Remote Sensing and Machine Learning for Disaster Response

Junshi Xia, Ph.D.
Senior Research Scientist (tenured)
RIKEN Center for Advanced Intelligence Project (AIP)

DOI: 10.5281/zenodo.12705925

WORLD DATA SYSTEM

Education

2011.10-2014.10 **PhD of Signal and Image Processing**, *GIPSA-lab, Grenoble Institute of Technology (INPG)*, France, *Excellent.*
Rank 2^{nd} lab of the Signal and Image processing in France
Advisor: Prof. Jocelyn Chanussot

2008.9-2013.6 **PhD of Photogrammetry and Remote Sensing**, *China University of Mining and Technology*, China, *GPA – 3.7.*
the project combines master and PhD degree (only for top 5% level student)
Advisor: Prof. Peijun Du

2004.9-2008.6 **Bachelor of Geographic Information Systems**, *China University of Mining and Technology*, China, *GPA – 3.5.*
Bachelor of Geographic Information Systems
Advisor: Prof. Peijun Du

Research Experience

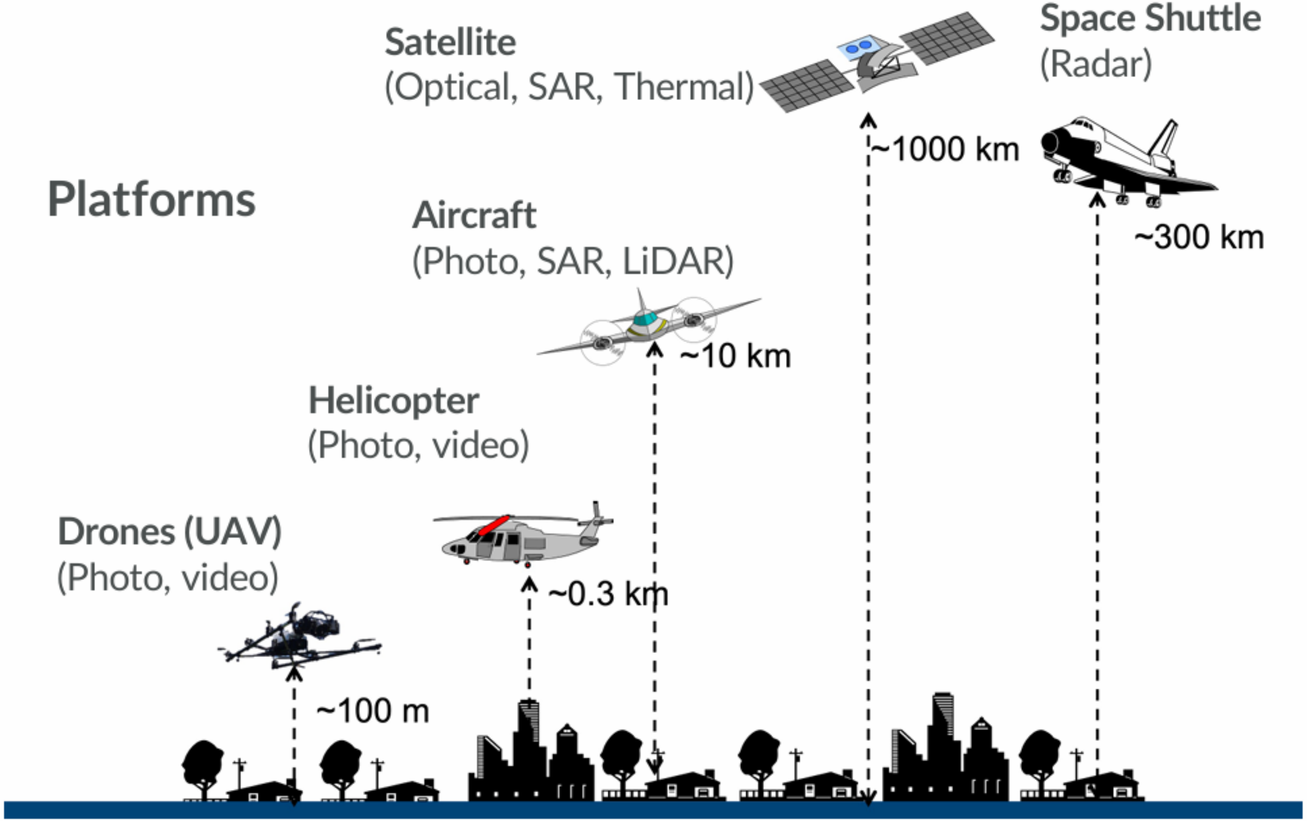
2018.5- **Research Scientist**, *RIKEN Center for Advanced Intelligence Project*, Tokyo, Japan.
Understanding of geographical processes via intelligent processing.

2016.5-2018.4 **Research Fellow**, *The University of Tokyo*, Tokyo, Japan.
Multi-sensor data classification based on ensemble learning: from algorithm to application domain.
Host: Prof. Akira Iwasaki

2015.5-2016.4 **Post-doctoral**, *University of Bordeaux*, Bordeaux, France.
Hyperspectral image analysis for bathymetry reconstruction and subtidal habitat identification.
Host: Prof. Lionel Bombrun, Prof. Yannick Berthoumieu and Prof. Christian Germain

2014.11-2015.4 **Visiting scientist**, *Nanjing University*, Nanjing, China.
Segmentation and classification of hyperspectral data.
Host: Prof. Peijun Du

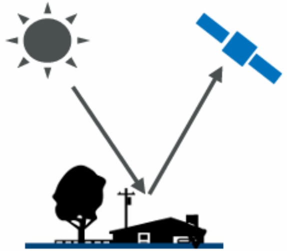
EARTH OBSERVATION PLATFORMS



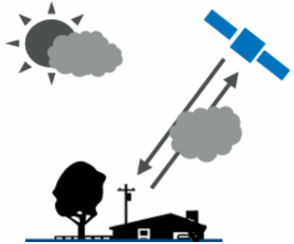
WORLD DATA SYSTEM

Sensors types

Optical Imaging



Synthetic Aperture Radar (SAR)



WORLD DATA SYSTEM

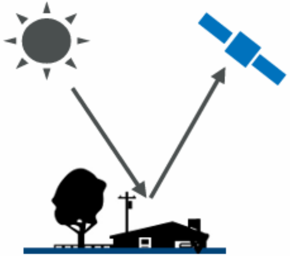
EARTH OBSERVATION SENSORS

Optical image

+ Easy to interpret
+ Useful for classification

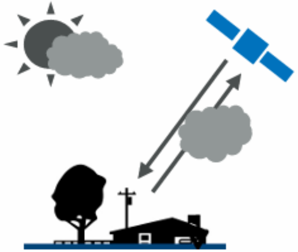
– Useless with cloud

Passive
Optical sensor

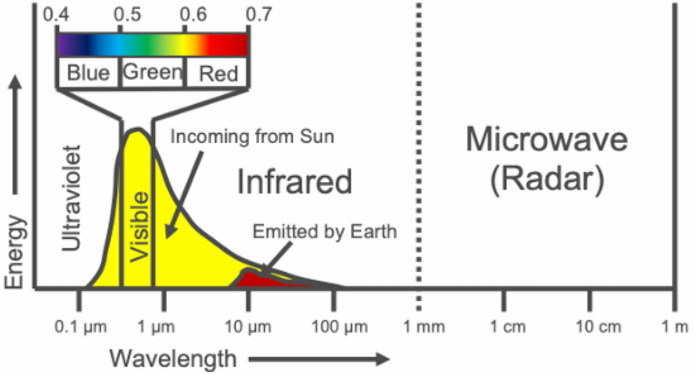


Reflection

Active
Radar sensor



Backscattering



Synthetic Aperture Radar (SAR)

+ Weather and daylight independence
+ Useful for 3D modeling & deformation calculations

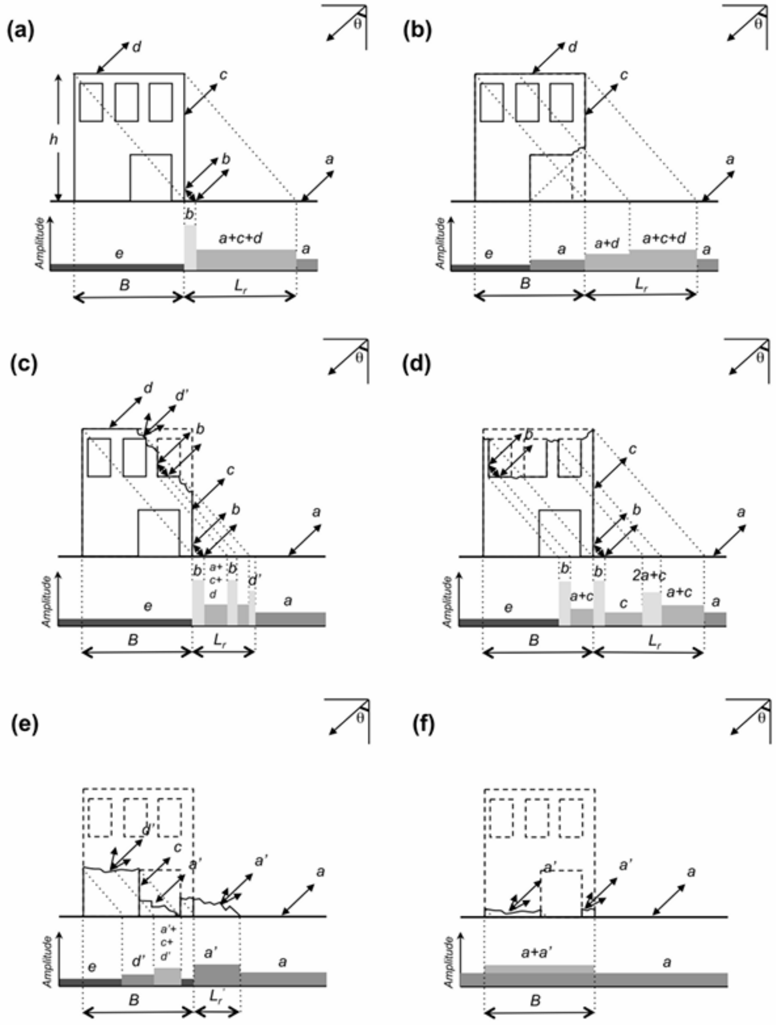
– Not easy to interpret
– Long processing chain

WORLD DATA SYSTEM

CHARACTERISTICS OF SAR BACKSCATTERING IN DAMAGED BUILDINGS

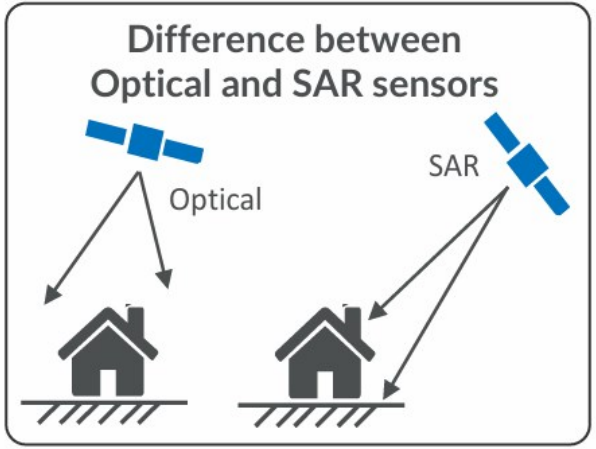
Electromagnetic Waves reflect and are sensed differently based on the conditions of the damaged building.

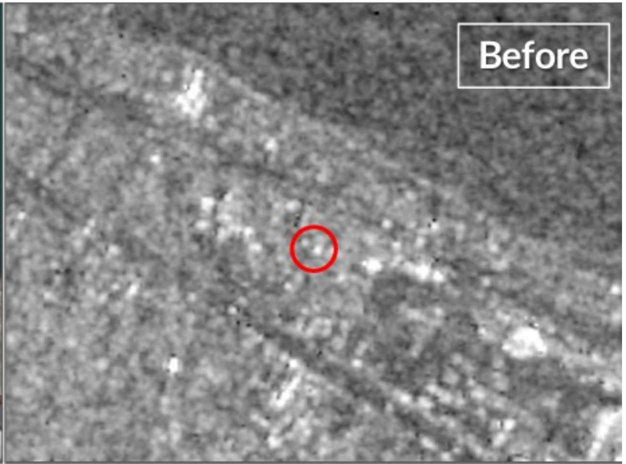
We use this feature to estimate the damage to buildings in an area after a disaster.

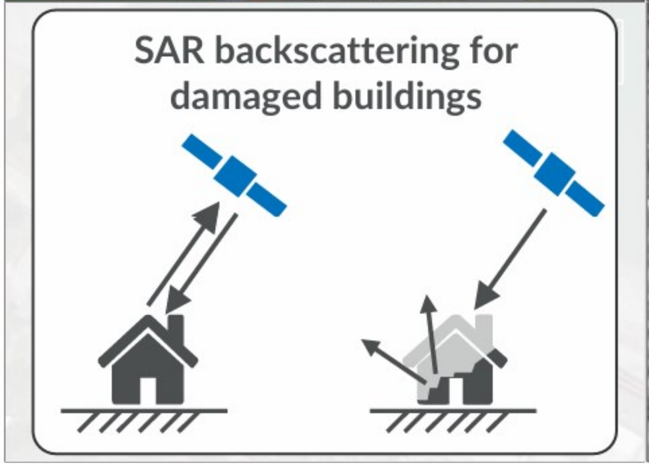


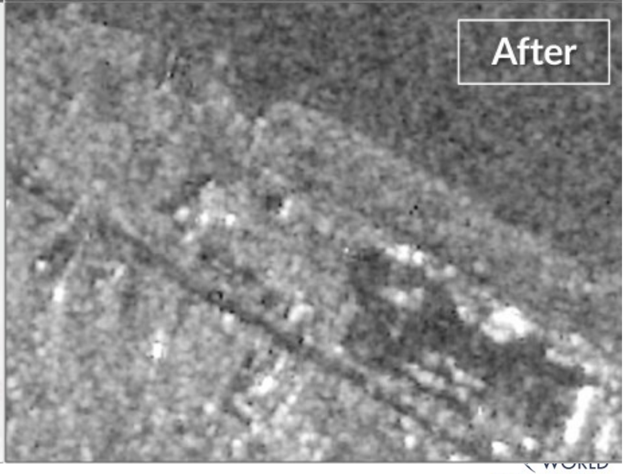
WORLD DATA SYSTEM

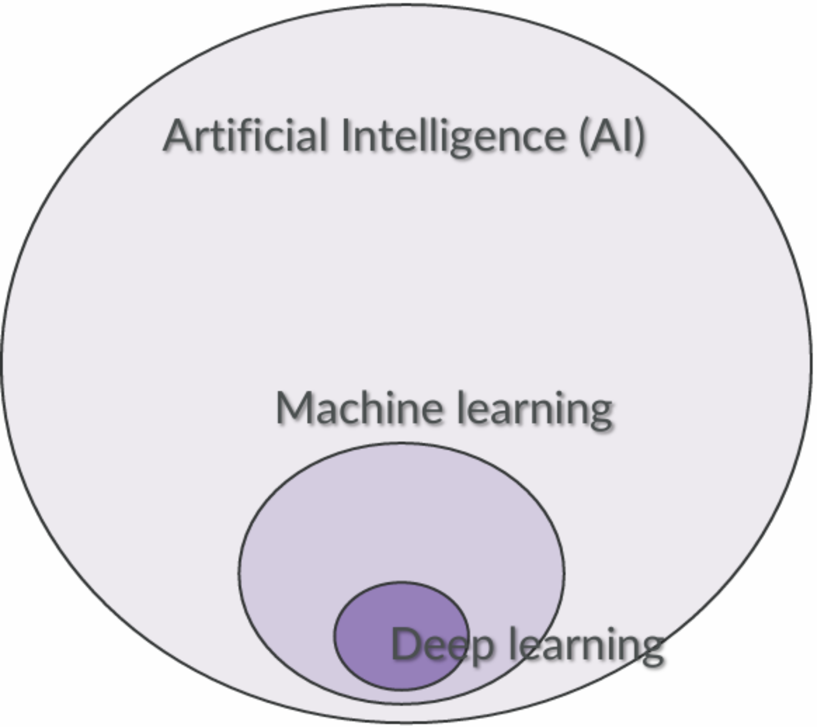
EO AND BUILDING DAMAGE









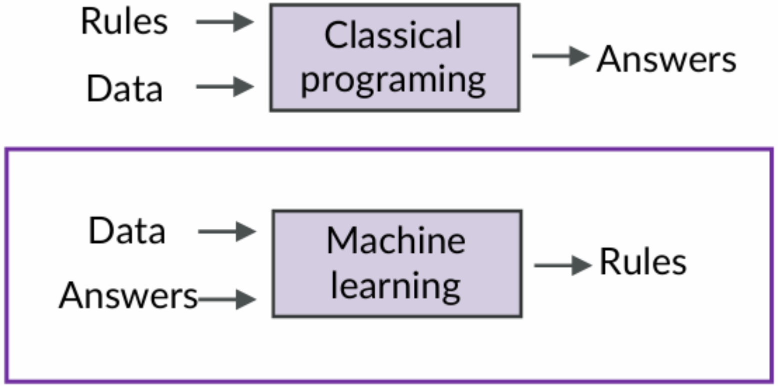


Machine learning (ML)

- *Perform a specified task by learning from data, using statistical algorithms, and generalize to unseen data.*

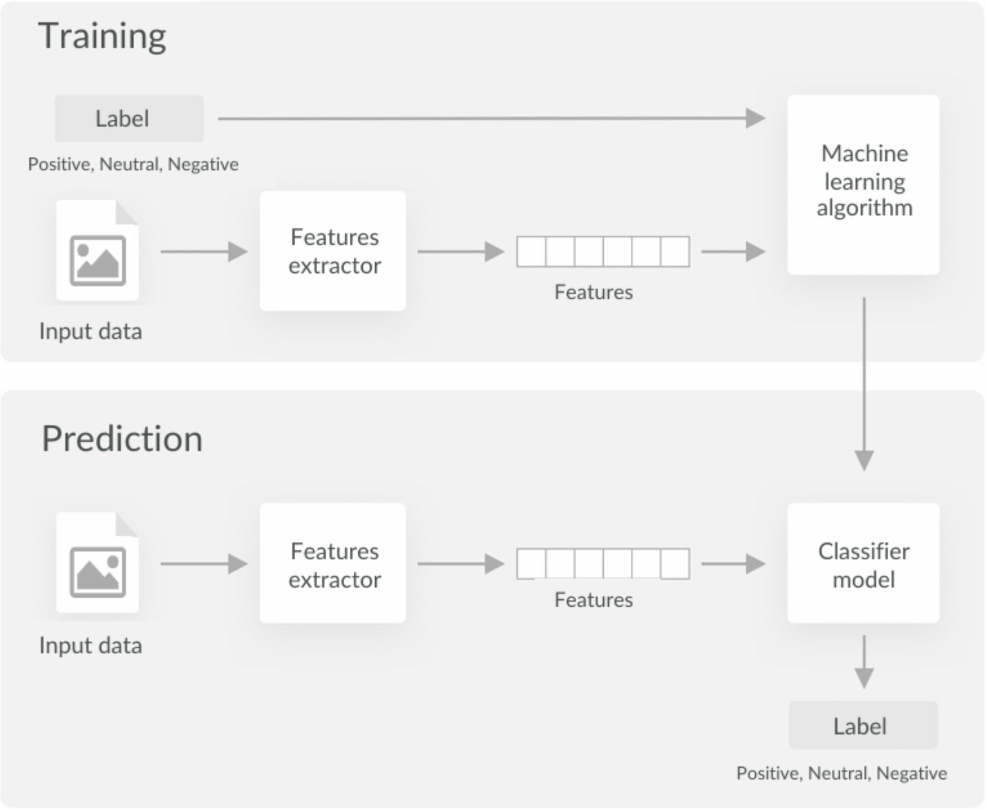
Deep learning (DL)

- *DL algorithms are inspired by the information processing patterns found in the human brain.*



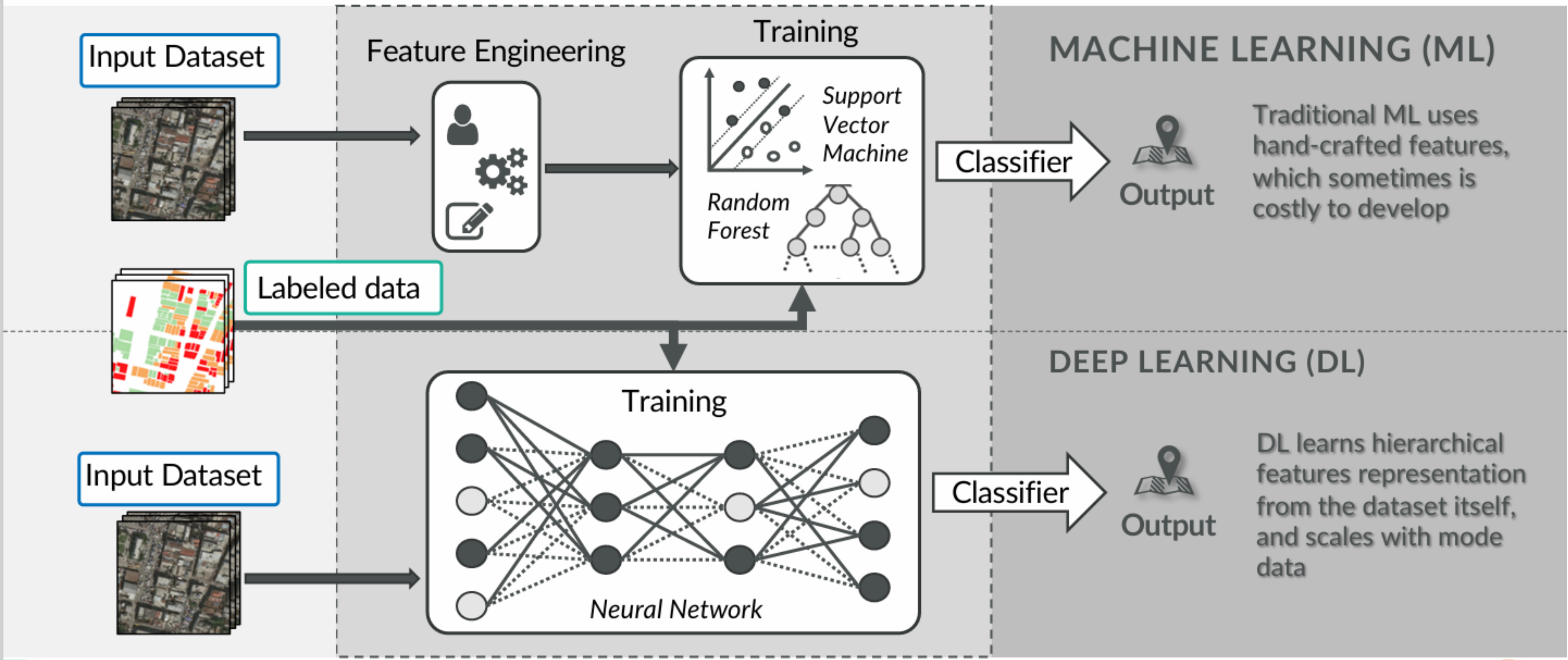
How does machine learning work?

- Feed a machine learning model training input data.
- Training labeled data with a desired output. The model transforms the training data into text vectors – numbers representing data features.
- Test your model by feeding it testing (or unseen) data.



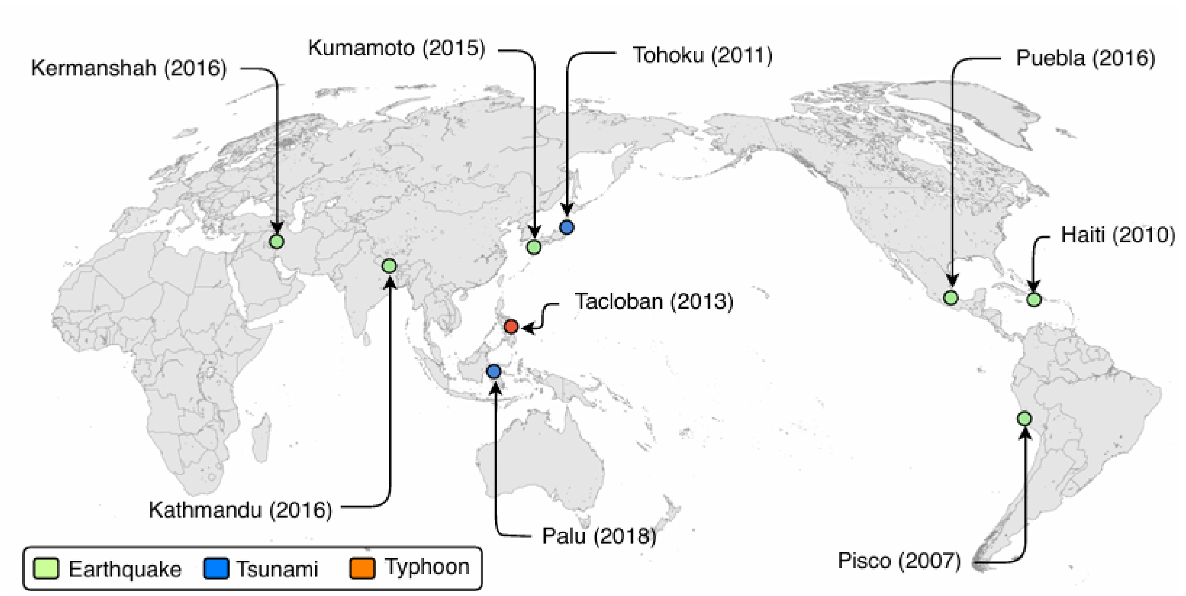
WORLD DATA SYSTEM

MACHINE LEARNING & REMOTE SENSING FOR DAMAGE MAPPING

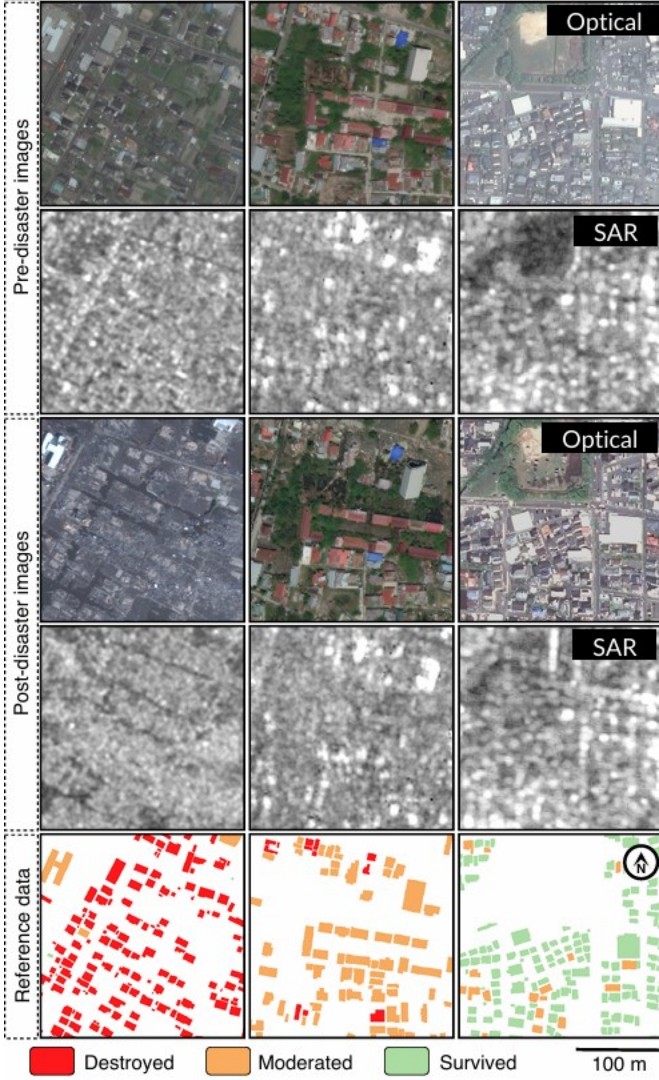


WORLD DATA SYSTEM

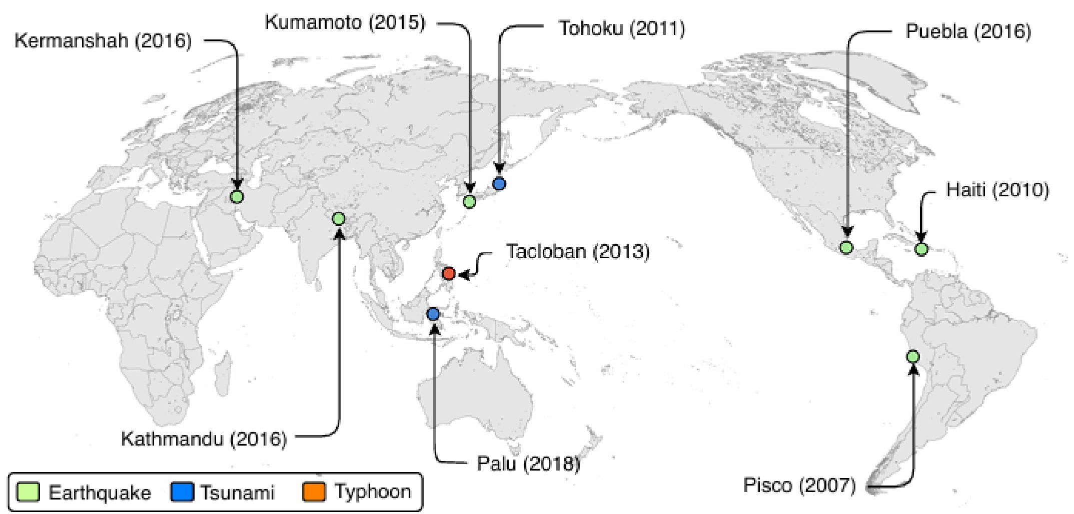
EARTHQUAKE DATASET TSUNAMI (BDD)



- Multitemporal optical dataset (WorldView-2/3, Pleiades, etc.)
- **Multitemporal SAR dataset (X-band and L-band)**
- Primary earthquake and tsunami disasters
- Three categories of building damage



EARTHQUAKE DATASET TSUNAMI (BDD)



Event	Remote sensing data		Building damage dataset	
	Optical	SAR	Source	Polygons
Pisco	QuickBird	ALOS	CISMID	3,164
Haiti	WorldView-2/3	TerraSAR-X	UNOSAT	2,036
Tohoku	WorldView-2/3	TerraSAR-X	MLIT	14,047
Haiyan	WorldView-2	COSMO-SkyMed	JICA	21,196
Nepal	SPOT 6/7	ALOS-2	UNOSAT	1,710
Kumamoto	Pleiades	TerraSAR-X	GSI	11,469
Puebla	SPOT 6/7	ALOS-2	UNOSAT	777
Kermanshah	WorldView-2/3	ALOS-2	UNOSAT	1,052
Palu	WorldView-2/3	COSMO-SkyMed	Copernicus EMS	5,745

Damage level	Buildings	Description
Destroyed	16,542	Completely collapsed or washed away
Moderately Damaged	28,112	Visible changes in and around the building
Survived	78,799	The building appears undisturbed

Specific objectives

- Modal fusion of Optical and SAR imagery for damage mapping.
- Cross-modal of optical and SAR imagery for damage mapping.

WORLD DATA SYSTEM

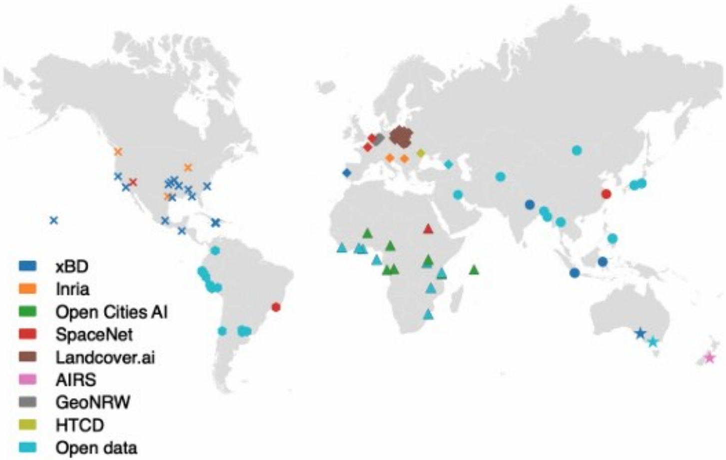

RIKEN AIP

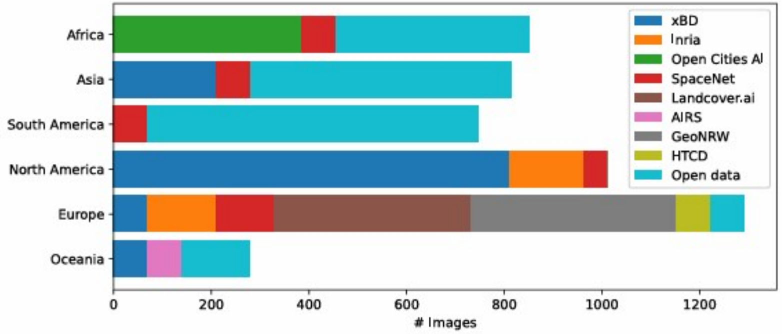
20190829_Flood_Kyushu
20191012_Typhoon_Japan
20191203_Typhoon_Philippines
20200101_Flood_Indonesia
20200107_Earthquake_PuertoRico
20200110_Wildfires_Australia
20200124_Earthquake_Turkey
20200222_Landslide_Peru
20200225_Flooding_Indonesia
20200406_Flood_Vanuatu
20200408_Covid19_Japan
20200508_Flood_BandaAceh
20200518_typhoon_Amphan
20200704_Flood_Kumamoto
20200714_Flood_Hiroshima
20200804_Lebanon_Explosion
20200901_Earthquake_Chile
20200906-Japan-Storm-00381
20201030_Neon_Karlovasion_Greece
20201030_Neon_Karlovasion_Greece_out
20210115_Earthquake_Indonesia
20210119_Earthquake_Argentina
20210207_Flooding_UTTARAKHAND
20210213_Earthquake_Japan
20210221_Flooding_Peru
20210223_Wildfire_Tochigi
20210406_Flooding_Indonedia
20210511-Tajikistan-Landslide-Other-00402
20210515-Philippines-Flood-00401
20210526-India-Flood-Storm-00404
20210615-Nepal-Flood-Landslide-00408
20210703_AtamiJapan_Landsile
20210717_Henan_Floods
20210814_Haiti_Earthquake
20210814_Japan_Floods

20210814_Japan_Floods
kyushu
out
out_dev
out_ver1
.sge_request
download_latest_data.py
nl_filt_geo.py
raiden_submit_nl_filt_geo.sh
raiden_submit_stack_creation_dev.sh
raiden_submit_stack_creation.sh
S1A_IW_SLC__1SDV_20210804T211718_20210804T211745_039085_049CAF_B620.zip
S1B_IW_SLC__1SDV_20210803T092153_20210803T092220_028080_035983_147B.zip
S1B_IW_SLC__1SDV_20210815T092153_20210815T092220_028255_035EEB_CE08.zip
stack_creation_dev.py
stack_creation.py
sub_raiden_stack_creation.e7277622
sub_raiden_stack_creation.e7646300
sub_raiden_stack_creation.o7277622
sub_raiden_stack_creation.o7646300
shikoku

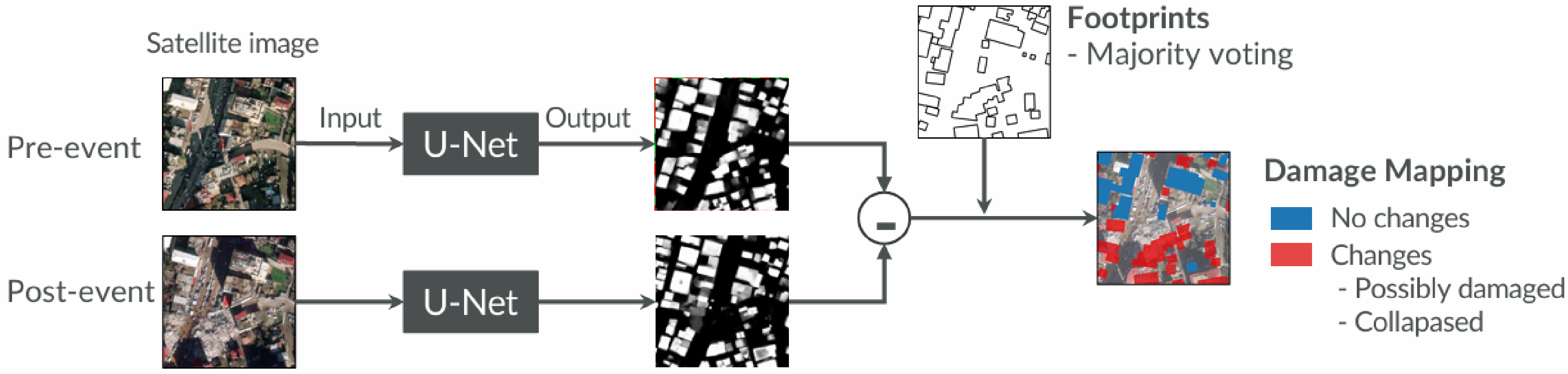
OpenEarthMap:
A Benchmark Dataset for Global High-resolution Land Cover Mapping

- A benchmark dataset for global sub-meter level land cover mapping
- Key features: **geographic diversity** & **annotation quality**
- OpenEarthMap models generalize across the globe

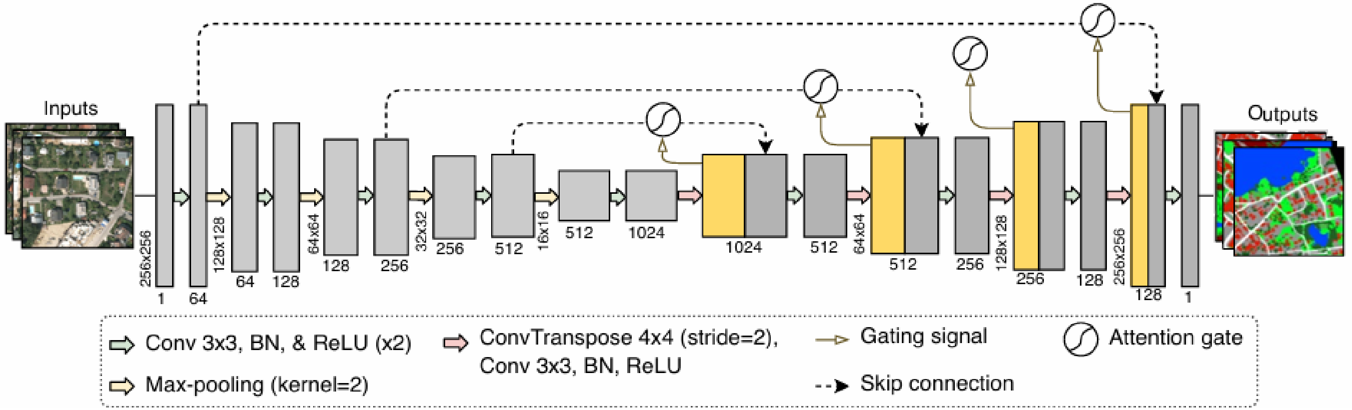


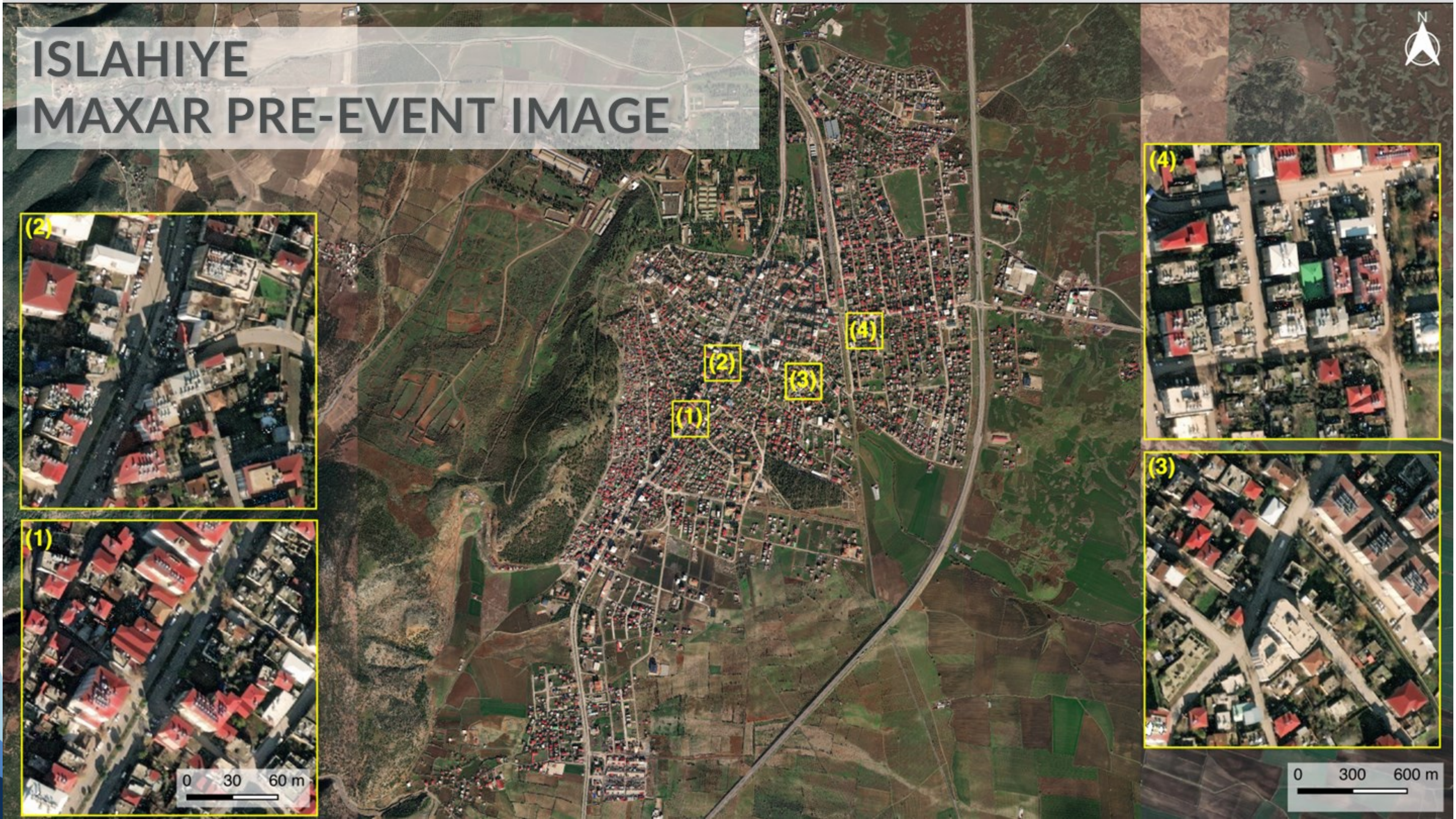


WORLD DATA SYSTEM

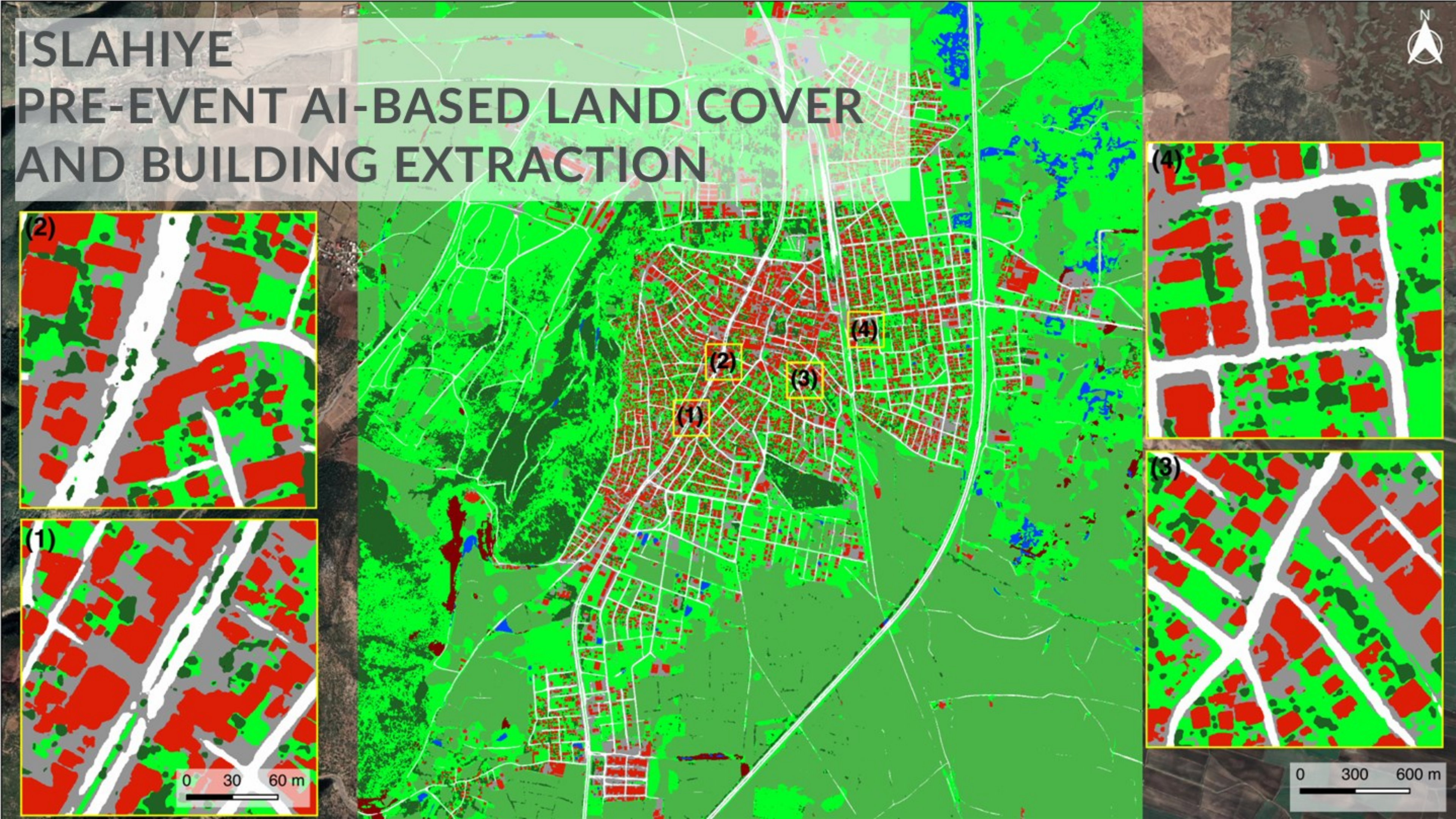


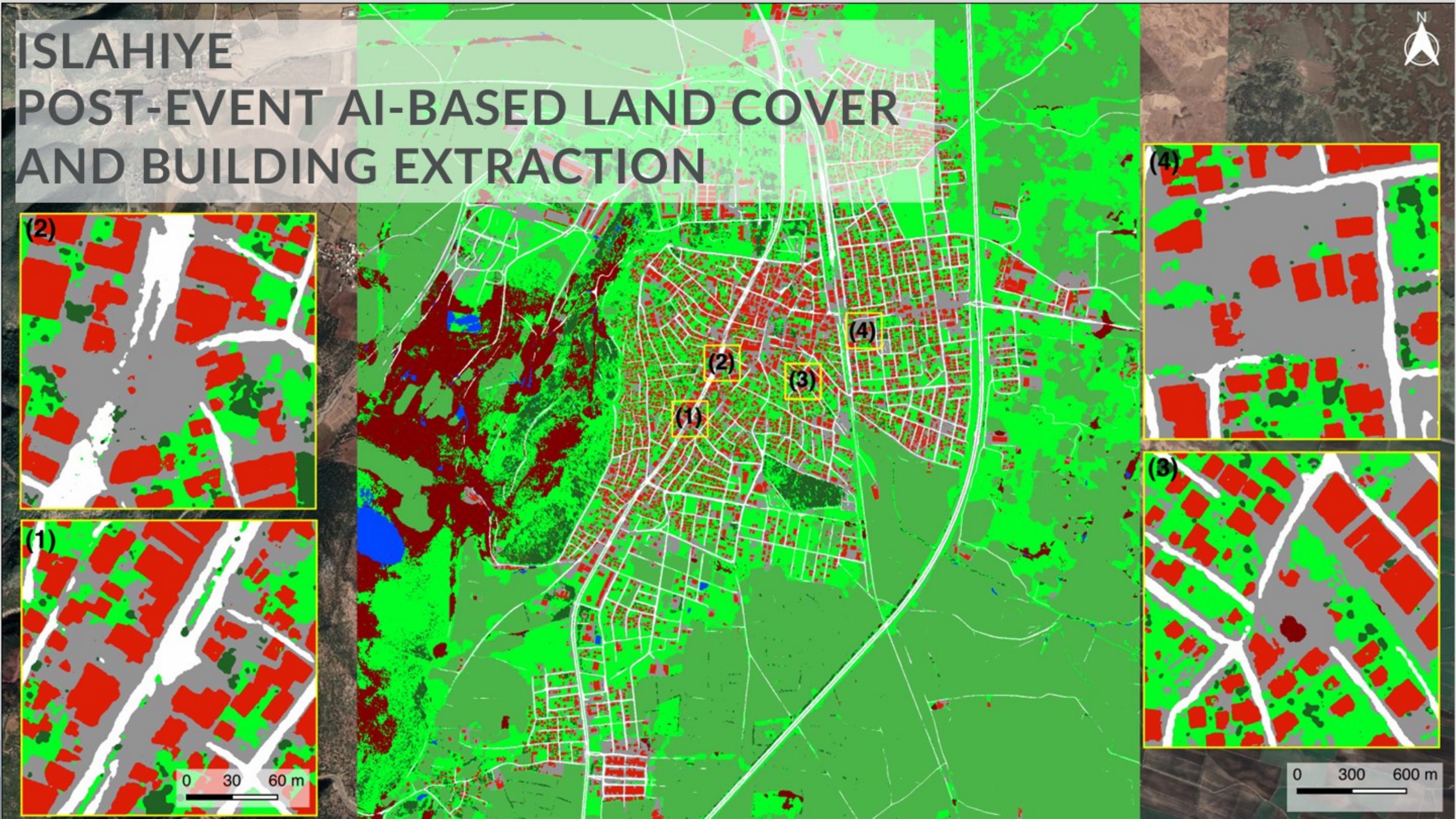
Network
- Attention U-Net




ISLAHIYE
MAXAR PRE-EVENT IMAGE
N
(1)
(2)
(3)
(4)
0 30 60 m
0 300 600 m


ISLAHIYE
MAXAR POST-EVENT IMAGE
N
(1)
(2)
(3)
(4)
0 30 60 m
0 300 600 m


ISLAHIYE
PRE-EVENT AI-BASED LAND COVER
AND BUILDING EXTRACTION
N
(1)
(2)
(3)
(4)
0 30 60 m
0 300 600 m


ISLAHIYE
POST-EVENT AI-BASED LAND COVER
AND BUILDING EXTRACTION
(1)
(2)
(3)
(4)
0 30 60 m
0 300 600 m
N


Islahiye
Building Footprint Changes
No changes (4,432)
Changes (819)
N
(1)
(2)
(3)
(4)
0 30 60 m
0 300 600 m

Q&A

Thank you!

WORLD DATA SYSTEM

World Data System
Webinar Series 2024

Fine Disaster Data Acquisition and Application

Feng Zhang

浙江大學
ZHEJIANG UNIVERSITY

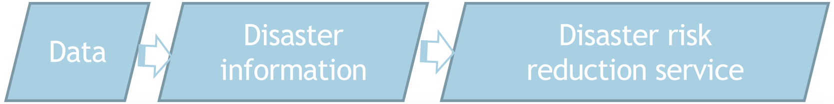
24 June 2024
9:00 PM EDT

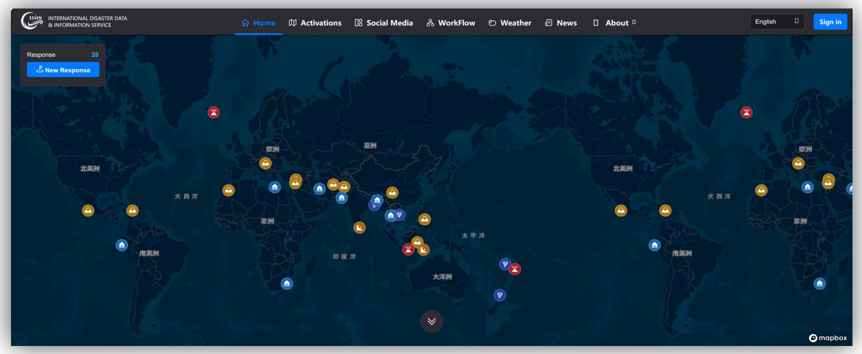
WORLD DATA SYSTEM

Contents

To couple satellite remote sensing with social media data, and establish an *intelligent, automated, and streamlined* service for disaster reduction response.

- ✓ Why precise AOI is vital for data retrieval
- ✓ How to collect remote sensing data and social media data automatically and effectively
- ✓ Extend damage dataset for Intelligent Disaster Information Extraction
- ✓ Disaster response case studies





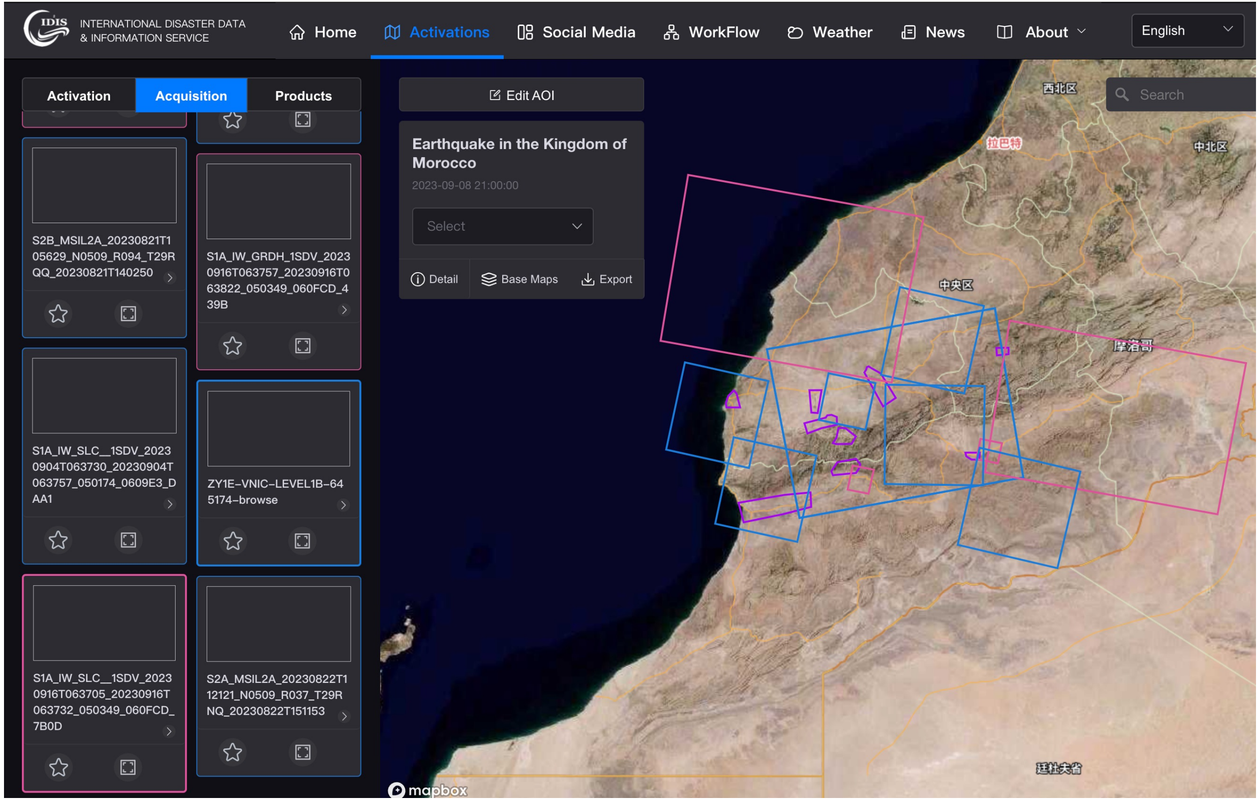
International Disaster Data & Information Service platform ID²IS

https://www.chinageoss.cn/iddis

WORLD DATA SYSTEM

I. Precise AOI is Vital for Disaster Data Retrieval

- **AOI， Area of Interest, the affected area of disaster.**
- **Provide a specific range to filter out which remote sensing images can reflect the situation of the disaster.**



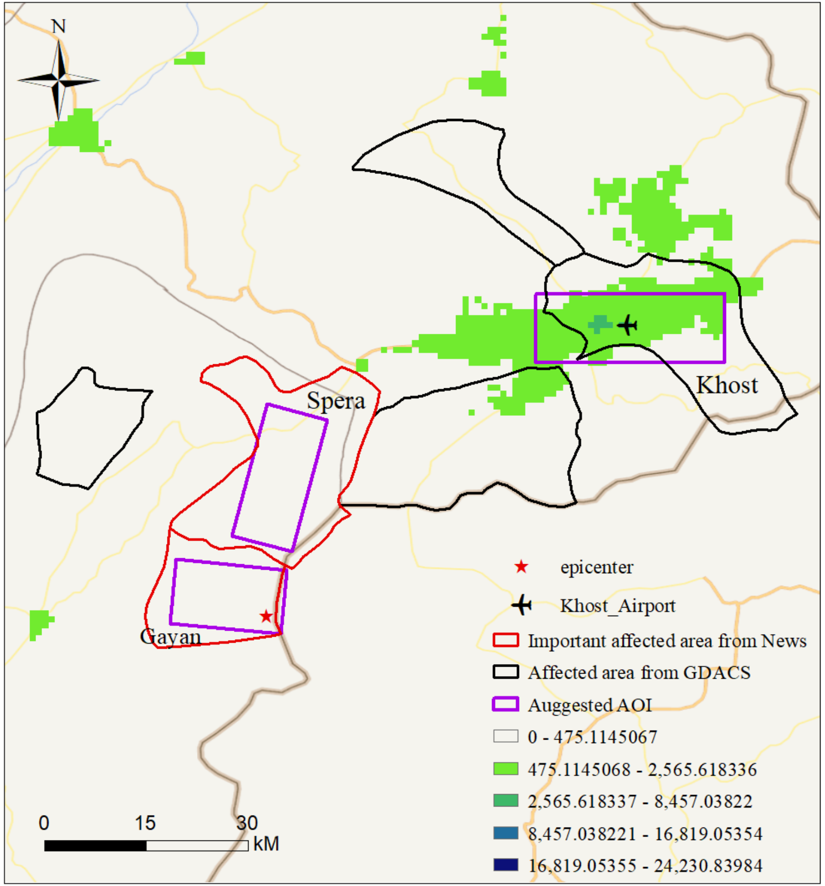
I. Precise AOI is Vital for Disaster Data Retrieval

- **Earthquake in Afghanistan October 2023**

On October 7, 2023, a strong earthquake had shaken parts of western Afghanistan, with up to 2,000 feared dead and many injured. It was followed by three very strong aftershocks, measuring magnitude 6.3, 5.9 and 5.5, as well as lesser shocks[1].

On October 11, 2023, another quake of the same magnitude struck nearby[2].

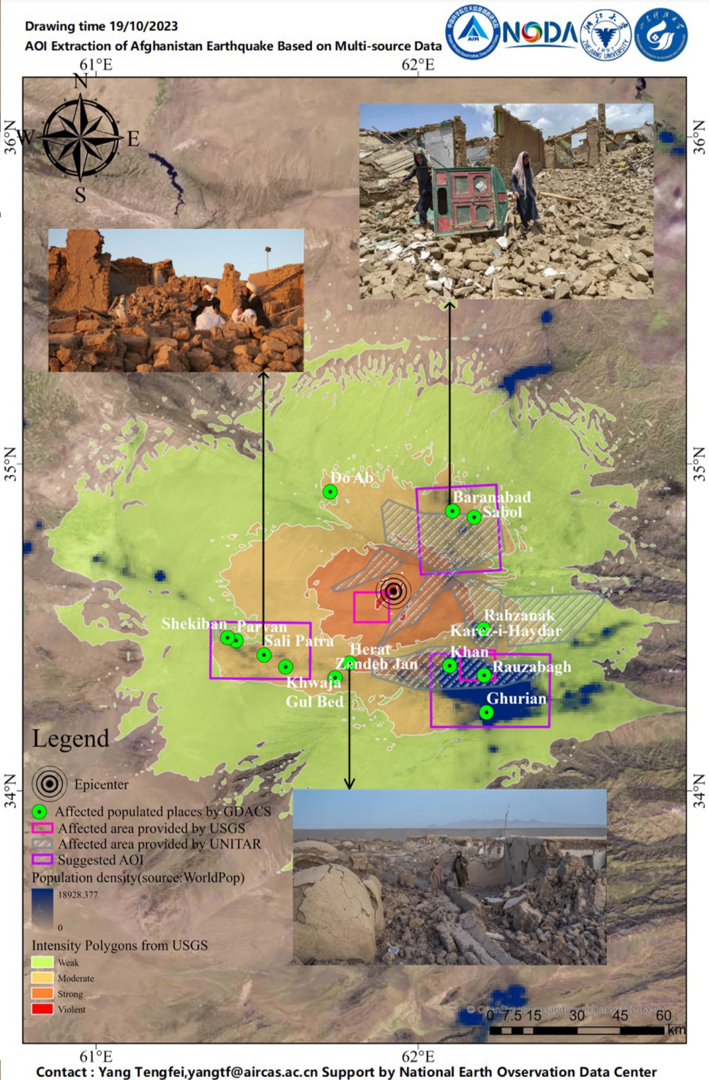
On October 15, 2023, 6.3 magnitude earthquake occurred in the same region. Four people have died and over 150 have been taken to a local hospital with injuries[3].

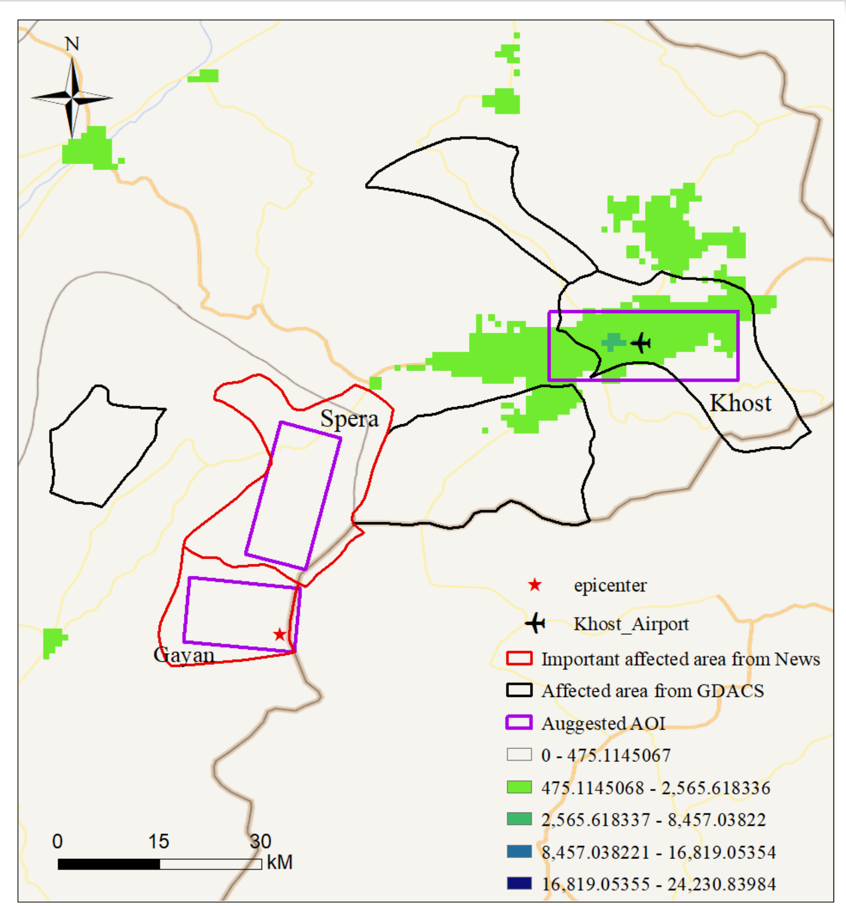


[1] "Earthquakes kill over 2,000 in Afghanistan." Accessed: Oct. 17, 2023. [Online]. Available: https://www.usatoday.com/story/news/world/2023/10/08/earthquakes-kill-over-2000-in-afghanistan/71109569007/
[2] "Quake in Afghanistan leaves rubble, funerals and survivors struggling with loss | AP News." Accessed: Oct. 25, 2023. [Online]. Available: https://apnews.com/article/afghanistan-earthquake-herat-07d767e0b1caf270485fb79deeaf324e
[3] "Afghanistan hit by powerful earthquake week after massive quake." Accessed: Oct. 17, 2023. [Online]. Available: https://www.usatoday.com/story/news/world/2023/10/15/afghanistan-hit-by-powerful-earthquake/71195014007/

r Disaster Data Retrieval

- **Earthqu**



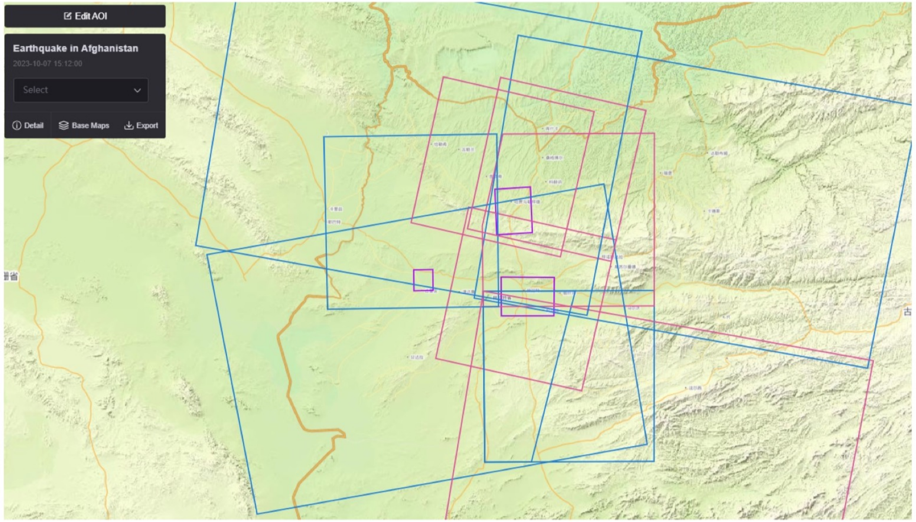


I. Precise AOI is Vital for Disaster Data Retrieval

- **Earthquake in Afghanistan October 2023**

Remote Sensing Data

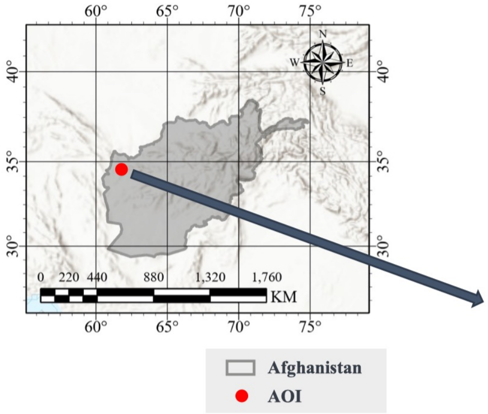
- **As of Oct. 23, 2023, 108 scenes of images including GF1, HJ2, CB04A, Sentinel, Maxer, etc. have been automatically collected.**
- **Images were filtered according to the quality description of the metadata, which requires the cloud cover to be less than 5%.**
- **70 scenes of pre-disaster images and 38 scenes of post-disaster images were collected.**

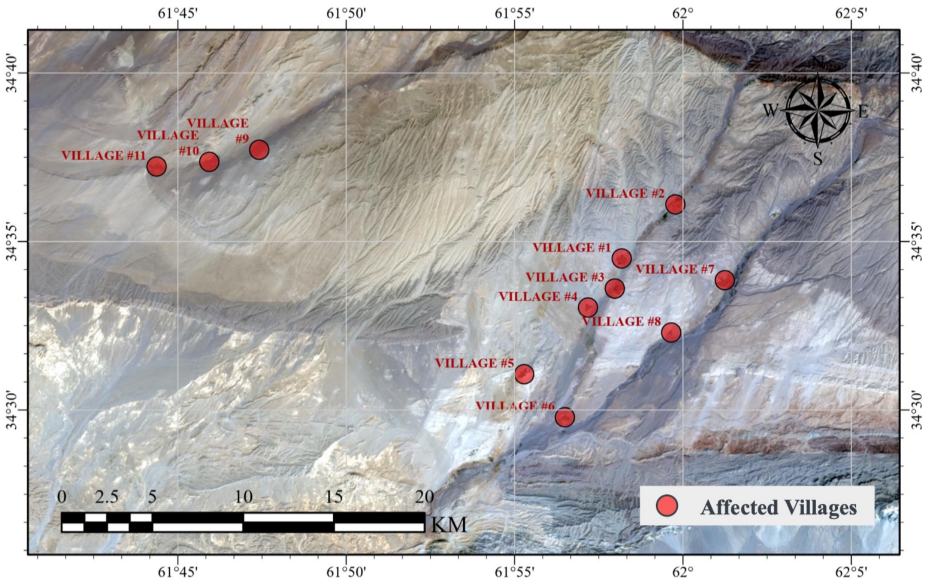


Pre-disaster image
Post-disaster image
Suggest AOI

I. Precise AOI is Vital for Disaster Data Retrieval

- **Earthquake in Afghanistan October 2023**





This report focuses on the Afghanistan earthquake on October 7, 2023. The hard-hit areas are mainly in rural areas in the north-west of Herat province. We conducted visual interpretation of building damage in the affected areas of more than 10 villages. The results showed that about 100% of the houses were damaged to varying degrees, and more than 75% were completely ruined.

All post-disaster images were from JiLin-1satellite, and all pre-disaster images were from Google Earth Pro platform.

Building Damage Statistics

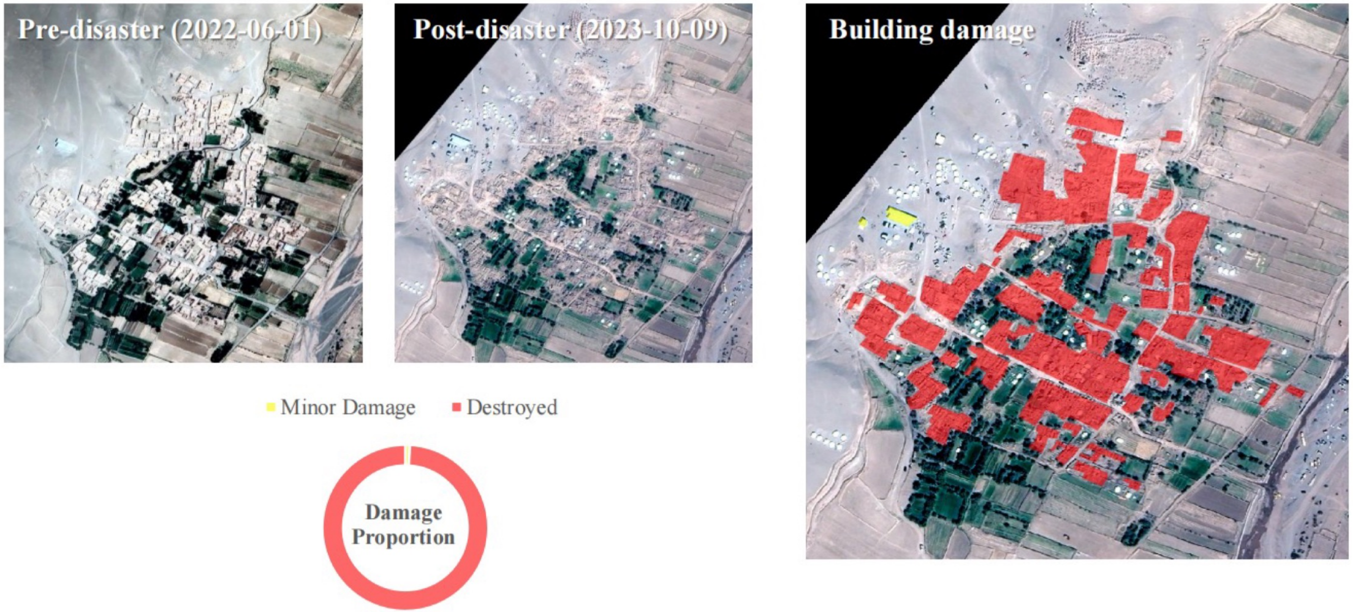
Damage Level	Area (m^2)	Proportion (%)
Minor Damage	22536.90	11.77
Major Damage	25097.97	13.11
Destroyed	143776.99	75.12
(Total)	191411.86	100

I. Precise AOI is Vital for Disaster Data Retrieval

- **Earthquake in Afghanistan October 2023**

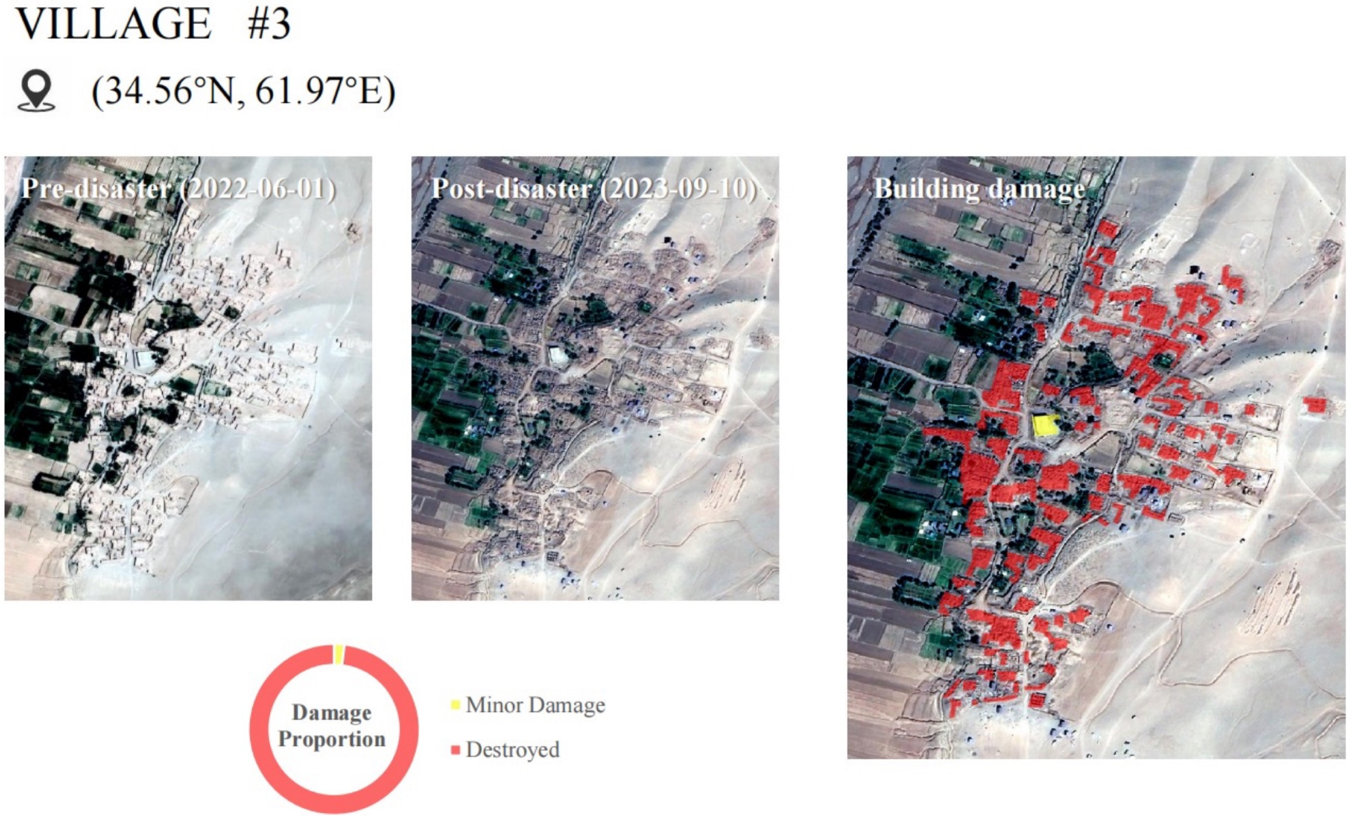
VILLAGE #1

(34.57°N, 61.97°E)



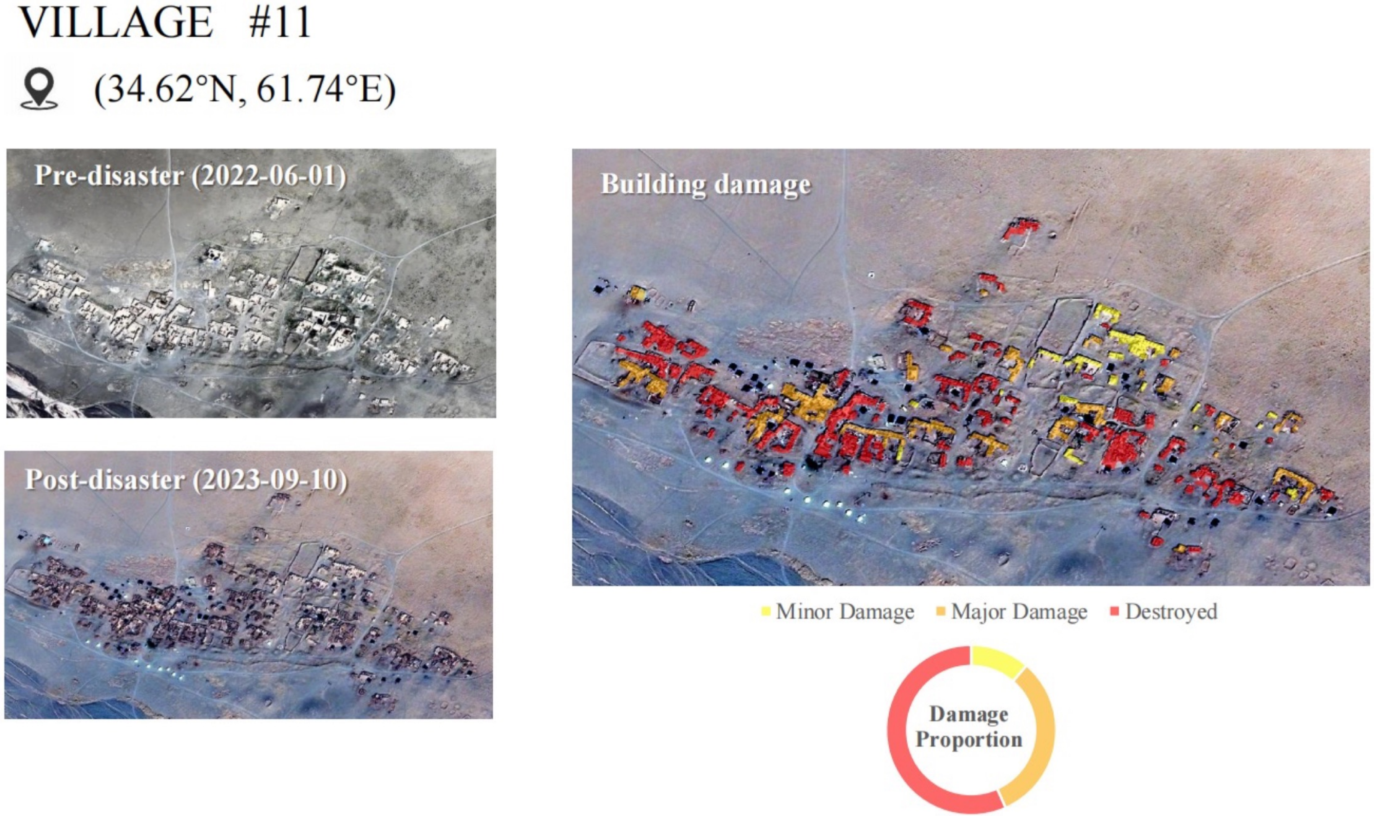
I. Precise AOI is Vital for Disaster Data Retrieval

- **Earthquake in Afghanistan October 2023**



I. Precise AOI is Vital for Disaster Data Retrieval

- **Earthquake in Afghanistan October 2023**



I. Precise AOI is Vital for Disaster Data Retrieval

- **Earthquake in Afghanistan October 2023**

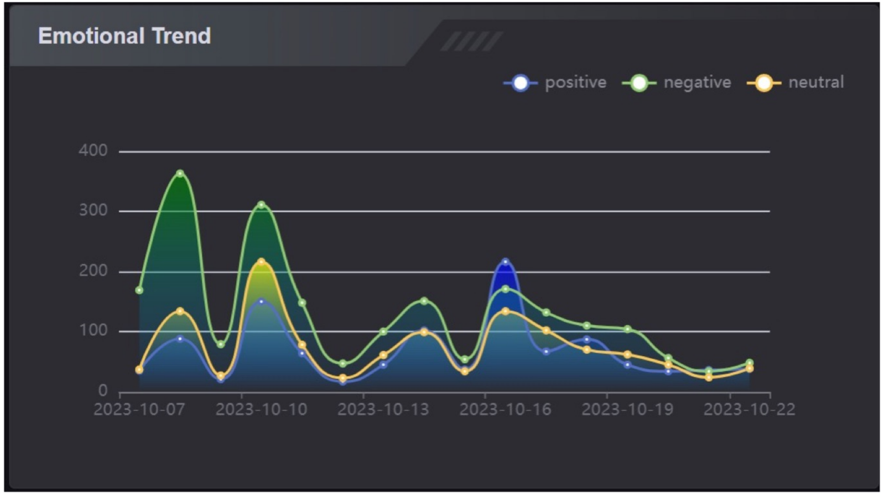
◆ **Human emotions changing along the time.**

October 8 — **negative emotions rose rapidly**

October 10 — **negative emotions rose rapidly and positive emotions increased**

October 14 — **the rise of negative emotions slowed down**

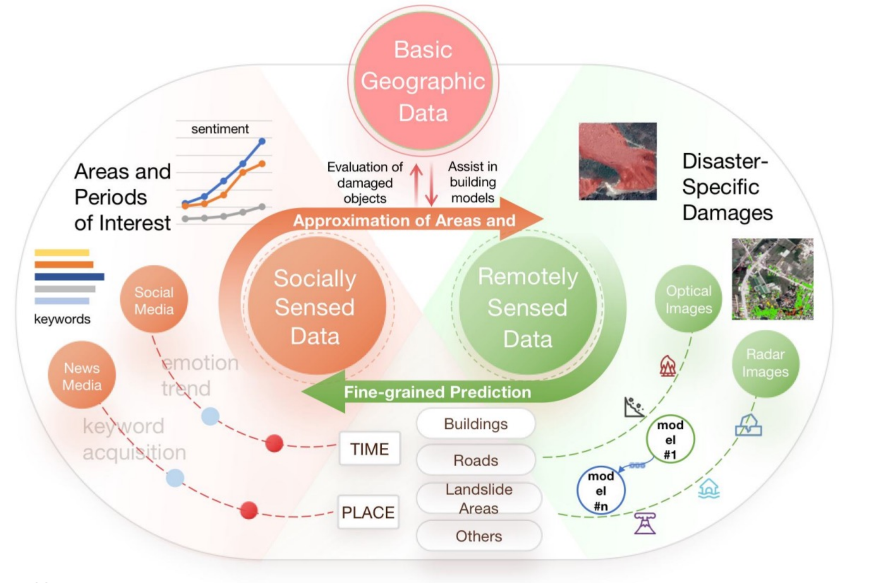
October 16 — **the rise of negative emotions slowed down, while the rise of positive emotions accelerated**



Twitter emotional trend / Oct. 07, 2023 — Oct. 23, 2023

II. Automated Acquisition & Collaborative Analysis of Disaster Data

- **Precise AOI extraction combining remote sensing and social media data**

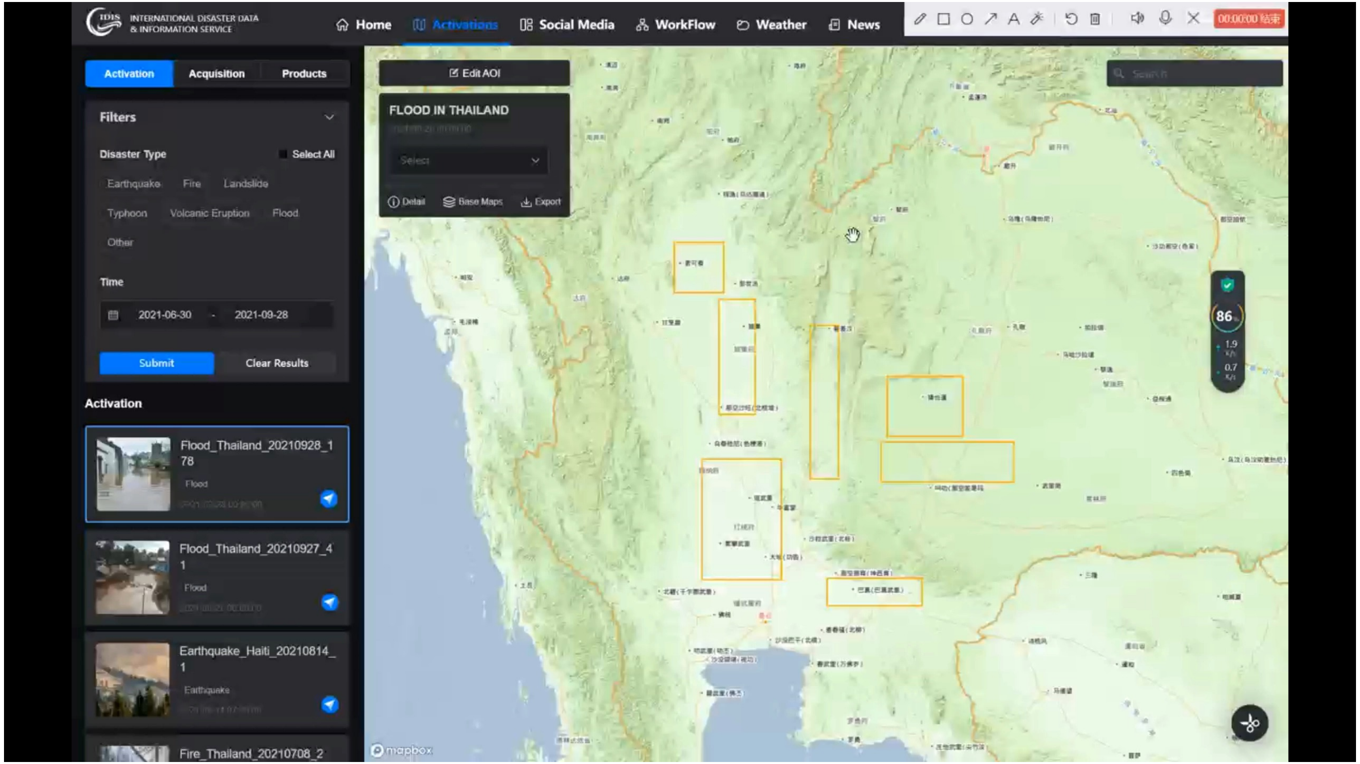


- **Collaborative extraction of disaster information from remote sensing and social media data**

- From social media data, extract affected areas using geo-parsing of places.
- Derive main AOIs by integrating: ① the affected extent from remote sensing data, ② affected areas extracted from social media data, and ③ officially reported disaster zones.

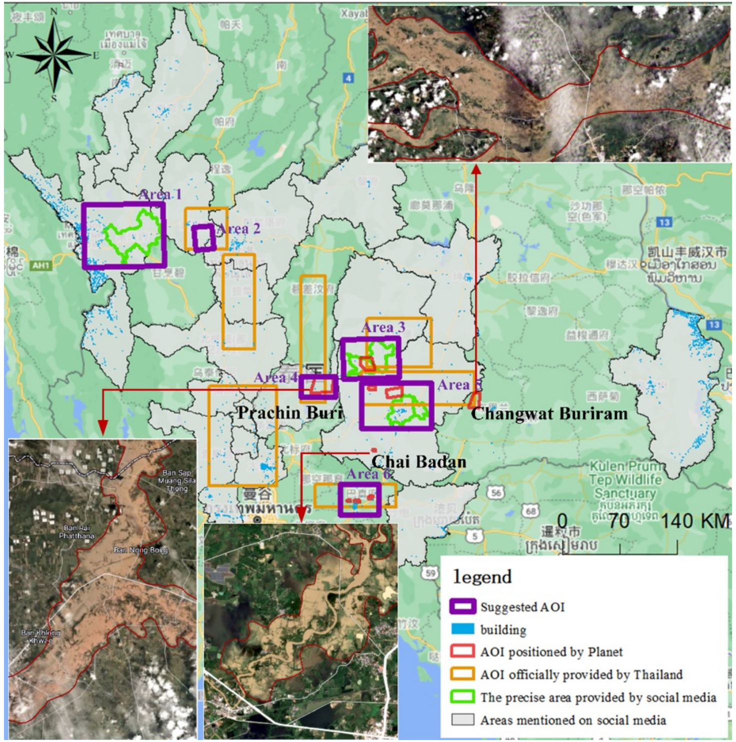
- Extract coarse disaster information from social media using geo-parsing and sentiment analysis
- Use remote sensing data for granular disaster information.
- Collaboratively leverage social media and remote sensing data to extract multi-perspective, multi-scale disaster information.

Precise AOI extraction from multi-source data (Thailand Flooding, 2021.9)



II. Automated Acquisition & Collaborative Analysis of Disaster Data

Precise AOI extraction from multi-source data (Thailand Flooding, 2021.9)



AOI extraction incorporates following data sources:

- Basic AOI data provided by the **Thai government**
- Disaster AOI from **Planet satellite** remote sensing data
- AOI from **social media** images posted on Twitter
- **Building distribution and administrative boundary** data from OpenStreetMap and DIVA-GIS platforms
- A comprehensive analysis identifies recommended AOI areas for focused attention.

★ Extracting precise AOI affected by the disaster provides a crucial spatial window for **coordinating satellite-based disaster data acquisition based on CDDR.**

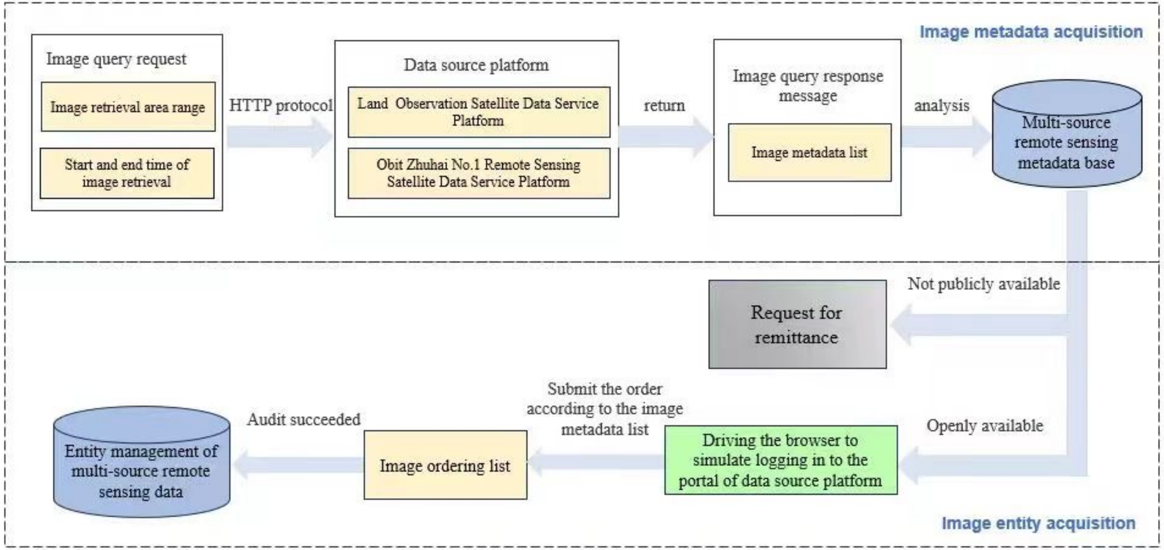
Multi-source Remote Sensing(RS) data retrieval, aggregation

- **Public RS data automated aggregation from domestic and international sources**

Employ an asynchronous acquisition strategy, utilizing open APIs provided by open data platforms.

- **Coordinate commercial RS data collecting from domestic and international sources**

Obtain data from the Chang Guang, Gaofen, Zhuhai-1, and etc. satellite constellations via **CDDR** (ChinaGEO Disaster Data Response) mechanism; access Planet data through the Charter mechanism.



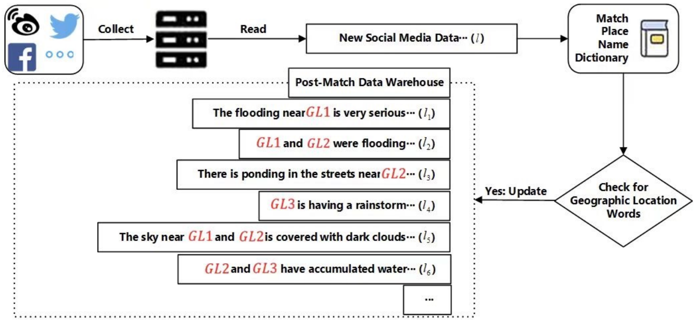
II. Automated Acquisition & Collaborative Analysis of Disaster Data

Social media disaster data retrieval, aggregation, and processing

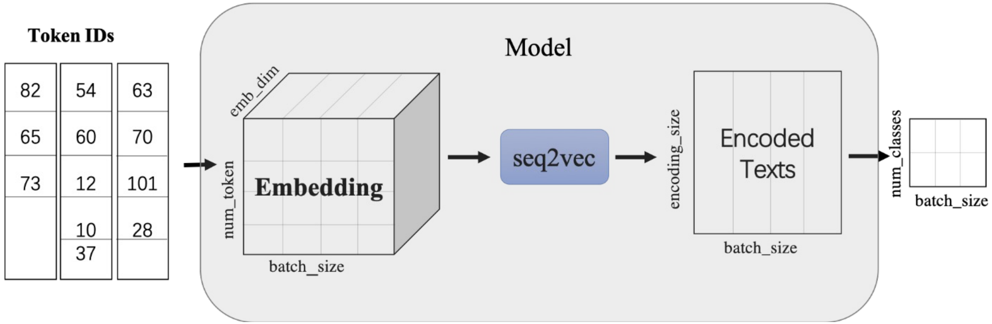
We have an integrated system for collecting multi-platform social media data:

- **Real-time** social media data acquisition based on the Twitter API
- **Historical Twitter** social media data retrieval based on web crawling
- **Chinese news** media data retrieval based on web crawling
- **English news** media data retrieval based on web crawling

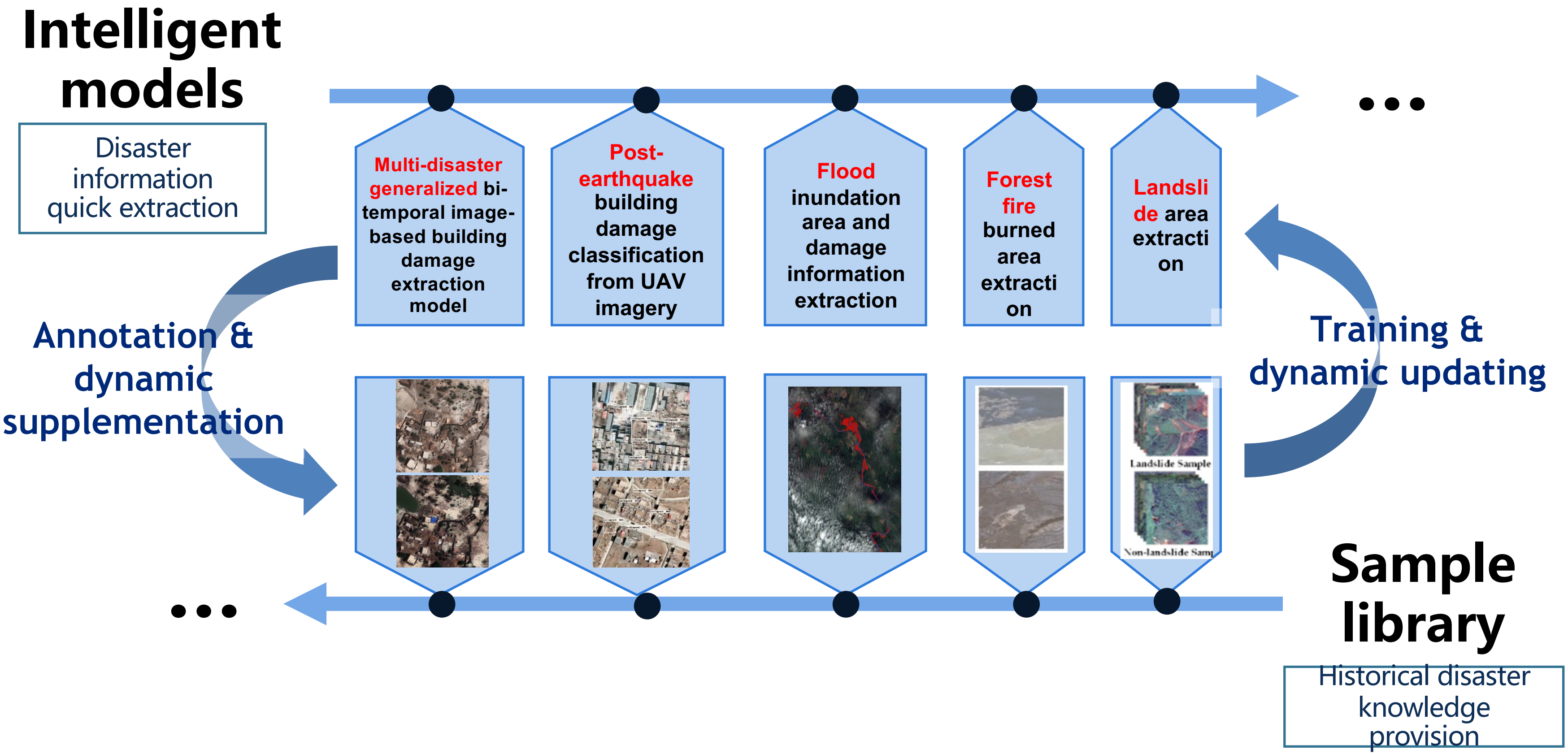
Extraction of location information



Training and information extraction by topic-based text models



III. Extend damage dataset for Intelligent Disaster Information Extraction

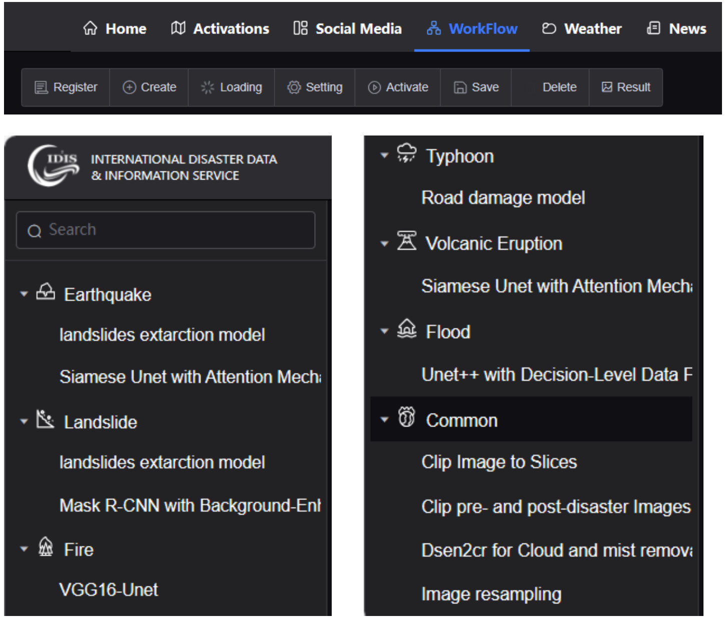


III. Extend damage dataset for Intelligent Disaster Information Extraction

- **Models， codes and datasets availability**

1. Online models at platform *ID²IS*

https://www.chinageoss.cn/iddis



2. Source codes of disaster information extraction model

- Building damage
- Landslide area
- Wildfire area
- Flood extraction
- Road flood extraction
- ……

https://github.com/Zeoyoon/DisasterModels_ZJUGIS.git

3. Data sharing of disaster RS sample library

- Extended Building Damage (EBD) dataset Covering 12 Natural Disaster Events Worldwide (2019-2023)
  https://doi.org/10.6084/m9.figshare.25285009.v1
- Road inundation dataset of Hurricane Delta (2020.10) and Hurricane Ian (2022.9)
  https://doi.org/10.6084/m9.figshare.25332451.v1

III. Extend damage dataset for Intelligent Disaster Information Extraction

Disaster information extraction at different spatial levels

Scene-level

- focuses on **the overall disaster assessment**, based on the global situation and high-dimensional features of the whole image, and has a medium-high spatial resolution

With the development of very-high-resolution satellite sensors such as **WorldView, SuperView, Gaofen**, and etc. , the details of ground objects reflected in images are becoming clearer

Object-level

- Focuses on the **localization and identification of damaged object** on post-disaster images

Pixel-level

- Focuses on the **fine-grained disaster information**, based on the pixel-level feature classification

Damage information extraction based on single-temporal (post-disaster) image

Post-disaster image → Damage object identification

Damage information extraction based on bi-temporal (pre- and post-disaster) images

Pre-disaster image
Post-disaster image
→ Pre-processing → Change (damage) information

11. Semi-supervised construction of Disaster Sample Library

Importance of sample library

1. **It establishes benchmarks** for precisely identify disaster-affected areas and systematically evaluating the disaster levels.
2. **Research site**: Sample library's accurately annotated examples across diverse scenarios allow development of robust machine learning models tailored for disaster applications
3. **Application site**: Sample library can serve as a knowledge base that can be referred to when a new natural disaster occurs, and aid emergency response and quick mapping

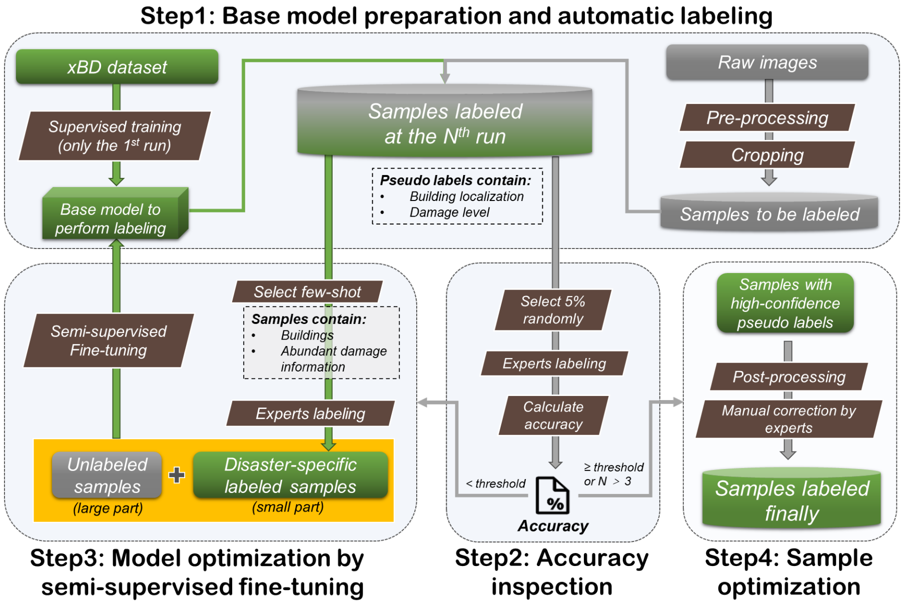
Challenges of sample library construction

1. Existing disaster-related RS datasets largely focus on specific disaster types or events, **lacking transferability** to new disaster scenarios.
2. Existing disaster-related RS datasets mostly remain static, **lacking scalability and extensibility**.
3. Manual annotation for constructing the library is **costly and inefficient**.

III. Extend damage dataset for Intelligent Disaster Information Extraction

Semi-supervised workflow of sample library construction

- mainly driven by **automatic model annotation**, supplemented by manual supervision



- **Step 1:** Train a base annotation model on the xBD dataset by following the supervised setting. For the 1st run, each sample will get the pseudo labels.

- **Step 2:** Randomly select a proportion of samples as the inspection set, and calculate the accuracy of pseudo labels. If the accuracy > threshold, proceed to Step 4 for sample post-processing; otherwise, proceed to Step 3 for model optimization.

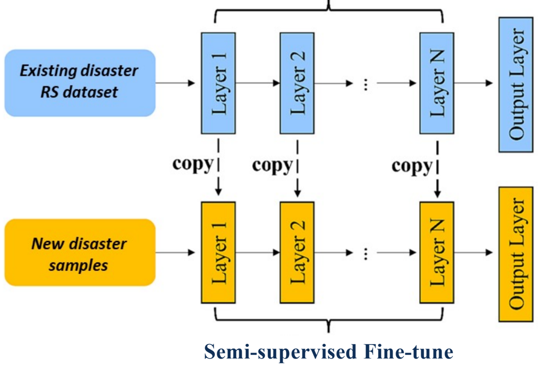
- **Step 3:** Select and label a proportion of samples as the fine-tuning set. With the remaining unlabeled samples, implement the model's semi-supervised optimization process.

- **Step 4:** Implement post-processing work on pseudo labels. Finally, experts perform a quick check for all samples and correct those mislabeled bad cases.

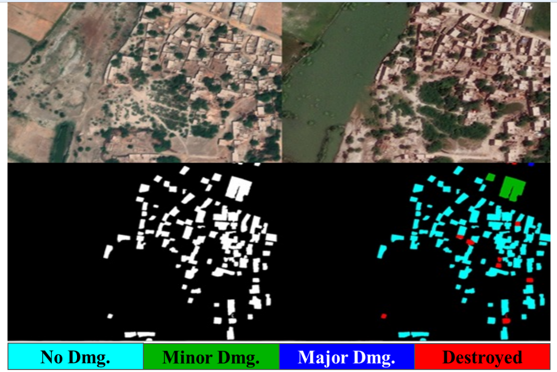
Transfer learning from existing disaster dataset to new disaster events

- Combining supervised fine-tuning with semi-supervised contrastive learning, ***utilizing only a small amount of manual annotation*** to achieve transfer optimization of the pre-trained model for the newly occurring disaster.
- The annotation model is able to perform automatic labeling of disaster images approximately consistent with the visual ground truth.
- In this way, the newly-labeled samples of new disaster events have ***expand the knowledge capacity of historical disaster sample library*** dynamically and effectively.

Transfer learning framework



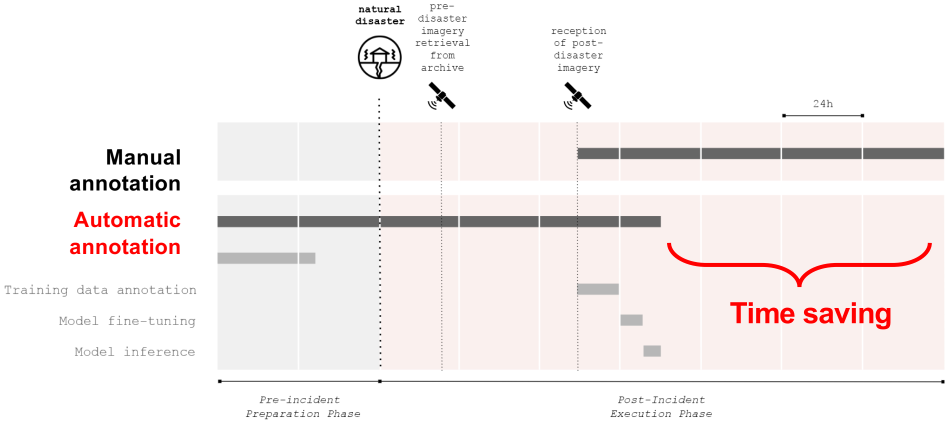
Annotation example of Pakistan Flooding



★ Potential usage of models and sample library in real emergency response

1. **Rapid disaster mapping:** After a disaster occurs, the intelligent models can significantly shorten the emergency response time by quickly mapping the damaged areas. Also, the disaster sample library serves as a knowledge base, forming the data foundation for model training and continuous improvement.

2. **Enhanced Accuracy**: By substituting on-the-ground surveys, these models improve the accuracy and granularity of post-disaster damage information. This leads to a more precise identification of affected areas and objects, facilitating better-informed decision-making in disaster management.



Bouchard, I.; Rancourt, M.-È.; Aloise, D.; Kalaitzis, F. On Transfer Learning for Building Damage Assessment from Satellite Imagery in Emergency Contexts. Remote Sens. 2022, 14, 2532. https://doi.org/10.3390/rs14112532

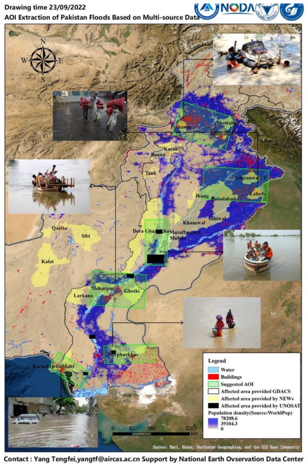
- Extended Building Damage (EBD) dataset Covering 12 Natural Disaster Events Worldwide (2019-2023)

  https://doi.org/10.6084/m9.figshare.25285009.v1

- Road inundation dataset of Hurricane Delta (2020.10) and Hurricane Ian (2022.9)

  https://doi.org/10.6084/m9.figshare.25332451.v1

2022.6 Pakistan Flooding



Since mid-June this year, more than 33 million people have been affected by heavy rainfall and floods across Pakistan, and more than one third of the country's land has been flooded[1]. Over 1 million houses were damaged or destroyed, while at least 5000 km of roads were damaged[2]. At the same time, the floods caused the overflow of Pakistan's largest lake, drowned hundreds of villages, leaving many surrounding residents in distress. The devastating floods in Pakistan are a "wake-up call" to the world on the threats of climate change[3] .

[1] Over 33 mln people, 72 districts of Pakistan affected by floods—Global Times. (2022, August 30). *Global Times*. https://www.globaltimes.cn/page/202208/1274189.shtml
[2]A third of Pakistan is underwater amid its worst floods in history. Here's what you need to know. (2022, September 2). *CNN*. https://www.cnn.com/2022/09/02/asia/pakistan-floods-climate-explainer-intl-hnk/index.html
[3] How Pakistan floods are linked to climate change. (2022, September 2). *BBC News*. https://www.bbc.com/news/science-environment-62758811

- Disaster Overview
- Comprehensive Mapping of Affected AOI

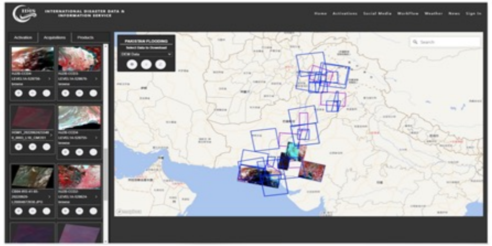
- Automated aggregation of multi-source remote sensing images
- Automated aggregation of disaster situation data from multi-platform social media

Remote Sensing Data

As of Sep. 22, 2022, 1,162 scenes of images including GF1, GF2, ZY1, Sentinel, Planet, etc. have been automatically collected. Images were filtered according to the quality description of the metadata, which requires the cloud cover to be less than 5%.

At the same time, coordinated by CDDR, 4 scenes of BJ-2 pre-disaster images were collected.

Domestic satellite data collection	Pre-disaster images (293 in total)	Post-disaster images (869 in total)
GF Satellites	129	221
ZY Satellites	89	112
CBERS	30	61



Social Media Data

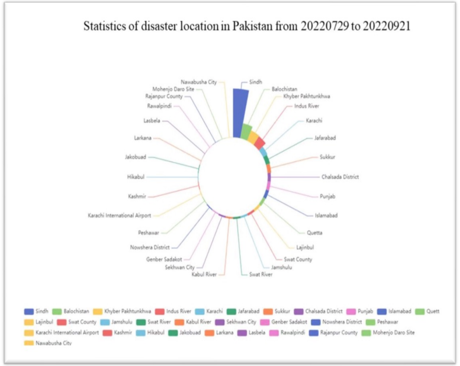
Human emotions changing along the time.

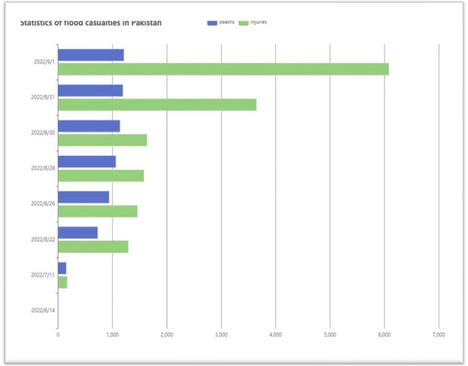
The floods lasted for a long time and had a wide range. Concerns about the flood disaster reached two peaks in late July and late August respectively.

At the end of July, the proportion of people's positive emotions was slightly higher. By the end of August, the negative emotions prevailed.

Twitter / Jul. 27, 2022 – Aug. 26, 2022 / 17451 tweets

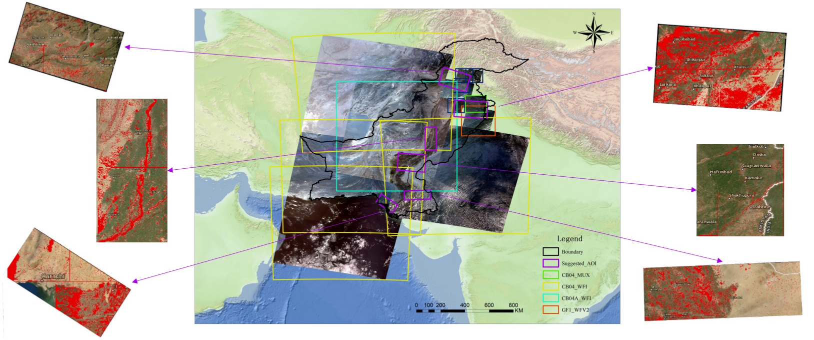
2022.6 Pakistan Flooding





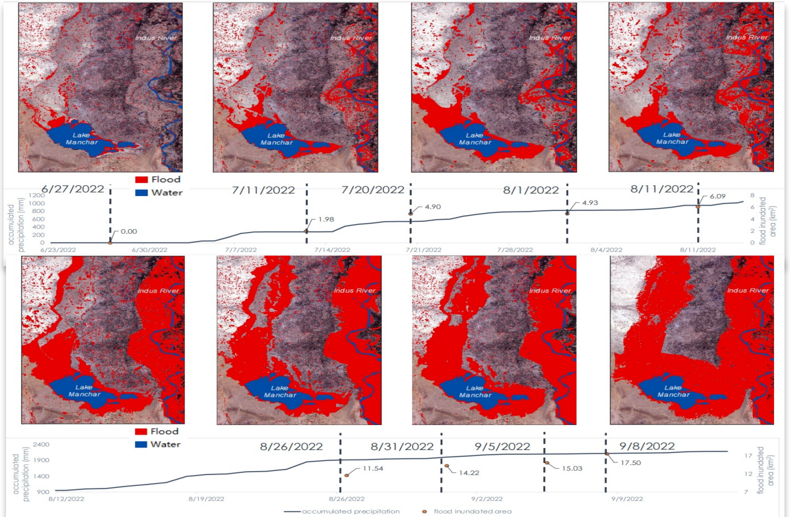
- Identifying disaster information from social media data based on natural language processing
- Analyzing changes in disaster-affected areas, casualties, etc., over time combined with temporal elements

- Based on precise extraction of disaster-affected AOI areas, extract flood-submerged areas from the selected remote sensing images



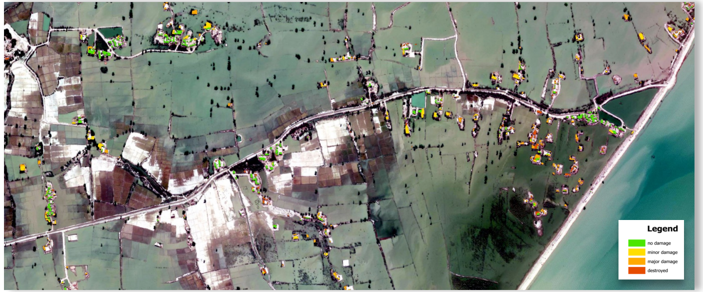
IV. Case Studies for Disaster Emergency Response

2022.6 Pakistan Flooding



- Extract flood-submerged areas around Manchar Lake using time-series remote sensing images.

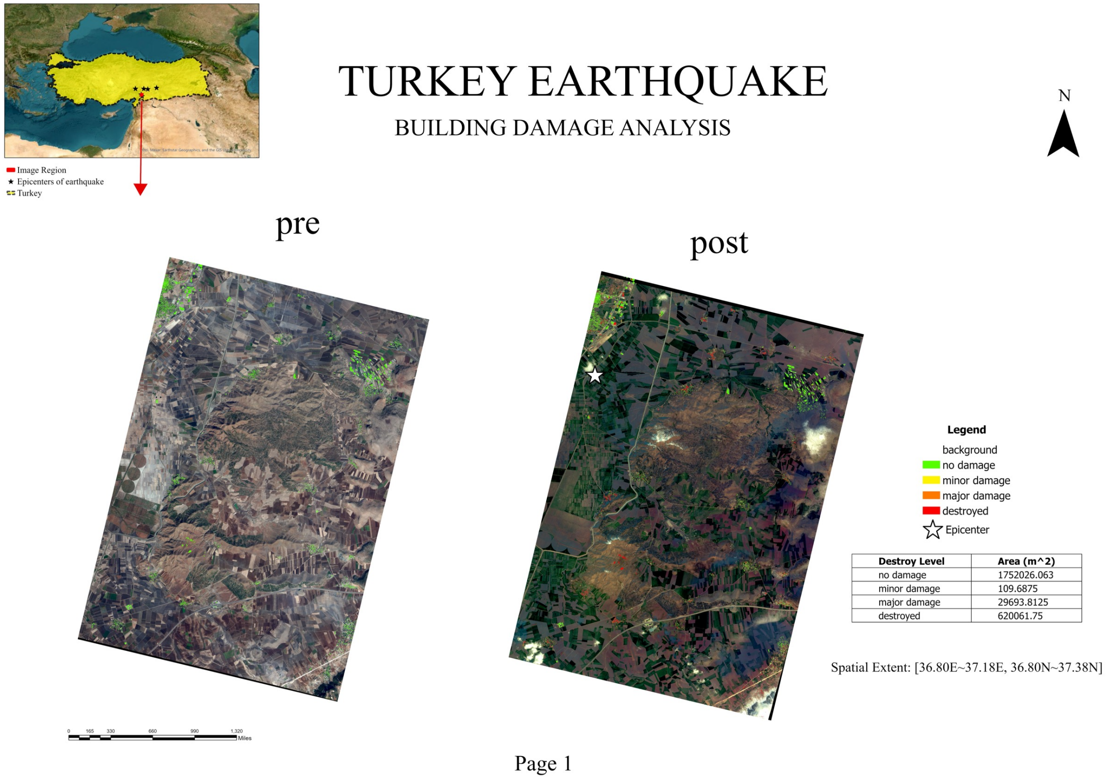
- Extract fine-grained building damage using WorldView-3 ultra-high-resolution remote sensing images.



On February 6, 2023, a strong earthquake occurred in southern Türkiye near the Syrian border.

Using the post disaster February 7, 2023 and pre disaster November 6, 2022 images of Jilin No.1 wide 01A satellite for analysis of building damage.

- ✓ The epicenter of this earthquake is located at the border of Kahramanmash Province and Gaziantep Province
- ✓ The proportion of building damage is about 30%, and the types of damage are mostly "severe damage" and "complete damage".



Destroy Level	Area (m^2)
no damage	1752026.063
minor damage	109.6875
major damage	29693.8125
destroyed	620061.75

Q&A

Thank you!

zfcarnation@zju.edu.cn

WORLD
DATA SYSTEM