A linear system model of dynamic throughfall rates beneath forest canopies

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[1] This paper describes a black box, linear system model to predict time-varying throughfall rates using only data of time-varying rainfall and storm total throughfall. For two forest stands in the Pacific Northwest the model predicted throughfall with mean efficiency of 0.84 when calibrated individually to 48 rainstorms and mean efficiency of 0.82 when calibrated to all storms simultaneously. The median of mean hydraulic residence times of precipitation in the canopy averaged across all storms ranged from 8 to 30 min by location within the two stands (overall median 12 min). Model predictions and performance were approximately equivalent for transfer functions based on either published equations describing storage and drip or of the form of exponential or gamma distributions. The model was insensitive to characteristics of rainstorms, so that calibrated models of water transfer through canopies were similar for storms of all sizes and intensities. *INDEX TERMS:* 1854 Hydrology: Precipitation (3354); 1894 Hydrology: Instruments and techniques; 1836 Hydrology: Hydrologic budget (1655); 1818 Hydrology: Evapotranspiration; *KEYWORDS:* canopy interception, convolution, forest canopy, linear modeling, throughfall, transfer functions

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1. Introduction

[2] Interest in the interception of precipitation by forest canopies has primarily been because of its importance as a component of evapotranspiration. Useful predictions of evaporation from wetted canopies have been made using models built upon Penman-Monteith estimates of evaporation [e.g., *Rutter et al.*, 1971; *Gash*, 1979] over a range of climates and vegetation types. The basic process these models describe is the accumulation of water on the canopy and its subsequent drip or evaporation. The variables that control evaporation have been extensively studied [e.g., *Murphy and Knoerr*, 1975; *Stewart*, 1977; *Teklehaimanot and Jarvis*, 1991; *Watanabe and Mizutani*, 1996; *Klaassen*, 2001], but the processes of storage and drip have received less attention.

[3] A more complete description of the dynamic behavior of canopy storage and drip during rainstorms would be useful for many applications. It has long been recognized that canopies modify rainfall intensity and erosivity [*Chapman*, 1948; *Trimble and Weitzman*, 1954]. Quantifying these effects is increasingly important as models of soil, hillslopes, and watersheds advance to include behaviors resulting from nonsteady infiltration [e.g., *Germann and Niggli*, 1998; *Reggiani et al.*, 1998; *Iverson*, 2000; *Torres and Alexander*, 2002]. Our specific interest in storage and drip is based on initial findings that canopies may reduce peak rainfall intensities sufficiently to reduce the probability of landslides initiating by infiltrating rainfall [*Keim and Skaugset*, 2003; *Keim et al.*, 2004].

[4] Available models of the canopy interception process, including the Rutter model [*Rutter et al.*, 1971], are not well suited to predicting dynamic throughfall rates. The reason is that most models require the stored mass of water in the canopy a parameter for predicting drip, but storage is not normally measurable in the field. Although direct measurement of water stored on canopies is possible [*Hancock and Crowther*, 1979; *Oszyczka and Crowther*, 1981; *Calder and Wright*, 1986; *Bouten et al.*, 1991, 1996; *Calder et al.*, 1996; *Klaassen et al.*, 1998], it is not a practical tool for applied work because it is difficult and expensive. As a result, canopy storage remains only a tunable parameter in most studies, and water balances are often achieved at the potential expense of the physical realism of predicted storage and drip. Many applications of Rutter-type models have only successfully predicted evaporation because of compensating errors [*Bouten et al.*, 1991; *Klaassen et al.*, 1998; *Klaassen*, 2001], indicating that it is a mistake to interpret strong overall performance of these models as evidence that they correctly represent all physical processes involved.

[5] Water balance models can rarely be constrained sufficiently for investigations of time-varying throughfall rates. The Rutter model and its derivates quantify water stored on canopy surfaces (S, dimension L) as the running difference (from start of rainfall, t_0, up to some time t), between accumulated measured gross incident precipitation (P_g, L T^{-1}) and the accumulated throughfall dripped from the canopy (P_t, L T^{-1}) (with which we include free throughfall, P_f, and stemflow, P_s), modified by an estimate of

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evaporation (E, L T^{-1}). Canopy storage and throughfall are therefore related by

$$S - \int_{t_0}^{t} P_t dt = \int_{t_0}^{t} P_g dt - \int_{t_0}^{t} E dt. \qquad (1)$$

While P_g can be measured relatively easily, E cannot. Estimating E using *Rutter et al.*'s [1971] application of the Penman-Monteith formula requires explicit knowledge of $S(t)$ (and an another ill-defined parameter, "canopy storage capacity"). All published expressions that predict P_t also require knowledge of $S(t)$ and at least one other parameter that must be fit empirically [*Rutter et al.*, 1971; *Rutter and Morton*, 1977; *Calder*, 1977; *Halldin et al.*, 1979; *Massman*, 1980, 1983; *Pitman*, 1989a, 1989b; *Domingo et al.*, 1998]. Therefore there is no way to use equation (1) to understand the relationship between S and P_t.

[6] In this paper, we present an alternate approach to predict dynamic throughfall rates. We show that considering the canopy as a black box linear operator on rainfall can provide useful predictions of time-varying throughfall. Because this method is mathematically based, it avoids the difficult parameterization inherent in existing physically based rainfall-throughfall models. In particular, it does not require explicitly considering canopy storage as a state variable controlling throughfall.

2. Systems Analysis and Transfer Functions

2.1. Theory

[7] Systems analysis is a common tool in engineering, in which a system is defined as a collection of inputs and outputs linked together by causative processes [*Mayhan*, 1984]. The analysis predicts the behavior of one portion of a system from knowledge of the rest of the system. Engineering applications often seek to predict output behaviors from known inputs and internal processes. It is possible, however, to use known inputs and outputs to predict behavior of the internal processes. We take this strategy here to identify the behavior of canopy storage and drip from measured rates of rainfall and throughfall (Figure 1). Once known, the properties of canopy storage as an operator on throughfall allow predictions of time-varying throughfall from rainfall data.

[8] Systems are linear if input, $x(t)$, produces response, $y(t)$, as a superposition of the responses to individual inputs that occurred at all time lags, τ, in the past:

$$y(t) = (x * g)(t) = \int_{0}^{t} x(t) g(t - \tau) d\tau, \qquad (2)$$

where asterisk denotes convolution. Equation (2) is known as the convolution integral, in which the signal, $x(t)$, is convolved with a unit response function, $g(t - \tau)$, to result in response $y(t)$. In a simple linear system, the unit response function, also known as a transfer function, uniquely and completely defines the action of the system on $x(t)$ to produce $y(t)$. A transfer function must satisfy

$$\int_{0}^{\infty} g(t - \tau) d\tau = 1 \qquad (3)$$

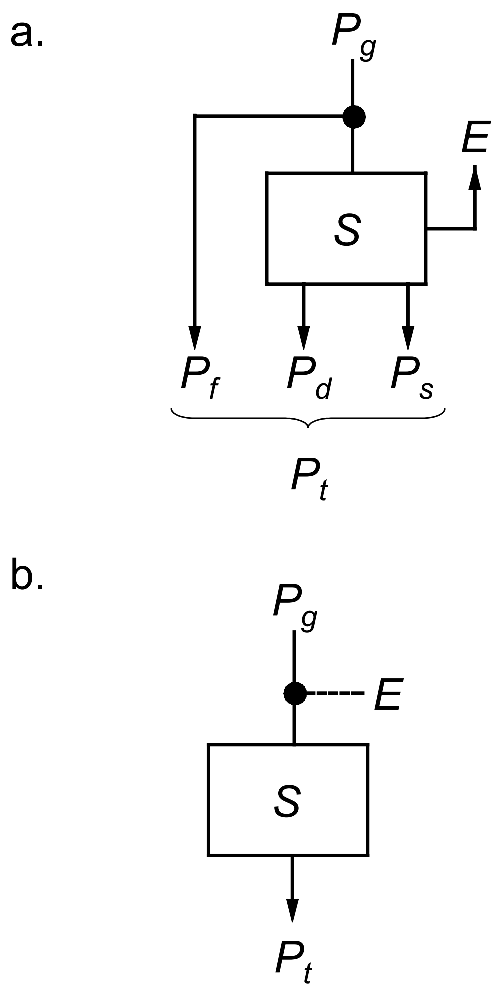

Figure 1. System representation of the process of canopy interception. (a) Full system described by equation (1). (b) Reduced system used in this study.

to conserve mass, and is characterized as the $g(t - \tau) = y(t)$ that results from a Dirac delta input $\delta(x)$ at $t = 0$.

[9] The most familiar application of linear systems in hydrology is instantaneous unit hydrograph theory, in which the input is rainfall, the output is streamflow, and the transfer function is the effect of a watershed on the routing of water to its outlet [*Dooge*, 1959, 1973; *Singh*, 1988; *Bras and Rodríguez-Iturbe*, 1993]. Other examples include using linear systems to model movement of solutes through watersheds [*Duffy and Gelhar*, 1985; *Barnes and Bonell*, 1996; *Kirchner et al.*, 2000, 2001] and rainfall-spring flow relations [*Labat et al.*, 2000].

2.2. Identifying Transfer Functions From Data

[10] Most hydrological data are sampled at discrete time intervals. In this case, equation (2) becomes

$$y(k) = (x * g)(t) = \sum_{i=1}^{k} x(i) g(k - i), \qquad (4)$$

where $k = (0, 1, 2, \ldots)$ is the index of sample periods, and i is the shift in sample periods analogous to τ in equation (2). A common approach is to assume some form of $g(k - i)$, convolve it with $x(k)$ using equation (4), and compare the result to observations. The best fit after iterating on candidate sets of parameters defining g can then be taken as the solution to equation (2).

[11] Deconvolution, in which a transfer function is obtained by solving equation (2) or equation (4) for g, is a poorly posed mathematical problem because noise in the input signal, x, can result in an unstable solution of g [*Eagleson et al.*, 1966; *Bree*, 1978; *Dietrich and Chapman*, 1993]. Despite efforts to develop methods [e.g., *Skaggs et al.*, 1998], deconvolution in the time domain remains a difficult problem numerically. A popular alternate method of deconvolution is to make the calculations in the Fourier domain. The input, output, and transfer function are related by

$$\mathcal{F}(g(t-\tau)) = \frac{\mathcal{F}(y(t))}{\mathcal{F}(x(t))}, \tag{5}$$

where $\mathcal{F}$ indicates the Fourier transform [*Mayhan*, 1984]. Analyses of data usually make use of the fast Fourier transform or power spectrum [*Duffy and Gelhar*, 1985; *Kirchner et al.*, 2000, 2001]. A disadvantage of this approach is that measurement errors and transformations of data introduce errors that often result in noisy or numerically unstable estimates of g. These problems are acute for rainfall-throughfall modeling at the temporal scale of individual storms because there are too few data available for robust estimation of power spectra at low frequencies. As a result, *Keim* [2003] found deconvolution in the Fourier domain to be less efficient than trial forward convolution in the time domain.

2.3. Time-Varying Transfer Functions

[12] It is not necessary to assume that a transfer function is invariant with time. Allowing the transfer function to vary with time means the response at any given time is no longer a superposition of responses governed by a single transfer function. Instead, the instantaneous response consists of superposed responses that are potentially different at each τ. This modifies equation (2) to

$$y(t) = \int_0^t x(\tau) g(t,\tau) d\tau. \tag{6}$$

Equation (6) is no longer strictly convolution because $(x(t) * g(t, \tau))$ is a meaningless expression, but converting (6) to the discrete time expression

$$y(t) = \sum_{i=1}^{k} x(i) g(k,i) \tag{7}$$

makes it possible to estimate a time-varying transfer function from data [*Kamen*, 1990].

3. Application Methods

3.1. Field Data

[13] We collected data of rainfall and throughfall at two coniferous forest stands in the Pacific Northwest for 14 months. We fitted troughs to tipping bucket rain gauges to collect data on throughfall intensity. Each gauge was fitted with a pair of troughs, each constructed by cutting a slot 19 mm wide longitudinally along a 2-m length of plastic pipe fitted to the tipping bucket at a 22.5° angle to the horizontal. This steep angle is slightly less than the funnel in a standard rain gauge, and minimizes travel time to the tipping bucket for recording accurate intensity data. The tipping buckets were calibrated to tip once per 0.254 mm of rainfall, but the area of the two troughs projected to the horizontal exactly doubled the normal catch area of the 8-inch-diameter gauge, so that each tip recorded 0.127 mm of throughfall. Rainfall data were from a normal tipping bucket rain gauge, also calibrated to tip once per 0.254 mm of rainfall, in a large opening <200 m away from the throughfall gauges.

[14] One stand is in the Cascade Mountains of southwestern Washington, USA. This stand originated about 600 years ago; the canopy is spatially inhomogeneous, and consists of some very large trees, up to 84 m tall and 3.1 m stem diameter, and many younger individuals of Douglas fir, western hemlock, and western red cedar. The other stand is in the Oregon Coast Range. This stand is 60 years old, dominated by Douglas fir trees up to 43 m tall and 0.8 m stem diameter, and the canopy is spatially homogeneous. Although we did not measure it, we estimate leaf area index (LAI) was between 7 and 9 for both stands, with perhaps lower LAI in the young stand than the old stand [*Bailey and Tappeiner*, 1998; *Thomas and Winner*, 2000]. The most important difference between the canopies at the two sites was the structure and spatial homogeneity of the canopy. Crown structure of the older trees was more complex, and included more woody surfaces and epiphytes [*Pike et al.*, 1977; *Ishii and Wilson*, 2001]. In addition, the canopy in the old stand was more spatially variable owing to mixed species and tree fall gaps [*Spies and Franklin*, 1989], which resulted in greater spatial variability in throughfall in the old stand [*Keim and Skaugset*, 2003]. We placed seven under-canopy trough rain gauges in the old stand, and three under-canopy trough rain gauges in the young stand.

[15] We converted the data recorded by data loggers in the rain gauges, which consisted of the times of bucket tips recorded to the nearest second, into depth of precipitation per one minute. To do this, we assumed constant intensities of rainfall and throughfall between tips, following *Habib et al.* [2001]. The bin size of one minute is near the minimum useful bin size for tipping buckets of the resolution we used. We estimate from *Habib et al.* [2001] that the instrumental error in individual bins is up to ±30% for the low intensities, but only ±10% during more intense rain. Increasing the length of the bin would have reduced these instrumental errors, but at the expense of sensitivity to time-varying intensity that were important to quantify according to the objectives of the study.

[16] The climate of this area is marine and strongly seasonal, with 80% of precipitation occurring in frontal storms during October to March, and only 5% occurring during the summer months; convective rainstorms are infrequent. Precipitation during the study period consisted mainly of rain in the young stand, but periods of snow were common in the old stand. We do not know all the periods that snow had accumulated in the canopy of either stand, but subjective assessment of the data allowed us to exclude times that exhibited atypical timing of precipitation in the opening and in throughfall. We were con-

servative in this regard by excluding storms for which there was any doubt.

3.2. Identifying Transfer Functions

3.2.1. Data and System Definition

[17] The first step in estimating transfer functions to describe the rainfall-throughfall process was to truncate field data to include only those periods when the canopy was fully wetted so as to eliminate the wetting-up process from the analysis. We termed each of these periods "storms." We had no field measure of canopy wetness to delineate these periods, so we relied on some well-established assumptions about canopy storage to make conservative estimates of times when the canopy was fully wet.

[18] Following *Leyton et al.* [1967], we fit a line to the upper envelope of points in a scatter plot of throughfall versus rainfall, and accepted the negative intercept on the throughfall axis as the rainfall required to fully wet the canopy. This method indicated saturation at ~2 mm for the young stand and ~4 mm for the old stand. We adopted a conservative minimum rainfall of 3 mm in the young stand and 5 mm in the old stand as the start of each storm. We defined the end of each storm as the time that rainfall intensity dropped below 0.25 mm hr^{-1} for at least one continuous hour.

[19] The next step in estimating transfer functions was to account for evaporative loss from canopy storage during rainfall. To satisfy our definition of the system (Figure 1b), we subtracted E from P_g, then used this adjusted P_g as effective input. Conceptually, this constitutes analyzing only the precipitation that will eventually drip, ignores any that will eventually evaporate, and assumes canopy storage is the same at the beginning and end of the simulation period. The field data lacked micrometeorological data required to estimate E by, for example, the Penman-Monteith equation, so we assumed that evaporation was constant during each storm, and the total evaporation was equal to the difference between $\int P_g$ and $\int P_t$. We subtracted the assumed evaporation from the rainfall data for each storm, using periods when precipitation exceeded evaporation. Total rainfall almost always exceeded total throughfall in the data, but there were a few exceptions when net condensation occurred; in these cases we treated E the same way but as a negative value.

[20] Measurements during storms have shown evaporation rates are generally small compared to rates of rainfall and throughfall [e.g., *Klaassen et al.*, 1998]. Therefore the assumption of constant evaporation during storms, while not strictly correct, should not unduly affect the model. Furthermore, if evaporation does not vary systematically during storms, the effect of assuming constant evaporation is to introduce white noise in the estimation of transfer functions. This effect degrades the goodness of fit, but does not affect the best fit parameters in the transfer functions.

3.2.2. Transfer Function Models and Parameterization

[21] Once rainfall data were truncated to wet periods only and adjusted for evaporation, we estimated transfer functions to find best fits for parameters to characterize $g(t)$ in equation (4) and $g(t, \tau)$ in equation (7) by trial-and-error forward convolution in the time domain. We optimized parameters for each of several forms of transfer functions for each storm and throughfall gauge, and for all storms simultaneously at each gauge. To do this, we used MATLAB (Mathworks) to perform a Nelder-Mead search [*Lagarias et al.*, 1998] of parameters to maximize the Nash-Sutcliffe efficiency,

$$\varepsilon = 1 - \frac{\sum_{i=1}^{N} (O_i - P_i)^2}{\sum_{i=1}^{N} (O_i - \overline{O})^2} \tag{8}$$

[*Nash and Sutcliffe*, 1970] (where O is the observed and P is the predicted value at time i, and $\bar{O}$ is the mean of all observations), of the time series of throughfall predicted from rainfall (ignoring the first eight minutes of each storm when calculating ε, to account for the fact that throughfall was normally nonzero at the start of the modeling period but the linear model requires $P_t = 0$ at $t = 0$). The advantage of using ε instead of the more familiar R^2 is that ε is sensitive to the overall variances of observations and predictions. Values of ε range from $(-\infty, 1]$; $\varepsilon = 1$ indicates perfect agreement and $\varepsilon < 0$ indicates that the observed mean $\bar{O}$ is a better predictor of the time series of observations than is the model [*Legates and McCabe*, 1999].

[22] We investigated six distinct forms of $g(t)$. Two forms are common statistical distributions: the exponential distribution,

$$g = P_t = ae^{-at}, \tag{9}$$

where a is a parameter; and the gamma distribution,

$$g = P_t = \frac{t^{a-1} e^{\left(\frac{-t}{b}\right)}}{\Gamma(a) b^a}, \tag{10}$$

where a and b are parameters and $\Gamma(\ )$ is the gamma function. The exponential distribution describes drainage from a linear reservoir, and the gamma distribution describes drainage from a series of linear reservoirs [*Haan*, 1977]. We chose to investigate these forms because they are common transfer functions often useful in hydrology. The other forms of transfer function originated as published equations to describe drip from canopies (Table 1). *Keim* [2003] gave details of the derivation of transfer functions from these drip equations, following *Singh* [1988].

[23] Most published drip equations imply transfer functions that do not conserve mass (to satisfy equation (3)) or cannot be solved analytically for conservation of mass. This corresponds to, for example, *Calder*'s [1977] observation that the original drip equation presented by *Rutter et al.* [1971] predicts finite drip even when the canopy is dry. Nevertheless, these equations produce good fits to data over periods of time characteristic of canopy storage and drip. One solution is to define a time period $t = 0 \ldots T$ over which to artificially impose conservation of mass. The extra parameter, T, can be chosen in many ways. On the basis of published studies and personal observations, we arbitrarily chose $T = 100$ min as the period over which nearly all water drips from a wet canopy.

[24] From 13 published drip equations emerged five unique useful transfer functions (Table 1) [*Keim*, 2003]. For three drip equations (*Massman* [1980] and two equations from *Pitman* [1989a]), there was no analytical solution for the initial drip rate, preventing explicit solutions for transfer functions. Two drip equations (one equation from *Pitman* [1989a] and *Domingo et al.* [1998]) produced transfer

Table 1. Published Drip Equations and Their Implied Transfer Functions[a]

Drip Equation	Source	Transfer Function
$P_t = a(S - C)$	*Calder* [1977]	$g = ae^{-at}$
$P_t = e^{(a+bS)}$	*Rutter et al.* [1971]	$g = \frac{-H(T)\left(e^{b}-1\right)}{b(T-t+te^{b})}$
$P_t = Ne^{\left(a+\frac{bS}{N}\right)}$	*Rutter and Morton* [1977][b]	$g = \frac{-H(T)\left(e^{b}-1\right)}{b(T-t+te^{b})}$
$P_t = ae^{(b(S-C))}$	*Lloyd et al.* [1988]	$g = \frac{-H(T)\left(e^{b}-1\right)}{b(T-t+te^{b})}$
$P_t = ae^{(bS)}$	*Pitman* [1989a]	$g = \frac{-H(T)\left(e^{b}-1\right)}{b(T-t+te^{b})}$
$P_t = (a - bI)\frac{S}{C}$	*Massman* [1983][c]	$g = \frac{-H(T)Ke^{(tK(bI-a))}(bI-a)}{e^{(TK(bI-a))}-1}$
$P_t = e^{a(S-b)} - 1$	*Pitman* [1989a]	$g = \frac{-H(T)e^{aT}(e^{a}-1)}{e^{aT}+e^{a+at+aT}-e^{at}-e^{a+aT}}$
$P_t = a(e^{(bS)} - 1)$	*Halldin et al.* [1979]	$g = \frac{-H(T)a\left(e^{-b}-1\right)}{e^{abt}+e^{-b}-e^{b(at-aT-1)}-1}$

[a]Common variables are as follows: P_t, throughfall rate (L T^{-1}); S, canopy storage (L); C, canopy storage capacity (L); T, length of time over which drip continues after rain. $H(\ )$ is the Heaviside step function.

[b]N is the number of layers in the canopy. Transfer function parameter $b = b/N$.

[c]I is rainfall intensity, equal to P_g; $K = 1/C$.

functions that too cumbersome in calibration because their parameter spaces contained numerous discontinuities where the function was undefined. Three drip equations (*Halldin et al.* [1979], *Massman* [1983], and one equation from *Pitman* [1989a]) each produced transfer functions of unique form, and another form of transfer function was produced independently by four different drip equations (*Rutter et al.* [1971], *Rutter and Morton* [1977], and *Lloyd et al.* [1988] and one equation from *Pitman* [1989a]). The drip equation of *Calder* [1977] produced the transfer function of the exponential distribution. The inability to derive useful transfer functions from several of the drip equations is best interpreted as a mathematical difficulty, rather than holding any physical meaning, because the main obstacle was lack of analytical solutions at some step in the derivation rather than poor fits to observed data. We omitted these equations from comparative analyses.

[25] We considered two time-varying transfer functions. The first was derived from the drip equation of *Massman* [1983], in which the form of the transfer function changes with $P_g(t)$. For the second time-varying transfer function, we allowed the parameter a in the exponential distribution (11) to vary with time as $a(t)$ using (7). Previous investigations have most commonly shown drip rates to be dependent on rainfall intensity [*Massman*, 1983], so we defined $a(t) = f(P_g)$; the most successful form was $a(t) = a \cdot P_g(t)$ (we also tested exponential and power forms). Therefore the time-varying exponential transfer function was

$$g = P_t = Iae^{-Iat}, \tag{11}$$

where $I = P_g(t)$. We applied the time-varying transfer functions in equation (7), rather than in equation (4) as with all other transfer function forms.

3.2.3. Analyses of Model Predictions and Fits

[26] We used the mean residence time (MRT) to compare best fit values of parameters among models and storms. The MRT is the first moment (mean) of the transfer function, and is also the mean lag between rainfall and throughfall. Although relevant to intensity smoothing effects, we did not analyze higher moments of most fitted residence time distributions. Transfer function forms do not have the flexibility to allow fitting of moments independently because the range of possible shapes is limited. For example, the exponential model equation (9) has mean = $1/a$, variance = $1/(a^2)$, skew = 2, kurtosis = 6.

[27] There is no analytical solution to the mean residence time for some of the transfer functions in this study. The MRT of these equations were therefore calculated numerically. Transfer functions that include the arbitrary maximum residence time, T, retain it in the equation for mean residence time, with the effect that residence time estimates depend on the assumption made about the maximum residence time. Thus MRTs reported in this paper are dependent on the assumption we made that T = 100 min. Mean residence time in this paper is the mean hydraulic residence time, in that $g(t)$ quantifies the statistical probability density of apparent travel times through the canopy but not actual particle travel times. This distinction has implications for proper interpretation of results in the context of, for example, chemical or biological reactions with water stored in the canopy.

[28] Frequency distributions of MRT predicted by each model for several storms were generally skewed, so we report the median of the observed MRTs for the purpose of comparing model predictions.

[29] After fitting all models for all storms, we compared the resulting mean residence times and concomitant efficiencies to draw inferences about relationships between rainfall and throughfall as well as the usefulness of each model in linear system modeling. Categorical variables potentially affecting model results and performance were stand, sampling location within each stand, and season. Continuous variables were storm length, total storm rainfall, mean rainfall intensity, maximum rainfall intensity, and storm multiscaling exponent [*Olsson et al.*, 1993]. We analyzed the continuous variables characterizing storms by performing a principle components analysis (PCA) ordination of all continuous variables for each storm, then examining correlations between PCA axes and model performance and MRT. The PCA did not effectively reduce dimensionality of the data: the first principle component was not statistically interpretable by the broken stick criterion for defining interpretability of ordination axes [*Jackson*, 1993], and all axes were poorly correlated with efficiencies and mean residence times of all models ($R^2 < 0.10$). Therefore we assumed statistical independence of all continuous rainfall variables for subsequent analyses.

[30] We analyzed categorical factors affecting model performance and results with linear, parametric analyses of variance (ANOVAs) with covariables, using variables transformed for normality and backward removal of nonsignificant variables at $\alpha = 0.05$. We evaluated statistical significance using least squares means (LSmeans), which are observed means adjusted for unbalanced statistical design and covariates, as the basis for least squares difference (LSD) multiple comparisons of factors within ANOVA.

4. Results and Discussion

4.1. Rainfall and Throughfall

[31] During the study period, a total of 48 storms exceeded minimum rainfall and were free of snow and

Table 2. Rainfall and Throughfall During the 14-Month Study Period[a]

Stand	Number of Storms	Total Rain, mm	Mean Rainfall Intensity, mm hr^{-1}	Total Throughfall, mm	Mean Throughfall Intensity, mm hr^{-1}
Old growth	32	937	1.34	730	1.05
Second growth	16	390	1.96	270	1.36
Total	48	1326	1.48	1000	1.12

[a]Data are truncated to periods when canopy was estimated to be fully wet.

equipment malfunctions: 32 at the old growth stand and 16 at the second growth stand (Table 2). Mean rainfall rates were generally low; maximum one-minute rates during the study period were 95 mm hr^{-1} at the old growth stand and 46 mm hr^{-1} at the young growth stand, but one-minute intensities rarely exceeded 15 mm hr^{-1} at either stand and intensities averaged over longer timescales were even lower. The largest storm total rainfall amounts occurred in low-intensity winter storms: 106 mm at the old growth stand (duration 25 h) and 92 mm (duration 36 h) at the young growth stand. The data were dominated by precipitation events with subannual statistical recurrence intervals, and there were no extreme events. Total evaporative loss during the wet-canopy periods was 25% (22% at the old growth stand and 31% at the young growth stand).

4.2. Efficiency of Models in Predicting Throughfall

4.2.1. Overall Efficiencies of Models

[32] The grand mean efficiency, ε, for all time domain transfer function forms predicting all storms at both sample stands was 0.84 (range −1.81 to 0.97). Only 0.4% of best fits resulted in $\varepsilon < 0$, indicating that the linear models were generally assets for predicting throughfall intensities from rainfall intensities (Figures 2–4). Efficiencies of models fit to all storms simultaneously averaged 0.82 over all ten sample locations in both stands. Overall, the most efficient model was the gamma distribution, and the least efficient was the time-varying exponential distribution (Table 3). All models generally performed efficiently, although the time-varying exponential distribution appeared to do so at the expense of overestimating residence times (see section 4.3).

[33] All published drip equations and the exponential distribution describe drainage from a reservoir, and thus imply transfer functions with monotonic drainage and modal residence times of zero. Consequently, these equations predict throughfall rates to be greatest when storage is greatest immediately upon input, and it is never possible for throughfall rate to increase without addition of more rain. In contrast, the gamma distribution is the only transfer function form we investigated that allowed modal hydraulic residence times greater than zero. In equation (10), this corresponds to $a > 1$. Because the gamma distribution was the most efficient transfer function, and because 21% of storms were best fit by $a > 1$, we infer that water is transferred through the canopy by a sort of temporary stem flow, in which intercepted rainfall travels along vegetative surfaces for some time before detaching and falling as throughfall (in the sense of *Herwitz* [1987]). This inference is supported by canopy interception models that have improved estimation of evaporative losses by explicitly accounting for movement of water through canopies [e.g., *Sellers and Lockwood*, 1981; *Calder*, 1996; *Jetten*, 1996; *Xiao et al.*, 2000].

[34] Model performance was most strongly affected by the shape of the recession. The single-parameter model of *Rutter et al.* [1971] results in a power law recession (i.e., linear in log-log space) so has the heaviest tail (mass response at late time) of all the tested models. As a result, best fit parameterizations of this model were characterized by the fastest initial recessions of all models (e.g., Figure 2). The tail was generally too heavy for efficient prediction of late time drip after rain (e.g., Figure 4). The single-parameter exponential and *Pitman* [1989a] models behaved similarly to each other, exhibiting slow initial recession followed by the fastest recession of all models for $t > \sim 10-20$ min. (Figure 2). These recession characteristics degraded model efficiency for the opposite reasons as the Rutter model - recessions were insufficiently slow initially, followed by too little drip predicted at late time (Figure 2). The gamma and *Halldin et al.* [1979] models, with two parameters, predicted recessions intermediate in shape between the exponential and Rutter types. The drip model of *Massman* [1983] had flexible recession because of its explicit consideration of rainfall intensity. Unfortunately, this added parameter did not increase overall efficiency of the Massman model above the simpler exponential, gamma, or Halldin models (Table 3).

[35] Although some behaviors of the best fit parameters of the time-varying exponential distribution were instructive for understanding intensity effects on storage and drip (see section 4.3.2), it was clearly the poorest model. We infer that better representation of intensity dependence of storage and drip requires additional parameters such as are incorporated in the drip equation of *Massman* [1983].

[36] Transfer function models with multiple parameters, even those forcing modal response at $t = 0$, were generally more globally efficient than single-parameter models (Table 3), indicating that flexibility of recession shape was important for modeling different storms. This variability in the recession of drip rate from canopies implies multiple controls on the storage-drip process. *Massman*'s [1983] model is based on recognition of the importance of rainfall intensity in this process, but that drip model was not an improvement over other multiparameter models.

4.2.2. Model Efficiencies Affected by Stand and Storm Characteristics

[37] The different forms of transfer function were variably efficient at modeling the spatial variability of throughfall within the study stands. Although throughfall in the young forest was generally similar at all collectors, there was considerable spatial variability within the old forest. Transfer functions with multiple parameters accommodated this spatial variability better than did single-parameter models. For example, the Rutter model was less efficient at predicting strongly damped throughfall, but efficiency of the gamma model was similar throughout the old stand (Figure 4 and Table 4).

[38] Efficiencies of models varied according to environmental variables. For the sake of simplicity and clarity, we present here the performance of linear systems governed by a gamma distribution transfer function. Other transfer func-

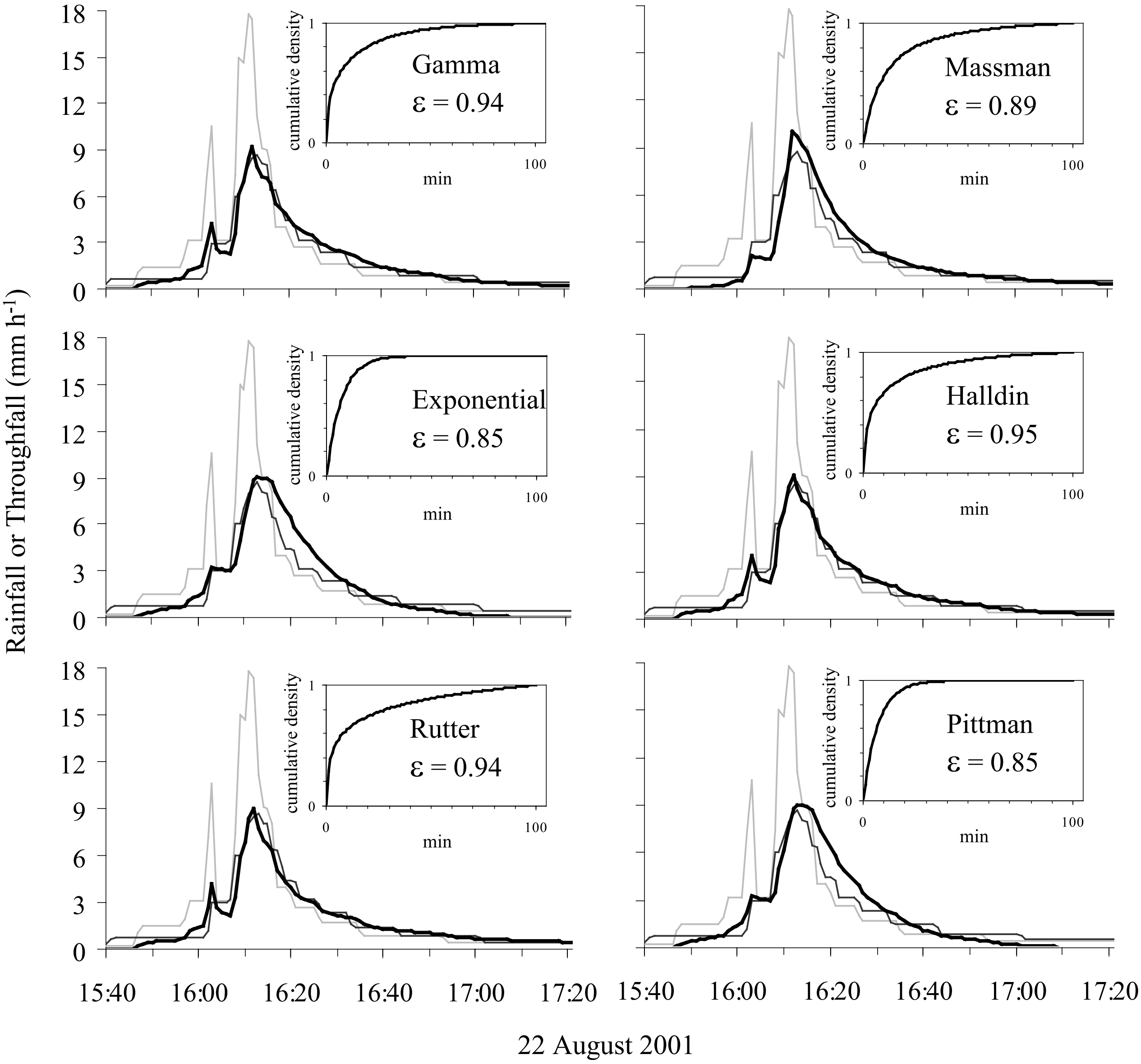

Figure 2. Throughfall in a Douglas fir forest in western Oregon, as modeled by six calibrated linear systems. In each plot, the thin solid line indicates throughfall measured at collector D2, the shaded line indicates rainfall measured in a nearby opening, and the thick solid line indicates throughfall modeled by a linear system governed by the transfer function in the inset (ε is model efficiency).

tion forms behaved similarly in response to environmental variables, but the overall superior behavior of the gamma distribution allows better analyses of these environmental effects alone. Relationships between gamma model performance and continuous storm variables (i.e., intensity, length, etc.) were weak ($R^2 < 0.06$ for all after transformations for linearity). Model predictions generally fit throughfall data better during warmer seasons (statistically insignificant) and at the old growth stand (Table 4). Model efficiencies may have been degraded in colder months by undetected ice and snow in the canopy or throughfall collectors, but we can think of no specific reason for better fits to occur at the site with the older, more structurally complex canopy.

[39] Adding intensity dependence to the linear model resulted in no gain in efficiency, either for the time-varying exponential distribution or the drip model of *Massman* [1983]. The time-dependent exponential transfer function predicted throughfall about as efficiently as the other models (median ε = 0.84), as did the intensity-sensitive Massman model (median ε = 0.86; Table 3). Insensitivity of the linear model to meteorological factors previously shown to affect canopy storage and drip rates is at least partially the result of the model being structured as a superposition of responses to rainfall through time. The parameters of the linear system appear to depend more on canopy characteristics than on storm characteristics.

[40] Model efficiencies were not statistically different among sample locations within stands (Table 3), regardless of varying characteristic MRT. Efficiencies were statistically negatively related to MRT, but with small effect size and

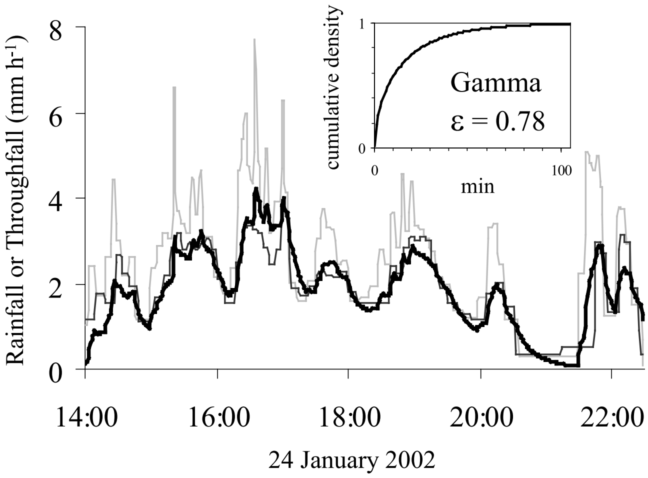

Figure 3. Throughfall in a Douglas fir forest in western Oregon, as modeled by a calibrated linear system governed by a gamma distribution transfer function. The thin solid line indicates throughfall measured at collector D2, the shaded line indicates rainfall measured in a nearby opening, and the thick solid line indicates throughfall modeled by a linear system governed by the gamma transfer function in the inset (ε is model efficiency).

low correlation coefficients ($R^2 \leq 0.20$, depending on model), suggesting the linear model was flexible enough to accommodate a range of canopy conditions.

[41] From the lack of structure in PCA of storm variables, weak correlations between model efficiency and PCA axes, and generally insignificant effects of all environmental variables on model efficiency, we expect that the model will perform similarly for storms different than the ones we measured. Because efficiency of the model was high in two contrasting stands as well as in strongly varying canopy conditions within stands, we infer that a linear system is generally appropriate for modeling throughfall at other locations.

4.3. Fitted Models

4.3.1. Comparison of Equations

[42] Most models indicated an experiment-wide median of mean hydraulic residence times of rainfall in the canopy of about 9–13 min, except the drip equation of *Rutter et al.* [1971], which indicated a median MRT of 17 min, and the time-varying exponential equation, which indicated a median MRT of 40 min (Table 3 and Figure 5). The differences in study average MRT among models were statistically significant.

[43] The shape of recession strongly affected the MRT indicated by each model. The longest MRTs were predicted by the Rutter model, and the shortest by the Pitman and exponential models, following the characteristic shapes discussed in section 4.2.1. Additionally, MRT was sensitively affected by selection of the T parameter (time to end of drip) included in models originating as drip equations. The heavy-tailed Rutter model was most sensitive to T, and the light-tailed Pitman model was least so. The best estimate of MRT is probably given by models based on the gamma distribution (study mean 12 min), both because of its generally superior model efficiency and its lack of dependence on T.

4.3.2. Comparison of Stand and Storm Characteristics

[44] Modeled MRT varied spatially within stands (Table 4 and Figure 6). Behavior of throughfall was similar for the three throughfall collectors in the young stand, but MRT was statistically different among collector locations in the old stand. One collector in the old stand, directly under a large tree with a deep, dense crown (Figure 6, C5), showed statistically longer MRT than for any other site. Three collectors in the old stand (C4, C6, and C7) were in gaps in the canopy. These sites showed generally shorter MRT than the other sites, but the differences were not all statistically significant (Table 4). Also, intensity smoothing at these sites was nearly always evident, suggesting that the gaps were not large enough to eliminate influence of adjacent trees. Models parameters fitted simultaneously to all storms at each throughfall collector were all comparable to the central tendency of the distribution of fits to individual storms at that collector (Figure 6).

[45] Best fit parameterizations of models predicted residence times statistically independently of all measured storm characteristics. Contrary to expectations, modeled MRT was not affected by rainfall intensity, storm length, or total storm precipitation (e.g., Figures 2–4).

[46] The best fit parameters of the time-varying exponential transfer function suggest that within-storm variations in intensity were not always the most important control on throughfall intensities. The fitted study-wide mean intensity factor (a from equation (11)) was 1.6, meaning that the exponential decay of drip rates after rainfall was positively correlated with rainfall intensity and residence times decreased with intensity ($I \propto -\text{MRT}$). However, the frequency distribution of a across storms was lognormal, with mode 0.6 and median 1.2. Therefore, while there was a strong negative correlation of residence time to intensity for some storms, there was a neutral or positive correlation for more than half of storms.

[47] Extrapolating the rainfall-throughfall relationships we measured to extreme events seems reasonable because best fit transfer function parameters were unrelated to total rainfall, event duration, or intensity. However, because we lack understanding of why transfer functions varied among storms, extrapolation to extreme events should be done with caution.

4.4. Implications for Canopy Storage During Rainfall

[48] Although linear systems do not explicitly model canopy storage, it is possible to calculate it from the water balance equation (1). Because the model ignores water that will eventually evaporate, modeled storage calculated as the residual difference between rainfall and simulated throughfall is in addition to saturation storage. The study average modeled storage is given by the product of average rainfall rate and mean residence time in the canopy, or $1.5 \text{ mm hr}^{-1} \cdot 12 \text{ min} = 0.3 \text{ mm}$ averaged across all storms and measurement sites for the gamma transfer function (Tables 2 and 3). This estimate roughly agrees with published field measurements of canopy storage in other forests, which have shown storage varying by ±1 mm during rainfall [*Calder and Wright*, 1986; *Bouten et al.*, 1996; *Klaassen et al.*, 1998]. *Keim and Skaugset* [2003] suggested an appropriate term for this additional storage is

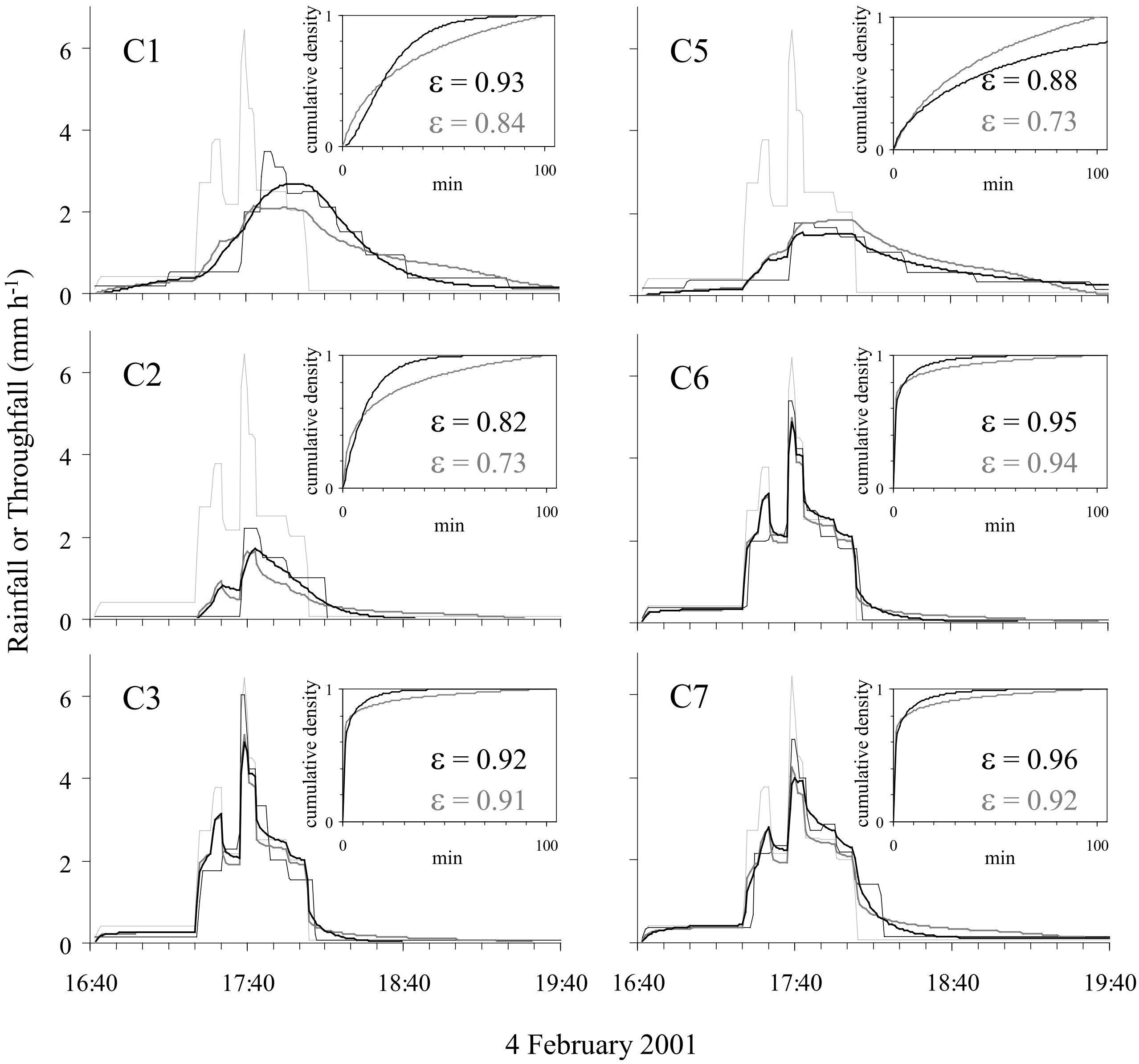

Figure 4. Throughfall at six locations (C1–C7) in an old growth mixed conifer forest in southwestern Washington, as modeled by two calibrated linear systems. In each plot, the thin solid line indicates throughfall measured at a collector noted in the top left corner, and the shaded line indicates rainfall measured in a nearby opening. Thick lines are throughfall predicted by linear models governed by gamma (thick solid lines) and Rutter (thick shaded lines) transfer functions in the inset (ε is model efficiency).

"dynamic storage," to distinguish transient storage that depends on rainfall intensity from the "static storage" that remains when rainfall ceases.

5. Conclusions

[49] This study has shown that a linear system is a useful model of dynamic throughfall rates at short time steps when the canopy is wet. The model was versatile over a range of microsite canopy conditions and storm properties, as evidenced by high model efficiency and lack of correlations between storm variables and the efficiency or parameters of models. Fitting the model to data from two forest stands over 48 storms in all seasons indicated stand median

Table 3. Comparisons of Transfer Function Forms Predicting Throughfall From Rainfall Data in a Linear System[a]

Transfer Function Form	Median Efficiency ε	Median Mean Residence Time, min
Statistical distributions		
Gamma	0.88 (a)[b]	12.0 (cd)[c]
Exponential	0.85 (bc)[b]	9.6 (e)[c]
Time-varying exponential	0.80 (f)[b]	40.4 (a)[c]
Drip equations		
Rutter et al. [1971]	0.85 (e)[b]	17.4 (b)[c]
Halldin et al. [1979]	0.86 (cd)[b]	10.5 (de)[c]
Massman [1983]	0.86 (b)[b]	12.9 (c)[c]
Pitman [1989a]	0.85 (d)[b]	9.0 (de)[c]

[a]Letters in parentheses indicate statistical similarity.
[b]Values in this group are statistically significant (α = 0.05).
[c]Values in this group are statistically significant (α = 0.05).

Table 4. Factors Affecting Predictions of Throughfall Rates From Rainfall Data in a Linear System Governed by a Gamma Distribution Transfer Function[a]

	Median Efficiency ε	Median Mean Residence Time, min
Season		
Spring	0.89[b]	10.7[c]
Summer	0.89[b]	8.6[c]
Fall	0.90[b]	8.2[c]
Winter	0.84[b]	16.6[c]
Stand		
Old growth	0.89 (b)[d]	9.5[e]
Second growth	0.86 (a)[d]	18.7[e]
Sample location in old growth stand[f]		
1	0.91[g]	10.7 (b)[h]
2	0.86[g]	16.6 (ab)[h]
3	0.90[g]	6.9 (c)[h]
4	0.84[g]	5.2 (c)[h]
5	0.88[g]	32.7 (a)[h]
6	0.90[g]	3.3 (c)[h]
7	0.89[g]	4.5 (c)[h]

[a]Letters in parentheses indicate statistical similarity.
[b]Values in this comparison are statistically similar.
[c]Values in this comparison are statistically similar.
[d]Values in this group are statistically significant (α = 0.05).
[e]Values in this comparison are statistically similar.
[f]There were no significant differences among the three sample locations in the young growth stand.
[g]Values in this group are statistically similar.
[h]Values in this group are statistically significant (α = 0.05).

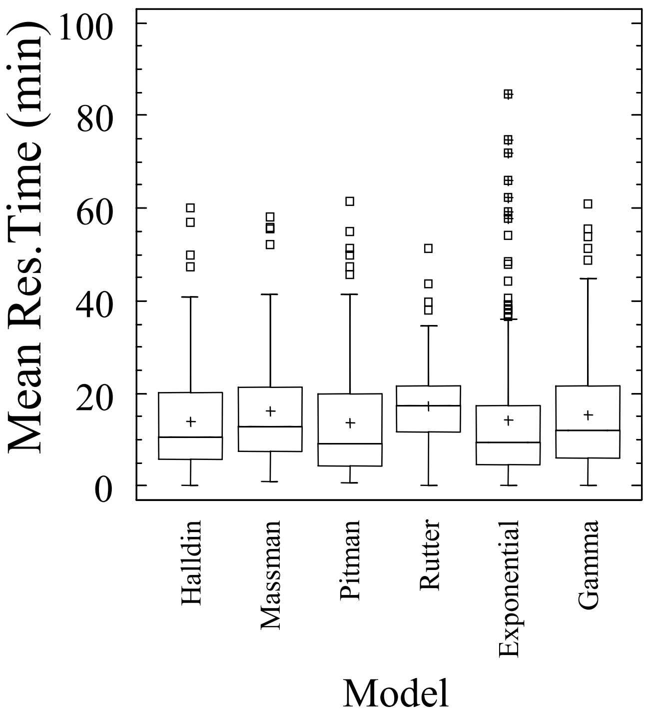

Figure 5. Mean hydraulic residence times of water stored in canopies predicted by each of six different models in two forests in the Pacific Northwest. The cross inside each box is the mean of all storms at all sites. The boundaries of each box indicate the middle two quartiles, the line splitting the box is the median, and whiskers extend 1.5 interquartile ranges above and below each box. Boxes outside the range of the whiskers are potential outliers.

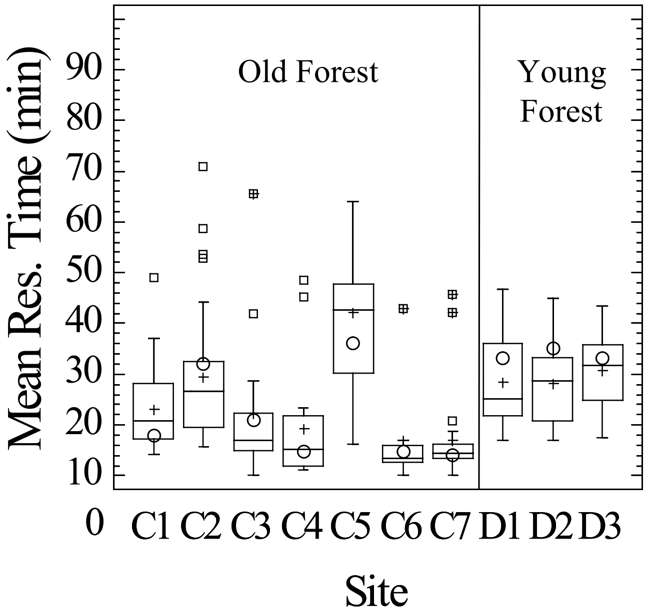

Figure 6. Mean hydraulic residence times of water stored in canopies predicted by a gamma transfer function in two forests in the Pacific Northwest. The cross inside each box is the mean of all storms at that site. The boundaries of each box indicate the middle two quartiles, the line splitting the box is the median, and whiskers extend 1.5 interquartile ranges above and below each box. Boxes outside the range of the whiskers are potential outliers. Circles indicate residence times for all storms optimized simultaneously at each site.

hydraulic residence times in the canopy of 12 minutes. Median residence times varied spatially within stands from less than 6 min to more than 30 min.

[50] While best fit transfer functions varied by local canopy characteristics, they did not vary according to rainfall intensities or season. Therefore we conclude transfer functions may be distinctive attributes of canopies useful for predicting dynamic canopy storage and drip. More work is required to reveal the sources of the variability of transfer function form among storms.

[51] Differences were minor among linear systems governed by any of several forms of transfer function. While the gamma distribution was most efficient at modeling time-varying drip rates, the exponential distribution and several transfer functions derived from published canopy storage-drip relationships were nearly as efficient.

[52] Further work to refine the use of linear systems in canopy interception should also include efforts to refine the treatment of evaporation to vary with time. Calibration of transfer functions for more forests and climates, and where more sources of variation are quantified will also lead to greater understanding of the flexibility of the model and suggest appropriate parameter sets for forests without measured throughfall intensities.

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