Localized Forest Fire Risk Prediction: A Department-Aware Approach for Operational Decision Support

Paper #3087

1		d
		• path_mean
	1 (1)	• prec24h16_max
2	1 Clustering target	• prec24h16_min
3	This section present figure 1. This figure shows more detailed on the	• prec24h_max
4	target clustering applied in this study.	• prec24h_min
		• prcp16_max
		• prcp16_min
5	2 Class imbalanced	• prcp_max
6	This section present figure 2. This figure shows more detailed on the	• prcp_min
7	imbalanced data problem faced in this study.	• precipitationIndexN3_max
,	inibataneed data problem faced in this study.	• precipitationIndexN3_min
		• precipitationIndexN5_max
8	3 Features list	• precipitationIndexN5_mean
0	Categorized Features	• precipitationIndexN5_min
9	Categorized reatures	• rhum16_max
10	This section shows the final list of features that have been used for	• rhum16_mean
11	predicting burned area and fire occurrence.	• rhum16_min
12	Meteorological:	• rhum_max
		• rhum_mean
13	• angstroem_max	• rhum_min
14	• angstroem_mean	• snow24h16_max
15	• angstroem_min	• snow24h16_min
16	• bui_max	• snow24h_max
17	• bui_min	• snow24h_min
18	• dailySeverityRating_min	 sum_consecutive_rainfall_max
19	• days_since_rain_max	 sum_consecutive_rainfall_min
20	• days_since_rain_mean	sum_rain_last_7_days_max
21	• days_since_rain_min	sum_rain_last_7_days_mean
22	• dwpt16_max	sum_rain_last_7_days_min
23	• dwpt16_min	sum_snow_last_7_days_max
24	• dwpt_max	sum_snow_last_7_days_min
25	• dwpt_min	• temp16_max
26	• fwi_max	• temp16_min
27	• fwi_min	• temp_max
28	• ffmc_max	• temp_min
29	• ffmc_mean	• wdir16_max
30	• ffmc_min	• wdir16_mean
31	• isi_mean	• wdir16_min
32	• kbdi_max	• wdir_max
33	• kbdi_min	• wdir_mean
34	• munger_max	wdir_min
35	• munger_mean	• wspd16_max
36	• munger_min	• wspd16_mean
37	• nesterov_max	• wspd16_min
38	• nesterov_mean	• wspd_max

9 • nesterov_min

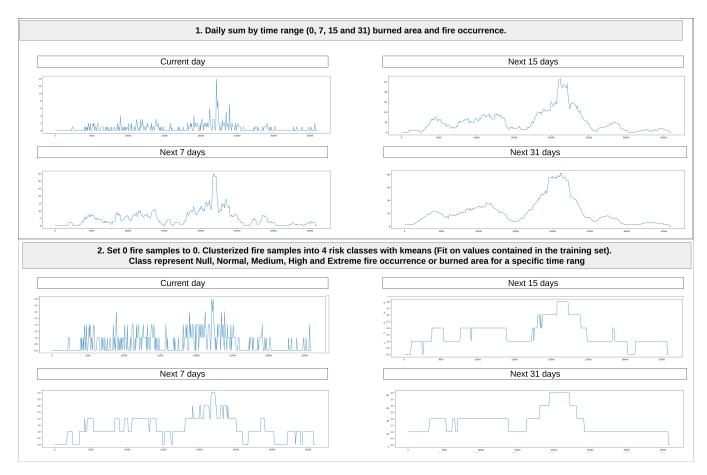


Figure 1: Process applied on each targets to obtain 5 classes risk. We use fire occurrence plots from Bouches du Rhone but same process has been applied at each department independently.

wspd_mean • Hêtre_mean 108 $wspd_min$ Lawn_max 109 Lawn_mean 110 Topographic: Lawn_min 111 Mélèze_max 112 Bare soil_max 88 Mélèze_mean 113 Bare soil_mean 89 Mixtes_max Bare soil_min 90 Mixtes_mean 91 Chênes décidus_max NDMI_mean 92 Chênes décidus_mean NDBI_max Chênes sempervirents_max NDBI_min 118 Conifères_max NDVI_max 119 Conifères_mean NDVI_mean 120 Conifer_max NDSI_max Conifer_mean 121 97 NDSI_mean 122 Crop_max NDSI_min 123 Crop_mean 99 NDWI_max 124 • Deciduous_max 100 NC_max 125 Deciduous_mean 101 NC_mean 126 102 Douglas_max NDVI_mean 103 Douglas_mean NDMI_mean 128 Feuillus_max NR_max • Feuillus_mean 129 105 PasDeRoute_max • Feuillus_min 130 106 • PasDeRoute_mean

• Hêtre_max

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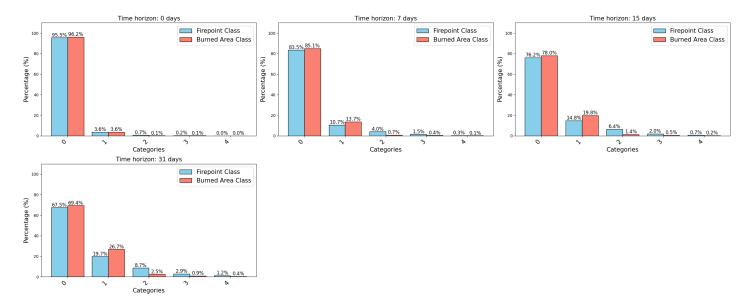


Figure 2: Distribution across time horizon in the test set for occurrence and burned area class. Classes 1, 2, 3, and 4 are outnumbered by class 0, especially classes 3 and 4, which make up barely 1.%.

133	path_mean
134	 Pin à crochets, pin cembro_max
135	• Pin d'Alep_max
136	 Pin laricio, pin noir_max
137	 Pin laricio, pin noir_mean
138	Pin maritime_max
139	Pin autre_max
140	Pin sylvestre_max
141	 Pin sylvestre_mean
142	 Pins mélangés_max
143	 Pins mélangés_mean
144	Peuplier_max
145	 Peuplier_mean
146	 Robinier_max
147	Robinier_mean
148	 Sapin, épicéa_max
149	 Shrubland_max
150	Shrubland_min
151	argile_encoder_max
152	 argile_encoder_mean
153	 cosia_encoder_max
154	 cosia_encoder_mean
155	 cosia_encoder_min
156	elevation_max
157	elevation_mean
158	• elevation_min
159	 foret encoder max

• foret_encoder_mean

foret_encoder_min

Socio-Economic:

calendar_maxcalendar_sumconfinement

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162 163

165

• path_max

• couvrefeux	166
 dayofweek 	167
 holidays 	168
 holidaysBorder 	169
 isweekend 	170
• month	171
• motorw	172
• motorw	173
 population_max 	174
 population_mean 	175
• population_min	176
• primary_max	177
• primary_mean	178
secondary_max	179
secondary_mean	180
• tertiary_max	181
• tertiary_mean	182
• ramadan	183
Historical:	184
Past_burnedarea	185
• Past_risk	186
• cluster_encoder	187
• id_encoder	188

189 4 Length of time series

This section present the length of the time series selected for training and testing time models. Results are shows in 1.

5 Tree based configuration

Table 2 presents the configuration of tree based models.

194 6 Deep learning layers configuration

This section present the layers parameters for each deep learning model used in this study.

197 6.1 MLP

Table 3 shows the configuration of the MLP models.

199 6.2 GraphCast

Table 4 shows the configuration of the GraphCast model. Edges channels is set to 4 as in the original paper containing the x, y, z positions of the mesh node and the length of the edge. Similarly, the input mesh data is the 3D position of the node.

204 6.3 GRU

Table 5 shows the configuration of the GRU model.

206 6.4 LSTM

Table 6 shows the configuration of the LSTM models.

208 6.5 DilatedCNN

Table 7 shows the configuration of the DilatedCNN models.

210 6.6 GRUGNN

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Table 8 shows the configuration of the GRUGNN models. 100 refers to the number of temporal features, 79 to the number of spatial features.

7 Comparis between binary models and multi classification

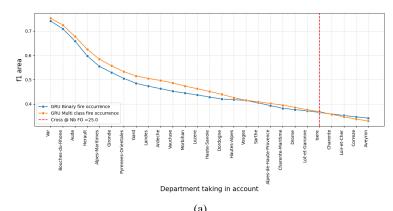
This section present the comparison between multi-classification and binary on Catboost, GRU and MLP models.

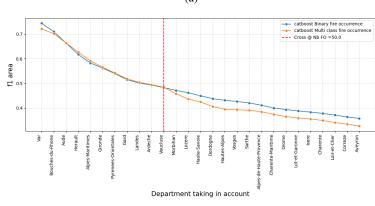
218 7.1 0 day horizon

Figure 3 shows the comparison between multi-classification and binary models at 0 day horizon.

221 7.2 7 day horizon

Figure 4 shows the comparison between multi-classification and binary models at 7 day horizon.





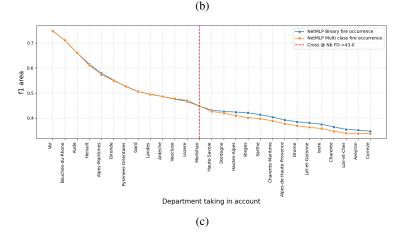


Figure 3: Comparison of multi-classification and binary F1 score area performance depending of the number of department for GRU (a), Catboost (b) and MLP (c) at 0 day horizon.

7.3 15 days horizon

Figure 5 shows the comparison between multi-classification and binary models at 15 day horizon.

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Table 1: Time series length selected for each model and prediction horizon

Table 1. Time series length selected								
Fire Occurrence								
Models	31 days							
LSTM	10	5	15	5				
GRU	10	15	15	5				
GRU Binary	10	10	5	10				
GRUGNN	10	5	5	5				
DilatedCNN	15	10	1.5	15				

Burned Area								
Models	0 days	7 days	15 days	31 days				
LSTM	10	5	15	10				
GRU	15	10	5	5				
GRUGNN	10	10	5	5				
DilatedCNN	15	10	15	5				

Table 2: Configuration of each tree based model

Parameters	XGBoost	Catboost
Early Stopping Rounds	15	15
Learning Rate	0.001	0.001
Max Depth/Num Leaves	6	4
Min Child Weight	1.0	-
Max Delta Step	1.0	-
Subsample	0.5	0.7
Col Sample Bytree	0.7	0.6
Reg Lambda	1.7	1
Reg Alpha	0.7	0.27
N Estimators	10000	10000
Tree Method	hist	-

Table 3: MLP configuration

Linear 1	Linear 2	Linear 3	Linear 4
179, ReLU	179, ReLU	64, ReLU	5

Table 4: GraphCast configuration. PP refers to message passing

	- 1			6 I	8	
Grid2Mesh	Mesh MP	Mesh2Grid 3	Linear 1	Linear 2	Linear 3	ı
179	179, 6 MLP MP layers	256	256	64	5	l

Table 5: GRU configuration

	Table 3. GRO configuration						
	GRU	Norm 1	Dropout	Linear 1	Linear 2	Linear 3	
ı	2 layer 0.03 dropout 170 Pel II	Ratch Norm	0.03	256 Pal II	64 Rel II	- 5	

Table 6: LSTM configuration

			C		
LSTM	Norm 1	Dropout	Linear 1	Linear 2	Linear 3
1 layer, 64, ReLU	BatchNorm	0.03	64, ReLU	64, ReLU	5

Table 7: DilatedCNN configuration. Dil refers to dilation

1	Conv 1	Conv2	Conv 3	Norm, Dropout 1, 2, 3	Linear 1	Linear 2	Linear 3
ı	179, Dil 1	179, Dil 3	Dil 3	Batchnorm, 0.03	64	64	5

Table 8: GRUGNN configuration.

			G		
GRU	GCN	Norm, Dropout	Linear 1	Linear 2	Linear 3
2 layer, 0.03 dropout, 100	79	Batchnorm, 0.03	256	64	5

7.4 31 days horizon

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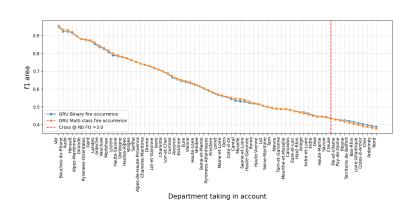
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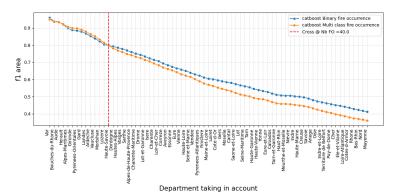
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Figure 6 shows the comparison between multi-classification and binary models at 31 day horizon.

8 Features importance

This section features importance based on shap values for Catboost models. Figure 7 shows features importance of Burned area prediction of Catboost model.





(a)

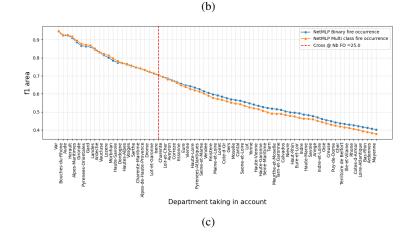


Figure 4: Comparison of multi-classification and binary F1 score area performance depending of the number of department for GRU (a), Catboost (b) and MLP (c) at 7 days horizon.

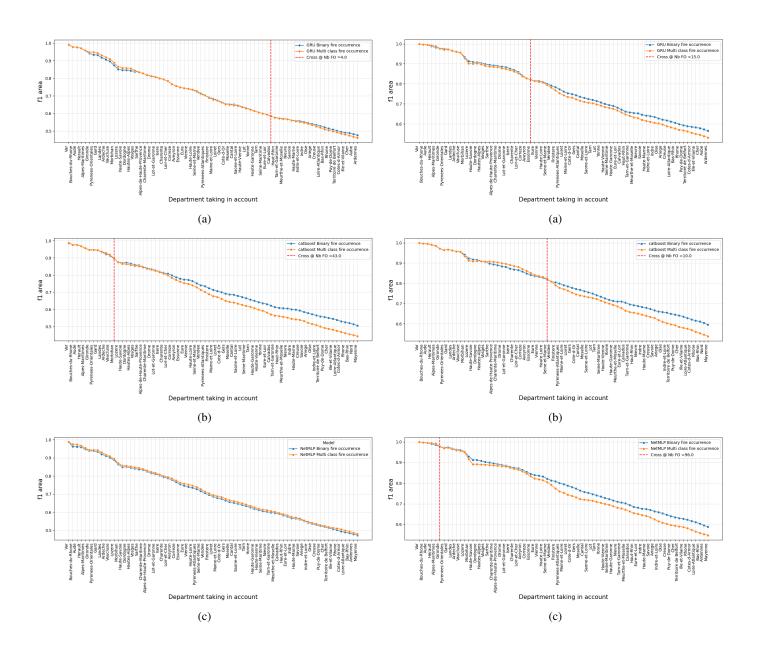


Figure 5: Comparison of multi-classification and binary F1 score area performance depending of the number of department for GRU (a), Catboost (b) and MLP (c) at 15 days horizon.

Figure 6: Comparison of multi-classification and binary F1 score area performance depending of the number of department for GRU (a), Catboost (b) and MLP (c) at 31 days horizons.

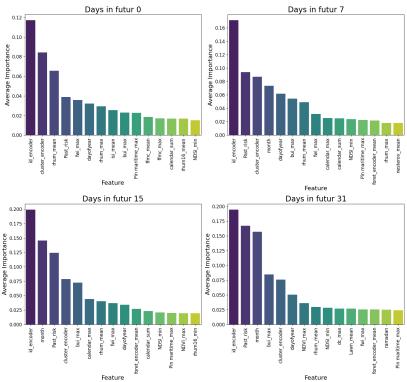


Figure 7: Top 15 shap values computed on multi-classification Catboost model on different time horizons for Burned area prediction. ID encoder correspond to Department ID