# Bayesian conditioning of a rainfall-runoff model for predicting flows in ungauged catchments and under land use changes

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[1] A novel method is presented for conditioning rainfall-runoff models for ungauged catchment and land use impact applications. The method conditions the model on information from multiple regionalized response indices using a formal Bayesian approach. Two indices that hold information about soil type and land use effects are the base flow index from the Hydrology of Soil Type (HOST) classification and curve number from the U.S. Department of Agriculture's Soil Conservation Service soil and land use classification. These indices are used to constrain a five-parameter probability distributed moisture model for subcatchments of the Wye (grazed grassland) and Severn (mainly afforested) catchments in the United Kingdom. The base flow index and curve number constrain only two of the five model parameters, indicating that ideally, other sources of information would be sought. Nevertheless, the procedure significantly reduces the prior uncertainty in runoff prediction and gives predictions close to those of the calibrated models. For the case study, the introduction of the curve number in addition to the base flow index has only a small effect on model performance and uncertainty; however, it allows a distinction between the effects of soil type and land management for the purpose of scenario analysis. The principal assumptions used in the method are the applicability of the curve number classification system and its mapping to UK soil types and the likelihood function used for Bayesian conditioning.

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## 1. Introduction

[2] Although there has been a 40 year history of successful application of hydrological models to simulate rainfall-runoff processes in gauged catchments, several problems remain fundamental challenges. Two of these are the representation of flow in ungauged catchments and the representation of nonstationarity in catchment response, in particular, the effects of rural land use and land management change. There has been extensive discussion of the role and limitations of physics-based models in addressing these problems [e.g., *Beven and Binley*, 1992; *Wheater et al.*, 1993; *Beven*, 2000, 2001; *Wheater*, 2002]. While *Jackson et al.* [2008] provide a strategy for the use of physics-based models to represent the effects of land use and land management change based on detailed experimental data, in general, the data support for such approaches is limited, and the application of such models to ungauged catchments is associated with high levels of uncertainty, reflecting uncertainty in the prior distribution of parameter values [e.g., *Lukey et al.*, 2000]. In this paper we focus on the use of simpler, conceptual model structures, with more parsimonious parameterizations, and consider the potential for conditioning based on regional data.

[3] In conceptual modeling, it is well known that catchment physical properties cannot be used directly as model parameters; hence, an alternative strategy for parameter specification is required. The problem is made harder by the fact that the strategy often cannot rely on fitting the model to observed hydrological data since a common purpose of modeling is not just to emulate observed responses but also to predict responses at ungauged locations or under future land use or land management changes. Consequently, parameters are often estimated using statistical relationships between parameter values and physical properties of the catchment, called parameter regionalization. This has been tackled using at least two different general approaches. The first links model parameters directly to physical catchment characteristics (e.g., catchment area, steepness, soil permeability, and geographical location [*Lamb and Kay*, 2004; *Lee et al.*, 2006; *McIntyre et al.*, 2005; *Young*, 2006]), and the second conditions parameters on flow response indices (e.g., mean annual discharge and daily discharge standard deviation) that have previously been regionalized [*Bardossy*, 2007; *Yadav et al.*, 2007; *Zhang et al.*, 2008]. While the former approach has been more common, an advantage of the latter is that a number of regional models linking flow indices to catchment properties are available [e.g., *Boorman et al.*, 1995; *U.S. Department of Agriculture* (*USDA*), 1986], hence avoiding, or at least reducing, the need to build new regional models.

[4] Despite the considerable research into rainfall-runoff model regionalization, arguably, there are no satisfactory methods for modeling the effects of rural land use and land management. This is because there are few data on the

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effects of rural land management on physical properties (for example, soil-plant hydrology) and even less data on how relevant changes affect catchment-scale response [*O'Connell et al.*, 2004; *Parrott et al.*, 2009]. Interpretation of data from comparative catchment studies has been difficult because of differences in catchment and climate characteristics (e.g., geology, soil, topography, and rainfall [*Calder*, 1993; *Kirby et al.*, 1991; *McIntyre and Marshall*, 2010]), and in catchments that have undergone significant land use change, the confounding effects of climatic variability and data uncertainty make the effects of these changes difficult to identify [*Beven et al.*, 2008]. Because of the uncertainties of physics-based approaches for predicting land use effects [*Jackson et al.*, 2008] and the lack of catchment-scale evidence, modeling studies of land use effects have been based on speculative changes to catchment-scale model parameters [e.g., *Packman et al.*, 2004; *Rose and Rosolova*, 2007].

[5] A resource that may help avoid such speculation is the USDA's Soil Conservation Service curve number system [*USDA*, 1986]. The Soil Conservation Service model was originally derived using data from small agricultural basins in the Midwest, including extensive areas of single land uses. As they were derived under specific conditions, the importability and relevance of curve number values to other locations is a hypothesis that has been suggested by several previous studies [*Godwin and Dresser*, 2003; *Holman et al.*, 2003]. Note that curve numbers are not intended here to be applied directly for simulation of design rainfall-runoff events but as values that characterize the asymptotic features of rainfall-runoff time series [*Hawkins*, 1993; *Van Mullem et al.*, 2002]. Moreover, estimating curve number values with sufficient accuracy appears to be difficult especially considering that the estimated runoff amount may be more sensitive to the curve number value than to the rainfall depth [*Hawkins*, 1975]. Because of the uncertainty in the suitable values of curve number for any particular catchment, we propose treating it as a random variable with published values treated as its sample mean [*USDA*, 1986].

[6] The curve number index adaptation extends our previous work [*Bulygina et al.*, 2009], where models were conditioned on the base flow index, as regionalized by the Hydrology of Soil Type (HOST) classification [*Boorman et al.*, 1995]. Using the regionalized base flow index alone proved a powerful method of conditioning models of ungauged catchments; however, there was considerable uncertainty in results, and land use change effects could only be introduced using speculative changes in the base flow index values [*Bulygina et al.*, 2009]. The information in the curve number data will, we propose, reduce prediction uncertainty and allow evidence-based representation of land use change. We test the proposition by applying a Bayesian regionalization method that integrates the information in the HOST and curve number databases while formally considering the dependencies between these two data sources. To the best of our knowledge, this is the first time that the curve number (CN) has been treated as a stochastic variable within a formal conditioning method and the first time the dependencies between two regionalized sources of information have been explicitly treated. With the exception of the concurrent work of *Hess et al.* [2010], it also seems to be the first evaluation of whether the CN data, derived in the United States, can usefully contribute to land management impacts analysis in the United Kingdom. The method is tested on the Plynlimon paired catchments in Wales [*Beven and Binley*, 1992; *Kirby et al.*, 1991; *Marc and Robinson*, 2006; *Robinson and Dupeyrat*, 2005]. The catchments are similar in terms of topography, soil, and climate but are distinctively different in terms of land use: one of the catchments is mainly afforested, while the other is grazed pasture. The Probability distributed moisture (PDM) conceptual rainfall-runoff model [*Moore*, 2007] is used to represent hourly time scale catchment hydrological response.

## 2. Method

[7] The proposed parameter conditioning method uses uncertain and limited information about the catchment response in a formal Bayesian framework. This information is represented as hydrological indices that describe different aspects of the expected rainfall-runoff time series behavior. The indices must be derived from a regionalization procedure, thus allowing model parameter estimation for ungauged catchments both in current and future (hypothetical) conditions. In this study, we rely on two regionalized indices: base flow index (BFI) and CN. The indices are treated as random variables due to natural variability in hydrological response (aleatory uncertainty) and the limited number of physical properties being considered in their estimation (epistemic uncertainty).

### 2.1. Regionalized Indices as Sources of Information

[8] BFI is the proportion of the total catchment discharge that is considered to be base flow. BFI has been regionalized in the United Kingdom as a part of the HOST classification system [*Boorman et al.*, 1995] on the basis of the following soil characteristics: depth to gleyed/slowly permeable layer, depth to groundwater, presence of a peaty surface layer, and soil substrate. This results in 29 soil classes with expected BFI values ($\mathrm{BFI}^*_{\mathrm{HOST}}$) and corresponding standard deviations (Table S1 in the auxiliary material).[1] In this study, BFI values for the simulated flow are defined using the hydrograph separation procedure of *Gustard et al.* [1992]: the procedure used in the HOST classification.

[9] The CN relates rainfall volume to corresponding storm runoff volume. Adopting the CN derivation described by *Hawkins* [1993] and *Van Mullem et al.* [2002] for each catchment, our procedure is as follows.

[10] 1. Partition the rainfall-runoff time series into individual events and calculate rainfall and storm runoff depths [*Boorman et al.*, 1995].

[11] 2. Order the data, i.e., sort the individual rainfall and runoff depths independently in descending order to match rainfall and runoff return periods.

[12] 3. Determine the CN for each event using the following equations:

$$Q = \frac{(P - I_a)^2}{P - I_a + S}, \quad (1a)$$

$$I_a = 0.2S, \quad (1b)$$

[1]Auxiliary materials are available in the HTML. doi:10.1029/2010WR009240.

$$S = \frac{1000}{\mathrm{CN}} - 10\,, \tag{1c}$$

where $Q$ is the direct surface runoff depth (inches), $P$ is the rainfall depth (inches), $I_a$ is the initial abstraction (inches), and $S$ is the potential maximum retention (inches). CN is dimensionless and can vary between 0 (no storm runoff) to 100 (all rainfall becomes storm runoff).

[13] 4. Fit the equation $\mathrm{CN}(P) = \mathrm{CN}^*_{\mathrm{USDA}} + (100 - \mathrm{CN}^*_{\mathrm{USDA}})e^{-kP}$ to the $\{P, \mathrm{CN}\}$ pairs by optimizing parameters $\mathrm{CN}^*_{\mathrm{USDA}}$ and $k$ using least squares.

[14] On the basis of data from experimental catchments, estimated values of $\mathrm{CN}^*_{\mathrm{USDA}}$ were regionalized within the Soil Conservation Service runoff curve number system [*USDA*, 1986] based on hydrological soil group, land use, and land management (where the latter is expressed as a land "condition"). Table S2 in the auxiliary material gives the hydrologic soil group description, and Table S3 gives selected $\mathrm{CN}^*_{\mathrm{USDA}}$ values.

### 2.2. Parameter Conditioning to Satisfy Soil Hydrology and Land Use Specifications

[15] If the hydrology of soil type class (HOST*) and land use type (LU*) are known, then following Bayes' law the posterior distribution of model parameter set $\theta$ (for model structure $M$) is

$$p(\theta|\mathrm{LU}^*,\mathrm{HOST}^*,M) = \frac{p(LU^*,\mathrm{HOST}^*|\theta,M)^* p(\theta|M)}{p(\mathrm{LU}^*,\mathrm{HOST}^*|M)}\,, \tag{2}$$

where $p(\theta\,|\,M)$ is a prior model parameter distribution, $p(\mathrm{LU}^*,\mathrm{HOST}^*|\,\theta,M)$ is the likelihood that a parameter set $\theta$ represents soil type HOST* and land use LU*, and $p(\mathrm{LU}^*,\mathrm{HOST}^*|M)$ is a normalizing constant. The likelihood equals the following product of two conditional distributions:

$$p(\mathrm{LU}^*,\mathrm{HOST}^*|\theta,M) = p(\mathrm{LU}^*|\mathrm{HOST}^*,\theta,M)^* p(\mathrm{HOST}^*|\theta,M)\,, \tag{3}$$

where $p(\mathrm{HOST}^*|\,\theta,M)$ is the likelihood that parameter set $\theta$ represents soil type HOST* and $p(\mathrm{LU}^*|\,\mathrm{HOST}^*,\theta,M)$ is the likelihood that parameter set $\theta$ characterizes land use LU* on soil of type HOST*.

[16] Application of equation (3) first requires us to estimate $p(\mathrm{HOST}^*|\theta,M)$ and $p(\mathrm{LU}^*|\mathrm{HOST}^*,\theta,M)$ using knowledge of expected flow responses under given soil and land use types. Although other choices might be made (e.g., other indices from the HOST classification system), this knowledge is derived here from the two regionalized flow response indices already described, $\mathrm{BFI}^*_{\mathrm{HOST}}$ and $\mathrm{CN}^*_{\mathrm{USDA}}$, which are treated as observed data from Bayesian point of view, so that

$$p(\mathrm{HOST}^*|\theta,M) = p\left(\mathrm{BFI}^*_{\mathrm{HOST}}|\theta,M\right)\,, \tag{4a}$$

$$p(\mathrm{LU}^*|\mathrm{HOST}^*,\theta,M) = p(\mathrm{CN}^*_{\mathrm{USDA}}|\mathrm{HOST}^*,\theta,M)\,. \tag{4b}$$

[17] The first likelihood function (4a) may be rewritten as $p\left(\mathrm{BFI}^*_{\mathrm{HOST}}|\theta,M\right) = p\left(\mathrm{BFI}^*_{\mathrm{HOST}}|\mathrm{BFI}_{M,\theta}\right)$, where $\mathrm{BFI}_{M,\theta}$ is the base flow index simulated by model $M$ using a parameter set $\theta$ and is treated as a "true" value of base flow index for soil type HOST*. The likelihood function $p\left(\mathrm{BFI}^*_{\mathrm{HOST}}|\mathrm{BFI}_{M,\theta}\right)$ is defined separately for each of the 29 HOST types and is assumed to be proportional to a normal probability density function with the expected value $\mathrm{BFI}_{M,\theta}$ (true value of base flow value index for soil type HOST*) and standard deviation $\sigma^*_{\mathrm{HOST}} = \sqrt{\sigma^2_{\mathrm{HOST}} + \sigma^2_{\mathrm{CV}}}$, where $\sigma_{\mathrm{HOST}}$ is provided by the HOST classification (Table S1 in the auxiliary material), reflecting the epistemic uncertainty, and $\sigma_{\mathrm{CV}} = 0.05$ [*Gustard et al.*, 1992], reflecting aleatory uncertainty. The standard deviation $\sigma^*_{\mathrm{HOST}}$ is not simply set to each of the HOST type standard deviations $\sigma^*_{\mathrm{HOST}}$ because a short-term BFI estimate varies around a long-term BFI value (as in the case study in section 3). In situations when a long-term (decadal) flow time series is available, $\sigma_{\mathrm{CV}}$ might be set to zero.

[18] The second likelihood function (4b) may be written $p(\mathrm{LU}^*|\mathrm{HOST}^*,\theta,M) = p(\mathrm{CN}^*_{\mathrm{USDA}}|\mathrm{CN}_{M,\theta})$, where $\mathrm{CN}_{M,\theta}$ is the curve number simulated by model $M$ using a parameter set $\theta$ and treated as a true value of curve number for given soil type and land use. Although there is no direct translation between hydrologic soil types in the United States and the United Kingdom would allow estimation of a suitable value of $\mathrm{CN}^*_{\mathrm{USDA}}$, we propose a mapping based on comparing the HOST and USDA soil descriptions. The HOST classification is based on a number of conceptual models (11 models, from model A to model K) that describe dominant pathways of water movement through the soil and, where appropriate, substrate [*Boorman et al.*, 1995]. For example, model A describes the dominant water movement in permeable, well-drained soils with permeable substrates and deep groundwater table. On the basis of the USDA soil group description (see *USDA* [1986] and Table S2 in the auxiliary material), these soils might be classified as USDA hydrological soil group A. Often, the link is not that straightforward; for example, often, HOST does not explicitly provide information about the water transmission rate, one of the key USDA soil class descriptors. In these cases the $\mathrm{BFI}^*_{\mathrm{HOST}}$ value might be used for guidance. For the purpose of this study, soils with $\mathrm{BFI^*}_{\mathrm{HOST}}$ higher than 0.79 are classified as belonging to the USDA hydrological group A, soils with $\mathrm{BFI}^*_{\mathrm{HOST}}$ between 0.61 and 0.79 are classified as belonging to USDA hydrological group B, soils with $\mathrm{BFI}^*_{\mathrm{HOST}}$ between 0.38 and 0.61 are classified as belonging to the USDA hydrological group C, and the rest are classified as the USDA hydrological group D (see Table 1 and Table S1 in the auxiliary material). Soils with $\mathrm{BFI}^*_{\mathrm{HOST}}$ close to the cutoffs are classified as either of two USDA classes, e.g., HOST type 15 is classified as the USDA soil type C or D. Although this mapping contains significant uncertainty, it is presumed to be useful in that it

**Table 1.** Proposed Mapping Between U.S. Department of Agriculture (USDA) and Hydrology of Soil Type (HOST) Soil Classifications

| USDA Class[a] | HOST Class |
|---|---|
| A | 1, 2, 3, 5, 11, 13 |
| A, B | 4, 7 |
| B | 6, 8, 9, 10, 16 |
| B, C | 17 |
| C | 18, 19, 20 |
| C, D | 14, 15, 28 |
| D | 12, 21-27, 29 |

[a]Two letters indicate uncertainty in mapping from the HOST to USDA soil classification.

provides information about land use and management effects that would otherwise not be available for UK applications. The proposed HOST to USDA soil group mapping is similar to the mapping hypothesized by *Hess et al.* [2010].

[19] The likelihood function (4b) is then assumed to be proportional to a normal distribution centered on the land use and management and soil type specific $CN_{M,\theta}$ with some chosen standard deviation, which gives equal weights to values that are higher or lower than $CN_{M,\theta}$. Since there is no quantification of standard deviation in the USDA report, subjective choices need to be made. On the basis of the interseparation of $CN^*_{USDA}$ values across land use and management classes [*USDA*, 1986] we chose a standard deviation of 3 so that the overlap of the normal distributions is limited (although still significant, as will be seen in the case study results). This value is arbitrary, representing a judgment about how much weight should be given to a $CN_{M,\theta}$ value. An analysis of the sensitivity of model performance to different standard deviations ranging from 0.5 to 15 (using the case study data) suggests that the performance is insensitive to this assumption, but parameter distributions for some soil–land use combinations are sensitive (see section 3.4 for more details), indicating that the assumption about standard deviation might be critical for some catchments. In cases where the suitable USDA soil class is uncertain, the likelihood function (4b) is assumed to be proportional to a bimodal normal distribution with the modes corresponding to the two curve numbers thought to be equally suitable (e.g., soils under HOST class 4; see Table 1). An illustrative example is shown in Figure 1, where the modes have the same $BFI^*_{HOST}$ value but different $CN^*_{USDA}$ values because of the mapping uncertainty. The likelihood function is unimodal where significant mapping uncertainty is not thought to exist.

## 3. Case Study

### 3.1. Catchment Description

[20] The proposed parameter regionalization method is demonstrated using data from the Plynlimon experimental catchments [*Beven and Binley*, 1992; *Kirby et al.*, 1991; *Marc and Robinson*, 2006; *Robinson and Dupeyrat*, 2005]. The Plynlimon catchments are located in Wales and comprise the Wye and Severn river headwaters (Figure 2), herein called the "upper Wye" and "upper Severn." The altitude ranges between 319 and 738 m, and average slopes are 67 m/km in the upper Severn and 36 m/km in the upper Wye. The upper Wye catchment (10.55 km$^2$) is almost exclusively under extensively grazed grassland, while for the upper Severn catchment (8.7 km$^2$) most of the area is covered with mature coniferous forest (Table 2), although this coverage declined after the mid-1980s when tree felling started. Both catchments are humid: the annual average precipitation is about 2500 mm, and the ratio of long-term precipitation to potential evapotranspiration is about 5. The soils in both catchments are dominated by blanket peats, with peat topsoils >40 cm thick at higher altitudes, podzols at lower altitudes, and valley bottom alluvium, peat, and stagnohumic gleys along the stream channels. Data from *Boorman et al.* [1995] and *Kirby et al.* [1991] are used to tabulate the distributions of land use classification and HOST (Table 2) in the catchments. Land use is classified as forest and pasture in good condition for the Severn and as pasture in fair condition for Wye.

[21] Automatic weather stations in the catchments (Figure 2) provide hourly records of precipitation, incoming solar and net radiation, wet and dry bulb temperature, and wind speed and direction, allowing estimation of potential evapotranspiration using the Food and Agriculture Organisation (FAO) recommendations for implementing the Penman-Monteith equation with crop coefficients representing extensive grazing (0.75) and coniferous forest (1) [*Allen et al.*, 1998]. Streamflow is measured by a trapezoidal critical depth flume on the Severn and a Crump weir on the Wye, as well as by six flumes on tributary streams (Figure 2). This paper uses hourly data from May 1980 through June 1981, before the Severn tree felling started and when gap-free AWS data are available.

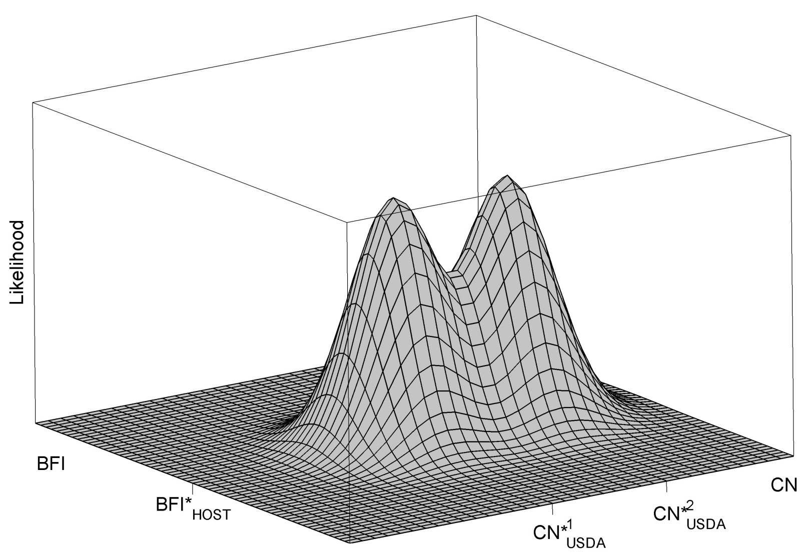


**Figure 1.** An illustrative example of likelihood function (3) based on base flow index (BFI) and curve number (CN) information with two modes, ($CN^{*1}_{USDA}$, $BFI^*_{HOST}$) and ($CN^{*2}_{USDA}$, $BFI^*_{HOST}$).

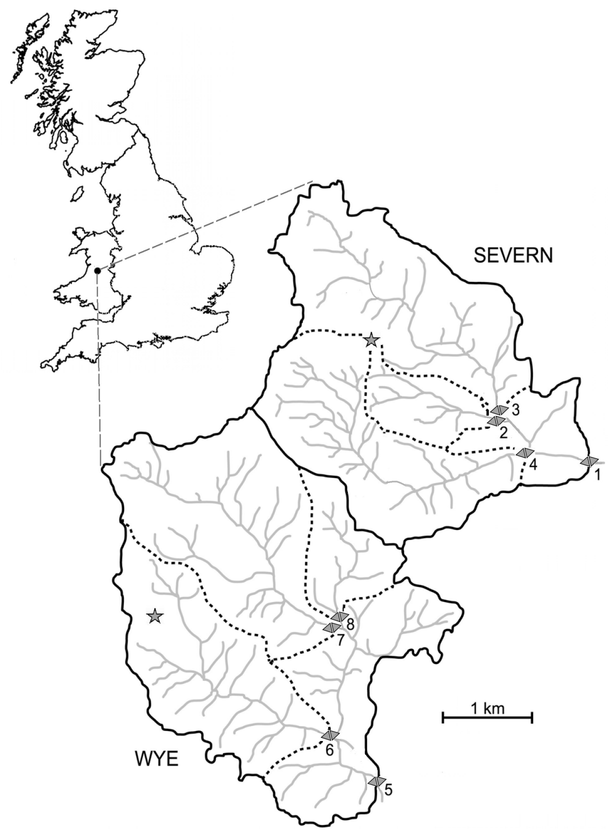


**Figure 2.** Plynlimon catchments, Wales, UK. Stars represent automatic weather stations, and diamonds are streamflow stations: 1, Severn; 2, Tanllwyth; 3, Hafren; 4, Hore; 5, Wye; 6, Gwy; 7, Cyff; 8, Iago. Adapted from *Kirchner* [2009].

### 3.2. Model Description

[22] The chosen rainfall-runoff model is the PDM model with two parallel linear routing stores [*Moore*, 2007]. The choice of the PDM model has two motivations: its structural simplicity is thought appropriate given the imposed data limitations (i.e., the information used to condition the model comes from only two flow indices), and it has been extensively applied to other catchments in upland Wales and other UK regions [*Calver et al.*, 2005; *Lamb and Kay*, 2004; *Lee et al.*, 2005]. This model has five parameters: $C_{\max}$ is the maximum soil water storage capacity within the modeled element, $b$ is a shape parameter defining the storage capacity distribution, $K_f$ and $K_s$ are fast and slow routing store residence times, and $\alpha$ is the proportion of the total flow going through the fast routing store. Although $\alpha$ is conceptually close to BFI, the $\mathrm{BFI}^*_{\mathrm{HOST}}$ values originate from an empirical streamflow disaggregation procedure [*Boorman et al.*, 1995], and the relationship $\alpha = 1-\mathrm{BFI}^*_{\mathrm{HOST}}$ cannot be presumed to hold [e.g., *Wagener and McIntyre*, 2005; *Lee et al.*, 2006]. The initial soil storage (at the start of May 1980) was assumed equal to $C_{\max}$, and the subsequent month was neglected when assessing performance to reduce sensitivity to this assumption.

[23] Prior ranges for the model parameters are given in Table 3. Parameter $K_f$ is restricted to vary between 1 and 10 h because of the low fast runoff residence times typically found for small, steep catchments in this region [e.g., *Lees*, 2000; *Young and Beven*, 1994; *McIntyre and Marshall*, 2010]. Other parameter ranges are defined within broad bounds based on UK catchment experience [*Wagener et al.*, 2004].

**Table 2.** Plynlimon Catchment Statistics and HOST Type Distribution[a]

| | Severn | Tanllwyth, | Hafren | Hore | Wye | Gwy | Cyff | Iago |
|---|---|---|---|---|---|---|---|---|
| Area (km$^2$) | 8.7 | 0.89 | 3.67 | 3.08 | 10.55 | 3.98 | 3.13 | 1.02 |
| Main channel slope (m/km) | 63 | 109.5 | 59.4 | 70.5 | 36.3 | 20.3 | 27.6 | 30.7 |
| Forest (%) | 67 | 100 | 48 | 78 | 1 | 0 | 0 | 3 |
| Soil (HOST) (%) | | | | | | | | |
| 15 | 58 | 75 | 42 | 64 | 64 | 67 | 70 | 69 |
| 17 | 1 | 0 | 3 | 0 | 13 | 0 | 16 | 0 |
| 22 | 0 | 0 | 0 | 0 | 2 | 0 | 2 | 0 |
| 26 | 15 | 14 | 15 | 14 | 12 | 14 | 11 | 14 |

[a]See *Kirby et al.* [1991] and *Hudson et al.* [1999] for Plynlimon and *Boorman et al*. [1995] for HOST.

**Table 3.** Parameter Ranges Used in Analysis

| Parameter | $C_{max}$ (mmol) | $b$ | $\alpha$ | $K_f$ (h) | $K_s$ (h) |
|---|---|---|---|---|---|
| Range | 0–500 | 0–2 | 0–1 | 1–10 | 50–1000 |

### 3.3. Model Conditioning Procedure

[24] To represent the five-dimensional posterior parameter distribution, the importance sampling technique is implemented [*Doucet et al.*, 2000]. Ten thousand parameter sets are sampled uniformly from the prior distributions (Table 3) using the Latin hypercube method. The model is run for each sample, and the $\mathrm{BFI}_{M,\theta}$ and $\mathrm{CN}_{M,\theta}$ values are calculated. Then, each parameter set is prescribed a weight (which is equal to parameter likelihood described in equations (2)–equations (4)) on the basis of the closeness of $\mathrm{BFI}^*_{\mathrm{HOST}}$ and $\mathrm{CN}^*_{\mathrm{USDA}}$ to the corresponding $\mathrm{BFI}_{M,\theta}$ and $\mathrm{CN}_{M,\theta}$ values. Hence, the posterior parameter distribution for each soil type–land use–land management combination is approximated as a discrete multivariate distribution with values defined by the sampled 10,000 parameter sets and corresponding probabilities equal to the (normalized) prescribed weights.

[25] For each sampled parameter set, the simulated response for a catchment is the average of the responses for all relevant soil type–land use–land management combinations weighted by their relative contributing areas. Averaging of responses in this way does not explicitly consider possible time lag differences between the response components. Identified time lags in the Plynlimon catchments and similarly small and steep catchments in Wales have varied between 0 and 1.5 h [*Kirby et al.*, 1991; *Young and Beven*, 1994; *Lees*, 2000; *McIntyre and Marshall*, 2010]; therefore, the timing errors introduced are expected to be one time step at the most (and the possibility of using a distributed model to resolve this is discussed in section 4). The posterior distribution of simulated flow for each catchment is then approximated by the sample of simulated responses and their associated likelihoods.

### 3.4. Results

[26] An example of the resulting marginal distribution for each of the parameters is shown in Figure 3 and 4. Figure 3 represents HOST class 15, the most abundant soil type in both catchments, and three different land use–management types: pasture in fair condition, pasture in good condition, and forest in good condition. Figure 4 represents only pasture in good condition but with all the soils present in Plynlimon: HOST classes 15, 17, 22, 26, and 29. In both sets of results, the two parameters for which the marginal distributions are most clearly different from the prior distributions are the split coefficient $\alpha$ and the slow residence time $K_s$. These two parameters interact somewhat for low values of $K_s$ (see Figure 3, bottom right, which represents projection on the ($\alpha$, $K_s$) plane of resampled parameter sets from the approximating discrete multivariate distribution described in section 3.3). The median values of parameter $\alpha$ for HOST class 15 under forest in good condition and pasture in good and fair conditions are approximately 0.6, 0.63, and 0.68 (Figure 3), indicating that there is more fast flow under pasture in fair condition than under either pasture or forest in good condition. The median values of parameter $\alpha$ under pasture in good condition for the five soil types (HOST classes 15, 17, 22, 26, and 29) are 0.63, 0.36, 0.66, 0.69, and 0.69, respectively, illustrating that the values are close to $1 - \mathrm{BFI}^*_{\mathrm{HOST}}$ for all classes, except classes

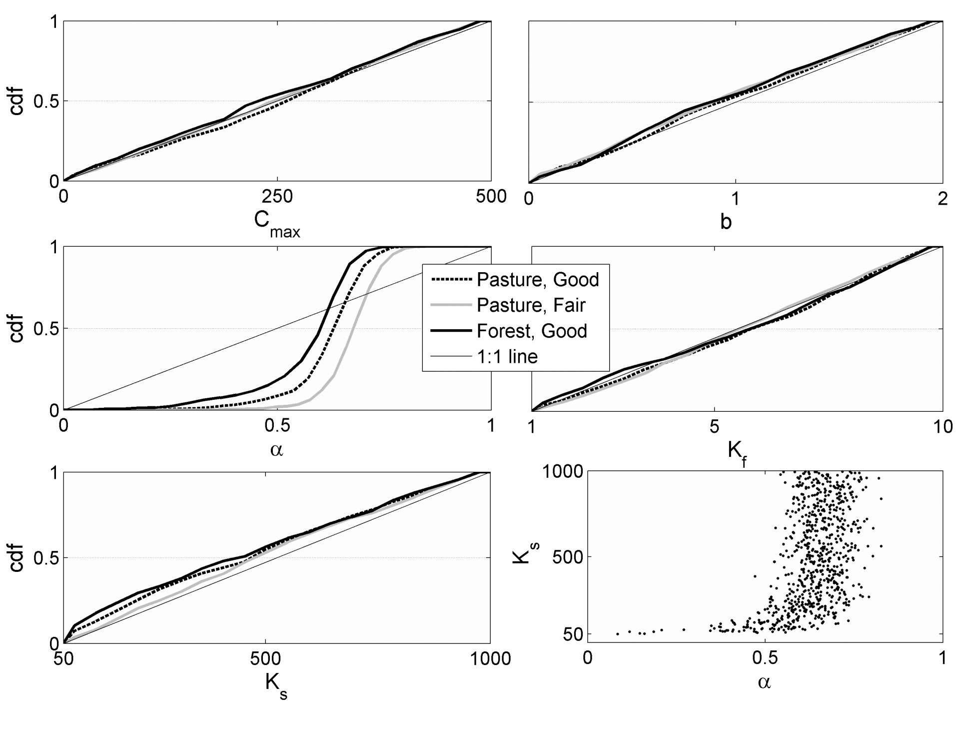


**Figure 3.** Marginal posterior distributions of the probability distributed moisture (PDM) model parameters for Hydrology of Soil Type (HOST) class 15 under three different land uses and management conditions, and sample draws from joint distribution of parameters $\alpha$ and $K_s$.

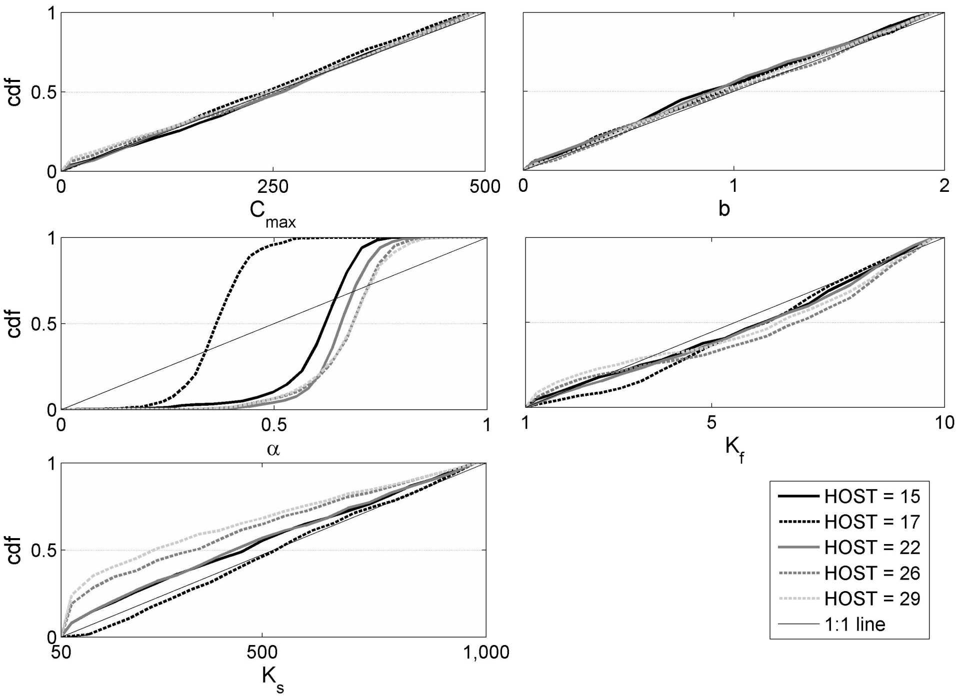


**Figure 4.** Marginal posterior distributions of the PDM model parameters for HOST classes 15, 17, 22, 26, and 29 under pasture in good condition.

26 and 29, and hence illustrating that $\alpha$ is more or less equivalent to $1 - \mathrm{BFI}^{*}_{\mathrm{HOST}}$ in this case.

[27] The influence of using BFI, CN, and both indices together in the parameter conditioning is shown in Figure 5a. CN information adds sharpness to the $\alpha$ and $K_s$ parameter distributions previously conditioned on BFI only. The marginal parameter distributions derived using parameter regionalization (using both CN and BFI) were also compared with those derived by conditioning the parameters directly on observed flows (Figure 5b), defining behavioral parameter sets as those that give results with Nash-Sutcliffe efficiency (NS) values greater than 0.7 (using the method of generalized likelihood uncertainty estimation [*Beven and Binley*, 1992]). Neither the direct conditioning nor the regionalization restrict the $C_{\max}$ and $b$ parameters (which will be discussed in section 4). The posterior distribution for the other parameters varies between the two methods, as would be expected when fundamentally changing the fit criterion, for example, we expect the NS values to be especially sensitive to timing of flow peaks and this is reflected in the better defined posterior for $K_f$ when using this criterion. If the criterion used for direct conditioning is altered (to log-transformed flow fitting), as expected, significantly different posteriors for $K_f$, $\alpha$ and $K_s$ are obtained again.

[28] Figure 6a and 6b show the predictions for the Severn and Wye catchments, respectively, for 2 weeks in March 1981, using a sample of 100 parameter sets (using all 10,000 sets was not practicable because of computer memory limitations, and a random sample of 100 was found to provide a good approximation to larger samples in terms of derived confidence intervals). Figure 6 compares the 95% prediction intervals after the parameter conditioning on BFI and CN information (dark gray) with those conditioned on BFI only (medium gray) and with those that are unconditioned (light gray) for the Severn and Wye catchments. Figure 6 also compares the conditioned predictions with the optimized deterministic prediction. The optimization was carried out using the NS as the objective function and the shuffled complex evolution algorithm of *Duan et al.* [1992]. The performances of the conditioned model for the data period June 1980 to June 1981 were assessed using the probabilistic formulation of the NS [*Bulygina et al.*, 2009] (also see Appendix A).

[29] Performance with respect to observed flow was considered generally good: the prior uncertainty was reduced by a large degree throughout the simulated periods (Figure 6 and Table 4); the confidence intervals, with exceptions, enclosed the observations. The exceptions were mainly at flow peaks where the simulations tended to underestimate the large flow peaks while overestimating the smaller peaks (this is discussed in section 4). The performance relative to the calibrated model was very good, with the NS values approaching the optimized values (Table 4), and with the estimated confidence intervals quite consistently enclosing the optimized simulation. Table 4 compares the performance of three regionalization strategies: (1) using BFI information only, (2) using CN information only, and (3) using information from both indices together. The probabilistic NS as well as the median 95% prediction interval width (i.e., the median interval width over the 1 year simulation period) is similar for the three methods, with prediction intervals being somewhat tighter for the Wye catchment when both indices are used.

[30] A primary assumption in the method is the standard deviation assigned to $\mathrm{CN}^{*}_{\mathrm{USDA}}$ values. The use of alternative values ranging from 0.5 to 15 suggests that the NS performance measure is insensitive to this assumption when $\mathrm{BFI}^{*}_{\mathrm{HOST}}$ and $\mathrm{CN}^{*}_{\mathrm{USDA}}$ are used together (the maximum

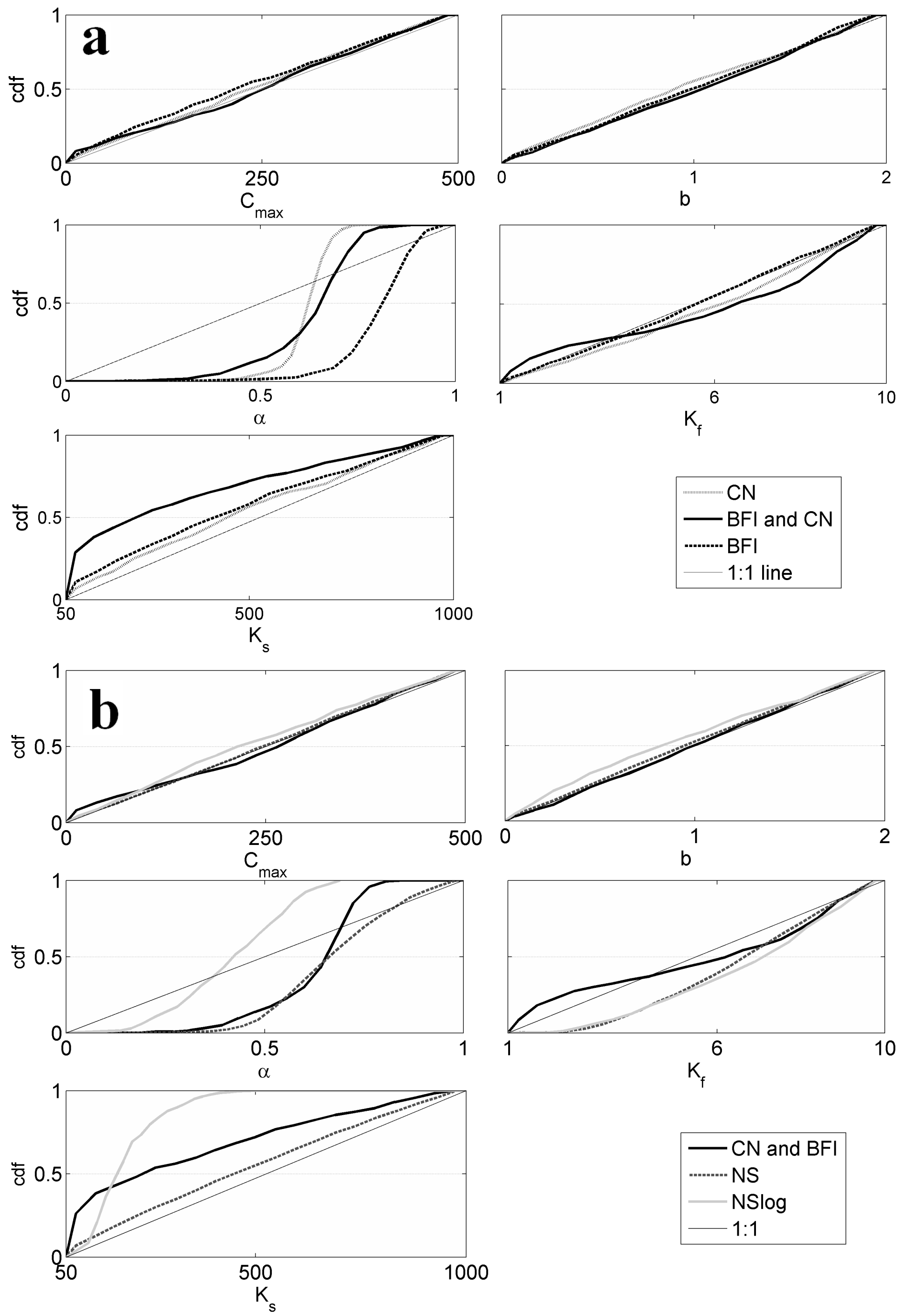


**Figure 5.** Marginal posterior distributions of the PDM model parameters for HOST class 29 (a) conditioned on BFI information only, CN information only, and on both BFI and CN information and (b) conditioned on both CN and BFI and on observed flow using NS as an objective function applied to raw or log-transformed streamflow data.

difference in NS is 0.02; see Table S4 in the auxiliary material). Under these circumstances, prediction uncertainty remains constrained by $BFI^*_{HOST}$, independent of the level of constraint provided by $CN^*_{USDA}$. Of course, when only $CN^*_{USDA}$ is used for conditioning and corresponding standard deviations grow, the posterior parameter distribution approaches the prior distribution, and NS efficiency drops to the prior distribution efficiency (Table 4). Furthermore, changing the standard deviation of $CN^*_{USDA}$ considerably influences posterior parameter distributions for certain combinations of soil type and land use. For example, while the parameters for HOST class 15 under forest in good condition were found to be insensitive (Figure 7a), the parameters for HOST class 29 were sensitive (Figure 7b). This might be explained by the prior (model specific) BFI-CN joint distribution (see Figure S1 in the auxiliary material),

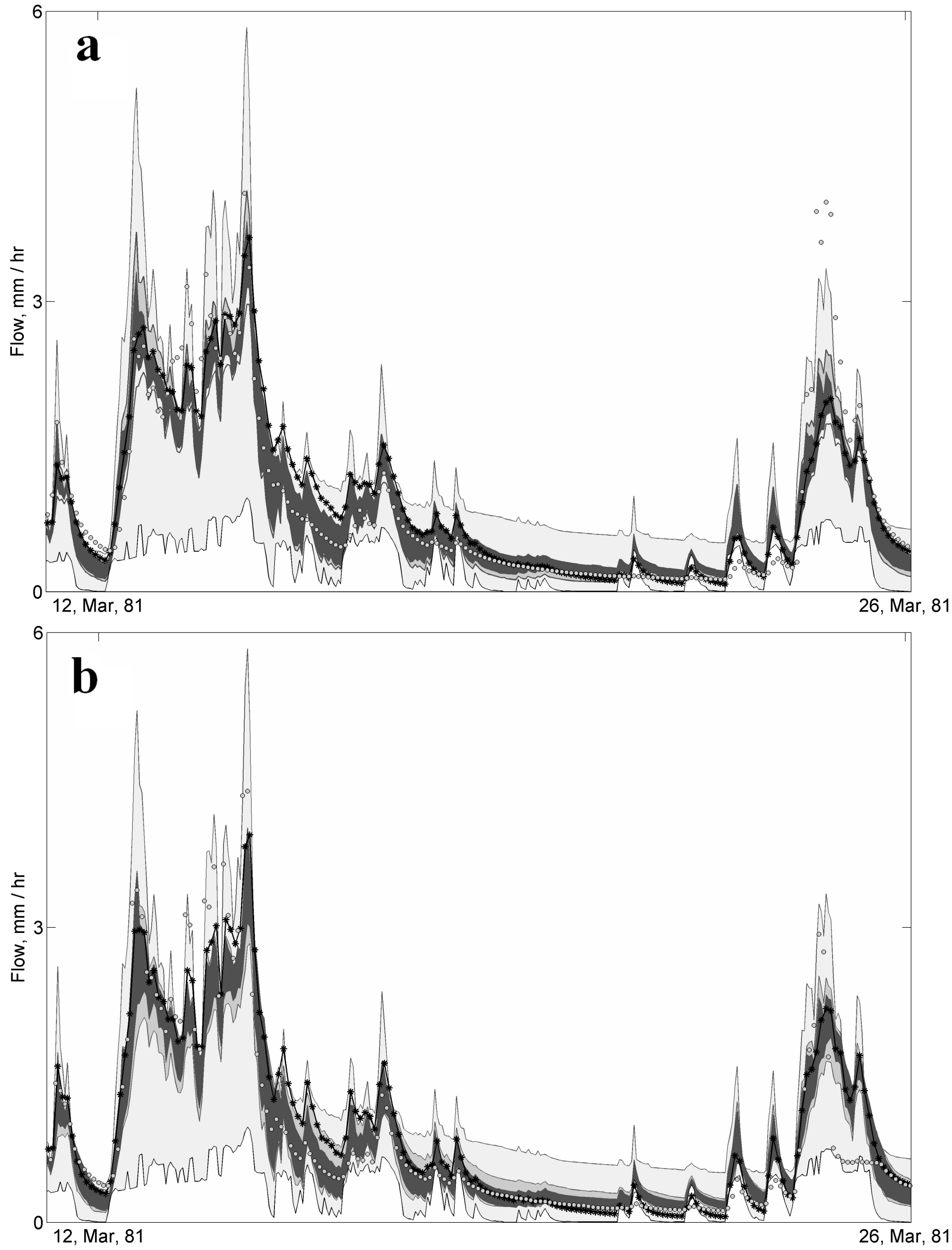


**Figure 6.** Prediction uncertainty bounds for (a) the Severn and (b) Wye for 2 weeks in March 1981. The prior 95% confidence intervals are represented by the light gray area; the BFI-based 95% confidence intervals are shown as the medium gray area; and the BFI- and CN-based 95% confidence intervals are shown as the dark gray area. The light gray circles are measured data, and the connected black dots are calibrated model predictions

which is generated by running the PDM model with samples of parameter sets from the uniform priors. If the regionalized (BFI, CN) pair is (0.23, 77) (HOST class 29 and forest in good condition), then the prior BFI-CN joint probability density function value is very small (close to 0) because of the nature of the model and the parameter priors and is strongly skewed around this value. The posterior CN distribution also becomes significantly skewed toward higher values of (BFI, CN) when standard deviation for curve number is high enough. Hence, for HOST class 29, median values of the posterior CN and parameter distributions become dependent on the curve number standard deviation (Figure 7b). While HOST class 29 is not dominant in the case study, in other cases the assumption about the $CN^*_{USDA}$ standard deviation may become more critical.

[31] As an illustration of the potential applicability of the method, two simple land use change scenarios were considered: (1) the upper Severn becomes pasture in good condition and (2) the upper Wye becomes forest in good condition. For each scenario the appropriate potential evaporation for the changed land use was used, and the prior model was conditioned on the appropriate $CN^*_{USDA}$ and

**Table 4.** Nash-Sutcliffe Efficiency and Median Width of 95% Prediction Interval for Different Parameter Estimation Methods

| | Severn | | | | Wye | | | |
|---|---|---|---|---|---|---|---|---|
| Parameter Estimation Method[a] | Severn | Tanllwyth | Hafren | Hore | Wye | Gwy | Cyff | Iago |
| *NS Efficiency* | | | | | | | | |
| Prior uncertainty | 0.59 | 0.55 | 0.56 | 0.57 | 0.62 | 0.58 | 0.63 | 0.6 |
| Regionalized BFI | 0.78 | 0.71 | 0.73 | 0.77 | 0.8 | 0.76 | 0.8 | 0.78 |
| Regionalized CN | 0.78 | 0.68 | 0.76 | 0.74 | 0.81 | 0.76 | 0.82 | 0.79 |
| Regionalized BFI and CN | 0.78 | 0.7 | 0.76 | 0.76 | 0.81 | 0.76 | 0.81 | 0.79 |
| Calibration | 0.78 | 0.74 | 0.75 | 0.76 | 0.85 | 0.81 | 0.88 | 0.83 |
| *Median Width of 95% Prediction Interval (mmol/h)* | | | | | | | | |
| Prior uncertainty | 0.62 | 0.06 | 0.26 | 0.22 | 0.80 | 0.30 | 0.24 | 0.08 |
| Regionalized BFI | 0.19 | 0.03 | 0.07 | 0.08 | 0.30 | 0.12 | 0.10 | 0.03 |
| Regionalized CN | 0.17 | 0.03 | 0.06 | 0.07 | 0.25 | 0.10 | 0.08 | 0.03 |
| Regionalized BFI and CN | 0.17 | 0.03 | 0.06 | 0.07 | 0.22 | 0.09 | 0.07 | 0.02 |

[a]BFI, base flow index; CN, curve number.

$BFI^*_{HOST}$ values taken from the classifications in Table 1–Table 3. Ten thousand parameter sets were sampled, and likelihoods were assigned to each as described in section 3.3. For each sampled parameter set the model was run over the May 1980 to June 1981 period. Figure 8 shows predictions for the event with the highest flow peak (5–6 October 1980) for which the modeled initial soil moisture deficit was low with little variability between realizations. In Figure 8, black lines represent 95% confidence intervals for the existing land use conditions, and gray lines represent 95% confidence intervals for the scenario. The median peak flow in the Severn increases by 9% when the afforested area becomes pasture; in the Wye it reduces by 13% when the pastureland is afforested.

## 4. Discussion and Conclusions

[32] This study proposed a probabilistic method for conditioning rainfall-runoff models on regionalized flow indices. The method was developed around two indices in particular: BFI (as estimated by the UK HOST soil classification system) and CN (as estimated from the USDA Soil Conservation Service soil and land use–management classification system). The methodological advance made over previous work is that information in interdependent regionalized flow indices has been assimilated into a model using a formal Bayesian approach to uncertainty analysis (although we do not attempt to include all sources of uncertainty, only those in the flow indices). Previous efforts at model conditioning using regionalized flow indices have either used only one regionalized index [*Bulygina et al.*, 2009] or have neither formally treated uncertainty in indices nor formally treated dependencies between indices [*McIntyre et al.*, 2005; *Yadav et al.*, 2007; *Zhang et al.*, 2008].

[33] The practical value of introducing regionalized information about soil hydrology and land use effects is the potential for improved predictions of runoff in ungauged catchments and under land use change scenarios. Previous UK work on catchment-scale land use effects is based on the assumption that land use effects can be represented by analog changes to soil classification [*Packman et al.*, 2004; *Rose and Rosolova*, 2007]. By integrating measured effects of land use as contained in the CN data, our new method allows a more evidence-based approach to land use effect analysis. The evidence stems from Soil Conservation Service research in the United States [*USDA*, 1986] under the bold assumption that the U.S. soil and land use classification can be usefully mapped to the UK classifications. This assumption of intercontinental applicability of the CN system to estimating storm runoff is quite commonly used [*Godwin and Dresser*, 2003; *Holman et al.*, 2003; *Young et al.*, 1987;

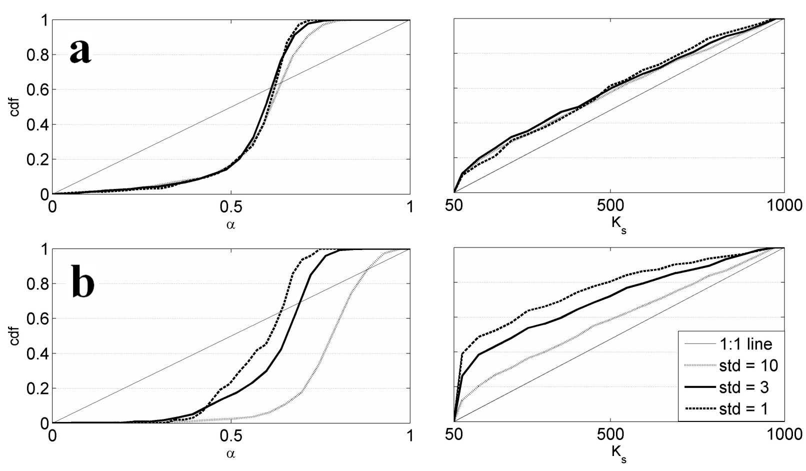


**Figure 7.** Parameter sensitivity to standard deviations in the CN likelihood: (a) HOST = 15, under forest in good condition, and (b) HOST = 29, under forest in good condition.

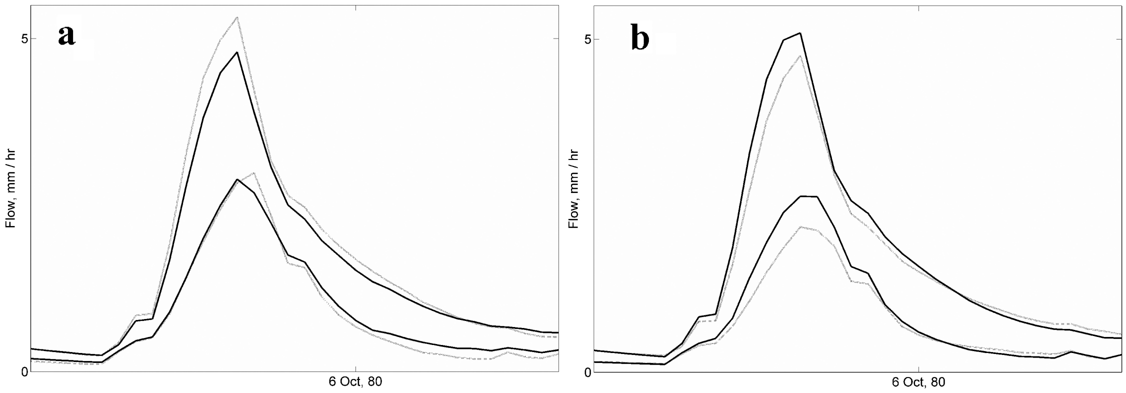


**Figure 8.** Predictions during a large flood event. (a) Severn becomes pasture in good condition; (b) Wye becomes forest in good condition. Black lines represent 95% confidence intervals for the existing land use, and gray lines represent 95% confidence intervals for the scenario.

*Williams*, 1995; *Arnold et al.*, 1996], although in a manner that neglects the uncertainty in the mapping and the uncertainty in the original CN data. Treating the CN information as stochastic and integrating it with the more local BFI index from HOST allows the available evidence about ungauged catchments and land use effects to be exploited in a more scientifically defendable manner.

[34] Demonstrating the practical value of the approach relies on being able to show that the CN adds new information over and above that derived from HOST and that information is consistent with measured evidence of land use effects in UK catchments. In an attempt to do so, the approach was applied to a data set from the Plynlimon paired catchment study in Wales. The paired catchments (the upper Wye and upper Severn) have similar topography, soil distribution, and climate but different land use: the upper Wye catchment is under pasture, and the upper Severn catchment is mainly under forest. Observed flows from eight gauges, four in the Wye and four in the Severn, were used to test the method. The results show that the Bayesian approach that uses regionalized CN and BFI information significantly reduces uncertainty in runoff prediction when compared to prior (unrestricted) uncertainty. Furthermore, the posterior predictions are close to calibrated model predictions in terms of visual assessment (Figure 6) and NS values (Table 4). The posterior predictions capture low flows better than the NS-calibrated model, providing a "trade-off" between fitting to high and low flows, which the NS is renowned for failing to do [e.g., *Wagener and McIntyre*, 2005]. When CN and BFI are used together the NS values are similar to those when using just BFI or just CN (Table 4), with some further reduction in prediction bound width. The marginal difference in prediction quality arises partly because of the overlap in the information contained within the BFI and CN data sets, as defined by the mapping (Table 1), partly because the high uncertainty in both indices does not allow noticeable improvements in performance (as measured by the stochastic NS), and also because of the model structure and/or data uncertainty, which prevents good performance even for the calibrated model. This is consistent with former findings [e.g., *Beven et al.*, 2008] that land use signals are easily disguised by measurement noise, model error, and lack of information on catchment properties.

[35] It was noted that the performance of the approach, despite being impressive compared to the performance of a calibrated model, was not especially impressive compared to the observed flow with the NS values ranging from 0.70 to 0.81 (Table 4). In particular, the simulated flow responses (using both regionalized and calibrated model parameters) are generally flashier than the observed responses for small events, and large peak flows are usually underestimated with a significant number of observations outside the confidence limits (Figure 6). This may be attributed to nonlinearity, which was not included in the PDM model. For example, nonlinear kinematic effects would tend to increase flashiness of larger events while limiting flashiness of smaller events. Another reason for high peak flow underestimation could be the presence of pipe flow in the peat which can introduce significant variability into high-flow response [*Chapman*, 1994]. However, attempts to include additional complexity were not fruitful, and improving the model structure remains a challenge. Notwithstanding the potential for improving the model structure, the use of the simple PDM model was sufficient to demonstrate the theoretical and practical attractions of the conditioning approach.

[36] The methodology mainly restricted two of the five PDM model parameters: the flow split coefficient $\alpha$ and slow flow residence time $K_s$ (Figures 3 and Figure 4). Hence, the marginal distributions refine their shapes when CN information is added to information on BFI (Figure 5) and are sensitive to land use and management types (Figure 3). Apparently, the CN and BFI indices applied to the Plynlimon catchments do not contain sufficient information to restrict all the model parameters, calling for the inclusion of some other sources of information. The lack of restriction of parameters $C_{\max}$ and $b$ (also barely restricted by direct calibration and also showing insignificant sensitivity if varied while fixing the other parameters) describing available soil moisture storage might be due to the wet climatic conditions (the long-term precipitation to potential evaporation ratio is approximately 5), so that soil remains near saturated for most of the time and so the role of $C_{\max}$ and $b$ is small. The lack of restriction of these parameters also exposes a limitation of the indices: BFI is designed to distinguish between storm runoff and base flow, and CN is designed to provide information about runoff coefficients under asymptotically

wet conditions. Neither can be expected to provide much information about soil moisture accounting parameters. In our application, this means that the increased evapotranspiration expected in forest is mainly represented by higher potential evapotranspiration rates and that the value of the regionalized indices for distinguishing between land use effects lies only in the information it provides about the partitioning coefficient and residence time. Another poorly identifiable parameter was the fast flow residence time $K_f$. This was partly because it had been restricted a priori on the basis of the range of values previously found for comparable catchments [*Young and Beven*, 1994; *Lees*, 2000; *McIntyre and Marshall*, 2010] and may have also been because of the trade-off between fitting the smaller and larger flow peaks, as discussed. If a more spatially discretized catchment representation had been used [see, e.g., *Bulygina et al.*, 2009], then surface topography, in particular the channel network characteristics, may have been used to add some physics-based constraints to this parameter. This was not attempted here because of the lack of high-resolution spatial data, but it provides opportunity for refining the application in future. In general, it is likely that further constraints could be found for the model parameters without resorting to calibration: either physics-based prior constraints, additional regionalized flow indices [*Winsemius et al.*, 2009], or information generated by a metamodeling procedure [e.g., *Bulygina et al.*, 2010]. A general challenge would be the increasing difficulty of estimating the dependencies between multiple sources of information and including them in the Bayes' equation.

[37] On the basis of the conclusion that the Bayesian approach using CN and BFI indices can distinguish between the Wye and Severn responses, we tentatively estimated the effects of hypothetical land use changes: the afforested area of the Severn becomes pasture, and the Wye becomes fully afforested. The estimation of effects was facilitated by a change in expected curve numbers under current and future land use and management, avoiding the arbitrary changes to base flow index used in previous work [*Bulygina et al.*, 2009]. The former scenario led to 9% median increase in the highest flow rate (June 1980 to June 1981 period), and the latter scenario led to a 13% median decrease in the peak flow. There is a significant uncertainty in these values; for example, the lower and upper 90% confidence intervals for change in peak flow for the afforestation scenario were −49% (decrease) and 28% (increase). That mature forest is predicted to increase peak flows in some realizations is perhaps surprising. This arises because the normal distributions of BFI and CN used to represent uncertainty lead to overlaps in the range of possible responses from one land use to another. Following *Bulygina et al.* [2009], we could simply reject all parameter samples that caused outcomes that we perceive to be unrealistic. For example, in our Wye afforestation scenario, if we rejected all parameter set samples that caused an increase in peak flows, our new median result would be a 22% decrease. This, however, places a lot of weight on prior perceptions of what is realistic.

[38] It may be noted that the estimated 13% difference between peak flow for the Wye catchment under the 1980 conditions and after full afforestation is consistent with the difference in event-averaged unit hydrographs between the Wye and Severn catchments found by the Institute of Hydrology in their Plynlimon study [*Kirby et al.*, 1991, Figure 28]. However, because of the uncertainties involved, Kirby et al. did not conclude that there is a statistically significant difference in unit hydrograph peaks between the catchments. The significance of our 13% result is also questionable considering its high uncertainty and that it is based on only a single event. To apply the method in a practical context for assessing land use effects on flooding, the uncertainty would need to be addressed by using additional sources of information and potentially more complex models.

[39] In conclusion, this paper has presented an approach to integrating regionalized information into model conditioning. While previous work had approached this task using either a single source of information or by using arbitrary rules for combining sources of information, we have combined dual sources of information (from the CN and HOST classification systems) in a more formal Bayesian approach. Applied to the Plynlimon paired catchment data set (representing grazed and forested upland catchments), it was concluded that both CN and HOST are potentially valuable sources of information for hydrological modeling of ungauged catchments and the effects of land use change if used appropriately within a stochastic modeling framework. By including information on CN in addition to information on BFI, the method allows a more evidence-based approach to parameter estimation analysis under land management change, avoiding the arbitrary changes to base flow index used in previous work [*Bulygina et al.*, 2009]. The primary assumptions used relate to the applicability of the curve number classification system to the United Kingdom, in particular, the mapping between the HOST and curve number classifications and the likelihood function structure. A more extensive evaluation under this framework, introducing more sources of information and covering a range of UK conditions, is recommended.

## Appendix A

[40] *Bulygina et al.* [2009] describe the Nash-Sutcliffe efficiency (NS) analog for probabilistic predictions given by a sequence of random variables $\{\xi_t\}$ as

$$\mathrm{NS} = \left\{ 1 - \frac{\sum_{t=1}^{T} \left(E[\xi_t] - q_t^0\right)^2}{\sum_{t=1}^{T} \left(q_t^0 - q^0\right)^2} \right\} - \frac{\sum_{t=1}^{T} \mathrm{Var.}[\xi_t]}{\sum_{t=1}^{T} \left(q_t^0 - q^0\right)^2}, \tag{A1}$$

where $q_t^0$ is a data point at time $t$, $q^0$ is an average value for the $\{q_t^0\}$ data series, Var.[ ] denotes variance, $E$[ ] denotes mathematical expectation, and $T$ is the number of time steps in the sequence. In the current context, $\{\xi_t\}$ is the simulated time series of flow and $q_t^0$ is the time series of observed flow.

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