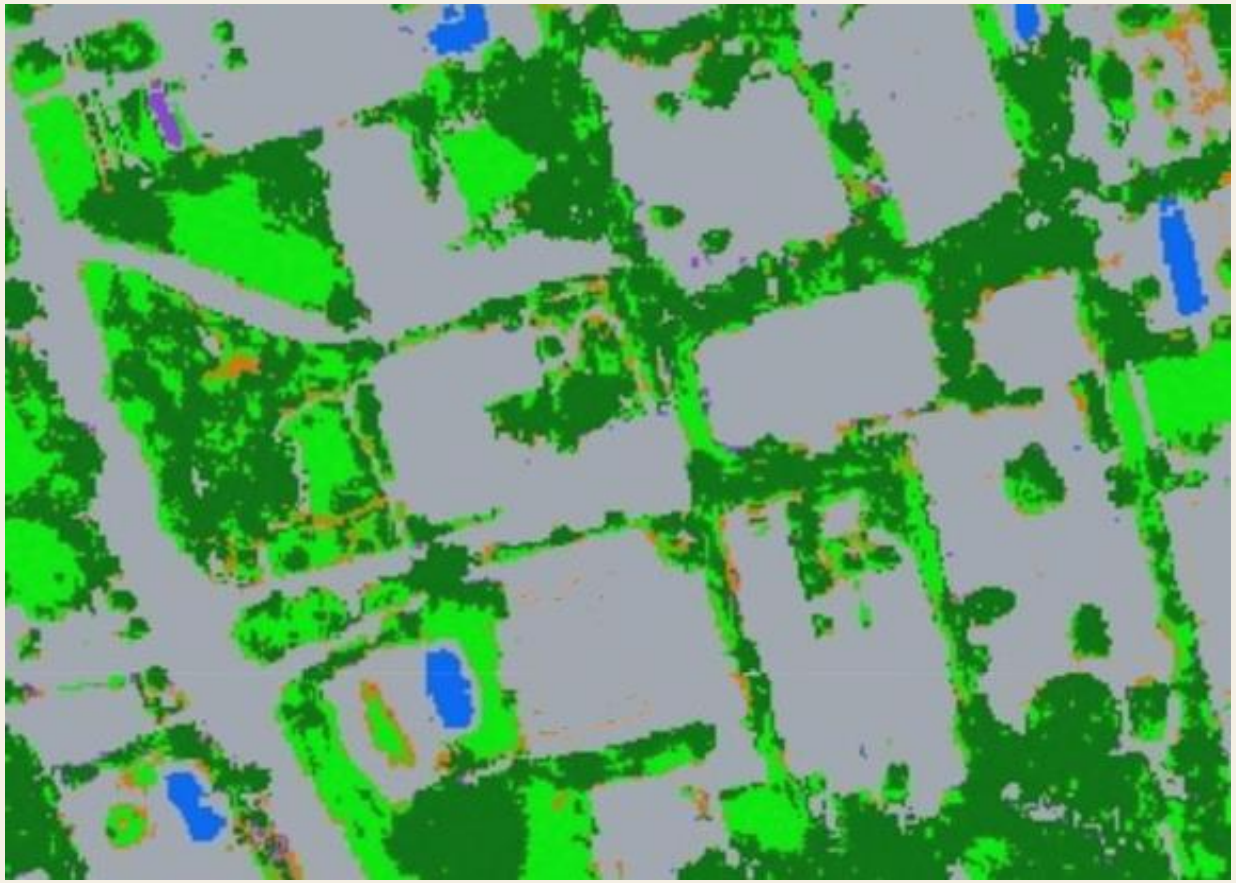

Urban Insights

better choices for healthier cities, one pixel at a time

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Thank you!

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IMAGINE

Urban Insights

Problem

Worst Drought in California in 1200 years!

Solution

Land Cover* Detection & Classification Insights

Use Cases

Impact on Microclimate and Correlation with Median Household

Deliverables

Research Paper, API & Website

*land cover indicates the physical land type such as water, grass, trees, impervious surfaces, soil and turf

Welcome to Urban Insights

Better choices for healthier cities... One pixel at a time!

Read More

ABOUT

OUR MISSION

Contents

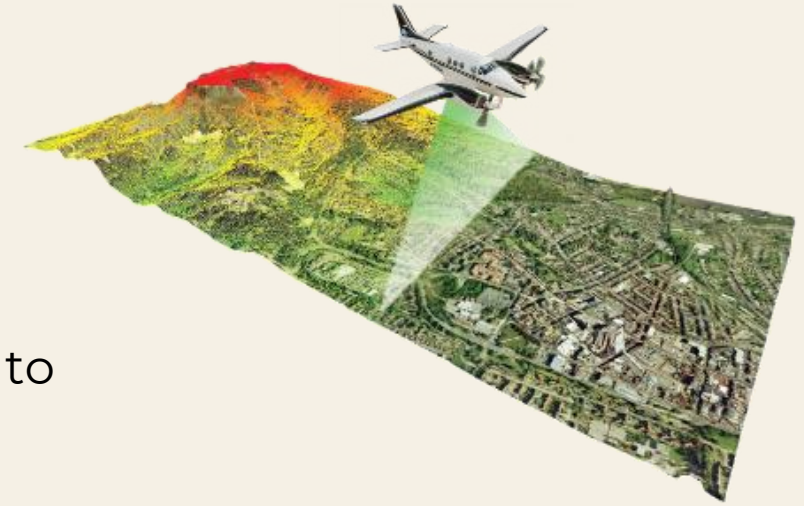
Data Sets

1. NAIP

Extract Aerial Images Containing 4 Channels:

- **Red**
- **Green**
- **Blue**
- **Near-Infrared**

Apply transformations to extract insights, e.g.:



$$NDVI = \frac{NIR - Red}{NIR + Red}$$

0< NDVI <0.33

0.33 < NDVI < 1

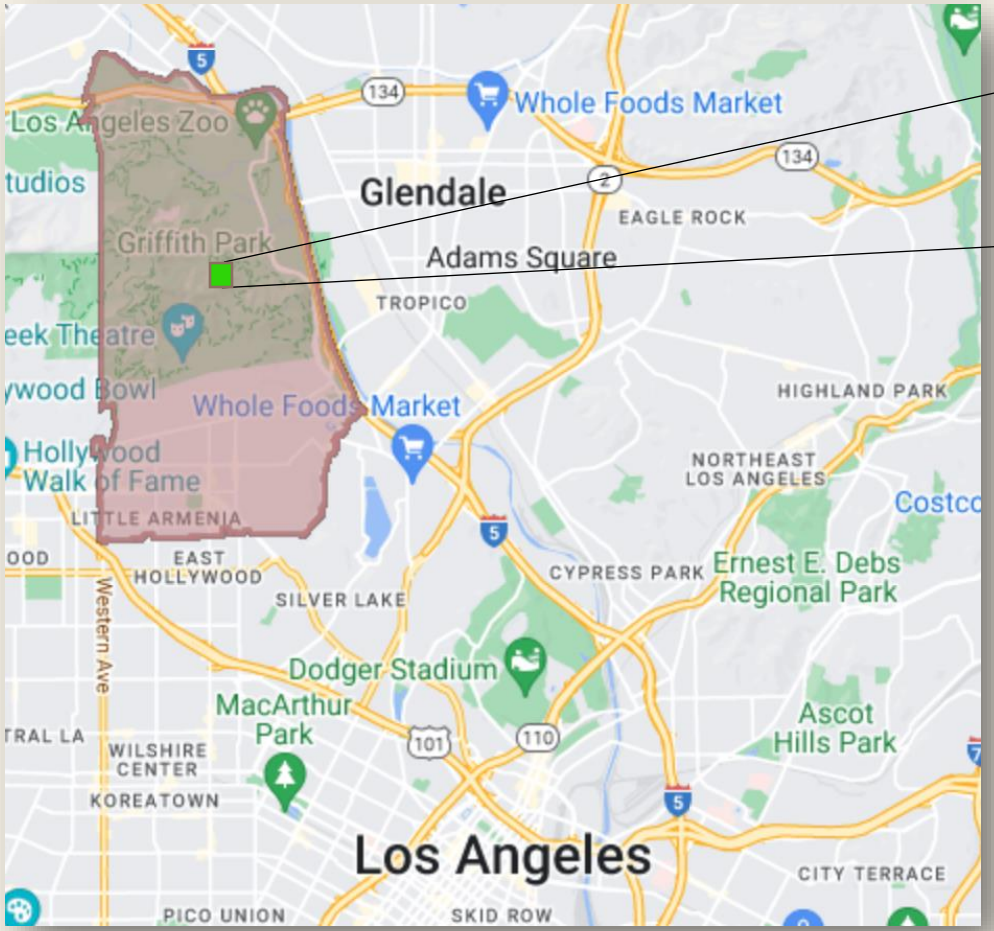
2. CENSUS

3. Land Surface Temperature Data

***NAIP:** National Agriculture Imagery Program
***NDVI:** Normalized Difference Vegetation Index

Implementation

Google Earth Engine



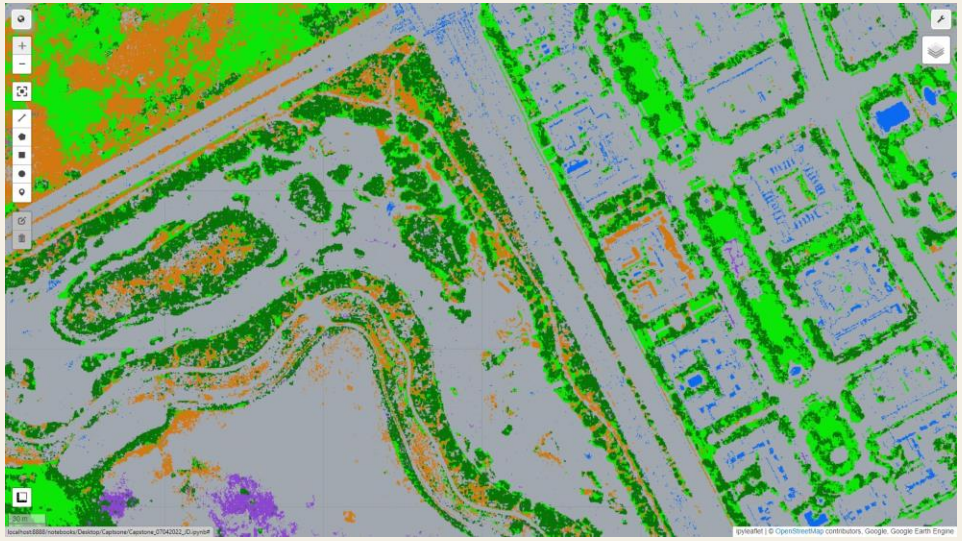
1 m²

CLASS = GRASS

FEATURES = [
R,
G,
B,
NIR,
NDVI,
NIR_Entropy,
NIR_Contrast,
NIR_Gearys
]

1 m^2 : 1 square meter

GEE Baseline Model



- 80/20 split on pixels → 80/20 split on polygons
- GEE* provided ML toolkit (Random Forest)
- Macro F_1

Classes Classified by the Model

- Water
- Trees
- Grass
- Turf
- Impervious
- Soil

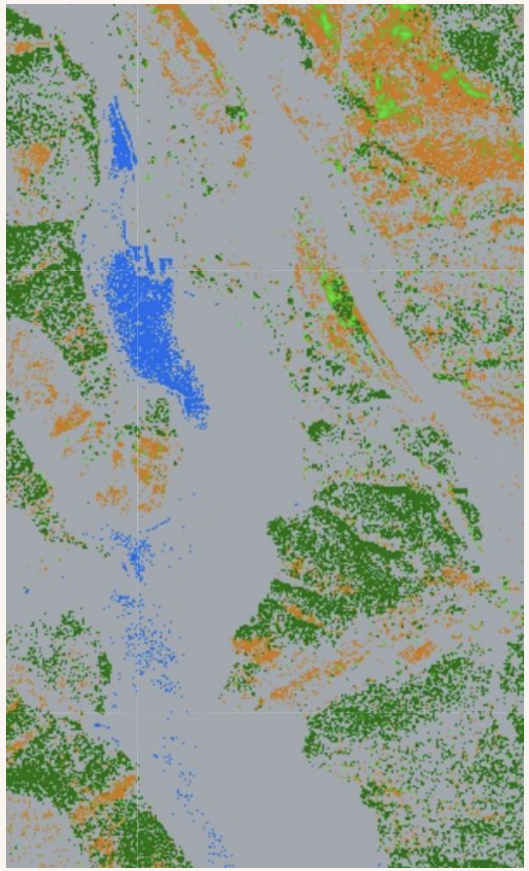
*Google Earth Engine

Model Iterations

Satellite Image

NAIP Image

Neural Net V1



Biased towards impervious

Neural Net V2

Biased towards water

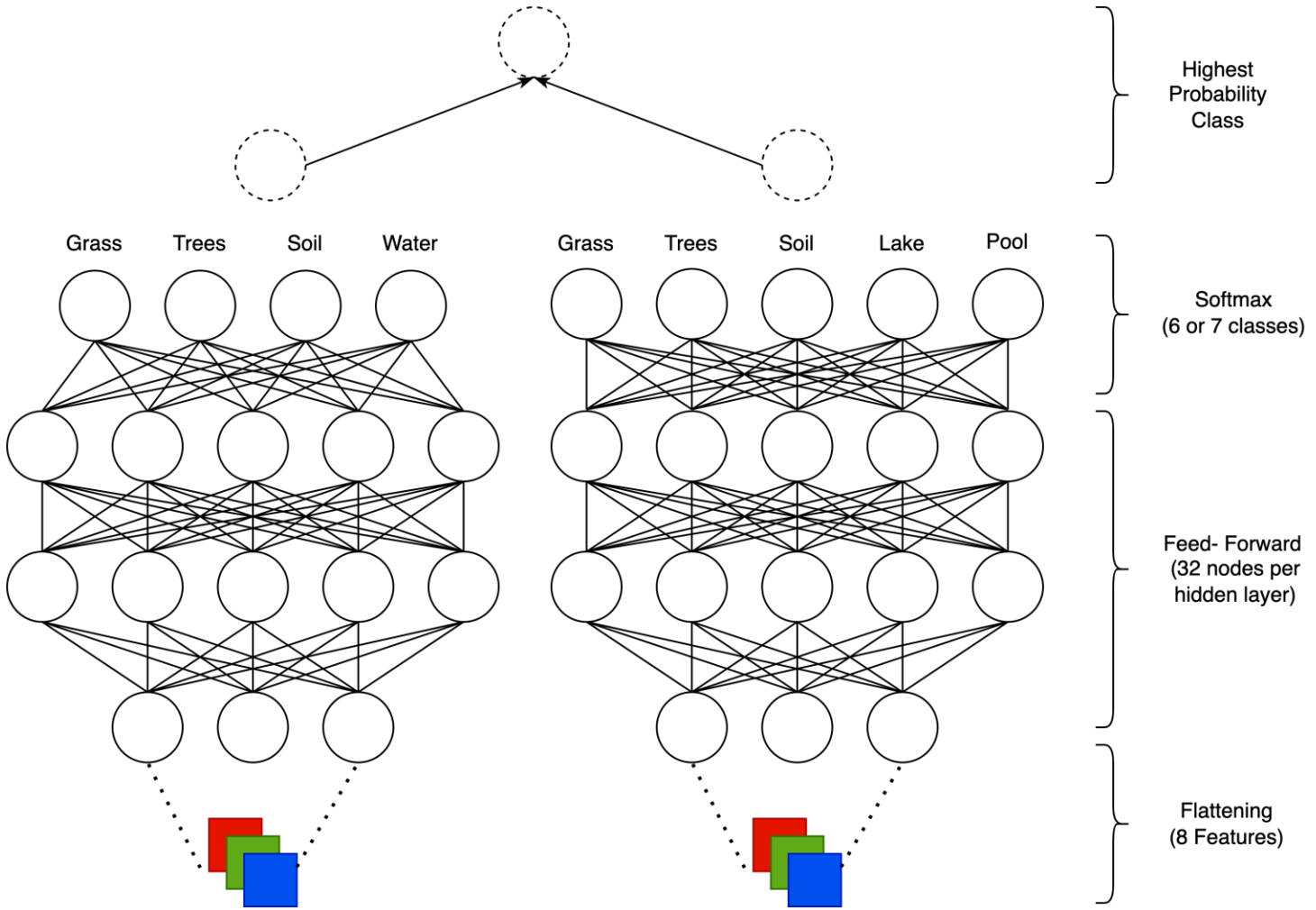
Neural Net Ensemble

Max probability class from both models

Neural Network Ensemble Model

Hyperparameters

Layers	3
Nodes	32
Dropout	0.05
Learning Rate (Adam)	0.01
Activation	ReLU
Batch Size	120



Model Performance Comparison

F_1 Score	Baseline (RF)	Neural Net V1	Neural Net V2	Ensemble
grass	0.88	0.88	0.89	0.90
trees	0.85	0.80	0.86	0.85
turf	0.84	0.94	0.91	0.93
soil	0.92	0.92	0.94	0.94
impervious	0.86	0.87	0.89	0.89
natural water	---	---	0.77	---
pool water	---	---	0.99	---
all water	0.67	0.84	---	0.99
Macro F_1 Average	0.84	0.88	0.89	0.92

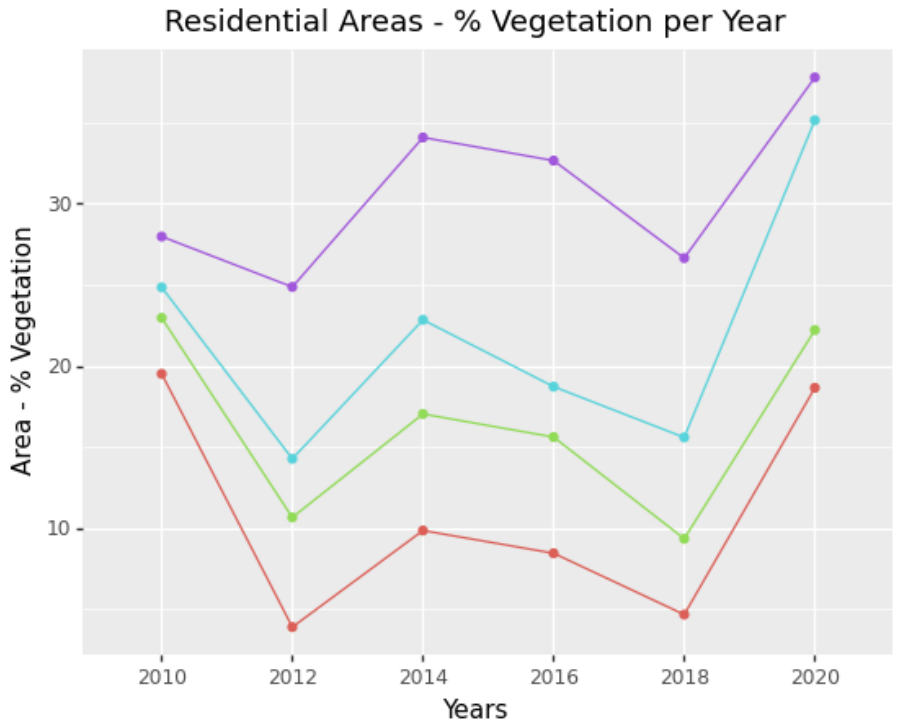
Correlation with Median Household Income

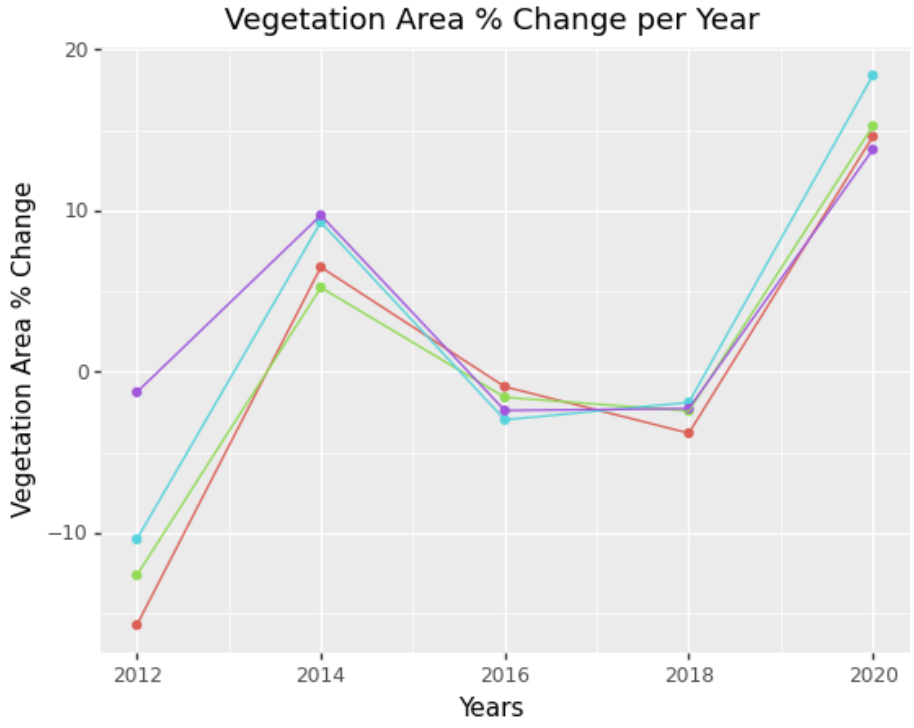
2.97%

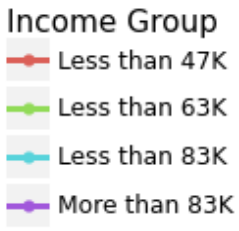
Area Increase for every 10K USD in Median Household Income

0.5%

Rate of Change Positive Increase for every 30K USD in Median House Income







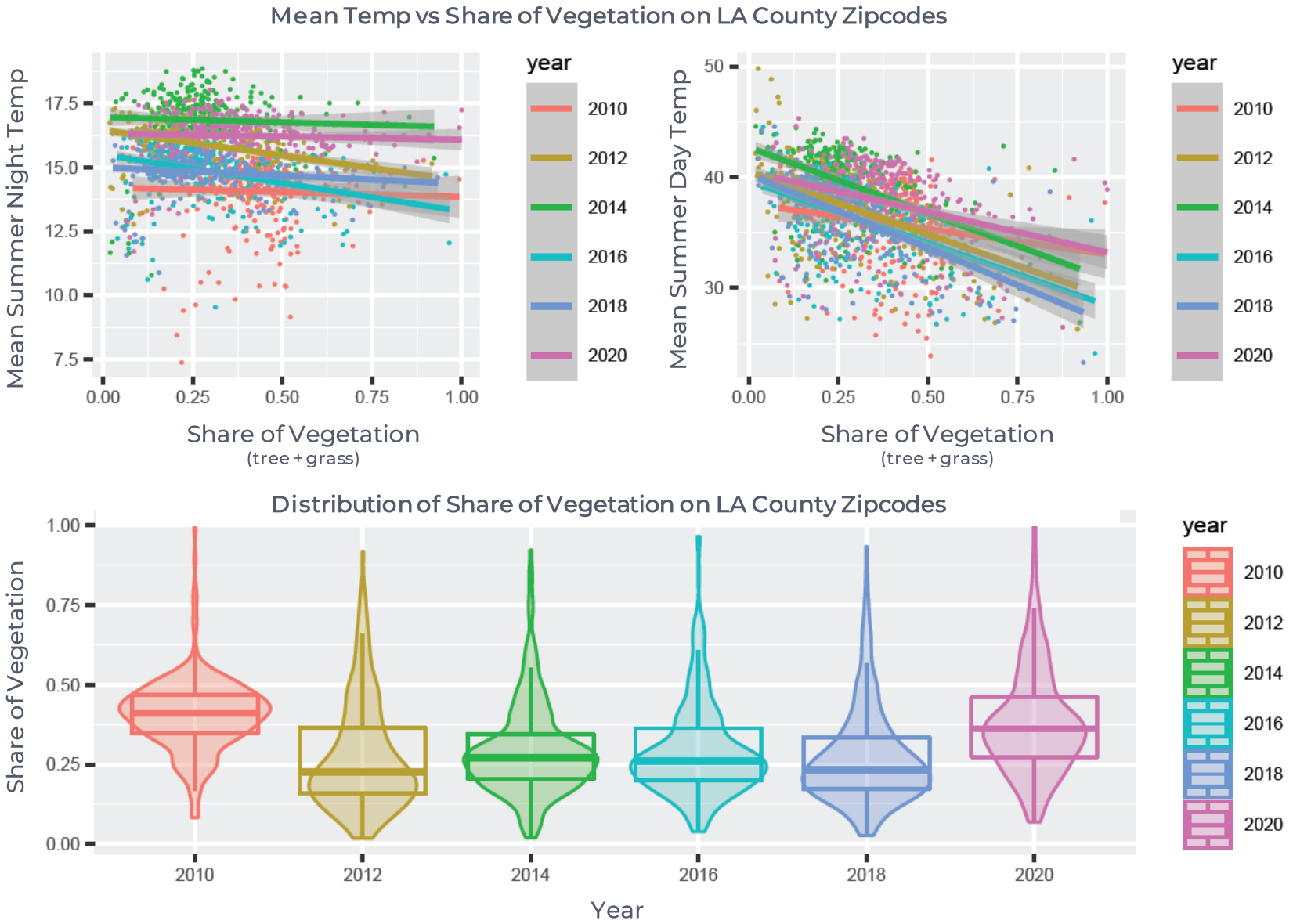
Impact on Microclimate

-2.25° C

Grass areas are on average cooler than impervious

-2.16° C

Tree areas are on average cooler than impervious



Layered Architecture

Input

Google Earth Engine

ArcGIS

Modeling

Google Earth Engine

TensorFlow

Integration

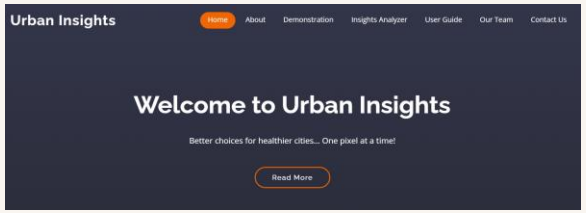
FastAPI

PostgreSQL

docker

aws

Output



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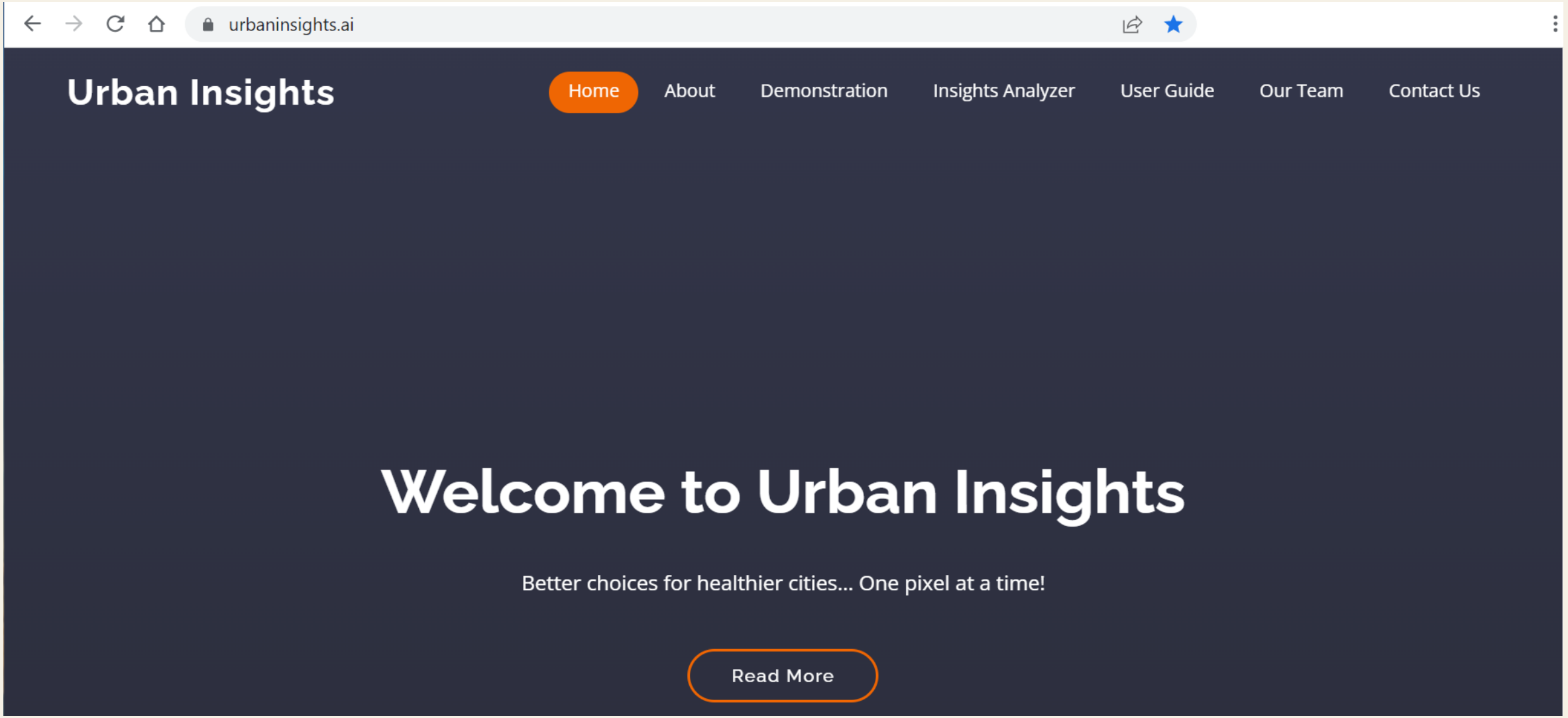
Shiny

R

N+

Live Demonstration



Summary

Worst climate crisis of generations

Urban Insights provides eco-friendly insights

Policy makers can use this to design incentives to curb outdoor residential water usage

Urban planners can use this to plan and redevelop cities

Thank you!

~ from team Urban Insights

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https://bit.ly/3SCnZoB

GitHub https://github.com/urbaninsights

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