Using Artificial Neural Network to estimate surface convective fluxes

Jomé, M.[1], Lohou, F.[1], Fautrez, L.[1], Lothon, M.[1], Kelley, J.[2], Pardyjak, E[3], Zouzoua, M[4].

[1]Laboratoire d'Aérologie, CNRS, Université de Toulouse, Toulouse, France

[2]Asperatus Consulting, Corvallis, Oregon, OR 97333, USA

[3]Department of Mechanical Engineering, University of Utah, Salt Lake City, UT 84112, USA

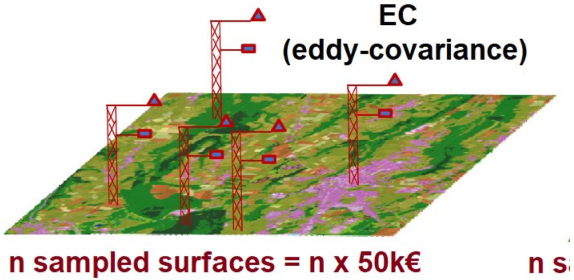
[4]Laboratoire Atmosphères, Milieux, Observations Spatiales, Institut Pierre-Simon Laplace, CNRS, Guyancourt, France

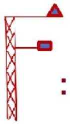
INTRODUCTION

SURFACE FLUXES ARE THE 2nd SOURCE OF ERRORS IN THE GLOBAL AND REGIONAL NUMERICAL MODELS[1] (WGNE)

Several local measurements are needed to sample different land surfaces

↪ <u>**one**</u> eddy-covariance station to sample <u>**one**</u> land surface





[1] **Carolyn Reynolds, Keith Williams, Ayrton Zadra:** *WGNE Systematic Error Survey Results Summary*, February 2019.

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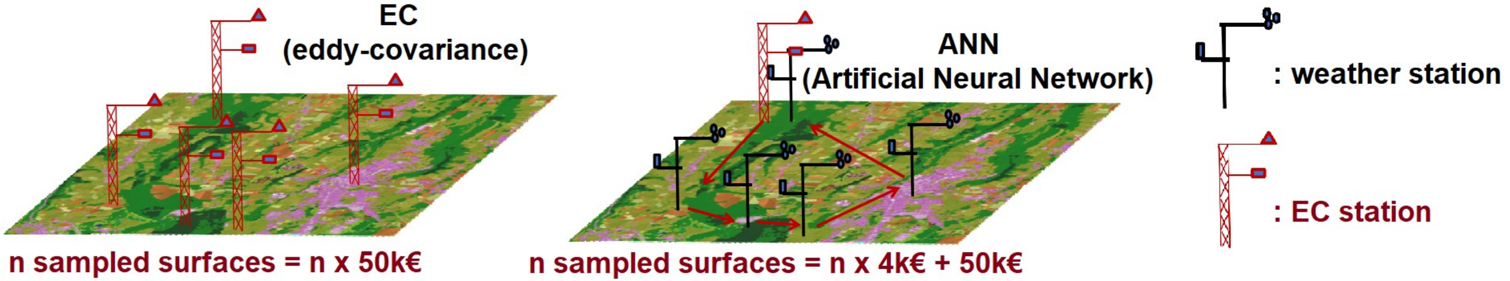

Recent studies[2,3] show that we can **estimate those fluxes using standard weather stations** (4k€) **and ANN** (trained with eddy-covariance measurements as references)

[1] **Carolyn Reynolds, Keith Williams, Ayrton Zadra:** *WGNE Systematic Error Survey Results Summary*, February 2019.
[2] **Jason Kelley, Eric Pardyjak,** *Using Neural Networks To Estimate Site-Specific Crop Evapotranspiration with Low-Cost Sensors,* 23 February 2019.
[3] **M. Kumar, N. S. Raghuwanshi, R. Singh,** *Artificial neural networks approach in evapotranspiration modeling: a review,* 5 August 2010.

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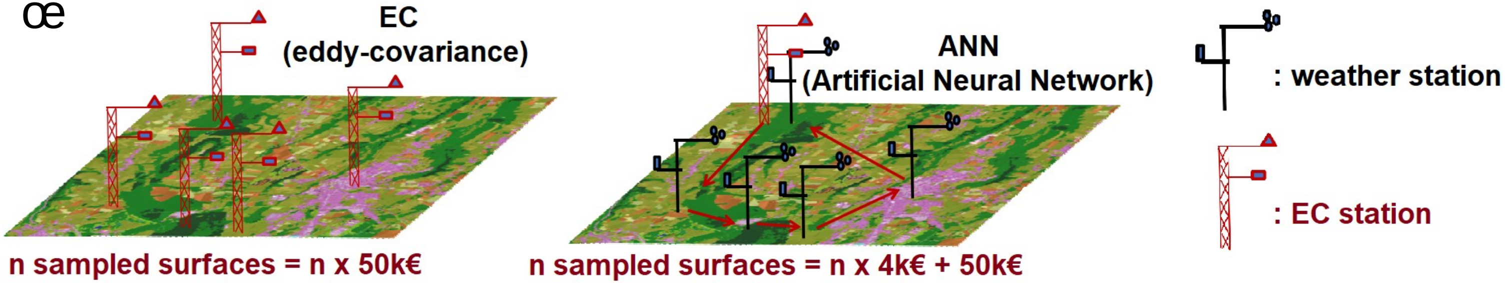
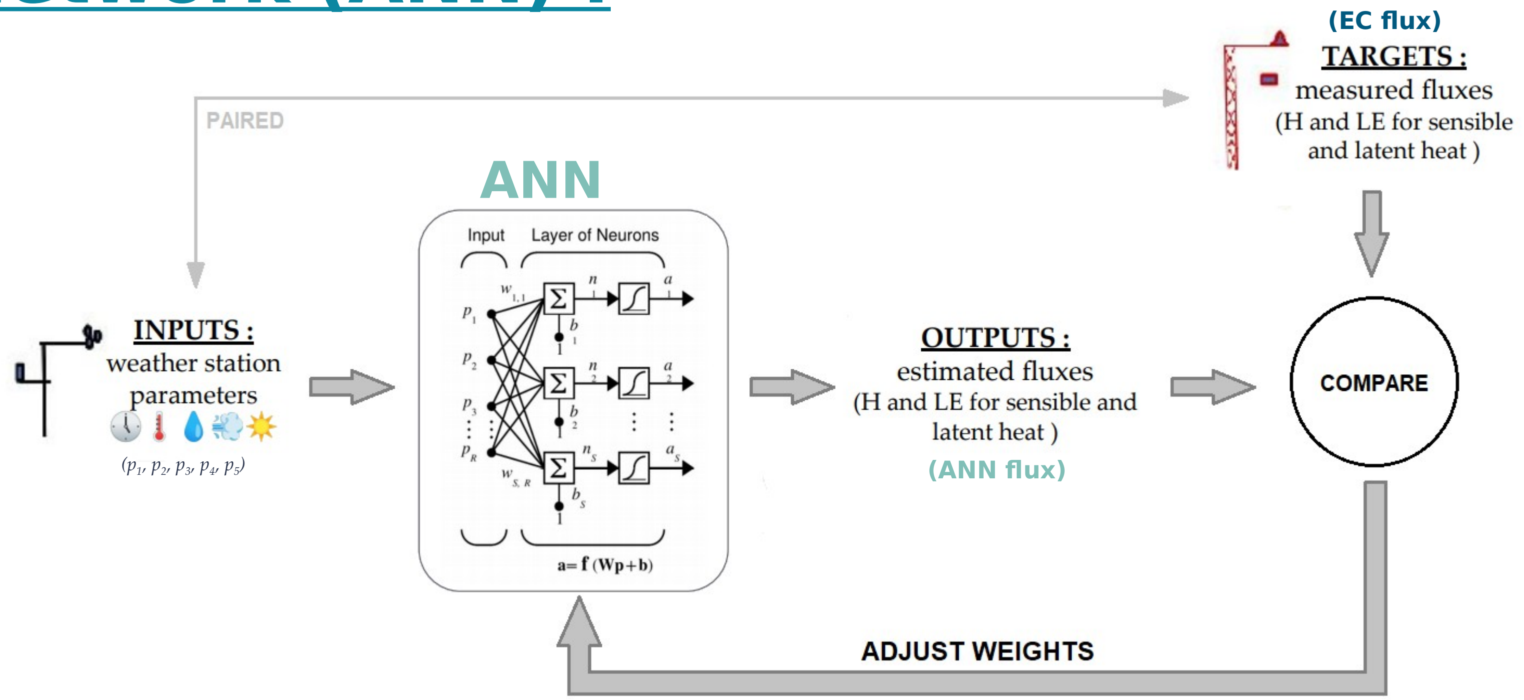


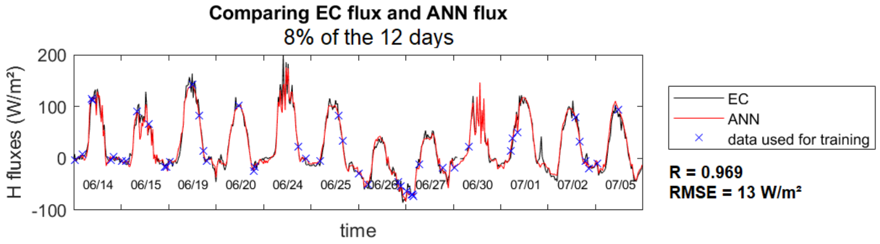
Recent studies[2,3] show that we can **estimate those fluxes using standard weather stations** (4k€) **and ANN** (trained with eddy-covariance measurements as references)

GOAL : Test this method in order to propose an experimental deployment plan to apply it during field campaigns

Use of Artificial Neural Network (ANN) :



ONE YEAR-LONG DATASET : VARIABILITY OF THE CONDITIONS (2m tower over a prairie)

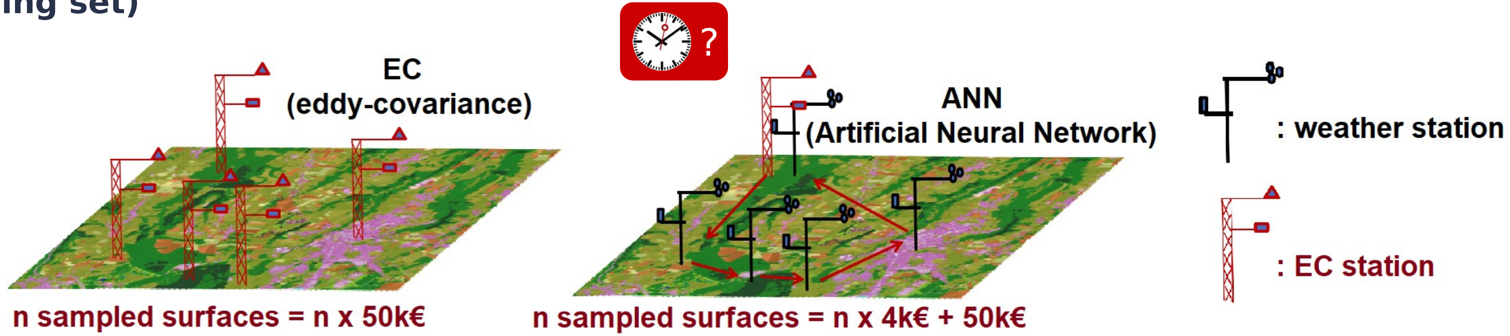


↪ definition of the **input variables :**

- **time** (cyclical)
- **air temperature**
- **air humidity**
- **two horizontal wind components** (u,v)
- **shortwave income**

↪ definition of an optimised **architecture** (architecture/dataset **co-dependency**)

↪ definition of the **rotation frequency (importance the variety of conditions** encountered in the **training set)**



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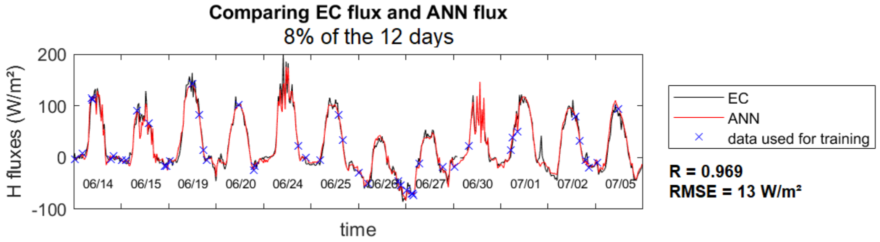

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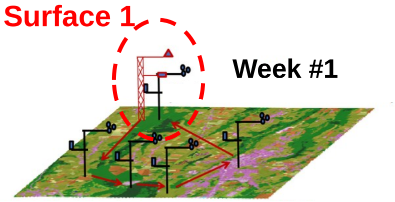
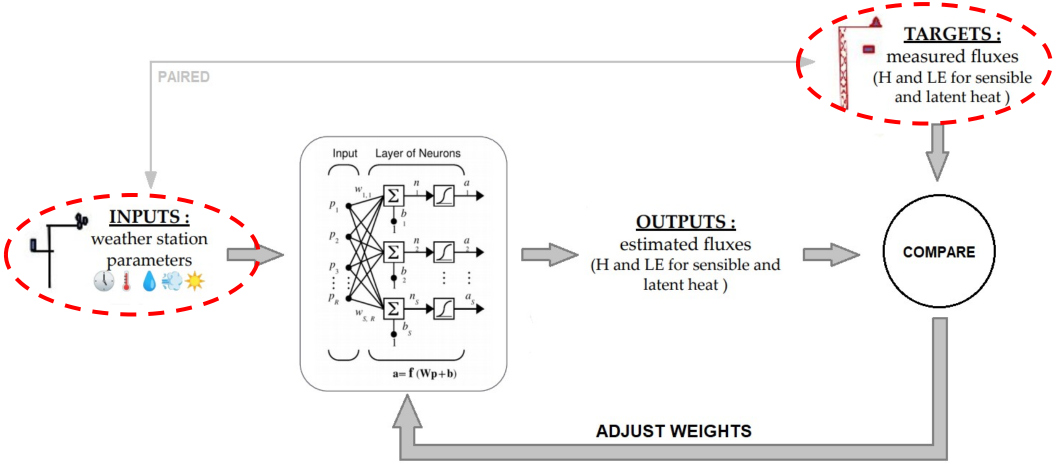
Scenario 1	Scenario 2	Scenario 3
1 week for training	2 weeks for training	3 weeks for training
4 weeks for test	8 weeks for test	12 weeks for test

Scenario 1

1 week for training
4 weeks for test





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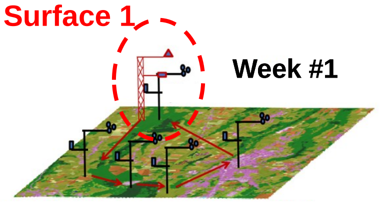

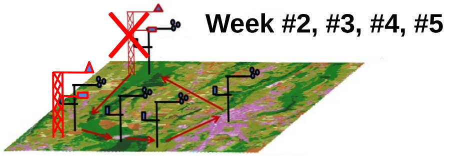

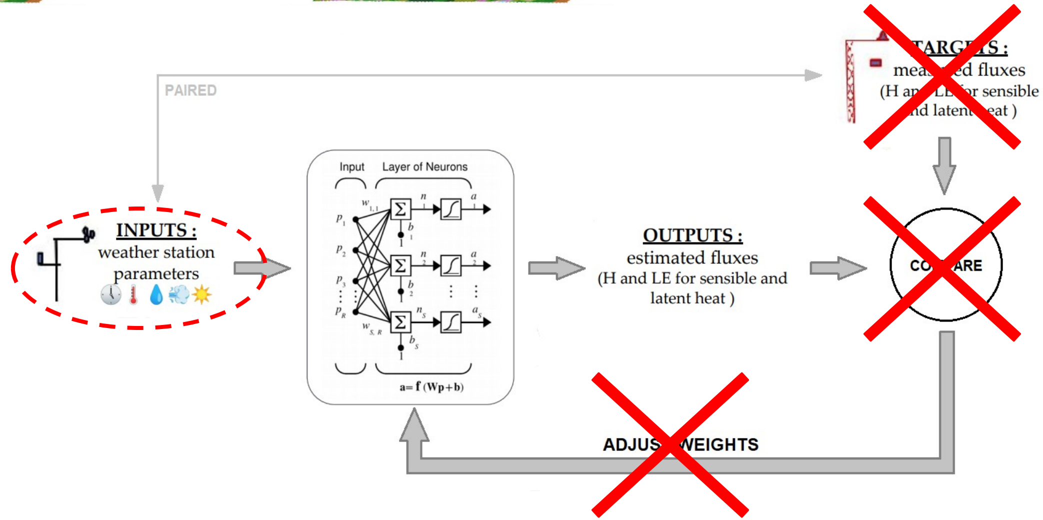

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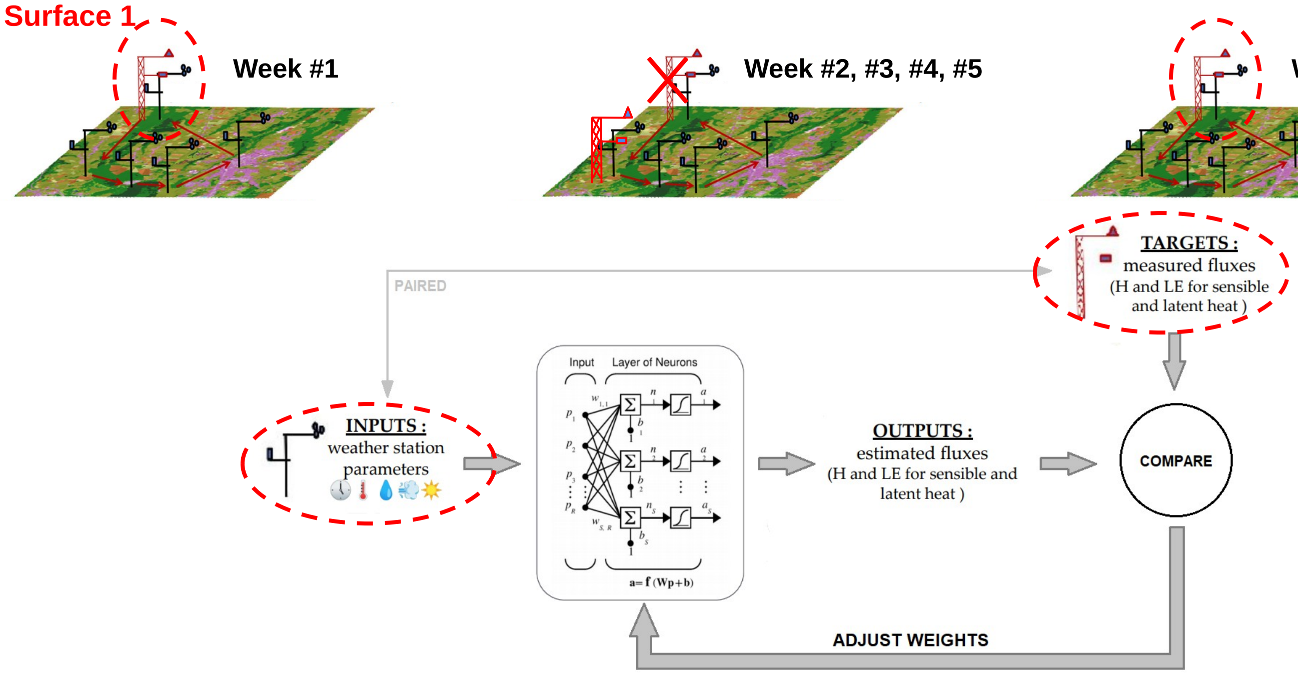

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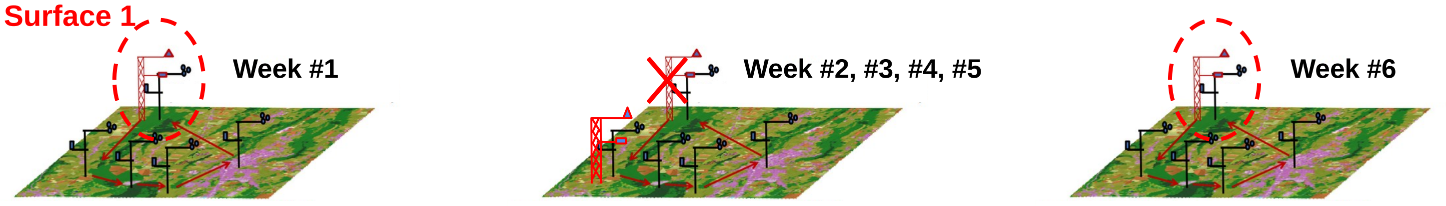
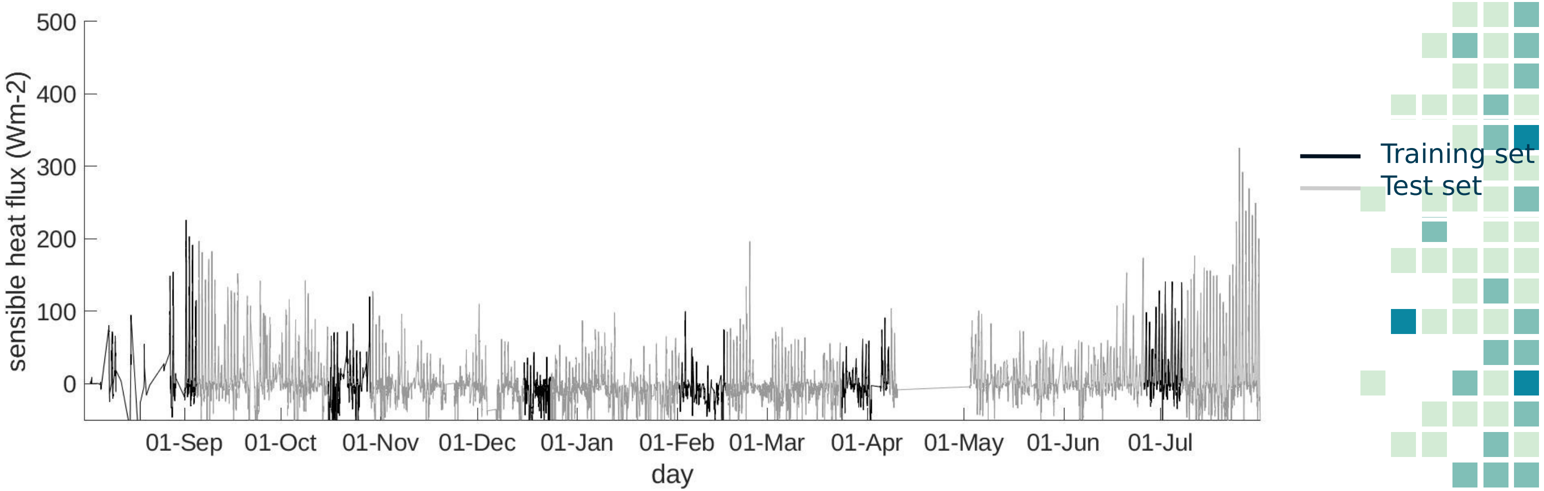
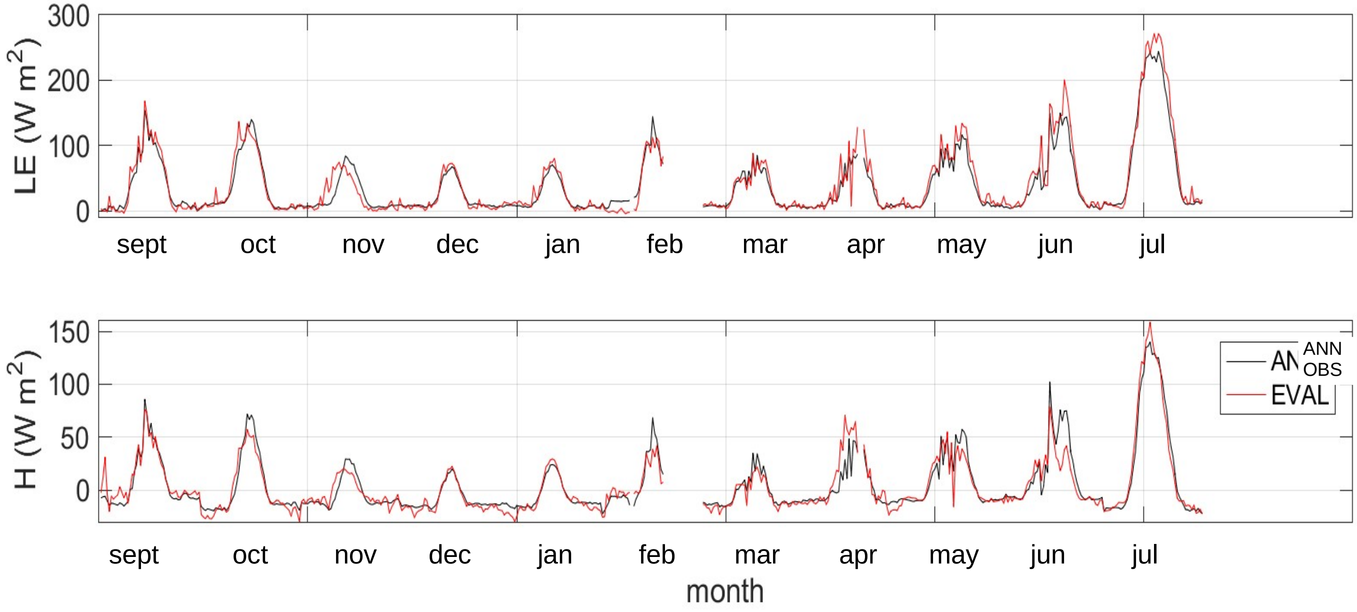




ESTIMATED FLUXES

Composite days for **scenario 3**, **5 neurons** and **1 hidden-layer** (monthly basis)



the **seasonal cycle** is well represented

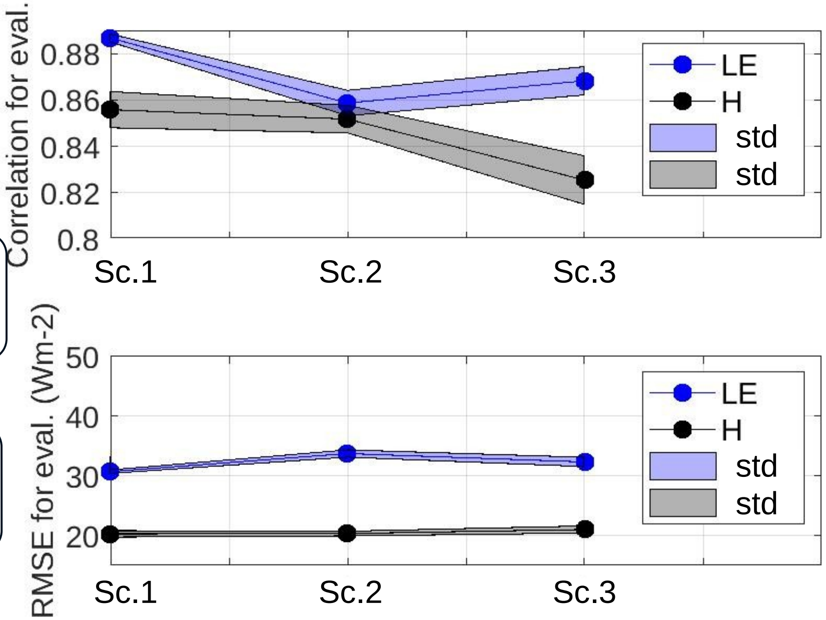
ROTATION FREQUENCY RESULTS

Test the influence of the different scenarios

Scenario 1
1 week for training
4 weeks for test

Scenario 2
2 weeks for training
8 weeks for test

Scenario 3
3 weeks for training
12 weeks for test

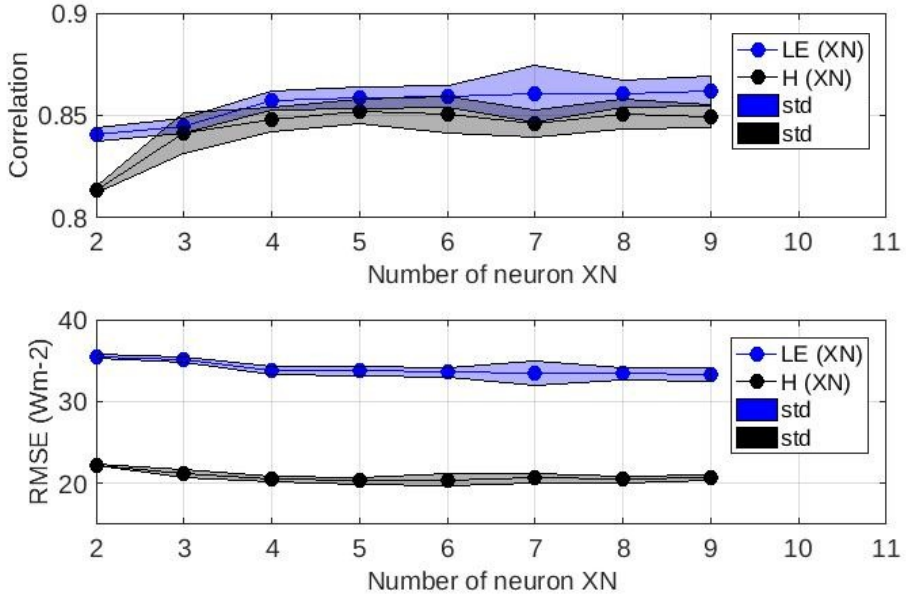


Architecture tested here :
1 hidden layer | 5 neurons

The 3rd scenario (3 weeks for training) seems to be a good compromise (sampling weather conditions/logistics)

NETWORK TOPOGRAPHY RESULTS

Test the influence of the architecture

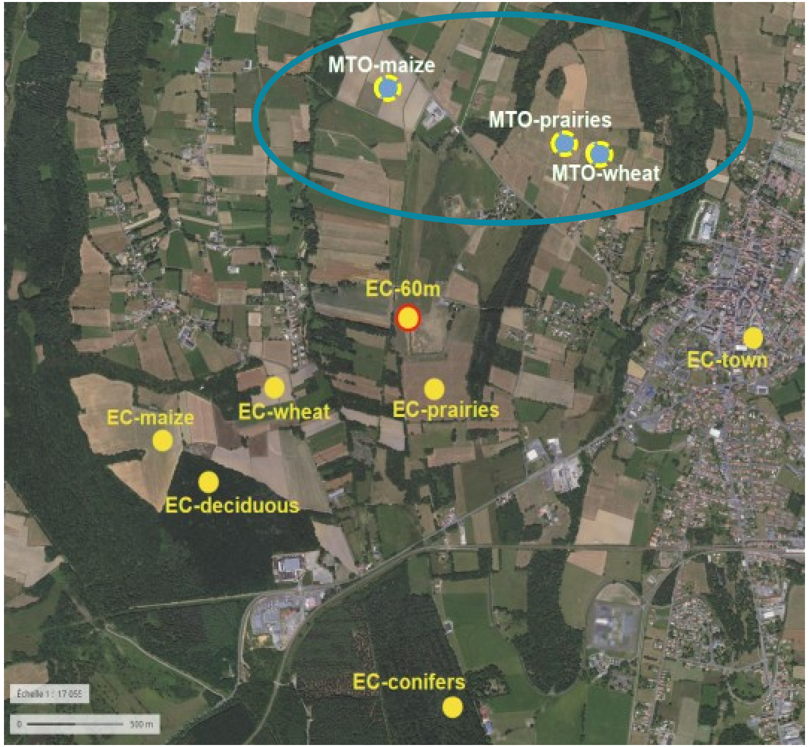


<u>Scenario tested here :</u> Scenario #2

5 neurons on 1 hidden-layer seems to be enough here to properly estimate fluxes

The simpler, the better !

THE MOSAI CAMPAIGN :



<u>frequency rotation :</u> 3 weeks

<u>architecture :</u> 1HL | 5N

Deployment of the method during the **P2OA campaign (april 2023)**

Three sites instrumented with standard weather stations :

Maize

Prairie

Wheat

THANKS !

Any questions ?

You can find me at :

mathilde.jome@aero.obs-mip.fr