> Novel Microwave- and Lidar Remote Sensing Techniques for Monitoring of In-Land Water Resources

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acatech MATERIALIEN – NR. 7

Diskussionspapier für die acatech Projektgruppe
„Georessource Wasser – Herausforderung Globaler Wandel"

acatech
DEUTSCHE AKADEMIE DER TECHNIKWISSENSCHAFTEN

Impressum

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Projekt:
Georessource Wasser – Herausforderung Globaler Wandel

Empfohlene Zitierweise:
Wolfgang Wagner, Michael Vetter, Annett Bartsch: Novel Microwave- and Lidar Remote Sensing Techniques for Monitoring of In-Land Water Resources, acatech Materialien Nr. 7, München 2011.

Reihenherausgeber:
acatech – Deutsche Akademie der Technikwissenschaften, 2011

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ISSN: 2191-8481/ISBN: 978-3-942044-12-7

Redaktion: PD Dr. Knut Kaiser, Monika Damm
Layout-Konzeption: acatech
Konvertierung und Satz: Fraunhofer-Institut für Intelligente Analyse- und Informationssysteme IAIS, Sankt Augustin

CONTENT

FOREWORD

This report was prepared in response to a request from the project "Geo-resource Water – The Challenge of Global Change" of the German Academy of Science and Engineering (acatech[1]). The overarching objective of this project is the development of a strategy for sustained water resource management under the conditions of global change, whereas the geographic focus of the project is on sensitive regions in Germany[2]. The aim is not to carry out original research, but to create a synthesis of existing research results in order to identify gaps in our knowledge and technology. The project shall deliver impulses for the research community and recommendations for policy makers, administration and industry.

Within the context of this acatech project, this report discusses some recent advances made in microwave- and lidar remote sensing in support to monitoring and assessing of in-land water resources. The intention is not to provide an all-encompassing state-of-the art-review, but rather it represents an attempt to identify gaps in our scientific understanding and barriers to a successful implementation of operational earth observation capacities for monitoring of water resources.

While much of the material presented in this report is original, some chapters are based on journal papers or reports authored or co-authored by Michael Vetter, Annett Bartsch and myself. These sources are listed at the end of the report. All graphics shown in this report were produced within the framework of projects carried out by TU Wien and I would like to thank Markus Hollaus, Christine Gschöpf, Stefan Schlaffer, Hubert Lehner, Luca Brocca, Gottfried Mandlburger, Sebastian Hahn, Marcela Doubkova, Richard de Jeu and Wouter Dorigo for kindly providing the figures. I also would like to thankfully acknowledge the financial support from the Austrian Space Applications Programme, ESA, EUMETSAT, European Commission, and the Austrian Science Fund.

1 http://www.acatech.de/
2 http://www.acatech.de/uk/home-uk/work-and-results/current-projects/water-as-a-geo-resource.html

1. INTRODUCTION

Observing and monitoring the different components of the global water cycle and their dynamics are essential steps to understand the climate of the Earth, forecast the weather, predict natural disasters such as floods and droughts, and improve water resources management (Su et al. 2010). Therefore, many of the essential variables governing the water cycle, such as precipitation or river discharge, are regularly recorded using ground based observation networks. Yet, ground based observations often do not adequately capture the high spatio-temporal variability of atmospheric- and land surface processes governing the water cycle. Therefore, it is important to complement the in-situ networks with airborne data and satellite observations.

The importance of earth observation (EO) for monitoring of the water cycle will increase as little doubt remains that climate change, in combination with continued population growth and economic development, will have strong impacts on the global water cycle. For example, projections indicate decreasing water availability in many regions of the world, manifest as reductions in river discharge, ground water resources and soil moisture (Gerten et al. 2007). In Europe, it is estimated that the number of areas and people affected by droughts went up by almost 20 % between 1976 and 2006. One of the most widespread droughts occurred in 2003 when over 100 million people and a third of the EU territory were affected. According to a Communication of the European Commission[3], the cost of the damage to the European economy was at least € 8.7 billion. The total cost of droughts over the past thirty years amounts to € 100 billion. The yearly average cost quadrupled over the same period.

Public concerns about the geo-resource "water" were recently also expressed by the journal *Nature* which devoted in March 2008 a special news feature to the topic of "Water under Pressure". As more than a billon people in developing nations lack access to safe drinking water, and more than 2 billion lack proper sanitation, *Nature* highlighted that our planet is already facing a water crisis in public health. And in the near future, water shortages are likely to spread into other key sectors – notably agriculture and energy – as well. In fact, the recent price surges of agricultural crops may already be interpreted as signs for the strong interdependencies of water resource issues, agriculture[4] and energy markets. Besides increased global food demand, speculations, poor harvests (e.g. caused by the 2007 droughts in Ukraine and Australia) and the introduction of biofuels are seen as the main reasons why food prices have doubled over the last couple of years[5].

Equally perturbing is how floods and other hydrometeorological disasters – may it be for reasons of population growth, poor management or the severity of the natural disasters themselves – are increasingly affecting the life of more and more people. Large events may affect several millions of people, killing hundreds to thousands of the most vulnerable (Table 1). Also, economic damages have been increasingly significantly over the past decades[6]. Despite this, disaster alert and response systems are often not well developed or lacking at all, as the flood in Pakistan and the drought induced fires in Russia have once more demonstrated in 2010.

Table 1: Top six most important flood disasters for 2009 sorted by numbers of total affected people at the country level. Source: "EM-DAT: The OFDA/CRED International Disaster Database, www.em-dat.net – Université Catholique de Louvain - Brussels - Belgium", created on: Aug-26-2010, data version: v12.07.

COUNTRY	DATE	NUMBERS OF TOTAL AFFECTED PEOPLE
China P Rep, General Flood	01.07.2009	39372000
China P Rep, General Flood	01.04.2009	5630000
India, General Flood	25.09.2009	2000000
India, General Flood	July 09	1886000
Brazil, General Flood	22.04.2009	1150900
Viet Nam, General Flood	03.07.2009	700000

This short discussion shows that operational earth observation capabilities for monitoring of the water cycle are much needed. Fortunately, the capacity of earth observation to observe different components of the water cycle accurately and in an operational fashion has greatly improved over the past decade. But considering the significant investments in space technol-

3 Communication COM(2007) 414 final from the Commission to the European Parliament and the Council on "Addressing the challenge of water scarcity and droughts in the European Union".
4 The major link between food and water crises is irrigated agriculture which produces a large portion of the world food supplies.
5 Washington Post, 04/06/2008, "World's hungry look for hope from food summit".
6 The costliest natural disaster was Hurricane Katrina which caused the flooding of New Orleans in 2005. Costs were estimated to be US$ 129 billion.

ogy[7] and the maturity of the remote sensing community, one should nevertheless be surprised that there are not yet more operational earth observation services available. The problem does not appear to reside in the space infrastructure (on average, one remote sensing satellite is launched almost every other week[8]), but in the shortage of high-end processing infrastructure which is required to transform the satellite measurements into geophysical parameters and to assimilate them in application-specific models. Therefore there is a certain risk that the high potential of existing and planned EO missions will not be properly tapped.

The report aims to identify the gaps in our knowledge and technology that stop us from using earth observation more effectively. The discussion will focus on microwave- and lidar remote sensing techniques which promise to bring about significant advances in monitoring of in-land water resources within the next tens years.

7 According to the European Space Policy Institute (ESPI) the total institutional spending on space in 2009 was about $ 67.8 billon (Pagkratis, S. 2010. Space Policies, Issues and Trends in 2009/2010. ESPI Report 23, European Space Policy Institute (ESPI), Vienna), whereas about $ 5 billon were spent on civil government earth observation activities (estimate for the year 2008 cited by International Telecommunication Union, http://www.itu.int/, based on the Euroconsult report "Satellite-Based Earth Observation - Market Prospects to 2018" published in 2008).

8 About 260 civil earth observation satellites are expected to be launched between 2009 and 2018, compared to 128 in the period 1999-2008 (source Euroconsult report "Satellite-Based Earth Observation - Market Prospects to 2018" published in 2008 cited by International Telecommunication Union, http://www.itu.int/).

2. RECENT TRENDS IN REMOTE SENSING

Space age, and with it the era of earth observation, began in the 1950s with the launches of Sputnik-1 on October 4, 1957 by the Soviet Union (Kramer 2002) and Explorer 1 on January 31, 1958 by the United States (Neufeld 2009). Sputnik's beeping radio signals did not only serve to demonstrate the technological capabilities of the Soviet Union, they were also used to gather information about the electron density of the ionosphere. Likewise, Explorer 1 was in the first place a technology demonstrator, but it also carried a cosmic ray detector designed to measure the radiation environment in Earth orbit. In legacy of Sputnik and Explorer 1, most of the Earth observation satellite missions that were to follow served multiple purposes. Unfortunately, up to this day, political and technological motives may be more important drivers for the design of remote sensing missions than the requirements and needs of the geoscientific community (Wagner et al. 2009d). It is probably for this reason that remote sensing continues to be underutilized in many Earth science applications. Hydrology and water resource management are not an exception.

This mismatch of technological capabilities and use of remotely sensed data has increasingly been recognised in the 1990s (Wagner et al. 2009d). Consequently, an increasing number of space-related programmes with the goal to bridge the gap between remote sensing data providers and users have been initiated. In Europe the most important programme is GMES[9] (Global Monitoring for Environment and Security), a joint programme of the European Commission (EC) and the European Space Agency (ESA) designed to establish a European capacity for the provision and use of operational information for monitoring and management of the environment and for civil security. At the international level GEOSS[10] – the Global Earth Observation System of Systems – aims at creating a comprehensive, coordinated and sustained observation system, in order to improve monitoring of the state of the Earth, increase understanding of its processes, and enhance prediction of the behaviour of the Earth system. It is within this international context that significant advances have been made in recent years that made remote sensing more useful to the user. In particular the range of geophysical products retrieved from spaceborne and airborne remote sensing data has now much expanded beyond the traditional land cover maps and digital elevation models. Of relevance to the hydrologist and water resource manager are, for example, highly dynamic land surface parameters such as soil moisture, evaporation, snow cover, and freeze/thaw status, and seasonally varying land surface features such as vegetation structure or hydrodynamic roughness.

Yet, there are still many political and scientific concerns. From a scientific point of view the accuracy of the products and their error characterisation needs to be improved. Also, it is often not well understood if and how remote sensing data can be used for solving hydrologic problems, such as e.g. formulated by the PUB (Prediction in Ungauged Basins) initiative (Sivapalan et al. 2003). From a political point of view, the problem is that the development of geophysical parameter retrieval services is still not funded at an adequate level. Still today, more than 90 % of the funding is normally used only for the development of the spacecraft and the ground segment. Too little is thus left to develop higher-level EO products that can be taken up by the user community. One example for these problems is the Sentinel programme currently under development within the framework of the GMES programme. While funding for the different Sentinel spacecrafts and ground segment is already largely secured, no concrete planning exists for the development of higher level EO data production chains. Given that the first few Sentinel satellites are planned to be launched in the 2012-2014 time frame this will mean that during the first few years of Sentinel operations there will be only very limited capability to uptake these new and very valuable observations by the different applications.

The strong imbalance of funding for the satellite segment and the higher-level ground segment thus continues to be the most important barrier to the successful use of novel EO data in the applications[11]. This problem is aggravated by quasi exponentially growing data volumes. So far, advances in the information technology (IT) sector have always made it possible to cope with the latest sensor technology. Having faith in Moore's law, most remote sensing experts also do not worry too much about the rapidly increasing EO data volumes. But the fact is that already today there are not enough facilities for near-real-time processing and distribution, and not to speak of meeting the needs for reprocessing. Again, one example is mentioned to highlight this

9 http://www.gmes.info/
10 http://www.earthobservations.org/index.html
11 For airborne systems this is usually not a problem because airborne remote sensing activities are more market oriented, i.e. airborne campaigns are carried out if there is a clear and identified need for a remote sensing data product, e.g. a digital terrain model or a topographic map.

problem: Currently, the German Remote Sensing Data Center (DFD) has probably the largest storage and processing capabilities in Europe, supporting several satellite missions (German missions TerraSAR-X, TanDEM-X, EnMAP; European missions ERS, ENVISAT, MSG, Sentinels; and the international missions IKONOS, NOAA-Series, Terra, and Aqua[12]). Within the next 2-3 years DFD plans to upgrade its storage capacities to several tens of Peta Byte[13]. While this is an impressive number, one needs to consider that already one of the Sentinel missions, Sentinel-1, can be expected to create a data volume (raw data plus higher level products) of 2-3 Peta Byte per year. So even for DFD it would be a significant challenge to free sufficient IT resources for storing and processing of the complete Sentinel-1 data set, while most universities, research organisations and private companies will not stand a chance.

Data storage capacities are only one worrying aspect of the rapidly increasing EO data volumes, processing costs and speed are other reasons for concern. Concerning processing speed it is essential to make use of distributed processing capabilities. Distribution can be applied at different levels, ranging from hardware (massively parallel processing CPU architectures), operations system (processes over multiple CPUs), network (Grid/Cloud job distribution protocols) to application level (distribution of processing requests to processing nodes). The selection of the applicable distribution models depends on various aspects such as the parallelism of the processing algorithm, available network infrastructure and policies, and the data transfer rates (input/output data distribution versus processing distribution). From a technological point of view the problem is certainly solvable but one needs to be aware of the higher IT infrastructure- and software development costs.

[12] http://www.dlr.de/caf/en/desktopdefault.aspx/tabid-5280/8852_read-15882/. Access on 3/12/2010.
[13] Personal Communication, Dr. Erhard Diedrich, Head of International Ground Segment of the German Remote Sensing Data Center (DFD), October 2010.

3. MICROWAVE REMOTE SENSING

3.1 SENSORS AND TECHNOLOGICAL TRENDS

In microwave remote sensing, one distinguishes active and passive techniques. Active microwave sensors (altimeters, scatterometers, synthetic aperture radars) transmit an electromagnetic pulse and measure the energy scattered back from the Earth's surface. For passive sensors (radiometers), the energy source is the target itself, and the sensor is merely a passive receiver (Ulaby et al. 1982). Radiometers measure the intensity of the emission of the Earth's surface that is related to the physical temperature of the emitting layer and the emissivity of the surface. Despite the different measurement processes, active and passive methods are closely linked through Kirchhoff's law which, applied to the problem of remote sensing of the Earth's surface, states that the emissivity is one minus the hemisphere integrated reflectivity (Schanda 1986). Therefore, both active and passive techniques deal in principle with the same physical phenomena, though the importance of different parameters on the measured signal may vary depending on the sensor characteristics (Wagner et al. 2007a). Microwave sensors may operate in one or more frequency bands, which are designated by letters. For land surface studies, the most important bands are: L-band (1-2 GHz), C-band (4-8 GHz), and X-band (8-12 GHz).

For all four instrument groups (altimeters, scatterometers, synthetic aperture radars, radiometers) there are now well established sensor heritage lines. For example, the United States has been operating multi-frequency radiometers with (almost) no interruptions since 1978. Europe has been flying C-band scatterometer and synthetic aperture radar (SAR) instruments since 1991 also with few interruptions. In addition to these established sensor lines, there is an increasing number of specialised microwave instruments that cross the border between these four traditional instrument groups. A good example is the Synthetic Aperture Interferometric Radar Altimeter (SIRAL) on board of ESA's CryoSat satellite which combines different microwave technologies to measure surface elevation with a high spatial resolution (Wingham et al. 2006). The technical design of these specialised instruments is typically pushed to a limit to achieve the best possible sensitivity of the measurements to the parameters of interest while maximising the spatio-temporal sampling. As technology demonstrators these instruments normally receive significant attention by both the scientific community and the public. However, from an application point of view one needs to be aware that it often takes many years before a new sensor type delivers data of high-enough quality to be of use in applications. Also, the technical characteristics of such new instruments normally undergoes several cycles before a stable design is reached. Thus, from an application perspective it may be more attractive to use data derived from established sensor lines, even though these data may be of lesser quality than the one from the new instruments.

In the following, the current state of art in microwave remote sensing to derive four hydrologic land surface parameters is described (soil moisture, snow, freeze/thaw, water surfaces). The retrieval of soil moisture is discussed in more depth than for the other parameters.

3.2 SOIL MOISTURE

The degree to which active and passive sensors offer different capacities for soil moisture retrieval has been an important research question since the first experiments with both sensor types in the 1970s (Eagleman and Ulaby 1975). Nowadays the dominating scientific view is that passive sensors are preferable over active sensors because the impact of roughness and vegetation on the observed signal can be more easily modelled in the passive case (Kerr 2007; Bindlish et al. 2009; Piles et al. 2009). This is because radiometers observe the non-coherent radiation emitted by the land surface (emanating from many directions from the sub-surface soil layer), while radars utilize a bidirectional coherent measurement process. Due to the coherent measurement principle of radars, the superposition of waves reflected by scatterers at the earth's surfaces leads to a high sensitivity of the measurements to the geometric arrangement of the scatterers and quasi unpredictable signal fluctuations which are referred to as "speckle" in synthetic aperture radar (SAR) imagery (Oliver and Quegan 1998). As a result, active measurements are very sensitive to the roughness of the soil surface (Verhoest et al. 2008) and the structure of the vegetation (Balzter 2001). Research has shown that the influences of surface roughness and vegetation on the backscattered signal are comparable or larger than the influence of soil moisture (Ulaby et al. 1986; Satalino et al. 2002). Nevertheless, all this does not mean that active measurements are less sensitive to soil moisture than passive measurements, it just appears to be more difficult to model backscatter than emissivity. Thus, if robust backscatter models that provide a good representation of the physical measurement process can be formulated then there is no reason to believe that active sensors should perform less well than passive sensors.

Another strong current scientific preference is for sensors operating at L-band (λ = 20 cm) because in many field and airborne experiments the best results were obtained in this band (Calvet et al. 2010). This is because longer wavelengths tend to penetrate vegetation and the upper soil layer better than shorter wavelengths (Wagner et al. 2007a). By choosing long wavelengths the sensitivity to the sub-surface soil moisture content can thus be maximised. However, using a longer wavelength also means that the antenna beamwidth and wave spreading losses increase (Ulaby et al. 1982). Thus satellite engineers must find a good trade-off between the wavelength and other sensor specifications, most importantly the spatial resolution, the on-board energy supply, and the radiometric accuracy. In other words, using longer wavelengths to enhance the sensitivity to soil moisture may lead to a lower spatial resolution, less frequent sampling and/or a poorer radiometric accuracy. Therefore, longer wavelengths do not automatically lead to "better" retrievals; rather it is a question of which signal-to-noise ratio can be achieved given a pre-defined spatio-temporal sampling. This is probably the reason why wavelengths longer than L-band (e.g. P-band) have not yet been seriously considered for spaceborne soil moisture missions.

As a result of the two current scientific preferences, the first two spaceborne missions that have been specifically designed for the purpose of soil moisture mapping rely (predominantly) on passive L-band measurements (Tsang and Jackson 2010). The first mission is the Soil Moisture and Ocean Salinity (SMOS) satellite that was launched in November 2009 (Kerr et al. 2001, 2010). The second one is the Soil Moisture Active Passive (SMAP) mission that is planned for launch in the 2014/15 timeframe (Entekhabi et al. 2010a). Nevertheless, also significant progress has been made in retrieving soil moisture from existing active and passive microwave instruments (Wagner et al. 2007b; de Jeu et al. 2008). The different sensors and techniques will be discussed in the following sections.

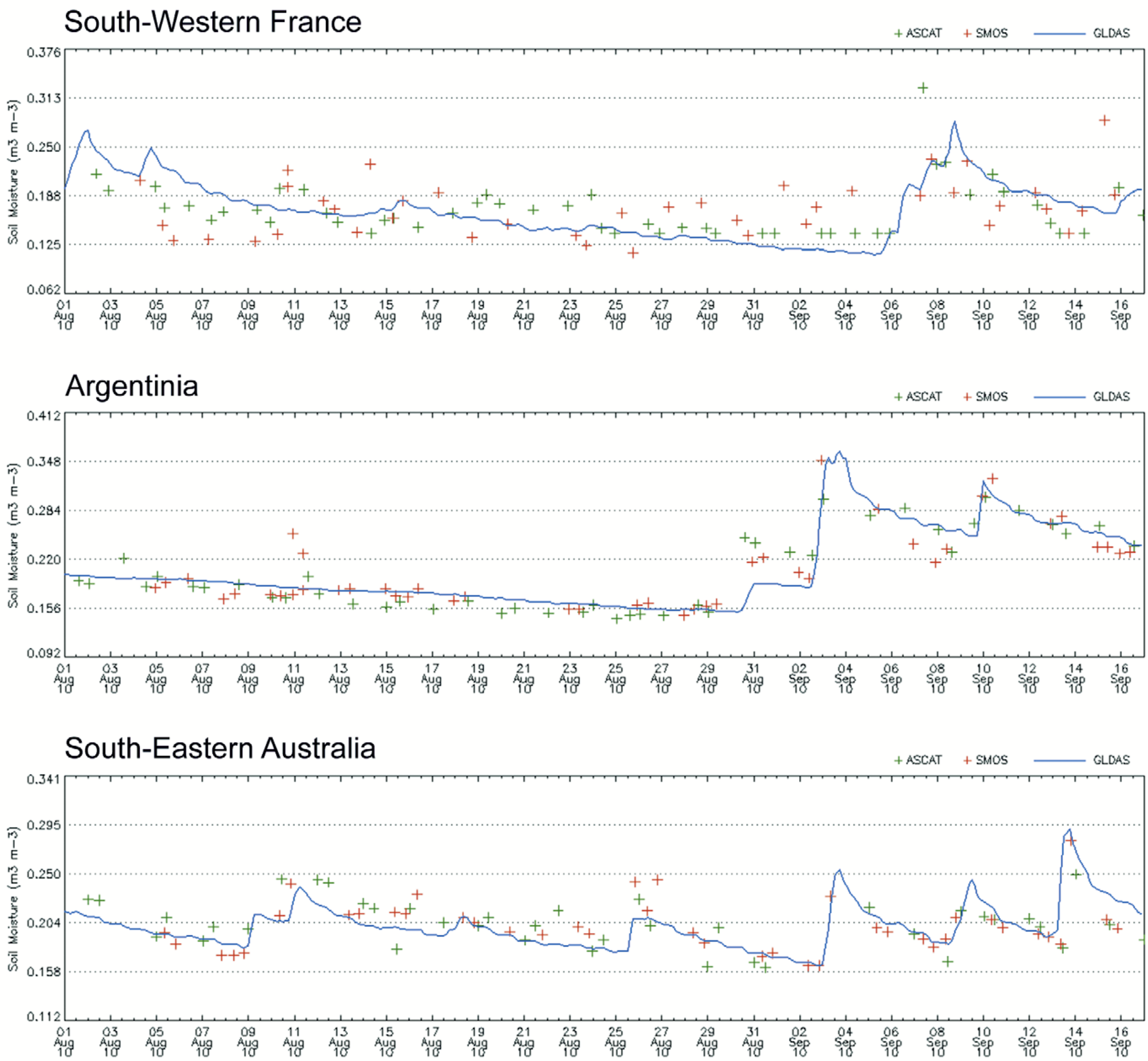
3.2.1 SOIL MOISTURE AND OCEAN SALINITY (SMOS)

The Soil Moisture and Ocean Salinity (SMOS) mission is the second Earth Explorer Opportunity mission of the European Space Agency (ESA) and was launched successfully on 2 November 2009. Because at L-band the spatial resolution of standard-size real-aperture radiometers is in the order of 100 km or even larger, SMOS uses as first satellite an interferometric design inspired by the very large baseline antenna concept used in radio astronomy (Kerr et al. 2001). SMOS uses a L-band 2D interferometric radiometer (1.4 GHz, 21 cm) to measure dual or fully polarized brightness temperatures at multiple incidence angles (-10 to +60 degrees) (Kerr et al. 2010). The satellite files in a polar sun-synchronous (6 am/6 pm) orbit and the swath is about 1000 km, meaning that global coverage is achieved every 2-3 days. The spatial resolution varies between 30 and 50 km depending on the position of the pixel within the swath, but nevertheless, all data are (over-)sampled to a discrete global grid (Ico-sahedron Snyder Equal Area Hexagonal grid) with a pixel spacing of 15 km.

The retrieval of soil moisture from SMOS brightness temperature data is challenging due to the (yet) limited knowledge of L-band processes at 50 km scale (Delwart et al. 2008). To deal with the many unknowns and to offer a sound physical solution for the retrieval of bias-free soil moisture data, it was decided to use a process-oriented radiative transfer model called L-MEB (L-band Microwave Emission of the Biosphere (Wigneron et al. 2007)). The retrieval is performed through an iterative procedure, minimising a cost function computed from the sum of squared weighted differences between measured and modelled brightness temperature data for all available incidence angles. To account for the strong heterogeneity of the land surface, the different cover types (bare soil, vegetated areas, open water, urban areas, etc.) present within the SMOS footprint are estimated from high-resolution land use maps. Brightness temperature data at SMOS pixel scale are thus computed by aggregating simulated values for each land cover type. Thus the algorithm requires a large number of auxiliary data, including static layers such as land cover and soil maps, and dynamic variables such as soil moisture, soil temperature and Leaf Area Index (LAI) to initiate the iterative retrieval process. Additionally, auxiliary data on surface water extent, topography, snow, and soil freezing are used for quantifying respectively masking non-valid retrievals.

Results from the first year of SMOS operations were presented at the SMOS Validation and Retrieval Team Workshop held at the European Space Agency in Frascati, Italy, on 29-30 November 2010. The workshop showed that despite several changes in the calibration the SMOS synthetic aperture processor already delivers brightness temperature measurements with an accuracy that is within instrument specifications (1.5 K at bore sight and 2.5 K at the edge of the swath). The biggest problem so far is Radio Frequency Interference (RFI), which is very strong over Europe, Asia and the Middle East despite the fact that SMOS works in a protected frequency band (Delwart et al. 2008). Some of the European RFI sources (terrestrial radars, illegal TV and radio links, etc.) have already been identified and shut down but since it will not be possible to deactivate all RFI sources, investigations are currently underway to identify and discard RFI affected measurements.

Figure 1: Comparison of SMOS (red/gray crosses), ASCAT (green/black crosses) and GLDAS (blue/black line) soil moisture time series for August-September 2010 for three locations in south-western France (43.78°N, 0.15°E), Argentina (36.58°S, 60.89°W), and south-eastern Australia (33.98°S, 146.52°E).



With respect to soil moisture, the workshop showed that the first SMOS retrievals are already comparable to soil moisture data derived using existing active and passive microwave instruments. As shown in Figure 1 SMOS soil moisture time series compare e.g. very well with soil moisture data retrieved from Advanced Scatterometer (ASCAT) backscatter measurements and modelled soil moisture data from the Global Land Data Assimilation System (GLDAS). These results are of course preliminary and with improvements in instrument calibration and retrieval, SMOS retrieval accuracy will also improve.

3.2.2 SOIL MOISTURE ACTIVE PASSIVE (SMAP)

The Soil Moisture Active Passive (SMAP) mission will be NASA's response to SMOS. It is based on the design of the Hyrosphere State (Hydros) mission (Entekhabi et al. 2004) which was cancelled in 2005 due to NASA budget constrains. Like for SMOS, L-band was chosen for enhancing the sensitivity to soil moisture. But instead of using a passive interferometric design to improve the spatial resolution, SMAP will use a large (6 m) parabolic reflector antenna that will rotate with 14.6 revolutions per minute (rpm) around the spacecraft's nadir axis. The use of a real aperture antenna is expected to provide more accurate brightness temperature data (1.3 K) with a spatial resolution of 40 km (Entekhabi et al. 2010a). Due to the size of the antenna, deployable mesh reflector technology, which was initially developed for spaceborne communications applications, is critical for the success of SMAP (Spencer et al. 2009). In addition to the passive measurements done at 1.4 GHz, SMAP will also make concurrent radar measurements at 1.26 GHz. Both the radar and the radiometer will share the parabolic mesh reflector and a single feedhorn. The radar employs pulse compression in range and Doppler discrimination in azimuth to achieve sub-footprint resolution (360 m at the swath edge to about 1.2 km at a distance of 150 km from the ground track).

Currently NASA plans to have two SMAP surface soil moisture products: one with a spatial resolution of 40 km derived solely from the passive measurements and one with 10 km derived by combining the passive and active measurements. No higher resolution soil moisture product based solely on the 1-3 km Level 1 backscatter measurements is currently foreseen. Like for SMOS the retrieval of soil moisture from the SMAP brightness temperature data will be based on radiative transfer theory (ω-τ model), but it seems that a more parsimonious forward model such as described by Jackson (1993) and Laymon et al. (2001) will be used (Crosson et al. 2010).

3.2.3 SCATTEROMETERS

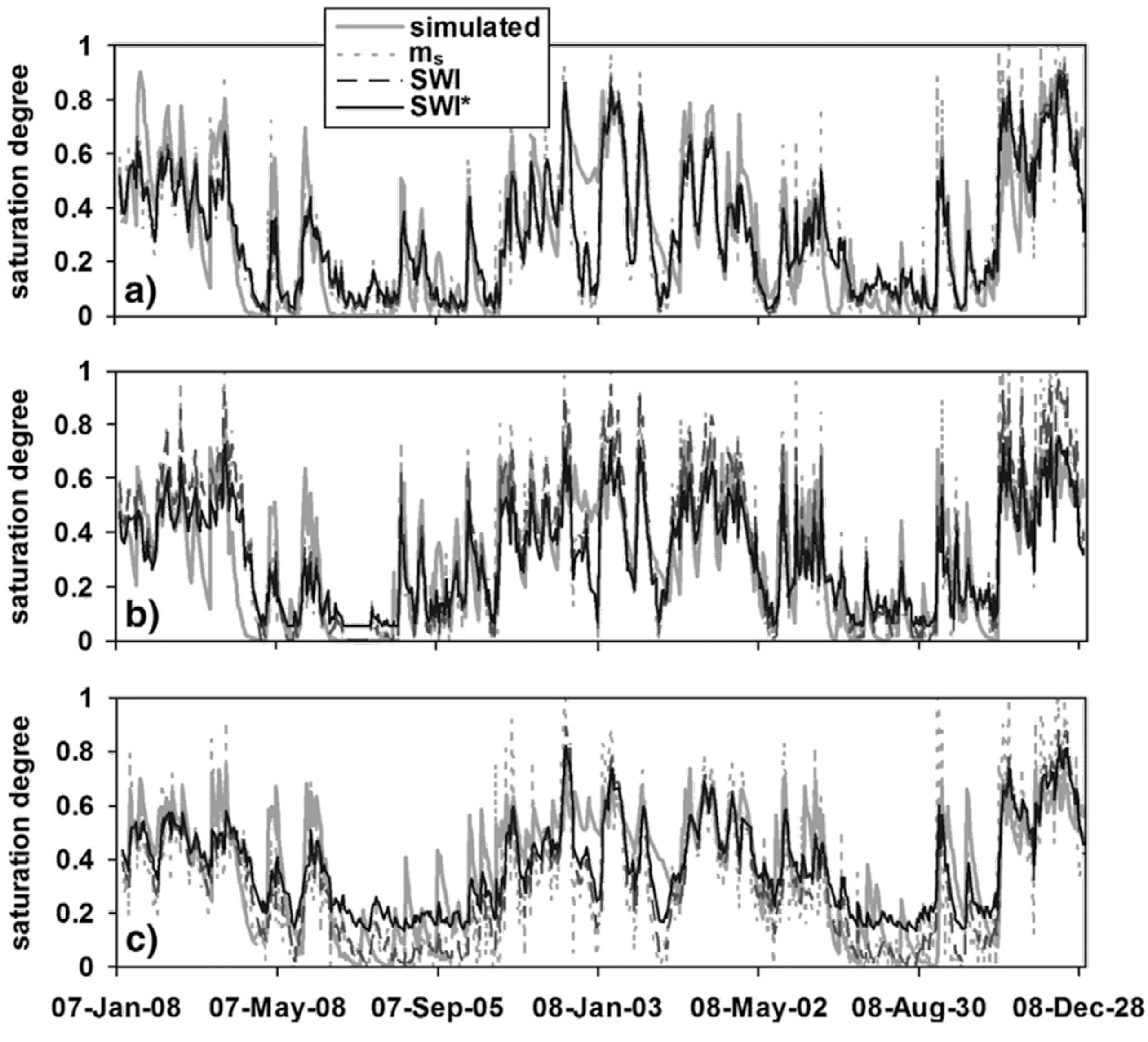
While not anticipated, major advances in the provision of global soil moisture data sets have recently been made with spaceborne scatterometers (Wagner et al. 2007a). Spaceborne scatterometers are used operationally for wind retrieval over the oceans and have been flown on a series of European and US satellites. While all US scatterometers have been operated in Ku-band (around 14 GHz), Europe relies on C-band scatterometers. Since scatterometers have initially not been foreseen for land applications, it took some time before first studies showed that these instruments may be useful for soil moisture monitoring over land. Because of their longer wavelength European scatterometers are better suited for soil moisture retrieval than the US scatterometers. Nevertheless, also some encouraging results were obtained using the QuikScat Ku-band backscatter measurements to track soil moisture changes (Mladenova et al. 2009).

The first multi-year, global soil moisture data set was derived from the ERS scatterometer data from the period 1992-2000 (Wagner et al. 2003). The ERS scatterometer is a C-band radar (5.3 GHz) which has acquired high-quality backscatter measurements with a spatial resolution of 50 km at vertical polarization (VV) since 1991. Its successor is the Advanced Scatterometer (ASCAT) which uses a very similar measurement concept while improving significantly on the spatial (25 km) and temporal (1-2 days) resolution. ASCAT has thus very comparable sampling characteristics like SMOS and the SMAP radiometer. Building on the heritage of the change detection algorithm developed for the ERS scatterometer (Wagner et al. 1999a, 1999b, 1999c), an operational near-real-time ASCAT soil moisture processor has been developed by EUMETSAT in cooperation with the Vienna University of Technology (Bartalis et al. 2007). Trial dissemination of the 25 km ASCAT soil moisture product commenced in May 2008 and since no major problems were observed EUMETSAT declared the service operational in December 2008. Even though some problems still exist with respect to the calibration of the ASCAT model parameters (Wagner et al. 2010), first independent validation studies (Albergel et al. 2009; Brocca et al. 2010a) have reported very good results (Figure 2). Further improvements are expected for the next update of the ASCAT soil moisture processor. Google Map visualisations of the ASCAT soil moisture products can be found at http://www.ipf.tuwien.ac.at/radar/dv/ascat.

3.2.4 RADIOMETERS

Like for scatterometers, recent progress in soil moisture retrieval using with multi-frequency radiometers has also not been fully anticipated. Multi-frequency microwave radiometers have been flown on US satellites since 1978. From 1978 to 1987 the Scanning Multichannel Microwave Radiometer (SMMR) provided

Figure 2: Simulated soil moisture expressed in terms of the saturation degree for a layer depth of 3 cm versus the three ASCAT saturation degree products: surface soil moisture (m_s), profile soil water index (SWI), and rescaled profile soil water index (SWI*) for the three investigated sites: a) Vallaccia, b) Cerbara, and c) Spoleto. From Brocca et al. (2010a).

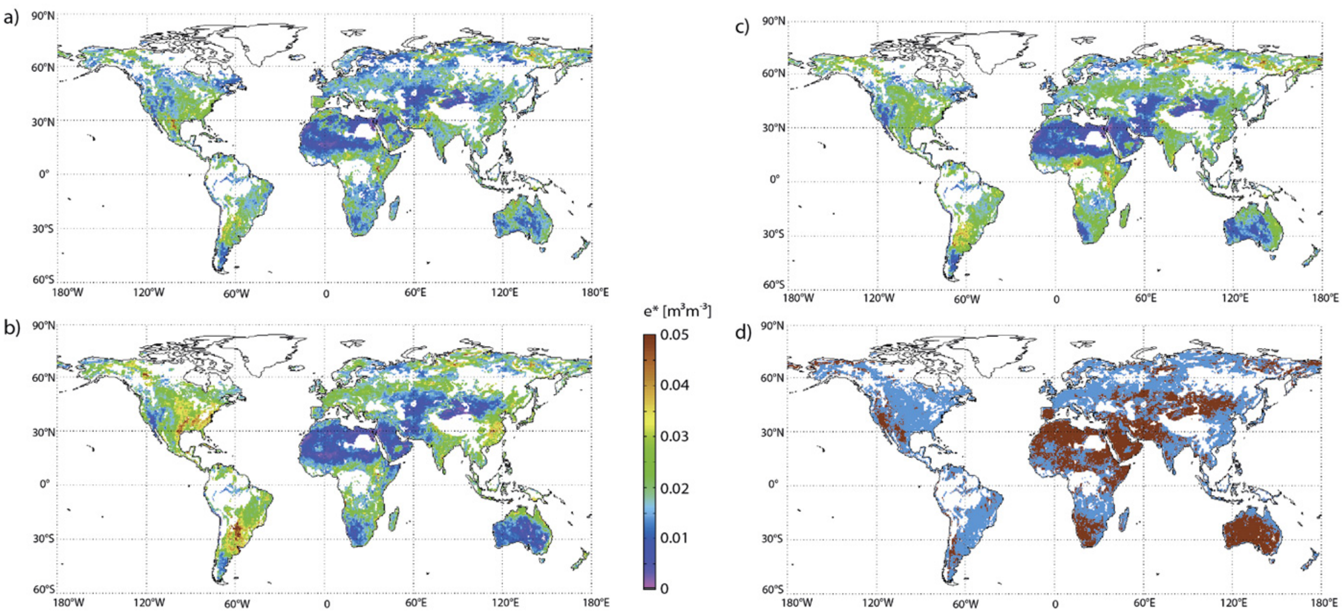


measurements of both horizontally and vertically polarized radiation at five frequencies: 6.6, 10.7, 18.0, 21.0 and 37.0 GHz. The spatial resolution varied between 148 km for the 6.6 GHz channel to 27 km for the 37.0 GHz channel. Since 1987 the Special Sensor Microwave Imager (SSM/I) has been providing an uninterrupted flow of passive data over land and oceans. Unfortunately, from the viewpoint of soil moisture retrieval, the lowest frequency of SSM/I is 19.4 GHz. Amongst the latest generation of radiometers are the Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI) launched in 1997, the Advanced Microwave Scanning Radiometer (AMSR-E), launched in 2002, and WindSat radiometer launched in 2003. These instruments receive again at the two low frequency channels of SMMR (with the exception of TMI which has only the 10.7 GHz channel) and several other higher-frequency channels, but at a much improved spatial resolution and a higher radiometric accuracy.

All these instruments can be used for soil moisture retrieval and in 2003 the US National Snow and Ice Data Center (NSIDC) started distributing the first AMSR-E soil moisture data retrieved using the algorithm of Njoku et al. (2003). Since then several other soil moisture data became freely available, most notably the multi-sensor soil moisture dataset produced by Vrije Universiteit Amsterdam (VUA) in cooperation with NASA (de Jeu et al. 2008, Owe et al. 2008), and the WindSat soil moisture dataset produced by the US Navel Research Laboratory (NRL) (Li et al. 2010). All retrieval algorithms are basically variants of the ω-τ model and try to make best use of the measurements in the 6-10 GHz range. Differences exist in the choice of the input channels (frequency, polarisation) and the paramerisation of vegetation, soil and temperature effects. Unfortunately, RFI is also often present at ~6 GHz which is why this channel is often discarded.

An increasing number of validation studies show that most soil moisture products are capable of depicting seasonal and short-term soil moisture changes well. Also the retrieval error estimated using different approaches, e.g. triple collocation (Scipal et al. 2008), compares well with theoretical expectations and results obtained with C-band scatterometers (Figure 3). Yet, biases in the absolute value and dynamic range may be large when compared to in-situ and modelled soil moisture data, which is why Jackson et al. (2010) still see much room for improvements in the algorithms. However, for most applications the remotely sensed soil moisture data have to be matched to the models in any case, so that any potential bias is removed at this stage (Drusch et al. 2005; Bolten et al. 2010; Entekhabi et al. 2010b).

Figure 3: Spatial errors of (a) ASCAT, (b) AMSR-E C-band, and (c) ERA-Interim surface soil moisture estimated using triple collocation. Errors are expressed in the climatology of ERA-Interim. (d) shows the areas in which either ASCAT (blue/light gray) or AMSR-E (red-brown/dark gray) shows the smallest error value. White areas indicate areas where not enough common observations were available for estimating the errors. From Dorigo et al. (2010).

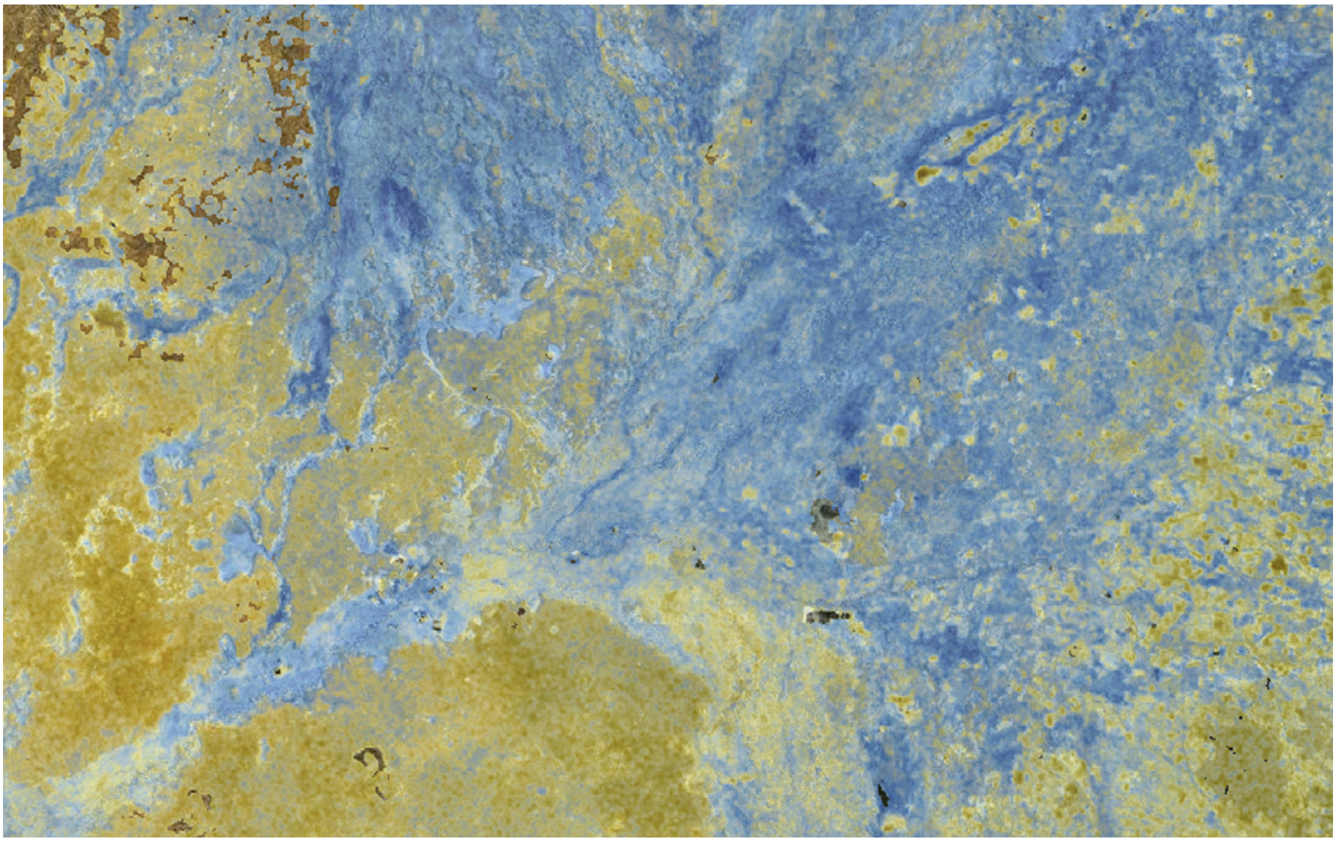


3.2.5 SYNTHETIC APERTURE RADAR (SAR)

Synthetic Aperture Radars (SARs) are imaging radars designed for achieving a fine spatial resolution (< 30 m) over regions of, typically, 100 x 100 km^2. For covering larger areas the so-called ScanSAR technique can be employed for imaging swaths of 300-500 km width. However, this comes at the cost of a degraded spatial resolution (> 100 m) and/or radiometric accuracy. Most spaceborne SAR satellites have operated at C-band, such as the European satellites ERS 1/2 and ENVISAT or the Canadian satellite Radarsat 1 and 2, but also X-band (TerraSAR-X) and L-band SAR (JERS, ALOS) have been available. These SAR systems typically do not offer frequent temporal sampling, which means that they cannot capture the high temporal dynamics of soil moisture (Wagner et al. 2007a). An exception is the Advanced Synthetic Aperture Radar (ASAR) on-board of ENVISAT which can be operated in the Global Monitoring (GM) mode. With this mode many regions worldwide have on average been covered about once or twice a week since December 2004, albeit with a rather poor radiometric accuracy. This situation will change with the launch of Sentinel-1 satellite series foreseen in 2012-2013. The SAR instrument on board of Sentinel-1 has four modes, but over land it will be operated mainly in Interferometric Wide Swath (IWS) mode which images a 250 km wide swath at 5 x 20 m spatial resolution in either VV+VH or HH+HV polarisation (Attema et al. 2007) With two satellites flying in parallel and a duty cycle of 20 minutes, Sentinel-1 can cover Europe in IWS mode within about 4 days and the entire global land mass within about 6-12 days.

As discussed above soil moisture retrieval from Synthetic Aperture Radar (SAR) is challenging due to the confounding influence of surface roughness and vegetation on the signal. A multitude of approaches utilising different backscatter mod-

Figure 4: Monthly average (March 2010) 1 km surface soil moisture derived from ENVISAT ASAR Global Monitoring (GM) mode over an arid region in eastern Australia. The soil moisture image is overlain over a true-colour satellite image to illustrate the effect of landscape morphology on the soil moisture patterns.



els (empirical, semi-empirical, theoretical models), inversion approaches (direct inversion, look-up tables, neural networks), and SAR techniques (multi-temporal, multi-frequency, interferometry, polarimetry) have been extensively studied. Yet, as Barrett et al. (2009) conclude in a recent review on the subject, only at large spatial scale some progress has been made while at field scales accurate soil moisture retrieval from SAR remains an enigma. As for the scatterometers, the most promising retrieval approach is change detection, where a reference image is subtracted from each individual SAR image in an attempt to correct for roughness and vegetation effects specific to each pixel of an image (Moran et al. 2000). Adapting the change detection method originally developed for the ERS scatterometer, Pathe et al. (2009) retrieved surface soil moisture data from ASAR GM time series acquired in HH polarisation over Oklahoma, USA. This method has since then been transferred to Africa, Australia and other continental scale areas worldwide. An independent validation over south-east Australia using data from the National Airborne Field Experiment (NAFE'05) showed good correlations to in-situ and airborne observations if the ASAR GM data were averaged to 5 km (Mladenova et al. 2010). An example of an ASAR GM soil moisture product, which illustrates the impact of landscape morphology on the local soil moisture patterns, is shown in Figure 4. This and many more examples can be viewed at http://www.ipf.tuwien.ac.at/radar/dv/asar. Given the encouraging results for ASAR it is expected that Sentinel-1 will become a very useful instrument for global monitoring of soil moisture at 1 km scale (Wagner et al. 2009c).

3.3 SNOW

Compared to the retrieval of soil moisture, mapping of snow cover in the visible and near-infrared part of the electromagnetic spectrum is a relatively straight forward task given the strong contrast between the reflectance of snow and the reflectances of vegetation and soil. Therefore, there are several mature snow extent products derived from optical sensors. Probably the most widely used snow products are the daily snow cover map from NASA's Moderate-resolution Imaging Spectroradiometer (MODIS) and the Interactive Multisensor Snow and Ice Mapping System (IMS) distributed by NOAA. Regarding the MODIS product, various validation studies have found it to be of good quality (Parajka and Blöschl 2006). Nevertheless, cloud cover and/or poor illumination conditions may cause many missing values which limits the usefulness of optical snow extent products in hydrologic applications (Dozier et al. 2008). Therefore, also microwave sensors have been considered for mapping snow cover extent as they overcome the problem of cloud cover and requirement for daylight. However, in the lower microwave range (1-10 GHz) dry snow is to a large extent transparent, making it nearly impossible to distinguish dry snow from snow-free ground. When the snow becomes wet, and provided that the snow surface is not too rough, then it may be distinguished from the surrounding snow free areas using Synthetic Aperture Radar at local to regional scales (Nagler and Rott 2000; Luojus et al. 2007). Nevertheless, no operational SAR derived wet snow extent product exists to date.

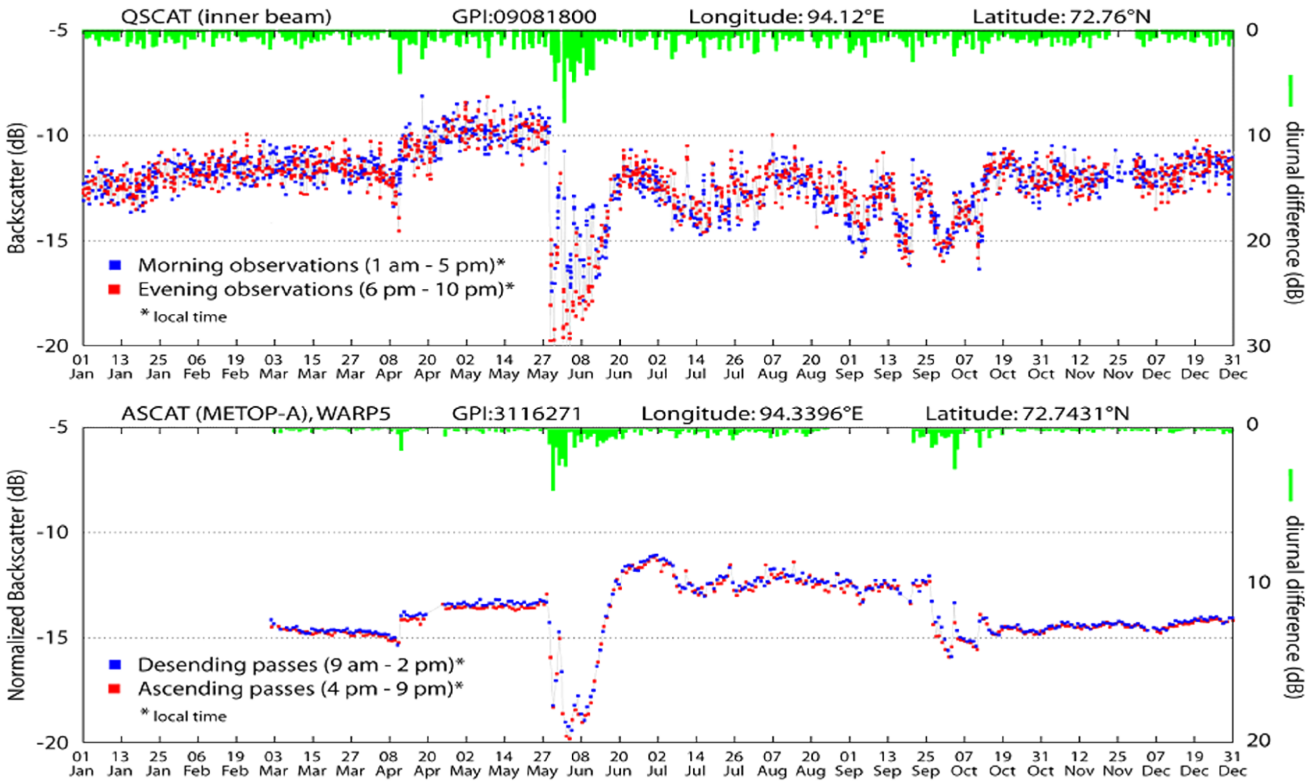
More progress has been made with coarse resolution microwave radiometers and scatterometers. In particular, microwave radiometers such as SSM/I, AMSR-E, etc. have been found to be useful for mapping of different snow parameters, most importantly snow water equivalent (SWE), snow depth and snow melt. These instruments measure the brightness temperature T_b emitted from the snow covered ground at several frequency channels in the range from about 6 to 90 GHz. Thus one can make use of the variable sensitivity of the T_b measurements to the snow pack characteristics. Snow melt can be derived from either solely using the 19V (19.35 GHz) channel (Ashcraft and Long 2005b) or a combination of 19H and 37V (Grippa et al. 2005). Snow depth and snow water equivalent is derived by contrasting the brightness temperature measurements at 19 and 37 GHz. Despite snow layering, crusting and other morphological changes of the snow pack may impair the SWE retrievals, several operational services exist and provide useful information to a range of applications (Kelly et al. 2003; Derksen et al. 2005).

3.4 FREEZE/THAW

Frozen surface conditions can be captured with C-band (5.3 cm) as well as Ku-band (2.1cm) scatterometers (Figure 5). The Ku-band QuikScat however has been determined to be most useful for the detection of snowmelt due to good coverage and sensitivity to snow grain size (Kimball et al. 2001). C-band is less sensitive to liquid water in snow than Ku-Band (Ashcraft and Long 2005a). Changes in backscatter are not only detectable at the beginning and end of snowmelt but also the primary or major thaw can be determined (Kimball et al. 2001). The snowmelt period can thus be even split up into specific stages. In Kimball et al. (2004) the onset of growing season (assumed to be equal to the end of snowmelt) is determined by a threshold based approach and reports a good correlation with the onset of growing season as determined by the start of xylem sap flow in pine trees. This approach has been further developed by Wang et al. (2008) with the use of an enhanced resolution QuikScat dataset (2.25 km).

Diurnal differences are investigated in a range of studies since they indicate exactly when melt water is released from the snow pack. These single days of thaw and refreeze are summed up to obtain the number of melt days, a method which has been specifically used with passive microwave systems over large ice caps such as the Greenland ice sheet and for mass balance studies over smaller ice caps (Tedesco 2007). Ashcraft and Long (2006) compare six different snow melt detection methods which use constant thresholds for both scatterometer and radiometer measurements over the Greenland ice sheet. Results from different radiometer methods agreed well with each other compared to ERS scatterometer observations and the diurnal difference method proposed by Nghiem et al. (2001) using Seawinds on QuikScat. By combination of ascending and descending orbits thaw and refreeze can also be captured with SSM/I radiometer and AMSR-E allowing the detection of incipient thaw timing as well as the number of melt days on glaciated terrain. SMMR provides diurnal acquisitions every other day. Data from this sensor are available from 1978 until 1987. Therefore long time series of spring thaw and autumn freeze can be derived in combination with SMM/I. The actual number of dates of snow thaw is of most interest for glacier mass balance studies but the final disappearance of snow together with the length of spring thaw is required in regions with seasonal snow cover. Clusters of consecutive days of diurnal cycling of freeze/thaw are characteristic for the final snowmelt period in boreal and tundra environments (Bartsch et al. 2007b). The start, end and duration of such periods give inside into spring CO_2 emissions and river runoff behaviour (Bartsch et al. 2007c).

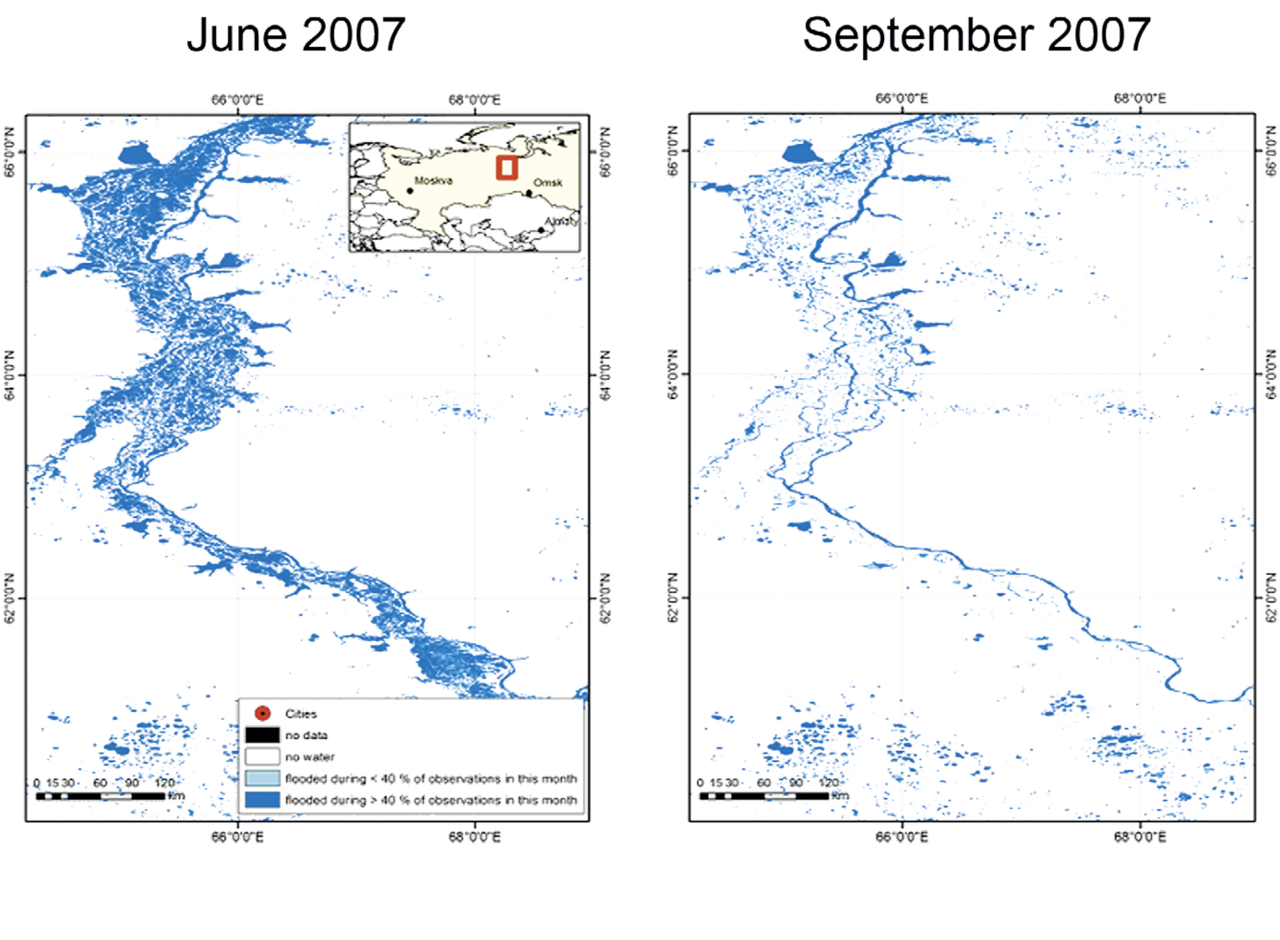
Figure 5: Ku-band (QuikScat SeaWinds) and C-band (METOP ASCAT) backscatter time series for a location in central Siberia for the years 2007. Also shown is the difference in backscatter between morning and evening (diurnal difference represented by the green/gray bars).



3.5 WATER SURFACES

Remote sensing techniques employing visible, infrared, and microwave observations offer varying degrees of success in providing quantitative estimates of wetlands and inundation extent and monitoring natural and anthropogenic variations. Sahagian and Melack (1996) review the various techniques over a range of spatial resolutions. Low spatial resolution (e.g., 30 km) limits detection to large wetlands or to regions where the cumulative area of small wetlands comprises a significant portion of the field of view, but has the advantage of frequent, often daily, coverage (Prigent et al. 2001; Papa et al. 2010). High spatial resolution (e.g., 100 m), while providing more environmental information, usually suffers from poor temporal resolution, often limiting observations over large regions to just high/low water or warm/cold seasons. Optical and infrared remote sensing provide good spatial resolution but are limited by their inability to penetrate clouds and dense vegetation cover, especially in tropical wet seasons. Synthetic Aperture Radar (SAR) can overcome this problem and are overall quite suited for mapping of open water surfaces (Schuhmann et al. 2009). When observed off-nadir, open-water surfaces are generally characterized by low backscattering coefficients and can be accurately delineated. Some misclassifications may occur when wind or vegetation increases backscatter. Nevertheless, there are different ways of dealing with these problems and there is now ample demonstration that SAR data can be used to map surface water and their dynamics from local to regional scales in tropical (Hess et al. 2003; Bartsch et al. 2009), temperate (Schuhmann et al. 2009; Zwenzner and Voigt 2009) and arctic environments (Bartsch et al. 2007a) (Figure 6). Unfortunately, also in this case no operational service exists yet.

Figure 6: Water cover maps of the Ob floodplain for June and September 2007 derived from multi-temporal 150 m wide swath images acquired by the ENVISAT Advanced Synthetic Aperture Radar (ASAR).



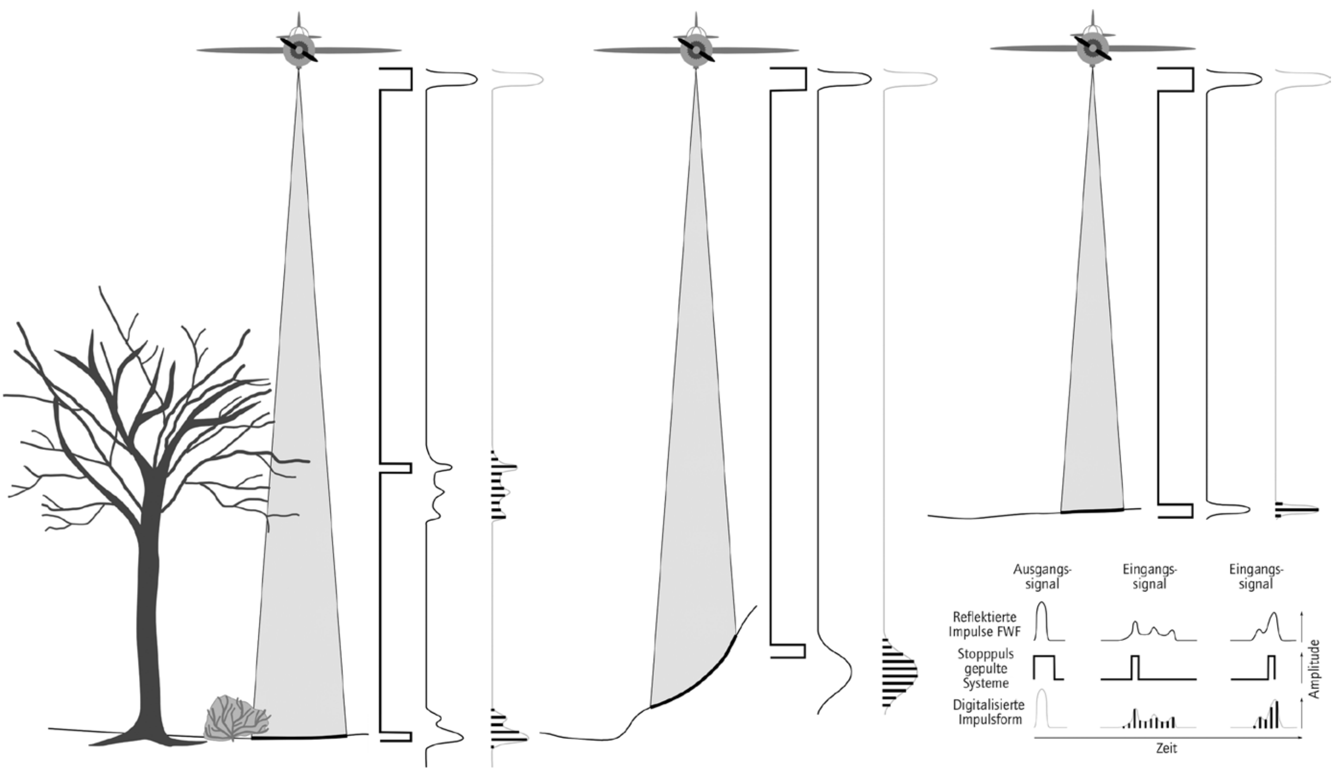
4. LASER SCANNING

4.1 SENSORS AND TECHNOLOGICAL TRENDS

Laser Scanning, also often referred to as lidar (Light Detection And Ranging), is used as a fast and accurate technique to collect topographic Earth information (Baltsavias 1999; Wehr and Lohr 1999). For capturing terrain data Airborne Laser Scanning (ALS) became a state of the art data source. ALS is a time and cost effective method to acquire topographic data with a low amount of users interaction, a high ground sampling density (typically 1-50 points per m²) and a height accuracy of less than 15 cm. It is used for area-wide 3D data acquisition in support to a range of scientific disciplines, including amongst others archaeology (Doneus et al. 2008), geology (Székely et al. 2009), geomorphology (Höfle and Rutzinger 2010), water surface mapping (Höfle et al. 2009), and glaciology (Abermann et al. 2010). For more detailed, smaller-scale investigations Terrestrial Laser Scanning (TLS) is used. TLS provides high ground sampling density (several hundred points per m²) but data acquisition is time consuming and the range is limited. TLS data can be used as independent source for validation of ALS data and as reference data sets for land cover mapping or roughness estimation of flood inundated areas (Straatsma et al. 2008). To bridge the scale gap between ALS and TLS, Mobile Laser Scanning (MLS), in which a TLS is mounted on a car or boat has increasingly been used in recent years (Alho et al. 2009).

The main principle of data collection is the same for all systems, which is shortly introduced here. A laser source is mounted in the system, which produces coherent and highly monochromatic light in the range from 905 nm to 1550 nm. Most laser scanners emit short pulses for range detection, but some close range TLS systems also utilise frequency modulated continuous waves (Wehr and Lohr 1999). Pulsed laser scanners transmit short laser pulses (4-10 ns) that are reflected by the object's surface and a part of the reflected energy can be recorded at the sensors receiver. The distance calculation is based on the travel time of the laser pulse between sensor and object, and back. Then, the range is connected to the position and attitude of

Figure 7: Discrete return and full-waveform airborne laser scanning. The graphics illustrate from left to right the interaction of the laser pulse with vegetation, sloped terrain and a flat target. Illustration modified after Hug et al. (2004).



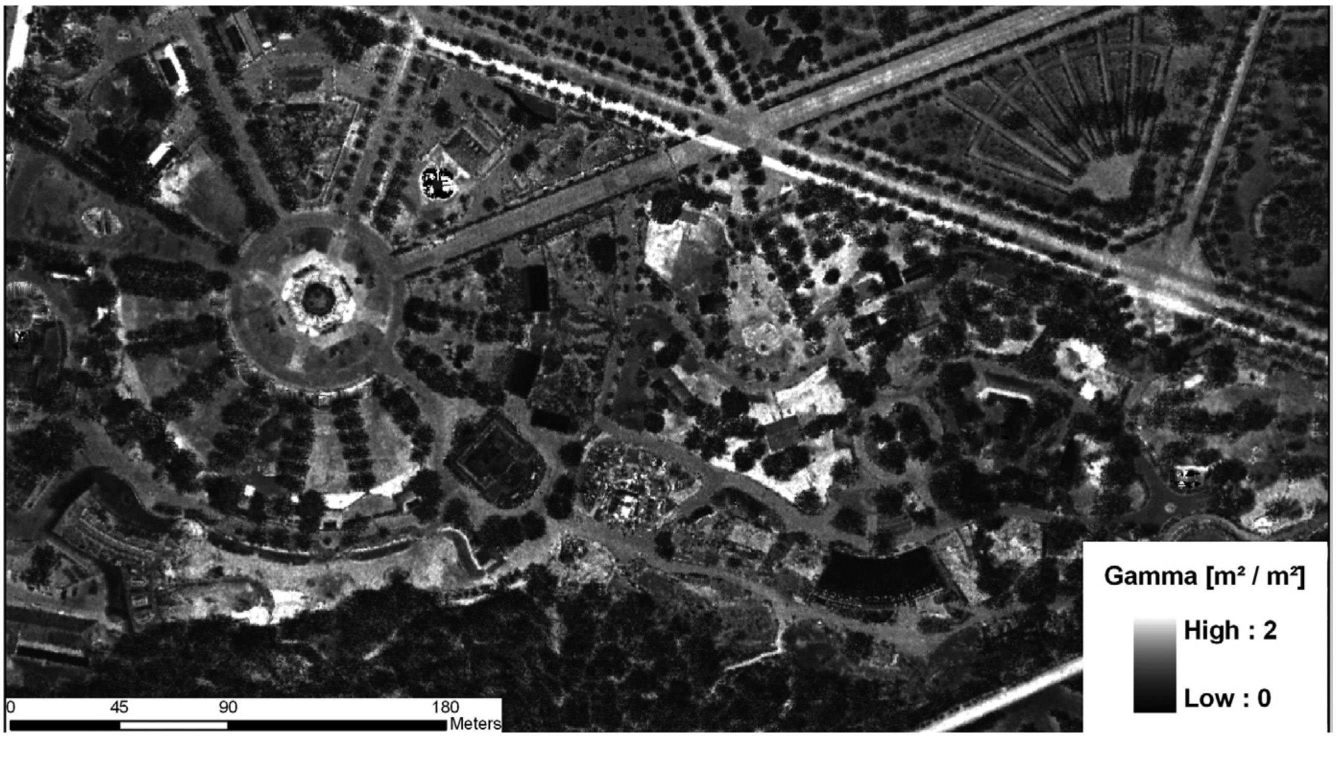
the remote sensing platform determined by Global Positioning System (GPS) and Inertial Measurement Unit (IMU). To calculate the x,y,z location of each measurement the angle of the oscillating mirror, which is installed to generate the scanning pattern, has to be added in the processing. The first generation of laser scanner collected the data as discrete echo recording system (first, intermediate and last pulse of each echo, max. 4 echoes). The new scanner generation (FWF systems) record the whole wave-form of the reflected pulse (Figure 7).

While most laser scanners operate at a single wavelength, two wavelength laser scanner systems have long been used in bathymetry (Guenther et al. 2000). The reason is that one needs two different frequencies (usually 1064 and 532 nm) to obtain reflections both at the water surface and the river bed/sea floor. Limitations of bathymetric lidar systems are that clear water conditions are required and a minimum water depth of about 1.5 m is necessary to distinguish the water surface from the riverbed targets depending on the used ALS system and pulse length (Allouis et al. 2010).

Full-waveform lidar sensors can also be operated from spaceborne platforms (Zwally et al. 2002). While many studies have already demonstrated the large potential use of spaceborne lidars for land surface characterization (Sun et al. 2008; Duong et al. 2009), the technology is not yet very robust. Most importantly, spatial sampling and laser life time will have to be improved for future satellite missions (Abdalati et al. 2010).

Meanwhile, hydrology and water management will mostly benefit from technological and scientific advances in airborne, mobile and terrestrial laser scanning. It can be expected that sensor weight and size will continue to decrease successively while functionality (full-waveform, multiple pulses in the air, two wavelengths, on-line radiometric calibration etc.) and usability will further improve. From a scientific perspective the realization that radiometric calibration of full-waveform data is possible will probably be a major impetus for future work into this direction (Pfennigbauer and Ullrich 2010; Wagner 2010). This means that laser scanners provide both precise geometric and radiometric information (Figure 8) which can be expected to be of use in multiple applications.

Figure 8: Image of the backscattering coefficient γ [$m^2 m^{-2}$] derived from full-waveform airborne laser scanner data acquired over the Vienna Zoo, Schönbrunn, Vienna. pulse with vegetation, sloped terrain and a flat target.



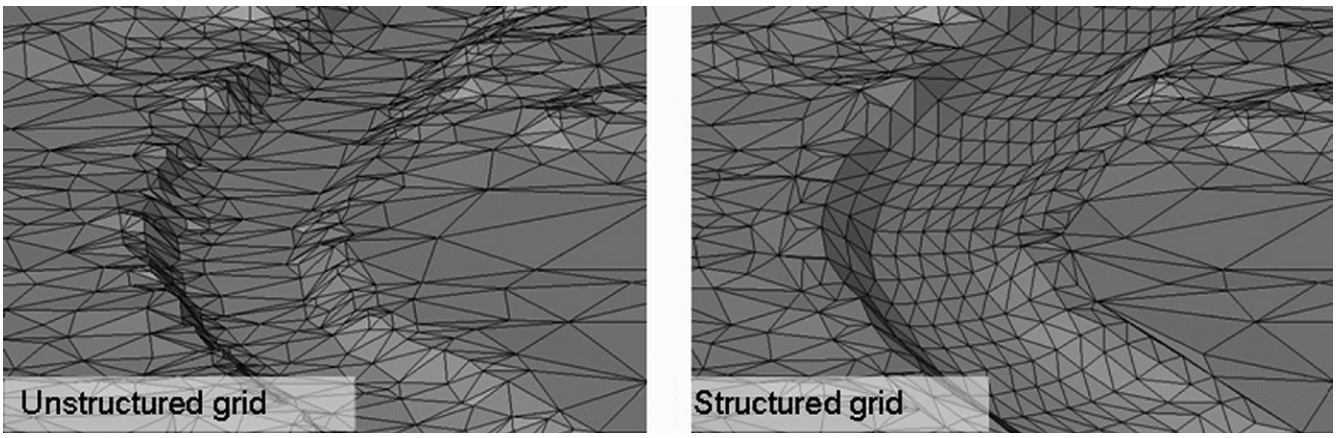
4.2 TERRAIN MODELS

Laser scanning has been a breakthrough technology for deriving precise digital terrain models (DTM) because of their capability to "see" though gaps in the vegetation canopy. As a result the 3D point cloud as acquired by laser scanners consists of both terrain and off-terrain echoes. The task of generating a DTM is thus essentially a classification that splits the 3D point cloud into terrain and off-terrain points. This process is usually called filtering and can be done in different ways. In the last few years many different algorithms have been developed which filter the ALS point cloud to eliminate off-terrain points (Sithole and Vosselman 2004). All these approaches have in common that they rely upon geometric criteria (typically the height relation of neighboured points) for the elimination of off-terrain points. Next to problems with big off-terrain objects and surface discontinuities, algorithms have often problems with the filtering of low vegetation, bushes and tree-trunks. Therefore the DTM surface may run through the lowest canopy levels in these areas. The fundamental reason for this problem is that conventional ALS systems cannot distinguish objects from the ground surface if these objects are shorter than the range resolution. Also in full-waveform ALS such objects do not produce distinguishable echoes. However, they lead to a broadening of the received waveform and can hence be eliminated. Following this reasoning Doneus et al. (2008) proposed a two step approach for DTM generation. In the first step, all last echo points with a significantly bigger echo width than the echo width of the system waveform are eliminated using a simple threshold value. Then, in the second step, a standard filtering procedure as described in Kraus and Pfeifer (1998) is used for classifying the remaining points into terrain and off-terrain points. Thus the combination of geometric and radiometric criteria as made possible through full-waveform systems may significantly improve our capabilities to model hydrologically relevant surface features (Wagner et al. 2008a).

For most hydrological applications the derived terrain model is represented as raster or vector data. However, there remain two major challenges in order to effectively use the DTMs for hydrodynamic simulations. The first challenge is that the DTM representation has to be optimised in order to be consistent with the physical equations used to model the water flow through the environment (Figure 9). The second challenge is that most hydrodynamic modeling software is, for pure computational reasons, not able to handle dense DTM data as input. Thus data reduction and data thinning become essential steps for the use of ALS derived DTMs in hydrodynamic simulations (Mandlburger et al. 2009). A close cooperation between remote sensing experts and hydraulic modellers is essential in order to obtain hydrodynamically realistic descriptions of the near-surface water flow.

The effect of more or less complex input data for numerical models are also presented in Wichmann et al. (2008) by using different DTM cell resolutions for modelling debris flow. The extent of the modelled debris flow fitted best to the in-situ measured extent by using a cell resolution of more than 5 m, which leads

Figure 9: Two representations of the river bed and surrounding terrain. From a pure geometric point of view both digital terrain models (DTMs) represent the true terrain equally well, but only the conditioned DTM on the right side allows realistic hydrodynamic simulations.



to three questions. Are the input ALS data too dense for the numerical model? Are the used numerical models optimized to less complex input data? Should future investigations concentrate on data reduction or on adapting natural process modelling algorithms for dense data set? The trends in sensor development and data collection techniques focus on increasing sampling density and accuracy. Therefore, data complexity increases and the DTM cell resolution decreases, while numeric models are not able to use this data. A challenge is to find a way to modify numerical models which use dense ALS data as input. Another challenge is to find a possibility to use the existing numeric models, reduce ALS data complexity and minimize the calibrating demand of the model. Calibration is normally used to reach the accuracy goal by changing some model parameters and values until the result is deemed acceptable. One is tempted to assume that the higher information content from dense ALS data can improve model outputs while reducing calibration demand, but this hypothesis may not necessarily be true.

4.3 VEGETATION STRUCTURE

Vegetation has a rather complex vertical structure. Therefore mapping of vegetation would preferably be done using 3D measurement techniques that allow separating objects found at different height above the Earth's surface. While so far 2D imaging techniques have been the state-of-the-art in remote sensing of vegetation, 3D measurements techniques have become more widely available in recent years.

One important approach is multi-image matching which is an extension of classical stereoscopic methods and refers to a technique to extract 3D information from two or more 2D digital images taken at different positions (Leberl et al. 2010). Over vegetated areas the challenge lies in finding corresponding points in at least two images that are the projections of the same vegetation point. Zhang and Grün (2006) demonstrate that high quality digital surface models can be obtained for forested areas by using a coarse-to-fine hierarchical solution and multiple matching primitives. However, due to shadow and occlusion the matching of vegetation points becomes increasingly difficult for lower canopy layers and the underlying ground surface. Therefore, in practice, multi-image matching techniques are suited to describe the top canopy layers, but provide only limited information about the lower canopy layers and the underlying terrain.

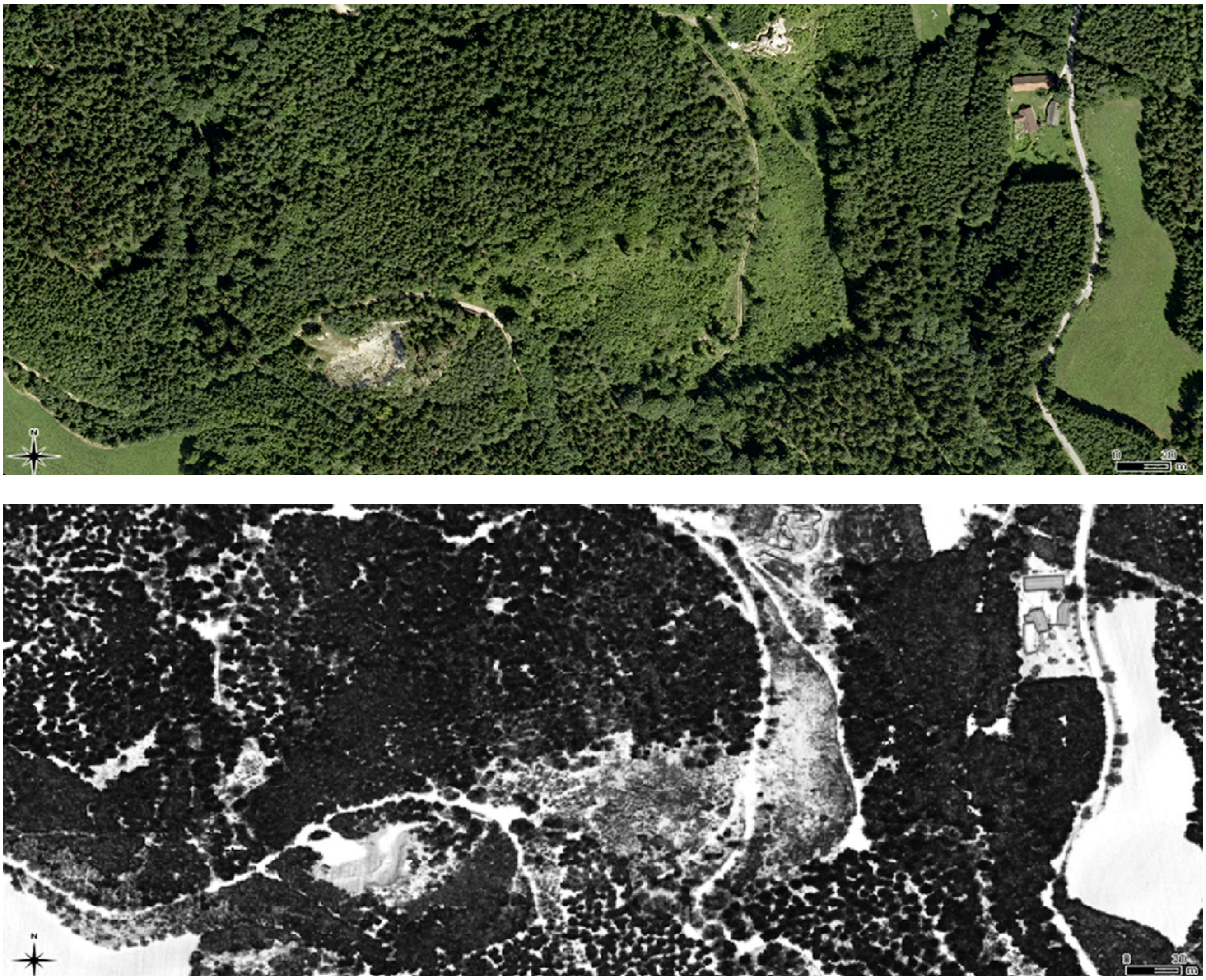
Active remote sensing techniques are better capable of resolving the vertical structure of vegetation. Particularly suited are radars that can penetrate the vegetation due to their long wavelength (centimetre to decimetre waves). For example, Hyyppä et al. (1997) used a helicopter-borne ranging scatterometer operating at two wavelengths (3.1 cm and 5.4 cm) to measure the backscattering characteristics of forest stands as a function of height with a vertical resolution of about 0.65 m along the flight line. Also SAR systems can in principle be used for 3D mapping of large areas by processing more than two SAR images acquired at different altitudes to synthesize an aperture in elevation (Reigber and Moreira 2000). However, much further research is still needed for assessing the real utility of this technique for vegetation mapping.

The third technique is laser scanning. A disadvantage of laser scanning compared to radar is that laser pulses can penetrate the vegetation canopy only through gaps, which means that below dense crown layers very little information about the ground surface and deeper canopy layers is obtained. However, laser scanners can more easily achieve a fine resolution both in the horizontal and vertical directions and produce a geometrically interpretable 3D point (i.e. echoes are from leaves, twigs, branches, stems etc.). This may sound trivial but it is not considering that in radar remote sensing the interaction of the waves with the canopy is more complex and hence the effective scattering centres of the measurements are usually not known. A similar problem arises in multi-image matching where matched points may not be associated with a real canopy element.

Thus, also in the case of vegetation mapping laser scanning can be considered to be a breakthrough technology. In fact, laser scanning has fostered the development of a steadily growing community in the forest and vegetation sciences that investigates methods for mapping of forest area and canopy height, stem volume and biomass estimation, species identification, etc. (Hyyppä et al. 2004; Höfle and Rutzinger 2010; Koch 2010). So far, studies have mostly exploited the geometric information provided by laser scanning, but more and more studies also make use of full-waveform attributes and thereof derived radiometric quantities (Reitberger et al. 2008; Wagner et al. 2008a; Alexander et al. 2010).

Vegetation influences water storage and fluxes in many different ways. Therefore, one needs to ask the question if the representation of vegetation in just a few land cover classes, as usually done in image classification and hydrological practice, is sufficient to reflect the different vegetation functions? The answer will of course be model dependent, but nevertheless it is clear that the capability of laser scanning to describe in three dimensions opens up the possibility to introduce new vegetation parameters that are better adapted for the processes under investigation. One example for such a new parameters is the 'Echo Ratio', which is the ration between the ground echo and all-off-terrain echoes (Figure 10). This parameter shows the degree of penetration of vegetation and has already be used for mapping vegetation structure in urban (Rutzinger et al. 2008) and rural (Aubrecht et al. 2010, Hollaus et al. 2011) environments. By calculating vertical vegetation structure, which is detrended from the elevation data it is possible to estimate the volume of vegetation in different layers above the terrain. This can be e.g. used in hydrological studies as input for vegetation friction coefficient (Vetter et al. 2011).

Figure 10: True-colour orthophoto (top) and echo ratio derived from airborne laser scanner data (bottom) over a forested area in Lower Austria. The echo ratio is a measure for the vertical structuring of the vegetation canopy, whereas flat targets are presented in white and highly structured canopies in black.



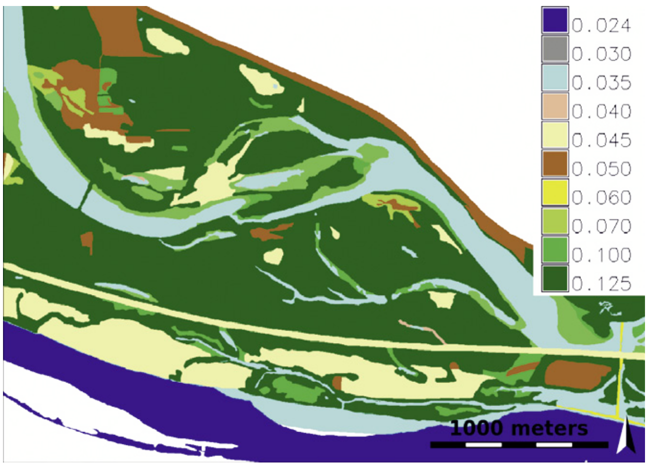
4.4 ROUGHNESS

The roughness of the terrain and the type of vegetation (trees, shrubs or grasses) has a big influence on how water flows over land. Thus, hydraulic models need to parameterize the effect of roughness, e.g. through the use of hydraulic friction coefficients such as the Manning-value or the Chézy coefficient. The state-of-the-art is to use land cover maps derived from areal images and/or field trips, and to select for all land cover class representative roughness values that yield the most realistic flood inundation patterns. As highlighted by Straatsma and Baptist (2008) this method is suspect because shortcomings in the model scheme, computation method or model input may be compensated using roughness values that are physically not representative.

Thanks to the capability of laser scanning to provide detailed information about the vegetation structure (Figure 11), the question is how ALS may be best used in support to hydraulic modelling? While one could immediately think of many different geometric roughness parameters that can be estimated from ALS data, it is unfortunately not clear which of these parameters would be suited for describing the physical phenomenon "hydraulic friction"? In other words, the problem is how to describe fluid mechanics in a complex environment with rather simple geometric descriptors? Some first interesting approaches using ALS data are e.g. presented in Mason et al. (2003), Straatsma and Baptist (2008) and Vetter et al. (2011), but it is clear that much further research is needed to fully exploit the novel information content of laser scanning. This research will also have to address the role of infiltrability (which is e.g. controlled by soil moisture) which has an important effect of the lateral flow in vegetated terrain.

Besides the overarching question of how to describe a complex physical phenomenon with comparable simple geometric models, scaling problems play also an important role. In this context it is important to release that due to their footprint size in the order from 10 cm to 1 m, ALS sensors are not be suited for directly capturing the geometric roughness of the non-vegetated terrain and the riverbed (grain size, bed form). At this fine spatial scales only TLS are able to capturing the geometric shape of the grains in the river bed (Heritage and Milan 2009). However, as the results obtained by Davenport et al. (2004) and Wagner et al. (2009b) suggests also sub-footprint resolution roughness values may be estimated by either calculating the root mean square height after detrending to remove topographic slopes or using the echo width and/or cross section derived from full-waveform acquisitions. Nevertheless, much more research is needed before firm conclusions can be drawn.

Figure 11: Manning's values as derived from optical imagery and field observations (left) and airborne laser scanning (right) used as input to a hydraulic model over the Lobau, Donau-Auen National Park south-east of Vienna, Austria (Vetter et al. 2011).

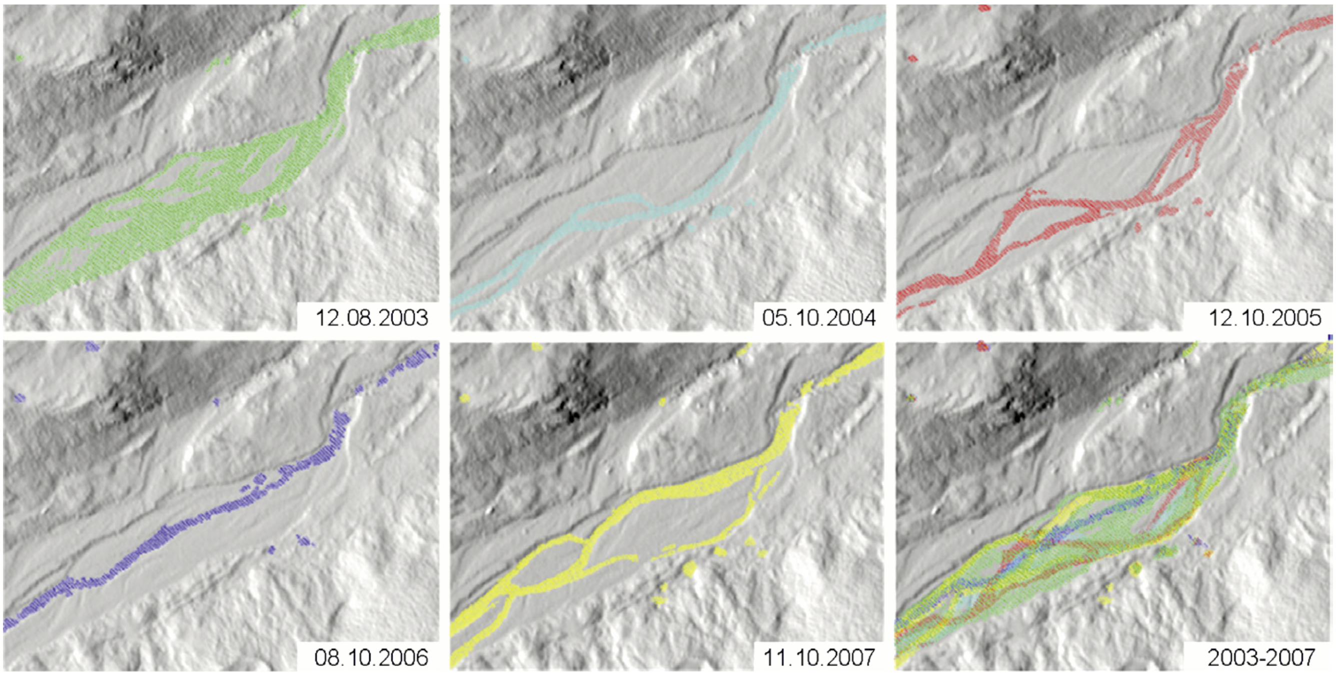


4.5 GLACIERS

Also in glacier monitoring the introduction of airborne laser scanning provided important new impetus (Favey et al. 2002). In Austria pioneering work by the Institute of Geography of the University of Innsbruck started in 2001 (Geist and Stötter 2007). Since then more than 20 single airborne LiDAR campaigns have been carried out by collecting data of the Hintereisferner, the Kesselwandferner and adjacent small glaciers and their surrounding areas (Ötztal Alps, Tyrol, Austria). This has allowed to much better understand glacier dynamics and alpine hydrology in this area. From a remote sensing point of view several new methods have been developed, e.g. methods for glacier outline and crevasses delineation and detection using local surface roughness (standard deviation) and radiometric data as input data (Kodde et al. 2007). Also, a classification method was developed to distinguish water from dry land on proglacial braided river system (Figure 12) based on surface roughness, radiometric information (corrected and adjusted to one data set) and laser shot dropouts, which are non-recorded echoes occur mainly from specular reflection in the opposite direction of the receiver on water surface, using multi-temporal data (Höfle et al. 2009; Vetter et al. 2009). Further, tools to compute and visualize the volume, elevation changes and the ice flow velocity at the glacier surface using multi-temporal data were first tested and, finally, routines for moraine ridge and rock glacier detection are produced, which work on break lines and curvature (Rutzinger et al. 2008).

Because of the strong absorption and specular reflection of laser pulses by water and ice surfaces, careful planning of the airborne campaigns is necessary. For example, by using a wavelength of 1064 nm, which is also commonly used in bathymetric LiDAR systems, the water and glacier surface can only be measured if the flying altitude is low enough (only a few hundred meters). However, if the altitude of the flight is low then the swath is small and spatial coverage is limited. In addition, a lot of nadir areas with comparably very high intensity values are in such recorded data. Those high values cause problems in the classification and delineation of surface classes (ice, firn, snow, water). Another challenge is the lack of tie-point features for strip adjustment, which is a general problem in high mountain regions, where no objects can be found for strip adjustment.

Figure 12: Surface water dynamics of an alpine stream captured by multiple airborne laser scanner acquisition campaigns organised by the University of Innsbruck, Austria. From Vetter et al. (2009).



5. APPLICATIONS

5.1 BENEFITING FROM UNCERTAIN EARTH OBSERVATION DATA?

One of the biggest problems in earth observation (EO) has been that it has frequently been oversold, i.e. too much was promised while the real use of many EO data turned out to be rather limited. Reasons for overselling are manifold, including the need to justify the high costs of spaceborne missions and wrong views about the real user requirements. As a result, many users have taken on a rather sceptical attitude towards the potential benefits of remote sensing in their scientific discipline. A good example is Keith Beven who wrote in 2001:

"There has been a commonly expressed hope that, in the future, remote sensing information would lead to the possibility of more robust estimates of spatially distributed parameter values for distributed hydrological modelling in applications to unique catchment areas ... However, the potential for remote sensing to provide the information required would appear to be limited. The digital numbers stored by the sensor do not give direct estimates of the hydrogical variables or parameters required at the pixel scale. They require an interpretative model. ... Thus, remote sensing information will also be subject to equifinality in interpretation and uncertainty in prediction. This will be compounded by the need to couple interpretative models for satellite or aircraft images which, except under unusual circumstances, give only information on near surface emissions, to models of the subsurface."

Indeed, these issues raised by Beven (2001) address the challenges for a successful use of EO in hydrology and water resource management at a very fundamental level. At the same time they make clear that remote sensing and hydrological sciences have many fundamental science questions in common (Wagner et al. 2009d). For example, one of the scientific issues that is often hotly disputed in both disciplines is model complexity. Complex models that try to solve the problem (e.g. runoff forecasting in hydrology or geophysical parameter retrieval in remote sensing) by considering sub-processes in as much physical detail as possible are, from a science-philosophical point if view, often regarded to be superior to more simple, phenological approaches. Yet, both in remote sensing and in hydrology one can make use of only a limited number of measurements for validating and driving the models. Therefore it is often not possible to falsify complex models, simply because different model structures and parameter sets may explain the observations equally well. This is the equifinality problem as mentioned by Beven (2001) above.

Additionally, the human perception of what processes are most important for the problem at hand may be deeply flawed in both disciplines. This problem was well described by Savenije (2009) for the hydrologic case. He argued that the human being is blinded by the scale at which he/she observes hydrologic processes, while at catchments scales ranging from a few to hundreds of kilometres the dominating processes may be completely different ones. The same is presumably true for remote sensing scientists who, intrigued by the complexity of the land surface, might miss to recognise those features which are most important for the interpretation of the remotely sensed data. This problem is aggravated when working with sensors operating outside the visible part of the electromagnetic spectrum. These wavelength regions (e.g. thermal- and microwave domain) are inaccessible for the human visual perception and are hence less accessible for human cognition.

Considering these challenges, is the often expressed hope that remote sensing can provide reliable data for validating and driving hydrological models really justified? Can we make better predictions by using more but nonetheless uncertain data? Probably the most appropriate answer to these question is a "Yes, but ...". Yes, because EO has been steadily advancing as discussed in the previous two chapters. The "but" comes from the fact that it is normally not possible to directly use EO data in existing applications and because not all new data will necessarily improve model predictions. Therefore, significant research is usually needed in order to adapt models for the use of remotely sensed data and to develop appropriate model-data interfaces. This process usually takes many years, whereas an initially negative to neutral impact of any new data sources on model predictions should not be taken immediately as evidence against the usefulness of the new data source. Only over time, a better understanding of the errors in both the model structures and the remotely sensed data sets emerges which will then allow to iteratively improve the model-date interface (e.g. through advanced data assimilation techniques) and hence model predictions.

In the following, some recent studies that demonstrated a measureable and positive impact of using real remote sensing data on model predictions are discussed. As it is not possible to cover the full diversity of remote sensing parameters and their use in a wide variety of hydrologic and water resource applications, this discussion limits itself to the successful use of global operational soil moisture products for runoff prediction, drought monitoring and climate change research.

5.2 SOIL MOISTURE APPLICATIONS

5.2.1 RUNOFF

Soil moisture is one of the most important controls on runoff. Because soil moisture is highly variable in space and time (Western et al. 2002) the notion that only high resolution (10-100 m) soil moisture data are of potential use for improving runoff predictions has often been expressed. If this would be correct then only spaceborne SAR systems would offer potential benefits to runoff forecasting. However, research on the scaling properties of soil moisture has increasingly provided evidence that temporal soil moisture patterns are similar across a wide range of spatial scales, a phenomenon usually referred to as temporal stability (Vachaud et al. 1985; Martinez-Fernandez and Ceballos 2005; Cosh et al. 2006; Wagner et al. 2008b). Temporal stability can be understood by considering that soil moisture variations in space and time can be related to both a small scale and a large scale component (Vinnikov et al. 1996). The small scale component leads to local variations in soil moisture due to soil properties, land cover attributes and local topography. The large scale component is related to atmospheric forcings, namely precipitation and evaporation processes, and is characterised by correlation lengths in the order of 400-800 km (Entin et al. 2000). Therefore, one should not exclude the possibility that also coarse (25-50 km) resolution scatterometer and radiometer sensors provide useful information about runoff generating processes, even though these processes take place on a very local scale.

Nevertheless, one naturally tends to assume that coarse resolution satellite data hold the largest potential for runoff predictions over large catchments. Therefore, research initially concentrated on comparing soil moisture and runoff dynamics over large catchments. For example, Scipal et al. (2005) compared ERS scatterometer derived soil moisture products to measured runoff of the Zambezi River in south-eastern Africa for several years (1992–2000). They found high correlations between basin-averaged soil moisture and runoff time series (R^2>0.85) demonstrating that the seasonal change from low runoff during the dry season to high runoff during the wet season was well captured. The first evidence that coarse resolution scatterometer data can contribute to runoff prediction also in small catchments was brought by Brocca et al. (2009) who used a scatterometer derived profile soil moisture index to estimate antecedent wetness conditions for an event-based rainfall-runoff model over three subcatchments of the Upper Tiber River in central Italy. They found that despite their catchments ranged only from 137 to 4150 km^2 in size it was possible to estimate the runoff depth with a Nash-Sutcliffe value greater than 0.94 and an error less than 20-30% for 80% of the rainfall-runoff events. In a follow-on study Brocca et al. (Brocca et al. 2010b) used ASCAT derived profile soil moisture data in an assimilation mode. This time they investigated five subcatchments, ranging in extension between 100 and 650 km^2, and interestingly, the assimilation of ASCAT lead to the best results over the smaller catchments (Figure 13). Of course, much further research work will be needed to test these methods also over other catchments and to better understand the mechanisms that contributed to a positive impact of remotely sensed soil moisture data on runoff predictions.

5.2.2 DROUGHT

As discussed by Mishra and Singh (2010) the assessment of droughts is of primary importance for freshwater planning and management and requires an understanding of historical droughts as well as drought impacts during their occurrences. As drought is a complex and multi-dimensional phenomena, and depending on which drought impacts one is interested in, different modelling approaches and input data sets are needed. Complementing existing drought indices, remotely sensed soil moisture data could become an important new source data for drought monitoring systems. Since for drought studies usually rather long time series are preferred, few studies have yet touched on the question on how the new satellite soil moisture data can be used for drought assessment. One of the first studies was carried out by Gouveia et al. (2009) who used Normalised Difference Vegetation Index (NDVI) and a scatterometer derived Soil Water Index (SWI) to study the spatial extent, severity and persistence of drought episodes over Continental Portugal, from 1999 to 2006. They found that the impact of dry periods (below average SWI) on vegetation was clearly observed in both arable land and forest, whereas arable land presented a higher sensitivity. Another study that used both SWI and NDVI data was carried out by Zribi et al. (2010) who investigated the relationship between soil moisture and vegetation in the Kairouan plain region of Tunisia. They found that it is possible to predict the next month's NDVI using the current month NDVI and SWI. These two studies thus indicate that one of the main benefits of using remotely sensed soil moisture data might be that drought conditions are signalled some weeks before there is any noticeable impact on the vegetation (see also Figure 14).

Figure 13: Cumulated runoff for the observed and simulated data with and without ASCAT data assimilation for five subcatchments of the Upper Tiber River in central Italy with a drainage area of (a) 137 km2, (b) 165 km2, (c) 100 km2, (d) 658 km2, and (e) 549 km2. From Brocca et al. (2010b).

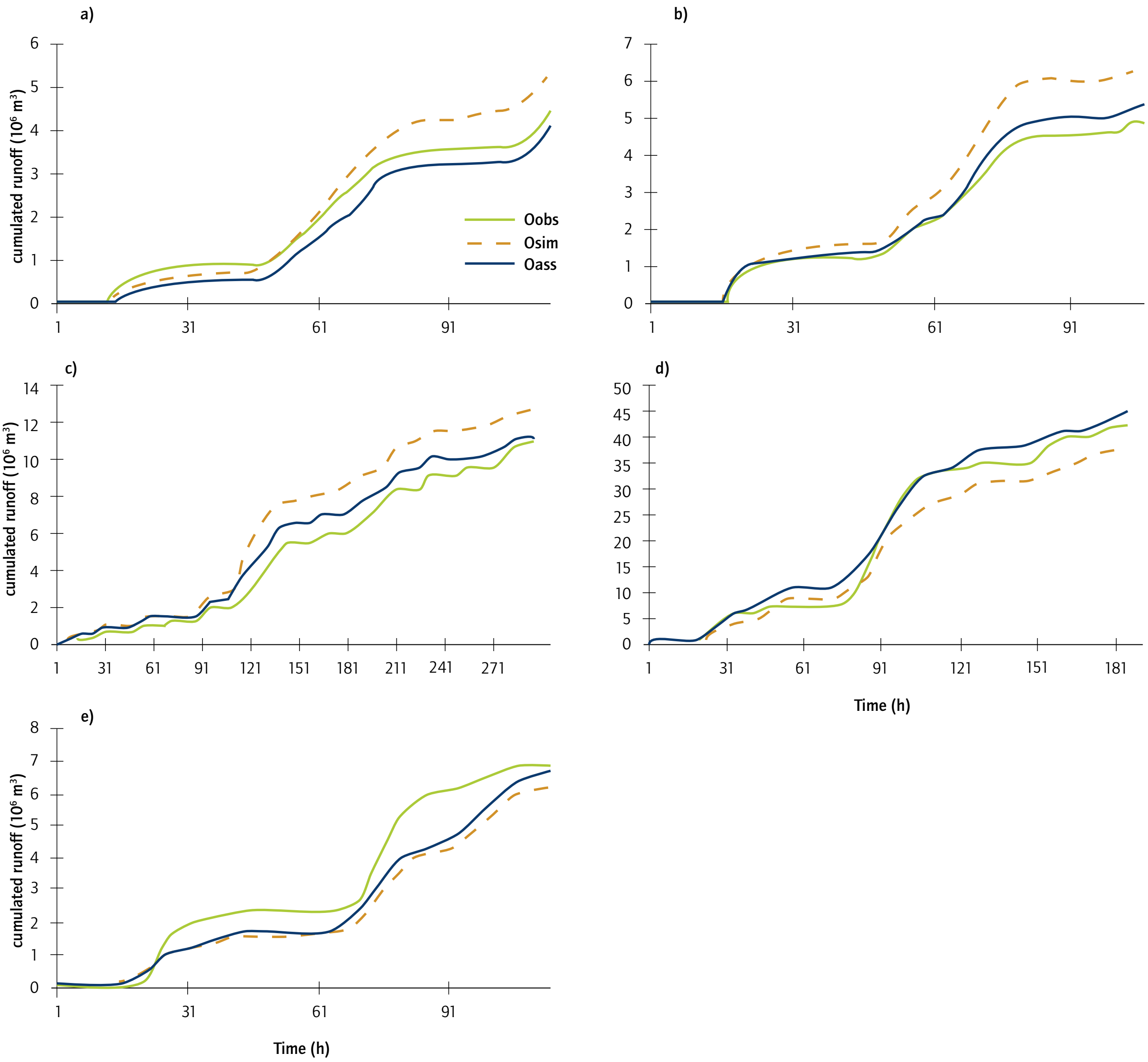
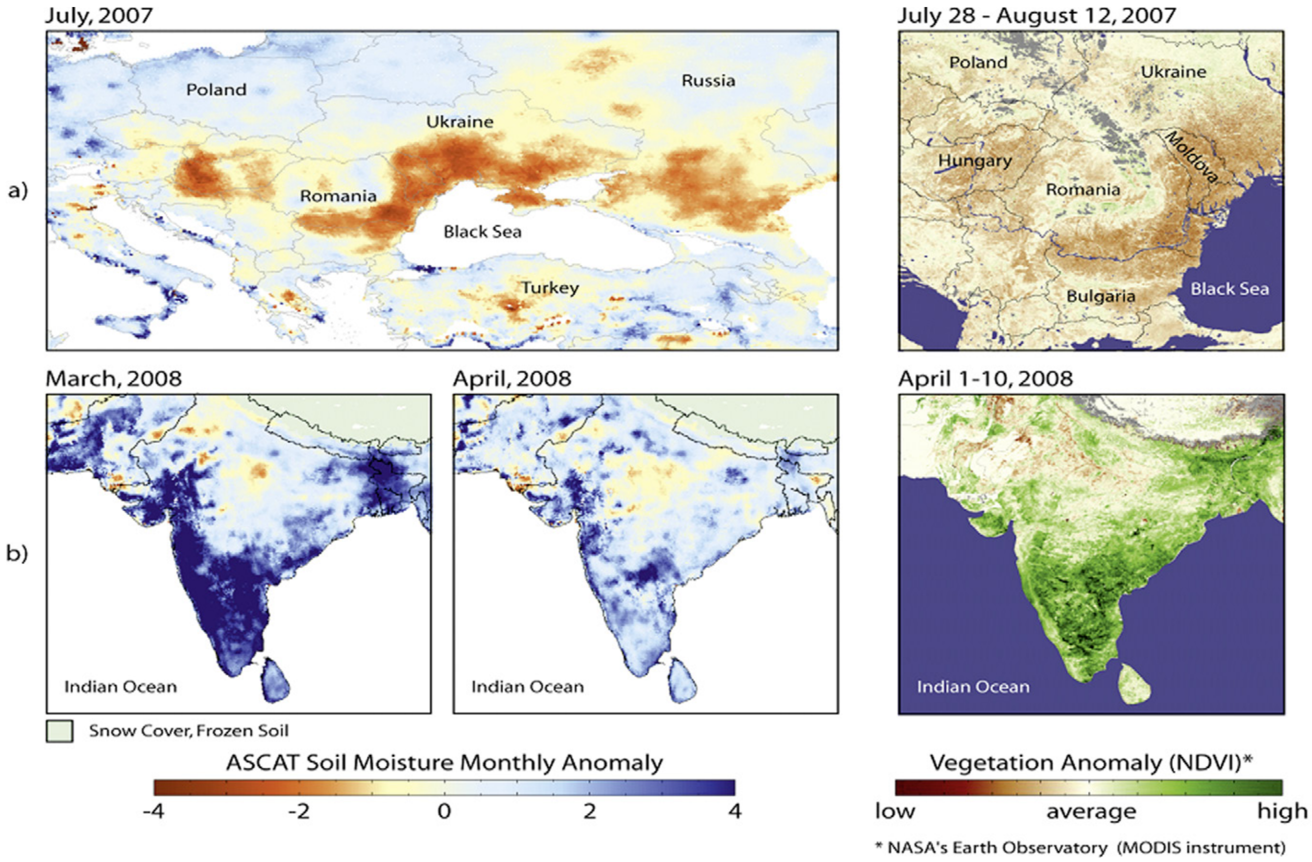


Figure 14: Anomalous soil moisture conditions are normally well reflected in vegetation status, as demonstrated by these two examples of extreme dry (top) and wet conditions (bottom). From Naeimi and Wagner (2010).



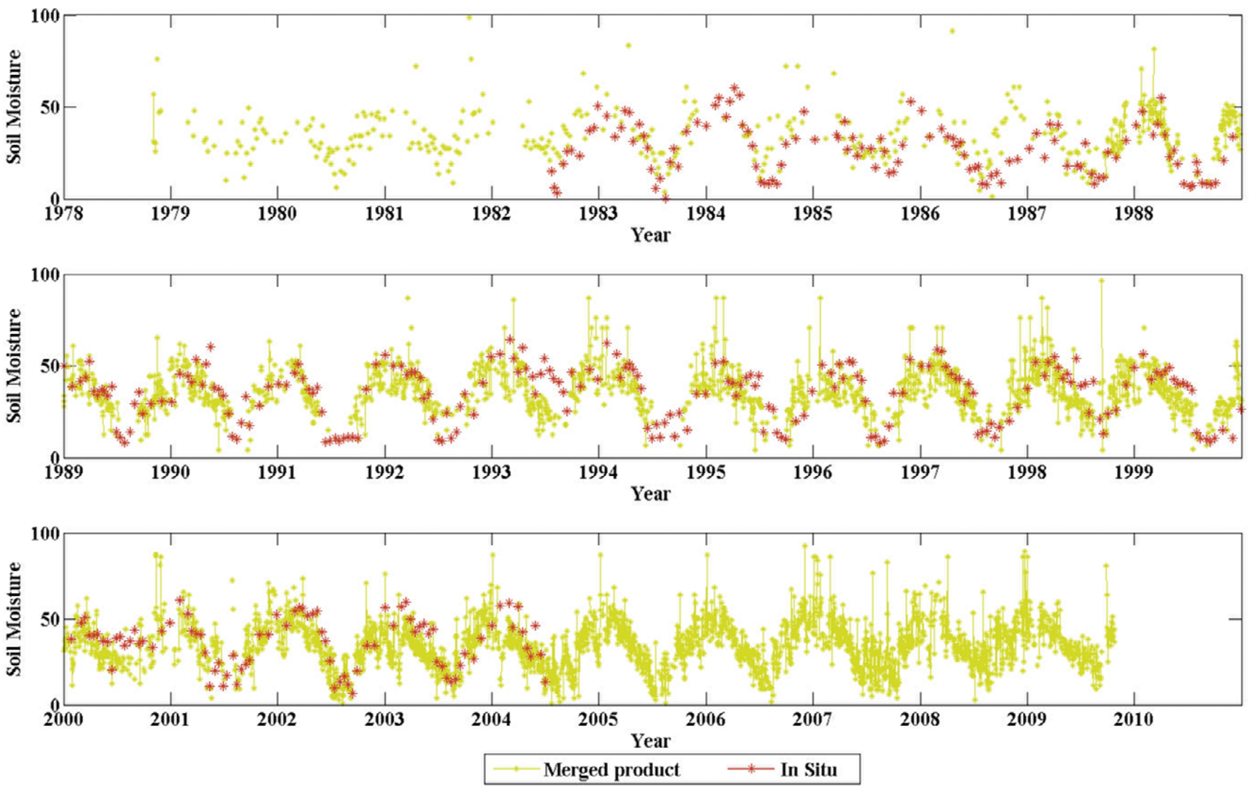
5.2.3 CLIMATE CHANGE

Many climate change simulations such as the one carried out by Gerten et al. (2007) suggest that soil moisture will decrease over the major part of the global land surface area due to climate warming. Yet, predictions of soil moisture are still uncertain because of the absence of suitable observations to refute the model results (Li et al. 2007). So far, long-term satellite records have not been available and in-situ measurements are sparse. This shortcoming was recognised at the workshop "Future Climate Change Research and Observations: GCOS, WCRP and IGBP Learning from the IPCC Fourth Assessment Report" organised jointly by the Global Climate Observing System (GCOS), the World Climate Research Programme (WCRP), and the International Geosphere-Biosphere Programme (IGBP) in Sydney, Australia, 4-6 October 2007. The workshop report pointed out that a more rigorous validation of models with observations of essential climate variables (ECVs), which are considered feasible for global observation, and essential for IPCC (Intergovernmental Panel on Climate Change) and UNFCCC (United Nations Framework Convention on Climate Change) needs, is essential. With respect to soil moisture, the report stated: "Datasets on effective soil moisture that can be used to constrain terrestrial models remain largely unavailable. Space-based capabilities to observe top-soil moisture (e.g., from ASCAT) and full moisture content (including ground water from GRACE) have become available, and provide, in combination with existing in situ soil moisture profile measurements, for the first time an opportunity to better understand the storage side of the water balance." As a result, soil moisture was endorsed as an official ECV at the 16th Session of the GCOS Steering Committee in Geneva, 14-17 October 2008, which means that the international community is called for action to generate long-term satellite soil moisture data sets.

As discussed in Section 3.2, soil moisture data sets from both active and passive microwave remote sensing instruments have become increasingly available and, very important for climate change research, soil moisture retrievals start to converge. This opens the possibility to construct long term time series by combing active and passive soil moisture retrievals (Wagner et al. 2009a). Merging of satellite-derived soil moisture data can be done using matching techniques such as the cumulative distribution matching used by Drusch et al. (2005). While the technical implementation appears straight forward, not all sensors are of course equally well suited for the task of soil moisture retrieval. Therefore, the quality of any long-term soil moisture record will be variable in space and time. Also, it needs to be considered that imperfections in the retrieval algorithm may have a strong impact on the quality of the soil moisture retrievals. For example, Wagner et al. (2007b) compared different soil moisture data sets derived from passive and active microwave observations over a validation site in Spain and found the best and worst results for two datasets derived from the same sensor, while the two best active and passive datasets were in reasonable agreement. The scientific challenge will therefore be to quantify the spatio-temporal error field for different sensor-algorithm combinations. New error assessment approaches such as the data assimilation approach proposed by Crow and Zhan (2007) or the triple-collocation method by Scipal et al. (2008) are fundamental for meeting this challenge.

The first steps towards the creation of an ECV soil moisture data sets are currently underway within the WACMOS project funded by ESA (Su et al. 2010). This project has the goal to create a 30+ year data set by firstly producing active and passive soil moisture time series separately, then characterising the errors using triple collocation and error propagation modelling, and finally merging of the active-passive data sets. A preliminary comparison of the merged data set with in-situ observations from the Illinois Climate Record is shown in Figure 15. First results of this project are described in more detail in Dorigo et al. (2010) and Liu et al. (2010).

Figure 15: Comparison of a merged active-passive soil moisture data set with in-situ soil moisture observations collected by the Illinois Climate Record.



6. CONCLUSIONS

This report has revealed a certain antagonism in the field of remote sensing and its application in hydrology and water resource management. On the very positive side, earth observation technology has made significant advances in recent years, reaching a point where it starts having a significant and positive impact for assessing and predicting water storages and fluxes from local to global scales. Yet, at the same time, one has to note that the enormous technological potential of earth observation is only partially tapped. The main reason for this probably is that the importance of building up operational services for higher level remote sensing data products has not been sufficiently recognised. Most space agencies define as their responsibility only the space segment and a rather limited ground segment that transforms unprocessed instrument and payload data at full resolution (so-called Level 0 data) to geometrically corrected data in sensor units (Level 1). The assumption behind this operation model is that public users and the „market" are able to uptake these basic data products and establish operational value-adding services. With few exceptions this operation model has not delivered the wished-for results. This becomes apparent when the output of earth observation missions that were set up under this operation model are compared to the achievements of earth observation programmes that go at least one step further, i.e. rather than to stop at Level 1 these advances programmes deliver geophysical variables in instrument geometry (Level 2) and value-added data products mapped on uniform space–time grid scales (Level 3 and Level 4).

This problem has already been recognised by various national and international programmes (GMES, GEOSS, etc.) that aim to bridge the gap between remote sensing data providers and users. However, the scientific and technological challenges that need to be overcome in order to establish user-friendly higher-level data services are still widely underestimated. Also, the significant efforts needed to adapt models to effectively use remote sensing data are also not properly appreciated. And this situation may get worse if no proper measures will be taken to handle the exponentially growing data volumes. Therefore, the recommendation is to pay significantly more attention to the task of building up higher-level data services and to apprehend the multi-faceted scientific and technological expertise behind this task. With this, earth observation will no doubt contribute significantly to a better management of water resources under a changing climate, and a more effective response to floods, droughts and other natural disasters.

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8. SOURCES OF THE CHAPTERS

SECTION	SOURCE
2, 5.1	Wagner, W., Verhoest, N.E.C., Ludwig, R., Tedesco, M. (2009): Remote Sensing in hydrological sciences. Hydrology and Earth System Sciences 13, 813-817.
3.2	Wagner, W., de Jeu, R. Brocca, L., Dorigo, W., Berry, P., Hahn, S., Beneviste, J. (2011): Recent advances in microwave remote sensing of soil moisture. Advances in Space Research, in preparation.
3.3, 3.4	Bartsch, A., Wagner, W., Kidd, R. (2010): Remote sensing of spring snowmelt in Siberia. Chapter 9 of "Environmental Change in Siberia". In: Balzter, H., ed., Springer Series on Advances in Global Change Research 40, Part 2, 135-155.
3.5	Bartsch, A., Blyth, E., Hayman, G. (2010): Preliminary Analyses Report. Report prepared for the project ALANIS methane. European Space Agency.
4.2, 4.3	Wagner, W., Hollaus, M., Briese, C., Ducic, V. (2008): 3D vegetation mapping using small-footprint full-waveform airborne laser scanners. International Journal of Remote Sensing 29(5), 1433-1452.
5.2.3	Wagner, W., de Jeu, R., van Oevelen, P. (2009): Towards multi-source global soil moisture datasets for unravelling climate change impacts on water resources. Proceedings of the 33rd International Symposium on Remote Sensing of Environment (ISRSE), 4-8 May 2009, Stresa, Italy, Joint Research Centre of the European Commission, 3.

MATERIALIEN DER PROJEKTGRUPPE „GEORESSOURCE WASSER – HERAUSFORDERUNG GLOBALER WANDEL"

Udo Wiesmann: *Historische Impressionen bei einer Spreefahrt durch Berlin,* acatech Materialien Nr. 2, München 2011.

Insa Theesfeld, Christian Schleyer: *Institutional Requirements for Integrated Water Resource Management in Germany,* acatech Materialien Nr. 3, München 2011.

Helmar Schubert: *Die Konzepte des Virtuellen Wassers und des Wasser-Fußabdrucks*, acatech Materialien Nr. 4, München 2011.

Hagen Koch, Uwe Grünewald: *Anpassungsoptionen der Wasserbewirtschaftung an den globalen Wandel in Deutschland*, acatech Materialien Nr. 5, München 2011.

Steffen Krauss, Christian Griebler: *Pathogenic Microorganisms and Viruses in Groundwater,* acatech Materialien Nr. 6, München 2011

Wolfgang Wagner, Michael Vetter, Annett Bartsch: *Novel Microwave- and Lidar Remote Sensing Techniques for Monitoring of In-Land Water Resources,* acatech Materialien Nr. 7, München 2011

Der aktuelle Stand der acatech Materialien zum Projekt „Georessource Wasser – Herausforderung Globaler Wandel" sowie einzelne Texte sind unter anderem im Internet unter http://www.acatech.de/de/projekte/laufende-projekte/georessource-wasser.html einsehbar. An gleicher Stelle sind auch Hinweise auf weitere Publikationen und auf Veranstaltungen im Rahmen des Projektes zu finden.