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Assimilation of an L-Band Microwave Soil Moisture Proxy to Compensate for Uncertainties in Precipitation Data

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Abstract—The accuracy of hydrological model simulations is dependent on the reliability of model input data like, for example, meteorological information or land cover and soil information. Uncertainties of simulations of soil water fluxes are hereby directly related to the accuracy of available precipitation data. As precipitation is characterized by small temporal and spatial correlation lengths, the uncertainties in precipitation data increase with decreasing density of available precipitation gauges. As soil moisture directly depends on precipitation dynamics, its variation can be used as a proxy for precipitation variability. Remote sensing techniques allow for monitoring of surface soil moisture dynamics at different spatiotemporal scales. In particular, low-frequency microwave data are most sensitive to soil moisture dynamics. This paper investigates the potential of integrating L-band (1–2 GHz) microwave radiometer data into a simple model for soil wetness to compensate for uncertainties in *a priori* information of precipitation. The study is based on a short-term ground-based L-band radiometer data set over grassland. A high correlation between the microwave signature and surface soil moisture was found, which is consistent with previous findings. An analytical data assimilation scheme for the integration of that information into a soil wetness model, based on an antecedent precipitation index (API), was established. The results revealed that the data assimilation filter adds or removes an amount of water partially compensating for the actual precipitation error. The correlation coefficient between the filter update and the actual precipitation error was found to be $0.6 \leq r \leq 0.8$, and the model simulations did show a better coincidence with *in situ* soil moisture records when integrating the microwave data. The results indicate high potential for use of L-band microwave data to compensate for uncertainties in precipitation data.

Index Terms—Data assimilation, European Soil Moisture and Ocean Salinity (SMOS) mission, land surface processes, L-band, microwave radiometry, model calibration, precipitation, remote sensing, soil moisture, water fluxes.

I. INTRODUCTION

HYDROLOGICAL models are typically used to simulate land surface water and energy fluxes. Their applicability and accuracy highly depend on the availability of the required model input data like, for example, meteorological data, soil

and land cover information, and the quality of the hydrological model itself.

Accurate precipitation information is crucial in simulating the surface water fluxes. The availability of reliable rainfall data is hereby often hampered by a lack of sufficiently dense precipitation measurement networks. The density of rainfall measurement networks highly varies between different parts of the world [1], while remote sensing techniques allow for a distributed mapping of precipitation patterns and the estimation of rainfall rates at the regional to global scale [2]. However, these remote-sensing-based rainfall estimates might often contain substantial errors, particularly over land. As the dynamic of surface soil moisture content is highly correlated with the precipitation dynamics, observations of the surface soil water variability are an indicator for the temporal and spatial rainfall variability.

Microwave remote sensing has proven its capability to derive quantitative information on surface soil moisture from active and passive sensor systems at various spatial resolutions. The microwave response from natural vegetated and bare soil surfaces has been studied, and it has been shown that the microwave emission or backscattering coefficient are mainly a function of surface roughness, moisture content, as well as vegetation characteristics [3]–[8].

Longer wavelength microwave systems are more sensitive to surface soil moisture as vegetation influence is reduced compared to higher frequency systems. Dedicated forthcoming soil moisture missions like the National Aeronautics and Space Administration Soil Moisture Active/Passive (SMAP) mission [9] as well as the forthcoming European Soil Moisture and Ocean Salinity (SMOS) mission, to be launched in 2009 [10], [11], operate in L-band (1.4 GHz).

Ground-based surveys are typically used for calibration purposes and for estimating the accuracies of the remote sensing data. However, a direct intercomparison of *in situ* measured soil moisture data with satellite measurements is often hampered by the different spatial scales (point scale for field measurements and tens of kilometers in case of passive microwave satellite data) [11]. Although it has been shown that coarse resolution remote sensing products with high temporal frequency contain valuable information about surface and root zone soil water dynamics, an intercomparison of *in situ* measurements with coarse scale satellite data remains a challenge [12]–[14]. An alternative method of assessing the value of remote sensing data is therefore to evaluate the impact of the remote sensing data for an improved characterization of land surface fluxes.

A simple method to assimilate surface soil moisture observations into a hydrological model has been proposed by Crow [15]

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Fig. 1. Data-processing flowchart.

to compensate for uncertainties of land surface model input data (deficits in rainfall estimates). The approach has been applied at the continental scale using different kinds of coarse resolution soil moisture products. It was found by Crow and Zhan [16] that surface soil moisture observations could be used to compensate for the impact of uncertainties in globally available rainfall estimates as, for example, provided by the Tropical Rainfall Measuring Mission [2].

Although the suggested data assimilation approach itself is rather simplistic, it was found that integrating the satellite measurements into a hydrological model could result in a considerable improvement of the model performance. Such an analysis could also be used to assess the quality of remote-sensing-based soil moisture products. Satellite calibration and validation approaches might therefore benefit from such an analysis.

The objectives of this paper are listed as follows: 1) To evaluate the potential of using L-band (1.4 GHz) microwave data to improve the spatial interpolation of coarsely spaced rain gauge observations. The analysis is based on a ground-based L-band radiometer data set measured over a grass-covered area throughout the vegetation period in 2004 [5]. The used approach might be exploited as an alternative for the validation of coarse-scale satellite soil moisture estimates in the absence of ground-based soil moisture networks. 2) To demonstrate that the applied methodology provides valuable additional information that helps in the assessment of the uncertainties associated with microwave soil moisture estimates. 3) To analyze the impact of different diurnal observation times and effects of sensor noise on the robustness of the suggested methodology.

While previous works have investigated the potential and limits of using satellite-based X- and C-band data for an improvement of satellite based precipitation products [16], this work extends the analysis to L-band microwave data, which is expected to have a higher sensitivity to soil moisture than higher frequency systems. The microwave measurements are integrated into a simple soil wetness model, which is based on an antecedent precipitation index (API), for that purpose.

The general concept of the used methodology is presented in Section II. Data sets are described in Section III and are

analyzed in Section IV. The used model and data assimilation framework are then introduced in Section V. The results of the experiment are presented in Section VI. Finally, conclusions are drawn in Section VII.

II. METHODOLOGY

The method of assessing the merit of microwave brightness temperature observations is based on the combined analysis of a simple model of soil water dynamics and soil moisture observations obtained from microwave radiometric observations. The impact of integrating the microwave data is assessed, and its relationship to uncertainties in the precipitation data is investigated. To quantify the latter, a reference precipitation data set is used for verification purposes. Fig. 1 shows the general data flow of the approach, which consists of the following steps.

- 1) Meteorological measurements are obtained from a network of rainfall stations, denoted as S_k , while observations from a ground-based microwave radiometer are available at a single location (S_0). In addition, rainfall data are measured at the location of the radiometer. Rainfall data from the different stations are used to mimic the uncertainties that result from the spatial variability of rainfall and its underrepresentation using a network of point-like rainfall gauges. The rainfall data are described in Section III-B, and the radiometric data set is introduced in Section IV.
- 2) The rainfall data are used to drive a simple soil water model. Each rainfall gauge is hereby used independently, which results in a range of model-predicted soil moisture for the different stations (θ_k). These simulations are denoted as *open-loop* simulations in the following. The used model is described in Section III-C.
- 3) Observations from ground-based microwave radiometry are assimilated into the soil water model. To compare the microwave data against model simulations, soil moisture information has to be derived from the microwave measurements. This could be achieved using either soil moisture retrieval models [17], [18] or using an appropriate

soil moisture proxy derived from the microwave observations. The latter is used in this study as it showed a higher sensitivity to measured soil moisture dynamics. To relate the microwave observations to the simulated soil water content θ_k , an observation model is calibrated for each station using the microwave observations and *open-loop* simulations of soil water content. The assimilation is done each time an observation becomes available and updates the state of the soil water model to obtain a more reliable estimate of the soil water conditions. The data assimilation approach is described in Section V.

- 4) The differences between model-based soil water predictions and observations of soil water content from the microwave data are assumed to reflect the uncertainties in the rainfall data. Integrating the remote sensing data into the model is therefore expected to improve the model predictive skills by adding or removing water to the model, denoted as filter increments Δ . Their amount is dependent on the actual difference between the model prediction and the microwave observations and their respective uncertainties.
- 5) To quantify, whether the simulation of soil water dynamics is improved, a) the final model results can be compared against *in situ* soil moisture measurements and b) the model increments can be analyzed and compared against the actual precipitation error ($R_0 - R_u$), which is defined as the difference in precipitation between station S_k and the reference station S_0 .

The analysis is made on the basis of individual stations, and the entire data assimilation experiment is repeated for each of the rainfall gauges independently. The analysis is based on the following assumptions and limitations.

- 1) *Local study*: The study is based on ground-based radiometric measurements, made at a given fixed location. Precipitation gauges are within a distance from 6 to 28 km around the location of the radiometer. Thus, the study mimics the case when the density of available precipitation gauges is less than the footprint size of an observation system. For large parts of the world, precipitation gauge density is less than the spatial resolution of available actual satellite measurements. For forthcoming satellite missions like, for example, SMAP, the spatial resolution of the sensor will be on the order of 10 km globally, which is finer than the average spacing between rain gauges over a vast majority of the world.
- 2) *Heterogeneity*: The study does not consider the influence of subpixel scale land surface heterogeneity on the sensor observations, like it would be necessary for satellite applications.
- 3) *Limited data set*: The used data set is limited to one land cover type (grassland) and a limited period. Conclusions drawn from that study can therefore only be valid for the particular conditions observed throughout the experiment.

III. DATA SETS AND MODELS

A. Field Measurements

The used data set was collected within the frame of an experiment carried out on an agricultural field at the Institute

Fig. 2. L-band radiometer ELBARA mounted on the tower at the test site.

of Plant Sciences, Eschikon (550 m above sea level), 15 km away from Zurich (Switzerland). A detailed description of the experimental setup and measurements can be found in [5].

Fig. 2 shows the basic setup of the experiment performed between May 27, 2004, corresponding to Julian Day (JD) 148, and July 27, 2004 (JD 209). The L-band (1.4 GHz) microwave radiometer ELBARA [19] mounted on a tower collected microwave signatures over a growing grass cover. L-band brightness temperatures T_b^p were measured at horizontal ($p = H$) and vertical ($p = V$) polarizations at the observation angles $45^\circ \leq \alpha \leq 75^\circ$, with increments of 5° .

The microwave measurements were accompanied by hourly ground-truth measurements at two locations close to the radiometer tower (Fig. 2). Soil permittivities and temperatures were measured *in situ* with horizontally installed two-rod time domain reflectometer (TDR) probes, connected to a Campbell TDR100 reflectometer, and with thermistors (Campbell S-TL107) both connected to a CR10X data logger. The sensors were placed in depths of 2, 4, 6, 10, 20, 30, and 50 cm. Soil water content was calculated from the TDR measurements using a dielectric mixing model [20]. Details on the soil hydraulic characteristics can be found in [21].

Total precipitation during the investigation period was 224.8 mm, with highest precipitation rates on JD 155 and JD 190 with 55 and 32 mm d⁻¹, the latter being a hailstorm, which significantly affected the structure of the vegetation canopy [5]. The longest dry period was from JD 159 to JD 163. For most parts of the experimental period, the soil moisture variations within the upper soil layer (0–5 cm) were between 0.13 and 0.29 m³ m⁻³.

The experiment started with bare soil conditions before JD 154. The grass grew with a rate of approximately 1.7 cm d⁻¹, and the column density of the fresh biomass increased with approximately 86 g m⁻² d⁻¹, reaching a maximum value of approximately 3 kg m⁻². The relative vegetation water content, defined as the fraction of water per unit fresh biomass (in kilograms per kilogram), was constant at about 85% throughout the entire growing period. The hailstorm at JD 190 deteriorated the vegetation structure, reducing the canopy height from

TABLE I
LIST OF METEOROLOGICAL STATIONS (ORDERED BY DISTANCE TO EXPERIMENTAL SITE)

Station	Lon [DEG]	Lat [DEG]	height [m]	rainfall source	Distance [km]
Eschikon	8.68	47.45	567	field experiment	-
Winterthur	8.78	47.50	453	FOEN	6.4
Kloten	8.56	47.46	436	MeteoSwiss	11.5
Meteo Swiss Zurich	8.54	47.41	556	MeteoSwiss	11.9
Neubrunn	8.89	47.44	608	FOEN	12.6
Reckenholz	8.52	47.42	443	MeteoSwiss	12.7
Niederglatt	8.51	47.49	410	FOEN	14.1
Taenikon	8.91	47.48	536	MeteoSwiss	17.1
Birmensdorf	8.44	47.35	466	FOEN	21.0
Schaffhausen	8.63	47.70	437	MeteoSwiss	27.1
Mettmenstetten	8.46	47.24	453	FOEN	28.4

approximately 60 to 20 cm. As will be shown later, the microwave measurements before and after that event were not comparable. The investigations of this study will therefore only focus on the time series before JD 190.

B. Precipitation Data

Precipitation information was available from a dense network of rain gauges. These are either operated by the Meteorological Service of Switzerland (MeteoSwiss) or by the Swiss Federal Office for the Environment (FOEN). In both cases, daily precipitation totals are used. The distances of the precipitation stations from the radiometer location (Eschikon) ranges from 6 to 28 km (Table I).

C. Soil Water Model

A simplistic model is used to simulate soil water dynamics. It is based on the concept of the so-called *API*. As the *API* is exclusively based on precipitation data as model input, it has been widely used in rainfall–runoff applications to parameterize the soil moisture conditions in a hydrological catchment [22]–[25]. The API_i for day i is defined as

$$API_i = \gamma_i API_{i-1} + P_i \quad (1)$$

where P_i is the observed precipitation (in millimeters), and γ_i is the corresponding *API* recession coefficient at that day which is used to parameterize the loss of water in the soil column due to evapotranspiration, groundwater recharge, and lateral soil water fluxes. In general, more complex land surface schemes might be used to simulate the land surface energy and water fluxes [26], [27]. However, more physically based approaches require very detailed information on the land surface as well as detailed meteorological forcing data.

Different approaches to parameterize γ_i have been proposed. Its value might vary between 0.7 for dry conditions and 1.0 for wet soil conditions [15]. An exponential decay of the form $\gamma = e^{-\delta}$ has been proposed, whereas the factor δ is the inverse of the characteristic time of soil moisture depletion. Its value might be empirically calibrated, or it might be parameterized using additional information like, for example, the ratio of potential evapotranspiration to maximum available soil moisture [24], [28].

In this study, we follow the parameterization proposed by Crow [15], where the seasonal variation of γ_i is defined as

$$\gamma_i = A + B \cos(2\pi JD/365) \quad (2)$$

Fig. 3. Time series of API_0 simulations using precipitation data from the station in Eschikon (red bold) and from different meteorological stations (gray) together with precipitation records of the Eschikon station.

with the parameters $A = 0.85$ and $B = 0.1$ and JD being the Julian Day, which is a very simple approach to roughly estimate the seasonal effects of evapotranspiration loss. The model parameters could be calibrated using available *in situ* soil moisture data. To keep the model as general as possible, no calibration of the model is done for the test site in this study.

For each available meteorological station, the *API* model is evaluated to simulate the soil wetness using the rainfall data from that particular station. Model spin-up time was found to be shorter than a week when starting before the first rainfall event on JD 155. Fig. 3 shows the evolution of *API* using the rainfall data from the different meteorological stations, compared to the simulation one obtains using the rainfall data from the Eschikon reference station (API_0). A large variability of the *API* in the order of 15–25 mm (standard deviation) is observed after the first significant rainfall event around JD 155. The meteorological stations are quite close to each other. However, using the rainfall data from the different stations results in a large variability of the *API* values. This illustrates the large impact that uncertainties in the precipitation data might have on the simulations of soil water fluxes and, thus, on the estimation of the land surface energy and water budget. These uncertainties might be either reduced using improved precipitation data or by compensating for the deficits using ancillary information. The latter is investigated in this study.

IV. DATA ANALYSIS

A. Land Surface Microwave Emission

The microwave emission from a vegetation-covered ground is often described using the zero-order τ - ω radiative transfer model [29], [30]. The effects of soil and vegetation on the measured brightness temperature T_b^p are given by [17], [31]

$$T_b^p = (1 - \Gamma_s^p) T_s \Upsilon_v^p + T_v(1 - \omega)(1 - \Upsilon_v^p) + T_v(1 - \omega)(1 - \Upsilon_v^p) \Gamma_s^p \Upsilon_v^p. \quad (3)$$

The reflectivity of a rough soil Γ_s^p is typically described as a function of the Fresnel reflectivities of a smooth surface, modified by a surface roughness component [29], [30], [32]. The vegetation parameters are the vegetation single-scattering albedo ω and the vegetation transmissivity Υ_v^p . The latter is described as function of the vegetation optical thickness τ_0^p at nadir and the observation angle α (Beer's law), i.e.,

$$\Upsilon_v^p = e^{-\tau_0^p / \cos \alpha}. \quad (4)$$

The basic underlying assumption of the τ - ω model is that the vertical vegetation profile is homogeneous in terms of temperature and extinction [31].

The microwave signatures of soil and vegetation exhibit distinct differences in different polarizations. There is a large polarization difference in the emission from bare and vegetated soils when the view angle α exceeds 30° [4]. Polarization differences for a given observation angle α are commonly expressed using the polarization ratio $PR(\alpha)$, defined as [4], [33], [34]

$$PR(\alpha) \equiv \frac{T_b^v(\alpha) - T_b^h(\alpha)}{T_b^v(\alpha) + T_b^h(\alpha)}. \quad (5)$$

Decreasing PR indicates a depolarization of the signal, which is either caused by an increase of the vegetation influence or a decrease of the soil water content, leading to less polarized soil emission. A major advantage of PR is that it is less influenced by the surface temperature. In case of thermal equilibrium between the vegetation layer and the soil surface, PR becomes independent of the physical temperature if the vegetation scattering is negligible.

B. Polarization Ratio

The time series of measured brightness temperatures T_b^p at the observation angle $\alpha = 45^\circ$ is shown in Fig. 4. It shows distinct response to precipitation events. After a rainfall, T_b^p decreases due to decreasing surface emissivity $(1 - \Gamma_s^p)$ in (3). The strong rainfall event at JD 155 resulted in a very sharp increase of PR , which is expected to be an indicator for intercepted water within the canopy [35]. The data analysis started therefore after that strong rain event.

At the beginning of the vegetation period, T_b^p showed a pronounced angular dependency at both polarizations, which diminishes in the course of the vegetation development (not shown; for details, see [5, Fig. 8(a)]). Furthermore, the polarization ratio PR shows a pronounced angular response at the beginning of the experiment, which is then reduced in the course of the growing period [Fig. 4(b)].

The latter indicates an increasing depolarization of the emission with increasing vegetation optical depth. It is observed

Fig. 4. Measured brightness temperatures at (a) $\alpha = 45^\circ$ for h and v polarization and rainfall data (precipitation scaled by a factor of 2) and (b) multiangular polarization ratio.

that the decrease of PR is stronger for higher than for smaller observation angles, as the path through the vegetation and, thus, the depolarization is increased. Less vegetation effects are therefore expected for relatively steep observations corresponding to small observation angles α .

The polarization ratio PR_{45} at $\alpha = 45^\circ$ shows a similar course as the observed soil moisture throughout the investigation period until JD 190 (Fig. 5). While a decreasing sensitivity of PR to soil moisture was found for larger observation angles, the sensitivity of PR_{45} did not change in the course of the investigation period. It is therefore assumed that PR_{45} could be used as an applicable proxy for surface soil moisture, at least for the biomass level encountered during the experiment. Fig. 5 compares PR_{45} against the measured soil moisture at 2 and 4 cm. It is observed that PR_{45} follows very well the surface soil water content until JD 190. The polarization ratio increases with increasing soil moisture and decreases when the soil becomes drier. However, a considerable decrease of PR_{45} is observed after JD 190 as the result of the deteriorated vegetation due to the hail storm on that day. Fig. 5(b) shows the correlation between $\theta_{2\text{cm}}$ and PR_{45} before and after the hail event on JD 190 on a daily basis. While the strong correlation ($r = 0.89$) between PR_{45} and $\theta_{2\text{cm}}$ is obvious before the event, the correlation is lost after the hail event. The data assimilation experiment will

Fig. 5. (a) Time series of measured θ (2 cm, 4 cm) and polarization index PR_{45} and (b) relationship between PR_{45} and $\theta_{2\text{ cm}}$ before and after the hail event; polarization ratio scaled by a factor of 2.

therefore only rely on T_b^p ($p = h, v$) data measured earlier than the hail event.

Algorithms for an operational retrieval of surface soil moisture from radiometer measurements are typically based on a minimization of the deviations between measured brightness temperatures and those simulated by using the τ - ω model (3). The advantage of using a forward model for the retrieval process is that it might be easily adapted to different land cover types and that it enables to explicitly take into account the spatial heterogeneity within the sensors footprint, which makes it a suitable approach for global-scale satellite-based applications [18], [29]. It has been shown that the polarization ratio is a good indicator for soil moisture dynamics under bare soil conditions [36], while it was found that its sensitivity might diminish in case of dense vegetation cover.

To compare PR against the output of a soil moisture retrieval model, the retrieval approach in [18] was applied to invert surface soil moisture from the radiometer measurements. The model is based on an analytical solution for the relationship between PR and the vegetation optical depth τ [37]. For the characterization of surface roughness and vegetation, single-scattering albedo parameters valid for L-band have been used [29], [34]. It was found that best soil moisture retrievals were obtained at an incidence angle α of 45° . Table II gives an

overview about the obtained correlation coefficients and rms errors for each incidence angle. Only the period before JD 190 was used for the analysis. The rms error ranges between 0.05 (0.03) and 0.08 (0.10) for the different incidence angles and *in situ* soil moisture measurements at 2 cm (4 cm).

However, it was found that PR_{45} showed a better correlation and higher sensitivity to the observed surface soil moisture compared to the LPRM retrievals. The polarization ratio was therefore used as a soil moisture proxy in further analysis of this study. However, as the relationship between the observed surface soil moisture and either PR or the retrieved soil moisture is linear, the data assimilation approach introduced in the following section could easily be applied for both.

Either daily mean values for PR_{45} or a value that is measured at 6:00 A.M. are used in further analysis. The latter corresponds to the early morning overpass time of the SMOS satellite [11]. The morning observations allow for the assumption that vertical temperature gradients within the vegetation canopy can be neglected, which results in a significant simplification of the radiative transfer modeling of the microwave emission [31]. The impact of using different observations in the analysis shall be investigated in the following.

V. DATA ASSIMILATION APPROACH

The baseline for integrating the microwave data into the API model and assessing the value of the data assimilation is outlined in the following. An observation of soil moisture θ_i , obtained either directly via *in situ* measurements or indirectly via a soil moisture proxy might be used to update (1) using a Kalman filter as [38]

$$API_i^+ = API_i^- + K_i [\theta_i - Z(API_i^-)] \quad (6)$$

where “+” denotes values after, “−” denotes values before model update, and Z is a linear observation operator that relates the model output to the observations. The following relationship is used in this study:

$$Z(API) = a + b API. \quad (7)$$

In general, one might use time series of observations with coincident model simulations to calibrate a statistical relationship for (7). In case of satellite images, this can, for example, be accomplished by the analysis of time series of remote sensing images and spatially distributed API model simulations. The procedure to calibrate the observation operator parameters a and b in this study is specified later on.

The *a posteriori* value API_i^+ is assumed to be a better representation for the true soil moisture state than simulations without the observations. The Kalman gain K_i weights the observations against the model predictions and their respective uncertainties. It is given by [38]

$$K_i = bT_i^- / (b^2T_i^- + S) \quad (8)$$

where S (in millimeters) denotes the uncertainties in the observations of θ , and T (in millimeters) denotes the model forecast error that is integrated over time as [39]

$$T_i = \gamma_i^2 T_{i-1} + Q \quad (9)$$

TABLE II
CORRELATION COEFFICIENT (r) AND RMS ERROR BETWEEN *In Situ* SOIL MOISTURE MEASUREMENTS (θ) AND RETRIEVED SOIL MOISTURE FROM LPRM (θ_{inv}) AND POLARIZATION INDEX (PR) FOR DIFFERENT INCIDENCE ANGLES (α)

α [deg]	r				RMS error [cm ³ /cm ³]	
	θ_{2cm} vs. θ_{inv}	θ_{4cm} vs. θ_{inv}	θ_{2cm} vs. PR	θ_{4cm} vs. PR	θ_{2cm} vs. θ_{inv}	θ_{4cm} vs. θ_{inv}
45	0.70	0.83	0.90	0.94	0.05	0.03
50	0.68	0.82	0.86	0.93	0.04	0.04
55	0.64	0.79	0.83	0.92	0.05	0.06
60	0.52	0.69	0.80	0.91	0.08	0.10
65	0.27	0.47	0.77	0.89	0.16	0.19
70	0.16	0.36	0.72	0.87	0.36	0.39

where Q (in millimeters) relates to the model uncertainty added to an API forecast as it is propagated in time.

Both observation error S and model error Q are typically not known. The update of T through the filter is given by

$$T_i^+ = (1 - bK_i)T_i^- \quad (10)$$

The update of API^- is given by the so-called filter increments Δ_i (in millimeters), which add or remove water to the model. They are defined as

$$\Delta_i = API_i^+ - API_i^- \quad (11)$$

The filter increments represent a direct measure of the impact of the remote sensing observations on the model simulations. The underlying assumptions of the Kalman filter are given as follows: 1) The model is linear; 2) the relationship between the measurements and models are linear and unbiased; and 3) the error of the model as well as of the observations are Gaussian white noise [39]. In case that these assumptions hold, the sequence of normalized filter innovations v should be serially uncorrelated and have mean zero with a variance of one. The normalized filter innovation at a given update is given by [39]

$$v_i = [\theta_i - (a + bAPI_i^-)] / \sqrt{(b^2T_i^- + S)}. \quad (12)$$

As the model and observation errors are typically not known with sufficient accuracy, the filter innovations can be used as a diagnostic tool to optimize the filter performance [40]. They therefore allow assessing the reliability of the error parameterization used and of the validity of the basic assumptions of the Kalman filter. A numerical optimization of Q and S is performed in this case until the filter innovations are serially uncorrelated and have mean zero [16].

The analysis is made for each of the stations individually. The data processing comprises the following analysis steps.

- 1) *Initial error definition*: Define an initial value for the model and observation uncertainties Q and S . Initial values of $Q = 10.0$ and $S = 10.0$ mm are chosen.
- 2) *Open-loop simulation*: Run the API model (1) with the precipitation data from the station under investigation, which yields the *open-loop* estimate API_0 .
- 3) *Observation operator*: Compare API_0 against the observed PR_{45} to calibrate a and b in (7). To avoid a bias between PR_{45} and API and to compensate for different dynamic ranges, the polarization ratio is rescaled to PR_R to match the statistics of the *a priori* API_0 estimate as

$$PR_R = \frac{PR - \overline{PR}}{\sigma_{PR}} \sigma_{API_0} + \overline{API_0}. \quad (13)$$

TABLE III
LINEAR OBSERVATION OPERATOR FOR THE INDIVIDUAL STATIONS AS DERIVED FROM PRIOR DATA ANALYSIS WITHOUT DATA ASSIMILATION

Station	a	b	r-value
Winterthur	0.0121	0.0020	0.7055
Kloten	0.0047	0.0016	0.7494
Meteo Swiss Zurich	0.0295	0.0010	0.7045
Neubrunn	0.0186	0.0013	0.7560
Reckenholz	-0.0008	0.0016	0.7598
Niederglatt	0.0152	0.0018	0.7436
Taenikon	-0.0016	0.0021	0.7353
Birmensdorf	0.0031	0.0014	0.7317
Schaffhausen	-0.0023	0.0026	0.8026
Mettmenstetten	0.0366	0.0010	0.7414

The subscript R denotes rescaled data, and $\overline{PR}$ and $\overline{API_0}$ are the expected values of PR and API_0 , while σ_{PR} and σ_{API_0} are their standard deviations, respectively. A linear relationship between PR_R and API_0 is then calibrated by a least square fit to obtain the coefficients of the observation operator in (7). The values for a and b as well as the correlation coefficient for the linear relationship are summarized in Table III. The rescaled polarization ratio PR_R is then assimilated into the model using (6), whereas PR_R is used as a soil moisture proxy, instead of using θ directly in the formulation. Thus, for each of the stations, (6) becomes

$$API_i^+ = API_i^- + K_i [PR_R - (a + bAPI_i^-)] \quad (14)$$

- 4) *Model run*: The API model is used to simulate the soil water dynamics using the precipitation data from the actual station using (1). The uncertainties of the model simulations are propagated using (9).
- 5) *Assimilation*: In case of available observations of PR , these are assimilated into the model. API^- as well as the error of the model T^- is updated using (6) and (10). The filter increments Δ_i and innovations v_i are stored.
- 6) *Innovation analysis*: After the completion of the model runs, the time series of normalized filter innovations v is analyzed whether they are serially uncorrelated and with mean zero. Numerical iteration of Q and S is done until these optimal filter criteria are matched. This is achieved by iterating the two variables using a numerical method [41] and repeating steps 4)–6) until convergence is achieved.
- 7) *Validation*: For the final model run, the filter increments Δ are compared against the precipitation error, defined as the difference between the precipitation data used for the simulation and the precipitation observed at the reference station close to the radiometer. The correlation coefficient (r), bias, and rms error are calculated between

Fig. 6. (a) Daily precipitation and (b) precipitation error compared against daily filter increments Δ and (c) scatterplot for the stations Winterthur and Meteo Swiss Zurich. Analysis at 6:00 A.M.

the Δ and the rainfall error. The impact on the model simulations are assessed by comparing the *open-loop* and assimilation run soil water content against the *in situ* soil moisture data.

In case of satellite measurements, observations are typically only possible at distinct times during the day. In case of dedicated soil moisture passive microwave missions (SMOS, SMAP), the sensor overpass time will be around 6:00 A.M. (equator passing time). The early-morning overpass is expected to be superior to other sensing times as it allows for the assumption of thermal equilibrium between the soil and the vegetation cover, which considerably simplifies surface parameter retrieval approaches [29], [31]. To investigate the impact of the sensor overpass time on the experimental results, early-

morning observations of *PR* (6:00 A.M.) and daily average values are compared.

VI. RESULTS

The results of the data analysis are presented in the following. The filter increments provide a diagnostic tool to evaluate whether the amount of water added or removed by the filter is in agreement with actual uncertainties of the precipitation data. Fig. 6 shows an example of the comparison between precipitation error against the filter increments Δ for the stations in Winterthur and Zurich, using the 6:00 A.M. microwave observations. A strong correlation between the actual precipitation error and the filter increments is found. The correlation coefficients are $r = 0.80(0.60)$ for Winterthur (Zurich).

TABLE IV

STATISTICS OF THE CORRELATION BETWEEN THE FILTER INCREMENTS Δ AND PRECIPITATION ERROR FOR DAILY MEASUREMENTS AT 6:00 A.M.

Station	r		bias [mm]		rms [mm]	
	Daily	06:00	Daily	06:00	Daily	06:00
Winterthur	0.70	0.80	-0.07	-0.07	2.15	2.00
Kloten	0.63	0.71	-0.62	-0.64	3.17	2.91
Zurich Meteo Schweiz	0.51	0.60	-0.59	-0.58	4.37	4.49
Neubrunn	0.64	0.75	-0.51	-0.52	3.03	2.70
Reckenholz	0.55	0.60	-0.83	-0.85	3.63	3.32
Niederglatt	0.68	0.72	-0.17	-0.19	2.74	2.32
Taenikon	0.70	0.78	-0.30	-0.30	2.34	2.37
Birmensdorf	0.59	0.65	-1.00	-1.00	4.36	4.92
Schaffhausen	0.71	0.75	-0.26	-0.27	2.18	1.99
Mettmenstetten	0.67	0.73	-0.53	-0.52	4.03	3.67

TABLE V

CORRELATION COEFFICIENTS (r) BETWEEN API AND θ_{4cm} FOR THE OPEN-LOOP AND ASSIMILATION RUNS

station	no noise	noise T_b^p		
		1K	2K	3K
Winterthur	0.80	0.77	0.71	0.61
Kloten	0.71	0.68	0.61	0.50
Zurich Meteo Schweiz	0.60	0.57	0.50	0.42
Neubrunn	0.75	0.72	0.65	0.56
Reckenholz	0.60	0.57	0.51	0.44
Niederglatt	0.72	0.71	0.64	0.55
Taenikon	0.78	0.76	0.69	0.60
Birmensdorf	0.65	0.60	0.53	0.45
Schaffhausen	0.75	0.73	0.65	0.57
Mettmenstetten	0.73	0.69	0.63	0.57

Table IV lists the rms error as well as the correlation coefficient (r) and bias of the analyzed filter increments against the actual precipitation error. It is observed that all stations show a positive correlation between Δ and the rainfall error, which indicates that the model simulations benefit from the integration of the microwave data, as the filter adds or removes an amount of water that is comparable to the precipitation error. In case of early-morning observations, the correlation between the precipitation error and the filter increments is higher than for daily observations for all stations.

The direct impact on the API simulations can be evaluated by comparing the simulation results against *in situ* soil moisture measurements. The correlation between the *in situ* soil moisture θ_{4cm} $m^3 m^{-3}$ and the API (in millimeters) was therefore calculated for the *open-loop* as well as the assimilation runs. Table V shows the correlation coefficients r between θ_{4cm} and API for the daily mean or the early-morning observations, respectively. It is observed that r is higher for the assimilation runs than for *open-loop* simulations in both cases, which indicates that the integration of the microwave data results in more realistic simulations of θ . The results that are based on the early-morning observations result in slightly better improvements in case of the daily average values.

Measurements of microwave brightness temperatures T_b^p are typically affected by noise. The noise level of the ELBARA instrument is less than 2 K standard deviation [5]. In case of the forthcoming SMOS mission, the noise level is expected to be on the order of 2 K [10].

As the accuracy of T_b^p will directly reflect on PR_{45} , it is expected that the uncertainties of T_b^p will also have an influence on the impact of the suggested data assimilation methodology. A sensitivity analysis on the robustness of the suggested methodology is therefore made in the following.

Additive white Gaussian noise with standard deviations of $\sigma = 1, 2, 3$ K is added to T_b^p at both polarizations $p = h, v$,

Fig. 7. Relationship between the filter increments without noise Δ_0 and the increments from noisy measurements Δ with noise of 1, 2, and 3 K.

TABLE VI

CORRELATION BETWEEN FILTER INCREMENTS Δ AND PRECIPITATION ERROR FOR NOISY MEASUREMENTS (6:00 A.M.)

station	r_{4cm} , daily		r_{4cm} , 6:00	
	open loop	assimilation	open loop	assimilation
Winterthur	0.82	0.86	0.85	0.89
Kloten	0.75	0.79	0.78	0.81
Zurich Meteo Schweiz	0.82	0.84	0.82	0.84
Neubrunn	0.79	0.83	0.81	0.84
Reckenholz	0.80	0.83	0.81	0.83
Niederglatt	0.77	0.82	0.80	0.84
Taenikon	0.82	0.86	0.84	0.88
Birmensdorf	0.76	0.80	0.79	0.83
Schaffhausen	0.72	0.75	0.77	0.80
Mettmenstetten	0.73	0.78	0.75	0.80

while the noise of the two channels is assumed to be independent. The obtained brightness temperatures are used to calculate PR_{45} , which was then assimilated similar to the previous experiment. The filter increments Δ are compared against those without noisy observations (Δ_0).

Fig. 7 shows the relationship between Δ_0 and Δ for the station in Winterthur. It is obvious that the filter increments show a higher variability compared to Δ_0 when increasing the noise level of the observations. The correlation coefficient r decreases with increasing uncertainties of the measurements.

Table VI shows the correlation coefficients of the filter increments versus the rainfall error observed at each of the stations. A decrease of r with increasing noise and positive values for r are observed in all cases. In Winterthur, the correlation coefficient decreases from $r = 0.80$ to 0.77, 0.71, and 0.61 in the case of noise of 1, 2, and 3 K, respectively. However, a positive correlation between Δ and the precipitation error was found for all stations, which indicates that given uncertain measurements of T_b^p , the suggested method provides a useful approach to compensate for deficits in precipitation information.

VII. CONCLUSION

This paper has investigated the potential to use L-band microwave data as a proxy for surface soil moisture dynamics and to use that information for an improved characterization of soil water dynamics. A strong correlation between the polarization ratio PR_{45} and the surface soil moisture θ was found in this study. It needs to be investigated in further studies whether PR_{45} can be used as a suitable soil moisture proxy also in

case of other land cover types or higher vegetation biomass levels than those present in the data set used. Such an evaluation might be of particular importance for the applicability of PR_{45} in case of operational observations. However, the used data assimilation approach is, in general, also applicable to soil moisture products obtained from appropriate retrieval models and should therefore allow application of the methodology in combination with forthcoming satellite data like, for example, those provided by SMOS or SMAP. The rationale of using PR_{45} in this study was that it showed highest sensitivity to observed surface soil moisture and was therefore assumed to be the best proxy for surface soil moisture dynamics.

The polarization ratio was assimilated into a simplistic model for soil wetness. It was found that the integration of the microwave observations improves the model simulation skills as it partly compensates for uncertainties in precipitation information.

It was shown for the first time that L-band radiometer data have large potential to improve the simulations of a simple soil water index model by compensating for uncertainties in the precipitation information based on an assimilation approach proposed in [15]. It has also been shown that early-morning observations are superior to daily average T_b^p estimates, which is a common assumption for passive microwave soil moisture retrieval concepts. The effect of sensor noise on the robustness of the data assimilation approach has been investigated, making realistic assumptions on noise levels as they are expected from satellite-borne L-band missions. Positive correlations between the precipitation error and filter increments Δ were diagnosed for all investigated stations. This indicates that L-band radiometry might provide useful information for the correction of precipitation error even under noisy conditions, which is an interesting result for potential applicability of the methodology for satellite data.

Although the available microwave data were rather limited and measured over growing grass, the results indicate the potential to improve precipitation data for hydrological model simulations. The availability of longer time series of low-frequency microwave (L-band) brightness temperature measured over a variety of different land cover types would be essential to validate the generality of the suggested methodology. The potential of existing multiyear L-band data sets like, for example, SMOSREX [36], might be exploited for that purpose. The transferability of the applied methodology from the field scale to satellite observations will be dependent on the sensitivity of the microwave signature on soil moisture changes. That might be reduced by the superposition of the radiances emitted from different land cover types within a resolution cell of the sensor system [42].

Using more deterministic land surface models instead of the simple *API* model might result in a better description of the surface water fluxes as a function of the meteorological boundary conditions. It is expected that the integration of a microwave surface soil moisture proxy such as PR_{45} might help in improving those model simulation skills as well.

The potential of using L-band microwave data to compensate for precipitation errors offers an interesting perspective for the improvement of hydrological model input data for regional to global scale applications using global satellite data as they are expected from the SMOS or SMAP missions. The application

of the suggested approach to more physically based land surface models on the one hand and different land cover types on the other hand, as well as the transferability to satellite-based soil moisture estimates from L-band missions will be the subject of further research.

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