USING ARTIFICIAL NEURAL NETWORK TO BETTER EVALUATE SURFACE TURBULENT HEAT FLUXES IN WEATHER AND CLIMATE NUMERICAL MODELS

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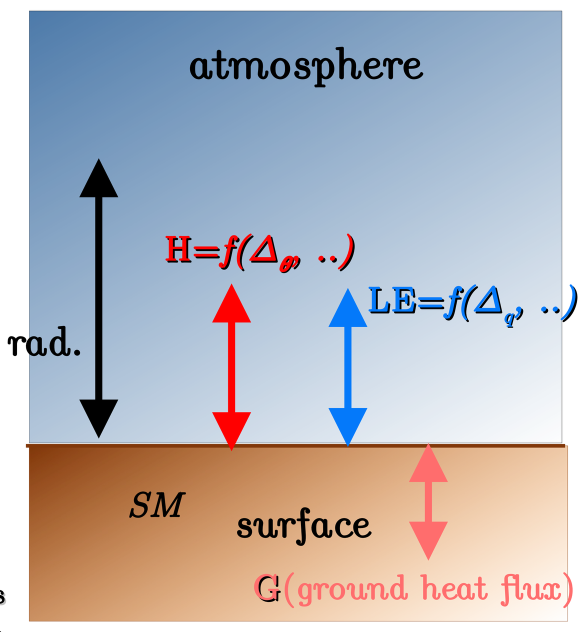
CONTEXT AND OBJECTIVES

The surface turbulent heat fluxes (**H** : sensible and **LE** : latent) are major terms of Surface-Energy-Budget (SEB) and key drivers of atmospheric boundary layer processes (turbulent mixing, low convective clouds triggering, ...). Therefore, their realistic representation in numerical weather and climate models is crucial to properly simulate the meteorological conditions within the low troposphere. However, formulation of these fluxes is the second source of uncertainty, which leads to incorrect surface-atmosphere interactions in numerical simulations.

θ ; q and Δ_α : temperature, humidity and gradient of **α** in atmospheric air near the surface ;
SM : soil moisture.



(SEB) : $R_{net} = \mathbf{H} + \mathbf{LE} + \mathbf{G}$

Assuming horizontally homogenous surface and overlying atmosphere in steady state (Stull, 1988).

Model evaluation is an essential task for developing improvements guidelines. Existing methods compare directly modelled and observed surface turbulent fluxes, blending many sources of errors such as inconsistent grid-scale representation, inaccurate environmental and meteorological forcings (soil and vegetation types, radiative fluxes, temperature, moisture, wind, ...).

Our work is part of the French **MOSAI** (**M**odel and **O**bservation for **S**urface-**A**tmosphere **I**nteractions) project. It aims at proposing a novel evaluation approach to better shed light on the shortcomings of **H** and **LE** formulations in numerical models. The idea is to use a multi-layer perceptron (MLP), trained to estimate surface fluxes ($\hat{H}$ and $\hat{LE}$) from variables describing atmospheric conditions near the surface, to freeze the errors caused by other sources.

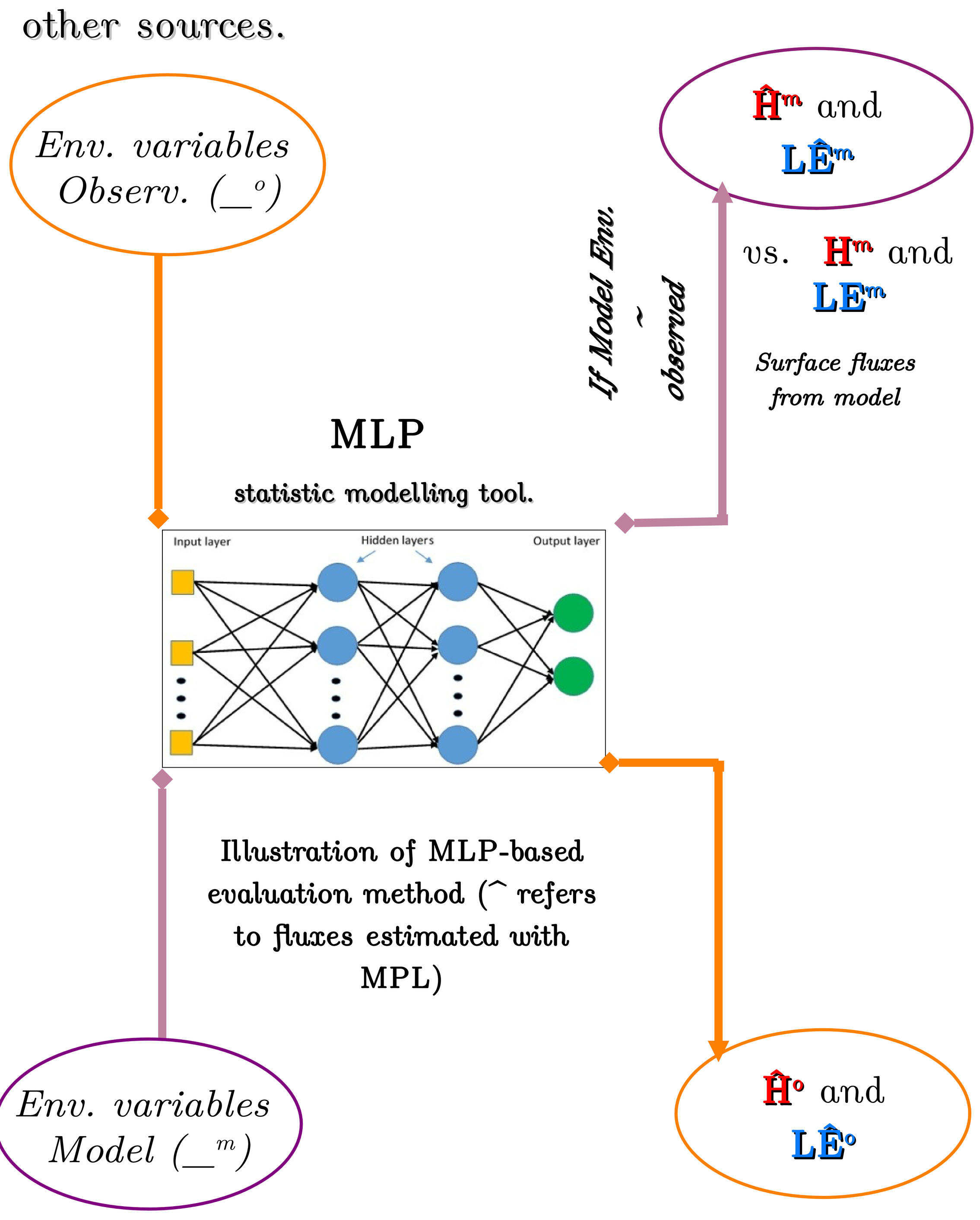
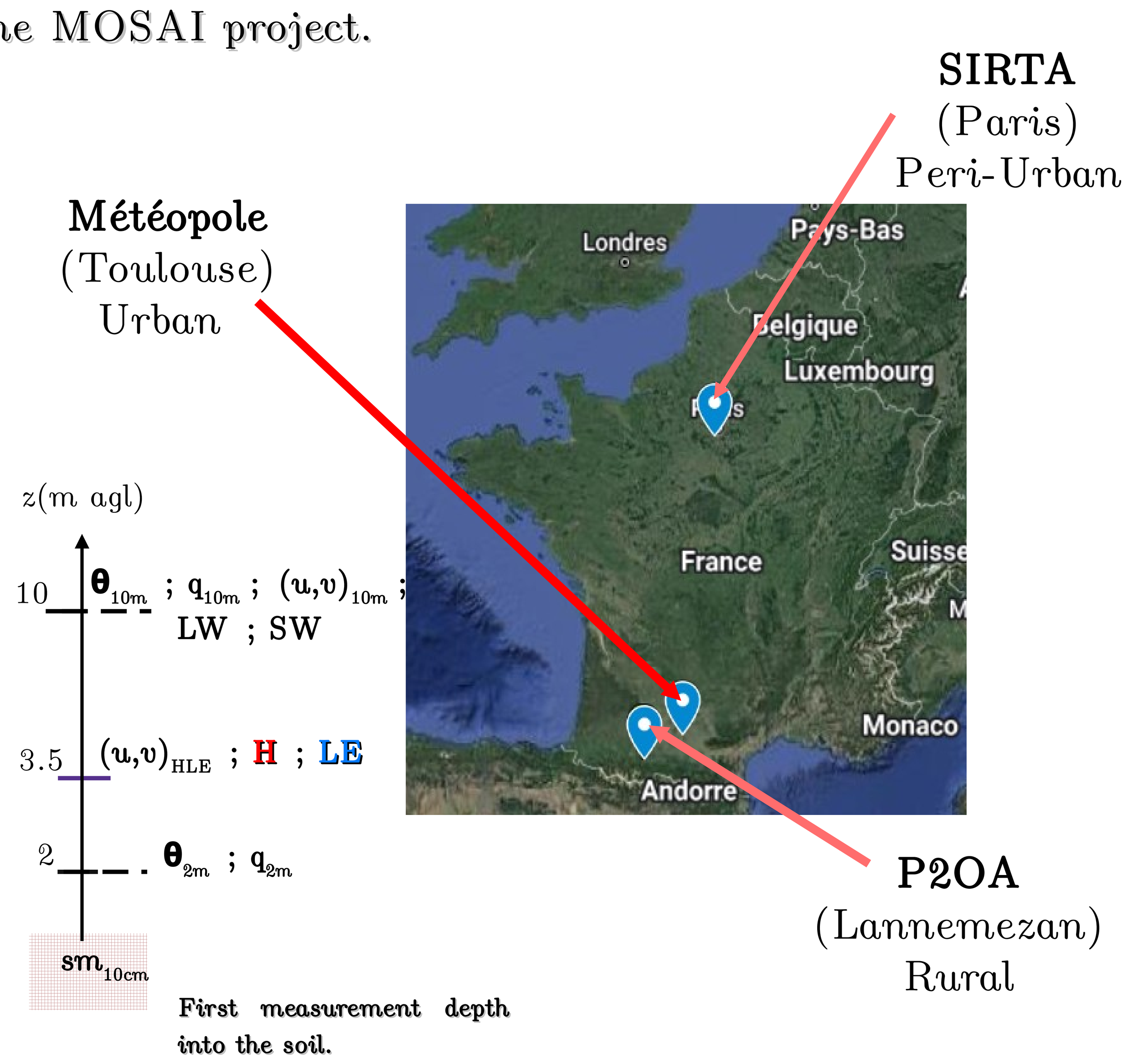


Illustration of MLP-based evaluation method (^ refers to fluxes estimated with MPL)

This method allows comparison in meteorological conditions described by the numerical model.

DATA AND METHODS

This study takes advantage of 30 min or hourly data collected over several years at three operational instrumented sites belonging to ACTRIS-France research infrastructure. The sites are mainly different by large scale forcing and surrounding urbanization. Four numerical models (**RegIPSL, LMDZ, AROME and ARPEGE**), developed and used by the French scientific community for weather forecasts and climate projections, are involved in the MOSAI project.



A pilot study is being conducted using Météopole 30 min observational data (*11 Nov. 2012 to 04 Fev 2021*) and 3 hourly data (*Jan. 2012 – Dec. 2016*) extracted at the nearest gridpoint from RegISPL model (WRF coupled to ORCHIDEE surface scheme). Only timestep without rainfall are taken into account. A single MLP is implemented with **tensorflow/keras** (Abadi et al., 2015) to ouput both $\hat{H}$ and $\hat{LE}$. It has learned (*train+validation*) with observational data from the five most covered years. Its ability to generalise is evaluated on the remaining data (*test*).

MPL configuration	
Normalisation	x = (X-min(X)) / (max(X) - min(X))
Initialization of MLP weights	normal (mean=0, stdv=0.05)
Hidden, output layer(s) activation	Hyperbolic tangent, Linear
Optimization algorithm	Adam
Training	MSE, batch mode

As MLP **input**, we use **13 variables** characterizing meteorological conditions within the surface layer such as :

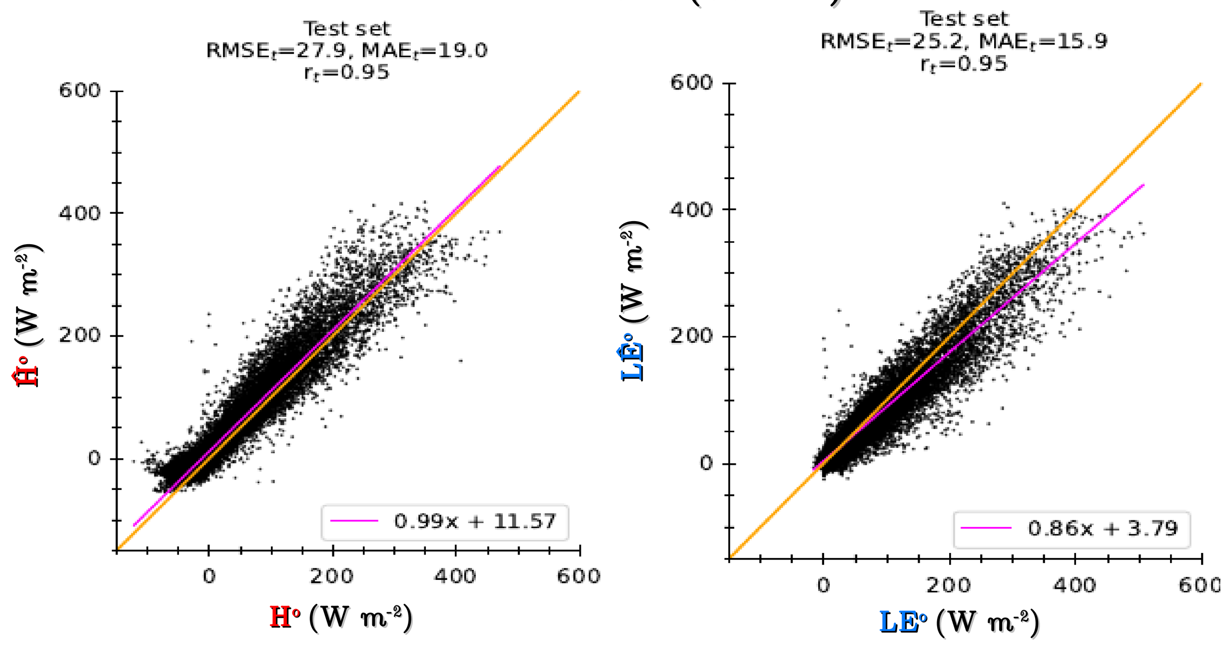
Input description	Observations	RegIPSL
Rad. forcing	R_{net}=sum(SW,LW)	same
Thermodynamic and dynamic	• θ_{sl}=mean(θ_{10m},θ_{2m}) ; Δ_θ=grad(θ_{10m},θ_{2m}) • q_{sl}=mean(q_{10m},q_{2m}) ; Δ_q=grad(q_{10m},q_{2m}) • $(u,v)_{sl}$=mean[$(u,v)_{10m}$, $(u,v)_{HLE}$] ; Δ_U=grad(U_{10m},U_{HLE})	• θ_{sl}=$\theta_{M=1}$; Δ_θ=grad($\theta_{M=1}$,θ_{2m}) • q_{sl}=$q_{M=1}$; Δ_θ=grad($q_{M=1}$,q_{2m}) • $(u,v)_{sl}$=$(u,v)_{M=1}$; Δ_U=grad(U_{10m},$U_{M=1}$)
Soil moisture	sm_{10cm}	sm_{12cm} *(nearest available depth)*
Time	• d_x=cos(2π*dd/N_d) ; d_y=sin(2π*dd/N_d) • h_x=cos(2π*Δh/24) ; h_y=sin(2π*Δh/24)	same

dd : julian day ; Nd : number of days a year ; Δh : hours relative to sunrise on dd
M=1 refers to the first half-eta level of RegIPSL (~8.1 m agl)

FINDINGS

A MLP with two hidden layers including 9 and 4 neurones respectively was found to provide satisfactory $\hat{H}$ and $\hat{LE}$ comparing to observations. It is then used as final architecture.

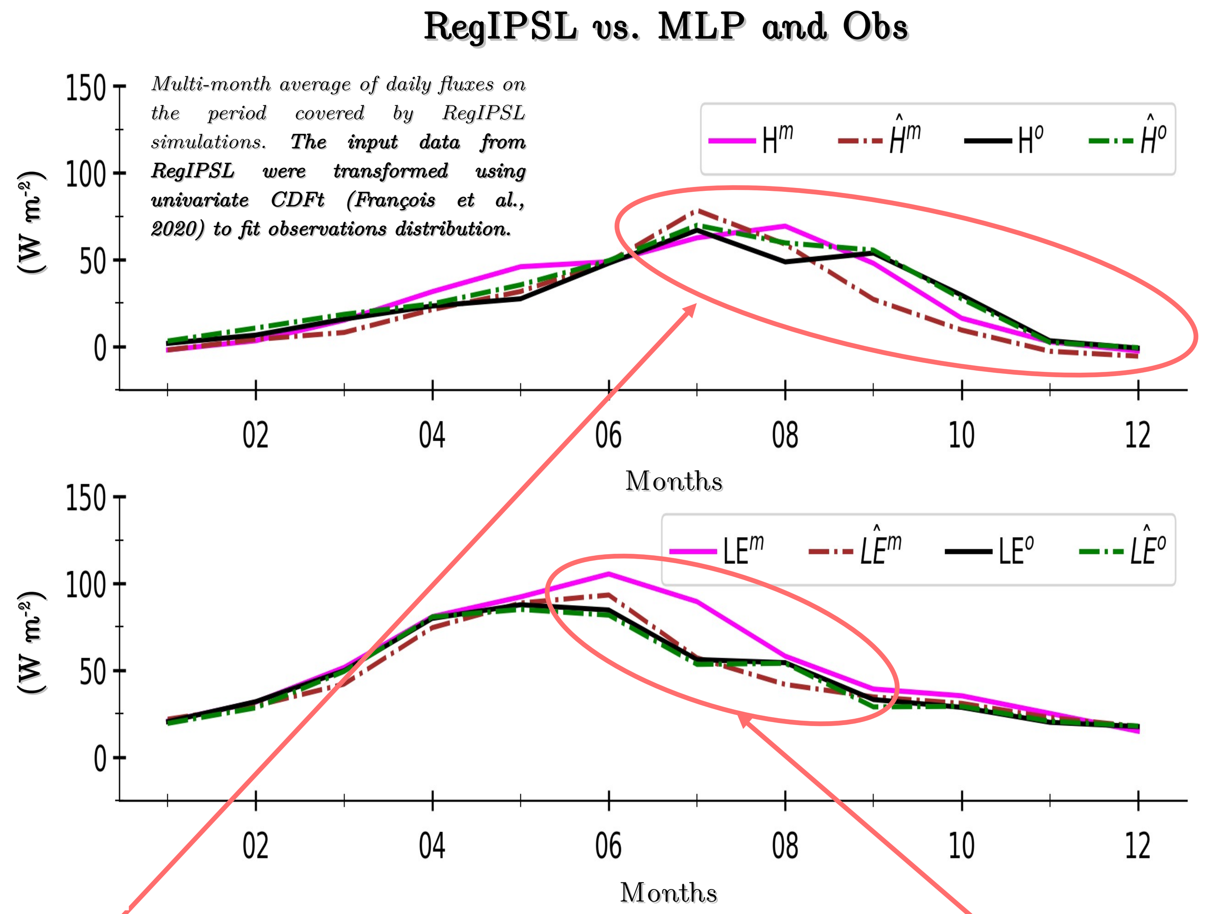
MLP vs. Obs (30 min)



RMSE ~ 25 W m⁻² and correlation ≥ 0.9 on test set (similar results on learning set). The MLP estimates well the surface fluxes and has a good generalization ability. Nonetheless, the variability of LE seems too complex to be fully described by the MLP entries.

Moreover, diurnal and seasonal cycles of $\hat{H}$ and $\hat{LE}$ are quite similar to observations and no fundamental modification of SEB is observed.

RegIPSL vs. MLP and Obs



Simulated latent heat flux is higher than the references (Obs and MLP). Overestimation of LE between May and September is clearly a characteristic weaknesses of the surface scheme in RegIPSL.

Observation and MLP estimates associated with model env. point out opposite systematic errors of simulated sensible heat flux between July and November. According to MLP, the deficiency of the surface scheme is instead overestimation of H.

PERSPECTIVES

- Further analyse the surface fluxes from RegIPSL simulations ;
- Extend the methodology to the other numerical models and instrumented sites ;
- Perform MLP-based inter-comparison of simulated surface turbulent fluxes.

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