High resolution image processing and land cover classification for hydro-geomorphological high-risk area monitoring

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CLOSE TO THE EARTH

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RPASInAir

Integrazione dei Sistemi Aeromobili a Pilotaggio Remoto nello spazio aereo non segregato per servizi

UNIONE EUROPEA
Fondo Sociale Europeo
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PON RICERCA E INNOVAZIONE 2014 - 2020

Outline

- Photogrammetry and classification studies for hydro-geomorphological high-risk areas
- The ReCaS-Bari data center and the Close to the Earth and RPASInAir projects
- A new workflow for photogrammetry studies
  - METHOD
  - WORKFLOW IMPLEMENTATION
  - RESULTS
  - NEW HPC ReCaS-Bari CLUSTER VALIDATION
- CNNs for territorial classifications using an original dataset
  - MODELS
  - RESULTS
- Conclusions

The importance of photogrammetry and classification studies for hydro-geomorphological high-risk areas

- Our collaboration comes from the need to develop an original and optimized photogrammetric workflow to perform territorial mapping and change detection analysis using aerial images and the one to create an original well-populated dataset to develop Machine Learning tasks for territorial feature classification

- Photogrammetric workflow which returns different output, also manages large amount of data exploiting FOSS (MicMac, GDAL and Orfeo ToolBox libraries) and computing cluster hosted by ReCaS-Bari data center, to deploy the most computationally expensive steps and optimize the processing time

- Large datasets of UAV images of two reaches of the Basento river (Basilicata, Italy) with a very high-resolution were used

- The high resolution aerial images are meant to be used to train different Convolutional Neural Networks performing territorial classification of hydro-geomorphological high-risk areas

- We tested the performance of different NNs on an original dataset of aerial images previously used on satellite dataset (EUROSAT – Sentinel 2)

- The HTC cluster and the new HPC cluster belonging to **ReCas-Bari data center** were used

- This work is being developed in the context of **Close to the Earth** and **RPASInAir projects**
    - **Call:** ''Avviso MIUR n. 1735 del 13/07/2017
    AVVISO PER LA PRESENTAZIONE DI PROGETTI DI RICERCA INDUSTRIALE E SVILUPPO SPERIMENTALE NELLE 12 AREE DI SPECIALIZZAZIONE INDIVIDUATE DAL PNR 2015-2020''

The CLOSE and the RPAS in Air Projects

CLOSE TO THE EARTH

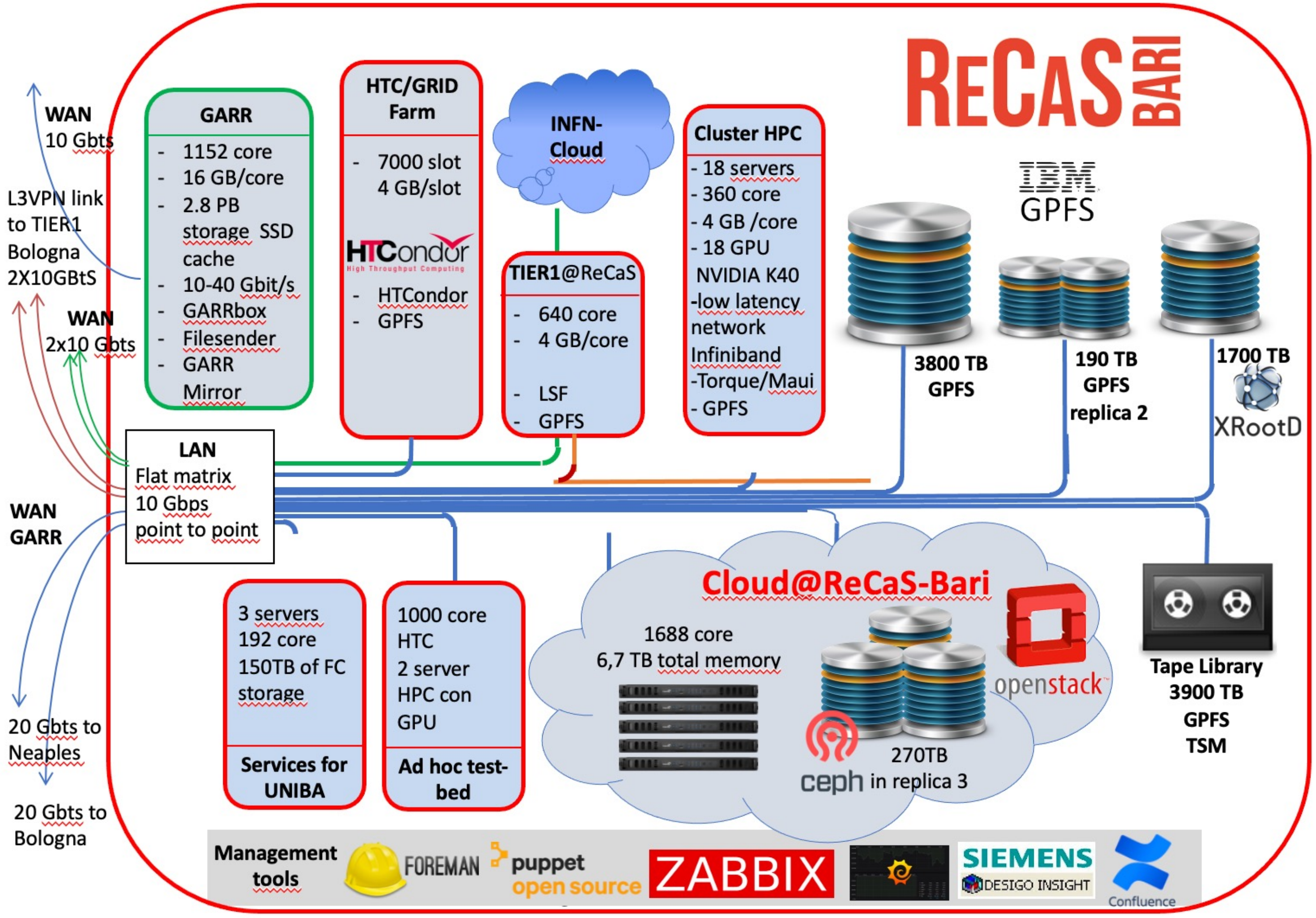
- The CLOSE project
  - **cofunded by European Union – SIF, Ricerca e Innovazione 2014-2020**
  - aims to build a technological prototype opening the access to the missions at Very Low Earth Orbit (lower than 250 km)
  - GOAL: design a low mass vehicle (LOW MASS= below 500 kg, including the propulsion system and payload) with an operating life of at least three years
  - The design of the vehicle and its subsystems for the CLOSE mission is a major challenge for the proposing DTA group
  - The final objective of the project is to obtain the elements that make it possible to carry out a mission at VLEO

RPASInAir

- The RPASInAir project
  - **cofunded by European Union – SIF, Ricerca e Innovazione 2014-2020**
  - The UAS (Unmanned Aircraft Systems) is increasingly applied in civilian applications in the field of natural disaster management, assets monitoring and patrolling (coastal patrol, power lines, pipelines…), migration flows and crops observation.
  - GOAL: enable innovative service which aims at land monitoring through the employment of data collected by RPAS (Remotely Piloted Aircraft Systems)
  - Need to manage new categories of critical events directly linked to the flight of these systems loss of datalink between air platform and pilot station, loss of ATM-pilot station connection, loss of vehicle cognitive capacities.
  - Need to realize a Synthetic Environment (SE) to simulate the behavior of RPAS in order to project operations with new types of RPAS in complex scenarios with controlled risk.

The RaCaS-Bari data center

- The ReCaS-Bari data center has been built by the University of Bari "Aldo Moro" and the National Institute of Nuclear Physics (INFN) in the framework of the ReCaS project
- The aim of the data center is to satisfy the growing need for scientific computing coming from experimental and theoretical groups operating within the INFN Section and the Department of Physics of Bari (Italy)
- Several services available (HTC, HPC, IaaS, PaaS)
- In our study we deploy the FOSS photogrammetric workflow on HTC cluster
  (128 servers, 8000 CPU core, 4GB of RAM
  per core, and 4PB of disk space)
- The GPFS distributed file system is used for storage management.
- **HTCondor** batch system
  - Docker containers using Singularity



Credits: G. Donvito, A. Italiano, S. Nicotri

METHOD

- Photogrammetry is a technique that allows to extrapolate three-dimensional information by overlapping two-dimensional images

- In order to perform this task, the Structure from Motion (SfM) algorithm follows 3 steps **[1]:**
  - detection of key features and tie-points of the images,
  - estimation of calibration parameters and camera positions and orientations,
  - dense-matching and point cloud generation

- To achieve high-resolution information on wide areas of the Earth surface a photogrammetric workflow based on MicMac, GDAL and Orfeo ToolBox open source libraries was developed using High-Throughput Computing environment (HTC)

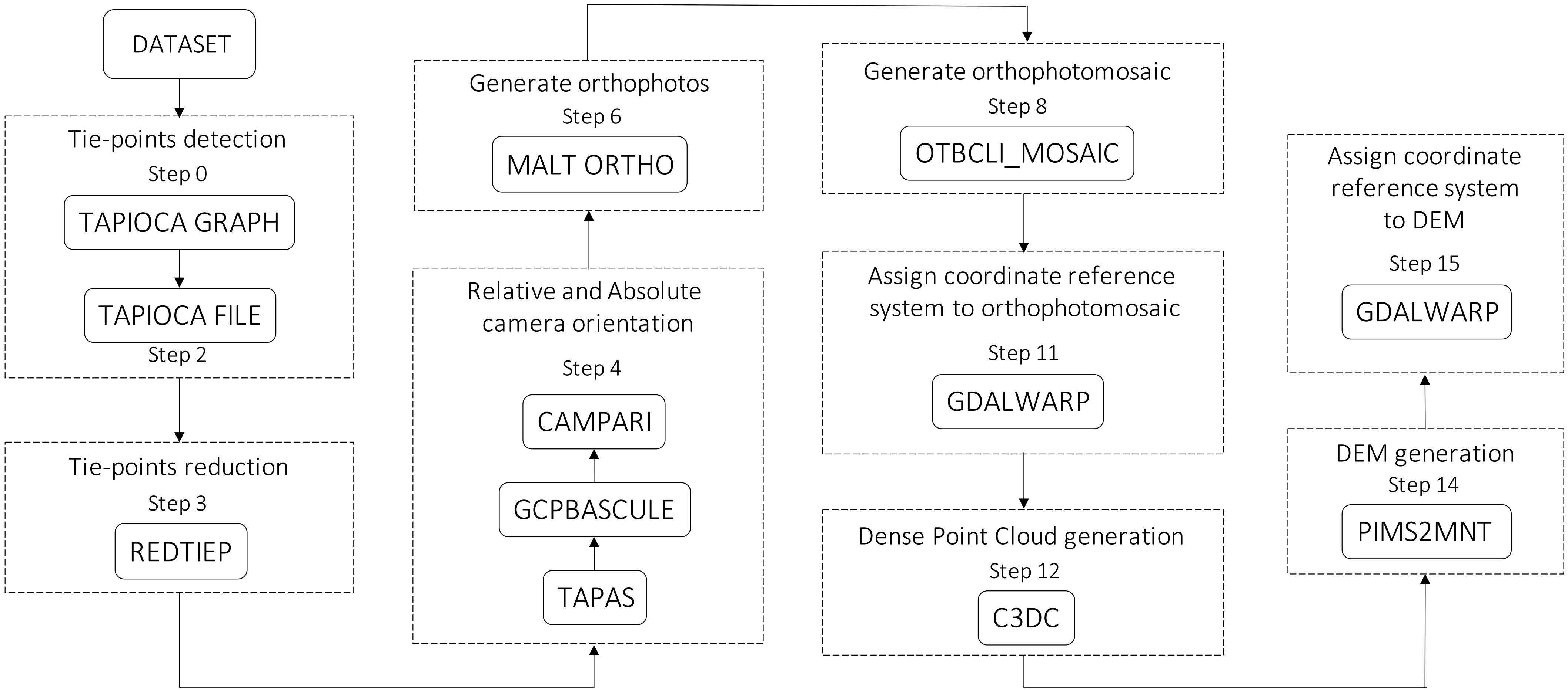
- This approach was fundamental to leverage the resources of the ReCaS-Bari computing cluster and managing large image datasets to return different output. In our work:

  - **3 OUTPUT:** Orthophotomosaic, Dense point cloud and Digital Elevation Model (DEM)

  - Task to accomplish: elasticity of managing each step of the workflow in the most efficient way to get the output in a good range of time

The processing chain of the FOSS photogrammetric workflow

- Photogrammetric workflow characterized by a sequence of 15 steps summarized here:



Just few info on the main commands...

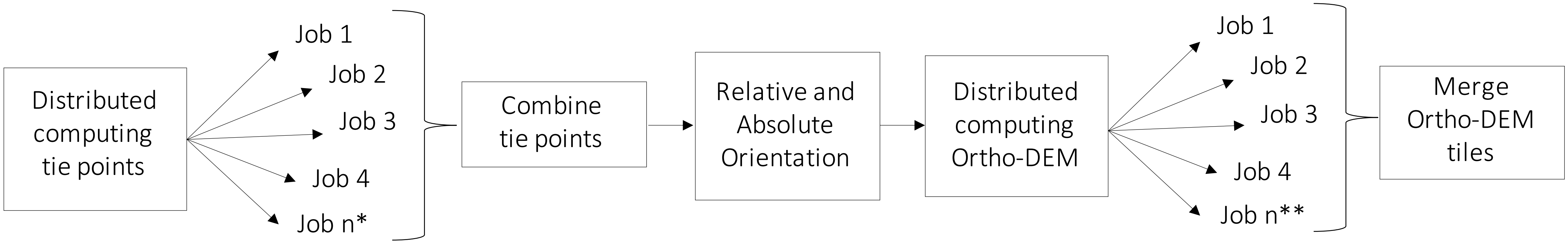
- **STEP1 - MicMac "Tapioca Graph":**
  - Extracts the key features and finds the candidate matching features of images creating a list of all overlapping image pairs (that potentially have common key features) by leveraging embedded GPS data recorded during the UAV flight missions;
- **STEP2 - MicMac "Tapioca File":**
  - Computes the homologous features (tie-points) of the images and removes the outlier initial features matched. It uses the list of overlapping image pairs and the tie points extraction option based on one-third of the pixel width of the image;
- **STEP3 - MicMac "Tapas":**
  - Performs the bundle adjustment operation to retrieve the 3D positions of key features and camera parameters so that internal and external orientation parameters are generated
- **STEP8 - "otbcli_Mosaic" Orfeo ToolBox:**
  - Generates orthophotomosaic. In order to produce seamless mosaic, this operation blends all previous orthophotos on the maximum overlapping area through a feathering method (mean convolution filter that replaces each pixel value with the mean value of its neighbors);
- **STEP10 – MicMac "C3DC":**
  - Generates dense point cloud identifing pixel-to-pixel matches within an image pairs, computes the 3D coordinate and, for each image generates a depth map (grey-scale image that contains information relating to the distance of the surfaces of scene objects from a viewpoint);
- **STEP11 – MicMac "PIMs2Mnt"**
  - Generates Digital Elevation Model (DEM) that blends the individual depth maps.

Test Results and Performance Evaluation

- **AREA OF INTEREST**: two reaches of the Basento river (Basilicata, southeastern Italy)
- **2 DATASETS**: **1139** and **2190** images acquired through low altitude UAV flight missions (50 m above ground level of take-off location)
- **HIGH-RESOLUTION AERIAL IMAGES**: **1,09 cm/pixel**
- **MOST CHALLENGING ISSUES**:
  - Overcoming the computational load related to the determination of tie-points, orthophoto and DEM
  - Parallelization of the most computational demanding steps on independent WNs
  - Each job must perform the parallel calculation of tie-points on a small subset of the original image dataset and then combine
  - Similar approach must be developed for orthophoto and DEM

*Parallel computing of tie points
on indipendent worker node

**Parallel computing of orthophoto and DEM
on indipendent worker node



Workflow implementation

- Processing time 1475 mins:
  - Good command configuration of the photogrammetric workflow
  - 50 images per jobs
  - 23 worker nodes

- In the same configuration a significant **reduction in processing time** was due to:
  - number of input images per job reduced from 50 to 3 images
  - number of worker nodes increased from 23 to 56

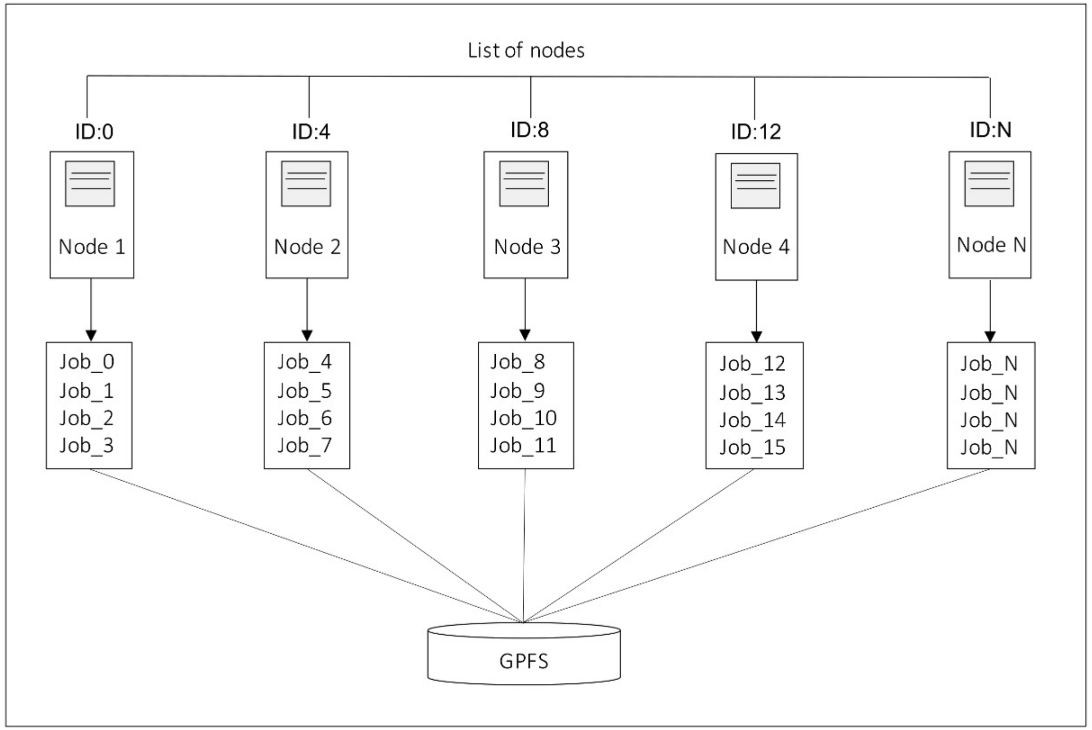
- **Issues** related to:
  - cluster's queue that manages the execution of user's jobs
  - computing resources and performance of the worker nodes
  - several parallel jobs running on a single node greatly affecting the performance since the photogrammetric workflow is characterized by some multi-thread MicMac command

Table 1
Processing time of 1139 images with different nodes configuration.

	Processing time [min]		
	workflow_final		workflow_pssh
STEP	23 nodes	56 nodes	103 nodes
Tie points computation	755	451	235
Relative and absolute camera orientation	120	85	85
Orthophotomosaic	370	152	73
Point Cloud	75	60	38
DEM	155	151	151
Overall	**1475**	**899**	**582**
	>24 hrs	~15 hrs	

Workflow implementation

- Further improvement in workflow performances using a dedicated slot on each worker node of the cluster to run a single job via "pssh"
  - Higher deployment on different nodes
  - Parallel access to a higher number of nodes overcoming the batch system job management
  - Generation of a 103 node list associated with an ID number to create a jobs execution scheme



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	>24 hrs	~15 hrs	<10 hrs

Results

- Optimizing our workflow mainly implied a significant time reduction of the workflow's distributed steps.
- Comparing to the 56-nodes test (1139 images):
  - a time reduction of 50% was recorded in the overlapping image pairs computation,
  - ~ 59% in tie points computation,
  - ~25% in the orthophoto generation,
  - ~67% in the orthophotomosaic generation,
  - ~37% in the dense point cloud generation.
- This represents a very good result, especially compared to the processing time of the same dataset using a commercial SfM software (Pix4D) on a single workstation
  - In this case there was a significant reduction of the processing time of ~ **73%**

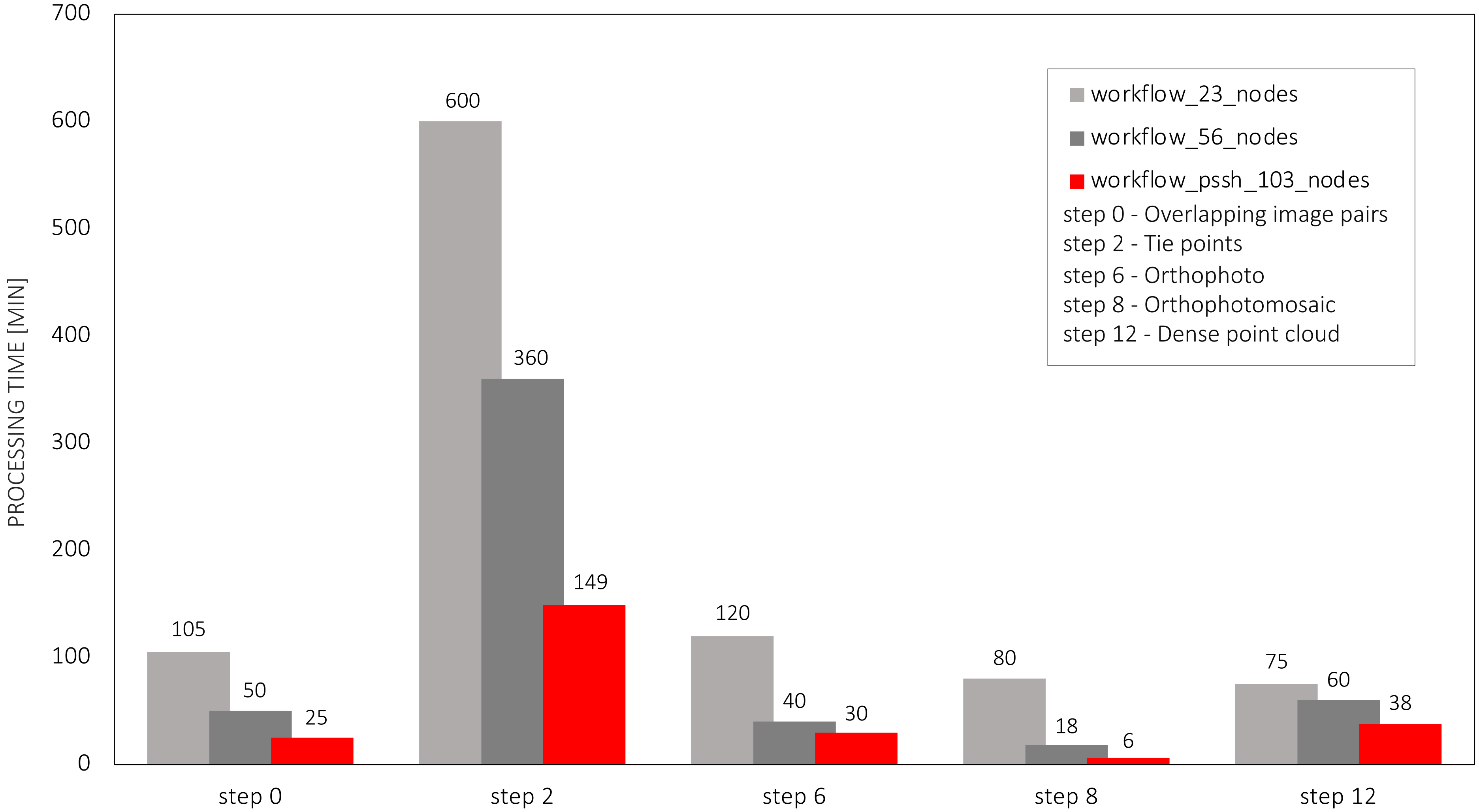
Table 2
Processing time with different dataset and software.

	Processing time [min]		
	1139 images		2190 images
STEP	workstation (Pix4D)	cluster (FOSS workflow)	cluster (FOSS workflow)
Tie points and camera calibration	240	320	705
Point Cloud	1260	38	114
DEM and Orthophotomosaic	637	224	480
Overall	**2137**	**582**	**1299**
	> 35 hrs	< 10 hrs	< 22 hrs

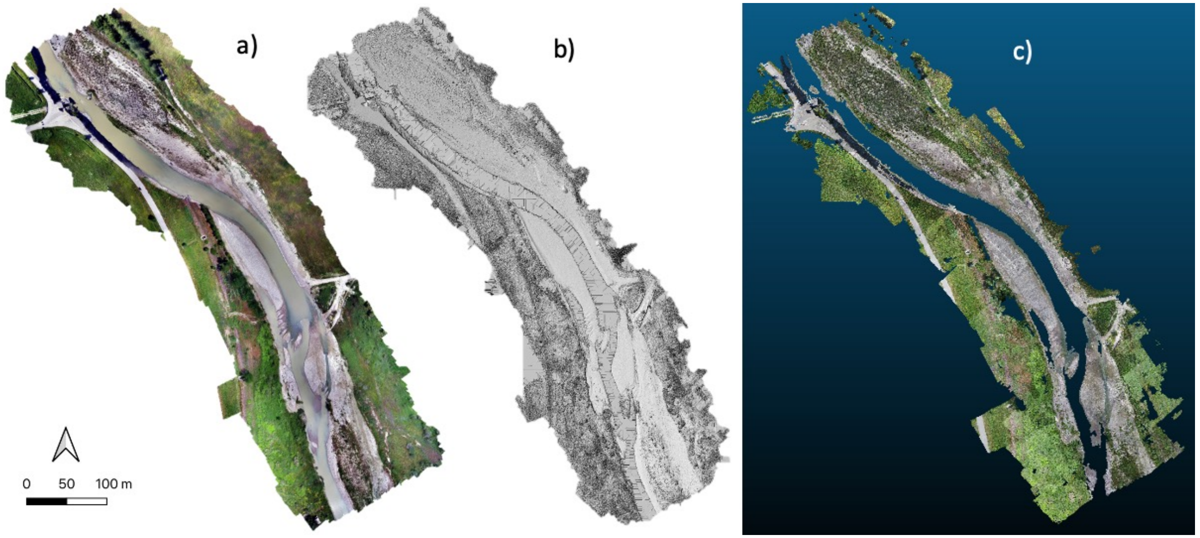
- In order to verify the computing capacity of the FOSS photogrammetric workflow, a dataset of 2190 was also processed
  - The total amount of processing time in this case is less than 22 hrs

Processing time of the workflow's distributed steps with different node configuration

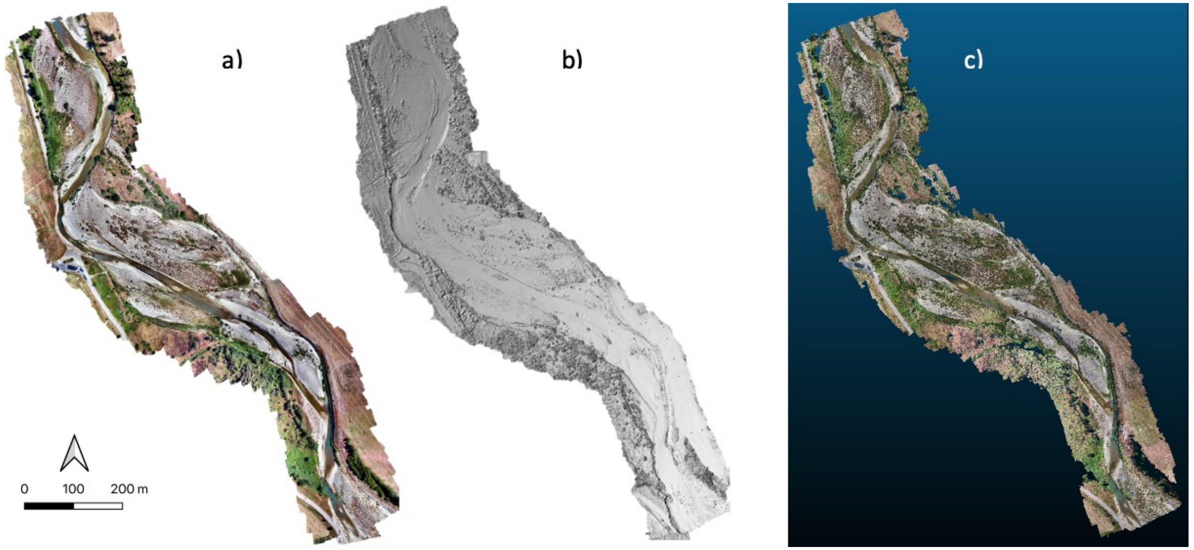
DATASET: 1139 imgs



Output



1139 images:
a) Orthophotmosaic (1.3 cm/pixel);
b) Digital Elevation Model (2.5 cm/pixel);
c) Dense point cloud (~95.000.000 densified points)



2190 images:
a) Orthophotmosaic (1.3 cm/pixel);
b) Digital Elevation Model (2.5 cm/pixel);
c) Dense point cloud (~200.000.000 densified points)

New HPC Cluster @ ReCaS-Bari

- Currently, the cluster is composed of 5 machines. Each one counts:
  - 4 GPU NVIDIA V100 32GB
  - 96 CPUs
  - 753.5 GB RAM
  - 6 TB SSD Disk

- Thanks to the high number of cores, the GPUs allow the running of high-performance parallel algorithms reducing the overall execution time

- The configured cluster is able to run batch jobs or open interactive environments where users are able to write code and test it in real time

- The new cluster was exploited both to test the performance of our workflow and validate the powerful potential of this machine configuration and to train ML models built for territorial classification

- In our study we used interactive mode implementing algorithms directly with Jupyter/Tensorflow

Credits: G. Vino

Testing the performance of the new HPC Cluster @ReCaS-Bari using a single-server configuration

- All the results presented were achieved by running the photogrammetric workflow using the CPU cores (up to 64 cores per node) and RAM (4 GB RAM per core) provided by ReCaS-Bari HTC cluster, using both batch and interactive modes

- In order to test the performance of the new HPC Cluster @ReCaS-Bari, our SfM algorithm was run on an available single-server belonging to this cluster

- The multi-thread behaviour of some commands could certainly take advantage of a higher number of cores, a Solid State Drive (SSD) and a higher amount of RAM, improving the performance by speeding-up the I/O operations (read and write) of each workflow step

- 2 approaches were used:
  - METHOD 1: executing all the workflow commands on the whole dataset
  - METHOD 2: executing in parallel single-thread and multi-phase commands (initial multi-thread phase that converges into single-thread or vice versa), on a subset of the original dataset.

Results for single-server configuration on 1139 imgs dataset

METHOD 1

- Important reduction of the overall processing time compared to the previous pssh-test
- Considerable time saving was recorded for most of the multi-thread and single-thread commands
- A non-negligible increase in some multi-phase commands due to a deficit of process parallelization on all available cores during the single-thread phases.

METHOD 2

- dataset divided into 9 subsets
- Parallel multiple execution of the single-thread and multi-phase commands on each subset (126 images)
- Processing time Reduction of about 60% of the overall time compared to pssh-test

1139 images

STEP	PROCESSING TIME [min]		
	1) Pssh 103 nodes HTC	2) Single server	3) Single server parallel-exe
Tapioca Graph	25	5	5
Tapioca File	149	120	120
RedTieP	60	4	4
Tapas-GCPBascule-Campari	85	39	39
Malt Ortho	30	100	44
otbcli_Mosaic	44	18	8
C3DC	38	70	5
PIMs2Mnt	151	6	6
Overall	**582**	**362**	**231**
	< 10 hrs	~6 hrs	< 4 hrs
		METHOD 1	METHOD 2

Results for single-server configuration on 2190 imgs dataset

METHOD 2

- overall temporal reduction of about 56% compared to the pssh test
- still a bottleneck was noted in the **Tapioca File** command:
    - poor reduction of its processing time for the 1139 img dataset
    - time increase for the 2190 img dataset
        - probably due to different behavior of this command to manage very large datasets (study still ongoing).

2190 images

STEP	PROCESSING TIME [min]	
	1) Pssh 103 nodes HTC	**2) Single server parallel-exe**
Tapioca Graph	74	12
Tapioca File	251	302
RedTieP	165	5
Tapas-GCPBascule-Campari	214	92
Malt Ortho	87	91
otbcli_Mosaic	93	15
C3DC	114	13
PIMs2Mnt	301	37
Overall	**1299**	**567**

< 22 hrs

< 10 hrs

METHOD 2

Land Cover Classification using NNs

- The images taken by the drone can be used to create an **original dataset of aerial images** that can be divided in classes. This part of our work is currently ongoing to reach the most suitable approach.

- It was performed a resolution downgrade (~80 cm/pixel, size of 64 x 48) of 3554 drone images, for a first exploration of the classes and a first study of ML models to be built for classification purpose

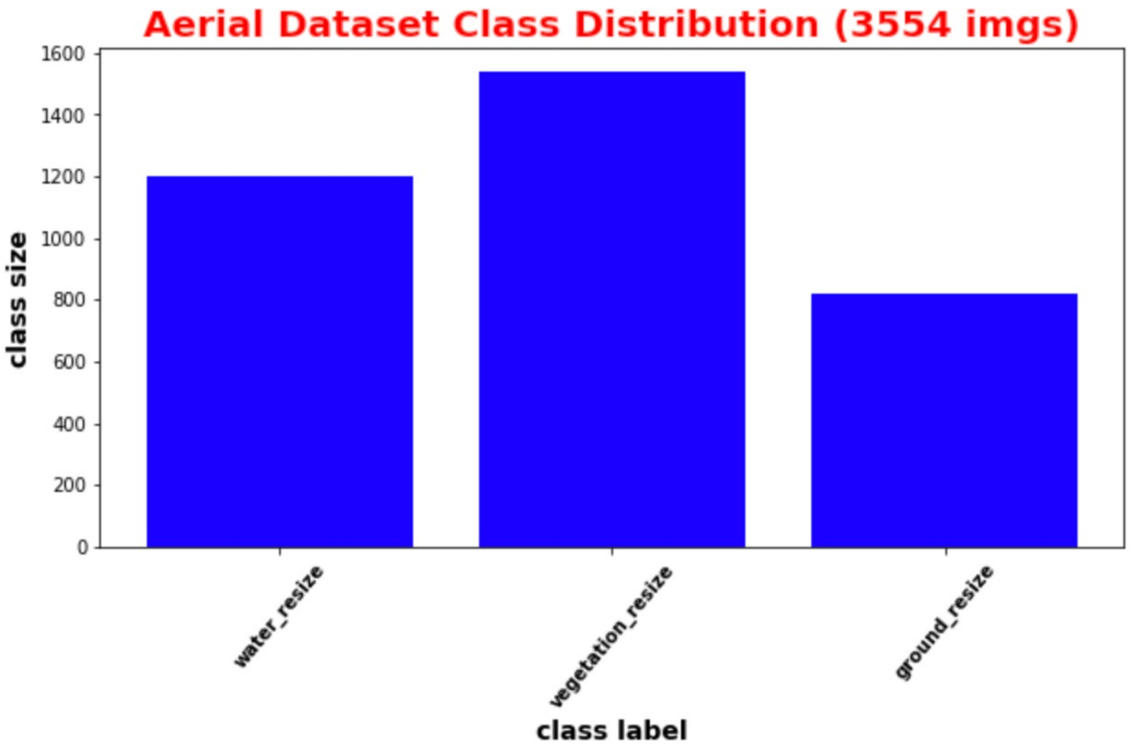
- The dataset has been divided into 3 basic classes: «**Ground**», «**Vegetation**» and «**Water**».

- Different models have been tested for territorial classification of the original dataset and only the best two are here presented

- This is a preliminary study in order to define the best way to correctly produce an aerial image dataset for land-cover classification and change detection monitoring.

Aerial Dataset Class Distribution

Class Label	Class Name	Population
0	**Ground**	817
1	**Vegetation**	1539
2	**Water**	1198



water_resize

vegetation_resize

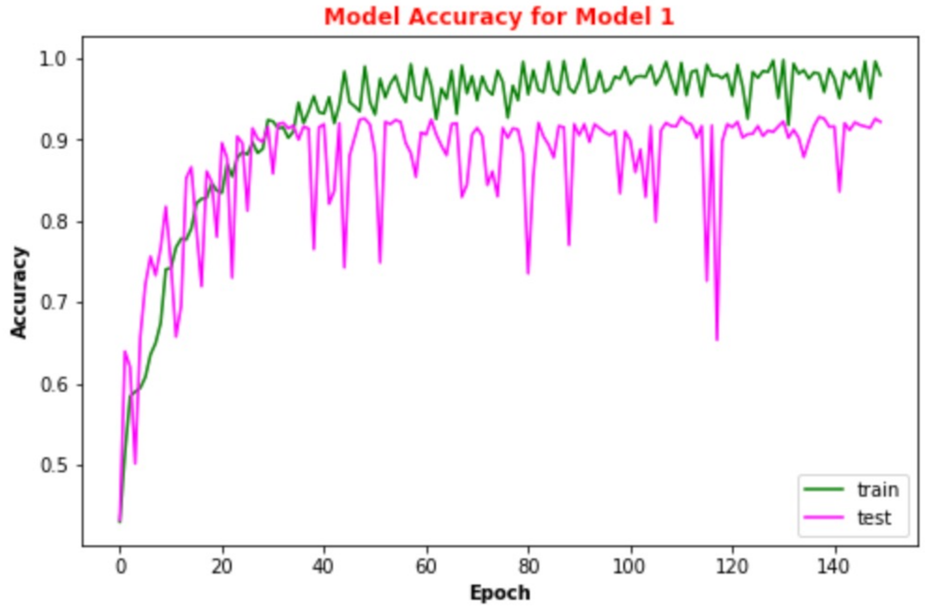
ground_resize

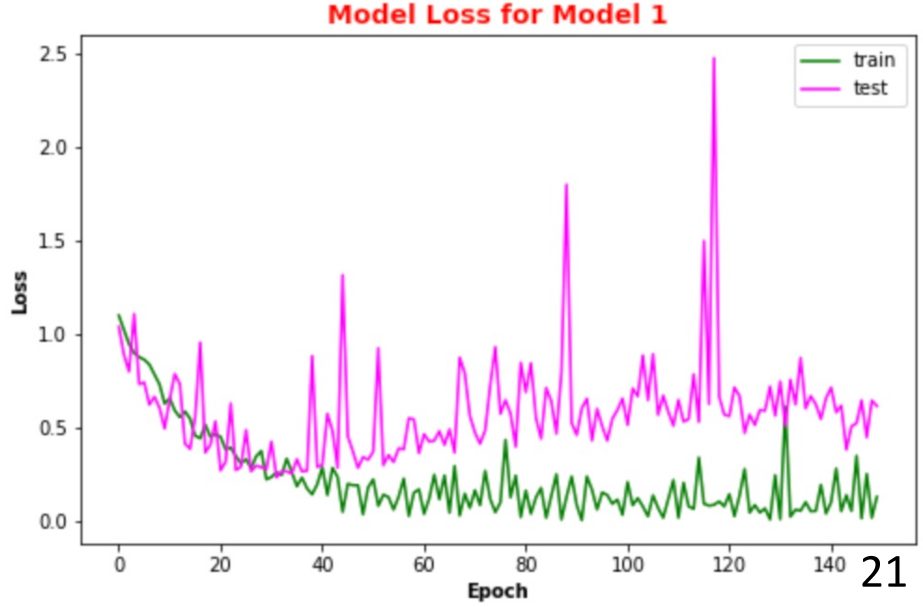
MODEL 1: MAX POOLING

MODEL 1: a sequence of pairs of max pooling and convolution layers ending with a dropout layer (30%) and a dense layer.

Epochs=150
Test accuracy: 92.18 %

	index	y_true	accurate_preds	label_count	class_acc	overall_acc
0	0	b'ground_resize'	353	409	0.863081	0.921778
1	1	b'vegetation_resize'	732	769	0.951886	0.921778
2	2	b'water_resize'	553	599	0.923205	0.921778





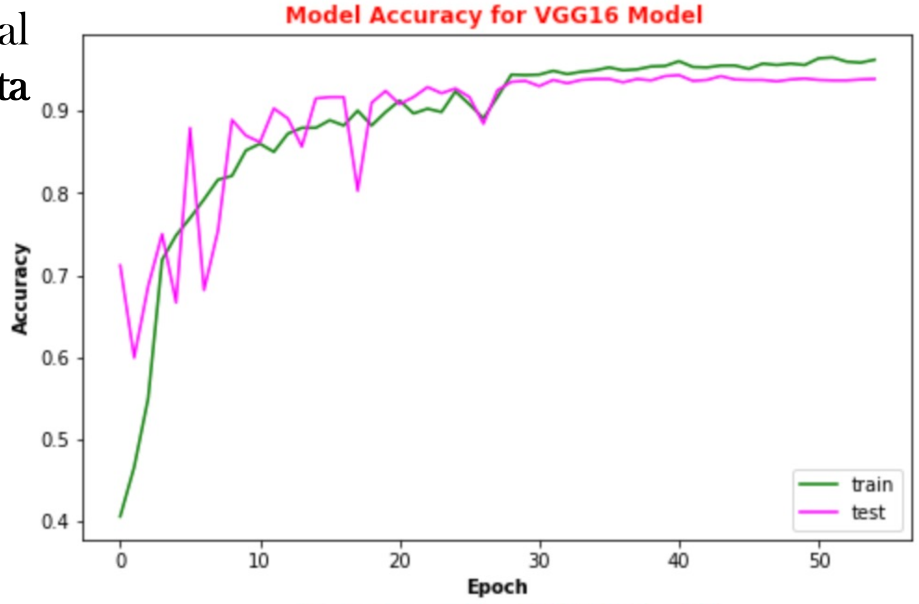
MODEL 2: VGG16 MODEL

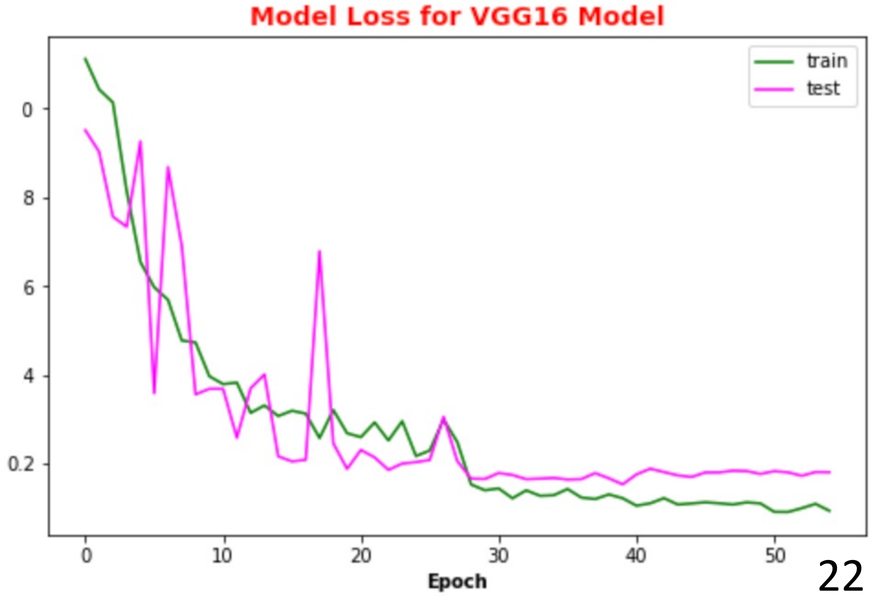
- MODEL 2: For this training we use a different approach adding convolutional base of the VGG16 Keras Model (pre-loaded weights) to exploit **data augmentation** technique and improving the results **[2]**

- In addition to **Model Checkpoint**, the **EarlyStopping** and **ReduceLROnPlateau** callback functions were added to limit the overfitting and reduce the learning rate if no improvements are seen after a fixed number of epochs

Epochs=150 early stopped after 55 epochs
Test accuracy: 94,03%

	index	y_true	accurate_preds	label_count	class_acc	overall_acc
0	0	b'ground_resize'	363	409	0.887531	0.940349
1	1	b'vegetation_resize'	738	769	0.959688	0.940349
2	2	b'water_resize'	570	599	0.951586	0.940349





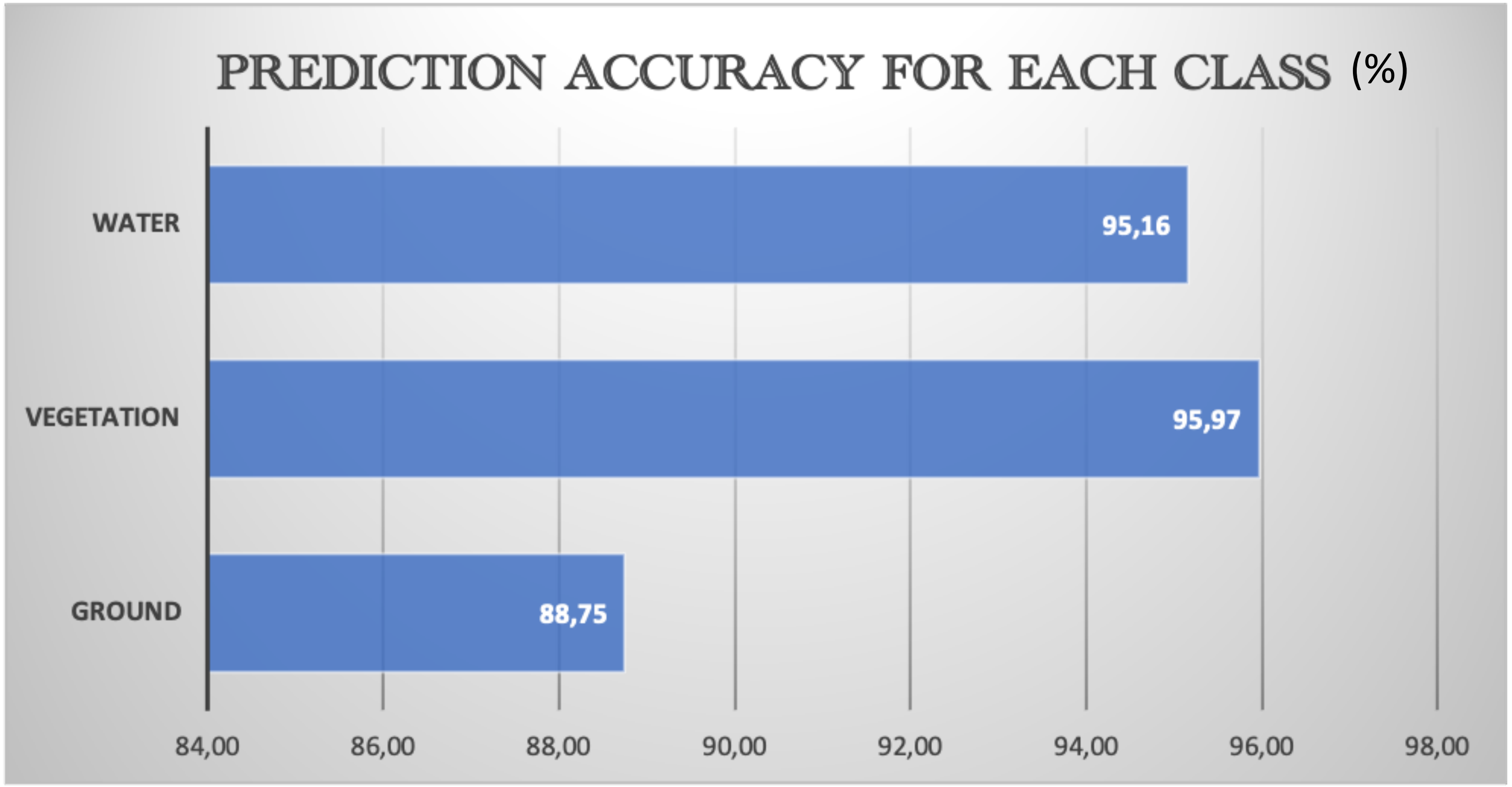
MODEL ACCURACY SUMMARY

	y_true	label_count	Mod1_class_acc	Mod1_overall_acc	Mod2_class_acc	Mod2_overall_acc
0	b'ground_resize'	409	0.863081	0.921778	0.887531	0.940349
1	b'vegetation_resize'	769	0.951886	0.921778	0.959688	0.940349
2	b'water_resize'	599	0.923205	0.921778	0.951586	0.940349

NNs RESULTS FOR BASENTO DATASET

BEST MODEL: VGG16 MODEL

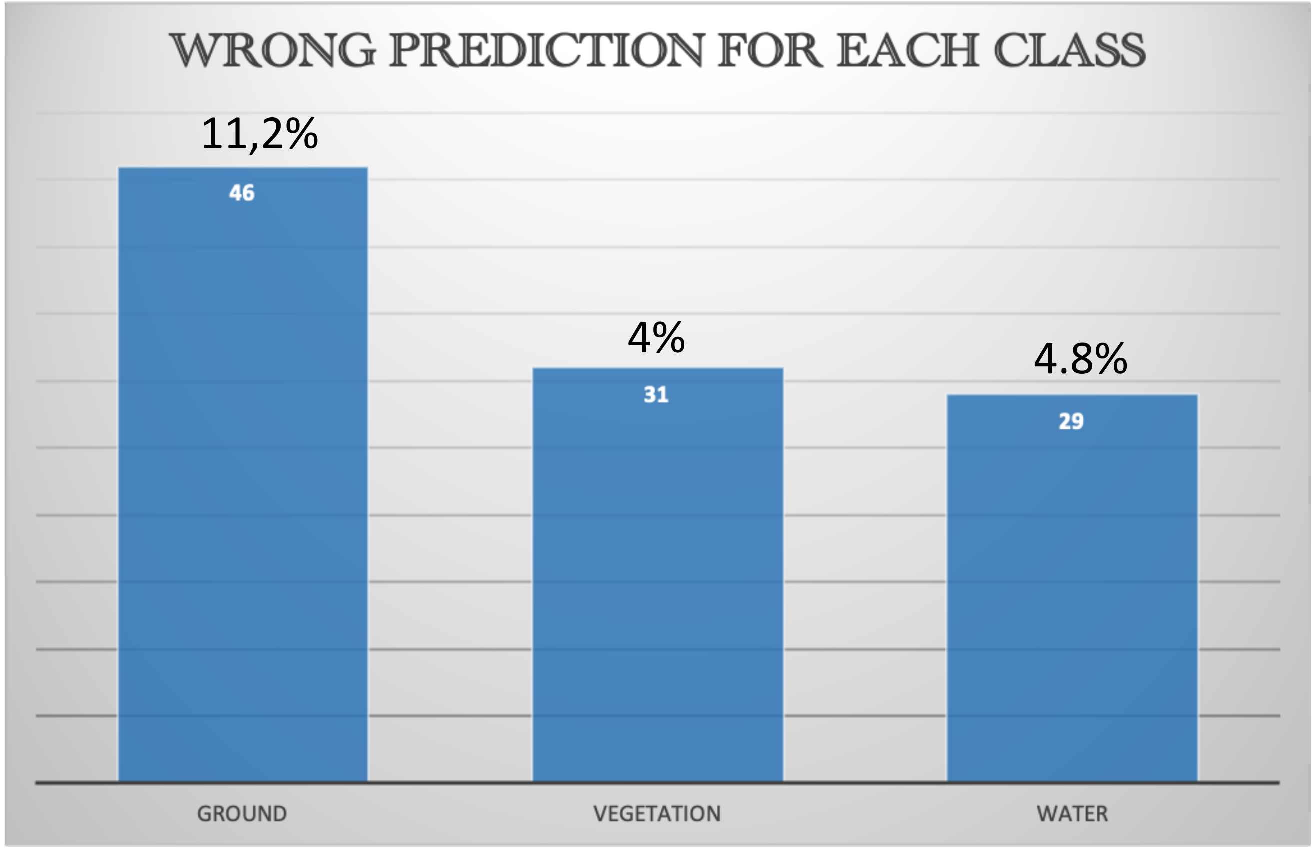
	index	y_true	accurate_preds	label_count	class_acc	overall_acc
0	0	b'ground_resize'	363	409	0.887531	0.940349
1	1	b'vegetation_resize'	738	769	0.959688	0.940349
2	2	b'water_resize'	570	599	0.951586	0.940349



NNs RESULTS FOR BASENTO DATA CLASSIFICATION

- Misclassification and percentage of wrong predictions for each class for the best model

Class Label	Class Name	Mostly misclassified for…
0	**Ground**	Vegetation
1	**Vegetation**	Ground
2	**Water**	Ground



- Dataset must be more populated
- Better selection of images per classes considering that using UAVs the images are closer to the surface of the Earth w.r.t satellites
- Upgrade the image resolution up to 20-30 cm/pixel

CONCLUSIONS

- An **original FOSS photogrammetric workflow** to process a large dataset of geotagged high-resolution images in a single run was presented
- Processing time has been optimized distributing the most computationally expensive steps on cluster nodes
- A comparison of the processing time with different configurations of computing resources was presented
- Results showed that **increasing the number of the jobs (thus reducing their workload) and the number of WNs the processing time is drastically reduced**
  - this ensured parallel execution and faster file writing performed by each node on the File System (GPFS).
- **1139 and 2190 high-resolution images (1.09 cm/pixel)** have been processed in a relative short time, **generating** respectively the **orthophotomosaic** (1.3 cm/pixel), **the dense point cloud** (∼ 95.000.000 and ∼ 200.000.000 densified points) and **DEM** (2.5 cm/pixel) of the detected areas.
- All these objects are useful to **perform detailed hydro-geomorphological analysis** of the investigated area
- A single-server configuration was also use to test and validate the performance of the new ReCaS-Bari HPC Cluster, obtaining further improvements w.r.t. our best result using pssh-configuration
- An original dataset of aerial images has been generated to perform land-cover classification
- We applied **NNs to our original dataset made of 3554 aerial** imgs to test 2 different models for land cover classification
  - Our **best model was a VGG16 Keras Model** (pre-loaded weights) in which we used **data augmentation** technique **reaching an overall accuracy of ∼94% and also reducing test loss to ∼15%**

ACKNOLEDGEMENTS

- We would like to thank our supervisors prof. G. P. Maggi, prof. D. Capolongo and prof. S. Stramaglia for scientific supports and advises constantly provided for this work

- We want also to thank G. Donvito, A. Italiano and S. Nicotri for proving us technical support and implementation without which we could’t get the improvements we had in our results

The computational work has been executed on the IT resources of the ReCaS-Bari data center, which have been made available by two projects financed by the MIUR (Italian Ministry for Education, University and Re-search) in the "PON Ricerca e Competitività 2007-2013" Program:

- ReCaS (Azione I - Interventi di rafforzamento strutturale, PONa3_00052, Avviso 254/Ric)
- PRISMA (Asse II - Sostegno all'innovazione, PON04a2_A)

The Aerospace Technology District (DTA Scarl) is the leading proponent for the CLOSE to the Earth and the RPASInAir projects

The photogrammetry study activities described are part of the objectives of a PhD project in Geosciences “Application of UAV system and SfM techniques to assess the hydrogeological hazard of a fluvial system” at the Department of Earth and Environmental Sciences of Bari and of the “RPASinAir - Integrazione dei Sistemi Aeromobili a Pilotaggio Remoto nello spazio aereo non segregato per servizi”, PON ricerca e innovazione 2014-2020.

REFERENCES

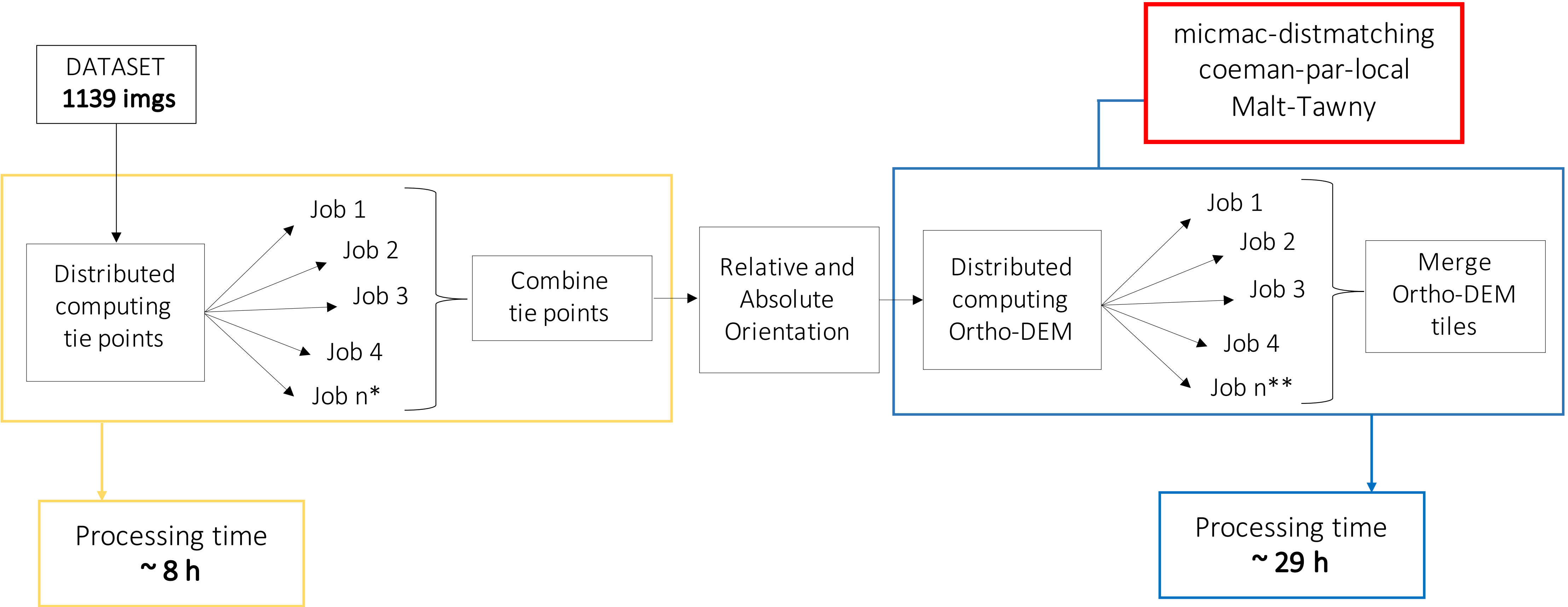
[1] *Ullman, 1979; Snavely et al., 2008; Wang et al., 2019*

[2] *K. Simonyan, A. Zisserman,* **Very Deep Convolutional Networks for Large-Scale Image Recognition,** International Conference on Learning Representations, 2015

BACKUP

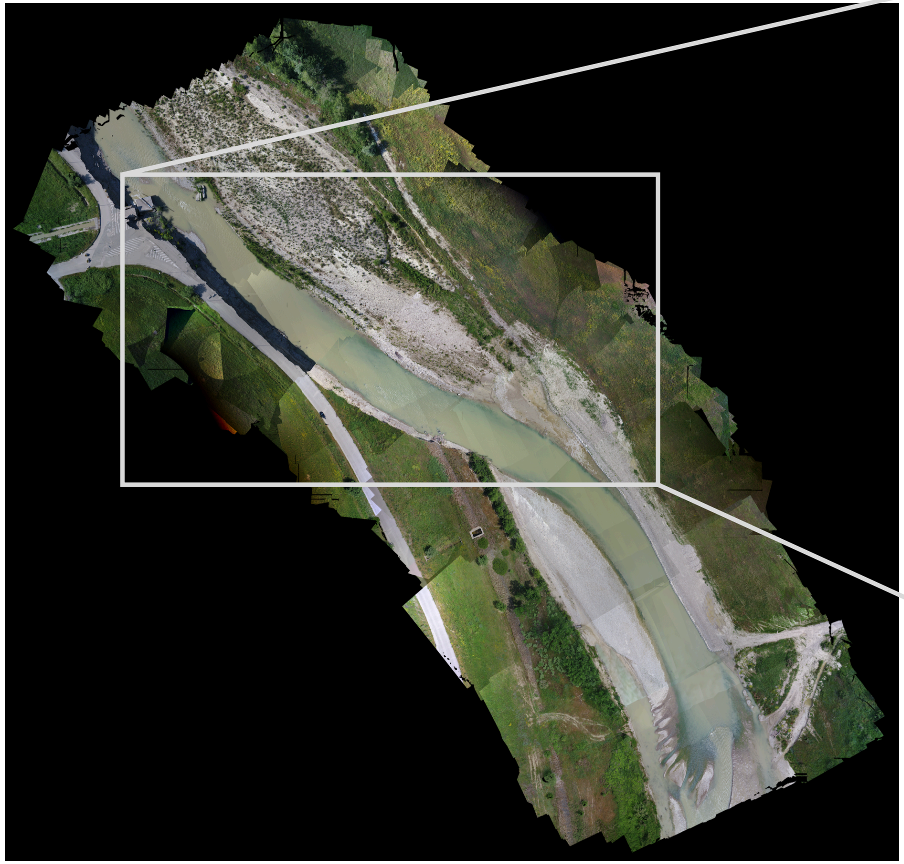
Configuration 1: Time Perfomances

- Different configurations of photogrammetric workflow and different number of images have been carried out to evaluate workflow best performances
- 1139 images took a wall time of ~ 37 hours **(previous version)**



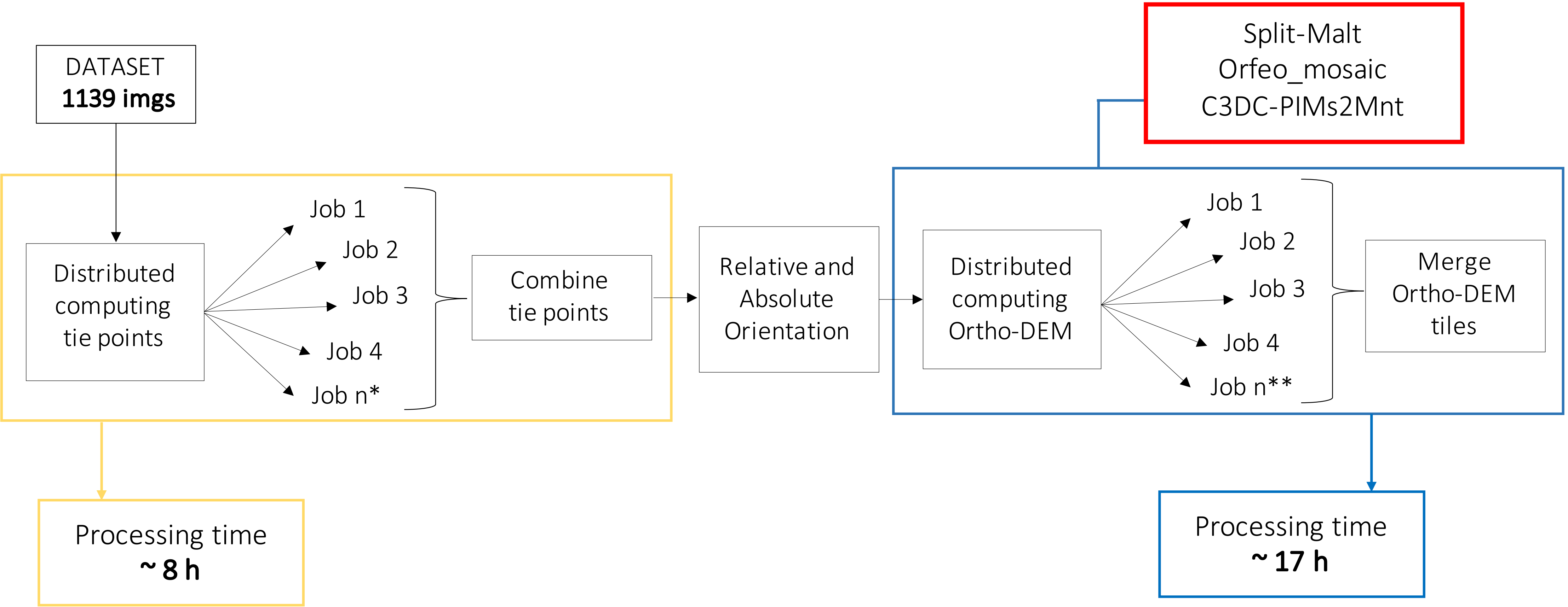
Configuration 1: Calibration Stability

- An incorrect radiometric equalization of the final orthophotomosaic has been found (exposure compensation and multi-band blending of tiles), due to incorrect configuration and poor stability of the MicMac commands on large dataset



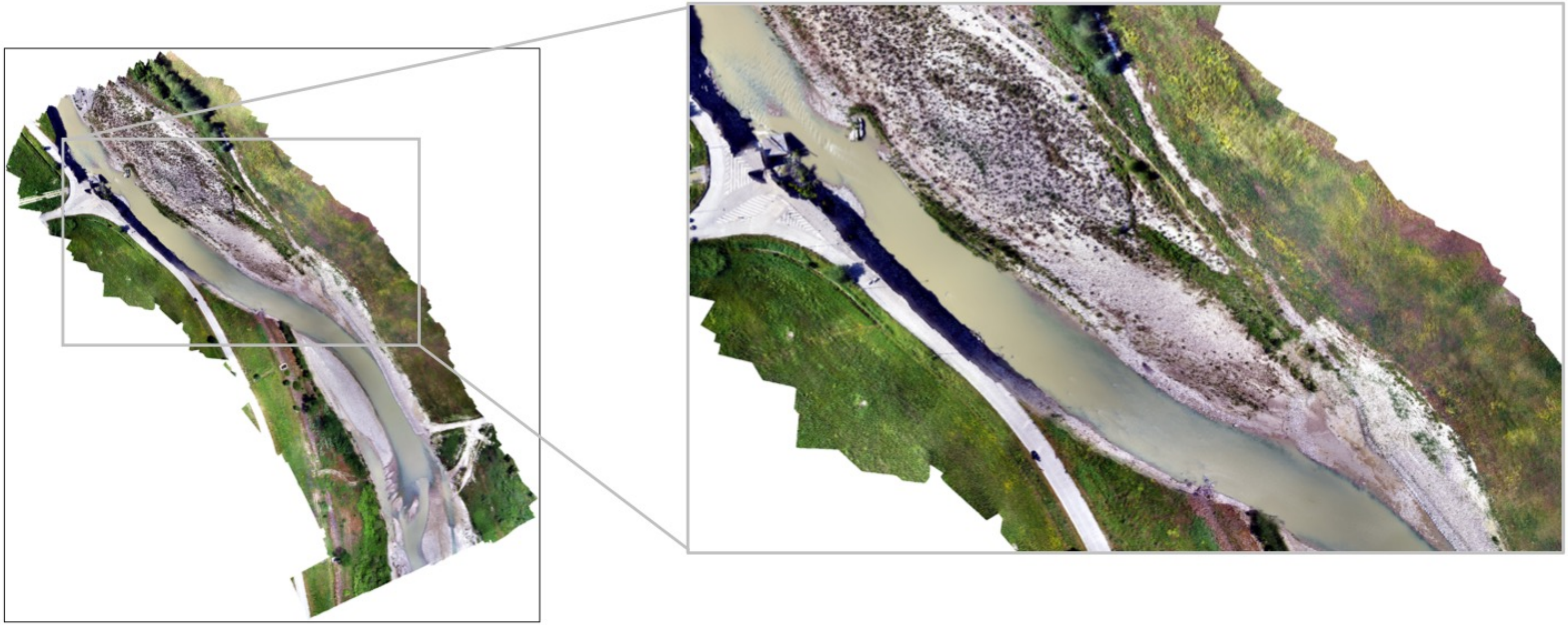
Configuration 2: Time Performances

- 1139 images took a wall time of about 25 hours **(current version)**
- ~33% time reduction compared to the previous configuration

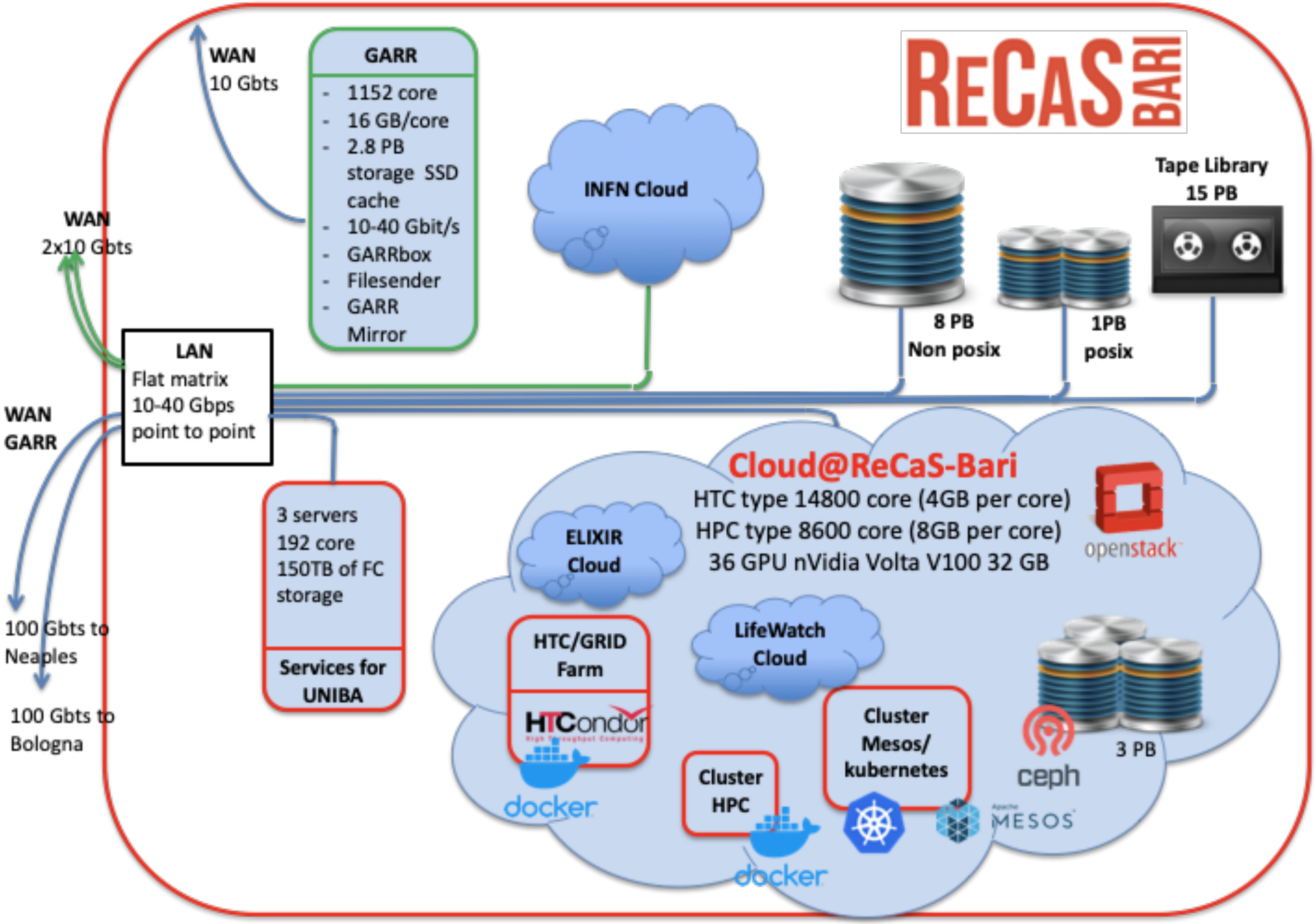


Configuration 2: Calibration Stability

- The box on the right shows a perfect radiometric equalization, obtained by Orfeo Tool Box feathering-method.



ReCaS-Bari future configuration



TERRITORIAL CLASSIFICATION USING NNs

- Both the images taken by the drone and the final ortophotomosaic, once opportunely cut, can be used to create an original dataset of aerial images that can be divided in classes. This part of our work is currently ongoing to get the most suitable arrangement. **(WORK IN PROGRESS)**

- Comparing our images to those used in other datasets built for the purpose, a considerable resolution downgrade will be operated

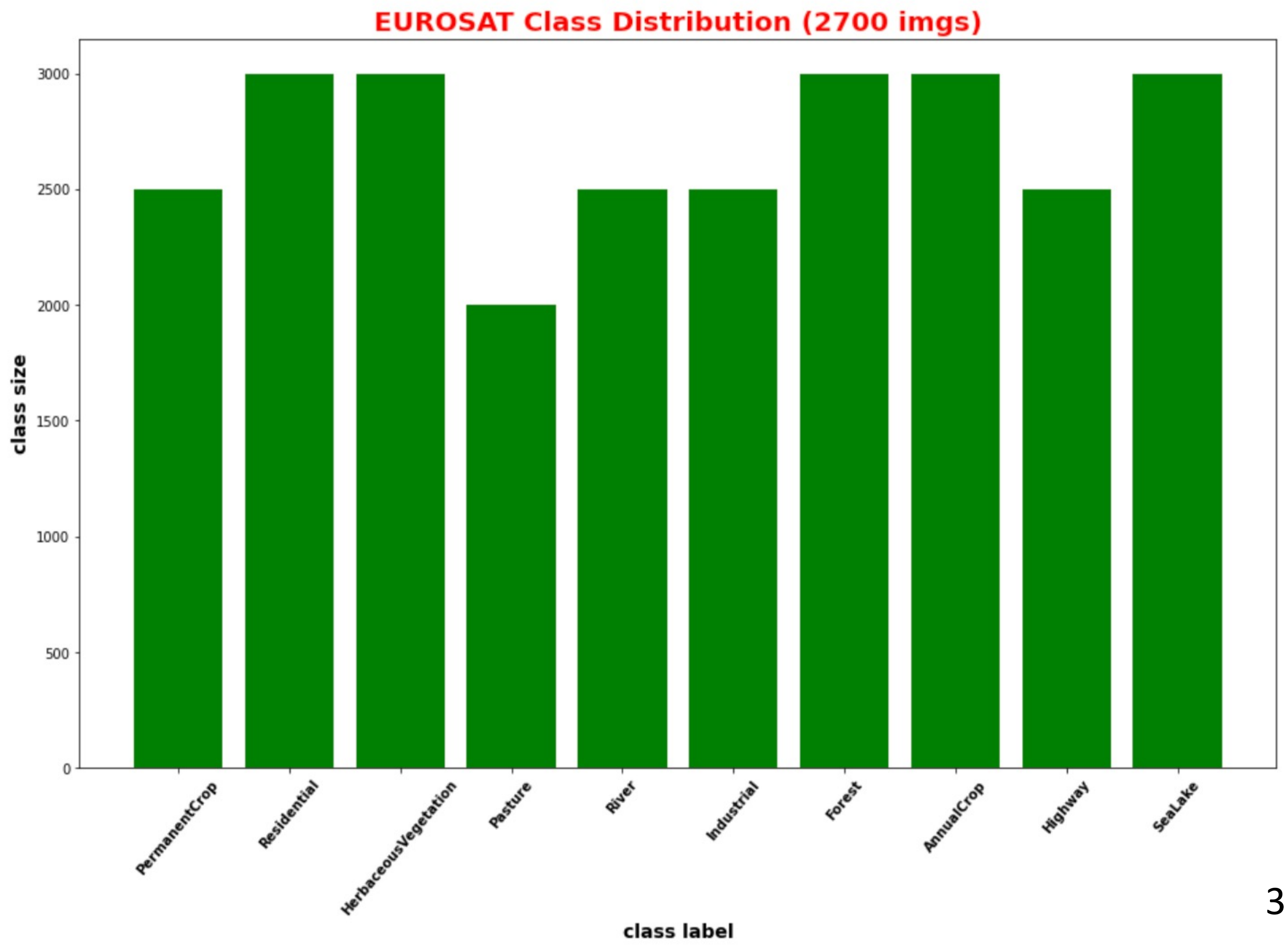
- For change detection studies, the most important classes that must be included in our work must be «Terrain», «Water» and «Vegetation»

- Two different models have been tested for territorial classification on the **EuroSAT dataset** [2] (available at https://github.com/phelber/eurosat), which was explored as a first approach for the next step of our studies

- The **EuroSAT dataset** consists of a collection of 27,000 Sentinel-2 satellite images made of 13 spectral bands and 10 pre-labeled classes : 'Annual Crop','Forest', 'Herbaceous Vegetation’, 'Highway', 'Industrial', 'Pasture', 'Permanent Crop', 'Residential', 'River','Sea Lake’.

EUROSAT Class Distribution

Class Number	Class Name	Population
1	Permanent Crop	2500
2	Residential	3000
3	Herbaceous Vegetation	3000
4	Pasture	2000
5	River	2500
6	Industrial	2500
7	Forest	3000
8	Annual Crop	3000
9	Highway	2500
10	Sea Labe	3000
TOTAL		27000

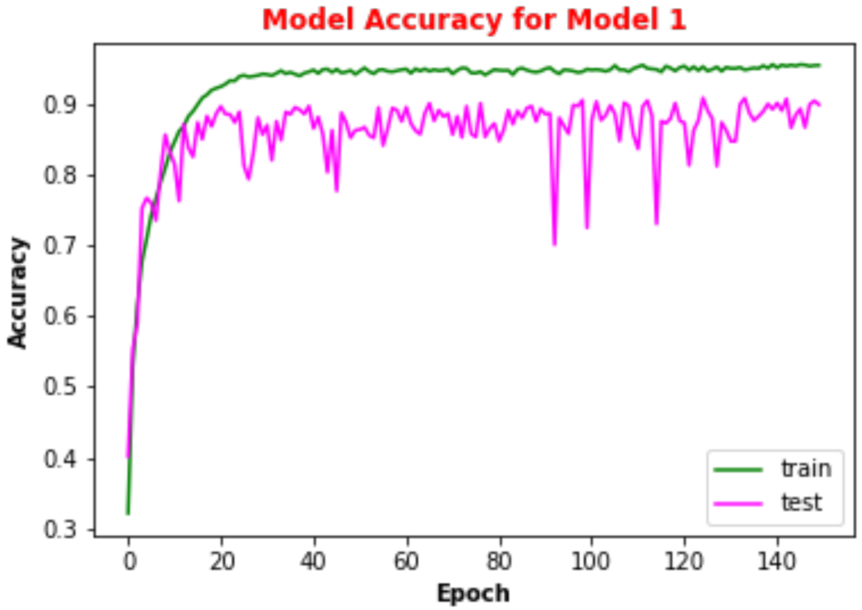


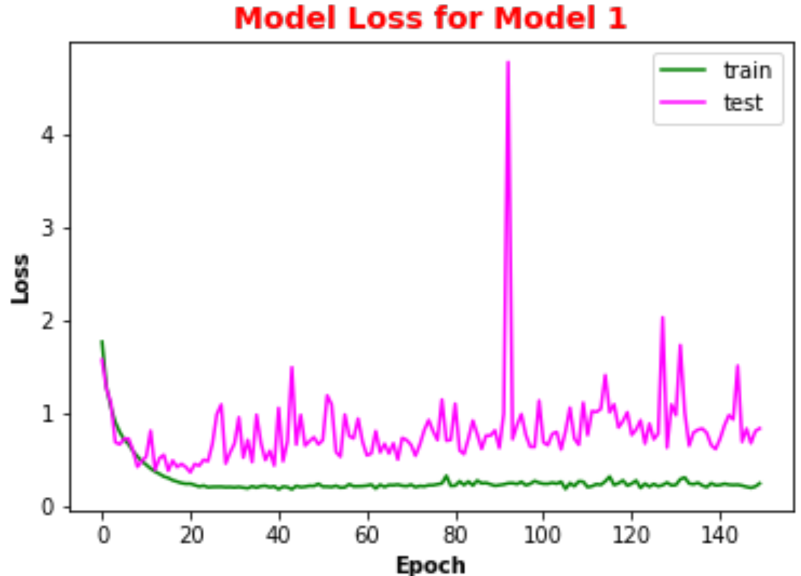
MODEL 1: MAX POOLING

MODEL 1: A model with a sequence of pairs of max pooling and convolution layers ending with a dropout layer (30%) and a dense layer.

Epochs=150
Test accuracy: 0.90

	index	y_true	accurate_preds	label_count	class_acc	overall_acc
0	0	b'AnnualCrop'	1276	1500	0.850667	0.900148
1	1	b'Forest'	1426	1500	0.950667	0.900148
2	2	b'HerbaceousVegetation'	1311	1500	0.874000	0.900148
3	3	b'Highway'	1082	1250	0.865600	0.900148
4	4	b'Industrial'	1176	1250	0.940800	0.900148
5	5	b'Pasture'	912	1000	0.912000	0.900148
6	6	b'PermanentCrop'	999	1250	0.799200	0.900148
7	7	b'Residential'	1406	1500	0.937333	0.900148
8	8	b'River'	1124	1250	0.899200	0.900148
9	9	b'SeaLake'	1440	1500	0.960000	0.900148



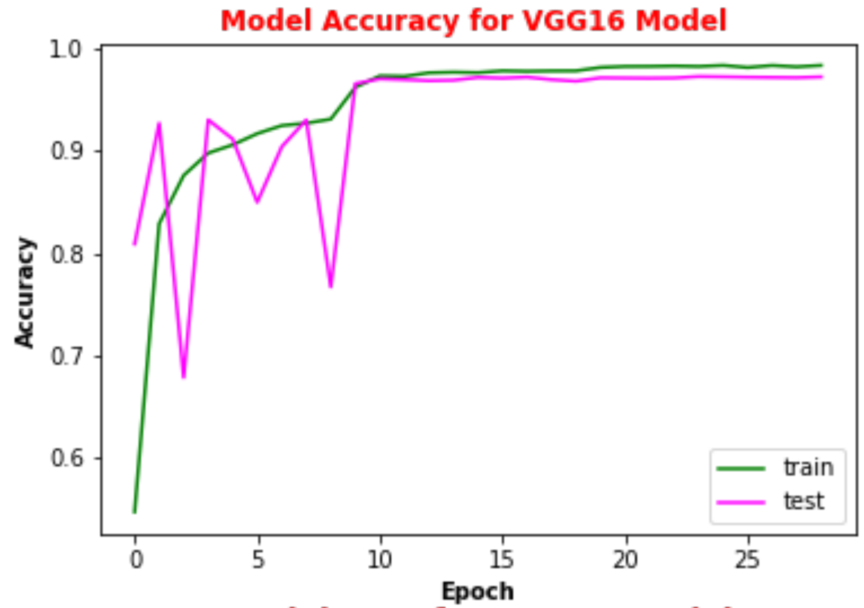


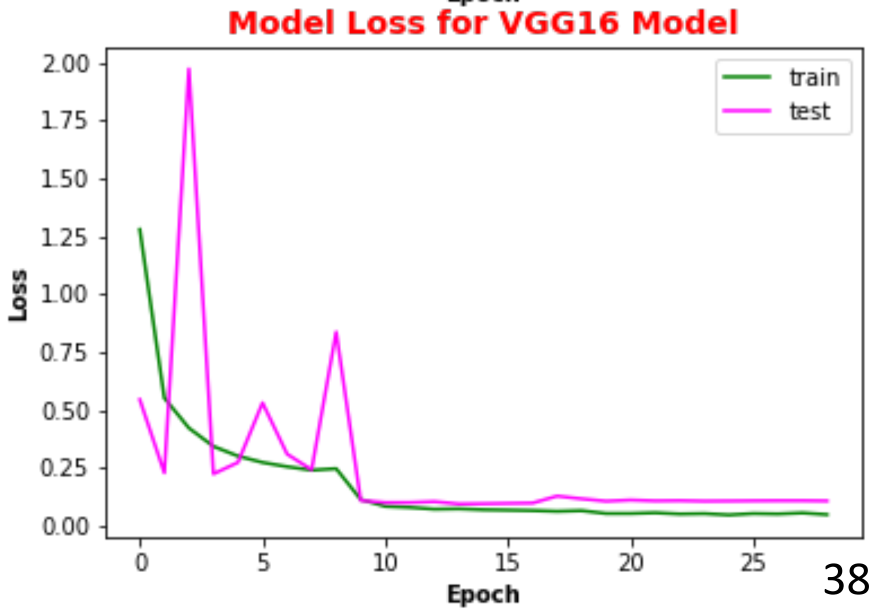
MODEL 2: VGG16 MODEL

- For this training we use a different approach adding convolutional base of the VGG16 Keras Model (pre-loaded weights) to exploit **data augmentation** technique and improving the results **[3]**
- In addition to **Model Checkpoint**, the **EarlyStopping** and **ReduceLROnPlateau** callback functions were added to limit the overfitting and reduce the learning rate if no improvements are seen after a fixed number of epochs

Epochs=150 early stopped after 30 epochs
Test accuracy: 0.97

	index	y_true	accurate_preds	label_count	class_acc	overall_acc
0	0	b'AnnualCrop'	1405	1500	0.936667	0.969778
1	1	b'Forest'	1491	1500	0.994000	0.969778
2	2	b'HerbaceousVegetation'	1387	1500	0.924667	0.969778
3	3	b'Highway'	1206	1250	0.964800	0.969778
4	4	b'Industrial'	1232	1250	0.985600	0.969778
5	5	b'Pasture'	970	1000	0.970000	0.969778
6	6	b'PermanentCrop'	1203	1250	0.962400	0.969778
7	7	b'Residential'	1490	1500	0.993333	0.969778
8	8	b'River'	1225	1250	0.980000	0.969778
9	9	b'SeaLake'	1483	1500	0.988667	0.969778

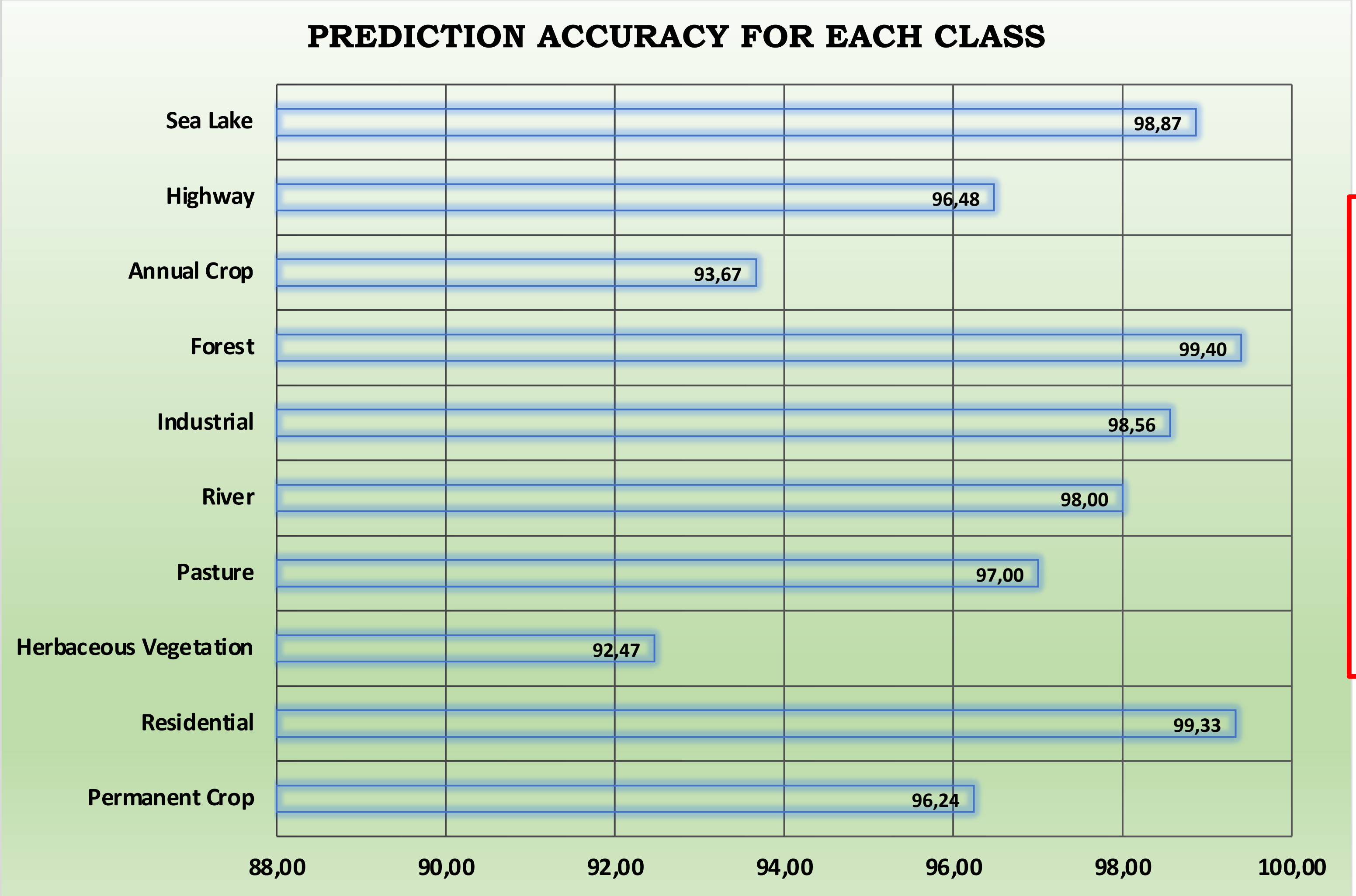




MODEL ACCURACY SUMMARY

	y_true	label_count	Mod1_class_acc	Mod1_overall_acc	Mod2_class_acc	Mod2_overall_acc
0	b'AnnualCrop'	1500	0.875333	0.840963	0.936667	0.969778
1	b'Forest'	1500	0.879333	0.840963	0.994000	0.969778
2	b'HerbaceousVegetation'	1500	0.760667	0.840963	0.924667	0.969778
3	b'Highway'	1250	0.718400	0.840963	0.964800	0.969778
4	b'Industrial'	1250	0.981600	0.840963	0.985600	0.969778
5	b'Pasture'	1000	0.836000	0.840963	0.970000	0.969778
6	b'PermanentCrop'	1250	0.826400	0.840963	0.962400	0.969778
7	b'Residential'	1500	0.688000	0.840963	0.993333	0.969778
8	b'River'	1250	0.943200	0.840963	0.980000	0.969778
9	b'SeaLake'	1500	0.916667	0.840963	0.988667	0.969778

NNs RESULTS FOR EUROSAT DATA CLASSIFICATION



BEST MODEL: VGG16 MODEL

	index	y_true	accurate_preds	label_count	class_acc	overall_acc
0	0	b'AnnualCrop'	1405	1500	0.936667	0.969778
1	1	b'Forest'	1491	1500	0.994000	0.969778
2	2	b'HerbaceousVegetation'	1387	1500	0.924667	0.969778
3	3	b'Highway'	1206	1250	0.964800	0.969778
4	4	b'Industrial'	1232	1250	0.985600	0.969778
5	5	b'Pasture'	970	1000	0.970000	0.969778
6	6	b'PermanentCrop'	1203	1250	0.962400	0.969778
7	7	b'Residential'	1490	1500	0.993333	0.969778
8	8	b'River'	1225	1250	0.980000	0.969778
9	9	b'SeaLake'	1483	1500	0.988667	0.969778

NNs RESULTS FOR EUROSAT DATA CLASSIFICATION

- Misclassification and percentage of wrong predictions for each class for the best model

Class Number	Class Name	Mostly misclassified for class …
1	**Permanent Crop**	Herbaceous Vegetation
2	**Residential**	Industrial
3	**Herbaceous Vegetation**	Permanent Crop
4	**Pasture**	Forest
5	**River**	Highway
6	**Industrial**	Residential
7	**Forest**	Pasture
8	**Annual Crop**	Permanent Crop
9	**Highway**	River
10	**Sea Lake**	Annual Crop/Forest