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Correcting satellite-based precipitation products through SMOS soil moisture data assimilation in two land-surface models of different complexity: API and SURFEX

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ABSTRACT

Global rainfall information is useful for many applications. However, real-time versions of satellite-based rainfall products are known to contain errors. Recent studies have demonstrated how the information about rainfall intrinsically contained in soil moisture data can be utilised for improving rainfall estimates. That is, soil moisture dynamics are impacted for several days by the accumulated amount of rainfall following within a particular event. In this context, soil moisture data from the Soil Moisture Ocean Salinity (SMOS) satellite is used in this study to correct rainfall accumulation estimates provided by satellite-based real-time precipitation products such as CMORPH, TRMM-3B42RT or PERSIANN. An algorithm based on the SMOS measurements data assimilation is tested in two land-surface models of different complexity: a simple hydrological model (Antecedent Precipitation Index (API)) and a more sophisticated state-of-the-art land-surface model (SURFEX (*Surface Externalisée*)). We show how the assimilation technique, based on a particle filter method, generally leads to a significant improvement in rainfall estimates, with slightly better results for the simpler (and less computationally demanding) API model. This methodology has been evaluated for six years at ten sites around the world with different land use and climatological features. The results also show the limitations of the methodology in regions highly affected by mountainous terrain, forest or intense radio-frequency interference (RFI), which can notably affect the quality of the retrievals. The satisfactory results shown here invite the future operational application of the methodology in near-real time on a global scale.

1. Introduction

Precipitation is a key variable of the water cycle, whose estimation is crucial for many applications (Brocca et al., 2016). Accurate estimates of the amount of water which reaches the ground at specific areas in near-real time are needed for hydrological applications, including flood (Wake, 2013; Jongman et al., 2014; Casse et al., 2015; Lievens et al., 2015) or landslide (Van Asch et al., 1999; Guzzetti et al., 2007; Iverson, 2000; Pennington et al., 2014) emergency response planning. Rainfall accumulation estimates are also very important for agricultural strategy and modelling (Fisher, 1925; French and Schultz, 1984; Akponikpe et al., 2011; Ramarohetra et al., 2013). Besides, accurate precipitation data is certainly decisive for data assimilation in numerical weather prediction models, since it highly affects surface energy fluxes that will drive the evolution of the planetary boundary layer (Pielke et al., 1998) which is linked to the formation of mesoscale and/or synoptic weather systems. Finally, the link between the spatio-temporal distribution of precipitation and the freshwater availability at several regions of the Earth is crucial for decision-making to mitigate extreme situations (Hou et al., 2014; Shannon et al., 2008), such as intense droughts.

Rain gauges provide the most accurate and reliable data to obtain the amount of rainfall at a point on the Earth's surface (Lanza and Vuerich, 2009). However, the heterogeneous (temporal and spatial) characteristic of rainfall makes the use of the information provided by one (or a few) station(s) not sufficient to address the large-scale

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applications listed above. Therefore, very extensive deployment of rain gauges is needed to appropriately quantify rainfall accumulation over relatively-large areas using spatial analysis techniques (Creutin and Obled, 1982; Jones et al., 2009). This is possible in some areas of economically developed countries, such as in the United States (e.g. Allen and Naney, 1991) or France (e.g. Delrieu et al., 2004). However, in developing regions (especially those in Africa), the number of available rain gauges has decreased over the last two decades (Ali and Lebel, 2009), mainly due to maintenance costs or political unrest. In order to improve the spatial coverage of rainfall information in areas with a limited number of rain gauges, the complementary use of ground-based weather radar data is a very useful technique. However, weather radars suffer from many issues that affect the reliability of the estimates (Krajewski and Smith, 2002) and are not available everywhere in the world.

To address these issues, important efforts have devoted during the last few years to develop and improve precipitation estimates from satellites (Ebert et al., 2007). These satellite-based precipitation products (SPPs) are based on the use of infrared (IR) sensors on-board geostationary satellites and/or microwave (MW) sensors on polar satellites. IR sensors use cloud-top temperatures to indirectly infer the associated precipitation and have the advantage of a larger spatial and denser temporal coverage, but they suffer from accuracy and false-alarm issues due to the indirect retrieval of precipitation (which is not always in accordance with the brightness temperature of the cloud top). MW sensors are more accurate, since they are based on the direct signal of hydrometeors (rain, drizzle, snow or haze) falling from the cloud base, but they have a significantly lower spatio-temporal resolution (Pellarin et al., 2013). To solve this issue, information provided by IR sensors is combined with MW sensors to generate improved multi-sensor SPP. However, even using this combination, several studies have demonstrated how precipitation from these products is biased when compared to real (and spatially averaged) values observed at ground level (e.g. Prasetia et al., 2013; Cai et al., 2015). These issues can be addressed in a post-processing step by correcting the real-time SPP data with ground-based observations, such as for example in the Global Precipitation Climatology Project (GPCP) (Huffman et al., 1997; Adler et al., 2003). However, due to lags in the availability of rain gauges observations, these adjusted products are available only after several days (or even several weeks/months). Moreover, even the adjusted products can be inaccurate in some cases (e.g. Yin and Gruber, 2010).

In this context, the use of near real-time soil moisture retrieved from satellites has been demonstrated as a very promising tool to improve precipitation estimates (Pellarin et al., 2008; Brocca et al., 2013). Soil moisture has the advantage of having a useful memory of rainfall events occurring several days in the past (Seneviratne et al., 2006; McColl et al., 2017). Hence, several studies have recently used this relation with the aim of improving precipitation estimates using different methodologies. Crow and Bolten (2007) used a Kalman filter for the assimilation of soil moisture data from the Advanced Microwave Scanning Radiometer - Earth Observing Systems (AMSR-E) within an Antecedent Precipitation Index (API) model, in order to estimate errors of different SPPs in the Southern United States. Pellarin et al. (2008) also used soil moisture data from AMSR-E to remove erroneous rain events from an IR satellite sensor using the API model. Almost simultaneously, Crow et al. (2009) used a conceptually similar approach to directly correct rainfall events of several SPPs and, later, Crow et al. (2011) improved their assimilation and modelling techniques to create the Soil Moisture Analysis Rainfall Tool (SMART). A similar methodology was applied in Wanders et al. (2015), by using a particle-filter assimilation technique for correcting precipitation over the US. In a different approach, Brocca et al. (2013) and Brocca et al. (2014) used satellite soil moisture data to directly infer rainfall quantities by inverting the soil-water balance equation via the so-called SM2RAIN methodology. SMART, SM2RAIN and the API-based methodologies were recently tested in Australia in the study of Brocca et al. (2016), where soil moisture data from the Soil Moisture and Ocean Salinity (SMOS) satellite was used to correct the real-time Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA) product.

In the present study, a particle-filter (DeChant and Moradkhani, 2011; Yan et al., 2015) assimilation technique, similar - but not identical - to the one applied by Wanders et al. (2015) is applied in two models of different complexity: an API model (an improved version of the one presented in Pellarin et al. (2008)) and the more complex *Surface Externalisée* (SURFEX) land-surface model (Masson et al., 2013). To our knowledge, this is the first time that a complex state-of-the-art land-surface model is compared to a simple one for the aim of correcting rainfall by assimilating satellite soil moisture data. It is hypothesised that the use of a more complex model would improve upon the API model in some conditions (e.g., under large run-off after intense rain events or in dense-vegetated areas highly affected by evapotranspiration). The results provided by using these two models are evaluated in terms of correction for three different real-time SPPs over ten sites around the world with different land cover and climate features (e.g., surface and vegetation characteristics, rainfall climatology, latitude, and closeness to mountainous areas). Past correlation approaches were typically tested in only a few specific locations or regions (e.g. in Australia, US and/or West Africa). In this work, reliable and extensive ground-based precipitation datasets from rain gauges are available at ten diverse sites, providing an excellent framework to test the methodology under different conditions and therefore strengthen the final conclusion of a potential real-time application at ungauged locations worldwide.

The paper is organised as follows: Section 2 details the data used, the API and SURFEX models and the particle filter assimilation technique. Results are presented in Section 3 and the discussion of these results is provided in Section 4. Finally, the main conclusions are summarised in Section 5.

2. Data, models and methodology

This section is divided in three main parts. The observational data needed to perform this work are described in the first one. The second part provides a brief description of the two land surface models used and compared in this study. In the third part, the land-surface model assimilation algorithm (LMAA) is described with equations, references and an example figure.

2.1. Observational data

This study aims at improving precipitation estimates by using SMOS soil moisture retrievals combined with data from a SPP (the correction is tested for three different ones). Spatially-averaged *in situ* rainfall data from different hydrological networks are used as the reference for the evaluation of the methodology at ten sites around the world. Some additional data were also needed to initialize or to force the land-surface models. All these datasets are explained in the following subsections.

2.1.1. Satellite-based precipitation products (SPPs)

Three different satellite-based precipitation products are used: 1) The Climate Prediction Center morphing method (CMORPH) product (Joyce et al., 2004), 2) the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) product (Sorooshian et al., 2000), and 3) the TRMM-3B42RT from the Tropical Rainfall Measuring Mission real-time product (Huffman et al., 2010).

All of these products combine information from IR and MW sensors to estimate precipitation accumulation with a resolution of 3 h and 0.25°. Due to the spatial mismatch between the grid of these rainfall products and the SMOS grid, the SPP pixels which ar closest to the