Citizen Scientists Tackling Devastating Floods and Disaster Relief with Semi-supervised Deep Learning

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ESA-ECMWF Workshop 2021

Code: bit.ly/etci-code | Paper: bit.ly/etci-paper

https://www.ml4esop.esa.int/

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Agenda

- What are floods and who does it impact?
- Where are we today in Flood segmentation?
- How can **YOU** as a citizen scientist make a difference?
- How can you get started **today**?

About Floods

- Cause more than $40 billion/year in damages worldwide
- 40% of the world’s population lives close to coasts
- Flooding events are on the rise due to climate change, increasing sea levels and extreme weather events (cloud bursts)
- Flood levels estimation needs to be done **remotely** as physical access to flooded areas is limited
- Deploying instruments in potential flood zones can be dangerous

Current state of Floods Segmentation

What's SOTA in Flood Segmentation?

- **No joint directive** - all organizations are doing their own thing.
- **WorldFloods Dataset** and techniques provides Sentinel-2 flood maps for 119 global flood events. Deployed on Intel Movidius Myriad2 on PhiSat (launched via SpaceX in 2021) https://www.nature.com/articles/s41598-021-86650-z.
- **UNOSAT** provides public data consumable by domain scientists http://floods.unosat.org/geoportal/.

How to evaluate solutions?

- Scalability (is this useful for my community and country?)
- Generalizability (is this useful for my geographic location?)
- Accessibility (can ***I*** use it?)
- Deployment in real time (will the result be ready quickly enough?)

How can **YOU** as a citizen scientist make a difference?

- Crowdsource AI+ML knowledge for interdisciplinary high-value public impact work.
- Push boundaries of research and deployment.
- Bring disaster preparedness in society & work towards Climate Change.
- A citizen science team devised a semi-supervised based pseudo-labeling solution for the NASA IMPACT flood segmentation challenge. The team used NVIDIA V100 GPUs for training on the Google Cloud Platform and released all the code and trained models in open source, encouraging future citizen scientists to join the climate security challenge.

What is Semi-Supervision in Deep Learning?

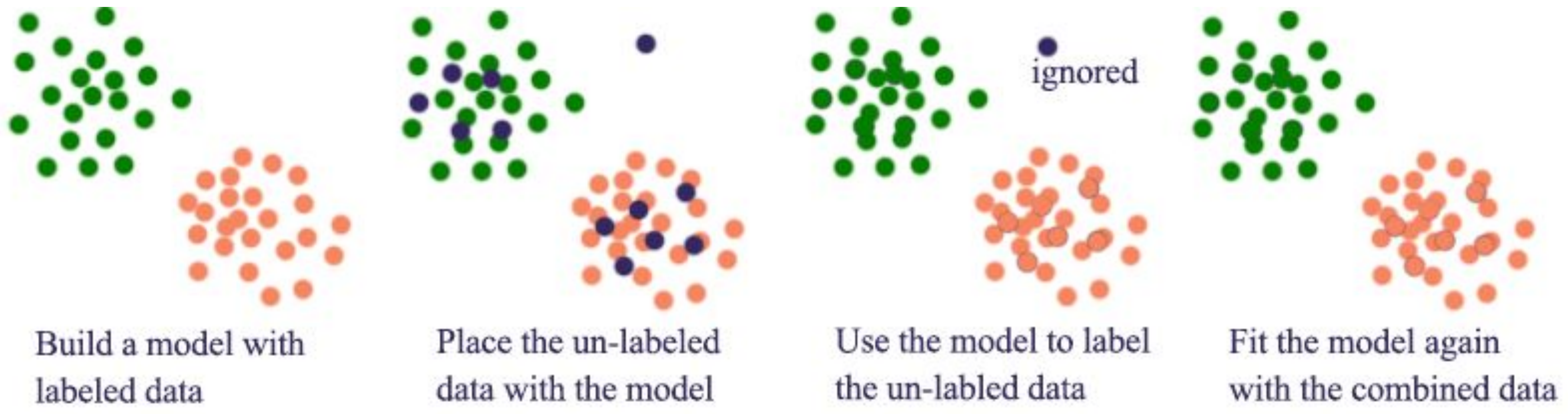

Figure: https://jhui.github.io/2017/01/15/Machine-learning-nonsupervised-and-semi-supervised-learning/

Why Semi Supervised Deep Learning methods?

- Feature based machine learning techniques are intractable as human annotators and featurizers cannot scale.
- Manual annotation in real time can easily exceed $62,500 daily.
- Not scalable for petabytes worth of data captured by satellites every day.
- Cannot get flood images from every single part of the world.

How can **YOU** use this work?

- For Government organizations:
  - Use the new state of the art AI based flood segmentation method to monitor and plan for flooding events
  - Disaster planning and relief
- For citizen scientists:
  - Educate communities about the impact of floods
  - Learn about AI techniques
  - Understand reproducibility
  - Create plan-of-action for potential flooding event in your area
- Climate Change

Get started **TODAY**

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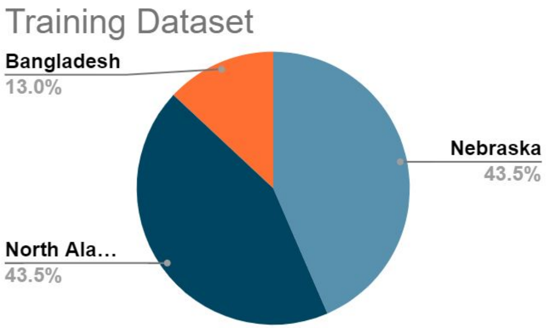
Get started **TODAY**:

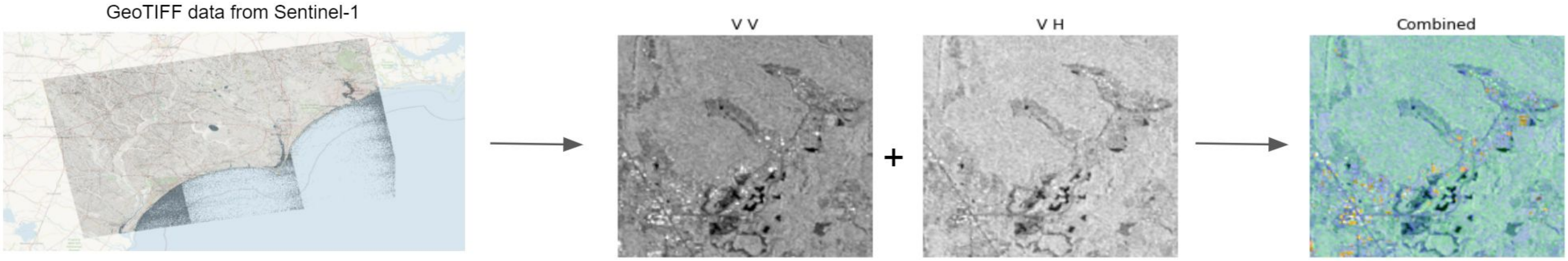
Use the #2 winning solution from the NASA Impact ETCI Competition

Data Analysis

- 66k tiled images from Nebraska, North Alabama, Bangladesh, Red River North, and Florence



- **Validation** = Florence
- **Test** = Red River North



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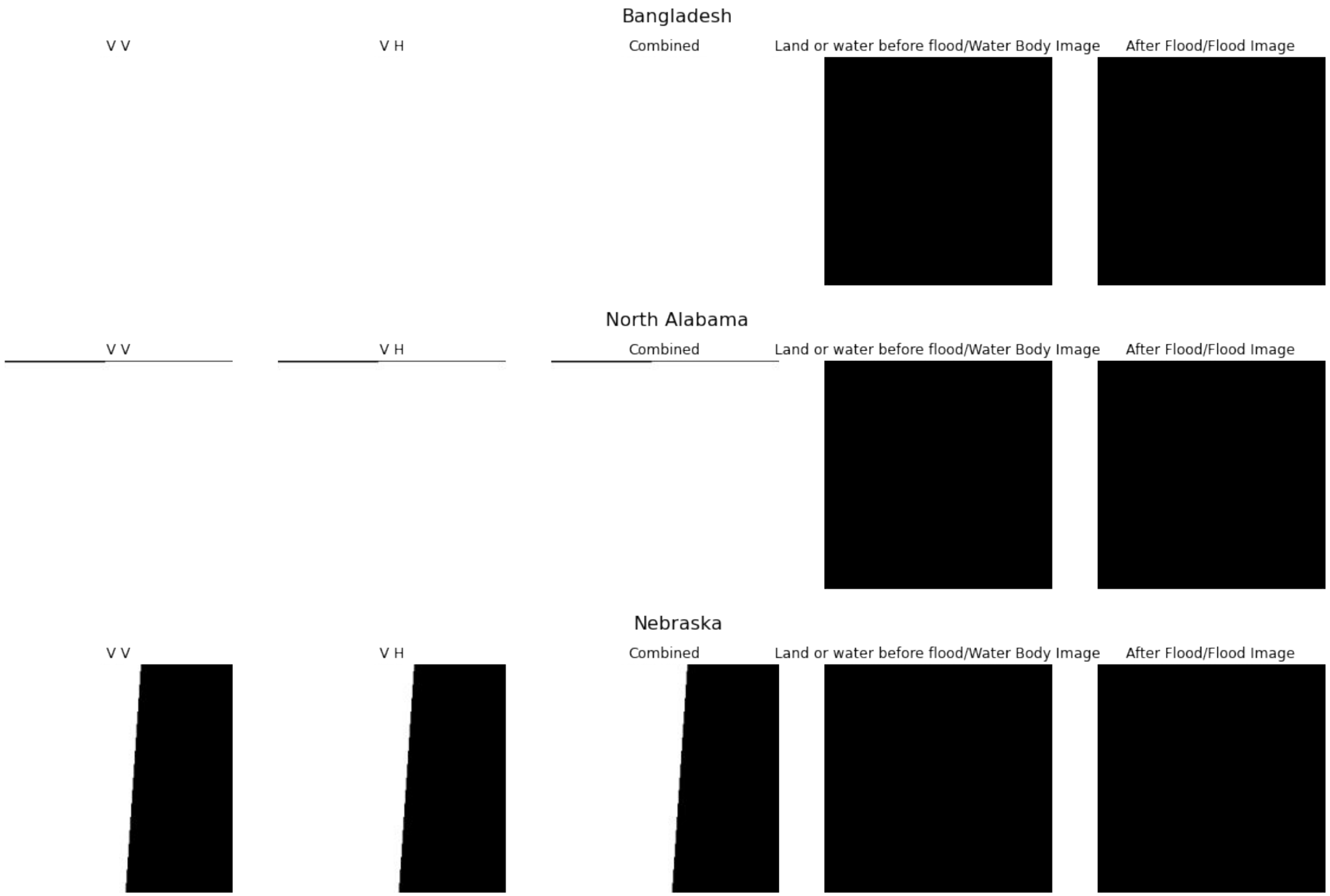
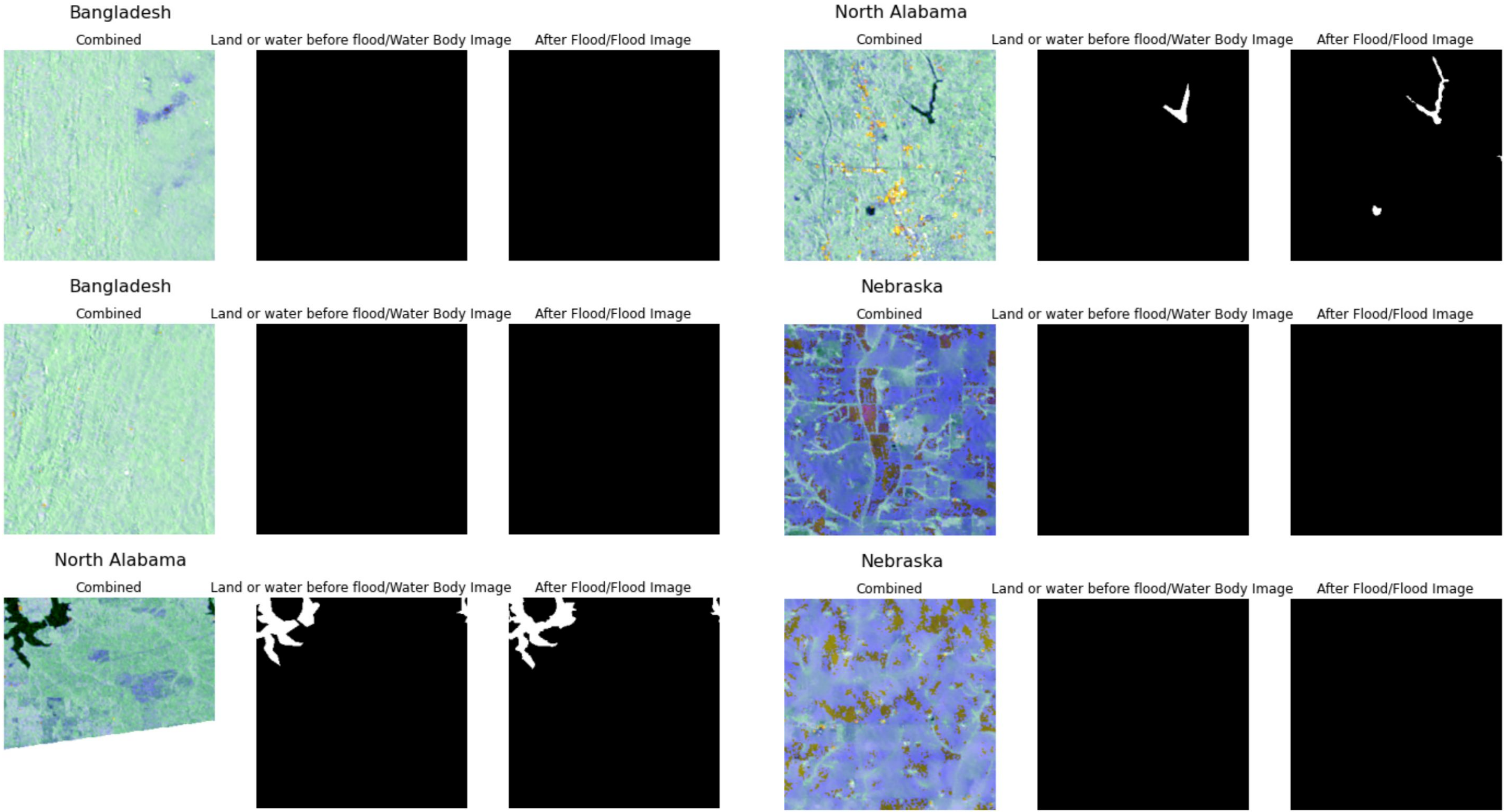
Data Processing - Removing images with swath gaps



Data Processing - Generating RGB tiles with ESA Polarimetry



Sampling data

- Timestamps
  - Intuitively could tell the progress of flooding events.
  - Empirically no impact with random sampling or maintaining ordered pairs.
- Stratified sampling
  - Each training batch contained at least 50% of samples having flood levels.
  - This also helps mitigating the class imbalance problem in the dataset.

Augmentation

- **Training**: horizontal flips, rotations, and elastic transformations.
- **Test-time**: horizontal, vertical flips, transpositions and 90 rotations (*Dihedral Group D4*).

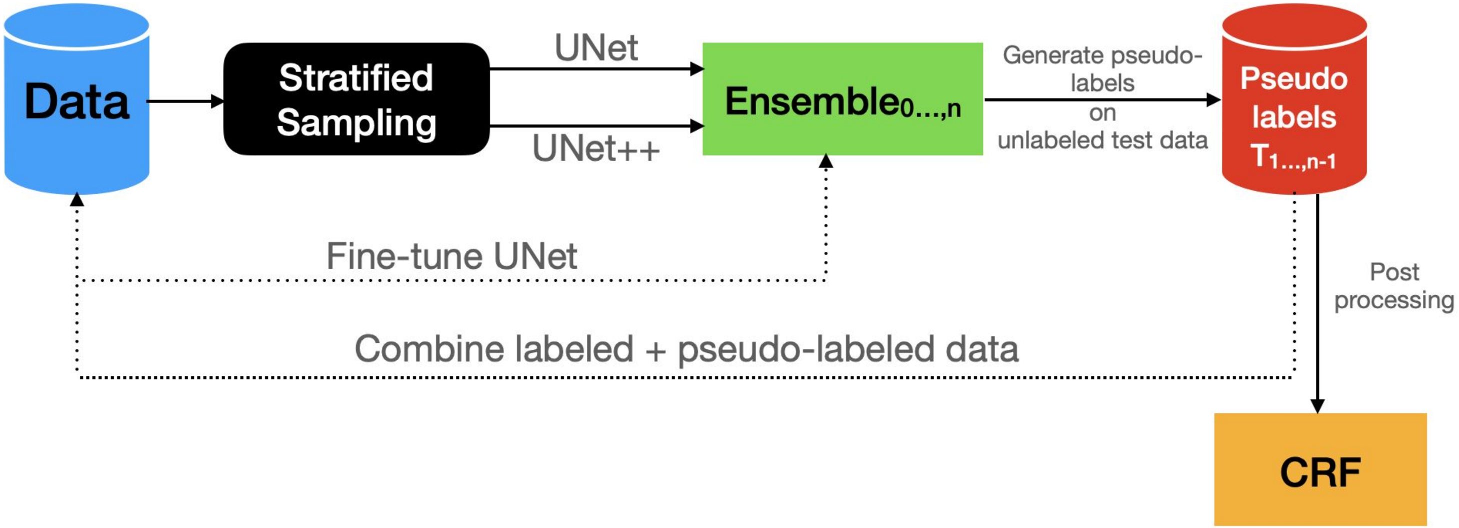
Training details

- **Encoder backbone**: MobileNetV2 due to its pointwise convolutions and performance consistency.

Model Architecture + Encoder Backbone	IoU
U-Net + ResNet34 [13]	0.55
U-Net + RegNetY-002 [29]	0.56
DeepLabV3Plus + MobileNetV2	0.52
DeepLabV3Plus + RegNetY-002	0.46
U-Net + MobileNetV2	**0.57**

- **Segmentation architectures**: UNet and UNet++.
- **Loss function**: Performance improvement with *Dice loss* alone compared to Focal loss and the two combined.

Training with pseudo labeling



Training with pseudo labeling

- **Step 1:** Training on available data, performing inference on entire test data, and generating Pseudo Labels
- **Step 2**: Filtering quality pseudo labels
- **Step 3**: Combining Pseudo Labels + Original Training data
- Repeat Steps 1,2,3
- Post processing with CRFs

Inference

- Using **test-time augmentation (TTA)** during inference in our case significantly helped boost performance. The trained model in both cases is consistent with a U-Net architecture with MobileNetV2 backend.

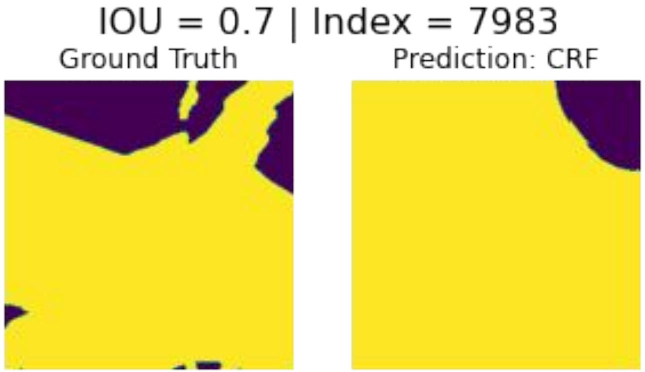
Method	**IoU**
U-Net	0.52
U-Net + TTA	**0.57**

Post processing with CRFs

- We used Conditional Random Fields (CRF) to post-process the predictions.
- CRFs helped refining the segmentation boundaries resulting in better final performance.

Results

Method Description	**IoU ↑**
Random Baseline (all zeroes)	0.00
Competition Provided Baseline	0.60
Standard U-Net	0.57
Ensemble with CRF post processing	0.68
Pseudo labeling + Ensembles with CRF post processing	**0.7654**

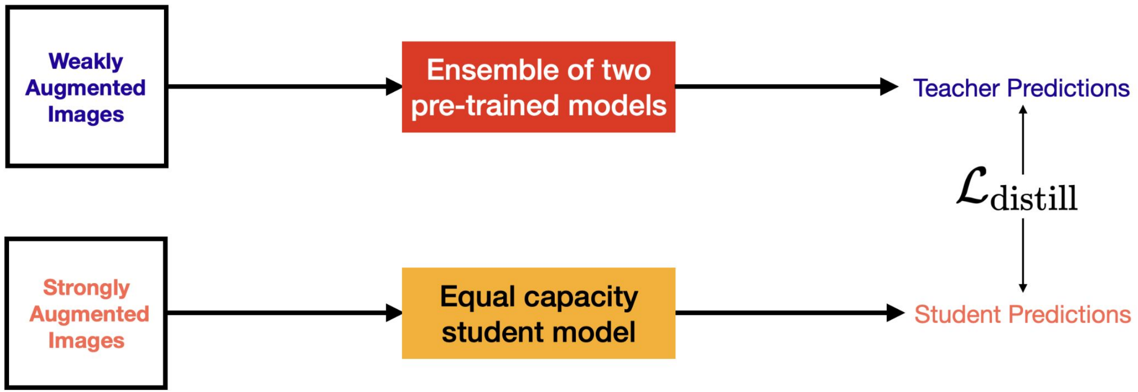


Importance of ensembling

- Paramount in modeling the uncertainty.
- It’s pros lie in its simplicity.
- We used ensembling in two flavours:
  - Standard geometric ensembling of models during inference.
  - Test-time augmentation during inference.

Noisy Student Experiments

- NST is an interesting semi-supervised learning paradigm introduced by Google Brain in 2019.
- It is also particularly helpful when dealing with distribution shifts.



Noisy Student Experiments

- Our extension of NST used the same method for obtaining quality pseudo-labels.
- It also helped cutting down the iterative training procedure drastically reducing the overall training time.
- For inference, we used UNet and UNet++ trained with our NST extension.
- Performance-wise it yields **0.75 IoU**.

Other training details

- Frameworks and others
  - **PyTorch** primarily for model training, other open-source frameworks like **`timm`**, **`smp`** for model building, and **`pydensecrf`** for applying CRF.
  - Standard Adam optimizer with the default from `torch.optim.adam.`
  - Mixed-precision and distributed training with `torch.cuda.amp` and `torch.nn.parallel.`
- Hardware
  - 4 x V100 GPUs on GCP.

Benchmarking

- Segmentation masks are generated in approx 3 seconds per Sentinel-1 tile.
- Covers an area of approximately 63,152 squared kilometers!
- Larger than the area covered by Lake Huron, the second largest fresh water Great Lake of North America.

Future work

- Eliminate CRFs because they are computationally expensive.
- Develop a single end-to-end training workflow to make the process more streamlined.
- More suitable architectures for segmenting satellite imagery.
- **Collaborating with the competition organizers and UNOSAT team to benchmark real time runtimes and to evaluate the scalability of our solution.**

Acknowledgements

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* https://developers.google.com/programs/experts/