RNN-based Multi-Source Land Cover Mapping: Application to a West African Agricultural Landscape

Gbodjo Y.J.E.*, Ienco D., Leroux L., Interdonato R., Gaetano R. and Ndao B.

* Corresponding author : jean-eudes.gbodjo@irstea.fr

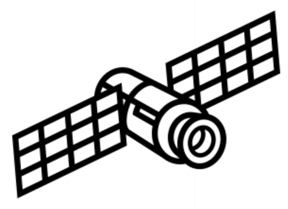
INTRODUCTION

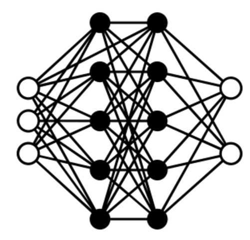
In the southern countries, most of the population lives in rural areas where agriculture is the main source of income and food.

Timely and accurate land cover maps are crucial inputs for crop monitoring and early warning systems to ensure food security.

Nowadays, a huge amount and varied source of remote sensing data are publicly available and can be leveraged to improve land cover mapping.

OBJECTIVES





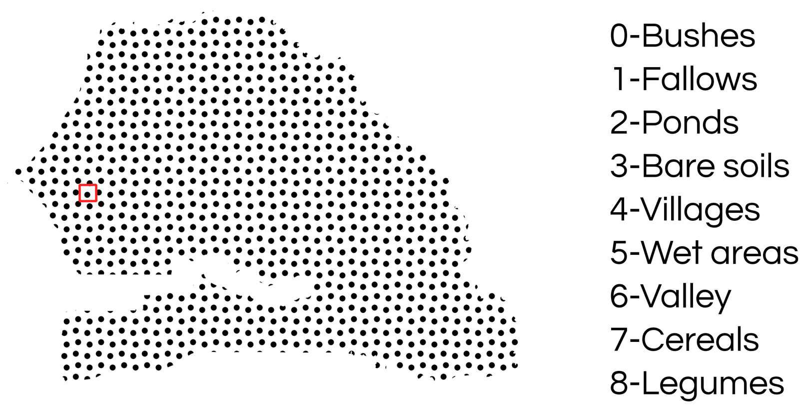
1- Design a RNN-based DL architecture to deal with a heterogeneous agricultural landscape land cover mapping combining radar and optical time series.

2- Explore via an attention mechanism how the parameters learned by the model can supply insights towards the explanation of its decisions.

DATA

Case study:
Groundnut Basin in Senegal

3084 Samples over 9 classes



Multi-Source Time Series:

- Sentinel-1 (16 timestamps, 2 dims)
- Sentinel-2 (19 timestamps, 5 dims)

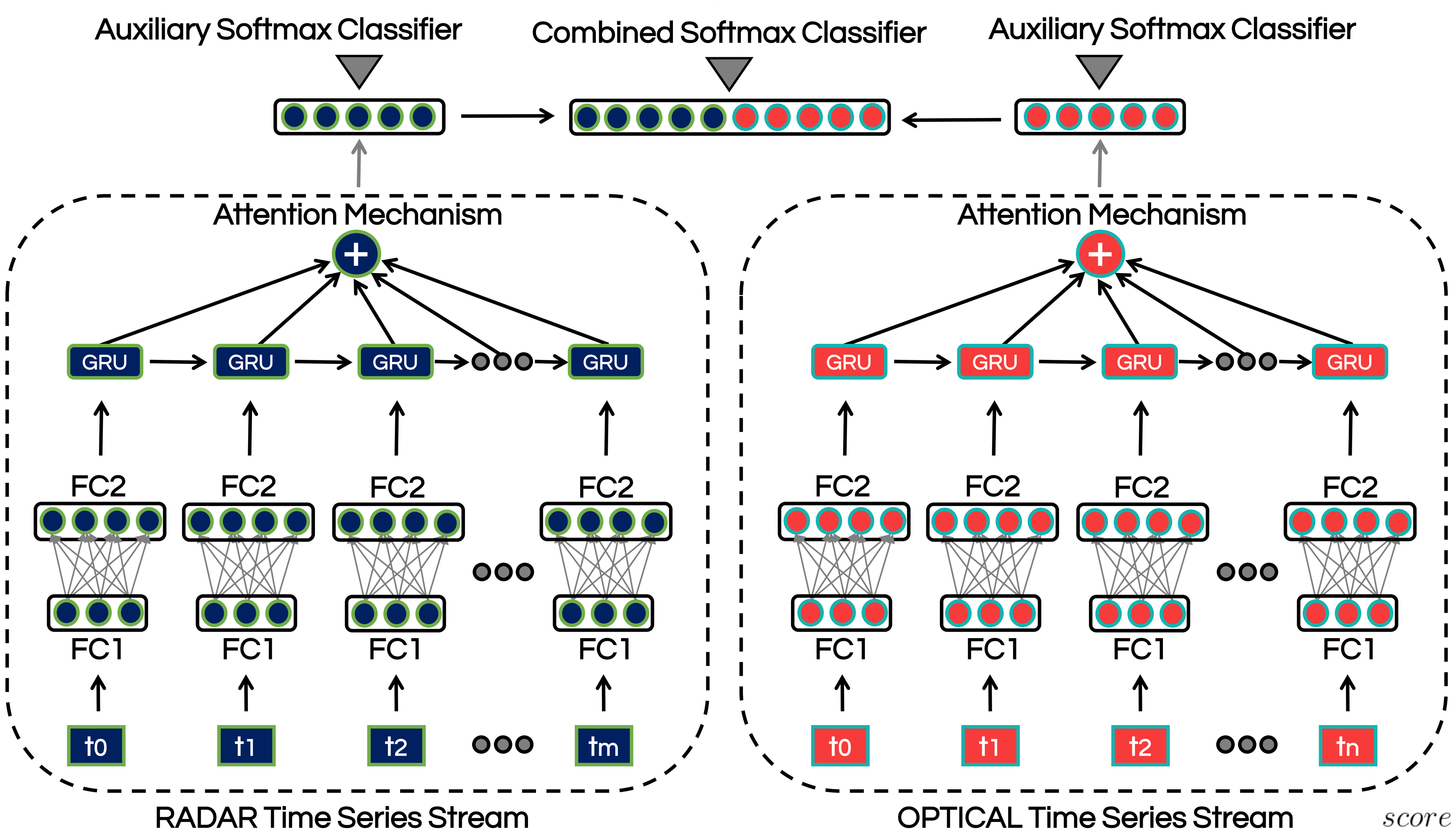
METHODS

The OB2SRNN architecture involves two streams one for radar and one for optical TS.

3 Stages for each stream

- 2 FC layers with ReLU activation to enrich data
- GRUs layer to manage temporal dependencies
- Attention Mechanism to weight GRU units outputs

Each stream output features that are successively concateneted to perform classification.



Auxiliary SofMAX classifiers enforce the complementarity and discriminative power of each stream output features

Attention Formulation

$$v_a = tanh(H \cdot W_a + b_a)$$
$$\lambda = SoftMax(v_a \cdot u_a)$$
$$stream_{feat} = \sum_{i=1}^{N} \lambda_i \cdot h_{t_i}$$

Loss function

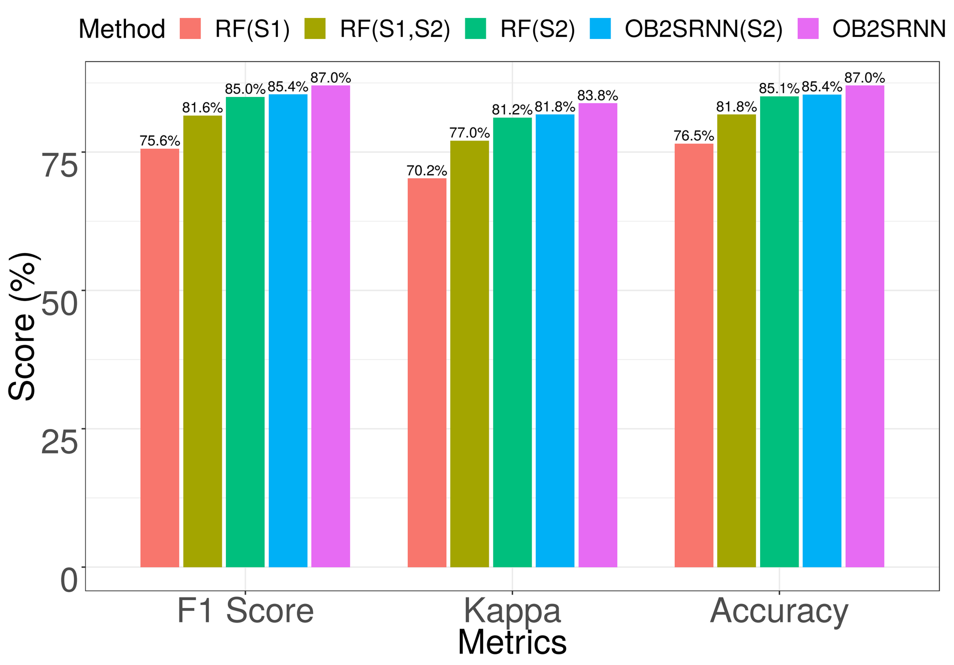
$$L_{total} = 0.5 \times L_1(feat_{rad}) + 0.5 \times L_2(feat_{opt}) + L_{fus}([feat_{rad}, feat_{opt}])$$

Scoring function

$$score = 0.5 \times score_{rad} + 0.5 \times score_{opt} + score_{fus}$$

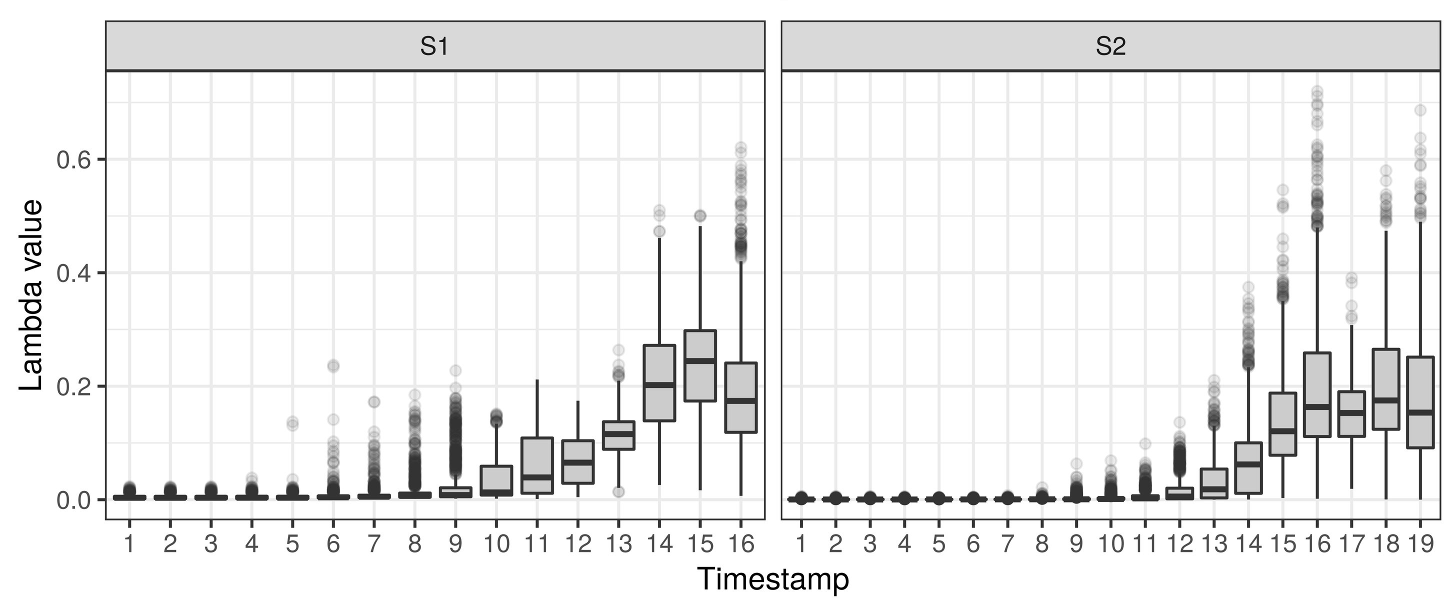
RESULTS

Evaluation Metrics

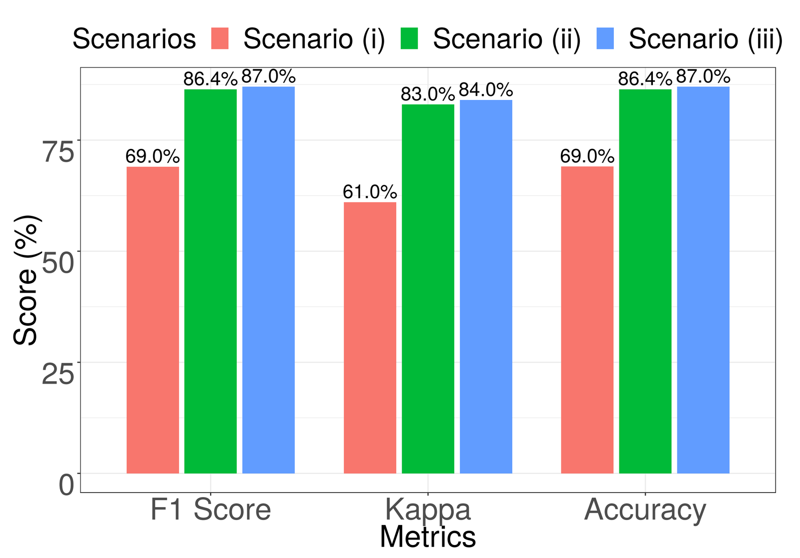


- The OB2SRNN model outperforms its Random Forest competitors: RF(S1,S2) , RF(S1) and RF(S2).
- RF(S1,S2) performs worst than RF(S2) and confirm that the Random Forest algorithm is not tailored to deal with multi-source data.
- The radar time series ablation on the OB2SRNN model shows the capacity of the DL model to leverage both radar and optical information to improve land cover mapping.

Attention weigths inspection

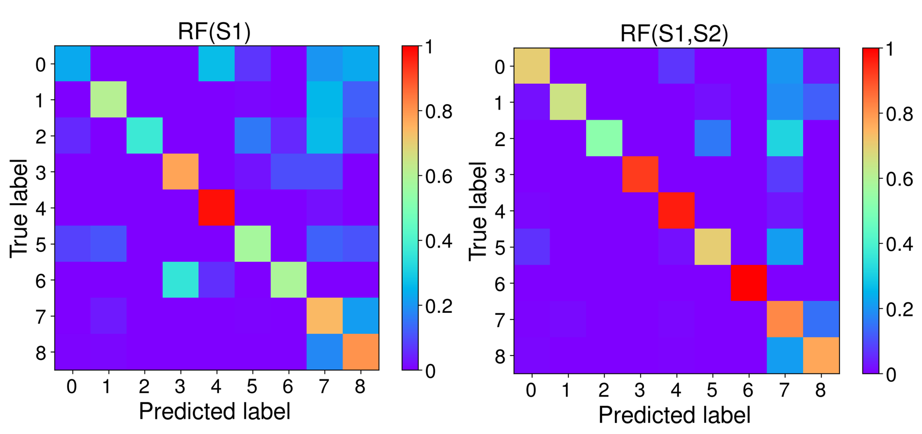


The OB2SRNN model learns two set of weights (λ_{rad} and λ_{opt}) to combine radar and optical timestamps. The Boxplots show timestamp attention weights distribution, the majority of the information is contained in the last portion of the considered time series. This is inline with the agronomic knowledge of the study site where agricultural season spans from June to October with occuring chlorophyll activity peak in August.

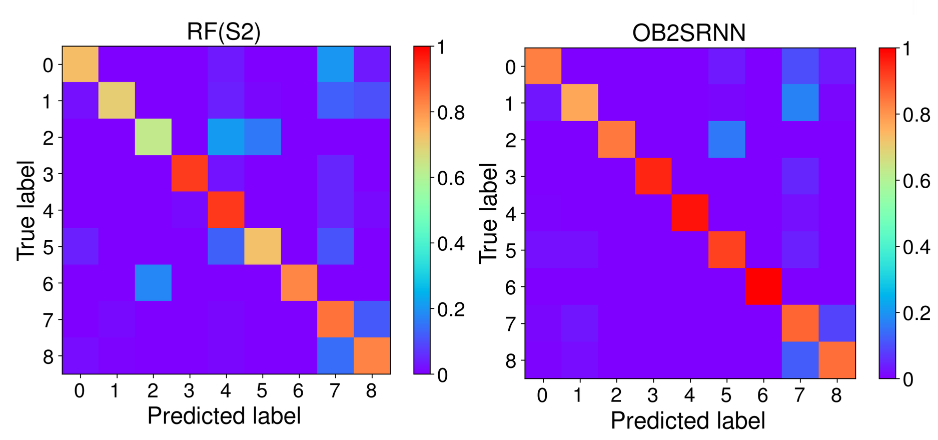


Based on the attention weigth analysis, three scenarios were considered. In scenario (i) we considered the OB2SRNN model on the time series spanned from May to June (5 timestamps for S1 and 8 for S2) while scenario (ii) involved the time series from July to October (11 timestamps for both S1 and S2). The scenario (iii) covers the whole temporal period. Scenario (ii) effectively performs similar to scenario (iii) while serious performances degradation can be noticed in the scenario (i).

Confusion Matrices



The OB2SRNN model clearly exhibits less confusions than its Random Forest competitors which have some issues to deal with classes like 0-Bushes, 1-Fallows, 2-Ponds and 5- Wet areas. The DL model was also able to capture complex temporal dependencies characterising agricultural classes (7-Cereals and 8-Legumes).



EXP. SETTINGS

- Model Parameters
  Learning rate: 1×10^{-4} ; Optimizer Adam
  1000 Epochs ; Batch size: 32
  GRU units 512 (S2) / 256 (S1) ; Dropout : 0,4
  FC units: 32 and 64 (S2) / 16 and 32 (S1) ; Dropout: 0,4
- Evaluation Metrics
  F1 Score ; Kappa Coefficient ; Global Accuracy
- 10 Random splits
  50% Training ; 20% Validation ; 30% Test
- Competing Methods
  Random Forest: RF(S1,S2) ; RF(S2) ; RF(S1)
  Radar Time Series Ablation: OB2SRNN(S2)

CONCLUSION

- The proposed deep learning architecture have demonstrated it capability to cope with the multi-temporal and multi-source land cover mapping in the Senegalese Groundnut basin heterogeneous landscape outperforming the Random Forest competitors.
- In the analysis of the DL model attention parameters, an existing correlation has been highlighted between the learnt attention weights and the informativeness of the optical as well as the radar time series. Therefore, attention parameters can supply insights contributing to the interpretability of the decisions made by the neural network architecture.

Acknowledgments: This study was supported by the French National Research Agency under the Investments for the Future Program, referred as ANR-16-CONV-0004 and the Programme National de Télédétection Spatiale (PNTS), grant no PNTS-2018-5.