Sensing and Big Data Analytics for Natural Disaster Management

N. Militsis, V. Mygdalis, Prof. I. Pitas
Aristotle University of Thessaloniki
pitas@csd.auth.gr
www.aiia.csd.auth.gr

Version 4.2

Artificial Intelligence & Information Analysis Lab

Big Data Analytics for Natural Disaster Management

- **Natural Disaster Management**
- NDM Concept and Objectives
- NDM Sensing
- Big NDM Data Analytics
- Horizon Europe R&D project TEMA

Natural Disaster Management

Natural Disaster Management (***NDM***) examples:

- forest fires, floods.

Big data issues in NDM:

- precise semantic mapping and phenomenon evolution predictions in ***real-time.***
- ***Heterogeneous extreme data sources***:
  - AI-capable autonomous devices and smart sensors at the edge
  - satellite images,
  - topographical data,
  - official meteorological data and predictions/warnings published in the Web
- ***Multilingual data***
  - geosocial media data (including text, image and videos).

Artificial Intelligence & Information Analysis Lab

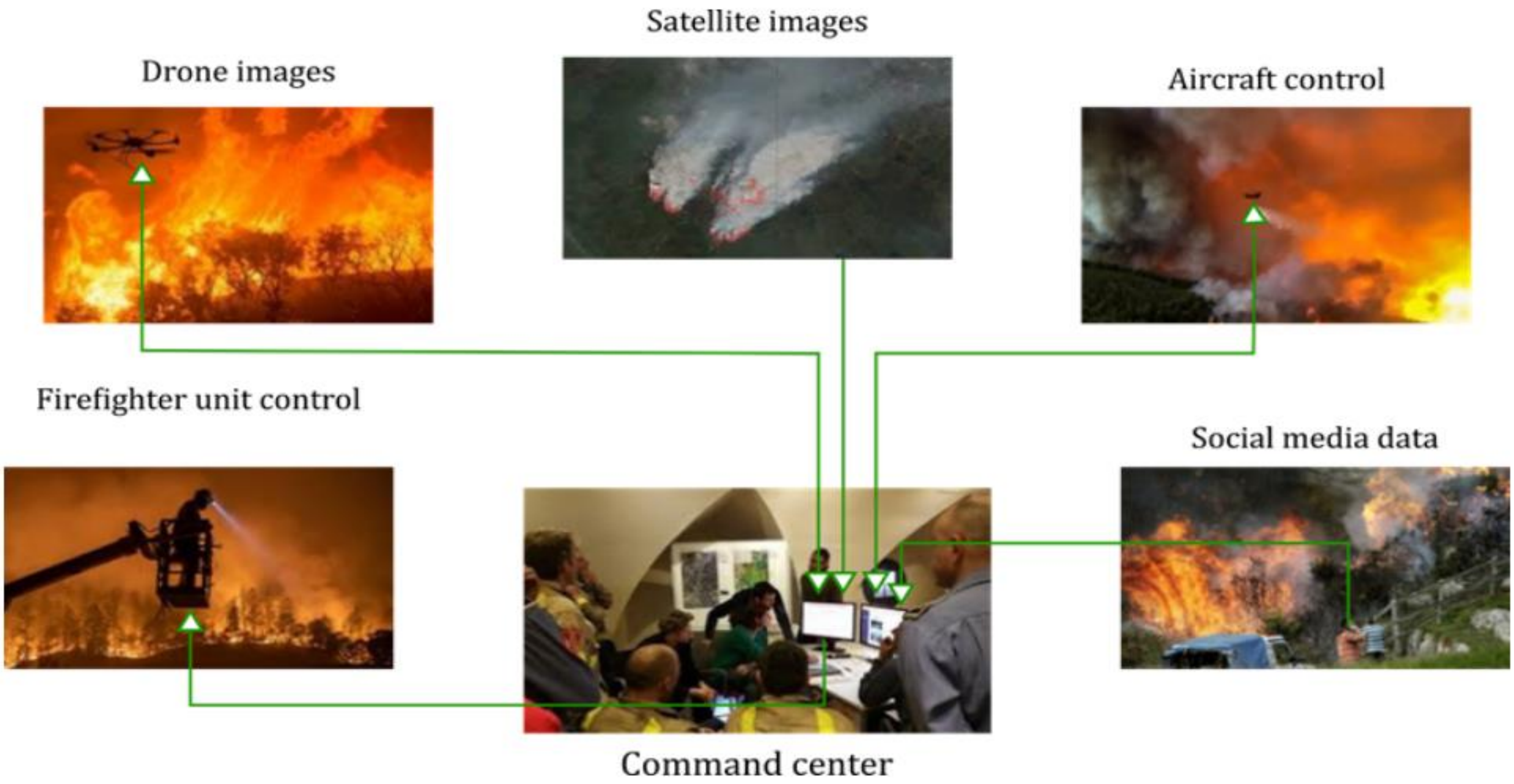
Natural Disaster Management

Trusted Extremely Precise Mapping and Prediction for Emergency Management (***TEMA***):

- It aims to aid and improve NDM for forest fires, floods.
- It will employ automated means for ***precise semantic mapping*** and ***phenomenon evolution predictions*** in real-time, by performing ***analysis of extreme data sources***:
    - AI-capable autonomous devices and smart sensors at the edge
    - satellite images,
    - topographical data,
    - official meteorological data and predictions/warnings published in the Web
    - geosocial media data (including text, image and videos).

Artificial Intelligence & Information Analysis Lab

Natural Disaster Management

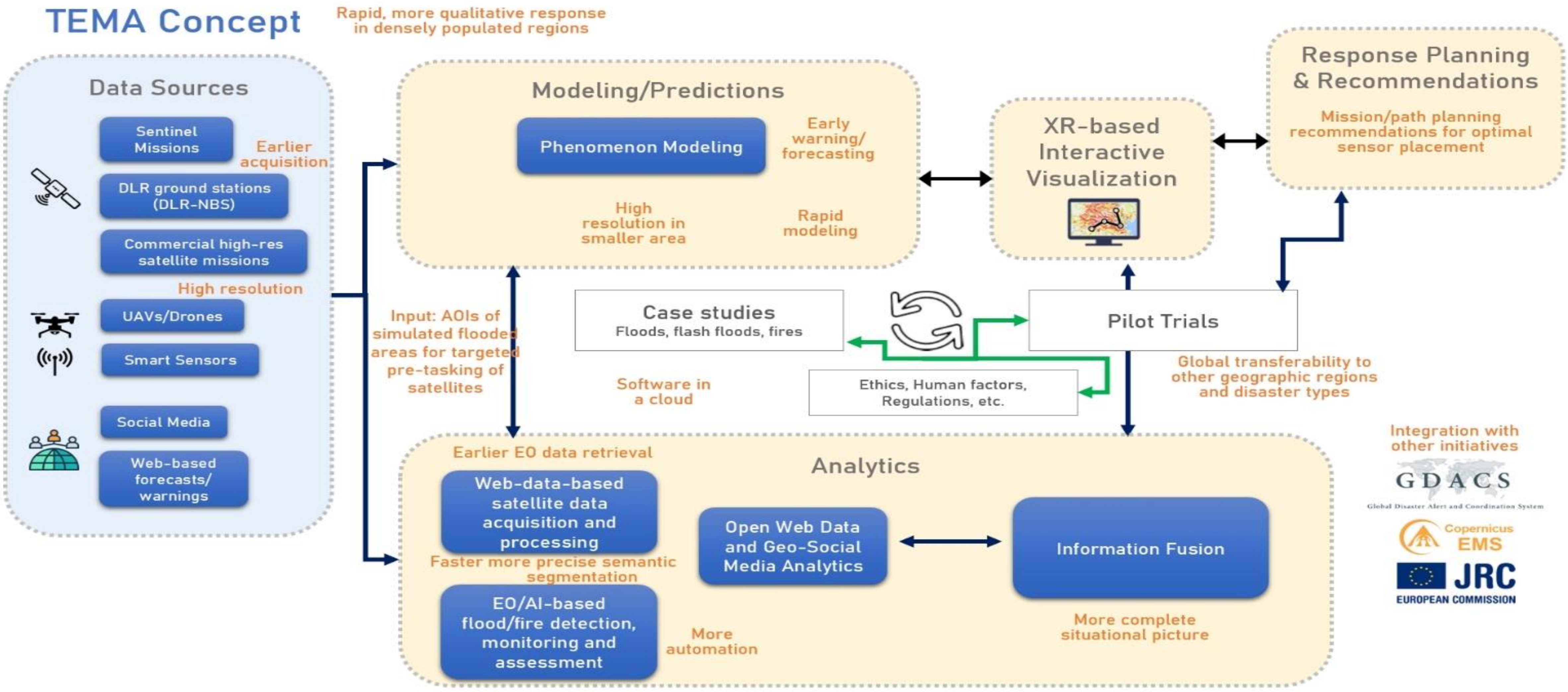


NDM Overview.

Big Data Analytics for Natural Disaster Management

- Natural Disaster Management
- **NDM Concept and Objectives**
- NDM Sensing
- Big NDM Data Analytics
- Horizon Europe R&D project TEMA

NDM Concept and Objectives



TEMA NDM Architecture.

NDM Concept and Objectives

Objectives

- Improve and accelerate ***extreme data analytics***.

- Improve and accelerate ***emergency phenomenon modeling, evolution predictions***, simulation and interactive visualization

- Improve NDM using new digital technologies and extreme data analytics.

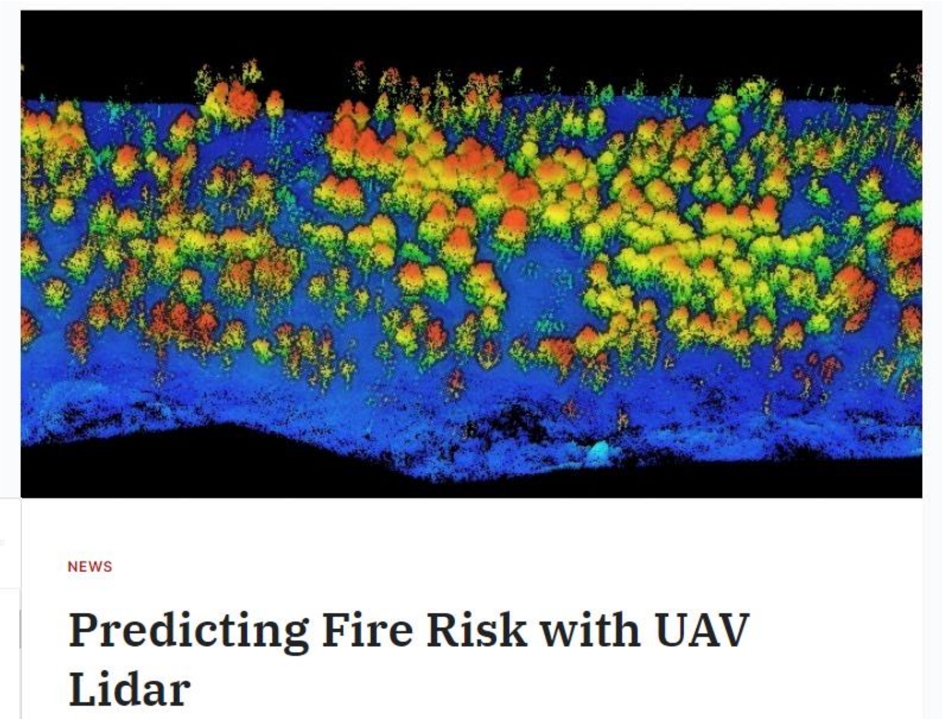
NDM Concept and Objectives

Improve and accelerate extreme data analytics

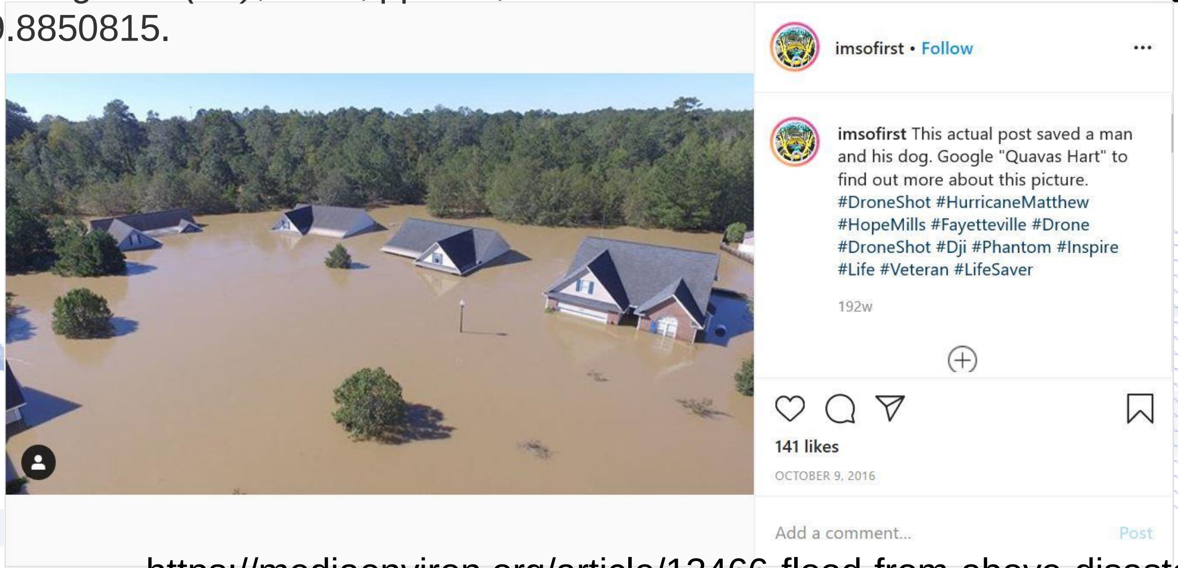
- ***Increase trustworthiness of extreme data analysis algorithms***
  - Speed of local & global XAI explanations.
- ***Increase accuracy of extreme data analysis algorithms***
  - Semantic/instance segmentation, object detection, Image recognition
- ***Increase responsiveness/speed of extreme data analysis algorithms***
  - Visual analysis, social media analysis speed.
- ***Reduce latency by innovative federated data analysis on a cloud-to-edge continuum***
  - Reduce computational latency, data migration.

NDM Concept and Objectives

Z. Jiao *et al*., "A Deep Learning Based Forest Fire Detection Approach Using UAV and YOLOv3," *2019 1st International Conference on Industrial Artificial Intelligence (IAI)*, 2019, pp. 1-5, doi: 10.1109/ICIAI.2019.8850815.



https://www.gim-international.com/content/news/predicting-fire-risk-with-uav-lidar



https://mediaenviron.org/article/13466-flood-from-above-disaster-mediation-and-drone-humanitarianism

Artificial Intelligence & Information Analysis Lab

Trustworthy federated analytics.

NDM Concept and Objectives

Improve and accelerate emergency phenomenon modeling, evolution predictions, simulation and interactive visualization

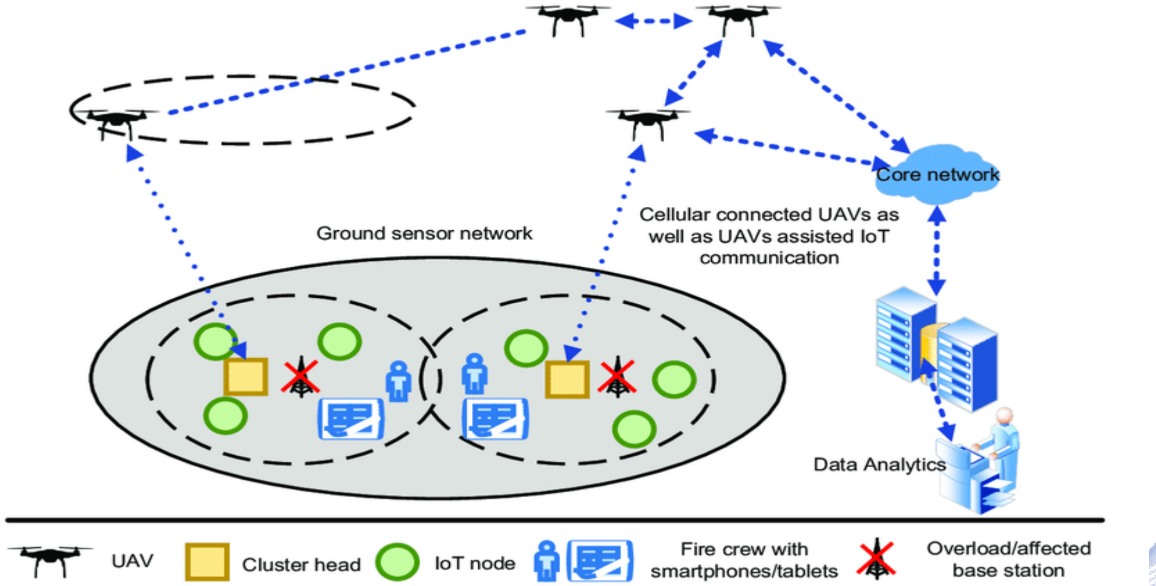
- ***Increase model-based prediction responsiveness/speed for evolving phenomena***
  - Increase dispersion model, flood model update rates.
- ***Increase model-based prediction accuracy for evolving phenomena***
  - Fire simulation, estimated smoke plume and concentration distribution, flood simulation.

NDM Concept and Objectives

Improve and accelerate emergency phenomenon modeling, evolution predictions, simulation and interactive visualization

- ***Improve responsiveness and interactivity of visualization mechanisms for evolving phenomena***
  - Responsiveness of visualization mechanisms, content customization increase in Augmented Reality Immersion score).
- ***Improve accuracy of visualization mechanisms for evolving phenomena***
  - Digital Twin accuracy, merged spatial 3D map resolution increase.

NDM Concept and Objectives



Sun H, Dai X, Shou W, Wang J, Ruan X. An Efficient Decision Support System for Flood Inundation Management Using Intermittent Remote-Sensing Data. *Remote Sensing*. 2021; 13(14):2818. https://doi.org/10.3390/rs13142818

Ejaz, Waleed & Azam, Muhammad Awais & Saadat, Salman & Iqbal, Farkhund & Hannan, Abdul. (2019). Unmanned Aerial Vehicles enabled IoT Platform for Disaster Management. Energies. 12. 10.3390/en12142706.

NDM predictions and decision-making.

Artificial Intelligence & Information Analysis Lab

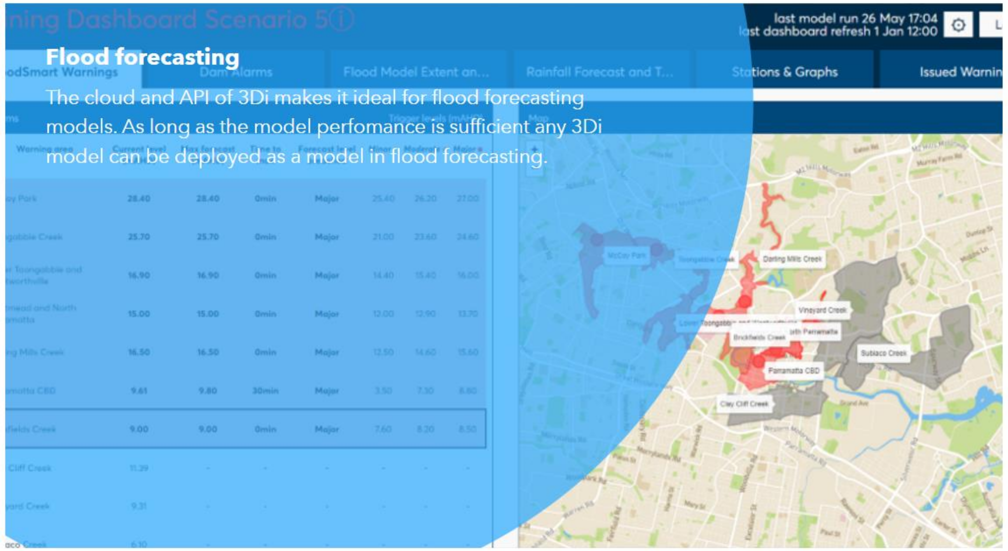
NDM Concept and Objectives

Improve NDM using new digital technologies and extreme data analytics.

- ***Reduce latency in NDM***
  - Speed of satellite-based crisis mapping, Frequency of wildfire burnt area product availability, reduction of time between sensing and satellite data availability.
- ***Increase situational awareness in NDM***
  - Heterogeneous data sources/modalities to semantically annotate the 3D map, Evaluation of contingent response alternatives ,Temporal resolution of map updates.
- ***Reduce mental load for human operators in NDM***
  - Workload from retrieval of satellite position and acquisition data, Transparency, automation and improvement of communication.
- ***Prototype a proof-of-concept TEMA system for NDM in forest fires, flash floods, and regional floods.***

NDM Concept and Objectives

TSYL Wildfire Analyst®



NS 3Di ® Flood forecasting

Simulation and visualization.

NDM Concept and Objectives

NDM Tasks

Requirements/Specifications

Trustworthy federated analytics

- *Trustworthy AI*
- *Visual data analysis and remote sensing*
- *Geosocial media and news analysis*
- *Federated analytics on an edge-to-cloud continuum*

Predictions and decision-making

- *Decision support service for remote sensing*
- *Information fusion*
- *NDM phenomenon modeling*
- *Automated response recommendations*

Simulation and visualization

- *Digital Twin*
- *Geovisual analytics*
- *Interactive visualization*

Integration and validation

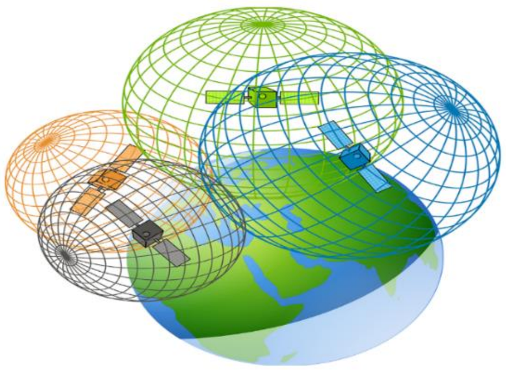
- *HW/SW integration*
- *Pilot trials*

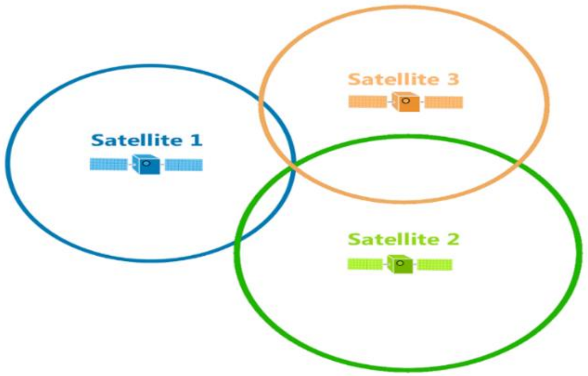
Big Data Analytics for Natural Disaster Management

- Natural Disaster Management
- NDM Concept and Objectives
- **NDM Sensing**
- Big NDM Data Analytics
- Horizon Europe R&D project TEMA

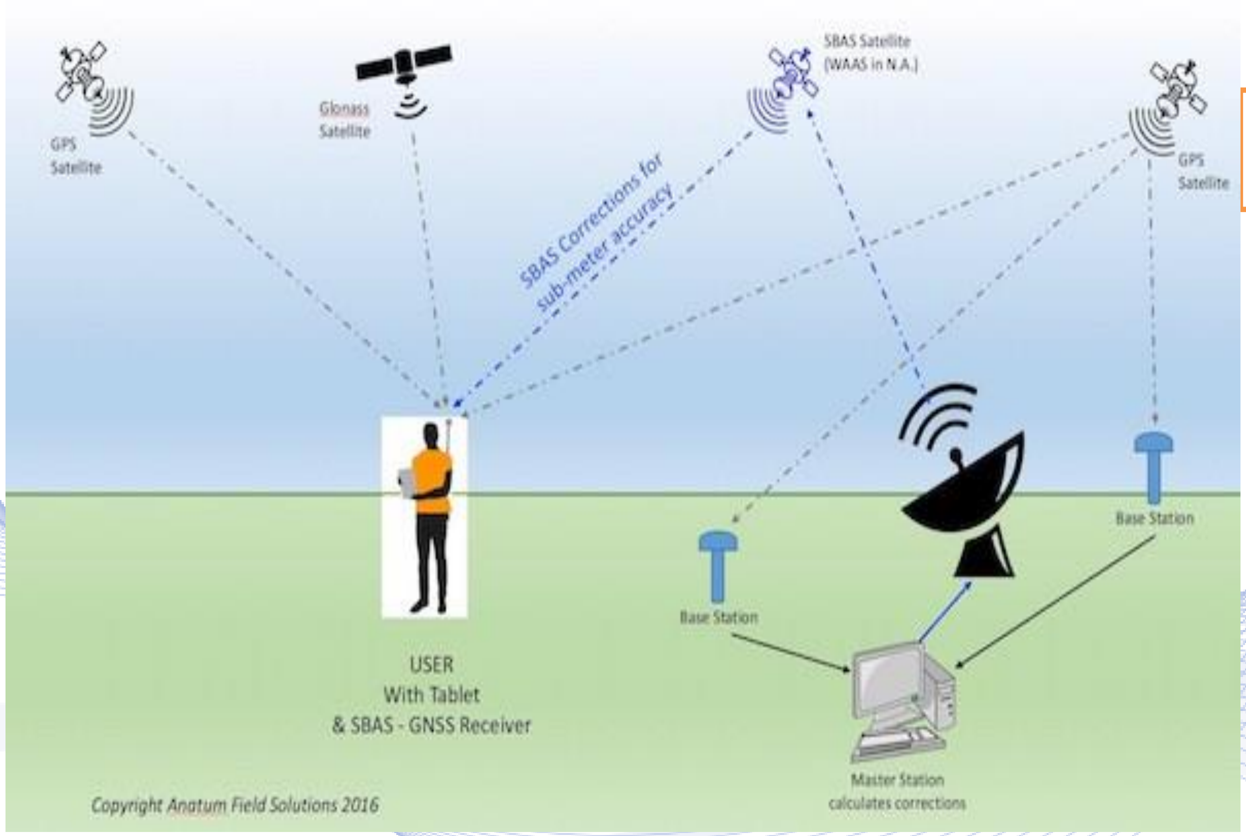
GPS

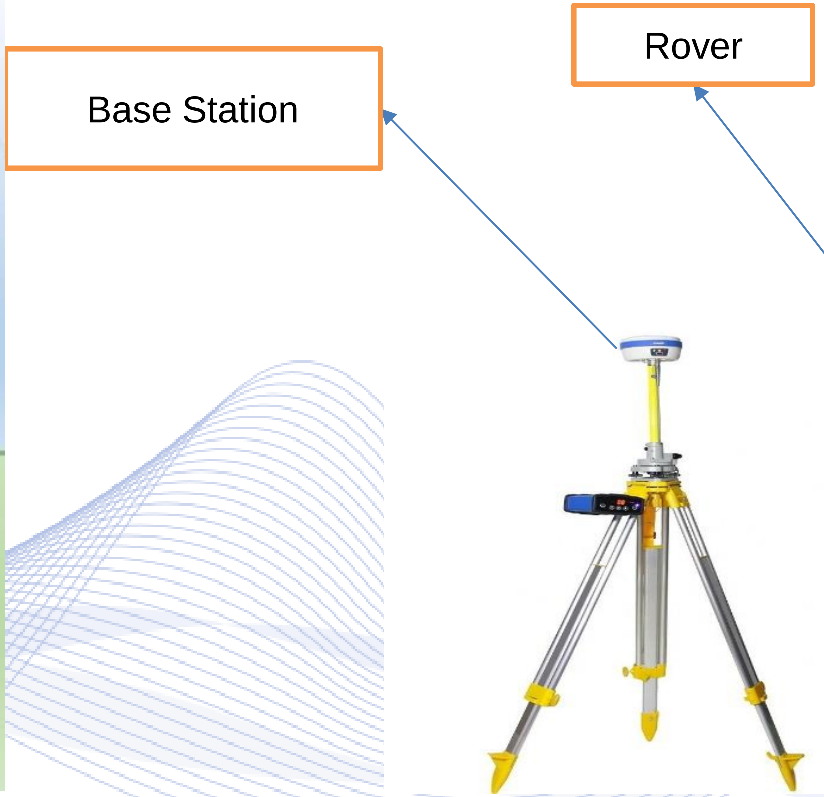
- The ***Global Positioning System*** (***GPS***) is a constellation of 27 Earth-orbiting satellites (24 in operation and three extras, in case one fails).
- GPS receivers receive position information from ***GPS satellites*** and then calculate the device geographical position (difference from Satellite position).





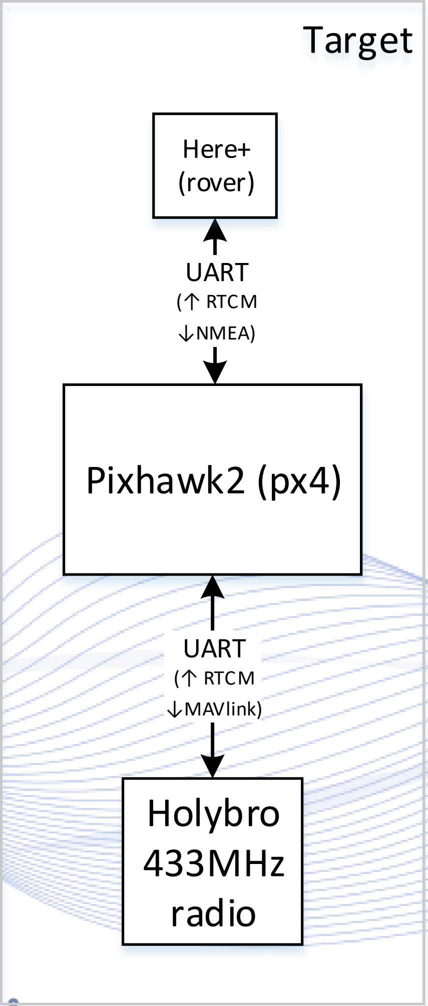
RTK GPS

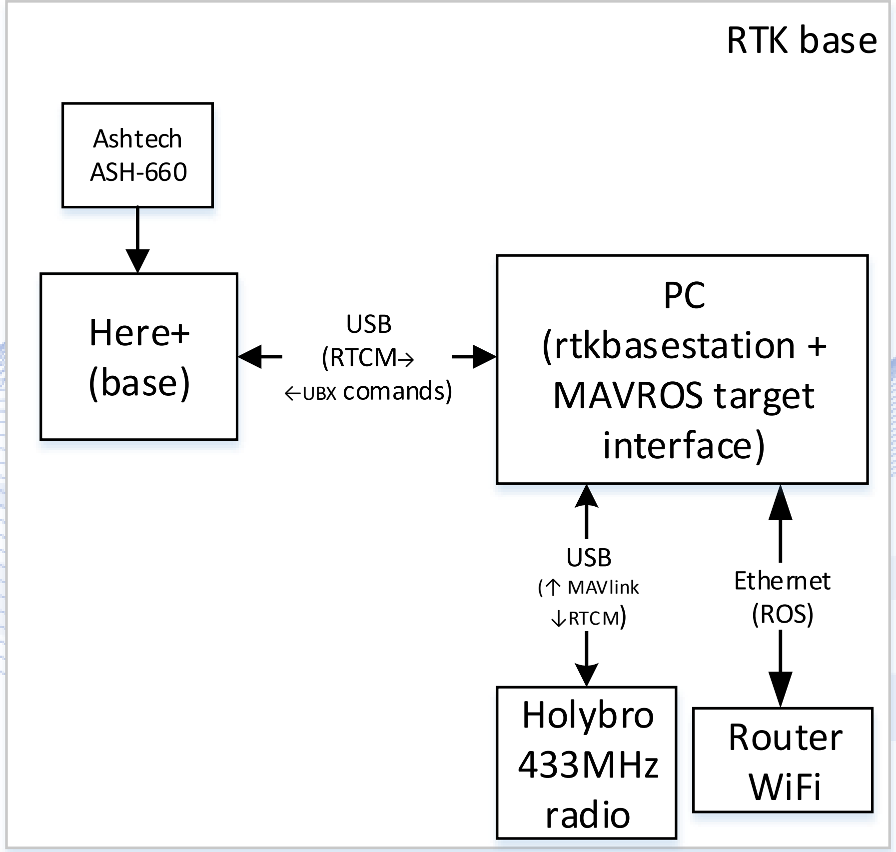




RTK-GPS receiver.

GPS Target Tracking





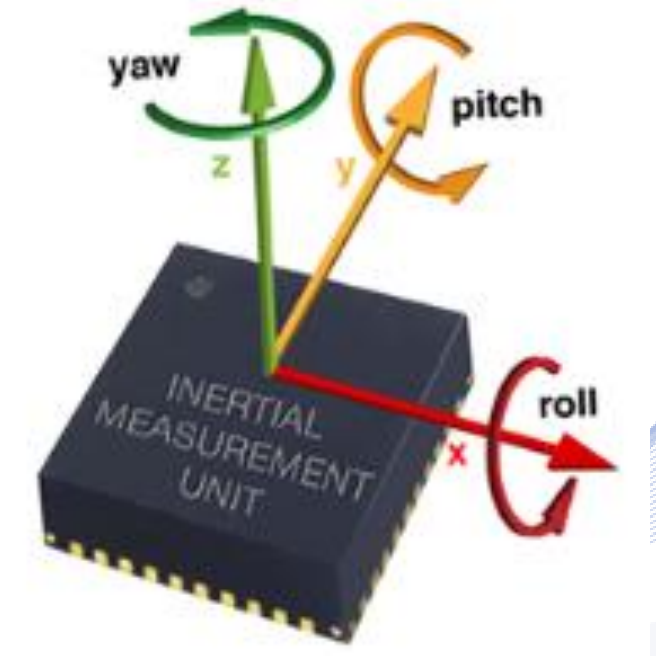
On-target RTK-GPS receiver.

IMU

Inertial Measurement Unit **(*IMU*)**:

- It measures and reports a body's specific force, angular motion rate and, sometimes, the magnetic field surrounding the body.

- It uses a combination of accelerometers, gyroscopes and, sometimes, also magnetometers/electronic compass.



Monocular images

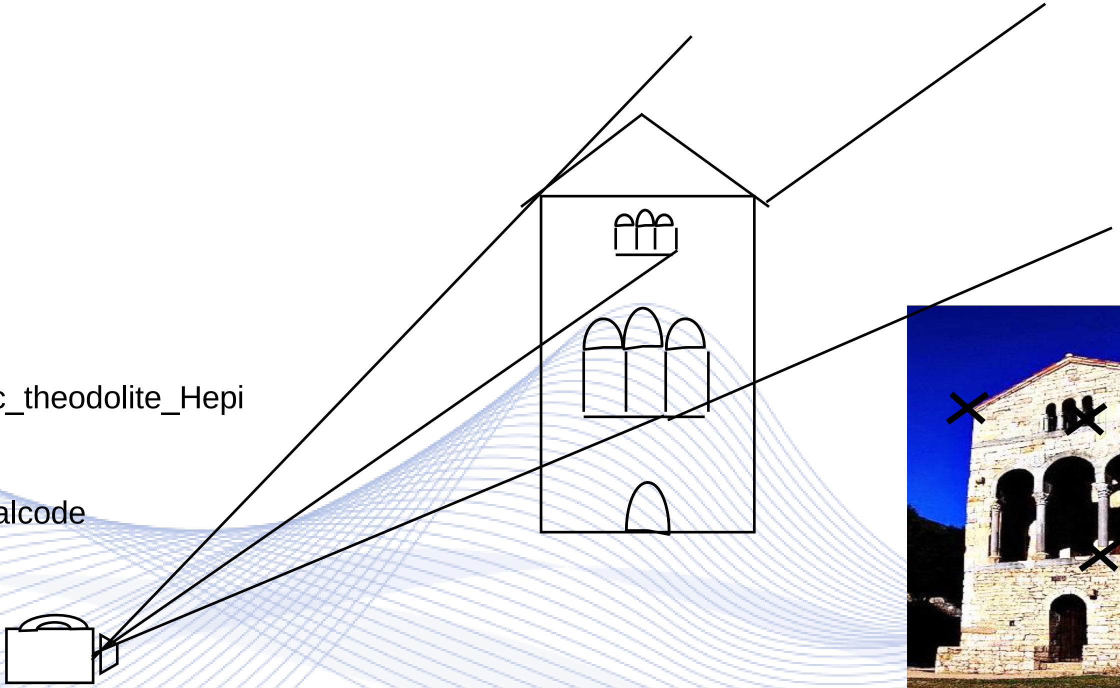
- A single monocular image does not convey depth information.
- But it can detect points at any range.

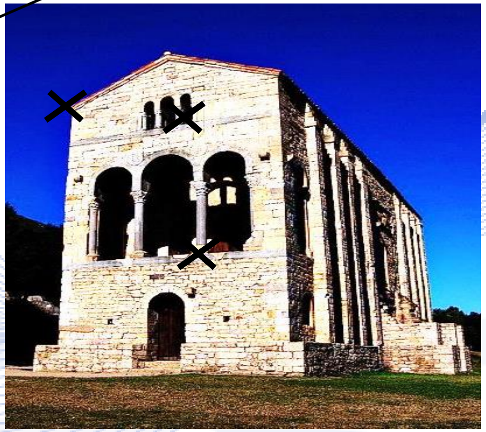
https://www.youtube.com/watch?v=8LWZSGNjuF0

Calibrated monocular image

- Light rays can backproject a target image to the 3D world model.
  - ***Azimuth*** and ***elevation*** angles per pixel of this light ray can have accuracy ranging from $0{,}1^o$ to $0{,}01^o$ degrees.
  - Color of the reflected light is available for each scene point on a per pixel basis.
  - Millions of pixels per image.
  - Tens of images per second.

Calibrated monocular image



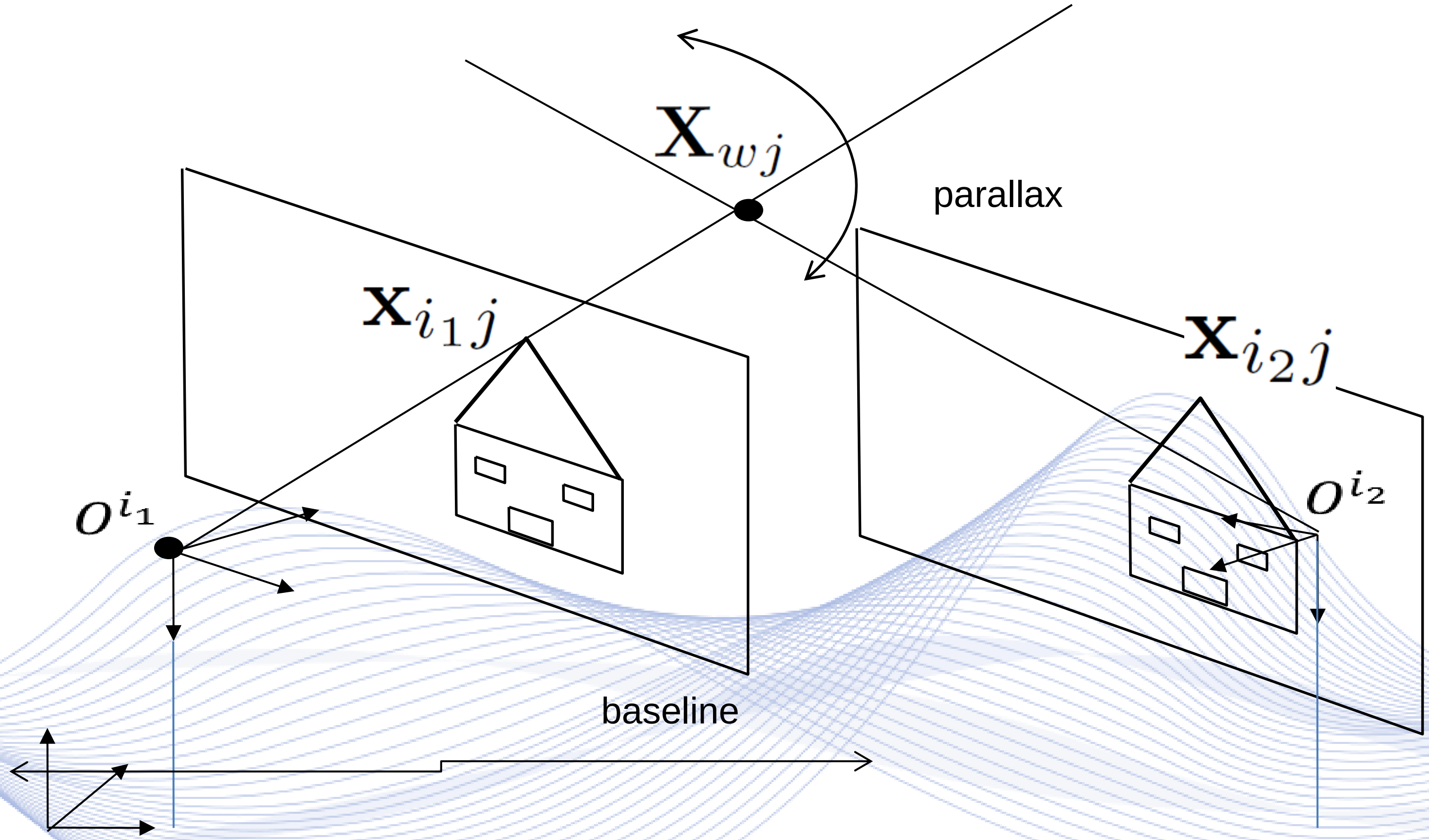


Stereo imaging

- Two cameras in known locations.
- Calibrated cameras.
- Stereo images can create a disparity (depth) map.
- Their range (in m) is limited, when high accuracy is desired.

Stereo image pair of a forest road.

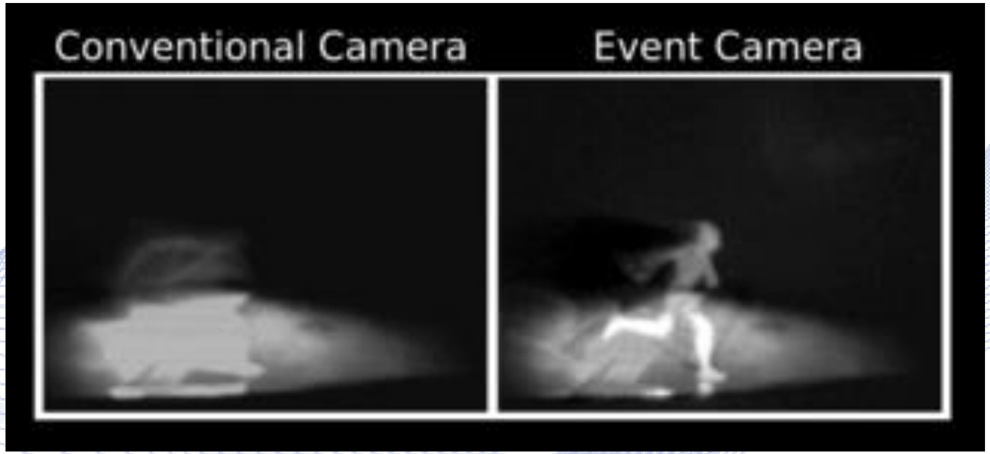
Stereo Imaging



Geometrical accuracy depends on parallax angle.

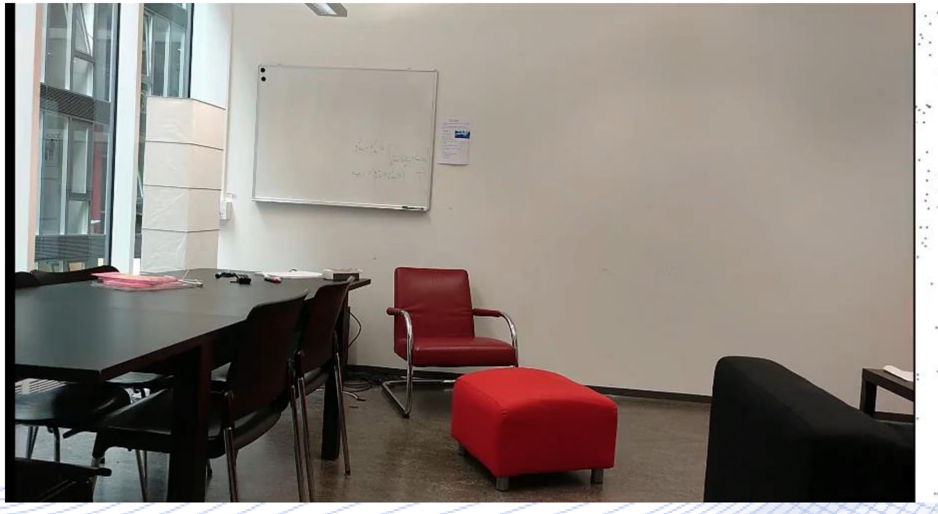
Event cameras

- Novel sensor that measures only ***scene motion***.
- Low-latency (~ 1 μs).
- No motion blur.
- High dynamic range (140 dB instead of 60 dB).
- Ultra-low power (1mW vs 1W).
- Traditional vision algorithms do not work!

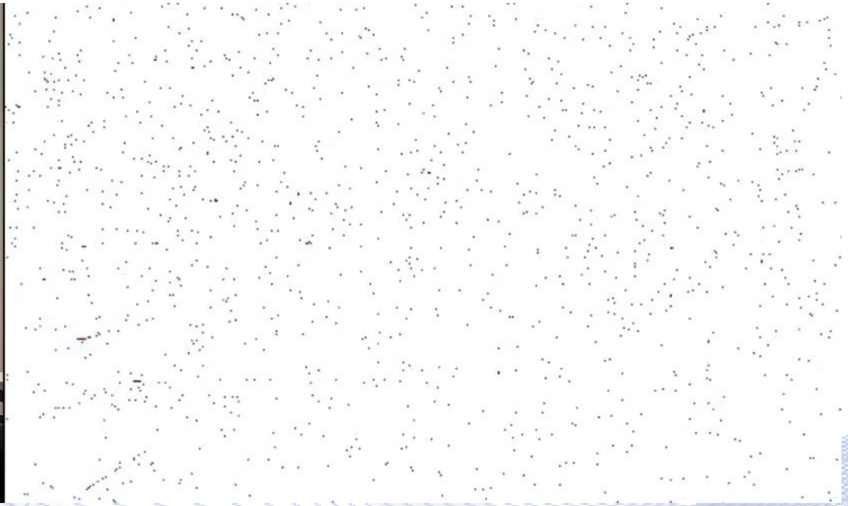


Event cameras

Standard Camera



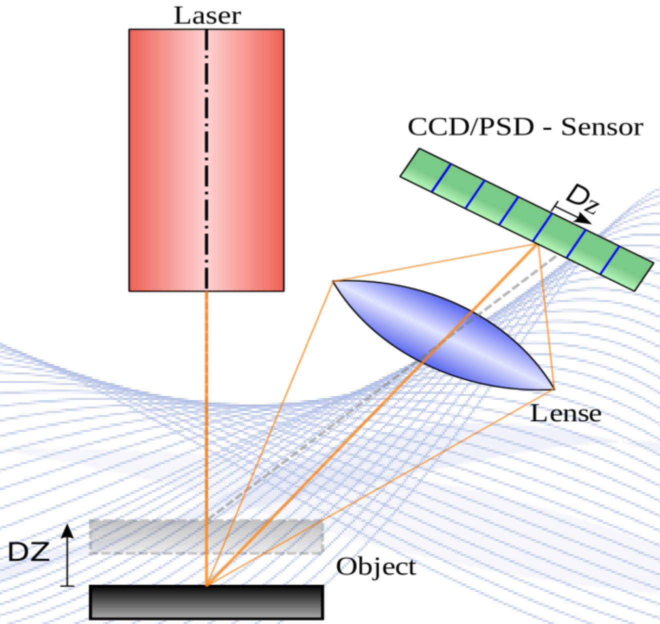
Event Camera (ON, OFF events)



Δt = 40 ms.

Laser scanning

A ***3D laser scanner*** uses a technique that employs reflected laser pulses to create accurate digital models of existing objects.



Laser scanning.

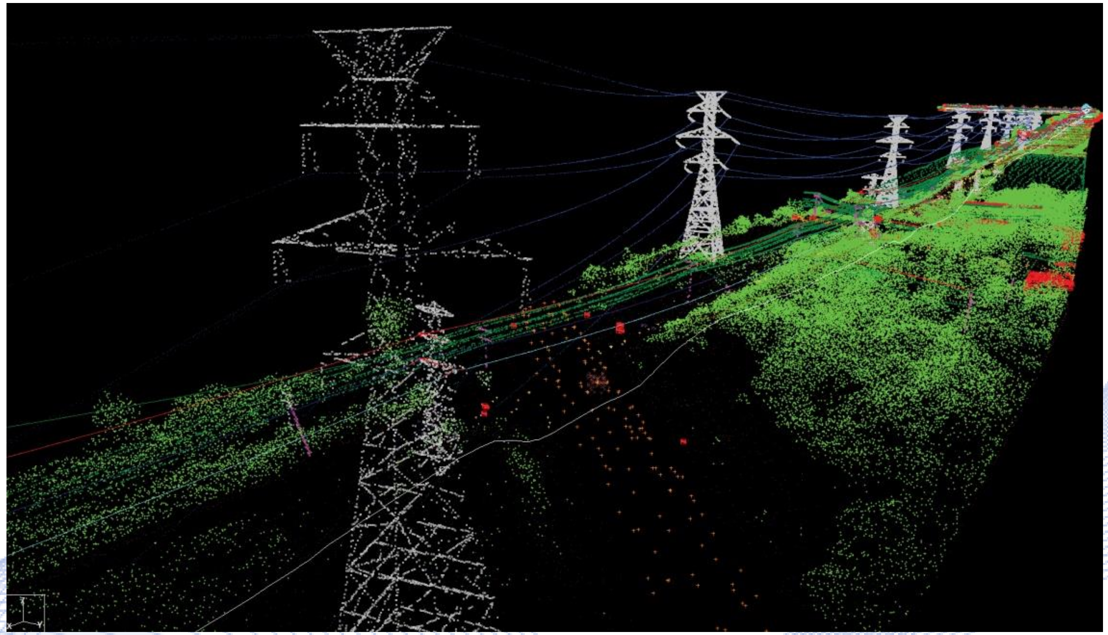
Laser Range Finder

- It emits laser pulses which travel to the ground/obstacle surface, where they are reflected.
- Part of the reflected radiation is detected by the device and stops a time counter started when the pulse was sent out.
- The distance is calculated using the speed of light.

  Typical range 1200 m.
- ***Laser altimeter*** measures the altitude (height) above a fixed ground level.

Lidars

- Lidar measures the distance to a target by illuminating the target with laser light and measuring the reflected light with a sensor.
- Differences in laser return times and wavelengths can then be used to make digital 3D representations of the target.



http://eijournal.com/print/articles/understanding-the-benefits-of-lidar-data?doing_wp_cron=1517767340.6914100646972656250000

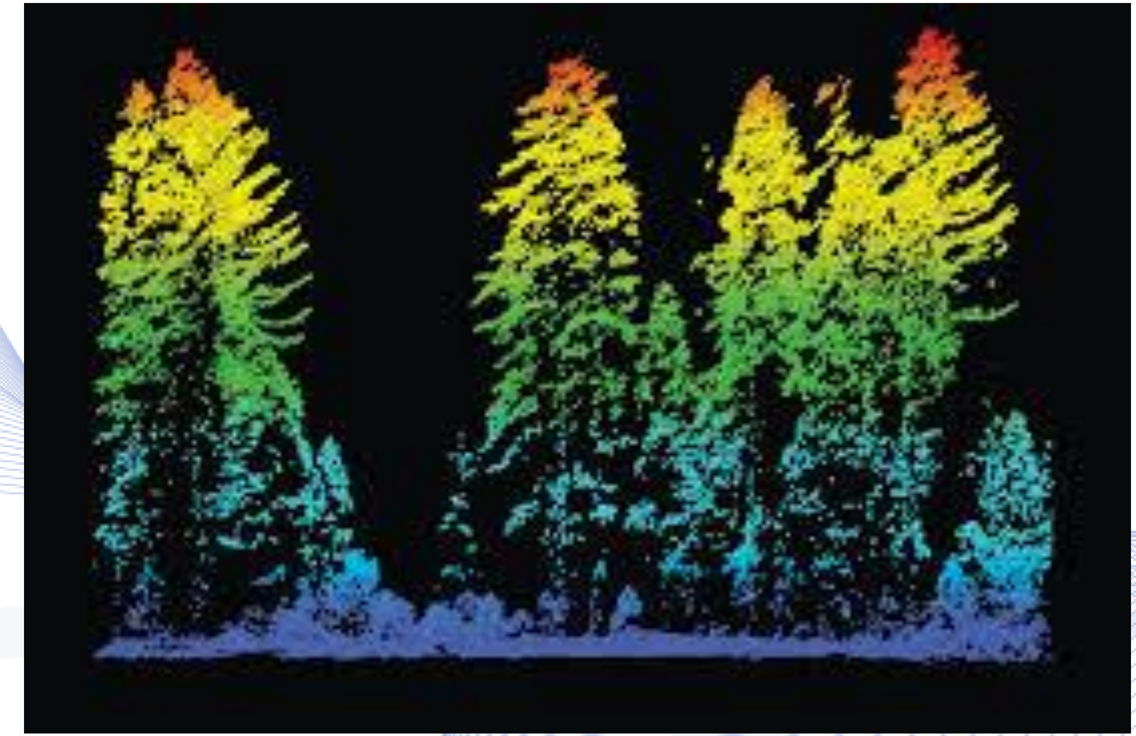
Lidars

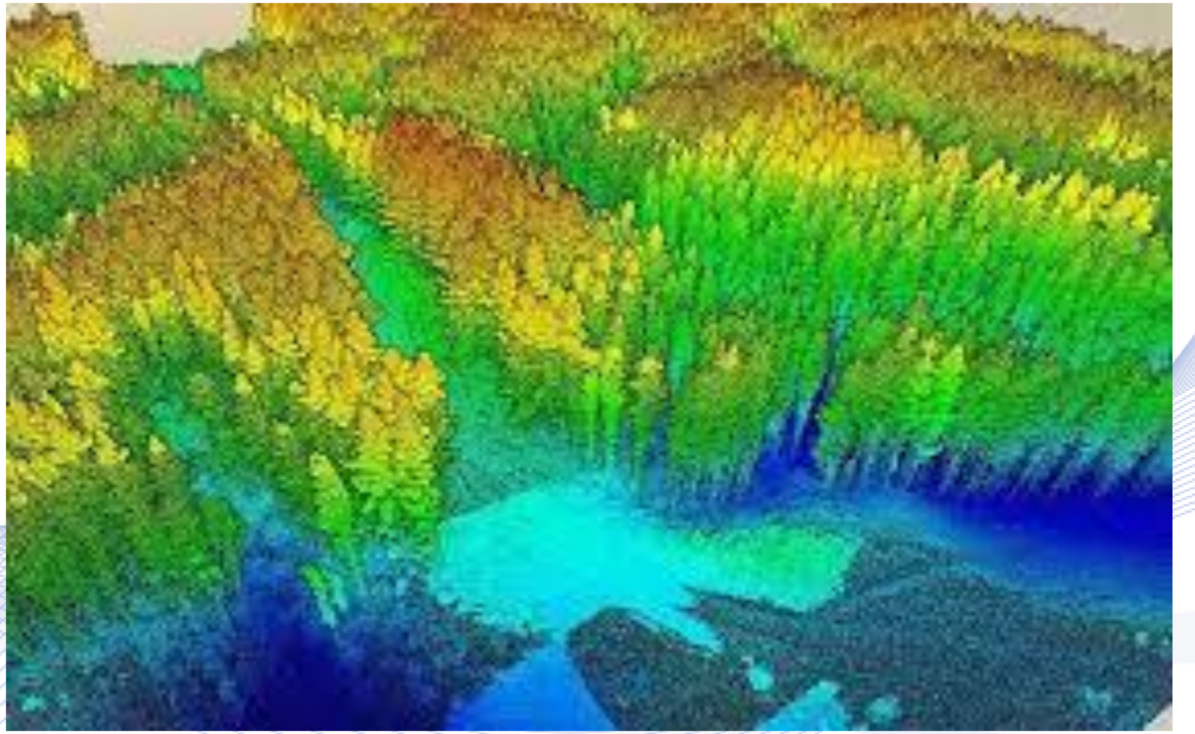
- Lidars provide depth acquisitions at a range of 100 m with a good spatial analysis.
- 3D geometry can be represented by:
  - 3D point clouds;
  - Octomaps or triangulated surfaces.
- Higher-level depth features can be obtained:
  - Depth segmentation.
  - Semantic depth information analysis.

Lidars

- Lidar-generated 3D point clouds are very accurate (much more precise than those provided by cameras).
- Laser pulses may be affected by heavy rain or low hanging clouds, because of ***light refraction***.
- Laser scanning technology does not work well when:
  - there are high sun angles or
  - huge light reflections.
- Lidar laser beams may occasionally affect the human eye.

Lidars





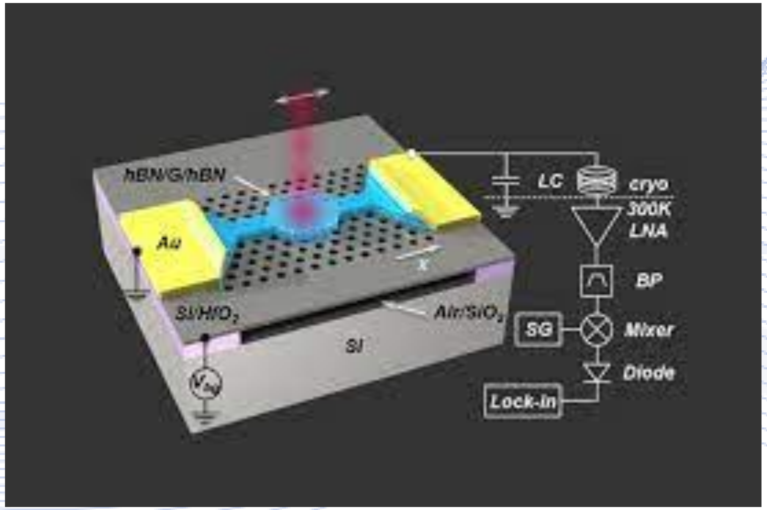
Lidars and forest imaging.

Artificial Intelligence & Information Analysis Lab

IR measurement and imaging

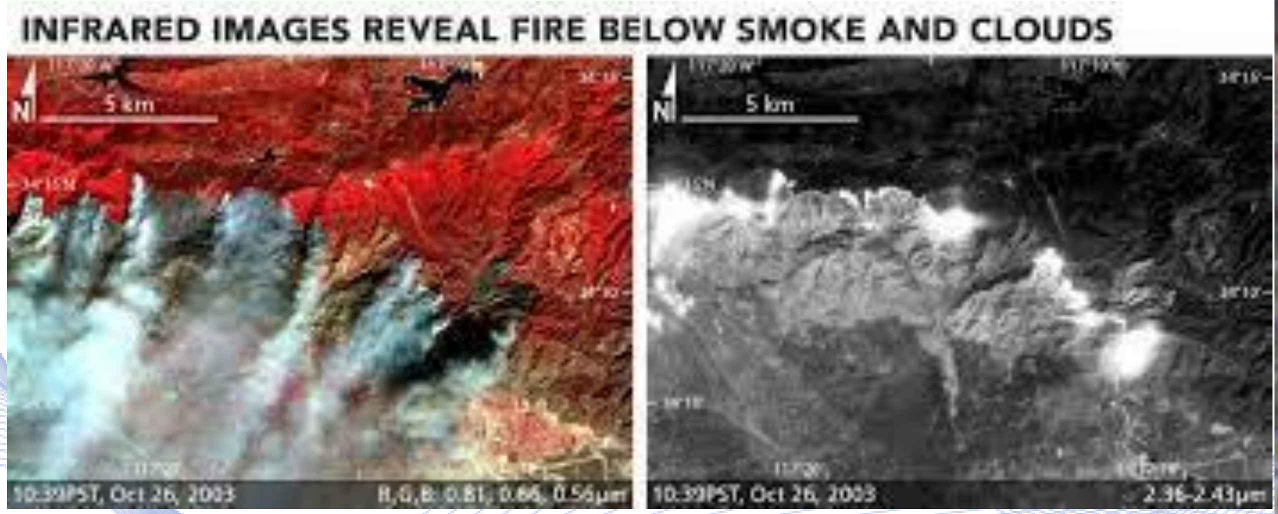
- ***IR cameras*** produce thermal images of an object.
- ***Bolometer*** measures the radiant heat.

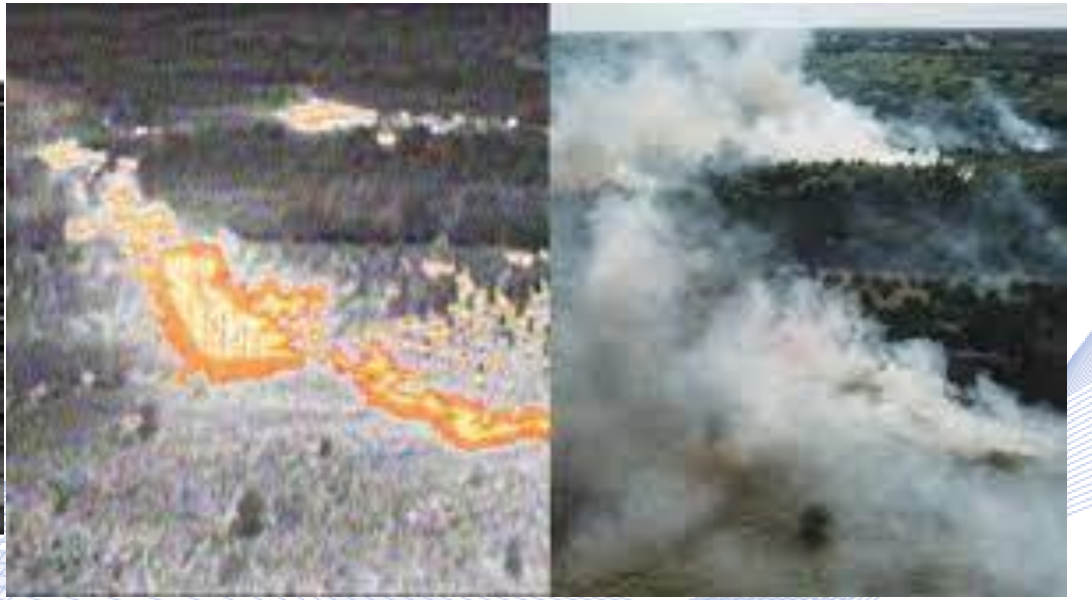
https://www.phase1vision.com/blog/understanding-the-benefits-of-infrared-imaging-cameras



https://phys.org/news/2018-06-bolometer-faster-simpler-wavelengths.html

IR measurement and imaging





IR imaging of forest fires.

Optical Fire Detection Systems

InsightFD Wildfire Detection System (Insight Robotics).

ADELIE (Alert Detection Localization of Forest Fires, Paratronic).

Artificial Intelligence & Information Analysis Lab

Optical beam smoke detection

Detecting absorption or scattering of light.

- It consists of a light transmitter and a photosensitive receiver.
- Portable, can be used for in-situ and remote measurements.
- Prone to false alarms (dust/dirt).

Smoke detector.

Ionization smoke detection

- It uses radioactive element (Americanium-241) to ionize air.
- ***Fire aerosoles change the ionization current***, triggering a detection.
- They are widely used in consumer market for fire detection.
- They provide in-situ measurements only.

Ionization smoke detector.

Lidar smoke detection

It detects smoke instead of fire.

- Remote 3D monitoring.
- Area with ~5 km radius.
- Spatial resolution 15 meters, temporal resolution 5 minutes.

Lidar smoke detector.

Meteorological Sensors

- ***Wind sensors*** determine the wind speed, direction and temperature.
  - Temperature range: [-20°C, +70°C].
  - Altitudes up to 4000m.
  - Lightweight, low power design.

- ***Temperature sensors.***
- ***Humidity sensors.***

UAV Wind sensor.

Drones for ND observation

- External hardware can be attached to drones (e.g., PEC, XR cameras).

- ***Optimal sensor placement.***

- Obstacle Detection technologies.

- SDK for high-level UAV control.

- IP45 ISO Protection level for flight resilience.

Drones for ND observation

UAV Sensors

DJI ZENMUSE H20T and Gimbal.
- Visual Camera: 23x zoom, 20 Mpx, Focal Length (FL): 7-120 mm.
  - Video: 3840×2160(px) @ 30 fps
  - Images: 5184×3888(px)
- Wide angle camera: 12 Mpx, FL 24mm.
- Radiometric Thermal Camera: 640x512px, FL: 13.5 mm, 30Hz
- Laser RangeFinder: 1200m Range.

Drones for ND observation

UAV Sensors

WIRIS PRO camera+ gimbal.

- Full HD 10x Optical Zoom Camera
- IR Camera Resolution px, 18º,32º,45 and 69º IR Lenses
- 7,5-13.5um Vox microbolometer.

Drones for ND observation

Fotokite Sigma

Actively tethered drones

Pros :

- Thermal camera
- Autonomous flight
- Robust Wind Performance
- 24 hour capacity.

Cons :

- Wired connection
- Does not provide 3D information

https://fotokite.com/situational-awareness-system/

Artificial Intelligence & Information Analysis Lab

Drones for Fire Fighting

Extinguish fires using drones (Portugal).

Autonomous Fire Fighting Drones

BEHA M1-AT

- Autonomous flight.
- 10 tons payload capability.
- Possible drone fleet operation.
- ‘Triple box-wing’ configuration which allows it to takeoff and land in a very short time.

Autonomous Fire Fighting Vehicles

https://www.popsci.com/technology/estonian-firefighting-robot/

Autonomous NDM Vehicles

Clemson University
Deep orange

- Off road autonomous driving
- Equipped with lidars, cameras, and high-accuracy GPS.
- Energy management strategies.

MISSION SCENARIOS

COLD WEATHER
DISASTER RELIEF

URBAN
RECONNAISSANCE

http://cuicardeeporange.com/project/do13/

Artificial Intelligence & Information Analysis Lab

Autonomous NDM Vehicles

Colossus

- Remotely controlled.
- High autonomy: up to 12 hours in operational situations.
- Power: 500 kg carrying capacity and 500 kg pulling capacity.
- Resistant to thermal waves.
- Sized to intervene in both indoor and outdoor environments.

https://www.shark-robotics.com/shark-robots

Big Data Analytics for Natural Disaster Management

- Natural Disaster Management
- NDM Concept and Objectives
- NDM Sensing
- **Big NDM Data Analytics**
- Horizon Europe R&D project TEMA

Artificial Intelligence & Information Analysis Lab

Big NDM Data Analytics

Underlying DNN and CV technologies

- Object detection
- Region segmentation

NDM cases

- Fire detection/segmentation
- Flood detection/segmentation

Big NDM Data Analytics

Social Media Analytics

- Geosocial analytics
- Semantic topic extraction
- Text sentiment analysis

Fast NDM Data Analytics

- DNN acceleration

Big NDM Data Analytics

Trustworthy NDM Data Analytics

- DNN robustness
- Privacy protection
- DNN Explainability

Other NDM Data Analytics Issues

- Information fusion
- Visualization tools

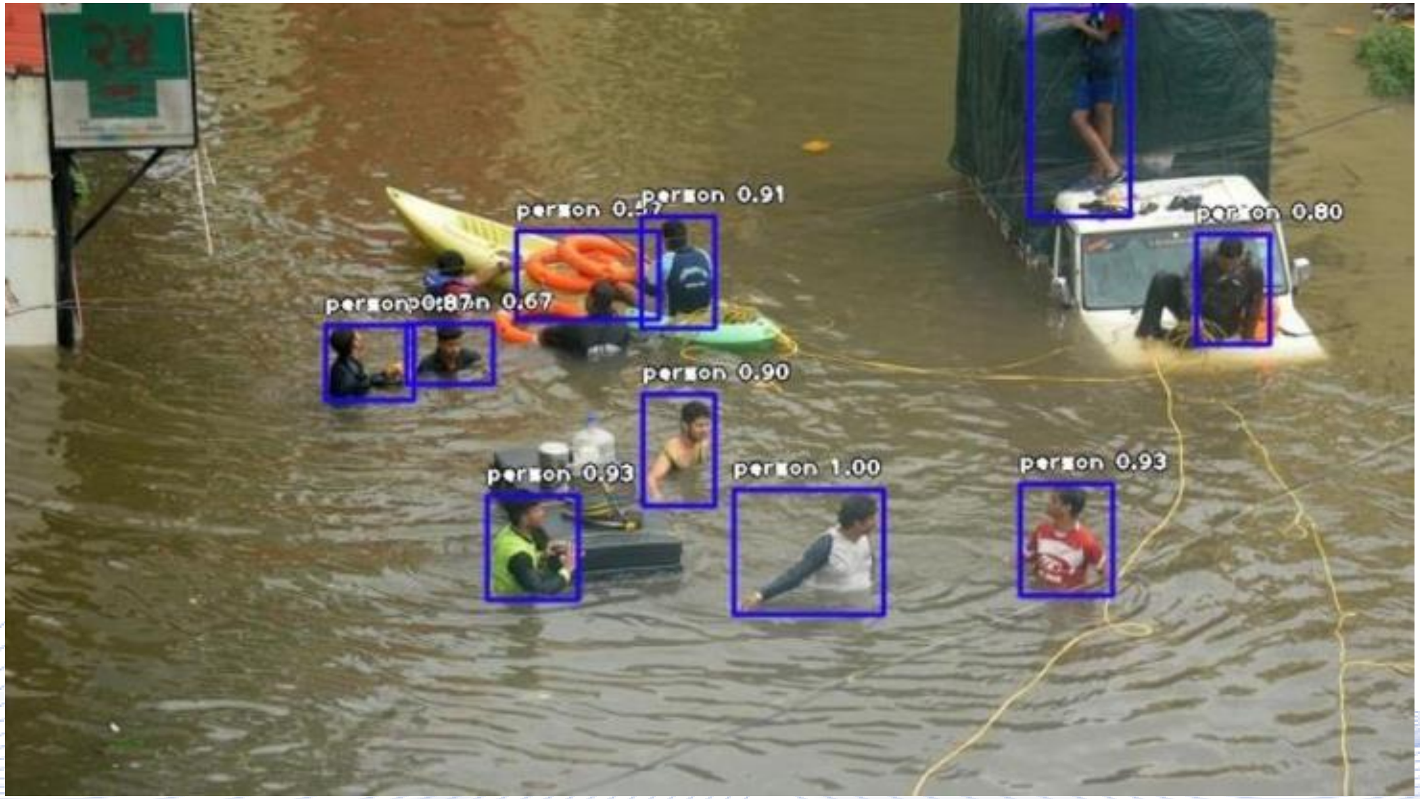
Object Detection

Object detection and tracking.

- Periodical object detection followed by object tracking.
- Tracking is much faster than DNN object detection.

- Problems due to occlusion, self-occlusion or clutter.

Person Detection



Person detection in a flooded area.

Image Segmentation

Crowd detection, segmentation and tracking.

Segmentation of a crowd area.

Image Segmentation

Flooded and burnt area segmentation.

Segmentation of a flooded area.
This video is from the flood in Mandra, Attica region, Greece (2017).

Fire Detection

Why new Mean Average Precision?

- Fire is an object with no fixed shape, leading e.g., to over/mis-segmentation.
- In this scenario, classical Mean Average Precision is not a good detection performance measure.
- The proposed new Mean Average Precision uses the ***Intersection over Union*** (IoU) of all predicted and all ground truths bounding boxes.
-

Fire region bounding box predictions.

Fire Detection

Intersection Over Union between a prediction and a ground truth (IOU)

$$IOU(PRED, GT) = \frac{area(PRED \cap GT)}{area(PRED \cup GT)}$$

Intersection Over Union between all predictions and all grounds truths (IMIOU)

$$IMIOU(PRED, GT) = \frac{area((PRED_1 \cup ... \cup PRED_N) \cap (GT_1 \cup ... \cup GT_M))}{area((PRED_1 \cup ... \cup PRED_N) \cup (GT_1 \cup ... \cup GT_M))}$$

3 TP – 0 FP

1 TP – 2 FP

0 TP – 3 FP

Based on IOU

IMIOU=0.78 -> TP

IMIOU=0.6 -> TP

IMIOU=0.51 -> TP

Based on IMIOU

Fire Detection

- Training Dataset:
  31.000 images(over 15.000 annotated fire images).

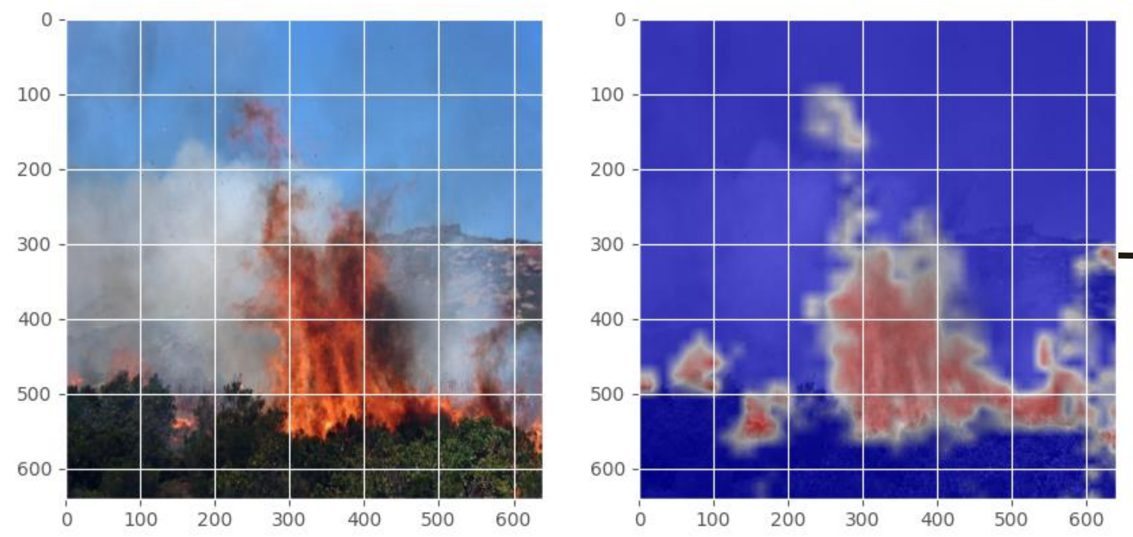
- Trained object detection architectures:
  CNNs as backbone (ResNet50).
  Transformers as backbone (Visual Transformers - ViT).

Results on a new Mean Average Precision (IoU threshold = 0.5).

CNN	ViT
89.97	87.66

Fire Detection

Improved Visual Transformers as backbones for fire detection tasks.



A vector embedding mechanism adds more weight on the corresponding ‘fire’ vectors of the ViT output.

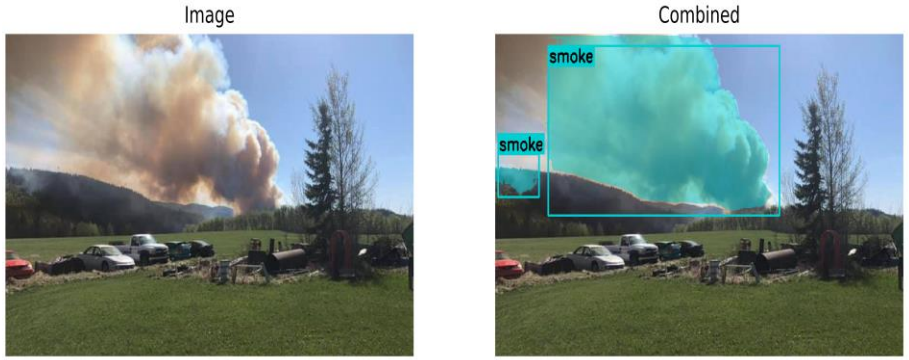
Improved new Mean Average Precision.

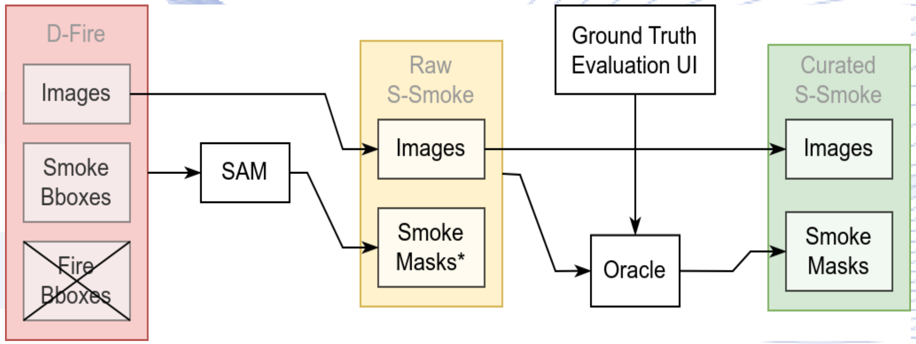
CNN	ViT	Weighted ViT
89.97	87.66	92.05

Fire Segmentation

Framework for smoke region segmentation annotation.

- Smoke bounding box coordinates are used as prompts to SAM API.
- SAM generates smoke region segmentation mask within these bounding boxes.





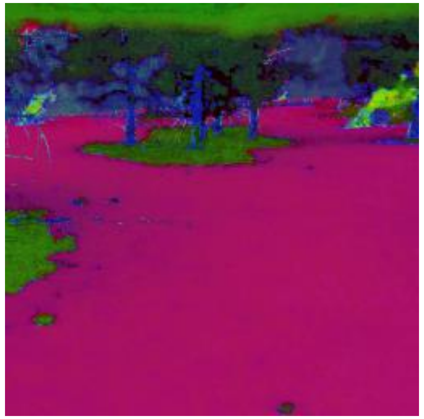
Artificial Intelligence & Information Analysis Lab

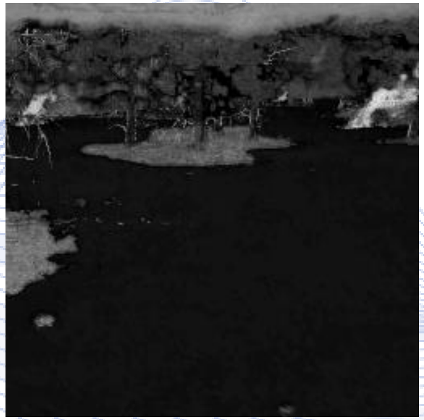
Fire Segmentation

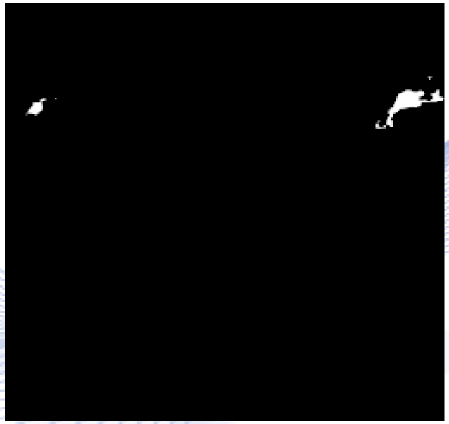
Evaluation of BiSeNet, I2I-CNN and PID-Net region segmentation architectures on:

- Raw RGB images.
- HSV images.
- RGBS images.


RGB input image


HSV transformation of RGB


Saturation channel (S)


Thresholding channel (S)

Interpretable evaluation based on:

- number of fire instances,
- average fire region area (in pixels),
- spatial dispersion of fire region instances.

Fire Segmentation

- Average number of fire sources:

$$D_N = \frac{1}{|I|}\sum_{i=0}^{|I|-1} |N_i - N_i'|$$

- Average fire region area (in pixels):

$$D_A = \frac{1}{|I|}\sum_{i=1}^{|I|} |A_i - A_i'|$$

- Spatial dispersion of fire sources:

$$D_S = \frac{1}{|I|}\sum_{i=0}^{|I|-1} |s_i - s_i'|$$

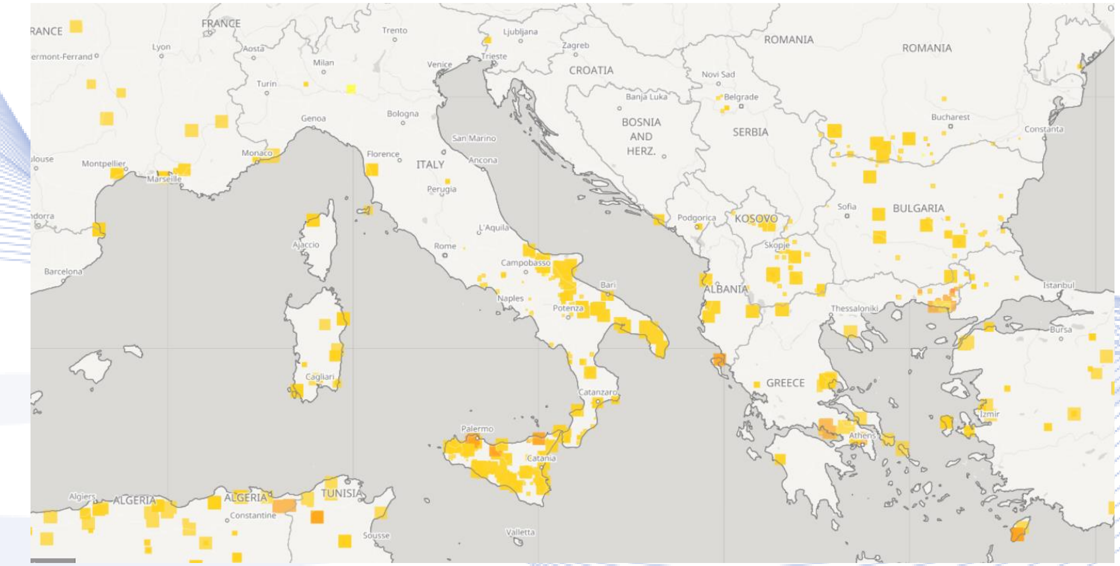
Fire source centers:

$$s_i = \frac{1}{|N|}\frac{1}{|N|-1}\sum_{j=1}^{|N|}\sum_{k=1, j\neq k}^{|N|} \|p_j - p_k\|_2$$

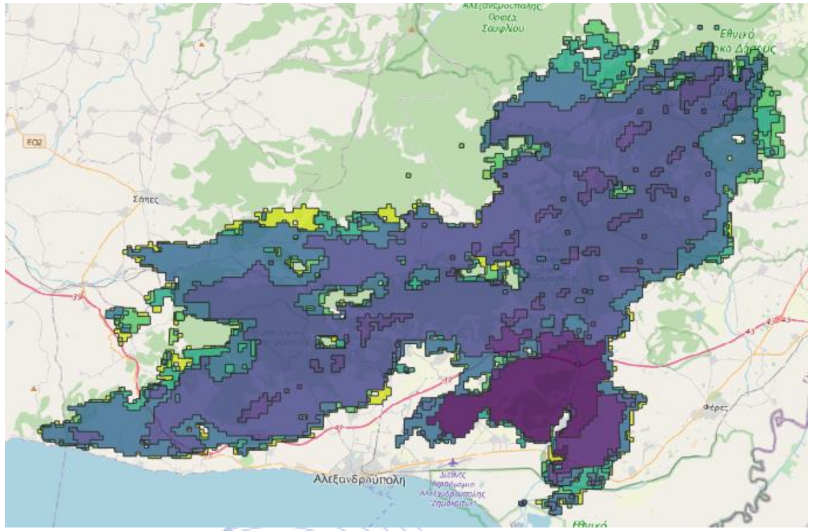
CNN Architecture	Input Data	Evaluation metric			
		mIoU	DN	DA	DS
PID-Net-R18	RGB	**0.914**	0.300	0.150	0.0149
	RGB+HSV	0.911	0.308	0.185	0.016
	RGBS	0.912	0.269	0.148	0.013
I2I-CNN-R18	RGB	0.895	0.702	0.326	0.055
	RGB+HSV	0.826	0.961	0.453	0.082
	RGBS	0.829	**0.989**	**0.514**	**0.082**
BiSeNet-R18	RGB	0.904	0.414	0.205	0.019
	RGB+HSV	0.907	0.353	0.190	0.019
	RGBS	0.904	0.372	0.196	0.020
BiSeNet-R101	RGB	0.873	0.45	0.247	0.026
	RGB+HSV	0.865	0.456	0.254	0.027
	RGBS	0.817	0.628	0.390	0.037

Satellite-based Burnt Area Detection

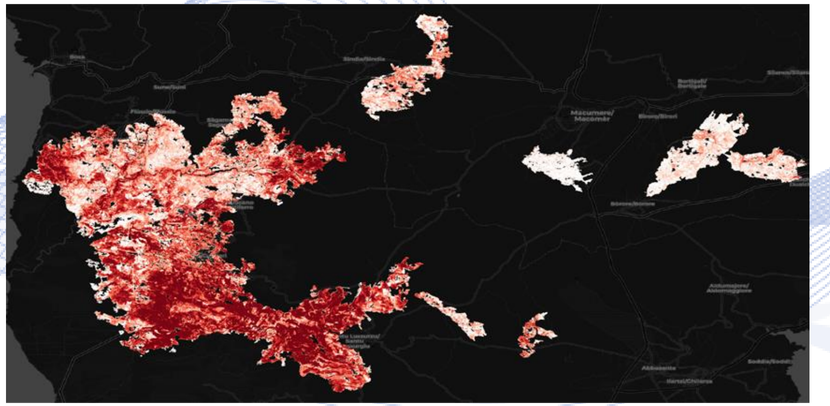
- **Near-real time AI-based burnt area monitoring** with Copernicus Sentinel-3 and MODIS satellite imagery (DLR-DFD)
- Burnt areas, burn severity, fire evolution over time
- It allows monitoring of current wildfire activity throughout Europe (four overpasses per day)



Wildfires South East Europe, from August 01 to September 03, 2023



Wildfire Greece, temporal evolution from August 20 to 30, 2023



TEMA Use case: Montiferru Fire, Sardinia / Italy Sentinel-2, 2021-08-14 10:20:31, Burn Severity

Artificial Intelligence & Information Analysis Lab

DLR

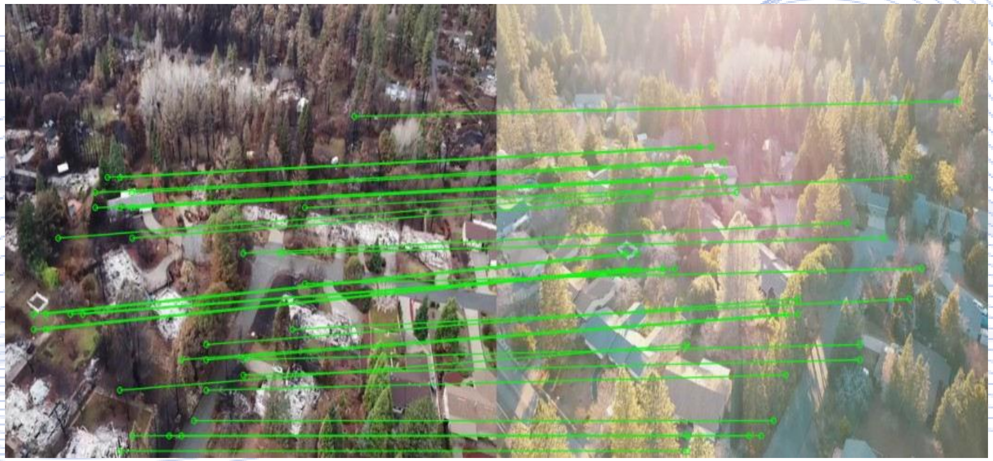
Georegistration

Geovisual analytics refers to the ***analytical reasoning with visual geospatial information***.

- Geospatial data include location information on Earth surface.
- Disaster area images/videos must be geolocalized on ***orthophotomaps***.
- Geolocalized pre-event images and videos.
- ***Georegistration***
  - Visual place recognition DNNs can be used to retrieve a ***pre-event image*** from a database, given a ***post-event image***.
  - RANSAC can find patch correspondences between the two such images.
  - Then the centers of these patches are given as prompts to a region segmentation algorithm to acquire a ***region similarity map***.

Georegistration

Burnt region georegistration.



Burnt region, pre-fire image, and their correspondences.

Georegistration

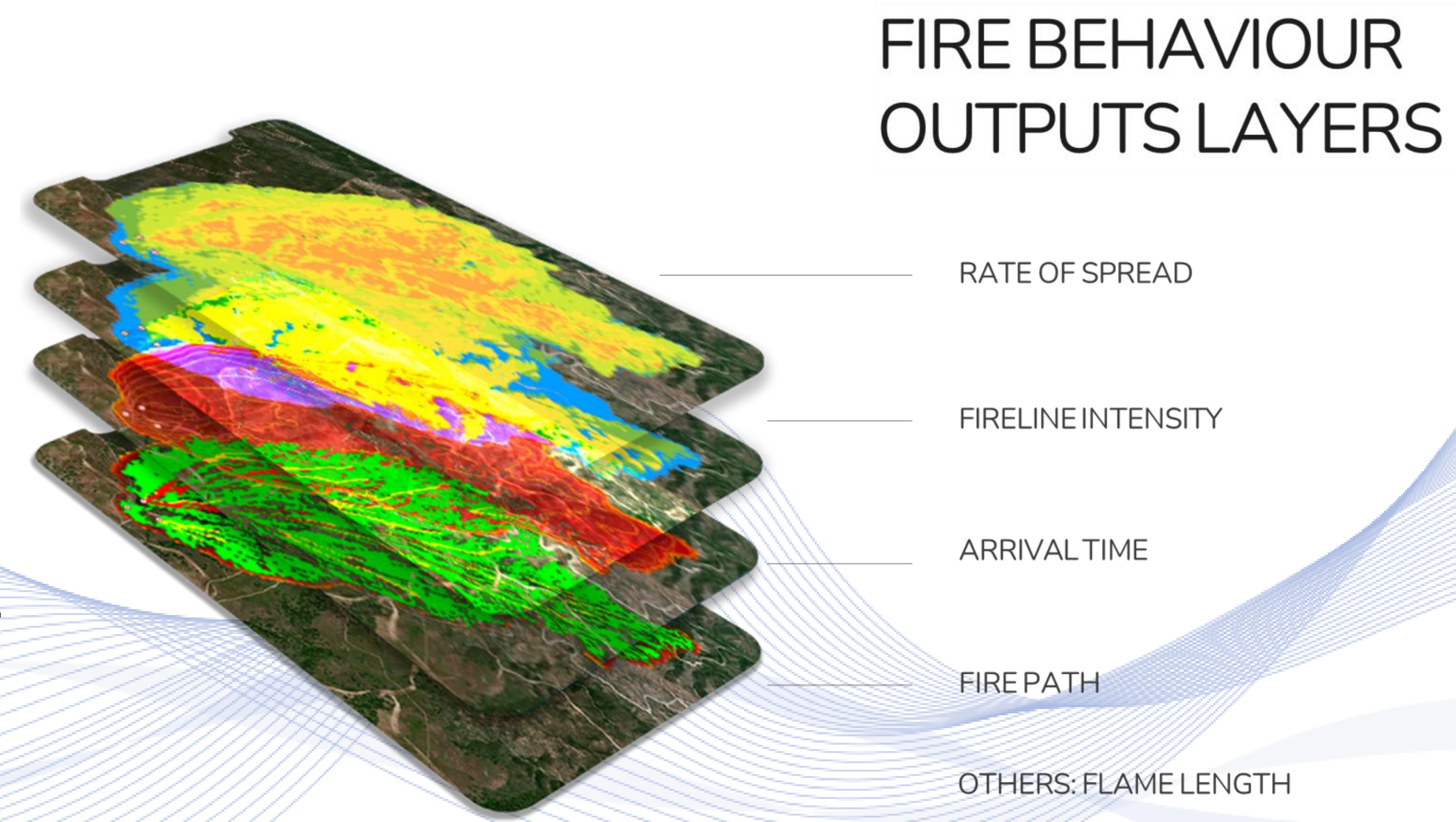
Burnt region georegistration.

Burnt region, pre-fire image, and their similarity map.

Forest Fire Modeling

Simulation of the ***wildfire spread and behavior*** in space and time (Technosylva).

- Effect of meteorological factors and forest modeling.
- Real-time analysis of wildfire behavior.
- Decision making for suppression activities, resource allocation and population evacuation.



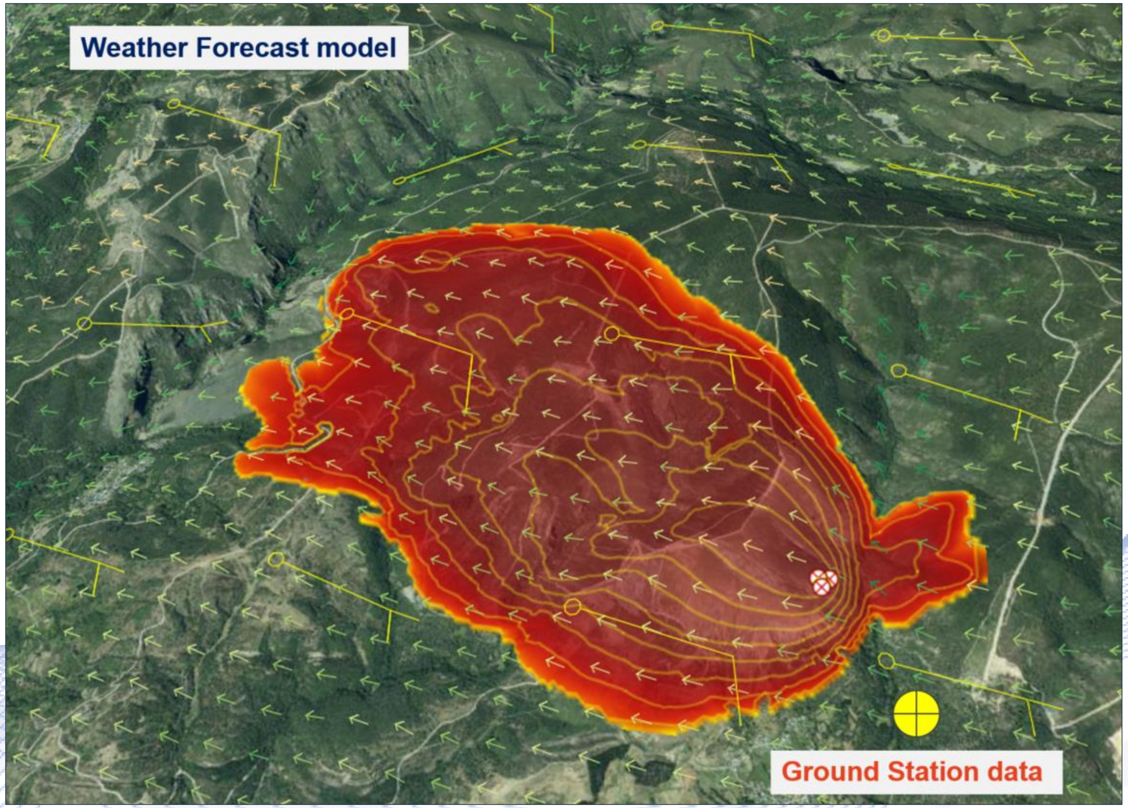
Wildfire Analyst® FireSim.

Artificial Intelligence & Information Analysis Lab

Forest Fire Modeling

Weather Data Model

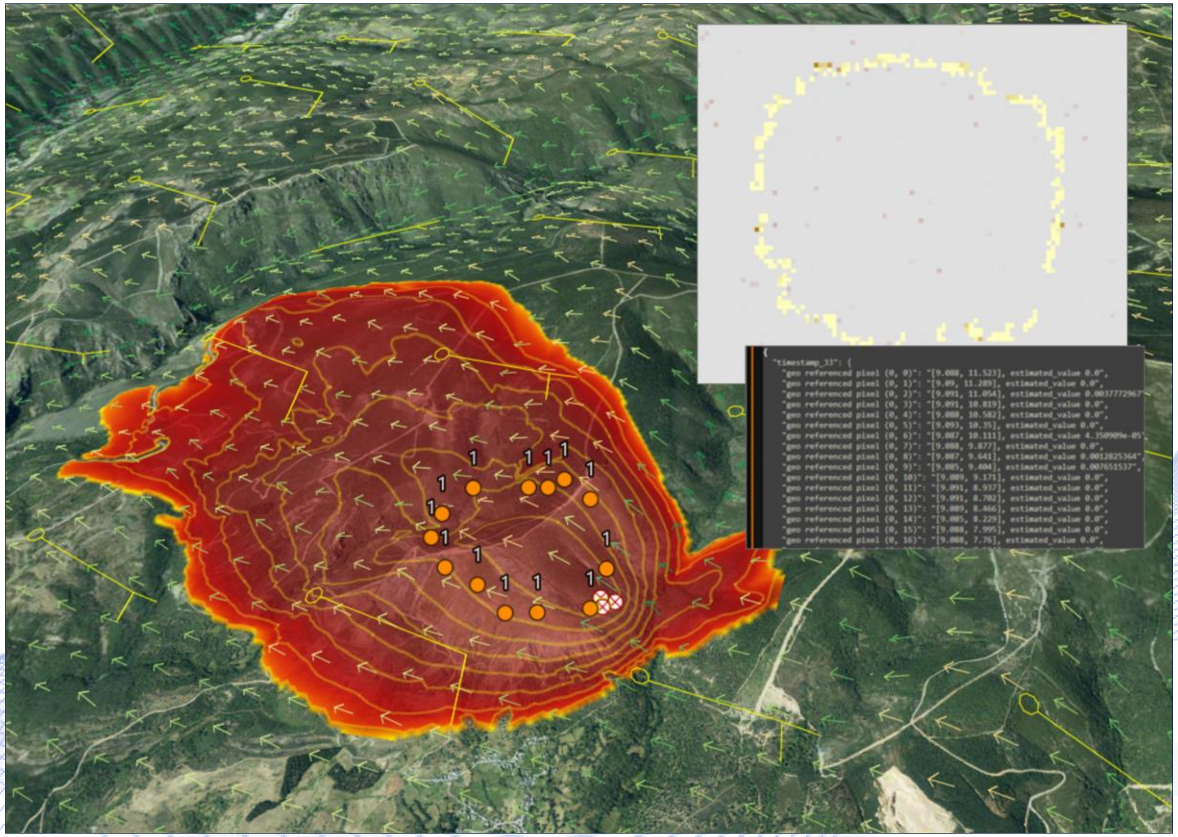
- Weather forecast data: HARMONIE-AROME, GFS.
- Real-time weather data from in-situ sensors.
- Spatio-temporal interpolation (IDW).
- Enhanced weather data model.



Forest Fire Modeling

Simulation Calibration

- Probability maps from Information Fusion.
- Set a probability threshold.
- GeoJSON ingestion for adjustment points.
- Adjustment parameters calculation.
- Run adjustment simulation every time new information is received.



Flood Segmentation

FloodSeg Dataset

FloodSeg training dataset images.

Flood Segmentation

FloodSeg: Training, Validation, Test data sets

- 548 annotated flood images from 3 different sources
- Train-Validation split (ratio 3:1)
- 2 manually annotated videos for testing purposes
- Greek video: 567 frames Italian video: 1204 frames.

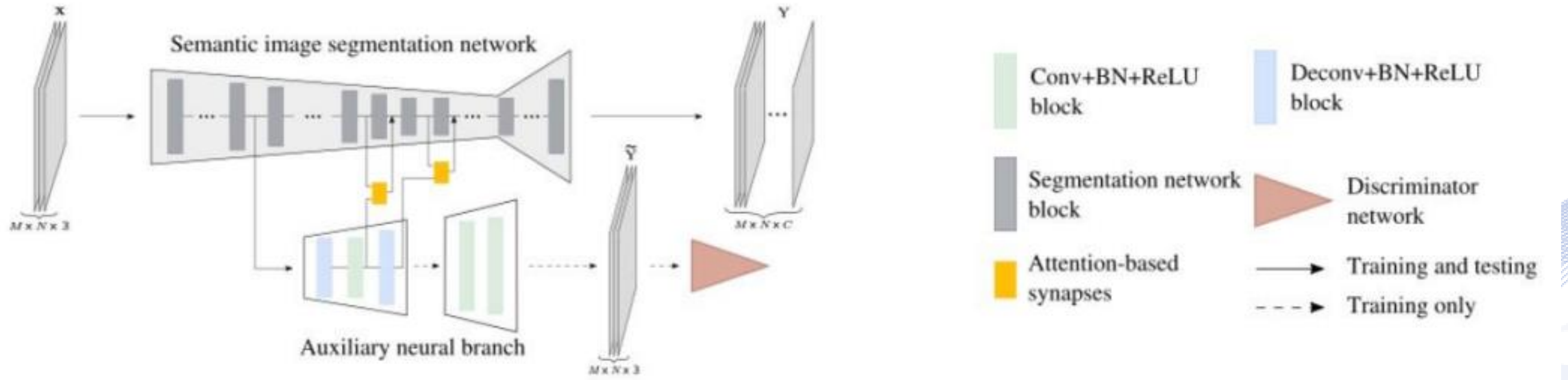
Extended FloodSeg Dataset

- It comprises nlabeled subsets to use via semi-supervised training.
- It contains unlabeled subsets as well as new validation and test sets for distinct geographic regions (Greek and central European floods).

Flood Segmentation

CNN-i2i is a SotA real-time DNN semantic region segmentation model.

- A parallel neural generative branch reconstructs the semantic RGB masks.
- Its features are propagated to the main branch via attention based synapses.
- The chosen main branch is a **Bisenet network** with **Resnet18** as backbone.

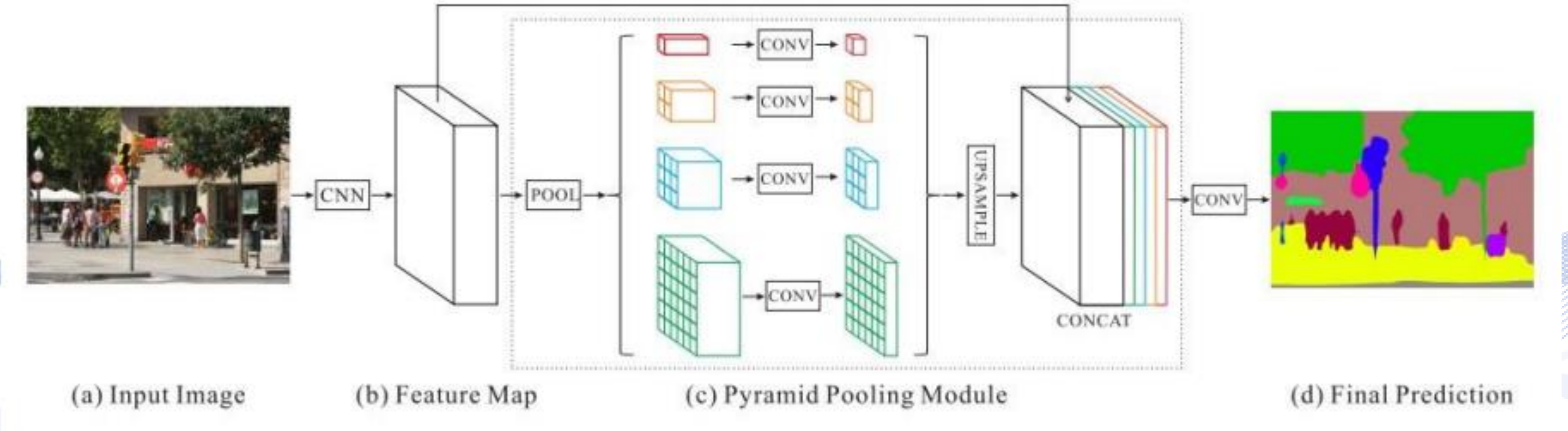


CNN-i2i Architecture.

Flood Segmentation

PSPnet is a benchmark model for semantic segmentation tasks.

- It employs a Pyramid Pooling module, concatenates feature maps of different scales and captures “global” features.
- We chose **Resnet50** as backbone for a lighter implementation.

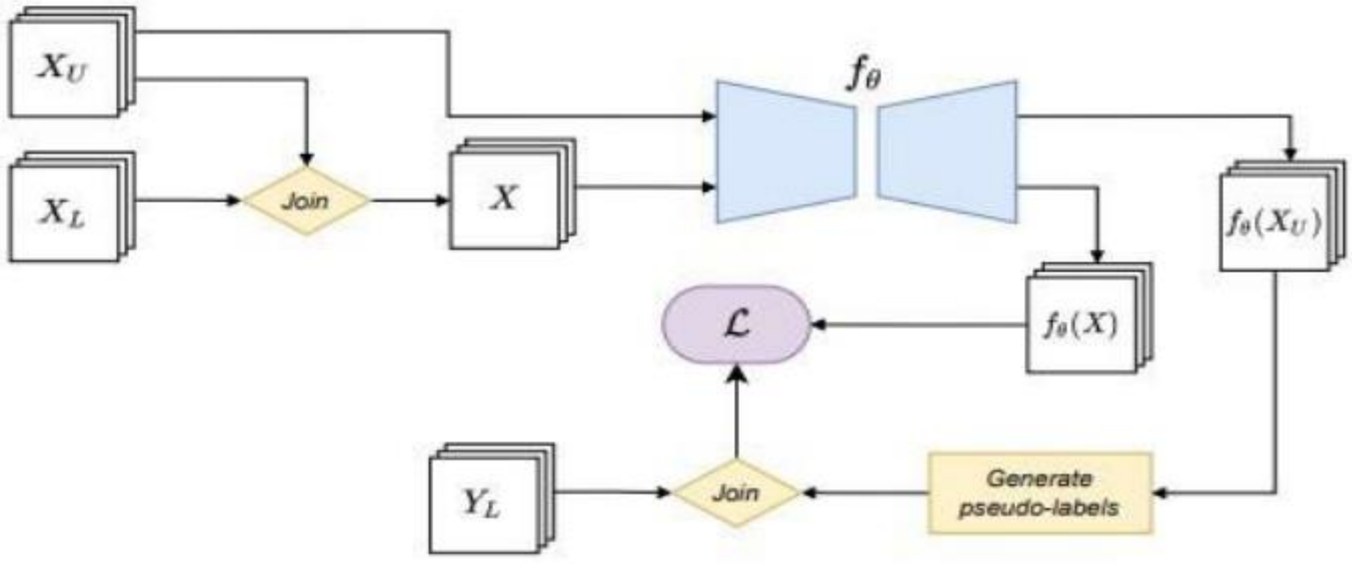


PSPnet Architecture.

Flood Segmentation

Semi Supervised Learning

- **ST++**is a SotA state-of-the-art self-training method for semi-supervised training.
- It pseudo-labels the unlabeled images in two steps (reliable, unreliable).
- Strong unlabeled image dataset augmentation can prevent overfitting to wrong predictions.



ST++ Semi-supervised DNN Architecture.

Flood Segmentation

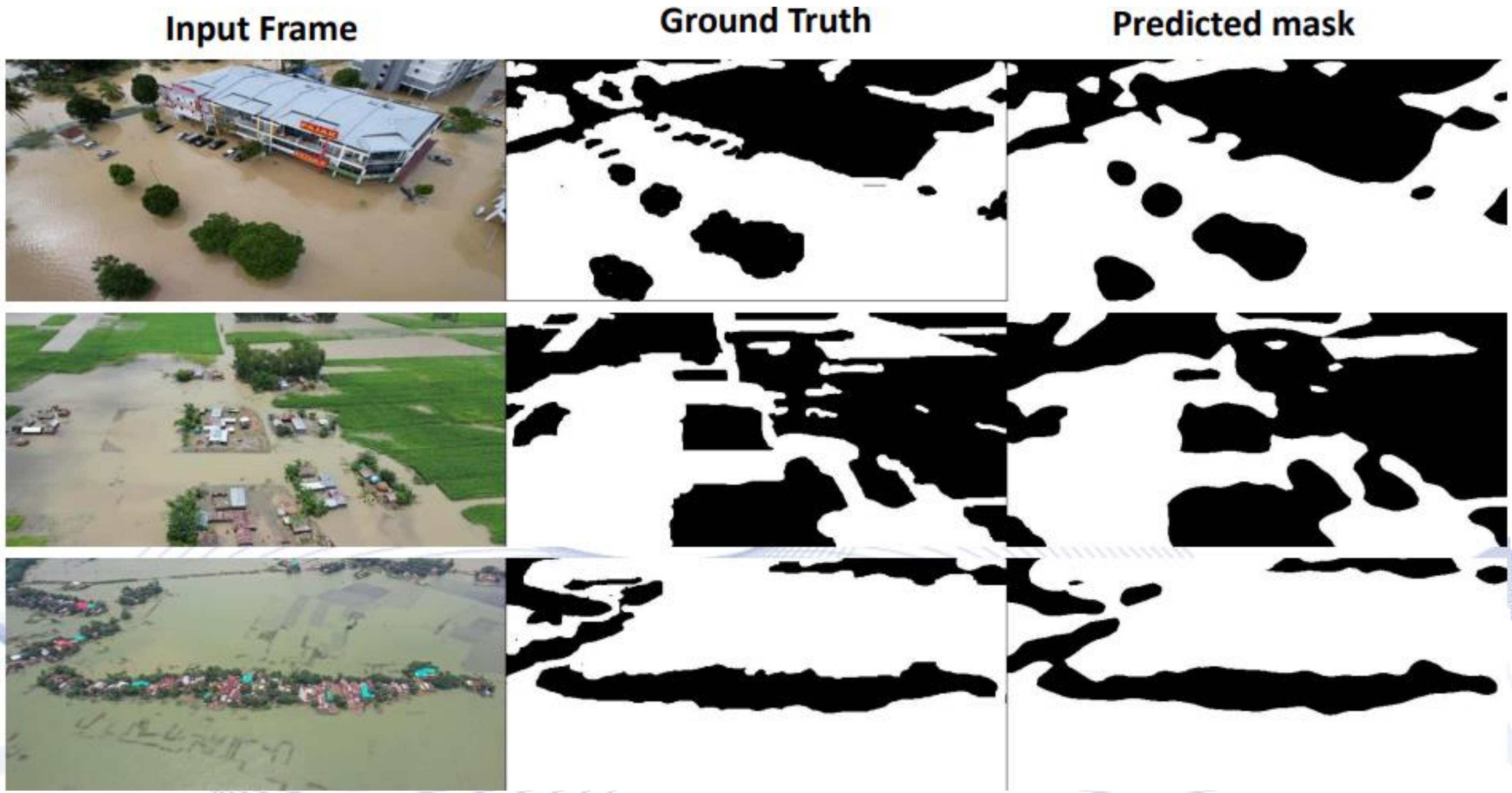
Experimental evaluation of Supervised region segmentation architectures trained on The loodSeg dataset.

Model	FloodSeg val (mIoU)	Greek Test (mIoU)	Italian test (mIoU)	Speed (ms)	FPS
CNN-i2i	**87.65%**	81.48%	**83.07%**	**9.82**	**101.85**
PSPnet	87.49%	**82.94%**	81.84%	12	79.5

Semi-supervised training results with varying number of unlabeled amount of flood image augmentation (PSPnet model).

Unlabeled data amount	FloodSeg val (mIoU)	Greek Test (mIoU)	Italian test (mIoU)
827	88.43%	86.06%	**84.36%**
2430	88.74%	**86.55%**	83.88%
4647	**88.94%**	86.51%	83.89%

Flood Segmentation



PSPnet flood region segmentation.

Flood Segmentation

CNN-i2i flood region segmentation on Ahrtal flash flood images (Germany).

Artificial Intelligence & Information Analysis Lab

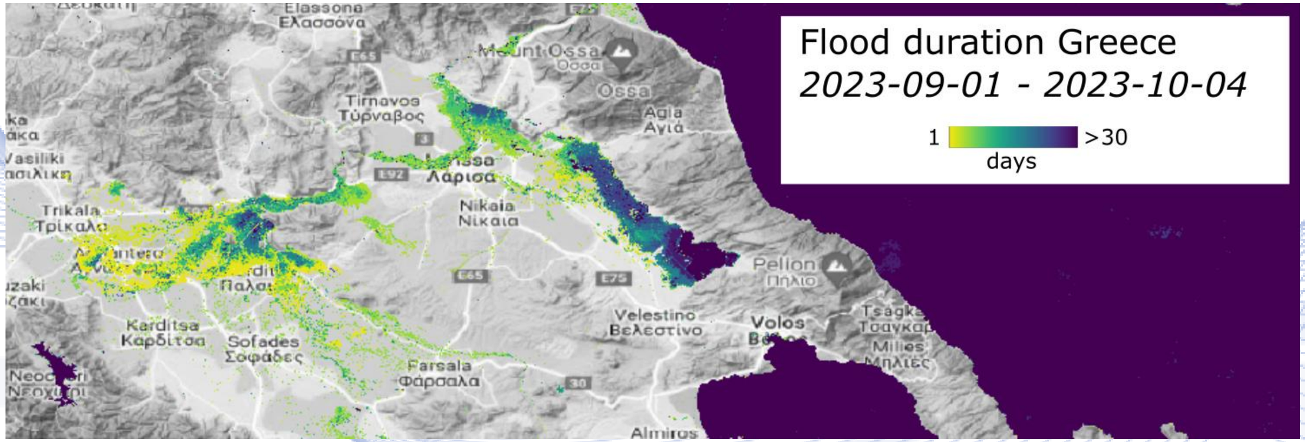
Object Detection and Tracking in Floods

DNN models, pretrained on COCO dataset were used to detect classes of interest (***cars, persons***) that may be in danger.

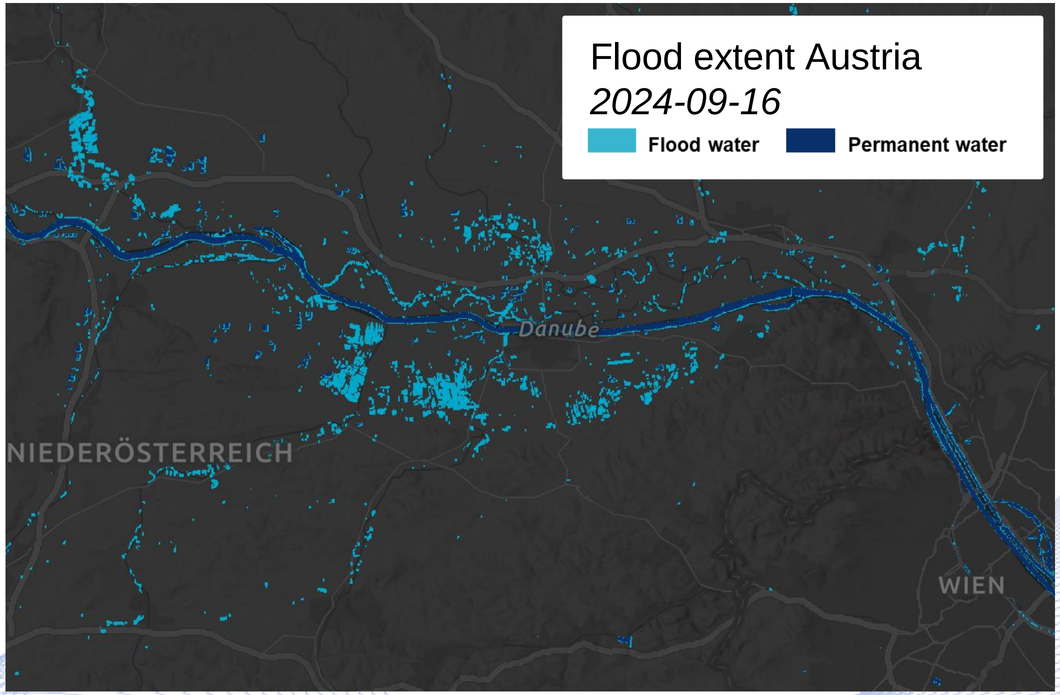
YOLOv6s 4.0 person and car detection in Thessaly floods, Greece (September 2023).

Satellite-based Flood Detection

- **Real-time AI-based flood extent mapping** (DLR-DFD)
- Continuous flood monitoring with Copernicus Sentinel-1/-2 satellite imagery
- Detection of flooded areas, permanent water bodies and flood duration
- Object detection in very high-resolution satellite and aerial images



Flood duration in Greece, September/October 2023, analyzed from Sentinel-1 and Sentinel-2 satellite images



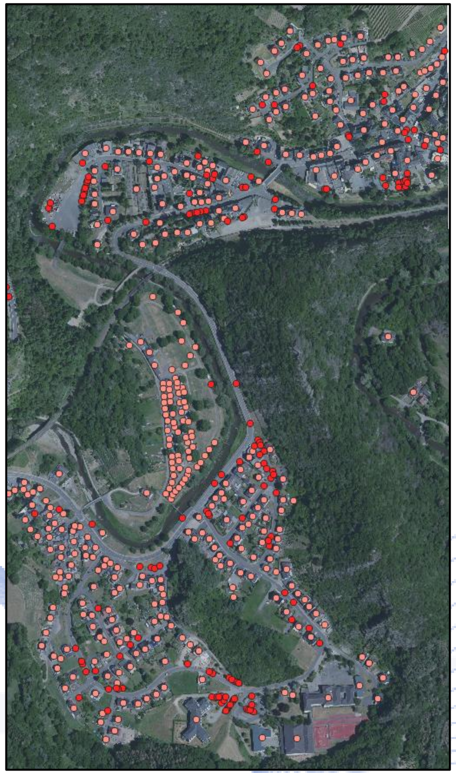
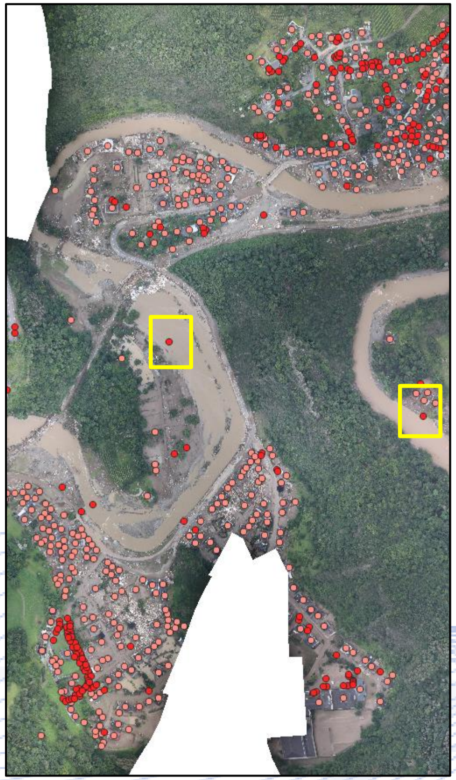
Flood situation, Austria, September 2024

Detected Vehicles
2024-06-04
DLR 3K aerial images

Artificial Intelligence & Information Analysis Lab

DLR

Satellite Flood Image Analysis

Buildings Vehicles

Flood mapping using satellite and aerial images.

Artificial Intelligence & Information Analysis Lab

DLR

Flood Modeling

Hydrodynamic simulation software

(Nelen & Schuurmans)

- Flood modelling in urban-suburban areas.
- Projection of results in a 2D map.

https://3diwatermanagement.com/learn/publications/

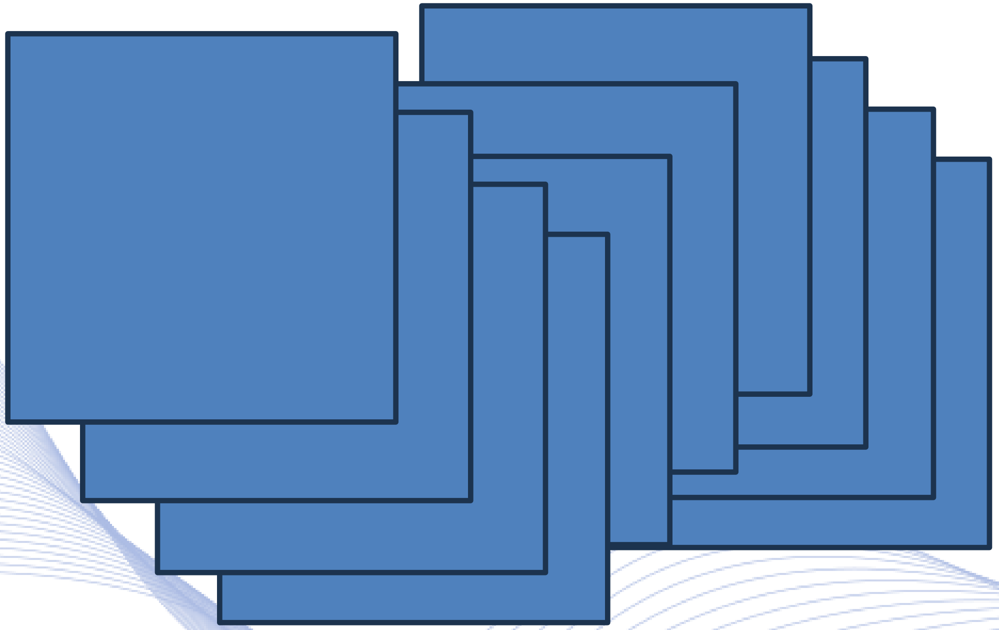
Digital Twins

Generating georeferenced 3D digital twin models (Northdocks)

- Use of drone images/videos and historical data.

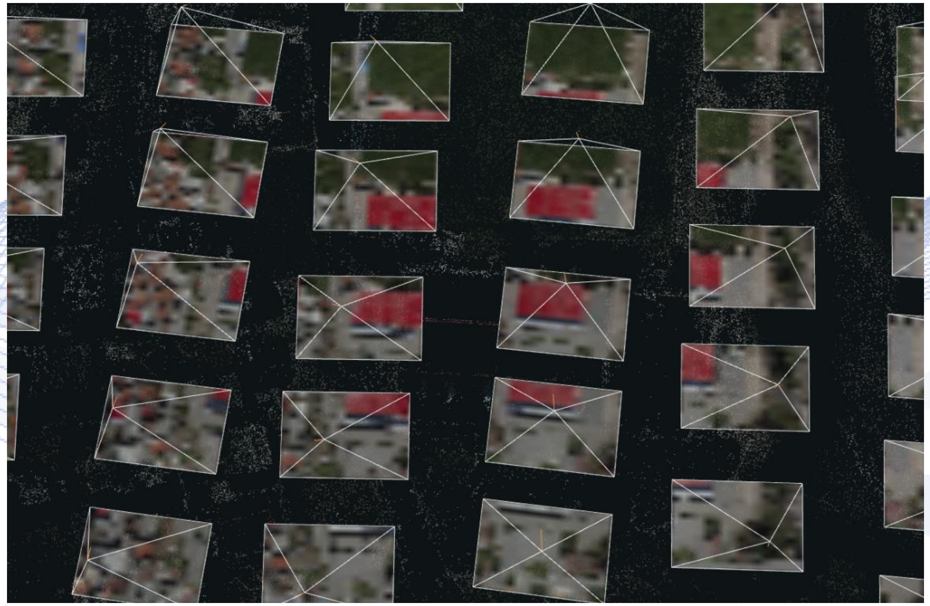
Drone image acquisition and digital twin of Larissa floods (Greece, 9/2023).

Digital Twin



Drone imaging rules.

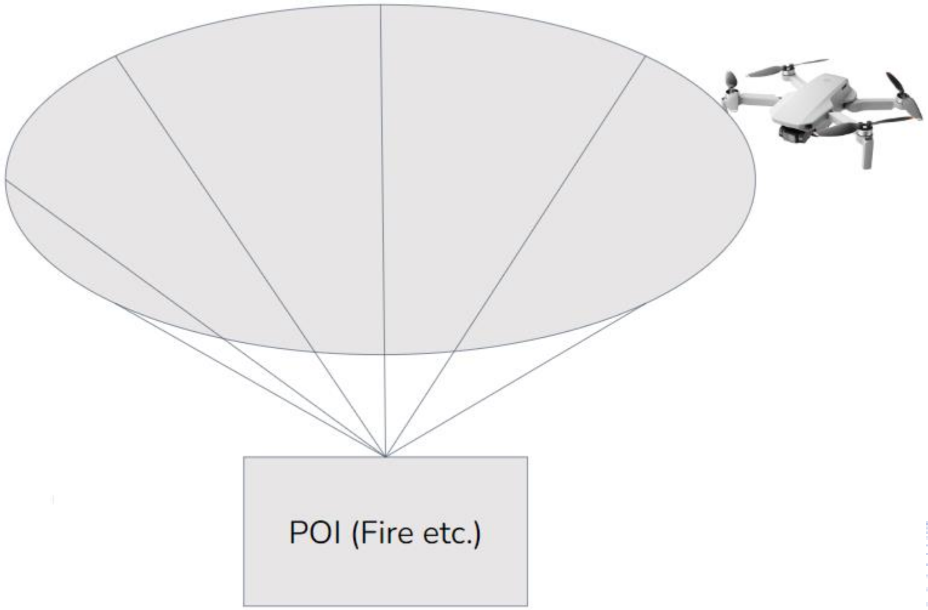
- images must overlap to generate a 3D model from images via SfM algorithms.
- The overlap should be above 70% in every image axes.

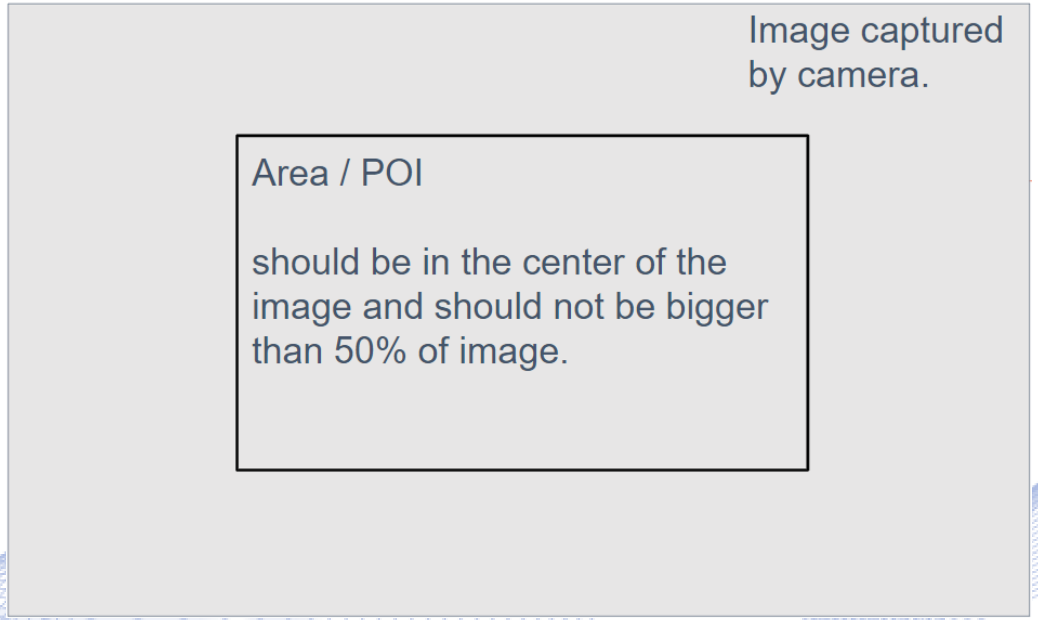


Red roof image overlap in different drone images.

Digital Twin

Drone imaging rules.





- Visualizing a small Point-Of-Interest (POI), e.g., a small fire.
- This drone image acquisition mode can be done by an experienced drone pilot or automatically.

Digital Twin

Figure 22. Screenshot of the 3D model of a flood in the Larissa region using state-of-the-art algorithms.

Figure 23. Screenshot of the 3D model of a flood in the Larissa region (Greece) generated using our optimized processes.

Artificial Intelligence &
Information Analysis Lab

NORTHDOCKS

Digital Twin

Visualization Tools

*Smart desk (*KAMK*)*

- The SmartDesk is an application running on a custom-built touchscreen computer
- The application is a mission management tool for civil protection
- It unifies the information and functionalities of TEMA in a single place
- It can be installed on any Windows PC
- Touch input, mouse, and keyboard are supported

AR visualization

Artificial Intelligence & Information Analysis Lab

KAMK • University of Applied Sciences

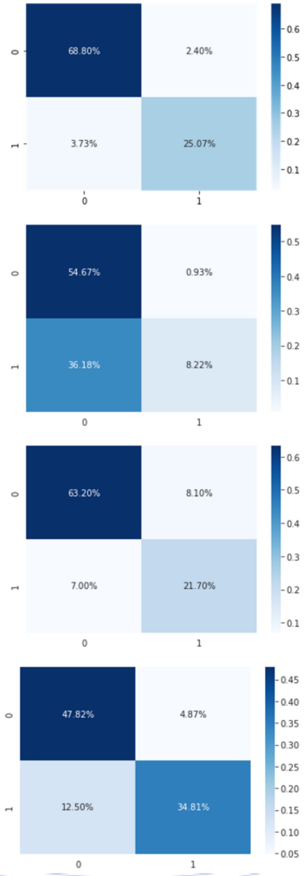
Geosocial Media Analytics

Natural Language Processing (NLP) for Semantic Topic Extraction (U Salzburg)

Understanding what posts talk about:

- Text pre-processing.
- Identification of semantic topics in social media text
- Semantic filtering (relevance).
- Currently testing GPT-3 and GPT neo

Vergleich von semantischen ML-Algorithmen



BERT: Accuracy (F1 Score): 97.3%, Training Accuracy: 99.2%

BERTopic: Accuracy (Current Best - F1 Score): 63%

GuidedLDA: Accuracy (F1 Score): 85%

LDA: Accuracy (F1 Score): 83%

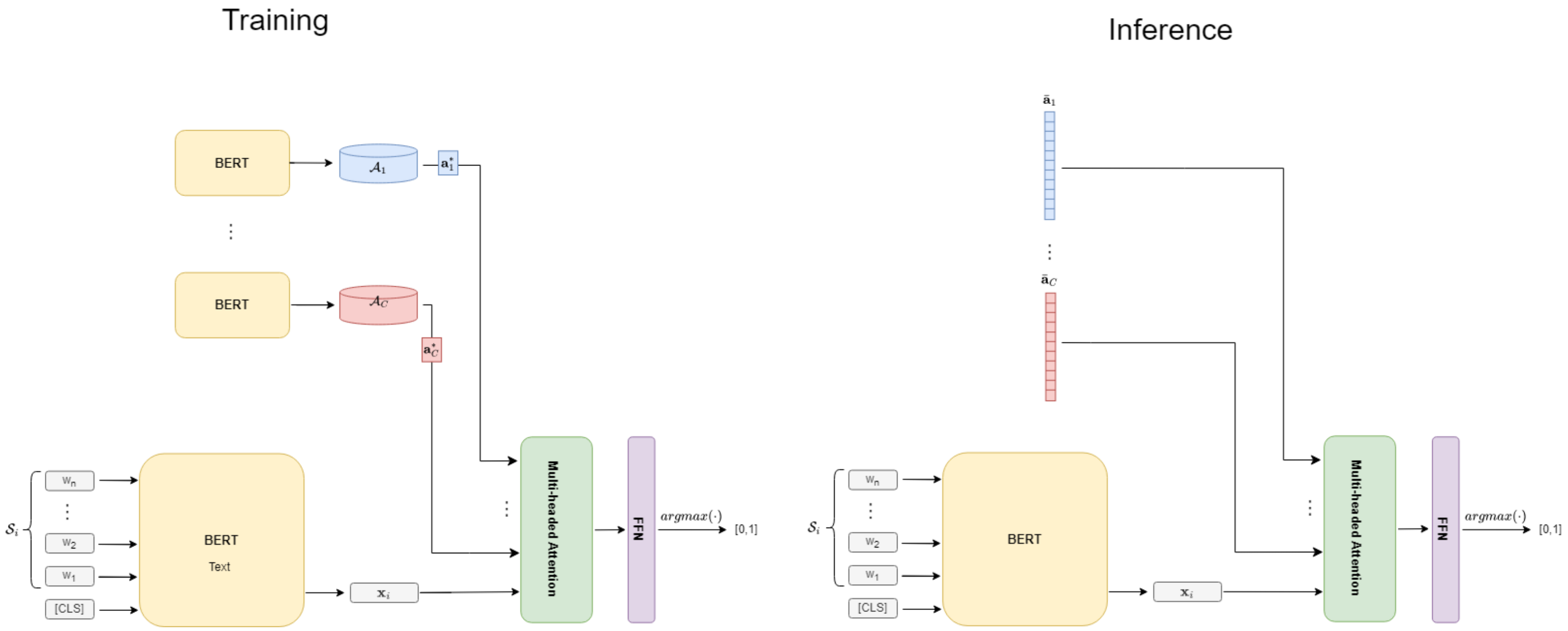
Artificial Intelligence & Information Analysis Lab

PARIS LODRON UNIVERSITÄT SALZBURG

Geosocial Media Analytics

NLP for Text Sentiment Analysis

- Anchor-based sentiment classification
- ***Anchor*** is the average tweet feature that represent 1 emotion.
- Attention compares current tweet with anchors.
- Output considers both tweet and relationship with other emotions.



Artificial Intelligence & Information Analysis Lab

Geosocial Media Analytics

Text sentiment analysis
Anchor-based sentiment classification

Results on HurricaneEMO (supervised learning).

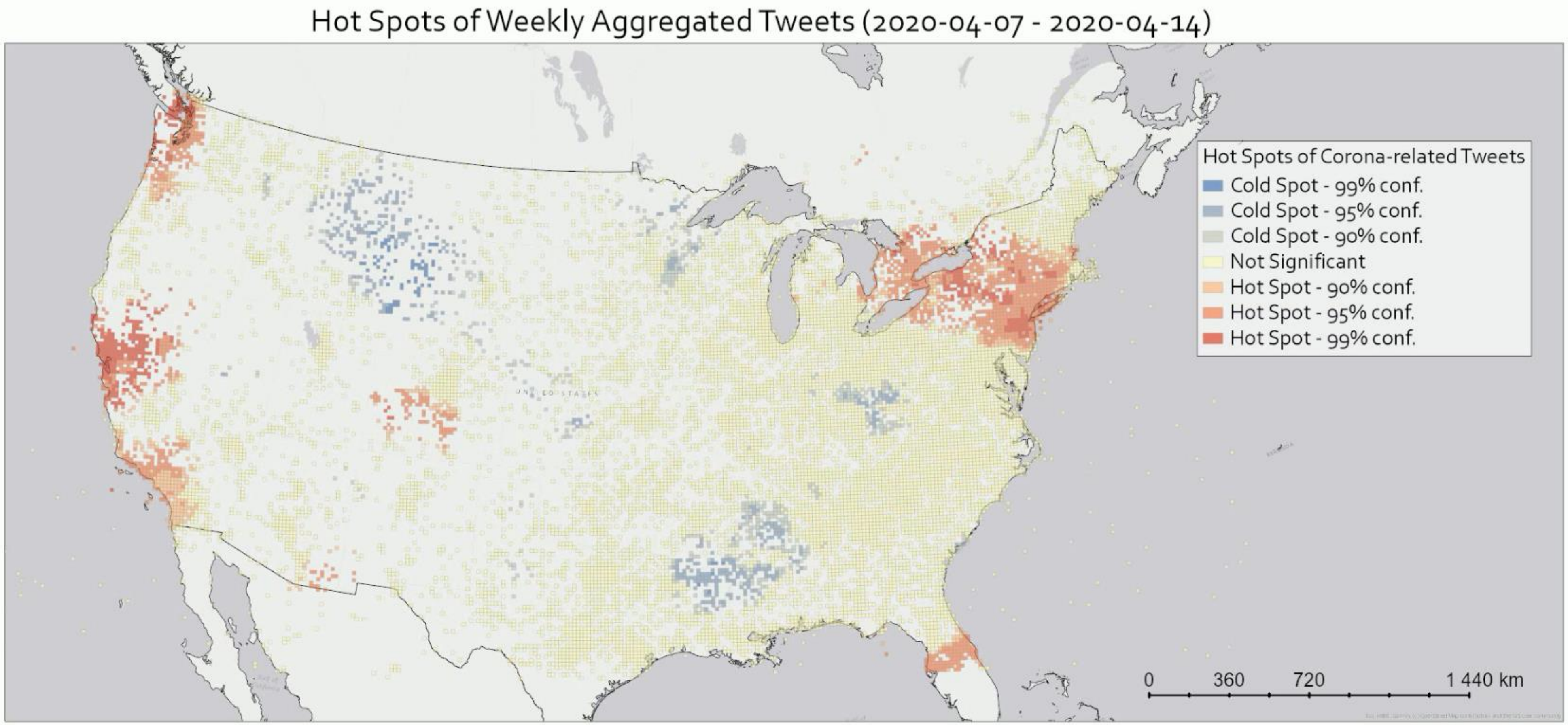
model	Agg	Awe	Con	Dis	Lov	Opt	Rem	Sub	Avg
BERT base	67.6	68.3	66.8	55.7	54	75	58.5	67.4	64.1
Our model	**71.4**	67.9	**67**	**56.4**	**55.7**	74.9	**61.5**	**69.1**	**65.5**

Results on CovidEMO (domain adaptation).

model	Ang	Ant	Dis	Fea	Joy	Sad	Sur	Tru	Avg
BERT base	73.5	57.7	62.9	64.4	72.5	71.7	61.7	52	64.55
Our model	**75.9**	**58.4**	**65.2**	**66**	**74.7**	**73.5**	**63.7**	**55.24**	**66.6**

Geosocial Media Analytics

Georeferenced tweet analysis.

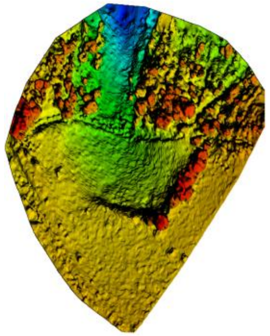


Spatio-temporal hotspot view.

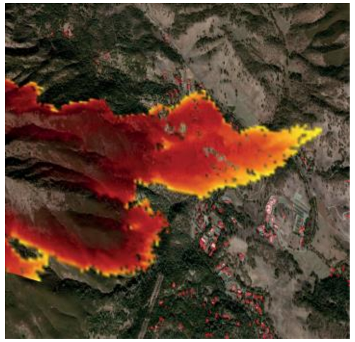
Information Fusion

Input data

Digital Elevation maps
Satellite imagery

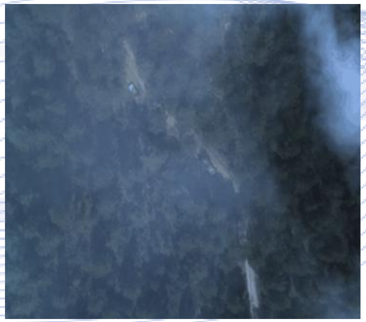


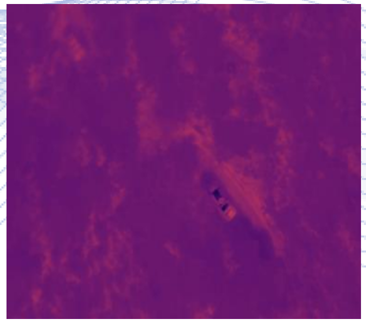
Fire simulators



Non-visual sensing (chemical + wind)

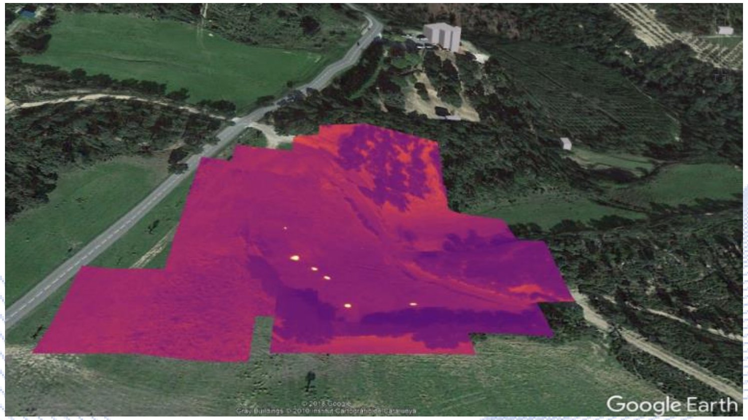
RGB and Thermal Infrared





Fused information (U Seville)

Geo-Referenced Thermal Pictures/ improved situation awareness

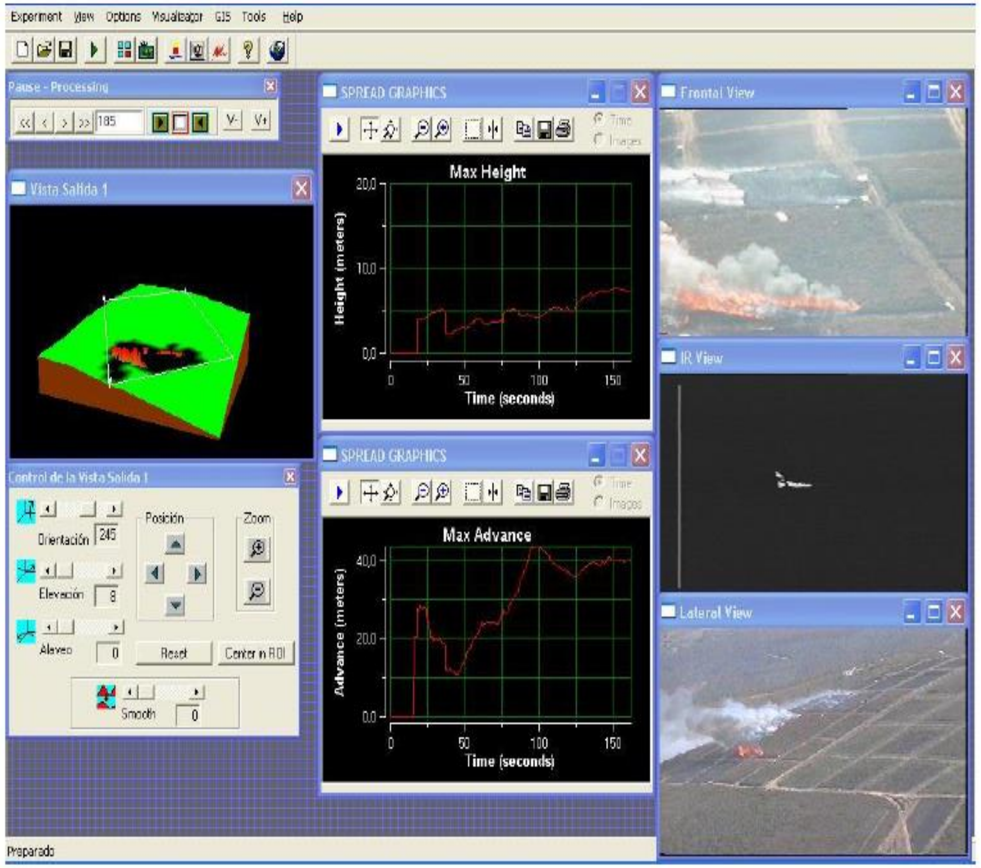


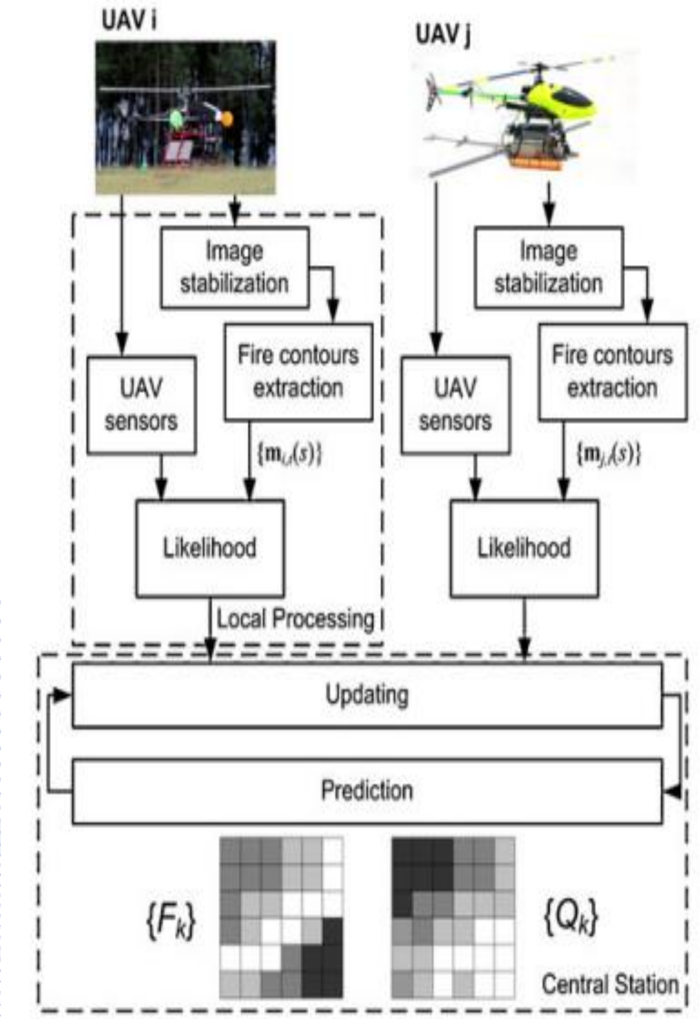
Geo-Referenced Digital models of wind and smoke

Information Fusion

Georeferenced Probabilistic Occupancy Grids

- Enables heterogeneity in observations temporal and spatial resolutions.
- Robust to occasional lack of observations.
- Robust to inconsistencies between observations.
- Enables multi-resolution observations.
- Provides georeferenced augmented maps (semantics).



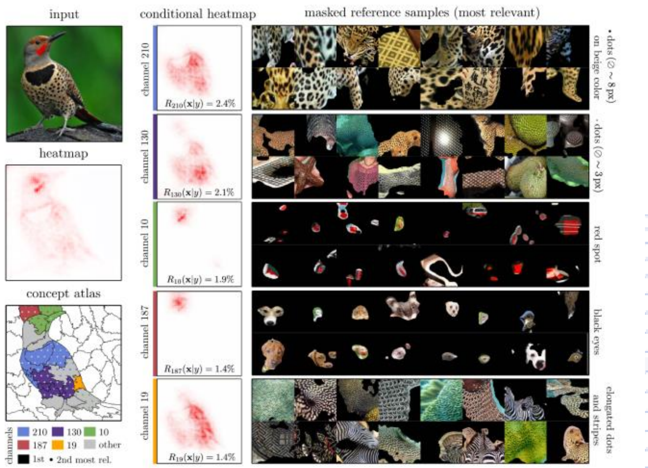


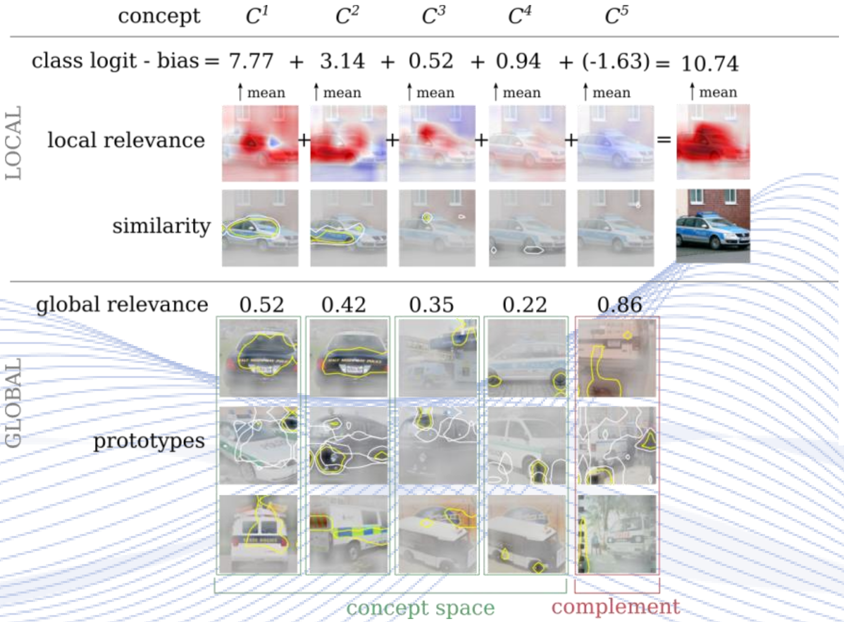
Artificial Intelligence & Information Analysis Lab

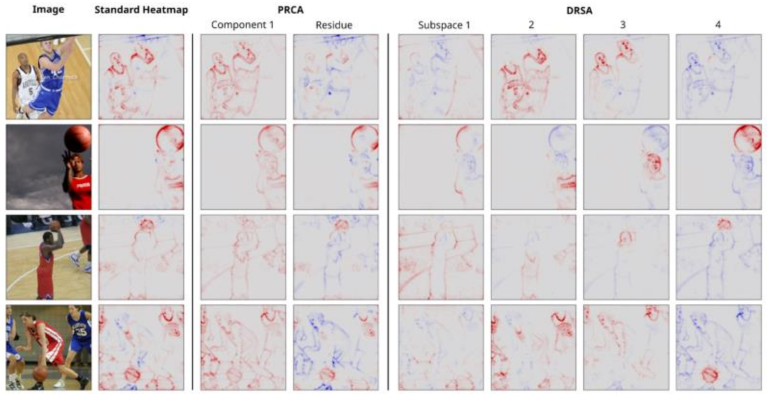
DNN Explainability

Concept-based explainability (Fraunhoffer HHI)

- Interpretability of explanations by decomposition into concepts with prototypes for context.







Relevant concept subspaces leveraging LRP

CRP: extension of LRP for glocal explanations.

MCD: dissecting feature space into concept subspaces

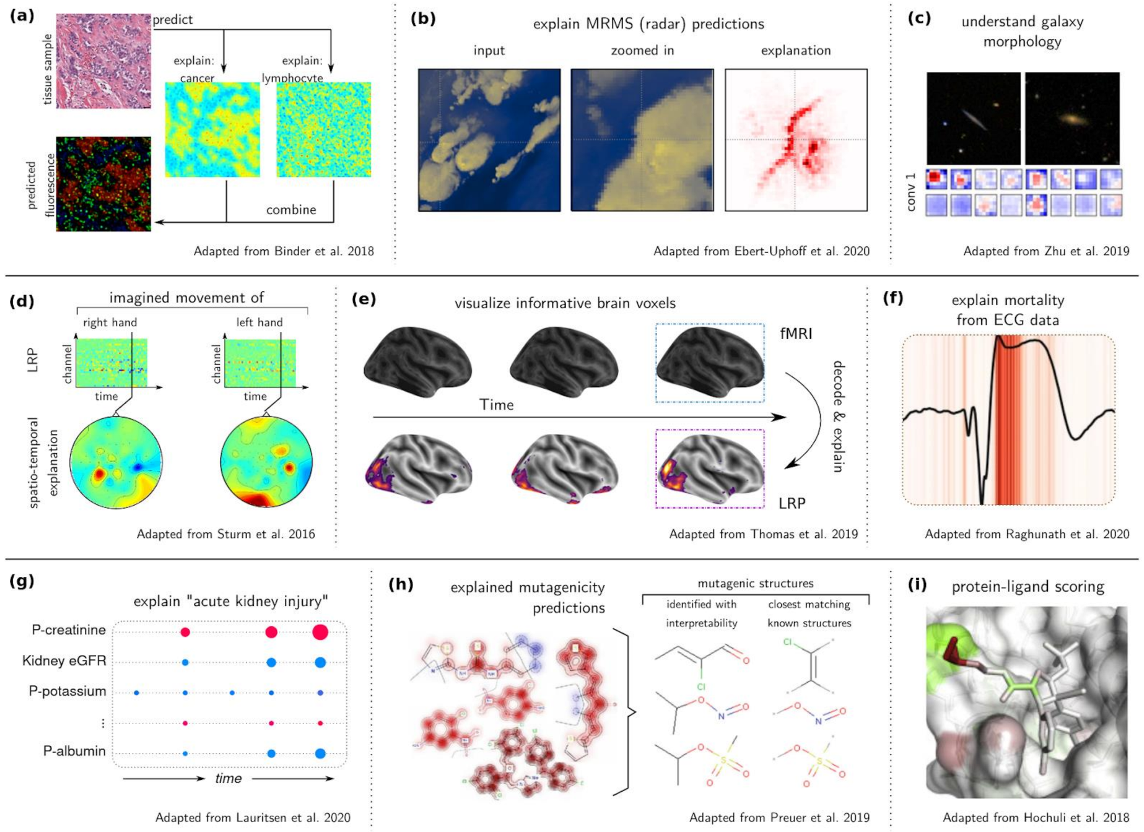
Artificial Intelligence & Information Analysis Lab

Fraunhofer

DNN Explainability

Layerwise relevance propagation

- Use the structure of the neural network to compute ***relevance scores*** for the input features.
- Tasks: DNN classification and regression.
- Data modalities: NLP, sensor data, audio, images, tabular, ...



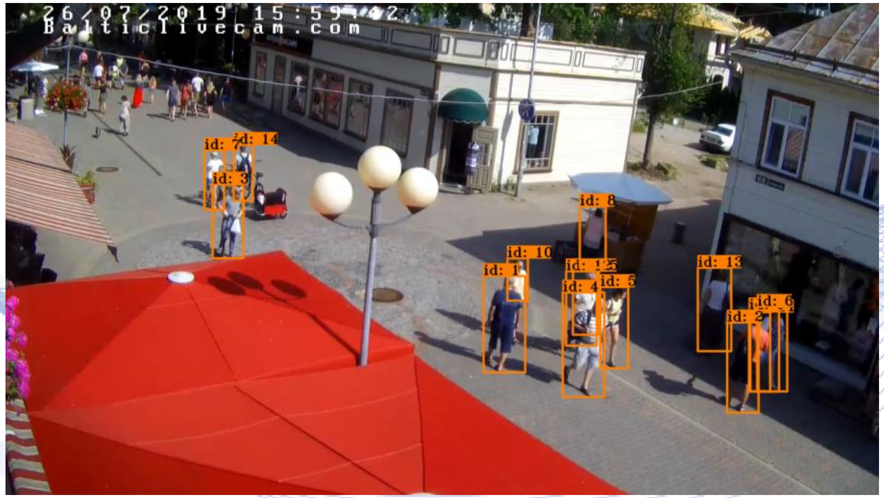
Person Re-identification

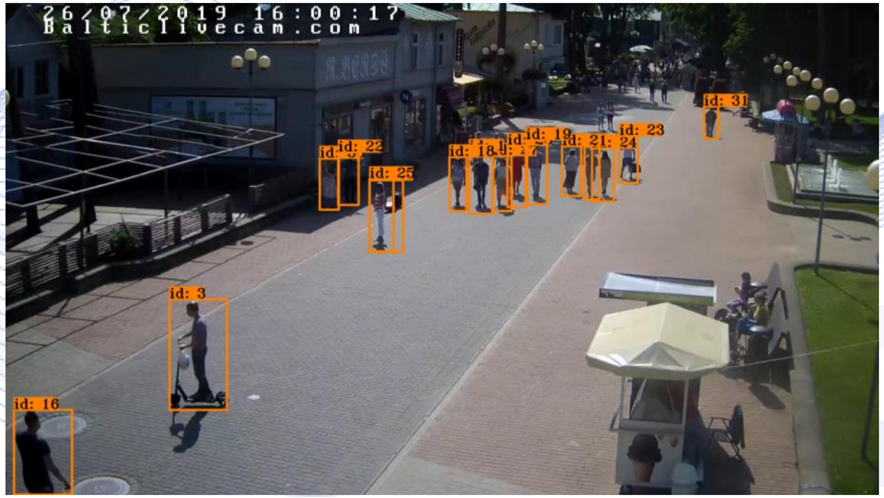
Person Re-identification (ATOS)

•YoloV8 performs person detection.

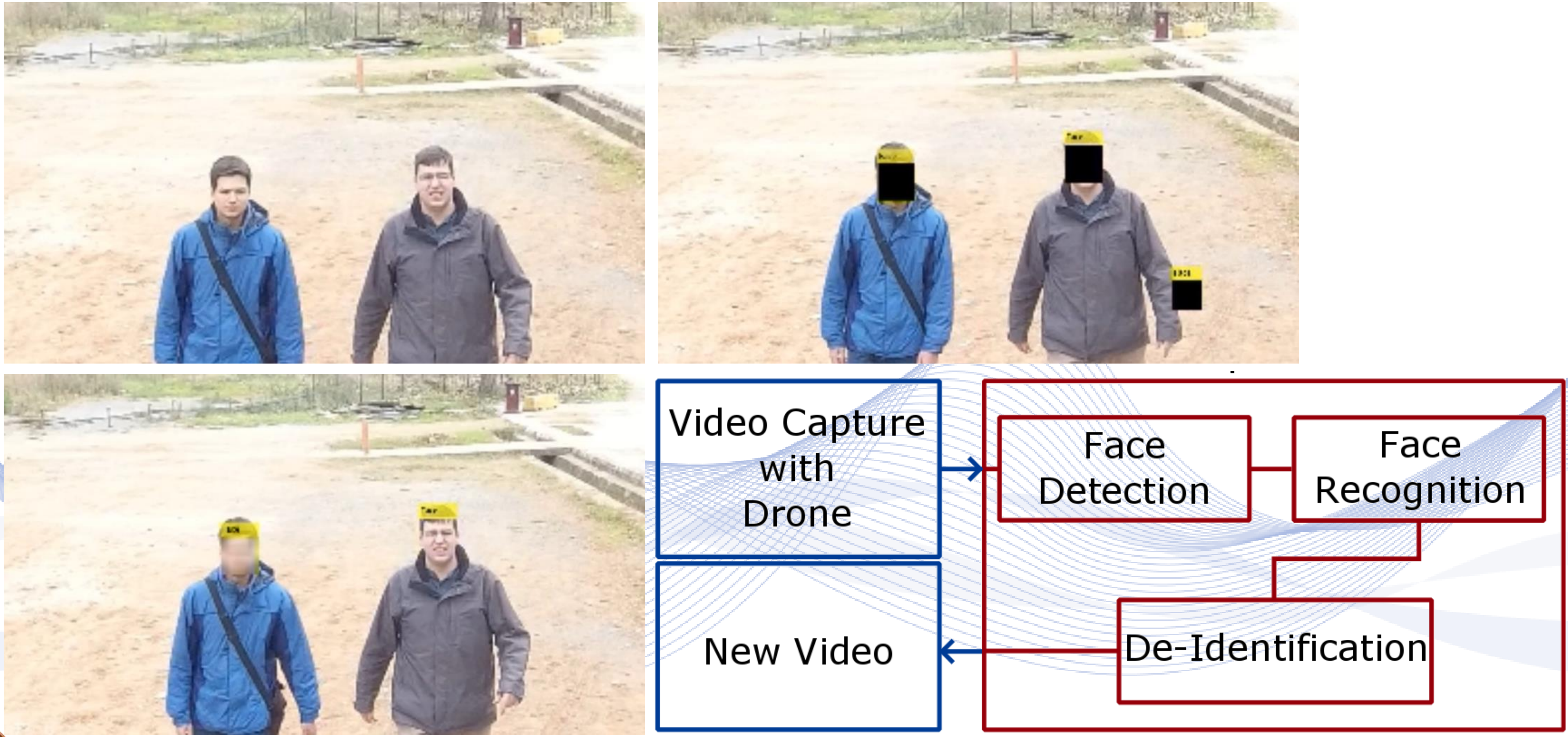
•DeepOCSORT tracker provides a unique person ROI id.

•Persons are re-identified on the same video stream further in time or in another stream.





Privacy Protection



Face de-identification on drone videos.

Privacy Protection

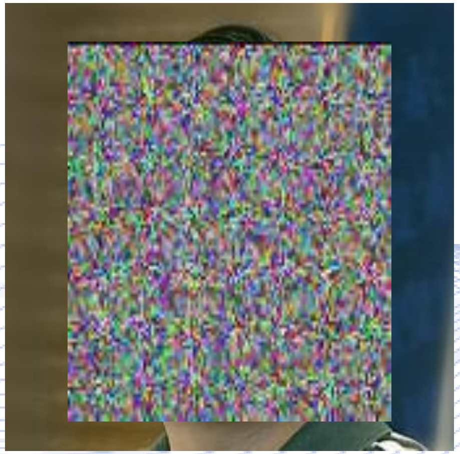
Adversarial attacks for privacy protection against automated classification systems.

- Generate unperceivable perturbations to fool DNN classifiers.
- Theoretical privacy guarantees.

Privacy Protection

Privacy Protection via Adversarial Reprogramming.

- Reprogramming the target DNN model (e.g., the face classifier), thereby effectively concealing sensitive information while maintaining model functionality



Big Data Analytics for Natural Disaster Management

- Natural Disaster Management
- NDM Concept and Objectives
- NDM Sensing
- Big NDM Data Analytics
- **Horizon Europe R&D project TEMA**

TEMA project

Acronym: TEMA

Call: RIA, HORIZON-CL4-2022-DATA-01

Grant agreement number: 101093003

Duration: 01/12/2022 - 30/11/2026

Total Project Funding: 11,340,223.50 €

Funding for AUTH (coordinator): 1,381,875.00 €

TEMA Consortium

- 19 Partners all over Europe
- AUTH is the coordinator

Acknowledgements

- This lecture has received funding from the European Union's European Union Horizon Europe research and innovation programme under grant agreement 101093003 (TEMA).

- ***Several TEMA partners, provided material that was incorporated in this presentation.***

- This lecture reflects only the authors' views. The European Commission is not responsible for any use that may be made of the information it contains.

Q & A

Thank you very much for your attention!

More material in
http://icarus.csd.auth.gr/cvml-web-lecture-series/

Contact: Prof. I. Pitas
pitas@csd.auth.gr