Using a model-of-models approach and remote sensing technologies to improve flood disaster alerting

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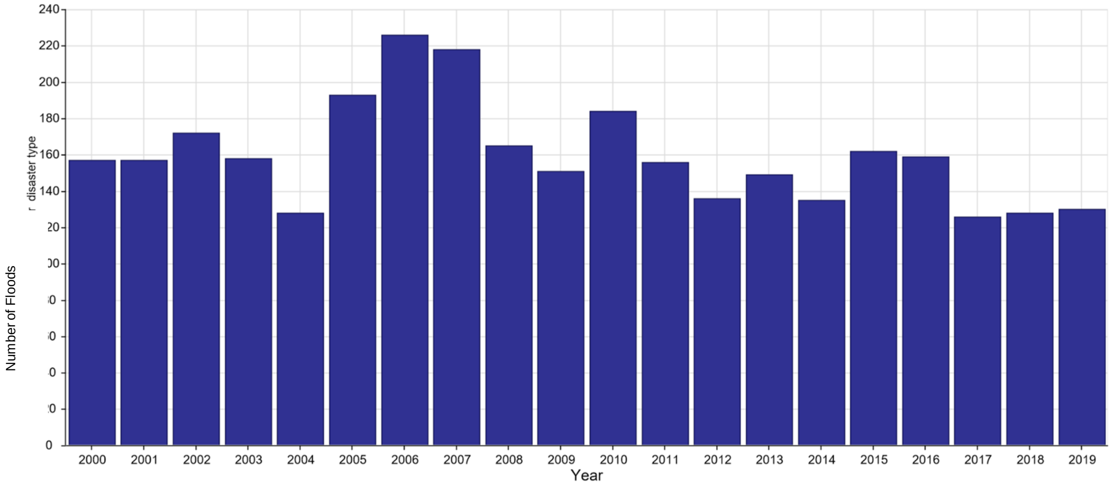
PDC | GLOBAL

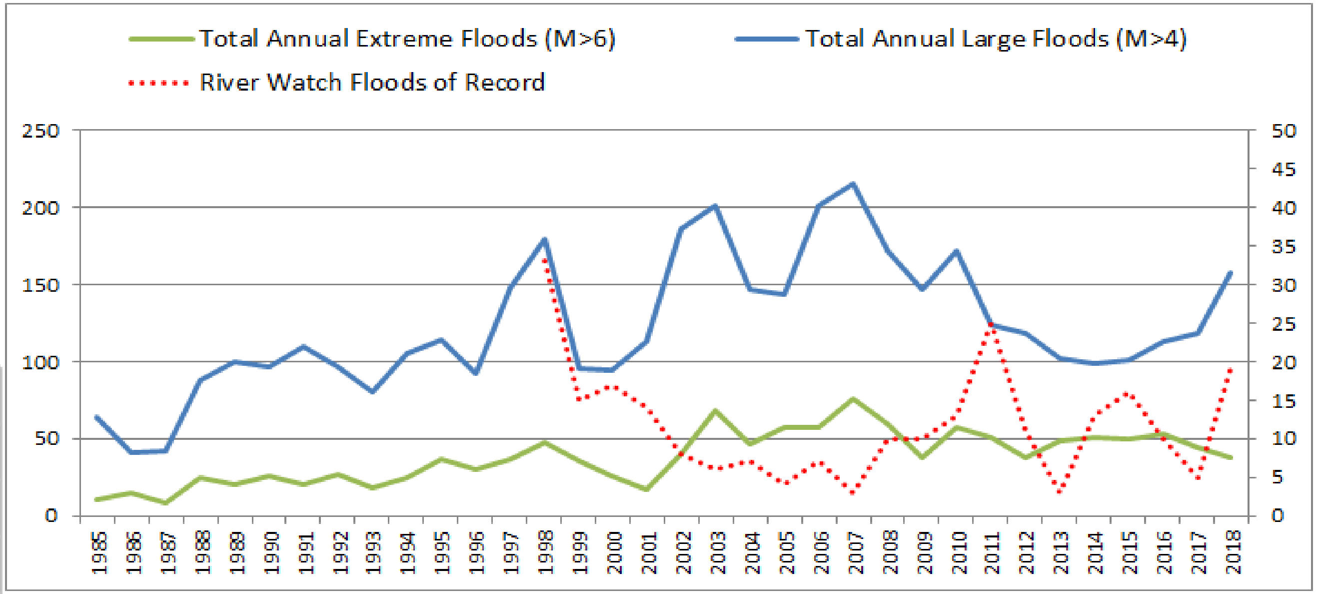
Outline of presentation

- Global Flooding
- Project context and overview
- Project tracks
  - Model of Models
  - EO Based Inundation and Flood Depth
  - EO Based Damage Assessment
- Validation
- Development infrastructure
- Integration with PDC
- Potential synergies

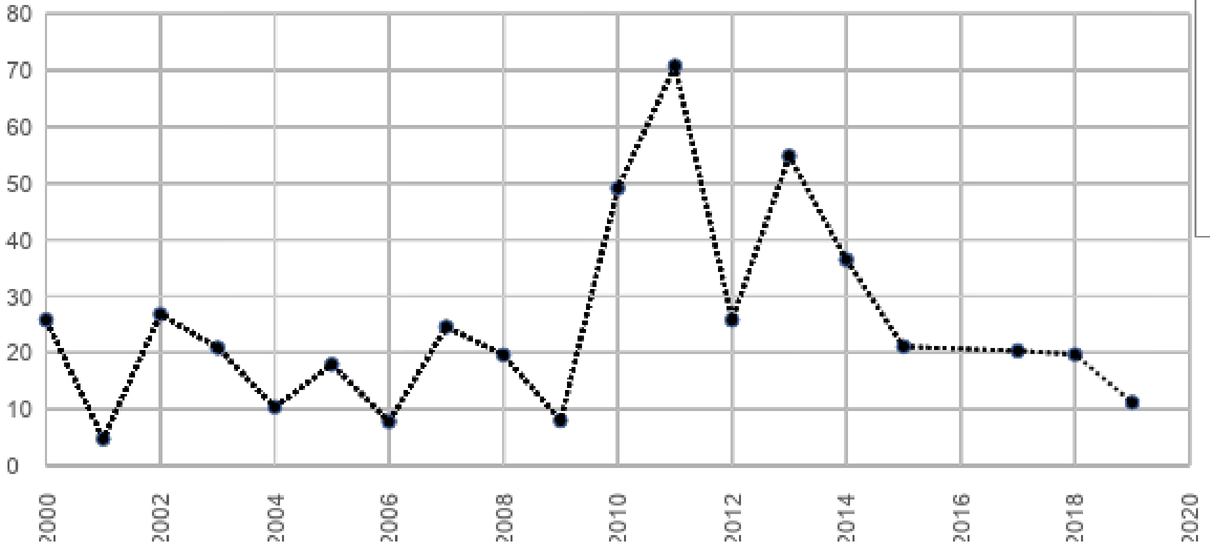
Global Flood Status



Number of Floods during 2000 – 2019
Source: https://www.emdat.be/

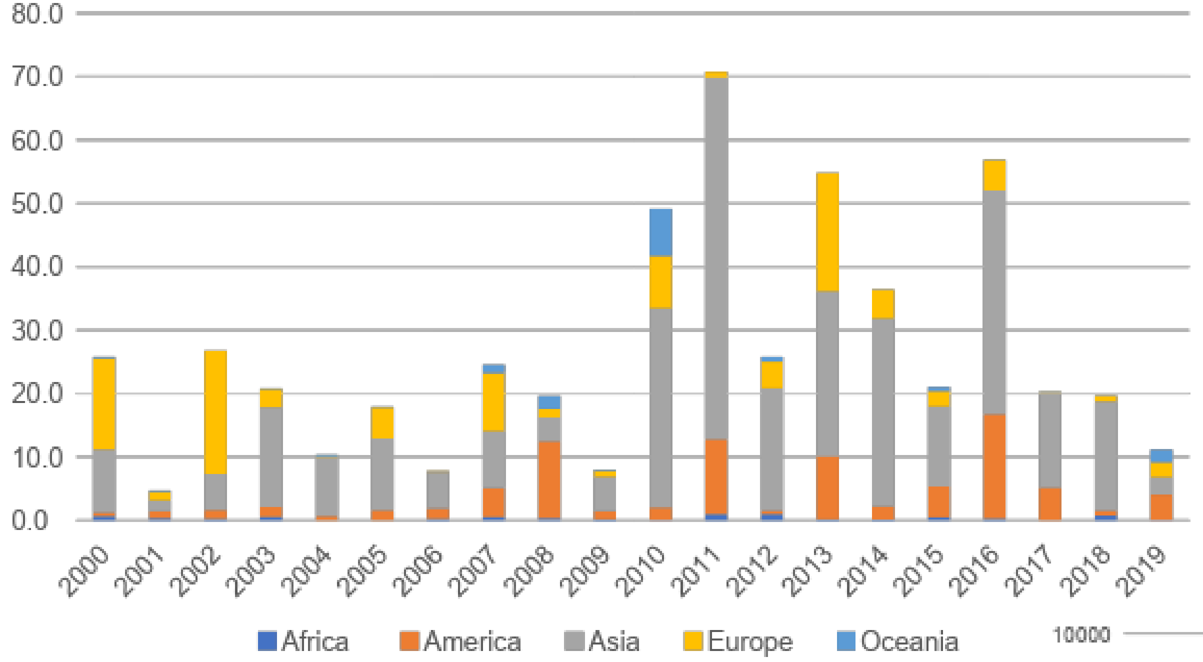


Large and Extreme floods as recorded in media and government reports- listed in the DFO Flood Archive

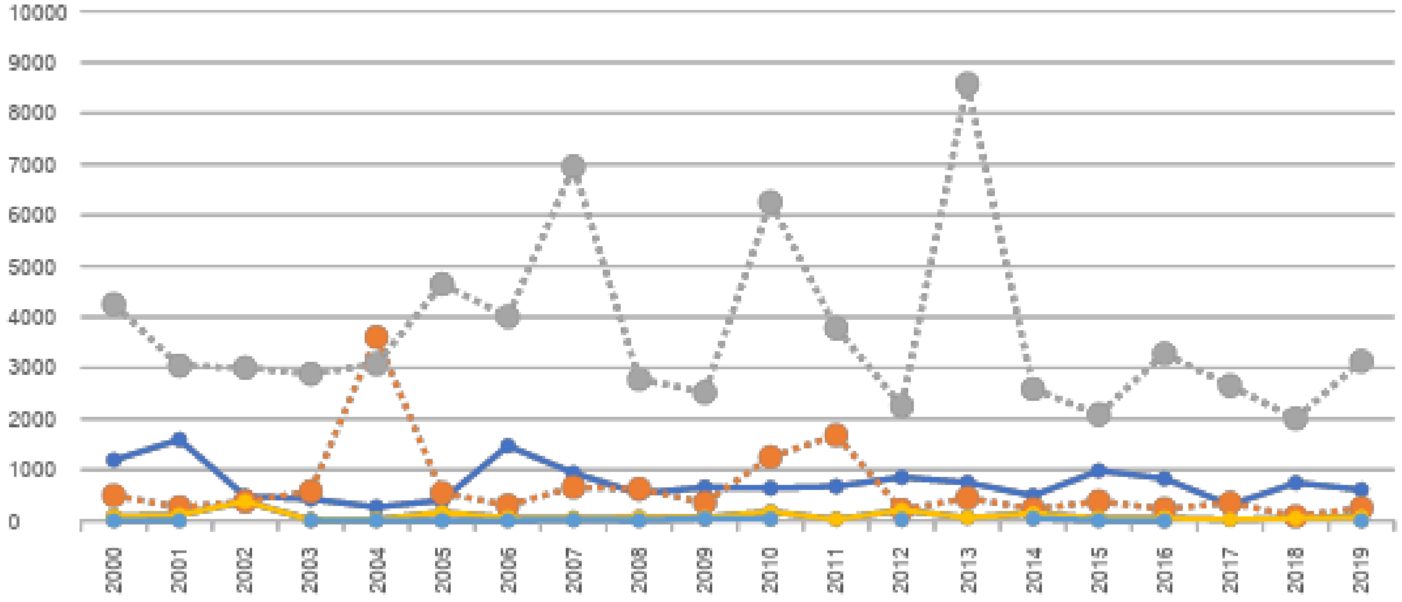


Global Flood Damage (in USD Billion) During 2000 – 2019
Source: https://www.emdat.be/

Global Flood Impact by Continent



Continent Level Flood Damage (in USD Billion) During 2000 – 2019
Source: https://www.emdat.be/



Continent Level Deaths During 2000 – 2019
Source: https://www.emdat.be/

Why this project?

This project encompasses several key features that makes it valuable to the A.37 portfolio:

- Partnership with PDC that would facilitate reaching hundreds or more of their users
- Establishes an integrated model of models for the global flood community that does not currently exist
- Leveraging machine learning research being performed by several Co-Is
- Use of validation data provided through project collaborator - DFO
- Excellent opportunity to demonstrate research efficacy and value of EO information for Disaster Management

Project Team

JPL
Project management, DAART team engagement, assisting with modeling as appropriate

Earth Observations

ImageCat
Testing, calibration, and validation of simulation results using EO-based data and historic case studies

UC Boulder
SAR and optical mapping of flood extent

Machine Learning

UMKC
Machine learning for hazard and loss mapping; software integration and linking to the platform systems

ORNL
Software integration and linking flood prediction output with current project - EAGLE-I for impact assessment

Framework

IU
Design of system middleware, coordination with other project components

PDC
Integration of framework into DisasterAWARE; Model of models implementation. Impact analysis and potential severity based on hazard, exposure and vulnerability.

RSS/DFO
Assisting with assessment of model of models implementation, integration of framework into NASA SBIR

Project Focus

Use DisasterAWARE - an open access, global flood alerting system – to effective dissemination of flood risks and potential impacts to aid with emergency response.

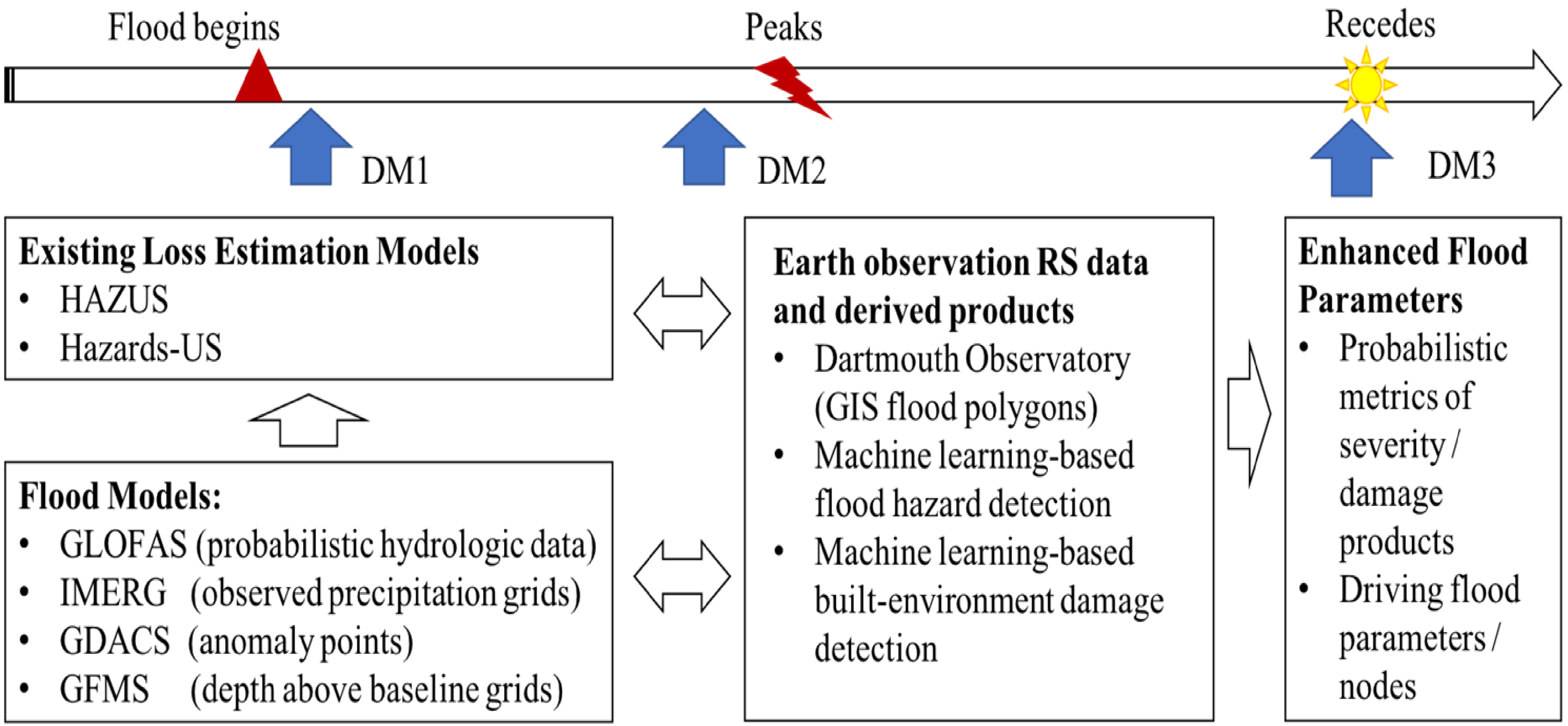
The main components of the project are:

i. A Model of Models (MoM) to forecast flood severity at global scale by integrating flood outputs from two simulation models – GloFAS and GFMS in near real-time;
ii. Derive inundation outputs from Earth observation data sets in the MoM for validation and calibration;
iii. Implement machine learning based flood damage assessment pipeline to generate impact outputs for vulnerable locations;
iv. Implement an end-to-end pipeline integrating the above-mentioned components.

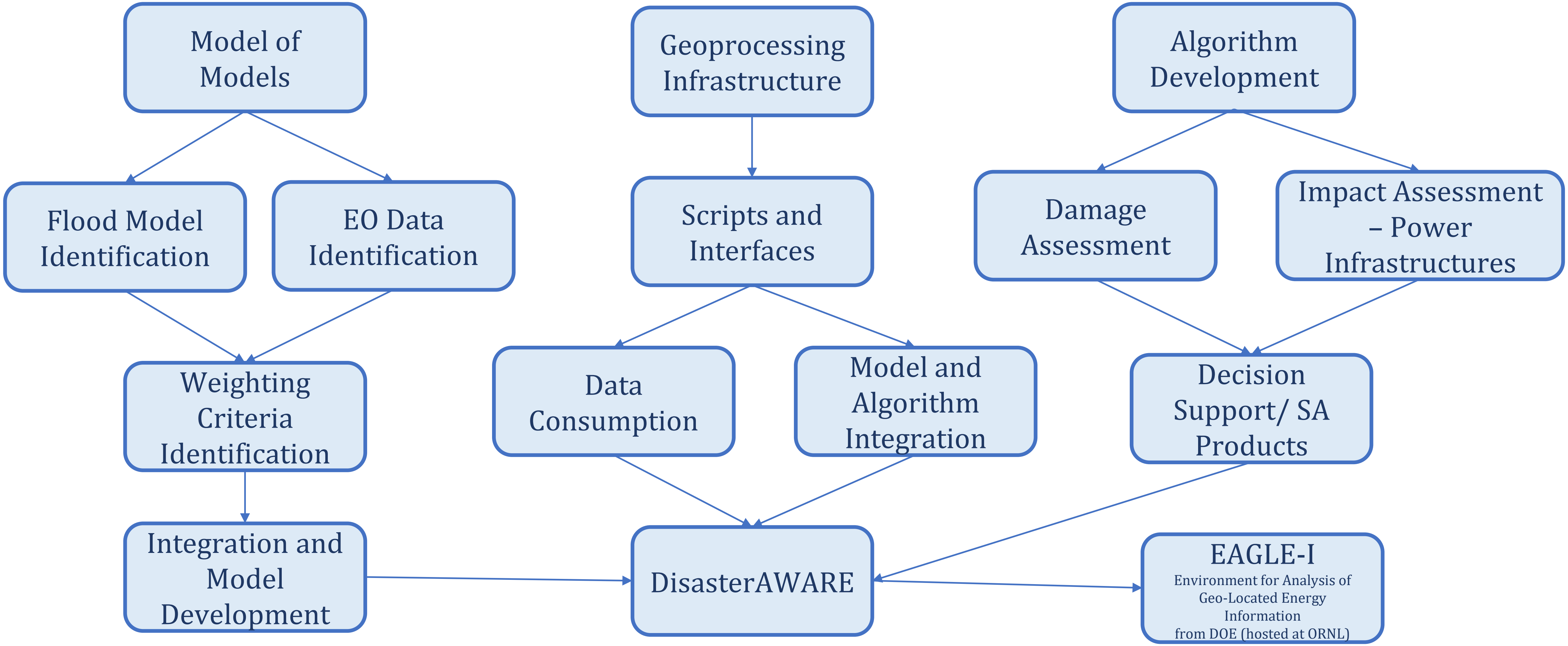
Central to the project is the incorporation of flood model outputs and remote sensing derived products from multiple platforms to help with flood risk mitigation and increase resilience of impacted communities.

Project Overview

Global Flood Alerting – Similar to the USGS PAGER rapid severity analysis for earthquakes.



Project Components

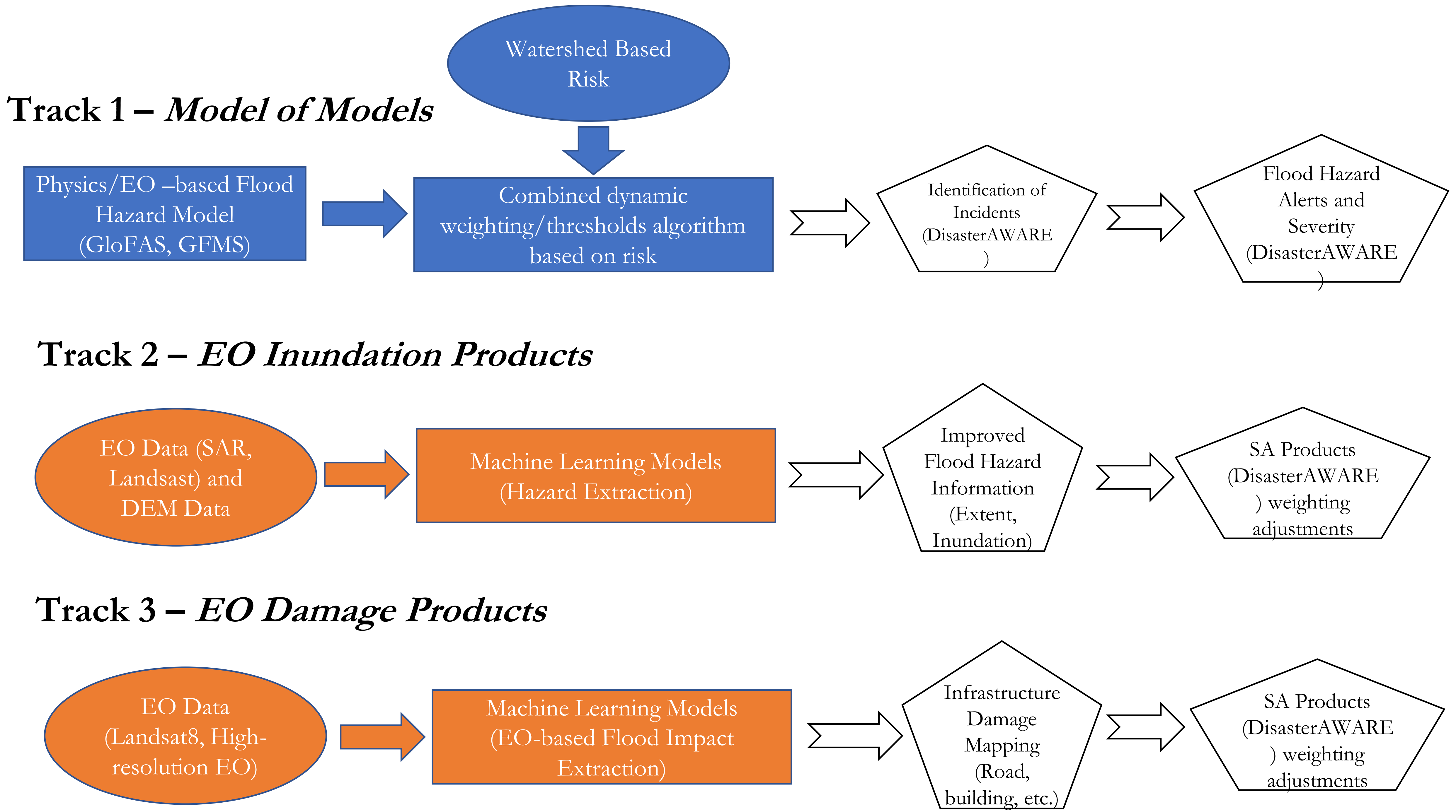


Project Tracks

Track 1
- Model of Models for Flood Forecasting and Severity Based Alert Dissemination

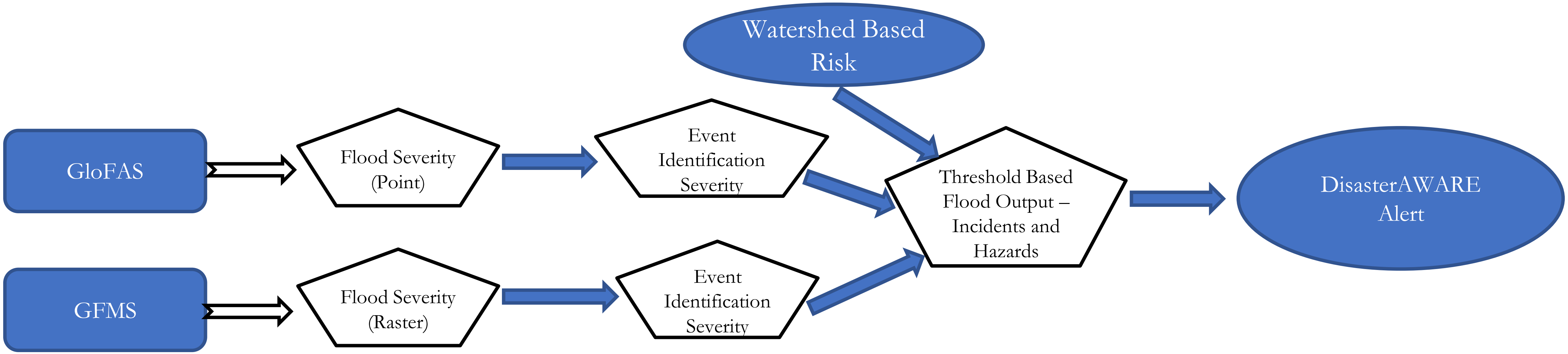
Track 2
- Earth Observation Based Flood Extent Extraction

Track 3
- Machine Learning Based Damage Assessment Model Using EO Data


Track 1 – Model of Models
Watershed Based Risk
Physics/EO –based Flood Hazard Model (GloFAS, GFMS)
Combined dynamic weighting/thresholds algorithm based on risk
Identification of Incidents (DisasterAWARE)
Flood Hazard Alerts and Severity (DisasterAWARE)
Track 2 – EO Inundation Products
EO Data (SAR, Landsast) and DEM Data
Machine Learning Models (Hazard Extraction)
Improved Flood Hazard Information (Extent, Inundation)
SA Products (DisasterAWARE) weighting adjustments
Track 3 – EO Damage Products
EO Data (Landsat8, High-resolution EO)
Machine Learning Models (EO-based Flood Impact Extraction)
Infrastructure Damage Mapping (Road, building, etc.)
SA Products (DisasterAWARE) weighting adjustments

1. Model of Models

Weighting Criteria for Flood Forecasting



GloFAS

Weighting Factors

1. 20yr %(20 year level)
2. 5yr% (5 year level)
3. 2yr% (2 year level)
4. Alert Level (Med., High, Severe)
5. Peak Forecasted - Days

GFMS

Weighting Factors

1. Total Area (km)
2. Percent Area
3. Mean Depth
4. Max Depth
5. Duration of Flooding

WATERSHED RISK (WRI Riverine Risk Score)

[Aqueduct 3.0](#):

Riverine Flood Risk (0-5, section 3.6)

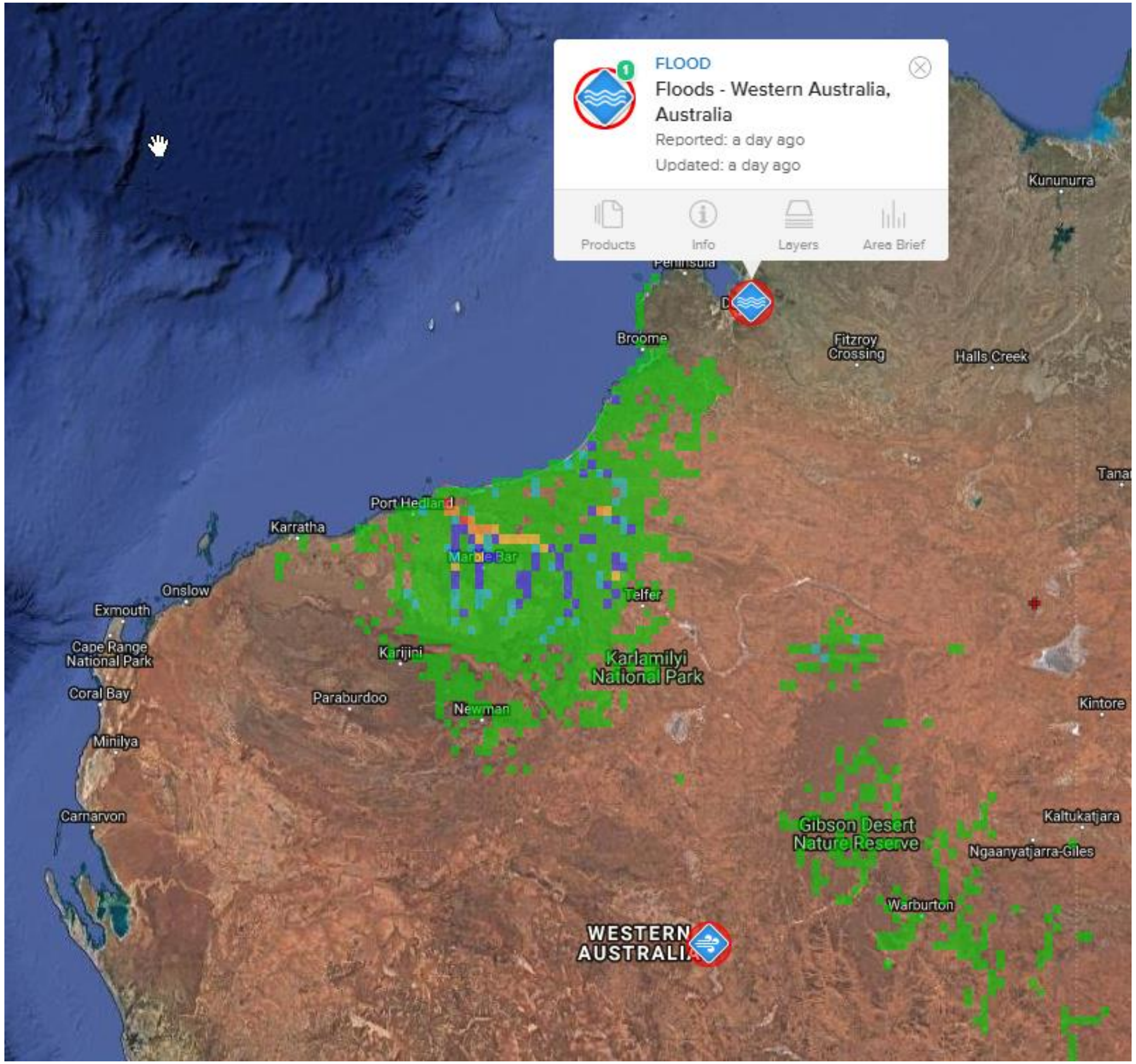
- HydroBASIN 6 intersect scale (~3,400 basins)
- Considers 9 event return periods
- Incorporates current levels of flood protection (FLOPROS model)
- Expected annual affected population
- WRI update planned for March release

Global Flood Monitoring System (GFMS)

Provides global, 0.125 degree grids updated every 3 hours.

Hazard Severity Indicators:

- Size (area and % area)
- Depth above baseline (mean and max)
- Duration (days)

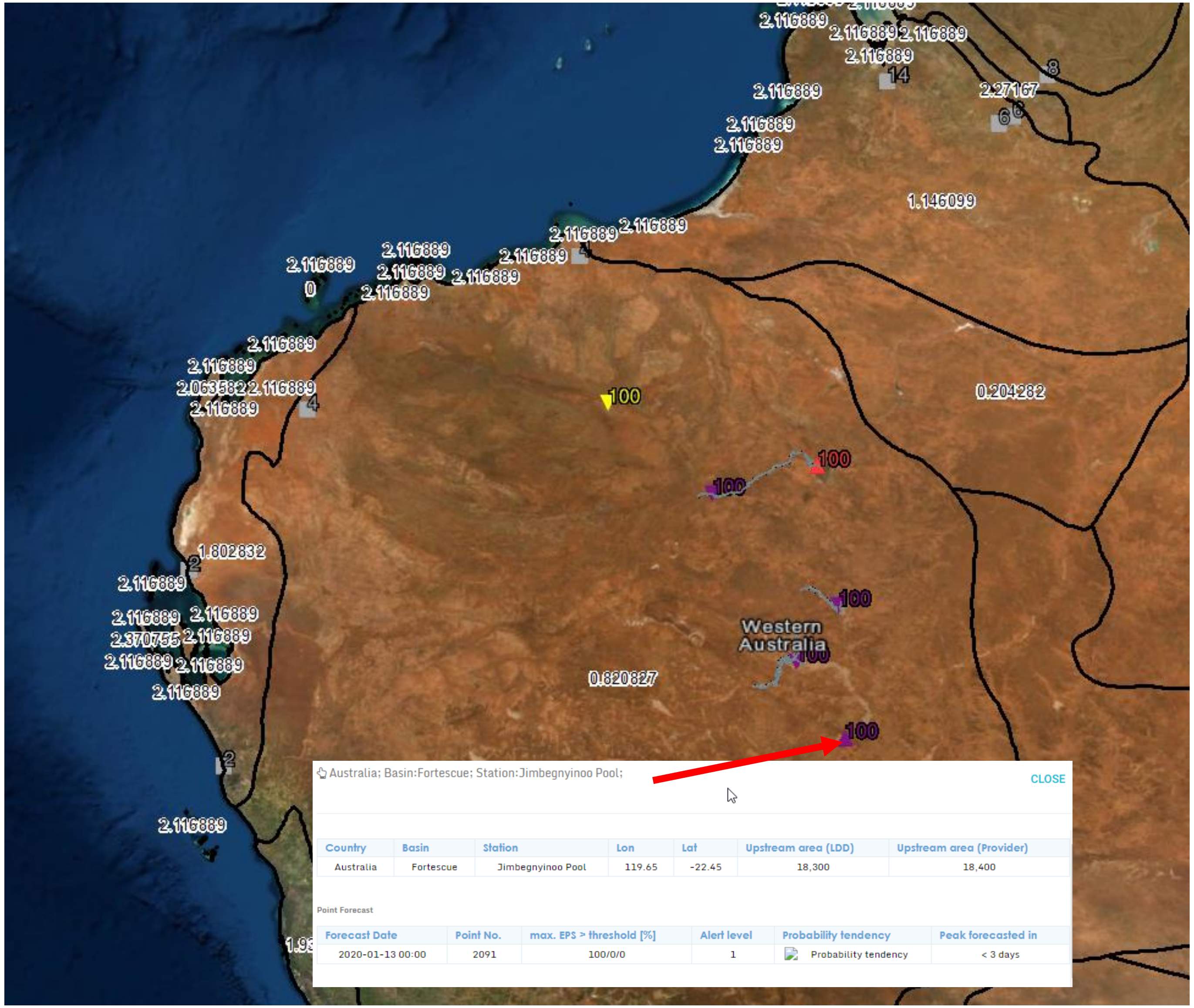


Global Flood Awareness System (GloFAS)

Couples weather forecasts with hydrologic models, updated daily, 30-day forecast, tabular global observation point data

Hazard Severity Indicators:

- Probability of return period events (2, 5 and 20 year)
- Alert level (Medium, High, Severe)
- Peak forecast (days)

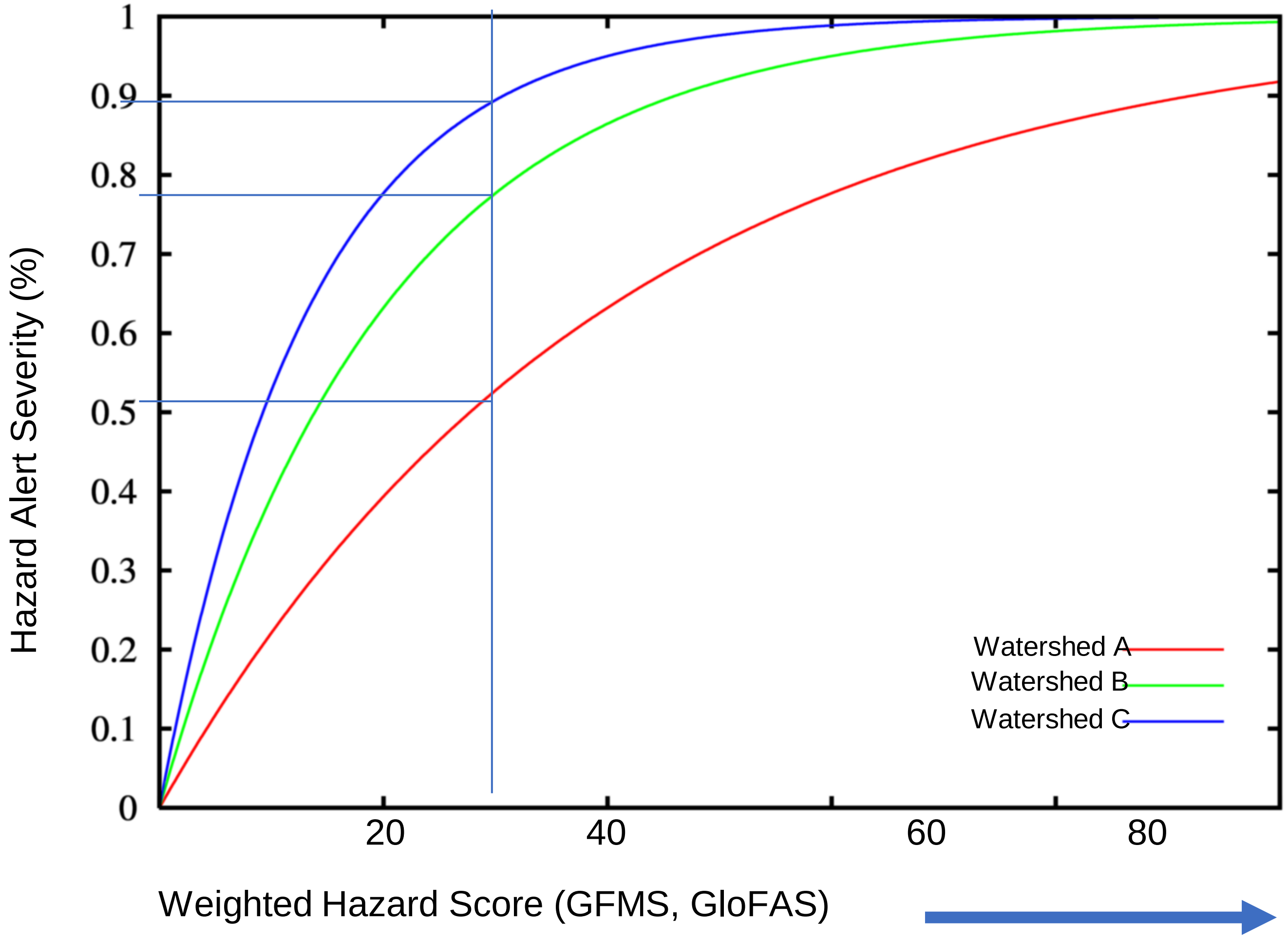


RISK FUNCTION METHODOLOGY

Based on cumulative distribution function (CDF):

- Watershed A-52%
- Watershed B-77%
- Watershed C-89%

Hazard weighting is continuously updated through machine learning

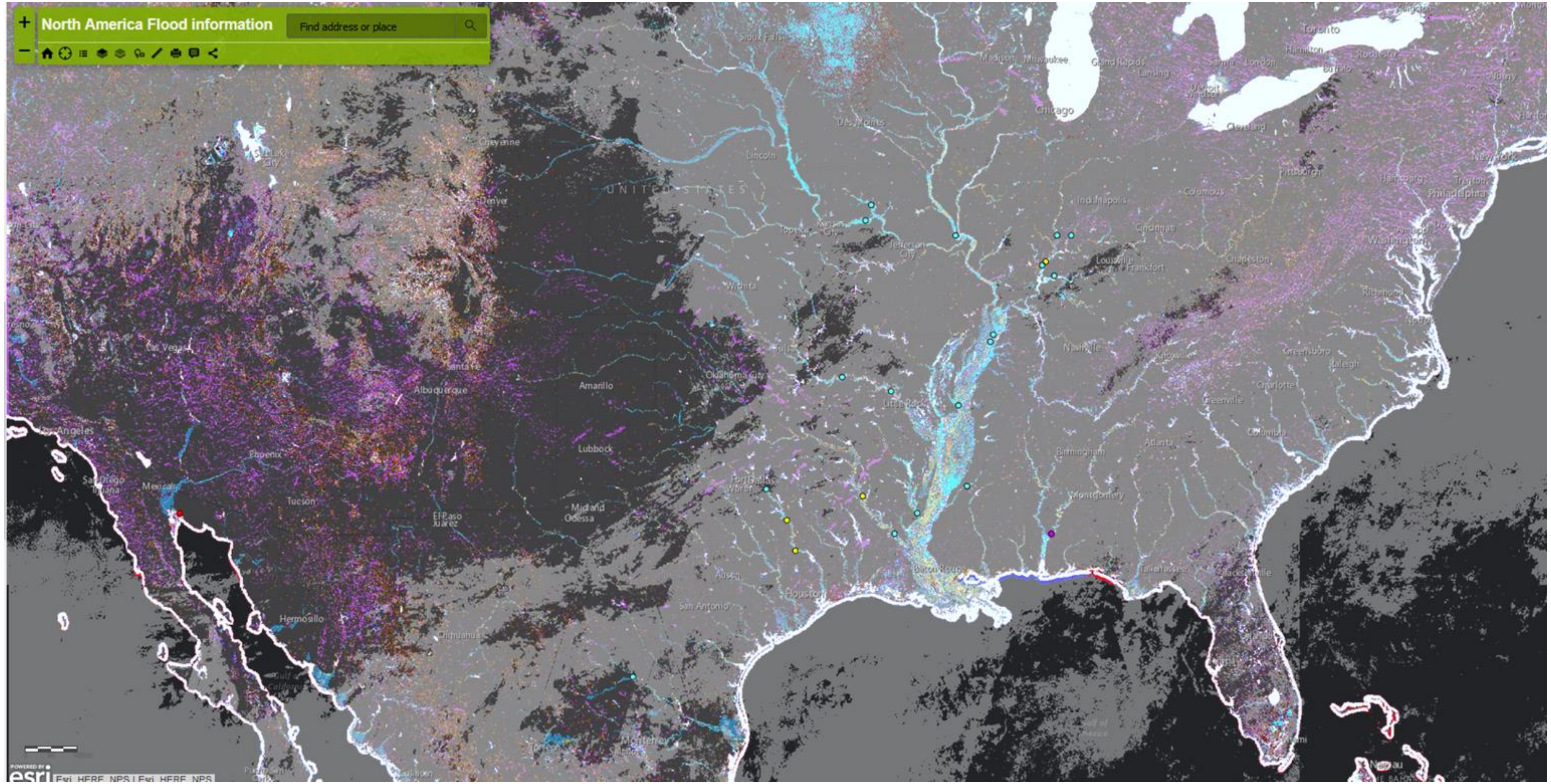


2. EO Based Inundation and Flood Depth

Leveraging the results of the NASA SBIR Phase II - DSS

Remote Sensing Solutions Inc. in collaboration with the DFO

Global event maps from MODIS, SAR and other sensors
DFO Web Map Server for the globe (all events 2013 - present)

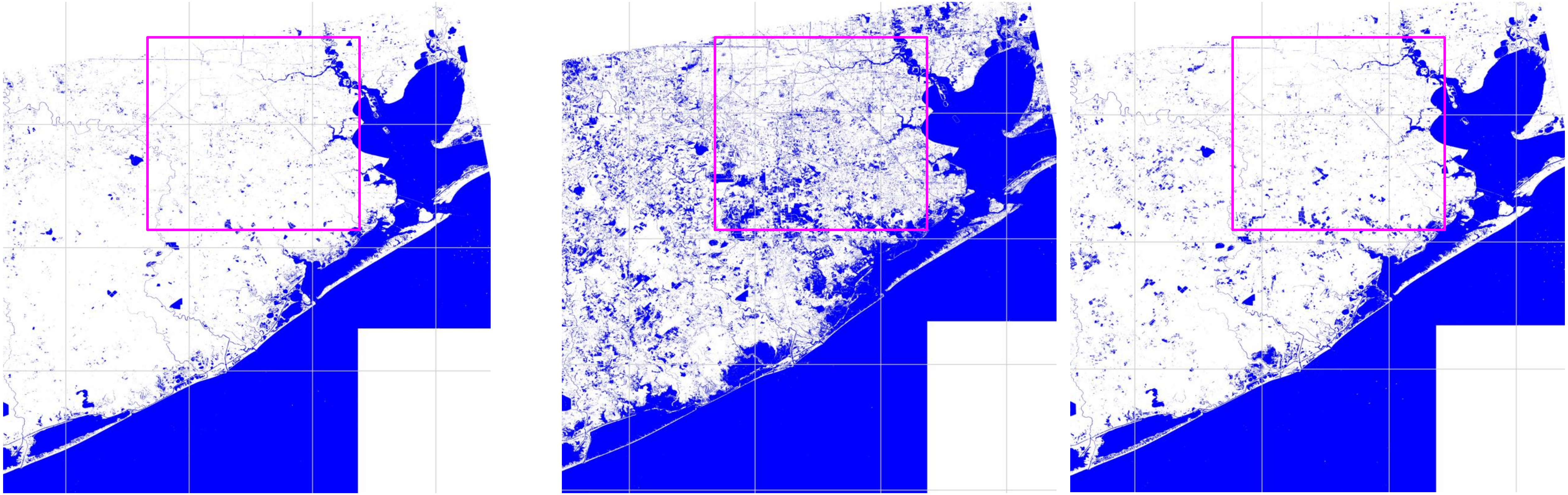


Mobile App version

SAR and Optical Mapping of Flood Extent During Harvey (2017)

Flood inundation maps for Houston, TX during Hurricane Harvey (2017) from Synthetic Aperture Radar (SAR) amplitude thresholding:

BEFORE	DURING	AFTER
August 5, 2017	August 29, 2017	September 10, 2017



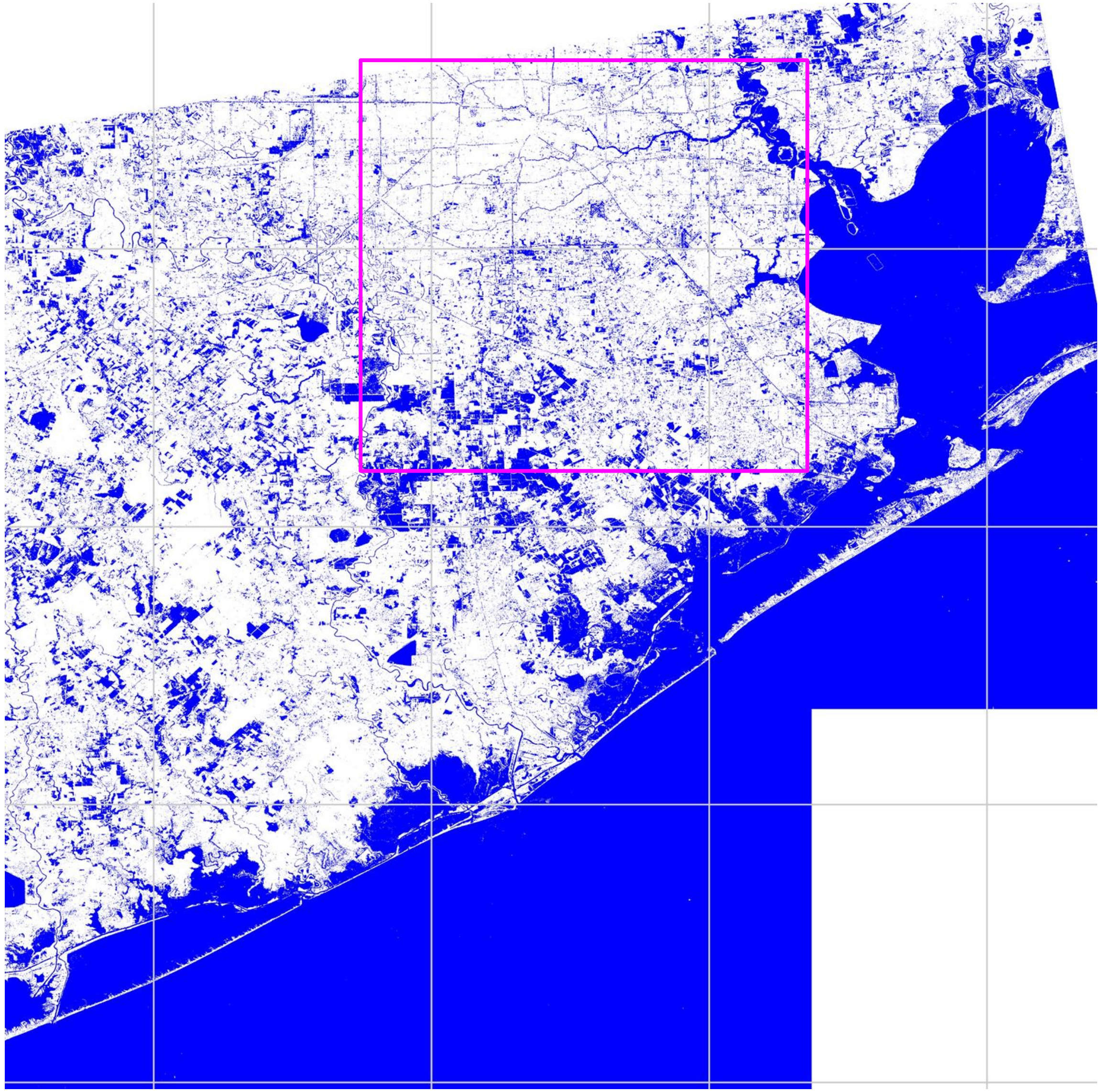
Pixel resolution is 20 meters; blue is water. Houston and its suburbs are outlined in the pink box.

SAR and Optical Mapping of Flood Extent - Next Steps

Houston, TX
August 29, 2017

Next steps of flood inundation maps:

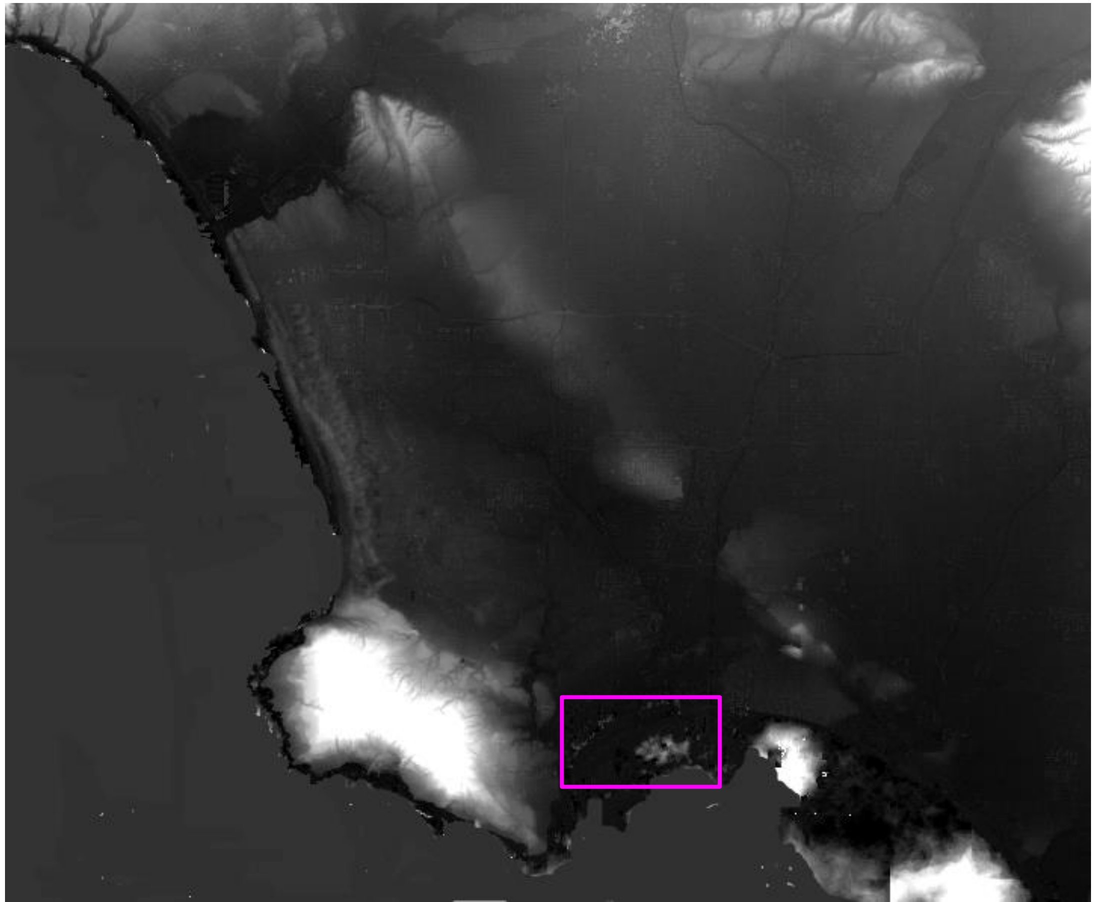
- Improve resolution to 10 meter pixel spacing
- Incorporate coherence metric water identification algorithm with thresholding
- Develop algorithm to combine information from Sentinel-2 optical data into inundation maps and time series
- Apply machine learning pixel identification to improve discrimination between water and land pixels

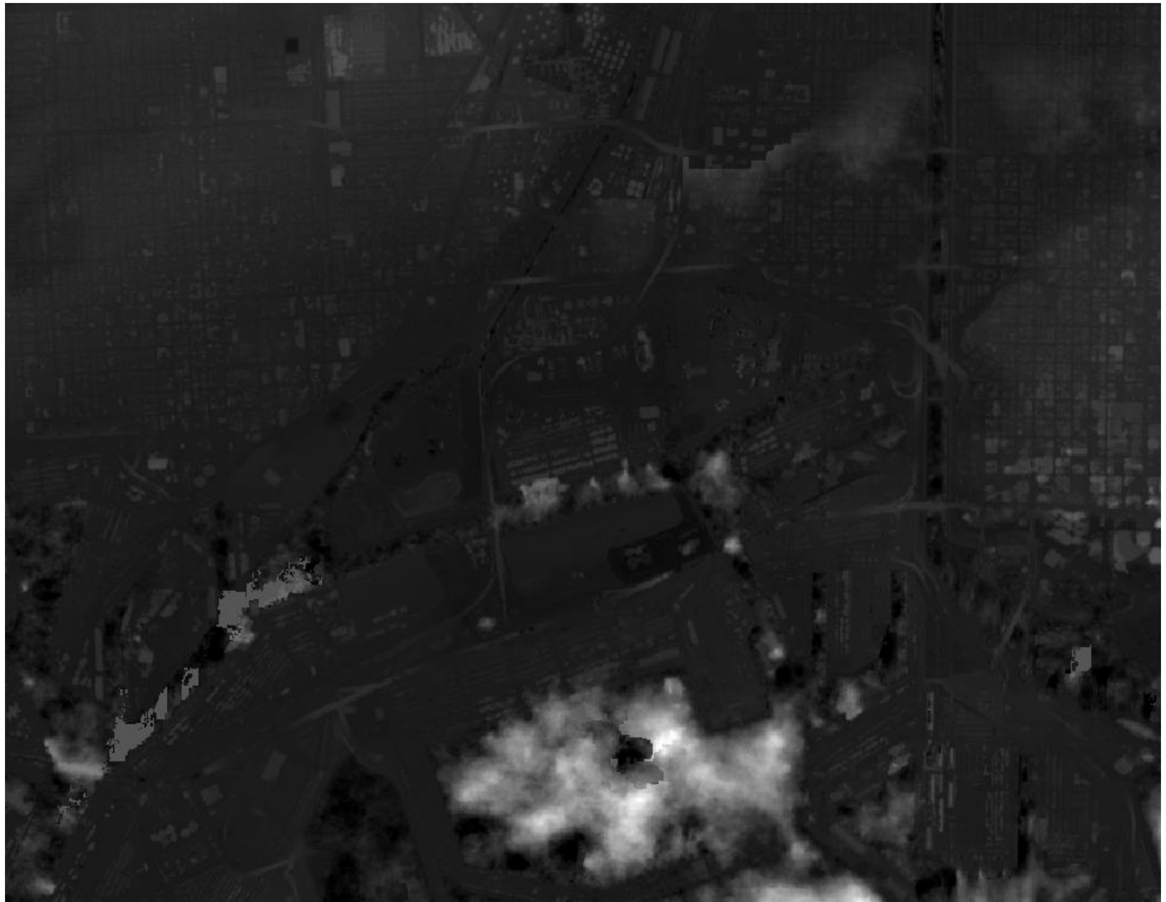


Steps to Improve SAR Derived Flood Extent Outputs

High-resolution digital surface models (DSMs): Created from Digital Globe optical data, with a resolution ranging from 2-10 meters, these can be used to both improve the SAR flood maps and produce higher resolution inundation maps.

Below is shown Long Beach, south of Los Angeles. On the left is the 10 m for the larger region; on the right is an enlargement of the box in pink. Note the infrastructure detail available at 10 m. We currently have completed or are in the process of completing 10 m DSMs for coastal US cities and selected regions.





3. EO Based Damage Assessment

Track 3 - Motivation

The state-of-the-practice flood hazard (FH) and flood loss (FL) mapping products

1. Flood hazard mapping uses predictive simulation, RS data, or both:
    a. GMFS/GLOFAS etc. provide FH at low-resolution (~ 1k m)
    b. MODIS/SAR etc. provide moderate-resolution (~ 100 m)
    c. This project: Sentinal/DEM etc. provide high-resolution (~ 10 m)
2. HAZUS-MH provides loss estimation at census block level (~ 100 - 1000 m)
3. This project: improved flood vulnerability/risk at ~ 10 m resolution

The state-of-the-art RS products and AI advances

1. Abundance in high-resolution (submeter or m / pixel) RS data: Worldview 2 / Geoeye 1/ Aerial images including UAVs;
2. Abundance in time-series moderate resolution imagery (~ 10 m; Sentinel 2; Landsat 8) with global coverage
3. Microsoft developed AI methods and extracted 125,192,184 building footprints in 50 states.
4. Advances in deep (machine) learning for rapid, semantic, and quantitative understanding of images.

Research gaps and practical needs

- Extends RS-based damage detection, monitoring, and mapping products
- End-users and the public demand near real-time property damage alerting.

Objectives of Track 3

Track 3 Technical Objectives

1. Develop end-to-end machine (deep) learning frameworks for flood-scene understanding
   a. Built object-level damage detection in high-resolution images (Worldview 2; UAV or aerial)
      i. Building footprint extraction
      ii. Bitemporal damage classification
      iii. Post-event image only damage classification
   b. Semantic attention-based segmentation for direct and rapid flood scene severity mapping in moderate-resolution image series

Track 3 Technical Objectives

2. Provide cross-validation to
   a. damage detection results (e.g. against MH-Hazus flood)
   b. flood hazard mapping (e.g., against moderate-resolution inundation data)

2. To generate enhanced and integrated RS-based and predictive damage mapping (as analogous to GFMS)

Building Footprint Detection

Our technique

- Conduct transfer learning based on XView2 dataset using the Mask R-CNN model for building footprint extraction

- To Extend - more semantic or post-event only flood damage detection

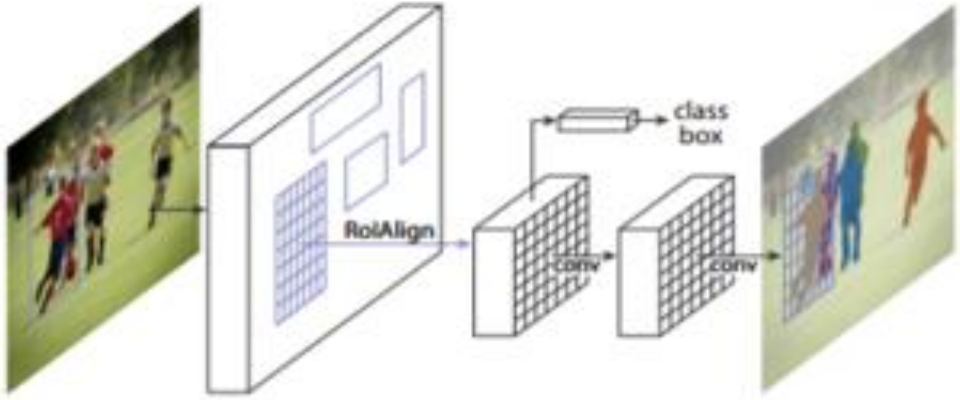
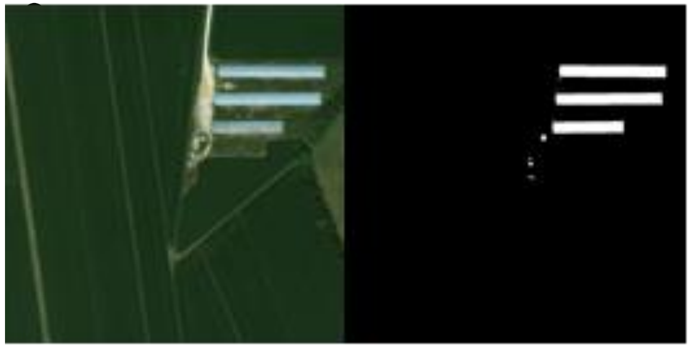


Figure 1. The **Mask R-CNN** framework for instance segmentation.

He, K., Gkioxari, G., Dollár, P., & Girshick, R. (2017)

Building Footprint Detection using Modified Mask R-CNN

- Trained using XSEDE’s Bridges-AI infrastructure (two 2 volta 16GB GPU)



Original image Mask

Original image Mask

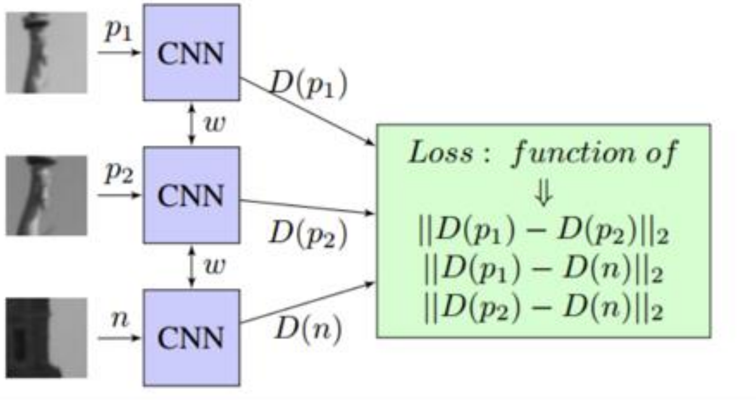
Original image Mask

- Accuracy report
  - mAP = 0.689
  - Precision = 0.770
  - Recall = 0.338

Bitemporal Building Damage Classification

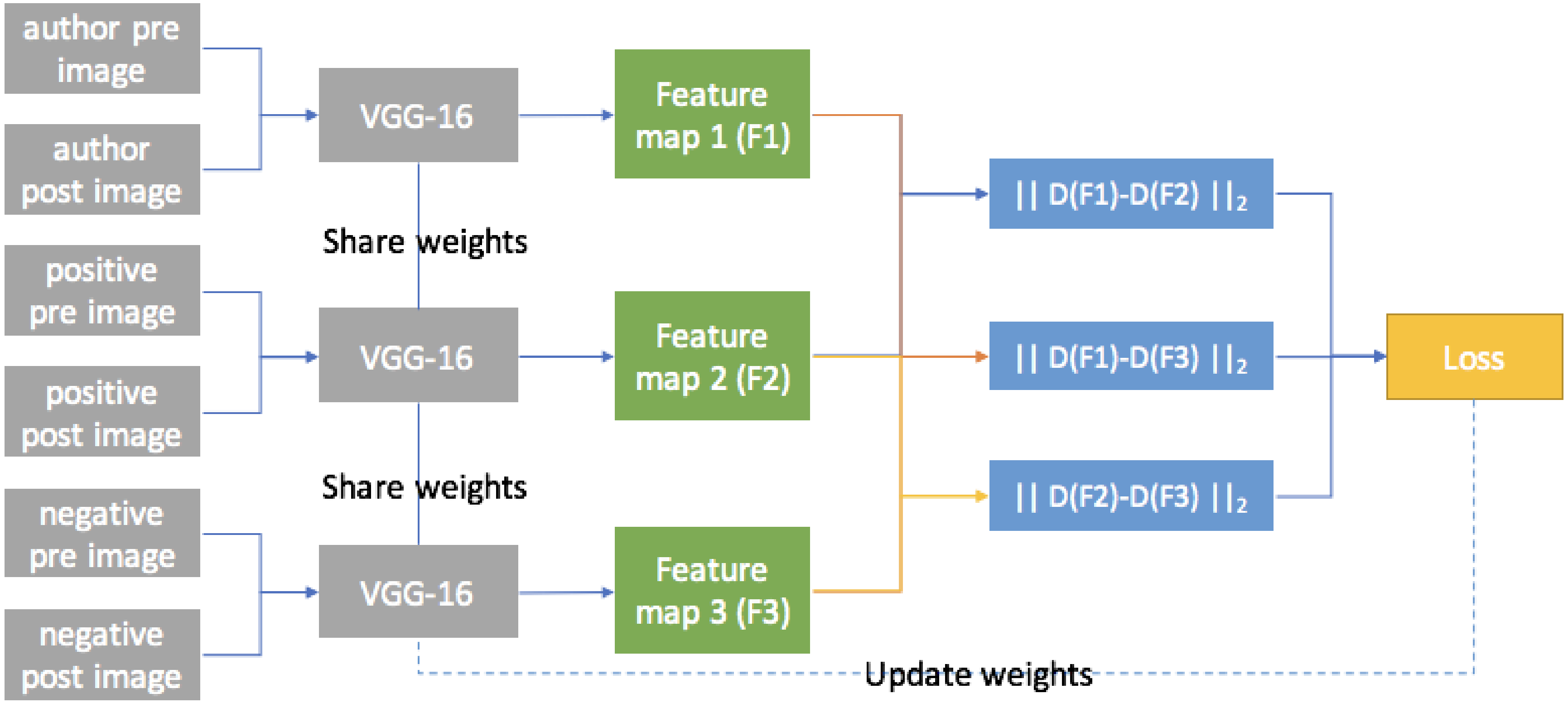
- This is a classical change detection problem.
- Previous methods (feature extraction + machine learning)
  - tend to overfit particular data;
  - lack of consideration of inter- and intra-class variations

- Inspired by Triplet deep network (TDD), we have designed a novel Triplet Bitemporal Damage Detection Network (Tri-BDDN)



Original Triplet network's baseline
[Olivier Moindrot,Triplet Loss and Online Triplet Mining in TensorFlow]

Triplet Bitemporal Damage Detection Network (Tri-BDDN)



We calculate the loss based on these formula:

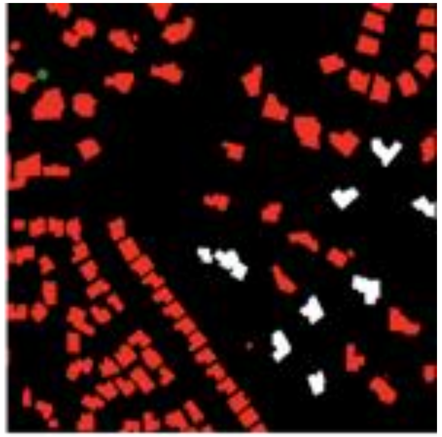
$$\left(\frac{e^{\sqrt{\Sigma(author_i - positive_i)^2}}}{e^{\sqrt{\Sigma(author_i - positive_i)^2}} + e^{\sqrt{\Sigma(author_i - negative_i)^2}}} - \frac{e^{\sqrt{\Sigma(author_i - negative_i)^2}}}{e^{\sqrt{\Sigma(author_i - positive_i)^2}} + e^{\sqrt{\Sigma(author_i - negative_i)^2}}} + 1\right)^2$$

Triplet Bitemporal Damage Detection Network (Tri-BDDN) - Sample Results

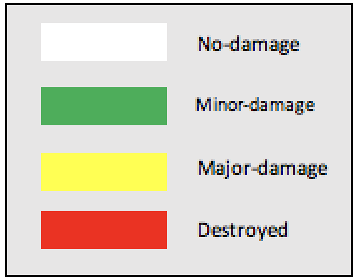
Original image

Mask

Original image



Mask



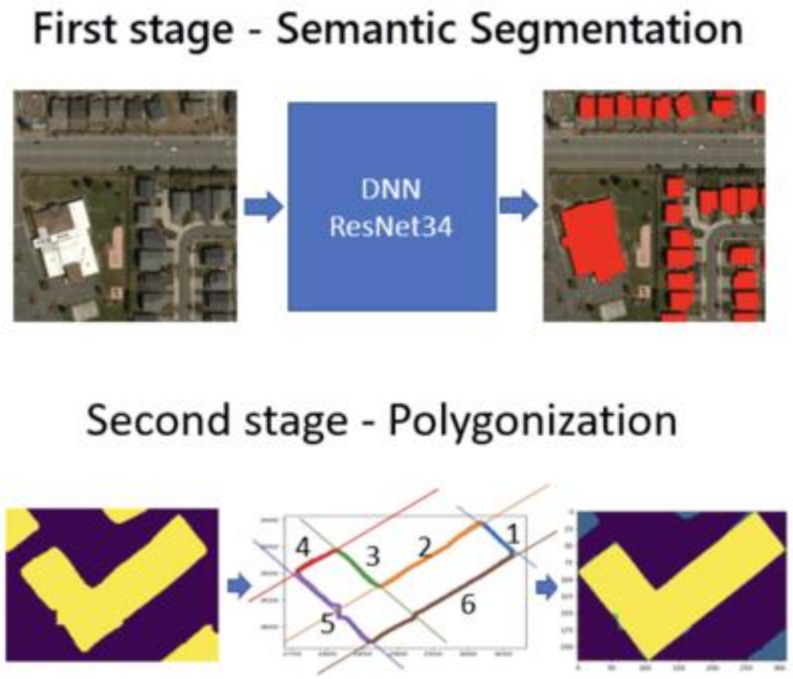
1.Train loss: after 20 epochs, the train loss is 0.067.

2. Test loss: the mean test loss is 0.1033.

3. Test accuracy: Test accuracy is 67.33%.

Other input data to integrate: Microsoft Building Footprints Data

- Using Deep Neural Networks and the ResNet34 with RefineNet up-sampling layers
- Extraction of 124 millions buildings in 50 states



- A performance comparison is being summarized in a technical paper between the microsoft technique and ours modified Mask-RCNN approach.

Other input data to integrate: OpenStreet Map

- OpenStreetMap is an open source project to create free, user generated maps of every part of the world.
- It contains two primary layers:
  - street data
  - Building data / Microsoft building data has been integrated.

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Strategy for implementation with Microsoft Building Footprints + OpenStreet Map

- For many US urban areas, we will use Microsoft building footprints data for the basis of flood damage detection

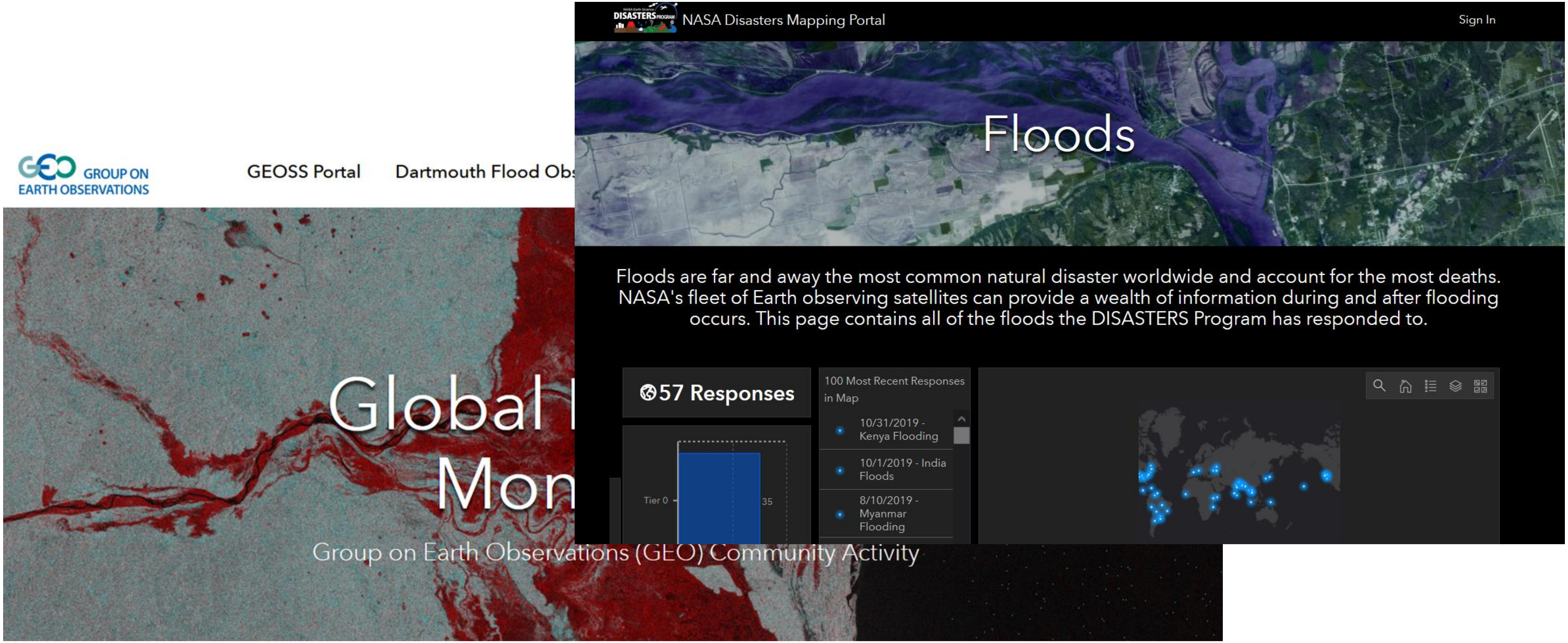
- For rural/remote areas and global areas, we will consider the use of Openstreet as the prior information further updated by our optimized building footprint extraction model

Next steps

1. Integration of Microsoft Footprints/Openstreet data for bitemporal damage detection in high-resolution images
2. Post-event only damage detection in high-resolution images
3. Semantic flood-severity attention-based segmentation and mapping in moderate-resolution images
4. Develop workflow for processing Geotiff images
    a. Google earth engine for GIS/image processing
5. Cross validation and integrated modeling with GIS-ready damage mapping products

4. Validation

Utilizing the NASA Disasters Floods Portal & linking NASA GEO efforts



Leveraging the results of the NASA SBIR Phase II - DSS

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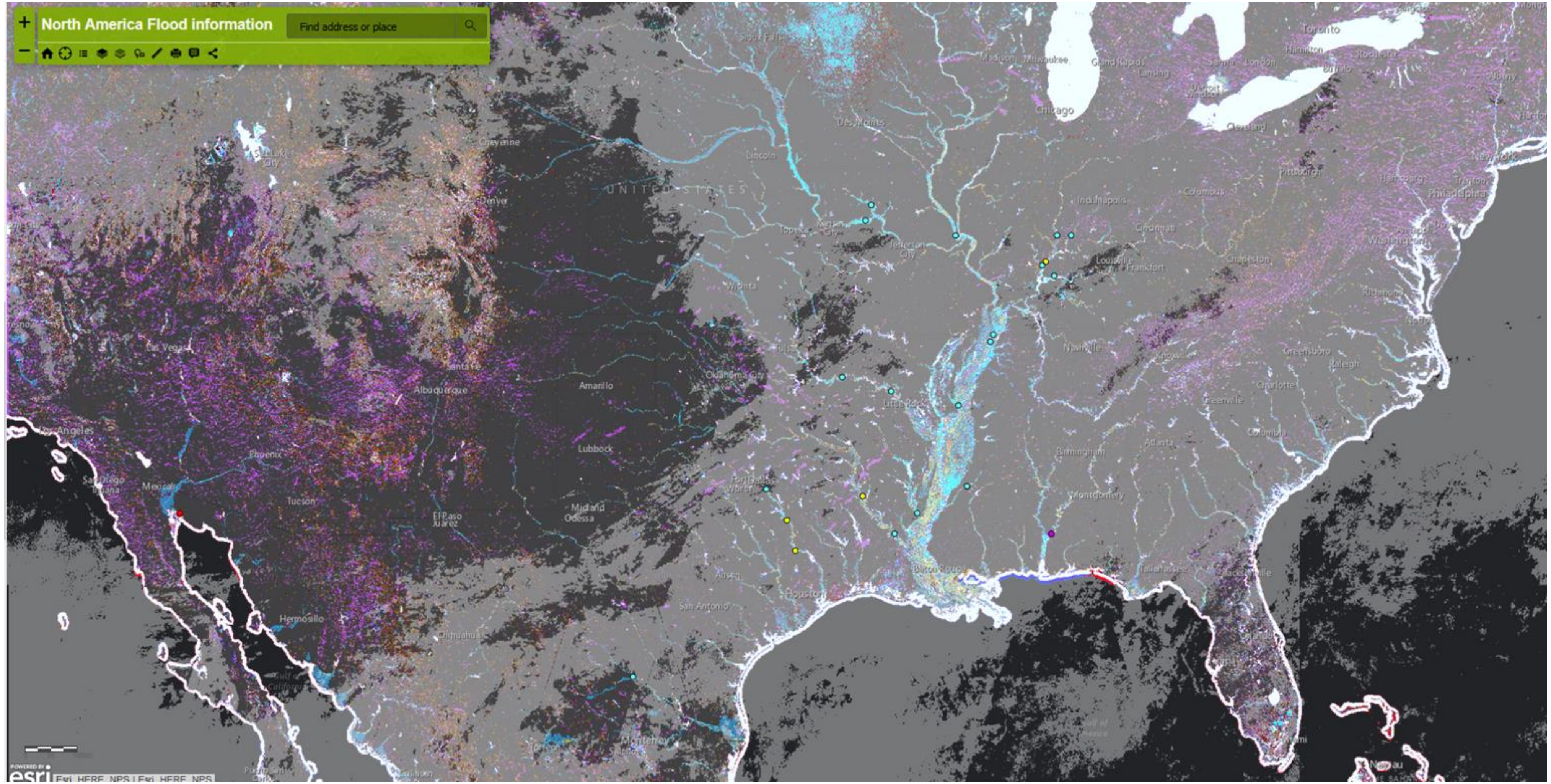
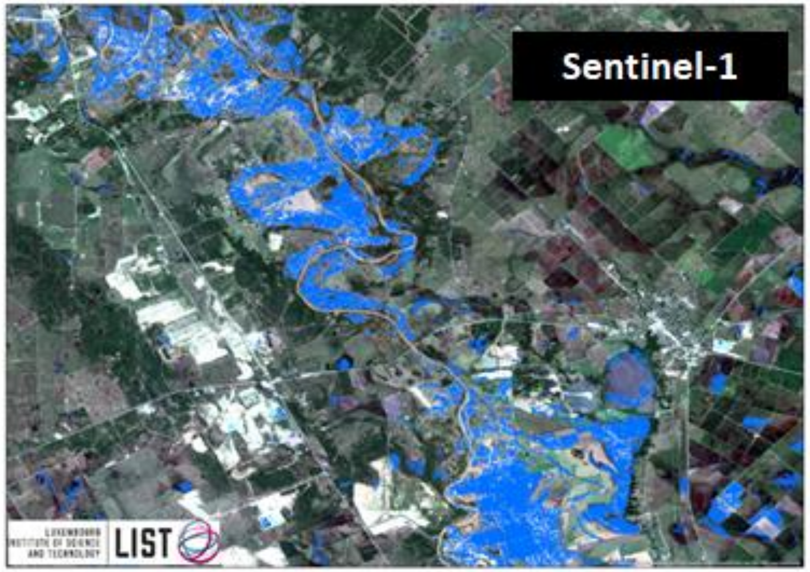


Mobile App version

Cross-evaluation with available event-specific models & ground data

Example:
Harvey event

Colorado River, La Grange



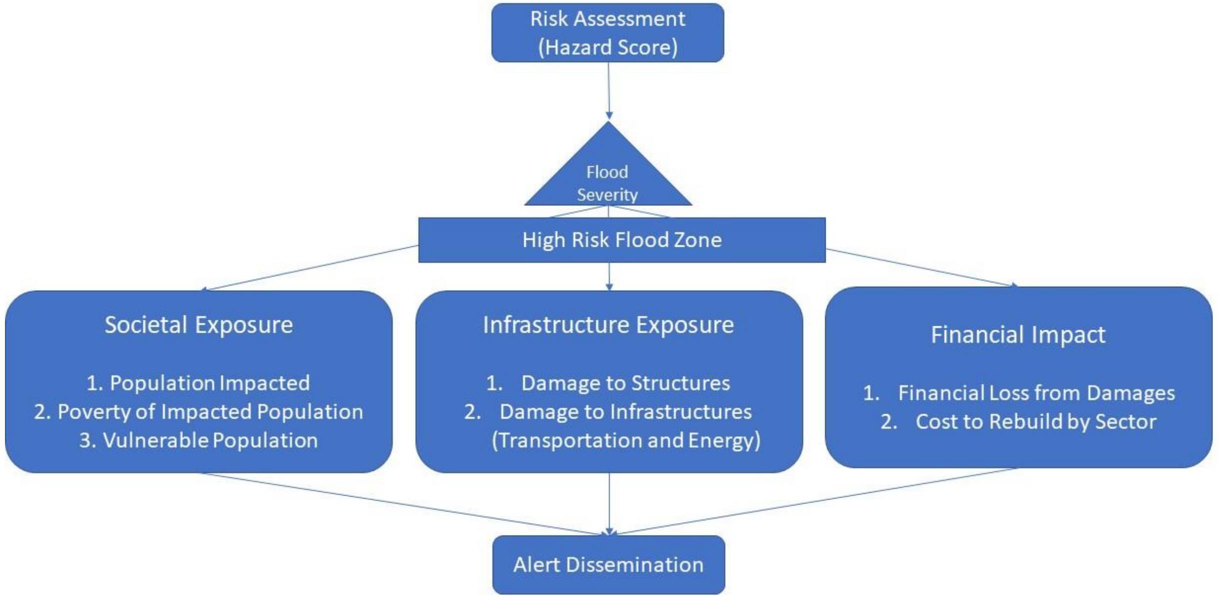
Photos posted on Twitter

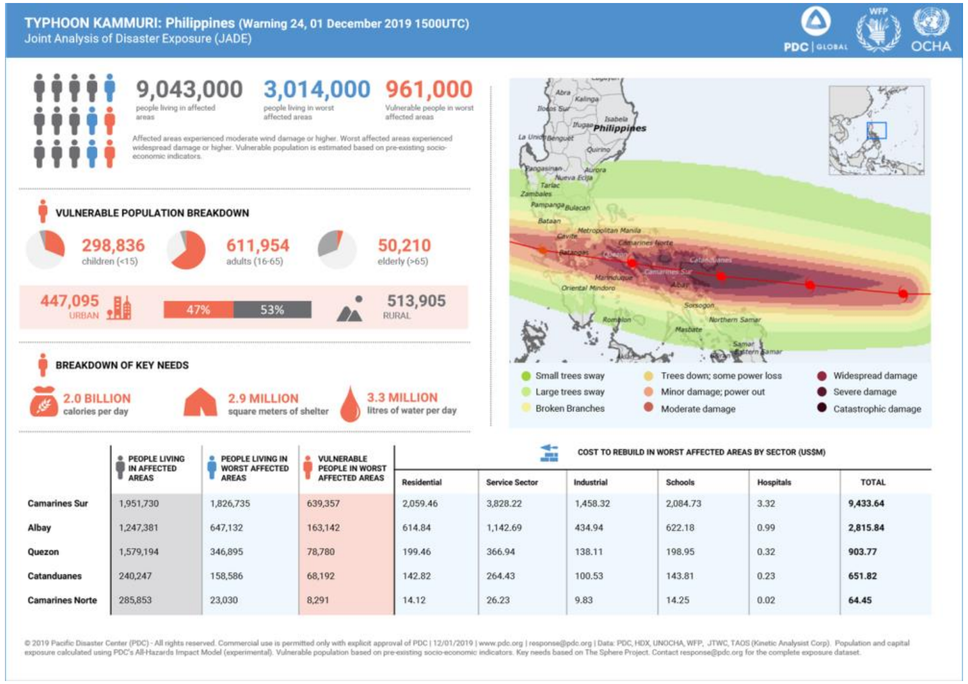
Fairly good agreement of optical EO, radar EO and model, but:

- SAR under-detects in densely vegetated areas and urban areas
- Model tends to overestimate extent of flooding when topography not well represented (cf. "tipping points")
- Twitter-derived flood information difficult to geo-localize as they refer to a city or a neighbourhood

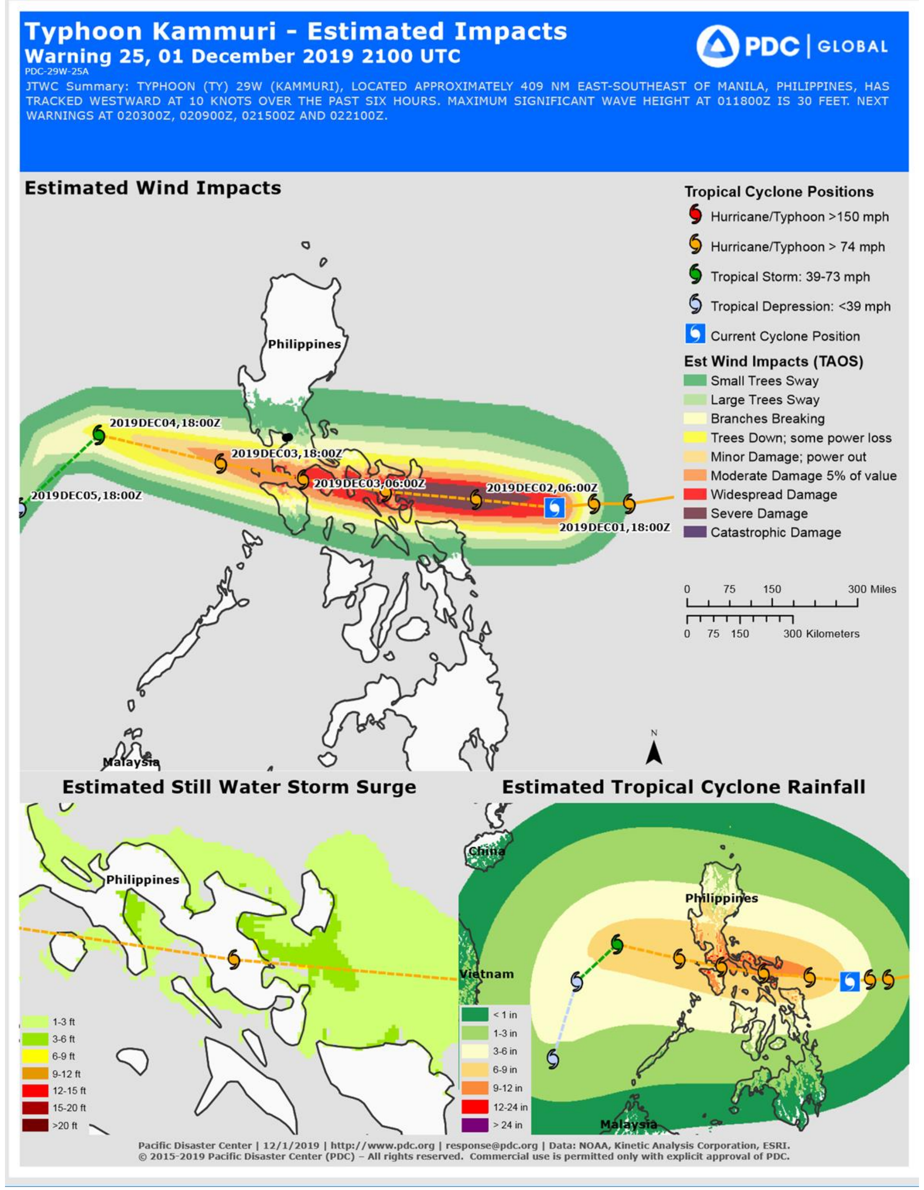
Using social media feeds from public-access databases

Exposure and Impact Assessment





	PEOPLE LIVING IN AFFECTED AREAS	PEOPLE LIVING IN WORST AFFECTED AREAS	VULNERABLE PEOPLE IN WORST AFFECTED AREAS	COST TO REBUILD IN WORST AFFECTED AREAS BY SECTOR (US$M)					
				Residential	Service Sector	Industrial	Schools	Hospitals	TOTAL
Camarines Sur	1,951,730	1,826,735	639,357	2,059.46	3,828.22	1,458.32	2,084.73	3.32	**9,433.64**
Albay	1,247,381	647,132	163,142	614.84	1,142.69	434.94	622.18	0.99	**2,815.84**
Quezon	1,579,194	346,895	78,780	199.46	366.94	138.11	198.95	0.32	**903.77**
Catanduanes	240,247	158,586	68,192	142.82	264.43	100.53	143.81	0.23	**651.82**
Camarines Norte	285,853	23,030	8,291	14.12	26.23	9.83	14.25	0.02	**64.45**



5. Development Infrastructure

Jetstream

XSEDE

Extreme Science and Engineering
Discovery Environment

BRIDGES

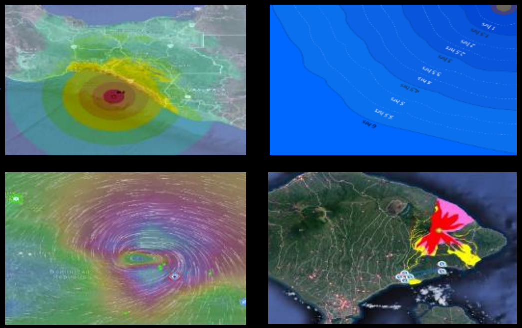
A PITTSBURGH SUPERCOMPUTING CENTER RESOURCE

APACHE
AIRAVATA

PDC's integrated approach

Observational and collection

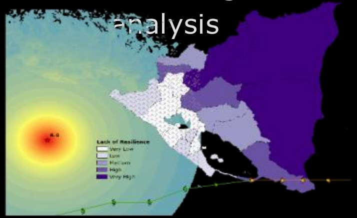
GIS and visualization systems



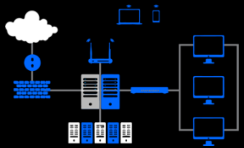
Improved

decision support capabilities

Advanced modeling and risk analysis



Computing and communication technologies



Informed decision making

Current Capabilities of DisasterAWARE

DisasterAWARE currently lacks a global flood identification and alerting component and does not integrate remote sensing components to enable near real-time validation of simulated flood modeling results. The use of remote sensing images and derivative products will enable users (domestic and global) to validate in near real-time the results of flood models (e.g. flood depths and boundaries) that will be incorporated into DisasterAWARE and used for situational awareness and impact estimation (e.g., Hazus) to quantify disaster impacts. The integration of publicly available global flood modeling sources with available remote sensing platforms (satellite and airborne) will create a robust and comprehensive platform for flood damage assessment and alerting that will help communities build their resilience.

PDC Users

Currently, the DisasterAWARE platform has over 7K users globally and the Disaster Alert app more than 1.4 M.

Thank you!

Questions?

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