FIRO: A Deep-neural Network for Wildfire Forecast with Interpretable Hidden States

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Abstract

Several wildfire danger systems have emerged from decades of research. One such system is the National Fire-Danger Rating System (NFDRS), which is used widely across the United States and is a key predictor in the Global ECMWF Fire Forecasting (GEFF) model. The NFDRS is composed of over 100 equations relating wildfire risk to weather conditions, climate and land cover characteristics, and fuel. These equations and the corresponding 130+ parameters were developed via field and lab experiments. These parameters, which are fixed in the standard NFDRS and GEFF implementations, may not be the most appropriate for a climate-changing world. In order to adjust the NFDRS parameters to current climate conditions and specific geographical locations, we recast NFDRS in PyTorch to create a new deep learning-based Fire Index Risk Optimizer (FIRO). FIRO predicts the ignition component, or the probability a wildfire would require suppression in the presence of a firebrand, and calibrates the uncertain parameters for a specific region and climate conditions by training on observed fires. Given the rare occurrence of wildfires, we employed the extremal dependency index (EDI) as the loss function. Using ERA5 reanalysis and MODIS burned area data, we trained FIRO models for California, Texas, Italy, and Madagascar. Across these four geographies, the average EDI improvement was 175% above the standard NFDRS implementation.

1 Introduction

Wildfires have caused billion-dollar disasters [14] and taken the lives of many people [5]. The threat of wildfires has been exacerbated by climate change through more frequent droughts and longer wildfire seasons. An important tool in tackling this problem are wildfire risk index models. Such models are typically driven by atmospheric data (e.g., precipitation, wind, humidity) and are used as an early warning system for people to be evacuated and preventative action taken.

Over the years, several fire index systems have been developed. Examples of index systems are the Canadian Forest Service Fire Weather Index Rating System (FWI) [16], the Australian McArthur rating systems (Mark 5) [13] and National Fire-Danger Rating System (NFDRS) [8]. These index systems are based on both physical and empirical conditions and, to this date, are used to generate risk maps which inform agencies, individuals and companies the risk in their particular areas (e.g., [1], with source code in [11]).

Internally, these fire index models compute intermediate variables which are combined to produce a set of fire danger indices. These internal variables are meaningful in that they correspond to

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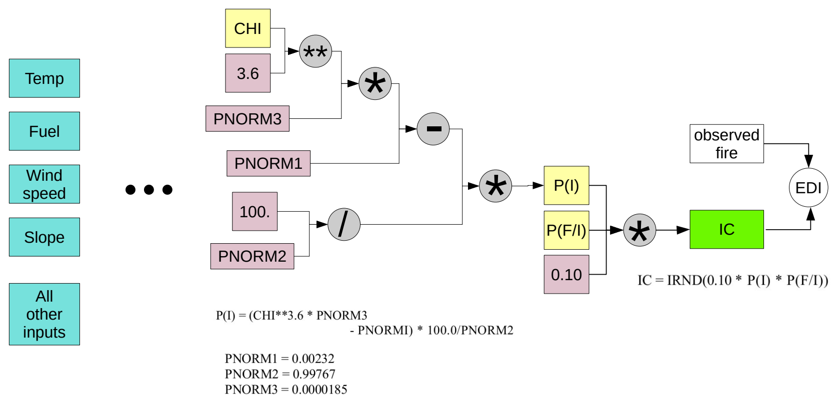


Figure 1: Head of the model. Yellow boxes are intermediate variables, pink boxes are parameters, light blue boxes are inputs, and operations are in grey. The Extremal Dependency Index (EDI) is the optimization criterion (loss function).

(possibly) measurable quantities; e.g., the equilibrium moisture content, which represents the steady state moisture content of woody material, and the slope effect coefficient, among many others. The relations among the internal variables and the indices are established empirically, with parameters that have been estimated throughout the years. These parameters, however, may not be the most appropriate for all regions and future climate conditions. Our hypothesis in this short paper is that we can adjust the internal parameters to best fit the particular regions and current conditions in which one intends to use the wildfire risk indices. This approach has two major advantages: (1) one can train the index models using actual observed fire, but starting with an already proven index, and (2) it preserves the internal variables which are meaningful for wildfire specialists.

In order to test our hypothesis, we implemented the *ignition component* (IC) index of the National Fire Danger Rating System (NFDRS) as a smooth function so that we can apply stochastic gradient descent (SGD) and optimize the internal parameters. This approach is the same as a regular neural network though with the difference that it is not a traditional architecture but a smooth version of a fire index model. In this paper, we present results comparing the unmodified model against a trained model (trained with observed fire from 2010 to 2015) for the period 2016 to 2020 in four separate regions.

2 Model

In order to produce the Ignition Component index, a number of *input variables* is used, such as temperature, relative humidity, vegetation stage, vegetation type, etc. From those, *intermediate variables* are computed. Most of these intermediate variables have concrete meaning and could be measured. For example, dead-fuels moisture, live-fuel moisture variables, reaction velocity, etc. The relations among inputs, intermediate variables, and the final IC index, were estimated in laboratory and field experiments and they are embedded through specific *parameters* in the NFDRS model. The head of the model can be seen in Figure 1 (all relations up to inputs can be found in [7]).

Our hypothesis in this paper is that we can optimize the internal parameters of the IC index so that it better predicts fire danger for particular regions and climate conditions, but keeps the internal variables. The major benefit of this approach is that one can still interpret the internal variables and possibly measure them. In order optimize the internal parameters, we need an optimization criterion and procedure to adjust parameters.

There are many possible optimization criteria (aka loss functions). All of them will compare the prediction (in our case the IC index) with a measure of fire danger and assign a score. However, it is not easy to obtain an accurate measure of fire danger. Therefore, one needs a proxy that may not be perfect but correlates with wildfire risk. Observed fire is obviously the most appropriate proxy, but one needs to keep in mind that a region may experience a high risk of wildfire though no wildfire eventuates. Moreover, fire events are extremely rare compared to non-fire events in a large area over time. This leads to a very unbalanced scenario in which a trivial solution (that is, no-fire ever) will perform statistically very well depending on the optimization criterion. Consequently, a loss function needs to be less dependent on the base rate. We therefore use the extremal dependency index (EDI) [10].

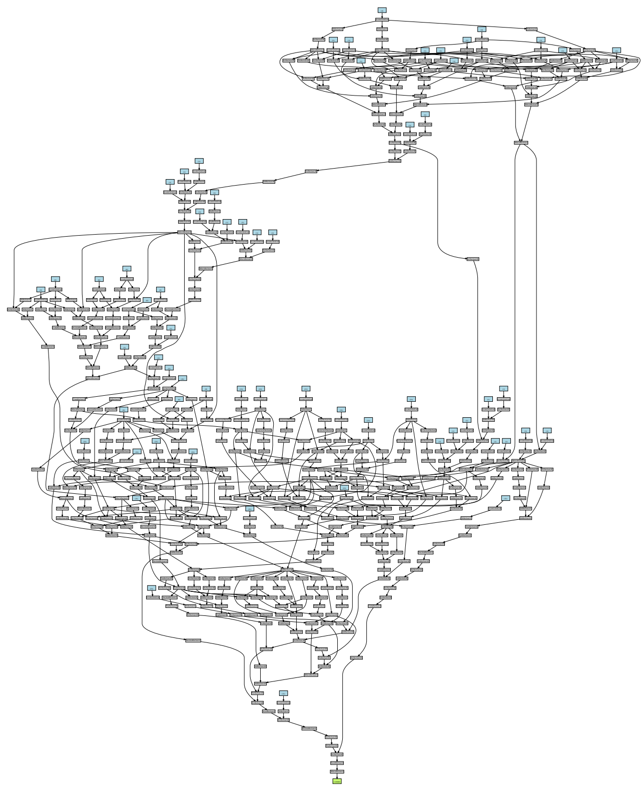


Figure 2: Network architecture illustrating the depth of the model. Green box is the output (IC index), grey boxes are operations, and light blue boxes are inputs. Intermediate variables and parameters are not shown.

As for the procedure to adjust parameters, we use gradient descent and use a validation procedure to avoid overfitting. In order to use gradient descent, we implemented the IC index as a differentiable function with PyTorch [15]. In addition to the sheer size of the model (see Figure 2 where blue boxes are inputs, gray boxes are operations and the green box is the IC index output), implementing the IC computations as a differentiable function poses a few challenges. All of them are related to hard-branches in the original code and infinite or undefined gradients. To tackle these, we make smoother versions of the branches, clip gradients and make constant the parameters which may cause the gradient to be undefined.

3 Evaluation

For the purpose of evaluating our model, we compared the original IC index with a trained model. The training data is daily and goes from November 2000 to 2015, and the testing data, also daily, from 2016 to 2020. We computed EDI for California, Texas, Madagascar and Italy in the testing set to make our comparison.

Weather input data (temperature, RH, wind speed, cloud cover and precipitation) comes from the ERA5 reanalysis dataset. We did not use forecasted weather data so as to avoid errors in the forecast that would impact the performance of the index (both trained and original). Consequently these results represent the potential predictability of wildfire. Climatic zones were obtained from [6], the

USA fuel map from [2] and the Europe fuel map [11], slope was obtained from [3], vegetation cover is built from the GLCC dataset [12], and vegetation stage classes are derived from [4]. Finally, fire observations are obtained from the MODIS/Terra+Aqua Burned Area Monthly L3 product.

All datasets were placed in the same resolution of 25km over the same grid points. This resolution is the same as the results presented in [9]. Continuous variables were interpolated linearly, while classes were interpolated by nearest neighbors.

In order to evaluate the skill, the observed fire dataset was pooled into the same resolution as the input, i.e. if at least one fire event is observed in the original resolution, the resulting grid point in the target resolution will record a fire. In addition, a fire prediction in a neighboring grid point where fire did not occur counts as hit (using the "fuzzy" pixel strategy as has been done in [9]).

A fire is forecast when the IC index value is above the median of the index distribution. The median of the index distribution has been previously computed from the training set. This forecast along with the observed fire dataset is fed into the EDI function for evaluation.

Results can be seen in figs. 3 to 6 for California, Texas, Italy, and Madagascar respectively in the Appendix A. The first sub-figure in that sequence represents EDI for the untrained model (the original NFDRS IC index), the second sub-figure has EDI for the trained model (the optimized NFDRS IC index), and the last sub-figure is the difference between trained and untrained. EDI can take values from 1 to -1, and one representing perfect forecast and 0 for random forecast.

Overall one can see improvements of the model skill over most of the areas in the testing set. Particularly, for California in Sierra Nevada and Central Valley, the skill improves compared to the baseline. At the extreme south, however, the trained model performs worst. This region, nevertheless, has few fire events in the testing set (now shown), so we hypothesize this is due to outliers. The Italy map shows similar behavior in which most places show improvements. Texas has more mixed results. The original (untrained) model is close to random, with just a few good places mainly in the Edwards plateau. The trained model improves skill in sparse areas in the north but at the cost of some other areas also in the north.

One possible explanation for the mixed results over Texas is the input data. Fuel maps have a large impact on the IC index as well as vegetation stage. Our model can in principle be used to optimize input maps by using gradient descent all the way up to the inputs and adjusting them as if they were parameters. We are not exploring this idea in this paper however.

4 Final remarks

Fire indices have been used worldwide to tackle wildfire. These models have been developed over many years as a mixture of physical and empirical models. Internally, they have many meaningful variables which can be measured and interpreted by experts.

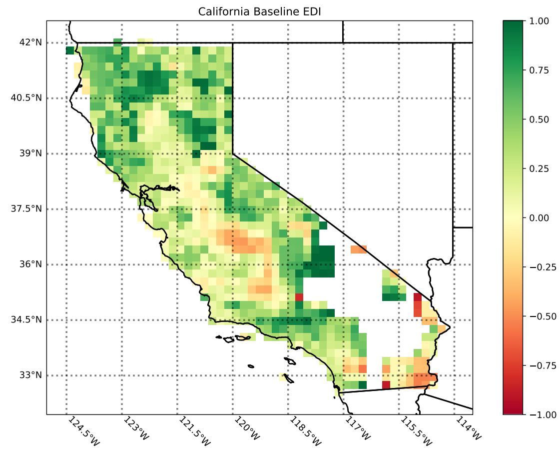
In this paper, we presented a new approach for fire indices. Our hypothesis is that the parameters that relate internal variables and indices may not be the most appropriate as climate changes. Consequently, one can find better parameters in the space of all possible values.

In order to search the space of parameters for specific regions, we propose to recast an existing model as a differentiable function, similar to a neural network. However, instead of a meaningless hidden layer, our model has the same internal variables as the original model we implemented. Consequently, our index preserves the meaning of the internal variables.

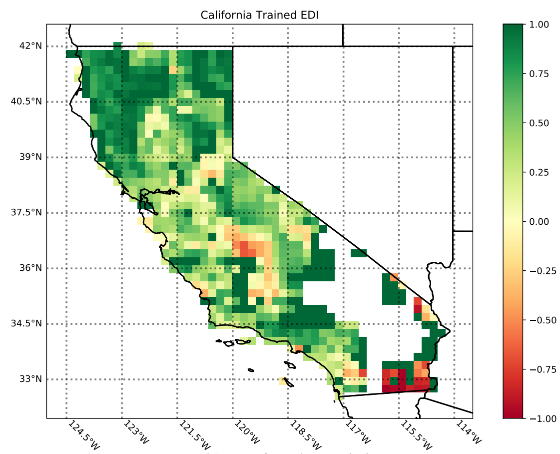
To evaluate our model, we ran experiments over three separate regions: California, Texas, Italy and Madagascar. Skill improved in most places when using the trained model. In addition, the resulting parameters differ among the regions indicating they adjusted to the particularities of the specific location. We intend to evaluate with experts the meaning of the adjustments found by the optimization procedure. We also intend to explore constraints to the parameters, so that the range in which the internal parameters vary does not go beyond what is coherent. For this, however, we will also need expert knowledge. Altogether, our strategy is intended to be used in close partnership with experts, enhancing their ability to explore changes to the model, but relying on them to provide meaning.

A Appendix

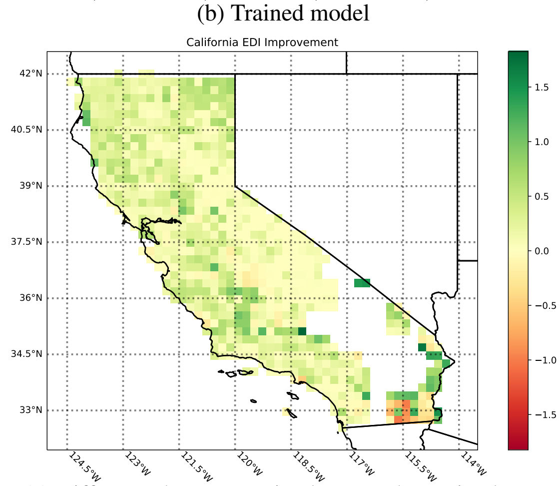
Comparison between the Extremal Dependence Indices (EDI) of the original untrained Ignition Component (IC) of the National Fire-danger Rating System (NFDRS) and IC trained with Fire Index Risk Optimizer (FIRO).



(a) Untrained model

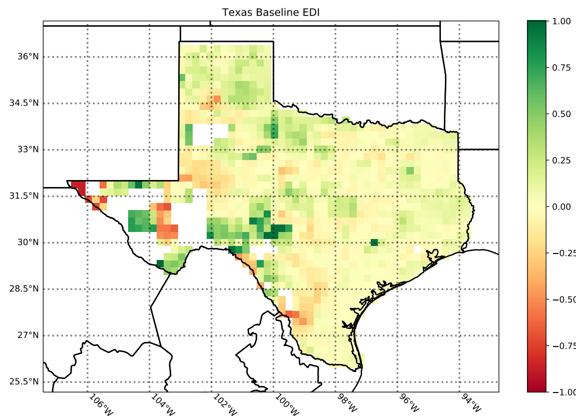


(b) Trained model

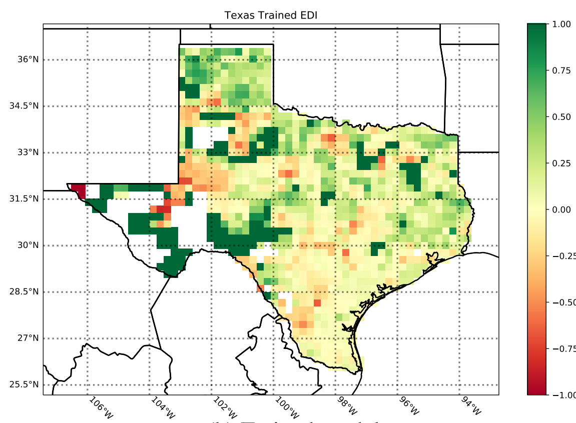


(c) Difference between trained EDI and untrained EDI

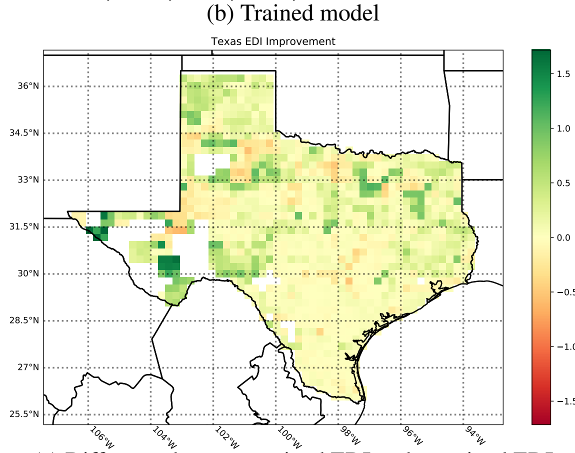
Figure 3: Evaluation of IC for California over the period from 2016 to 2020 (training set from 2000 to 2015)



(a) Untrained model

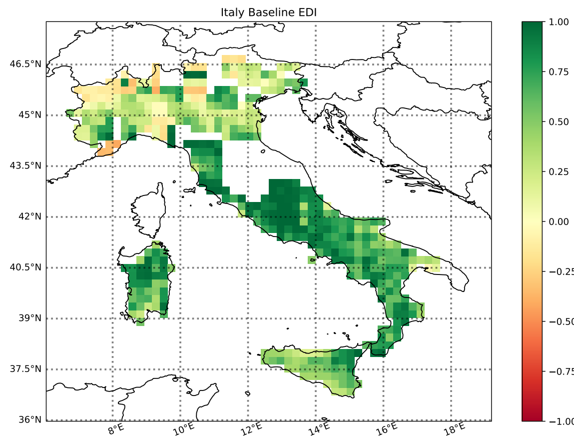


(b) Trained model

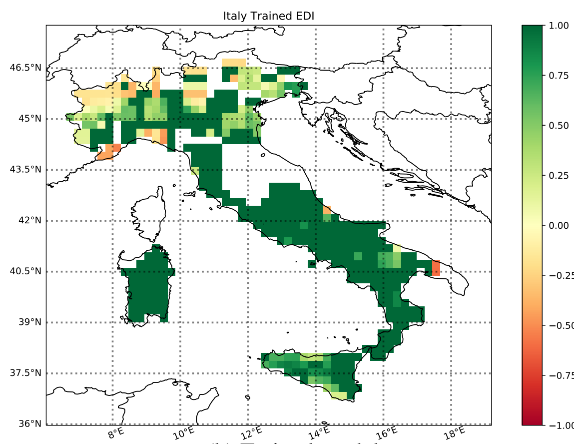


(c) Difference between trained EDI and untrained EDI

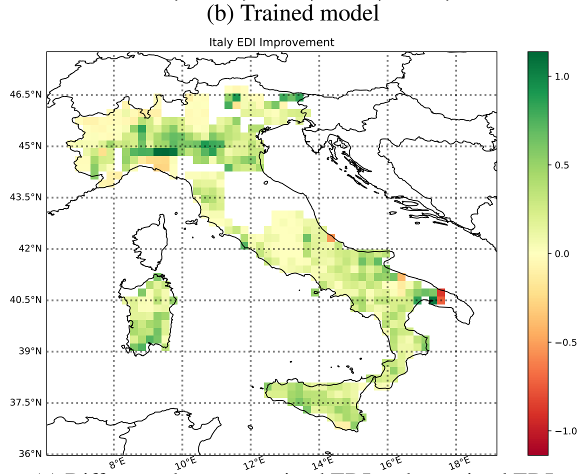
Figure 4: Evaluation of IC for Texas over the period from 2016 to 2020 (training set from 2000 to 2015)



(a) Untrained model

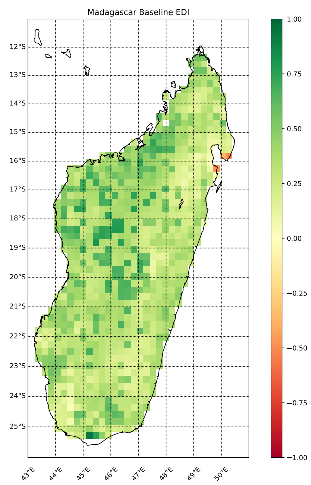


(b) Trained model

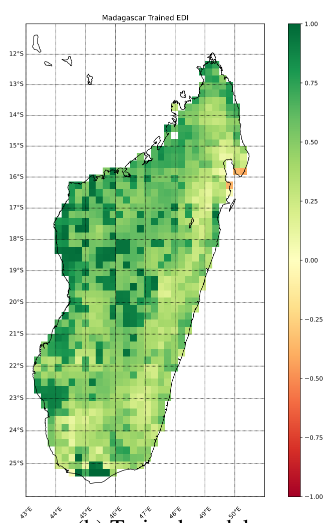


(c) Difference between trained EDI and untrained EDI

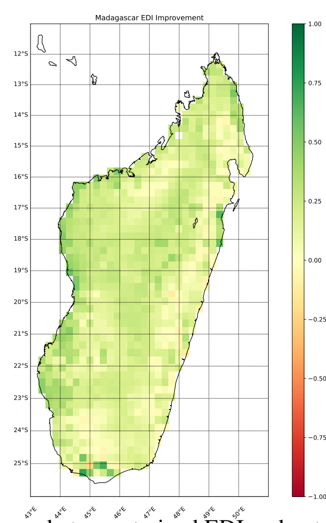
Figure 5: Evaluation of IC for Italy over the period from 2016 to 2020 (training set from 2000 to 2015)



(a) Untrained model



(b) Trained model



(c) Difference between trained EDI and untrained EDI

Figure 6: Evaluation of IC for Madagascar over the period from 2016 to 2020 (training set from 2000 to 2015)

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