

A MODEL BASED RADIOMETER DISAGGREGATION TECHNIQUE USING RADAR BACKSCATTER INFORMATION FOR SMAP

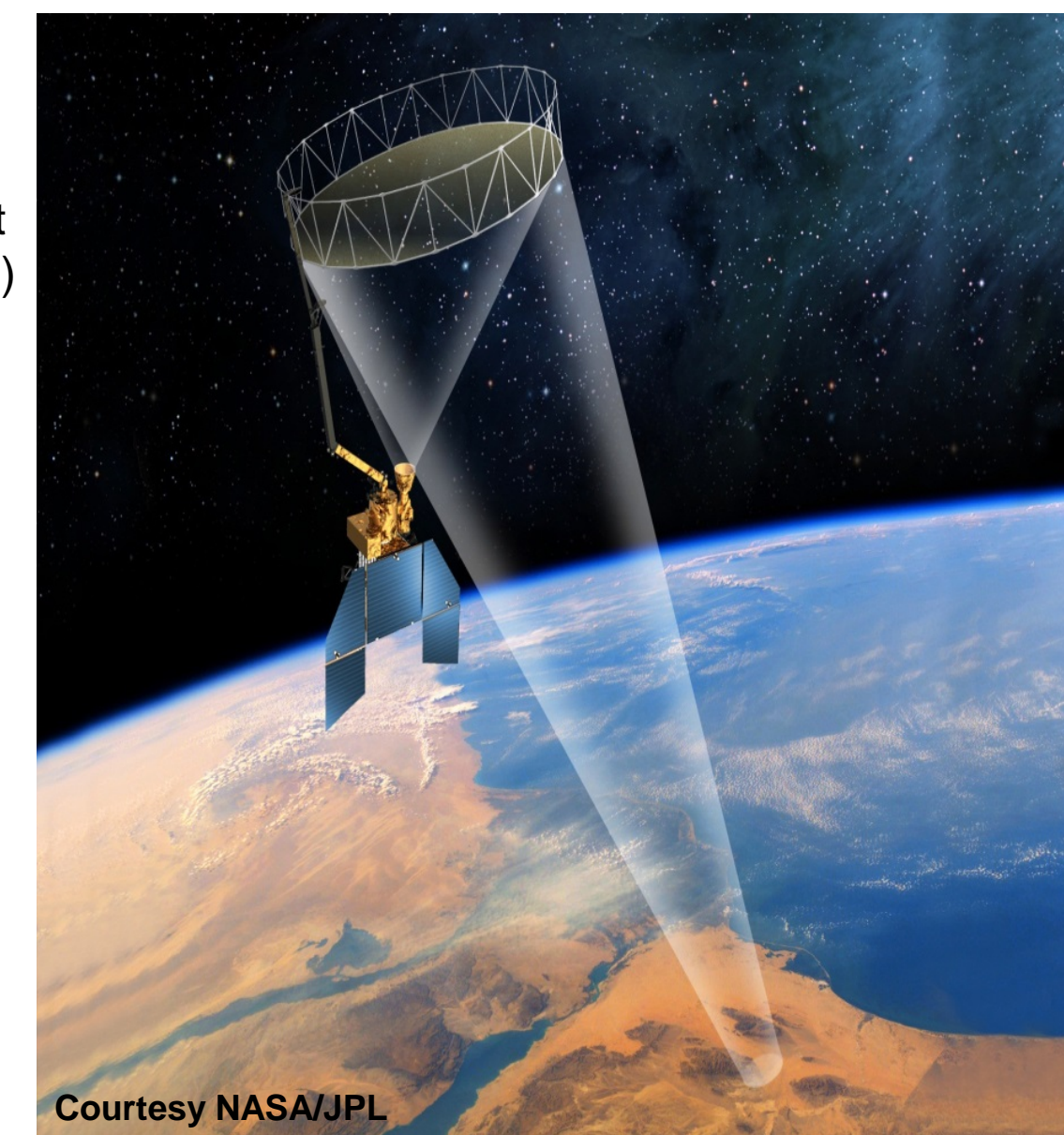
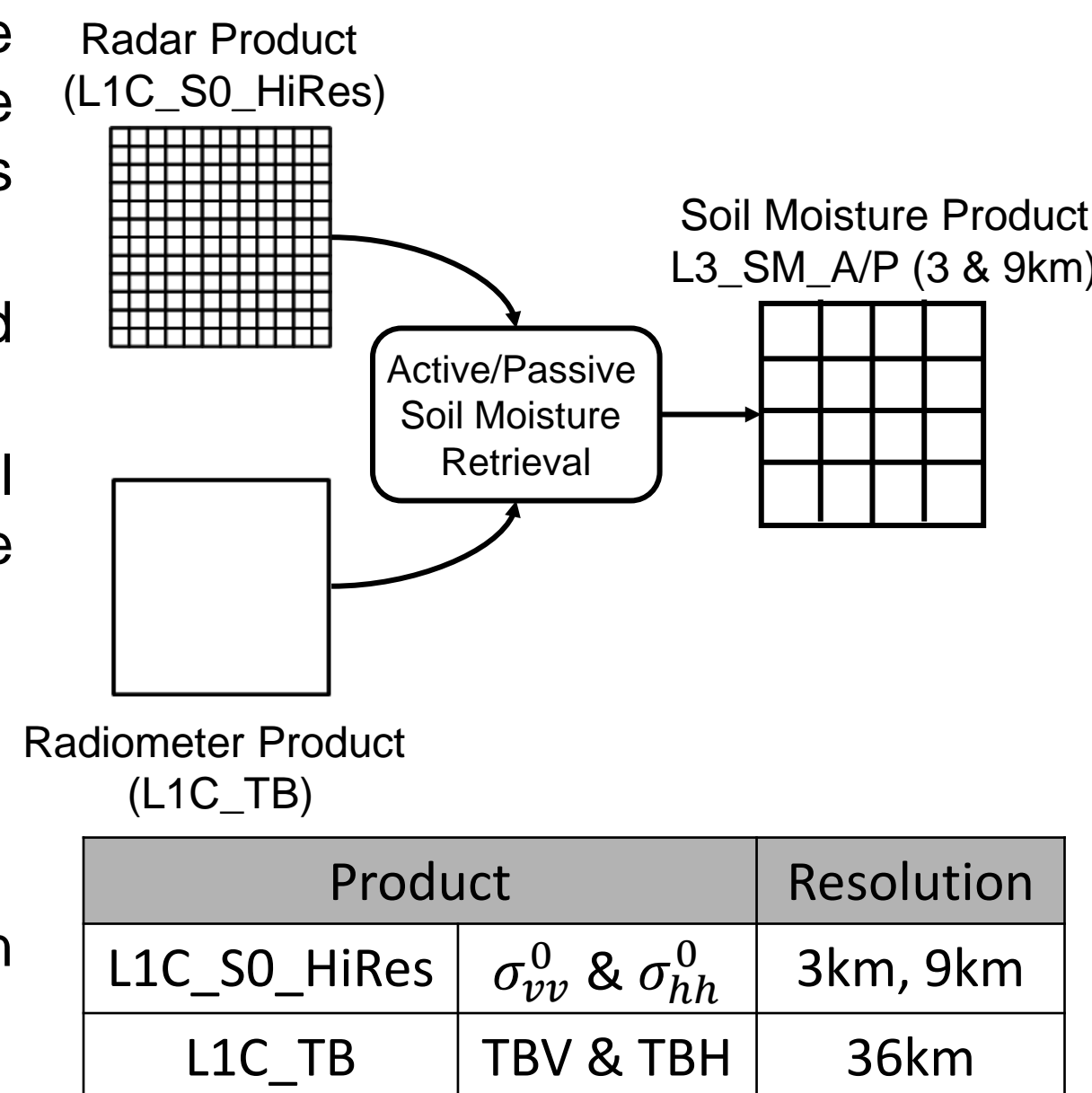
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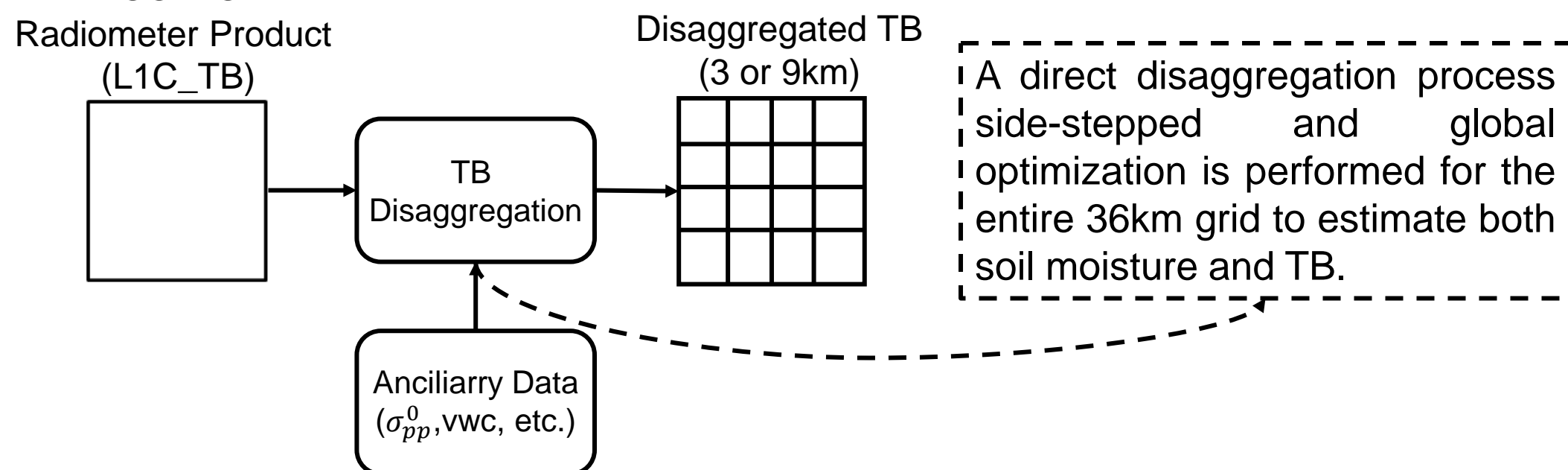
Motivation, Overview and Objectives: SMAP and Active-Passive Remote Sensing

- The NASA Soil Moisture Active Passive (SMAP) mission aims to provide the science community with unprecedented global surface soil moisture estimates to address many of the pressing and current climate dynamics questions
- To achieve mission goals, SMAP will utilize an L-band SAR and L-band Radiometer to monitor global surface soil moisture.
- Improved soil moisture estimates both in terms of accuracy and spatial resolution are expected by effectively combining measurements from the SMAP radar and radiometer.
- A complete algorithm for SMAP must address
 - How to effectively combine radar and radiometer measurements
 - How to address the spatial resolution disparity
- This work aims to address these two issues simultaneously in an optimization/retrieval framework



Estimation and Disaggregation Approach

- Numerical optimization is used to retrieve soil moisture and perform TB disaggregation



- A cost function $L(\bar{X})$ is set up such that it includes both Radar backscatter contributions σ_{pp}^0 at 3km and Radiometer TB_p at 36km resolution:

$$L(\bar{X}) = L_{active}(\sigma_{pp}^0, \bar{X}) + L_{passive}(TB_p, \bar{X}).$$

- The detailed mathematical form of the cost function is

$$L(\bar{X}) = \frac{1}{2} \left[\sum_{i=1}^N \sum_{pp=hh,vv} \left| \frac{\sigma_{pp}^0 - FM(X_i)}{\sigma_{pp}^0} \right|^2 + \sum_{p=H,V} \left| \frac{TB_p - \frac{1}{N} \sum_{i=1}^N TB(X_i)}{TB_p} \right|^2 \right]$$

- \bar{X} is the vector of all N unknown soil moisture values for every pixel (N=144 at 3km & N=16 at 9km Resolution)
- Minimization of the cost function follows the method of Simulated Annealing. Optimization exit and convergence criteria are:
 - $L(\bar{X}) < \delta$: cost function becomes smaller than a threshold
 - The number of forward model evaluations passes a certain limit
 - For a certain number of iterations the algorithm converges to a local minimum
- While simultaneously constrained to the grid mean TB difference i.e. bias $TB_p - \frac{1}{N} \sum_{i=1}^N TB(X_i)$ soil moisture estimation is performed for all radar pixels.
- Optimum \bar{X} which minimizes $L(\bar{X})$ is reported as the retrieved soil moisture
- High resolution disaggregated TB_d is then derived based on grid soil moisture estimates X_i i.e. $TB_d \sim \tau\omega(\bar{X}, VWC, T_c, b, \omega, h)$
- This process is forward model driven and dependent on correct and accurate model parameterization

Numerical Monte-Carlo Analysis Parameter setup

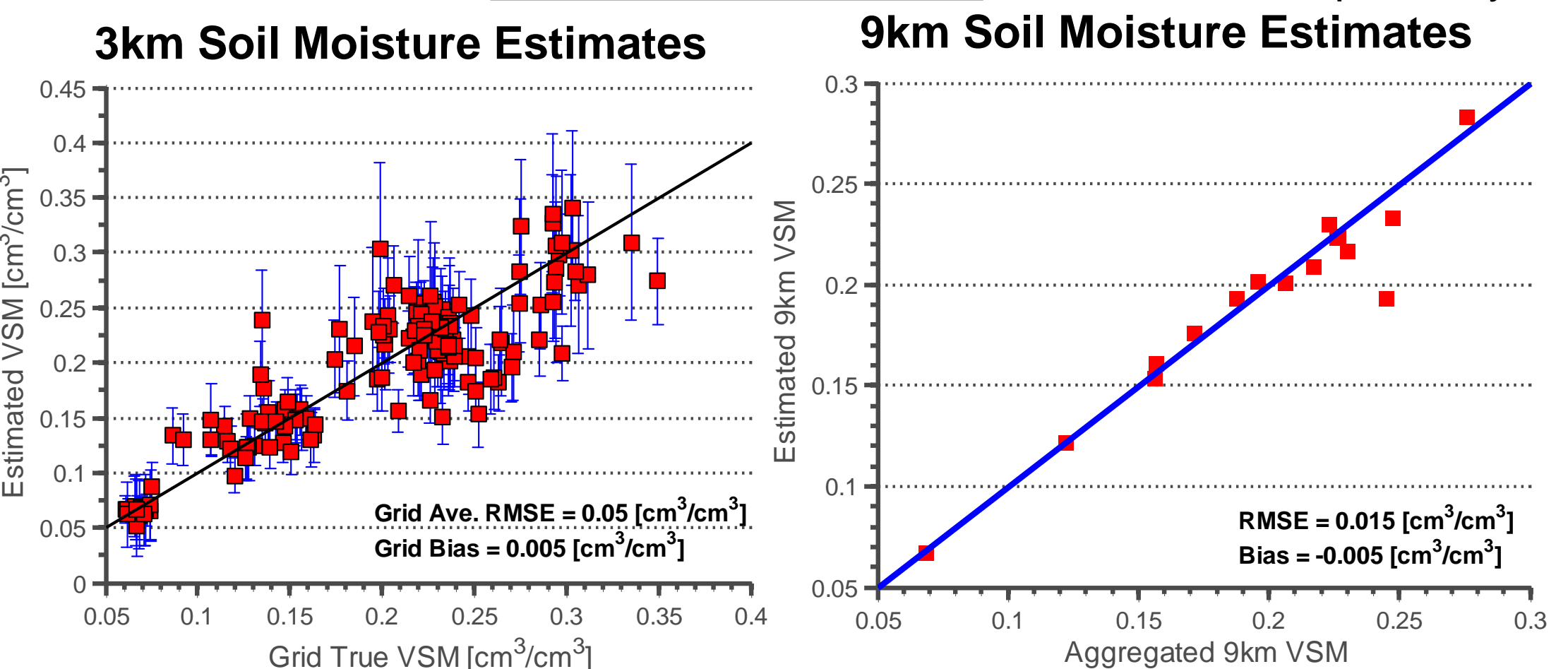
Parameter	Range	Parameter	Uncertainty
VSM (cm ³ /cm ³)	0.04-0.4	Radar Noise (K _p)	0.5 dB
VWC (kg/m ²)	0-5	Radiometer Noise	1.5 K
Temperature (K)	280-310	VWC	10%
Roughness (k's)	0-0.3	Temperature	10%
		b, ω & h	10%

Note: errors reported include both data noise and parameter uncertainty

Analysis Results: Disaggregation & Soil Moisture Estimation

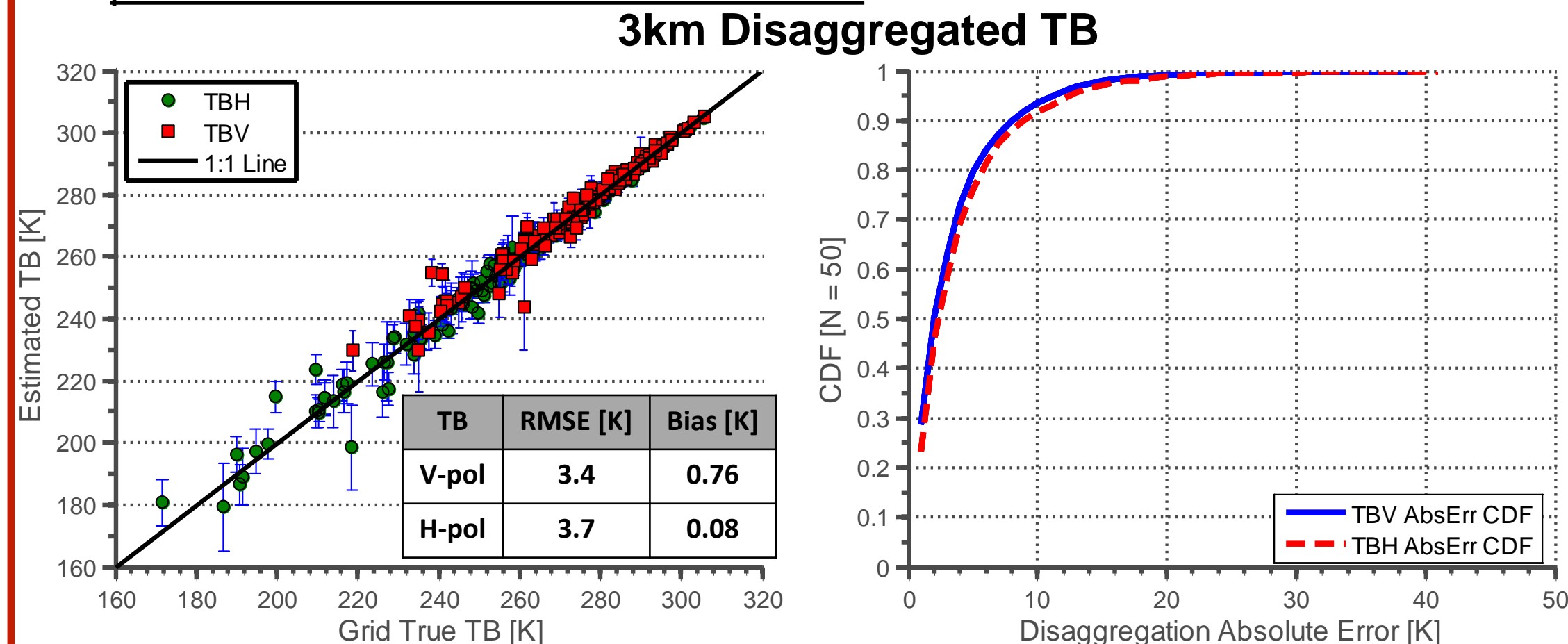
- 3 and 9km Soil Moisture estimates are based on Monte-Carlo numerical analysis

- Grid Mean RMSE is 0.05 and 0.015 cm³/cm³ for 3 and 9km respectively



- H and V-pol high resolution TB product is determined from grid soil moisture estimates

- TB estimation CDF, based on Monte-Carlo analysis, indicates ~90% of all pixels have 10K or less absolute error.



- 9km TB_d are derived by aggregating 3km estimates
- Therefore, RMS error, bias and CDF performance statistically improve

