Modelling and monitoring forest evapotranspiration. Behaviour, concepts and parameters
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ABSTRACT

This study aims at identifying the parameters of a rainfall interception model from throughfall and canopy storage measurements using \textit{PIMA} \textit{I} (Parameter Identification Method based on the Localization of Information). It is shown that every rainfall event and both measurement types contain different information with respect to the model parameters. The uniqueness of model parameters turned out to be much better when identified from storage measurements compared to throughfall measurements. Independent throughfall and canopy storage measurements were both better predicted with parameters calibrated on storage measurements. From throughfall measurements, exclusively the interception fraction could be identified with comparable accuracy as with canopy storage measurements.

5.1 INTRODUCTION

Interception and evaporation of rainfall are important hydrological processes in forest ecosystems. In the past, several physically based (Gash, 1979; Rutter et al., 1971) and stochastic models (Calder, 1986) were developed to simulate throughfall, evaporation and canopy storage. New model extensions, based on these models, were suggested by many authors (Calder, 1996; Gash et al., 1995; Valente et al., 1997).

If only long-term values of interception losses, measured over a range of storm sizes and durations, are available only very simple models can be constructed with a minimum of parameters (Calder and Hall, 1997). It is evident that a too complex model generates problems for the identification of unique parameters with high accuracy. It is also known that the identification of model parameters is far more dependent on the information content of the data than the amount of data (Gupta and Sorooshian, 1985; Gupta et al., 1998; Kuczera, 1982; Sorooshian et al., 1983; Yapo et al., 1998). A unique parameter set with high accuracy is a prerequisite to understand the system, or to find transfer functions.
that link these unique parameters to independently measured properties and to use the parameters for extrapolation in time and space. Recently, a new Parameter Identification Method based on the Localisation of Information (PIML) (Musters and Bouten, 2000; Vrugt et al., 2000) was developed to assess the information content of measurements. The idea of this method is that each measurement in a time series contains a different amount of information with respect to a specific model parameter. Only measurements with high information content are used to identify that parameter.

In most studies, model parameters of a rainfall interception model were identified by using only throughfall measurement (Aboal et al., 1999; Jetten, 1996; Loustau et al., 1992). However, other measurement types can also be used to identify these parameters. For instance, Bouten et al. (1991) have used storage canopy measurements to identify the model parameters of a four-layer rainfall interception model and recently, Gash et al. (1999) have measured evaporation from wet canopies with measurements using the combined eddy correlation/energy balance method.

Throughfall, canopy storage and evaporation processes are all dependent of each other. If rainfall interception model parameters are identified from a time series in which all these three processes occur at the same time, then a dependency between the parameters can be found. In this study, the uniqueness and accuracy of the rainfall interception model parameters are assessed by using the information content of throughfall and canopy storage measurements. Therefore, a simple four-parameter model is used. PIML is applied to assess the criteria for selecting measurements with highest information content yielding unique parameter with high accuracy. Artificial simulated measurements were used to first avoid problems with systematic errors. As soon the selection criteria are known for all parameters, true measurements were used to identify the parameters.

5.2 MATERIALS AND MEASUREMENTS

Research site

The research site, Speuld is located in a 2.5 ha Douglas fir forest stand, in the central Netherlands, near Garderen. The stand is dense with 780 firs ha⁻¹ without understorey and planted in 1962. Average tree height between is 18 m and the single sided leaf area in summer ranges from 9.0 m² m⁻² to 12.0 m² m⁻² (Jans et al., 1994). The 30-year average rainfall is 834 mm y⁻¹ and is evenly distributed over the year.
Measurements

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 0.8 km away with a resolution of 0.05 mm of rainfall. Half-hourly measurements of meteorological driving variables were measured by the Royal Meteorological Institute of the Netherlands (KNMI) (Bosveld et al., 1998) on a 36 meter high guyed mast to calculate the potential evaporation ($E_{0}$) (Monteith, 1965). Stemflow was never observed.

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 5.1). But even with mean weekly values, up to 70 mm throughfall, a minimum $CV$ of 20% was found. The measurement resolution of one funnel was 0.02 mm. Smaller values of throughfall, plotted in Figure 5.1, were calculated by averaging the funnels.

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 15 m apart. Every half-hour six complete vertical scans were carried out during which 20 measurements per second were performed. From April to December 1989, the system was

![Figure 5.1](image_url): The coefficient of variation ($CV$) of the mean automatic throughfall measurements, averaged over 0.25 hour, 1 hour, 3 hour, 1 day and 7 day.
operational for about 88% of the total time. Estimated measurement error on average half-hourly measurements was 0.04 mm (Bouten et al., 1996).

Model

Bouten et al. (1996) have modelled the canopy water storage by using a numerical multi-layer interception model based on the Rutter Model (Rutter et al., 1971). In this study, for simplicity, a single-layer model was used. The water balance is calculated according to:

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

(5.1)

where \( S \) (mm) is the water storage in the canopy, \( t \) (d) is 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:

\[
I = a P 
\]

(5.2)

where \( a \) (\%) is the interception efficiency parameter and \( P \) (mm d\(^{-1}\)) is 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:

\[
D = b (S - c) 
\]

(5.3)

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

Evaporation rate is calculated with

\[
E = d \frac{S}{c} 
\]

(5.4)

in which \( d \) is an empirical evaporation efficiency and \( E_n \) is determined by (Monteith, 1965):

\[
E_n = \frac{s R_n + \rho C_p D(z_s + z_e)}{\lambda (s + \gamma)} 
\]

(5.5)

where \( s \) the slope of the saturated water vapour curve, \( R_n \) the net radiation, \( \rho \) the density of air, \( C_p \) the specific heat capacity of air, \( D \) the vapour pressure deficit, \( \gamma \) the
psychrometer constant, \(g_v\), the aerodynamic resistance, \(g_f\), the excess resistance and \(\lambda\) is the latent heat of vaporisation.

The model contains four parameters that must be identified. Bouten et al. (1996) found a yearly trend of the optimised \(c\) model parameter, which reflects the biomass dynamics.

**Parameter Identification Method based on Localisation of Information (PIMLI)**

The identification of parameters is dependent on the properties of the data, meaning that parameter identification problems will not simply disappear with the availability of more measurements. PIMLI was used to establish the criteria for selecting measurements with highest information content yielding unique parameters with high accuracy (Musters and Bouten, 2000; Vrugt et al., 2000). ‘Artificial measurements’ were simulated with a reference set of parameters, deduced from Bouten et al. (1996), to first avoid problems with systematic errors. In the identification procedure, PIMLI uses the confidence interval \((\alpha)\) of a measurement was used to discriminate between parameter sets, for which a simulation does or does not fit a measurement.

PIMLI is an iterative procedure. Before the iteration starts, a large number of parameter sets is drawn from pre-set parameter ranges using the Latin-Hypercube method (McKay et al., 1979). As a first step of the iteration, the model is run for all these parameter sets. In the second step, at each measuring point, parameter sets are accepted if the difference between the model result (\(y\)) and the measurement is smaller that \(\alpha\). The information content \((IC)\) of an individual measurement (\(i\)) with respect to a parameter (\(p\)) is defined as:

\[
IC_i(p) = 1 - \frac{\sigma(p)_i}{\sigma(p)_b}
\]  

(5.6)

where \(\sigma(p)_i\) is the standard deviation of accepted parameter values at an individual measurement and \(\sigma(p)_b\) is the standard deviation of the pre-set parameter range at the start. The \(IC\) of a measurement varies with the parameter. A high \(IC_i(p)\) stands for a measurement that yields a parameter estimate with high accuracy.

The third step of PIMLI is to find criteria that can be used to select conditions that lead to a high \(IC_i(p)\). In other words, we select conditions where the model sensitivity to a parameter \((\partial y/\partial p_i)\) is high while the model sensitivity to the other parameters

\[
\frac{\partial y}{\partial p_j}
\]
(\frac{\partial s}{\partial (p_2, \ldots, p_4)}) is low and the confidence interval of the measurement is small. Once a subset with these specific conditions is localised for a specific parameter, the mean and standard deviation of accepted parameter values are calculated. Then, in the fourth step, new parameter sets are drawn with a normal distribution with this mean and standard deviation. Hereafter the iteration starts again. As soon as the selection criteria are known for all parameters, true measurements instead of ‘artificial measurements’ are used and steps two and three are by-passed. The iteration is repeated until the standard deviation of the parameter estimate no longer decreases.

Parameter Identification with throughfall and canopy storage measurements

As can be expected from equation 5.1-5.4, the throughfall, canopy storage and evaporation processes and parameters can be separated in time. The \(a\)-parameter can be derived from rainfall and throughfall or storage measurements and is independent of other parameters if storage has not yet reached its saturation point (no drainage) and if \(E_0\) is negligible. As the measurement errors decrease with increasing precipitation, this means that the \(a\)-parameter is best identified from measurements with low evaporation during night-time and just before saturation. However, the maximum accumulated precipitation until the storage reaches saturation, is dependent on the lowest possible value of the \(c\)-parameter and the maximum value of the \(a\)-parameter \((P < \epsilon_{\text{min}} / a_{\text{max}})\). This means that only measurements at the start of the event can be used for the identification of the \(a\)-parameter as long as the values of these two parameters are uncertain.

Equation 5.1 and 5.3 show that canopy water storage measurements reflect the \(c\)-parameter and are independent to drainage or evaporation in periods after heavy rainfall \((P > \epsilon_{\text{max}} / a_{\text{min}})\) has ceased and when \(E_0\) is negligible. The difference between accumulated precipitation and throughfall at that point determine the \(c\)-parameter. The uncertainty of the parameter value is dependent on the \(a\)-parameters, the uncertainty of the throughfall measurement and the uncertainty of the evaporation. As the uncertainty of throughfall measurements increases with higher precipitation amounts, events that are just large enough to saturate the canopy with minimal drainage are optimal for identification of the \(c\)-parameter.

Drainage is only active if canopy storage is above saturation. Equation 5.3 shows that \(S\) and \(c\) must be known to be able to identify the \(b\)-parameter. With throughfall measurements only, \(S\) is not known and therefore \(b\) can only be identified if storage measurements are available. The \(b\)-parameter is best identified at low \(E_0\) and high rainfall.
By the end of a rain event the difference between precipitation and throughfall equals the sum of the storage capacity and the cumulative evaporated amount. The \( d \)-parameter also determines the slope \( \partial V/\partial t \) in a drying time series. It can best be identified during conditions without rain starting from the point that \( I_{in} \) increases to a high \( I_{in} \).

At first, \( PIMLI \) is applied on rain events with simulated throughfall and storage, calculated with the reference parameter set of Table 5.1. In this first step, the above hypotheses are tested, selection criteria are assessed and \( PIMLI \) is used to find out if the reference parameter set is retrieved. To calculate the \( IC_{p}(p) \), 1000 parameter sets were drawn within the parameter ranges of Table 5.1 (last 2 columns). The confidence interval for the simulations was based on the function from Figure 5.1 for throughfall measurements and 0.04 mm for storage measurements (Bouten et al., 1996).

**Table 5.1**: Model parameters calculated by Bouten et al. (1996) for total year and for Day Number of the Year (DOY) 258, 211. Last two columns are minimum and maximum values of parameters.

<table>
<thead>
<tr>
<th></th>
<th>average</th>
<th>DOY258</th>
<th>DOY211</th>
<th>min</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>0.83</td>
<td>0.83</td>
<td>0.83</td>
<td>0.5</td>
<td>1</td>
</tr>
<tr>
<td>b (d)</td>
<td>135</td>
<td>135</td>
<td>135</td>
<td>1</td>
<td>1000</td>
</tr>
<tr>
<td>c (mm)</td>
<td>2.07-2.58</td>
<td>2.13</td>
<td>2.50</td>
<td>0.5</td>
<td>5</td>
</tr>
<tr>
<td>d</td>
<td>0.79</td>
<td>0.79</td>
<td>0.79</td>
<td>0.1</td>
<td>2.0</td>
</tr>
</tbody>
</table>

After the selection criteria are assessed and tested for all parameters, true measurements of throughfall and canopy storage are used to identify the model parameters and to calculate their accuracy.

Finally, the accuracies of model predictions \( (\sigma_{model}) \) are evaluated on the basis of time series of measurements that were not used for the calibration. Model accuracies for both throughfall and canopy storage are calculated by drawing parameter sets within the parameter ranges obtained by both throughfall and canopy storage calibration.

### 5.3 Results

**Accuracy of the interception (a) and storage capacity (c) parameter estimates**

The rain event during night at day number of the year (DOY) 257 has the best characteristics to identify the parameters \( a \) and \( c \). Figure 5.2A shows the cumulative
precipitation and the cumulative potential evaporation for this period. Accumulated throughfall and storage, simulated with the parameter set of Table 5.1 are shown in Figure 5.2B. For this reference simulation, the storage reached saturation ($Y = c$) at a cumulative precipitation of 2.56 mm ($c / a$).

The first PIMLI iteration starts with the parameter ranges of Table 5.1. The $IC(a)$ and $IC(c)$ of throughfall measurements was calculated and plotted in Figure 5.2C (thick lines). The $IC(a)$ increases to a maximum of 0.85, with a mean value of the $a$-parameter ($\mu_a$) of 0.83 and standard deviation ($\sigma_a$) of 0.0402. In the same iteration, the minimum value of the $c$-parameter range increases from 0.5 to 1.45 mm. As a result, the canopy storage reaches saturation at a cumulative precipitation of at least 1.7 mm ($c_{\text{min}} / a_{\text{min}}$). At this point the $IC(a)$ equals 0.82, with $\mu_a=0.83$ and $\sigma_a=0.0456$. In the second iteration of PIMLI, $IC(a)$ and $IC(c)$ were calculated again and plotted in Figure 5.2C (thin lines). The $a$-parameter is best identified at a cumulative precipitation of 2.08 mm ($c_{\text{min}} / a_{\text{min}}$), denoted as a dot in Figure 5.2C. The $c$-parameter is best identified after rain at the end of the period, also denoted as a dot in Figure 5.2C. Final parameter estimates and accuracies are shown in Table 5.2. By using these artificial measurements, the original reference parameter values were retrieved.

True measured throughfall is shown in Figure 5.2D. From the simulations that fit within the $\alpha$ of the two selected cumulative points, mean and standard deviations of the $a$ and $c$-parameter were calculated (Table 5.2). Standard deviations of the model results and the measurement accuracy are plotted in Figure 5.2D. Parameter ranges are slightly larger than obtained with the sensitivity analysis as the $\mathcal{CI'}$ is higher at low cumulative throughfall amounts than used with the analysis of artificial measurements.

| Table 5.2: Mean parameter estimates ($\mu$) and accuracy ($\sigma$) using artificial (artf) and true measurements (meas) for DOY 258 for both throughfall and canopy storage calibration. |
|-----------------|-----------------|-----------------|-----------------|
|                  | $\mu_{\text{artf}}$ | $\sigma_{\text{artf}}$ | $\mu_{\text{meas}}$ | $\sigma_{\text{meas}}$ |
| **Throughfall**  |                  |                  |                  |                  |
| $a$              | 0.83             | 0.035            | 0.78             | 0.08             |
| $c$ (mm)         | 2.15             | 0.35             | 2.01             | 0.55             |
| **Canopy Storage** |                  |                  |                  |                  |
| $a$              | 0.823            | 0.027            | 0.83             | 0.046            |
| $c$ (mm)         | 2.18             | 0.036            | 2.15             | 0.040            |
Figure 5.2: Rain event at DOY 257: For explanations see text. Thick lines in (C) and (E) are first iteration, dots are selected measurements and thin lines are second iteration. In (D) and (F), dots are measurements, line is model and dotted lines are $\sigma$ of model results.

With the same rain event, the $a$ and $c$ parameters were also identified from storage measurements. The $IC(a)$ and $IC(c)$ of the first PI/MLI iteration are plotted in Figure 5.2E. The $IC(a)$ was calculated from the storage increase determined from the start of the rainfall event. The confidence interval of 0.04 mm was doubled because two measurements were now used. At a cumulative precipitation of 0.5 mm ($c_{\text{min}}/a_{\text{max}}$), the $IC(a)$ was 0.85, with a $\mu_a = 0.825$ and $\sigma_a = 0.037$. In the second iteration the maximum $IC(c)$ equalled 0.97 with $\mu_c = 2.15$ and $\sigma_c = 0.04$.

The best identification of the $a$-parameter is reached at a cumulative precipitation of 2.38 mm ($c_{\text{min}}/a_{\text{max}}$). All measurements between a cumulative precipitation of 0.5 and 2.38
mm were used to identify $a$. The best identification of $c$ is achieved with measurements without precipitation and with a low $E_0$ of 4 mm d$^{-1}$. After DOY 258.4 the $IC(c)$ decreases due to the increase of $I_{e0}$. Selected measurements are plotted in Figure 5.2E and results are shown in Table 5.2. Again the original reference parameter values were retrieved.

For these two selected periods, the parameter estimates and accuracies were again calculated with the true measurements (Table 5.2). Standard deviation of the model results are plotted in Figure 5.2E.

**Accuracy of the drainage (b) and evaporation efficiency (d) parameter estimates**

The drainage parameter ($b$) and evaporation efficiency parameter ($d$) were identified with the rain event at DOY 211. Cumulative precipitation and potential evaporation are shown in Figure 5.3A. Reference simulations of cumulative throughfall and canopy storage, again simulated with the reference parameters of Table 5.1, are shown in Figure 5.3B. In the first PIMLI iteration, only information on the $a$ and the $c$-parameters was found from throughfall measurements (Figure 5.3C). However, due to higher drainage amounts, the $IC(c)$ was now much lower.

In the second iteration, the $IC(b)$ and $IC(d)$ remained zero, even with the $a$ and $c$ accuracy obtained from the first analyses. As expected from equation 5.3, $b$ cannot be identified if $S$ is unknown. At the end of the rain event, total simulated reference evaporation was 2.96 mm while the measurement error of throughfall was 6.7 mm. On half-hourly basis, maximum $E_0$ during rain was only 10 mm d$^{-1}$ while it can reach 80 mm d$^{-1}$. Using equation 5.4 and assuming an $S/c$ of 1.0 and $0.1<d<2$, the evaporation was between 0.02 and 0.41 mm for a half-hourly measurement and was lower than the measurement error. Figure 5.3D shows the measured cumulative throughfall and model results. It is shown that the confidence interval for the measurements is even larger than the model uncertainties, meaning that the initial parameter ranges of $b$ and $d$ were chosen too small.

From canopy water storage measurements, however, far more information was found. In the first PIMLI iteration, information on the $a$-parameter was found again during the wetting stage of the canopy. Dots are plotted at the position with cumulative precipitation between 0.5 and 2.4 mm, shown in Figure 5.3F. In the second iteration, the $IC(c)$ was again at its maximum after rain and with a low $I_{e0}$ of 4 mm d$^{-1}$ (around DOY 212.2). Measurements that satisfy the criteria are plotted as dots in Figure 5.3F and results are shown in Table 5.3.
Figure 5.3: Rain event at DOY 211: For explanations see text. Figure (B), throughfall is divided by 5. Lines in (C) are first iteration. In (D) and (F), dots are measurements, line is model and dotted lines are $\sigma$ of model results.

In the third PiMILI iteration, information was found for $b$ and $d$, shown in Figure 5.3E. The $IC(b)$ was at its maximum at periods with a saturated canopy and with precipitation rates of more than 50 mm d$^{-1}$ for a half-hourly measurement. Measurements are plotted as dots in Figure 5.3E. The $IC(d)$ is at its maximum during the drying cycle of the canopy storage and is calculated by $\Delta S$, starting from the point that $E_0$ is larger than 4 mm d$^{-1}$. Half way the drying cycle, at the maximum first derivative, the information is at its maximum. Final parameter estimates and accuracy are shown in Table 5.3. Again, the reference parameter values were retrieved.
Table 5.3: Mean parameter estimates (μ) and accuracy (σ) using artificial (art) and true measurements (meas) for DOY 211 for both throughfall and canopy storage calibration.

<table>
<thead>
<tr>
<th></th>
<th>μ_{art}</th>
<th>σ_{art}</th>
<th>μ_{meas}</th>
<th>σ_{meas}</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Throughfall</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>b (d⁻¹)</td>
<td>0.815</td>
<td>0.035</td>
<td>0.78</td>
<td>0.08</td>
</tr>
<tr>
<td>c (mm)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>d</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Canopy Storage</strong></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>a</td>
<td>0.823</td>
<td>0.027</td>
<td>0.83</td>
<td>0.046</td>
</tr>
<tr>
<td>b (d⁻¹)</td>
<td>135</td>
<td>15</td>
<td>170</td>
<td>52</td>
</tr>
<tr>
<td>c (mm)</td>
<td>2.50</td>
<td>0.041</td>
<td>2.70</td>
<td>0.062</td>
</tr>
<tr>
<td>d</td>
<td>0.79</td>
<td>0.025</td>
<td>0.96</td>
<td>0.15</td>
</tr>
</tbody>
</table>

True canopy storage measurements are plotted in Figure 5.4F. With the same selection criteria, the parameter ranges were calculated from true measurements. Results are shown in Table 5.3 and in Figure 5.4F. The measurements during the wetting stage and the steady state period, dealing with the a and c-parameters, fit all within the accuracy range. However, during the first drainage peak, the model can only fit the measurements with μₕ = 900 d⁻¹ and σₕ = 130 d⁻¹, while the other two peaks can only be described with μₕ = 170 d⁻¹ and σₕ = 52 d⁻¹. It is also shown that the simulated storage is lower than the measurements at the end of the drying cycle. However, to fit this part, μₖ = 0.6 must be used while then large deviations were found halfway the drying period.

**Model evaluation**

The parameter sets p_{through} obtained from throughfall measurements, and p_{stor}, obtained from storage measurements, are both evaluated on a time series of measurements containing 389 half-hourly measurements between DOY 238 and 285. A linear decreasing trend of the c-parameter between the calibrated values at DOY 211 and 258 was used (Bouten et al., 1996). Accumulated throughfall is predicted with both parameter sets. Small differences in model performance were found, resulting for p_{through} in R² = 0.664 and for p_{stor} in R² = 0.684. The model error (σ_modₖ), calculated as the mean σ at the end of the period was 10.6 mm with p_{through} and 4.2 mm with p_{stor}, while the
measurement error ($\sigma_{w,df}$) was 10.3 mm. This means that the model with $p_{stor}$ can estimate throughfall more accurately than as it was measured. However, due to the dominating $\sigma_{w,df}$, the model performances were almost equal. Canopy water storage was also predicted for the same period. Large differences in model performance were found, resulting for $p_{through}$ in $R^2 = 0.825$ and for $p_{stor}$ in $R^2 = 0.912$. The $\sigma_{model}$ for $p_{through}$ is 0.42 mm and for $p_{stor}$ is 0.12 mm.

5.4 DISCUSSION

As shown in the above analysis, parameters can be estimated more accurately with storage measurements. From canopy storage measurements, Bouten et al. (1996) found a yearly trend of the calibrated c-parameter following the biomass dynamics. With throughfall measurements, however, this trend can never be established. In the total data set of 158 days, only six suitable rain events with a cumulative precipitation between 2.5 and 4.0 mm were found. The $\mu$, of these events ranges from 1.55 to 2.75 mm with a mean $\sigma_r$ of 0.65, while a yearly trend was not found.

In summary, throughfall measurements have limited information. In fact, only the $a$-parameter range was identified with satisfying accuracy. As Calder and Hall (1997) pointed out, only a very simple model, in this case a one-parameter model, can be used if only throughfall measurements are available. Therefore, all model parameters of drainage and evaporation functions from studies with only throughfall measurements must be taken with care due to the problems of non-uniqueness of the parameters. It seems to be premature to compare parameter estimates of different species, that were obtained by throughfall measurements only (e.g. Hertwitz, 1985; Klaassen et al., 1998; Rutter et al., 1975; Valente et al., 1997) or to develop models with more parameters.

The throughfall measurements obtained with funnels have a too low accuracy to assess the four model parameters. Lundberg et al. (1997) have therefore developed a new measurement approach, with weighing troughs, with an accuracy of 0.1 mm and a time resolution of 1 minute. Using the same analysis of artificial data, an equal result of the a-parameter ($\sigma_d = 0.035$) and a much better result of the c-parameter ($\sigma_r = 0.043$) are found for DOY 258. To identify evaporation, the end of the rain event of DOY 211 was used. Using the uncertainties in the other parameters, d can be reduced to $\mu_d = 0.80$ and $\sigma_r = 0.053$. This uncertainty is still twice as high as found with storage measurements due to the correlation with the $b$ and $d$-parameters, while $b$ can still not be identified.
With PI MIL, the uniqueness and accuracy of the parameters was identified by analysing individual periods. As a result, specific positions, for instance the first drainage peak at DOY 211 and the evaporation period, can be marked and be used to improve the model. For the evaporation function it can mean that the linear decrease \( \frac{S}{c} \) may not be correct. However, using a classical calibration, based on the best fit of the total data set, systematic model errors can be compensated by the calibration. Therefore, the discrepancies at individual points are much more difficult to interpret.

5.5 CONCLUSIONS

This study shows that every measurement of throughfall or canopy water storage has a different information content to identify each of the parameters of a rainfall interception model. From throughfall measurements, only the interception fraction could be identified with comparable accuracy as with canopy storage measurements. The best identifications of the interception fraction and the storage capacity parameter were achieved during nights with low evaporation and rather low rainfall amounts. The drainage parameter can never be identified, as storage is not measured directly while the evaporation parameters could not be identified in a unique way due to correlation between the parameters and high measurement errors. If only throughfall measurements are available, than it is concluded that unique parameters can only be achieved with a very simple model with only one parameter.

With canopy storage measurements, parameters were identified during the independent stages of the drying and wetting cycles. A much higher accuracy of all parameter estimates was thus obtained. It was further shown that the uncertainty in throughfall predictions simulated with the parameter set based on storage measurements was even lower than the standard deviation of the throughfall measurements. It is finally shown that by using PI MIL, specific situations can be selected to improve the model.
REFERENCES


