ML-based fire hazard model trained on thermal infrared satellite data

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A global problem

Wildfires

About 10% of global CO_2 emissions

Hundreds of direct and thousands of indi human fatalities

Destroyed ecosystems and natural habitats for animals

Tens of billions in economic damages

Data Gathering Mission

OroraTech

Yesterday

Founded in 2018 as a spin-off from Technical University of Munich.

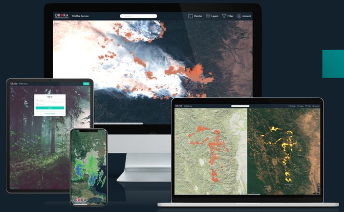
Today

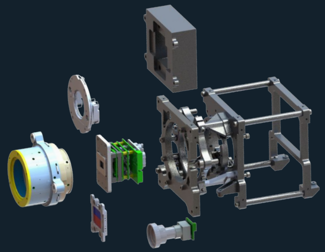
Combining over 20 external satellites for the best wildfire monitoring system.

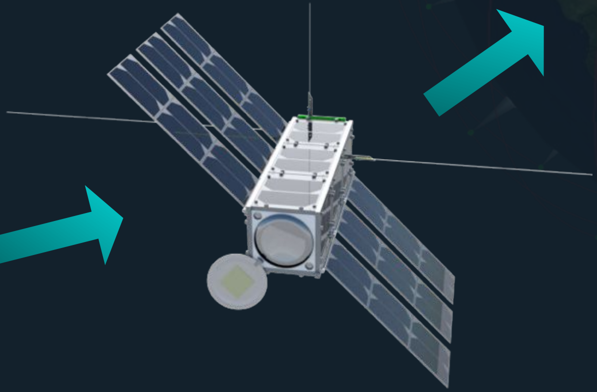
Launching our own satellites with thermal infrared & RGB imaging, FOREST-1 in orbit since Jan 22

Tomorrow

Having a full constellation of >100 nano satellites in orbit







Problem statement Fire Risk

“Fire Risk”

wishlist

High spatial resolution

High temporal resolution

Focus on buildings

Focus on forests

Local

global

vs.

Computation

Reasonably sized datasets

Reusable code

Fast model training, fast inference

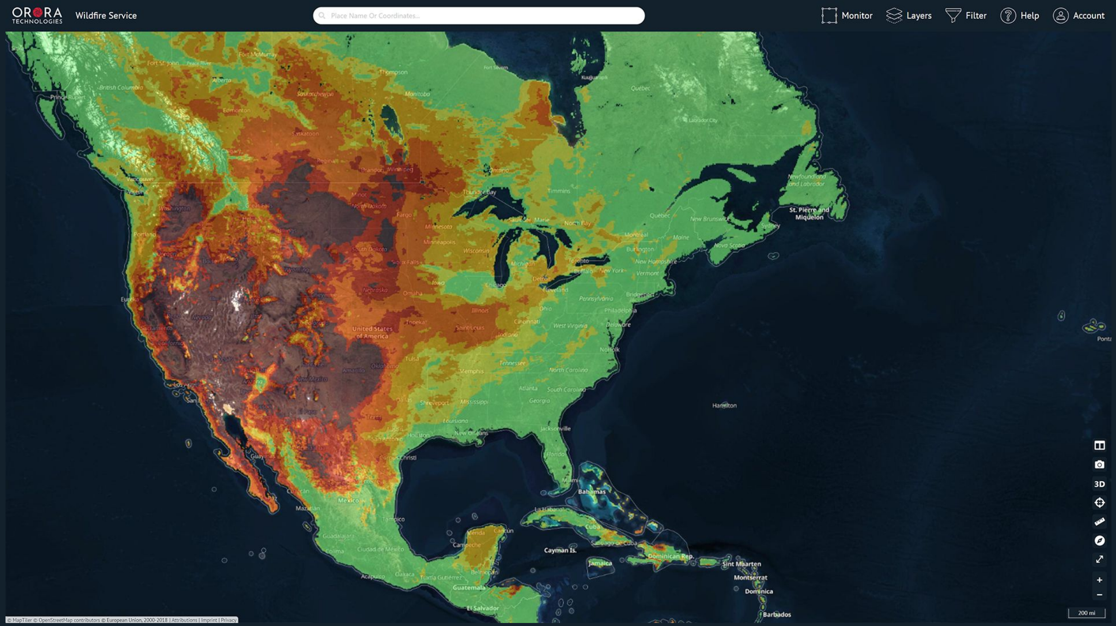
generalize well across many land use types

generalize well across many locations

Problem Statement: Status Quo

FIRE HAZARD / RISK MODELLING

BEFORE | DURING | AFTER



Problem Statement

Machine Learning Approach

Goal: Predicting next weeks fire risk.

- Multivariate model
- Dynamic (learning) from historic active fire data
- Using our data in the future as a unique ground truth to update model near real time

ML Approach

1. **Baseline**: Emulating Fire Weather Index via Regression
2. **Classification**: Active fire
3. **Transfer**: to ICON weather forecasts (= Fire Risk Forecast)

Problem Statement

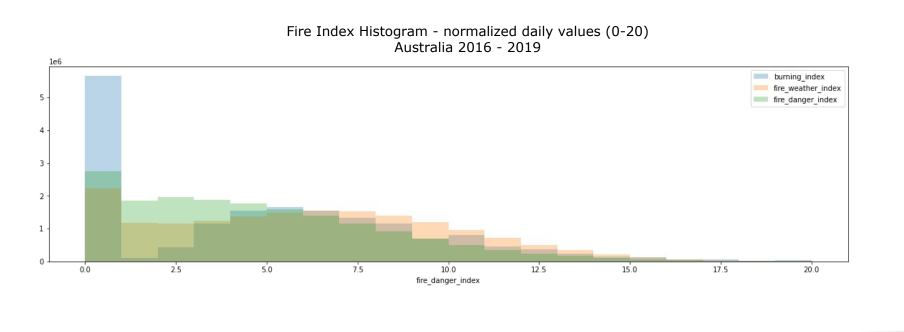
Region of Interest

- Region: Australia
- Time range: 4 years (2016-2019)
- Resolution: 0.1 x 0.1 deg

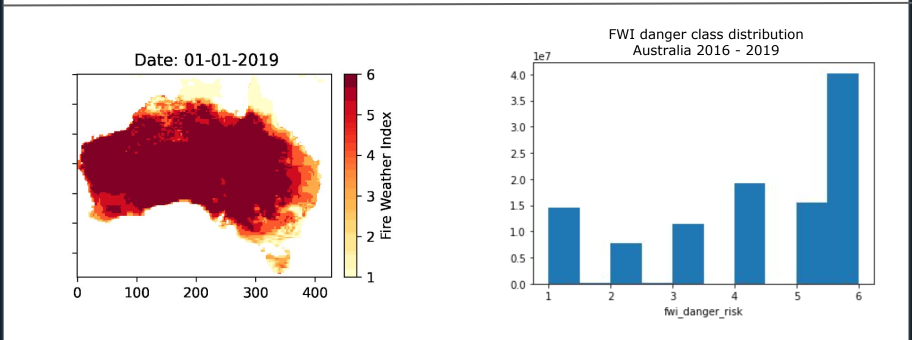
Baseline: Emulating FWI via Regression

Q: Is it possible to emulate an existing fire risk index via ML?

Target - Fire Weather Index (FWI)



Available fire indices from the Fire danger indices historical (Copernicus Emergency Management Service) perform similar on the area of interest



Danger rating: reduced FWI to 6 classes of danger, accordingly to EFFIS danger class levels definition (very low, low, medium, high, very high and extreme).

Source: climate data store

Baseline: Emulating FWI via Regression

Input Data

Input vars: ERA5 ‘sp', 't2m', 'skt', 'v10', 'u10', 'tp'

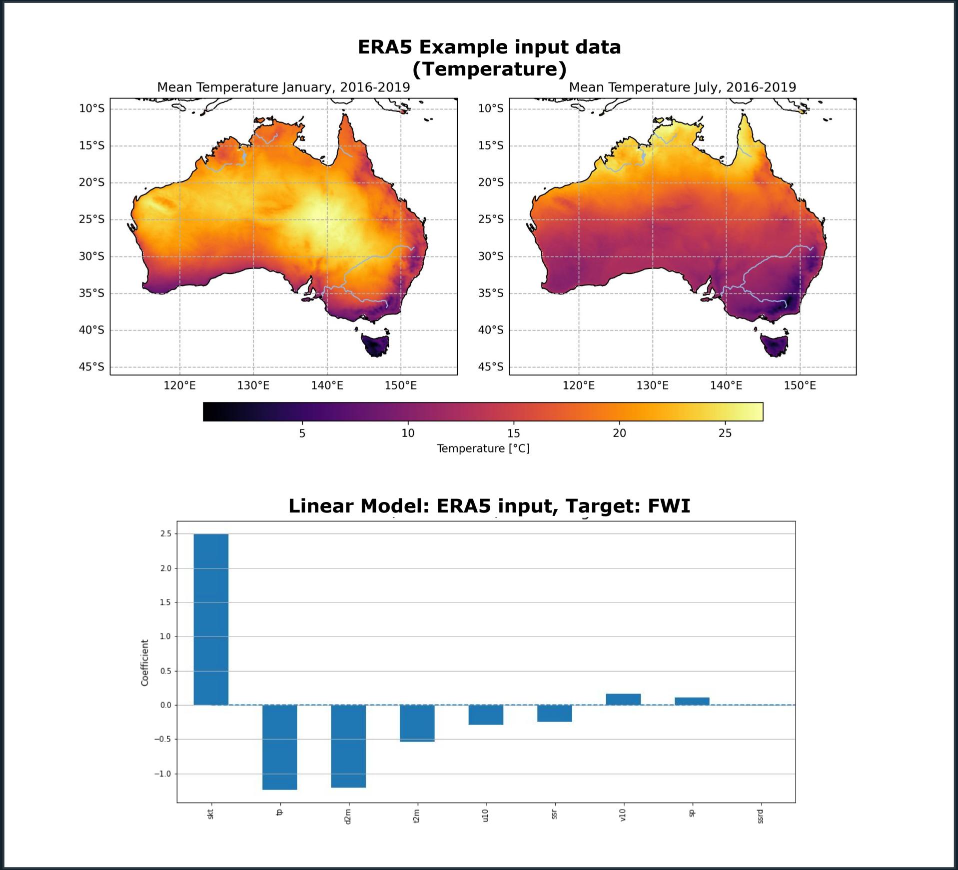
- 2 m temperature
- skin temperature
- 2 m dew point temperature
- 10 metre U & V wind component
- surface pressure
- total precipitation

Input sequence: 3 days

Target variable: FWI

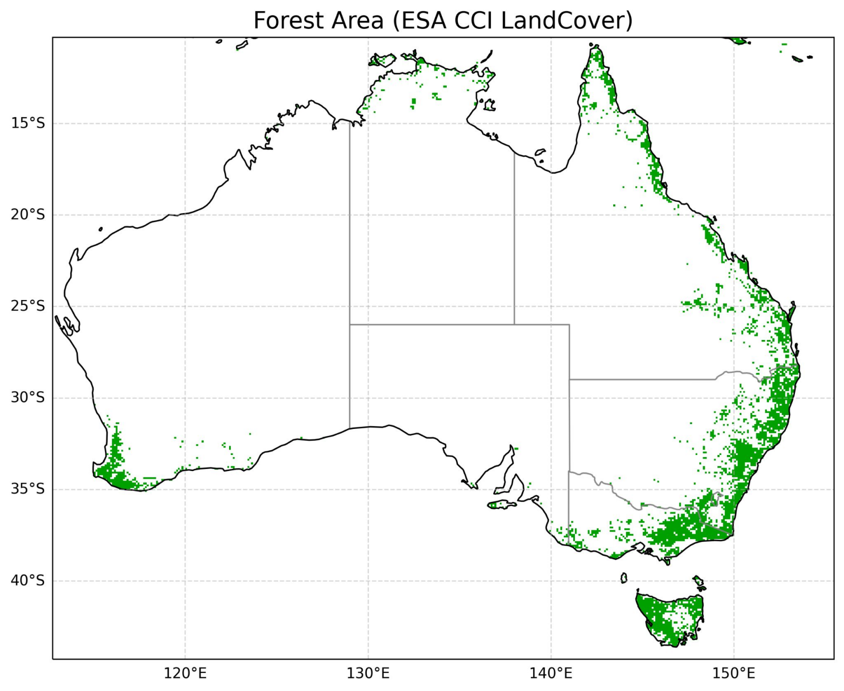
Feature Selection:

- linear model coefficient analysis
- Overlap with ICON weather forecast data



Input Data

- Optional: ESA CCI Land Cover classification maps



Model types

Pixelwise classification

Keras: Dense, CNN, LSTM with Sequential pixelwise input

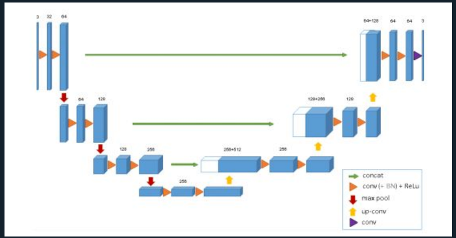
`Input shape:  [num_samples, seq_len, features]`

Segmentation-based approach

Torch: 3D Unet:

`Input shape: [features, seq_len, height, width]`

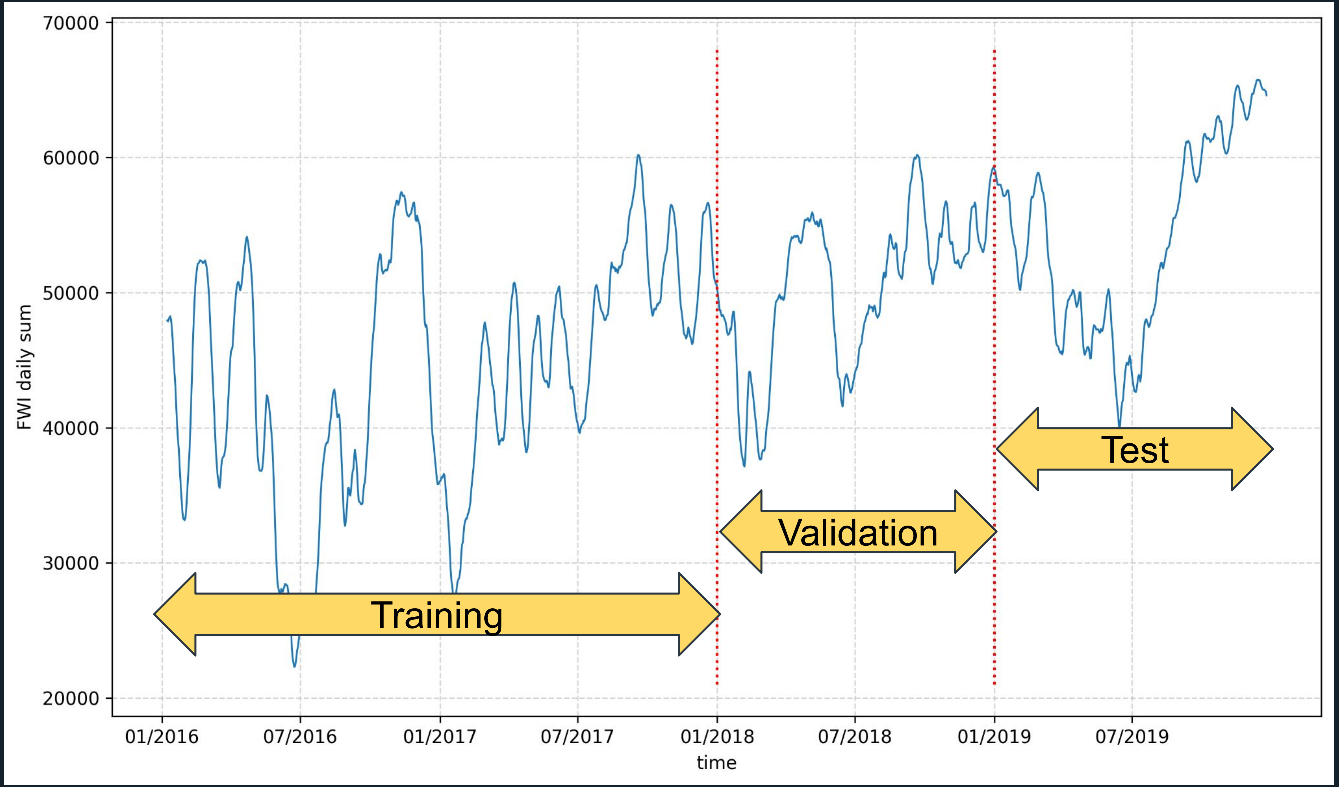
[Wolny et. al, 2020]



Evaluation Strategy - Regression (Target: FWI)

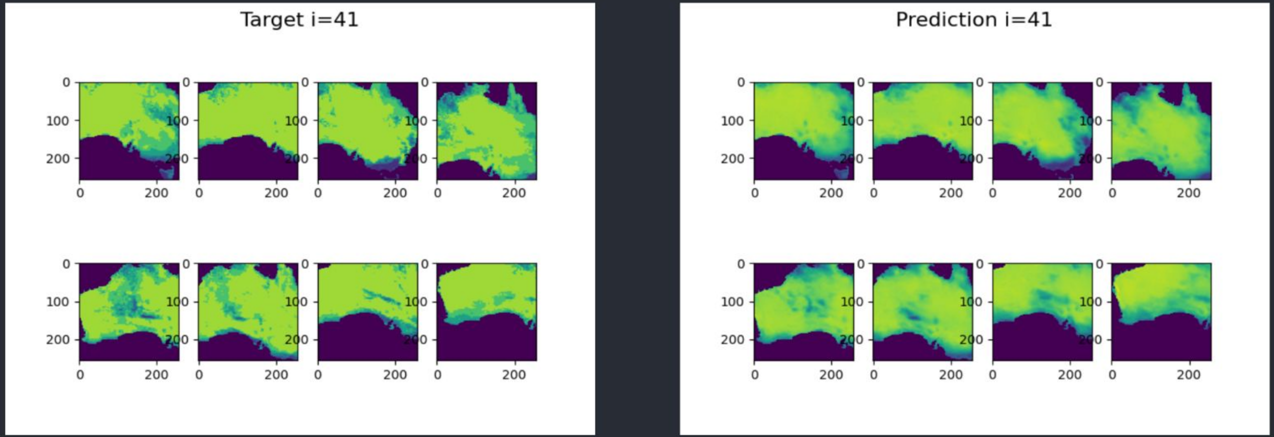
Time-based

Evaluation split



Emulating FWI via Regression - results

Model Type	MSE on test
Dense (pixelwise)	0.035
3D UNet	0.088

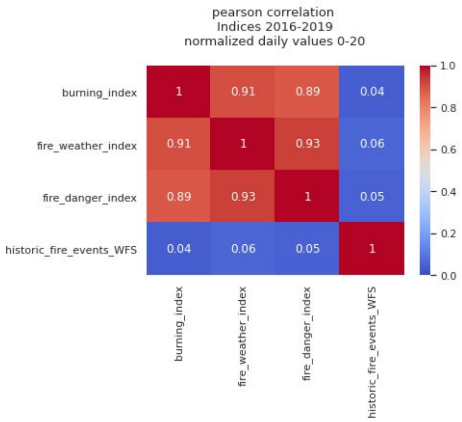


Active fire classification

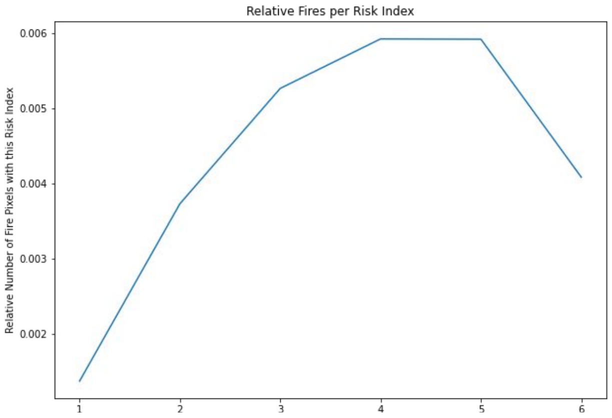
Q: Can a DL model learn “fire risk” from highly imbalanced active fire data?

Motivation

Comparison between active fires + fire risk indices



Comparison between active fire class 1 + FWI danger classes Australia, 2016-2019



Classification: Active fire

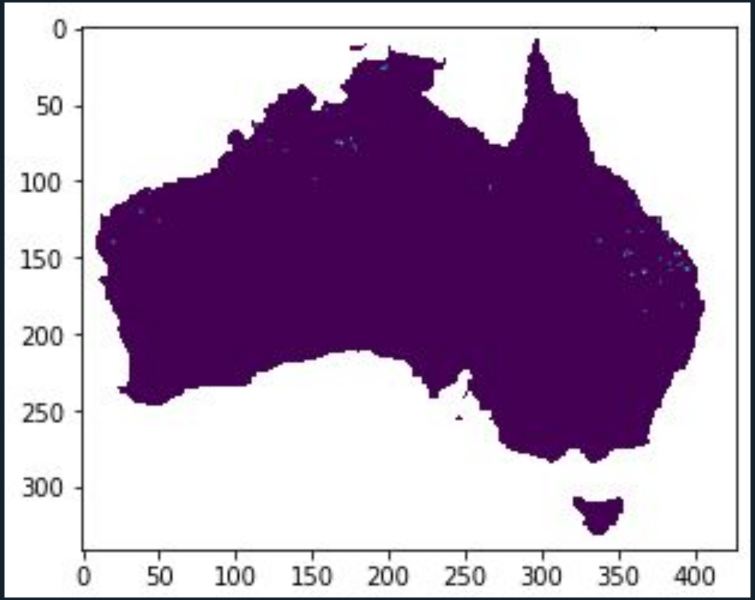
Time range: 4 years (2016-2019)

Resolution: 0.1 x 0.1 deg / Timestep: daily

Input vars: ERA5 ‘sp', 't2m', 'skt', 'v10', 'u10', 'tp'

Input sequence: 3 days

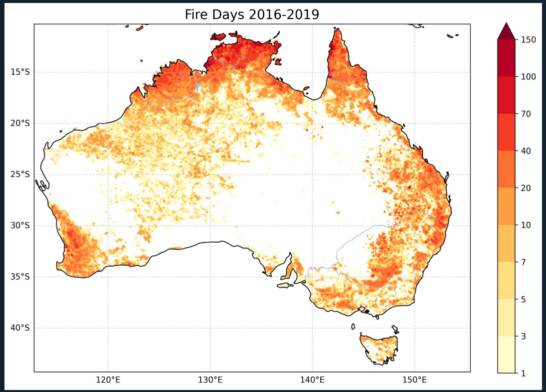
Target variable: active fire (binary)

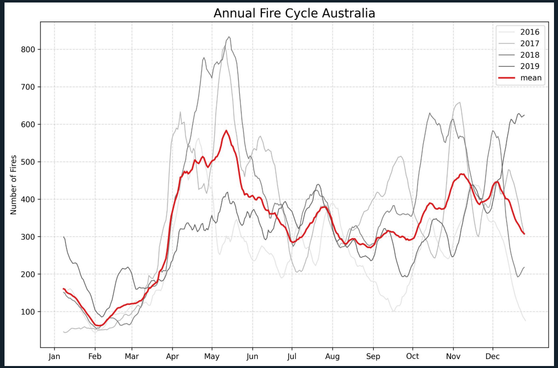


Active Fire classification based on thermal infrared data

Labels - Active Fires

- Active fire detections from satellites(Aqua, Terra, Suomi-NPP)
- Only hotspots that have been detected by at least 2 satellites are taken into account
- Hotspot clustering (concave hull)
- Rasterization of fire cluster perimeters to ERA5-Land spatial resolution (0.1°x0.1°)





Model types

Pixelwise classification

Keras: Dense, CNN, LSTM with Sequential pixelwise input

```
Input shape:  [num_samples, seq_len, features]
```

Sklearn: HistGradientBoosting

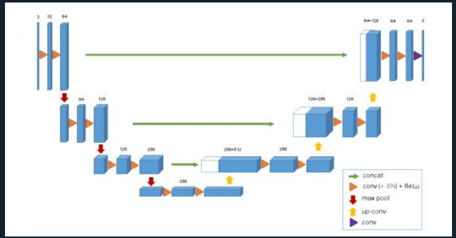
```
Input shape:  [num_samples, features * seq_len]
```

Segmentation-based approach

Torch: 3D Unet:

```
Input shape: [features, seq_len, height, width]
```

Wolny et. al, 2020



Evaluation Strategy - Classification (Target: active fire)

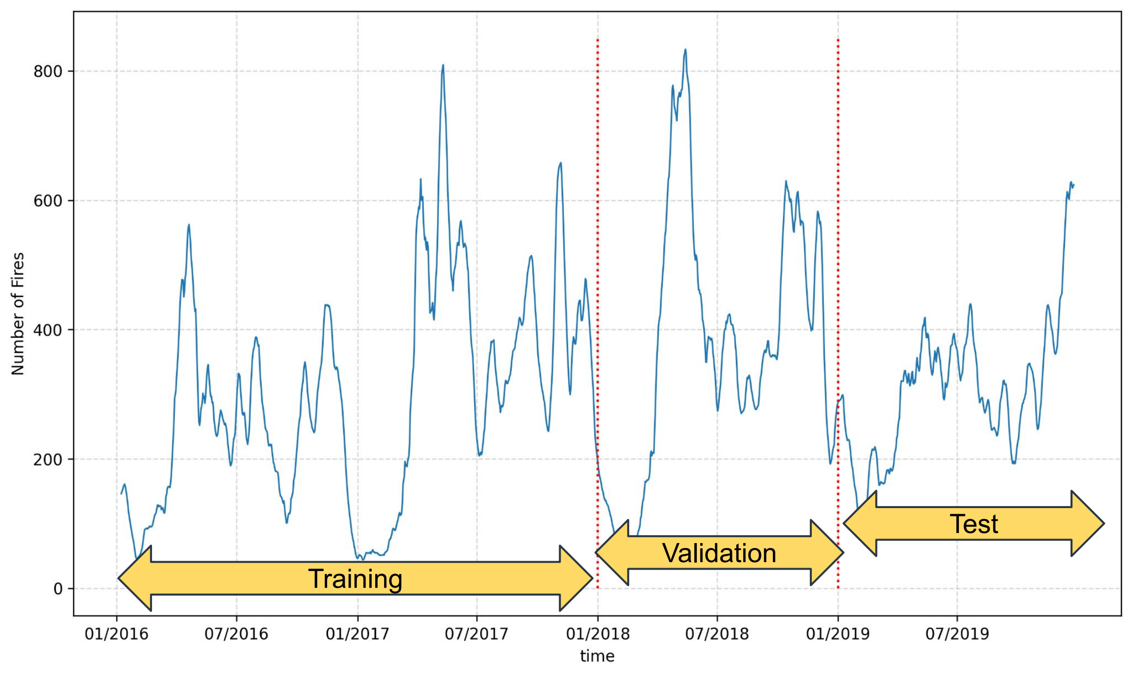
Evaluation split for active fire:

Split Statistics - high imbalance:

train : class counts: 0: 99.90%, 1: 0.10%

validation : class counts: 0: 99.92%, 1: 0.08%

test : class counts: 0: 99.96%, 1: 0.04%



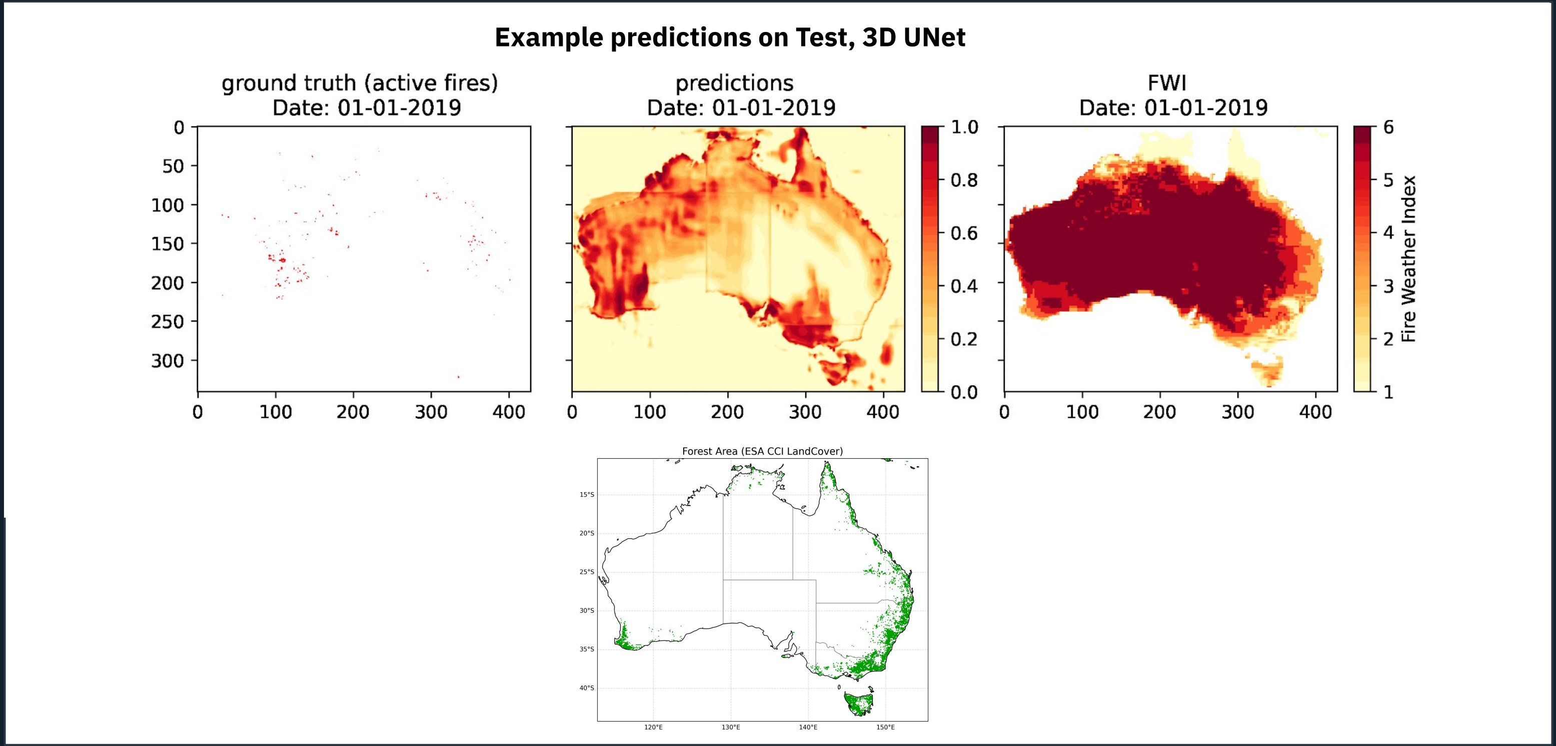
Results - Active Fire

Model Type	F1 (macro-avg)
3D UNet	0.46 (w landcover: 0.40)
HistGradBoosting (pixelwise)	0.45
Dense (pixelwise)	0.28

Example predictions on Test, 3D UNet

Active Fire classification based on thermal infrared data

Results - Active Fire - Compared to FWI



Transfer to ICON weather forecast

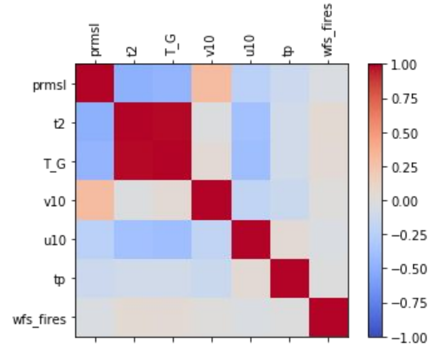
Q: Can we apply the trained DL models on weather forecast data to produce a "fire risk forecast"?

Test Data

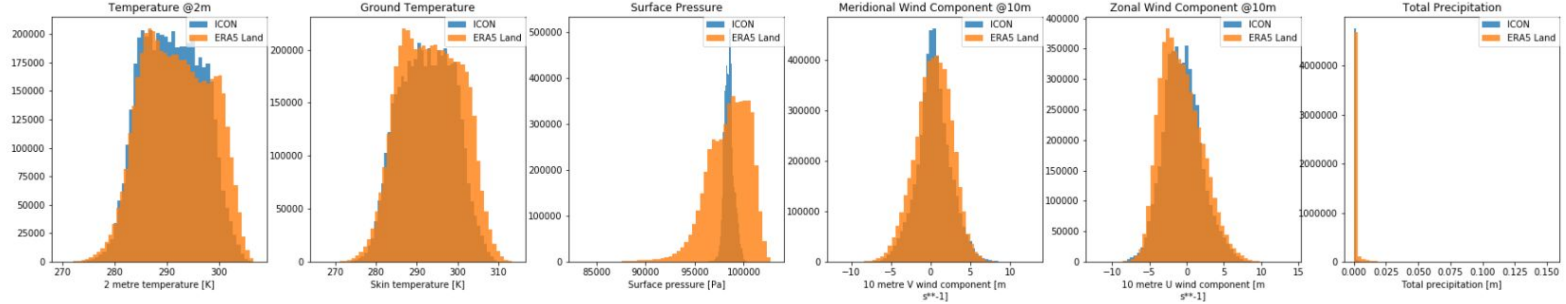
Icon Weather Forecast Data (DWD)

- Daily means from hourly forecasts, avail. up to ~7days
- Regridded to ERA5 grid
- VARS: ['prmsl', 't2', 'T_G', 'v10', 'u10', 'tp']
- Timerange: 2021/07/22 - 2021/09/30
- Fire to non-fire ratio in labels: 0.002719

Correlation, active fires vs. ICON vars, 07/2021 - 09/2021



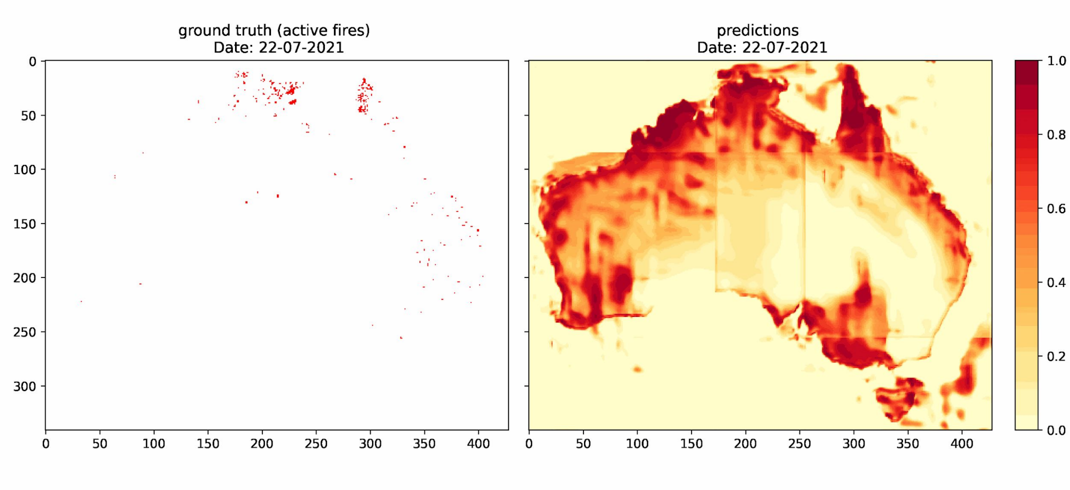
Histogram: ERA5 vs. ICON vars, 07/2021 - 09/2021



Transfer from active fire classification to fire risk forecasting

Inference using ICON data

Model Type	F1
3D UNet	0.50



Outlook / future work

- Expanding input data by DEM, human proximity and lightning as fire source & grouping land cover
- Experimenting with the threshold in active fire classification
- K-fold evaluation over a longer period of time (10 years)
- Using high res weather data to reduce resolution from 0.1x0.1
- 2-headed model: burned area + active fire

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ORORA TECHNOLOGIES

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