FORWARD AND INVERSE L-BAND RADIATIVE TRANSFER MODELING OVER THE DRY CHACO, USING SMOS OBSERVATIONS, LAND SURFACE MODELING AND IN SITU DATA

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***Abstract*— Passive microwave L-band remote sensing is well known for its sensitivity to surface soil moisture over land. The signal is also affected by other dynamic variables such as vegetation and soil salinity. In this research, L-band microwave observations of the Soil Moisture Ocean Salinity (SMOS) mission are used to explore soil surface salinity, moisture and vegetation, in the Argentinean Dry Chaco, an area with possible emerging dryland salinity. A Radiative Transfer Model (RTM) with inclusion of a correction to the soil's dielectric constant for salinity was used in forward and inverse mode, using either in situ data or Catchment Land Surface Model (CLSM) simulations as RTM input. The forward analysis pointed out shortcomings in the modeled soil moisture and soil surface temperature estimates. The impact of salinity on forward simulations over the Dry Chaco was limited. The RTM inversion using 10 years of SMOS brightness temperature observations resulted in realistic estimates of vegetation and roughness, both with and without optimizing a correction term for the dielectric constant in terms of salinity equivalents. However, the retrieval of the correction term to the dielectric constant was very uncertain and not representative of soil surface salinity, but rather of open water, texture uncertainty or soil moisture bias.**

Keywords—L-band, SMOS, SMAP, Dry Chaco, dryland salinity, land surface modelling

I. INTRODUCTION

Soil salinity in the surface and root-zone causes the global annual loss of 1.5 million ha of productive land and that area might increase further under climate change scenarios [1]. Global soil surface salinity monitoring is limited by the lack of data with large coverage and high temporal resolution. Remote sensing has been successfully applied to explore soil salinity at a large scale, with the use of optical [2, 3, 4], and thermal remote sensing data [5, 6] and machine learning techniques [7]. Alternatively, microwave remote sensing might prove useful for salinity detection. It has been demonstrated that the dielectric constant of the soil (ε), and especially the imaginary part of ε, is influenced greatly by salinity at microwave L-band frequencies (1-2 GHz, [8]) and several authors have reported on the potential of microwave L-band data for salinity retrieval [9, 10] but so far no consistent attempts at the actual retrieval have been made. For this study, an intensive field campaign was organized in the Dry Chaco to collect land surface properties, and these data were compared to model simulations and L-band satellite observations. The South American Dry Chaco is characterized by a potential salinity hazard caused by the ongoing deforestation of its native dry forests, and forms a unique testbed for the exploration of land surface properties with L-band data.

II. METHODS

The research started with a field campaign, which took place in the Argentinean Dry Chaco in the months of July and August 2019 (Vincent et al., 2021a). Fig. 1 gives an overview of the sampled area, along with background Harmonized World Soil Database (HWSD) salinity estimates. In situ data on surface (upper 5 cm) soil moisture, salinity, temperature and ε was collected. Data was gathered at multiple points (between 3 and 27) along a transect in a 36 km Equal Area Scalable Earth version 2 grid pixel (EASEv2). A total of 26 pixels was sampled. The point samples were then upscaled to the EASEv2 grid scale by calculating a weighted average based on elevation classes within a pixel.

Next, a simple zeroth order RTM was extended to include salinity in the soil water. In the dielectric mixing model of Wang and Schmugge [11], we substituted the equations for the dielectric constant of pure water by a formulation for the dielectric constant of saline water, established by Swift and Klein [12].

After a sensitivity analysis, the RTM was used in forward mode to simulate L-band brightness temperatures (T_B). Simulations were performed using either in situ data, with or without salinity, or model simulations of the Catchment Land Surface Model (CLSM, [15]). RTM simulations were compared to SMOS (SCLF1C.v620) and SMAP (SPL1CTB.v004) level 1 T_B observations.

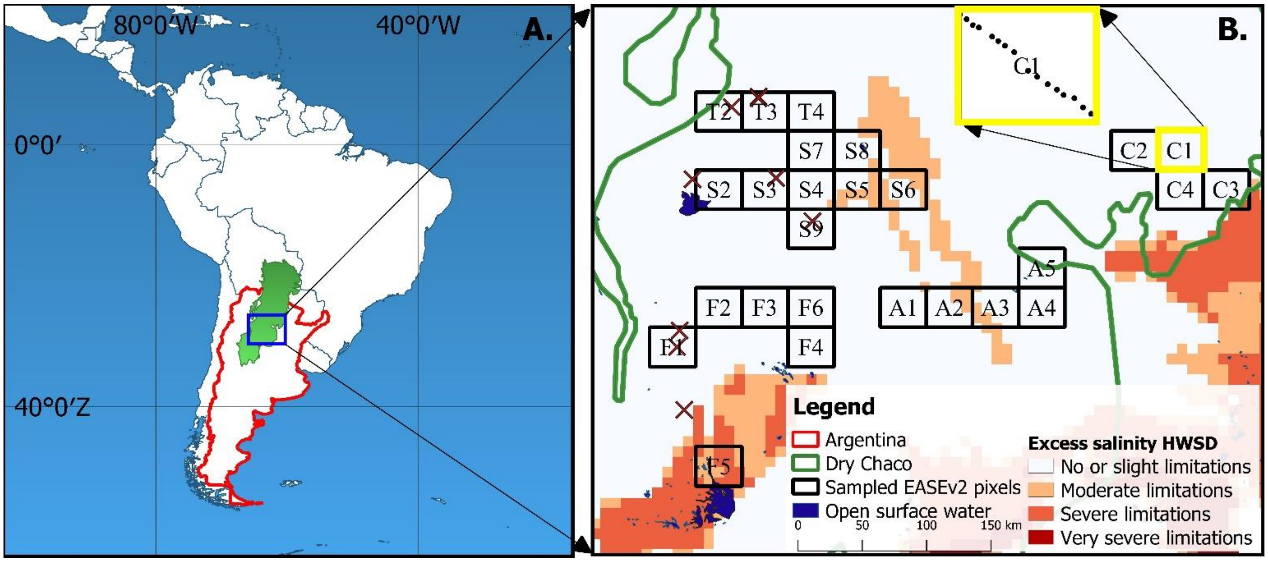

Fig. 1: A. Location of the Dry Chaco in South America with an indication of the area of the field campaign and B. the 26 EASEv2 pixels where sampling took place with in the background the Harmonized Soil World Database excess salinity map and open surface water. The zoom in illustrates the sample sites along a transect in one EASEv2 pixel.

Finally, an RTM inversion followed, using SMOS data and a Markov Chain Monte Carlo algorithm, i.e. DiffeRential Evolution Adaptive Metropolis (DREAM(zs), [13], with similar settings as in [14], to calibrate RTM parameters that characterize land surface properties related to microwave parameters and a correction to the dielectric constant, in terms of salinity equivalents. For the latter, we calibrated two parameters, a and b, to allow for the calculation of salinity (S) based on temporal soil moisture (SM) information, following:

$$S = a + b \cdot SM \tag{1}$$

Where a is assumed to be a positive number, while b is assumed negative. The equation assumes that in time, soil moisture and salinity are inversely related, as observed in field experiments by [16]. (Note that in space, wetter areas correspond to more saline areas, but this is beyond the scope of this short summary paper.) Further details about the RTM inversion are provided in Vincent et al. (2021b).

III. MAIN CONCLUSIONS

An evaluation of in situ data, CLSM simulations and satellite retrieval observations illustrated discrepancies between the in situ and model soil moisture and temperature estimates, and in situ data were therefore used for bias-correction of land surface model simulations. We established a linear regression between model and in situ temperature to bias-correct the model estimates for further use in this research. However, a comparison of subsequent RTM inversions of vegetation optical depth using the model with and without our corrected surface temperature illustrated that the in situ based correction does not perform equally well over all vegetation types and should be temporally and spatially localized in order to be suitable everywhere.

The forward T_B simulations performed better when in situ data was used versus when model data (including a temperature bias correction) was used, most likely due to poor absolute spatial estimates of CLSM soil moisture.

The addition of salinity to the RTM input did not affect the T_B simulation performance relative to SMOS or SMAP observations, confirming the low sensitivity of T_B to salinity found in the sensitivity analysis. While in the dielectric mixing model, salinity greatly influenced the imaginary part of the dielectric constant, only a small effect on the T_B is propagated throughout the RTM, hard to disentangle from alternative influences introduced by uncertainty on other RTM variables.

Both with and without inclusion of the correction to the dielectric constant in terms of salinity equivalents, the calibration of the RTM parameters using DREAM(zs) led to physically realistic RTM parameters. The vegetation opacity retrievals (VOD) in particular matched well (spatial correlation of 0.9 over the Dry Chaco) with independent observations of above ground biomass and SMOS VOD retrievals. However, the retrieval of the correction to the dielectric constant in terms of salinity equivalents (S) resulted in a very noisy and too high estimate, which could not be related to in situ observed surface salinity, and rather represents uncertainties introduced by various erroneous RTM variables such as soil moisture and texture, and missed open water.

Our study shows that the surface salinity level in the Dry Chaco is still low and does not affect the T_B much yet, which consequently does not allow to accurately retrieve salinity at the coarse scale using SMOS data. It is recommended to test salinity retrieval in an area where salinization is in a further stage than in the Dry Chaco to overcome these sensitivity issues.

However, the inclusion and calibration of a correction to the dielectric constant in terms of salinity within the RTM revealed the potential to correct ill-represented land surface properties, such as open water, absolute soil moisture level, soil texture or organic matter. It is also shown that a bias-correction to input CLSM estimates of land surface variables (temperature bias correction, dielectric constant bias correction) can locally help to obtain more realistic estimates of microwave radiative transfer parameters, which all together result in a better description of a whole set of land surface properties for the Dry Chaco.

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