Fire risk prediction

1. Next day fire prediction: Problem definition and background
2. Current status: Establishment of a complete/reliable ML workflow
3. Operational system presentation
4. Future steps: adaptation of DL methods for handling problem specificities

Problem definition and background

Problem overview

- 2019 : 1.65 million hectares burned in New South Wales of Australia and 83% increase in 2019.
- Brazilian Space Agency has reported an 83% increase in fire occurrences compared to the same period of the previous year.
- 2018 Attica wildfires spread up to a speed of 124 km/h resulting to more than a hundred casualties.
- 2021 Greece wildfires burned>10^6 hectares
- Climate change provoke more and more

Need

Systems that provide valuable information to the civil protection services for prevention and preparness, like fire incidents online alerting and monitoring, fire risk prediction and and spread prediction

Concept

Data-driven models are good in discovering unknown relations between data. Exploit historical data from fire events and fire related parameters to train machine learning algorithms for predictive modeling.

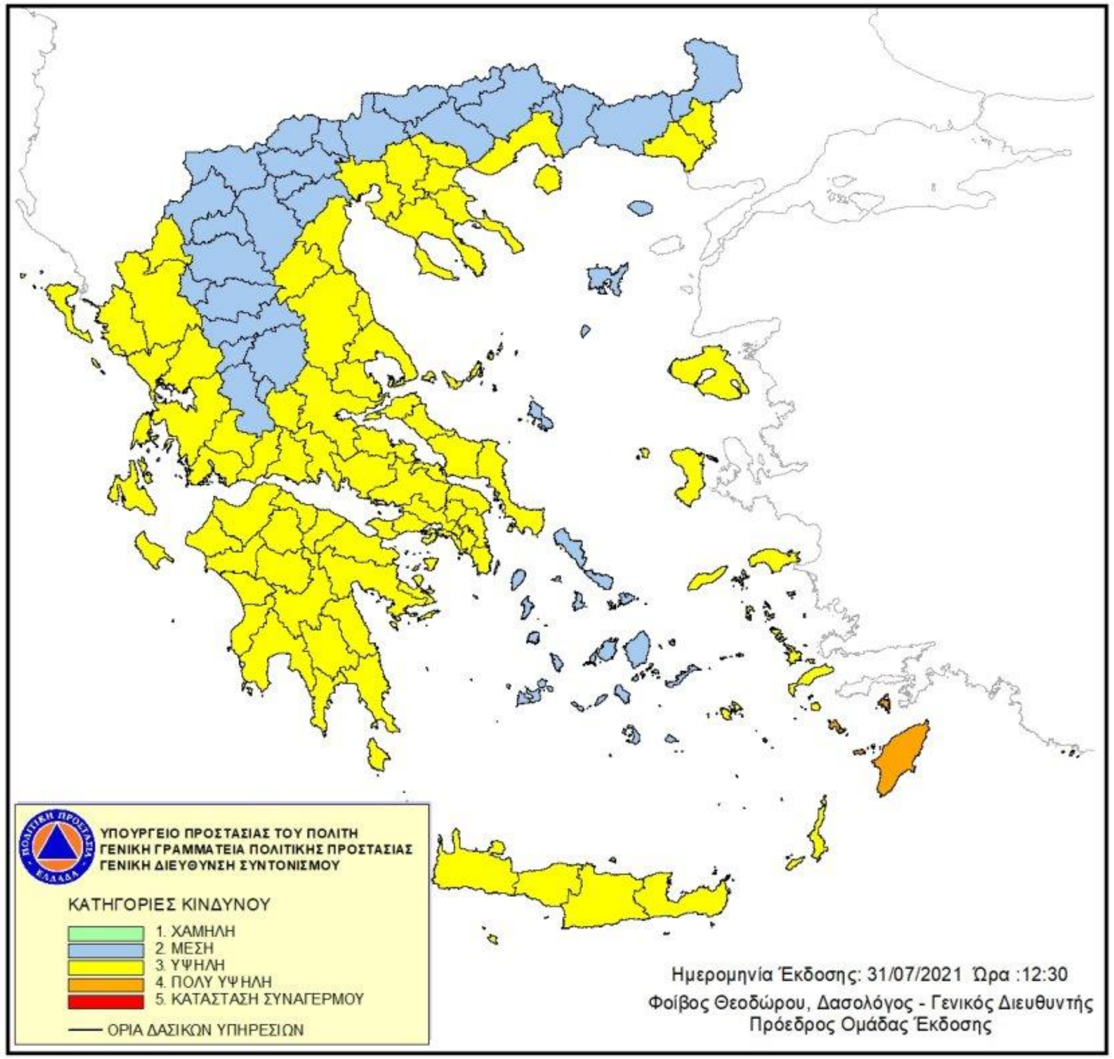
Complexity

Forest fire occurrence and behaviour are the product of several interrelated factors, including ignition source, fuel composition, weather, and topography. The mathematic relations of those factors are not known, thus it is not easy to model the behaviour using physics based/theoretical models.

Motivation

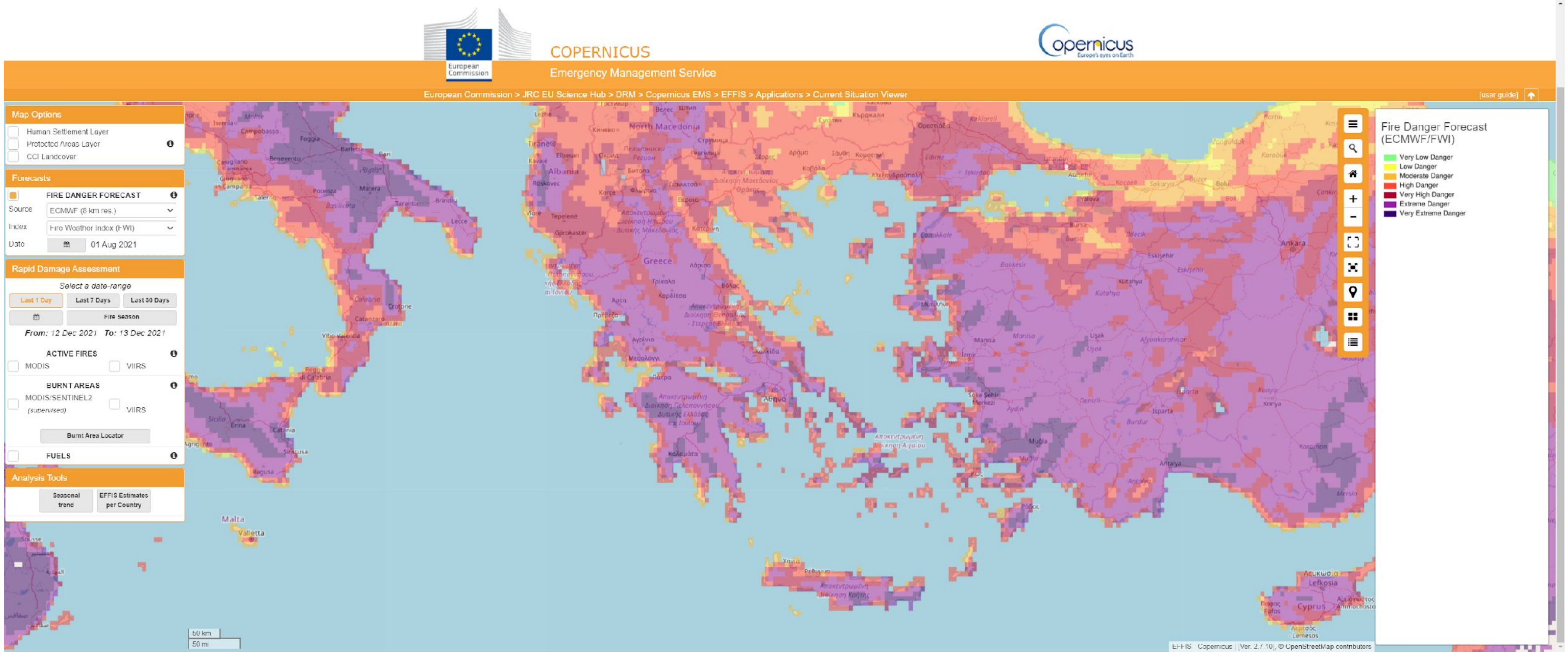
- Essential tool for **daily operational organization** of fire services
- Current service of Civil Protection

ΧΑΡΤΗΣ ΠΡΟΒΛΕΨΗΣ ΚΙΝΔΥΝΟΥ ΠΥΡΚΑΓΙΑΣ ΠΟΥ ΙΣΧΥΕΙ ΓΙΑ
Κυριακή 01/08/2021



Motivation

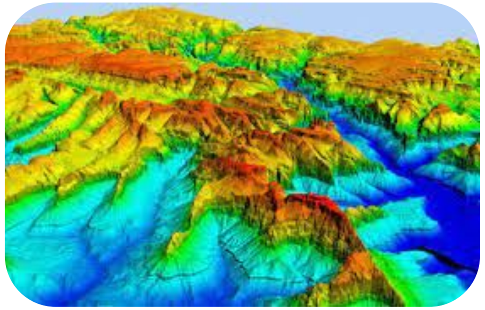
- Essential tool for **daily operational organization** of fire services
- Current service of Copernicus EFFIS



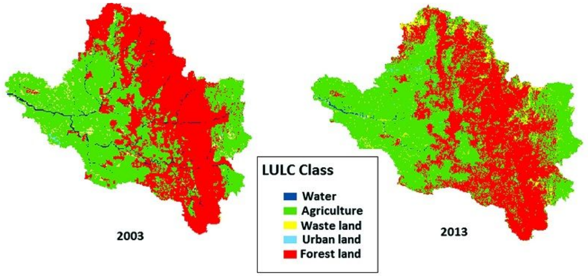
The Fire Drivers usually adopted in literature that form the input features for the modeling

Static or slow change

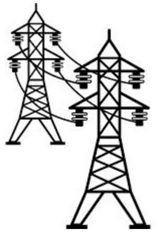
Ground Morphology: Elevation, Slope, Curvuture



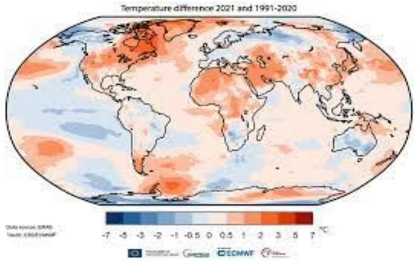
Land Use - Land Cover



Location Related: Distance from roads, urban environment, power grids, machinery, rivers

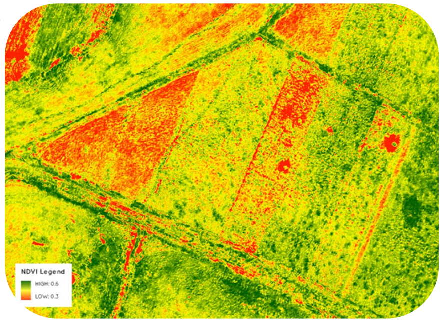


Climate: statistics of weather parameters

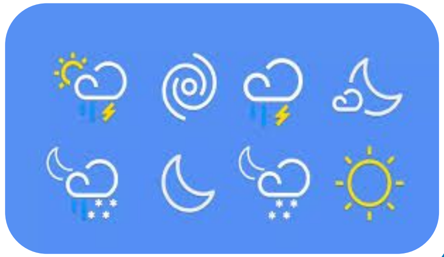


Dynamic

Satellite :
Vegetation indices
Surface temperature
Soil moisture



Meteorology / Weather forecast: Temperature, Wind, Precipitation, Humidity



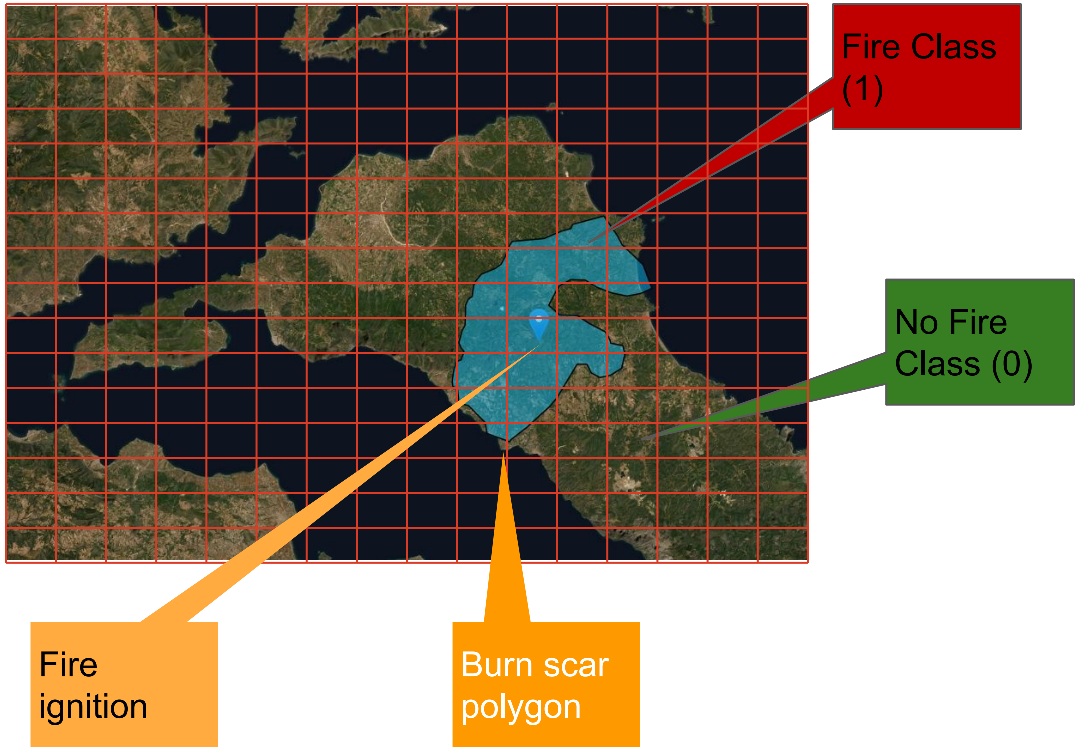
Target variable - Fire / No Fire classes

Use of burn scar maps to annotate fire class on a specific area at a specific time frame

Problem is solved as supervised classification.

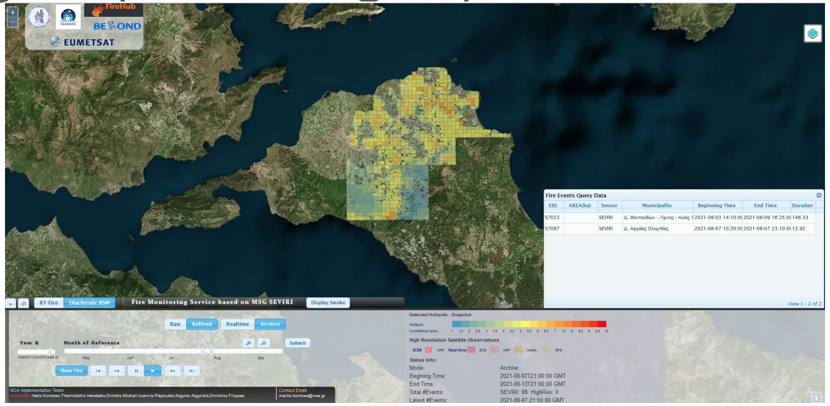
For each day all cells which suffered a fire event are assigned the "fire" class whereas all other cells belong to the "no fire" class. Right? Not exactly!

Each parameter input vector is assigned to a cell grid for a specific date



Problem definition - Next day Fire risk prediction

- Predict the risk of fire occurrence in an area for a day *k*, exploiting information for the area exclusively gathered up until day *k-1*
- Essentially handled as binary *{fire, no-fire} classification problem,* due to label availability (historical fires)
  - Ideally, a reliable confidence (probability of risk) level should be output
- Each area corresponds to a 500m cell of a grid (fireHub grid)
  - Grid covers the whole Greek territory
- Detailed historical data from 2010-2020
  - > 800M instances



Problem complications and usual pitfalls

- Annotating absence of fire as "no fire" class does not mean zero probability for fire. "No-fire" class is essentially a pseudo-absence.

  Bar Massada, Avi; Syphard, Alexandra D.; Stewart, Susan I.; Radeloff, Volker C. 2012 Wildfire ignition-distribution modelling: a comparative study in the Huron-Manistee National Forest, Michigan, USA. International Journal of Wildland Fire.

- Data Leakage may occur creating the train and validation datasets.

  Alexis Apostolakis, Stella Girtsou, Charalampos Kontoes, Ioannis Papoutsis, and Michalis Tsoutsos. "Implementation of a Random Forest Classifier to Examine Wildfire Predictive Modelling in Greece Using Diachronically Collected Fire Occurrence and Fire Mapping, 2021

- Huge imbalance between classes "fire" and "no fire"

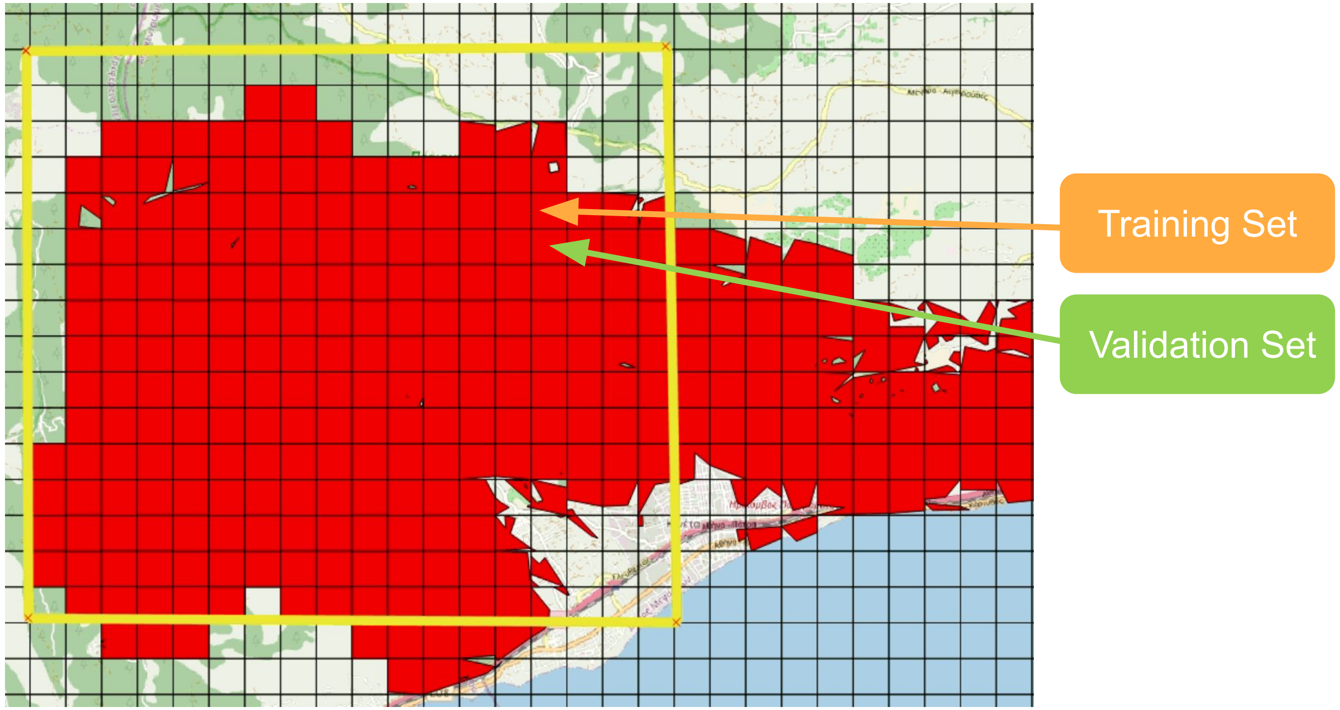
  Girtsou, Stella, Alexis Apostolakis, Giorgos Giannopoulos, and Charalampos Kontoes. "A Machine Learning Methodology for Next Day Wildfire Prediction." In *IGARSS 2021*

- Which metric to optimize?

  Alexis Apostolakis, Stella Girtsou, Giorgos Giannopoulos, Nikolaos S. Bartsotas, and Charalampos Kontoes. "Estimating Next Day's Forest Fire Risk via a Complete Machine Learning Methodology, 2022

Problem complications and usual pitfalls

Classifier may become "too successful" when shuffling instances to produce train-validation sets



ERA5Land cell | Grid 500x500m | Fire cells

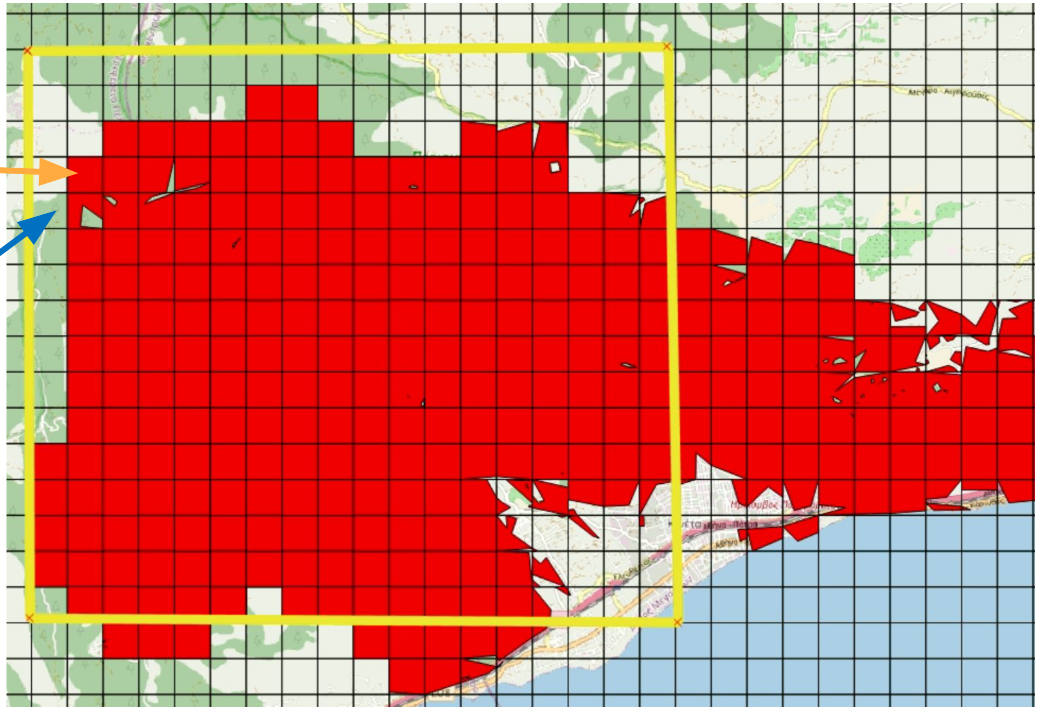
When shuffling, cells from the same fire event with almost same feature vectors may participate both in training and validation set, causing data leakage

Problem complications and usual pitfalls

Non-fire cells may have a very similar feature vector with fire cell

Fire Cell

No fire Cell



ERA5Land cell

Grid 500x500m

Fire cells

Problem complications and usual pitfalls

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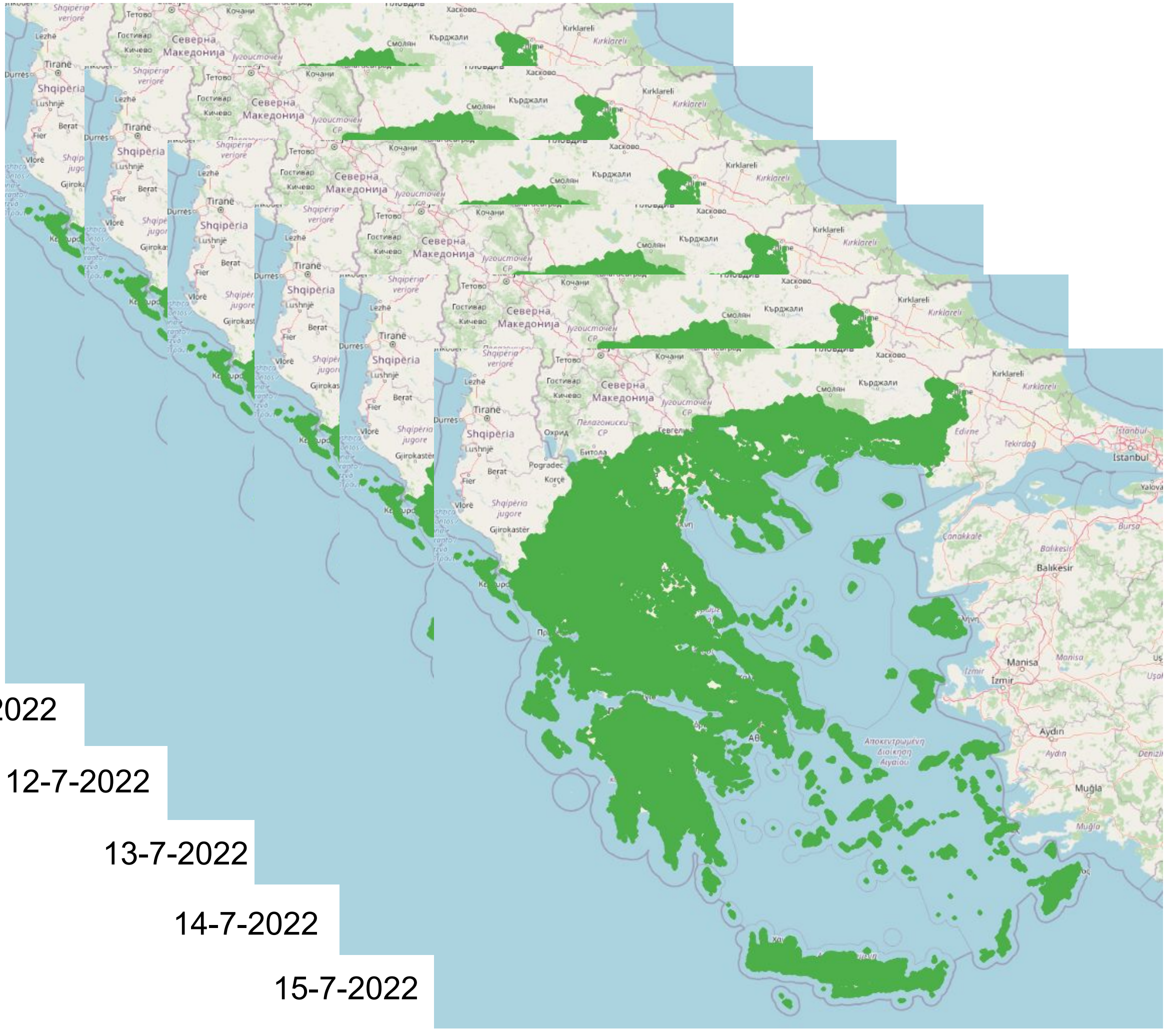


11-7-2022
12-7-2022
13-7-2022
14-7-2022
15-7-2022

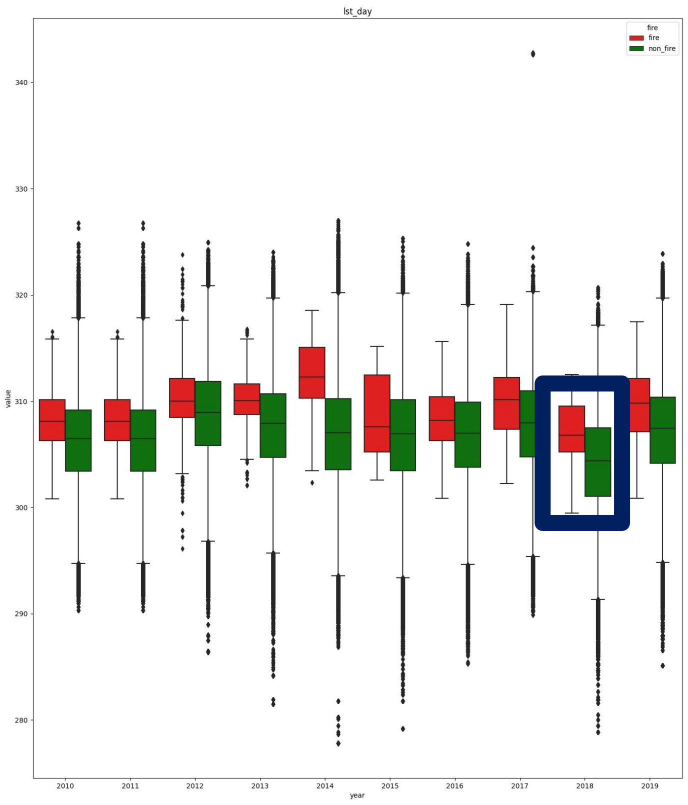
....

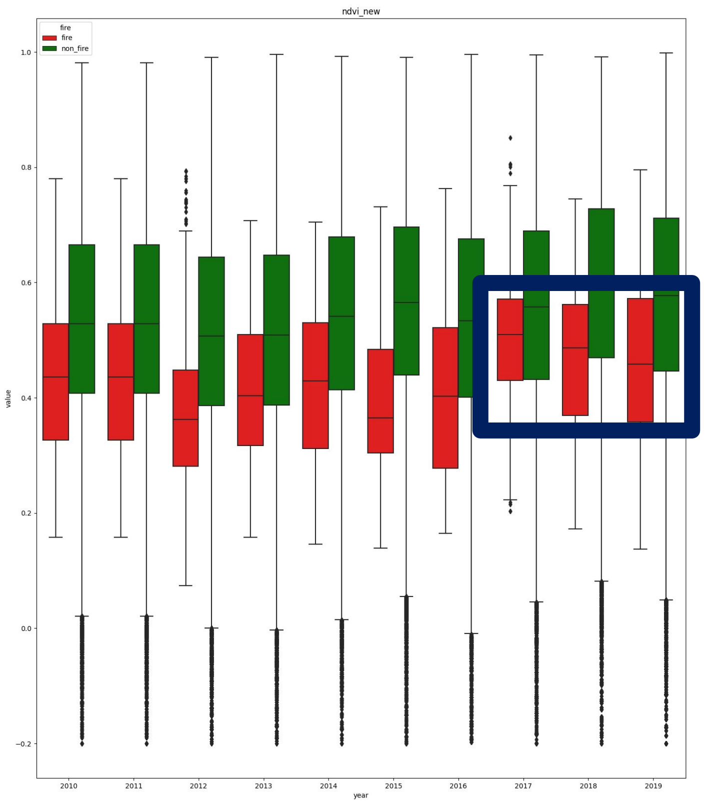
Big data and huge class imbalance

Real world Dataset comprise of ~270000 feature vectors (grid cells) per day. Each vector has 90 parameters (including one-hot). Only 1/100000 is a fire cell

Problem complications and usual pitfalls

- Concept drift





Problem complications and usual pitfalls

- Extreme data imbalance
  - Ratio of ~1:100K between fire/no-fire cells
- Large data scale
  - Challenging to properly perform model selection
- Absence of fire phenomenon
  - Areas that should have a fire occurrence but did not *by chance*
  - Chance = lack of impossible to capture features
    - (i.e. a person's decision to start a fire, a cigarette thrown by a driver, a lightning)
- Spatio-temporal correlations
  - Adjacent cells are expected to be nearly-identical
  - Previous years' incidents might affect the short-term behavior of an area
- Optimization metric
  - Which is the ideal metric to optimize? A high recall/sensitivity does not mean anything if it is combined with a low specificity on a "real world" dataset

Problematic even for imbalance handling methods

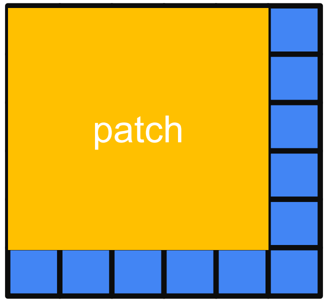
Problem complications and usual pitfalls

Related works – General observations

- Unfit model selection/assessment poor generalizability
  - Balanced train/validation/test setting
  - Usually poor/non-existent hyperparameter search

Related works – Deep learning

Convolutional NNs label every "patch" as fire or no-fire oversampling fire class and lowering the prediction resolution arbitrary (according the patch size)



Works that employ simple Deep NNs instead of applying an extensive hyperparameterization methodology to determine the network's architecture, they define the depth of the network a priori.

Motivation

- What comprises a meaningful/useful result?
  - Predict most of the fires
  - Try not to predict for the majority of the territory (country) high risk for fire
- Translation: a good balance between sensitivity/specificity*
  - Ideal: {>95%, >90%}
  - Realistic:
    - {>90%, >70%}
    - {>80%, >80%}
    - Depends on the exact application setting/needs
    - □ could reach the ideal if reformulate the problem □ mid-term work

*Sensitivity = $\frac{TP}{P}$ (P=TP+FN) → $\frac{\text{Fires predicted corrrectly}}{\text{Actual fire}}$

*Specificity = $\frac{TN}{N}$ (N=TN+FP) → TN >> FP, TN+FP ≈ TN, N >> P, N+P ≈ N → $\frac{\text{Area of Low Risk}}{\text{Area of whole territory}}$

ML Method and Results

Establishment of a complete ML workflow

- Formalize the problem as binary classification
  - Utilize model’s prediction confidence for quantifying risk probability

1. Extract an extended set of features
   - Meteorological, topographical, vegetation, earth observation, and historical characteristics of the areas
2. Utilize state of the art classification algorithms
   - Random Forest, XGBoost, ExtraTrees, Neural Networks
   - Explore large hyperparameter spaces of the algorithms

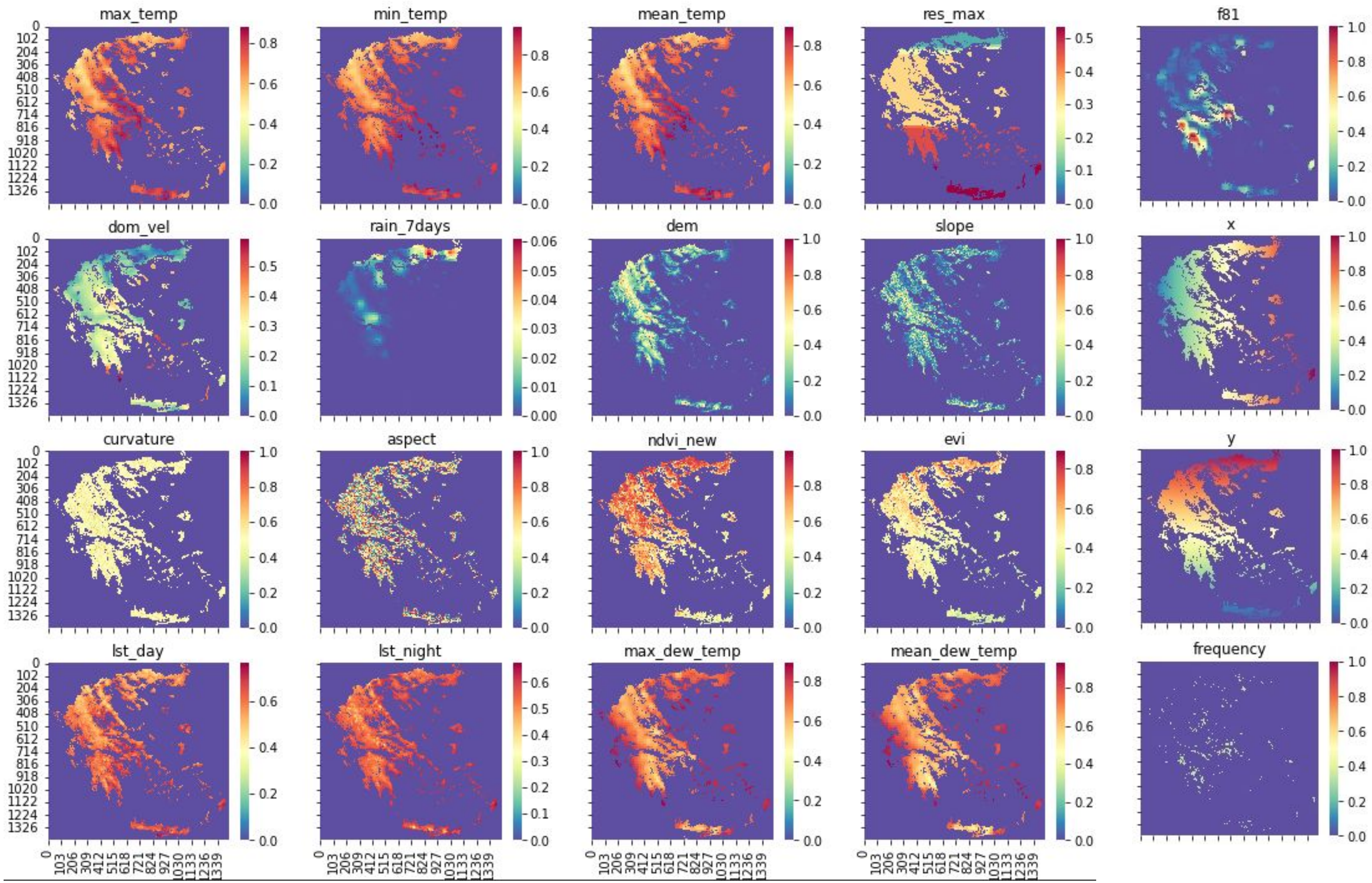
Establishment of a complete ML workflow

3. Perform appropriate cross-validation
   - Proper train-validation-test splits
   - Ensure
     - Avoiding data leakage
     - Assessing the methods on the real-world dataset distribution
     - Agility in adjusting sensitivity/specificity trade-off
     - Generalizability

4. Select/define appropriate measures for model selection and evaluation
   - In our extremely imbalance setting, distinguishing between model selection and evaluation is important

1. Feature extraction

Category	Features	Spatial Res.	Temp.Res.	Source
DEM	Dem, slope, curvature	25 m	-	Copernicus DEM
Land cover	corine	100 m	3 years	Corine Land Cover
Temperature	max, min, mean	9 km	hourly	ERA5 land
Dewpoint	max, min mean	9 km	hourly	ERA5 land
Wind speed	dom_vel	9 km	hourly	ERA5 land
Wind direction	dir_max, dom_dir	9 km	hourly	ERA5 land
Precipitation	rain_7days	9 km	hourly	ERA5 land
Vegetation	ndvi, evi	500 m	8 days	NASA MODIS
LST	lst_day, lst_night	1 km	8 days	NASA MODIS
Fire history	Frequency, f81 (smoothed)	500 m	daily	FireHub BSM
Coordinates	xpos, ypos	500 m	daily	FireHub cell grid
Calendar Cycles	month, wkd	500 m	daily	Fire Inventory date field


max_temp
min_temp
mean_temp
res_max
f81
dom_vel
rain_7days
dem
slope
x
curvature
aspect
ndvi_new
evi
y
lst_day
lst_night
max_dew_temp
mean_dew_temp
frequency

2. Classification algorithms

- Neural Networks
  - Up to 5 layers depth
  - Up to 2000 nodes per layer
  - With/out dropout
  - Adam optimizer
- Tree Ensembles
  - Random Forest
  - XGBoost
  - ExtraTrees

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- Tree Ensembles
  - Random Forest
  - XGBoost
  - ExtraTrees
- Exploration of a large hyperparameter space

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[
(0, {’layer_1_0_nodes’: hp.quniform(’layer_1_0_w_nodes’, 100, 2100,
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’layer_2_1_nodes’: hp.quniform(’layer_2_1_w_nodes’, 100, 2100,
100)}),
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100)}),
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(3, {’layer_1_3_nodes’: hp.quniform(’layer_1_3_nodes’, 10, 100, 10),
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’layer_4_4_nodes’: hp.quniform(’layer_4_4_nodes’, 10, 100, 10),
’layer_5_4_nodes’: hp.quniform(’layer_5_4_nodes’, 10, 100, 10)})
]
),
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{0:2,1:3},
{0:1, 1:5}, {0:1, 1:10}]),
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{’name’:’Adam’,’adam_params’:hp.choice(’adam_params’,[None])}]),
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500, 750, 1000,1400, 1500]),
’min_samples_split’: hp.choice(’min_samples_split’,[2, 10, 50, 70,100,120,150,180,
200, 250,400,600,1000, 1300, 2000]),
’min_samples_leaf’ :hp.choice(’min_samples_leaf’,[1, 10,30,40,50,100,120,150]),
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’max_features’:hp.quniform(’max_features’, 1,10,1), # the x/10 of the total features
’bootstrap’:hp.choice(’bootstrap’,[True, False]),
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])
}
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1000]),
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’max_depth’: hp.quniform(’max_depth’,2, 40, 2),
’min_samples_split’: hp.choice(’min_samples_split’,[2, 10, 50, 70, 100, 120, 150, 180,
200, 250, 400, 600, 1000, 1300, 2000]),
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’max_features’: hp.quniform(’max_features’, 1,10,1), # the x/10 of the total features
’bootstrap’: hp.choice(’bootstrap’,[True, False]),
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’gamma’: hp.choice(’gamma’,[0, 0.001, 0.01, 0.1, 1, 10, 100, 1000]),
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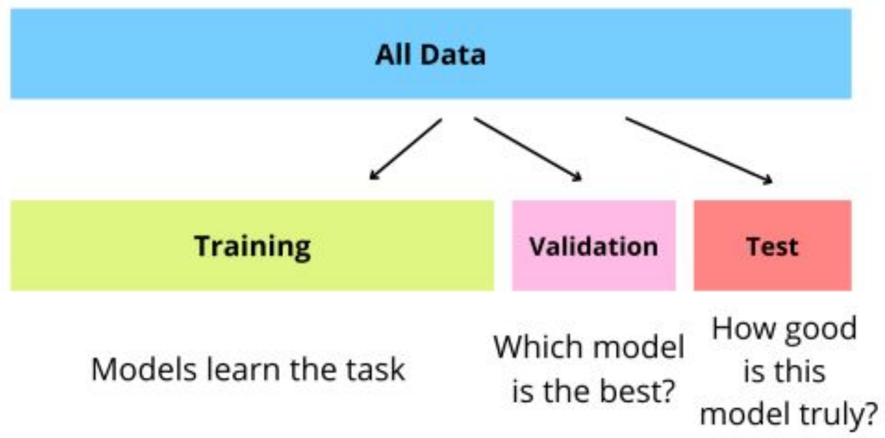
’feature_drop’: [],
}
```

3. Cross validation

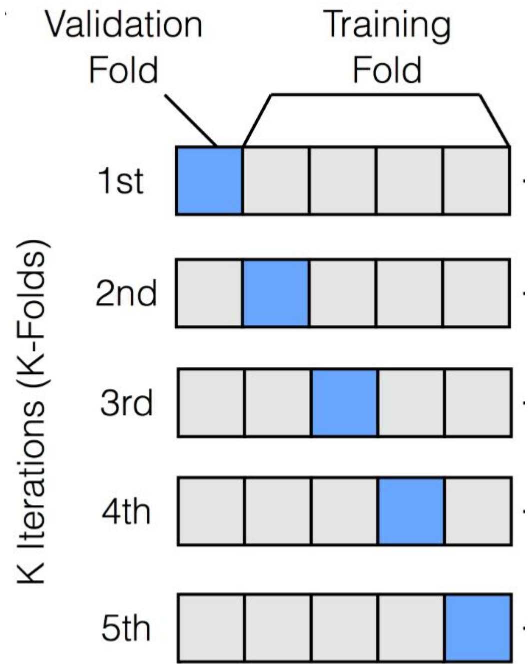
- Train-validation-test

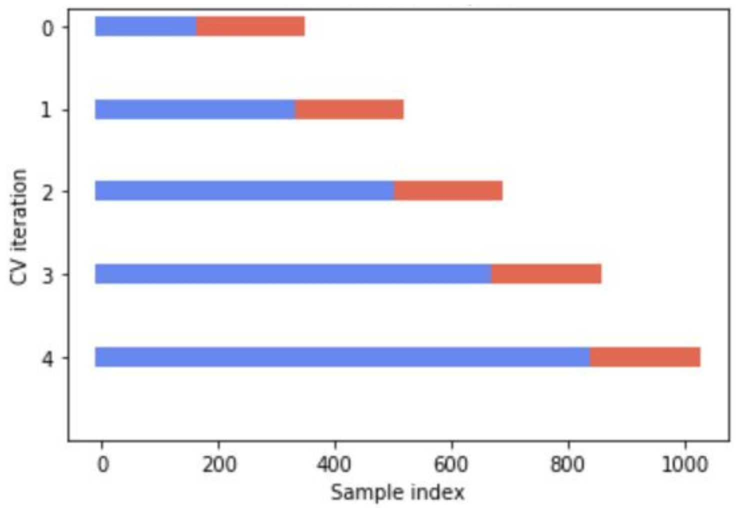


- Two schemes for cross validation on train-validation splits
  - Train-validation set on years **2010-2018**
- Proper dataset splitting for model selection and evaluation
  - Ensure that events from the same day/fire event are not distributed in different folds
- Test sets always maintains the initial, extremely imbalanced distribution
  - Years **2019 and 2020**

3. Cross validation

- Two alternative schemes for cross validation
  - Default:
    - Consider all the fire (minority) instances of the training set
    - Geographically sample the no-fire (majority) instances to create a balanced set
    - Perform k-fold cross-validation and select models on the average best validation scores
  - Alternative:
    - Make the training set balanced, but keep the validation sets highly imbalanced
    - Adjust so that each training set precedes the respective validation set on a yearly level
    - Perform model selection on highly imbalanced folds closer to the real distribution





https://androidkt.com/pytorch-k-fold-cross-validation-using-dataloader-and-sklearn/

4. Measures for model selection

- Adjusted evaluation measures for model selection
  - Evaluated on the validation set
  - Variable weighting between sensitivity and specificity
- $rhybrid_k = \frac{sensitivity * specificity}{sensitivity + k * specificity}$
- $shybrid_k = k * sensitivity + specificity$

Results

- Realistic targets (sensitivity/specificity):
  - {>90%, >70%}
  - {>80%, >80%}
- Achieved:
  - {90%, 67%}, {95%, 67%}

	2019		2020	
	Sensitivity	**Specificity**	**Sensitivity**	**Specificity**
RF-sh5-defCV	0.9	0.55	0.97	0.56
ET-rh5-altCV	0.92	0.59	0.96	0.59
XGB-sh2-altCV	0.91	0.59	0.96	0.58
NN-rh5-defCV	**0.9**	**0.66**	**0.95**	**0.67**
NNd-rh5-defCV	0.91	0.65	0.95	0.66
NNd-sh2-defCV	**0.9**	**0.67**	**0.95**	**0.67**
NNd-sh5-defCV	0.93	0.59	0.96	0.62
NN-auc-altCV	0.9	0.61	0.97	0.59
NN-rh5-altCV	0.9	0.61	0.97	0.58
NN-sh5-altCV	0.91	0.61	0.96	0.58
NN-sh10-altCV	0.93	0.62	0.97	0.58
NNd-sh10-altCV	0.91	0.61	0.97	0.6

Results

- Agility for different configurations:

	AUC		f-Score		rh2		rh5		sh2		sh5		sh10	
	Sens.	**Spec.**	**Sens.**	**Spec.**	**Sens.**	**Spec.**	**Sens.**	**Spec.**	**Sens.**	**Spec.**	**Sens.**	**Spec.**	**Sens.**	**Spec.**
Default Cross-Validation														
RF	0.87	0.66	0.86	0.67	0.78	0.71	0.88	0.59	0.87	0.61	0.9	0.55	0.94	0.47
ET	0.57	0.83	0.79	0.69	0.75	0.73	0.81	0.68	0.79	0.69	0.94	0.54	0.79	0.68
XGB	0.54	0.8	0.57	0.75	0.67	0.74	0.74	0.69	0.68	0.71	0.91	0.56	0.93	0.51
NN	0.71	0.77	0.67	0.8	0.72	0.78	0.9	0.66	0.83	0.68	0.92	0.58	0.96	0.47
NNd	0.66	0.84	0.77	0.78	**0.79**	**0.76**	0.91	0.65	0.9	0.67	0.93	0.59	0.97	0.47
Alternative Cross-Validation														
RF	0.74	0.8	0.13	0.99	**0.82**	**0.71**	0.87	0.64	0.91	0.47	0.91	0.47	0.91	0.47
ET	0.32	0.96	0.27	0.97	0.85	0.69	0.92	0.59	0.94	0.52	0.93	0.52	0.95	0.45
XGB	0.7	0.77	0.34	0.94	0.74	0.69	0.82	0.62	0.91	0.59	0.95	0.46	0.95	0.46
NN	0.9	0.61	0.48	0.88	0.84	0.67	0.9	0.61	0.84	0.64	0.91	0.61	0.93	0.62
NNd	0.81	0.71	0.51	0.87	0.85	0.68	0.89	0.64	0.88	0.66	0.91	0.59	0.91	0.61

Results

- Agility for different configurations:

	AUC		f-Score		rh2		rh5		sh2		sh5		sh10	
	Sens.	**Spec.**	**Sens.**	**Spec.**	**Sens.**	**Spec.**	**Sens.**	**Spec.**	**Sens.**	**Spec.**	**Sens.**	**Spec.**	**Sens.**	**Spec.**
Default Cross-Validation														
RF	0.87	0.66	0.86	0.67	0.78	0.71	0.88	0.59	0.87	0.61	0.9	0.55	0.94	0.47
ET	0.57	0.83	0.79	0.69	0.75	0.73	0.81	0.68	0.79	0.69	0.94	0.54	0.79	0.68
XGB	0.54	0.8	0.57	0.75	0.67	0.74	0.74	0.69	0.68	0.71	0.91	0.56	0.93	0.51
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Sensitivity/Specificity

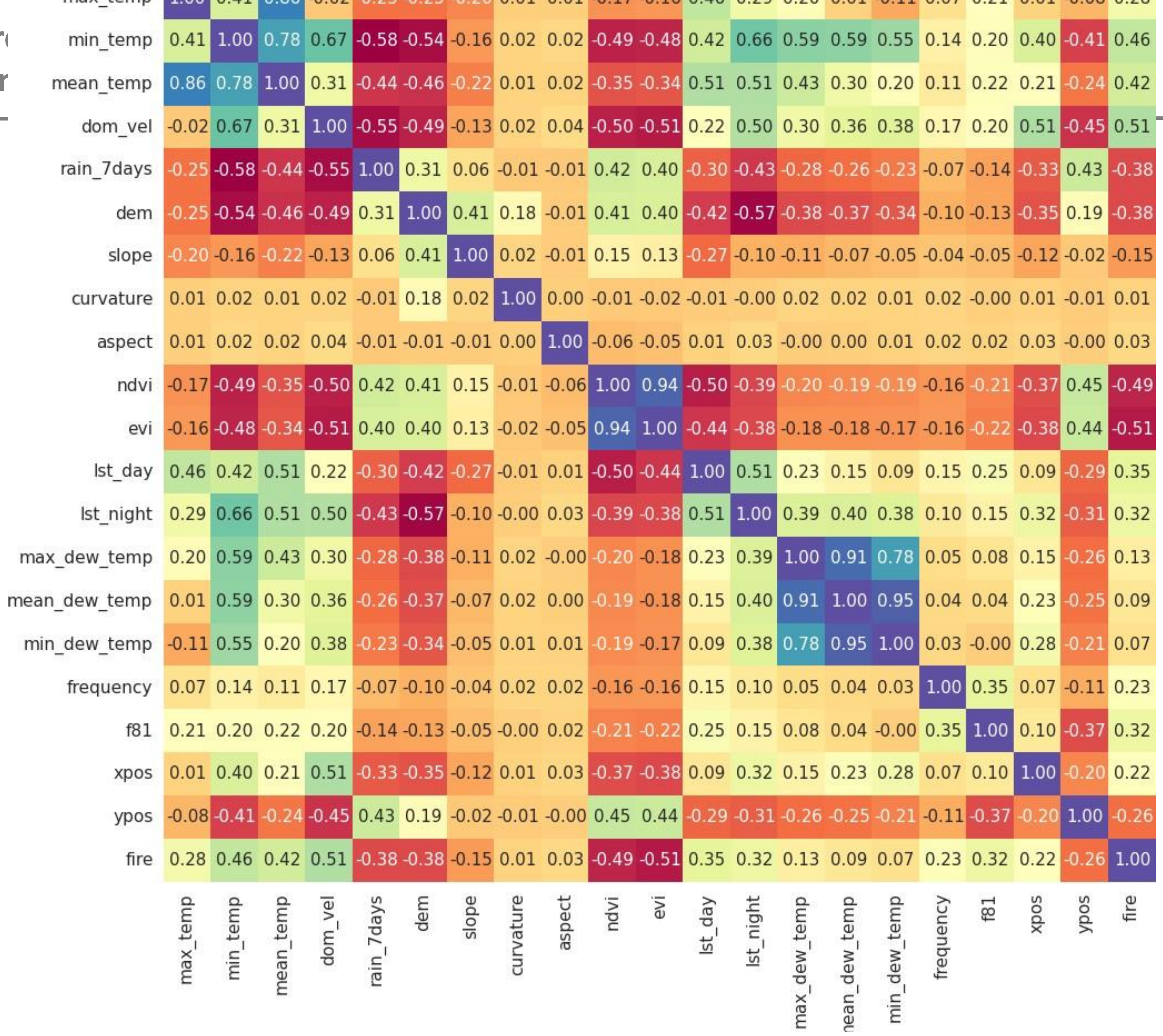
Results

- Feature importance
  - Measured via feature permutation

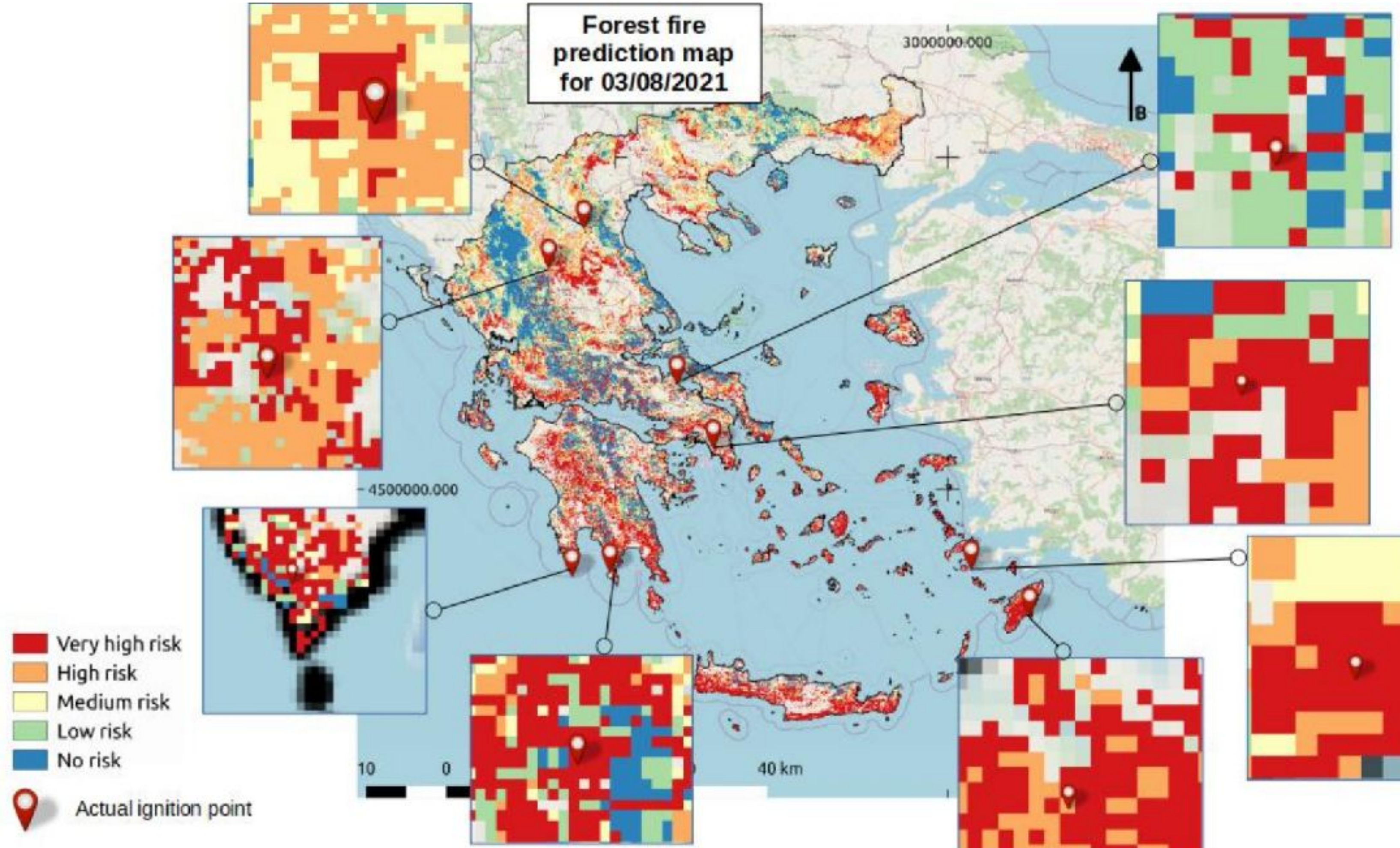
Rank	NNd (rh2-defCV) Feature Imp. (%)		RF (rh5-defCV) Feature Imp. (%)		XGB (rh5-defCV) Feature Imp. (%)	
1	dom_vel	6.07	dom_vel	12.94	dom_vel	7.47
2	evi	2.38	evi	2.37	evi	2.24
3	**f81**	1.99	**f81**	2.18	dem	1.68
4	**xpos**	1.47	ndvi_new	2.13	max_temp	1.63
5	**ypos**	1.18	mean_temp	1.72	**xpos**	1.58
6	dem	1.17	max_temp	1.71	**pos**	1.48
7	rain_7days	0.57	**lst_day**	1.48	**f81**	1.36
8	max_temp	0.44	**xpos**	1.2	rain_7days	0.8
9	**frequency**	0.26	**ypos**	1.12	**mean_dew_temp**	0.67
10	slope	0.19	**mean_dew_temp**	1.11	**mean_temp**	0.47

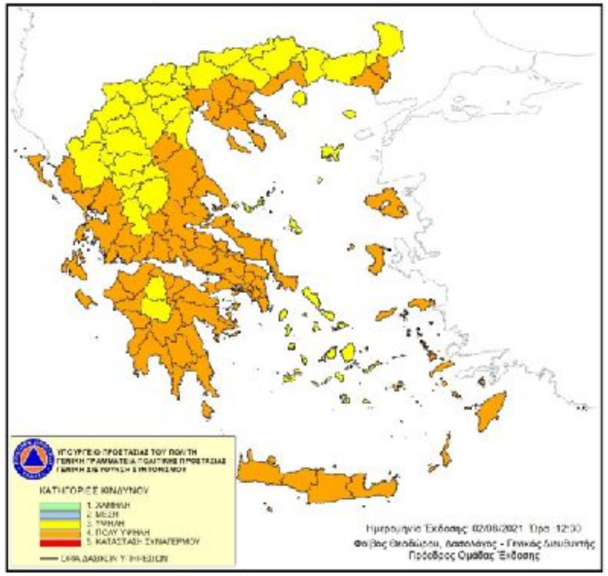
Results

- Feature importance
  - Measured via feature correlation



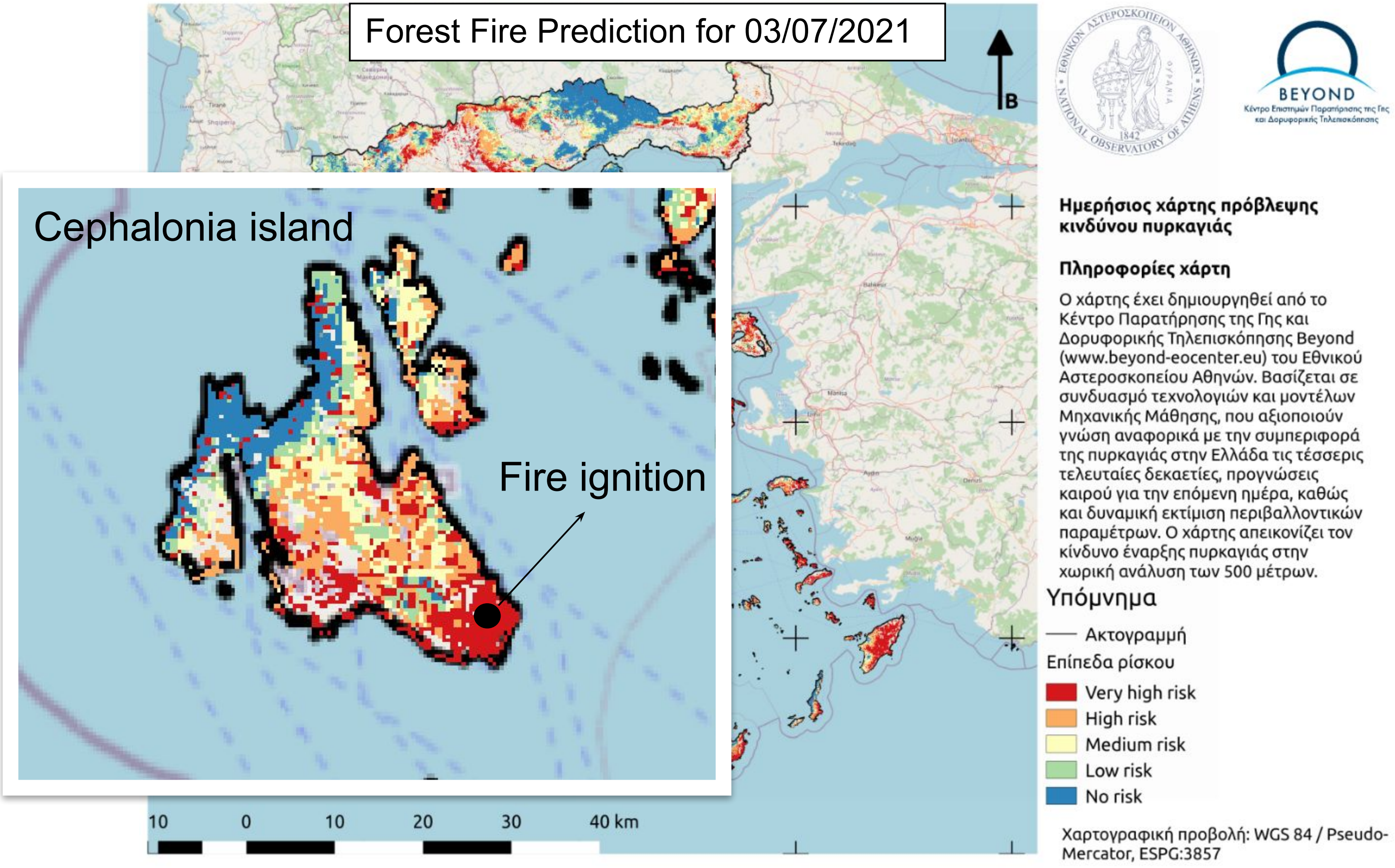
Results





[redacted]

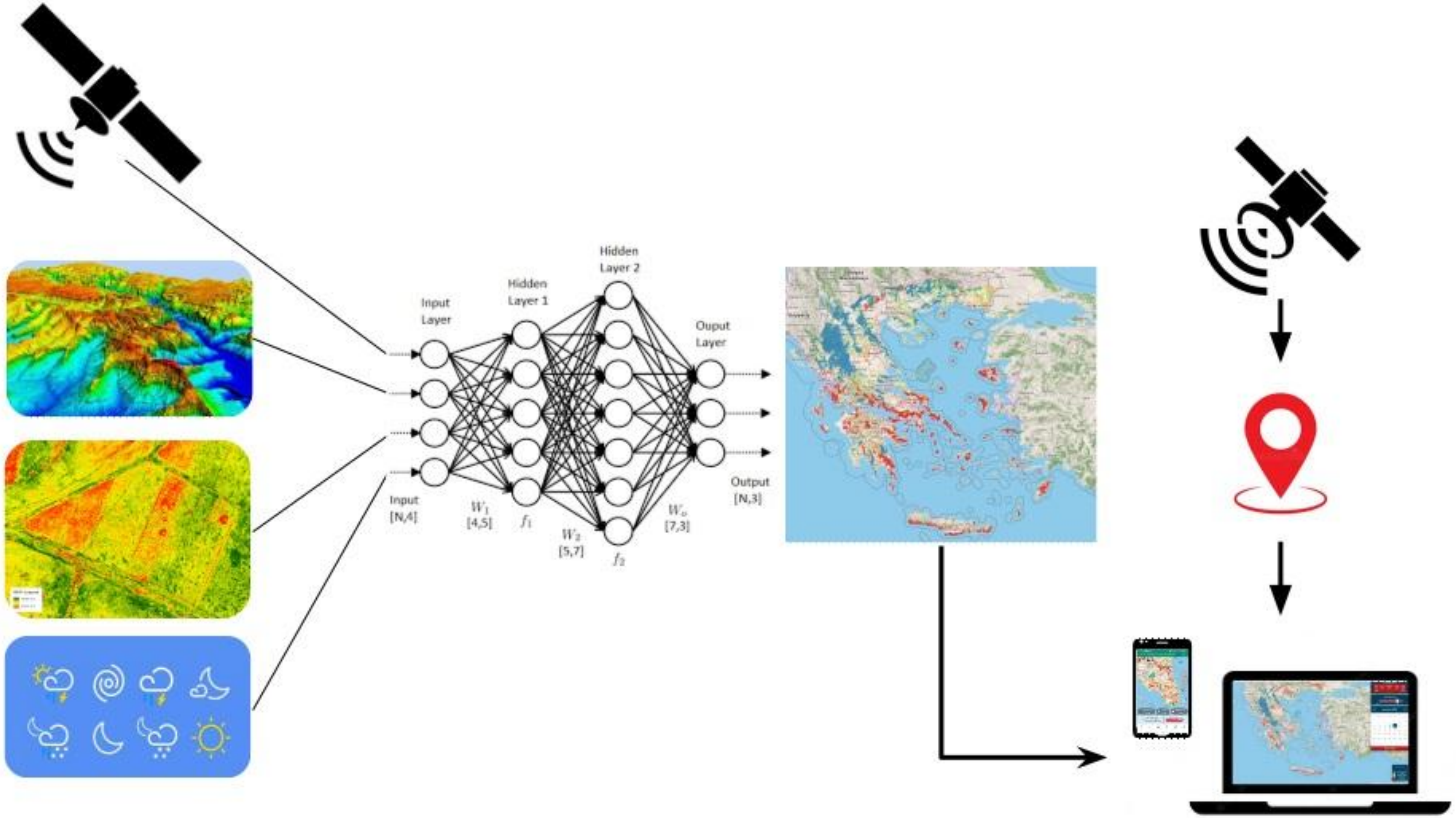
Results


Forest Fire Prediction for 03/07/2021
Cephalonia island
Fire ignition
B
10 0 10 20 30 40 km
Ημερήσιος χάρτης πρόβλεψης κινδύνου πυρκαγιάς
Πληροφορίες χάρτη
Ο χάρτης έχει δημιουργηθεί από το Κέντρο Παρατήρησης της Γης και Δορυφορικής Τηλεπισκόπησης Beyond (www.beyond-eocenter.eu) του Εθνικού Αστεροσκοπείου Αθηνών. Βασίζεται σε συνδυασμό τεχνολογιών και μοντέλων Μηχανικής Μάθησης, που αξιοποιούν γνώση αναφορικά με την συμπεριφορά της πυρκαγιάς στην Ελλάδα τις τέσσερις τελευταίες δεκαετίες, προγνώσεις καιρού για την επόμενη ημέρα, καθώς και δυναμική εκτίμιση περιβαλλοντικών παραμέτρων. Ο χάρτης απεικονίζει τον κίνδυνο έναρξης πυρκαγιάς στην χωρική ανάλυση των 500 μέτρων.
Υπόμνημα
Ακτογραμμή
Επίπεδα ρίσκου
Very high risk
High risk
Medium risk
Low risk
No risk
Χαρτογραφική προβολή: WGS 84 / Pseudo-Mercator, ESPG:3857

System architecture

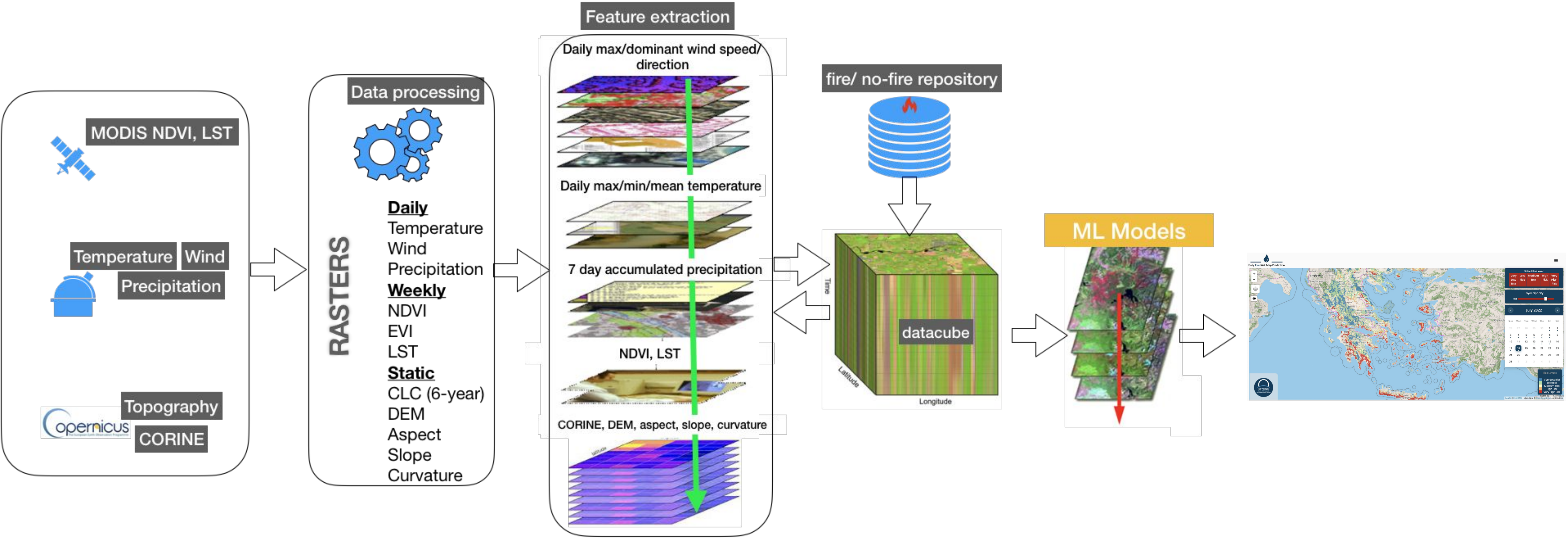
Operational system

Architecture concept



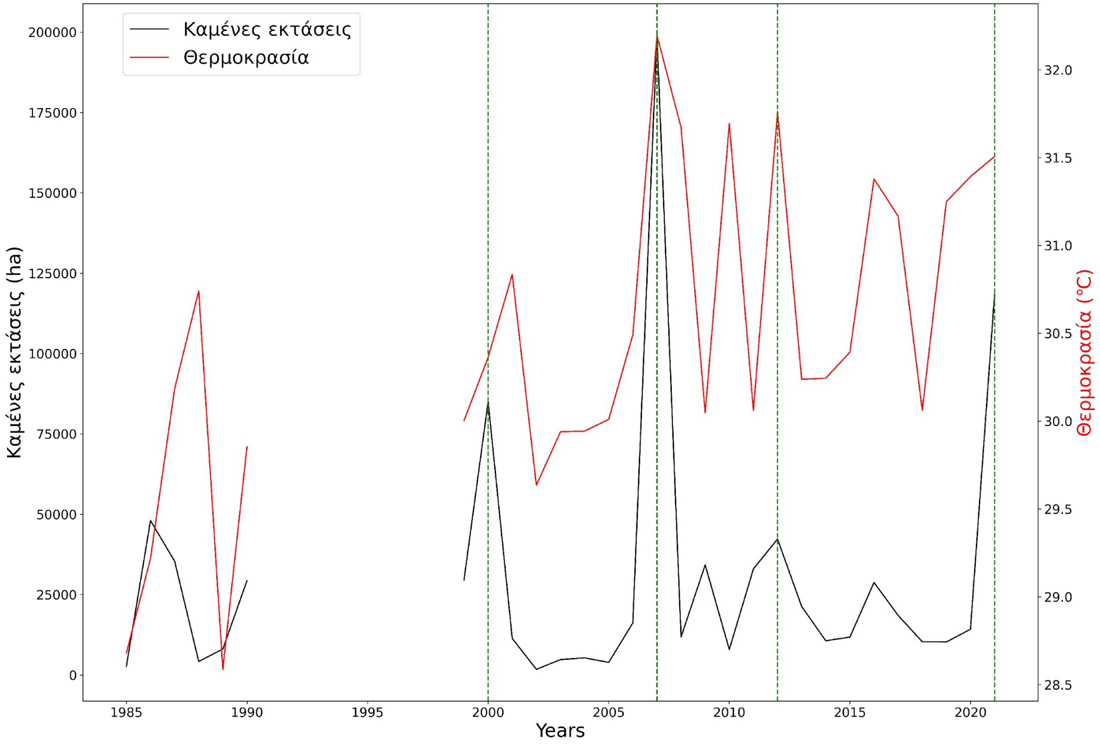
Operational system

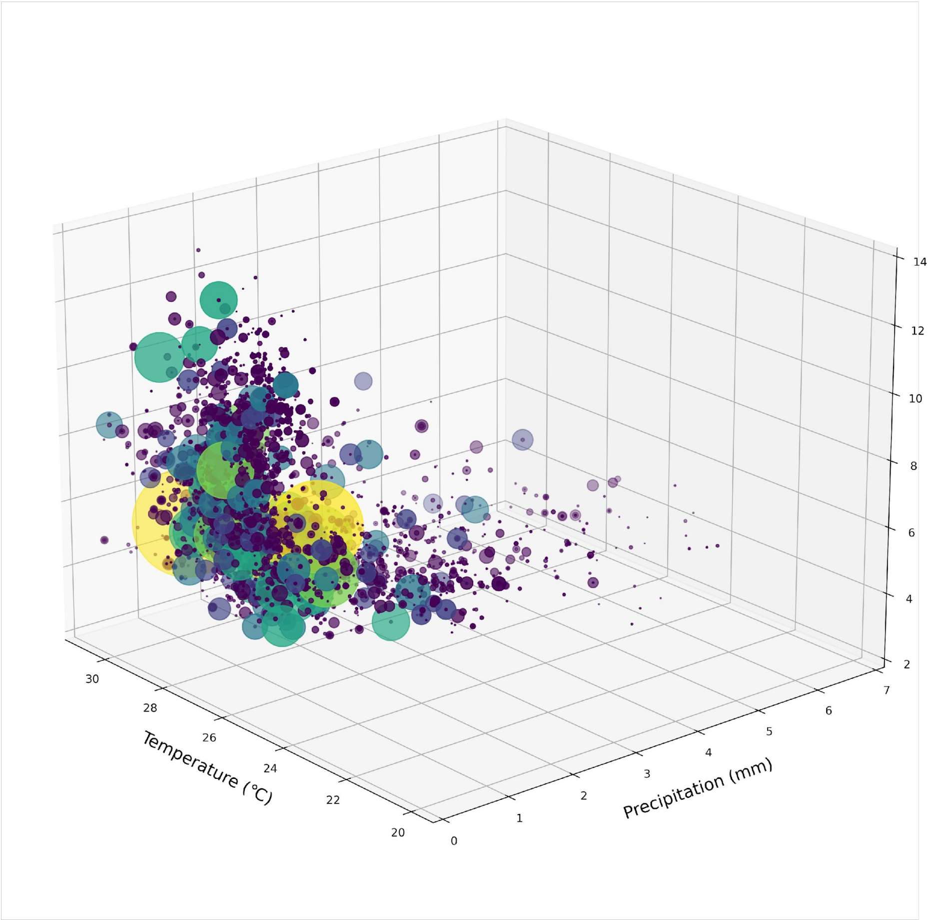
Back-end processing



Operational system

Datacube insights

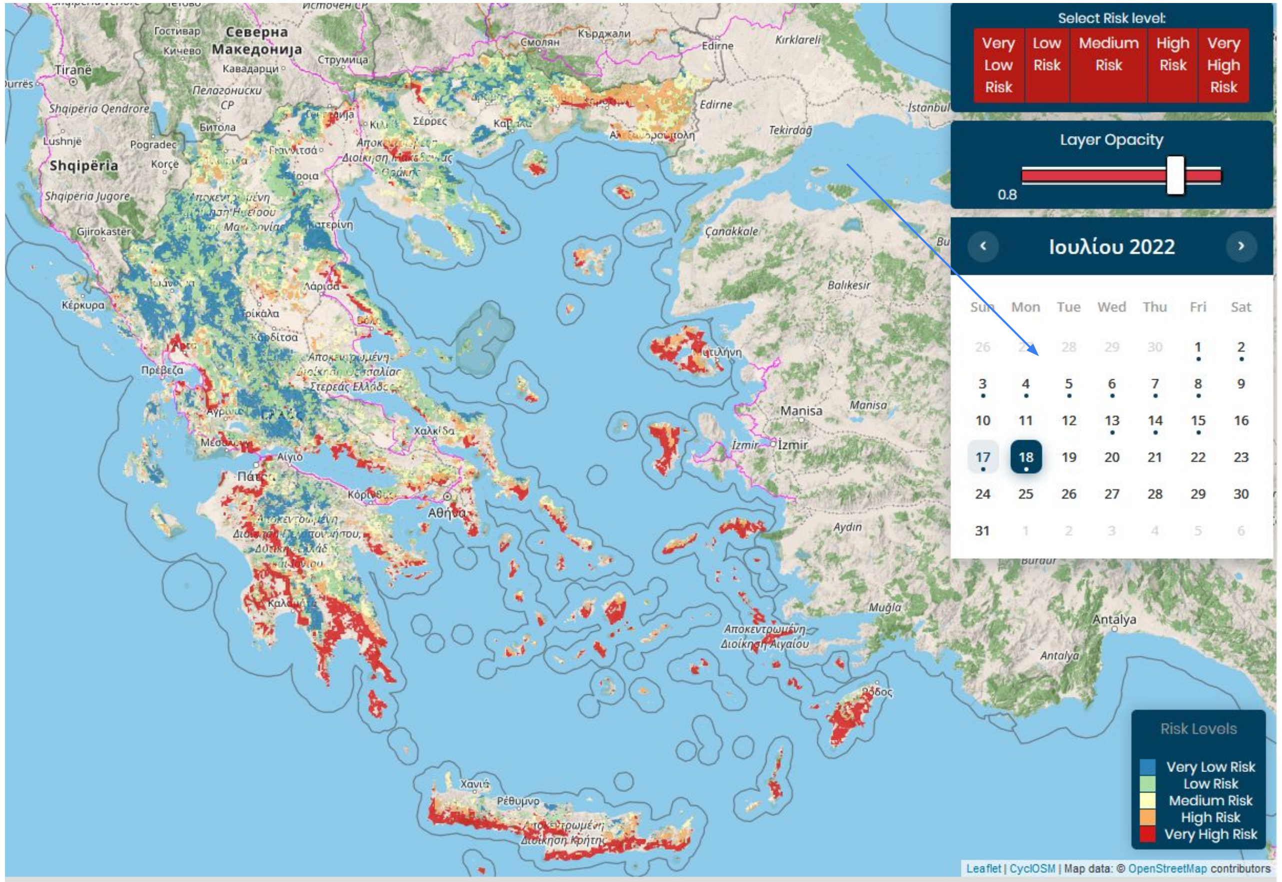




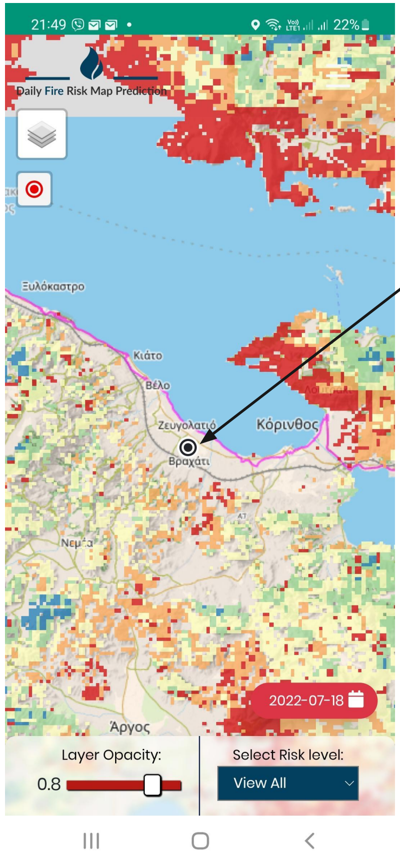
Operational system

Desktop/mobile front-end

Desktop



Mobile



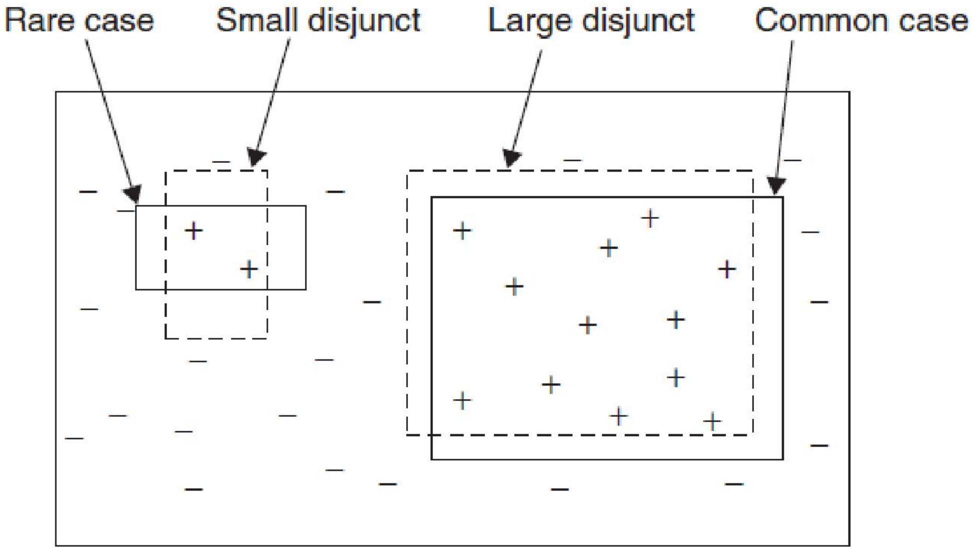
GNSS Location

https://riskmap.beyond-eocenter.eu/

Future work

Directions

- Handle absence of fire phenomenon
  - No-fire instances that are very close to fire instances
    - Problematic for learning proper boundaries
    - Reduces specificity by default
- Better handle imbalance
  - Existing schemes are only half-measures
  - Training/validation/test on different distributions
- Examine rare cases and small disjuncts
  - Indications that fire instances form discrete clusters within the hyperspace
- Handle data sizes
  - Try to limit undersampling as much as possible to exploit the whole dataset



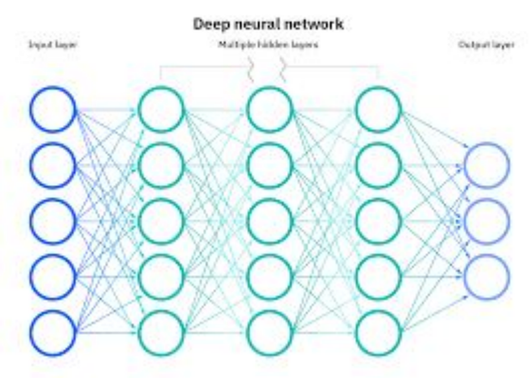
Imbalanced Learning_ Foundations, Algorithms, and Applications (2013, Wiley-IEEE Press)

Centre of EO Research &
Satellite Remote Sensing

Why Deep learning : A DL model is a neural network model composed of multiple processing layers. They have proven to be highly efficient in finding intricate structures and learning data with multiple levels of abstraction

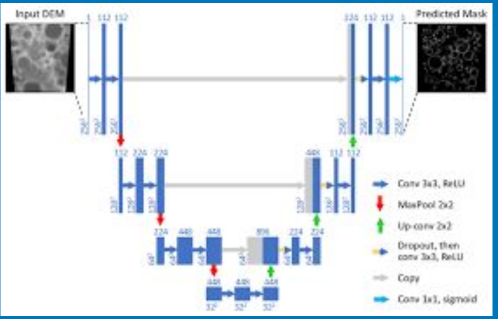
Complex feature correlations

Deep neural networks (DNN) may produce more meaningful representations in deeper layers.



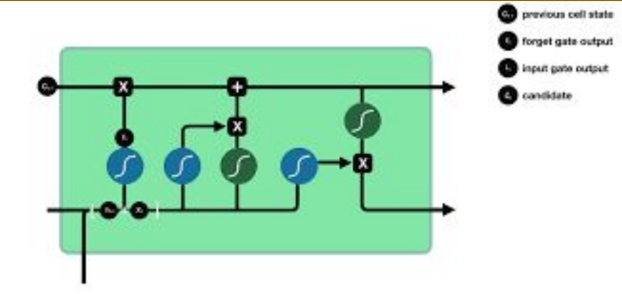
Dimensionality of the input data.

The instances in this problem refer to specific locations that have spatial correlations. Convolutional NNs can discover that kind of relations where traditional ML algorithms (such as ANN, SVM, weak learner ensembles) are likely to fail.



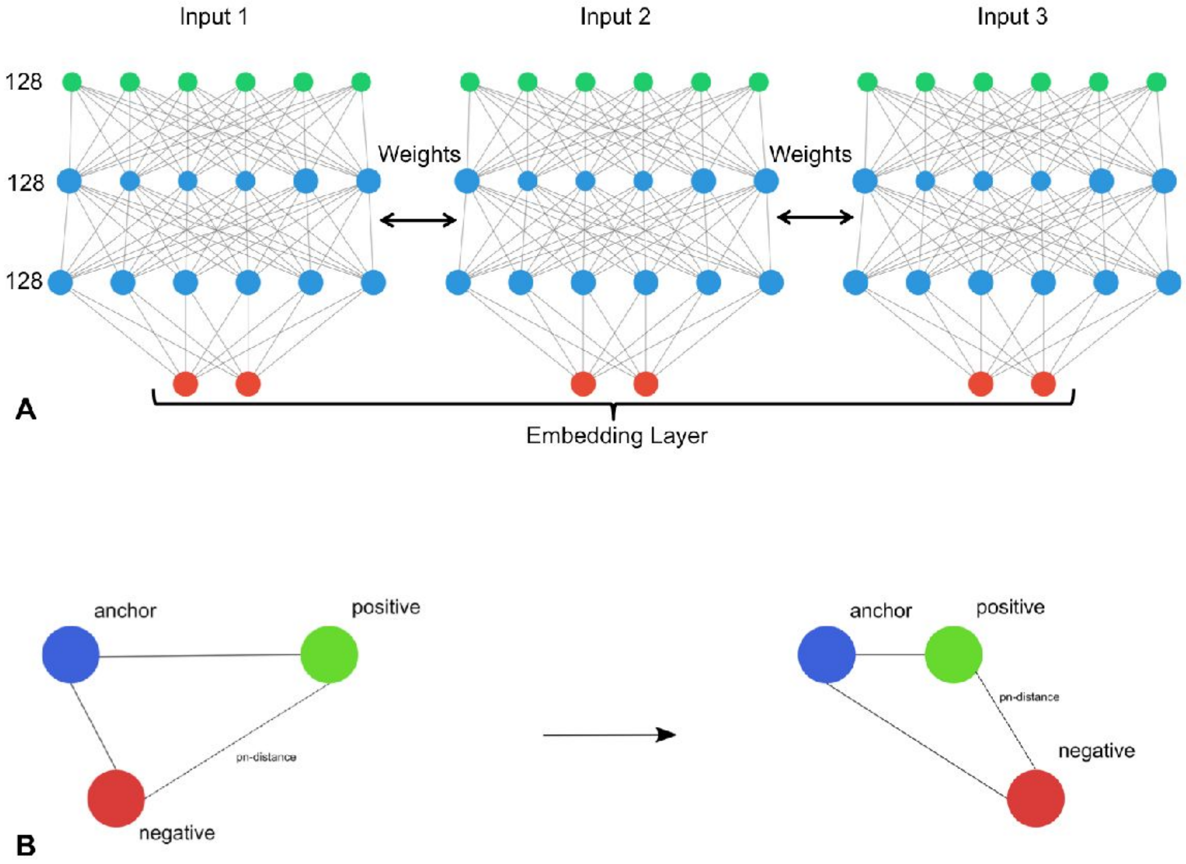
Time Series

The risk of fire ignition and spread can be related to long periods of drought or periods with high temperatures (long heat waves) that form the suitable conditions for a fire to start. DL LSTM takes into account past states for learning and are suitable to detect those correlations.



Approach 1: Siamese NNs

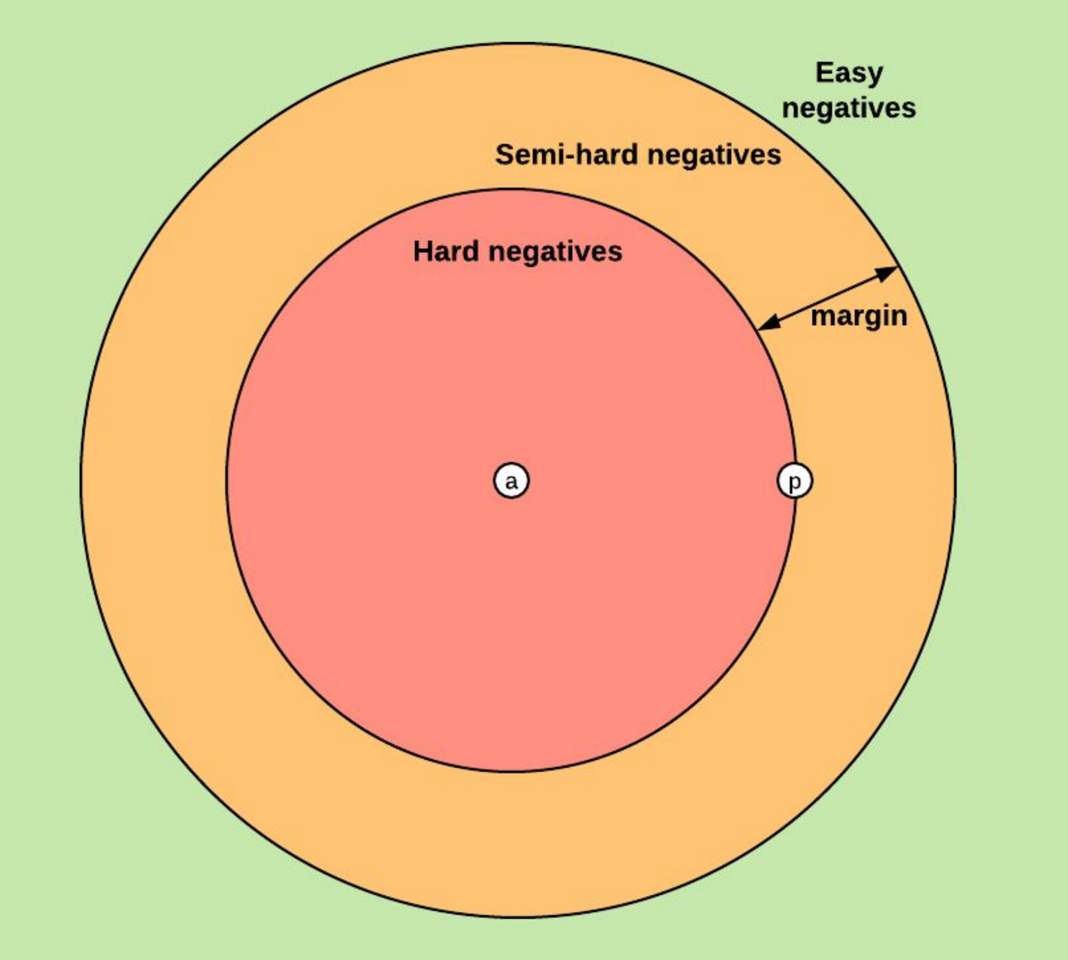
- Architectures that aim at learning a similarity function
  - Comprise of parallel NN architectures that receive different inputs but learn the same parameters
- SNNs provide the framework for handling several of the aforementioned issues
  - Particularly triplet loss based SNNs
  - Input as triplets of {anchor, positive, negative}



Structure-preserving visualisation of high dimensional single-cell datasets

Approach 1: Siamese NNs

- **Absence of fire** and **extreme imbalance** can be handled to some extent by properly constructing {anchor, positive, negative} triplets
  - Hard negatives can be ignored or transformed into positives
  - Semi-hard should probably be emphasized



https://medium.com/@enoshshr/triplet-loss-and-siamese-neural-networks-5d363fdeb

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- **Absence of fire** and **extreme imbalance** can be handled to some extent by properly constructing {anchor, positive, negative} triplets
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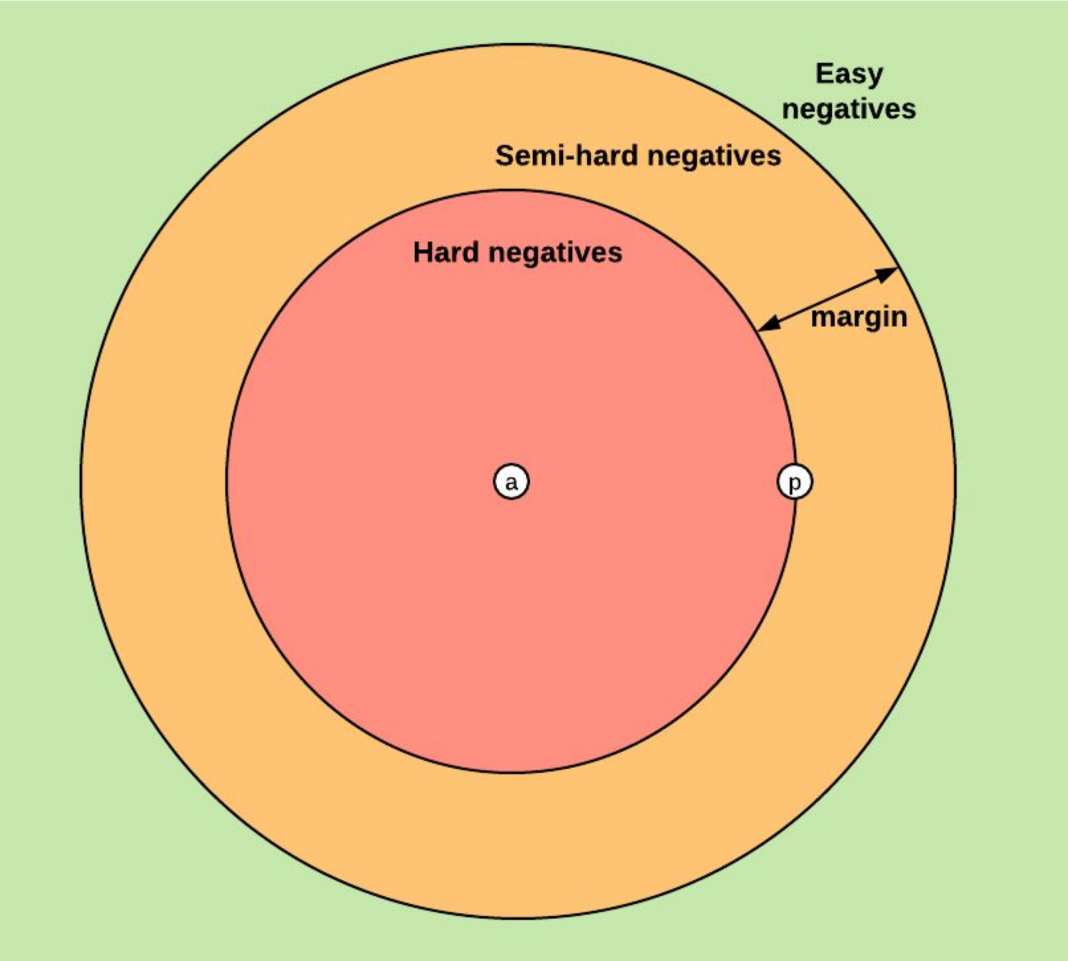
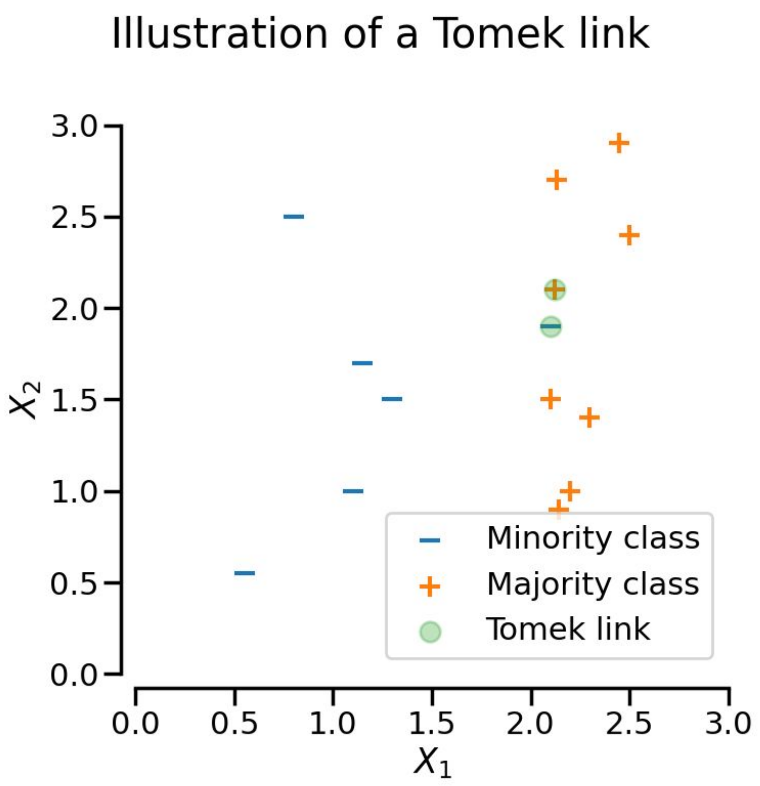
- Variations of undersampling techniques can be combined



https://medium.com/@enoshshr/triplet-loss-and-siamese-neural-networks-5d363fde
b

Approach 1: Siamese NNs

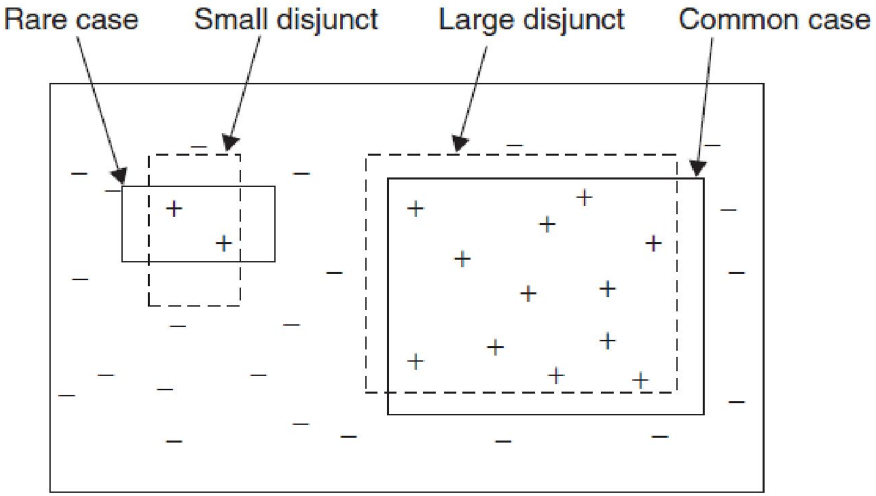
- Variations of undersampling techniques can be combined
  - E.g. Tomek links
  - Removing majority instances
  - Transforming majority into minority instances

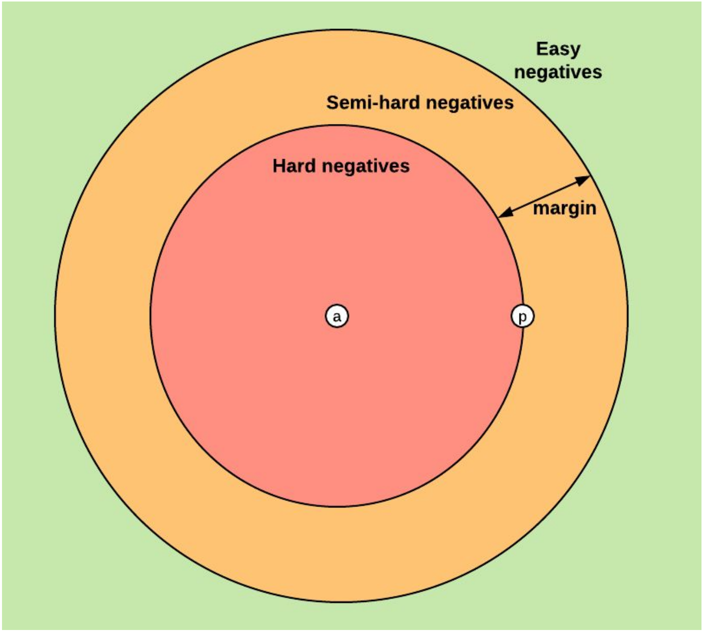


https://imbalanced-learn.org/stable/under_sampling.html

Approach 1: Siamese NN

- Rare cases and small disjuncts
  - Consider more than one *fire* classes
    - E.g. by clustering
  - Properly adjust the triplet generation function
  - Learn more “clear” boundaries per fire class
    - Limit the absence of fire phenomenon





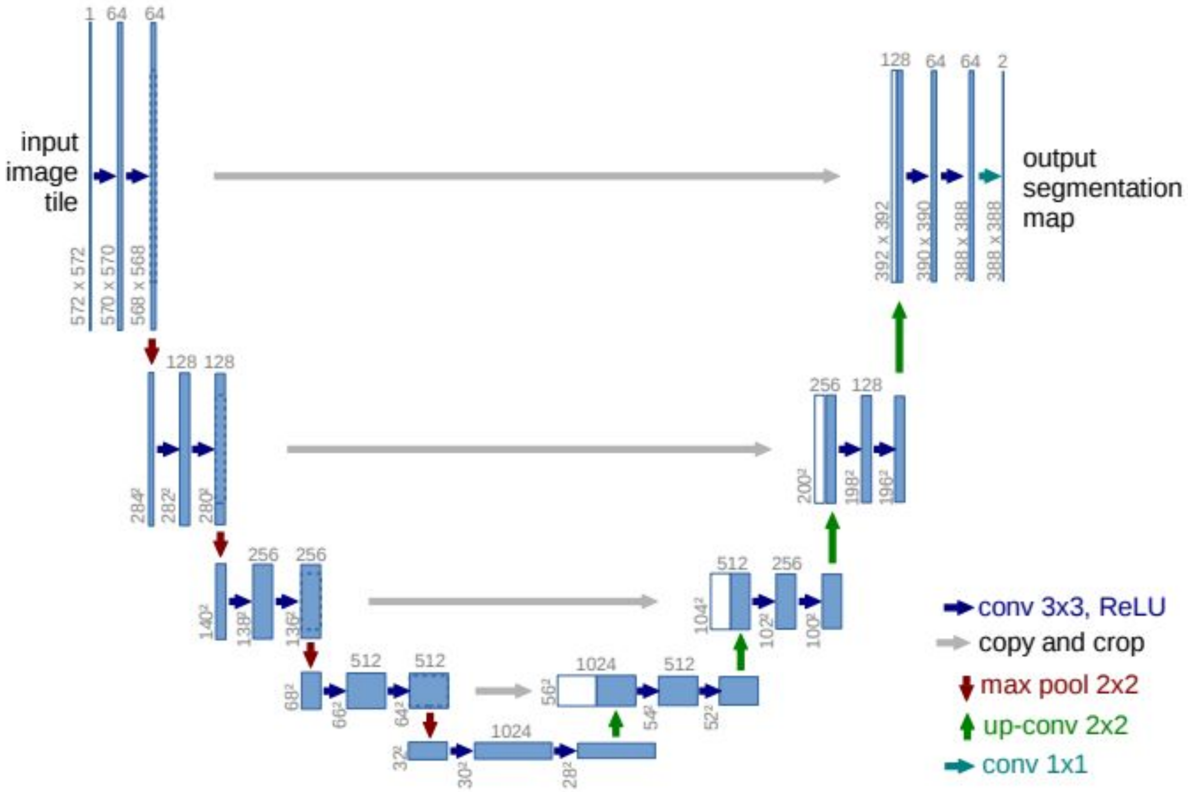
Approach 1: Siamese NNs

- Data sizes (~800M instances)
  - Can scale decently in 11M instances in a mediocre GPU
- Initial findings
  - Vanilla Siamese* reached similar effectiveness scores with tuned baseline ML models
    - Without any triplet tuning or over/undersampling
    - With moderate network tuning

* https://bering-ivis.readthedocs.io/en/latest/metric_learning.html

Approach 2: Semantic Segmentation

- CNN architectures that aim at performing image classification on the pixel level
  - Utilized when the exact shape of an item (class) needs to be identified
  - Applications
    - Aerial images
    - Medical images



https://towardsdatascience.com/semantic-segmentation-with-deep-learning-a-guide-and-code-e52fc8958823

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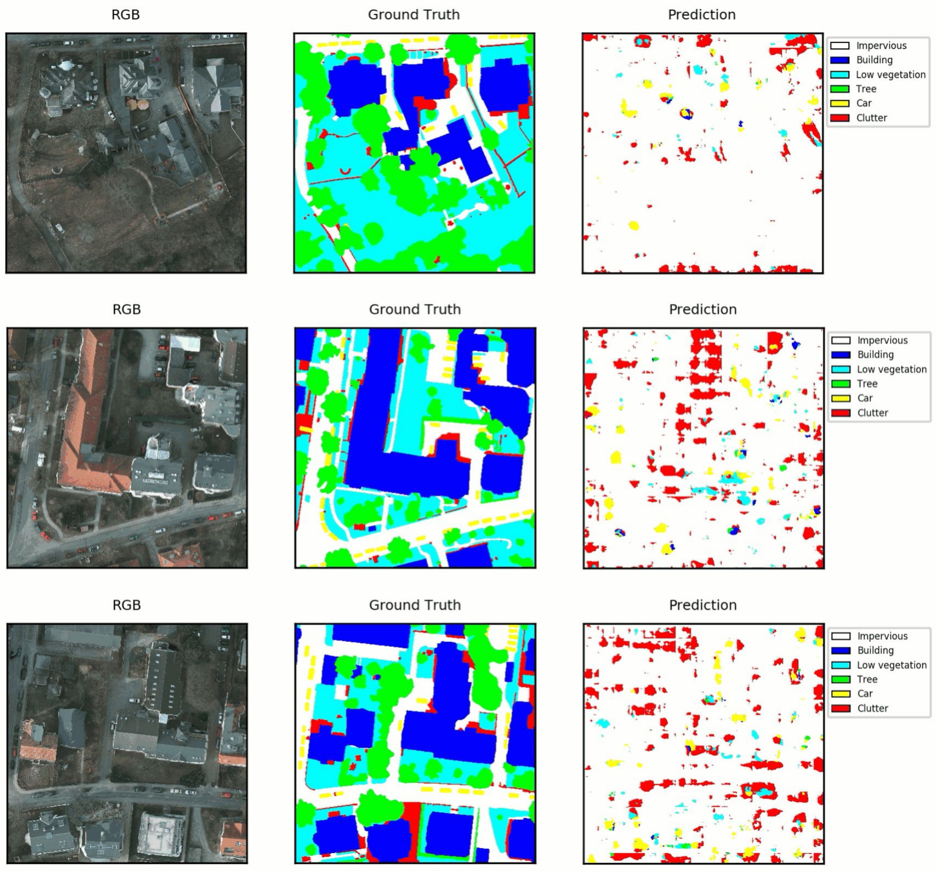


https://www.azavea.com/blog/2017/05/30/deep-learning-on-aerial-imagery/

Approach 2: Semantic Segmentation

- But we do not have images in our setting?
  - Each grid cell can be considered as a pixel of an image corresponding to the whole considered territory
  - Each feature of each cell can be considered as a different channel of the image
- Potential gains
  - Direct consideration of spatial correlations
  - Dataset significantly reduced to a few tenths of thousands of images
    - manageable
  - Imbalance can be handled orthogonally

Other Directions

- Model Explainability
  - A difficult challenge in machine learning and especially deep learning is to provide explanations for the model's predictions.
  - New methods have been developed (SHAP, DL adjusted permutation importance, Partial Dependence Plots) to assist the interpretation of the results of deep learning as applied to provide
- Potential gains
  - Identify most influencing factors for each prediction
  - Determine/discover meaningful latent features

Other Directions

- Model Uncertainty
  - The model's decision of NNs is based on the computation of a certain likelihood by the model. However, the certainty of this likelihood is unknown.
  - Introducing Bayesian methodology it is possible to compute the uncertainty in the model's prediction
- Potential gains
  - Provide a measure of the certainty for each model's prediction.

Results

- Real-world, significant task
  - Practically not handled until now
- Establishment of a complete/sound ML methodology
  - Good/exploitable effectiveness
  - Daily provision of a fire risk map to the Fire Service
- Several promising research directions
  - Several gaps to be handled

Publications

- A. Apostolakis, S. Girtsou, G. Giannopoulos, N. S. Bartsotas, and C. Kontoes, “Estimating Next Day’s Forest Fire Risk via a Complete Machine Learning Methodology,” Remote Sensing, vol. 14, no. 5, p. 1222, Mar. 2022, doi: 10.3390/rs14051222.

- S. Girtsou, A. Apostolakis, G. Giannopoulos, and C. Kontoes, “A Machine Learning Methodology for Next Day Wildfire Prediction,” Jul. 2021. doi: 10.1109/igarss47720.2021.9554301.

- A. Apostolakis, S. Girtsou, C. Kontoes, I. Papoutsis, and M. Tsoutsos, “Implementation of a Random Forest Classifier to Examine Wildfire Predictive Modelling in Greece Using Diachronically Collected Fire Occurrence and Fire Mapping Data,” in MultiMedia Modeling, Springer International Publishing, 2021, pp. 318–329. doi: 10.1007/978-3-030-67835-7_27.

- A. Apostolakis, “Next Day Forest Fire Risk Prediction in Greece Using Machine Learning,” SafeGreece 2021.

- CEST 2021 conference, oral presentation: “Daily Forest Fire Prediction modeling and Forest Fire Information System (FFIS)”

- Συγγραφή κεφαλαίου στην Επιτροπή Έρευνας της Ανθεκτικότητας των Ελληνικών Δασικών Οικοσυστημάτων (Ε.Α.Δ.Ο.)

Team

- Beyond center of excellence of the National Observatory of Athens
- Team
  - Alexis Apostolakis
  - Stella Girtsou
  - Giorgos Giannopoulos
  - Nikos Mpartsotas
  - Charalampos Kontoes

Thank you !!

Questions?

?

Existing research approaches

- Unfit model selection/assessment poor generalizability
  - Balanced train/validation/test setting
  - Usually poor/non-existent hyperparameter search
- Practically no utilization of Deep Learning methods
  - While fitting on the setting
    - Data sizes
    - Spatial correlations

Results

- Realistic targets (sensitivity/specificity):
  - {>90%, >70%}
  - {>80%, >80%}
- Achieved:
  - {90%, 66%}, {93%, 62%}
  - {82%, 71%}, {79%, 76%}

- Agility on balancing the trade-off between sensitivity/specificity
  - Via combinations of cross-validation schemes and model selection evaluation measures
- A proper problem formulation and baseline methodology

Problem definition

- Features
  - Earth Observation features: NDVI, EVI
  - Meteorological features: Temperature (max, min, mean), Wind speed (max, dominant), Wind direction (wind_direction, dominant_direction), Cumulative Precipitation
  - Geomorphological/natural features: DEM (DEM, aspect, slope, curvature), Land use/Land cover

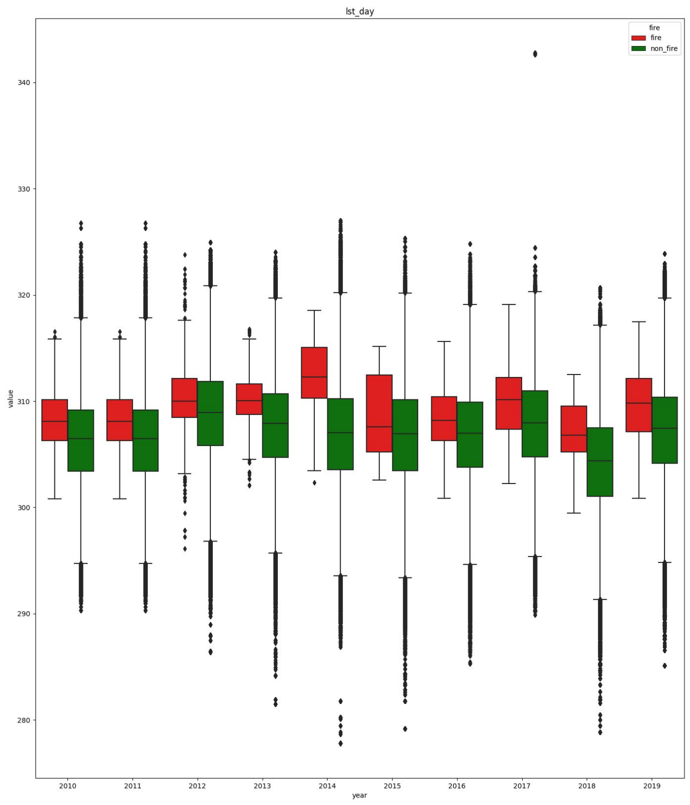
Domain specificities

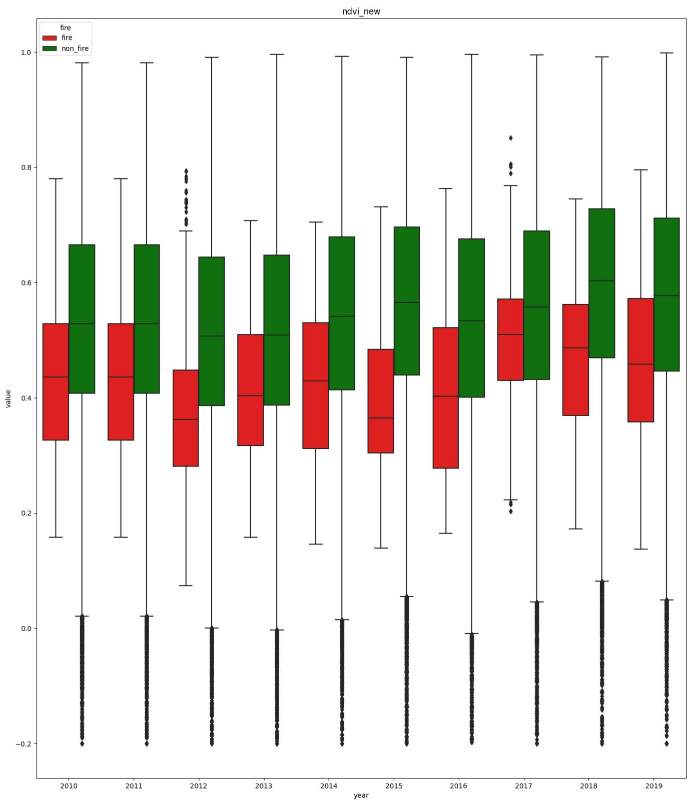
- Extreme data imbalance
  - Ratio of ~1:100K between fire/no-fire cells
- Large data scale
  - Challenging to properly perform model selection
- Absence of fire phenomenon
  - Areas that should have a fire occurrence but did not *by chance*
  - Chance = lack of impossible to capture features
    - (i.e. a person's decision to start a fire, a cigarette thrown by a driver, a lightning)
- Spatio-temporal correlations
  - Adjacent cells are expected to be nearly-identical
  - Previous years' incidents might affect the short-term behavior of an area

Problematic even for imbalance handling methods

Domain specificities

- Concept drift

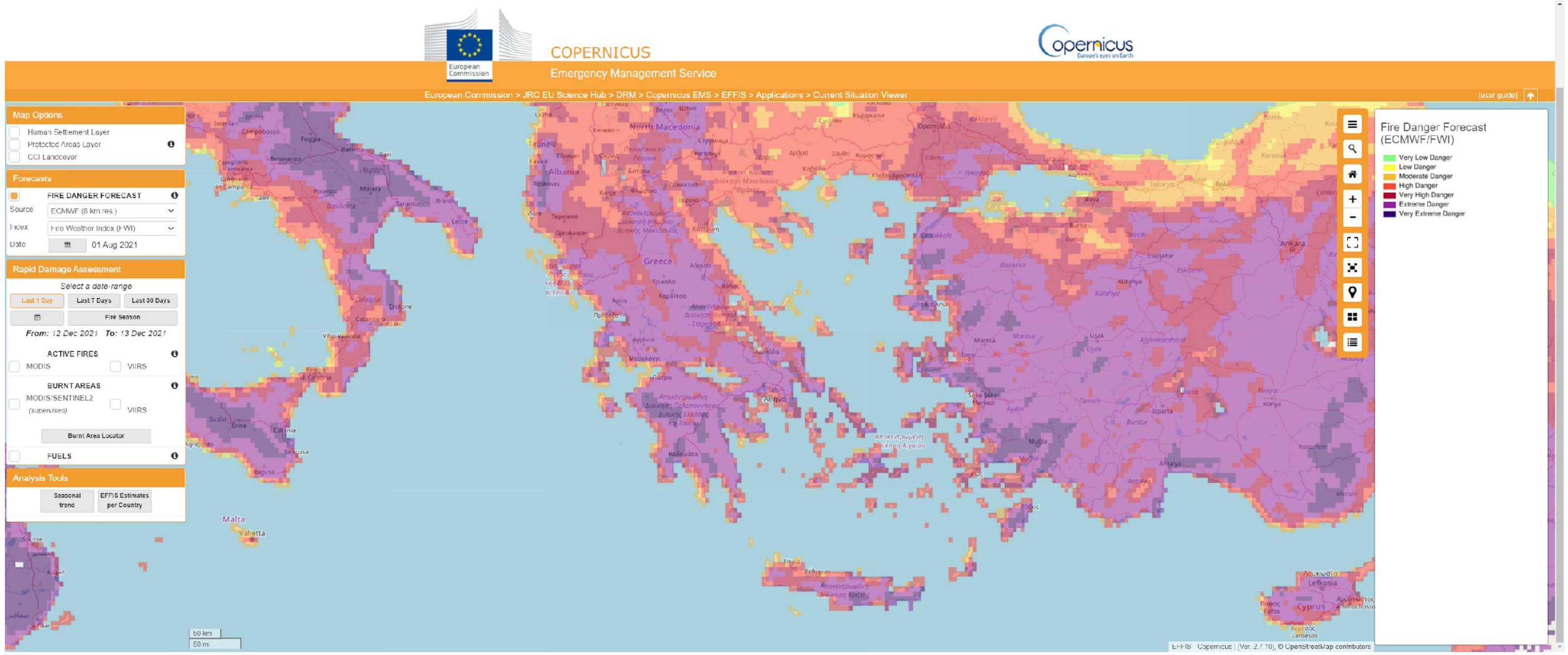




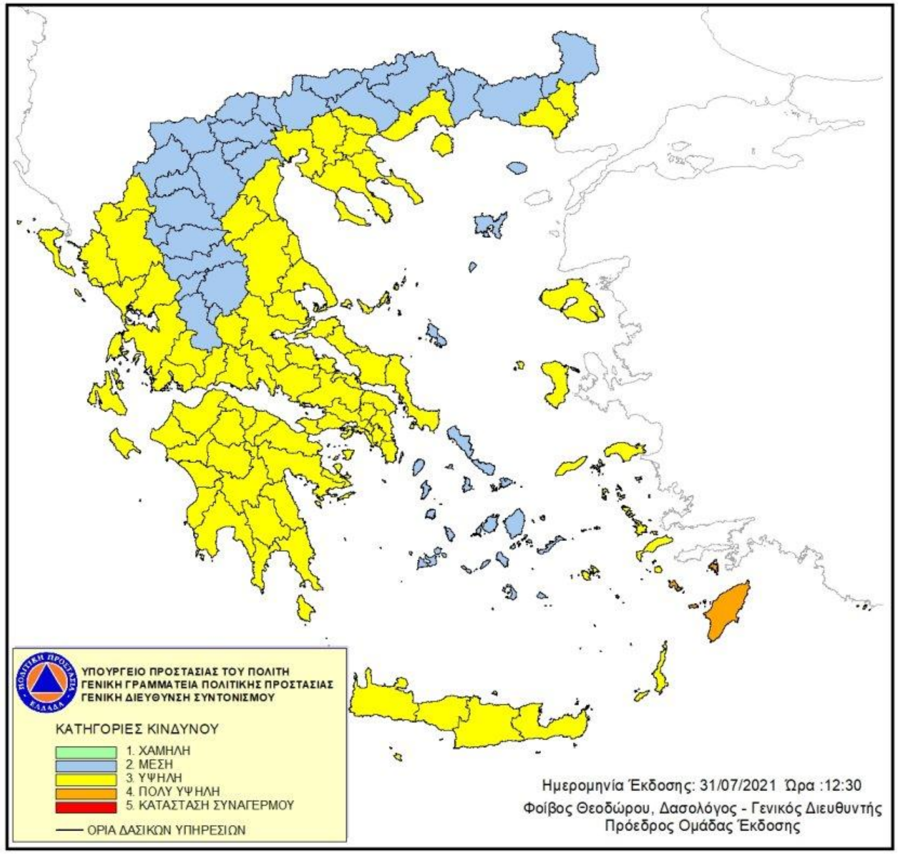
Existing research approaches

- Simplified variation of the problem: *fire susceptibility*
  - Risk of fire occurrence within a large period (e.g. month, year)
  - Imbalance and size significantly reduced
  - Much less use for real-world operational organization
- Methodological errors unreliable results
  - Instances shuffled before train/validation/test split information leakage
  - Instances' class changes propagated into the test set

Existing applied approaches



ΧΑΡΤΗΣ ΠΡΟΒΛΕΨΗΣ ΚΙΝΔΥΝΟΥ ΠΥΡΚΑΓΙΑΣ ΠΟΥ ΙΣΧΥΕΙ ΓΙΑ
Κυριακή 01/08/2021



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- Agility for different configurations:

	AUC		f-Score		rh2		rh5		sh2		sh5		sh10	
	Sens.	**Spec.**	**Sens.**	**Spec.**	**Sens.**	**Spec.**	**Sens.**	**Spec.**	**Sens.**	**Spec.**	**Sens.**	**Spec.**	**Sens.**	**Spec.**
Default Cross-Validation														
RF	0.87	0.66	0.86	0.67	0.78	0.71	0.88	0.59	0.87	0.61	0.9	0.55	0.94	0.47
ET	0.57	0.83	0.79	0.69	0.75	0.73	0.81	0.68	0.79	0.69	0.94	0.54	0.79	0.68
XGB	0.54	0.8	0.57	0.75	0.67	0.74	0.74	0.69	0.68	0.71	0.91	0.56	0.93	0.51
NN	0.71	0.77	0.67	0.8	0.72	0.78	0.9	0.66	0.83	0.68	0.92	0.58	0.96	0.47
NNd	0.66	0.84	0.77	0.78	**0.79**	**0.76**	0.91	0.65	0.9	0.67	0.93	0.59	0.97	0.47
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RF	0.74	0.8	0.13	0.99	**0.82**	**0.71**	0.87	0.64	0.91	0.47	0.91	0.47	0.91	0.47
ET	0.32	0.96	0.27	0.97	0.85	0.69	0.92	0.59	0.94	0.52	0.93	0.52	0.95	0.45
XGB	0.7	0.77	0.34	0.94	0.74	0.69	0.82	0.62	0.91	0.59	0.95	0.46	0.95	0.46
NN	0.9	0.61	0.48	0.88	0.84	0.67	0.9	0.61	0.84	0.64	0.91	0.61	0.93	0.62
NNd	0.81	0.71	0.51	0.87	0.85	0.68	0.89	0.64	0.88	0.66	0.91	0.59	0.91	0.61