The Simulation and Subseasonal Forecasting of Hydrological Variables

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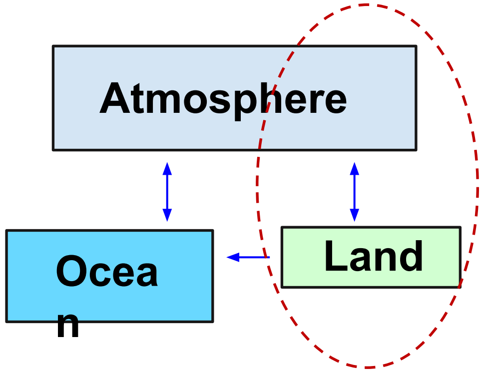
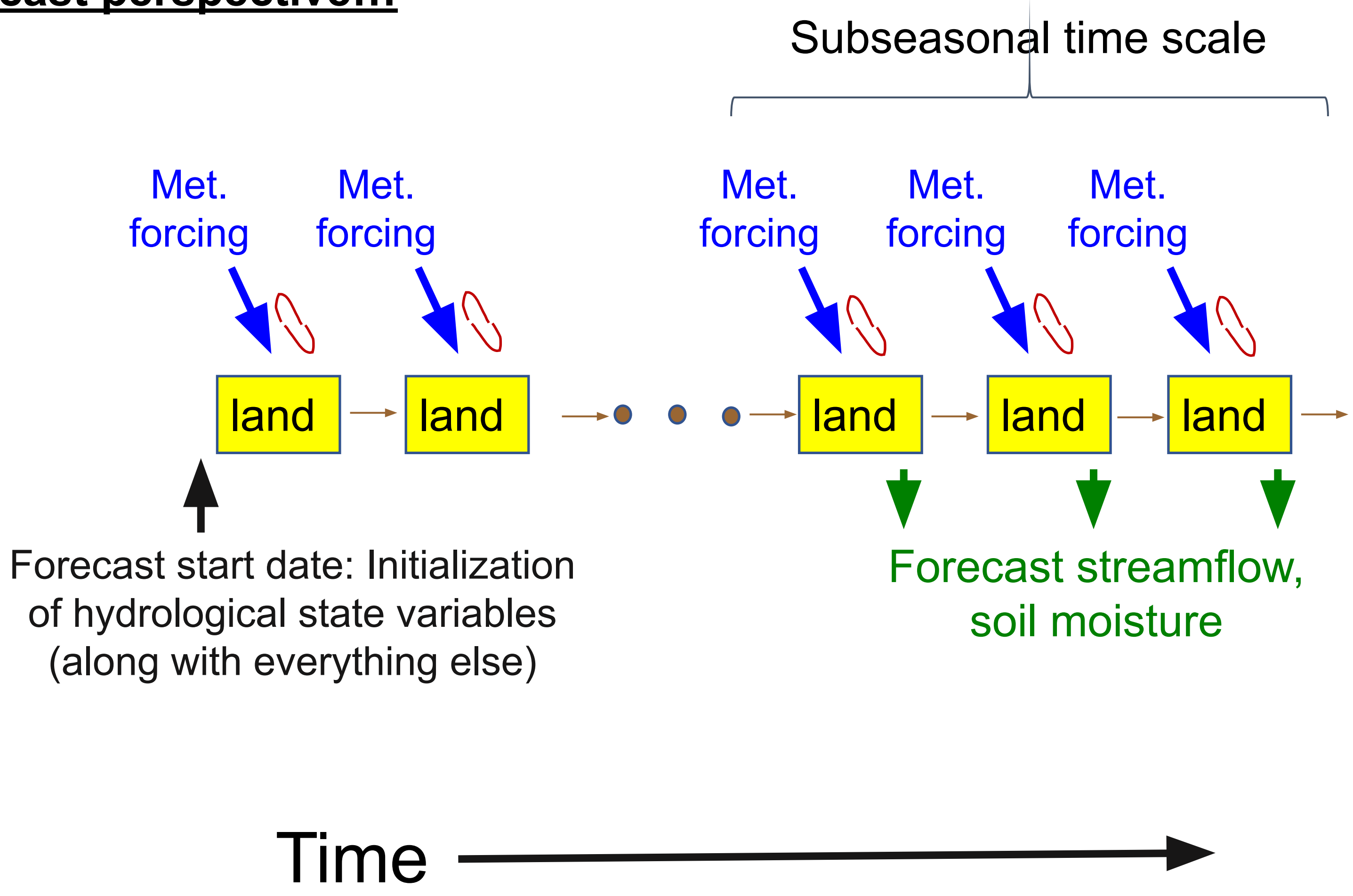
Hydrological variables: Important to predict at subseasonal time scales.

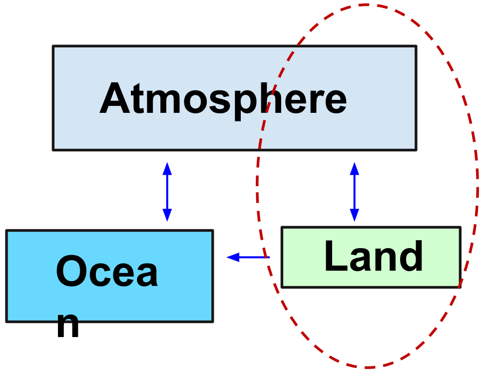
- Soil moisture anomalies (e.g., agricultural planning)
- Streamflow anomalies (e.g., water resources planning, flooding preparedness)

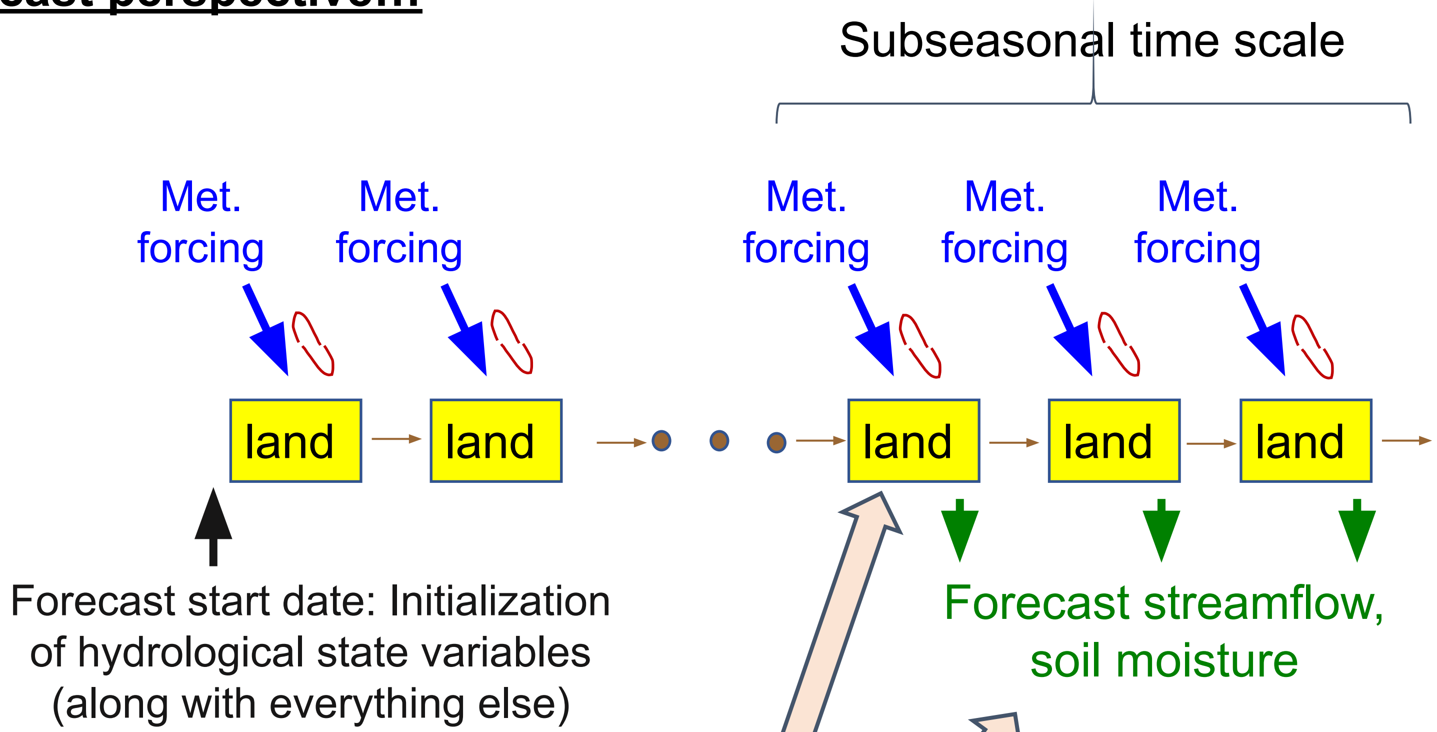
From a hydrological forecast perspective…





From a hydrological forecast perspective…

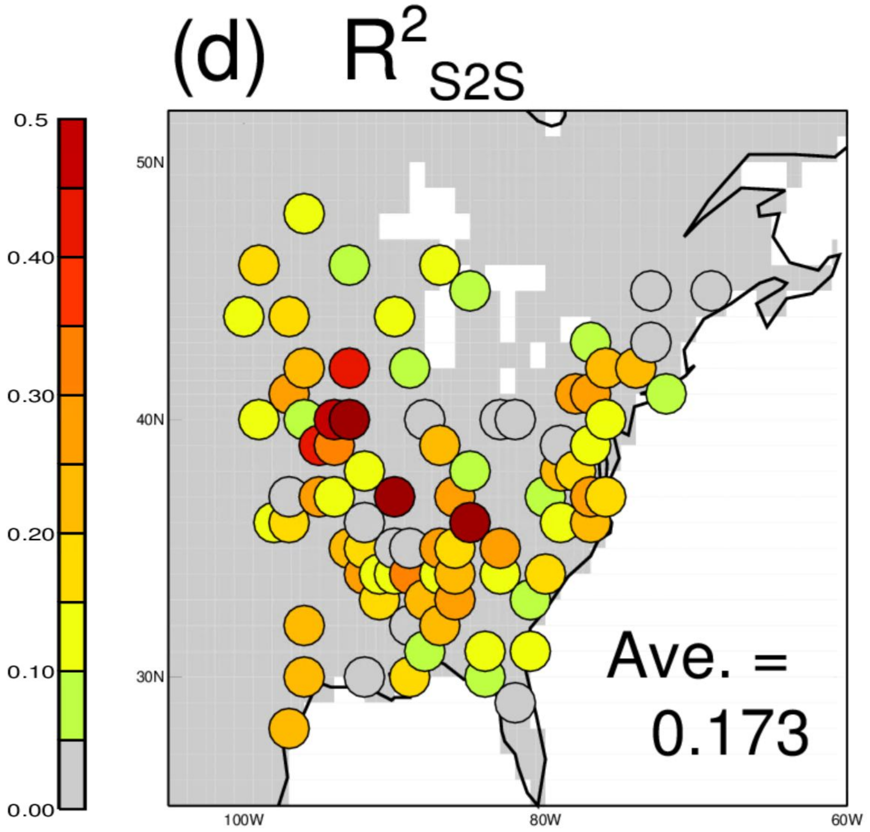




To what extent does a land model's design, all by itself, affect hydrological forecast skill (in terms of anomaly prediction, not just absolute magnitudes), regardless of how good the meteorological forecasts are?

That is, can we improve hydrological forecast skill by optimizing the land model itself?

Current level of skill for the GMAO S2S forecast system: Forecast soil moistures vs. in situ observations



Soil moisture forecast skill (anomaly R^2) at 11-20 day lead, as determined against in-situ soil moisture measurements. Hindcast period considered: May-September of 1999-2020.

(from https://doi.org/10.1175/JHM-D-22-0050.1)

How do we go about improving on this?

Step 1 of Approach:

Examine problem with a “bare bones” representation of a land surface model.

Bare-bones representation: the “WBM”, based on water balance equation

Soil profile water holding capacity

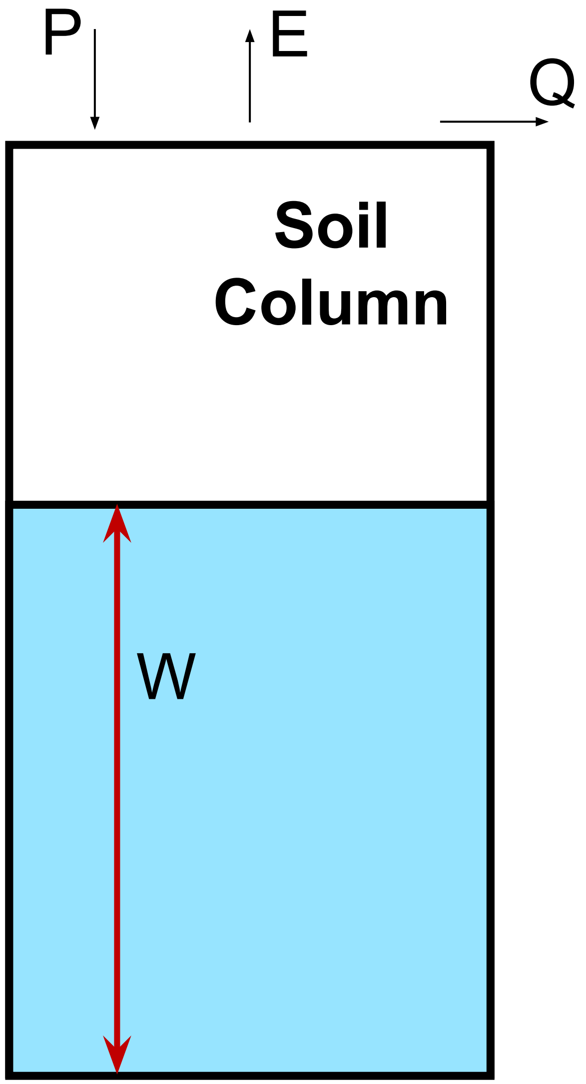
Precipitation

Evapotranspiration

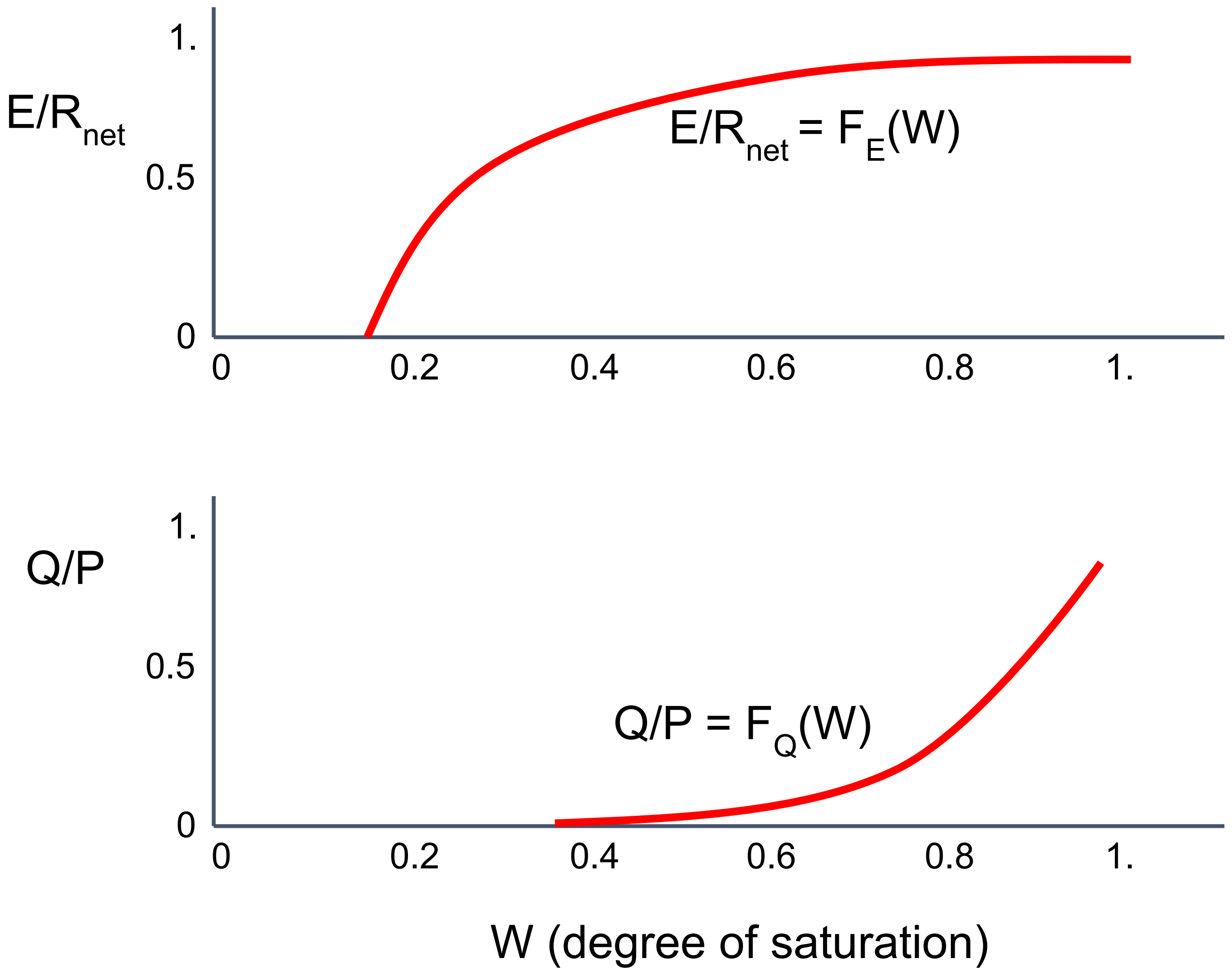
$$C\,W_{n+1} = C\,W_n + P_n - E_n - Q_n,$$

Total runoff

Soil moisture at start of day n (degree of saturation)

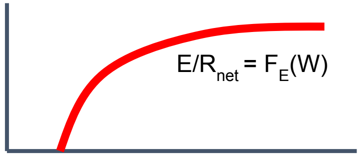


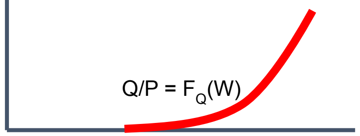
We can impose simple relationships between W and both E and Q:



 Replace

$$C\ W_{n+1} = C\ W_n + P_n - E_n - Q_n$$





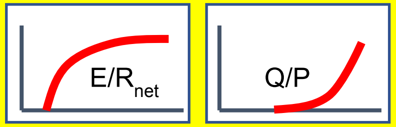
with

$$C\ W_{n+1} = C\ W_n + P_n - F_E(W_n)\ R_{net\text{-}n} - F_Q(W_n)\ P_n$$

This, in a nutshell, is the bare-bones representation.

Time series of meteorological forcing (rainfall, radiation, etc.)

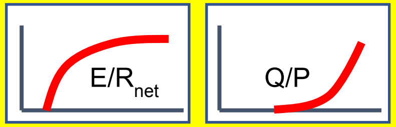
WBM: bare-bones representation of LSM



Time series of hydrological variables (streamflow, soil moisture)

Time series of meteorological forcing (rainfall, radiation, etc.)

WBM: bare-bones representation of LSM



Time series of hydrological variables (streamflow, soil moisture)

Time series of meteorological forcing (rainfall, radiation, etc.)

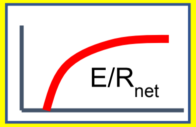
Full LSM

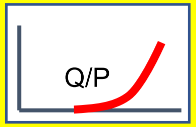
Time series of hydrological variables (streamflow, soil moisture)

Can we calibrate the WBM curves so that this…

Time series of meteorological forcing (rainfall, radiation, etc.)

WBM: bare-bones representation of LSM





Time series of hydrological variables (streamflow, soil moisture)

…looks like this?

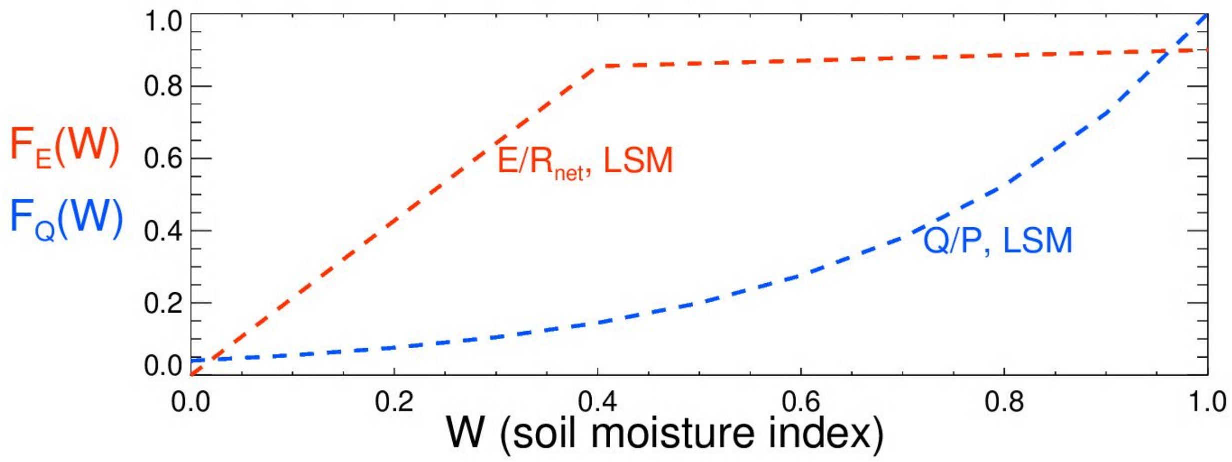
Time series of meteorological forcing (rainfall, radiation, etc.)

Full LSM

Time series of hydrological variables (streamflow, soil moisture)

YES!

-- Calibrate curves to the behavior of a full LSM (the Catchment LSM, part of the MERRA-2 reanalysis) using data from 1980-1998.



-- Run the bare-bones model over 1999-2020

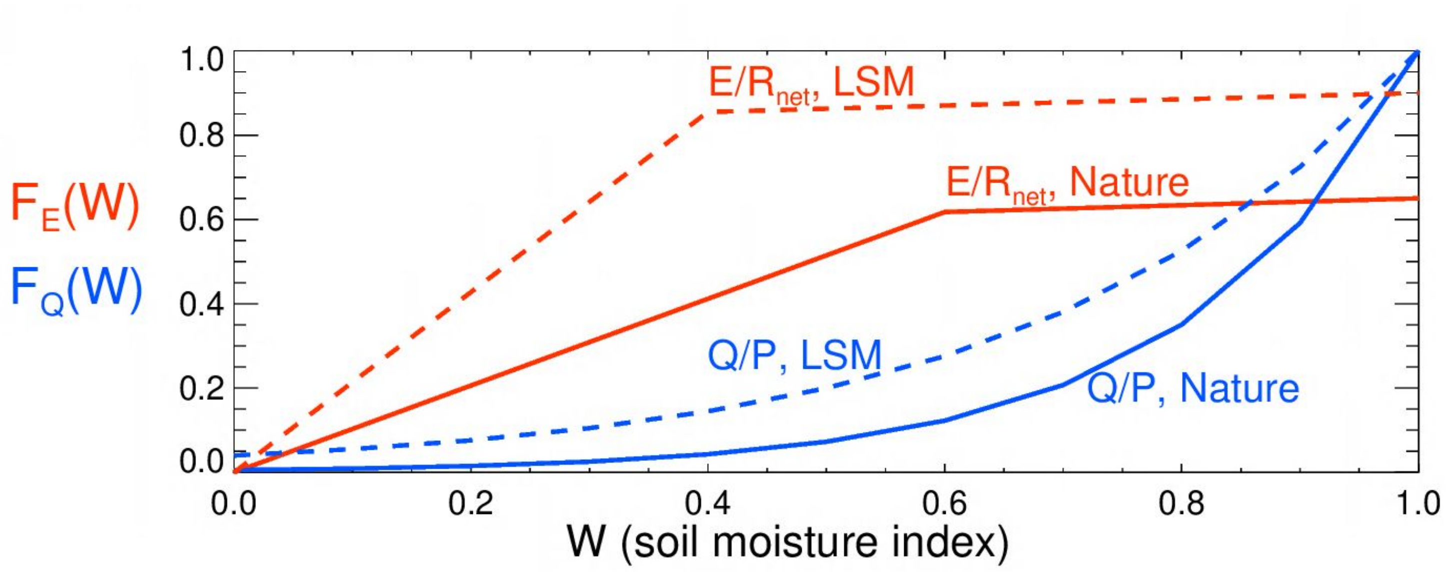
-- Compare the simulated hydrology to that of the full Catchment LSM, as produced in MERRA-2 during that latter period

 Nice agreement!

(not shown here due to time constraints, but see doi:10.1175/JHM-D-22-0050.1)

But – are the calibrated curves optimal?

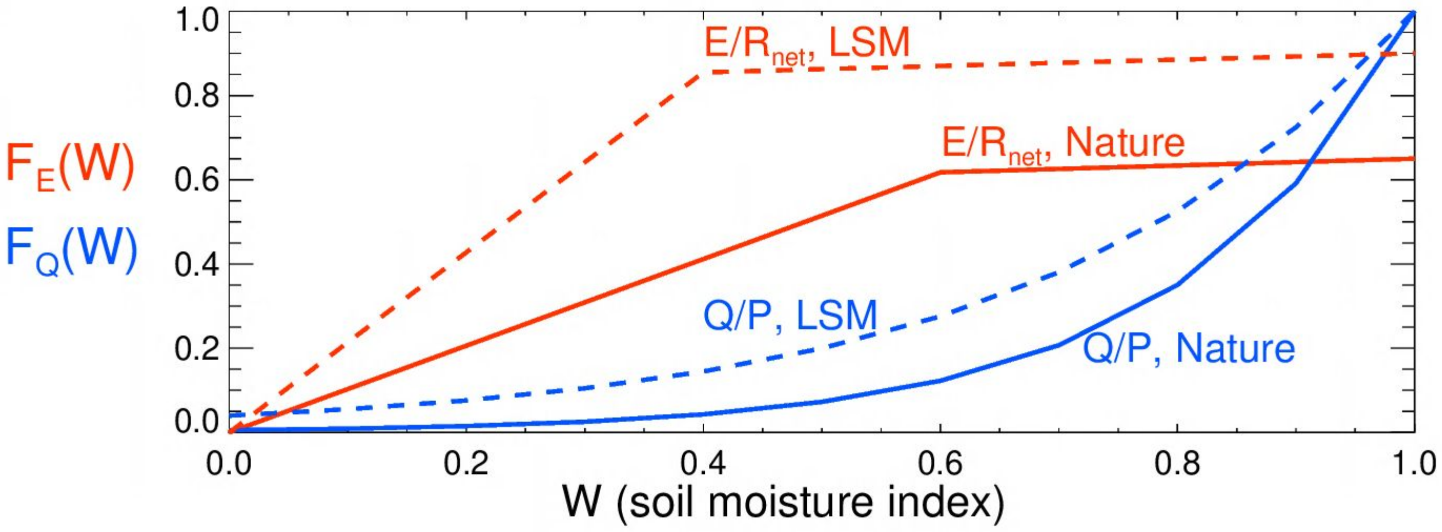
Recalibrate curves during the 1980-1998 period using observed streamflow as the calibration target get a different set of curves.



But – are the calibrated curves optimal?

Recalibrate curves … erved streamflow as the c… curves.

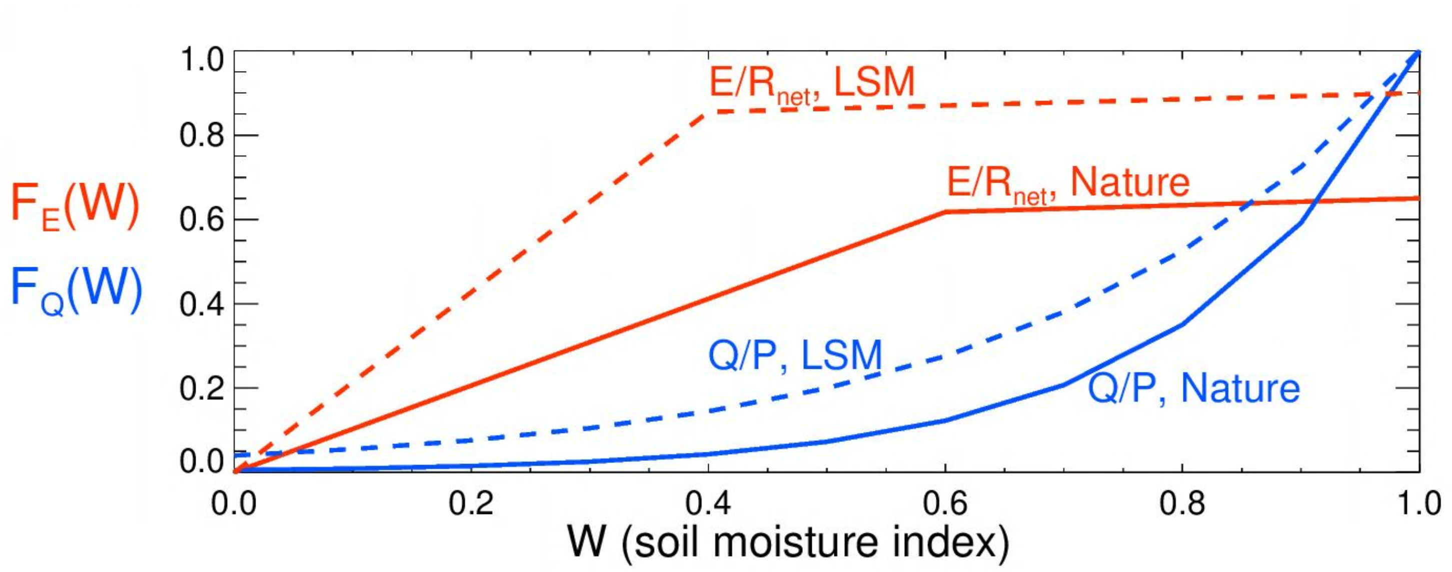
A technical detail (just for completeness): it's not so much that the solid curves lie below the dashed curves that's important…



… it's that the solid curves are closer together than the dashed curves.

But – are the calibrated curves optimal?

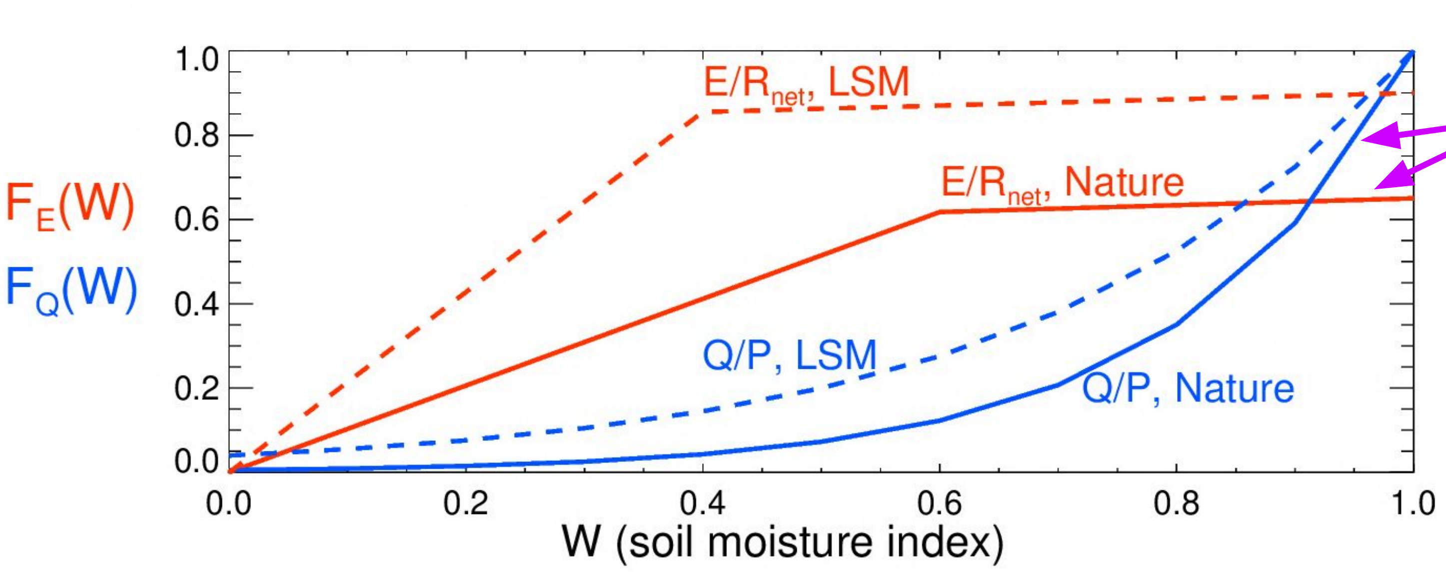
Recalibrate curves during the 1980-1998 period using observed streamflow as the calibration target get a different set of curves.



When both sets of curves are used in the WBM, and the WBM is driven with forcing in an independent time period, the "Nature" curves continue to agree with observations best.

But – are the calibrated curves optimal?

Recalibrate curves during the 1980-1998 period using observed streamflow as the calibration target get a different set of curves.

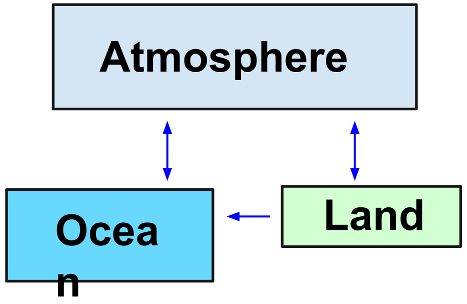


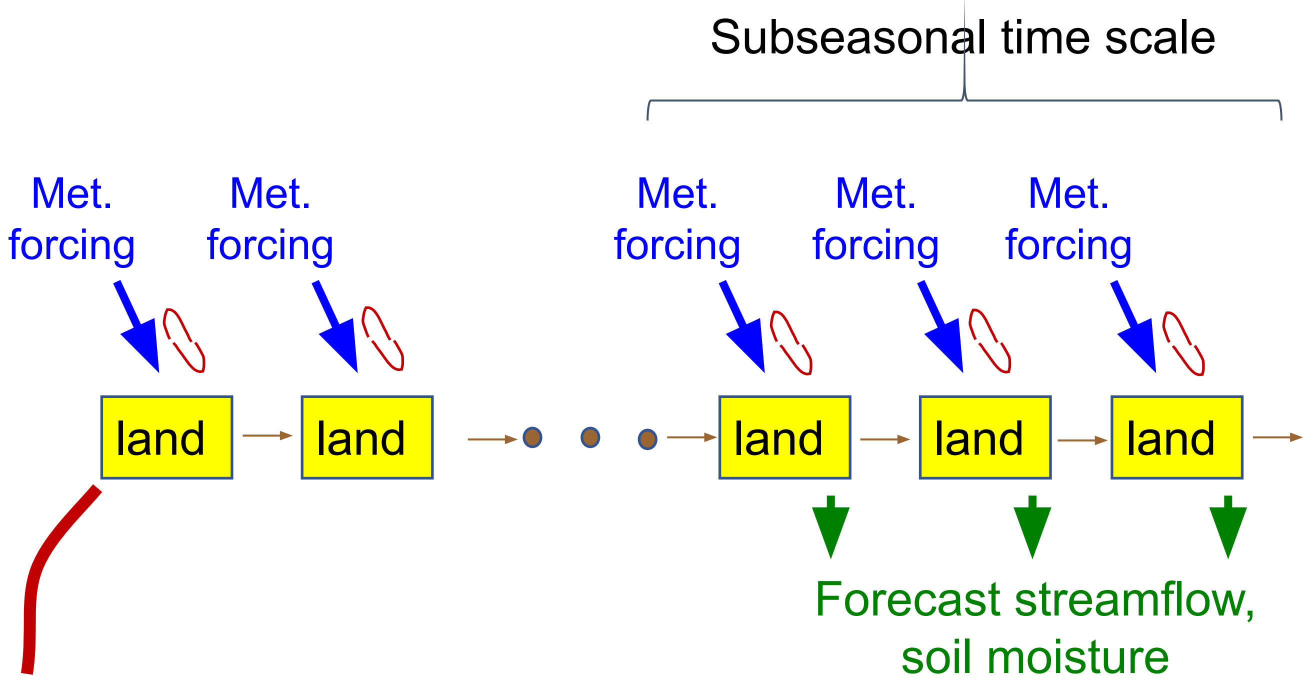
The "Nature" curves will thus serve as our development target when improving the land surface model.

Step 2 of Approach:

Examine the prediction problem with actual changes to the S2S system's land surface model.

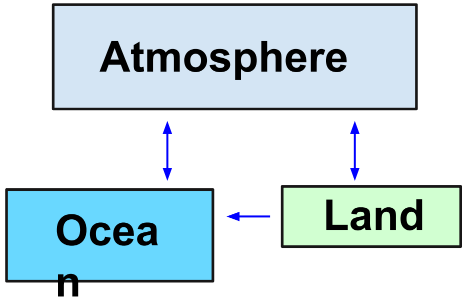
Land model impacts could be studied online…

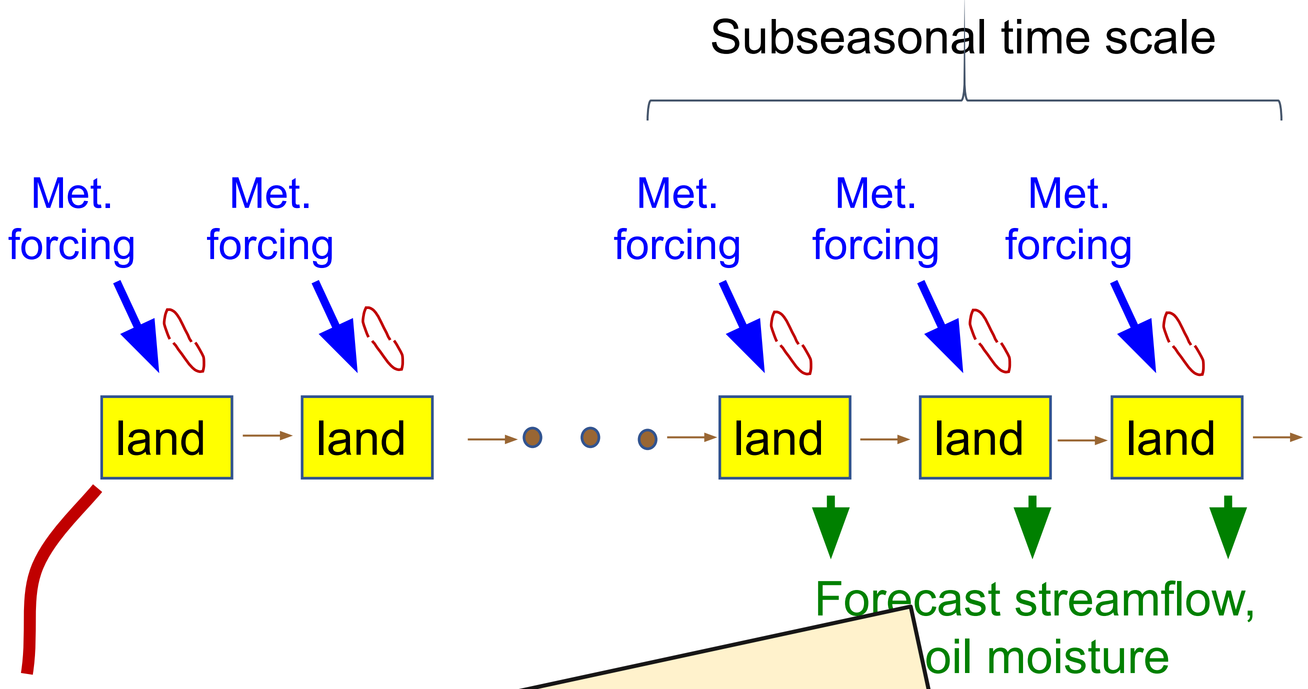




In a series of hindcast experiments, modify the land model and see if you get better hydrological predictions

Land model impacts <u>could</u> be studied online…

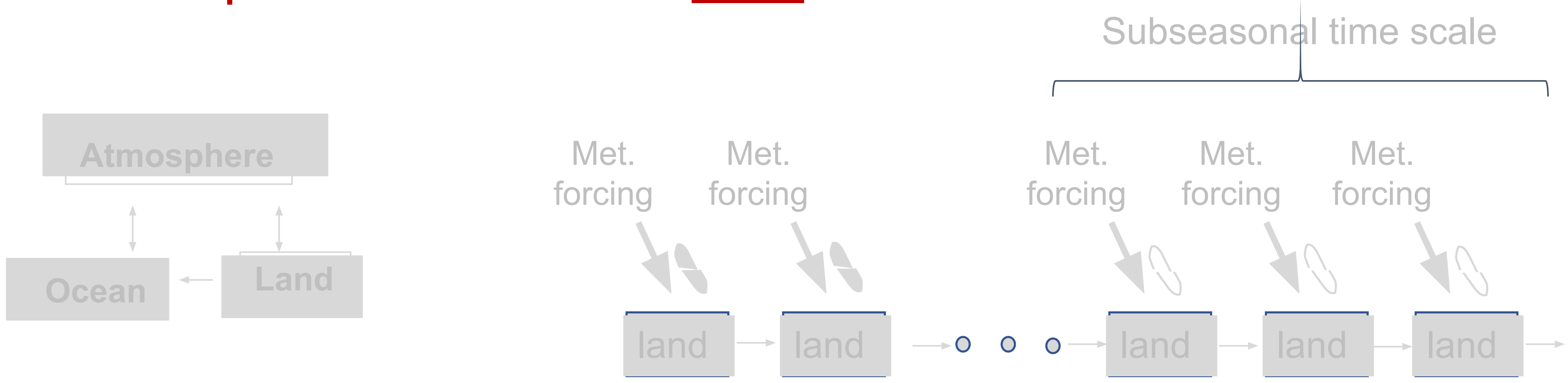




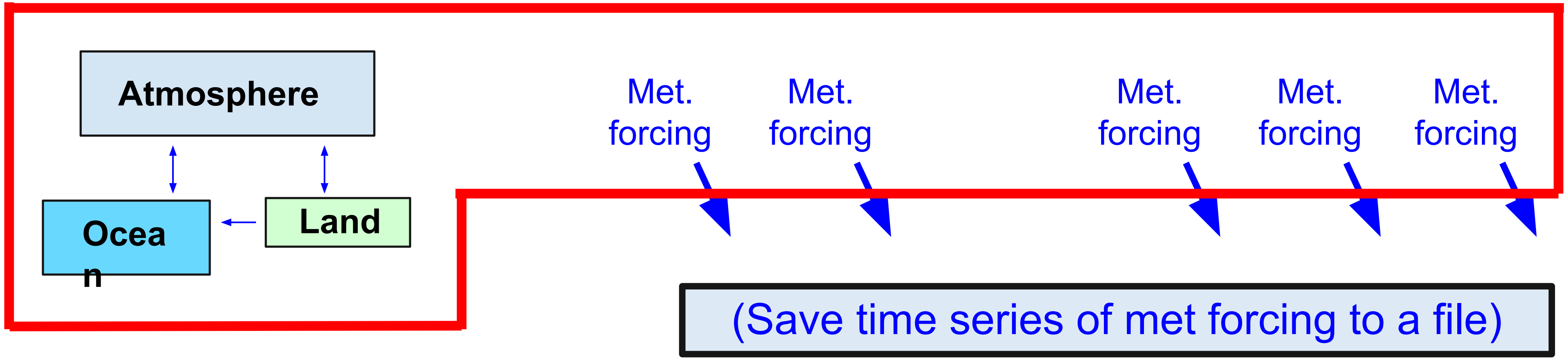
In a series of hindcast experiments
modify the land model and see if y
get better hydrological predictions

No – overwhelmingly expensive!

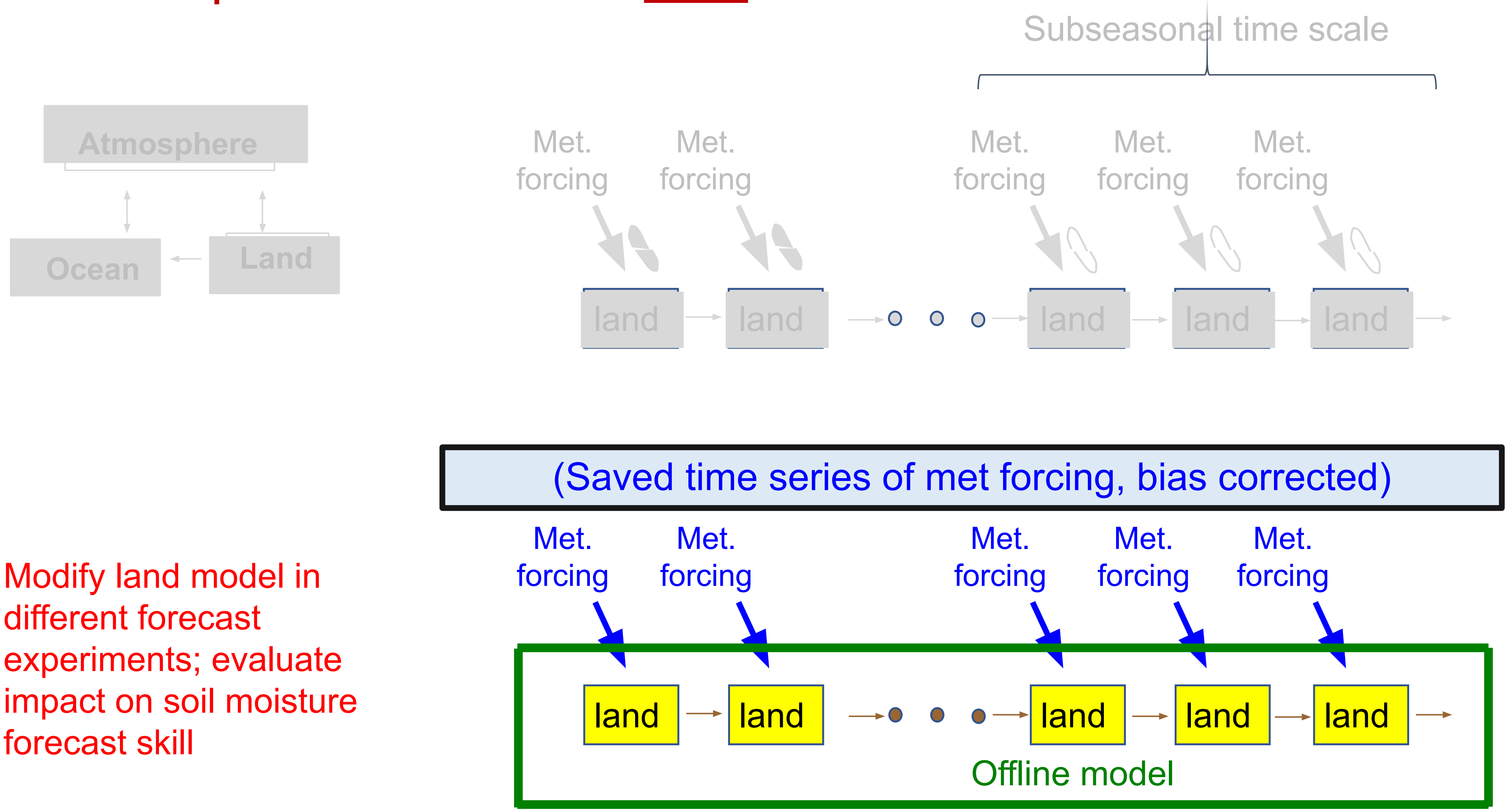
Land model impacts can also be studied offline



Run the full S2S set of hindcasts once, ahead of time!

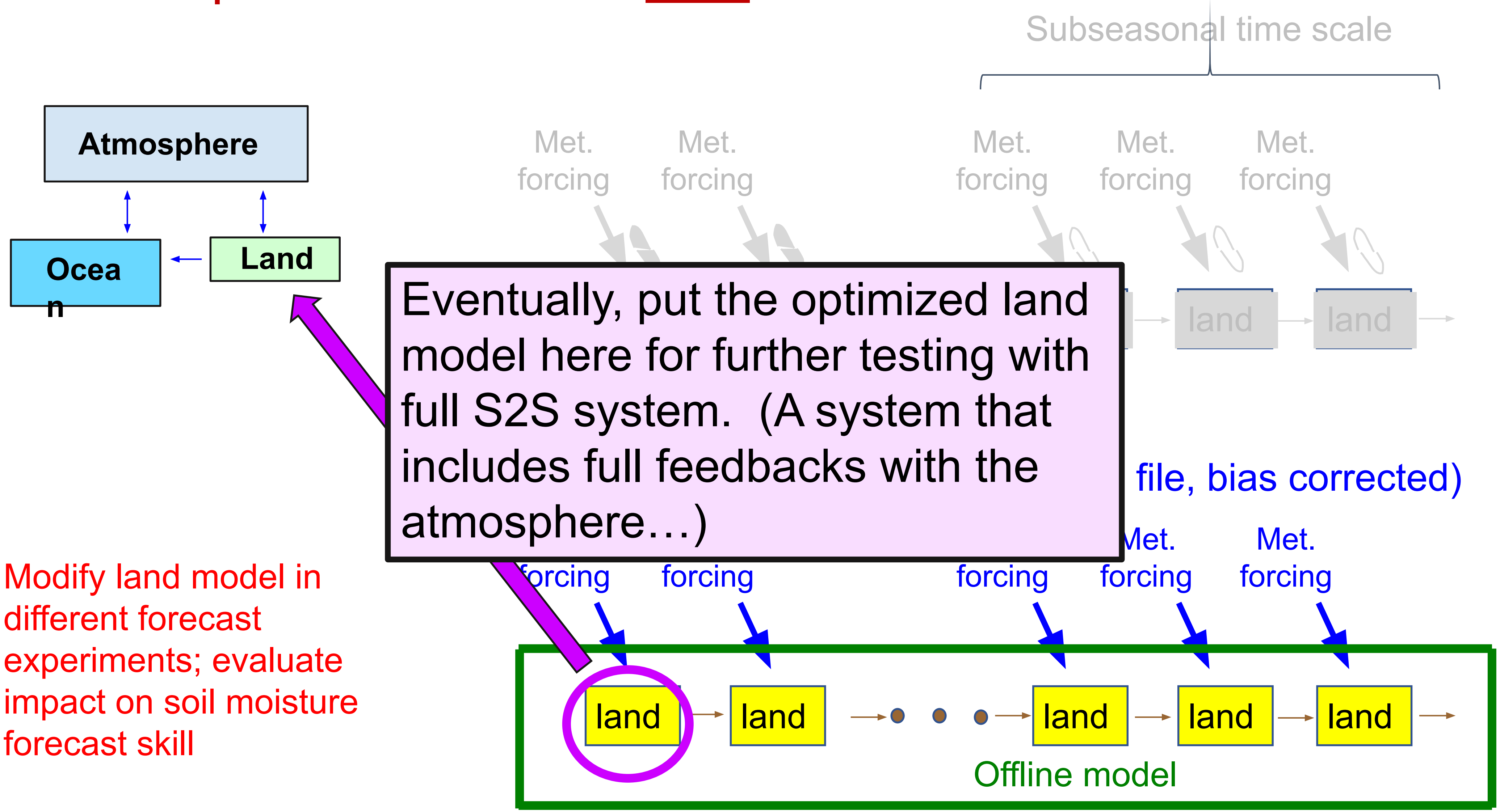


Land model impacts can also be studied <u>offline</u>



Modify land model in different forecast experiments; evaluate impact on soil moisture forecast skill

Land model impacts can also be studied offline



Modify land model in different forecast experiments; evaluate impact on soil moisture forecast skill

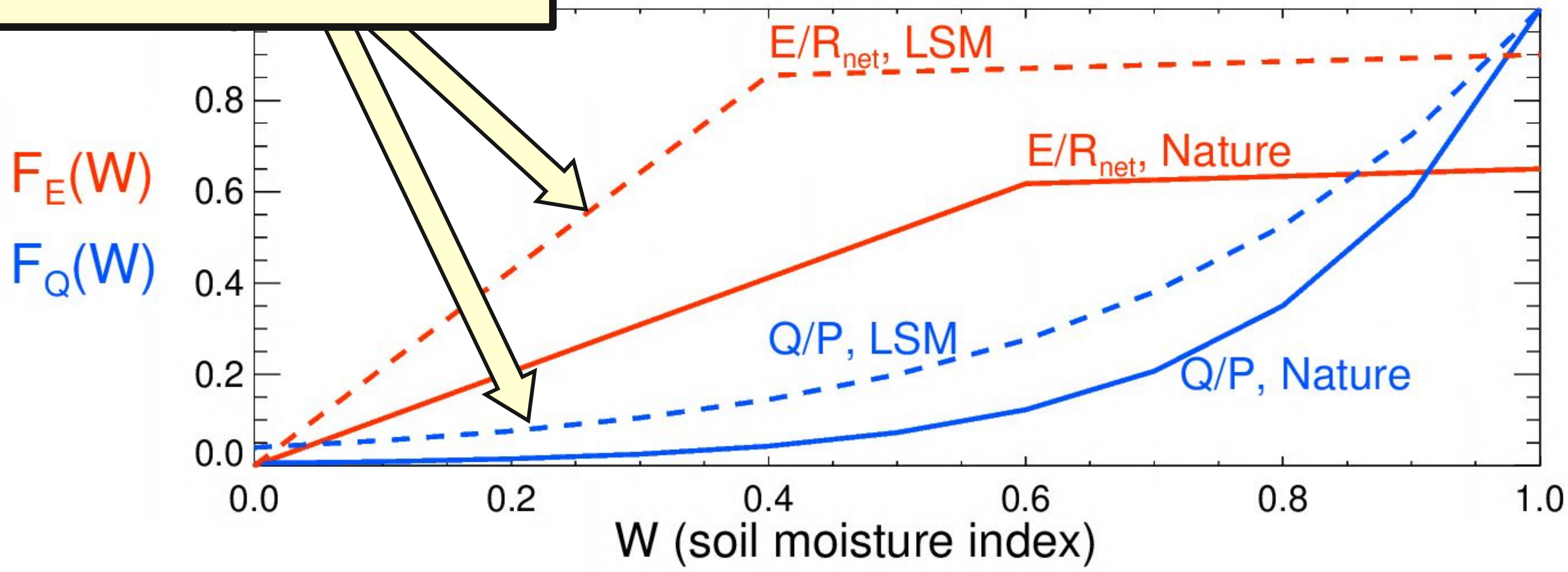
We use the offline testing environment to improve our land model for hydrological forecasts. (Note – even with imposed bias corrections to the forcing, we will still be studying <u>fair</u> forecasts.)

<u>BUT</u>, do we know how to improve the land model?

Yes! From the "bare bones" analysis!

That is, make the curves for the model look more like "Nature's curves"

…hips between land model's soil moisture variable …ency [$F_E(W)$] and runoff efficiency [$F_Q(W)$]:



https://doi.org/10.1175/JHM-D-22-0050.1

Offline "control" forecast experiment

Initializations: June 1, July 1, August 1 of 2001-2020, as taken from a long-term offline simulation forced with reanalysis forcing

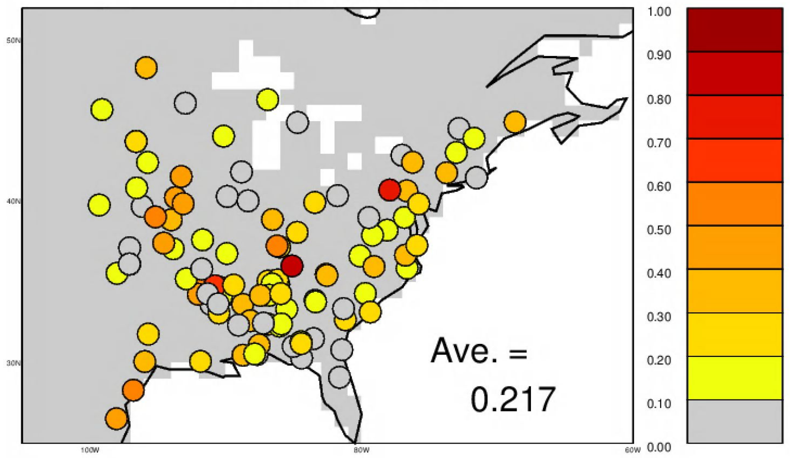
All met forcing was derived from full GMAO S2S system's set of hindcasts, bias corrected to MERRA-2 climatologies determined during an independent period

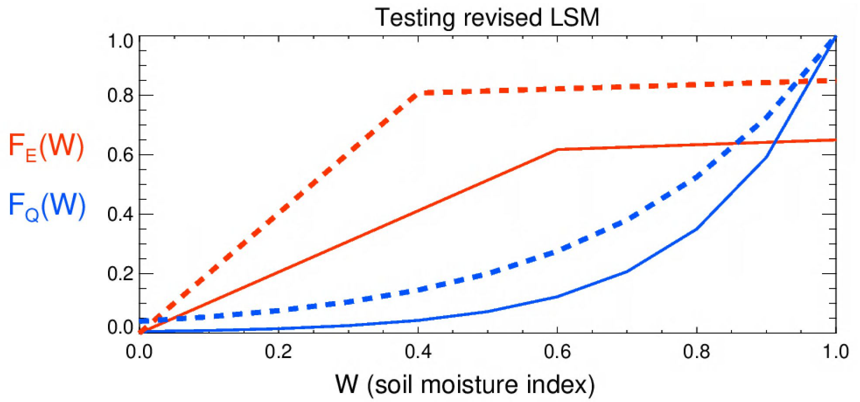
Variable examined and compared to in-situ observations: root zone soil moisture

Lead considered in all analyses below: Days 11-20 of forecast

Thanks to Yuna Lim for all forecast production work!

Offline forecast skill for soil moisture (R^2)

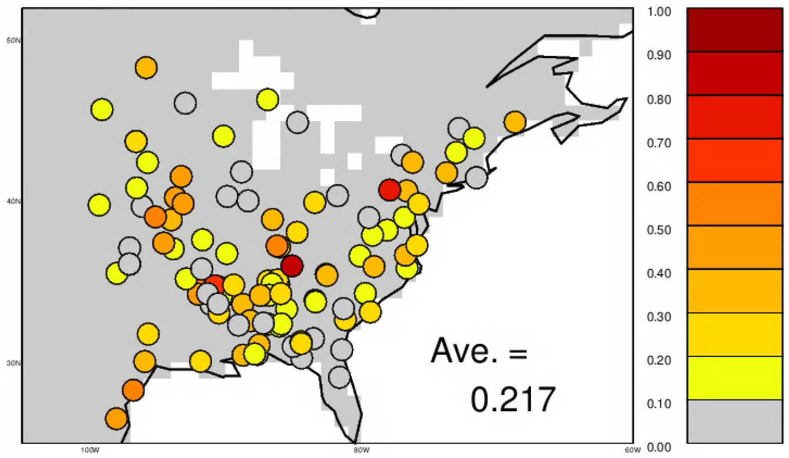


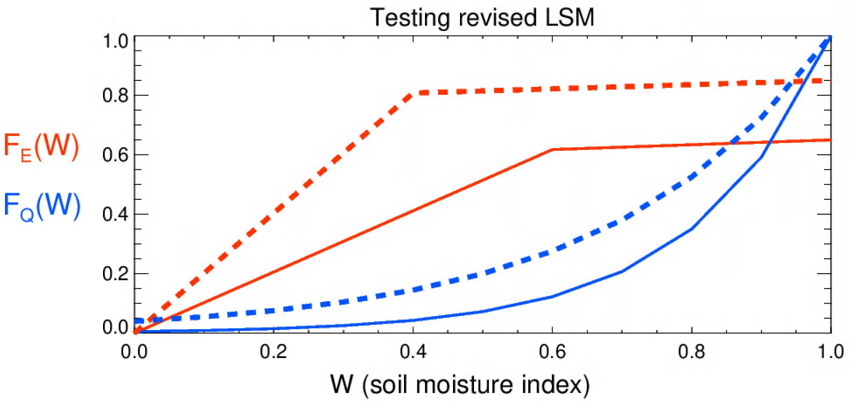


Dashed lines: inferred model curves

Solid lines: inferred Nature curves

Offline forecast skill for soil moisture (R^2)





Dashed lines: inferred model curves

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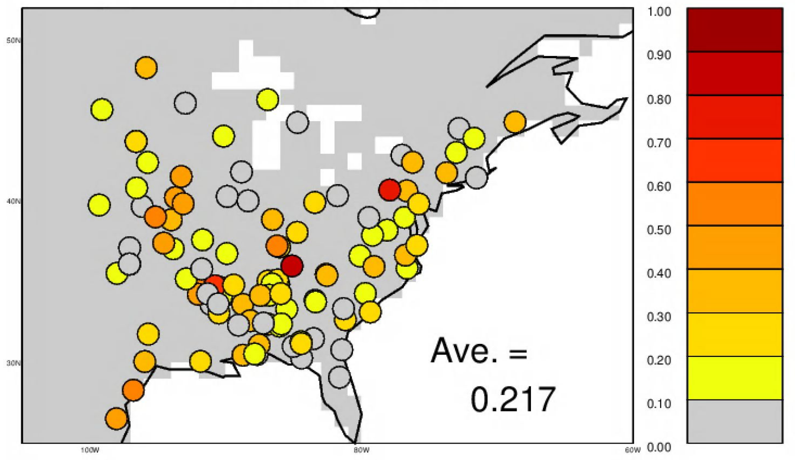
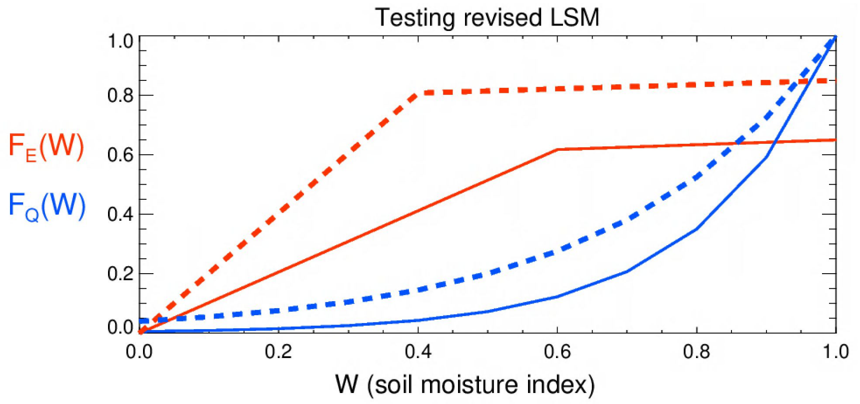
And now – some results from a first test, where we move the red curve a little bit in the right direction. (We're just getting started with the optimization…)

Thanks to Yujin Zeng for initial offline testing of modification!

Offline forecast skill for soil moisture (R^2)





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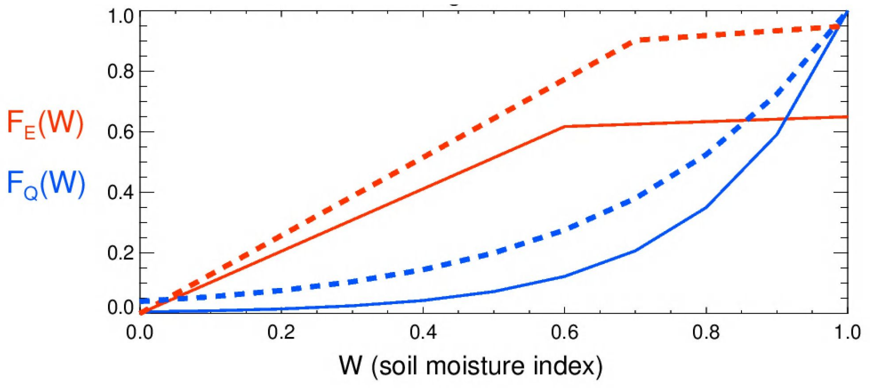
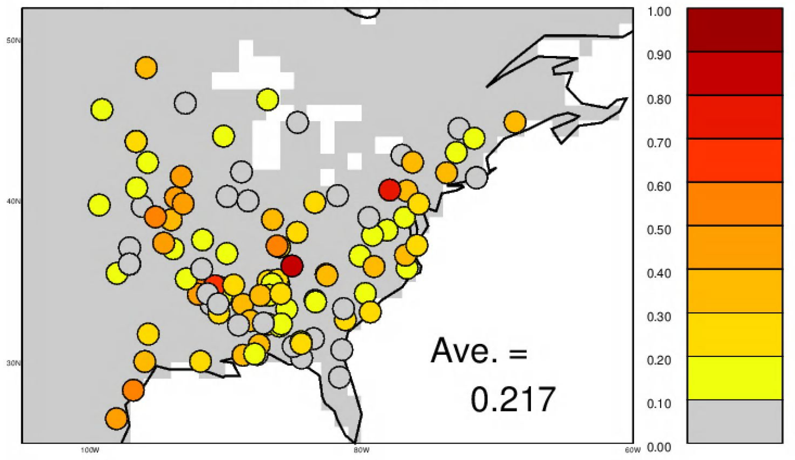
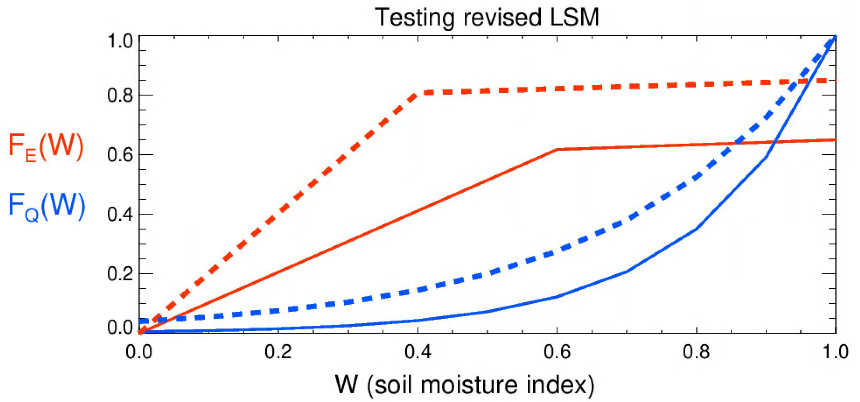
Modify land surface model: strengthen soil moisture stress function



Offline forecast skill for soil moisture (R^2)





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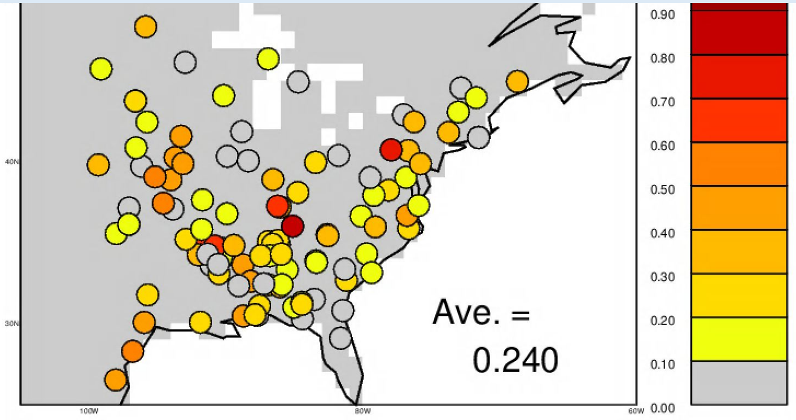
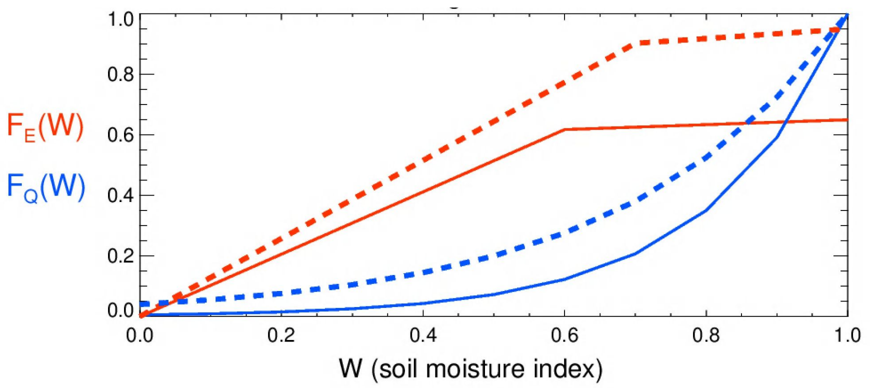
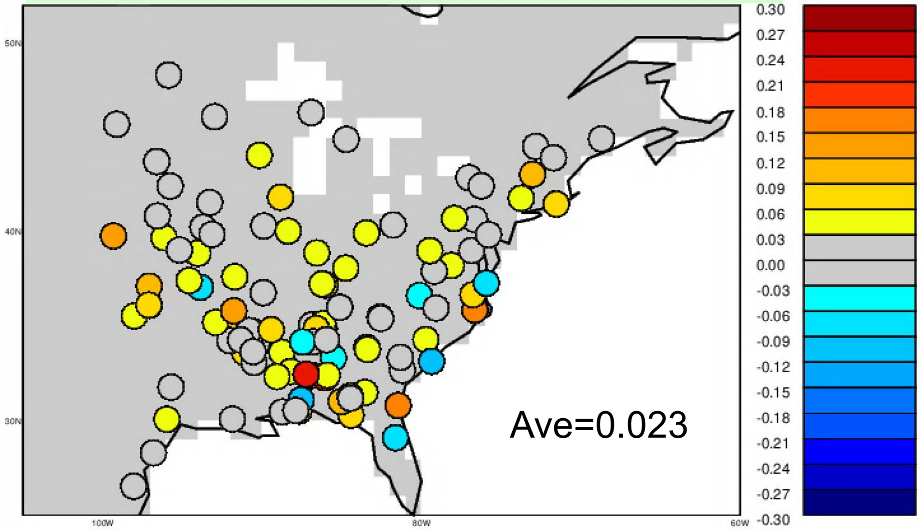
Modify land surface model: strengthen soil moisture stress function

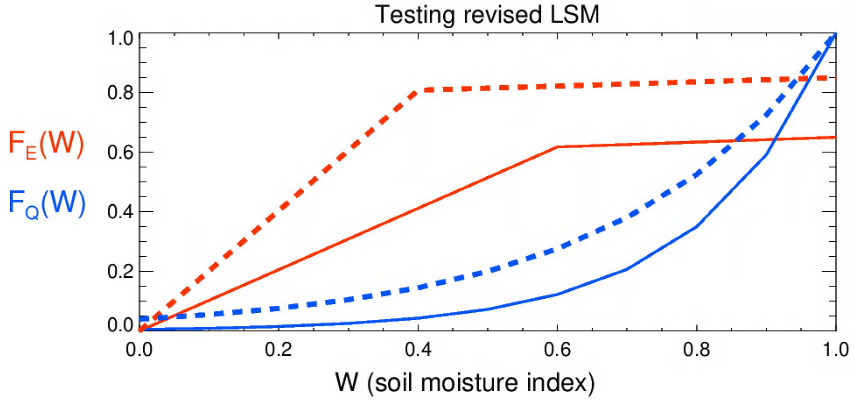
Offline forecast skill for soil moisture (R^2); revised model





Differences: Increase in skill due to model revision





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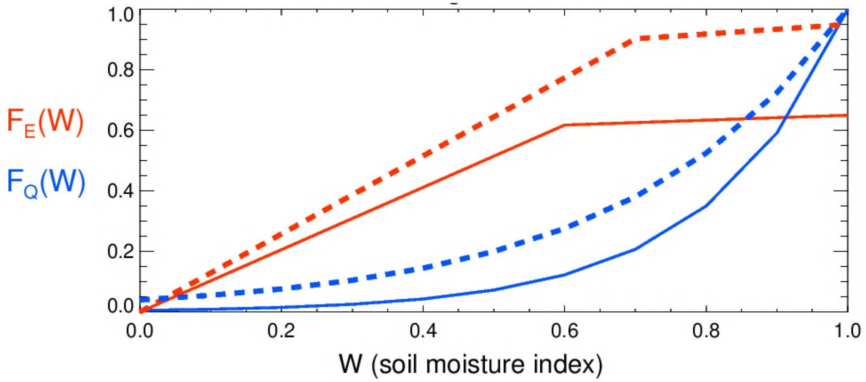

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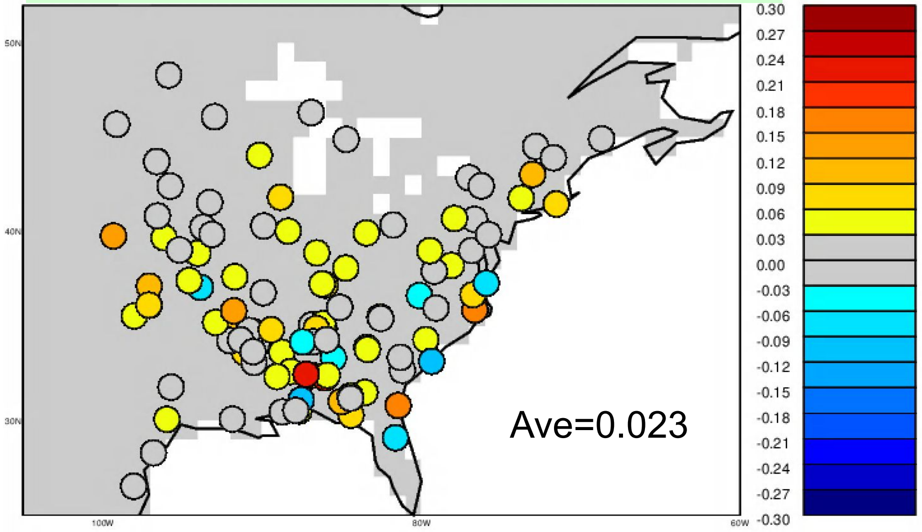
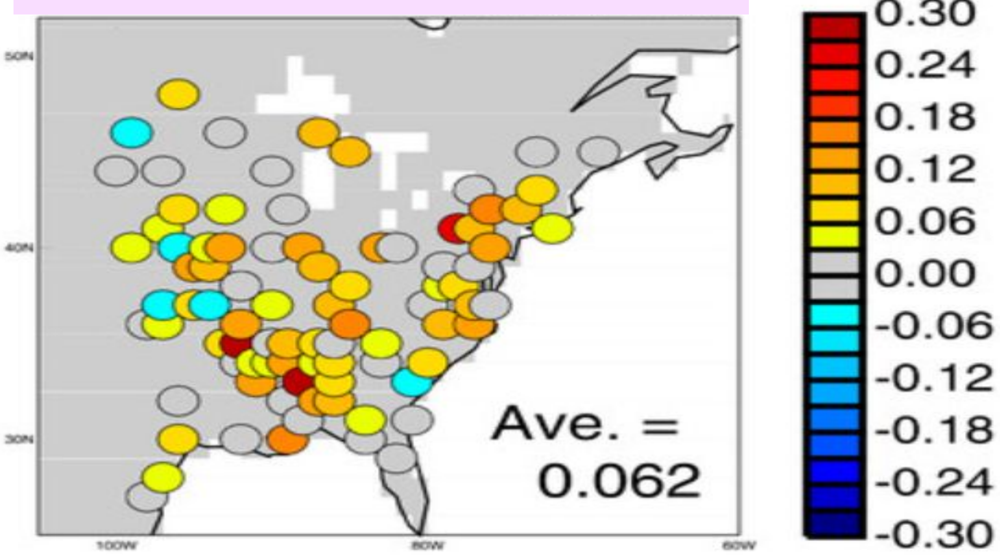


Potential increases in skill, based on “bare bones” analysis (from before)



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This experiment also led to a much-smaller-in-magnitude *degradation* of streamflow prediction skill. Overall, there was still an improvement in forecast hydrology

Again, this was only our first test…

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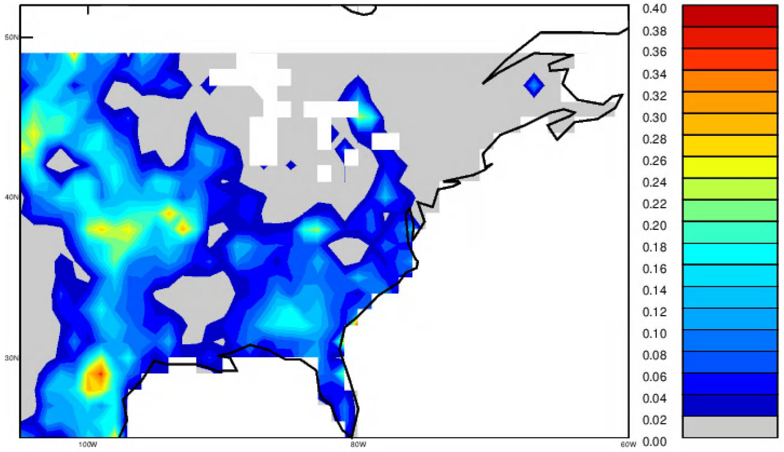
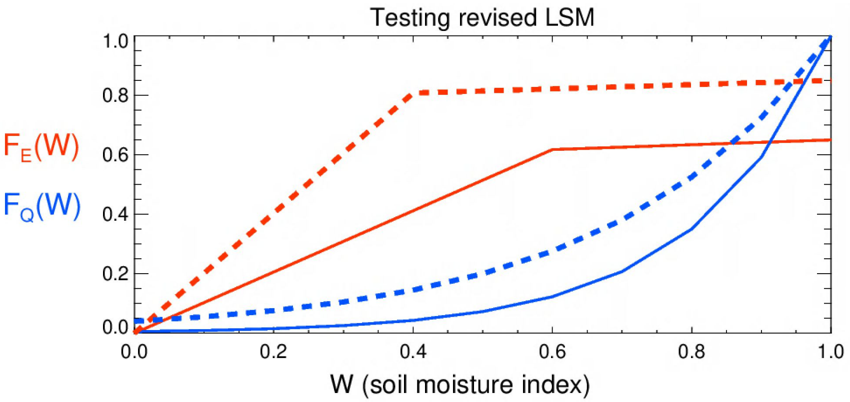
Again, this was only our first test…

Could the land model modification contribute to improved air temperature forecast skill, if it were put into the full S2S system? (i.e., allow land-atmosphere feedbacks?) We think so!

R^2 between negative of forecast ET and observed day-night T2M difference





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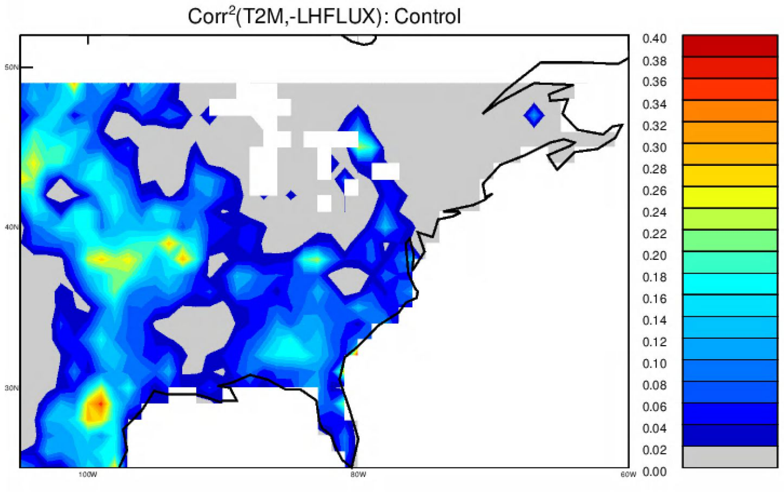
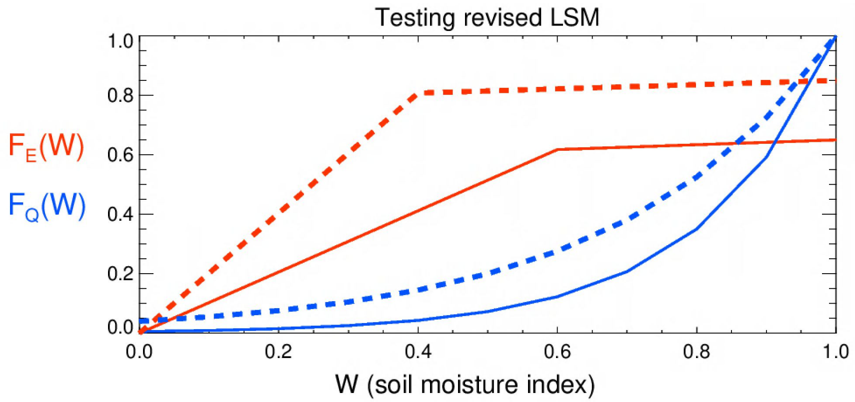
R^2 between negative of forecast ET and observed day-night T2M difference





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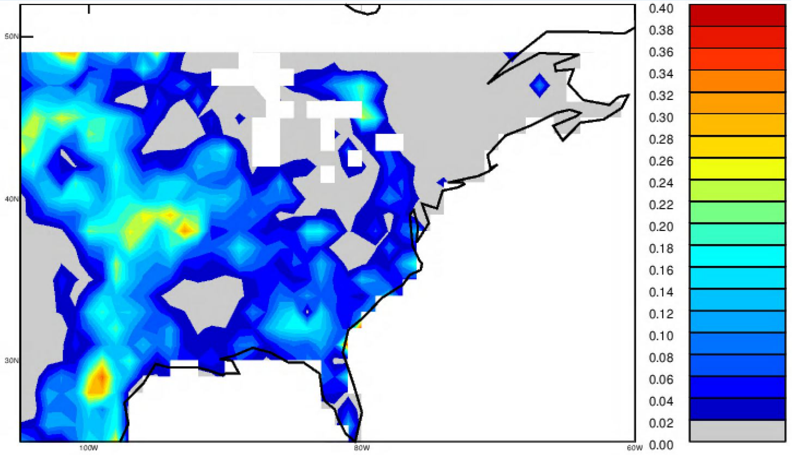
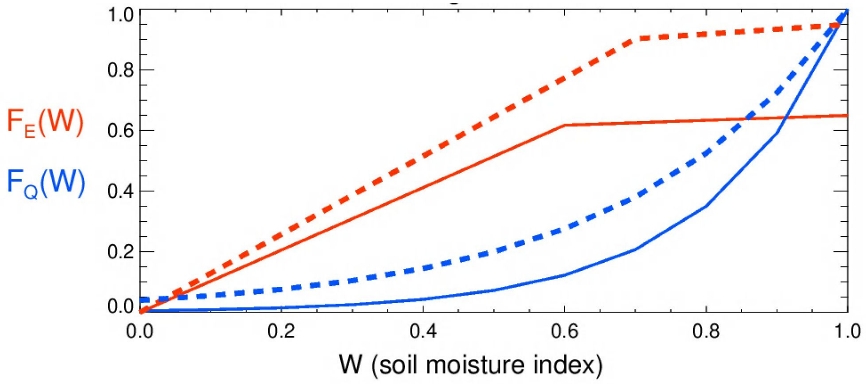
Modify land surface model: strengthen soil moisture stress function

Same, but using revised land model





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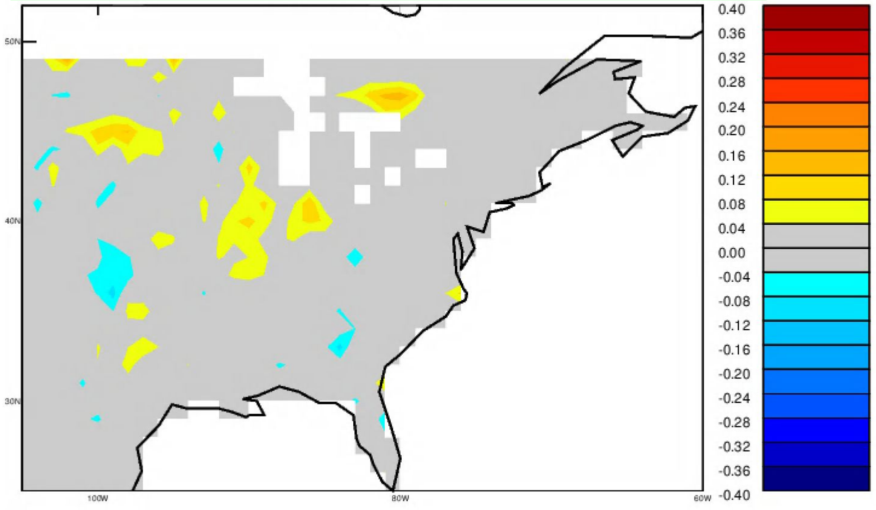

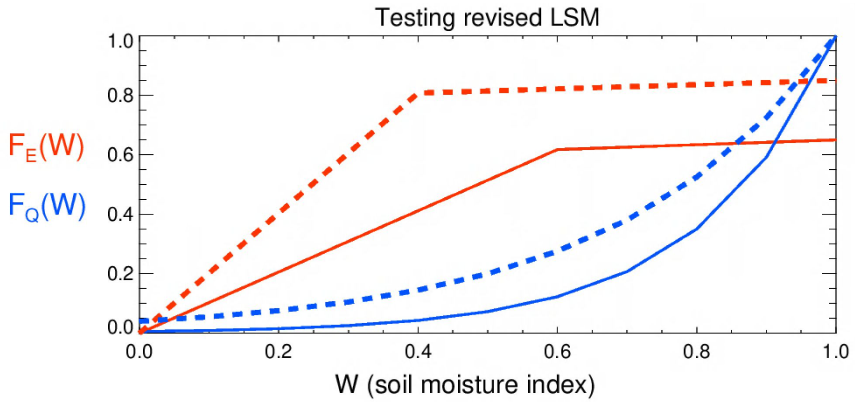

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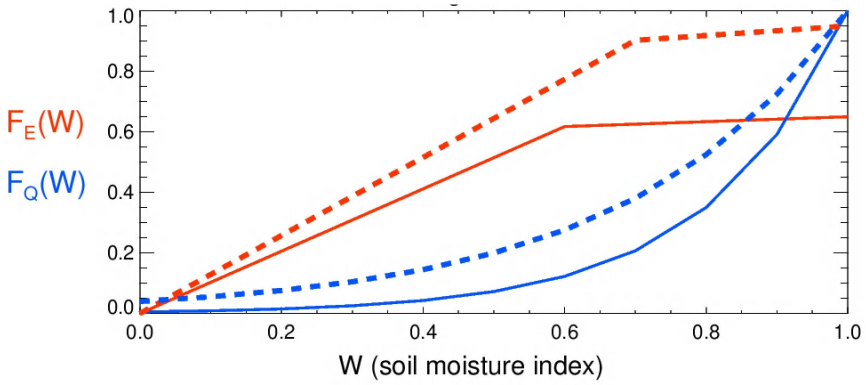
Modify land surface model: strengthen soil moisture stress function



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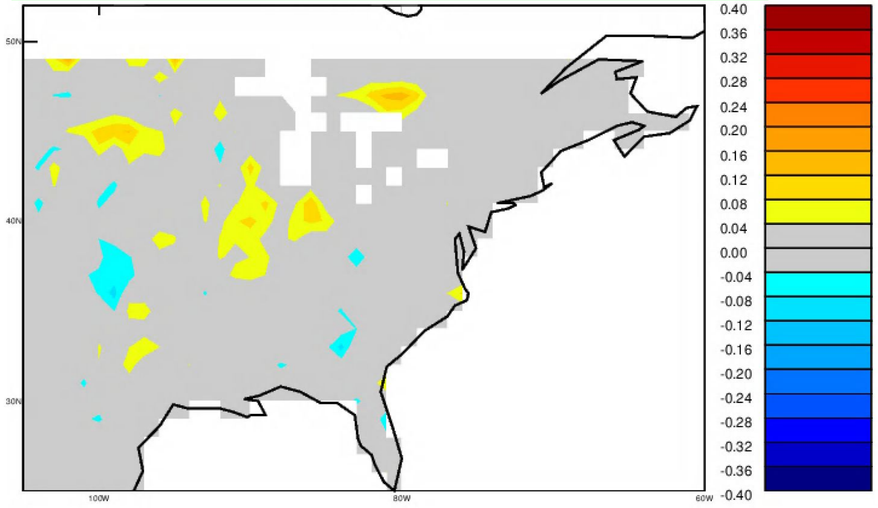
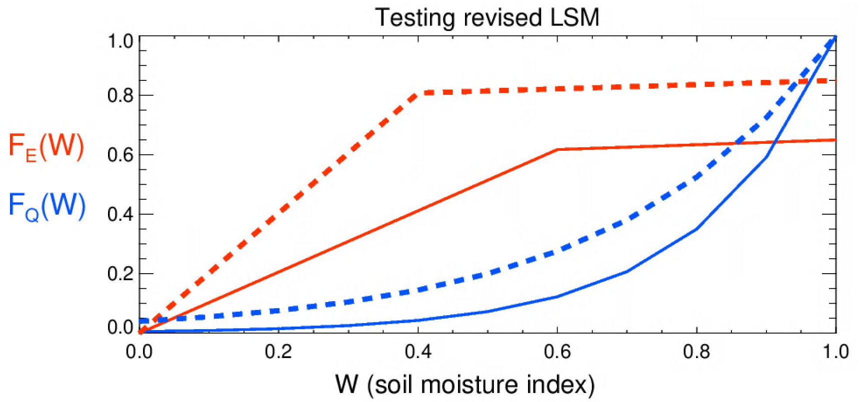


Far from conclusive – but maybe this is real! Maybe, through feedback, the land improvements would improve T2M forecasts!



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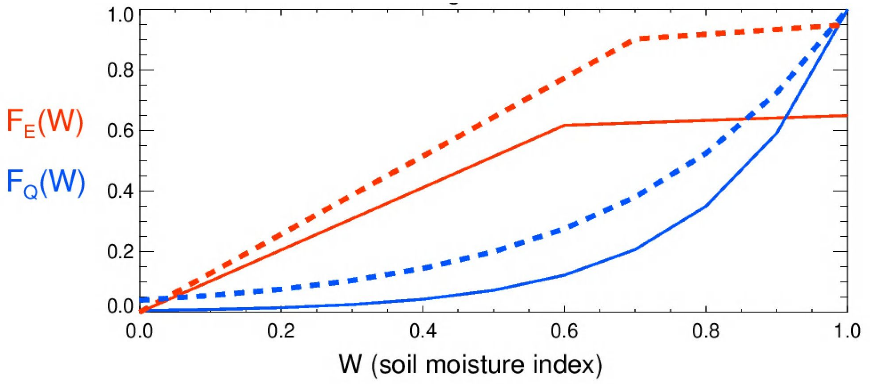

Summary

1. We performed a “bare bones” analysis with a simple water balance model to determine the ET efficiency and runoff efficiency curves that we should target for model development.

2. We have developed an offline forecast system that is driven by bias-corrected meteorological forcing from a full S2S system.

3. The offline forecast system is tractable enough for extensive hindcast experiments aimed at optimizing a land surface model for improved hydrological prediction – under the assumption that feedbacks to the atmosphere are of secondary importance (relative to land model structure) for things like soil moisture forecasts.

4. A first test of the system shows how a modification in the ET formulation does lead to expected, though small, improvements in soil moisture forecasts (anomaly R^2) at the subseasonal lead.

With these sets of curves in place, do a forecast analysis

Compare warm season (May – September) offline (land-only) subseasonal forecasts of streamflow and soil moisture (at 11-20 day lead) to independent in-situ observations at a collection of measurement sites across the eastern continental US:

Two forecast experiments:

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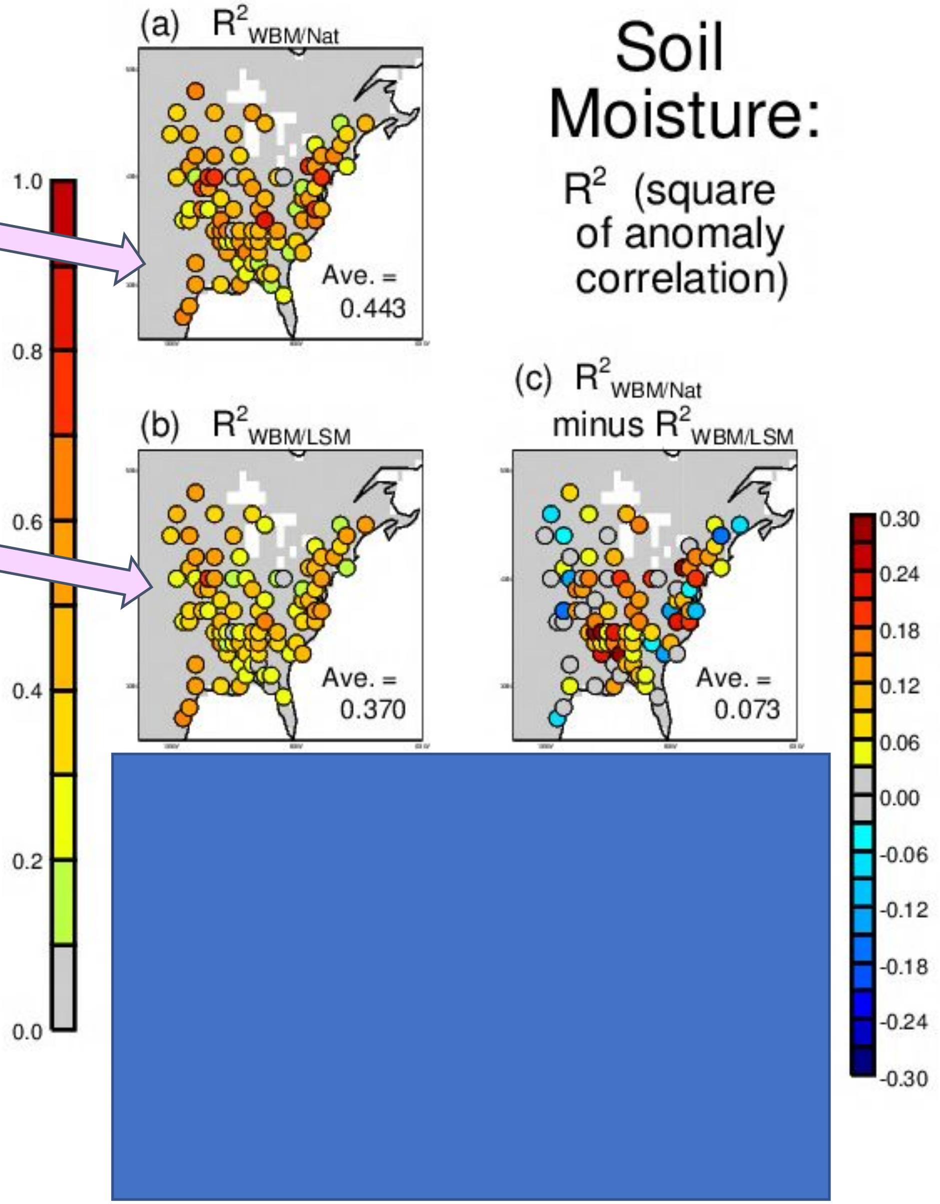
For full details on experimental design and more results, see:

doi:10.1175/JHM-D-22-0050.1

Skill (R^2 vs obs.) assuming <u>"perfect" meteorological forecasts</u> – basically, the skill of a hydrological simulation with observed forcing.

WBM fit to Nature

WBM fit to Catchment LSM



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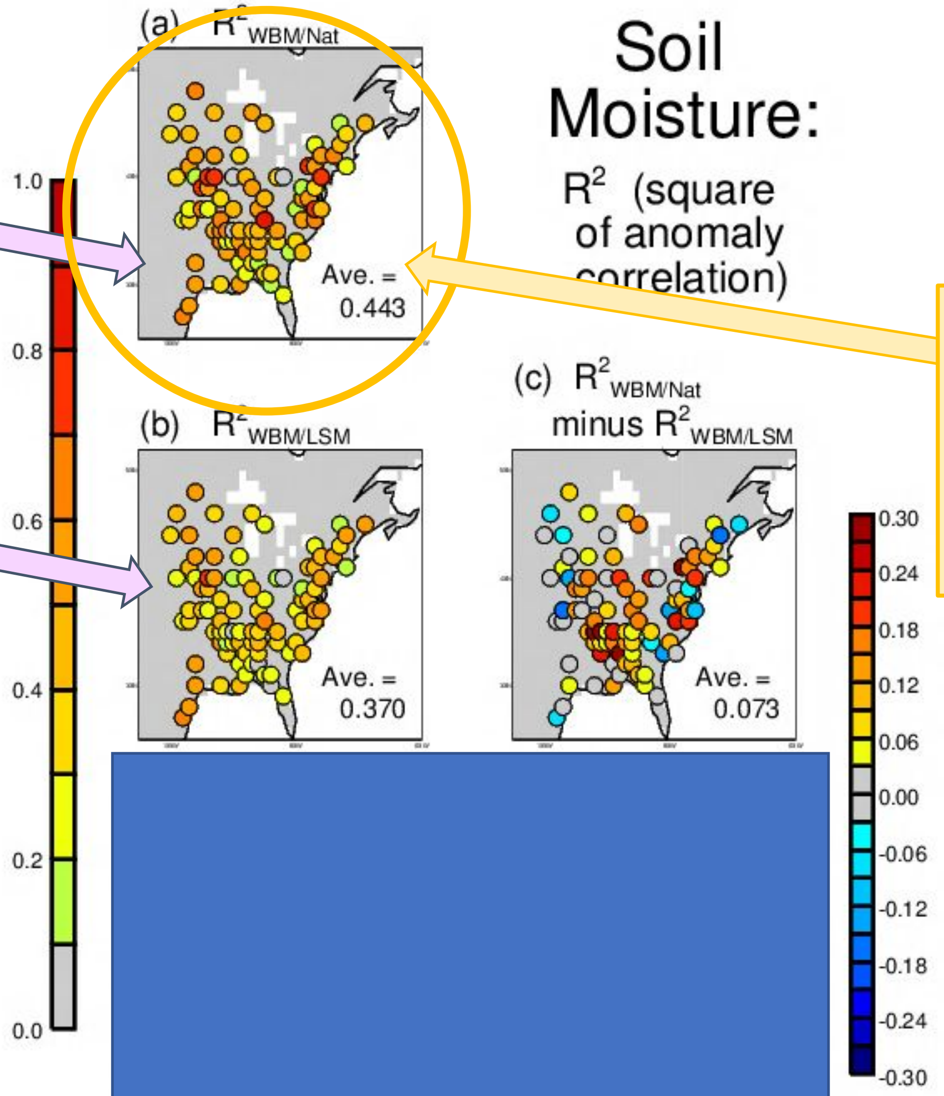

Soil Moisture:

R^2 (square of anomaly correlation)

Using Nature's curves works better than using the LSM's curves.

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WBM fit to Nature

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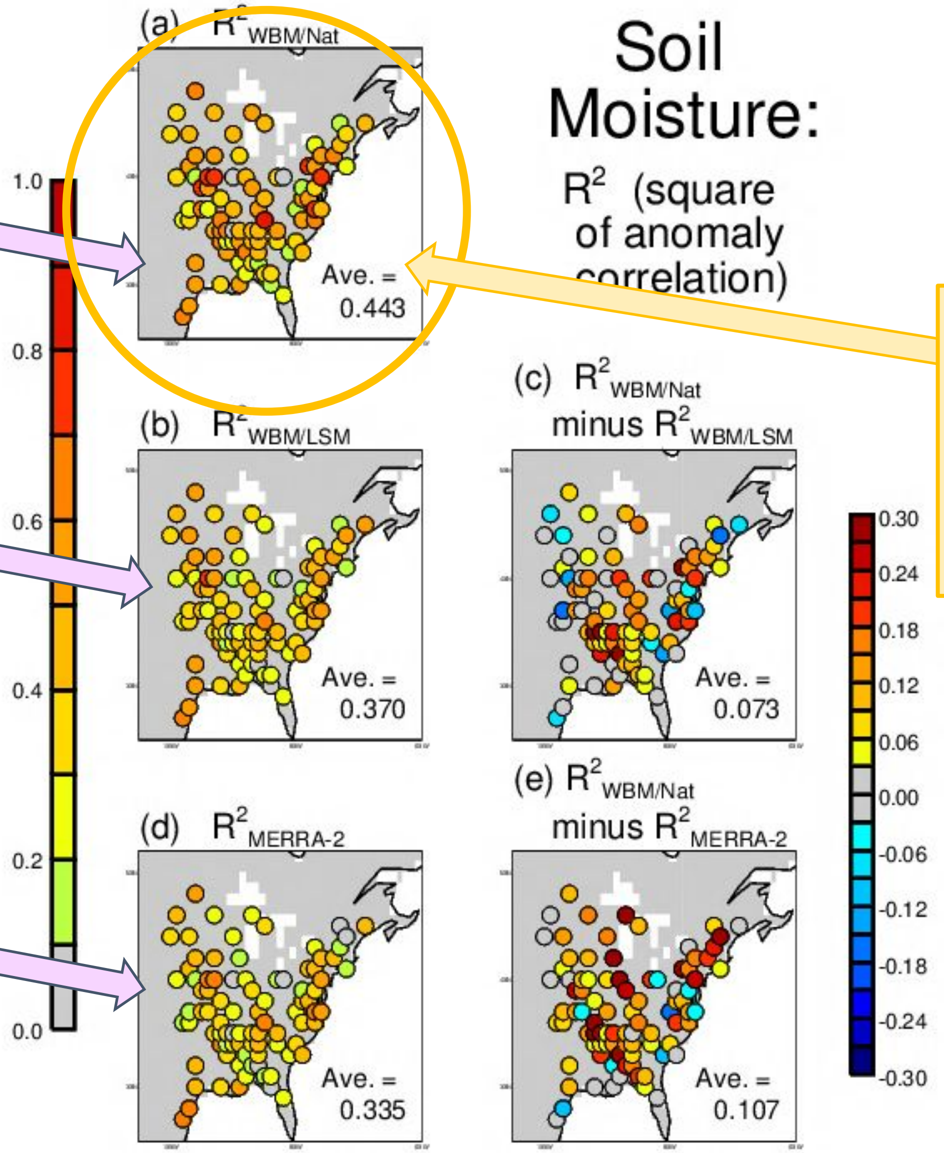
MERRA-2 skill (using full Catchment LSM



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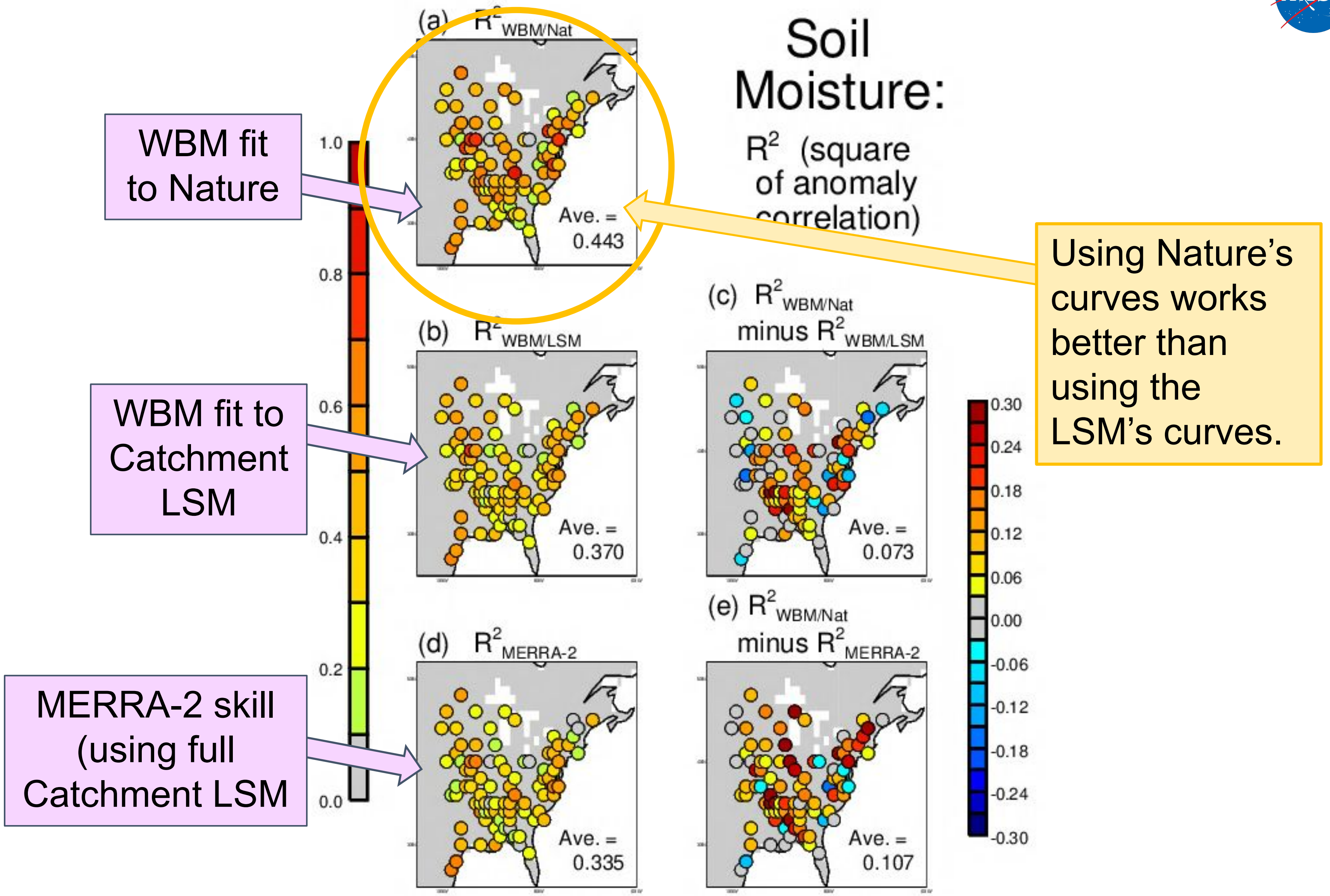
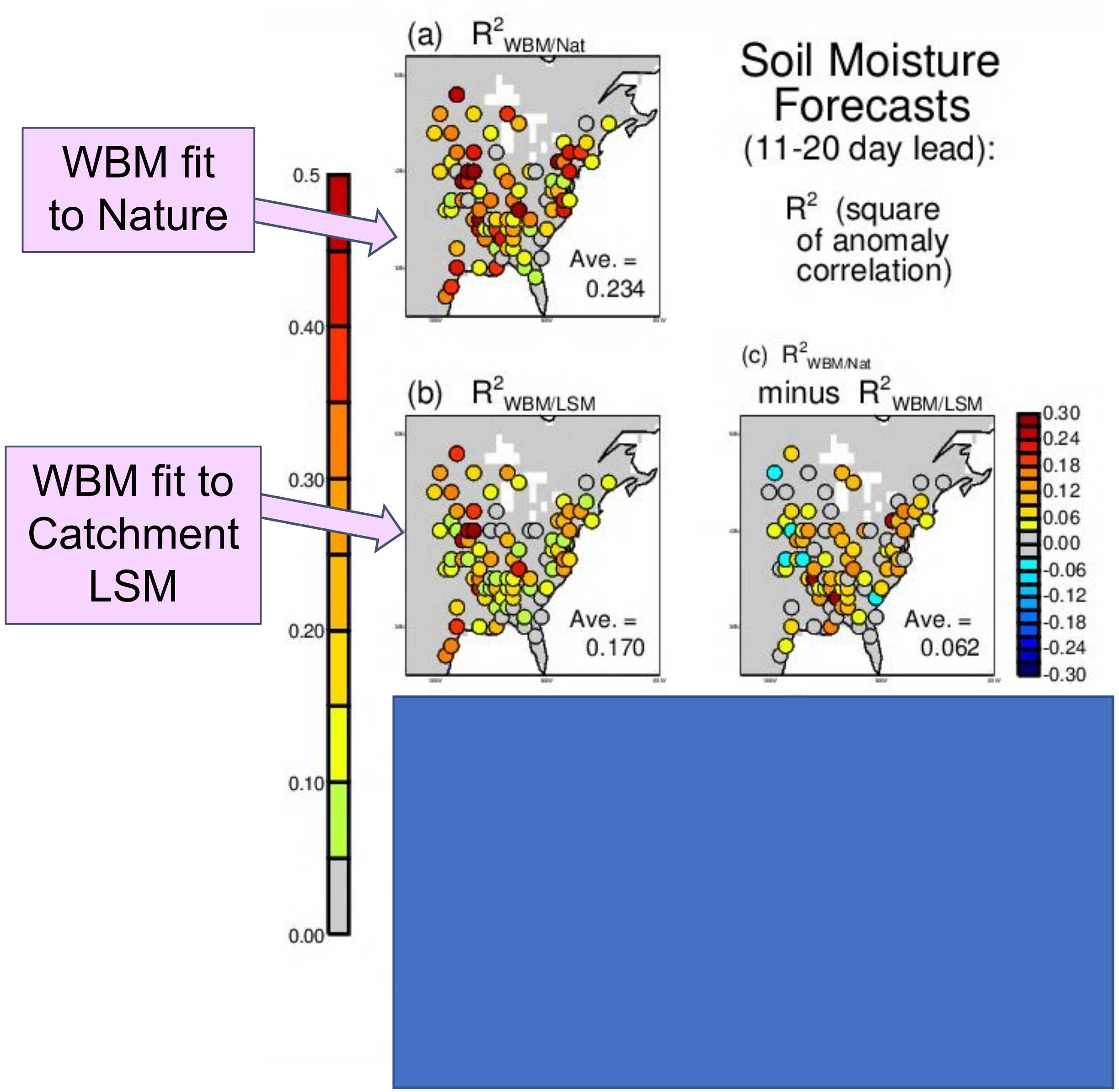


Results for streamflow are similar!

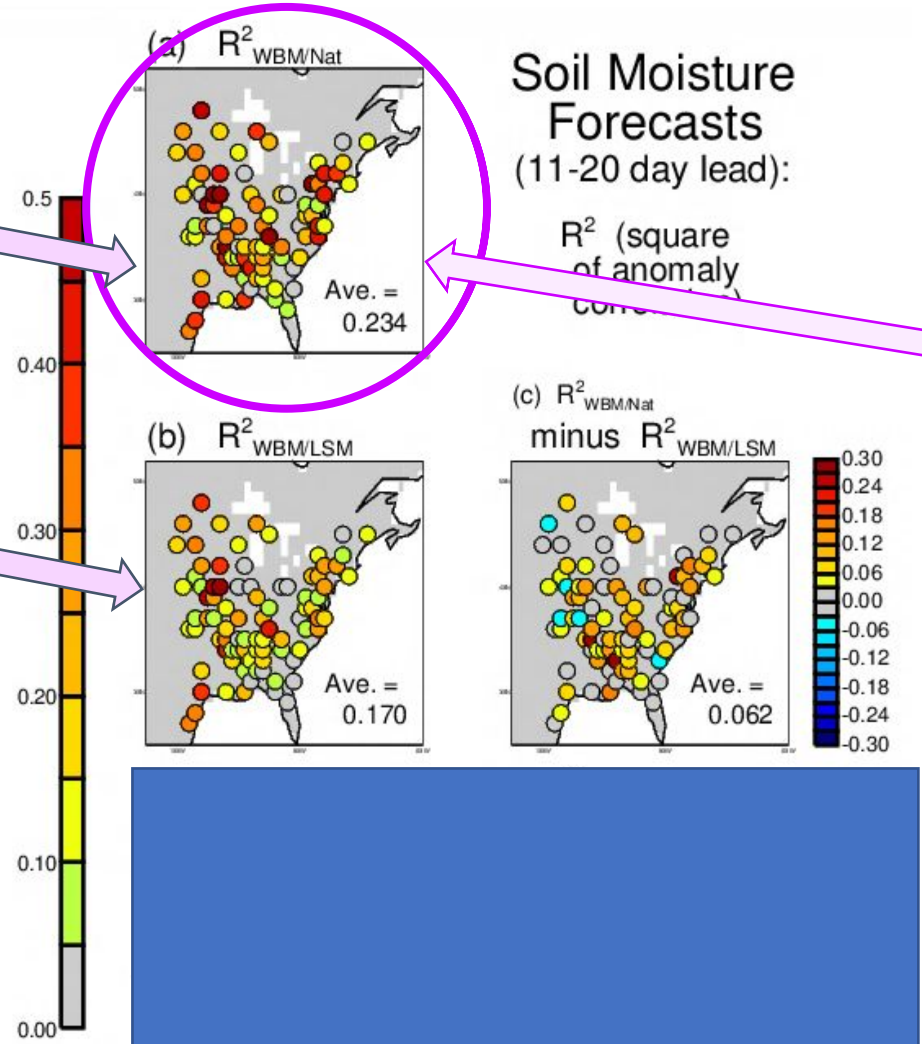
Skill (R^2 vs obs.) assuming <u>zero-skill meteorological forecasts</u> <u>(</u>climatological P, R_{net} during the forecast period)



Skill (R^2 vs obs.) assuming [zero-skill meteorological forecasts](#) (climatological P, R_{net} during the forecast period)

WBM fit to Nature

WBM fit to Catchment LSM



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Skill (R^2 vs obs.) assuming ***zero-skill meteorological forecasts*** *(climatological P, R_{net} during the forecast period)*

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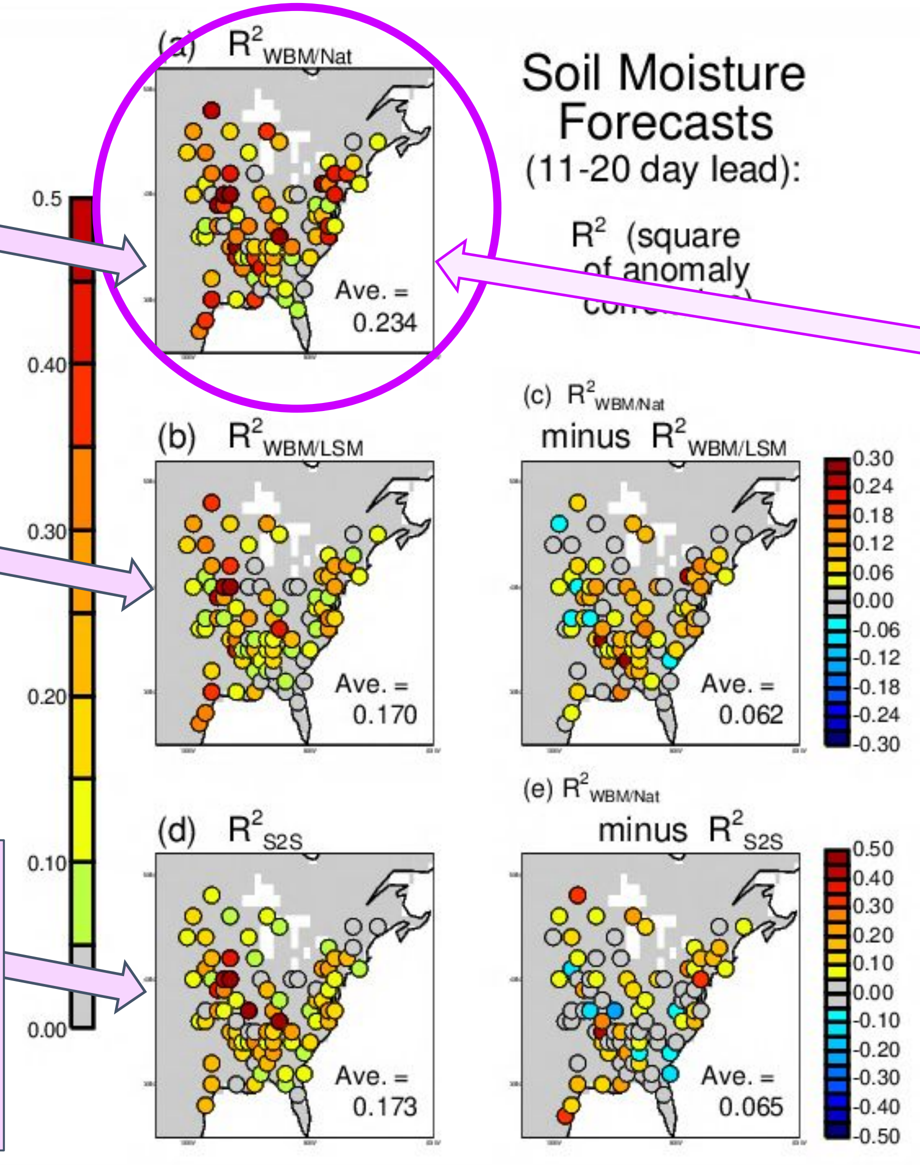
GMAO S2S forecast system skill (using full Catchment LSM and actual met forecasts)



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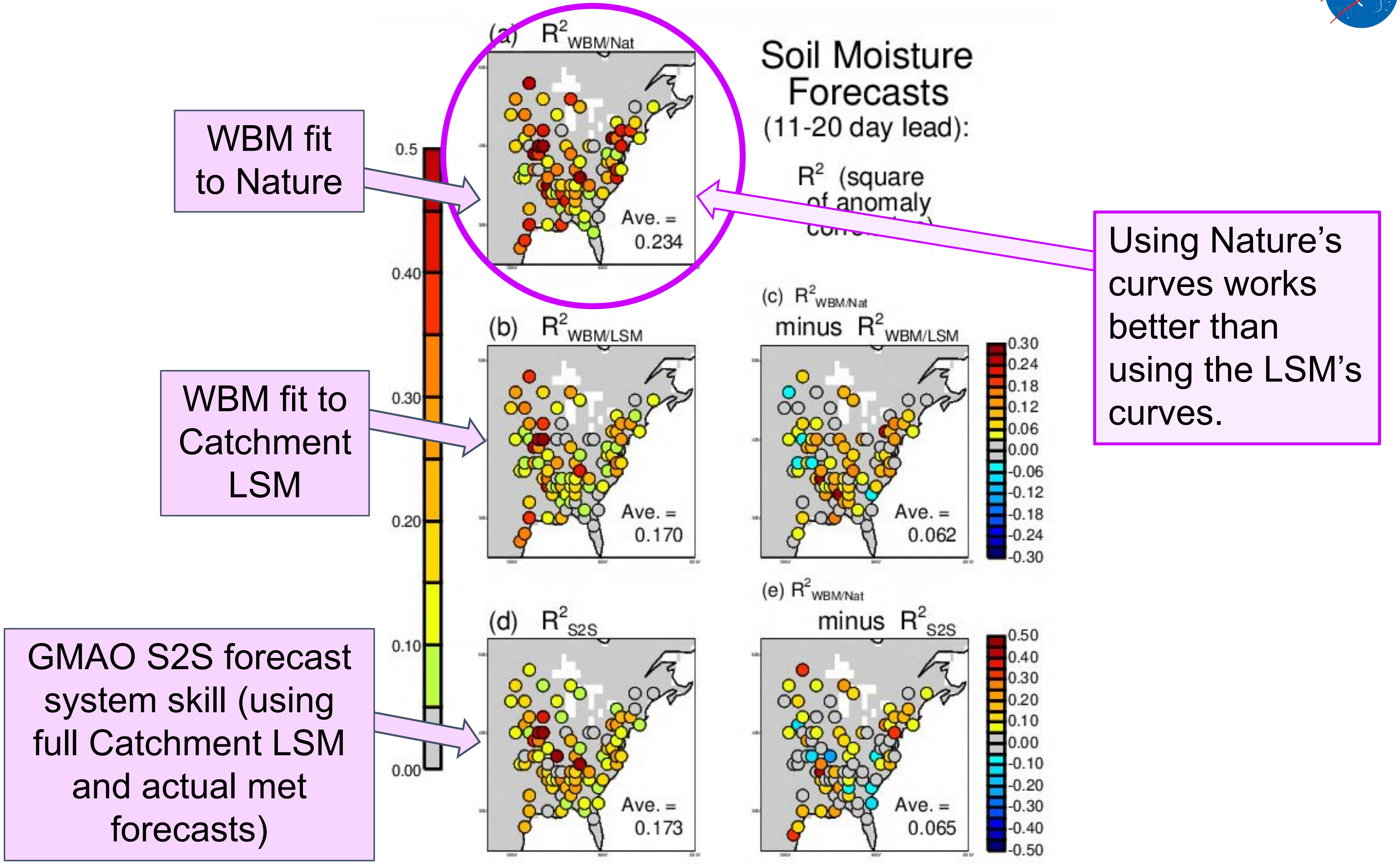


Approach: Examine problem with a “bare bones” representation of a land surface model.

Bare-bones representation: the "WBM", based on water balance equation

Soil profile water holding capacity

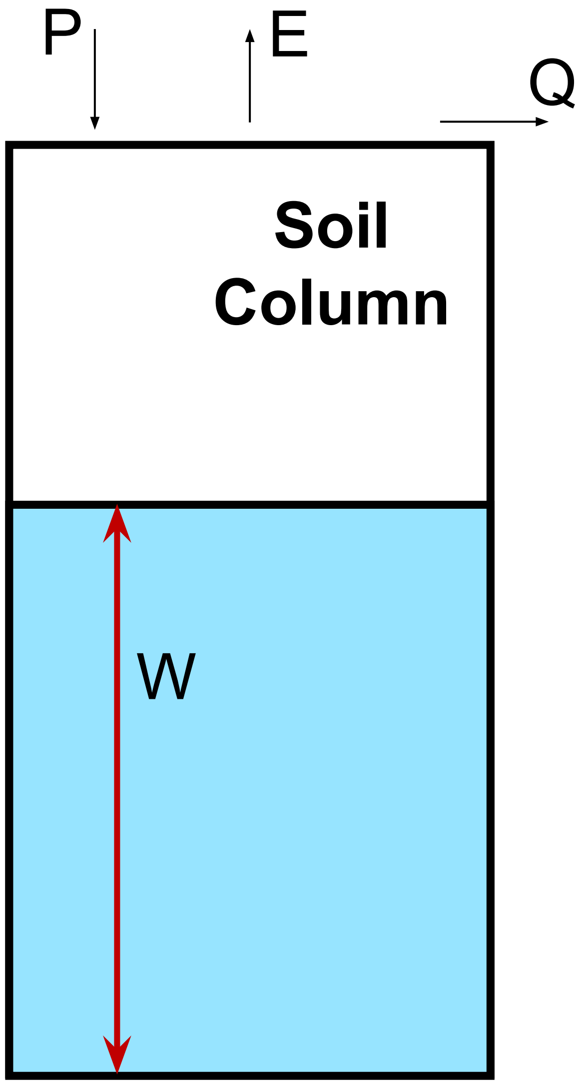
Precipitation

Evapotranspiration

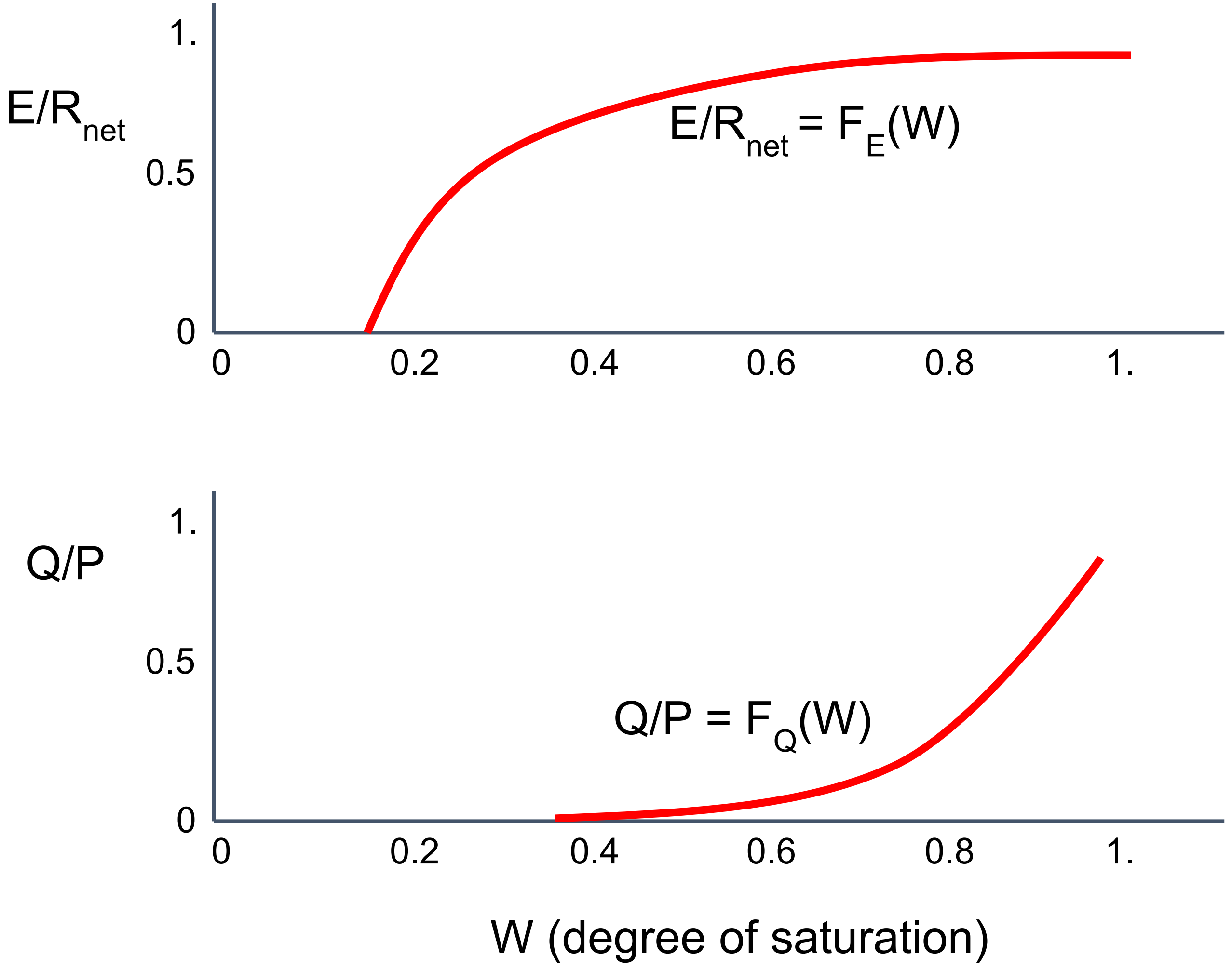
$$C\,W_{n+1} = C\,W_n + P_n - E_n - Q_n,$$

Total runoff

Soil moisture at start of day n (degree of saturation)

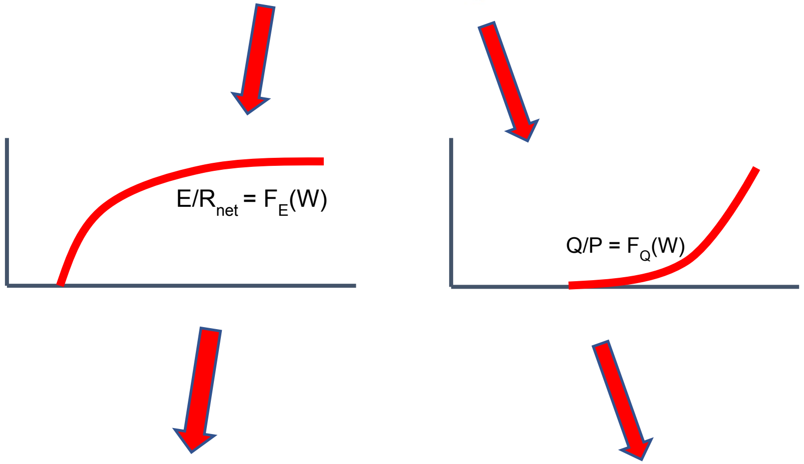


We can impose simple relationships between W and both E and Q:



 Replace

$$C\ W_{n+1} = C\ W_n + P_n - E_n - Q_n$$



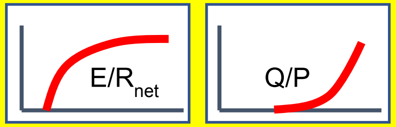
with

$$C\ W_{n+1} = C\ W_n + P_n - F_E(W_n)\ R_{net\text{-}n} - F_Q(W_n)\ P_n$$

This, in a nutshell, is the bare-bones representation.

Time series of meteorological forcing (rainfall, radiation, etc.)

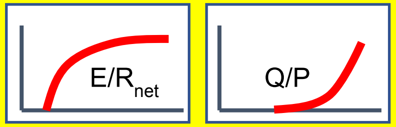
WBM: bare-bones representation of LSM



Time series of hydrological variables (streamflow, soil moisture)

Time series of meteorological forcing (rainfall, radiation, etc.)

WBM: bare-bones representation of LSM



Time series of hydrological variables (streamflow, soil moisture)

Time series of meteorological forcing (rainfall, radiation, etc.)

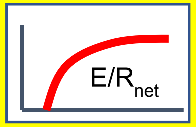
Full LSM

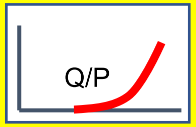
Time series of hydrological variables (streamflow, soil moisture)

Can we calibrate the WBM curves so that this…

Time series of meteorological forcing (rainfall, radiation, etc.)

WBM: bare-bones representation of LSM





Time series of hydrological variables (streamflow, soil moisture)

…looks like this?

Time series of meteorological forcing (rainfall, radiation, etc.)

Full LSM

Time series of hydrological variables (streamflow, soil moisture)

With these sets of curves in place, do a forecast analysis

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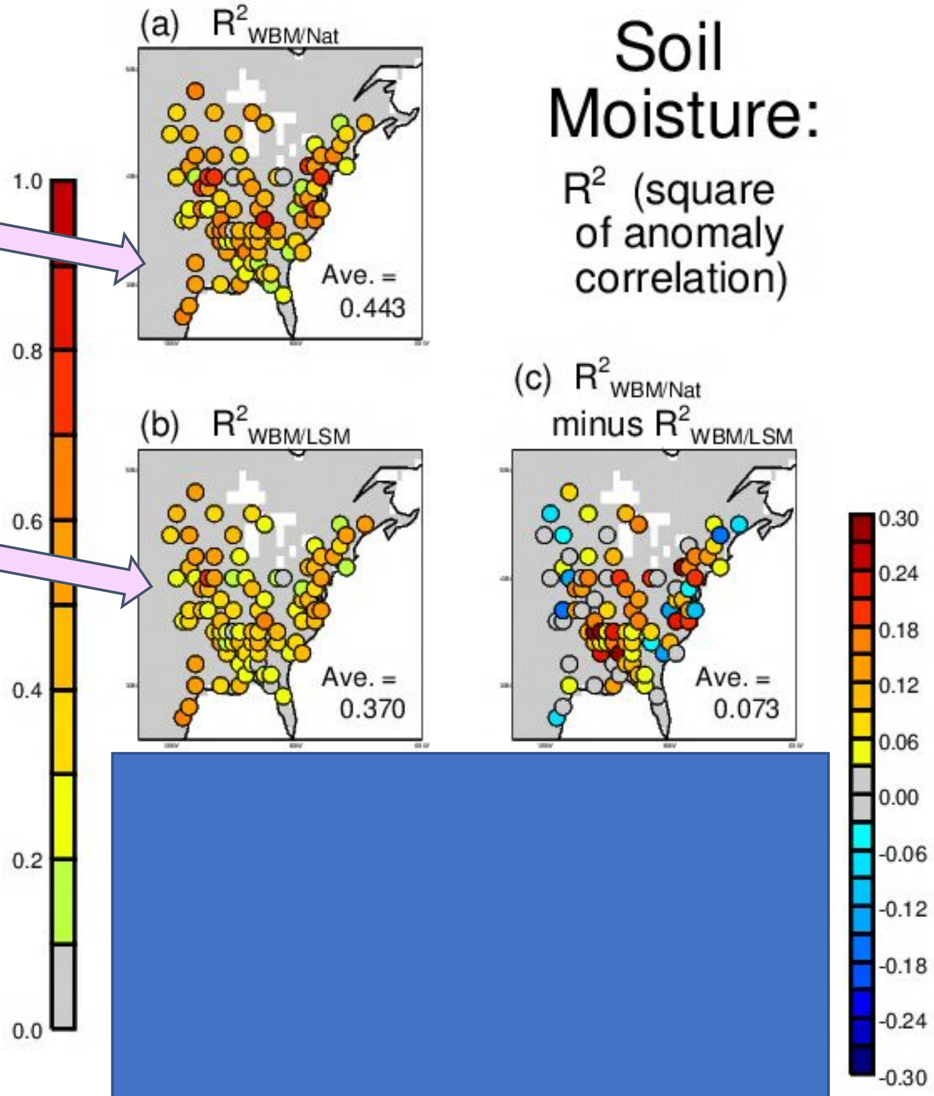

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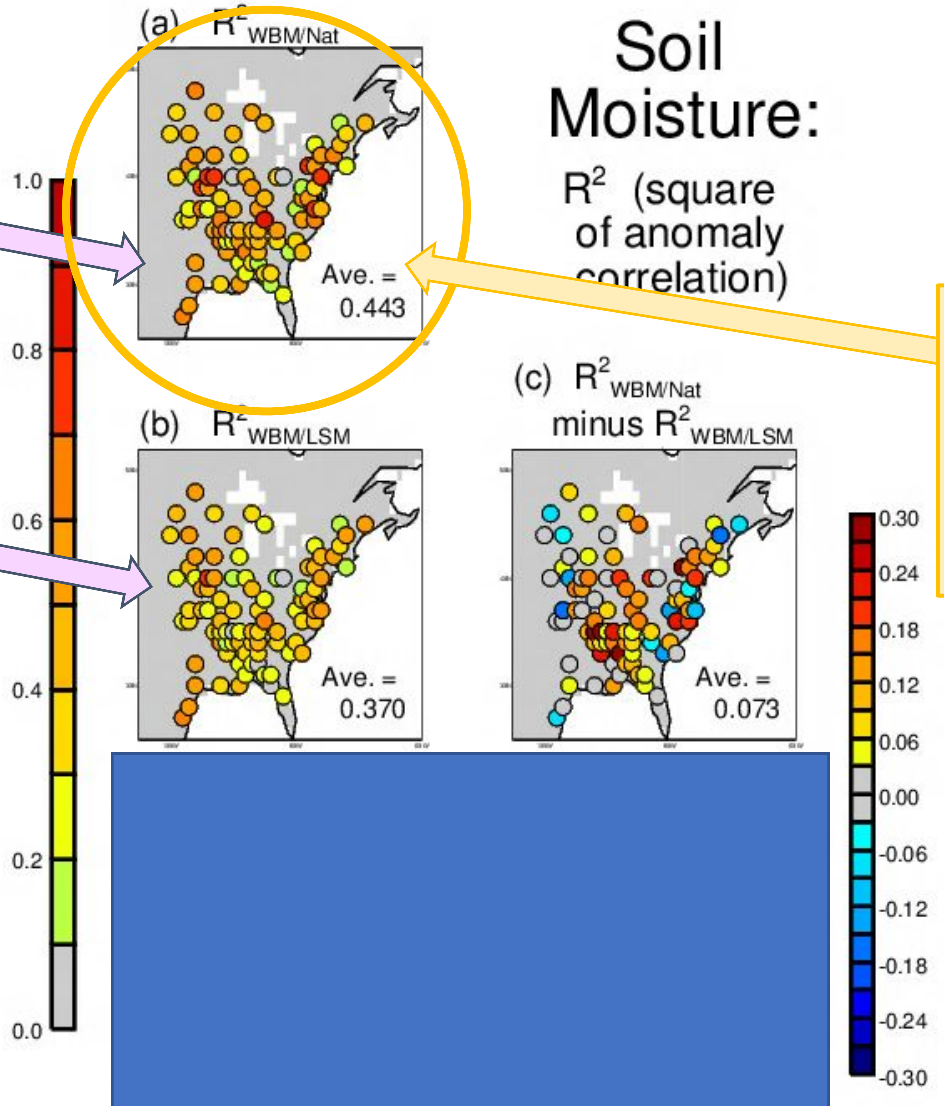

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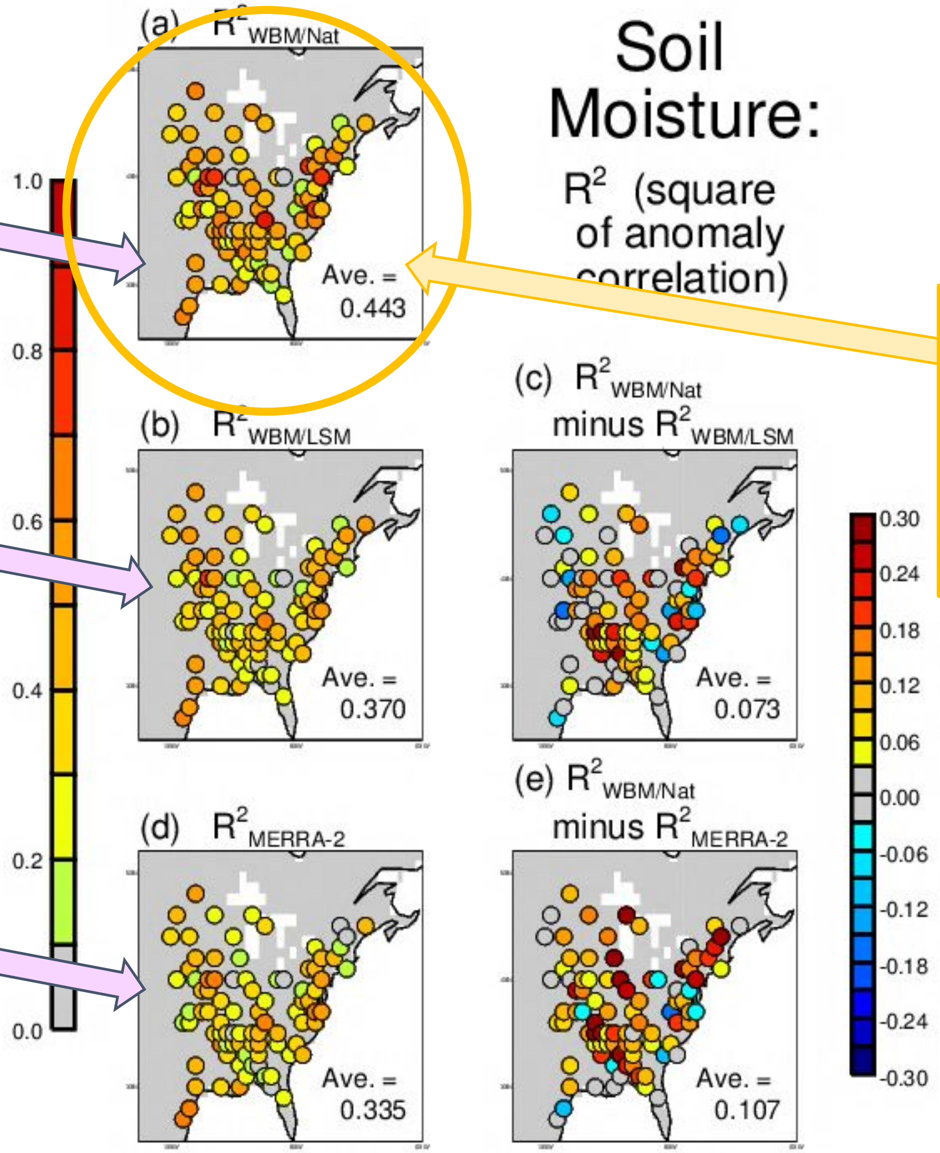

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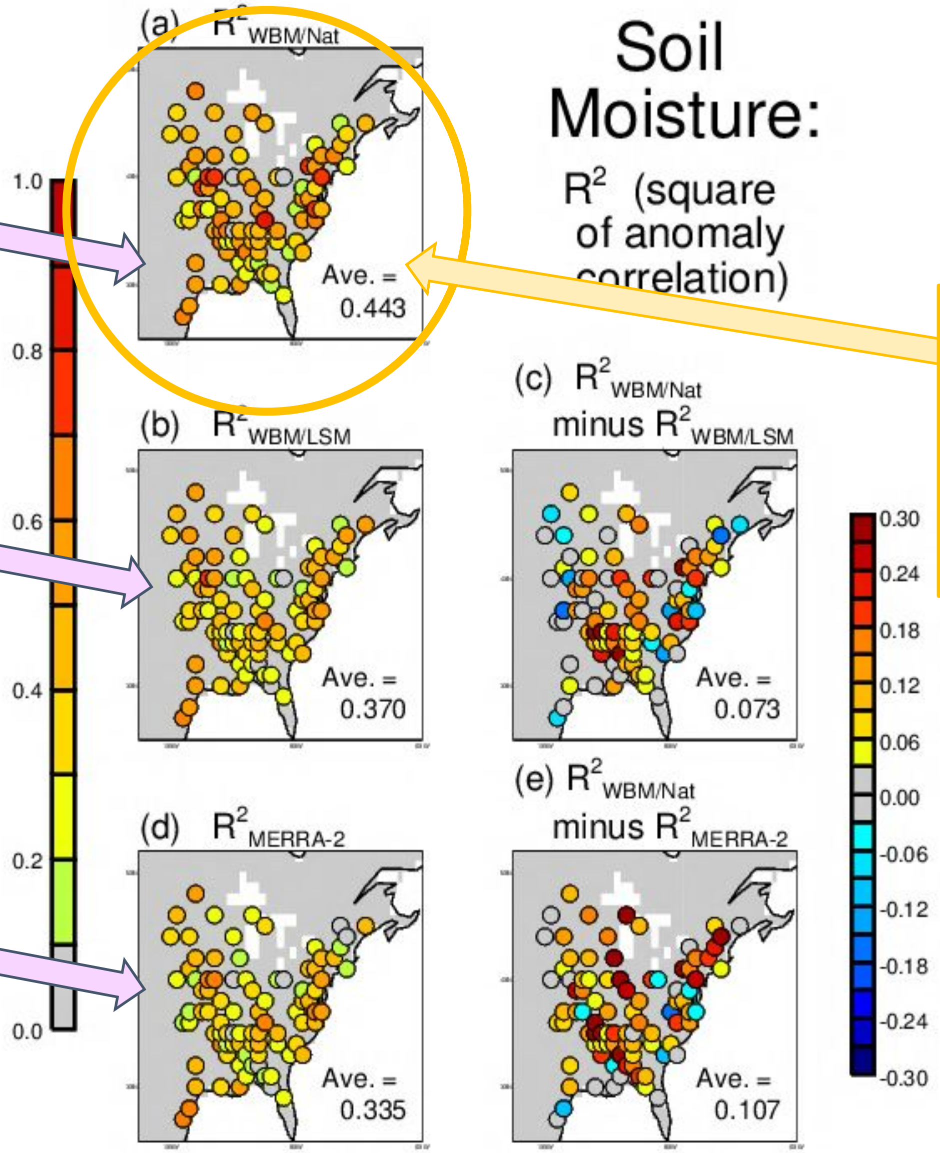

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Results for streamflow are similar!

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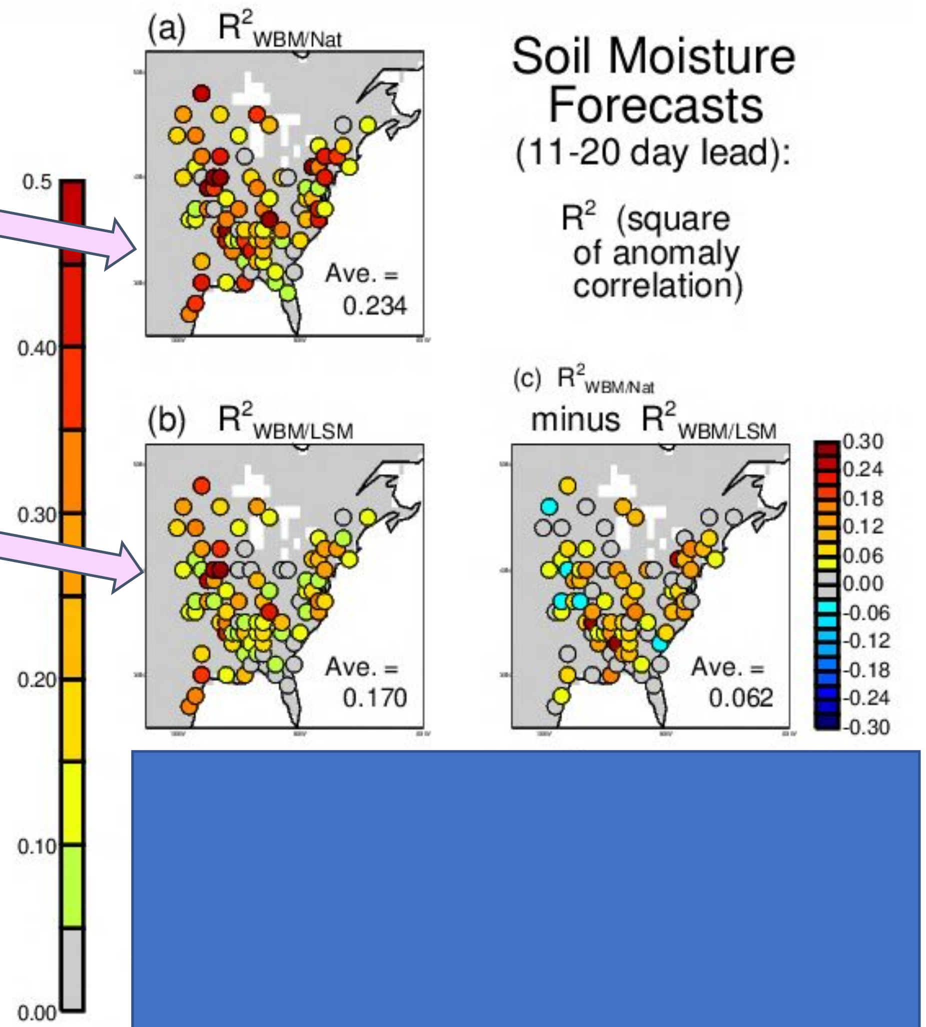

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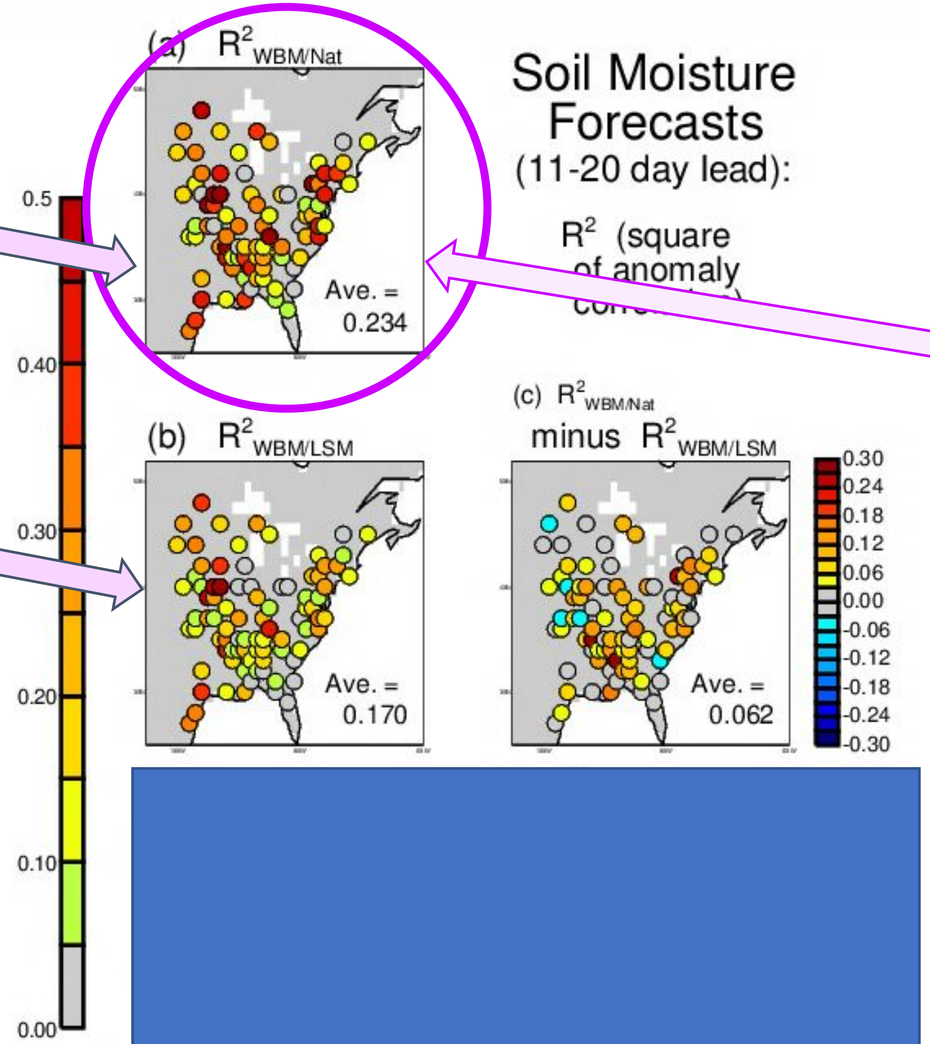

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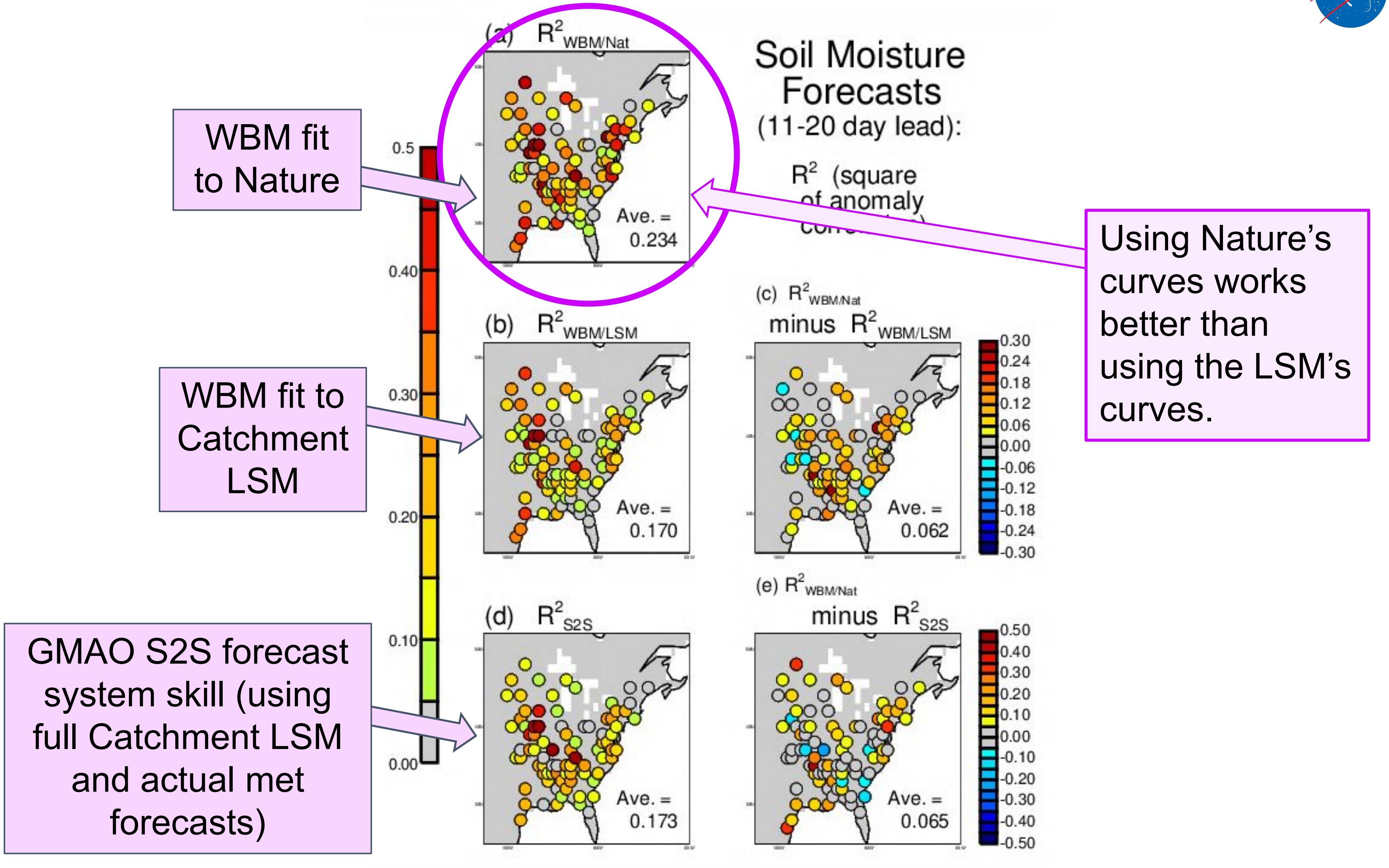

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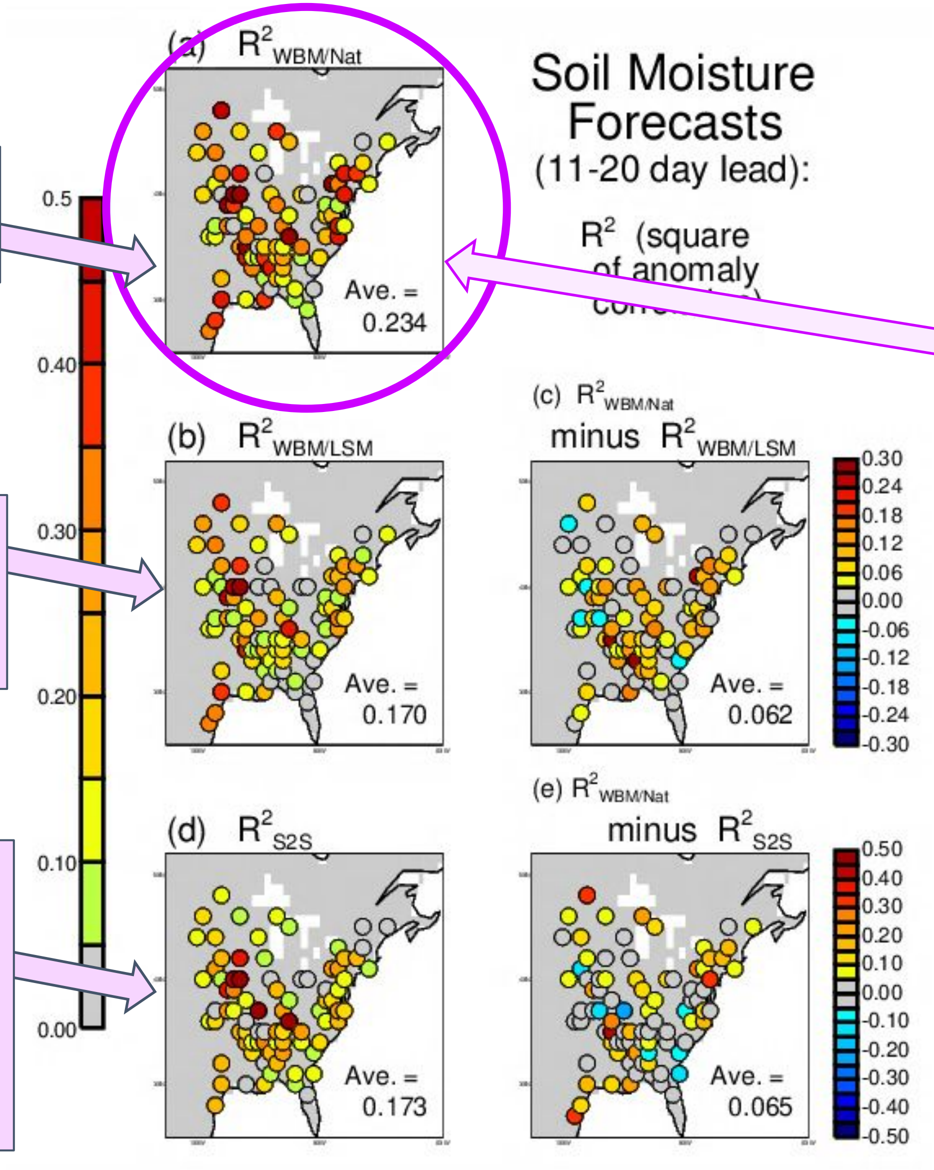
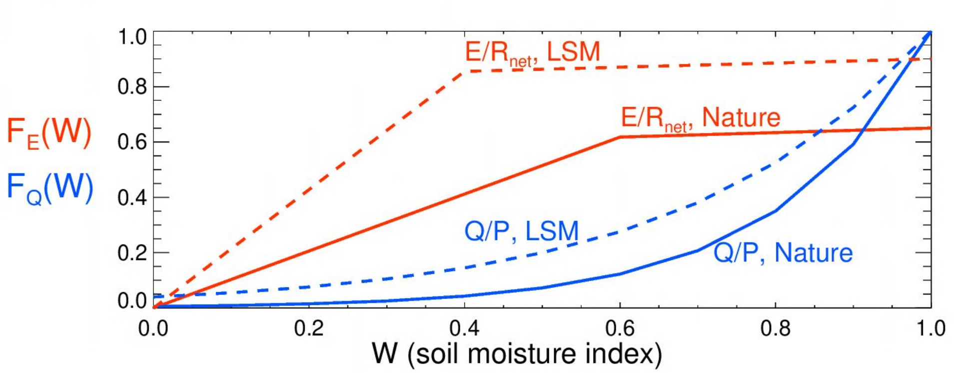


Using Nature's curves works better than using the LSM's curves.

Results for streamflow are similar!

Implications of all this:

- As illustrated here and in past work, an LSM's implicit E/R_{net} vs. W and Q/P vs. W relationships control, to first order, its hydrological behavior.
- An LSM's relationships may be sub-optimal.



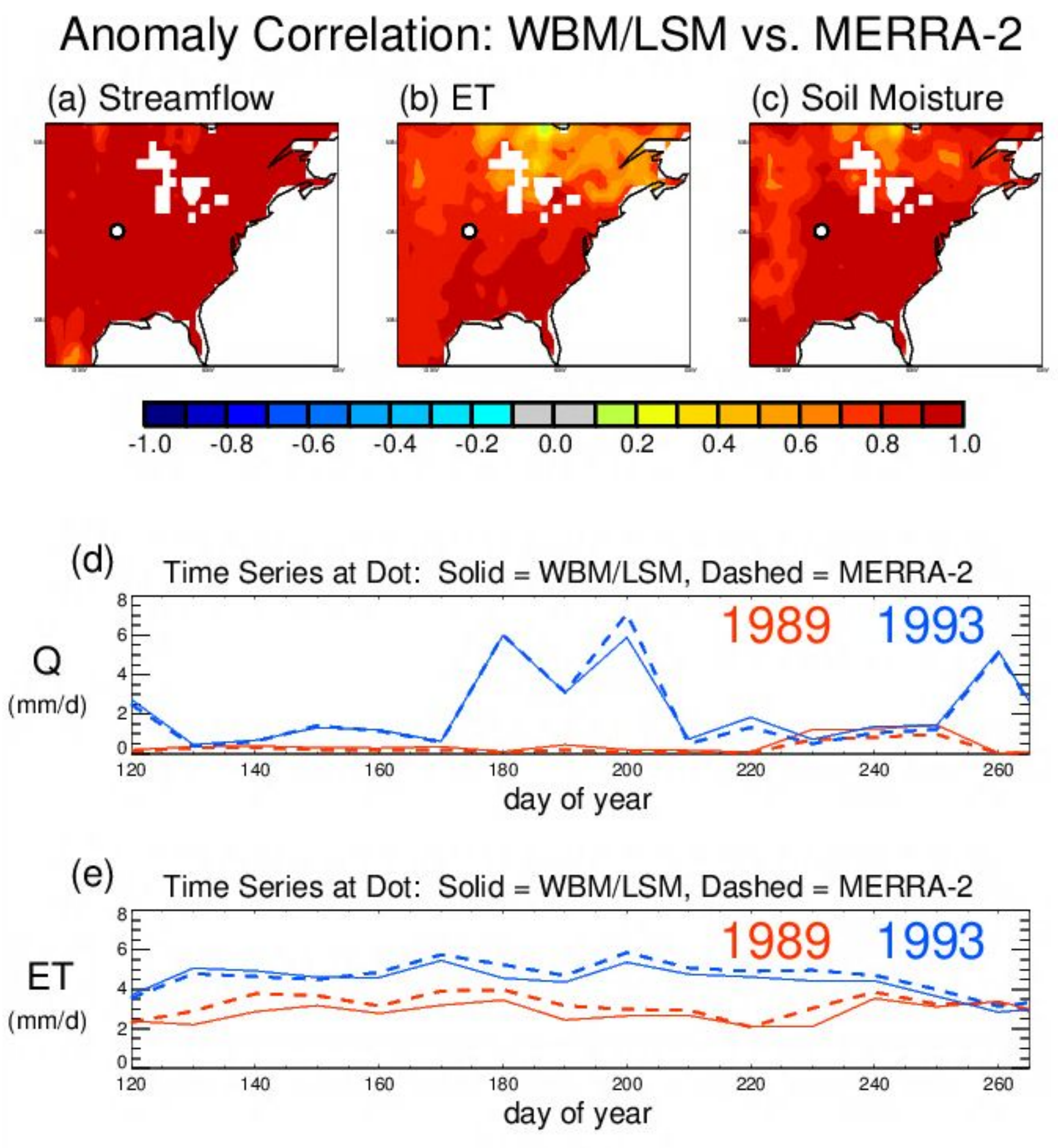
Again, see:
doi:10.1175/JHM-D-22-0050.1

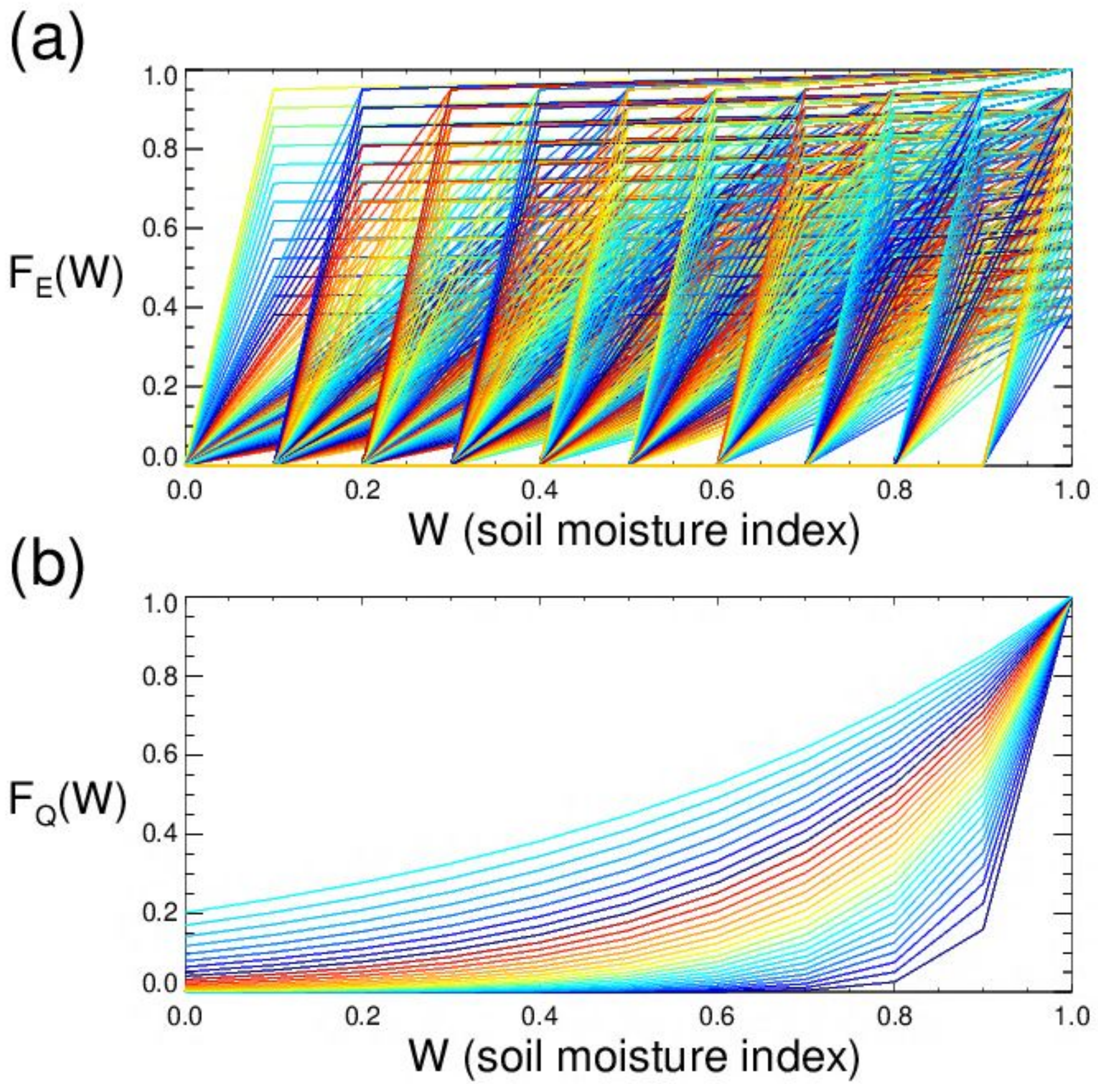
- Calibrating the LSM's parameterizations to bring the relationships more in line with "Nature's curves" should lead to improved performance in subseasonal hydrological forecasting.
- Important side note: the WBM could never replace a full LSM in a complex reanalysis or forecast system given other important roles played by the LSM.

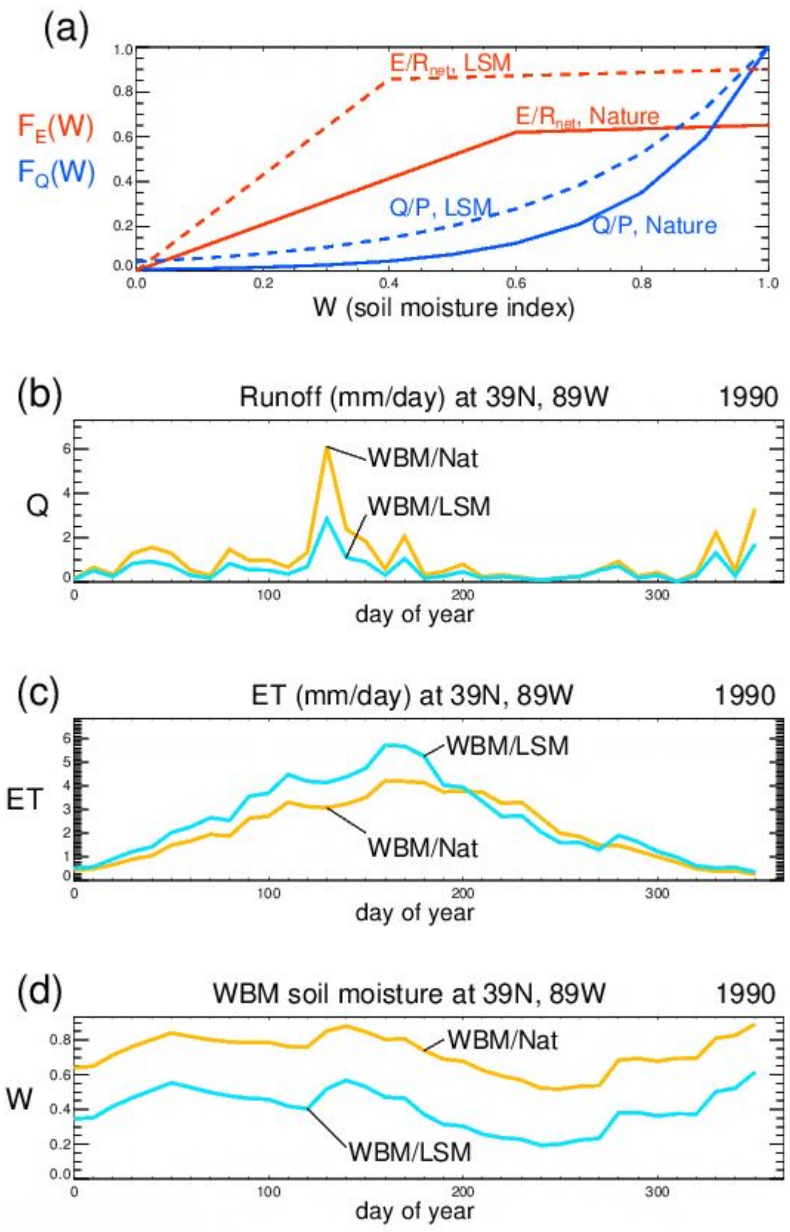
High anomaly correlations between the bare-bones representation (the “WBM”) and the full Catchment LSM as used in MERRA-2

Sample time series comparisons

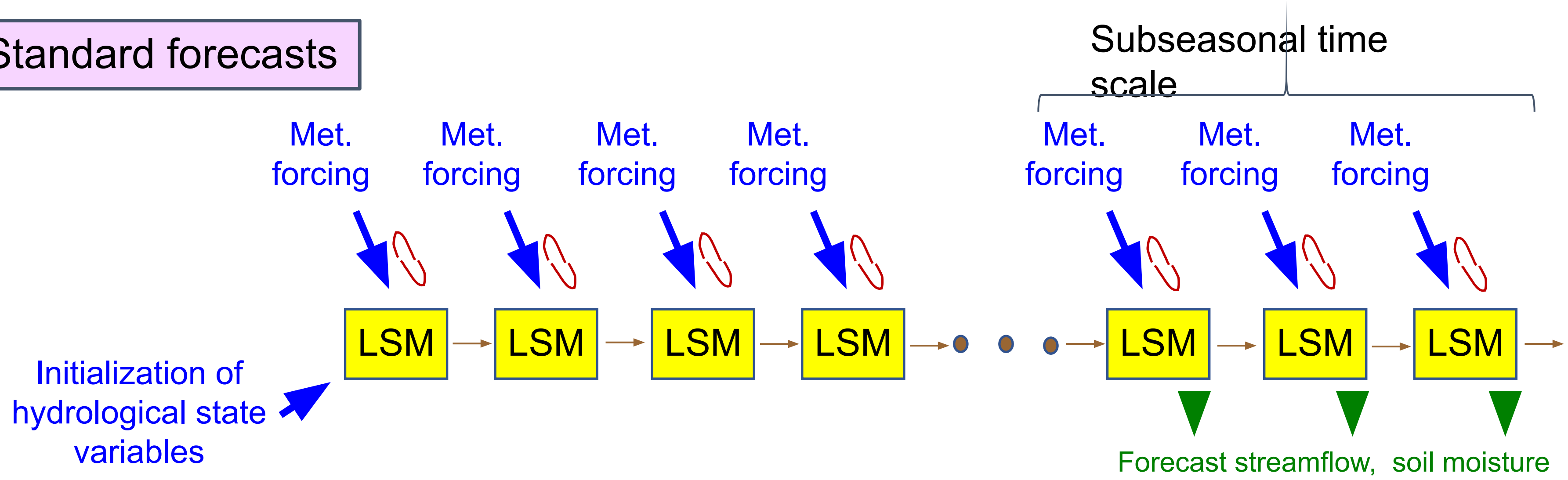
The bare-bones representation <u>does</u> capture the hydrological behavior of the full LSM!



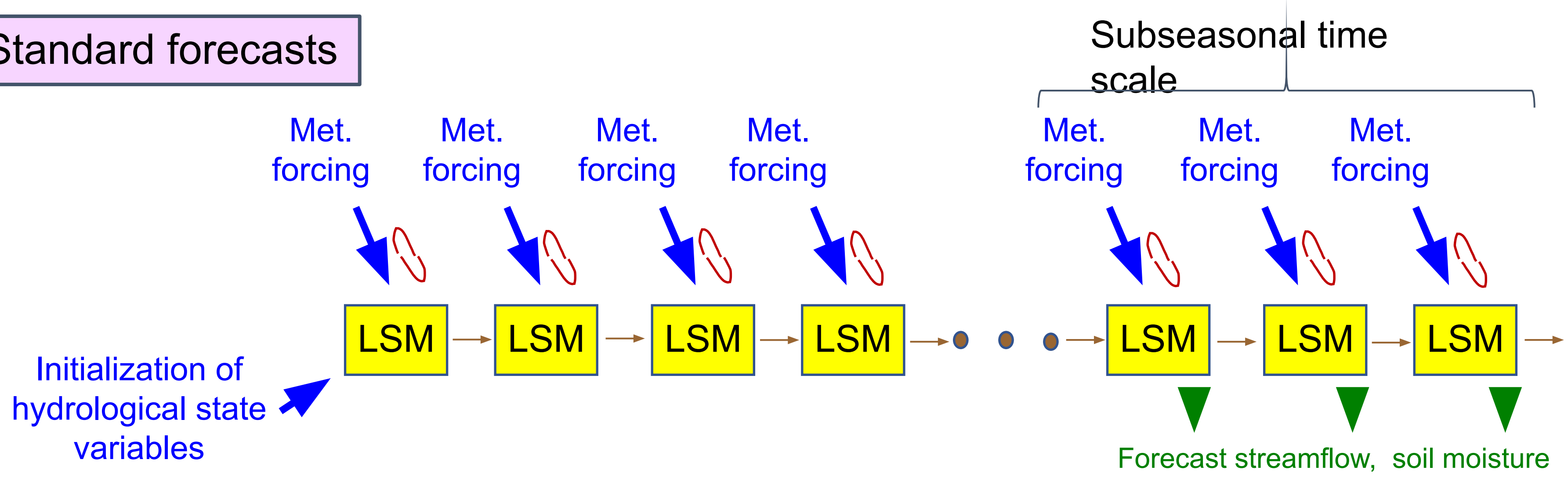

(a)
F_E(W)
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
W (soil moisture index)
(b)
F_Q(W)
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
W (soil moisture index)


(a)
$F_E(W)$
$F_Q(W)$
E/R_{net}, LSM
E/R_{net}, Nature
Q/P, LSM
Q/P, Nature
W (soil moisture index)
(b)
Runoff (mm/day) at 39N, 89W
1990
Q
WBM/Nat
WBM/LSM
day of year
(c)
ET (mm/day) at 39N, 89W
1990
ET
WBM/LSM
WBM/Nat
day of year
(d)
WBM soil moisture at 39N, 89W
1990
W
WBM/Nat
WBM/LSM
day of year

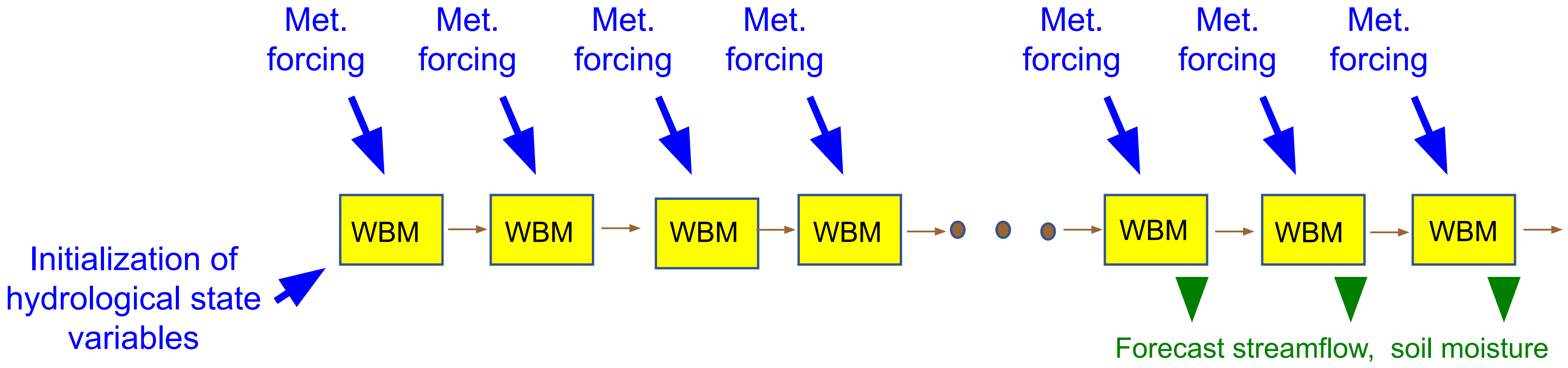
Standard forecasts



Standard forecasts



Offline forecasts using bare-bones (WBM) representation



Let WBM represent Catchment LSM

Standard forecasts

Subseasonal time scale

Met. forcing | Met. forcing | Met. forcing | Met. forcing | Met. forcing | Met. forcing | Met. forcing

Initialization of hydrological state variables → LSM → LSM → LSM → LSM → • • • → LSM → LSM → LSM →

Forecast streamflow, soil moisture

Offline forecasts using bare-bones (WBM) representation

Met. forcing | Met. forcing | Met. forcing | Met. forcing | Met. forcing | Met. forcing | Met. forcing

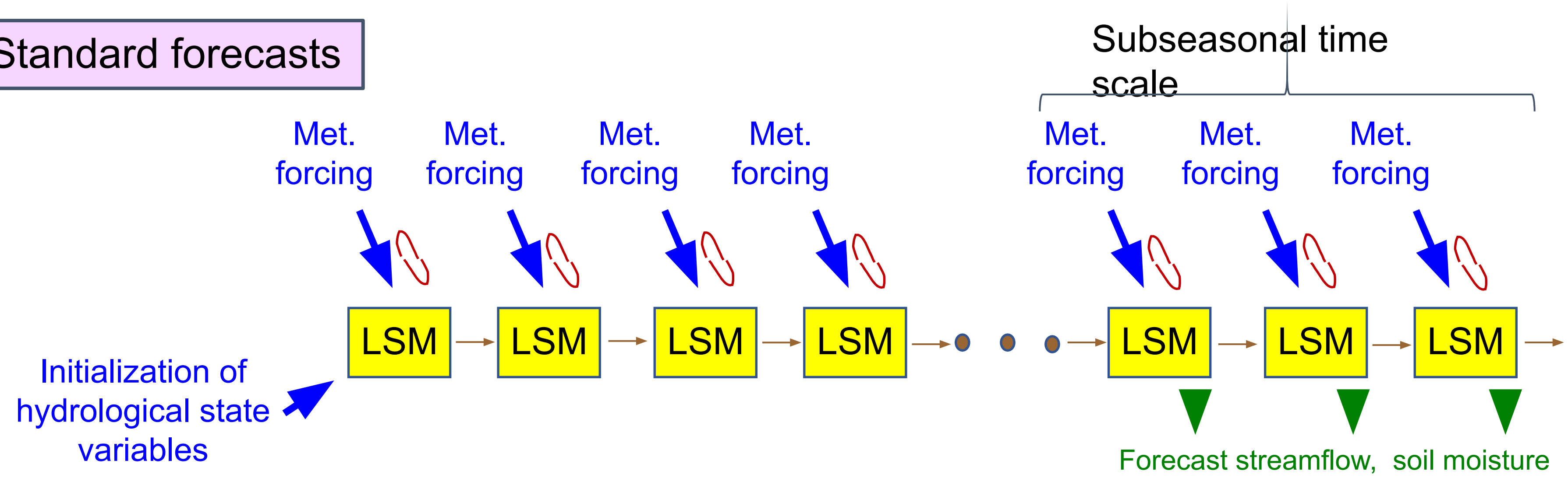
Initialization of hydrological state variables → WBM → WBM → WBM → WBM → • • • → WBM → WBM → WBM →

Forecast streamflow, soil moisture

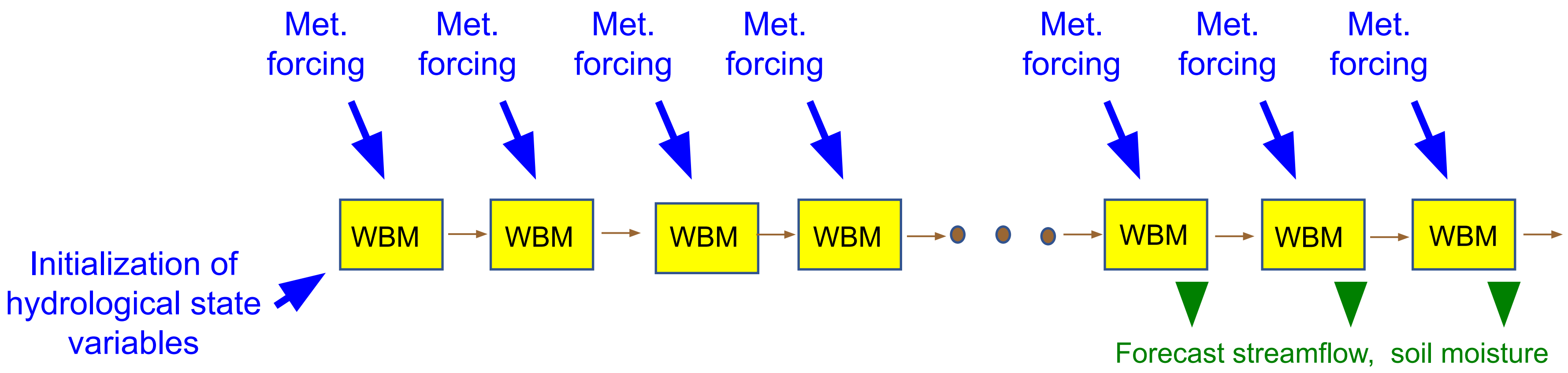
If met forecast is the same, hydrological forecast skill should be similar

Let WBM represent Catchment LSM

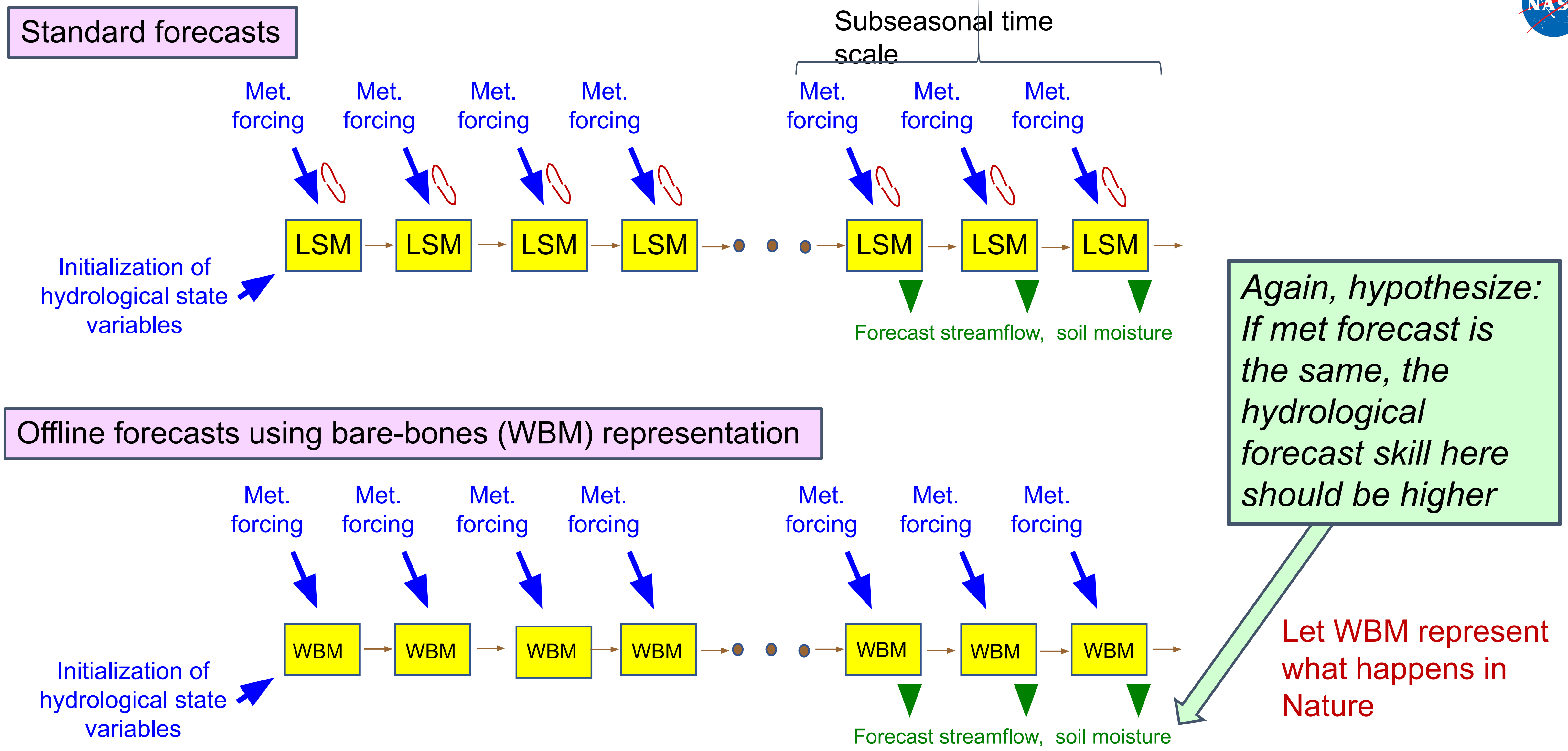
Standard forecasts



Offline forecasts using bare-bones (WBM) representation



Let WBM represent what happens in Nature

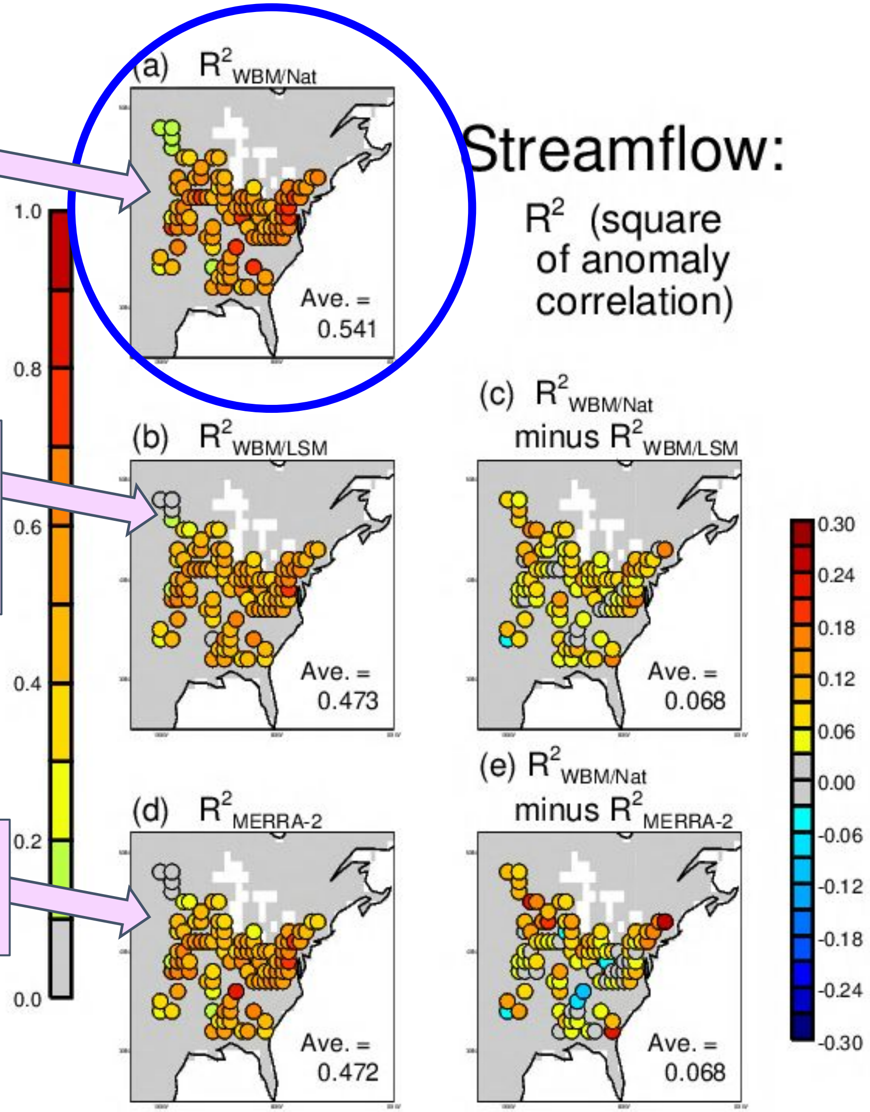

Standard forecasts
Subseasonal time scale
Met. forcing
LSM
Initialization of hydrological state variables
Forecast streamflow, soil moisture
Offline forecasts using bare-bones (WBM) representation
Met. forcing
WBM
Initialization of hydrological state variables
Forecast streamflow, soil moisture
Again, hypothesize: If met forecast is the same, the hydrological forecast skill here should be higher
Let WBM represent what happens in Nature

Skill (R^2 vs obs.) assuming <u>"perfect" meteorological forecasts</u> – basically, the skill of a hydrological simulation with observed forcing

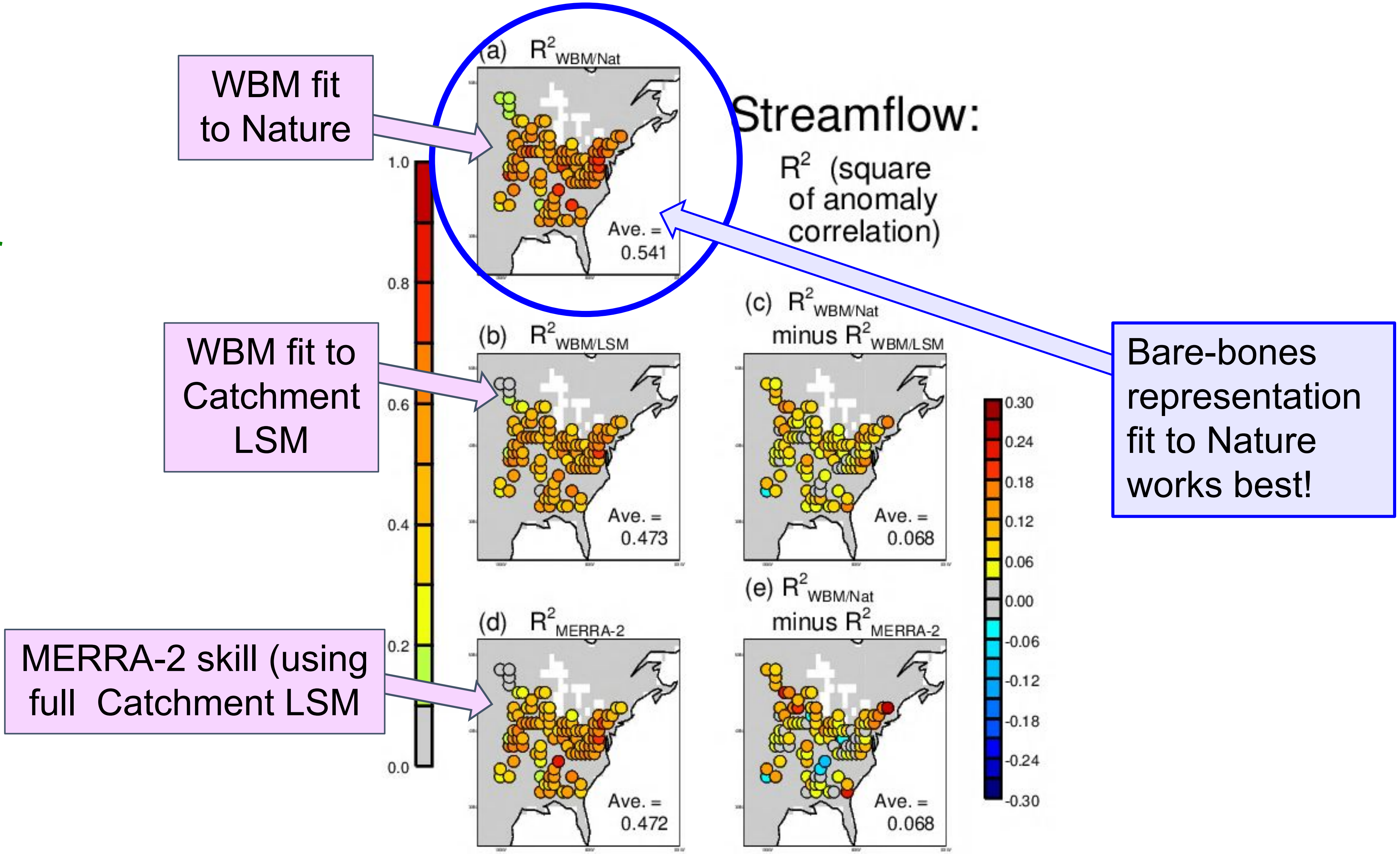
WBM fit to Nature

WBM fit to Catchment LSM

MERRA-2 skill (using full Catchment LSM



Skill (R^2 vs obs.) assuming "perfect" meteorological forecasts – basically, the skill of a hydrological simulation with observed forcing



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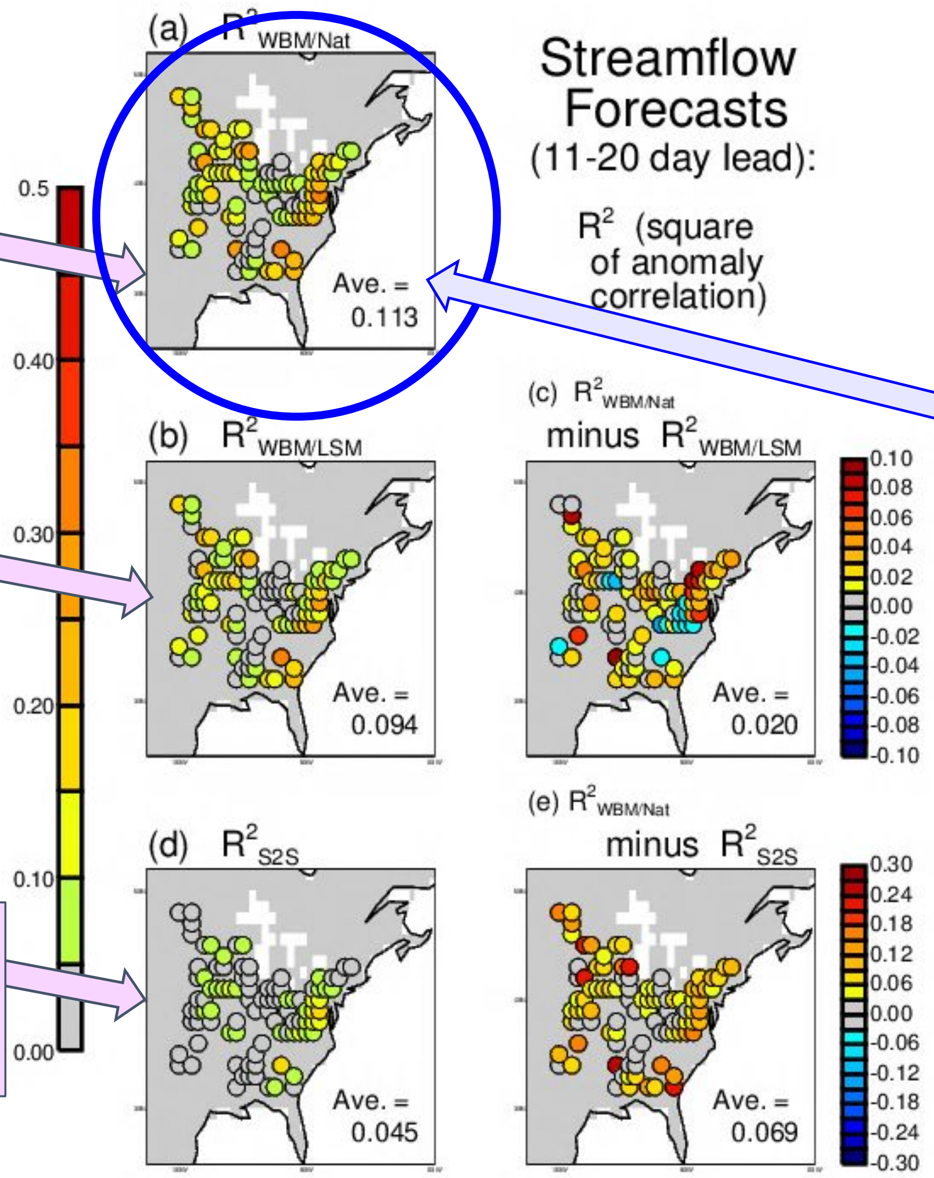
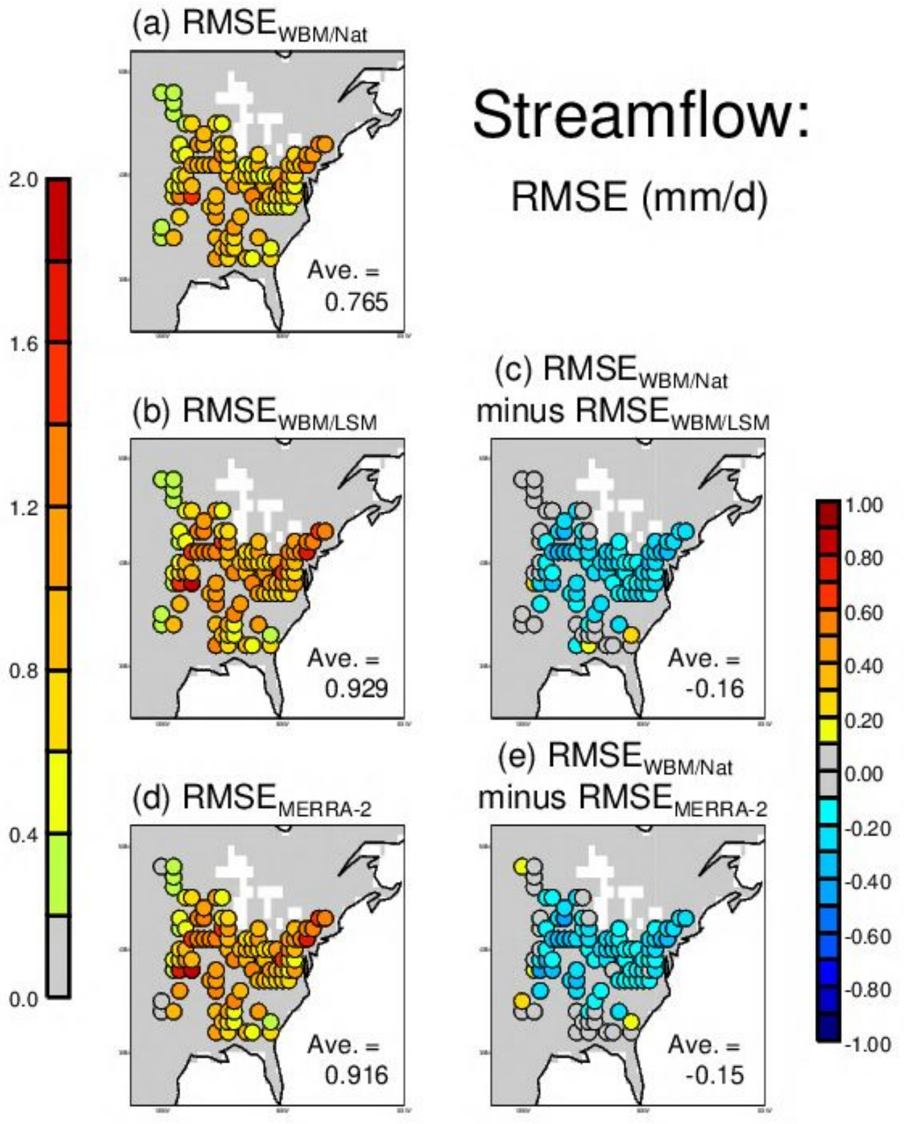
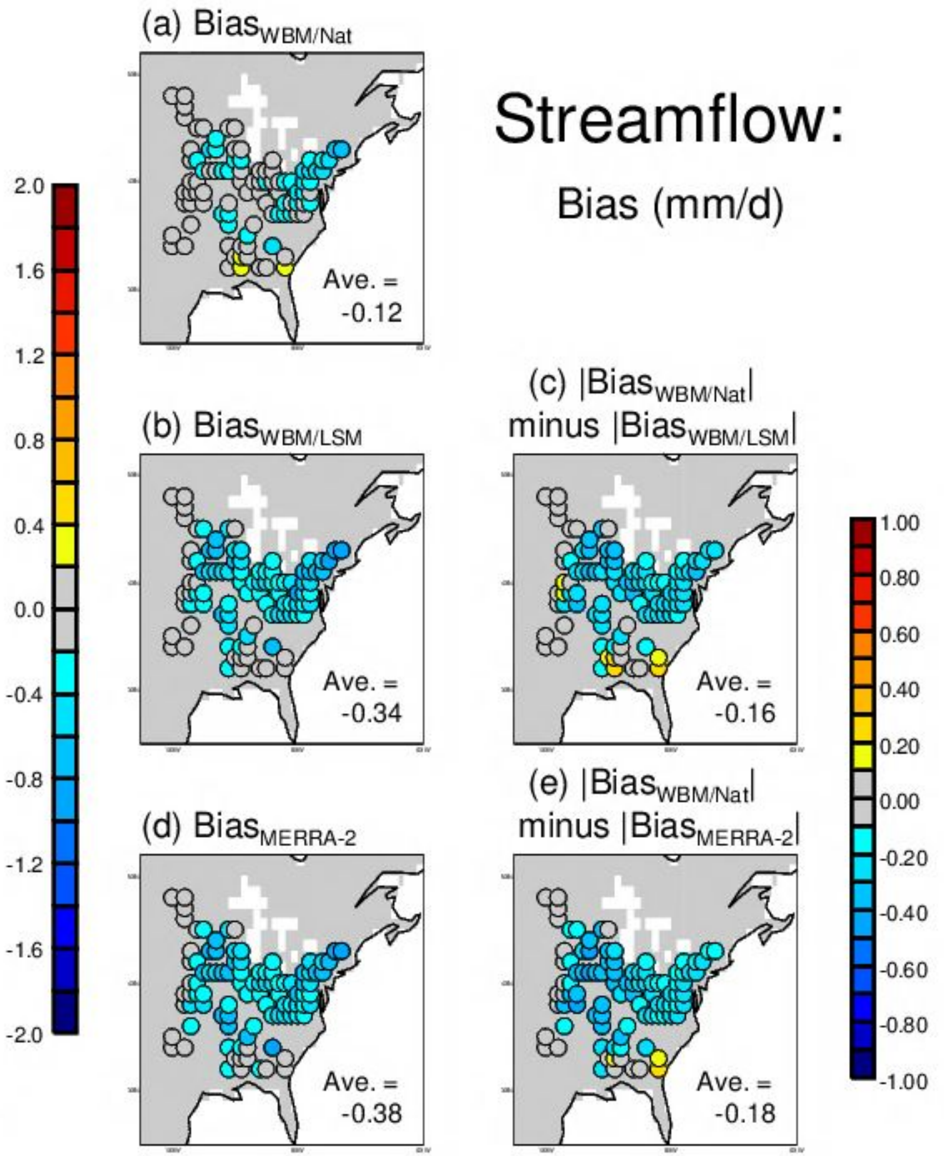


The bare-bones representation fit to Nature again works best!

Streamflow:

RMSE (mm/d)





Streamflow:
Bias (mm/d)
(a) $Bias_{WBM/Nat}$
Ave. = -0.12
(b) $Bias_{WBM/LSM}$
Ave. = -0.34
(c) $|Bias_{WBM/Nat}|$ minus $|Bias_{WBM/LSM}|$
Ave. = -0.16
(d) $Bias_{MERRA-2}$
Ave. = -0.38
(e) $|Bias_{WBM/Nat}|$ minus $|Bias_{MERRA-2}|$
Ave. = -0.18
2.0
1.6
1.2
0.8
0.4
0.0
-0.4
-0.8
-1.2
-1.6
-2.0
1.00
0.80
0.60
0.40
0.20
0.00
-0.20
-0.40
-0.60
-0.80
-1.00