Politecnico di Torino

Doctoral Program in Computer and Control Engineering (33.rd cycle)

Data science for geo-referenced and heterogeneous data analysis

With applications in the emergency management domain

Candidate
Alessandro Farasin

Supervisor
Prof. Paolo Garza

Doctoral Examination Committee
Prof. Annalisa Appice, Referee, Università degli Studi di Bari
Prof. Giacomo Boracchi, Referee, Politecnico di Milano
Prof. Davide Cavagnino, Università degli Studi di Torino
Prof. Silvia Chiusano, Politecnico di Torino
Prof. Dino Ienco, UMR Tetis – INRAE, Montpellier

Outline

Introduction

State of the Art

Supporting EM using Social Media data

Supporting EM using Satellite data

Rapid Mapping and Damage Assessment Platform

Conclusions

Natural hazard

Definition (*UNISDR, 2009*)

"**Natural process** or phenomenon **that may cause loss of life**, **injury** or other health impacts, **property damage**, loss of livelihoods and services, **environmental damage**, or **social and economic disruption**".

Life losses
& injuries

Environment

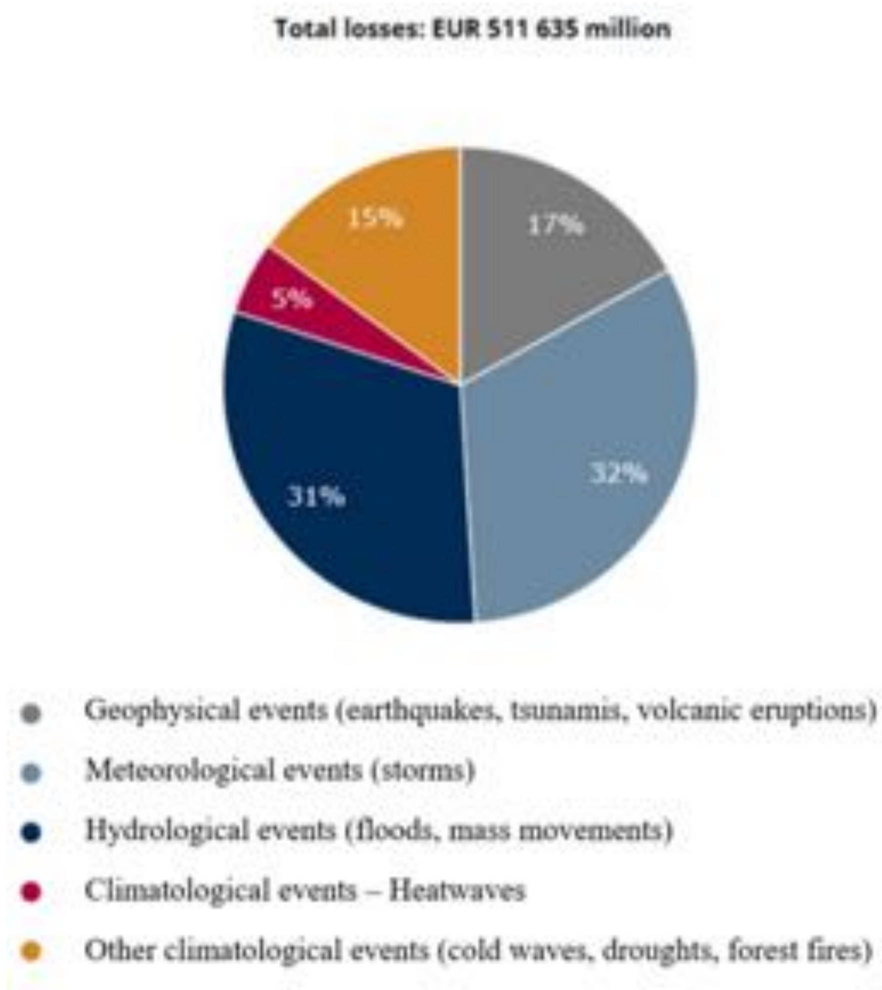
Cost

Natural hazards

The European Commission estimated that, between 1980 and 2017, natural hazards caused, in the EU:

- **Loss of ~ 90’000 lives**
- **Economic loss > 500 M€**

Climate-related events (floods, wildfires) are more frequent and intense due to global warming (IPCC, 2019)



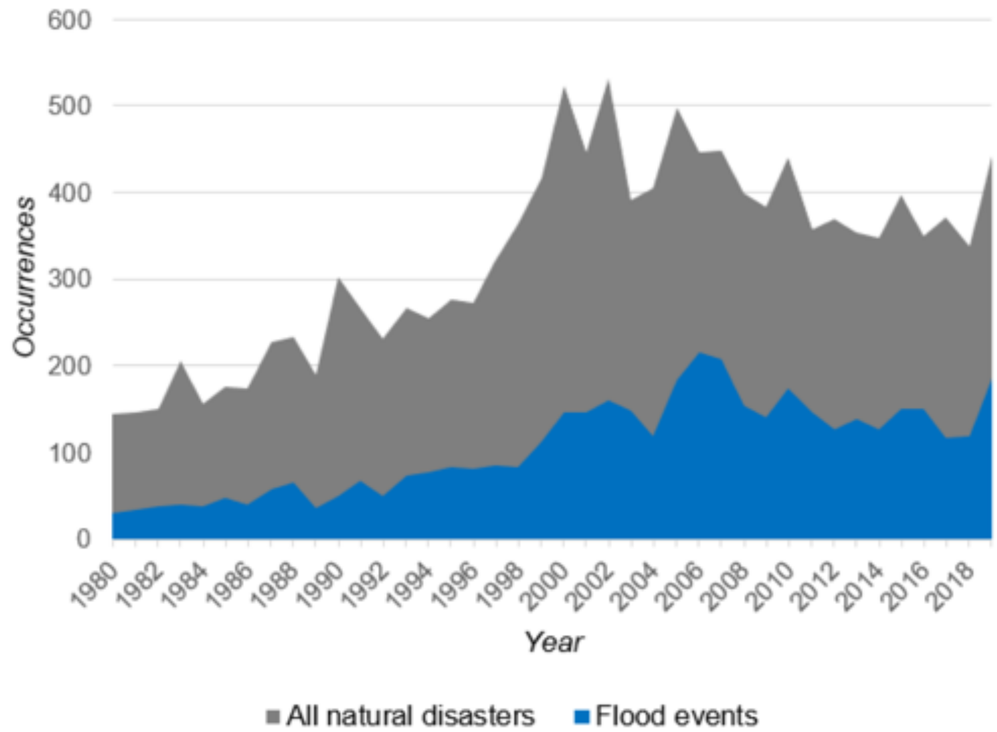
Economic losses from disasters caused by natural hazards, EU, 1980-2017

Floods

Global warming causes the retention of water in atmosphere (~+7% over 1°C):

- storms are more likely to produce extreme precipitation events
- increased risk of flood events

On average, the 30% of all natural disasters occurred are floods.



Occurrence of flood events compared to all other natural disasters – Centre for research on the Epidemiology of Disasters (CRED)

Wildfires

According to the Joint Research Centre (JRC) **annual report on wildfires, in 2019**, more than **3800 wildfires** (>30 ha) were observed in **40 countries** (EU), involving a **total burnt area of** ~$7900\ \mathrm{km}^2$:

- nearly **4 times** more than **the total surface burnt** in 2018
- nearly **3 times** more the **average number of wildfires in the past decade**

Wildfire in Athens, Greece, 7th Aug 2021 – Reuters.com

Emergency Management cycle

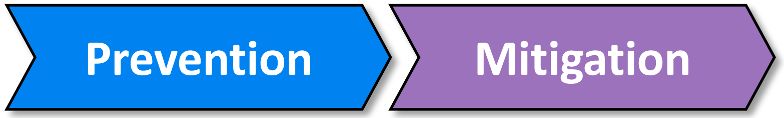
Emergency Management cycle

Prevention

Prevention

Actions taken **to prevent** an emergency (e.g. monitoring of the water level, cleaning river banks)

Emergency Management cycle



Prevention

Actions taken **to prevent** an emergency (e.g. monitoring of the water level, cleaning river banks)

Mitigation

Structural **measures to reduce** the risk or the **impact** of new disasters **if prevention is not possible** (e.g. earthquake resistant buildings)

Emergency Management cycle

Prevention

Actions taken **to prevent** an emergency (e.g. monitoring of the water level, cleaning river banks)

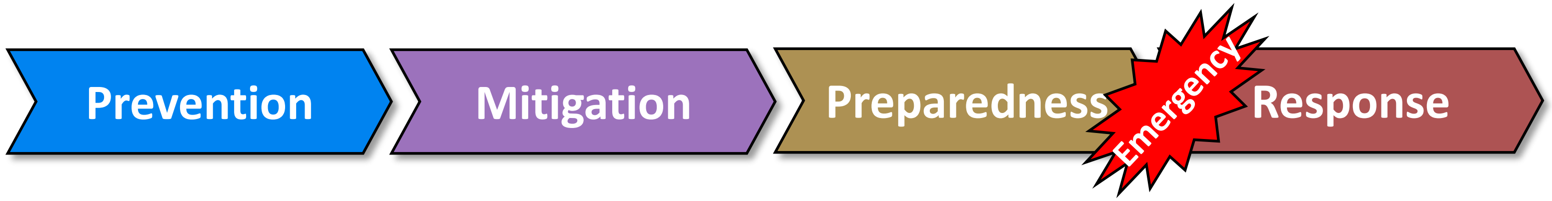
Mitigation

Structural **measures to reduce** the risk or the **impact** of new disasters **if prevention is not possible** (e.g. earthquake resistant buildings)

Preparedness

Equipment and **procedures** aimed to increase a community's ability **to respond when a disaster occurs** (e.g. emergency drills)

Emergency Management cycle



Response

Actions carried out immediately before, during, and immediately after a hazard impact, which is **aimed at saving lives**, **reducing economic losses**, and **alleviating suffering** (e.g. rapid assessments, rescue operations)

Emergency Management cycle

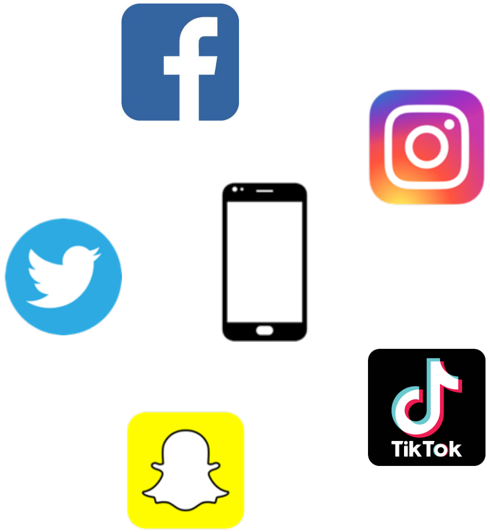
Response

Actions carried out immediately before, during, and immediately after a hazard impact, which is **aimed at saving lives**, **reducing economic losses**, and **alleviating suffering** (e.g. rapid assessments, rescue operations)

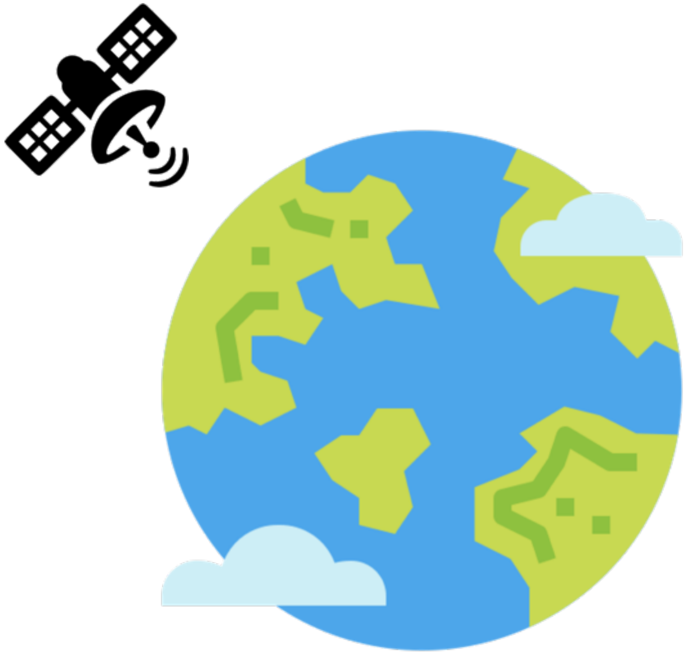
Recovery

Actions taken to **restore** normal conditions, repairing of **physical**, **social** and **economical damages**

How can EM operations be supported?



Social media data



Satellite acquisitions

Focus

Social media analysis for informative features extraction during flood events

Earth observation for automatic burned areas/flood mapping

Involvement in European H2020 Projects

(Research and Innovation Actions - RIA)

Politecnico di Torino 1859 — I REACT Shelter — LINKS ISMB STI

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State of the Art
-
Exploiting Social media in Emergency Mgmt

User5 @user5
More trucks drive through flooded roads in Lakewood Park.

Exploiting Social media in Emergency Mgmt

Emergency management applications involve:

- *Computer vision*
- *Natural Language Processing*

Computer Vision

- *Detection of the hazard* and/or visible subjects in the image (people, vehicles, infrastructures)

- *Semantic segmentation of the hit area* and/o of visible subjects in the image (people, vehicles, infrastructures)

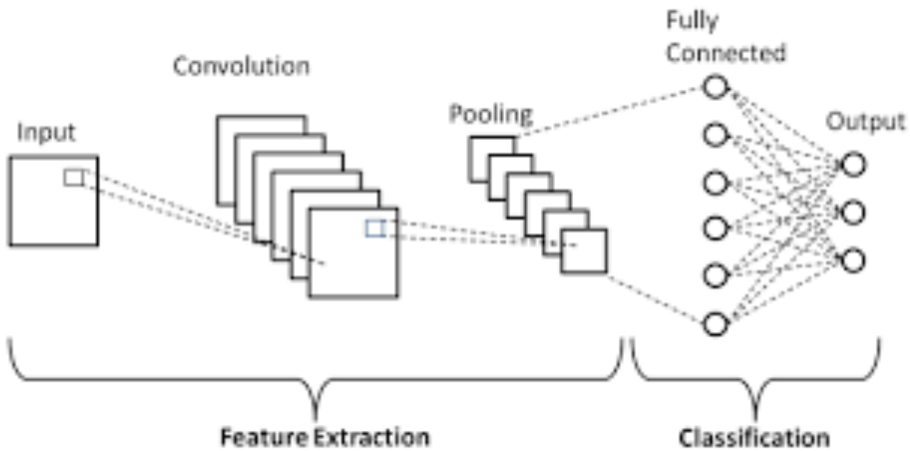
Image of a flooded region

Semantic segmentation of water

Computer vision – Detection tasks

Classification problems

- since the creation of AlexNet (2012), Convolutional Neural Networks (CNNs) have been widely adopted in computer vision with a variety of versions (DenseNet, Inception, ResNet, VGG)
- composed of two parts:
  - feature extraction
  - classification



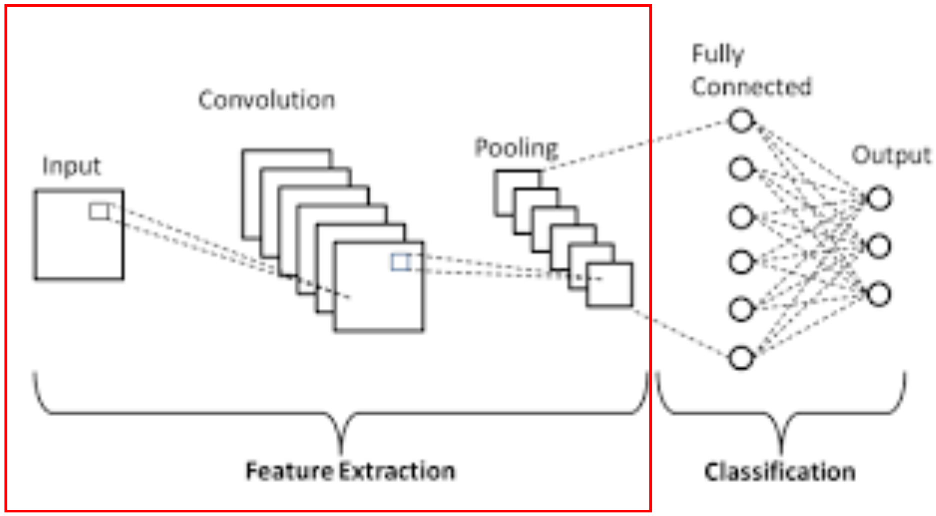
Computer vision – Detection tasks

Features extraction

Convolutional layers interleaved with pooling layers

Descriptors:

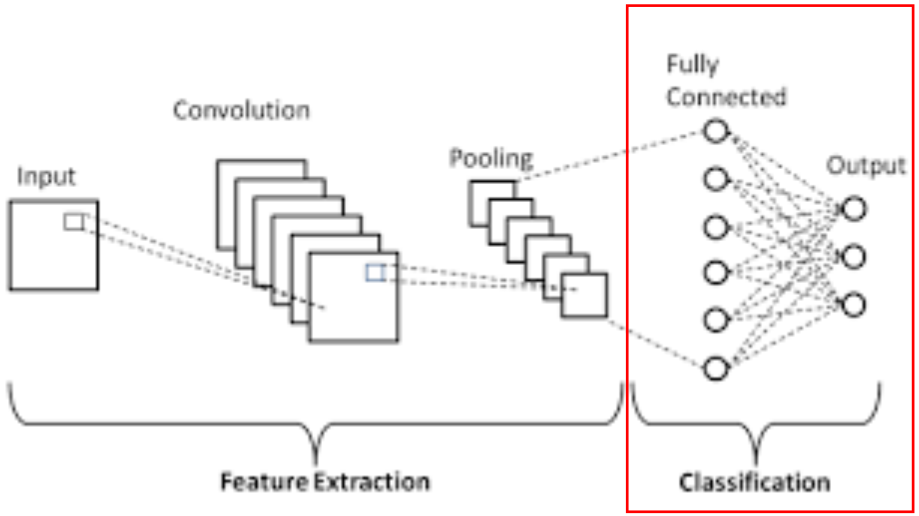
- Color and Edge Descriptor (CEDD)
- Color Layout (CL)
- Joint Composite Descriptor (JCD)
- Morphological descriptors
- Other



Computer vision – Detection tasks

Classification

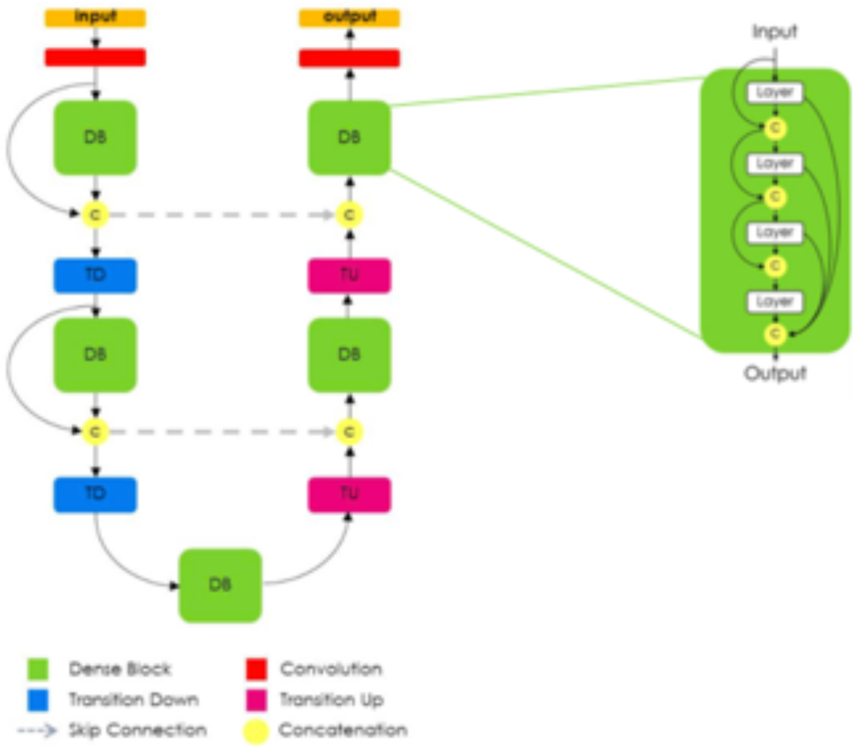
- Through *Feed Forward Neural Networks*
- Through other ML algorithms, such as *Decision tree, Support Vector Machines*



Computer vision – Semantic segmentation

Semantic segmentation problems

- Classification CNNs are adapted to Fully convolutional networks (Long et al., 2014)
- Introduction of bilinear interpolation and upsampling to restore original image resolution
- Introduction of skip connections to merge high frequency information with spatial representation



Exploiting Social media in Emergency Mgmt

Applications related to emergency management are usually related to *Computer vision* and *Natural Language Processing* approaches.

Natural Language Processing (NLP)

- *Detection of the hazard* and/or information about the context (people, vehicles, infrastructures)

Natural Language Processing – Detection

Text Preprocessing

- Tokenization
- Stopwords filtering,
- Lemmatization

Feature representation

- One-hot encoding
- Word embeddings (Word2Vec, GloVe)

Classification approaches

- Machine Learning (SVM, Decision Tree, Random Forest)
- Recurrent Neural Networks (LSTM)
- Transformers (BERT)

Social Media - Limitations & Challenges

Limitations
Detection or segmentation of objects in the content
(e.g. hazard, people, infrastructures)

Challenges
Deduction of deeper information from the context
(e.g. road viability, flood depth)

Goals: Social Media

Floods

- evaluation of roads conditions to determine their viability
- estimation of flood depth, to detect places and people potentially in danger

State of the Art

Exploiting Satellite data in Emergency Mgmt

The European Union's Earth Observation Programme

Goal: monitor and forecast environment conditions:

- on the land
- in the sea
- in the atmosphere

It is based on satellite Earth Observation and in situ (non-space) sensors

Sentinel mission

Sentinel-1

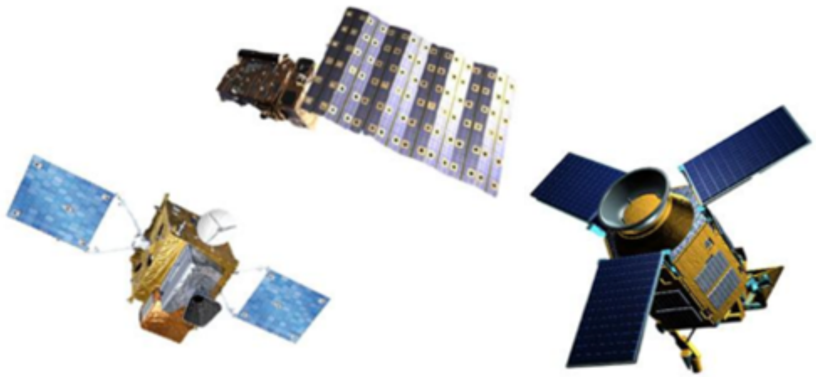
- Radar imagery
- Monitors land surfaces and oceans

Sentinel-2

- High-resolution optical imagery
- Land surfaces monitoring

Sentinel-3

- Optical, radar and altimetry data
- Marine and coastal monitoring



Sentinel-4, 5 and 5P

- Atmospheric composition monitoring, such as ozone, nitrogen dioxide, sulphur dioxide, carbon monoxide, methane, formaldehyde, and aerosol properties

Sentinel-1

- Fleet of 2 satellites
- Equipped with Synthetic Aperture Radar (SAR)
- Revisit time (~1-2 days at European latitudes)

Acquisitions are performed through **radio waves**: they are **not shielded by atmospheric conditions**:

- avoids imagery occlusions or disturbances like clouds and fog

Radar signal is transmitted:

- in horizontal (H) polarisation
- In vertical (V) polarisation

Products are available in **single** (HH or VV) **or dual polarisation** (HH+HV or VV+VH)

For land monitoring the Interferometric Wide Swath (IW) mode is largely adopted with resolution of 5m x 20m and VV+VH polarization

Sentinel-2

- Fleet of 2 satellites
- Equipped with high-resolution, multi-spectral imaging sensors
- Revisit time (~1-2 days at European latitudes)

Band	Description	Central Wavelength (μm)	Spatial resolution (m)
1	Coastal aerosol	0.443	60
2	Blue	0.490	10
3	Green	0.560	10
4	Red	0.665	10
5	Vegetation red edge	0.705	20
6	Vegetation red edge	0.740	20
7	Vegetation red edge	0.783	20
8	Near Infrared (NIR)	0.842	10
8A	Narrow NIR	0.865	20
9	Water vapour	0.945	60
10	Short wavelength infrared (SWIR)	1.375	60
11	Short SWIR (SSWIR)	1.610	20
12	Long SWIR (LSWIR)	2.190	20

Copernicus – Emergency Management Service

The census of natural hazards is an essential activity for:

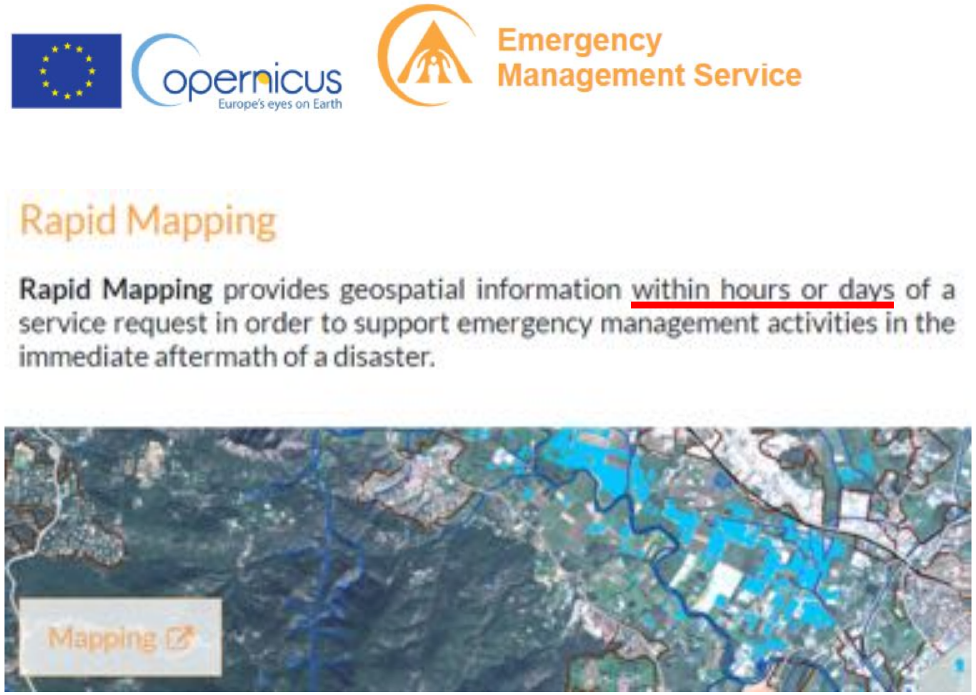
- the **delineation** of the phenomena, to **prepare proper interventions** and **limit the disaster**
- the **estimation of the damage** to **buildings** and **natural environment habitats** (economical impact, life losses, injuries);
- **planning a proper restoration**

Copernicus Emergency Management Service portal

Copernicus – Emergency Management Service

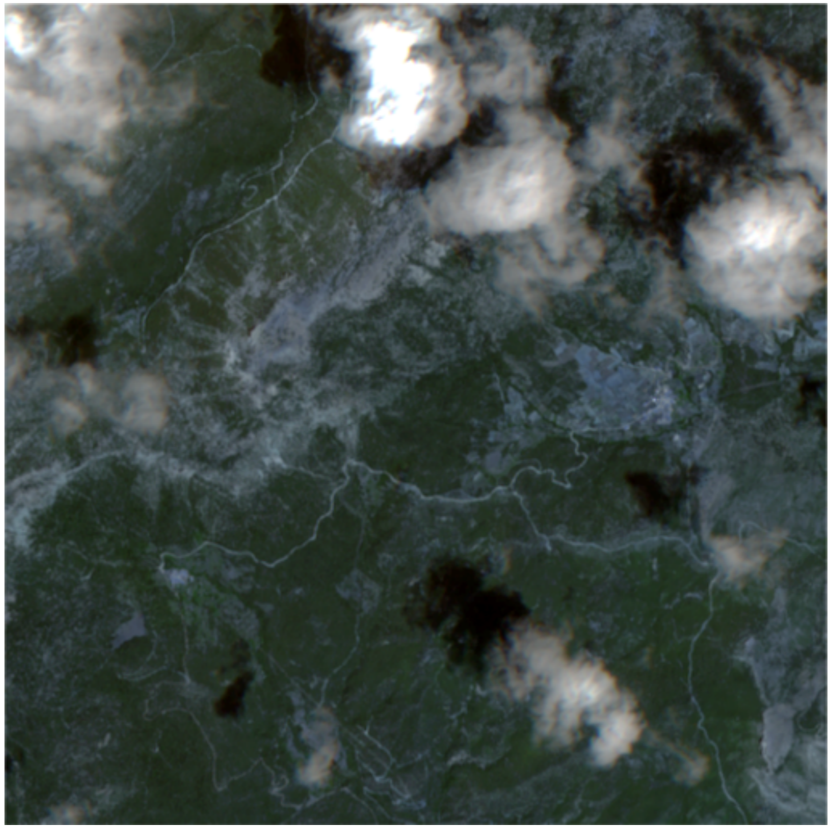
Currently, mappings are **hand-made** by public bodies or designated agencies with the help of **semi-automatic techniques**

Mappings can take hours or days to be delivered

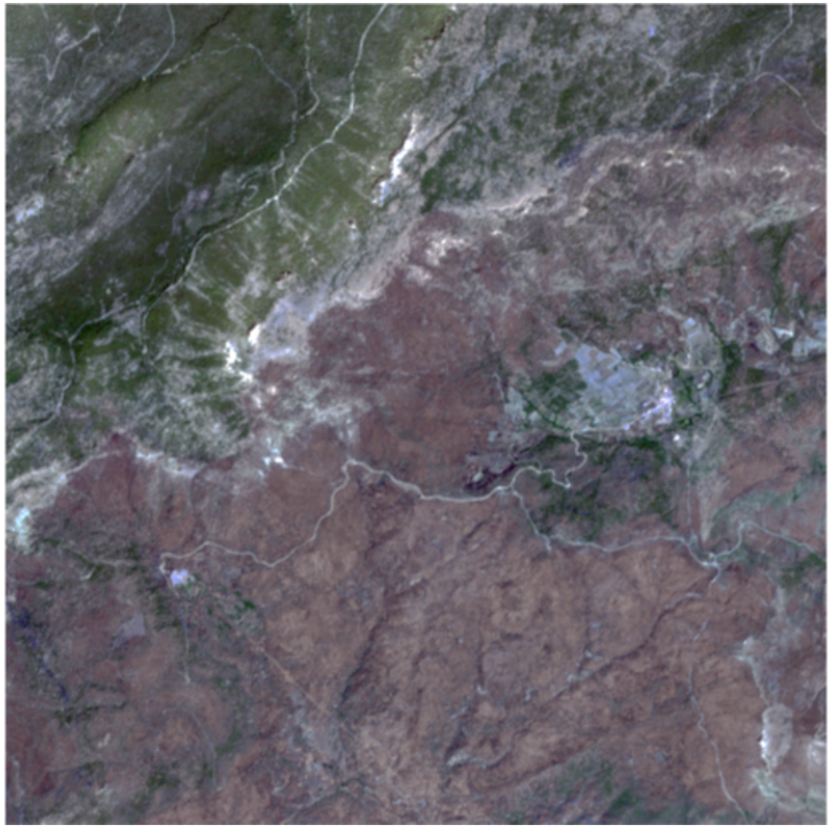


Copernicus Emergency Management Service portal

Copernicus EMS – Delineation maps

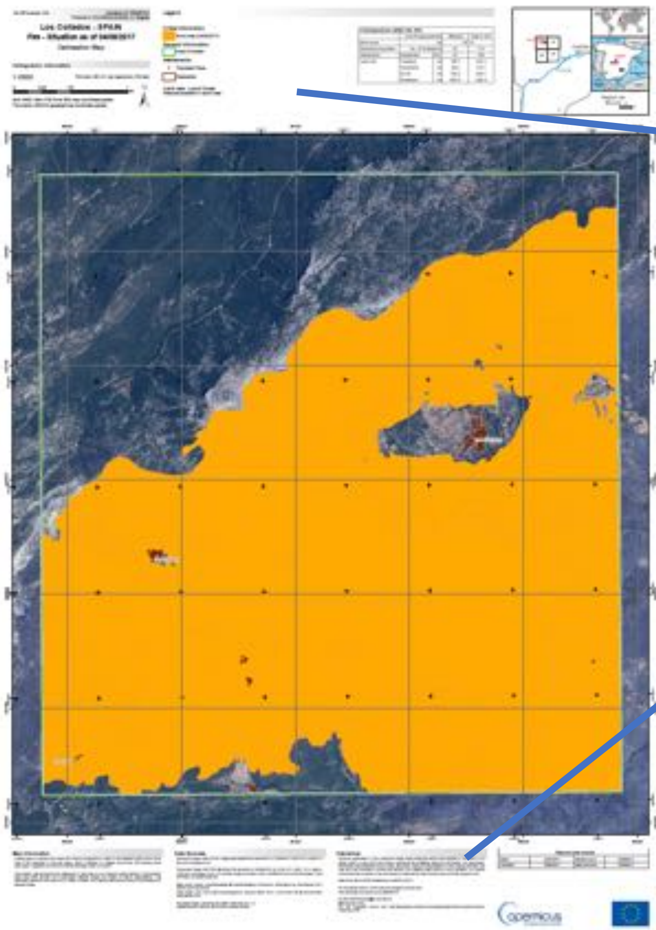


Sentinel-2 Pre Wildfire acquisition



Sentinel-2 Post Wildfire acquisition

Copernicus EMS – Delineation maps



Crisis Information

Burnt Area (04/08/2017)

General Information

Area of Interest

Settlements

Populated Place

Residential

Data Sources

Pre-event image: ESRI World Imagery © DigitalGlobe (acquired on 12/08/2013, GSD 0.5 m, approx. 0 % cloud coverage in AoI.

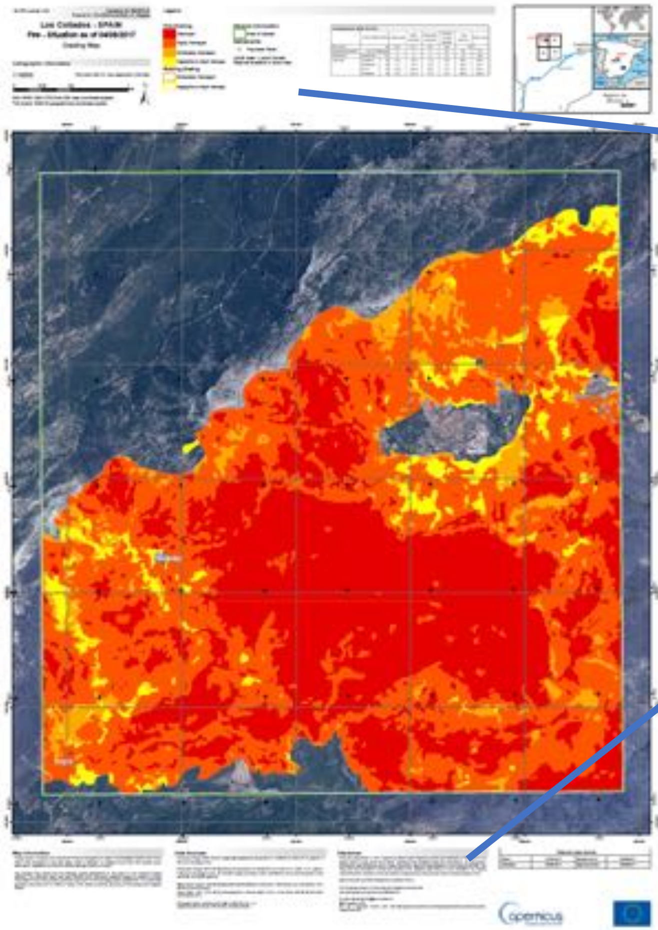
Post-event image: SPOT6/7 © Airbus DS (acquired on 04/08/2017 at 10:34 UTC, GSD 1.5 m, approx. 0 % cloud coverage in AoI, 8° off-nadir angle) provided under COPERNICUS by the European Union and ESA, all roghts reserved.

Base vector layers: OpenStreetMap © OpenStreetMap contributors, Wikimapia.org, GeoNames 2017, refined by the producer.
Inset maps: JRC 2013, © EuroGeographics, Natural Earth 2012, CCM River DB © EUJRC2007, GeoNames 2013.

Population data: Landscan 2010 © UT BATTELLE, LLC
Digital Elevation Model: SRTM 90m (NASA/USGS)

Relevant date records			
Event	27/07/2017	Situation as of	04/08/2017
Activation	03/08/2017	Map production	04/08/2017

Copernicus EMS – Grading maps



Fire Grading

- Destroyed
- Highly Damaged
- Moderately Damaged
- Negligible to slight damage

General Information

- Area of Interest

Settlements

- Populated Place

Land use - Land Cover

Features available in vector data

Data Sources

Pre-event image: ESRI World Imagery © DigitalGlobe (acquired on 12/08/2013, GSD 0.5 m, approx. 0 % cloud coverage in AoI.

Post-event image: SPOT6/7 © Airbus DS (acquired on 04/08/2017 at 10:34 UTC, GSD 1.5 m, approx. 0 % cloud coverage in AoI, 8° off-nadir angle) provided under COPERNICUS by the European Union and ESA, all roghts reserved.

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Relevant date records			
Event	27/07/2017	Situation as of	04/08/2017
Activation	03/08/2017	Map production	04/08/2017

Burned area - Delineation

Based on thresholding of spectral indexes, that may vary from region to region (manually assessed)

Usually evaluated through the Separability Index (SI)

$$\mathrm{SI} = \frac{|\mu_b - \mu_u|}{\sigma_b + \sigma_u}$$

- $SI > 1$ indicates good separability
- $SI <= 1$ indicate poor separability (histogram

overlap between the burned and unburned classes).

Thresholding (Otsu) or ML algorithms (SVM, DTree) support manual evaluation:

- **in specific regions**, such as forests or deserts
- **using pre- wildfire images** that requires manual selection (no clouds, fog, shadows, same season, ..)

$$\mathrm{NBR} = \frac{\mathrm{B08} - \mathrm{B12}}{\mathrm{B08} + \mathrm{B12}}$$

$$\mathrm{MIRBI} = 10 \cdot \mathrm{B12} - 9.8 \cdot \mathrm{B11} + 2$$

$$\mathrm{NBR2} = \frac{\mathrm{B11} - \mathrm{B12}}{\mathrm{B11} + \mathrm{B12}}$$

$$\mathrm{BAIS2} = \left(1 - \sqrt{\frac{\mathrm{B06} \cdot \mathrm{B07} \cdot \mathrm{B8A}}{\mathrm{B04}}}\right) \cdot \left(\frac{\mathrm{B12} - \mathrm{B8A}}{\sqrt{\mathrm{B12} + \mathrm{B8A}}} + 1\right)$$

Burned area - Damage severity estimation

The $dNBR$ index is a widely acknowledged estimator of the damage severity level.

$$\mathrm{dNBR} = \mathrm{NBR}_{PRE} - \mathrm{NBR}_{POST}$$

After its computation, it is quantized in 5 different classes:

- Unburned
- Low damage
- Moderate damage
- High damage
- Very High damage / destroyed

Aerial or in-situ inspections are performed to correct the estimates

Copernicus Europe's eyes on Earth

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Fire severity is estimated using the difference Normalized Burnt Ratio (dNBR), as proposed by Key and Benson (2005) and verified through correlation with field-estimated fire effects (Twele, 2004). The thresholds used for the fire severity classes in EFFIS are as follows:

Fire Severity Class	Range of dNBR
Unburned/Very Low	< 0.1
Low	0.1 - 0.255
Moderate	0.256 - 0.41
High	0.42 - 0.66
Very High	> 0.66

References

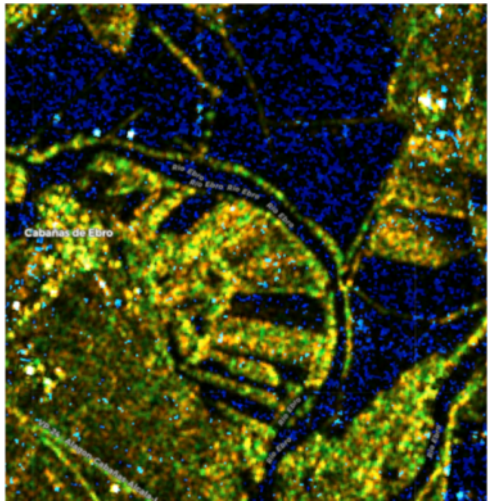
Key, C. H., & Benson, N. C. (2005). Landscape assessment: Remote sensing of severity, the Normalized Burn Ratio. In D. C. Lutes (Ed.), FIREMON: Fire Effects Monitoring and Inventory System. Ogden, UT: USDA Forest Service, Rocky Mountain Research Station, General Technical Report, RMRS-GTR-164-CD (pp. LA1–LA51).

Twele, A., 2004, Post-fire vegetation regeneration: The case studo of the Massif the l'Etoile Fire, JRC Technical Report EUR 21010, European Communities.

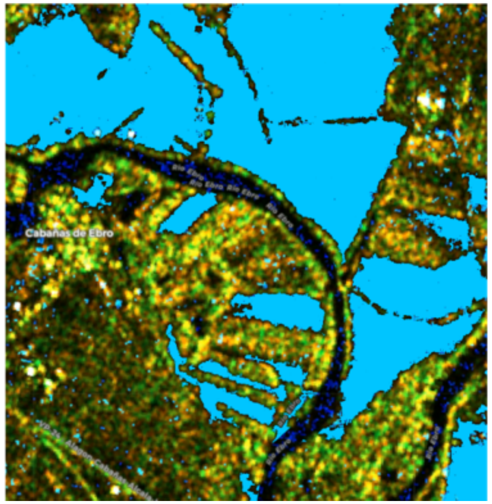
About the Copernicus EFFIS damage severity estimation algorithm (visited in 08-2021)

Flood Delineation

Sentinel-2 acquisition of a flooded region



Sentinel-1 acquisition of the same region



Delineation maps distinguish flooded regions from natural water sources

Flood delineation

Sentinel-1 – SAR data

Acquisitions are inherently affected by speckle noise

- Despeckling operations are usually performed (Gaussian filtering, Non-local Means filtering)

Natural water sources are estimated from:

- Acquisitions before the event (must be assessed)
- Digital Elevation Maps (DEM), through the computation of the Height Above Nearest Drainage (HAND) index

Common approaches are:

- histogram thresholding (Otsu)
- region growing
- change detection algorithms
- Machine learning approaches (SVM, Decision Tree)

Satellite data - Limitations & Challenges

Limitations

Pre-hazard image is usually required

- Need to be assessed and processed to be comparable with the current or post-hazard acquisition

Spectral indexes are location dependent

- More effective in some regions than in others
- Thresholds may vary from region to region
- No existing approaches for visible-light only (wildfires)

Mappings are delivered in hours or days (manual assessment)

Satellite data - Limitations & Challenges

Challenges

Reliable mappings based on current or post- hazard acquisitions only

Location-independent approaches

Fast mapping process, to promote near-real-time mappings
(e.g. from aircraft monitoring)

Goals: Satellite Data

Wildfires

Fast and **automatic generation** of:

- **delineation** maps
- **grading** maps (dmg severity estimation)

using **post-wildfire acquisition only**

Goals: Satellite Data

Floods

- **Fast** and **automatic generation** of **delineation** maps using **current satellite acquisition** only

- Evaluating long lasting flooded region, to assess after-hazard intervention

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Estimation of Road Viability during Flood Events

User5 @user5
More trucks drive through flooded roads in Lakewood Park.

Estimating road viability

Goal
Provide a **reliable approach** to **estimate viable roads** from tweets during a flood event, suitable for real-world applications.

If geolocalized, those tweets can help addressing rescue operations during the emergency.

Problem statement

Input: Tweet post, containing both image (RGB) and metadata

Output

Determine whether:

- There is **Evidence of any Road** (**ER**) (1 for positive ER, otherwise 0)
- In case ER = 0, estimate if the road is still passable (**Evidence of Road Passability**, **ERP**) (1 for positive ERP, otherwise 0)

Dataset – Visual data

Dataset	Total	# Evid. of Roads YES	NO	# Passable Roads YES	NO
development set	5818	2130	3688	951	1179
test set	3017	-	-	-	-

No evidence of road

Evidence of road

Passable road

Evidence of road

No road passability

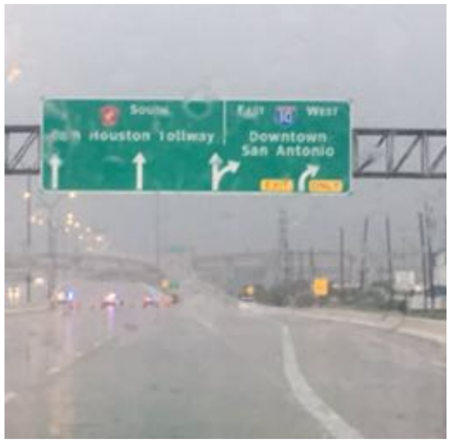
Dataset – Visual data

Dataset	Total	# Evid. of Roads		# Passable Roads	
		YES	NO	YES	NO
development set	5818	2130	3688	951	1179
test set	3017	-	-	-	-

Images difficult to be classified

Evidence of road

Passable road



Evidence of road

No road passability

Dataset – Metadata

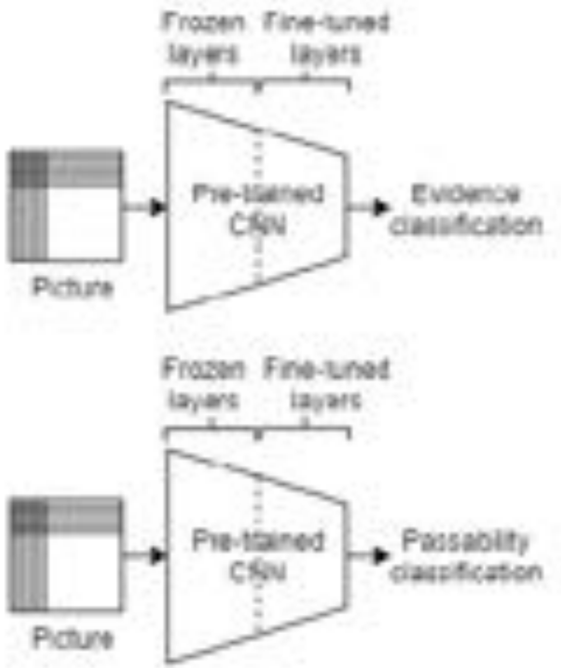
Field	Description	Type
Created at	UTC time when this tweet was created	datetime
Entities	Dictionary of the entities which have been parsed out of the text, such as the hashtags	object
Extended entities	Dictionary of entities extracted from the media, such as the image size	object
Favorite count	Indicates how many times the tweet has been liked	int64
Favorited	Indicates whether the tweet has been liked	bool
Id	Unique identifier of the tweet	int64
Id str	String version of the unique identifier	string
Is quote status	Indicates whether this is a quoted tweet	bool
Lang	Indicates the language of the text (machine generated)	string
Possibly sensitive	When the tweet contains a link it indicates if the content of the URL is identified as containing sensitive content	bool
Retweet count	Indicates how many times has the tweet been retweeted	int64
Retweeted	Indicates whether the tweet has been retweeted	bool
Source	Utility used to post the tweet	object
text	Text written by the user	string
Truncated	Whether the value of the text parameter was truncated	bool
User	Dictionary of information about the user who posted the tweet	object

Visual Information - Results (F1-Score)

Approach	EVIDENCE OF ROAD [%]			EV. OF ROAD PASSABILITY [%]		
	Validation set	Test set (MediaEval)	Test set (Own)	Validation set	Test set (MediaEval)	Test set (Own)
Human annotation	87.32*	-	-	47.71*	-	-

* Evaluation performed on a subset of 50 images

Independent tasks: Single CNN approach



CNN used: InceptionV3
Loss function: Binary Cross Entropy

Visual Information - Results (F1-Score)

Approach	EVIDENCE OF ROAD [%]			EV. OF ROAD PASSABILITY [%]		
	Validation set	Test set (MediaEval)	Test set (Own)	Validation set	Test set (MediaEval)	Test set (Own)
Human annotation	87.32*	-	-	47.71*	-	-
Single CNN	86.48	-	84.88	62.84	-	59.99

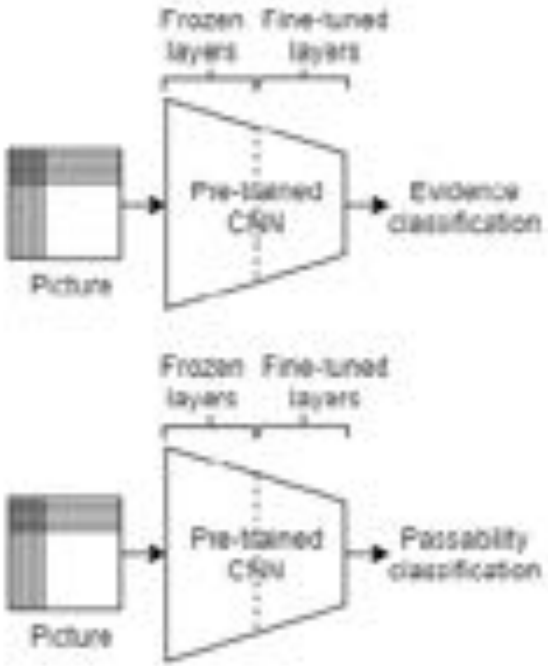
* Evaluation performed on a subset of 50 images

Independent tasks: network ensemble (90)

Architectures adopted

DenseNet101
DenseNet201
InceptionV3
MobileNet
NaSnetLarge
ResNetV2
VGG16
VGG19
Xception

Training strategy



Aggregation strategy

$$\mathrm{pred}(p_1, ..., p_n, x, y) = \\ = \begin{cases} 1 & \text{if } \left(\overline{p} > 0.5 - x \text{ and } voting(p_1, ..., p_n) \geq \frac{n}{2}\right) \text{ or} \\ & \left(\overline{p} > 0.5 \text{ and } voting(p_1, ..., p_n) > \frac{n}{2} - y\right), \\ 0 & \text{otherwise.} \end{cases}$$

Visual Information - Results (F1-Score)

Approach	EVIDENCE OF ROAD [%]			EV. OF ROAD PASSABILITY [%]		
	Validation set	Test set (MediaEval)	Test set (Own)	Validation set	Test set (MediaEval)	Test set (Own)
Human annotation	87.32*	-	-	47.71*	-	-
Single CNN	86.48	-	84.88	62.84	-	59.99
Networks Ensemble (90)	90.14	87.79	90.17	70.56	68.38	65.91

* Evaluation performed on a subset of 50 images

Visual Information - Results (F1-Score)

MediaEval Benchmark
MediaEval Benchmarking Initiative for Multimedia Evaluation

Approach	EVIDENCE OF ROAD [%]			EV. OF ROAD PASSABILITY [%]		
	Validation set	Test set (MediaEval)	Test set (Own)	Validation set	Test set (MediaEval)	Test set (Own)
Human annotation	87.32*	-	-	47.71*	-	-
Single CNN	86.48	-	84.88	62.84	-	59.99
Networks Ensemble (90)	90.14	87.79	90.17	70.56	68.38	65.91
A. Mountzidou et al. [107]	-	-	-	-	66.65	-
B. Bischke [7]	-	87.70	-	-	66.48	-
N. Said et al. [132]	-	-	-	-	65.03	-
D. Dias [30]	-	-	-	-	64.81	-
Y. Feng et al. [46]	-	-	-	-	64.35	-
Z. Zhao et al. [170]	-	87.58	-	-	63.13	-
M. Hanif et al. [63]	-	74.58	-	-	45.04	-
A. Kirchknopf et al. [79]	-	-	-	-	24	-

Best model for the task "Emergency Response for Flooding Events" – MediaEval 2018

* Evaluation performed on a subset of 50 images

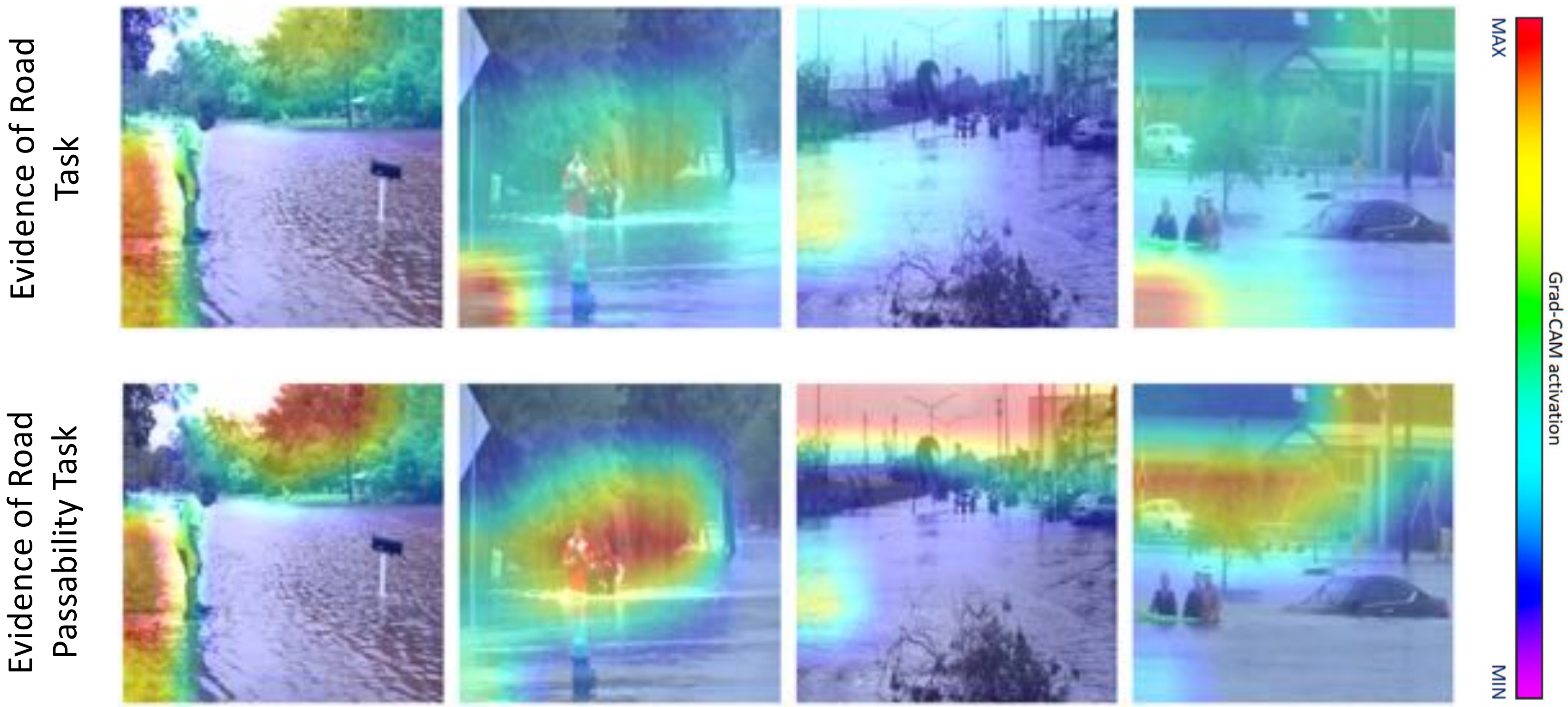
Visual Information - Results (F1-Score)

Approach	EVIDENCE OF ROAD [%]			EV. OF ROAD PASSABILITY [%]		
	Validation set	Test set (MediaEval)	Test set (Own)	Validation set	Test set (MediaEval)	Test set (Own)
Human annotation	87.32*	-	-	47.71*	-	-
Single CNN	86.48	-	84.88	62.84	-	59.99
Networks Ensemble (90)	90.14	87.79	90.17	70.56	68.38	65.91
Networks Ensemble (30)	88.91	-	89.45	70.18	-	65.28

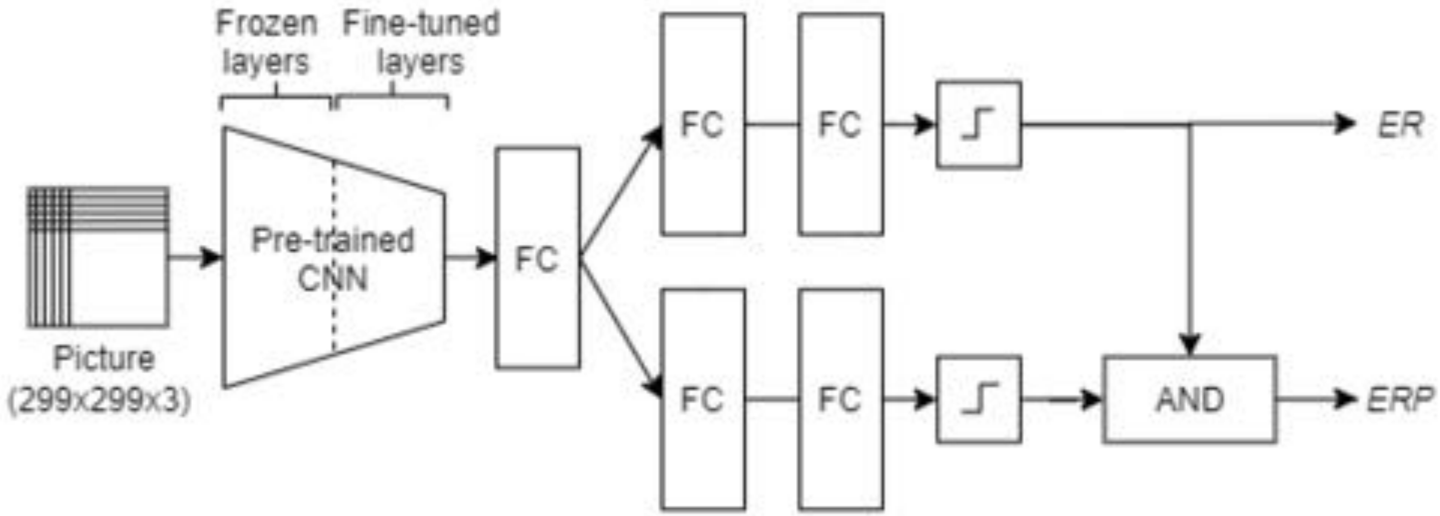
Net Ensemble (30) is "lighter", but still unsuitable for real world applications

* Evaluation performed on a subset of 50 images

Idea: considering both tasks as related



Related tasks: Double-ended network



CNN used: InceptionV3
Loss function: Binary Cross Entropy

Visual Information - Results (F1-Score)

Approach	EVIDENCE OF ROAD [%]			EV. OF ROAD PASSABILITY [%]		
	Validation set	Test set (MediaEval)	Test set (Own)	Validation set	Test set (MediaEval)	Test set (Own)
Human annotation	87.32*	-	-	47.71*	-	-
Single CNN	86.48	-	84.88	62.84	-	59.99
Networks Ensemble (90)	90.14	87.79	90.17	70.56	68.38	65.91
Networks Ensemble (30)	88.91	-	89.45	70.18	-	65.28
Double-ended network	88.73	-	85.00	67.51	-	67.91

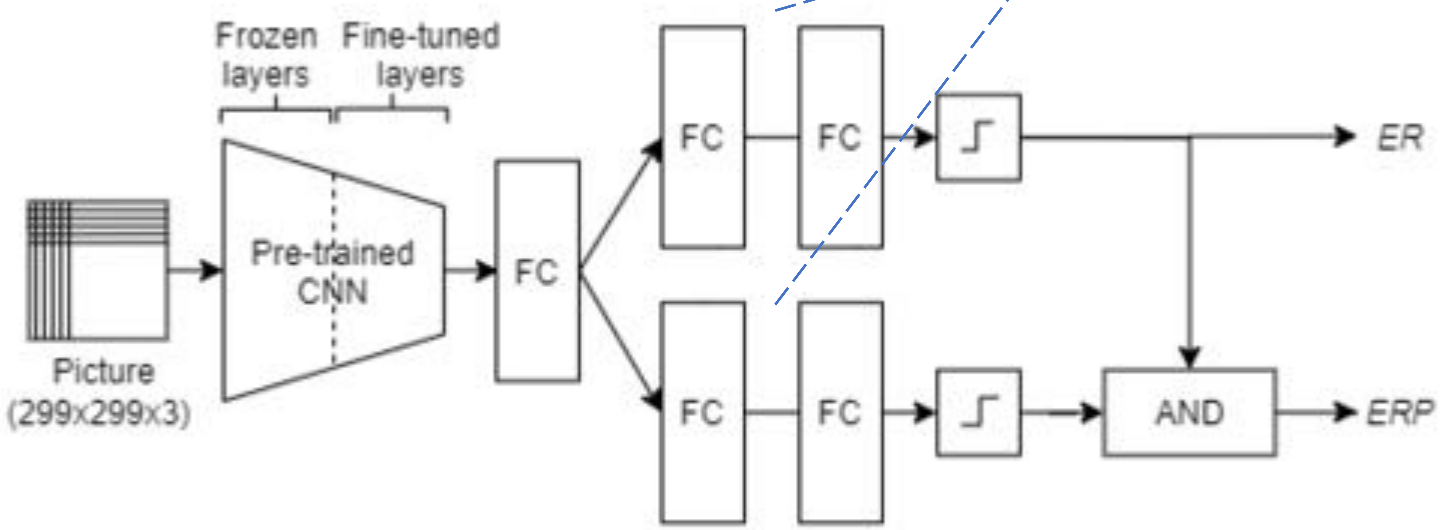
The Double-ended network performed:

- In **ER task**, similar to SingleCNN, worse than Net Ensemble (90)
- In the **ERP task**, it overcame the performances

* Evaluation performed on a subset of 50 images

Related tasks: Double-ended network

$$l(t) = \min_g C\big(g(t)\big) + D(g(t))$$



$g(t)$: deep feature representation for the training data $\boldsymbol{t}$
$C(g(t))$: compactness loss (sample variance of the target class)
$D(g(t))$: descriptiveness loss (binary cross entropy)

Visual Information - Results (F1-Score)

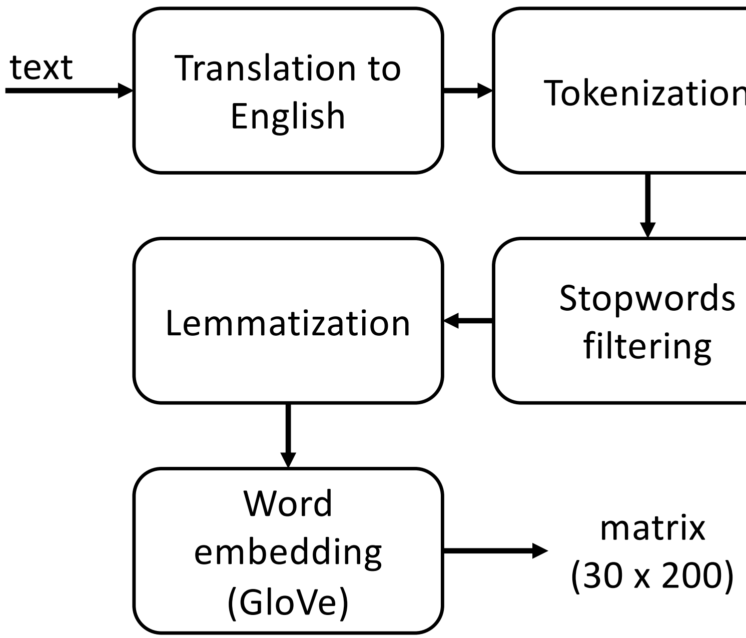
Approach	EVIDENCE OF ROAD [%]			EV. OF ROAD PASSABILITY [%]		
	Validation set	Test set (MediaEval)	Test set (Own)	Validation set	Test set (MediaEval)	Test set (Own)
Human annotation	87.32*	-	-	47.71*	-	-
Single CNN	86.48	-	84.88	62.84	-	59.99
Networks Ensemble (90)	90.14	87.79	90.17	70.56	68.38	65.91
Networks Ensemble (30)	88.91	-	89.45	70.18	-	65.28
Double-ended network	88.73	-	85.00	67.51	-	67.91
Double-ended with comp. loss	87.78	-	86.42	67.49	-	68.53

The **comp. loss** furtherly **improves the F1-Score** by ~1.4 % for ER and by ~0.6%

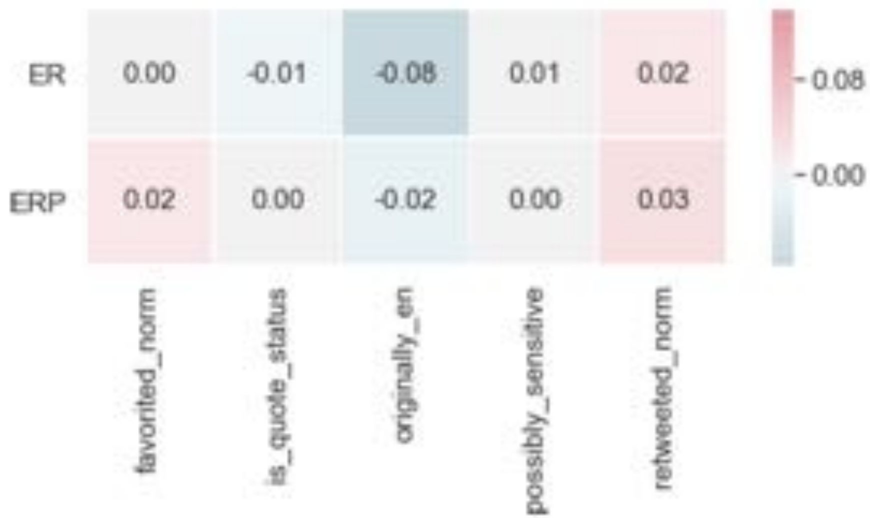
* Evaluation performed on a subset of 50 images

Dealing with Metadata

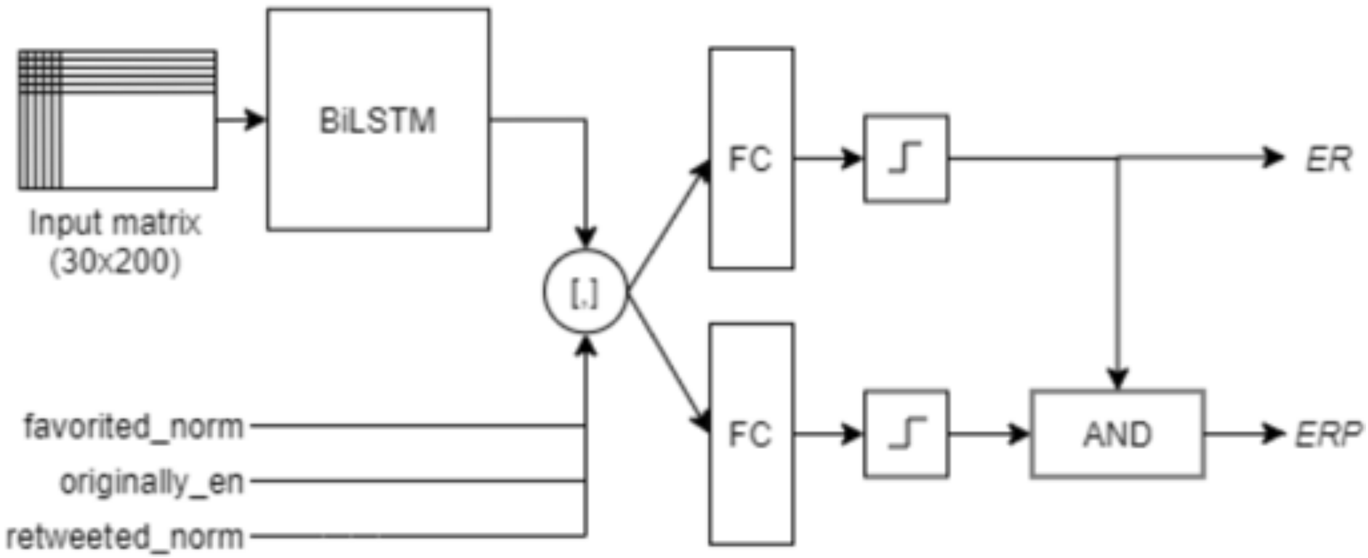
Text pre-processing



Structured feature selection



Metadata approach

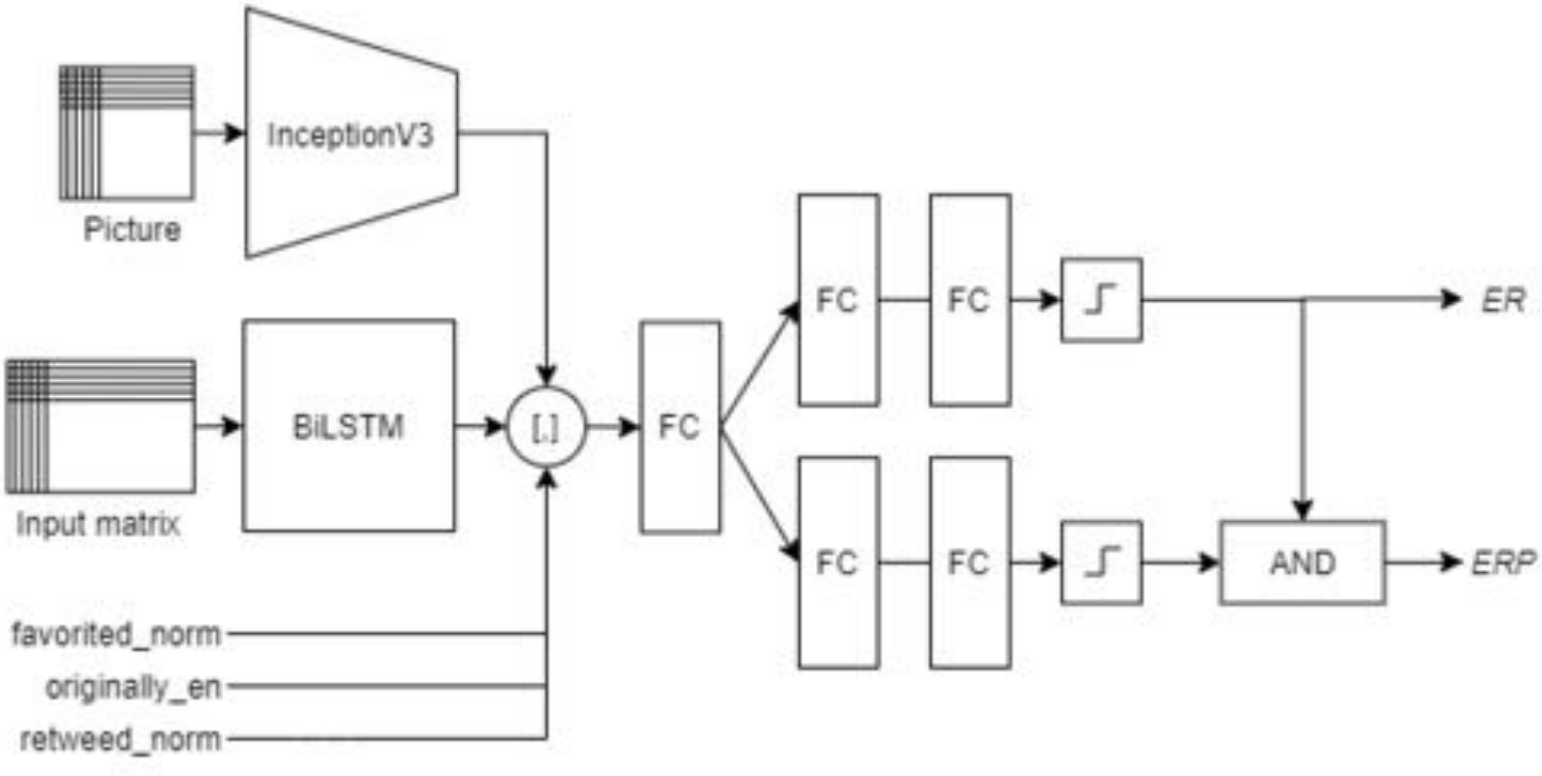


Overall results

	Approach	EVIDENCE OF ROAD [%] Validation set	Test set	EV. OF ROAD PASSAB. [%] Validation set	Test set
V	Double-ended network	88.73	85.00	67.51	67.91
V	Double-ended (comp. loss)	87.78	86.42	67.49	68.53
M	Metadata approach	59.93	65.56	56.82	57.05

V: Visual information only
M: Metadata information only

Combining Visual content and Metadata



Overall results

	Approach	EVIDENCE OF ROAD [%] Validation set	Test set	EV. OF ROAD PASSAB. [%] Validation set	Test set
V	Double-ended network	88.73	85.00	67.51	67.91
	Double-ended (comp. loss)	87.78	86.42	67.49	68.53
M	Metadata approach	59.93	65.56	56.82	57.05
VM	Double-ended network	78.96	86.99	61.06	62.96
	Double-ended (comp. loss)	77.85	84.56	73.61	75.93

Visual + Metadata approaches

- ER task: similar or slightly worse performances
- ERP task: compactness loss significatively improved the performances

V: Visual information only
M: Metadata information only
VM: Visual and Metadata information

Text can disambiguate road passability

Evidence of road
Not passable road

Evidence of road
Passable road

Considerations

- **Networks ensemble (90)** was the **best model** for the Flood **challenge in MediaEval2018**, but it is **unpractical for real world problems**
- Proposed "**Double-ended network**", a **novel** architecture, **lighter** and **faster**, **ready for real world applications**
- **Compactness loss improved the performances**
- Using **visual information**, **performances are comparable** to the **Network ensemble (90) in the ER task**, **better in the ERP task**
- The Double-ended network was then **extended using metadata**, which furtherly **improved the performance when using the compactness loss**

Outline

Introduction

State of the Art

Supporting EM using Social Media data

Supporting EM using Satellite data

Rapid Mapping and Damage Assessment Platform

Conclusions

Automatic Delineation of Burned Areas

Automatic delineation of burned areas

Goal

- **Reliable and fast approach** for delineating burned areas caused by wildfires, **using post-wildfire acquisitions only**.
- The approach should be **location-independent**

The assessment foresees two steps:

- **using visible light only**, for aircraft monitoring with low-cost mounted cameras
- **using all spectral data**

Problem statement

Input: $I \in \mathbb{R}^{w \times h \times d}$, post-wildfire Image acquired from Sentinel-2 (L2A)

Visible light task: d = 3 (B02, B03, B04)

All bands task: d = 12

Output: $O \in \{0,1\}^{w \times h}$, the burn delineation map (1 = burned area, 0 otherwise)

Sentinel-2 L2A acquisition

Burned area delineation

Dataset

- 5 countries involved: Finland, France, Italy, Spain, Portugal

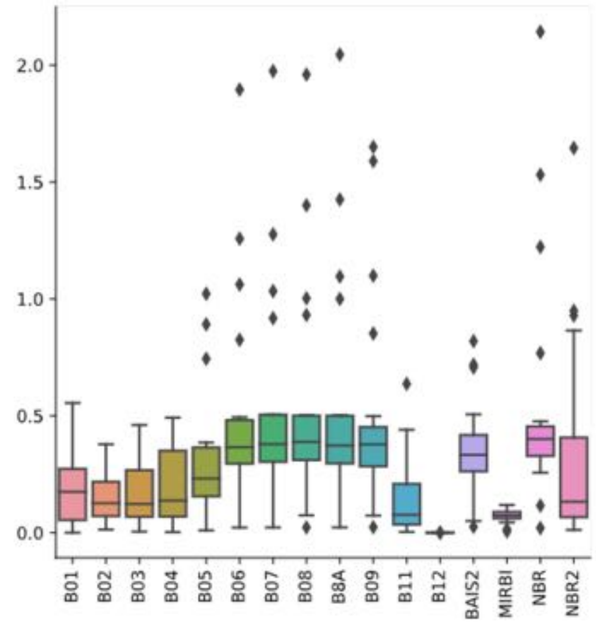
- 21 Copernicus EMS Delineation maps involved
- Each Satellite acquisition is tiled in 135 images of 480x480 px

- 7 folds are created, according to geographical proximity, having the following cardinality:
  - Blue fold: 8
  - Brown fold: 9
  - Pink fold: 30
  - Green fold: 16
  - Orange fold: 18
  - Red fold: 12
  - Yellow fold: 42

Data Analysis

	B01	B02	B03	B04	B05	B06	B07	B08	B8A	B09	B11	B12	DNBR	GT
B01	1.000	0.876	0.833	0.786	0.777	0.576	0.498	0.456	0.447	0.512	0.688	0.723	0.001	-0.059
B02	0.876	1.000	0.972	0.936	0.886	0.679	0.598	0.591	0.546	0.538	0.779	0.795	-0.078	-0.124
B03	0.833	0.972	1.000	0.978	0.950	0.783	0.708	0.702	0.659	0.637	0.853	0.831	-0.170	-0.232
B04	0.786	0.936	0.978	1.000	0.961	0.761	0.685	0.678	0.640	0.614	0.897	0.882	-0.144	-0.211
B05	0.777	0.886	0.950	0.961	1.000	0.868	0.803	0.771	0.765	0.734	0.927	0.860	-0.263	-0.335
B06	0.576	0.679	0.783	0.761	0.868	1.000	0.988	0.962	0.975	0.926	0.772	0.589	-0.558	-0.606
B07	0.498	0.598	0.708	0.685	0.803	0.988	1.000	0.974	0.992	0.940	0.711	0.505	-0.611	-0.650
B08	0.456	0.591	0.702	0.678	0.771	0.962	0.974	1.000	0.974	0.918	0.687	0.476	-0.628	-0.651
B8A	0.447	0.546	0.659	0.640	0.765	0.975	0.992	0.974	1.000	0.946	0.688	0.463	-0.648	-0.679
B09	0.512	0.538	0.637	0.614	0.734	0.926	0.940	0.918	0.946	1.000	0.670	0.448	-0.639	-0.686
B11	0.688	0.779	0.853	0.897	0.927	0.772	0.711	0.687	0.688	0.670	1.000	0.937	-0.190	-0.286
B12	0.723	0.795	0.831	0.882	0.860	0.589	0.505	0.476	0.463	0.448	0.937	1.000	0.084	-0.027
DNBR	0.001	-0.078	-0.170	-0.144	-0.263	-0.558	-0.611	-0.628	-0.648	-0.639	-0.190	0.084	1.000	0.853
GT	-0.059	-0.124	-0.232	-0.211	-0.335	-0.606	-0.650	-0.651	-0.679	-0.686	-0.286	-0.027	0.853	1.000

Correlation Matrix (Pearson)



Separability Index (SI)

- Mostly correlated features are spectral bands used in burned area indexes (B06, B07, B08, B8A, B11)
- The Separability index states NBR is the most suitable spectral index for this dataset

Approaches: idea from the biological field

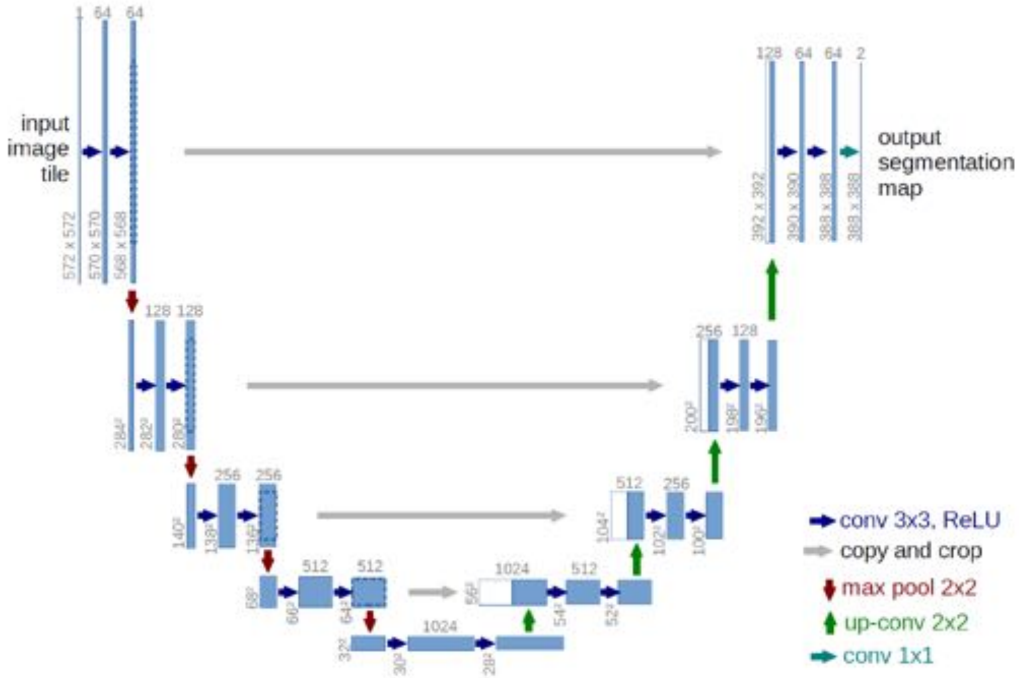
Burned areas can be interpreted as circumscribed shapes presenting irregular borders, sometimes presenting branches or protruding parts.

With some abstraction, this rough description can be applied to biological cells

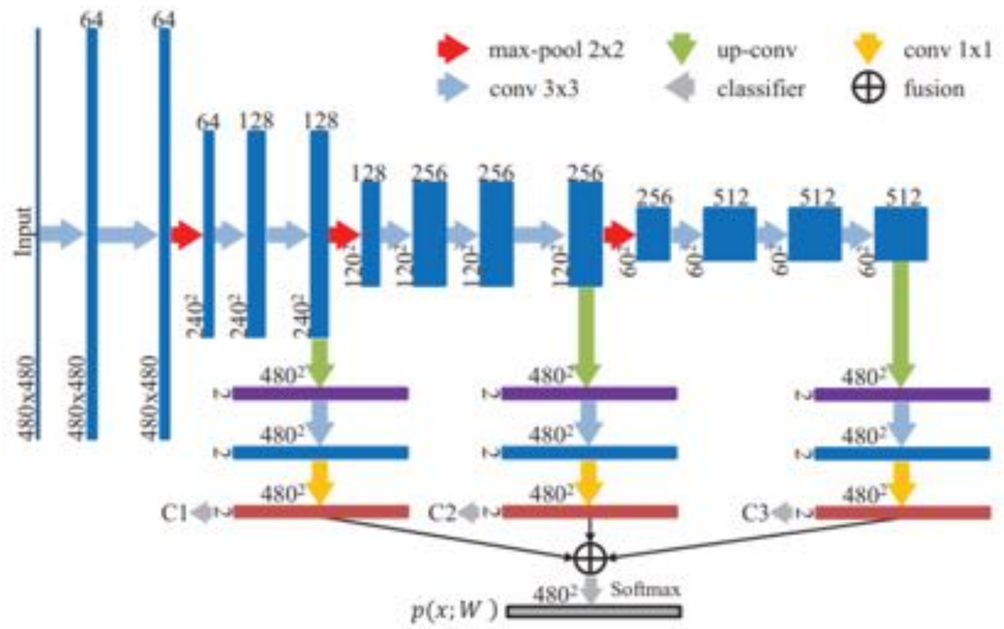
Burned region
(binary mask)

Biological cells
(binary mask)

Approaches



U-Net



CuMedVision

- “Reduced” number of params (20-30 Mln) if compared with other CNNs used as a backbone (e.g. VGG16 ~138 mln)
- Can be successfully trained in small datasets (hundreds/ thousands of pictures)

U-Net: loss function

Original U-Net's loss

$$E = \sum_{\mathbf{x}\in\Omega} \underline{w(\mathbf{x})} \log(p_{\ell(\mathbf{x})}(\mathbf{x}))$$

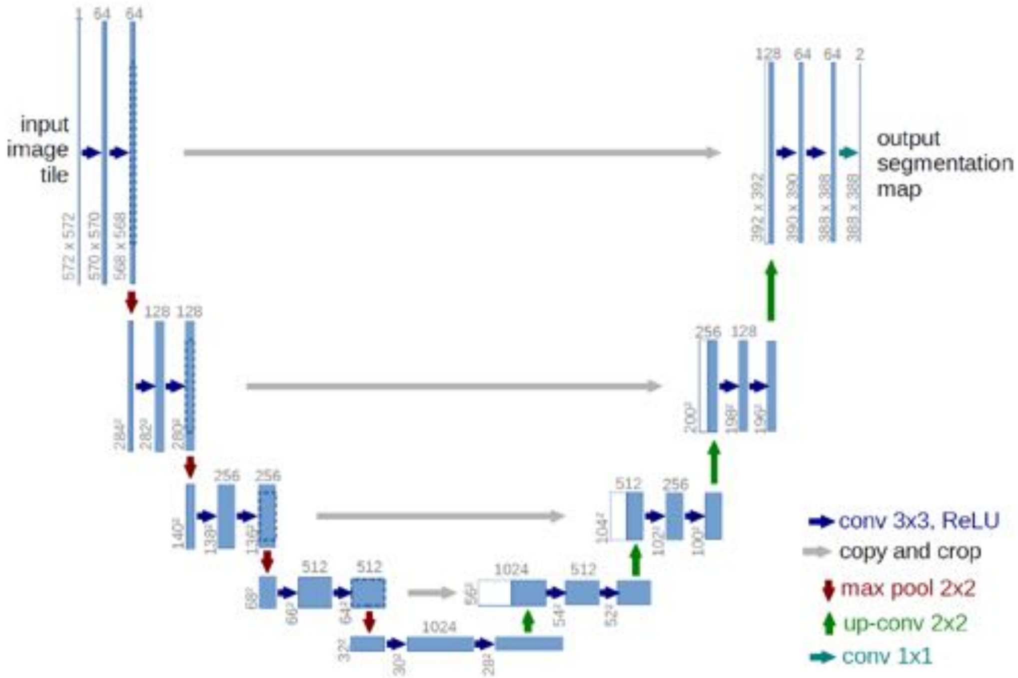
Each pixel x has a weight w(x) associated, which give more importance to:

- errors at cell **borders**
- classes with **lower frequencies**

Loss function used in our work (both CNNs):

Soft Dice Loss: $DL(y\hat{p}) = 1 - \frac{2y\hat{p}+1}{y+\hat{p}+1}$

Dimensions of Input, output adapted according to the tile size (480x480px)



Results – Visible light

Fold	CuMedVision			U-Net		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score
blue	0.33	0.99	0.49	0.34	0.99*	**0.51**
brown	0.98†	0.15	0.22	0.44	0.39*	**0.41**
fucsia	0.89	0.67*	**0.77**	0.95†	0.54	0.69
green	0.86	0.93*	**0.95**	0.98†	0.89	0.93
orange	0.86†	0.45	0.59	0.74	0.61*	**0.66**
red	0.23	0.99*	0.37	0.80†	0.91	**0.85**
yellow	0.82	0.84	0.83	0.80	0.97*	**0.87**
Avg.	0.71	0.72	0.60	0.72†	0.76*	**0.70**

- Both tend to misclassify regions presenting deep water sources (blue, brown folds) or bare soil, like bare rocks or arable lands (orange fold).
- U-Net presents more accurate and stable results

† best Precision; * best Recall; **bold** best F1-Score

Results – All spectral bands

Fold	NBR (Best Threshold)			CuMedVision			U-Net		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score	Precision	Recall	F1-Score
blue	0.55	0.98*	0.63	0.42	0.96	0.58	0.91†	0.95	**0.93**
brown	0.80†	0.94	**0.85**	0.79	0.83	0.81	0.45	0.98*	0.61
fucsia	0.90	0.75	0.82	0.85	0.97	0.90	0.93†	0.98*	**0.95**
green	0.92	0.83	0.87	0.98	0.95*	**0.96**	0.99†	0.91	0.95
orange	0.80†	0.77	0.74	0.64	0.99	0.78	0.71	0.99*	**0.82**
red	0.78	0.83	0.81	0.73	0.98	0.84	0.84†	0.99*	**0.91**
yellow	0.75	0.92	0.80	0.94†	0.87	**0.91**	0.78	0.99*	0.87
Avg.	0.79	0.86	0.79	0.76	0.94	0.83	0.80†	0.97*	**0.86**

- NBR, with best threshold (manual operation) result to be accurate
- Both approaches significatively improve the performance and are robust to water and bare soil
- U-Net confirms to be the best model for this task

† best Precision; * best Recall; **bold** best F1-Score

Coastal area

Ground Truth

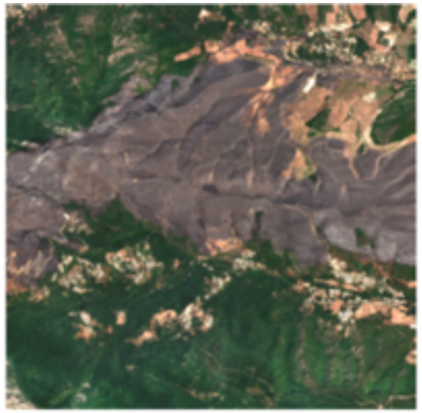
Visible light

All spectral bands

CuMedVision

U-Net

Forest area



Ground
Truth

Visible light

All spectral bands

CuMedVision U-Net

Arid area

Ground
Truth

Visible light

All spectral bands

CuMedVision U-Net

Computational time evaluation

Table 3.4: Inference times of the assessed methods for the delineation task, considering input tiles of dimension 480×480 px.

Bands	Method	# params	Inference time (ms)			
			Avg (CPU)	Std (CPU)	Avg (GPU)	Std (GPU)
RGB	CuMed.	21 Mln	516	20	41	0.2
	U-Net	28 Mln	719	27	45	0.3
ALL	NBR	-	2	3	-	-
	CuMed.	24 Mln	624	22	47	0.3
	U-Net	31 Mln	796	30	61	0.4

Computational time linearly dependent with the number of parameters
Overall inference time < 0.8 s on CPU, < 0.062 s on GPU

Hardware
- CPU: Intel Core I9 7940x
- RAM: 128 GB, DDR4
- GPU: 1 x NVIDIA 1080 Ti

Considerations

- U-Net and CuMedVision are reliable approaches for this task
- In visible light, both tend to misclassify water and bare soil (arable land, bare rocks), but they can be affordable for a rough analysis
- Using all the spectrum, both approaches are highly reliable (F1-Score > 0.82)
- U-Net produce best mappings, and tend to be more stable to different land types. Differences in computation time are negligible on GPU (< 0.062s)

Acknowledged as a runner up for the best paper award
International Conference on Information Systems for Crisis Response and Management

Automatic Damage Severity Estimation of Burned Areas

Automatic damage severity estimation in burned areas

Goal

- **Reliable and fast approach** for estimating the damage severity in burned areas, **using post-wildfire acquisitions only**.
- The approach should be **location-independent**

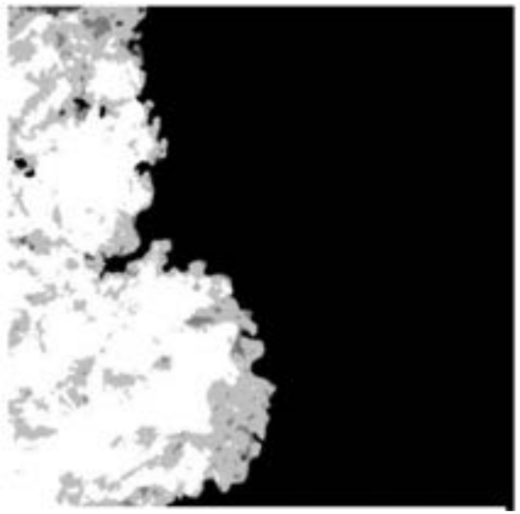
The assessment foresees the use of **all spectral data**

Problem statement

Input: $I \in \mathbb{R}^{w \times h \times d}$, Image acquired from Sentinel-2 (L2A), d = 12 (all bands)
Output: $O \in \mathbb{R}^{w \times h}$, $0 \leq O_{x,y} \leq 4$, the burn grading map

Where severity levels match the Copernicus defined levels:
0: no damage
1: negligible to slight damage
2: moderate damage
3: high damage
4: destroyed

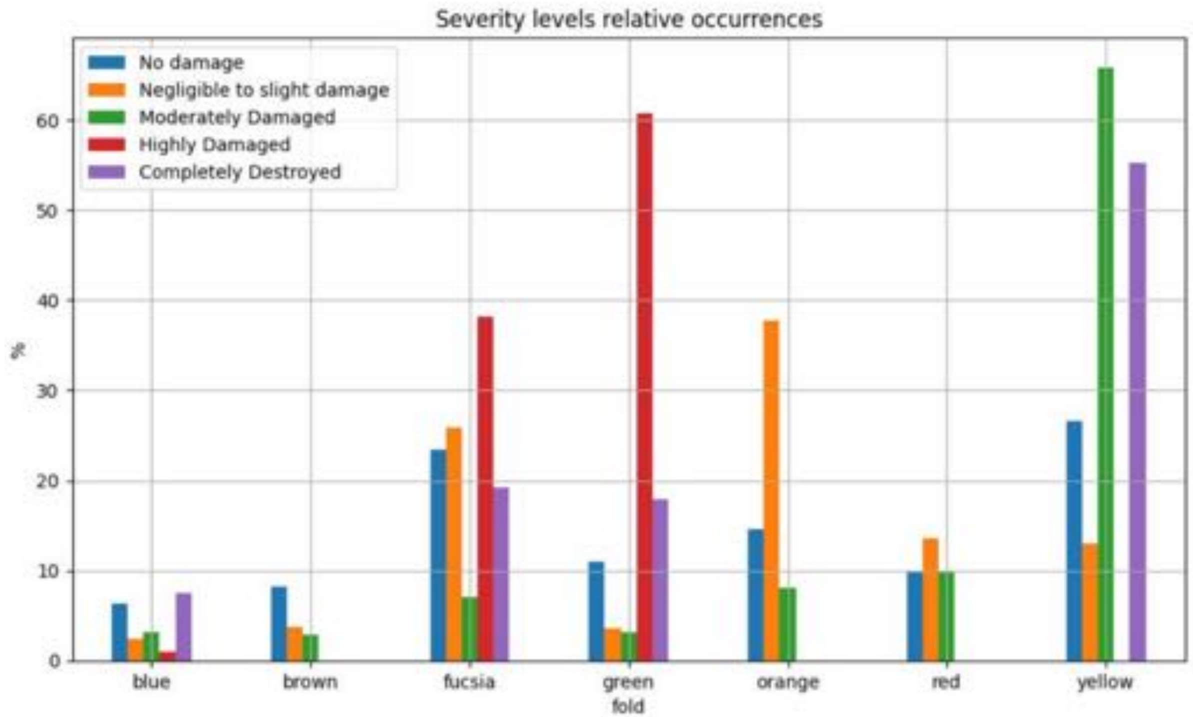
Sentinel-2 L2A acquisition



Burned area grading map*

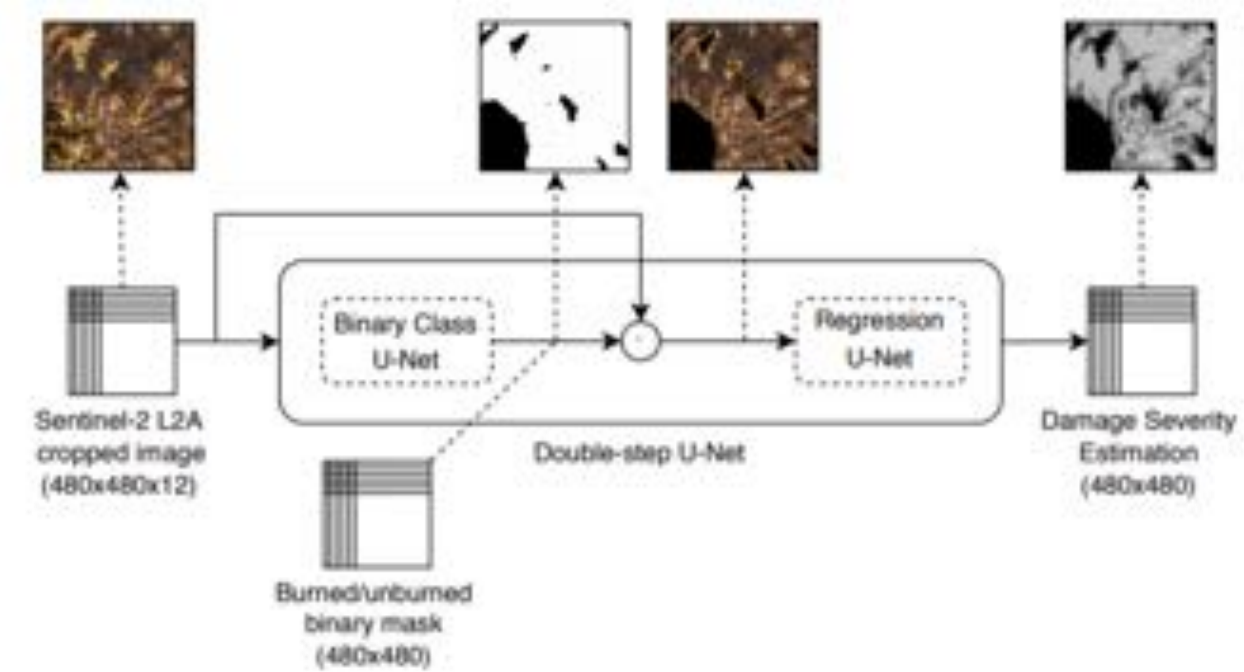
*Illustrated colors range from black (= no damage) to white (= destroyed)

Data analysis – Severity levels distribution



Unbalanced folds, not all severity levels in each fold

Approach: Double-Step U-Net (DSU)

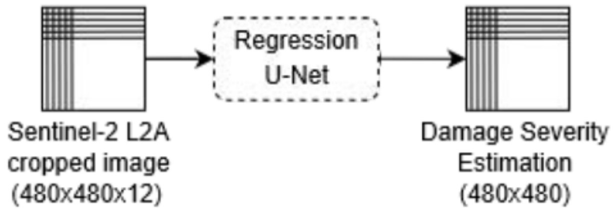


Idea: what about splitting the problem in two subtasks?
1) Segmenting the burned area (burned/not burned)
2) Estimating the damage severity in the burned regions

Loss functions
- Binary U-Net: Soft Dice loss
- Regression U-Net: MSE loss

Ablation study

Single U-Net (regression)

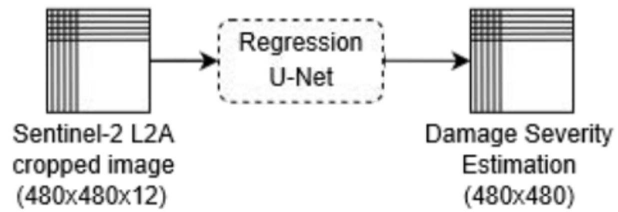


Loss functions

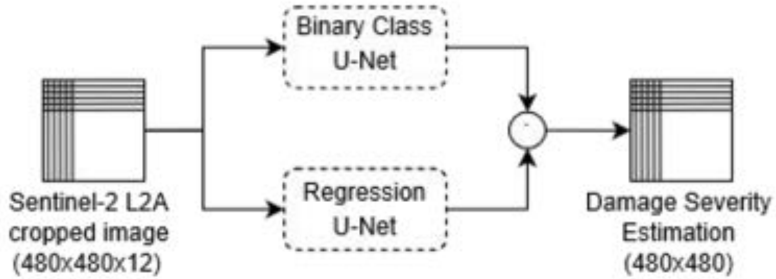
- Regression U-Net: MSE loss

Ablation study

Single U-Net (regression)



Parallel U-Net

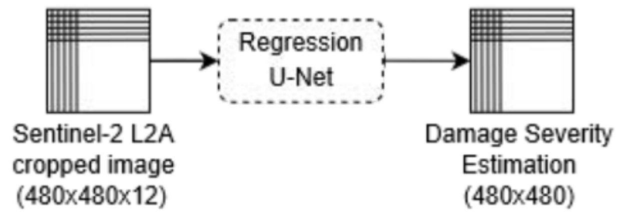


Loss functions

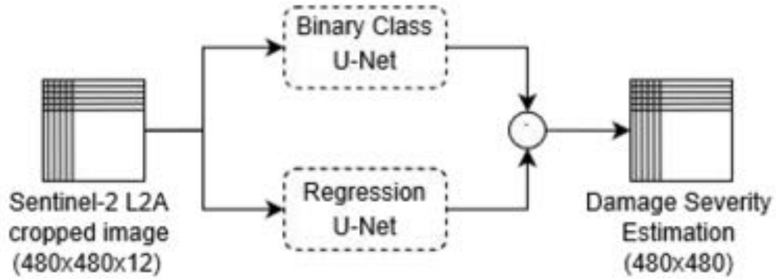
- Binary U-Net: Soft Dice loss
- Regression U-Net: MSE loss

Ablation study

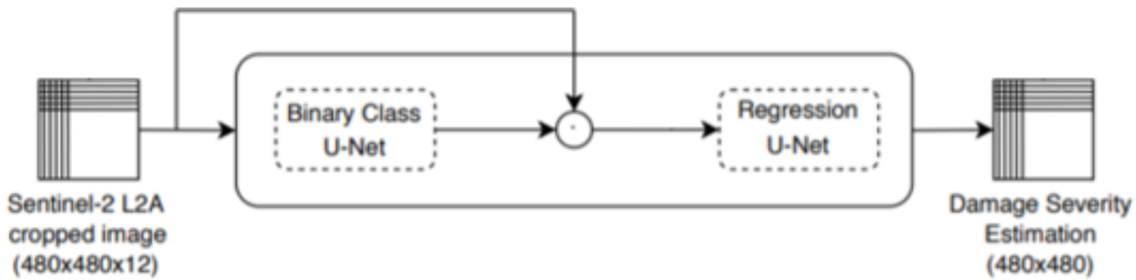
Single U-Net (regression)



Parallel U-Net



Double-step U-Net



Results

Severity	Overall Per-Class Performance (RMSE)			
	dNBR	Single U-Net	Parallel U-Net	Double-Step U-Net
0	0.62	0.42	0.20 *†	0.35
1	0.95 †	1.07	1.08	1.03 *
2	1.09	1.01	1.02	0.94 *†
3	1.02	0.95	0.97	0.76 *†
4	0.91 †	1.45	1.46	1.30 *
Avg.	0.92	0.98	0.94	0.88*†

- **Considering U-Net** based **models**, **DSU achieves best performance** in 4/5 severity levels
- **Considering dNBR** (which uses pre- and post- fire acquisitions), **DSU performed better**

Fold	Severity	Performance (RMSE)			
		dNBR	Single U-Net	Parallel U-Net	Double-Step U-Net
Blue	0	0.78	1.06	0.23 *†	0.27
	1	1.07	0.89	0.89	0.73 *†
	2	1.23	0.71	0.80	0.62 *†
	3	0.82	0.63	0.65	0.52 *†
	4	0.62 †	0.93 *	0.96	1.44
Brown	0	0.65	0.22	0.20 *†	0.47
	1	0.97	0.94	0.94	0.92 *†
	2	1.01	0.65 *†	0.65 *†	0.86
	3	0.70	0.35 *†	0.35 *†	0.39
	4	0.48 †	1.26 *	1.28	1.49
Fucsia	0	0.82	0.39	0.16 *†	0.24
	1	1.37	1.40	1.41	1.02 *†
	2	1.12	1.35	1.35	1.00 *†
	3	1.10	0.97	0.97	0.75 *†
	4	1.67	1.26 *†	1.28	1.49
Green	0	0.20	0.28	0.04 *†	0.18
	1	0.64 †	1.03	1.03	0.80 *
	2	1.18 †	1.78	1.78	1.40 *
	3	1.46	1.87	1.90	1.38 *†
	4	1.09	1.57	1.58	1.00 *†
Orange	0	0.42 †	0.40	0.39 *	0.43
	1	1.10 †	1.68	1.68	1.47 *
	2	1.04	1.14	1.14	1.02 *†
	3	-	-	-	-
	4	-	-	-	-
Red	0	0.20	0.21	0.15 *†	0.33
	1	0.66 †	0.71 *	0.71 *	1.21
	2	0.80	0.56 *†	0.56 *†	0.97
	3	-	-	-	-
	4	0.58 †	1.96	1.96	1.21 *
Yellow	0	1.31	0.37	0.25 *†	0.54
	1	0.83 †	0.83*	0.84	1.04
	2	1.24	0.89	0.89	0.71 *†
	3	-	-	-	-
	4	0.99 †	1.70	1.71	1.18 *

† best among all approaches, * best among U-Net-based approaches

Statistical significance

For each fold and test case, we considered the RMSE scores for all the tiles in the dataset.

- **Friedman test** was performed to recognize statistical differences in the RMSE scores

- If the Friedman's test H_0 is rejected, we performed the **Nemenyi test** to assess the best approach

Ticks (✓) indicate statistical relevance in both tests (H_0 rejected twice). Best approaches are highlighted by the best results (shown in the previous slide)

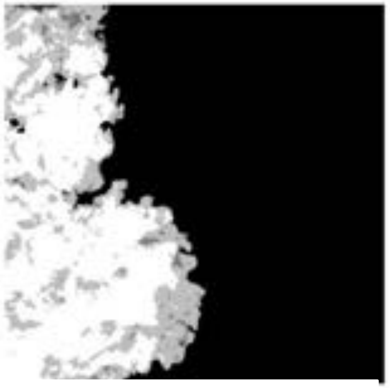
- **Parallel U-Net perform better than Single-UNet on severity 0** (thanks to Binary U-Net)
- **Double-Step U-Net produce significatively different results than the other approaches**
- **On average, DSU provide better results**

Table 3.6: Statistical significance between grading maps produced by the approaches shown in Table 3.5, considering different folds (shortened to the second letter) and severity levels. The Nemenyi test was performed with $\alpha = 0.05$. Check marks (✓) highlight statistical relevance (null hypothesis is rejected). Dashes (-) mark unavailable severity for the corresponding fold.

Test	Severity	Fold: Bl	Br	Fu	Gr	Or	Rr	Ye
Single U-Net - Parallel U-Net	0	✓		✓	✓		✓	✓
	1							
	2							
	3					-	-	-
	4						-	-
Single U-Net - Double-Step U-Net	0	✓	✓	✓	✓	✓	✓	✓
	1	✓	✓	✓	✓	✓	✓	✓
	2	✓	✓	✓	✓	✓	✓	✓
	3	✓	✓	✓	✓	-	-	-
	4	✓	✓	✓	✓	✓	-	-
Parallel U-Net - Double-Step U-Net	0	✓	✓	✓	✓	✓	✓	✓
	1	✓	✓	✓	✓	✓	✓	✓
	2	✓	✓	✓	✓	✓	✓	✓
	3	✓		✓	✓	-	-	-
	4	✓	✓	✓	✓	✓	-	-
dNBR - Double-Step U-Net	0	✓	✓	✓			✓	✓
	1	✓	✓	✓	✓	✓	✓	✓
	2	✓	✓	✓	✓		✓	✓
	3	✓		✓	✓	-	-	-
	4	✓	✓	✓		✓	-	-

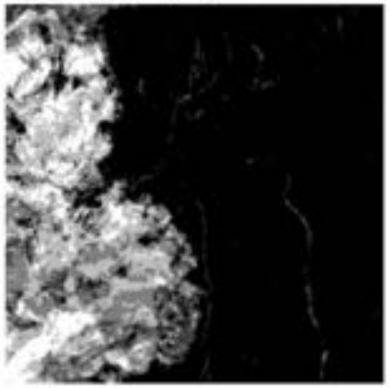
Examples

Sentinel-2

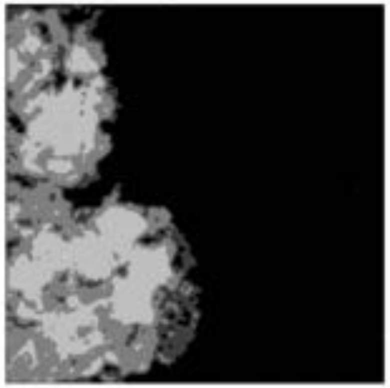


Ground Truth

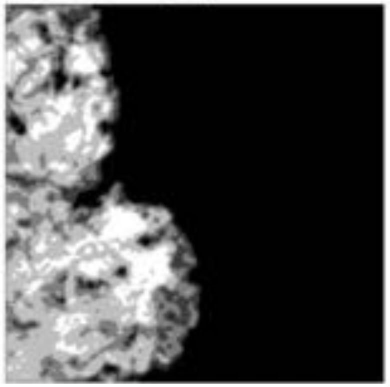
Binary U-Net



dNBR

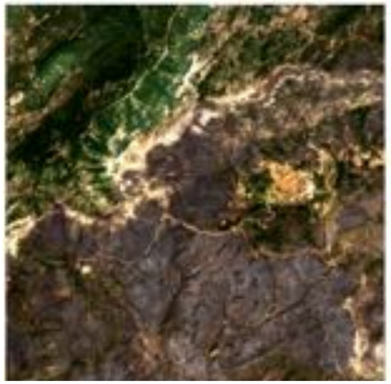


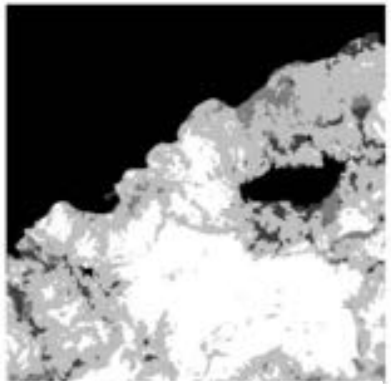
Single U-Net



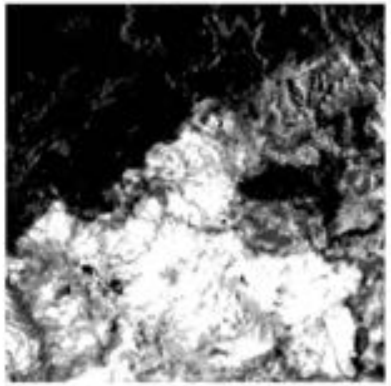
Double-Step U-Net

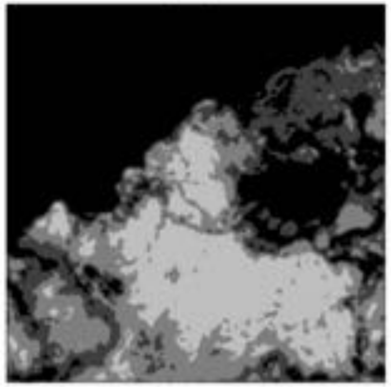
Examples

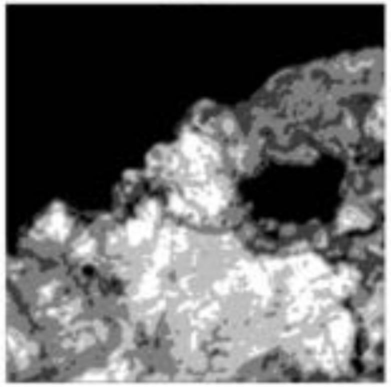

Sentinel-2


Ground Truth


Binary U-Net


dNBR


Single U-Net


Double-Step U-Net

Computational time evaluation

Table 3.7: Inference times of the assessed methods for the damage severity estimation task, considering input tiles of dimension 480×480 px and 12 bands.

Method	# params	Inference time (ms) Avg (CPU)	Std (CPU)	Avg (GPU)	Std (GPU)
dNBR	-	3	2	-	-
Single UN	31 Mln	788	31	62	0.3
Parallel UN	62 Mln	1582	43	104	0.5
Double-Step UN	62 Mln	1511	53	103	2

Computational time linearly dependent with the number of parameters
Overall inference time ~ 1.5s on CPU, ~ 100ms on GPU

Hardware
- CPU: Intel Core I9 7940x
- RAM: 128 GB, DDR4
- GPU: 1 x NVIDIA 1080 Ti

Considerations

- Proposed a **novel method**, named **Double-Step U-Net** (DSU)
  - splitting in two sub-problems enhances the performances
  - ablation study confirmed the hypothesis

- **Compared to the literature** (**dNBR**), **DSU performs better** and with only **half of the information** (only post-wildfire images)

- **Computation times** are **fast:** 1.5s on CPU, 100ms on GPU

Automatic Delineation of ongoing Flood Events

Ongoing Flood delineation

Prevention → Mitigation → Preparedness → **Response** → **Recovery**

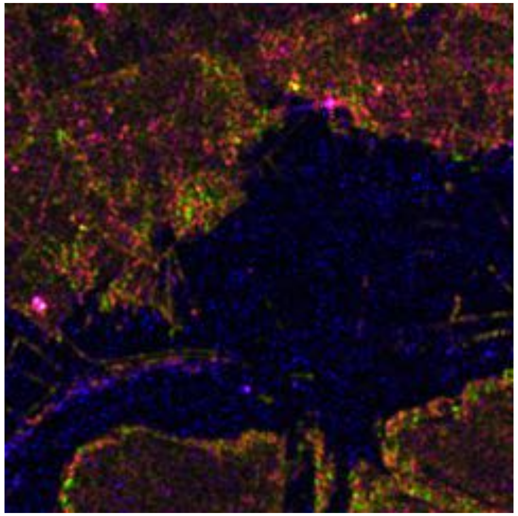
Goal

- **Reliable and fast approach** for estimating the damage severity in burned areas, **using current-acquired content** and **cartography data**.

- The approach should be **location-independent**

Problem statement

Input: $I \in \mathbb{R}^{w \times h \times d}$, $0 \leq I_{x,y,z} \leq 1$, a normalized image acquired from Sentinel-1 (VV, VH, VV/VH)
$C \in \{0,1\}^{w \times h}$, a cartography map, involving hydrography
Output: $O \in \{0,1\}^{w \times h}$, the flood delineation map (1 = flooded area, 0 otherwise)



Sentinel-1 acquisition

Flood delineation
(no natural water sources)

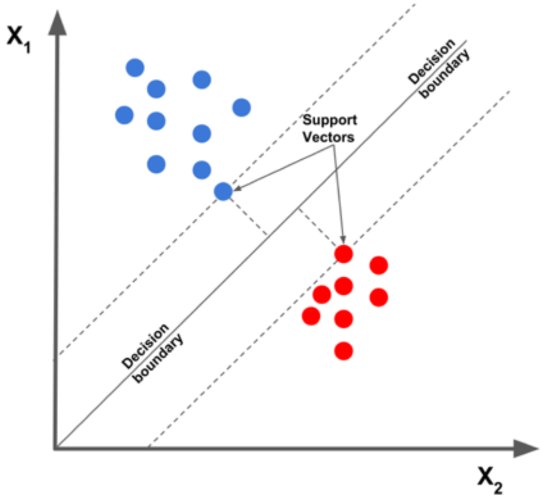
Dataset

- 5 countries involved: Austria, Greece, Ireland, Italy, United Kingdom
- Contains 64 satellite acquisitions of size 480x480 px, 3 channels
- 5 folds are identified, with the following cardinality:
  - AU fold: 8
  - GR fold: 8
  - IR fold: 21
  - IT fold: 11
  - UK fold: 16

Country	Activation Code	Location Name
AU	EMSR184	JEMALONGCONDOBOLIN
GR	EMSR122	01STRYMONAS
	EMSR122	04MAVROTHALASSA
IR	EMSR149	05ENNIS
	EMSR149	08GORT
	EMSR149	13PORTUMNA
	EMSR149	02ATHLONE
	EMSR149	06COROFIN
	EMSR149	04CASTLECONNEL
	EMSR156	02LOUGHFUNSHINAGH
IT	EMSR192	04ASTI
	EMSR192	10CASALEMONFERRATO
	EMSR192	14ALESSANDRIA
	EMSR192	13SALE
UK	EMSR147	01CARLISLE
	EMSR147	04KENDAL
	EMSR150	01YORK
	EMSR150	02SELBY
	EMSR150	08LEEDS

Assessed approaches

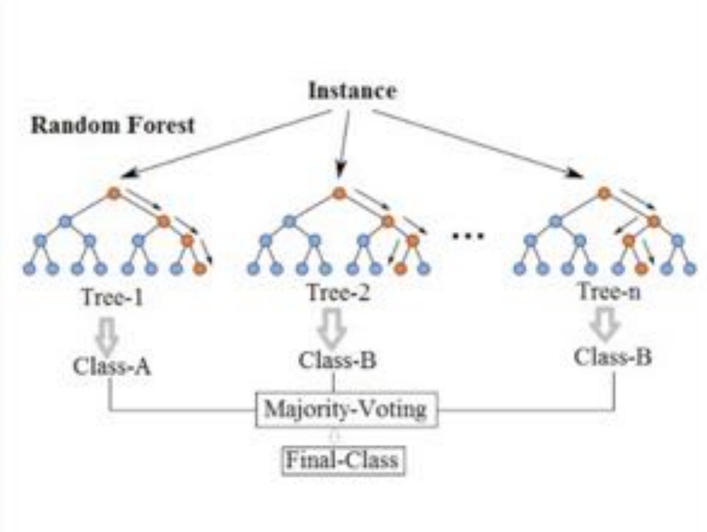
Support Vector Machine (SVM, baseline)



- Hinge loss and L2 regularization

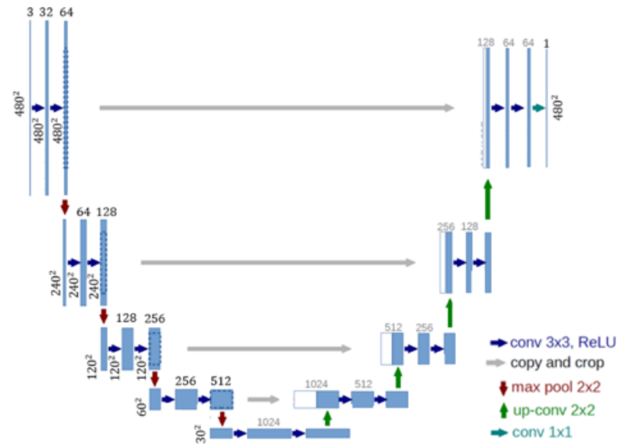
$$L(x_j, y_j) = H(x_j, y_j) + L2$$

Random Forest (RF)



- # Decision trees: empirically assessed
- Purity criterion: Gini index

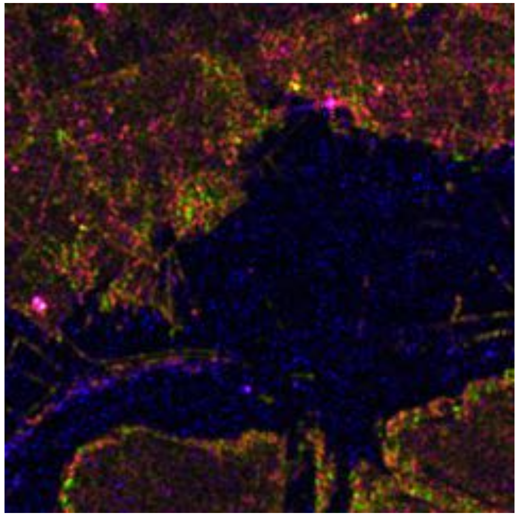
U-Net



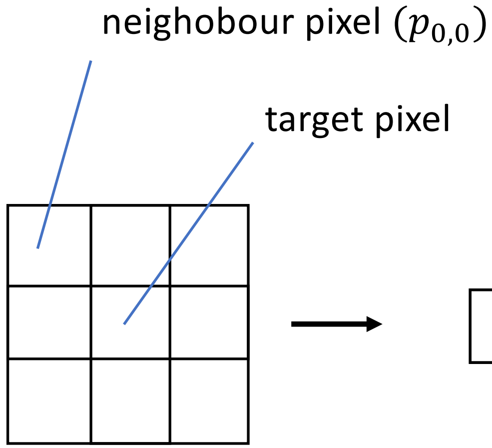
- Same as burned area delineation
- Loss function, Dice Loss:

$$DL(y, \hat{p}) = 1 - \frac{2y\hat{p} + 1}{y + \hat{p} + 1}$$

Preprocessing: windowing (SVM & RF)



Input tile: 480 x 480 px, 3 ch



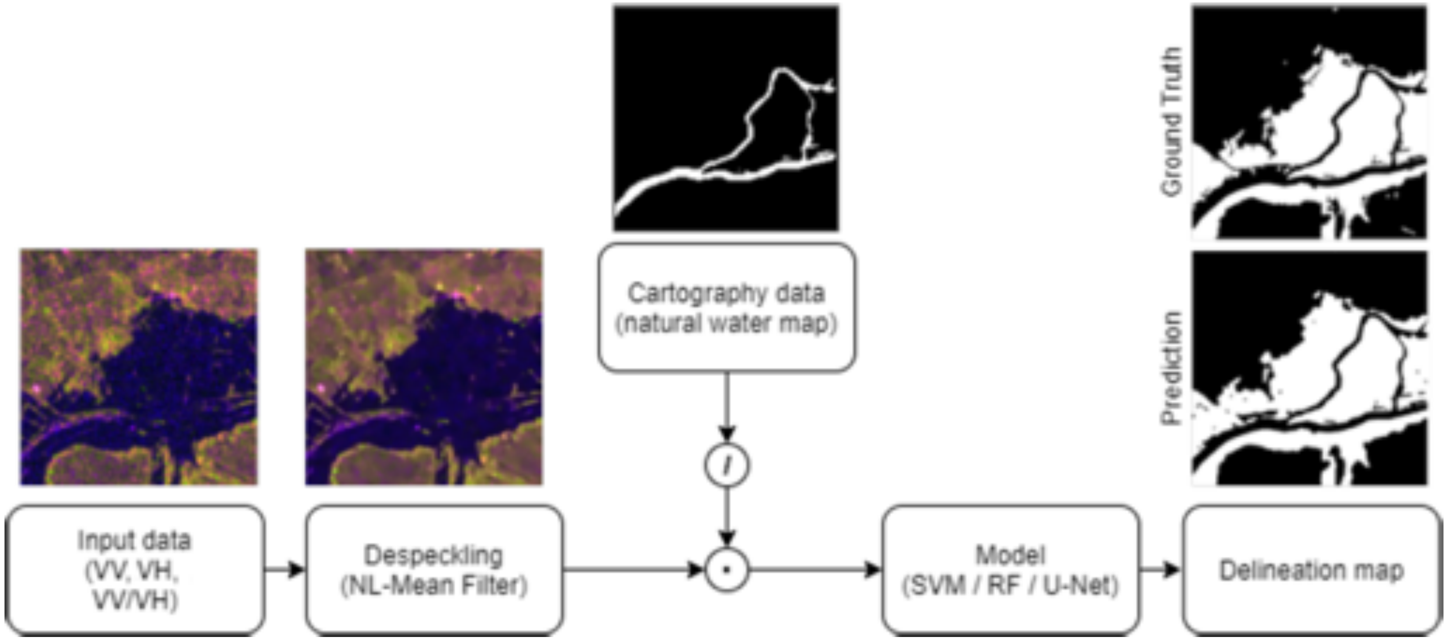
Window
($w \times w$ pixels, w odd)

$p_{0,0,0}$	$p_{0,0,1}$	$p_{0,0,2}$	$p_{0,1,0}$	…	$p_{w-1,w-1,2}$

Vectorized window
Length: $w \times w \times$ **3**

Transformed input dimensions: $\underbrace{(480 \times 480)}_{\text{rows}} \times \underbrace{(w \times w \times 3)}_{\text{columns}}$

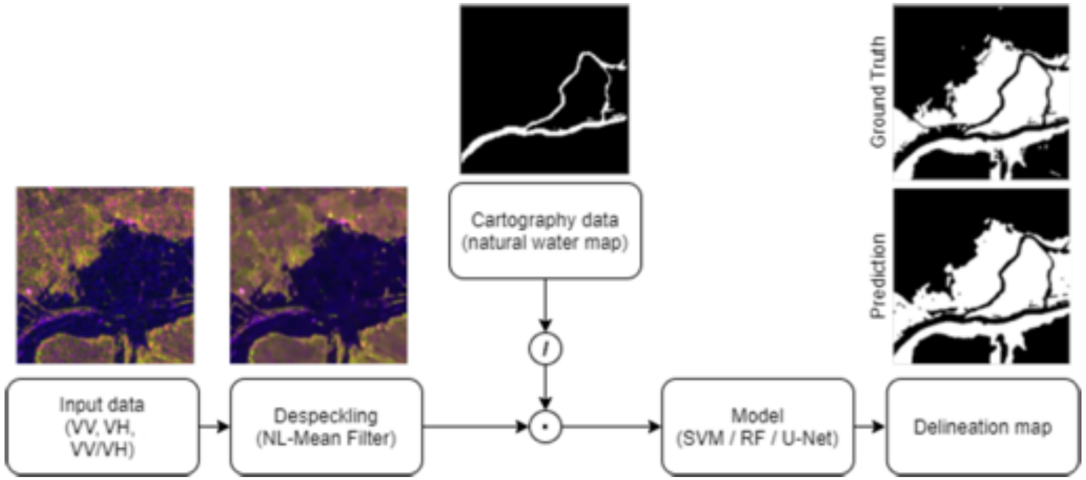
Flood Delineation from Satellite data



Flood Delineation from Satellite data

Ablation Study:

- Test case #1: Using only raw data (Input data)
- Test case #2: Using despeckled data (Input data + despeckling)
- Test case #3: Using the full approach (despeckled data + hydrography)



Overall Average Results

Test #1: Raw data

Test	SVM			RF			U-Net		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score	Precision	Recall	F1-Score
#1	0.61	0.79	0.69	0.78†	0.71	0.74	0.77	0.82*	**0.80**

Overall Average Results

Test #1: Raw data
Test #2: Despeckled data

Test	SVM			RF			U-Net		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score	Precision	Recall	F1-Score
#1	0.61	0.79	0.69	0.78†	0.71	0.74	0.77	0.82*	**0.80**
#2	0.79	0.73	0.75	0.78	0.72	0.75	0.82†	0.79*	**0.80**

Despeckling operation:
- significantly improves SVM performance (+6% F1)
- does not affect either RF our U-Net

Overall Average Results

Test #1: Raw data
Test #2: Despeckled data
Test #3: Despeckled data + Hydrography

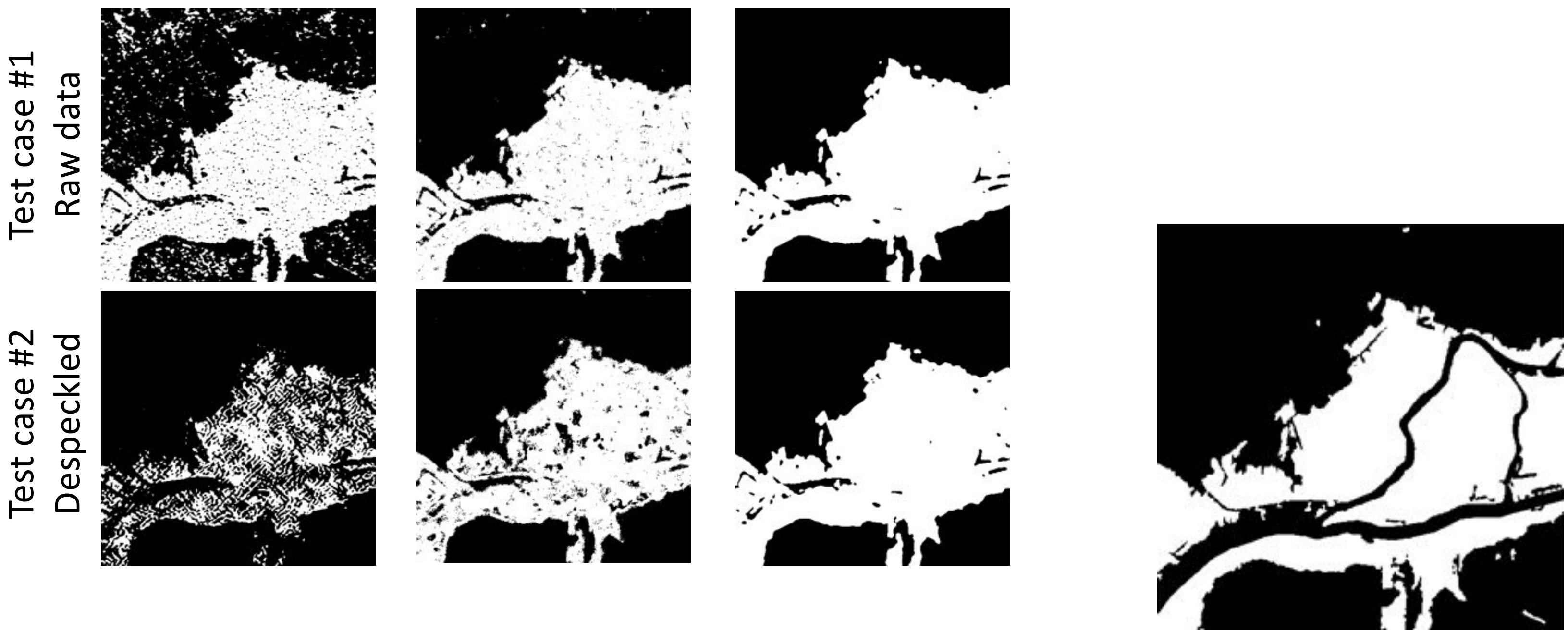
Test	SVM			RF			U-Net		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score	Precision	Recall	F1-Score
#1	0.61	0.79	0.69	$0.78^{\dagger}$	0.71	0.74	0.77	$0.82^{\star}$	**0.80**
#2	0.79	0.73	0.75	0.78	0.72	0.75	$0.82^{\dagger}$	$0.79^{\star}$	**0.80**
#3	0.80	0.76	0.76	$0.89^{\dagger}$	0.83	0.85	0.85	$0.87^{\star}$	**0.86**

Despeckling operation:
- significantly improves SVM performance (+9% F1)
- does not affect either RF our U-Net

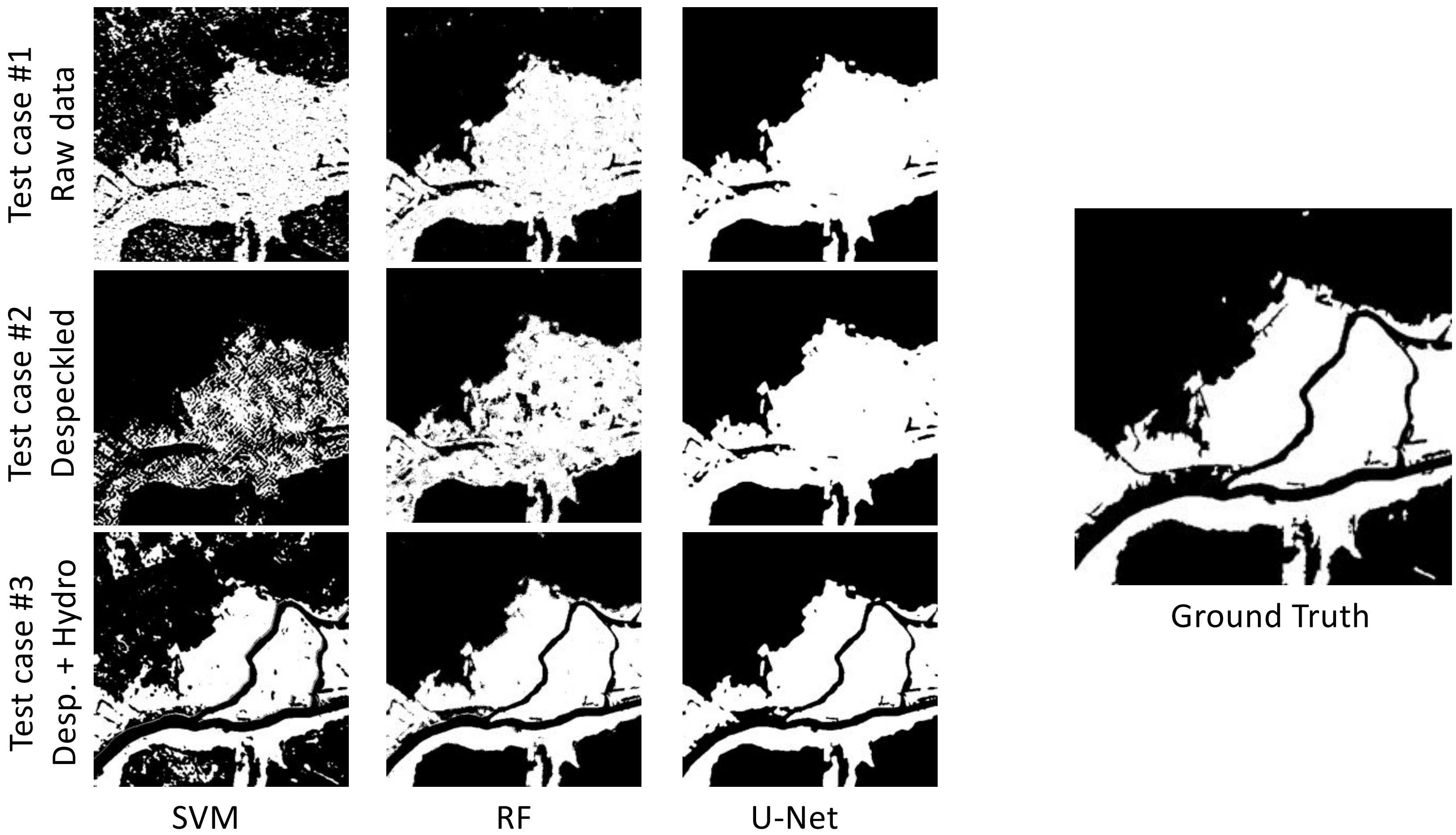
Hydrography:
- slightly improves SVM performance
- significantly improves RF and U-Net performance (+10% and +6% F1, resp.)

Delineation examples

Delineation examples



Delineation examples



Are RF and U-Net’s maps significatively different?

McNemar’s statistical test

For each fold and test case, we considered the predictions of all the delineation maps generated by RF and U-Net.

Given A and B, two different approaches, we formulated:

- **Null hypothesis** (H_0): delineation maps generated by RF and U-Net are equal
- **Alternative hypothesis** (H_1): delineation maps generated by RF and U-Net are significantly different

Considering α = 0.05, H_0 **was rejected for each test case**, therefore:

RF and U-Net produce significatively different maps

Computational time evaluation

Table 4.5: Inference times of the assessed methods for the delineation task, considering input tiles of dimension 480 × 480 px and 3 channels.

Method	# params	Inference time (ms)			
		Avg (CPU)	Std (CPU)	Avg (GPU)	Std (GPU)
SVM	< 100	217	15	-	-
RF	21 Mln	593	33	-	-
U-Net	28 Mln	716	24	47	0.4

Hardware

- CPU: Intel Core I9 7940x
- RAM: 128 GB, DDR4
- GPU: 1 x NVIDIA 1080 Ti

Considerations

- **U-Net and RF**, with **Despeckling** and **Hydrography** provide **highly affordable delineation maps**

- Considering evaluation scores (Precision, Recall, F1) **U-Net performs**, on average, **slightly better than RF**

- Considering **computational execution time**, **RF is faster on CPU** (because of the reduced number of params), **U-Net is way faster on GPU**

This study proved that **U-Net** and **RF are valid methods** that provide **high accurate delineation map** in **near-real time**, **considering** the **current satellite acquisition**

Outline

Introduction

State of the Art

Supporting EM using
Social Media data

Supporting EM using
Satellite data

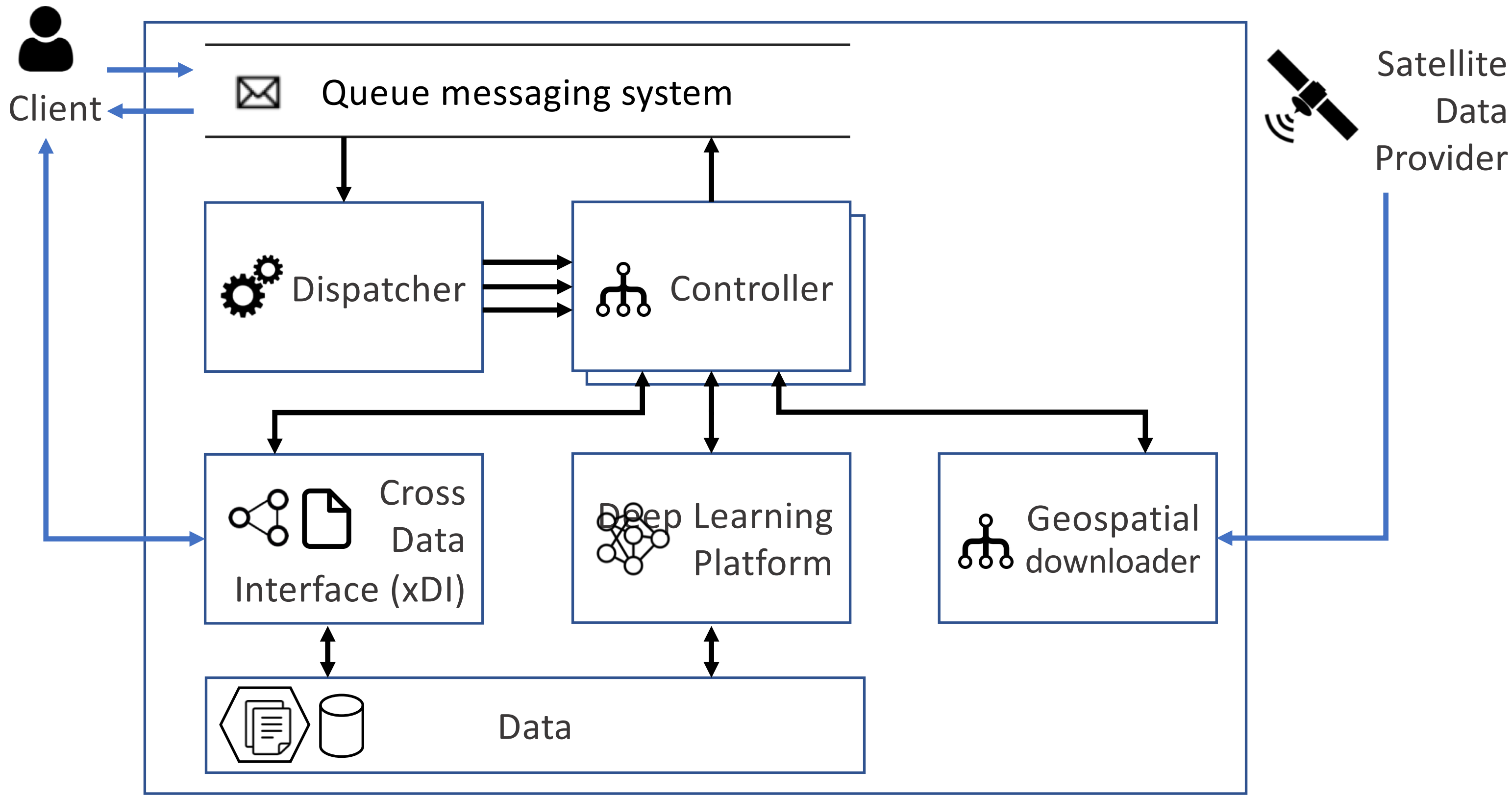
Rapid Mapping and Damage Assessment Platform

Conclusions

Rapid Mapping and Damage Assessment Platform

Microservices architecture able to **process and deliver mapping requests automatically**.

Delineation and **grading models presented are operative** in this platform.



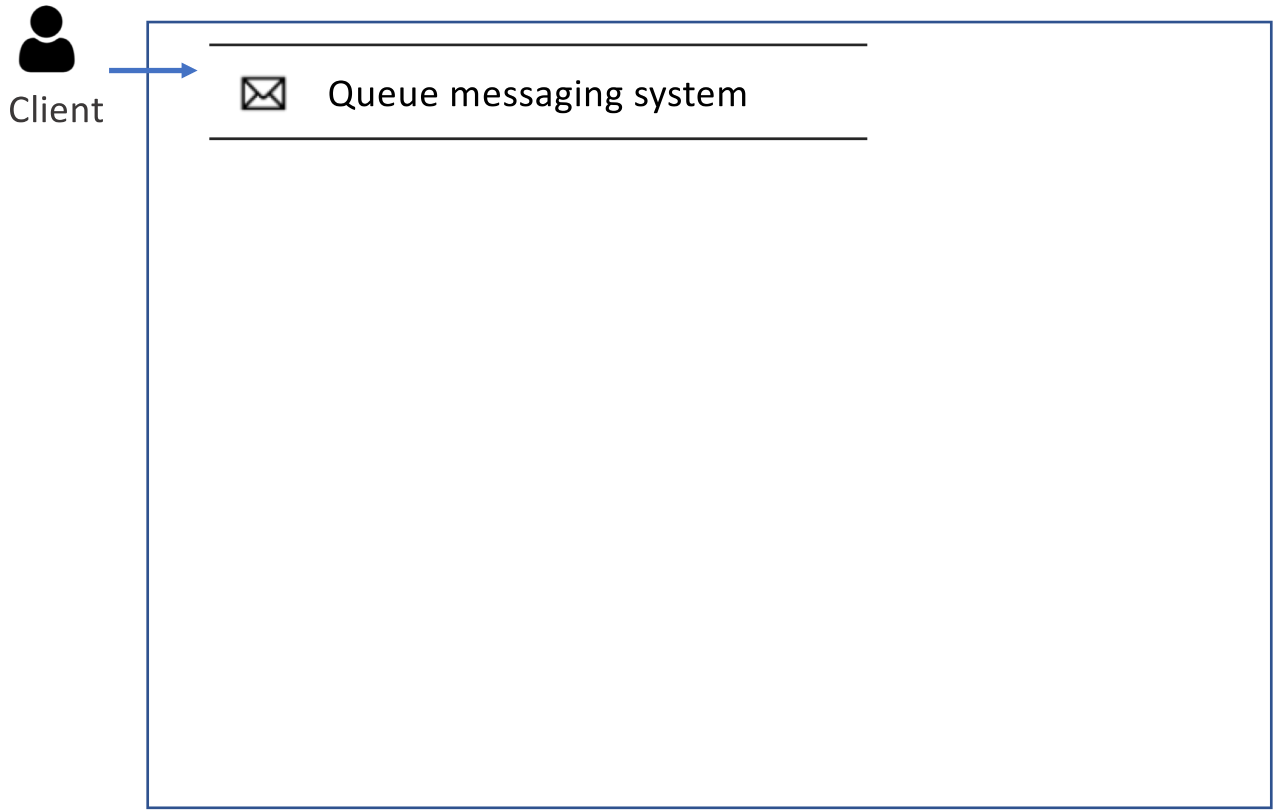
sentinelhub by SINERGISE · docker · NGINX · swagger · gunicorn · FastAPI · dramatiq · ONNX

Rapid Mapping and Damage Assessment Platform

Any authorized Client sends the request containing:

- Area of Interest
- Date range,
- Hazard type
- Mapping type

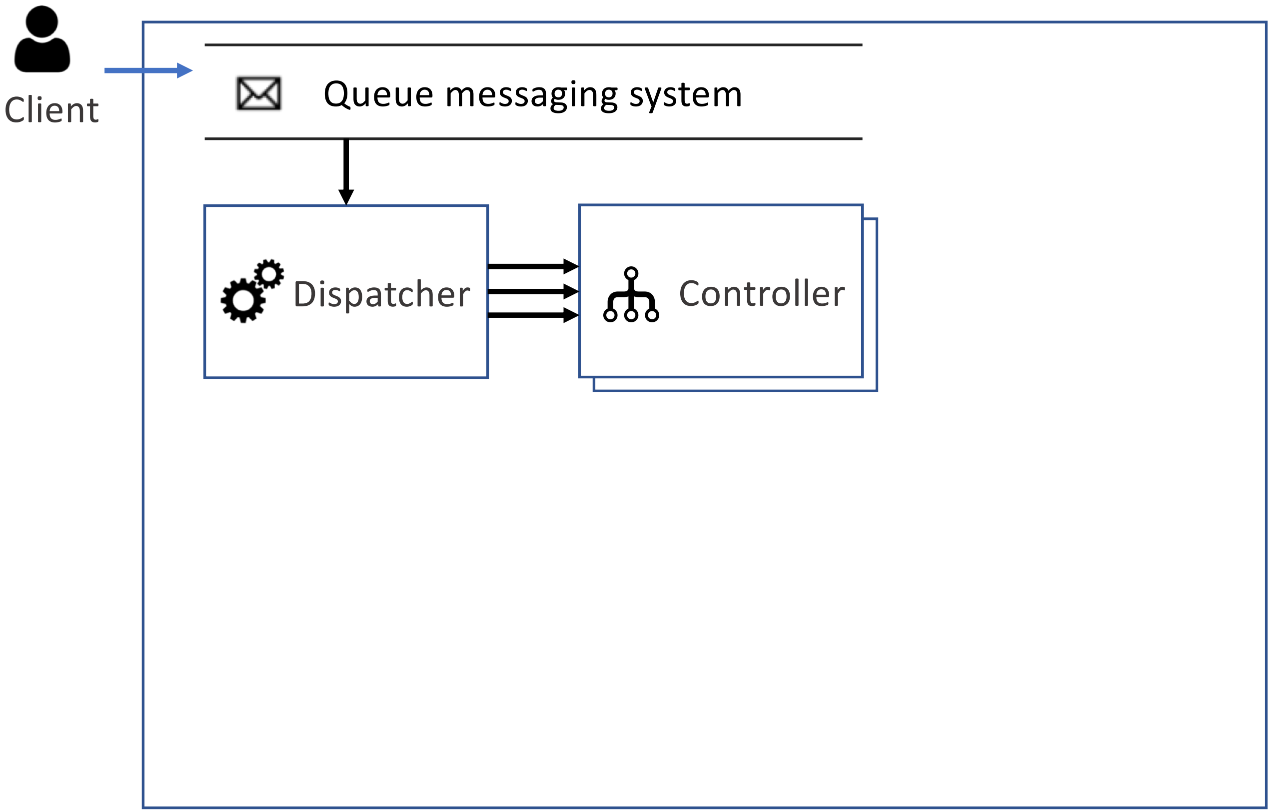
The **Queue messaging system** handles the communication with the other modules



Rapid Mapping and Damage Assessment Platform

The **Dispatcher** determine the requests to be processed, according to the available hardware resources

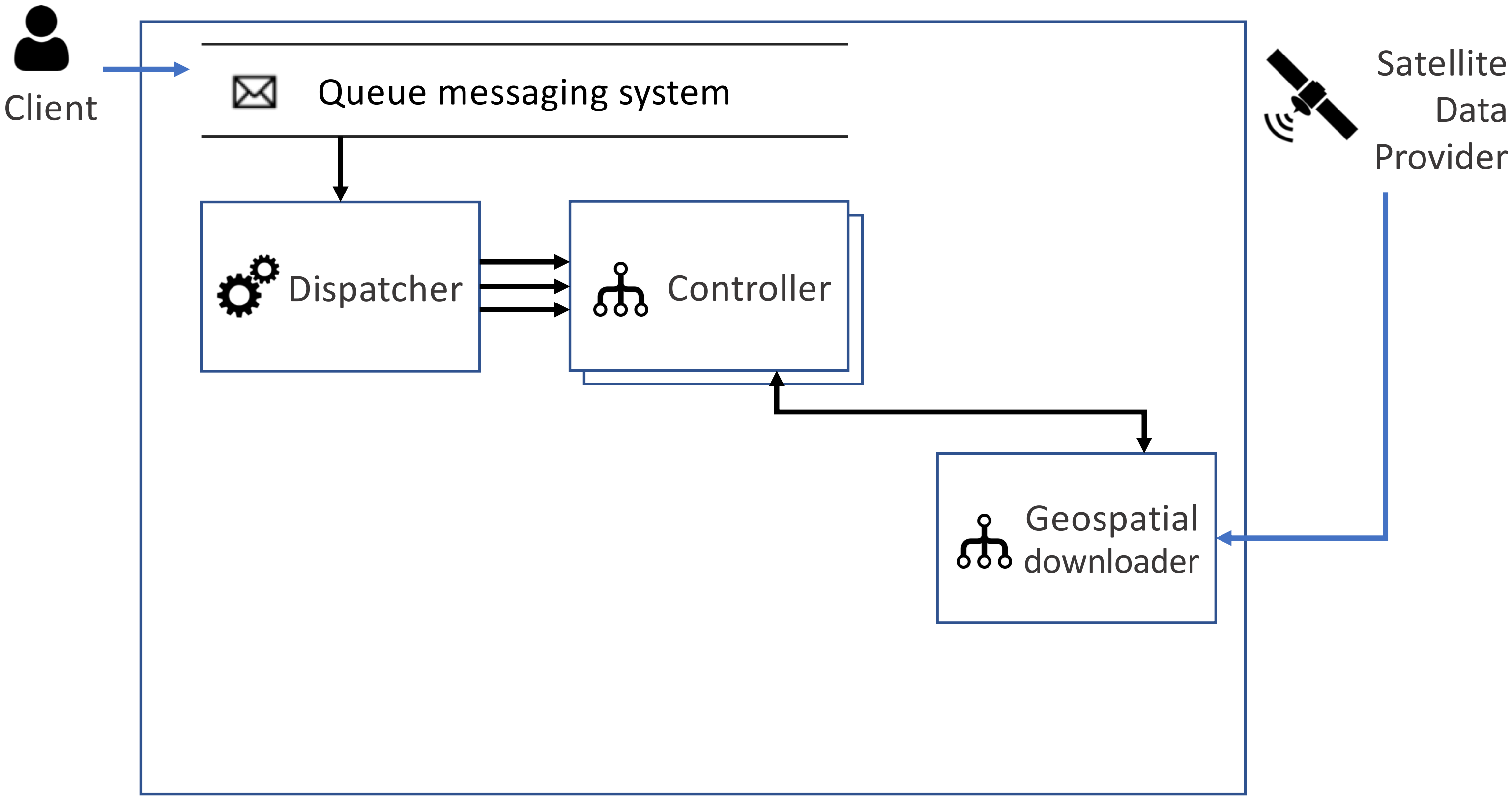
The **Controller** handles the whole mapping process, coordinating the flow of information among the other modules in the platform



Rapid Mapping and Damage Assessment Platform

The **Controller** requests to the Geospatial downloader, satellit acquisitions.

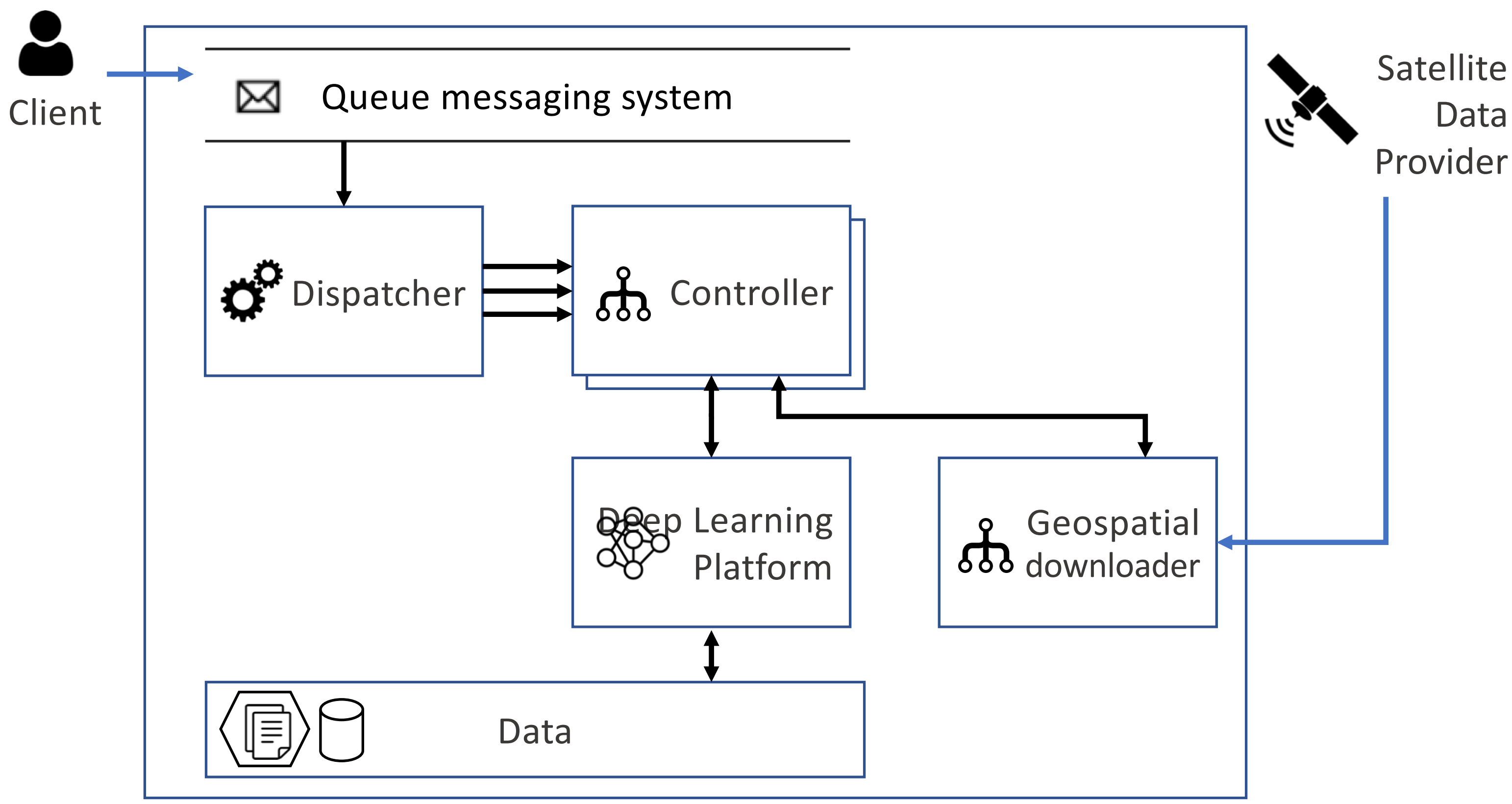
The **Geospatial Downloader** retrieves Sentinel 1 and 2 acquisitions, according to quality constraints of cloud coverage and data coverage



Rapid Mapping and Damage Assessment Platform

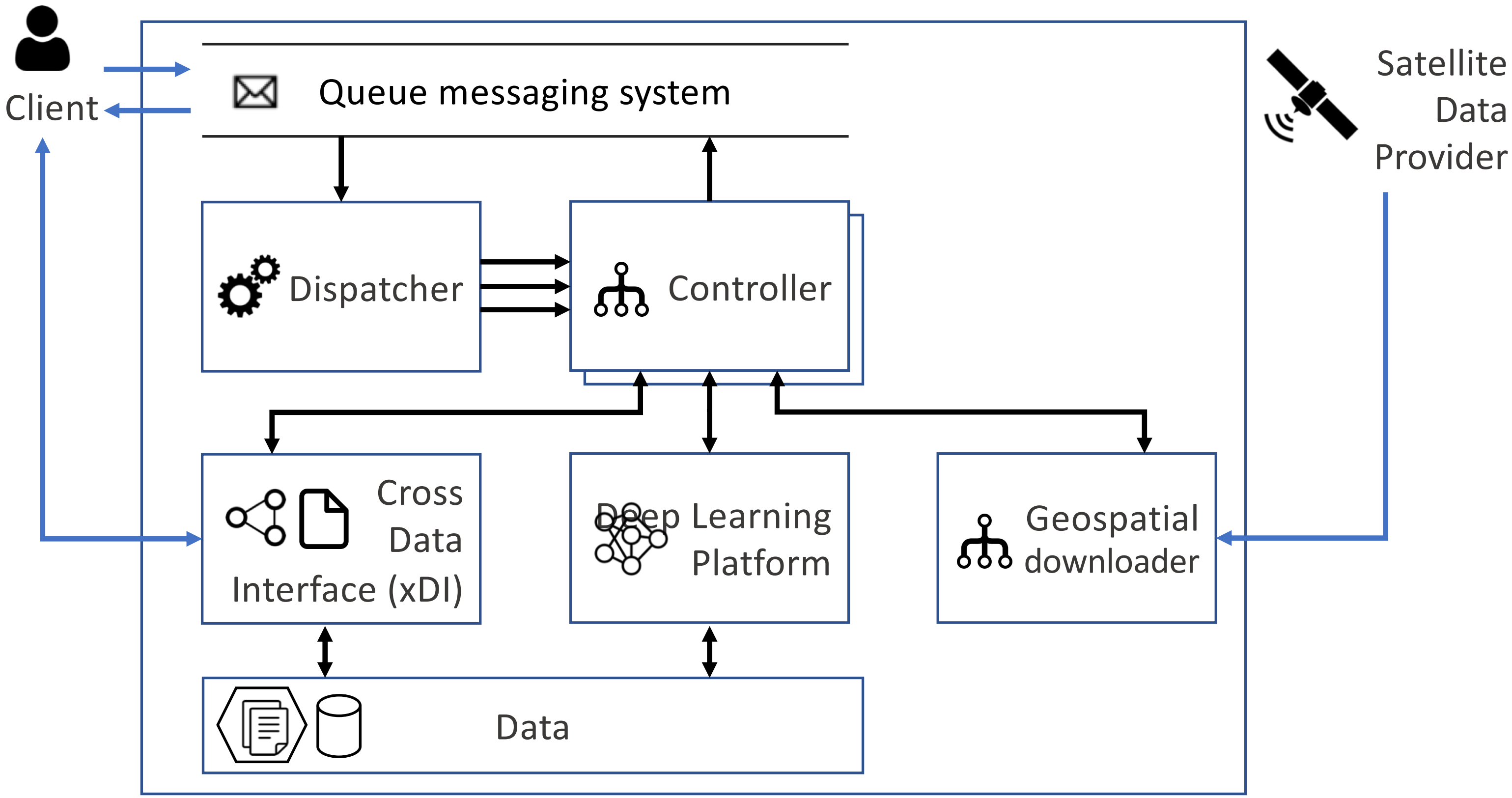
The **Controller** creates tiles from the satellite acquisition, sending them to the **Deep Learning (DL) Platform**.

The **DL platform** instantiate the right model and perform the mapping activity. Mapped tiles are returned to the **Controller**.



Rapid Mapping and Damage Assessment Platform

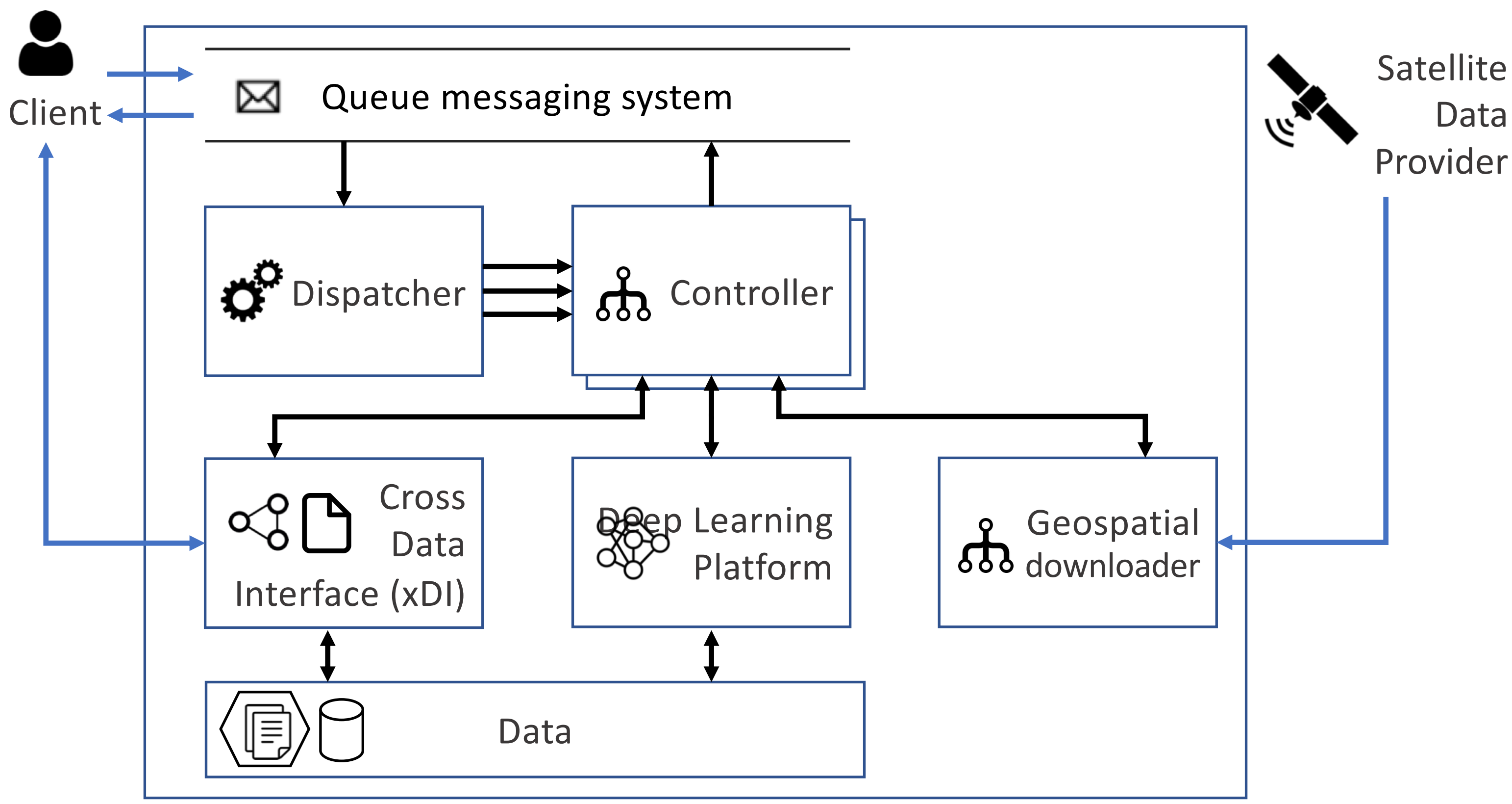
The **Controller** retrieves and merges the mapped tiles into the final map. Then, it delivers satellite acquisitions and the map to the **Cross Data Interface (xDI)**.



Rapid Mapping and Damage Assessment Platform

The **xDI** is an open source Data Management System, makes available and editable all the received information to the client, through a web portal.

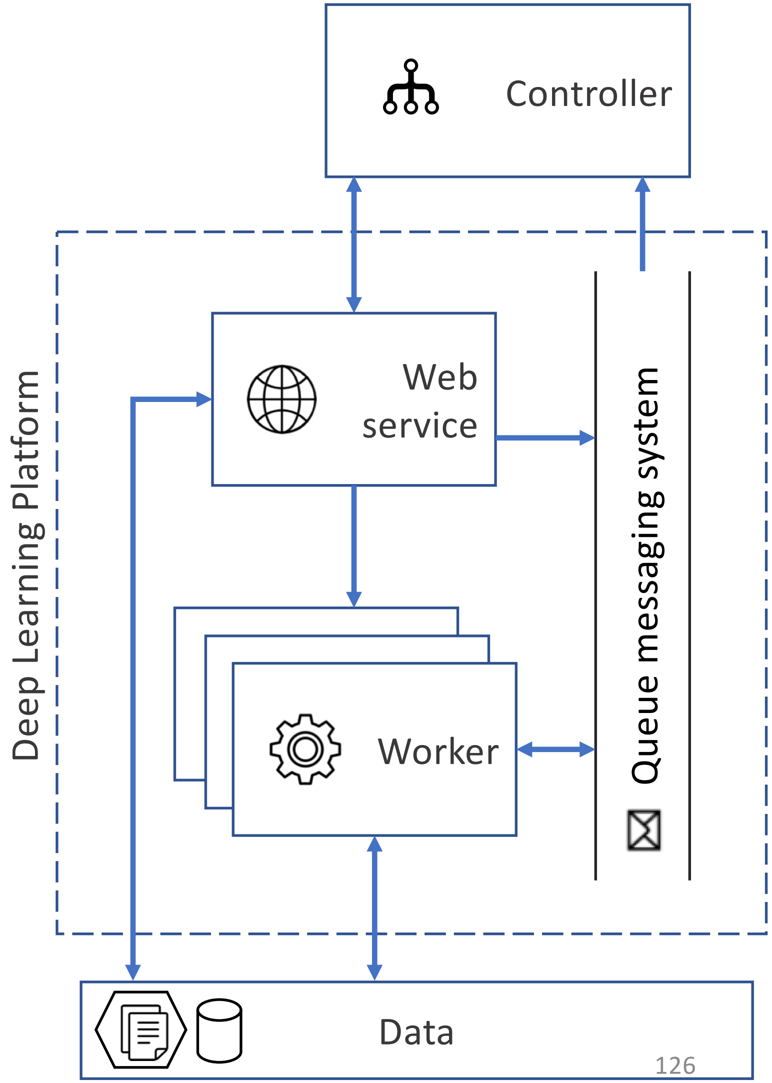
Finally, the **Controller** notifies the Client the completion of the mapping request.



Deep Learning Platform

Platform for the deployment of Deep Learning Models (Onnx standard)
<u>It can be used for both Geospatial and Social Media models</u>

Main tasks:
1. **handles the upload** of a new deep learning model
2. **operationalizes a model**, loading it in memory and enabling it to receive inputs and to return inference predictions
3. **handles a model inference** request
4. **return the inference results**



Deep Learning Platform – Performance evaluation

Input

- Tile of 480x480 px x 12 channels (11.5 km^2)
- Tests performed in the dataset presented for burned area delineation and grading tasks (135 tiles)

Model

- Double-Step U-Net

Hardware

- CPU: Intel Core I9 7940x
- RAM: 128 GB, DDR4
- GPU: 1 x NVIDIA 1080 Ti

Step	Time (ms)					
	Batch size: 1		Batch size: 2		Batch size: 4	
	avg	std	avg	std	avg	std
Request	139	10	268	16	505	23
Inference	110	7	215	14	443	31
Response	66	3	140	3	305	10
Total	313	20	624	33	1253	64

Deep Learning Platform – Performance evaluation

Results

- The **average mapping time** is **~313 ms per tile**, with a standard deviation of 20 ms
- **Batch size** and **execution time** are **linearly dependent**
- **Inference time** is **coherent** with the **assessment performed in the related chapter**

Step	Time (ms)					
	Batch size: 1		Batch size: 2		Batch size: 4	
	avg	std	avg	std	avg	std
Request	139	10	268	16	505	23
Inference	110	7	215	14	443	31
Response	66	3	140	3	305	10
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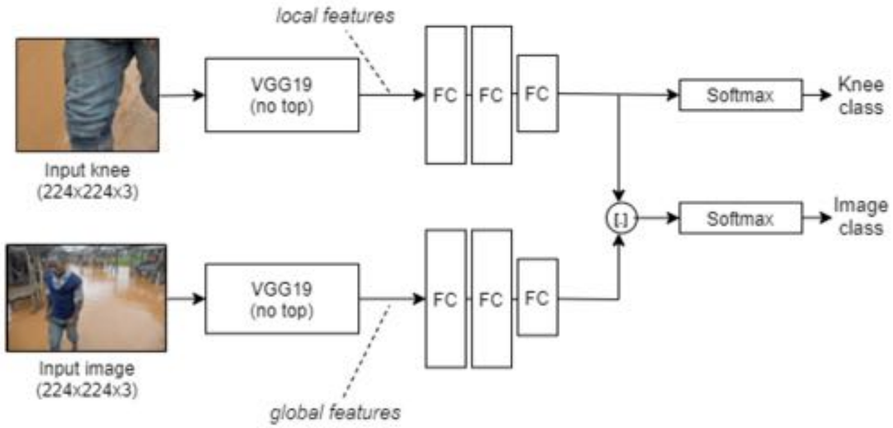
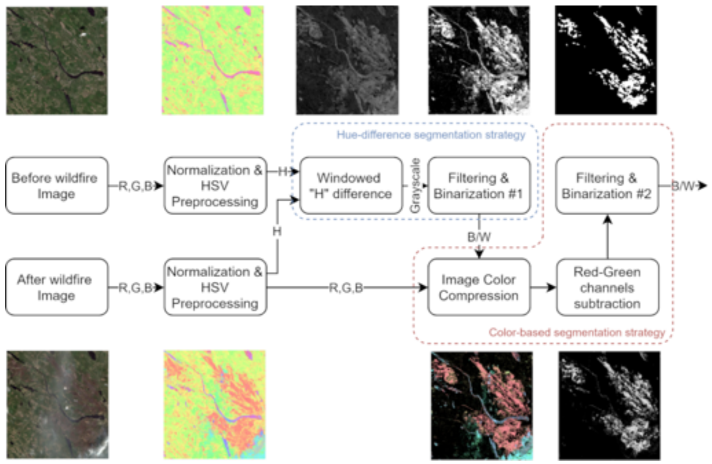
Other contributions (Emergency Mgmt.)



Floods: estimation of flood depth, to detect places and people potentially in danger

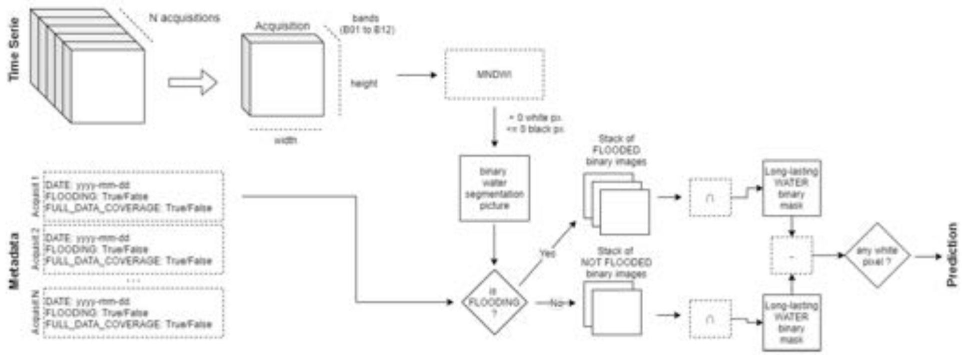
Other contributions (Emergency Mgmt.)

Response



🔥**Wildfires:** *unsupervised* burned area estimator (pre + post wildfire acquisitions, visible light only)

Recovery **Mitigation**



💧**Floods:** expert system for the *automatic evaluation* of long-lasting flooded regions from timeseries and metadata

Scientific Accomplishments

Prevention → Mitigation → Preparedness → Response → Recovery

Social Media data

- Proposed two novel techniques for the inference of viable roads during flooded events
- Novel flood depth estimation model, to identify dangerous places and people at risk

Satellite data

- Solutions for the automatic delineation of those phenomena from post-event satellite acquisition, which leverage on optical data, radar data, and cartography. (1 Flood, 3 Wildfires)
- Novel approach for the post-event damage severity estimation of regions affected by wildfires, validated through in-field tests

Architecture

- Development of a micro-services architecture, which operationalizes the models published during the PhD, currently adopted in SHELTER (European funded project)

Future works

Politecnico di Torino

Social Media data

- Evaluation of structural damages to buildings
- Evaluation of injured people that would need hospitalization

Satellite data

- Combination of Sentinel-1 and Sentinel-2 data to overcome occlusions (clouds) and delineate ongoing wildfires
- Models to forecast the wildfire evolution exploiting extra data (weather information, digital elevation maps)
- Delineation of other natural hazards (e.g. earthquakes)

Thanks for your attention ☺

Publications list

Natural Hazards Delineation and Damage Severity Estimation from Satellite data

1. **(Journal) Farasin, A., Colomba, L., & Garza, P. (2020). Double-Step U-Net: A Deep Learning-Based Approach for the Estimation of Wildfire Damage Severity through Sentinel-2 Satellite Data. Applied Sciences, 10(12), 4332.**
2. Farasin, A.; Colomba, L.; Palomba, G.; Nini, G.; Rossi, C. Supervised Burned Areas delineation by means of Sentinel-2 imagery and Convolutional Neural Networks. In Proceedings of the 17th ISCRAM Conference, Blacksburg, VA, USA, 24–27 May 2020.
3. Palomba, G., Farasin, A., & Rossi, C. (2020). Sentinel-1 Flood Delineation with Supervised Machine Learning. In Proceedings of the 17th ISCRAM Conference, Blacksburg, VA, USA, 24–27 May 2020.
4. Farasin, A., Nini, G., Garza, P., & Rossi, C. (2019). Unsupervised Burned Area Estimation through Satellite Tiles: A multimodal approach by means of image segmentation over remote sensing imagery. MACLEAN workshop, ECML/PKDD conference. Würzburg (Germany); Sep. 2019.

Flood Events information extraction using social media data

1. **(Journal) Lopez-Fuentes, L., Farasin, A., Zaffaroni, M., Skinnemoen, H., & Garza, P. (2020). Deep Learning Models for Road Passability Detection during Flood Events Using Social Media Data. Applied Sciences, 10(24), 8783**
2. Zaffaroni, M., Lopez-Fuentes, L., Farasin, A., Garza, P., & Skinnemoen, H. (2019). AI-based flood event understanding and quantification using online media and satellite data. MediaEval2019; 27-30 Oct 2019;
3. Lopez-Fuentes, L.; Farasin, A.; Skinnemoen, H.; Garza, P. Deep Learning Models for Passability Detection of Flooded Roads; MediaEval2018; 29-31 Oct 2018; CEUR-WS: Aachen, Germany, 2018; p. 2283.

Air Quality estimation & Weather correlations

1. **(Journal) Arnaudo, E., Farasin, A., & Rossi, C. (2020). A Comparative Analysis for Air Quality Estimation from Traffic and Meteorological Data. MDPI Applied Sciences, 10(13), 4587.**
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3. Rossi, C., Farasin, A., Falcone, G., & Castelluccio, C. (2019, November). uAQE: Urban Air Quality Evaluator. In European Conference on Ambient Intelligence (pp. 337-343). Springer, Cham.
4. Farasin A., Garza P., PERCEIVE: Precipitation Data Characterization by means on Frequent Spatio-Temporal Sequences. In Proceedings of the 15th International Conference on Information Systems for Crisis Response and Management (ISCRAM 2018)

Ionospheric Scintillaton Detection

1. **(Journal) Linty, N., Farasin, A., Favenza, A., & Dovis, F. (2018). Detection of GNSS ionospheric scintillations based on machine learning decision tree. IEEE Transactions on Aerospace and Electronic Systems, 55(1), 303-317.**
2. Favenza, A., Farasin, A., Linty, N., & Dovis, F. (2017, September). A machine learning approach to GNSS scintillation detection: automatic soft inspection of the events. In Proceedings of the 30th International Technical Meeting of the Satellite Division Of the Institute of Navigation (ION GNSS+ 2017), Portland, OR, USA (pp. 25-29).

Other works (Virtual Reality)

1. Zaffaroni, Mirko; Grangetto, Marco; Farasin, Alessandro. Estimation of Speed and Distance of Surrounding Vehicles from a Single Camera. In: International Conference on Image Analysis and Processing. Springer, Cham, 2019. p. 388-398.
2. Farasin, A., Peciarolo, F., Grangetto, M., Gianaria, E., & Garza, P. (2020). Real-time object detection and tracking in mixed reality using Microsoft HoloLens. In 15th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications, VISIGRAPP 2020 (Vol. 4, pp. 165-172). SciTePress.

Candidate: Alessandro Farasin
Supervisor: Paolo Garza

Politecnico di Torino