A Bayesian approach to retrieve soil parameters from SAR data: Effect of prior information

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Introduction and Motivation

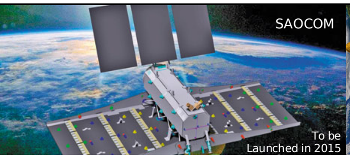
Surface soil moisture is a key variable related to:

- ❖Climatic modeling (heat and mass transfer between Earth and atmosphere).
- ❖Hydrological applications (water dynamics and runoff, both closely related with water erosion, risk of floods).
- ❖Agronomical applications (vegetation and crops development).

Argentina is building an L-Band full polarimetric SAR system named SAOCOM (scheduled for 2015):

- ❖Offering the opportunity of monitoring surface soil moisture content.
- ❖In this context the goal of this work is to assess the effect of prior information in a Bayesian retrieval scheme.

Which are the necessary requirements of the prior information to ensure an acceptable estimate of soil parameters, mainly soil moisture?



Limiting factors for retrieval from SAR data

Concerning the surface soil moisture:

•It is a very heterogeneous variable across scales (high spatial and temporal variability)

Concerning the surface roughness:

•It is very dependent on the tillage practice

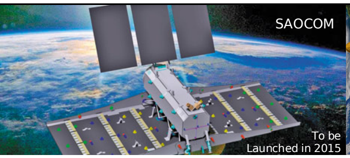
Concerning the forward models:

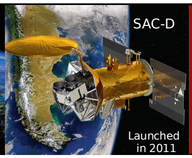
•Non-negligible mismatches between model parameters and measured data (statistical fluctuations, difficulty on parameterization of model variables, target’s heterogeneity)

Concerning the speckle noise:

•Decreases the contrast and radiometric quality of SAR images.

•It is usually reduced by spatial averaging at the expense of spatial resolution.





Why a Bayesian retrieval scheme?

Because…

- Needs only a forward model (as the Bayesian approach itself is the inversion procedure applied to forward model data).
- Gives an estimator of soil parameters as well as their associated error.
- Can include prior information in order to improve the retrieval.

Bayes' Theorem: Basics

Posterior Likelihood Prior

$$P(m,ks|z_1,z_2,z_3) = \frac{P_{Z_1Z_2Z_3}(z_1,z_2,z_3|m,ks)P_{MKS}(m,ks)}{P_{Z_1Z_2Z_3}(z_1,z_2,z_3)}$$

Evidence

The *Posterior* is conditional probability of measuring m and ks given measured SAR backscattering coefficients Z_1, Z_2, Z_3 (hh, vv, vh from now on).

The *Likelihood* involves forward model as well as speckle model.

In the *Prior* is included all a priori information about m and ks.

The *Evidence* is an overall normalization factor.

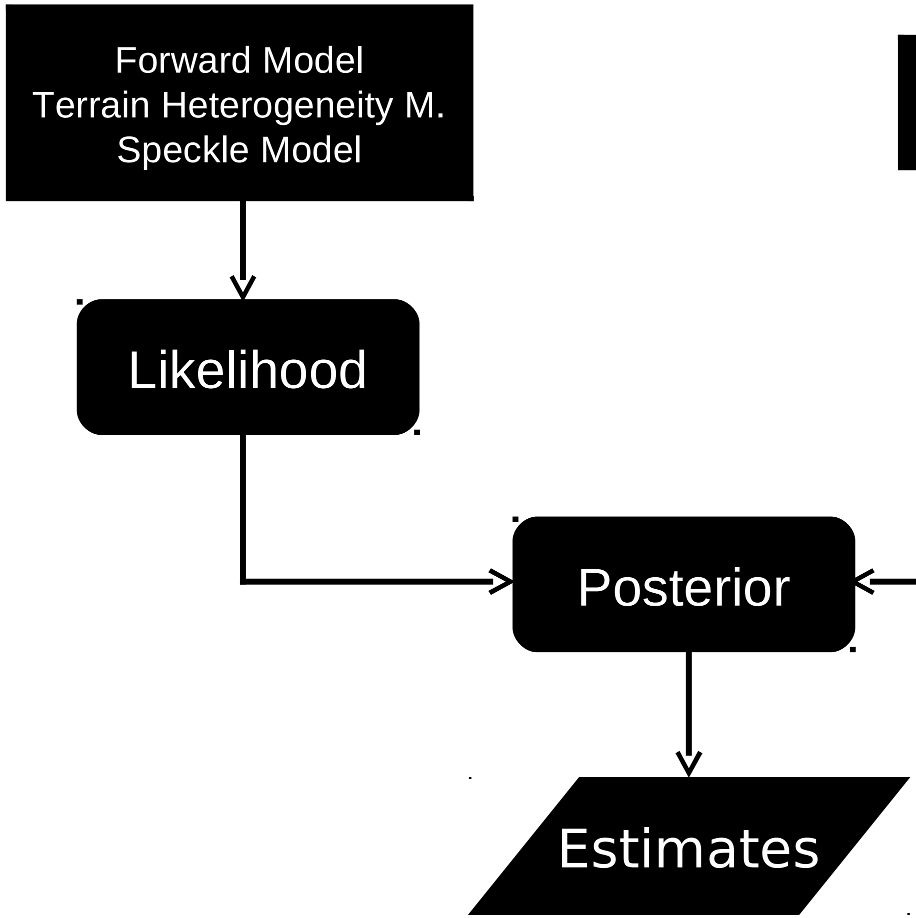
Providing the conditional density function the optimal unbiased estimators are:

$$m_{mean} = \iint_D mP(m,ks|z_1,z_2,z_3)dksdm$$

$$m_{std} = \iint_D (m - m_{mean})^2 P(m,ks|z_1,z_2,z_3)dksdm$$

Integration is made over the feasibility region D of forward model used

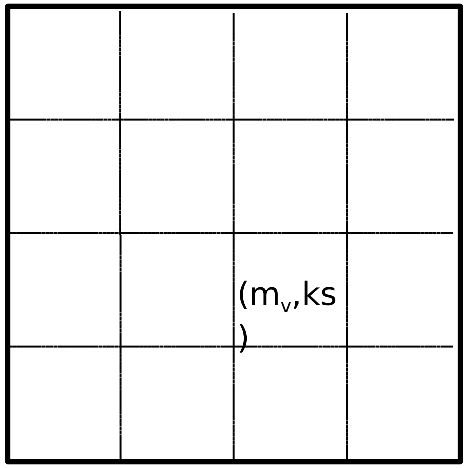
Algorithm Block Diagram



Modeling the likelihood function (I)

Forward model

Forward Model
Terrain Heterogeneity M.
Speckle Model



$$(m_v, ks) \xrightarrow{\text{Forward Model}} \begin{pmatrix} hh = f_1(m_v, ks) \\ hv = f_2(m_v, ks) \\ vv = f_3(m_v, ks) \end{pmatrix}$$

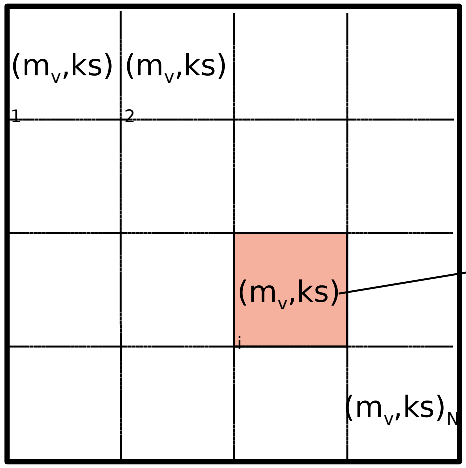
m_v = volumetric soil moisture [cm^3/cm^3]

ks = normalized roughness [-] ($k=2\pi/\lambda$)

Modeling the likelihood function (I)

Terrain Heterogeneity Model

Forward Model
Terrain Heterogeneity M.
Speckle Model



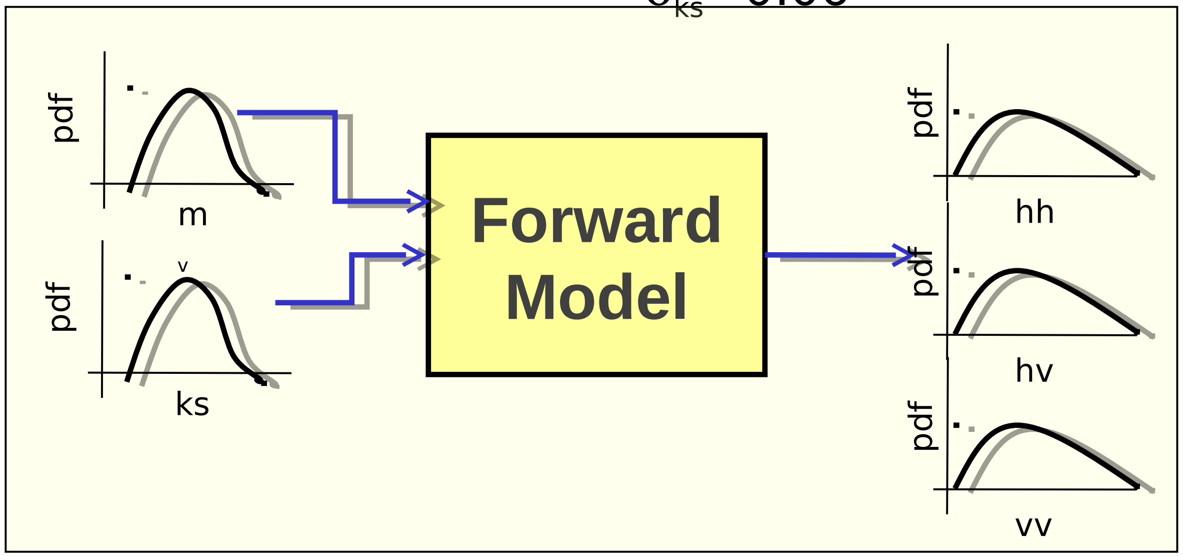
$$\begin{Bmatrix} (m_v, ks)_1 \\ (m_v, ks)_2 \\ \vdots \\ (m_v, ks)_i \\ \vdots \\ (m_v, ks)_N \end{Bmatrix}_{i=1,\dots,N} \xrightarrow{\text{Forward Model}} \begin{Bmatrix} (hh, hv, vv)_1 \\ (hh, hv, vv)_2 \\ \vdots \\ (hh, hv, vv)_i \\ \vdots \\ (hh, hv, vv)_N \end{Bmatrix}_{i=1,\dots,N}$$

Gaussian model for the heterogeneity

Typical values of deviation:

$\sigma_{mv} \sim 0.05 cm^3/cm^3$

$\sigma_{ks} \sim 0.06$



Modeling the likelihood function (I)

Forward Model
Terrain Heterogeneity M.
Speckle Model

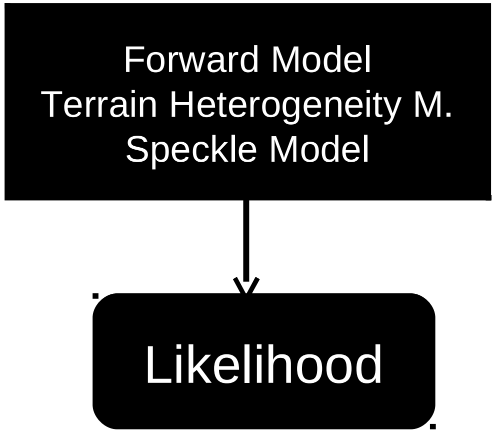
Speckle model derived from a Wishart distribution

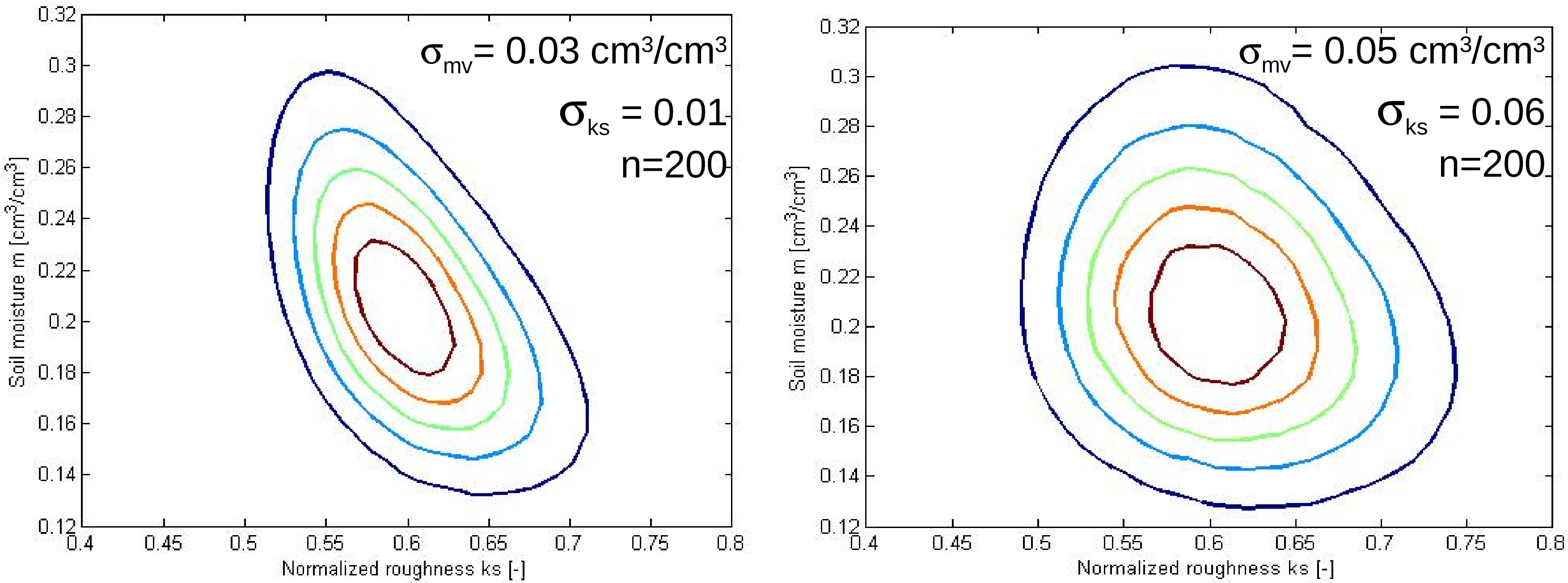
In this paper it reduces to the distribution of the ratio of two multilooked intensity variables
(Barber et al., “Speckle noise and soil heterogeneities as error sources in a bayesian soil moisture retrieval scheme for sar data," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,* **5**, 942-951 (Jun 2012))

The main parameter is the number of looks, *n*. When increasing *n*, decreasing the negative effect of the speckle noise.

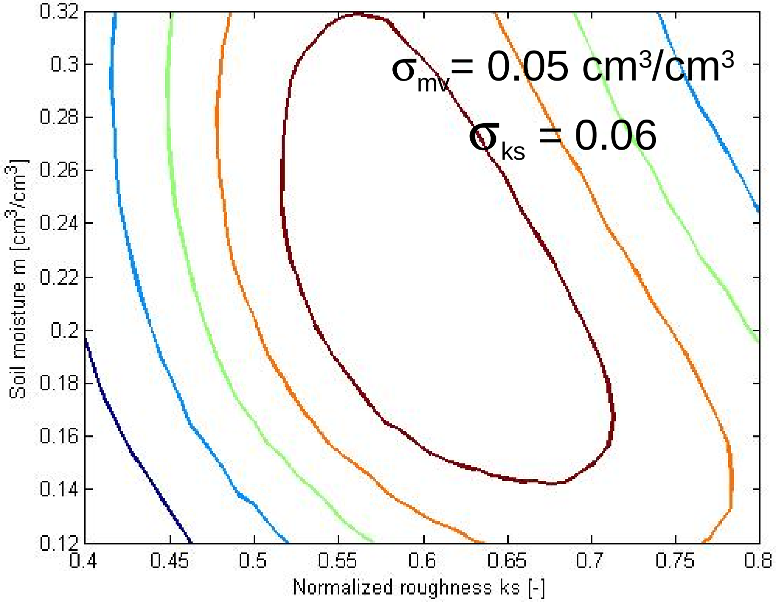
Modeling the likelihood function (II)

Measures the degree of compatibility between a certain SAR measurement and certain soil parameters constrained to some given forward model.
The higher the values, the more likely that the SAR measurement come from that specific combination of soil parameters.
The spread of the likelihood is a consequence of the soil parameter heterogeneity and the speckle noise.
(For the mathematical details involved, please refer to Barber et al

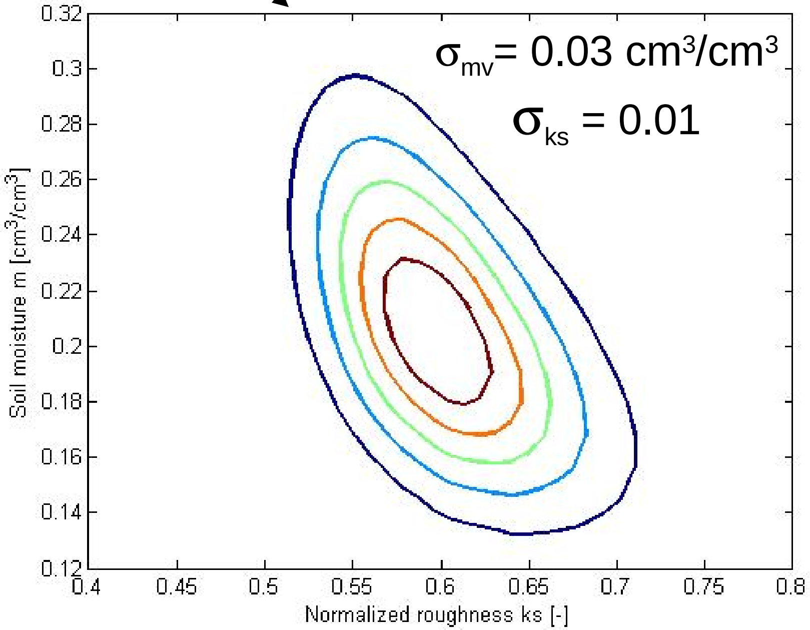




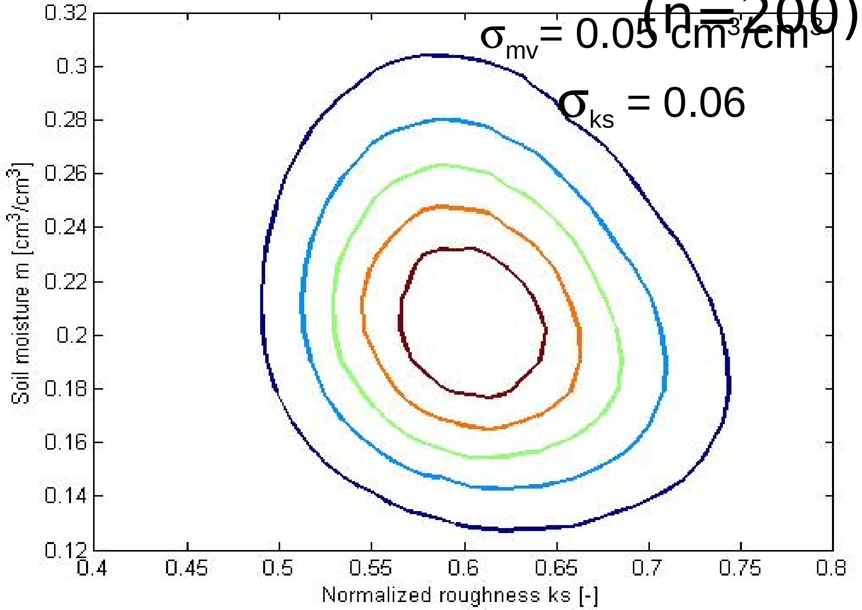
Affected by speckle (n=16)



Almost no speckle (n=200)

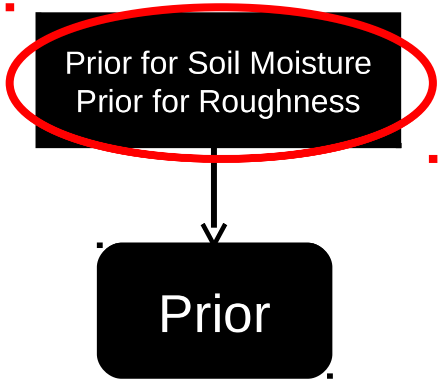


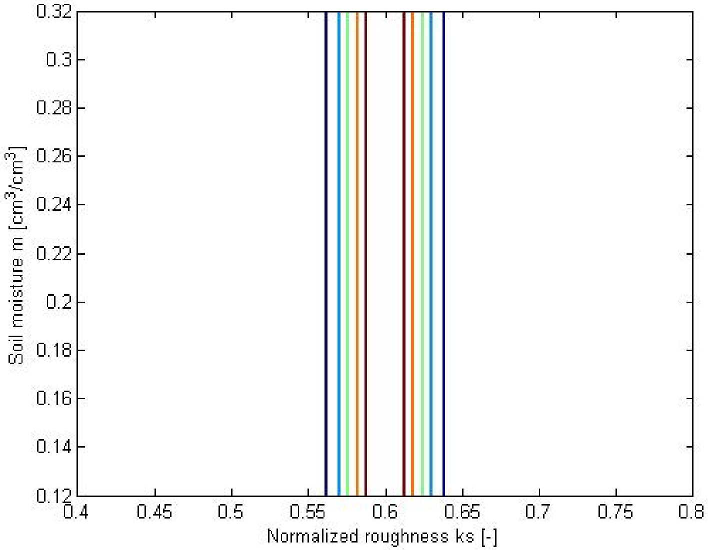
Almost no speckle (n=200)



Modeling the Prior distribution

The prior involves all the information available about the terrain parameters.
It can be available from historical records, estimation from other sensors, in-situ data and/or contextual information.
It will be assumed independence between soil moisture and roughness parameter, $P_{MKS}(m,ks)= P_{M}(m)P_{KS}(ks)$.





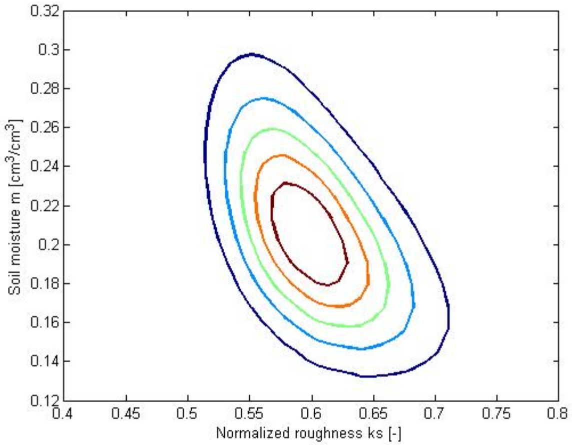
$P_{M}(m)=U[0.04,0.35]$

$P_{KS}(ks)=N[\mu,\sigma]$

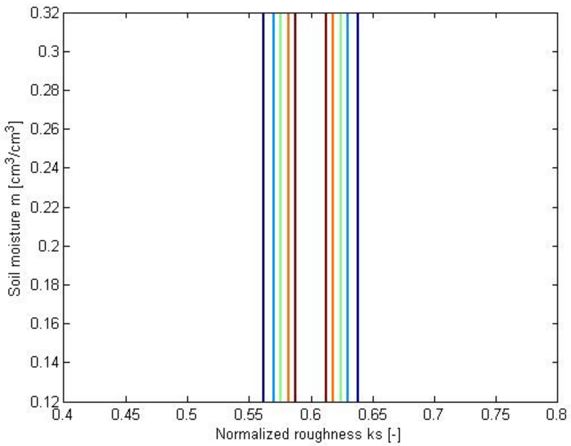
The Posterior

It is the point-by-point product of the likelihood by the posterior.

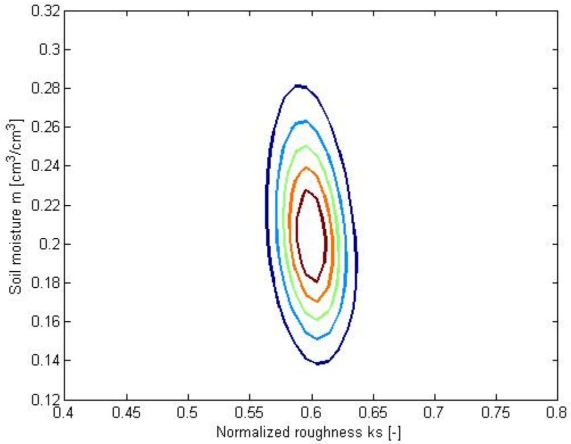
Likelihood



Prior



Posterior



Simulation

Estimates for different values of the roughness prior.

In order to perform a numerical simulation, the following functions and model parameters are required:

1) Forward Model → Oh Model
2)Terrain Heterogeneity M. → Gaussian model
3) Speckle Model --> Wishart-derived
4) Soil moisture prior → Uniform
5) Roughness prior → Gaussian $N(\mu_{ks}, \sigma'_{ks})$.

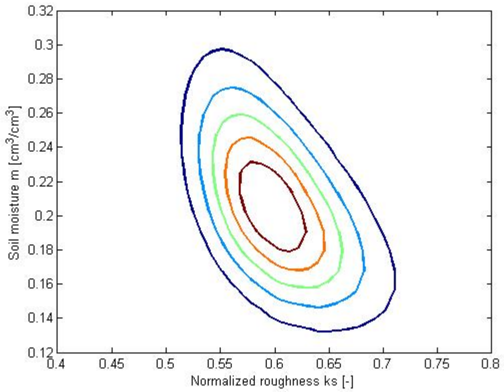
A study of the estimates mv and ks as a function of:

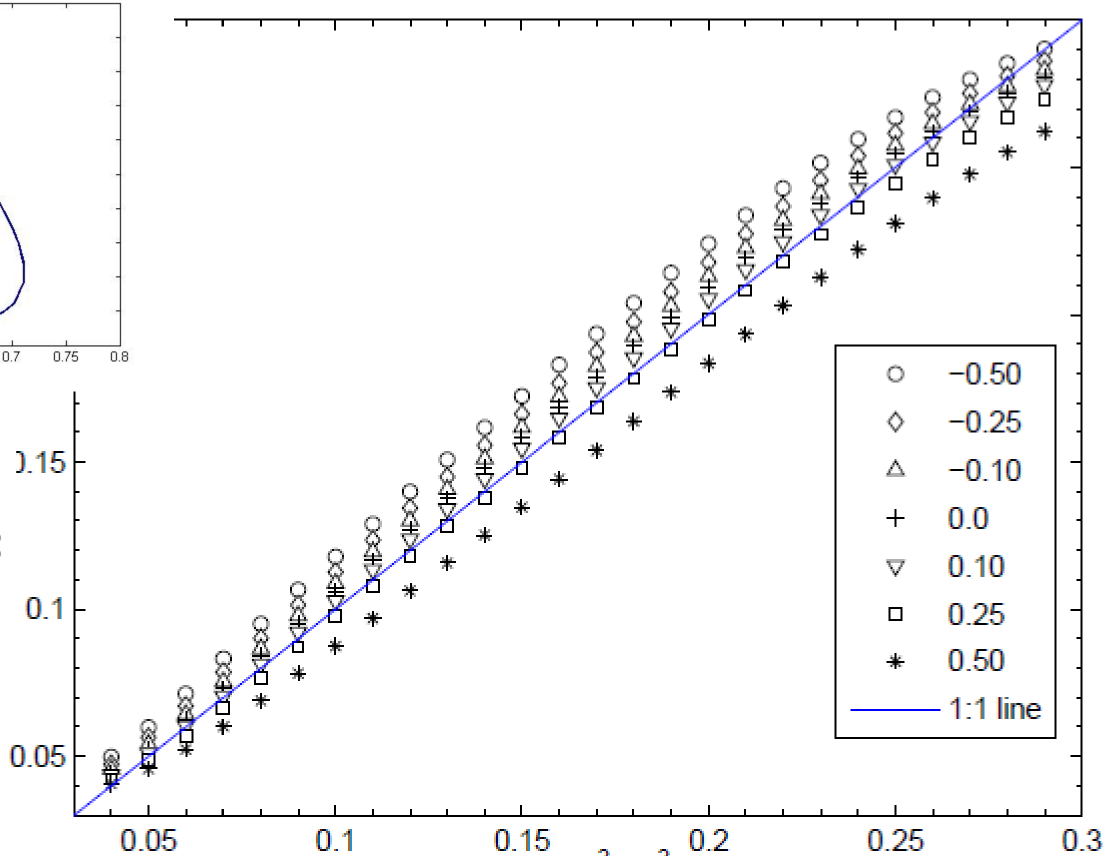
-> Bias
-> Deviation

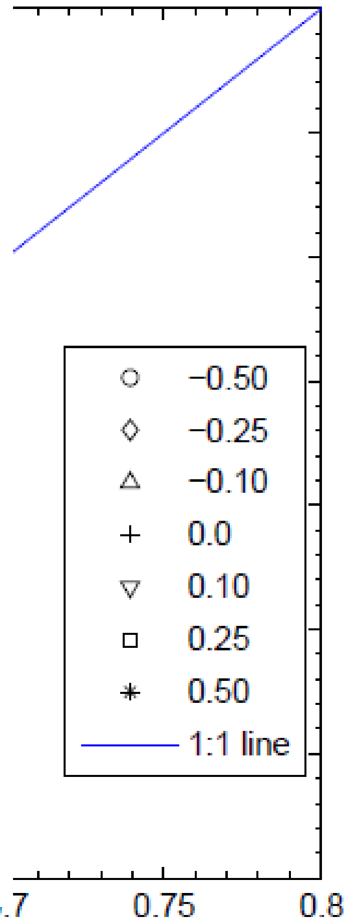
of the roughness prior will be performed. Moisture prior is fixed (Uniform).

Results

Estimates for different porcentual bias of the roughness priors, i.e. -0.10 refers to a prior underestimation of 10% with respect to the real value ks_{true}=*0.60.*







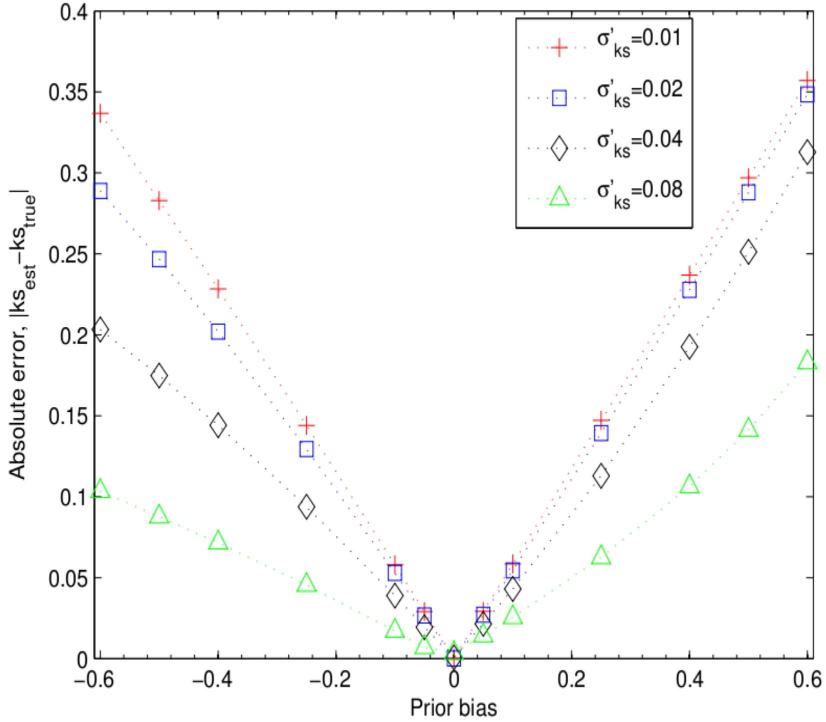
mv_{est} [cm

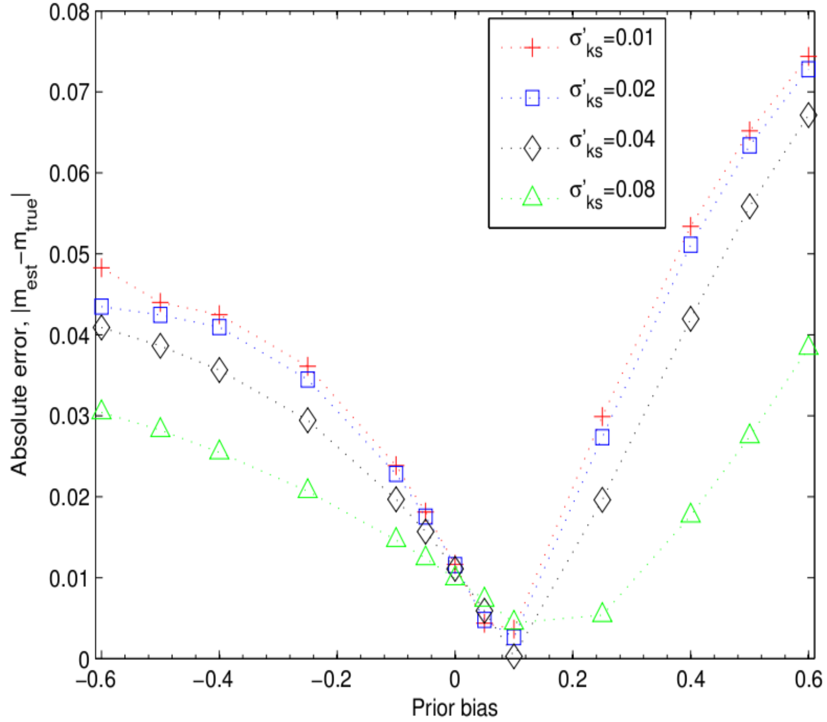
]mv_{true} [cm³/cm³

ks_{true}

Results

Absolute error as a function of the bias of the roughness prior $N(\mu_{ks}, \sigma'_{ks})$. Different standard deviations σ'_{ks} are taken into account. Uniform prior is used for soil moisture.

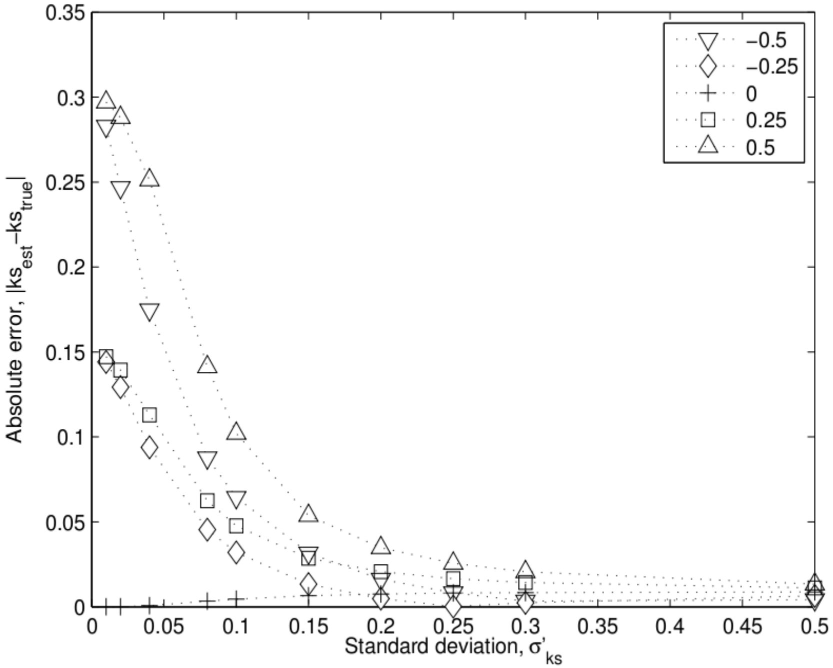


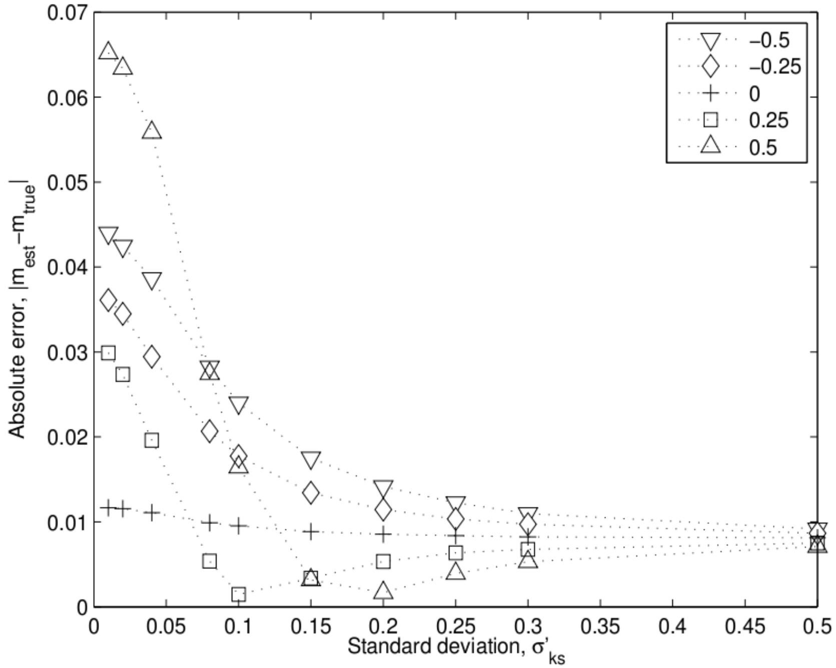


The error is minimum for bias 0 and increases with increasing the absolute value of the bias. When comparing several standard deviations, it turns out that the smaller the standard deviation, the higher the absolute error. In other words, if the prior is narrow, small biases strongly affect the mean value of the likelihood.
Same remarks hold, except for the fact that the smallest error is for bias 0:10. The soil moisture estimate is very dependent on the center of the roughness prior when the moisture prior is Uniform.

Results

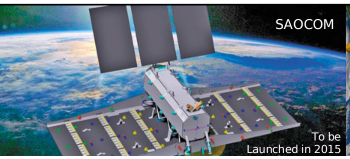
Absolute error as a function of the standard deviation of the roughness prior $N(\mu_{ks}, \sigma'_{ks})$. Different biases are taken into account. Uniform prior is used for soil moisture.





For the unbiased case ('+'-marks) the error decreases when the standard deviation decreases, approaching zero. On the contrary, for the biased cases, the higher the standard deviation the smaller the error. This is because the bias of the prior is compensated by the increasing σ_{ks}.

For soil moisture and the unbiased case, an absolute error lesser than 0:01cm3=cm3 is achieved provided the standard deviation σ_{ks} is not smaller than 0:08. When a bias is present, a higher standard deviation would be preferable



Concluding remarks

- Speckle noise and soil parameter heterogeneity are the main reasons for the uncertainties present in a soil moisture retrieval scheme using SAR data.

- Based on simulations, the effect of prior information in a Bayesian retrieval scheme has been analyzed for the case when speckle can be neglected.

- Uniform distribution $U(0{:}04;\ 0{:}291)$ for soil moisture.
- Gaussian distribution $N(\mu_{ks};\ \sigma_{ks})$ for the normalized soil roughness.

- Soil moisture estimate is very dependent on the choice of the roughness prior parameters. If a bias is present, a high standard deviation will compensate the bias.

- The standard deviation of the prior needs to be chosen carefully, because a prior with a wrong mean and a small standard deviation would lead to errors in the retrieval.

THANK YOU