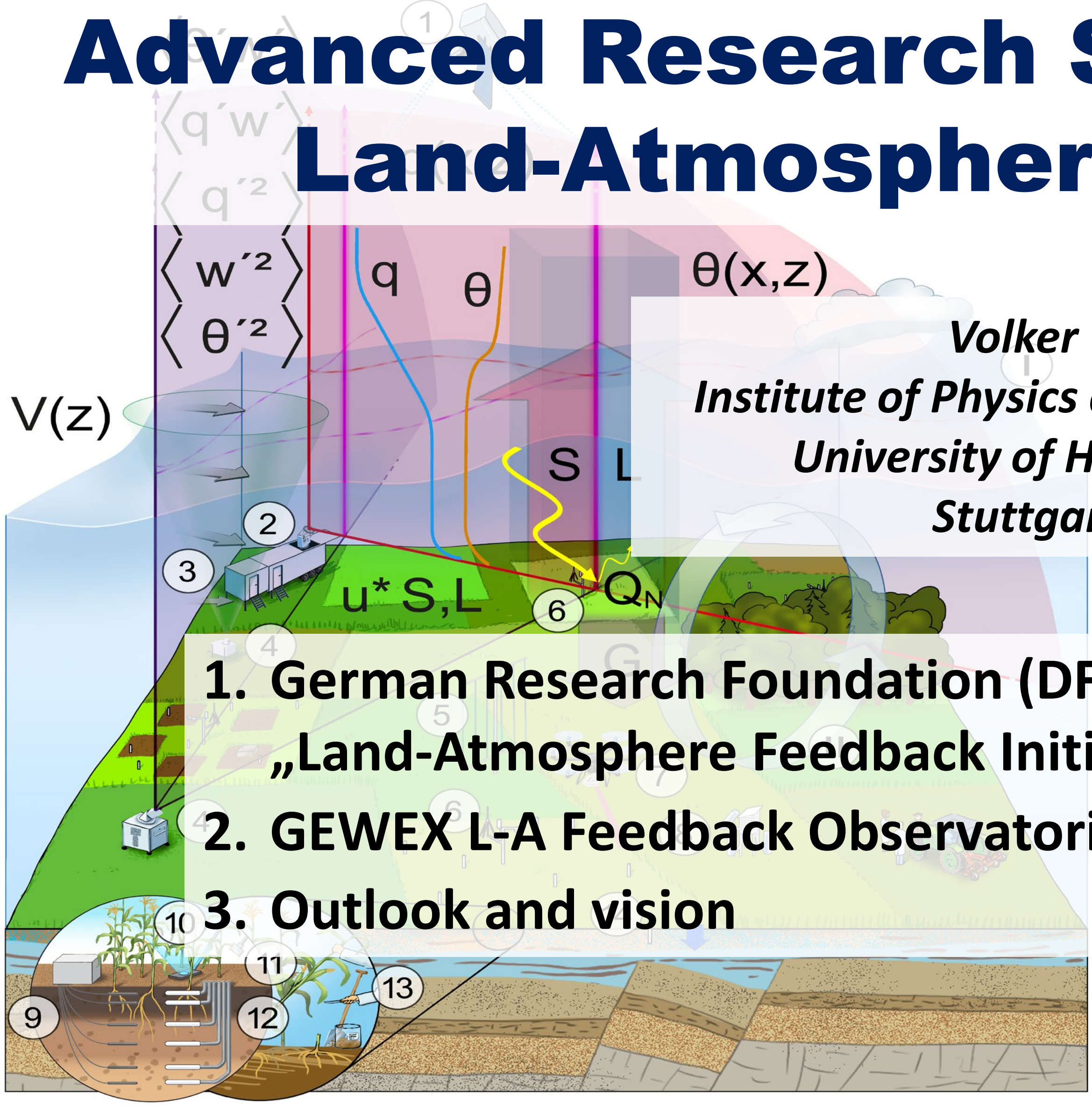
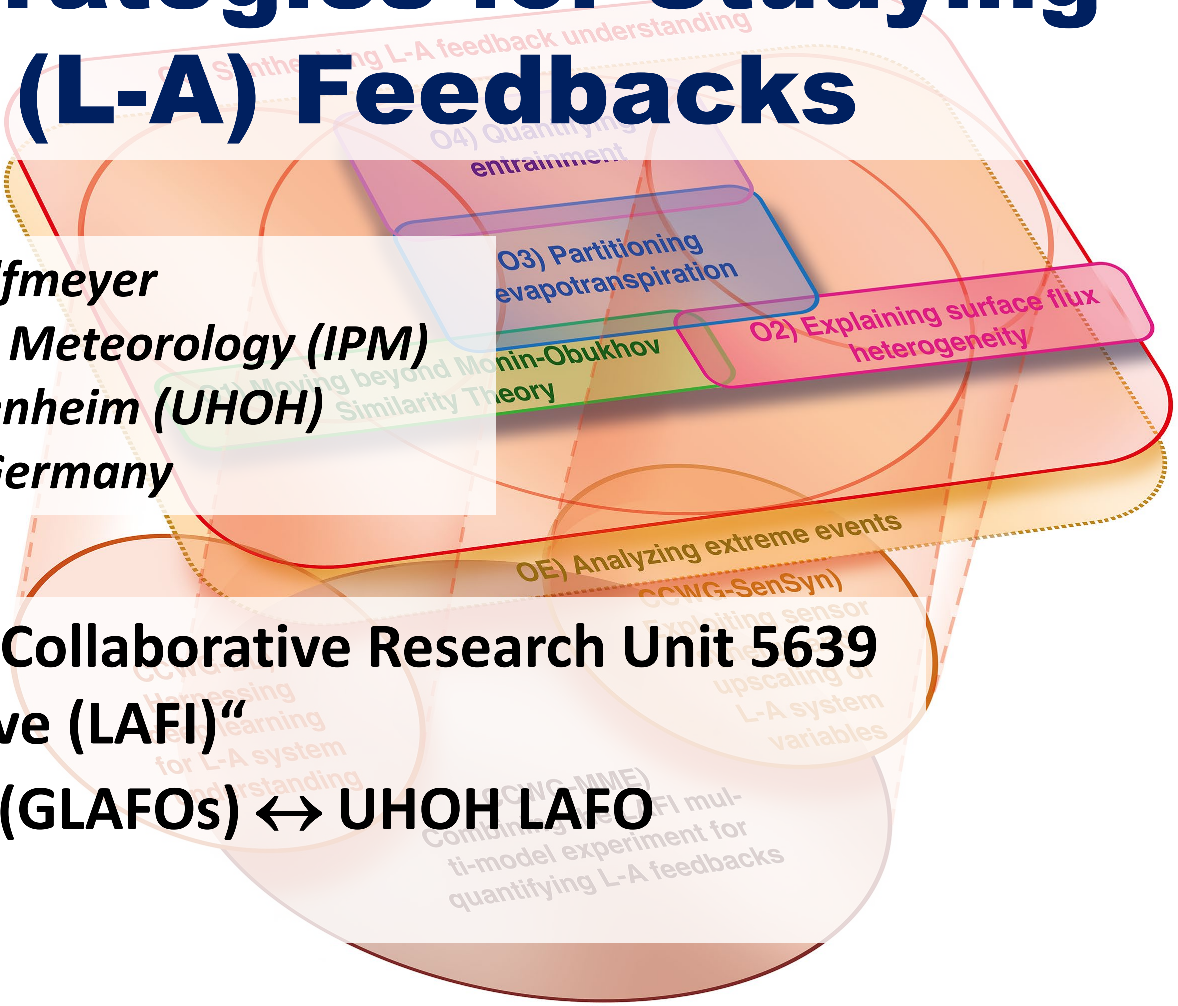
Advanced Research Strategies for Studying Land-Atmosphere (L-A) Feedbacks





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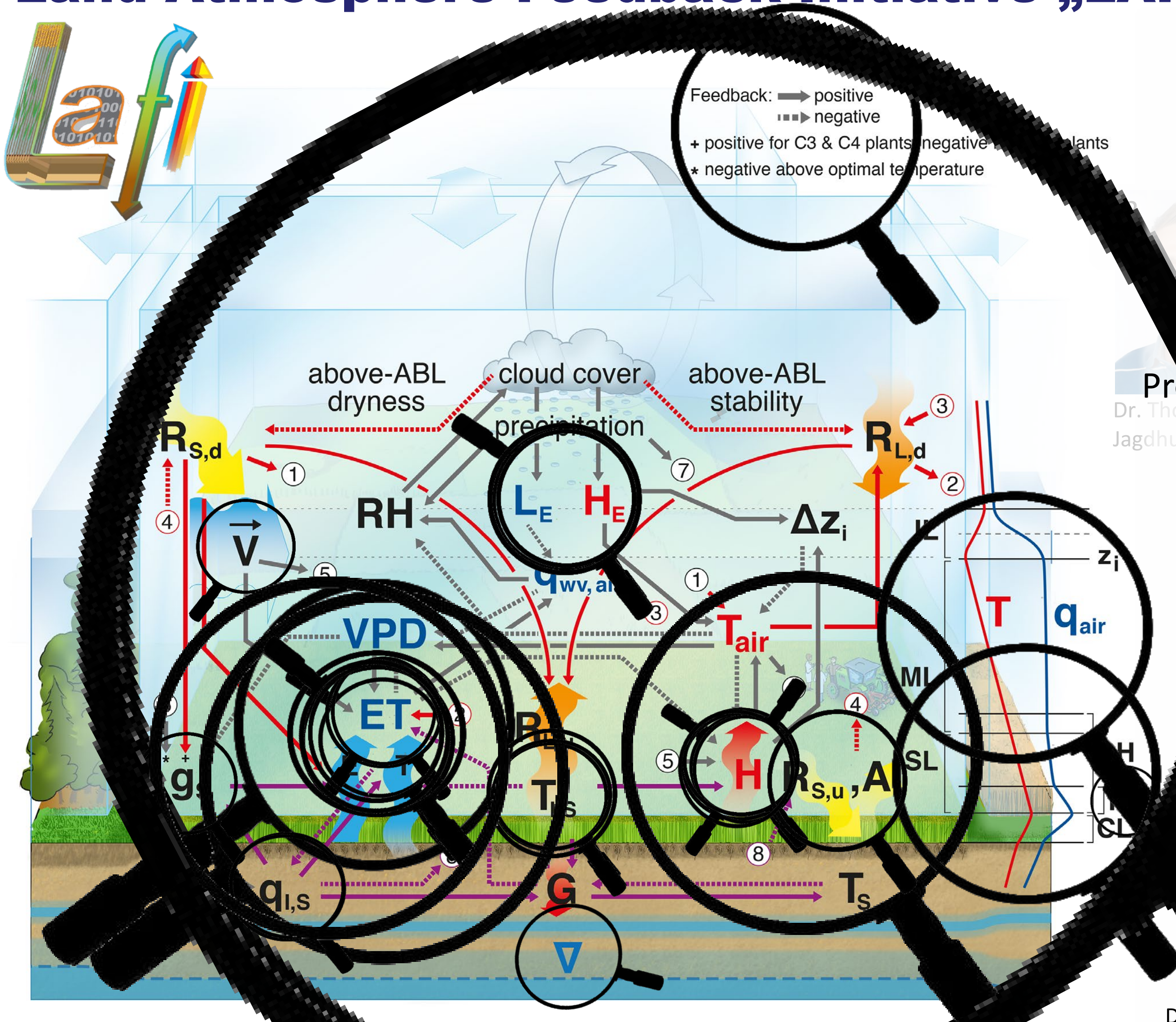
1. German Research Foundation (DFG) Collaborative Research Unit 5639 „Land-Atmosphere Feedback Initiative (LAFI)“
2. GEWEX L-A Feedback Observatories (GLAFOs) ↔ UHOH LAFO
3. Outlook and vision

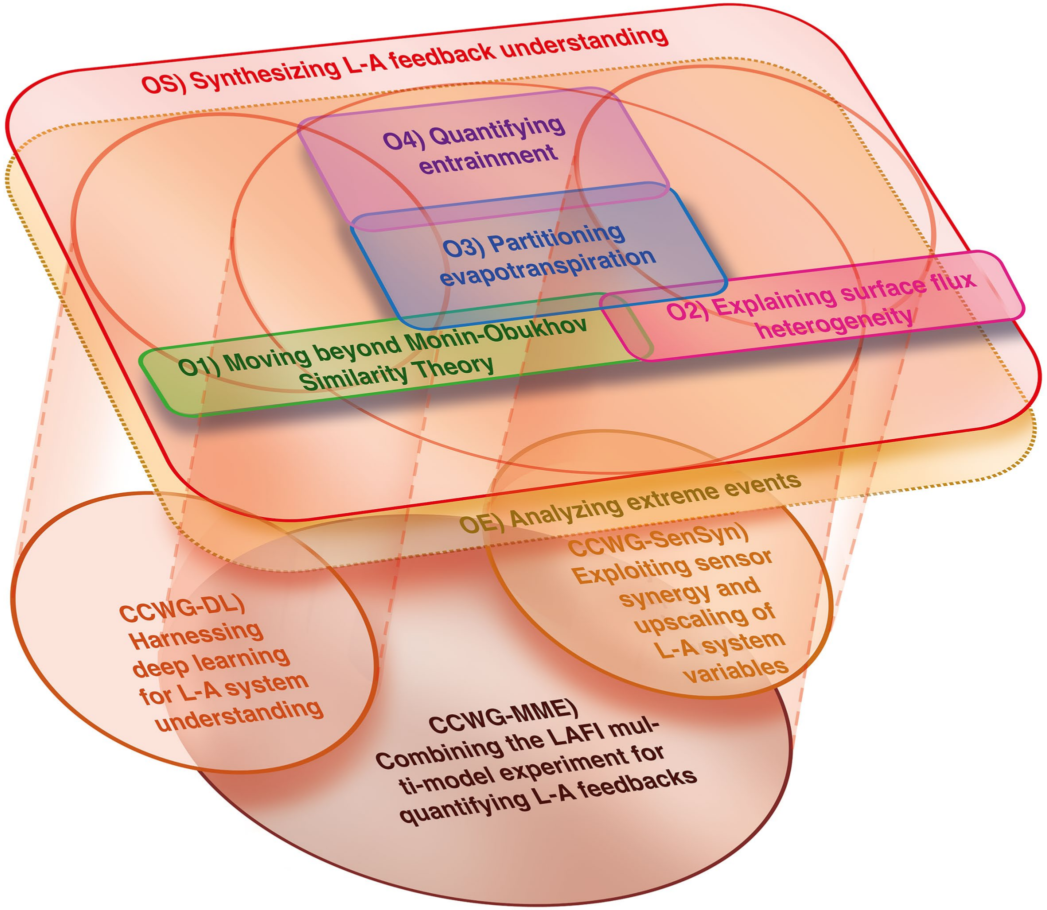
1. DFG Research Unit 5639

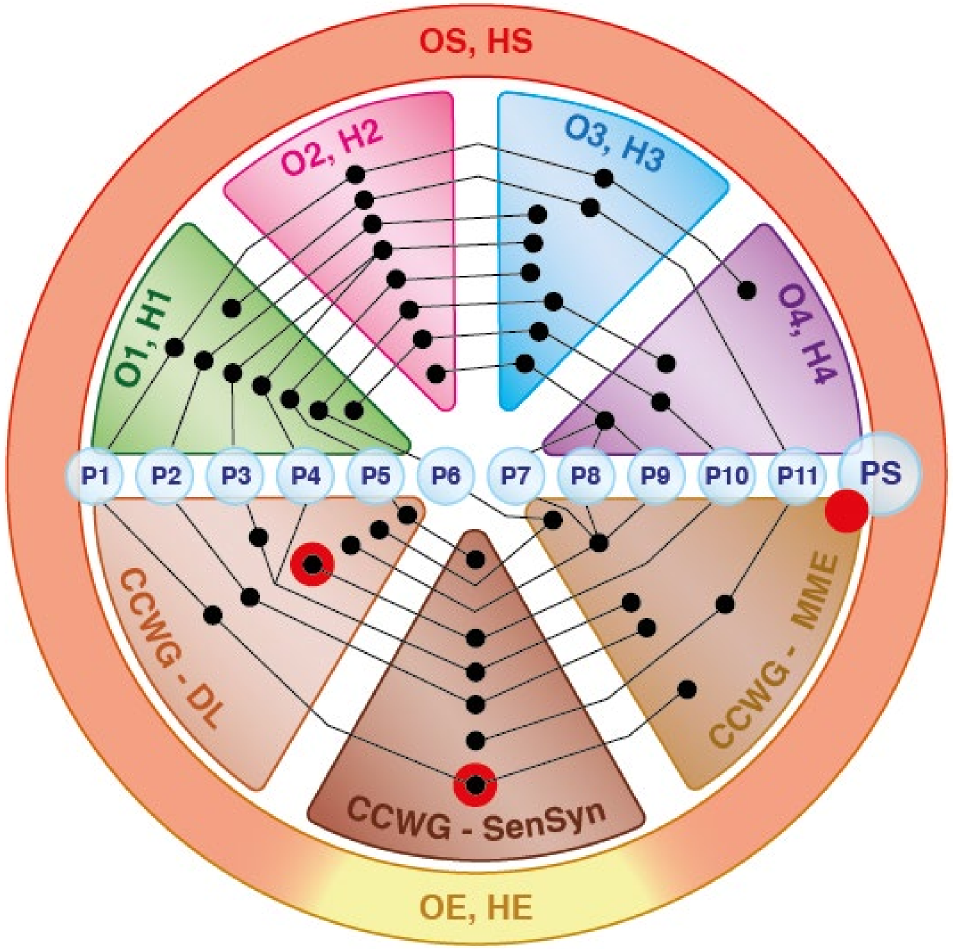
Land-Atmosphere Feedback Initiative „LAFI“



Objectives and Collaboration

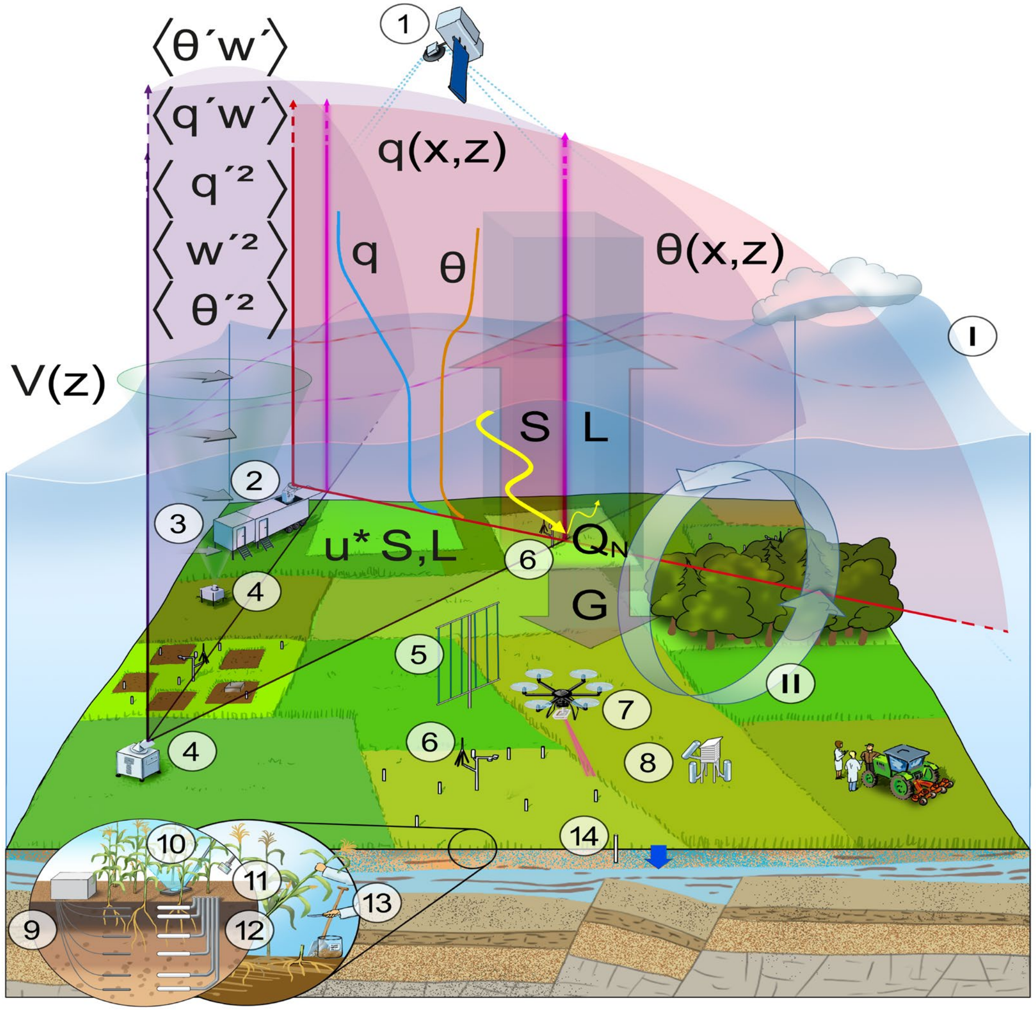
Our goal is to understand and quantify L-A feedbacks via unique synergistic observations and model simulations from the micro-γ (≈ 2 m) to the meso-γ (≈ 2 km) scales across diurnal to seasonal time scales.





1. GEWEX LAFO (GLAFO) Project

Holistic observation of the L-A system

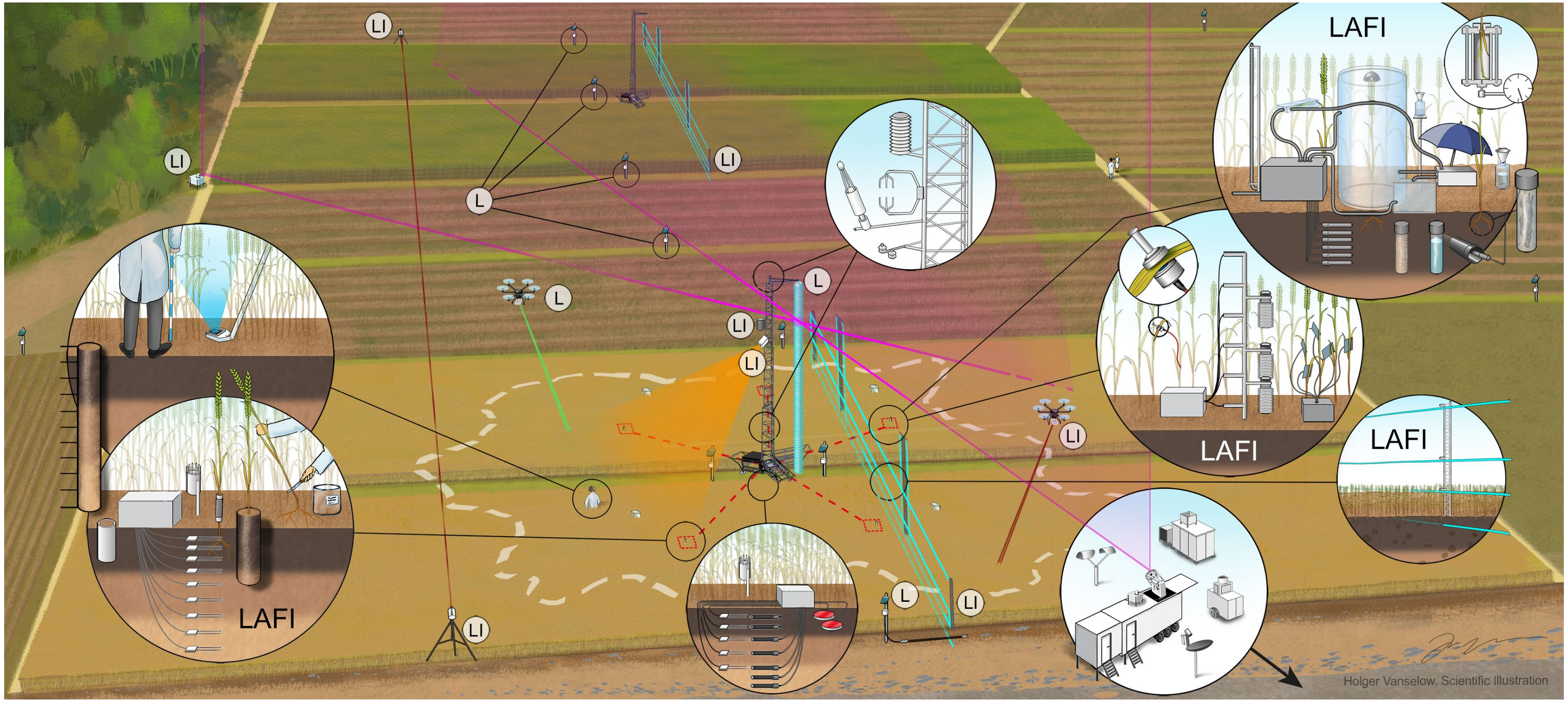


Proposed sensor synergy:
I: PBL top, II: mesoscale vortex
1: Satellite remote sensing
2: Vertically staring Doppler, water vapor, temperature, and CO_2 lidar systems, infrared spectrometer (IRS), microwave radiometer (MWR), cloud radar
3: Scanning Doppler, water vapor, temperature, and CO_2 lidar systems
4: Scanning Doppler lidar systems
5: Fiber-based distributed sensors
6: Energy balance and eddy covariance stations
7: Unmanned aerial vehicle (UAV)
8: Water vapor and CO_2 isotope sensor
9: Time-domain reflectometers (TDRs)
10: Leaf area index (LAI) measurement
11: Gas exchange system for photosynthesis and transpiration rates
12: Tensiometers
13: In-situ canopy measurements such as biomass and canopy height
14: Soil moisture and temperature network

Confirmed: DWD MOL-RAO; Ruisdael Observatory; Huancayo, Peru

Wulfmeyer et al. GEWEX Newsletter 2020, GLAFO White Paper 2021 (see https://www.gewex.org/panels/global-landatmosphere-system-study-panel/glass-projects)

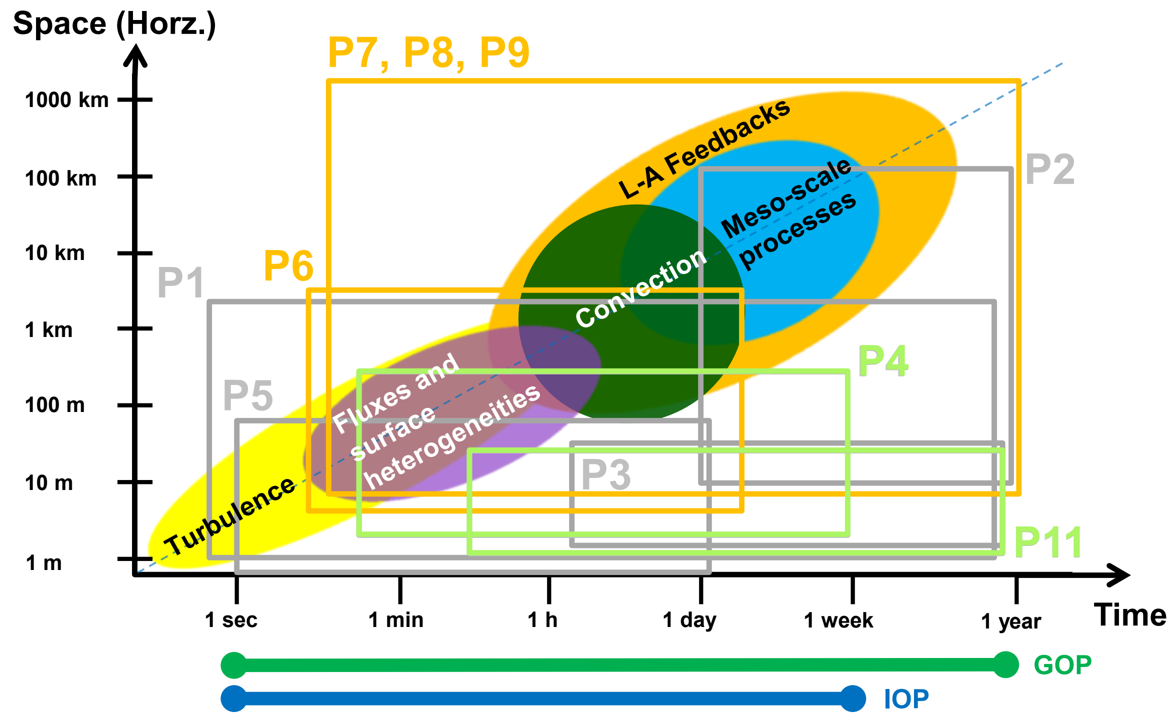
Research Component 1: Enhancement of the Land-Atmosphere Feedback Observatory (LAFO)



L: LAFO equipment
LI: LAFI enhancement

Worldwide unique observatory: Profiling and horizontal measurements through all compartments, simultaneously, in the atmosphere with turbulence resolution. CCWG-SenSyn exploits its sensor synergy.

Research Component 2: The Multi-Model Experiment (MME)



L-A SYSTEM MODELS

PALM (P6):
- Resolves turbulent transport in heterogeneous terrain with very high spatial resolution.

WRF-NoahMP-Gecros (P7):
- Operates with different resolutions simultaneously and uses a sophisticated representation of crop dynamics.

ICON-JSBACH (P8):
- Enables to study mesoscale effects of microscale surface heterogeneities and provides carbon fluxes.

WRF-NoahMP-Hydro-Iso (P9):
- Provides a more sophisticated representation of hydrology and links to the isotope measurements of P3.

- **Fundamental to understand the effects of heterogeneity on local to regional feedbacks**
- **Provide uncertainty estimates for metrics (PS)**

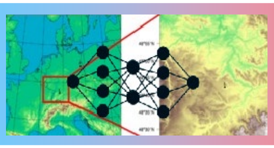
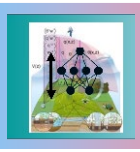
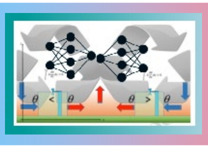
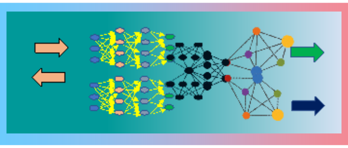
Offline LAND-SURFACE MODELS

NoahMP-Gecros (P4):
- Improves the representation of E and T of crops and of the soil water regime.

Vegetation Optimality Model (VOM) (P11):
- Realizes a detailed study of stomatal resistance models.

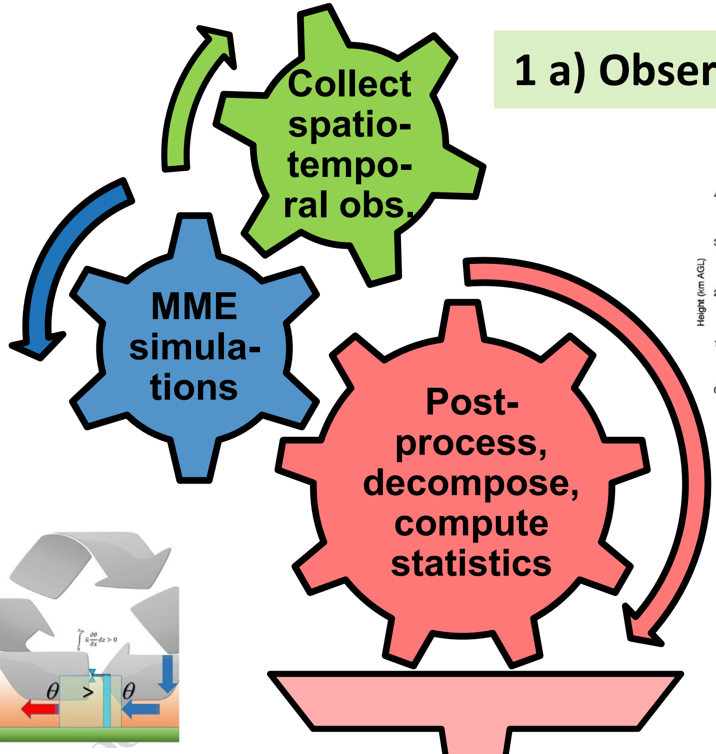
- **Fundamental to advance representation of water transport in the soil-plant system**

Research Component 3: Deep Learning

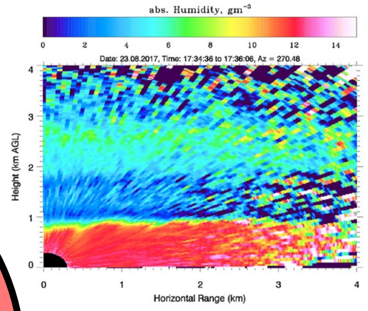
Aim	LAFI Research	Methodology		Process and system understanding
General similarities	Downscaling (satellite data of T_{LS}) (**P2**)	**Convolutional networks**		**Insight in the role of land-surface heterogeneity**
Process similarities	Fluxes and drivers (*ET, u*, H, H_E, L_E*), *(Wulfmeyer et al. 2023)* (**P5, P1, P3**)	**Machine learning with importance weighting**		**Alternative to MOST, turbulence similarities**
Process similarities + physics-informed	Fluxes and drivers (*ET, u*, H*) + energy conservation (**P5, P3, P1**), EBC (**P6**)	**Deep learning with regularization**		**Refined alternative to MOST with physical constraints, EBC**
Study of multi-dimensional phase space of L-A system	Structures and metrics in L-A system (**PS**)	**Foundation models**		**L-A system understanding and metrics**

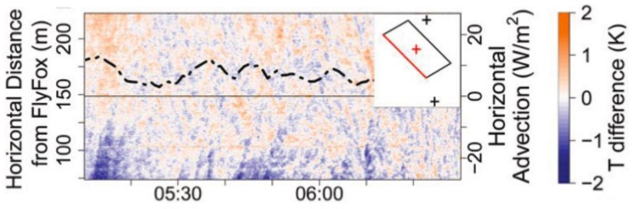
Research Component 4: Process Understanding Example: Objective 2 (O2) and Hypothesis 2 (H2)

Objective O2: Explaining surface flux heterogeneity. Key research on scaling and partitioning of surface fluxes as well as on the energy balance closure (EBC) across agricultural landscapes (P1-P11)

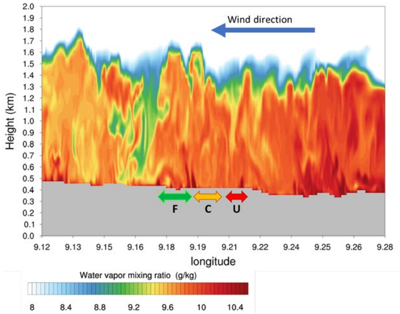


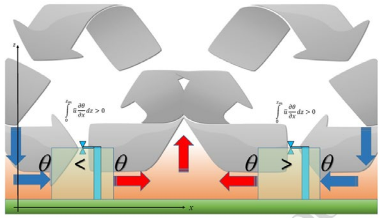
1 a) Observe L-A system states and variables



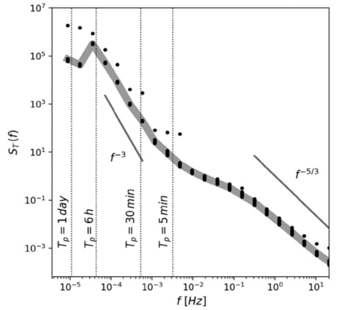


1 b) Simulate L-A system variables with MME:





2) Post-process, filter, scale-decompose



3 a) Synthesize:

- Analyze short-comings of measured and simulated fluxes
- Propose alternative scaling of fluxes dependent upon flow conditions as well as micro- and mesoscale circulations

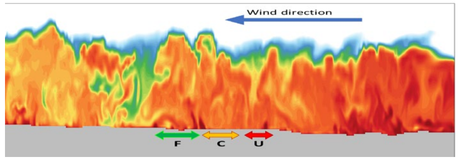
3 b) Evaluate hypothesis H2 (lead P6):

- Identify norm for comparing MME output and observations
- Incorporate co-spectral modifications and dispersive fluxes to correct surface fluxes and recompute EBC

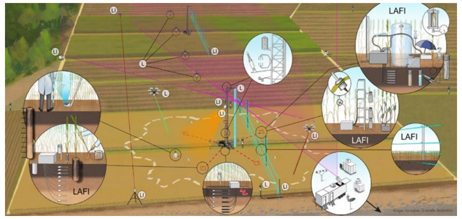
Conclusion and Vision

Highlights

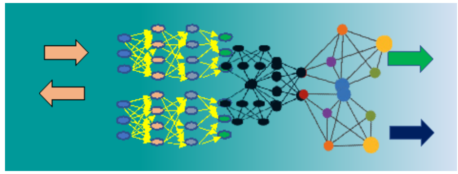
Ultra-high resolution MME



Unique sensor synergy

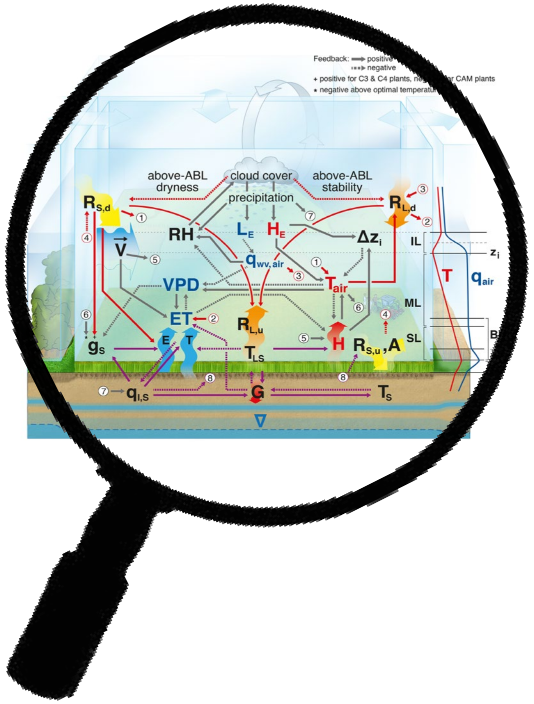


Deep learning

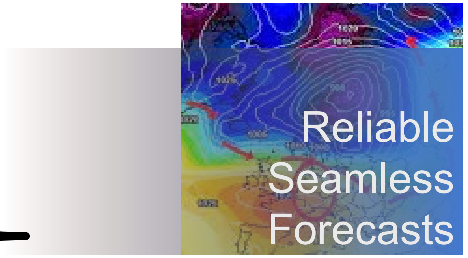


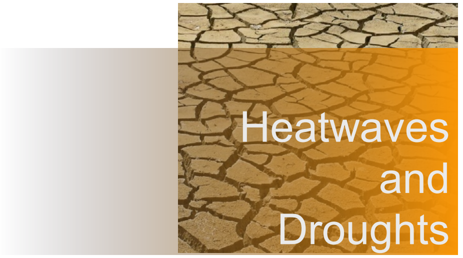
Interdisciplinary Teams

Advanced process understanding of land-atmosphere feedbacks



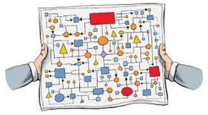
Implications



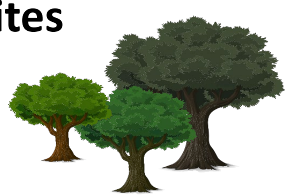


Outlook

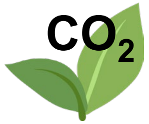
Develop and implement parameterizations for heterogeneous terrain



Expand studies at different sites (e.g., GLAFOs)

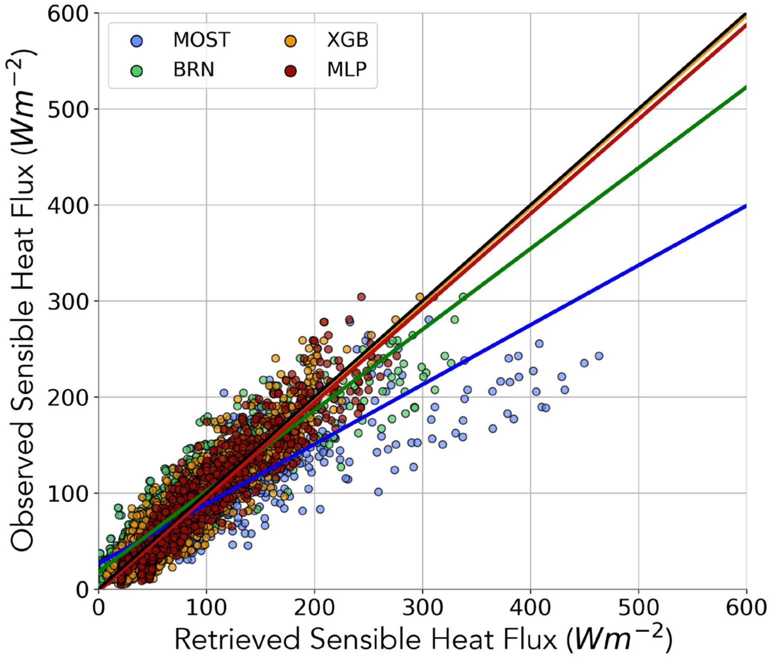


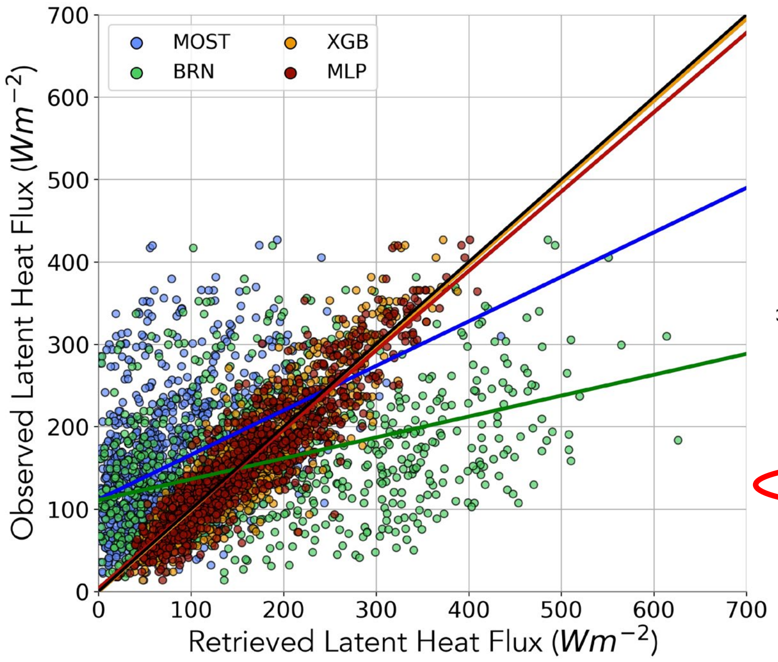
Include coupling of carbon and water cycles

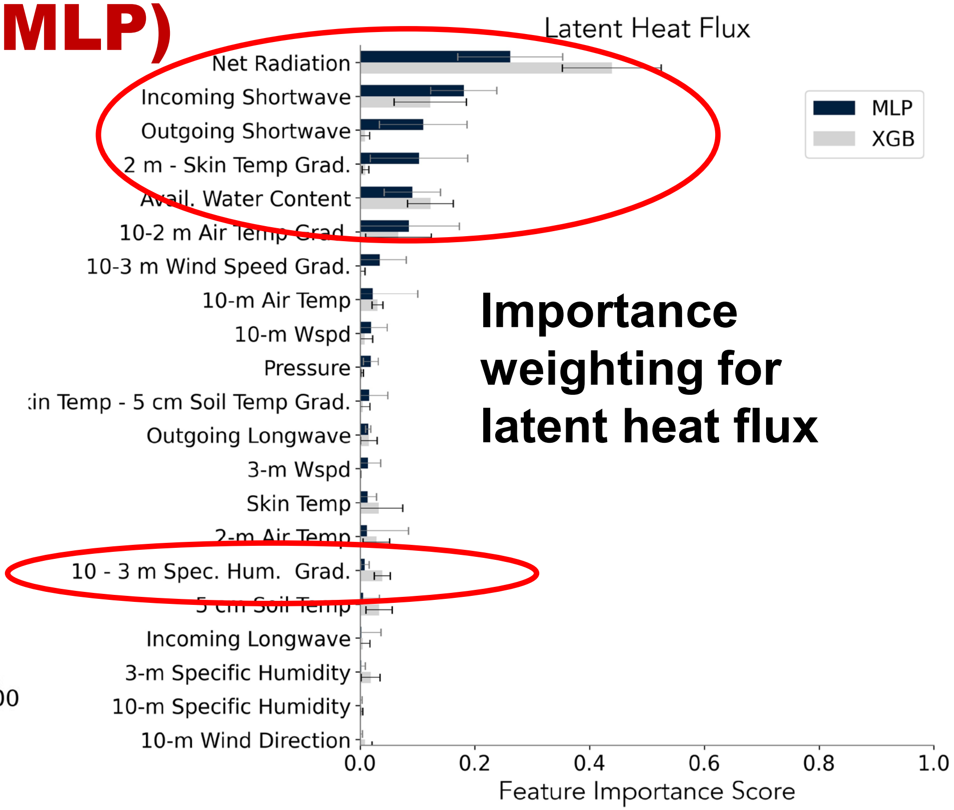


LAFE Result: Surface Fluxes

Comparison of Monin-Obukhov Similarity (MOST), Bulk Richardson Number (BRN) and Machine Learning (ML) with Extreme Gradient Boosting (XGB) and Multilayer Perceptron (MLP)



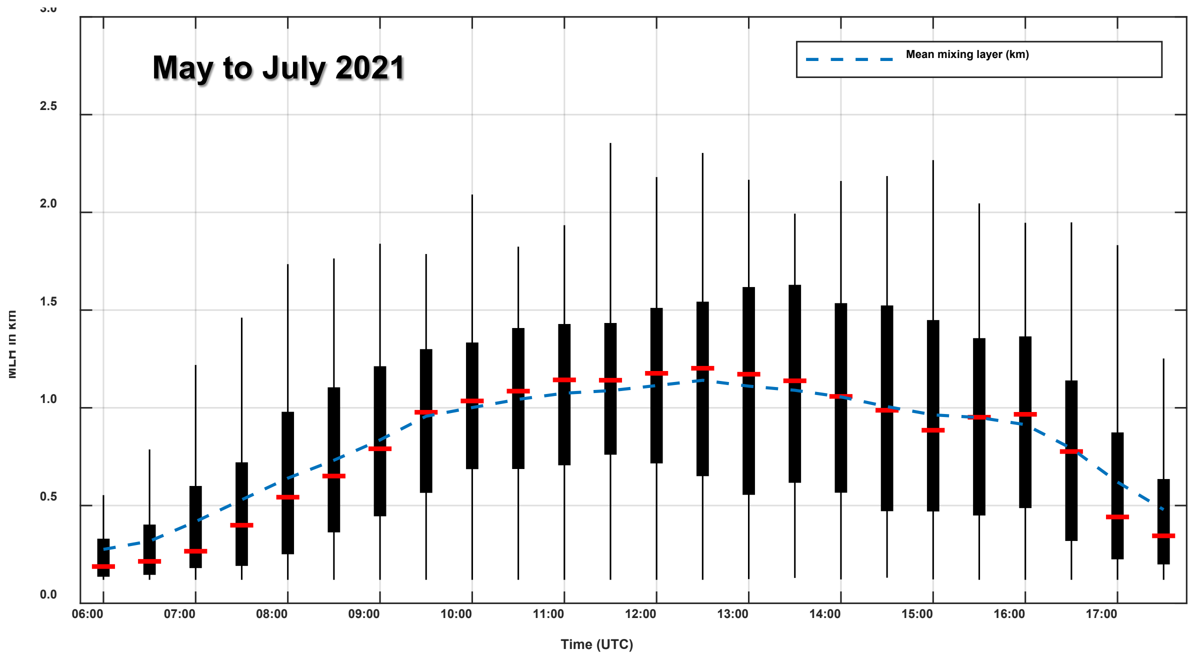


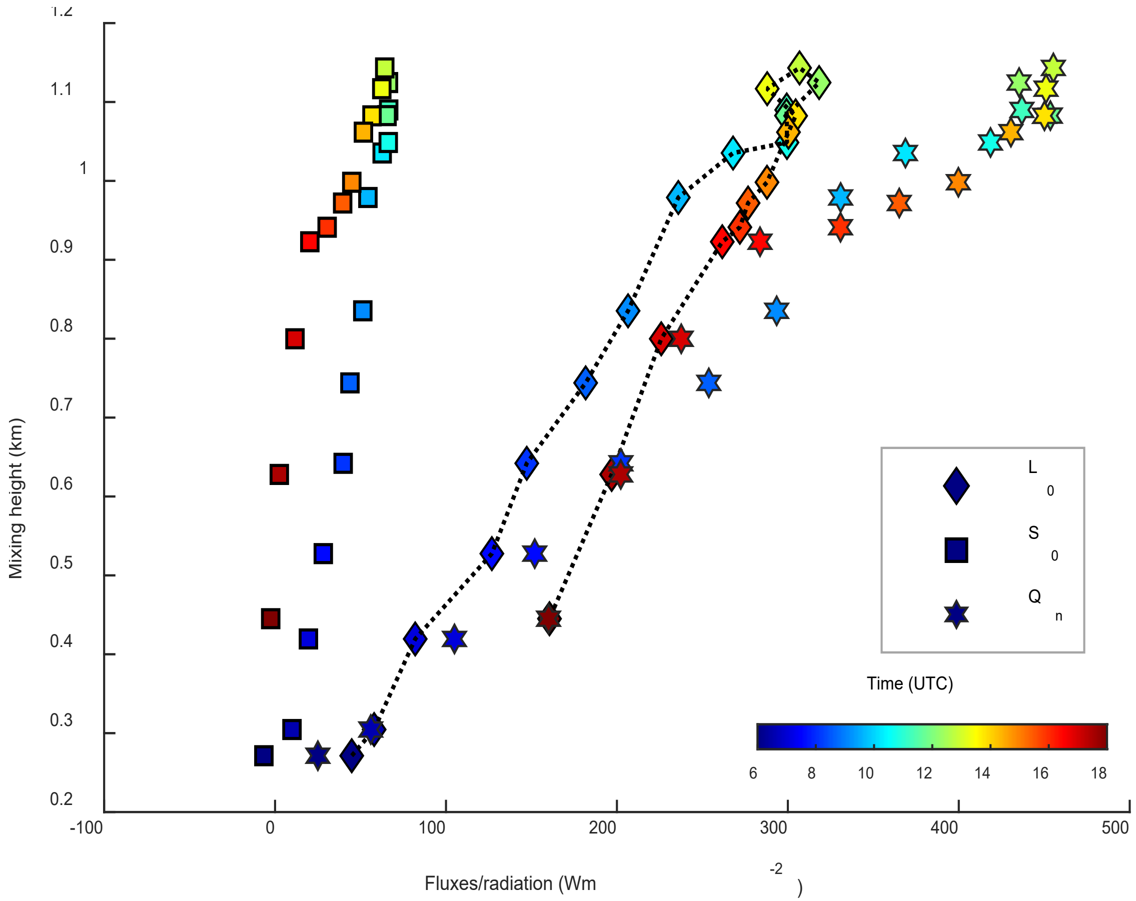


Importance weighting for latent heat flux

ML outperforms MOST and BRN. ML has great potential to improve surface layer flux relationships ***(Lee and Buban JAMC 2020, Lee et al. MWR 2021, Lee and Meyers 2023, Wulfmeyer et al. BLM 2023).***

LAFO Diurnal Cycle Statistics and Feedback Metrics





With (G)LAFO data, process-based feedback metrics can be derived routinely

(see also *Santanello et al. BAMS 2018, Wakefield et al. JH 2021, JAMC 2022*).