Soil Moisture Retrieval using Sliced Regression Inversion Technique

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   - Synthetic Data
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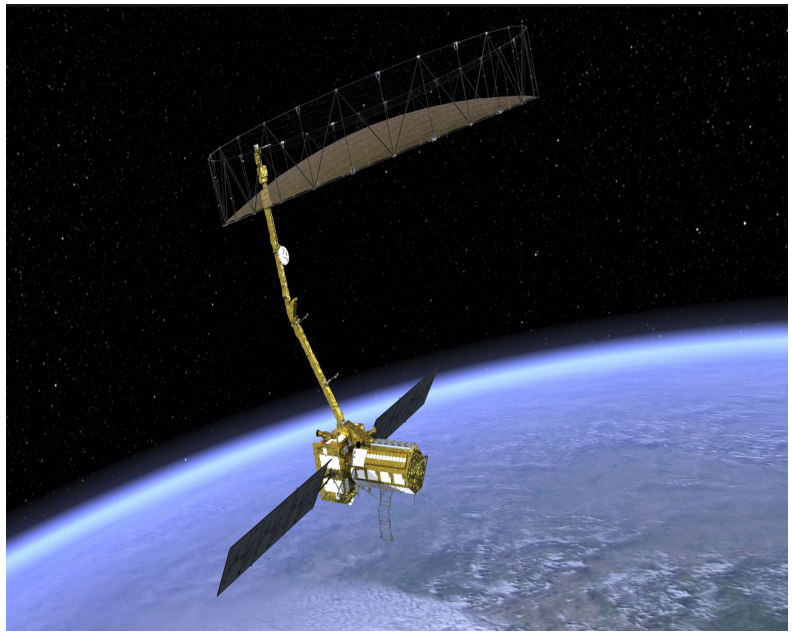
Soil Moisture - Why does it matter?

Figure: Applications of soil moisture measurements[1]

[1] Entekhabi, Dara, et al. "The soil moisture active passive (SMAP) mission." Proceedings of the IEEE 98.5 (2010): 704-716

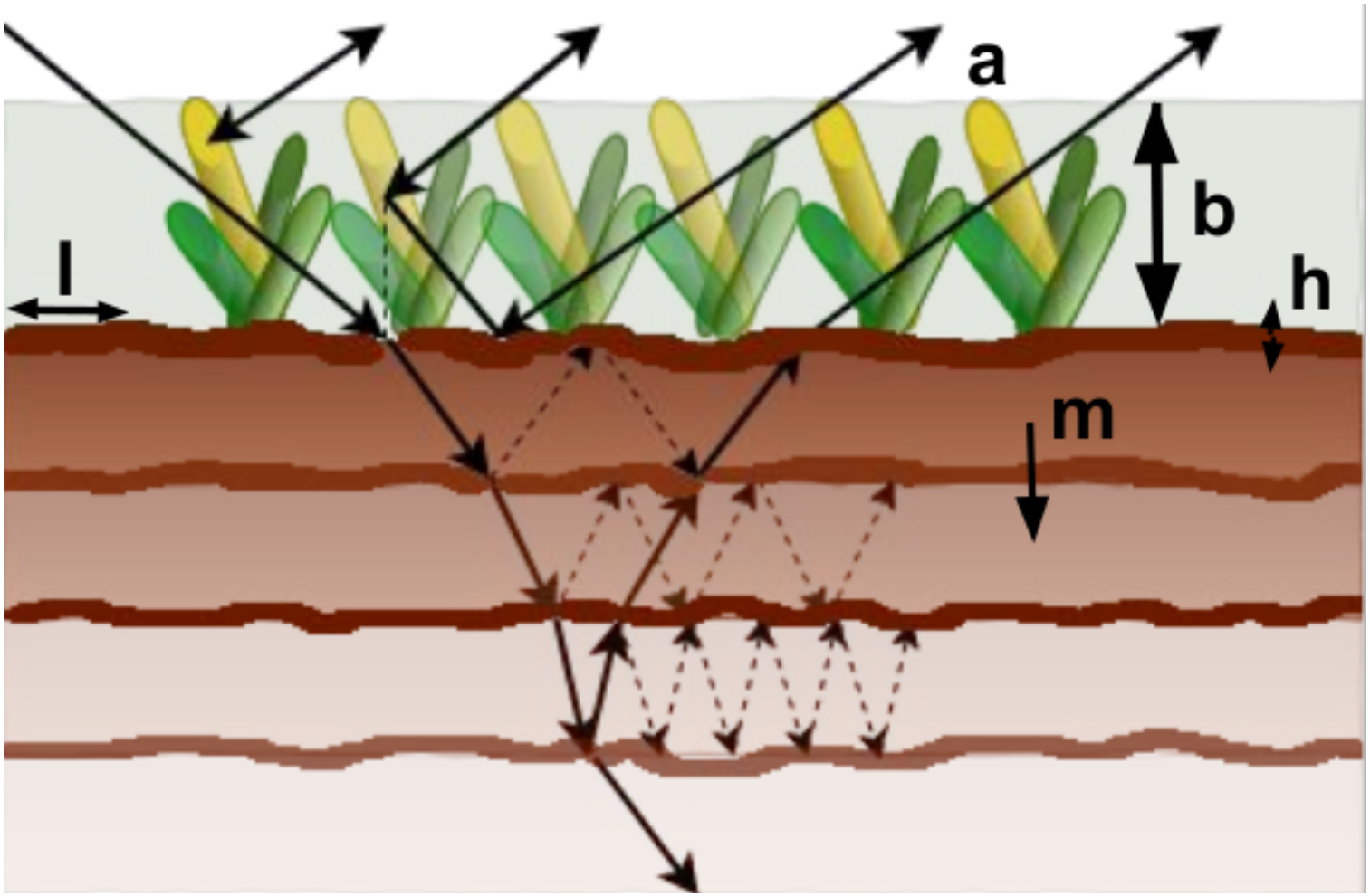
NASA-ISRO Synthetic Aperture Radar (NISAR) Mission[2]

- Joint Mission by ISRO-NASA (2021)
- Operated bands: L and S
- All-Weather Day and Night Imaging
- Mission Objectives:
  1. Agricultural Monitoring
  2. Glacier and coastal studies
  3. Disaster monitoring and assessment



[2]Rosen, Paul A., et al. "Global persistent SAR sampling with the NASA-ISRO SAR (NISAR) mission." 2017 IEEE Radar Conference (RadarConf). IEEE, 2017

Forward Model - Schematic



Forward Model - Block Diagram

1. RMS Surface Height: h
2. Correlation Length: l
3. Soil Moisture Content: mv

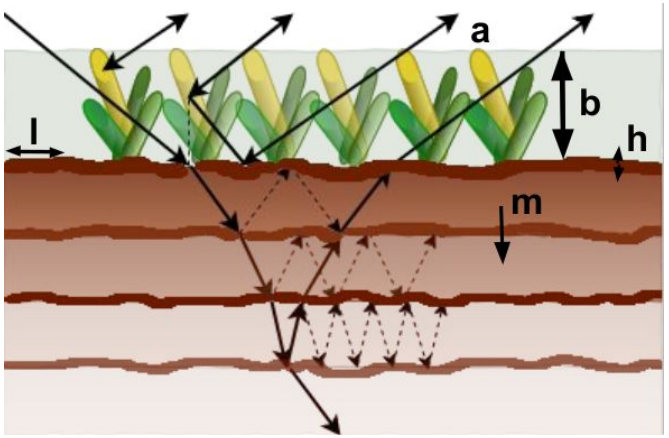
Soil Parameters

1. Frequency : f
2. Polarization : pq
3. Radar Incidence Angle : θ

Radar Parameters

1. Vegetation Moisture : vm
2. Cylinder Radius : a
3. Cylinder Height : b
4. Density of Scatterers : ρ

Vegetation Parameters



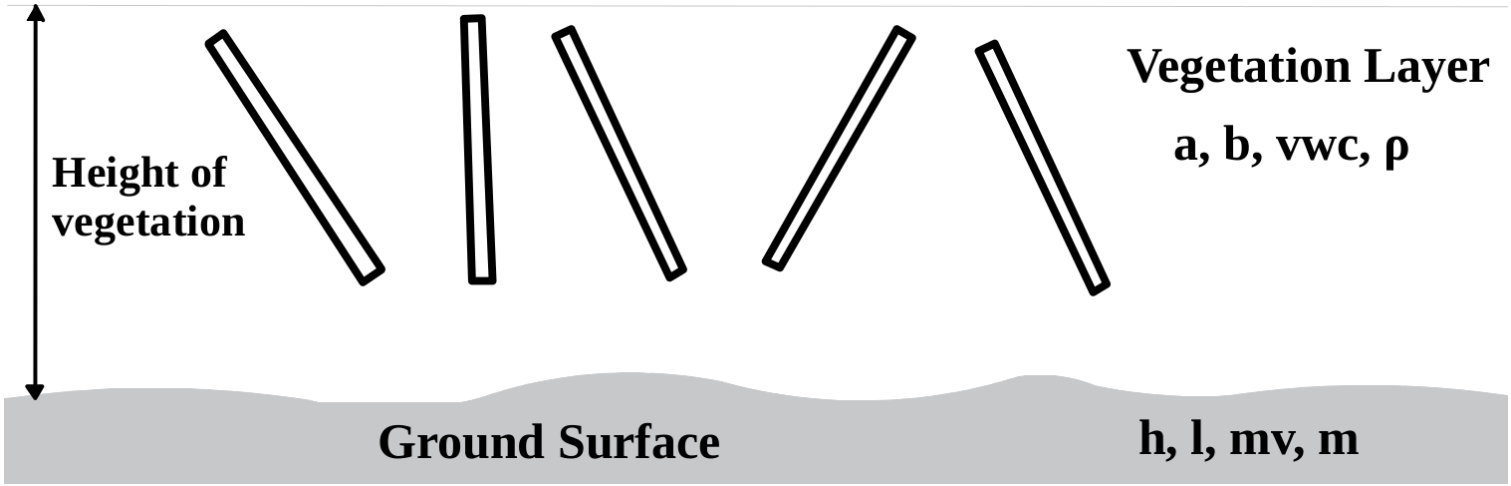
Ground (l^2EM) Backscatter

Vegetation Backscatter

+

$\sigma^{pq,f}(\theta)$

Modeling Vegetation Backscatter[3]



[3] van Zyl, Jakob J. Synthetic aperture radar polarimetry. Vol. 2. John Wiley & Sons, 2011.

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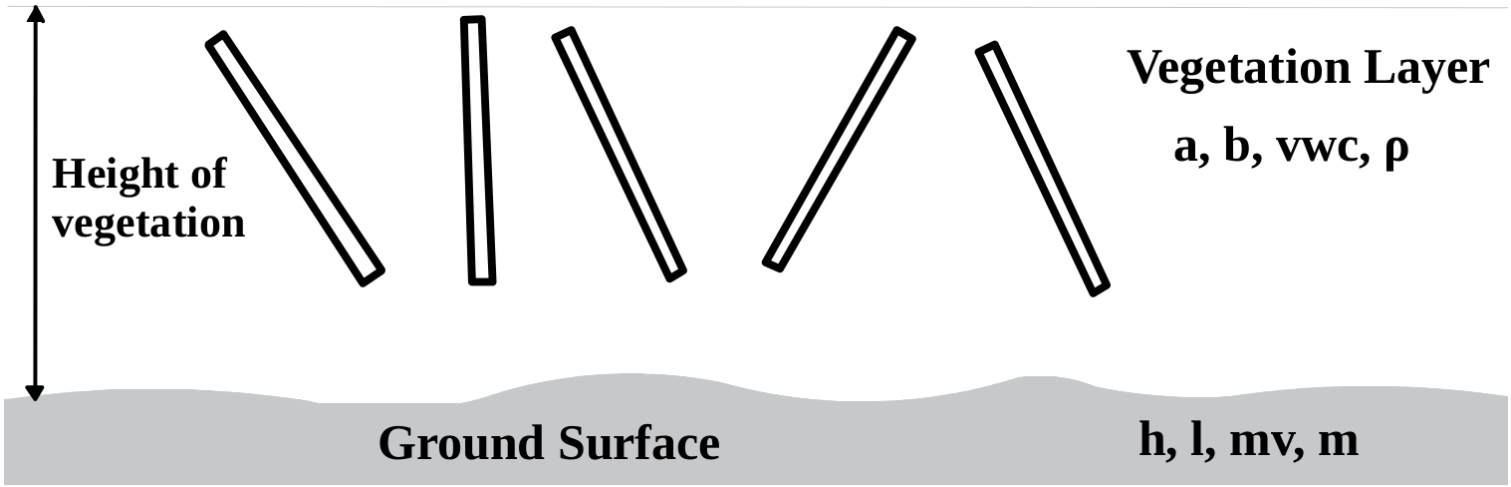

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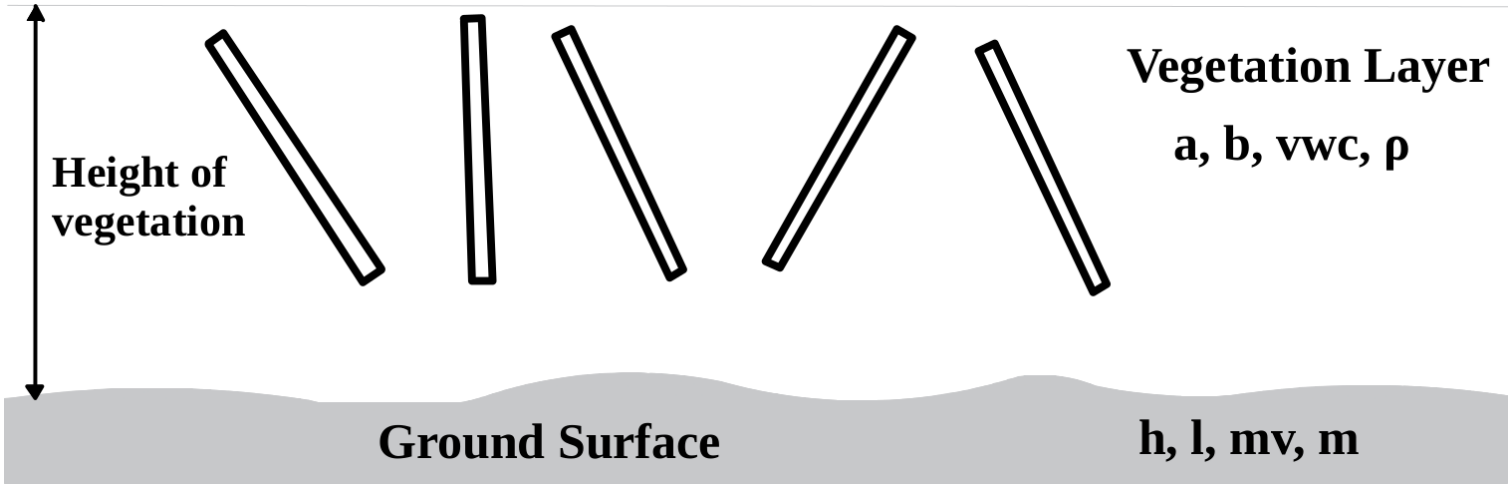

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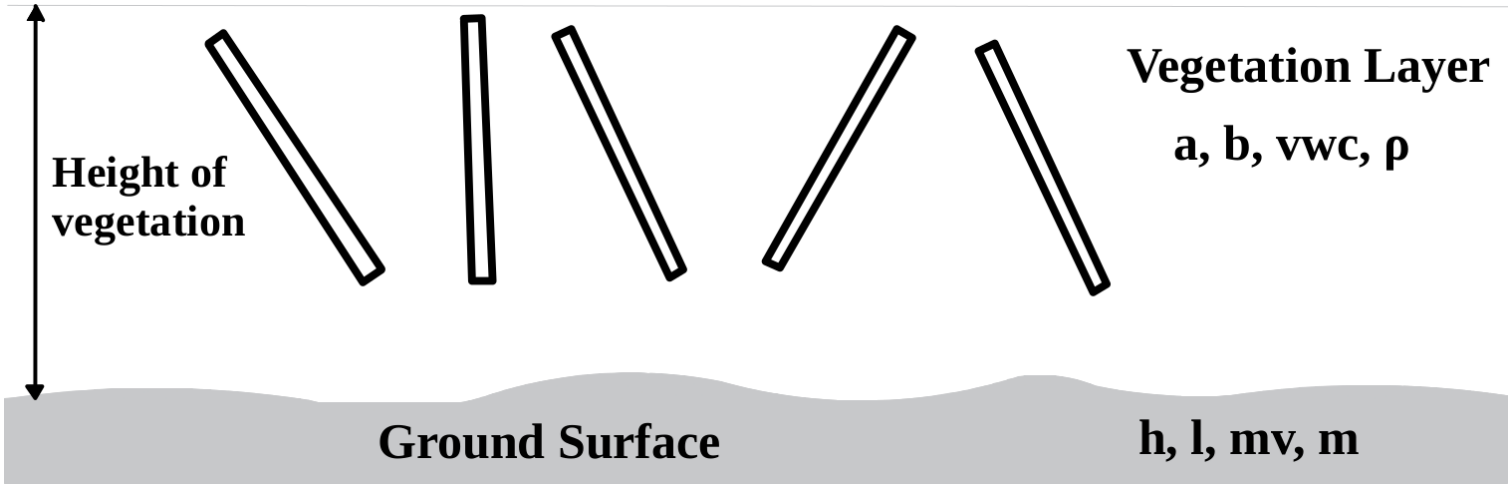

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- Describes scattering from grasslands, pasture lands, etc.
- Spatial distribution of cylinders governed by a cosine-squared PDF

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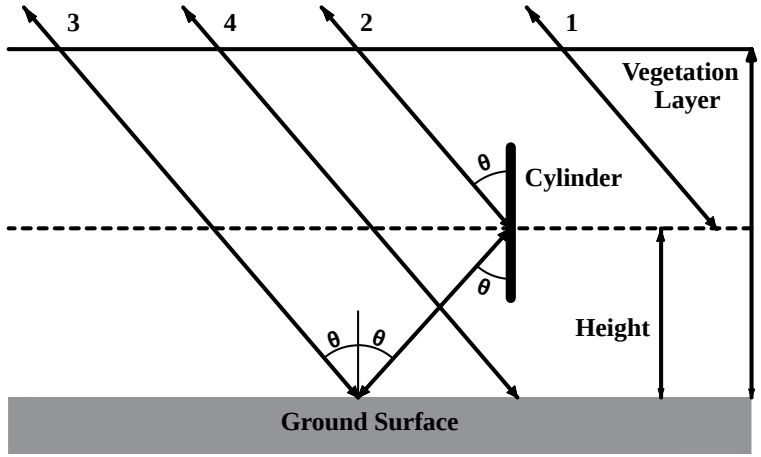
Single Layer Vegetation Model [4]

1. Scattering from the Vegetation Layer **Path-1**
2. Double Reflection Scattering **Paths-2,3**
3. Backscatter from the Ground Surface **Path-4**



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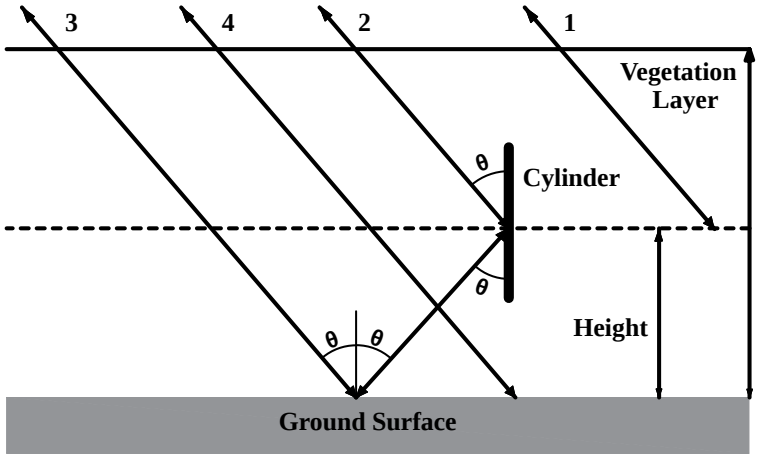

Backscatter Contributions from soil and vegetation

$$\sigma_{total} = \sigma_{veg}(vwc, a, b, \rho_s) + \tau^2 \sigma_{IEM}(h, l, \epsilon) + \sigma_{db}(vwc, a, b, \rho_s, h, l, \epsilon)$$

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Bistatic Scattering Matrix of a Cylinder[5]

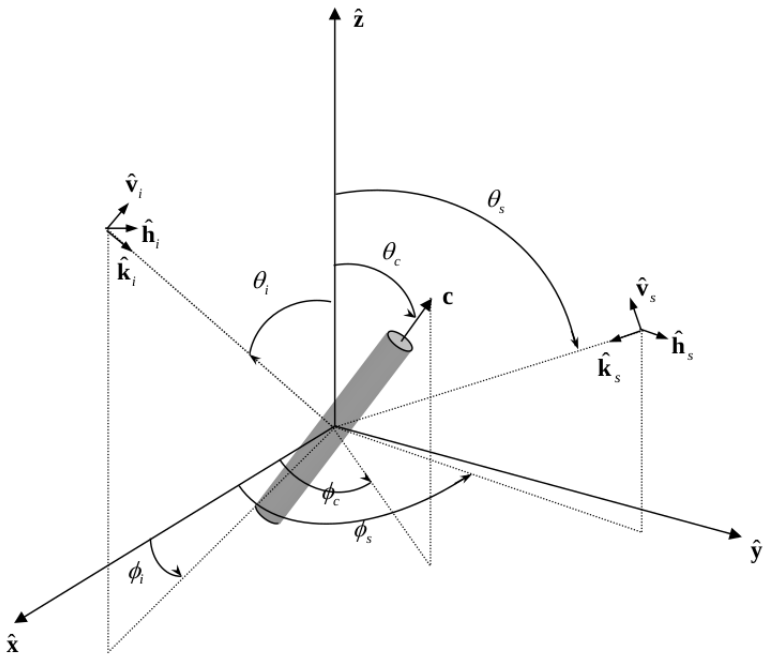

Figure: Global backscattering alignment coordinate system

Scattering Matrix

$$\mathbf{E}^{sc} = [\mathbf{S}]\mathbf{E}^{inc}\frac{e^{ikr}}{r}$$

where

$$\mathbf{S} = \begin{bmatrix} S_{HH} & S_{HV} \\ S_{vh} & S_{VV} \end{bmatrix}$$

[5] van Zyl, Jakob J. Synthetic aperture radar polarimetry. Vol. 2. John Wiley & Sons, 2011.

Vegetation Backscatter[6]

1. Scattering Coefficient of a Single Cylinder

$$S_{HH} = -\frac{il \sin\theta_s}{\pi \sin\theta_i} \frac{\sin V}{V} \sum_{m=-\infty}^{\infty} (-1)^m C_m^{TM} e^{im(\phi_s - \phi_i)}$$

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2. Averaging over all possible orientations: $p(\theta_c, \phi_c) = 1/2\pi \cos^2\theta_c$

$$\langle S_{HH} S_{HH}^* \rangle = \int_0^{2\pi} \int_0^{\pi} S_{HH} S_{HH}^* \, p(\theta_c, \phi_c) \sin\theta_c d\theta_c d\phi_c$$

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3. Calculating the Backscattering Coefficient

$$\sigma_{HH} = 4\pi \frac{b\rho_s cos\theta_i}{4\tau_{hm}} \langle S_{HH} S_{HH}^* \rangle$$

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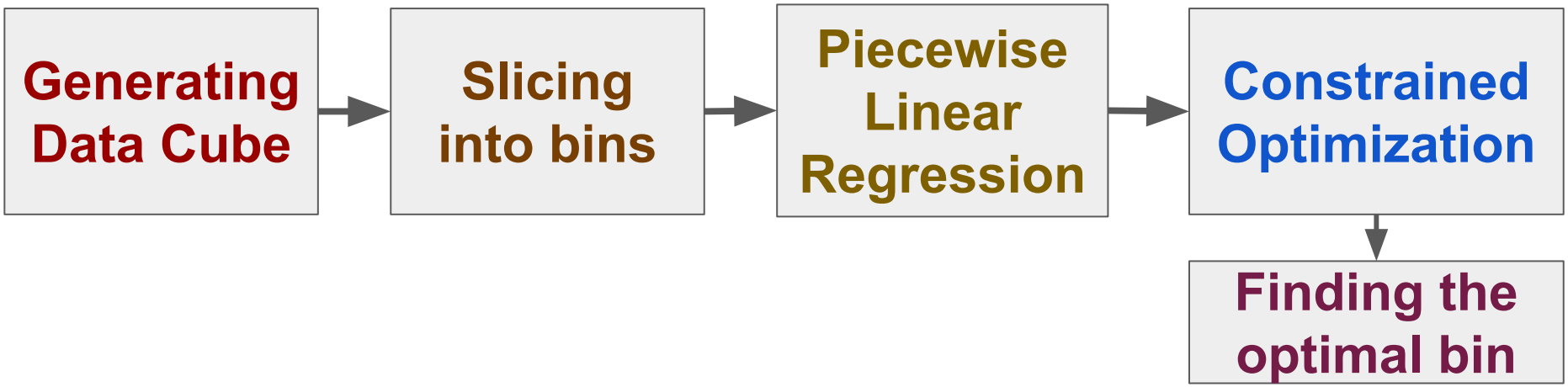
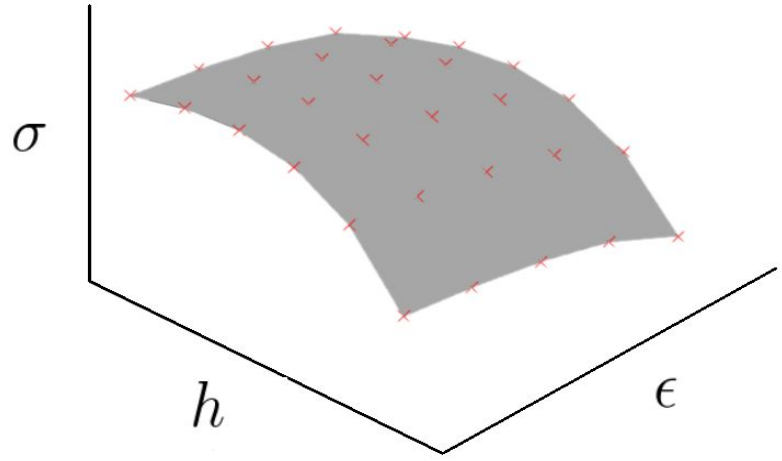
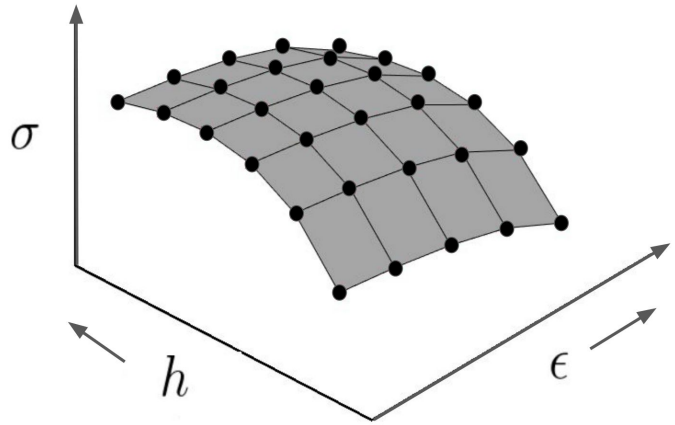
Sliced Regression Inversion Algorithm







SRI - Data Cube Generation

Data Cube Generation

$$\sigma^{pq,f} = F(h_i, l_i, m_{v_i}, v_{m_i}, pq, f) \forall\, i \in \{1, n\}$$

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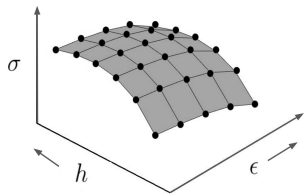
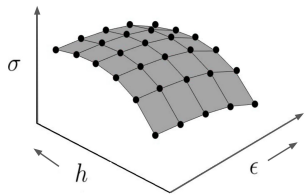
$$\sigma^{pq,f} = F(h_i, l_i, m_{v_i}, v_{m_i}, pq, f) \forall\, i \in \{1, n\}$$

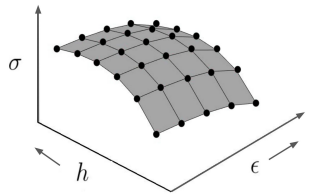
For polarization $pq = \{HH, VV, HV\}$ and frequency bands $f = L, S$:



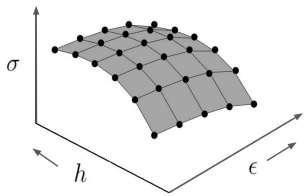
$\sigma^{HH,L}$



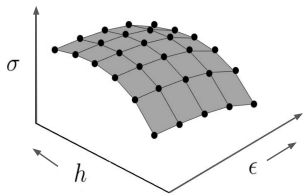
$\sigma^{HV,L}$



$\sigma^{VV,L}$



$\sigma^{HH,S}$



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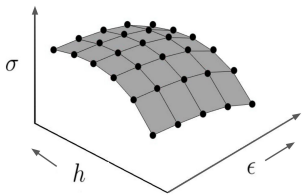

$\sigma^{VV,S}$

SRI - Inversion

$$\underbrace{\begin{bmatrix} \sigma_k^{HH,L} - \beta_{0,k}^{HH,L} \\ \vdots \\ \sigma_k^{HV,S} - \beta_{0,k}^{HV,S} \end{bmatrix}}_{\vec{z}} = \underbrace{\begin{bmatrix} \beta_{1,k}^{HH,L} & \cdots & \beta_{d,k}^{HH,L} \\ \vdots & \ddots & \vdots \\ \beta_{1,k}^{HV,S} & \cdots & \beta_{d,k}^{HV,S} \end{bmatrix}}_{\boldsymbol{\beta}} \underbrace{\begin{bmatrix} x_1 \\ \vdots \\ x_d \end{bmatrix}}_{\vec{x}}$$

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- Define $y = \bar{\sigma}^{pq,f} - \beta_{0,k}^{pq,f}$, where $\bar{\sigma}^{pq,f}$ is the value measured by SAR

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Retrieving the soil moisture using the β for the k^{th} slice

$$\hat{\vec{x}} = \underset{\vec{x}}{\operatorname{argmin}} \|\vec{y} - \boldsymbol{\beta}\vec{x}\|^2 \; s.t. \; \vec{x} \in \mathcal{B}_k$$

Retrieval Accuracy on Synthetic Dataset

Measurement	Vegetated Land		Bare Soil	
	RMSE	R2	RMSE	R2
[HH+HV]-L	0.11	0.44	0.14	0.14
[VV+VH]-S	0.11	0.45	0.12	0.29
[HH+VV]-[L,S]	0.09	0.66	0.07	0.71
[HH+VV+HV]-[L,S]	**0.06**	**0.79**	**0.05**	**0.81**

Table: Comparison of single and dual band soil moisture retrieval accuracy. $h = [0.5 : 0.7 : 4]$ cm, $l = [5, 25]$ cm, $mv = [0.05 : 0.05 : 0.5]$ cm^3/cm^3,, $vm = [0.05 : 0.1 : 0.5]$ cm^3/cm^3, $l_{veg} = [50 : 100 : 250]$ cm, $r_{veg} = [2 : 3 : 8]$ mm.

- **Error Metric:** RMSE - Root Mean Squared Error (cm^3/cm^3), R2 - Correlation Coefficient

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- **Error Metric:** RMSE - Root Mean Squared Error (cm^3/cm^3), R2 - Correlation Coefficient
- Dual band performs better than single band
- Adding cross polarized backscatter leads to better accuracy

NISAR Operating Bands (L and S) - Bare Soil

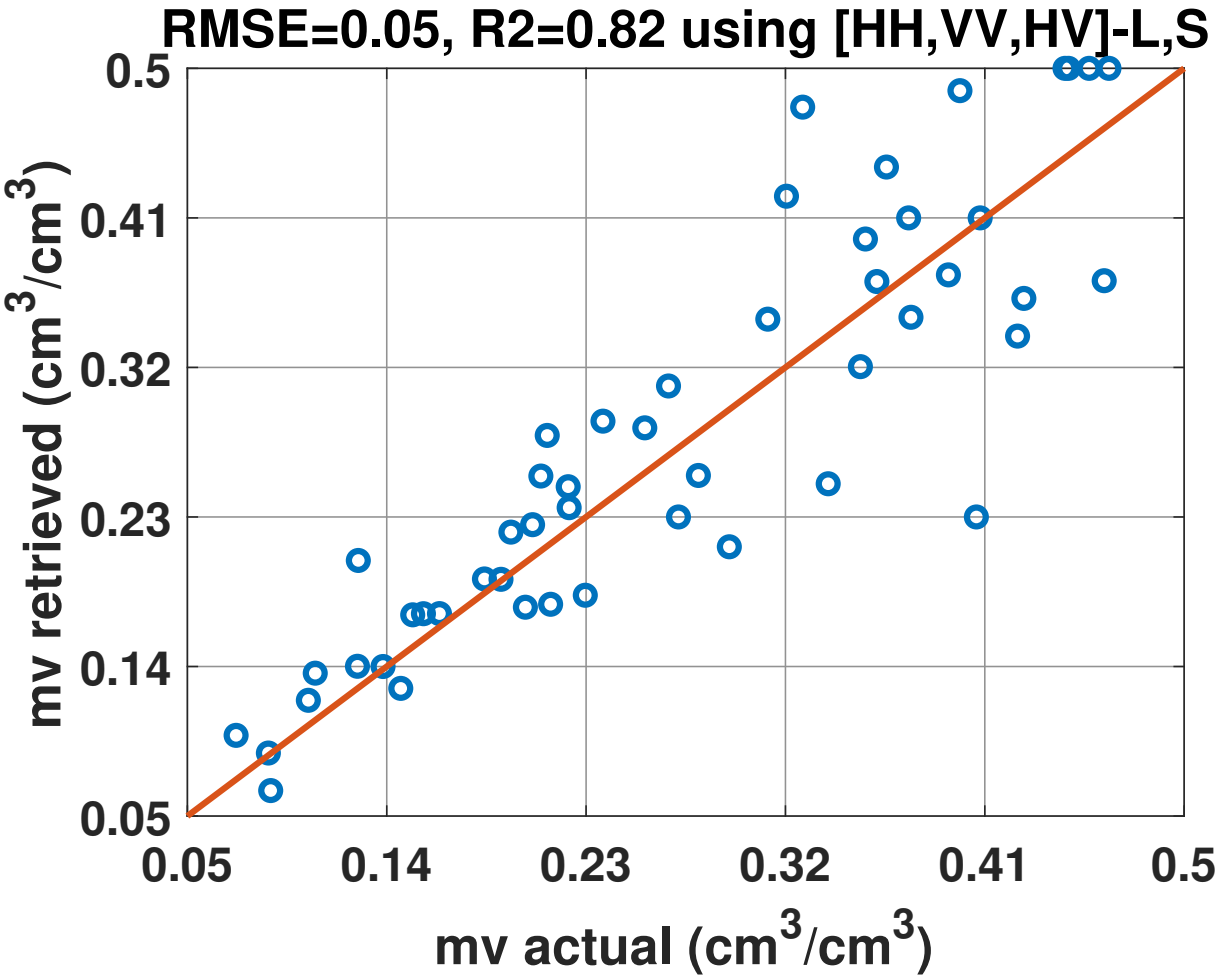
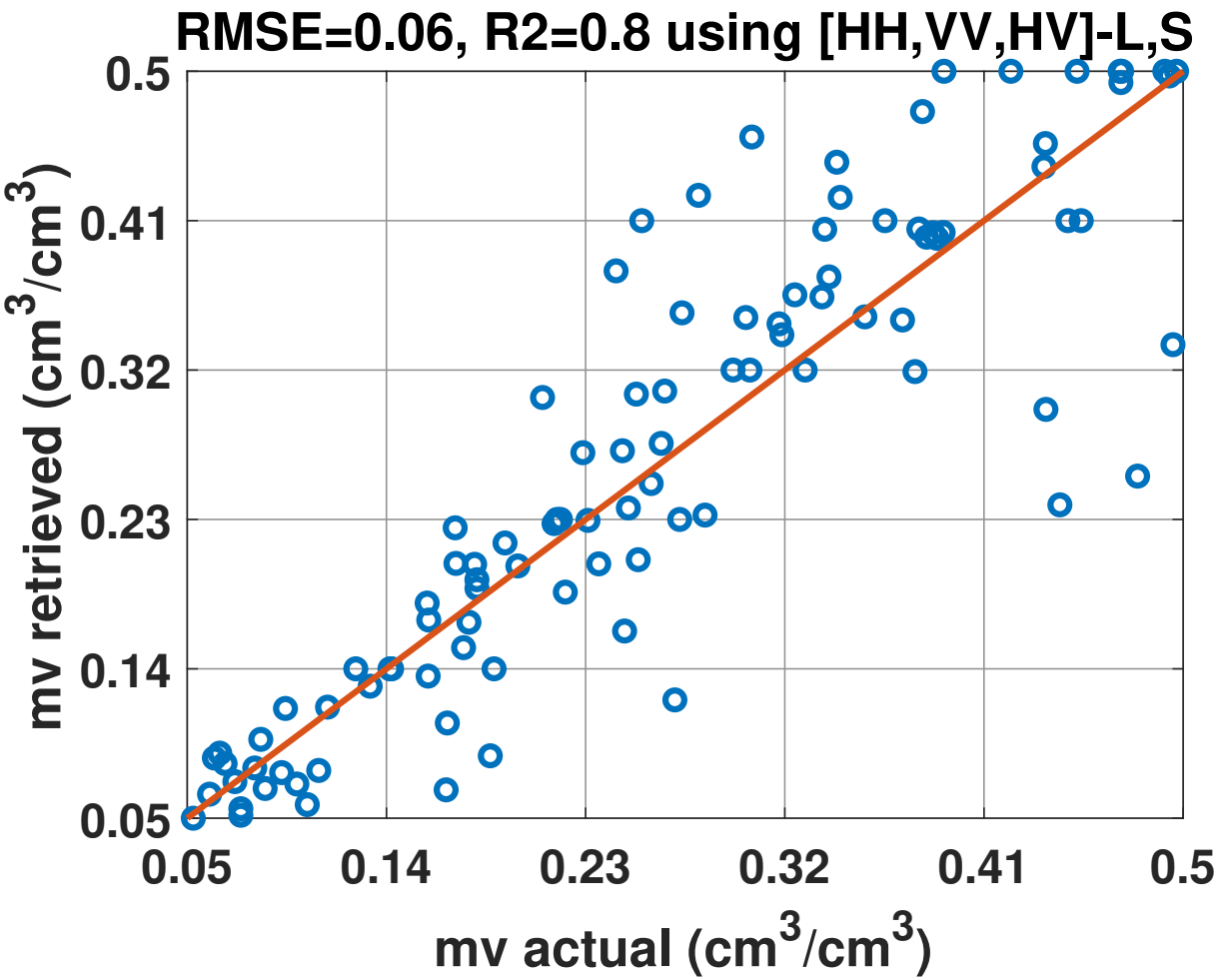


Figure: Scatter plot showing performance of SRI algorithm for soil moisture retrieval using dual (L+S) band (synthetic) data over bare soil

NISAR Operating Bands (L and S) - Vegetated Lands



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Ground Truth Data Collection

- **Collecting Agency:** Space Applications Centre (ISRO)
- **Collaborators:** Dharmendra Pandey & Shivani Tyagi - SAC/ISRO
- **Area:** Agriculture fields spread over Guntur, Andhra Pradesh
- **Satellites:** ALOS PALSAR (L-band), SENTINEL (C-band)

Accuracy on Real Dataset - Bare Soil and Maize Crop

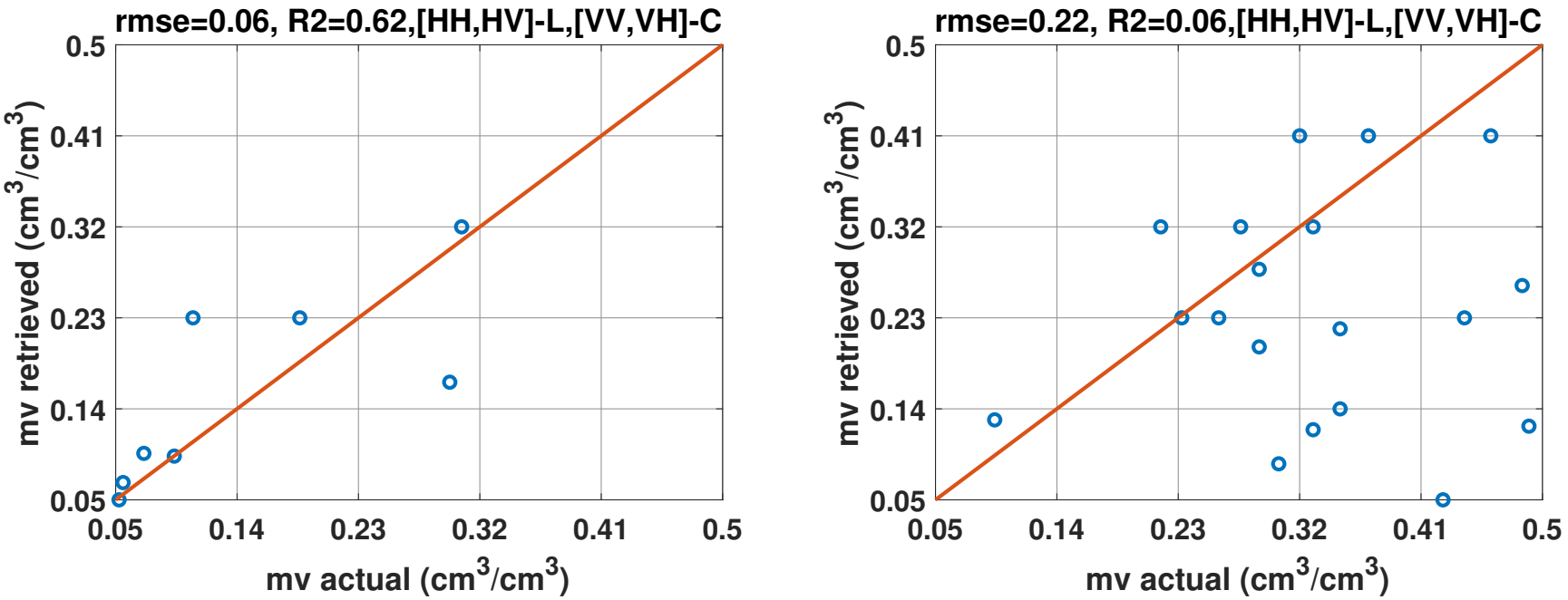
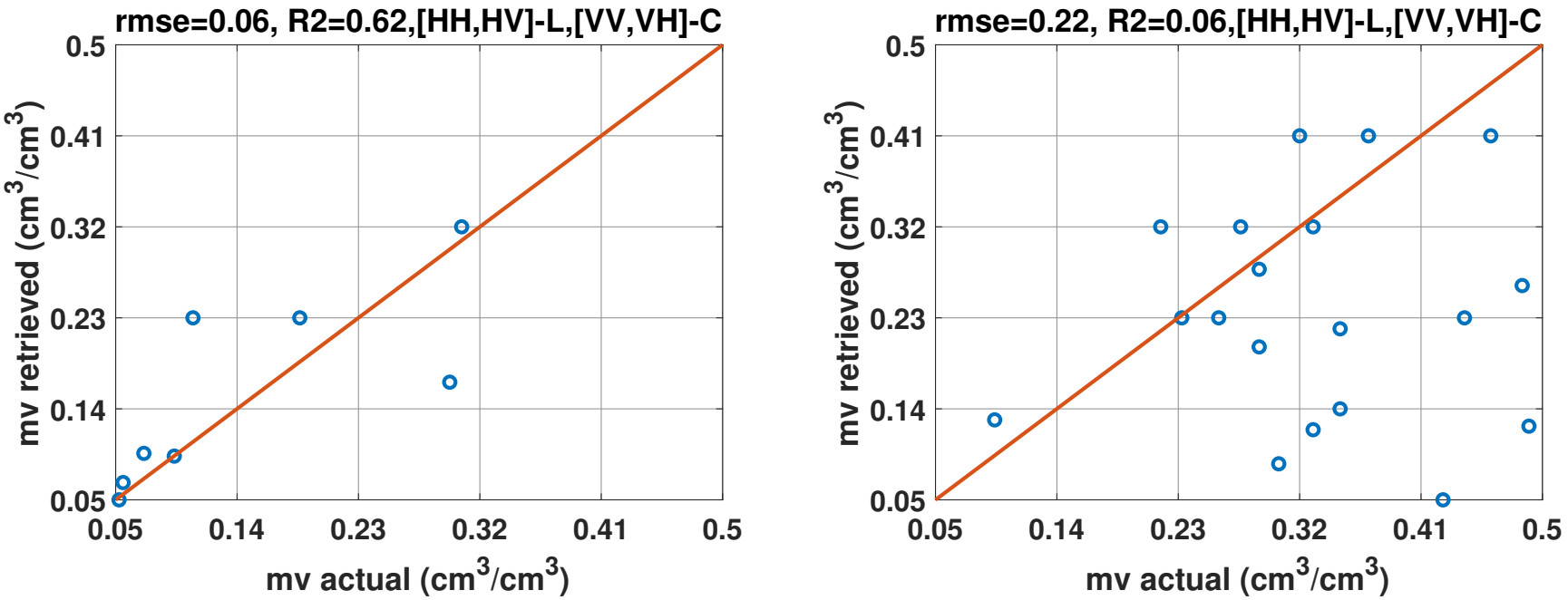


Figure: Retrieval accuracy of SRI for (1) bare soil and (2) maize crop using experimental data.

Accuracy on Real Dataset - Bare Soil and Maize Crop



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- For maize crop, the radius is fixed at 5mm and length is retrieved.

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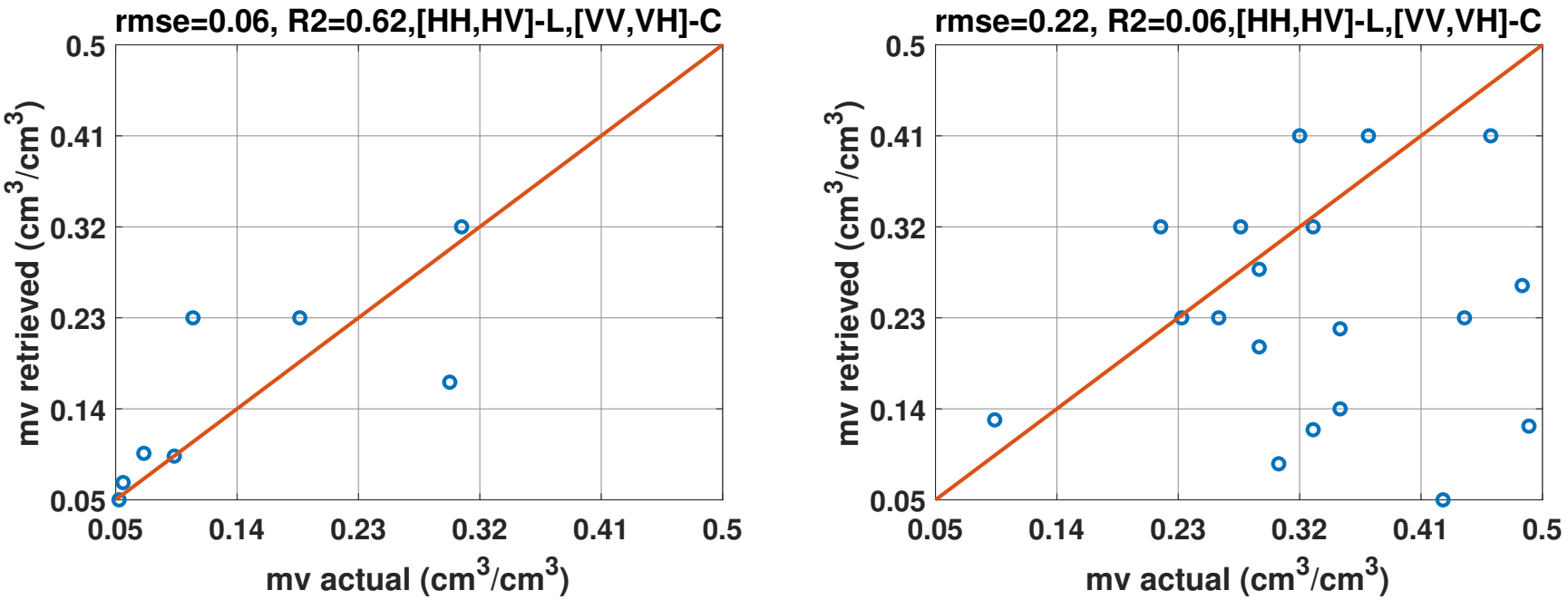

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- For maize crop, the radius is fixed at 5mm and length is retrieved.
- There must be either a modelling error or an incorrect fixed parameter causing the mismatch.

Accuracy on Real Dataset - Chilli Crop

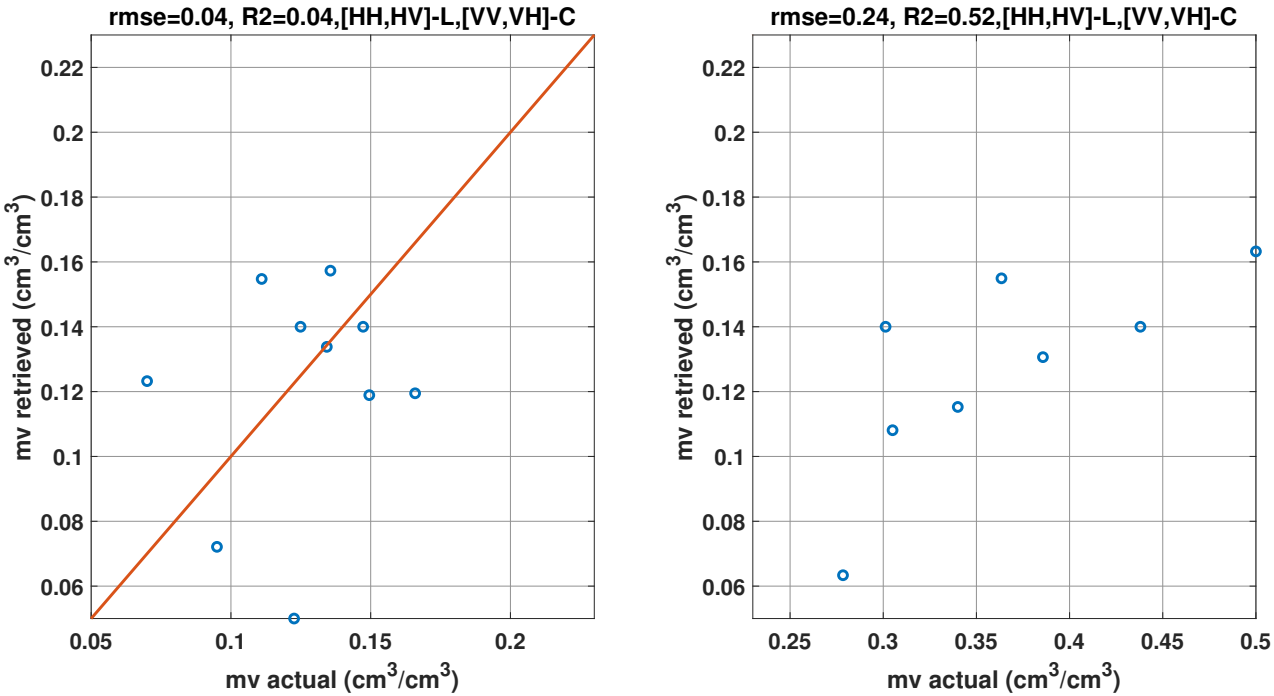

Figure: Retrieval accuracy of SRI approach for chilli crop using the experimental data. Cylinder radius and length are fixed at 2mm and 50 cm respectively.

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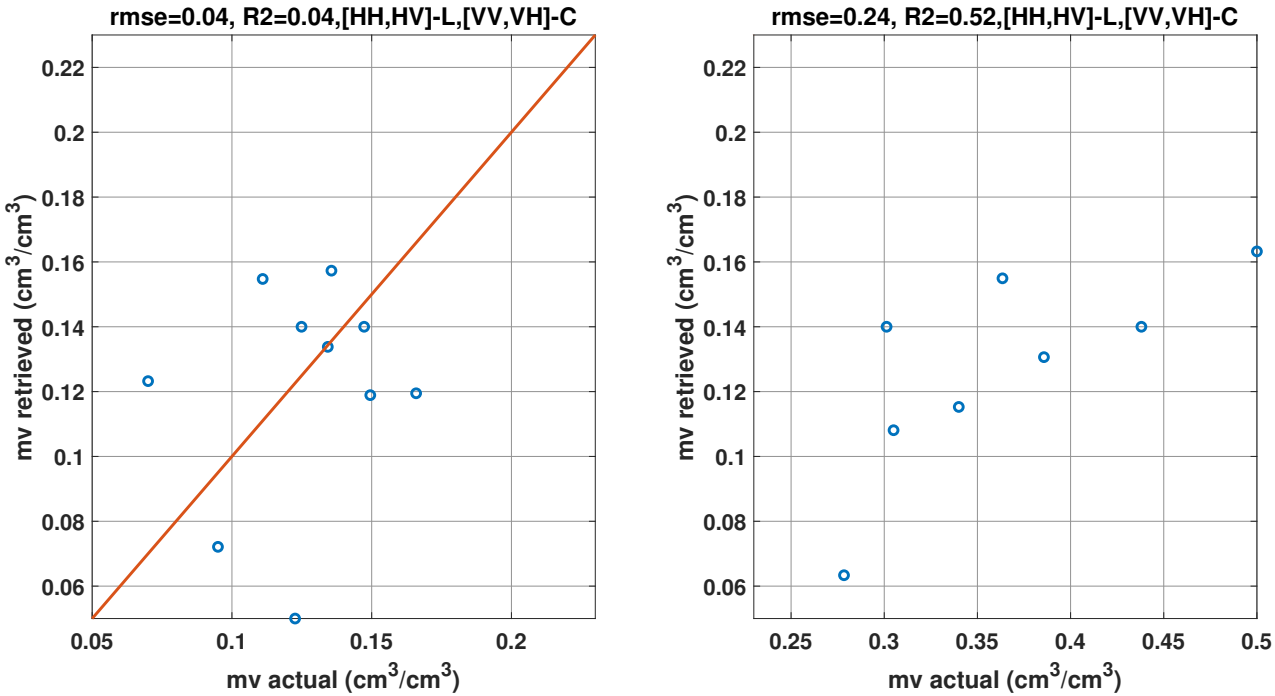

Figure: Retrieval accuracy of SRI approach for chilli crop using the experimental data. Cylinder radius and length are fixed at 2mm and 50 cm respectively.

- Low values of soil moisture ($mv < 0.25$) retrieved with good accuracy (0.04 cm^3/cm^3)

Accuracy on Real Dataset - Chilli Crop

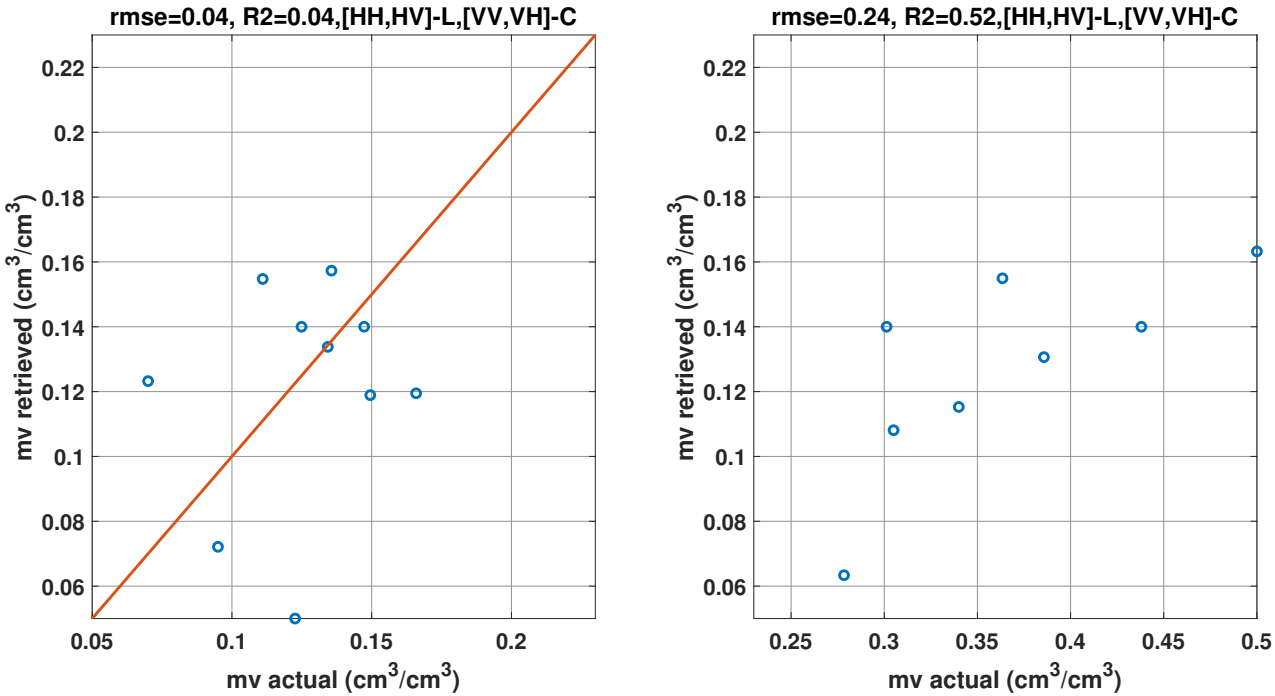

Figure: Retrieval accuracy of SRI approach for chilli crop using the experimental data. Cylinder radius and length are fixed at 2mm and 50 cm respectively.

- Low values of soil moisture ($mv < 0.25$) retrieved with good accuracy (0.04 cm^3/cm^3)
- For wet soil with moisture content greater than 0.25 cm^3/cm^3, accuracy is poor.

Comparison with LUT approach [Seung-Bum Kim 2013]

Algorithm	Maize	Chilli	Jowar	Bare Soil
SRI	0.2	0.18	0.26	0.06
LUT	0.43	0.27	0.47	0.17

Table: Retrieval Accuracy using the ALOS-PALSAR (L-band) and SENTINEL-1A (C-band) data.

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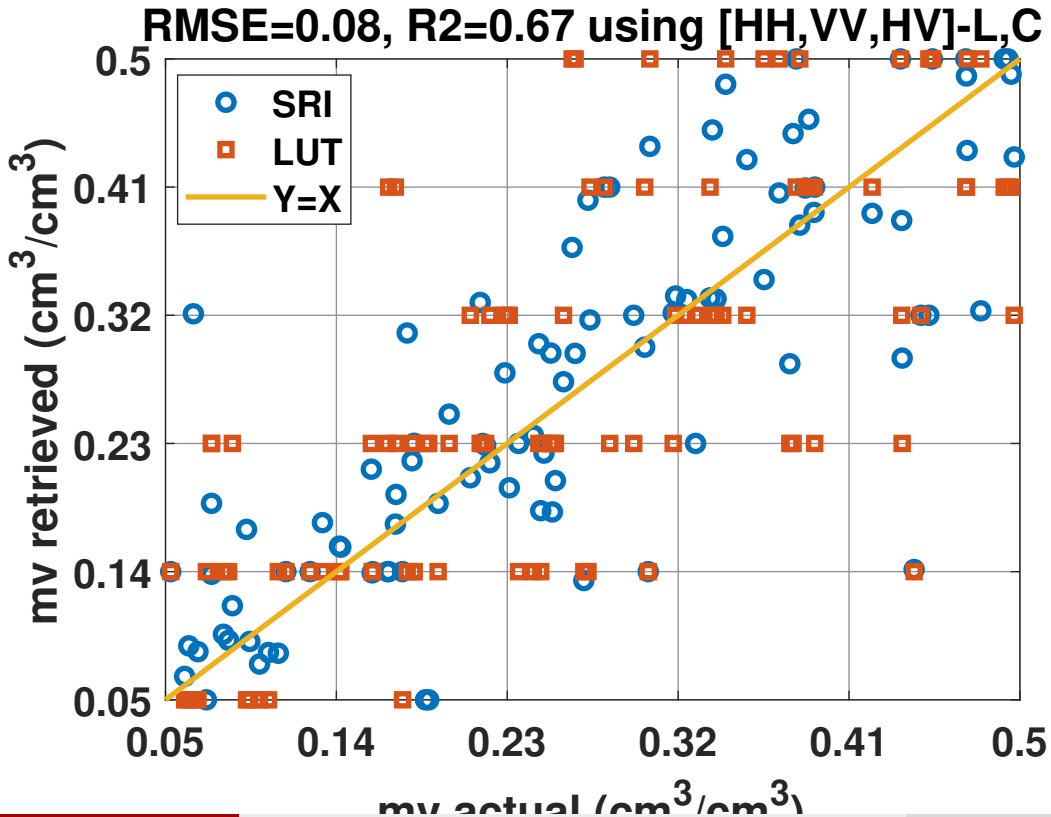
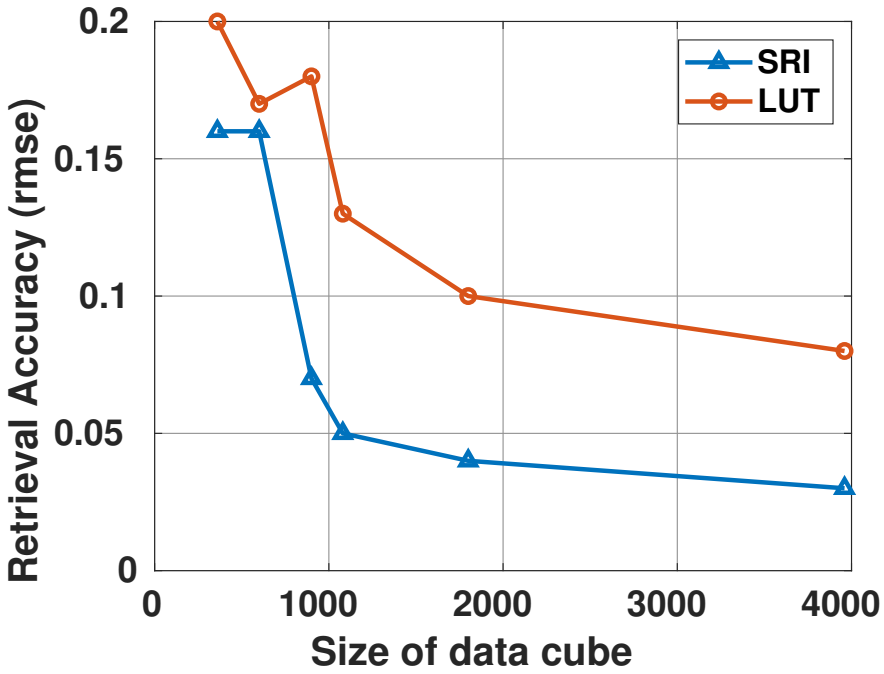
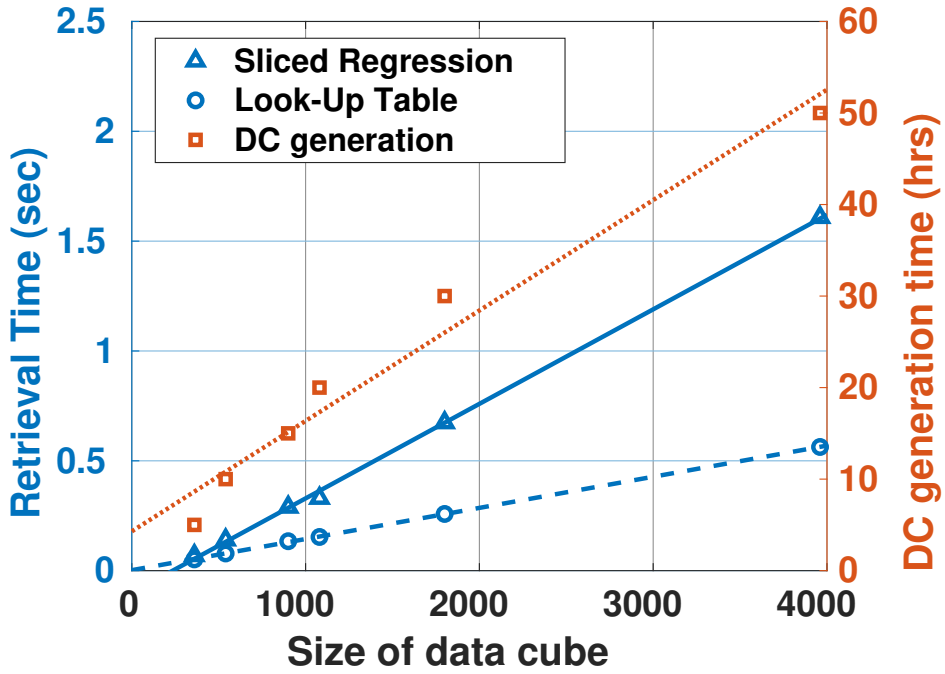


Accuracy and Time Consideration - SRI vs LUT[7]





[7] Kim, Seung-Bum, et al. "Models of L-band radar backscattering coefficients over global terrain for soil moisture retrieval." IEEE Transactions on Geoscience and Remote Sensing 52.2 (2013): 1381-1396.

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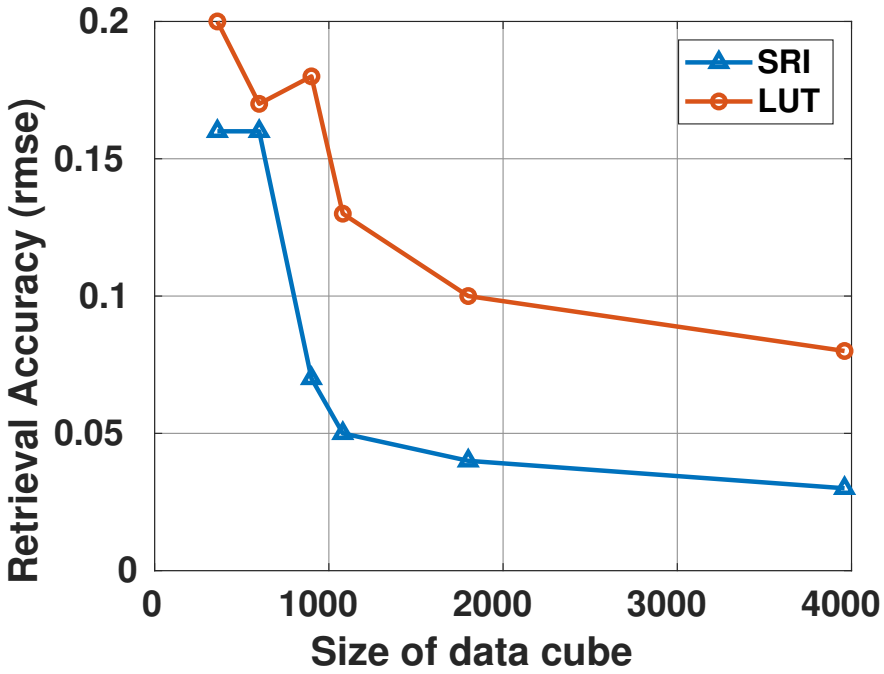

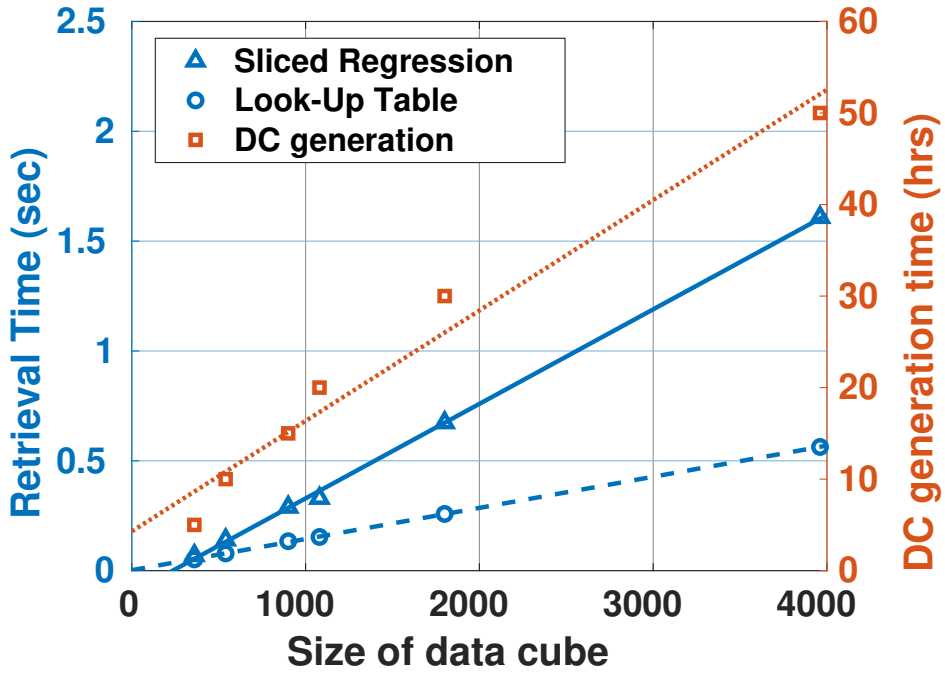

- Linear dependence of retrieval time on datacube size

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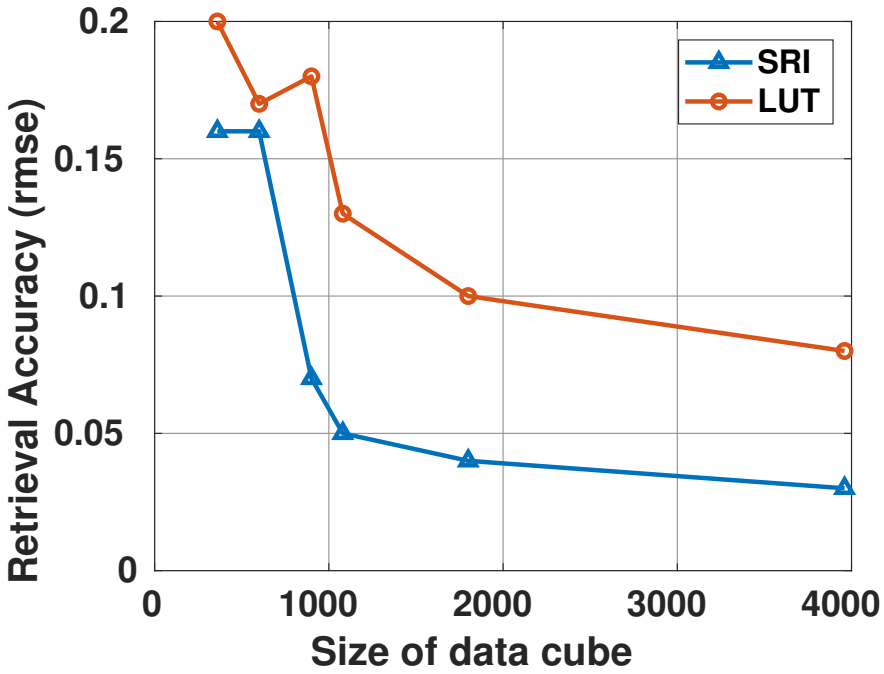

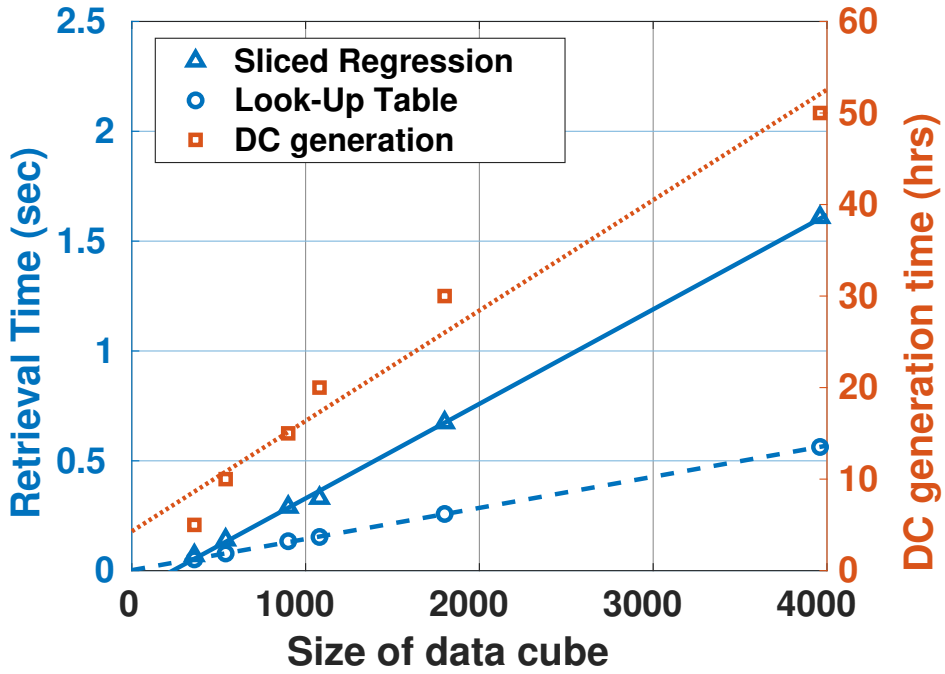

- Linear dependence of retrieval time on datacube size
- For a given RMSE, DC generation time different-SRI:20 hrs,LUT:50 hrs

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Conclusion

- Presented a new soil moisture inversion algorithm, termed Sliced Regression Inversion
  - Approximates the relationship between the backscatter and physical parameters by piece-wise linear models
  - Performs linear regression within each slice to obtain an estimate of the physical parameters
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- SRI more accurate and computationally efficient than the lookup table approach

Publications

Manuscripts under Preparation:

1. **Siddhant Gautam**, Dharmendra K Pandey, Uday K Khankhoje, "**Soil Moisture Retrieval from Multi-Frequency Multi-Polarization SAR Data Using a Sliced Regression Inversion Technique**"

Peer Reviewed Conferences:

1. **Gautam, S.**, S. V. Chidambaram, N. Gunturu, and U. K. Khankhoje, **Retrieval of soil moisture using sliced regression inversion technique**. In 2019 PhotonIcs and Electromagnetics Re-search Symposium-Spring (PIERS-Spring). IEEE, 2019