COUPLED MODELLING OF LAND SURFACE MICROWAVE INTERACTIONS USING ENVISAT ASAR DATA

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ABSTRACT

In the last decades microwave remote sensing has proven its capability to provide valuable information about the land surface. New sensor generations as e.g. ENVISAT ASAR are capable to provide frequent imagery with an high information content. To make use of the multiple imaging capabilities of those sensors, sophisticated parameter inversion and assimilation strategies have to be applied.
The objective of the presented work is the analysis and quantitative description of the backscattering processes of vegetated areas by means of microwave backscattering models. The effect of changing imaging geometries is investigated and models for the description of bare soil and vegetation backscattering are developed. Spatially distributed model parameterisation is realized by synergistic coupling of microwave scattering models with a physically based land surface process model. This enables the simulation of realistic SAR images, based on bio- and geophysical parameters.
The approach is validated using nine ENVISAT ASAR images. A pixelwise comparison between simulated and observed backscattering coefficients revealed a mean deviation of 0.5 dB with a corresponding standard deviation of 2.8 dB.

1. INTRODUCTION

A prerequisite for sustainable development and management of the limited natural resources of the Earth are integrative analysis and monitoring tools and techniques. Earth observation by means of remote sensing techniques has become a powerful tool for the characterization and description of the biosphere system at regional and global scales. It is therefore an ideal tool to provide necessary geospatial datasets for land surface process models and decision support systems.

Recent operational spaceborne SAR systems as e.g. ENVISAT ASAR and RADARSAT and forthcoming systems as e.g. RADARSAT-II or TerraSAR, allow frequent, multipolarised observations of the Earth surface. Contrary to their predecessors, as e.g. the ERS and JERS satellites, the new sensor generation is capable to acquire data under different imaging geometries. This enables the frequent observation of an area of interest, which is crucial for operational applications as e.g. flood forecasting or disaster management.

Due to the different imaging geometries and highly variable surface characteristics, the interpretation of these multiple datasets becomes more complicated than that of a system with a unique geometry. Sophisticated models and analysis tools, applicable for various sensor types, are therefore needed to analyse and predict the backscattering coefficient in relationship to the current state of land surface variables.

The presented work concentrates on the understanding, separation and quantitative description of the various backscatter contributions. A theoretical land surface microwave backscattering model is suggested for bare soil and vegetated areas. By means of a synergistic coupling approach with a land surface process model, it enables the realistic simulation of SAR images and the spatially distributed comparison with real image datasets.
After a description of the general concept and available datasets, the backscattering models are introduced and validated on the point scale. The approach is then transferred to spatially distributed simulations of realistic SAR images, using the output of a land surface process model to parameterise the microwave backscattering model.

2. METHODOLOGY AND DATASETS

2.1 Testarea and datasets

The investigations for this study were done on a testsite, situated 25 km southwest of the Bavarian Capital of Munich (Germany). It is an heterogeneous agricultural area, mainly dominated by winter cereals and grassland.

A total of 17 ENVISAT ASAR alternating polarisation image products (HH/VV polarisation) were analysed for the study. The images have multiple imaging geometries, covering the entire ENVISAT ASAR swath and were acquired in year 2003 during the crop development.

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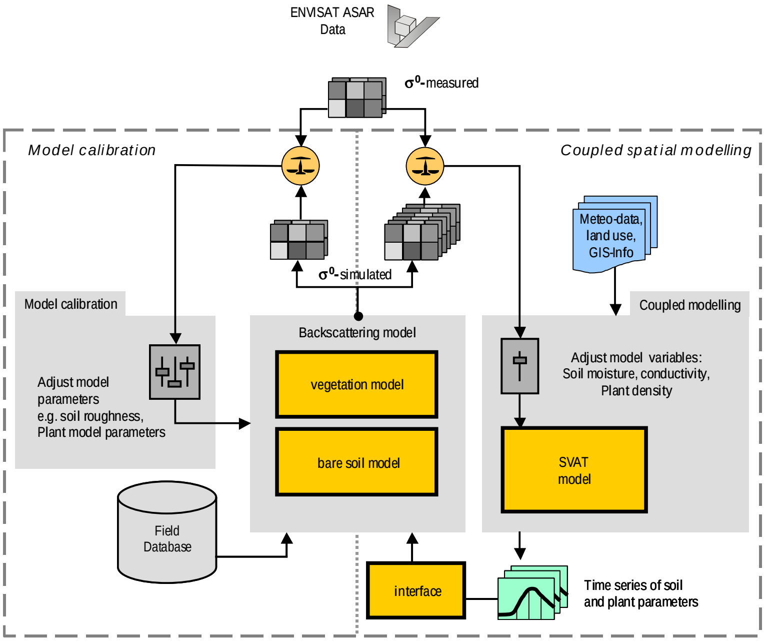

Fig. 1: Calibration of a SAR backscattering model and coupled modelling of land surface microwave interactions

All image datasets were carefully calibrated and terrain geocoded using a rigorous approach [1]. The resulting geocoded images are free of geometric and radiometric terrain distortions.

Extensive ground measurements of soil and plant parameters were carried out during the sensor path. The ground measurements were made for a wheat and a triticale field. Soil moisture was measured in different depths and at various sampling points. The wet and dry biomass of the different plant components (stalk, leaf, fruit) as well as the vegetation height and leaf area index (LAI) were measured.

2.2 Approach

The calibration and validation of empirical surface parameter inversion and backscattering models is difficult for images with multiple imaging geometries as provided by ENVISAT ASAR. Numerous field measurements, combined with ASAR acquisitions would be needed. Even for a minimal specification, the number of necessary ground measurements exceeds the capabilities for ground based data acquisitions. To overcome this problem, a combination of empirical with theoretical backscattering models was chosen for this study. These are calibrated, using a reduced number of ground measurements, and then used for the generalized prediction of the backscattering coefficient for various imaging geometries and ground conditions. Together with a plant growth model, which can predict the plant and soil parameters of heterogeneous areas for each instant, the number of field measurements can be reduced significantly. Such a model can also be used, to provide spatially distributed time series of land surface parameters, needed as input variables for a backscattering model.

Fig. 1 shows the general concept of the presented approach, which is mainly separated into two major parts. The first deals with the derivation and calibration of soil and vegetation backscattering models for various imaging geometries. The models are calibrated and validated using ground measurements and image data. To reduce the number of necessary model input parameters, a bare soil backscattering model is recommended, which requires only two input parameters. This helps to simplify the description of bare soil surfaces and allows the accurate prediction of the bare soil backscatter. A vegetation backscattering model is then calibrated and validated, using available ground measurements and SAR image data. The resulting forward backscattering model allows for a precise prediction of the backscattering coefficient of vegetated areas, based on bio- and geophysical variables.
The second part of the study transfers the developed backscattering models for spatially distributed simulation of the backscattering coefficient in heterogeneous areas. The necessary spatially distributed backscattering model input parameters are provided as output of a physically based land surface process model. The coupling of the backscattering and process models is realized by an appropriate interface. This enables the spatially distributed prediction of the backscattering coefficient based on bio- and geophysical parameters.

3. BACKSCATTER MODEL CALIBRATION

3.1 Bare soil backscatter model

To predict the backscattering coefficient of vegetated areas, the bare soil and vegetation contributions have to be separated. The bare soil backscattering model used for the investigations is a simplified two-parameter bare soil backscattering model developed by [2]. It expresses the backscattering coefficient σ_s of a bare surface as function of a surface roughness parameter A and the surface reflectivity Γ_0 at normal incidence angle as

$$\sigma_s = A(\theta)\, \Gamma_0^{b(\theta)} \quad (1)$$

The dielectric properties of the surface are represented by the surface reflectivity Γ_0 defined as

$$\Gamma_0 = (1-\varepsilon_r^{0.5}) / (1+\varepsilon_r^{0.5}) \quad (2)$$

The empirical parameters A and B can be described as function of the incidence angle. The surface roughness parameter A needs to be estimated empirically or can be derived from multitemporal image datasets. Spatially distributed informations of the surface roughness are derived from ENVISAT ASAR alternating polarization datasets, using the algorithm proposed by [2].

The bare soil model predictions are validated, using four ENVISAT ASAR alternating polarization datasets from spring 2003, where the vegetation cover was still sparse. Soil moisture information was available for the testfields from the ground measurements. The bare soil backscattering coefficients are simulated using Eq. 1 and the soil moisture information and then compared to the image data (Fig. 2). The backscattering coefficients are predicted well for both polarisations. The RMSE between the modelled and measured values is 1.6 and 1.7 dB for HH and VV polarisation respectively and the coefficient of determination exceeds 0.85. The gain of the regression line is near unity.

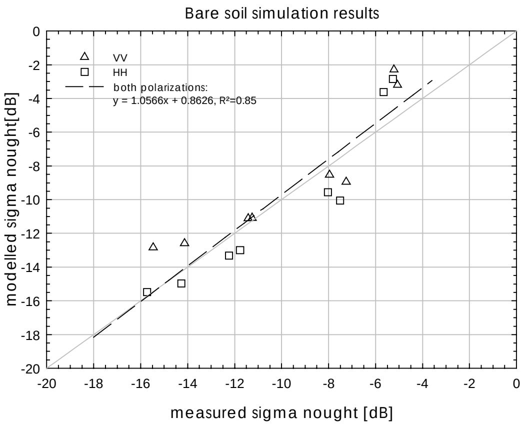

Fig. 2: Bare soil backscatter simulation results

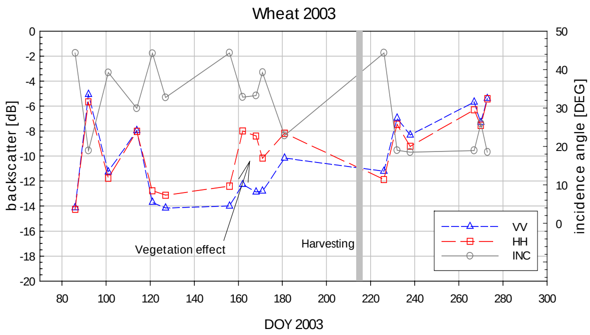

Fig. 3: Temporal development of the backscattering coefficient of a wheat field for both copolarisations and various incidence angles

3.2 Vegetation model calibration

An adequate parameterisation of the vegetation influence on the backscattering signal is mandatory for the modelling of the backscattering coefficient over the vegetation period. Different imaging geometries have to be taken into account in this context, to make use of the multiple imaging capabilities of ENVISAT ASAR.

The changing imaging geometry has a major influence on the signal as can be seen in Fig. 3, where the temporal development of the backscattering coefficient of a wheat field is shown exemplary. Over the entire vegetation period, the backscatter is inversely proportional to the incidence angle (e.g. DOY 156-181). This main mechanism is superposed by the plant development and changing surface soil moisture contents. It can also be observed, that the temporal development of the backscattering coefficient differs for different polarisations. VV is lower than the HH backscattering coefficient, which is caused by the stronger attenuation effects of the canopy, due to the vertically oriented stalks of the wheat plants. The incidence angle effect is stronger for HH than for VV polarisation during the vegetation period, as can be observed on DOY 155-181. A similar incidence angle dependency is also observable for bare soils (e.g. before DOY 120) indicating that soil contributions have a major influence on the HH backscattering coefficient of vegetated areas.

A semi empirical approach is developed to describe the vegetation's influence on the signal (Fig. 4). The method is based on the theoretical modelling of the bare soil backscatter contribution σ_s using the bare soil model given by (1). The necessary soil moisture information is taken from ground measurements. The remaining residuals $\Delta\sigma$ between the measured backscattering coefficient σ^0 and the simulated bare soil backscatter σ_s are analysed and empirically related to the imaging geometry and vegetation parameters. This enables the derivation and calibration of species specific vegetation backscattering models.

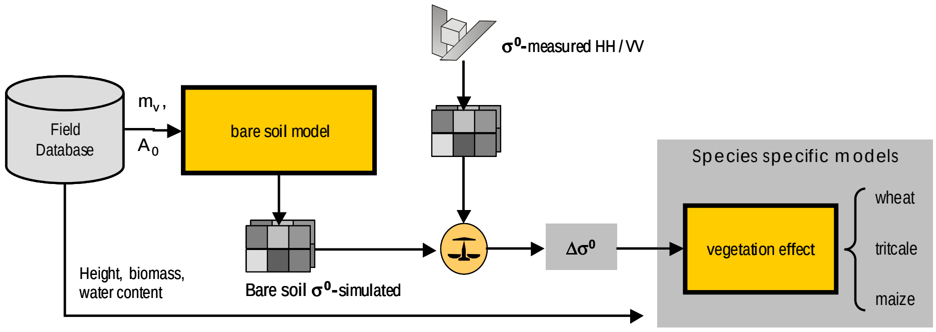

Fig. 4: Calibration of species specific vegetation scattering models using image data and ground measurements

3.3 Relating image parameters to vegetation properties

The distinct, polarisation dependant vegetation interactions can be expressed in terms of the copolarisation ratio *CP*, defined as

$$CP = \sigma_{HH} / \sigma_{VV} \tag{3}$$

This ratio is mainly influenced by the different attenuation and scattering properties of the canopy for different polarisations. The attenuation of the electromagnetic field by the vertically oriented stalks has a major influence for wheat. High values of the *CP* therefore indicate a strong attenuation of the signal in VV polarisation and vice versa. Thus, the copol ratio may be treated as a measure of the extinction properties of the plants which can be directly derived from the image data. As reported by [4], a strong relationship exists between the copol ratio and the vegetation biomass.

The copol ratio *CP* is an ambiguous variable. The same copol ratio can be observed under different conditions. If a low vegetation cover is illuminated by a shallow electromagnetic incident field, the radiation path through the canopy is quite large, resulting in strong interactions with the canopy. The same value of *CP* can also be observed, if the vegetation cover is higher and the incident ray has a smaller incidence angle. Thus the path through the vegetation remains the same. Under the assumption of the same extinction and scattering properties, the copol ratio can therefore not be used to characterize the extinction properties of a vegetation cover in an unambiguous, incidence angle independent, manner.

If the vegetation height *h* and the incidence angle are known, *CP* can be normalized to get a normalized copol ratio CP_N defined as

$$CP_N = CP \cos(\theta)\, h^{-1} \tag{4}$$

This parameter contains information about the intrinsic scattering and attenuation properties of the canopy, as observed by the SAR system. It is independent of the imaging geometry and therefore allows for the multitemporal analysis and comparison of different ENVISAT ASAR images. After [3], the normalized copol ratio can be related to plant biophysical parameters P as absolute vegetation water content or vegetation biomass as

$$\log(CP_N) = a \log(P) + b \tag{5}$$

where a and b denote species specific parameters. Fig. 5 shows the relationship between the normalized copol ratio and the dry biomass for cereals.

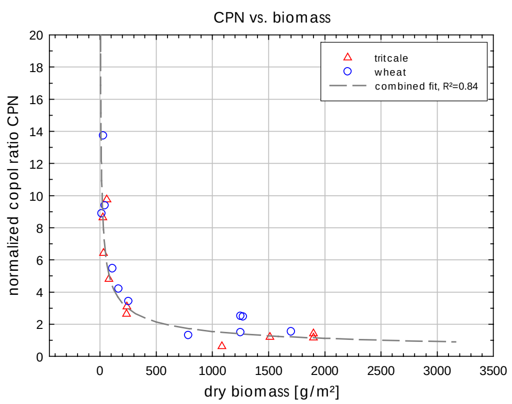

Fig. 5: Relationship between vegetation dry biomass and normalized copol ratio for cereals

The fact, that the copol ratio can be directly related to plant biophysical variables indicates, that it can be used to parameterise the vegetation influence on the signal. Using alternating polarisation data, this information can be extracted from the image data itself. It might also be used to invert vegetation biomass or water content. A priori information about the vegetation height is needed in this context to estimate the normalized copol ratio.

To estimate the influence of the vegetation on the backscattering coefficient, expressed in terms of CP_N, the residuals between simulated bare soil backscatter and observed backscattering coefficients can be used. It can be shown, that stable relationships (R^2=0.93) exist

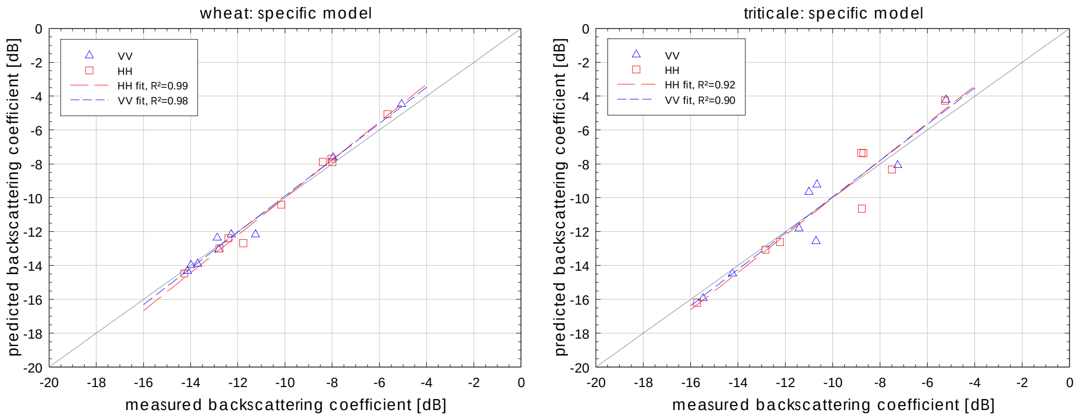

Fig. 6: Simulated and measured ENVISAT ASAR backscattering coefficients for cereals

between CP_N and the backscatter residuals [3]. This allows for the derivation of plant biophysical parameters from ENVISAT ASAR alternating polarization data and enables the accurate prediction of the backscattering coefficient of agricultural areas. The vegetation influence on the signal is compensated, using the copol ratio and additional a priori vegetation height information. Using available SAR images and ground measurements, the microwave backscattering model, consisting of the bare soil model, given by Eq. 1 and the vegetation model, is used to predict the backscattering coefficient of the investigated test fields during crop development. Fig. 6 shows the predicted and measured backscattering coefficients. It can be seen, that the model provides excellent predictions of the backscattering coefficient. The regression lines for both species (wheat and triticale) as well as both polarisations are near unity. The coefficients of determination range from 0.90 to 0.99. The RMSE is 0.4 dB for wheat and 1.1 dB for triticale respectively.

4. COUPLED MODELLING OF LAND SURFACE MICROWAVE INTERACTIONS

Land surface process models can be used for the parameterization of remote sensing models, as e.g. the backscattering models, introduced in the previous section [5,6]. A linkage between those and a physically based land surface process model is established to allow for spatially distributed validation of the proposed backscattering model. A quantitative analysis of the deviations between model results and SAR images is made.

4.1 Land surface process model

The process-oriented land surface model PROMET-V (PROcess-oriented Multiscale Environmental and Vegetation model) was developed to simulate plant growth, water and nitrogen fluxes. A brief introduction and examples for assimilation of remote sensing data in PROMET-V can be found in [5]. It was designed to allow for the spatially distributed modelling of land surface processes. Based on spatially distributed input datasets, it calculates time series of land surface parameters. Its raster structure makes it suitable for comparison and coupling with remote sensing data products. It has been shown, that the model can provide reliable input data series for remote sensing models, and that it can be used for assimilation strategies [5-7].

The land surface process model output variables as e.g. soil moisture are not necessarily applicable as such for the backscattering model where the dielectric constant is needed instead of the volumetric soil moisture. Therefore a functional interface has to be defined which derives appropriate input parameters for the backscattering model from regular PROMET-V outputs. The process model can then be used to predict the state of land surface variables for each image pixel.

4.2 Spatially distributed simulation of the backscattering coefficient

The backscattering coefficient of agricultural fields can then be simulated based on the land surface model outputs for any instance. For a total of nine ENVISAT ASAR acquisitions (see Tab. 1), synthetic SAR images

Tab. 1: ENVISAT ASAR images used for coupled backscatter modelling

DATE	DOY	DIRECTION	INCIDENCE ANGLE [°]
02.04.2003	92	ASC	18.9
11.04.2003	101	ASC	39.2
24.04.2003	114	ASC	29.9
01.05.2003	121	DESC	43.0
07.05.2003	127	DESC	32.7
05.06.2003	156	DESC	43.0
11.06.2003	162	DESC	32.8
17.06.2003	168	ASC	33.2
20.06.2003	171	ASC	39.3

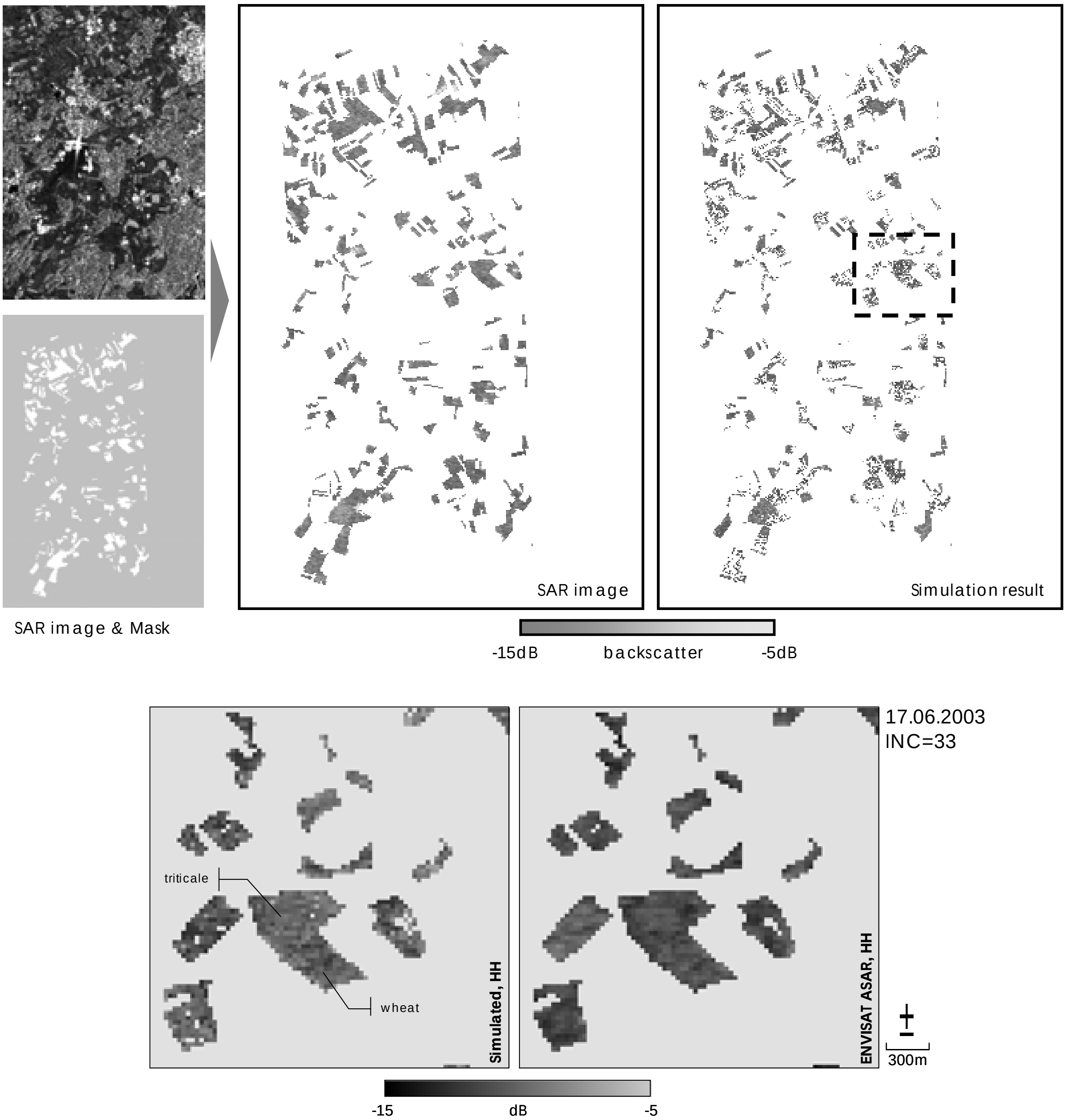

Fig. 7: Simulated and observed SAR image (HH polarisation); the original image is masked to simplify comparisons with the modelling results

are generated, using this coupled modelling approach. It is emphasized that the images cover a wide incidence angle range.

An example of a simulated SAR scene is given in Fig. 7. The fields with available simulation results, corresponding to wheat and triticale, are extracted from the original image dataset for better comparability. It can be seen, that the backscattering coefficients have the same magnitude and even similar features can be observed in both datasets.

The accuracy of the simulated backscattering coefficients is assed by correlating simulated and measured backscattering coefficients and by analysing the residuals. This is done for all dates on a pixel by pixel basis without any filtering applied to the datasets, which is the most sophisticated approach. A total of 35357 image pixels was used for the comparisons. Fig. 8 shows the pixelwise correlation of the simulated and measured backscattering values and the frequency distribution of the residuals for all images used for the investigation. Positive residuals indicate an overestimation of the backscattering coefficient by the model and vice versa.

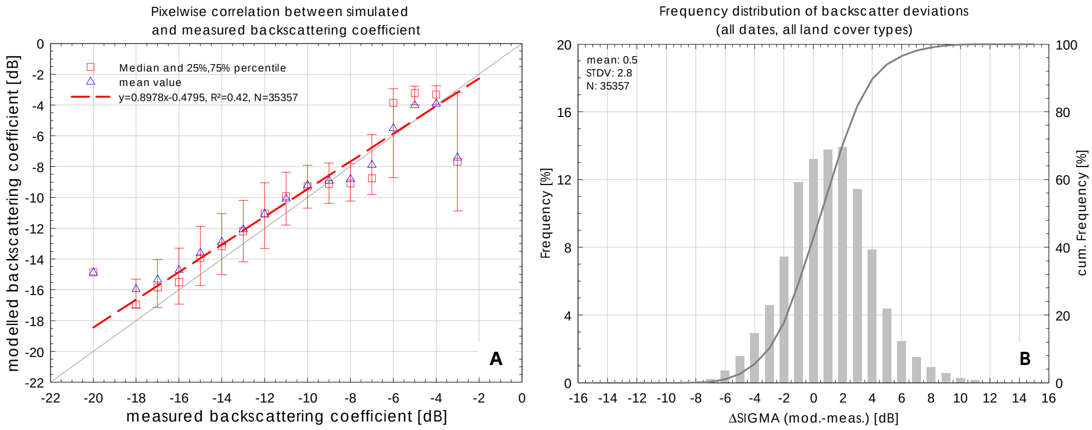

Fig. 8: Pixelwise correlation between measured and simulated backscattering coefficients (left) and frequency distribution of the remaining residuals - analysis for all nine ENVISAT ASAR images

It can be seen, that the backscattering coefficients are generally well predicted by the backscatter model. The gain of the regression line is almost unity. The residuals are normally distributed with an average of 0.5 dB. The residuals have a standard deviation of 2.8 dB. Around 70% of all values are within the interval of ±2 dB. It can be seen from Fig. 8, that the variances are rather similar for the backscatter range, corresponding typically to agricultural fields (-18 … -6 dB).

This indicates, that the model generally provides good estimates of the backscattering coefficient. The simulated input parameters, provided by PROMET-V, have lower dynamics within an agricultural field than in reality. The reason is that the land surface model input parameters as e.g. soil texture are rather homogeneous over larger areas. In reality, the microscale variations of soil hydrological properties are more heterogeneous. Due to similar other input variables, as e.g. temperature and precipitation fields, the land surface model predictions have a lower spatial variance than in reality.

5. CONCLUSIONS

Sensors with multiple imaging capabilities, as e.g. ENVISAT ASAR, are the basis for frequent and accurate monitoring of the environment. A method was presented, being capable to predict the backscattering coefficient of bare soils and vegetated areas over a wide incidence angle range. The vegetation influence on the signal can be assessed using dual polarisation datasets. Spatially distributed modelling of the backscattering coefficient was achieved by a synergistic coupling of the backscattering models with a physically based land surface process model. The method is transferable to heterogeneous landscapes.

Remaining residuals between simulated and measured backscattering coefficients contain valuable informations about imprecise parameterisations of the land surface model and therefore allow for the derivation of land surface parameters and adjustment of spatially distributed parameter sets as e.g. soil texture. This will be a subject of further investigations.

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