Deep Learning & Observation spatiale des précipitations

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…

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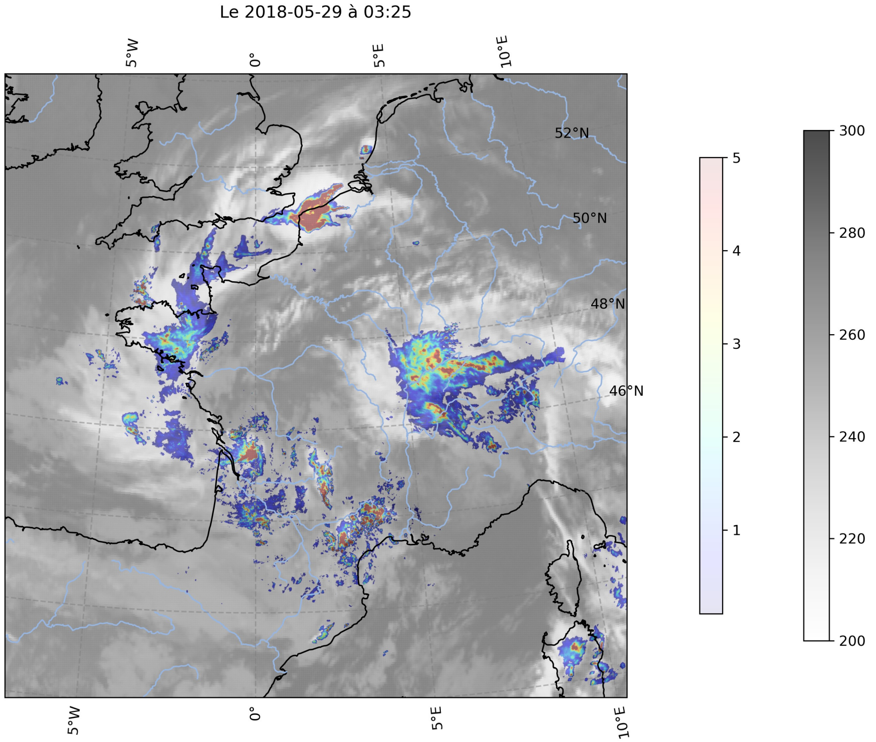
Context

- Rain is a very special variable
  - Spatial intermittence
  - Temporal intermittence
  - Extremely scale dependent
  - Surface rain is dependent on 3-D structure

- End users require < 1km, < 5minutes
  - "Direct" rain measurement on LEO
  - Geostationary offer only IR

➔ We probably need some sort of fusion in the end…



MOTIVATION: from BRAIN to… DRAIN

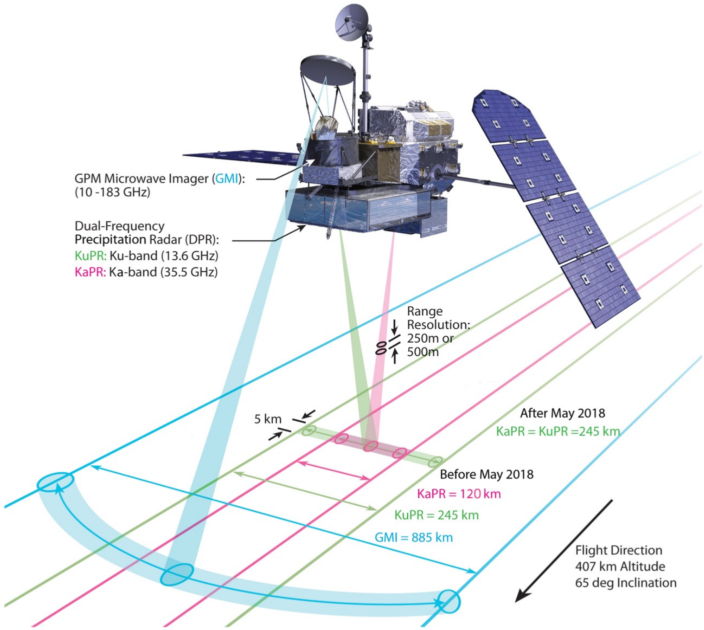
(from Bayesian to Deep-Learning)

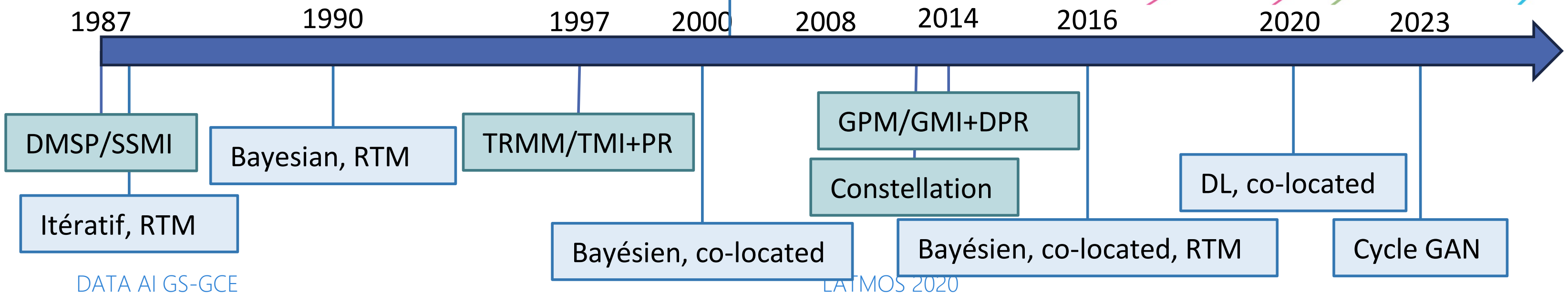
❑Passive microwave (10 to 100th of GHz)

  - ❑ Spatial resolution ~10 km but frequency dependent
  - ❑ Measures integrated over the whole column
  - ❑ Highly ill-posed problem

❑Active microwave (14 and/or 35 GHz)

  - ❑ Spatial resolution closer to 5 km
  - ❑ Measures a profile
  - ❑ Strong dependance on DSD…





ML, co-located

1987 1990 1997 2000 2008 2014 2016 2020 2023

DMSP/SSMI

Itératif, RTM

Bayesian, RTM

TRMM/TMI+PR

Bayésien, co-located

GPM/GMI+DPR

Constellation

Bayésien, co-located, RTM

DL, co-located

Cycle GAN

DRAIN DATABASE

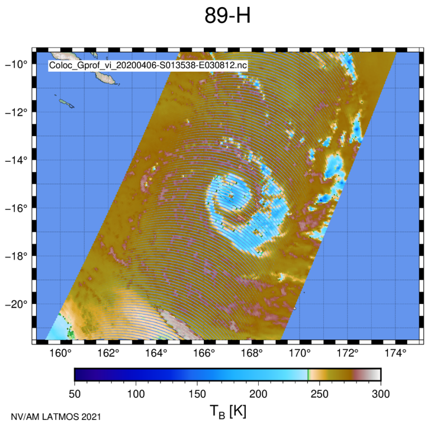
☐Database made of co-located data over 7 years ~70 000+33 000 images

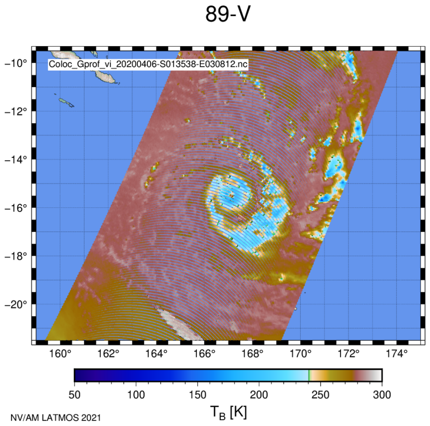
☐Test database: 2019

☐T_Bs as input, *surface rain* from DPR as target:

  ☐89 GHz & 37 GHz H and V

  ☐No other a-priori information



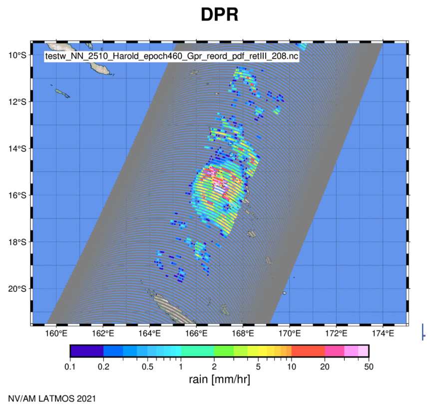


☐ U-net 64 layers (➔ de-cluttering of MF radar data)

☐ Training:

  ☐ 128x128 pixels sub-setted with random position

  ☐ 90° random rotation

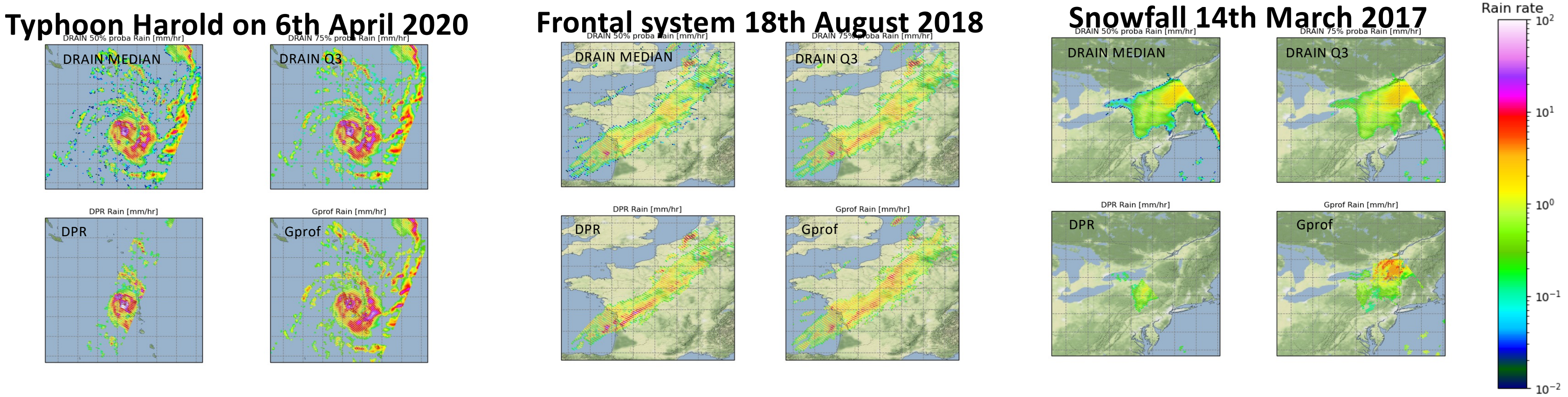


☐ *Quantile loss function* =>Estimating the CDF of rain intensity for a given a-priori T_Bs input vector

☐ No a priori on on the CDF shape

DRAIN Results: examples

GPROF: reference algorithm from NASA (with fair amount of aux. data), pixel by pixel



Typhoon Harold on 6th April 2020

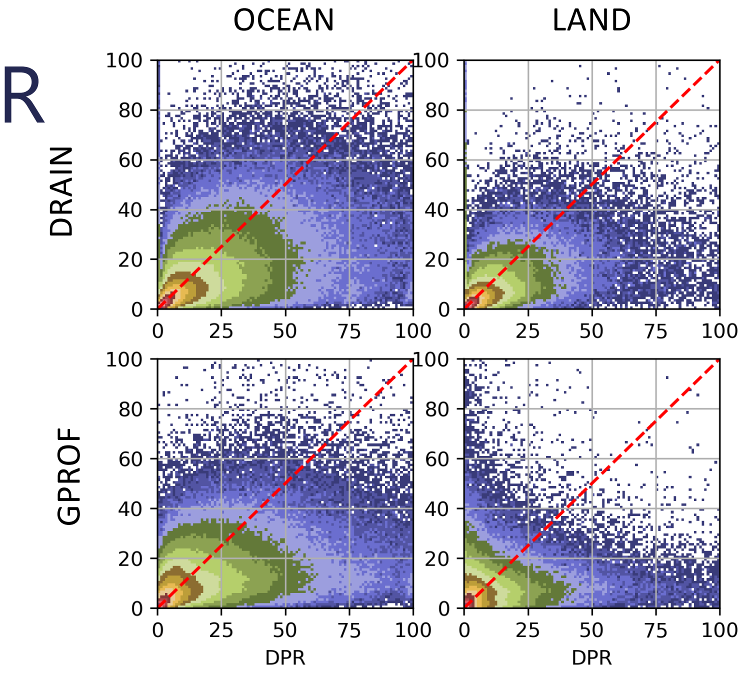
Frontal system 18th August 2018

Snowfall 14th March 2017

- ❑ Excellent rain/no-rain discrimination w/r to DPR
- ❑ Excellent retrieval of both structure and intensity in very different situations
- ❑ Equivalent to GPROF without any auxiliary data !

Test database : 2019
« Pixels » resolution, to DPR

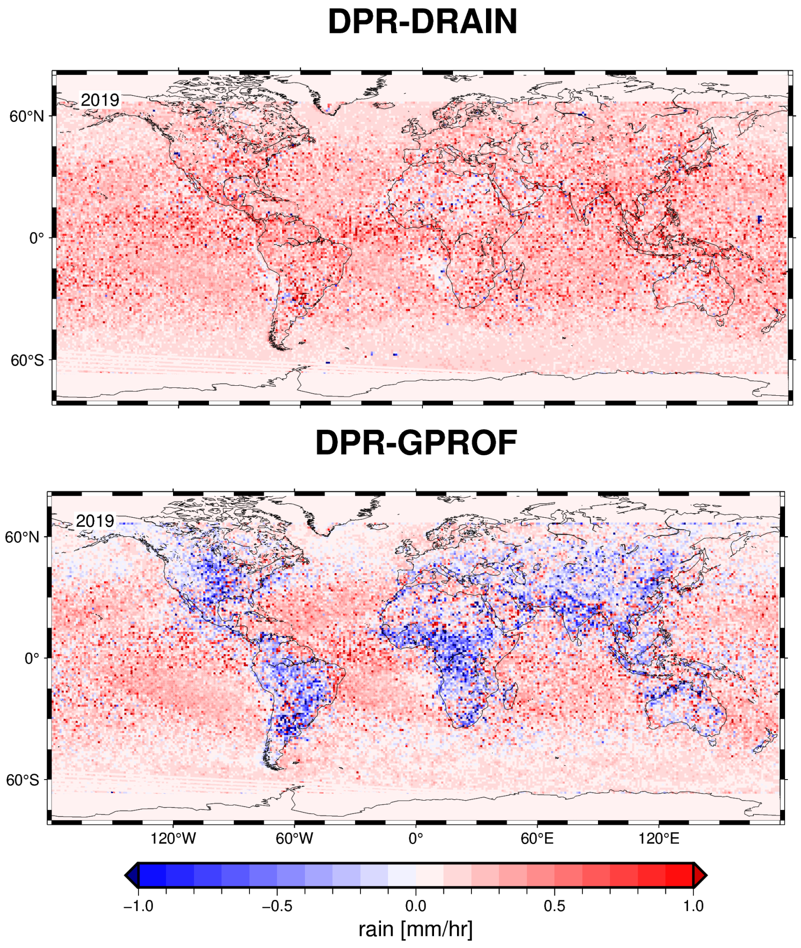
	DRAIN		GPROF	
	Bias	RMSE	Bias	RMSE
LAND	0.31	2.67	-0.24	3.39
OCEAN	0.26	2.98	0.08	3.18
TOTAL	0.27	2.92	0.01	3.22



mm/hr

- DPR is used for training so logically better than GPROF
- GPROF bias slightly better but due to compensation

Base de test : 2019
2°x2° resolution, to DPR



NV/AM LATMOS 2021

- Homogeneity of the error structure
- Slight N/S error structure

- Unlike GPROF, no Land/Ocean difference

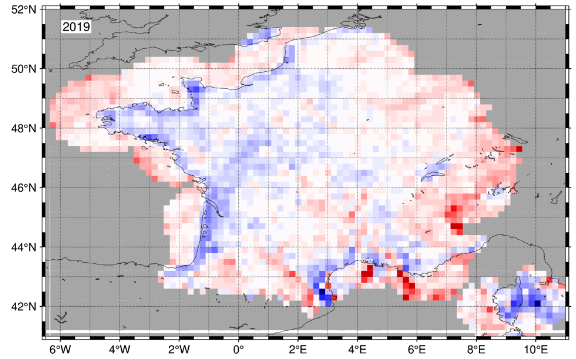
Base de test : 2019,comparaisons avec MF
Résolution 0.2°x0.2°

Ref.\GPROF	Positive	Negative	POD
Positive	7.38 %	7.26 %	0.50
Negative	4.49 %	80.88 %	FAR
Precision	0.62		0.38
F1-score	0.56		

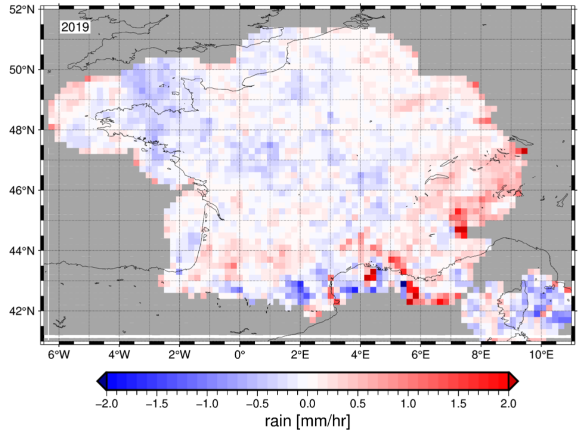
Ref.\DRAIN	Positive	Negative	POD
Positive	4.85 %	9.81 %	0.33
Negative	0.36 %	84.98 %	FAR
Precision	0.93		0.07
F1-score	0.49		

- Bad detections due to DPR threshold
- GPROF coastal effect
- Effect of mountains ➔degraded MF mosaic ?

Mosaic-GPROF, 0.2ºx0.2º



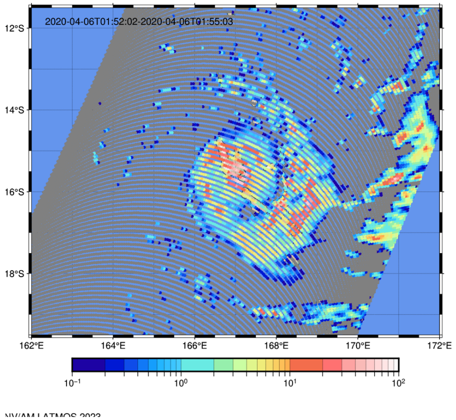
Mosaic-DRAIN, 0.2ºx0.2º



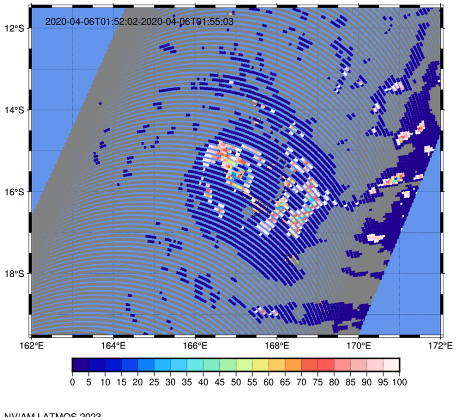
NV/AM LATMOS 2021

Exploitation of PDF/CDF

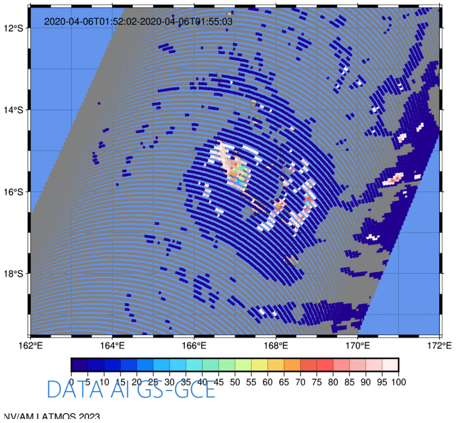
DRAIN RAIN mm/hr



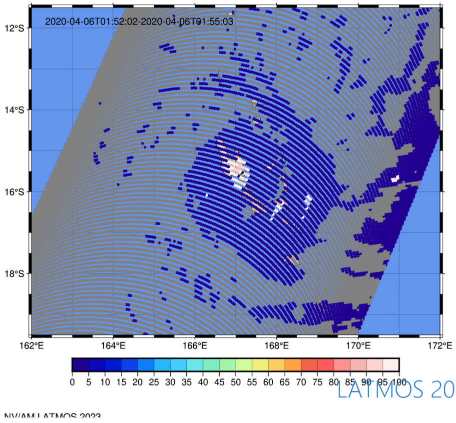
DRAIN Proba RR > 30.0 mm/hr



DRAIN Proba RR > 50.0 mm/hr



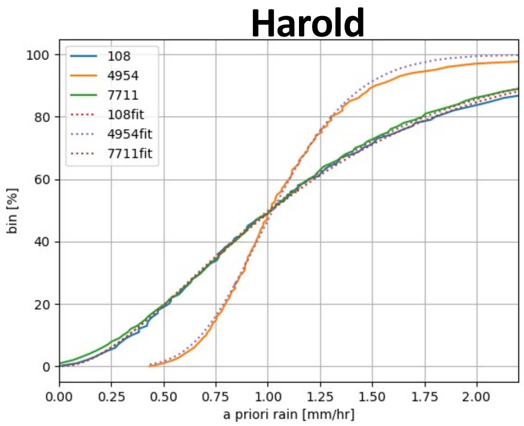
DRAIN Proba RR > 100.0 mm/hr



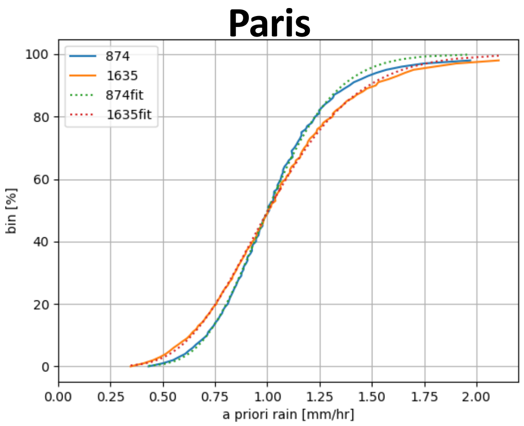
- ☐ Probability of exceedance:
  - ☐ Pixels where RR has a probability to reach a certain threshold

➔useful for hydrological applications

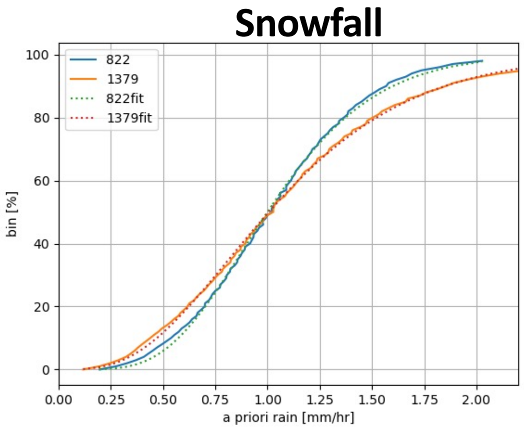
Exploitation of PDF/CDF



Harold



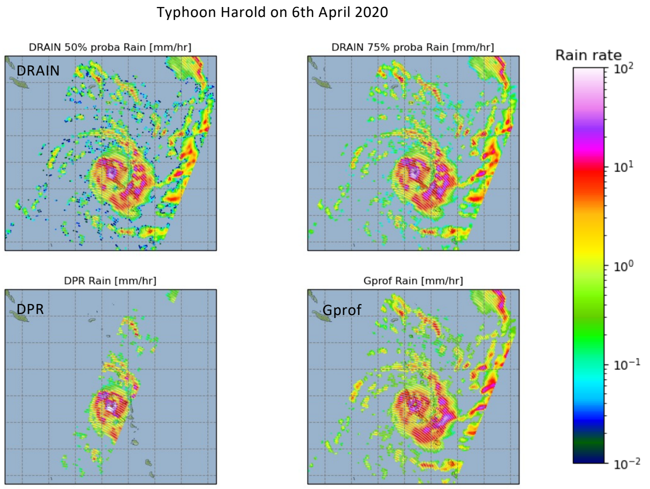
Paris



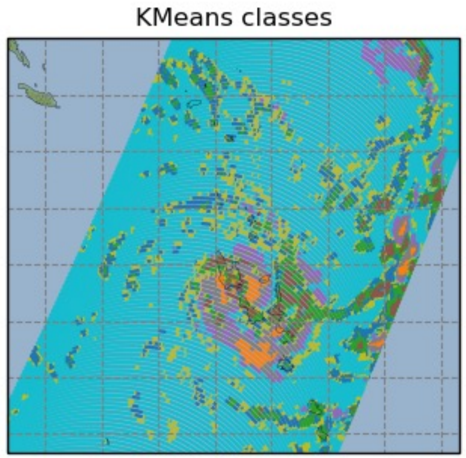
Snowfall

- CDF for 1 mm/hr (median, random pixels)
- There seem to be different CDFs for different regimes

Unsupervised classification from CDF



- K-means from quantiles
- Are the classes spatially structured ?

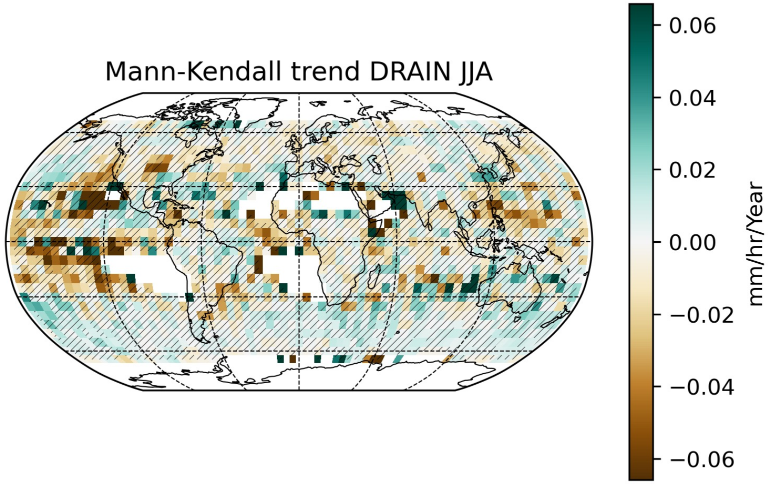


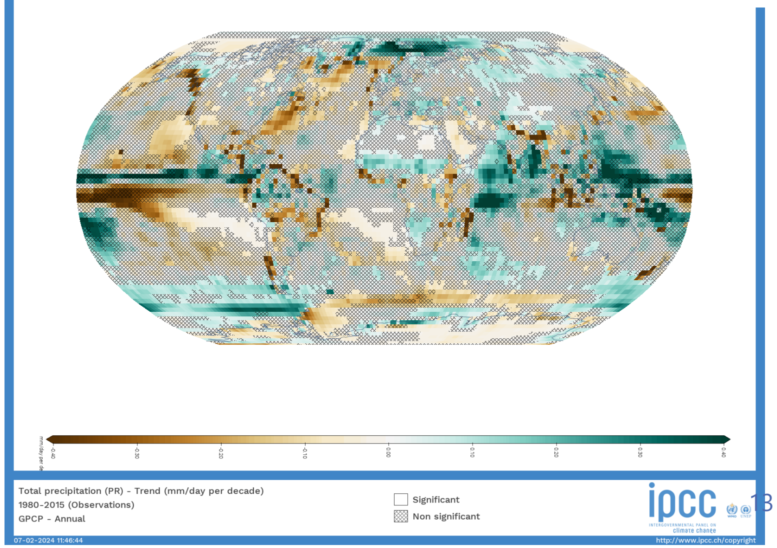
☐ Yes !
☐ But we didn't go much further for the moment …

With DL, we were able to process the 10 year of GPM data…

Trends over 2014-2024 period

- ❑ Study the rain properties at Global scale
- ❑ Expected acceleration of WC? (JJA 2014-2023)
  - ❑Weak + trend at midlatitudes
  - ❑Weak - trend in Tropics
  - ❑But inconclusive Mann-Kendall…
- ❑How to study CC using pre-trained methods…?



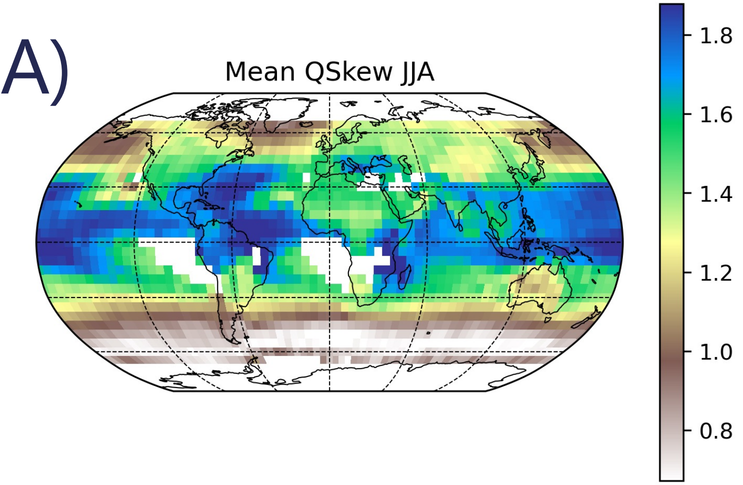


Total precipitation (PR) - Trend (mm/day per decade)
1980-2015 (Observations)
GPCP - Annual

07-02-2024 11:46:44

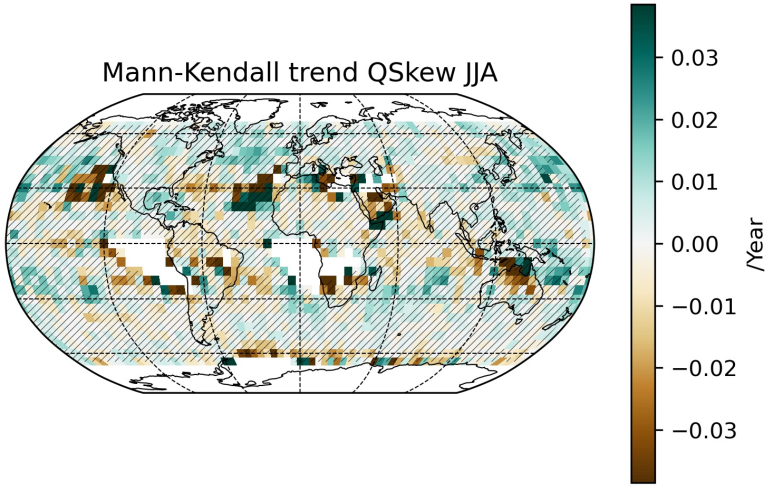
http://www.ipcc.ch/copyright

Trends over 2014-2024 period (JJA)


Mean QSkew JJA

- ❑ Skewness computed from retrieved quantile
- ❑ Zonal structure of Skewness ➔ regime ?

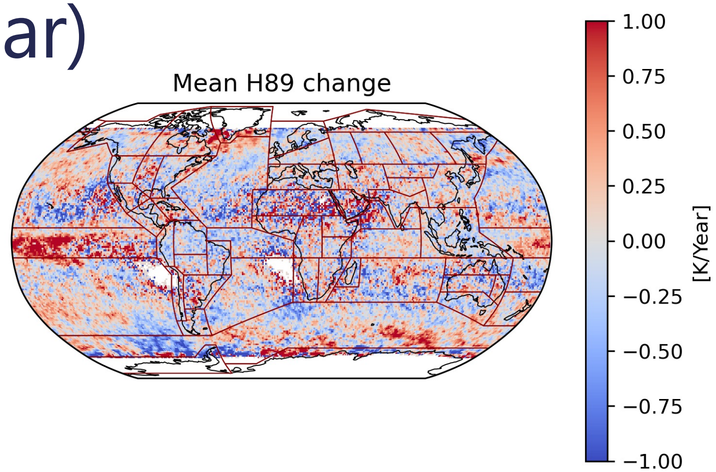
- ❑Inconclusive trend except locally:
  - ❑Cabo Verde
  - ❑Mediterranean
  - ❑North of Australia
  - ❑…

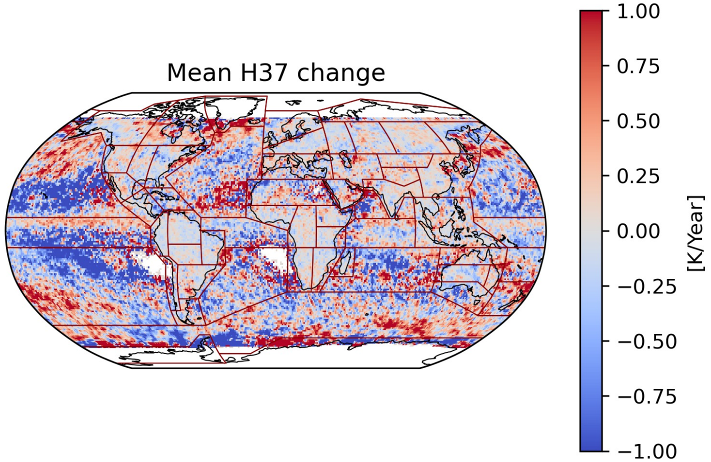

Mann-Kendall trend QSkew JJA

Trends over 2014-2024 period (Year)

- TB evolution is the signature of an evolution of the rain regimes
  - Colder 89H ➔ intensification of convection
  - Colder 37H ➔ idem or colder SST…

- But trends are actually inconclusive (Mann-Kendall)





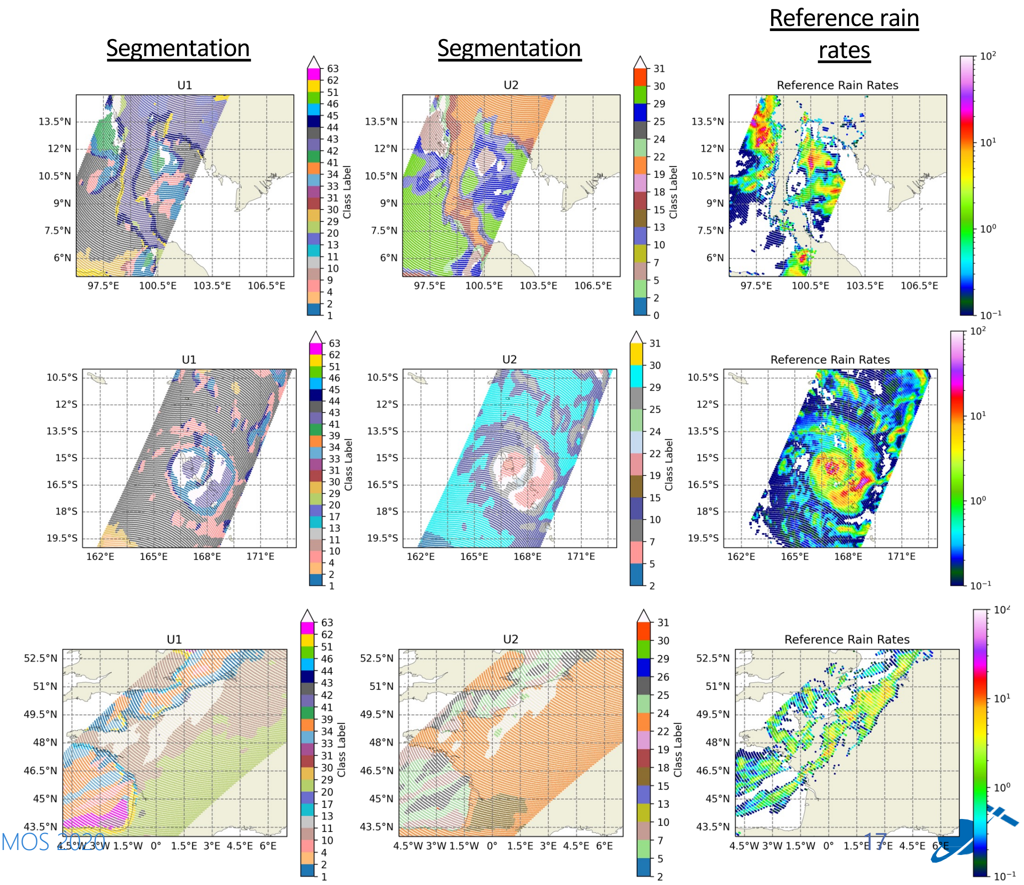
If rain intensities give an inconclusive trend, and T_B trends are unclear, let's look at…

Segmentation non-supervisée de T_Bs pour étudier les changements dans le Cycle de l'Eau.

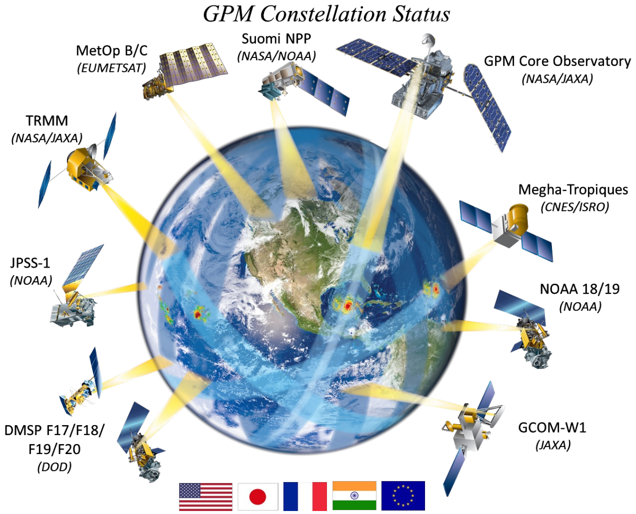
Thèse AMX V. SAMBATH

- unsupervised semantic image segmentation on brightness temperature images using a model by Kim et al. 2020.

- The result of the segmentation is compared quantitatively and qualitatively to precipitation and sea surface temperature. After the validation, the evolution of the segmented classes will be analyzed.



Using transfer learning/domain adaptation to go from GPM to constellation



Using cycle-GAN for Unsupervised Domain Adaptation

On GPM-core

❑GMI

  ❑89 GHz, 3x13.4 km^2

  ❑36.64 GHz, 6x13.4 km^2

On NOAA-F18, close but different…

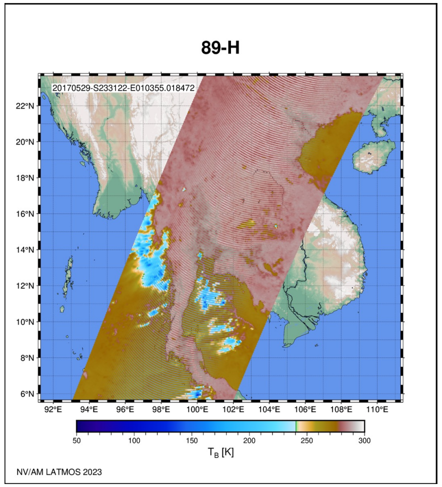
❑SSMI/S

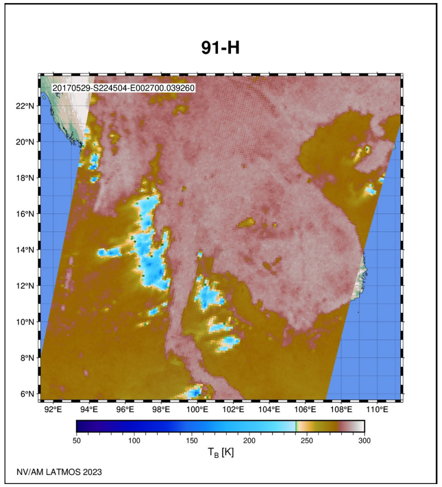
  ❑91.65 GHz, 12.5x12.5 km2

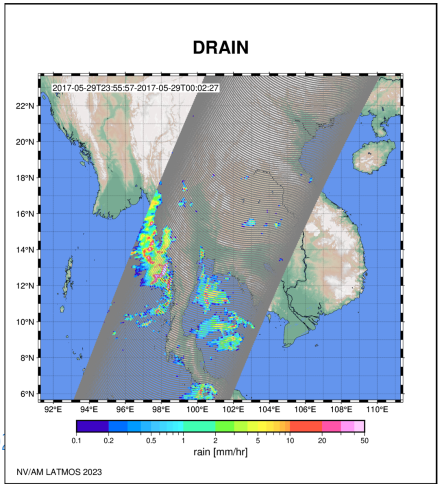
  ❑37 GHz, 12.5x25 km2

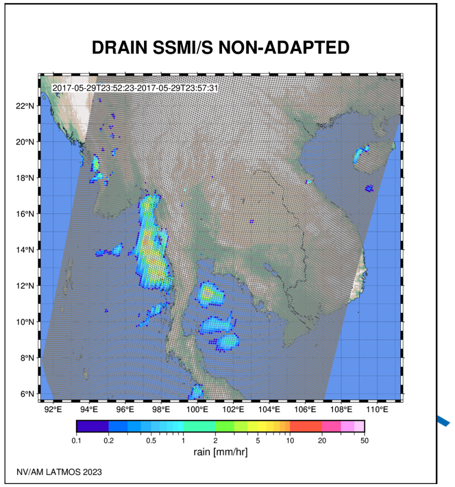
❑ DRAIN on GMI

❑ DRAIN on raw SSMI/S

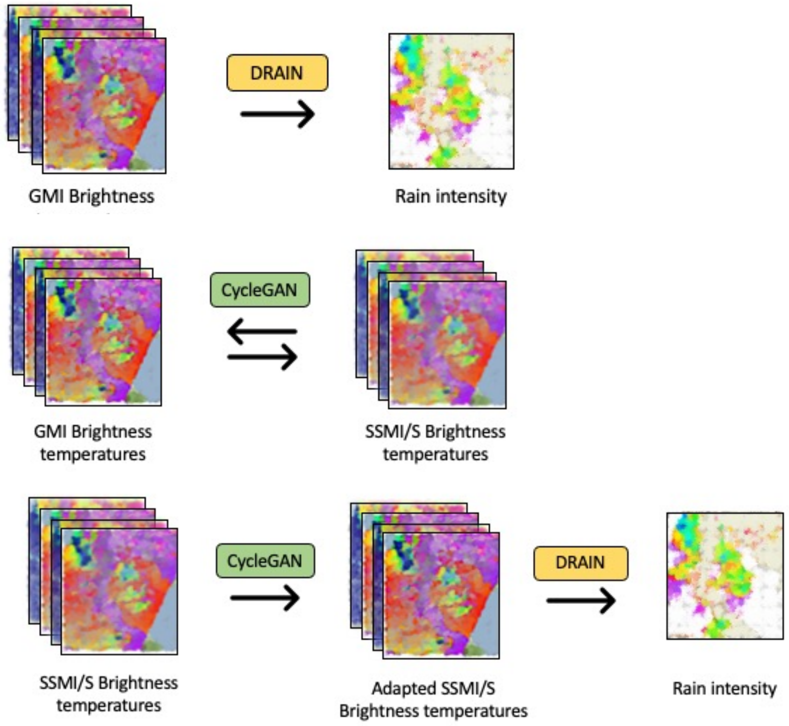








Using cycle-GAN...



GMI Brightness

DRAIN

Rain intensity

GMI Brightness temperatures

CycleGAN

SSMI/S Brightness temperatures

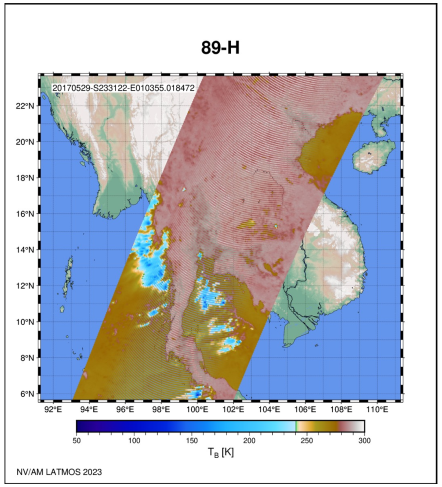
SSMI/S Brightness temperatures

CycleGAN

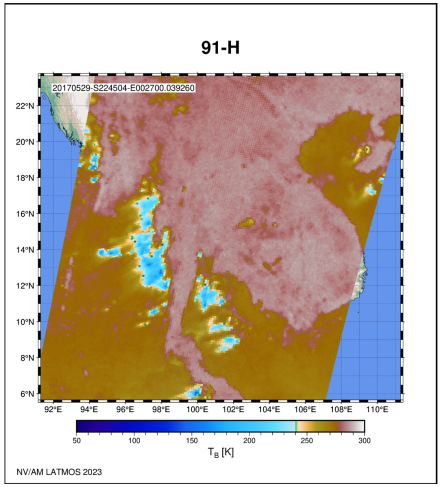
Adapted SSMI/S Brightness temperatures

DRAIN

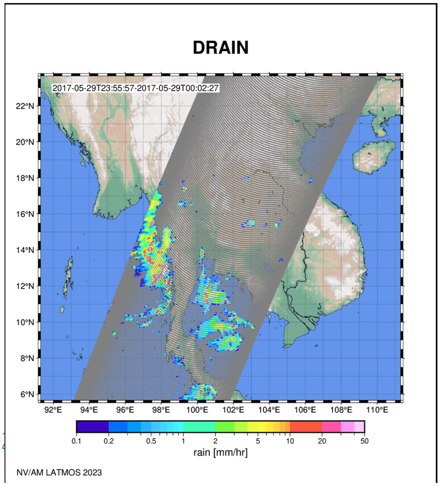
Rain intensity



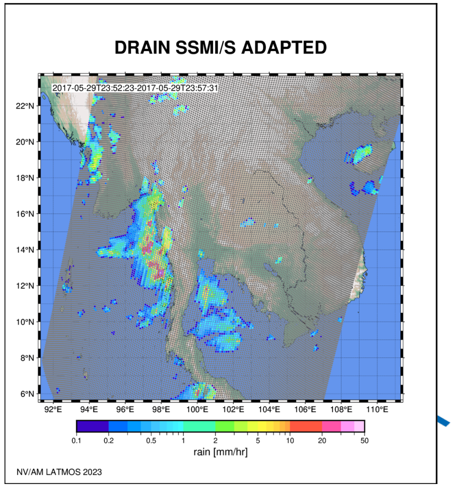
89-H



91-H

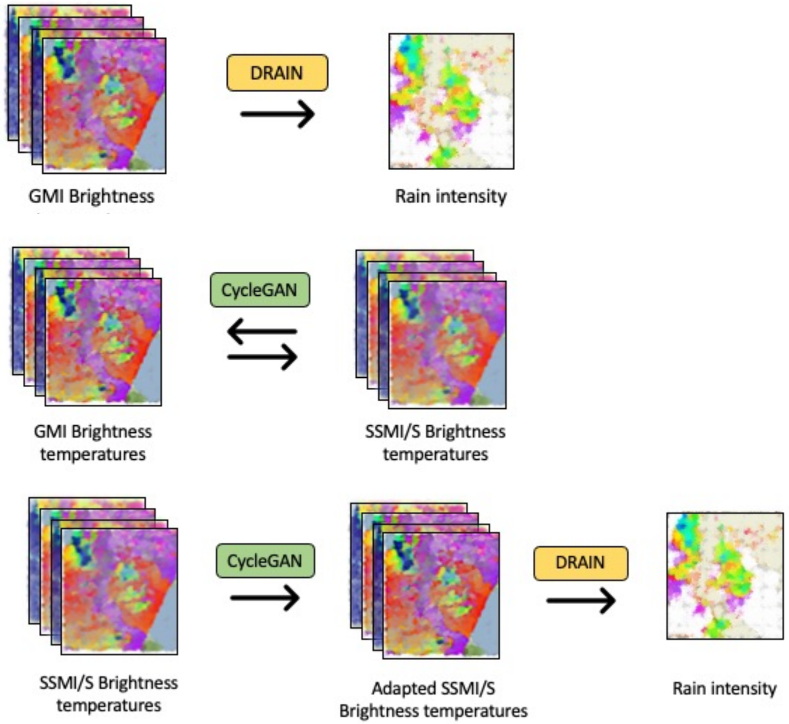


DRAIN



DRAIN SSMI/S ADAPTED

Validation over France on MF mosaic data



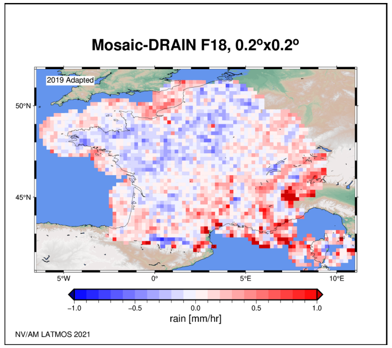
GMI Brightness → **DRAIN** → Rain intensity

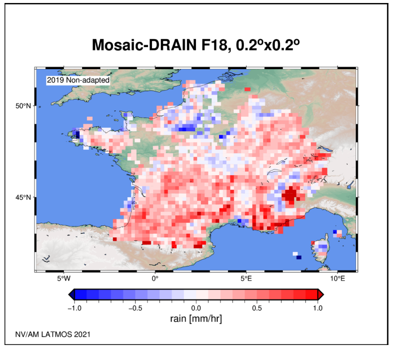
GMI Brightness temperatures ⇆ **CycleGAN** ⇆ SSMI/S Brightness temperatures

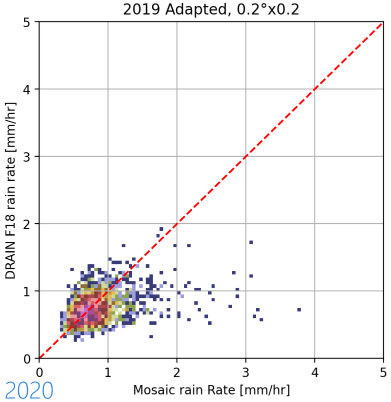
SSMI/S Brightness temperatures → **CycleGAN** → Adapted SSMI/S Brightness temperatures → **DRAIN** → Rain intensity

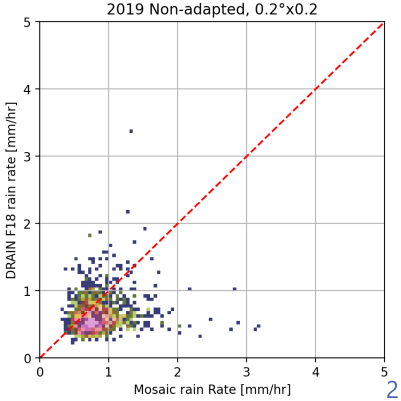
DRAIN adapted

DRAIN non-adapted









Conclusions

- A real breakthrough using ML:
  - Mostly due to pixel ➔ image

- Able to perform climatological studies…

- Tried multitask➔ inconclusive…
- Tried cycle GAN ➔ Yes, but really difficult to balance
- Developing the same approach for IR

- Collaborative work between ML experts and remote-sensing experts !

Perspectives and thoughts

- ☐Next breakthrough: domain adapatation ?
- ☐ML and CC ?
- ☐Data fusion IR+MW ? In-situ/ground based data ?
  - ➔AOS suborbital component
- ☐How to properly anticipate the DL rush to come ?

Merci

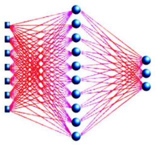
www.latmos.ipsl.fr

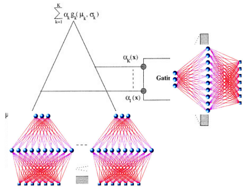
QPE from Space key steps for NN

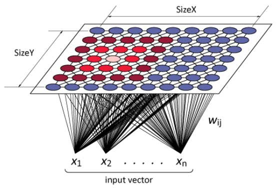
[Phd E. Moreau (2000) M.A. Pérez Chavarria (2007) V. Sambath (in progress)]

Increasing capacity of neural models

pixewise algorithm







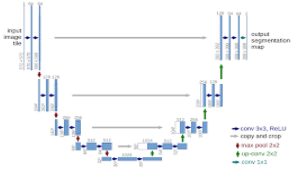
Multilayer Perceptron

Multi-Expert

MLP + Self Organising Map

Combining classification/clustering and regression

Image inversion



=> Image time series inversion

3D convolutionnal network

1990

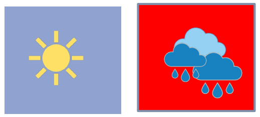
1997

201
4

202
0

Increasing quality and quantity of training dataset

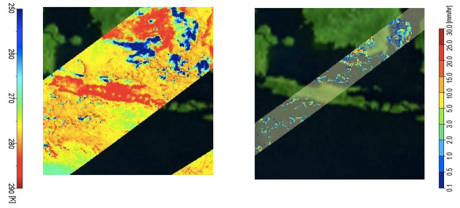
radiative transfer algorithm simulation



horizontal homogeneity
simplified diffusion
process

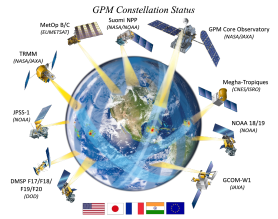
more realistic simulation

Co-located observations(TB;RR)



Microwave Imager + Radar RR
Tropical Rainfall Measuring Mission

Microwave Imager Constellation

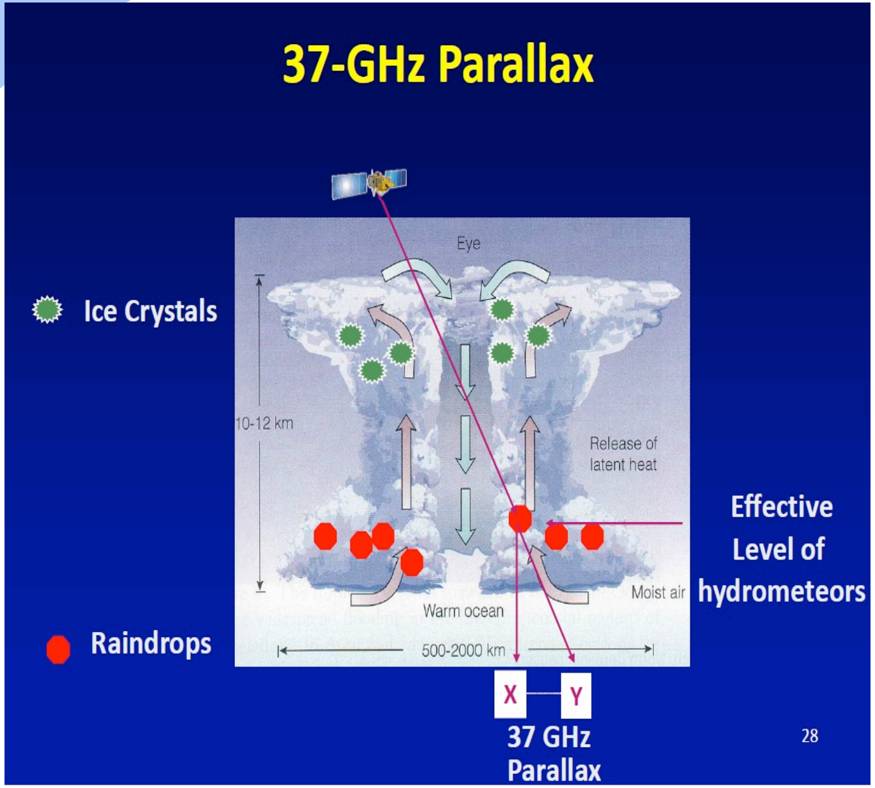


=> + Geostationary satellites (IR Imager)

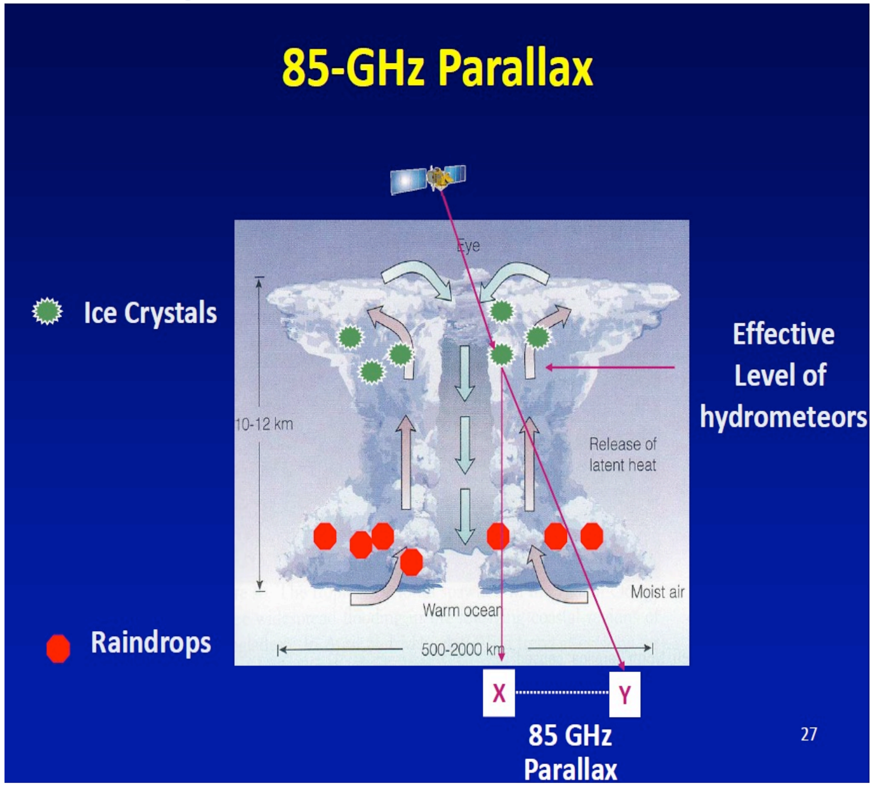
Global Precipitation Mission

Performance evaluation is a complex and fundamental task for quantitative study of earth climate

Microwave Imager



37-GHz Parallax



85-GHz Parallax

Sensitivity to liquid rain drops contained in low layers :

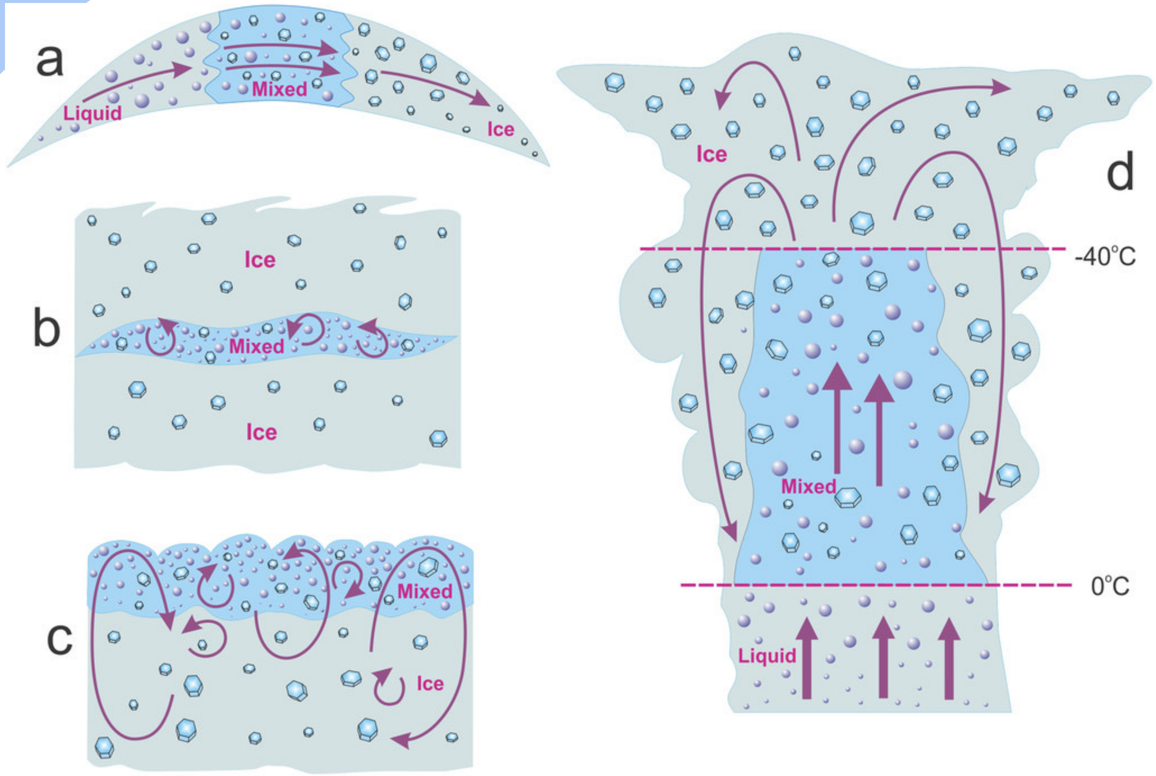
warm temperatures

small parallax error

Sensitivity to ice particles in higher atmospheric layers

Cold temperatures

High parallax error



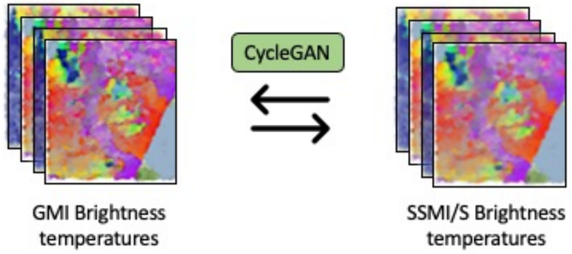
Conceptual model of the effect of dynamic forcing on the formation of the mixed-phase in different types of cloud:

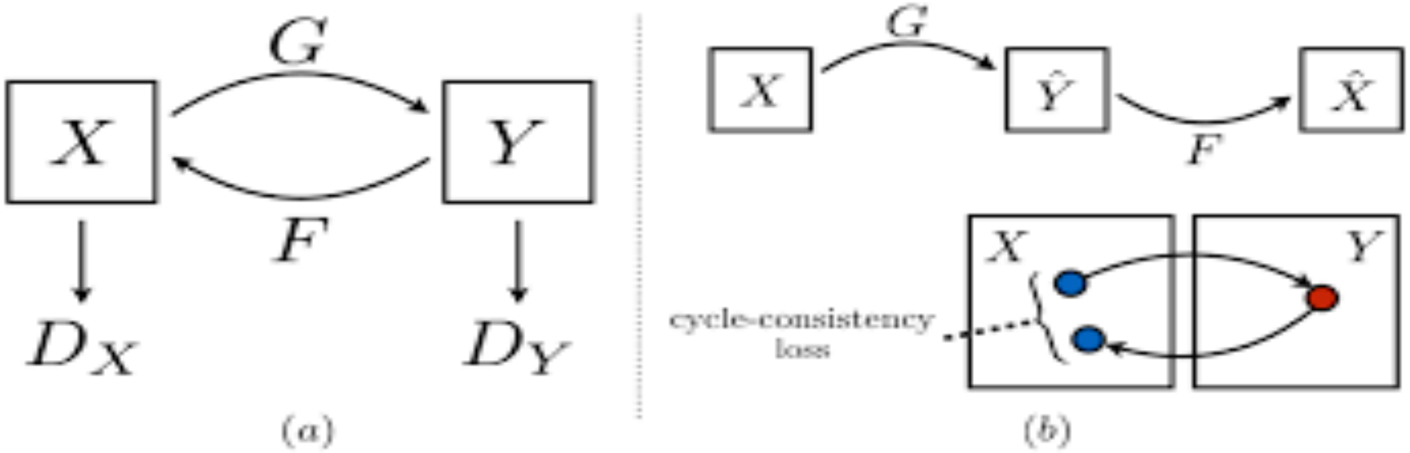
a) Wave clouds, Ac lenticular
b) frontal cloud, Cs–Ns
c) boundary layer clouds, St–Sc
d) deep convective clouds, Cb, convective storms

Meteorological Monographs 58, 1; 10.1175/AMSMONOGRAPHS-D-17-0001.1

UDA

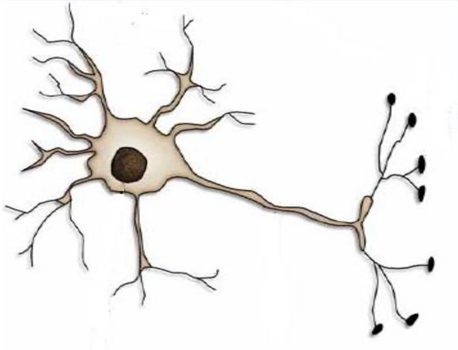
- Unsupervised domain adaptation for GPM satellite constellation using Cycle Generative Adversarial Nets



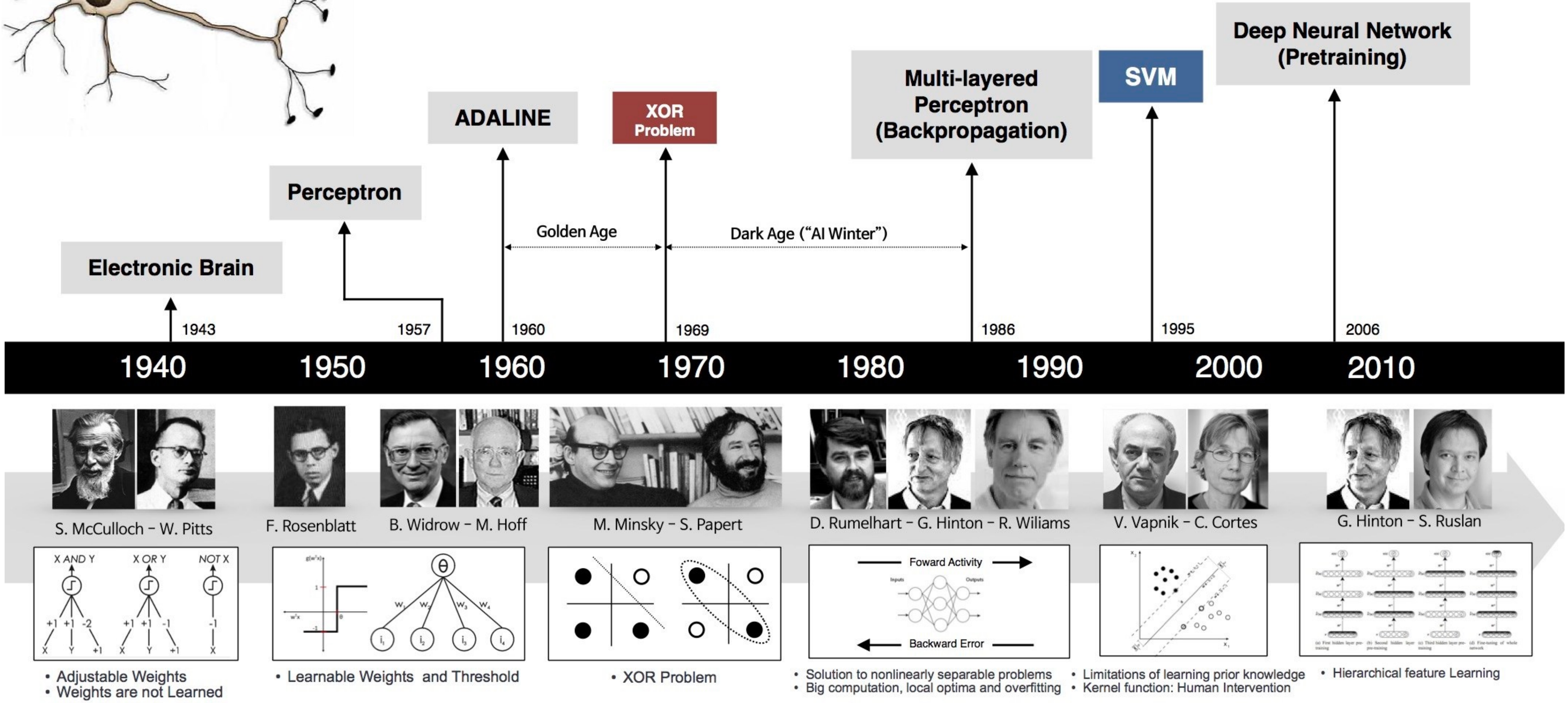


- **translate an image from a source domain X (SSMI) to a target domain Y (GMI) in the absence of paired examples.**
- **learn a mapping G: X -> Y such that the distribution of images from G(X) is indistinguishable from the distribution Y using an adversarial loss.**
- **Because this mapping is highly under-constrained, it is couple it with an inverse mapping F: Y -> X and introduce a cycle consistency loss to push F(G(X)) ~ X (and vice versa).**

Refrence : Zhu, J. Y., Park, T., Isola, P., & Efros, A. A. (2017). Unpaired image-to-image translation using cycle-consistent adversarial networks. In *Proceedings of the IEEE international conference on computer vision* (pp. 2223-2232).



Réseaux de neurones : une complexité croissante



Electronic Brain — 1943

Perceptron — 1957

ADALINE — 1960

XOR Problem — 1969

Multi-layered Perceptron (Backpropagation) — 1986

SVM — 1995

Deep Neural Network (Pretraining) — 2006

Golden Age

Dark Age ("AI Winter")

1940 1950 1960 1970 1980 1990 2000 2010

S. McCulloch – W. Pitts
- Adjustable Weights
- Weights are not Learned

F. Rosenblatt
- Learnable Weights and Threshold

B. Widrow – M. Hoff

M. Minsky – S. Papert
- XOR Problem

D. Rumelhart – G. Hinton – R. Wiliams
- Solution to nonlinearly separable problems
- Big computation, local optima and overfitting

V. Vapnik – C. Cortes
- Limitations of learning prior knowledge
- Kernel function: Human Intervention

G. Hinton – S. Ruslan
- Hierarchical feature Learning

Une brève histoire de l'apprentissage profond de Sophie Donnet et Christophe Ambroise https://stateofther.github.io/post/deep_learning/deep-learning-history.html#1