# Closing the Domain Gap – Blended Synthetic Imagery for Climate Object Detection

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Duke University

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*for* ENERGY, ENVIRONMENT
& SUSTAINABILITY

Wind Turbines

Transmission Lines

Solar Panels

Storage Tanks

## Motivating Problem

Accurate information on the location of energy infrastructure is important for policymakers to make climate decisions, however key data are often lacking.

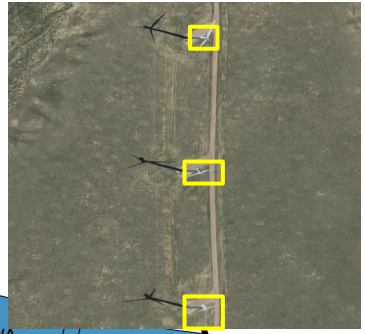
## Proposed Solution

Object detection models trained on remotely-sensed data.

## Challenges

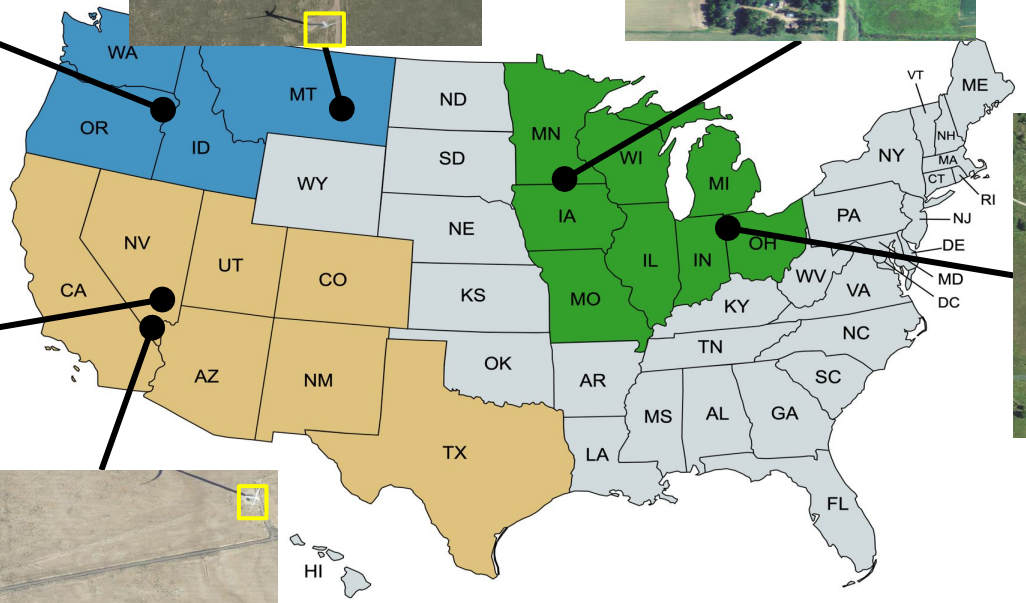
- Cost of acquiring and labeling data
- Generalizability of model

Northwest



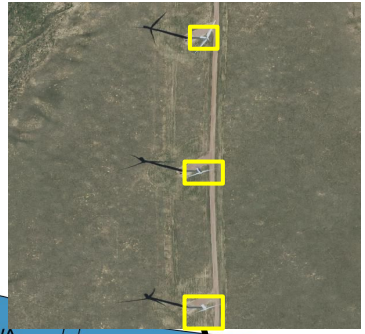
Eastern Midwest

Southwest



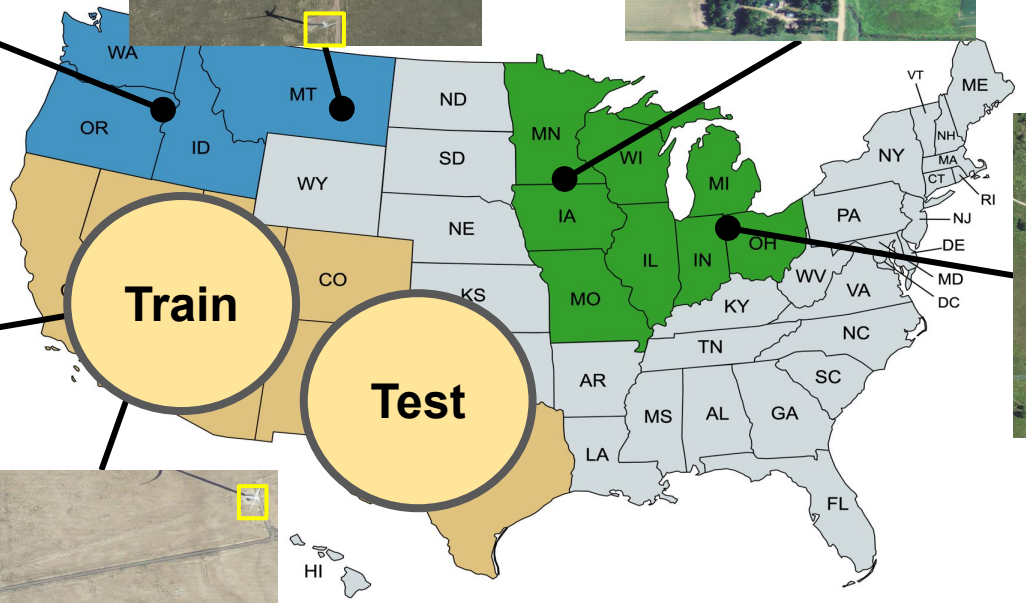

**Domains can be visually distinct**

Northwest



Eastern Midwest

Southwest

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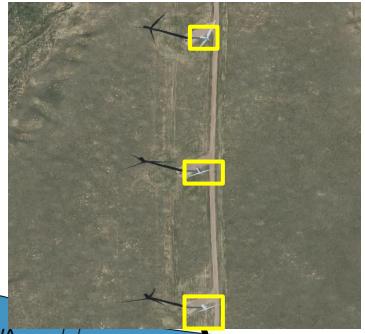

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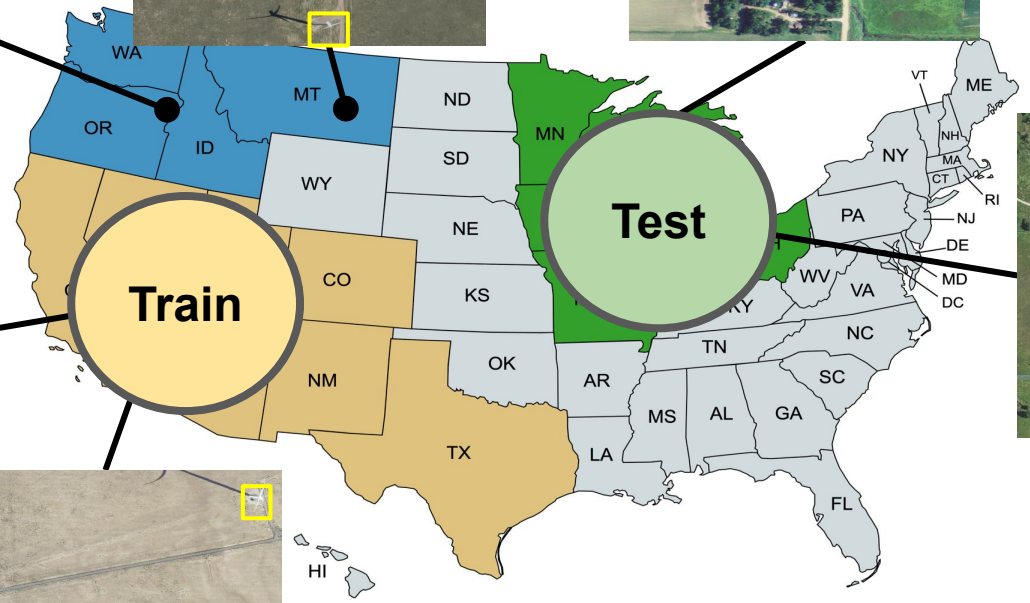
Southwest




**Domains can be visually distinct**

# Our method:

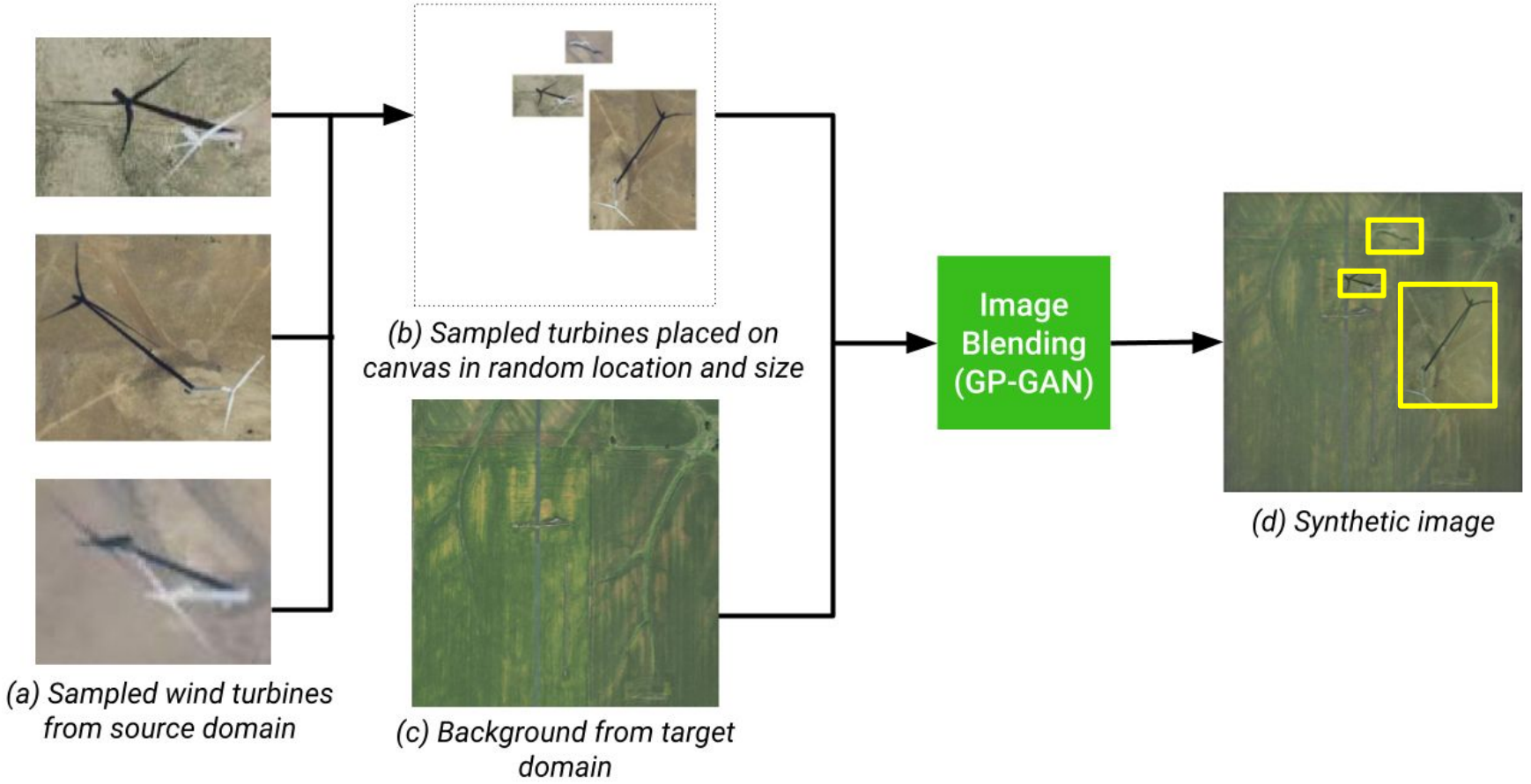


Image Blending (GP-GAN)
(a) Sampled wind turbines from source domain
(b) Sampled turbines placed on canvas in random location and size
(c) Background from target domain
(d) Synthetic image

# Our method:

Background Image

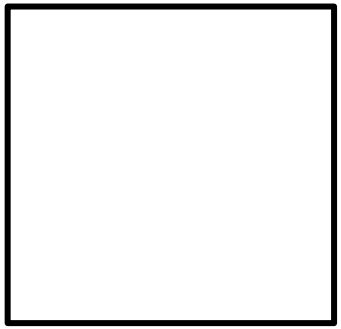
Synthetic Image

## Training Data

## Test Data

**Baseline Experiments**

100 real images



100 real images

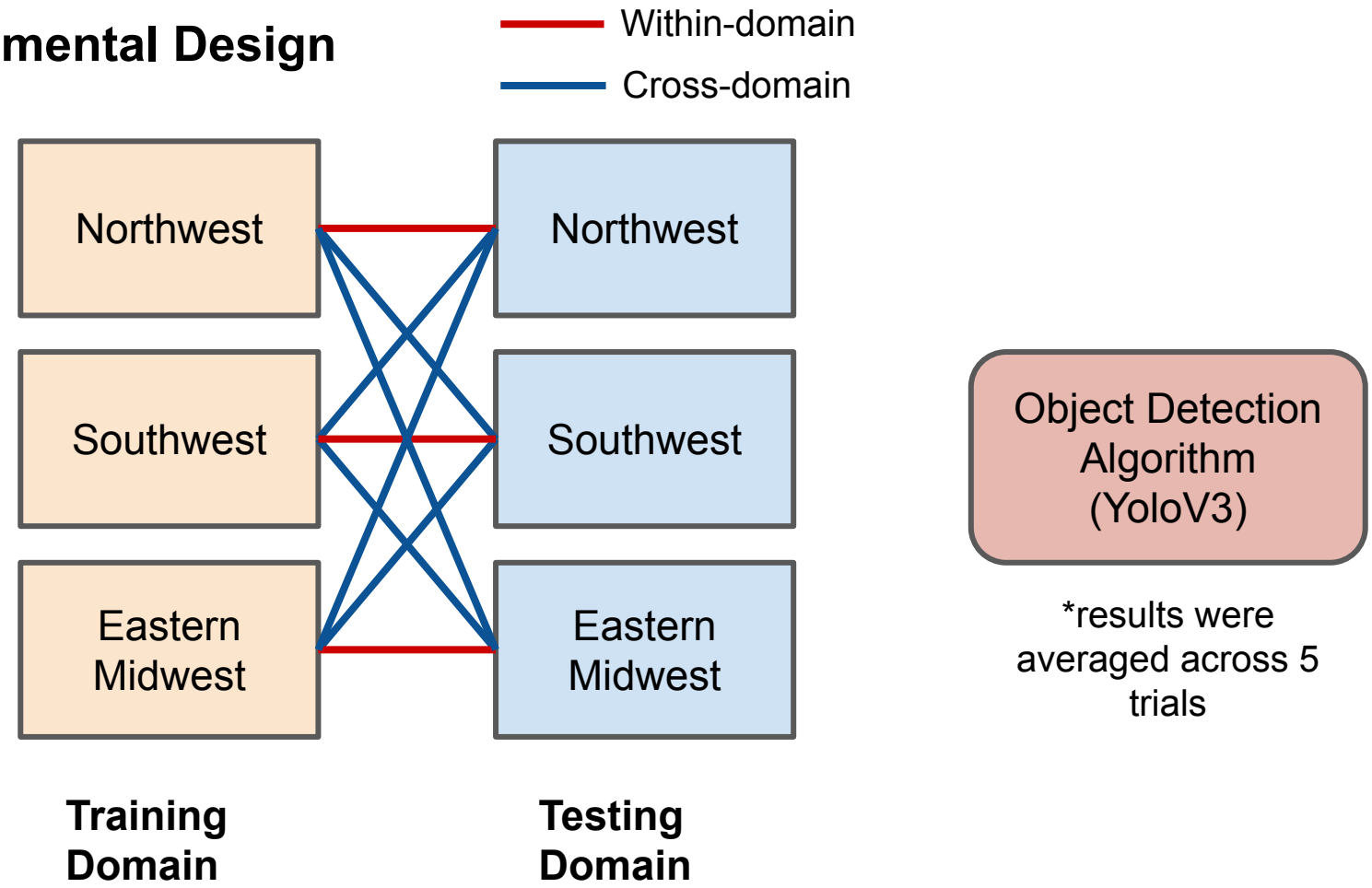
**Domain Adaptation Experiments**

100 real images

100 supplemental images

100 real images

# Experimental Design



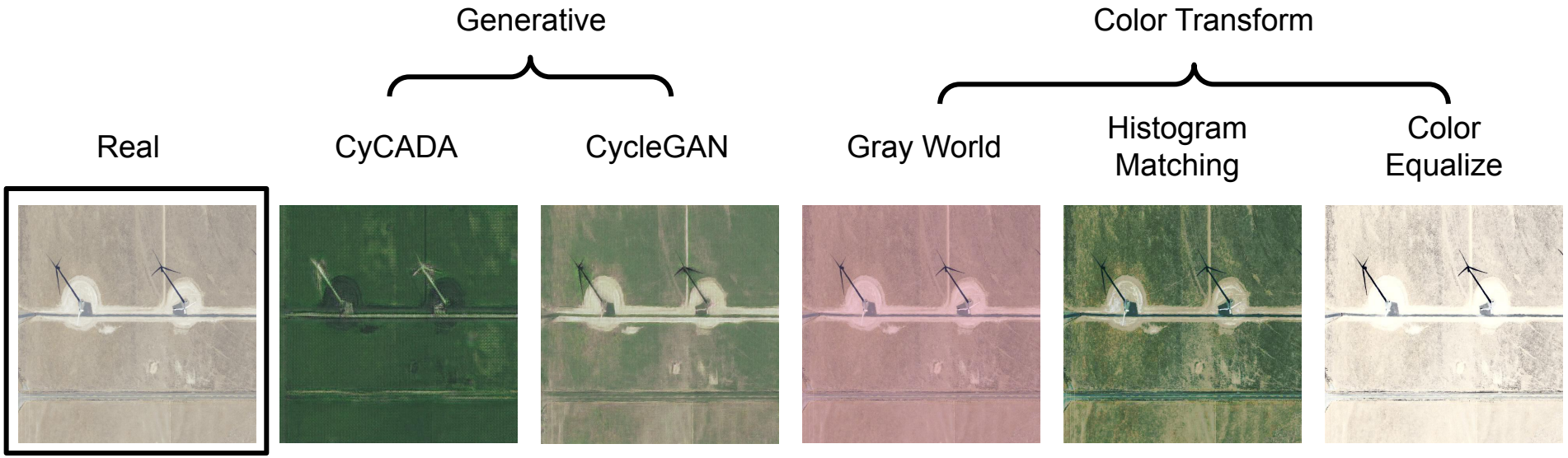

Object Detection Algorithm (YoloV3)

*results were averaged across 5 trials

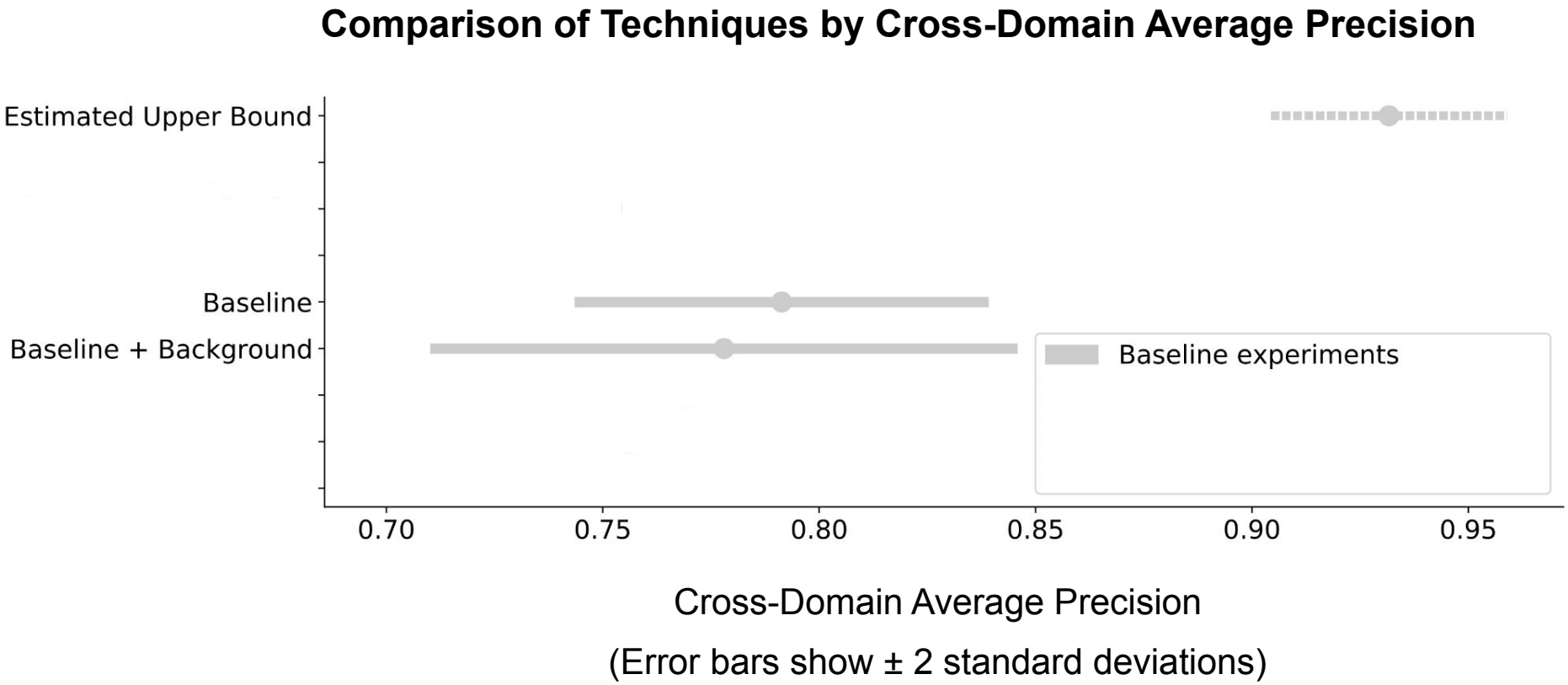
# Results

## Average Precision

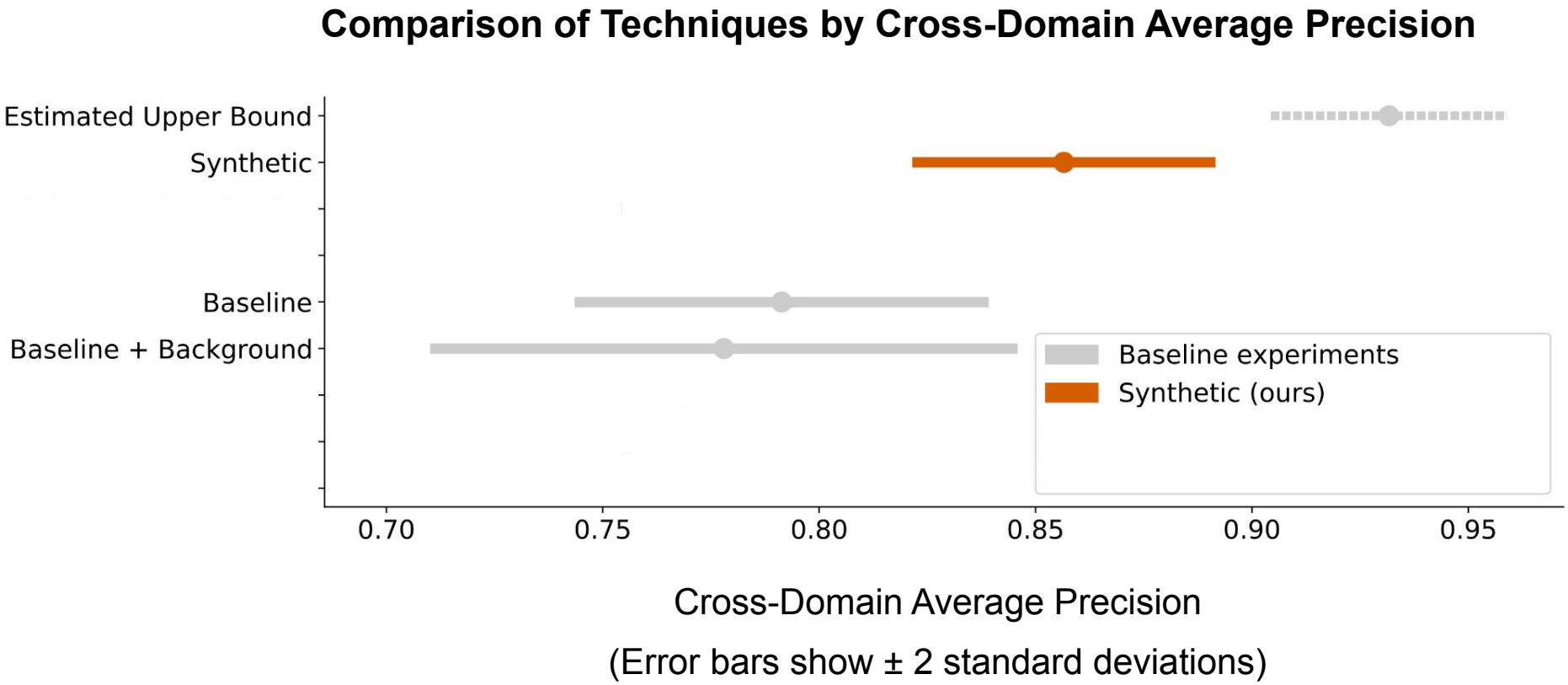
# Current Domain Adaptation Techniques



# Results


Comparison of Techniques by Cross-Domain Average Precision
Estimated Upper Bound
Baseline
Baseline + Background
Baseline experiments
0.70
0.75
0.80
0.85
0.90
0.95
Cross-Domain Average Precision
(Error bars show ± 2 standard deviations)

# Results


Comparison of Techniques by Cross-Domain Average Precision
Estimated Upper Bound
Synthetic
Baseline
Baseline + Background
Baseline experiments
Synthetic (ours)
0.70
0.75
0.80
0.85
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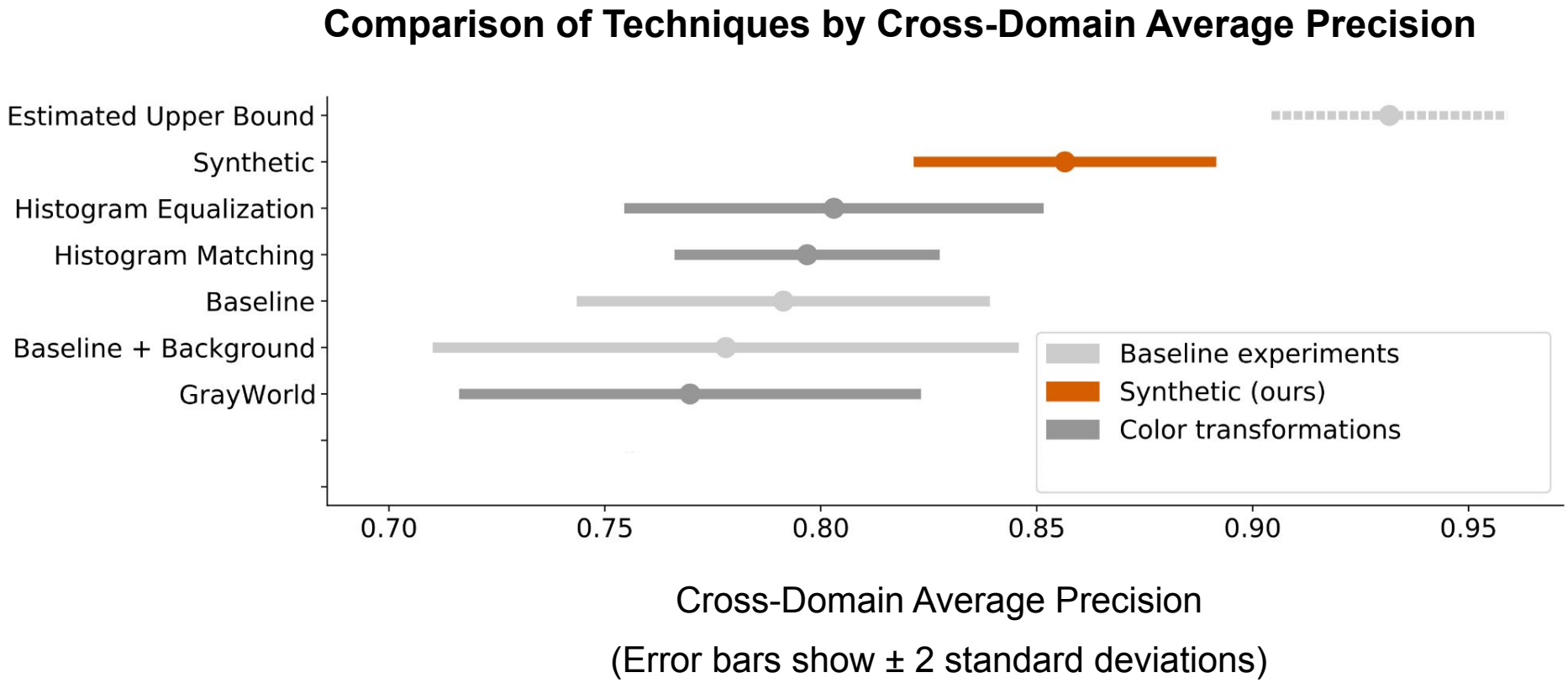
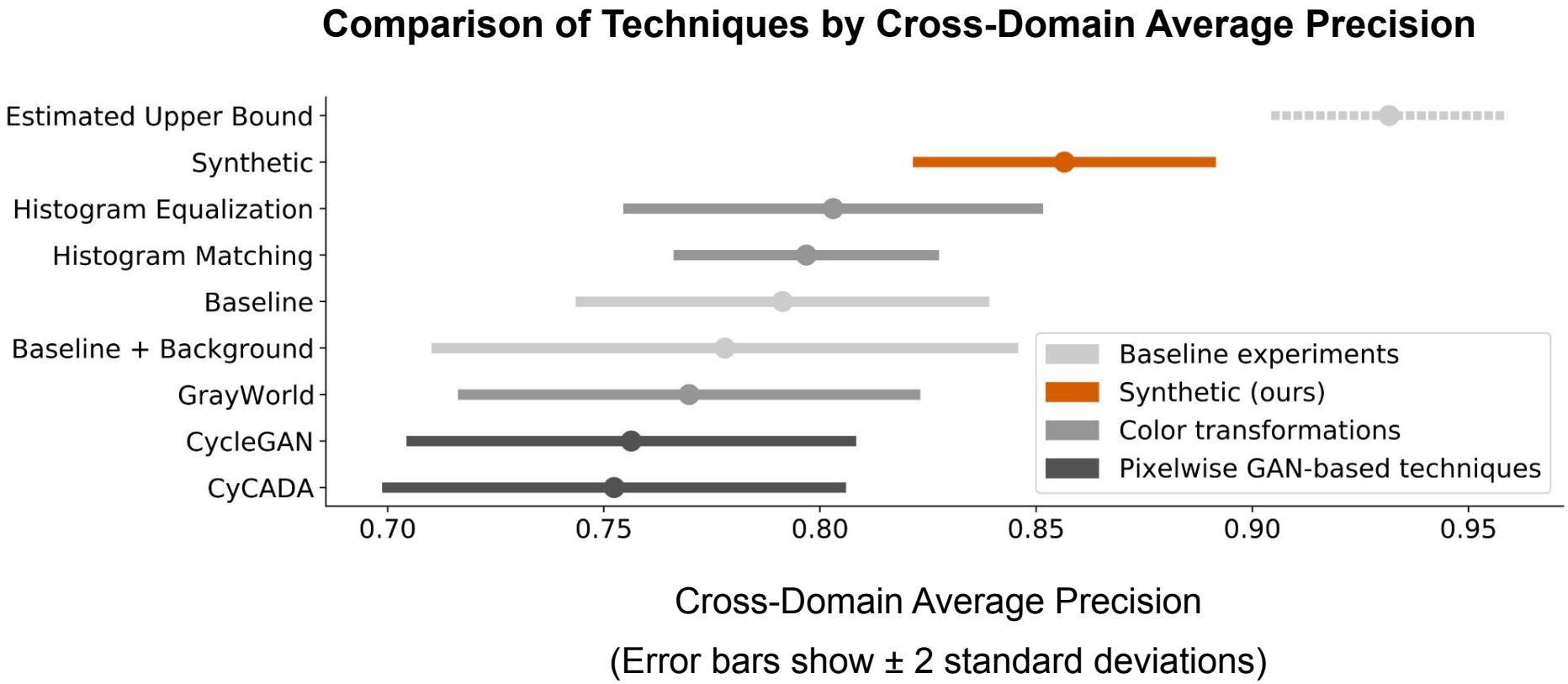
Cross-Domain Average Precision
(Error bars show ± 2 standard deviations)

# Results


Comparison of Techniques by Cross-Domain Average Precision
Estimated Upper Bound
Synthetic
Histogram Equalization
Histogram Matching
Baseline
Baseline + Background
GrayWorld
Baseline experiments
Synthetic (ours)
Color transformations
0.70
0.75
0.80
0.85
0.90
0.95
Cross-Domain Average Precision
(Error bars show ± 2 standard deviations)

# Results


Comparison of Techniques by Cross-Domain Average Precision
Estimated Upper Bound
Synthetic
Histogram Equalization
Histogram Matching
Baseline
Baseline + Background
GrayWorld
CycleGAN
CyCADA
0.70
0.75
0.80
0.85
0.90
0.95
Baseline experiments
Synthetic (ours)
Color transformations
Pixelwise GAN-based techniques
Cross-Domain Average Precision
(Error bars show ± 2 standard deviations)

# Key Takeaways

1. **Synthetic images can help** object detection **models generalize** to new geographies.
2. **Synthetic images can be easy to create** – our technique uses unlabeled background images and requires minimal labeled examples.

We thank our collaborators Wei Hu, Madeleine Jones, Alena Zhang, Maddie Rubin, Alexander Kumar, Aya Lahlou, Boya (Jennie) Sun, and Katie Wu.