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# Radar-based surface soil moisture retrieval over agricultural used sites – A multi-sensor approach

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**Abstract:** Spatial distributed information of isochronal surface soil moisture is very important to compensate the inaccuracy of initial conditions and the uncertainty of parameters in hydrological models at the landscape scale. In this paper the conceptual procedure to derive spatial distributed surface soil moisture values from synthetic aperture radar data by using ancillary optical remote sensing data is presented. Different biophysical vegetation parameters like vegetation water content and leaf area index overlay the soil moisture information on the microwave signal and hamper the application of many existing models. Therefore the objective of the proposed study is to test the performance of artificial neural networks to extract soil moisture information from radar data. Multi- and hyperspectral remote sensing data provide spatial distributed information about above ground vegetation parameters and can thereby used as ancillary network input to support the soil moisture extraction. The results of the study are expected to provide an improved database (initial conditions, plant parameters, etc.) for hydrological models.

***Keywords:*** Surface Soil Moisture; Remote Sensing; Artificial Neural Network

## 1. INTRODUCTION

Synthetic Aperture Radar (SAR) data from satellite may provide robust estimates of spatially distributed surface soil moisture (SSM) values for different applications of distributed hydrological modelling in catchment areas. It has been shown that SSM can be derived with a root mean square error of 3-7 vol.% [Loew et al., 2006; Wagner et al., 2007]. The spatial resolution of information derived from remote sensing data is often similar to or even finer than the scale of distributed model elements; and in many images it is easy to detect spatial patterns visually.

However, especially the vegetation cover and its spatial and temporal dynamics represent a problematic factor for the useful applicability of the most existing methods or models. The scattering behaviour of the radar signal from vegetated areas is thereby not only controlled by the soil dielectric properties but also by the dielectric properties of the vegetation and its geometric structure (leaves, stems, fruits). Over the last three decades fundamental research and many case studies have been performed to handle the active microwave signal in terms of SSM retrieval. Therefore, several different kinds of modelling techniques were performed. Theoretical models like the Kirchhoff Model as well as the prevalently used Integral Equation Model (IEM) [Fung et al., 1992] are electromagnetic backscattering models and describe the radar backscattering as a function of sensor configurations and surface characteristics e.g. soil roughness or soil moisture. The parameterization of these models is very difficult and thus limited for operational applications on large areas. Simultaneously many empirical and semi-empirical models show in fact good results but must be explicitly designed for the research area. Furthermore, these methods require a large ground truth database to adopt simple linear or nonlinear regression analyses [Attema and Ulaby, 1978; Loew et al., 2006; Quesney et al., 2000; Zribi and Dechambre 2003] for a reliable model performance. An alternative solution that hasn't been applied that much for the retrieval of radar-based SSM is the application of an Artificial Neural Network (ANN). ANN techniques are readily available and have the ability to learn the relationships between input and output pairs given in a training phase. After the training, the network can be applied to new sets of input data. The demand on training data is in the most cases extensive and similar to empirical approaches. Hence, the presented study aims at the integration of appropriate other available remote sensing data to provide input information about the vegetation cover.

Based on the described background this paper outlines an ANN based SSM modelling on the basis of SAR data and ancillary optical remote sensing information. In this connection a moderate number of in-situ soil moisture values as well as in-situ vegetation parameters will be used to calibrate several remote sensing based vegetation indices and the network itself. Correlations of remote sensing data and many different bio- and geophysical parameters are in the most cases nonlinear. This is the reason why neural networks are inherently suitable for addressing remote sensing based vegetation and SSM information retrieval especially for input data collections with very different natural background and units.

The primary objectives of this presented study are focused to a) find the optimal set of remote sensing based indices to derive the leaf area index (LAI) and vegetation water content (VWC) information for different cereals; b) describe a moderate way for the ground truth sampling of SSM and vegetation parameters; and c) discuss the application constraints of radar based SSM retrieval.

## 2. MATERIAL AND METHODS

The data, used for the study, consist of space born multispectral and horizontal-horizontal as well as vertical-vertical polarized SAR data. For C-band SAR information ENVISAT-ASAR (Environmental Satellite-Advanced Synthetic Aperture Radar) Alternating Polarization Mode Products obtained by ESA EO Cat-1 Proposal 5086 are applied. SAR X-band data are provided by the new German TerraSAR-X satellite by Proposal HYD0315 through the German Aerospace Centre (DLR). The multispectral information will be obtained from the ASTER instrument on the NASA satellite Terra. Additionally it is planned to obtain further spectral data from the air born hyperspectral sensor AISA by an own flight campaign. The ground truth campaign will take place near the acquisition time of the ASAR data during spring and early summer 2008.

### 2.1 Remote Sensing based vegetation parameter estimation

Subsequently, the retrieval of vegetation parameters from SAR data and optical remote sensing data will be described. LAI and VWC are one of the most important parameters for vegetation canopy characterisation and can be related to different spectral vegetation indices (VI) or the radar backscatter coefficient. Normally multi- or even hyperspectral band information is reduced to a single numerical index on the basis of some spectral intervals. Generally, different VI must be analysed to find the most appropriate one, in terms of phenological stage and soil signal fraction, for simple linear or nonlinear regression modelling of LAI and VWC. Correlation analyses will be applied to quantify the relationship between SAR backscatter coefficient and vegetation parameters.

*SAR based biomass information*

The SAR C-band data can be used as SSM reference data set [Ulaby et al., 1996]. To provide radar based information about the above ground vegetation layer X- band SAR data can be applied. Therefore, the relation of co-polarisation ratios and the biomass respectively the vegetation structure (e.g. LAI) and VWC itself as well as their temporal change during the growing season can be analysed focused on biomass quantifications on the C-band signal.

*LAI information*

Spectral vegetation indices are designed to measure the greenness in which the amount of green leaves and the chlorophyll content plays a major role. Because of differences in canopy density and plant structure itself during the growing season it is obvious that different VI need to be taken into account.

For LAI estimations different VI derived from the multi- and hyperspectral data, e.g. like the Ratio Vegetation Index (RVI), the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Water Index (NDWI) or the Modified Soil Adjusted Vegetation Index (MSAVI) and Modified Soil Adjusted Vegetation Index 2 (MSAVI2), can be analysed focused on their applicability to establish simple linear and nonlinear empirical relationships to model spatial distributed LAI values.

*Vegetation water content information*

Vegetation water content has an important influence on the microwave signal especially at C- and X-band frequencies in terms of scattering and attenuation. By estimating the VWC the accuracy of the final SSM value is more accurate [Jackson et al. 2004, Anderson et al. 2004]. Therefore, different spectral remote sensing indices can be calculated from the ASTER and AISA data to obtain spatial distributed VWC estimations. A performance test to define the most proper indices will at least analyse the Normalized Difference Water Index (NDWI), the Moisture Stress Index (MSI) and the Equivalent Water Thickness of the canopy ($EWT_{canopy}$).

## 2.2 Ground Truth

The ground truth observations will be performed on three testsites in the south of the Parthe catchment in south-eastern Germany. Land management in the catchment is dominated by crop rotations such as winter barley, winter rye and winter rape. Presently five field campaigns in the period of March and June 2008 are planned. Table 1 gives an overview of different sampling variables and the time schedule. Due to the high diurnal dynamics of surface soil water content the corresponding SSM field measurements will take place in three-hours-periods around the ENVISAT ASAR overpass. Measurements will be carried out within the upper 6 cm of the soil surface by using mobile TDR probes. An average of five single measurements will be taken as representative value every 50 m along two or three profiles per testsite (see Figure 1). The profiles are parallel to the machine tracks on the field to ensure the accessibility during later campaigns in the growing cycle. To study the influence of SSM heterogeneity inside an ENVISAT ASAR pixel an extensive in-situ SSM sampling will take place in a defined grid (60m x 60m) on the winter rye field. Therefore 49 additional sampling points will be observed.

**Table 1.** Time table for in-field sampling

| **Variable** | **Time Window around ENVISAT overpass** |
|---|---|
| *Vegetation and Land Cover* | 1 day |
| - Phenological stage | |
| - Plant height | |
| - Stand density | |
| - Leaf Area Index | |
| - Biomass samples, to get fresh and dry weight of stems, leaves and ears | |
| - Spectral Emission | 1 week |
| *Soil Moisture* | 3 hours |
| *Soil and Surface Temperature* | 3 hours |
| *Surface Roughness* | before campaign starts |
| - Row spacing, row direction | |

Field LAI measurements will be performed by using a LI-COR, Inc. (Lincoln, Nebraska, USA) LAI-2000 Plant Canopy Analyzer. A destructive biomass sampling is scheduled to retrieve vegetation water content. Several single plants from different parts of each field will therefore be separated into stems, leaves and ears focused to a) analyse their single influence on the C- and X-band SAR signal and b) to obtain the $EWT_{canopy}$ on the basis of the leave water content information. In the framework of this study the data acquisition from the hyperspectral sensor AISA (Airborne Imaging Spectrometer for Applications) [Mäkisara et al., 1993] shall be tested from a microlight aircraft. For that purpose field spectrometer measurements will be performed for the validation of several hyperspectral indices.

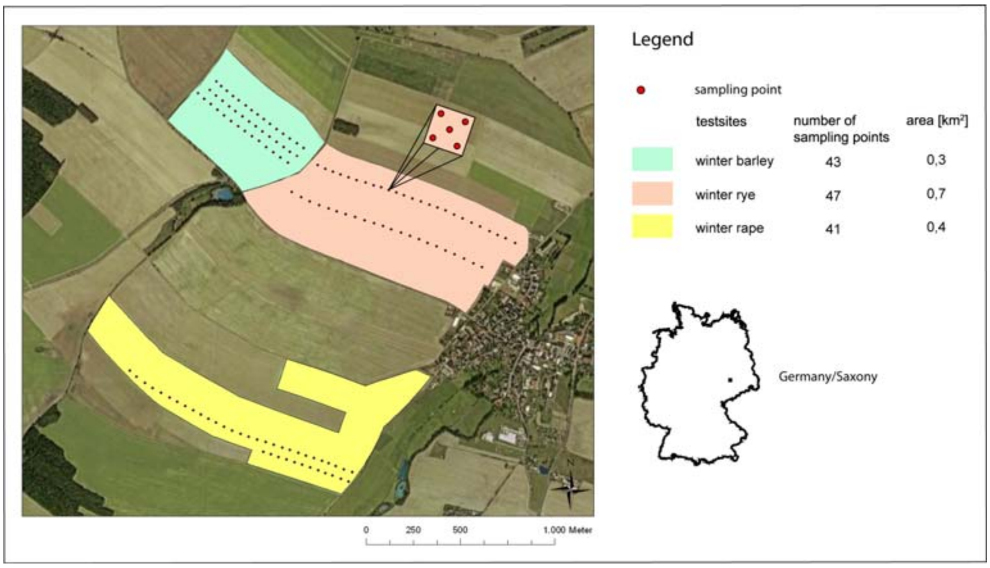


**Figure 1.** Testsites and schematic demonstration of the SSM sampling strategy (map source: Google Earth)

## 2.3 Methodology

All ASAR and TerraSAR-X data sets will pass an automated calibration and geocoding procedure. The rectification will include a digital elevation model to compensate terrain induced distortions. The temporal and spatial variations of the radar backscatter coefficient will be regarded as an influence of soil moisture and vegetation parameters in the case of identical sensor properties (incidence angle, acquisition track). The soil surface roughness will be assumed to be constant due to the fact that winter cereals are cultivated on it and the soil surface remains untilled from sowing during the experiment period until harvest.

Inferring SSM values from the C-band data among using other remotely sensed ancillary information implies that a functional relationship of the different vegetation parameters, the radar backscatter coefficient and the SSM itself must be made. The fact of the dynamics and complexity of many different environmental parameters (e.g. soil moisture, vegetation water content, plant geometry, plant interception) which are interacting to the signal formation limits a mathematical representation and its actual further application, respectively.

Artificial Neural Network training algorithms attempt to find the best nonlinear approximation based on a defined network complexity and structure without the constraint of linearity or pre-defined nonlinear relationships. A supervised network map inputs to the desired outputs by learning the mathematical function underlying the system. With this method it is possible to relate inputs and outputs without any assumptions about the mathematical relations. It is also a proven method to find a proper set of input parameters out of a large number to perform an essential modelling. Figure 2 shows the fundamental NN structure consisting of a M-dimensional input layer, a hidden layer and one output.

In the framework of this study a feed-forward multilayer perceptron (MLP) with some hidden layers of neurons between the input and output is designated. To train the weights of the network the backpropagation learning algorithm will be applied and a sigmoid activation function to introduce nonlinearity will be used. For example Brogioni et al. (2007) presented reasonable ANN based soil moisture results with a regression coefficient of $R^2$ = 0,82 by using only the C-band backscattering as input. An improvement to $R^2$ = 0,91 was obtained by using the backscattering and an ancillary soil surface roughness information.

To train the networks a set of ground truth vectors (GTV) will be created on the basis of the measured data for each testsite. The different inputs are indices adapted from direct ground truth measurements and the radar backscatter coefficients itself, the corresponding output is an aggregated in-situ SSM value. A second and only remotely sensed dataset for applying the learnt rules contains all input vectors where no direct ground truth information for the different indices exists.

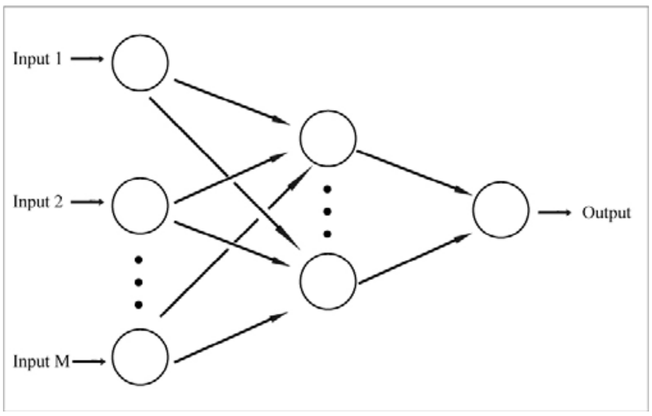


**Figure 2.** Principle Neural Network Structure

## 3. RESULTS

This paper introduces to a multi-sensor based method to derive spatial distributed SSM values through the application of an ANN and is currently under development. Results in form of modelled SSM or analysed empirical relationships of remote sensing data and different biophysical vegetation parameters can not be given yet, because the acquisition of necessary data is planned for the next months.

## 4. DISCUSSION

During the last three decades, many studies were performed to retrieve bio- and geophysical parameters from optical and active microwave remote sensing data. Significant correlations were carried out that provide important input for environmental modelling applications.

Surface soil moisture is highly variable in space and time and plays an important role for many hydrological processes (e.g. infiltration, surface runoff, evaporation) occurring at the land-atmosphere boundary. By proper selection of sensor parameters SAR C-band data mainly depend on SSM even on vegetation covered soils while the attenuation and vegetation contribution itself are larger observed in X- band SAR data [Fung und Ulaby, 1978; Ulaby and Wilson, 1985]. Multispectral and especially hyperspectral data may provide detailed information about vegetation phenological state and condition (e.g. VWC) which is important to quantify the effect of vegetation on the active microwave signal. Hence, the ancillary use of optical remote sensing data encourages radar- based SSM retrieval with a focus on moderate ground truth effort. Unfortunately, the availability of optical images is often limited through cloud cover. Therefore, the potential of X- band SAR data to quantify the effect of vegetation promises a further ancillary possibility to quantify the SSM information on the C-band signal. In general microwave systems, like radiometer and SAR systems, are quite reliable sources for remote sensing data, which is caused by their weather independency. Occurring problems are in the most cases limited to user conflicts by ordering the SAR data in a special sensor mode.

Regarding the complexity of radar signals the problem is that the final backscatter coefficient can be the result of a variety of corresponding conditions and the quantification of the several parameters is strongly hampered through its nonlinear nature. However, neural networks provide the potential to handle complex nonlinear systems and need to get studied and applied in future remote sensing applications especially with focus in minimizing the ground truth effort.

## 5. CONCLUSION

SSM and their spatial variability play a key role for many hydrological processes and are a major factor in watershed science and modelling. Satellite SSM products are an important component for long term observations of the earth surface and provide high potential to perform that task. However, there is a need to improve SSM retrieval from spaceborn SAR in respect of reliability and operational applications. The aim of the outlined project is to prepare an optimal processing chain for multi-sensor (optical and SAR) data and indices to quantify the vegetation content on the C-band SAR signal and to built up a NN based SSM retrieval procedure.

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