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

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

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P1 – Observation and Investigation of L-A System, ABL Processes and Fluxes

P9 – PS – Understanding and Quantification of L-A Feedbacks
Objectives and Collaboration

Our goal is to understand and quantify L-A feedbacks via unique synergistic observations and model simulations from the micro-$\gamma$ ($\approx 2$ m) to the meso-$\gamma$ ($\approx 2$ 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 CO₂ lidar systems, infrared spectrometer (IRS), microwave radiometer (MWR), cloud radar
3: Scanning Doppler, water vapor, temperature, and CO₂ 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 CO₂ 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

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

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.

**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 understand the effects of heterogeneity on local to regional feedbacks
- Provide uncertainty estimates for metrics (PS)
- Fundamental to advance representation of water transport in the soil-plant system
## Research Component 3: Deep Learning

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<th>Process and system understanding</th>
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<td>Downscaling (satellite data of $T_{LS}$) (P2)</td>
<td>Convolutional networks</td>
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<td>Process similarities</td>
<td>Fluxes and drivers ($ET, u^*, H, H_E, L_e$), (Wulfmeyer et al. 2023) (P5, P1, P3)</td>
<td>Machine learning with importance weighting</td>
<td>Alternative to MOST, turbulence similarities</td>
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<tr>
<td>Process similarities + physics-informed</td>
<td>Fluxes and drivers ($ET, u^*, H$) + energy conservation (P5, P3, P1), EBC (P6)</td>
<td>Deep learning with regularization</td>
<td>Refined alternative to MOST with physical constraints, EBC</td>
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<td>Study of multi-dimensional phase space of L-A system</td>
<td>Structures and metrics in L-A system (PS)</td>
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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:

MME simulations

Collect spatio-temporal obs.

Post-process, decompose, compute statistics

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

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June 3, 2024
Noah-MP International Workshop

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Conclusion and Vision

Highlights
- Ultra-high resolution MME
- Unique sensor synergy
- Deep learning
- Interdisciplinary Teams

Implications
- Advanced process understanding of land-atmosphere feedbacks
- Regional Climate Change
- Reliable Seamless Forecasts
- Crop growth and yield assessment
- Heatwaves and Droughts

Outlook
- Develop and implement parameterizations for heterogeneous terrain
- Expand studies at different sites (e.g., GLAFOs)
- Include coupling of carbon and water cycles

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**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)

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).