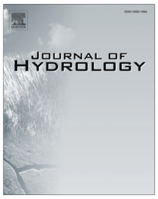
Journal of Hydrology 538 (2016) 109–116

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol



# A comparison of five forest interception models using global sensitivity and uncertainty analysis

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ARTICLE INFO

*Article history:*
Received 16 March 2016
Received in revised form 30 March 2016
Accepted 5 April 2016
Available online 13 April 2016
This manuscript was handled by Andras Bardossy, Editor-in-Chief, with the assistance of Sheng Yue, Associate Editor

*Keywords:*
Interception
Sensitivity analysis
Uncertainty analysis
Canopy storage capacity

## SUMMARY

Interception by the forest canopy plays a critical role in the hydrologic cycle by removing a significant portion of incoming precipitation from the terrestrial component. While there are a number of existing physical models of forest interception, few studies have summarized or compared these models. The objective of this work is to use global sensitivity and uncertainty analysis to compare five mechanistic interception models including the Rutter, Rutter Sparse, Gash, Sparse Gash, and Liu models. Using parameter probability distribution functions of values from the literature, our results show that on average storm duration [$Dur$], gross precipitation [$P_G$], canopy storage [$S$] and solar radiation [$Rn$] are the most important model parameters. On the other hand, empirical parameters used in calculating evaporation and drip (i.e. trunk evaporation as a proportion of evaporation from the saturated canopy [$\epsilon$], the empirical drainage parameter [$b$], the drainage partitioning coefficient [$p_d$], and the rate of water dripping from the canopy when canopy storage has been reached [$Ds$]) have relatively low levels of importance in interception modeling. As such, future modeling efforts should aim to decompose parameters that are the most influential in determining model outputs into easily measurable physical components. Because this study compares models, the choices regarding the parameter probability distribution functions are applied across models, which enables a more definitive ranking of model uncertainty.

## 1. Introduction

Forests will face unprecedented stressors in the coming decades from changes in climate, threats from invasive species, and additional societal pressure for ecosystem services (Vose et al., 2012). These stressors will alter how water and nutrients move through watersheds, beginning with canopy-atmosphere interactions. In forested landscapes, the forest canopy is the first major storage compartment encountered by rainfall, which can dramatically transform the fate and transport of water and nutrients. Annually, the average forest canopy intercepts 18% of incident precipitation (Llorens and Domingo, 2007), although the variability of canopy interception is large and depends on forest composition (Siegert and Levia, 2014), rainfall characteristics (Staelens et al., 2008; Van Stan Ii et al., 2011), and meteorological conditions (Herwitz and Slye, 1995).

Interception by the forest canopy plays a critical role in determining net hydrologic parameters by diverting significant quantities of precipitation that would otherwise be directed to soil moisture, transpiration, and surface and groundwater recharge. Canopy interception ($I$) has long been estimated from the equation $I = P_G - (P_T + P_S)$, where $P_G$ is gross precipitation measured above the forest canopy or in a nearby clearing, $P_T$ is throughfall, and $P_S$ is stemflow (Helvey and Patric, 1965). Direct measurements of $P_G$, $P_T$, and $P_S$ provide reasonable estimates of $I$, but do not account for the variability that is introduced through the diversity of canopy characteristics, seasonality, or storm and meteorological conditions nor do they provide a means to incorporate these effects into dynamic or scenario-based models. In contrast, interception models often rely on indirect estimates of canopy partitioning that are derived from canopy storage capacity, rainfall characteristics, canopy drainage, and evaporation (e.g., Deguchi et al., 2006; Gash, 1979; Rutter et al., 1972; Zeng et al., 2000). Additionally, laboratory-controlled wetting experiments have been employed to model interception under variable environmental conditions (e.g. Calder, 1996; Keim et al., 2005; Toba and Ohta, 2008).

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http://dx.doi.org/10.1016/j.jhydrol.2016.04.011
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*Abbreviations*

| | |
|---|---|
| $b$ | empirical drainage parameter (mm) |
| $C$ | actual canopy storage (mm) |
| $c$ | canopy cover (unit area) |
| $D_s$ | rate of water dripping from the canopy when $C = S$ (mm h$^{-1}$) |
| $D_C$ | rate of water dripping from the canopy (mm h$^{-1}$) |
| $Dur$ | storm duration (h) |
| $e_a$ | actual vapor pressure (kPa) |
| $e_s$ | saturation vapor pressure (kPa) |
| $\bar{E}$ | mean evaporation (mm h$^{-1}$) |
| $E_P$ | potential evaporation (mm h$^{-1}$) |
| $E_C$ | canopy evaporation (mm h$^{-1}$) |
| $E_t$ | trunk evaporation (mm h$^{-1}$) |
| $\epsilon$ | trunk evaporation as a proportion of evaporation from the saturated canopy (%) |
| $G$ | soil heat flux density (MJ m$^{-2}$ h$^{-1}$) |
| $H_{max}$ | maximum humidity (%) |
| $H_{min}$ | minimum humidity (%) |
| $I$ | interception (mm) |
| $m$ | number of storms insufficient to saturate the canopy |
| $n$ | number of storms which saturate the canopy |
| $N_i$ | first order sensitivity index for each model parameter |
| $N_{ij}$ | second order sensitivity index for each model parameter |
| $N_{Ti}$ | total sensitivity index |
| $p$ | free throughfall coefficient |
| $p_d$ | drainage partitioning coefficient (%) |
| $p_t$ | stemflow coefficient |
| $P_G$ | cumulative gross rainfall (mm) |
| $P'_G$ | rainfall necessary to saturate the canopy (mm) |
| $P_S$ | stemflow (mm) |
| $P_T$ | throughfall (mm) |
| PDF | probability distribution function |
| $q$ | number of storms that fill the trunk storage and produce stemflow |
| $\bar{R}$ | mean rainfall (mm h$^{-1}$) |
| $R_n$ | net radiation (MJ m$^{-2}$ h$^{-1}$) |
| $S$ | maximum canopy storage capacity (mm) |
| $S_C$ | canopy capacity per unit area of cover (mm) |
| $Sf$ | Stemflow (mm) |
| $S_t$ | trunk storage capacity (mm) |
| $T_{Cmax}$ | maximum temperature (°C) |
| $T_{Cmean}$ | mean air temperature (°C) |
| $T_{Cmin}$ | minimum temperature (°C) |
| $u_2$ | wind speed 2 m above the ground surface (m s$^{-1}$) |
| $V_i$ | first order effect for each model parameter |
| $V_{ij}$ | second order interaction for each model parameter |
| $y$ | model output |
| $z$ | number of model parameters |
| $\Delta$ | slope of the vapor pressure curve (kPa °C$^{-1}$) |
| $\gamma$ | psychometric constant (kPa °C$^{-1}$) |

Because of the significance of interception in the water budget, it is important to understand the most suitable models for use in any particular circumstance. There are a variety of existing forest interception models including simple empirical models (Ponce and Hawkins, 1996), probabilistic models (Calder, 1977), and physical or mechanistic models (e.g., Gash, 1979; Rutter et al., 1972). Physical models are particularly useful because they allow investigation into the system's processes and inner workings.

While there are a number of existing physical models of forest interception, few studies have summarized or compared these models (Bryant et al., 2005; Klingaman et al., 2007; Liu, 2001; Muzylo et al., 2009; Valente et al., 1997). Conclusions from these studies emphasize the need for more comparative studies, model validation, and uncertainty analysis. However, very few studies have assessed the sensitivity or uncertainty of interception models (Bartlett et al., 2006; Hedstrom and Pomeroy, 1998; Rutter and Morton, 1977; Xiao et al., 2000). Most of these studies use cursory sensitivity analysis techniques varying parameters one at a time by fixed percentages. Estimating forest canopy interception at large spatial scales results in a degree of uncertainty that carries over into calculations of hydrologic water budgets and associated biogeochemical budgets. To reduce sources of model uncertainty, physical and mechanistic models should be developed that focus on reducing uncertainty in the parameters that most strongly influence model results.

Sensitivity and uncertainty analyses assess model reliability (Saltelli et al., 2008; Scott, 1996) and can be used to assign confidence to model results (Linhoss et al., 2012). Uncertainty analysis quantifies the total model uncertainty, and sensitivity analysis apportions that uncertainty to each of the parameters. While local sensitivity and uncertainty methods use a simple one at a time approach to assess parameter importance, global methods systematically and quantitatively assess model sensitivity throughout the global parametric space and are able to account for the interactions between parameters, which are often important in complex models (Saltelli et al., 2008). Variance based global sensitivity and uncertainty analysis techniques are quantitative methods in which the output variance is defined as the sum of the variances assigned to each parameter and also the interactions between the parameters. Understanding the uncertainty associated with a model and the sensitivity of the model parameters allows users to (1) assess the value of a model for its use in the decision making process, (2) acknowledge the reliability of models when assessing forecasts, and (3) simplify models by setting unimportant parameters to constants, thus reducing the risk of over-parameterization (Beven, 2006; Linhoss et al., 2013; Saltelli et al., 2008). For these reasons, sensitivity and uncertainty analysis is a critical step in the modeling process.

Our objective is to use global uncertainty and sensitivity analysis techniques to compare five mechanistic interception models including the Rutter (Rutter et al., 1972), Rutter Sparse (Valente et al., 1997), Gash (1979), Sparse Gash (Gash et al., 1995), and Liu (1997) models. We assess model uncertainty and also identify the important and unimportant processes and parameters within each model. Because we are comparing models, the choices regarding the parameter probability distribution functions (PDFs) are applied across models, which enables us to definitively rank model uncertainty.

## 2. Methods

The following section describes the evaporation and interception models, their equations, and the global sensitivity and uncertainty analysis methodology. Each interception model simulates a single storm event and assumes a previously dry canopy. The parameters for the interception models are listed in Table 1.

### 2.1. Penman-Montieth reference evaporation

The FAO Penman-Montieth reference evaporation equation was used to calculate hourly potential evaporation [$E_P$] in all of the