Estimation of soil moisture using radar and optical images over Grassland areas

Mohamad El Hajj*, Nicolas Baghdadi*, Gilles Belaud, Mehrez Zribi, Bruno Cheviron, Dominique Courault, Olivier Hagolle, François Charron

* IRSTEA, UMR TETIS, 500 rue François Breton, 34093 Montpellier cedex 5, France

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Outline

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- Sensitivity analysis of X-band
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- Modelling and inversion of X-band
  - Methodology
  - Results
  - Conclusions

Context

- In agriculture areas, information on soil and vegetation conditions is key for water and crop management
- In situ sensors to measure soil and vegetation parameters is not effective, especially over large areas, due to the punctual information provided by these measurements
- Space-borne SAR remote sensing is a useful tool for mapping soil parameters due to its capacity to provide continuous coverage over large areas at high spatial and temporal resolutions.

Objectives

- **Analyze the sensitivity of radar signal in X-band at medium incidence angle to irrigated grassland conditions**

    - Is the X-band radar signal sensitive to soil moisture in dense grassland?

    - Can the X-band detect the beginning of irrigation and monitor the duration of irrigation for each plot, even when the vegetation is well developed?

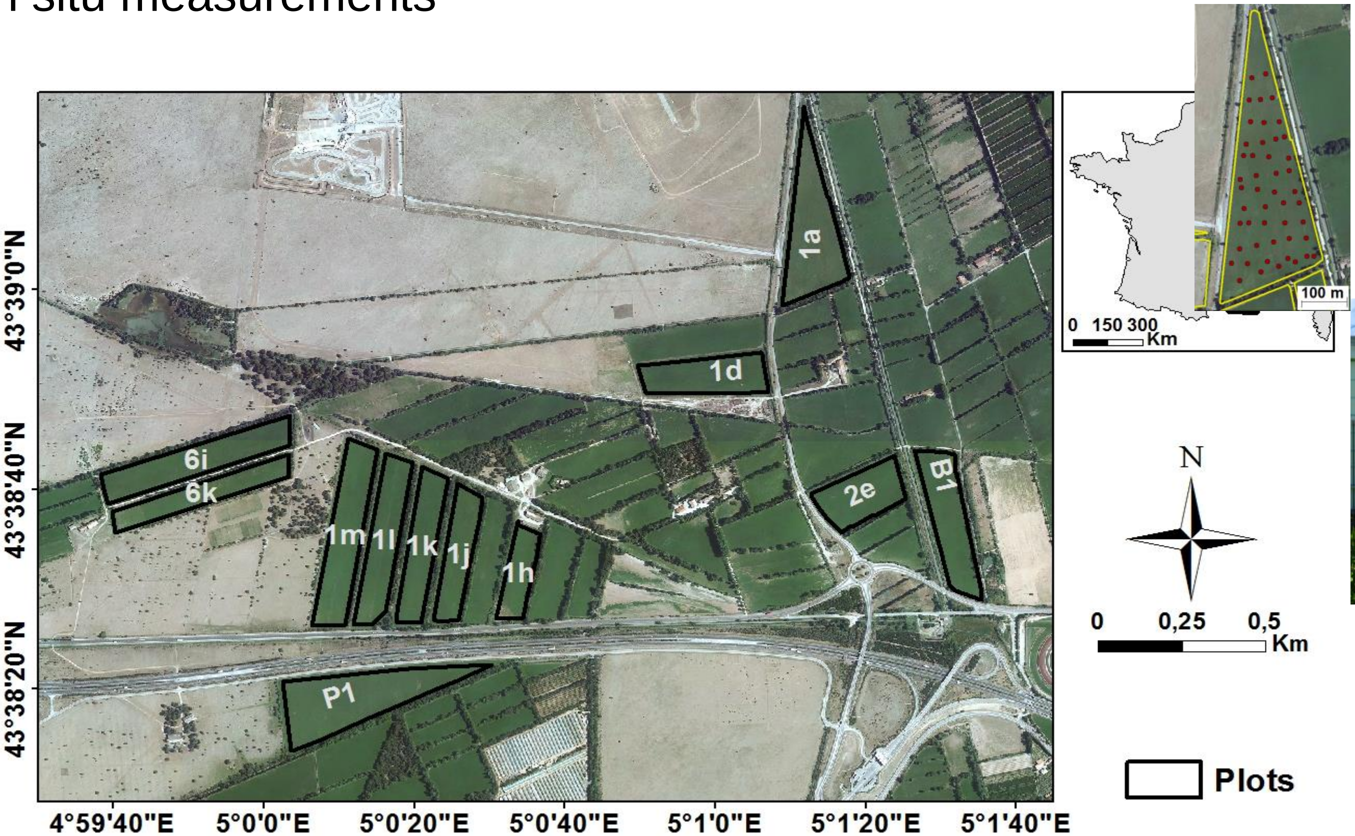
- **Show the potential of the X-band radar signal at medium incidence angle for soil moisture estimation over grassland areas**

Study area

- Soil texture: loam with depth varying between 30 and 80 cm
- Gravity irrigation (border irrigation)
- Irrigation rotation is about 10 days
- Plots harvested three times a year, in May, June and September.

Database (1)

- In situ measurements



- Water content (VWC)
- Vegetation height (HVE)
- Leaf Area Index (LAI)

Database (2)

- In situ measurements

Range of Mv (cm^3/cm^3)	Range of BIO (kg/m^2)	Range of VWC (kg/m^2)	Range of HVE (m)	Range of LAI m^2/m^2	Range of Rmse (cm)
[0.109 - 0.470]	[0.28 - 4.14]	[0.12 - 2.35]	[0.08 - 1.20]	[0.09 - 5.88]	[0.35- 0.55]
25-30/plot	2/plot	2/plot	20/plot	25-30/plot	10/plot

Database (3)

- Spatial data

  - SAR data

SAR Sensor	Bande	Polarization	Incidence angle	Acquisition mode	Resolution	Number
CosmoSkyMed (Csk)	X	HH and HV	28.5°-30.2°	PINGPONG	8 m x 8 m	16
TerraSAR-X (TX)	X	HH and HV	29.3° - 32.6°	STRIPMAP	3 m x 3 m	9

  - Optical data in in the visible and infrared spectral range:

SPOT-4/Take5, SPOT-5, LANDSAT-7/8

Database (4)

- Spatial data
  - Spatial data acquisitions dates (Year 2013)

	April							May						Jun												July								
	14	17	19	22	24	25	30	03	04	11	14	22	27	03	04	06	10	11	12	13	14	18	26	28	30	05	08	12	14	16	19	22	29	30
TSX			X	X			X				X	X															X							X
CSK																X	X	X			X		X				X	X		X				
SPOT-4 & 5	X				X				X		X						X			X		X			X	X								
LANDSAT-7 & 8		X	`			X		X		X			X		X				X					X					X			X		X
In situ meaurments			X				X	X			X	X		X		X	X	X			X		X				X	X		X	X		X	X

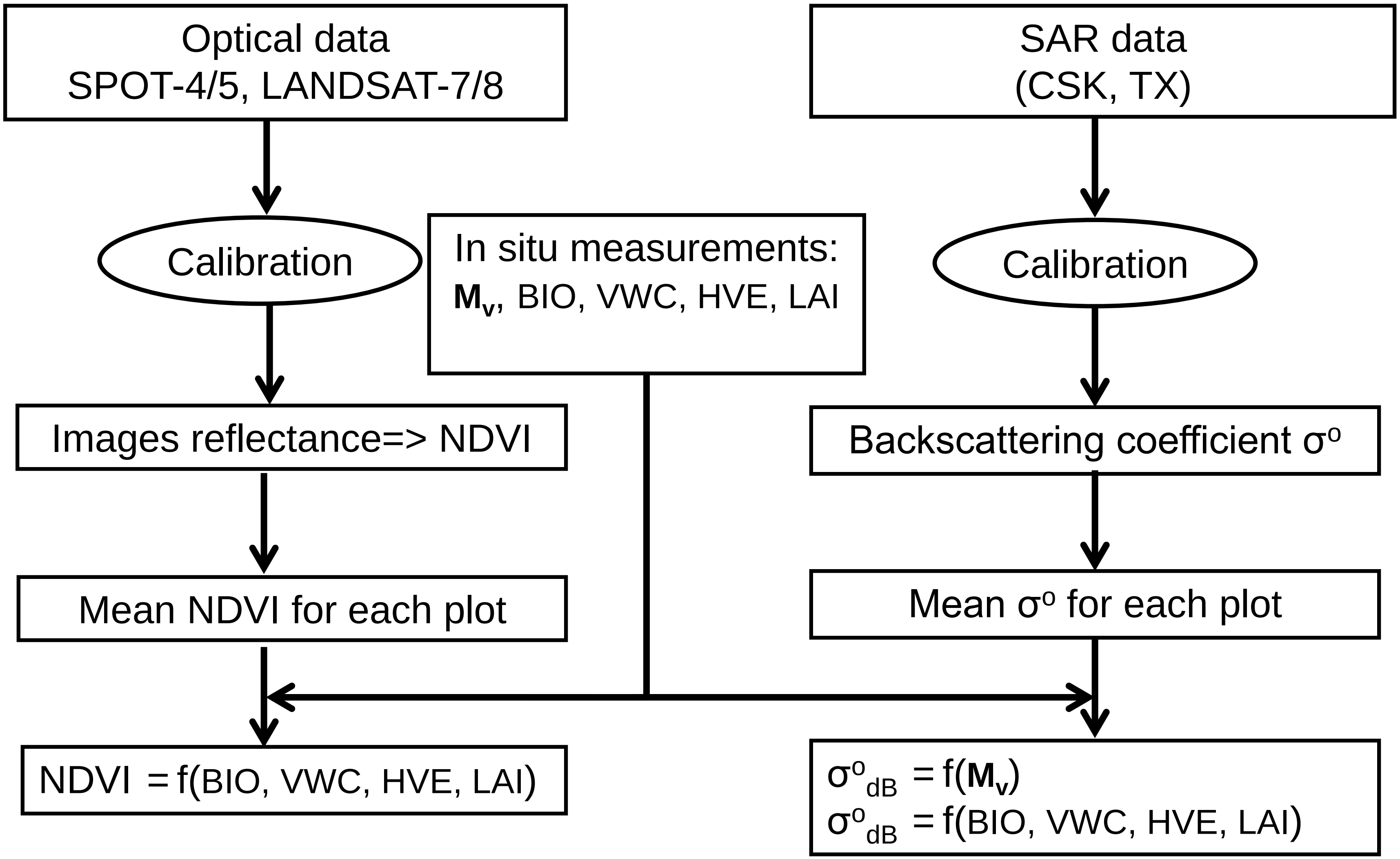
	August												September							October				
	01	09	13	15	18	20	21	22	23	26	29	31	02	03	04	10	16	22	24	01	04	06	11	16
TSX					X															X				
CSK	X	X								X	X		X			X					X			X
SPOT-4 & 5	X					X												X				X	X	
LANDSAT-7 & 8				X					X			X					X		X					
In situ meaurments	X	X	X	X			X	X		X	X		X	X	X	X				X	X	X		X

Sensitivity analysis of X-band

Irrigated Grassland Monitoring Using a Time Series of TerraSAR-X and COSMO-SkyMed X-Band SAR Data

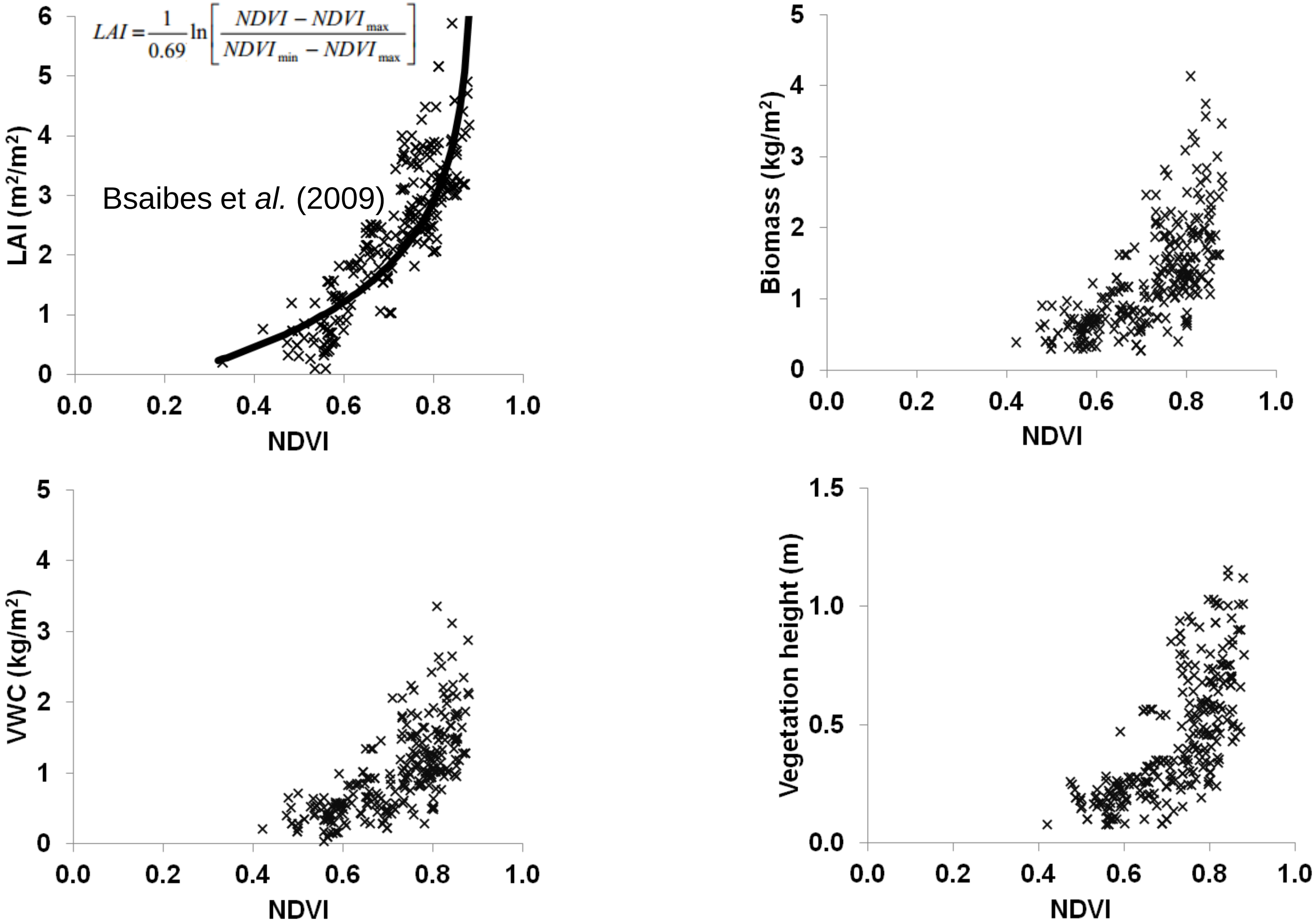
El Hajj, M., Baghdadi, N., Belaud, G., Zribi, M., Cheviron, B., Courault, D., Hagolle, O., and Charron, F. (2014). Irrigated Grassland Monitoring Using a Time Series of TerraSAR-X and COSMO-SkyMed X-Band SAR Data. Remote Sens. *6*, 10002–10032.

Methodology



Results (1)

➢ Sensitivity of optical data to LAI, BIO, VWC, and HVE

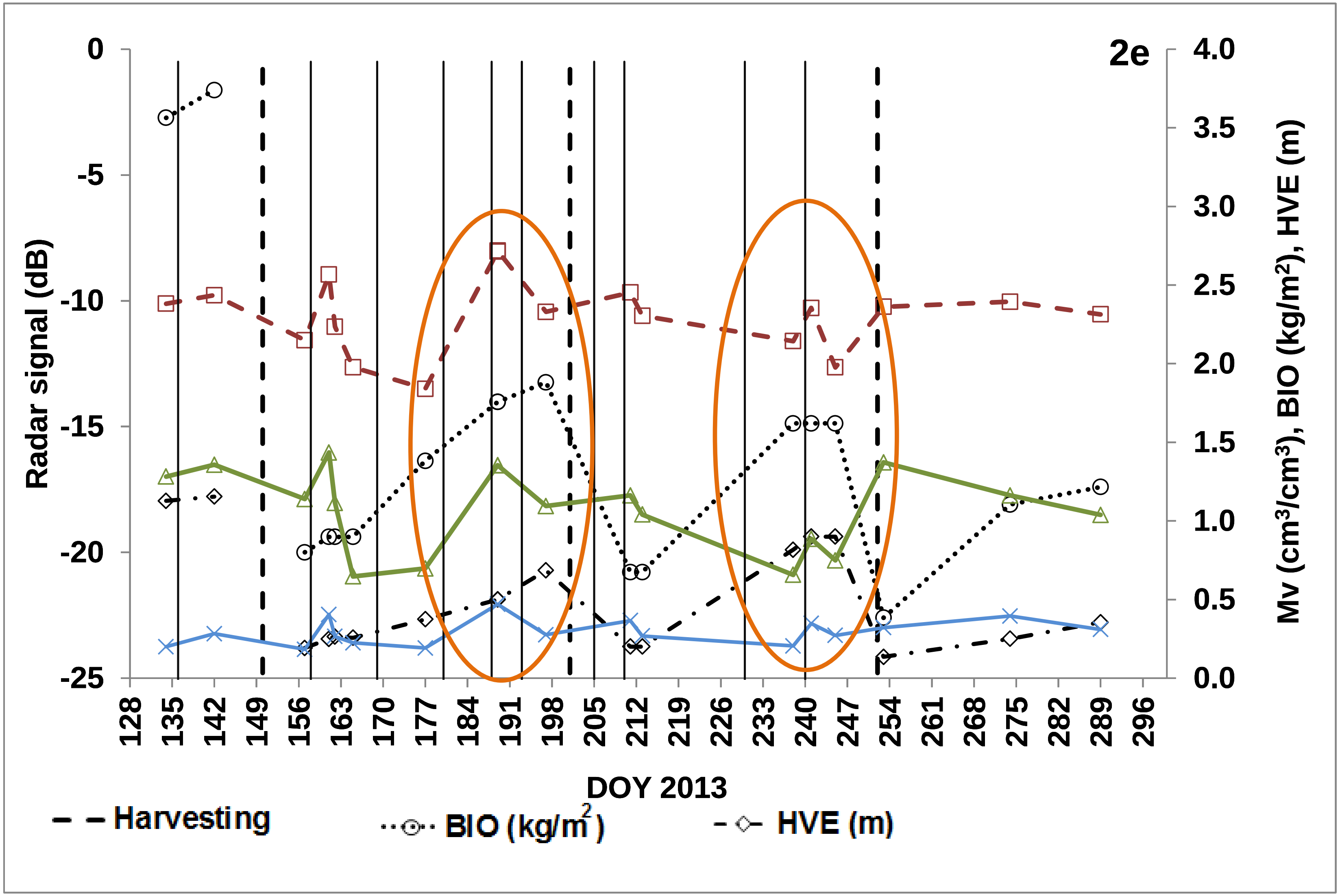


Anderson *et al.* (2004) showed that the NDVI saturates when the LAI of corn and soybean reaches 3.5 m^2/m^2

Payero *et al.* (2004) reported that the NDVI saturated when the height of alfalfa exceeded 40 cm.

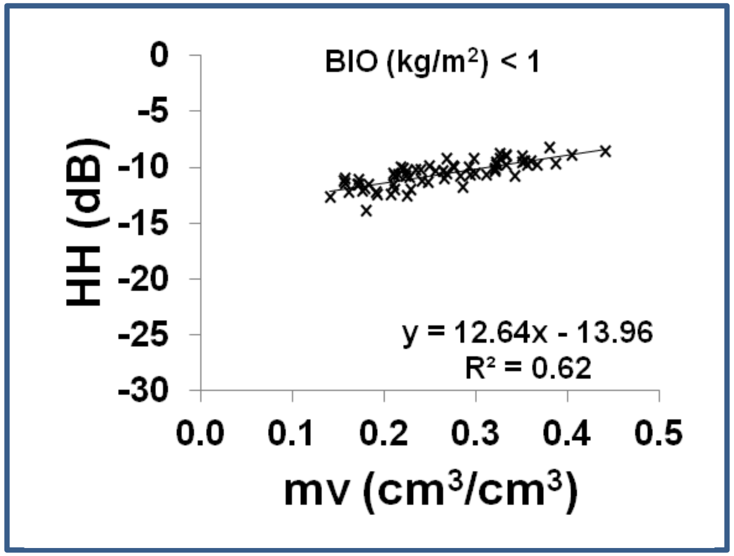
Results (2)

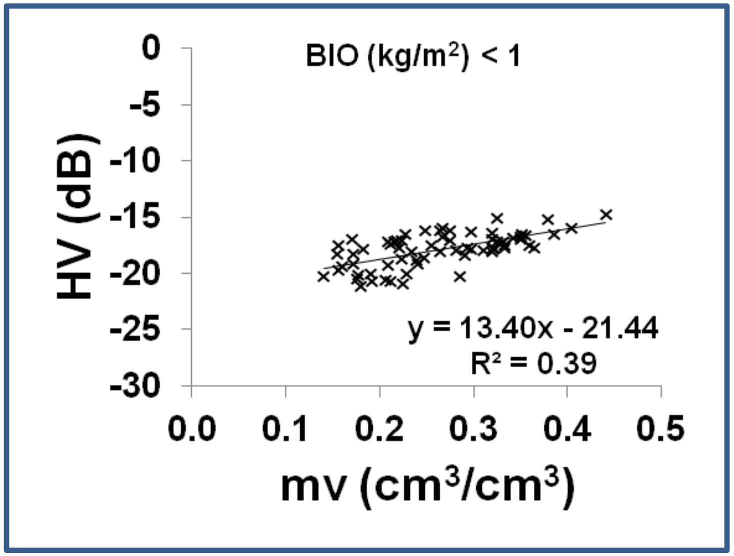
➢ The radar response according to soil moisture variations

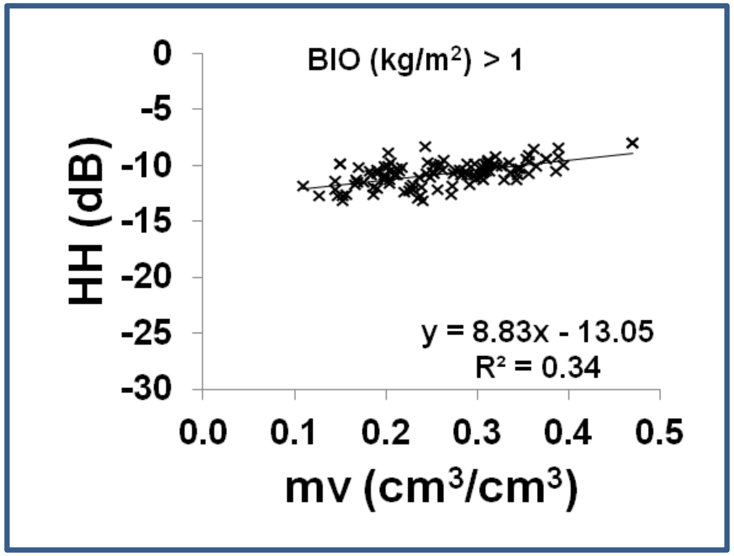


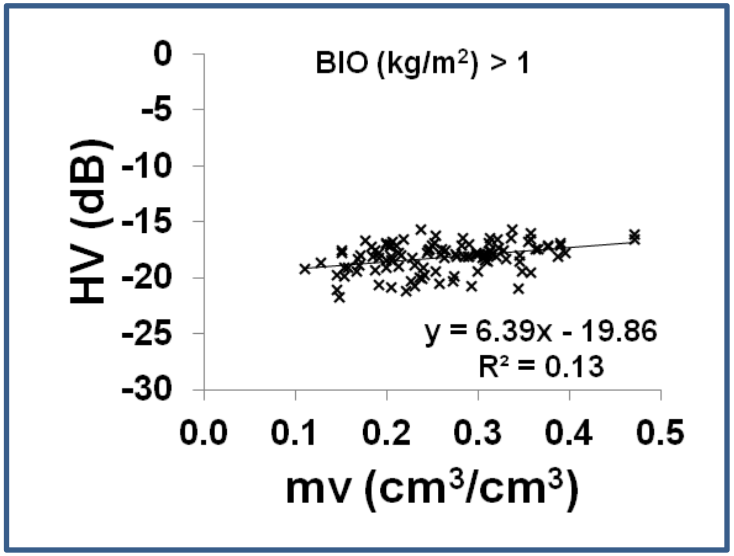
Results (3)

➢ Sensitivity of radar signal to soil moisture



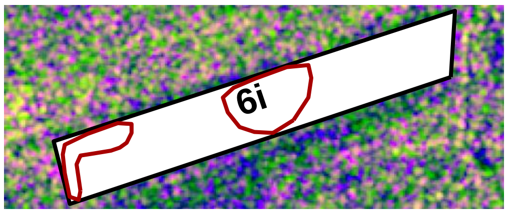




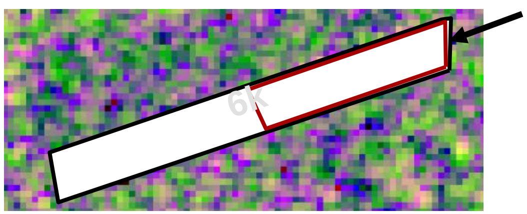


Results (4)

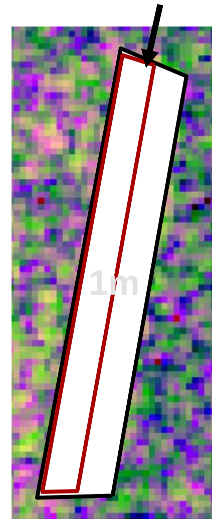
- Detection of flooded plots



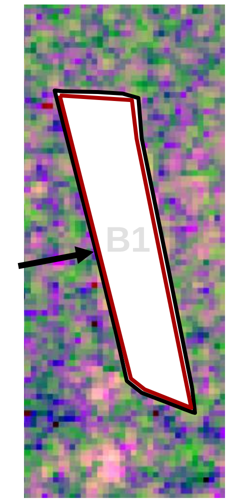
HVE=19 cm; BIO=0.74 kg/m²
Δt_b = 18 h; Δt_e = 5 h; Wd = 4 cm



HVE=102 cm; BIO=3.9 kg/m²
Δt_b = 6 h; Δt_e = -10 h; Wd=30 cm



HVE=56 cm; BIO=1.34 kg/m²
Δt_b =12 h; Δt_e = -10 h; Wd=8 cm



HVE=71 cm; BIO=1.92 kg/m²
Δt_b= 9 h; Δt_e = -1 h; Wd=30 cm

Images are in RGB composite colors (R:HH, G: HV, B:HH-HV)

Δt_b (in hours)= SAR acquisition time – start irrigation time

Δt_e (in hours)= SAR acquisition time – end irrigation time

Wd = Water bodies' depth

Black arrows indicate open canal locations used for border irrigation

Conclusions

- The X-band radar signal at both HH and HV is always sensitive to soil moisture variations, even with dense vegetation cover (HVE up to 1 m): Higher sensitivity for biomass less than 1 kg/m^2

- The X-band radar signal penetrates vegetation cover and allows for the tracking of irrigation practices

- The X-band at HV polarization is more sensitive to grassland parameters

- The X-band radar signal at HV polarization is useful to monitor vegetation height for HVE up to 50 cm.

Inversion of X-band radar signal for soil moisture estimation using neural networks

TETIS

Water-Cloud model (Attema and Ulaby 1978)

$$\sigma^0_{tot} = \sigma^0_{veg} + T^2 \sigma^0_{sol}$$

$$\sigma^0_{veg} = A.V_1.\text{Cos}\,\theta \;\; (1- T^2)$$

$$T^2 = \text{Exp}\,(-2.B.V_2.\sec\theta)$$

$$\sigma^0_{sol} = C(\theta)\exp\,(D.M_v)$$

- σ^0_{tot} **:** Total backscattered radar signal (linear unit)
- $\boldsymbol{\sigma^0_{veg}}$ **:** Vegetation contribution (linear unit)
- $\mathbf{T^2}$ **:** Two-way attenuation
- $\boldsymbol{\sigma^0_{sol}}$ **:** Soil contribution (linear unit)
- $\mathbf{V_1 = V_2}$ **:** Vegetation descriptors (BIO (kg/m^2), VWC (kg/m^2), HVE (m), LAI (m^2/m^2), FAPAR, FCOVER, and NDVI)
- $\boldsymbol{\theta}$ **:** Radar incidence angle
- **A et B:** Parameters depending on the canopy descriptors and radar configurations
- $\mathbf{M_v}$**:** Volumetric soil moisture (Vol.%)
- **C:** dependent on roughness and incidence angle
- **D:** sensibility of radar signal to $\mathbf{M_v}$ in the case of bare soils, dependents on radar configurations

Methodology: WCM parameterization

➢Fit the WCM against SAR data and ground-truth measurements:

❖ Estimate the sensitivity parameter D for both HH and HV polarization

❑σ^0_{tot} = f (Mv) : Plots recently harvested

❖ Estimate parameters A, B, and C: for each radar polarization and each vegetation descriptor (i.e A_{HH-LAI} , B_{HH-LAI})

Mv	BIO	VWC	HVE	LAI	FAPAR	FCOVER	NDVI	HH	HV

Fitting (47 %)

$$F = \sum_{i=1}^{N} \left(\sigma^{o}_{measured} - \sigma^{o}_{simulated}\right)^2_i$$

Validation (53 %)

Methodology: Generating synthetic datasets

A, B, C, D

M_v **(0.10:0.05:0.45)**

LAI (0.001:0.2:6) → Modèle WCM → σ^0_{tot} (HH and HV)

- LAI is better to represent the vegetation canopies (wheat, sugarcane, cherry, rice, and grassland) (Champion 1991, Champion and Guyot 1991, and Said et *al.* 2012)

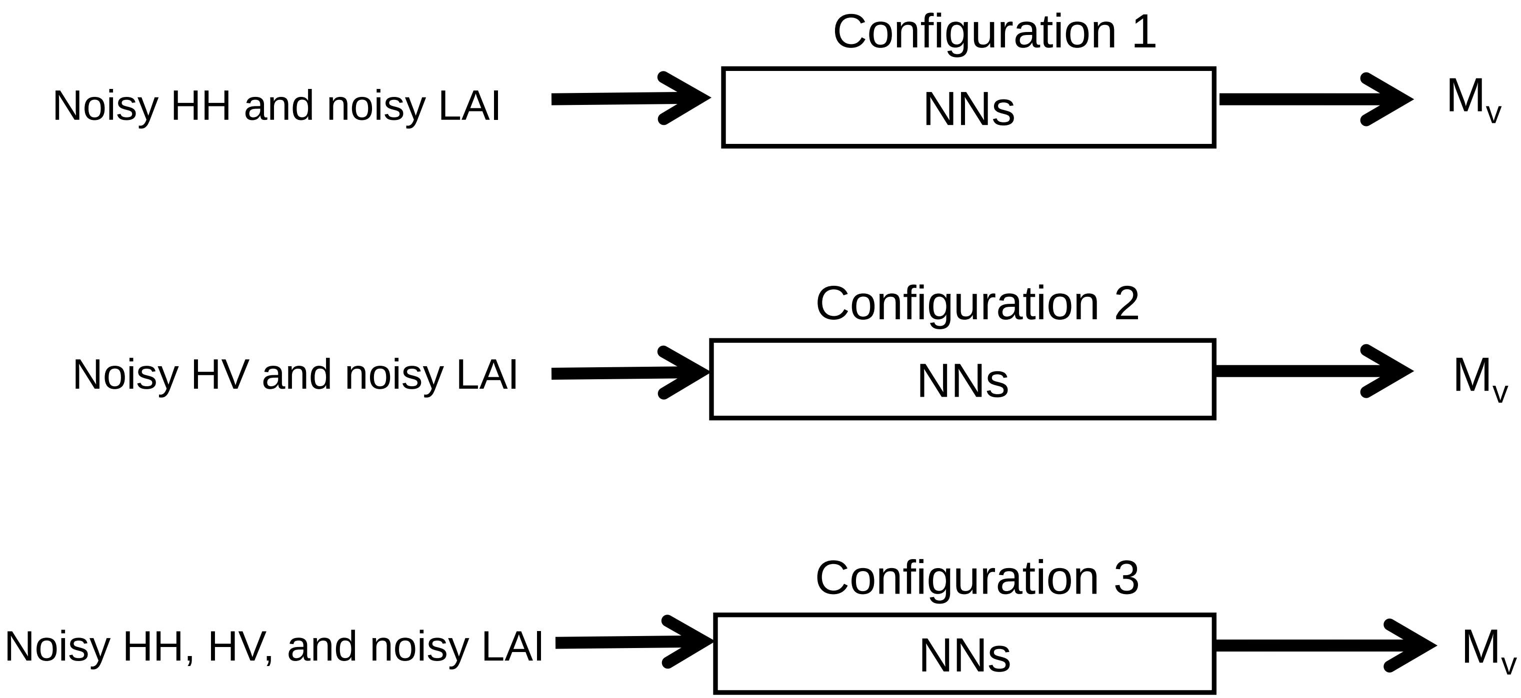
- To make WCM simulations more realistic absolute erros of ±1 dB were added to simulated radar signal (Agenzia Spaziale Italiana, 2007; Coletta et al., 2007; Iorio et al., 2010; Schwerdt et al., 2008; Torre et al., 2011)

- To assimilate LAI values as they will be estimated from optical data, relative error of 30 % was added to LAI values. This relative error was obtained by comparing LAI (BV-NNET) to in situ LAI.

- 500 random sampling of zero-mean Gaussian noises with a standard deviation equal to absolute and relative errors were added to radar signal and LAI

Methodology: Soil moisture retrieval (Synthetic dataset)

- 5-fold cross-validation (80% training, and 20% validation data samples)



Methodology: Soil moisture retrieval (Real dataset)

- Applied the trained NNs to real dataset of validation: 53 % of the real dataset not used in the WCM paramerizatiion were used in the validation phase

Configuration 1

Measured HH and in situ LAI → Trained NNs → M_v

Configuration 2

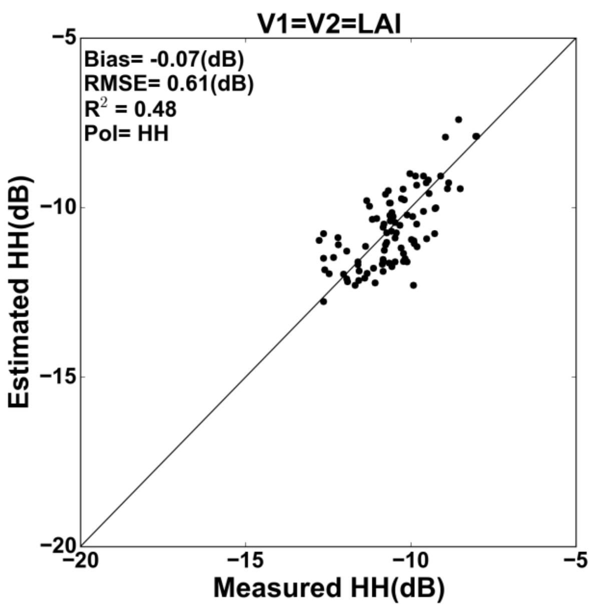
Measured HV and in situ LAI → Trained NNs → M_v

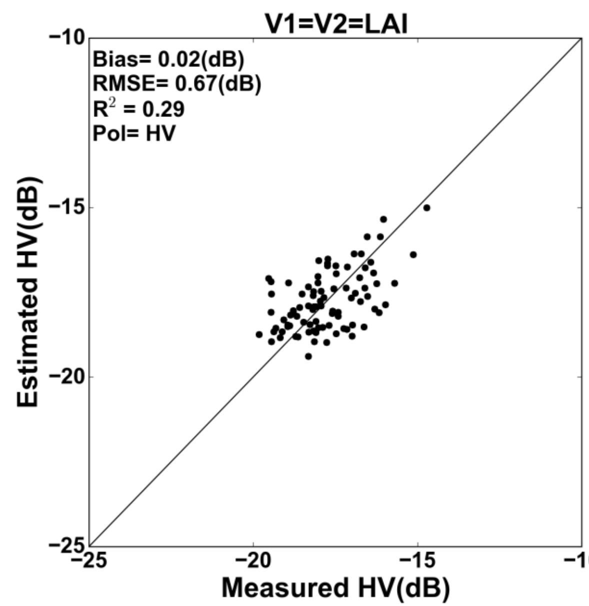
Configuration 3

Measured HH, HV, and in situ LAI → Trained NNs → M_v

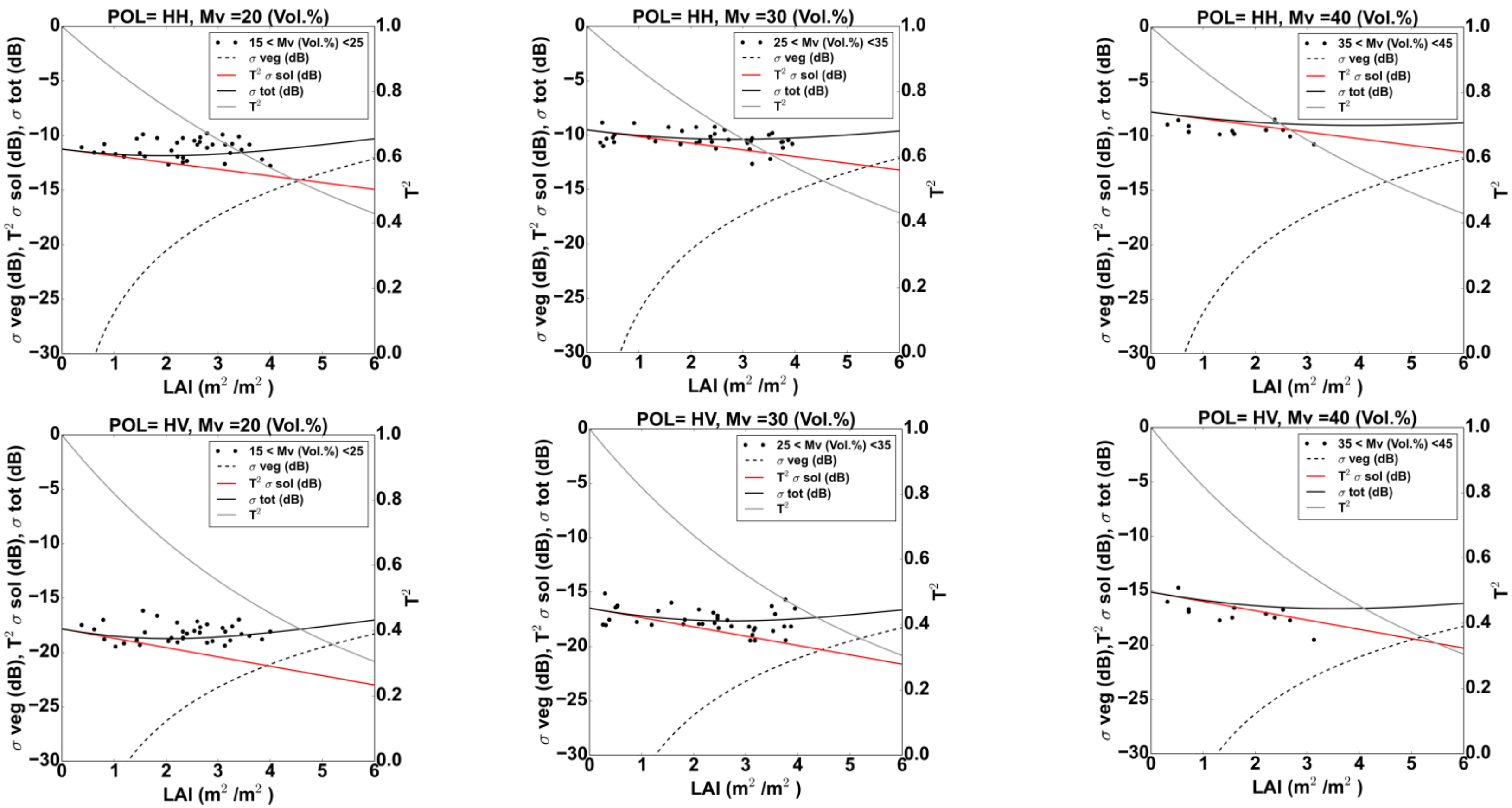
Results : WCM parametrization

V1=V2	A_{HH}	B_{HH}	C_{HH}	D_{HH}	A_{HV}	B_{HV}	C_{HV}	D_{HV}	R^2_{HH} (R^2_{HV})	$RMSE_{HH}$ ($RMSE_{HV}$) (dB)
BIO	0.0345	0.0995	0.0334	3.971	0.0068	0.1850	0.0093	3.116	0.49 (0.37)	0.60 (0.60)
VWC	0.0438	0.1047	0.0324	3.971	0.0084	0.1927	0.0088	3.116	0.49 (0.38)	0.61 (0.61)
HVE	0.1045	0.4314	0.0357	3.971	0.0207	0.7882	0.0105	3.116	0.52 (0.40)	0.56 (0.60)
LAI	0.0205	0.0613	0.0338	3.971	0.0041	0.0856	0.0088	3.116	0.48 (0.29)	0.61 (0.67)
FAPAR	0.0911	0.3275	0.0354	3.971	0.0177	0.4662	0.0096	3.116	0.47 (0.26)	0.57 (0.66)
FCOVR	0.1021	0.3696	0.0355	3.971	0.0203	0.5212	0.0095	3.116	0.48 (0.28)	0.58 (0.66)
NDVI	0.0767	0.7944	0.0644	3.971	0.0101	0.9032	0.0221	3.116	0.51 (0.33)	0.51 (0.66)





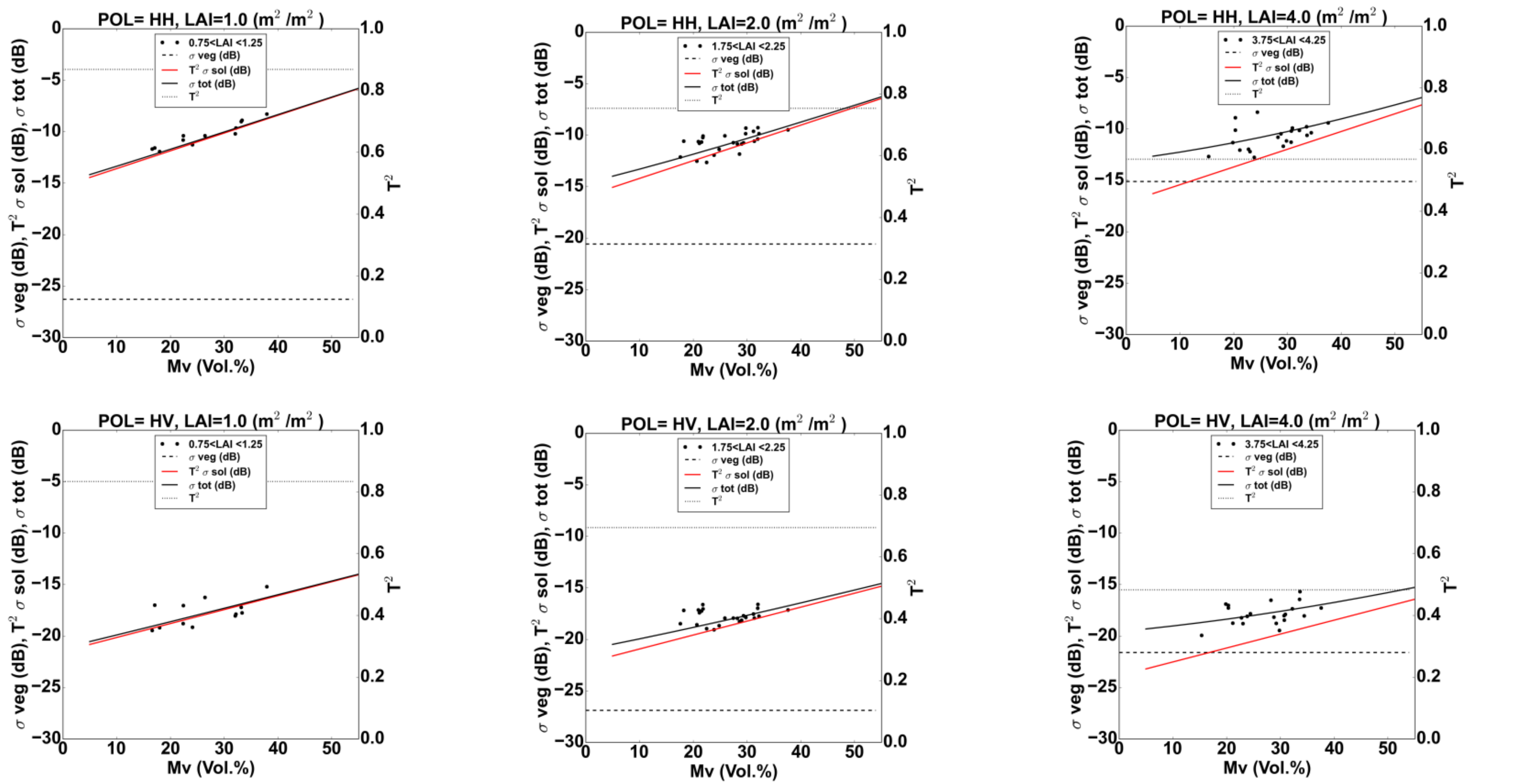
Results : Modelling results



Behaviour of WCM components ($\sigma°_{veg}$, $T^2\sigma°_{sol}$, and $\sigma°_{tot}$) in both HH and HV according to LAI.

Black points represent SAR data ($\sigma°_{tot}$: validation dataset) associated to M_v measurements situated at ±5 vol. % of the M_v used in the modelling.

Results : Modelling results



Behaviour of WCM components ($\sigma°_{veg}$, $T^2\sigma°_{sol}$, and $\sigma°_{tot}$) in both HH and HV according to M_v.

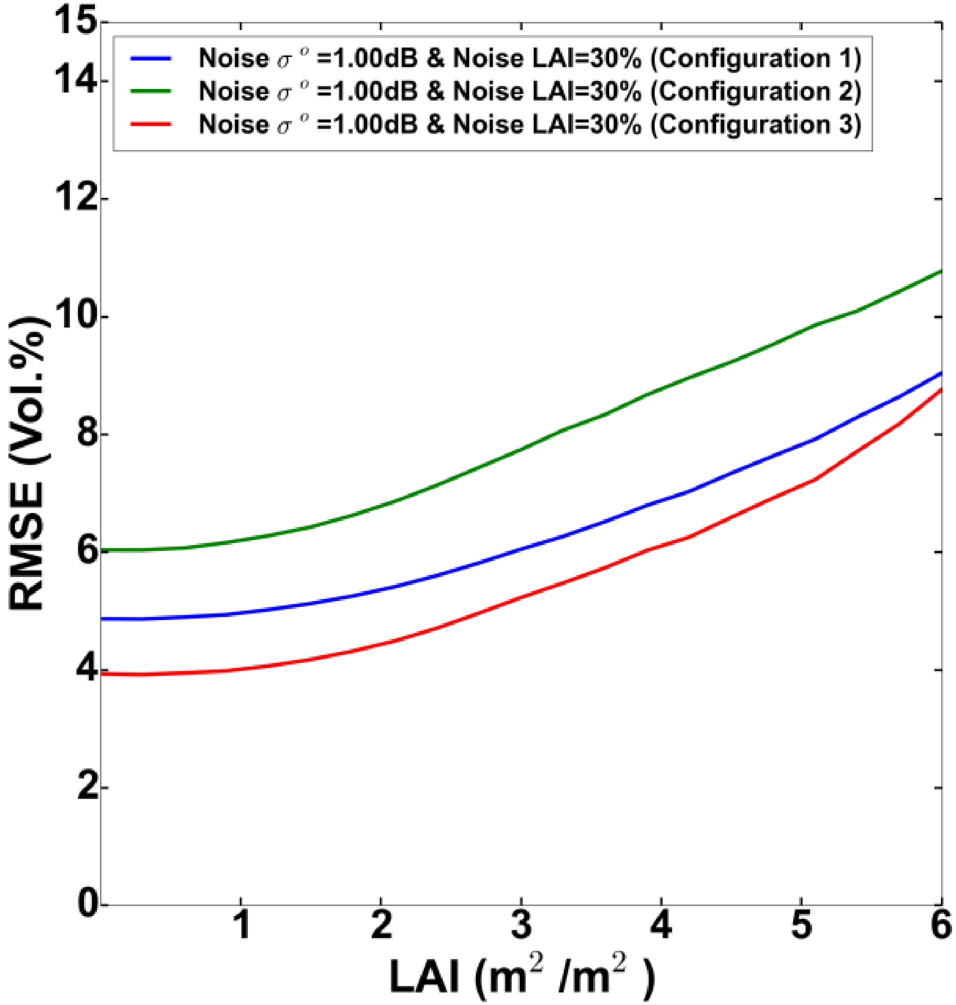
Black points represent SAR data ($\sigma°_{tot}$: validation dataset) associated to LAI measurements situated at ± 0.25 m^2/m^2 of the LAI used in the modelling.

Results: Soil moisture retreival (Syntetic dataset)

	Noise on σ^0_{tot} : $\pm$1.00 dB
Configuration 1 (HH+LAI)	6.5/0.0
Configuration 2 (HV+LAI)	8.1/0.0
Configuration 3 (HH+HV+LAI)	5.8/0.0

RMSE and Bias on M_v estimates according to the three inversion configurations (RMSE/Bias in vol. %). Relative noise on LAI=30%.

Results: Soil moisture retreival (Syntetic dataset)



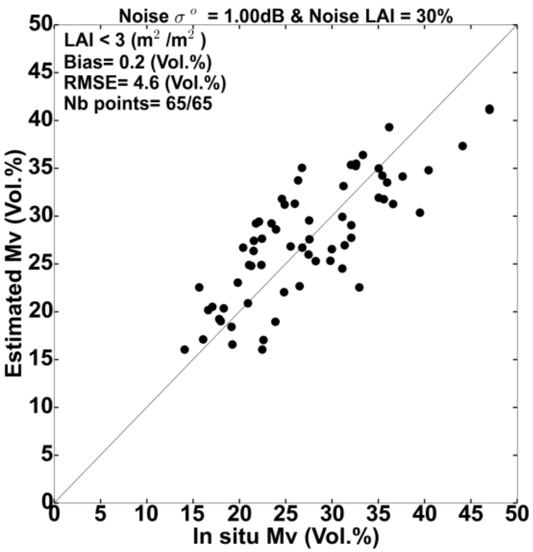
Evolution of RMSE on M_v estimates according to the three inversion configurations as a function of LAI for noise conditions on modeled radar signal of ±1 dB.

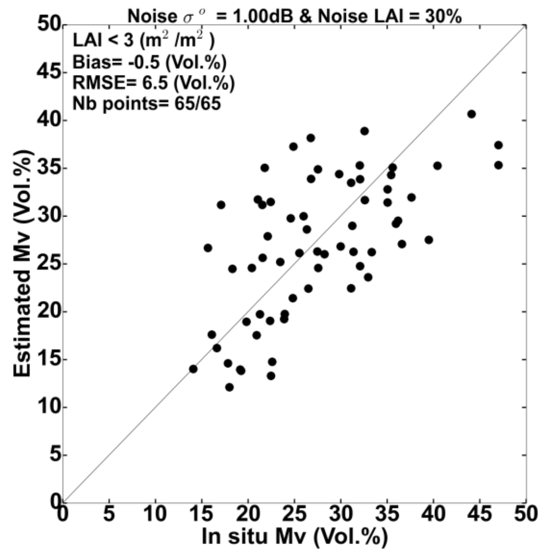
Results: Soil moisture retreival (real dataset)

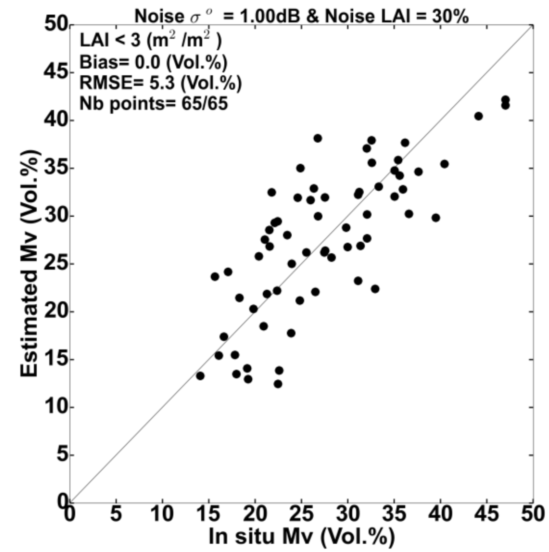
	Noise on σ^0_{tot} : ±1.00 dB
	LAI = [0-6] m^2/m^2
Configuration 1 (HH+LAI)	5.7/-0.2
Configuration 2 (HV+LAI)	7.6/-1.1
Configuration 3 (HH+HV+LAI)	6.8/-0.8

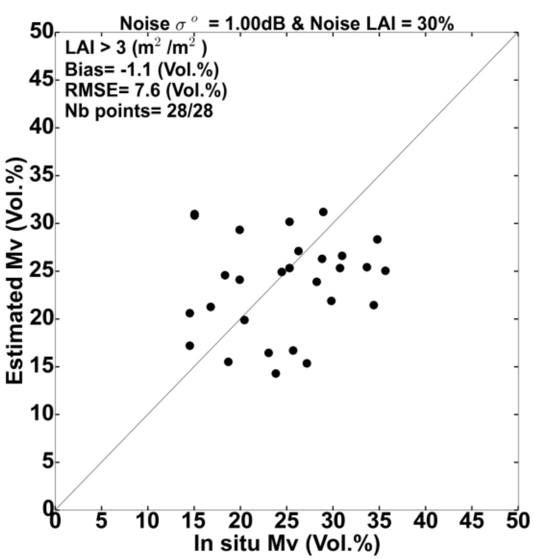
RMSE and Bias on M_v estimates according to the three inversion configurations (RMSE/Bias in vol. %).

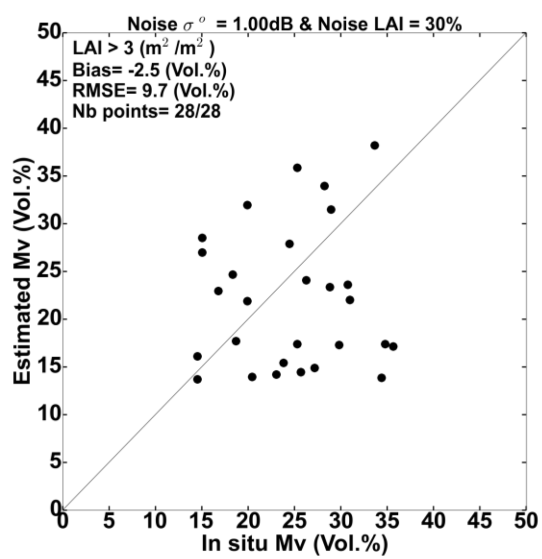
Results: Soil moisture retreival (real dataset)

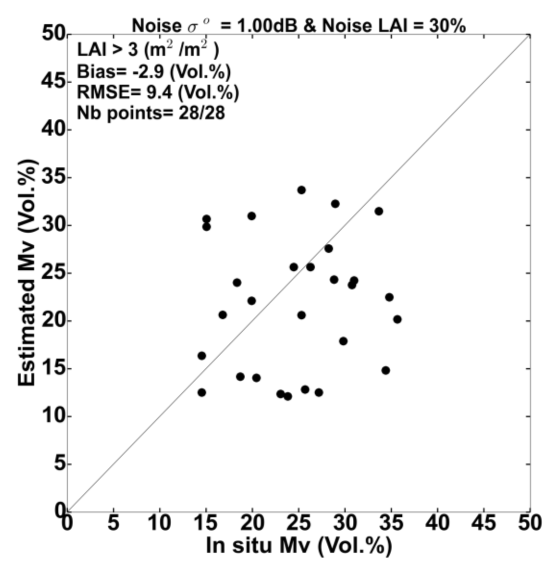




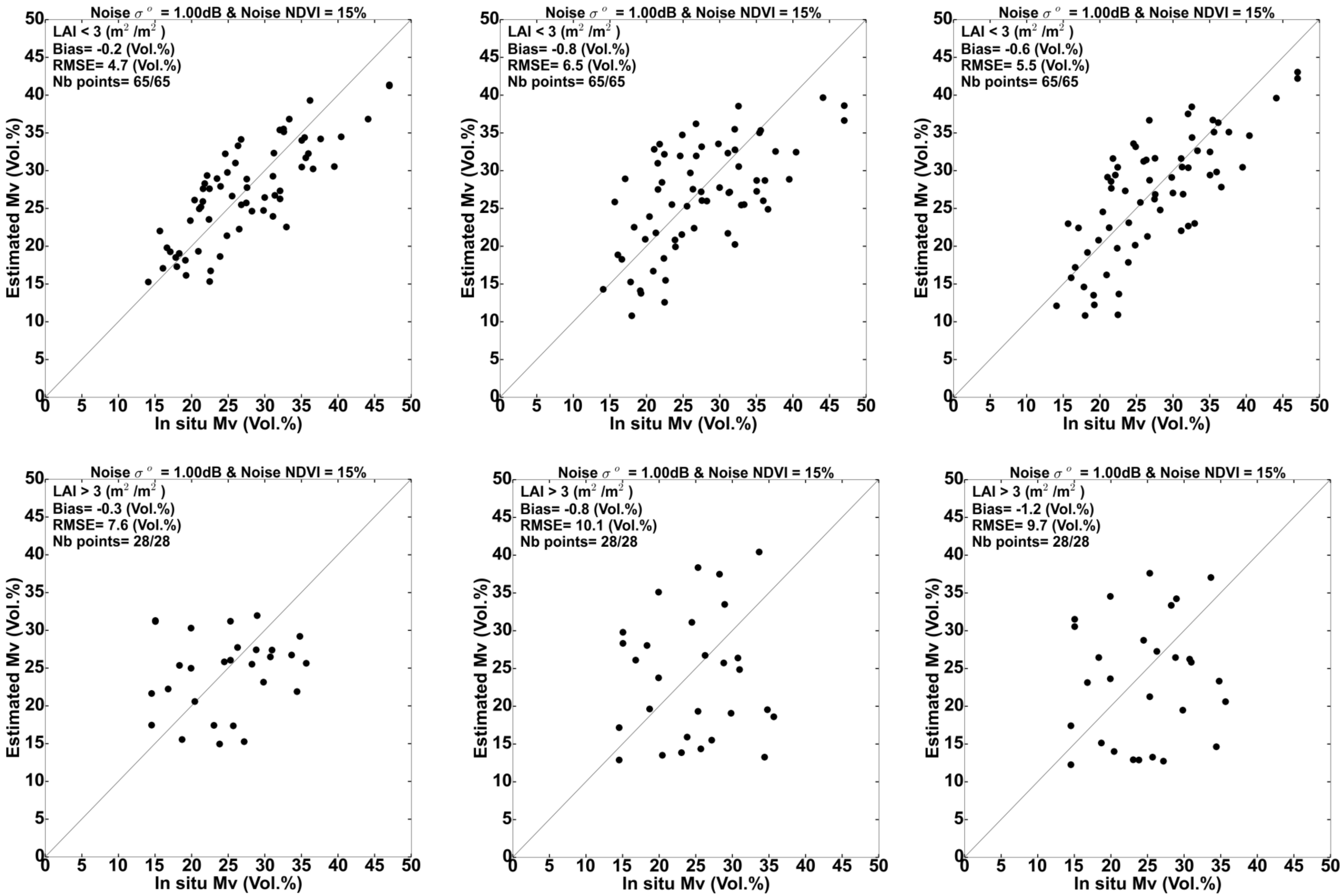








Results: Soil moisture retreival (real dataset)



Conclusions and perspective

- RMSE on Mv estimates increases with LAI

- It is relevant to use LAI or NDVI derived from optical images in WCM.

- The use of HH provides a better estimation of the soil moisture with **RMSE of 4.6 and 7.6 vol. %** for LAI lower and higher than 3 m^2/m^2, respectively.

- Operational methods based on coupling between SAR and optical images could be developed (Sentinel 1 with Sentinel 2 and Landsat)

Thanks

Questions