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A sensitivity assessment of the TOPKAPI model with an added infiltration module

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SUMMARY

In this paper we extend the usefulness of the TOPKAPI model by adding a Green-Ampt infiltration module and make the model and source code freely available on the internet as PyTOPKAPI. Then, we investigate the sensitivity of the PyTOPKAPI hydrological model to systematic bias in the variables rainfall and evapotranspiration, as well as the physically based soil properties that describe the model behaviour. The model sensitivity is assessed in terms of relative changes in the Soil Saturation Index (SSI), which is defined as the percentage of soil pore space filled by water. The volumetric soil moisture content, can be calculated from SSI using location dependent soil properties, if required.

The model sensitivity is calculated at 7200 sites in South Africa, for a 2.5 year simulation period with a time-step of three hours. This large spatial extent gives results for a wide array of climates and land properties. Overall, the sensitivity of the model turns out to be a closely linear function of, and the same order of magnitude as (or less than), the forcing/parameter bias. This indicates that the model is robust to errors in forcing/parameters.

The results also show that the best estimates of soil water can be obtained by improving estimates of the storage parameters and rainfall forcing. However, the storage parameters must be obtained from static soil property data-sets and we show that there is value in making improvements to the rainfall forcing (in this case TRMM 3B42RT) for places where it is biased relative to observed rainfall.

This work is particularly relevant for model application in ungauged basins, where the quality of forcing variables and physical parameters cannot be calibrated.

1. Introduction

The TOPKAPI semi-distributed hydrological model (Liu and Todini, 2002) uses a physical representation of catchment characteristics, with the relevant physical parameters (slopes, soil properties, etc.) typically available from reference data-sets. Unfortunately the uncertainty in these physical parameters is often poorly known and there is little work in the literature to quantify the sensitivity of the TOPKAPI model to it's physical parametrization or the accuracy of the forcing variables. Foglia et al. (2009) and Finger et al. (2011) examined the parameter sensitivity of the calibration of their implementation of TOPKAPI in two Swiss catchments. However, there does not appear to be any similar work in conditions that match those typical of South Africa, which experiences a range of climates from desert to sub-tropical and where the preponderance of the vegetation is savannah.

PyTOPKAPI is an open-source extension and implementation of TOPKAPI, which was described in Vischel et al. (2008a) and Vischel et al. (2008b), with the detail of our current application of the model described in Sinclair and Pegram (2010). The model code is freely available under an open source license at http://sahg.github.com/PyTOPKAPI/.

The work presented in this paper aims to determine which model input variables and parameters have the largest effect on the dynamics of the soil store, and therefore does not attempt to validate the absolute accuracy of the estimates. This information is particularly relevant for model application in ungauged basins, where the quality of forcing variables and physical parameters cannot be calibrated. The paper also adds to the limited information in the literature on the sensitivity of the TOPKAPI model to variability in parameters and forcing.

We describe the addition of an infiltration module to the PyTOPKAPI model in order to provide a mechanism for the model to generate rapid overland runoff when subjected to high intensity rainfall. The main thrust of this paper is then to simulate the soil moisture state at 3 hourly time-steps over South Africa for a 2.5 year period. In addition to describing the new infiltration module, we investigate the sensitivity of the PyTOPKAPI model to systematic bias in the model forcing variables (rainfall and evapotranspiration) and the physical parameters describing the model's behaviour. The model sensitivity is assessed in terms of relative changes in the Soil Saturation Index (SSI, which is the percentage

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of available soil pore space filled by water) to known changes to each of the forcing variables and soil parameters independently. SSI is directly related to the volumetric soil moisture content, which can be calculated from SSI using location dependent soil properties. The reason we use local SSI to quantify sensitivity, and not streamflow from selected catchments, is that SSI is directly related to the soil properties, the local climate and weather, whereas hydrological response is a function of catchment location, configuration and size, complicating the sensitivity of SSI to the primary parameters.

Section 2 describes the Green-Ampt (Green and Ampt, 1911) based infiltration module that is a new addition to PyTOPKAPI, a significant change from the original TOPKAPI formulation described by Liu and Todini (2002), which was implemented in the first version of PyTOPKAPI by Vischel et al. (2008a). The sensitivity analysis carried out is described in Section 3 and the results of the analysis presented and discussed in Section 4. Finally, conclusions are drawn in Section 5.

2. Description of the infiltration module

The purpose of this section is to describe the changes applied to the PyTOPKAPI model formulation by including infiltration as a new model process. We begin by describing the motivation for our selected infiltration model before moving on to a presentation of the PyTOPKAPI implementation details. We compare the response of both the original and revised versions of PyTOPKAPI to selected scenarios of high and low-intensity rainfall in Section 4.1.

2.1. Motivation for the infiltration model

The original TOPKAPI formulation (Liu and Todini, 2002) does not include an infiltration process. In that formulation, all rainfall enters the soil store directly and overland runoff is generated purely by saturation excess. Liu et al. (2005) made several adaptations to the TOPKAPI formulation, which included an infiltration model where the infiltration was calculated as a fraction of the precipitation, depending on the land-cover. Since overland flow generation during high-intensity rainfall events can be important for flash flood modelling in small catchments, we considered this an important addition but elected to add a more physically based infiltration module to our version of the model.

We chose to use the model of Green and Ampt (1911) as the infiltration module for PyTOPKAPI. Apart from the fact that the model is well known, our choice was based on the following factors: (1) The Green-Ampt parameters could be easily estimated from the available soil information in South Africa; (2) some authors have shown that Green-Ampt performs well relative to observed data and a full 1D solution of Richards equation in certain situations (Ma et al., 2010); (3) we prefer to avoid unnecessary complexity in PyTOPKAPI and Green-Ampt is robust and relatively straightforward to code.

The infiltration depth during each interval is calculated using the Green-Ampt method (e.g. Chow et al., 1988). The Green-Ampt cumulative infiltration during an infiltration event is determined by solving the difference equation

$$F_{t+\Delta t} - F_t - \psi\Delta\theta \ln\left(\frac{F_{t+\Delta t} + \psi\Delta\theta}{F_t + \psi\Delta\theta}\right) = K_s\Delta t$$

where $F_{t+\Delta t}$ is the cumulative infiltration depth at time $t + \Delta t$,F_t is the cumulative infiltration depth at time t, ψ is the soil suction head at the wetting front and K_s is the saturated hydraulic conductivity of the soil. $\Delta\theta$ is the change in moisture content as the wetting front passes and is therefore equal to the difference between the porosity η and the initial soil moisture content θ at the start of the infiltration event. If the residual soil moisture content is θ_r, then the effective porosity η_e is defined as

$$\eta_e = \eta - \theta_r$$

and effective saturation is

$$s_e = \frac{\theta - \theta_r}{\eta_e}$$

so

$$\Delta\theta = \eta - \theta = \eta - \theta_r - s_e\eta_e = (1 - s_e)\eta_e$$

Since PyTOPKAPI records the time-varying water volumes in the soil, overland and channel stores, the model keeps track of the effective saturation s_e, which is updated at each time-step. Therefore $\Delta\theta$ can be updated and the initial accumulated infiltration F_t reset to zero at the start of each new time interval. This is done for computational convenience, reducing the Green-Ampt cumulative infiltration equation to

$$F_{t+\Delta t} - \psi\Delta\theta \ln\left(\frac{F_{t+\Delta t} + \psi\Delta\theta}{\psi\Delta\theta}\right) - K_s\Delta t = 0$$

This equation is non-linear in $F_{t+\Delta t}$ and the roots must be obtained by an iterative technique. The solver used in PyTOPKAPI is a modified version of the Powell hybrid method (Powell, 1970), accessed via the Scipy (Jones et al., 2001) wrappers of the MINPACK library (Moré et al., 1980).

The parameters of the Green-Ampt model are K_s,$\Delta\theta$ and ψ. K_s and $\Delta\theta$ are already easily obtainable from the original formulation of the PyTOPKAPI model. Therefore ψ must be estimated. Since the suction head ψ varies as a function of θ and soil type (e.g. Chow et al., 1988), it is necessary to obtain a functional form for $\psi(\theta)$ by soil type, in order to describe the time-varying value of ψ with location. El-Kadi (1985) evaluated a number of well-known models for $\psi(\theta)$ by fitting them to measured data for a selection of soil samples and comparing the model fits. In general El-Kadi (1985) found that there was relatively little difference in the model performances, but suggested that the Brooks and Corey relationship (Brooks and Corey, 1964) was least sensitive to the number of ψ samples near saturation. This suggests that the model is most robust out of those tested by El-Kadi (1985) and is one of the reasons for selecting the Brooks Corey model for use in PyTOPKAPI. The model is given by

$$s_e = \left[\frac{\psi_b}{\psi}\right]^{\lambda}$$

which we rearrange as

$$\psi = \frac{\psi_b}{(s_e)^{\frac{1}{\lambda}}}$$

where ψ_b is the bubbling pressure and λ is a pore size distribution index for the soil.

A second (more practical) reason to choose the Brooks and Corey model is the availability of model parameter estimates (ψ_b and λ) for a large number of soil samples in the United States produced by Rawls et al. (1982). The Brooks and Corey model parameters are presented by Rawls et al. (1982) for 11 different soil texture classes, which are readily available for South Africa from Middleton and Bailey (2009), and are already used to estimate other parameters of the PyTOPKAPI model in our work. The spatial distributions of ψ_b and λ are obtained by mapping the geometric means of ψ_b and λ reported in Table 2 of Rawls et al. (1982) to the soil texture classes from Middleton and Bailey (2009).