Deep Learning applied to cryosphere Earth Observation data

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General context

Boom of **AI in remote sensing !**
- Phi-Lab at ESA organizing PhiWeek event, see LPS Milan

Some AI startups
- Annotation platform: Biggle, Scale , DataVlab (ESA BIC nord: nouvelle startup 2019)
- Optical images: EarthCube (France)
- Analytics with images SAR (descarteslab, URSA),…

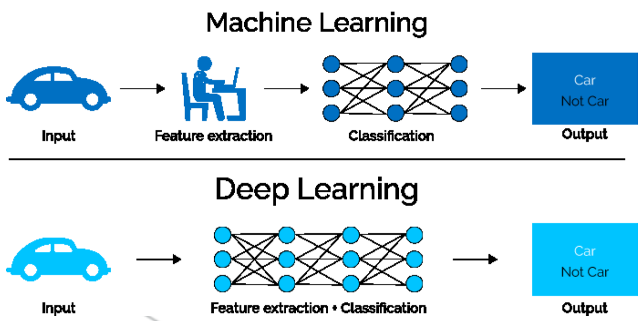
Context of **data analytics platform** (DIAS, PEPS…)

Recent interest of community
- 1st workshop Leveraging AI in the Exploitation of Satellite Earth Observations & Numerical Weather Prediction by NOAA
- Ice charting working group (IICWG) with recent discussion on “big data and Machine Learning”
- Journées thématique IA/ocean/climate/atmosphere
- …

So far limited studies for SAR-based cryosphere applications
- Kaggle by C-Core for iceberg versus vessel detection from SAR images
- SAR-based sea ice classification: one group from Univ Waterloo Canada
- **Oceanography: nothing, except our IFREMER/IMT-A/CLS initiative !**

What about altimetry community ?

Deep Learning technics ?



Classification/segmentation of images and Machine Learning ?
-> Need for handcrafting features
ML applicable to oceanic SAR images ?

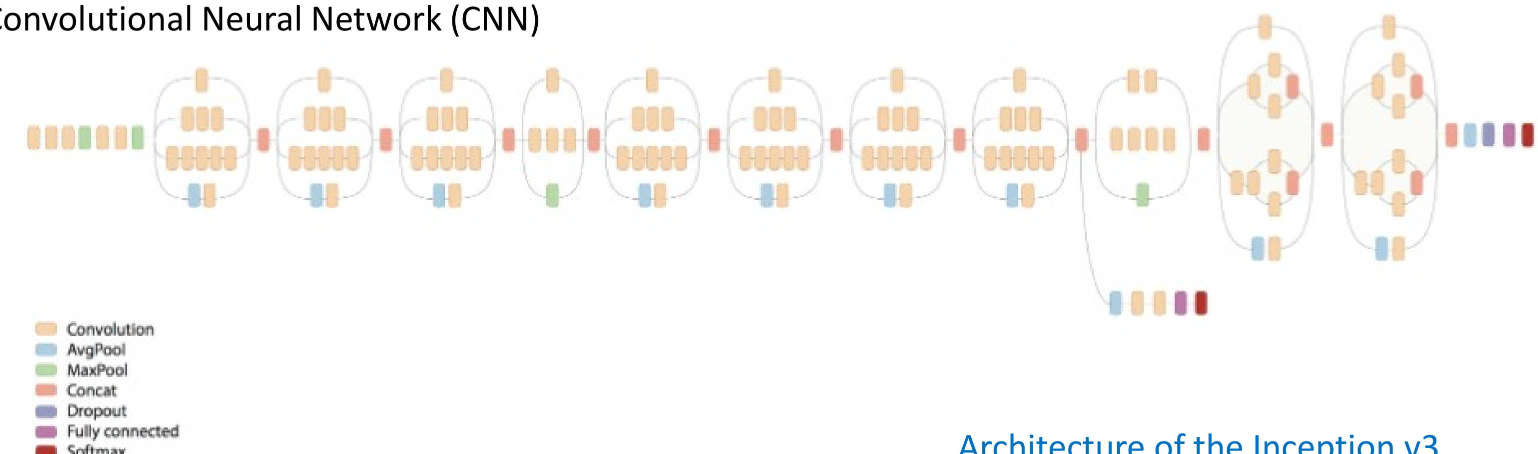
- Intrinsic variability for a given phenomenon
- Depending on metocean and observation conditions

Deep Learning -> data-based feature extraction + classification
DL applicable to oceanic SAR images?

- Need for training database with annotated/labelled SAR images

Computing Power (GPU…) + Frameworks by Google/Facebook/… + Crowdsoucing capabilities with Internet (ImageNet) + Data availability => Boom of Deep Learning

Challenge classification ILSVRC (ImageNet), 1001 classes, 1M+ images
Deep Convolutional Neural Network (CNN)



Architecture of the Inception v3

Used AI - Deep Learning technics

Image classification CNN

Semantic segmentation FCN

Time series analysis RNN / LSTM

Used AI - Deep Learning technics

Image classification CNN

Context for ocean SAR images

Overwhelming amount of data from Copernicus satellites:

- Every day representing **a daily average of 3,45 TB of S1a/S1b data** published

A significant amount covers ocean surface, used for a wide range of applications involving public and private stakeholders.

- Few operational services from SAR: sea ice, oil spill, EMSA/Frontex…
- Few other operational products: wind field (for EMR), waves (see CMEMS),…

Do we really exploit the full imaging capabilities of these C-band SAR data acquired over the ocean's surface?

To name a few, atmospheric fronts, oceanic fronts, rain cells, micro convective cells, internal waves, gravity waves, biologic slicks, upwelling or wind streaks can be observed !

- being **totally discarded in the SAR images.**

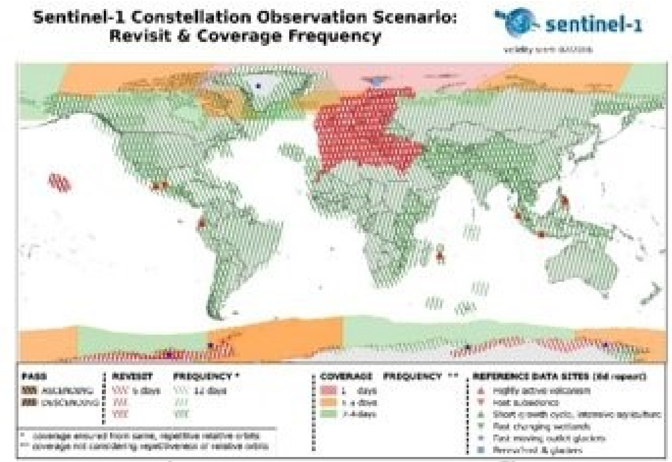
Short/mid term objectives: **automatically and systematically tagged all the observed phenomena**

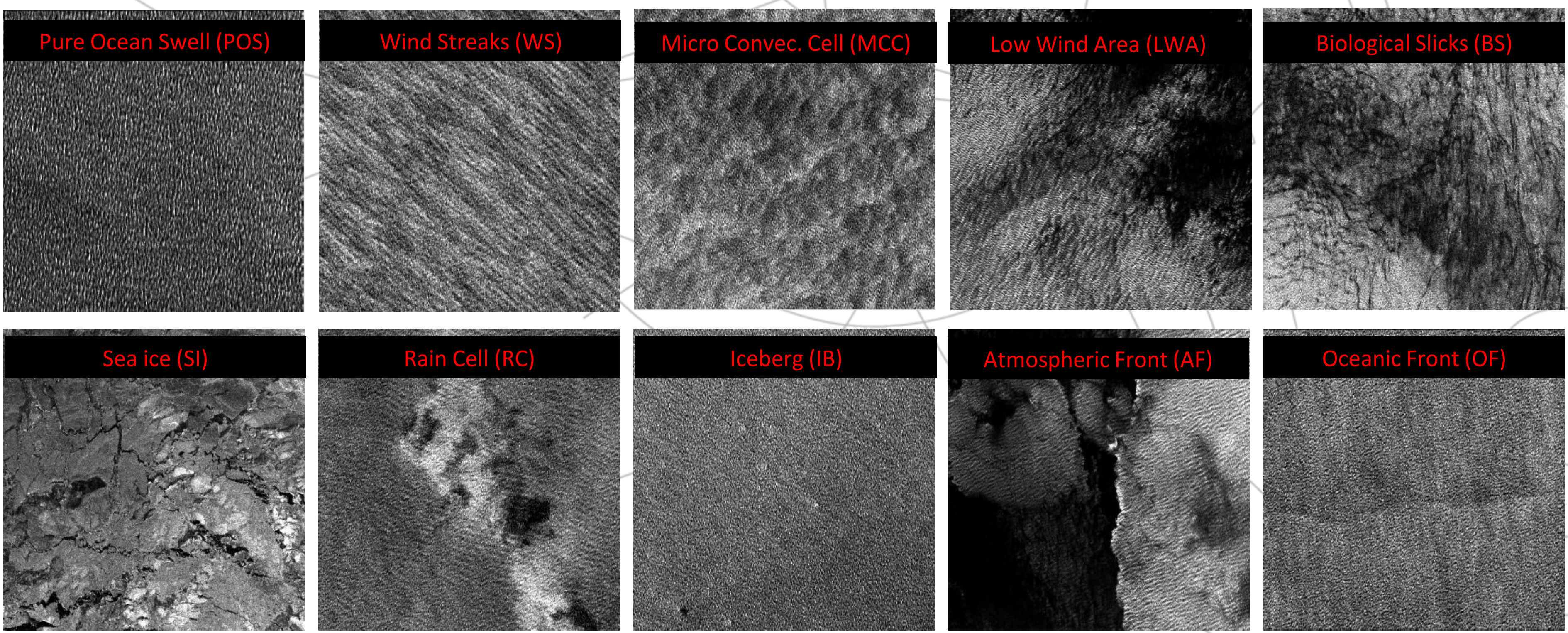
Opening many potential perspectives:
Sciences, operational services, space data

Training database

Based on **Wave Mode imagettes (20 x 20 km).**
Mode by default: see in White ->

- See TenGeoP-SARwv (https://doi.org/10.17882/56796)
- 37k + 10k labelled imagettes with one label per imagette
- 10 classes
- Resampled with 50 m spatial resolution



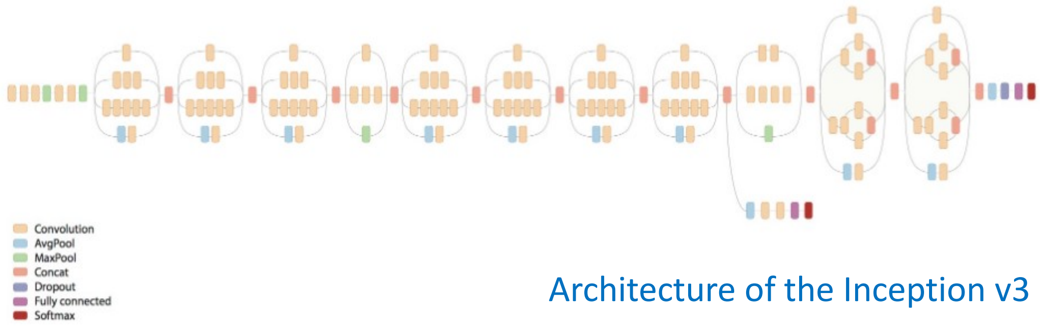


General results

Training/cross-validation/testing: 75/20/5%

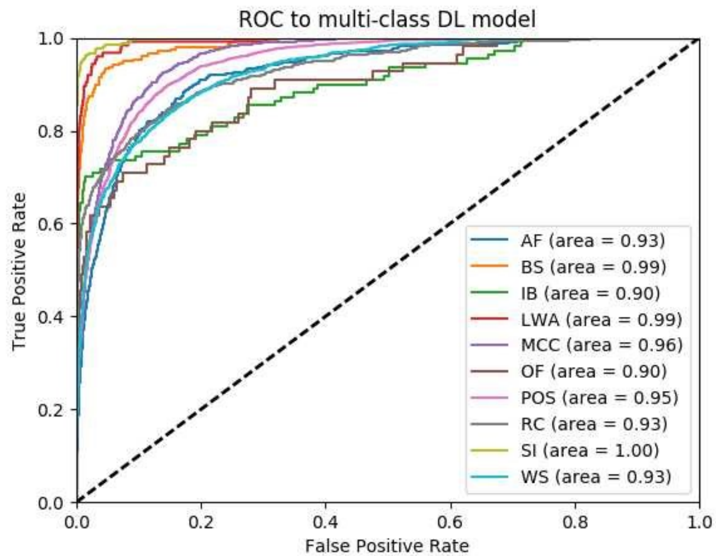
Fine-tuned Inception-V3 Model:
97.5 % accuracy on cross validation(CV)
97.1% on test set.

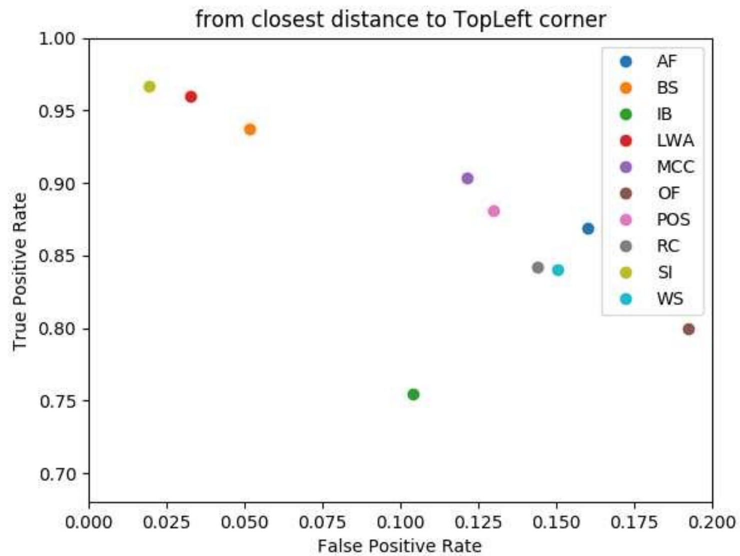
"Fine-tuned": Starting weights of the model comes from training on the ImageNet dataset



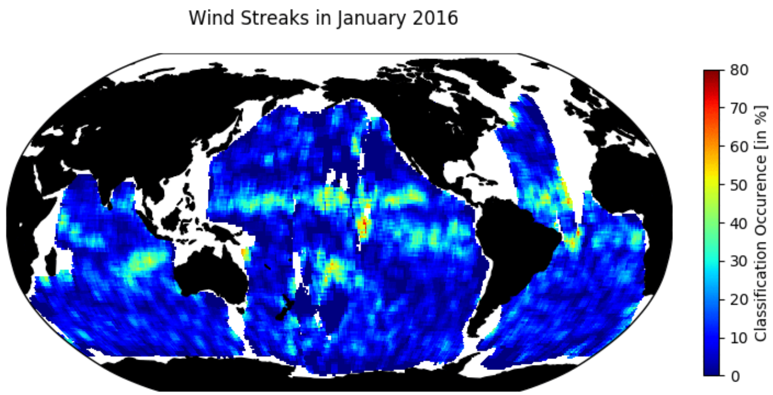
Architecture of the Inception v3

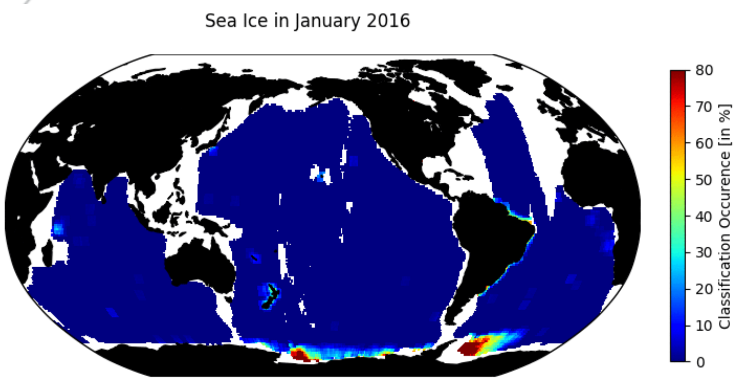
Assessment with independent 10k database: interest for multi-labelling, establishment of classification confidence

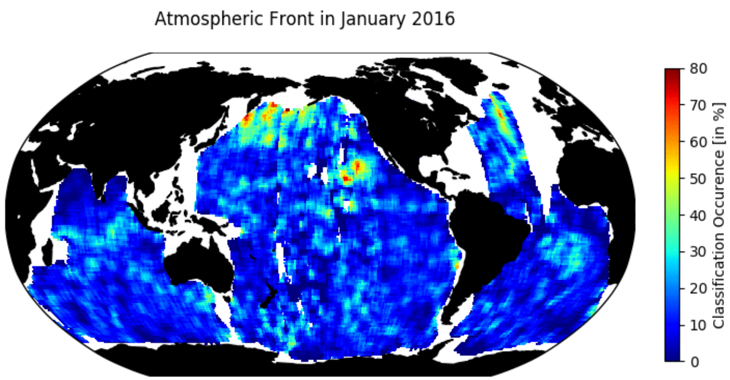


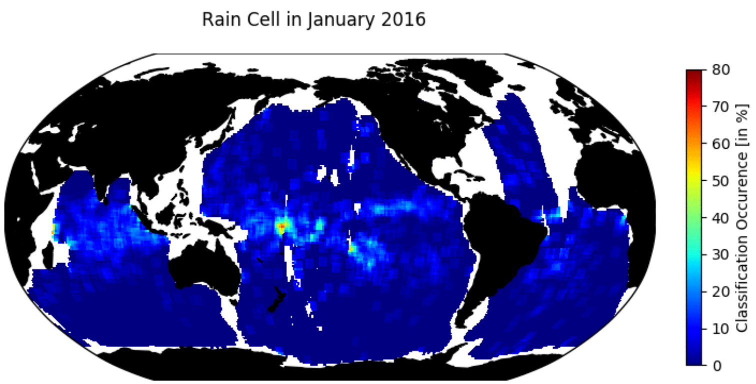


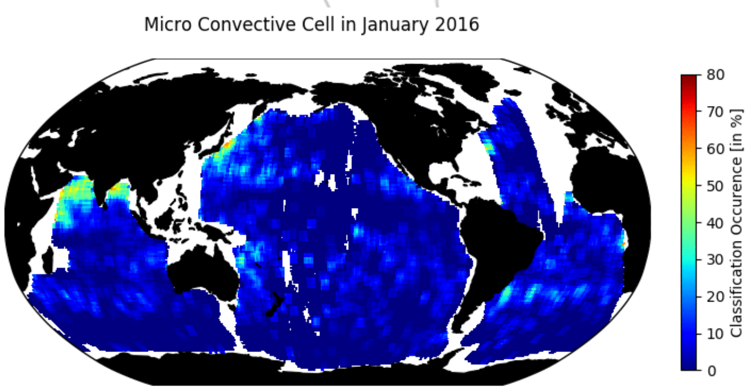
AI-based automatic detection of metocean features on WM imagettes









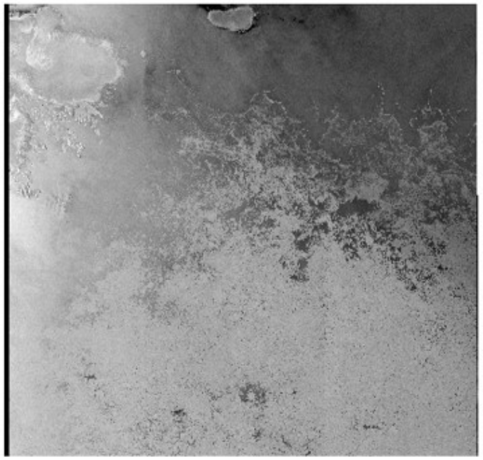


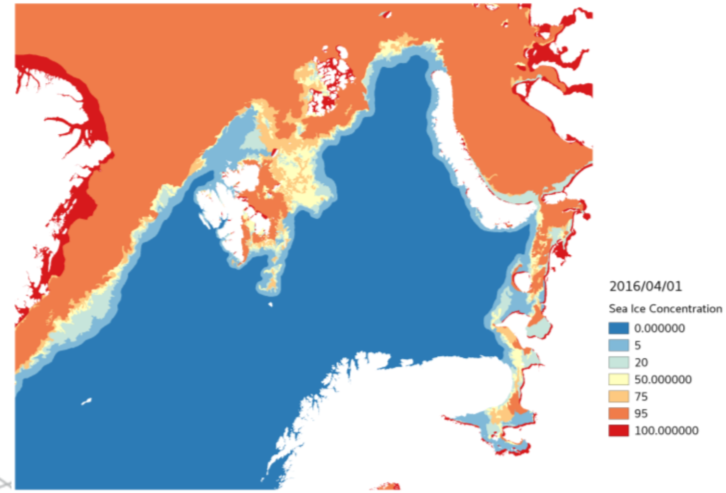
Used AI - Deep Learning technics

Semantic segmentation FCN

Semantic segmentation (Objective)

- Estimation of SIC in Arctic from SAR image





- Sentinel-1 (S1A/S1B) : SAR
  - HH et HV
- 2016 – 2017 – 2018
- 1528 EW images

--> 400 km par 400 km

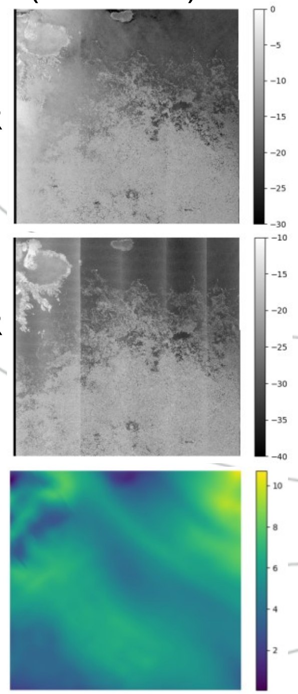
Architecture - FCN –UNet [1]

Sentinel 1
(S1A/S1B)

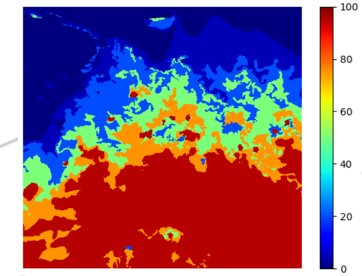
SAR
HH

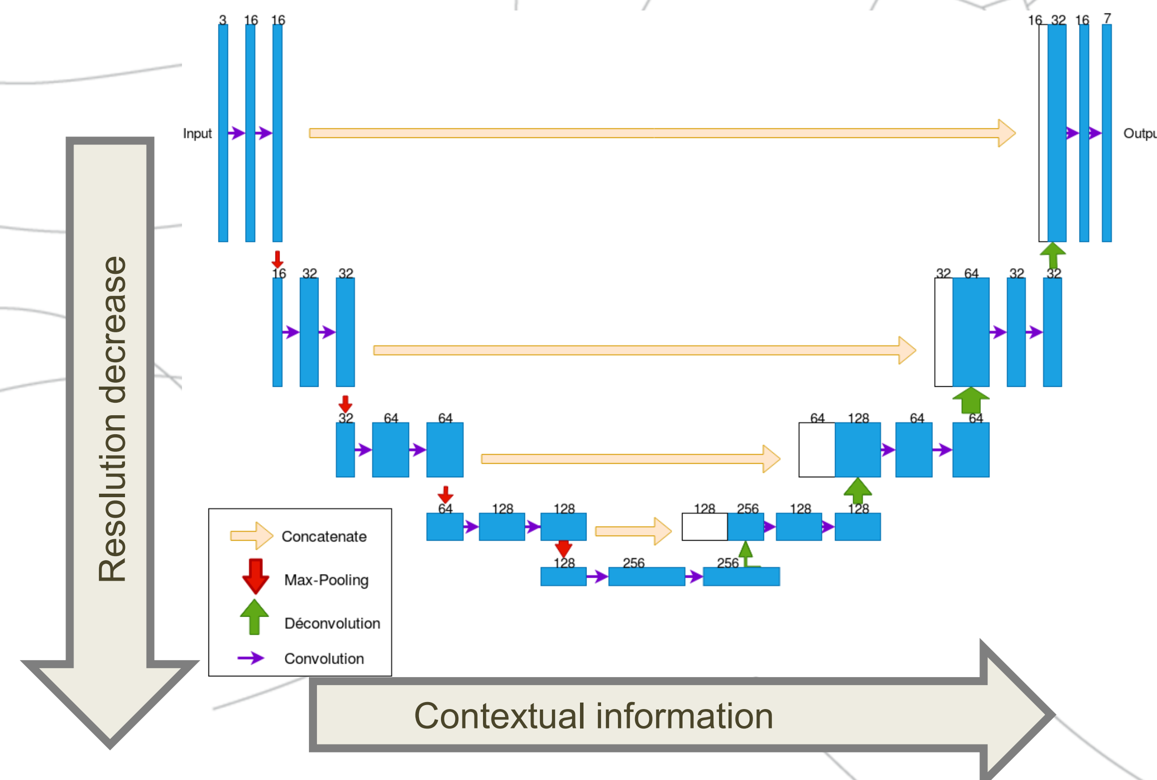
SAR
HV

Wind
Speed
model



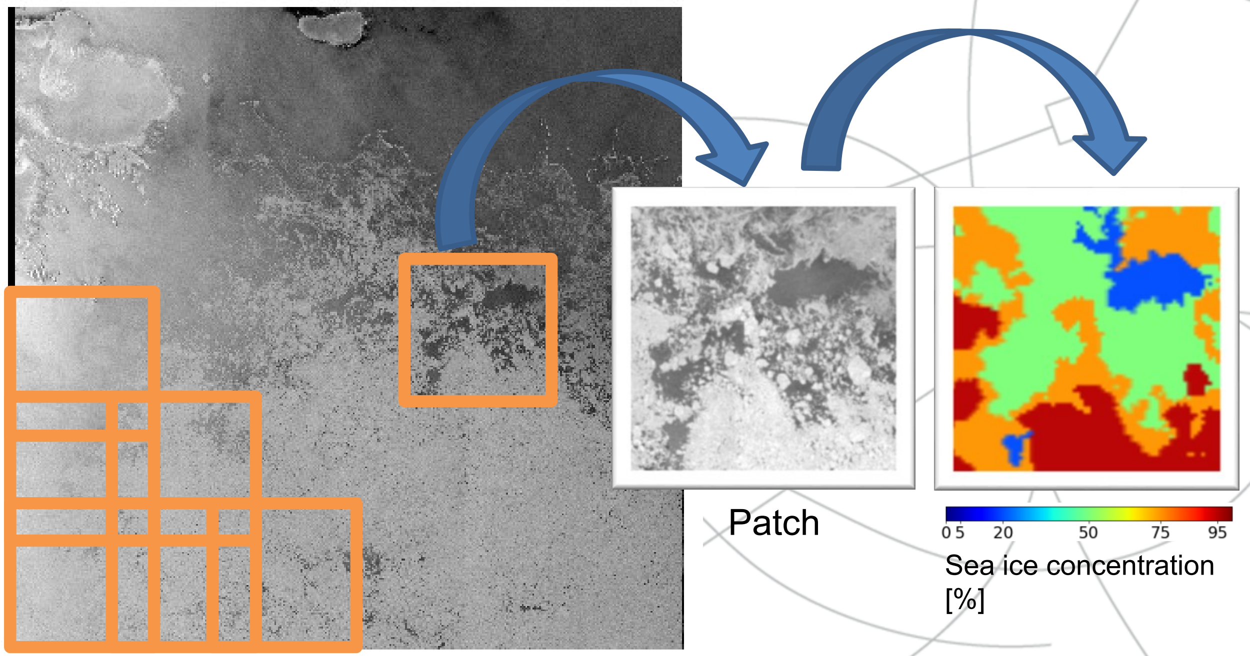
MetNo-like
ice chart

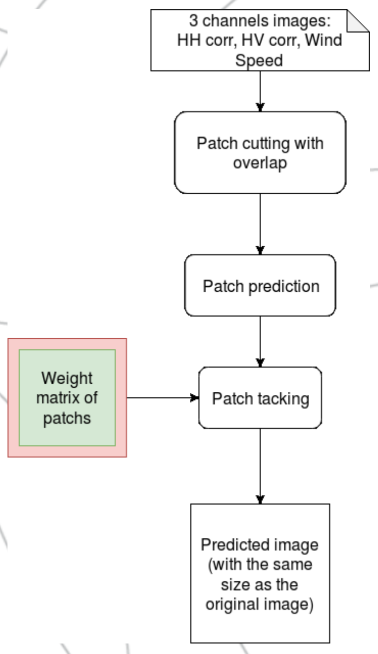




[1] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. “U-net : Convolutional networks for biomedical image segmentation”. In: International Conference on Medical image computing and computer-assisted intervention. Springer. 2015, pp. 234–241.

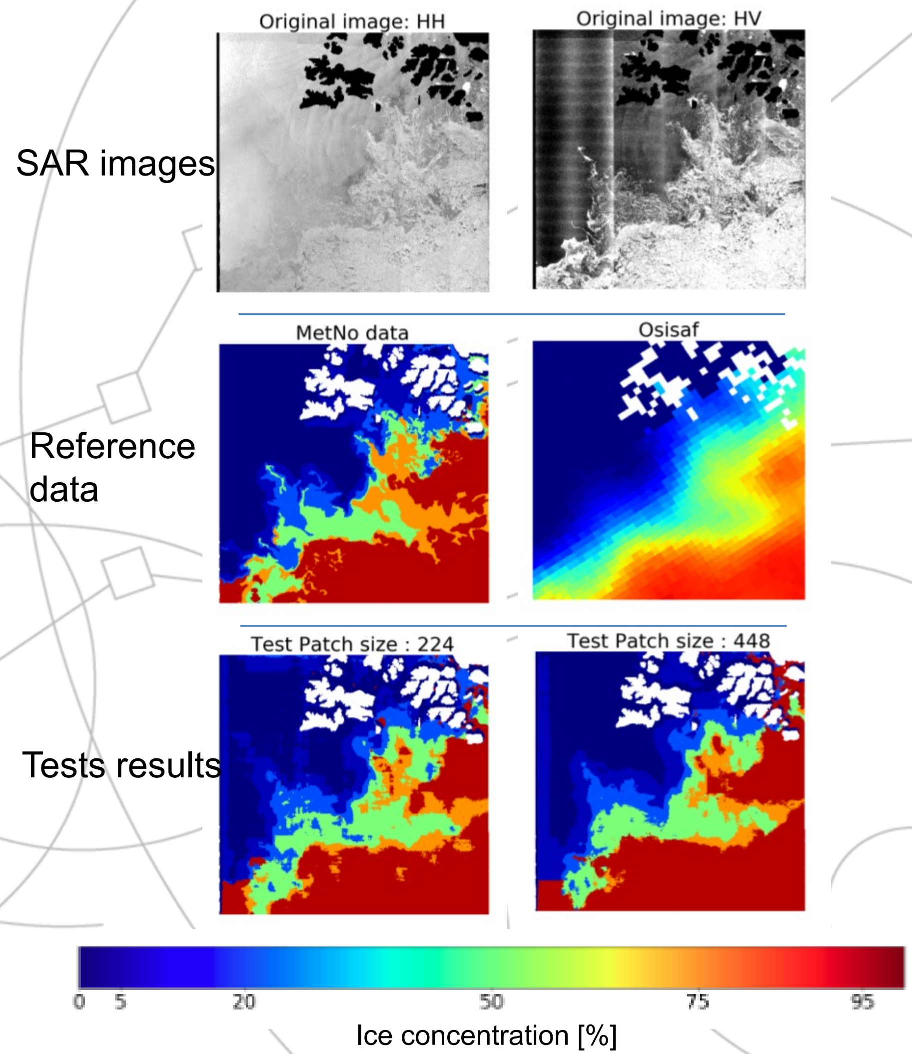
Prediction by patches





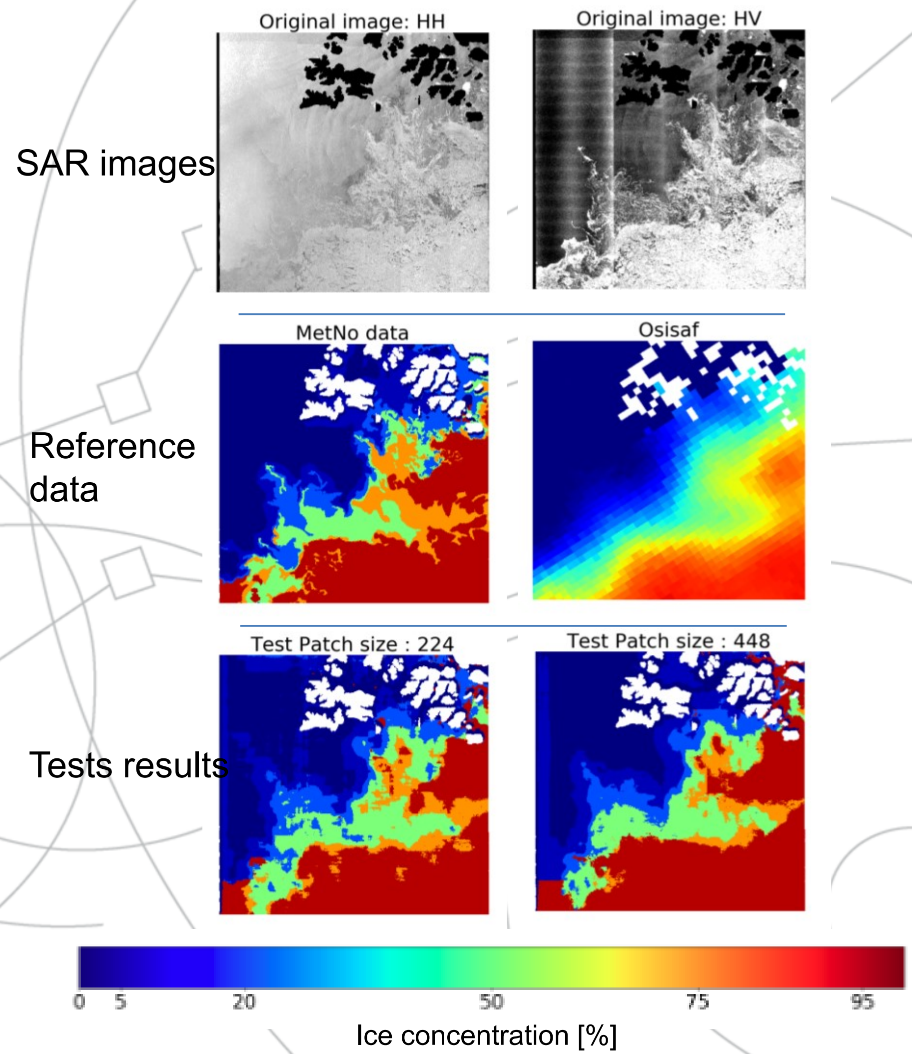
Results

- Overall good prediction



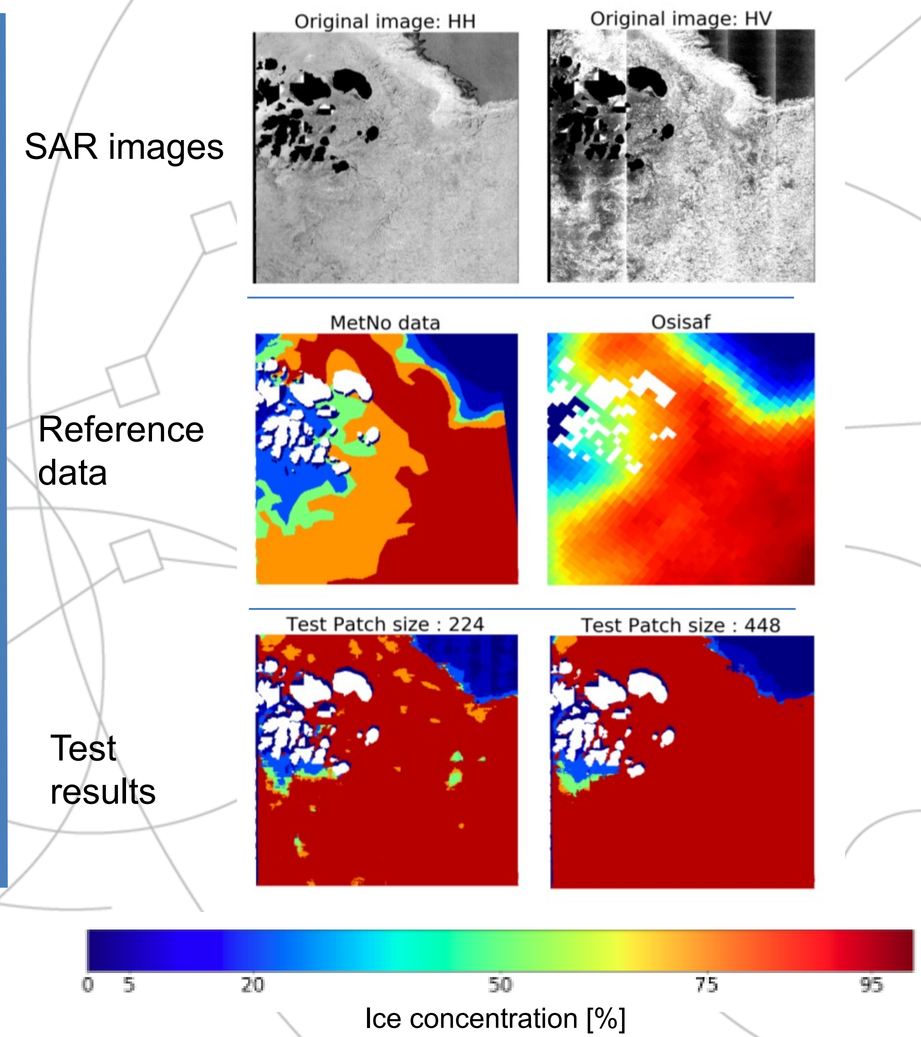
Results

- Overall good prediction
- Better generalisation with deeper network (patch size 448 with 5 layers)



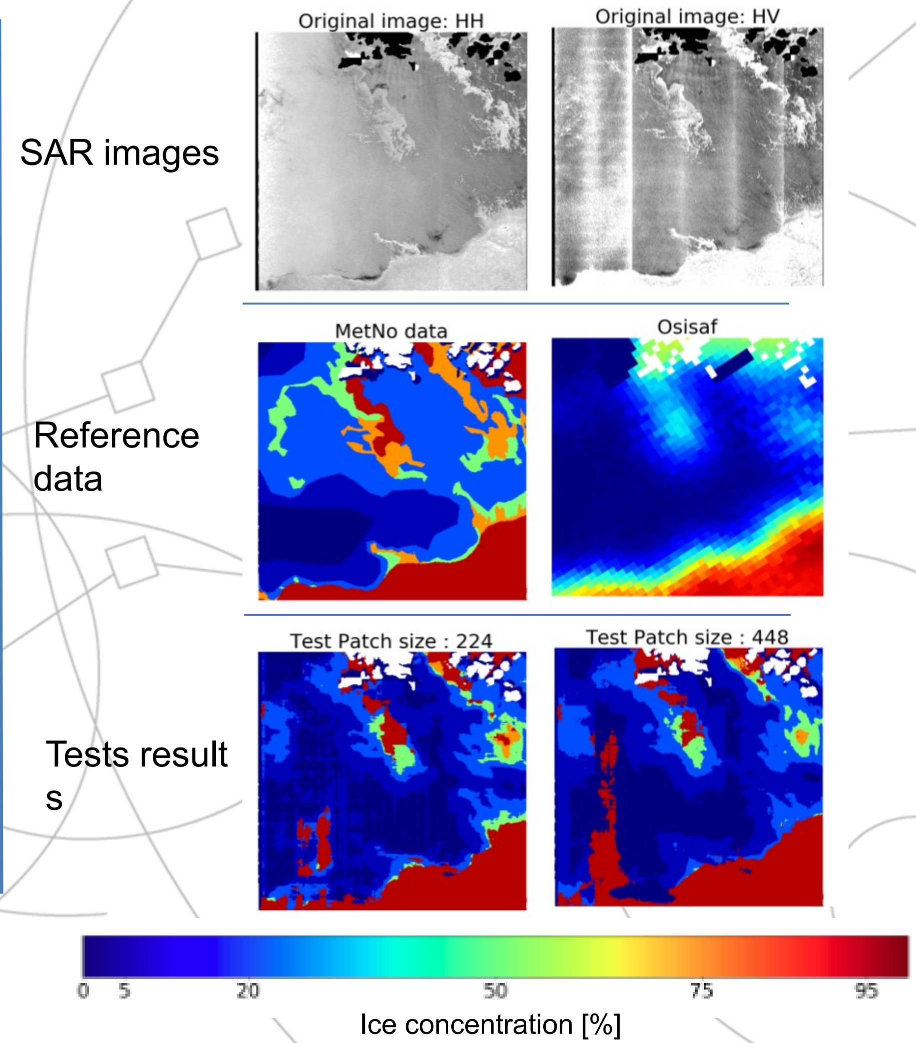
Results

- Overall good prediction
- Better generalisation with deeper network (patch size 448 with 5 layers)
- Overprediction for 95% SIC class



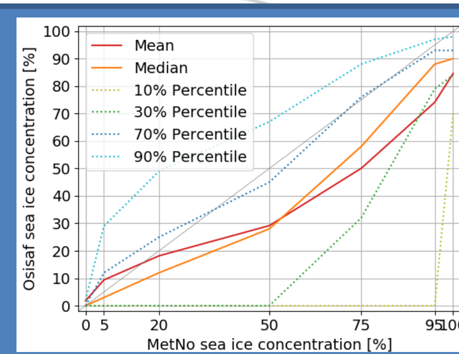
Results

- Overall good prediction
- Better generalisation with deeper network (patch size 448 with 5 layers)
- Overprediction for 95% SIC class
- Better agreement with OSISAF for low SIC

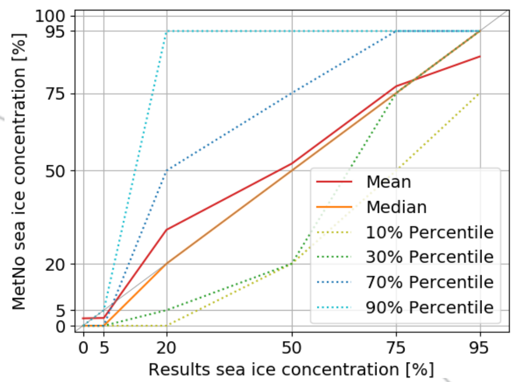


Validation

MetNo contre
OSI SAF

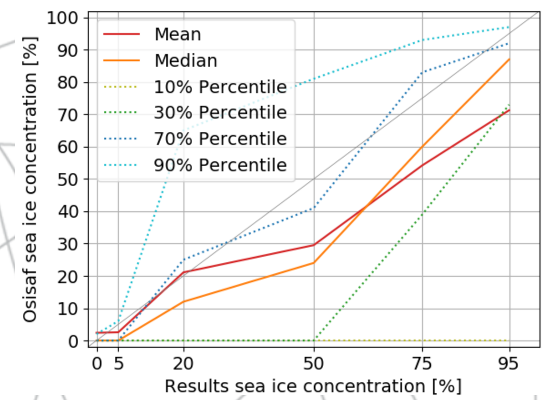


METNO



- Median and mean values consistent
- Spead for intermediate classes (20% -> 75%)

OSI SAF



- Overestimation compared to OSISAF SIC (same with MetNo)

Used AI - Deep Learning technics

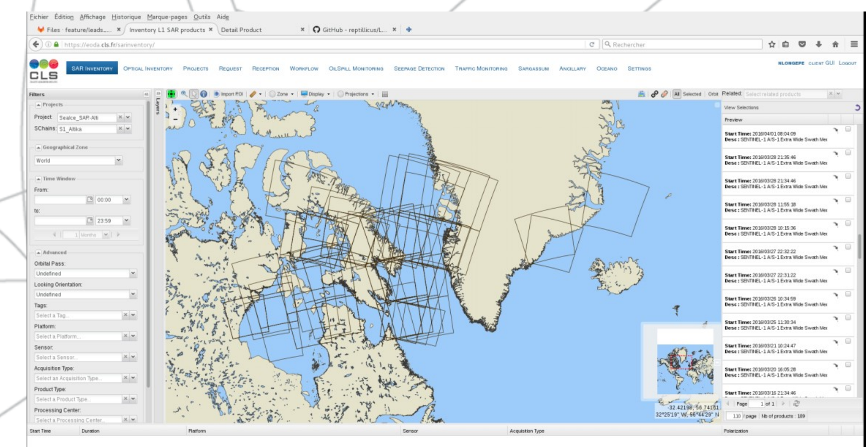
Time series analysis RNN / LSTM

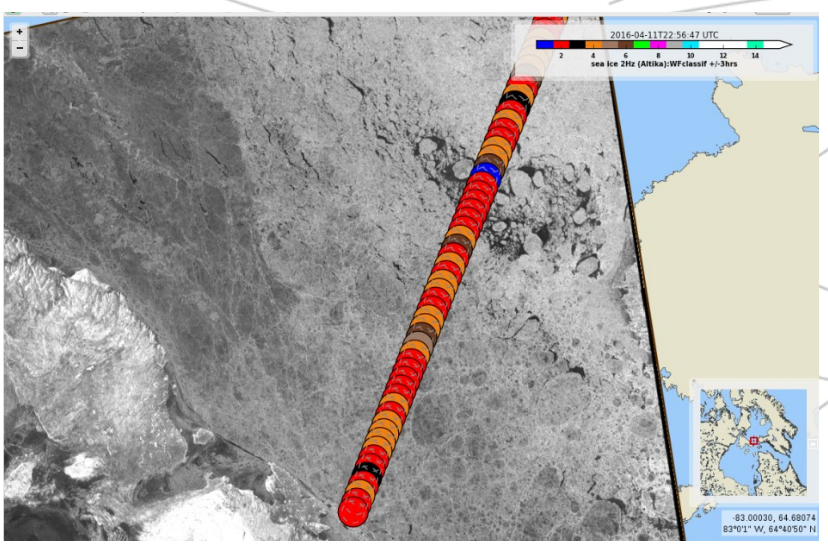
Database AltiKa with "ground truth" provided by S-1 lead data

Collocation between AltiKa/SARAL tracks and S-1 data during winter 2015-2016 for AltiKa

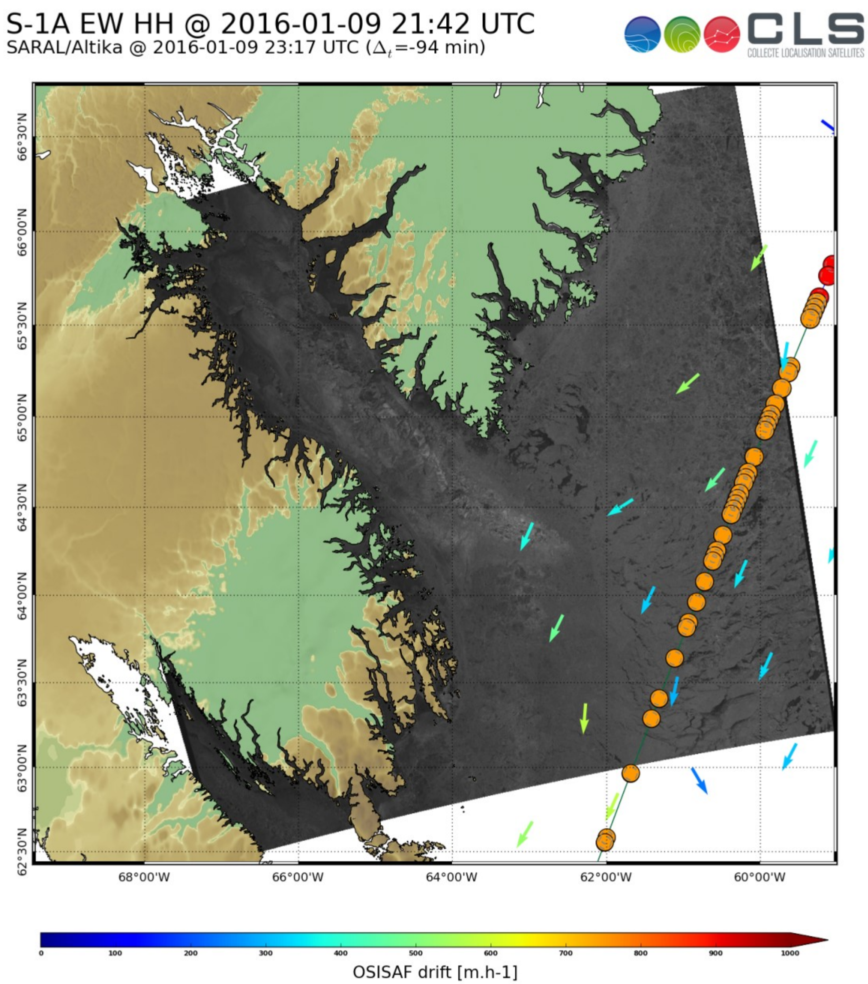
About 100 images selected with consolidated sea ice (SIC > 50%)

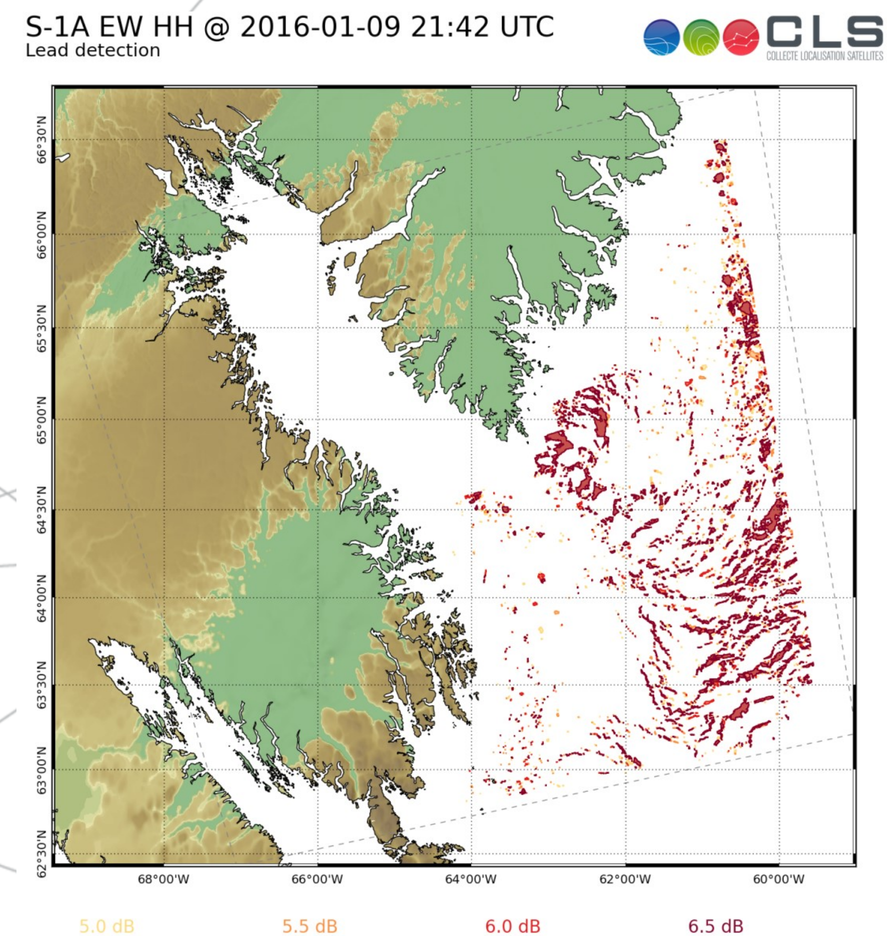
About 1h time lag at best





Database AltiKa with ground truth provided by S-1

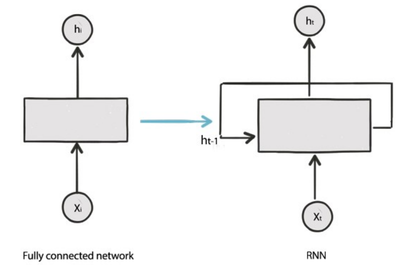


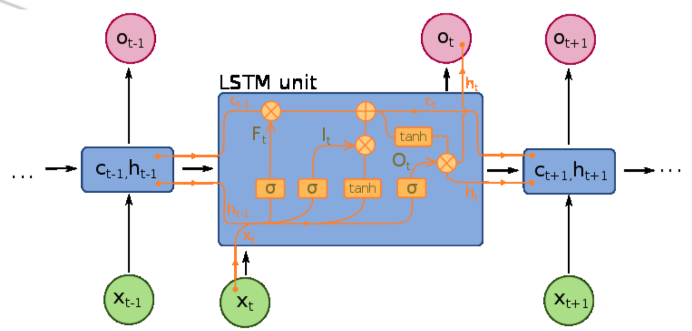


For each 40Hz WF: Compute distance from nadir to closest lead
If distance below a given threshold, consider "lead" as ground truth, otherwise "not lead"

Build RNN / LSTM (experimental)

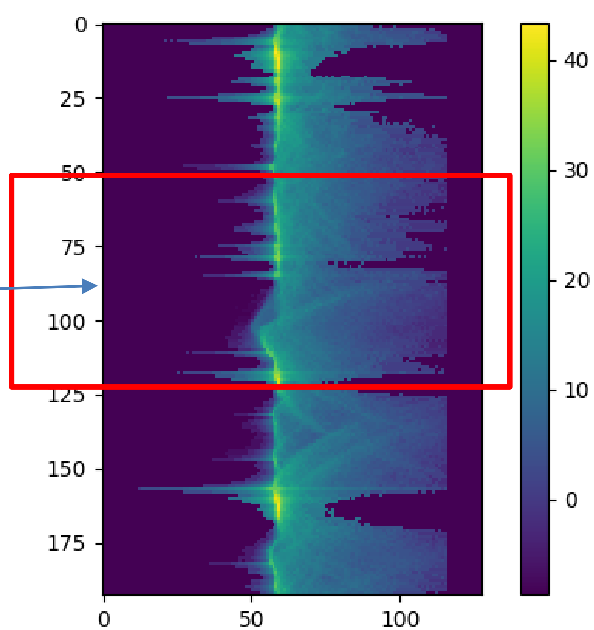
Recurent neural Network: networks with loops allowing persistence of information, adapted to time series analysis





Time steps : 128 per WF
Nb features : 71 WF
For each block of 71 WF, one label "lead/non lead" corresponding to the central WF

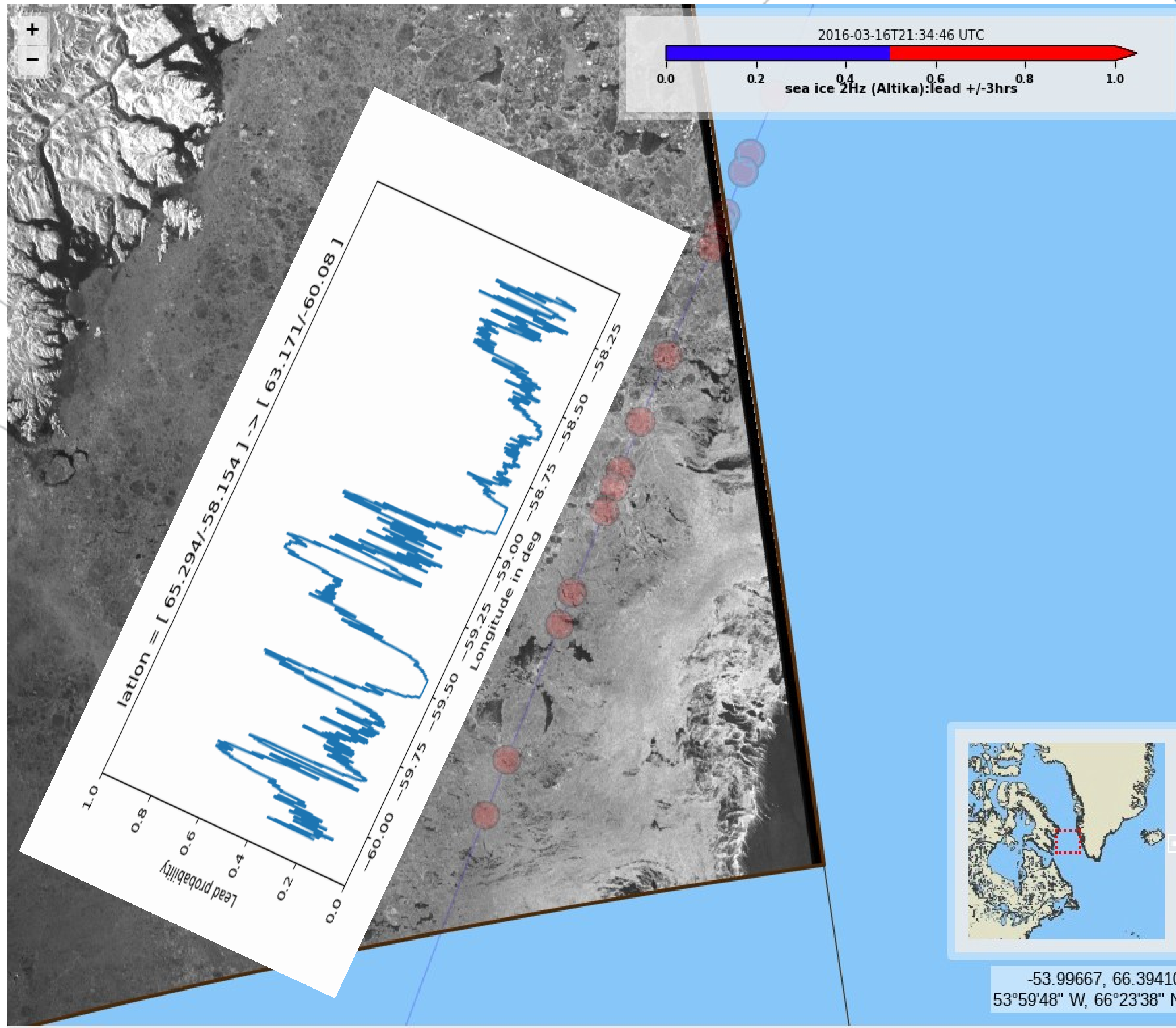
Lead or not lead provided by SAR lead product for central position



About 40 000 samples (128x71) for training

About 10 000 samples (128x71) for testing/validation

Some very preliminary results



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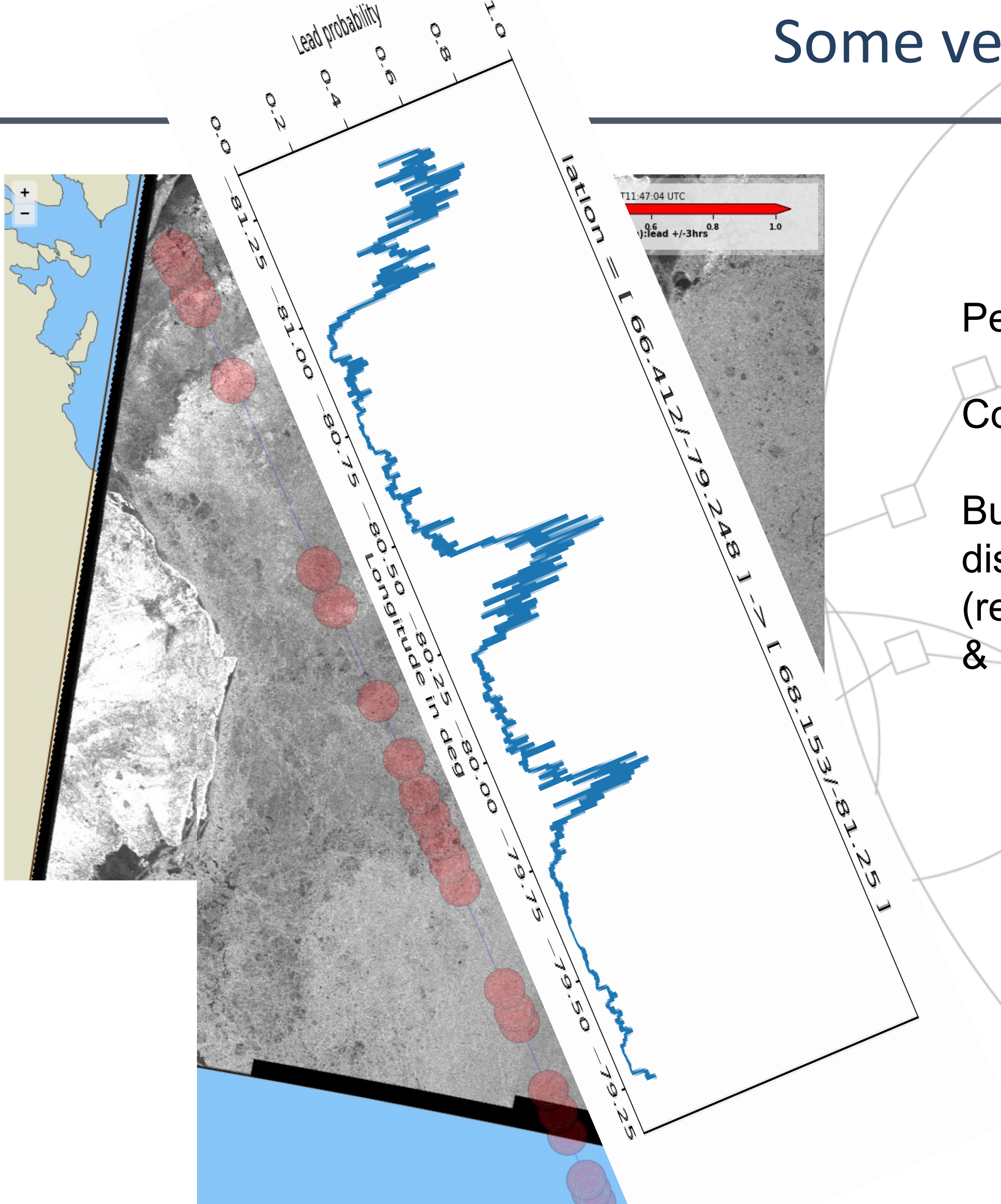

Perspectives:

Consolidate the approach !!

Build DL model to estimate distance of leads from nadir (reprocess data with no AGC & no tracker accounted for)