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

Anna C. Linhoss^a, Courtney M. Siegert^b

a. Department of Agricultural and Biological Engineering

Mississippi State University

Starkville, Mississippi 39762 USA

alinhoss@abe.msstate.edu

Corresponding author

b. Department of Forestry

Mississippi State University

Starkville, Mississippi 39762 USA

courtney.siegert@msstate.edu

Abstract

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 [ϵ], 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. Additionally, the free throughfall coefficient [p] and drainage partitioning coefficient [p_d] have relatively low levels of importance. 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.

Keywords

Interception; Sensitivity Analysis; Uncertainty Analysis; Canopy Storage Capacity

36 Abbreviations

37	b	empirical drainage parameter (mm)
38	C	actual canopy storage (mm)
39	c	canopy cover (unit area)
40	D_s	rate of water dripping from the canopy when $C = S$ (mm hr ⁻¹)
41	D_C	rate of water dripping from the canopy (mm hr ⁻¹)
42	Dur	storm duration (hr)
43	e_a	actual vapor pressure (kPa)
44	e_s	saturation vapor pressure (kPa)
45	$\overline{E}$	mean evaporation (mm hr ⁻¹)
46	E_p	potential evaporation (mm hr ⁻¹)
47	E_C	canopy evaporation (mm hr ⁻¹)
48	E_t	trunk evaporation (mm hr ⁻¹)
49	ϵ	trunk evaporation as a proportion of evaporation from the saturated canopy (%)
50	G	soil heat flux density (MJ m ⁻² hr ⁻¹)
51	H_{max}	maximum humidity (%)
52	H_{min}	minimum humidity (%)
53	I	interception (mm)
54	n	number of storms which saturate the canopy
55	N_i	first order sensitivity index for each model parameter
56	N_{ij}	second order sensitivity index for each model parameter
57	N_{Ti}	total sensitivity index

58	m	number of storms insufficient to saturate the canopy
59	p	free throughfall coefficient
60	p_d	drainage partitioning coefficient (%)
61	p_t	stemflow coefficient
62	P_G	cumulative gross rainfall (mm)
63	P_G^*	rainfall necessary to saturate the canopy (mm)
64	P_S	stemflow (mm)
65	P_T	throughfall (mm)
66	PDF	probability distribution function
67	q	number of storms that fill the trunk storage and produce stemflow
68	$\bar{R}$	mean rainfall (mm hr ⁻¹)
69	R_n	net radiation (MJ m ⁻² hr ⁻¹)
70	S	maximum canopy storage capacity (mm)
71	S_c	canopy capacity per unit area of cover (mm)
72	S_f	Stemflow (mm)
73	S_t	trunk storage capacity (mm)
74	T_{Cmax}	maximum temperature (°C)
75	T_{Cmean}	mean air temperature (°C)
76	T_{Cmin}	minimum temperature (°C)
77	u_2	Wind speed 2 m above the ground surface (m s ⁻¹)
78	V_i	first order effect for each model parameter
79	V_{ij}	second order interaction for each model parameter

80	y	Model output
81	z	Number of model parameters
82	Δ	slope of the vapor pressure curve ($\text{kPa } ^\circ\text{C}^{-1}$)
83	γ	psychometric constant ($\text{kPa } ^\circ\text{C}^{-1}$)

84

85 1. Introduction

86 Forests will face unprecedented stressors in the coming decades from changes in climate,
87 threats from invasive species, and additional societal pressure for ecosystem services (Vose et
88 al., 2012). These stressors will alter how water and nutrients move through watersheds,
89 beginning with canopy-atmosphere interactions. In forested landscapes, the forest canopy is
90 the first major storage compartment encountered by rainfall, which can dramatically transform
91 the fate and transport of water and nutrients. Annually, the average forest canopy intercepts
92 18% of incident precipitation (Llorens and Domingo, 2007), although the variability of canopy
93 interception is large and depends on forest composition (Siegert and Levia, 2014), rainfall
94 characteristics (Staelens et al., 2008; Van Stan li et al., 2011), and meteorological conditions
95 (Herwitz and Slye, 1995).

96

97 Interception by the forest canopy plays a critical role in determining net hydrologic parameters
98 by diverting significant quantities of precipitation that would otherwise be directed to soil
99 moisture, transpiration, and surface and groundwater recharge. Canopy interception (I) has
100 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).

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 models (Allen et al., 1998). The Penman-Montieth equation requires observational measurements of maximum and minimum temperature, maximum and minimum relative humidity, solar radiation, and wind speed (Eq. 1). Here, Δ is

the slope of the vapor pressure curve, R_n is net radiation, G is the soil heat flux density, T_c is air temperature, u_2 is wind speed at 2 m height, e_s is saturation vapor pressure, e_a is actual vapor pressure, H is humidity, and γ is the psychrometric constant.

$$E_p = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T_c + 273} u_2 (e_s - e_a)}{1} \quad \text{Eq. 1}$$

2.2. Rutter Model

The Rutter model is one of the foundations of modern interception modeling (Rutter et al., 1972; Rutter and Morton, 1977; Rutter et al., 1975, Equations 6-11). It is a numerical model that uses a continuous running using equations describing the canopy water balance (Eq. 2), trunk water balance (Eq. 3), rate of drainage from the canopy (Eq. 4), evaporation from the canopy (Eq. 5), stemflow (Eq. 6), and evaporation from the trunks (Eq. 7).

$$(1 - p - p_t) \int R dt = \int D dt + \int E dt + \Delta C \quad \text{Eq. 2}$$

$$p_t \int R dt = Sf + \int E_t dt + \Delta C_t \quad \text{Eq. 3}$$

$$D_c = \begin{cases} D_c \exp[b(C - S)] & C \geq S \end{cases} \quad \text{Eq. 4}$$

$$E_c = \begin{cases} E_p \frac{C}{S} & C < S \\ E_p & C \geq S \end{cases} \quad \text{Eq. 5}$$

$$Sf = \begin{cases} C_t - S_t & C_t \geq S_t \\ 0 & C_t < S_t \end{cases} \quad \text{Eq. 6}$$

$$E_t = \begin{cases} \epsilon E_p \frac{C}{S} & C_t < S_t \\ \epsilon E_p & C_t \geq S_t \end{cases} \quad \text{Eq. 7}$$

Here, $\bar{R}$ is the mean rainfall rate, p is the free throughfall coefficient, p_t is the stemflow coefficient, S is maximum canopy storage capacity, S_t is trunk storage capacity, C is actual canopy storage, E_p is potential evaporation, E_c is evaporation from the canopy, E_t is evaporation from the trunk, ϵ describes the evaporation from the trunk as a proportion of the evaporation from the saturated canopy, D_c is the rate of water dripping from the canopy, D_s is the rate of water dripping from the canopy when canopy storage capacity has been reached, b is an empirical drainage parameter, and I is interception. Fitted parameters in the model equations (b , ϵ , and S) were calibrated with empirical measurements from a Corsican pine stand (*Pinus negra*).

2.2. Rutter Sparse Model

The Rutter Sparse model (Valente et al., 1997, Equations 12-17) is a reformulation of the Rutter model designed for sparse forests and treats rainfall passing through canopy gaps and rainfall intercepted by canopy cover and trunk separately (Eq. 8 and 9). The Rutter Sparse model also simplifies the calculation of canopy drip (Eq. 10) and uses a canopy drainage coefficient to partition the rainfall between the canopy and trunk (Eq. 11 and 12).

$$S_c = \frac{S}{c} \quad \text{Eq. 8}$$

$$S_{t,c} = \frac{S_t}{c} \quad \text{Eq. 9}$$

$$\int D_c dt = \begin{cases} C_c - S_c & C_c \geq S_c \\ 0 & C_c < S_c \end{cases} \quad \text{Eq. 10}$$

$$\int E_c dt = \begin{cases} (1 - \epsilon) E_p \frac{C}{S_c} & C < S_c \\ (1 - \epsilon) E_p & C \geq S_c \end{cases} \quad \text{Eq. 11}$$

$$\int E_t dt = \begin{cases} \epsilon E_p \frac{C}{S_c} & C_t < S_{t,c} \\ \epsilon E_p & C_t \geq S_{t,c} \end{cases} \quad \text{Eq. 12}$$

205

206 The Rutter Sparse model was developed in Portugal based on sparse eucalypt and pine forests.

207 Here, c is the canopy cover, S_c is the canopy storage capacity per unit area of canopy cover,

208 p_d is the drainage partitioning coefficient, and ϵ is trunk evaporation as a proportion of

209 evaporation from the saturated canopy..

210

211 2.3. Gash Model

212 Over the years, a number of analytical models based on the Rutter model have been

213 developed. One of the first was the Gash model (1979, Eq. 13 and 14), which treats rainfall

214 events as three categories: (1) the canopy wetting phase, (2) the canopy saturation phase, and

215 (3) the canopy drying phase. Parameters in this model are derived from measurements of S , p ,

216 S_t , and p_t from a Scotts pine stand (*Pinus sylvestris*). Here, n is the number of storms which

217 saturate the canopy, m is the number of storms insufficient to saturate the canopy, q is the

218 number of storms with stemflow, P_G is gross precipitation, P_G^* is the rainfall necessary to

219 saturate the canopy, and $\overline{E_p}$ is the average potential evaporation rate.

220

$$\sum_{j=1}^{n+m} I_j = n(1 - p - p_t)P_G^* \quad \text{Eq. 13}$$

222

223

$$P_G^* = -\frac{\overline{RS}}{\overline{E_p}} \ln \left[1 \right] \quad \text{Eq. 14}$$

224

2.4. Gash Sparse Model

The Gash Sparse canopy model (Gash et al., 1995, Eq. 15 and 16) provides an improvement to the original Gash model. This model estimates evaporation based on canopy area rather than the ground area. Parameters in the Gash Sparse model are derived from measurements of S , S_t , and p_t from a Maritime pine stand (*Pinus pinaster*). Here $\bar{E}_c$ is the average evaporation rate from the canopy

$$\sum_{j=1}^{n+m} I_j = ncP_G + \left(\frac{c\bar{E}_c}{R}\right) \sum_{j=1}^n (P_{G,j} - P_G) \quad \text{Eq. 15}$$

$$P_G = -\frac{\bar{R}S_c}{\bar{E}_c} \ln \left[1 \right] \quad \text{Eq. 16}$$

2.6. Liu Model

The Liu model is based on the Rutter model. It was developed to minimize data requirements by using only four parameters including rainfall amount, the ratio of mean wet canopy evaporation to rainfall intensity, canopy gap fraction, and canopy storage capacity (Liu, 1997; Liu, 2001). To reduce other parameters, the model removes the dynamic prediction of stem interception and discards the empirical drainage parameters (Liu, 2001). The Liu model was developed based on data from cypress wetlands (*Taxodium distichum*) and slash pine uplands (*Pinus elliottii*) and explained 89% of interception variability in these stands. For our comparison testing, we use the single storm form of the Liu model that assumes a dry canopy at the model start (Liu, 1997; Liu, 2001; Eq. 17).

$$I = (S + S_t) \left[1 - \exp \left(-\frac{(1-p)}{S + S_t} P_G \right) \right] \left[1 - \frac{\bar{E}_p}{(1-p)\bar{R}} \right] \quad \text{Eq. 17}$$

2.7. Global Sensitivity Analysis/Uncertainty Analysis Methods

Variance based Global Sensitivity Analysis/Uncertainty Analysis (GSA/UA) methods are particularly useful because they are both quantitative and model independent (Saltelli et al., 2005). Variance GSA/UA methods explore the entire parametric space of a model by simultaneously using different combinations of values for each uncertain parameter. The Sobol method is an example of a variance based GSA/UA method. Sobol uses a quasi-Monte-Carlo based method to decompose the model variance. The total variance of the model is partitioned in terms of increasing dimension, which represents the contribution of single, paired, tripled, etc. parameters to the overall model uncertainty, according to equation 18 (Sobol, 1993). Here, y is the model output, z is the total number of parameters, V_i is the first order effect for each parameter, V_{ij} is the second order interaction between two parameters, etc.

$$V(y) = \sum_i V_i + \sum_i \sum_{j>i} V_{ij} + \dots \quad \text{Eq. 18}$$

The first order sensitivity index $[N_i]$ and the second order sensitivity index $[N_{ij}]$ for each parameter is given by equations 19 and 20. Thus, the total sensitivity index $[N_T]$, which is given in equation 21, represents the total contribution to the output variance by a single parameter from first and higher order interactions.

$$N_i = \frac{V_i}{V(y)} \quad \text{Eq. 19}$$

$$N_{ij} = \frac{V_{ij}}{V(y)} \quad \text{Eq. 20}$$

269
270
271
272
273
274
275
276
277
278
279
280
281
282
283
284
285
286

$$N_{T_i} = N_i + \sum_{1 \neq j} N_{i,j} \quad \text{Eq. 21}$$

8,192 ensembles of the five interception models, using the Sobol GSA/UA method, were simulated while varying the evaporation and canopy characteristic parameters according to each equation. The parameters include maximum temperature [T_{Cmax}], maximum relative humidity [H_{max}], wind [u_2], net solar radiation [R_n], cumulative gross precipitation [P_G], storm duration [Dur], free throughfall coefficient [p], stemflow coefficient [p_t], drainage partitioning coefficient [p_d], canopy storage capacity [S], canopy drip when *canopy storage capacity is reached* [D_S], empirical drainage parameter [b], trunk evaporation as a proportion of evaporation from the saturated canopy [ϵ], trunk storage capacity [S_t], and canopy cover [c]. Minimum temperature [T_{Cmin}] and minimum relative humidity [H_{min}] were represented in the models by subtracting the average difference between maximum and minimum hourly values from the maximum value for temperature and relative humidity. This ensures that the maximum temperature and relative humidity were always higher than the minimum temperature and relative humidity.

2.8. Parameter Probability Distributions

Probability distribution functions (PDFs) for each of the 15 model parameters were set according to measured data and literature values. The PDF for each parameter was set to a uniform distribution [U] due to a lack of data indicating a more informed distribution such as

normal or log normal, and in order to provide consistency across PDFs. Since the models were each run to simulate a single storm event, climatic inputs were defined using a single data point versus time series data.

PDFs for the climatic variables (*i.e.*, maximum temperature, maximum relative humidity, wind speed, net solar radiation, rainfall depth, and storm duration) were determined based on hourly measurements made in Perthshire, Mississippi (33.97⁰, -90.90⁰) from May through October from 2010 through 2015 (Delta Agricultural Weather Center, 2015) and are representative of diurnal conditions. The site was chosen because it is a reliable data source and because the conditions represent a large portion of the eastern U.S., which occupies a temperate, humid climate. Average daily maximum and minimum temperatures were 22.5°C and 10.4°C, respectively. Average annual precipitation was 1,064 mm. To isolate conditions appropriate for interception model simulation, climatic data were selected only from periods when rainfall occurred. To isolate leaf-on conditions, climatic data was only selected from May through October. A total 328 individual rainfall events were represented by this selection of data. The PDF for each climatic variable is based on the 95% confidence interval from this subset of meteorological observations.

PDFs for canopy parameters were developed from literature values. These values are representative of temperate forest conditions across a variety of species assemblages and stand conditions (*i.e.*, pines, hardwoods, and mixed; bottomlands and uplands; unmanaged and plantation), all under leafed conditions (Table 1). The PDF for canopy storage capacity [*S*] was

313 set to $U(0.29, 2.24)$ (Bryant et al., 2005; Herbst et al., 2008; Návar, 2013; Šraj et al., 2008;
314 Xiao and McPherson, 2015). The PDF for the free canopy cover $[c]$ was set to $U(0.43, 0.95)$
315 (Bryant et al., 2005; Návar, 2013). Trunk storage capacity $[S_t]$ was set to $U(0.0037, 0.9800)$
316 (Bryant et al., 2005; Herbst et al., 2008; Limousin et al., 2008; Návar, 2013; Šraj et al., 2008;
317 Xiao and McPherson, 2015). The PDF for canopy drip when canopy storage capacity is reached
318 $[D_s]$ was determined to be $U(0.024, 0.74)$ based on literature values (Massman, 1983). The PDF
319 for the empirical drainage parameter $[b]$ was set to $U(3.0, 4.6)$ (Rutter et al., 1972). The PDF for
320 the free throughfall coefficient $[p]$ was set to $U(0.06, 0.55)$ (Herbst et al., 2008; Šraj et al.,
321 2008). The PDF for stemflow coefficient $[p_t]$ was set to $U(0.0031, 0.06)$ (Bryant et al., 2005;
322 Návar, 2013). The PDFs for the drainage partitioning coefficient $[p_d]$ and trunk evaporation as a
323 proportion of evaporation from the saturated canopy $[\epsilon]$ were set to $U(0.0076, 0.0324)$ and
324 $U(0.022, 0.024)$, respectively (Valente et al., 1997).

325

Table 1. Model parameter descriptions, abbreviations, and probability distribution functions (PDFs). *R* = Rutter, *RS* = Rutter Sparse, *G* = Gash, *GS* = Gash Sparse, and *L* = Liu. An “X” indicates that the parameter is used in the corresponding model.

Abb.	Parameter Description	R	RS	G	GS	L	Parameter PDF
P_G^*	cumulative gross precipitation (mm)	X	X	X	X	X	$U(0.254, 45.700)$
Dur	Duration (hr)	X	X	X	X	X	$U(1, 14)$
S	canopy storage capacity (mm)	X	X	X	X	X	$U(0.29, 2.24)$
S_t	trunk storage capacity (mm)	X	X	X	X	X	$U(0.0037, 0.9800)$
p	free throughfall coefficient (%)	X		X		X	$U(0.06, 0.55)$
p_t	stemflow coefficient (%)	X		X	X		$U(0.0031, 0.0600)$
p_d	drainage partitioning coefficient (%)		X				$U(0.0076, 0.0324)$
c	canopy cover (unit area)		X		X		$U(0.43, 0.95)$
b	empirical drainage parameter (mm)	X					$U(3.0, 4.6)$
D_S	canopy drip when $C = S$ (mm hr ⁻¹)	X					$U(0.024, 0.740)$
ϵ	trunk / canopy evaporation (%)	X	X				$U(0.022, 0.024)$
R_n	net radiation (MJ m ⁻² hr ⁻¹)	X	X	X	X	X	$U(0.00, 2.37)$
T_{Cmax}	maximum temperature (°C)	X	X	X	X	X	$U(10.8, 31.9)$
H_{max}	maximum humidity (%)	X	X	X	X	X	$U(68, 98)$
u_2	wind speed (m s ⁻¹)	X	X	X	X	X	$U(0.7, 6.9)$

* The Rutter and Rutter Sparse models use *R* rather than P_G . However we calculate *R* directly from P_G using *Dur*.

3. Results

Results from the Sobol global sensitivity and uncertainty analysis are given below. Uncertainty is interpreted through statistics and histograms. Sensitivity is interpreted through the Sobol first and higher order sensitivity indices (Eq. 22).

3.1. Uncertainty Analysis

Results from the uncertainty analysis provide a ranking of the models according to the confidence in the results. These results show the maximum, minimum, mean, median,

confidence interval, skew, and kurtosis (Table 2). The Rutter Sparse and Gash Sparse models are the most uncertain of the five models in predicting canopy interception with the largest 95% CI while the Gash model is the most certain with the smallest 95% CI (Table 2). The kurtosis for each of the models is positive indicating that the distribution of predicted canopy interception are all more peaked than a standard normal distribution (Table 2). The Gash model has a particularly high kurtosis (1.1). The skew for each of the models is positive indicating that the predictions of canopy interception are skewed to the left when compared to a normal distribution (Table 2). A two sided Kolmogorov-Smirnov test shows that there is a statistical difference between each of the model uncertainty analyses. However, visually, this difference does not appear critical, except perhaps for the case of the Gash model which is more peaked and skewed compared to the other models.

Table 2. Sobol global uncertainty analysis results. The units for max, min, mean, median, and 95% confidence interval (CI) are mm of interception. Skew and kurtosis are both unitless.

	Rutter	Rutter Sparse	Gash	Gash Sparse	Liu
Max	7.6	7.9	6.6	8.4	9.1
Min	0.3	0.3	-0.3	0.3	0.2
Mean	2.8	2.9	2.2	3.3	3.3
Median	2.7	2.8	2.2	3.3	3.2
95% CI	4.6	4.9	3.5	5.0	3.0
Skew	0.6	0.6	0.6	0.4	0.4
Kurtosis	0.5	0.4	0.9	0.4	0.1
# parameters	13	11	10	10	9

Figure 1. Sobol global uncertainty analysis.

3.2. Sensitivity Analysis

The results from the sensitivity analysis identify the most important and the least important parameters for each of the interception models (Figure 2). Interestingly, for these fairly simple models, higher order sensitivities are important for characterizing the total model sensitivity. Overall, the five models behave similarly, with the most and least important parameters fairly consistent across models. On average, the most important model parameter was cumulative gross precipitation [P_G], which accounted for 16% to 34% of the total model sensitivity. This was followed closely by duration [Dur] which accounted for 18% to 31% of the total model sensitivity. Canopy storage [S], solar radiation [Rn], and maximum temperature [T_{max}] were also important parameters accounting for 14% to 28%, 12% to 20%, and 5% to 8% of total model

sensitivity, respectively across all five of the models. In both the Rutter Sparse and Gash Sparse models, canopy cover $[c]$ was also important, as expected. Additionally, trunk storage $[S_t]$ was important in the Gash Sparse and Liu models.

The specific ranking of the top four most important parameters did vary between models. In the Rutter model, the four most important parameters, in order of importance, were gross rainfall $[P_G]$, duration $[Dur]$, solar radiation $[Rn]$, and canopy storage capacity $[S]$. In the Rutter Sparse model, the four most important parameters, in order of importance, were gross rainfall $[P_G]$, canopy storage capacity $[S]$, duration $[Dur]$, and solar radiation $[Rn]$. In the Gash model, the four most important parameters, in order of importance were duration $[Dur]$, solar radiation $[Rn]$, gross rainfall $[P_G]$, and canopy storage capacity $[S]$. In the Gash Sparse model, the four most important parameters, in order of importance were canopy storage capacity $[S]$, duration $[Dur]$, gross rainfall $[P_G]$, and solar radiation $[Rn]$. In the Liu model, the four most important parameters, in order of importance, were duration $[Dur]$, gross rainfall $[P_G]$, solar radiation $[Rn]$, and canopy storage capacity $[S]$.

There were a number of parameters that were relatively unimportant in all of the models. Trunk evaporation as a proportion of evaporation from the saturated canopy $[\epsilon]$, the empirical drainage parameter $[b]$, the drainage partitioning coefficient $[p_d]$, and wind speed $[u_2]$ were all responsible for less than 1% of the total model sensitivity in each of the models where these parameters were employed. Maximum humidity $[H_{max}]$, free throughfall coefficient $[p]$,

stemflow coefficient [p_t], and the rate of water dripping from the canopy when canopy storage capacity is reached [Ds], were each responsible for 2% of the total model sensitivity.

Figure 2. Global Sensitivity analysis of the a) Rutter, b) Rutter Sparse, c) Gash, d) Gash Sparse, and e) Liu models. The figure shows the first and higher orders sensitivity indices for each of the model parameters. The total sensitivity index is the sum of first and higher order indices.

4. Discussion

This study provides three general insights regarding (1) model development, (2) model reliability, and (3) model application. First, the sensitivity analysis identified the most and least important parameters. This allows future modeling efforts to deliberately select between the five models and also aids in strategic calibration, monitoring, and algorithm development based

on the most important processes. Second, the uncertainty analysis enables a direct comparison of model reliability across the five models. Third, the sensitivity and uncertainty can inform and guide modeling at large scales based on readily available meteorological data and general canopy characteristics.

4.1 Model Development

Our results show that gross cumulative precipitation [P_G], storm duration [Dur], solar radiation [Rn], and canopy storage capacity [S] are the most important parameters. Precipitation amount and duration are obvious parameters that determine the total quantify of water in the model systems while solar radiation is the driving meteorological component of evaporation processes. Canopy storage capacity is also important across all five models. Although the total quantity of water that is stored by the canopy (see Table 1) is minimal, correct parameterization of this value is significant to model results. While the former three meteorological variables are easily measured, measurement of the latter is much more difficult to obtain. Indirect measurements of canopy storage capacity can be obtained using the Leyton method of regression (Leyton et al., 1967), in laboratory artificial wetting experiments for foliage (Hutchings et al., 1988), in laboratory submersion experiments for woody surfaces (Herwitz, 1985), or with elaborate *in situ* direct measurements such as trunk compression sensors (Van Stan et al., 2013) or whole-tree lysimeters (Crockford and Richardson, 1990). As such, the consistently high importance of canopy storage capacity [S] in these five models highlights the need for accurate input data. For example, Xiao et al. (2000) developed a complex interception model using detailed simulation of tree architecture to explain 84-90% of

the variation of canopy interception and found that canopy storage capacity [S] was a significant model parameter. While the Xiao et al. (2000) approach is compelling, their model parameterization is cumbersome because of the number of difficult to measure parameters (e.g., leaf and stem zenith angles, stem area index). As such, future modeling efforts should focus on decomposing canopy storage capacity into physical components that are commonly and easily measured.

4.2 Model Reliability

In an overall comparison of the five models a number of general conclusions can be drawn. While all of the models behaved differently, they did display similar patterns in both uncertainty and sensitivity. The Gash and Liu models are very similar in the ranking of parameter importance (Figure 2). The advantages of the Liu model include the low number of parameters and lack of empirical parameters (Table 1). Both the Gash Sparse and Rutter Sparse models show canopy cover [c] as somewhat important. These are the only two models that utilize canopy cover as a parameter. In the Liu, Gash, and Rutter models the free throughfall coefficient [p] is used in a conceptually similar manner to canopy cover [c]. However, the free throughfall coefficient [p] has less importance compared to canopy cover [c]. This is likely because of the frequency that the two parameters are used in the calculations. For example, the Gash Sparse utilizes canopy cover [c] in eight locations including the calculation of canopy and trunk evaporation. Whereas, the Gash model utilizes the free throughfall coefficient [p] in only three locations and does not include it in evaporation calculations. Both the Rutter and Rutter Sparse models contain additional empirical parameters used in calculating evaporation

and drip (i.e. trunk evaporation as a proportion of evaporation from the saturated canopy [ϵ], the empirical drainage parameter [b], the drainage partitioning coefficient [p_d], and the rate of water dripping from the canopy when $C = S$ [D_s]). These parameters add to model complexity and involve additional parameterization. However each of these parameters is responsible for less than 3% of the total model sensitivity. It is not the purpose of this study to determine which model is capable of producing the most accurate measures of canopy interception. Instead, our results show how each of these five interception models function given similar parameter ranges. Future work will provide experimental results of canopy interception that will be used for model calibration to assess model accuracy.

When conducting a GSA/UA the choice in how the parameter PDFs are defined plays a critical role in the results (Linhoss et al., 2015). In this study, the PDFs are not based on values from site specific or canopy specific studies. Furthermore, climatic parameter PDFs represent the full suite of seasonal and diurnal conditions. As such, this study is not designed to understand the model uncertainty when applied to a particular location or circumstance. Instead, the PDFs represent a broader range of parameter values that describe the variety of conditions under which the models may be applied, given leafed conditions. Therefore, this uncertainty identifies the maximum range in interception.

4.3 Model Application

Easily measured field parameters that may be used to parameterize foliar canopy storage include canopy gap fraction, leaf area index, and leaf water repellency characteristics. However,

storage by canopy foliage responds to rainfall events in a much different way than storage by bark and stem surfaces. For example, Van Stan et al. (2011) showed that wind-driven rainfall can initiate new stemflow pathways on tree trunks. As such, we hypothesize two theoretical curves for the response of aboveground storage compartments during rainfall events (Figure 3). The current models assume that maximum canopy storage capacity is attained when rainfall exceeds canopy storage. In reality, canopy storage capacity is rarely saturated and follows an asymptotic curve (Keim et al., 2005; Xiao and McPherson, 2015). Likewise, trunk storage capacity probably undergoes a series of stair-step increases as additional trunk flowpaths are saturated and begin to generate stemflow. Given the importance of canopy and stem storage capacity parameters in the five interception models, considerable effort should be directed towards quantifying these values across a broader range of tree species. Parameters for describing trunk storage may include bark thickness, bark surface area, diameter at breast height (DBH), and tree height. DBH can be used to infer bark surface area via allometric formulas developed by Whittaker and Woodwell (1967). Alternatively, surface area index can be measured using an LI-8100 during leafless canopy conditions. The former measurement provides total surface area of woody surfaces while the latter measurement provides one sided surface area. The actual quantity of woody surface area that can be wetted and saturated during storm events is probably somewhere in-between.

Figure 3. Theoretical relationship between a) canopy storage capacity and precipitation and b) trunk storage capacity and precipitation.

5. Conclusions

This work uses sensitivity and uncertainty analysis to compare the reliability and identify the most and least important parameters for five interception models (Rutter, Rutter Sparse, Gash, Gash Sparse, and Liu). Our results show that the most important parameters are gross precipitation [P_g], storm duration [Dur], canopy storage [S] and solar radiation [Rn]. As such, future modeling efforts, should aim to (1) obtain reliable measurements of canopy spatial characteristics, (2) decompose canopy storage capacity variables into easily measureable physical components, and (3) use high quality rainfall and solar radiation data.

This analysis shows how particularly well suited sensitivity and uncertainty is for model comparisons. In cases where a sensitivity and uncertainty analysis is applied to a single model there are limitations in the study's applicability based on how the PDFs are defined. For example, we used the 95% confidence interval from data from one weather station to define the PDFs for the climatic variables. This is a somewhat arbitrary cutoff and if we had instead chosen the 80% confidence interval, the model uncertainty would be reduced. Similarly, we set the range of values for canopy storage capacity based on data from a variety of leafed stand

types. If instead, we had set this PDF based on data from a specific species or a specific region then the model uncertainty would also be reduced. However, because we are comparing models the choices regarding the parameter PDFs are applied across models enabling us to more definitively rank the model uncertainty and parameter importance. As a result, this comparative study is particularly useful in guiding decisions for the choice of future model applications.

Acknowledgments

This material is based upon work supported by the National Institute of Food and Agriculture, U.S. Department of Agriculture, under award numbers 160000-010-300-02700 and MISZ-069390. We would also like to thank the anonymous reviewers for their thoughtful comments and suggestions.

References

- Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. Crop evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56. FAO, Rome, 300: 6541.
- Bartlett, P.A., MacKay, M.D., Verseghy, D.L., 2006. Modified snow algorithms in the Canadian Land Surface Scheme: model runs and sensitivity analysis at three Boreal forest stands. *Atmosphere-Ocean*, 44(3): 207-222.
- Beven, K., 2006. A manifesto for the equifinality thesis. *Journal of Hydrology*, 320(1): 18-36.

529 Bryant, M.L., Bhat, S., Jacobs, J.M., 2005. Measurements and modeling of throughfall
530 variability for five forest communities in the southeastern US. *Journal of Hydrology*,
531 312(1–4): 95-108. DOI:<http://dx.doi.org/10.1016/j.jhydrol.2005.02.012>

532 Calder, I., 1977. A model of transpiration and interception loss from a spruce forest in
533 Plynlimon, central Wales. *Journal of Hydrology*, 33(3): 247-265.

534 Calder, I.R., 1996. Rainfall interception and drop size—development and calibration of the
535 two-layer stochastic interception model. *Tree Physiology*, 16(8): 727-732.
536 DOI:10.1093/treephys/16.8.727

537 Crockford, R.H., Richardson, D.P., 1990. Partitioning of rainfall in a eucalypt forest and pine
538 plantation in southeastern australia: IV the relationship of interception and canopy
539 storage capacity, the interception of these forests, and the effect on interception of
540 thinning the pine plantation. *Hydrological Processes*, 4(2): 169-188.
541 DOI:10.1002/hyp.3360040207

542 Deguchi, A., Hattori, S., Park, H.-T., 2006. The influence of seasonal changes in canopy
543 structure on interception loss: Application of the revised Gash model. *Journal of*
544 *Hydrology*, 318(1–4): 80-102. DOI:<http://dx.doi.org/10.1016/j.jhydrol.2005.06.005>

545 Delta Agricultural Weather Center, 2015. Weather Data. Mississippi State University
546 Extension Service.

547 Gash, J., 1979. An analytical model of rainfall interception by forests. *Quarterly Journal of*
548 *the Royal Meteorological Society*, 105(443): 43-55.

549 Gash, J., Lloyd, C., Lachaud, G., 1995. Estimating sparse forest rainfall interception with an
550 analytical model. *Journal of Hydrology*, 170(1): 79-86.

551 Hedstrom, N., Pomeroy, J., 1998. Measurements and modelling of snow interception in the
 552 boreal forest. *Hydrological Processes*, 12(1011): 1611-1625.

553 Helvey, J., Patric, J., 1965. Design criteria for interception studies, Symposium on Design of
 554 Hydrological Networks 1, W.M.O. Publ., Quebec, 67 (1965), pp. 131–137, pp. 131-
 555 137.

556 Herbst, M., Rosier, P.T.W., McNeil, D.D., Harding, R.J., Gowing, D.J., 2008. Seasonal variability
 557 of interception evaporation from the canopy of a mixed deciduous forest.
 558 *Agricultural and Forest Meteorology*, 148(11): 1655-1667.
 559 DOI:<http://dx.doi.org/10.1016/j.agrformet.2008.05.011>

560 Herwitz, S.R., 1985. Interception storage capacities of tropical rainforest canopy trees.
 561 *Journal of Hydrology*, 77(1): 237-252. DOI:[http://dx.doi.org/10.1016/0022-](http://dx.doi.org/10.1016/0022-1694(85)90209-4)
 562 [1694\(85\)90209-4](http://dx.doi.org/10.1016/0022-1694(85)90209-4)

563 Herwitz, S.R., Slye, R.E., 1995. Three-dimensional modeling of canopy tree interception of
 564 wind-driven rainfall. *Journal of Hydrology*, 168(1–4): 205-226.
 565 DOI:[http://dx.doi.org/10.1016/0022-1694\(94\)02643-P](http://dx.doi.org/10.1016/0022-1694(94)02643-P)

566 Hutchings, N.J., Milne, R., Crowther, J.M., 1988. Canopy storage capacity and its vertical
 567 distribution in a Sitka spruce canopy. *Journal of Hydrology*, 104(1–4): 161-171.
 568 DOI:[http://dx.doi.org/10.1016/0022-1694\(88\)90163-1](http://dx.doi.org/10.1016/0022-1694(88)90163-1)

569 Keim, R.F., Skaugset, A.E., Weiler, M., 2005. Temporal persistence of spatial patterns in
 570 throughfall. *Journal of Hydrology*, 314(1–4): 263-274.
 571 DOI:<http://dx.doi.org/10.1016/j.jhydrol.2005.03.021>

572 Klingaman, N.P., Levia, D.F., Frost, E.E., 2007. A comparison of three canopy interception
 573 models for a leafless mixed deciduous forest stand in the Eastern United States.
 574 Journal of Hydrometeorology, 8(4): 825-836.

575 Leyton, L., Reynolds, E., Thompson, F., 1967. Rainfall interception in forest and moorland,
 576 International symposium on forest hydrology. Pergamon Press, New York, USA, pp.
 577 168.

578 Limousin, J.-M., Rambal, S., Ourcival, J.-M., Joffre, R., 2008. Modelling rainfall interception in
 579 a mediterranean Quercus ilex ecosystem: Lesson from a throughfall exclusion
 580 experiment. Journal of Hydrology, 357(1-2): 57-66.
 581 DOI:<http://dx.doi.org/10.1016/j.jhydrol.2008.05.001>

582 Linhoss, A.C. et al., 2013. Decision analysis for species preservation under sea-level rise.
 583 Ecol. Model., 263(2013): 264-272.

584 Linhoss, A.C., Muñoz-Carpena, R., Kiker, G., Hughes, D., 2012. Hydrologic modeling,
 585 uncertainty, and sensitivity in the Okavango Basin: Insights for scenario assessment:
 586 Case Study. J Hydrol Eng, 18(12): 1767-1778.

587 Linhoss, A.C., Tagert, M.L., Hazel, B., 2015. Factors affecting parameter importance in a
 588 sensitivity analysis: Application to an irrigation scheduler. Biosys. Eng., Submitted.

589 Liu, S., 1997. A new model for the prediction of rainfall interception in forest canopies. Ecol.
 590 Model., 99(2-3): 151-159. DOI:[http://dx.doi.org/10.1016/S0304-3800\(97\)01948-0](http://dx.doi.org/10.1016/S0304-3800(97)01948-0)

591 Liu, S., 2001. Evaluation of the Liu model for predicting rainfall interception in forests
 592 world-wide. Hydrological Processes, 15(12): 2341-2360. DOI:10.1002/hyp.264

593 Llorens, P., Domingo, F., 2007. Rainfall partitioning by vegetation under Mediterranean
 594 conditions. A review of studies in Europe. *Journal of Hydrology*, 335(1–2): 37-54.
 595 DOI:<http://dx.doi.org/10.1016/j.jhydrol.2006.10.032>
 596 Massman, W.J., 1983. The derivation and validation of a new model for the interception of
 597 rainfall by forests. *Agricultural Meteorology*, 28(3): 261-286.
 598 Muzyllo, A., Llorens, P., Valente, F., Keizer, J., Domingo, F., Gash, J., 2009. A review of rainfall
 599 interception modelling. *Journal of Hydrology*, 370(1): 191-206.
 600 Návar, J., 2013. The performance of the reformulated Gash's interception loss model in
 601 Mexico's northeastern temperate forests. *Hydrological Processes*, 27(11): 1626-
 602 1633. DOI:10.1002/hyp.9309
 603 Ponce, V.M., Hawkins, R.H., 1996. Runoff curve number: Has it reached maturity? *Journal of*
 604 *Hydrologic Engineering*, 1(1): 11-19.
 605 Rutter, A., Kershaw, K., Robins, P., Morton, A., 1972. A predictive model of rainfall
 606 interception in forests, 1. Derivation of the model from observations in a plantation
 607 of Corsican pine. *Agricultural Meteorology*, 9: 367-384.
 608 Rutter, A., Morton, A., 1977. A predictive model of rainfall interception in forests. III.
 609 Sensitivity of the model to stand parameters and meteorological variables. *J. Appl.*
 610 *Ecol.*: 567-588.
 611 Rutter, A., Morton, A., Robins, P., 1975. A predictive model of rainfall interception in forests.
 612 II. Generalization of the model and comparison with observations in some
 613 coniferous and hardwood stands. *J. Appl. Ecol.*: 367-380.
 614 Saltelli, A. et al., 2008. *Global Sensitivity Analysis: The Primer*. John Wiley & Sons, West
 615 Sussex, England.

616 Saltelli, A., Ratto, M., Tarantola, S., Campolongo, F., 2005. Sensitivity analysis for chemical
617 models. *Chemical Reviews*, 105(7): 2811-2828.

618 Scott, E.M., 1996. Uncertainty and sensitivity studies of models of environmental systems,
619 Proceedings of the 28th conference on Winter simulation. IEEE Computer Society,
620 pp. 255-259.

621 Siegert, C.M., Levia, D.F., 2014. Seasonal and meteorological effects on differential stemflow
622 funneling ratios for two deciduous tree species. *Journal of Hydrology*, 519, Part A:
623 446-454. DOI:<http://dx.doi.org/10.1016/j.jhydrol.2014.07.038>

624 Sobol, I., 1993. Sensitivity analysis for nonlinear mathematical models. *Mathematics and*
625 *Computers in Simulation*, 1(4): 407-414.

626 Šraj, M., Brilly, M., Mikoš, M., 2008. Rainfall interception by two deciduous Mediterranean
627 forests of contrasting stature in Slovenia. *Agricultural and Forest Meteorology*,
628 148(1): 121-134. DOI:<http://dx.doi.org/10.1016/j.agrformet.2007.09.007>

629 Staelens, J., De Schrijver, A., Verheyen, K., Verhoest, N.E.C., 2008. Rainfall partitioning into
630 throughfall, stemflow, and interception within a single beech (*Fagus sylvatica* L.)
631 canopy: influence of foliation, rain event characteristics, and meteorology.
632 *Hydrological Processes*, 22(1): 33-45. DOI:10.1002/hyp.6610

633 Toba, T., Ohta, T., 2008. Factors affecting rainfall interception determined by a forest
634 simulator and numerical model. *Hydrological Processes*, 22(14): 2634-2643.
635 DOI:10.1002/hyp.6859

636 Valente, F., David, J., Gash, J., 1997. Modelling interception loss for two sparse eucalypt and
637 pine forests in central Portugal using reformulated Rutter and Gash analytical
638 models. *Journal of Hydrology*, 190(1): 141-162.

639 Van Stan li, J.T., Siegert, C.M., Levia Jr, D.F., Scheick, C.E., 2011. Effects of wind-driven
640 rainfall on stemflow generation between codominant tree species with differing
641 crown characteristics. *Agricultural and Forest Meteorology*, 151(9): 1277-1286.
642 DOI:<http://dx.doi.org/10.1016/j.agrformet.2011.05.008>

643 Van Stan, J.T., Martin, K., Friesen, J., Jarvis, M.T., Lundquist, J.D., Levia, D.F., 2013. Evaluation
644 of an instrumental method to reduce error in canopy water storage estimates via
645 mechanical displacement. *Water Resources Research*, 49(1): 54-63.
646 DOI:10.1029/2012WR012666

647 Vose, J.M., Peterson, D.L., Patel-Weynand, T., 2012. Effects of climatic variability and change
648 on forest ecosystems: a comprehensive science synthesis for the US forest sector. US
649 Department of Agriculture, Forest Service, Pacific Northwest Research Station
650 Portland, OR.

651 Whittaker, R.H., Woodwell, G.M., 1967. Surface area relations of woody plants and forest
652 communities. *Am. J. Bot.*, 54(8): 931-939.

653 Xiao, Q., McPherson, E.G., 2015. Surface water storage capacity of twenty tree species in
654 Davis, California. *Journal of Environmental Quality*. DOI:10.2134/jeq2015.02.0092

655 Xiao, Q., McPherson, E.G., Ustin, S.L., Grismer, M.E., 2000. A new approach to modeling tree
656 rainfall interception. *Journal of Geophysical Research: Atmospheres*, 105(D23):
657 29173-29188.

658 Zeng, N., Shuttleworth, J.W., Gash, J.H., 2000. Influence of temporal variability of rainfall on
659 interception loss. Part I. Point analysis. *Journal of Hydrology*, 228(3): 228-241.
660