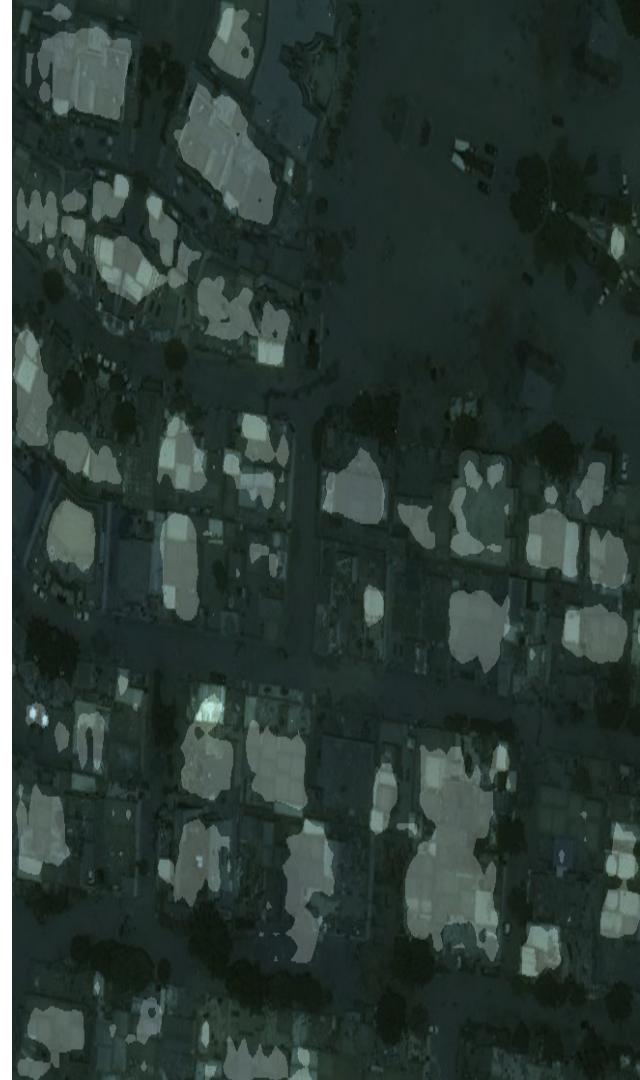


# Leveraging Domain Adaptation for Low-Resource Geospatial Machine Learning

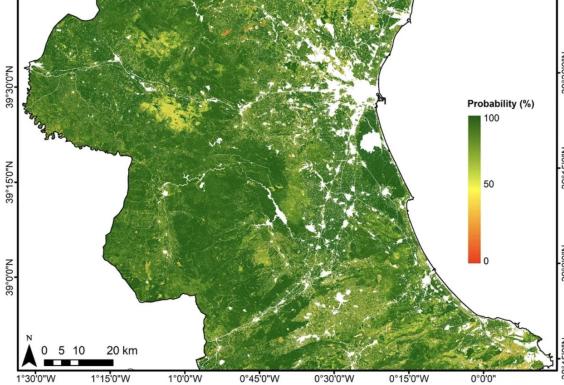
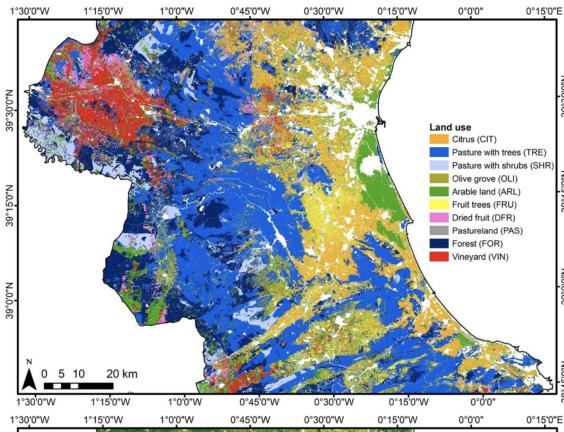
Jack Lynch<sup>1, 2</sup>, Sam Wookey<sup>1</sup>

jmlynch3@ncsu.edu,  @\_lychrel

Masterful AI<sup>1</sup>, NC State University<sup>2</sup>



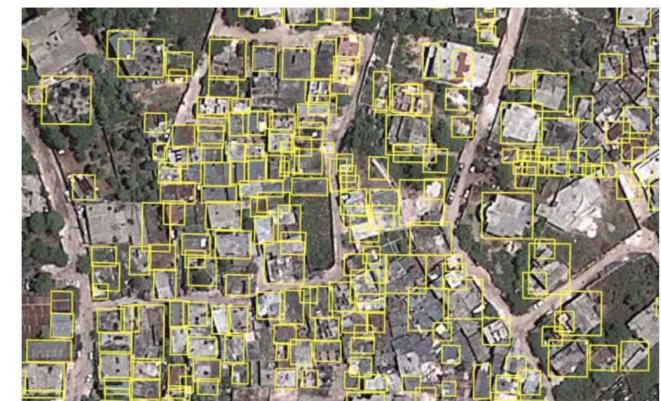
(Campos-Taberner et al., 2020)



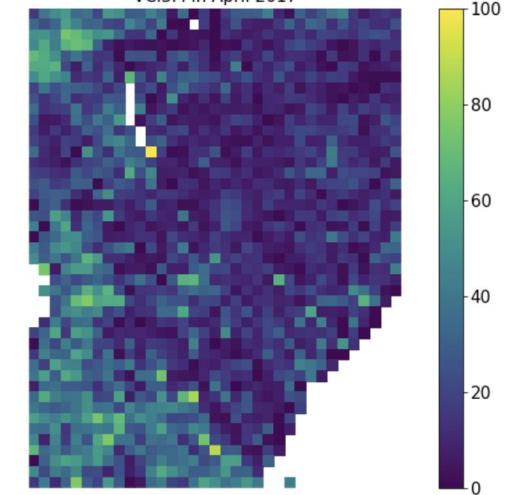
(Cerrón et al., 2020)



(Xu et al., 2019)



VCI3M in April 2017



(Lees et al., 2019)

Geospatial ML is growing.

[https://commons.wikimedia.org/wiki/File:Flag\\_map\\_of\\_Spain\\_\(without\\_Catalonia\).png](https://commons.wikimedia.org/wiki/File:Flag_map_of_Spain_(without_Catalonia).png)



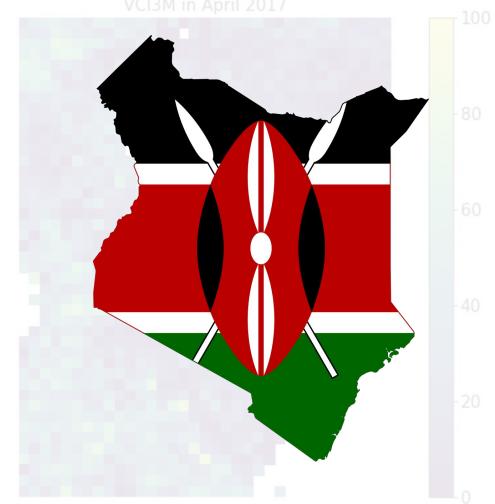
[https://commons.wikimedia.org/wiki/File:Flag-map\\_of\\_Peru.svg](https://commons.wikimedia.org/wiki/File:Flag-map_of_Peru.svg)



[https://commons.wikimedia.org/wiki/File:Flag\\_map\\_of\\_Haiti.svg](https://commons.wikimedia.org/wiki/File:Flag_map_of_Haiti.svg)

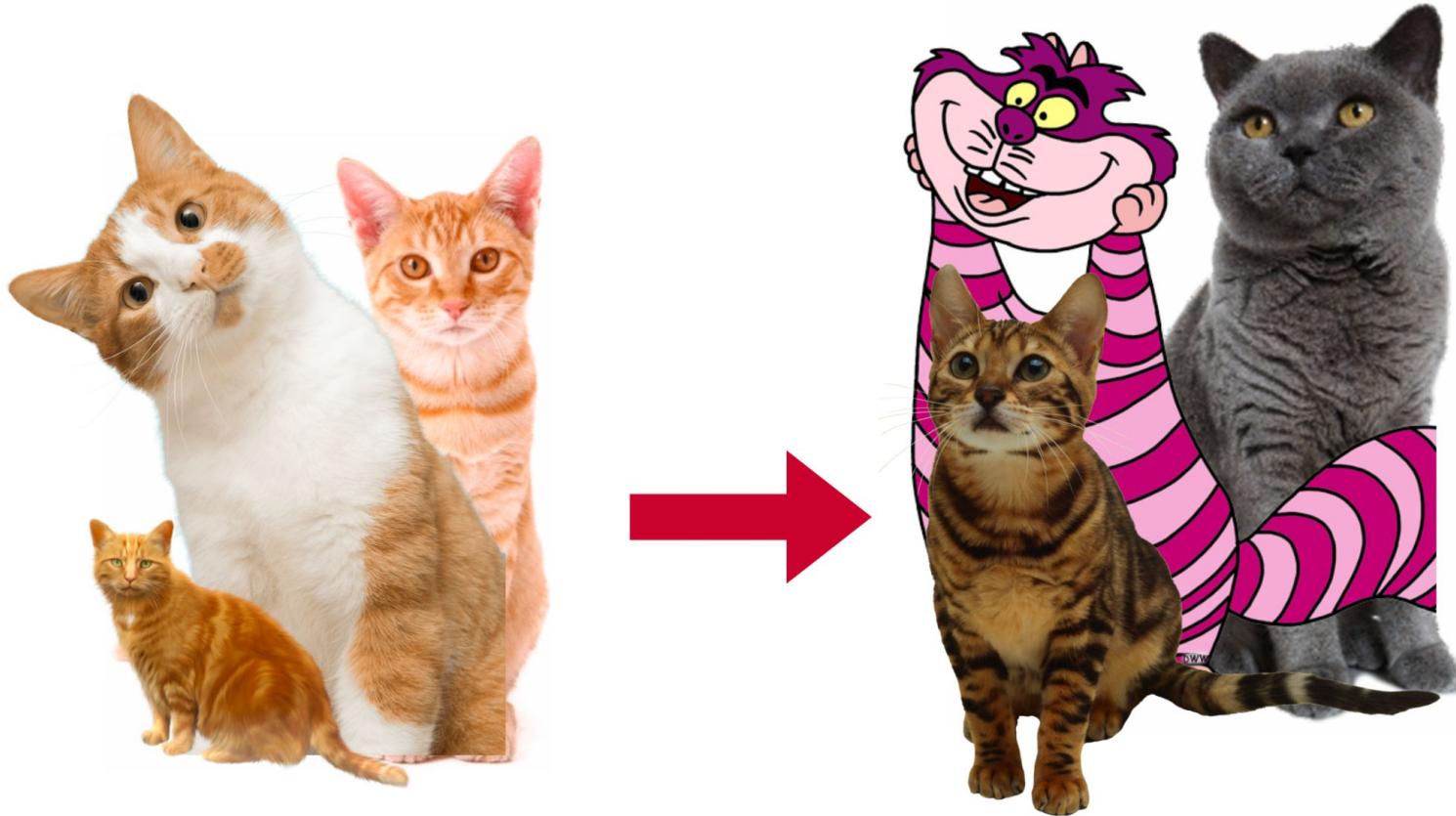


VCIBM in April 2017



Geospatial ML is (often) domain-specific.

[https://en.m.wikipedia.org/wiki/File:Flag-map\\_of\\_Kenya.svg](https://en.m.wikipedia.org/wiki/File:Flag-map_of_Kenya.svg)



**Domain adaptation** can help!

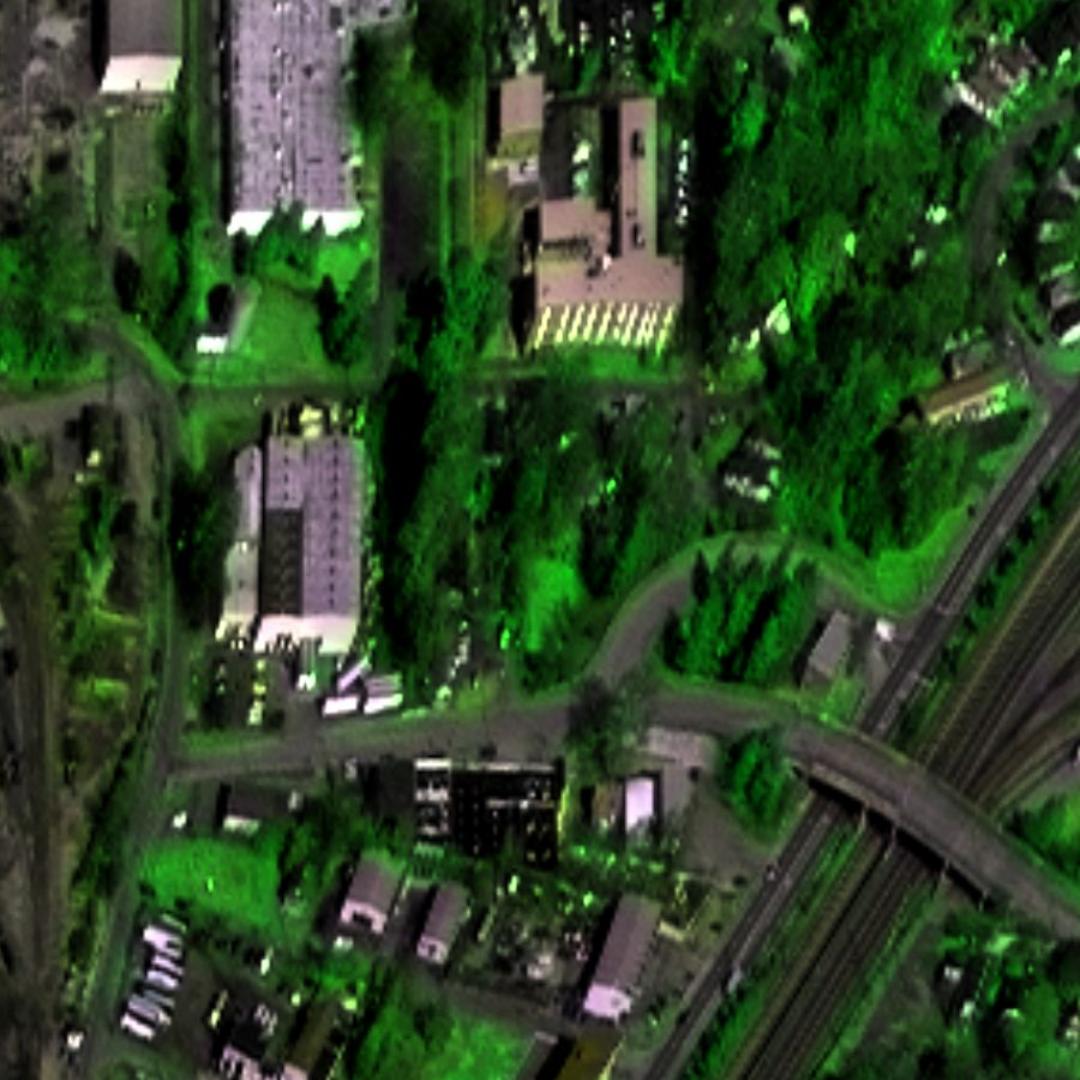
**Khatagam**

SpaceNet 2:  
**City-to-City** Adaptation

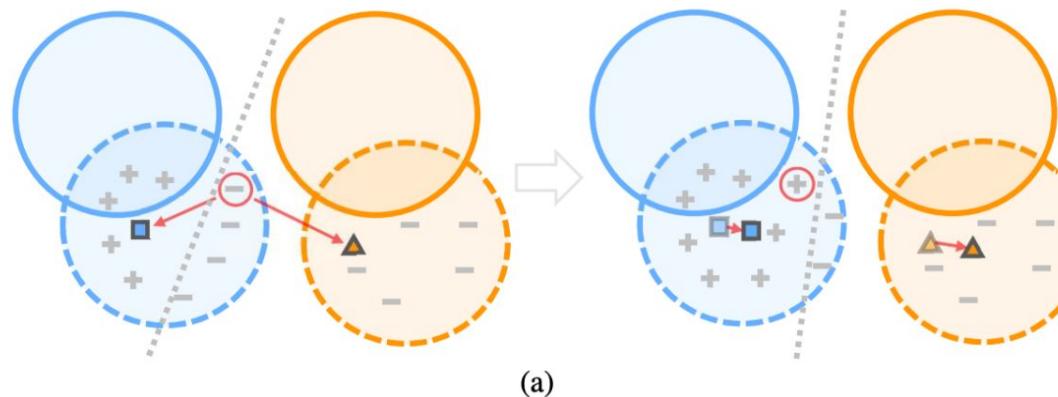


**VerON-Nadir**

SpaceNet 4:  
**On-to-Off-Nadir** Adaptation

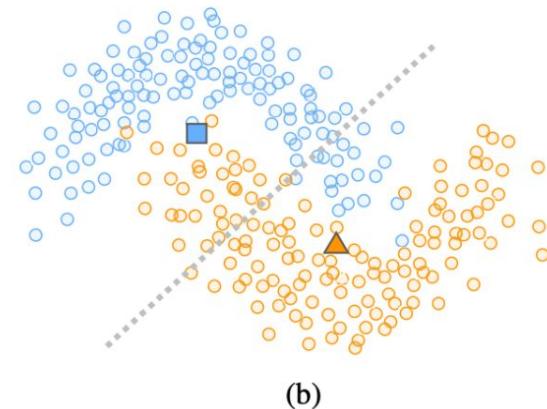


○ Source domain, class A    ○ Source domain, class B + Pseudo label of class A  
○ Target domain, class A    ○ Target domain, class B – Pseudo label of class B  
■ Prototype of class A    ▲ Prototype of class B    ..... Decision boundary



(a)

○ Target domain, class A    ○ Target domain, class B  
■ Prototype of class A    ▲ Prototype of class B    ..... Decision boundary



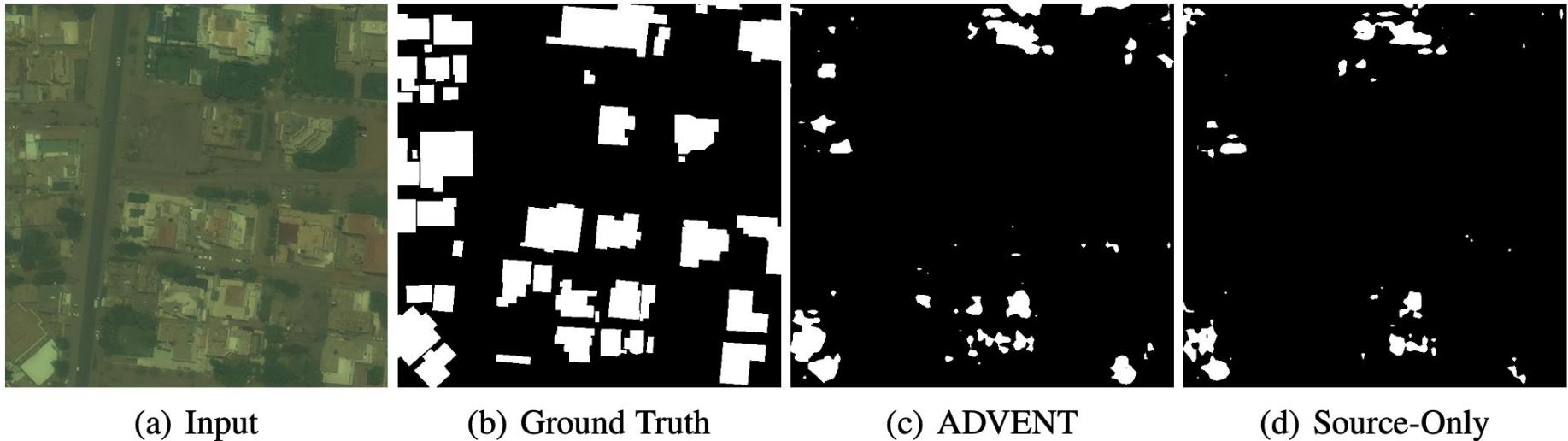
(b)

ADVENT

Zhang et. al., 2021

Tsai et. al., 2018

Vu et. al., 2019



(a) Input

(b) Ground Truth

(c) ADVENT

(d) Source-Only

|                | GTA → CS | V → K | V, P → K | P, S → K | V, S, P → K | ON → V. OFF |
|----------------|----------|-------|----------|----------|-------------|-------------|
| IoU (ADVENT)   | 47.6     | 13.59 | 9.95     | 26.36    | 25.05       | 11.03       |
| IoU (SRC-ONLY) | 36.6     | 15.09 | 17.56    | 23.62    | 30.09       | 14.77       |
| Δ IoU          | +11.0    | -1.50 | -7.61    | +2.74    | -5.04       | -3.74       |

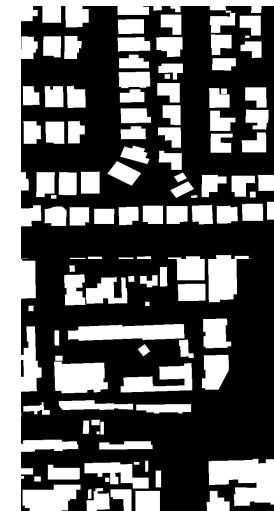
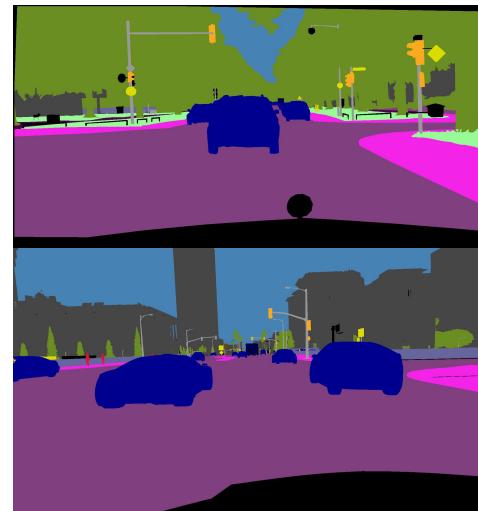
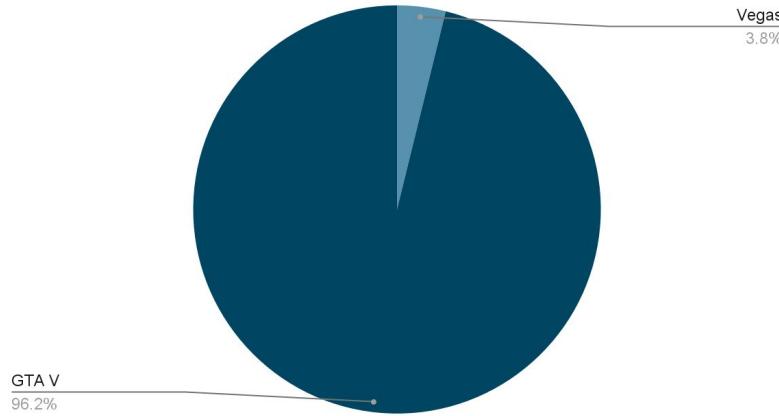
Adaptation failure

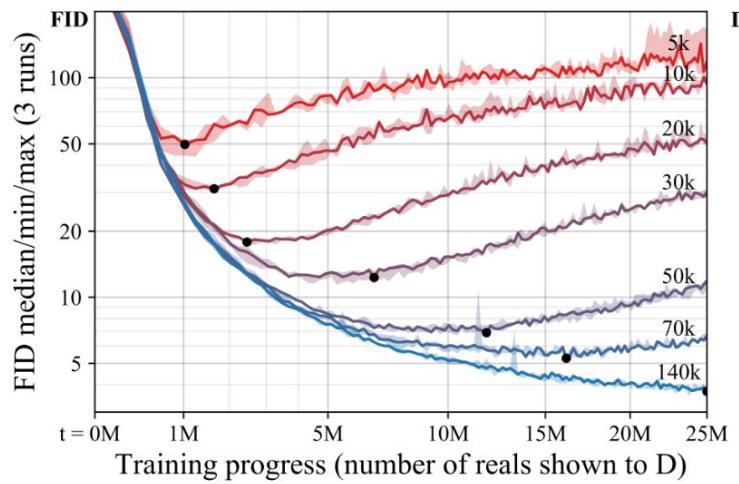
*Vu et. al., 2019*

# Core Assumptions of Adversarial Domain Adaptation

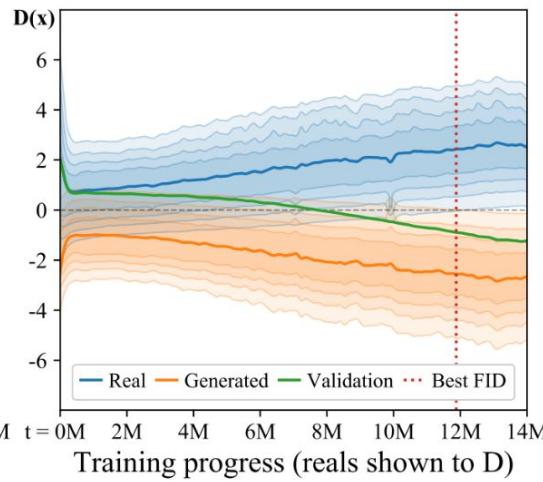
- You have sufficient labeled **source data**.
- The source and target **label distributions** are fairly similar.

Number of Labeled Training Samples

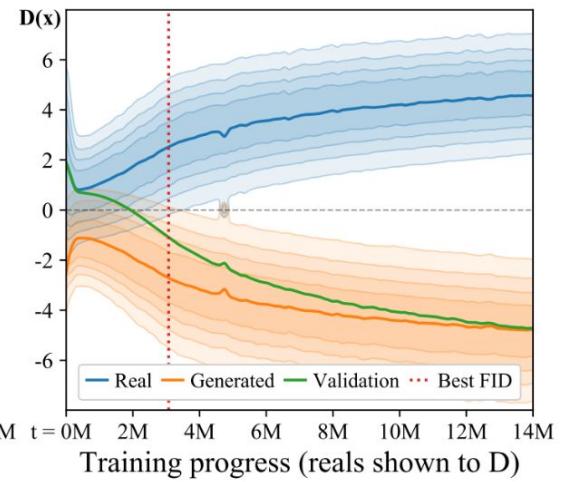




(a) Convergence of FFHQ ( $256 \times 256$ )



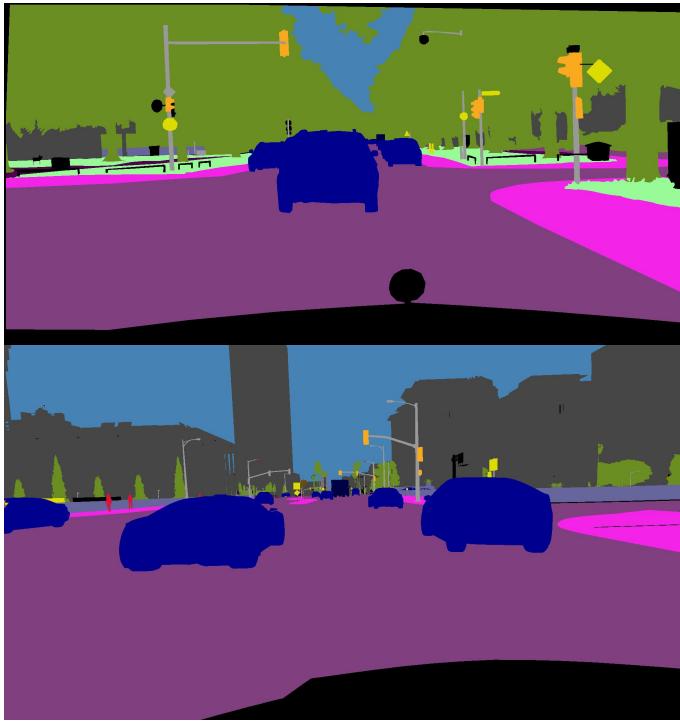
(b) Discriminator outputs, 50k



(c) Discriminator outputs, 20k

Discriminator **overfitting** (Karras et al., 2020)

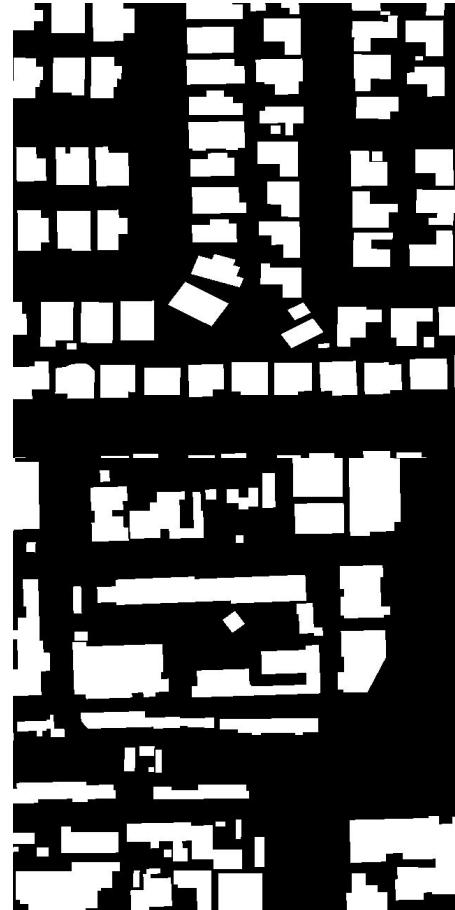
CityScapes



GTA V



Label distribution **discrepancies**



Vegas

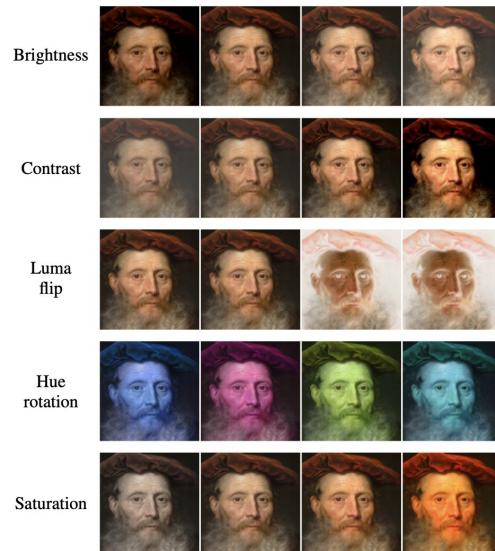
Khartoum

Percentile: 5<sup>th</sup> 35<sup>th</sup> 65<sup>th</sup> 95<sup>th</sup>

### Pixel blitting

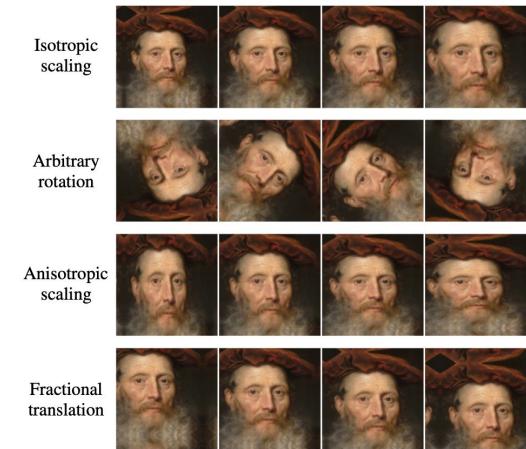


### Color transformations

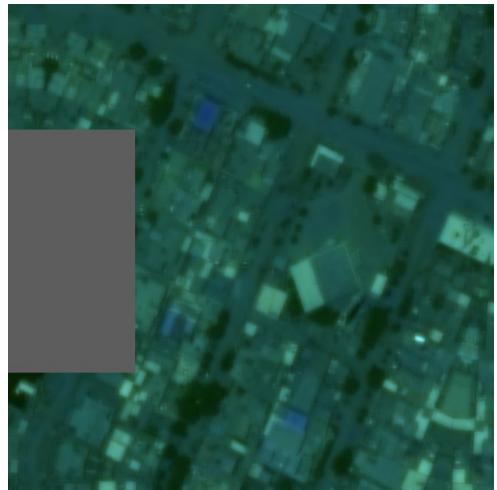


(Karras et al., 2020)

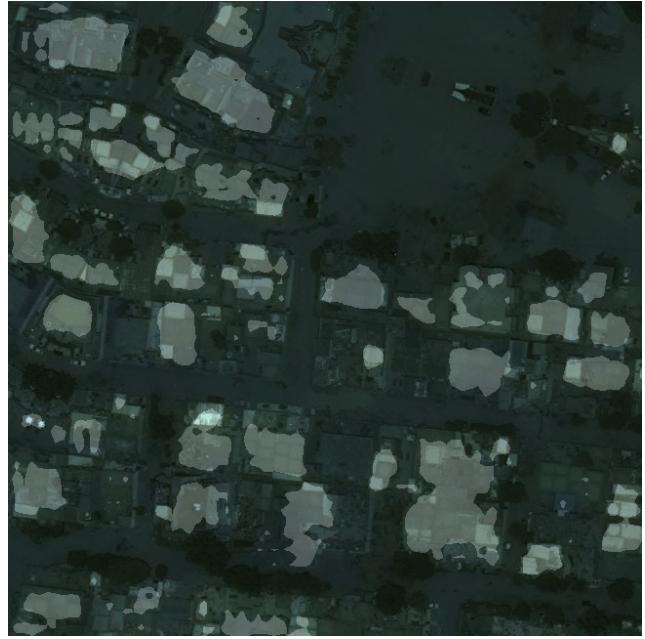
### General geometric transformations



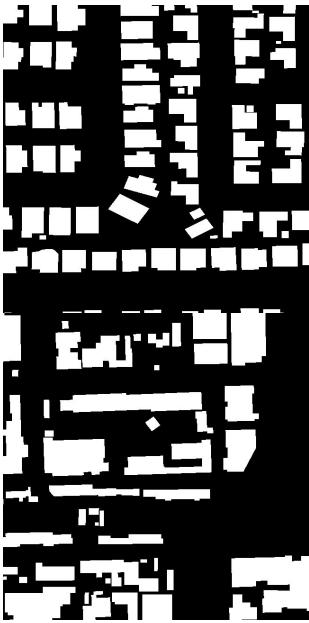
Solution: (adaptive?) augmentation



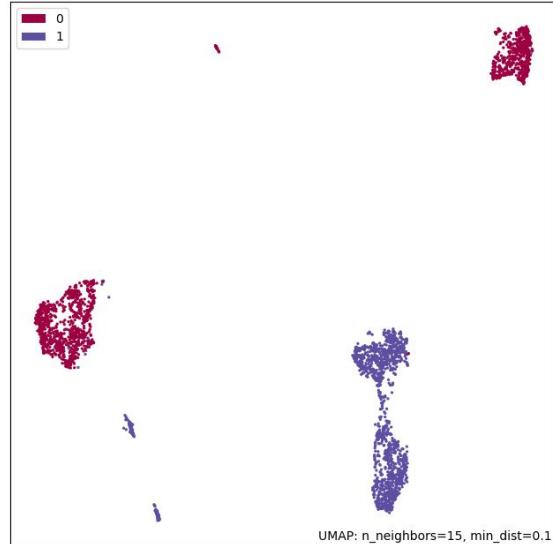
**Solution: (adaptive?) augmentation**



Augmentations **reduce** discriminator overfitting.



UMAP

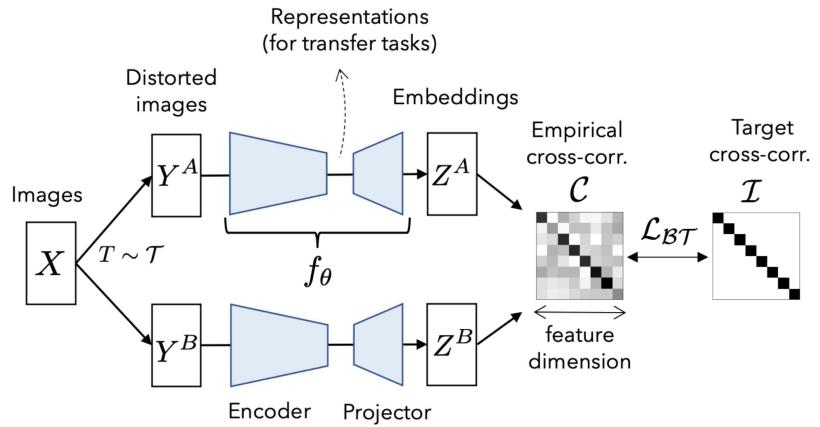


0D Persistent  
Homology  
Label Purity  
Estimation

Relative Class  
Similarity Metric

Comparing **Label-Distribution Similarities** (with UMAP)

(Zbontar et al., 2021)



Opportunities in **self-supervised** Geospatial ML

# References

- Campos-Taberner, M., García-Haro, F. J., Martínez, B., Izquierdo-Verdiguier, E., Atzberger, C., Camps-Valls, G., and Gilabert, M. A. Understanding deep learning in land use classification based on sentinel-2 time series. *Scientific Reports*, 10(1):17188, Oct 2020. ISSN 2045- 2322. doi: 10.1038/s41598-020-74215-5. URL <https://doi.org/10.1038/s41598-020-74215-5>.
- Cerrón, B., Bazan, C., and Coronado, A. Detection of housing and agriculture areas on dry-riverbeds for the evaluation of risk by landslides using low-resolution satellite imagery based on deep learning. Study zone: Lima, Peru. In ICML 2020 Workshop: Tackling Climate Change with Machine Learning, 2020.
- Karras, T., Aittala, M., Hellsten, J., Laine, S., Lehtinen, J., and Aila, T. Training generative adversarial networks with limited data, 2020.
- Lees, T., Tseng, G., Dadson, S., Hernández, A., G. Atzberger, C., and Reece, S. A Machine Learning Pipeline to Predict Vegetation Health. In ICML 2020 Workshop: Tackling Climate Change with Machine Learning, 2020.
- Tsai, Y.-H., Hung, W.-C., Schulter, S., Sohn, K., Yang, M.- H., and Chandraker, M. Learning to adapt structured output space for semantic segmentation, 2020.
- Vu, T.-H., Jain, H., Bucher, M., Cord, M., and Pérez, P. Advent: Adversarial entropy minimization for domain adaptation in semantic segmentation, 2019.
- Xu, J. Z., Lu, W., Li, Z., Khaitan, P., and Zaytseva, V. Building damage detection in satellite imagery using convolutional neural networks, 2019.
- Zbontar, J., Jing, L., Misra, I., LeCun, Y., and Deny, S. Barlow twins: Self-supervised learning via redundancy reduction, 2021.
- Zhang, P., Zhang, B., Zhang, T., Chen, D., Wang, Y., and Wen, F. Prototypical pseudo label denoising and target structure learning for domain adaptive semantic segmentation, 2021.