CNN CLASSIFICATION OF WET SNOW BY PHYSICAL SNOWPACK MODEL LABELLING

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Introduction: In this work, we propose a new approach for wet snow detection in Synthetic Aperture Radar (SAR) images by using a convolutional neural network (CNN) designed to learn with respect to snowpack outputs from the state-of-the-art snow model Crocus. The CNN was trained to classify the wet snow states based on features extracted from the SAR images, using 2 polarimetrics channel (VV, VH) and the ratio of these channels with those obtained with a snow-free reference image acquired in summer.

Dataset

Localisation

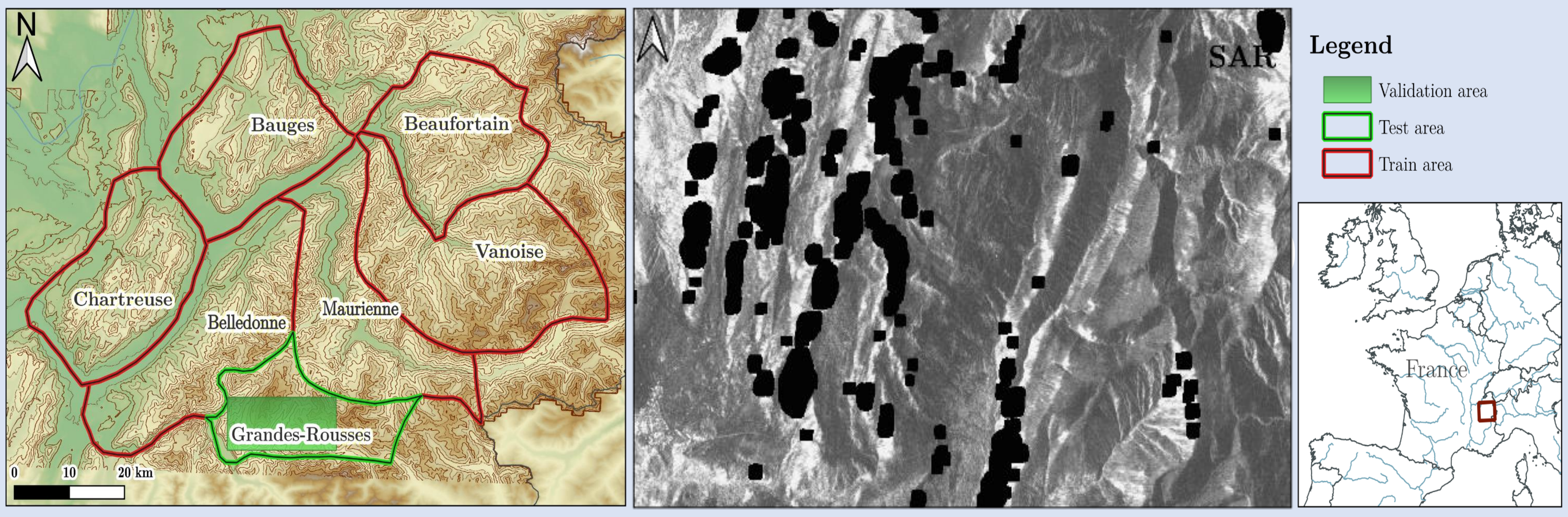

Fig 1: Localisation and repartition of the train/test area. Overview of the SAR image

Description

SAR data: Sentinel-1 Ground Range Detected (GRD)

- 69 images (2020-2021) with 2 polarisations (VV, VH)
- Nagler features: polarimetric ratio with a reference image (09/08/2020)
- Sample size: 16 x 16 x 4 pixels
- 18659 samples with **wet** label and 472696 with **not wet** label
- Balanced subset for the evaluation

Labelling rule

Crocus physical snowpack model

Wet Snow = Tn ≥ 0 and Hs ≥ 0.4,

Tn = minimal temperature of the snowpack

Hs = height of the snowpack

An extensive version of the dataset can be found in Zenodo: LSD4WSD

Methodology

CNN architecture

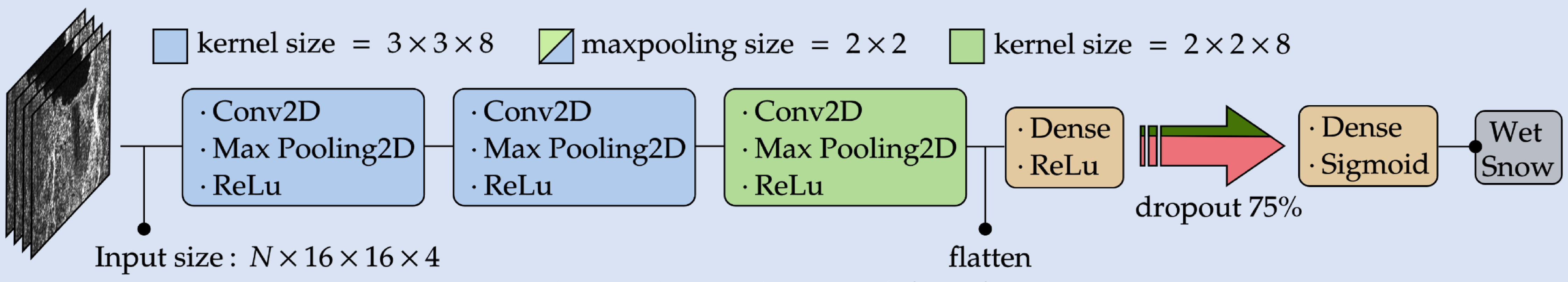

Fig 2: Convolutional Neural Network (CNN) architecture

- Conv2D: 2-dimensional feature extractor
- Maxpooling2D: reduction of the number of learning variables
- ReLu: non-linearity, induces model complexity to the learning process
- Dense layer: learns the optimal combination of the learned features
- Drop-out layer: avoid overfitting (drop 75% of the features randomly during the training)

Random Forest (RF) architecture

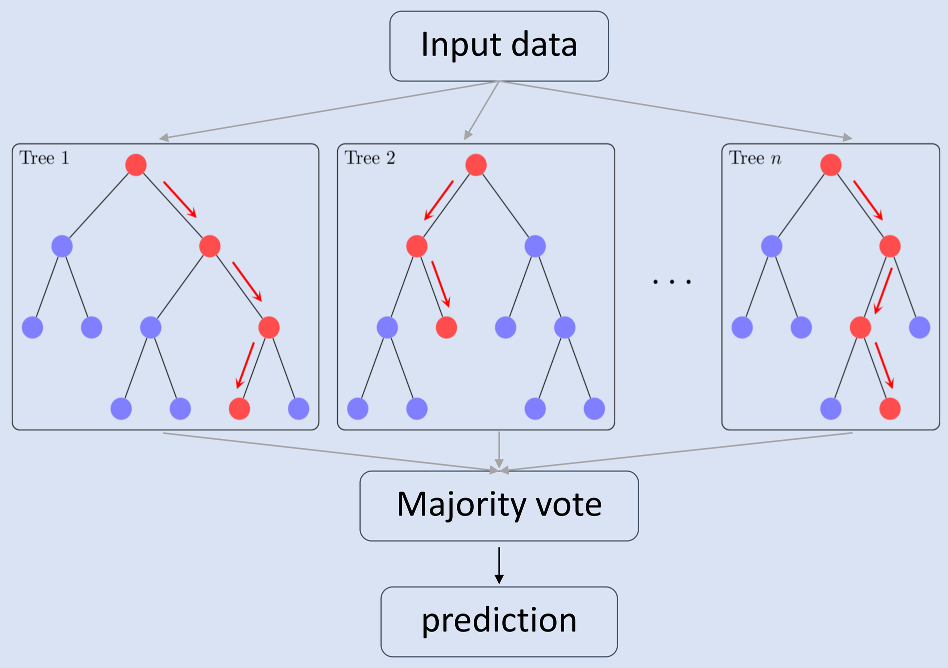

Fig 3: Random Forest general architecture

Results

Wet Snow Maps of 31st March 2021

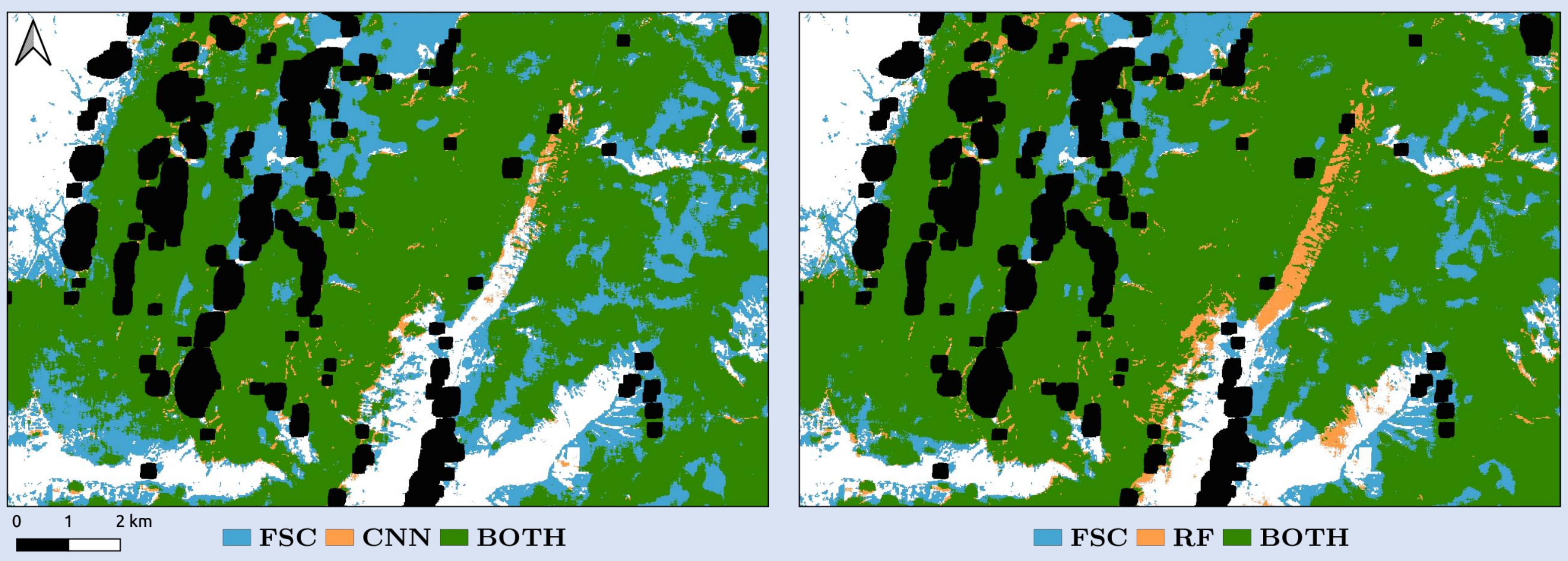

Fig 4: Comparison between the Fractionnal Snow Cover (FSC) and the two algorithms (RF & CNN)

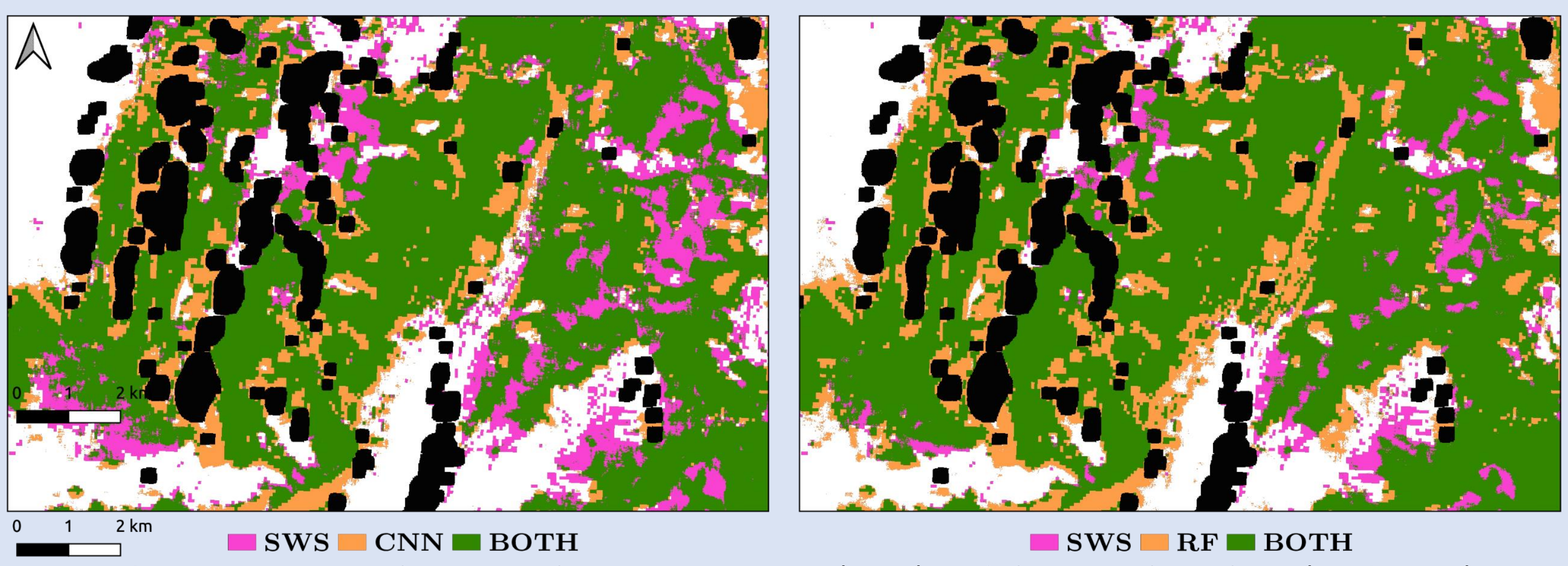

Fig 5: Comparison between the SAR Wet Snow (SWS) and the two algorithms (RF & CNN)

We see that the 2 algorithms trained on the Crocus-labelled data produce maps **close** to the existing Copernicus products, with better **definition** than the SAR SWS product. The RF tends to **overestimate** the zones compared with the CNN but gives more **homogenous** results.

Quantitative results

FCROC: Threshold on the output probability, learned on train data for a constant (5%) False Positive Rate (rather than the traditional threshold at 0,5)

	F1	AUC	κ	FRCOC
RF	75.2 +/- 0.2	83.6 +/- 0.1	50.6 +/- 0.4	68.8 +/- 0.4
CNN	76.3 +/- 1.8	83.9 +/- 0.6	52.8 +/- 3.2	69.3 +/- 0.9

Confusion matrices

FCROC CNN (%)		
Not Wet	47.5	2.5
Wet	28.2	21.8
	Not Wet	Wet

FCROC RF (%)		
Not Wet	47.6	2.4
Wet	29.1	20.9
	Not Wet	Wet

Conclusion: We compare models on a study area at a given date. The wet snow map obtained by CNN and RF are compared with the existing Copernicus products (FSC and SWS). This evaluation allowed us to assess the relatively **good** correspondence between the 2 results and the 2 products. The main limitation of this machine learning approach is the **reliability** of the physical model used to determine the labels of the samples. The codes are available on **Github**.

References:
[1] R.Nijhawan, J.Das, and B.Raman, "A hybrid of deep learning and hand-crafted features based approach for snow cover mapping," International Journal of Remote Sensing (2019).
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[3] Tsai, Dietz, Oppelt, and Kuenzer, "Wet and dry snow detection using Sentinel-1 SAR data for mountainous areas with a machine learning technique," Remote Sensing (2021).
[4] V. Vionnet, E. Brun, S. Morin & al, "The detailed snowpack scheme Crocus and its implementation in surfexv7.2," Geoscientific Model Development (2012).
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