Comparing ERA-40-Based L-Band Brightness Temperatures with Skylab Observations: A Calibration/Validation Study Using the Community Microwave Emission Model

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ABSTRACT

The Community Microwave Emission Model (CMEM) has been used to compute global L-band brightness temperatures at the top of the atmosphere. The input data comprise surface fields from the 40-yr ECMWF Re-Analysis (ERA-40), vegetation data from the ECOCLIMAP dataset, and the Food and Agriculture Organization’s (FAO) soil database. Modeled brightness temperatures have been compared against (historic) observations from the S-194 passive microwave radiometer onboard the Skylab space station. Different parameterizations for surface roughness and the vegetation optical depth have been used to calibrate the model. The best results have been obtained for rather simple approaches proposed by Wigneron et al. and Kirdyashev et al. The rms errors after calibration are 10.7 and 9.8 K for North and South America, respectively. Comparing the ERA-40 soil moisture product against the corresponding in situ observations suggests that the uncertainty in the modeled soil moisture is the predominant contributor to these rms errors. Although the bias between model and observed brightness temperatures are reduced after the calibration, systematic differences in the dynamic range remain. For NWP analysis applications, bias correction schemes should be applied prior to data assimilation. The calibrated model has been used to compute a 10-yr brightness temperature climatology based on ERA-40 data.

1. Introduction

Satellite-borne passive microwave observations at L-band will become routinely available for the first time through the European Space Agency’s (ESA) Soil Moisture and Ocean Salinity mission (SMOS) foreseen in 2009. The sensitivity of L-band measurements to soil moisture has been thoroughly analyzed (e.g., Ulaby et al. 1986), and the applicability of soil moisture retrievals has been demonstrated over the previous decades (e.g., Jackson et al. 1999). In recent years, data assimilation studies have also demonstrated the potential benefit of this observation type for hydrological modeling (e.g., Reichle and Koster 2005) and numerical weather prediction (NWP; e.g., Balsamo et al. 2007; Drusch 2007).

For NWP centers, SMOS data will be most beneficial for the soil moisture analysis, which is used to initialize operational weather forecasts. For the atmospheric and surface analyses, the medium-range forecast system at the European Centre for Medium-Range Weather Forecasts (ECMWF) receives observations within three hours of sensing. The analyses are then produced within 1.5 h to guarantee a timely start of the forecast computations and to minimize the latency between forecast initialization and forecast dissemination times (Haseler 2004). For short-range forecasts and nowcasting, the operational production schedule can be even tighter. The operational constraints have a significant...
influence on the design of the data assimilation system and how a specific dataset can be used.

Producing the SMOS level 2 soil moisture product will take more than 24 h but brightness temperatures will be available in near-real time (NRT; i.e., within three hours of sensing). Consequently, a land surface microwave emission model is needed to transfer the model state variables (e.g., soil moisture, soil temperature, etc.) into observation space (brightness temperature). Auxiliary datasets (e.g., soil temperature, profiles of atmospheric temperature and relative humidity) used for this computation are also required in NRT and should be consistent with the first-guess state variables. In the current operational data assimilation system, approximately 18 million satellite observations are used, and the radiative transfer calculations for the model first guess are based on short-range forecasts.

Because of the limited time available and the high computational costs of an advanced variational data assimilation system, operational analyses are often produced at a low spatial resolution. Although the ECMWF medium-range forecast is currently produced at \( \approx 25\)-km resolution, the atmospheric four-dimensional variational data assimilation (4DVAR) analysis is based on analysis increments with \( \approx 120\)-km resolution. It is likely that the surface analysis system will be operated at a similar reduced resolution.

In this study, we compare modeled brightness temperatures based on ECMWF’s 40-yr reanalysis (ERA-40) and observations from the Skylab satellite mission in 1973. The ERA-40 land surface scheme is comparable to the current version used in the Integrated Forecast System (IFS), and its spatial resolution matches that of the data assimilation system. The Skylab dataset is limited and comprises only nine overpasses. However, these observations are the only spaceborne L-band data available. It should be noted that they cover a large variety of landscapes, vegetation types, and climates. In addition, the measurements were taken during different seasons. As a consequence, we have to wait at least half a year after launch to get calibrated SMOS observations covering a similar period; the operational data monitoring should start much earlier.

Skylab data are briefly introduced in section 2. In sections 3 and 4, we introduce the Community Microwave Emission Model (CMEM) and the operational NWP datasets used in the future SMOS-based soil moisture analysis. To provide a timely calibration and validation benchmark for adaptation to SMOS, the model is calibrated using the Skylab observations. Systematic and random model errors, which have to be known for data assimilation, are quantified and discussed in section 5. With ERA-40 data, a L-band climatology for the period from 1990 to 2000 is produced and discussed in section 7.

2. Skylab S-194 observed brightness temperatures

The National Aeronautics and Space Administration (NASA) Skylab mission was the first example of a space station. It operated between May 1973 and July 1977 on a polar orbit at 435-km nominal altitude; the orbit period was 93 min. The Skylab S-194 instrument was a nadir-viewing passive microwave radiometer operating at 1.4 GHz with a hard-mounted antenna. The resolution of a single observation was approximately 110 km; the distance between the centers of two consecutive footprints was 2.5 km. The sensor calibration was based on fixed cold and hot load inputs, and the absolute antenna temperature was obtained with an accuracy of 1 K (Eagleman and Lin 1976).

Collecting data from S-194 required the astronauts on board the satellite. Consequently, the number of observations is limited to the following periods: 14 May–22 June 1973, 28 June–25 September 1973, and 16 November 1973–8 February 1974. The S-194 data and a comprehensive description are now available [available online at http://disc.gsfc.nasa.gov; Jackson et al. (2004)].

In total, nine tracks of observations are available (Fig. 1). Although the number of observations is quite limited, it should be emphasized that a large variety of landscapes, vegetation types, climates, and seasons is covered. This spatial coverage could hardly be achieved from airborne field campaigns; consequently, the S-194 measurements are the best dataset available to perform a first calibration of land surface emission models at L-band for global NWP applications.
Table 1. Modular configuration of CMEM. For each component, the key variable is indicated and the list of options is provided. The soil module includes four components: the dielectric mixing model ($\varepsilon$), the effective temperature model ($T_{\text{eff}}$), the smooth surface emissivity model ($\varepsilon_{s,p}$), and the rough surface emissivity, $\varepsilon_{r,p}$. For each of the components, several parameterizations are proposed. The vegetation module key variable is the vegetation optical thickness $\tau_{\text{veg},p}$. The snow module computes the snow reflectivity $\rho_{\text{sn},p}$, and the atmospheric module provides the atmosphere optical thickness $\tau_{\text{ atm},p}$. Options in bold are those used in this paper.

<table>
<thead>
<tr>
<th>Module</th>
<th>Output</th>
<th>Parameterizations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\varepsilon_{s,p}$</td>
<td>Fresnel</td>
</tr>
<tr>
<td>Snow</td>
<td>$\rho_{\text{sn},p}$</td>
<td>Pulliainen et al. (1999)</td>
</tr>
</tbody>
</table>

3. The Community Microwave Emission Model

Land surface emission modeling in NWP centers relies mainly on results published in the peer reviewed literature due to practical constraints on resources. As a consequence, there is a substantial latency between the latest developments and their beneficial impact on operational applications. In addition, feedback from operational users to the various research groups developing algorithms and parameterizations is often difficult to obtain.

ESA’s calibration, validation, and retrieval study provides the framework for a timely and direct exchange of information between the SMOS Validation and Retrieval Team (SVRT) members working on parameterizations and forward modeling problems, the NWP community, and ESA. CMEM is the appropriate common tool for emission model developments and applications. The detailed CMEM documentation and the source code can be obtained on the Internet (available online at http://www.ewcmf.int/research/ESA_projects/SMOS/cmem/cmem_index.html).

CMEM comprises the physics and parameterizations used in the Land Surface Microwave Emission Model (LSMEM; Drusch et al. 2001) and the L-Band Microwave Emission of the Biosphere (L-MEB; Wigneron et al. 2007). It is based on a simplified solution for the vector radiative transfer equation (e.g., Kerr and Njoku 1990; Drusch and Crewell 2005). For polarization $p$, the brightness temperature over snow-free areas at the top of the atmosphere (TOA) $T_{\text{Btoa},p}$ can be expressed as

$$T_{\text{Btoa},p} = T_{\text{Bau},p} + \exp\left(-\tau_{\text{ atm},p}\right)T_{\text{Btv},p}$$  \hspace{1cm} (1)

$$T_{\text{Btv},p} = T_{\text{Bsoil},p}\exp\left(-\tau_{\text{veg},p}\right)$$
$$+ T_{\text{Bveg},p}\left[1+r_{p}\exp\left(-\tau_{\text{veg},p}\right)\right]$$
$$+ T_{\text{Bad},p}r_{p}\exp\left(-2\tau_{\text{veg},p}\right),$$  \hspace{1cm} (2)

where $T_{\text{Bau},p}$ is the upwelling atmospheric emission, $\tau_{\text{ atm},p}$ is the atmospheric optical depth, and $T_{\text{Btv},p}$ is the top-of-vegetation brightness temperature when the vegetation is represented as a single-scattering layer above a rough surface; $T_{\text{Bsoil},p}$, $T_{\text{Bveg},p}$, and $T_{\text{Bad},p}$ are the soil, vegetation layer, and downward atmospheric contributions, respectively. Here, $r_{p}$ is the soil reflectivity of the rough surface (one minus the emissivity $\varepsilon_{r,p}$), and $\tau_{\text{veg},p}$ is the vegetation optical depth along the viewing path. Snow is represented through the Helsinki University of Technology (HUT) snow emission model (Pulliainen et al. 1999) as a single additional homogeneous snow layer with low attenuation and an additional dielectric boundary.

CMEM comprises four modules for computing the contributions from soil, vegetation, snow, and the atmosphere. The code is designed to be highly modular and for each microwave modeling component, a choice of several parameterizations are considered. Table 1 summarizes the modular structure and lists the options provided in CMEM. The following paragraphs address surface roughness and vegetation contribution because these components have been used for calibrating the model.

Wang and Choudhury (1981) propose a semiempirical approach to represent soil roughness effects on the microwave emission. The rough emissivity is computed as a function of the smooth emissivity and three parameters $Q$, $h$, $N$:

$$r_{p} = \left[Qr_{p} + (1-Q)r_{q}\right]\exp\left(-h\cos^{N}\psi\right),$$  \hspace{1cm} (3)

where $p$ and $q$ refer to the polarization states, $Q$ is the polarization mixing factor, $N$ describes the angular dependence, $h$ is the roughness parameter, and $\psi$ is the incidence angle. The mixing factor $Q$ is considered to be very low at low frequencies and is generally set to 0 (Wigneron et al. 2007; Njoku et al. 2003).
For the roughness parameter $h$, a number of parameterizations exist. They are based on (i) empirical coefficients, wavenumber, and the rms surface height $\sigma$ (Choudhury et al. 1979; Wegmüller and Mätzler 1999); (ii) empirical coefficients, wavenumber, the rms surface height, and correlation length (Wigneron et al. 2001); (iii) soil moisture and soil texture (Expert Support Laboratories 2007); or (iv) soil moisture and vegetation type (Wigneron et al. 2007).

In CMEM, vegetation is represented through $\tau - \omega$ approaches in which the vegetation layer has a direct contribution to the TOA signal and attenuates the emission from the underlying soil:

$$T_{B_{\text{veg,p}}} = T_c (1 - \omega_p) [1 - \exp(-\tau_{\text{veg,p}})],$$

where $T_c$ is the canopy temperature and $\omega_p$ is the single scattering albedo at polarization $p$.

With Eq. (4), Jackson and Schmugge (1991) propose a simple parameterization to compute the vegetation optical thickness:

$$\tau_{\text{veg,p}} = b \frac{VWC}{\cos \psi},$$

where $b$ and VWC are the vegetation structure parameter and the vegetation water content, respectively. The single scattering albedo is assumed constant at $\omega = 0.05$ for low vegetation types (grass and crops) and for high vegetation types (forests).

The Wigneron et al. (2007) vegetation optical thickness model also describes the vegetation effect with Eq. (4). In their formulation, the single scattering albedo depends on vegetation type and polarization. The polarized optical thickness is expressed as

$$\tau_{\text{veg,p}} = \tau_{\text{nadir}} (\cos^2 \psi + t_p \sin^2 \psi) \frac{1}{\cos \psi},$$

$$\tau_{\text{nadir}} = b' \text{LAI} + b'' \text{ for low vegetation, and}$$

$$\tau_{\text{nadir}} = b'' \text{ for high vegetation},$$

where $t_p$ parameters represent the angular effect on vegetation optical thickness for each polarization and vegetation types (at nadir, $t_p$ has no effect on the simulations). The vegetation structure parameters $b', b''$, and $b'''$ and the single scattering albedo are obtained from lookup tables (Wigneron et al. 2007).

The Kirdyashev et al. (1979) parameterization expresses the vegetation optical thickness as a function of the wavenumber $k$ (between 1 and 7.5GHz), the dielectric constant of saline water, $\varepsilon''_{\text{sw}}$ (imaginary part), VWC, incidence angle $\psi$, water density $\rho_{\text{water}}$, and a vegetation structure parameter $d_{\text{geo}}$:

$$\tau_{\text{veg,p}} = a_{\text{geo}} k \frac{VWC}{\rho_{\text{water}}} \varepsilon''_{\text{sw}} \frac{1}{\cos \psi}.$$

Again, the single scattering albedo is assumed constant at $\omega = 0.05$.

Here, $T_{B_{\text{tov,p}}}$ is computed for each model grid box, taking the subgrid-scale variability of the land surface into account. Up to seven tiles can be considered in each CMEM grid box: bare soil, low vegetation, high vegetation (each are either free of snow or snow covered), and open water. For the vegetation tiles, the dominant vegetation class is obtained from an auxiliary land-use classification dataset. The gridbox averaged brightness temperature is computed using the weighted sum of the brightness temperatures obtained for the individual tiles.

### 4. CMEM input data and calibration strategy

The calibration of a complex model system is often an ill-posed problem because the number of parameters exceeds the number of observations at a given location. Therefore, it is essential to focus on the key parameters in the emission modeling process. Jones et al. (2004) ranked the main variables and parameters entering passive microwave land surface emission models according to their impact on $T_{B_{\text{toa}}}$.

Although values are strictly valid at C- and X-bands, they can give an indication of the relative importance of the individual parameters at L-band. In the following paragraphs, we discuss the availability and accuracy of the key products entering the land surface emission model. A summary on the input parameters is given in Table 2. It should be noted that our focus lies on global near-real time applications. For hindcast, reanalyses, and soil moisture retrievals, better products may be available, especially on local to regional scales.

Volumetric soil moisture ($\theta$) is routinely analyzed in NWP systems and is directly linked to soil, vegetation, and atmospheric parameters. For this study, $\theta$ is obtained from the ERA-40 reanalysis dataset (Uppala et al. 2005). The observations used in the analysis comprise various satellite datasets as well as ground-based measurements and conventional synoptic data. These
datasets were assimilated through a 3DVAR analysis scheme, making use of the IFS at T159 spectral resolution (~1.125° horizontal spacing) with 60 vertical levels. The surface scheme within the IFS is the Tiled ECMWF Scheme for Surface Exchanges over Land (TESSEL) model as described in van den Hurk et al. (2000). The soil is discretized in four layers of 0.07, 0.21, 0.72, and 1.89-m depth (from top to bottom). We use the soil moisture analyzed for the first model layer, representing a depth of 0.07 m.

VWC is not used by the NWP model and is poorly known on large spatial scales. A number of empirical formulas exist that relate vegetation water content to the normalized difference vegetation index or leaf area index (LAI) from satellite data such as Advanced Very High Resolution Radiometer (AVHRR) or Moderate Resolution Imaging Spectroradiometer (MODIS; e.g., Jackson et al. 1999). However, vegetation datasets from optical instruments are not available in near-real time, and NWP centers have just started to explore the capabilities of offline LAI analysis systems (e.g., Jarlan et al. 2008). Currently, static vegetation datasets are used by the NWP community, and VWC has been derived from the ECOCLIMAP LAI dataset (Masson et al. 2003) following Pellarin et al. (2003).

\[
\text{VWC} = 0.5 \times \text{LAI}, \quad (10)
\]

for grasslands and crops; the vegetation water content for rain forests, deciduous forests, and coniferous forests has been set to 10, 4, and 3 kg m\(^{-2}\) (Holmes et al. 2008), respectively, for the first-guess model calibration setup. However, these values have not been validated on the continental scale and represent the branch water content rather than the entire biomass. In this study, we consider the vegetation water content of forests as a calibration parameter.

The brightness temperatures at the top of the atmosphere also depend on the effective soil temperature \(T_{\text{eff}}\) and canopy temperature \(T_c\). The effective temperature depends on the vertical profile of soil temperature close to the surface; it has been parameterized following Wigneron et al. (2001) using ERA-40 soil temperatures. We also use ERA-40 soil temperature fields at 0.035-m depth as an approximation for canopy temperatures. Because the influence of these parameters on the brightness temperature is comparably low (Jones et al. 2004), these approximations do not introduce a substantial error.

Soil texture data from the Food and Agriculture Organization (FAO) are static at 10-km spatial resolution and are of one of three soil texture classes: coarse, medium, and fine (FAO 2000). Sand and clay fractions have been computed from a lookup table according to Salgado (1999). The 10-km datasets have been aggregated to T159 spectral resolution.

Snow water equivalent data and snow density have also been obtained from the ERA-40 dataset. The reanalysis is based on a short-range weather forecast and in situ observations (Drusch et al. 2004a); fractional snow coverage is set to 100% in the presence of snow.

Open water (i.e., lakes, rivers, flood areas, and so on) represents a challenge for soil moisture retrievals as well as for data assimilation applications (Gao et al. 2006). Global NRT datasets for surface temperatures do not exist, and the emission of rough water surfaces is difficult to estimate. For the future soil moisture analysis, observations with open water fractions exceeding 5% will be flagged and excluded. For this study, soil temperature has been used as a proxy for lake and sea temperatures. The salinity of open water in a land pixel is set to 0 psu; the salinity for sea pixels is 32.5 psu. Using the Klein and Swift (1977) parameterization for the dielectric constant of saline water, Fresnel

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### Table 2. CMEM input parameters

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Relative influence</th>
<th>Value</th>
<th>Source</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\theta)</td>
<td>Volume soil moisture</td>
<td>1.0</td>
<td>Dynamic</td>
<td>ERA-40</td>
<td>Uppala et al. (2005)</td>
</tr>
<tr>
<td>VWC</td>
<td>Vegetation water content</td>
<td>0.63</td>
<td>Static</td>
<td>ECOCLIMAP</td>
<td>Masson et al. (2003)</td>
</tr>
<tr>
<td>(T_{\text{eff}})</td>
<td>Effective soil temperature</td>
<td>0.13</td>
<td>Dynamic</td>
<td>ERA-40</td>
<td>Uppala et al. (2005)</td>
</tr>
<tr>
<td>(\omega)</td>
<td>Vegetation single scattering albedo</td>
<td>0.08</td>
<td>Constant</td>
<td>–</td>
<td>Holmes et al. (2008)</td>
</tr>
<tr>
<td>–</td>
<td>Soil bulk density</td>
<td>0.05</td>
<td>Static</td>
<td>FAO</td>
<td>FAO (2000)</td>
</tr>
<tr>
<td>–</td>
<td>Vegetation temperature</td>
<td>0.03</td>
<td>Dynamic</td>
<td>ERA-40</td>
<td>Uppala et al. (2005)</td>
</tr>
<tr>
<td>–</td>
<td>Soil temperature</td>
<td>0.01</td>
<td>Static</td>
<td>FAO</td>
<td>FAO (2000)</td>
</tr>
<tr>
<td>–</td>
<td>Snow water equivalent</td>
<td>NA</td>
<td>Dynamic</td>
<td>ERA-40</td>
<td>Uppala et al. (2005)</td>
</tr>
<tr>
<td>–</td>
<td>Snow density</td>
<td>NA</td>
<td>Dynamic</td>
<td>ERA-40</td>
<td>Uppala et al. (2005)</td>
</tr>
</tbody>
</table>

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The relative impact has been derived from the normalized perturbation response at C- and X-bands given in Jones et al. (2004). We distinguish between three types of parameter values: i) dynamic: NWP model output varying in space and time; ii) static: a database representing parameters with a limited spatial and/or temporal variability; and iii) constant: a single value. VWC is obtained from ECOCLIMAP LAI using Pellarin et al. (2003); soil bulk densities have been derived from the FAO soil texture dataset following Hillel (1980). Parameters that are used to calibrate CMEM are described in Table 3.
reflectivities of \( \sim 0.6 \) have been obtained from these values.

Soil roughness, vegetation structure coefficient, and vegetation water content for dense vegetation are used for the emission modeling only. They do not feed back into the NWP model or only indirectly and are poorly known on large spatial scales. For the calibration process, we tune these parameters, and we use different parameterizations for the rough surface reflectivity and the vegetation opacity. A discussion on other error sources will be given in section 6.

The setup for the different CMEM runs presented in the study including parameter values used for the calibration is summarized in Table 3. Model setup A provides the first-guess setup based on parameterizations and parameter values used in previous studies. The other three configurations outlined in Table 3 have been selected from more than 20 experiments.

### 5. Calibration and validation

Skylab observations and the corresponding ERA-40 grid boxes are matched using the nearest neighbor technique. To produce a set of independent data pairs, Skylab observations for a specific grid box were averaged. This is a reasonable approach because (i) the S-194 footprints are smaller than an ERA-40 grid box and (ii) averaging should be preferentially applied to brightness temperatures rather than geophysical parameters to avoid errors introduced through nonlinearities in the radiative transfer calculation (Drusch et al. 1999a, b; Crow et al. 2001). The spatial variability of the observations within each ERA-40 grid box has been used as a quality check for the observation–model data pair. Whenever the range of observed brightness temperatures for a specific grid box exceeded 10 K, the aggregated observation–model data pair is rejected. This test removes data pairs in coastal areas and grid boxes with large open water bodies (e.g., the Amazon), which may not be represented correctly in the ERA-40 dataset.

Four tracks covering North and South America and including both winter and summertime passages have been selected for the CMEM calibration (Fig. 1, black tracks). The comparison between setup A brightness temperatures and the observations is shown in Fig. 2. The spatial distribution of brightness temperature differences (observation – model) shows good coverage of calibration data for North America. In South America, one transect including the Amazon region and the Mato Grosso has been obtained. The differences for North America can be as large as 40 K and overall, the observed \( T_{\text{B}} \text{toa} \) are cooler than the corresponding model values. The maps suggest that the differences over the eastern United States are generally larger than over the central and western United States. The scatterplots reveal a correlation of 0.52 and a bias of \(-8.4 \) K for the South America data (Fig. 3b). The data pairs over North America exhibit a correlation of 0.34 and a bias of \(-8.4 \) K. The January 14 data present little bias (Fig. 3a). This is somewhat surprising because large parts of the western and central United States were snow covered during the overpass time, and winter conditions are generally difficult to capture by emission models.

In total, 10 combinations of different roughness and vegetation parameterizations have been used to compute brightness temperatures. For these computations, the recommended parameter values from the reviewed literature have been applied. They are performed to gauge the output space and to determine sensitivities. Setup B is one example configuration, which gave promising results when data from field experiments

<table>
<thead>
<tr>
<th>Setup</th>
<th>Reference</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Wigneron et al. (2001)</td>
<td>( h ) (cm)</td>
<td>0.77</td>
</tr>
<tr>
<td>B</td>
<td>Wigneron et al. (2007)</td>
<td>( h_{\text{bare soil}} )</td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( h_{\text{decid. forest}} )</td>
<td>1.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( h_{\text{conif. forest}} )</td>
<td>1.6</td>
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<tr>
<td></td>
<td></td>
<td>( h_{\text{rain. forest}} )</td>
<td>1.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( h_{\text{C3/C4grass}} )</td>
<td>( f(\theta) )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( h_{\text{C3/C4crops}} )</td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( h_{\text{C3/C4crops}} )</td>
<td>0.6</td>
</tr>
<tr>
<td>C</td>
<td>Wigneron et al. (2001)</td>
<td>( h )</td>
<td>0.73</td>
</tr>
<tr>
<td>D</td>
<td>Wigneron et al. (2001)</td>
<td>( h )</td>
<td>0.77</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>Setups</th>
<th>Reference</th>
<th>Parameter</th>
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<td></td>
<td>Jackson and Schmugge (1991)</td>
<td>( b_{\text{forests}} )</td>
<td>0.33</td>
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<tr>
<td></td>
<td></td>
<td>( b_{\text{C3/C4grass}} )</td>
<td>0.20</td>
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<td>( b_{\text{C3/C4crops}} )</td>
<td>1.6</td>
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<tr>
<td></td>
<td>Wigneron et al. (2007)</td>
<td>( b_{\text{C3/C4grass}} )</td>
<td>0.0375</td>
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<td></td>
<td></td>
<td>( b_{\text{C3/C4crops}} )</td>
<td>0.05</td>
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<tr>
<td></td>
<td></td>
<td>( b_{\text{C3/C4crops}} )</td>
<td>0.05</td>
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<tr>
<td></td>
<td></td>
<td>( b_{\text{C3/C4crops}} )</td>
<td>0.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( b^{*} )</td>
<td>0.7</td>
</tr>
<tr>
<td></td>
<td>Kirdyashev et al. (1979)</td>
<td>( a_{\text{geo(high/low)}} )</td>
<td>0.33/0.66</td>
</tr>
<tr>
<td></td>
<td>Kirdyashev et al. (1979)</td>
<td>( a_{\text{geo(high/low)}} )</td>
<td>0.33/0.33</td>
</tr>
</tbody>
</table>
were used (Wigneron et al. 2007). In combination with the ECMWF model fields and the NWP auxiliary datasets, the systematic and random errors are comparably large. For North America, we obtain 0.04 and 23.1 K for the correlation coefficient and the bias, respectively (Fig. 3c). The corresponding values for the South American data are 0.58 and 27.9 K (Fig. 3d). The best results for both continents have been obtained using Wigneron et al. (2001) for describing the effects of surface roughness and Kirdyashev et al. (1979) for the parameterization of vegetation.

In the subsequent model runs, the roughness height and the vegetation structure coefficient have been modified to fine-tune CMEM. Figures 3e and 3f show the brightness temperatures for setup C (Table 3). The correlations for North and South America have been increased and the biases of −1.2 and −3.0 K, respectively, are comparably low.

The vegetation structure coefficient in Eq. (9) should vary between 0.66 for a vegetation layer with elements in the form of small discs and 0.33 for cylinders. For setup D, $a_{geo}$ is set to 0.33 for low and high vegetation types (Figs. 3g,h). For the North American datasets, the correlation is 0.5 and the bias is −0.7 K. Over South America, the modeled $T_{geoa}$ are slightly too low (correlation is 0.56) when compared against the corresponding observations. However, this configuration leads to the best agreement between model-based brightness temperatures and observations.

Observations from five overpasses (Fig. 1, gray tracks) have been used to validate CMEM setup D. For three ERA-40 grid boxes over the Amazon region, the modeled brightness temperatures are more than 16 K higher than the corresponding observations. The northernmost data pair (Figs. 4a,b) showing a difference of almost 20 K includes the Serra da Mocidade plateau and the Rio Branco; the footprint further to the south is strongly influenced by the Rio Negro, and the southernmost data pair is located over an extended swamp area, the Ilha Tupinambarama. It is likely that these complex terrains with a significant amount of open and vegetation-covered water bodies are not represented correctly by the land surface scheme in ERA-40. In general, the results for the validation dataset are better than the ones obtained for the calibration dataset, indicating that the data sample size is too small to capture the full variability over the two continents. However, the results for the two data samples provide an estimate of the accuracy range that can be obtained with a continental scale calibration.

The calibration/validation experiments also show that it is not possible to reproduce the observed dynamical range of brightness temperatures. For the June, August, and September dates, the observed values range from 220 to 275 K. The corresponding model data vary from 230 to 265 K. We discuss this systematic difference and its implication for data assimilation applications in the following section.

### 6. Error discussion

The weights of the observations and the model first guess in the analysis are determined through their respective error characteristics. The rms errors obtained in this study include both the first guess uncertainty and the observation error. Because the calibration error of the observations is below 1 K and the observations taken every 2.5 km along the orbit path are averaged to represent an ERA-40 grid box, it is assumed that the main contribution to the random errors originates from the model brightness temperatures.

Random errors in the ERA-40 soil moisture fields have been analyzed using data from the Southern Great Plains Hydrology Experiment 1999. In general, root-mean-square errors varying from 2.5% to 5% have been found for dry and wet scenes, respectively (Drusch et al. 1999).
Around selected Skylab overpasses, gravimetric soil moisture samples were taken in Texas and Kansas. Details on the data, the field sites, and the synoptic situations can be found in Jackson et al. (2004). A comparison between spatially averaged in situ measurements and the corresponding ERA-40 grid box values shows the systematic differences between soil moisture datasets (Fig. 5). The original in situ observations comprise values from ~1% to 51% volumetric soil moisture, resulting in area averages from 3% to 33%. The dynamic range of the model is much smaller with a higher mean value. A first order correction for these systematic differences is a linear transformation to model space:

\[ \theta_{\text{trans}} = \theta_{\text{wp}} + \frac{\theta_{\text{in-situ}}}{50} (\theta_{\text{fc}} - \theta_{\text{wp}}), \]  

where \( \theta_{\text{wp}} \) and \( \theta_{\text{fc}} \) are the model volumetric soil moisture at wilting point and field capacity, respectively; \( \theta_{\text{in-situ}} \) is the original observation; and \( \theta_{\text{trans}} \) is the transformed value. This transformation reduces the bias to ~0.3% and results in a root-mean-square error of 1.97% when compared against the model data (Fig. 5b). Over sparsely vegetated areas, a 1% change in soil moisture results in a 2.5 K change in top of the atmosphere L-band brightness temperatures. Consequently, the random error in the ERA-40 soil moisture fields translates into brightness temperature uncertainties from 5 K (assuming a 2% error as obtained in Fig. 5b) to 12.5 K [for a 5% error obtained in Drusch et al. (2004b)].

Systematic differences between observations and the model background should be minimized prior to data assimilation applications to obtain statistically optimal
analyses of soil moisture. Calibrating the forward operator reduces the bias between the modeled brightness temperatures and the observations. However, a systematic difference in the dynamic ranges of observed and predicted brightness temperatures remains.

Using Eq. (11), we transform the ERA-40 soil moisture data to the observed dynamic range and repeat the calibration and validation computations under setup D for North America. This simple correction results in a modeled variability that is almost identical to the observed one (Fig. 6). It should be noted that the bias after normalization is due to systematic differences between the in situ measurements and the Skylab observations. An advanced bias correction scheme applied in brightness temperature space will effectively reduce any remaining systematic differences after CMEM calibration. In addition, the difference in the vertical resolution between the two datasets can result in brightness temperature uncertainty exceeding ±5 K (Wilker et al. 2006), which is included in the errors given in Figs. 2 and 3. Ideally, the top soil layer representing a depth of 1/10 of the wavelength should be discretized in more than 10 layers (Wilheit 1978) to produce an accurate estimate of the soil dielectric constant.

Another major source of uncertainty is introduced through the vegetation dataset. The ECOCLIMAP data used in the forward model represent an annual cycle but do not take interannual variability or variability on short time scales into account. In addition, ERA-40 adopted a different vegetation dataset, which can lead to local inconsistencies with geophysical parameters (e.g., soil temperature). However, this is a common problem in many retrieval and forward modeling approaches in which datasets from different sources are necessarily combined.

The observations over South America also reveal potential problems with the treatment of water bodies (i.e., lakes, rivers, and swamps) in the NWP model.
fields and the microwave emission model. Although an accurate estimate of the fractional coverage of static open water can be obtained for each model grid box and satellite footprint from high-resolution land cover datasets, it is hardly possible to determine the corresponding surface temperature and salinity. In ECMWF’s IFS, a model grid box is treated as land if the fractional coverage of water is less than 50%. As a consequence, water bodies up to 5500 km² cannot be described correctly at ERA-40 resolution.

Potentially, the different spatial resolution of the satellite observations and the ERA-40 grid boxes and the matching procedure described above can introduce errors as well. To estimate the errors of the spatial aggregation procedure, a subset of data pairs with ERA-40 grid boxes, which are represented by at least 50 Skylab observations, has been extracted. This number of observations results in a track of 125 km and ensures that the model grid box is well covered by measurements. The changes in rms errors and biases were marginal when only the subset of data pairs were analyzed; the results and conclusions did not change.

7. ERA-40 climatology

Based on the ERA-40 dataset and CMEM, a climatology for L-band brightness temperatures has been computed for the period 1990–2000. Mean values for
July and the corresponding standard deviations are shown in Fig. 7. As one would expect, densely forested areas in the tropics and deserts are characterized by high brightness temperatures exceeding 280 K, wet areas, and the Tibetan Plateau exhibits values around 230 K. It is interesting to note that the interannual variability is comparably small: large parts of the earth show values below 6 K. The tropical rain forest in the Amazon region is particularly stable and brightness temperature standard deviation is below 0.5 K. However, this area is comparably small and with the SMOS field of view exceeding 1000 km, it remains questionable whether the rain forest could be used as a calibration target.

The mean annual cycle has been computed for North and South America (Fig. 8). Again, the interannual variability on the continental scale is low compared with the biases found in the calibration study. For North America, the largest variability is found in wintertime, which is probably related to the variability in snow. During summertime, monthly mean brightness temperature variations hardly exceed 5 K. The values
for South America are even lower as a result of the large coverage of tropical forests. The (calibrated) ERA-40 brightness temperature climatology will allow us to obtain a first check on the SMOS monitoring shortly after launch. However, comparisons should be based on large spatial scales only. Locally, the static ECOCLIMAP vegetation database can introduce errors. Similar climatologies will be produced for different SMOS viewing angles and for longer periods covering the presatellite era.

8. Summary and implementation strategy

Apart from the S-194 data used in this study, no spaceborne passive microwave L-band observations have been available on the continental scale. Parameterizations and coefficients for the land surface emissivity modeling have been derived from laboratory measurements and field experiments covering local to regional scales. In this study, we focus on the continental scale due to the limited number of observations available and the coarse spatial resolution of the observations and the model fields. This study demonstrates that it is possible to calibrate a state-of-the-art emission model for NWP data assimilation applications and for operational soil moisture retrievals using the S-194 data.

However, backward and forward emission modeling depend on a number of auxiliary datasets and geophysical parameters. Each of these datasets has systematic and random errors, which are difficult to quantify and which partly determine the choice of the parameterizations in the emission model, the value of a calibration parameter or the coefficients in a retrieval algorithm. For ECMWF’s Integrated Forecast System, setup D (Table 3) using parameterizations suggested by Kirdyashev et al. (1979) and Wigneron et al. (2001) gives the best results for the calibration and validation datasets. Our study demonstrates that it is important to develop new parameterizations not only on the local scale using high-quality experimental data but also on larger scales with global datasets. CMEM is a convenient tool for these applications because it comprises a number of optional parameterizations and different input/output interfaces.

Within the Project for the Intercomparison of Land-Surface Parameterization Schemes (PILPS), it was shown that different land surface models can produce substantially different surface energy and water budgets even when they are driven by the same meteorological forcings (Koster and Milly 1997). Consequently, model soil moisture is systematically different from satellite-derived products and in situ measurements representing the point scale. These systematic differences cannot be avoided and are inherent in retrieval methods using auxiliary datasets and data assimilation applications alike. It has been shown that the bias between the model brightness temperatures and the observations can be minimized through the CMEM calibration. However, systematic differences in the brightness temperature’s dynamic range as a result of the model’s soil moisture climatology remain present and have not been reduced.

Any systematic differences between the model and the observation should be minimized prior to data assimilation applications to obtain statistically optimal analyses. In the NWP community, this preprocessing step is referred to as bias correction. Various methods with different complexity levels have been applied in atmospheric data assimilation systems (e.g., Dee and da
Silva 1998; Harris and Kelly 2001; Auligné et al. 2007). For hydrological applications, cumulative distribution function matching has been applied successfully (Reichle and Koster 2004; Drusch et al. 2005). However, our comparison confirms that it will be necessary to develop bias correction methods for the assimilation of SMOS observations.

At ECMWF, CMEM will be implemented for the direct assimilation of brightness temperatures over snow-free areas. Near-real time applications will have to be based on brightness temperatures: (i) the generation and acquisition of auxiliary datasets and the soil moisture retrieval itself will cause an unacceptable latency; and (ii) the retrieved soil moisture product will be based on archived model fields, which are available at 3-hourly resolution. During the assimilation process, the corresponding model fields are available every 12 min and should give more accurate estimates of the surface parameters (e.g., for the temperature fields at a specific overpass time).

During the SMOS commissioning phase, the SMOS data will be monitored operationally, for example, model-based brightness temperatures will be compared against the corresponding observations. The configuration will be based on the values and parameterizations defined in this study. It is envisaged that CMEM is updated 6 months after launch, and a second calibration can be performed based on the observations available and the latest results from the SMOS calibration/validation study. In the subsequent preoperational phase, the influence of SMOS observations on the forecast will be evaluated and it is planned to start with the operational application approximately 18 months after launch.

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