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Article

Estimating the Leaf Area Index of Agricultural Crops using multi-temporal dual-polarimetric TerraSAR-X Data: A case study in North-Eastern Germany

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Keywords: TerraSAR-X, agricultural crop, leaf area index, stepwise regression, water cloud model

Summary: Leaf area index (LAI) is one of the most important indicators of agricultural variables because of its relation to biophysical and biochemical properties of agricultural crops. Variations in LAI can be related to changes in leaf scattering properties, and these variations in leaf scattering properties can lead to changes in canopy backscattering behaviour. The objective of this study was to explore the potential of estimating LAI using multi-temporal dual polarimetric TerraSAR-X data in three different agricultural field crops, including winter wheat (*Triticum aestivum* L.), barley (*Hordeum vulgare* L.), and canola (*Brassica napus* L.). The relationship between LAI and the scattering coefficient (σ^0) in TerraSAR-X was explored using three different approaches, including univariate regression, i.e., simple linear and nonlinear regression, multivariate regression, i.e., stepwise regression, and a semi-empirical water cloud model (WCM). The multivariate stepwise regression showed its capability to retrieve the LAI without any external input data, such as soil moisture, based solely on the polarization channels, i.e., HH or VV, and polarization variables, e.g. HH/VV or HH+VV. However, unlike the WCM, the stepwise method is not applicable with just one polarization channel. The results indicate that the leaf area index (LAI) was significantly and consistently correlated with σ^0 throughout the growth stages using the stepwise regression and WCM approaches, whereas simple linear and nonlinear regression yielded relatively poor results except with barley.

Zusammenfassung: *Abschätzung des Blattflächenindexes von Anbaukulturen mittels dual-polarimetrischer TerraSAR-X Daten: Eine Fallstudie in Nordostdeutschland.* Der Blattflächenindex (LAI) zählt wegen seiner Beziehung zu biophysikalischen und biochemischen Eigenschaften von Anbaufrüchten zu den interessantesten Parametern im Kontext der Landwirtschaft. Unterschiede im LAI können zu Streuungseigenschaften der Blätter in Beziehung gesetzt werden. Die Variationen der Streuungseigenschaften von Blättern können zu Änderungen im Rückstreuverhalten der Vegetationsoberfläche führen. Gegenstand der vorliegenden Studie war es, das Potenzial einer LAI-Abschätzung mit Hilfe von multitemporalen, dual-polarimetrischen TerraSAR-X-Daten zu ermitteln, und zwar für drei verschiedene landwirtschaftliche Anbaufrüchte: Winterweizen (*Triticum aestivum* L.), Gerste (*Hordeum vulgare* L.) und Raps (*Brassica napus* L.). Die Beziehung zwischen LAI und dem Streuungskoeffizienten (σ^0) bei TerraSAR-X wurde mit Hilfe von drei verschiedenen methodischen Ansätzen untersucht: mittels univariater Regression (einfache lineare und nichtlineare Regression), multivariater Regression (schrittweise Regression) und mit Hilfe eines semi-empirischen Water/Cloud-Modells (WCM). Die multivariate schrittweise Regression erwies ihr großes Potenzial für eine LAI-Abschätzung ohne Hinzunahme weiterer Informationen wie etwa der Bodenfeuchte. Die Abschätzung erfolgte allein auf der Grundlage der Polarisationskanäle (HH und VV) und der Polarisationsvariablen (HH/VV und HH+VV). Im Gegensatz zum WCM ist die schrittweise Methode jedoch bei Verwendung nur eines Polarisationskanals nicht anwendbar. Die Ergebnisse zeigen, dass der Blattflächenindex über die ganze Vegetati-

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onsperiode hinweg signifikant und konsistent mit σ^0 korreliert, wenn mit schrittweiser Regression und WCM gearbeitet wird. Dagegen erzielten die Ansätze mit einfacher linearer und nicht-linearer Regression, außer für Gerste, vergleichsweise schwache Ergebnisse.

1 Introduction

Leaf area index (LAI) measures the amount of leaf material in an ecosystem. The measurement of LAI is of fundamental importance to understanding vegetation photosynthesis, respiration, rain interception, and other processes that link vegetation to different environmental processes for different categories of vegetation, such as agricultural crops (Chen et al. 2009, Jiao et al. 2011). It is one of the key variables required in primary production and global climate studies (Myneni et al. 1997) and ecological research, such as global land surface phenology (Jones et al. 2011), because this variable correlates directly with canopy foliage content and crown structure (Gower & Norman 1991, Hosseini et al. 2015). LAI can be considered an indicator of plant growth and health (Hosseini et al. 2015). LAI directly affects the interception and absorption of light by the canopy and influences heat balance and evaporation from the landscape, which is an important component of vegetation-atmosphere interaction models and crop yield models (Hosseini et al. 2015).

Optical satellite imagery faces the problem of illumination conditions that limit the acquisition of high quality remote sensing data, and the availability of remote sensing images from satellite and aerial platforms is often severely limited by frequent cloud cover (Mulla 2013). Multispectral reflectance data have been used to create different vegetation indices (Baret & Guyot 1991). Sharp contrast in reflectance values between the red and NIR bands of the remote sensing data was the motivation for development of vegetation indices (Mulla 2013). These indices demonstrate a correlation between different vegetation parameters, such as LAI (Baret & Guyot 1991). However, these indices reach a saturation level asymptotically with increasing LAI values, and the sensitivity of these indices to LAI become increasingly weak beyond a particular threshold value (Carlson & Ripley 1997), which is typically between 2 and 4 (Ahmadian et al. 2016a, Mulla 2013, Thenkabail et al. 2000), depending on different factors, such as vegetation, crop type, and experimental and environmental factors (Baret & Guyot 1991). In this situation, the use of radar sensors becomes a feasible means for acquiring remote sensing data in a given period of time. The past decade has seen a significant growth in research activities focused on developing approaches using radar remote sensing to study vegetation characteristics and parameters for ecological, agronomy and meteorological application. Several studies have examined the sensitivity between radar data and LAI at different frequencies and polarizations. Applicability of X-band sensors to LAI estimation was assessed by Fontanelli et al. (2013) using COSMO-SkyMed and TerraSAR-X data. These scientists observed a relatively high sensitivity of backscatter to LAI at both HH and VV polarizations for wheat.

Previous research on SAR sensitivity to LAI has been mostly empirical and semi-empirical. Simple statistical models (linear and non-linear) developed and inverted to estimate LAI as the most commonly used empirically based approach (Fontanelli et al. 2013) and water cloud model as a semi-empirical approach. Empirical models are generally derived from experimental measurements to establish useful empirical relationships for inversion of vegetation characteristics from backscattering observations. The empirical model usually is divided into two categories: first are univariate models and the second are multivariate models, e.g. stepwise regression. The most common technique used as a semi-empirical approach is the "water cloud model" (Attema & Ulaby 1978). This model describes the dependence between the radar signal and the vegetated surface parameters. In water-cloud models, the vegetation has been considered as a cloud containing water droplets randomly distributed within the canopy and the total backscattering signal from the surface is the sum of the backscattering signals from the soil multiplied by two-way attenuation and the direct reflected signal from the vegetation.

The results of previous studies reveal that the backscattering from crops is a complex combination of different mechanisms (LIN et al. 2009). The backscattering coefficient changes during different growing stages of crops (Cable et al. 2014b, Kim et al. 2013), and the aforementioned mechanisms, include direct backscatter from the underlying ground, e.g. soil, direct backscatter from the plant components (leaves, stems, fruit), double-bounce backscatter between the soil surface and crop canopy, and, in some cases, ground-vegetation-ground and multiple scattering mechanisms (Adams et al. 2014, Cable et al. 2014a). It was also demonstrated that when seeds are still below the surface, the main contributor to a radar signal is single-bounce backscatter due to soil moisture and surface roughness (van Zyl 2009). As crops emerge and the canopy develops, the characteristics of scattering from agricultural fields change and the co-polarized backscatter intensities tend to increase. The increase in co-polarized backscatter is due to a combination of single bounce backscatter directly off leaves or stems, etc., and soil-vegetation double-bounce backscatter (Cable et al. 2014a). Consequently, this study evaluated the sensitivity of combinations of several polarimetric parameters, e.g. HH+VV or HH/VV, to LAI. The research presented here examines the potential of multi-temporal dual polarimetric TerraSAR-X data (X-band) for LAI estimation over wheat and barley (narrow-leaf crops) and canola (broad leaf crop) canopies using simple linear and nonlinear, stepwise regression (empirical approaches) and semi-empirical WCM methods and compares the capability of each method to retrieve and estimate the LAI of aforementioned crops. For the validation of the models, the root-mean-square error (RMSE) and correlation coefficient, i.e. R^2, were reported for the simple linear and nonlinear approach, the leave one out cross validation (LOOCV) method was used to report the RMSE, the correlation between the observed and predicted responses (cross-validated R^2) and Adjusted R^2, the mean-absolute error (MAE), the coefficient of variation (CV), and p-value of the stepwise approach. Moreover R^2, RMSE and MAE were also reported for the WCM approach.

2 Test Site and Study Area

The study area is located in North East Germany, in the Durable Environmental Multidisciplinary Monitoring Information Network (DEMMIN). The DEMMIN project, established in 1999, is managed by the Neustrelitz "Thematic Processor Development and Validation DEMMIN" team in the German Remote Sensing Data Center's National Ground Segment department (Gerighausen et al. 2007). This reference site is approximately 50 by 50 km² and extends from 53°45'40.42"N, 13°27'49.45"E to 54°2'54.29"N, 12°52'17.98"E. Within this test site, a study area including three winter wheat, barley and canola fields was chosen to carry out the ground truth data collection. The sizes of the fields were approximately 225 ha, 117 ha, and 25 ha for winter wheat, barley, and canola, respectively. For more information, please refer to DLR (2016).

3 Materials and Methods

3.1 *Field Data*

The ground truth data collection was carried out for 20 weeks from 17 April until 28 August 2013 at weekly intervals during the crop growing season. During the field campaign, almost all growing stages of the winter wheat, barley, and canola were recorded. During each sampling expedition, two random centers in each field were chosen, and five sampling locations were established with five (50 cm × 50 cm) squares around each center (Fig. 1). The squares were used to collect the soil samples, i.e., approximately 10 samples were collected in each crop field during each field trip. LAI was measured using a handheld LAI-2200 plant canopy analyzer (LI-COR) close to the squares (Fig. 2). The 270° view cap was used to hide the operator from the sensor. Normally, LAI can be computed using two readings, the above (A) and below (B) canopy readings. To evaluate the number of below (B) readings necessary to decide with 95% confidence that the true LAI mean is within ± 10% of the measured LAI, the operator took an LAI reading based on 6 below (B) readings that included both the thinnest and densest parts of the canopy. Next, the standard error of the LAI (SEL) was divided by the LAI (SEL/LAI), and a table provided by LI-COR was used to determine the number of B readings necessary for all further readings. After collecting the LAI values in the field, post-processing of data was performed in the lab using the software from LI-COR, i.e. FV2200 (Ahmadian et al. 2016a).

The GPS coordinates of the measurements were recorded with a handheld Trimble, i.e., GeoExplorer 2008 series or GeoXH handheld, GPS device for mapping of the data in a Geographic Information System (GIS). The accuracy is between 2 m – 5 m.

Gravimetric (GSM) and volumetric (VSM) soil moisture was measured, and using a

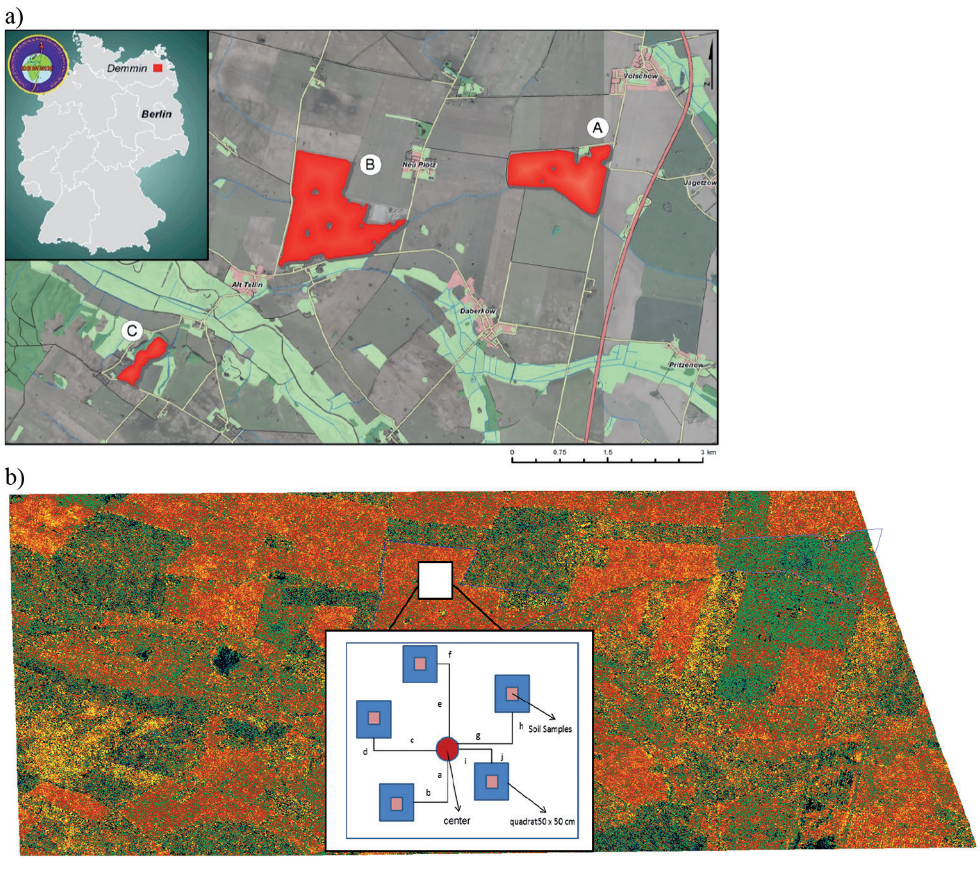

Fig. 1: a) Study area including barley (A), winter wheat (B), and canola (C) in the Durable Environmental Multidisciplinary Monitoring Information Network (DEMMIN). The background data were taken from GeoBasis (M-V) (DOP40), GeoBasis (M-V) (ATKIS), and GeoBasis (DE). b) The study area was shown by dual polarimetric TerraSAR-X using PDR index and colour slicing (3) on 21 June 2013. As an example of ground truth data collection, the light-orange squares show the locations of the soil samples, and the blue squares show the squares.

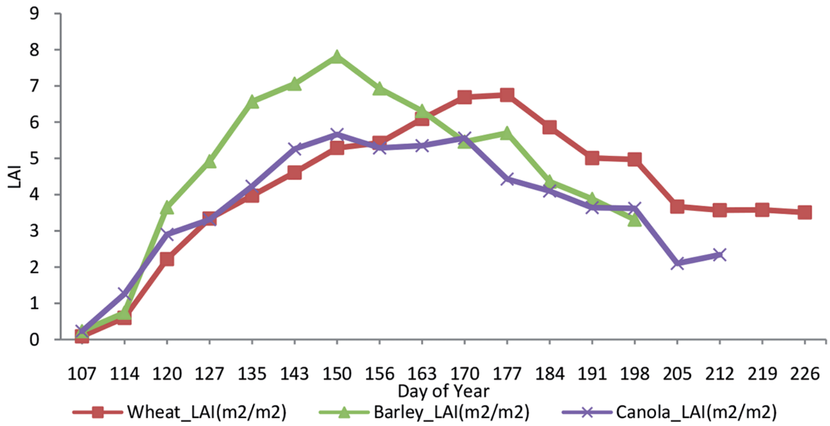

Fig. 2: LAI of agricultural crops using ground truth data collection during the complete growing season.

hand sledge and five 5.6 cm diameter cylinder/rings (corresponding to five squares) were used for laboratory analysis. All soil samples were weighed, i.e., weight of wet soil, and then dried in an oven for approximately 24 hours at 105 °C to obtain constant weight. Bulk density (BD) was calculated using the oven dry weight and the inner volume of the cylinder/ring.

(1) and (2) show the formulas for computing the GSM, and VSM. The soil moisture content was determined by averaging the weight of samples as the ratio of the water mass present in the soil to the dry weight of the soil sample using (1), and by volume as the ratio of water volume to the total volume of the soil sample for volumetric soil moisture using (2) (Fig. 3).

$$GSM\ (g/g) = (W1(g) - W2(g))/W2(g) \quad (1)$$

$$VSM\ (g/cm^3) = GSM\ (g/g) \times BD\ (g/cm^3) \quad (2)$$

where W1 is the weight of wet soil in grams, and W2 is the weight of oven dry soil in grams.

3.2 *Satellite Images*

To study the LAI variation during the whole growing season, TerraSAR-X (TSX) satellite images were used for the acquisition of high-resolution SAR images in Stripmap mode (SM) during the year 2013. The specifications of the aforementioned images as well as the related growing stages of each crop are summarized in Tab. 1. The Feekes scale was used to identify the phenological development stages of winter wheat and barley (Large 1954). The BBCH-scale was also used to describe the phenological development of canola plants (Lancashire et al.1991).

In this study, Multi Look Ground Range Detected product operated in SM with co-polarized channels, i.e., HH and VV, was used (all images). This product, i.e., Multi Look Ground Range Detected, is a detected multi look product with reduced speckle and approximately square resolution cells. The image coordinates are oriented along the flight direction and along the ground range. The pixel spacing is equidistant in azimuth and in ground range. A simple polynomial slant to ground projection is performed in range using a WGS84 ellipsoid and an average, constant terrain height parameter (Roth et al. 2005). The spatial resolution of all images is approximately 6 m × 6 m.

Initially, all the images were georeferenced using SRTM 1-arc-sec (Shuttle Radar Topography Mission). Since all the delivered images were already multilooked, a time series of images was built and co-registered in order to perform De Grandi multi-temporal filtering (De Grandi et al. 1997). All images were

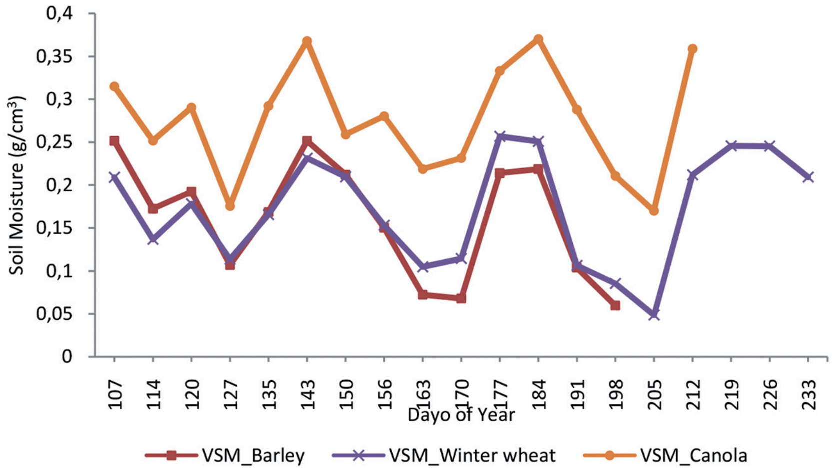

Fig. 3: Volumetric soil moisture (VSM) (g/cm³) of agricultural crops using ground truth data collection during the complete growing season.

geocoded and afterward radiometrically calibrated in order to retrieve the sigma nought (σ^0) using the SARScape 5.1 module of ENVI 5.1. Sigma nought (σ^0), expressed in decibels (dB), is the conventional measure of the radar backscattering coefficient. This parameter is defined as a normalized dimensionless number that compares the strength of the signal observed to that "expected" from an area of one square meter (Raney 1998).

3.3 *Analysis*

Three different approaches were considered in this study to estimate the LAI of different agricultural crops during the whole growing season. Using ground truth data collection, and the closest acquisitions of TSX images, a linear or nonlinear relationship was constructed between the ground truth data, i.e. LAI, and the corresponding pixel values, i.e., polarization channels and variables, from TSX images, i.e., the same GPS coordinates of the measurements and TSX pixels. A linear and nonlinear regression model was used to simplify the complex relationship between radar backscattering and vegetation characteristics, i.e. LAI. The polarization variables, e.g. HH+VV and HH/VV, were retrieved from the satellite data based on a pixel to pixel calculation. The disadvantages of these simple regression models are the dependence of model parameters and the little information provided on the physics of the scattering events involved (Richards 1990). It is also worth noting that the following index was also used as a polarization variable to assess the biophysical parameters of the crops, i.e. LAI (Singh 2006):

Polarization discrimination ratio

$$= \frac{(\sigma 0VV\text{-}\sigma 0HH)}{(\sigma 0HH+\sigma 0HH)} \tag{3}$$

The correlation coefficient (R^2) and the root-mean-square error (RMSE) were reported for the linear and nonlinear regressions.

For the second approach, stepwise regression was used to identify the optimal set of polarization channels (HH, VV) and polarization variables, e.g. HH/VV, for providing accurate estimates of LAI for the aforementioned agricultural crops. In stepwise regression models, the sigma nought of HH and VV polarization and polarization variables were set as the independent variables, while canopy characteristics, i.e. LAI, of the agricultural crops were set as the dependent variables. For the stepwise method, in addition to R^2 and RMSE values, adjusted R^2, p-value and F-stat were also

Tab. 1: Overview of TSX imagery dates and phenological development of each crop. IA and P stand for Incidence Angle and polarization, respectively. Feekes scale for growing stages of winter wheat, and barley (Large 1954). The BBCH-scale for growing stages of canola (Lancashire et al. 1991), MGD = Multi Look Ground Range Detected.

Crop field(s)	Mission	Mode	Product	Pass	Date	IA (°)	P	Growing Stage
Canola	TSX	SM	MGD	D	20130504	~ 27	HH&VV	Inflorescence emergence (55)
Wheat	TSX	SM	MGD	A	20130519	~ 31	HH&VV	Stem extension (8)
Barley								Stem extension (10)
Canola								40% of flowers on main raceme open (64)
Wheat	TSX	SM	MGD	A	20130621	~ 31	HH&VV	Beginning of flowering (10.5.1)
Barley								flowering (10.5.3)
Canola								Ripening (80)
Wheat	TSX	SM	MGD	D	20130709	~ 27	HH&VV	Flowering over at base of ear (10.5.3)
Barley								Milky ripe (11.1)
Barley	TSX	SM	MGD	A	20130713	~ 31	HH&VV	Kernel hard (11.3)
Wheat	TSX	SM	MGD	D	20130724	~ 27	HH&VV	Milky ripe (11.1)
Canola								Plant dead and dry (97)
Wheat	TSX	SM	MGD	A	20130804	~ 31	HH&VV	Mealy ripe, kernel soft but dry (11.2)
Wheat	TSX	SM	MGD	D	20130822	~ 27	HH&VV	Ripe for cutting, straw dead (11.4)

reported for assessment of the goodness of fit. In this study, forward stepwise regression was used to build the models. This technique starts with no model terms then adds the most statistically significant term, i.e., polarization channels or variables. This significant term is the one with the highest F statistic or the lowest p-value at each step until there are no terms left (Matlab Statistics Toolbox User's Guide). In other words, inclusion of other parameters would not contribute positively to the success of the model.

For the third approach, The Water Cloud Model (WCM) that was developed by Attema & Ulaby (1978) was used to assess the relationships between the polarization channels, i.e., HH and VV, and the LAI of each crop. In this model, total backscatter σ^0 is expressed as the incoherent sum of backscatter from vegetation σ^0veg and backscatter from the underlying surface σ^0soil, which is attenuated by the vegetation layer through the two-way attenuation factor τ^2.

$$\sigma^0 = \sigma^0_{veg} + \tau^2 \sigma^0_{soil} \tag{4}$$

$$\sigma^0_{veg} = AV_1 \cos\theta (1 - \exp\left(-\frac{2BV_2}{\cos\theta}\right)) \tag{5}$$

$$\tau^2 = \exp\left(-\frac{2BV_2}{\cos\theta}\right) \tag{6}$$

In these equations, Parameter A relates to the radar backscatter from a vegetation canopy, parameter B relates to canopy attenuation (Alastair et al. 2003), and θ is the incidence angle. V1 and V2 are descriptors of the canopy, and backscatter (σ^0) is expressed in power units.

The backscatter from the soil surface σ^0 soil can be expressed as follows:

$$\sigma^0_{soil} = C + D(VSM) \tag{7}$$

Parameters C and D are dependent on soil moisture, and VSM is the volumetric soil moisture, (8) is obtained by grouping these terms (4) – (7):

$$\sigma^0 = AV_1 \cos\theta (1 - \exp\left(\frac{2BV_2}{\cos\theta}\right)) + (C + D(VSM)) \cdot \exp\left(-\frac{2BV_2}{\cos\theta}\right) \tag{8}$$

Because an important part of the scattering and attenuation is controlled by the leaves, some studies propose using the LAI as the canopy descriptor (Hosseini et al. 2015, Inoue et al. 2014a, Kumar et al. 2015). Furthermore, some studies propose V1=1 and V2= LAI (van Leeuwen & Clevers 1994, Ulaby et al. 1984), therefore, (9) can be written as:

$$LAI = -\frac{\cos\theta}{2B} Ln \frac{\sigma^0 - A\cos\theta}{C + D(VSM) - A\cos\theta} \tag{9}$$

All parameters of the model, i.e., A, B, C, D, are calculated using the non-linear least-squares method. The "brute-force" algorithm was chosen to evaluate residual sum of squares (RSS) for the parameter values. In this algorithm, one can introduce a two-row data frame as the upper and lower values, and the algorithm assumes the lower value as the start value, creates a grid between these two values of each parameter, runs an optimization starting at each point on the grid and returns the best value. This model is calibrated for each crop type and polarization, and different parameters are obtained for each crop-polarization.

To determine how well the models are created, a validation procedure was also performed. In this part, the LOOCV approach was used in order to validate the models (Stone 1974). LOOCV has been shown to be superior to split-sample validation, particularly for smaller sample sizes (Goutte 1997). This approach omits a single observation from the dataset, and then predicts its response using the regression model created with the remaining observations. This procedure is then repeated, in turn, for each observation in the dataset (Davidson et al. 2006). In other words, we fit a model to a subset, i.e., original data minus omitted single observation, of the total measured data, and then we evaluate how well the model predicts the remaining data. To evaluate the ability of each model to predict the biophysical characteristics of the crops, the root-mean-square error (RMSE), the correlation between the observed and predicted responses (cross-validated R^2), adjusted R^2, the mean-absolute error (MAE), p-value and the coefficient of variation (CV) were also reported. All of these terms are commonly used measures of model uncertainty. The RMSE is often used to quantify model precision, while R is often used to assess model accuracy (Olden & Jackson 2000). Furthermore, MAE is less sensitive to extreme data values (Willmott 1982). CV gives an indication of the difference compared to the mean of the observed variable (Kross et al. 2015).

4 Results

The polarization channels and variables values of the images collected during the whole growing season were correlated with LAI data of the corresponding field measurement campaigns (closest in time). As the first approach in the relationships between radar backscattering and the LAI, simple linear and nonlinear degree of determination R^2 and RMSE were calculated. Tab. 2 presents the results of the correlation analysis between LAI of crops and the remotely sensed parameters extracted from TerraSAR-X satellite images. All coefficients in the aforementioned Table are significant, with p-values less than 0.01. A high correlation between LAI values and radar backscatter, especially in the HH/VV polarization variable was observed on the barley field ($R^2 = 0.9437$), whereas this polarization variable shows moderate correlation ($R^2 = 0.4946$) for winter wheat (narrow leaves)); on the other hand, for canola, the maximum determination coefficient is 0.5331 for HH polarization. Overall, the LAIs were not strongly correlated with polarization channels and variables, especially for the winter wheat. The results included some weak or negligible relationships, as well as strong relationships, especially for barley. However, both low and high correlation between the variables of dual polarimetric TSX data and LAI are presented here to clearly show the inherent limitations and potential for accurate assessment of LAI (Inoue et al. 2014a) of different crops using simple linear and nonlinear regression.

For the second approach, stepwise regression was used to establish a minimum and optimal set of polarization channels and variables to estimate the LAI of crops. To meet the assumption of the stepwise regression for the validation models, four diagnostic plots were studied, including the residuals versus the fitted values plot, Quantile-Quantile normal plot, scale-location plot, and the standardized residuals against leverage plot. Recall that a least-squares regression assumes that the errors (residuals) are normally distributed, that they are centered on the regression line, and that their variance does not change as a function of x, i.e., homoscedasticity. All assumptions of the regression appeared to be upheld. Furthermore, in order to study the multicollinearity between the predictors, i.e., polarization variables, multicollinearity analysis was performed, and the polarization variables, i.e. predictors, which had high correlation with the most significant term of stepwise regression were omitted from the analysis. The collinearity between the predictors is less than 0.3 ($r < 0.3$) in all equations of Tab. 3. This analysis should be performed when the independent variables are not independent from each other.

As can be observed from Tab. 3, the performance of polarization variables employed for selecting the coefficients for use in predictive models varied between vegetation types. As observed from Tab. 3, stepwise regression successfully predicted the amount of LAI of different agricultural crops, and a strong correlation was observed between LAI and the polarization variables using this approach for all three crops. The amount of error is an important factor for the practical use of any given model. Therefore, the LOOCV method was employed to ensure the normality of residuals and to improve the statistical models for predicting the LAI of crops. As observed from Tab. 4, some values of R^2 and adjusted R^2 of cross validation are higher than those of the original dataset, and the others are lower. Nonetheless, the results show values that are close to those of the original models.

Following the first two approaches, the Water Cloud Model (WCM) was parameterized using LAI, volumetric soil moisture and TSX dual polarimetric data. Estimating LAI from the backscatter using the water-cloud model was also successful, and a strong relationship, i.e. R2, between estimated and derived LAI was observed. The results of the inversion are provided in Fig. 4.

Tab. 5 shows the relation between the estimated and the observed LAI values using the WCM for all three crops. The R^2, RMSE and MAE statistics as well as the coefficients, i.e., a, b, c, d, are provided in the Tab. 5. An obvious underestimation was observed for the LAI > 7 of winter wheat. This is in agreement with findings of MORAN et al. (1998), who showed that there is an underestimation at the higher values and overestimation of LAI of barley between 3.5 and 4 m^2/m^2 (Fig. 4).

Tab. 2: Summary of the correlation coefficients between the X-band $\sigma 0$ of TSX and LAI of winter wheat, barley, canola using simple linear and nonlinear regression. " ", * and ** represent the linear, power and exponential relationships, respectively.

Index	Stat Info	LAI		
		Winter Wheat	Barley	Canola
HH	R^2	0.0770	0.0668	0.5331
	RMSE	0.8483	0.9729	0.6732
HH/VV	R^2	0.4946*	0.9437	0.1486**
	RMSE	0.6277*	0.2391	0.9091**
HH-VV	R^2	0.2916*	0.00728*	0.1571
	RMSE	0.7432*	1.003*	0.9046
HH+VV	R^2	0.06742	0.1352*	0.5156
	RMSE	0.8527	0.9366*	0.6857
PDR	R^2	0.2679*	0.002678*	0.1586
	RMSE	0.7555*	1.006*	0.9038
VV	R^2	0.1194	0.2816*	0.4704
	RMSE	0.8286	0.8536*	0.7171
VV/HH	R^2	0.2674**	0.2674**	0.1473**
	RMSE	0.7558**	0.7558**	0.9098**
VV*HH	R^2	0.2645*	0.0652	0.0408*
	RMSE	0.7572*	0.9738	0.965*

The accuracy is relatively the same for HH and VV but a slightly higher correlation of VV polarization was observed for the barley and canola. This is because the trend in the radar backscattering is generally similar in VV as in HH polarization. For X band TSX and aforementioned crops, the correlation coefficients (R^2 values) between the observed and estimated LAI were approximately 0.7 using WCM.

5 Discussion

Our analysis using high-resolution satellite images taken by TSX has determined clear and consistent relationships between X-band sigma naught and canopy LAI variables using different statistical approaches. Although a correlation coefficient and accuracy of LAI retrieval can be affected by the underlying mechanisms, the reasonable interpretation of our consistent results strongly suggests the potential capability of X-band TSX SAR for the timely monitoring of different agricultural crops such as wheat, barley, and canola growth.

When the LAI is low (LAI < 2), the prevailing phenomenon is the attenuation of the soil contribution by the vegetation (Jiao et al. 2011, Prévot et al. 1993). In contrast, when the LAI is high (LAI > 4), the soil contribution is negligible, and the backscattering is dominated by the vegetation contribution (Prévot et al. 1993). Jiao et al. (2011) reported a loss in sensitivity at LAI values more than 3.0 m^2/m^2 for combinations incorporating one or more co-polarizations. In the results presented here, no saturation occurs, even for higher LAI values (Fig. 4). This behaviour is similar to that reported by Prévot et al. (1993) and Ulaby et al. (1984). Prévot et al. (1993) showed that for a given soil moisture, the function relating the backscattering coefficient in X-band to LAI is approximately monotonic when LAI > 2. Thus, even if one is only interested in LAI estimation, a unique radar configuration can be

Tab. 3: Transfer functions and statistical information of the calibration of LAI of winter wheat, barley, and canola. HHdVV, HHpVV, VVmHH, and VVmulHH correspond to σ0HH/σ0VV, σ0HH+σ0VV, σ0VV-σ0HH, σ0HH×σ0VV, respectively.

Transfer Function	R2	RMSE	Adj-R²	F-stat	p-value
$LAI - Winter\ Wheat = (5.016 \times HHdVV) + (0.546 \times HHpVV) + (-1.08 \times HH) + 0.664$	0.64	0.543	0.62	43.9372	< 0.05
$LAI - Barley = (5.263 \times HHdVV) + (0321 \times HHmVV) + 0.675$	0.949	0.229	0.947	514.87	< 0.05
$LAI - Canola = (0.72145 \times HH) + (-0.1855 \times HHmVV) + (-0.0086256 \times VVmulHH) + 9.932$	0.7866	0.4639	0.7742	63.8733	< 0.05

Tab. 4: Statistical information of validation of LAI models of winter wheat, barley, and canola using leave-one-out approach.

Models	R2	Adj-R²	RMSE	MAE	CV	p-value
LAI-Winter Wheat	0.6305	0.6159	0.5968	0.4589	28.8454	<0.05
LAI-Barley	0.944	0.941	0.2485	0. 2063	3.5821	<0.05
LAI-Canola	0.7629	0.7489	0.4841	0.3745	13.1209	<0.05

Tab. 5: Parameter values and statistics retrieved in the water cloud model for this study. Parameters (A, B, C, D) were calculated using (9).

	A	B	C	D	R²	RMSE	MAE
HH-LAI-Wheat	-0.14	-0.3	-0.13	0.11	0.7289	0.6709	0.5375
VV-LAI-Wheat	-0.14	-0.29	-0.13	0.11	0.6947	0.6863	0.5472
HH-LAI-Barley	-1.06	-0.33	-0.87	-0.2	0.7496	0.7084	0.5807
VV-DB-Barley	-1.56	-0.33	-1.28	-0.3	0.7516	0.7084	0.5910
HH-DB-Canola	-1.39	-0.07	-0.1	-1.3	0.7552	0.6107	0.4697
VV-DB-Canola	-0.5	-0.11	-0.06	-0.53	0.7861	0.5703	0.4581

adequate if the optimum set of satellite data acquired is especially for narrow leaf crops. Although information on crop growth must be temporally frequent in order to adequately characterize crop productivity, as it was observed for the retrieval of barley using simple regression by the HH/VV variable, the optimum choice of satellite data during the whole growing season can be sufficient for accurate estimation of LAI. The estimation of LAI for barley is correct since its precision given by the RMSE is 0.23 m²/m² using the HH/VV variable. The relatively good accuracy obtained is most likely related to the optimal choice of satellite data in a specific growth stage, as mentioned before, and the choice of suitable radar data acquisition likely accounts for these encouraging results. Further validation of this point is needed, and more research is necessary to investigate this assumption in detail. The HH/VV polarization ratio at a steep incidence angle, i.e., ~ 27° and ~ 31°, was strongly correlated with wheat LAI (Satalino et al. 2006), and the same polarization ratio has been correlated with the LAI of rice (Chen et al. 2009) and with corn (Jiao et al. 2011). The results with barley confirm the results mentioned above, but winter wheat shows moderate correlation with the ratio.

The linear co-polarizations are less sensitive to volume scattering from within a vegetation canopy (Jiao et al. 2011). This low-

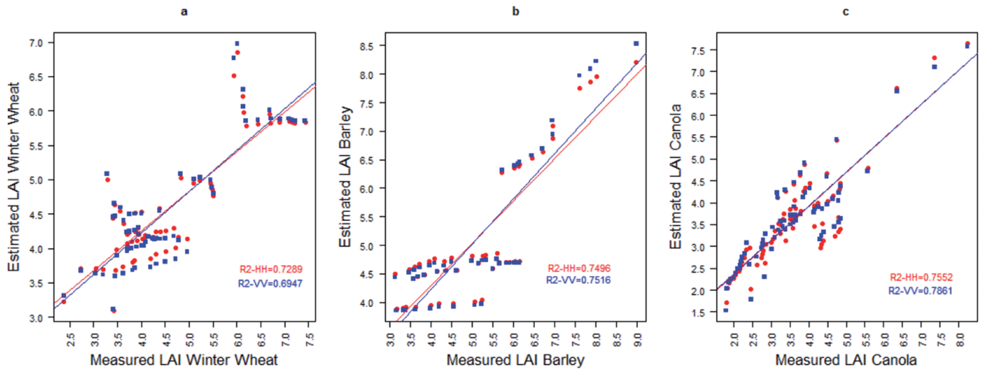

Fig. 4: Relationship between measured and predicted the LAI of winter wheat, barley, and canola using the WCM model. The VV and HH indicate simulated σ^0 values in VV and HH polarization, respectively.

er sensitivity was reflected in weaker correlations with LAI for HH and VV, as well as the co-polarization variable for the wheat and canola. The backscatter signal from vegetated surfaces is affected by many factors, including the physical structure of the plants and canopy volume (biomass, leaf size, stem density, LAI, etc.), the surface volumetric moisture of the soil below the canopy (Inoue et al. 2014b), as well as sensor configurations, such as frequency, polarization, and incidence angle, strongly affect backscattering coefficients (Inoue et al. 2002, Lopez-Sanchez & Ballester-Berman 2009). Direct scattering from the canopy and the soil, double-bounce backscatter between the soil surface and crop canopy, as well as multiple interactions between the vegetation components and the soil, contribute all to the magnitude and scattering characteristics of the SAR response. Therefore, simple linear or nonlinear expressions based only on intensity values fail to adequately express and explain the interaction of microwaves with a complex vegetation-over-soil target. More sophisticated models, such as dual polarimetric decomposition techniques (Jagdhuber et al. 2013a, Jagdhuber et al. 2013b), seem to be necessary to quantify this concept to separate ground scattering from vegetation scattering and studying different vegetation polarimetric mechanisms, e.g. single bounce and/or double bounce, using multi-temporal dual polarimetric TSX data. Our dual polarimetric TSX data suffer from a lack of HV polarization channels, which are related to volume scattering (Cable et al. 2014a). Therefore, a multiple variable stepwise regression approach, i.e., polarization channels and polarization variables, was used to more accurately estimate the LAI of agricultural crops without any input variables, e.g. soil moisture, since theoretical and semi-empirical models need some input variables to calibrate the model. The stepwise models can be built using at least two polarization channels. With such an approach, a priori knowledge of soil moisture is not required in order to estimate LAI. These results demonstrate that combinations of polarization channels and variables using a stepwise approach produce better LAI estimations when compared to simple linear and nonlinear regression, except for barley. This approach was superior to WCM in terms of RMSE, as shown above.

Stepwise regression analysis which uses polarization variables is expected to be a more robust approach than a simple linear or nonlinear regression analysis. Multiple crop variables are required to fully explain variations in backscatter, as explained by McNairn et al. (2002). The same concepts were applied here. The coefficients provided in Tab. 3 suggest that multiple polarization channels are required to better explain variations in crop variables such LAI. As can be observed from Tab. 3, different polarization channels and variables such as HH-VV and HH+VV have been presented in the models discussed above. However, the effect of the VV×HH variable is not fully understood and should be investigated in more detail in the future. It is also worth mentioning that we were not able to study any phase-relation between HH and VV since we were using the MGD data based on intensity only (MGD = Multi Look Ground Range Detected). This means that it was not possible to process the single bounce or the double bounce, or any other polarimetric feature using this format (MGD). The authors predict that the correlation will be even better once one can include true polarimetric indices/information, e.g., entropy/alpha decomposition features or Pauli elements. However, this would require processing the single look slant range complex (SSC) data of TSX.

In the past, many different formulations of the WCM have been proposed (Graham & Harris 2003a). Since there is no general agreement upon the precise setup of the WCM, we used the LAI parameter as the indicators. Because an important part of the scattering and attenuation is determined by the leaves, many studies propose the LAI as a vegetation indicator, e.g. Lievens & Verhoest (2011) and Prévot et al. (1993). There is no general theoretical background defining the best set of canopy descriptors and predicting the values of the A and B parameters (Prévot et al. 1993). For the possibility of inversion, the model should involve as few variables as possible, and its mathematical form must permit inversion (Prévot et al. 1993). The water-cloud model adequately simulated LAI as the canopy developed demonstrating the potential of dual polarimetric X band SAR data for monitoring indicators of crop productivity.

The errors in estimating the LAI parameter of the above crops can be attributed to two different facts: first the complexity of the vegetation structure is difficult to summarize in a bulk vegetation parameter as needed for the WCM (Prévot et al. 1993), second for estimation of LAI, rough estimates of the soil moisture content on a 4 – 5 day basis are sufficient to carry out the retrievals of LAI and obtain useful information on crop growth (Wigneron et al. 1999). However, the authors believe that simultaneous timing of ground-truth sampling with respect to the satellite overpasses can reduce the uncertainties in the estimation of crop-related parameters, i.e. LAI. The acquisition times for the ascending and descending orbits of TSX are different (18:00 hrs ascending pass (± 0.25 hrs), 06:00 hrs descending pass (± 0.25 hrs)). The presence of dew drops in the morning may act to change the dielectric constant of soil and vegetation and, may have directly introduced errors into the soil and vegetation parameters retrieval. However, these error sources are not severe (He et al. 2014).

Each of these approaches has its advantages and disadvantages; the stepwise regression approach does not need the soil moisture as an input variable, but since this approach is empirical, it is site- and study-specific and requires further research to assess robustness for LAI estimation. The stepwise regression approach cannot be used with just one polarization channel. WCM can be implemented with single polarimetric data, but it requires information about soil moisture.

6 Conclusion

In this study, the applicability of X-band TSX (SAR) for estimating leaf area index (LAI) was assessed for three major crops: wheat, barley and canola. The comprehensive analysis of the relationship of X-band multi-temporal dual polarimetric TSX in HH and VV with the LAI variable shows the response of SAR signatures to wheat, barley, and canola canopies. Although the X-band is not the best frequency for monitoring soil and vegetation parameters due to the weak penetration of the canopy and soil, a rather high sensitivity of the polarization channels and variables of TSX sensors to wheat, barley, and canola LAI was observed during this research work using different statistical approaches. We observed that the coefficients of determination of the stepwise and WCM approaches between the polarization channels/variables and LAI were higher than 0.64.

The LAI of barley had a significantly high correlation with the HH/VV variable, and these relationships were consistent throughout all the growth stages. This relationship was expressed by simple linearity with high coefficients of determination. This was most likely due to optimum use of satellite images. Simple linear and nonlinear regressions were not able to estimate the LAI of winter wheat or canola accurately. In addition to the positive results, some of the negative results would be useful for basic studies on backscattering processes and for operational applications of SAR sensors in the future. On the other hand, stepwise and WCM approaches showed their capability for the estimation of winter wheat and canola. The stepwise approach showed its superiority in terms of RMSE. The WCM model was calibrated for the HH, and VV polarizations. These calibrated models were then used to estimate LAI. The root-mean-square error (RMSE), mean-absolute error (MAE) and correlation coefficient (R^2) statistics were used to evaluate the model's accuracy.

The results from both the model calibration and validation confirmed that when using X-band TSX data, the strongest correlations and lowest errors of estimation were found when these two approaches were used. This was true for both winter wheat and canola.

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