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SMAP L3_SM_A/P High Resolution Soil Moisture Algorithm Status and Issues

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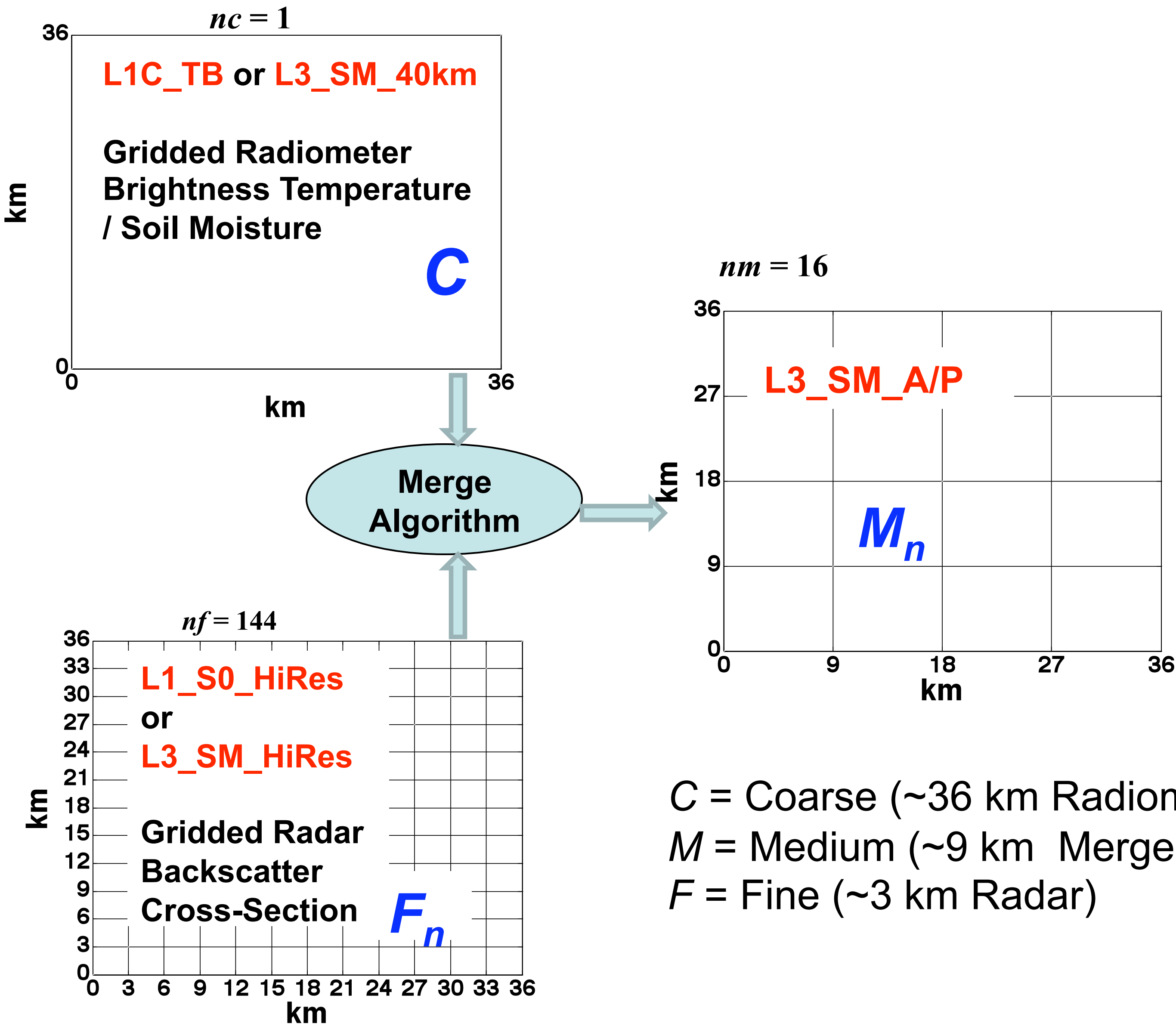
Grid Definitions



C = Coarse (~36 km Radiometer)
M = Medium (~9 km Merged Product)
F = Fine (~3 km Radar)

Approaches

Approach 1:

Begins with L3 Retrieved Soil Moisture Products

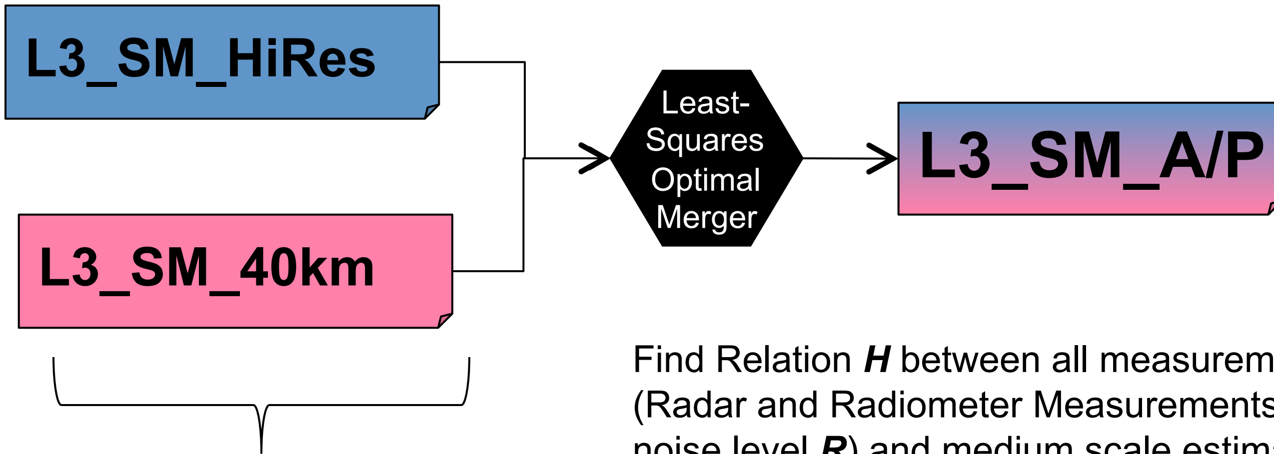
L3_SM_HiRes
L3_SM_40km
Least-Squares Optimal Merger
L3_SM_A/P

L1C_S0_HiRes
L1C_TB
β(C) Linear T_B-σ^0
TB 3 km Disaggregated
Least-Squares Optimal Merger
TB 9 km
tau-omega T_B SM retrieval
L3_SM_A/P

Approach 2:

- Begins with L1C T_B Data
- Disaggregates T_B (using Hi-res sigma0)
- Retrieval With tau-omega

Approach 1



Find Relation ***H*** between all measurements (Radar and Radiometer Measurements ***Z*** with RMSE noise level ***R***) and medium scale estimates of soil moisture.

Collect multiple scale data into an observation vector:

$$Z = \begin{bmatrix} \theta_C \\ \theta_{F1} \\ \theta_{F.2} \\ \vdots \\ \theta_{F.nf} \end{bmatrix}$$

Pose Least-Squares Estimation Problem:

$$E = [Z - H \cdot \theta(M_n)]^T R^{-1} [Z - H \cdot \theta(M_n)]$$

Solution:

$$\theta(M_n) = \left[\left(H^T R^{-1} H \right)^{-1} H^T R^{-1} \right] \cdot Z$$

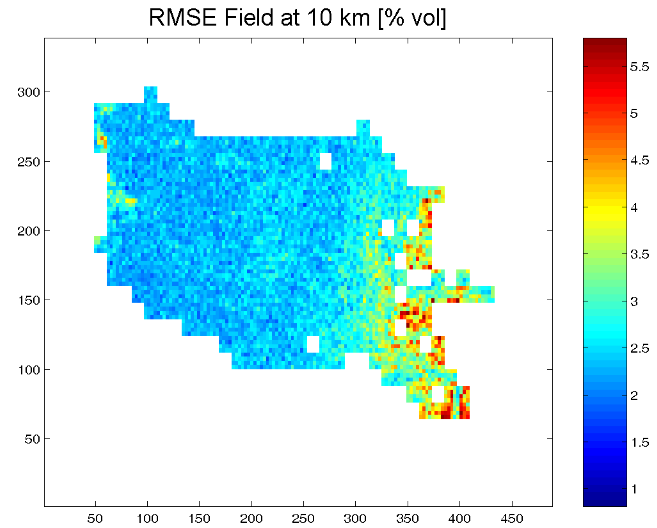
<u>Advantages</u>:

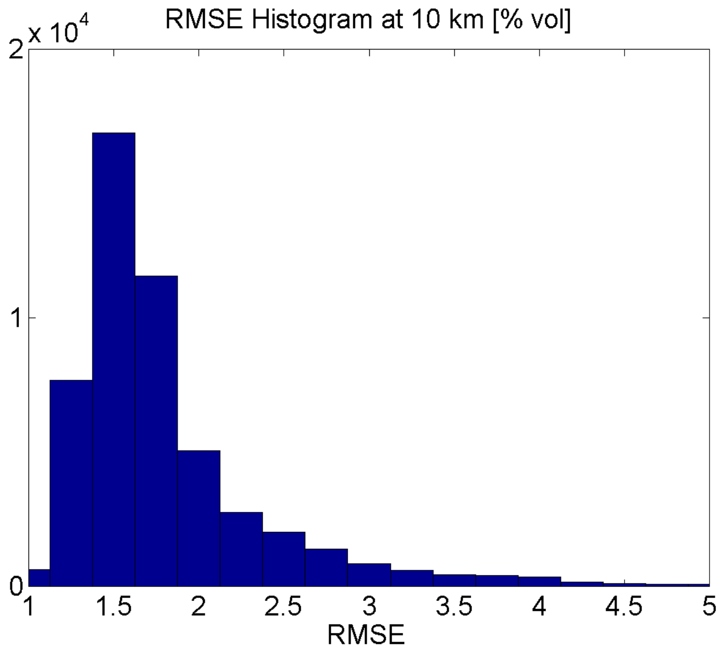
1. Least-Squares Beats Down Error (Oversampling)
2. Provides Confidence Limits on Estimates

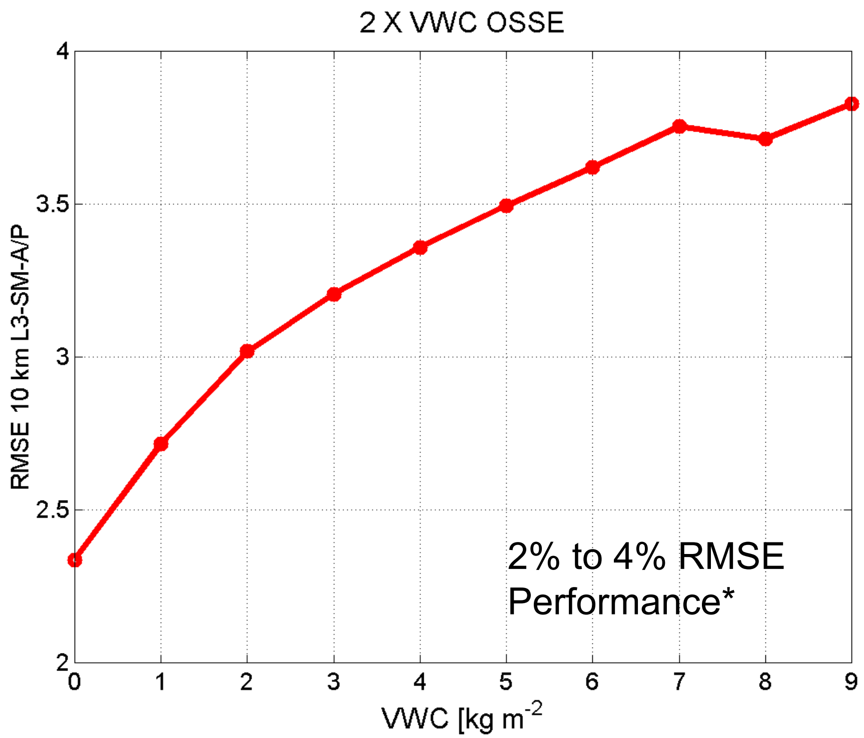
<u>Disadvantages</u>:

1. Relies on L3 Retrieved SM Products
2. Needs *Unbiased* L3 Products

Approach 1

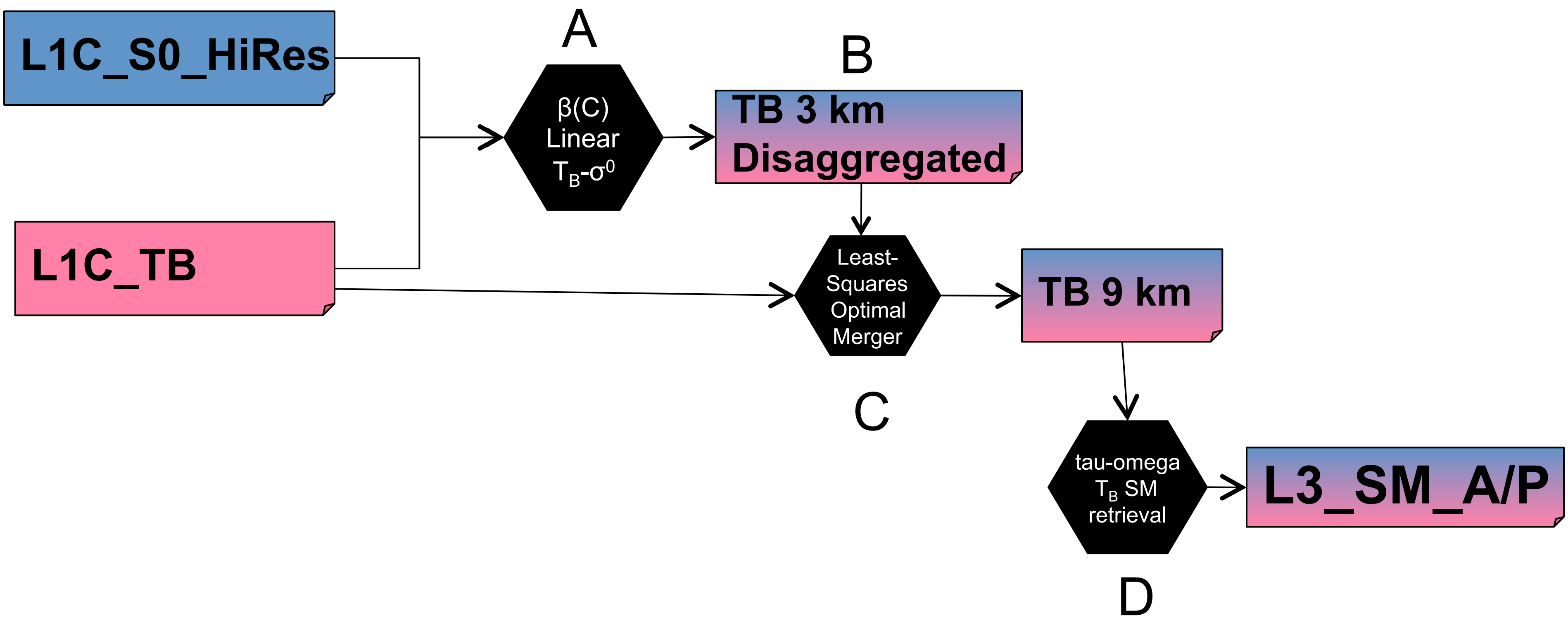






Approach 1 Performance Over Red-River OSSE (1 Month) With Noise Added

Approach 2



Advantages:

1. Uses L1C_TB Instrument Data directly
2. Removes Bias through T_B Aggregation Rule
3. Uses Least-Squares to Beats Down Error
4. Uses same tau-omega Retrieval Code as L3_SM_40km
5. Can Use PALS T_B and σ^0 Data to Test

Disadvantages:

1. Assumes Linear Relation Between T_B and σ^0 (dB)
2. Linear Coefficient is Vegetation-Dependent and assumed to be spatially homogeneous within 36 km

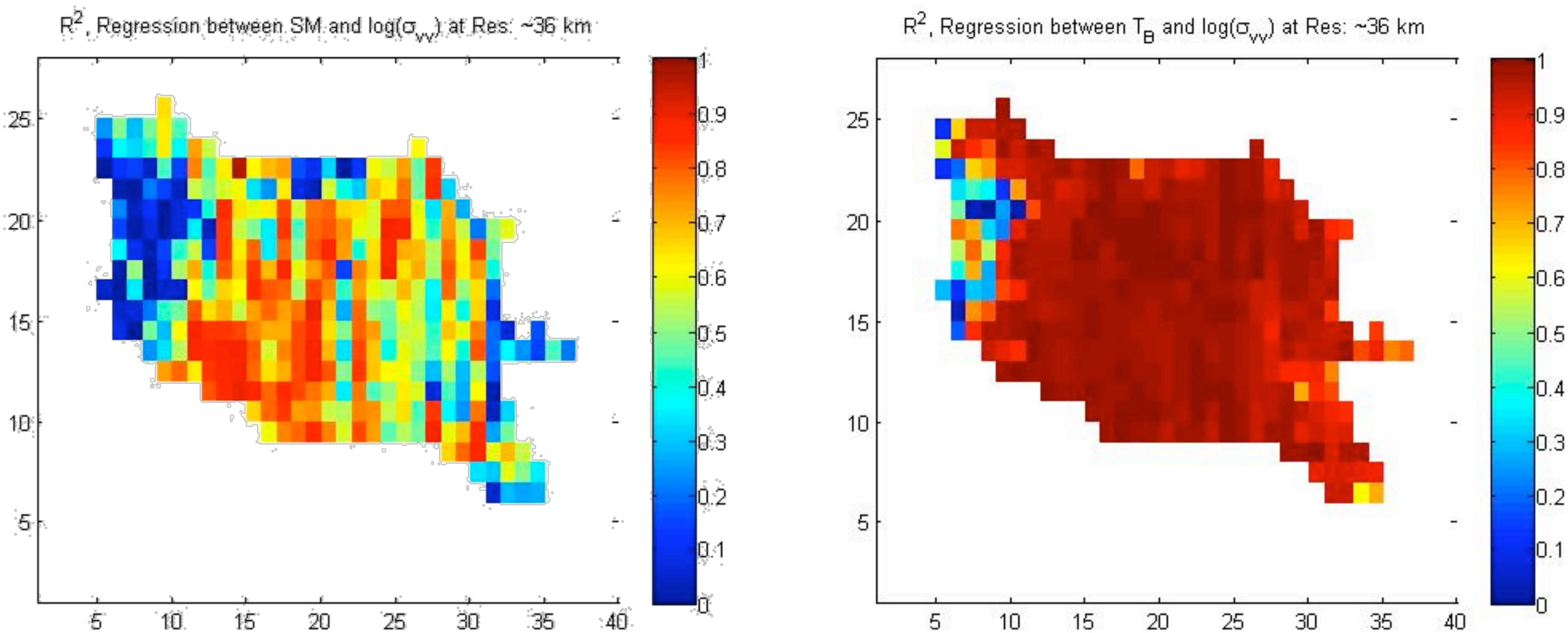
Linear Relationship between T_B and Sigma0

Part (**A**) of Approach 2

At the radiometer scale-*C* use time-series of brightness temperature and aggregated radar backscatter ($\log_{10}$) to develop linear model.

$$SM(C,t) = \alpha(C) + \beta(C)\log_{10}\left(\frac{1}{nf}\sum_{i=1}^{nf}\sigma_{vv}(F_i,t)\right)$$

$$T_B(C,t) = \alpha(C) + \beta(C)\log_{10}\left(\frac{1}{nf}\sum_{i=1}^{nf}\sigma_{vv}(F_i,t)\right)$$



Better R^2 values are observed for (TB and Mean[log(σ_{vv})]) as compared to (SM and Mean[log(σ_{vv})])

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Disaggregation of T_B using Fine Scale Sigma0

Part (**B**) of Approach 2

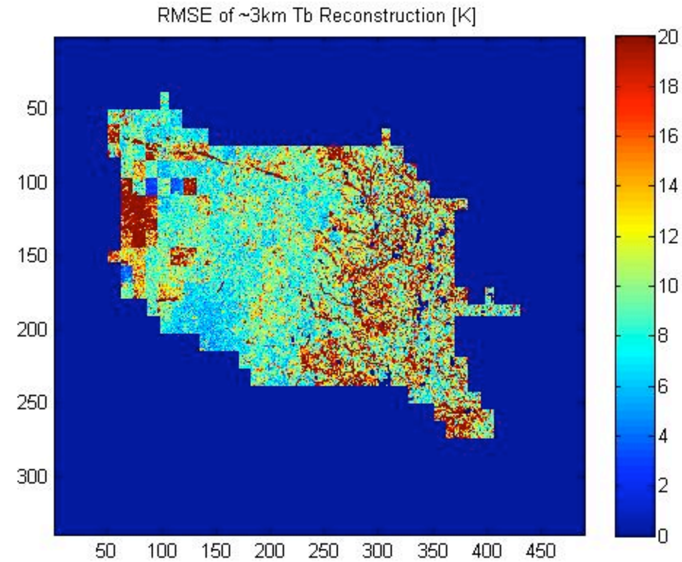
The fine-scale brightness temperature is taken to be the coarse-scale brightness temperature adjusted by radar-based spatial anomalies (symbolized by *δ*)as in

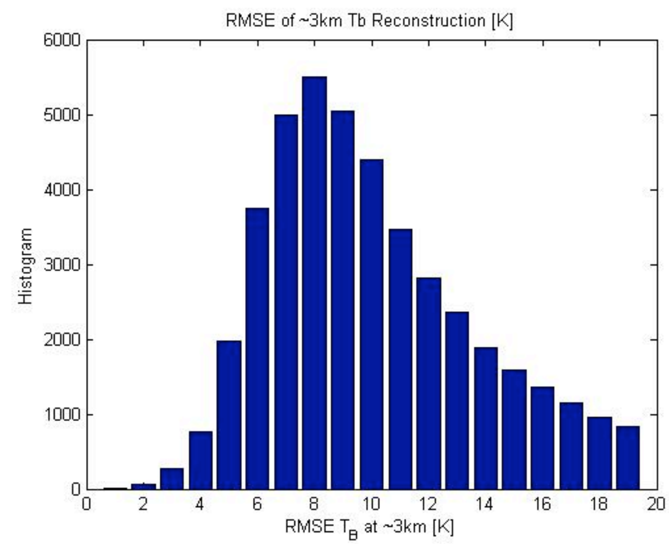
$$T_B(F_i,t) = T_B(C_i,t) + \beta(C)\cdot\delta\log_{10}(\sigma_{vv}(F_i,t))$$

Parameter *β*(*C*) is assumed to be applicable at the finer scales, i.e. heterogeneity at larger scales and homogeneous within coarse scale

Bias is removed from the reconstruction by requiring that

$$\boldsymbol{T_B}(\boldsymbol{C},\boldsymbol{t}) = (1/\boldsymbol{nf})\left(\sum_{\boldsymbol{i}=1}^{\boldsymbol{nf}}\log_{10}(\boldsymbol{T_B}(\boldsymbol{F_i},\boldsymbol{t}))\right)$$



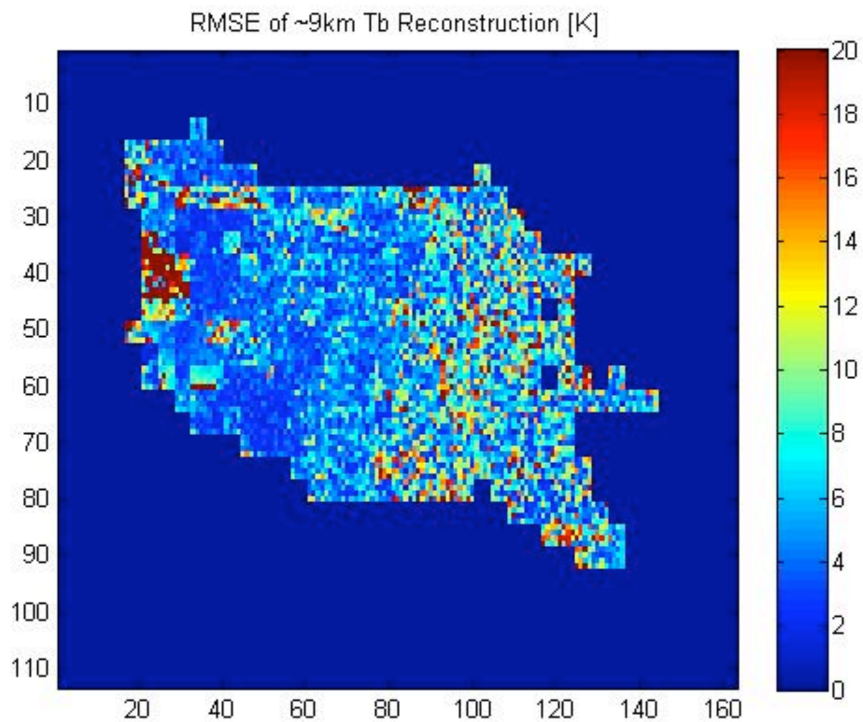


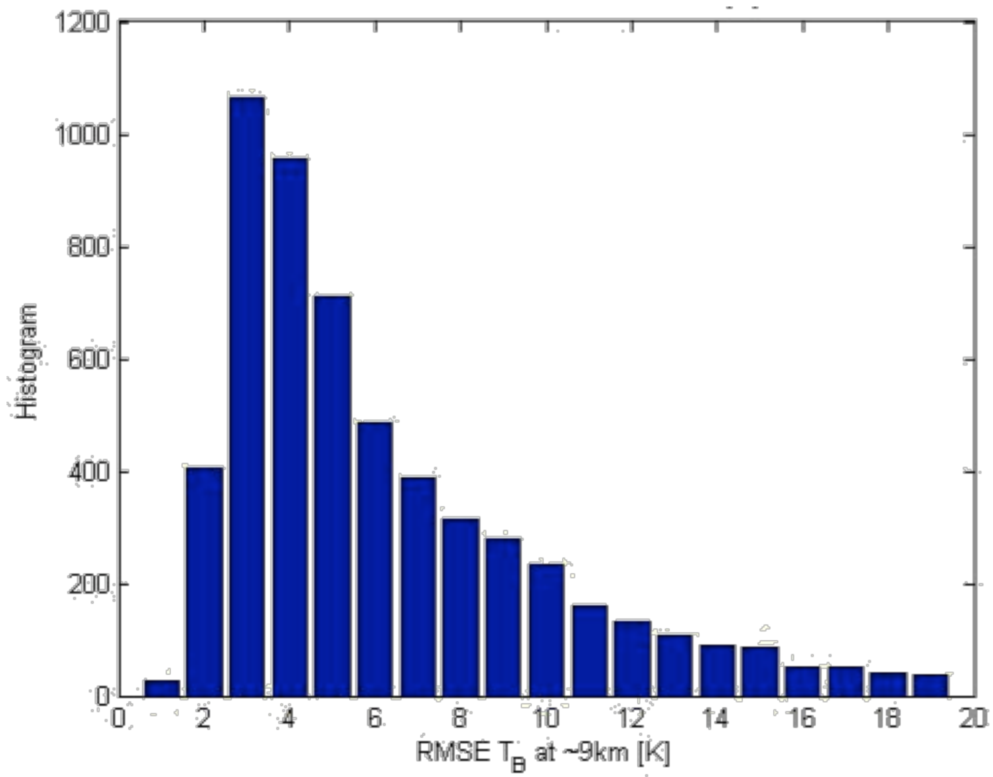
RMSE of 3km Reconstructed T_B in the SMAP OSSE.
Anticipated radar and radiometer noise levels are added.

Optimal Merger of Coarse Scale T_B with Fine Scale T_B

Part (**C**) of Approach 2

Coarse Scale TB (~36 km) blended with fine scale TB (~3 km) using optimal merger to obtain medium resolution TB (~9 km)



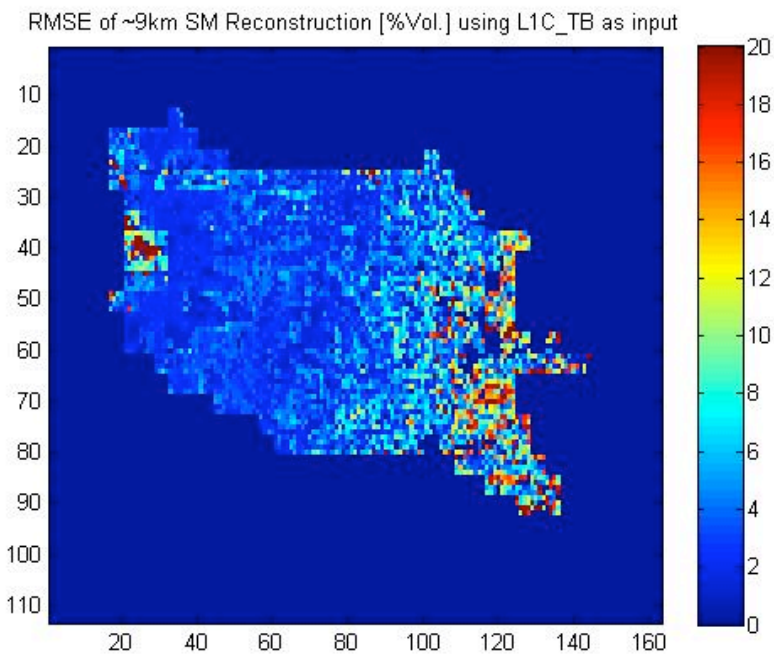


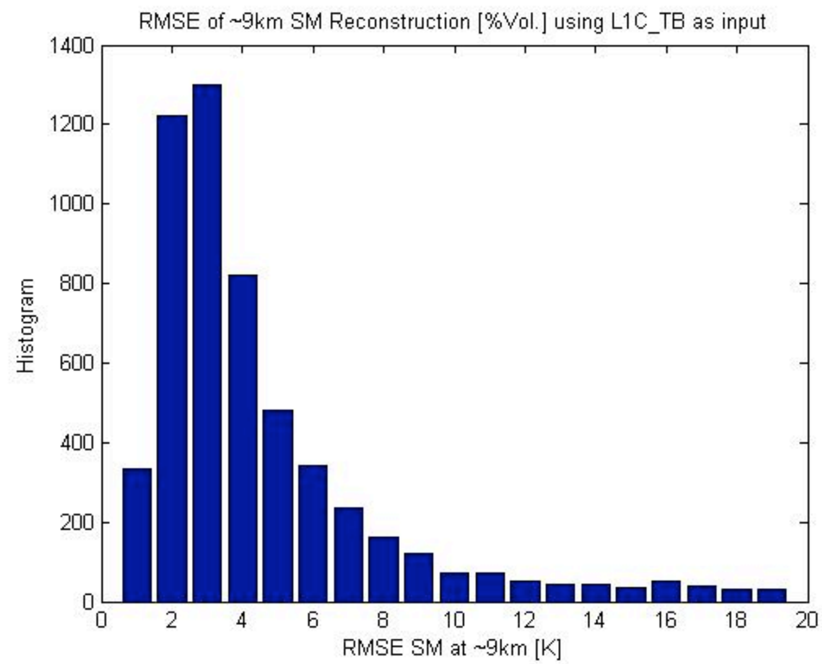
RMSE of 9km Reconstructed T_B in the OSSE.
Anticipated radar and radiometer noise levels are added.

Soil Moisture Performance at Scale of L3_SM_A/P

Part (**D**) of Approach 2

The radiometer retrieval algorithms (see L3_40km_SM) are now applied to retrieve soil moisture. Required ancillary data are provided at 9 km.





RMSE of 9km Reconstructed soil moisture in the OSSE using Single-Channel Radiometer Algorithm. Anticipated radar and radiometer noise levels are added. The errors are largest where there is significant vegetation (East) or where β could not be estimated well due to persistent soil dryness (West).

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Application of Approach 2 to Airborne Passive/Active L-/S-band (PALS) microwave data from SMEX02

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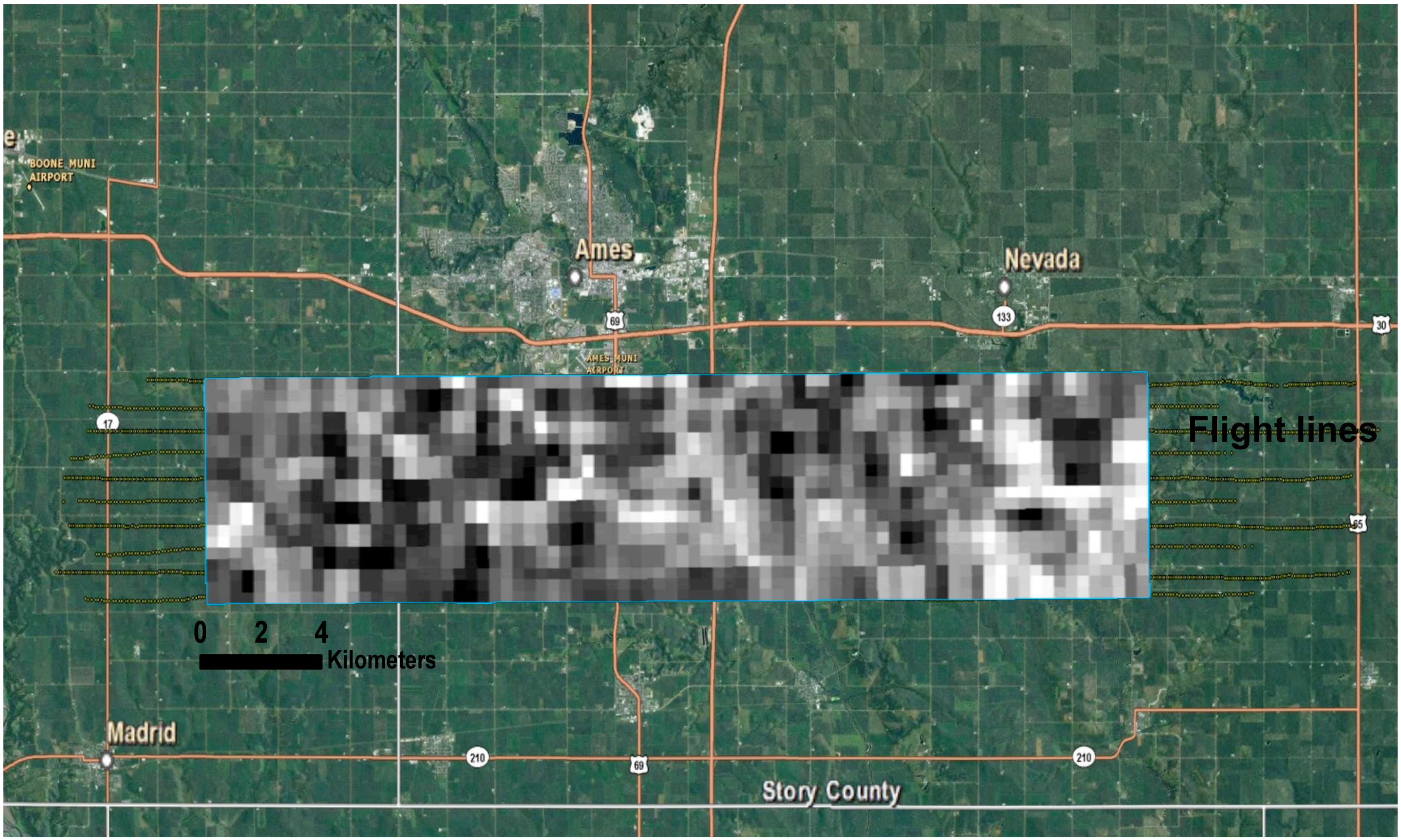
Gridding of PALS Flight lines Data



TB data gridded at 4 km, and Sigma0 gridded at 0.4 km

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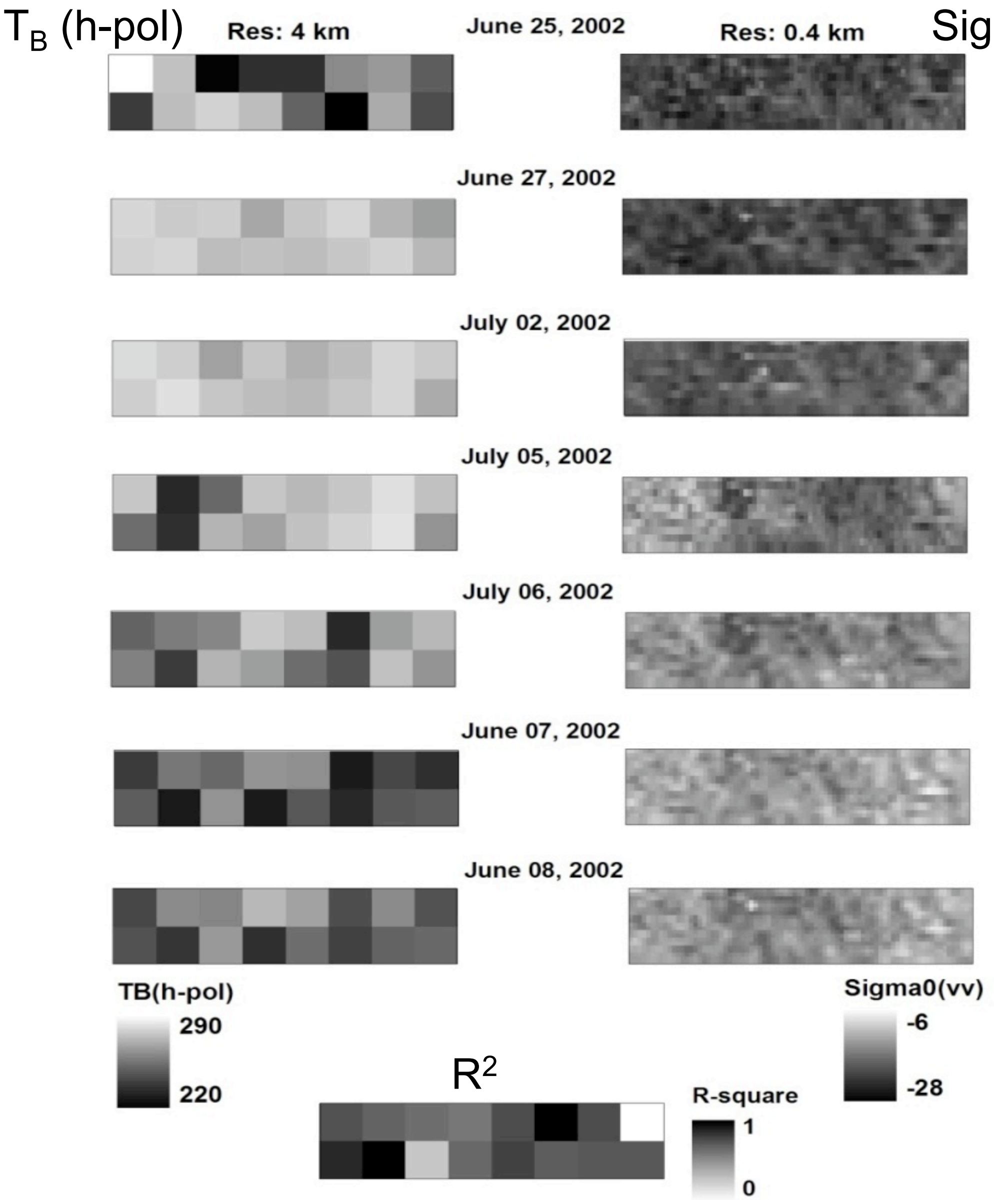
Evaluation of Linear Relationship Between T_B and Sigma0 for PALS Data



<u>PALS Explained Variance</u>

7-days of SMEX02 PALS T_B and σ^0

T_B aggregated to form the same scale differences as with SMAP (T_B ~4 km and σ ~ 0.4 km)

For 7-days the R^2 field has Median value of 0.75
(Max value of 0.91)
(Min value of 0.44)

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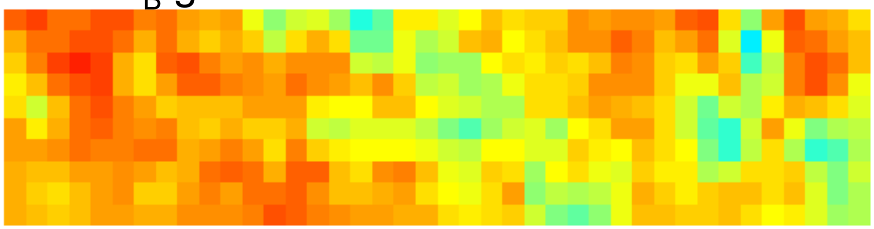
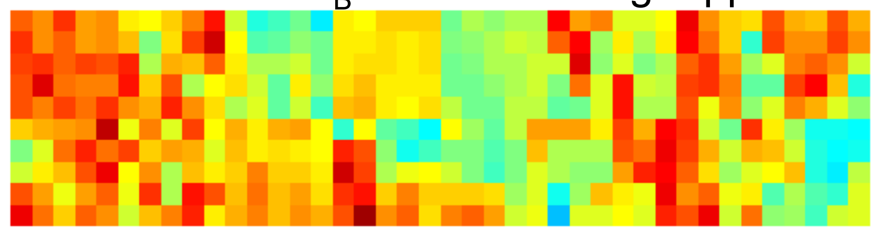
Comparison of Reconstructed T_B at 0.8 km with Gridded PALS data

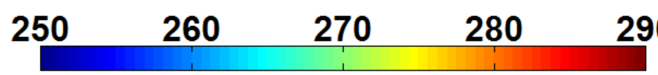
PALS T_B gridded at 0.8 km



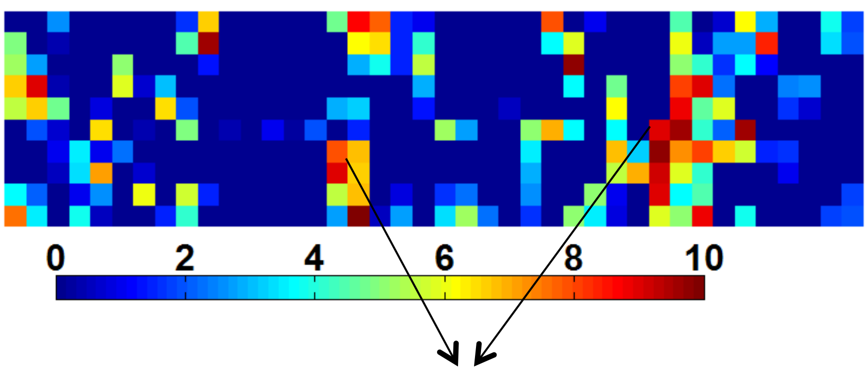
Reconstructed T_B at 0.8 km using Approach 2



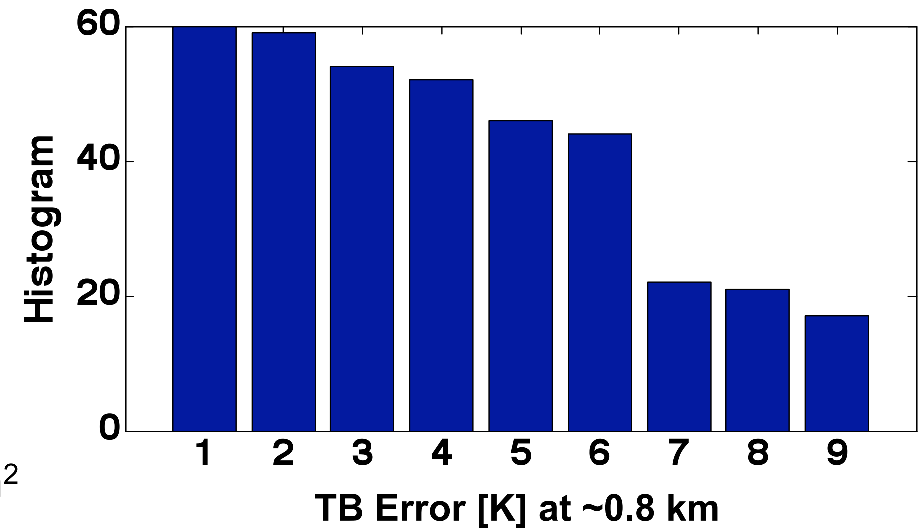
July 02, 2002



Errors in reconstructed T_B at Res: 0.8 km



High errors are observed for pixels having trees with VWC > 5 kg/m^2



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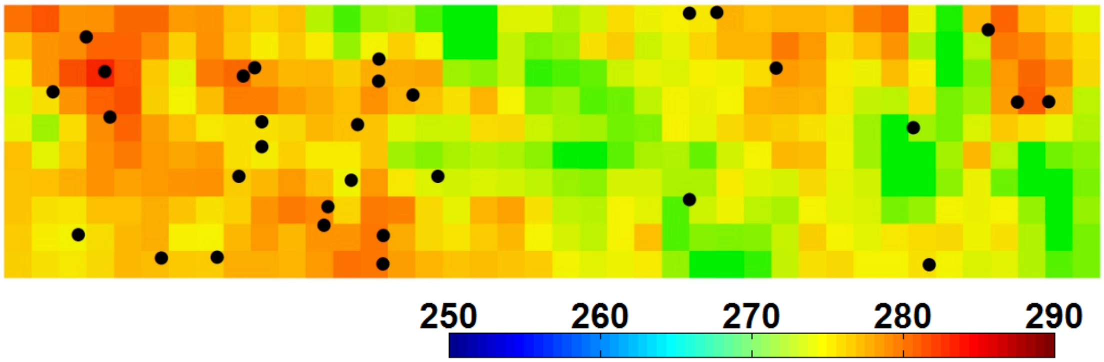
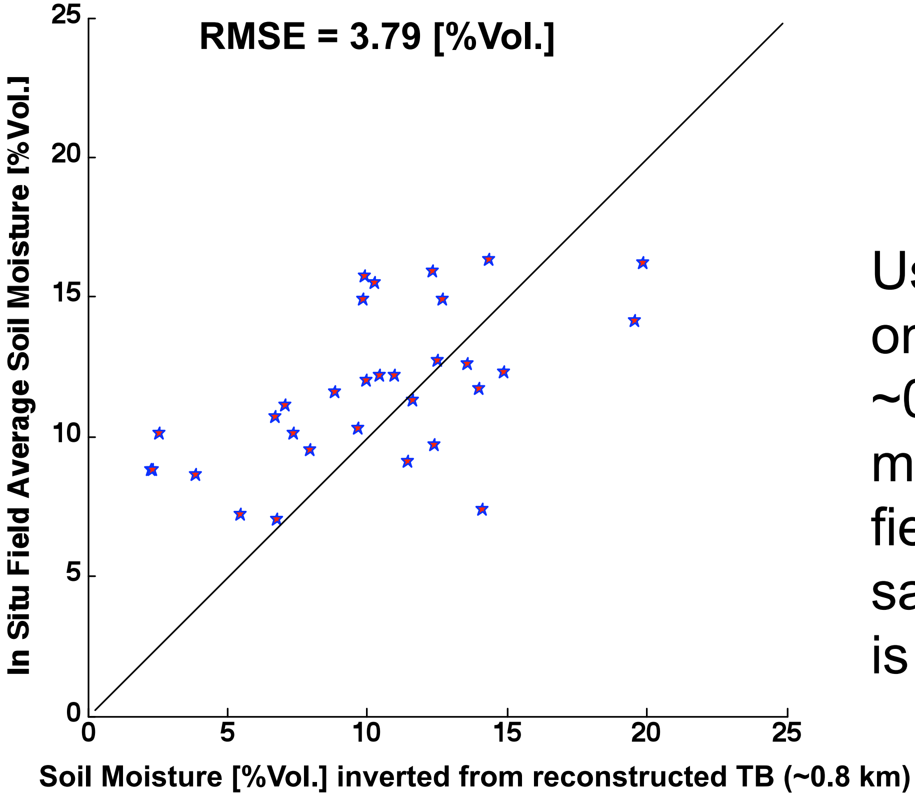
Soil moisture Retrieval from Reconstructed T_B at 0.8 km

July 02, 2002





- Soil moisture sampling site

Using single channel algorithm (tau-omega model) disaggregated T_B (h-pol) at ~0.8 km is inverted to volumetric soil moisture and compared with the in situ field averaged soil moisture for the sampling sites. An RMSE of 3.79 [%Vol.] is obtained.

Conclusion and Issues

Conclusion

1. Feasibility of combined active/passive algorithm approach has been demonstrated using simulated and PALS SMEX02 dataset

2. Retrieval accuracy within 4 [%Vol.] for VWC < 5 kg/m2 at 10 km spatial resolution is achievable

Issues

1. Simulated data (OSSE) do not test every assumption/approximation in the algorithm. However, PALS data are used to verify algorithm assumptions (e.g., linear *TB*-log[σ] relationship assumption).

2. Optimization of algorithm details is needed (e.g., time-horizon for β-estimation; treatment of sub-40km heterogeneity through relating β to ancillary data).

3. Implementation of algorithm options over larger domains (e.g., CONUS) is in progress with inclusion of appropriate errors and biases in the inputs due to satellite orbital sampling.

4. Additional time series approaches are being considered to improve algorithm

Backup

Product Objectives

Mapping radars are capable of a very high spatial resolution but, since radar backscatter is highly influenced by surface roughness, vegetation canopy structure and water content, they have a low sensitivity to soil moisture. Various algorithms for retrieval of soil moisture from radar backscattering have been developed, but they are only valid in low-vegetation water content conditions. In contrast, the spatial resolution of radiometers is typically low, the retrieval of soil moisture from radiometers is well established and radiometers have a high sensitivity to soil moisture. To overcome the individual limitations of the passive and active approaches, the Soil Moisture Active and Passive (SMAP) mission is combining the two technologies. The accurate retrievals of soil moisture at the coarse resolution of the radiometer need to be combined with the relatively less accurate soil moisture information from the high resolution radar measurements in order to yield an intermediate scale soil moisture data product. The merging of radar and radiometer measurements and retrieved information yields the SMAP Hydrometeorology Product at intermediate (10 km) scale called L3_SM_A/P.

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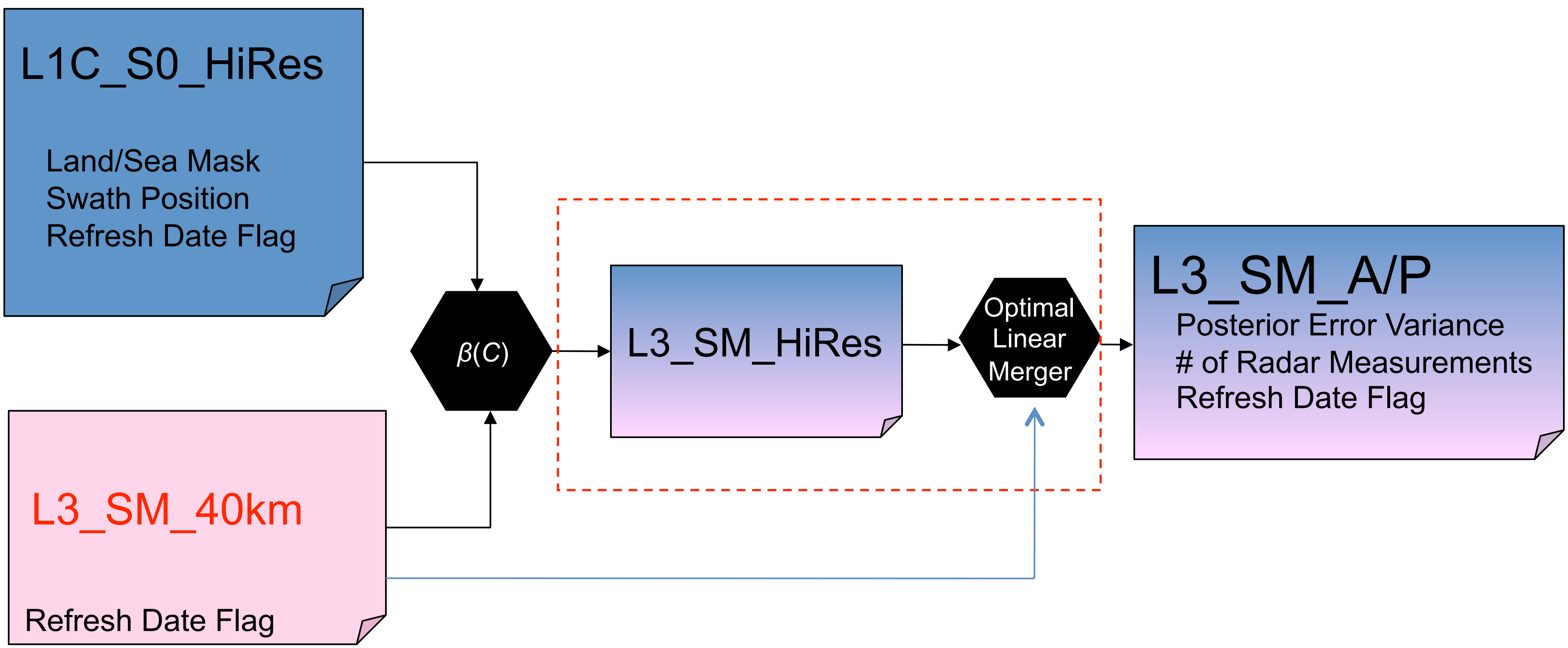
Data Flow: L3_SM_A/P Time-Series Algorithm

Approach 3

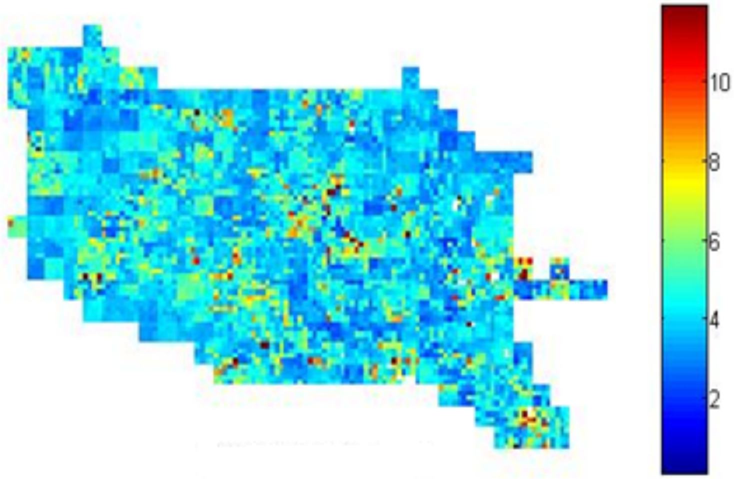


<u>Other Inputs</u>:

1. Bias error statistics of input products
2. Squared error statistics of input products

Approach using L3_SM_40km

Output from 4 month OSSE data



$$\theta(C,t) = \alpha(C) + \beta(C)\log_{10}\left(\frac{1}{nf}\sum_{i=1}^{nf}\sigma_{vv}(F_i,t)\right)$$

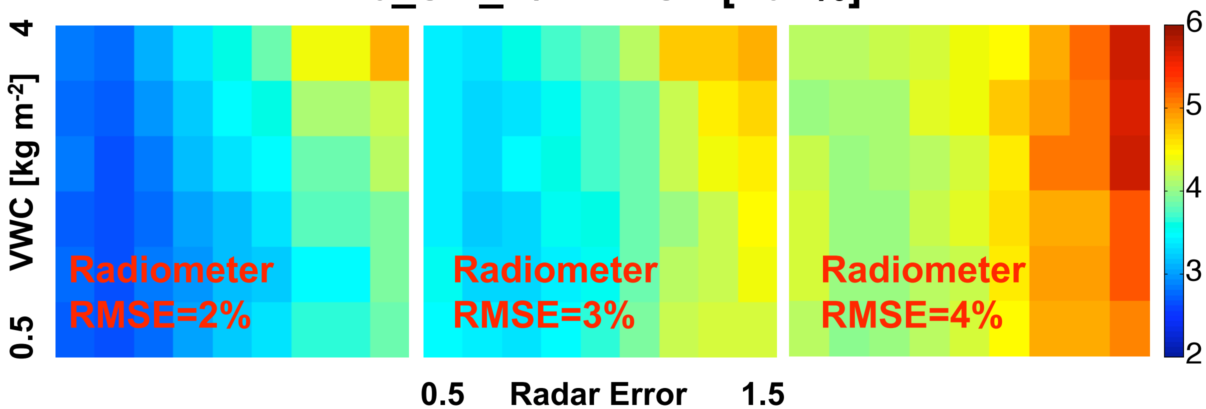
$$\Delta(\cdot)_t = (\cdot)_t - (\cdot)_{t-t_R} \qquad \delta(\cdot) = (\cdot) - \langle\cdot\rangle$$

$$\theta(M_n,t) = \theta(M_n,t-t_R) + \beta(C)\,\Delta\log[\sigma(M_n,t)]$$

$$\theta(M_n,t) = \theta(C,t) + \beta(C)\,\delta\log[\sigma(M_n,t)]$$

Pixelwise RMSE at Res: ~9 km
for input Radiometer RMSE: 4 [%Vol.]

L3_SM_A/P RMSE [Vol.%]



The results show that RMSE of L3_SM_A/P is always dependent and greater than on the input RMSE of L3_SM_40km