



GSTM 2017
Austin, Texas

Bart Forman

Motivation

TWS

Assimilation

Sensors

Study Domain

3D-EnKF

Validation

L-band

Assimilation

RTM

Validation

K-,Ka-,X-band

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Machine

Learning

Validation

Joint Assimilation

Framework

Validation

Challenges

Multi-scale

Spatial Errors

Conclusions

Merging Space-based Gravimetry and Radiometry to Improve Regional-scale Estimates of Terrestrial Water Storage

Bart Forman

Assistant Professor, University of Maryland
Department of Civil and Environmental Engineering

Co-authors: Jing Wang¹, Yuan Xue¹,
Manuela Girotto^{2,3}, and Rolf Reichle²

¹University of Maryland; ²NASA GSFC; ³USRA/GESTAR

Session B5: Hydrology

October 12, 2017

Remote Sensing of Falling Snow

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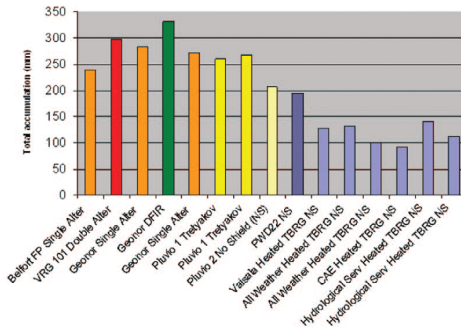
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Rasmussen et al., *"How well are we measuring snow?"*, BAMS, 2012

- Motivates hydrologic modeling + snow assimilation
 - ▶ state update to correct improper boundary conditions

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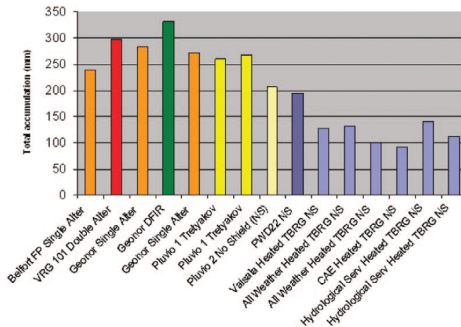
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Background and Motivation

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- Leverage suite of remotely-sensed **satellite** observations
 - ▶ **Visible** information $\mapsto$ snow cover extent
 - ▶ **Passive MW** information $\mapsto$ soil moisture & snow mass
 - ▶ **Gravimetric** information $\mapsto$ terrestrial water anomalies
- Need for **computationally efficient** observation operator
 - ▶ Eventual use in **data assimilation** framework
 - ▶
$$\underbrace{\mathbf{y}_i^+}_{\text{posterior}} = \underbrace{\mathbf{y}_i^-}_{\text{prior}} + \underbrace{\mathbf{K}}_{\text{Kalman gain}} \left[\underbrace{\mathbf{Z}}_{\substack{\text{observation} \\ \text{via satellite}}} - \underbrace{h(\mathbf{y}_i^-)}_{\substack{\text{observation} \\ \text{operator}}} \right]$$
- Goal is to **improve TWS** (snow + soil moisture + GW + ...) across **regional scales** based on **conditional probability**, $p(y|z)$



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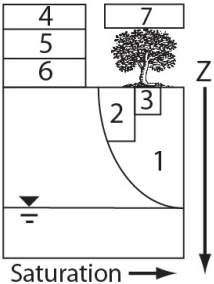


Multi-Sensor Approach

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GRACE
assimilation
(core routine to
improve TWS
via SWE, soil
moisture, and
ground-water
updates)



$$\underbrace{y_i^+}_{\text{posterior TWS}} = \underbrace{y_i^-}_{\text{prior TWS}} + \underbrace{\mathbf{K}}_{\text{Kalman gain}} \left[\underbrace{Z}_{\substack{\text{measurements} \\ \text{GRACE TWS} \\ \text{and/or} \\ \text{L-band PMW} \\ \text{and/or} \\ \text{K-,Ka-,X-band PMW}}} - \underbrace{h(y_i^-)}_{\substack{\text{observation operator} \\ \text{spatiotemporal } \mathbf{H} \\ \text{and/or} \\ \text{radiative transfer} \\ \text{and/or} \\ \text{machine learning}}} \right]$$

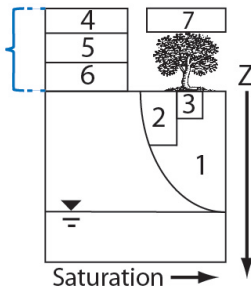


Multi-Sensor Approach

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(core routine to
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AMSR-E (>10 GHz)
updates SWE when
snow exists



$$\underbrace{\mathbf{y}_i^+}_{\text{posterior TWS}} = \underbrace{\mathbf{y}_i^-}_{\text{prior TWS}} + \underbrace{\mathbf{K}}_{\text{Kalman gain}} \left[\underbrace{\mathbf{Z}}_{\substack{\text{measurements} \\ \text{GRACE TWS} \\ \text{and/or} \\ \text{L-band PMW} \\ \text{and/or} \\ \text{K-,Ka-,X-band PMW}}} - \underbrace{h(\mathbf{y}_i^-)}_{\substack{\text{observation operator} \\ \text{spatiotemporal } \mathbf{H} \\ \text{and/or} \\ \text{radiative transfer} \\ \text{and/or} \\ \text{machine learning}}} \right]$$

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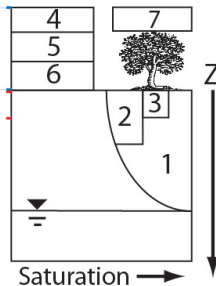


Multi-Sensor Approach

GRACE assimilation
(core routine to improve TWS via SWE, soil moisture, and ground-water updates)

AMSR-E (>10 GHz)
updates SWE when
snow exists

L-band (1.4 GHz) updates
soil moisture during
non-frozen soil conditions



$$\underbrace{y_i^+}_{\text{posterior TWS}} = \underbrace{y_i^-}_{\text{prior TWS}} + \underbrace{\mathbf{K}}_{\text{Kalman gain}} \left[\underbrace{Z}_{\substack{\text{measurements} \\ \text{GRACE TWS} \\ \text{and/or} \\ \text{L-band PMW} \\ \text{and/or} \\ \text{K-,Ka-,X-band PMW}}} - \underbrace{h(y_i^-)}_{\substack{\text{observation operator} \\ \text{spatiotemporal } \mathbf{H} \\ \text{and/or} \\ \text{radiative transfer} \\ \text{and/or} \\ \text{machine learning}}} \right]$$

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Experimental Setup

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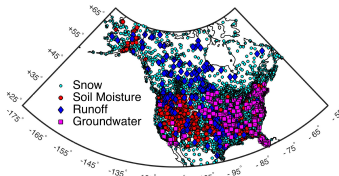
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Domain

- North America (9-km)
- 1 Sept. 2002 – 1 Sept. 2011

Model

- GEOS-5 Catchment model
- MERRA2 forcing

SVM (snow) Training Targets

- AMSR-E nighttime overpass
 - ▶ 10.65, 18.7, and 36.5 GHz
 - ▶ V- and H-polarization

RTM (soil moisture) Calibration

- SMOS L-band
 - ▶ Multiple incidence angles
 - ▶ V- and H-polarization

3D-Ensemble Kalman Filter in “Two Steps”

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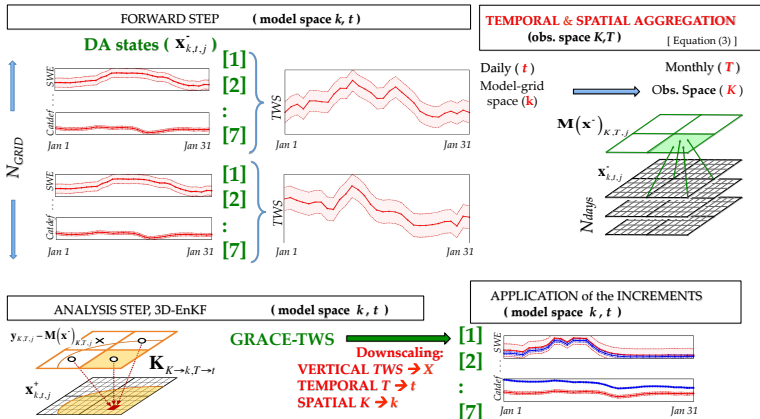
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Giroto et al., WRR, 52, 4164-4183, 10.1002/2015WR018417, 2016.

KEY: **Compute** *monthly-averaged analysis increments*

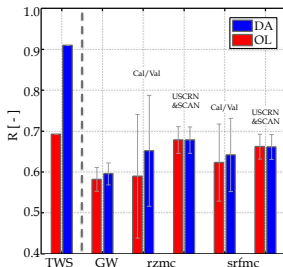
Validation across CONUS (GRACE only)

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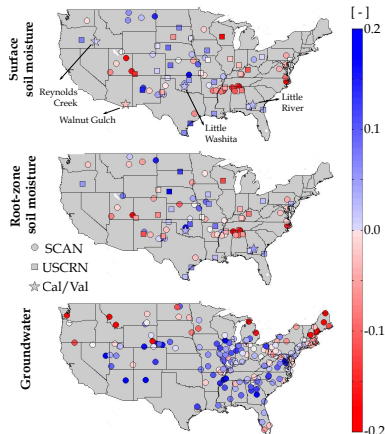
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- Improvements to groundwater
- Relatively minor improvements to soil moisture

Bulk Statistics:



$$\Delta_R = R_{DA} - R_{OL} \text{ [BLUE = Improvement]}$$



Giroto et al., WRR, 2016.

Measuring Soil Moisture from Space

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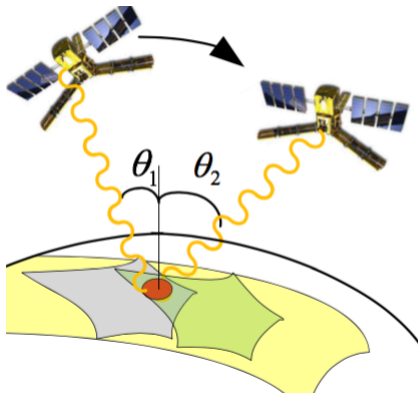
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Soil Moisture and Ocean Salinity (SMOS) Mission:

- Launched November 2009
- L-band radiometer → measures PMW brightness temperature (T_b) at multiple incidence $\angle$'s



PROS:

- $T_b \propto$ soil moisture
- Global coverage ($\sim 2-3$ days)
- 40-km spatial resolution

CONS:

- Only sensitive to surface layer (~ 5 cm)

Radiative Transfer Model (Obs. Operator)

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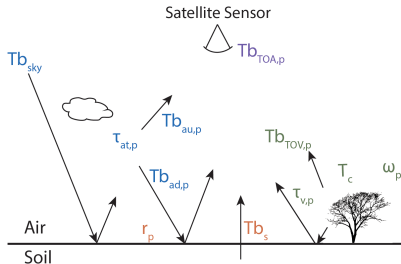
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where

$p, q \in [H, V]$; $p \neq q$

θ = Incidence angle

Atmospheric components

$Tb_{TOA,p}$ = Tb at top of atmosphere

$Tb_{au,p}$ = Atmospheric radiation (upward)

$Tb_{ad,p}$ = Atmospheric radiation (downward)

Tb_{sky} = Extra-terrestrial brightness temperature

$\tau_{at,p}$ = Atmospheric optical thickness

Vegetation components

$Tb_{TOV,p}$ = Tb at top of vegetation

T_c = Canopy temperature

Tb_v = Vegetation brightness temperature

ω_p = Single scattering albedo

$\tau_{v,p}$ = Vegetation optical thickness

Soil components

Tb_s = Soil brightness temperature

r_p = Rough surface reflectivity

R_p = Smooth surface reflectivity

Q = Polarization mixing factor

h = Roughness parameter

$$Tb_{TOV,p} = Tb_s \exp(-\tau_{v,p}) + Tb_v [1 + r_p \exp(-\tau_{v,p})] + Tb_{ad,p} r_p \exp(-2\tau_{v,p})$$

$$Tb_v = T_c (1 - \omega_p) [1 - \exp(-\tau_{v,p})]$$

$$Tb_{TOA,p} = T_{au,p} + \exp(-\tau_{at,p}) Tb_{TOV,p}$$

$$r_p = [(1 - Q) R_p + Q R_q] \exp(-h \cos^2 \theta)$$

Assumptions:

1. Non-frozen soil
2. Applicable for L-band (1.4 GHz) radiometry only

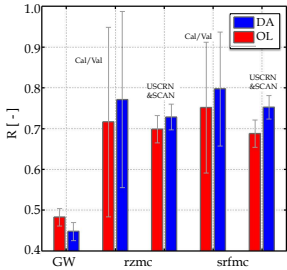
Validation across CONUS (SMOS only)

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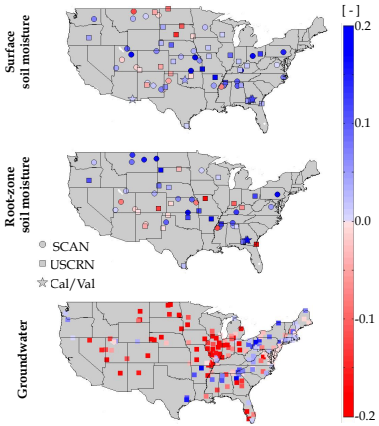
- Improvements to soil moisture
- Degradation of groundwater
- Competing vs. complementary information

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AMSR-E Background

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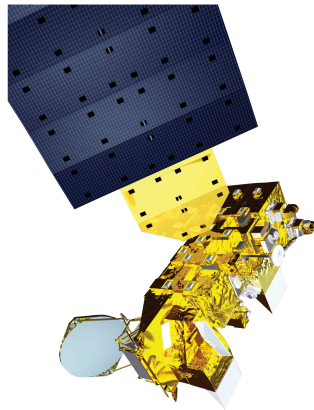
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Conclusions

- Advanced Microwave Scanning Radiometer EOS (AMSR-E)
- Measures multi-frequency, multi-polarization **passive microwave** radiation
 - ▶ 10.65, 18.7, and 36.5 GHz
 - ▶ V- and H-polarization
- Twice daily estimates (utilize **nighttime** only)
- Utilize **~25 km** EASE grid product
- Data record from 1 Sep 2002 to 1 Sep 2011 (**9 years**)



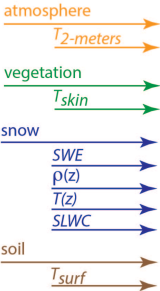
<http://aqua.nasa.gov/reference/publications.php>



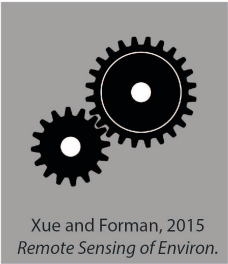
Machine Learning Approach

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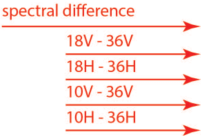
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NASA Catchment
Land Surface Model
(Koster et al., 2000)



Tb Observation Operator
(Forman et al., 2014;
Forman and Reichle, 2014;
Xue and Forman, 2016;
Forman and Xue, 2016)

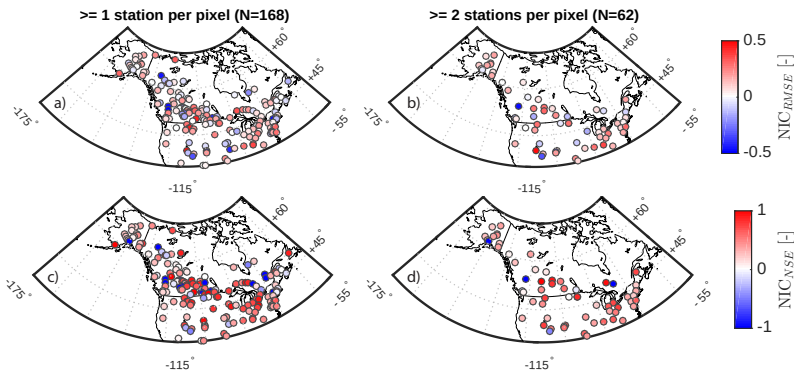


Multi-frequency,
Multi-polarization
Training Targets

;

Validation across NA (AMSR-E only)

Snow Depth [RED = improvement over Open Loop]



River Discharge (not shown) → 11 of 13 basins improved (~85%)

Xue et al., WRR, In Preparation

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Joint (SMOS+GRACE) Assimilation

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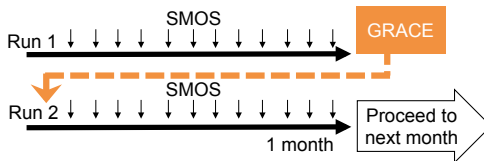
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Run 1:

- Conduct one month forecast ensemble integration
- SMOS-Tb assimilation
- Calculate model TWS observation prediction [spatial aggregation: model-to-observation grid & temporal aggregation: daily to monthly]
- Calculate increments via 3DEnKF

Run 2:

- Rewind the model to the beginning of the month and apply the GRACE Increments
- Integrate the model from the 1st - to the last day and re-perform SMOS-Tb assimilation



Joint (SMOS+GRACE) Validation

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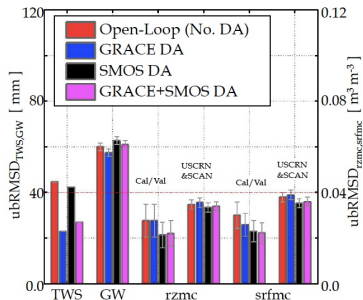
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Conclusions

- Joint assimilation **improves** surface (and root zone) soil moisture
- Joint assimilation maintains **high skill** in TWS estimation
- Joint assimilation **does not** degrade GW

Bulk Statistics:



Multi-scale Assimilation and Oversampling

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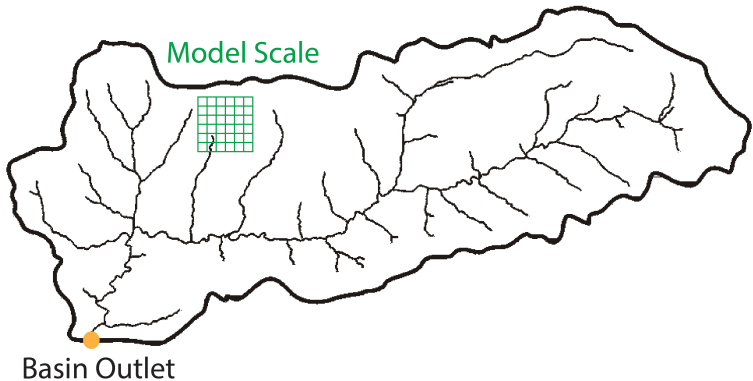
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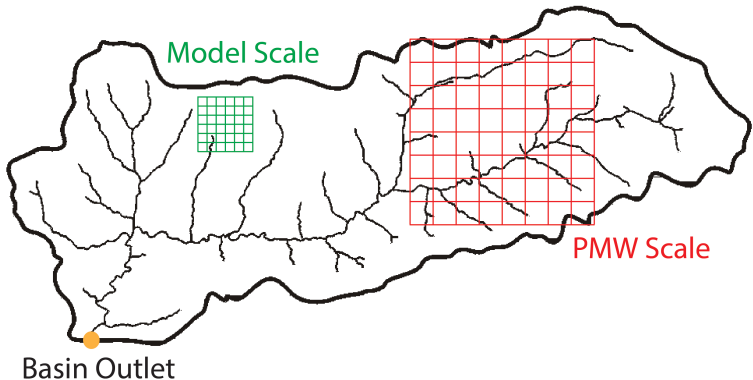
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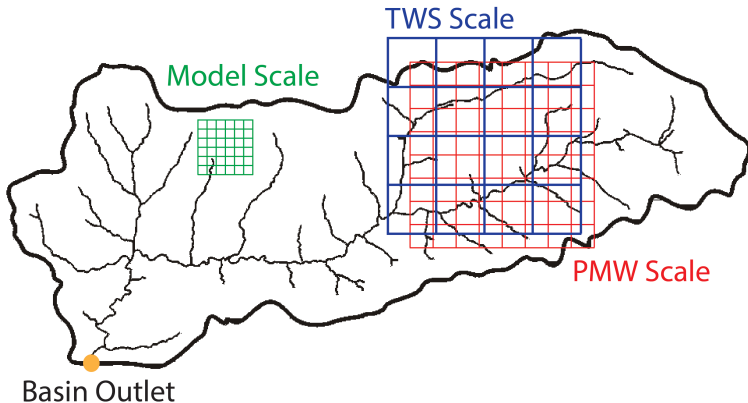
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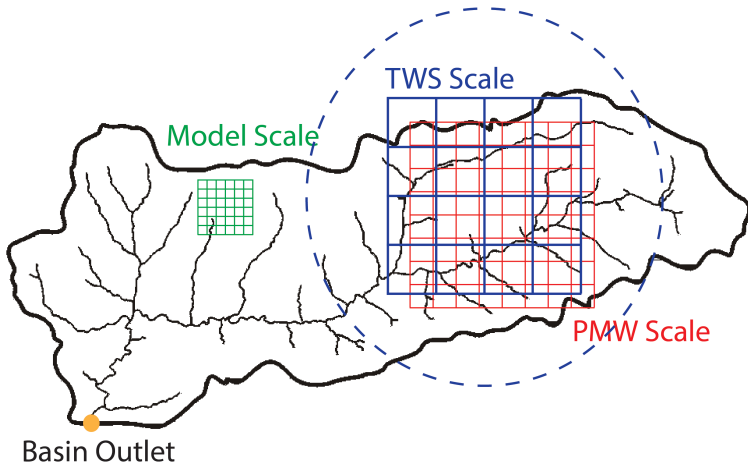
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Characterizing Spatially-correlated Errors

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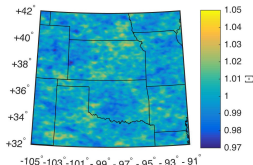
Challenges

Multi-scale

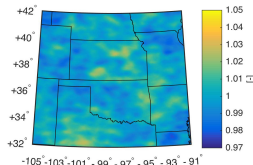
Spatial Errors

Conclusions

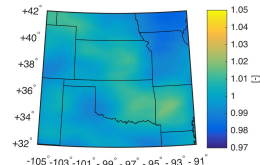
var03: $\bar{X} = 1$; $\sigma_X = 0.0599$; $\mathcal{L} \sim 10$ km;



var03: $\bar{X} = 1$; $\sigma_X = 0.0602$; $\mathcal{L} \sim 25$ km;



var03: $\bar{X} = 1$; $\sigma_X = 0.0651$; $\mathcal{L} \sim 100$ km;



increasing error correlation length scale ($\mathcal{L}$) $\longrightarrow$



Research Summary

GSTM 2017
Austin, Texas

Bart Forman

Motivation

TWS

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3D-EnKF

Validation

L-band

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K-,Ka-,X-band

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- Land surface models possess **skill due to improved forcings**
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Thank You.

Questions and/or Comments?

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