Impact of spatial variability in land surface characteristics on regional-scale evapotranspiration and runoff

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Abstract Numerical experiments have been carried out with a Soil-Vegetation-Atmosphere Transfer model to study the impact of spatial variability in soil and land surface parameters on regional-scale water balance components in a 27 km^2 catchment in SE Australia. A statistical-dynamical approach has been used to account for the spatial variability of the selected properties and to determine the seasonal evolution of the impact on water budget components. The method uses point data to derive probability-density functions for the thickness of the permeable top soil layer, coefficients for the water retention and hydraulic conductivity curves, the Leaf Area Index and the minimum stomatal resistance and incorporates these distributions in the model's mathematical framework in order to generate univariate distributions (sensitivity patterns) for evaporation, transpiration, evapotranspiration and runoff . The means of these univariate distributions of outputs yield *catchment-scale averages*. The study obtains catchment-scale evaporation estimates by running simulations with *aggregated parameters* obtained as statistical descriptors of parameter distributions. The difference between the *catchment scale averages* and values obtained with *aggregated parameters* describes the non-linear response of the model to spatial variability of the particular parameter. The study also investigates several *effective parameters* based on recently described hydrometeorological aggregation rules. Results show significant differences in sensitivity patterns between individual parameters and between seasons.

1 INTRODUCTION

Understanding the large-scale water and energy cycles requires investigative studies over a range of time and space scales of the relative importance of the various transfer mechanisms. There is increasing interest in providing scaling definitions and establishing scaling rules for use in regional-scale land surface process studies. This clearly requires interdisciplinary approaches. However, hydrologists and meteorologists have not yet reached a consensus on the optimum strategy to be adopted for moving between scales. Approaches to dealing with land surface heterogeneity and up-scaling usually involve (1) subdividing the land surface into homogeneous patches and calculating fluxes for those individual patches, and (2) defining aggregated parameters representing a uniform, composite surface. Sub-gridscale homogeneous areas may be defined *deterministically*, i.e. as a pattern of homogeneous surface units (e.g. Boulet et al. [1995]). Patches may also be defined *stochastically*, ie. as an occurrence of a given probability density function of a key parameter (the "statistical method"; see Avissar [1992]).

The "statistical dynamical method" has been used in meteorology by Avissar [1995] and Bonan et al. [1993] and in hydrology by Famiglietti and Wood [1992]. These studies investigate the impact of selected univariate distributions of relevant parameters such as stomatal resistance and soil- hydraulic properties on the variability in water fluxes. In the case of dependent variables one must define a common "scaling factor" (see Sposito and Jury, [1985] or Braud et al. [1995a]). The variability of the "scaling factor" then provides a substitute for the variability of the original surrogate variables. Such a relationship has been developed for the soil hydraulic parameters. Depending on the reliability accredited to current capillary models, the correlation is either derived analytically (cf. Miller and Miller [1956] or statistically (as in Noilhan and Lacarrère [1995]).

This paper reports on a numerical experiment which uses and extends the "statistical dynamical method". We have used a one-dimensional Soil-Vegetation-Atmosphere Transfer (SVAT) model and applied this model to 14 months of climate forcing. The objectives of this study are: to determine the impact of spatial distributions of selected soil and land surface parameters on regional-scale evapotranspiration and runoff; to determine the seasonal evolution of these impacts; and to investigate several aggregation procedures. This paper discusses the results obtained for transpiration (T), evaporation from the soil surface (E), total evapotranspiration (ET=E +T), and runoff (RO). A more detailed explanation of the methods used and discussion of the results obtained will be presented elsewhere (Boulet et al., submitted).

2 METHODS AND AVAILABLE DATA

2.1 Description of study area

The 27 km^2 Lockyersleigh catchment in SE NSW is gently undulating (with elevations ranging from 600 to 762 m + msl). Some 70% of the catchment comprises grazing lands and the remainder is open woodland. The local duplex soils are characterised by a 30-50 cm thick sandy loam layer overlaying a more impervious clayey layer. Because of the small range in elevations and the relatively high values of incoming solar radiation, heat and mass exchanges are considered to be mainly vertical, and lateral redistribution of water is assumed to be restricted to surface overflow processes shortly after rainfall (see Kalma et al. [1995]).

The catchment's landscape does not show strong discontinuities in its organisation, and therefore can not easily be sub-divided into distinctly homogeneous surfaces. Spatial heterogeneity can thus be parameterised more easily by adopting a stochastic approach involving integration over assumed distribution functions rather than with a deterministic approach based on homogeneous (field-scale) surface units (cf. Boulet et al. [1995]).

The regional climate is characterised by strong diurnal and seasonal climate variations and short-duration rainfall events, which necessitate the use of a realistic climate forcing sampling frequency and a computational time-step of less than one day.

The above assumptions have led to the use of a one-dimensional SVAT model, which transfers instantaneously the runoff generated at a particular location (represented in the stochastic approach by a point of the probability density function) to the catchment outlet.

2.2 Model description

The SVAT model SiSPAT (Braud et al. [1995b]; Braud [1996b]) is forced with air temperature, humidity, wind speed, incoming solar and long-wave radiation and rainfall. In the soil, coupled heat and mass transfer equations are solved for temperature T and matric potential h. They include both liquid and vapour transfers as formulated by Milly [1982]. The model deals with vertically heterogeneous soils. The upper boundary conditions are obtained by the solution of the soil-plant-atmosphere interface, which results in the surface soil heat and mass fluxes and the surface matric potential h_1 and temperature T_1. If saturation of the surface occurs, the matric potential is set to zero and surface runoff is calculated from the mass budget. At the soil-plant-atmosphere interface, bare soil and vegetation are considered separately in a two-source model (Shuttleworth and Wallace [1985]; Taconet et al. [1986]).

In the soil, a root extraction term is included and modelled with a resistance network. The assumption that the total root-extraction is equal to the plant transpiration allows for the computation of the leaf water potential which is used to compute the stomatal resistance water stress function. The incoming energy is partitioned between bare soil and vegetation through a shielding factor (Taconet et al.[1986].

For the solutions of moisture and heat transfer equations into the soil, two functions need to be specified which characterize soil hydrodynamic properties as a function of volumetric water content θ: the retention curve $h(\theta)$ and the hydraulic conductivity curve $K(\theta)$. These functions are described by the Van Genuchten [1980] model:

$$\text{Relative saturation } Se = (\theta - \theta_{res})/(\theta_{sat} - \theta_{res}) \quad (1)$$

$$Se = \{1 + (h/hg)^n\}^{-m} \quad \text{with } m=1-2/n \quad (2)$$

$$K(Se) = K_{sat}(Se)^2 \left[1 - \{1-(Se)^{1/m}\}^m\right] \quad (3)$$

These three expressions contain five parameters: one shape parameter m and four scale parameters: h_g for the pressure, the residual and saturated water content θ_{res} and θ_{sat} respectively, and hydraulic saturated conductivity K_{sat}. The shape parameter m is related to the texture of the soil and the scale parameters depend mainly on the structure of the soil. The spatial variability of the scale parameters is usually larger than that of shape parameters.

2.3 Distribution of model parameters

Previous studies using other land-surfaces schemes (Avissar [1995]), as well as local sensitivity studies (Boulet et al. [1995]) have shown that critical parameters for the description of the local water budget are depth of the top sandy layer (A horizon) z_{sand}, scale (θ_{sat} , K_{sat} and h_g) and shape (m) parameters of the water retention and hydraulic conductivity curves, Leaf Area Index (LAI) and minimum stomatal resistance (R_{stmin}). Additional sensitivity studies have indicated that variation in maximum root density, critical leaf water potential, vegetation height and albedo are insignificant and those parameters have not been included in this experiment.

Distributions of these soil parameters have been based on local field data and field work carried out by Geeves et al. [1995] in the Tablelands region of southern NSW and northern Victoria. All statistical descriptors for these two sets of data are given in Boulet et al. (submitted). In this study, we use the Lockyersleigh data set for mean values of all parameters and standard deviation of storage capacity, z_{sand} and θ_{sat}, and standard deviations taken from Geeves et al. [1995] for K_{sat}, h_g and m.. An insight into the spatial variability of the vegetation parameters LAI and R_{stmin} has been obtained from airborne mapping of the Normalised Difference Vegetation Index $NDVI$ and from the available literature, respectively. Values for "short grass" minimum stomatal resistance range from 20 s m^{-1} up to 200 s m^{-1}.

The distributions have all been fitted to data sets using normal or log-normal frequency distributions, except for the depth of the sandy surface layer z_{sand} (see **Table 1**). This depth has been related to total storage capacity (SC) of the soil. Kalma et al. [1995] obtained SC estimates from the difference between maximum and minimum water content observed over three years at 35 NMM tube

Table 1

Statistical models used for the scaling factors of six soil and land surface parameters. The mean of each scaling factor is unity.

Parameter	Symbol	Analytical statistical law	Standard deviation
Depth of sandy top layer	z_{sand}	Xinanjiang*	0.34
Miller and Miller coefficient	α	Log-normal	0.82
Saturated water content	θ_{sat}	Normal	0.11
Van Genuchten shape parameter	m	Normal	0.34
Leaf Area Index	LAI	Normal	0.3
Minimum stomatal resistance	R_{stmin}	Normal	0.5

* Cumulative probablity density function given by $F(s) = 1 - [(1-s)/(1-s_{min})]^{\beta}$ where $s = z_{sand}/130$, $s_{min} = 0.2$ and $\beta=4$

locations. They noted that the SC distribution could be represented with the empirical ("Xinanjiang") distribution used by Zhao et al. [1980], Dumenil and Todini [1992] and Wood et al. [1992]. *SC* is closely related to the depth of the sandy layer which approximates the "hydrologically active depth". We assumed that the same analytical expression can be applied to the depth of the sandy layer and fitted the available data on the depth of the A horizon with this model. Similar distribution parameters were obtained for *SC* and z_{sand}, and these values have been used in the numerical experiment.

2.4 Selection of parameters.

Stochastic simulations are usually performed with the Monte-Carlo approach whereby values are randomly drawn from its distribution. In order to get statistically representative results numerous simulations would be required, involving prohibitively large amounts of computing time. Boulier and Vauclin [1987] have shown that the number of simulations can be reduced significantly to as low as 10 simulations provided equi-probable parameters are drawn which are representative of the distribution. In this study we have extracted ten mid-point values each representing a 10% wide sub-range of the total population. Distributions of non-dimensional "scaling factors" are then used to relate these equi-probable values to their arithmetic mean, except for the soil physical properties h_g and K_{sat} which have been related by the similarity theory of Miller and Miller [1956]. Thus, for *LAI* and R_{stmin} and z_{sand}, q_{sat} and m values of the top sandy layer we write:

Equi-probable value=scaling factor mean value (4)

Covariations for h_g and K_{sat} of the sandy A-horizon are described with the same scaling factor coefficient α:

Equi-probable K_{sat} value= mean K_{sat} value*α^2 (5)

Equi-probable h_g value = mean h_g value * α^{-1} (6)

Cumulative probability distributions for the scaling factors are shown in the figure below.

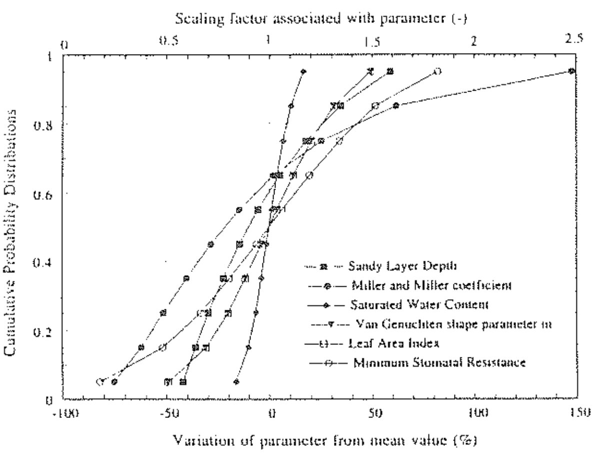

Figure 1: Cumulative probability distributions for the scaling factors associated with the selected parameters.

3 RESULTS AND DISCUSSION

3.1 Local deviation and sensitivity patterns

All simulations were done for grassland and considered the period from 8 July 1987 till 15 September 1988. The initial soil moisture profile used in all simulations was an average profile based on neutron moisture meter measurements made throughout the catchment on 8 July 1987. For each parameter ten equi-probable scaling factors have been obtained with the specific statistical model fitted to their distribution (cf. Boulier and Vauclin [1987], Braud et al. [1995a] and Braud [1996a]). These equi-probable scaling factors correspond with the mid-points of each of the ten 10% ranges. The mean value of each parameter is kept constant throughout the year, except for *LAI*. The time series of *LAI* throughout the experimental period is shown in Figure 2 together with the temporal distribution of rainfall. The ten scaling factors are then used to calculate the surface water budget components while all other parameters have their respective scaling factor kept at unity.

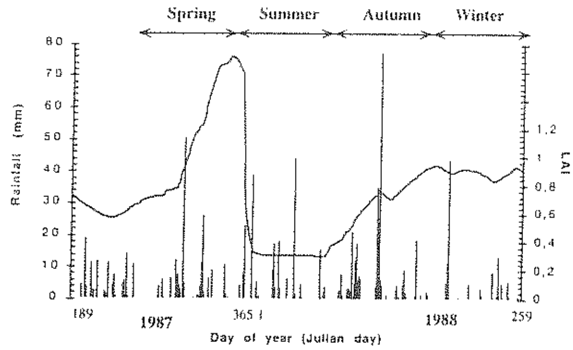

Figure 2: Daily time series between DOY 189 and DOY 365+259 of Leaf Area Index (m^2/m^2) and rainfall (mm/day)

The difference between the *equiprobable* value calculated for each of the ten local scale factors and an *aggregated* values computed with the arithmetic mean of the parameter's distribution (i.e. the class for which the scaling factor equals 1) is expressed as a percentage of the aggregated value and is shown in (7)

$$\text{Local Deviation (\%)} = 100 * \frac{\text{equiprobable value - aggregated value}}{\text{aggregated value}} \quad (7)$$

These Local Deviation values have been used to develop sensitivity patterns for E, T, ET and RO over the entire experimental period of 437 days, as shown in Figure 3, where each symbol can be associated with one-tenth of the catchment area. The steeper the slope near the origin, the more sensitive the parameter. If straight lines are obtained, the variation of output variable can be considered as linear with the parameter. Finally the range of variation of a given output as a response to a given parameter is directly linked to the range of variation of the input parameter (i.e. its spatial variability as quantified by the coefficient of variation).

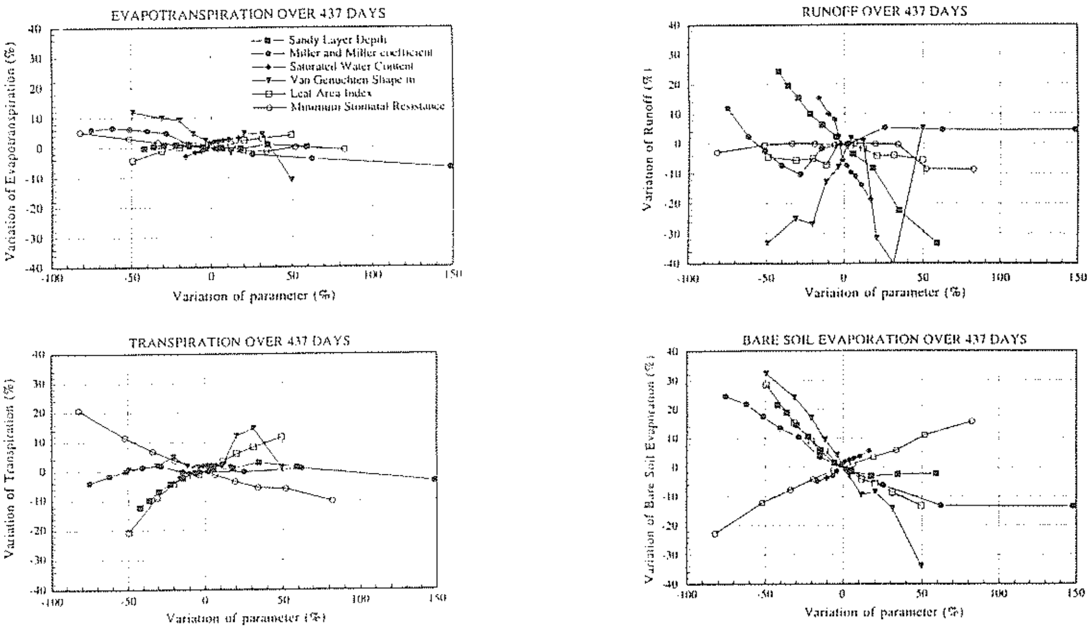

Figure 3: Sensitivity patterns for runoff, evapotranspiration, evaporation and transpiration over 437 days.

Variations in ET occur mainly during the stages of intermediate drying of soils. However, since impacts on E and T tend to compensate each other, sensitivity of ET to variation in the parameters is less significant than for T and E separately. Annual sensitivity patterns for E and T are rather regular without any break of slope except for the highest values of the Miller and Miller scaling factor α (when variations reach a threshold value) and m.

Sensitivity patterns for RO are far more complicated, since RO is modelled by a conditional "yes/no" command. For RO the most sensitive parameters are θ_{sat} and z_{sand}, for which the steepest slopes occur near the origin. The variation with those parameters is rather linear in contrast to what is observed with m or α. The largest variation in RO is obtained with z_{sand} and m ($\pm30\%$ and $\pm40\%$ respectively). Note that RO in this environment is mainly sensitive to soil parameters and insensitive to vegetation parameters.

For ET, m is the most critical parameter. This is mainly associated with the high sensitivity of E to this parameter (both in terms of slope near the origin and total variability: -40% to +30%). E is also sensitive to z_{sand}, LAI, α, θ_{sat} and R_{stmin} in decreasing order, whereas for T the importance of R_{stmin} exceeds that of α. The largest sensitivity is found for E (more than $\pm30\%$) but is reduced for T ($\pm20\%$), thus resulting in a maximum deviation of $\pm10\%$ for ET.

3.2 Regional deviation

The mean of ten local *equi-probable* output values also allows for the determination of an *average* value which is a measure of the particular water budget component for the entire catchment. The difference between *average* and *aggregated* values (computed with the arithmetic mean of the parameter's distribution) expressed as a percentage of *aggregated* value provides a measure of Regional Deviation as expressed in (8):

Regional Deviation (%) =

$$100 * \frac{[\text{average ET - aggregated ET}]}{\text{aggregated ET}} \qquad (8)$$

The Regional Deviation values shown in Figure 4 for ET and RO indicate that the differences between *averaged* and the *aggregated* values are significant for m, α, and also for z_{sand} and LAI. This effect is very obvious in summer. The existence of such Regional Deviation values may be attributed to the following factors:

(i) Non-linear expressions (e.g. LAI)
LAI affects absorption of solar radiation by vegetation, the amount of precipitation intercepted by vegetation, aerodynamic and stomatal resistances to transpiration, intercepted water evaporation and bare soil evaporation through the energy partition factor. This study shows that use of the *LAI* expressions induces considerable non-linearity into the simulations and that LAI represents a geometric feature of the complex system. This finding is similar to the results in Bonan et al. [1993] but it is verified for a much longer period.

(ii) Non-symmetrical probability density functions. The distribution functions of z_{sand} and α indicate that both have a greater probability of occurrence for low parameter values.

(iii) Use of conditional commands
It has been noted that the infiltration excess mechanism for runoff generation generates cut-offs in runoff sensitivity curves.

In this study the third factor appears to dominate. However, at a field scale and for a shorter period, Braud et al. [1996a] found with SiSPAT that Regional Deviations between average and aggregated values were largely caused by non-symmetrical distributions.

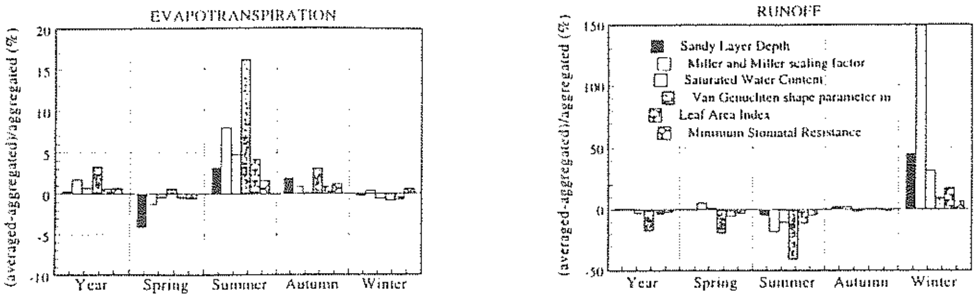

Figure 4: Annual and seasonal differences between "average" and "aggregated" values of evapotranspiration and runoff.

3.3 Effective parameters.

The Regional Deviation between *averaged* and *aggregated* ET as expressed by (8) reflects the non-linear behaviour of the simulation model. The parameter that yields with a single simulation ET values equal to the average value obtained with ten simulations is called an *effective parameter*. A zero value for the regional deviation then implies that the mean parameter can be used as an effective parameter.

When the probability density function is asymmetrical (as for the thickness of the sandy top layer z_{sand} and the Miller and Miller scaling factor α) the median may differ significantly from the mean. Some authors have suggested that the median (i.e. the geometric mean in the case of a log-normal distribution) of the distributions may be used as effective parameter value. In meteorology "aggregating rules" have been established to derive effective parameters from analytical evaluation of the "flux matching" condition (which states that water and energy fluxes aggregate linearly). For the minimum stomatal resistance, Raupach [1995] and Dolman [1992] have analysed the Penman-Monteith formulation for ET and have shown that the harmonic mean of the stomatal resistance is a better "effective" parameter than the arithmetic mean, because its inverse value, the stomatal conductance, aggregates approximately linearly.

To test whether geometric of harmonic means satisfy the above-mentioned definition of an *effective parameter*, we have simulated the one-dimensional water budget components using as effective parameters the geometric means of the distributions of z_{sand} and α respectively, and the harmonic mean of the R_{stmin} distribution. In Figure 5 we show the differences between *average* and *effective* values (based on effective parameters) for ET and RO.

A comparison of Figures 4 and 5 shows the efficiency of such aggregation rules. For example it is shown that summer runoff non-linearity is considerably reduced when the median of the Miller and Miller coefficient α or the sandy layer thickness z_{sand} distribution is used. When looking at the impact of z_{sand} , significant deviations appear for summer ET when the effective parameter is used. Effective minimum stomatal resistance increases the bias between *aggregated* and *averaged* water budget, as compared to the *aggregated* value derived from the arithmetic mean of the statistical distribution of R_{stmin}.

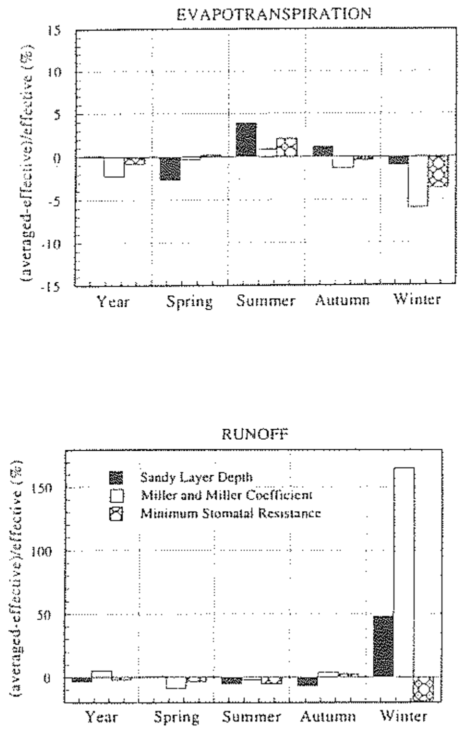

Figure 5: Annual and seasonal differences between "average" and "effective" values of evapotranspiration and runoff. (See text for explanation).

4. CONCLUSIONS

This study has provided examples of the impact of simulated spatial variability in landsurface parameters on the four water budget components: evaporation, transpiration, evapotranspiration and runoff. Local Deviation values used to develop sensitivity patterns for these four components over the entire year display how water budget components will vary in response to changes in key input parameters.

A statistical method is used to investigate the effectiveness of using the arithmetic mean of an input parameter as "effective parameter" in reproducing the average behaviour of the system. Results are encouraging in spring, autumn and winter, when the complexity of the interactions between different processes and the high frequency of rainfall is not very great. Differences ("regional deviations") between average values and aggregated outputs based on arithmetic means of input parameters for these three seasons are of the same order of magnitude as the mass-balance uncertainty allowed by the computational constraints on time cost-efficiency. However, in summer regional deviation is considerable if the arithmetic mean of the distributions is used.

Aggregating rules based on median values of the input parameter improve the accuracy of the one-dimensional catchment-scale water budget simulation. However, several existing aggregation rules developed from simplified parameterizations do not adequately consider the analytical complexity of the model or, therefore, the possible interactions between the transfer phenomena. In our case, the rules derived in this way for the minimum stomatal resistance R_{stmin} fail to reproduce the averaged water budget. Runoff variability has been found to be an important mechanism responsible for spatial heterogeneity and non-linear sensitivity. Finally, we note that spatial rainfall variability has been neglected. In drier environments, the impact of spatial and temporal rainfall variability on heat and mass exchange must also be investigated.

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