Evaluation of artificial intelligence based models for the spatial prediction of forest fire risk

Fidel Bonet Vilela

Area	**Artificial Intelligence**
Tutor	**Dr. Samir Kanaan Izquierdo**
Responsible teacher	**Dr. Carles Ventura Royo**

1. Motivation
2. Method
3. Data. Previous analysis
4. Models
5. Evaluation and optimization
6. Implementation. Risk maps
7. Conclusions

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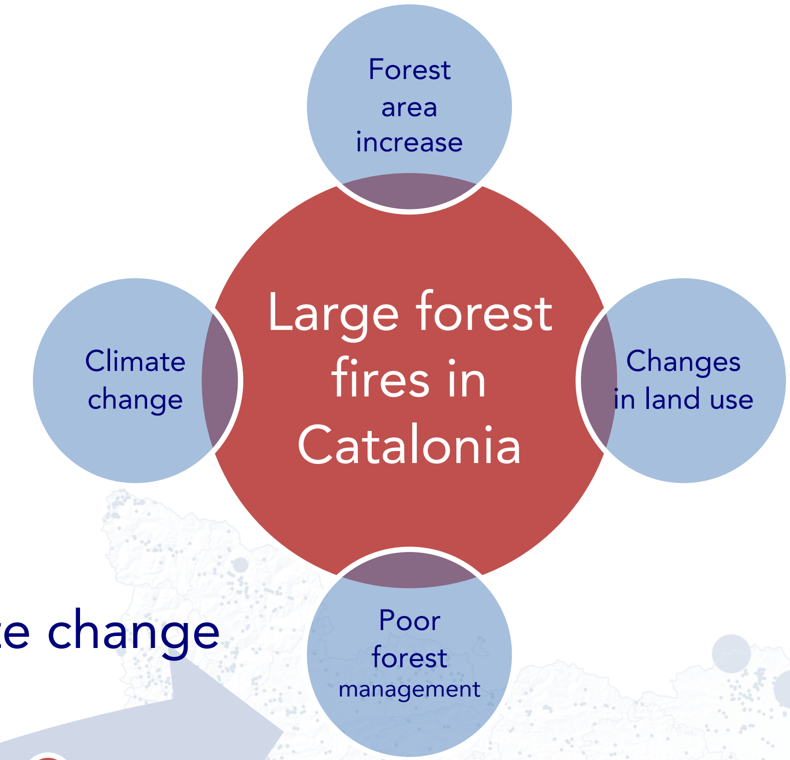
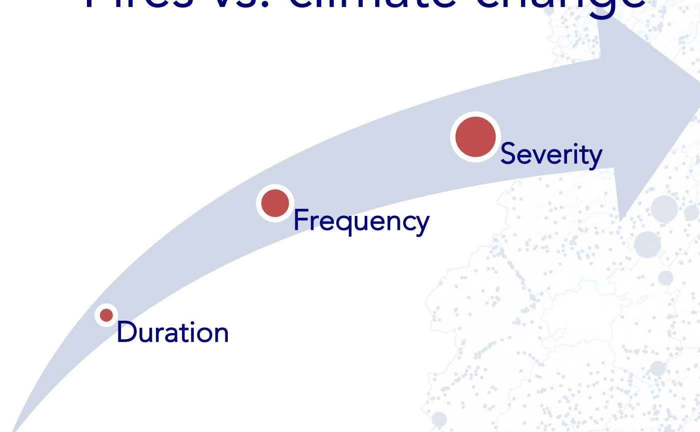
Motivation



Fires vs. climate change



Motivation

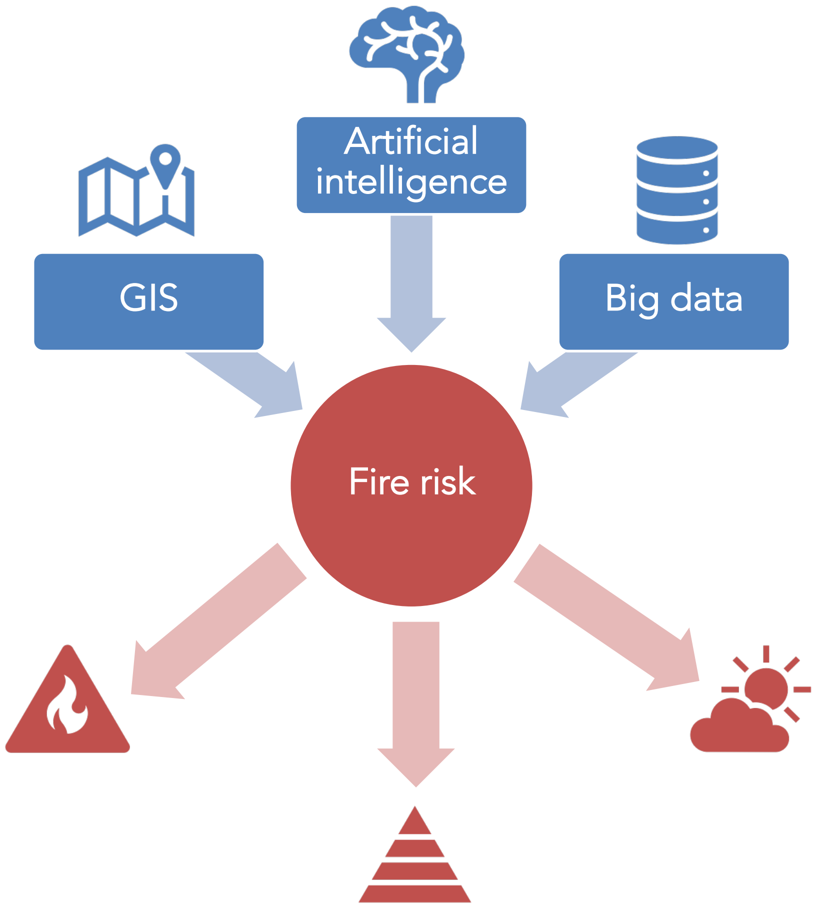
Models

Management:
- Territory
- Fire

Decrease:
- Damage to the territory
- Damage to residential areas
- Life damage of extinguishing teams
- Extinction costs

Promote:
- Early warning
- Controlled burns
- Resource planning
- Assigning tasks

Method



Study areas

- Catalonia
- Natural Park

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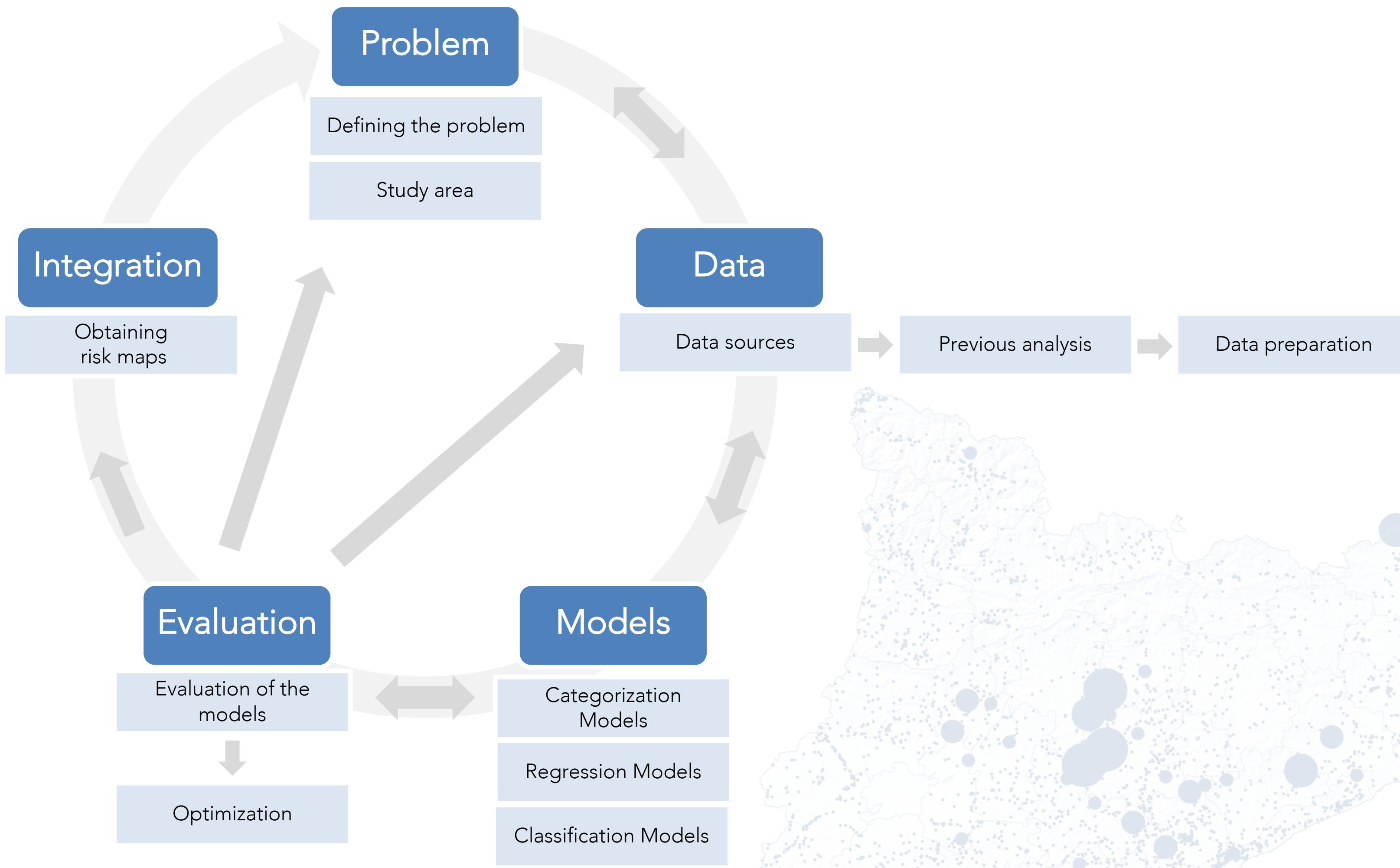
Method



Data

Fire	Terrain	Meteorology	Vegetation and land covers
• Coordinates • Start time • Burned surface	• Altitude • Orientation • Slope	• Relative humidity • Specific humidity • Temperature • *U* wind component • *V* wind component • Analogues	• NDVI • Land use and cover
Forest Fire Prevention Service (Catalan Government)	ICGC, own generation	Climate Data Store, ECMWF, Meteorological Service of Catalonia	EarthData, Department of Territory and Sustainability (Catalan Government)

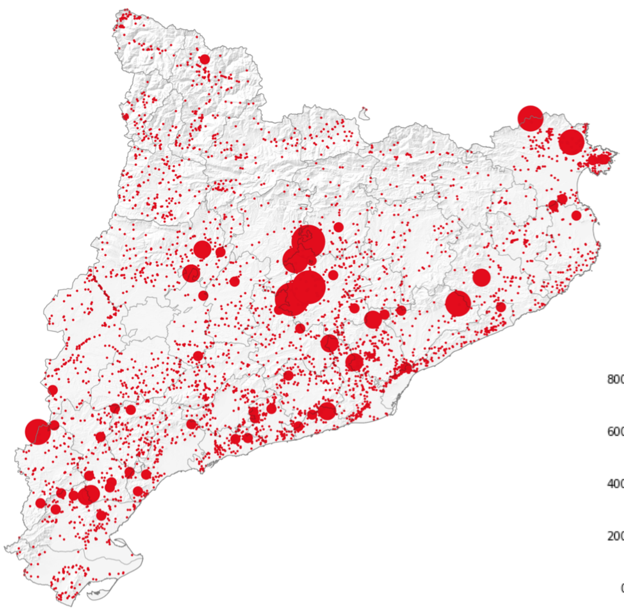
Sources: see the last row of the table above.

Previous analysis

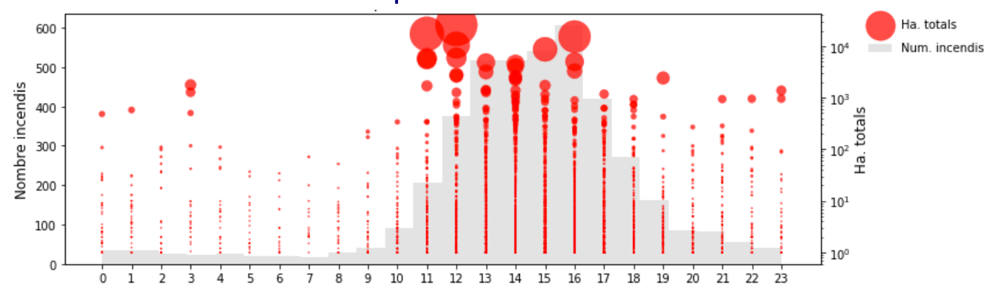
Fires

Fire	Period	Source
4.249	32 years	Forest Fire Prevention Service

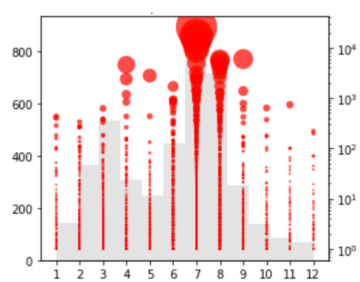
Spatial distribution



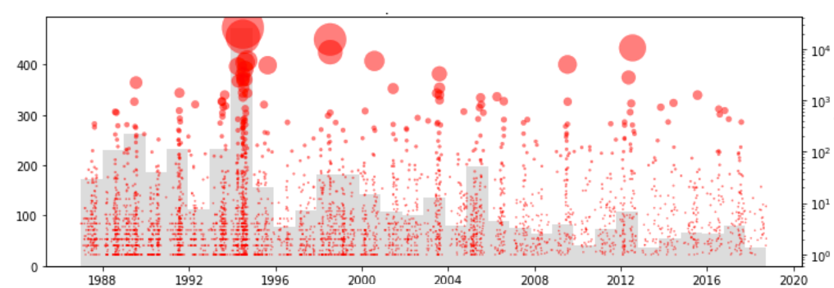
Temporal distribution



Time



Month

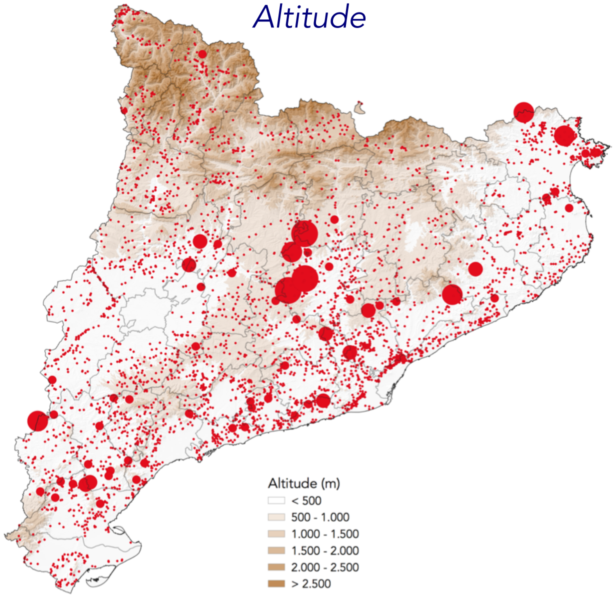


Date

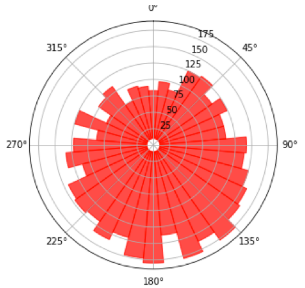
Previous analysis

Terrain

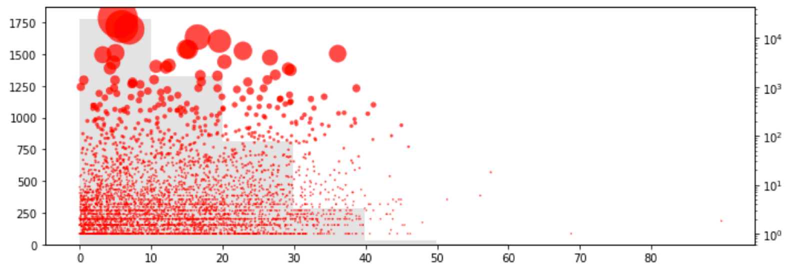
Altitude



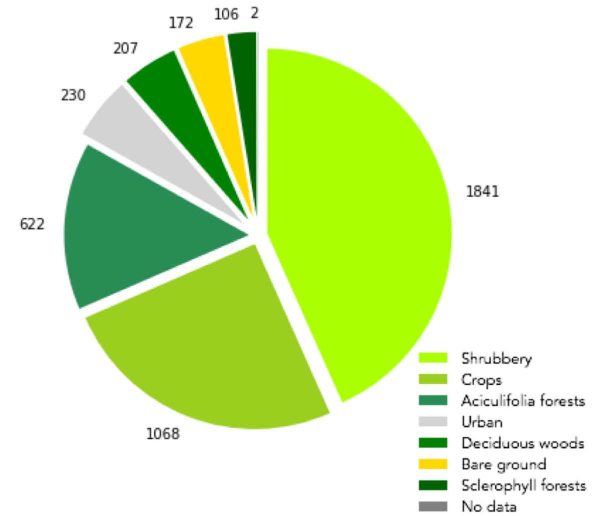
Orientation



Slope



Vegetation

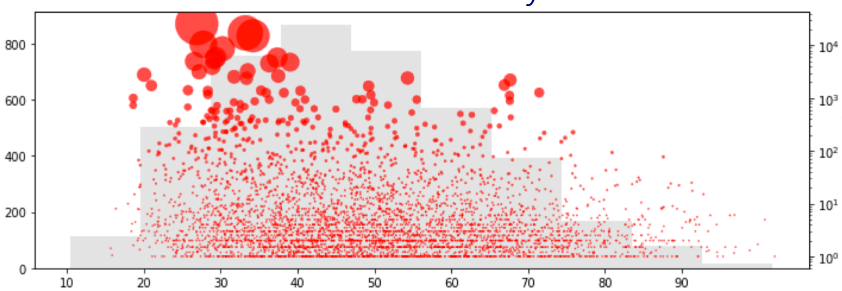


Previous analysis

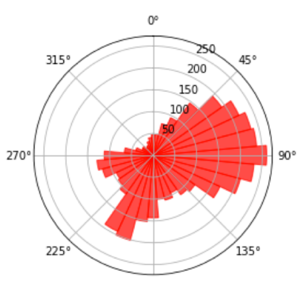
Meteorology

Type	Period	Source
Analogues	5 summer months of the years 2017 and 2018	Meteorological Service of Catalonia
Reanalysis	32 years	ECMWF

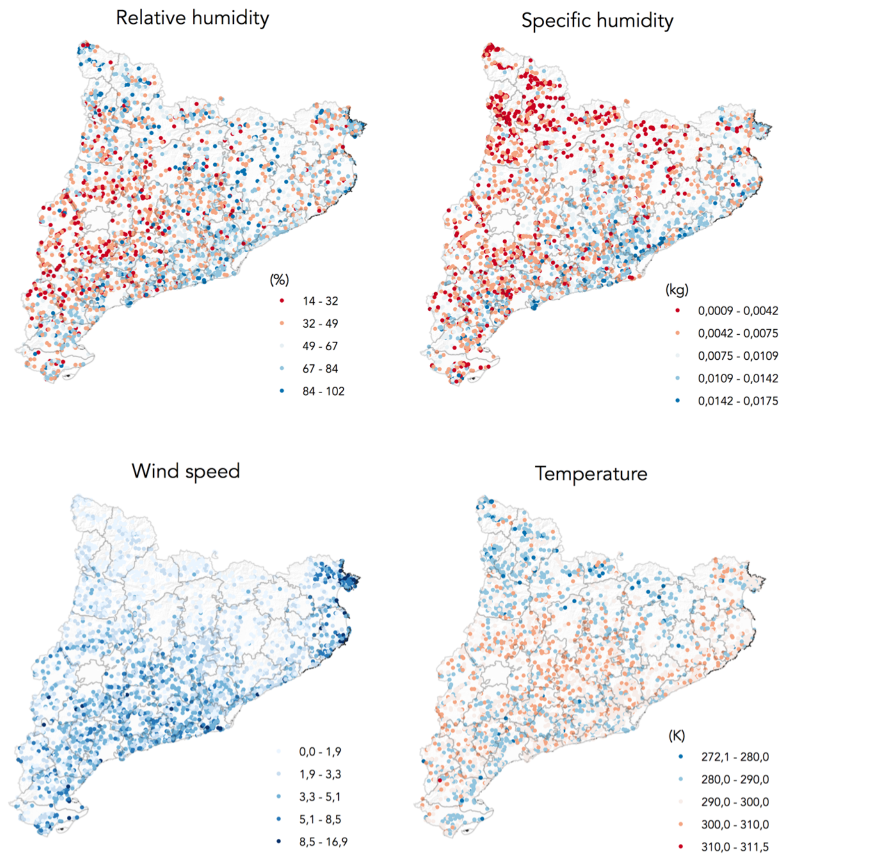
Relative humidity



Wind direction



Spatial distribution



Models

Grouping of risk areas according to weather conditions

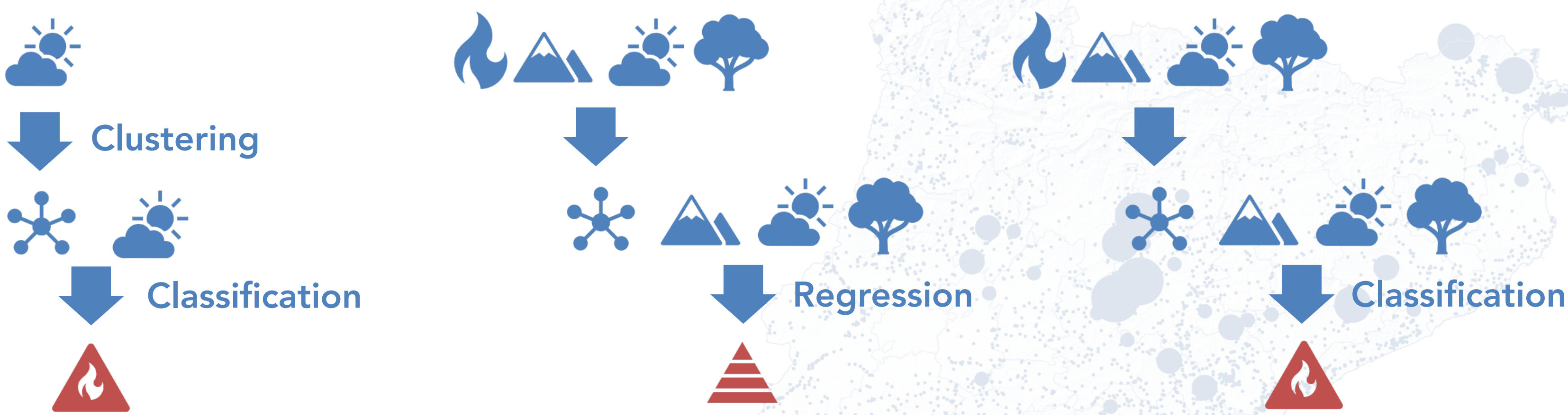
- Clustering algorithms
- Number of groups
  - Reanalysis: 10 groups
  - Analogues: 5 groups

Predicting the size of fires at the time of ignition

- Supervised regression algorithms

Risk of forest fire estimation

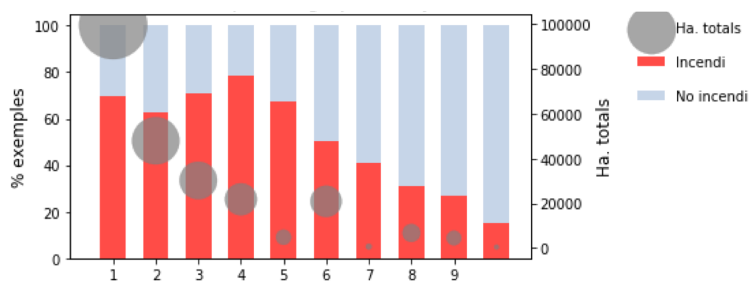
- Classification supervised algorithms
- Risk: probability of belonging to the fire class
- Calibration



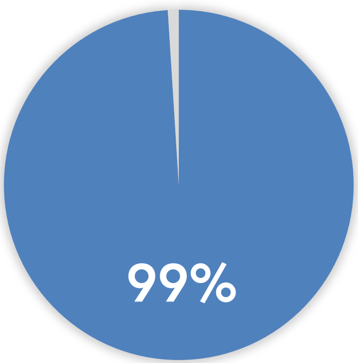
Evaluation

Risk zone grouping algorithms according to weather conditions (reanalysis)

Clusters



Accuracy



Cluster	1	2	3	4	5	6	7	8	9	10
Meteorological characteristics										
Relative humidity (%, average)	34,4	48,3	47,6	55,7	42,2	57,5	64,8	77,5	70,2	78,0
Temperature (average)	28,1	16,3	24,1	26,2	17,5	19,0	15,2	22,9	10,2	14,1
U wind component (average)	2,09	4,85	-2,00	0,49	0,16	0,31	0,83	-0,47	0,81	-2,07
V wind component (average)	0,95	-2,22	2,42	3,22	0,39	-4,92	2,86	0,06	-0,92	-0,19
Fire characteristics										
Fire	518	636	509	911	363	249	177	354	433	97
Non-fires	227	374	210	251	177	245	254	797	1172	543
Forestal (Ha, mitjana)	145	62,6	44,2	20,8	12,6	71,5	3,9	17,5	10,1	4,6
Non-forestry (Ha, average)	47,0	12,8	15,1	3,1	0,8	12,3	0,0	1,6	0,4	0,1
Orientation (average)	181	179	178	178	177	175	171	172	165	175
Slope (average)	13	12	11	13	21	13	13	15	17	13
Altitude (average)	499	313	322	279	982	250	356	326	747	306
NDVI (average)	0,45	0,44	0,44	0,43	0,41	0,48	0,46	0,45	0,43	0,48
Land cover (predominant)	Crops									

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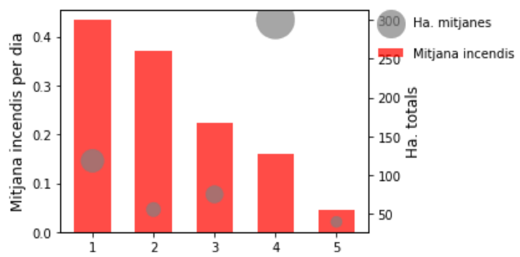
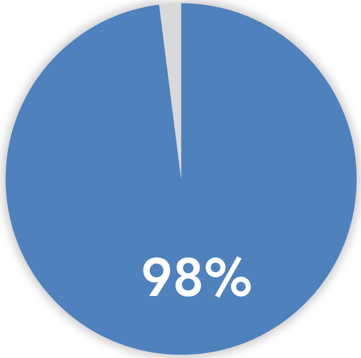
Evaluation

Risk zone grouping algorithms according to weather conditions (analogues)

Clusters



Accuracy



Cluster		1	2	3	4	5
Characteristics of analogues						
No. Analogues		55	82	12	1	3
Wind		0,014	0,0147	0,0184	0,0433	0,0048
U wind component		6,98	6,6919	7,0445	6,2009	6,8667
V wind component		7,813	8,0942	7,925	6,1852	6,7222
Relative humidity	500 hPa	-0,827	-1,071	-1,946	-2,035	-1,522
	850 hPa	-0,95	-1,079	-1,181	1,579	-0,008
Temperature		10,825	14,372	11,54	19,881	18,511
Precipitation		27,688	36,532	55,409	145,78	93,526
Fire characteristics						
Fire		855	906	181	11	9
Fires per day (average)		0,43	0,37	0,22	0,16	0,05
Forest (Ha, average)		88,3	45,1	66,8	273,9	5,7
Non-forestry (Ha, average)		30,2	10,5	8,5	26,5	34,1
Month (predominant)		7	7	7	9	6
Start time (average)		14:41	14:56	14:41	13:32	13:00
Relative humidity (%, av.)	1000 hPa	48,9	50,3	43,9	49,2	37,8
Temperature (average)		299,1	298,9	299,7	298,6	302,3
U wind Component (average)		0,44	0,13	0,51	-0,38	-0,23
V wind Component (average)		1,24	1,07	2,16	2,00	2,83
Orientation (average)		172,8	179,3	181,9	168,4	235,5
Slope (average)		13,5	13,5	13,3	17,1	17,6
Altitude (average)		325,0	343,7	313,5	372,3	410,7
NDVI (average)		0,44	0,44	0,45	0,47	0,42
Land cover (predominant)		Crops	Crops	Crops	Aciculifolia forests	Crops

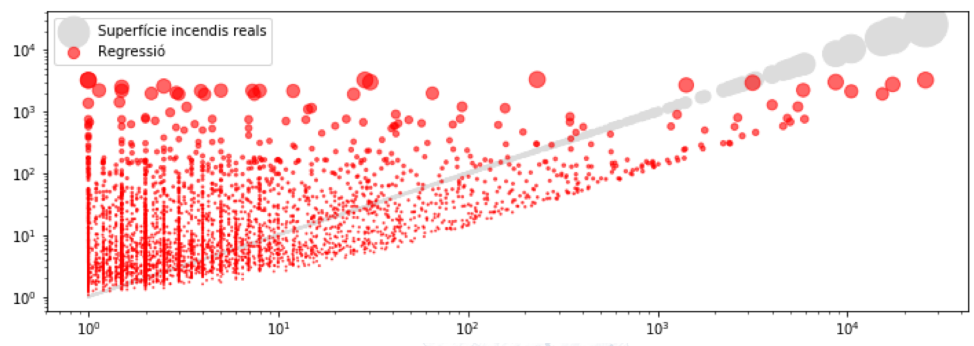
Evaluation

Regression algorithms for prediction of the size of wildfires at the time of ignition

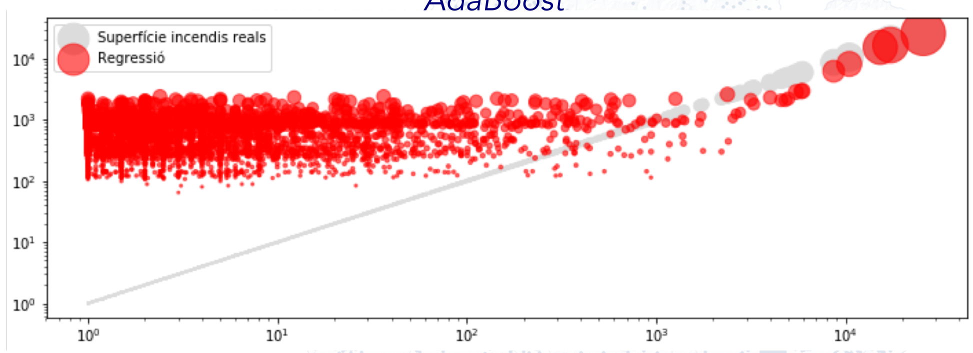
Methods

kNN
SVM
Decision trees
AdaBoost
Decision trees + AdaBoost
Logistic regression
Kernel ridge
Neural networks

kNN



AdaBoost



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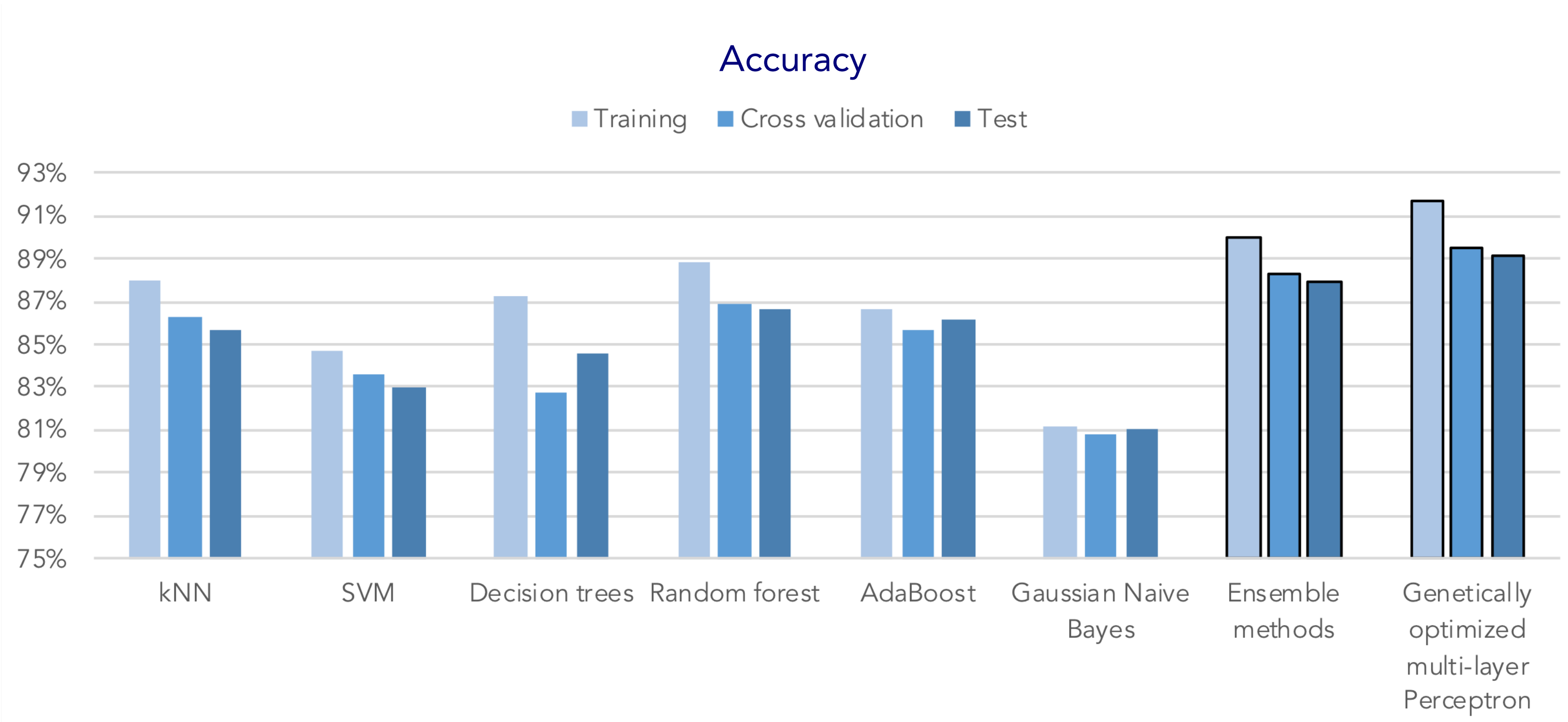
Evaluation

Classification algorithms for estimating forest fire risk



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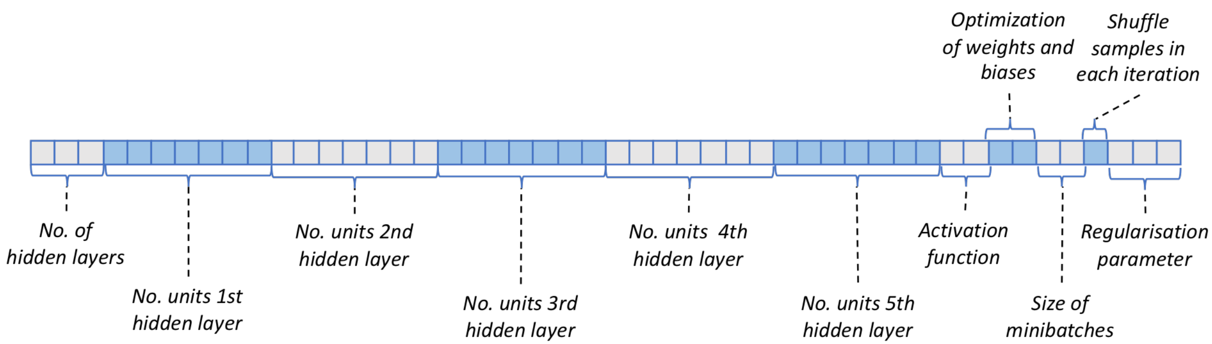
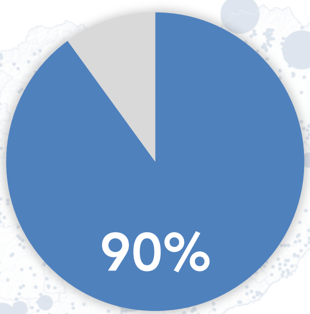
Optimization

Multi-layer Perceptron optimization using genetic algorithms



Experiment	1	2	3	4	5
Hidden layers	1 to 5	1 to 5	1 to 5	1 to 5	1 to 5
Population	50	75	70	100	70
Generations	50	50	50	12	70
Probability crossing	10%	10%	10%	10%	15%
Mutation probability	25%	30%	30%	30%	25%
Training time	22h58′15′′	21h33′36′′	19h35′31′′	8h15′	32h09′05′′
Accuracy improvement (cross-validation)	0,011	0,015	0,006	0,014	0,02

Accuracy



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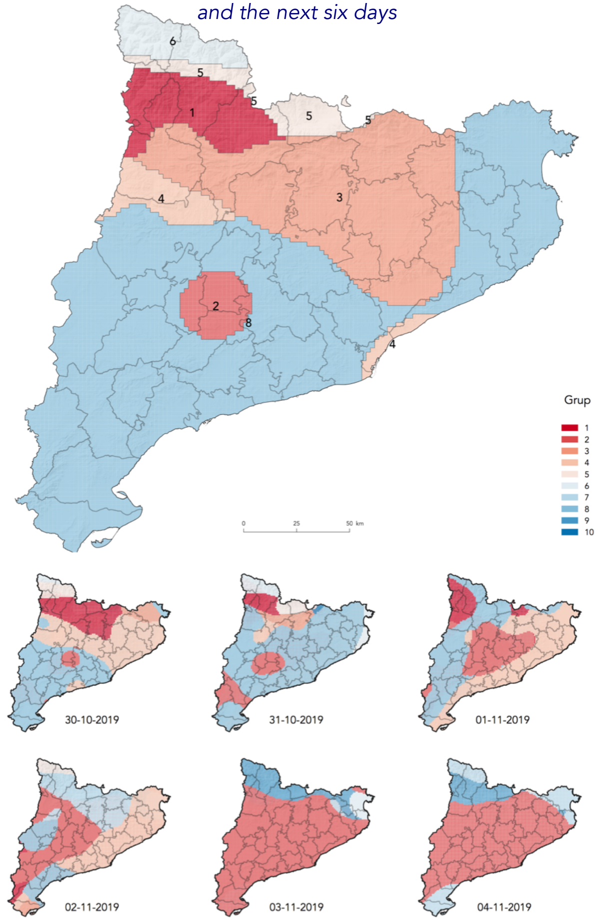
Implementation

Risk maps of forest fire according to weather conditions

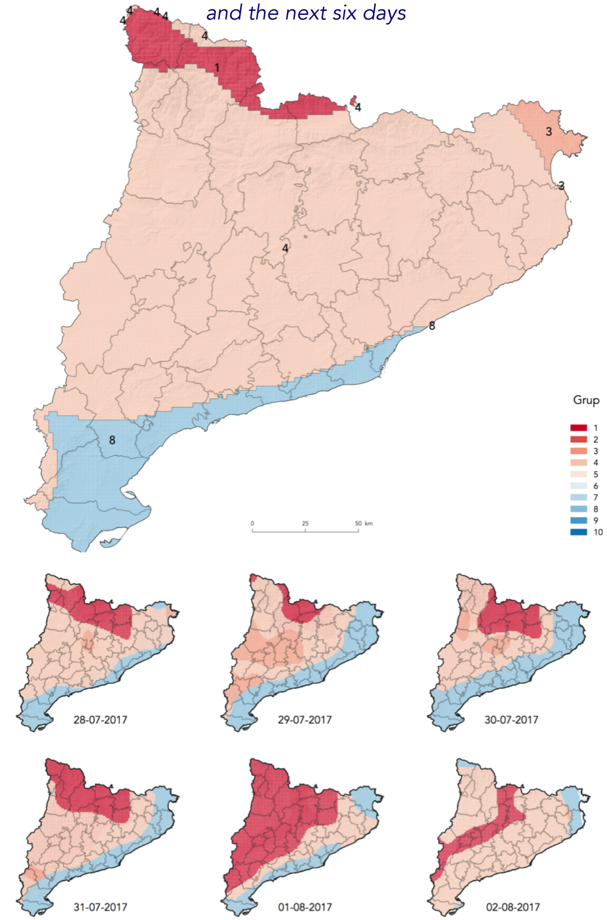
October 29th (12:00)

and the next six days



July 27th (12:00)

and the next six days



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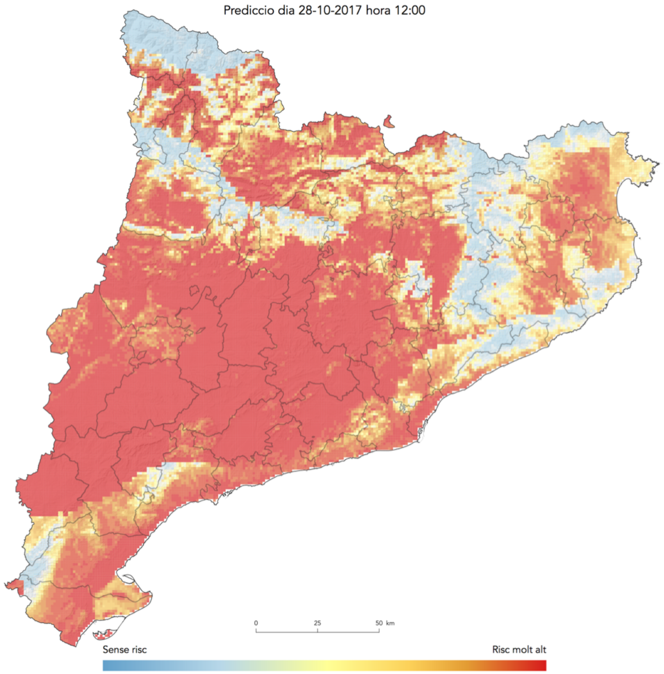
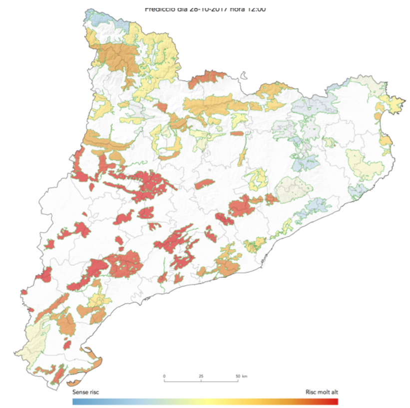
Implementation

Forest fire risk estimation maps

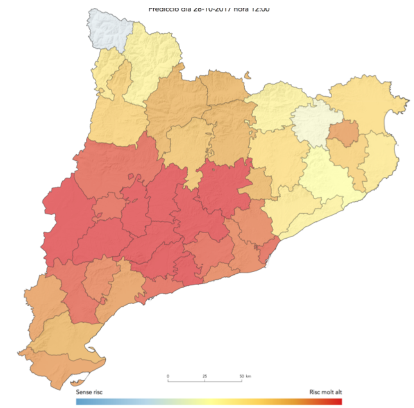
Multi-layer Perceptron



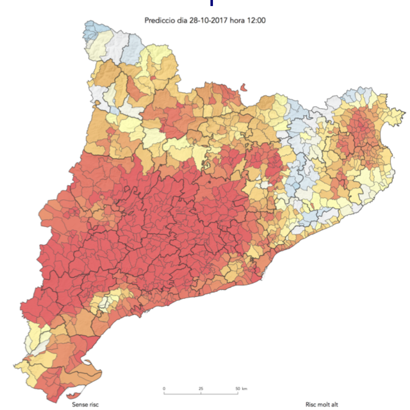
Natural Parks



Counties



Municipalities



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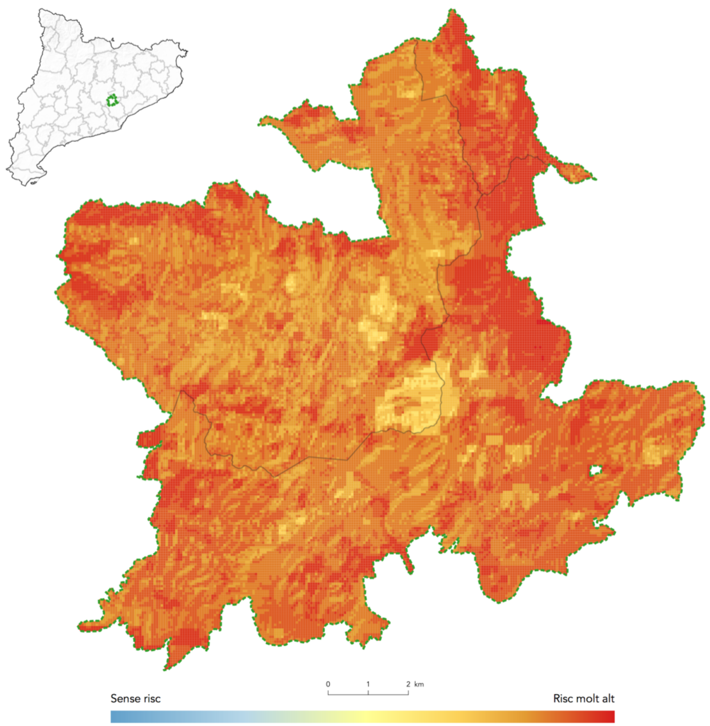
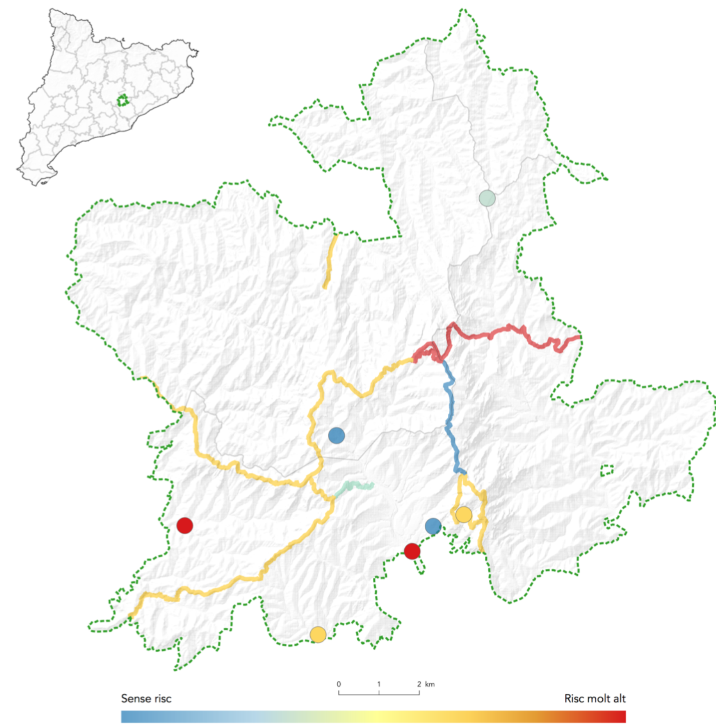
Implementation

Forest fire risk estimation maps

Natural Park



Main paths and parking areas



Conclusions

- Suitability of machine learning to estimate the risk of forest fires.
- Fast method that does not require complex or difficult to obtain data.
- Need to use big data technology due to the large volume of data used.
- Good results with the two sets of meteorological data used:
  - the reanalyzes offer enough detail to obtain risk areas.
  - the usefulness of using weather data from the days before and after the fires has been confirmed.
- Importance of obtaining a valid set of negative examples for training. Use of Pearson's Similarity.
- Best results for fire risk estimation : genetically-optimized multi-layer perceptron with 90% accuracy.
- Best results for grouping risk zones based on weather conditions: accuracy between 98% and 99%.
- Good spatial resolution (60m) of the models obtained, even valid for specific areas as natural parks.
- Method developed reproducible in any area.

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