# Derivation of a root zone soil moisture algorithm and its application to validate model data*

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**Abstract** A retrieval algorithm for soil moisture within the uppermost metre of soil is presented. As calibration data, longtime soil moisture measurements from the former Soviet Union are used. The retrieval works in two steps. First, the distribution of longtime mean soil moisture is derived by using precipitation, soil texture, vegetation density and terrain slope. In a second step, the temporal variability at each location is deduced by using microwave radiation measurements available from satellite together with precipitation and air temperature data. This soil moisture algorithm is applied in Northern and Central Europe to validate a climate simulation from the regional model REMO.

**Keywords** Model validation; passive microwave; REMO; retrieval algorithm; soil moisture

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## Introduction

The Baltic Sea region is one of the continental scale experiment regions within GEWEX (Global Energy and Water Cycle Experiment), where the interactions between the different climate components are studied in detail to enhance our understanding of the energy and water cycle (Raschke *et al.*, 2001). The REgional MOdel (REMO), run by the Max Planck Institute for Meteorology in Hamburg, is a central tool for this purpose (Jacob, 2001; Jacob *et al.*, 2001). Within the German research program DEKLIM, REMO, originally confined to the atmosphere, is coupled with an ocean model of the Baltic Sea (BSIOM, Baltic Sea Ice Ocean Model) (Lehmann and Hinrichsen, 2002) and a hydrological model (LARSIM, Large Area Simulation Model) (Eisele and Leibundgut, 2002). It is expected that the hydrological coupling will substantially improve the modelling of soil moisture, which has so far been rather frugal despite its widely accepted importance for the climate. However, the progress attained by the coupling needs to be proved and documented. The evaluation of modelled soil moisture by independent data is therefore crucial to assess the advances made by the model system developed. In this study, the soil moisture of REMO is validated to assess the initial model skill, which may serve as a reference level for future improvements.

Spatial direct measurements of soil moisture appropriate for model validation are not available for the BALTEX region. Microwave measurements from satellite might be useful, but reliable retrieval algorithms for soil moisture currently exist only for semi-arid regions (Seuffert *et al.*, 2004), where the disturbance from vegetation remains small. Further limitations for microwave satellite remote sensing are caused by their small ground penetration depth, which allows us to detect soil moisture only within the uppermost centimetres of soil. Information from the soil lying below this level is thus only indirectly attainable. However, for hydrological purposes a much thicker layer, often referred to as the root zone, is of greater interest. It comprises approximately the uppermost metre, which

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we use in this paper as a synonym for the root zone. As soil moisture to such depths is not derivable from satellite data alone, supplementary information is required.

In the first part of this paper, we present an algorithm that is able to derive soil moisture from the uppermost metre of soil. Besides microwave measurements from satellite, the algorithm needs information about precipitation, air temperature, soil texture, vegetation density and terrain slope. In the second part, the retrieval algorithm is applied to derive soil moisture estimates in the REMO model domain, covering Northern and Central Europe. This retrieved soil moisture is then used to validate the modelled soil moisture of a REMO climate simulation from 1979–1988.



## The soil moisture retrieval algorithm

For the derivation of the retrieval algorithm, longtime measurements of soil moisture from the former Soviet Union are analysed. The data compiled by Vinnikov and Yeserkepova (1991) cover a broad spectrum of climate zones existing between the subtropical deserts and the arctic tundra (Figure 1). The data set comprises soil moisture measurements of the upper 1 m soil layer at 50 stations. In general, measurements are taken every 10 d during the period 1952–1985. The temporal data coverage is, however, incomplete, resulting in 17 748 observations available for our analysis. Furthermore, we restricted our calculations to the period 1979–1985, for which all additional supplementary data sets (see below) are available.

The variance of soil moisture is decomposed following Lindau (2003). The idea is to consider subsamples of the entire data set. The total variance is then principally equal to the mean variance within all subsamples plus the variance between the averages of the subsamples. The first can be denoted as internal, the latter as external variance. In the present case, data from each of the 50 stations is considered as one subsample, so that the external variance is purely spatial, whereas the internal variance is equal to the mean temporal variability at each station. The major part of the observation errors remains in the internal part, since here individual observations are considered. The external variance is much less affected by observation errors as it is based on differences between averages. However, assuming random errors the exact error effect is calculated and taken into account, as described in detail by Lindau (2003).

The analysis shows a pronounced dominance of the spatial variability between the longtime means at each station. About 85% of the total variance is attributed to this purely spatial variance. Thus, aiming at a quantitative soil moisture algorithm the first and most important step is to explain this temporally constant variance. In this context it is beneficial that globally available fields of climatological means are sufficient for this purpose.

We used the following four parameters to determine the climatological soil moisture: the longtime mean precipitation from GPCP (Global Precipitation Climatology Project)

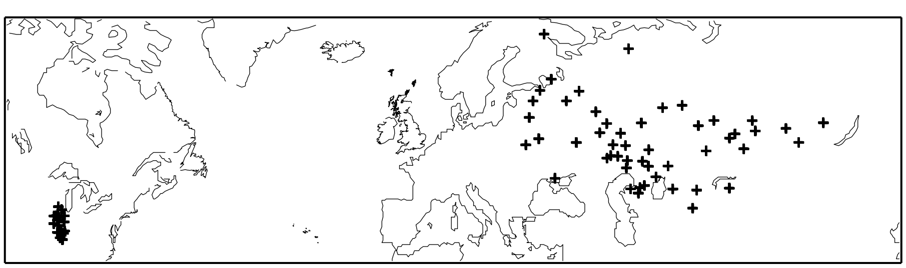

**Figure 1** Location of the used soil moisture stations. 50 stations in the former Soviet Union are used for the derivation of the algorithm. 19 stations in Illinois, USA, are used for the validation

(Adler *et al.*, 2003), the vegetation density from the UMD-1 km Land Cover Data of Maryland University (Hansen *et al.*, 2000) and soil texture and terrain slope both from FAO (Food and Agriculture Organization, 1970–1979).

With a regression of the form

$$SM_0 = 600(1 - \exp(-p/p_0)) + 30.0T - 1.58S - 15.8V - 6.6 \quad (1)$$

we found a correlation of 0.854 (Figure 2) between the measured 7-yr station averages and the theoretically predicted values $SM_0$. $p$ denotes the annual climatological rainfall and $p_0$ is a constant of $1000\,\mathrm{mm\,yr}^{-1}$. $T$ denotes the soil texture class between 1 for sand texture to 7 for organic soils, $V$ gives the vegetation class from 1 for high density to 12 for bare soil and $S$ denotes the average slope in per cent.

Although the major part of the variance is explained by Equation (1), $SM_0$ can only provide a temporally constant soil moisture at each station, so that an improvement by a second step is necessary. We used three temporally varying parameters to capture the temporal variance at each station. These are the precipitation fallen during the last weeks (again from GPCP), the air temperature from Willmott and Robeson (1995) and the brightness temperature from SMMR (Scanning Multichannel Microwave Radiometer flown on Nimbus-7) (Knowles *et al.* (2002).

A linear regression for the local temporal anomaly of soil moisture, $SM_1$, yields

$$SM_1 = -1.32t' + 21.52rr'' - 1.341tb_{10v} + 5.5 \quad (2)$$

where $t'$ denotes the anomaly against the longtime local air temperature averaged over the last 3 months. $rr''$ is the anomaly against the longtime local annual cycle of rainfall averaged

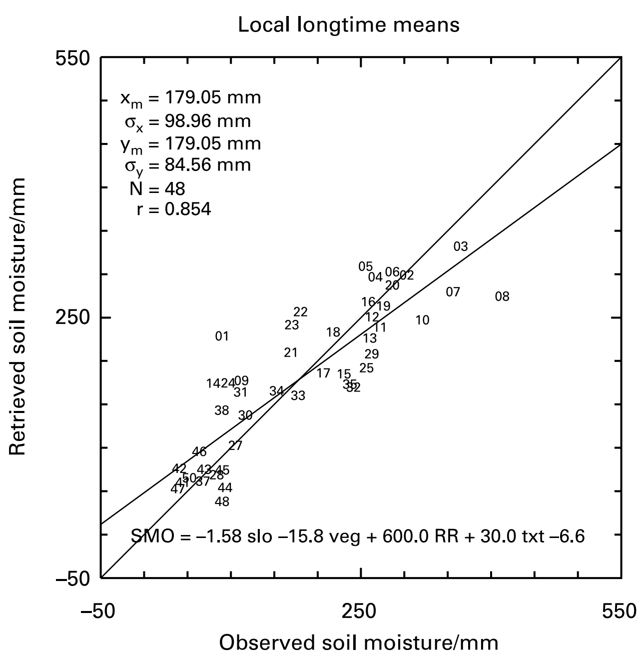


**Figure 2** Mean soil moisture for the period 1979–1985 within the uppermost metre as measured at 48 stations (the station numbers are plotted) in the former Soviet Union compared to the retrieval calculated by Equation (1) as given at the bottom. *slo*, *veg* and *txt* denote here slope, vegetation and texture. RR is the precipitation index specified in the text. For both data sets, mean and standard deviation are given, as well as the number *N* and the correlation *r*. Two regression lines are shown, taking the observations as independent and the retrieval as dependent parameter, and *vice versa*

over the past 2 months and $tb_{10v}$ is the vertically polarised brightness temperature of 10 GHz from SMMR on the Nimbus satellite. A correlation of 0.602 is attained, which might appear weak on first glance. But we have to keep in mind that only the remaining yet unexplained part of the total variance (about 15% of the total variance) is considered here, which also includes the complete error variance of the soil moisture observations. Hence, it becomes increasingly difficult to explain a larger part of it by independent information.

By combining Equations (1) and (2), soil moisture can be derived with a correlation of nearly 0.8 to ground measurements. About three quarters of the spatial variance is explained in this way, as it is treated explicitly in Equation (1) (see Figure 2). For the temporal variance the circumstances are more complicated since observation errors, annual cycle and interannual variability are lumped together. To assess the performance of the algorithm we computed the monthly soil moisture averaged over all station locations and compared the results to the measurements. The mean annual cycle is reproduced with an excellent correlation of 0.979. An analogous procedure provides for the retrieval of the interannual variability with a correlation coefficient of 0.525.

In order to assess the algorithm quality, it has to be applied to independent data. Spread over Illinois, USA, 19 soil moisture stations have operated for several decades (Hollinger and Isard, 1994). We extracted measurements from 1979–1999 and computed the longtime mean soil moisture in the uppermost metre at each station. The same temporal averages are alternatively derived with our retrieval algorithm (Equation (1)) by using globally available information about four climatological parameters, resulting in a good agreement with the measurements (Figure 3). The measured total mean of 330 mm is reproduced with a deviation of only 4 mm. This quality control is a hard test since the algorithm is transferred to

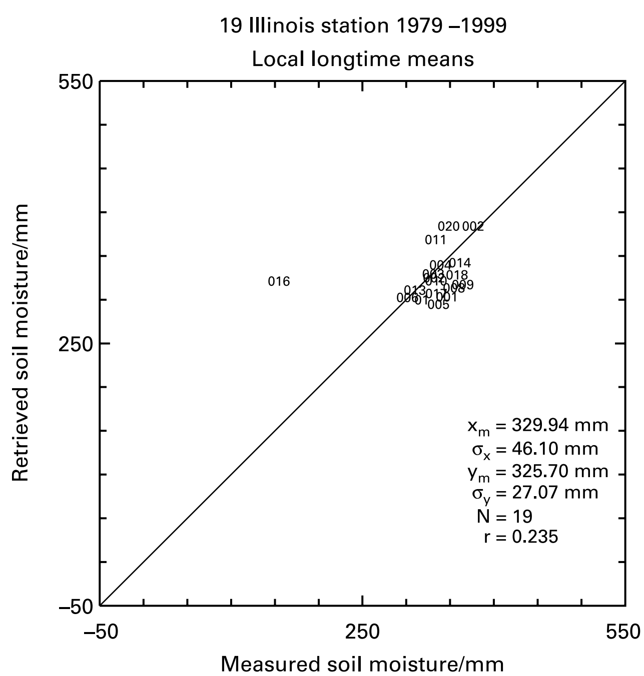


**Figure 3** Comparison of the retrieved mean root soil moisture for the period 1979–1999 to independent measurement from 19 stations in Illinois (the station numbers are plotted). For abscissa and ordinate, the same ranges are used as in Figure 2 to make the variabilities comparable. Mean and standard deviation are given for both data sets, as well as the number *N* and the correlation *r*

another continent and into a climate region with soil moistures much higher than those prevailing in the former Soviet Union where the algorithm has been derived.

At first glance, the correlation between measurements and retrieval appears (correlation coefficient $= 0.3$) rather low. The reason is that the variability range covered by the Illinois stations is small compared to the error variance of the algorithm. The Russian data, on which the algorithm is based, have a spatial variance of 9793 mm$^2$, corresponding to a value of $\sigma_x = 98.96$ mm in Figure 2. The algorithm is able to explain about 73% of it, thus 7150 mm$^2$ (compare $\sigma_y$ and $r$ in Figure 2). The remaining unexplained variance (2643 mm$^2$) is the error variance of the algorithm, corresponding to an uncertainty of about 51 mm.

In the Illinois data, the spatial variance is only 46 mm (see $\sigma_x$ in Figure 3), which is lower than the uncertainty of the algorithm. Thus, considered on a continental scale, all 19 stations in Illinois are located in their immediate mutual proximity. Their longtime means cover such a small range that they represent effectively only a single site. The detected low correlation follows directly from this fact.



## Model validation

In the following, the algorithm presented above is used to validate the soil moisture modelled by REMO. A ten-year climate simulation provided by the MPI for Meteorology in Hamburg is examined in two aspects with the two-step retrieval algorithm. First we compare the longtime averages and second we address the temporal variance. As an example the Oder catchment is analysed.

### Comparison of the longtime mean soil moisture

As discussed in the previous section, four parameters are used as input data for the longtime mean soil moisture $SM_0$ (Equation (1)): climatological precipitation, vegetation density, soil texture and terrain slope. Three of them have a rather coarse resolution: however, these four data sets turned out to be the best combination to predict the soil moisture measurements in the former Soviet Union, although several other data sets were tested.

The spatial resolutions of the chosen four data sets differ considerably. Vegetation density is available with a resolution of 1 km, whereas the other data sets have a much coarser resolution, i.e. 2.5° by 2.5° for precipitation and 1° by 1° for soil texture and slope. For a comparison with REMO, the four input fields are scaled to a resolution of a sixth degree, which is the spatial resolution of the model. For the high-resolution vegetation data, 18 by 18 vegetation pixel values are averaged for each REMO grid box (Figure 4(a)). Forests, which are characterised by low vegetation classes, prevail in Northern Europe. The wooded mountain regions of the Alps, the Apennines and the Carpathians become clearly apparent, whereas higher vegetation classes, indicating crop fields, extend from the Ukraine to the North Sea.

To obtain analogous maps also for the other coarser resolved parameters we interpolated these data sets to REMO resolution. For each REMO grid box a weighted average of the data points in the vicinity is calculated by using an exponential weighting function $w$:

$$w(d) = \exp(-d/d_0) \tag{3}$$

with $d$ denoting the distance between a specific REMO grid midpoint and the surrounding grid points of the interpolated parameter. The constant $d_0$ controlling the decrease of spatial influence is set to 50 km for all parameters. Applying this interpolation procedure to the entire REMO model area, three fields are obtained providing the remaining input parameters on REMO resolution (Figures 4(b), (c) and (d)). Figure 4(b) shows that the maximum climatological precipitation of GPCP data is found at the Norwegian coast and in the Alps. All over Western Germany precipitation is higher than 1000 mm yr$^{-1}$, exceeding the commonly assumed estimates for this region, whereas the dryer climate found in Eastern Europe is in

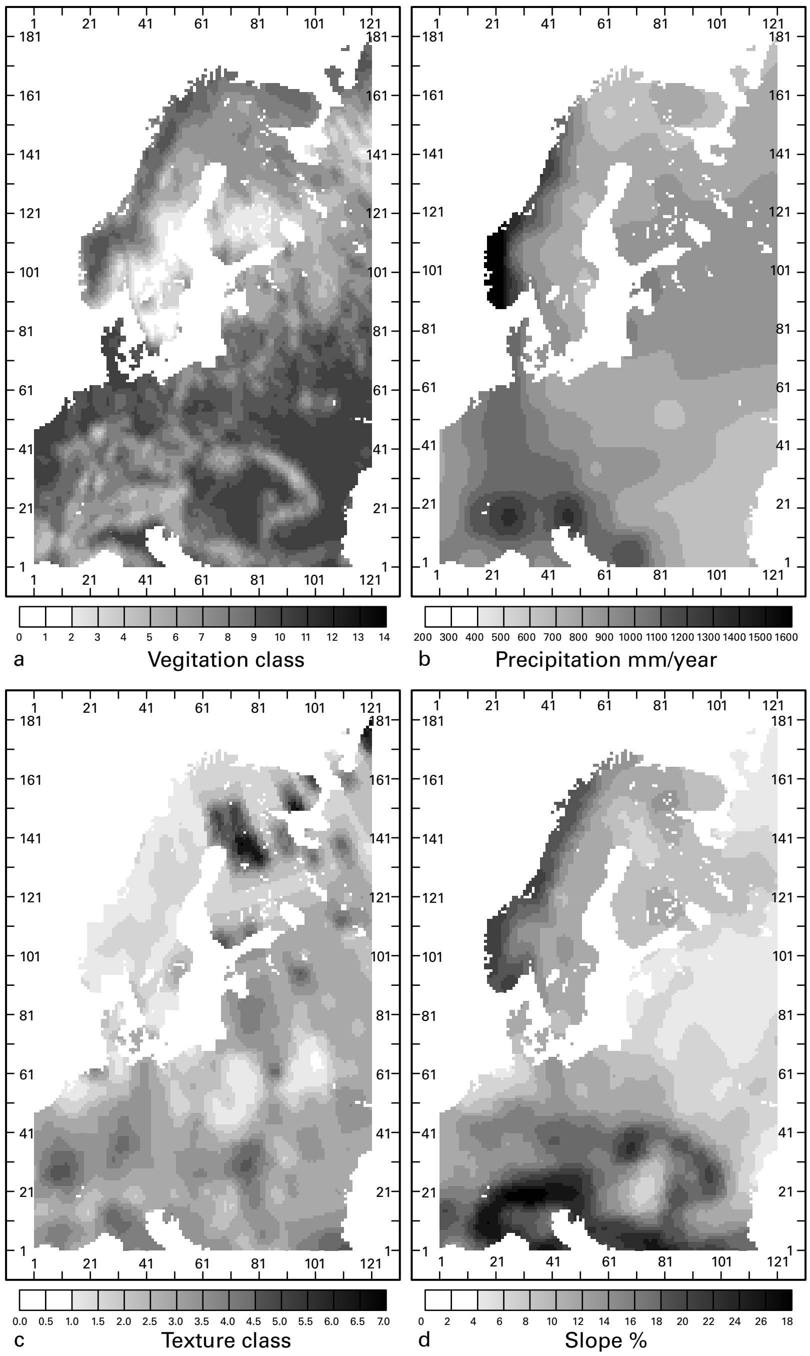


**Figure 4** Maps of the REMO model area for the four input parameters, which are used in Equation (1) to derive the climatological soil moisture in the uppermost metre. (a) shows the vegetation class, (b) the mean precipitation for the period 1979–1999, (c) the soil texture class and (d) the mean terrain slope. The parameters are scaled to REMO resolution by averaging (a) or interpolation (b–d)

better agreement with expectation. In Poland and Belarus the texture distribution (Figure 4(c)) shows sandy soils, which tend to be dry, whereas the peat areas in Lapland are able to store large amounts of water. The average terrain slope (Figure 4(d)) reflects the commonly known distribution of mountains and lowlands in Europe. On the basis of these four maps, the longtime mean climatological soil moisture can be calculated for each REMO box by applying Equation (1). The resulting soil moisture map is shown in Figure 5. Wet soils containing about 350 mm water within the uppermost metre are found in the Middle European forests and in Northern Finland, where peat soils are able to store larger amounts of water.

For the comparison a ten-year simulation of REMO is analysed. In REMO soil moisture *WS* is calculated as the equivalent water column (measured in metres) within a soil layer of unspecified thickness. The soil moisture estimate retrieved by our algorithm (Figure 5) refers, however, to a 1 m layer of soil. In order to make both values comparable, we estimated the 1 m soil moisture from the model data as follows. The model parameter *WSMX* gives the maximum possible soil moisture (measured in metres) within the local soil layer of unknown thickness. The model parameter *FCAP* also gives the maximum soil moisture, but measured in per cent. Thus, the fraction *WSMX*/*FCAP* enables us to recover the assumed local soil thickness of the model (Figure 6). Consequently, the soil moisture *WS* has to be divided by this recovered soil thickness to obtain the mean soil moisture *W* within 1 m of soil:

$$W = WS \times FCAP/WSMX. \tag{4}$$

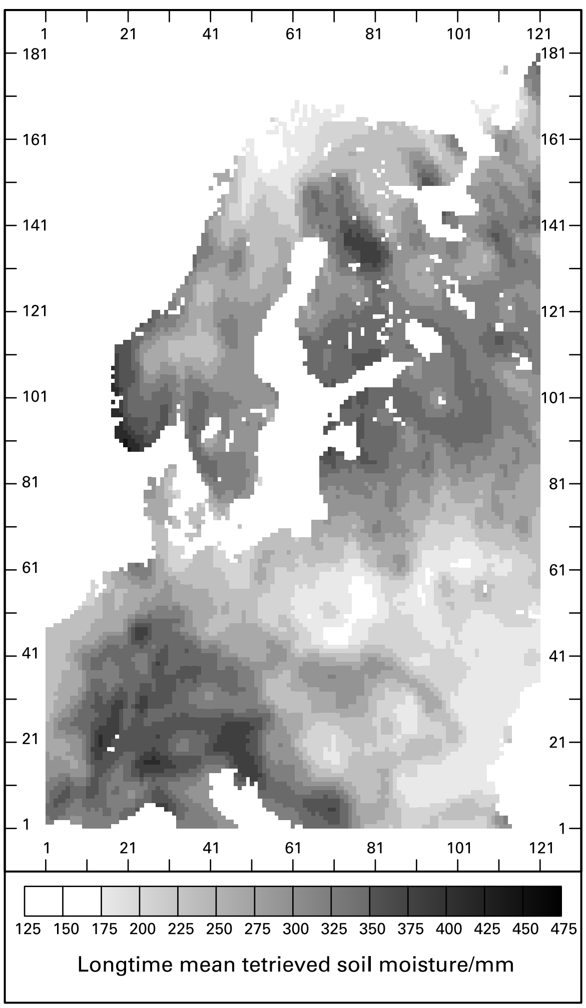


**Figure 5** Mean root zone soil moisture for the period 1979–1988 as calculated by Equation (1) using the four input parameters shown in Figure 4

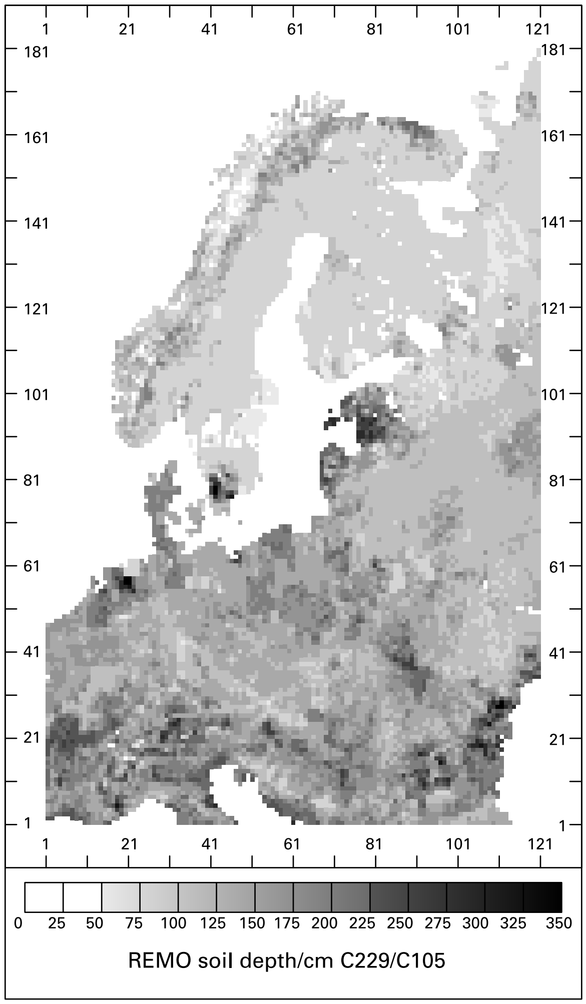


**Figure 6** REMO soil depth as concluded indirectly by dividing the two model parameters *WSMX* and *FCAP*, which both describe the maximum soil moisture, but the first is measured in metres and the second in per cent. The derived soil depth is used as normalisation of the soil moisture model output (total depth of water column) to estimate the soil moisture of the uppermost metre

Figure 7 shows the estimated model soil moisture $W$ within 1 m of soil. This estimate corresponds to the soil moisture in the uppermost metre under the assumption that soil moisture content does not change vertically.

Comparing Figures 5 and 7 reveals first that the retrieved soil moisture is based on rather coarse data. Thus fine structures apparent in the model output are not resolved in the retrieval. However, the broad structures are similar to dry soils at the Black Sea and in Poland, whereas wet soils prevail in Southern Germany and Lapland. The overall averages of the entire model domain shown on the maps are in good agreement with 262 mm for the model and 274 mm for the retrieval. The correlation coefficient based on all 14 494 land points is, however, very weak, with only 0.236 (Figure 8(a)), partly caused by the high spatial model resolution. The true resolution of the retrieval is much coarser. For a more appropriate comparison, we averaged both data sets over $10 \times 10$ grid boxes (180 km $\times$ 180 km), leading to a correlation of 0.457 (Figure 8(b)). By the averaging process, the standard deviation of the model decreases considerably from 92 mm to 44 mm,

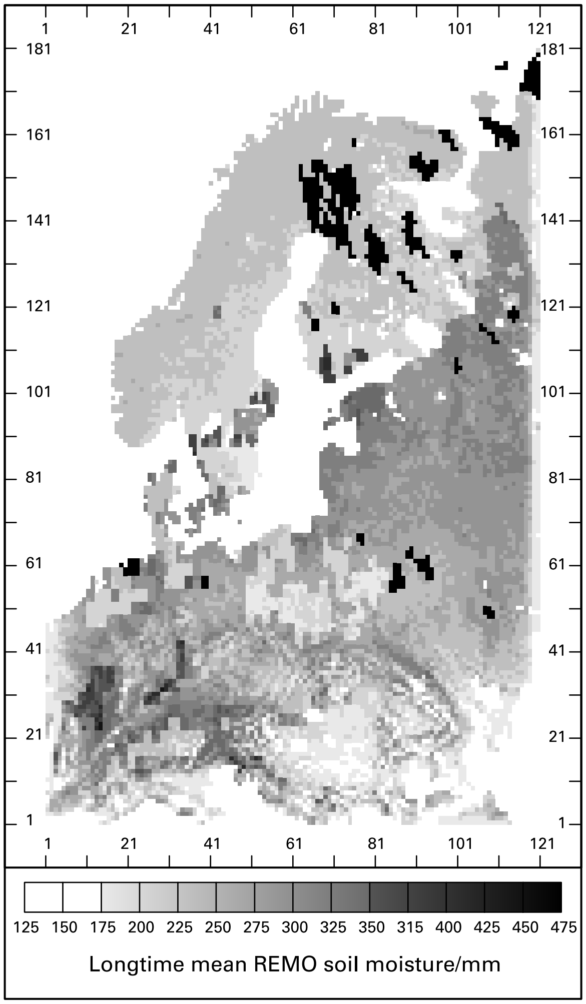


**Figure 7** Mean soil moisture of REMO for the period 1979–1988 as obtained after normalisation with the model soil depth shown in Figure 6

whereas it remains almost constant for the retrieval data. This proves that the small-scale variability of the model, not included in the retrieval, is removed as intended. Despite the increase from 0.236 to 0.457, the correlation is still poor. Thus, if the retrieval is regarded as a better estimate of soil moisture, it seems that the longtime mean soil moisture of REMO is indeed improvable. However, we have to take into account that a climate simulation of REMO is validated here. A climate simulation is free to produce weather structures in the inner model area, which are typical, but not identical to the actually observed weather.

#### Comparison of the local temporal variation of soil moisture

For the following comparison of modelled and retrieved soil moisture the Oder catchment is chosen as an example. As the retrieval is already available on REMO grid, we used the catchment boundaries of the model to identify the included grid boxes. The temporal evolution discussed in the following is a spatial average over the respective 358 REMO grid boxes encompassing the Oder catchment. The analysed period covers nearly 9 years from the beginning of 1979, when the model simulation starts, to August

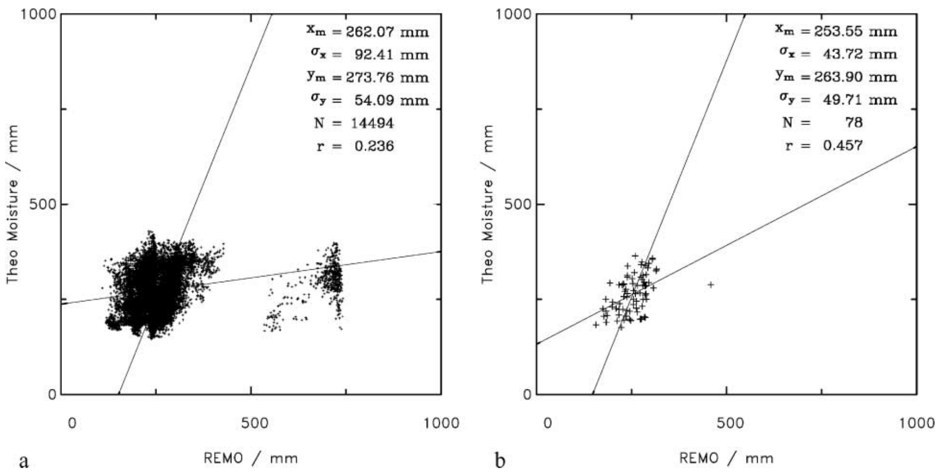


**Figure 8** Comparison of the mean soil moisture for the period 1979–1988 as modelled by REMO, see Figure 7, and as retrieved, see Figure 5. (a) shows a comparison of the original REMO resolution, in (b) averages of 10 × 10 grid boxes are compared. Both regression lines are shown, taking the model as independent and the retrieval as dependent, and *vice versa*

1987, when satellite observations from SMMR were no longer available. The time series of the local soil moisture anomaly is now retrieved by Equation (2), using precipitation, air temperature and the 10 GHz brightness temperature from SMMR. According to Equation (2), the retrieved soil moisture anomaly can be regarded as a composite of the contributions from the three input parameters. Figures 9(a–c) show these components separately. The variation range of all three parameters is similar, showing that each parameter has a comparable contribution to the resulting soil moisture retrieval. The additive combination of the three time series finally yields the soil moisture variation in the Oder catchment (Figure 9(d)). Seasonal events, such as the dry summer of 1982, are reproduced by the precipitation data, whereas the prominent annual cycle of soil moisture is adequately modelled by the course of air temperature. The brightness temperature is used to detect shortterm variations of soil moisture.

So far, only the anomalies of soil moisture resulting from Equation (2) have been considered. The absolute amount of soil moisture is obtained by adding to this anomaly the longtime mean discussed above. Applying Equation (1) to the Oder catchment grid boxes, this longtime mean soil moisture is equal to 233 mm. The thick line in Figure 10 gives the time series of soil moisture for the 312 daily decades from January 1979 to August 1987. The REMO soil moisture, again normalised to 1 m as described in the previous section, is accordingly averaged over 10 d and spatially over the Oder catchment. The thin line in Figure 10 shows the soil moisture evolution modelled by REMO. The temporal variance is dominated by the annual cycle for both model and retrieval. The model shows a higher amplitude of the annual cycle, and thus more variance, than the retrieval (38.7 mm standard deviation for the model instead of 20.3 mm for the retrieval). However, the total means are almost identical with 231 mm and 233 mm. The two time series show a correlation coefficient of 0.728.

A detailed inspection of Figure 10 indicates that the model soil moisture trends have a time lag in comparison to the retrieved time series. This becomes more evident in Figure 11, where the mean annual cycle averaged over the entire 9 yr period is depicted. The soil moisture retrieval leads and the model is delayed by about one month. An analysis of the model precipitation could help to find the reason for it.

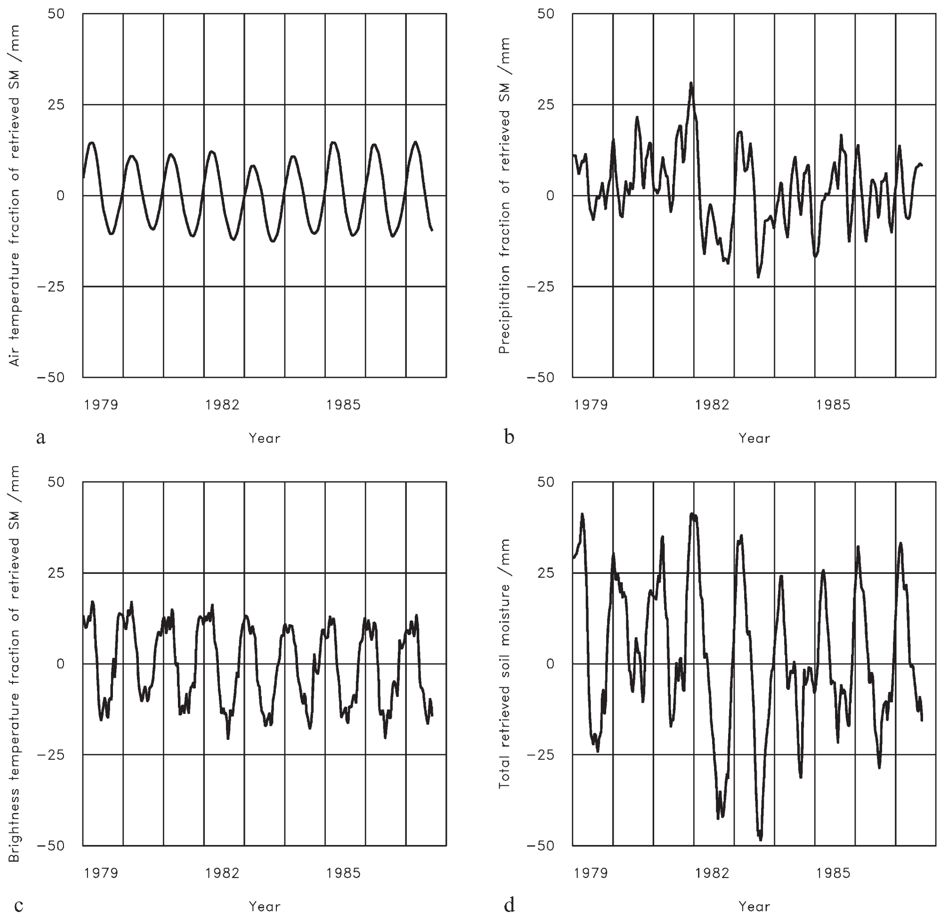


**Figure 9** 10-d soil moisture anomaly (and its three fractions) as retrieved for the period January 1979 to August 1987, averaged over the Oder catchment. The retrieval is calculated by Equation (2) so that three components can be separated. In (a) only the component caused by the air temperature is shown, in (b) that for precipitation, and in (c) the microwave component. (d) summarises the components according to Equation (2)

## Summary and discussion

For the derivation of a soil moisture algorithm ground measurements from the former Soviet Union are analysed. The major part of the soil moisture variance originates from spatial differences between longtime means at each location. Consequently, we first concentrate on the explanation of this temporal invariant soil moisture pattern. Our algorithm is capable of reproducing its variance to a large extent by using easily available data, i.e. precipitation, vegetation density, soil texture and terrain slope. The temporal variance is explained in a second step. Its retrieved annual cycle is also in good agreement with the measurements. Independent soil moisture measurements from Illinois are used to assess the performance of the retrieval algorithm presented. Only the total mean of all 19 stations is meaningful for a comparison of longtime means, as the distances between the Illinois stations are small, if they are considered on a continental scale. The total mean is well reproduced, confirming the good performance from the presented algorithm.

Using the retrieval algorithm as validation for the modelled soil moisture from REMO, large differences occur in both the regional distribution of longtime mean soil moisture and its temporal variance. The two longtime means for the entire model area are,

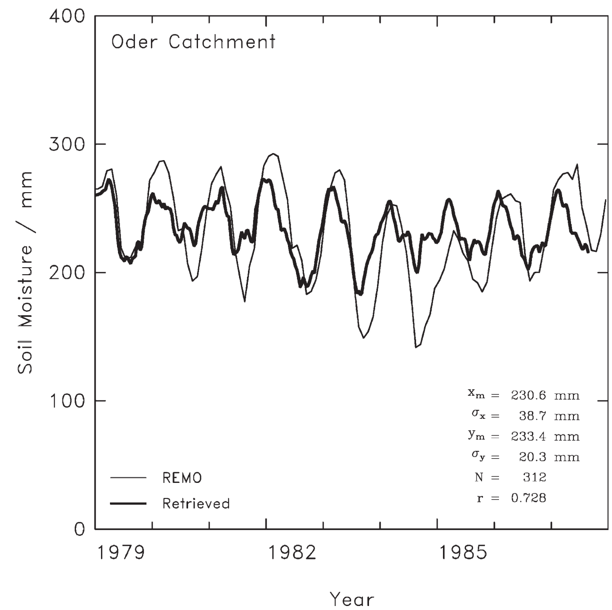


**Figure 10** Soil moisture within the uppermost metre as retrieved (thick line) and as modelled by REMO (thin line) from 1979–1987 for the Oder catchment. Mean and standard deviation are given for both data sets on the basis of 10-d averages. *N* gives the number of decades and *r* the correlation coefficient

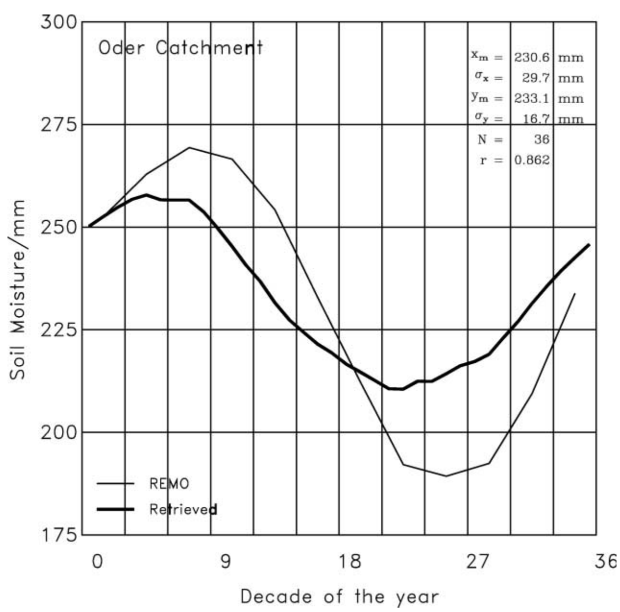


**Figure 11** As Figure 9, but additionally averaged over the considered nine years to obtain the mean annual cycles of the retrieved and the modelled soil moisture

however, in good agreement: they differ only by about 10 mm, corresponding to 4% of the total mean. This result was not expected because both data sets have been derived from totally independent information. As the retrieval is based on rather coarse data, it cannot resolve the details in the fine structures of REMO's longtime mean soil moisture pattern. To compensate for the different resolutions of model and retrieval, we averaged results from both data sets over $10 \times 10$ grid boxes and found a correlation coefficient of 0.457 between them. This low value shows that soil moisture modelling is still improvable.

The ability of REMO to reproduce the temporal evolution of soil moisture is studied for the Oder catchment. Almost nine years of data are exploited. The average soil moisture for this particular region is reproduced very well by the model (231 mm) when compared to the retrieval results (233 mm). However, the model exhibits a much stronger annual cycle reflected in a standard deviation twice as high as that retrieved by the algorithm. Above that, the annual cycle of REMO is shifted backward. The model seems to be delayed by about one month.

Compared to the observation-based retrieval, large deficiencies are obvious in the modelled soil moisture. This comparison has been performed with a one-way-coupled climate simulation of REMO. Key numbers characterising the model skill are now available, which can be used as reference to assess the improvements attained by the intended two-way-coupling with the hydrological model and future model development.



## Conclusions

A two-step soil moisture algorithm is presented using precipitation, soil texture, vegetation density and terrain slope to derive in a first step the longtime mean soil moisture, and in a second step the temporal variability of soil moisture at each location by using precipitation, air temperature and the satellite-observed microwave brightness temperature. The major conclusions are:

- A comparison with independent soil moisture measurements shows that the algorithm performs well, so that the retrieval can be used to validate model soil moisture.
- The mean soil moisture from a climate simulation of REMO, averaged over the entire 10 yr period and the entire model domain is in good agreement with the retrieval.
- The spatial pattern of the longtime mean soil moisture is, however, not well reproduced by the model. The correlation with the retrieved soil moisture is only 0.457.
- For the Oder catchment, the temporal variability of soil moisture is analysed. We found that the general variation of soil moisture is well reproduced, showing a correlation of 0.728 with the retrieval.
- In the model the annual cycle of soil moisture is delayed by about one month.

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