

Automatic detection of weather events in high-resolution NWP outputs

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Plan

- 1 Motivations and methods
- 2 Texture-based segmentation of rainfall
- 3 Tropical cyclone wind structure
- 4 Conclusions and future works

- ▷ The classical use of EPS includes
 - a visual examination of each member : time-consuming
 - point-based probabilities and percentiles : lack of spatial consistency, mostly univariate, hide some small-scale multivariate features (e.g. MCS)
- ▷ Automatic detection of relevant weather patterns in NWP outputs could provide an additional useful information
 - Occurrence of some events in ensemble members
 - Pattern-based probabilities
 - Pattern-based verification, weighting and clustering of ensemble members

1 - Detection methods

- ▷ Object detection is not new ... but the methods have evolved
- ▷ 2 main approaches can be used to automate this task
 - **Expert systems**
a set of empirical rules are specified by the expert (e.g. size and intensity thresholds)

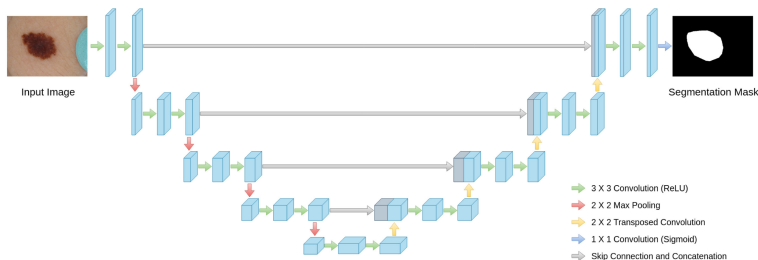


- **Supervised machine learning**
classification rules are learnt by the algorithm from the statistical properties of the data



1 - Weather objects detection

- ▷ Several objects detected in the French [Arome/Arome-EPS outputs](#) : rainfall patterns (intensity, texture), tropical cyclones, bow echoes (A. Mounier's poster), weather fronts (L. Rottner's poster)
- ▷ Detection is performed with a standard [convolutional neural network](#) : the [U-Net](#) encoder-decoder (Ronneberger et. al 2015)



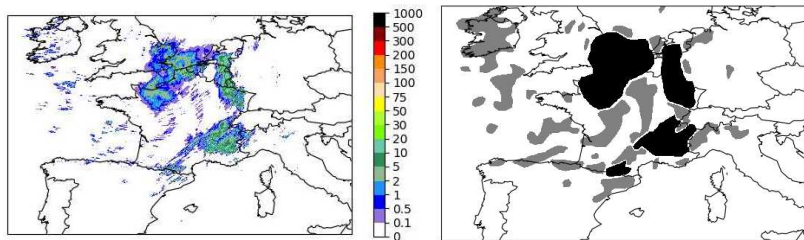
- ▷ The U-Net is known to work well with small training datasets

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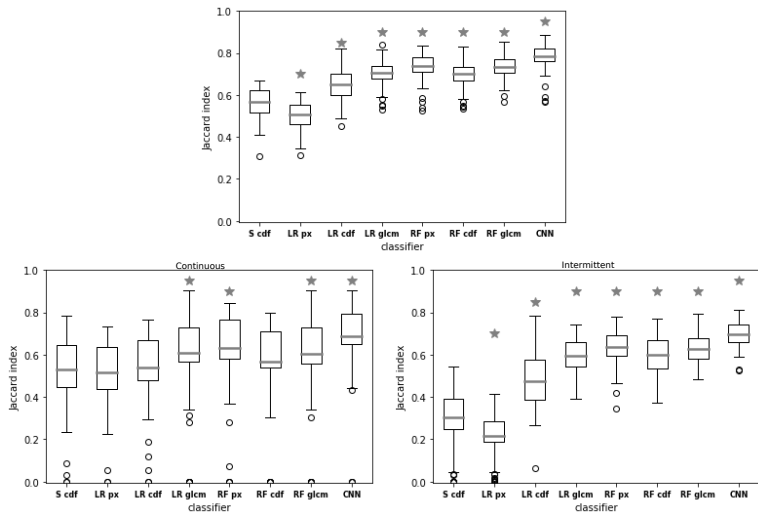
2 - Training

- ▷ Detection of categories ‘no precipitation’, ‘continuous precipitation’ and ‘intermittent precipitation’
- ▷ Training database : 180 Arome 1hr-accumulated rainfall forecasts + corresponding manual labels



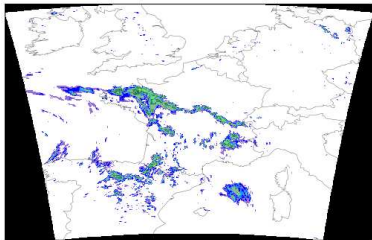
- ▷ U-Net is trained on small patches randomly extracted from each Arome image

2 - Prediction - Performances

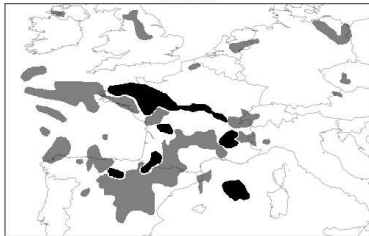


▷ U-Net performs best, but it is only slightly better than RF

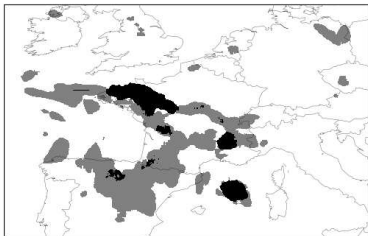
2 - Prediction - Case study



Ground truth

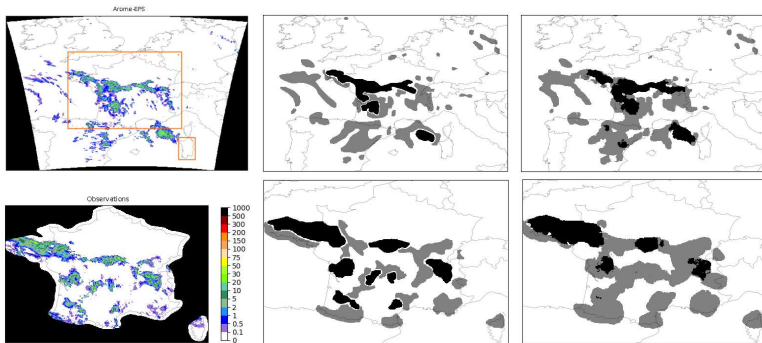


U-Net



2 - Transfer learning

- ▷ Similar detections can be done on Arome-EPS and observations
- ▷ **Transfer learning** is efficient and removes the need for new databases



Plan

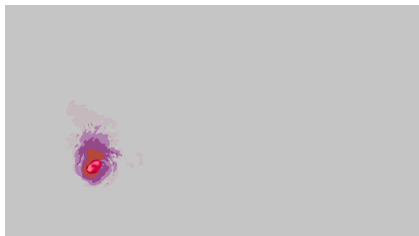
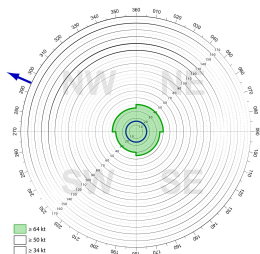
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3 - TC trackers

- ▷ Existing TC trackers are based on expert systems
- ▷ Heming, 2017 : TC tracking and verification techniques at UKMO
 - “1. The 850RV must be above a predetermined threshold*
 - 2. The nearest point of lowest MSLP must be below a predetermined threshold*
 - 3. A closed isobar check is applied*
 - 4. The TC centre detected must be equatorwards of 37.5 latitude*
 - 5. The TC centre must be over or very close to sea points in the model*
 - 6. The TC centre must be over sea with a model analysed SST above a predetermined threshold.”*
- ▷ If all these conditions are met a TC is considered to have been detected in the model forecast.
- ▷ TC trackers can be complex to develop and computationally expensive.

3 - TC trackers

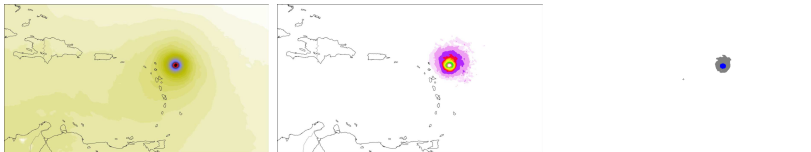
- ▷ TC trackers also report **cyclonic (64kt)** and **maximum winds radii**
- ▷ Only in each quadrant of the storm



- ▷ The U-Net can be used to get a finer description of wind structure by directly identifying **areas of cyclonic and maximum winds**

3 - Training

▷ Training : 311 Arôme-West Indies forecasts of 10-meter wind speed and Z850 + corresponding manual labels of wind areas

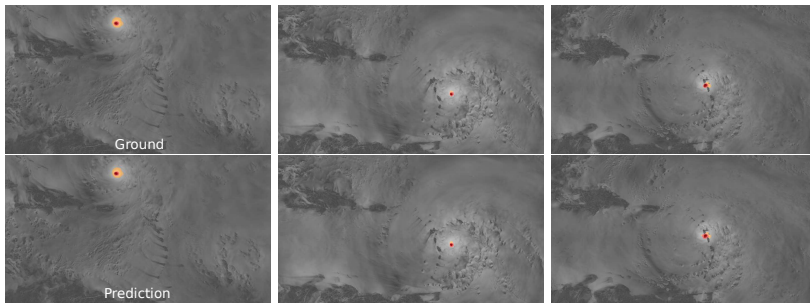


▷ Training data are highly imbalanced : $\sim 5\%$ of pixels are labeled as TC

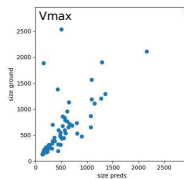
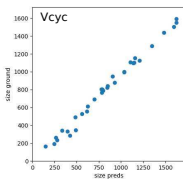
- we impose a ratio ‘empty’ patches/‘TC’ patches = 2
- we use the weighted cross-entropy :
⇒ higher weights are given to TC categories

3 - Prediction

- ▷ On 77 validation TCs : no miss, 2 false alarms on Vmax
- ▷ $\text{Jaccard}(V_{\text{cyc}})=0.87$, $\text{Jaccard}(V_{\text{max}})=0.72$

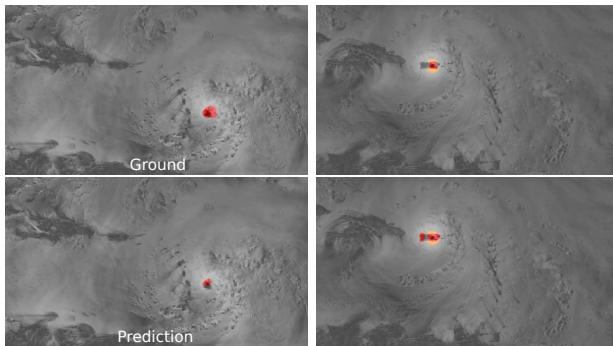


- ▷ Good correspondance of object sizes



3 - Prediction

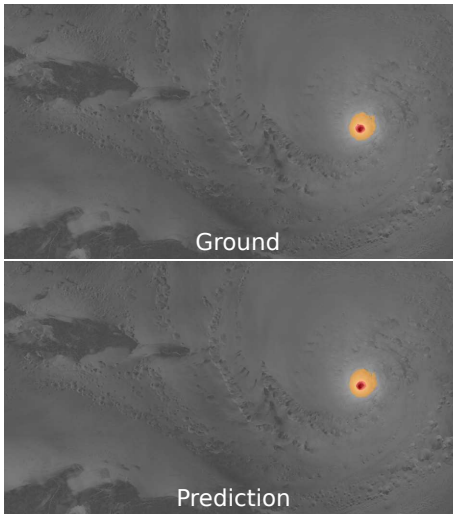
- ▷ Some problems to fix for e.g. for low-intensity TCs and landing



- ▷ Refine the training data and re-tune weights

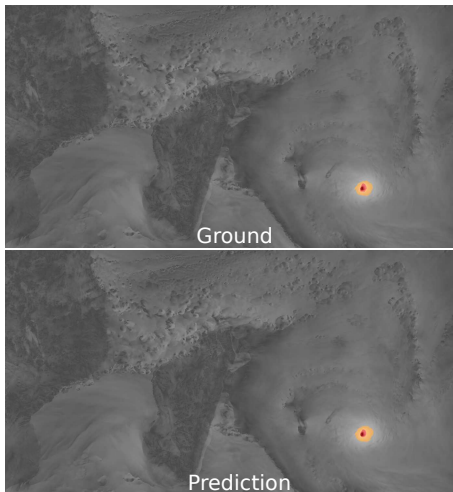
3 - Transfer learning - Model resolution

▷ From Arome 2.5km outputs to Arome 1.3km outputs



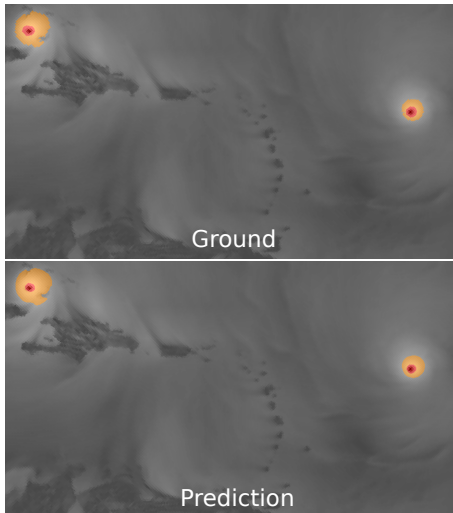
3 - Transfer learning - Domain

▷ From the West Indies domain to the Indian Ocean domain



3 - Transfer learning - Model formulation

▷ From Arome outputs to Arpège outputs



4 - Conclusions and future works

- ▷ The U-Net is an efficient method for the detection of a variety of complex, multivariate objects
- ▷ But a lot of efforts has to be put on the labelling of training data
- ▷ Transfer learning is very promising
- ▷ Extend the detection to other objects (e.g., ongoing work on supercells, weather fronts)
- ▷ Introduce and promote the use of objects in daily forecasters practice :
 - “Direct” use : help for zoning, identifying and characterizing areas of risk
 - “Indirect” use : [objet-based metrics](#) for [weighting](#) (Raynaud et al. 2019), [clustering](#) and [verification](#) of EPS members