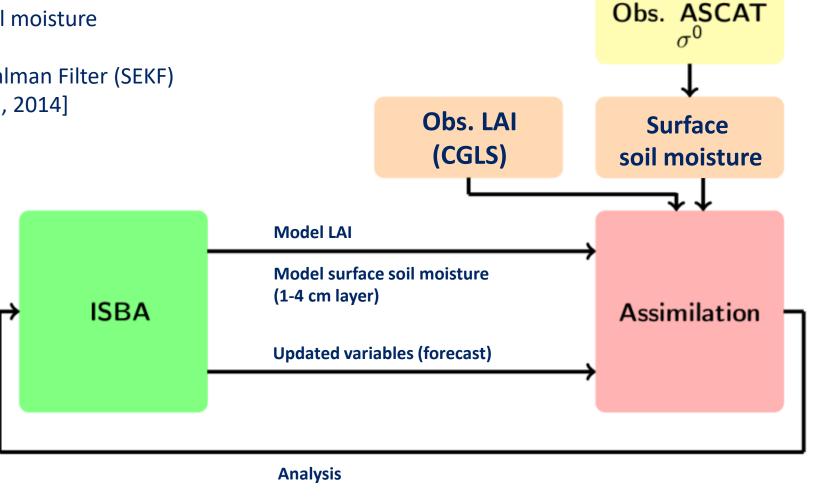




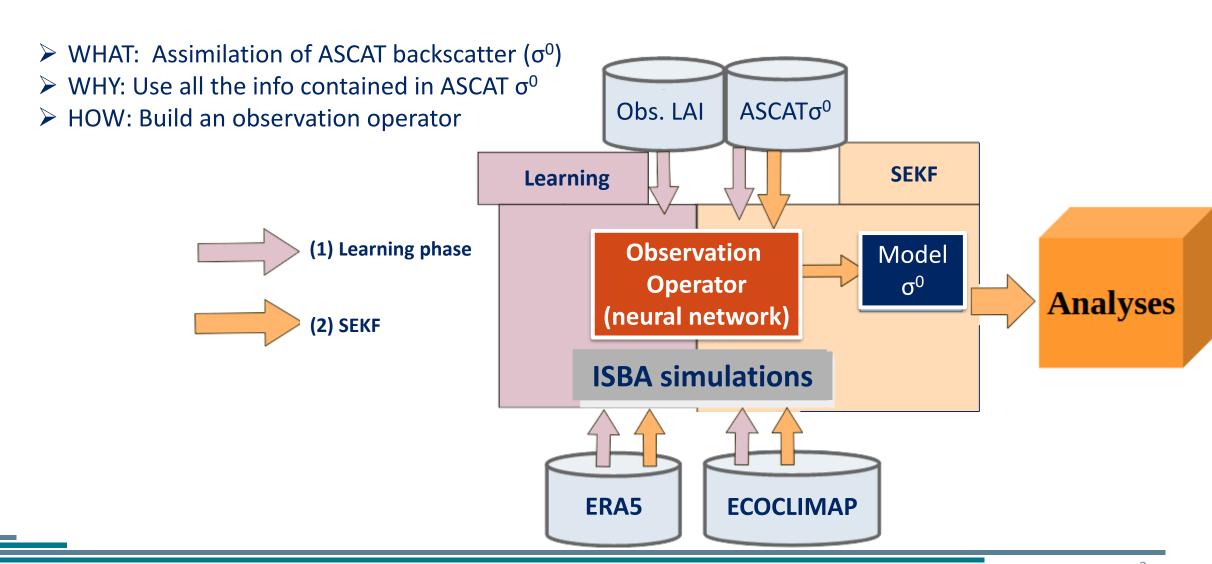
# Assimilation of level 2 products in LDAS-Monde

- ➤ Leaf area index and/or Surface soil moisture
- Frechnique: Simplified Extended Kalman Filter (SEKF) [Mahfouf et al., 2009; Barbu et al., 2014]
- Analyzed variables:
  - Soil moisture of 7 soil layers (1 to 100 cm depths)
  - Leaf biomass





## Assimilation of level 1 products in LDAS-Monde





# Why machine learning?

	Semi-empirical model	Machine learning
Approach	Water cloud model (Attema and Ulaby 1978, Shamambo et al. 2019)	Many possible approaches
Complexity	4 parameters per grid cell	As many as needed
Input variables	<ul><li>Observed LAI</li><li>ISBA surface soil moisture</li></ul>	<ul> <li>Observed LAI</li> <li>ISBA surface soil moisture</li> <li>ISBA surface soil temperature</li> <li>ISBA interception reservoir</li> </ul>



## **Observation operator**

#### MACHINE LEARNING MODELS

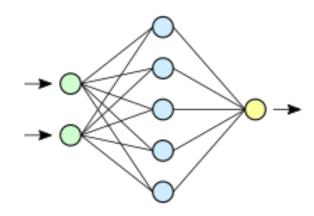
- Support Vector Regression (SVR)
- Gradient Boosting
- Random Forest
- Neural Network (NN)



## **Observation operator**

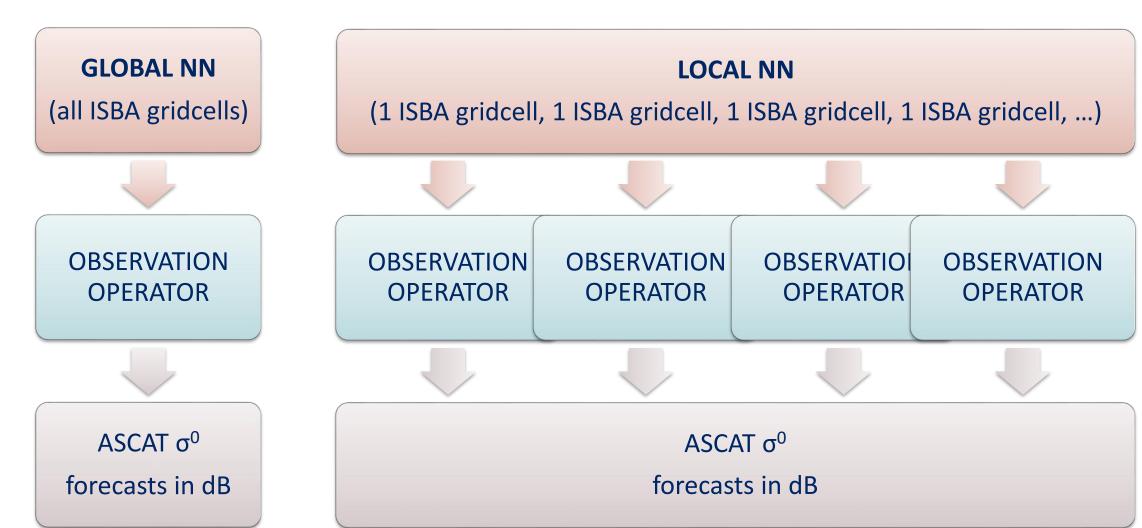
#### MACHINE LEARNING MODELS

- Support Vector Regression (SVR)
- Gradient Boosting
- Random Forest
- Neural Network (NN)





## **Observation operator (neural network)**





## **Model requirements**

**PERFORMANCE** 

o good scores (RMSD, R, ...)

> PARSIMONY

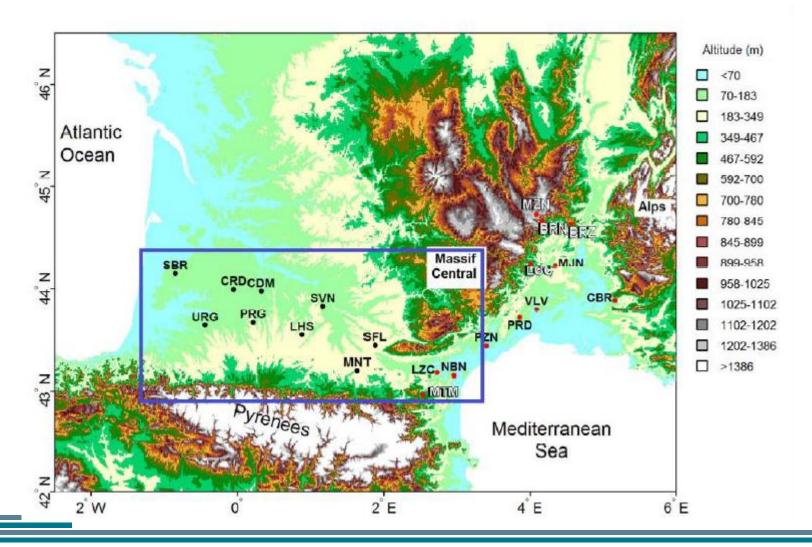
- low number of parameters
- low computing time
- > USABILITY IN APPLICATIONS
- LDAS-Monde

**EXPLICABILITY** 

physical processes



#### Assimilation of ASCAT $\sigma^0$



12 stations of the SMOSMANIA network in southwestern France



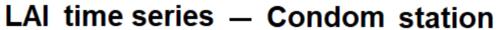
## **Performance of observation operator**

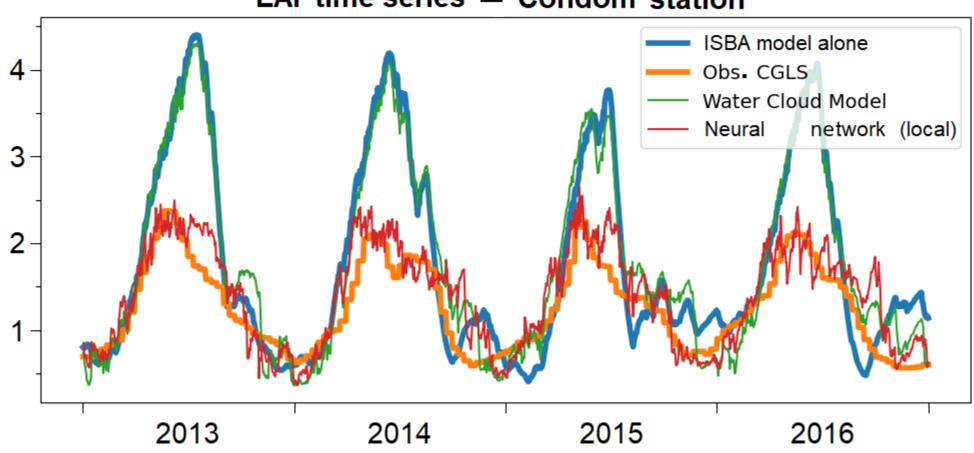
 $\triangleright$  Simulated vs. Observed ASCAT  $\sigma^0$  (all stations, 2013-2017 validation time period)

LOCAL MODEL	CONFIGURATION	R SCORE	RMSD SCORE (dB)	Nb parameters per gridcell
Water Cloud Model	4 parameters (A,B,C,D)	0.80	0.44	4
LOCAL NN	1 layer, 40 neurones	0.84	0.40	241



#### **Assimilation results: LAI**







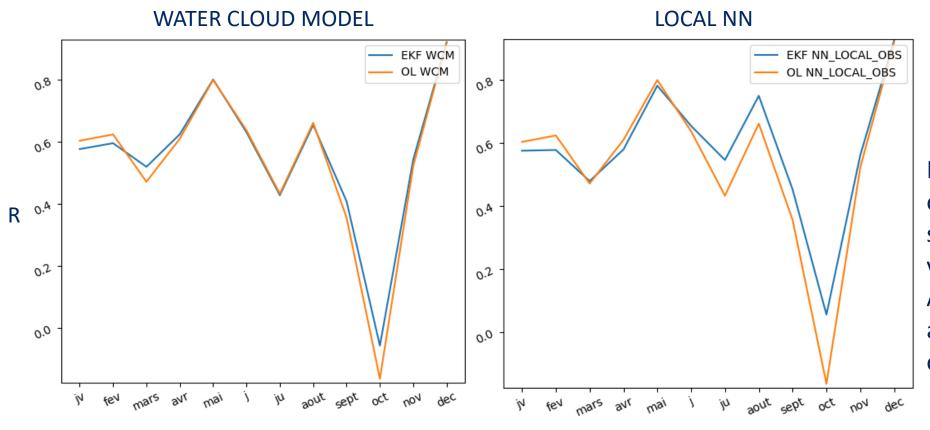
### **Assimilation results: LAI**

SMOSMANIA station	ISBA LAI RMSD	Improvement using local NN
SBR	0.86	14 %
URG	0.97	8 %
CRD	0.56	12 %
PRG	1.16	59 %
CDM	0.89	65 %
LHS	1.25	63 %
SVN	0.75	<b>57</b> %
MNT	1.20	<b>52</b> %
SFL	1.44	<b>57</b> %
MTM	0.81	- 6 %
LZC	0.77	7 %
NBN	0.60	4 %

Assimilation of ASCAT  $\sigma^0$  markedly improves the simulated LAI, mainly over agricultural areas



#### Assimilation results: surface soil moisture



In situ soil moisture observations at the CDM station shows the added value on R of assimilating ASCAT  $\sigma^0$  using a NN approach w.r.t. the ISBA open-loop simulation



#### **Conclusions**

- > MARKED IMPROVEMENTS OF ANALYSED VARIABLES
  - $\circ$  ASSIMILATING ASCAT  $\sigma^0$  ONLY
  - USING LOCAL NN OBSERVATION OPERATOR

- > POSSIBILITY TO ACCOUNT FOR NEW PREDICTORS
  - RAINWATER INTERCEPTION BY VEGETATION
  - **O SOIL TEMPERATURE**



#### **Prospects**

- > GLOBAL NN IN CONTRASTING CONDITIONS
- > APPLICATION TO SMOS TB
- > APPLICATION TO OTHER VARIABLES (e.g. ALBEDO, SIF, ...)



### MANY THANKS FOR YOUR ATTENTION ©

More info on LDAS-Monde:

https://www.umr-cnrm.fr/spip.php?article1022