Identification of Rainfall Interception Model Parameters from Measurements of Throughfall and Forest Canopy Storage

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ABSTRACT

The majority of canopy interception models, simulating the driving processes that control the energy and water exchange between the canopy and the atmosphere, contain parameters that can not be measured directly, but can only be meaningfully inferred by calibration against a measured record of input – output data. The aim of the present paper is to explore the suitability of two different types of measurements for the identification of parameters in a single layer forest canopy interception model. The first information source consists of measured throughfall dynamics, whereas the second consists of measured canopy water storage dynamics. The latter measurements were obtained using the attenuation of a microwave signal over 12.5 m propagation line while scanning vertically through the forest canopy. Results demonstrate that measured throughfall dynamics contain only very limited information for the calibration of a canopy interception model, and are particularly inadequate to identify the storage capacity and evaporation rate of the forest canopy. On the contrary, microwave-measured canopy water storage dynamics contain sufficient information to be able to identify the interception model parameters with a high degree of confidence.

Keywords: Parameter Identification, Rainfall Interception, Canopy Water Storage, Throughfall, Markov Chain Monte Carlo, Recursive Parameter Estimation.

1. INTRODUCTION AND SCOPE

Interception and evaporation of rainfall are important hydrologic processes in forest ecosystems. Modeling these complex processes involves an understanding of the observations, models and equations that are formulated to describe the energy and water exchange between the forest canopy and the atmosphere. In the past, several physically based [*Gash*, 1979; *Rutter et al*., 1971] and stochastic models [*Calder*, 1986], ranging from single-layer models [*Rutter al al*., 1971; *Halldin et al*., 1979; *Massman*, 1983] to more elaborate multi-layer models [*Calder*, 1977; *Sellers and Lockwood*, 1981], were developed to simultaneously simulate throughfall, evaporation from the wetted canopy, and the resulting temporal and spatial dynamics in canopy water storage. Despite their crucial role in the water balance of hydrologic models, relative limited research has been conducted towards the validity of canopy interception models or the appropriate use of their parameters in larger scale hydrologic models. As such, it is possible that poor interception models or biased values of the parameters in these models are in widespread use, which of course has important consequences for regional water management.

The development of canopy interception models is hampered by the lack of measurement techniques available to independently validate each of the simulated hydrologic processes controlling canopy water storage dynamics. Canopy interception models typically calculate the canopy water balance on the basis of precipitation, drainage, and evaporation rates, the last two being dependent upon the actual canopy water storage. The increasing complexity of the physical processes represented within the canopy interception models has resulted in an increasing number of parameters that can not be measured directly, but only by calibration against a measured record of input – output data. Principally, canopy interception model parameters can be identified on the basis of measured throughfall, canopy storage and evaporation dynamics from the wetted surface. However, as evaporation from the rain-wetted canopy and drainage during and after the rain event is difficult to measure, these models are usually calibrated against measured throughfall dynamics only [*Lousteau et al*., 1992; *Jetten*, 1996; *Aboal et al*., 1999; *Schellekens et al*., 1999; among others], thereby casting doubt about the physical realism of the values of some of the model parameters. Hence, if rainfall interception model parameters are identified from a time series in which throughfall and evaporation occur simultaneously, then a strong interdependency between at least some of the model parameters can be expected.

Several contributions to the hydrologic literature have demonstrated the usefulness and applicability of attenuation methods for the direct measurement of canopy water storage dynamics. For instance, *Calder and Wright* [1986] measured the γ-ray attenuation over a 25-35 m horizontal transmission line, scanning vertically, right across the canopy. They succeeded in calibrating their measuring system and obtained direct measurements of canopy water storage. Unfortunately, because of safety standards, this equipment is not suitable for unattended automated monitoring. To circumvent this problem, *Bouten et al.* [1996] applied a microwave transmission technique to directly measure canopy water storage dynamics. The principal advantages of this method over, for example γ-ray attenuation are that it involves no radiological hazards and that the method is sensitive to small changes in water content due to its high spatial and temporal resolution.

Whether interception model parameters are well identifiable is primarily determined by the duration and intensity of rainfall events, the quality and type of measurements used for model calibration and the complexity of the underlying model structure. This issue of parameter identifiability and its antithesis parameter uncertainty has drawn on a growing interest over the last two decades, partly because it influences the reliability of all further applications of models. Only recently have methods for realistic assessment of parameter uncertainty in hydrologic models begun to appear in the literature. Because traditional statistical theory based on first-order approximations and multinormal distributions is typically unable to cope with the nonlinearity of complex models, Markov Chain Monte Carlo (MCMC) algorithms have become increasingly popular as a class of general purpose approximation methods for problems involving complex inference, search, and optimization [*Gilks et al.*, 1996].

The MCMC method for assessing parameter confidence intervals in nonlinear models is based on the idea that instead of explicitly computing the probability distribution, $p(\theta|\boldsymbol{y})$, as done with traditional first-order approximations, it is sufficient to approximate the form of the density by drawing a large random sample from $p(\theta|\boldsymbol{y})$. Diagnostic measures of central tendency and dispersion of the posterior distribution can be estimated by computing the mean and standard deviation of the sample. As MCMC methods, thoroughly exploit the global parameter space and therefore explicitly account for parameter interdependence and non-linearity of the employed hydrologic processes, this class of algorithms is suited to generate a useful description of parameter identifiability. An effective and efficient MCMC sampler has recently been developed in collaboration with colleagues at the University of Arizona, entitled the Shuffled Complex Evolution Metropolis algorithm (SCEM-UA), which is suited to simultaneously infer the most likely parameter set and its underlying probabilistic posterior distribution within a single optimization run [see *Vrugt et al.*, 2003].

The aim of the present paper is to explore the suitability of measured throughfall and microwave-measured canopy storage dynamics for the identification of parameters in a simple four-parameter canopy interception model. An identifiability analysis of the parameters in an interception model using different types of information constitutes important information for studies that aim to find transfer functions, relating these parameters to independently measured system properties. The remainder of this paper is organized as follows. In Section 2 we present the rationales of the single-layer interception model used throughout this study, describe the research site and measurements used for the identification of the model parameters in the interception model, and briefly discuss the SCEM-UA global optimization algorithm. Subsequently, in Section 3 we test the usefulness of measured throughfall and water storage dynamics for the identification of the parameters in the single-layer interception model. In this Section we are especially concerned with the temporal variability in information content of the two different measurement types for the various model parameters by identifying portions of the dataset with maximal and independent information about the interception model parameters. Finally, a summary of the work presented in this paper is given in Section 4.

2. MATERIALS AND METHODS

The fundamental problem with which we are concerned is to estimate parameter values and their uncertainty from observed hydrologic data (inputs) using a specified mathematical model that simulates actual input-output relations. Several models have been proposed to mathematically describe the hydrologic process of interception of rainfall by forest canopies. In the present study, for simplicity, a parsimonious single-layer interception model with four model parameters was used.

2.1. The single-layer interception model

Bouten et al. [1996] have modeled the canopy water storage by using a numerical multi-layer interception model based on the Rutter Model [*Rutter et al*., 1971]. The canopy water balance is calculated according to:

$$\frac{\Delta S}{\Delta t} = I - D - E \qquad [1]$$

where S (mm) is the water storage in the canopy, *t* (d) denotes time, D (mm d^{-1}) is drainage rate and E (mm d^{-1}) is the evaporation rate. The water interception rate, I (mm d^{-1}), is calculated with:

$$I = aP \qquad [2]$$

where *a* is a unit-less interception efficiency parameter and P (mm d^{-1}) denotes the gross rainfall. It is assumed that drainage only occurs if S is larger than the storage capacity *c* (mm) and for simplicity a linear threshold model was used:

$$D = b(S - c) \quad \text{if} \quad S > c \qquad [3]$$

in which *b* (d^{-1}) is an empirical drainage parameter.

The evaporation rate is computed according to:

$$E = dE_0 \frac{S}{c} \qquad [4]$$

in which *d* is an unit-less empirical evaporation efficiency and E_0 is calculated according to [*Monteith*, 1965]:

$$E_0 = \frac{sR_n + \rho C_p VPD(g_a + g_b)}{\lambda(s + \gamma)} \qquad [5]$$

where s is the slope of the saturated vapor pressure with temperature (Pa K^{-1}), R_n the net radiation (W m^{-2}), ρ the density of air (kg m^{-3}), C_p the specific heat of air, taken as 1005 (J kg^{-1} K), VPD the vapor pressure deficit (Pa), γ the psychrometer constant (Pa K^{-1}), g_a the aerodynamic conductance (m s^{-1}), g_b the excess resistance (m s^{-1}) and λ is the latent heat of vaporization (J kg^{-1}) . The g_b is derived from the formula of *Hicks et al.* [1985] and g_a was calculated from the wind speed at 30 m and roughness length as a function of wind direction. Corrections were made for temperature stability. For more details, please refer to *Bouten et al.* [1996]. All together the model has four parameters, *a*, *b*, *c* and *d* that need to be identified on the basis of either throughfall or canopy water storage measurements.

While classical statistics consider the model parameters *a*, *b*, *c* and *d* (hereafter referred to as θ) in the interception model to be fixed but unknown, the Bayesian statistics treat them as probabilistic variables having a joint posterior probability density function (pdf), which captures the probabilistic beliefs about the parameters θ in the light of the observed data $\boldsymbol{y}$. The posterior pdf $p(\theta|\boldsymbol{y})$ is proportional to the product of the likelihood function and the prior pdf. The prior pdf with probability density (or mass) function $p(\theta)$ summarizes information about θ before any data are collected. This prior information usually consists of realistic lower and upper bounds on each of the parameters (see Table 1), thereby defining the feasible parameter space and imposing a uniform prior distribution on this rectangle.

2.2. Research site

The research site Speuld is located in a 2.5 ha Douglas fir forest stand, in a large forested area near Garderen in the Netherlands (52°15’N, 5°41’W, 52 m above sea level). The 27-year-old stand is dense with 780 firs ha^{-1} without understorey. The 30-year average rainfall is 834 mm

y^{-1} and is evenly distributed over the year. The stand is surrounded by stands of Scotch Pine, oak, beech, larch and Douglas fir.

Gross rainfall was measured every 2.5 minutes just above the forest with two funnels with a resolution of 0.02 mm rainfall, and additionally with one funnel in a large clearing area, 0.8 km away with a specified resolution of 0.05 mm of rainfall. The Royal Meteorological Institute of the Netherlands (KNMI) [see *Bosveld et al.*, 1998] performed half-hourly measurements of meteorological driving variables on a 36 meter high guyed mast to calculate the potential evaporation (E_0) [*Monteith*, 1965].

Throughfall was measured every 2.5 minutes with 11 automatic funnels (480 cm^2) from July to September and with 18 automatic funnels from October to December. The coefficient of variation (CV) of the throughfall measurements is large due to spatial variability between the funnels and decreases with the amount of throughfall (Figure 1). But even with mean weekly values, up to 70 mm throughfall, a minimum CV of 20% was found. The specified measurement resolution of one funnel is 0.02 mm. Smaller values of throughfall, as indicated in Figure 1, are caused by averaging the different automated funnels. In this study half-hourly measurements of throughfall were used, obtained when averaging measured throughfall amount with the automated funnels over 30 minute intervals. Stemflow was never observed within the experimental plot.

Water storage was measured using a microwave transmitter and receiver [*Bouten and Bosveld*, 1991; *Bouten et al.*, 1991] mounted in a hoist attached to towers standing 12.5 m apart. Every half-hour six complete vertical scans were carried out during which 20 measurements per second were performed. Every vertical meter of displacement, the mean attenuation, based on more than 100 measurements, and its standard deviation were calculated and stored. Conversion of the measured attenuation values to canopy water storage was done using measured precipitation and throughfall rates on nights with low wind speeds (less than 2 m s^{-1}), low vapor pressure deficit (less than 0.5 g kg^{-1}) and an absence of solar radiation. Under these circumstances, evaporation from the wetted canopy was expected to be negligible [*Bouten and Bosveld*, 1991]. The vertically integrated attenuation increment compared to dry conditions was found to be highly correlated with these calculated storage amounts. The slope of the regression line, can therefore be used to convert attenuation measurements to canopy water storage. A complete description of the experimental design and calculation of canopy water storage amounts from attenuation measurement is given by *Bouten et al*. [1991] and *Bouten and Bosveld* [1991], respectively, and so will not be repeated here. In the present study 36 days with half-hourly measured values of canopy water storage, synchronized with the throughfall measurements, were used with the SCEM-UA algorithm for the identification of the model parameters in the single-layer interception model. During this 36 day selection period both measurement systems were working properly. Moreover, each of the days contained at least one significant rainfall event.

The data of DOY 211 and 258 are extensively used for calibration throughout this paper, whereas the remaining 34 days of measured throughfall and water storage dynamics were used for evaluation purposes. For two main reasons longer data sets of measured throughfall and water storage dynamics were not used for calibration purposes. In the first place, application of the Parameter Identification Method based on the Localization of Information (PIMLI) method, a Sequential Optimization Methodology developed by *Vrugt et al*. [2002], demonstrated that one day of half-hourly measurements of throughfall and canopy water storage yielded very similar results than to those using longer data sets for the identification of the interception model parameters. In other words, the gain in information for the calibration of the interception model parameters can be considered marginal when using more than one day of half-hourly observations. In the second place, a significant yearly trend in the storage capacity of the canopy, caused by biomass dynamics, is found in the measured attenuation profiles [*Tiktak et al*., 1991]. The Leaf Area Index (LAI) for the Douglas fir stand ranges between 8 m^2 m^{-2} in spring to about 12 m^2 m^{-2} in early summer. Restricting the analysis to two short time series of one day circumvents the problem of a variable canopy water storage parameter throughout the year in the interception model.

2.3. The Shuffled Complex Evolution Metropolis (SCEM-UA) optimization algorithm

The SCEM-UA algorithm is a general-purpose method suited for optimization and uncertainty assessment of hydrologic model parameters. The SCEM-UA algorithm is related to the successful SCE-UA global optimization method [*Duan et al*., 1992], but uses the Metropolis Hastings (MH) strategy [*Metropolis et al*, 1953; *Hastings*, 1970] instead of the Downhill Simplex method for population evolution, and is therefore able to simultaneously infer both the most likely parameter set and its underlying posterior probability distribution within a single optimization run. A detailed description of the method is given by *Vrugt et al*. [2003] and so will not be repeated here. In brief, the SCEM-UA method involves the initial selection of a population of points randomly distributed throughout the feasible parameter space. In the absence of any information about the posterior distribution, a Latin hypercube sampling strategy is used. The population is partitioned into several complexes and in each of these complexes a parallel sequence is launched starting at that point that exhibits the highest posterior probability. Subsequently, a new candidate point in each of the sequences is generated using the current draw in the sequence in combination with the covariance structure of that particular complex. The Metropolis-annealing [*Metropolis et al*., 1953] criterion is utilized to test whether the candidate point is added to the current sequence. Finally, the new candidate point is shuffled into the original population of complexes. This ability of the SCEM-UA algorithm to exchange information between parallel launched sequences in the parameter space significantly reduces the number of model simulations needed to infer the posterior distribution of the parameters as compared to traditional Metropolis Hastings samplers. The evolution and shuffling procedures are repeated until the Gelman – Rubin convergence diagnostic for each of the parameters demonstrates convergence to a stationary posterior target distribution [*Gelman and Rubin*, 1992].

When using the SCEM-UA algorithm to estimate the posterior distribution of the model parameters, the likelihood of each single parameter set needs to be calculated. Assuming that the residuals are mutually independent, and Gaussian distributed with constant variance, the likelihood of a parameter set θ for describing the observed data **y** can be computed using [*Box and Tiao*, 1973],

$$\mathrm{L}(\theta \mid \boldsymbol{y}, \beta) = \exp\left[-\frac{1}{2}\sum_{j=1}^{n}\left|\frac{\boldsymbol{y}_j - \hat{y}_j(\theta)}{\sigma}\right|^2\right] \qquad [6]$$

in which $\hat{y}$ is a n x 1 vector of model predictions, $\boldsymbol{y}$ denotes the time series of observed output (in this case either observed throughfall or measured canopy water storage dynamics) and σ denotes the error standard deviation of the observations (see Section 2.4).

Once, the SCEM-UA algorithm has converged to a limiting distribution, the covariance matrix of the parameters (**P**) within this distribution can be computed. This matrix **P** contains all the necessary information to infer the identifiability of the parameters and to assess how many parameters are supported by the data. Based on recommendations in our previous work [*Vrugt et al*., 2003], the stationary posterior distribution corresponding to the likelihood criterion specified in Eq. [6] was estimated using a population size of 500 points in combination with a total of 10,000 model evaluations. Moreover, we use a uniform distribution on θ as the prior distribution p(θ). In the remaining part of this paper, the stationary posterior distribution of the parameters is also referred to as the High Probability Density (HPD) region of the parameter space.

2.4. Inferences regarding the error standard deviation (σ) of the throughfall and canopy water storage measurements

Assigning each residual between model and measurement in the right hand side of Eq. [6] a weight relative to the reliability of the measurements preserves all the statistical information. When dealing with throughfall or canopy storage measurements, the value of σ in Eq. [6], should not only be based on the instrumental error of the measuring devices, but should also explicitly include some measure of the uncertainty associated with the spatial variability in measured throughfall and canopy storage amounts within the Douglas fir stand. Hence, the parameters in the single-layer interception model, outlined in Section 2.1, are averages for the Douglas fir stand. Consequently, the value of σ for the throughfall measurements was derived from the standard deviation of measured half-hourly throughfall amounts with the automated funnels. Additionally, the measurement error of the half-hourly canopy water storage measurements was set to 0.25 mm, constituting an error of 0.05 mm in measured water storage amounts due to the influence of the wind [*Bouten et al*., 1996], in combination with an additional error of 0.20 mm, obtained when translating microwave attenuation measurements to actual canopy water storage amounts [*Bouten and Bosveld*, 1991] for this particular Douglas fir stand.

3. RESULTS AND DISCUSSION

Table 2 presents the posterior mean, standard deviation, coefficient of variation (CV), and correlation structure induced between the parameters of the single layer interception model, obtained when assimilating and processing the throughfall and canopy water storage measurements of DOY 211 with the SCEM-UA algorithm. The algorithm converged to a stationary posterior distribution after 2,500 iterations (function evaluations). The high coefficients of variations (CV) and standard deviations of the parameters in Table 2 demonstrate that measured throughfall dynamics contain only very limited information for the calibration of a canopy interception model. Although there does not exist an exact quantitative threshold to help judge whether a parameter is identifiable or not, the rationales on the identifiability of the interception model parameters that we adopt in this paper are based on the extent of the HPD region in the physical plausible or prior parameter space. For instance, it is clear that the storage capacity, the evaporation efficiency and drainage parameter are poorly defined by calibration to measured throughfall dynamics, as for each of these parameters there does not exist a well-defined region, in the sense of a compact region, interior to the physical plausible or prior parameter space. Moreover, there is considerable correlation between the *c* and *d*-parameter of the interception model, further deteriorating the identifiability of these parameters as illustrated in Figure 2. On the contrary, measured water storage dynamics contain sufficient information to be able to identify most of the model parameters with a high degree of confidence. Hence, the CV-values and standard deviation of the parameters, as reported in Table 2, illustrate that for most of the parameters the HPD region occupies only a very small portion of the prior parameter space. Especially, the storage capacity and the evaporation efficiency parameter are very well determined by calibration to measured water storage dynamics. Unfortunately, like measured throughfall dynamics, canopy water storage measurements contain insufficient information to identify the drainage (b) parameter with a satisfying accuracy.

To understand these results consider Figure 3 that presents the evolution of the High Probability Density (HPD) region of the posterior probability density, in the form of one-dimensional projections for each of the model parameters, derived when stepwise assimilating and processing the throughfall (Fig. 3B-E) or canopy water storage (Fig. 3G-J) measurements of DOY 211 with the SCEM-UA algorithm. The approach followed here is similar as the Bayesian Recursive Estimation (BaRE) methodology recently developed by *Thiemann et al*. [2001], with the small adaptation that the recursive SCEM-UA methodology followed here resamples the parameter space after each measurement is assimilated and processed, thereby preventing the collapse to a single best parameter estimate and thus addressing a deficiency of the BaRE algorithm. To allow comparison between uncertainties of different parameters, the HPD region was scaled according to the prior uncertainty bounds of the parameters, previously defined in Table 1, to yield normalized ranges between 0 and 1. The dark-shaded line marks the evolution of the most likely parameter set at each time step, whereas the asterisks denote the most likely parameter values derived using the Shuffled Complex Evolution (SCE-UA) global optimization algorithm developed by *Duan et al*. [1992].

Starting at t = 211.4, the size of the HPD region of the parameters, reflects the initial or prior uncertainty of the parameters before any data are collected and processed. Immediately after the first rain event at t = 211.55, the uncertainty associated with the interception efficiency parameter, *a*, decreases, and remains rather constant thereafter, demonstrating that rain events during the wetting stage of the forest canopy contain the most information for the identification of the *a*-parameter. Notice the striking similarity in the evolution of the HPD region of the *a*-parameter when using throughfall and canopy water storage measurements separately with the SCEM-UA algorithm. Although the *a*-parameter is reasonable well determined by calibration to measured throughfall dynamics (see Fig. 3B), the additional throughfall measurements between the first rain-event and the drying cycle starting at the beginning of DOY 212 contain very limited information for the model parameters. Hence, the one-dimensional projections of the evolution of the HPD region of the posterior probability density defined in Eq. [6] for *b*, *c*, and *d* (see. Fig. 3C-E) suggest that for these parameters there does not exist a well defined region in the sense of a compact region interior to the prior parameter space when calibrating on measured throughfall dynamics. On the contrary, the evolution of the Bayesian confidence intervals of the parameters depicted in the Figures 3G-J, illustrate that measured canopy water storage dynamics contain sufficient information to uniquely identify at least three of the interception model parameters (*a*, *c*, and *d*). Moreover, these parameters are identifiable at different stages during the wetting and drying cycles, thereby facilitating the identification of a unique set of parameters. Again, the interception efficiency parameter, *a*, is best defined during the wetting stage of the canopy, whereas the *c* and *d*-parameter are best defined when the canopy water storage reaches its saturation ($211.6 < t < 212.2$), and during the drying stage of the canopy respectively ($212.3 < t < 212.6$). Unfortunately, no information is found for the drainage parameter. Also notice, the excellent correspondence between the most optimal parameter values derived using a conventional batch calibration approach (SCE-UA algorithm) for the entire period and the location of the HPD region, centered around the most likely parameter set, derived with the sequential SCEM-UA approach. The characteristic jumping behavior of the bounds of the HPD region in the parameter space, so evident in Figure 3, is caused by the presence of errors in the augmented boundary conditions, model structural inadequacies, errors in measured throughfall and canopy water storage dynamics and the stochastic properties of the SCEM-UA sampler. Nevertheless, Figure 3 demonstrates very well that adding more data does not simply solve the problem of parameter identifiability. Only specific data periods with high information content can reduce the uncertainty associated with the interception model parameters.

To check whether the calibration results of the interception model parameters using the observations of throughfall and canopy water storage of DOY 211 are consistent, consider Table 3 that presents the posterior mean, standard deviation, coefficient of variation (CV), and correlation structure induced between the parameters of the single layer interception model, obtained when calibrating the interception model parameters using the throughfall and canopy water storage measurements of DOY 258. Indeed, the results presented in Table 3 are quite similar to our earlier results presented in Table 2 thereby illustrating the consistency of the results when using different measurement days for the calibration of the interception model and further confirming the poor identifiability of the interception model parameters using measured throughfall dynamics.

Notwithstanding the results presented here, the Bayesian framework for inferring the posterior probability distribution of the parameters operates under the central assumption that the predefined model structure of the single layer interception model, outlined in Section 2.1, is correct. To verify the correctness of the interception model, consider Figure 4 that presents the prediction uncertainty ranges of the interception model associated with the posterior parameter estimates (light-gray region), for DOY 211 and 258 of 1989 using the throughfall and canopy water storage measurements. The solid circles correspond to the measured throughfall and canopy water storage amounts respectively. Note that the prediction uncertainty ranges generally bracket the observed throughfall and water storage amounts, indicating that the predefined model structure is capable for the purpose of predicting throughfall and water storage dynamics.

To verify the consistency and reliability of the calibration results, the performance for each of the parameter samples in the HPD region obtained when using throughfall and water storage measurements separately for DOY 211 and 258 were evaluated for a time series of 816 half-hourly measurements of throughfall and canopy water storage amounts not included in the calibration set. To account for seasonal fluctuations in biomass, a linear decreasing trend of the *c*-parameter between the calibrated values at DOY 211 and 258 was used [*Bouten et al*., 1996]. In this particular case, the cross-validation is no longer based on a single "best" parameter set, but is based on an ensemble of model structures, each having a different posterior density. Figure 5 presents the results of this analysis, in terms of the prediction uncertainty ranges for the evaluation period associated with the HPD region obtained for DOY 211 with the throughfall (Fig. 5A and C) and canopy water storage measurements (Fig. 5B and D). The solid circles correspond to the measured throughfall and canopy water storage amounts respectively. Also indicated in the Figure is the mean Root Mean Squared Error (RMSE), and mean percent BIAS statistics of the residuals for the evaluation period. Note that the results in the Figures B and C denote cross-validations and that cumulative throughfall is set to zero after a prolonged dry period. The prediction uncertainty ranges associated with the HPD region of the parameters, obtained when calibrating the single layer interception model on measured cumulative throughfall dynamics of DOY 211, do not only show considerable bias in the cross validation when predicting measured storage dynamics, but perhaps more importantly, also exhibit significant bias when predicting measured throughfall dynamics during an independent evaluation period. This demonstrates that on longer time scales, the performance of a canopy interception model, when calibrated on measured throughfall dynamics, can be considered quite poor. Additionally, the results in Figure 5B illustrate that one should be careful in using the parameter estimates obtained by calibration to measured throughfall dynamics to predict canopy water storage dynamics. On the contrary, the prediction uncertainty ranges associated with the HPD region of the parameters obtained by calibration to measured water storage dynamics at DOY 211, not only generate consistent forecasts of measured water storage observations over the independent evaluation period, thereby encompassing the observations, but in the cross-validation also simultaneously generate more reliable predictions of measured throughfall dynamics over the evaluation period, resulting in considerably less bias and lower RMSE values. The systematic deviations between the observed and predicted throughfall amounts over the evaluation period are primarily caused by errors in the augmented boundary conditions (measured rainfall amounts). Nevertheless, the results presented here emphasize that canopy water storage dynamics contain better and more reliable information than measured throughfall dynamics for the calibration of a canopy interception model, thereby increasing the prospects of finding the preferred parameter solutions.

Summarizing, throughfall measurements have only limited information for the identification of interception model parameters. Based on investigations of two days of measured throughfall dynamics, the only parameter that is warranted by the data is the interception fraction or *a* parameter in the single layer interception model [see also *Calder and Hall*, 1997]. Although not explicitly demonstrated here, the use of longer observational time series of throughfall dynamics for calibration purposes, leads to similar findings. While it might seem speculative to generalize the conclusions regarding the identifiability of the interception model parameters using measured throughfall dynamics to other climates, species, or biomasses situations, additional investigations with numerically generated throughfall "measurements" for other situations than what was presented in this paper yielded similar results. We subscribe ourselves, therefore, to the view that model parameters of drainage and evaporation functions, which are obtained by calibration against measured throughfall dynamics must be interpreted with care as these parameters are subject to considerable uncertainty. From this perspective, it seems, therefore, premature to compare parameter estimates of different species, that were obtained by calibration against throughfall measurements [*Rutter et al*., 1975; *Hertwitz*, 1985; *Valente et al.*, 1997; *Klaassen et a*l., 1998] or to develop more complex interception models containing a larger number of parameters [*Gash et al.*, 1995; *Calder*, 1996; *Valente et al*., 1997].

4. CONCLUSIONS

The aim of the present paper was to explore the suitability of canopy water storage observations and measured throughfall dynamics for the identification of parameters in a single layer forest canopy interception model. Most significantly, results demonstrate that measured throughfall dynamics contain only very limited information for the calibration of a four-parameter canopy interception model, and are particularly inadequate to identify the storage capacity and evaporation efficiency from the forest canopy. On the contrary, canopy water storage dynamics contain sufficient information to be able to identify the interception model parameters with a high degree of confidence. Moreover, using canopy water storage dynamics, it was shown that the parameters in the canopy interception model are identifiable at different stages during the wetting and drying cycles, thereby reducing parameter interaction and facilitating the identification of a unique set of parameters. The interception efficiency parameter, a, is best defined during the wetting stage of the canopy, whereas the canopy storage and evaporation efficiency parameter are best determined when the canopy water storage reaches its saturation, and during the drying stage of the canopy respectively. Unfortunately, neither half-hourly throughfall measurements nor canopy water storage measurements contain sufficient information for the identification of the drainage parameter. Summarizing, the results in this paper demonstrate that measured canopy water storage dynamics contain better and more reliable information than measured throughfall dynamics for the calibration of a canopy interception model, thereby increasing the prospects of finding the preferred parameter solutions. Moreover, as only one drying and wetting cycle of the canopy is needed for a reliable model calibration using measured canopy water storage dynamics, these observations are well suited to assess temporal variations in the values of the interception model parameter throughout the year.

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Table 1. Prior ranges of the parameters in the single-layer interception model

Par.	Description	Min.	Max.	Unit
a	Interception Efficiency	0.5	1.0	[-]
b	Drainage Parameter	1	1000	[d^{-1}]
c	Storage Capacity	0.5	5.0	[mm]
d	Evaporation Efficiency	0.1	2.0	[-]

Table 2. SCEM-UA derived posterior mean, standard deviation, coefficient of variation (CV [%]), and Pearson correlation coefficients between the parameters in the single-layer interception model obtained when using half-hourly measurements of throughfall or canopy storage at DOY 211. This information was derived from the matrix **P**, as generated with the SCEM-UA algorithm.

	---------------------Throughfall-------------------------							----------------------Canopy Storage---------------------						
Par.	Mean.	Std.	CV [%]	*a*	*b*	*c*	*d*	Mean.	Std.	CV [%]	*a*	*b*	*c*	*d*
a	0.92	0.043	4.63	1.00	-0.12	-0.00	-0.06	0.94	0.037	3.97	1.00	-0.01	-0.10	-0.03
b	496.08	191.22	38.55	-----	1.00	0.13	-0.01	663.42	144.81	21.82	-----	1.00	0.35	0.06
c	1.92	0.62	32.53	-----	-----	1.00	-0.86	2.64	0.040	1.51	-----	-----	1.00	0.40
d	1.26	0.24	18.87	-----	-----	-----	1.00	1.09	0.086	7.91	-----	-----	-----	1.00

Table 3. SCEM-UA derived posterior mean, standard deviation, coefficient of variation (CV [%]), and Pearson correlation coefficients between the parameters in the single-layer interception model obtained when using half-hourly measurements of throughfall or canopy storage at DOY 258.

	---------------------Throughfall------------------------							----------------------Canopy Storage---------------------						
Par.	Mean.	Std.	CV [%]	*a*	*b*	*c*	*d*	Mean.	Std.	CV [%]	*a*	*b*	*c*	*d*
a	0.93	0.034	3.68	1.00	0.16	-0.26	-0.15	0.72	0.055	7.61	1.00	0.10	0.11	0.24
b	471.45	235.11	49.87	-----	1.00	0.05	-0.04	501.06	240.01	47.90	-----	1.00	-0.09	-0.07
c	1.85	0.16	8.54	-----	-----	1.00	-0.15	2.16	0.053	2.44	-----	-----	1.00	0.55
d	0.97	0.44	45.03	-----	-----	-----	1.00	0.69	0.12	16.88	-----	-----	-----	1.00

Figure captions:

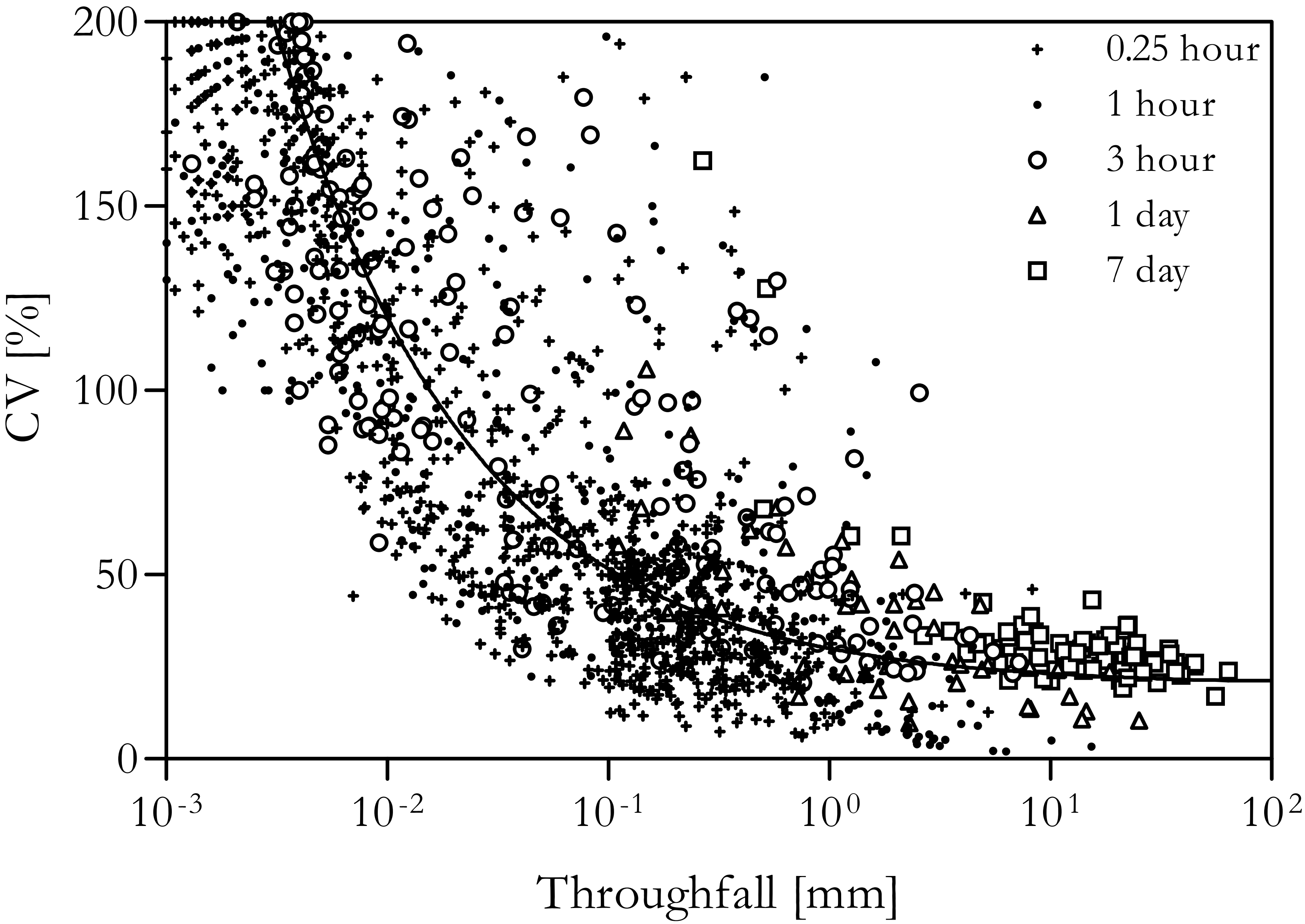
Figure 1: The coefficient of variation of the mean automatic throughfall measurements, averaged over 0.25 hour, 1 hour, 3 hours, 1 day and 7 days.

Figure 2: Scatter plot of 1000 SCEM-UA generated *c*,*d* samples in the High Probability Density (HPD) region of the parameter space after convergence has been achieved to a stationary posterior distribution using measured throughfall dynamics at DOY 211.

Figure 3: Evolution of the HPD region of the posterior probability density in the form of one-dimensional projections of the parameters (light-gray region) using measured throughfall dynamics (B-E), or canopy water storage observations (G-J). The dotted line denotes the evolution of the most likely parameter set, whereas the asterisks indicate the "best" parameter values obtained using a traditional batch calibration with the SCE-UA global optimization algorithm. The solid circles in the figures A and F denote measured values of throughfall and canopy water storage respectively, whereas the dotted line in these figures denote the model predicted values corresponding to the parameter set with the highest posterior probability.

Figure 4: Prediction uncertainty ranges (light-gray region) associated with the HPD region of the parameters using observed throughfall dynamics at DOY 211 (A), and DOY 258 (B), or measured canopy water storage dynamics at DOY 211 (C), and DOY 258 (D). The solid circles correspond to the observations, whereas the dark dotted line indicates the model predicted values corresponding to the parameter set with the highest posterior probability.

Figure 5: Evaluation and cross-validation of the HPD region of the parameters corresponding to measured throughfall (HPD-T) and canopy water storage dynamics (HPD-C) at DOY 211; A,C) Prediction uncertainty ranges of HPD-T and HPD-C when predicting cumulative throughfall dynamics; B,D) Prediction uncertainty ranges of HPD-T and HPD-C when predicting canopy water storage dynamics. The solid circles denote observations. Also indicated are the mean RMSE and mean BIAS statistics of the residuals over the evaluation and cross-validation period. For more explanation see text.



200
150
100
50
0
CV [%]
10^{-3}
10^{-2}
10^{-1}
10^{0}
10^{1}
10^{2}
Throughfall [mm]
0.25 hour
1 hour
3 hour
1 day
7 day

Figure 1.

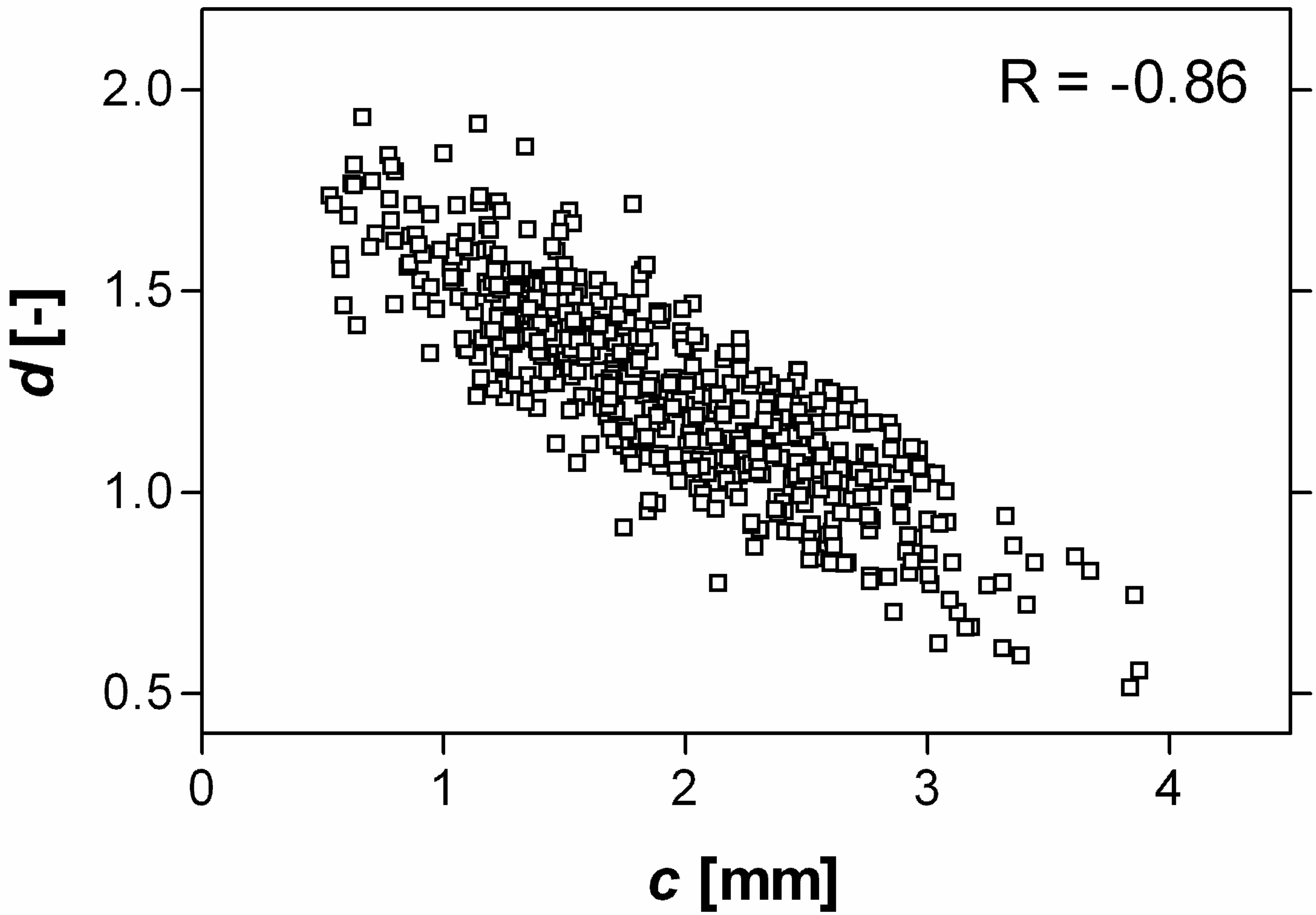
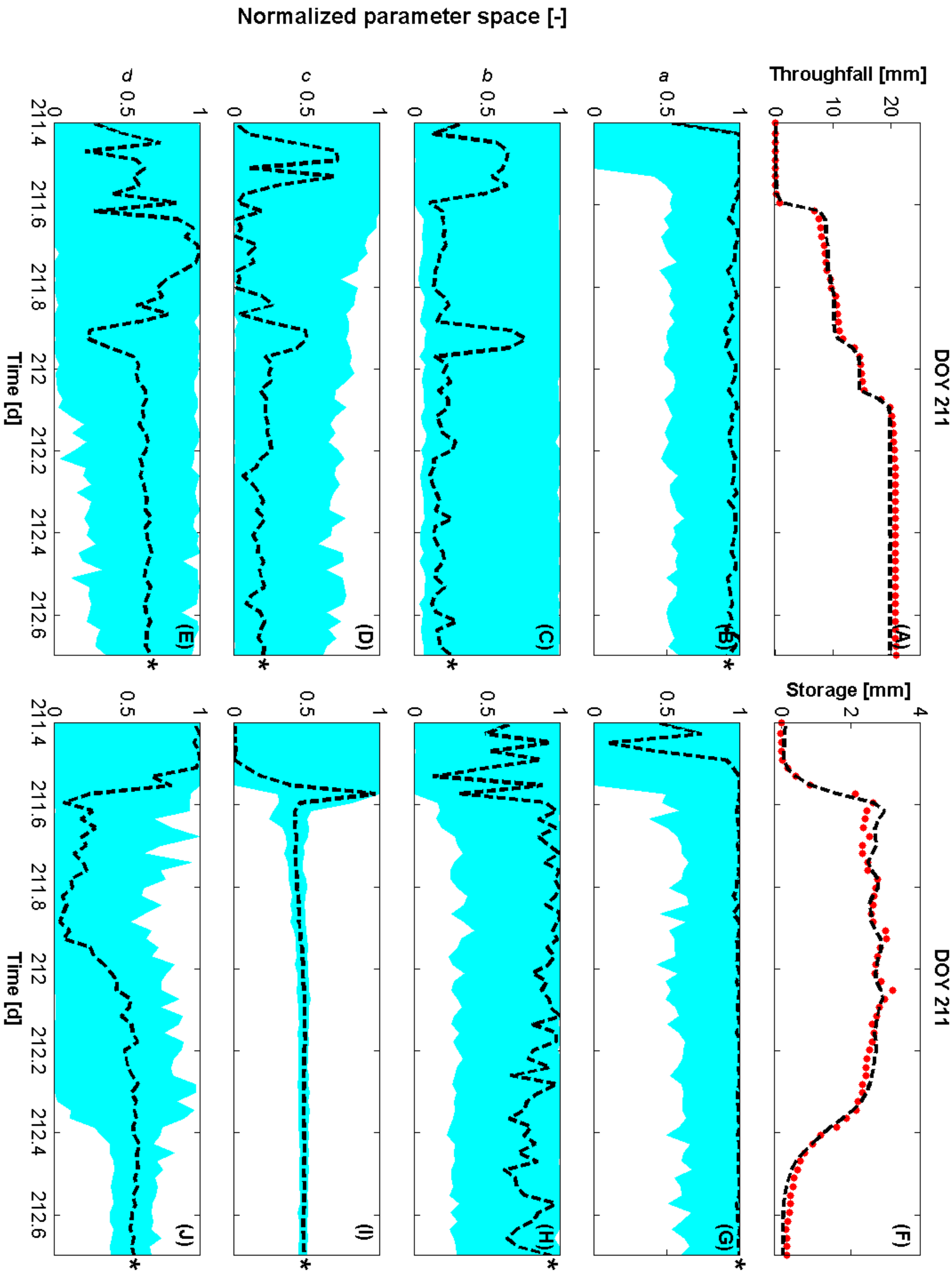


Figure 2.



Normalized parameter space [-]
Throughfall [mm]
Storage [mm]
DOY 211
DOY 211
a
b
c
d
(A)
(B)
(C)
(D)
(E)
(F)
(G)
(H)
(I)
(J)
Time [d]
Time [d]

Figure 3.

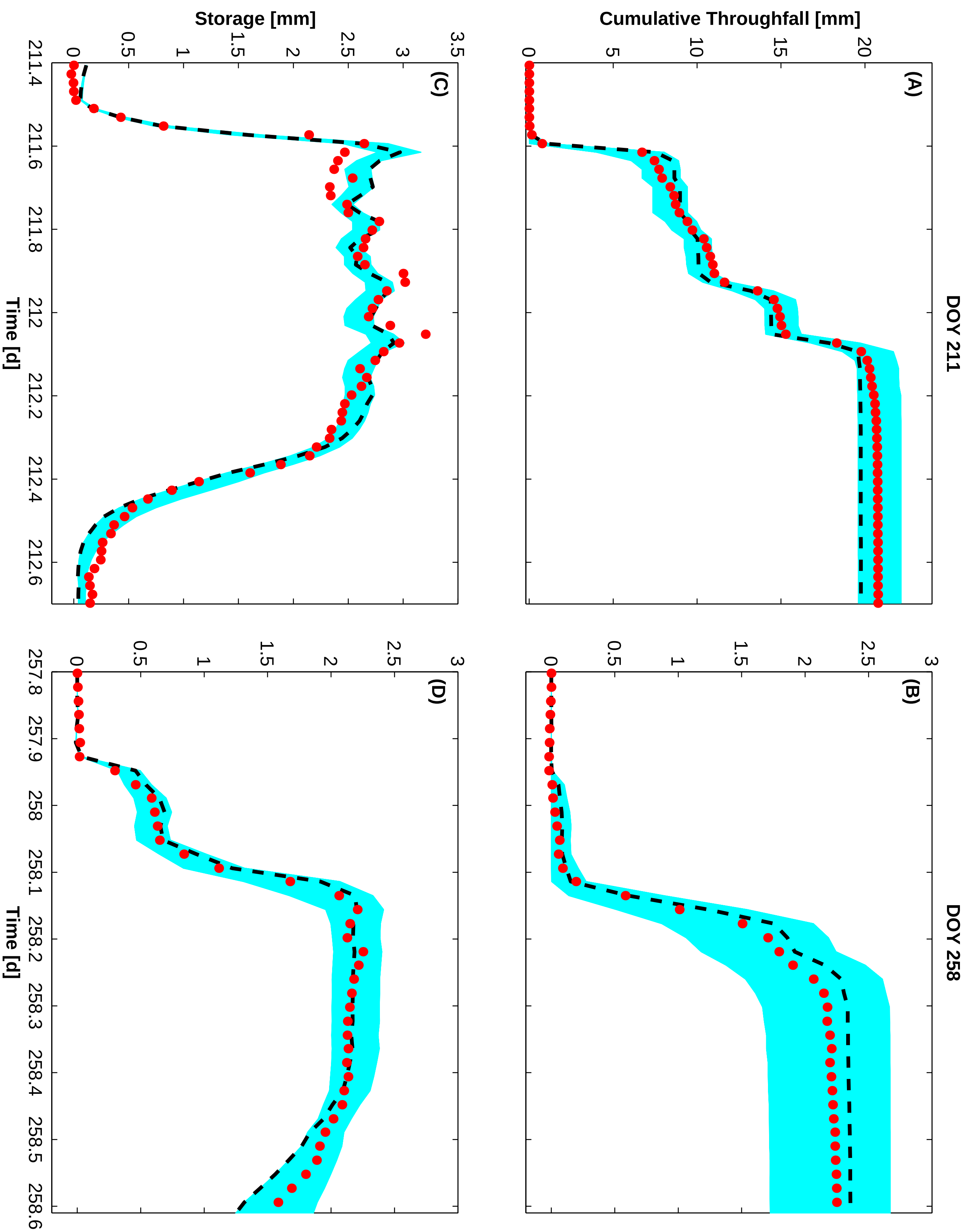

DOY 211
DOY 258
(A)
(B)
(C)
(D)
Cumulative Throughfall [mm]
Storage [mm]
Time [d]
0
5
10
15
20
0.5
1
1.5
2
2.5
3
3.5
211.4
211.6
211.8
212
212.2
212.4
212.6
257.8
257.9
258
258.1
258.2
258.3
258.4
258.5
258.6

Figure 4.

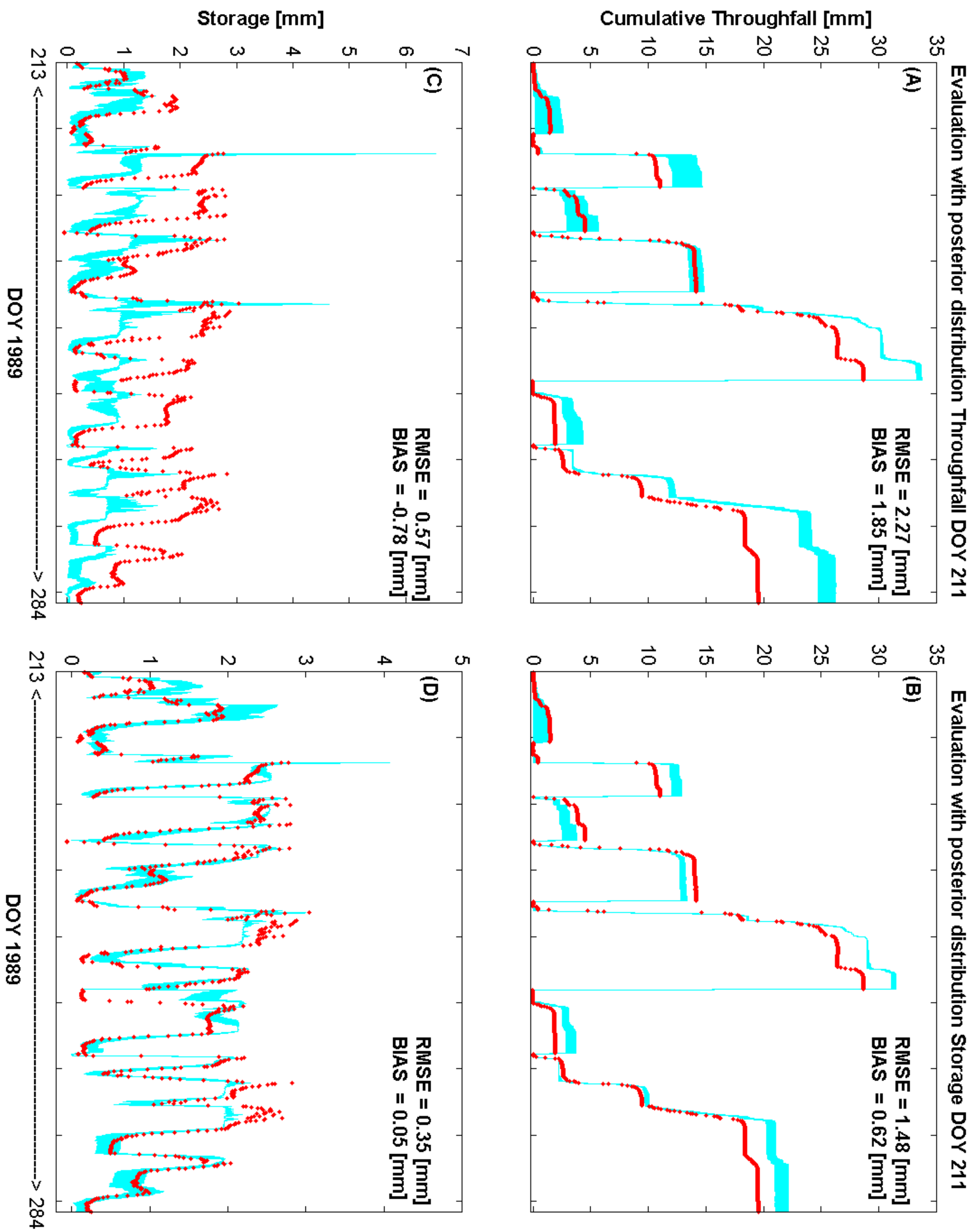

Evaluation with posterior distribution Throughfall DOY 211
Evaluation with posterior distribution Storage DOY 211
(A)
(B)
(C)
(D)
Cumulative Throughfall [mm]
Storage [mm]
RMSE = 2.27 [mm]
BIAS = 1.85 [mm]
RMSE = 1.48 [mm]
BIAS = 0.62 [mm]
RMSE = 0.57 [mm]
BIAS = -0.78 [mm]
RMSE = 0.35 [mm]
BIAS = 0.05 [mm]
213 <------------------------------------> 284
DOY 1989

Figure 5.