Local versus Remote Contributions of Soil Moisture to Near-Surface Temperature Variability

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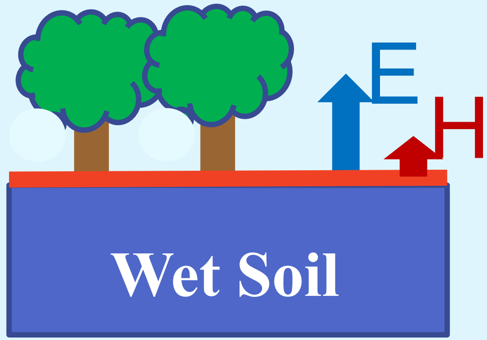
Local land-atmosphere feedback is intuitive:

Wet soil ⇨ higher evaporation, lower sensible heat flux

This can affect local air temperature:

⇨ more evaporative cooling

⇨ lower air temperature



It can also affect local precipitation:

⇨ boundary layer modification

⇨ conditions influencing onset of moist convection

What about impacts of soil moisture on <u>remote</u> meteorology?

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Impacts of Local Soil Moisture Anomalies on the Atmospheric Circulation and on Remote Surface Meteorological Fields during Boreal Summer: A Comprehensive Analysis over North America

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In a recent J. Climate paper, we analyzed a series of "imposed drought" simulations with the NASA GEOS-5 atmospheric GCM.

Results: a quantification of the impact of a locally-imposed drought on remote temperature, precipitation, and circulation fields.

Some results (from paper)

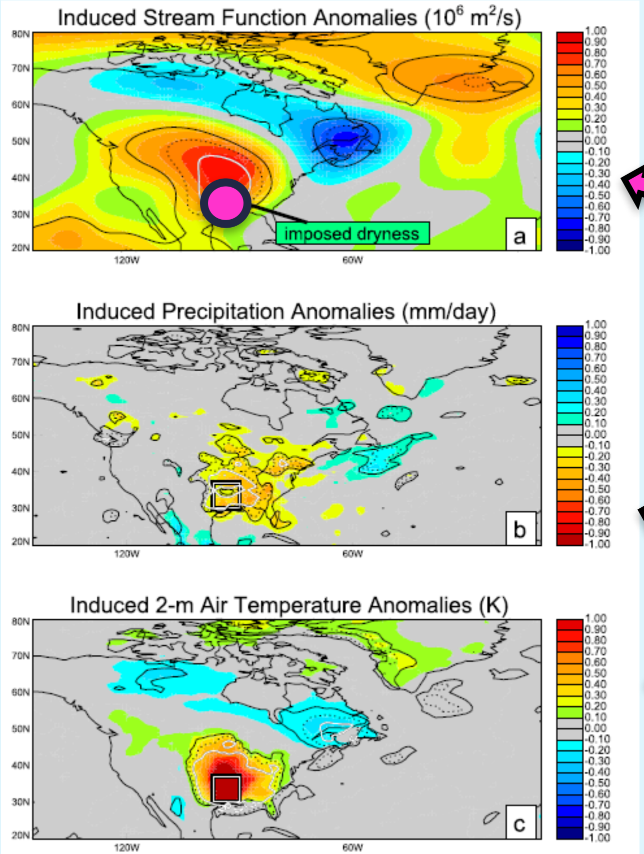


FIG. 6. (a) Anomalies (10^6 m^2 s^{-1}) in June–July 250-hPa streamfunction (experiment minus control) for experiment AGCM-S. The imposed dryness in region S has induced a wavelike pattern in the streamfunction field. (b) As in (a), but for June–July precipitation anomalies (mm day^{-1}). (c) As in (a), but for June–July 2-m air temperature anomalies (K).

Imposing dry soil moisture at the pink dot…

…leads to changes in the ensemble-mean atmospheric circulation (streamfunction)…

… which has consequent impacts on precipitation and temperature outside the region.

The 2016 study used an extensive control experiment – one consisting of a 768-member ensemble of 4-month (April-July) simulations.

In the present talk, we examine an alternative analysis approach:
The quantification of local vs. remote soil moisture impacts through a statistical analysis of the control ensemble in isolation.

Lots of data – nice statistics!

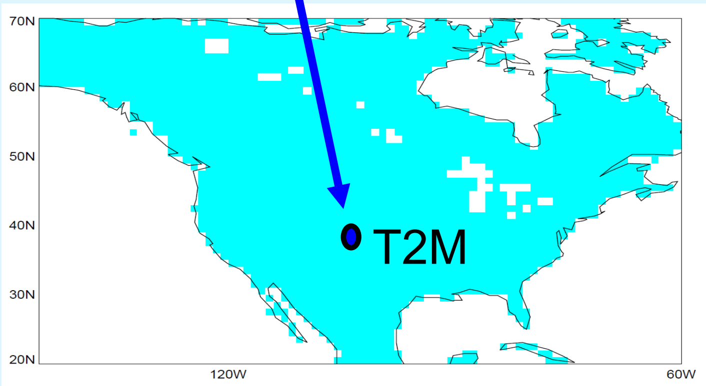
In this simplistic statistical study, we quantify a soil moisture contribution to a subsequent meteorological variable X in terms of r^2, the square of the correlation coefficient between them.

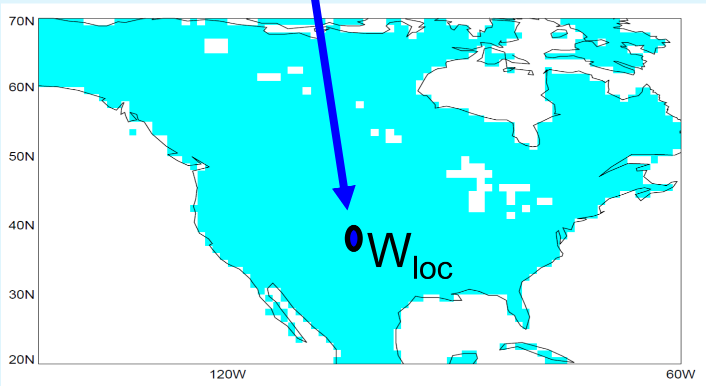
> ⇨ *In essence, we interpret r^2 as the fraction of σ^2_X "explained" by the antecedent soil moisture variable(s). (Causality is suggested but not demonstrated.)*

Step 1: Simple regression of local met. variable on local soil moisture

Regress T2M here…

…against local (and earlier) soil moisture here.





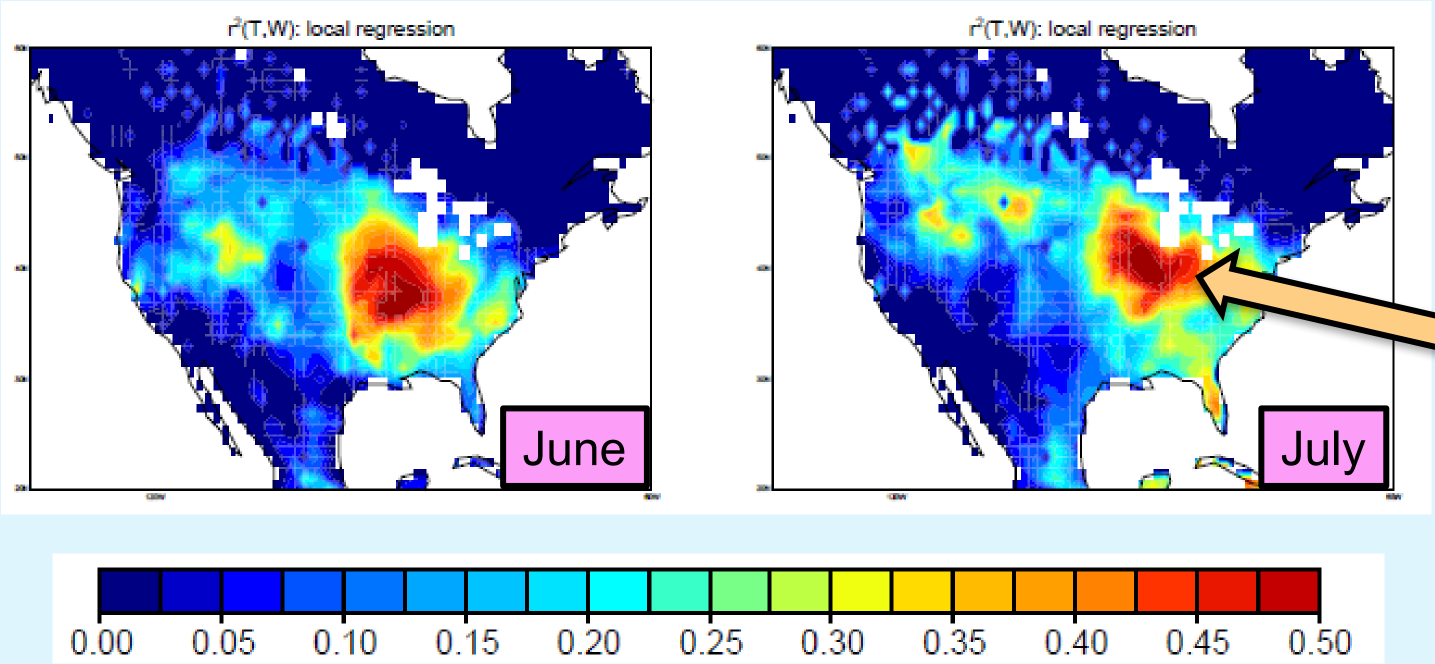
At each grid cell: Determine r^2 along with predictor equation:

$$T2M_{loc} = const. + c_{loc} \, W_{loc} \; ;$$

Temperature Results: r^2 (W_0, T2M)

Soil moisture at start of month

Local overlying air temperature averaged over month

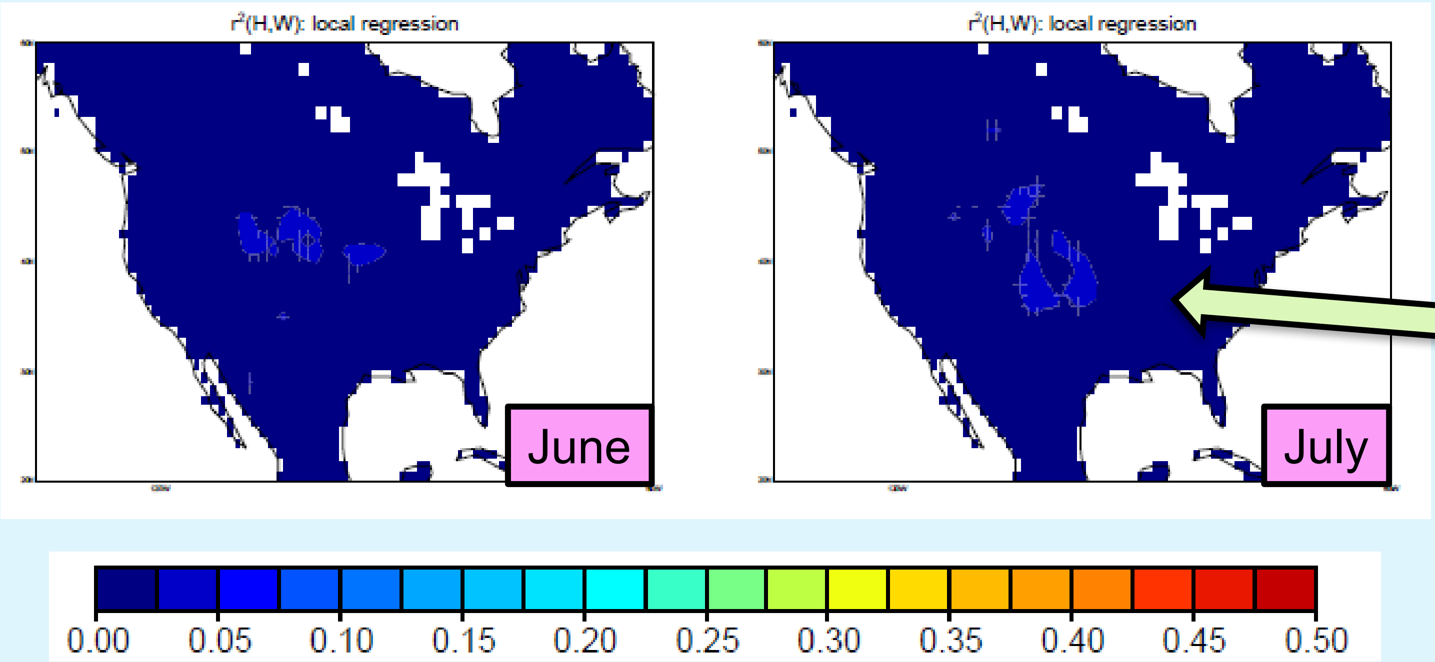


Strong (and unrealistic) local connection here between initial soil moisture and subsequent T2M.

Geopotential Height Results: r^2 (W_0, H250)

Soil moisture at start of month

local 250 mb height



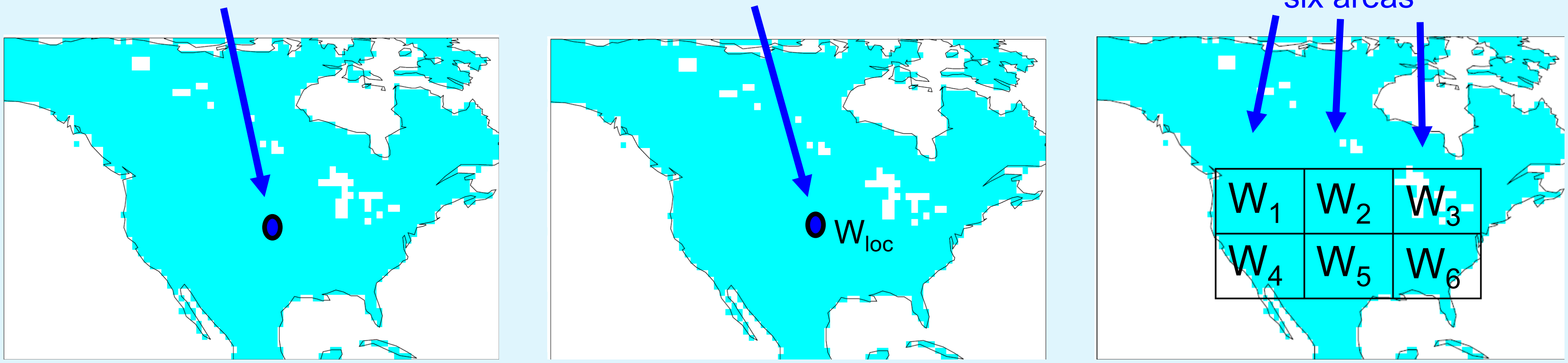
Almost no local connection between initial soil moisture and subsequent H250.

Step 2: Multiple regression of local met. variable on local soil moisture and large-scale spatial pattern of soil moisture.

Regress T2M here…

…against local (and earlier) soil moisture here…

…and against large scale soil moisture contents in six areas



From multiple regression,

(i) Determine square of multiple correlation coefficient.

(ii) Determine predictor equation:

$$T2M_{loc} = \text{const.} + c_{loc}\, W_{loc} + c_1\, W_1 + c_2\, W_2 + \ldots + c_6\, W_6 = f(7 \text{ variables})$$

Isolation of Remote Impacts

Fraction of variance "explained" by local W and remote W:

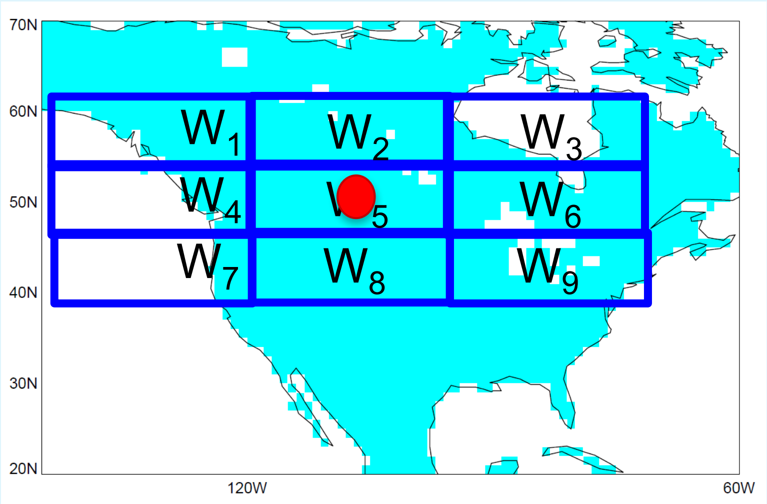
r^2 from multiple regression against W_{loc}, W_1, W_2, … , W_6

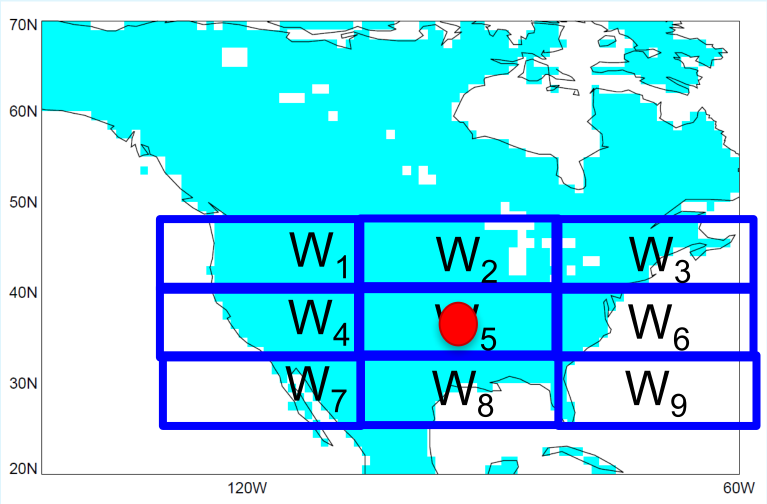
Fraction of variance "explained" by local W alone:

r^2 from regression against W_{loc} (from before)

⇨ Subtract the second r^2 from the first r^2 to get the remote contribution.

Note: we tried variants of this breakdown; results are essentially the same…

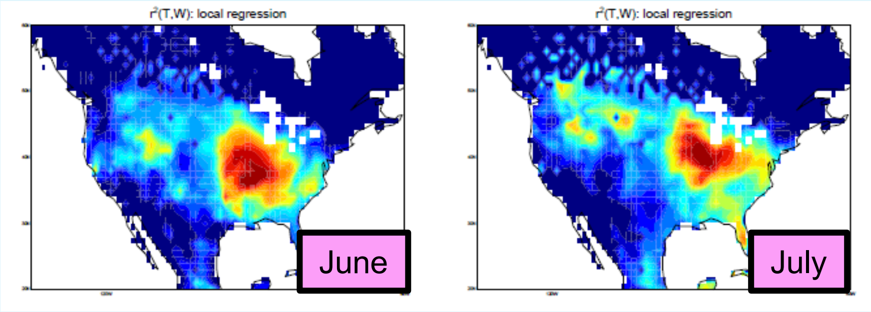


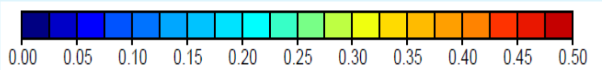


e.g., 9 areas – a 3x3 grid centered on the local point in question

T2M Results: r^2 from predictor equations

Local regression (from before)



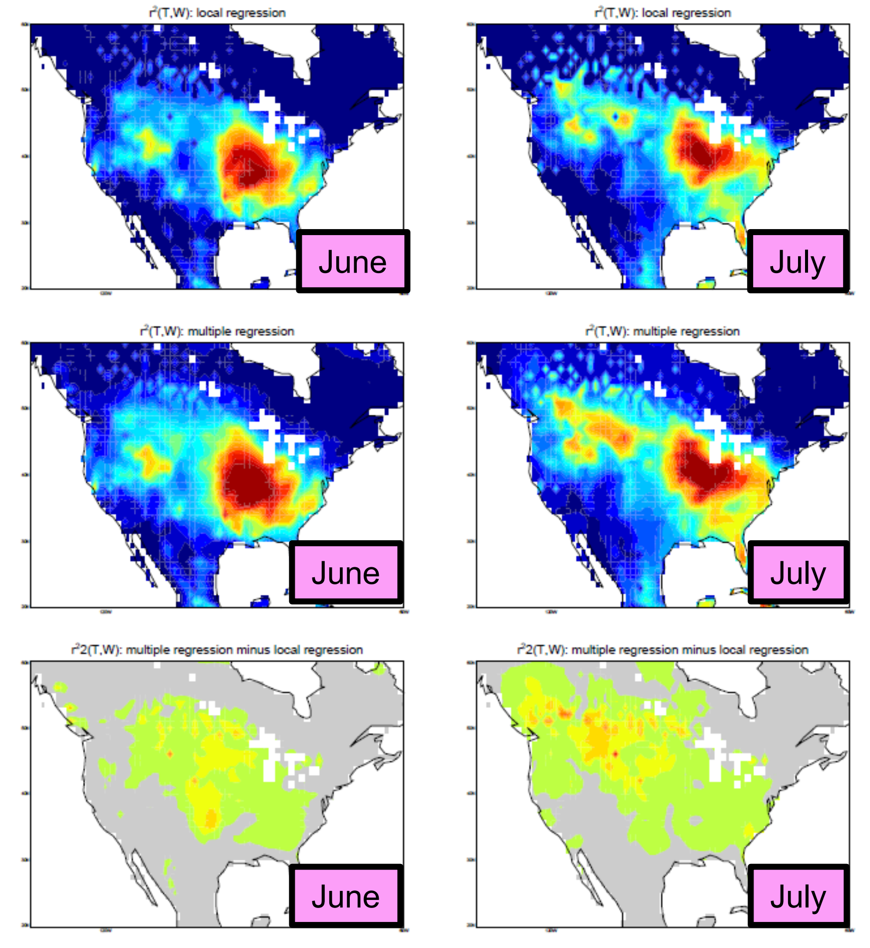


T2M Results: r^2 from predictor equations

Local regression (from before)

Multiple regression

Differences

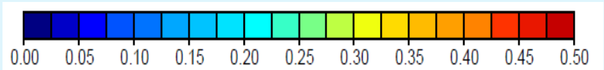


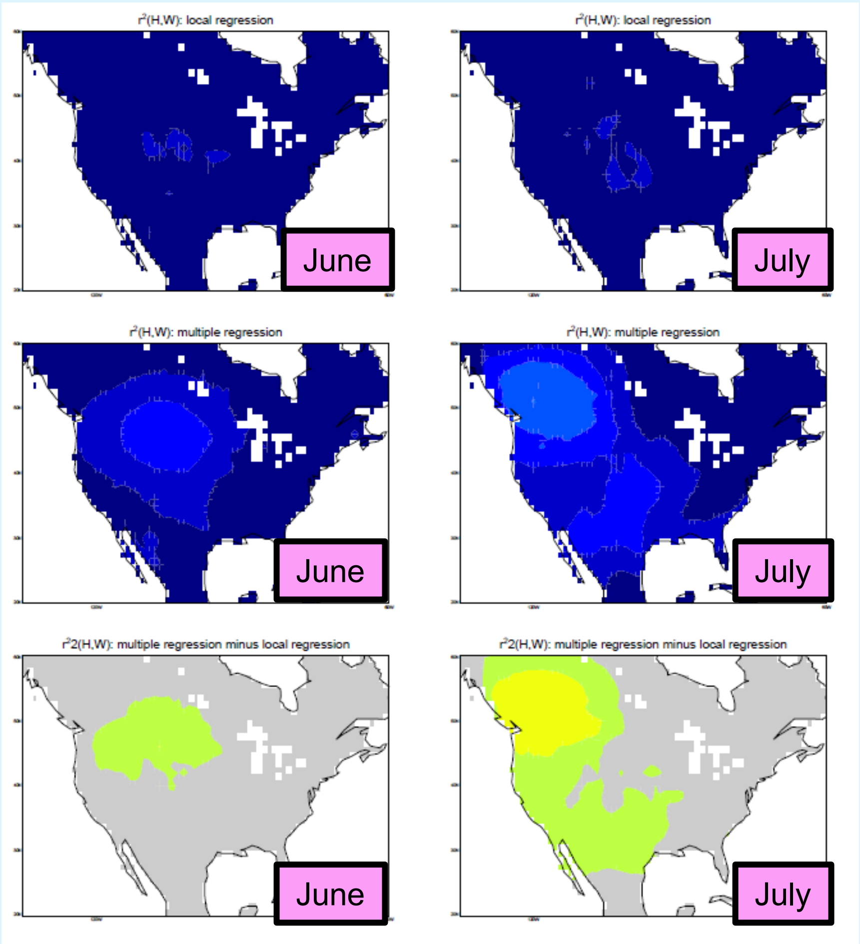
H250 Results: r^2 from predictor equations

Local regression (from before)

Multiple regression

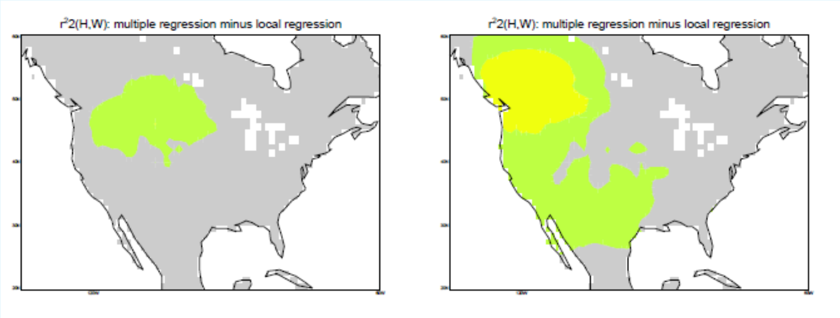
Differences





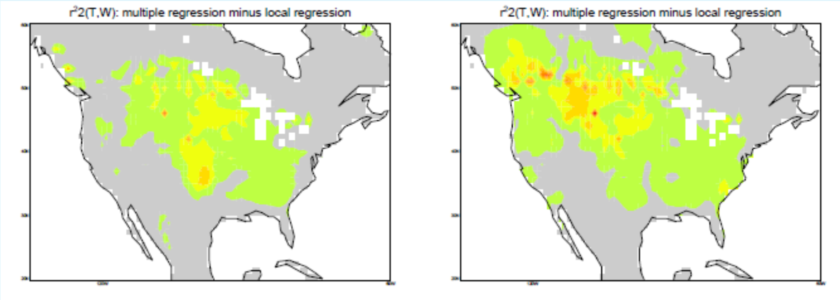
The contributions of the large-scale soil moisture pattern to the height field…

H250:
r^2 from multiple regression
minus
r^2 from local regression



… is not inconsistent with its contribution to the T2M field.

T2M:
r^2 from multiple regression
minus
r^2 from local regression



Obvious question:

What relevance does this have to the real world?

Observations-based data considered (1979-2013)

Soil moistures: MERRA-2 product (reflects gauge-based precipitation) (Gelaro et al. 2017)

⇨ *Consider soil moisture patterns at start of predicted month*

Temperatures: ERA-Interim 2-meter temperatures (Dee et al. 2011)

250 mb height fields: ERA-Interim H250 fields (Dee et al. 2011)

From the GCM data, we have determined coefficients c_{loc}, c_1, c_2, …, c_9 such that

$$T2M_{loc} = \text{const.} + c_{loc}\, W_{loc} + c_1\, W_1 + c_2\, W_2 + \ldots + c_6\, W_6 = f(7 \text{ variables})$$

Can these be used to predict observed monthly temperature from the *completely independent* observed local soil moisture and large-scale soil moisture patterns?

Soil moisture from observations, t= 0 days

→ Apply regression coefficients from AGCM analysis →

Estimated temperatures, t=0-29 days

→ Compare with actual observed temperatures →

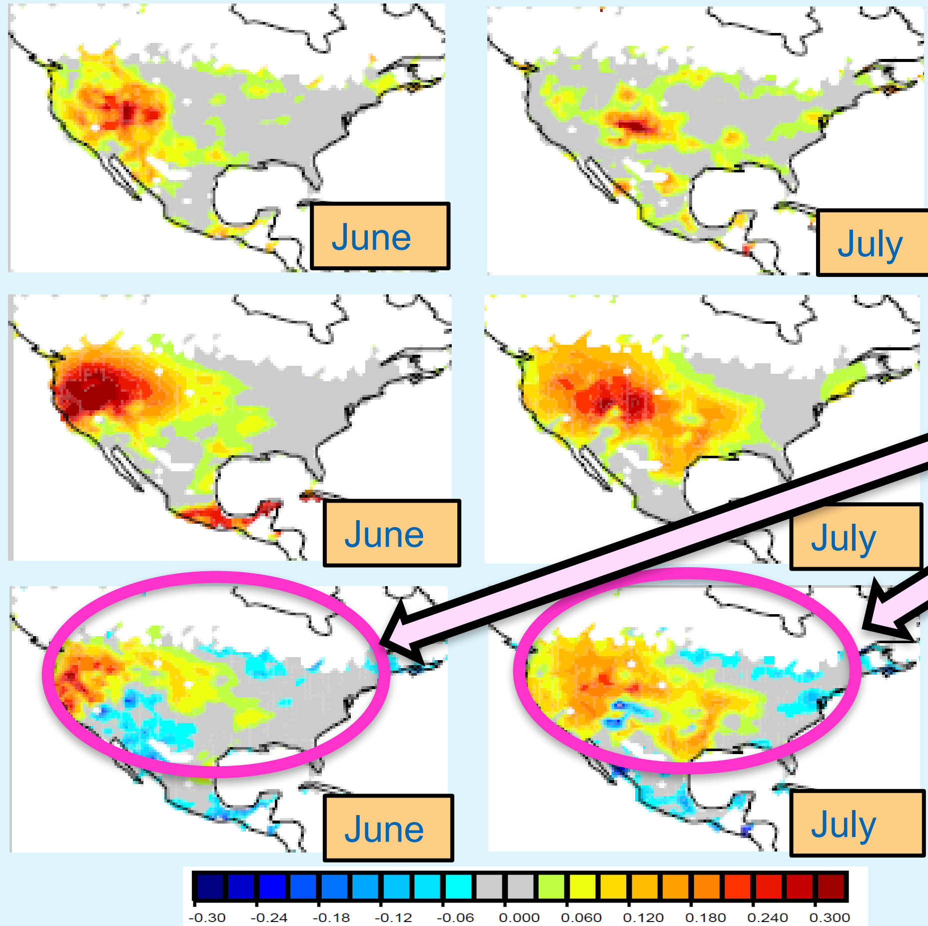
Map of forecast skill

H250 Results: Skill of prediction (r^2 vs observations)

Using predictor equation from simple linear regression

Using GCM-based predictor equation from multiple regression

<u>Differences:</u>
Contribution of large-scale pattern to skill



Warm colors outweigh cold colors ⇨ indication of true remote contribution to skill?

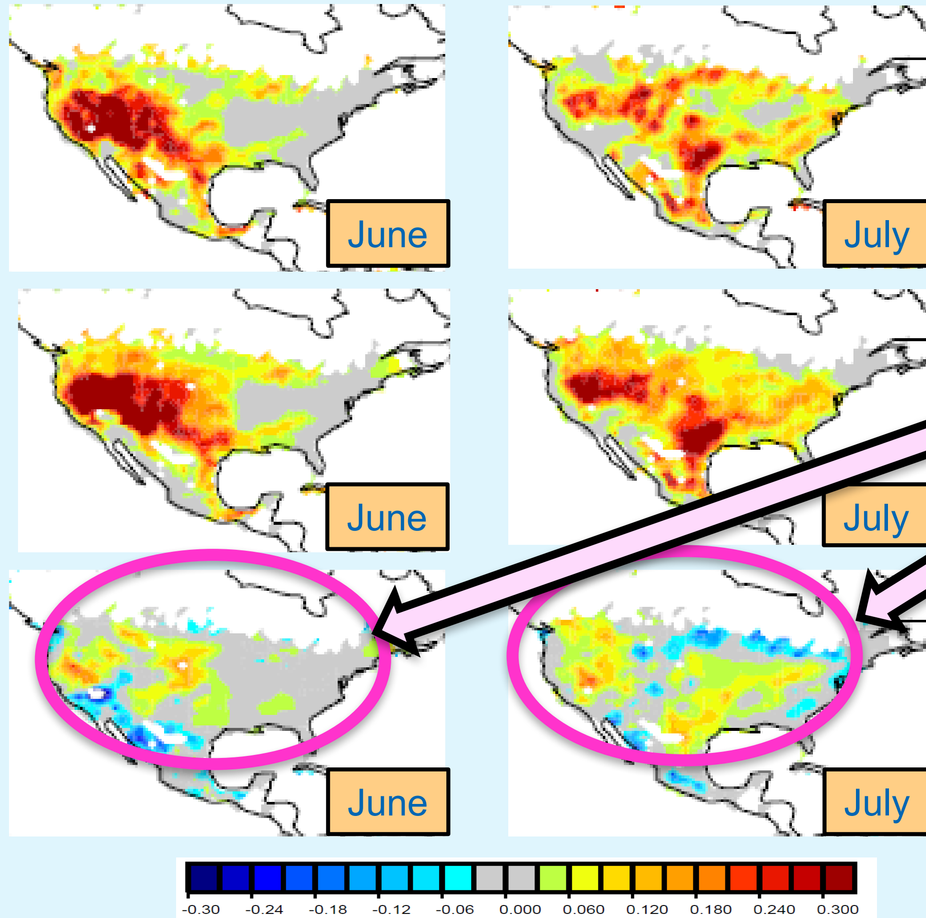
lead 0

T2M Results: Skill of prediction (r^2 vs observations)

Using predictor equation from simple linear regression

Using GCM-based predictor equation from multiple regression

Differences: Contribution of large-scale pattern to skill



Positive impact on temperature skill is also somewhat apparent

lead 0

Summary

1. A large set of AGCM ensemble members can be analyzed statistically to isolate apparent local impacts of land moisture from remote impacts.

2. The multiple regression-based predictor equation derived from the AGCM ensembles, when applied to antecedent observations-based soil moistures, shows some skill in reproducing observed T2M and H250 anomalies

    ⇨ the statistical relationships derived from the AGCM may have some relevance to the real world.

3. With a statistical analysis like this, causality (soil moisture affecting meteorology) cannot be demonstrated; causality is at best only suggested.