ANALYSES OF CHRIS DATA OF THE AQUIFEREX TEST-SITES IN TUNISIA APPLYING RADIATIVE TRANSFER MODELS

Heike Bach1), Silke Begiebing1, Wolfgang Eder 1)
1) Vista Geowissenschaftliche Fernerkundung GmbH, Gabelsbergerstrasse 51, 80333 München, Germany,
Email: bach@vista-geo.de, begiebing@vista-geo.de

ABSTRACT

The evaluation of CHRIS data of the AquiferEx test-sites in Tunisia concerning their information content for advanced land use classifications will be presented. As first essential step, the data need a careful atmospheric correction. A new approach is developed for the two test-sites where atmospheric measurements were missing. The atmospheric parameters i.e. the optical thickness and the water vapour were derived from the CHRIS data themselves using the hyperspectral and directional capabilities of the sensor. The methodology is presented and resulting BRDF functions of this arid region are demonstrated.

The classification approach uses the soil-leaf-canopy reflectance model SLC to interpret the signatures measured by CHRIS. Bio-geophysical land surface properties like LAI and surface soil moisture are retrieved that in a next step are translated into land use classes. Comparison with results obtained from the hyperspectral airborne sensor will be given. Synergistic and complementary use of SAR data is investigated.

1. INTRODUCTION

ESA has initiated several projects in the frame of the TIGER initiative of UNESCO supposed to help African countries to better manage their water resources [http://www.tiger.esa.int/about.asp]. The Aquifer project is one of them, focusing on transboundary water resources management (Saradeth & Weißmann, 2006). The project team is led by GAF AG. For details visit http://www2.gaf.de/aquifer/.

Based on remote sensing data of presently available satellites, Aquifer has defined a consolidated list of required products and services as a result of several meetings and intense discussions with the Aquifer users on their requirements and expectations. Products include land-use and land-cover maps, change maps, surface water extent and dynamics, digital terrain models and estimates of water consumption and extraction. In support of the science product development within Aquifer (e.g. refined land use maps), the AquiferEx airborne campaign has been conducted in Tunisia in November 2005. This campaign was financed by the Data User Element (DUE) of ESA. During AquiferEx two sensors were operated in parallel from the same aircraft, namely the E-SAR sensor of DLR [Scheiber et al., 2007] and the AVIS hyperspectral sensor of the University of Munich (LMU) [Mauser, 2003]. In parallel a ground measurement campaign was conducted with the support of the Tunisian organisations CRDA (Commissariat Regional des Development Agricole) and IRA (Institut des Regiones Arides).

The Tunisian partners selected two test-sites typical for the southern Tunisian Djeffara, i.e. a sub-aquifer of SASS (Systeme d’Aquifer du Sahara Septentrional), which extends across the borders of Algeria, Libya, and Tunisia. The test areas are situated in the Ben Gardane and Gabès regions, each about 10 000 has in size. The AquiferEx campaign was complemented by satellite data acquisitions. Apart from SAR data of ERS and ENVISAT, hyperspectral directional CHRIS data were acquired. The combined analyses of these advanced sensors using a model based approach will be presented.

2. MATERIALS AND METHODS

2.1 Sensors

Two hyperspectral sensors were used for the analyses presented in this paper, CHRIS and AVIS. CHRIS (Compact High Resolution Imaging Spectrometer) on PROBA is the first high-resolution multangular imaging spectrometer in space within an ESA Third Party Mission. CHRIS covers a spectral range of 400 to 1000 nm at a spatial resolution of 17m or 34m. The specific feature of CHRIS is that it allows the acquisition at five observation angles during one data take. This is important for the observation of the bi-directional reflectance distribution function (BRDF) of different surfaces, which describes the change of reflectance with observation geometry and sun position. The airborne AQUIFEREX campaign delivered hyperspectral images from AVIS, the Airborne Visible/infrared Imaging Spectrometer [Mauser, 2003]. AVIS (www.gteo.de) covers a similar spectral range as CHRIS, but with a ground resolution of 4m that allows up-scaling analyses.

2.2 Atmospheric correction

The atmospheric correction is performed using the MODTRAN-4 radiative transfer code in order to simulate the absorption and scattering properties of the atmosphere. The PULREF procedure (Bach & Mauser,
1994) provides the environment to utilise MODTRAN for reflectance retrieval under consideration of the adjacency effect. Although MODTRAN provides a list of pre-defined atmosphere models (e.g. desert), it further requires information on the visibility (optical thickness) and on the relative water vapour content (relative to its nominal value in the model atmosphere) in order to simulate the atmospheric properties correctly. If meteorological measurements like radiosonde profiles are available, this information can be used, however in many regions the available information is not adequate for the parameterisation of the atmospheric conditions. Therefore a methodology was developed and tested that derives this information from the CHRIS scene itself.

For the determination of the water vapour factor the hyperspectral capabilities of CHRIS are used. As illustrated in Fig. 2, the spectral range of the atmospheric water vapour absorption around 940 nm is analysed for this purpose. The reflectance spectra are retrieved assuming a variable set of water vapour factors. An overestimation of the water vapour then leads to a sharp absorption at 940nm whereas an underestimation results in a peak. The water vapour factor that provides the smoothest reflectance curve in this spectral range is then calculated.

In the example in Fig. 2 a value of 1.28 was retrieved. If the SNR of the sensor allows it, the retrieval can be made pixel-wise. For CHRIS however, sensor noise dominates the retrieved water vapour distributions at least in the investigated test-sites due to the spatially low variability of water vapour. Therefore a scene average for water vapour was retrieved and used in the atmospheric correction.

As a second step the directional observation capabilities of CHRIS are used for the assessment of the atmospheric visibility. The concept can be demonstrated most easily for bare soils. Fig. 3 shows how the reflectance of a soil is expected to vary with the 5 observation angles of CHRIS. The spectra are results from the SLC (Soil-Leaf-Canopy) reflectance model (Verhoef & Bach, 2003 and 2007).

The input parameters to SLC comprise structural and physiological information on the vegetation, soil optical properties and the observation geometry. A non-Lambertian soil BRDF sub-model for the soil reflectance and its variation with moisture is incorporated in SLC. The canopy is modelled with a two-layer modernized version of the model SAILH. Reflectances and transmittances of green and brown leaves are calculated using the PROSPECT sub-model.

For the retrieval of the visibility from the CHRIS scene the concept is to first apply the atmospheric correction to retrieve multi-angular soil reflectance spectra under the assumption of different atmospheric visibilities. A kind of ensemble run is conducted. The visibility is then selected within the ensemble by comparing the retrieved BRDF functions with the ones simulated with SLC and determining the most similar one.

Fig. 4 shows an example of such a procedure for the bare soil spectra shown in Fig. 3. One can observe that a visibility of 5km results in a too pronounced BRDF whereas a visibility of 40km is slightly underestimating the BRDF. In this example a visibility of 23km is selected as most realistic.

2.3 Advanced classification concept

Standard land use classifications either label spectral classes determined using an unsupervised classifier, or using a supervised classifier by defining the optical properties of the land use classes with example spectra selected in the scene. These training areas are then used to compare each pixel with, and find the land use class spectrally most similar to the pixel signature. Also visual interpretation is still widely used. For an automatic classification these options are however not adequate.

Therefore a methodology is introduced to use a model based approach for the classification that has the potential to work fully automatic and delivers comparable results also when using different sensors. The concept
Fig. 3: Multidirectional reflectance spectra for bare soil simulated with the Soil-Leaf-Canopy (SLC) reflectance model using the CHRIS acquisition specifications.

Fig. 4: Multidirectional reflectance spectra as retrieved from CHRIS using variable atmospheric visibilities in the atmospheric correction.

is to retrieve geophysical parameters from a scene using RT-model inversion. The retrievable parameters depend on the used sensor. As illustrated in Fig. 5 this varies between optical and SAR data. A GIS based expert system then combines the retrieved geophysical parameters in a land use map.

3. RESULTS

For the geophysical parameter retrieval from hyperspectral data again the SLC model is applied. The optical and geometrical parameters of SLC were adapted according to the spectral and acquisition configuration of CHRIS as well as AVIS. This allows the simulation of surface reflectances as observed with the respective sensor. Via model inversion, land surface parameters like the LAI (leaf area index) are retrieved by minimizing the root mean square error between observation and model result. For the Aquiferex test site a standard vegetation canopy assuming spherical leaf distribution was assumed, applying a characterisation of the optical properties from literature values. Thus only the LAI was allowed to be retrieved for the vegetation layer.

The soil layer had two options to vary. First the substrate could be different since e.g. a ferrous soil differs spectrally from a calcareous surface. Secondly the moisture status was allowed to have two classes, dry and wet. According to the climatic conditions during data acquisition it can be assumed that wet soil is under irrigation.

Examples for vegetation spectra modelled with SLC under variable conditions are illustrated in Fig. 6. It is observable that the dry, bright soil and the wet, dark soil have a strong effect on the canopy reflectance that differs strongly depending on the moisture status even assuming the same LAI.

The model inversion finds the configuration of parameters that brings the simulated spectra closest to the observations. Thus maps of LAI distributions and soil properties result from the hyperspectral analyses. In order to derive a land use map from this information, decision rules need to be established.
3.1 Multisensoral classification concept

How these decision rules could look like is illustrated in Fig. 7 for the Aquiferex test-sites. The land use classes to be separated were defined by the Tunisian users. In the first level cultivated and non cultivated land needs to be separated. Since in this climatic conditions vegetation with a high LAI needs irrigation and is thus cultivated, the LAI can serve as decision criteria here.

The cultivated lands can further be separated in irrigated and non irrigated fields by additionally combining the LAI information with the soil information. If a hyperspectral or SAR observation determines a wet soil, irrigation can be assumed. It must however be noted that multitemporal observations are required in order to identify the complete region under irrigation. Multitemporal analyses are further required in the third level of the classification when temporary and non-temporary / perennial and non perennial land surfaces are to be separated.

Even more complex land use classes can be classified e.g. when texture information from SAR data are used for the detection of olive tree plantations.

---

**Fig. 6: Examples for modelled vegetation spectra on dry, bright soil (left) and dark, wet soil (right)**

**Fig. 7: Proposed expert system for refined classification using multisensoral information (hyperspectral and SAR; land use classes as defined by users)**
Fig. 8: Comparison of model-based classification results of cultivated land differentiating areas under irrigation within the Gabès test-site; CHRIS (Nov 1st), right: AVIS (Nov 9th)

Fig. 9: Multi-sensoral model-based landuse map derived for the Gabès test site
A comparison of the model-based classification differentiating the first two levels in the classification scheme is illustrated in Fig. 8 using the CHRIS sensor as input or AVIS. Both sensors provide pretty much the same patterns in the cultivated land, as well as in the irrigation. Some differences in irrigation can be expected due to the time difference of 8 days between the two acquisitions. With both sensors clear field structure can be observed in the irrigation patterns that illustrate the man-made influences.

A result of the multisensoral classification for the Gabès test-site is shown in Fig. 9. The information from hyperspectral observations is in this case complemented with olive plantations. These can hardly be identified in the hyperspectral data due to the very low LAI values and densities of the olive trees. The SAR sensor is however very sensitive to the vertical structure of the olive stems and allowed a distinct classification of the olive trees especially when using cross-polarized L-band data of E-SAR with a spatial resolution of 2m.

4. DISCUSSION

Based solely on radiative transfer model techniques for the atmosphere (MODTRAN) and the land surface (SLC), it is possible to derive

- the atmospheric properties (water vapour and visibility) needed for reflectance calibration
- bio-geo-physical parameters of the land surface that can be translated into an advanced classification.

Multiangular CHRIS data in full spectral mode are most suitable for this task. Full spectral mode guarantees a high spectral resolution in the water vapour absorption, allowing a more precise retrieval of said parameter. For the derivation of visibility without vicarious data, the BRDF information of the CHRIS data is utilized, since different visibilities change the position of the different spectra for each angle towards each other.

Using the radiative transfer model SLC and the hyperspectral remote sensing data, different soils, cultivated and non cultivated vegetation areas, and irrigated and non irrigated crops could be distinguished. Including additional data E-SAR data, olive plantations could also be classified. For irrigation it has to be said that the remote sensing data show only one moment in time. To classify the complete extend of the irrigated area, time series are necessary.

The developed model based approach showed promising results, but is only a very first step towards a model based automatic land use classification. Further developments, extensions and applications to a wider set of geographical region are necessary in order to make it a general applicable tool.

ACKNOWLEDGEMENTS

ESA kindly supported this activity within the AQUIFER project. Our special thanks go to Stefan Saradeth from GAF AG for coordinating the project. Thanks also to the Aquiferex team of DLR and the University of Munich. ESA provided the CHRIS scenes of this activity within AO2978.

REFERENCES


