Convolutional Autoencoder for the unsupervised extraction of fire footprints from Sentinel-1 time-series

Poster · May 2022

DOI: 10.13140/RG.2.2.11886.69449

4 authors:

Thomas Di Martino
CentraleSupélec

Laetitia Thirion-Lefevre
CentraleSupelec

Elise Colin
The French Aerospace Lab ONERA

Régis Guinvarc'h
CentraleSupélec

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Thomas Di Martino[1,2], Laetitia Thirion-Lefevre[2], Elise Colin[1], Régis Guinvarc'h[2]

1 ONERA, Traitement de l'information et systèmes, Université Paris-Saclay, 91123 Palaiseau, France
2 SONDRA, CentraleSupélec, Université Paris-Saclay, 91190 Gif-sur-Yvette, France

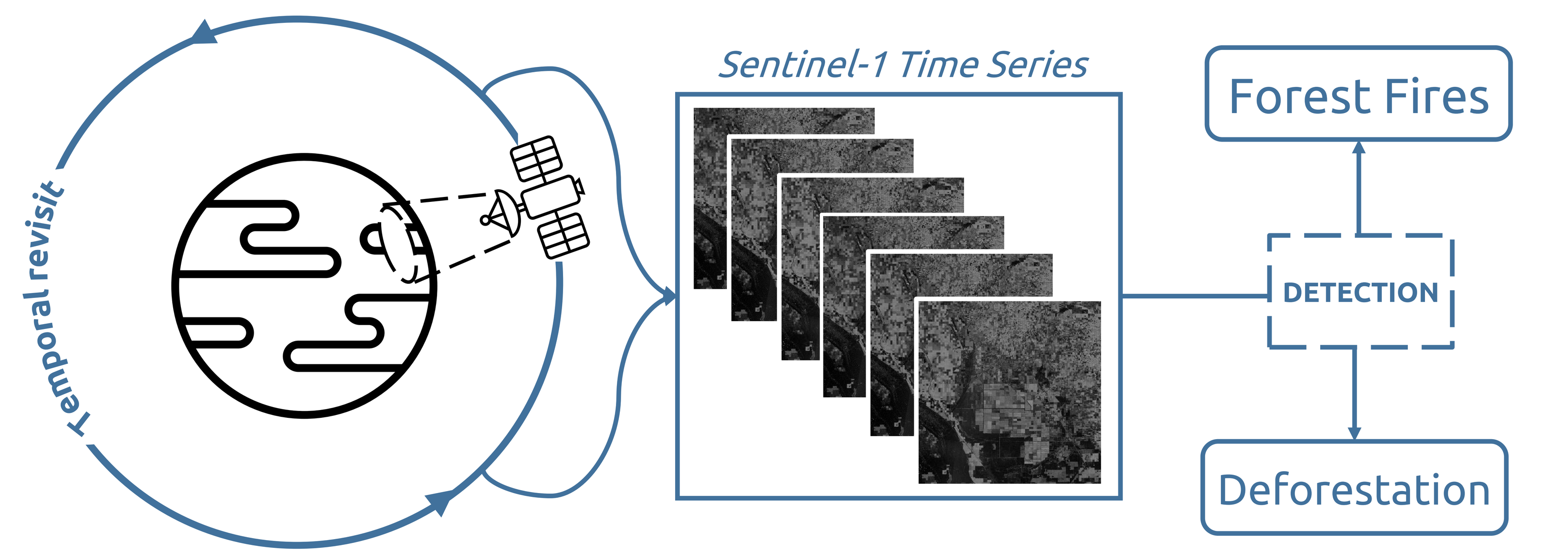
Session C1.09 Representation learning in remote sensing: from unsupervised, to self-and meta-learning

living planet symposium BONN 23–27 May 2022

INTRODUCTION

Detection of forest perturbations is possible with Sentinel-1 time series, through temporal processing:

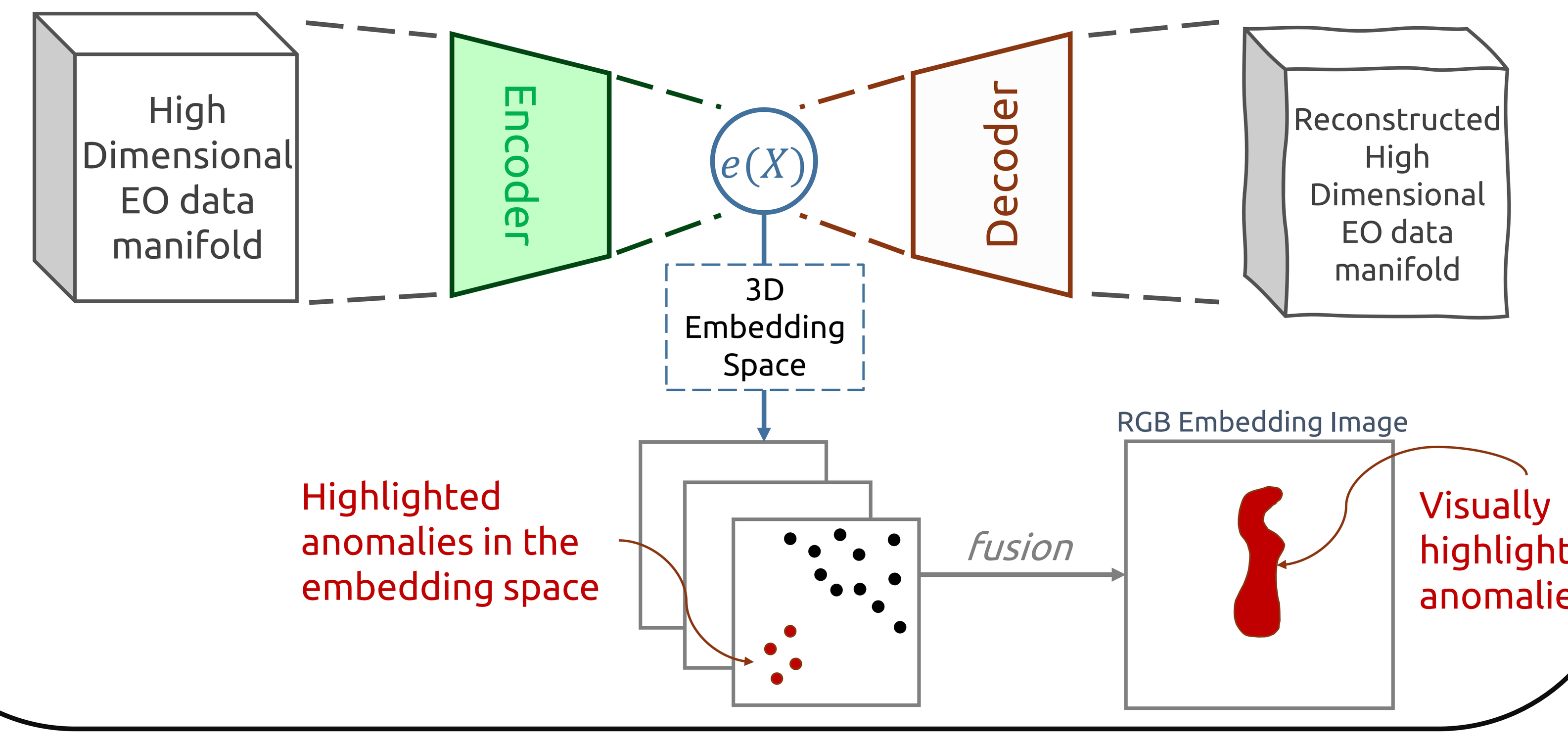
- Detection of deforestation [1,2]
- Detection of wildfires [3]



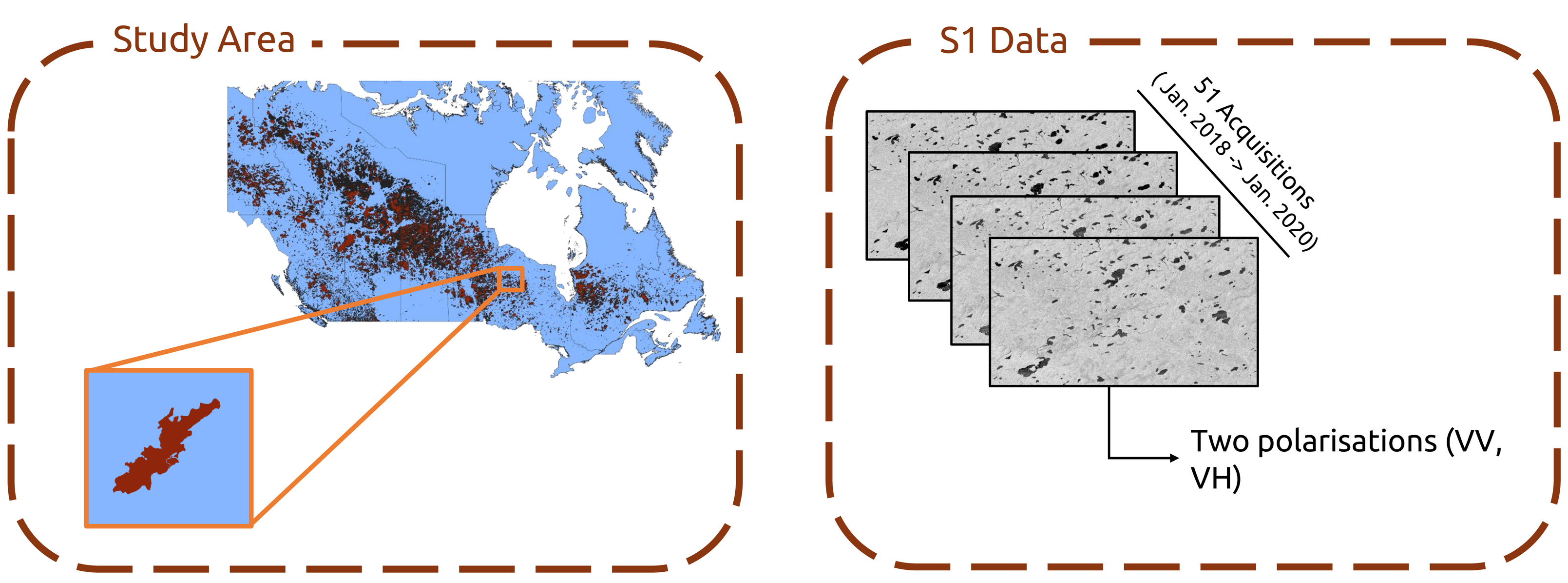
METHOD

Unsupervised temporal anomaly detection method:

1. **Model** radiometric temporal profile of forests using Convolutional Autoencoders [4].
2. **Visualize** variations in the profiles of forest using the generated embedding space.
3. **Isolate** profiles deviating from a norm as being fire.

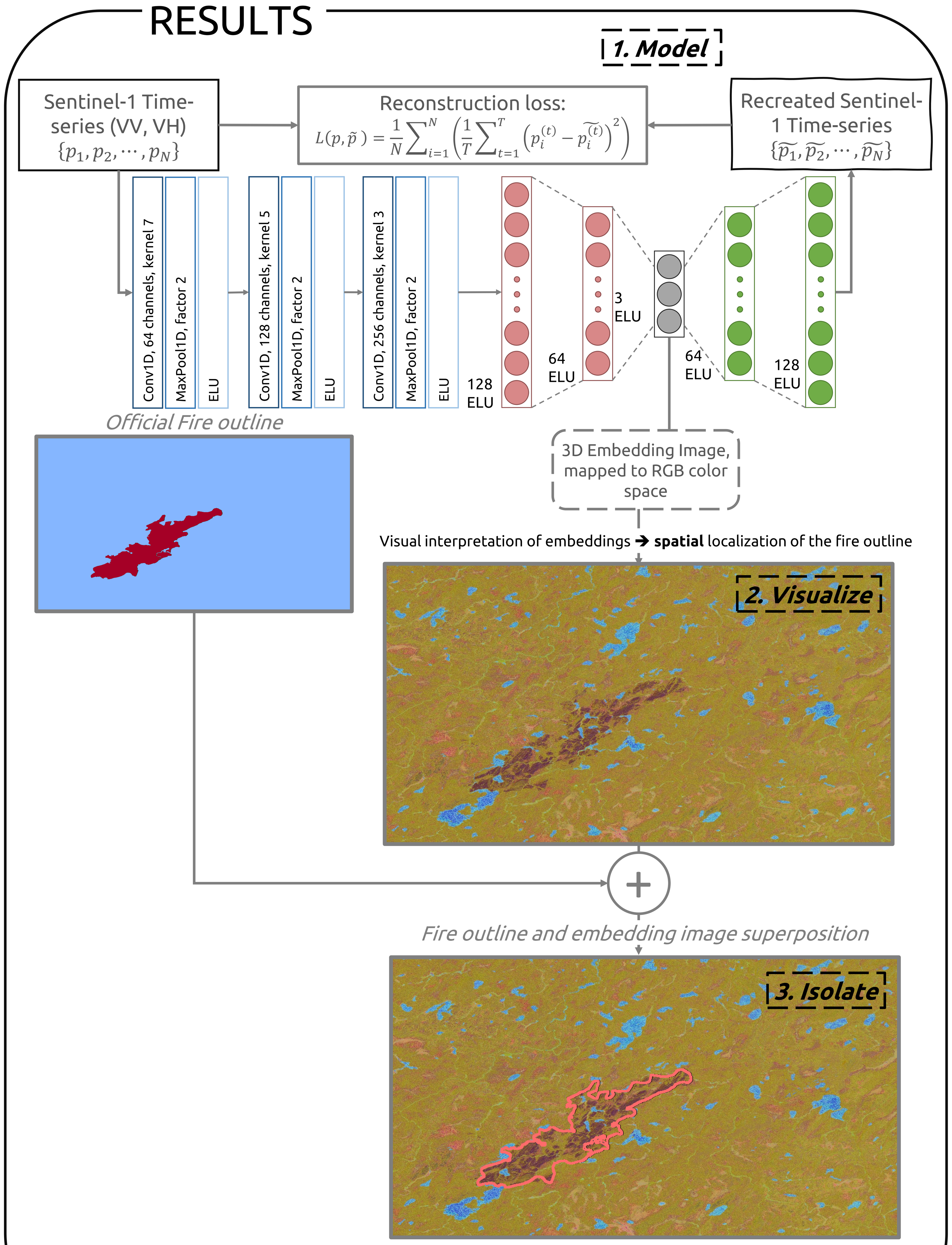


STUDY DATASET



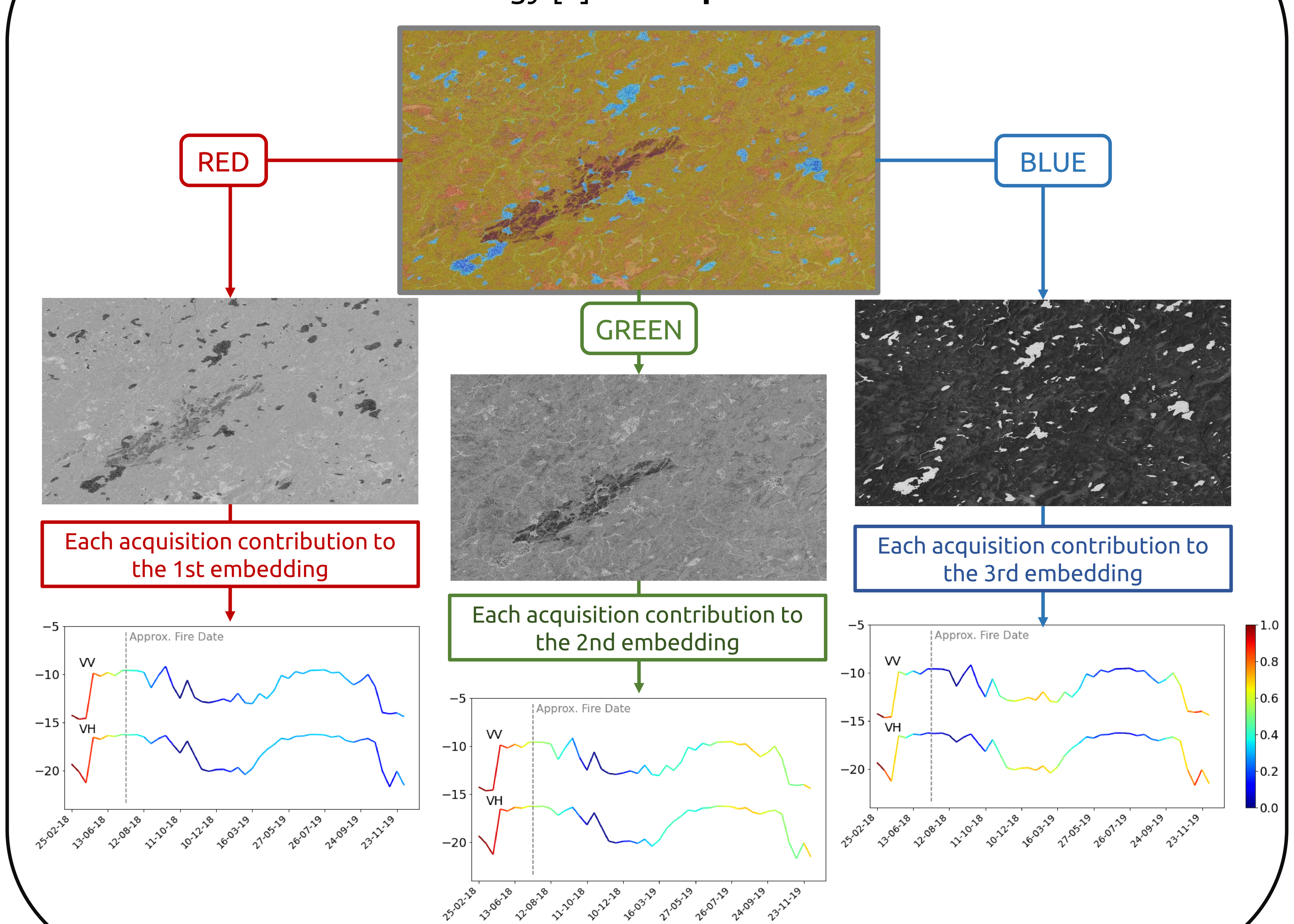
- Ontario Fire, starting date: 21st of June 2018.
- Superficies: ~760 Ha.
- Fire outline data source: *2021 Canadian National Fire Database product*

RESULTS



EXPLAINABILITY

Custom Grad-CAM methodology [5] ➔ **temporal** localization of the fire outline



CONCLUSION

Thanks to the modeling of SAR time series of forested environments with Convolutional Autoencoders, we can:

- **Extract** and **visualize** the main temporal profiles within a forested scene.
- **Adopt** an **anomaly detection** viewpoint to **model** "**normal**" forest temporal signatures, and the **extraction** of "**abnormal**" forest temporal signatures.
- Leverage this viewpoint to **retrieve fire outlines** as "abnormal" profiles **without supervision.**

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Extraction of variations in agricultural practices over rice fields using unsupervised learning

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DOI: 10.13140/RG.2.2.26986.18880

4 authors:


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CentraleSupélec


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A3.04 Agriculture - Methods and Algorithms, Science, Applications and Policy

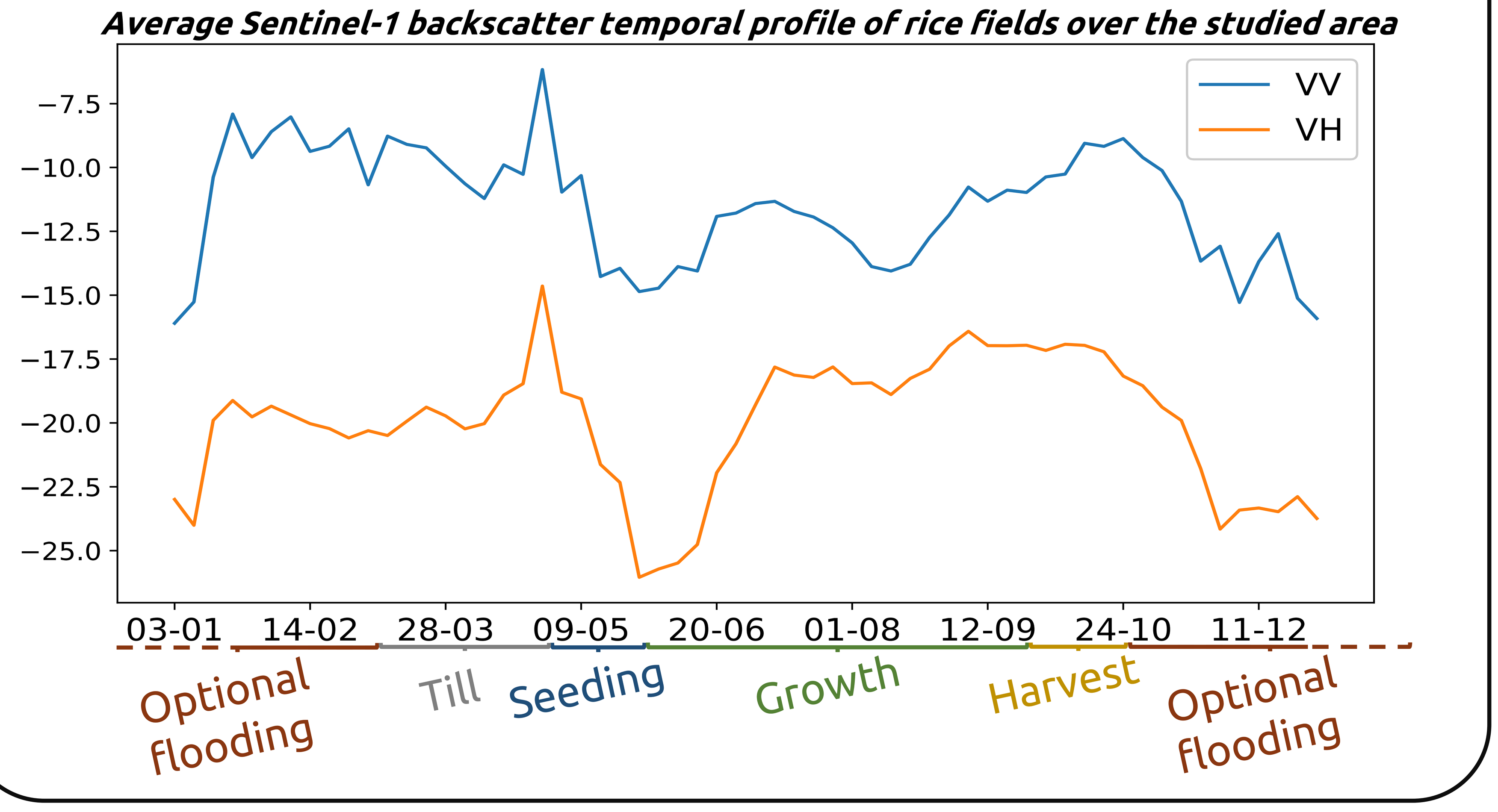
living planet symposium BONN 23–27 May 2022

INTRODUCTION

Existing variations of agricultural practices within a single crop type:
- Various sowing, harvesting dates [1].
- Optional flooding of rice fields, for bird resting areas [2], seeding period...

Convolutional Autoencoders [3] can model and **extract variations within a single crop type** and **group them**, using different semantic criteria, **without supervision**.

Average Sentinel-1 backscatter temporal profile of rice fields over the studied area

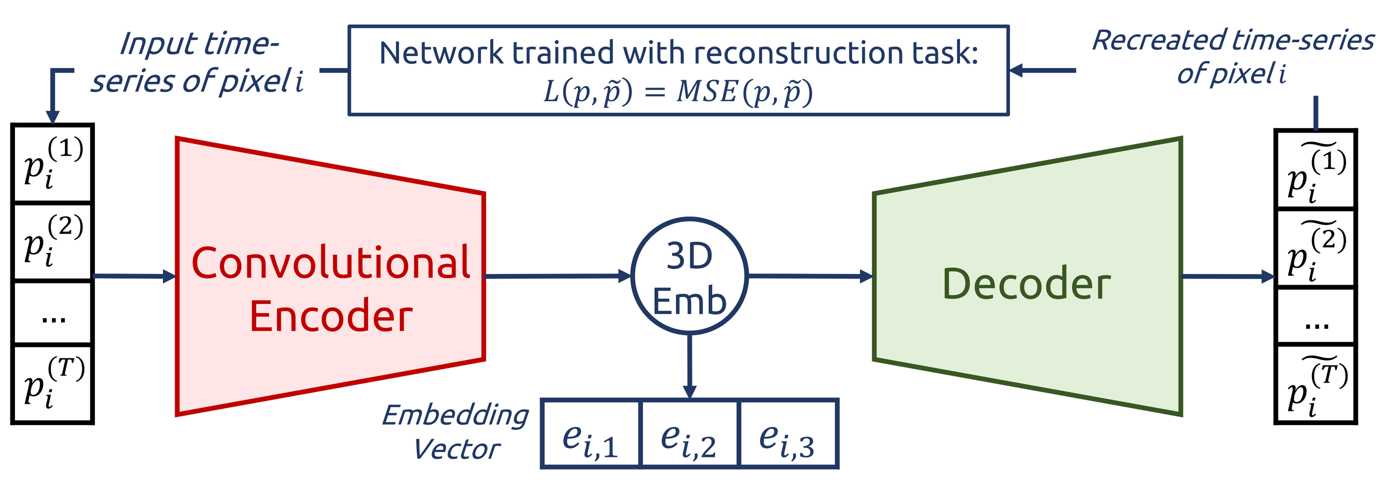


USED DATA

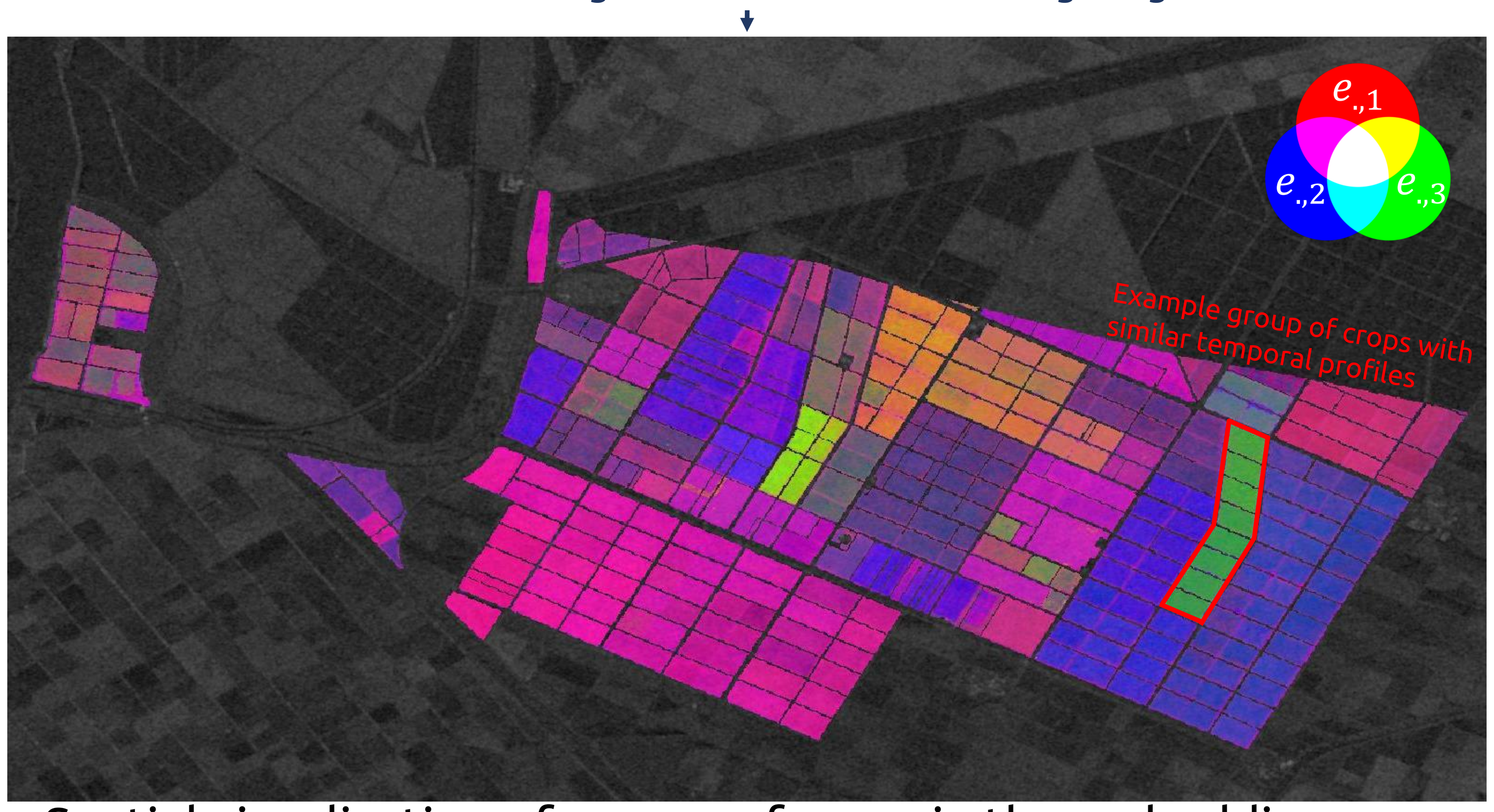
- Location of rice crops: Sector BXII, near Sevilla, Spain
- Details: 3500 ha of crops, growing in 2017.
- Sentinel-1 Data: 61 acquisitions (Jan 2017 to Dec 2017), dual-pol (VV, VH), preprocessing in [4]

Rice fields, in a Guadlquivir Marshes landscape, Andalucia, Spain (Source: [5])

AUTOENCODERS AND APPLICATION



3D Embedding vectors ➔ RGB Embedding image



Spatial visualization of groups of crops in the embedding space

Optional Flooding Period — Approximate Seeding Period — End of the year Flooding Period

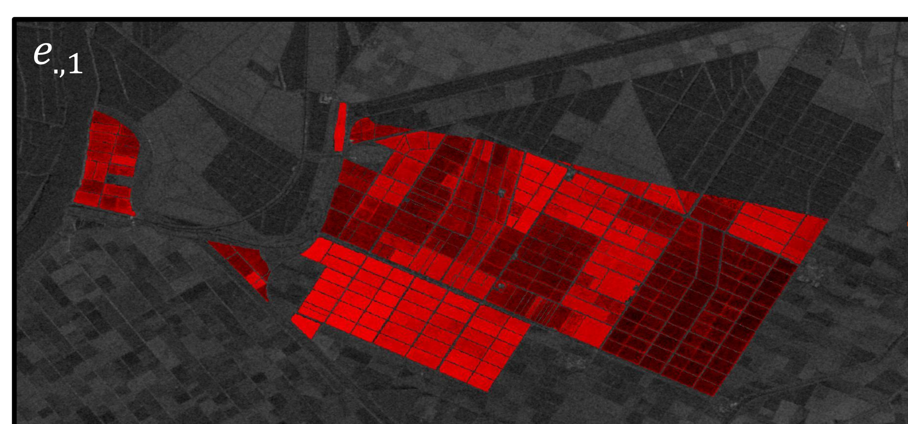
CONCLUSION

The application of an autoencoder to SAR time series of rice crops allows to:

- Generate a 3D **embedding image** that **highlights groups** of crops.
- **Visualize** these **groups** of crops by mapping the embedding space to the **RGB** color space.
- Find out **which period** of a field contributes to **making the groups** of crops using the Grad-CAM methodology.

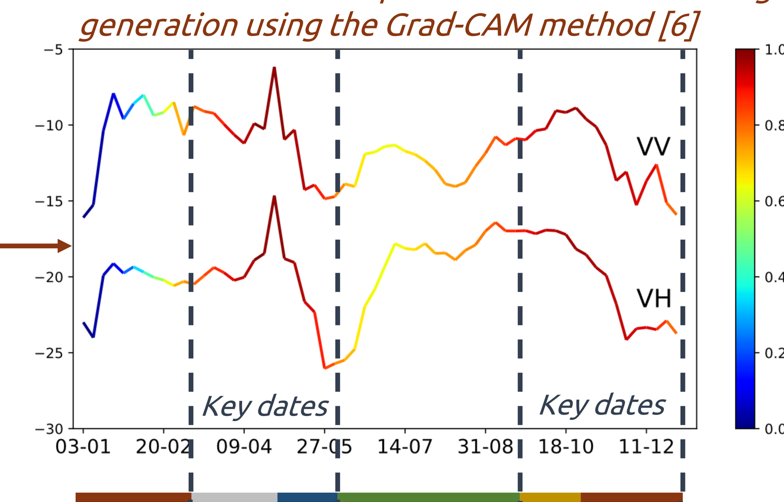
RESULTS AND VISUALISATION

Red channel: 1st embedding dimension



Similarities between crops in shades of red imply similarities in harvest strategies in key periods (i.e. Till, Seeding, Harvest, End of the year flooding)

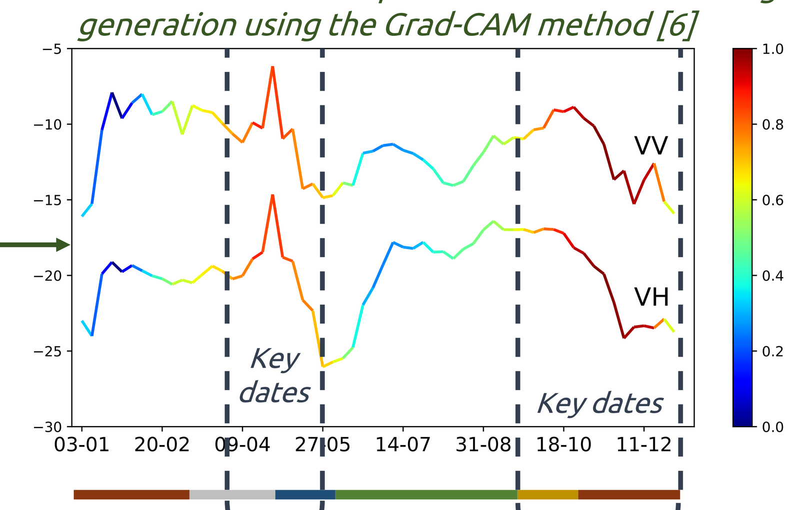
Extraction of date importance for 1st embedding generation using the Grad-CAM method [6]



Periods of interest for 1st embedding:
- All, but start of the year *optional flooding*

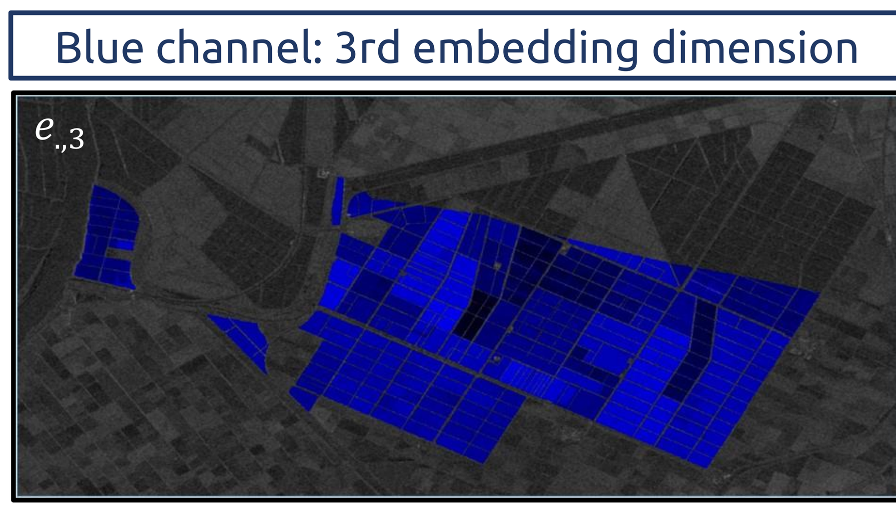
Green channel: 2nd embedding dimension

Extraction of date importance for 2nd embedding generation using the Grad-CAM method [6]

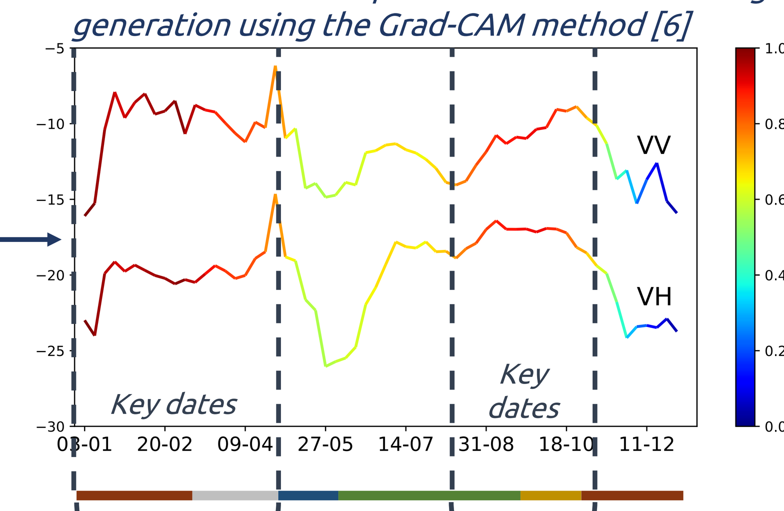


Periods of interest for 2nd embedding:
- End of *Field preparation*
- *Seeding*
- *Harvest*
- End of the year *optional flooding*

Blue channel: 3rd embedding dimension



Extraction of date importance for 3rd embedding generation using the Grad-CAM method [6]



Periods of interest for 3rd embedding:
- Start of the year *optional flooding*
- *Growth*

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