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Research Paper

Automated Parameterization of Land Surface Process Models Using Fuzzy Logic

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Abstract
All land surface process models require parameters that are proxies for spatial processes that are impractical or impossible to measure. Recent developments in model parameter estimation theory suggest that information obtained from calibrating such models is inherently uncertain in nature. As a consequence, identification of optimum parameter values is often highly non-specific. A calibration framework using fuzzy logic is presented to deal with such uncertain information. An application of this technique to calibrate the sub-canopy controls on transpiration in a land surface process model demonstrates that objective estimates of parameter values and expected ranges of predictions can be obtained with suitable choices for objective functions. An iterative refinement in parameter estimates was possible with conditional sampling techniques. The automated approach was able to correctly identify parameter tradeoffs such that two strongly different sets of parameters could

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produce almost equal daily average canopy transpiration for two upland deciduous tree species. The approach failed to correctly identify such idealized model parameter tradeoffs for upland conifer and wetland tree species. There remains a need for expert knowledge to choose among a range of parameter values. Due to its computational simplicity and flexibility, the framework presented and its associated algorithms can easily be embedded within a GIS to support the parameterization of land surface models. However, the core analytical tools would need to be augmented by human expertise or some form of expert system to reliably generate model parameters.

1 Introduction

Major research efforts to integrate GIS with modeling can be viewed as part of a wider GIS community effort to improve the analytical capabilities of GIS (Fotheringham and Rogerson 1994, Goodchild et al. 1992). The emphases in this area include making the GIS a framework for model integration (e.g. Mackay et al. 1993, 1994; numerous papers in Goodchild et al. 1993, 1996; Robinson and Mackay 1996; Taylor et al. 1999), and extending the analytical capabilities to include uncertainty handling, model sensitivity analysis, and error propagation (e.g. Heuvelink 1998, Mackay and Robinson 2000, Crosetto and Tarantola 2001). It is clear from all this effort that simpler, purely quantitative analytical tools are easier to implement within GIS, and these simpler tools have a more widespread appeal. One analytical capability that seems like a logical addition to the analytical GIS is automated model parameterization. In general, model parameterization refers to the assignment of parameter values as proxies for variables or processes that cannot be directly measured. No matter how much spatial detail is captured by a model, at some level it must rely on parameters. It is rarely possible to obtain direct measurements for all of the required parameter values due to high degrees of spatial heterogeneity (Beven 1989). Land surface process models require diverse types of spatial observations, and schemes for parameterizing spatial properties that cannot be directly observed. There are numerous strategies for such parameterization. For example, hydrologists routinely use parameters organized according to the geomorphic structure of the watershed (e.g. Band et al. 1993, Arnold et al. 1998), or on surface flow paths (e.g. Band et al. 1993, 2000; Wigmosta et al. 1994; Vertessey et al. 1996). The global modeling community organizes parameters based on area-derived means (e.g. Running and Hunt 1993, Foley et al. 1996) or by implicitly capturing the spatial covariation of key variables using distributional information (Famiglietti and Wood 1994, Sellers et al. 1997, Foley et al. 2000).

When values for model parameters cannot be measured, an alternative is to estimate them through a calibration process in which the parameters are adjusted until one or more predicted variables match observations. In an automated calibration framework, this involves selecting a model-parameter combination from the feasible model-parameter space, which can include multiple models and multiple parameter sets or values. Typically, the best simulation output is the one with the highest degree of fit to some calibration data, determined using evaluation criteria or objective functions. It may not be possible to identify a single set of parameters that gives a prediction that uniquely satisfies the evaluation criteria. For example, it has been shown that output from hydrological simulations with widely different parameter sets produce nearly equal levels of measured degree of fit, making it difficult to select among these solutions (Beven

1993). The ranking of simulations based on performance may change when a different data set is used for calibration (Beven 1993) or a different set of objective functions is used (Gupta et al. 1998). One reason for this non-unique solution to the calibration exercise is that model parameters are not mutually independent. Parameters can compensate for each other in ways that allow for many parameter combinations to yield almost equivalent results. Furthermore, poor representation of processes within the model structure, as well as the use of aggregated data, can sometimes be compensated for with an adjustment of parameters. As such, model parameterization remains partly an art requiring considerable domain experience and knowledge of the model structure.

In this paper, we present a framework to automate the parameterization of land surface process models, and to quantify the range of variability in model output that results from predictive uncertainty in model parameters. The framework is evaluated in its application to a regional model of forest canopy transpiration, parameterized by tree species. A series of algorithms are presented, which successively restrict the range of parameter values used by the model. Simple, iteratively applied filters are used to restrict an initial large set of parameter values obtained from Monte Carlo sampling. Our assumption is that simple algorithms, which can be built into a GIS framework, are sufficient for parameterizating our model of canopy transpiration. We evaluate this assumption and then discuss the implications, with reference to the physiology of transpiration, for constructing automated tools for the parameterization of land surface processes models.

2 Fuzzy Calibration Framework

2.1 Outline of the Problem

Comparison and subsequent selection of the optimum simulation in a traditional automated calibration system is based on the following premise:

$$x_i, x_j \in M : f(x_i) > f(x_j) \Rightarrow x_i \text{ is a better simulator of the system than } x_j, \qquad (1)$$

where x_i and x_j are two different simulations (i.e. a model and a single parameter set) in the discrete set of feasible simulators M, and $f()$ is the objective function that is maximized. This premise is true if the relative ranking of x_i and x_j is not sensitive to a change in the definition of $f()$ or a change to the calibration data. For reasons discussed in the introduction, this assumption is not strictly valid for most calibration problems and a set of simulations may have to be accepted as the solution to the calibration exercise. Consequently, a revised goal of calibration may be stated as that of identifying the smallest possible simulation solution set within the constraints imposed by the models and data available.

For a calibration process to be successful, some amount of information regarding relative suitability of simulations obtained from $f()$ must not depend on the choice of data or objective function. The value of $f(x_i)$ provides some estimate of the possibility that x_i is an acceptable simulation compared to the other simulations in M. This notion is used in the Generalized Likelihood Uncertainty Estimation (GLUE) framework (Beven and Binley 1992) where $f()$ values are scaled to sum to one and then interpreted as the likelihood of a simulation to be optimal. The acceptable simulation set is defined by a threshold value of $f()$ based on a statistical confidence limit. However, in most cases, the errors from land surface process models do not strictly conform to the assumptions associated with probabilistic methods. The probabilistic interpretation of the scaled

objective function value is too restrictive and using a threshold on the objective function value to obtain the set of acceptable simulations under this assumption may seem arbitrary (Gupta et al. 1998).

An alternative approach is to build a parameter selection technique using set theory, as is done with Multi-Objective Complex Evolution (MOCOM-UA) (Yapo et al. 1998, Gupta et al. 1998). The set of acceptable simulations, which is called the Pareto set, is defined in such a way that it contains a single member when only one objective function is used. This approach explores only part of the uncertainty in parameter values because it assumes that the best simulation for one objective function can be identified unequivocally, and the uncertainty arises only as a result of tradeoffs among objective functions. Consequently, if this best simulation is a result of over-fitting to the objective function, incorporating information from other objective functions cannot subsequently reject it. In order to work well in practice, this approach requires careful selection of objective functions as well as calibration data. An alternative interpretation is proposed here, in which the set of acceptable simulations is considered a fuzzy set. To characterize this fuzzy set, $f()$ is interpreted as a fuzzy membership grade function. The fuzzy set approach relaxes the assumption made by MOCOM-UA by accepting the possibility of nonspecific simulation selection even when a single objective function is considered.

2.2 Solution Based on Information Theory

A set of simulations accepted as a solution to the calibration problem can be considered an expression of the inability to precisely identify a unique solution. This uncertainty arises from the fact that it is known that the simulation of interest belongs to a set of alternatives that cannot be distinguished from each other. This type of uncertainty is called non-specificity and can be estimated by the Hartley Function (Hartley 1928) in the context of crisp sets. The Hartley Function is a measure of the additional information that is required to remove this non-specificity. It is defined as:

$$H(A) = \log_2 | A | \tag{2}$$

where $H(A)$ is the Hartley Function for a finite crisp set A and $| A |$ is its cardinality. The greater the cardinality of the retained simulation set in proportion to the population of simulations, the greater the non-specificity in the model calibration.

When the acceptable set of simulations is considered a fuzzy set, F, within the domain, X, of all feasible simulations, uncertainty related to the cardinality of F is expressed as a measure of the non-specificity of F. One measure of non-specificity is the U-uncertainty of subnormal fuzzy sets proposed by Higashi and Klir (1982) and refined in Klir and Wierman (1998):

$$U(F) = \int_0^{h(F)} \log_2 | {}^{\alpha}F | \, \mathrm{d}\alpha + (1 - h(F)) \log_2 | X | \tag{3}$$

where $U(F)$ is the U-uncertainty associated with F, $| {}^{\alpha}F |$ is the cardinality of an α-cut of F (i.e. number of members that remain in the set if all members with a membership grade less than α are taken out of F), $h(F)$ is the height of F (or maximum membership grade in F), and $| X |$ is the cardinality of the universal set X (or in this paper, the population of simulations created by sampling the parameter space). An approximate solution to Equation 3 is:

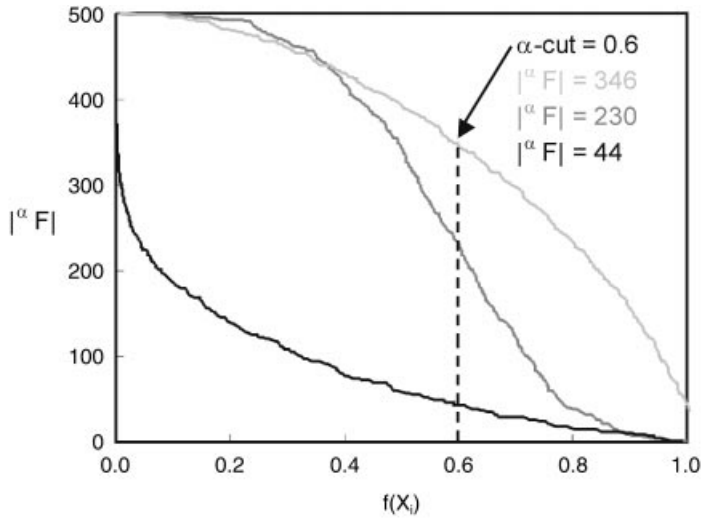

Figure 1 These hypothetical distribution functions illustrate how cardinality of a candidate set of models varies by value obtained from a measure of goodness-of-fit. At a given level (or α-cut) a low cardinality indicates a high level of specificity in the set of candidate models. A high cardinality indicates a high level of non-specificity.

$$U(r) = \sum_{i=2}^{n} (r_i - r_{i+1}) \log_2 i + (1 - r_1) \log_2 n \tag{4}$$

where r is the ordered possibility distribution (Zadeh 1978) derived from the fuzzy set F and r_{n+1} is assumed to be 0. Figure 1 shows a series of hypothetical relationships between the α-cut and $|\,{}^{\alpha}F\,|$. In this figure $f(x_i)$ refers to the goodness-of-fit for each simulation. At an α-cut of $f(x_i) = 0.6$ the three relationships shown yield very different cardinalities. Relations that are skewed towards the low end, and thus have only a few high $f(x_i)$ simulations, are better than relations having too many high $f(x_i)$ values. The ideal is to have a single simulation with its respective $f(x_i) = 1.0$ and all other simulations have $f(x_i) = 0.0$. This gives a cardinality of 1.0 for the fuzzy set and a cardinality of one for the crisp set. The more usual case is one in which the cardinality of the fuzzy set is greater than 1.0.

The shape of the α-cut versus $|\,{}^{\alpha}F\,|$ curve provides a basis for estimating the useful calibration information provided by the given objective function. The key is to objectively define the α-cut and the cardinality of the simulation set that must be retained as the solution to the calibration based on the available information. One way to do this is to use the principle of uncertainty invariance (Klir and Wierman 1998), which forms a crisp set of acceptable simulations that approximates the respective fuzzy sets by virtue of having the same *U*-uncertainty. Consider for example the ordered fuzzy set $F = \{0.9, 0.8, 0.8, 0.7, 0.6, 0.4, 0.1, 0.1\}$. The cardinality of F is the sum of fuzzy memberships in the set, which in this case is 4.4, and the associated *U*-uncertainty is 2.2. To decide how many members must be retained given this evidence, an integer, k, is calculated such that the value of $|\,U(r) - \log_2 k\,|$ reaches a minimum (Samanta and Mackay 2002). This is obtained by equating the *U*-uncertainty of the fuzzy set (Equation 4) to the Hartley function (Equation 2) for the desired crisp set. The value of k (5 in this example)

is the required cardinality of the retained simulation set, which means the top five simulations in F are retained and the α-cut is placed at 0.6. Note that the simulations are no longer ranked within the restricted set. This is based on the assumption that all the information obtainable from a particular objective function has been extracted in constructing the restricted set. No further ranking is allowed within this set based on the same objective function (Samanta and Mackay 2002). The parameter values associated with this crisp set (henceforth called the α-restricted set) can fill all or part of the multi-dimensional parameter space defined by the initial ranges or distributions used for sampling.

3 Application to Modeling Forest Canopy Transpiration

3.1 Study Site and Data Description

Data for this study was obtained in northern Wisconsin, in a 4.1 km × 3.1 km region centered on a communications tower (WLEF tower) instrumented to measure energy, water and carbon exchange between the forest landscape and the atmosphere (Berger et al. 2001). The bedrock is comprised of Precambrian metamorphic and igneous rock overlain by 8 to 90 m of glacial and glaciofluvial material deposited approximately 10 k to 12 K years before present. The topography is slightly rolling with a range of 45 m within the defined study area. Outwash, pitted outwash, and moraines are the dominant geomorphic landforms. The growing season is short and the winters are long and cold. Mean annual July and January temperatures are 19°C and –12°C, respectively. The forest vegetation reflects glacial topography (Fassnacht and Gower 1997) and forest management activities, such as thinning, selective and clear-cut harvests.

Five primary species were selected for intensive study including red pine, sugar maple, trembling aspen, white cedar, and speckled alder. These species represent over 80% of the tree basal area (Burrows et al. 2002) and about 85% of the land surface area (Mackay et al. 2002) in the region around the WLEF tower. The average leaf area index for each stand was 3.6 and did not change significantly throughout the measurement period (Ewers et al. 2002). A total of 64 trees in four stands were instrumented to record sap flow in the hydroactive xylem. Sap flow measurements were taken from June 22 through August 15, 2000 on all species except alder, for which measurements were made from July 25 through August 15, 2000 (Ewers et al. 2002). In each stand, soil moisture, air temperature and relative humidity were recorded. Radiation and precipitation were recorded above the cedar stand. Additional measurements of wind speed, air temperature, precipitation, soil moisture, and relative humidity were made at the WLEF tower and in mixed hardwood, red pine, and alder stands surrounding the WLEF tower.

3.2 The TREES Model and Its Parameterization

To illustrate the automated calibration framework, it was applied to the Terrestrial Regional Ecosystem Exchange Simulator (TREES) (Ahl 2002, Mackay et al. 2003), a land surface process model that is based on earlier work on coupling vegetation and hydrologic models (Mackay and Band 1997, Mackay 2001). TREES has a mechanistic diurnal canopy model for photosynthesis and transpiration, which allows TREES to use detailed meteorological, sap flux, eddy covariance, and soil moisture data that is being collected around the WLEF eddy flux tower in northern Wisconsin and other sites.

Canopy transpiration is calculated with the Penman-Monteith (P-M) equation (Monteith 1965):

$$E_c = \frac{\Delta R_n + C_p \rho_a \dfrac{D}{r_a}}{\rho_w \lambda \left(\Delta + \gamma \left(1 + \dfrac{r_c}{r_a} \right) \right)} \tag{5}$$

where E_c is canopy transpiration, Δ is the slope of the saturation vapor pressure-temperature curve, R_n is canopy net radiation, C_p is specific heat capacity of air, ρ_a is the density of air, D is vapor pressure deficit from canopy to air, r_a is the bulk vegetation aerodynamic resistance, ρ_w is the density of water, λ is the latent heat of evaporation, γ is the psychrometric constant, and r_c is canopy resistance. Aerodynamic resistance, r_a, is affected by canopy properties and the flow of air through and above the canopy. Canopy resistance, r_c, is affected by the environmental and physiological conditions of the leaf stomata. It is calculated as follows:

$$r_C = \frac{1}{g_S L} \tag{6}$$

where g_S is the leaf-level stomatal conductance determined from a multiple constraint function (Jarvis 1976):

$$g_S = g_{S\max} \cdot f_1(\delta) \cdot f_2(Q_{\min}) \cdot f_3(\Psi_L) \tag{7}$$

where $g_{S\max}$ is a theoretical maximum canopy average stomatal conductance as occurs under optimal environmental conditions and leaf health, δ is sensitivity of stomatal conductance to vapor pressure deficit (D), $Q_{\min}$ is minimum light level for stomatal opening to occur, and Ψ_L is leaf water potential. The key parameter determining the potential rate of canopy transpiration is $g_{S\max}$. The functions in Equation (7) compensate for the choice of $g_{S\max}$ value by calibrating δ, $Q_{\min}$ and parameters that affect Ψ_L.

TREES parameter estimation was conducted for each species (Ahl 2002, Mackay et al. 2003). The range for each parameter was adjusted after an initial set of simulations to minimize under sampling. This involved running the model with a range of parameter values and then comparing simulation output to stand-level sap flux transpiration. Based on this initial analysis the most sensitive parameters were selected. The selected parameters, their respective ranges, and the source of the ranges were $Q_{\min}$(30 to 790 W m^{-2} L^{-1}) (Running and Coughlan 1988), $g_{S\max}$(0.4 to 5 mm s^{-1}) (Kelliher et al. 1995), and δ (0.07 to 0.74 kPa^{-1}) (Jarvis 1976). Other parameters that were varied included a parameter used in calculating aerodynamic resistance, a precipitation interception coefficient, and a soil hydraulic parameter that affects Ψ_L. However, these other parameters did not show any relationship to $g_{S\max}$. For each species, TREES was run 15,000 times using random parameter values within the ranges defined for each parameter. Simulations were run over the period covered by the sap flux data, using 30-minute time-steps and 30-minute average micrometeorological data collected for each stand type. E_C output was on a daily time-step.

Each simulation was evaluated using a linear regression analysis of the form:

$$Y = b_0 + b_1 X \tag{8}$$

where b_0 and b_1 are regression coefficients referred to as the intercept and slope, respectively, Y is the simulation estimate of E_C(mm day^{-1}) and X is the sap flux estimate of

E_C(mm day^{-1}). Simulation results were evaluated using the regression coefficients and the coefficient of determination calculated as:

$$R^2 = \left\{ \frac{\sum_{i=1}^{N} (X - \overline{X})(Y - \overline{Y})}{\left[\sum_{i=1}^{N} (X - \overline{X})^2 \right]^{0.5} \left[\sum_{i=1}^{N} (Y - \overline{Y})^2 \right]^{0.5}} \right\}^2 \quad (9)$$

The regression coefficients and R^2 were combined into a single index (Ahl 2002):

$$f(x_i) = 1 - \max\{[w_1 | b_0 - 0|^2 + w_2 | b_1 - 1|^2 + w_3(1 - R^2)^2]^{0.5}, 0\} \quad (10)$$

where $f(x_i)$ describes the relative deviation of the regression parameters and R^2 from an ideal simulation, and $[f(x_i) = 1]$ and $w_1 + w_2 + w_3 = 1$ are weighting factors. A simulation was considered to be a good predictor of transpiration when its respective regression with sap flux data had an intercept near 0, a slope near 1, and a high R^2. For this study, $w_1 = w_2 = w_3$ to avoid giving preferential weight to any one criteria of the goodness-of-fit.

An ordered possibility distribution, r, was derived by sorting the $f(x_i)$ scores (Equation 10) from highest to lowest. The k simulations having scores higher than the simulation that minimizes $| U(r) - \log_2 k |$ were retained as the α-restricted set. Further automated restrictions were then applied to this set to isolate individual parameters or combinations of parameters. Consider, for example, the parameters δ and Q_{min}, which are proxies for stomatal response to the rate of water loss and to low light conditions, respectively. An increase in δ causes stomatal conductance to reduce more rapidly in response to increases in vapor pressure deficit (VPD). VPD typically increases during mid-day, which means δ is responsible for reducing mid-day transpiration. An increase in Q_{min} forces stomatal closure (and reduced transpiration) early and late in the day when light levels are low. It is clear that either an increase in δ or Q_{min} can reduce daily total transpiration, and this tradeoff allows for many parameter combinations to produce a similar daily total transpiration. Ewers et al. (2002) found that VPD explained most of the variance in transpiration in our study site. For this reason we applied a further restriction to reduce the variability of Q_{min} in a more refined solution set. We developed a simple filtering algorithm to apply this restriction. First, the α-restricted set was sorted from low to high Q_{min}. Filters were then defined on Q_{min} using a window size of 3 Wm^{-2}L^{-1} for all species except for alder, which had a window size of 10 Wm^{-2}L^{-1}. The window size was chosen to retain a sufficient number of simulations to capture a range of variation in g_{Smax}. The windows were moved through the respective α-restricted sets and within-window ranges of g_{Smax} were recorded. Windows containing the largest variation in g_{Smax} for each species, respectively, were retained as Q-restricted sets. End-member simulations of low and high g_{Smax} within each Q-restricted set were used to parameterize TREES for the respective species. The end members of the Q-restricted sets can be viewed as worse case uncertainty arising from any residual ambiguity in the choice of g_{Smax} after we have exhausted all knowledge available. It should be noted that we could have sorted on δ and applied filters defined on this parameter if the analysis of Ewers et al. (2002) had indicated that light levels were the primary control on transpiration. Furthermore, if additional knowledge can be obtained on how to restrict the parameter ranges, then parameter non-specificity can be further reduced.

3.3 Mapping Canopy Transpiration

TREES was run at 30 m resolution using a forest land cover classification derived from airborne imagery (Mackay et al. 2002) and leaf area index derived from co-kriging of optically measured leaf area with tree species type (Burrows et al. 2002). Each cell in a raster field of 137 × 104 grid cells was individually parameterized using the dominant species for the respective cell. All conifer-dominated cells were parameterized using the red pine parameters. All upland hardwoods were parameterized using the maple parameters. Alder and cedar represent species cohorts in most of the forested wetland areas, and so these species were each simulated in every forested wetland cell. We ran TREES once using low $g_{S\max}$ for the respective species, and again using high $g_{S\max}$. This provided a direct way to quantify the uncertainty in transpiration that results from non-specificity in $g_{S\max}$.

4 Results and Discussion

Figure 2 shows the possibility distributions for the respective species. The values for the α-cuts span a relatively small range of 0.575 for aspen to 0.683 for red pine, while the cardinalities of the restricted sets corresponding to the α-cuts are from 1608 for alder to 3759 for red pine. This result shows that canopy parameterization is most non-specific for the conifer species (cedar, red pine) and most specific for alder. Maple and aspen parameterizations are intermediate with respect to specificity. The significance of this non-specificity for making predictions depends on how clustered the parameter values are within the α-restricted set. A tight clustering suggests that parameter trade-offs may be predictable. The relationships between $g_{S\max}$ and δ in the α-restricted and Q-restricted simulation sets are shown in Figure 3. There is generally a well-defined non-linear relationship between these two parameters. As $g_{S\max}$ is increased there is a necessary increase in δ. This relationship is consistent with plant water relations theory, which has shown that stomata close in response to increasing rates of water loss associated with high VPD at the leaf-atmosphere interface (Jarvis 1980, Monteith 1995). Plants with high stomatal conductance rates under optimal conditions show greater sensitivity to VPD, and this can be attributed to stomatal control of leaf water potentials in the plant to prevent hydraulic failure (Sperry et al. 1998, Oren et al. 1999, Ewers et al. 2000).

Although cedar has the second highest cardinality in its α-restricted set, the simulations are tightly clustered in the two-parameter space. This suggests that cedar may have low predictive uncertainty. This may be attributed to the fact that the cedar individuals are very well coupled to the atmosphere. This coupling makes cedar canopy transpiration easier to model since stomatal control of transpiration dominates over the influence of boundary-layer conductance (McNaughton and Jarvis 1991), which was not considered in the current study. For less coupled canopies there is a greater need to resolve sub-canopy processes. For example, the short, broad-leaf alder responds more to light than to vapor pressure deficit (Ewers et al. 2002) and so within the α-restricted set there is no apparent relationship between $g_{S\max}$ and δ. A further refinement of the simulations into Q-restricted sets (Figure 3) provides further insight on the sub-canopy parameterizations among the species. Red pine, sugar maple and alder show clustering within narrow ranges of $Q_{\min}$. Aspen and cedar do not. Since the simulations for cedar are

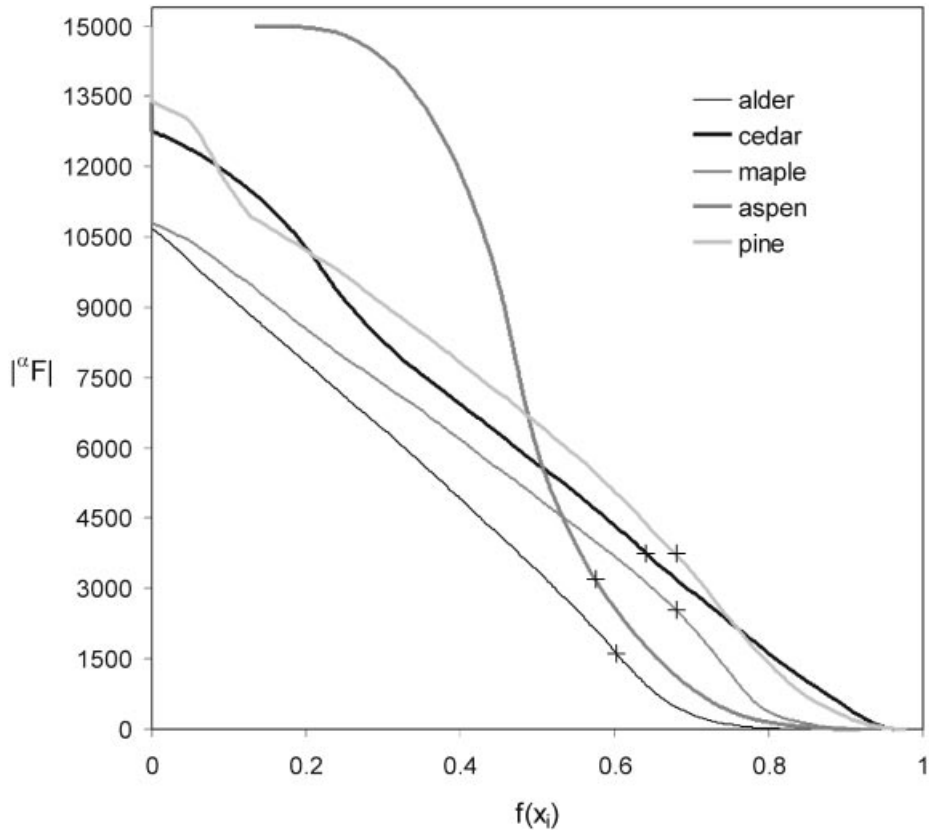

Figure 2 This figure shows the possibility distributions for the 15000 simulations for the respective species. The crosses are located at the α-cut obtained by minimizing $| U(r) - \log_2 k |$ in each distribution

tightly clustered in parameter space, this leaves aspen as the only species in this analysis to retain a high degree of parameter variability. This result highlights a weakness of fully automated parameter estimation techniques, as further insight into the refinement of the aspen and other species parameterizations may be possible by taking into consideration knowledge of plant water relations. Nevertheless, the automated approach allows for a considerable refinement of the parameter space without resorting to *ad hoc* rules or subjective judgment.

The results of TREES simulations parameterized with low and high maximum stomatal conductance are shown in Plate 2, see plate section. Based on the residual canopy transpiration (Plate 2c) the conifers show the greatest variation in canopy transpiration of up to 0.63 mm day^{-1}, followed by the forested wetland at about 0.25 mm day^{-1}. Aspen and hardwoods show negligible variation. Based on the percent change in canopy transpiration the forested wetland shows the greatest uncertainty due to parameter selection, followed by red pine. The hardwoods have a small uncertainty and aspen is simulated with almost no predictive uncertainty attributed to g_{Smax}. The results for the wetlands and upland conifers appear to be in direct conflict with the equifinality notion that simulations of equal fit should give essentially the same answer (Beven 1993). However,

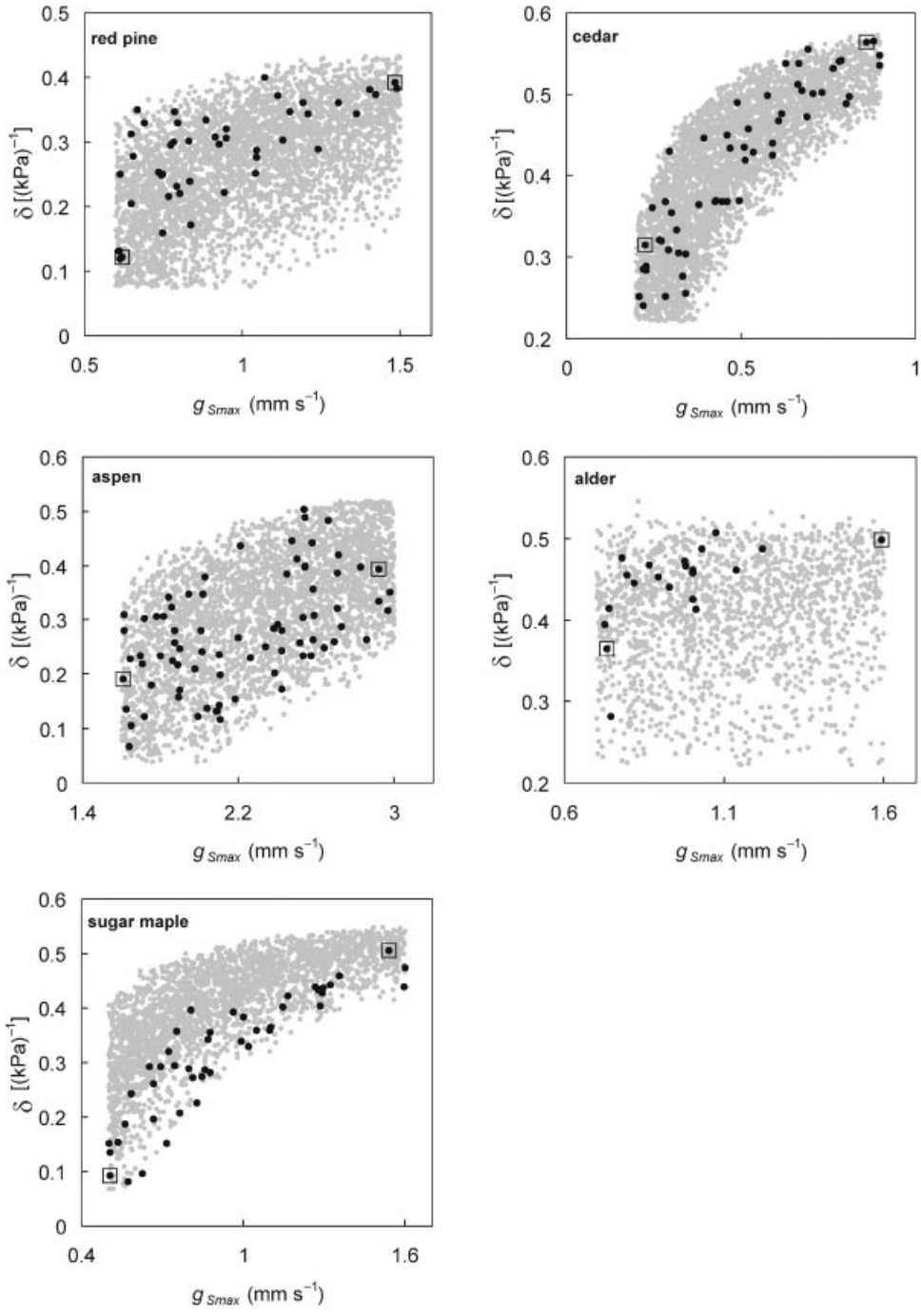

Figure 3 These plots represent a projection of δ versus g_{Smax} from the parameter spaces for the respective species. The gray dots represent α-restricted sets. The black dots are the Q-restricted sets. The squares bound the models selected for parameterizing TREES

the variability in predictions among the simulations may be attributed to properties of the objective function used (Equation 10). One possibility is that the use of equal weights in Equation 10 means that the regression slope and intercept may deviate from 1 and 0, respectively, and hence bias in the prediction may be tolerated by accepting a simulation with a high coefficient of determination. Caution must therefore be exercised in selection and application of objective functions. Although a multi-objective approach could be used to minimize bias, the choice of these additional objective functions may add further uncertainty to the analysis. Adding more objective functions cannot eliminate the problem of parameter over-fitting.

It may be easier to reject over-fitted parameters using rule-based criteria instead of strictly calculated objective functions. The ability to separate out clusters of parameter values using a fuzzy logic framework would make it easier to formulate knowledge-based rules useful for this purpose. Overall, a fuzzy relaxation of the premise of calibration (Equation 1) without a probabilistic interpretation of objective function values can still obtain reasonable estimates of predictions and parameter values. It also offers the ability to reject simulations that may be a consequence of over-fitting to a specific objective function.

5 Conclusions

The calibration and uncertainty estimation framework described in this paper provides a basis for making an objective estimate of parameters and expected range of predictions. A fuzzy ranking of simulations instead of a strict one can result in a non-specific solution to the calibration problem. However, the iterative approach proposed here supports a nonlinear, but continual refinement that is useful in determining reasonably well-defined parameter values. The method can, in some cases, avoid parameter over-fitting by identifying parameter clusters that emerge as a result of functional limits on the degree of variability in the modeled system. However, as seen from the results, careful choice and evaluation of the membership grade function is necessary to obtain reliable parameter estimates. The flexibility provided by this approach makes it suitable for implementation in an automated calibration framework. It uses simple, iterative algorithms, which are currently implemented in C++. The approach needs to be extended to handle spatially distributed parameters. Further work is needed to determine the extent to which expert, model-specific knowledge is needed to make the approach work. Future advances in both the model integration and uncertainty handling aspects of GIS are clearly needed to make automated parameterization a viable component of the analytical GIS.

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