D.3 PARAMETERIZATION POOL

Parameterization Pool for Remote Sensing Data

OVERVIEW

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<thead>
<tr>
<th>Parameter</th>
<th>Objective</th>
<th>Sensor type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leaf Area Index</td>
<td>Leaf Area Index, LAI, quantifies the amount of foliage per unit ground surface area. It is one of the “driving” biophysical variables and is therefore an important input to many models, e.g. hydrological, ecological and climate models.</td>
<td>optical</td>
</tr>
<tr>
<td>Land Cover</td>
<td>The term land cover relates to the type of feature present on the surface of the earth.</td>
<td>optical</td>
</tr>
<tr>
<td>Soil moisture</td>
<td>Soil moisture is storage of water between precipitation and evaporation that acts as a regulator of one of the more fundamental hydrological processes, infiltration and runoff production from precipitation and which must be accounted for in any water or energy balances. It is an environmental descriptor that integrates much of the land surface hydrology, acts as the interface between the earth’s surface and the atmosphere and plays a crucial role in life and bio-geochemical cycles.</td>
<td>radar</td>
</tr>
<tr>
<td>Catchment topography</td>
<td>Catchment topography is the base for hydrological processes related to flow and accumulation of surface water. Parameters derived from a Digital Elevation Model (DEM) like slope angle and aspect are often used.</td>
<td>optical</td>
</tr>
<tr>
<td>Water Quality</td>
<td>Water quality is a general term used to describe the physical, chemical, thermal, and/or biological properties of water. In broader terms the quality of water affects all components of the aquatic ecosystem. It is a parameter that relates to land cover, anthropogenic disturbances, management, and hydrologic dynamics of rivers controlled by spatially distributed catchment properties.</td>
<td>optical</td>
</tr>
<tr>
<td>Soil Erosion</td>
<td>Soil erosion causes both physical (i.e. gullies, rills) and visible (i.e. exposure of different coloured soil layers) changes in the surface properties of soils. Remote sensing techniques can measure qualitative and quantitative information on changes in the soil surface roughness and on visible features.</td>
<td>optical</td>
</tr>
<tr>
<td>Snow</td>
<td>Snow melt is responsible for large amounts of annual runoff in numerous catchments in higher latitudes and mountainous regions. The snow cover is a temporal intermediate storage, releasing the ecologically and economically important melt water in warmer periods.</td>
<td>optical</td>
</tr>
<tr>
<td>Evapotranspiration</td>
<td>The actual evapotranspiration is responsible for 70 % of global energy exchange through latent heat fluxes (MAUSER &amp; SCHÄDLICH 1998). It therefore has a significant relevance for the water cycle concerning the distribution of water resources and runoff.</td>
<td>optical</td>
</tr>
<tr>
<td>Precipitation</td>
<td>The estimation of the precipitation amount is the base for the observation of large scale hydrological processes since it represents the input of the hydrological cycle. It should therefore be quantified as accurate as possible.</td>
<td>optical</td>
</tr>
</tbody>
</table>
PARAMETERIZATION METHODS FOR REMOTE SENSING DATA

Leaf Area Index

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<thead>
<tr>
<th>Sensor type</th>
<th>Digital Image Preprocessing</th>
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<tbody>
<tr>
<td>optical</td>
<td>Radiometric Calibration</td>
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<tr>
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<td>Geocoding of optical Data</td>
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<td></td>
<td>Topographic Correction</td>
</tr>
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<td></td>
<td>Index Images</td>
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</table>

1 OBJECTIVE

Leaf Area Index, LAI, quantifies the amount of foliage per unit ground surface area. It is one of the "driving" biophysical variables and is therefore an important input parameter to many models, e.g. hydrological, ecological and climate models. LAI varies with plant/tree species as well as with mean annual temperature, length of the vegetation period, water supply (WULDER 1998) and stock age (SPANNER et al. 1994).

The hydrological meaning consists in the fact that species with high LAI like e.g. oak or beech have a higher interception capacity during the vegetation period than species with low LAI like e.g. pine or larch (DANSON 1995). LAI also influences the photosynthesis as well as the amount of perspired water and both the amount of absorbed CO2 and emitted O2 through the leaf surface area. It is therefore an important steering parameter of the plant water balance and of the energy and mass exchange between vegetation and atmosphere (SPANNER et al. 1990, WULDER 1998).

The LAI is defined as the projected leaf surface area per unit ground surface. However, recently LAI has been defined as one half the total green leaf area per unit ground area (CHEN & BLACK 1992, as referred in CHEN & CIHLAR 1996 & CHEN et al. 1997). Estimates based on these two definitions can differ by a factor between 1.28 and 2, depending on the form of the object that is described. The change in definition is related to the fact that optical instruments respond to half the total area of foliage elements rather than to the projected area (op cit.). LAI = 0 means that no leafs or needles exist, LAI = 1 indicates that the leaf area equals the horizontal ground surface, LAI = 2 means that the leaf area is double the size as the ground surface area etc. The maximum value of LAI = 16 has been reached in evergreen forests at the west coast of the USA.

2 METHOD DESCRIPTION

LAI can be quantified either using direct and/or indirect field methods (which are very time and cost consuming) or indirect satellite remote sensing methods. The recognition that reflectance measurements offered the opportunity for "scaling up" from the plot level to larger areas has produced sustained interest over the last three decades in development of empirical algorithms relating LAI to surface reflectance and to spectral vegetation indices (SVIs) derived from reflectance.

Optical instruments measure light transmittance beneath/within a canopy; i.e. gap fraction over a range of zenith angles is measured and gives the effective LAI, LAIₑ (CHEN et al. 1997). The assumption for optical measurements is random distribution of foliage. This implies that LAIₑ can be derived from the probability that a beam of direct radiation will pass unobstructed through a canopy. LAI can be derived from LAIₑ by correcting for contribution of woody materials and for canopy architecture (i.e. nonrandom foliage distribution). However, none of these correction factors can be measured with commonly applied optical instruments (op cit.). The major workload in making optical measurements of LAI is in obtaining these two correction factors (op cit.).

The assumption of random foliage distribution is fulfilled for closed canopy deciduous forest. However, for open canopy forests (e.g. coniferous, aspen) where this assumption is not fulfilled, it is of importance to correct the LAIₑ in order to obtain realistic estimates of LAI. Otherwise the LAI might be estimated with an error of 100% (GOWER et al. 1999). Thus, in cases of non-random distribution of foliage an accurate description of canopy architecture, e.g. gap size, is essential. Gap size is described by two components: clumping within a shoot and clumping at scales larger than the shoot.
CHEN et al. (1997) discuss how these can be quantified. Typically LAIe measured in coniferous stands are 50-70% of LAI due to foliage clumping (op cit).

**Direct field methods**

**Area harvest**

Area harvest is applied to determine Specific Leaf Area, SLA. SLA is the ratio of fresh foliage surface area to unit dry foliage mass. SLA provides the coefficient to convert foliage mass to leaf area. It is a problem that there is no consistent way for defining SLA. GOWER et al. (1999) suggest its definition as half the total needle surface area, referred to as hemisurface area (HAS). SLA is species dependent.

**Allometry**

Allometry is the relationship between the mass or area of a part (e.g. leaf mass or area), and an independent variable. Stem diameter and sapwood cross sectional area are commonly used as independent variables. Such a relation can be used to directly estimate LAI if SLA is known. Both biotic and abiotic factors influence the allometry coefficient, thus these relations are site specific and moderate to large errors can result if applied to stands where other biotic and abiotic factors dominate.

**Pipe model**

The Pipe model is a slight variation of the allometric equation. It correlates the cross-sectional area of a stem or branch that is responsible for water transport (i.e. sapwood) to foliage mass or to leaf area.

**Indirect field methods**

LAI can be estimated by measuring light transmission within stands by means of a photometer. Numerous commercially available instruments, such as Decagon ceptometer, LI-COR LAI-2000 plant canopy analyser (LI-COR 1992, DEBLONDE & PENNER 1994), DEMON & TRAC, are used to indirectly estimate LAI: all of the instruments assume foliage is randomly distributed in the canopy and generally give biased estimates. Consequently, conversion factors are required to convert output from the photometer to the actual LAI.

**Indirect satellite remote sensing methods**

Satellite remote sensing provides a unique way to obtain distribution of LAI over large areas. Two approaches are generally used to estimate LAI from spectral reflectance measurements:

**Deterministic or stochastic canopy radiation models**

The first approach is based on the use of deterministic or stochastic canopy radiation models. Such models are developed for homogenous canopies (agriculture), however, for heterogeneous canopies (forest) it has proved difficult to adequately simulate the variability. Models for forest canopies also require data for parameterisation at scales and resolutions that generally are unavailable (NEMANI et al. 1993).

**Empirical spectral vegetation indices (SVI)**

The second approach is based on empirical spectral vegetation indices (SVI). LAI can be related to SVIs because they are sensitive to photosynthetic activity and hence, in one way or another, to leaf area. Commonly it is the Red, NIR and/or MIR/SWIR, e.g. respectively TM3, TM4 and TM5, that are used to calculate the SVI.

Both the Red and MIR band have a strong inverse curvilinear relationship to LAI, of which the MIR relationship is strongest (SPANNER et al. 1990). This inverse relationship is in accordance with the expected trend for these bands over vegetation; i.e. as the vegetation coverage increase the spectral reflectance decrease due to high absorption for vegetation (respectively pigments and leaf water content). However, NIR has a less consistent behaviour; i.e. the spectral reflectance decrease as LAI increases for low LAIs, while there is a positive correlation for high LAIs. This pattern is due to the combined effect of an increase in NIR reflectance caused by increased vegetation coverage and of decrease in NIR reflectance caused by increased shadowing from overstory vegetation (trees). The net effect will be dominated by the shadowing factor at low LAIs and by the canopy factor at higher LAIs.

In general the SVI-LAI relationship is influenced by canopy closure and as the canopy opens the influence from understory vegetation and background reflectance increases. It is a challenge to remove/minimise the influence of the latter two factors on the SVI - LAI relationship. Another challenge is to increase the low sensitivity of this relationship at mid to high LAIs. Both for the single bands and for SVIs there is saturation around a LAI of 35. Vegetation with LAI above 35 occupies one third of the terrestrial land surface (TURNER et al. 1999).

Different SVIs have been related to LAI (Table 1), and several authors have made comparisons among these SVIs. Among SVIs based on Red and NIR, NDVI, SR and SAVI have been related to LAI. TURNER et al. (1999) compared these SVIs, derived from Landsat TM, across three temperate
zone sites. Different pre-processing is also done in this study and they conclude that atmospherically
corrected imagery give stronger cross-site LAI-SVI relationship than those based on DN, radiance, or
top of atmosphere reflectance.
Topographic corrections had, however, little effect on the LAI-SVI relationship. They do not conclude
that one SVI gives a better LAI relation than another but rather that the optimal relationship depends
both on vegetation -type and -density. In a study by HUETE et al. (1997) it is, however, argued that
while NDVI is sensitive to fraction of absorbed photosynthetic active radiation, SARVI (a SAVI type of
index) is more sensitive to structural canopy parameters such as leaf area index and leaf morphology.
On the other hand, Brown et al. concludes that SAVI minimise background effects but has a
decreased sensitivity to LAI compared to SR. CHEN & CIHLAR (1996) study NDVI and SR and
recognise the limitations of these indices to remove the effects of background. In order to minimise this
effect they suggest selecting imagery from an optimal season, in their case late spring before the full
growth of the understory and moss cover. They found no statistical significant difference in terms of
the accuracy in retrieving LAI from NDVI and SR.

Table 1: Overview of Spectral measures of LAI used in different studies with different sensors over
varying vegetation types (forests) and obtained regression coefficients

<table>
<thead>
<tr>
<th>Spectral measures of LAI</th>
<th>Sensor</th>
<th>Regression coefficient (standard error, vegetation type)</th>
<th>Author</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDVI = (NIR-R)/(NIR+R)</td>
<td>TM</td>
<td>0.302-0.597 (0.093, temperate conifer forest)</td>
<td>Spanner et al., 1990</td>
</tr>
<tr>
<td></td>
<td>TM</td>
<td>0.32 (-, boreal conifer forest)</td>
<td>Nemani et al., 1993</td>
</tr>
<tr>
<td></td>
<td>TM</td>
<td>0.74 (0.04, various)</td>
<td>Turner et al., 1999</td>
</tr>
<tr>
<td></td>
<td>NOAA AVHRR</td>
<td>0.50-0.52 (-, boreal conifer forest)</td>
<td>Chen and Cihlar, 1996</td>
</tr>
<tr>
<td></td>
<td>TM</td>
<td>0.46 (-, boreal forest)</td>
<td>Boyd et al., 2000</td>
</tr>
<tr>
<td>SR = NIR/R</td>
<td>TM</td>
<td>0.122-0.554 (-, boreal forest)</td>
<td>Brown et al., 2000</td>
</tr>
<tr>
<td></td>
<td>TM</td>
<td>0.255-0.537 (2.153, temperate conifer forest)</td>
<td>Spanner et al., 1990</td>
</tr>
<tr>
<td></td>
<td>TM</td>
<td>0.59 (0.19, various)</td>
<td>Turner et al., 1999</td>
</tr>
<tr>
<td></td>
<td>TM</td>
<td>0.53 (-, boreal conifer forest)</td>
<td>Chen and Cihlar, 1996</td>
</tr>
<tr>
<td>SAVI = [NIR-R]/(NIR+R+L)(1+L)</td>
<td>TM</td>
<td>0.54 (0.14, various)</td>
<td>Huete 1988</td>
</tr>
<tr>
<td></td>
<td>TM</td>
<td></td>
<td>Turner et al., 1999</td>
</tr>
<tr>
<td>NDVIc = (NIR-R)/(NIR+R)</td>
<td>TM</td>
<td>0.64 (-, boreal conifer forest)</td>
<td>Nemani et al., 1993</td>
</tr>
<tr>
<td></td>
<td>TM</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RSR = (NIR/R)*?1-?(MIR_{max}-MIR_{min})/(MIR_{max}-MIR_{min})</td>
<td>TM</td>
<td>0.551-0.703 (boreal forest)</td>
<td>Brown et al., 2000</td>
</tr>
<tr>
<td>VI3 = (NIR-MIR)/(NIR+MIR)</td>
<td>TM</td>
<td>0.620-0.626 (temperate conifer forest)</td>
<td>Spanner et al., 1990</td>
</tr>
<tr>
<td></td>
<td>TM</td>
<td>0.76 (-, boreal forest)</td>
<td>Boyd et al., 2000</td>
</tr>
<tr>
<td>SR(MIR) = NIR/MIR</td>
<td>TM</td>
<td>0.524-0.553 (Temperate conifer forest)</td>
<td>Spanner et al., 1990</td>
</tr>
<tr>
<td>NDVI and texture</td>
<td>casi</td>
<td>0.92 – (0.68, canadian subalpine forest)</td>
<td>Wulder et al., 1996</td>
</tr>
</tbody>
</table>

# L is an empirically determined factor to minimize the soil background influence;
? MIR_{max} and MIR_{min} are radiances from completely close and completely open canopies respectively
(NEMANI et al. 1993)
Several other studies (BOYD et al. 2000, BROWN et al. 2000, NEMANI et al. 1993, SPANNER et al. 1990) have focused on a comparison of a SVI based on NIR and Red, and an equivalent SVI including MIR. The advantage of the MIR band is both its similar reflectance across different background types and its larger sensitivity to LAI (BROWN et al. 2000). All these studies conclude that indices including MIR perform better than the equivalent NIR-R indices. However, SPANNER et al. (1990) finds only small improvements by their MIR-based indices. BROWN et al. (2000) find that the RSR has the potential to unify deciduous and coniferous species, a fact that suggests the possibility of not requiring cover type stratification prior to LAI retrieval.

Another approach to improve the SVI-LAI relationship is tested by WULDER et al. (1996). They included a texture component derived from the high resolution Compact Airborne Spectrographic Imager (casi) in the NDVI-LAI relationship and consequently retrieved a stronger correlation to LAI.

One general conclusion from the individual LAI-SVI studies is that there is considerable sensitivity to LAI, but more so at relatively low LAI values. R-NIR SVIs typically increase over an LAI range from 0 to about 3-5 before an asymptote is reached. The upper limit of sensitivity, and the relative importance of R and NIR reflectance in determining this limit, apparently differ among vegetation types.

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Land Cover

<table>
<thead>
<tr>
<th>Sensor type</th>
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<tbody>
<tr>
<td>optical</td>
<td>Radiometric Calibration</td>
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<td>Geocoding of optical Data</td>
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<td></td>
<td>Topographic Correction</td>
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<td></td>
<td>Image Fusion</td>
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<td>Index Images</td>
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<td>Spectral Signatures</td>
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<td>Classification of optical Data</td>
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<td>Accuracy Assessment</td>
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<tr>
<td>radar</td>
<td>Radar Calibration</td>
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<td>Geocoding of radar Data</td>
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<td>Speckle Filtering</td>
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<td>Coherence Images</td>
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<td></td>
<td>Classification of radar Data</td>
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<td>Accuracy Assessment</td>
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</tbody>
</table>

1 OBJECTIVE

The term land cover relates to the type of feature present on the surface of the earth. Recognition of land cover in images is based on the different spectral reflections of these features. With regard to hydrology land cover provides information on the imperviousness and roughness of the surface, necessary for modelling surface run-off, or on the type of agricultural crops, relevant for estimating nutrient leaching into water bodies.

A number of classification schemes has been set up for use with remote sensing imagery, usually providing a hierarchical structure, where the degree of detail increases with the level of the hierarchy. Well known nomenclatures are the one from the USGS (United States Geological Survey) (Anderson et al, 1976) and the CORINE land cover nomenclature from the EC (see table 1, EUR 1993). The different levels of the nomenclatures are related to the different resolution of the image data and thus to the scale of the final land cover map. While the first two levels are designed for information on a continental or national scale, further levels are related to regional and local applications. For hydrological applications on a catchment basis the requirements will be related to the third level.

2 METHOD DESCRIPTION

Deriving land cover from satellite images requires at first the right choice of image data. The most widely used type of imagery are multispectral data with a resolution between 20 and 30m (such as Landsat TM or SPOT). Multispectral data are a prerequisite for the differentiation of the required land cover types. However, there is an increasing use of panchromatic data with a spatial resolution between 5 and 10m (such as IRS-1C/D PAN or SPOT PAN). These data can be used directly for the derivation of various land cover types, but also can be combined with the multispectral data to improve their spatial resolution. Depending on the image data used the final scale will be in a range between 1:25000 to 1:100,000. In the following paragraphs a short description is presented of how to derive the major land cover types that occur in a cultural landscape. It is based on the availability of image data described above.

Built-up areas

Built-up areas are composed of man-made objects such as buildings or traffic infrastructure. In a wider sense they might also include mineral extraction and dump sites. Classification of multispectral data will allow the derivation of two or three urban density classes, and industrial or commercial centres. Linear elements such as roads and railroad track will not be detected, unless they have a significant width. The mapping of industrial and commercial units will in most cases need ancillary information or local expertise.

Due to the pixel size of multispectral data urban areas will have a large portion of mixed pixels and thus spectral confusion will occur between these areas and agricultural or natural land cover. This can be solved by analysing textural characteristics of higher resolution panchromatic imagery. Derivation of a texture mask allows the separation of built-up areas from agricultural or natural areas. Intersection
with the multispectral classification results will limit the multispectral analysis to the actual settlement areas and avoid confusion with non artificial land cover types.

**Agricultural areas**

Agricultural areas include pastures and arable land, that is further separated into permanent and non-permanent crops. While pastures and permanent crops can be recognised in a single multispectral image, the mapping of non-permanent crops requires multitemporal imagery. A mono-temporal satellite image will only offer information on the status of these crops at the moment of data capture. A time series of three or more images acquired during spring and summer of one year provides information of the development of the single plants. Differentiation of crop types can thus be based not only on the spectral response of the crops but also on their phenological development and time of harvest.

When estimating the acreage of crops one should be aware that mixed pixels will occur at the borderline between fields. Image fusion techniques allow the increase of the spatial resolution of the multispectral images by combining them with higher resolution panchromatic images. The resulting sharpened multispectral image will have a reduced amount of mixed pixels and will increase the quality of the classification product.

**Forest**

Classification of forest from satellite images is hampered by the spatial resolution of the imagery. While aerial photographs allow the interpretation of single trees - including their shape and texture - the pixel in a satellite image usually covers at least one tree including its surroundings. Classification of forest parameters such as tree species, crown coverage or age is therefore a complex task.

Standard multispectral classification for differentiation of broadleaf and coniferous forest leads to satisfactory results. This also includes the detection of clear-cuts and windfall. Identification of tree species and crown closure is possible to a certain extent but requires more complex data analysis and high quality reference data. The use of multitemporal data from spring and autumn can help to separate certain species.

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**REFERENCES**

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EUR 12585 (1993):  
CORINE land-cover project - Technical guide. Luxembourg


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Table 1: CORINE land cover nomenclature

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<th>Level 2</th>
<th>Level 3</th>
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<td>1.1 Urban fabric</td>
<td>1.1.1 Continuous urban fabric</td>
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<td>1.2 Industrial,</td>
<td>1.2.1 Industrial or commercial units</td>
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<td></td>
<td>commercial and transport units</td>
<td>1.2.2 Road and rail networks and associated land</td>
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<td></td>
<td>1.3 Mine, dump and construction sites</td>
<td>1.2.3 Port areas</td>
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<td>1.2.4 Airports</td>
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<td>1.3.2 Dump sites</td>
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<td>1.3.3 Construction sites</td>
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<td></td>
<td>1.4 Artificial non-agricultural vegetated areas</td>
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<td>2. Agricultural areas</td>
<td>2.1 Arable land</td>
<td>1.4.2 Sport and leisure facilities</td>
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<td>2.1.1 Non-irrigated arable land</td>
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<td>2.1.2 Permanently irrigated land</td>
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<td>2.1.3 Rice fields</td>
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<td>2.2 Permanent crops</td>
<td>2.2.1 Vineyards</td>
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<td>2.2.2 Fruit trees and berry plantations</td>
<td>2.2.2. Fruit trees and berry plantations</td>
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<td>2.2.3 Olive groves</td>
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<td>2.3 Pastures</td>
<td>2.3.1 Pastures</td>
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<td></td>
<td>2.4 Heterogeneous agricultural areas</td>
<td>2.4.1 Annual crops associated with permanent crops</td>
</tr>
<tr>
<td></td>
<td>2.4.2 Complex cultivation patterns</td>
<td>2.4.2 Complex cultivation patterns</td>
</tr>
<tr>
<td>3. Forests and semi natural areas</td>
<td>3.1 Forests</td>
<td>2.4.3 Land principally occupied by agriculture, with significant areas of natural vegetation</td>
</tr>
<tr>
<td></td>
<td>3.1.1 Broad-leaved forest</td>
<td>2.4.4 Agro-forestry areas</td>
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<td>3.1.2 Coniferous forest</td>
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<td></td>
<td>3.1.3 Mixed forest</td>
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<td>3.2 Shrub and/or herbaceous vegetation associations</td>
<td>3.2.1 Natural grassland</td>
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<td></td>
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<td>3.2.2 Moors and heathland</td>
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Soil moisture

Soil moisture is storage of water between precipitation and evaporation that acts as a regulator of one of the more fundamental hydrological processes, infiltration and runoff production from precipitation and which must be accounted for in any water or energy balances. It is an environmental descriptor that integrates much of the land surface hydrology, acts as the interface between the earth’s surface and the atmosphere and plays a crucial role in life and bio-geochemical cycles.

In situ measurements of soil moisture are time consuming, and are often not feasible for studies covering large areas which are involved in hydrological modelling. The large spatial and temporal variability that soil moisture exhibits in the natural environment is precisely the characteristic that makes it very difficult to measure and use in earth science applications.

2 METHOD DESCRIPTION

Recent advances in remote sensing have shown that soil moisture can be measured by a variety of techniques using all parts of the electromagnetic spectrum. However, only microwave technology has demonstrated a quantitative ability to measure soil moisture under a variety of topographic and vegetation cover conditions so that it could be extended to routine measurements from a satellite system (ENGMAN & Chauhan, 1995). The two most promising technologies for this purpose are passive and active microwave sensors. The advantage of passive microwave systems include frequent coverage, low data rates and simpler data processing. The disadvantages include poor resolution. In the case of active microwave systems, the advantages include high resolution, but comes at the expense of larger data volumes and more complex processing.

The theoretical basis for microwave’s sensitivity to soil moisture lies in the strong dependence of both radar backscatter and passive radiometric brightness temperatures on the dielectric constant. Dry soil has a real dielectric constant $\varepsilon'$ of about 2-3 and water has an $\varepsilon'$ of about 80. When these two materials are mixed, the resulting dielectric constant can range from 3 to over 25 for very moist soil.

Many experiments indicate that soil moisture could indeed be measured accurately with spaceborne SAR under certain conditions and especially with ERS-1 (Borgeaud et al. 1993; LE TOAN et al. 1993; FELLAH et al. 1995; Dabrowska-Zielinska et al., 1997). For this, a number of SAR pre-processing steps need to be applied. It concerns the full calibration of the SAR data (LAUR et al. 1996), a selection of particular observation scale for which soil moisture could be derived with sufficient confidence (FELLAH, 1997) and finally, a selection of surfaces for which soil moisture could be potentially derived (bare soils, sparse vegetated areas). The last could be by using synergies of EO data and GIS approaches.

There are two approaches to radar measurement of soil moisture. The first uses instantaneous estimation of absolute near-surface soil moisture and the second relies on change detection procedures to estimate increases/decrease to near-surface water content. The accuracy of the first depends by the capability to correct the estimated volumetric soil moisture for the effects of the other components (vegetation cover, surface roughness and topography). The change detection approach minimises the impact of these components as they tend to change slowly as a function of time.

Theoretical Models

Theoretical models like the optics model (PO) and the geometrical optics model (GO) predict the trend of radar backscatter in response to both changes in roughness and soil moisture; however they can rarely be used to invert data measured from natural surfaces, mainly because of the restrictive assumptions made when deriving them. More recently a model based on the integral equation (IEM), (FUNG et al. 1992) which although more complicated, should be applicable to a wider range of surfaces. Work is currently in progress to evaluate this model as a candidate for soil moisture inversion.
Empirical and Semi-Empirical Models
Because of the difficulties in applying theoretical models to data measured from natural surfaces, empirical (or semi-empirical) models were developed to infer soil moisture.

Soil moisture estimation of bare soil
Assuming the selection of a transmission and reception polarisation configuration, the following simplified model can be applied for bare soils (BERNARD et al. 1982; LE TOAN 1982; ULABY et al. 1982; DOBSON & ULABY, 1986). In this case, there is linear relationship between the backscattering coefficient $s^o s$ and soil moisture $H_s$.

$$s^o s = aH_s + b \quad (1)$$

$s^o s$ = backscattering coefficient  
$H_s$ = soil moisture  
$a$ and $b$ = coefficients depending on the radar system configuration and the surface roughness.

Soil moisture estimation under vegetation
With radar the effect of the vegetation canopy adds more complexity. For vegetated surfaces, the total backscatter observed by the radar $s^o t$ (at a given frequency, polarisation, and angle of incidence) could be decomposed as follow (ULABY et al., 1982):

$$s^o t = s^o v + \frac{s^o s}{L^2} \quad (2)$$

$s^o t$ = total backscatter observed by the radar  
$s^o v$ = backscattering contribution from vegetation  
$s^o s$ = backscattering contribution from soil  
$L^2$ = two way attenuation loss due to the canopy

Outlook
In the near future ENVISAT, RADARSAT-2 with polarimetric capabilities will offer more opportunities for soil moisture measurement and will bring the EO community therefore one step closer to providing important variables to help understand and routinely monitor the hydrological cycle.

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Catchment topography

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1 OBJECTIVE

Catchment topography is the base for hydrological processes related to flow and accumulation of surface water. Parameters derived from a Digital Elevation Model (DEM) like slope angle and aspect are often used.

Digital Elevation Models (DEM) are used to derive parameters describing catchment topography, e.g. drainage systems, catchment boundaries, slope angle and aspect. DEM are produced through field measurements using geodetic instruments or GPS systems, digitizing of contour lines from topographic maps, parallax measurements in stereo images using photogrammetric instruments or digital matching, radar interferometry and airborne laser systems. DEM are stored in regular raster form or in a TIN (triangular irregular network) structure. DEM are essential for geometric transformation (and radiometric correction) of remote sensing data in hilly or mountainous terrain. DEM and derived data like topographic features can be used to calculate solar irradiation, determine soil properties related to topographic position and to estimate e.g. erosion risk using models.

Basic software to derive from a DEM parameters relevant for hydrologic modeling are contained in most GIS systems. This include extraction of drainage systems, catchment boundaries, slope angle and slope aspect. More sophisticated software calculates slope length, extraction of topographic features like peaks, ridges and depression and corrects for typical errors like artificial depressions due to raster spacing in a DEM.

2 METHOD DESCRIPTION

DEM generation

Contour lines
Tradtitionally DEMs have been derived through digitizing of contour lines from existing maps and conversion to a regular grid or TIN structure with spot elevations.

Photogrammetry
Contour lines, profiles or spot elevations are measured in photogrammetric instruments using stereo images for DEM generation and orthophoto production.

Digital image matching
In the last 30 years matching of scanned aerial photographs or optical remote sensing data (e.g. SPOT) using digital image processing was developed. Height accuracy typically is of the same order of magnitude as pixel size, e.g 5 to 10 meters with panchromatic SPOT data, around 1 m with new high resolution spaceborne scanner data (e.g. IKONOS) and down to a few decimeters or centimeters with airborne systems depending on equipment and flying height. Typically the elevation of the upper layers of a dense vegetation cover, e.g. in forests, is determined and not the ground surface.

Radar interferometry
Interferometric methods using radar data have been developed in the last 10 years (Sawaya-Lacoste, H, 1999, Toutin, T & Gray, L,2000). During a 10 day space shuttle mission the American / German SRTM project collected radar data to create a global DEM for most of the land surfaces with a 30 m grid (e.g. Schmullius, C. et al, 2000). With C or X band typically elevation of the upper layers of a dense vegetation cover is determined. Longer wavelength radar systems, now available from aircraft, can penetrate vegetation cover and provide ground elevation data (e.g. Schwäbisch, M. & Moreira, J., 2000)

Laser
With Airborne laser systems vegetation top and ground elevation can be determined and over water surfaces elevation and water depth (depending on visibility in the water).
Extraction of catchment topography

Different algorithms are used to extract slope angle and azimuth, drainage systems, catchment boundaries, topographic elements etc, resulting in often minor differences in derived data. Random or systematic errors in a DEM can cause significant errors in derived data, e.g. slope angle (e.g. Giles, P.T. & Franklin, S.E., 1996), and may require significant modifications of algorithms. DEM grid size can affect computed topographic parameters significantly (e.g. Zhang, W. & Montgomery, D, 1994)

Slope angle and aspect

Surface normals are calculated and slope angle and azimuth derived from them. With raster data a plane through the nearest 4, 9 or 16 points is used. With a TIN structure the triangular plane between three corner points is used.

Catchment boundaries and drainage system

Catchment boundaries and drainage systems can be extracted from a DEM (Tribe, A. 1992, Martz, L.W. & Garbrecht, J., 1993). Typical problems are artificial depressions, caused by a DEM grid spacing of 100 or 50 m (or even 10 m), errors in the DEM and low precision in flat areas. Different approaches are used to reduce these problems, e.g. DEM filtering, searching for flow directions across small depressions and using an additional layer with real sinks or depressions. Accumulation maps with the number of upstream raster elements draining through a raster element are produced.

Topographic features

Topographic features like peaks, ridges, valleys and escarpments can be extracted from a DEM. Algorithms typically assess changes in local slope or approximate local morphology by second or third order polynomials. These topographic features can e.g. support delineation of erosion risk zones, rock or soil types.

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Water Quality

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1 OBJECTIVE

Water quality is a general term used to describe the physical, chemical, thermal, and/or biological properties of water. In broader terms, the quality of water affects all components of the aquatic ecosystem. It is a parameter that relates to land cover, anthropogenic disturbances, management, and hydrologic dynamics of rivers controlled by spatially distributed catchment properties.

Monitoring and assessing the quality of water in streams, reservoirs, lakes, estuaries, and oceans are critical for managing and improving the quality of the environment. Classical techniques for measuring indicators of water quality involve in situ measurements and/or the collection of water samples for subsequent laboratory analyses. Although these technologies give accurate measurements for a point in time and space, they are time consuming, expensive, and do not give either the spatial or temporal view of water quality needed for accurate monitoring, assessing, or managing water quality for an individual water body or for multiple water bodies across the landscape. Remote sensing of indicators of water quality offers the potential of relatively inexpensive, frequent, and synoptic measurements using sensors aboard aircraft and/or spacecraft.

2 METHOD DESCRIPTION

Major factors affecting water quality in fresh waters, estuaries, and oceans are suspended sediments, turbidity, chlorophylls (algae), chemicals, dissolved organic matter (DOM), nutrients, pesticides, thermal releases, and oils. Suspended sediments (turbidity), chlorophylls, DOM, and oils produce visible and/or thermal changes in surface waters that can change the energy of reflected solar and/or emitted thermal radiation from surface waters. Such changes in the spectral signals from surface waters are measurable by remote sensing techniques from many platforms. Substances can also change the thermal properties of water thus affecting the heat content and thus water temperature that can be measured remotely with thermal sensors. Most chemicals do not directly affect or change the spectral or thermal properties of surface waters. Measuring water properties affected by chemicals can only be inferred indirectly from remotely sensed measurements of other water quality parameters affected by these chemicals. Measurements of these surrogate properties may then be used in mathematical modeling and analyses to indirectly infer chemicals in water (RITCHIE & SCHIEBE 2000, p. 288).

Application of remote sensing for measuring water quality parameters depends on the ability to measure these changes in the energy spectral signature backscattered from water in the direction of
the sensor. Visible and near-infrared light energy in specific wavelengths can indicate the presence and concentration of substances in surface waters (THIEMANN AND KAUFMANN 2000, SCHIEBE et al. 1992, GITELSON et al. 1994). The optimal wavelength used to measure different water quality parameters is dependent on the substance being measured and the sensor characteristics.

Water samples analysed for the substance of interest should be collected at the same time or on the same day that the remote sensing data is acquired. Water systems are very dynamic and rapidly change so that the substances in the water are continuously changing. Location of sample sites should be determined with GPS (Global Positioning System) so that the correct data can be extracted from the remote sensing data for comparison. Often 3 to 5 pixel arrays are averaged to obtain the remote sensing data to account for the dynamic nature of the water body. Remote sensing data must be converted to radiance or reflectance data if the algorithms developed are to be applicable to other conditions. Data from satellite sensors and high altitude aircraft sensors should be corrected for atmospheric interference.

Three general methods are discussed to determine relationships between radiance or reflectance and the concentration of constituents in water: an empirical approach, a semi-empirical approach and an analytical approach.

**Empirical and semi-empirical approach**

The general form of the empirical and semi-empirical equation is:

\[
Y = A + BX \quad \text{or} \quad Y = ABX
\]

where:

- \(Y\) = measured radiance, reflectance, or energy
- \(X\) = water quality parameter of interest (suspended sediment, chlorophyll, etc.)
- \(A, B\) = empirically derived factors or empirical factors modified based on a knowledge of the interaction of water quality parameters and optical/thermal properties of water.

In the empirical approach a statistical relationship is determined between measured spectral properties and measured water quality parameters. In the semi-empirical approach, information about the spectral/optical characteristics of the water quality parameter is used in statistical analyses to aid in the selection of best wavelength(s) or best model. In both approaches the empirical characteristics of the relationships limit their applications to the condition for which the data were collected (RITCHIE AND SCHIEBE 2000, p. 289).

**Analytical approach**

In the analytical approach, optical properties of water and water quality parameters are used to model spectral characteristics of the water being studied. DEKKER et al. (1995) proposed the following analytical model derived from the physical relationship between water quality parameters, optical properties, and remote sensing measurements:

\[
R = \frac{n}{a + b} = n\omega_0
\]

where:

- \(R\) = reflectance
- \(ri\) = radiance to reflectance conversion
- \(a\) = absorption
- \(b\) = scattering
- \(?0\) = backscattering albedo

They found \(ri\) ranged between 0.12 and 0.50 and was apparently specific for each water body.

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Soil Erosion

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1 OBJECTIVE

Soil erosion and consequent land degradation (i.e. reduction or loss of biological or economic productivity and complexity of cropland, pasture, forest and woodlands) is resulting from various factors, including climatic variations and human activities (BALABANIS et al. 1999). A considerable amount of soil loss from the land surface is carried downstream into lakes, reservoirs and estuaries where it reduces storage capacity and affects water quality, navigation, and biological productivity. Soil erosion causes both physical (i.e. gullies, rills) and visible (i.e. exposure of different coloured soil layers) changes in the surface properties of soils. Remote sensing techniques can measure qualitative and quantitative information on changes in the soil surface roughness and on visible features.

2 METHOD DESCRIPTION

Assessing and monitoring soil erosion occurs in the two dimensions stage and time (CIHLAR 1987), while stage refers to the type of soil erosion (i.e. sheet, rill, or gully) and time refers to actual or
potential soil erosion. Both the stage and time of erosion can affect the physical and spectral properties of soil surfaces. Since remote sensing techniques measure spectral and physical properties, EO data can provide information on these changes in surface properties of the soil caused by erosion. (RITCHIE 2000, p. 273). A wide range of digital data with differing spectral and spatial resolution are available from airborne and spaceborne sensors. They need to be corrected for atmospheric interference and need to be georeferenced for best results.

**Photointerpretation**

Ground-based and aerial photographs are a very popular remote sensing technique used to study and map soil erosion using photointerpretation. This technique is based on the ability of the observer to identify and delineate objects based on pattern, texture, and colour and provides information on spectral differences in the soil surface which is interpreted to delineate areas affected by soil erosion. Photointerpretation of digital radiance data from optical spaceborne sensors like Landsat TM/ETM, SPOT HRV, IRS LISS/PAN, NOAA AVHRR, and radar satellites like ERS-1/2, JERS-1, RADARSAT etc. is also used to map areas of soil degradation. Both photographs and digital imagery can be used to map actual/potential soil erosion areas, to determine spectral patterns and differences in the surface soils related to soil erosion, and to determine land cover and conservation practices for input to soil erosion models (RITCHIE 2000).

**Digital Image Processing (Classification)**

Soil erosion removes the surface soil layer exposing different layers with different spectral properties. Based on this concept, albedo differences between multitemporal airborne or spaceborne images serve to monitor arid land soil erosion and degradation. Decreases in albedo can be caused by improved land use patterns (more soil moisture, organic matter, and increased vegetation productivity), and increases in albedo caused by soil degradation (erosion, low soil moisture, organic matter, and productivity).

By digital classification methods the spectral properties can be classified into information about the characteristic of the landscape surface properties related to soil erosion rates and patterns. Image classification and vegetation indices are widely used for erosion studies (JENSEN 1996).

**Photogrammetric Techniques**

Photogrammetry has been defined as the science, art, and technology of obtaining reliable information about physical objects and the environment from photographs (GREVE 1996). Photogrammetric techniques are used with stereo ground-based and aerial photographs as well as digital stereo satellite imagery (e.g. SPOT HRV) to measure physical changes in soil surface elevation, thus quantifying soil loss (THOMAS and WELCH 1988). Sequential photographs and digital data can be used to determine changes in areas of erosion or deposition over time.

**Laser Altimetry**

Ground-based and airborne lasers are also used to measure landscape features related to soil erosion such as surface roughness and topography, stream channels, gullies, and canopy cover. The laser system can measure physical changes in the soil surface to within a few millimetres from ground platforms and within a few centimetres from aerial platforms allowing estimates of soil loss or of surface roughness. Data related to changes in landscape topography, both micro and macro changes, provide basic information for determining soil erosion rates and patterns (RITCHIE 2000). Both profile and imaging laser systems can be used in erosion research (RITCHIE 1996).

**Radar Interferometry**

Interferometric Synthetic Aperture Radar (InSAR) is a rapidly developing technology for the generation of Digital Elevation Models (DEMs). InSAR techniques based on data acquired from aircraft or satellite are successfully used for the mapping of land surface topography (PAC et al. 1999, SCHMULLIUS et al. 2000).

Furthermore, with differential InSAR the detection and monitoring of surface displacements with a precision in the centimetre and even millimetre range is feasible (LUDWIG et al. 2000). The DEMs can be provided on a local scale with high resolution by airborne systems, and on a regional or global scale by spaceborne sensors. Thus radar interferometry contributes to erosion research by providing information of topographic parameters like e.g. altitude, terrain slope, or aspect.
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Snow

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1 Objective

Snow melt is responsible for large amounts of annual runoff in numerous catchments in higher latitudes and mountainous regions. The snow cover is a temporal intermediate storage, releasing the ecologically and economically important melt water in warmer periods. Therefore monitoring of the areal snow cover extent and estimation of the snow water equivalent with remote sensing data play a significant role in the regional hydrological modelling of snow melt and runoff (Swamy & Brivio 1996). Field measurements of the areal extent of the snow cover are difficult to obtain, especially in remote areas. Due to the strong spatial and time dependent dynamics of snow covers short observation cycles are necessary.

2 Method Description

For the areal monitoring of snow covers optical as well as active microwave data is used, the quantitative estimation of parameters like water equivalent, density or layering is done by evaluating data from gamma spectrometers or active microwave sensors, because they are able to penetrate into the snow cover. On continental ice sheets like Greenland or Antarctica it enables the distinction between dry and wet snow. In general there is only a weak sensitivity of L - and C -Band for snow parameters (ULABY 1998).

The literature on remote sensing of snow is manifold, meanwhile the work of HALL & Martinec (1985) is of paramount importance, some general overviews on remote sensing in hydrology cover also chapters on snow (ENGMAN & GURNEY 1991, BAUMGARTNER et al. 1997, SCHULTZ & ENGMAN 2000). Considerable work on microwave remote sensing of snow was done by ULABY et al. (1982), ULABY et al. (1986), Parlow (1996), ISRSE (1998) or HENDERSON & Lewis (1998). A plethora of references is provided by Mätzler (1987) and NASA (1986, 1989). Operational programmes from weather satellite data (GOES or METEOSAT) provide areal snow cover distributions for North America (Rango 1996), the European Alps (BAUMGARTNER 1987) or the Himalayas (Kumar et al. 1991). In catchments up to 200 km² also Landsat data have been used (Rango 1990). BAUMGARTNER et al. (1985) provided a standardized processing scheme.

Areal monitoring of snow covers

Optical data
Operational programmes from weather satellite data (GOES or METEOSAT) provide areal snow cover distributions for North America (Rango 1996), the European Alps (BAUMGARTNER 1987) or the Himalayas (Kumar et al. 1991). In catchments up to 200 km² also Landsat data have been used (Rango 1990). The difference between snow covered and other areas is most distinct in the red part of the electromagnetic spectrum (0.6-0.7 µm). The distinction between snow covered and cloud covered areas is done with the mid-infrared TM-channel 5 (1.55-1.75 µm), where clouds have a higher reflection than snow. This enables an automatic detection (Dozier 1989). BAUMGARTNER et al. (1985) provided a standardized processing scheme.

Microwave data
In contrast to optical data, radar imagery show not only the surface structuring but also information about subsurface layers within the snow cover. The backscatter coefficient $s_\theta$ is determined by the reflection on the snow surface, the scattering in the snow cover and the reflection on the boundary layer snow/soil or snow/ice. Since the backscatter coefficient contains relief information, in areas of high relief energy an adjustment in form of a local incidence correction has to be done, to make the signal relief independent. Polarimetric SAR was found to be effective for mapping snow and glacier covered areas without topographic information required when analyzing single polarized radar data.
Snow covers alter their dielectrical conditions due to the liquid water content. Because of the large differences between the dielectrical constants of water (60) and ice (3.17), only small variations of the liquid water content within the snow cover influence the resulting radar backscattering. The attenuation of the microwaves within the snow cover is raising with increasing liquid water content, reducing the penetration depth at the same time. Dry snow is transparent for microwaves, the backscattering is determined by the underlying ground. With increasing thickness of homogeneous fine grained snow the amount of volume scattering is stronger so that the backscattered power is low. Therefore in C Band SAR imagery areas of dry snow appear dark, areas of wet snow are bright. On glaciers the percolation zone in between zones of dry and wet snow is even brighter due to the development of ice lenses and ice layers within the snow cover causing a significant increase of the backscatter coefficient.

Haefner & Piesbergen (1997) developed a method of synergistic use of optical and microwave data for snow cover monitoring in high mountain areas. Their system MORA (Multitemporal Optimal Resolution Approach) is using ERS data to cover the periods between cloud free Landsat TM acquisitions. To overcome the strong terrain effects in the SAR data, they integrate ascending and descending orbits.

### Snow water equivalent determination

**Gamma Radiation**

Apart from the areal monitoring of snow covers, estimations of the snow water equivalent play a crucial role for the simulation and forecast of snow melt events. The only method for the measurement of the snow water equivalent for all snow types is an airborne Gamma radiation acquisition (Kuittinen 1990). It is based on the attenuation of the natural radioactive terrestrial radiation by the mass of water in the overlying snow cover. The emissions result from the top 20 cm of the soil from radioisotopes like potassium (40K), uranium (238U) and thorium (208Tl). The intensity of the gamma radiation is measured with a gamma radiation spectrometer from a low-flying airplane (150 m). In autumn a comparison flight is acquired before snow accumulation, which is redone during winter when snow covered. The major limitation of this method is the contribution of soil moisture to the measurements of the snow water equivalent. Here in-situ measurements of the soil moisture under the snow cover could help to increase the accuracy of the snow water equivalent estimations (Rango et al. 2000). A description of the physical background and the calibration methods of airborne gamma spectrometer measurements is given by Fritzche (1982).

**Thresholds of SAR-Intensity**

GUNERIUSSEN (1997) gives an overview of the theoretical physical background of microwave backscattering inside a snow cover. He is using ERS-1 data for the determination of snow water equivalent in mountaineous relief. The SAR-data first were calibrated with a correction of the range spreading loss and the antenna gain and were converted to $s^\circ$. Afterwards a geometric rectification was applied using a DEM, excluding pixels affected by layover and shadowing effects from further analysis. Then a mean backscatter coefficient was calculated for each testsite and compared to in-situ measurements of the snow wetness. A decrease in $s^\circ$ of 3 dB between dry and wet snow has been observed.

Another method for the derivation of areas of wet snow from ERS SAR data was developed by Nagler & Rott (1997). They worked in the central alps in an area of high mountain relief with change detection methods on repeat pass SAR. The SAR imagery has to be preprocessed due to the strong distortions and terrain effects. As input to the snow mapping procedure, a snow image and a snow free reference image with the same imaging geometry (repeat pass) are needed. After co-registration and speckle reduction, the ratio of the backscattering coefficient of the snow image ($s^\circ$ ws) to the backscattering coefficient of the reference image ($s^\circ$ ref) is calculated. For segmentation of wet snow areas a threshold of 3 dB is applied on the ratio image, where a pixel is classified as wet snow if the condition $s^\circ$ ws / $s^\circ$ ref = -3 dB. The method is applicable to ERS C-Band VV and RADARSAT C-Band HH. The results have been compared with evaluations of optical remote sensing data and show good coincidence. The snow cover maps were used as input for snowmelt runoff models producing good correlations between measured and simulated runoff.

**Multisensoral**

But also from historical optical data and modified snowmelt runoff curves areal water equivalents could be calculated. Moorman (1998) is evaluating aerial photography as well as TM, ERS, JERS and RADARSAT data to characterize the snow and ice development during the course of the year. In this case the radar data is useful to monitor the decay of the snow as well as for the detection of runoff systems under the snow. Studies for the quantitative determination of the snow water equivalent are
using often airborne multifrequency and multipolarized systems. Operational approaches are rare and just in the beginning.

**Conclusion**

The evaluation of multitemporal microwave data shows clearly the capability of active microwave data to detect the beginning of snowmelt. It is not possible to detect the liquid water content of snow quantitatively due to a lot of parameters influencing the backscatter coefficient, but a qualitative estimation is possible as well as the extension of the dry and wet snow zone on polar ice sheets. This enables the determination of the mean annual temperature (temperature in a 10 m deep) borehole as well as the definition of areas where an analysis of isotopes is possible. Concluding it can be mentioned, that the largest potential for future comprehension of snow from remote sensing data will be the synergy of different sensors (spatial, spectral, temporal resolution) as well as in the use of additional topographic information.

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Evapotranspiration

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1 OBJECTIVE

The quantitative assessment and the acquisition of the spatial distribution of the evaporation have always been of major interest to science. Evaporation means the transition of water from the liquid to the vapor phase, occurring at or underneath the soil surface. Transpiration is the process occurring in plant leaves. So evapotranspiration means evaporation from a mixture of vegetation and soil. Point data and derived products interpolated through geostatistical methods have been inferior to remote sensing data with the acquisition of the spatial variance. Although it is not possible to derive evaporation directly from remote sensing data, there is a lot of useful information about the atmosphere and the land surface, which is important for the estimation of evaporation. Surface temperature, soil moisture, albedo, vegetation cover and received radiation could be recorded area covering with an acceptable accuracy for the parameterization of "Soil-Vegetation-Atmosphere-Transfer"-models (SVAT, SHUTTLEWORTH & WALLACE 1985, FAMIGLIETTI & WOOD 1994, RAUPACH 1995).

2 METHOD DESCRIPTION

From remote sensing data only brightness temperatures can be derived. They are not directly suitable for the determination of heat transfer, which is also dependent on the thermodynamical surface temperature including the emissivity e. In all cases an atmospheric correction has to be applied. Since the moisture and energy balance on the ground are closely connected, the moisture transfer and the surface heat transfer are connected either. TACONET et al. (1986) present a numerical SVAT-model. The evapotranspiration is controlled by the opening and closing of vegetation stomata, linking it to the absorption of atmospheric carbon. Since the evapotranspiration is a non-linear function of the stomata exchange, there exists a scaling problem with the regional determination of the evapotranspiration. A solution are really distributed models, which consider the spatial variability of geophysical parameters (RAST 1999). Important input parameters for the determination of the evapotranspiration are:
- fractional vegetation cover
- canopy structure for the determination of interception
- vegetation type for surface roughness estimations
- snow covered area for estimation of water storage and snow melt forecast

The challenge to all remote sensing methods to estimate land evaporation is how to determine model variables not directly related to feasible observations, since not all required model variables are observable by remote sensing (i.e. air temperature, vapor pressure or aerodynamic resistances for heat and vapor transfer) (MENENTI 2000). Evapotranspiration estimations could therefore only be seen within the context of heat balance and net radiation.

The heat balance on the land surface is as follows:
\[ R_n + G + H + LE = 0 \] (Wm⁻²)
where \( R_n \) is the net radiation, \( G \) is the soil heat flux, \( H \) is the sensible heat flux and \( LE \) is the latent heat flux.

The net radiation is composed of:
\[ R_n = S + R + L + E \]
where \( R_n \) is the net radiation, \( S \) is the shortwave incoming radiation, \( R \) is the reflected shortwave radiation (Albedo), \( L \) is the longwave atmospheric radiation and \( E \) is the longwave terrestrial emission.

Surface temperature and evapotranspiration are affected by the albedo, the ratio between received and reflected solar radiation. It is determined by the land cover, varying from 8 (dark objects) to 45% (bright objects), but could also reach 95% for a fresh snow cover. An increased albedo is often caused by a reduced vegetation cover, resulting in a reduced evaporation and an increased surface temperature (BECKER et al. 1988). Problematic are the directional satellite measurement and the extrapolation from measurement intervals (channels) onto the total spectrum. DUGUAY and LeDREW
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(1992) calculated the albedo separately for different land cover classes from Landsat-TM data (i.e. vegetation):

\[ a = 0.526 \cdot \rho_{TM\,2} + 0.362 \cdot \rho_{TM\,4} + 0.112 \cdot \rho_{TM\,7} \]

where \( \rho \) is the surface reflectance corrected for the sensor radiance and the solar irradiance.

**Simple approaches assuming linear relationships**

Simple approaches (Laguarde 1991, SEGUIN 1993, OTTLE and Vidal-Madjar 1994) assume a linear relationship between evapotranspiration, soil moisture and surface temperature and calculate the daily evaporation from the difference between surface and air temperature. Because it needs clear sky conditions, the application in Middle and Northern Europe is limited.

\[
LE - R_n = b - a\, (T_s - T_a)
\]

\( LE \) = daily evapotranspiration  
\( R_n \) = daily net radiation  
\( a, b \) = coefficients of the vegetation roughness (statistically)  
\( T_s \) = surface temperature  
\( T_a \) = air temperature

The surface temperature could be derived from Landsat-TM 5 data after algorithms from SCHOTT and VOLCHOK (1985). The TM Band 6 represent mean values of the long wave radiance (IFOV 120 m, after atmospheric propagation).

\[
K = \frac{1260.56}{\ln \left( \frac{60.776}{L_{\lambda}} + 1 \right)}
\]

\( K \) = temperature in Kelvin  
\( L_{\lambda} \) = mean spectral radiance  
\( N \) = TM Band 6 digital value

The algorithms were successfully applied in a study for estimating soil water content around Stockholm (LUNDEN 1987) and are transferable to Scandinavia and Central Europe.

**Combination of RS data and numerical energy balance models**

More sophisticated approaches (CAMILLO et al. 1983) combine from remote sensing data derived surface temperatures with numerical energy balance models:

\[ G = R_n + LE + H \]

\( G \) = net radiation  
\( R_n \) = net radiation  
\( LE \) = latent heat flux  
\( H \) = sensible heat flux

**Complex approach with a multitude of datasets**

MAUSER & SCHÄDLICH (1998) present a complex approach, considering a multitude of datasets (meteorological point data, digital maps, multitemporal remote sensing data) as input for a physically based model, applicable to different scales (micro and meso scale). LAI is used together with sun elevation to calculate the canopy resistance. Vegetation height and albedo are used for the calculation of the aerodynamic resistance and the energy balance in the Penman-Monteith equation.

For the modelling of the evapotranspiration on two different scales remote sensing data (Landsat TM, NOAA) is used for the derivation of the land cover. Together with soil data, climatological and field data the evapotranspiration has been simulated on a hourly basis. The validation of the spatial distribution of the evapotranspiration was done with thermal data, assuming that the evapotranspiration influences the surface temperature through cooling. The results of the microscale (7 x 13 km, 30 m raster) and mesoscale (100 x 150 km, 500 m raster) testsites coincide with cold lakes, warm cities and forests as the coldest vegetation areas.
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Precipitation

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1 OBJECTIVE

The estimation of the precipitation amount is the base for the observation of large scale hydrological processes since it represents the input of the hydrological cycle. It should therefore be quantified as accurate as possible.

In general the point measurements of rain gauges on the ground are not sufficient to acquire the precipitation process in a satisfying temporal and spatial resolution for operational water resources management. Measurement mistakes (wind, etc.) underestimate the actual precipitation, furthermore the extrapolation is problematic. The determination of the precipitation with remote sensing data has therefore a large practical importance (SCOFIELD 1991). Assemblies of the most important methods are found in BARRETT (1989), ENGMAN & GURNEY (1991), HAEFNER & SCHUMANN (1992), PETTY (1995), PETTY & KRAJEWSKI (1996) und BARRETT (1997).

The presented remote sensing methods are applicable due to the high temporal resolution of geostationary satellites, enabling the acquisition of the large variability of precipitation events in weekly or monthly averages. Certainly most of the studies have an insufficient validation (PETTY 1995), which is complicated by a missing objective basis (also rain gauges measurements have mistakes). Altogether the methods are only limited applicable for regional scales, in certain circumstances they could also be better than the ground measurement network (i.e. Kenya, MENZ 1996).

2 METHOD DESCRIPTION

There are three methods in general: The derivation of precipitation
a) from the cloud surface temperature with the thermal infrared,
b) passive microwave radiometers which provide direct information of water and ice particles in the atmosphere (BARRETT 1991) and
c) active microwave systems, either spaceborne or ground based (GABELLA et al. 1998, LEGATES 2000).

Derivation from cloud surface temperature

The derivation from cloud surface temperature is an indirect empirical method, which requires more meteorological observations beside optical remote sensing data (VIS/NIR/TIR-channels from weather satellites like NOAA or METEOSAT). The Cloud-Index-Method classifies the clouds and estimates the amount of precipitation from the number, area and the period of transfer of the clouds. The threshold method assumes, that all clouds below a certain surface temperature are rain clouds. So called Life-History-Methods consider the rates of change of convective clouds. An example is mentioned in GABELLA & BARRETT (1989). In general the optical/thermal methods provide better results with the generation of weakly and monthly averages.

Passive microwave radiometers

The acquisition with passive microwave radiometers is based on the fact, that rain clouds reduce the thermal radiation of the earth and reflecting cosmic background radiation simultaneously. The higher the precipitation rate, the higher is the heat reduction or the higher is the reflection. The advantage of passive microwave radiometers is the direct dependence of the microwave radiation from the drop size in the center of the cloud, which enables a more immediate measurement than on the cloud surface and is therefore clearly better than optical/thermal methods with direct derivation. The disadvantage is the low spatial resolution and the weak signal which is difficult to measure.
Active microwave
New methods exist since 1997, when the TRMM (Tropical Rainfall Measurement Mission), a high resolution active microwave system (13.8 GHz, 2.2 cm) was launched into orbit to measure the precipitation vertically. The system provides macro scale precipitation data for tropical and subtropical regions enabling the calculation of seasonal and yearly sums. The engagement of the typical tropical daily variation could not be realized with that either.

Active ground based radar systems
Active ground based radar systems are especially suitable for the detection of storm rainfall areas and the estimation of rainfall intensity. Their mode of operation is based similar to the spaceborne radar systems on the scattering of the horizontally transmitted signal by the rain. But the receiving circle is limited to approximately 100 km due to earth curvature and the used frequency (C-Band, SCHULTZ 1989). Two methods are used here:

Single parameter measurement
The single parameter measurement derives the rainfall intensity from the backscattered radiation

\[ Z = aR^b \]  

(1)

\( Z \) = the backscattered radiation in dB
\( R \) = the rainfall intensity in mm/h
\( a, b \) = calibration parameter

Multi parameter measurement
The multi parameter measurement works with multifrequent backscattering for the determination of the precipitation amount and also the drop size distribution. (ENGMAN & GURNEY 1991).

General Comments
The spatial resolution of such systems comes to several kilometers (4 x 4 km of the WSR-88D, Weather Surveillance Radar 1988 Doppler), nevertheless these ground based radar systems represent the spatial rainfall distribution much better than conventional rain gauges. However, also these ground based radar systems show some sources of errors, which should be considered with the estimation:

- the ground based radar underestimates storm rainfall, but overestimates small rainfall;
- between the radar reflection and the precipitation rate is no exact relationship, because the precipitation rate is dependent on drop volume and not on the surface. Therefore the drop size is estimated to derive the precipitation rate from the reflection through a Z-R-algorithm;
- rain is falling on other locations than the measurement in 2 km height due to strong winds;
- precipitation is evaporating before reaching the surface;
- especially at the margins of the receiving circle there is an underestimation, so that the maximum of the overlapping area is used;
- there are problems in mountaineous areas due to shadow, so that the systems are unsuitable for macro scale modelling.

In general a calibration with rain gauges is recommended to enhance the accuracy (COLLIER 1986). LEGATES (2000) presents a method for the real-time calibration with rain gauges and variable ZR-algorithms, which is able to estimate precipitation with a high resolution and high accuracy, particularly with storm rainfall and historical flooding events. Although there was an enormous progress in the systems accuracy within the last five years, the operational application is still restricted to industrialized countries like the US (LEGATES 2000), Germany, UK, Netherlands (ASSEM 1990) or Italy (GABELLA et al. 1998), which have a dense network.
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EU-Project

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(ARSGISIP)

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