GMAO Seminar

March 3, 2008

Soil moisture data assimilation:

Error modeling, adaptive filtering, and the contribution of soil moisture retrievals to land data assimilation products

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Outline

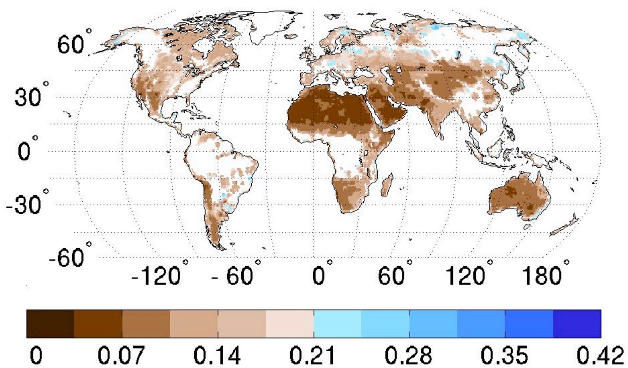
- *Motivation*
  - Soil moisture data assimilation
- *Part 1* *(doi:10.1029/2007WR006357)*
  - Impact of input error parameters on soil moisture estimates
  - Adaptive filtering
- *Part 2* *(doi:10.1029/2007GL031986)*
  - Contribution of soil moisture retrievals to land assimilation products

http://userpages.umbc.edu/~reichle/

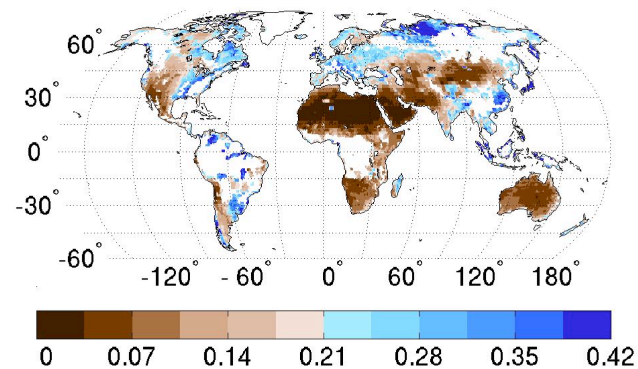
Introduction

Large-scale soil moisture is needed, for example, for water cycle studies and for initializing weather/climate models. It is available from:

AMSR-E surface soil moisture
Upper 1cm, ~50km, ~daily.



Catchment land surface model forced w/ observed meteorology. ***Complete space-time coverage, incl. root zone.***



Weights based on respective uncertainties.

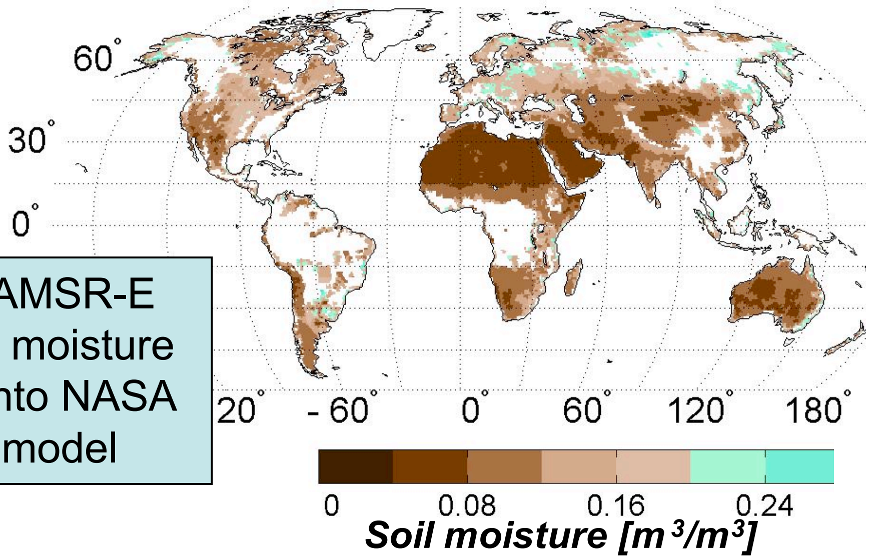
Soil moisture retrievals (subject to error) → Assimilation ← Model soil moisture (subject to error)

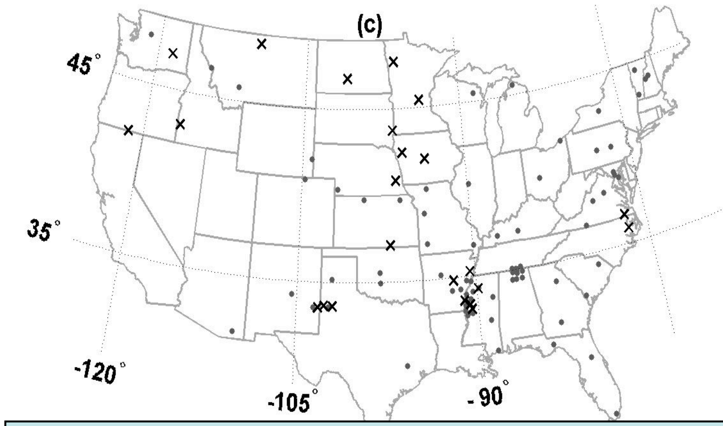
Assimilation → "Optimal" soil moisture

a.k.a. "Level 4 product"

Global assimilation of AMSR-E soil moisture retrievals

Assimilate AMSR-E surface soil moisture (2002-06) into NASA Catchment model





Validate with USDA SCAN stations (only 23 of 103 suitable for validation)

		Anomaly time series correlation coeff. with in situ data [-] (with 95% confidence interval)			Confidence levels: Improvement of assimilation over	
	N	**Satellite**	**Model**	**Assim.**	**Satellite**	**Model**
Surface soil moisture	23	**.38±.02**	**.43±.02**	**.50±.02**	**>99.99%**	**>99.99%**
Root zone soil moisture	22	**n/a**	**.40±.02**	**.46±.02**	**n/a**	**>99.99%**

Assimilation product agrees better with ground data than satellite or model alone.

Modest increase may be close to maximum possible with *imperfect* in situ data.

Reichle et al., *JGR*, 2007

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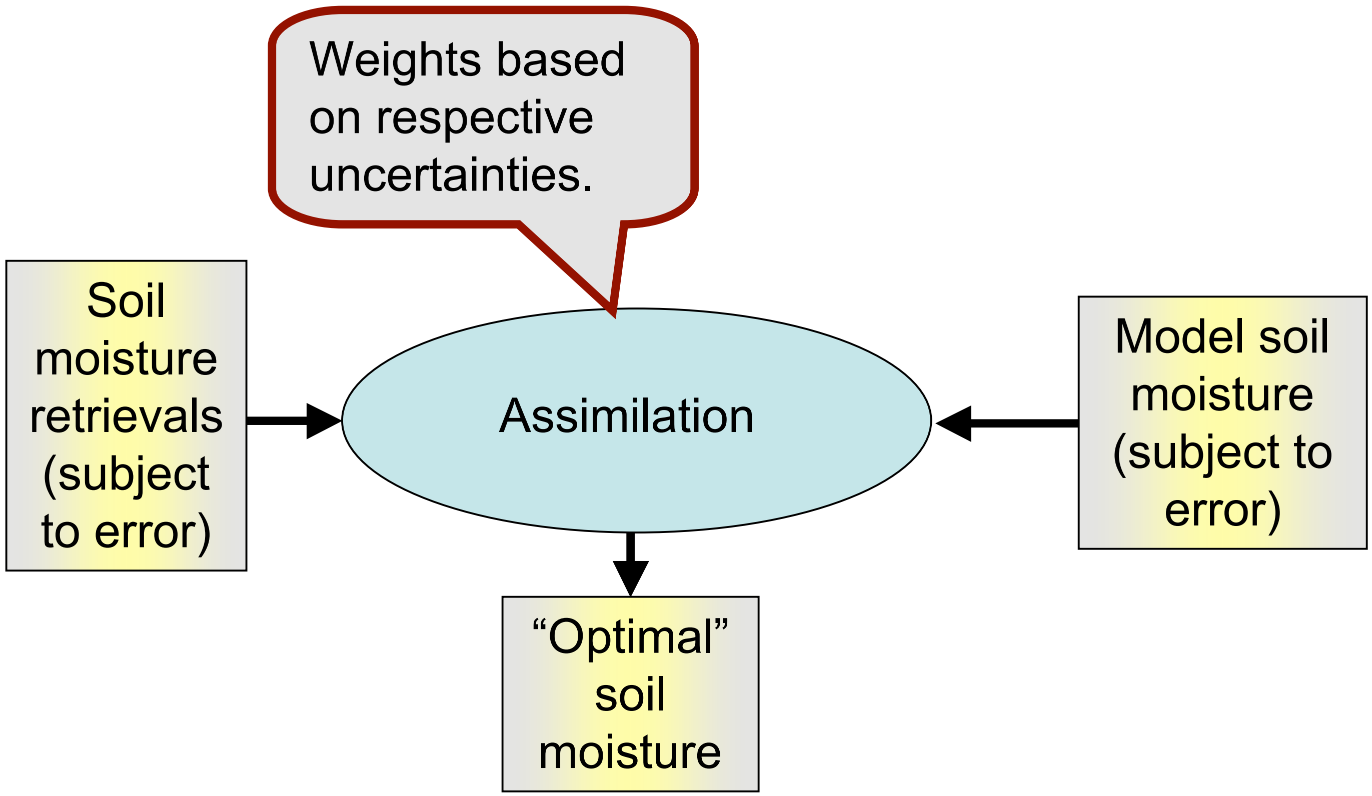
Input error parameters Q and R



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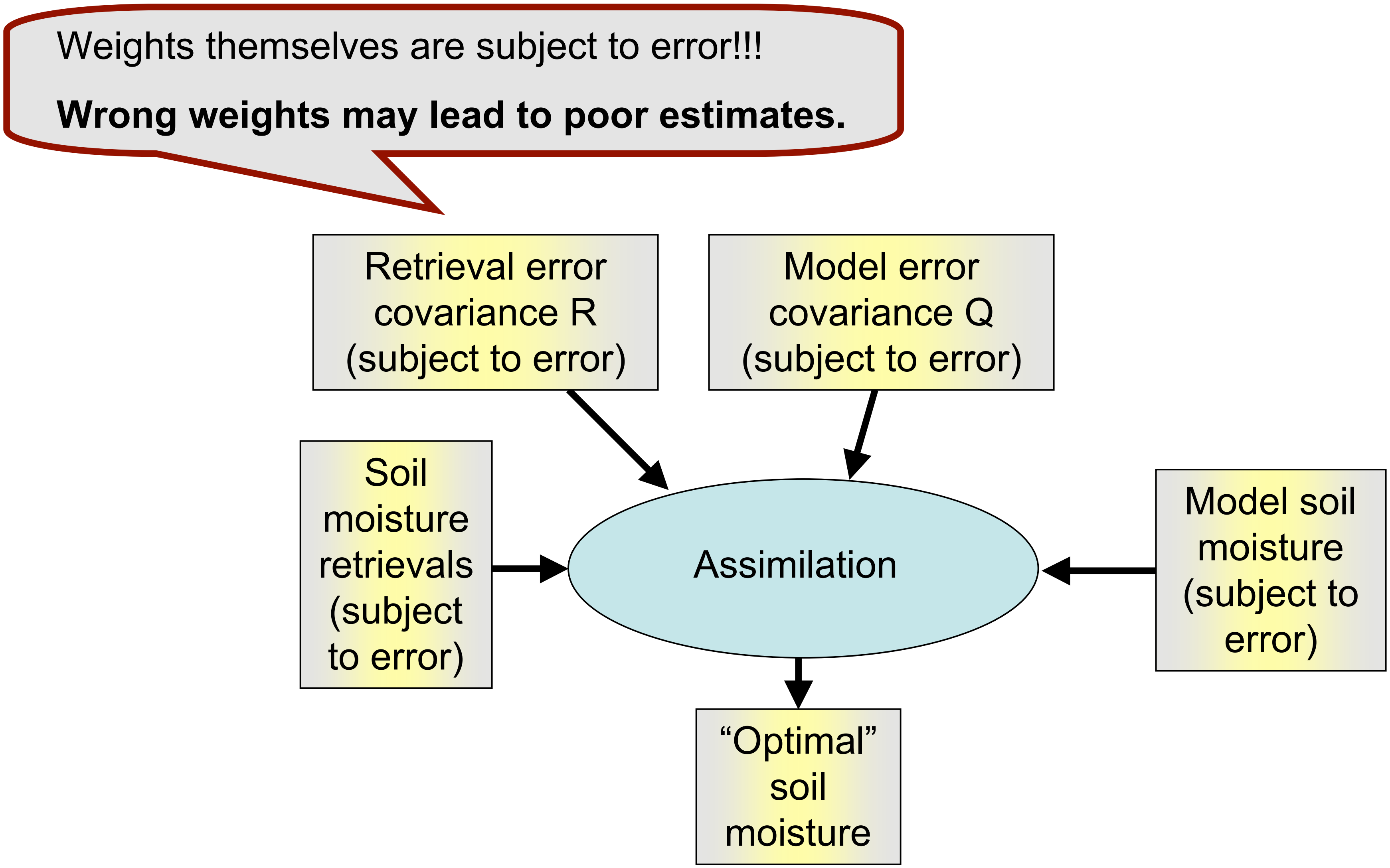
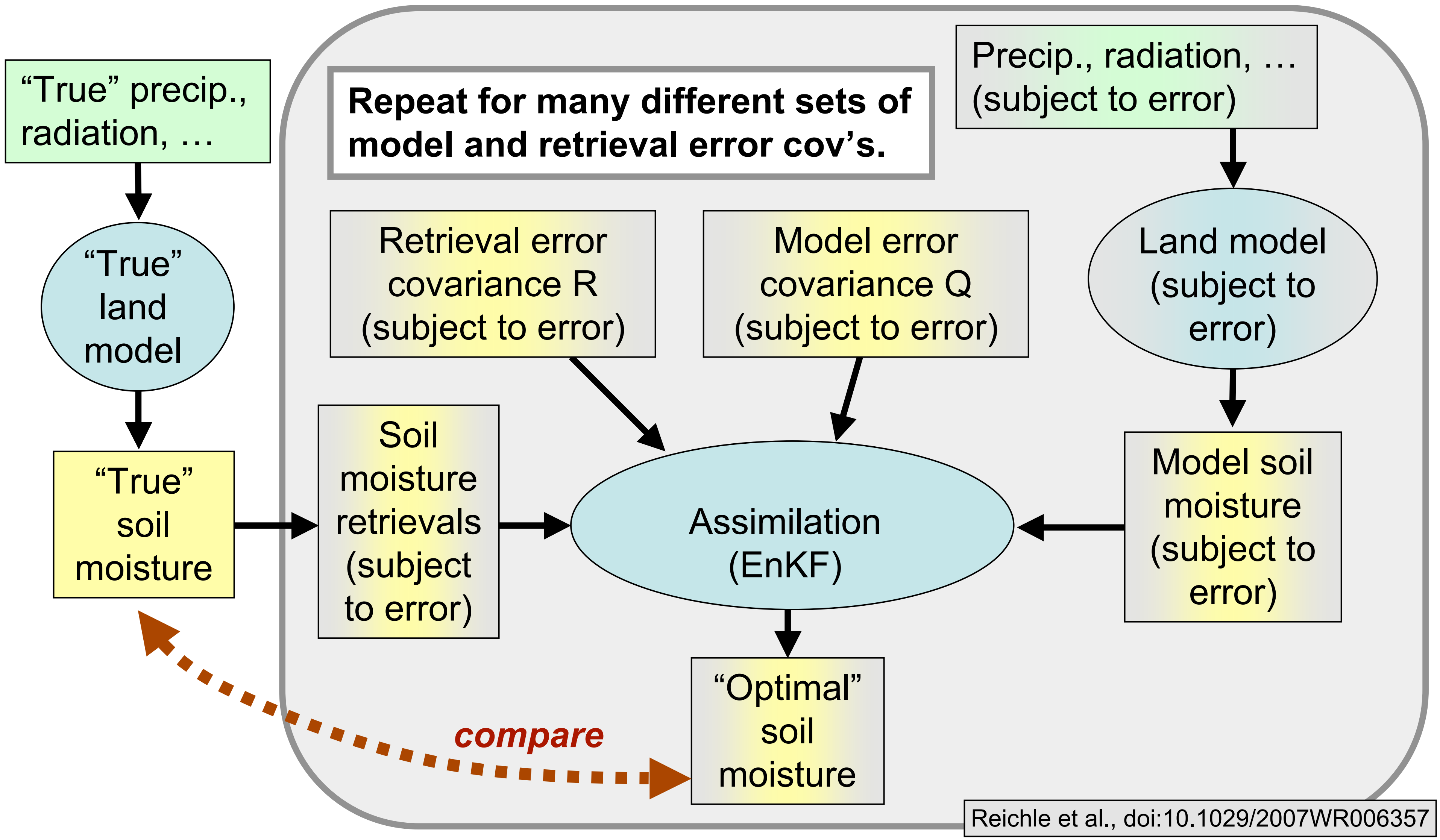


Synthetic assimilation experiment

Investigate impact of wrong model and obs. error inputs on assimilation estimates:

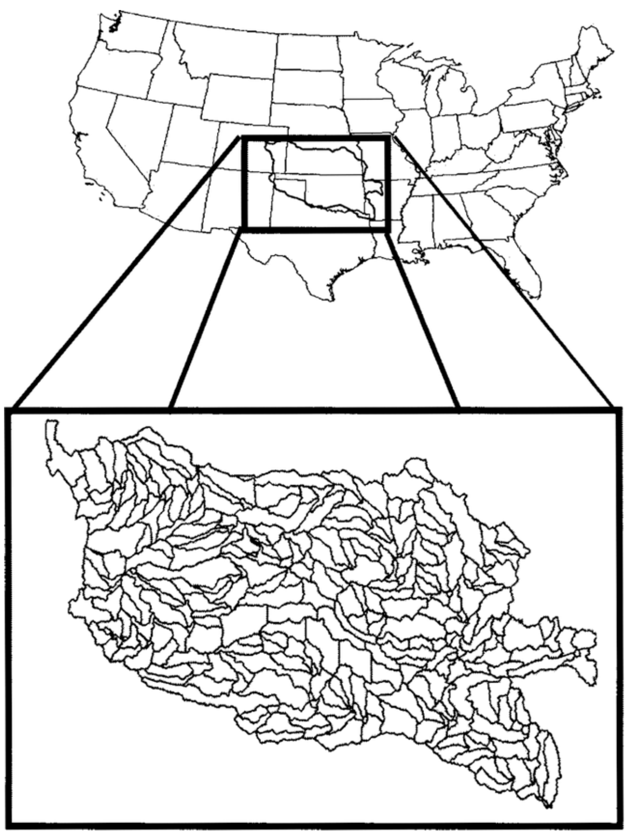


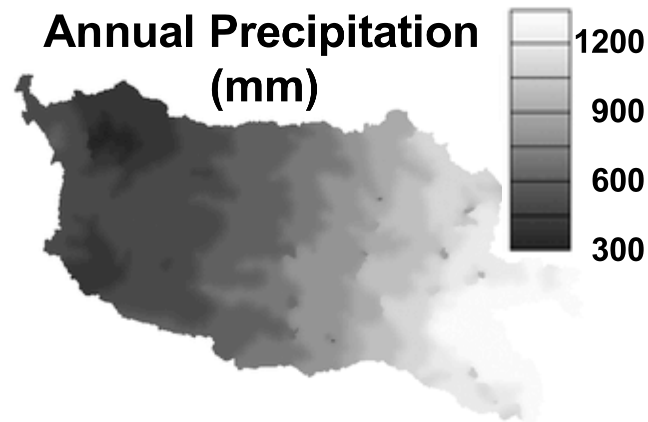
Red-Arkansas river basin

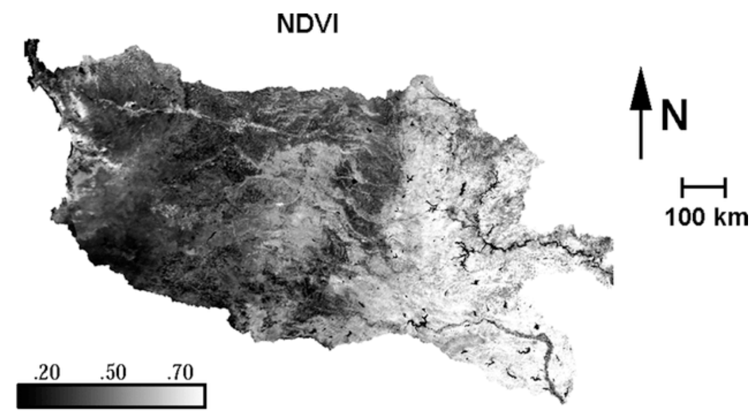
Red-Arkansas river basin (308 catchments)

Hourly forcing data (1981−2000)

NASA Catchment land surface model
(identical twin experiment)







West: Dry with sparse vegetation

East: Wet with dense vegetation

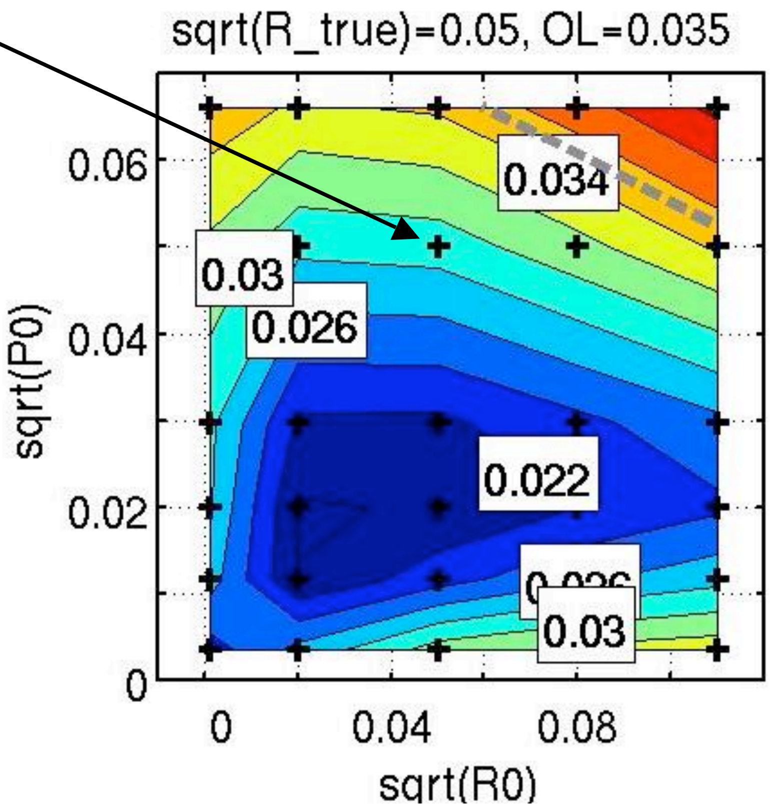
Sharif et al., JHM, 2007

Impact of Q and R on assimilation estimates

RMSE of assimilation estimates v. truth for:

Surface soil moisture m^3/m^3

Each "+" symbol represents one 19-year assim. experiment over the Red-Arkansas with a unique combination of input model and observation error parameters.



input obs error std-dev

forecast error std-dev

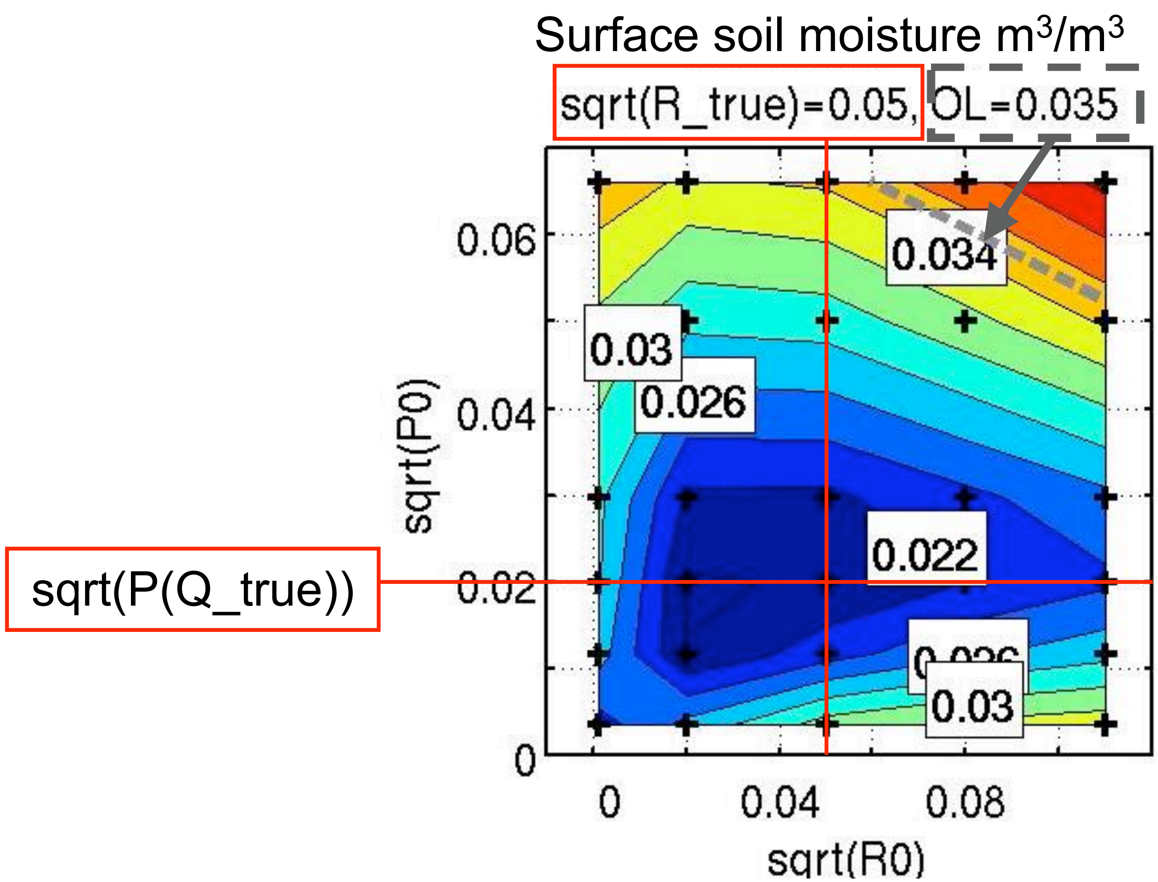
Q = model error (including errors in precip, radiation, and soil moisture tendencies)

P = P(Q) = soil moisture error variance

Reichle et al., doi:10.1029/2007WR006357

Impact of Q and R on assimilation estimates

RMSE of assimilation estimates v. truth for:

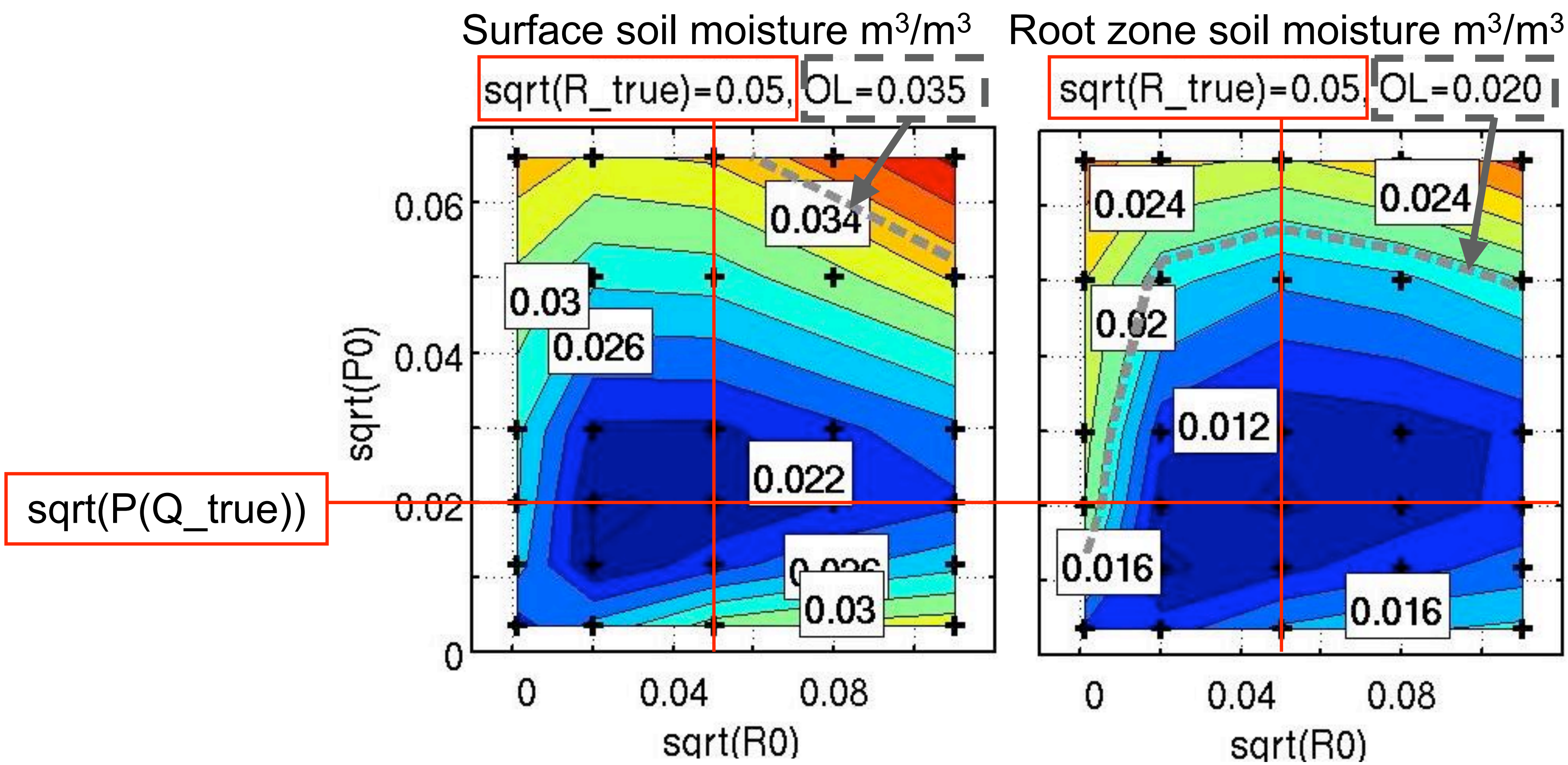


- "True" input error covariances yield minimum estimation errors.
- Wrong model and obs. error covariance inputs degrade assimilation estimates.
- In most cases, assimilation still better than open loop (OL).

Reichle et al., doi:10.1029/2007WR006357

Impact of Q and R on assimilation estimates

RMSE of assimilation estimates v. truth for:

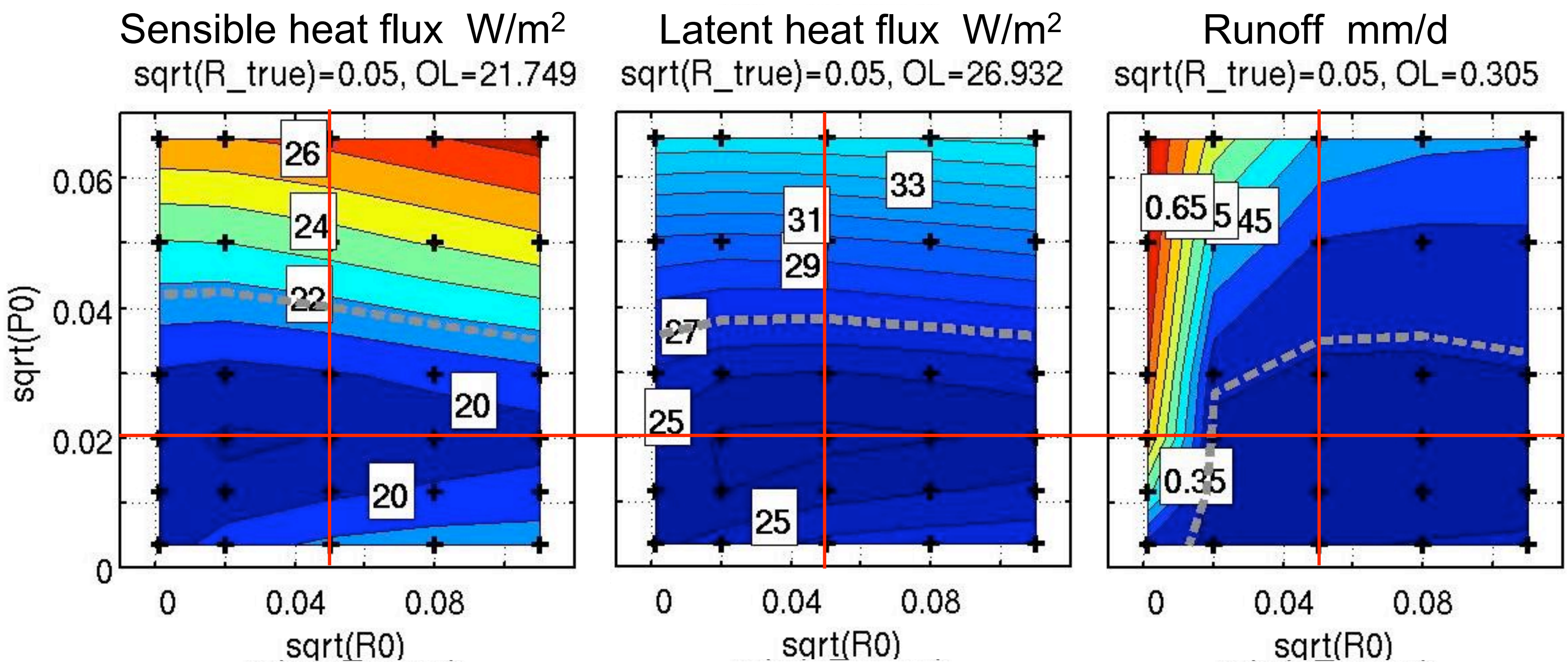


• Root zone more sensitive than surface soil moisture.

Reichle et al., doi:10.1029/2007WR006357

Impact of Q and R on assimilation estimates (fluxes)

RMSE of assimilation estimates v. truth for:



- Fluxes more sensitive to wrong error parameters than soil moisture.
- Sensible/latent heat more sensitive to model error cov than obs error cov (probably related to ensemble propagation).

Reichle et al., doi:10.1029/2007WR006357

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Diagnostics of filter performance and adaptive filtering

Find true Q, R by enumeration?

- RMSE plots require "truth" (not usually available).
- Too expensive computationally.

Use diagnostics that are available within the assimilation system.

Filter update: $\mathbf{x^+ = x^- + K(y - x^-)}$

$\mathbf{K = P\,(P + R)^{-1}}$ **= Kalman gain**

Diagnostic: $\mathbf{E[(y - x^-)\,(y - x^-)^T] = P + R}$

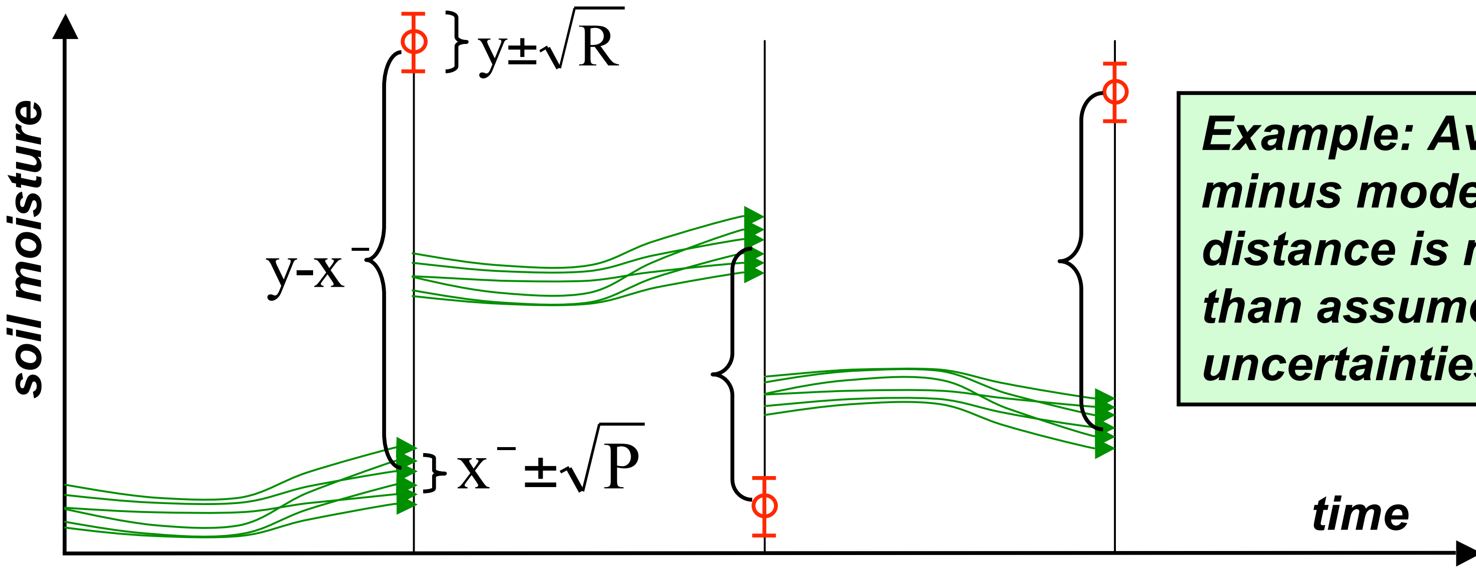
$\mathbf{x^-}$ = model forecast

$\mathbf{x^+}$ = "analysis"

$\mathbf{y}$ = observation

innovations ≡ obs – model prediction (internal diagnostic)

state err cov + obs err cov (controlled by inputs)



Example: Average "obs. minus model prediction" distance is much larger than assumed input uncertainties

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Diagnostic: $E[(y - x^-)(y - x^-)^T] = P + R$

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x^+ = "analysis"
y = observation

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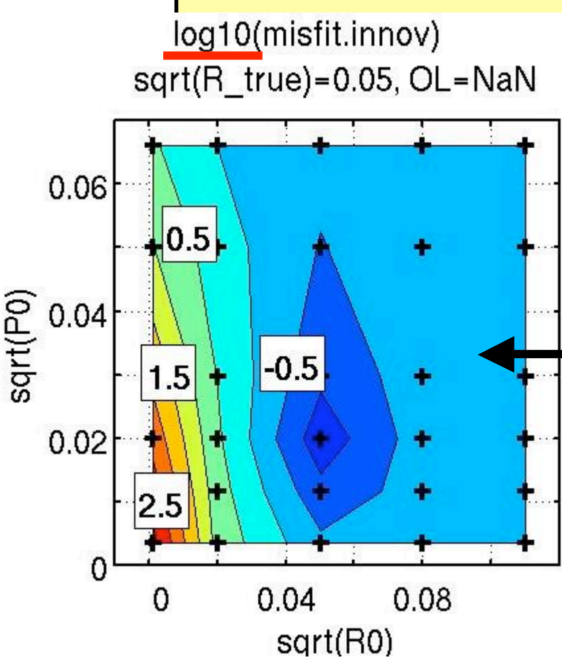

Contours: misfit between diagnostic and what it "should" be.

Adaptive filter: Nudge input error parameters (Q, R) during assimilation to minimize misfit.

Reichle et al., doi:10.1029/2007WR006357

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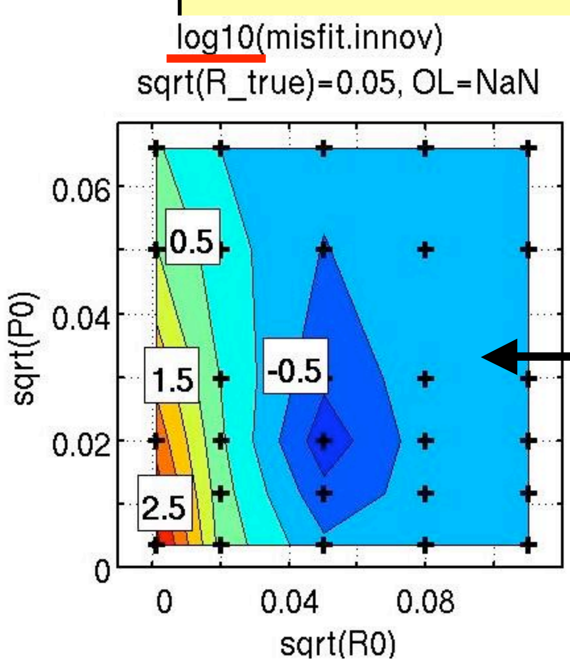


Contours: misfit between diagnostic and what it “should” be.

Adaptive filter: Nudge input error parameters (Q, R) during assimilation to minimize misfit.

Diagnostic 1: $E[(y - x^+)\,(y - x^-)^T] = R$
Diagnostic 2: $E[(x^+ - x^-)\,(y - x^-)^T] = P(Q)$

Reichle et al., doi:10.1029/2007WR006357

Adaptive algorithm

$t=1$

Initialize: $x_{0,i}^{+}$, $Q_1=Q_0$, $q_{1,i}$, $R_1=R_0$, $\alpha_{Q,0}=\alpha_{R,0}=1$
$MA[u\,v^T]_0=MA[HPH^T]_0=MA[w\,v^T]_0=MA[R]_0=R_0$

Propagate model: $x_{t,i}^{-} = f(x_{t-1,i}^{+}, q_{t,i})$

Forecast error cov.: $P_t = E\{(x_{t,i}^{-} - E\{x_{t,i}^{-}\})^2\}$
Kalman gain: $K_t = P_t H_t^T (H_t P_t H_t^T + R_t)^{-1}$
Analysis update: $x_{t,i}^{+} = x_{t,i}^{-} + K_t\,(y_{t,i} - H_t\,x_{t,i}^{-})$

1. EnKF propagation and update

Innovations: $v_t = E\{y_{t,i} - H_t\,x_{t,i}^{-}\}$
Analysis departures: $w_t = E\{y_{t,i} - H_t\,x_{t,i}^{+}\}$
Analysis increments: $u_t = E\{H_t(x_{t,i}^{+} - x_{t,i}^{-})\}$

a.)
$$MA[u\,v^T]_t = (1-\gamma)\,MA[u\,v^T]_{t-1} + \gamma\,u_t\,v_t^T$$
$$MA[w\,v^T]_t = (1-\gamma)\,MA[w\,v^T]_{t-1} + \gamma\,w_t\,v_t^T$$
$$MA[HPH^T]_t = (1-\gamma)\,MA[HPH^T]_{t-1} + \gamma\,H_t P_t H_t^T$$
$$MA[R]_t = (1-\gamma)\,MA[R]_{t-1} + \gamma\,R_t$$

2. Moving average of filter diagnostics

$t=t+1$

b.)
$$f_Q = \beta\,MA[u\,v^T]_t \,/\, MA[HPH^T]_t$$
$$f_R = MA[w\,v^T]_t \,/\, MA[R]_t$$

c.)
$$\alpha_{Q,t} = \alpha_{Q,t-1}\max(\min(f_Q,f_{max}),f_{min})$$
$$\alpha_{R,t} = \alpha_{R,t-1}\max(\min(f_R,f_{max}),f_{min})$$

d.)
$$\alpha_{Q,t} = \max(\min(\alpha_{Q,t},\alpha_{max}),\alpha_{min})$$
$$\alpha_{R,t} = \max(\min(\alpha_{R,t},\alpha_{max}),\alpha_{min})$$

e.)
$$\boxed{Q_{t+1} = \alpha_{Q,t}\,Q_0}\ \text{(and generate } q_{t,i}\text{)}$$
$$\boxed{R_{t+1} = \alpha_{R,t}\,R_0}$$

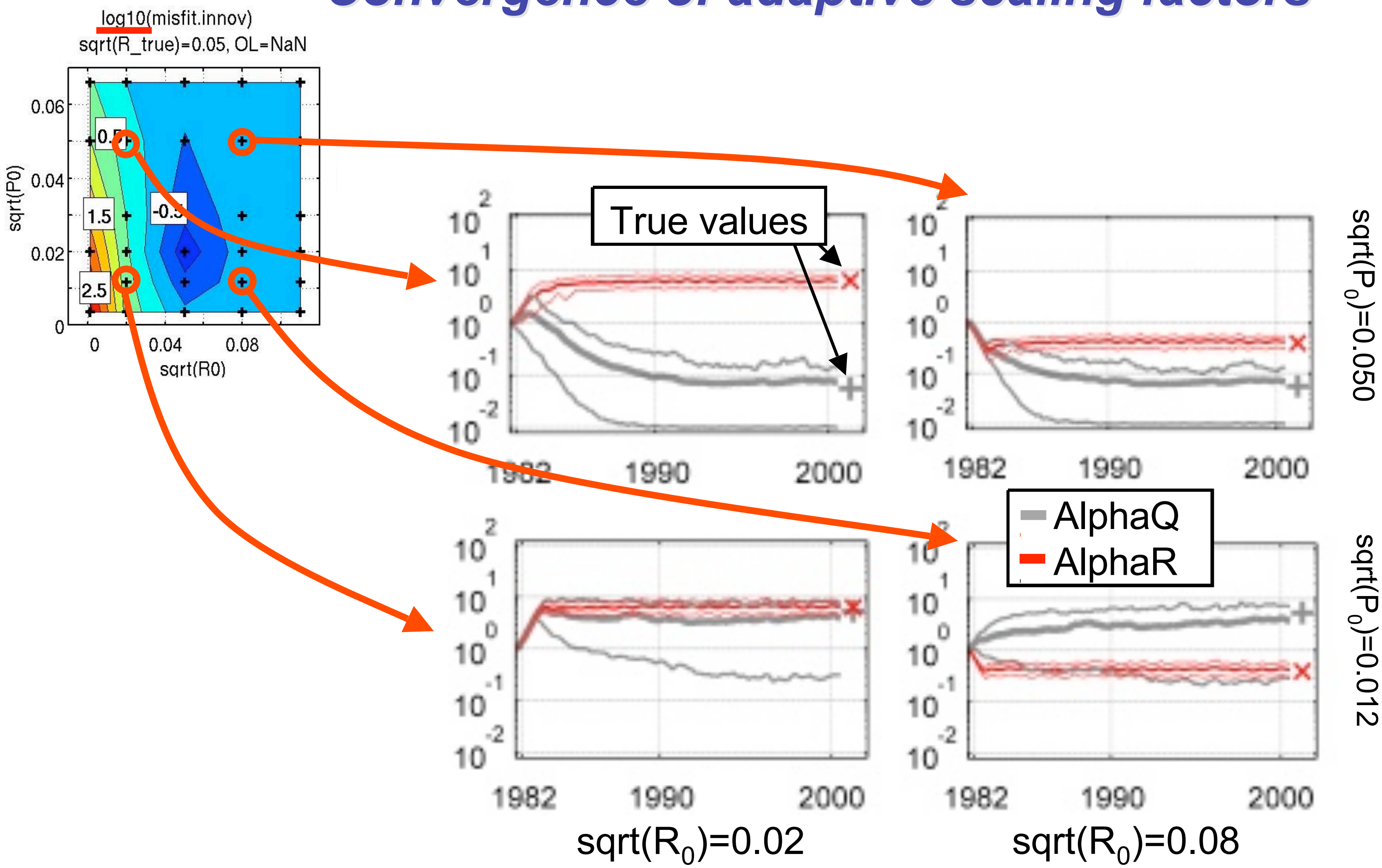
$\gamma = 0.02$
$\beta = 1.06$
$\delta = 0.005$
$f_{min} = (1+\delta)^{-1}$
$f_{max} = (1+\delta)$
$\alpha_{min} = 0.01$
$\alpha_{max} = 100$

3. Adaptive scaling coefficients

- Adapted *Dee* et al. for land
- Cheap
- Need parameters

Reichle et al., doi:10.1029/2007WR006357

Convergence of adaptive scaling factors



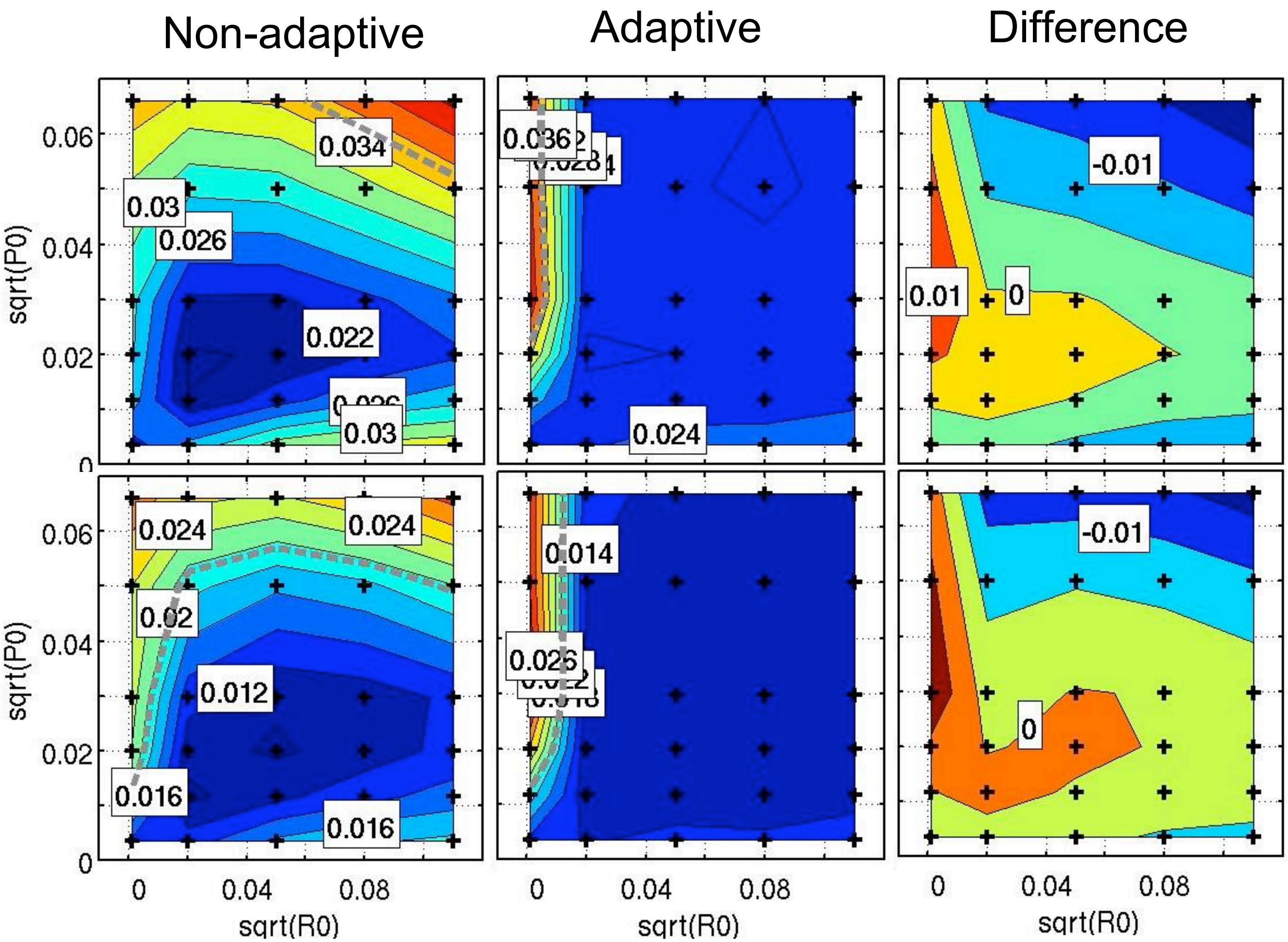
- Adaptive scaling factors generally converge to true values (thick lines).
- Convergence is slow (order of years).
- Spatial variability (thin lines) much greater for alphaQ than for alphaR.

Reichle et al., doi:10.1029/2007WR006357

Adaptive v. non-adaptive EnKF (soil moisture)

Surface soil moisture m^3/m^3

Root zone soil moisture m^3/m^3



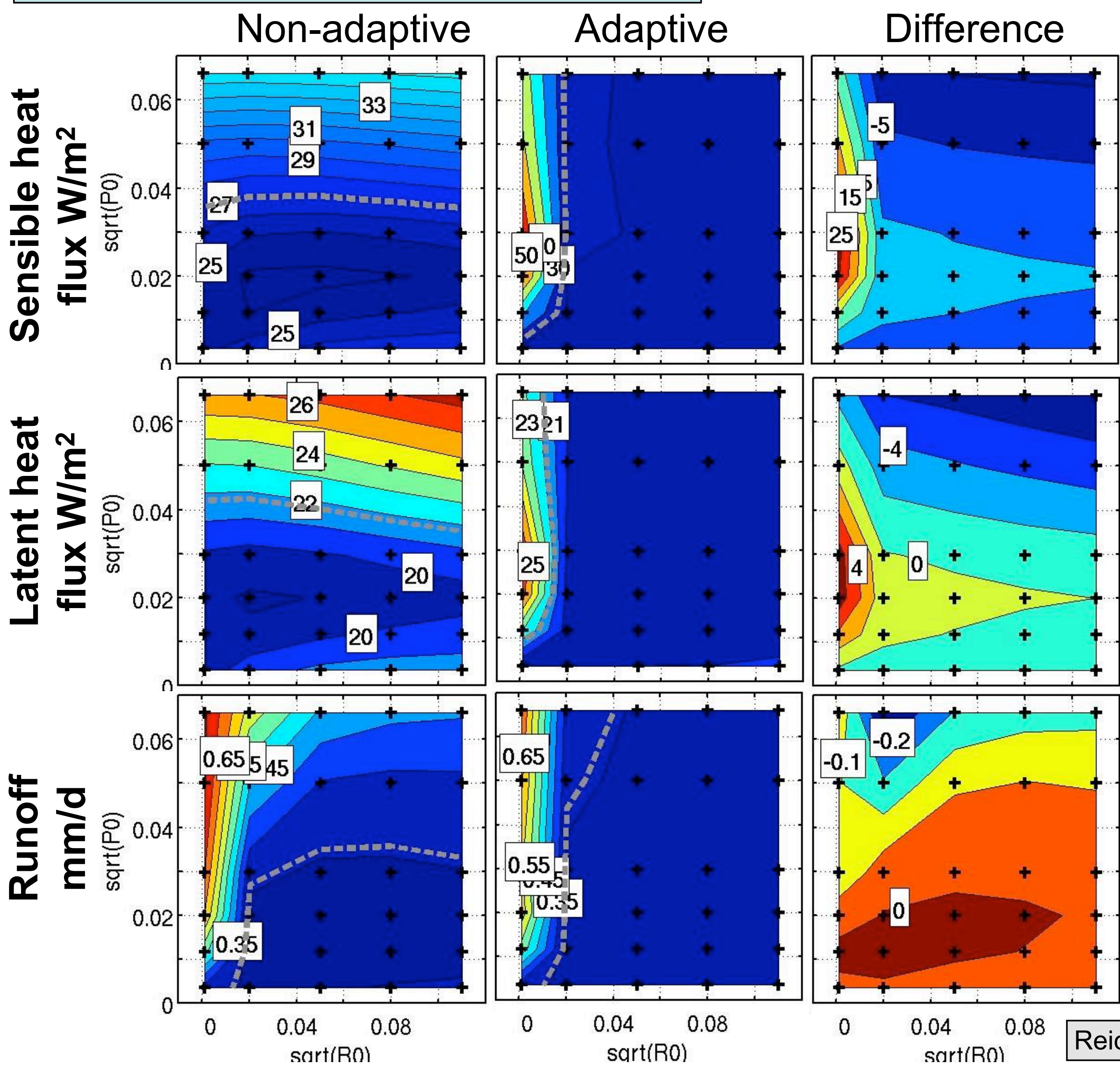
Contours: RMSE of assim. estimates v. truth

• Adaptive filter: Map experiment onto contour plot based on initial guess of R, P(Q).
• Adaptive filter yields improved assimilation estimates for initially wrong model and observation error inputs (except for R_0=0).

Reichle et al., doi:10.1029/2007WR006357

Adaptive v. non-adaptive EnKF (fluxes)

Contours: RMSE of assim. est. v. truth



- Adaptive filter generally yields improved flux estimates.
- Degradation when R is severely underestimated.
  → Simply choose large R at the start and let the filter adapt it.

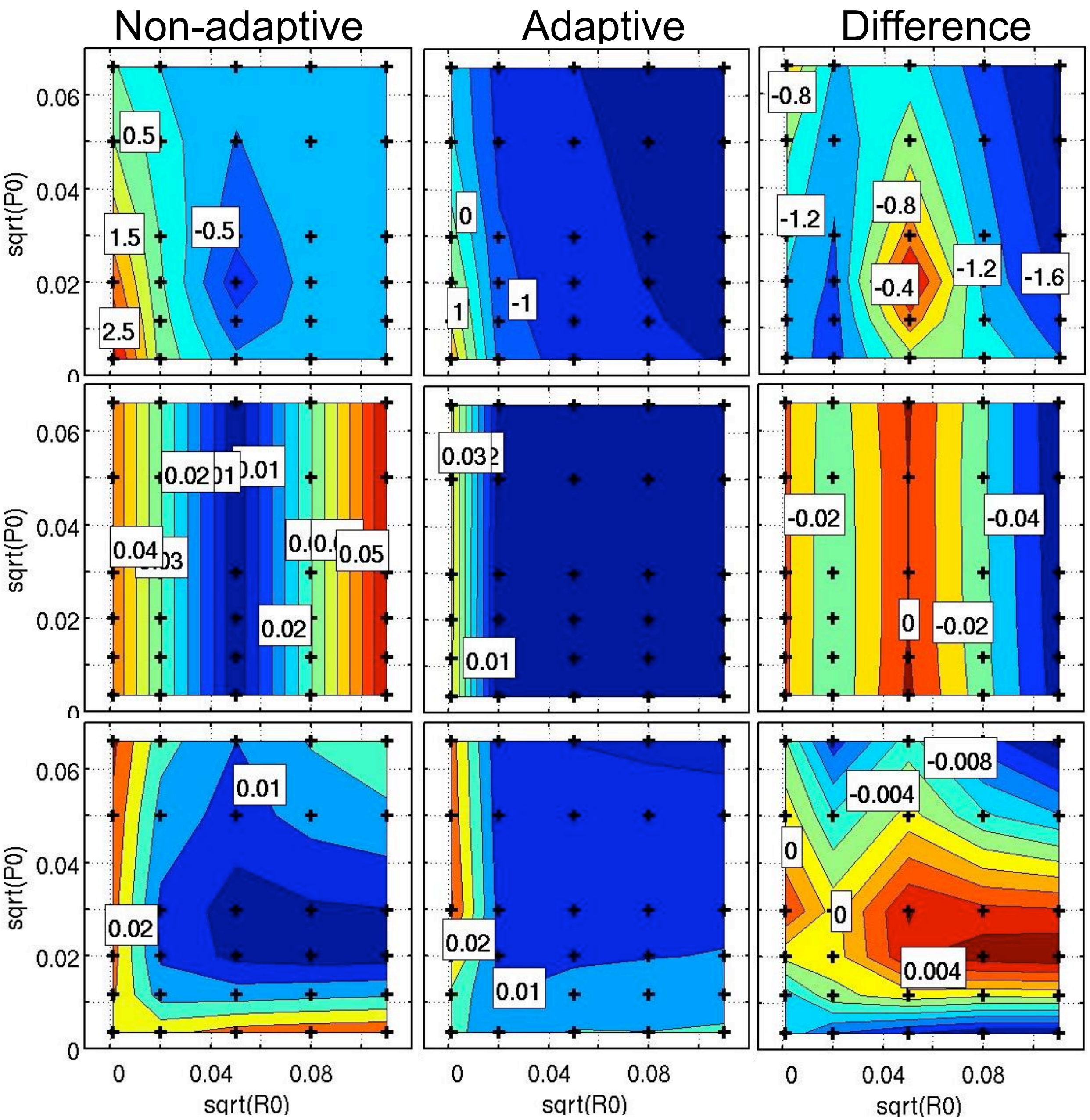
Reichle et al., doi:10.1029/2007WR006357

Adaptive v. non-adaptive EnKF (filter diagnostics)

Log10 of innov. misfit

Error in estimate of obs error std sqrt(R) m^3/m^3

Error in estimate of analysis error std "sqrt(P^+)" m^3/m^3



- Adaptive filter (by design) improves innovations stats.
- Adaptive filter retrieves obs error std (except for R_0=0).
- On balance, adaptive filter improves estimate of error bars on assimilation product (surface soil moisture).

Adaptive filter summary

Wrong model and observation error inputs degrade assimilation estimates.

Degradation quantified with synthetic experiment over Red-Arkansas river basin.

Adaptive EnKF:

+ Generally improves assimilation estimates.

+ Better at estimating obs. error cov. R than model error cov. Q.

+ Cheap.

Future applications:

Use for AMSR-E soil moisture assimilation.

Estimates of AMSR-E obs. error variance (not provided by official NASA product).

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Problem statement

Design problem for future satellite missions
(eg. NASA Soil Moisture Active Passive "SMAP" mission)

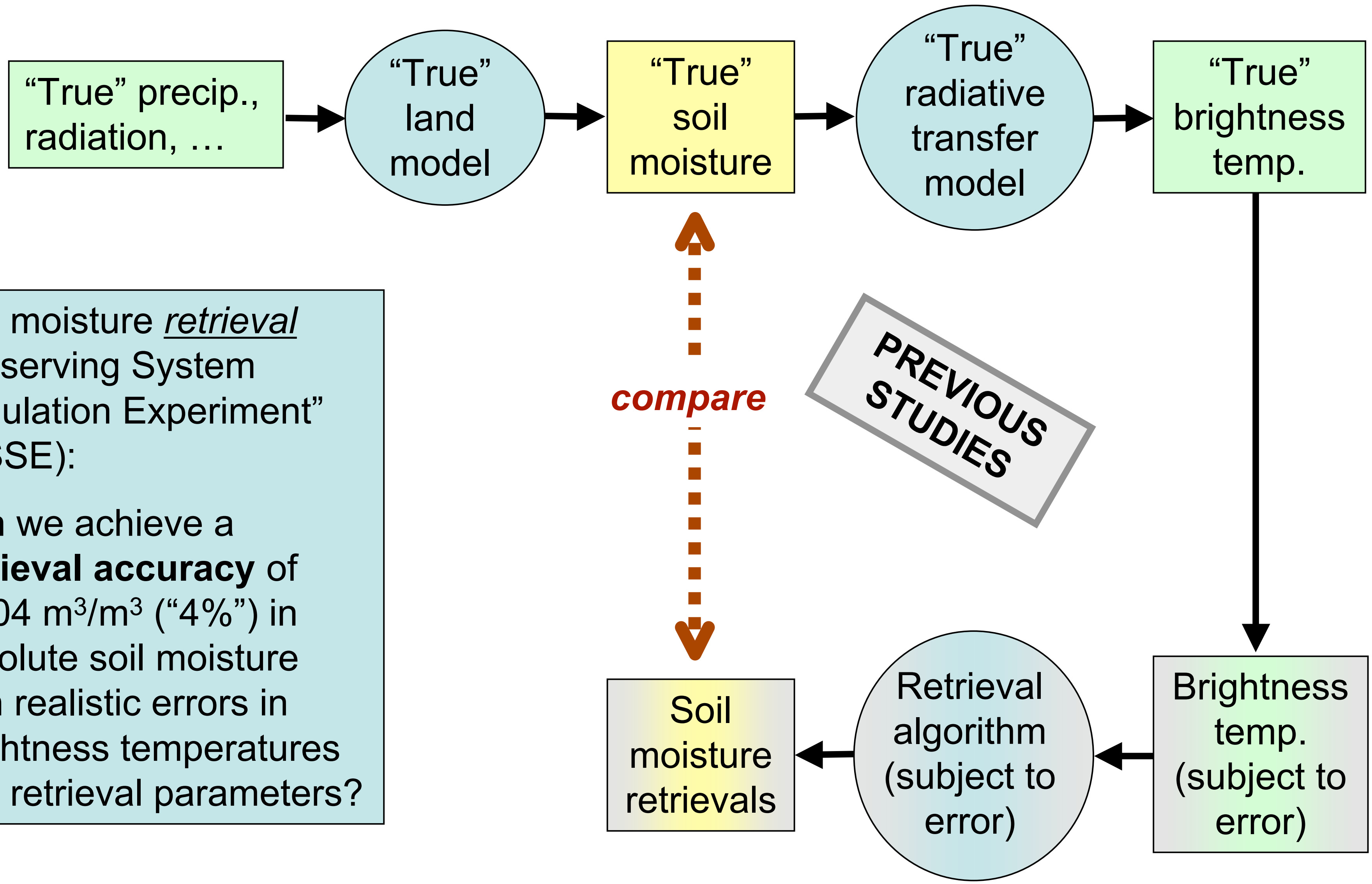
How uncertain can retrievals be and still add useful information in the assimilation system?

		Anomaly time series correlation coeff. with in situ data [-] (with 95% confidence interval)		
	N	**Satellite**	**Model**	**Assim.**
Surface soil moisture	23	**.38±.02**	**.43±.02**	**.50±.02**

Example: **If target skill=0.5 and model skill=0.43, need retrieval skill≥0.38.**

Goal: **Contour plot based on many such triplets of numbers.**

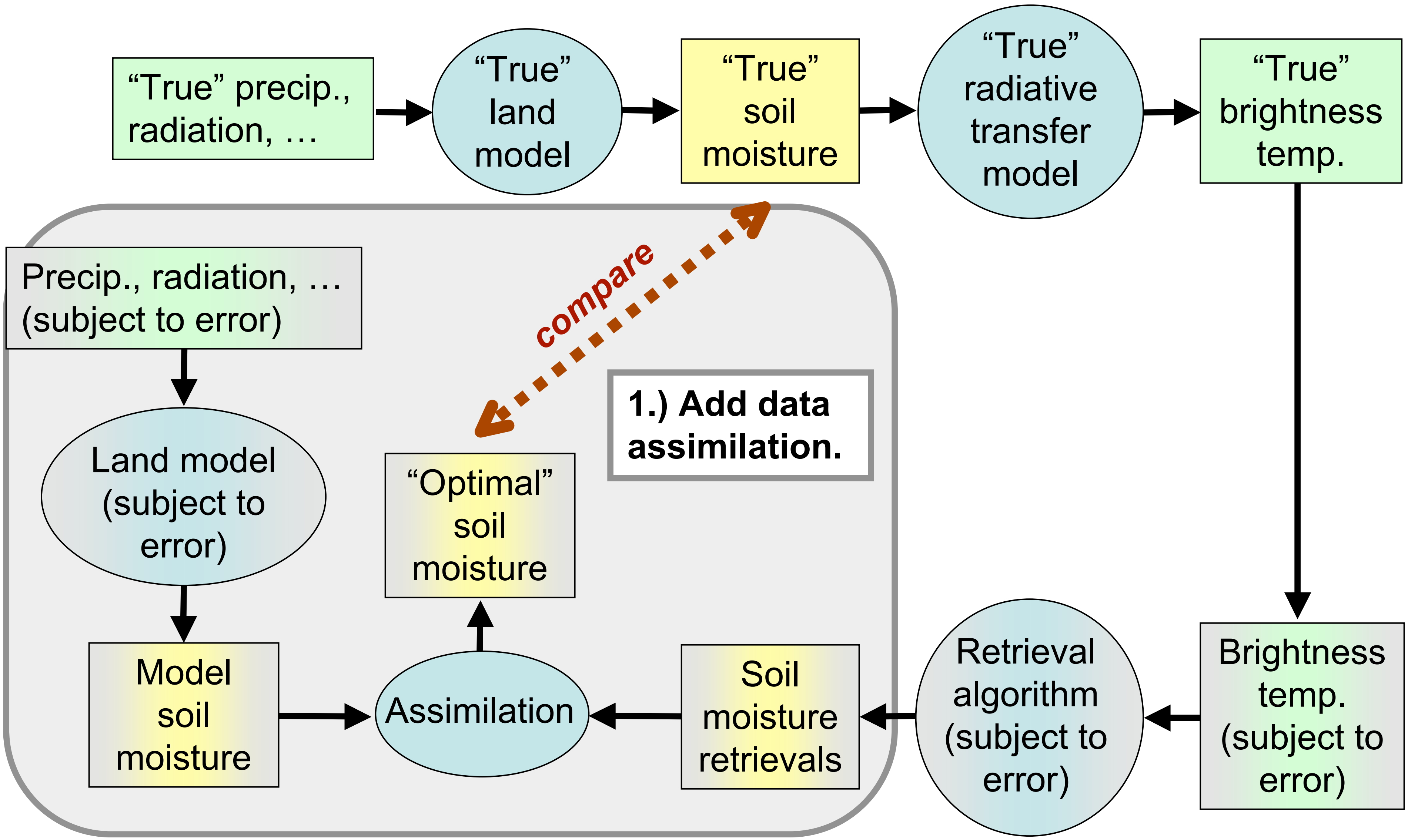
Previous work: Soil moisture retrieval OSSE



Soil moisture *retrieval* "Observing System Simulation Experiment" (OSSE):

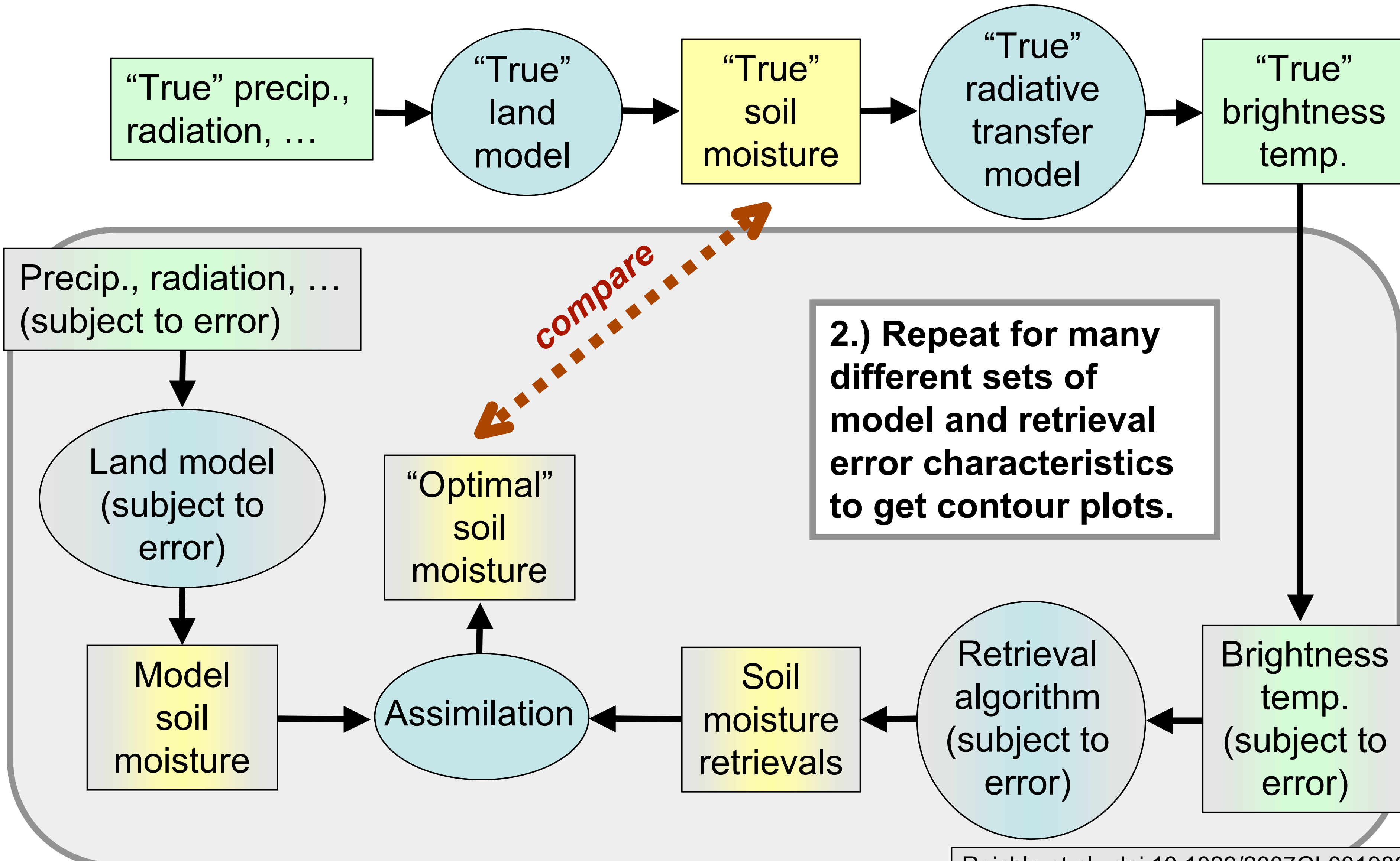
Can we achieve a **retrieval accuracy** of ~0.04 m^3/m^3 ("4%") in absolute soil moisture with realistic errors in brightness temperatures and retrieval parameters?

Soil moisture assimilation OSSE: Design



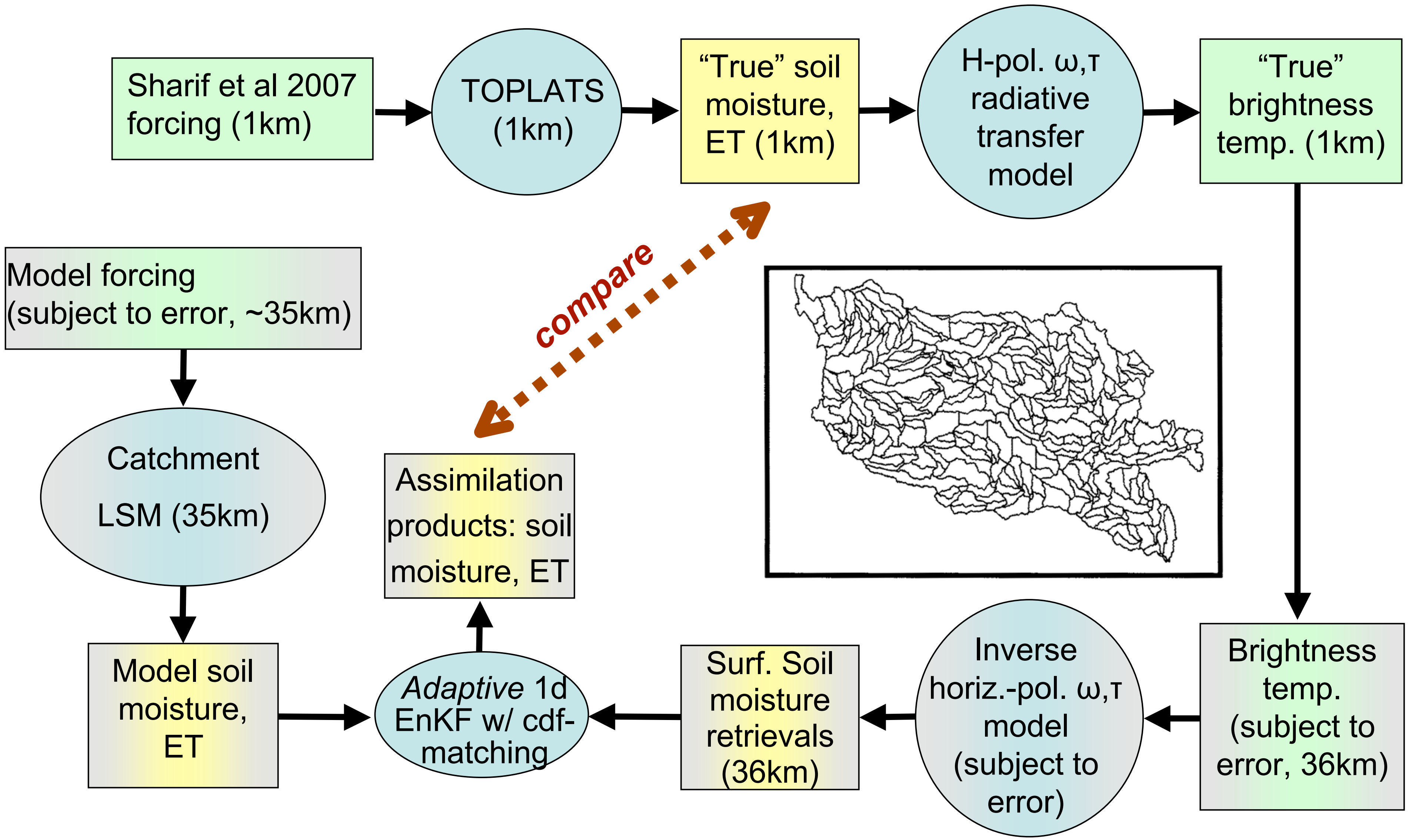
Reichle et al., doi:10.1029/2007GL031986

Soil moisture assimilation OSSE: Design



Reichle et al., doi:10.1029/2007GL031986

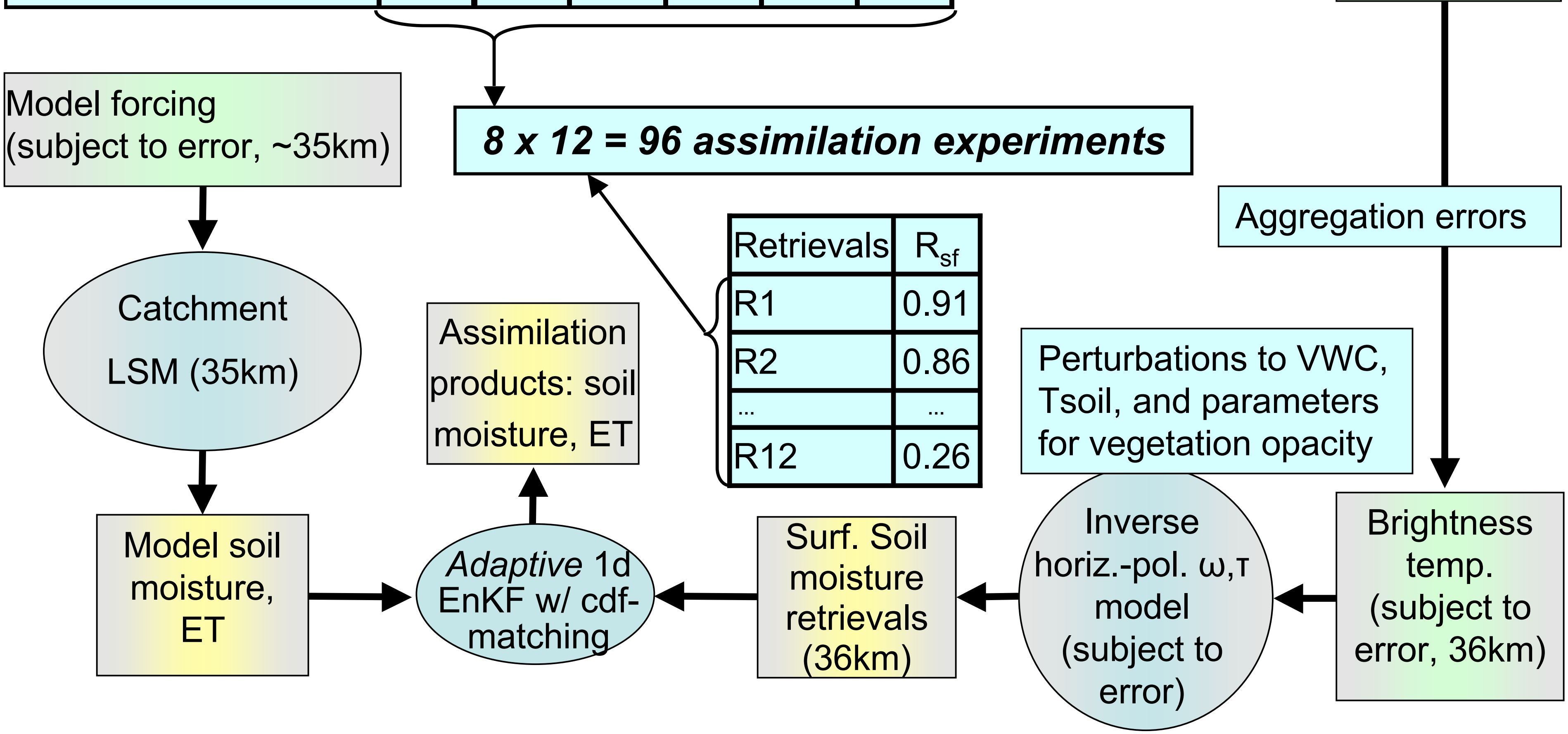
Soil moisture assimilation OSSE: Implementation



Reichle et al., doi:10.1029/2007GL031986

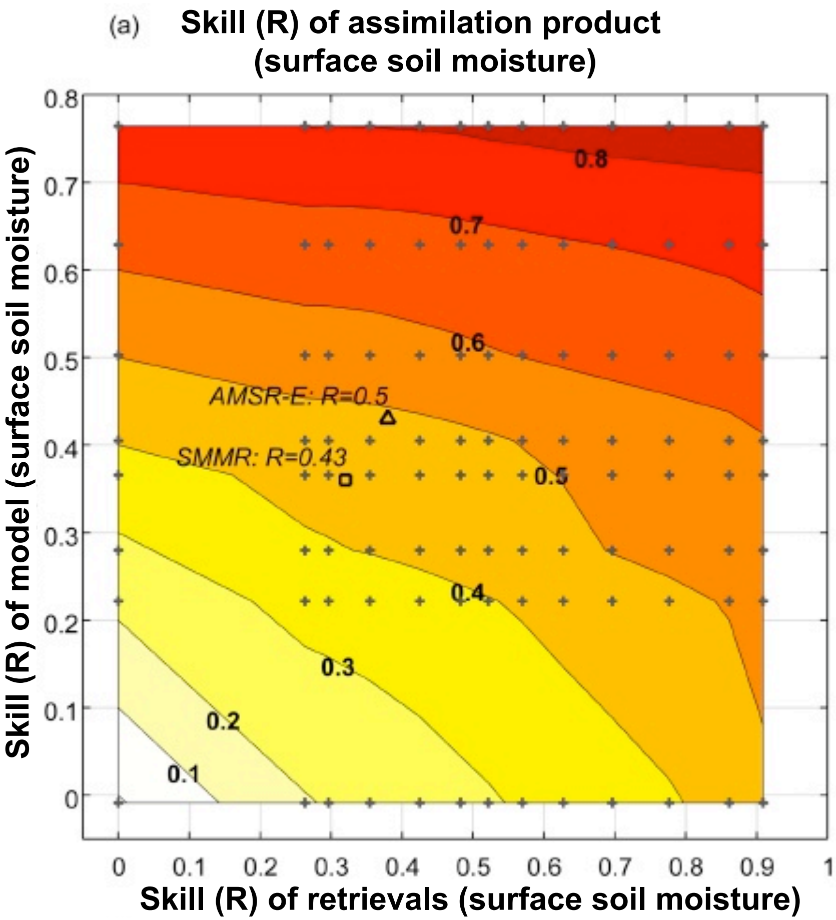
Soil moisture assimilation OSSE: Implementation

Model scenario	**M1**	**M2**	**M4**	**M3**	**…**	**M8**
Base forcing dataset	**F1**	**F2**	**F3**	**F1**	**…**	**F1**
Forcing shift [days]	**n/a**	**n/a**	**n/a**	**7**	**…**	**365**
R_{sf} (skill)	**0.76**	**0.63**	**0.41**	**0.5**	**…**	**-0.01**
R_{rz} (skill)	**0.78**	**0.55**	**0.46**	**0.64**	**…**	**0.01**
R_{ET} (skill)	**0.65**	**0.38**	**0.37**	**0.58**	**…**	**0.02**



Reichle et al., doi:10.1029/2007GL031986

Skill of soil moisture estimates



Skill is measured in terms of R
(=anomaly time series correlation coefficient against truth).

Contours show the skill of the assimilation product

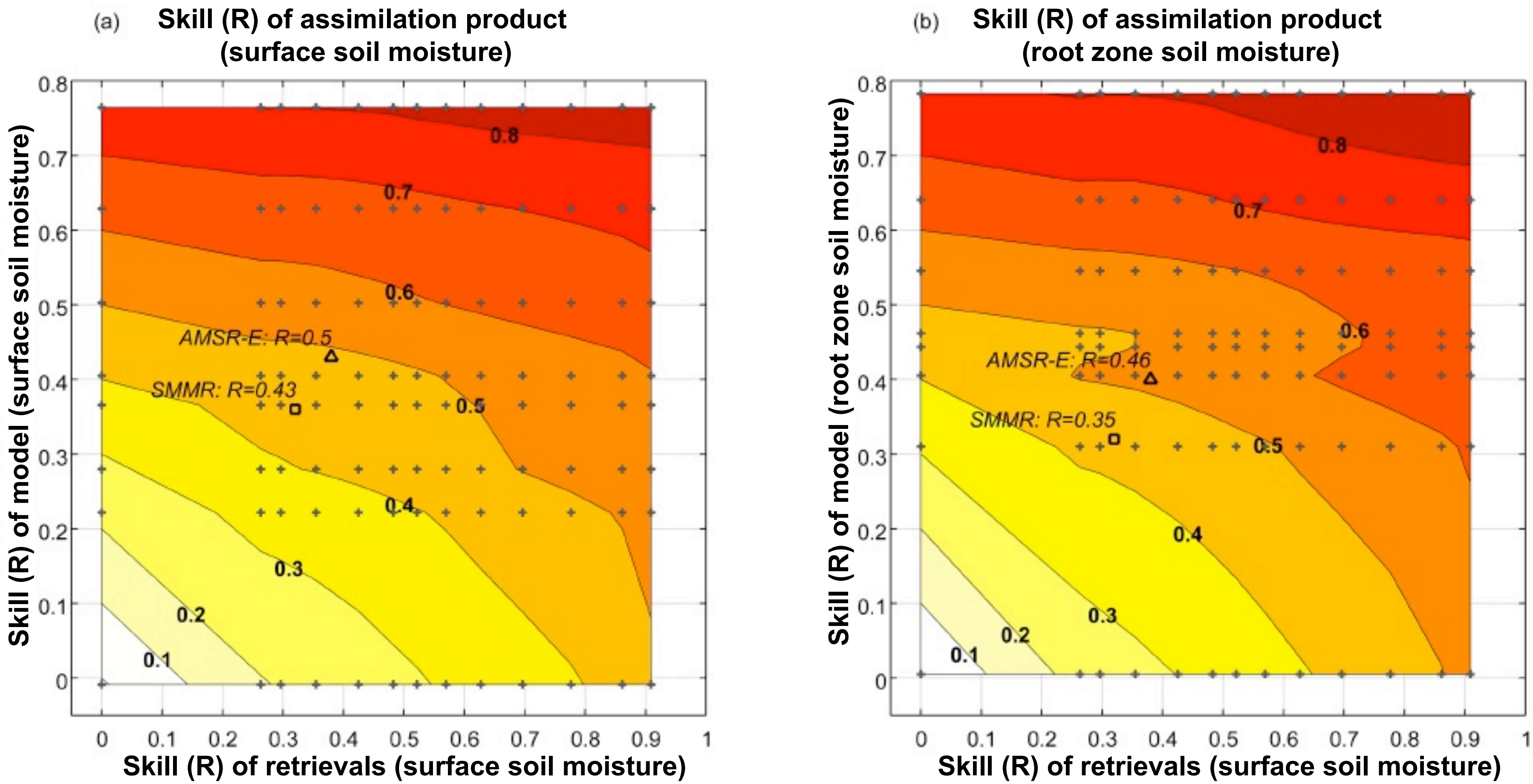
X-axis: Skill of retrievals

Y-axis: Skill of model product

Each plus sign indicates the result of one 19-year assimilation integration over the entire Red-Arkansas domain.

Reichle et al., doi:10.1029/2007GL031986

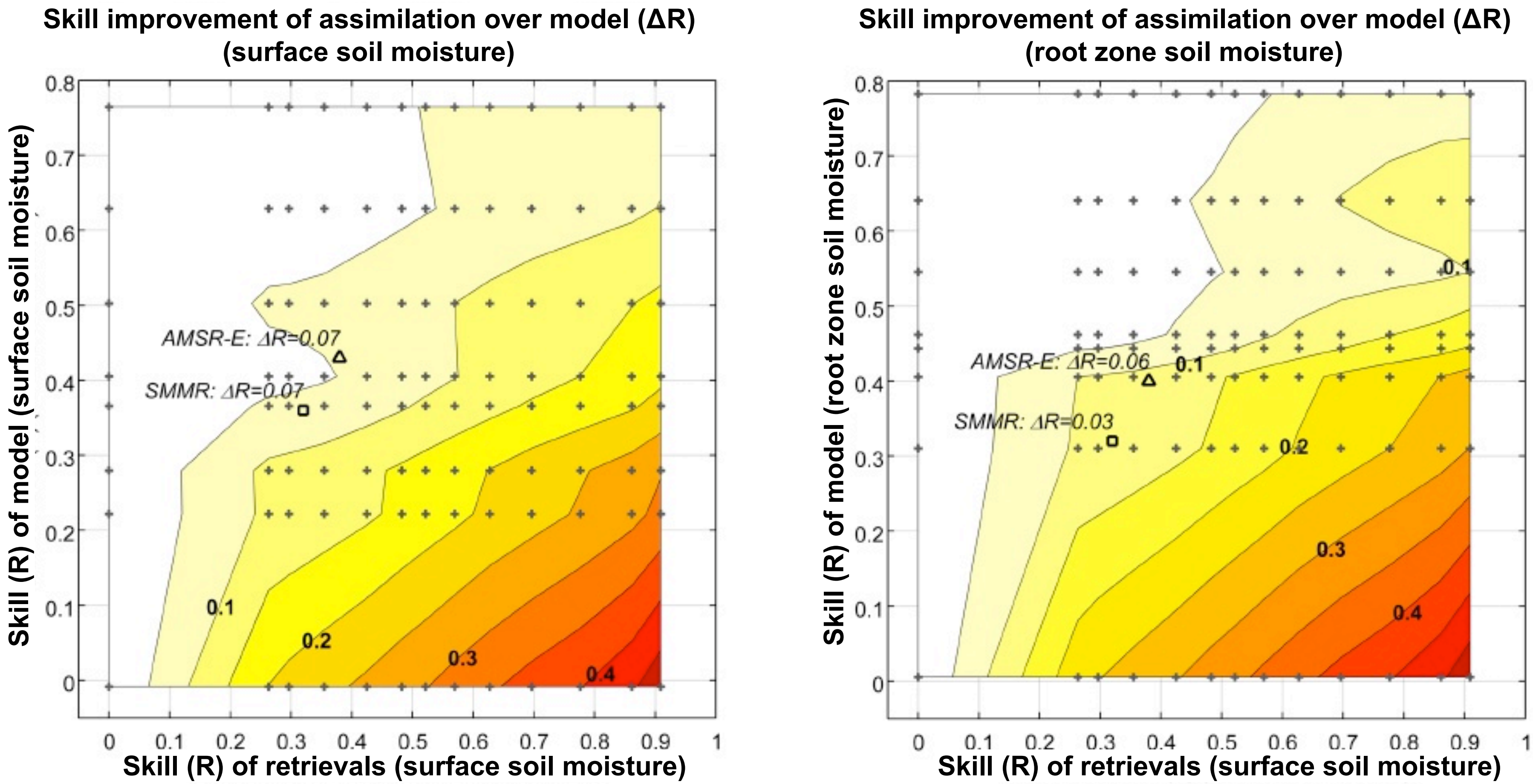
Skill of soil moisture estimates



- The skill of the soil moisture (surface and root zone) assimilation product increases with the skill of the retrievals and the skill of the model.
- The skill of the assimilation product is more sensitive to model skill than to retrieval skill.

Reichle et al., doi:10.1029/2007GL031986

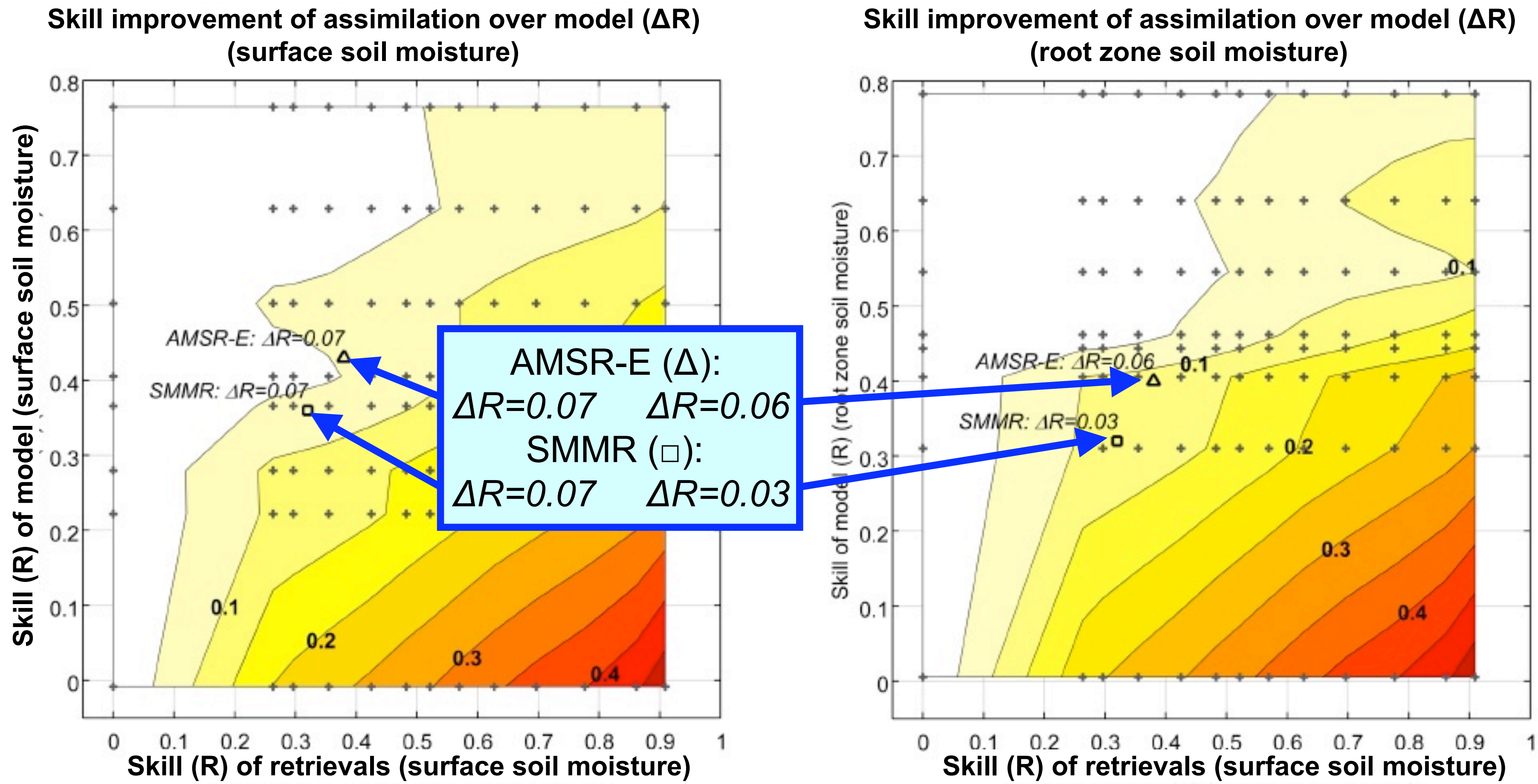
Skill improvement (soil moisture)



- Assimilation of soil moisture retrievals adds skill (relative to model product).
- Even retrievals of poor quality contribute information to the assimilation product.

Reichle et al., doi:10.1029/2007GL031986

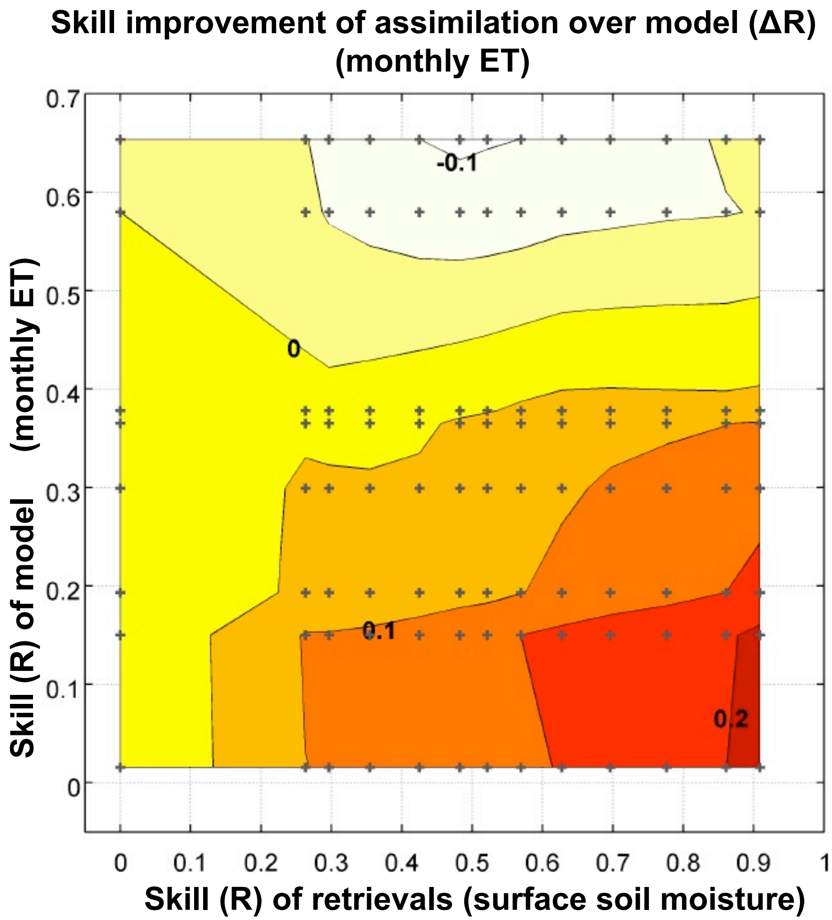
Skill improvement (soil moisture)



- Assimilation of soil moisture retrievals adds skill (relative to model product).
- Even retrievals of poor quality contribute information to the assimilation product.
- Published AMSR-E and SMMR assimilation products are consistent with expected skill levels for surface soil moisture, to a lesser degree also for root zone soil moisture.

Reichle et al., doi:10.1029/2007GL031986

Skill improvement (ET)



- Assimilation of surface soil moisture retrievals yields, on average, modest improvements in ET estimates.
- Negative ΔR related to technicalities (EnKF bias issues and adaptive filtering).

Reichle et al., doi:10.1029/2007GL031986

DA-OSSE summary

- **General DA-OSSE framework developed:**
  - Quantify the information added to land assimilation products by satellite retrievals for detailed and comprehensive error budget analyses for data assimilation products.
  - **Adaptive filtering** is major component of the DA-OSSE.
  - Success of DA-OSSE depends on realism of imposed model errors.

- **Soil moisture assimilation study for the Red-Arkansas:**
  - Even retrieval data sets of poor quality contribute information to the assimilation product.
  - Published AMSR-E and SMMR assimilation products are consistent with expected skill levels for surface soil moisture, to a lesser degree also for root zone soil moisture.

- **Future applications:**
  - Extending the DA-OSSE to continental/global scales is straightforward but computationally demanding.
  - Same applies for higher-resolution soil moisture retrievals (e.g. from active/passive MW sensor).