



Cloud to Street



STREET TO CLOUD

Improving Flood Maps With Crowdsourcing and Semantic Segmentation

Veda Sunkara, Matthew Purri, Bertrand Le Saux, Jennifer Adams

Tackling Climate Change with Machine Learning workshop at NeurIPS 2020

veda@cloudtostreet.info

www.cloudtostreet.info

Twitter: [@Cloud2Street](https://twitter.com/Cloud2Street)

NEED

Near Real Time Flood Mapping

Rising frequency and magnitude of flood disasters (UNDRR 2015)

Growing populations affected, disproportionate impacts due to social vulnerability (Tellman et. al. 2020)



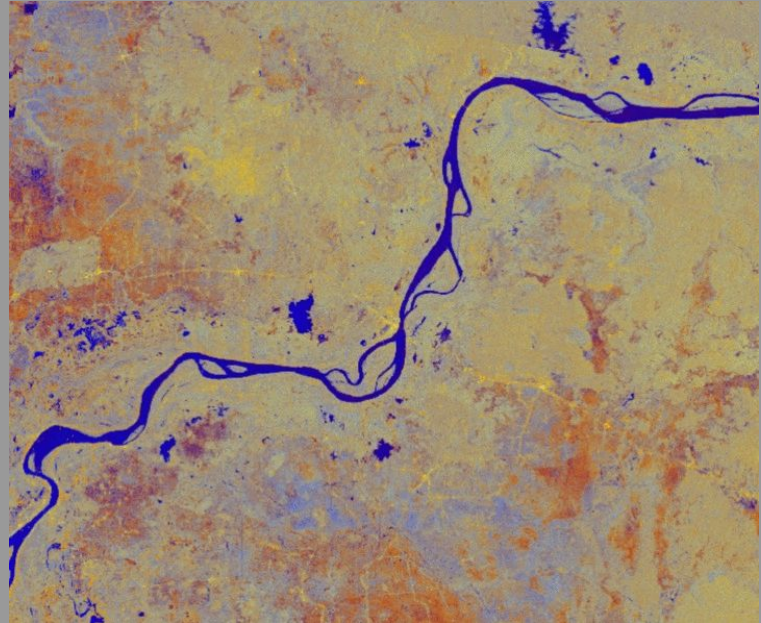
Milkmen wade through a flooded road after Cyclone Amphan, in North 24 Parganas district.
(Photo: PTI)

THE SCIENCE

Satellite Imagery, Remote Sensing, and ML

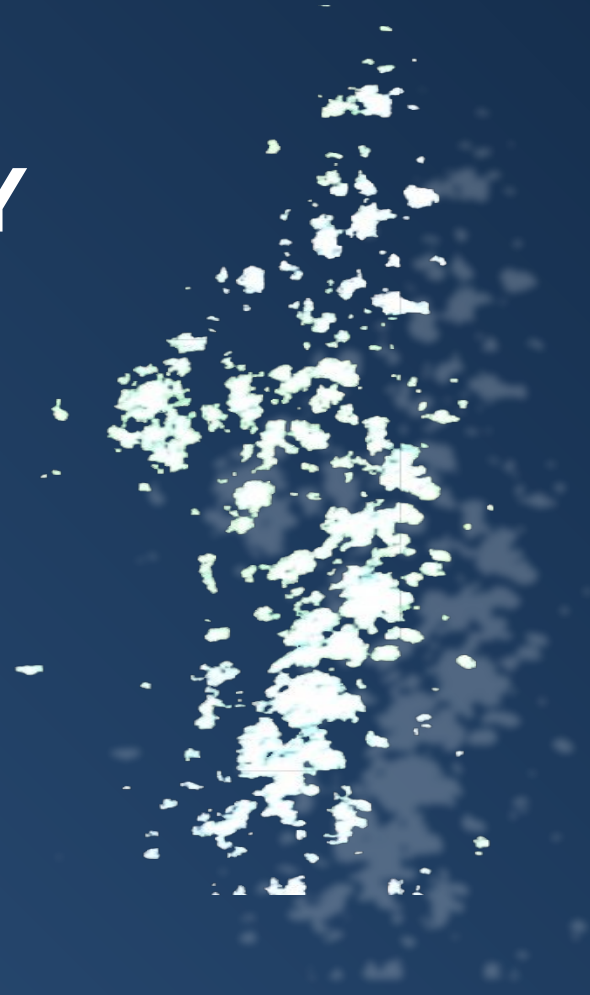
maps made from optical, radar,
and microwave satellites

Nowcast flood extents and
impacts → disaster relief



CHALLENGES WITH SATELLITE IMAGERY

- Infrequent revisit times
- Varying resolutions
- Adverse weather conditions
- Lack of precision in urban areas
- Unlikely to capture flood peak



LIMITATIONS OF EXISTING TECHNIQUES

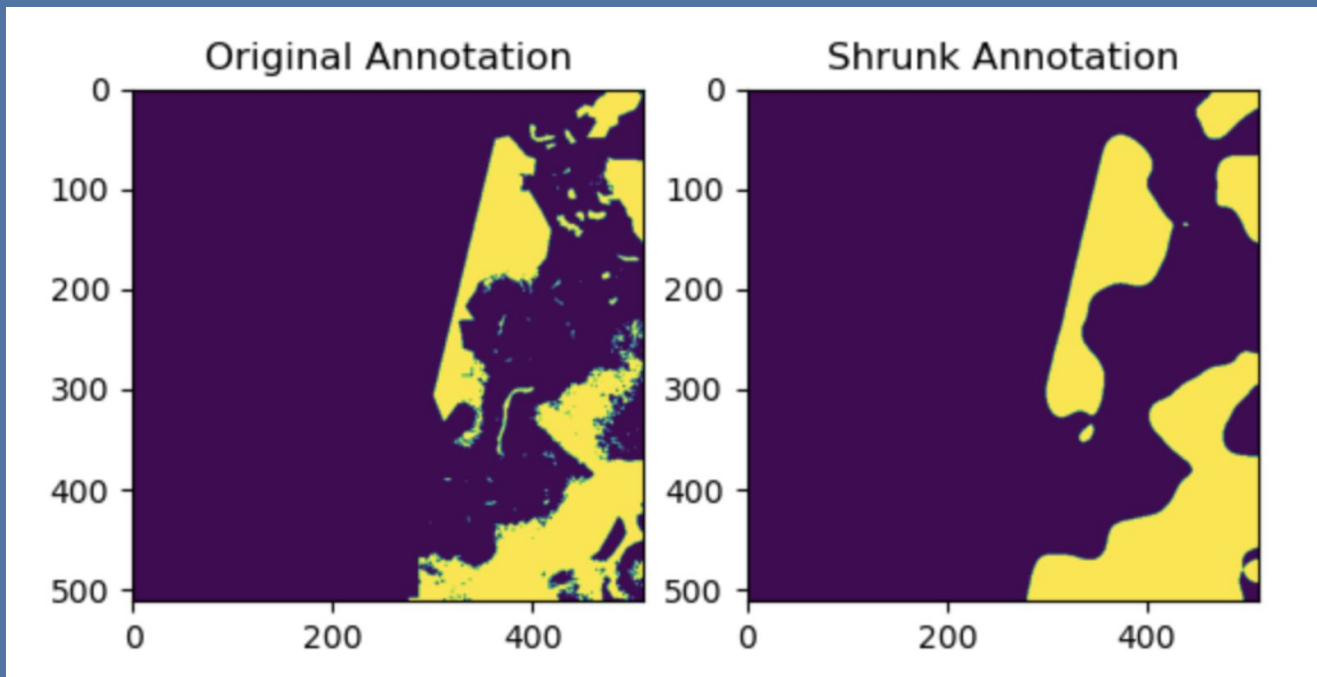
- Manual thresholding and quality assurance
- Availability of training data

SOLUTION: CROWDSOURCING

Simplified training labels, multimodal network, community engagement

METHODOLOGY: TRAINING LABELS

1. *reference*: fine, hand labeled flood masks ([Sen1Floods11](#))
2. Coarse, simplified flood masks (Gaussian blur of Sen1Floods11)

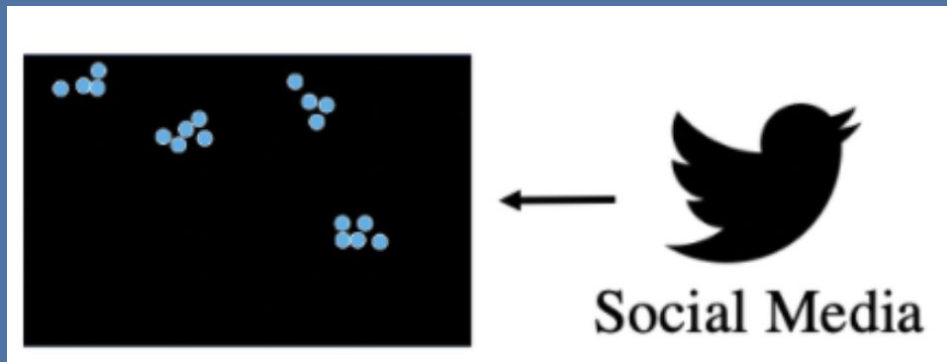
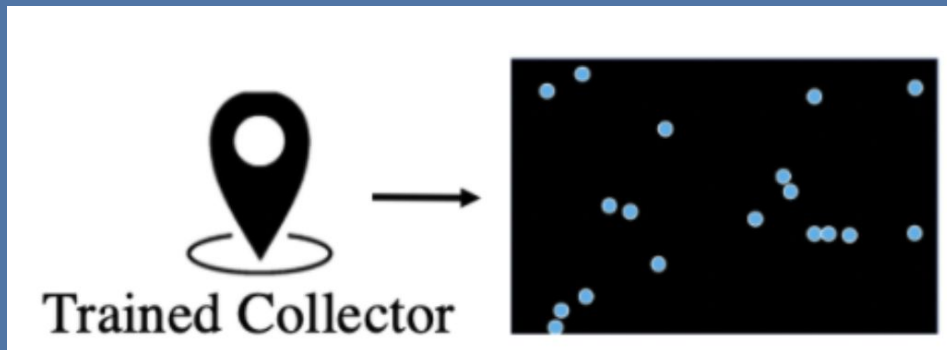


METHODOLOGY: CROWDSOURCED DATA POINTS

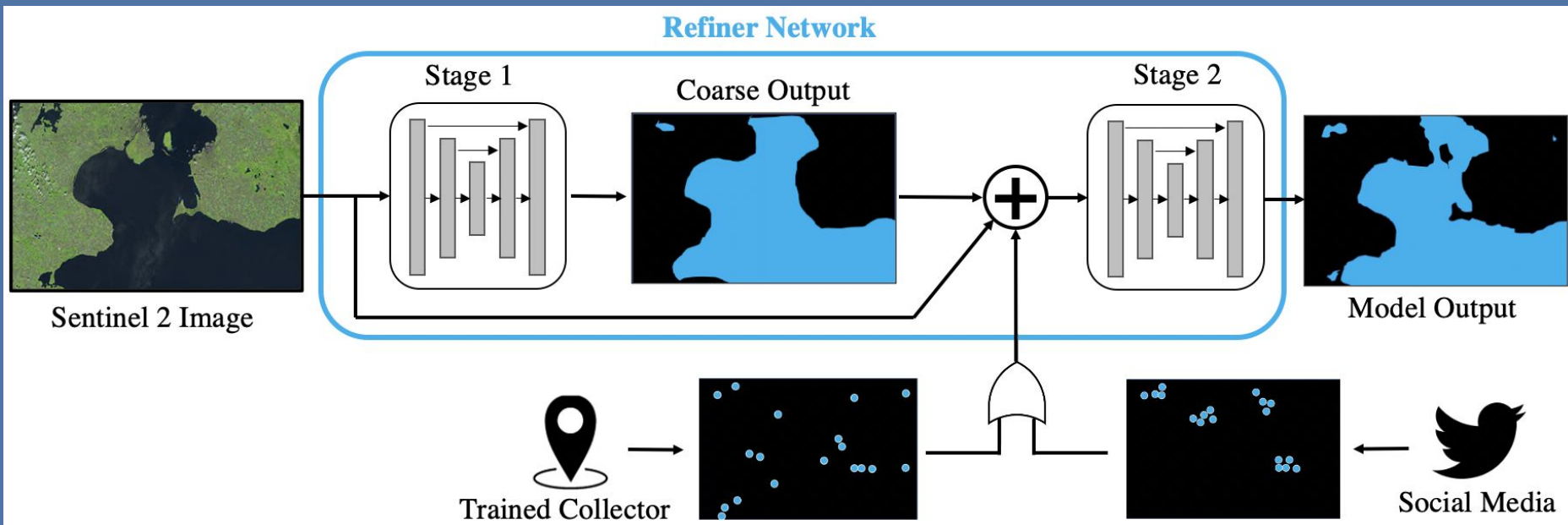
PERIMETER DATA POINTS

Two strategies to collect street information:

1. Social media scraping (low dispersion)
2. Trained data collector (high dispersion)



METHODOLOGY: TRAINING



RESULTS

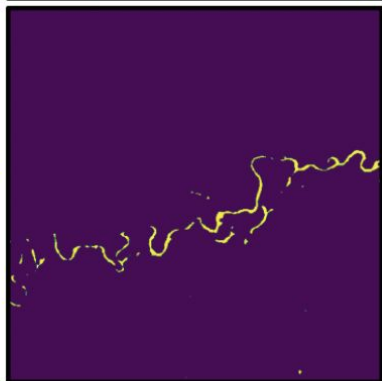
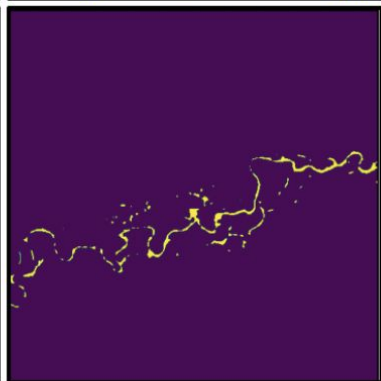
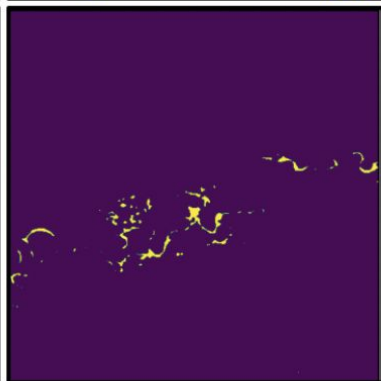
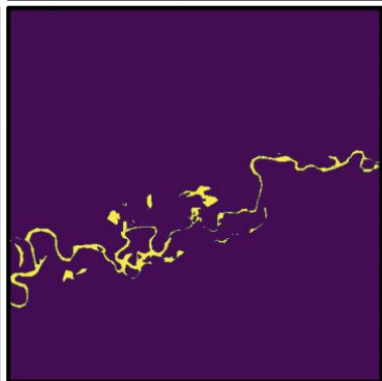
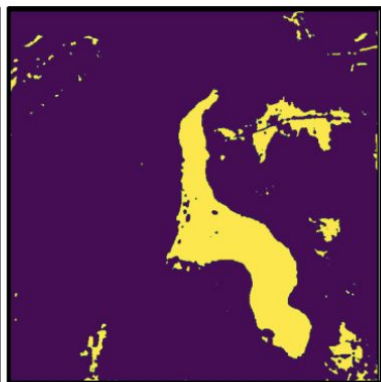
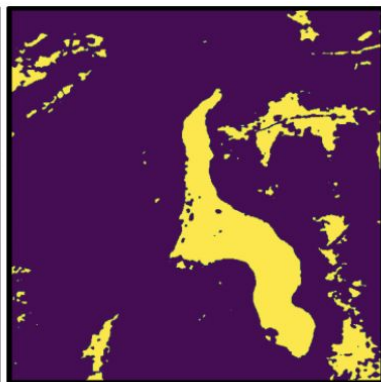
Model	Training Labels	Acc	mIoU
UNet	Coarse	95.2	53.8
Refiner	Coarse	95.6	56.5
Refiner	Coarse+Points	97.2	61.8
<i>UNet</i>	<i>Fine</i>	<i>97.0</i>	<i>62.4</i>
<i>Refiner</i>	<i>Fine</i>	<i>98.1</i>	<i>64.9</i>

Gains in accuracy and mIoU over coarse labels, fine labels in single input architecture

RESULTS

Dispersion	Noise	Acc	mIoU
No Points	No Points	95.6	56.5
Low	Low	95.9	59.6
Low	High	96.9	61.0
High	Low	97.2	61.8
High	High	97.0	60.9

Gains with any crowdsourcing form, with the best results from the trained data collector simulation (high dispersion) with low noise.



Sentinel-2 Image

Ground Truth

UNet

Refiner

Refiner+Points

FUTURE WORK

- Crowdsourcing viability
- Sensitivity analysis
- Unsupervised/weakly supervised training
- Case study on urban areas

HIGH-RESOLUTION IMAGERY OF MAKOTIPOKO,
SKYSAT SATELLITE 2019, PLANET LABS

Thank you.



Cloud to Street

Questions? Contact veda@cloudtostreet.info