# Spatio-Temporal Learning for Feature Extraction inTime-Series Images

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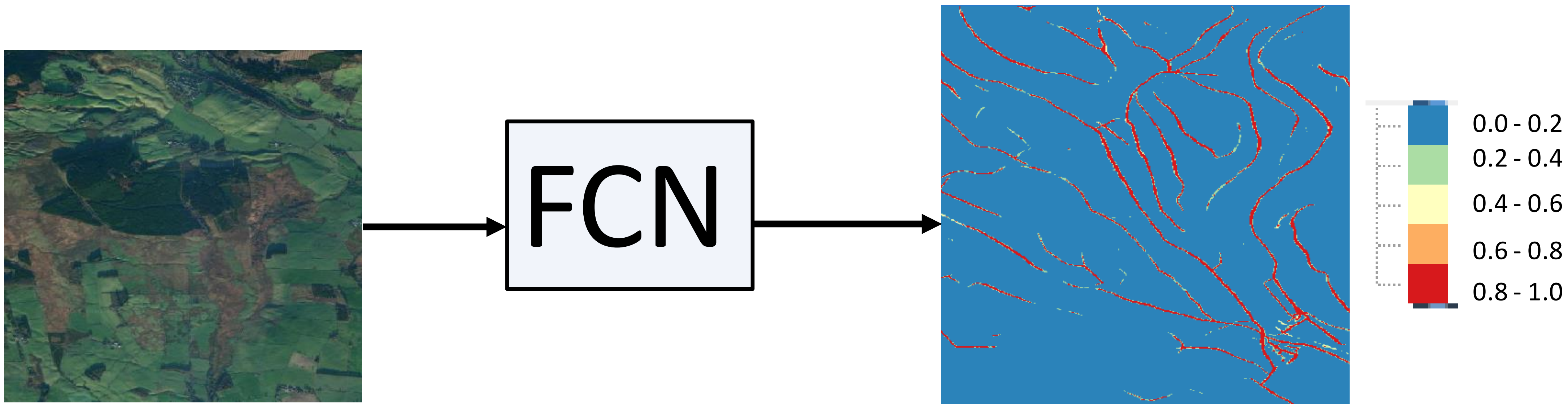
# Introduction

- Sentinel
- Pleiades
- SPOT
- Landsat

- huge volume of medium to high resolution multi-spectral images
- Acquisition every day and organized in time series

- Production of accurate land cover maps
- Monitoring of environmental changes

# Fully Convolutional Neural Network

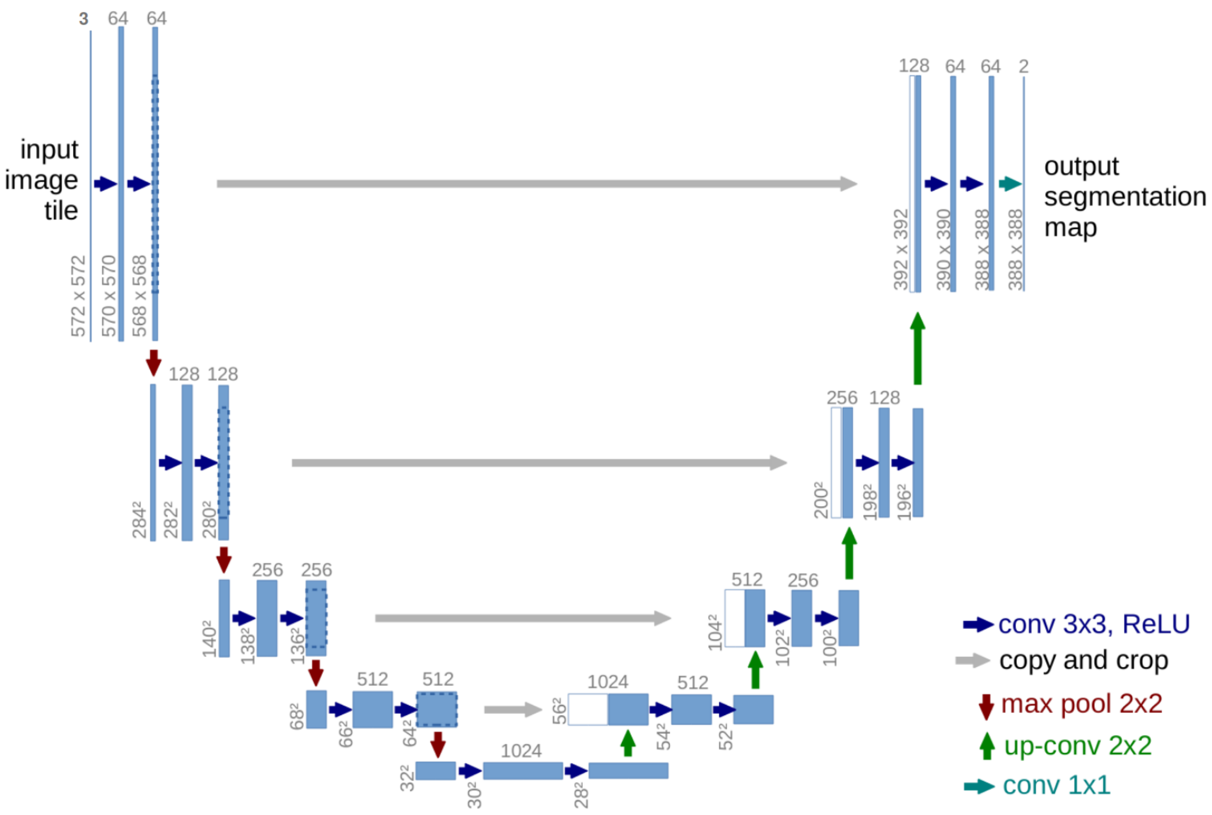



**Input Image**

**Probability Map**

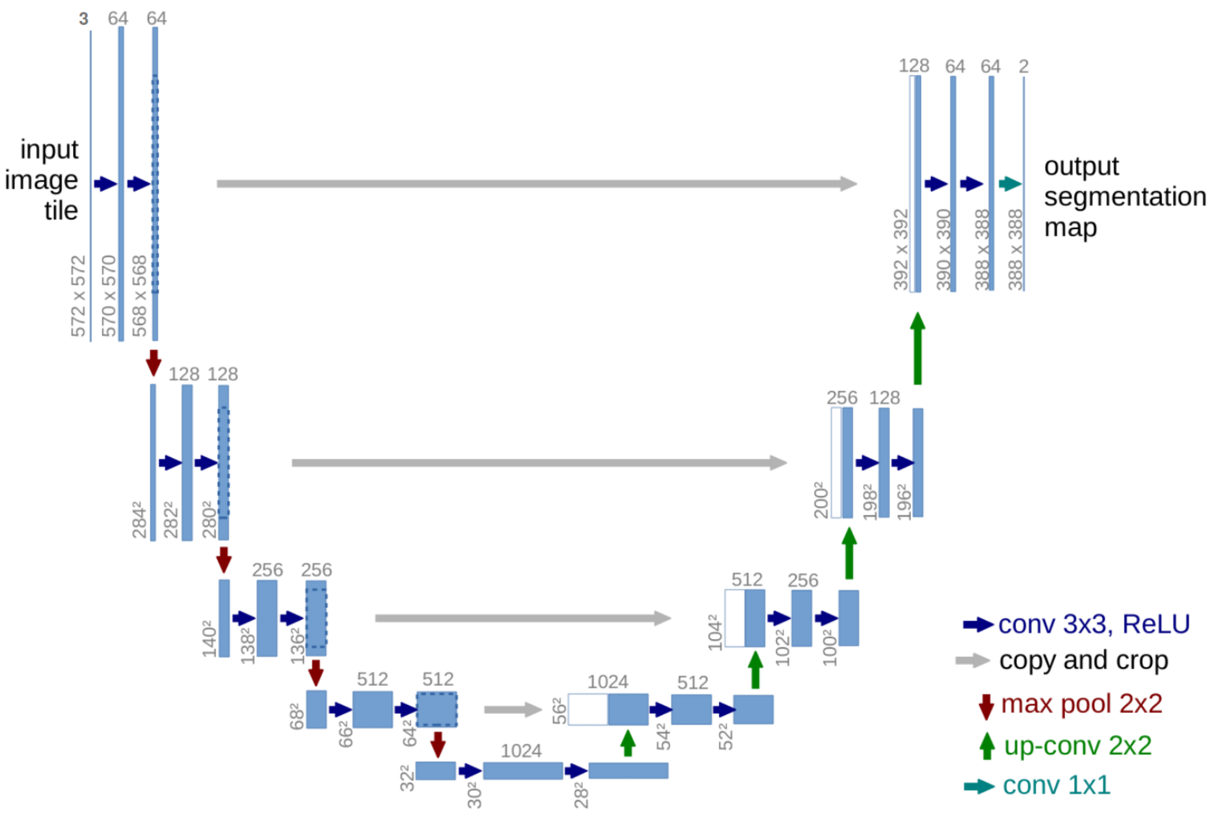
Road network

# Fully Convolutional Neural Network




U-NET

# Fully Convolutional Neural Network




U-NET

- First we used 32 filters instead of 64 in the first level convolutional layers

- Second we inserted batch normalization after each convolutional layer to speed up convergence.

# Reducing the variance of the model

April 4, 2020

February2 , 2020

January 11, 2020

Toulouse

**Surface Reflectance**

Difference of illumination and variation of the proportion of light reflected from the ground to the satellite sensor.

**Varies because of**

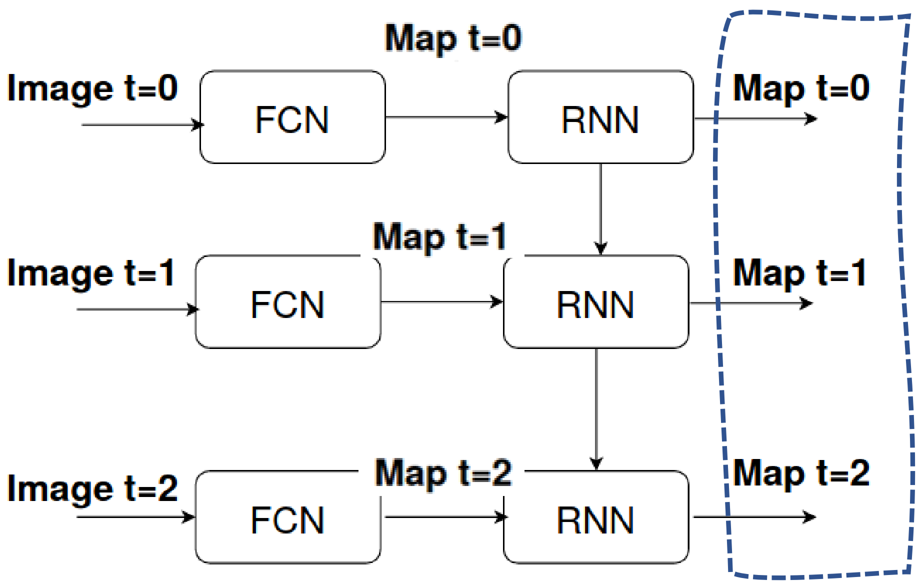
- sun-target-sensor geometry
- Light polarization
- Etc,,

Pixel energy = F(Surface Reflectance) = F(time)

**Need to introduce time dependency**

# Recurrent Neural Network

Update

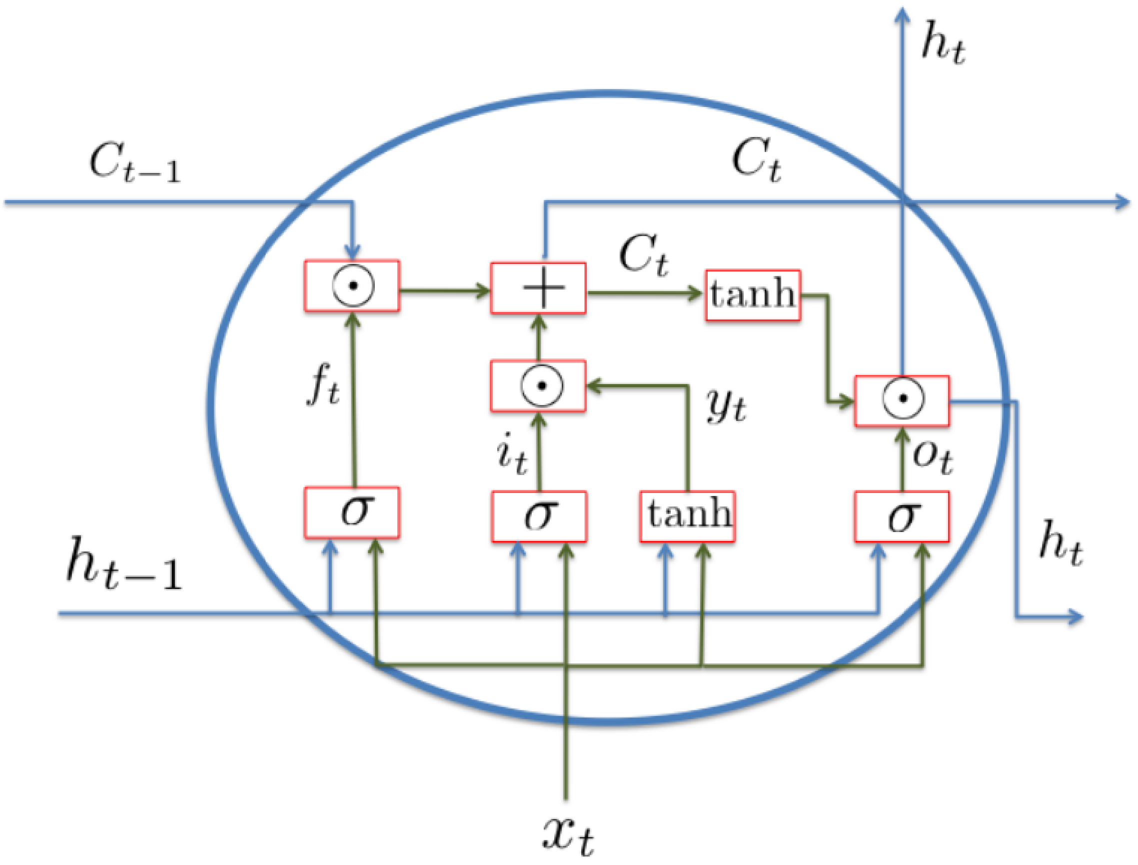



**Encoding temporal dependencies with RNN**

- At each time step t, the FCN generates a noisy Pmap
- The RNN combines this Pmap with a hidden state coming from the previous time step to generate a more accurate and up-to-date Pmap

Overal model

# Recurrent Neural Network- LSTM



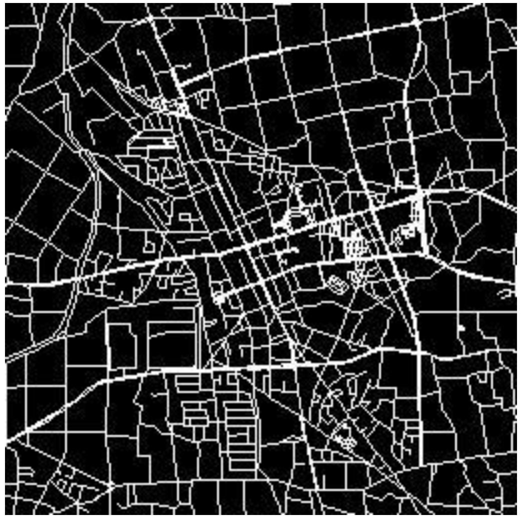

LSTM structure

# Dataset

- 16 cities chosen in Canada, USA, Africa, Europe and South America
- Reference data obtained from Open StreetMap
- Patches of size 512x512 generated from 10900x10900 images
- Data augmentation with vertical/horizontal flips and rotations

Patch

Reference data



# Results

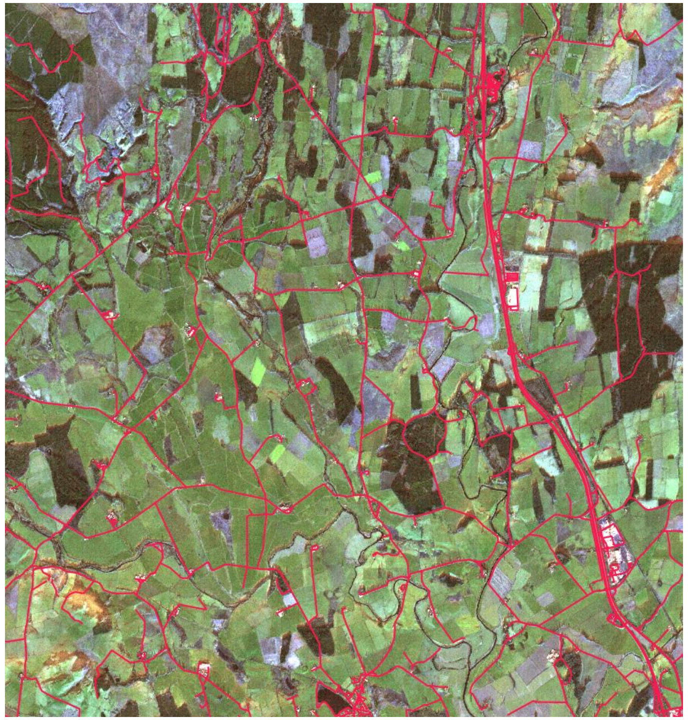
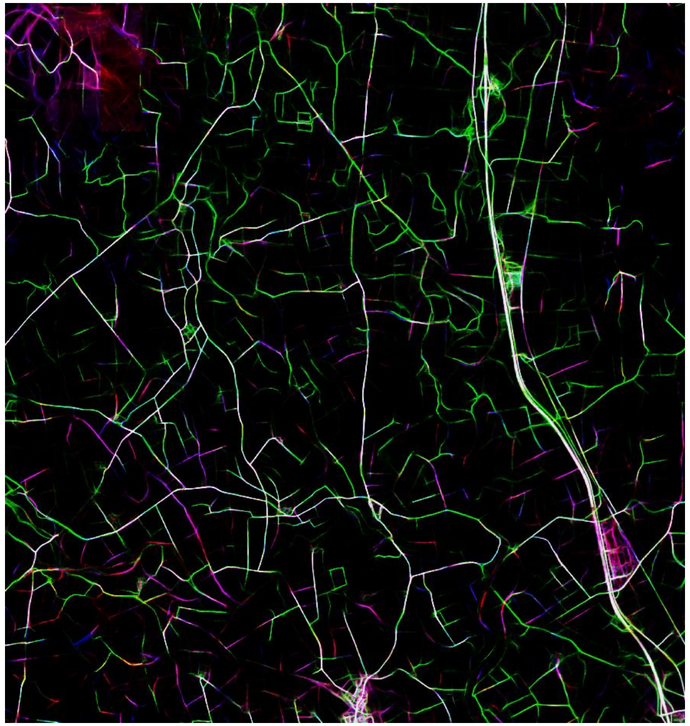


Image and Ground truth



Individual PMap for 3 days

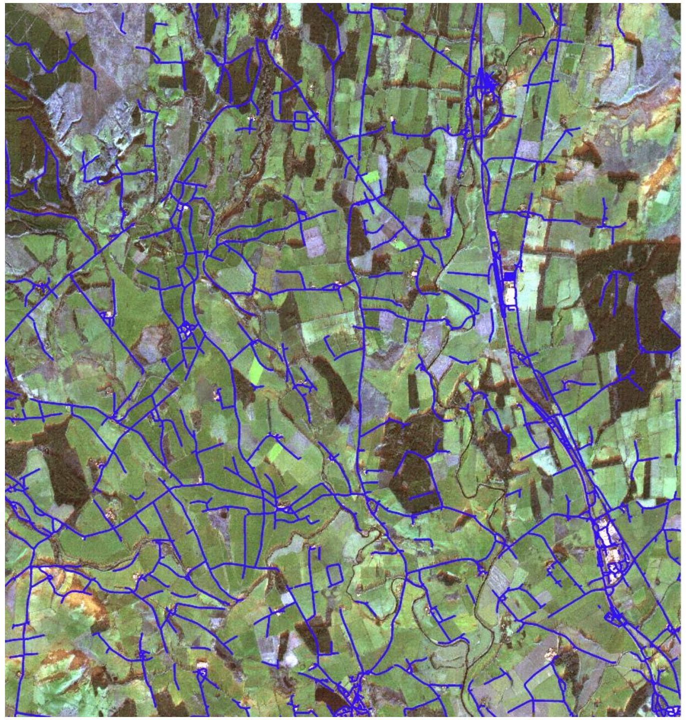
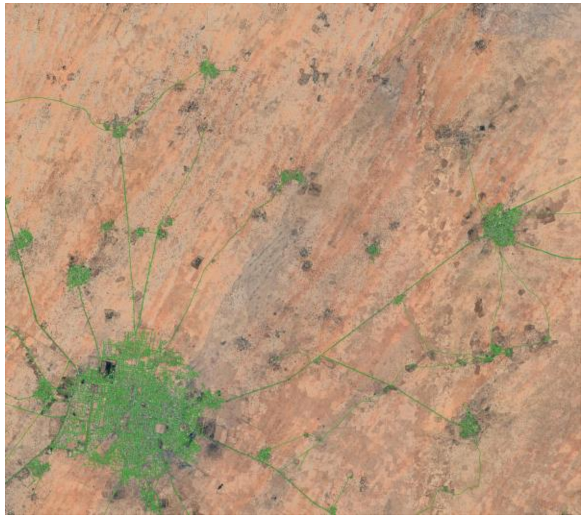
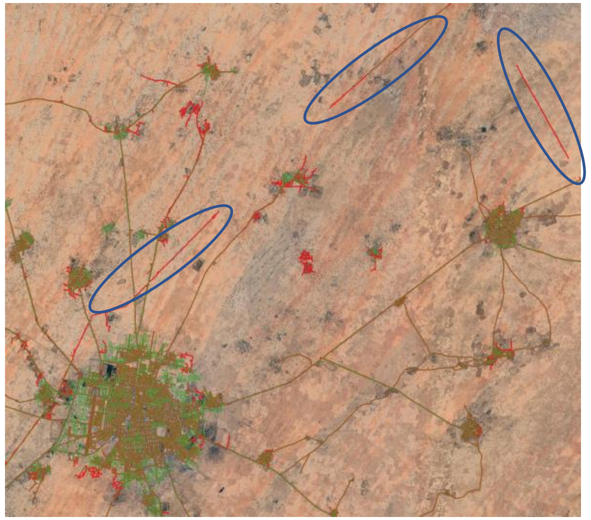


Image and overal predicton

# Results



Saint Louis, Senegal 2016



Saint Louis, Senegal 2020

2020

2016

# Conclusion

- Generation of accurate and up-to-date land cover maps
- Use of temporal and spatial information
- In the next steps, measurement of changes of anthroprogenic and natural features on the West African Littoral.

# References

[1] Andrei Stoian, et al. ”Land Cover Maps Production with HighResolution Satellite Image Time Series and Convolutional Neu-ral Networks: Adaptations and Limits for Operational Systems”MDPI, Remote Sensing 2019

[2] C. Pelletier, G. I. Webb and F. Petitjean, ”Deep Learning for theClassification of Sentinel-2 Image Time Series,” IGARSS 2019 -2019 IEEE International Geoscience and Remote Sensing Sym-posium, Yokohama, Japan, 2019, pp. 461-464

[3] Emmanuel Maggiori, Guillaume Charpiat, Yuliya Tarabalka,Pierre Alliez. Recurrent Neural Net-works to Correct SatelliteImage Classification Maps. IEEE Transactions on Geoscience an-dRemote Sensing, Institute of Electrical and Electronics Engi-neers, 2017, 55 (9), pp.4962-4971

[4] Hochreiter, S.; Schmidhuber, J. Long Short–Term Memory. Neu-ral Compution Journal. 1997, 9, 1735–1780.