Tackling Climate Change with Machine Learning

NeuIPS 2020

“Deep fire topology: Understanding the role of landscape spatial patterns in wildfire susceptibility ”

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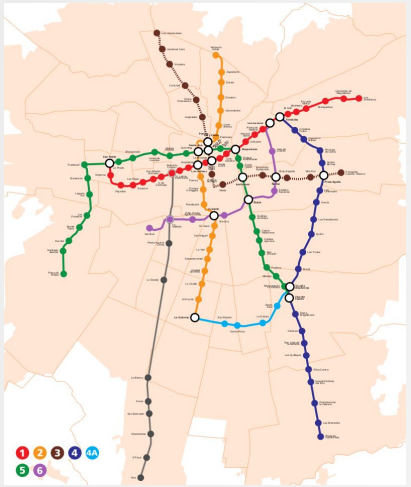
Motivation: landscape topology

- We want to understand how different landscape and rural/urban interface structures impact the potential wildfire risk, in order to provide useful insights to trigger actions to mitigate future expected losses.

- Identify and extract useful topological features that can be used in related models.
- Analyze the role of connectivity, continuity, adjacency, and dispersion of the land cover when predicting future wildfire risk.

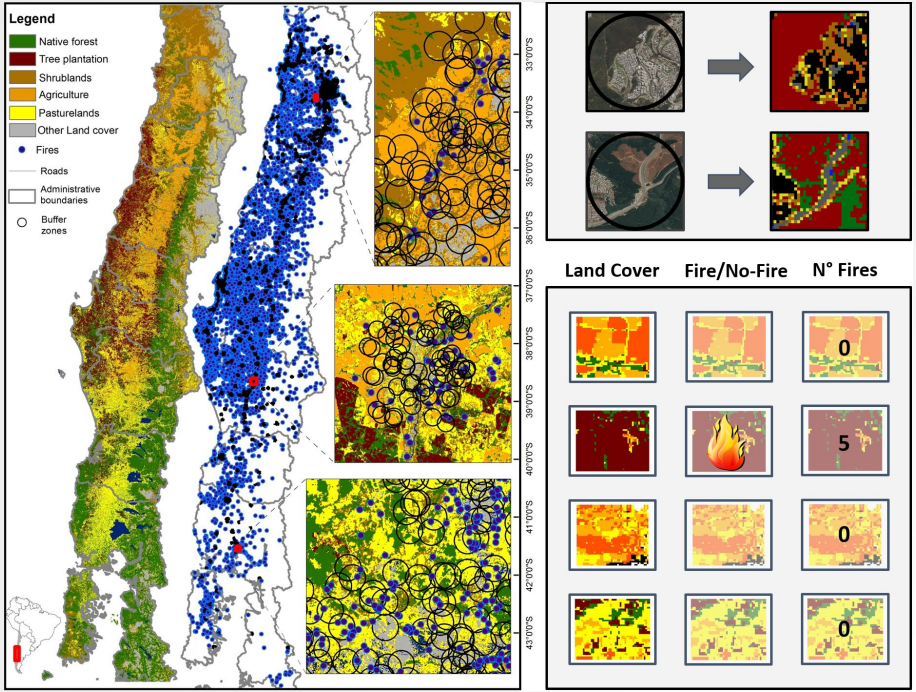
Geometrical

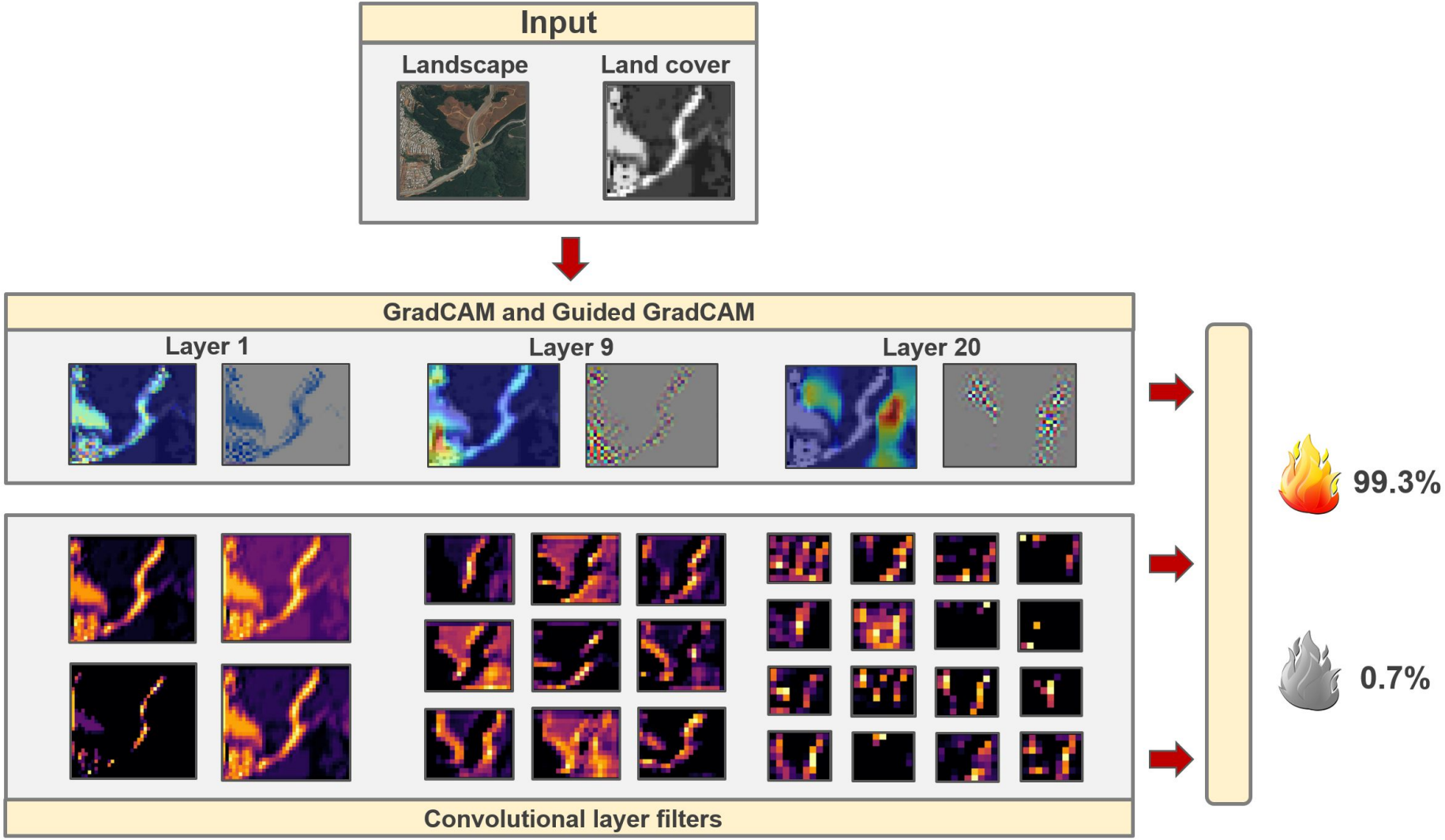


Topological

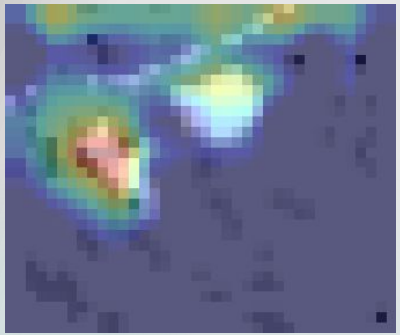
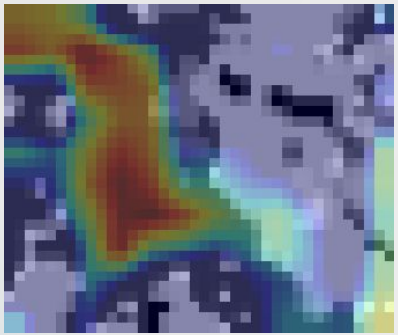
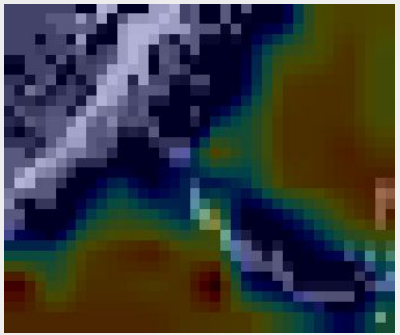
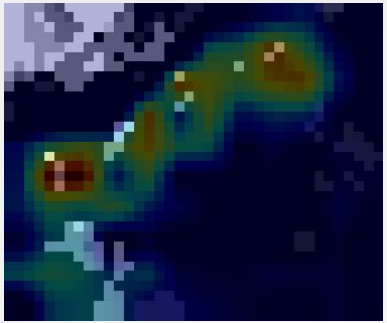
Data mining

- **Dataset**: ~ 18,000 satellite images from Google Earth Engine. Land cover layer obtained from spectral analysis (30m resolution) is transformed into a grayscale 32x32 geotiff file.
- **Location**: south-central Chile (212,000 km2), corresponding to 28% of the country which accounts for 98.5% of the historical fire occurrence.
- **Binary label "*fire*":** Classification label (1: fire positive, 0: negative) between 2013 – 2015.




Input
Landscape
Land cover
GradCAM and Guided GradCAM
Layer 1
Layer 9
Layer 20
Convolutional layer filters
99.3%
0.7%

Risk levels

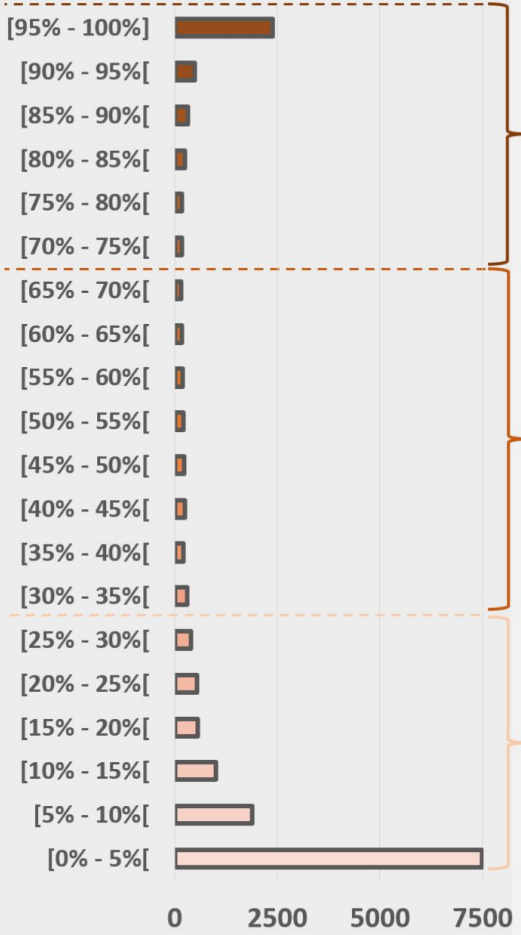





The model is able to determine dangerous/risky topologies based on the combination, adjacency, area covered, and discontinuities of different land-covers in the landscape.

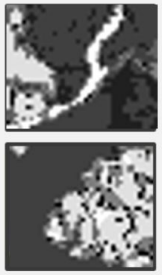
E.g., Dense urban areas with certain grass/trees.

Large areas of continuous flammable land covers

Classification risk frequency



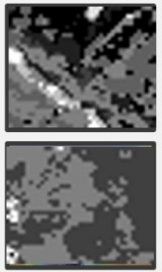
Landscape



Dominant LCs: shrublands (29.6%), grasslands (20.3%)

Components: 118

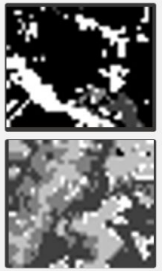
Simpson index: 0.26



Dominant LCs: shrublands (31%), grasslands (22.7%)

Components: 103

Simpson index: 0.29

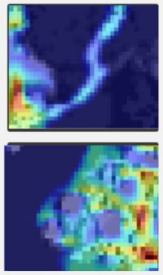


Dominant LCs : shrublands (30%), croplands (26.5%)

Components: 88

Simpson index: 0.39

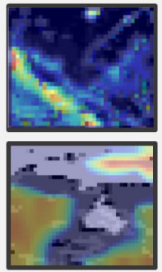
Attention maps



Dominant LCs: shrublands (28%), grasslands (19%)

Components: 45

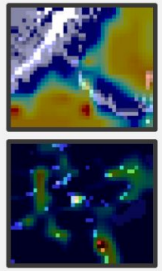
Simpson index: 0.40



Dominant LCs: shrublands (29%), grasslands (22%)

Components: 35

Simpson index: 0.49



Dominant LCs : Croplands (29.2%), shrublands (25.7%)

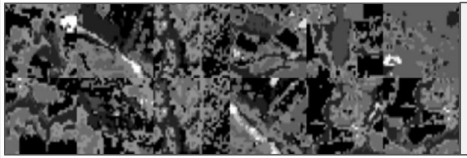
Components: 29

Simpson index: 0.55

Risk analysis: full dataset summary

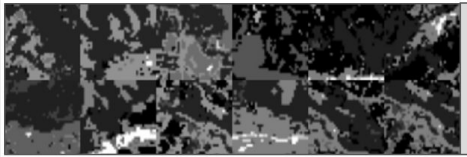
High risk

Low diversity landscapes dominated by forest plantation, agriculture land, and high population density.



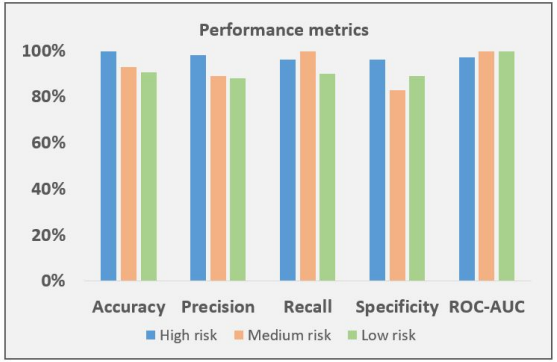
Medium risk

Heterogeneous landscapes characterized by a similar proportion of the most common land covers and low population density.

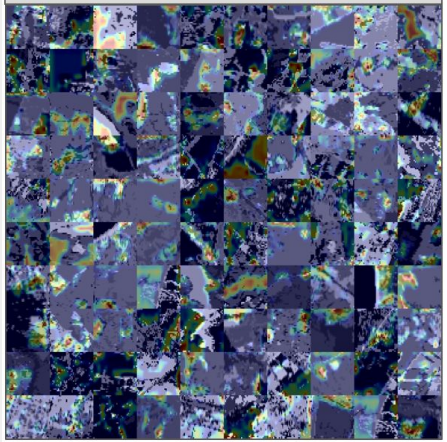


Low risk

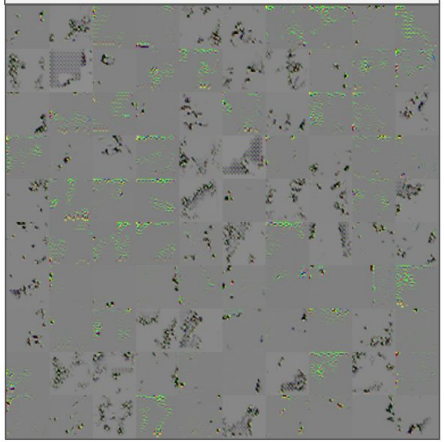
Homogeneous landscapes dominated by native forest and low population density



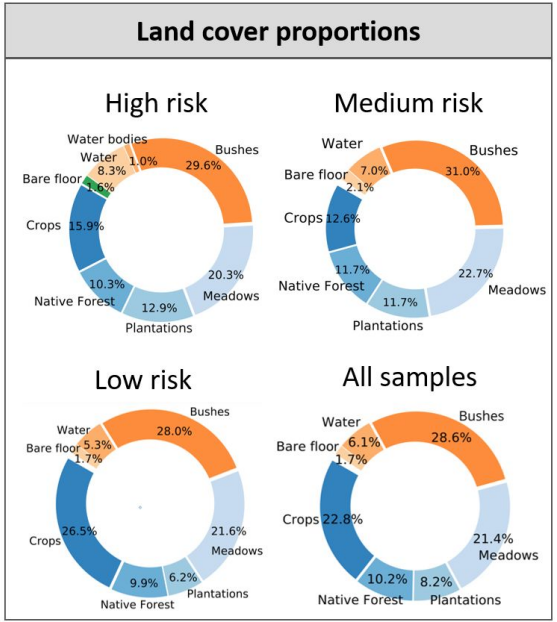
Grad-CAM



Guided backpropagation



Land cover proportions



Future work

- Global implementation results including millions of fires and extra layers (climatic, demographic, etc.) as part of the images or inputs of independent networks.
- Derive/evaluate meaningful and realistic actions to transform high risk landscapes into low risk ones.
- Deploy the open source version in GitHub and Azure services.

Thanks for your attention

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