# Toward the Development of New Parameterizations for Surface Fluxes


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## Focal Area:

In this work we seek to improve surface-layer parameterizations of heat, moisture, and momentum exchange for use in numerical weather prediction (NWP) models. We will use data from a variety of sources and locations as input into a physics-guided neural network-driven spatiotemporal sequence forecasting method to develop a new approach for calculating these land-atmosphere interactions.

## Science Challenge:

For more than 50 years (e.g., Monin and Obukhov 1954, Obukhov 1971) Monin-Obukhov Similarity Theory (MOST) has been used to represent near-surface exchanges of heat, moisture, and momentum in NWP models (e.g., Foken 2006, Jiménez et al. 2012). However, limitations of MOST are well-known. In brief, MOST assumes a homogenous near-surface flux layer, which is oftentimes not valid, and suffers from autocorrelation (Andreas and Hicks 2002). Limitations such as these motivate the need to modify the functional forms of the similarity equations used to represent fluxes in NWP models.

## Rationale:

Lee and Buban (2020) recently suggested that using a bulk Richardson ($Ri_b$) approach yielded better predictions of near-surface temperature, moisture, and wind than using classical similarity relationships derived from MOST. However, the $Ri_b$ parameterizations from Lee and Buban (2020) were developed only in the lowest 10 m of the atmospheric boundary layer (ABL) for unstable conditions only and over one land surface type. In order for the parameterizations that they developed to be used to improve heat, moisture, and momentum exchanges in NWP models, the parameterizations must be 1) extended to stable regimes, 2) evaluated over different land surface types with varying surface roughness length ($z_0$), and 3) above 10 m above ground level (AGL) and throughout the entire ABL depth. Applying new parameterizations to these different regimes and to areas with different $z_0$ is expected to yield improvements to the surface and ABL parameterization schemes used in NWP models, which will lead to improved weather forecasts including those leading to extreme hydrological events such as drought and flooding.

## Narrative:

We propose using datasets obtained from 1) targeted field campaigns funded through NOAA and the National Science Foundation, and 2) long-term DOE-operated sites at which a rich array of surface and ABL observations are available to test the recently-proposed $Ri_b$


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parameterizations and to make modifications to these parameterizations to account for variations in atmospheric stability and $z_0$. We will use datasets obtained from field campaigns conducted in regions of the US with different $z_0$ and within different US Global Change Research Program (USGCRP) climatic region divisions in which arrays of meteorological and flux measurements are available. Field campaign datasets will include, e.g. those obtained during the Land Atmosphere Feedback Experiment (LAFE) in Oklahoma in summer 2017 (e.g., Wulfmeyer et al. 2018) ($z_0 \approx 0.1$), the Verification of the Origins of Rotation in Tornadoes Experiment-Southeast (VORTEX-SE) in spring 2016 and 2017 in Alabama (e.g., Lee et al. 2019a, b) ($z_0 \approx 0.2$), the Chequamegon Heterogeneous Ecosystem Energy-balance Study Enabled by a High-density Extensive Array of Detectors (CHEESEHEAD) in summer-fall 2019 in Wisconsin (Butterworth et al., 2020) ($z_0 \approx 1$), and an ongoing study near Oak Ridge, Tennessee ($z_0 \approx 5$) in which small unmanned aircraft systems (sUAS) are being used to frequently sample ABL kinematic and thermodynamic fields.

We will then use long-term observations to test the new parameterizations that we developed using the aforementioned datasets and will compare the new parameterizations against classical parameterizations obtained from MOST to determine if the new $Ri_b$ parameterizations better predict near-surface fluxes of momentum, heat, and moisture. We will conduct this evaluation using datasets from at least two study regions which represent a range of surface roughness: 1) the DOE Atmospheric Radiation Measurement (ARM) Southern Great Plains (SGP) site near Lamont, Oklahoma that is characterized by relatively flat terrain, and 2) DOE and NOAA/ATDD observations near Oak Ridge, Tennessee which is an area characterized by ridge and valley terrain and much larger $z_0$ than Oklahoma. The DOE ARM site has multi-decadal meteorological observations, as well as supplementary measurements from numerous field campaigns conducted on-site. Long-term observations are also available from multiple meteorological and flux towers and ceilometers in and near Oak Ridge.

Besides allowing us to assess the impact of the new parameterizations on surface fluxes, datasets from the SGP site and east Tennessee will allow us to assess the impact the new parameterizations have on, e.g. ABL kinematic and thermodynamic fields, mixing height, etc. For example, at the Oak Ridge site, mixing heights are routinely overestimated in the North American Model (NAM) model as well as other NWP models (personal communication, ORNL meteorologist).

Our approach will use the recurrent neural network (RNN) form of spatiotemporal sequence forecasting (STSF) implemented as an Encoder-Forecaster. The method first takes geolocated measurements recorded as time series and stores each time step as a tensor for input into the encoder. The encoder is constructed of a series of convolutional layers, which converts the input into a high-dimensional representation that captures key correlations of informative spatial features in the original data for the given time step. This representation is then fed in series as input for the RNN, which discovers temporal correlations by learning an internal memory state that is triggered by informative patterns in the input sequence. The output of the RNN is then decoded using the forecaster (which includes an additional RNN and a de-convolutional step) so that multistep predications can be generated (Shi, 2018). In this particular instance, we will use the encoder-forecaster to simulate potential future flux states based on various initial flux states comprising known important combinations of parameters. Results will be compared to observations and reconciled with classical parameterizations. As this work will use pre-existing datasets from DOE assets and facilities and does not fully rely upon the collection of new datasets, the level of risk for this work is low.

In order to allow our findings from this work to be reproducible, in accordance with the FAIR (Findable, Accessible, Interoperable, Reusable) principles, we will make available the datasets, corresponding metadata files, and model code available through a NOAA/ATDD FTP server. Additionally, we will share results from this work with the broader scientific community through presentations at presentations at meetings hosted by the American Meteorological Society and through the submission of at least two publications to high-quality peer-reviewed journals.

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