Deep Learning Methods for Daily Wildfire Danger Forecasting

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Problem Formulation

- We use historical Earth observation and modern Machine Learning (ML) methods data to predict next-day's fire danger.
- We implement a variety of Deep Learning (DL) models which capture the spatial, temporal or spatio-temporal context of the input, which is important for the problem at hand [1].
- We model the joint probability that a fire ignites and becomes large (>30 hectares)

Challenges

Wildfire forecasting is not a typical ML problem and poses some major challenges that need to be considered:

- Wildfires caused by the **complex spatio-temporal interactions** of the fire drivers (climate, vegetation, human activity)
- Wildfire **occurrence is inherently stochastic**. The lack of a fire event does not mean lack of fire danger.
- Wildfires are rare events, leading to **dataset imbalance**.

Datacube

We **create and publish** a harmonized **1 km x 1 km x 1 day** datacube covering most of **Greece for years 2009-2020** [2], with variables that affect fire danger, and the historical burned areas:

Weather Data (min/max 2m temperature, min/max wind components, max total precipitation), **MODIS Satellite variables** (Fpar, LAI, Day/Night LST, NDVI and EVI), **Road Density**, **Population Density**, **Corine Land Cover**, **Topography Variables** (elevation, aspect, slope), post-processed **Historical Burned Areas** (EFFIS [3]).

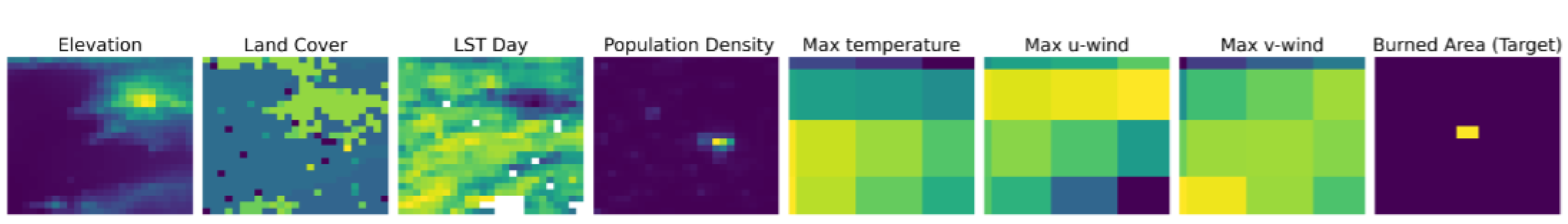

Figure 1: Visualization of some of the datacube variables

Experimental Setup

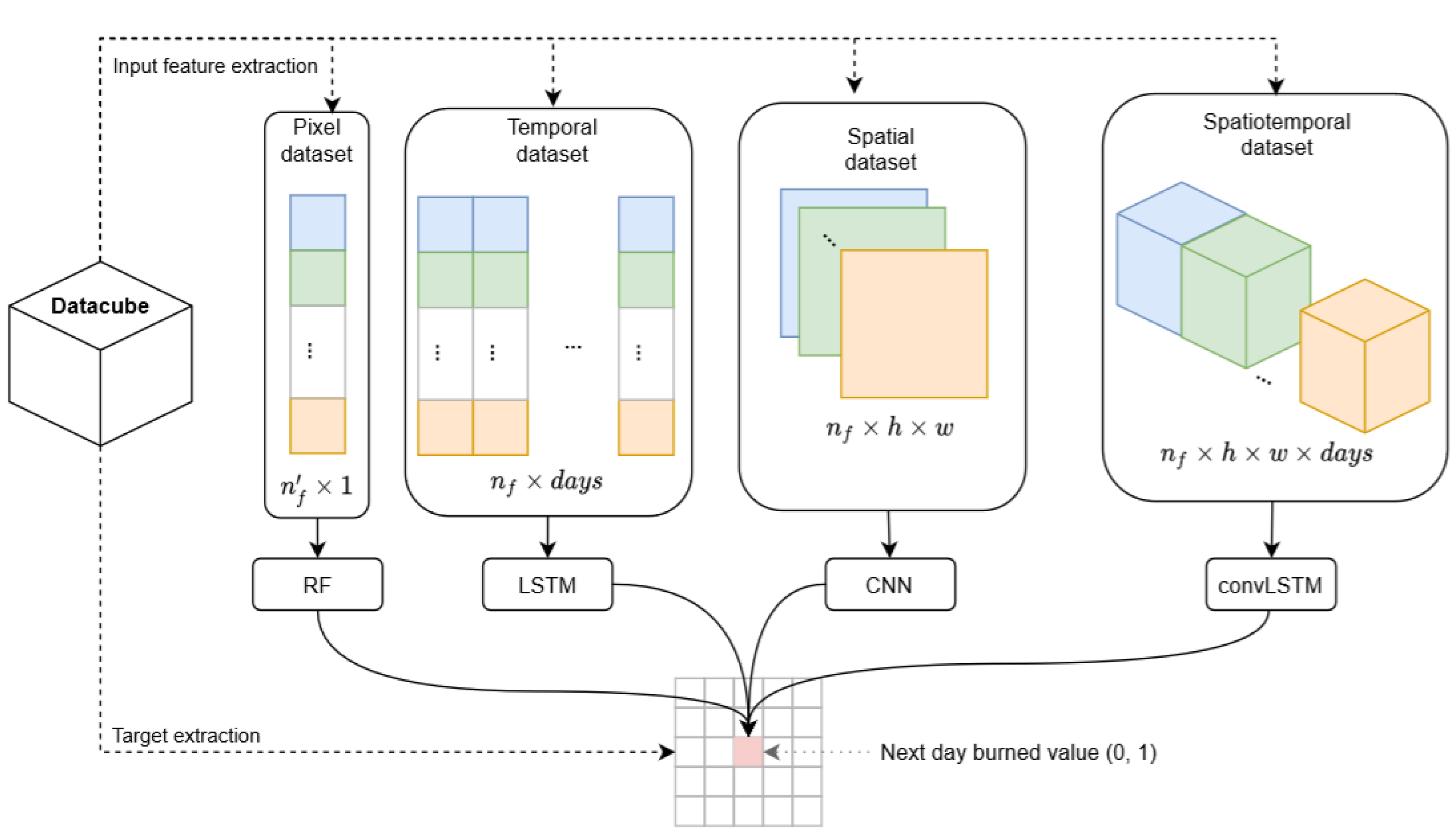

Figure 2: Dataset extraction and experimental setup

- From the datacube we extract four different types of datasets and apply a different model for each (Figure 2).
- Target is for all types of datasets the same; the next-day's burned value.
- Positive/Negative Sampling: Positives are all included. Negatives are two times more than the positives on days with no fire events.

Results

Model	Precision	Recall	F_1	AUROC
RF	**0.832**	0.508	0.631	0.898
LSTM	0.741	**0.762**	**0.751**	0.920
CNN	0.732	0.553	0.63	0.910
ConvLSTM	0.798	0.646	0.714	**0.926**

Table 1: Performance of the models on the test set (year 2020)

- All models achieve a good performance with $AUROC \approx 0.9$
- LSTM has a balanced performance between precision and recall.
- Best AUROC with ConvLSTM that exploits both spatial and temporal context.

Danger Maps

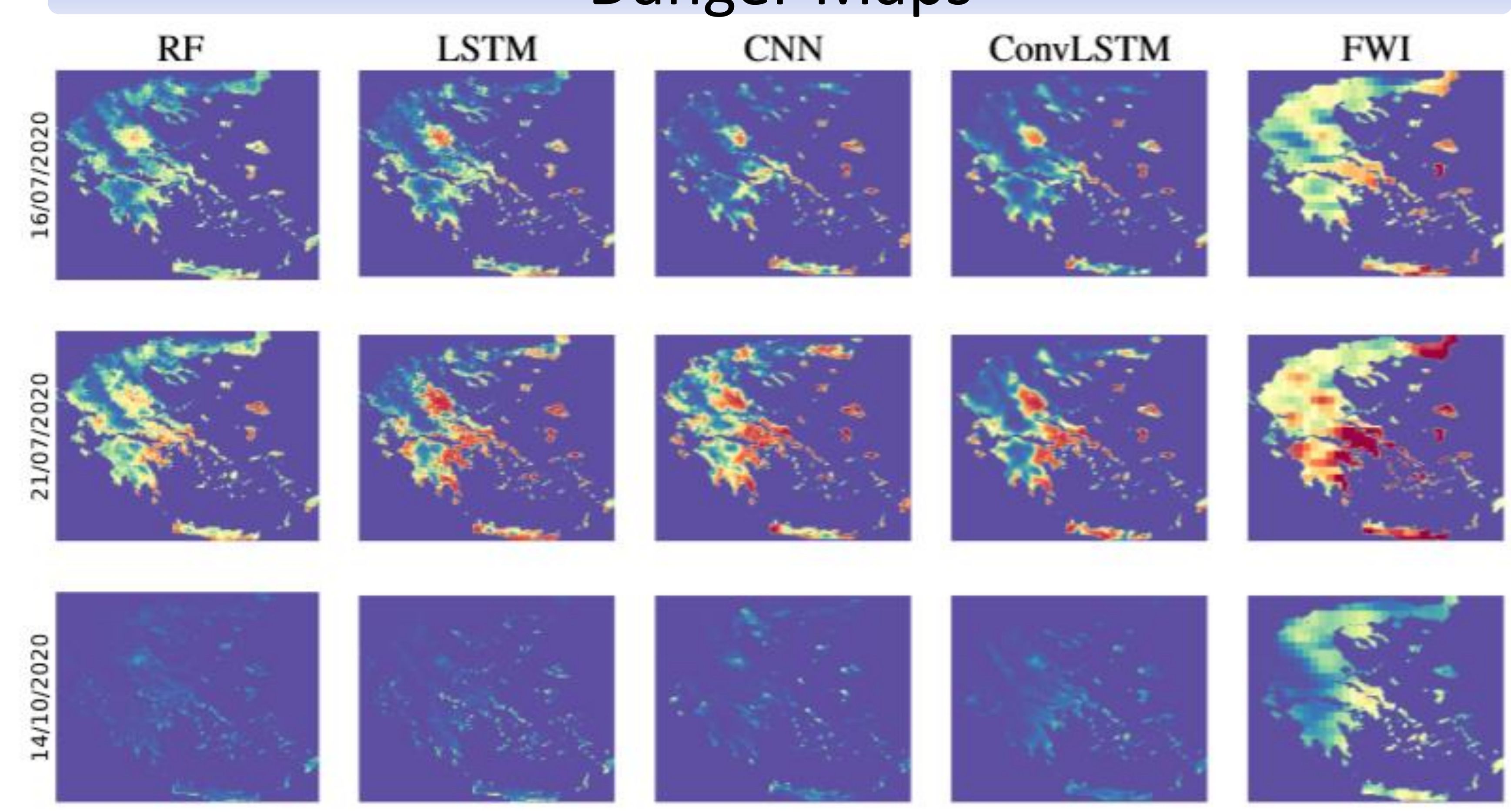

Figure 3: Fire danger maps and FWI (Fire Weather Index) for three different test days

- Data-driven models follow the FWI empirical model.
- Fire danger maps from ML models provide better susceptibility patterns than FWI that only considers meteorology.
- Differences between models are subtle and are not captured by the metric table.

Conclusion

- We formulated daily fire danger forecasting as a machine learning problem and published a harmonized country-wide datacube.
- We implemented some simple, yet effective DL models.
- We demonstrate that DL can be used for wildfire forecasting.

Further Research

- Scale to larger area (e.g. Mediterranean).
- Refine evaluation metrics to quantitatively compare models.
- Understand models' predictions with explainable AI methods.

References

[1] Reichstein et al. Deep learning and process understanding for data-driven Earth system science. *Nature (*2019)

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[3] San-Miguel-Ayanz et al. The european forest fire information system in the context of environmental policies of the european union. *Forest Policy and Economics.* (2013)

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