Leaf Area Index Prediction Using ConvLSTM: Application to South-Central US with Insights into Atmosphere-Vegetation Interactions

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Background

- Evaluating the two-way interactions between the atmosphere and land surface processes is crucial to our understanding of regional and global climate, vegetation dynamics, and watershed hydrology.
- Modeling vegetation phenology from weather is challenging due its interannual variations and complex spatial heterogeneity.
- We developed a novel machine learning model, ML-LAI, based on convolutional Long Short-Term Memory (LSTM) techniques to study regional-scale interactions between the atmosphere and Leaf Area Index (LAI).

Input Dataset

- **Weather variables**
  Surface air temperature and precipitation data are sourced from Global Historical Climatology Network(GHCN) daily dataset.
- **Vegetation data**
  Moderateb Resolution Imaging Spectroradiometer (MODIS) LAI product MCD15A3H, a 4-day composite dataset with a 500-meter pixel size.
- **Soil moisture data** (in progress)
- **Additional variables** are currently under investigation: terrain, geographic locations, etc.

Preliminary research area

- Trained on daily data from 2003-2020. All data is interpolated to a grid with 0.01 degree resolution.
- The initial focus is on the Southwestern United States, as shown in Fig. 1.

ML-LAI Model

- Built on convolutional LSTM (ConvLSTM) architecture. Fig. 2 illustrates the model diagram during the training process.
- Designed to learn temporal patterns within each sequence, capturing the temporal changes in LAI.
- Extract spatial relationships across multiple variables, enabling it to understand the interactions between weather and vegetation changes.

Model Training

- The current version of ML-LAI uses 14-day time series sequences of multivariate inputs to predict LAI values over the following 14 days.
- Data subsets, each covering a 1x1 degree area, are treated as individual samples. Figure 3 illustrates the location of these subsets within the research area.

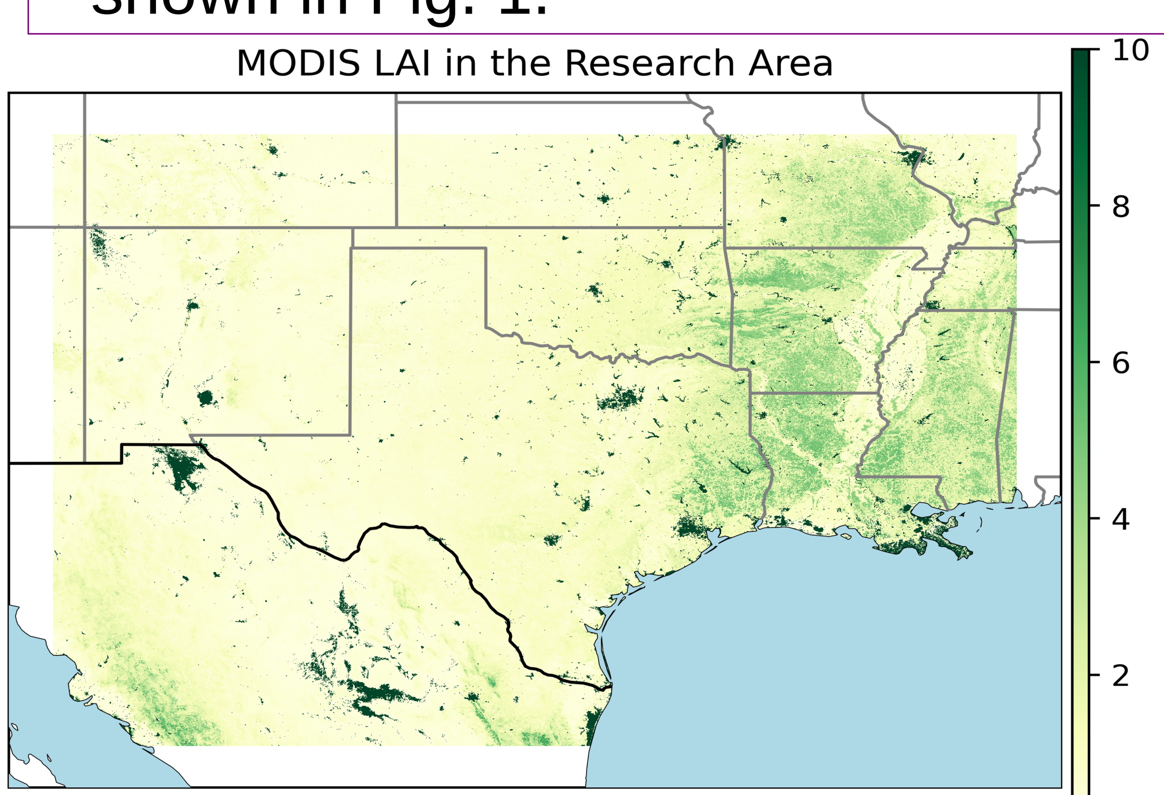


Fig. 1. MODIS LAI data in the research area

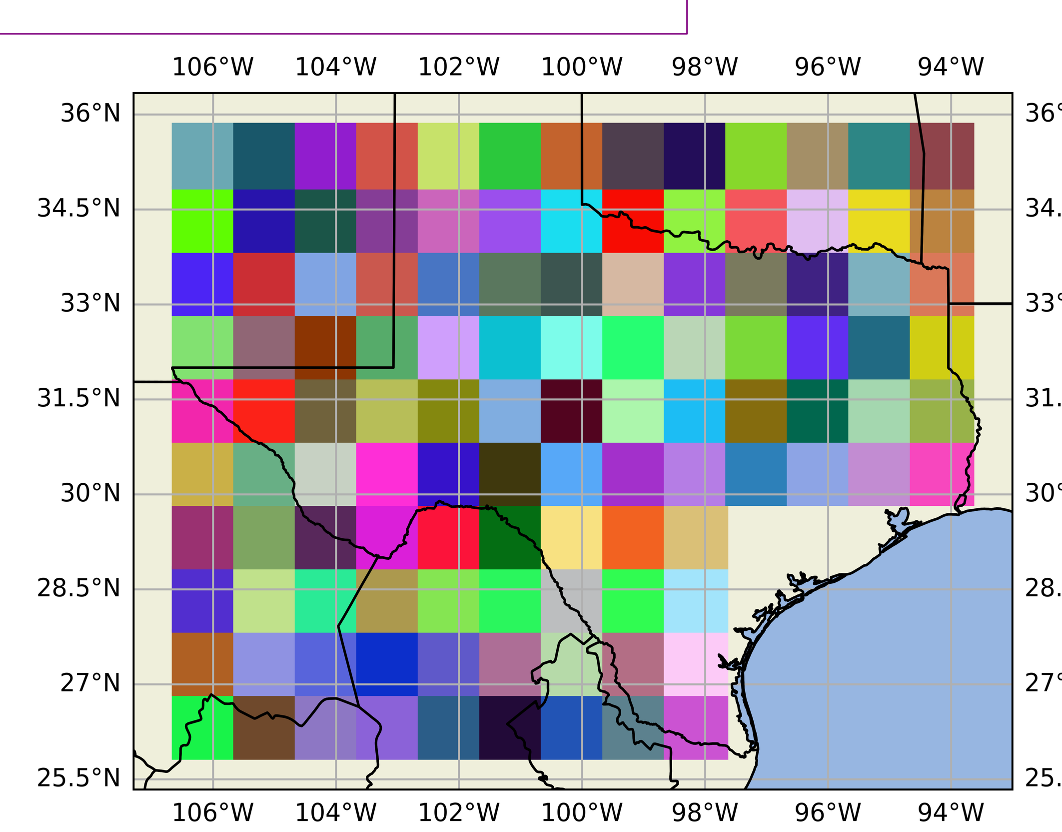


Fig. 3. Subsets selection for model training

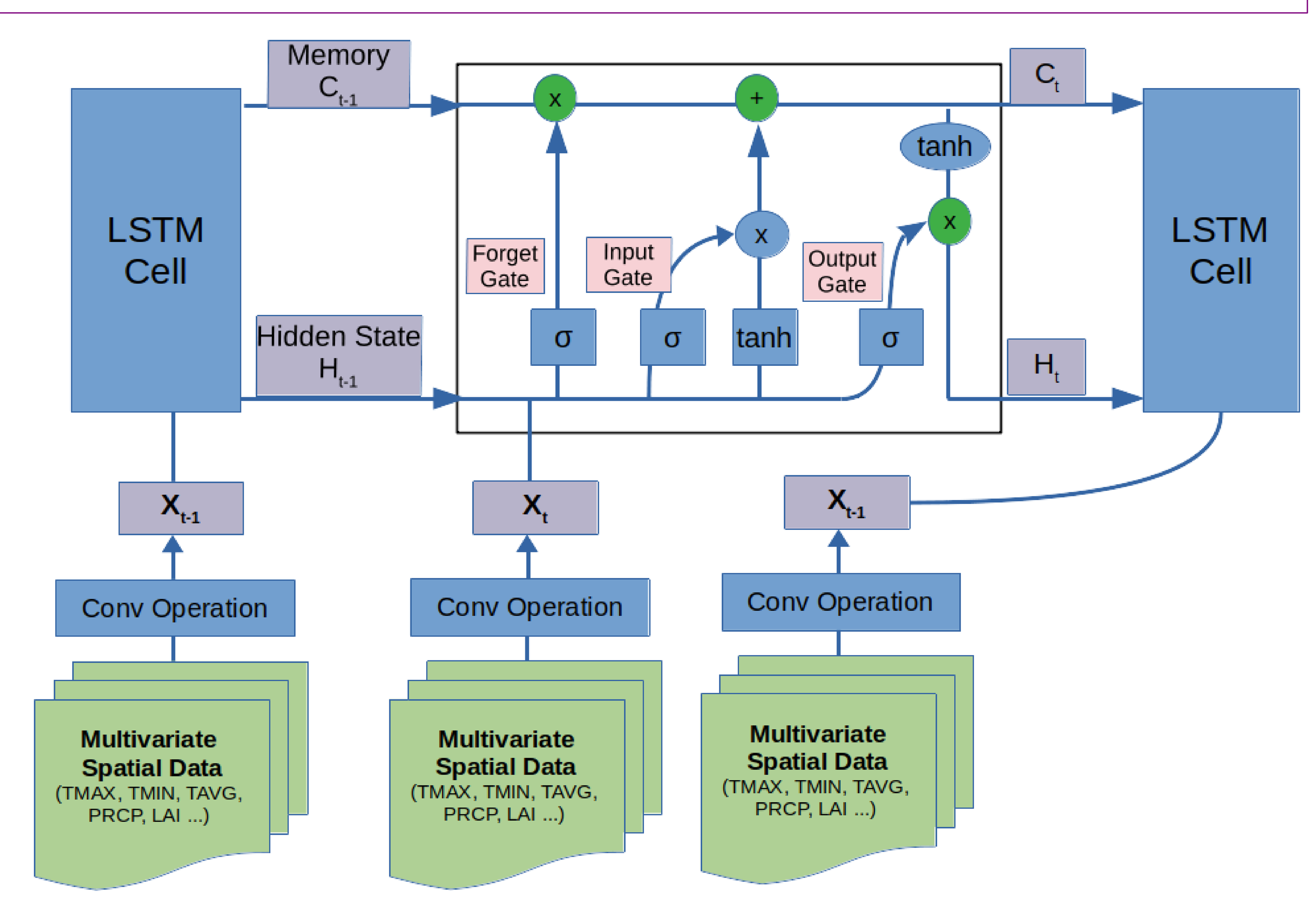


Fig. 2. ML-LAI model architecture diagram

Preliminary Results

- Fig. 4 is the comparison of the average LAI values across the domain area from ML-LAI prediction and from MODIS. The difference is less than 0.03, and effectively captured both seasonal and interannual variations.
- Fig. 5 illustrates the model's performance across different land cover types. Figure shows a subset of land types within the domain area. Overall, the ML-LAI model demonstrates robustness in predicting LAI for shrublands, croplands, evergreen needle leaf forest, grasslands, savannas and woody savannas.

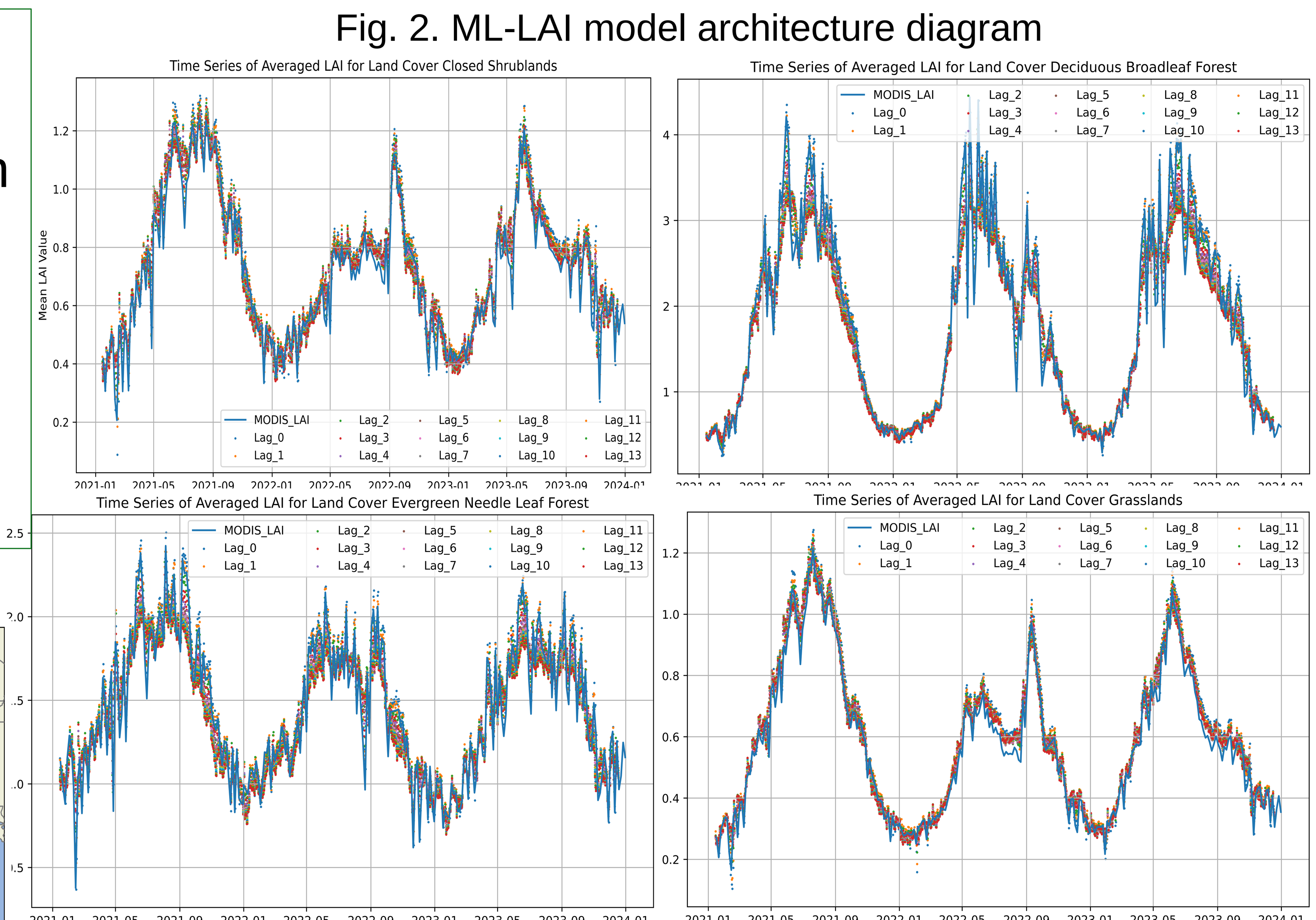
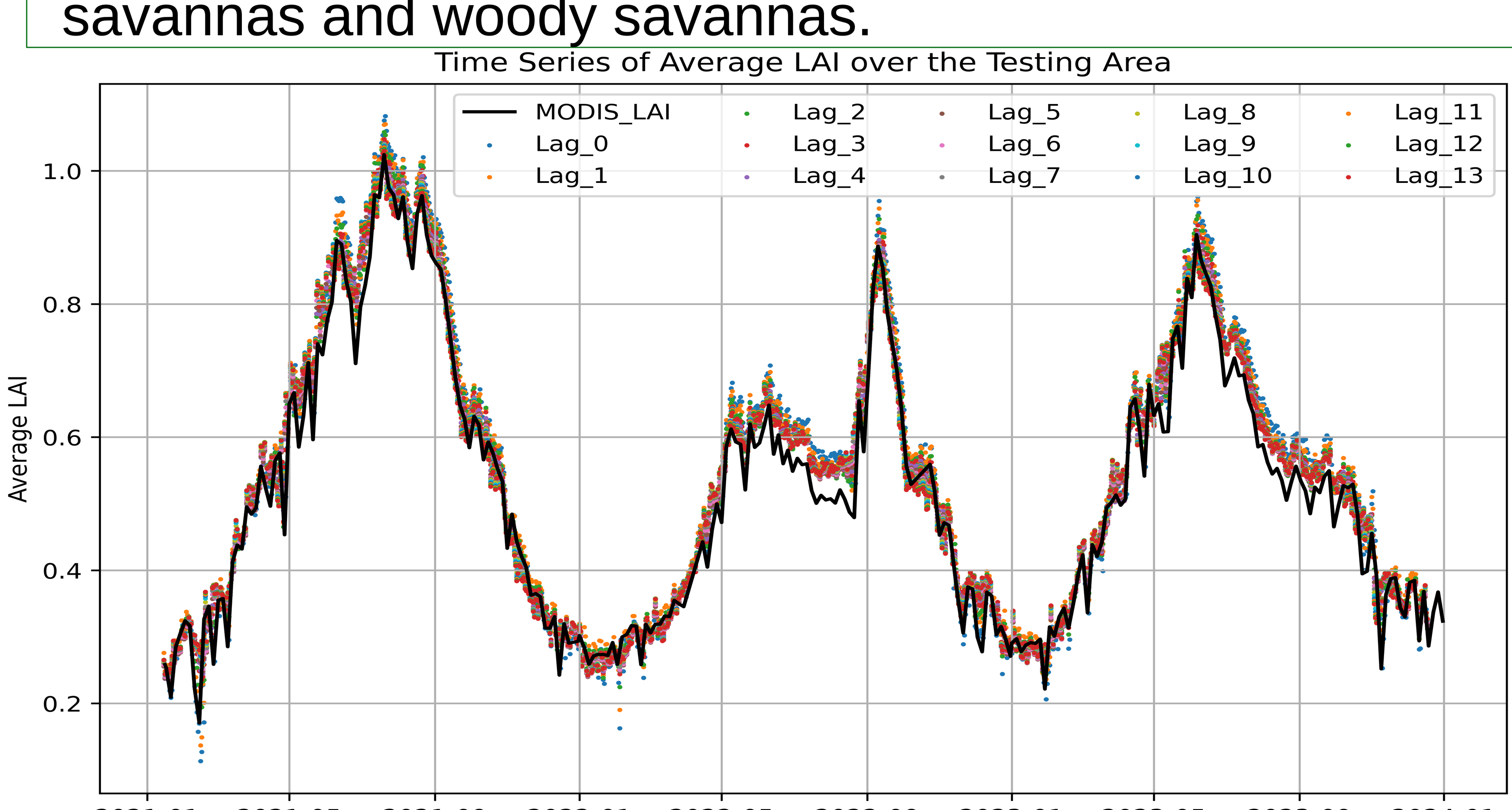


Fig. 5. Average LAI over different land covers: closed shrublands, broadleaf forest, evergreen needle leaf forest, grasslands.



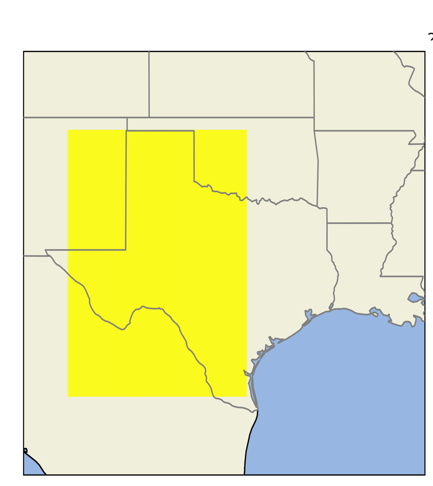


Fig. 4. Average LAI over the test domain area (yellow rectangle in the right plot)

Ongoing work

- Expand the model to cover the region of Continental United States.
- Compare with Noah-MP model in prognostic vegetation.
- Integrate ML-LAI with UFS atmospheric model.