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Using simulation and deep learning to derive synthetic high resolution daily fire danger maps

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Abstract

Diagnostic of next day wildfire danger typically relies on computation of meteorological indices, usually derived from weather forecast. These indices may represent the danger of ignition, potential rate of spread or droughts, and while it takes into account the vegetation state it does not represent exactly how it will burn, as this is dependent of the fuel distribution and landscape at a scale much finer than weather model allows. On the other hand, overall landscape danger is more and more often evaluated statistically using mass simulation, with a very large number of fires simulated over a variety of weather situation to estimate effective fire area burned (in Ha), reaching a very fine scale at a cost of a computational time too long for next day forecast. Deep learning and model emulation can be used to overcome this computational problem and compute this next day fire size distribution a very high temporal and spatial resolution. Nevertheless, such simulation still comes at a cost, the amount of generated data is large and challenges on how to create a synthesis that may actually be helpful and insightful in operations. In this study, several approaches are proposed to analyze results and provide new range of fire danger maps and ratings, it is applied to the real forecasts of 13 relatively large fires that occurred in Corsica and compared to corresponding forecasts using standard fire danger index used in operational conditions.

1. Introduction

Diagnostic of wildfire danger for the next day typically relies on computation of meteorological indices, usually derived from weather forecast. These indices may represent the danger of ignition, potential rate of spread or droughts. Fire danger rating systems include assessment and forecast of one or several discrete indices, rated from "low" to "extreme", but the notion of "rating" may also refer to scalar values composing the system. These indices relate to the proneness for ignition, spread and/or intensity of a wildfire according to the state of vegetation and its environment at a given time. Well known examples are The Canadian Forest Fire Danger Rating System (CFFDRS, cf. Lawson and Armitage (2008)) and the National Fire Danger Rating System (NFDRS, cf. Bradshaw et al. (1984)). Fire danger maps may be available among other data via internet-based information systems; for instance, covering the US as part of the Wildland Fire Assessment System (WFAS, cf. Burgan et al. (1997)). While these systems take into account the vegetation state it does not represent exactly how it will burn, as this is dependent of the fuel distribution and landscape at a scale much finer than weather model allows. On the other hand, overall landscape danger is more and more often evaluated statistically using mass simulation, with a very large number of fires simulated over a variety of weather situation to estimate effective fire area burned (in Ha), reaching a very fine scale at a cost of long computational time. The strategy to rely on fire spread simulations is common to Burn Probability modelling (e.g., Parisien et al. (2005), Finney et al. (2011), Parisien et al. (2019)) although the goal here is to provide a fire danger index focusing on potential for fire spread, instead of potential for a location to burn.

We have recently introduced a method to overcome the computational problem and pinpoint where and when the most critical situation of next day may occurs. DeepFire (Allaire et al. (2022)), based on deep learning emulation of wildfire simulation, to compute this next day fire size distribution at a very high temporal and spatial resolution. Nevertheless, this simulation comes at a cost, the amount of generated data is large and pose the challenge of creating a synthesis that may actually be helpful in operations. In this study, several approaches are proposed to analyze results and provide fire danger maps and ratings using this new simulation-based prediction system, it is applied to forecasts for 13 relatively large fires that occurred in Corsica and compared to corresponding forecasts using another fire danger index used in operational conditions.

2. Methodology

The new approach proposed to quantify fire danger consists in predicting, for a given time and location, the size of the burned surface that would result from one hour of free wildfire spread after an early stage where the fire has already ignited and spread over about one acre. Ignition probability is assumed homogeneous, except for locations without vegetation where it is considered null. A duration of one hour is generally more than the time necessary for the first attack on the fire to be carried out, even more so if one assumes that the fire has been detected in the early stage. These simplifying assumptions imply that fire danger mostly expresses potential for fire spread if it is not attacked rather than potential for ignition. The overall approach has already been presented in Allaire et al. (2022), tested and compared to the French IEP (Indice éclosion-Propagation, similar to the ISI Initial Spread Index) that range from low to severe in 5 classes. As DeepFire computes effective area burnt in one hour, there has been matched to fire size classes as in Table 1.

Table 1: Values of fire sizes used to determine a class of fire danger. The fire size classes follow the US classification and a correspondence of fire danger classes was made between DeepFire and IEP in the present study

Fire size (ha)	< 0.1	[0.1, 4.0[	[4.0, 40.5[	[40.5, 121.4[	[121.4, 404.7[	[404.7, 2023.4[	≥ 2023.4
Category	A	B	C	D	E	F	G
Corresponding IEP	None	very low (1)	low (2)	moderate (3)	severe (4)	very severe (5)	very severe (5)

3. Results

In Allaire et al. (2022), it has been shown that if the focus is on the vicinity of the ignition location, DeepFire predictions proved to be better (less false-positive area), or on par with standard index, with the added advantage of providing a quantifiable output. For the fire cases studied, we knew what were the when and where to focus on because the information was known a posteriori. However, in practice, information on the fires is not known before making fire danger predictions, and area of interest must be investigated on a full 24 hours ensemble simulation dataset that consists of 10.000 members (slightly different runs), 240 time steps on a 80m resolution grid. Computation is possible in 2 hours' time, but the analysis of this entire dataset is unrealistic in operational context unless it is guided with synthetic maps.

All these deepfires computations takes as input high resolution (600 m resolution) weather forecast initialized from the French Arome model. These computations are initiated at midnight (T0 here) and available at T6 (6:00UTC) all the evaluated forecasts are between T6 and T30 (6:00 of the first day to 6:00 on the next day).

These maps have been designed to attempt to address specific questions. First, what are the locations and time where/when fire danger is highest for the day to come? (cf. deterministic: Figure 1 & 2, and probabilistic: Figure 3 & 4) Then, starting from when and for how long is there high fire danger? (cf. Figure 5 and Figure 6.) Regarding these aspects, the question of uncertainty in the prediction is also addressed to some extent by comparing the deterministic maps to their probabilistic counterparts.

A focus on one small fire, Calenzana 2017

From the deterministic prediction of either DeepFire or IEP, the maximum value over the day can be computed easily for each location. The maps of the maximum between T+6 and T+30 of DeepFire (resp., IEP) and of the associated time of maximum are shown in Figure 1 (resp., Figure 2). On this fire day, a relatively strong south-westerly wind was definitely the driving factor, but this wind also brought some humidity, leaving area of high danger either where a downslope effect was strong. By looking at the time of the maximum of DeepFire on the right of Figure 1 it can be seen that although there is a high danger potential (some areas in red in map on the left), there is actually much contrast regarding time of highest danger in the area of Calvi, suggesting that if there is an event, a detailed local analysis is required. On the IEP map in Figure 2 such requirement is less obvious, with large areas marked in orange and less contrast, indicating a dangerous but more general situation (less discriminant) with an event having strong probabilities of occurring in the morning.

If the maximum is obtained at several forecast times (T, with T+6), we show the earliest one. Because the IEP has only 5 categories, the maximum value will most likely be predicted at several times. Figure 2 shows that the time of maximum is T+6 for most locations, making it hard to tell when fire danger is highest. In practice, this issue can be avoided by identifying the time of maximum of another a continuous quantity, such as the FFMC which is one of the two components of IEP. In Figure 1, although the maximum is represented by a categorical color scale, it corresponds to a continuous index, so this issue does not occur. The time of maximum for DeepFire predictions is between T+8 and T+18 on the majority of the island, but for some locations (even among these predicted in class F) the time of maximum is after T+18, notably around the ignition location where the fire occurred at T+16 while the maximum is more around T+22.

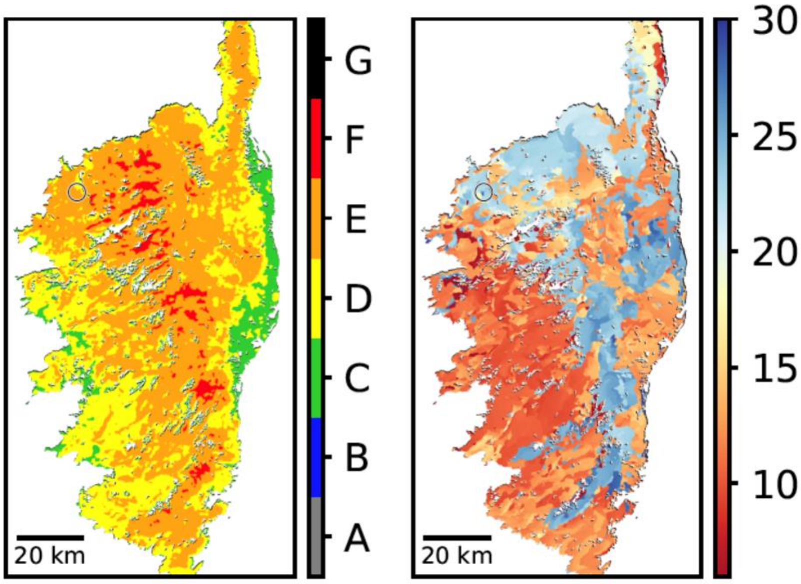

Figure 1: Maximum over the forecast between T+6 and T+30 (left) and time thereof (right) of the DeepFire prediction, location of actual fire in circle.

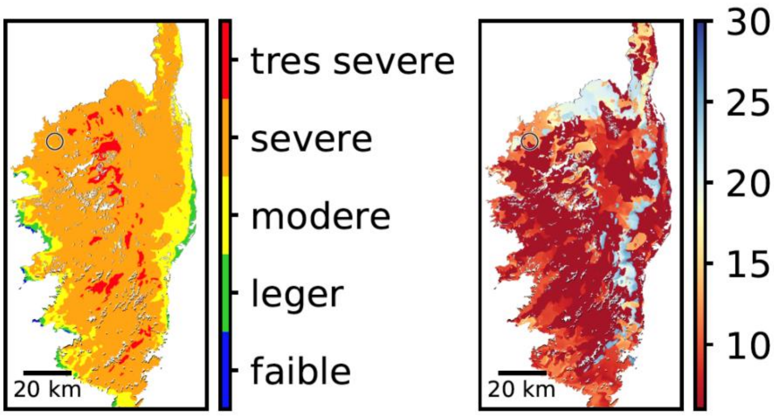

Figure 2: Same as Figure 1 but for IEP prediction

From the probabilistic forecast of DeepFire, the computation of a counterpart to Figure 1 is less direct. The ensemble can be summarized by a statistic such as the mean or a quantile. For either statistic, it makes more sense to first compute it for all locations and forecast times, then to identify the time of maximum. In the case of a quantile, for instance, the time of maximum can therefore be interpreted to that of a more or less optimistic predicted scenario. In Figure 3, the quantile for probability 0.8 was chosen. According to the Prométhée database, about 80% of the fires in Corsica have a final burned surface of 1 ha or less, which is quite low considering the range of DeepFire predictions. Although it is untuitive to define quantile from a meaningful fire size derived from a database of observations, it does not seem relevant here, and it makes more sense to interpret the chosen quantile as a quantity that represents a quite “pessimistic” scenario. However, as can be seen in Figure 3 (middle map) there are still many locations where fire danger is at least in class D. It might be possible to make a distinction among the high-danger areas by looking at the less intuitive continuous value (left map). Regarding the time of maximum, it is similar to that of the deterministic counterpart in Figure 1.

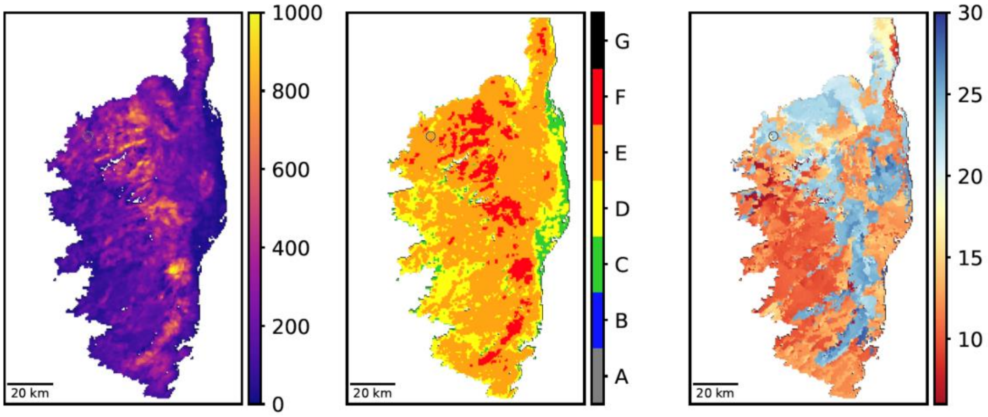

Figure 3: Maximum over the forecast between T+6 and T+30 of the quantile for probability 0.8 in the ensemble of DeepFire predictions. From left to right: continuous scale; categorical scale; time of the maximum.

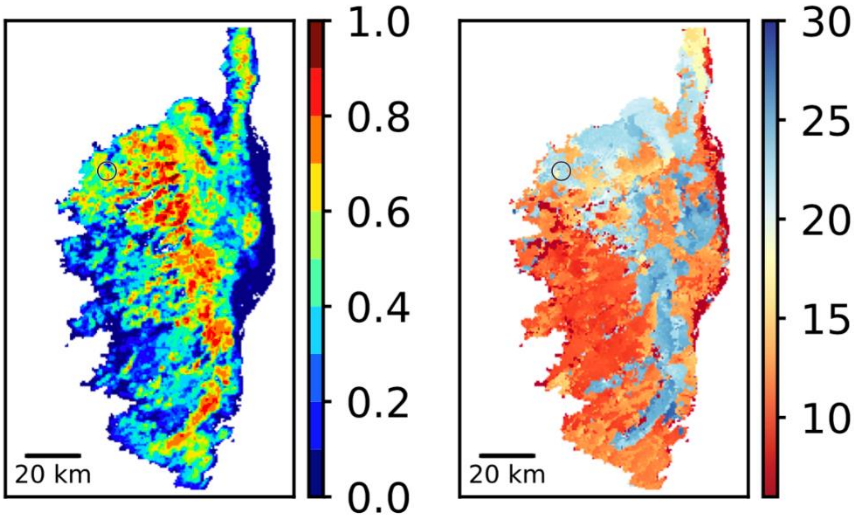

Figure 4: Maximum over the forecast between T+6 and T+30 of the probability of being into class E or higher (left) and time thereof (right).

Overview of the predictions for 12 fires

A number of numerical quantities that could serve as a daily indicator were proposed. Due to its ability to discriminate between locations with high fire danger in the cal_2017 fire case, the maximum over the forecast between T+6 and T+30 of the probability of being into class E or higher is chosen as a daily fire danger map for the 12 other fire cases. This map is shown for all 12 cases in Figure 5, together with the evolution of the proportion in the island of each class for both DeepFire and IEP according to the deterministic prediction to have an idea of how the overall spatial distribution of fire danger evolves over time.

Overall there is a general agreement in variations between T+6 and T+30 between IEP and DeepFire, with a general trend of more “contrasted” DeepFire predictions, indicating a better ability to pinpoint high danger locations (i.e. it is more discriminant). Alternatively, one may consider another maximum over time: that of the probability (based on the ensemble) of being into class E or higher. The resulting map for cal_2017 fire case is shown in Figure 4 together with the associated time of maximum. Compared to Figure 3, the maximum probability seems better suited to discriminate among locations with high fire danger during the day, whereas the time of maximum appears similar overall, except for some locations where the predicted probability is 0 over all 24 hours, resulting in a time of maximum at the value of T+6 by default.

In terms of danger, Figure 5 has been separated into two main classes that corresponds to winter and summer fires. More than the season, a difference that can be observes is that for most summer fires, the peak in fire danger corresponds to noon (or the solar maximum), does not stay very long in peak value and overall, a situation that is bad over a large area. In winter, peaks do not have a clear time, with situation prone to large fires for a longer period. Moreover, for winter fire, there is a strong contrast between areas upwind and downwind, each of the winter situations happened in very strong winds.

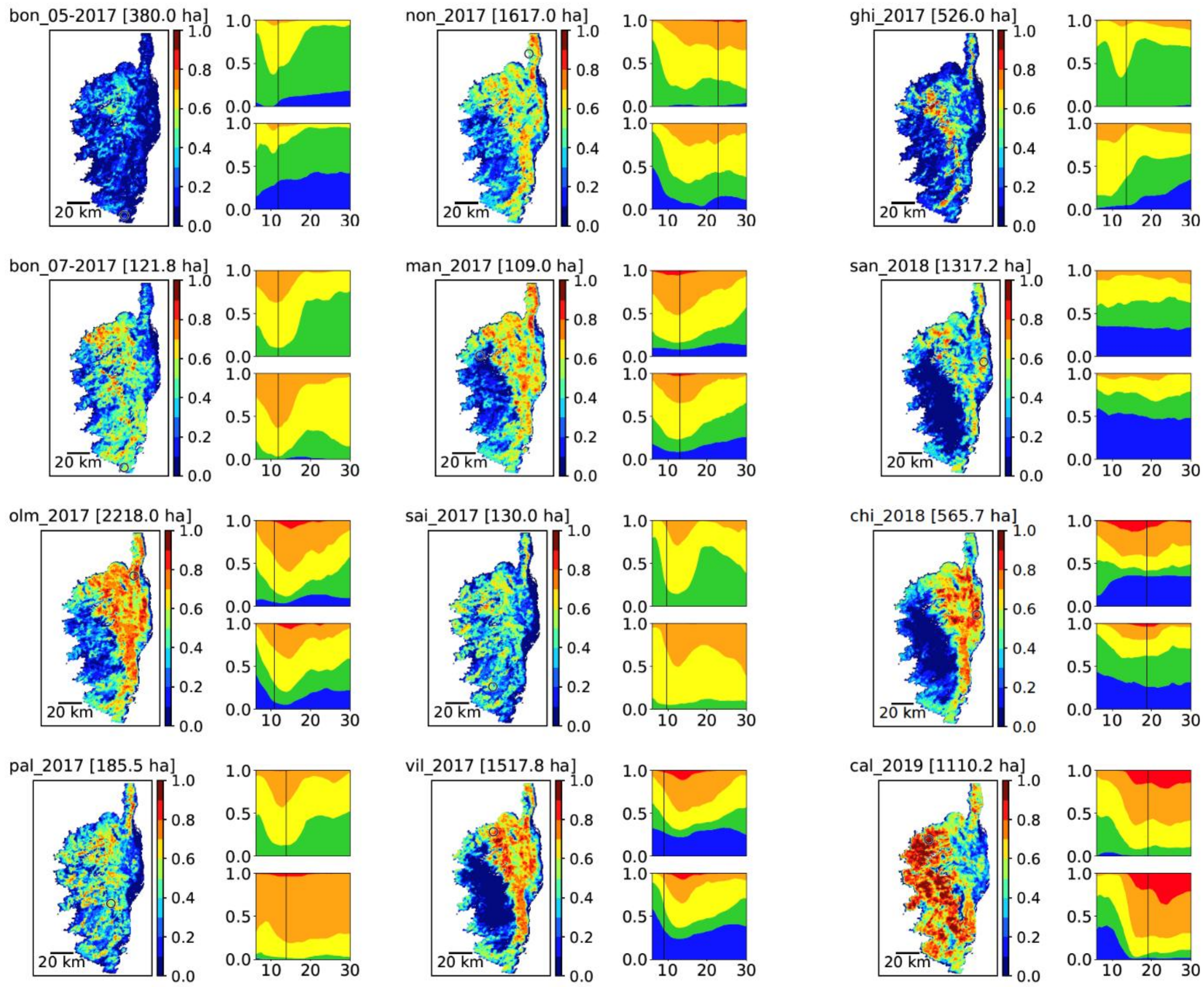

Figure 5: For all 12 complementary fire cases: maximum between T+6 and T+30 of the probability of being into class E or higher (left, cf. Figure 4), together with the evolution of the proportions over the island of DeepFire (top right) and IEP (bottom right) classes. First two columns: summer fires; last column: winter fires.

4. Conclusions

This works presents some insights on how to represent a synthesis of the large amount of data that results from fire danger predictions of potential fire size using DeepFire fire behaviour emulation.

Arguably, a daily rating of fire danger based on DeepFire should be computed on a relatively large area, at the sub-regional level for Corsica Island and the maximum value over the day can be considered. At this spatial scale, a representative fire danger rating could be the one associated to the DeepFire value that separates the 80% lower values from the 20% highest in a given area. As a complement to fire danger ratings, that are associated to a low spatial resolution, it only makes sense to use these predictions with high spatial resolution and high frequency weather predictions to analyze the situation in more detail.

A major strength of the prediction using DeepFire seems to be its spatial granularity allowing to be more discriminant. Compared to traditional fire danger indices that mostly rely on weather forecasts, the potential fire size estimated by DeepFire accounts for the influence of terrain on fire spread at via the variability over space in type of vegetation, presence of non-burnable areas, and slope. The high-resolution maps could be used as complement of fire danger ratings, that generally attribute a single value to a large area, for better anticipation but potentially to help to decide firefighting actions after a fire has started spreading. For instance, the maps can be used to finely identify locations that, if reached at some point, the fire will spread even faster and become harder to control. Moreover, another strength regarding its design, compared to other fire danger rating systems, is that it is not based on empirical knowledge, except for the actual choices of fire size for each class, these results are not based on experience of past fires, nor on expert analysis.

Current work is focused towards removing a simplification. Separation in fire categories based on a size factor poses the problem of defining these classes. As a first guess, defining this threshold based on observed fire sizes seems a logical answer, but it may not be that representative. In Corsica and Europe, a vast majority of fires are attacked early enough and do not spread far, even when fire danger is high. It may make more sense to reanalyze the situation of a high number of days (e.g., a hundred) and provide a “reference” fire danger category, regardless of whether a fire occurred or not. Then, the thresholds could be adjusted so as to optimize the match between reference and predicted values of fire danger. Information on the intermediate sizes of the fires, rather than that of final burned surfaces, would be most relevant for evaluating the prediction performance of DeepFire, but most of the time the fire is stopped early and, otherwise, the 1-hour fire size is difficult to measure. This feedback would be very valuable to adjust the thresholds, but also to evaluate the usefulness of such a prediction system for operational use. Overall, the amount of information and complexity is increasing with the increase in resolution of most of the forecasting systems, and performing a synthesis that can leverage the advances offered by such systems is a major concern for any operational research.

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6. References

Allaire F, Filippi JB, Mallet V (2022) Simulation-based high resolution fire danger mapping using deep learning. International Journal of Wildland Fire p. Just accepted, https://doi.org/10.1071/WF21143

Bradshaw LS, Deeming JE, Burgan RE, Cohen JD (1984) The 1978 National Fire-Danger Rating System: technical documentation. Gen. Tech. Rep. INT-169. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station. 44 pp.

Burgan RE, Andrews PL, Bradshaw LS, Chase CH, Hartford RA, Latham DJ (1997) Current status of the wildland fire assessment system (WFAS). Fire Management Notes 57, 14–17

Finney MA, McHugh CW, Grenfell IC, Riley KL, Short KC (2011) A simulation of probabilistic wildfire risk components for the continental United States. Stochastic Environmental Research and Risk Assessment 25, 973–1000, https://doi.org/10.1007/s00477-011-0462-z

Lawson B, Armitage O (2008) Weather Guide for the Canadian Forest Fire Danger Rating System. Natural Resources Canada, Canadian Forest Service, Northern Forestry Centre, Edmonton, Alberta. 84 p.

Parisien M, Kafka V, Hirsch K, Todd J, Lavoie S, Maczek P (2005) Mapping Wildfire Susceptibility with the BURN-P3 Simulation Model. Natural Resources Canada, Information Report NOR-X-405, Canadian Forest Service, Northern Forestry Centre, Edmonton, Alberta.

Parisien MA, Dawe DA, Miller C, Stockdale CA, Armitage OB (2019) Applications of simulation-based burn probability modelling: a review. International Journal of Wildland Fire 28, 913–926, 10.1071/wf19069