Land Model Testbed: Accelerating Development, Benchmarking and Analysis of Land Surface Models

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October 19, 2020

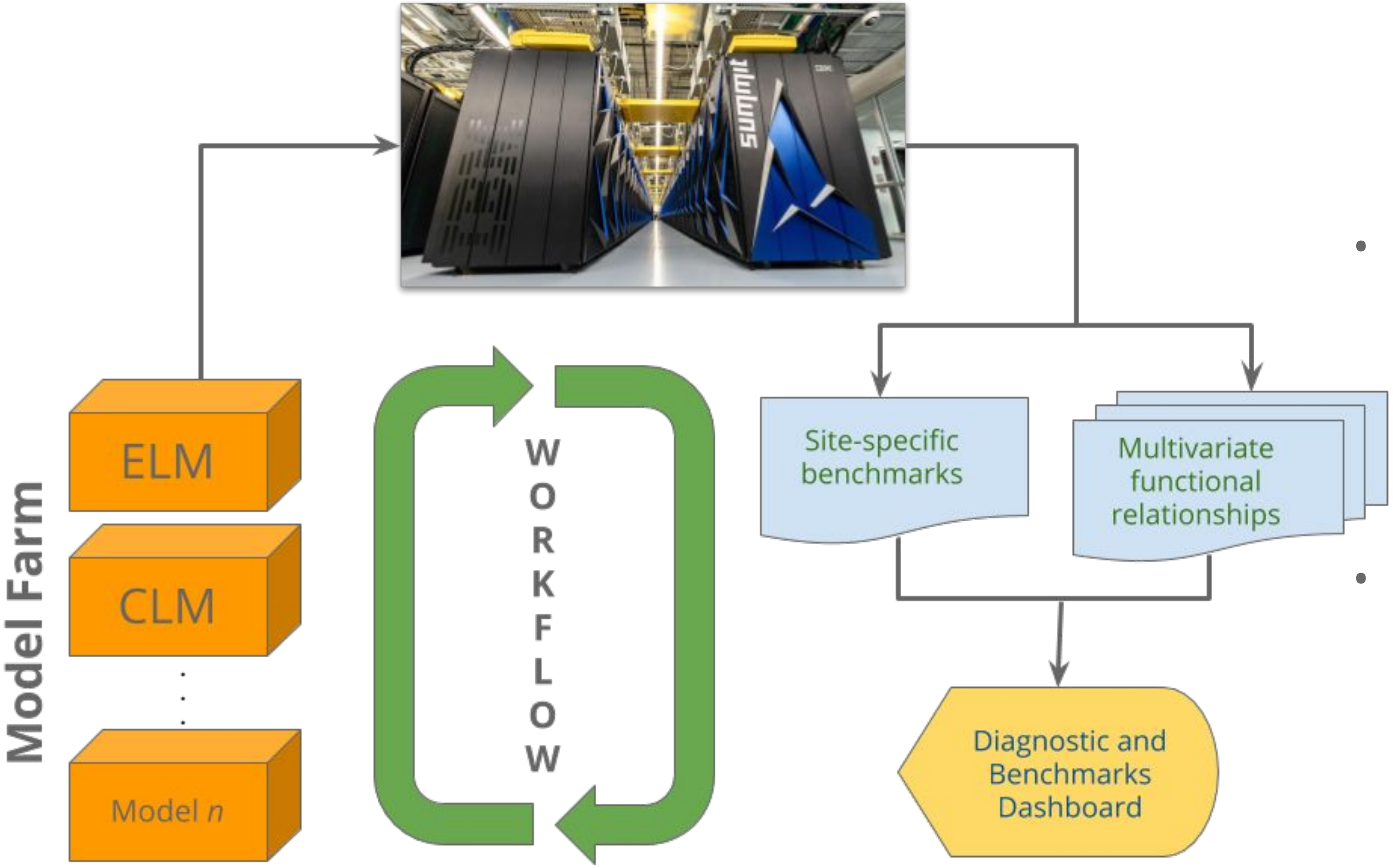
Gateways 2020 Conference

October 19–23, 2020

Land Model Testbed (LMT)

- Jupyter Notebooks for workflow prototype deployed on ORNL Cloud Computing Resources

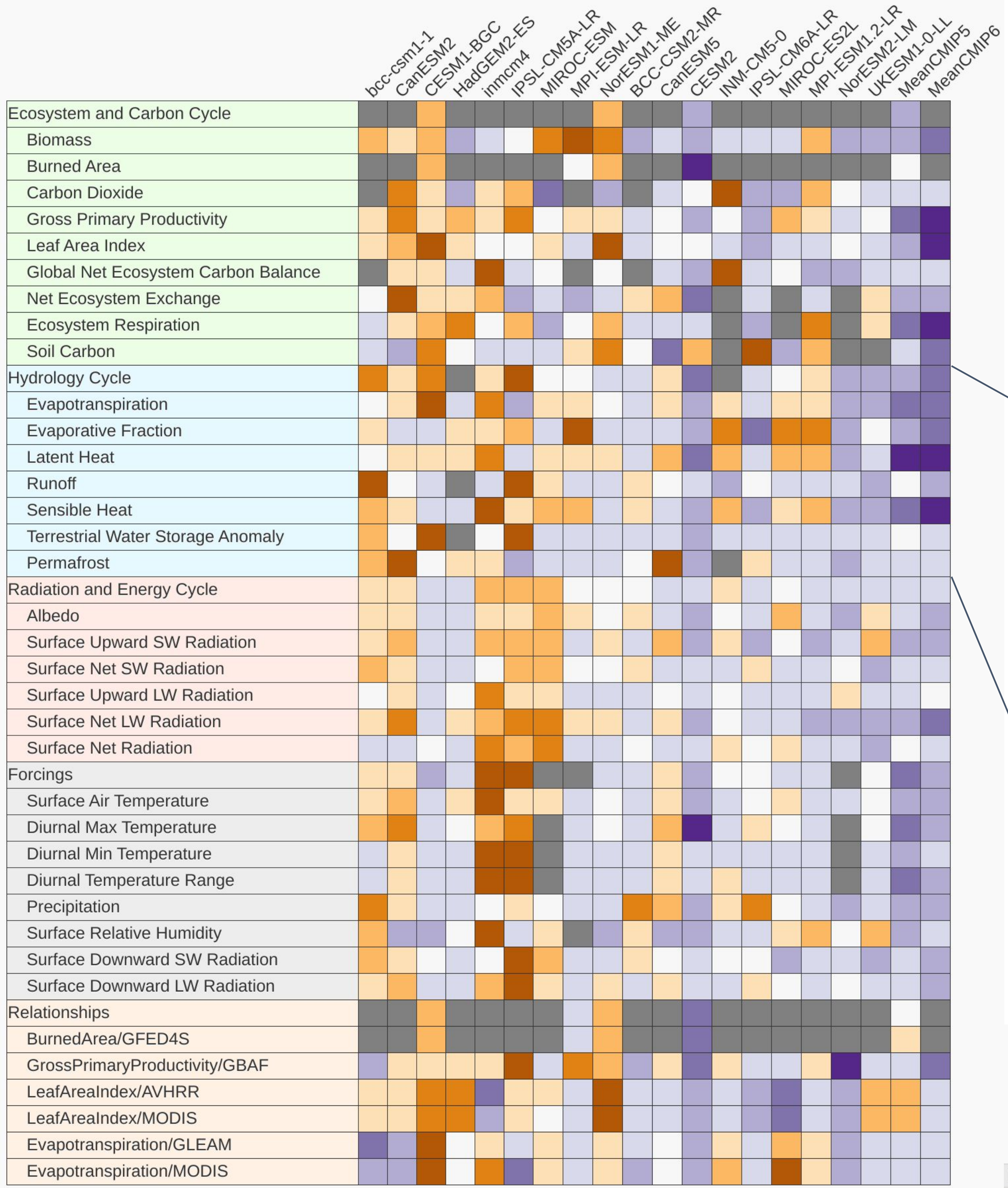
- Main workflow now tested and running on ORNL Cloud and Summit supercomputer (simulations)
- Model output post-processing tools developed

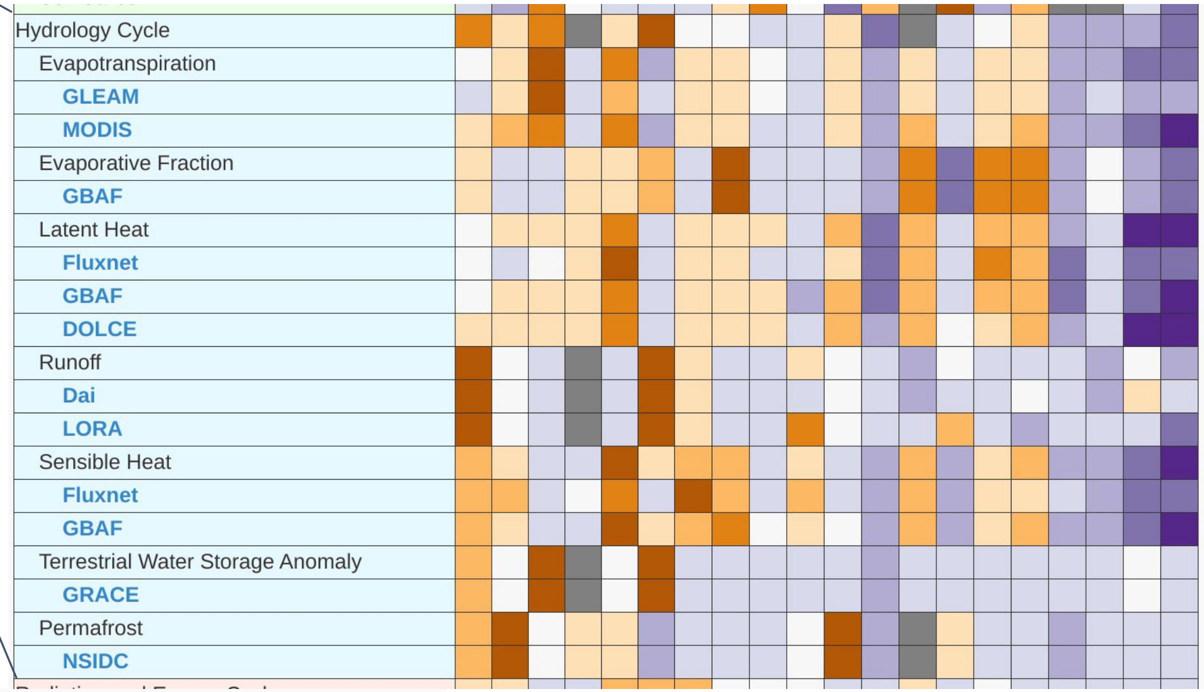


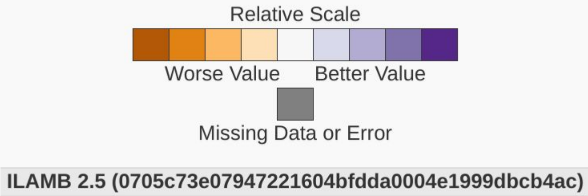
- Developing dashboard specific to climate phenomena-focused analysis
- Facilitating climate Coupled Model Intercomparison Project (CMIP) style analysis
- Evolutionary study (CMIP6 vs. CMIP5 models) to assess if complexity improved predictability

International Land Model Benchmarking (ILAMB) Package

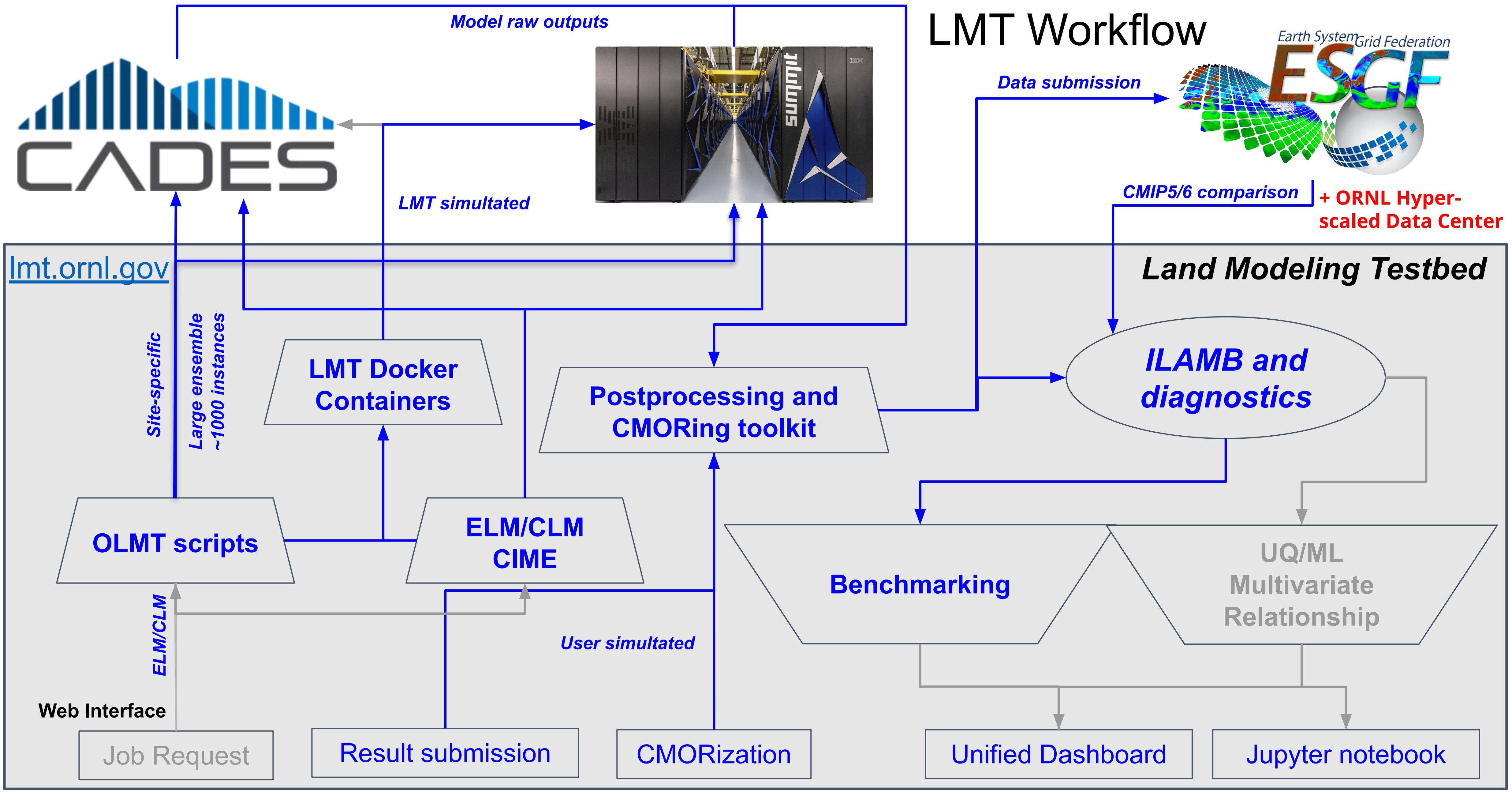
- ILAMB evaluates land model results by comparing with global-, regional-, and site-scale data
- For every variable, multiple observational datasets may be used to evaluate model results







Top-level portrait plot shows relative scores by variable for CMIP5 and CMIP6 models (Hoffman et al., in prep)



Our ensemble generation optimizations resulted in a 72× speed improvement.

Use Case: Perturbed Parameter Ensemble (PPE)

- Critical capability for model uncertainty quantification and parameter optimization
- Developed a framework with ability to launch thousands of model instances (ELM) with parameter variations
- Concurrent model execution on supercomputers like Summit
- Performance optimization to substantially improve ensemble generation workflow
- Required workflow time reduced from 12 hours to 10 minutes on a single node of Summit

JupyterLab: Interactive analysis environment

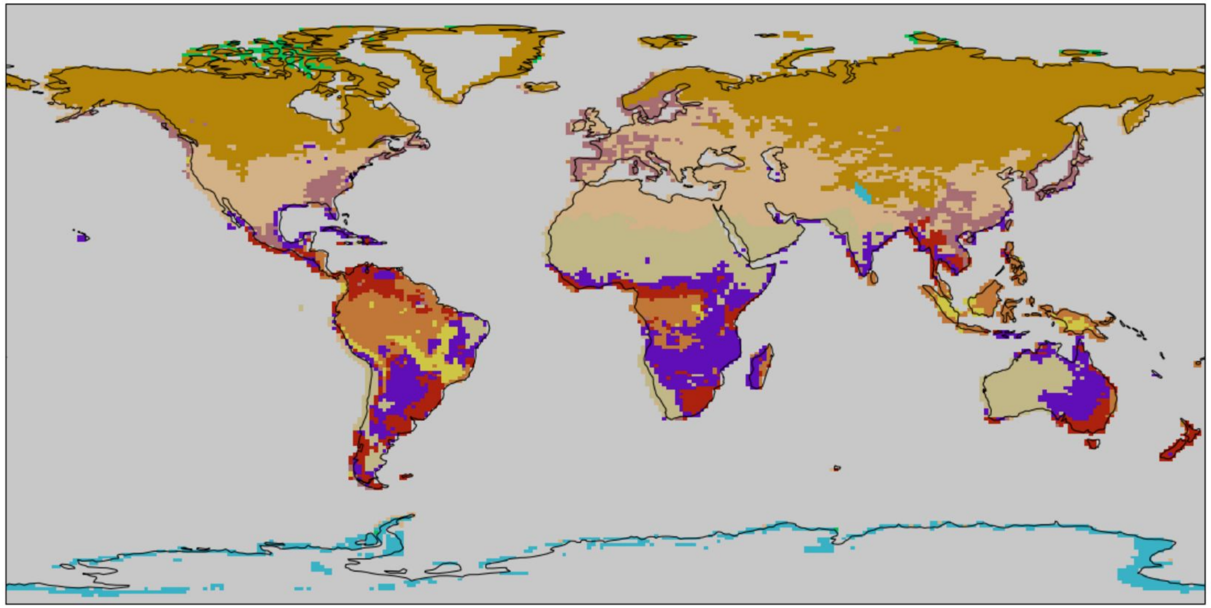
- Deployment on high memory computational nodes facilitates analysis of large datasets
- Allows reproducible and shareable analysis
- Investigating machine learning methods for analysis of model outputs and observations
- ILAMB enables computing standardized metrics and geospatial visualizations.

```
def regime_plotter(t):
    starttime = pd.to_datetime('1850-01-01')
    months_since = int((t - starttime)/np.timedelta64(1,'M'))
    print("%d months since"%(months_since))
    print(t)
    plot_cluster_at_t(months_since+1)


slider = widgets.SelectionSlider(
    options=dates,
    value=pd.to_datetime('2000-01-01'),
    description='Time [YYYYMM]',
    disabled=False,
    continuous_update=False,
    orientation='horizontal',
    readout=True
)
interact(regime_plotter, t=slider)
```

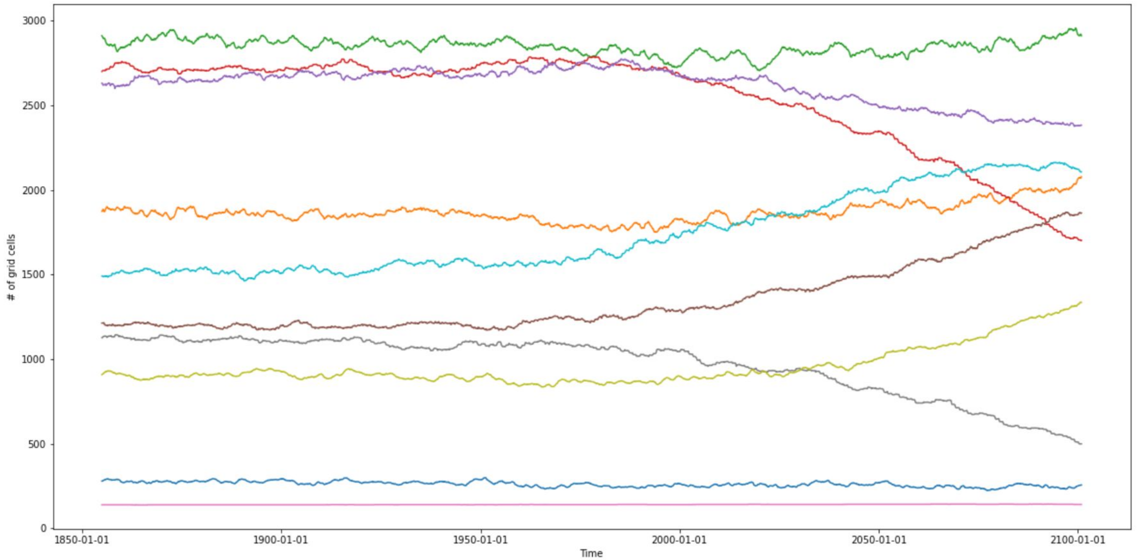
Time [YYY... 2000-01-01 00:

```
1799 months since
2000-01-01 00:00:00
```



```
[14]: <function __main__.regime_plotter(t)>
```

```
[20]: regime_extent_60, dates_60 = moving_average(regime_extent, 60)
      plot_regime_extent(regime_extent_60, dates_60)
```



Unsupervised clustering-based identification of spatial (right) and temporal (left) patterns of dynamic climate regimes under the SSP5-8.5 scenario for the future.

JupyterLab: Dynamic / Descriptive Prototyping

Prototype new functionality

Code refactoring/redesign

Ensemble analysis capability added to ILAMB

[1]:
```
from ModelResult import ModelResult
```

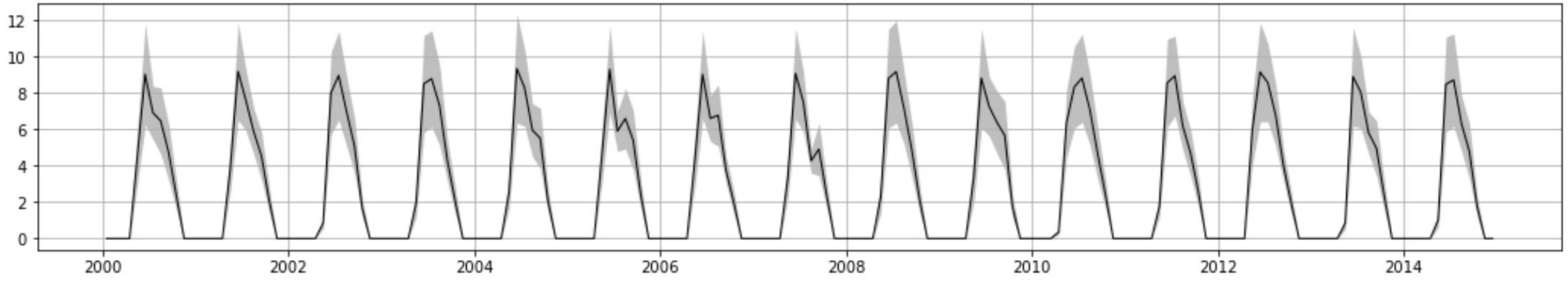
Model results can work as they did before with one small change that I do not automatically find all the files. This is because sometimes we will want a model to be a 'shell' and only really serve as a parent for child models.

[2]:
```
clm4 = ModelResult("/home/ncf/CLM/CLM4.0",name="CLM4").findFiles()
clm5 = ModelResult("/home/ncf/CLM/CLM5.0",name="CLM5").findFiles()
```

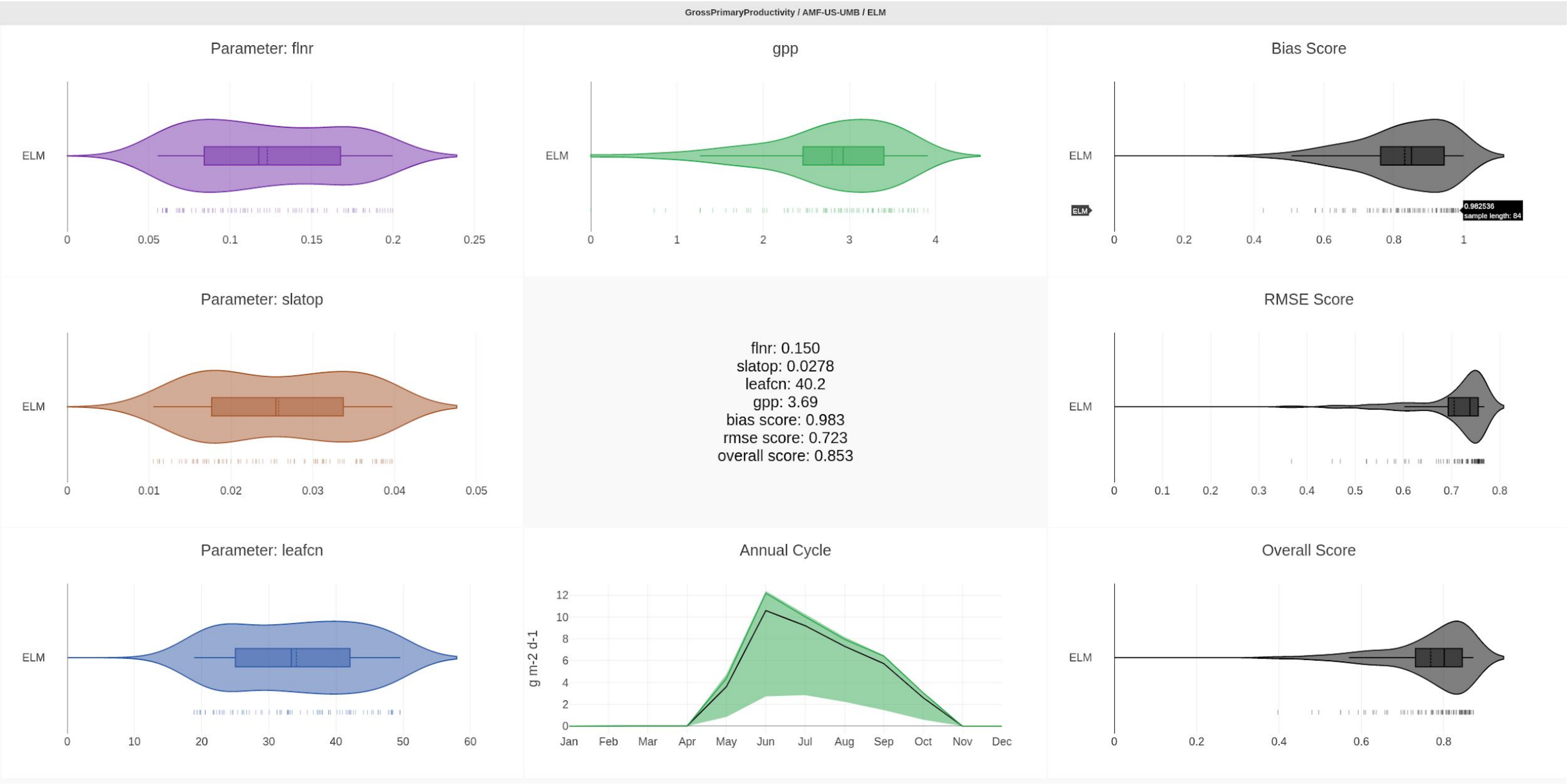
A model could also be a group / collection of models. You could use this to define a collection, like a MIP or to define an ensemble. There is a manual addition of models to the group, seen here:

[3]:
```
grp = ModelResult("/home/ncf/CLM/",name="CLM - manual")
grp.addModel(clm4)
grp.addModel([clm4,clm5]) # can add lists too, won't duplicate
print(grp)
```

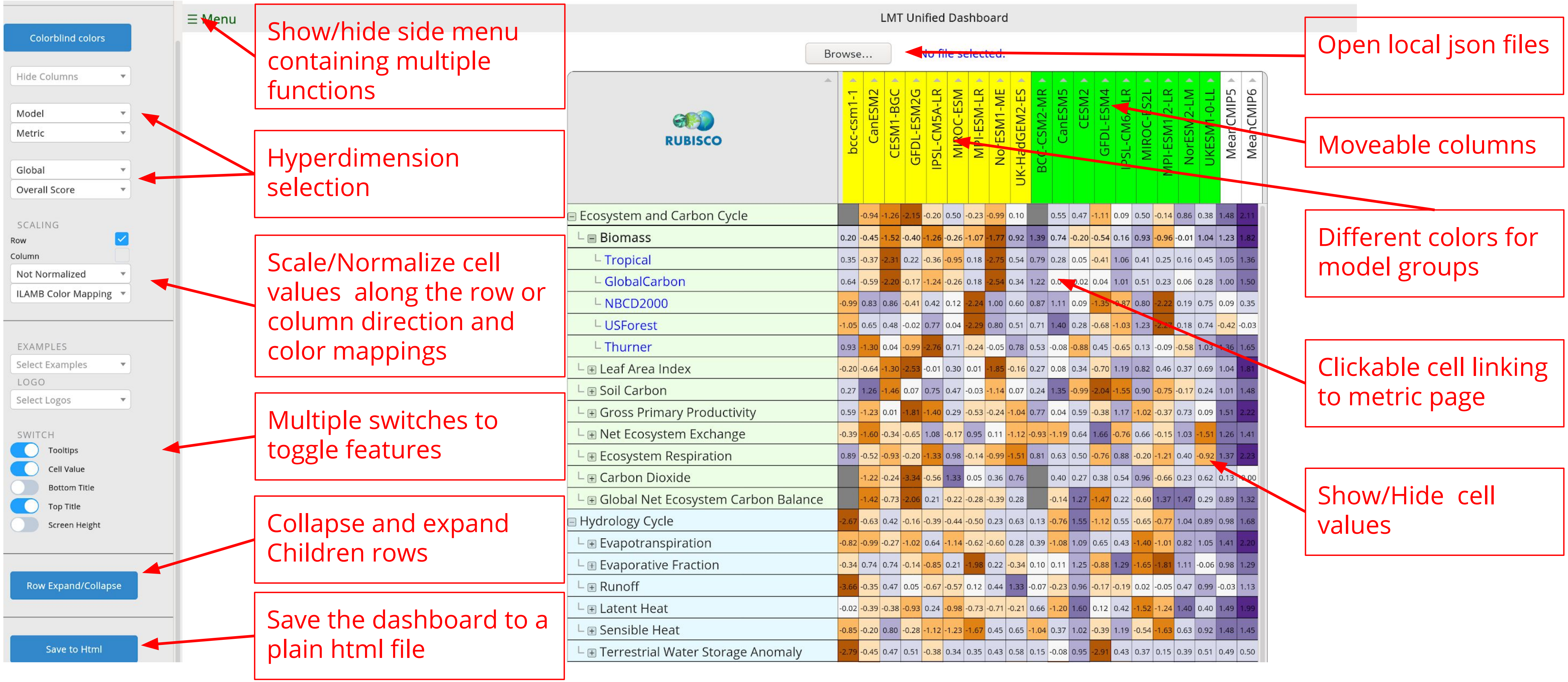
[26]:
```
import matplotlib.pyplot as plt
fig,ax = plt.subplots(figsize=(18,3))
mean_gpp.convert("g m-2 d-1")
mean_gpp.plot(ax)
plt.show()
```



Ensemble Diagnostics Prototype

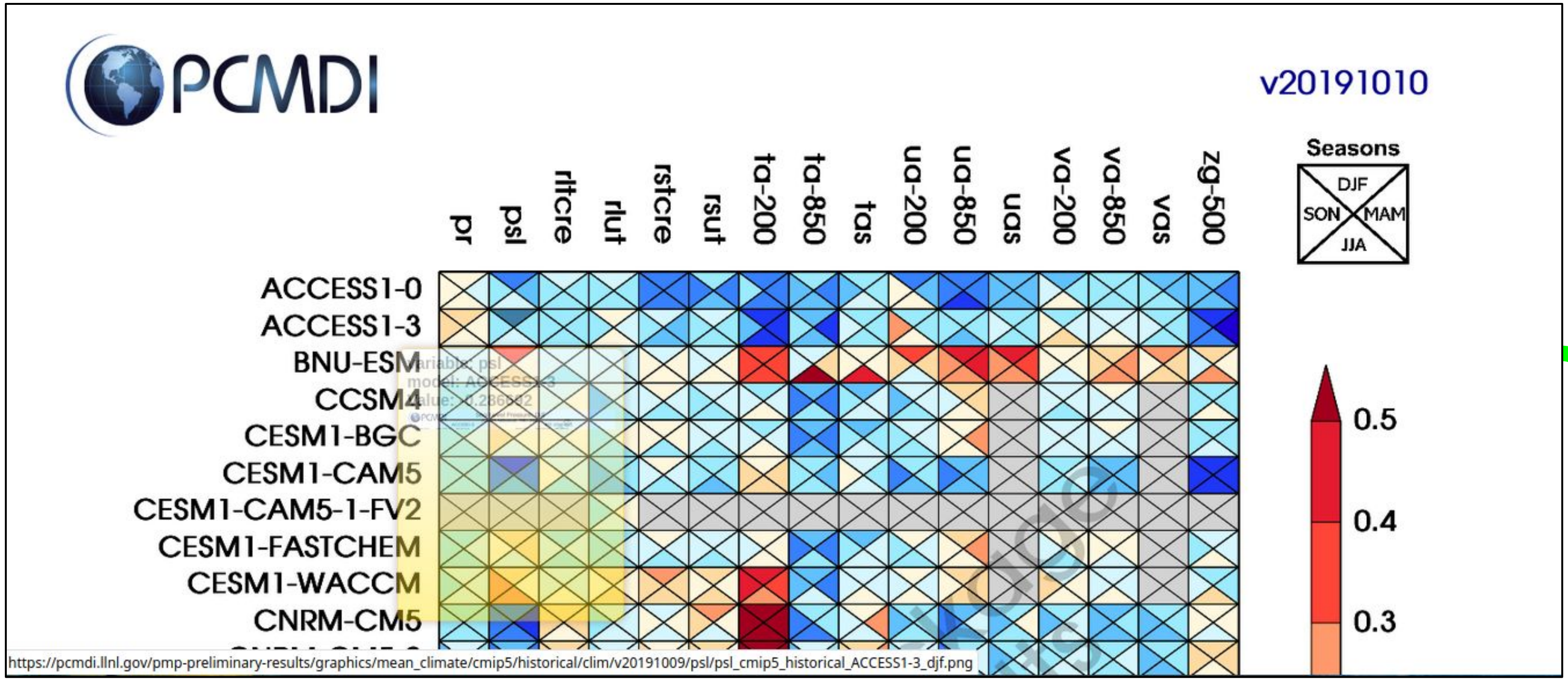


LMT Dashboard: https://lmt.ornl.gov/unified-dashboard/

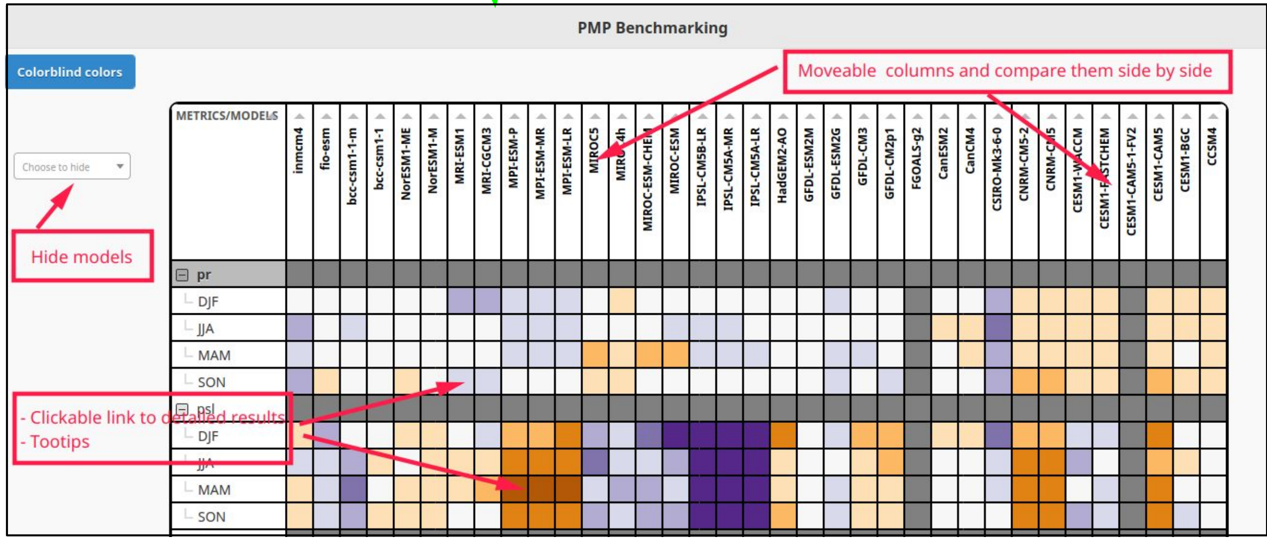


- **Tooltips:** show scores when mouse hovers the cells.
- **Column Hiding:** hide some models (columns) to focus into models of interest.
- **Column sorting:** sort the scores along the columns/models to see the best metric for the model.

Convert other diagnostic results for use in LMT dashboard



https://lmt.ornl.gov/tab_pmp



PMP: The Program for Climate Model Diagnostics and Intercomparison (PCMDI) Metrics Package (PMP)

- Clicking cell will go to maps of geographic distributions generated by PMP
- Our LMT dashboard can be used to study science questions like ENSO-BGC feedbacks

Interactive web-enabled tool (https://lmt.ornl.gov/ers4cmor/) for users to analyze and benchmark any land model results using LMT

Interactive Variable Mapping System For C4MIP

Refresh Table | E3SM variable list | C4MIP | E3SM | Lmon

Hide columns × | Search:

id	priority	long name	varname	units	relationship
Lmon (33 item)					
0	1,2	Precipitation onto Canopy	prveg	kg m-2 s-1	QINTR
1	1,2	Total Carbon Mass Flux from Litter to Soil	fLitterSoil	kg m-2 s-1	LITR1C_TO_SOI
2	1,2	Total Carbon Mass Flux from Vegetation to Litter	fVegLitter	kg m-2 s-1	LITFALL
3	1,2	Percentage of Land Which Is Anthropogenic Pasture	pastureFrac	%	
4	1,2	Total Runoff	mrro	kg m-2 s-1	QRUNOFF+QSN
5	1,2	Net Primary Production Allocated to Roots as Carbon Mass Flux [kgC m-2 s-1]	nppRoot	kg m-2 s-1	FROOTC_ALLO
6	1,2	Carbon Mass in Roots	cRoot	kg m-2	LIVECROOTC+I
7	1,2	Total Soil Moisture Content	mrso	kg m-2	SOILLIQ[0:14]
8	1,2	Carbon Mass in Leaves	cLeaf	kg m-2	LEAFC
9	1,2	Bare Soil Percentage Area Coverage	baresoilFrac	%	PCT_LANDUNIT

- Relationships and equations are saved and versioned in a repository
- Post-processing to standardize (CMORize) the model outputs.
- User defined relationships and mapping to CMIP6 variables

Machine Learning for Deriving Empirical Relationships

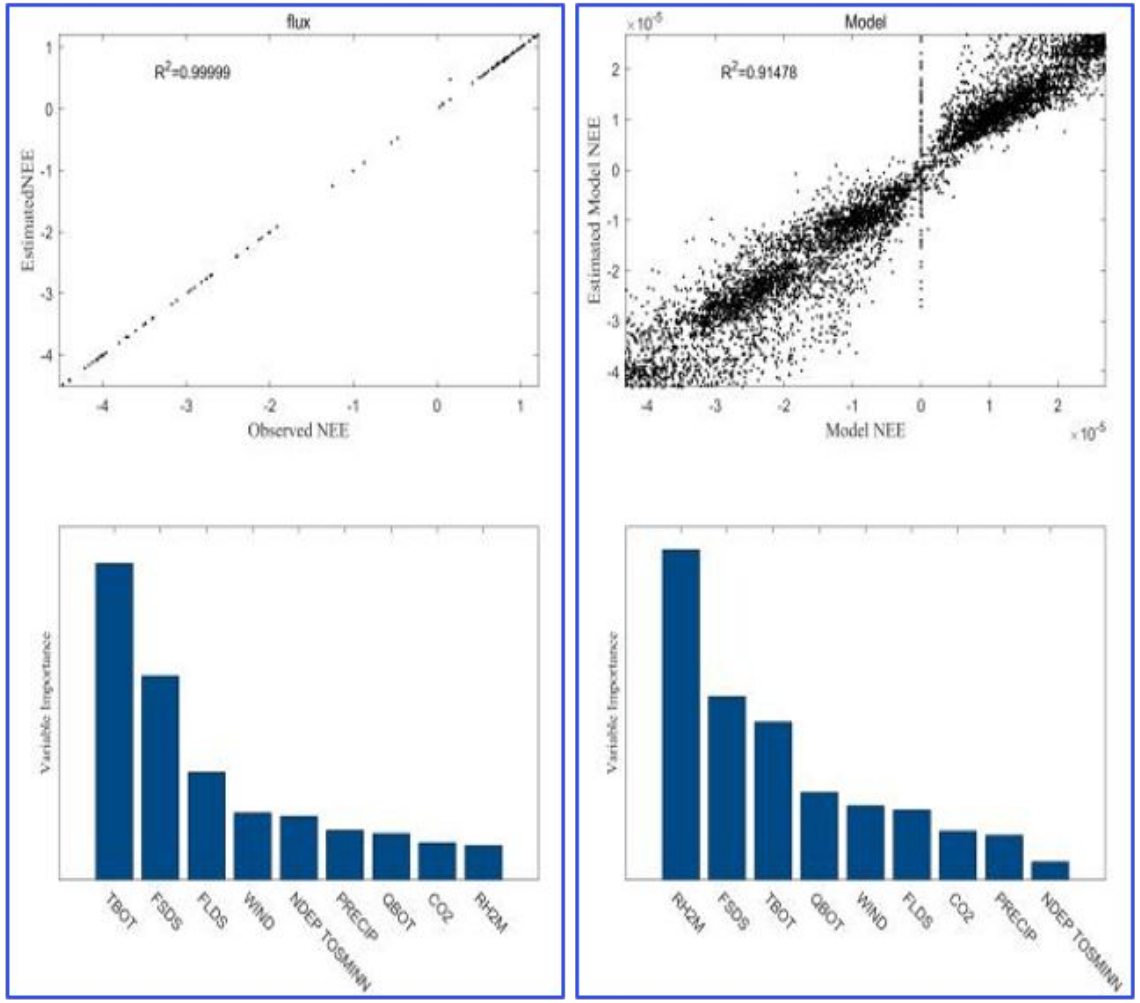


Figure: The relative importance of environmental factors in predicting (left) the observed and (right) the modeled net ecosystem exchange from a land surface model, using a random forest machine learning technique

- We employed a random forest machine learning method to quantitatively predict net carbon ecosystem exchange from observations and from land surface model output
- Various parameter perturbations were used for 84 simulations of the land surface model
- The monthly net ecosystem exchange was predicted accurately by environmental forcing variables in the observational and the model cases
- However, the importance of the environmental factors was very different between the observations and the model results
- This study indicates a need to further study driving relationships in the model

Summary and Future Work

- We developed a suite of tools and capabilities that could become part of an institute or center focused on modeling, model evaluation, and Earth system predictability
- We are extending Perturbed Parameter Ensemble (PPE) effort to test both the Community Land Model (CLM) and the Energy Exascale Earth System Model (E3SM) Land Model (ELM)
- Opportunities for future development include
  - Adding more models to the land model farm
  - Further development of ILAMB benchmarks and diagnostics for PPE
  - Collaborative extension of the Unified Dashboard across a suite of diagnostics packages through the Coordination Model Evaluation Capabilities (CMEC) activity supported by the U.S. Department of Energy
  - Library and tool development for collaborative analysis through JupyterHub
  - Additional analysis employing machine learning approaches to derive empirical relationships as another suite of methods for evaluating model performance