Cloud to Street

Making flood maps better and making them matter!

Machine learning, SmallSats, and iterative stakeholder design at Cloud to Street

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WHAT WE DO

We provide near real-time flood risk analytics in easy-to-use decision support tools to enable faster disaster response and long term risk reduction. Leveraging remote sensing, crowd intelligence, and machine learning, our mission is to ensure that all vulnerable communities have the information they need to prepare for and respond to disasters.

SELECT PARTNERS

WFP World Food Programme

THE WORLD BANK

planet.

Willis Towers Watson

African Risk Capacity

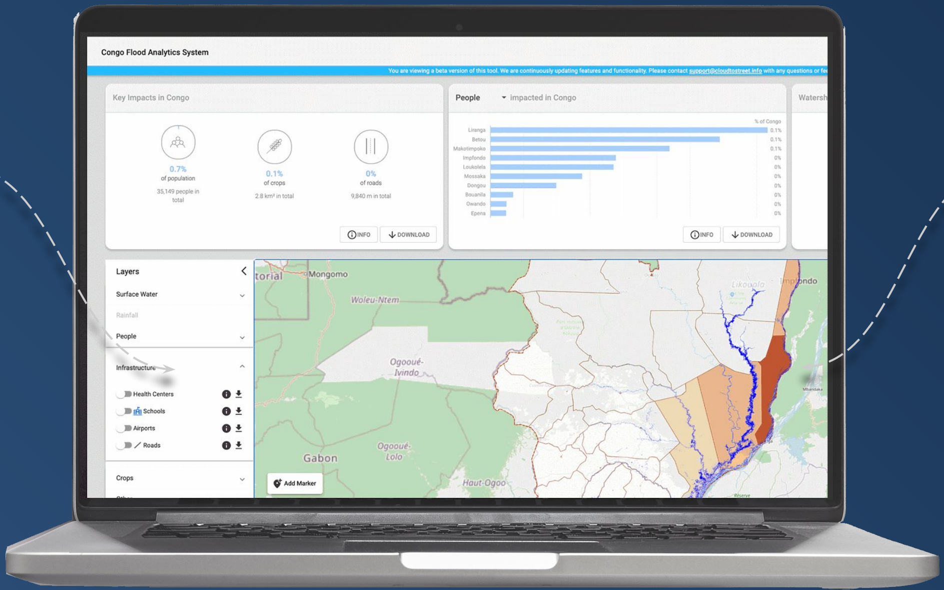
Capella Space

CLOUD

Analyze satellite data in the Google Earth Engine Cloud

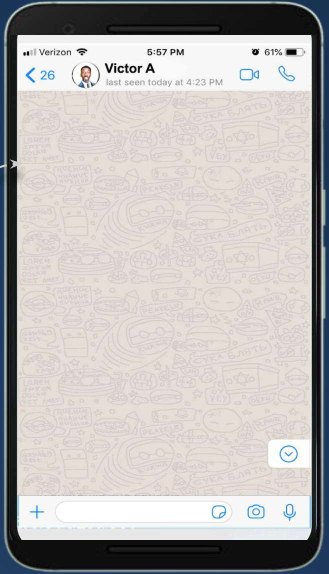
TO

Estimate affected population, infrastructure, and croplands, and create SMS alerts that syncs with conditions on the ground



STREET

Users upload observations and reach out for support



WHERE WE WORK

RISK REDUCTION & PLANNING

Sudan
South Sudan
The Republic of Congo
Uganda
Kenya
Rwanda
Tanzania
The Gambia
Ivory Coast
Democratic Republic of Congo

EMERGENCY RESPONSE

The Republic of Congo
Niger
Ghana
Ethiopia
Sri Lanka

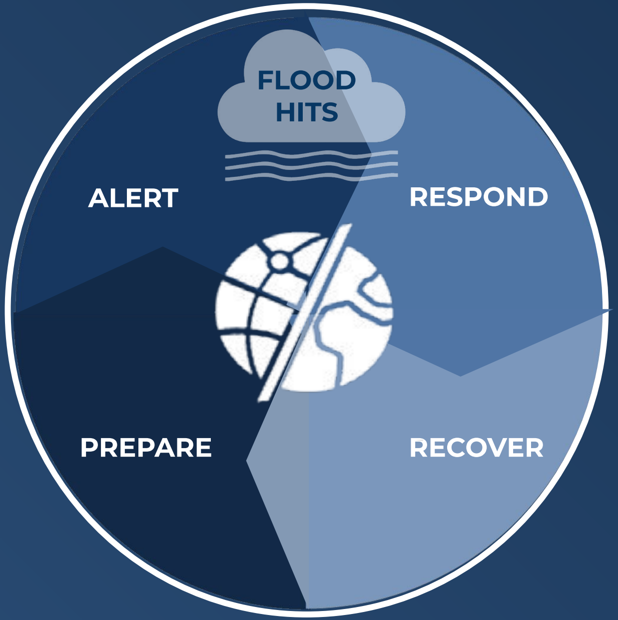
FINANCIAL SERVICES & INSURANCE

Ghana
The Gambia
United States
Indonesia
India

WE REDUCE RISK AND INCREASE CAPACITY THROUGHOUT THE DISASTER CYCLE

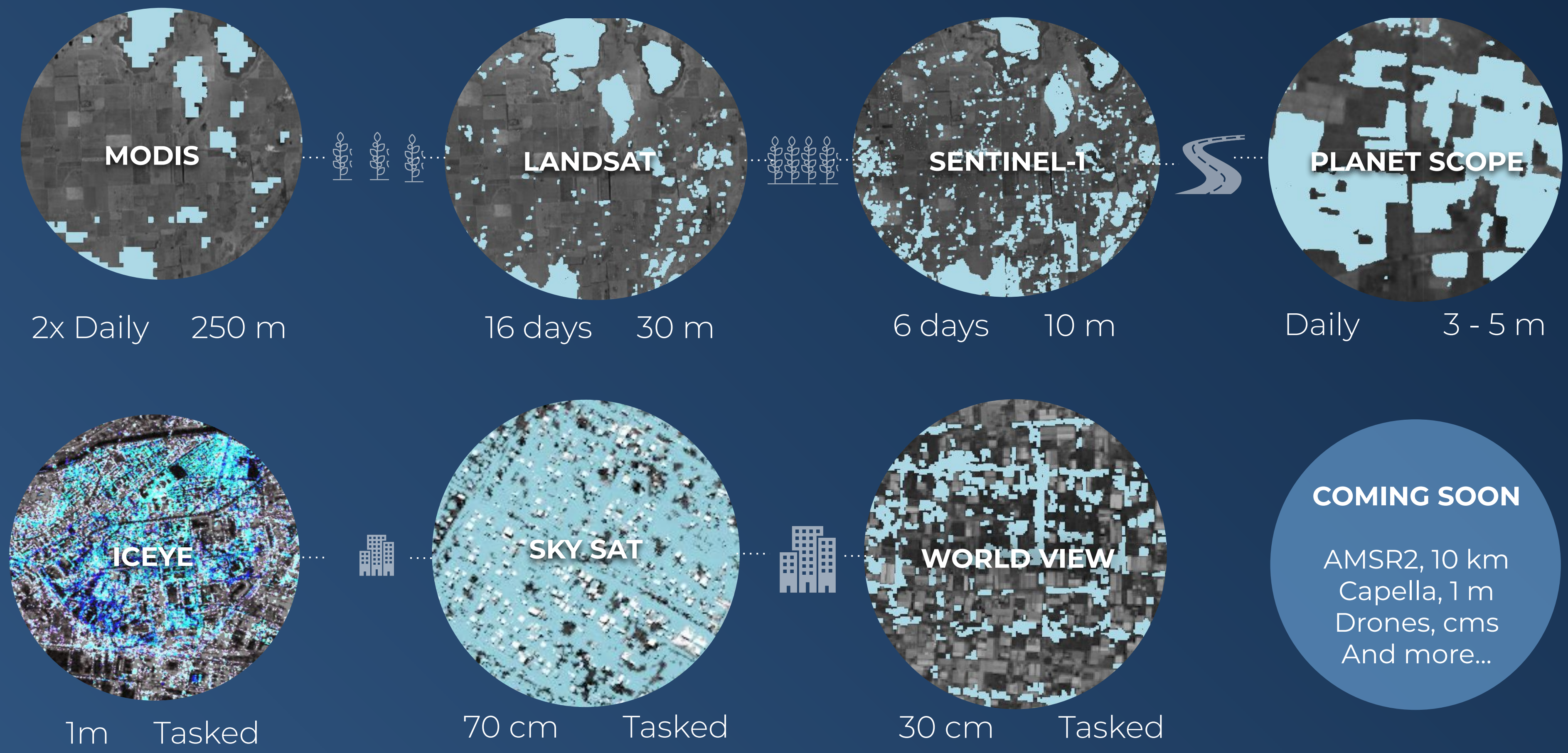
Enable governments and planners to map flood risk without ground gauges; support flood model calibration

Create a financial safety net for all communities by supplying insurers with data



Near real-time updates ensure timely evacuation

Increase efficiency of disaster relief, and trigger insurance payouts


MODIS
2x Daily 250 m
LANDSAT
16 days 30 m
SENTINEL-1
6 days 10 m
PLANET SCOPE
Daily 3 - 5 m
ICEYE
1m Tasked
SKY SAT
70 cm Tasked
WORLD VIEW
30 cm Tasked
COMING SOON
AMSR2, 10 km
Capella, 1 m
Drones, cms
And more...

OUR IMPACT with WFP Congo

2018 PREPARE

Historical Risk Maps

Supported the relocation of 7,000 refugees

2019 RESPOND

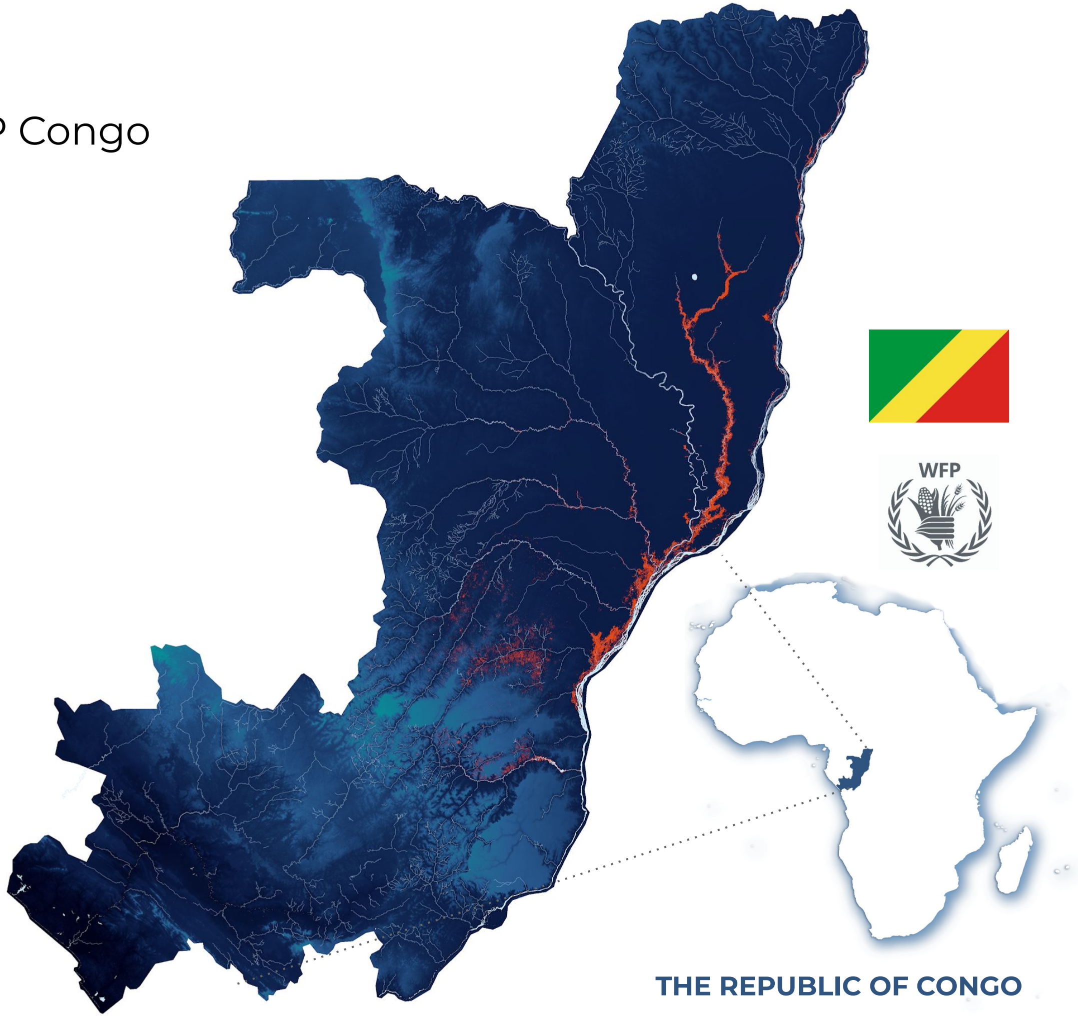
Emergency Activation

Presented to decision-makers to secure $11.5M in assistance

2020 RECOVER

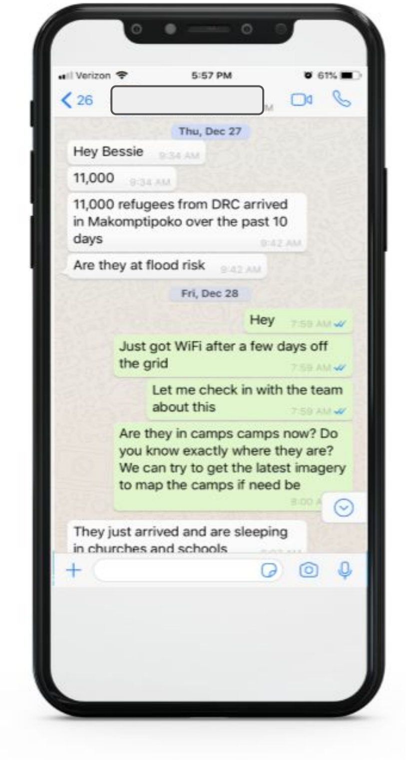
Monthly Reports

Distributed cash transfers to 145,000 civilians

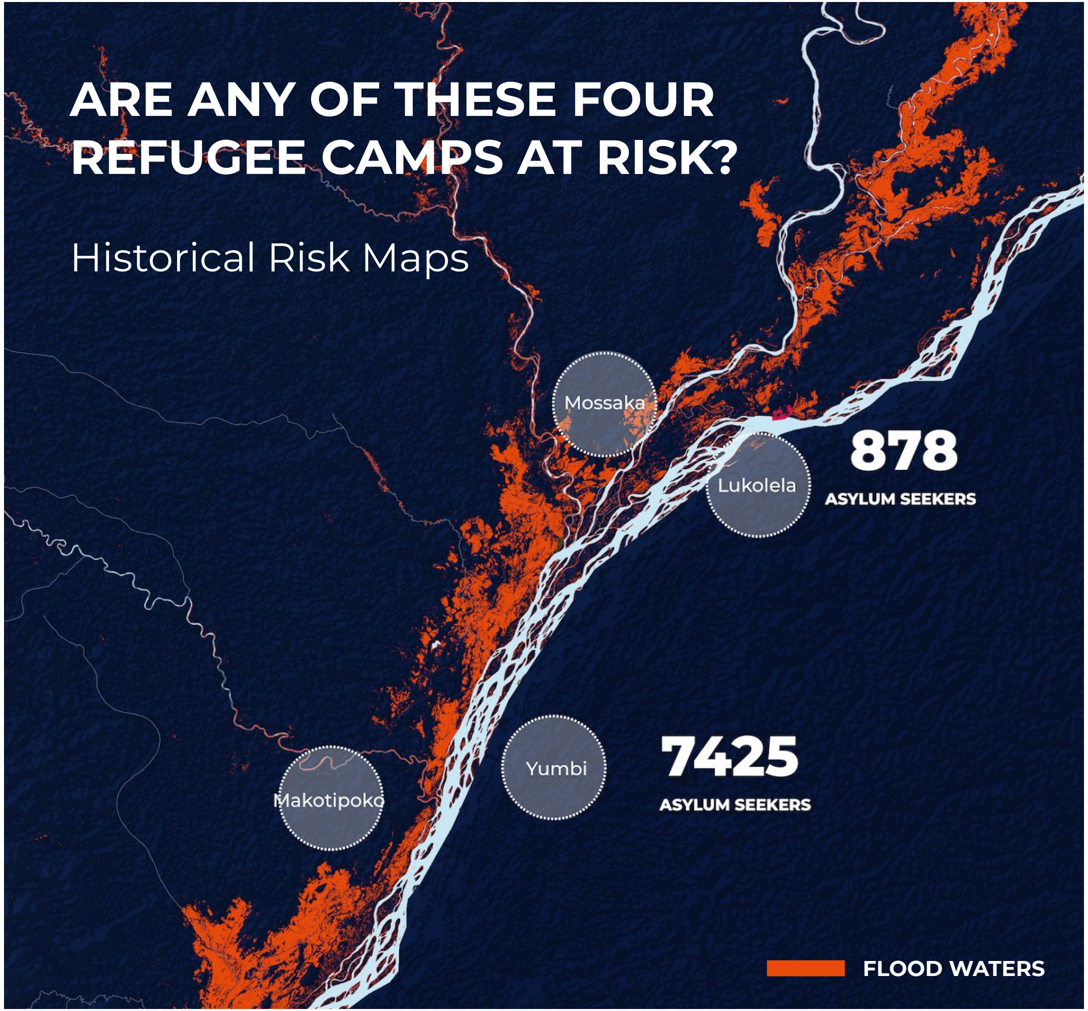


IS THIS COMMUNITY AT RISK?

Makopitoko, 2018



The WFP Country Director messaged us because they and the government needed to know if thousands of new refugees should be recoated



Historical flood mapping in 3 days indicate one of the camps (Makotipoko) was at high risk of flooding, supporting the Ministry of Social Affairs' recommendation to relocate 7,000 at risk refugees

RESPOND

Emergency Activation

In 2019, another catastrophic flood hits Congo, including Makotipoko. We used high resolution satellites, and provided emergency numbers in days that enabled **WFP Congo to secure $11.5 M in emergency funding.**

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

RECOVER

More Accurate Algorithms

Where will floods cause long term food insecurity? Global crop data was inaccurate (20% accuracy), so we used Google Earth Engine to make better crop maps (94% accuracy) in a week. These data identified **360,000 people with long term flood impacts, enabling WFP Congo to provide 145,000 cash-based transfers to affected households.**

Making flood maps better and more useful

Use Smallsats!

⬆ COVERAGE

⬆ RESOLUTION,

Invest in deep learning

-IMPROVE IMPACT DATA

-SEE THROUGH CLOUDS

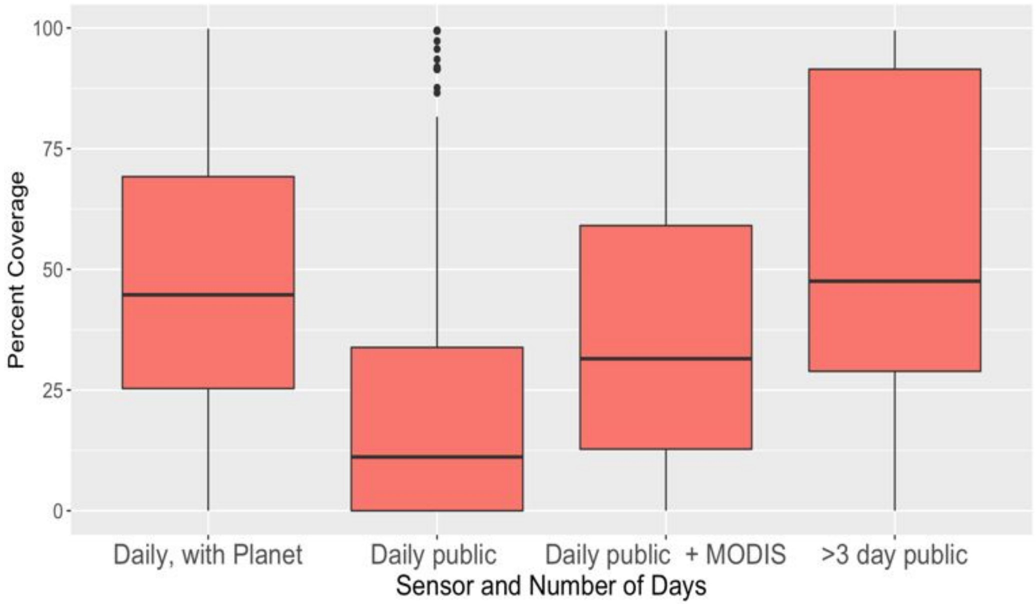
-CNNS + CROWDSOURCING IMPROVE FLOOD MAPS (SUNKARA ET AL 2021)

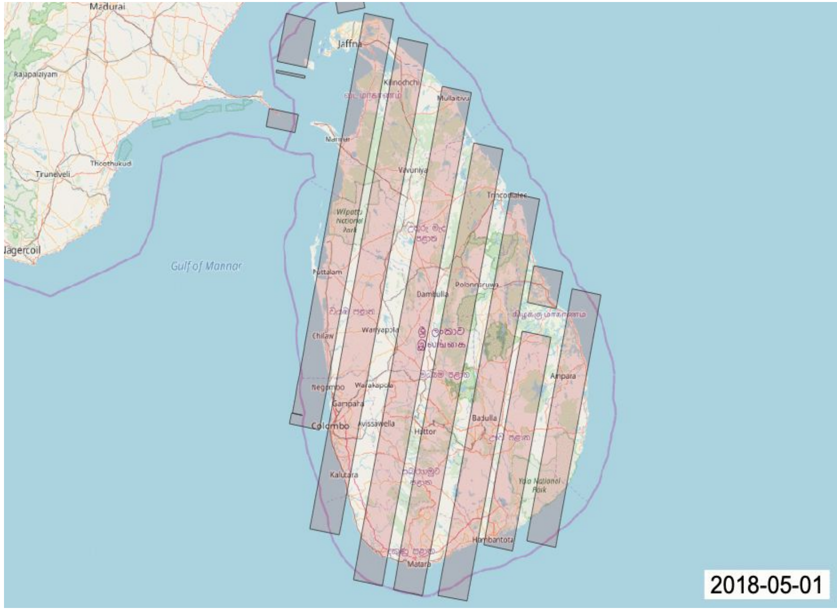
-USE GANS TO SIMULATE SWIR, IMPROVES ACCURACY 10%! (AKIVA ET AL 2021)

Practice human-centered design

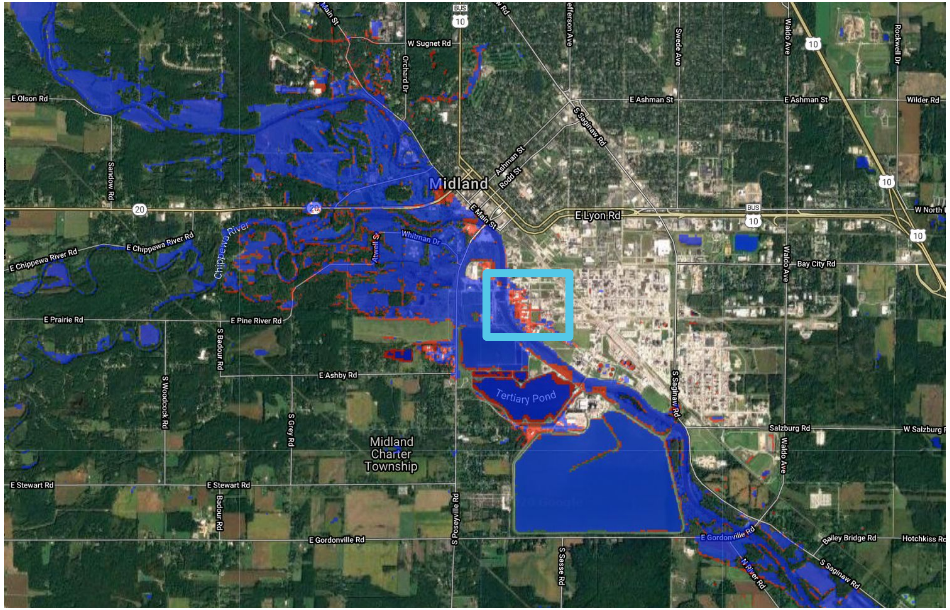
USERS ARE NOT A LAST MILE PROBLEM (THEY ARE THE FIRST 100 MILE SOLUTION!)

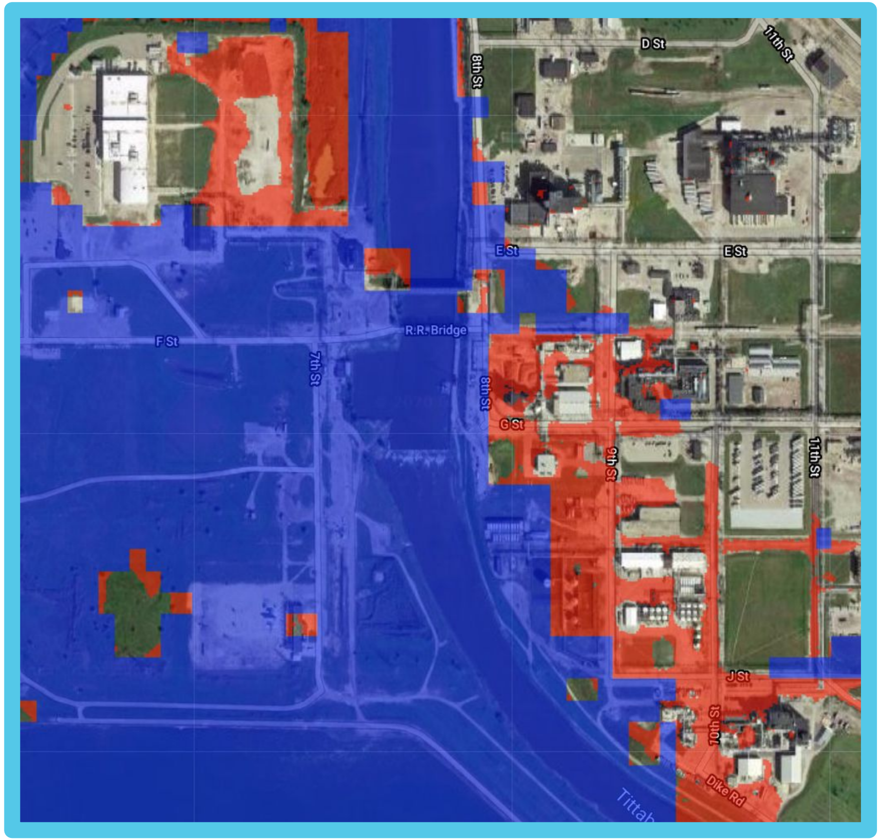
Gains in **consistency** and resolution with Smallsats-> Example: Planet





Dam Break, Michigan May 20th Imagery -- Landsat vs PlanetScope

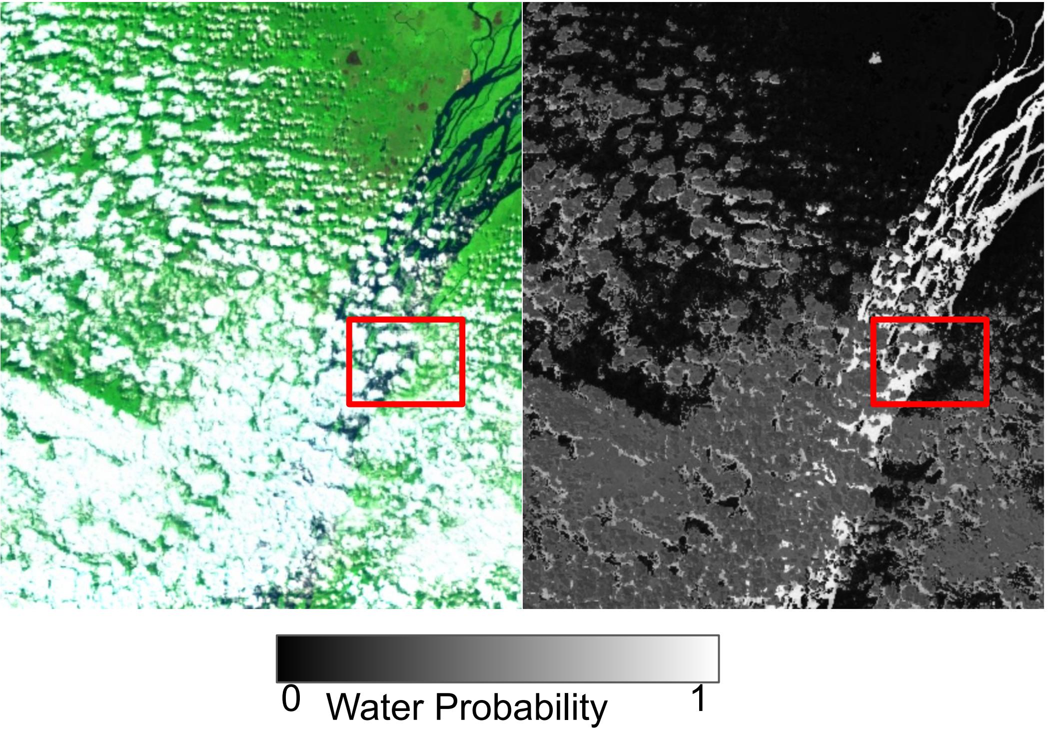


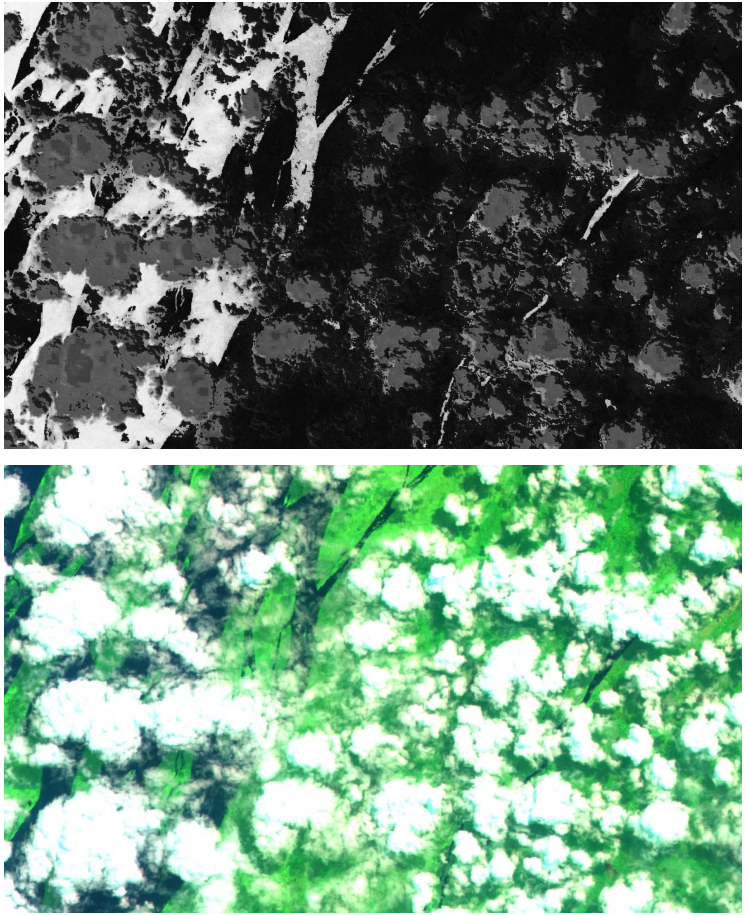


Landsat 8 (30 m)

PlanetScope (3 m)

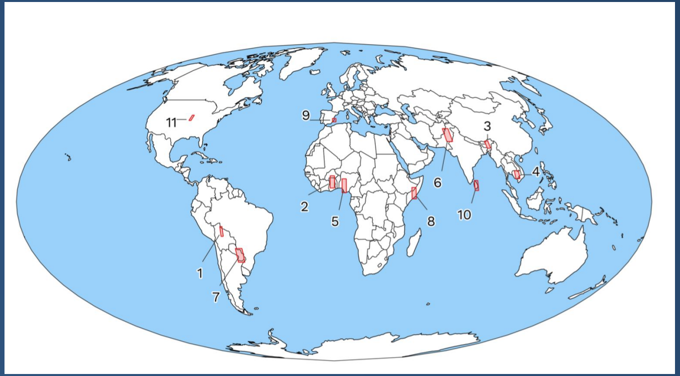
Random Forest maps floods through thin clouds

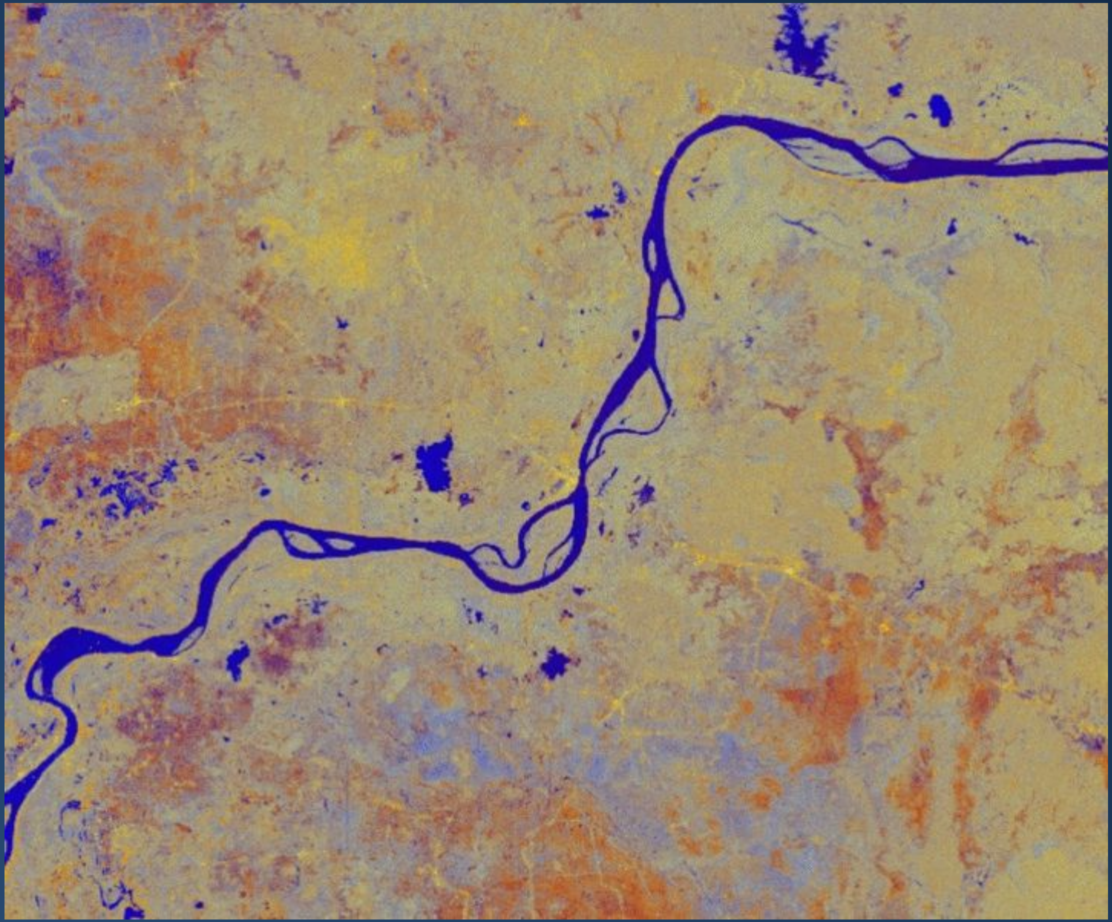




Use CNNs to get more spatial info into flood predictions (Peng et al 2019)

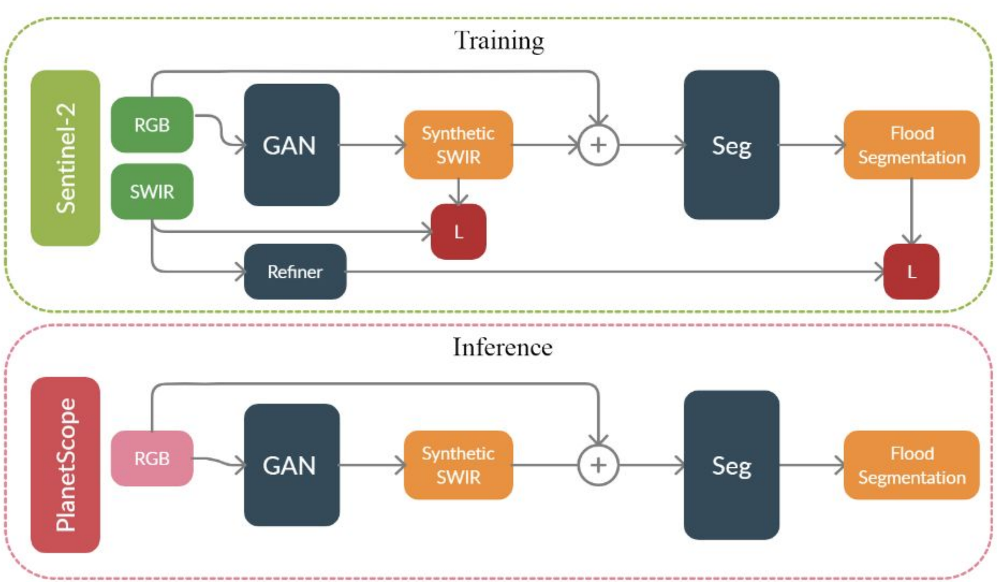
Can use labeled data -> Sen1floods11 (Bonafilia et al 2020), and SEN12FLOOD (Rambour et al 2020) for ML radar/optical model development

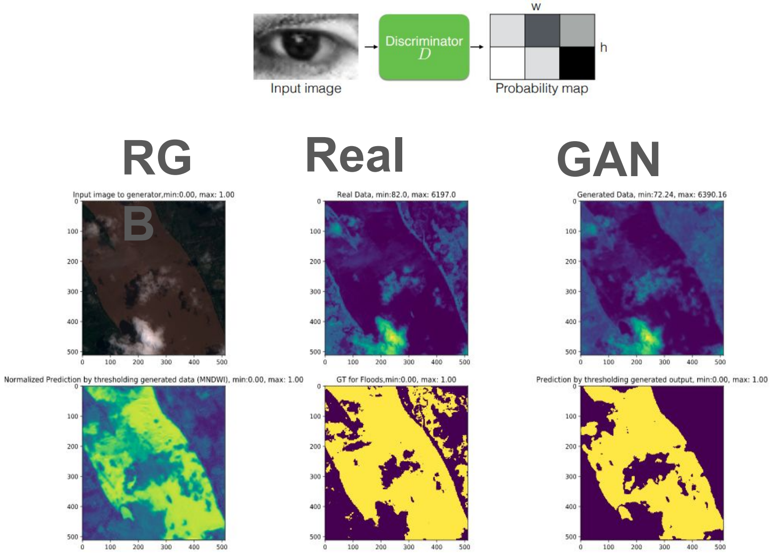




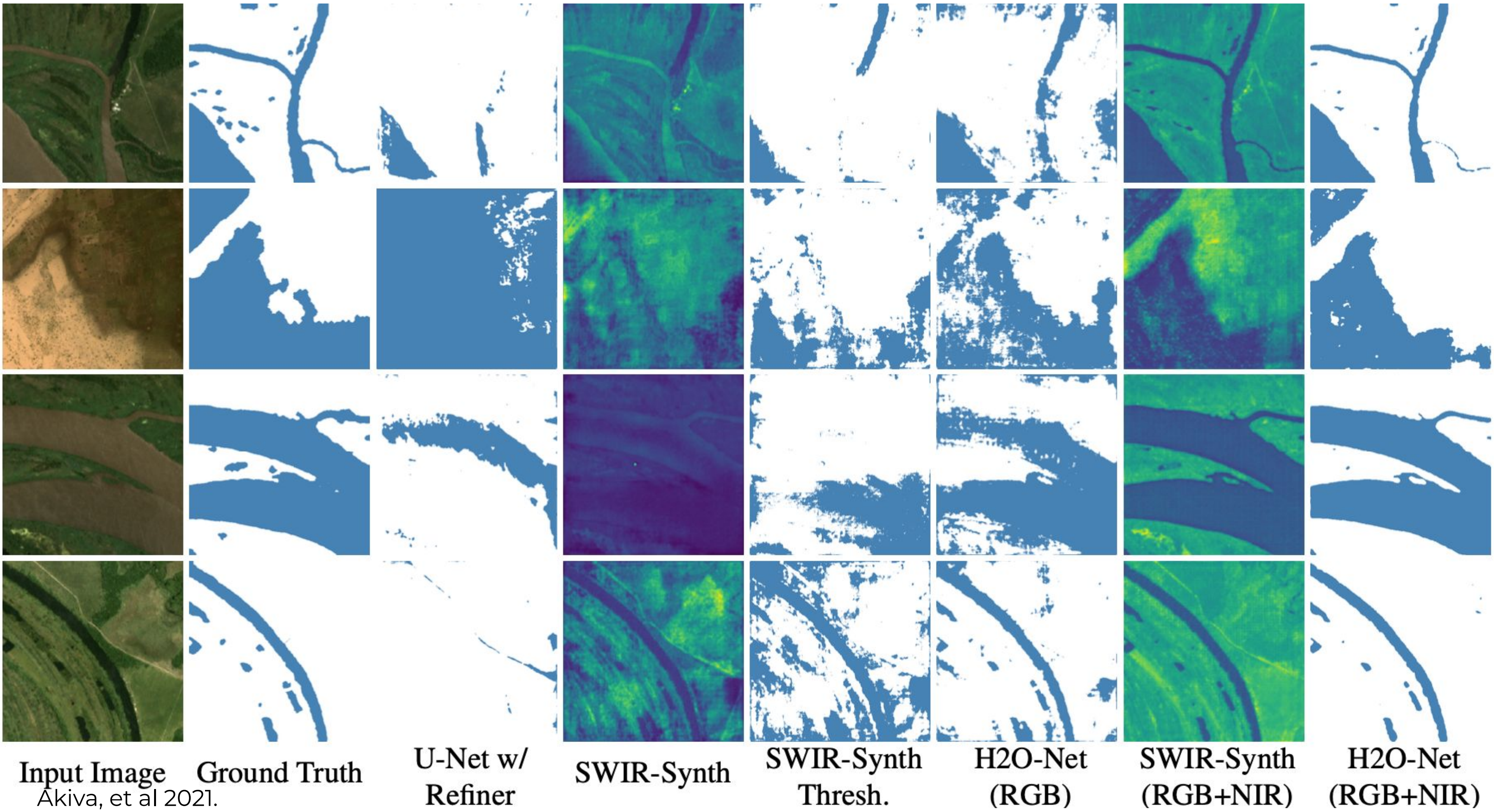
Bonafilia, D., Tellman, B., Anderson, T., Issenberg, E. 2020. Sen1Floods11: a georeferenced dataset to train and test deep learning flood algorithms for Sentinel-1. **The IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshop**

Self-Supervised Flood Segmentation via Adversarial Domain Adaptation and Label Refinement





Akiva, Peri, Matt Purri, Beth Tellman, Tyler Anderson, and Kristin Dana. “H20-Net: Self Supervised Flood Segmentation via Adversarial Domain Adaptation and Label Refinement.” In *2021 IEEE Winter Conference on Applications of Computer Vision (WACV)*. https://arxiv.org/abs/2010.05309.



Akiva, et al 2021.

Results- TL;DR

-synthesized SWIR from RGB increases accuracy of flood mapping for BOTH drone and Planetscope by ~10-15%

-if you don’t have enough labeling data for CNNs, refiners increase accuracy ~3-5%

Dataset	PlanetScope [2]			
Method	Bands Used	Pixel Accuracy (%)	mIoU (%)	FW-IoU (%)
NDWI Thresholding (≥ -0.1)[20, 58]	RGB+NIR	72.35	63.26	61.53
SWIR-Synth Thresholding (≥ 0.35)	RGB+NIR	85.47	71.93	74.49
H2O-Net (Ours)	RGB+NIR	**87.23**	**74.52**	**76.88**
DeepLab v3 [16]	RGB	57.03	31.46	29.61
DeepLab v3 (w/ refiner)	RGB	59.22	33.74	39.89
U-Net [64]	RGB	64.01	42.63	49.49
U-Net (w/ refiner)	RGB	66.81	48.18	50.98
SWIR-Synth Thresholding (≥ 0.35)	RGB	69.23	53.31	53.97
H2O-Net (Ours)	RGB	**76.19**	**60.92**	**62.42**

Akiva, et al 2021.

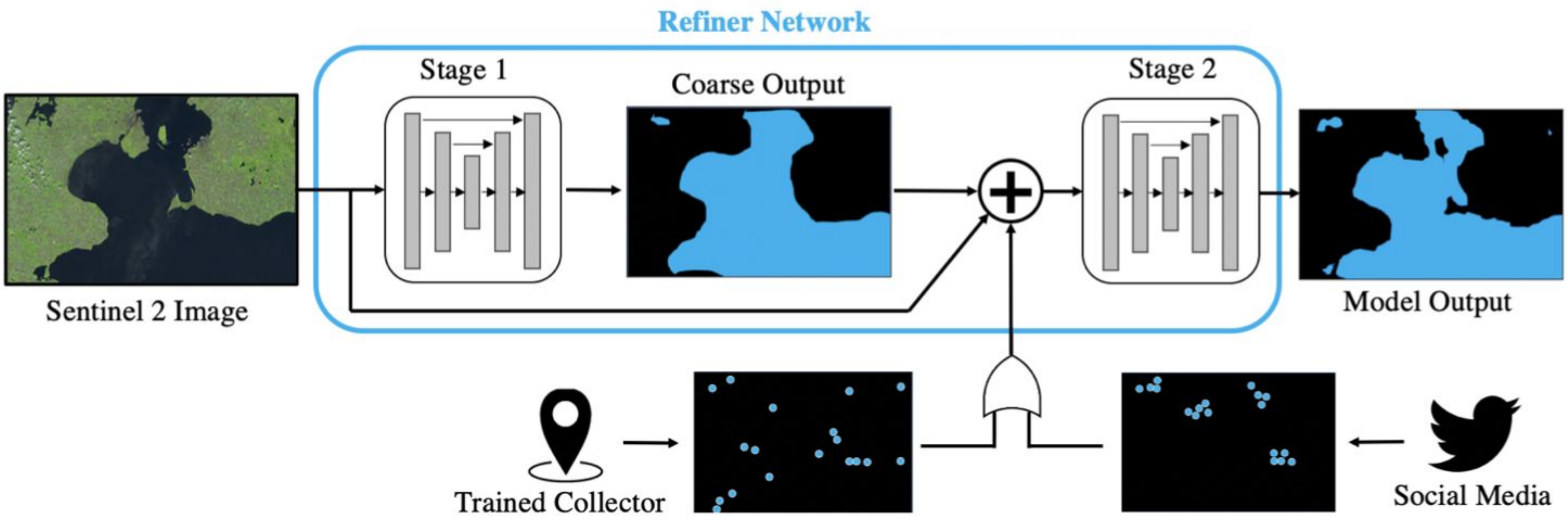
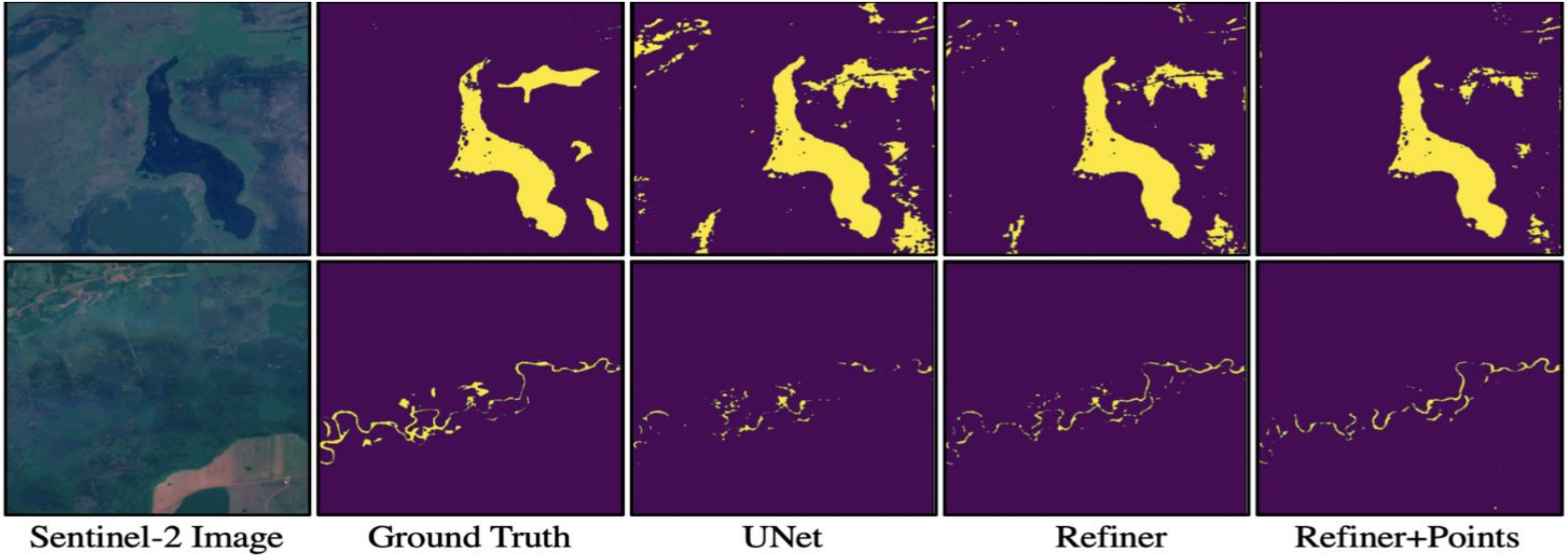


Figure 1: The inference pipeline of our model. The two-stage model first generates a segmentation mask from Sentinel-2 imagery in Stage 1, and then combines Sentinel-2 imagery, initial coarse output, and crowdsourced points in Stage 2 to generate the final segmentation mask. Points collected from either a Trained Collector or Social Media model can be used interchangeably in this model.

Sunkara, Veda, Matthew Purri, Bertrand Le Saux, and Jennifer Adams. "STREET TO CLOUD: IMPROVING FLOOD MAPS WITH CROWDSOURCING AND SEMANTIC SEGMENTATION." *NeurIPS Climate Change AI Workshop*, 2020, 5.

A few ground points (20-50) aid CNN accuracy by 3-5%; trained data collectors increase accuracy adt'l 1%

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



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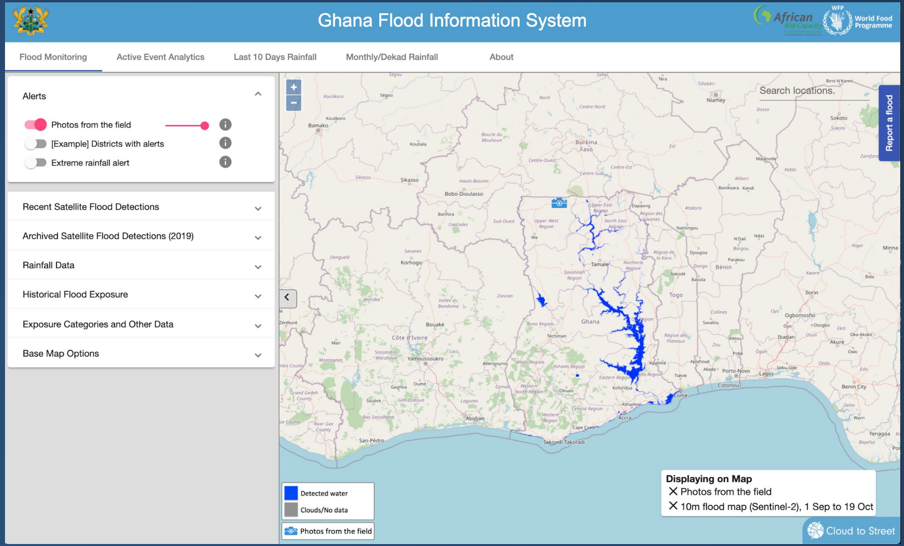
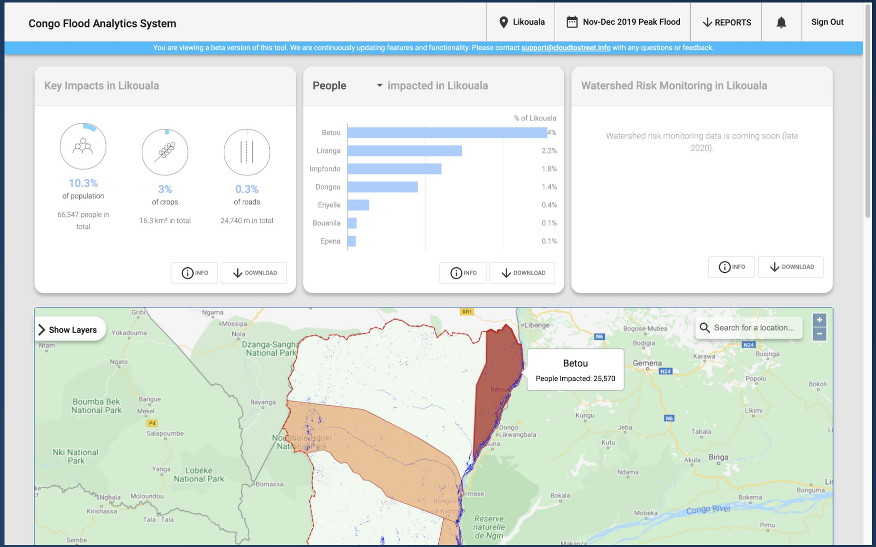
MAPS AREN'T ENOUGH

GET TO THE INSIGHT

Cloud to Street





"The information was not clear or broken down to local levels so we can't prioritize which to support"

—National Agency Disaster Management Organization, Ghana

"The data was very much appreciated by my partners, they don't have this kind of data at the moment...

—World Food Programme, Republic of Congo

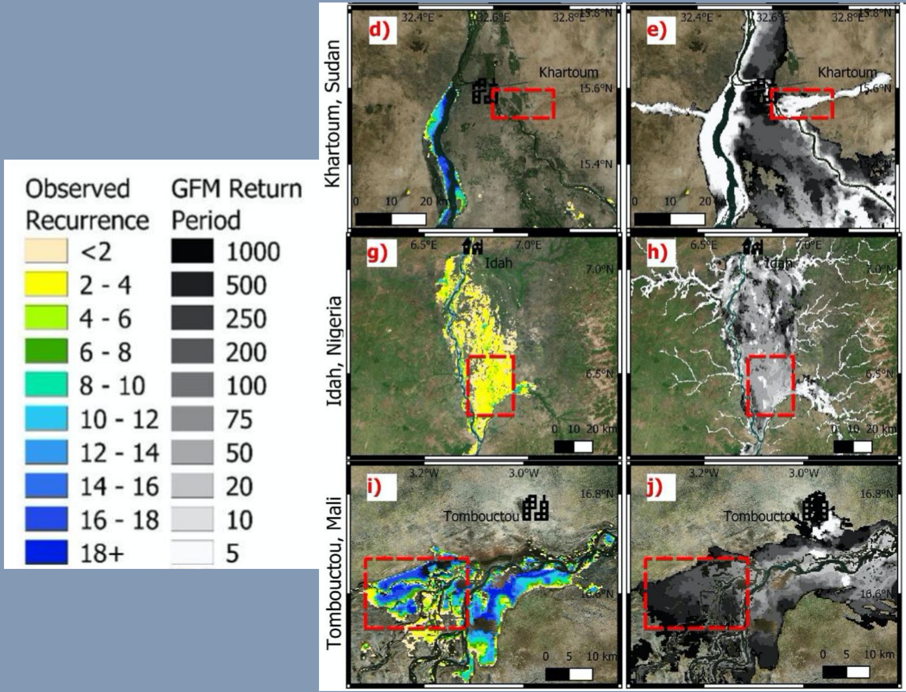
We have work to do together!

Together we can! GFP inspired collaboration comparing EO and Models HOT OFF THE PRESS!

-evaluate outcomes in user driven and defined contexts iteratively

-assess consistency and accuracy over time in publications

-understand how consistently deep learning can map floods operationally and extent of domain transfer possible



Hawker, Neal, Tellman, Liang, Schumann, Doyle, Sullivan, Savage, Tshimianga. *2020. Environmental Research letters.* Comparing earth observation and inundation models to map flood hazards .https://iopscience.iop.org/article/10.1088/1748-9326/abc216/meta

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