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Self-adaptive Green-Ampt infiltration parameters obtained from measured moisture processes

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Abstract

The Green-Ampt (G-A) infiltration model (i.e., the G-A model) is often used to characterize the infiltration process in hydrology. The parameters of the G-A model are critical in applications for the prediction of infiltration and associated rainfall-runoff processes. Previous approaches to determining the G-A parameters have depended on pedotransfer functions (PTFs) or estimates from experimental results, usually without providing optimum values. In this study, rainfall simulators with soil moisture measurements were used to generate rainfall in various experimental plots. Observed runoff data and soil moisture dynamic data were jointly used to yield the infiltration processes, and an improved self-adaptive method was used to optimize the G-A parameters for various types of soil under different rainfall conditions. The two G-A parameters, i.e., the effective hydraulic conductivity and the effective capillary drive at the wetting front, were determined simultaneously to describe the relationships between rainfall, runoff, and infiltration processes. Through a designed experiment, the method for determining the G-A parameters was proved to be reliable in reflecting the effects of pedologic background in G-A type infiltration cases and deriving the optimum G-A parameters. Unlike PTF methods, this approach estimates the G-A parameters directly from infiltration curves obtained from rainfall simulation experiments so that it can be used to determine site-specific parameters. This study provides a self-adaptive method of optimizing the G-A parameters through designed field experiments. The parameters derived from field-measured rainfall-infiltration processes are more reliable and applicable to hydrological models.

Keywords: Green-Ampt model; Levenberg-Marquardt algorithm; Parameter optimization; Ungauged basin; Pedotransfer function

1. Introduction

Infiltration plays an important role in terrestrial hydrologic processes. It affects the runoff generation process and is dramatically influenced by the soil hydraulic properties and soil porous texture (Sivakumar, 2015). Most physically based hydrologic models have described the relationships between rainfall, runoff, and infiltration processes implicitly or explicitly (Lee et al., 2015). The Green-Ampt (G-A) infiltration model (Green and Ampt, 1911) is one such model based on the soil porous media characteristics (Prevedello et al., 2009). It is widely used in the hydrologic field due to its reasonable physical mechanism and easy-to-solve solution (Govindaraju et al., 1996; Ma et al., 2010; O'Brien

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et al., 2009; Silburn and Connolly, 1995; Wang et al., 2010). For example, both the FLO-2D model in Maricopa County and the Water Erosion Prediction Project (WEPP) model of the U.S. Department of Agriculture (USDA) (Dun et al., 2009; Risse et al., 1995) have adopted the G-A model for rainfall-runoff prediction. Meanwhile, many researchers have improved the G-A model in order to adapt it to more complex soil systems (Gowdish and Munoz-Carpena, 2009). They have focused on solving the equations and estimating its parameters theoretically (Regalado et al., 2005; Verbist et al., 2010). The most common method is to make use of pedotransfer functions (PTFs) (Brooks and Corey, 1966) to calculate the parameters of the G-A model (Rawls et al., 1983; Regalado et al., 2005). They also suggest that it is reasonable to use half of the saturation conductivity as the effective conductivity (Bouwer, 1966). This hypothesis has been commonly accepted in practice. However, it has limitations when the G-A model is used in the field (van den Putte et al., 2013). In order to avoid the limitations, ring infiltrometers were used to measure the hydraulic conductivity by imposing ponded conditions in some field experimental methods (Angermann et al., 2002; Esteves et al., 2000; Galbiati and Savi, 1995; Mohamoud, 1991; Reynolds, 2010; Suleiman and Swartzendruber, 2003). However, this method is not fit for non-ponded initial conditions when the G-A model is used. On the other hand, some researchers have used rainfall simulators for the parameterization of the G-A model (Esteves et al., 2000; Rawls et al., 1992; Suleiman and Swartzendruber, 2003; Valiantzas, 2010; Taskinen et al., 2008). In those studies, the measured runoff data (the runoff process is an indirect part of the infiltration process) were used to calibrate the G-A model and to generate best fitting parameters for the model. However, the uncertainty of observed data series decreases the reliability of the parameters and at the same time prevents derivation of multi-parameters to describe the relationships between the coupled equations put forward by Athira and Sudheer (2015). To solve these problems, we designed an infiltration equipment for small-scale rainfall experiments through a moisture survey and developed a parameter optimization algorithm to derive the G-A parameters using the measured data.

In this study, rainfall simulators were set up in various experimental plots based on a typical pedologic background. Accumulated infiltration curves and moisture dynamic data were obtained in the experiments. High-intensity rainfall experiments were conducted in each plot and infiltration curves were yielded under the simulated rainfall conditions. Then, a new self-adaptive optimization approach based on the Levenberg-Marquardt (LM) algorithm (Marquardt, 1963) was validated theoretically, in order to estimate the G-A parameters directly from these data, and a quantified relationship between soil textures and the G-A parameters was built through comparison with the parameters derived directly from the PTF method. Based on these data, the method for extraction of the G-A parameters based on the pedologic background was developed for high-resolution distributed hydrologic models.

2. Materials and methods

2.1. Optimization setup

Since the G-A model was presented by Green and Ampt (1911), it has been modified by several researchers. Mein and Larson (1973) extended the model from ponded conditions to constant intensity conditions. Chu (1978) applied this model to unsteady rainfall intensities. In these studies, the G-A model was treated as two parts: under the steady state, the infiltration rate equals the rainfall intensity before ponding; as the wetting front moves downwards with time, ponding occurs and the integrated version of the G-A model after ponding can be expressed as

$$K_e\left[t-\left(t_p-t_s\right)\right]=I-\left(\theta_s-\theta_i\right)S\ln\left[1+\frac{I}{\left(\theta_s-\theta_i\right)S}\right]\quad t>t_p \tag{1}$$

where I is the vertical accumulative infiltration depth; S is the soil capillary drive at the wetting front; θ_i and θ_s are initial and saturated water contents, respectively; K_e is the effective hydraulic conductivity; t is time; the t_p is the ponding time, and $t_p = I_p/P$, in which P is the rainfall intensity ($P > K_e$) and I_p is the infiltration depth at t_p, which is calculated as follows:

$$I_p=\frac{\left(\theta_s-\theta_i\right)S}{P/K_e-1}\quad P>K_e \tag{2}$$

t_s is a virtual time defined as follows:

$$K_e t_s=I_p-S\left(\theta_s-\theta_i\right)\ln\left[1+\frac{I_p}{S\left(\theta_s-\theta_i\right)}\right] \tag{3}$$

To implicitly calculate I in Eq. (1), four parameters are needed: K_e, S, θ_s, and θ_i. In Eq. (1), S, θ_s, and θ_i always have an integrity form of $S(\theta_s - \theta_i)$. This can be simplified to one parameter M, where $M = S(\theta_s - \theta_i)$. The parameters to be optimized are then reduced to two: K_e and M.

The self-adaptive optimization algorithms can be categorized as local and global search methods. Depending on the hill-climbing strategy, search algorithms can be divided into direct and gradient-based methods. Gradient-based methods use the information about the gradient of the objective function and direct search methods use only the information about the objective function value. In this study, we chose a gradient-based method, the LM algorithm, as our optimization method. The general object of the LM algorithm is to minimize the sum of the square residuals (Eq. (4)) by gradually changing the optimized parameters. Its objective function is assumed to be the nonlinear least squares problems as follows:

$$F=\min\sum_{i=1}^{m}\left[y_i-f\left(x_i,\beta\right)\right]^2 \tag{4}$$

where y_i is the observed data series at time step i, $f(x_i, \beta)$ is the optimized series using the optimized parameter β, x_i is a variable, and m is the maximum series number. $f(x_i, \beta)$ in this study was solved implicitly through Eq. (1) using the Newton method because the G-A model is an implicit function for accumulated infiltration series. Each time step is recorded as i