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Simultaneous soil moisture and properties estimation for a drip irrigated field by assimilating cosmic-ray neutron intensity

Xujun Han [a,b,*], Harrie-Jan Hendricks Franssen [a,b], Miguel Ángel Jiménez Bello [c], Rafael Rosolem [d], Heye Bogena [a], Fernando Martínez Alzamora [c], André Chanzy [e], Harry Vereecken [a,b]

[a] Forschungszentrum Jülich, Agrosphere (IBG 3), Leo-Brandt-Strasse, 52425 Jülich, Germany
[b] Centre for High-Performance Scientific Computing in Terrestrial Systems: HPSC TerrSys, Geoverbund ABC/J, Leo-Brandt-Strasse, 52425 Jülich, Germany
[c] Institute of Water and Environmental Engineering (IIAMA), Universitat Politècnica de Valencia, Camino de Vera, s/n, 46022 Valencia, Spain
[d] Department of Civil Engineering, University of Bristol, Bristol BS8 1TR, UK
[e] INRA, UMR1114, Environnement Méditerranéen et Modélisation des AgroHydrosystèmes, Domaine Saint Paul, Site Agroparc, F-84914 Avignon, France

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SUMMARY

Neutron intensity measured by the aboveground cosmic-ray neutron intensity probe (CRP) allows estimating soil moisture content at the field scale. In this work, synthetic neutron intensities were used to remove the bias of simulated soil moisture content or update soil hydraulic properties (together with soil moisture) in the Community Land Model (CLM) using the Local Ensemble Transform Kalman Filter. The cosmic-ray forward model COSMIC was used as the non-linear measurement operator which maps between neutron intensity and soil moisture. The novel aspect of this work is that synthetically measured neutron intensity was used for real time updating of soil states and soil properties (or soil moisture bias) and posterior use for the real time scheduling of irrigation (data assimilation based real-time control approach). Uncertainty of model forcing and soil properties (sand fraction, clay fraction and organic matter density) were considered in the ensemble predictions of the soil moisture profiles. Horizontal and vertical weighting of soil moisture was introduced in the data assimilation in order to handle the scale mismatch between the cosmic-ray footprint and the CLM grid cell.

The approach was illustrated in a synthetic study with the real-time irrigation scheduling of fields of citrus trees. After adjusting soil moisture content by assimilating neutron intensity, the irrigation requirements were calculated based on the water deficit method. Model bias was introduced by using coarser soil texture in the data assimilation experiments than in reality. A series of experiments was done with different combinations of state, parameter and bias estimation in combination with irrigation scheduling.

Assimilation of CRP neutron intensity improved soil moisture characterization. Irrigation requirement was overestimated if biased soil properties were used. The soil moisture bias was reduced by 35% after data assimilation. The scenario of joint state-parameter estimation resulted in the best soil moisture characterization (50% decrease in root mean square error compared to open loop simulations), and the best estimate of needed irrigation amount (86% decrease in Hausdorff distance compared to open loop). The coarse scale synthetic CRP observation was proven to be useful for the fine scale soil moisture and soil properties estimation for the objective of irrigation scheduling.

1. Introduction

Globally, 70% of fresh water is used by agriculture (FAO – Food and Agriculture Organization of the United Nations). Therefore, it is necessary to increase the water use efficiency and reduce the water need for crop production, while maintaining crop yield. Enough water should be applied to meet the requirement of maximum crop evapotranspiration (ET). Farmers usually base irrigation scheduling on their own experience taking into account soil water status and crop growth. However, it is unlikely that the optimal scheduling of irrigation is acquired without the knowledge of crop water needs. Low cost sensors that measure soil moisture content can be of advantage. However, these sensors typically have a very small measurement volume which is much smaller than the scale of the fields where the crops are grown. Numerical models like crop growth models (Heng et al., 2009) and land surface models

* Corresponding author at: Forschungszentrum Jülich, Agrosphere (IBG 3), Leo-Brandt-Strasse, 52425 Jülich, Germany.
E-mail address: x.han@fz-juelich.de (X. Han).

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(Wood et al., 2011) can be used for the quantitative estimation of the irrigation requirement under specific soil water and crop growth conditions. The estimated irrigation amount can be applied accurately with new agricultural technology like drip irrigation (Sampathkumar et al., 2012). However, uncertain model input data and deficits in the model structure result in biased estimates of soil water status, crop transpiration and therefore irrigation requirement.

The optimal scheduling of irrigation is complicated given the high heterogeneity of soil moisture content in drip irrigated fields. An estimate of soil moisture content for the complete root zone is important in this context. It is difficult to achieve this with small-scale measurements (e.g., TDR – Time Domain Reflectometry, FDR – Frequency Domain Reflectometry or TDT – Time Domain Transmission) as a prohibitively large number of sensors is needed to cover large irrigated areas. Soil moisture information from remote sensing on the other hand is limited to the upper few soil centimeters, and often has a very coarse horizontal resolution (>10 km) (Entekhabi et al., 2010; Kerr et al., 2010; Montzka et al., 2013). A further limitation of satellite-derived soil moisture content is that it is not reliable for highly vegetated areas (Njoku and Chan, 2006) and high uncertainties (Merlin et al., 2009; Montzka et al., 2013). The spatial variability of soil moisture is controlled by soil hydraulic properties, meteorological forcing, land cover patterns and topographic features at different measurement scales. Small scale variability is more driven by soil hydraulic properties while large scale variability is also more driven by the other factors. Hence, strengths and weaknesses of each measurement method rely on the additional uncertainty given by these additional controlling factors (Crow et al., 2012).

A new promising method which can determine integral root zone soil moisture from the measured above ground fast neutron intensity (defined as the number of counted neutrons per unit of time – e.g., counts per hour) has been proposed (Zreda et al., 2012). This synthetic study focuses on the assimilation of cosmic-ray probe (CRP) neutron intensity (Bogena et al., 2013; Desilets et al., 2010; Rosolem et al., 2014; Shuttleworth et al., 2013; Zreda et al., 2008, 2012). Soil moisture measurements at the intermediate scale of the cosmic ray probe have the advantage that they are less affected by small scale variability of soil hydraulic properties. A further advantage is that soil moisture can be determined for a deeper layer (10–70 cm) in higher temporal frequency than remote sensing (Rosolem et al., 2014).

Primary cosmic rays originate from our galaxy and eventually collide with atmospheric nuclei, generating secondary cosmic rays mainly consisting of neutrons (Lal and Peters, 1967). Primary cosmic rays create cascades of secondary high-energy neutrons through colliding with atmospheric nuclei and the high-energy neutrons can penetrate the atmosphere and collide with nuclei in soils. These collisions in the soil generate fast neutrons. Some of these fast neutrons are eventually scattered back to the atmosphere and the fast neutron intensity can be measured with the CRP. The measured intensity of fast neutrons above the ground depends strongly on soil moisture content (Hendrick and Edge, 1966; Zreda et al., 2012). CRPs make use of this principle to estimate soil moisture content for an area of about 600 m diameter and variable measurement depth ($\sim$10–70 cm) depending on the soil moisture conditions (Zreda et al., 2012).

Measured neutron intensities above ground need to be corrected for variations in incoming high-energetic neutrons and atmospheric pressure (Zreda et al., 2012). Moreover, as the measured neutron intensity depends on additional sources of hydrogen (besides of soil moisture), these need to be taken into account in order to isolate the soil moisture signal. Corrections have been proposed for other hydrogen sources like atmospheric vapor (Rosolem et al., 2013), lattice water and organic carbon in the soil (Franz et al., 2013), hydrogen atoms stored in the litter layer (Bogena et al., 2013) and above-ground biomass (Baatz et al., 2015). Data assimilation studies have shown the advantage of using measured multi-source soil moisture observations for improving the soil moisture profile characterization of a land surface model (Crow et al., 2008; De Lannoy et al., 2007b; Han et al., 2012; Huang et al., 2008; Reichle et al., 2008; Walker et al., 2001). Measured neutron intensities have already been used for assimilation in a land surface model to improve estimates of soil moisture profiles, but the model parameters were calibrated a priori (Han et al., 2015a; Rosolem et al., 2014; Shuttleworth et al., 2013).

In this paper we will investigate the benefits of assimilating coarse scale (600 m) neutron intensity data into the Community Land Model (CLM) for the application of drip irrigation for citrus trees on a finer scale (100 m) than the CRP scale. The neutron intensity measured by a synthetic CRP affects a larger area than a typical irrigation management unit (1 ha in this work). In order to study the impact of soil moisture data assimilation on irrigation scheduling, the drip irrigation was therefore simulated at a finer spatial scale than the footprint of a CRP. The drip irrigation was applied at the vegetated area and resulted in a very heterogeneous soil moisture distribution with the alternation of patches of wet and dry soil. It is very CPU-intensive to explicitly model the irrigated patches and the non-irrigated parts, and a simplified implementation was adopted in this work, which will be further detailed in the methodology section. In the simulation experiments, CLM was driven by biased soil properties to mimic the intrinsic model uncertainties. The coarse scale CRP neutron intensity observations were used to update the field scale heterogeneous soil moisture field through data assimilation. The joint soil moisture and soil properties (or soil moisture bias) estimation scheme was evaluated. This is important because soil moisture content and crop transpiration are sensitive to model parameters (Hou et al., 2012; Rosolem et al., 2012; Schwinger et al., 2010). Typically, field measurements of parameter values are scarce and very uncertain, especially because of the scale mismatch between a local measurement and the model scale (Waller et al., 2014). Model parameter estimation in the context of a data assimilation framework was proven to be successful, using either an augmented state vector approach (Chen and Zhang, 2006), dual state parameter estimation (Moradkhani et al., 2005b) or parameter estimation in a loop external to the data assimilation filter (Vrugt et al., 2005). Successful applications are reported for such diverse areas as groundwater hydrology (Franssen and Kinzelbach, 2008; Kurtz et al., 2014; Schöniger et al., 2012), rainfall–runoff models (Moradkhani et al., 2005a; Vrugt et al., 2006), land surface models (Han et al., 2014a; Pauwels et al., 2009), vadose zone hydrology (Montzka et al., 2011; Wu and Margulis, 2013) and atmospheric models (Ruiz et al., 2013). A data assimilation framework can consider uncertain model forcing, model structure and initial conditions, as well as parameter uncertainties. Data assimilation has become a commonly used method for parameter estimation, especially for large scale applications (Wanders et al., 2014).

Joint soil moisture and soil moisture bias estimation has been proven to be helpful for improving data assimilation results (De Lannoy et al., 2007a; Kumar et al., 2012b) like soil temperature assimilation with bias correction (Bosilovich et al., 2007; Reichle et al., 2010). In this study, we also evaluated the impact of the soil moisture bias estimation method (Dee, 2005) on improving the soil moisture assimilation and irrigation scheduling and compared it with joint state-parameter estimation.

In Han et al. (2015a), we studied the joint updating of soil moisture, soil temperature and leaf area index by assimilating CRP neutron intensity and land surface temperature. In this study however, we considered in addition the joint updating of soil moisture and soil properties, or soil moisture and soil moisture bias, and the