Synthetic Imagery Aided Geographic Domain Adaptation for Rare Energy Infrastructure Detection in Remotely Sensed Imagery

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Overview

Motivation:

Energy systems are important anthropogenic greenhouse gas emission sources

Remote sensing and computer vision to obtain and update energy systems information

Challenge:

Visual variability of imagery across geographies

Rare objects detection

Approach:

Use **synthetically generated data** to augment real training data

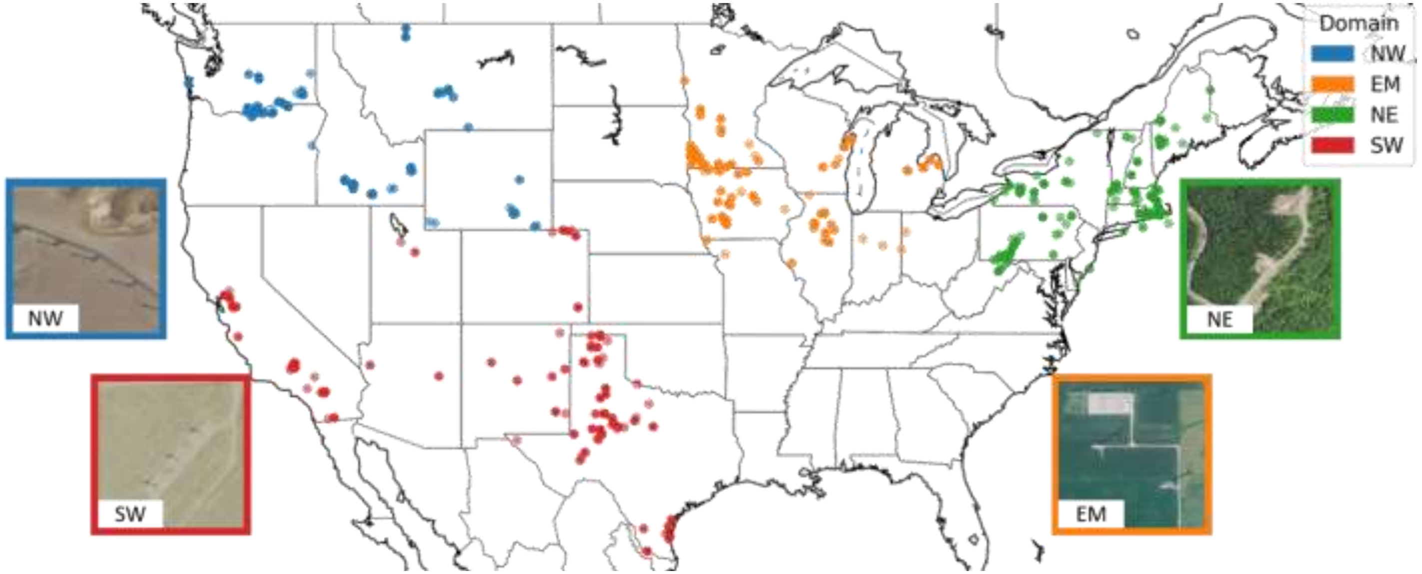
1 Dataset Creation

Real Imagery Sampling

4 geographic domains:
Northwest (NW), Northeast (NE), Eastern Midwest (EM), and Southwest (SW)

At each domain:
100 images for training, 100 for validation

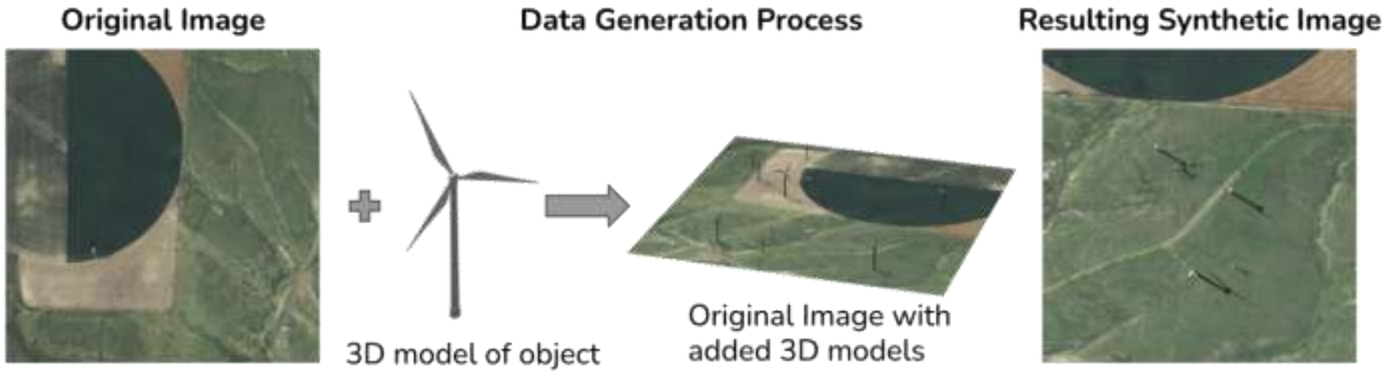
Imagery resolution:
0.6 meter/pixel



Synthetic Imagery Generation

Superimpose 3D models on real background images

No wind turbines present in background images



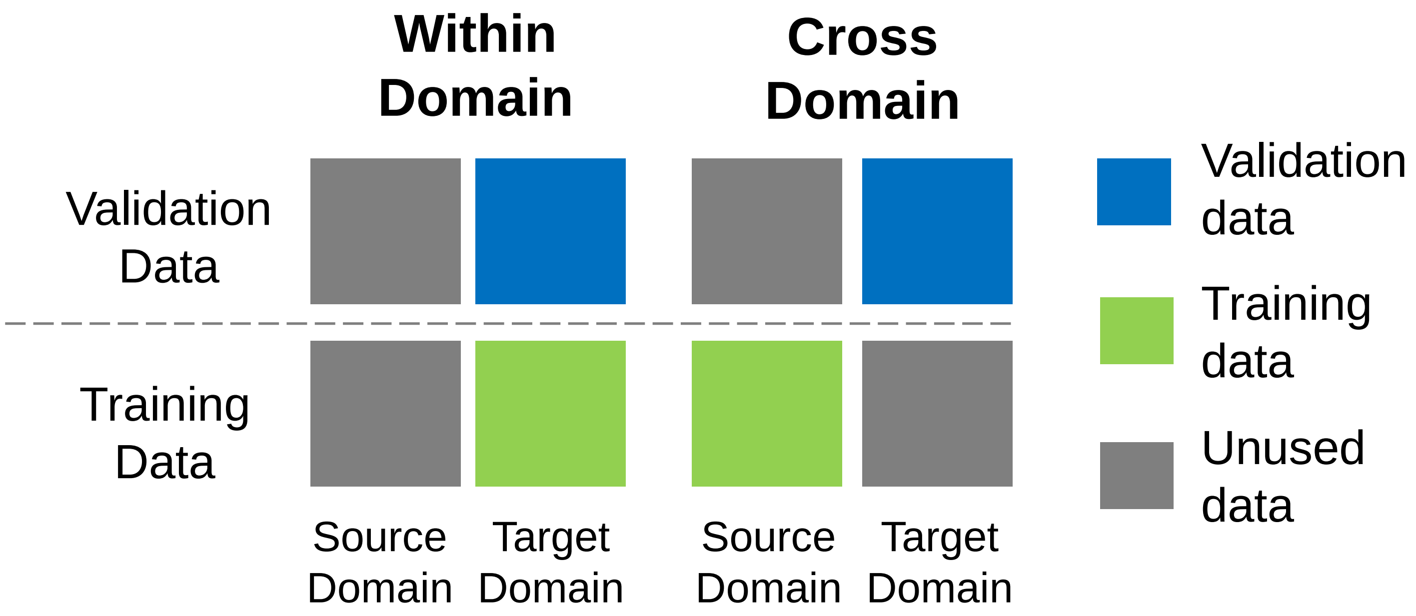
2 Impact of Adding Synthetic Imagery

Experimental setup

Object detection model:
YOLOv3, repeat 4 times for each experiment

Within-domain:
Source domain is target domain

Cross-domain:
Target domain different from source domain



2 Impact of Adding Synthetic Imagery

Experimental setup

Object detection model:
YOLOv3, repeat 4 times for each experiment

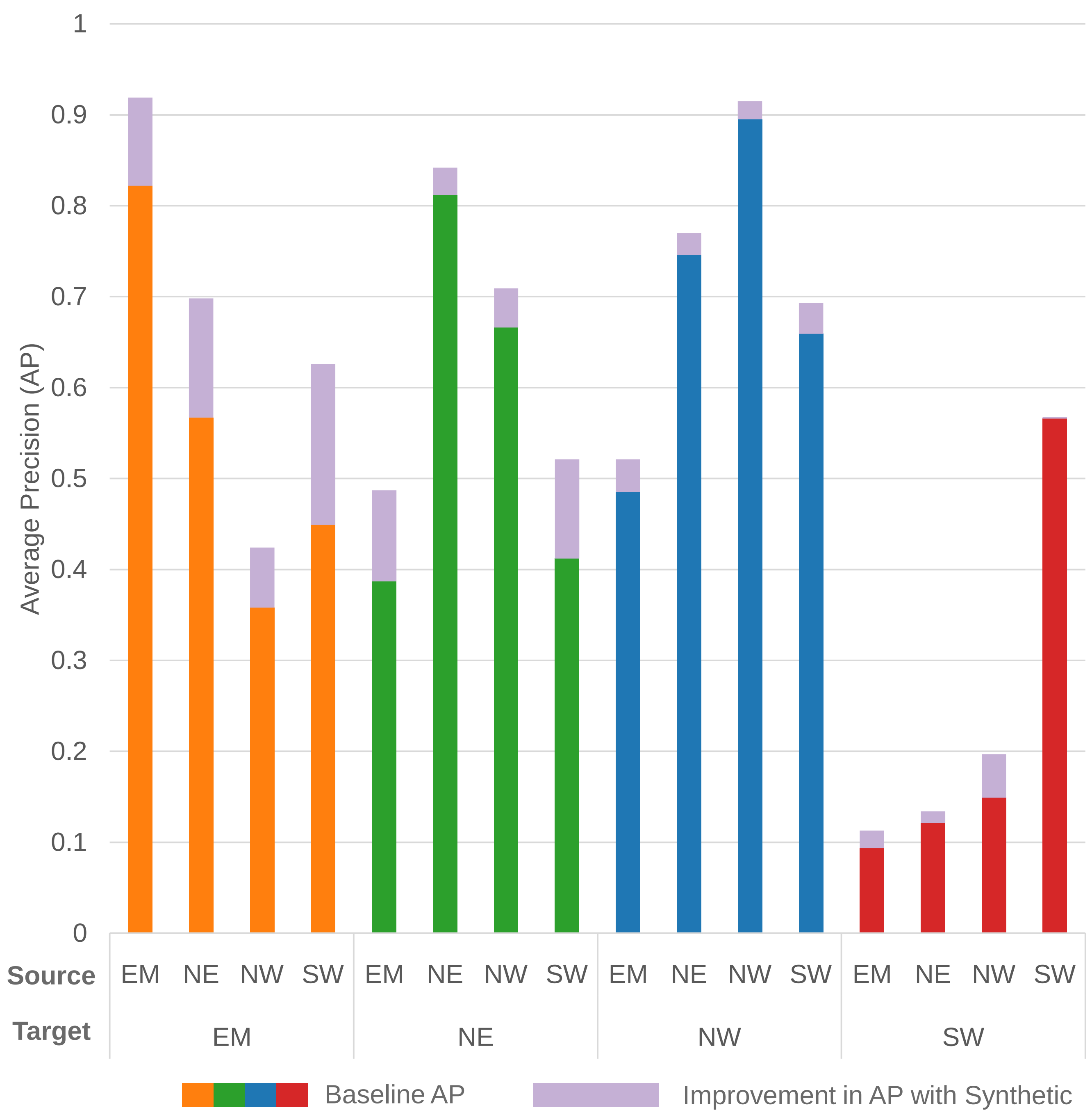
Within-domain:
Source domain is target domain

Cross-domain:
Target domain different from source domain

Baseline:
100 real training images from source domain

Experiments with added synthetic:
100 real training images from source domain + 75 synthetic training images from target domain

Evaluation metric:
Average precision (AP)



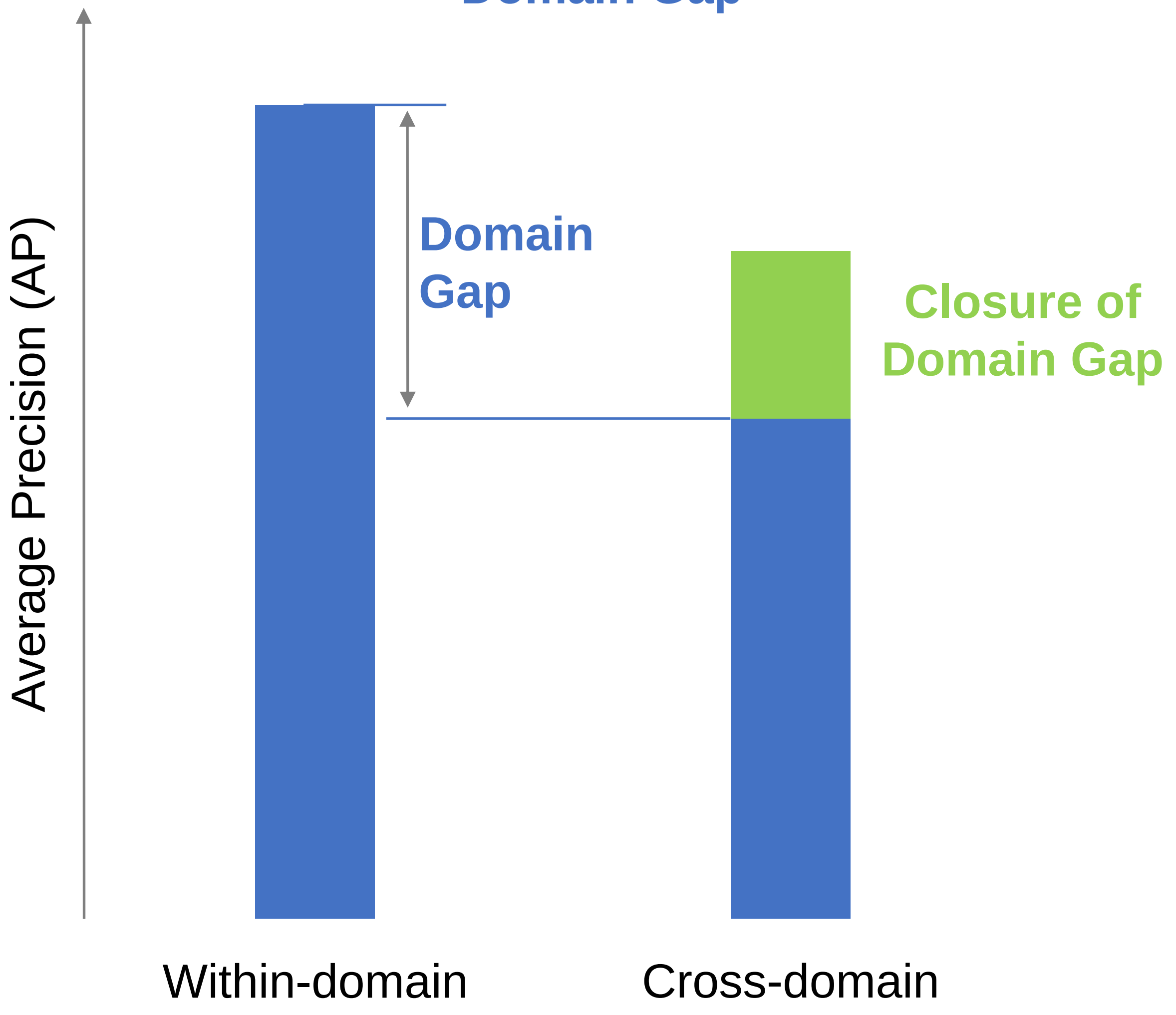
2 Impact of Adding Synthetic Imagery

Results Evaluation

Percent Improvement in AP

Percent Closure of Domain Gap (CDG%)

$$\%\ \text{Closure of Domain Gap} = \frac{\text{Closure of Domain Gap}}{\text{Domain Gap}} \times 100\%$$



2 Impact of Adding Synthetic Imagery

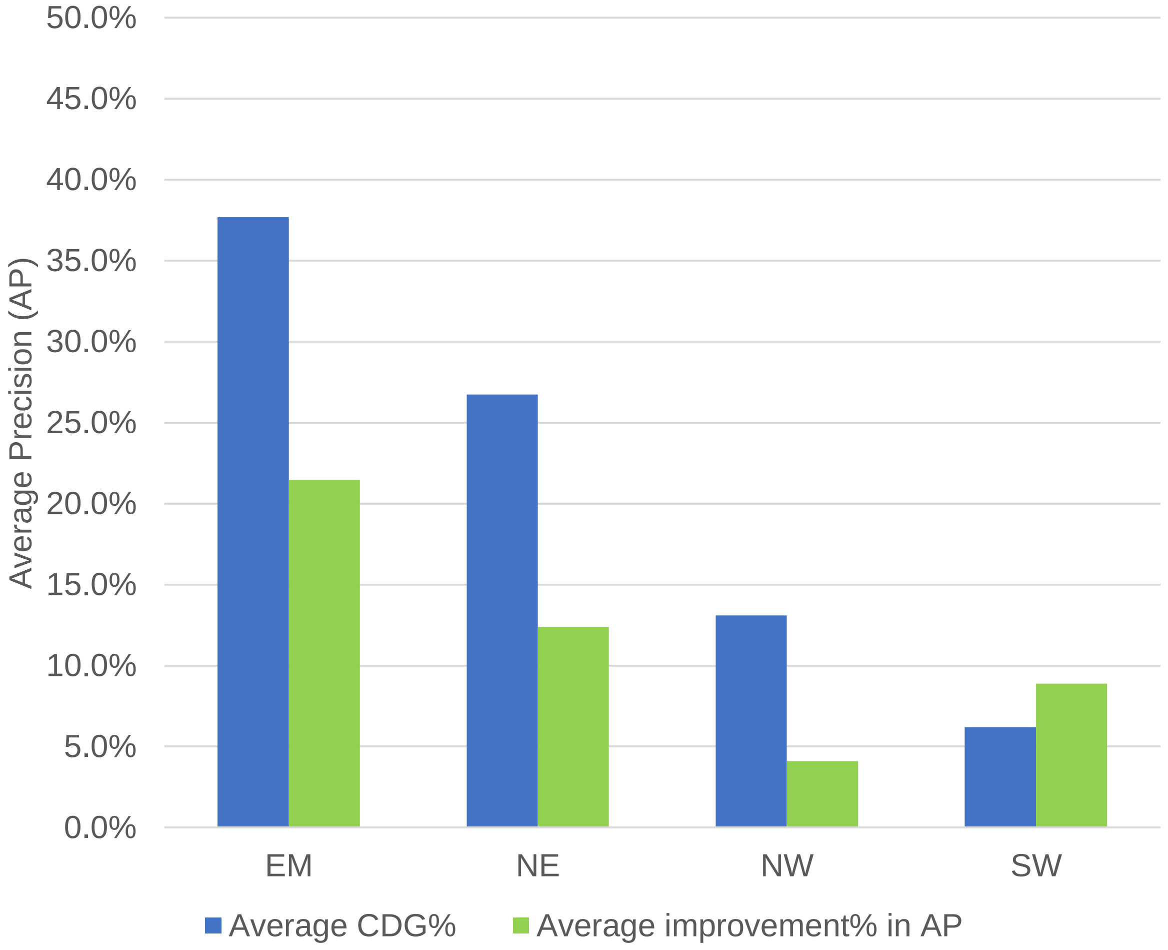
Results Evaluation

Percent Improvement in AP

Percent Closure of Domain Gap (CDG%)

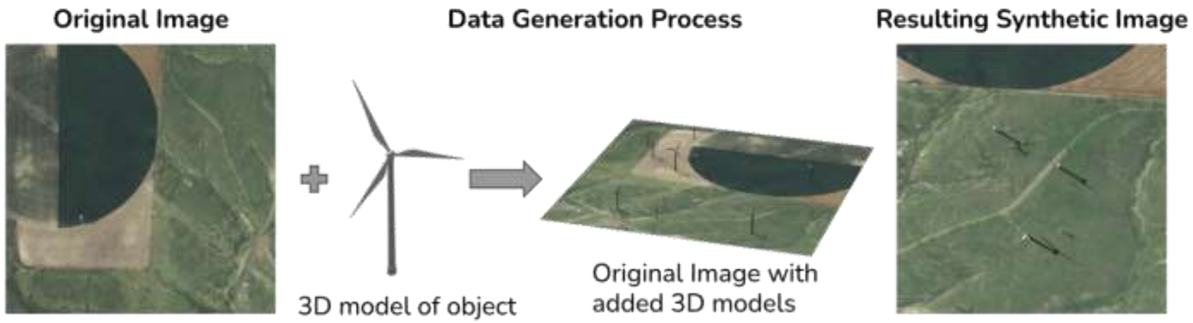
Results Summary

	Within-domain	Cross-domain
Baseline $\pm 2\sigma$	0.774$\pm$0.050	0.425$\pm$0.054
Adding synthetic $\pm 2\sigma$	**0.811**$\pm$0.039	**0.491**$\pm$0.067
Average improvement% in AP	4.8%	15.7%
Average CDG%	-	20.9%



Summary

Synthetic data generation approach for domain adaptation



1 Created a wind turbine dataset with labeled real and synthetically augmented imagery from 4 geographies.

Synthetic Imagery Improves Cross-domain Performance

	Within-domain	Cross-domain
Baseline $\pm 2\sigma$	0.774±0.050	0.425±0.054
Adding synthetic $\pm 2\sigma$	**0.811**±0.039	**0.491**±0.067
Average % improvement in AP	4.8%	15.7%
Average % closure of the domain gap	-	20.9%

2 Adding synthetic training data closed the domain gap by **20.9%** on average and improved object detection average precision (AP) by **15.7%**.