Toy model preliminaries

Goal: Form an expression for T' and Var(T).

Surface energy budget,

- Tools: Soil moisture budget,Parameterization of land surface fluxes.
 - Focus on inter-annual variability:
 - Use monthly-averaged variables,
 - Decompose each variable around monthly climatology:

$$X'_{i,j} \equiv X_{i,j} - \overline{X}_j \tag{3}$$

where i: year index, j: month index.

Surface energy and soil moisture anomaly budgets:

$$\frac{\mathrm{d}}{\mathrm{d}t} \left(C_{eff} T' \right) = F' - LE' - H'_s - F_{lw}^{\dagger'} - G' \tag{4a}$$

$$\frac{\mathrm{d}\,m'}{\mathrm{d}\,t} = P' - E' - R' - I' \tag{4b}$$

T: 2-meter temperature ,

 $C_{\!\it{eff}}$: effective heat capacity of land surface ,

P: Precipitation , R: Surface Runoff , I: Infiltration .

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Assume that m is the moisture content in the top 10 cm of soil

Surface energy and soil moisture anomaly budgets:

$$\frac{\mathrm{d}}{\mathrm{d}t}(\mathbf{x}_{l}^{\dagger}T') = F' - LE' - H'_{s} - F_{lw}^{\dagger'} - G' \tag{4a}$$

$$\frac{dP}{dI} = P' - E' - R' - I' \tag{4b}$$

Scale analysis reveals that both storage terms are negligible.

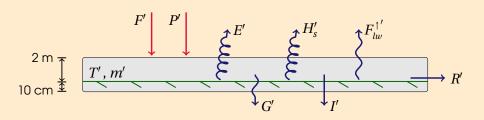
Surface energy and soil moisture anomaly budgets:

$$\frac{\mathrm{d}}{\mathrm{d}t}(T') = F' - LE' - H'_s - F_{lw}^{\dagger'} - G' \tag{4a}$$

$$\frac{dn}{dt} = P' - E' - R' - I' \tag{4b}$$

X Define
$$G' \equiv F' - LE' - H'_s - F^{\dagger'}_{hv}$$
 and $I' \equiv P' - E' - R'$

Toy model assumptions



- 1. F' and P' are **external forcings**, independent of $E', H'_{s}, F^{\dagger'}_{lm}, G', I', R'$.
- 2. Parameterize $E', H'_s, F^{\dagger'}_{lw}, G', I', R'$ as functions of T', m', F', P' only.

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Step 1: Regress G' as:

$$G' = G'_0 + aY'$$
 where $Y' = \{T', m', F', P'\}$ (5)

Best predictor has $\min \left[\left\langle G_0', G_0' \right\rangle \right]$



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Step 2: \triangle If T' is a candidate

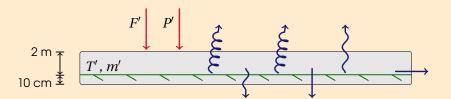
Substitute G' = aT' into surface energy anomaly budget:

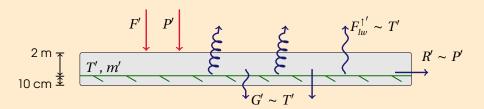
$$\widehat{T}'_{tm} = a^{-1} \left[F' - LE' - H'_{s} - F^{\dagger}_{lw} \right]$$
 (6)

Evaluate performance with RMS $[\widehat{T}'_{tm} - T'_{dataset}]$

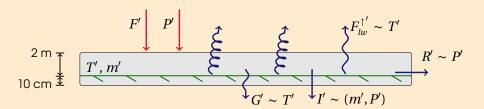
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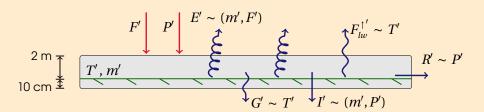




3 out of 6 processes were easy to parameterize



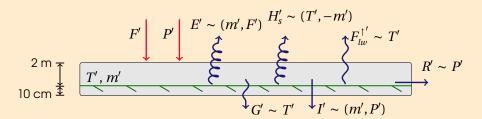
 \aleph 2 predictors for inflitration m' and P'



Special algorithm for E' to model both E regimes:

If $\langle E', m' \rangle > 0$: 2 predictors m' and F' (moisture-limited)

Otherwise: 1 predictor F' only (energy-limited)



Surprising result: H'_s is best predicted by m'!



Use 2 predictors T' and m'

After some algebra:

$$\widehat{T}'_{tm} = \frac{1}{\gamma} \left[\left(1 - \lambda \right) F'_0 - L \alpha \left(1 - \lambda \right) P' - L \left(v_E - v_{Hs} \right) m' \right]$$
 (7a)

$$\widehat{m}'_{tm} = \frac{1}{\nu_I + \nu_E} \left[\left(1 + \alpha \lambda - \beta \right) P' - \left(\frac{\lambda}{L} \right) F'_0 \right] \tag{7b}$$

$$F' = F'_0 - L\alpha P'$$
** Recall

L: specific latent heat of vaporization

After some algebra:

$$\widehat{T}'_{tm} = \frac{1}{\gamma} \left[(1 - \lambda) F'_0 - L\alpha (1 - \lambda) P' - L (\nu_E - \nu_{Hs}) m' \right]$$
(7a)
$$\widehat{m}'_{tm} = \frac{1}{\nu_I + \nu_F} \left[(1 + \alpha \lambda - \beta) P' - (\frac{\lambda}{L}) F'_0 \right]$$
(7b)

Surface temperature resistance (Wm⁻²K⁻¹)

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 (7b)

Evapotranspiration efficiency (unitless)

After some algebra:

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 (7b)

Fraction of P' **loss to** I' **and** R' (unitless)

After some algebra:

$$\widehat{T}'_{tm} = \frac{1}{\gamma} \left[(1 - \lambda) F'_0 - L\alpha (1 - \lambda) P' - L (v_E - v_{Hs}) m' \right]$$
 (70)

$$\widehat{m}'_{tm} = \frac{1}{\nu_I + \nu_F} \left[\left(1 + \alpha \lambda - \beta \right) P' - \left(\frac{\lambda}{L} \right) F'_0 \right] \tag{7b}$$

Net effect of soil moisture anomalies on T'



All v's have units of s⁻¹

After some algebra:

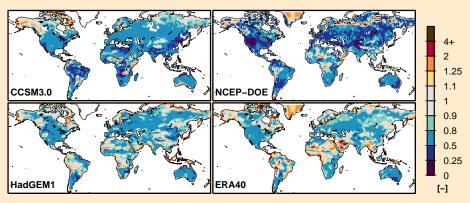
$$\widehat{T}'_{tm} = \frac{1}{\gamma} \left[(1 - \lambda) F'_0 - L\alpha (1 - \lambda) P' - L \left(v_E - v_{Hs} \right) m' \right]$$
(7a)
$$\widehat{m}'_{tm} = \frac{1}{v_I + v_E} \left[(1 + \alpha \lambda - \beta) P' - \left(\frac{\lambda}{L} \right) F'_0 \right]$$
(7b)

Define
$$\frac{v_E - v_{Hs}}{v_I + v_E}$$
 (unitless) the coupling coefficient

Modulates net effect of m' on T'

Toy model performance

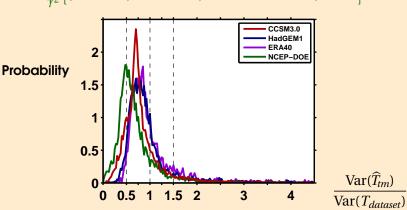
$$\mathrm{Var}(\widehat{T}_{tm}) = \frac{1}{\gamma^2} \left[\left(1 - \lambda(1 - \mathcal{X}) \right)^2 \mathrm{Var}(F_0) + L^2 \left(\alpha(1 - \lambda) + \mathcal{X}(1 + \alpha\lambda - \beta) \right)^2 \mathrm{Var}(P) \right]$$



$$ilde{\mathsf{X}}$$
 Plotted as $\dfrac{\operatorname{Var}(\widehat{T}_{tm})}{\operatorname{Var}(T_{dataset})}$

Toy model performance

$$\mathrm{Var}(\widehat{T}_{tm}) = \frac{1}{\gamma^2} \left[\left(1 - \lambda (1 - \mathcal{X}) \right)^2 \mathrm{Var}(F_0) + L^2 \left(\alpha (1 - \lambda) + \mathcal{X}(1 + \alpha \lambda - \beta) \right)^2 \mathrm{Var}(P) \right]$$



 \implies Toy model underestimates dataset outputs by \sim 20% to 40%.