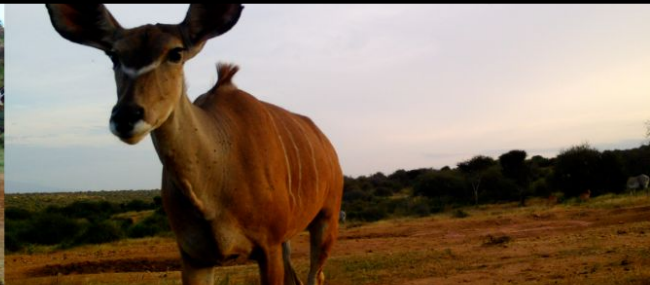




Computer Vision for Global-Scale Biodiversity Monitoring



Sara Beery | Harvard AI for Science | 2-1-24



A satellite view of Earth showing the Americas and surrounding oceans, with a central text box.

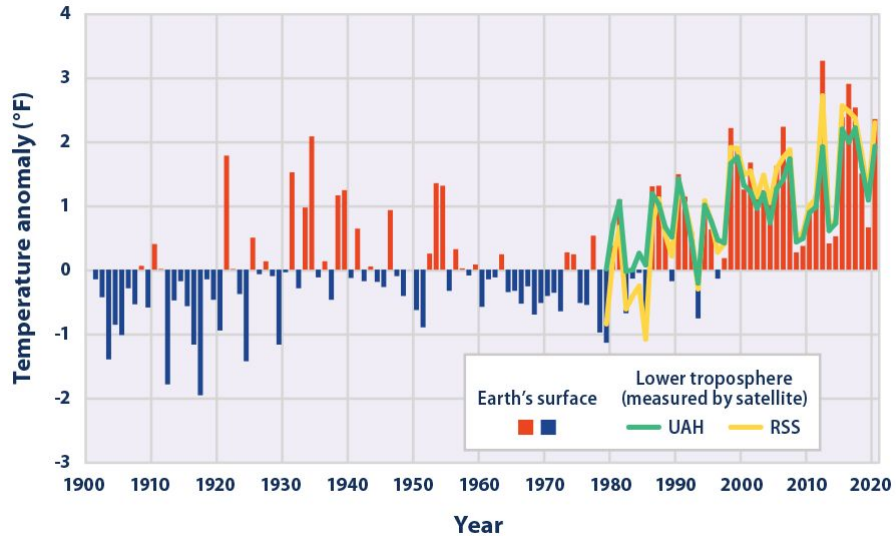
**Big Goal: monitoring biodiversity and
detecting change, across scales, globally,
and in real time**

Why monitor biodiversity?

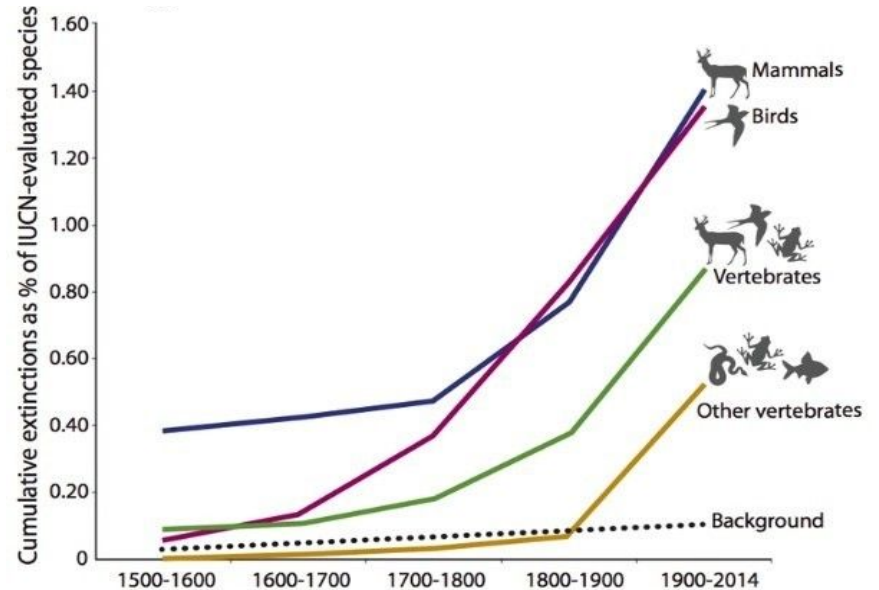


Why monitor biodiversity?

Increase in global temperatures



Mass extinction of species



Biodiversity data is diverse and large-scale

Mobile Sensors

Satellite (optical, SAR, LiDAR)



UAV (RGB, thermal, LiDAR)



On-Animal Sensors

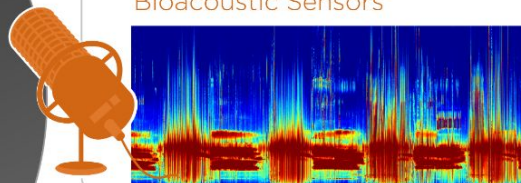


Stationary Sensors

Camera Traps

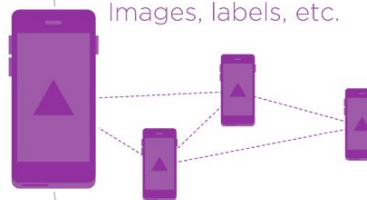


Bioacoustic Sensors

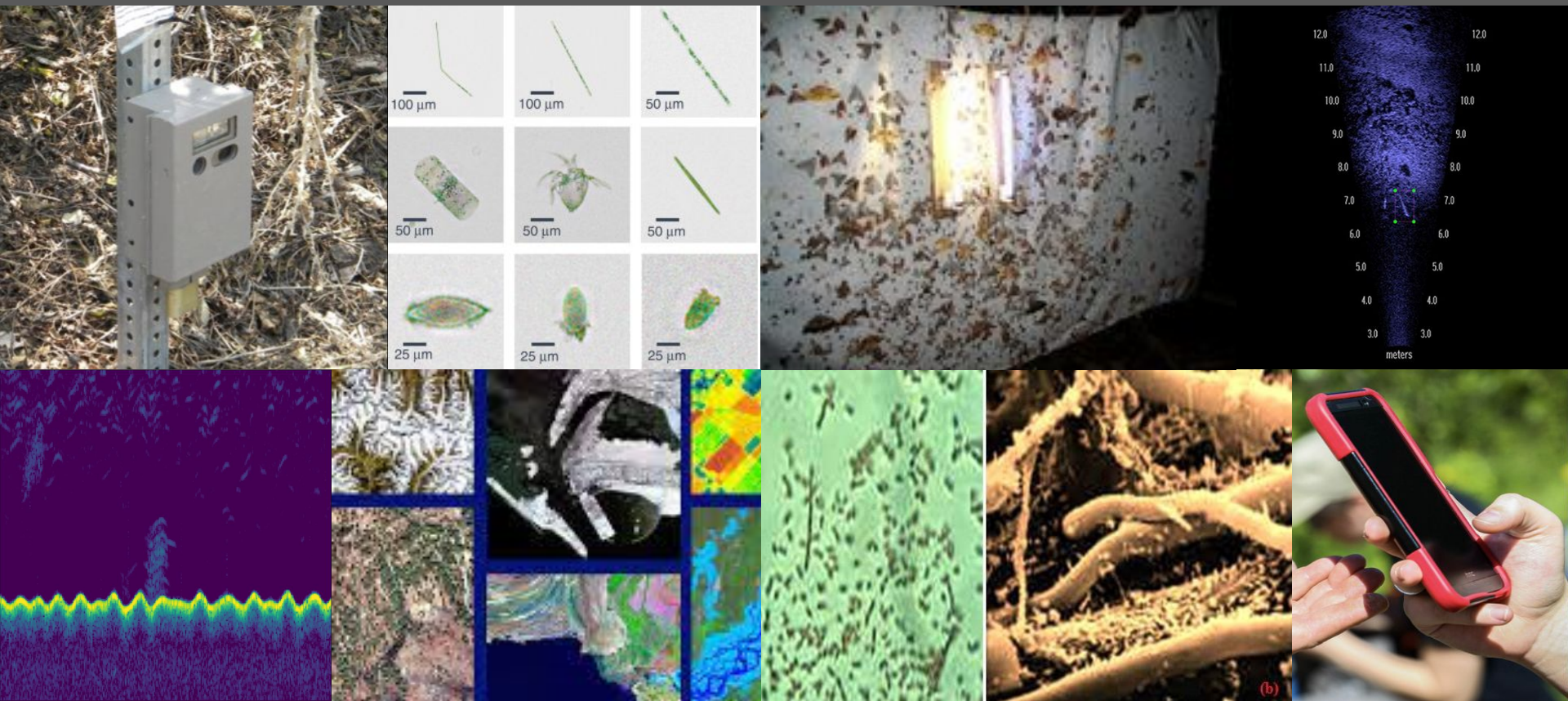


Community Science

Images, labels, etc.



No direct sensor for biodiversity across taxa & scale



Manual data processing can't keep up

Camera Traps



One project can collect >10M images/season

Community Scientists



>64M Species observations in iNaturalist

Aerial Surveys



One survey can generate >200TB of video

Manual data processing can't keep up

Camera Traps



One project can collect >10M images/season

Community Scientists



>170M!
~~>64M~~ Species observations in iNaturalist

Aerial Surveys



One survey can generate >200TB of video

Manual data processing can't keep up

Camera
Traps



Community
Scientists



Aerial
Surveys



Use CV/ML to automate data processing



One project can
collect >10M
images/season



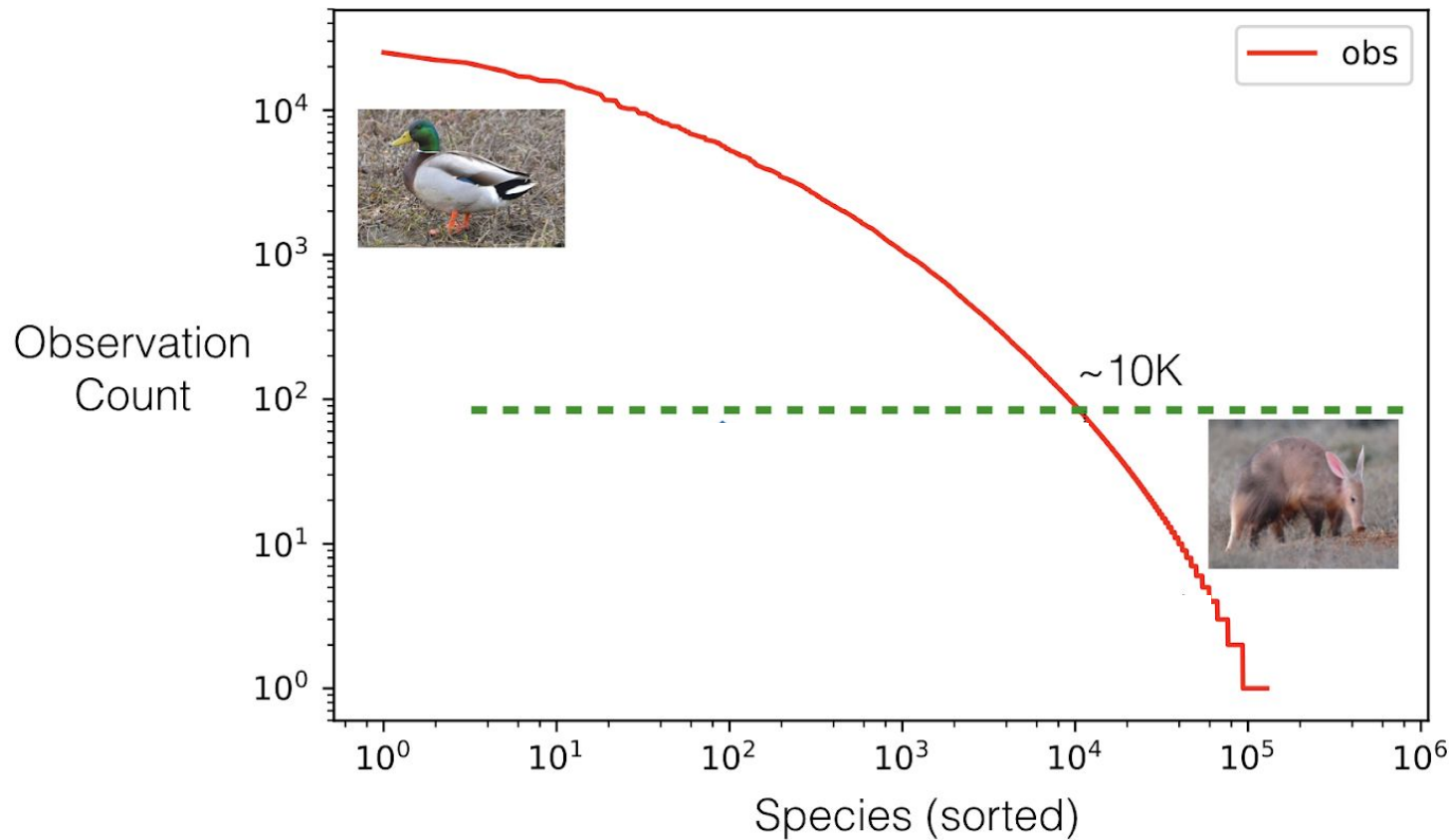
~~>64M~~ **>170M!**
Species
observations in
iNaturalist



One survey can
generate >200TB
of video

Biodiversity data has a long tail

Observations per iNaturalist Species: 16 M total



Biodiversity data is fine-grained

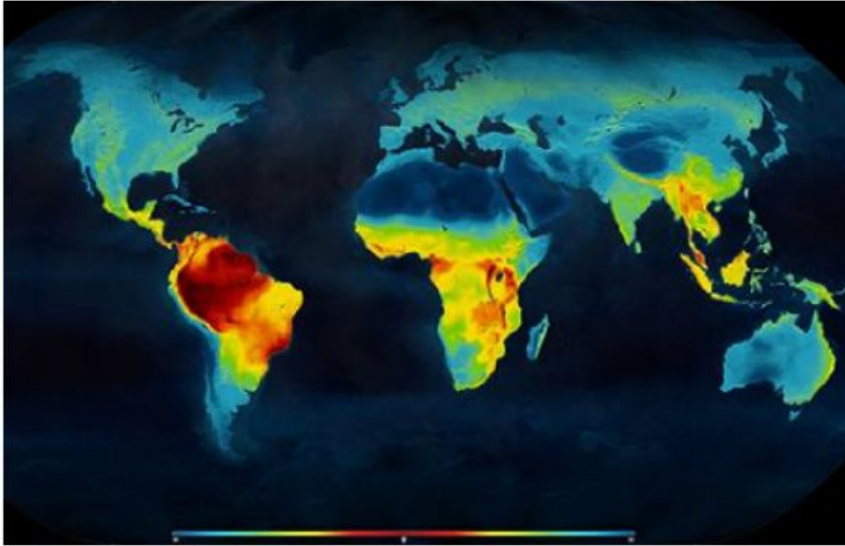


American Crow



Common Raven

Biodiversity data is not IID - spatially, temporally, or taxonomically



**Map of global
biodiversity**



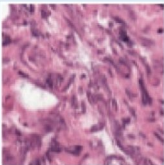



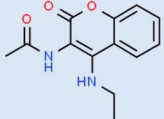
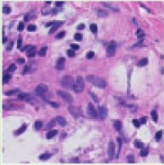



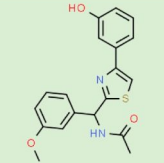
**Species occurrence
data in GBIF**

Distribution shifts are ubiquitous in real-world scenarios

WILDS

<https://wilds.stanford.edu/>

Pang Wei Koh*, Shiori Sagawa*, Henrik Marklund, Sang Michael Xie, Marvin Zhang, Akshay Balsubramani, Weihua Hu, Michihiro Yasunaga, Richard Lanus Phillips, Sara Beery, Jure Leskovec, Anshul Kundaje, Emma Pierson, Sergey Levine, Chelsea Finn, and Percy Liang

	Camelyon17	iWildCam	PovertyMap	FMoW	Amazon	CivilComments	OGB-MolPCBA
Shift	Hospitals	Locations	Countries	Time	Users	Demographics	Scaffold
Train					Overall a solid package that has a good quality of construction for the price.	What do Black and LGBT people have to do with bicycle licensing?	
Test					I *loved* my French press, it's so perfect and came with all this fun stuff!	As a Christian, I will not be patronizing any of those businesses.	
Adapted from	Bandi et al. 2018	Beery et al. 2020	Yeh et al. 2020	Christie et al. 2018	Ni et al. 2019	Borkan et al. 2019	Hu et al. 2020

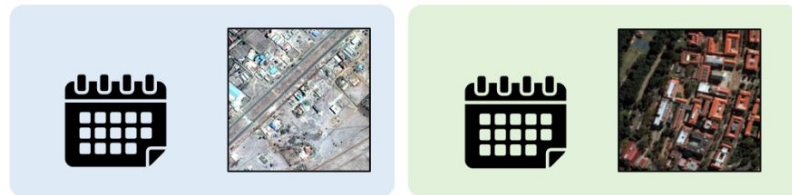
Performance degradation is also ubiquitous

shifts across hospitals in histopathology



ID accuracy 93.2% $\xrightarrow{-22.9\%}$ OOD accuracy 70.3%

shifts across time in satellite imagery



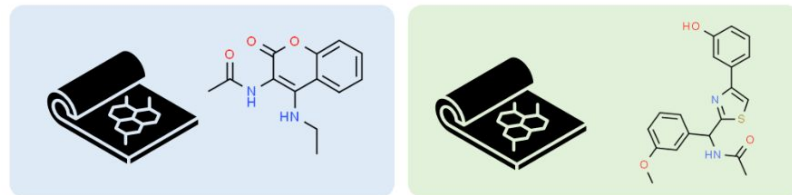
ID accuracy 48.6% $\xrightarrow{-16.3\%}$ OOD accuracy 32.3%

shifts across regions in wheat head detection



ID accuracy 63.3% $\xrightarrow{-13.7\%}$ OOD accuracy 49.6%

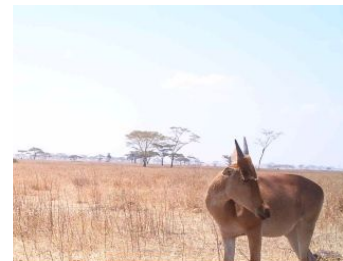
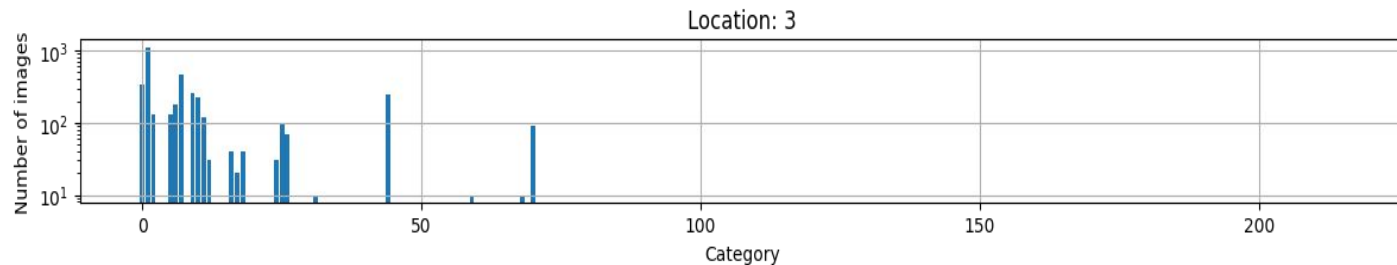
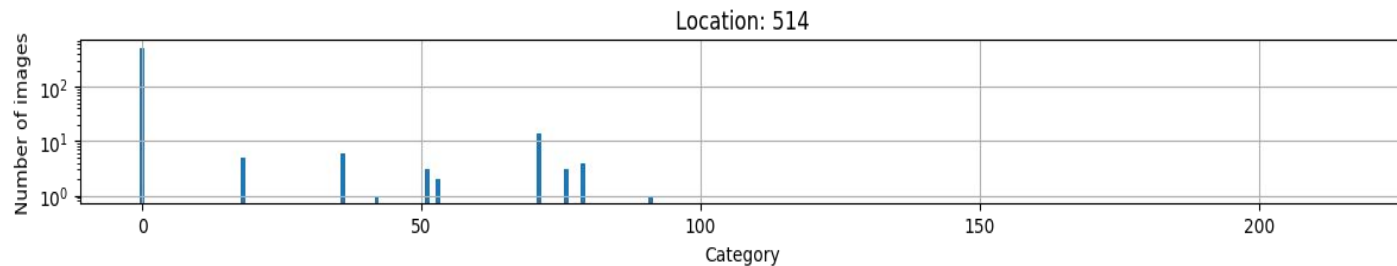
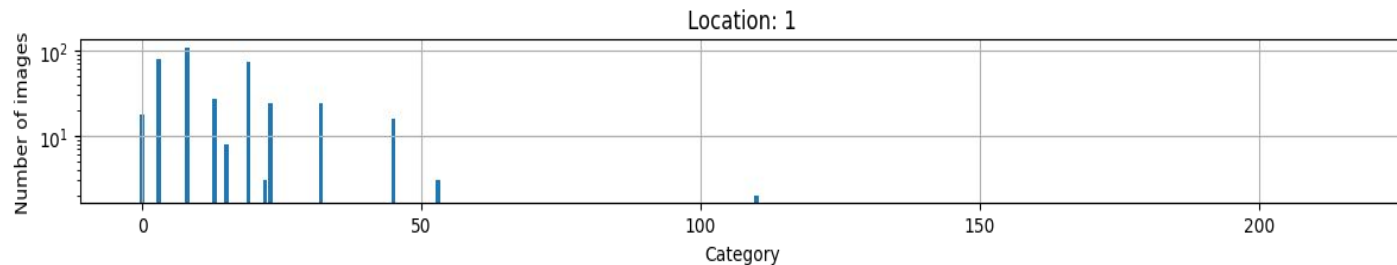
shifts across scaffold in bioassay prediction



ID AP 34.4% $\xrightarrow{-7.2\%}$ OOD AP 27.2%

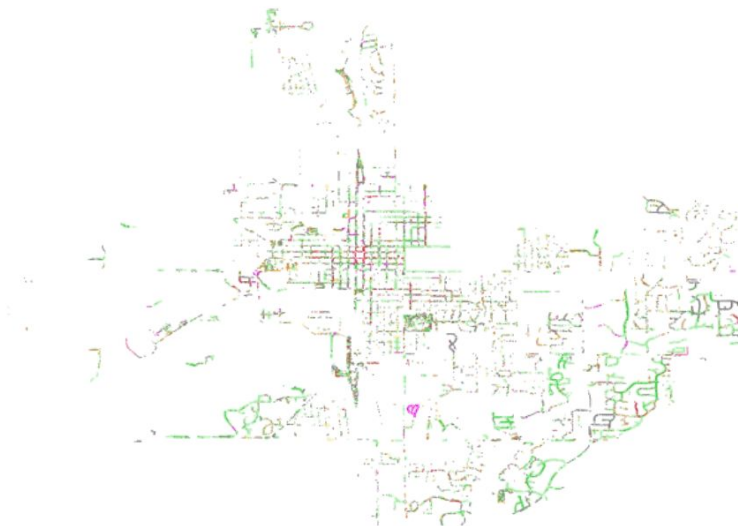
[Koh et al., 2021]

Each geospatial location has a distinctive habitat and class distribution



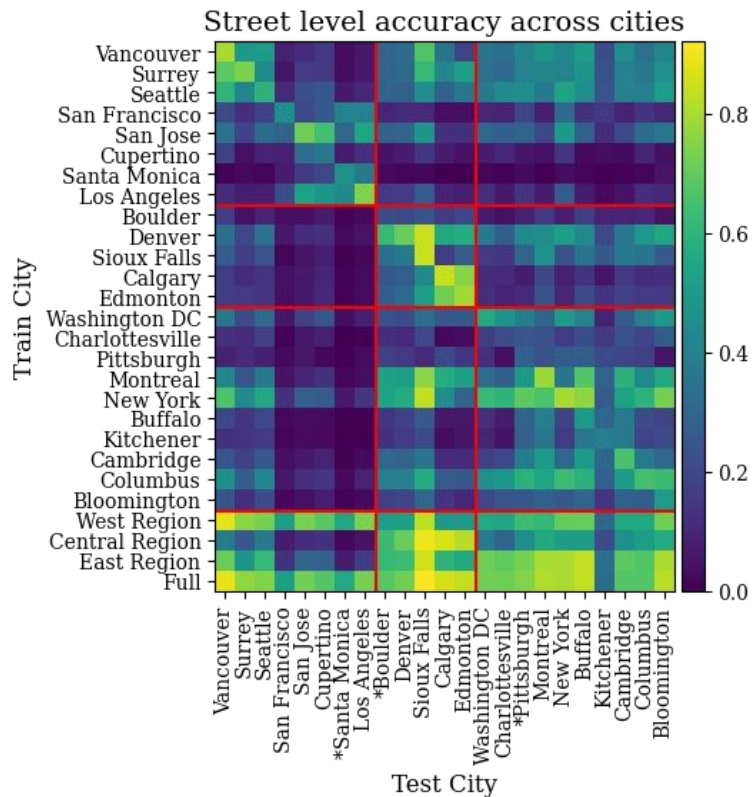
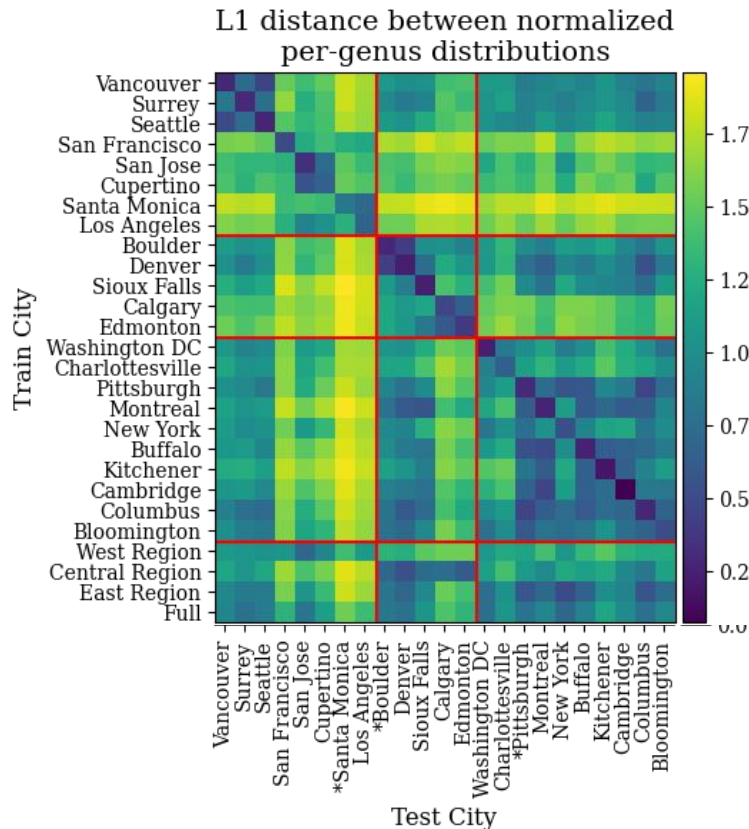
The distribution of urban tree species changes dramatically across North America

Bloomington



- Acer (Maple)
- Fraxinus (Ash)
- Ulmus (Elm)
- Quercus (Oak)
- Picea (Spruce)
- Prunus (Plum)
- Tilia
- Platanus
- Gleditsia
- Populus
- Pinus (Pine)
- Liquidambar
- Lagerstroemia
- Washingtonia
- Ficus
- Afrocarpus
- Other

Performance has strong correlation with distribution similarity in urban forests



2015-01-25 1:46:42 AM M 5/10 18°C



**Class-agnostic
localization
generalizes:
less impact from
context,
distribution shift,
and the long tail**

<https://github.com/microsoft/CameraTraps/blob/main/megadetector.md>

*Efficient Pipeline for Camera Trap
Image Review*, Beery, et al., DMAIC @
KDD 2019

INO1





Sarah Bassing @S_Bassing · May 19



Thank goodness for the [#MegaDetector](#) helping me find the ONE animal image mixed in with 170,787 pictures of blowing grass and clouds from this [#CameraTrap](#)! Image recognition software is a game changer. [#painless](#) [#tech4wildlife](#) [#WAPredatorPreyProject](#)



Active learning to adapt models to new regions efficiently



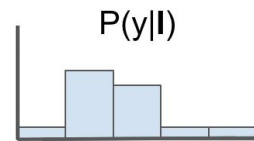
- Use the MegaDetector to crop
- Cluster animals based on visual similarity in new cameras
- Humans ID examples from each cluster (active learning criteria)
- Gets same accuracy with **99.5% fewer labels**

Learn a spatiotemporal prior to provide context

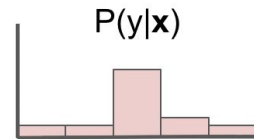
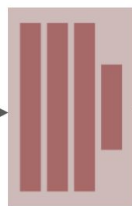
$$P(y|I, \mathbf{x}) \propto P(y|I)P(y|\mathbf{x})$$



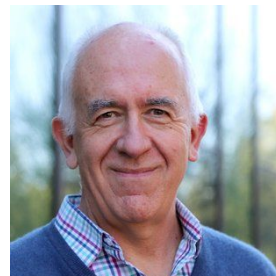
Image Classifier



Spatio-Temporal Prior



Combine



$\mathbf{x} = (\text{longitude, latitude, day})$

A photograph of a tree-lined street with a white text overlay. The street is paved and has a white dashed line down the center. The trees are lush green and their shadows are cast on the road. The text is centered and reads:

**Exploring global model performance across
data modalities:
Multiview Urban Forest Monitoring**

Benefits of the Urban Forest



Biodiversity

Cities support regional biodiversity

Large trees and a diverse, connected urban forest supporting a rich array of wildlife, particularly birds



Reduces Air Pollution

Removes some 784k tons of air pollution annually

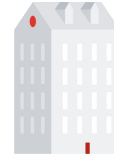
Implied global value: \$15-20B/yr
Potential impact: \$1.5B-\$5B/yr



Carbon Sequestration

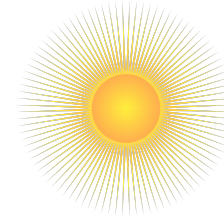
Total opportunity for additional carbon sequestration ranges from 1GT to 2.4GT

At \$50/ton, that's a value of \$50B-\$120B, cumulatively (i.e., not annually)



Reduced Energy Use

Trees reduce building energy use and avoided pollutant emissions (\$8B+ value in U.S. alone)



Extreme Heat Islands

Lowers surface and air temperatures by providing shade and through evapotranspiration

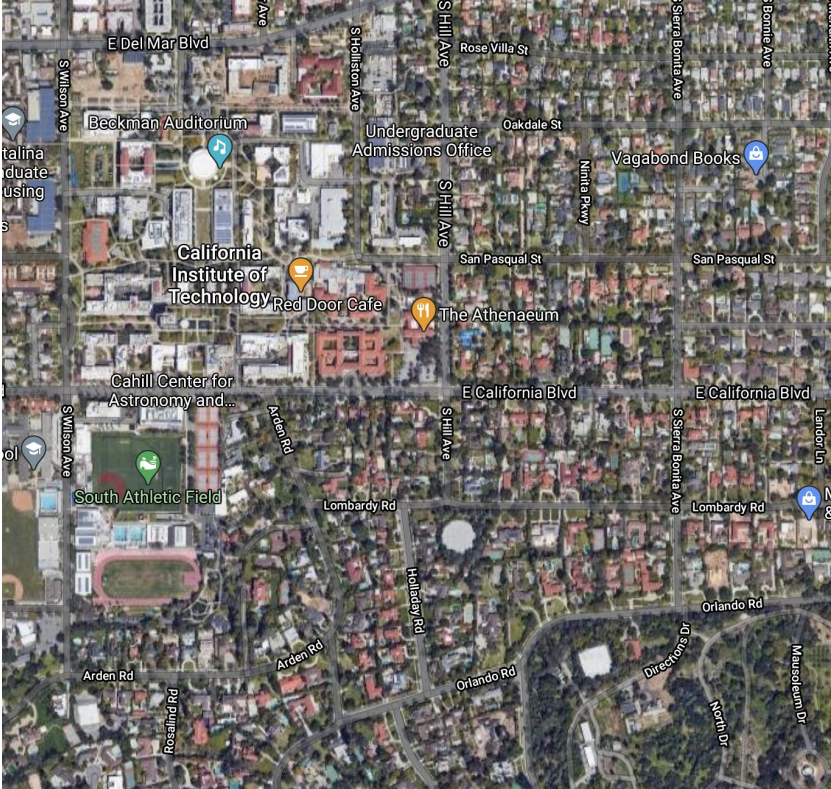


Physical + Mental Health

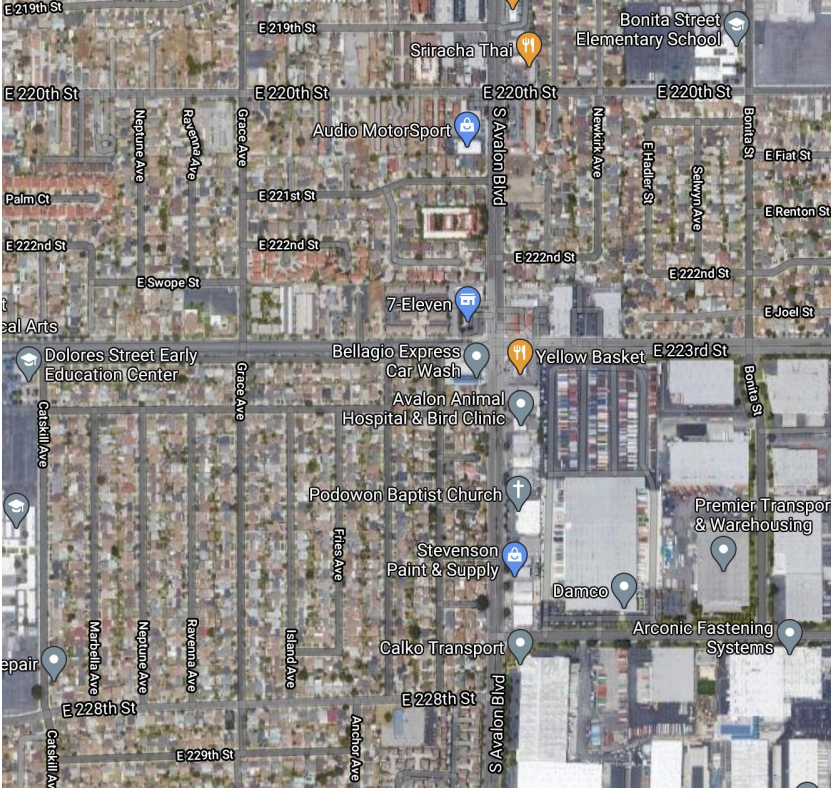
Trees in a community correlate with lower asthma rates, reduced hospital visits during heat waves and improved mental health

These benefits are not accessible to all

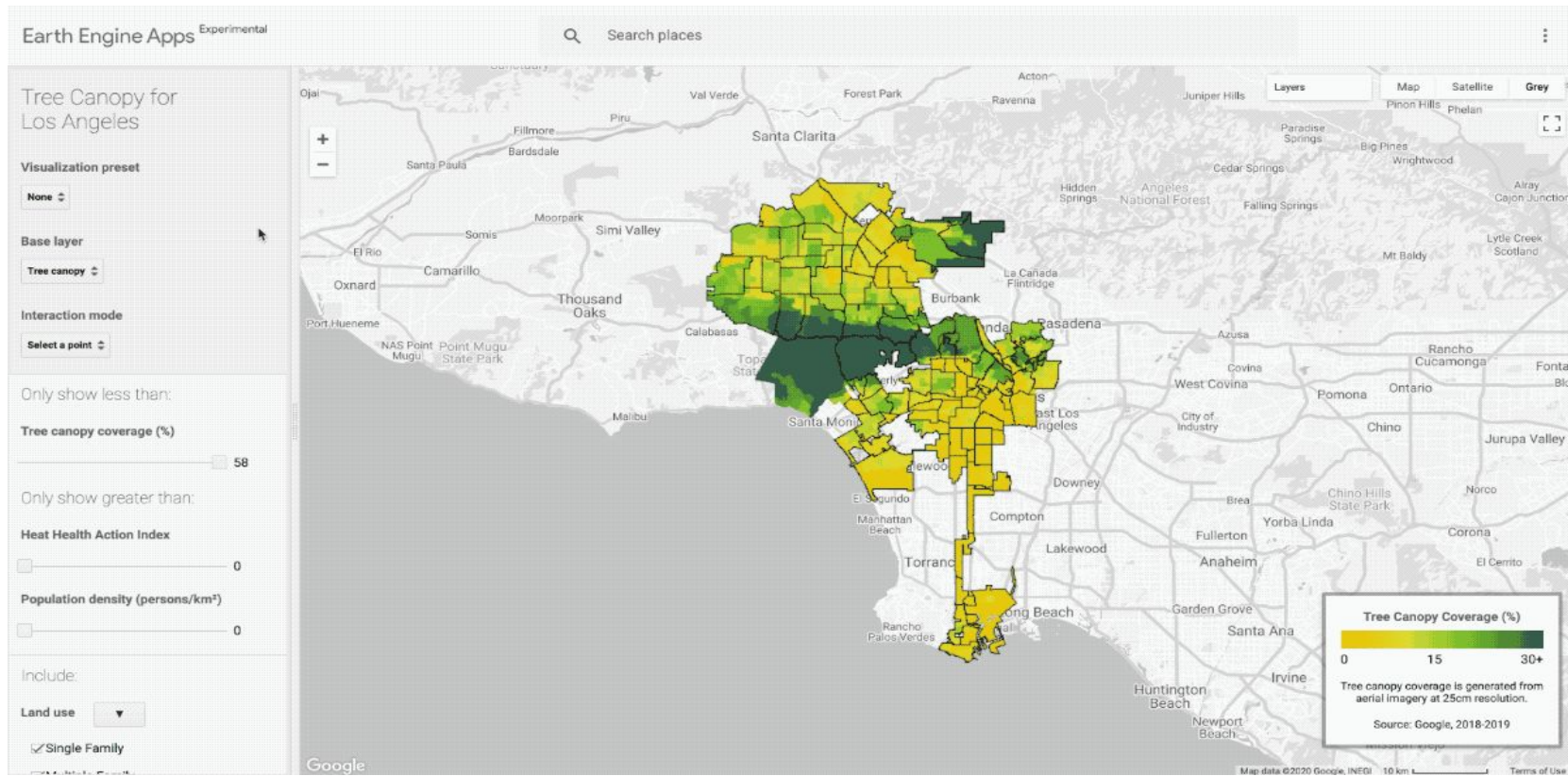
Pasadena



Carson



Tree canopy prediction via Google's Urban Ecology Team

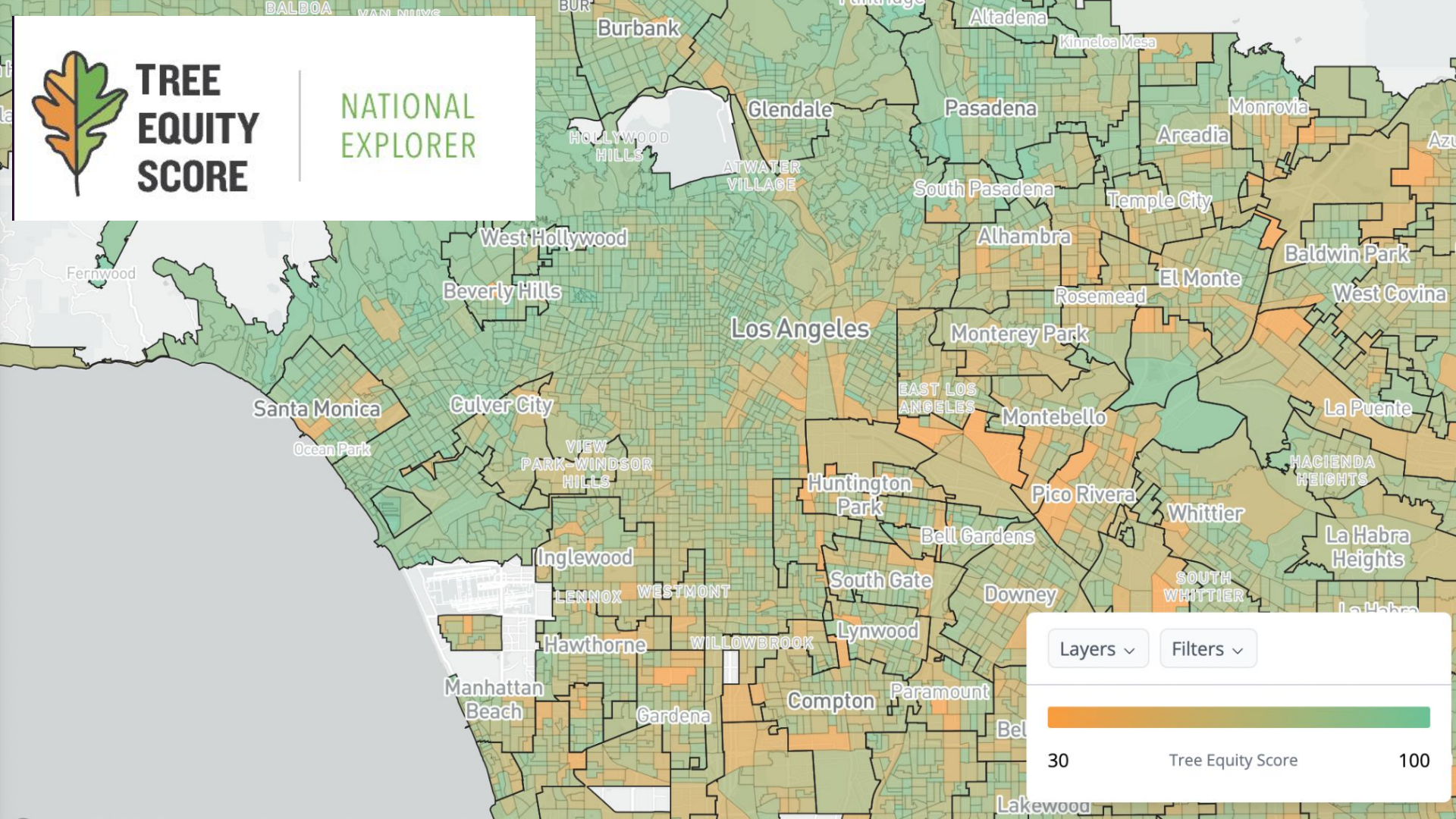


<https://insights.sustainability.google/labs/treecanopy>



**TREE
EQUITY
SCORE**

NATIONAL
EXPLORER



Layers ▾

Filters ▾



Tree canopy prediction is not enough

Instance locations and species identification is needed to:

- Estimate water retention
- Estimate carbon sequestration
- Estimate potential heat reduction
- Monitor species' reaction and resilience to our changing climate at scale
- Strategically plan planting to maximize biodiversity



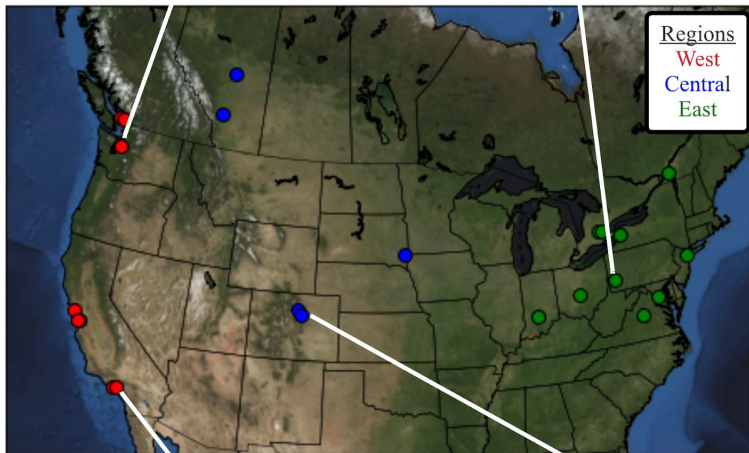
The Auto Arborist Dataset:

23 cities, 344 genera, 2.6M tree records, >1M trees w/ imagery

City: Seattle, Genus: Malus



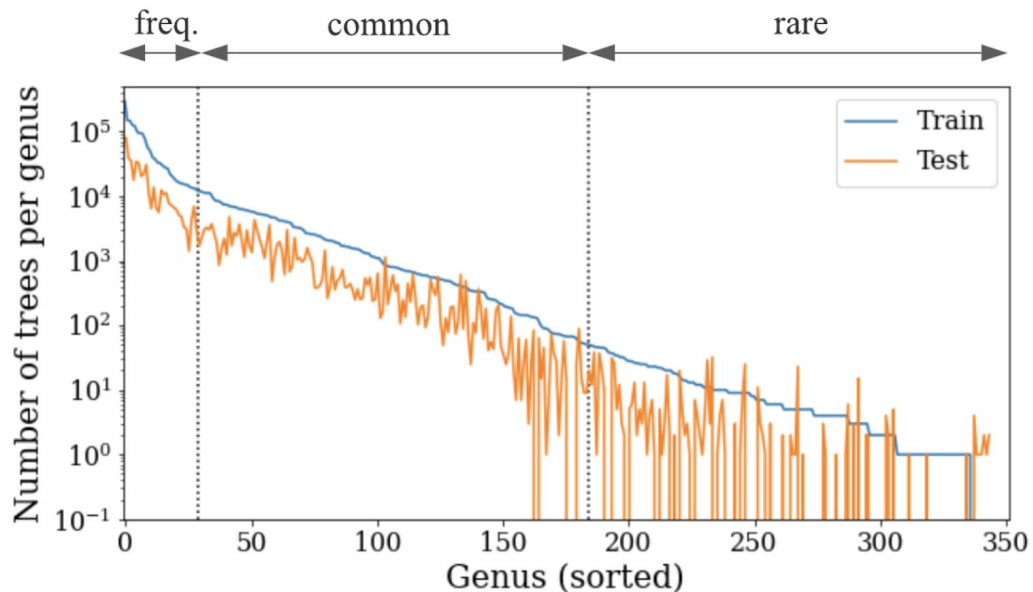
City: Pittsburgh, Genus: Platanus



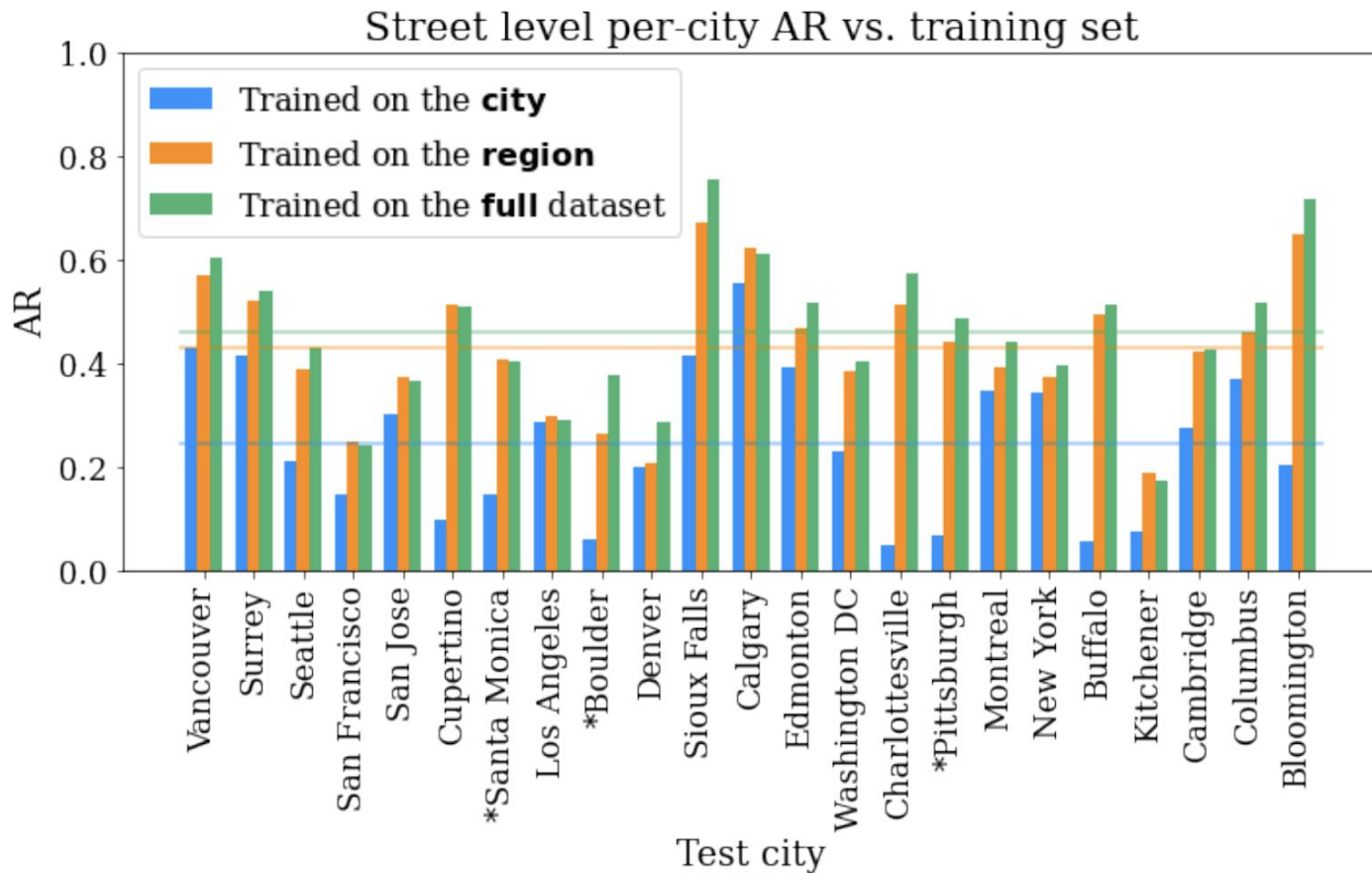
City: Los Angeles, Genus: Washingtonia



City: Denver, Genus: Quercus

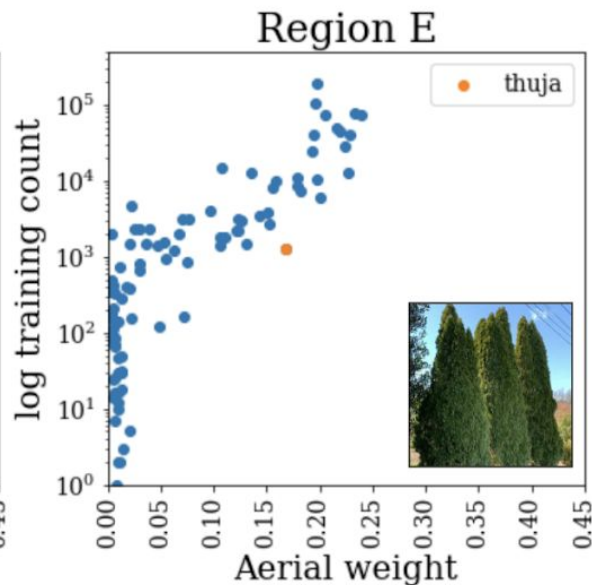
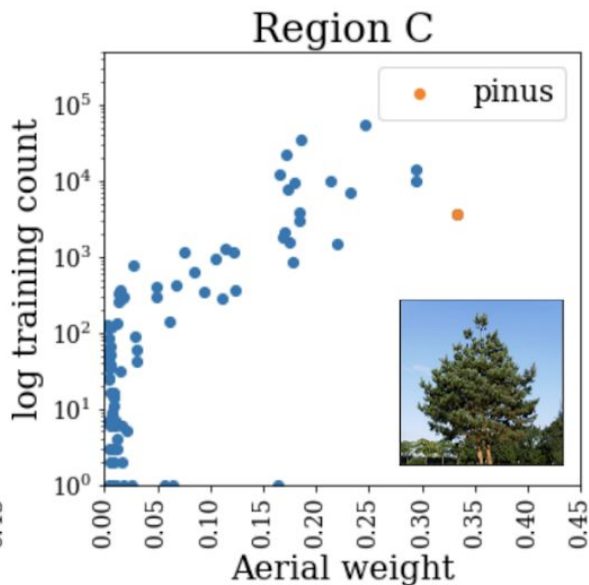
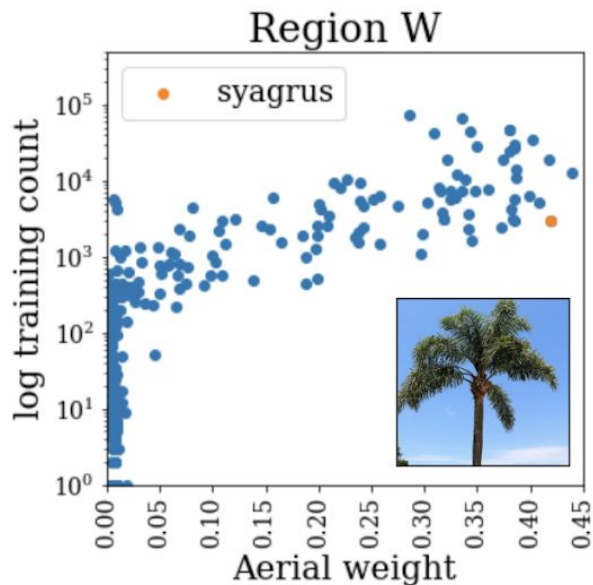


Models trained on the full dataset *often* outperform city-specific or region-specific models, *but not always*



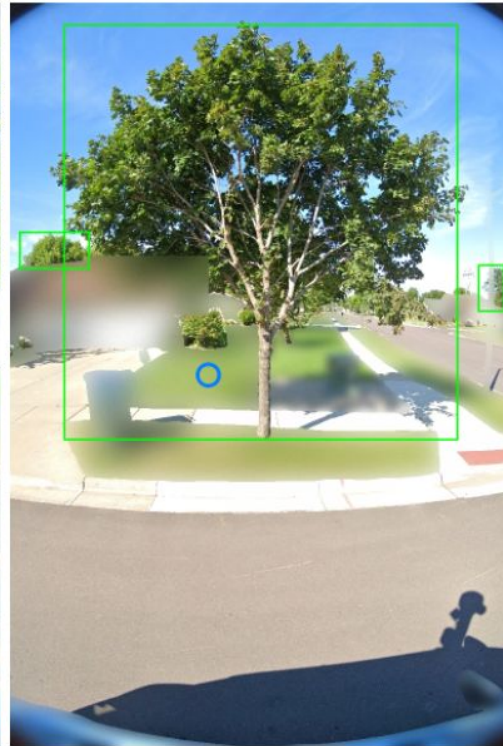
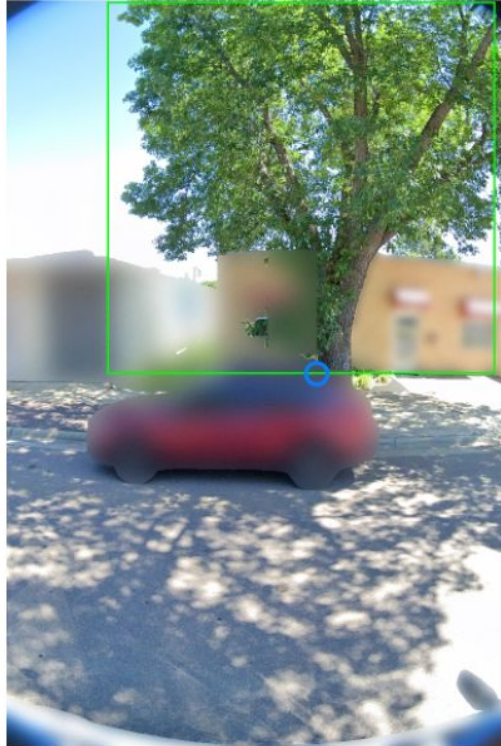
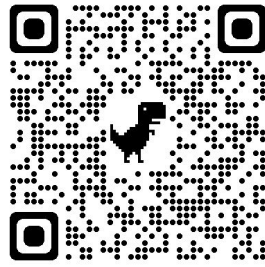
Combining information across data modalities achieves best results

Train Set	Aerial	1 SL	3 SL	A+SL
Region W	20.63	41.53	45.12	46.07
Region C	18.8	44.77	46.91	47.12
Region E	17.54	43.25	45.13	46.21
Full	18.7	46.13	49.0	49.23
Full w/ Regional MoE				49.96



Dataset Release

<https://google.github.io/auto-arborist/>



Going beyond images-

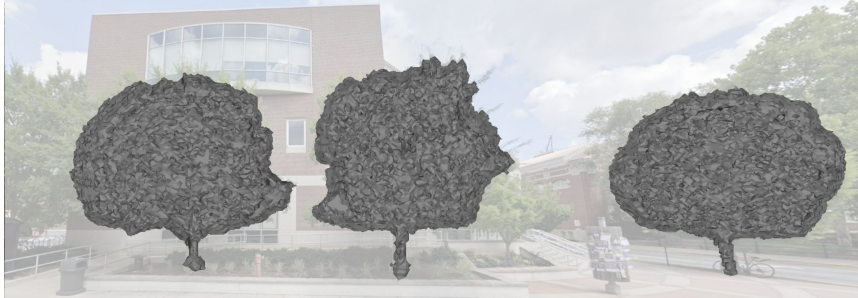
Understanding urban forests in 4D



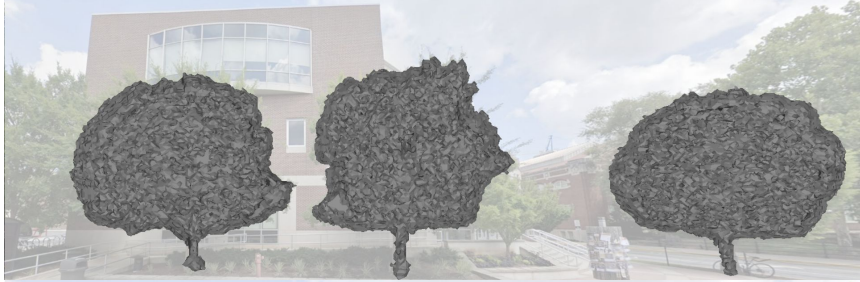
Generate tree structure from images



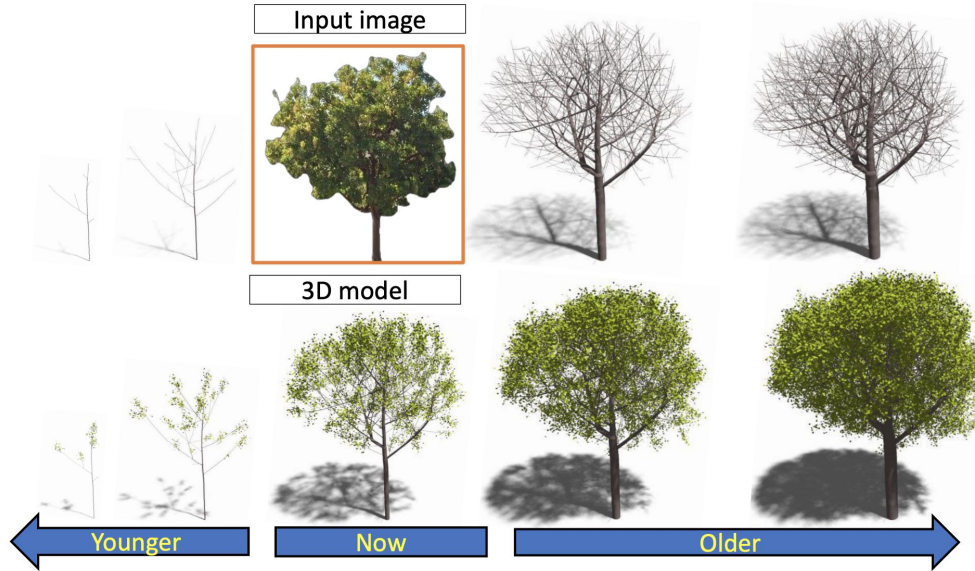
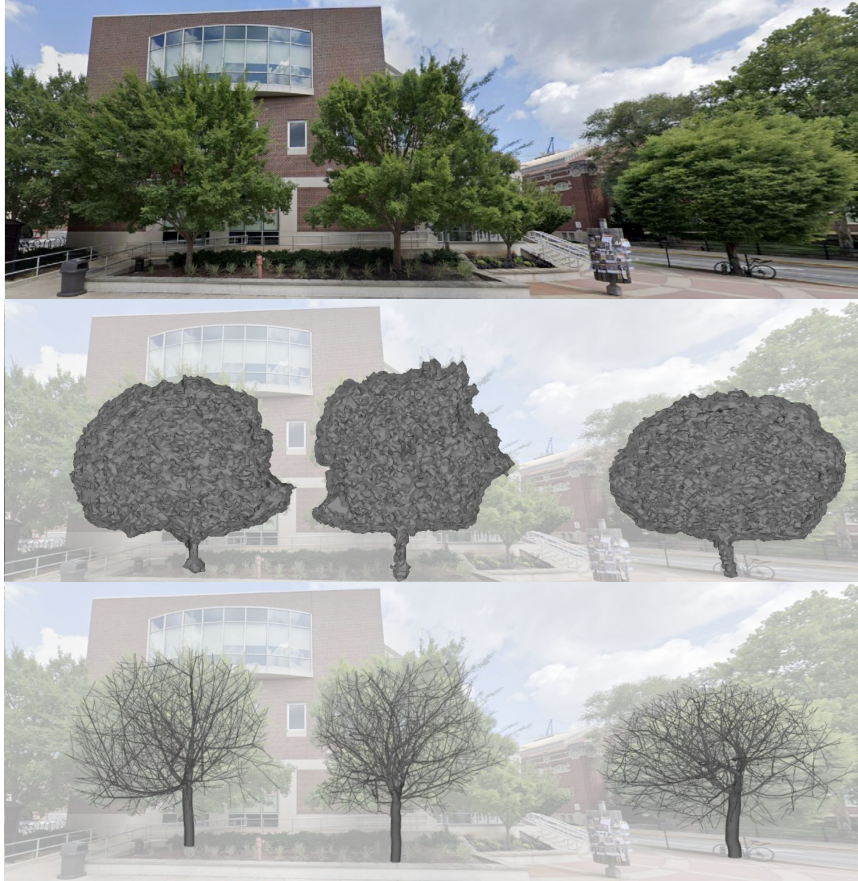
Generate tree structure from images



Generate tree structure from images



Measure and predict urban forest change



Open challenges in CV4Ecology

- Global and local distribution shift
- Long-tailed distributions
- Sparse, low-quality, biased data
- Interactive ecologist-AI systems
- Multimodal, multiview systems
- Detecting and categorizing change
- Limited Interdisciplinary capacity

Interested? Join our slack channel by
emailing aiforconservation@gmail.com



Thanks!
Questions?

