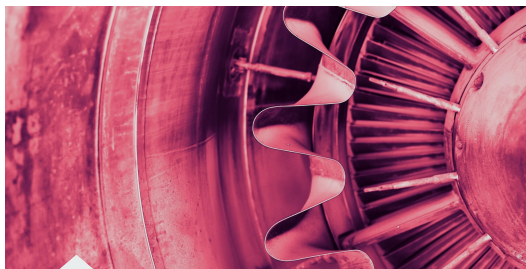




Hazard Mapping and vulnerability Monitoring



Introducing HaMMon



Funded by PNRR

Backed by ICSC's spoke 3



Industrial Project

Capitalizing the acquired skills applying them to real world's issues



15 partners

Public bodies and private companies across Italy

Goals

Facing the hazardous and extreme events **more frequent** due to the **Climate Change**





Work Packages

0

Management

1

Technological infrastructure to run and deploy the applications

2

Post-event analysis

3

Seasonal forecasts and weather generator

4

Building features extraction from images

5

Vulnerability curves for earthquakes and landslides



Work Packages involving INAF

0

Management

1

Technological infrastructure to run and deploy the applications

2

Post-event analysis

3

Seasonal forecasts and weather generator

4

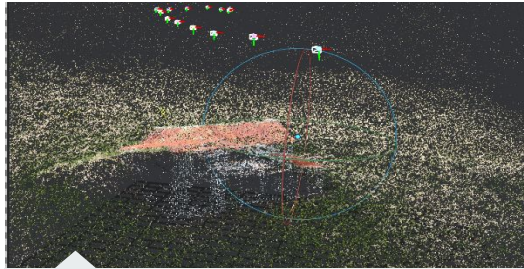
Building features extraction from images

5

Vulnerability curves for earthquakes and landslides



Which are the goals?



WP2

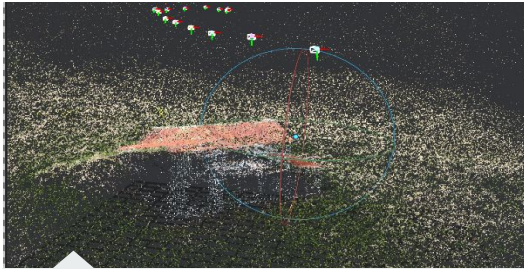
Carry on assessment activities on the Digital Twin

WP4

Getting better estimates on the danger to which building are exposed



Which are the tasks?



WP2

- Flying drones to take pictures
- Segmenting the pictures automatically
- Doing photogrammetry
- Finalizing the Digital Twin

WP4

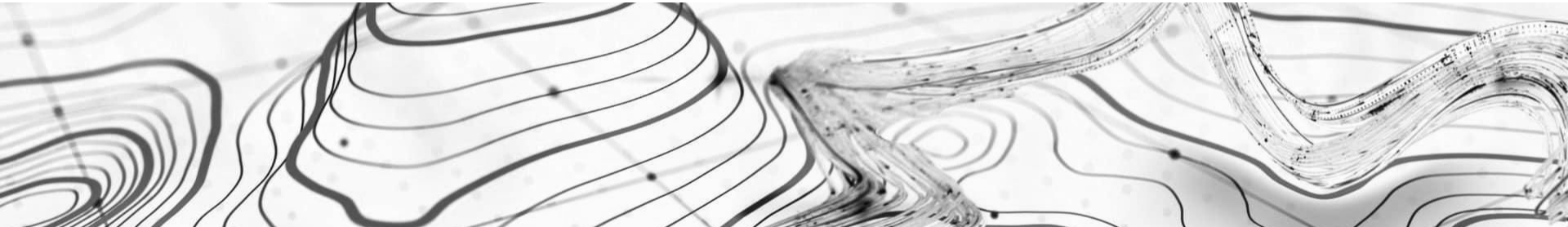
- Modelling the vulnerability curves
- Collecting aerial images
- Doing feature extraction

[Listen to Nicoletta Sanvitale for more info!!](#)



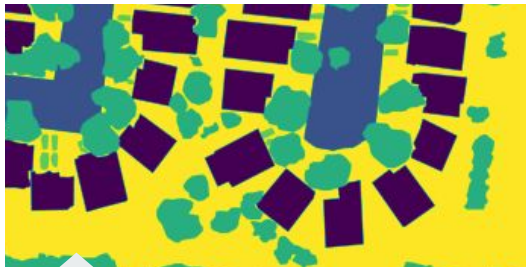


Digging deeper into WP2

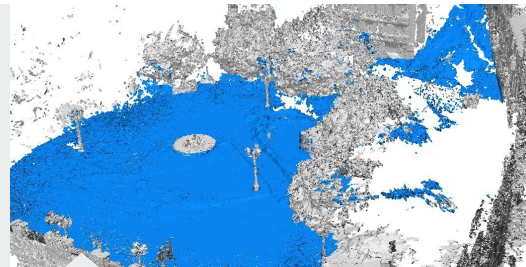




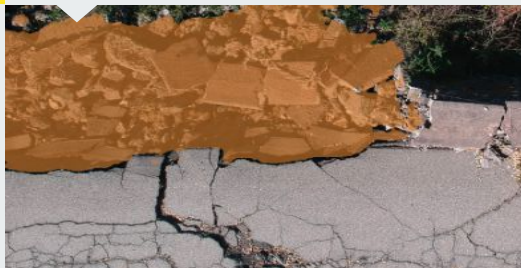
Why Segmenting?



Estimating areas



Shape-aware



Estimating volumes
(with photogrammetry)



How to segment?

Tiramisù

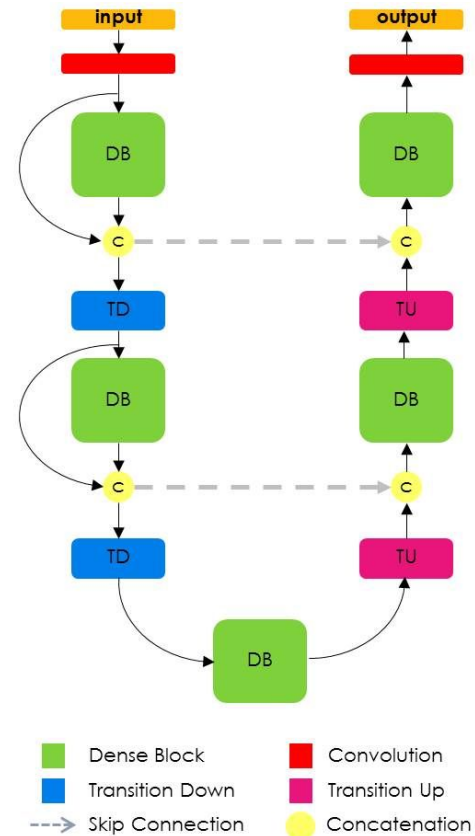
Fully Convolutional Densely Connected U-Net

How to segment?

Tiramisù

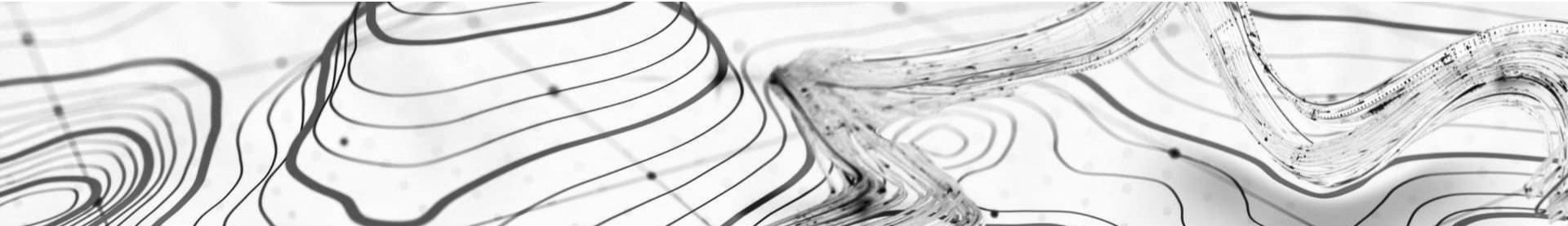
Fully Convolutional Densely Connected U-Net

- The Dense Blocks accumulate different feature maps for the input
- The Transition Down decrease size and increase feature space
- The Transition Up decrease feature space and increase size
- The Skip Connections force conditioning on the output





Experimental setup





FloodNet dataset

- Images from a drone survey made in 2017
- Presents damages left from Harvey hurricane
- Taken in Texas and Louisiana (USA)

2.343

Labelled images

10

Class of objects

Background, Building-flooded,
Building-not-flooded, Road-flooded,
Road-not-flooded, Water, Tree, Vehicle
Pool, Grass

13GB

of Hi-Res images



Training architecture

- The architecture is a Kubernetes cluster provided by the WP1
- The training runs on two nVidia Tesla V100 32GB
- The network storage is modular and shared



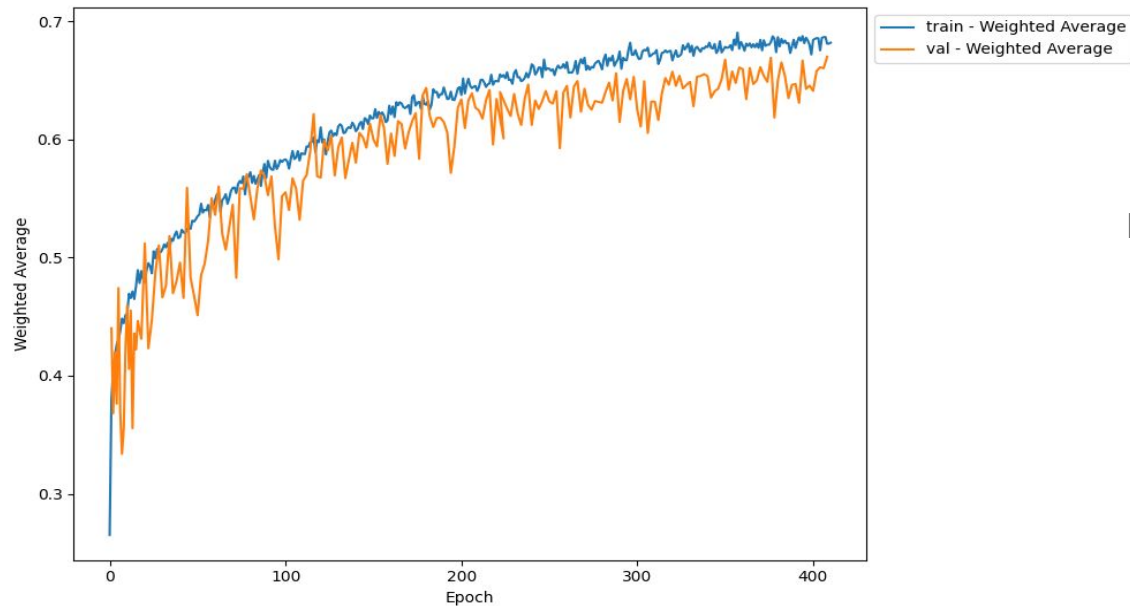


Training setup

- Random crops of the dataset images at 600x600 px
- Data augmentation (flipping, scaling)
- ~ 400 epochs
- Average training time of around 100 hours



Results so far

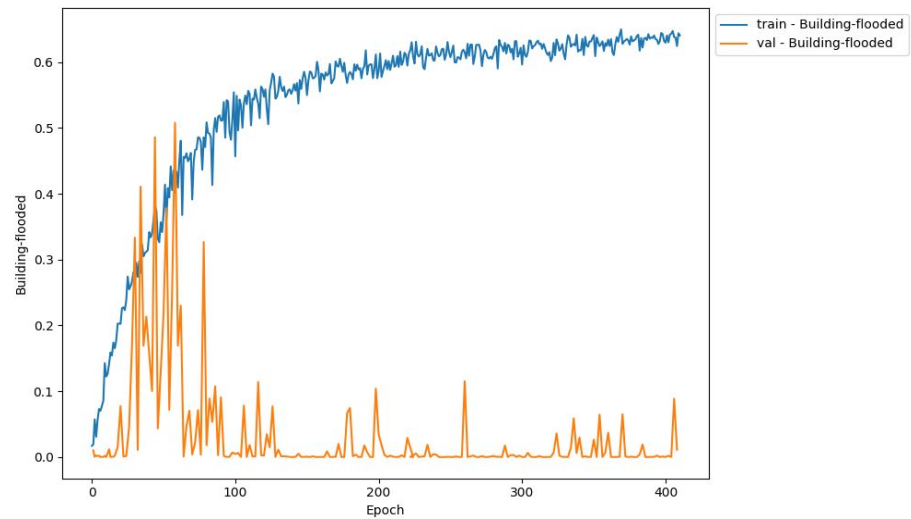
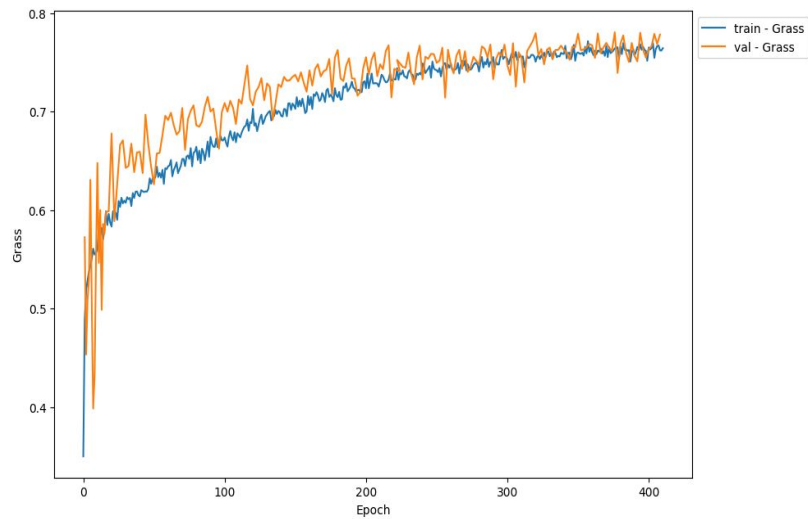


Weighted average of the
IoU of the different classes

Promising but...

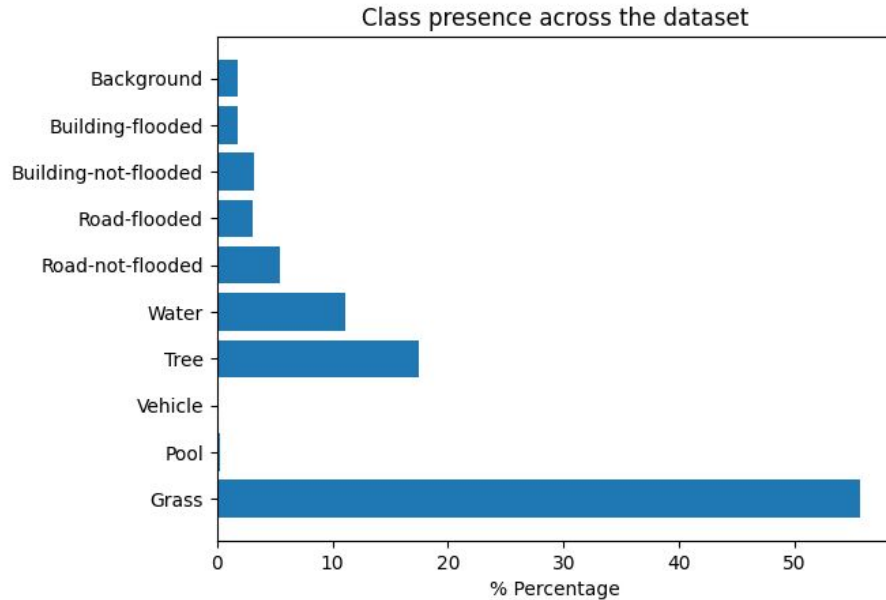


Results so far





Results so far



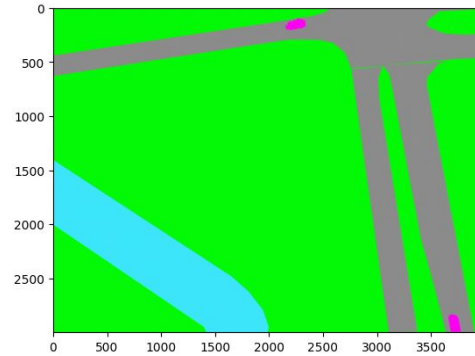
Some classes are
practically missing!



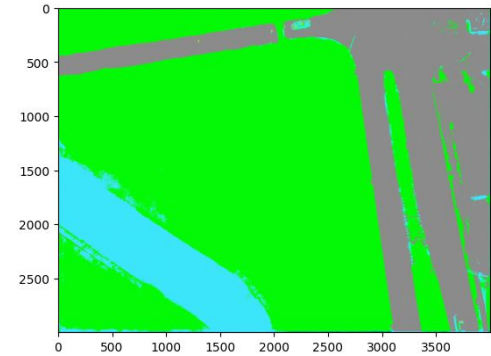
Results so far



Image



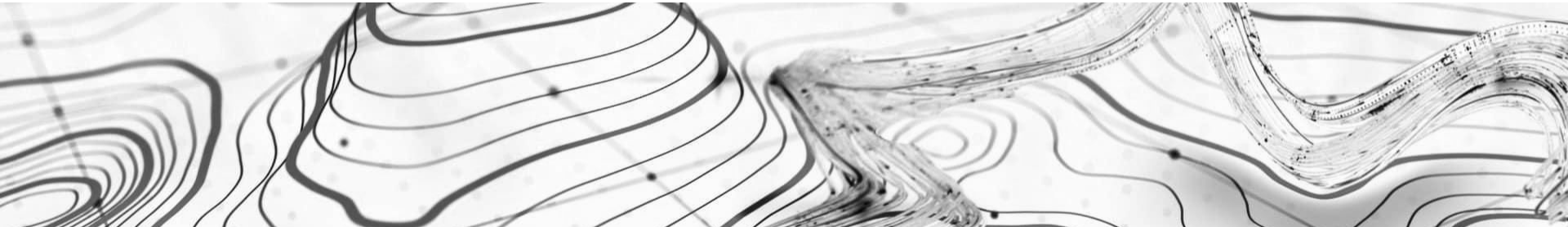
Ground Truth



Prediction



What we are improving





Transfer-learning on RescueNet dataset

- Images from a UAV made in 2018
- Presents damages left from Michael hurricane
- Taken in different USA locations

4.494

Labelled images

11

Class of objects

Background, Water, Building_No_Damage,
Building_Minor_Damage, Building_Major_Damage,
Building_Total_Destruction, Vehicle,
Road-Clear, Road-Blocked, Tree, Pool

22.6GB

of Hi-Res images



Hi-Res inference

CPU/GPU

Heterogeneous computing

12MP

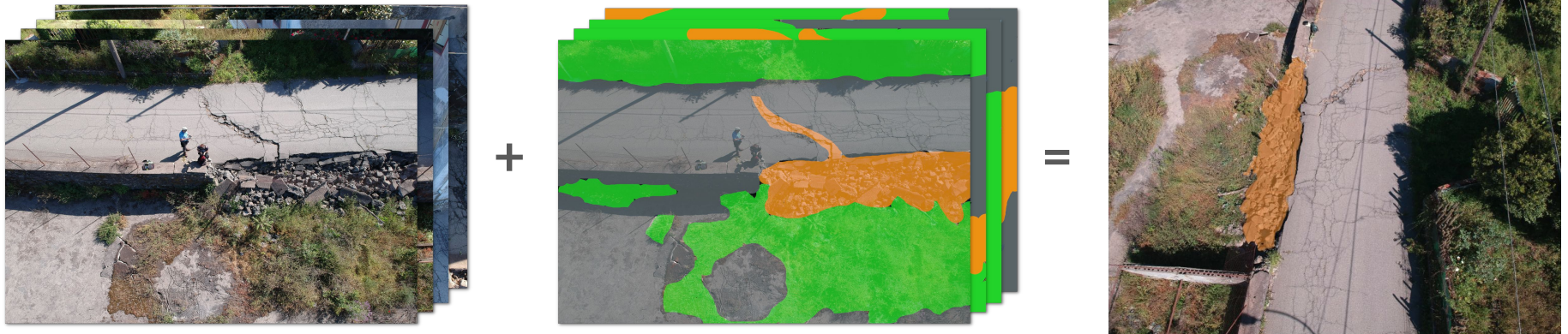
3000x4000 px

1 min

per image



Digital Twin augmentation



↑ Tiramisù



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INAF OACT

Thank you.