→ THE ESA EARTH OBSERVATION Φ-WEEK

EO Open Science and FutureEO

12–16 November 2018 | ESA-ESRIN | Frascati (Rome), Italy

CNN assessment for land cover map production from S2 image time series

V. Poulain, V. Poughon, J. Inglada, A. Stoian, A. Galimberti

Agenda

- Context
- Method
- Results
- Conclusion

Agenda

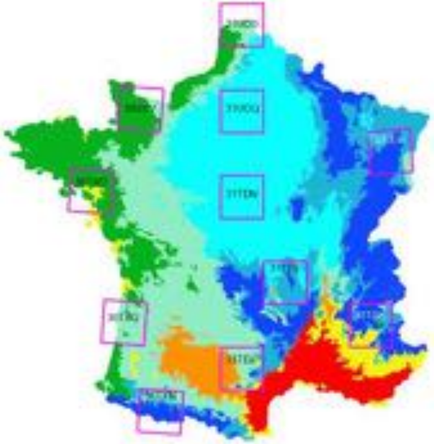
- Context
- Method
- Results
- Conclusion

Context

- Land cover maps
  - Classify ground content into classes
  - Applications in cartography, country and urban planning, agriculture, etc…
  - Need for automation
- Operational land cover map production by French Space Agency
  - Iota2 processing chain with Random Forest (RF) pixel-based method
  - No use of context
- Deep learning
  - Impressive results in computer vision applications
  - Requires a huge amount of data

Data

- Sentinel2 images
  - Tiles of 100x100km over France
  - Multi-spectral (10 bands at 10m or 20m resolution) and multi temporal (33 dates over year 2016) data
  - 11 tiles with 330 channels (33 dates x 10 bands)
- Reference data
  - Used for training and validation
  - Fusion of various sources (CLC, Urban Atlas, BD TOPO, RPG, RGI) ➔ Sparse labelled data
  - Polygons split in train (66%) and test (34%) datasets
  - 17 thematic classes



Agenda

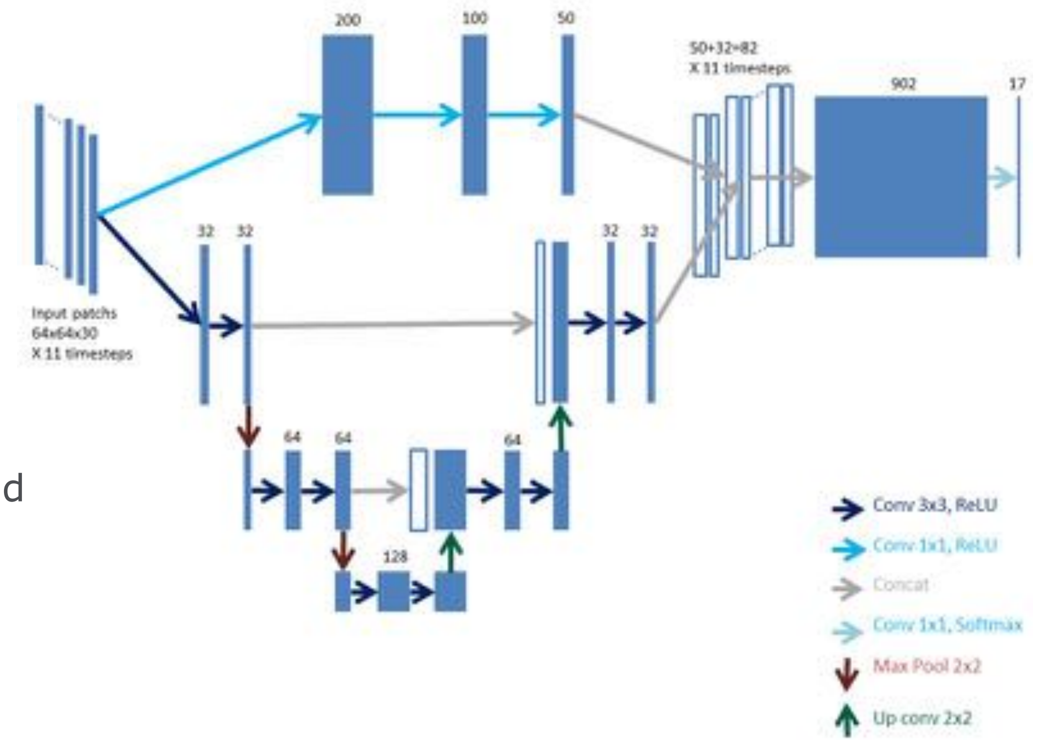
- Context
- Method
- Results
- Conclusion

Method – Network FG-UNET

- Fine Grained UNET (FG-UNET) :
  - Adaptation of UNET
  - Pixel wise 1x1 path

➔Able to deal with sparse data, to produce detailed land cover maps

- Configuration :
  - Keras with TensorFlow backend
  - Horovod to distribute training over a HPC cluster



THALES

Method

- Loss function : weighted categorical cross entropy
  - Weights according to class frequency
  - Unlabelled pixels not taken into account

$$\mathcal{L} = \sum_{pixels} \sum_{k=1}^{class\_nb} weight_k \cdot y_{true_k} \cdot \log\left(y_{pred_k}\right)$$

- Patch generation
  - 64x64 patched generated on the fly
  - Patch normalisation
  - Class randomly chosen for each patch
  - Data augmentation

THALES

cnes

Agenda

- Context
- Method
- Results
- Conclusion

Results - methodology

- Learning on train datasets of 11 tiles, and evaluation on test datasets
- Classification of tiles 512x512 (memory limitations) with 16 pixels of overlap
- Evaluation :
    - Statistical measures (Cohen's Kappa coefficient, F-Scores)
    - Visual analysis of the level of detail
- Comparison with Random Forest (currently used in an operational processing chain)

Method	Parameters	Learning time	Learning time on 1 CPU
Random Forest	-	25h	25h
FG-UNET	525 997	13h	3 300h

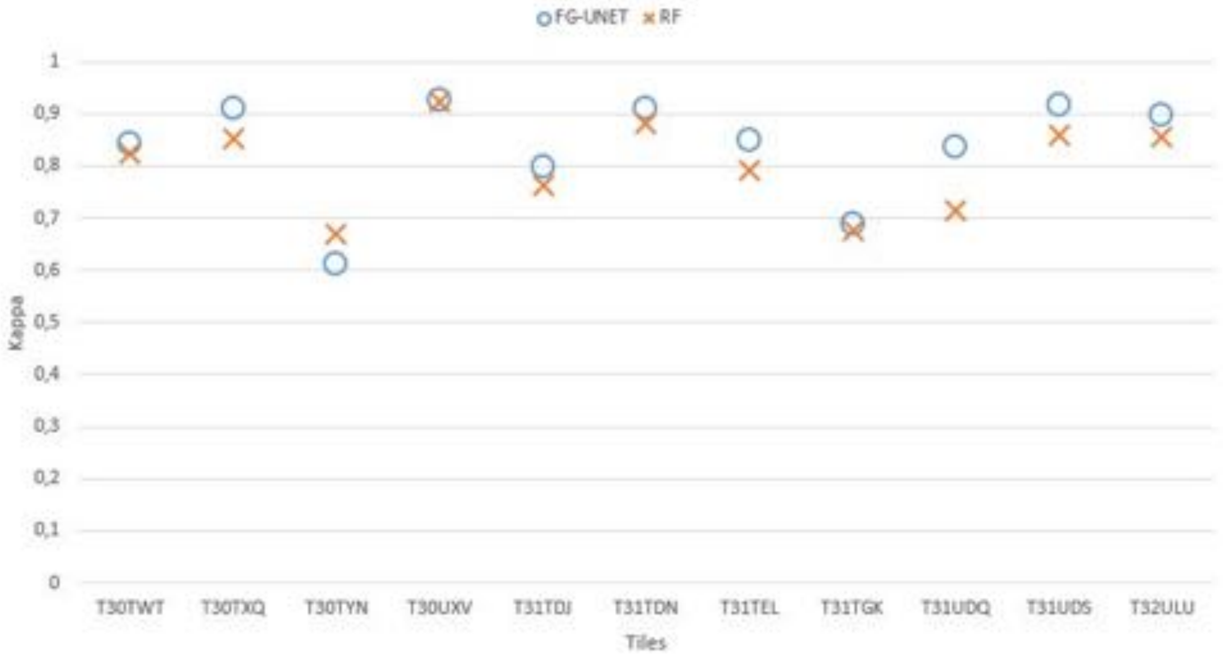
Results – land cover maps examples

FG-UNET	RF	Image
		

Results – land cover maps examples

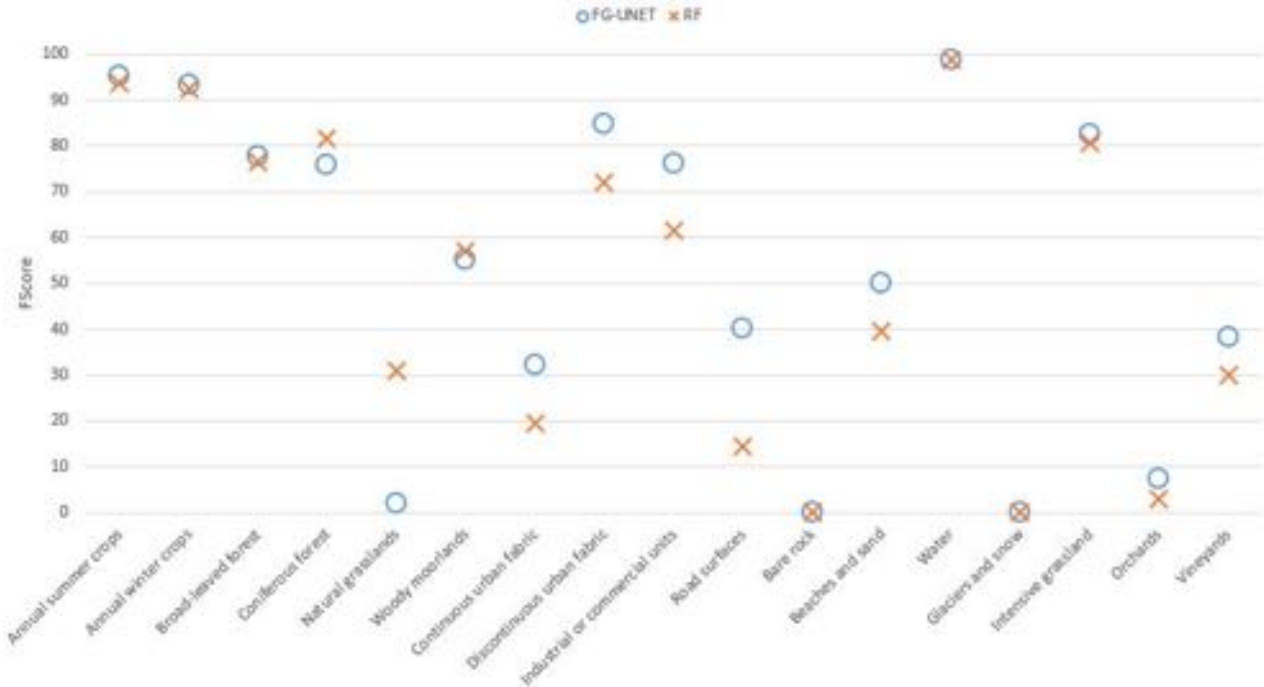
FG-UNET	RF	Image
		

Results – Kappa for each S2 tile



➔ The more the tile contains urban areas, the better is FG-UNET

Results – Fscore for each class



➔ FG-UNET significantly better on urban areas, thanks to the use of context

Agenda

- Context
- Method
- Results
- Conclusion

Conclusion

- Use of a fully convolutional network to classify S2 time series at the country scale
- Adaptation of the classical U-Net model to deal with sparse data
- Results equivalent or better than classical method (RF)
- Importance of the quality of training data