A SOIL MOISTURE RETRIEVAL ALGORITHM BASED ON
METEOSAT IMAGERY

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Abstract

Global carbon budget studies are currently dominated by temperature analysis since the importance of
this meteorological variable on photosynthesis processes and soil carbon dynamics. Yet, the strong
coupling between the carbon and hydrological cycles is a longstanding acquisition of the bio-
geophysical sciences. To take the important aspect of water limitation in carbon studies into account,
water availability of vegetation is to be estimated firstly. Evidently soil moisture is an essential part of
plant water availability.

We present a strategy to retrieve soil moisture content from optical and thermal information using
coarse resolution METEOSAT imagery with a robust pre-processing chain and an operational
capacity: the integral METEOSAT Processing Chain (iMETEOSAT-Chain).

Soil moisture is derived using the concept of thermal inertia, whereby the ratio of albedo with the
difference of day and night land surface temperatures is combined. A soil moisture saturation index is
calculated from thermal inertia data and processed by a 1st order Markov filter which converts surface
values to soil moisture values of a 1 m soil profile.

For the region of interest of Europe, for the growing season of 1997, we present soil moisture time
series validated against EUROFLUX tower measurements.

With spatial values of soil moisture content on a regional/continental scale, water limitation can then
be incorporated into continental/global carbon budgeting.

INTRODUCTION

In general, soil moisture is the water held in the soil within reach of plant roots. It is one of the most
important land environmental variables in perspective with land surface climatology, hydrology, and
ecology. The soil moisture content (SMC) generally refers to the water in the upper 1-2 m of soil,
which can potentially evaporate into the atmosphere, drain off to surface waters reservoirs or
percolate to the deeper soil layers towards the aquifers. Variations in SMC have strong impacts on
changes in the surface energy balance, regional run-off and vegetation productivity (crop yield
potential). Knowledge of the SMC conditions may serve as a warning for flooding but also as early
warning systems for (failure in) food production. In areas of active deforestation, SMC estimates help
to predict run-off as well as soil erosion. Despite the importance of SMC the standard procedure of
SMC determination is the gravimetric method which essentially is a point measurement. Local scale
variations in soil properties, terrain and vegetation cover make selection of representative field sites
difficult if not impossible. Moreover, field methods are complex, labour intensive and therefore
expensive. Contrarily, remote sensing (RS) techniques may be compromising because of the spatial
ability and the relatively low cost (Wagner et al., 1999).

General well known measurement techniques to determine soil moisture content are (i) the gravimetric
technique, (ii) nuclear techniques such as neutron scattering, gamma attenuation, the technique of
nuclear magnetic resonance, (iii) electromagnetic techniques such as resistive and capacitive sensors,
time and frequency domain reflectometer, (iv) the tensiometric technique, (v) hydrometric techniques,
(vi) earth observation techniques using passive and active microwave, thermal infrared remote
sensing, and (vii) optical techniques such as polarized light, fibre optic sensors, near-infrared (Zazueta
and Xin, 1994). A more basic field method (ix) is the ‘Feel and Appearance method’ using a soil

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moisture interpretation chart based on texture classification and squeezing of soil samples (Miles, 1998).

We demonstrate that optical and thermal information from an existing operational coarse resolution spaceborne sensor (METEOSAT) can be used to determine SMC on 10-daily intervals without the need of excessive ancillary data or direct coupling with SVAT models. We present the methodology, the product evaluation on one EUROFLUX site and a comparison with active microwave RS using the ERS Scatterometer (Wagner et al., 1999).

**SOIL MOISTURE RETRIEVAL METHODOLOGY**

Similar to the Integral NOAA/AVHRR-imagery processing Chain (iNOAA-Chain) (Verstraeten et al., 2005b) the Integral METEOSAT-imagery processing Chain (iMETEOSAT-Chain) was developed to produce spatially explicit information to detect water limiting conditions and to estimate hydrological variables such as evapotranspiration (Verstraeten et al., 2004, 2005b) and soil moisture content (Verstraeten et al., 2006b) in an operational mode in the framework of plant carbon relations (Field et al. 1995; Veroustraete et al., 2002, 2004; Verstraeten et al., 2006a). With the iMETEOSAT-Chain SMC is estimated combining visible and thermal satellite information at the regional scale.

A method to estimate SMC from optical and thermal spectral information of METEOSAT imagery based on thermal inertia (TI) was presented and validated for European forest in Verstraeten et al. (2006). TI is a body property of materials and describes their resistance to temperature variations. The approach of Mitra & Majumdar (2004) to infer the apparent thermal inertia (ATI) was adopted for its simplicity for routine calculations. ATI is computed using measurements of spectral surface albedo \( \alpha_0 \) and the diurnal land surface temperature range \( \Delta LST_0 \) (\( LST_{0,d} - LST_{0,n} \)). The apparent thermal inertia index is:

\[
ATI = C \cdot \frac{1 - \alpha_0}{\Delta LST_0}
\]  

(1)

From the surface thermal inertia time series minima and maxima are extracted and combined into the Soil Moisture Saturation Index (SMSI_0) for the earth’s surface:

\[
SMSI_0(t) = \frac{ATI(t) - ATI_{min}}{ATI_{max} - ATI_{min}} = \left( C \cdot \frac{1 - \alpha_0(t)}{\Delta LST_0(t)} \right) - \left( C \cdot \frac{1 - \alpha_0}{\Delta LST_0} \right)_{min}
\]  

(2)

In Equations (1) and (2); \( ATI_{min}, ATI_{max} \) and \( ATI(t) \) is the minimum, the maximum and the apparent thermal inertia at time t \( [K^{-1}] \); \( C \) is solar correction factor, function of latitude and solar declination \([-]\); \( \alpha_0 \) is broadband albedo \([-]\); \( \Delta LST_0 \) is the difference between the day and night brightness temperatures \([K]\); and SMSI_0(t) is the remotely sensed surface moisture saturation index at a time t \([-\]).

The soil moisture saturation index (SMSI) is the degree to which the soil is at maximum water content and is written as:

\[
SMSI(t) = \frac{\theta(t) - \theta_{res}}{\theta_{sat} - \theta_{res}}
\]  

(3)

Since saturated and residual soil moisture contents are determined under laboratory conditions, field soil moisture values are unlikely to be equal to extremely high or low values, especially with at coarse spatial resolution pixels. Hence, \( \theta_{sat} \) and \( \theta_{res} \) are substituted by a maximal and minimal SMC (\( \theta_{max} \) and \( \theta_{min} \)) respectively. To convert SMSI_0(t) of the surface to SMSI(t) of the 1 m soil profile, a Markov type filter is used based on a simple two layered water balance equation (the surface layer and the reservoir below) with an autocorrelation function added in a similar way as Wagner et al. (1999) and Ceballos et al. (2005). SMC of the 1 m soil profile is then estimated from:
\[
\theta(t) = \text{SMSI}_p(t) \cdot (\theta_{\text{max}} - \theta_{\text{min}}) + \theta_{\text{min}} = \sum \text{SMSI}_p(t_i) \cdot e^{-\frac{(t - t_i)}{T}} \cdot (\theta_{\text{max}} - \theta_{\text{min}}) + \theta_{\text{min}}
\]  

In Equations (3) and (4): SMSI_0 is the soil moisture saturation index from the surface layer derived from remote sensing [-]; SMSI_p(t) is the soil moisture saturation index for a 1 m soil profile at time t [-]; t_i is the time at which a discrete change of SMSI takes place [day]; T is the time constant or characteristic time length [day] needed for a specific amount of change of SMSI_p to occur at a certain moment t in time, after a discrete change of SMSI_0 at time t_i whereby time t > t_i; T depends on climate and soil type; \( \theta \) is volumetric soil moisture content at a time t \( [m^3 m^{-3}] \); \( \theta_{\text{res}}, \theta_{\text{sat}}, \theta_{\text{max}}, \theta_{\text{min}} \) is the volumetric residual, saturated, maximum and minimum soil moisture content respectively \( [m^3 m^{-3}] \).

**EARTH OBSERVATION AND FIELD DATA**

METEOSAT imagery was collected and processed for the region of interest of Europe for the growing season of 1997 (March-October). The imagery was pre-processed with processing steps such as image unpacking, calibration, geometric and atmospheric correction. End products are broadband albedo, LST, evaporative fraction, evapotranspiration and soil moisture content. To calculate ATI, the brightness temperatures of image 6 and 30 (out of 48) were used, corresponding to the slot times of 3 AM and 3 PM. The albedo is retrieved for image 30. LST is derived from the heat balance expressing infrared radiant exitance as a resultant of the heat flux emitted by the land surface and the infrared irradiance part reflected by the surface (Gellens-Meulenberghs et al., 1994; Gellens-Meulenberghs, 2000). The albedo is calculated from calibrated radiances obtained by Govaerts et al. (1998).

To enable the spatially explicit input of \( \theta_{\text{max}} \) and \( \theta_{\text{min}} \) in the iMETEOSAT-Chain, the European soil database (JRC - INRA, 1999) can be used. The soil texture of the database is combined with class pedotransfer functions from Wösten et al. (1999). From these pedotransfer functions the soil retention parameters are derived and hence \( \theta_{\text{max}}, \theta_{\text{min}} \).

The field data used in this study originate from the EUROFLUX of Brasschaat in Flanders. The Brasschaat site is characterized as Pinus sylvestris stand on a coarse soil texture at 10 m above sea level located at 51°18’N and 04°31’E. The EUROFLUX sites came into full operation in 1997 and are located in European forested areas as can be verified in Valentini et al. (2000). For the Brasschaat site in Flanders (BE2), in-situ soil properties were derived, the soil moisture profile was simulated with the hydrological field scale model WAVE, calibrated and validated on a dataset measured during a field campaign in 2000 and 2002 (Verstraeten et al., 2005a) and recalculated for the year 1997.

**SOIL MOISTURE FROM VISIBLE AND THERMAL EARTH OBSERVATION**

In Figure 1 an illustration is given of the different steps to obtain SMC. Starting point is the requirements of time series of albedo and day and night LST. ATI is calculated from these time series with Equation (1). ATI values are rescaled to SMSI of the surface using minimum and maximum ATI of the time series for each pixel with Equation (2). The surface SMSI is then converted to the 1 m soil profile with Equation (4) using a low pass filter based on the autocorrelation function of the two layered water balance. Finally, SMSI in rescaled to SMC using soil physical properties and Equation (4). For the Brasschaat site the characteristic length T is set on 20 days. The scatter graph, SMC derived from METEOSAT against SMC from the EUROFLUX site of Brasschaat, shows a linear fit with slope, intercept and R² of respectively 1.12, -0.03 and 0.71. The Root Mean Square Error is 0.02 m³ m⁻³. The rapid fluctuations of the albedo may be explained by undetected (sub-) clouds and wet surfaces (after rainfall). Perhaps also a BRDF effect plays. The main reason for the albedo fluctuations is suggested due to an incomplete cloud detection algorithm. Moreover, most albedo products (eg MODIS, MSG) are composite products, filtering out some of the fluctuation.
Figure 1: Illustrative data flow of the calculations of Soil Moisture Content (SMC) of the 1 m soil profile from optical and thermal information of METEOSAT imagery. Example for the pixel covering the Brasschaat EUROFLUX site for the growing season March-October 1997. A) Day (black squares) and night land surface temperatures time series (white diamonds). B) Albedo and Apparent Thermal Inertia (ATI) time series; ATI is calculated according to Equation (1). C) The surface Soil Moisture Saturation Index (white diamonds) computed according to Equation (2); the 1 m soil profile Moisture Saturation Index (black squares) based on Equation (4); SMC (grey triangle) computed according to Equation (4).
Due to parameter interactions and non-linearity’s it is likely that more than one parameter set achieves the condition of the best fit between simulated and observed data. Hence, all model evaluations are subjected to uncertainty since no single model is a true representation of processes of bio-geophysical systems. Errors arise due to model structure, assumptions/simplifications, errors in boundary and forcing conditions and error in observations with which the model is compared or fed. Separating these error sources is difficult and likely even impossible. Model boundary conditions cannot be defined with absolute accuracy and the observational data for model calibration and evaluation and model input is not error free.

Multiple parameter sets can be constructed using Monte-Carlo sampling to randomly extract parameter sets from pre-defined ranges. The model is run with each set of parameter values. Assuming some confidence in the model exists, it is reasonable that within these multiple simulations a number of model realisations that reflect the actual land surface observations are presented. The Generalised Likelihood Uncertainty Estimation (GLUE) methodology is based on Monte-Carlo to sample parameters sets (Franks and Beven, 1997; Beven and Freer, 2001). The fundamental principle of the GLUE approach is the rejection of the idea of an optimum parameter set or model structure in favour of the concept of ‘equifinality’ or equivalence of model structures and parameter sets. This implies that only the relative model performance in terms of some likelihood measure can be evaluated. Table 1 gives the absolute errors assumed on the model inputs for two cases. Table 2 shows the results of the Monte-Carlo approach to generate the model uncertainty for the different steps as given in Equations (1), (2) and (4). Model simulation were conducted using 1000 randomly chosen parameter sets from an uniform distribution with the errors (or intervals) taken from Table 1.

<table>
<thead>
<tr>
<th>Absolute errors</th>
<th>Case</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔLST_o,d [K]</td>
<td>1.0</td>
</tr>
<tr>
<td>ΔLST_o,n [K]</td>
<td>1.0</td>
</tr>
<tr>
<td>Δα_0 [-]</td>
<td>0.01</td>
</tr>
<tr>
<td>Δθ_max [m^3 m^-3]</td>
<td>0.010</td>
</tr>
<tr>
<td>Δθ_min [m^3 m^-3]</td>
<td>0.005</td>
</tr>
</tbody>
</table>

Table 1: The absolute error values of the model parameters of Equation 1, 2, 3 and 4 for two case scenarios.

<table>
<thead>
<tr>
<th>Error intervals</th>
<th>ATI</th>
<th>SMSI_o</th>
<th>SMSI_o</th>
<th>SMC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case</td>
<td>Max</td>
<td>Min</td>
<td>Average</td>
<td>Stdev</td>
</tr>
<tr>
<td>1</td>
<td>0.42</td>
<td>0.00</td>
<td>0.05</td>
<td>0.08</td>
</tr>
<tr>
<td>2</td>
<td>0.49</td>
<td>0.00</td>
<td>0.10</td>
<td>0.14</td>
</tr>
</tbody>
</table>

Average observed SMC from METEOSAT is 0.20 m^3 m^-3

Table 2: The maximum, minimum, average and standard deviation of the absolute errors (expressed as half the 95% confidence interval) on time series of ATI, SMSI_o, SMSI_o, and SMC from Brasschaat for the two error scenarios of Table 1.
Figure 1: The uncertainty on the time series of ATI, SMSI₀, SMSIₚ and SMC derived from the iMETEOSAT-Chain (growing season of 1997) using the two error scenarios of Table 1.
DISCUSSION, CONCLUSION AND RECOMMENDATIONS

As shown by Verstraeten et al. (2006b) the comparison results (METEOSAT versus EUROFLUX) are in the same order of magnitude with other reported approaches. From the uncertainty analysis it is derived that an error of $0.02 \text{ m}^3 \text{ m}^{-3}$ on SMC may be expected, and that the magnitude of the uncertainty decreases from the SMSI$_0$ to the SMSI$_P$ step. Some preliminary results with larger errors on the parameters of Table 1 (errors on LST, albedo, min, max. SMC of 4 K, 0.1, 0.02 $\text{ m}^3 \text{ m}^{-3}$ and 0.1 $\text{ m}^3 \text{ m}^{-3}$ respectively), suggest errors in the order of $0.04 \text{ m}^3 \text{ m}^{-3}$ on SMC for the Brasschaat site.

The soil moisture related timeseries shown in Figure 1 are derived from short time series of LST and albedo. The filter used in Equation 4 requires time spans which is set to three times the time span of T (here T is set on 20 days) (Wagner et al., 1999). Due to the unavailability of a comprehensive METEOSAT dataset, the initial condition of SMSI$_0$ can be set to a default or initial value based on the assumption of periodicity of soil moisture at annual base for the time not covered by the imagery. The characteristic time length T is suggested to be related to conditions of climate, vegetation and soil. Also other T values such as 40 and 60 days may be possible. Using other T values, other initial conditions for the SMSI$_0$ timeseries must be set.

An exhaustive but incomplete list of to do’s or issues to be cleared out are

- more and in depth research focused on the physical basis of the characteristic time length T (for the conversion of surface values to the soil moisture of the 1 m soil profile) to fully understand the link of T with climate and soil (eco regions);
- to combine long and short term variations in soil moisture and to neutralize the disadvantages of microwave and optical and thermal remote sensing, to assimilate the microwave derived Soil Water Index and the optical and thermal remote sensing derived Soil Moisture Saturation Index should be assimilated into one parameter;
- introducing the thermal inertia methodology on other continents besides Europe with other satellite sensors such as NOAA/AVHRR and MODIS imagery; These sensors have higher spatial resolutions and a global coverage capacity;
- evaluating the thermal inertia methodology on non-forested areas and with multi-year datasets;
- bridging scales between field and earth observation should also be addressed more in depth; Up-scaling of ground ‘truth’ measurements for validation purposes; Use of distributed hydrological models to scale up soil moisture to satellite pixel?;
- a complete operational processing upset to produce SMC information in due time; Hitherto, a fully operational chain to produce spatial and temporal SMC values is not completed yet;
- reducing model uncertainty; A more comprehensive uncertainty study is recommended wherein more parameters sets are implemented and also the prior information is used to reduce the uncertainty; Applying the Monte-Carlo approach with other parameter distributions than uniform ones as applied now; The characteristic time length T should also be included in the Monte-Carlo analysis. The use of more parameter samples, applying prior information to produce posterior probabilities into for instance the C-Fix model;

Hence, lots of efforts still need to be done before the proposed methodology encompasses a complete spatial and temporal measuring and monitoring approach.

Once spatial and temporal soil moisture values can be produced in due time and at continental and global scales, then carbon fixation models can operate fully water limited and hence produce more realistic estimates on vegetation carbon fluxes and balances. Moreover, global Water Use Efficiency estimates become feasible combining ecosystem water consumption and net carbon uptake.

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