COMPLEMENTARITY OF LINEAR POLARIZATIONS IN C-BAND SAR IMAGERY TO ESTIMATE LEAF AREA INDEX FOR MAIZE AND WINTER WHEAT

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ABSTRACT

This paper presents results of LAI estimation from multi-polarimetric SAR data assessed for maize and winter wheat crop. Taking advantage of a large multi-year data set of RADARSAT-2 and ground observations collected in Belgium and in The Netherlands, this research aims at improving a method that takes benefits of all linear polarizations to optimize the LAI estimation. The semi-empirical Water Cloud Model (WCM) is implemented to derive maize and winter wheat LAI values from each linear polarization. The cross-polarization and the VV polarization were found the most relevant polarization to retrieve maize and wheat LAI through this model. A combination of the retrieved LAI and their associated errors for each polarization is then computed to improve the LAI estimation.

1. INTRODUCTION

In agricultural applications, development of information systems of monitoring of agricultural production has become a major objective to anticipate difficult situations. The Leaf Area Index (LAI) is a key biophysical variable for crop growth monitoring. SAR data are seen of great potential for LAI monitoring thanks to their systematic acquisition offering a good temporal resolution along the crop growing season. Moreover, an important opportunity has been offered by the launch of polarimetric spaceborne SAR sensors. The RADARSAT-2 sensor presents a quad-polarization mode that multiplies information in one image by the simultaneous acquisition of the four linear polarizations (HH, VV, VH, and HV). Furthermore, SAR signal is very sensitive to plant water content, a variable highly correlated with the LAI during the vegetative phase.

This relationship between the sensitivity of microwave dielectric constant and plant water content has led to much effort devoted to investigate the link of SAR sensors to the crop parameters. This sensitivity was observed for sugar beet [1], sugarcane [2], rice [3] and [4], maize [5] and [6] , potato [7] and wheat [8] and [9].

Interaction between polarized microwaves and scattering elements of the canopy lead to differences both in the energy backscattered in those different polarizations and in the penetration through the soil. Thus, it is expected that the combination of microwave signature at different polarizations may provide different and complementary information on vegetation conditions. Several authors already developed empirical relationships between dual polarization ratios and physical parameters of crop fields. For example, [6] investigated the sensitivity of radar to maize crop growth by considering a wide range of frequencies and angles and all linear polarizations. Good correlations (larger then 0.7) with maize biomass and height were achieved by the co-polarization and cross-polarization ratios at C-band and observation angles above 30°. From a simulated data set, [5] found that dual-polarizations indices were sensitive to maize growth; the VV/VH polarization ratios computed from signal recorded at high incidence angle (35° to 45°) could assess the crop growth till LAI reaches 4.9 m^2/m^2. The reference [10] showed that the L-band co-polarization ratio presents high correlation with grassland and winter wheat water content (R^2=0.68). Radar's sensitivity to biophysical parameters at different polarizations was observed for winter wheat [11]. The authors found the ratio HH/VV at C-band (with an incidence angle equal to 40°) to be strongly related to above-ground biomass with a correlation coefficient of 0.87. Reference [12] found a strong relation between the co-polarized ratio and wheat biomass water content. The cross-polarized ratio at C-band has been used for sugarcane LAI by [13]. Some attempts at using empirical relationships between HH/VV ratio and wheat LAI have been performed by [14], with a determination coefficient of 0.82. The reference [15] showed that biomass retrieval benefits from the availability of cross-polarization data. The reference [16] reported than L-HV backscatter was highly correlated (r=0.83) with vegetation biomass for broadleaf crops.

Next to various empirical relationships developed to retrieve crop variables from SAR data, semi-empirical model, such the Water Cloud Model (WCM) have been widely used for agricultural applications ([17]; [18]; [19]; [20]). Although these studies demonstrated the performances of the WCM to retrieve crop LAI from C-band SAR data, this research aims to use each linear polarization from polarimetric SAR images for maize and wheat LAI estimation. The objective is to improve maize and wheat LAI estimation and to reduce its associated uncertainty thanks to the potential of polarized C-band SAR sensors while using the WCM.

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2. METHODOLOGY

Use of SAR signal for crop growth monitoring often relies on radiative transfer models. In this study, the selected model for maize and winter wheat LAI estimation is the semi-empirical WCM [21]. In order to retrieve LAI values through model inversion, model parameters need to be calibrated first. Four parameters (A, B, C and D) are thus calibrated. During the calibration procedure, the model expresses the backscattering coefficient (σ°) as function of the LAI, the surface volumetric soil moisture (V_m) and the local incidence angle (θ). By contrast, during the inversion, the LAI is function of the surface volumetric soil moisture (V_m), the backscattering coefficient (σ°) and the local incidence angle (θ). The calibrations and inversions of the model were done separately for each linear polarization – VV, HH and HV – giving three estimations of the LAI – named LAI_{HH}, LAI_{VV} and LAI_{HV} – for each observation of each data set.

Calibrated parameters covariance and correlation matrices were estimated thanks to the Hessian matrix of the calibration objective function and permit to assess possible biases and instability problems in the calibration process. In order to analyze the impact of this instability, 1000 vectors of calibrated parameters – A, B, C, D – were simulated using a multivariate Gaussian assumption for their distribution. LAI distributions were then computed for each observation and polarization. This technique provides us a way to assess uncertainty on LAI values as the quality of the fit for the model varies. The standard deviations on LAI estimations were calculated for each polarization by averaging the LAI variance of each observation, named var_{VV}, var_{HH}, var_{HV}. Assuming those distributions as independent Gaussian, they were combined to give LAI estimates with minimum variance by using the following formulas for the expectation and variance:

$$LAI_{pond} = \frac{LAI_{VV}/\mathrm{var}_{VV} + LAI_{HH}/\mathrm{var}_{HH} + LAI_{HV}/\mathrm{var}_{HV}}{1/\mathrm{var}_{VV} + 1/\mathrm{var}_{HH} + 1/\mathrm{var}_{HV}} \quad (1)$$

$$\mathrm{var}_{pond} = \frac{1}{1/\mathrm{var}_{VV} + 1/\mathrm{var}_{HH} + 1/\mathrm{var}_{HV}} \quad (2)$$

This LAI estimation was named LAI_{pond}.

3. WATER CLOUD MODEL

The Water Cloud Model considers the canopy can be modeled as a water cloud whose droplets are held in place by the vegetation. The droplets are randomly distributed, have all the same size and are smaller than the wavelength [22]. The backscattering coefficient (σ^0_{total}) can be formulated as the incoherent sum of the direct contribution of the vegetation (σ^0_{veg}) and the contribution of the soil (σ^0_{soil}) attenuated by the vegetation (t^2):

$$\sigma^0_{total}\left[m^2/m^2\right] = \sigma^0_{veg} + t^2\sigma^0_{soil} \quad (3)$$

with: $$\sigma^o_{veg}\left[m^2/m^2\right] = A\cos\theta(1-t^2) \quad (4)$$

$$t^2 = \exp(-2B.LAI/\cos\theta) \quad (5)$$

$$\sigma^o_{soil}(dB) = C.V_m - D \quad (6)$$

where θ is the local incidence angle, V_m is the volumetric soil moisture, A, B, C, D the model coefficients. Parameter A is related to the scattering albedo of the canopy and B to its vertical depth [23]. C is assumed to be constant and represents the sensitivity of the signal to the soil moisture, D is assumed to be specific of the radar configuration and the soil roughness [23]. The linear relationship between soil backscattering coefficient and the volumetric surface soil moisture is based on experimental evidence indicating that the scattering coefficient of soil expressed in dB is approximately linearly dependent on the volumetric soil moisture content V_m (kg/m³) [21].

Water Cloud Model calibration

Calibration was run for each polarizations configuration. Four variables are needed: the LAI, the surface soil moisture (V_m), the SAR backscattering coefficient (σ^0_{total}) and the local incidence angle (θ). The four parameters (A, B, C and D) are calibrated by non-linear regression. Non-linear regression relies on the minimization of the Sum of Squared Deviations (SSD) between the measured signal (in dB) and the corresponding simulated values (in dB). The minimization function algorithm used is the Nelder-Mead type simplex search method [24].

Water Cloud Model inversion

The inverse equation (7) was used to estimate maize and winter wheat LAI from the backscattering coefficient, the local incidence angle and the surface soil moisture.

$$LAI_{sim} = \ln\left[\frac{10^{(\sigma_{dB}{}^0/10)} - A.\cos\theta}{10^{((C*Vm-D)/10)} - A\cos\theta}\right].\frac{\cos\theta}{-2*B} \quad (7)$$

The same SAR data and soil properties were used for both calibration and inversion. Thresholds were defined for signal values at which inversion led to values that don't fit to the model. Those signal values correspond to LAI of 0.001 and 4 m²/m². This inversion forces a retrieved LAI necessarily below 4. This threshold value was used as prior information because of the saturation effect of the SAR signal on plant development [25].

4. STUDY SITES AND DATA

For this research, two data sets containing values for maize and two data sets for winter wheat are considered. These data sets hold in values of the four variables needed for the calibration of the WCM, i.e. LAI, surface soil moisture, SAR backscattering coefficient and local incidence angle.

The first data set (i) was obtained during the AgriSAR campaign carried out by ESA in Flevoland [26]. The second (ii) was acquired over Belgium and Flevoland during the 2008 and 2009 maize growth seasons. The two last (iii) and (iv) were obtained during the 2009 and 2010 winter wheat growing season in Belgium.

(i) AgriSAR maize data set

The AgriSAR campaign was lead in Flevoland in central Netherlands. LAI data were derived from RapidEye optical imagery at three dates. More information about this LAI retrieval method can be found in [27]. Surface soil moisture (5 cm depth) data were measured on the ground using Thetaprobe [28]. Seventeen quad-polarization SLC RADARSAT-2 data were acquired from the 1st of June to the 9th of July, corresponding to the beginning of the maize growing season. The SAR preprocessing chain includes multi-looking, geocoding and radiometric calibration to convert SLC products into Geocoded Terrain Corrected (GTC) products with a spatial resolution of 20 m. The per-field mean backscattering coefficient and local incidence angle were extracted for each parcel. Only the maize fields where the row orientation is mainly perpendicular, i.e. 50° to 90°, to the SAR beam were kept. Indeed, [28] and [29] showed that the planting row direction effects can cause significant backscatter differences between fields with the same crop type and crop condition for linear co-polarizations. The reference [19] demonstrated also that the relative orientation of the maize row with respect to the SAR beam direction has to be considered. Tab.1 summarizes the AgriSAR 2009 data set, including the data of acquisition, the mean values of both soil moisture and LAI, and the number of observation.

Table 1. AgriSAR 2009 and Belgium and Flevoland 2008/2009 maize data sets

Date	**Site**	**Pass direction**	**Inc. angle (°)**	***Vm* (%)**	**LAI (m²/m²)**	**N. obs**
1/06/2009	Flevoland	Desc.	32.2	29.6	0.3	26
1/06/2009	Flevoland	Asc.	33.3	29.5	0.2	50
8/06/2009	Flevoland	Desc.	37.3	35.5	-	32
8/06/2009	Flevoland	Asc.	29	36.7	-	49
11/06/2009	Flevoland	Asc.	40.9	41.4	-	98
15/06/2009	Flevoland	Desc.	41	33.8	-	36
15/06/2009	Flevoland	Asc.	24.3	33.8	-	49
18/06/2009	Flevoland	Asc.	27.8	31.9	-	51
25/06/2009	Flevoland	Desc.	32.2	26.4	1.3	26
25/06/2009	Flevoland	Asc.	33.3	25.8	1.3	16
2/07/2009	Flevoland	Desc.	37.3	26.1	2	25
2/07/2009	Flevoland	Asc.	29	25.7	2	36
5/07/2009	Flevoland	Asc.	40.9	30.7	-	98
9/07/2009	Flevoland	Desc.	41	37.4	-	36
9/07/2009	Flevoland	Asc.	24.3	37.8	-	49
12/07/2009	Flevoland	Desc.	27.8	39.9	-	57
12/07/2009	Flevoland	Asc.	37.2	37	-	50
30/06/2008	Belgium	Asc.	27.1	19.3	1.8	5
1/05/2009	Belgium	Desc.	27.1	22.2	0.002	1
25/05/2009	Belgium	Desc.	28	20.2	0.08	7
1/06/2009	Belgium	Asc.	28	17.5	0.13	3
18/06/2009	Belgium	Desc.	27.1	22.3	0.5	7
25/06/2009	Belgium	Desc.	31	19.2	0.8	5
8/06/2009	Flevoland	Desc.	37.2	24.6	1	5
2/07/2009	Flevoland	Desc.	37.2	17.1	3.5	1

(ii) Belgium and Flevoland 2008/2009 maize data set

These data were acquired over various maize fields in Belgium and in The Netherlands along the beginning of the 2008 and 2009 growing seasons. Eight polarimetric RADARSAT-2 images were acquired on the 30th of June 2008 and from the 1st of May to the 2nd of July 2009. The SAR preprocessing chain includes multi-looking, geocoding and radiometric calibration with correction for the local incidence angle. A subset was applied excluding maize fields smaller than 3 ha and including only the perpendicular row-oriented fields to the SAR beam direction. In situ LAI measurements were collected on the ground during intensive field campaigns during 2008 and 2009 maize growing seasons in Belgium and in Flevoland. The LAI was either measured with LAI-2000 instrument (LiCor) or by taking hemispherical photographs processed with the CAN-EYE software[1]. For more details about this second technique, see [30]. Surface volumetric soil moisture was estimated thanks to the Soil, Water, Atmosphere and Plant model (SWAP). The SWAP model simulates transport of water, solutes and heat in the soil [31]. It was tuned to maize and winter wheat fields integrating a generic crop module WOFOST (World Food Studies). Soil surface moisture estimated through the SWAP model was found to be sufficiently accurate for maize LAI retrieval from SAR data through the Water Cloud Model by [32]. Tab. 1 summarizes the Belgium and Flevoland 2008/2009 data set.

Table 2. Belgium 2009 and 2010 winter wheat data sets

Date	**Site**	**Pass direction**	**Inc. angle (°)**	**Vm^+ (%)**	**LAI* (m²/m²)**	**N. obs**
14/04/2009	Belgium	Asc.	28	20.5	1.7	18
1/05/2009	Belgium	Desc.	27.1	20.3	2.5	16
8/05/2009	Belgium	Asc.	28	18.2	3.1	12
25/05/2009	Belgium	Desc.	28	19.1	3.7	20
1/06/2009	Belgium	Asc.	28	16.1	3.8	21
18/06/2009	Belgium	Desc.	27.1	20.5	3.4	21
25/06/2009	Belgium	Desc.	31	19.6	3.1	10
17/05/2010	Belgium	Dsc.	40.2	16.62	2.87	15
24/05/2010	Belgium	Dsc.	43.6	11.3	4.21	15
27/05/2010	Belgium	Dsc.	31.4	27.12	4.75	15
31/05/2010	Belgium	Dsc.	46.8	19.3	5.14	15
13/06/2010	Belgium	Dsc.	26.9	16.47	6.09	15
20/06/2010	Belgium	Dsc.	31.3	11.53	5.89	15
7/07/2010	Belgium	Dsc.	26.9	9.7	4.47	15
11/07/2010	Belgium	Dsc.	43.6	21.07	3.9	12
18/07/2010	Belgium	Dsc.	46.8	16.48	2.97	15
21/07/2010	Belgium	Asc.	22.1	10.85	2.48	15
28/07/2010	Belgium	Dsc.	40.2	11.02	1.46	15

[1] CAN-EYE software – http://www.avignon.inra.fr/can_eye

(iii) and (iv) Belgium 2009 and 2010 wheat data set

The research concerning winter wheat is based on two data sets in Belgium. Two temporal series of 7 RADARSAT-2 and 11 RADARSAT-2 have been acquired during the 2009 and 2010 wheat growing season (Tab. 2). The processing of the images series, the use of the SWAP model and the ground campaign is the same as the data set (ii).

5. RESULTS AND DISCUSSION

5.1. Water Cloud Model Calibration

The Water Cloud Model was calibrated for each data set and polarization. Fig. 1 shows the calibration results for the maize datasets. The mean Sum of Squared Deviations (SSD) between the measured signal and the corresponding simulated values varies from 0.73 to 1.83 dB. Cross-polarization calibration seems the most interesting because of its much larger range of observed backscattering coefficient. The evolution of depolarization properties showed by the maize canopy for various development stages provides more information than the progressive attenuation of the co-polarized signal by the vegetation.

Fig. 2 illustrate the results related to the calibration of the wheat 2009 data set. In this case, the dispersion is significant with a mean SSD between 2.3 and 6.47 dB. The large range of observed backscattering signal for both datasets shows that the polarization VV is the most interesting.

5.2. Analysis of the model stability

The covariance and correlation matrices of the calibrated parameters A, B, C and D were estimated thanks to the Hessian matrix. Tab. 3 presents the values of calibrated parameters, *A*, *B*, *C* and *D*, their variances and their variation coefficient for maize dataset. This shows the high sensitivity of the calibration to the data set and/or the low sensitivity of the model to this parameter. Parameters related to the soil moisture (*C* and *D*) present higher variation than vegetation related parameters (*A* and *B*) for all data sets. The calibrated parameters with highest variances are found for the (ii) data set. This latter presents the more inhomogeneous conditions while mixing agro-ecological regions and growing seasons. This lack of homogeneity could explain high variances values. Regarding winter wheat (data not shown), the (iv) dataset presents higher variation for parameters *A* and *B*, it could be the cause of a heterogeneity of incidence angles and a reduced set of LAI < 4.

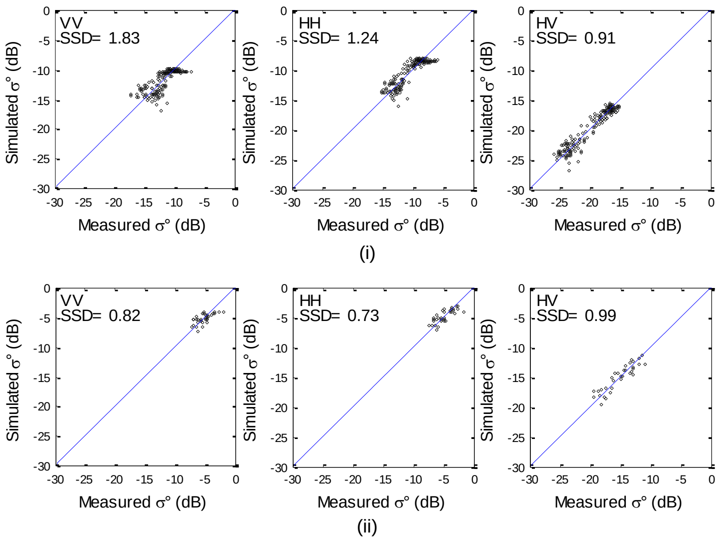


Figure 1. Measured versus simulated backscattering coefficient (σ°) after Water Cloud Model calibration for VV, HH and HV polarizations using the AgriSAR 2009 (n=180) (i), The Belgium and Flevoland 2008/2009 (n=34) (ii) data sets for the model calibration.

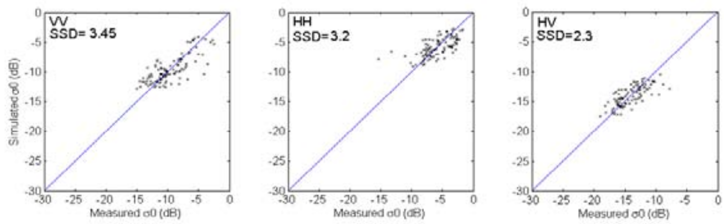


Figure 2. Measured versus simulated backscattering coefficient (σ°) after Water Cloud Model calibration for VV, HH and HV polarizations using the Belgium wheat 2009 (n=104) (iii) data sets for the model calibration.

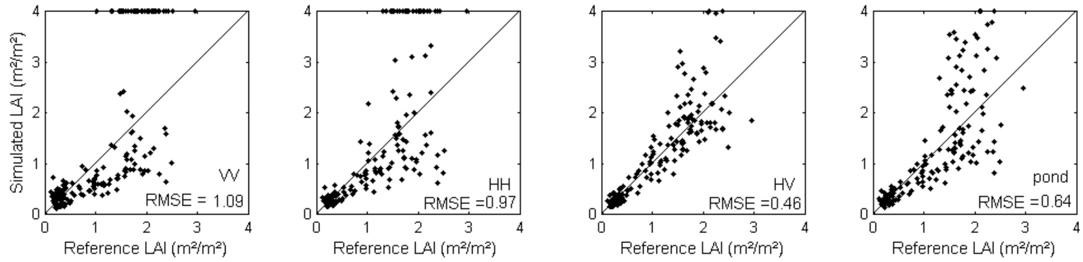
Table 3. Calibration parameters A, B, C and D values, variances and variation coefficients for each data set.

Data set	Pol	*A*	Var (*A*)	Var. coef.	*B*	Var (*B*)	Var. coef.	*C*	Var (*C*)	Var. coef.	*D*	Var (*D*)	Var. coef.
(i) Maize AgriSAR 2009	**VV**	0.12	0.00001	0.03	0.86	0.0026	0.06	4.7	1.9	0.29	618	6.3	0.00
	HH	0.18	0.00002	0.03	0.63	0.00098	0.05	4.7	1.3	0.24	526	5	0.00
	HV	0.04	0.00001	0.06	0.23	0.00028	0.07	5.0	0.9	0.19	803	0.4	0.00
(ii) Maize- Belgium & Flevoland 2008/2009	**VV**	0.39	0.0012	0.08	0.34	0.0239	0.43	46.9	101.1	0.21	15.2	4.3	0.13
	HH	1.27	2.6386	0.9	0.05	0.0087	1.40	36	52.1	0.2	13.3	2.4	0.12
	HV	0.13	0.0028	0.36	0.13	0.0071	0.59	70	115.6	0.16	32.4	5.6	0.08

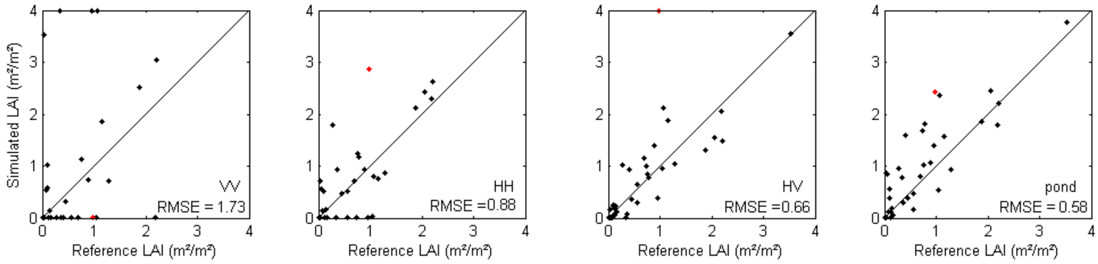
5.3. Water Cloud Model inversion and LAI retrieval

Maize and wheat LAI estimates were obtained after model inversion from the backscattering coefficient, the local incidence angle and the surface soil moisture using equation (7). The error affecting the LAI estimation was calculated thanks to a comparison with the reference

LAI values from the calibration data set. The Fig. 3 and 4 present the simulated LAI as a function of reference LAI for each polarization and each data set. RMSEs on LAI estimation vary from 0.46 to 1.76 m²/m² for maize and 0.54 to 1.88 m²/m² for winter wheat. Similar results are observed for the two maize data. For these latter, the cross-polarization offers the most promising results with a smaller RMSE value compared to the two co-polarizations. Especially at the very beginning of the growing season, small LAI are well estimated. By contrast, using VV polarization in particular, small LAI are often overestimated. LAI estimates from cross-polarization still present overestimated LAI throughout the growing period observed. These estimations reach often the threshold value fixed to 4 m²/m².



(i)



(ii)

Figure 3. Reference LAI versus simulated LAI, after Water Cloud Model inversion using VV, HH and HV polarizations and, after LAI recalculation by weighting VV, HH, and HV retrieved LAI using the AgriSAR 2009 data set (n=180 (i) and the Belgium and Flevoland 2008/2009 data set (n=34)(ii).

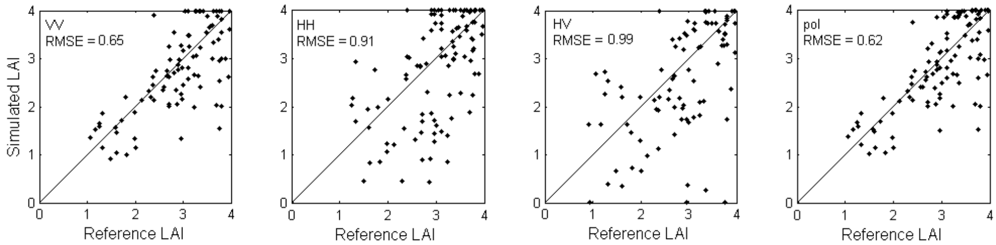


Figure 4. Reference LAI versus simulated LAI, after Water Cloud Model inversion using VV, HH and HV polarizations and, after LAI recalculation by weighting VV, HH, and HV retrieved LAI using the Belgium wheat 2009 data set (n=118) (iii).

In spite of high SSD obtained for the model calibration, the inversion performances are better for the 2009 wheat data set (iii) than for the 2010 (data not shown). The VV polarization for the year 2009 presents the best estimation with a RMSE of 0.65, compared to others polarizations. For small LAI (<3), this polarization shows a good estimation while HH and HV polarization tends to underestimate LAI. Concerning the year 2010, the LAI estimations are not explicit even for VV polarization where LAI are underestimated (data not shown). The heterogeneity of incidence angles and the absence of a larger range of LAI could explain this result for 2010.

The LAI distribution summary statistics are reported in Tab. 7 for maize and wheat data sets. This provides us a way to assess uncertainty on LAI values as the quality of the fit for the model varies. In maize, the cross-polarization and the LAI taking account all polarizations present a much lower standard deviation value compared to the co-polarization. Concerning the wheat data set, the VV polarization and the ponderation show the lower standard deviation for (iii) dataset, the most homogeneous.

Table 7. Correlation matrices of the calibration parameters for each data set.

Data set	Polarization	RMSE on LAI	Std on LAI
(i) Maize - AgriSAR 2009	VV	1.09	1.83
	HH	0.97	1.24
	HV	0.46	0.91
	Pond	0.65	**0.02**
(ii) Maize- Belgium & Flevoland 2008/2009	VV	1.76	1.02
	HH	0.87	1.17
	HV	0.66	0.52
	Pond	0.59	**0.25**
(iii) Wheat - Belgium 2009	VV	0.65	0.16
	HH	0.91	0.79
	HV	0.99	0.79
	Pond	0.62	**0.02**
(iv) Wheat - Belgium 2010	VV	1.25	0.55
	HH	1.6	1.11
	HV	1.88	1.15
	Pond	0.97	**0.18**

5.4. Polarimetric responses of the maize canopy

For a better understanding of these results, the different curves reported on Fig. 5 provide the simulated backscattered signal as a function of LAI for different soil moisture contents after WCM calibration for each polarization using the maize (ii) data sets. Large differences are observed concerning the soil contribution and consequently the total contribution. Looking first only at the contribution of the vegetation (blue curves), SAR signal seems to saturate the earliest with the VV polarization and the later with the cross-polarization involving a better LAI retrieval for medium LAI values with the cross-polarization.

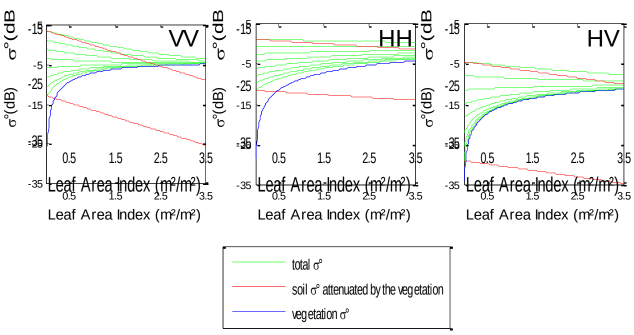


Figure 5. Backscattering coefficient simulation according to LAI for different soil volumetric moisture values after WCM calibration for each polarization using the Belgian and Flevoland data set (ii). Green curves represent the total backscattering at different soil moisture values (from 5 to 40% by step of 5%). The red curve represents the backscattering coefficient from the soil attenuated by the vegetation for soil moisture of 5 and 40%. The blue curve represents the vegetation backscattering coefficient.

The analysis of Fig.5 enables to explain the sensitivity of polarimetric responses of maize crops. The sensitivity of SAR signal to maize growth for different soil moisture levels differs from one polarization to another. Indeed, for VV polarization, the lowest sensitivity of SAR signal to crop LAI is observed for intermediate soil moisture values while for HV-polarization, this sensitivity is low for high soil moisture levels.

6. CONCLUSIONS AND PERSPECTIVES

This research analyzed methods for maize and wheat LAI retrieval from SAR data combining all information contained in polarimetric SAR data. The WCM was calibrated and inverted for each polarization and for four data sets. The C-band cross-polarization was found the more relevant to retrieve maize LAI from polarimetric SAR data using the WCM and allows a RMSE on LAI estimation of 0.46 m²/m² in the best case. Wheat LAI estimation with VV polarization was the most relevant with a RMSE of 0.16 for the (iii) dataset.

The RADARSAT-2 and the SENTINEL-1 sensors offer multi-polarized C-band information that can directly be used in order to retrieve LAI. A combination of the retrieved LAI weighting by their associated errors for each VV, HH and HV polarization was carried out and rather improved the LAI estimation and surely reduced its associated uncertainty compared to LAI retrieved from single polarizations. With this method, the standard deviation on LAI retrieval decreases significantly comparing to the single polarization use for its retrieval.

In the future, an analysis of the evolution of the WCM calibration with different incidence angles should be investigated.

Another foreseen perspective that may follow this study is its promising application to other kind of crops. The results are assumed to be applicable for other similar broad leaves crops as sunflower or sorghum. They can maybe be applicable to other kinds of crops because the maize can be considered as a transparent canopy for the C-band signal and presents as well the difficulty of its row-orientation influence on the SAR signal.

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