Detecting Aquaculture in the Brazilian Amazon using Deep Learning in a Low-Data Setting

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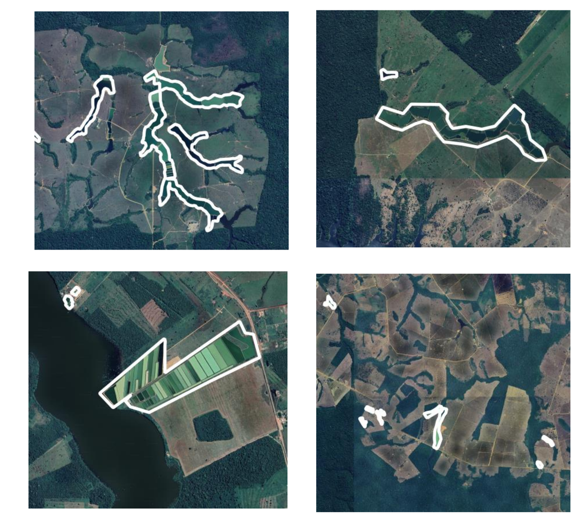
Motivation

- Aquaculture is the farming or cultivation of aquatic organisms, including fish, mollusks, and crustaceans
- Aquaculture has the potential **to produce high-quality animal protein** with **lower environmental impacts** than traditional livestock like cattle
- However, adverse impacts such as freshwater use, eutrophication, and greenhouse gas emissions can vary by over two orders of magnitude based on factors such as species farmed, land-use change, and production practices [1]
- We currently lack basic information on the **number** and **area** of aquaculture ponds and their **locations** in regions such as the Amazon Basin
- Therefore, detailed spatial information is needed to understand impacts of aquaculture across the Amazon basin

Problem Formulation

- **Detecting aquaculture from remote sensing data offers the possibility of scalable, low-cost mapping**
- We want to segment and classify waterbodies as aquaculture or non-aquaculture
- Random forests can reliably segment waterbodies, making the problem primarily a **classification** task

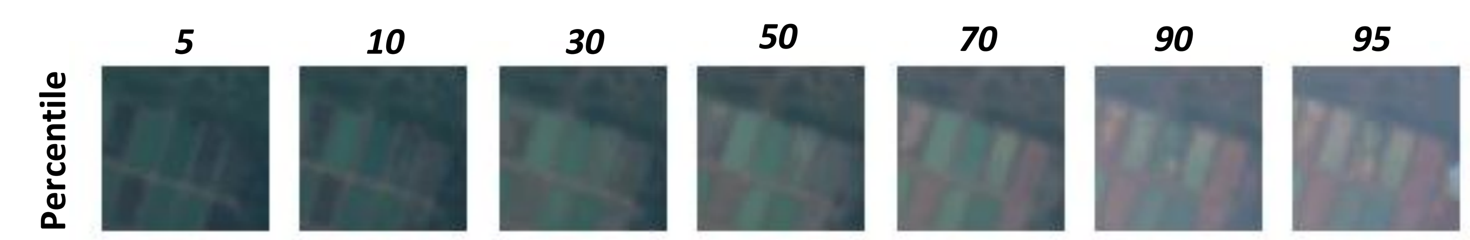


Example fish farms in Rondônia state

Can we train a model that performs well across the Amazon using a small number of examples from a few regions?

Data

- The Brazilian Agricultural Research Corporation, Embrapa, provided labels for over 2300 aquaculture operations in the Brazilian states of Rondônia and Amazonas, representing roughly 6000 waterbodies
- The National Water and Sanitation Agency (ANA) provided roughly 3000 negative examples (non-pond waterbodies) across both states
- We used Sentinel-1 and 2 data (14 spectral bands), taking images at 7 percentiles to capture temporal change, and processed the data into 32 x 32 tiles
- We trained the model on three subregions of Rondônia, each with 300-400 training examples, and tested the model's ability to generalize in both states

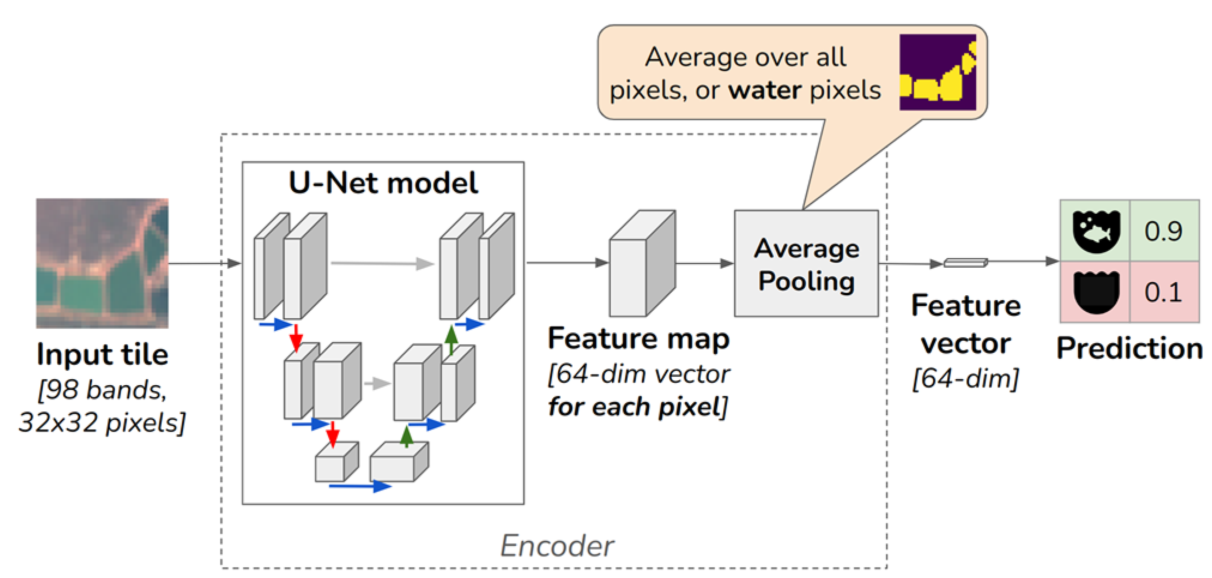


Deep Learning Methods

- Deep learning allows us to **learn** to extract predictive features from entire images, removing the need for feature engineering
- However, deep learning models often need large quantities of data to prevent overfitting
- **Supervised** models use **labeled** images to learn predictive features
- **Self-supervised** models use **unlabeled** images to learn features that separate images. A second classifier is then trained on these features to separate labeled images.
- Unsupervised models can make use of large quantities of unlabeled data

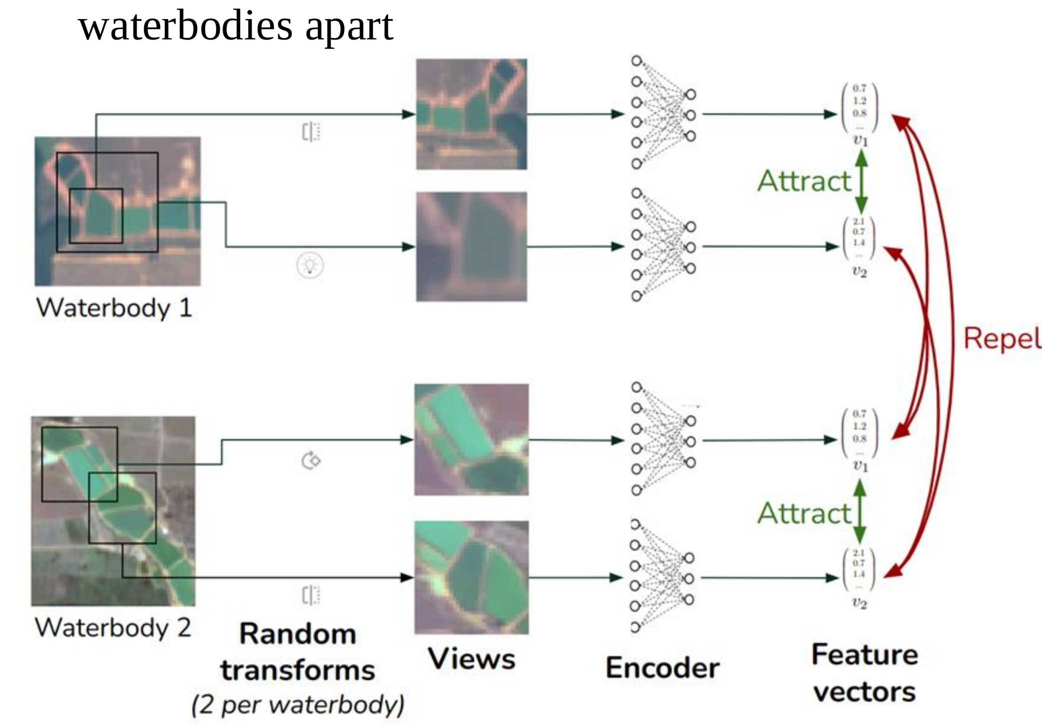
CNN/U-Net

- Supervised deep learning model
- Generates features for each pixel, uses **average pooling** to produce features for the full tile, then predicts waterbody type
- **Masked pooling:** only average over known water pixels to minimize overfitting on landscape features



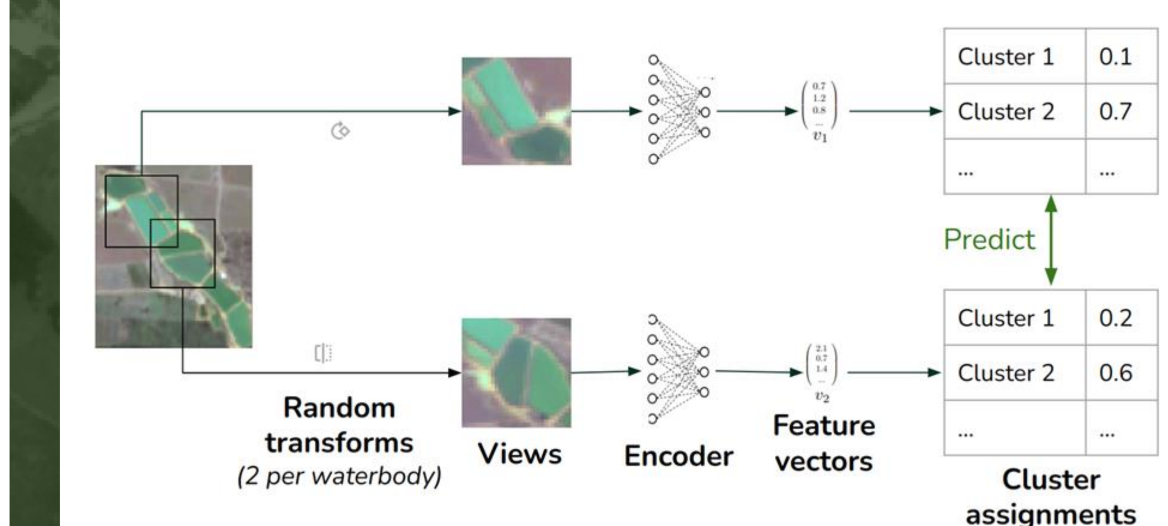
SimCLR

- Self-supervised contrastive deep learning model
- For each waterbody, generate two **views** by performing random transformations
- Learns representations by pushing views from the same waterbody closer and views from different waterbodies apart



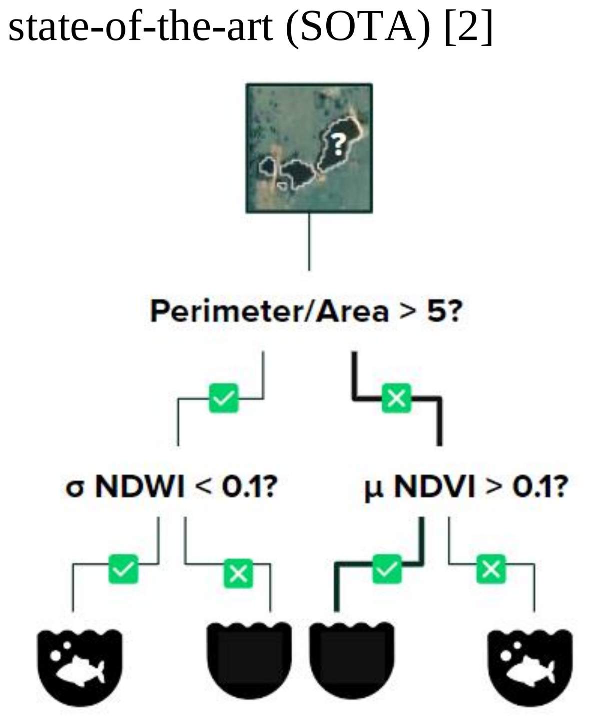
SWAV

- Self-supervised contrastive deep learning model
- Similar to SimCLR, except that images from different waterbodies are not necessarily pushed apart
- Instead, views from the same waterbody should be assigned to the same cluster



Baseline – Random Forests

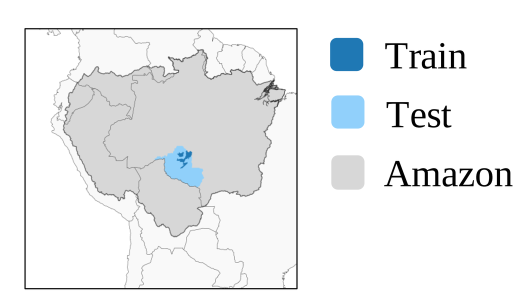
- Hand-engineer features, such as perimeter or mean NDWI, from NDWI mask of waterbody
- Then train a random forest to predict waterbody type
- Prior state-of-the-art (SOTA) [2]



Results

Rondônia → Rondônia (different parts)

	Random Forest	CNN	CNN + Masked Pooling	SimCLR[1]	SWAV[2]
F1	0.84 ± 0.01[3]	0.95 ± 0.01	0.95 ± 0.01	0.96 ± 0.01	**0.97 ± 0.00**
Accuracy	0.77 ± 0.01	0.93 ± 0.01	0.93 ± 0.02	0.94 ± 0.02	**0.96 ± 0.00**



Rondônia → Amazonas

	Random forest	CNN	CNN + Masked Pooling	SimCLR[1]	SWAV[2]
F1	0.35 ± 0.30	0.69 ± 0.04	0.87 ± 0.02	0.90 ± 0.03	**0.93 ± 0.00**
Accuracy	0.30 ± 0.29	0.78 ± 0.02	0.86 ± 0.03	0.89 ± 0.04	**0.93 ± 0.00**

[1]SimCLR results are with fine-tuning on labeled examples
[2]SWAV results are without fine-tuning, training a linear classifier on fixed features
[3]Format is mean ± standard deviation over 5 random seeds. For SimCLR and SWAV, seeds apply to the classifier.

See workshop paper for further results ➤

Conclusions

- Previous SOTA performed poorly in the Amazon basin
- Deep learning can achieve 90%+ accuracy only using hundreds of labeled examples, but generalization to new regions remains challenging
- Using contrastive learning to utilize large quantities of unlabeled data significantly improves generalization performance
- However, contrastive models are harder to train and sensitive to hyperparameters, initialization, and image transformations
- Future directions: investigate dataset **sampling bias** - we may be missing many challenging negative examples (e.g. small natural ponds)

References

[1] Jessica A Gephart, Patrik JG Henriksson,, et al. 2021. Environmental performance of blue foods. *Nature* 597, 7876 (2021), 360–365.
[2] Zilong Xia, Xiaona Guo, and Ruishan Chen. "Automatic extraction of aquaculture ponds based on Google Earth Engine." *Ocean & Coastal Management* 198 (2020): 105348.