Patterns and signatures charactering the partitioning of precipitation into ET and R in land surface parameterizations

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Outline

- Philosophy
- Experimental Design
- Results and Discussions
- Conclusions

How Can We Use Sophisticated Evaluation Methods To Guide LSM Development?

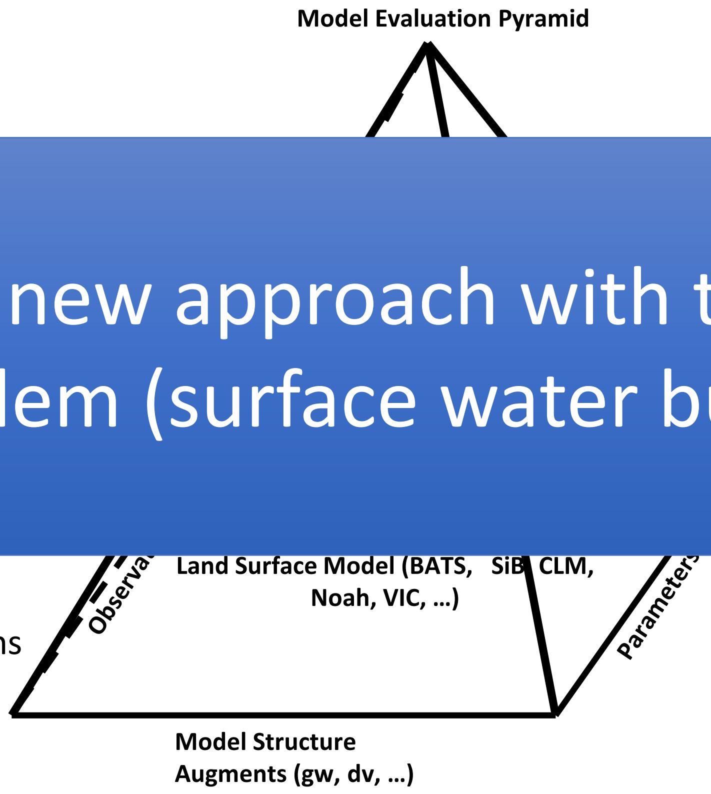
Two schools of thought in LSM development and evaluation

LSM developers consider

1. Increasing realism in representing key processes

predictions

5. Generalizing parameterzations across sites



LSM evaluators consider

1. Uncertainty in many subsurface parameters and

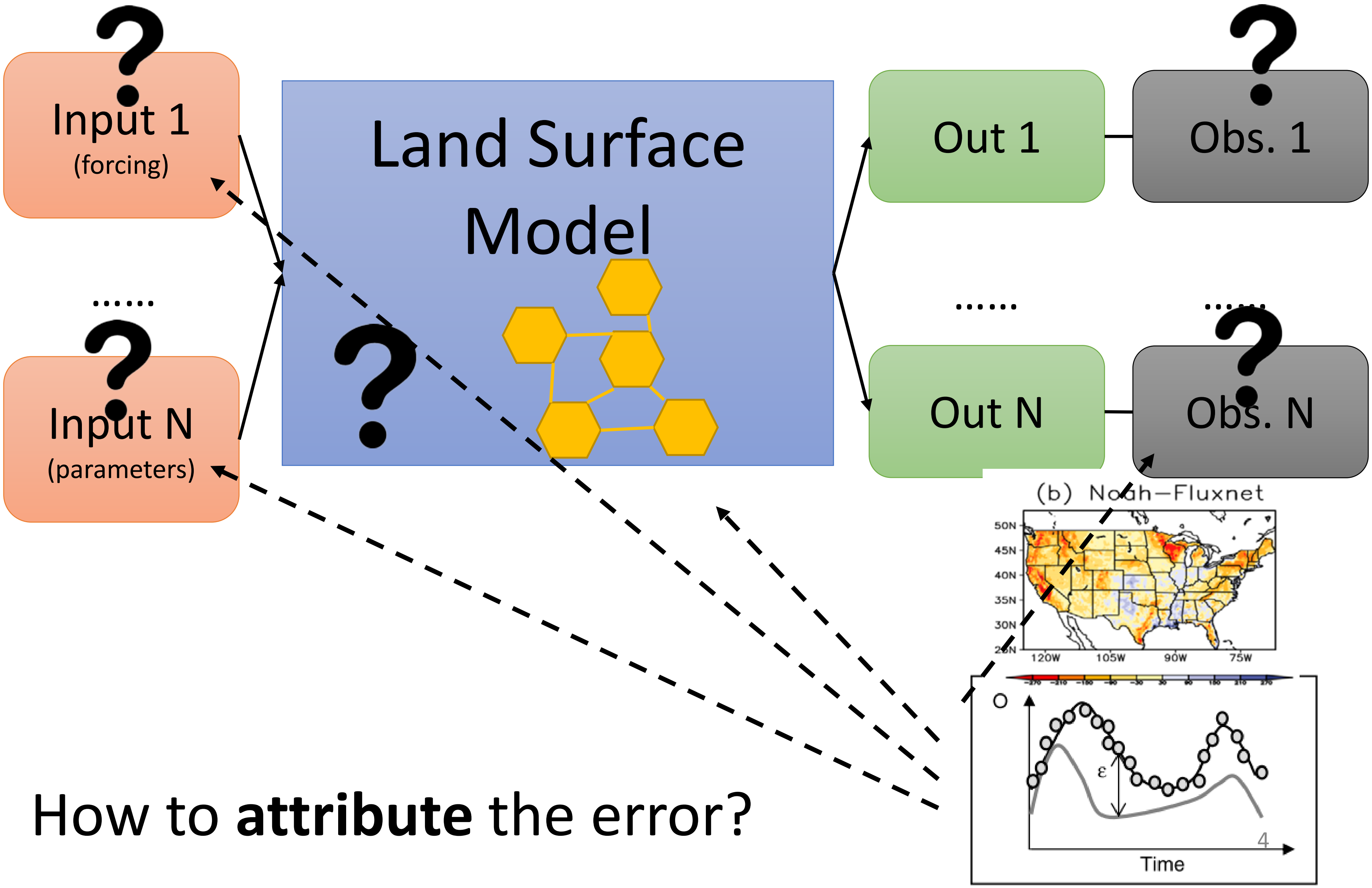
4. Evaluation in all dimensions
5. Equifinality?

Demonstrate a new approach with the water balance problem (surface water budgets)

LSM developers do not use automated, sophisticated evaluation tools.

LSM evaluators calibrate/evaluate LSMs that already exist.

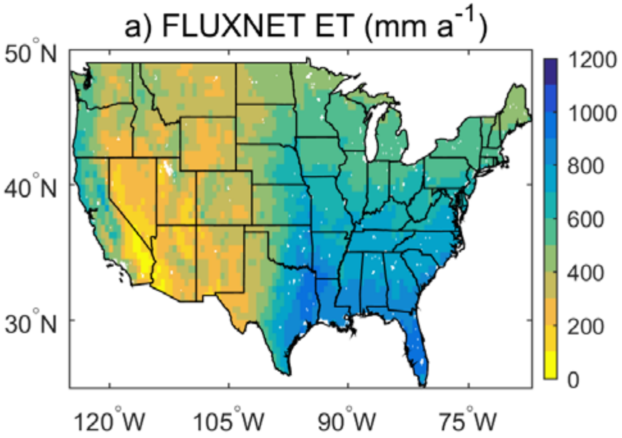
Introduction: error attribution
From evaluation to development

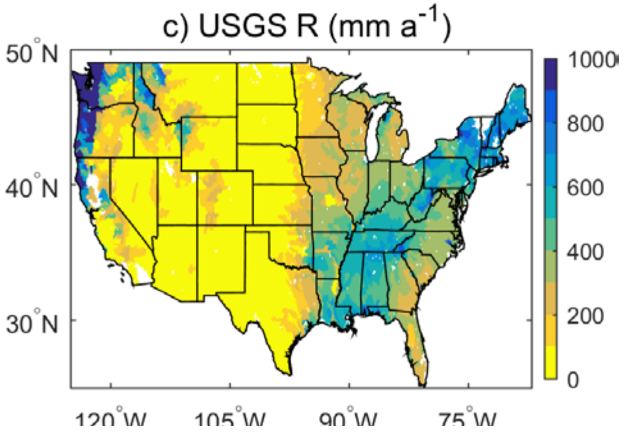


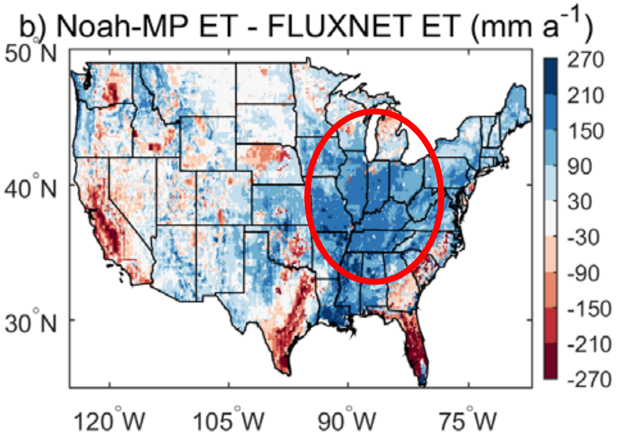
How to **attribute** the error?

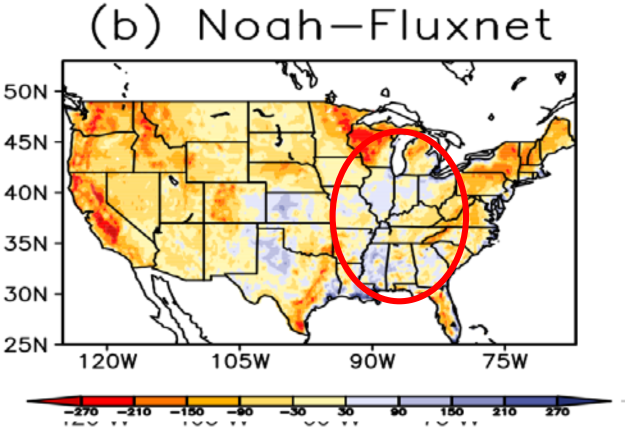
A Simple/Zero-order Problem
Long-term Surface Water Balance

$$P = ET + R$$ (30-year mean)


a) FLUXNET ET (mm a^{-1})

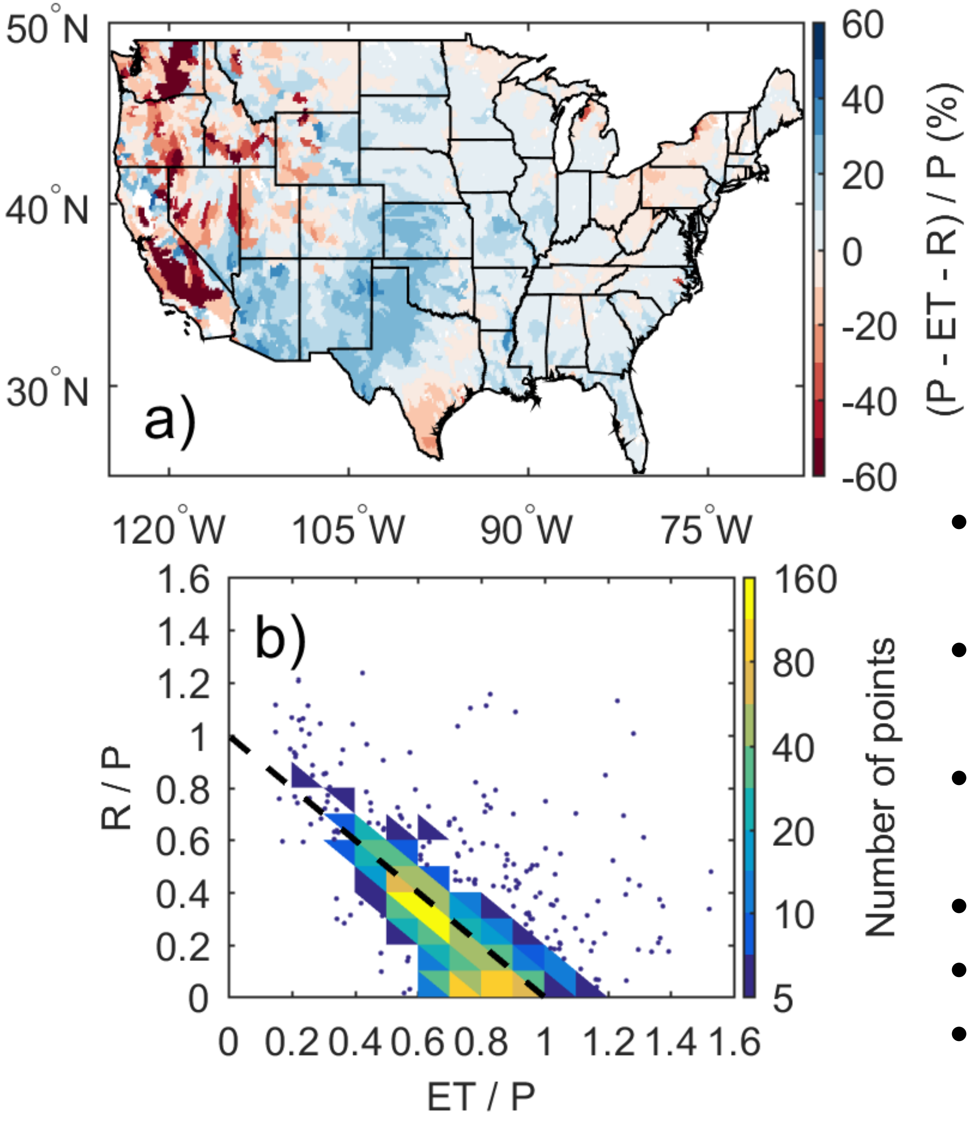

c) USGS R (mm a^{-1})


b) Noah-MP ET - FLUXNET ET (mm a^{-1})


(b) Noah–Fluxnet

What *may* cause the bias?

Can the “error” solely be attributed to the model in evaluation?



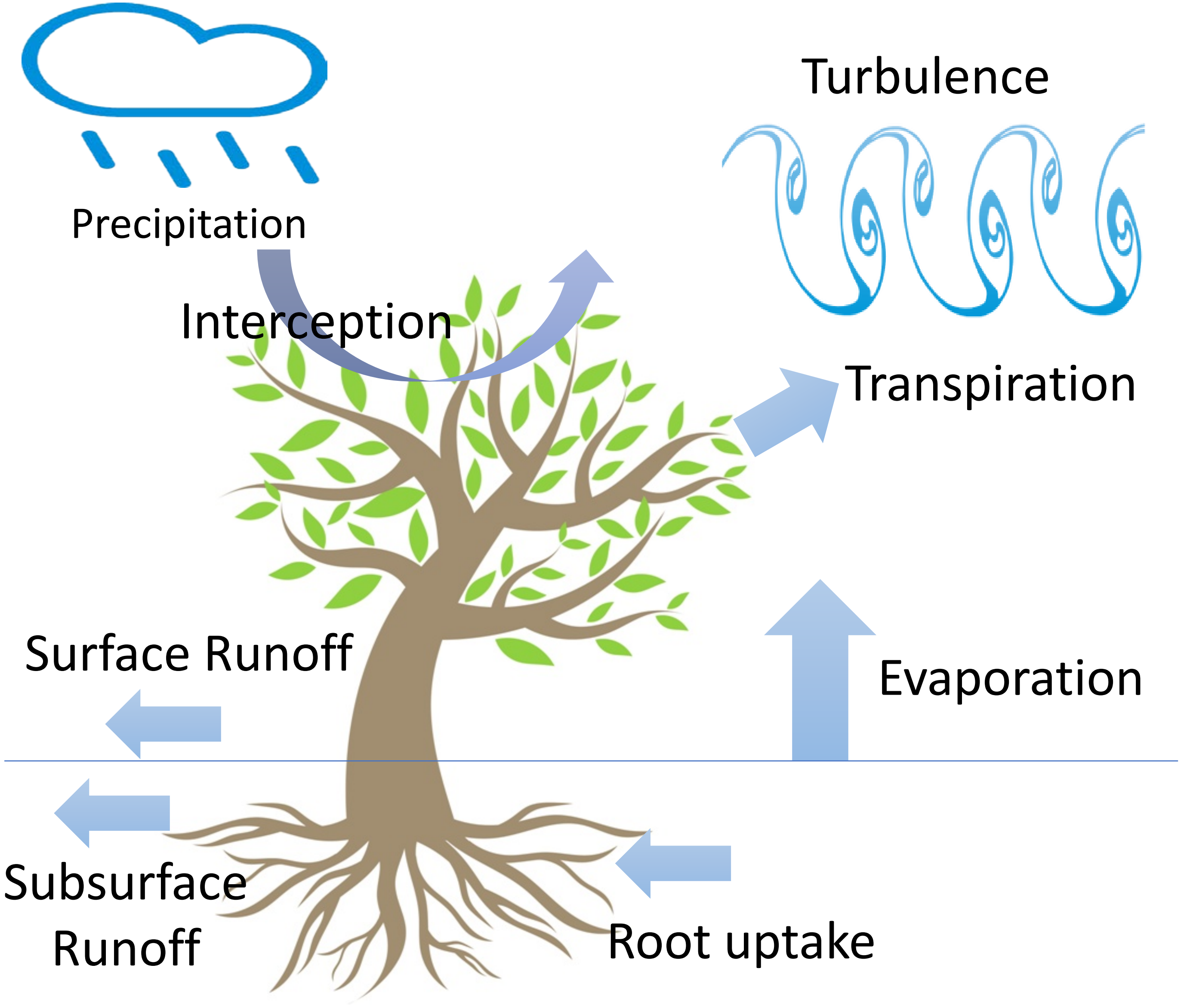
$$1 = \frac{ET}{P} + \frac{R}{P} + \epsilon$$

- Water budgets are not closed in the forcing and evaluation data.
- Water imbalance ~ 4% precipitation (CONUS)
- ~50% in the western US

- NLDAS P
- FLUXNET ET
- USGS R

Models do not have balance error.

Which parameterization is responsible for the overall model error?



Precipitation

Turbulence

Interception

Transpiration

Surface Runoff

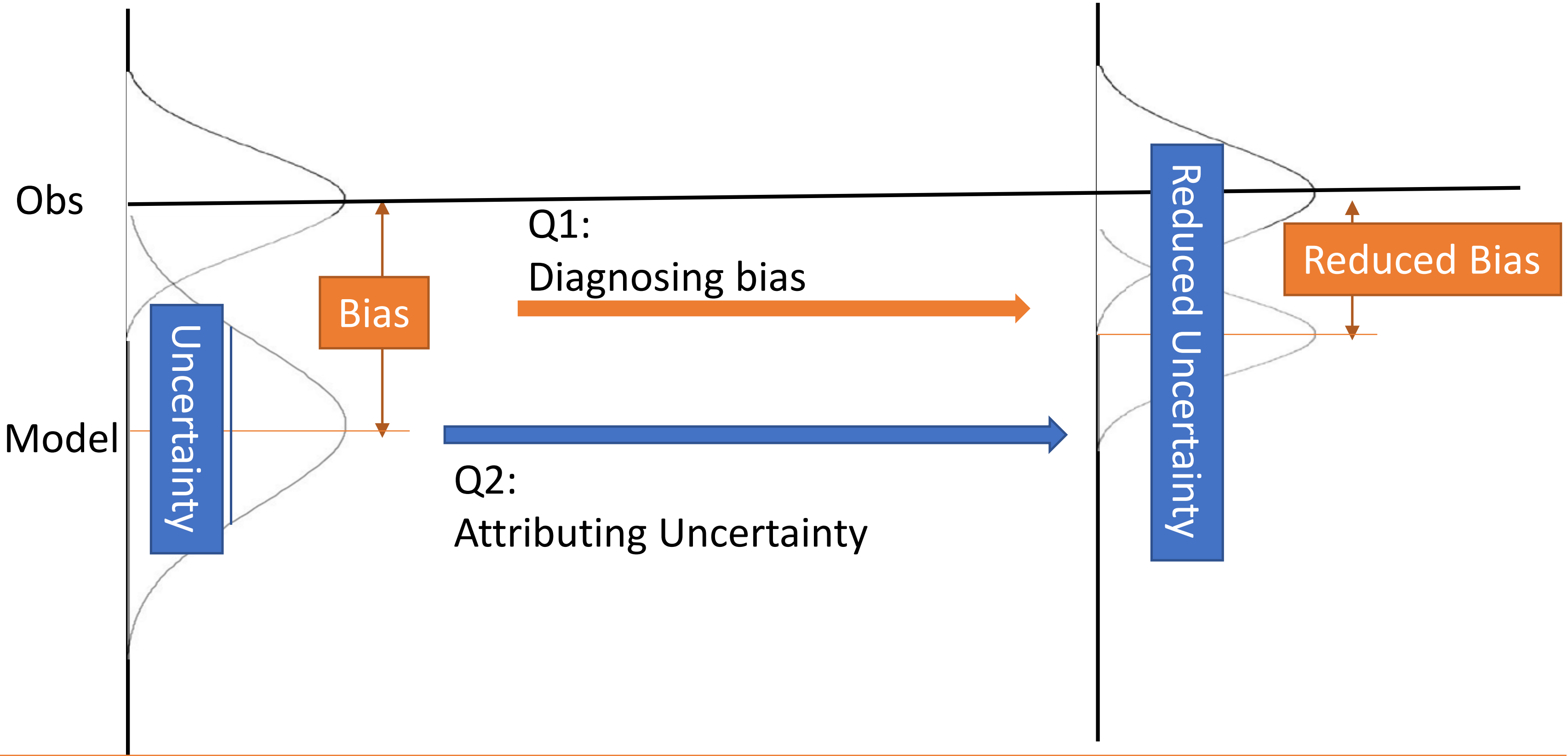
Evaporation

Subsurface Runoff

Root uptake

SiB、SSiB
BATS
CLM
Noah
…

A “Backward” and Iterative Approach for Model Developments



Q1:
Diagnosing bias

Q2:
Attributing Uncertainty

Conventional approach: Implement a new process -> sensitivity -> evaluation
Our approach: evaluation -> attribution -> developments and improvements

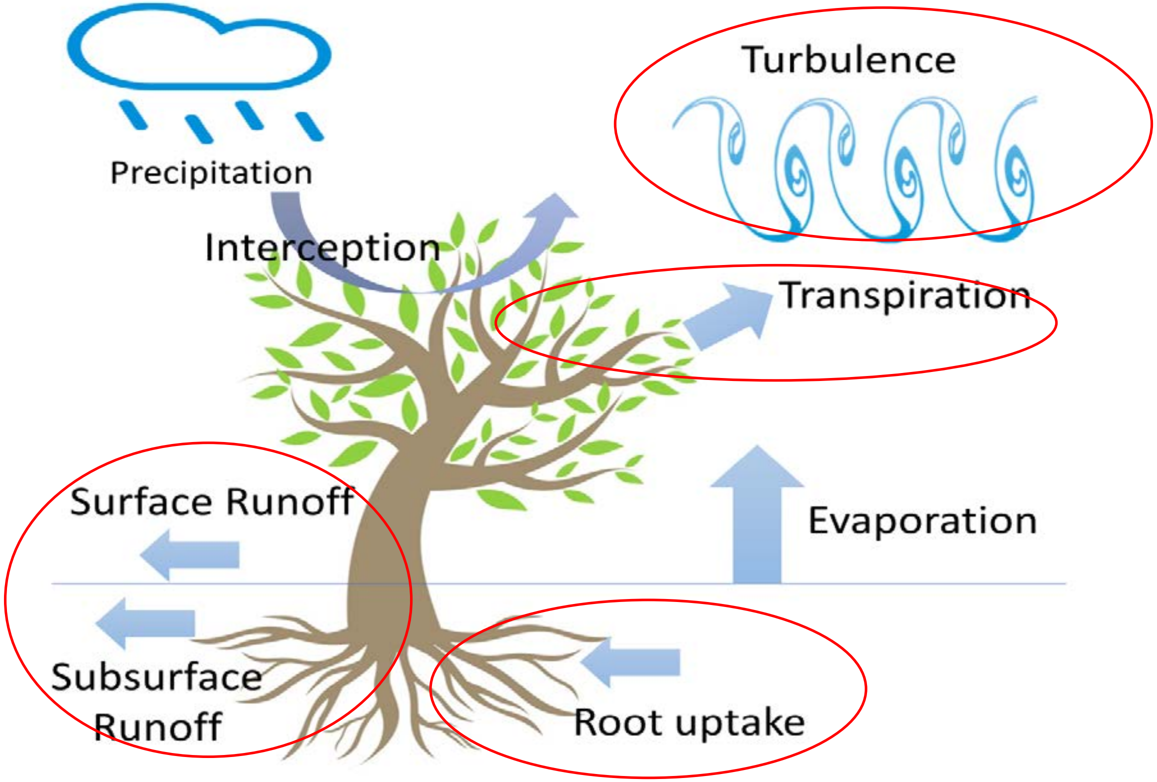
Questions

1. How to diagnose model bias using imbalanced water data?
    - Rejection-based evaluation [Beven, 2012]
    - Signature-based evaluation [Gupta et al., 2008]
    - Rejection-based evaluation of signature (This study)

2. How to attribute model uncertainty to multiple interactive processes?
    - process-based multi-hypothesis modeling [Clark et al., 2011; Clark et al., 2015]
    - Parameterization sensitivity (This study)

Noah-MP Multi-Parameterization Ensemble

Physics
Stomatal Conductance
β-factor (Soil moisture stress factor)
Runoff (Surface and subsurface)
Turbulence



$$2 \times 3 \times 4 \times 2 = 48$$

Noah-MP v3.6
NLDAS phase-2, 1/8 degree
Spin-up: 1979×100 + 1979 to 1982; Output: 1982 to 2011 (30 years)

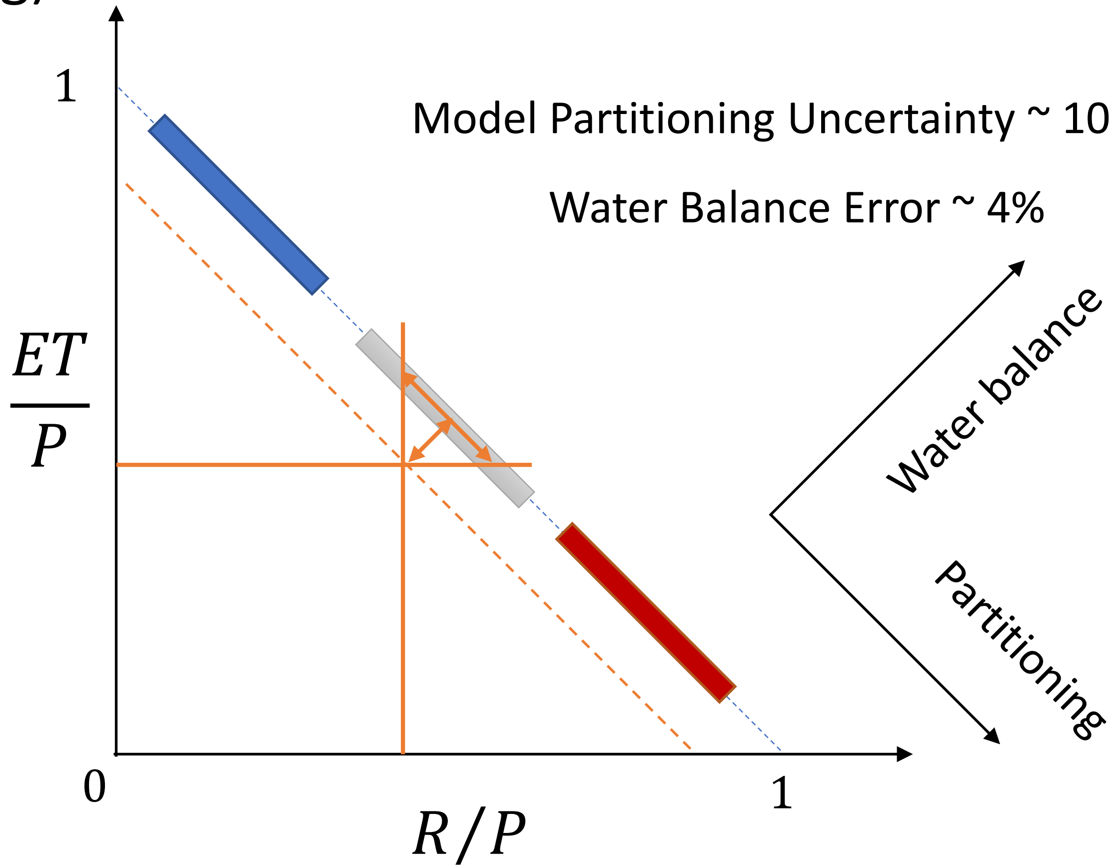
Represent the parameterizations adopted by CLM, BATS, SSiB, and Noah which are widely used in various applications and have influenced an array of LSMs.

Rejection-based evaluation of signature

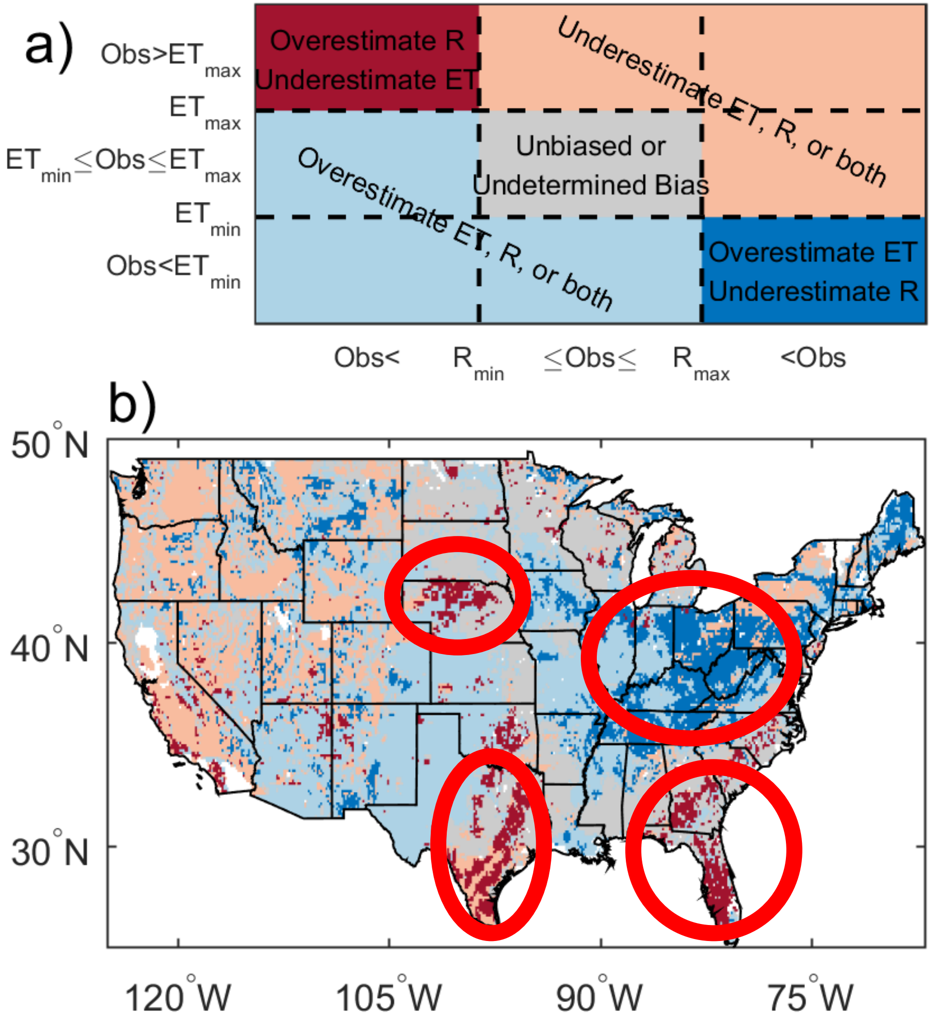
Model Signature
(Precip. Partitioning)

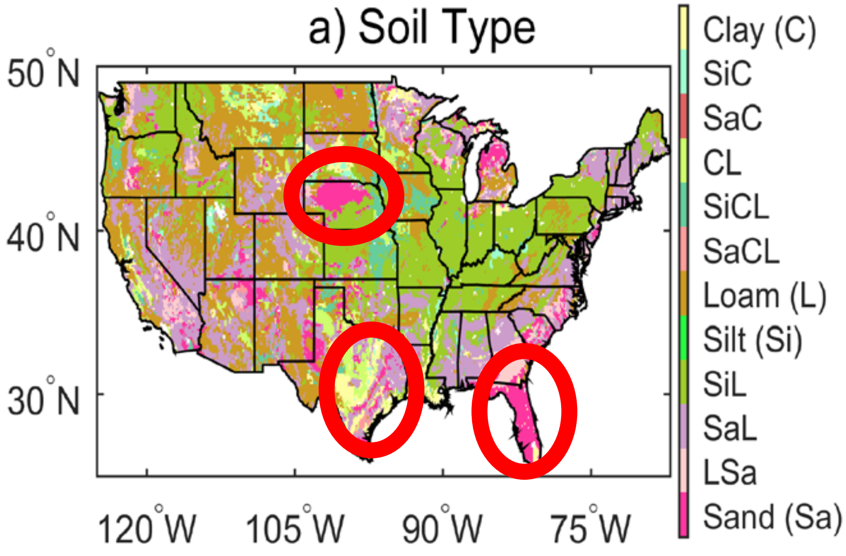
$$P = ET + R \longrightarrow 1 = \frac{ET}{P} + \frac{R}{P}$$

Rejection Rules
(the difference between the model and observation is larger than the data uncertainty)



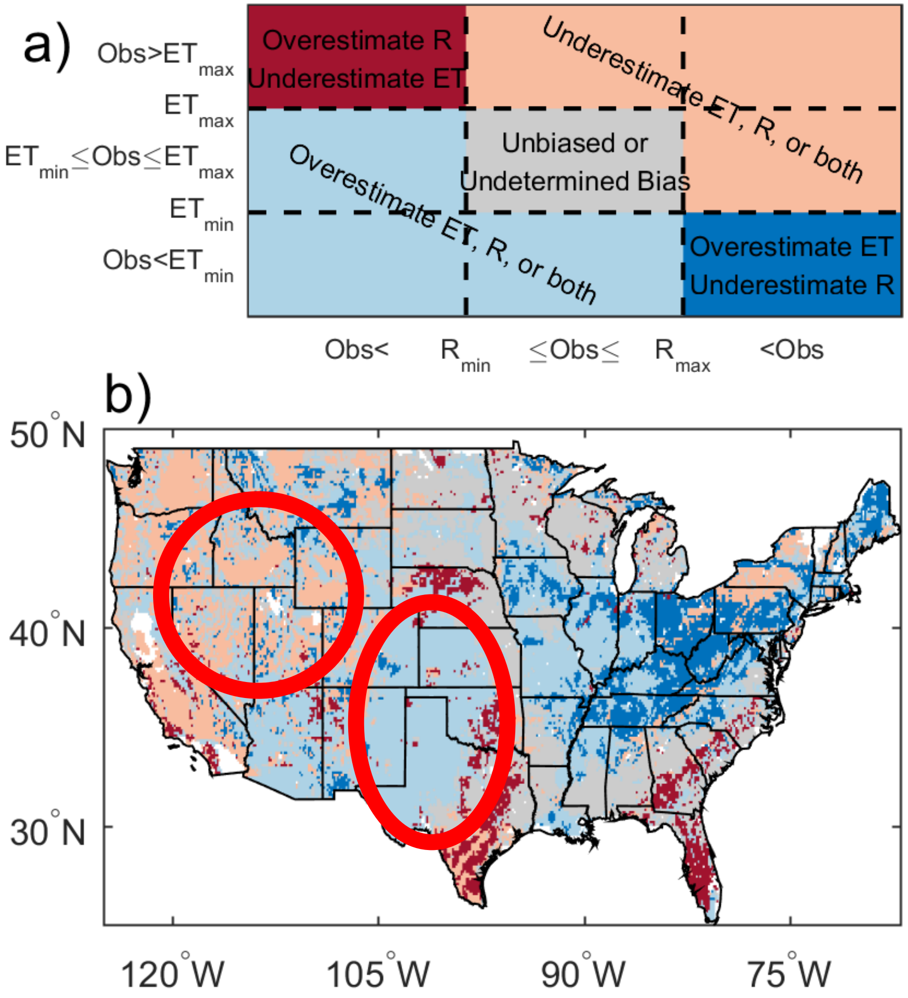
Rejection-based evaluation of signature

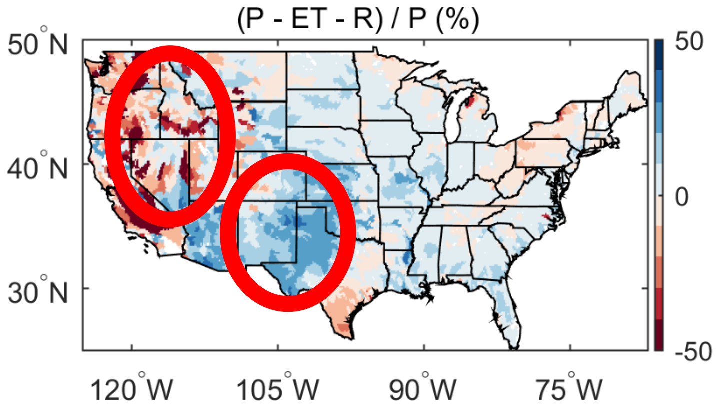




The parameters of the SAND soil type; ET overestimation in Ohio River Basin

Water Balance Error





In most areas:

- Imbalance of the data -> Bias of the simulations
- The bias does not reflect the inherent model error.

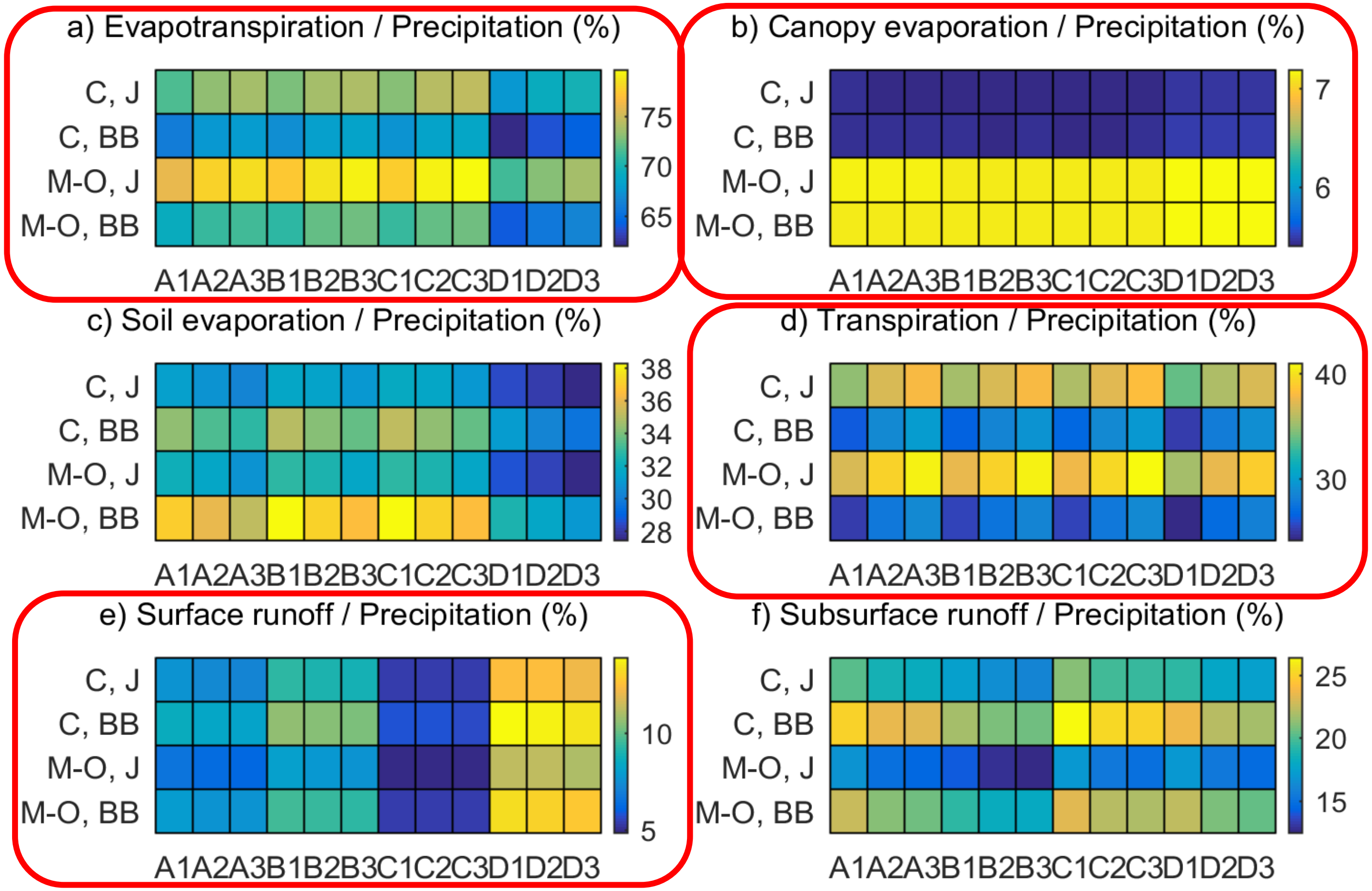
Q2, Uncertainty Attribution: Decomposition of the ensemble variance

$$Y = f(x_1, x_2, x_3, x_4)$$

Four parameterization in Noah-MP
x_1: stomatal conductance
x_2: β-factor
x_3: runoff
x_4: turbulence

Parameterization Sensitivity $S_i = \frac{E_{x_{\sim i}}\left(Var_{x_i}(Y|x_{\sim i})\right)}{Var(Y)}$

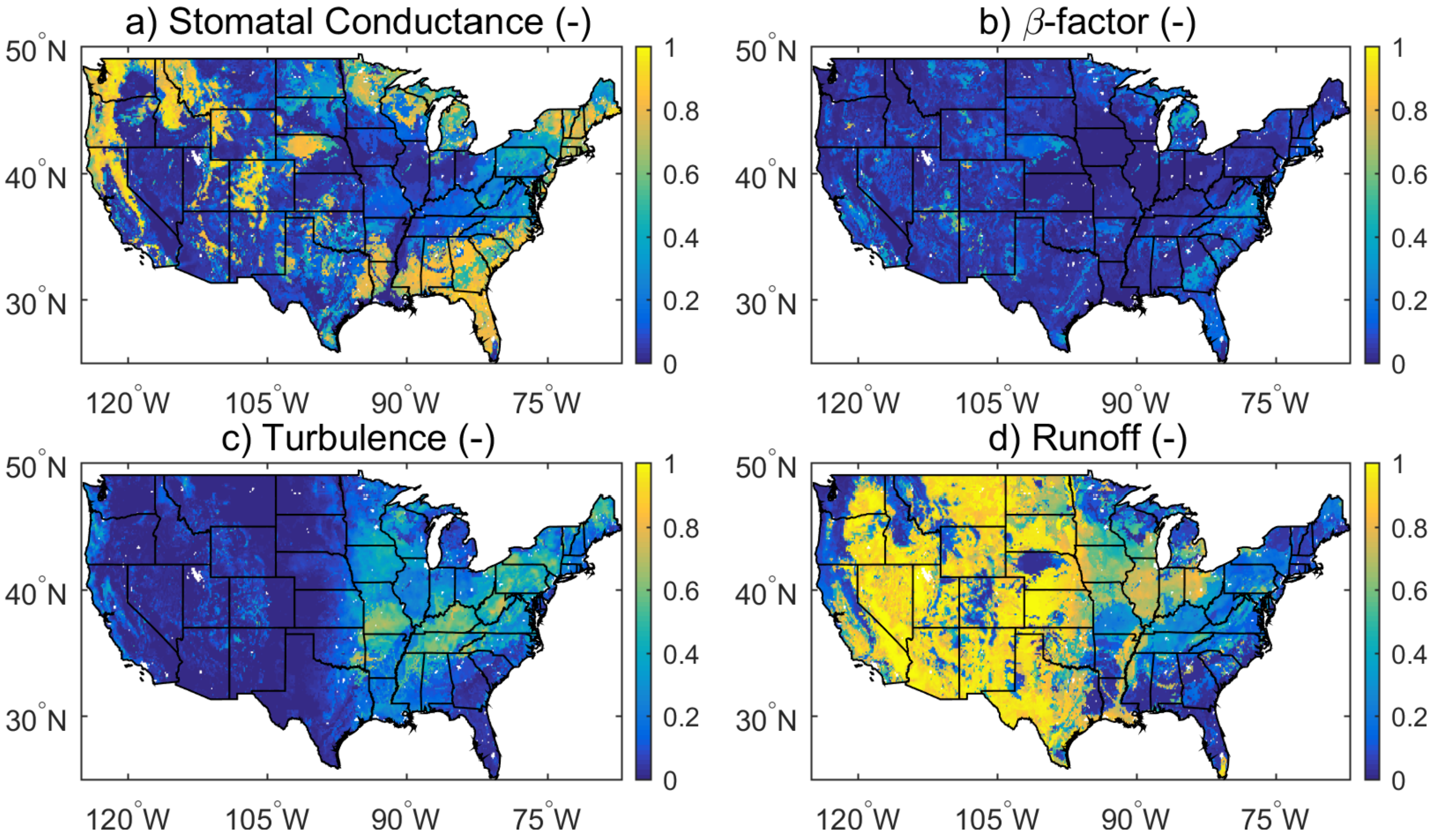
Decomposition of the ensemble variance



- For canopy evaporation, the turbulence parameterization accounts for 100%
- For transpiration, the stomatal conductance parameterization accounts for 92%
- For surface runoff, the runoff parameterization accounts for 93%

- For ET, stoma contributes 51%, runoff contributes 26%, turbulence contributes 21%

Spatial Pattern of the Parameterization Sensitivity



a) Stomatal Conductance (-)

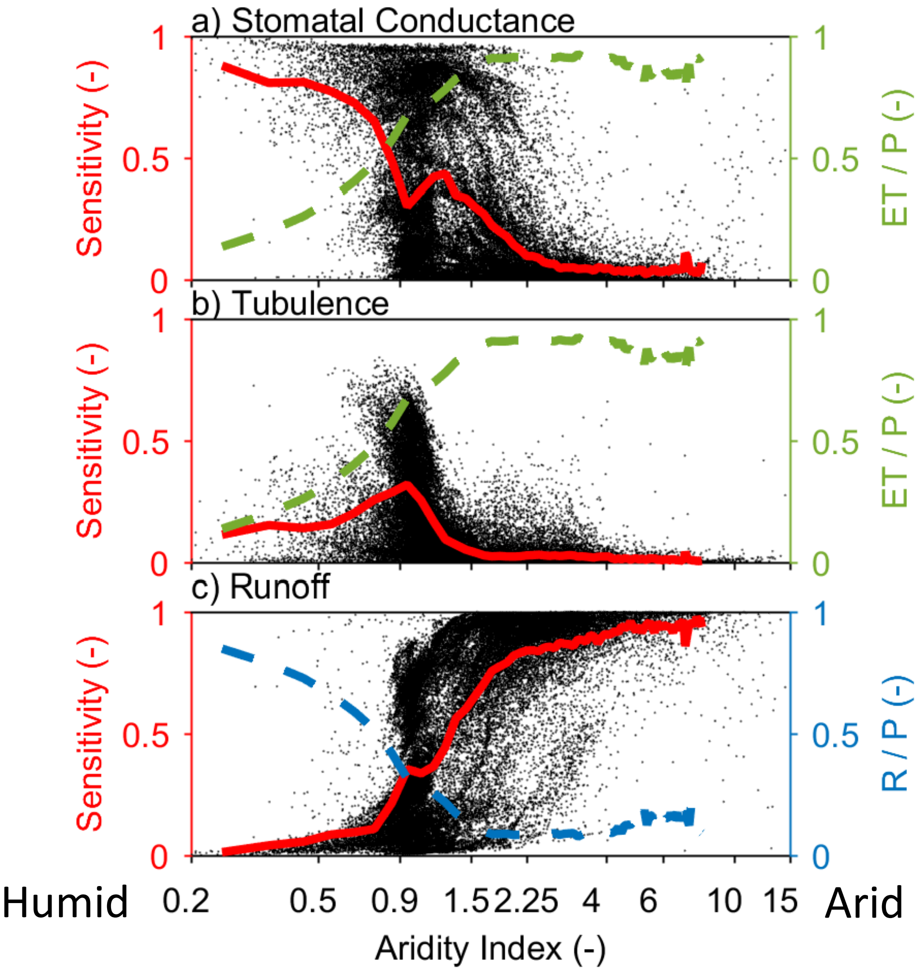
b) β-factor (-)

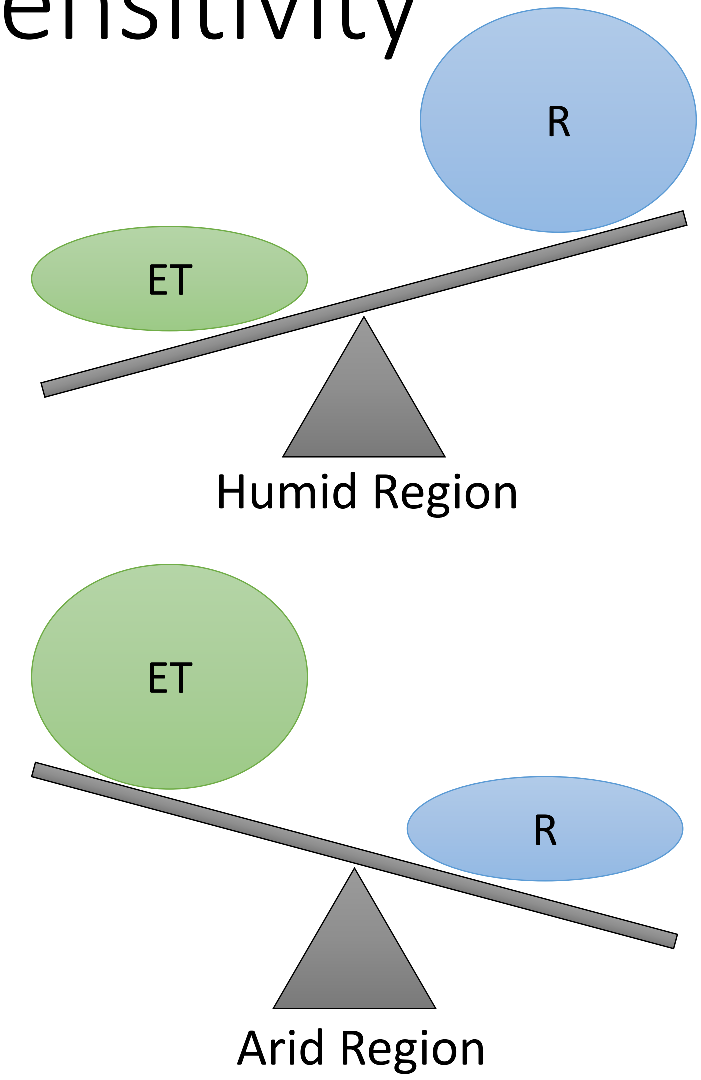
c) Turbulence (-)

d) Runoff (-)

- For the stoma, the area is limited, but it dominates the continental-aggregated water balance.
- The runoff parameterization in the interior and western U.S.

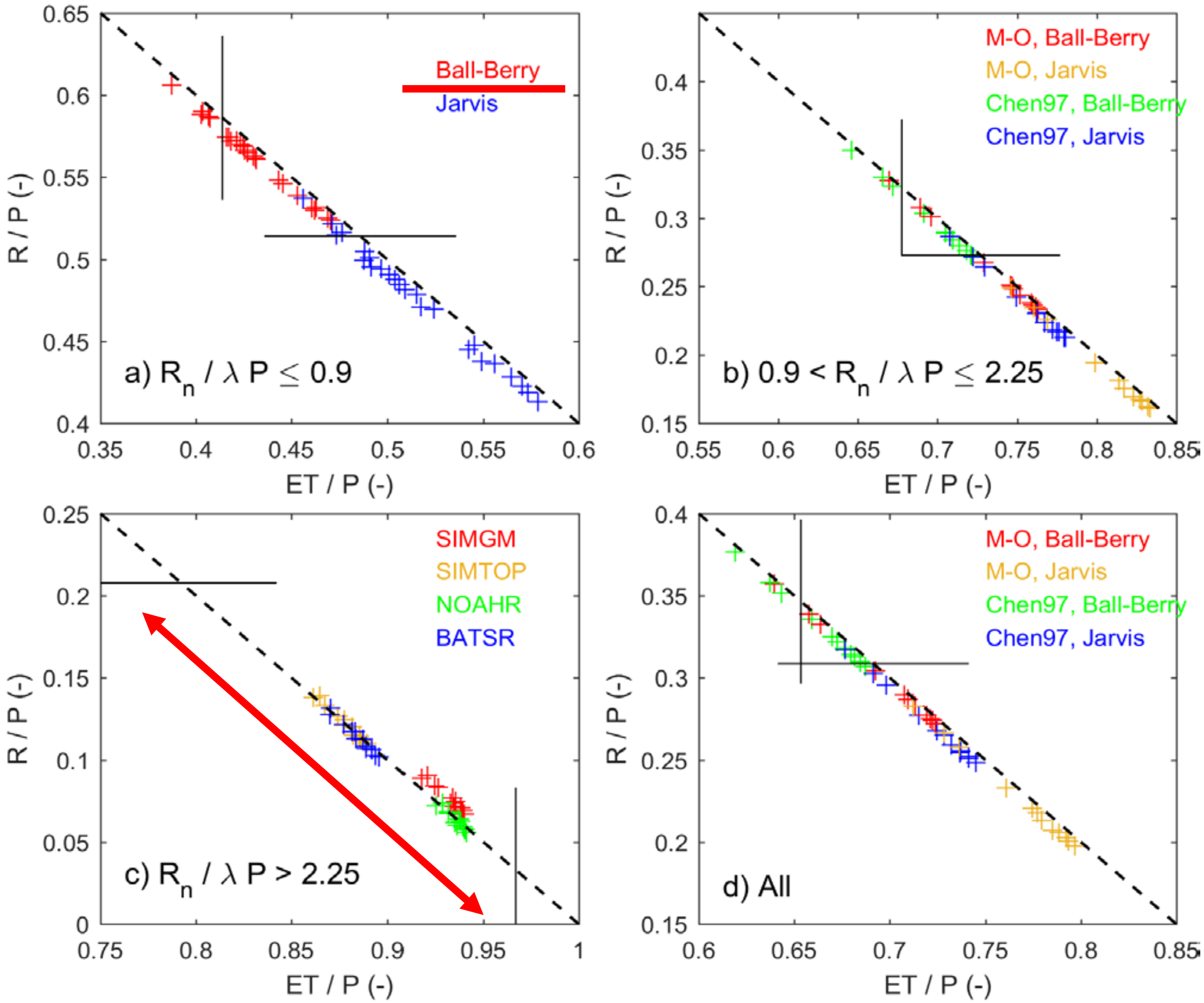
Spatial Distribution of the Parameterization Sensitivity





- Stoma in humid regions
- Runoff parameterization in arid regions
- Turbulence in transitional zones.

Evaluation with obs.

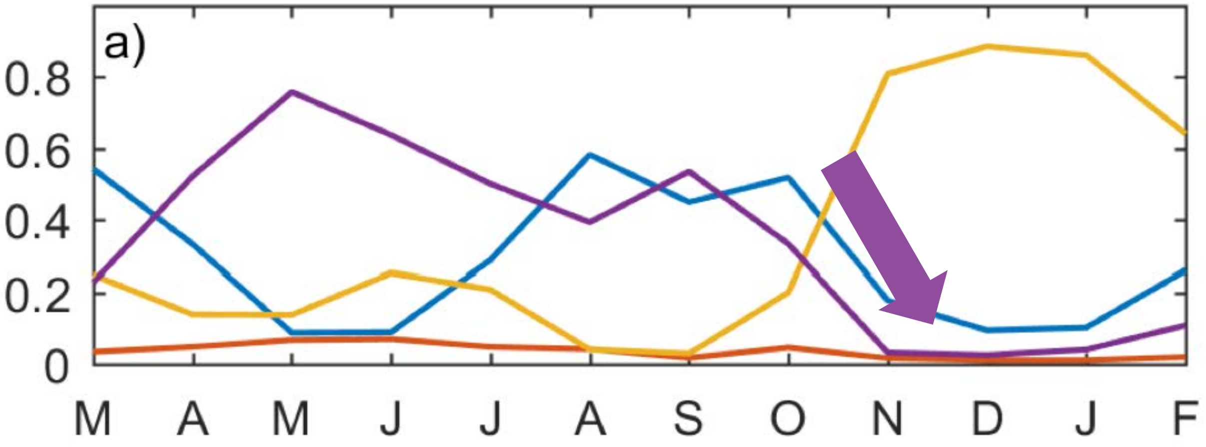


In humid regions, Ball-Berry outperforms Jarvis

In transitional zones, their performances are compensated.

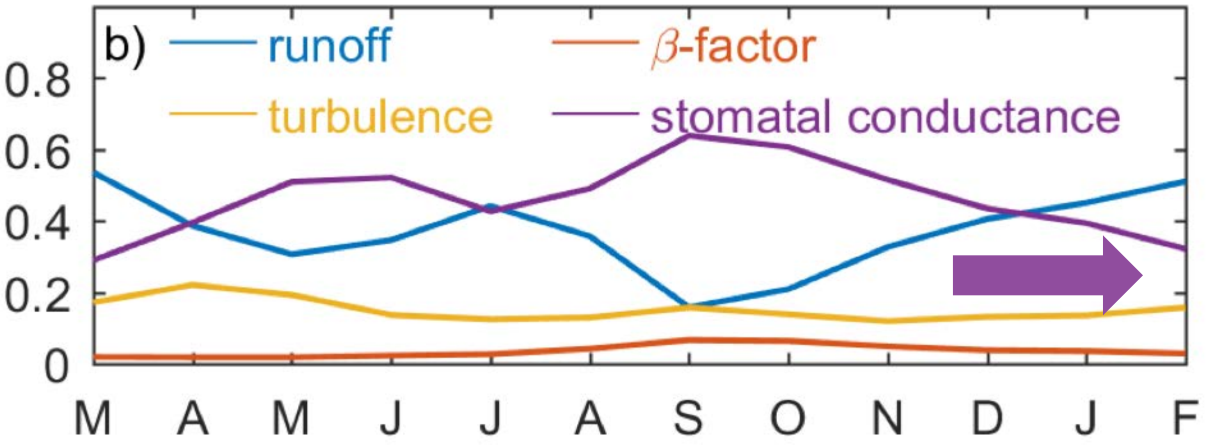
Seasonal changes in the parameterization sensitivity

Sensitivity of Evapotranspiration



The influence of stomatal conductance on ET ceases in winter.

Sensitivity of Runoff

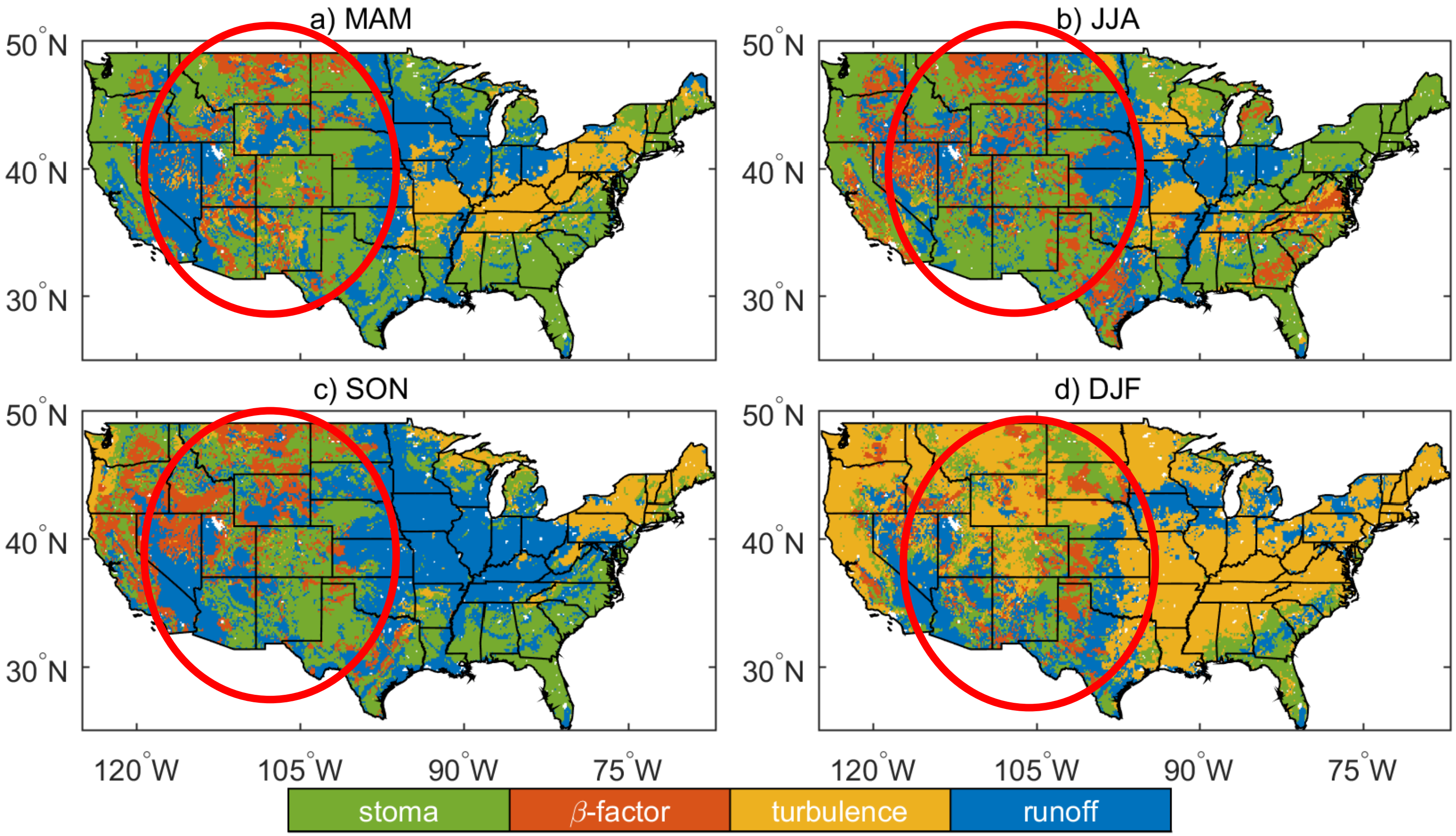


It still influence R in winter.

Memory of land surface states.

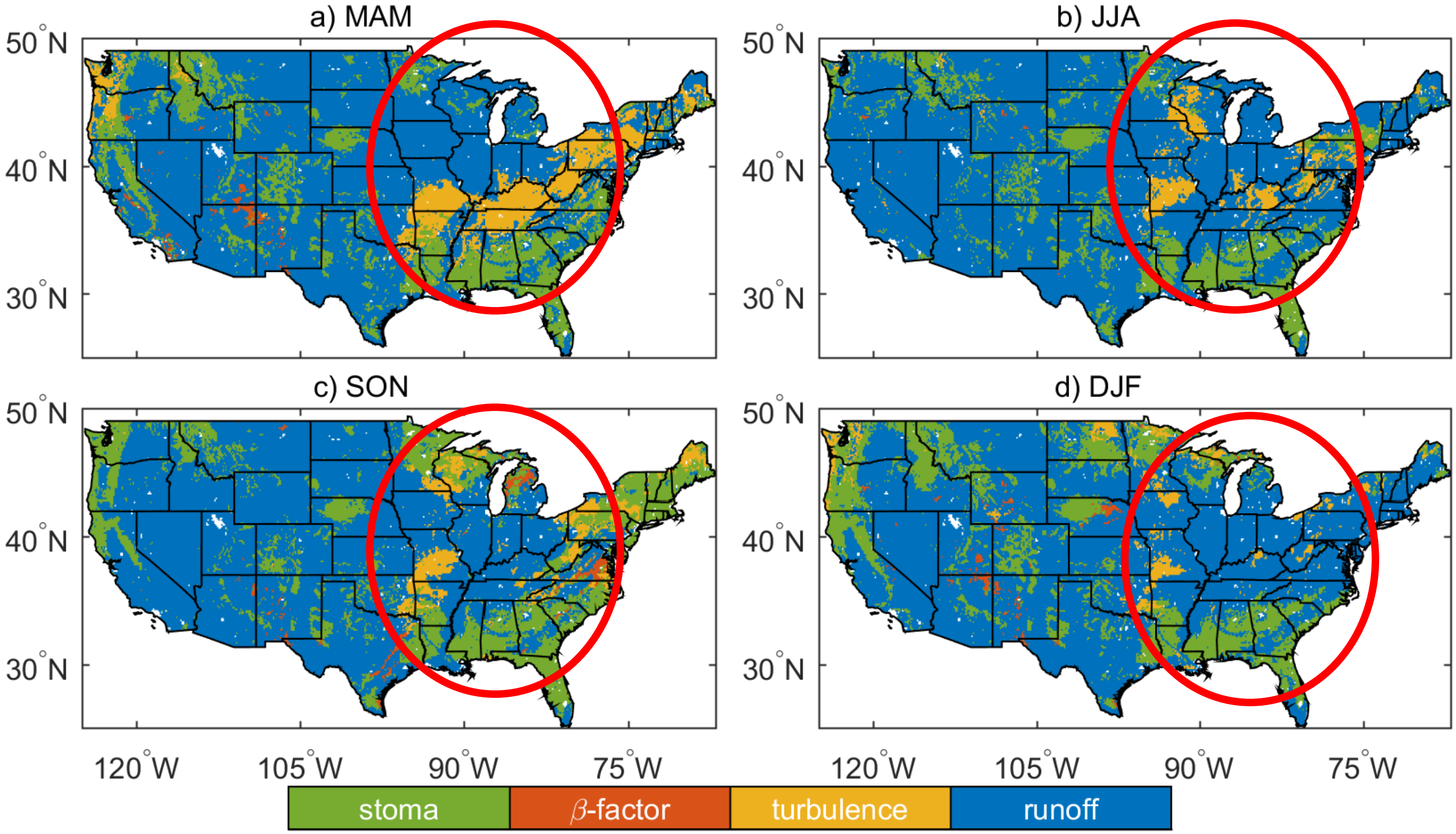
Seasonal influence on ET from the stoma and turbulence parameterizations <- vegetation
The influence of stoma on R persists from warm seasons to winter due to land surface memory.

Dominant parameterization for ET



- β-factor is more important on seasonal scales.
- ET-related parameterizations are more important to ET on seasonal scales than on the annual scale.
- From the annual mean to seasonality, the shifts of the dominant parameterizations are mainly located in transitional zones.

Dominant parameterization for R



- R-related parameterizations are more important on seasonal scales than on the annual scale.
- From the annual mean to seasonality, the shifts of the dominant parameterizations are mainly located in transitional zones.

Dominant area fractions of CONUS

Seasons	runoff	β-factor	turbulence	Stomatal conductance
		Evapotranspiration		
Spring (MAM)	33%	7.4%	15%	45%
Summer (JJA)	28%	16%	8.9%	47%
Fall (SON)	43%	14%	8.7%	35%
Winter (DJF)	22%	7.1%	53%	18%
Average	31%	11%	21%	36%
Annual mean	59%	1.1%	11%	29%
		Runoff		
Spring (MAM)	68%	0.9%	11%	20%
Summer (JJA)	78%	0.0%	4.8%	17%
Fall (SON)	70%	1.3%	5.1%	23%
Winter (DJF)	74%	1.0%	3.8%	21%
Average	72%	0.8%	6.2%	20%
Annual mean	59%	1.1%	9%	30%

ET-related processes, four seasons > annual mean

R-related processes, four seasons > annual mean

Discussions

- Limitations
  - The parameterization schemes are not exhausted but reflect the accomplishments of several widely used LSMs.
  - No dynamic vegetation, which is important especially during extreme events such as droughts. As this demonstration study focuses on climatology and seasonality, we used the monthly vegetation greenness fraction climatology and parameters that are provided by NLDAS and widely used in NLDAS simulations.
  - Have not included all snowpack-related processes (only the turbulence here), which are important for hydrology in spring and in mountainous regions.

  - Have not included the parameter sensitivity. The parameters have been pre-calibrated manually by the parameterization developers reflecting their practical estimations of the “truth”.
  - Have not consider the sensitivity to the atmospheric forcing dataset. However, we related the results to the climatic aridity. The findings here should be independent to the atmospheric forcing datasets and therefore robust.

Conclusions

- The backward approach and multi-parameterization models shed light on resolving the gaps between evaluation and development.

- Issues of the Noah-MP (and Noah) LSM need to be addressed: R overestimation over sand and ET overestimation over Deciduous Broadleaf Forest.

- The partitioning of P between ET and R is sensitive to the parameterization of stomatal conductance, suggesting the importance of plant physiology.
- The runoff parameterization is dominant in arid regions, the stomatal conductance parameterization is dominant in humid regions, and the sensitivity to the turbulence parameterization peaks in the transitional zone.

- ET-related parameterizations are more important on ET on finer time scales.
- R-related parameterizations are more important on R on finer time scales.
- The shifts of the dominant parameterization when the time scale is reduced from the climatology to seasonality mainly exists in transitional zones.

Next

- Extend the evaluation timescale from the climatology to finer scales (monthly, daily, diurnal).
- Include more processes.
  - Snow
  - CO2 and dynamic vegetation
- Synthetically analyze the sensitivities to parameters and parameterizations.

Ultimate Goals

- From model evaluation to parameterization evaluation.
- A synthetic quantification of model and data uncertainty may lead to a better land data assimilation.

Thanks for your attention!

Q & A

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References

- Zheng et al., A Rejection-based evaluation of hydrological simulations using multiple types of observations (in prep.)
- Zheng et al., On the sensitivity of the precipitation partition into evapotranspiration and runoff in land surface parameterizations (in revision)

Ensemble Spread

	σ_{hps} (ensemble spread)	σ_{total} (month-to-month variability)	$\frac{\sigma_{hps}}{\sigma_{total}}$
Runoff	38.0	98.2	0.387
Surface Runoff	19.8	24.9	0.793
Subsurface Runoff	30.3	76.5	0.396
Evapotranspiration	38.0	373	0.102
Evaporation from canopy	5.83	32.4	0.180
Evaporation from soil	23.3	117	0.199
Transpiration	43.0	252	0.171
Snow	0.194	7.91	0.0245
Soil moisture in top 10 cm	0.652	2.54	0.257
Soil moisture in top 1 m	10.3	22.4	0.461
Soil moisture in top 2 m	24.2	38.2	0.636
Groundwater	34.2	2.21	15.5

σ_{lss} and σ_{total} are defined as [Dirmeyer, 2006, BAMS]