Crop coefficients parameterization using remote sensing in basin-scale hydrological modelling

Parametrización de coeficientes de cultivo a partir de teledetección y su uso en modelización hidrológica a escala de cuenca

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Abstract

A distributed hydrologic model is used to evaluate how different methods to estimate evapotranspiration (ETc) influence the water balance and hydrologic response of basins. The study site, the upper Segura basin (~2500 km2) in Spain, is characterized by a wide range of terrain, soil, and ecosystem conditions. Input and calibration data for the hydrological model SPHY are obtained from best available data sources. The model was setup for a period of 15 year. Five crop coefficient parameterization methods are compared to explore the impact of spatial and temporal variations in these input datasets on actual evapotranspiration, streamflow and soil moisture. Methods include three that are based on remote sensing information; one based on FAO literature, and another that takes the crop coefficient equal to unity for the entire basin. The analysis shows that basin-level streamflow is hardly influenced by the choice in parameterization, but actual evapotranspiration and soil moisture are quite different, especially in the wet season and for the FAO-based method.

Keywords: evapotranspiration; satellite imagery; watershed hydrology.

Resumen

Se utiliza un modelo hidrológico distribuido para evaluar cómo diferentes métodos influyen en la estimación de la evapotranspiración (ETc) y el balance de agua a escala de cuenca. La zona de estudio se ubica en la cuenca alta del Segura (~ 2.500 km2) en el Sureste español, zona caracterizada por una elevada heterogeneidad de condiciones del terreno y usos del suelo. El modelo hidrológico SPHY fue desarrollado y calibrado para un período de simulación de 15 años. Se emplearon cinco métodos para parametrizar el coeficiente de cultivo y se compararon los patrones espaciales y las dinámicas temporales simuladas para la evapotranspiración, la humedad del suelo y los caudales. Tres de los cinco métodos utilizan información de satélite, otro los valores del coeficiente de cultivo establecidos por FAO, y el último asume un valor constante para toda la cuenca y periodo de simulación. El análisis muestra que la generación de caudales apenas se ve afectada por la selección del método de parametrización, aunque sí es importante a la hora de calcular la evapotranspiración real, especialmente durante épocas húmedas y para los valores tabulados de FAO.

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Palabras clave: evapotranspiración; imágenes satelitales; hidrología de cuenca.

1. INTRODUCTION

Improvements in data availability, including satellite imagery, have increased the use and applications of distributed high-resolution hydrological models [1-3]. Remote sensing information is also being increasingly used in applications on plot-scale using agro-hydrological models [4,5]. In spite of the potential of remote sensing information to parameterize evapotranspiration (ET) processes, models used by practitioners for planning, engineering design and other type of decision making on basin scale, generally consider relatively simple representations of the evapotranspiration process [5-7]. A better representation of ET has the potential to improve streamflow prediction [8], especially in semi-arid basins where evapotranspiration generally has a larger share in the water balance than runoff [9]. The size of the study area may also affect the influence of the crop parameterization method [10,11]. At the same time, crop evapotranspiration parameterization may be less important for streamflow estimation in larger basins, but it may be critical for other variables (e.g. soil moisture, recharge) [2,12,13]. Also, the choice of the crop evapotranspiration parameterization may be more relevant in certain seasons than in others, e.g. [14].

The objective of this study is to explore how different methods used for the parameterization of crop evapotranspiration affects hydrological model outcomes. This will improve our understanding of (i) the sensitivity of different output variables to the parameterization approaches, and (ii) the effect of catchment size and season (dry vs wet) on this parameterization.

2. METHODS

2.1 Study basin and model

The study is performed in the Upper Segura basin (SE Spain). The basin covers an approximate area of 2500 km^2 and the dominant lithology consists of marls and limestones. Average annual rainfall is 400 mm and elevation ranges between 488 and 1749 m.a.s.l. The landscape represents rainfed farming, forests (mainly pine tree) and shrublands. The basin includes four reservoirs, their main purpose being irrigation water storage.

The hydrological model used is SPHY (*Spatial Processes in Hydrology*). SPHY is a spatially distributed leaky bucket type of model that is applied on a cell-by-cell basis. More details on the model and its applications are given by [15]. Main input data used for this study are: digital elevation model (SRTM), rainfall and temperature station data (CHS, AEMET), Landcover (Corine) and maps with soil physical properties (CEBAS).

2.2 Crop coefficient parameterization scenarios

For this study we assume that the best available data related to crop coefficients are Normalized Difference Vegetation Index (NDVI) observations [16]. We use a linear parameterization for the NDVI-k_c relationship in which the minimum values for the crop coefficient ($k_{c,min}$) are reached in bare soils, and the maximum ones ($k_{c,max}$) are expected to be reached when vegetation/crop is growing at its optimum agronomic condition. The SPHY model forced with dynamic bi-monthly NDVI observations to derive crop coefficients can be considered as the most accurate model, hereafter called “reference model”. This reference model is calibrated using monthly reservoir inflow data for a period of 10 years (2001-2010), using data for three reservoirs. The validation period of the model is 2011-2015.

A second model is built by altering the crop coefficient parameterization of the calibrated model with the annual kc pattern based on standard FAO literature values per land use type. This model is compared to the NDVI-based reference model. To understand the impact of catchment size, a representative sample of different catchment size classes across the basin was collected. The catchment size classes were: 0.1, 1, 10, 100 and 1000 km^2. For example, for the first catchment size class, a total of 100 catchments in the basin were selected, all having a total drainage area of approximately 0.1 km^2.

3. RESULTS AND DISCUSSION

The model was calibrated and validated successfully (not shown here). Fig. 1 shows the deviation (mm/month) of streamflow and actual evapotranspiration at basin-scale for the FAO-based model. Streamflow is lower and more or less constant throughout the year, due to the higher evapotranspiration demands as compared to the reference model. This demonstrates the impact of soil moisture storage, which reaches its maximum at the start of the year (not shown here). From April onwards, soil moisture will limits actual evapotranspiration rates.

Streamflow is thus hardly affected by the choice of the crop coefficient parameterization method (Fig. 1). However, the difference in streamflow is more significant for smaller sub-watersheds as shown in Fig. 2, which shows that the Normalized RMSE, as an indicator of relative deviation from the reference model, generally increases for smaller watersheds, especially for actual evapotranspiration.

4. CONCLUSIONS

Overall, the choice of crop parameterization model is not important for monthly streamflow in the semi-arid basin studied at the basin scale. However, spatial and temporal differences in model outputs can be significant at smaller spatial and temporal scales. The classical FAO-based approach led to most significant deviations in streamflow and actual evapotranspiration estimates compared to the reference model. Further work should focus on the influence of soil moisture on the studied patterns and a more in-depth analysis of the impact of different spatial and temporal scales.

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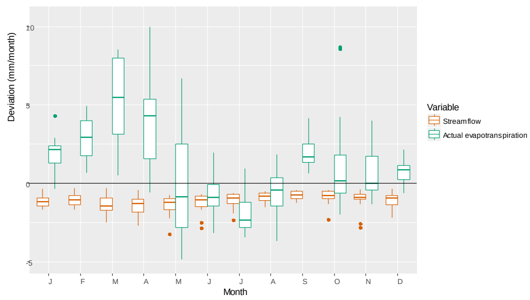

Figure 1: Boxplots showing the monthly deviation (mm/month) of the FAO method compared to the reference model for streamflow and ETa at basin-scale. Positive deviations mean higher values for the FAO-based model

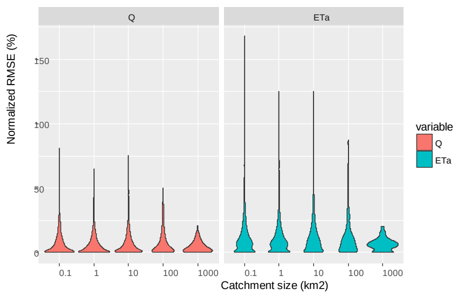

Figure 2: Violin plots (rotated histograms) of streamflow expressed as Normalized RMSE compared to reference run, for 5 catchment size classes based on monthly simulation outputs