncertainty in area and regression coefficient estimation from remote sensing maps
Lu et al. 2024

We need to talk (more) about uncertainty in geospatial machine learning

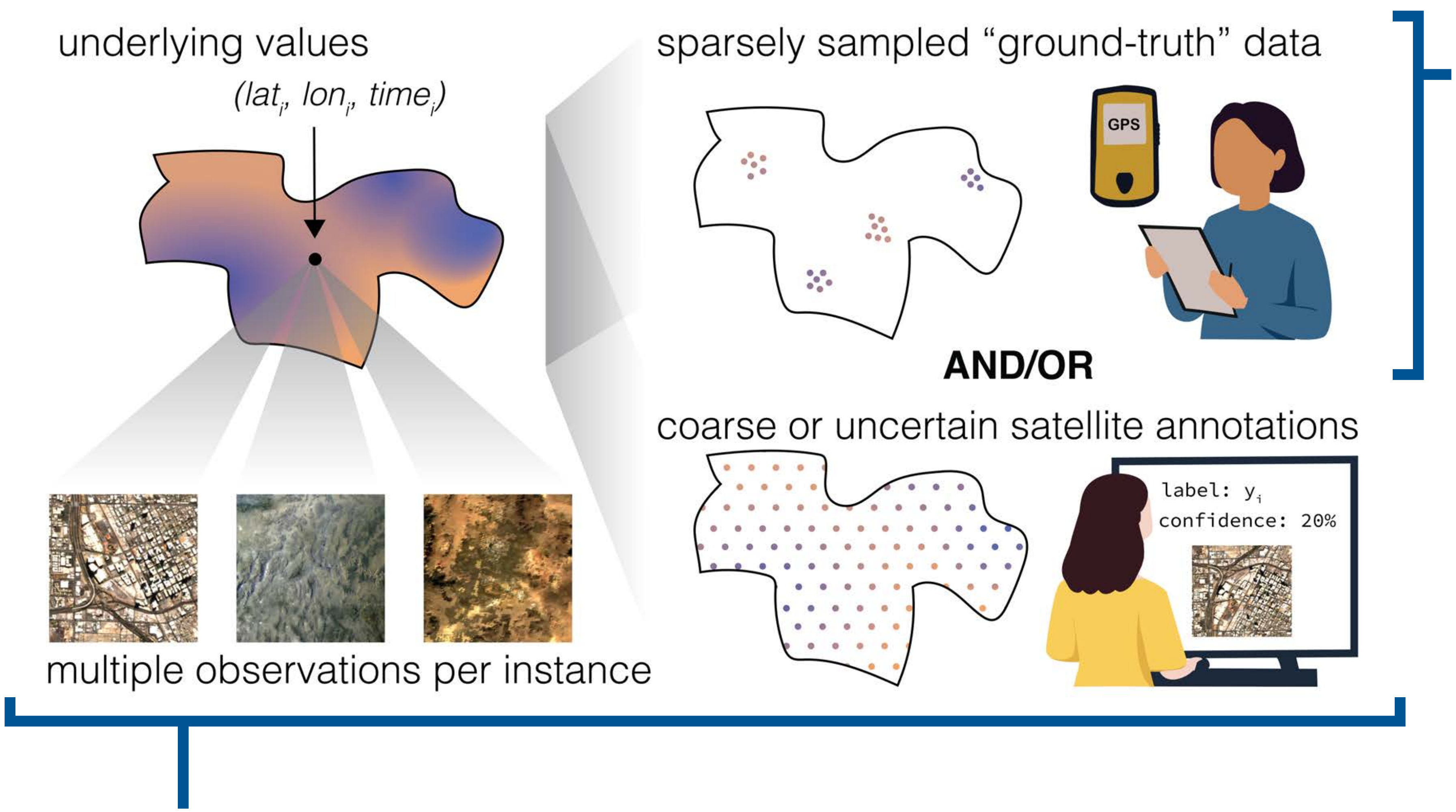
We need methods tailored for the uncertainties in geospatial data:



1. Uncertainty due to **partial representativity** of geospatial data

We need to talk (more) about uncertainty in geospatial machine learning

We need methods tailored for the uncertainties in geospatial data:



2. Uncertainty due to **spatially biased** distributions of data

1. Uncertainty due to **partial representativity** of geospatial data

We need to talk (more) about uncertainty in geospatial machine learning

Esther Rolf
Assistant Professor, CU Boulder Computer Science

estherrolf.com
estherrolf.bksy

HDSI | Harvard Data Science Initiative

CRCS Center for Research on Computation and Society
Harvard John A. Paulson School of Engineering and Applied Sciences

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Google PhD Fellowship Program