L-Band Microwave Satellite Data and Model Simulations Over the Dry Chaco to Estimate Soil Moisture, Soil Temperature, Vegetation, and Soil Salinity

Frederike Vincent ©, Michiel Maertens, Michel Bechtold ©, Esteban Jobbágy ©, Rolf H. Reichle ©, Veerle Vanacker ©, Jasper A. Vrugt ©, Jean-Pierre Wigneron, and Gabriële J. M. De Lannoy ©

Abstract—The Dry Chaco in South America is a semi-arid ecoregion prone to dryland salinization. In this region, we investigated coarse-scale surface soil moisture (SM), soil temperature, soil salinity, and vegetation, using L-band microwave brightness temperature (T_B) observations and retrievals from the soil moisture ocean salinity (SMOS) and soil moisture active passive satellite missions, Catchment land surface model (CLSM) simulations, and in situ measurements within 26 sampled satellite pixels. Across these 26 sampled pixels, the satellite-based SM outperformed CLSM SM when evaluated against field data, and the forward L-band T_B simulations derived from in situ SM and soil temperature performed better than those derived from CLSM estimates when evaluated against SMOS T_B observations. The surface salinity for the sampled pixels was on average only 4 mg/g and only locally influenced the T_B simulations, when including salinity in the dielectric mixing model of the forward radiative transfer model (RTM) simulations. To explore the potential of retrieving salinity together with other RTM parameters to optimize T_B simulations over the entire Dry Chaco, the RTM was inverted using 10 years of multangular SMOS T_B data and constraints of CLSM SM and soil temperature. However, the latter modeled SM was not sufficiently accurate and factors such as open surface water were missing in the background constraints, so that the salinity retrievals effectively represented a bulk correction of the dielectric constant, rather than salinity per se. However, the retrieval of vegetation, scattering albedo, and surface roughness resulted in realistic values.

Index Terms—L-band microwave, land surface model, salinity, soil moisture, soil moisture active passive (SMAP), soil moisture ocean salinity (SMOS), soil temperature, vegetation.

I. INTRODUCTION

Soil-vegetation processes and their interaction with the atmosphere determine the characteristic features of terrestrial biomes around the world. Soil moisture and vegetation are at the center of the coupling between water, energy, and carbon cycles, they regulate land surface fluxes and are constrained by environmental factors such as soil chemical properties, terrain, land use, or human interventions [1], [2]. In dry regions, the soil salinity plays an important role in land surface processes because it influences vegetation growth, and alters the water, energy, and carbon budgets [3], [4]. Therefore, an integrated large-scale assessment of soil moisture SM, vegetation, and soil salinity is crucial in drylands or biomes with very dry seasons, often found in tropical and subtropical regions.

Large-scale estimates of surface soil moisture (SM) and vegetation are routinely available from land surface and vegetation model simulations and from satellite observations or combinations thereof [5]. The L-band microwave soil moisture ocean salinity (SMOS [6]) and soil moisture active passive (SMAP [7]) missions were launched with the explicit purpose to monitor SM globally, and also provide estimates of vegetation optical depth [8]–[10].

In contrast to SM and vegetation, large-scale estimates of salinity are scarce and often characterized by a low temporal resolution. Some global estimates are provided by, e.g., the Harmonized World Soil Database (HWSDv1.21, hereafter HWSD) [11]. However, those salinity estimates are typically classified in a few categories and the information is time-invariant, often relying on soil samples of decades ago. Remote sensing offers the potential to address these limitations.

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Optical remote sensing satellites have localized areas affected by excess soil salinity using spectral salinity indices [12], vegetation proxies [13], or machine learning techniques using a stack of optical remote sensing data and other global datasets [14]. Thermal remote sensing has also been explored to map salinity [15]. Alternatively, microwave remote sensing might prove useful for salinity detection. Passive L-band microwave observations from the SMOS and SMAP missions are routinely used for sea surface salinity estimation [16], but the potential for soil surface salinity monitoring has not been fully explored yet. Given that at L-band, the soil water dielectric constant is sensitive to salinity [17], it may be possible to improve brightness temperature \( T_B \) simulations, improve SM retrievals in saline areas, and perhaps even estimate soil surface salinity by including the effect of salinity in the computation of the dielectric constant for water [18], [19], as part of the microwave radiative transfer model (RTM).

Chaturvedi et al. [20] suggested that a combination of L- and C-band microwave remote sensing data might allow to differentiate between soil salinity and SM effects on the microwave signal. Jackson and O’Neill [21] used the equations of [19] in the dielectric mixing model of [22] to conclude that salinity below 5 parts per thousand (PPT, mg/g) is most likely undetectable using L-band and would therefore not affect SM retrievals. In contrast, for areas with higher salinity levels, up to 128 PPT, McColl et al. [23] reported significant overestimations of simulated \( T_B \) when salinity is not accounted for, leading to errors in SM retrieval.

In short, L-band microwave remote sensing has a proven capability to routinely estimate large-scale SM and vegetation optical depth, and it is also affected by salinity, as shown in laboratory and small-scale studies. However, the \( T_B \) sensitivity to salinity at the coarse spatial resolution of spaceborne passive microwave radiometers has not yet been widely studied. The key question of this article is therefore what we can learn from L-band \( T_B \) observations about land surface variables such as soil salinity, SM, soil temperature, and vegetation. To this end, the South-American Dry Chaco, with its naturally saline soils [24] at risk of future salinization, forms a unique large-scale testbed.

The objectives of this article are to 1) evaluate large-scale estimates of SM and soil temperature in the Dry Chaco, using data from an extensive field campaign, land surface model simulations, and SMOS and SMAP retrievals, 2) simulate L-band \( T_B \) with and without accounting for salinity and compare the simulations to satellite-based observations, and 3) investigate the possibility of jointly retrieving RTM parameters related to soil roughness, vegetation, and salinity over the Dry Chaco, using coarse-scale L-band radiometry and modeled constraints of SM and soil temperature. The latter constraints help to set the dominant moisture and temperature contributions of the \( T_B \) signal apart, and to focus on the estimation of less dominant variables, incl. salinity. Furthermore, the retrieved parameters could be used to optimize the forward RTM to produce improved \( T_B \) simulations for a \( T_B \) data assimilation system that inherently uses modeled SM and temperature, such as the SMAP Level 4 Surface and Root-Zone SM (L4_SM [5]).

In Section II, the field data are presented, as well as the ancillary data sources and models used for L-band \( T_B \) simulation. Section III describes the methods, including the adjustments to the RTM to account for salinity and how the RTM is used in forward and inverse mode to simulate microwave \( T_B \) and retrieve land surface properties, respectively. The results are shown in Section IV, a discussion is provided in Section V, and conclusions and recommendations for future article are summarized in Section VI.

II. DATA AND MODELS

A. Study Area

The South American Gran Chaco hosts a wealth of biodiversity in an area where native dry forests and expanding, mostly rainfed, agriculture for crops and cattle ranching are competing in a changing landscape [24], [25]. Despite its large latitudinal extent and vegetative and climatic variability, the Dry Chaco is a well-delineated ecoregion in the western part of the larger Gran Chaco and covers an area of about 787 000 km\(^2\) in southern Bolivia, western Paraguay, and northern Argentina [26], east of the Andean mountain range [Fig. 1(A)]. The vegetation is dominated by xerophytic shrubs and trees, making up the Earth’s largest subtropical dry forest and savannas. East of the Dry Chaco lies the Humid Chaco, characterized by wetlands and a lower tree coverage [25].

The Dry Chaco is one of the planet’s largest level plains with slopes <0.1% and a semi-arid climate. The mean annual temperature ranges between 18 °C and 26 °C, but maximum temperatures can easily exceed 40 °C [27]. Rainfall varies between 400 and 1000 mm/year and is concentrated in the southern hemisphere summer [26].

Saline soils are common in the region owing to its semi-arid climate, flat topography, and shallow groundwater table [24]. Large natural salt deposits occur in the presence of paleo-lakes [e.g., the Salinas de Ambargasta and Salinas Grandes, marked as open water in Fig. 1(B)], paleo-channels, or floodplains [28]. Large-scale deforestation and forest degradation for agriculture
pose a threat for soil salinization in this area. The dry forest conversion began in the early 20th century [29] and reached record high rates at the turn of the century. Multiple regional studies reported an increased downward mobilization of salts toward the water table after deforestation, followed by the rise of the saline water table, leading to the upward movement of salts [30], [25], suggesting the onset of changing hydrological conditions in the Dry Chaco. So far, however, there are no large-scale data to confirm these suggestions.

During the months of July and August 2019, a field campaign was organized in a part of the Argentinean Dry Chaco [Fig. 1(B)], discussed in Section II-E. Soil moisture, salinity, temperature, and vegetation were sampled near Añatuya, Chahar, Frías, Santiago del Estero, and Tucuman.

B. SMOS and SMAP Data

L-band $T_B$ (level 1), surface $SM$, and vegetation optical depth ($\tau$) retrievals (level 2) were collected from the SMOS and SMAP missions. The SMOS mission was launched in 2009 and provides data at a 3-day temporal resolution and a nominal (3 dB) spatial resolution of 43 km [6]. We used the multispectral SMOS SCLFL1C.v620 $T_B$ at horizontal and vertical polarization ($H_{pol}$ and $V_{pol}$), reprojected to the Equal-Area Scalable Earth (EASEv2) 36-km grid, and the SMOS-IC version 2 level 2 $SM$ and $\tau$ product [8], resampled to 36 km. The $T_B$ preprocessing and filtering were done as in [31], i.e., excluding pixels where $T_B$ observations are impacted by open water, radiofrequency interference, etc. as provided in the product quality flags. The SMAP satellite was launched in 2015 and collects data at a similar temporal and spatial resolution as SMOS [7]. The SMAP level 1 $H_{pol}$ and $V_{pol}$ $T_B$ data were extracted from the SPL1CTB.v004 product, and level 2 $SM$ retrievals were extracted from SPL2SMP.v006, which are both produced on the EASEv2 36 km grid. The $\tau$ retrievals were extracted from the 9-km SPL2SMP_E.004, using the “option 3” dual-channel algorithm [9], conservatively filtered using the provided quality flags and aggregated to 36 km.

The SMOS and SMAP $SM$ and $T_B$ data for July-August 2019 were compared to in situ and model $SM$, and to evaluate forward RTM simulations, respectively, at pixels visited during the field campaign. The multispectral SMOS $T_B$ for 2010–2019 were used for RTM inversions, whereas the time-average $<\tau>$ retrieval products for 2015–2019 (both SMOS and SMAP) were used to evaluate the $<\tau>$ estimates obtained from the RTM inversion. The SMOS and SMAP $\tau$ retrievals were earlier evaluated with a range of independent vegetation datasets [32].

C. Land Surface Modeling

The Catchment land surface model (CLSM [33]), part of the NASA Goddard Earth Observing System model, was forced with meteorological data from the Modern-Era Retrospective Analysis for Research and Applications version 2 (MERRA-2 [34]) to simulate land surface processes over the Dry Chaco on the 36-km EASEv2 grid from 2010 to 2019, after 30 years of spin-up. The CLSM version is similar to that used for the SMAP L4_SM product version 4 [5]. The system simulates soil moisture in the surface (0–5 cm) and root zone (0–100 cm), surface temperature in a layer of 0–5 cm, and soil temperature in six layers with the first layer pertaining to 5–15 cm depth. For surface $SM$, the simulated and in situ sampled layer depth is similar (0–5 cm), and both will be referred to as $SM$. For temperature, the CLSM surface temperature ($T_{surf}$, 0–5 cm) and soil temperature in the first layer ($T_{soil1}$, 5–15 cm) will be compared to the in situ temperature data collected in the upper 5 cm ($T_s$). Because the CLSM $T_{soil1}$ is used as temperature input to the forward RTM in the SMAP L4_SM product, a statistical relationship between $T_{soil1}$ simulations and in situ $T_s$ observations (frequently sampled during the day) was established to bias-correct the model $T_{soil1}$ toward in situ $T_s$, and also to extrapolate point-based in situ $T_s$ measurements to upscaled 36-km EASEv2 estimates at specific times of the day (Section IV-A). These bias-corrected CLSM soil temperature estimates will therefore also be referred to as $T_s$. The $SM$ and $T_{soil1}$ (or $T_{surf}$) simulations were compared to in situ measurements and satellite retrievals, and then used for forward $T_B$ simulation, or as a constraint to invert SMOS $T_B$ and derive land surface properties (RTM parameters, incl. salinity and $\tau$).

It is important to note some shortcomings of the CLSM. First, explicit deforestation or the vegetation response to salinity is not included in the CLSM, and a historical climatology is used to describe the vegetation instead. The CLSM leaf area index (LAI) values over the Dry Chaco are based on a multiyear average climatology, obtained from GEOShLAND2 [35]. This poses no problem for long-term deforested areas, but for recently deforested areas, the vegetation and $SM$ may locally deviate from historical climatological conditions [36]. Second, it can be expected that soil salinity alters the water retention curve in a soil and affects the soil moisture profile and evapotranspiration response [37]. That would affect the satellite-observed $T_B$ signal but is not captured in the CLSM or any other state-of-the-art land surface model.

D. L-Band RTM

Given static and dynamic information about the land surface, a zero-order omega-tau RTM was used to simulate L-band $T_B$ at the top of the vegetation at horizontal or vertical polarization $p$ ($H_{pol}$ or $V_{pol}$) as follows:

$$T_{B,p} = T (1 - r_p) A_p + T_C (1 - \omega_p) (1 - A_p) (1 + r_p A_p).$$

(1)

Atmospheric contributions were not included because they were already removed from the L-band satellite data, $T$ [K] is the effective soil temperature (either $T_s$ or $T_{soil1}$), $T_C$ [K] is the effective canopy temperature (assumed to equal $T$), $r_p$ [-] is the rough surface reflectivity, $\omega_p$ [-] is the scattering albedo, and $A_p$ [-] is the vegetation attenuation, calculated as follows:

$$A_p = \exp\left(\frac{-r_p}{\cos(\theta)}\right).$$

(2)

The vegetation optical depth $\tau_p$ [-] depends on a vegetation-structure parameter, $b_p$ [-], and the vegetation water content (VWC), which is the product of LAI [m²/m²] and leaf equivalent
TABLE I
OVERVIEW OF SAMPLED EASEv2 PIXELS IN JULY AND AUGUST 2019: NAME, NUMBER OF SAMPLE SITES PER PIXEL (#), SAMPLE DATE (DAY/MONTH) IN THE YEAR 2019 AND DESCRIPTION OF THE LAND COVER

| Name | # | Date  | Description                  | Name | # | Date  | Description                  | Name | # | Date  | Description                  |
|------|---|-------|-------------------------------|------|---|-------|-------------------------------|------|---|-------|-------------------------------|
| A1   | 27| 13/08 | Forest                        | F1   | 20| 22/08 | Forest and pastures           | S5   | 16| 25/07 | Mainly forest, cotton fields   |
| A2   | 19| 12/08 | Mainly forest, some bushes    | F2   | 19| 24/08 | Forest and pastures           | S6   | 13| 26/07 | Mainly forest                 |
| A3   | 25| 14/08 | Forest and bushes             | F3   | 19| 23/08 | Forest                        | S7   | 16| 29/07 | Forest, bushes (halophytic)    |
| A4   | 22| 16/08 | Agriculture                   | F4   | 20| 21/08 | Mainly bushes                 | S8   | 20| 31/07 | Mainly forest                 |
| A5   | 6 | 17/08 | Bushes, close to salt lakes   | F5   | 5 | 18/08 | Forest and bushes near saline lakes | S9   | 21| 01/08 | Agriculture                   |
| C1   | 20| 06/08 | Post-harvest agriculture      | F6   | 3 | 23/08 | Bushes                        | T2   | 20| 26/08 | Agriculture                   |
| C2   | 20| 07/08 | Post-harvest agriculture      | S2   | 11| 19/07 | Agriculture and forest         | T3   | 20| 27/08 | Agriculture, some bushes       |
| C3   | 21| 08/08 | Post-harvest agriculture      | S3   | 19| 23/07 | Mainly forest and bushes      | T4   | 16| 30/08 | Mainly dense forest            |
| C4   | 19| 09/08 | Post-harvest agriculture      | S4   | 19| 24/07 | Mainly forest                 |      |    |       |                                |

Names are based on the municipality closest to the pixel location: A = Añatuy, C = Charata, F = Frías, S = Santiago Del Estero, and T = Tucumán.

water thickness (LEWT) [kg/m²]

\[ \tau_p = b_p \text{VWC, and VWC} = \text{LEWT LAI}. \] (3)

The rough surface reflectivity, \( r_p [-] \), is defined as follows [38]:

\[ r_p = [QR_p + (1 - Q) R_p] \exp(-h) \cos^{N_p} (\theta) \] (4)

and requires \( Q \), the polarization mixing ratio [-] (assumed to equal 0 for L-band), \( \theta \), the incidence angle [rad], \( h \), an SM-dependent roughness parameter [-], and \( N_p \), the angular dependence [-]. The roughness \( h \) varies in time between \( h_{\text{max}} \) for SM at or below transition \( SM \) and \( h_{\text{min}} \) for SM at saturation. \( R_p \) is the smooth surface reflectivity [-], which is calculated using the Fresnel equations:

\[ R_H (\theta) = \left| \frac{\cos(\theta) - \sqrt{\varepsilon - \sin^2(\theta)}}{\cos(\theta) + \sqrt{\varepsilon - \sin^2(\theta)}} \right|^2, \text{ and} \]

\[ R_V (\theta) = \left| \frac{\varepsilon \cos(\theta) - \sqrt{\varepsilon - \sin^2(\theta)}}{\varepsilon \cos(\theta) + \sqrt{\varepsilon - \sin^2(\theta)}} \right|^2 \] (5)

with \( \varepsilon \) the complex dielectric constant of the soil, \( \varepsilon = \varepsilon' + i\varepsilon'' \), where \( \varepsilon' \) is the real part of the dielectric constant, \( \varepsilon'' \) is the imaginary part, and \( i \) is the solution of the equation \( i^2 = -1 \). As will be discussed below, \( \varepsilon \) is a function of soil texture, SM, \( T \), and \( S \).

This article used the same RTM structure as that used in Version 4 of the SMAP L4_SM product [5]. In short, the RTM uses dynamic CLSM SM and \( T(T_{\text{soil}} \) or \( T_5 \)) as input, along with seasonally varying climatological LAI, and a set of lookup or calibrated RTM parameters (see below). The lookup parameters were based on the dominant vegetation cover, determined by the MODerate resolution Imaging Spectroradiometer (MODIS) IGBP landcover map. The RTM simulations were also performed for a small sample of in situ SM and \( T_5 \) observations described below.

E. In Situ Data

During the months of July and August 2019, a total of 26 pixels on the EASEv2 36 km grid (Fig. 1) were sampled to facilitate comparison with satellite and model data. The pixels were chosen based on satellite imagery, deforestation history, expected salinity level (historical mapped data, unmapped natural or upcoming salinity as suggested by literature or satellite imagery), elevation, and accessibility. A multitude of sites were sampled within each pixel, each pixel was sampled entirely within a day, and each pixel was visited only once. In the Dry Chaco, the months of July and August are typically dry, and in 2019, there was a clear dry-down after an anomalously wet austral summer. Table I provides an overview of all sampled pixels, the number of sample sites within the pixel, and the dominant vegetation type.

We collected extensive surface soil data in areas with diversified levels of salinization, and deeper soil samples at locations where deforestation had taken place either recently or in the past. Surface (0–5 cm) soil data were gathered on SM, temperature \( T_5 \), electrical conductivity (EC), and dielectric constant (\( \varepsilon \)) at multiple sample sites along a transect within each sampled EASEv2 pixel. The transect was situated to best capture the variability of the pixel, and consisted of minimally three (F6) and maximally 27 (A1) sample sites. An example of a transect is depicted in Fig. 1(B). At 10 locations, marked with crosses in Fig. 1(B), additional deeper soil measurements were taken. Those are discussed in Appendix 1 to frame our findings within
the scientific discussion about the salinization potential of the Dry Chaco.

For SM, we used two different probes (Stevens HydraGO and the Delta-T Devices ThetaProbe). The HydraGO was used with the factory calibration that is also used for the widely used Soil Climate Analysis Network of the Natural Resource Conservation Service [39]. At each sample site, measurements were taken in two or three different pits (1 m apart) by horizontally inserting the probes into a cleared surface of an undisturbed soil at a depth of approximately 2.5 cm. The probes have a sensing volume that covers 5 cm in the vertical direction, i.e., the measurements represent the top 5 cm of soil. A high Pearson correlation \((R = 0.87)\) and a small bias \((0.028 \text{ m}^3/\text{m}^3)\) were found between all individual SM measurements from both probes (931 measurements with each sensor). Per site, an average SM was calculated based on the measurements of the HydraGO and the ThetaProbe in all pits. Given the strong agreement between both SM sensors and given that the composition of soils in the Dry Chaco is not too different from those used in the factory calibration of the HydraGO sensor, we believe that the averaged data are reliable to serve as reference in terms of relative accuracy metrics. Furthermore, 38 texture samples were collected.

To measure in situ dielectric properties and salinity in the field, several methods were used. The Stevens HydraGO probe was used to measure porewater EC and the real and imaginary parts of \(\varepsilon (\varepsilon' \text{ and } \varepsilon'')\) at 0.05 GHz (i.e., a much lower frequency than the L-band frequency of interest to this article). Two other probes, a Hanna sensor and the YSI proDSS, were used to measure the EC of a soil–water paste (hereafter referred to as EC) of a mixed soil sample that was taken from the top 5 cm at each sample location along the transect. With the soil sample, a soil–water mixture was prepared on a 1:1 ratio; adding 50 ml of water to 50 g of the sample. The 1:1 ratio was chosen to minimize probe sensitivity difficulties because of dilution (which occurs more at the typical 1:5 ratio) and to allow reproducibility. After mixing and resting, the EC was measured with both probes. The measurements by both probes correlated well \((R = 0.94)\) with a slight underestimation by the Hanna probe \((\text{bias} = -0.82 \text{ dS/m})\), due to saturation at 20 dS/m. In the following, only the YSI proDSS EC measurements were used. Where needed, these in situ EC measurements in dS/m were converted to salinity \((S)\) in PPT in the practical salinity scale, following the YSI proDSS’s internal conversion method, i.e., via regression equations (PSS 78 [40]) that only consider the EC and the temperature of the soil–water mixture. The equations are based on the salinity of seawater, and thus not fully representative for the ionic content of the Dry Chaco soil water, but the conversion error is expected to be small and consistent across all samples.

In situ surface soil temperature was measured with the HydraGO within the top 5 cm of the soil. Per sample site, \(T_5\) measurements in all pits were taken within less than 15 min and averaged to one value. All measurements were taken during the daytime, and a special effort was done to sample additional \(T_5\) data close to the SMOS and SMAP satellite overpass times.

Vegetation type was visually assessed at each location along the transect, and sampling was done in different vegetation types that were representative for that pixel, and in zones with different elevations and expected salinity, i.e., the sample sites were chosen after close inspection of satellite imagery and ancillary spatial datasets (see below).

F. Pixel-Scale In Situ Data

To allow for comparison with satellite observations and model simulations on the 36-km EASEv2 grid, point measurements of surface \(SM, S\) (measured as EC in the field) and \(\varepsilon\) were upscaled via a weighted average to obtain in-situ-based “observations” that are representative of a pixel area. The values of the limited number (mostly >15) of samples for the one pixel were weighted based on elevation from the 30 arc-second Multi Error Improved Terrain [41] digital elevation model. This choice was based on the notion that both \(SM\) and \(S\) vary spatially with depth to the water table and the proximity of streams, which in turn are linked to elevation.

The upscaling of in situ soil temperature \((T_5)\) measurements leveraged CLSM simulations (Section II-C). In short, the simulated diurnal cycle of CLSM \(T_{\text{soil}}\) at the 36-km pixel scale was compared to \(T_5\) site measurements taken at many different times in the day to establish a mapping function between both. This allowed to bias-correct the 36-km \(T_{\text{soil}}\) simulations to in situ \(T_5\) observations, and to obtain a pixel-scale “in-situ-based” \(T_5\) estimate at any time of the day.

The visual inspection of vegetation (Table I) within each sampled pixel was aggregated to a dominant impression of the landscape. For each visited EASEv2 pixel, a dominant vegetation class was selected by 3 observers during the field campaign from the 17 possibilities of the International Geosphere-Biosphere Program (IGBP) land cover classification [42].

Fig. 2 summarizes all surface soil data gathered during the field campaign. In panels a–c, the within- and between-pixel variability in \(SM, S\) (EC in dS/m), and \(T_5\) are shown. The variability also includes temporal variability, which is limited within a pixel for \(SM\), because each EASEv2 pixel was always completely sampled within a day. In contrast, the variability in \(T_5\) samples is largely driven by diurnal and daily temperature fluctuations. The blue dots indicate the upcaled values for \(SM\) and \(S\) (EC), whereas the red dots are \(T_5\) estimates at 6 am local time on the sample day (extrapolated to 6 am, discussed below). Except for \(T_5\), the upcaled values for all other variables are close to the simple pixel median values (center line of boxplot). For \(T_5\), the median value is associated with the sampled subset of the diurnal temperature variation, whereas the upcaled value is at a fixed time. The figure indicates that there is a large variability between pixels. For certain pixels and variables, there is also a large within-pixel variability. Our article only focuses on the variability between—and not within—pixels.

G. Ancillary Data for In Situ Pixels

Additional data sources complement the in situ data collection. For every sampled 36-km EASEv2 pixel, an LAI value was calculated from 4-day 500-m MODIS (onboard the NASA Terra and Aqua satellites retrievals (version 006) [43] for July and August 2019. Fig. 2(d) shows the pixel-average LAI and the in situ observed vegetation class.
A. Accounting for Salinity in the RTM

In the RTM, the soil dielectric constant $\varepsilon$ is calculated using a dielectric mixing model. Soil, water, and air components all contribute to the dielectric properties of the soil mixture. Salinity also has an influence on the dielectric properties of a soil, and reduces $T_D$, but is generally not included in global land RTMs. In line with the SMAP L4_SM product, we used the empirical [22] dielectric mixing model to calculate $\varepsilon$ based on the dielectric constants of air ($\varepsilon_a$), rock ($\varepsilon_r$), ice ($\varepsilon_i$), and water ($\varepsilon_w$) with a distinction between bound and free water (see Appendix 2 for detailed equations, similar results were found with the [49] model). The dielectric constant of free water ($\varepsilon_w$) can be calculated by the Debye expression:

$$\varepsilon_w(\omega) = \varepsilon_{\infty} + \frac{\varepsilon_{s} - \varepsilon_{\infty}}{1 + (i\omega T)^{-\alpha} - i\frac{\sigma}{\omega \varepsilon_0}} \tag{6}$$

where $\varepsilon_{\infty}$ is the dielectric constant at an infinite frequency (set to $\varepsilon_{\infty} = 4.9$), $\omega = 2\pi f$ with $f$ the frequency [Hz], $\varepsilon_0$ is the permittivity of free space (equal to $8.854 \cdot 10^{-12}$), and $\alpha$ is an empirical parameter describing the distribution of relaxation times, and is set to zero [19].

In most operational RTMs, $\varepsilon_w$ is calculated for pure water with the ionic conductivity $\sigma$ equal to zero. The remaining variables in (6), i.e., the ionic conductivity $\sigma$ [mhos/m], the relaxation time $t$ [s], and the static dielectric constant $\varepsilon_s$ [–], are calculated based on regressions equations using only $T$ as an explanatory variable [49].

In this article, we replaced these equations for $\sigma(T), t(T),$ and $\varepsilon_s(T)$ in pure water with $\sigma(S, T), t(S, T),$ and $\varepsilon_s(S, T),$ i.e., with the regression equations of [19] for saline water in the Debye expression (6) to calculate $\varepsilon_w$ for the dielectric mixing model of [22]. These regression equations of [19] build further on the equations of [18], which are valid for salinity ranging from 4 to 35 PPT. However, the authors note that the lower limit is not restrictive, and that only for distilled water a different set of

Soil texture information was derived from the HWSD, and soil hydraulic parameters were derived as in [44]. Fig. 2(e) gives the HWSD sand and clay fraction per EASEv2 pixel. A comparison with 38 soil samples (laboratory analysis, not shown) within 20 of the 26 sampled EASEv2 pixels showed high sand and low clay fractions in both datasets. Given the small set of in situ texture samples, we relied solely on HWSD estimates in the remainder of this article.

H. Regional Reference Data

We further consulted the HWSD excess salts map [Fig. 1(B)] as a reference for salinity over the entire Dry Chaco. This map indicates the historically observed and expected severity of growth limitations due to salinity, sodicity or both, and does not account for possible recent salinization. Fig. 1(B) illustrates that the occurrence of excess salinity is higher in proximity of (paleo-)lakes and streams. The static open water areas in the figure originate from the Global Wetland and Lake Database [45]. The 25-km dynamic open water estimates retrieved from the Advanced Microwave Scanning Radiometer 2 (AMSR2) [46] were also consulted to evaluate the results.

As a reference dataset for vegetation, 1-ha aboveground biomass (AGB) estimates for the year 2010 [47] were used. The 1-ha AGB data were obtained from a combination of radar, optical, and lidar data and were aggregated to the EASEv2 36-km resolution. Since AGB is the oven-dry weight of the woody parts (stem, bark, branches, and twigs) of all living trees excluding stump and roots, it represents a very different quantity than the L-band $\tau$, which is a microwave-based index that strongly varies with VWC. However, relative spatial patterns in AGB estimates can be reliably related to L-band $\tau$ patterns [48].

III. METHODOLOGY

Simulations with the EBODT model were performed as in (6), i.e., the ionic conductivity $\sigma$ equal to zero. The remaining variables in (6), i.e., the ionic conductivity $\sigma$ [mhos/m], the relaxation time $t$ [s], and the static dielectric constant $\varepsilon_s$ [–], are calculated based on regressions equations using only $T$ as an explanatory variable [49].

In this article, we replaced the equations for $\sigma(T), t(T),$ and $\varepsilon_s(T)$ in pure water with $\sigma(S, T), t(S, T),$ and $\varepsilon_s(S, T),$ i.e., with the regression equations of [19] for saline water in the Debye expression (6) to calculate $\varepsilon_w$ for the dielectric mixing model of [22]. These regression equations of [19] build further on the equations of [18], which are valid for salinity ranging from 4 to 35 PPT. However, the authors note that the lower limit is not restrictive, and that only for distilled water a different set of
equations should be used. For the detailed regression equations, we refer to [19].

Fig. 3(a) illustrates the $\varepsilon''_w$ and the $\varepsilon'''_w$ of pure (0 PPT) and saline (32.5 PPT) water at frequencies ranging from 0 to 100 GHz following [19]. Increasing salinity leads to a decrease in the real part and an increase in the imaginary part of the dielectric constant of saline water, in line with [17]. Fig. 3(b) and (c) illustrates the influence of soil water temperature on the sensitivity of $\varepsilon''_w$ and $\varepsilon'''_w$ to salinity at L-band (1.4 GHz). Fig. 3(c) indicates that $\varepsilon'''_w$ becomes more sensitive to salinity at higher soil water temperatures.

Note that adding salinity via $\varepsilon''_w$ in the free water solution is a simplification of reality, as salts can be found as ions in the bound water fraction or in the form of salt crystals. We assume that the salinity measured in the field equals the soil water salinity that influences $\varepsilon''_w$, and consequently the dielectric constant of the soil. In sensitivity tests (not shown), we found that the saline–water Double Debye dielectric model [50] created by William Ellison [51] produced very similar results to [19].

B. Forward $T_B$ Simulations

To understand the forward (and inverse) simulations with the adjusted RTM, a global sensitivity analysis of the modeled forward $T_B$ to various RTM input parameters was performed, considering first-order interactions between the various RTM input parameters. Sobol’s sensitivity indices [52] were computed to quantify how much an individual input parameter contributes to the variance in $T_B$ (either at $H_p$ or $V_{pol}$), using Monte Carlo simulation with $10^5$ samples. The framework of [53] was used to calculate Sobol indices for eight input parameters [$SM, T_5, S, porosity (P), wilting point (wp), VWC, h_{min}, and \omega$], with the margins based on the field campaign or literature (Lit2 [56]). The global sensitivity analysis is followed by a local sensitivity analysis focusing only on the influence of $S$ on $T_B$.

Next, forward $T_B$ simulations were performed using either up-scaled in situ data or CLSM input of $SM, T$, and vegetation for the sampled EASEv2 pixels. For both in-situ-based and model-based $T_B$ simulations, the RTM ran twice: once with and once without salinity as an input variable. $H_{pol}$ and $V_{pol}$ $T_B$ simulations at 40° incidence angle were evaluated with SMAP and SMOS $T_B$ observations at the time of the satellite overpass. The difference between both sensors is small (<3 K difference between SMAP and SMOS $T_B$ over land [54, 55]) and therefore SMOS and SMAP $T_B$ were used together to ensure sufficient observations for the evaluation of $T_B$ simulations at the time of field sampling.

The input of up-scaled in situ and CLSM $SM$ and $T$ ($T_5$ and $T_{soil}$) was as described in Section II-F and C, respectively. When $T_B$ was simulated with in-situ-based input, the LAI was obtained using MODIS imagery at the sampling time, whereas the $T_B$ simulation with CLSM input used CLSM LAI values based on the multiyear average seasonally varying GEOLAND2 climatology (Section II-C). For in-situ-based simulations, the vegetation-related lookup RTM parameters were based on the vegetation class observed in the field, whereas for the model-based simulations, lookup RTM parameters were based on the MODIS IGBP vegetation class used in the CLSM RTM. For both in-situ- and model-based simulations, the soil-related RTM parameters were based on the HWSD (Section II-G) and $T_B$ simulations that account for salinity use the in situ salinity measurements. The lookup table values for the parameters $b_p$, $LEWT$, $\omega_p$, $h$, and $N_{tp}$ per vegetation class were compiled from literature and are referred to as “Lit2” in [56].

C. Retrieval of Land Surface Properties

To retrieve land surface properties over the entire Dry Chaco, including RTM parameters related to salinity, vegetation optical depth $\tau$, microwave roughness $h$, and scattering albedo $\omega$, the RTM was used in inverse mode for each pixel individually. To estimate multiple unknowns, multiple types of independent observations and constraints are needed. An important complexity is that the presence of water and salinity both affect the $\varepsilon$ and subsequent $T_B$ simulations. Therefore, the estimation of salinity requires a priori knowledge or strong constraints for the other (more dominant) variables that influence $T_B$.

The multiangular (seven incidence angles [30°, 35°, ..., 60°]) and dual-polarized SMOS $T_B$ of the previous decade (July 2010–November 2019) were used as observational constraint, and CLSM-based $SM$, LAI, and $T$ input data (either with or without CLSM $T_{soil}$ bias correction, i.e., $T_5$ or $T_{soil}$) were used as modeled background constraint (i.e., assumed to be known) to 1) find parameters that are consistent with the modeling system and suitable for a subsequent forward RTM application, and 2) to exclude the dominant influence of SM and $T$ from the $T_B$ signal to retrieve less dominant factors. A set of parameters ($\alpha [-]$) was calibrated (or "retrieved") to minimize the multiangular and multipolarization misfit between long-term mean values and standard deviations of SMOS observed $T_B$ ($T_{obs}$) and forecasted $T_B$ [4$T_B(\alpha)$], following the procedure of [57], [58], i.e., using a Bayesian optimization with inclusion of priori parameter constraint. The $T_B(\alpha)$ were forecasted using the RTM [(1)] with CLSM-based input data.
The calibrated parameters included \( h \text{min} \) and \( \Delta h = h \text{max} - h \text{min} \) to parameterize an SM-dependent \( h \), the scattering albedo \( \omega \) \([1(1)]\) (here polarization-independent), \( b_h \) and \( \Delta b = b_v - b_h \) \([3]\) to parameterize the LAI-dependent \( \tau_p \) (i.e., five parameters), either with or without two additional parameters that mimic the presence of salinity: \( s_a \) and \( s_b \). In line with field experiments \([21]\), the \( s_a \) and \( s_b \) parameters describe that over time, when \( SM \text{ (m}^3\text{m}^{-3}\) decreases, \( S \text{ (PPT)} \) increases at a single pixel:

\[
S = s_a + s_b \times SM. \tag{7}
\]

The initial values and ranges were set to \( s_a = 5 \text{ [0.35] PPT} \) and \( s_b = -10 \text{ [-88 0] PPT/(m}^3\text{m}^{-3}\) based on trial-and-error \([59]\). The proposed equation does not consider temporal variation of salt mass in the soil caused, for example, by ongoing evaporation. A physically more complex alternative salt model formulation could not be justified, for lack of large-scale salinity observations to support it (and it will be shown later that the calibrated \( S \) does not actually reflect salinity but a bulk correction to the dielectric constant).

After calibration of \( s_a \) and \( s_b \) \([7]\) can be used to calculate \( S \) per pixel at any time, given its \( SM \) value. This allows for an evaluation of \( S \) for specific days of the field campaign, but our main evaluation will focus on spatial patterns in long-term 10-year average \( \langle S \rangle \) estimates. In line with \( S = f(s_a, s_b, SM) \), it should be noted that \( h = f(h \text{min}, \Delta h, SM) \) depends on time-varying \( SM \), and \( \tau_p = f(b_p, LAI) \) depends on time-varying LAI, and we will evaluate the 10-year average \( \langle h \rangle \) and \( \langle \tau \rangle \), where the latter is also an average of \( \tau_p \) at \( H_{pol} \) and \( V_{pol} \).

Four calibration cases were considered. In a reference case, the same five parameters \([\alpha]\) were calibrated as in \([57, 58]\) without inclusion of salinity or any correction to CLSM input variables, similar to what is used for the RTM calibration of the SMAP L4_SM product \([5]\). The three other cases either 1) include an in-situ-based bias-correction to CLSM \( T_{\text{soil1, in}} \) input, or 2) include the calibration of two additional parameters related to salinity (equivalents), or 3) include both 1) and 2).

The optimization was performed with a Markov Chain Monte Carlo algorithm, i.e., Differential Evolution Adaptive Metropolis with parallel direction and snooker sampling from past states \([\text{DREAM(ZS)}]\) \([60]\), with the same settings as in \([58]\). A major advantage of this method is that it provides the entire posteriori density distribution of the parameter estimates, i.e., with access to the maximum a posteriori density (or “best”) and ensemble mean parameter estimates, and the associated ensemble standard deviation. The latter quantifies the uncertainty of the retrievals.

The multitemporal retrieval approach with strong background constraints of modeled \( T \) and \( SM \), and the imposed inverse temporal relationship between \( SM \) and \( S \) limit the possibilities for equifinality: if \( S \) and \( SM \) would be retrieved simultaneously at individual time steps without strong background constraints, multiple combinations of \( SM \) and \( S \) would be found to be equally good. However, imposing modeled background \( SM \) also holds the risk that the \( S \) retrievals compensate for biases in the background data, as will be discussed below. Keeping the multitemporal approach and including a long-term \( T \) and \( SM \) bias estimation in the retrieval is feasible and recommended for future research.

IV. RESULTS

A. Data Analysis: Satellite Pixels With In Situ Sampling

We start with an inspection of the surface \( S, T (T_{\text{surf}}, T_{\text{soil1}}, \text{or } T_5) \), \( SM \), and vegetation in the sampled EASEv2 pixels, observed in situ or with satellite data, and simulated with CLSM. Given that the temperature shows a strong diurnal cycle, whereas the other variables are nearly constant within a day in this region during the dry season, we analyzed \( T_{\text{surf}}, T_{\text{soil1}}, \text{and } T_5 \) at individual sample times within a day, whereas in situ \( SM \) and salinity samples were first aggregated to an upscaled daily value prior to comparison with model and satellite data as discussed in Section II-F.

For \( S \), Figs. 1 and 4(a) show that two pixels with the highest in situ values \([F4 \text{ and } F5]\) are indeed located in or near areas identified as being limited due to salinity and/or sodicity in the HWSD. However, there is only a limited agreement between the in situ data and the general pattern of the HWSD, indicating that the HWSD estimates likely do not reflect surface salinity only or may not be representative of the current situation. Fig. 4(b) shows the associated \( SM \) at the times and locations of sampling. Pixels with a high in situ \( S \) [Fig. 4(a)] are also characterized by a high in situ \( SM \) [Fig. 4(b)].

For \( SM \), Table II gives an overview of spatiotemporal accuracy metrics, for various \( SM \) products for the 26 sampled EASEv2 pixels, where in situ \( SM \) is upscaled and each 36-km EASEv2 pixel is sampled only once. CLSM \( SM \) does not correlate well with in situ data, SMOS, or SMAP retrievals. The in situ measurements, on the other hand, have a high correlation \((R \sim 0.7)\) with SMOS and SMAP \( SM \) retrievals. The RMSD values are similar for model or in situ \( SM \) compared to satellite observations. Fig. 5(a) further illustrates that the bias between CLSM and SMAP \( SM \) is only \( 0.02 \text{ m}^3\text{m}^{-3}\) when computed across the years 2015–2019 and all 26 sampled EASEv2 pixels. For some individual pixels, however, large biases between in situ
Fig. 5. Comparison of (a) CLSM SM against 5 years of SMAP SM retrievals for the 26 sampled EASEv2 pixels (August 2015–2019). (b) CLSM soil surface temperature \( T_{surf} \) against in situ (IS) \( T_5 \) measurements at all sample sites of the field campaign. (c) CLSM soil temperature \( T_{soil1} \) (July–August 2019). Also shown is the 1:1 line. The blue dots represent pixels (3 of the 26) with an \( S > 4 \) PPT.

TABLE II

| Comparison of Different SM Data Products at 26 In Situ Pixels Sampled in July and August 2019 |
|---------------------------------------------------|-------------------|-------------------|-------------------|-------------------|
| Model                                             | R \([-\)          | RMSD [m³/m³]     | Bias [m³/m³]     | R \([-\)          | RMSD [K]         | Bias [K]         | In situ          |
| SMOS                                             | 0.32              | 0.08             | -0.01            | 0.71              | 0.08             | 0.05             |
| SMAP                                             | 0.14              | 0.06             | -0.03            | 0.73              | 0.07             | 0.03             |
| Model                                            | -                 | -                | -                | 0.09              | 0.11             | 0.06             |

The bias is relative to the reference product in the corresponding major row header. Correlations in boldface are significant at a level of \( \alpha = 0.05 \).

\( T_5 = 1.20 T_{soil1} - 52.44 \)  \( (8) \)

Equation (8) was thus used to rescale the model \( T_{soil1} \) at SMOS or SMAP satellite overpass times (at \( \sim 6 \) am or 6 pm local time) to obtain either extrapolated “in-situ-based” \( T_5 \) estimates for each visited EASEv2 pixel, or “bias-corrected” model \( T_{soil1} \) estimates in forward or inverse RTM simulations, as introduced in Section II-F.

Finally, the observed vegetation at the sampled pixels is either dominantly agriculture, open shrubland, or mixed forest, as summarized in Fig. 2(d). Fig. 4 illustrates that the sampled area is in the transition zone between agricultural, shrubland, and broadleaf dry forest. It is thus not surprising that only for 6 out of the 26 sampled pixels, the assignment of the model-based vegetation classes agrees with the field-based classification. Furthermore (not shown), the MODIS observed LAI is typically higher for the agricultural areas than for the dry forest during the field campaign.

**B. Data Analysis: Dry Chaco Region**

Satellite observations of \( T_B \) for the entire Chaco area give an integrated view of the land surface. Fig. 6(a) and (b) show 10-year averages of SMOS \( H_{pol} \) and \( V_{pol} \) \( T_B \) at 40° incidence angle, and the corresponding (cross-masked) 10-year averages of CLSM simulations of \( SM \) [Fig. 6(c)] and \( T_{soil1} \) [Fig. 6(d)]. The model \( T_{soil1} \) simulations show a smooth gradient over both the Dry Chaco and the area east of it (Humid Chaco) with higher temperatures in the northern Chaco and little differences between east and west. The 10-year average \( SM \) simulation pattern
is dominated by texture (areas with higher porosities have higher \( SM \) values) and climatological rainfall patterns. For example, the area east of the Dry Chaco is wetter both because of higher precipitation amounts and higher soil porosities. The long-term mean SMOS \( T_B \) (both \( H \)- and \( V_{pol} \)) observations combine real \( SM \) and temperature, along with vegetation information, resulting in a smoother spatial pattern than the modeled \( SM \) (which is patchy due to distinct soil hydraulic parameters associated with sharp soil class delineations), and a much stronger delineation between the Dry Chaco (high \( T_B \)) and the wetter region east of it (low \( T_B \)) than what could be expected based on CLSM \( SM \) or \( T_{soil} \) alone. In the northern Chaco, the denser forest vegetation in combination with the higher temperature contributes to the higher observed \( T_B \) values.

Some interesting features in the \( T_B \) patterns are highlighted in Fig. 6(a) and (b). The zoom in Fig. 6(a) is situated in the mid-west part of the Dry Chaco, and shows local low \( T_B \) and some missing pixels surrounding the Tucuman and Santiago Del Estero area of the field campaign. Pixels in the presence of a lake are filtered in the satellite data (Fig. 1), and land conversion in the area might contribute to the local decreases in \( T_B \). The zoom in Fig. 6(b) shows linear features spanning from east to north-west in the northern part of the Dry Chaco, matching the floodplains of the Bermejo and Pilcomayo River and areas with high excess salinity in the HWSD map. The same features can be found in the simulated \( SM \) map [Fig. 6(c)], but less distinctly than in the \( T_B \) map, nicely illustrating how the \( T_B \) pattern gives an integrated view of the land surface.

C. Forward \( T_B \) Simulations

Fig. 7(a) and (b) gives an overview of the first-order and total Sobol indices for \( T_B \) at \( H \)- and \( V_{pol} \) for soil- and vegetation-related RTM parameters, respectively.

This global sensitivity analysis confirms that \( SM \), \( T_5 \), vegetation, and roughness parameters have a significant contribution to the output \( T_B \) variability, whereas \( S \) only has a small influence. Therefore, we will use strong constraints of \( SM \) and \( T_5 \) (model background assumed to be known) in the following retrieval analysis to potentially tease out the marginal impact of the \( S \) signal.

The above analysis was supplemented with a local sensitivity analysis. Table III gives an overview of the simulated \( T_B \) sensitivity to \( S \) for a range of other RTM input variables. It should be noted that the tested salinity range of \( \Delta S = 35 \text{ PPT} \) is a stretch for most soil–water mixtures, i.e., values above \( 30 \text{ PPT} \) were only found in soils near salt lakes within the Dry Chaco. The change in \( T_B \) (\( \Delta T_B \)) for a \( \Delta S \) of \( 35 \text{ PPT} \) is limited to \(-3.6 \text{ K} \) at \( H_{pol} \) and \(-2.8 \text{ K} \) at \( V_{pol} \) for average field conditions marked as “initial settings” (open shrubland, loamy soil, \( T = 288 \text{ K}, \, SM = 0.2 \text{ m}^3/\text{m}^3 \), and \( \text{LAI} = 0.3 \)). Using uncalibrated “Lit2” values [56] for RTM parameters, such as \( b_{\text{min}}, b_{\text{max}}, \omega \), \( b_h \), and \( b_c \). However, the sensitivity \( |\Delta T_B| \) increases to \( \approx 7 \text{ K} \) with increasing \( T \), increasing \( SM \) (in correspondence with literature [61]), and decreasing \( \text{LAI} \). Note that if the canopy temperature \( T_c \) is varied independently from \( T \) and the sensitivity of \( T_B \) to salinity increases with decreasing \( T_c \) (not shown). Vegetation classes with a denser canopy cover, such as forests, lower the \( T_B \) sensitivity to soil salinity.

Fig. 8 illustrates the forward simulation via full time series of input variables and simulated \( T_B \) for one random pixel of the field campaign (EASEv2 pixel A1) for 1) 10 years with SMOS data and 2) the months of the field campaign. While model-based \( T_B \) simulations correctly follow the pattern of the satellite \( T_B \) observations, the absolute value is underestimated by as much as \( 20 \text{ K} \) because the model \( T_{soil} \) is not bias corrected here and the RTM parameters are not locally tuned. In contrast, the \( T_B \) simulation using in situ data at the day of field sampling agrees well with the satellite \( T_B \).

Both the model- and in-situ-based \( T_B \) simulations at the time and location of the sampled EASEv2 pixels were compared with the closest SMOS (~6 am/pm local time) and SMAP (~6 pm/am local time) \( T_B \) on the sample day. Table IV gives a summary of the (spatiotemporal) accuracy metrics using a total of 31 satellite \( T_B \) observations (both SMOS and SMAP, am and pm overpasses were combined to ensure a sufficiently large sample size) for the visited EASEv2 pixels. For some of the 26 pixels, no satellite \( T_B \) observation was found at the day of field sampling, for other pixels multiple overpasses were available. The in-situ-based
TABLE III

| Variable                | Initial | Range       | Effect on $T_B$ | Effect on sensitivity of $T_B$ to salinity (0 PPT – 35 PPT) |
|-------------------------|---------|-------------|-----------------|---------------------------------------------------------------|
| $T$ ** [K]              | 288     | [275 300]   | $T_B$ increases with $T$ | Sensitivity increases with rising $T$; $\Delta T_B$ is minimally $-7$ K at $T = 300$ K |
| $SM$ [m$^3$/m$^2$]      | 0.2     | [0.1 0.4]   | $T_B$ decreases with $SM$ | Sensitivity increases with rising $SM$; $\Delta T_B$ is minimally $-5$ K at $SM = 0.4$ m$^3$/m$^2$ |
| LAI [m$^2$/m$^2$]       | 0.3     | [0.1 3]     | $T_B$ increases with LAI | Sensitivity decreases with rising LAI; $\Delta T_B$ is minimally $-4$ K at LAI = 0.1 m$^2$/m$^2$ |
| Vegetation class        | 7: Open shrubland | [1 16] | Mixed effect | Lower sensitivity in denser vegetation covers; $\Delta T_B$ is minimally $-6$ K for grass- and wetlands |
| Soil class              | 2: Loamy sand | [1 12] | Mixed effect | Sandy classes have slightly higher sensitivity; $\Delta T_B$ is minimally $-4$ K for silt loam texture |

**Changing soil temperature $T$ simultaneously changes canopy temperature $T_c$ and the soil water temperature, which are all assumed equal.

RTM parameters depend on the vegetation class and are taken from literature-based lookup table “Lit2” in [53]. The last column quantifies the difference in $T_B$ ($\Delta T_B$) for a difference in $S$ ($\Delta S$) of 35 PPT.

Fig. 8. Time series illustrating the concept of forward simulation with the RTM for EASEv2 pixel A1, for (a) 10 years and (b) months of July and August 2019, when the field campaign took place. The top three panels show the CLSM LAI, SM, and $T_{soil1}$. The lowest two panels depict the observed $V_{pol}$ and $H_{pol}$ $T_B$ by (red dots) SMOS, (black dots) SMAP, the (•, indicated by the arrows) in situ-based $T_B$ simulation on the exact day of measurement in the field, and the (black line) model-based $T_B$ simulations.

forward $T_B$ simulations correlate better with satellite $T_B$ observations than model-based $T_B$ simulations, especially at $V_{pol}$. The low correlation between model-based $T_B$ simulations and $T_B$ observations is most likely due to the low correlation between $S$ and the model and in situ or satellite $SM$, and because the (soil- and vegetation-related) lookup RTM parameters are associated with model-based vegetation classes that differ from those observed in situ. $T_{soil1}$ bias correction adds bias to the $V_{pol}$ and reduces the bias in the $H_{pol}$, but generally brings the model-based $T_B$ simulations closer to the in-situ-based simulations. Across the 31 sample points, Table IV indicates a relatively small average $T_B$ bias compared to literature [57], but the ubRMSD suggests that large compensating differences are found across the sampled pixels.

In line with the low sensitivity of $T_B$ to $S$, there is a slight but consistent increase in $T_B$ simulation performance when $S$ is included. At $H_{pol}$, the R value increases from 0.77 to 0.79 and at $V_{pol}$ from 0.80 to 0.83. For saline pixels, defined as EASEv2

TABLE IV

| SPATIOTEMPORAL PERFORMANCE METRICS FOR THE FORWARD $T_B$ SIMULATIONS USING EITHER IN SITU (IS) OR MODEL DATA (M) INPUT WITHOUT OR WITH (+ S) IS SALINITY INPUT |
|-----------------|---------|----------|----------|----------|---------|
| Variable        | R [−]  | RMSD [K] | Bias [K] | ubRMSD [K] |
| $H_{pol}$       |         |          |          |           |
| $T_B$ IS        | 0.77    | 12.70    | -0.53    | 12.69    |
| $T_B$ IS + s    | 0.79    | 12.62    | -0.44    | 12.61    |
| $T_B$ m         | 0.18    | 25.74    | -9.35    | 23.98    |
| $T_B$ m + s    | 0.17    | 25.85    | -8.89    | 24.24    |
| $T_B$ m + s*   | 0.18    | 24.76    | -4.33    | 24.38    |
| $V_{pol}$       |         |          |          |           |
| $T_B$ IS        | 0.80    | 9.49     | 6.23     | 7.17     |
| $T_B$ IS + s    | 0.83    | 9.24     | 6.20     | 6.86     |
| $T_B$ m         | 0.13    | 14.67    | 0.77     | 14.56    |
| $T_B$ m + s    | 0.12    | 14.84    | 1.02     | 14.80    |
| $T_B$ m + s*   | 0.13    | 16.12    | 6.07     | 14.93    |

The $T_B$ simulations marked with * use bias-corrected $T_{soil1}$. The reference $T_B$ observations (obs) include all available SMOS and SMAP (together) $T_B$ at 40° incidence angle collected for the times and EASEv2 pixels of the field sampling. Correlations in boldface are significant at a level of $\alpha = 0.05$. The $T_B$ simulations marked with * use bias-corrected $T_{soil1}$. The reference $T_B$ observations (obs) include all available SMOS and SMAP (together) $T_B$ at 40° incidence angle collected for the times and EASEv2 pixels of the field sampling. Correlations in boldface are significant at a level of $\alpha = 0.05$.
pixels with in situ $S > 4$ PPT, accounting for $S$ causes an increase in $R$ from 0.66 to 0.70 at $H_{\text{pol}}$ and from 0.72 to 0.79 at $V_{\text{pol}}$. Given the small sample size, no statistically significant model improvement can be proven, but this finding shows that $S$ can have a locally important impact on $T_B$.

**D. Retrieval of Land Surface Properties**

The above $T_B$ simulations were limited to some in-situ sampled EASEv2 pixels, and indicated that the spatial pattern of CLSM input and lookup RTM parameter values were not ideal to represent the observed $T_B$. In a next step, the long-term (2010–2019) discrepancy between simulated and observed $T_B$ was leveraged to estimate some RTM properties at each pixel of the entire Dry Chaco. More specifically, vegetation, soil roughness, and possibly salinity, and their uncertainty, were estimated via RTM inversion, using CLSM background information of $T_S$ and $SM$ [which have a dominant effect on $T_B$, Fig. 7(a)]. The resulting estimates can be used as parameters for future forward RTM applications with consistent CLSM background information, or they can be interpreted as retrievals which are constrained by model background information (on $SM$ and $T$).

Fig. 9 shows the spatial distribution of the “best” and ensemble mean estimate for four diagnosed parameters retrieved (i.e., calibrated) with DREAM$_{(\text{ZS})}$ over the 569 EASEv2 pixels located within the Dry Chaco, for two calibration cases. The reference calibration optimizes five parameters without inclusion of $S$ or $T_{\text{soil1}}$ bias correction. The second case calibrates seven parameters, including $s_a$ and $s_h$ (to diagnose $S$), and applies a $T_{\text{soil1}}$ bias correction. For the latter, the spatial average best or ensemble mean value ± the spatial average ensemble standard deviation is also shown. The ensemble standard deviation is an indication of the retrieval uncertainty. In any case, the RTM inversion yields spatially continuous parameter values, unlike the literature-based values associated with the few different vegetation classes in the region. Not explicitly shown is that the difference in distributions for the two calibration experiments is due to the $T_{\text{soil1}}$ bias correction, whereas the calibration of $S$ has no significant impact on the spatial distribution of the retrieved parameters.

Overall, the inversion (or RTM calibration) yields realistic estimates of vegetation (long-term LAI-based vegetation optical depth $\langle \tau \rangle$ and scattering albedo $\omega$) and roughness (long-term $SM$-based $\langle h \rangle$) with a low associated uncertainty. Including a bias-correction of $T_{\text{soil1}}$ results in lower $\langle h \rangle$ and higher $\langle \tau \rangle$ (via higher $b$ parameters) and $\omega$ values.

The $\langle \tau \rangle$ estimates were evaluated against independent vegetation products, i.e., 2015–2019 average $\langle \tau \rangle$ retrievals from SMOS and SMAP, and 2010 AGB estimates. Fig. 10 illustrates that both (a) without and (b) with $T_{\text{soil1}}$ bias correction, a high spatial correlation is found between long-term best estimates of $\langle \tau \rangle$ and long-term SMOS-IC $\langle \tau \rangle$ ($R \approx 0.95$), long-term SMAP $\langle \tau \rangle$ ($R = 0.85–0.90$), and 2010 AGB estimates ($R \approx 0.80$), at locations where SMAP retrievals are assumed to be of high quality [i.e., excluding areas with too dense vegetation, indicated in Fig. 10(c)]. To assess the usefulness of the AGB dataset for 2010 to evaluate climatological $\langle \tau \rangle$ retrievals, we also computed the correspondence between the retrieved $\langle \tau \rangle$ with the SMOS-IC $\langle \tau \rangle$ for the year 2010, resulting in $R = 0.92$ and RMSD = 0.07 [–]. Land use changes in the area typically result in local mosaic patterns that probably have not significantly changed the coarse-scale $\tau$ patterns over the last decade. Again, the differences between Fig. 10(a) and (b) are mainly due to the $T_{\text{soil1}}$ bias correction, and the results only marginally differ with or without inclusion of $S$ calibration.

The smaller and lighter markers in Fig. 10(a) and (b) show that in dense vegetation areas (high $\langle \tau \rangle$ values) the inclusion of a $T_{\text{soil1}}$ bias correction possibly leads to an overestimation of absolute $\langle \tau \rangle$ values, esp. compared to the SMAP $\langle \tau \rangle$ (RMSD metrics not reported; too few high r values left after applying quality control). This finding, combined with locally increased misfits between long-term mean $T_B$ observations and $T_B$ simulations in case of $T_{\text{soil1}}$ bias correction (not shown), leads to the conclusion that our in-situ-based $T_{\text{soil1}}$ bias correction is not suitable everywhere, and that the use of $T_{\text{soil1}}$ as input for the SMAP L4_SM RTM is justified for this area.

Even though the calibration yields realistic estimates of $\langle \tau \rangle$, $\omega$, and $\langle h \rangle$ with a low associated uncertainty, Fig. 9 shows that the (10-year average) $\langle S \rangle$ takes on unrealistically high values in the Dry Chaco, especially so when the “best” values for $s_a$ and $s_h$ are used in the calculation of $S$. The retrieved space–time average value for the pixels sampled during the field campaign is ~12 PPT when $\langle S \rangle$ is calculated using the ensemble mean $s_a$ and $s_h$ values and ~28 PPT when the best values for $s_a$ and $s_h$ are used, whereas the average surface salinity measured in situ, which comprised only a small part of the Dry Chaco, was 4 PPT. Furthermore, the $S$ estimates computed at the sample days do not at all correlate ($R = -0.19$) with in situ measurements for the EASEv2 pixels of the field campaign. Fig. 9 also highlights a large ensemble uncertainty on the $\langle S \rangle$ estimates and a large discrepancy between the “best” estimate and the ensemble mean estimate, which is indicative of a wide and skewed a posteriori
Fig. 10. Comparison of long-term mean retrieved $\langle \tau \rangle$ (without and (b) with inclusion of $T_{soil1}$ bias correction against (black) SMOS $\langle \tau \rangle$, (red) SMAP $\langle \tau \rangle$, and (blue) linearly rescaled 2010 AGB ($AGB_{rs}$). $S$ calibration is included, but does not affect the skill metrics. The “best” $\langle \tau \rangle$ values are shown; the metrics are the same for the ensemble mean $\langle \tau \rangle$ values. The lighter and smaller markers correspond to (cyan) AGB and (gray) SMOS estimates where SMAP retrievals are masked out, and these are not included in the skill metrics. (c) Distribution of 36-km AGB values. Markers with black edges correspond to grid cells where quality SMAP retrievals are found.

Fig. 11. (a) 10-year averaged retrievals of the ensemble mean correction of the dielectric constant in terms of salinity $\langle S \rangle$ [PPT], calibrated without $T_{soil1}$ bias correction. (b) 2015–2017 standard deviation of AMSR2 open water fraction.

V. DISCUSSION

An evaluation of satellite-based SM retrievals using in situ measurements at the large 36-km pixel scale has so far only been done for a few dedicated calibration and validation (Cal/Val) sites [62]. For this article, in situ measurements were collected within 26 different satellite pixels during the dry season in the Dry Chaco and—despite the small sample size—they confirmed that SMOS and SMAP SM retrievals agree well ($R \sim 0.7$), and better than CLSM simulations, with ground measurements. However, when including all SMAP retrievals across the years 2015–2019, the CLSM simulations only showed a small bias of 0.02 m$^3$/m$^3$ across the sampled pixels, and a noteworthy wet bias in the retrievals for saline pixels (Fig. 5). The latter indicates that missing salinity may affect the SM retrievals because the salinity decreases $T_B$ by a few K, especially for high $T$ and low LAI, as in the Dry Chaco. As a rule of thumb, a 2–3 K decrease in $T_B$ (40˚) corresponds to an increase of 0.01 m$^3$/m$^3$ in SM retrievals [63].

The sensitivity analysis (Table III) showed that the influence of salinity on $T_B$ is only a few K, and thus is close to the uncertainty on individual (single angle) SMOS $T_B$ observations ($\sim 4$ K), and only marginally above the $T_B$ differences ($< 3$ K) between SMOS and SMAP sensors. This necessitates the combined use of multiple $T_B$ observations and strong modeled background information to tease out the influence of salinity on the $T_B$.

The long time series of multiangular and multipolarization SMOS $T_B$ data was used to obtain reliable retrievals of vegetation ($\tau, \omega$) and microwave roughness ($h$), but the retrieval of salinity ($S$) did not return realistic values and did not significantly affect the retrieval of other land surface properties. The unrealistic high $S$ values contrast with our own fieldwork and the level of dryland salinization indicated in literature, that is, the observed surface salinity is still low at this time, whereas the salinity is higher mainly in deeper layers (see Appendix 1). Because of the low sensitivity of the $T_B$ simulations to $S$, the low observed surface $S$, and the low spatial resolution of L-band radiometers, subpixel heterogeneity makes it hard to disentangle $S$ from other inaccurate sources of input to the $T_B$ signal, which explains the uncertainty in the $S$ retrievals. The $S$ estimates compensate for errors introduced in the computation of the dielectric constant $\varepsilon$ by inaccurate data other than salinity. For example, southeast of the Dry Chaco, the calibrated salinity equivalents are almost
certainly compensating for missed open water, organic material, and underestimated CLSM SM. Fig. 11(b) confirms that the area southeast of the Dry Chaco experiences temporal ponding, which is not included in the CLSM background simulations, and which was not persistent enough to flag SMOS $T_B$ prior to the inversion. The high S equivalents are effectively increasing $\varepsilon''$, resulting in a higher magnitude of $\varepsilon$, similar to how higher water amounts would affect $\varepsilon''$.

The retrieval approach could be further elaborated by improving the strong model background constraints, or by adding more observational constraints, e.g., by including information on water ponding. In this article, long-term $T_B$ signature statistics were optimized, using 1) simulated $T$ and $SM$ and 2) imposed time series relationships between $S$ and $SM$. While the first constraint ensures temporally and spatially consistent fields of RTM parameters that are readily applicable for forward modeling in a land surface data assimilation system [5], it may also introduce bias in the $S$ (and other) retrievals. The bias in the large-scale CLSM $SM$ and $T$ could originate from the MERRA-2 forcings or CLSM parameters. Such biases are unavoidable, unless extensive in situ observations are available for model optimization. Including a calibration of the long-term $SM$ and $T$ background bias as part of the inversion may reduce this problem. We verified (results not shown) that by keeping the modeled $SM$ dynamics, but including a rescaling factor (bias correction) for $SM$ (and consistent porosity) in the calibration, the $S$ values significantly decreased (by on average 5 PPT), and the inclusion of an $S$ retrieval has a local impact on the magnitude of the $SM$ rescaling factor. The latter reinforces that $SM$ retrieval might locally be affected when high $S$ is present. If available, it can be recommended to include knowledge about $S$ as ancillary information (constraint) to improve $SM$ retrieval accuracy over salt-affected areas. The constraint on the relationship between $S$ and $SM$ could also be improved by a more elaborate physically based model, which would then allow to better estimate the temporal variation of $S$.

Finally, the low spatial resolution of passive microwave remote sensing is great for large-scale ecosystem monitoring, but not ideal for agricultural applications. Even the largest farms in Argentina are on average only half the size of the SMOS and SMAP pixel scale [64]. Finer resolution active microwave data could solve that problem of spatial resolution, but decomposing the backscatter signal is not trivial.

VI. CONCLUSION

The Dry Chaco is a biogeographical region with a distinct land surface characterized by dry forest and expanding agriculture, possibly threatened by a changing water distribution and salinization. This article highlights limitations and possibilities of various data sources in capturing coarse-scale surface soil moisture ($SM$), soil temperature, soil salinity ($S$), and vegetation in the Dry Chaco. More specifically, we examine L-band microwave brightness temperature ($T_B$) observations and retrievals from the SMOS and SMAP satellite missions, CLSM simulations, and in situ measurements within 26 satellite pixels covering a part of the Dry Chaco.

First, data from an intensive field campaign in July–August 2019, CLSM simulations, and SMOS and SMAP SM retrievals are compared. Across the 26 pixels sampled in the field campaign (each observed once, on different days), the CLSM-based $SM$ does not correlate well with the in situ measurements, whereas SMOS and SMAP SM retrievals correlate much better with in situ data. The CLSM daytime surface soil temperature ($T_{surf}$) is slightly colder (2 K) than in situ temperature ($T_s$) measurements (both 0–5 cm), and CLSM’s first layer soil temperature at 5–15 cm ($T_{soil1}$) is colder by ~5 K compared to the 0–5 cm in situ $T_s$ data, due to differences in spatial (horizontal and vertical) representativeness. When comparing satellite-based $SM$ retrievals to CLSM SM across the years 2015–2019 for the sampled pixels, a wet bias in the $SM$ retrievals for saline pixels was detected.

Next, the effect of $S$ and other land surface variables on forward L-band $T_B$ simulations is quantified. To this end, we implemented the equations of [18] for saline water into the dielectric mixing model of [21] to estimate the dielectric constant of the soil–water–salinity mixture. When propagating these dielectric constant estimates through the L-band RTM, $T_B$ shows an overall low sensitivity to $S$ (decrease by ~4 K when $S$ increases from 0 to 35 PPT under average field campaign conditions, and using literature-based RTM parameters), with increases in sensitivity when $SM$ increases, vegetation decreases, or soil temperature increases. Because the 26 in-situ sampled satellite pixels have on average only an $S$ value of 4 PPT, the forward $T_B$ simulations only change marginally on average when accounting for $S$ in the RTM, but for some pixels strong local impacts are found. $T_B$ simulations using in-situ-based soil temperature and SM greatly outperform those using CLSM-based input data, when evaluated against SMOS and SMAP $T_B$ observations. In line with the SMAP L4_SM product, CLSM $T_{soil1}$ is an input to the RTM. An optional $T_{soil1}$ bias correction using the $T_s$ data of our field campaign only marginally improves the forward L-band RTM.

Finally, we use the RTM in inverse mode to estimate time-average vegetation ($\tau, \omega$), microwave roughness ($h$), and salinity and their uncertainty at each pixel within the Dry Chaco region, using Markov chain Monte Carlo simulations, 10 years of multiantennal and dual-polarization SMOS $T_B$ observations and constraints of CLSM $SM$, temperature, and LAI. The RTM inversion retrieves consistent spatial patterns for $h_{\text{min}}$, $\Delta h$ (related to microwave roughness $h$), $b_h$, $\Delta b$ (related to vegetation opacity $\tau$), and $\omega$ (related to vegetation). The calibrated pattern of 10-year average $\langle \tau \rangle$ agrees very well with independent SMOS and SMAP $\langle \tau \rangle$ retrievals ($R \geq 0.9$), and with AGB estimates. The inclusion of an in-situ-based $T_{soil1}$ bias correction in the retrieval is not recommended for the entire Dry Chaco. The inclusion of $S$ in the retrieval does not significantly alter the values of the retrieved vegetation and roughness parameters. However, the retrieved $S$ values themselves are unrealistically high with a large associated uncertainty over the Dry Chaco, but they help to slightly reduce the differences between simulated $T_B$ and SMOS $T_B$ observations. The $S$ retrievals should thus not be seen as $S$ estimates as such, but rather as a bulk correction of the dielectric constant that also compensates for inadequate CLSM SM values, neglected open water contributions, or other model deficiencies.
To retrieve soil surface \( S \) from the microwave L-band signal, the \( S \) levels should be high enough and the uncertainty on the “known” RTM input variables should be minimized to maximize the sensitivity to \( S \). For future research, we suggest improving the model background information, e.g., by including both local and seasonal soil temperature and \( SM \) bias corrections (incl. the impact of open water fraction) and more accurate soil texture information. Future research would also benefit from a study area where soil surface salinization is in a further stage than in the Dry Chaco to overcome \( T_B \) sensitivity issues at low \( S \).

APPENDIX A

At 10 locations [Fig. 1(B)], deeper soil measurements of EC and pH were collected. Like the surface soil EC measurements, the deeper EC measurements were performed in a home laboratory setting, and based on a 1:1 soil–water mixture sample. Eight of the sample locations were chosen based on deforestation history and were situated at the interface between forest and agriculture. At those locations, measurements were taken along three transects: one in the agricultural area, one in the forest, and one moving from agriculture to forest. Each of the transects consisted of two to five sample sites. A pit of approximately 40 cm deep was dug at each sample site and soil moisture, temperature, and dielectric properties were measured with the HydraGO and ThetaProbe at 5–10 and 20–40 cm depth. With a soil auger, deeper soil samples at 80–100 and 200 cm depth were collected for salinity analysis with the Hanna and YSI prodSS probes. Preparation and analysis of those samples followed the same steps as discussed for the surface soil samples. Following the same data collection strategy, a transect of six sample sites along a river and another one along an elevation gradient was sampled. Fig. 12 shows that, currently, the surface soil salinity in the Dry Chaco is still low, whereas deeper soil layers have significantly higher salinity values, and the correlation between surface and deeper salinity decreases with depth, i.e., \( R = 0.70 \) (184 samples) at 80–100 cm depth and \( R = 0.42 \) (34 samples) at 200 cm depth.

APPENDIX B

The dielectric mixing model of [22] calculates the dielectric constant of the soil based on the different constituents of the soil as follows:

1. Air: \( \varepsilon_a = 1 \).
2. Rock: \( \varepsilon_r = 5.5 + 0.2i \).
3. Tightly bound water approximated by the dielectric constant of ice: \( \varepsilon_t = 3.2 + 0.1i \).
4. Free water, \( \varepsilon_w \), based on our modified model of [19].

Further, the model differentiates between the dielectric constant of the soil when the \( SM \) content is below or above a certain transition level because the permeability to electricity differs for tightly bound water from free water. The transition water content \( W_t \) is calculated as

\[
W_t = 0.49wp + 0.165
\]

where \( wp [m^3/m^3] \) is the wilting point of the soil. When the \( SM \) content \([m^3/m^3]\) is lower than \( W_t \), the dielectric constant of the soil can be calculated as

\[
\varepsilon_{soil} = SM \varepsilon_x + (P - SM) \varepsilon_a + (1 - P) \varepsilon_r
\]

where \( P \) is the soil porosity and \( \varepsilon_x \) is the dielectric constant of the initially absorbed water, calculated as

\[
\varepsilon_x = \varepsilon_i + (\varepsilon_w - \varepsilon_i) \frac{SM}{W_t} y
\]

where \( y \) is a fit parameter: \( y = -0.57wp + 0.481 \). When \( SM \) is higher than \( W_t \), the dielectric constant of the soil can be calculated as

\[
\varepsilon_{soil} = W_t \varepsilon_x + (SM - W_t) \varepsilon_w + (P - SM) \varepsilon_a + (1 - P) \varepsilon_r
\]

with \( \varepsilon_x = \varepsilon_i + (\varepsilon_w - \varepsilon_i)y \).

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**Frederike Vincent** received the M.S. degree in bio-science engineering from the KU Leuven, Leuven, Belgium, in 2020, and the M.S. degree in international management and strategy from the Vlerick Business School, Gent, Belgium, in 2021.

**Rolf H. Reiche** received the M.S. degree (Diploma) in physics from the University of Heidelberg, Heidelberg, Germany, and the Ph.D. degree in environmental engineering from the Massachusetts Institute of Technology, Cambridge, MA, USA, in 2000. He is currently a Research Physical Scientist with the Global Modeling and Assimilation Office, NASA GSFC, Greenbelt, MD, USA. His research interests include land data assimilation, satellite-based remote sensing, and applications related to land–atmosphere interactions, weather prediction, and seasonal climate forecasting.

**Veerle Vanacker** received the M.S. and Ph.D. degrees from the KU Leuven, Leuven, Belgium. She is currently with the UC Louvain, Louvain-la-Neuve, Belgium.

**Michiel Maertens** received the M.S. degree in geography and the Ph.D. degree in bioscience engineering from the KU Leuven, Leuven, Belgium, in 2021. He is currently working with the VITO, Belgium.

**Jean-Pierre Wigneron** received the M.S./Eng. degree from the SupAéro, Ecole Nationale Supérieure de l’Aéronautique et de l’Espace (ENSAE), Toulouse, France, and the Ph.D. degree from the University of Toulouse, Toulouse, France. He is currently a Senior Research Scientist with the Institut National de la Recherche Agronomique and the Head of the INRA/ISPA remote sensing team, Bordeaux, France.

**Michel Bechtold** received the M.S. degree (Diploma) in geosciences from the University of Göttingen, Göttingen, Germany, and the Ph.D. degree in geosciences from the University of Bonn, Bonn, Germany, in 2012. He is currently holding a Research Expert position on water and carbon cycle processes with the KU Leuven, Leuven, Belgium.

**Gabrielle J. M. De Lannoy** received the M.S. degree in bioscience engineering, industrial automation, and academic education, and the Ph.D. degree in bioscience engineering from UGent, Ghent, Belgium, in 2006. She is currently a Full Professor with the KU Leuven, Leuven, Belgium, leading the research group on Land Surface Remote Sensing, Modeling and Data Assimilation. Her research interests include land data assimilation, satellite-based remote sensing, and applications related to soil moisture, snow, vegetation, and their interactions with the atmosphere and human activities.

**Esteban Jobbágy** received the M.S. degree in agronomy from the UBA Argentina, Buenos Aires, Argentina, and the Ph.D. degree in biology from the Duke University, Durham, NC, USA, in 2002. He is currently a Senior Scientist with the Universidad Nacional de San Luis, San Luis, Argentina.