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Towards simplification of hydrologic modeling: identification of dominant processes

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Abstract

An application of the Precipitation-Runoff Modeling System, a distributed-parameter hydrologic model, has been developed for the conterminous United States. In this study, two different aspects of the complexity in applying this model has been addressed: (1) the number of input parameters and (2) the interpretation of model output. Parameter sensitivity analysis was used to simplify the application of the hydrologic model through identification of parameters related to dominant hydrologic processes (baseflow, evapotranspiration, runoff, infiltration, snowmelt, soil moisture, surface runoff, and interflow) at various geographic scales. These processes correspond to variables for which objective functions (mean, autoregressive lag 1, and coefficient of variation) are computed.

Categories of parameter sensitivity were developed in various ways, on the basis of geographic location, hydrologic process and model response. Visualization of these categories provide insight into model performance and useful information about how to structure the modeling application to take advantage of as much local information as possible. The results of this study indicates that (1) the choice of objective function and output variables have a strong influence on parameter sensitivity, (2) the dimensionality of distributed-parameter hydrology models can be reduced by removing input parameters, output variables and objective functions from consideration on the basis of selection by hydrological process, (3) different hydrological processes require different numbers of parameters for simulation, and (4) some model sensitive parameters influence only one hydrologic process, while others may influence many.

1 Introduction

It has long been recognized that distributed-parameter hydrology models (DPHMs) are complex because of the subtlety and diversity of the hydrologic cycle which they aim to simulate (Freeze and Harlan, 1969; Amorocho and Hart, 1964). In this study, two different aspects of this complexity are addressed:

(1) DPHMs have too many input parameters (Jakeman and Hornberger, 1993; Kirchner et al., 1996; Brun et al., 2001; Perrin et al., 2001; McDonnell et al., 2007). Those who apply these models often have difficulty understanding what these parameters are and how they are used in the model. Regularly, there are several parameters that may have similar effect on the

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computations or may constrain the model in unintended ways. Despite the developer's claims that these DPHMs are more or less physically based, often there are not measurements or data sources available for reliable development of all of the input parameters. These unmeasured parameters, ostensibly tangible, are really empirical coefficients when it comes to application and calibration.

(2) The output produced by DPHMs is difficult to interpret (Schaefli and Gupta et al., 2008; Gupta et al., 2009; Gupta et al., 2012). Often, the meaning of output variables is not always intuitive and results sometimes can seem contradictory (e.g. when streamflow does not seem to correlate with climate information). Consequently, development of objective measures of model performance (hereafter referred to as *objective functions*) is often a subjective exercise that can lead to different interpretation depending on the choices made (Krause et al., 2005; Mendoza et al., 2015b; Mendoza et al., 2015a).

Developing effective DPHM applications require that the modeler address these two aspects of complexity at the same time (i.e. the uncertainty problem: "If I am uncertain when estimating input parameters, due to either incomplete or inaccurate information, what affect does it have on the output?", and the calibration problem: "I know the output I want, which parameters should I change and how much should I change them?").

These two issues are compounded as the spatial domain of the DPHM application expands. A common problem is that at large scale and with limited information, the effects of different hydrological processes can be indistinguishable from each other. For instance, groundwater recession and snowmelt from a receding snowpack can cause similar response in a streamflow hydrograph. If the prevailing hydrological process is not identified by the modeler, and subsequently parameterized in the model, the result can be "the right answer for the wrong reason" (Kirchner, 2006; McDonnell et al., 2007). This type of misunderstanding compounds both of the problems identified above as the modeler wastes resources working with insensitive input parameters and evaluating objective functions that do not relate with the real world physical processes. The result of these complex issues has led to study of parameter interaction (Clark and Vrugt, 2006) and equifinality (Beven, 2006).

Any particular DPHM must necessarily be complex because it must be able to simulate any and all hydrological process that may occur anywhere on the landscape. However, with the application of a DPHM to a specific site, it can become much less complex when the dominant hydrological process(es) are identified, as not all processes are active or at the same level of importance. The problem becomes less complex when hydrological processes not relevant to the modeled domain (or watershed) are removed from consideration (Bock et al., 2105). Dominant process concepts have been explored as a way to classify watershed and natural hydrologic systems for simplifying DPHMs by several researchers (Sivakumar and Singh, 2012; Sivakumar et al., 2007). Some have suggested the approach for use as a possible classification framework (e.g. Woods, 2002; Sivakumar, 2004). Pfannerstill et al. (2015) developed a framework for identification and verification of hydrologic process in simulation models on the basis of temporal sensitivity analysis. McDonnell et al. (2007) discuss the possibility of simplifying hydrologic modeling by identifying “fundamental laws” so that over parameterized models are not needed. However, in our opinion we have not made much progress on that front and DPHMs are, in many ways and for many reasons, more complex than ever.

This article describes a DPHM approach that has been applied to the conterminous United States (CONUS). Specifically, by aggregating a large collection of many small domain DPHMs, the large domain can be simulated. This has the advantage of being able to use all local information and match local conditions. The disadvantage is that all of these DPHMs must be set up in a uniform way or the result is a “patchwork quilt” of parameter values. Identification and simulation of these small-scale catchments is determined by the resolution of the available information and how the DPHM responds to geophysical (e.g., topography, vegetation and soils) and climatological variation. Specifically, we propose to reduce the complexity of the DPHM approach through identification of dominant hydrologic process(es) and reduce the number of inputs and outputs considered (Chaney et al., 2015). This is accomplished by relating a hydrologic process directly to parameters and objective functions. The questions addressed by this study are: (1) can DPHM application be simplified by reducing the dimensionality of the input, and (2) can geographic areas (regions, watersheds, HRUs, etc.) be categorized by hydrological process to aid identification of meaningful output?

2 Methods

2.1 Hydrologic model

The U.S. Geological Survey’s (USGS) Precipitation-Runoff Modeling System (PRMS) is the DPHM used in this study. PRMS is a modular, deterministic, distributed-parameter, physical-process watershed model used to simulate and evaluate the effects of various combinations of precipitation, climate, and land use on watershed response. Each hydrologic process simulated by the model is represented within PRMS by an algorithm that is based on a physical law (i.e. balance of energy required to melt the ice in a snowpack) or empirical relation with measured or estimated characteristics (i.e. a tank model used to simulate interflow). The reader is referred to Markstrom et al., (2015) for a complete description of PRMS.

To define the spatial domain for the CONUS application, the locations of major confluences, water bodies and stream gages have been located as georeferenced points. These points are mapped onto the natural river network of the entire CONUS, breaking the network into approximately 56,000 stream segments, which vary in length from approximately 1 meter to 175 kilometers, with 10 kilometers being typical. Using these stream segments, the left and right bank areas that contribute runoff directly to each segment have been identified, resulting in approximately 110,000 irregularly shaped hydrologic response units (HRUs) (Viger and Bock, 2014) (fig. 1). These HRUs as defined by the real world points represent the conceptualization of areal space within the DPHM and vary in size from approximately 500 square meters to 14,000 square kilometers, with 100 square kilometers being typical. HRUs in PRMS are simulated as homogenous units and tend to be finer in areas that have more information (i.e. stream gages) and produce more streamflow (i.e. denser stream network). This topological network of stream segments and HRUs allows for evaluation of streamflow simulation at almost 60,000 specific locations on rivers, including nearly 8000 stream gages.

This CONUS application is forced with values of daily precipitation and daily maximum and minimum air temperature from the DAYMET data set (Thorton et al., 2014). The one square kilometer gridded DAYMET data has been processed to provide mean daily HRU values on the basis of area weighted averaging using the USGS Geo Data Portal (Blodgett et al., 2011). The climate information covers a time period from 1980-2013 on a daily time step, but a shorter period (1987 – 1989 used for warmup and 1990 – 2000 used for evaluation) was selected for this study.

The version of PRMS used in this study has 108 input parameters. For this study, a parameter is an input value that does not change over the course of a simulation run. Of these parameters, most would never be modified from their initial values (hereafter referred to as *non-calibration parameters*) because they are (1) computed directly from digital data sets

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through the use of a geographic information system (e.g. land-surface characterization parameters) (Viger, 2014), (2) boundary conditions (e.g. parameters to adjust daily precipitation and daily min/max air temperature forcings), or (3) model configuration options (e.g. unit conversions and model output options). This leaves 35 parameters under consideration for improved model performance, hereafter referred to as *calibration parameters* (listed below in table 1 and described fully by Markstrom et al. (2015) in table 1-3).

2.2 Hydrologic processes

PRMS produces more than 200 output variables that indicate the hydrologic response of the simulation of a watershed through time (Markstrom et al., 2015, see table 1-5). In this study, eight of these output variables have been selected to represent the response of major hydrologic processes at the HRU resolution. These processes are: (1) baseflow (PRMS output variable *gwres_flow*) – the component of flow from the saturated zone to the connected stream segment; (2) evapotranspiration (*hru_actet*) – the total actual evapotranspitation lost from canopy interception, snow sublimation and soil and plant losses from the root zone; (3) runoff (*hru_outflow*) – the total flow from the HRU contributing to streamflow in the connected stream segment; (4) infiltration (*infil*) – the sum of rain and snowmelt that passes into the soil zone of the HRU; (5) snowmelt (*snowmelt*) – the amount of water that has changed from ice to liquid and becomes either surface runoff or infiltrates into the soil zone of the HRU; (6) soil moisture (*soil_moist*) – the storage state that represents the amount of soil water in the soil zone above wilting point and below total saturation in the HRU; (7) surface runoff (*sroff*) – water from a rainfall or snowmelt event that travels quickly over the land surface from the HRU to the connected stream segment; and (8) interflow (*ssres_flow*) – shallow lateral flow in the unsaturated zone to the connected stream segment. Details of how these processes are simulated by PRMS are described by Markstrom et al. (2015).

2.3 Objective functions

For DPHMs, there are many different objective functions that have been developed for different purposes (Krause et al., 2005; Gupta et al., 2008; Gupta et al., 2009). Because this study is an analysis of model sensitivity, the objective functions need only track changes in model output and do not necessarily need to include observed measurements. Consequently, objective functions can be developed for processes that are not normally evaluated by objective functions. Archfield et al. (2014) demonstrated that seven fundamental daily streamflow statistics (FDSS) can be used to group streams by similar hydrologic response and tend to provide non-redundant information. In this study, all seven FDSS were computed for each of the eight PRMS output variables corresponding to the processes. For the purpose of illustration, this paper focuses on three of the FDSS: (1) mean; (2) coefficient of variation (CV); and (3) the autoregressive lag-one correlation coefficient (AR-1). In an intuitive sense, objective functions based on these three statistics can be thought to represent changes in total volume, "spikiness" or "flashiness", and day-to-day timing, respectively. These objective functions are computed on the daily time series of the process variables for the 10 year evaluation period.

3 FAST analysis

Global parameter sensitivity analysis measures the variability of model output given variability of calibration parameter values. This is determined by partitioning the total variability in the model output or change in objective function values to individual calibration parameter (Reusser et al., 2011). The Fourier Amplitude Sensitivity Test (FAST) (Schaibly and Shuler, 1973; Cukier et al., 1973; Cukier et al., 1975; Saltelli et al., 2006) was selected for this study because it has been demonstrated that it can efficiently estimate non-linear hydrologic model parameter sensitivity (Pfannerstill et al. 2015; Reusser et al., 2011). FAST is a variance-based global sensitivity algorithm that estimates the first-order partial variance of model output explained by each calibration parameter (hereafter referred to as *parameter sensitivity*). Specifically, this first-order variance is the variability in the output that is directly attributable to variations in any one parameter and is distinguishable from higher order variances associated with parameter interactions. Selected parameters are varied within defined ranges at independent frequencies among different model runs. FAST identifies the variability of parameter sensitivities and their ranks, by means of their contribution to total power in the power spectrum. FAST has been implemented as the 'fast' library in the statistical software R (Reusser et al., 2011; R Core Team, 2015) in two parts. In the first part, the user identifies the calibration parameters and respective value ranges for the test, then FAST generates sets of test calibration parameter values (hereafter referred to as *trials*). Calibration parameter values are varied across the trials according to non-harmonic fundamental frequencies. The user then runs the DPHM for each trial and computes corresponding objective function values. Then the user runs the second part of the FAST package that performs a Fourier analysis of the objective function values over the trial space looking for the frequency signatures associated with each calibration parameter. The FAST methodology results in a simple procedure for computing parameter sensitivities on an HRU basis for all the CONUS (see fig. 1). The steps in this process are as follows:

1. Assign appropriate ranges for the 35 calibration parameters (Markstrom et al., 2015; as in LaFontaine et al., 2013).
2. Run the first part of the FAST procedure (as described above) to develop over 9000 unique parameter sets, comprised of value combinations for the calibration parameters. These parameter sets in the trial space are independent of each other so they can run in parallel on a computer cluster.
3. Compute the FDSS based objective function (mean, CV, and AR-1) values for each process.
4. Run the second part of the FAST procedure (as described above) using output from step 3, resulting in PRMS parameter sensitivities, at each HRU, for the 56 combinations of three objective functions and eight processes (plus totals).

4 Results

4.1 Sensitivity by process and objective function

Figure 2 shows parameter sensitivity as a set of maps ordered by process and objective function. This illustrates the spatial variability in parameter sensitivity and the importance that choice of objective function can make in terms of evaluation of hydrologic response. In these maps, the HRUs are colored according to the parameter sensitivity, which is computed by summing the first order sensitivity for all 35 parameters and then scaling (by average) each individual category of process and objective function to total sensitivity. These categories are indicated by their position in the rows and columns in figure 2. When looking at a single objective function for a single process, the cumulative parameter sensitivity can vary from near 0.0 (white colored HRUs) to near 1.0 (black colored HRUs). Low values in these maps indicate that there are no parameters that can be changed in any way to affect the objective function value (this situation is hereafter referred to as an *inferior process*). Likewise, each HRU has a cumulative sensitivity value which is highest for a particular process, which is referred to as the *dominant process*.

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An example of an inferior process is clearly seen in the case of the mean of the snowmelt process in the southern CONUS HRUs. This is because the occurrence of snow in these areas is very infrequent. Also, there were HRUs for which the value of some objective functions were mathematically undefined for certain processes (e.g. AR-1 and CV for the baseflow and snowmelt processes). These cases occur when the output variable representing the process does not change at all through time and are extreme examples of inferior processes. Likewise, a clear example of a dominant hydrologic process is the CV of interflow in the Intermountain West region of the CONUS (figs. 2 and 3). This means that for these HRUs, there exist some calibration parameters that can be varied that affect this process to a very high degree.

Also apparent from figure 2 is that there are clear spatial patterns in the parameter sensitivity on the basis of the geographical features of the CONUS. Generally, many of the maps show a sharp break in parameter sensitivity between mountain ranges and comparatively lower elevations, and northern contrasted with southern latitudes. Specific contrasts can be seen in several maps such as when examining the Humid Midwest as opposed to the Great Plains regions and the Pacific Coastal areas and the Desert Southwest region of the CONUS (fig. 3). Additionally, topographic features of the landscape are prominent (e.g. elevation for interflow), while in other maps, climate considerations seem to dominate (e.g. snowmelt). Another specific example is that the mean of each process, which indicates the ability of any particular parameter to change the total volume of water during a simulation, seems to have a low sensitivity band in the Great Plains region for all processes except for snowmelt (fig. 3). This band of low sensitivity has been noted in other modeling studies (Newman et al., 2015; Bock et al., 2015).

4.2 Parameter count required to parameterize each process

Figure 4 illustrates the extent to which it is possible to decompose the parameter estimation problem into a sub-set of independent problems, and hence reduce the dimensionality of the inference problem and avoid the troublesome nature of parameter interactions. It also illustrates that there is a strong spatial component to this decomposition. To identify the expected count of parameters required to parameterize a particular process, cumulative parameter sensitivity across all HRUs of the CONUS has been computed and plotted (fig. 4*A-H*). The sensitivity level accounted for by the most sensitive parameter, regardless of which parameter it is, for all HRUs across the CONUS is plotted in position 1 on the X axis of each of these plots (fig. 4*A-H*). Then, cumulative sensitivity is plotted for the parameter in rank 2, and so on, until the cumulative sensitivity of all 35 calibration parameters is accounted for. The plots in figure 4*A-H* show that far fewer than the full 35 parameters, on average, are needed to account for most of the parameter sensitivity. In fact, to account for 90% of the parameter sensitivity, this count varies from an average low value of just over two for snowmelt to an average high value of over 9 for runoff in selected HRUs.

The actual count of calibration parameters required to account for 90% of the parameter sensitivity varies by process and region, as shown by the maps in figure 4*I-P*. These maps were generated by counting the number of parameters required to obtain the 90% cumulative sensitivity level for each HRU. For example, figure 4*I* indicates that for the baseflow process between three and nine parameters are needed in specific HRUs to account for 90% of the parameter sensitivity in the HRUs across the CONUS, with the higher count needed in mountainous, Great Lakes and New England regions. The maps also indicate that between four and six parameters are required for parameterization of evapotranspiration (fig. 4*J*), five to 14 parameters are required for parameterization of runoff (fig. 4*K*), four to 13 parameters are required for parameterization of infiltration (fig. 4*L*), two to eight are required for parameterization of snowmelt (fig. 4*M*), three to six parameters are required for parameterization of soil moisture (fig. 4*N*), five to eight parameters are required for parameterization of surface runoff (fig. 4*O*), and two to 13 parameters are required for parameterization of interflow (fig. 4*P*). This analysis indicates that more parameters are needed to simulate the components of stream flow (e.g. baseflow, interflow, and groundwater flow) than processes that do not result directly in flow (e.g. snowmelt, evapotranspiration, and soil moisture).

Visually, these maps (fig. 4*I-P*) indicate that HRU calibration parameter counts vary regionally. For most processes, higher parameter counts are seen in the more mountainous regions of the Cascade, Sierra, Rocky, Ozark, and Appalachian mountains. Higher values also seem prevalent in New England and Great Lake regions (fig. 3). This result seems to indicate that, no matter which part of the hydrologic cycle is simulated, more parameters are required in these regions. In contrast, low parameters counts seem prevalent in the Great Plains and Desert Southwest of the United States.

In order to make the information presented in figure 4 more useful for DPHM application, the particular sensitive parameters have been determined for each HRU by ranking the calibration parameters by sensitivity for each category of process and objective function for each individual HRU (not shown). A summary of this information is produced by counting the occurrence of each parameter across the HRUs and ranking them within their respective category of process and objective function (table 1). Refer to Markstrom et al. (2015, table 1-3) for a complete description of these parameters.

When looking at the categorical parameter lists of table 1, it is expected that different parameters would associate with different processes (i.e. along a column), but it surprising to see how different the parameter lists are for different objective functions (moving across a row) for the same process. An example of this is the baseflow process: the baseflow coefficient (PRMS parameter *gwflow_coef*) is the most sensitive parameter for objective functions CV and AR1, but is not even in the list of sensitive parameters for the objective function related to the mean of the process. This implies that this parameter is the most important for effecting the timing of baseflow, while it does not have any effect on the total volume of baseflow.

Further inspection of table 1 indicates that some calibration parameters occur in many of the 24 categories (8 processes times 3 OFs), while some parameters do not occur at all. A count of how many times each parameter occurs provides insight into how important that particular parameter is to the DPHM simulation. To investigate this for the CONUS application, another view of the information in table 1 is shown in figure 5. The 25 calibration parameters identified as sensitive in some category from table 1 are listed on the y-axis of figure 5, ranked by order of the number of times that they appear. Furthermore, each appearance is indicated by an adjacent circle, with the color indicating the rank within the category in which it appeared. Specifically, a red circle indicates a first place appearance, blue indicates a last place appearance, and shades of purple indicate something in between.

Figure 5 shows that three specific parameters affect 18 or more process/objective function categories; seven parameters affect seven to 14 categories, and 15 specific parameters affect one to five categories. Finally, of the 35 parameters studied, 10 are never used for any combination of process/objective function (table 1 and fig. 5). It is apparent from figure 5, that for the CONUS application of PRMS, the most important parameters are *soil_moist_max* (maximum available water holding capacity), *jh_coef* (Jensen-Haise air temperature coefficient), and *dday_intcp* (intercept in degree-day equation). Modelers would be wise to invest their resources in developing the best values possible for these parameters. Ideally,

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these parameters could be estimated from reliable external data and set for the model and not calibrated. The least important parameters (aside from the parameters that are never sensitive) are *cecn_coef* (convection condensation energy coefficient), *ssr2gw_exp* (coefficient in equation used to route water from the soil to the groundwater reservoir), *emis_noppt* (emissivity of air on days without precipitation), *potet_sublim* (fraction of potential evapotranspiration that is sublimated), and *slowcoef_lin* (slow interflow routing coefficient). Ideally, these parameters could be set to default values and only calibrated if necessary. Also apparent from figure 5 is that there are many parameters between these two extreme groups. Parameters like *smidx_coef* (soil moisture index for contributing area calculation) can appear in several process/objective function categories, without any high rankings, while there are other parameters like *slowcoef_sq* (slow interflow routing coefficient) that appear in relatively few process/objective function categories, but have high rankings. These parameters may be the best candidates for calibration because they are sensitive, while at the same time interaction across processes is perhaps limited.

5 Discussion

5.1 Causes of parameter sensitivity

There are regions where parameter sensitivity is typically high for a particular objective function (e.g. New England region (fig. 3) for objective function based on mean of processes) or typically low (e.g. Great Plains region (fig. 3) for mean of processes) regardless of the process (fig 2). Why do the HRUs of some regions exhibit parameter sensitivity to almost all processes, while others exhibit parameter sensitivity to almost none? All other things being equal, there can only be two sources of these spatial patterns:

1. The physiography that is used to define the non-calibration parameters (e.g. elevation, vegetation type, soil type) renders all calibration parameters insensitive. A theoretical example of this could be if an HRU is characterized as entirely impervious, resulting in the non-existence of any simulated soil water.

2. Patterns in the climate data used to drive the model (e.g. daily temperature and precipitation) could control model response. A theoretical example of this could be an HRU that receives no precipitation. The hydrologic response of the HRUs in either case would always remain unchanged, regardless of changes in any parameter value.

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In either case, these sources of information are independent of the DPHM and could lead to the conclusion that the dominant processes identified by the methods outlined in this paper could correspond to perceptible dominant processes in the physical world (i.e. how the "real world" works).

The number of unique calibration parameters for each process in table 1 (i.e. counting the parameters across each row) may provide some insight into the complexity of each process. In theory, more "complicated" hydrologic processes would require more parameters for parameterization than the "simpler" ones. According to this view, runoff (17 calibration parameters) and infiltration (14 calibration parameters) are the most complex processes to simulate, with soil moisture (4) being the simplest. Interflow (12 calibration parameters), baseflow (11 calibration parameters), surface runoff, (10 calibration parameters), snowmelt (9 calibration parameters) and Evapotranspiration (8 calibration parameters) are in between. This reflects the fact that in PRMS, runoff is a much more complicated calculation with many of the other processes directly contributing information. Also apparent is that more parameters are needed to simulate the components of stream flow (e.g. baseflow, interflow, and surface runoff) than processes that do not result directly in flow (e.g. snowmelt, evapotranspiration, and soil moisture). The only process that does not follow this pattern is infiltration. Storm-event based infiltration is typically simulated with sub-daily time steps to account for the time/intensity variability of this process. It is possible that PRMS must compensate for this shortcoming in structure with a more complex parameterization of the process.

Table 1 indicates that there are 10 calibration parameters that are never sensitive regardless of the process or objective function. This indicates that these parameters should always be set to default value, with minimal resources used to estimate them, and never be calibrated. Additional modeling studies could reveal situations where these parameters actually do exhibit some sensitivity, perhaps in situations with smaller geographical domains or over different time periods. It is also possible that these parameters are never sensitive, indicating some structural problem or unwarranted complexity in the DPHM and the removal of some algorithms from the source code of the DPHM is advised. Additional study is required of these 10 non-sensitive calibration parameters and upon further review of the PRMS source code, a structural problem (e.g. unintended constraint, non-differentiable behavior, or software bug) might be revealed. Alternatively, the problem could be related to invalid parameter ranges in the FAST analysis or problems with the climate data used to drive the model. Finally, it could be that alternative or improved objective functions could resolve this issue.

5.2 Choice of objective function

The maps of figure 2 clearly illustrate the importance that choice of objective function can make in terms of evaluation of hydrologic response. When the maps of objective functions within a single hydrologic process are compared (i.e. the maps across a single row), the spatial patterns and magnitude of the parameter sensitivity can be very different. This could indicate that the objective functions based on the FDSS truly are non-redundant and are accounting for different aspects of the hydrological processes.

Table 1 indicates that the baseflow coefficient (PRMS parameter *gwflow_coef*) (Markstrom et al. 2015) is the most sensitive parameter for objective functions CV and AR1, but not sensitive to the mean of the baseflow process objective function. This indicates that despite knowledge of parameters being associated with the computations of simulation of a certain process, sensitivity analysis can reveal that the response of the simulation is completely different when the objective function changes. It also indicates that sensitivity analysis might be an important step in selection of an appropriate objective function and that uncritical application of objective functions may be misleading.

5.3 Identification of dominant and inferior processes by geographic area

To identify the dominant and inferior process(es) by geographic area, the following procedure is done for each HRU:

1. The parameter sensitivity scores are summed for each parameter, resulting in a score for each parameter for each output variable and objective function.
2. The parameter scores are averaged by objective functions, resulting in a score for each process.
3. The process scores are ranked for each HRU.
4. The top (and bottom) ranked process determines the most dominant (and most inferior) single process as shown in figure 6.

When the sensitivities are computed this way, it is possible that certain parameters are included in both the most dominate and most inferior processes at the same time. This apparent contradiction is not necessarily a conflict but indicates that the calibration parameters must work in concert with the evaluation method. For example, there exist HRUs where the evapotranspiration process is dominant and at the same time the runoff or infiltration processes are inferior (fig. 6*A* and 6*B*). The parameter *soil_moist_max* is indicated as being sensitive for all three of these processes (table 1). This parameter would demonstrate equifinality if evaluated within the context of the inferior processes (i.e. those output variables and objective functions) but would be a very effective calibration parameter resulting in optimal values when viewed within the context of the dominate process.

Generally, figure 6*A* shows that evapotranspiration is the most prevalent dominant process for the CONUS. This is probably because it a major component of the hydrologic cycle that is important in every HRU. However, this is not universal, and the dominant process varies by geographic region, with snowmelt being the dominant process in the northern Great Planes and northern Rocky Mountains, total runoff being the most important in the Pacific Northwest, and with interflow important in bands across the Intermountain West (fig. 3). Each process is dominant somewhere depending on local conditions. Equally informative are the locations of the most inferior processes (fig. 6*B*). This clearly shows that PRMS snowmelt parameters are not sensitive across the Central Valley of California, and in the Deep South and the Southwestern United States (fig. 3). Areas where runoff is more dominate that evapotranspiration, as in the Cascade and coastal areas of the Pacific Northwest, are locations where the runoff is a substantially greater part of the water budget. Interestingly, infiltration and baseflow appear to be equally inferior across most of CONUS, with pockets of HRUs that are insensitive to soil moisture, surface runoff, and interflow, depending on local conditions. There are no HRUs that rank evapotranspiration as the most inferior process.

Dominant and inferior process can be identified for HRUs at the watershed scale as well. Figure 6*C* shows the most dominant process by HRU for the Apalachicola – Chattahoochee – Flint River watershed in the Southeastern United States. This watershed has been the subject of previous PRMS modeling studies (LaFontaine et al. 2013). When using this information at a finer resolution, it shows that evapotranspiration is the most dominant process watershed wide, but with pockets of HRUs in the northern part of the watershed where runoff is the most dominant and a pocket in the southern part of the watershed where infiltration is most dominant. Likewise, the most inferior process for each HRU is identified in figure 6*D*. This clearly indicates that parameters and objective functions related to snowmelt, and to a lesser degree baseflow do not need to be considered when modeling this watershed. Figure 6*D* also indicates, that in the northern part of the watershed, infiltration and runoff are inferior processes as well, which could in part be due to impervious conditions around the Atlanta metropolitan area. This information could be use, in conjunction with table 1 to develop the most effective parameter estimation and objective function selection strategy when modeling this watershed.

This method of identification of inferior and dominate processes for a specific geographical location are defined within the context of the application of the DPHM and may not have the same meaning within a different context. This method of using the PRMS watershed hydrology model as the context resolves problems that researchers have had classifying watershed by dominate process. Indicating that classification not only depends on the physiographic nature of the watershed, but also, the scale, resolution, and purpose for classification.

5.4 Further study

Providing modelers with reduced lists of calibration parameters on an HRU-by-HRU, watershed-by-watershed, or region-by-region basis is the first step in the path of this research. This approach could be developed into more sophisticated methods where orthogonal output variables and objective functions could provide much more insight into methods of effective model calibration. Advancements in this approach may identify groups of parameters that effectively behave together, thus reducing the number of parameters and making specific model output respond more directly to a single or a few parameters, reducing parameter interaction. This suggests that model parameterization and calibration might benefit from a step-by-step strategy, using as much information as possible to set non-interactive parameters and remove them from consideration before the more interactive parameters are calibrated, reducing the dimensionality of the problem (Hay et al., 2006; Hay and Umemoto, 2006).

Another potential application is that it is possible that uncertainty maps related to the hydrological processes could be developed. A simple relation between the uncertainties of model output and input based on sensitivity can be described according to (Mishra, 2009):

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$$sens = \frac{\sigma_{input}}{\sigma_{output}}, \quad (1)$$

where *sens* is the parameter sensitivity, σ_{input} is the uncertainty associated with the input parameters, and σ_{output} is the uncertainty associated with the model output. If this equation is applied, process by process, using uncertainty estimates associated with the parameter groupings listed in table 1 and the spatially distributed objective function values shown in figure 2, it would be possible to develop maps of estimates of uncertainty by process and objective function. Developing estimates of spatially varying parameter uncertainty (σ_{input}) may be possible as more remotely sensed data sets become available. These maps of model output uncertainty, by process, could be an effective way to communicate DPHM uncertainty on the basis of geographic location and dominant process.

Another question for future research is does the classification of dominate hydrologic processes, both geographical and categorical, as described in this study apply to any other context? Comparable findings from other modeling studies, such as those by Newman et al. (2015) and Bock et al. (2015) might indicate that there could be a connection. These other studies use the same input information (i.e. being driven with the same climate data and using the same sources of information for parameter estimation) and thus simulation results and model sensitivity to this information might be similar. Also, can real world watersheds be classified by sensitivity analysis using DPHMs? Based on the findings of the work presented so far, the answer is inconclusive. Clearly there are some results that indicate that it might be possible. For example, the methods described here effectively identify "snowmelt watersheds" in the mountainous and northern latitudes, but, is all of this necessary to accomplish this? Might simpler methods (e.g. an isohyetal snowfall map) identify snowmelt watersheds just as effectively?

Questions remain about using parameter sensitivity for identification of structural inadequacies within the CONUS application and specifically, the PRMS model itself. In this application, certain hydrologic processes (e.g. depression storage, streamflow routing, flow through lakes, and strong groundwater/surface-water interaction) were not considered because of additional data requirements and parameterization complexity. Just as the spatial and temporal scope of any modeling project must be defined, the scope of the hydrologic processes, and the detail to which these processes are simulated must be likewise defined. Perhaps sensitivity analysis could help define this in a more objective way. Model

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development and application could perhaps proceed by first accounting for those processes that have the most effect.

6 Conclusion

Watersheds in the real world clearly exhibit hydrologic behavior determined by dominant processes based on geographic location (i.e. land surface conditions and climate forcings). A methodology has been developed to identify regions, watersheds and HRUs according to dominant process(es) on the basis of parameter sensitivity response with respect to a distributed-parameter hydrology model. The parameters in this model were divided into two groups – those that are used for model calibration and those that were not. A global parameter sensitivity analysis was performed on the calibration parameters for all HRUs of the conterminous United States. Categories of parameter sensitivity were developed in various ways, on the basis of geographic location, hydrologic process and model response. Visualization of these categories provide insight into model performance and useful information about how to structure the modeling application should take advantage of as much local information as possible.

By definition, an insensitive parameter is one that does not affect the output. Ideally, a distributed-parameter hydrology model would have just a few calibration parameters, all of them meaningful, each controlling the algorithms related to the corresponding process. This would result in low parameter interaction and a clear mapping between input and output. However, this is not always the case, and despite the fact that parameter interaction is unavoidable in these types of models, this behavior is also seen in the real world. For instance, in watersheds where evaporation is very high, antecedent soil moisture is affected, which has a direct influence on infiltration. The real world process of evaporation has an effect on infiltration, just as evaporation parameters have an effect on simulation of infiltration in watershed hydrology models.

In conclusion, results of this study indicate that it is possible to identify the influence of different hydrologic processes when simulating with a distributed-parameter hydrology model on the basis of parameter sensitivity analysis. Factors influencing this analysis include geographic area, topography, land cover, soil, geology, climate, and other unidentified physical effects. Identification of these processes allow the modeler to focus on the more important aspects of the model input and output, which can simplify all facets of the hydrologic modeling application.

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Data availability

The Precipitation-Runoff Modeling System software used in this study is developed, documented and distributed by the U.S. Geological Survey. It is in the public domain and freely available from their web site (http://wwwbrr.cr.usgs.gov/prms). Data analysis and plotting is done with the R software package (http://www.r-project.org), which is freely available, subject to the GNU General Public License.

The climate forcing data set used in this study came from the U.S. Geological Survey Geo Data Portal (http://cida.usgs.gov/climate/gdp). The HRU delineation and default parameterization came from the U.S. Geological Survey GeoSpatial Fabric (http://wwwbrr.cr.usgs.gov/projects/SW_MoWS/GeospatialFabric.html). Finally, the parameter sensitivity output values that were used to make the maps and table in this article are available at ftp://brrftp.cr.usgs.gov/pub/markstro/hess.

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Tables

Table 1. Ordered list of most sensitive Precipitation-Runoff Modeling System calibration parameters by process and objective function. The parameters listed in each cell of the table are those that are required to account for 90 percent of the cumulative sensitivity. These parameters are described by Markstrom et al. (2015, table 1-3).

Process	Objective Function		
	Mean (i.e. total volume)	CV (i.e. "flashiness")	AR 1 (i.e. day-to-day timing)
Baseflow	jh_coef, soil_moist_max, dday_intcp, soil2gw_max, radmax, carea_max, jh_coef_hru	gwflow_coef, soil_moist_max, jh_coef, soil2gw_max, smidx_coef, carea_max, tmax_allsnow, dday_intcp, smidx_exp	gwflow_coef, soil_moist_max, soil2gw_max, carea_max
Evapotranspiration	jh_coef, soil_moist_max, dday_intcp, radmax, jh_coef_hru, smidx_coef, dday_slope	radmax, jh_coef, soil_moist_max, dday_intcp, dday_slope, soil_rechr_max	jh_coef, radmax, dday_slope, soil_moist_max, dday_intcp, soil_rechr_max
Runoff	jh_coef, dday_intcp, soil_moist_max, radmax, jh_coef_hru, smidx_coef, dday_slope	gwflow_coef, soil_moist_max, fastcoef_lin, pref_flow_den, carea_max, jh_coef, smidx_exp, smidx_coef, soil2gw_max, tmax_allsnow	slowcoef_sq, soil2gw_max, gwflow_coef, carea_max, soil_moist_max, smidx_exp, smidx_coef, fastcoef_lin, pref_flow_den, jh_coef, slowcoef_lin
Infiltration	smidx_exp, soil_moist_max, carea_max, smidx_coef, jh_coef, srain_intcp	carea_max, tmax_allsnow, jh_coef, smidx_exp, srain_intcp, smidx_coef, tmax_allrain, radmax, freeh2o_cap, soil_moist_max, dday_intcp, rad_trncf	carea_max, soil_moist_max, smidx_exp, tmax_allsnow, srain_intcp, tmax_allrain, jh_coef, smidx_coef, freeh2o_cap, dday_intcp
Snowmelt	tmax_allsnow, tmax_allrain	tmax_allsnow, tmax_allrain, rad_trncf, freeh2o_cap, dday_intcp	tmax_allsnow, dday_intcp, rad_trncf, radmax, tmax_allrain, jh_coef, freeh2o_cap, cecn_coef, emis_noppt, jh_coef_hru, potet_sublim

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Soil moisture	soil_moist_max, jh_coef, dday_intcp, radmax	jh_coef, radmax, soil_moist_max, dday_intcp	soil_moist_max, jh_coef, dday_intcp, radmax
Surface runoff	smidx_exp, carea_max, soil_moist_max, smidx_coef, jh_coef, dday_intcp	carea_max, smidx_exp, jh_coef, tmax_allsnow, smidx_coef, srain_intcp, soil_moist_max, tmax_allrain	soil_moist_max, carea_max, jh_coef, smidx_exp, smidx_coef, tmax_allsnow, dday_intcp, srain_intcp, tmax_allrain, radmax
Interflow	soil_moist_max, soil2gw_max, pref_flow_den, jh_coef, carea_max, smidx_exp, dday_intcp, smidx_coef	fastcoef_lin, soil_moist_max, pref_flow_den, jh_coef, carea_max, soil2gw_max, smidx_exp, tmax_allsnow, dday_intcp	soil_moist_max, fastcoef_lin, slowcoef_sq, carea_max, jh_coef, pref_flow_den, smidx_exp, ssr2gw_exp, soil2gw_max, dday_intcp, tmax_allsnow
Parameters not sensitive			
adjmix_rain, fastcoef_sq, ppt_rad_adj, radj_sppt, radj_wppt, sat_threshold, ssr2gw_rate, tmax_index, transp_tmax, wrain_intcp			

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Figures

Figure 1. The Hydrologic Response Units defined for the conterminous United States. Each Hydrologic Response Unit is drawn in a different color to distinguish it from its neighbors.

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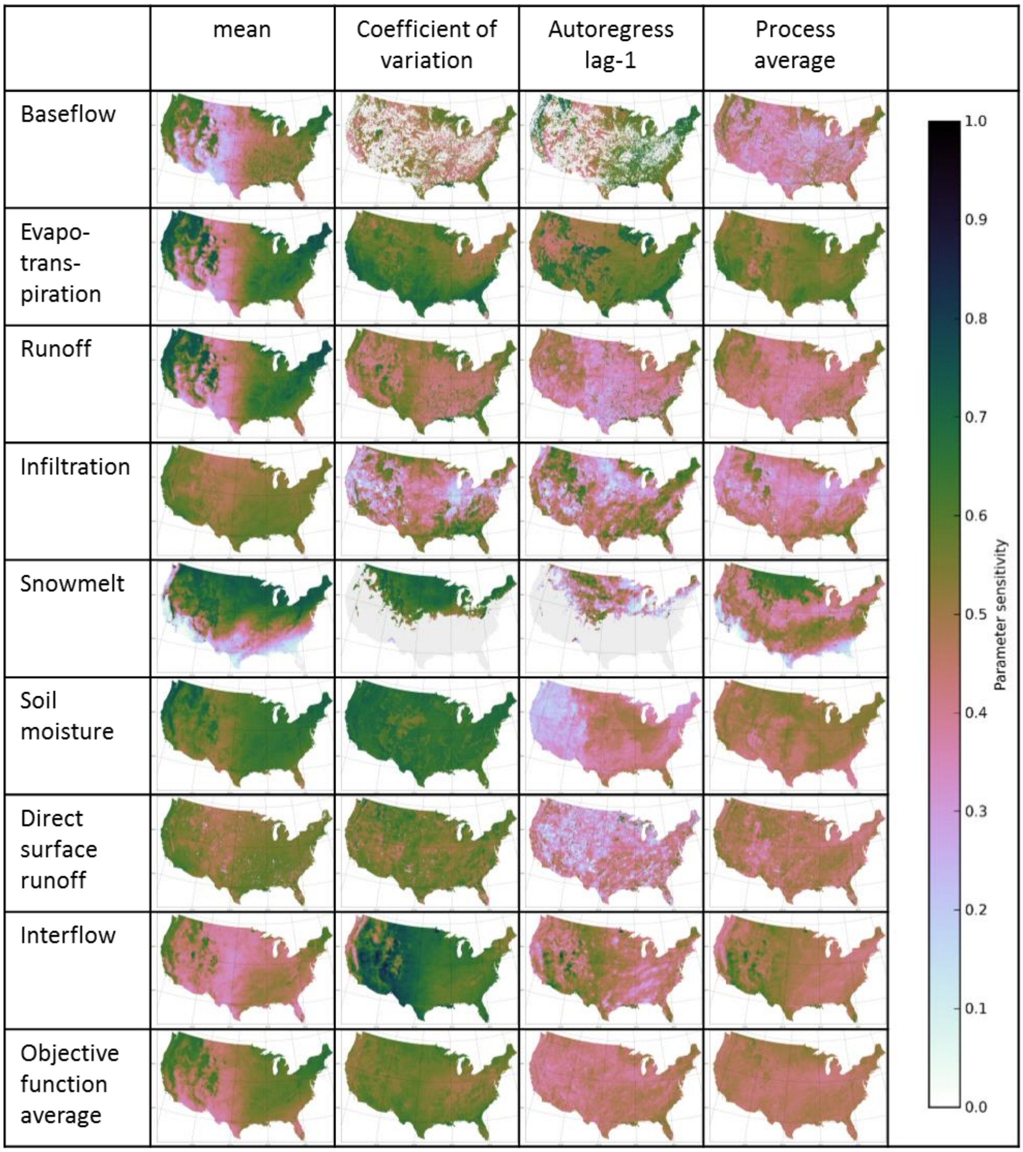

Figure 2. Maps of the conterminous United States showing Precipitation-Runoff Modeling System parameter sensitivity by Hydrologic Response Unit by process and selected objective function.

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Figure 3. Location Map of the conterminous United States showing the different geographic regions referred to this study.

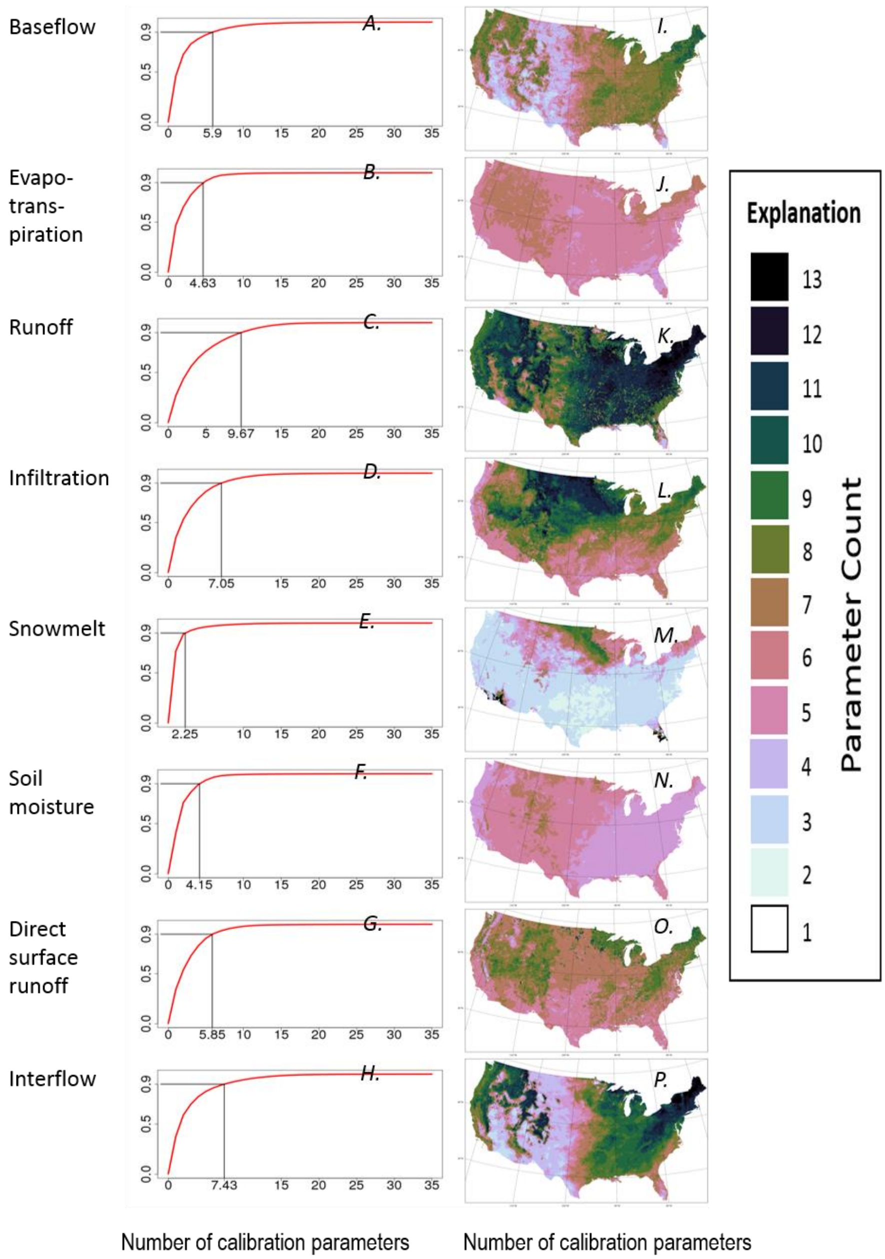

Figure 4. Cumulative Precipitation-Runoff Modeling System parameter sensitivity across all HRUs in the continental Parameters Related to Processes. Parameter sensitivities have been averaged across all objective functions. The plots A-F summarize the counts for all 110,000 HRUs shown in the corresponding maps (I – P).

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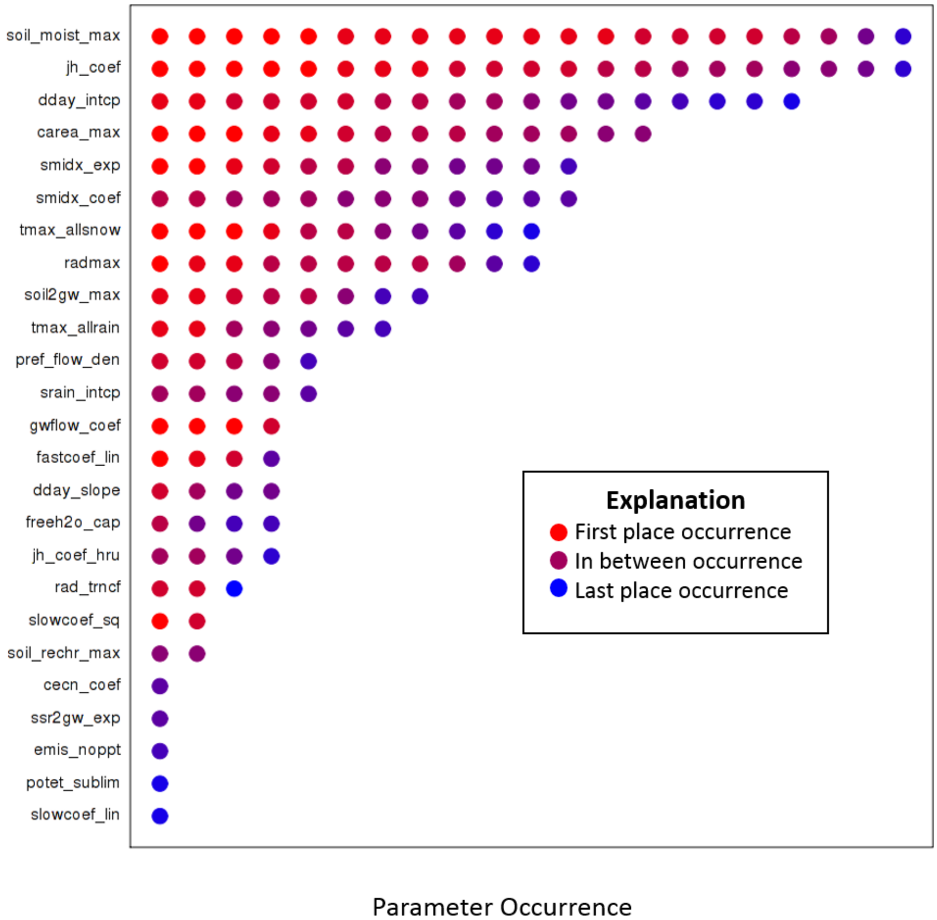

Figure 5. Frequency of occurrence of the different parameter counts. The count of circles in the row adjacent to the parameter name indicates how many times the respective parameter occurs in the different categories in table 1. The color of each circle indicates the ranking of that occurrence within the category, red corresponding to a higher ranking than blue.

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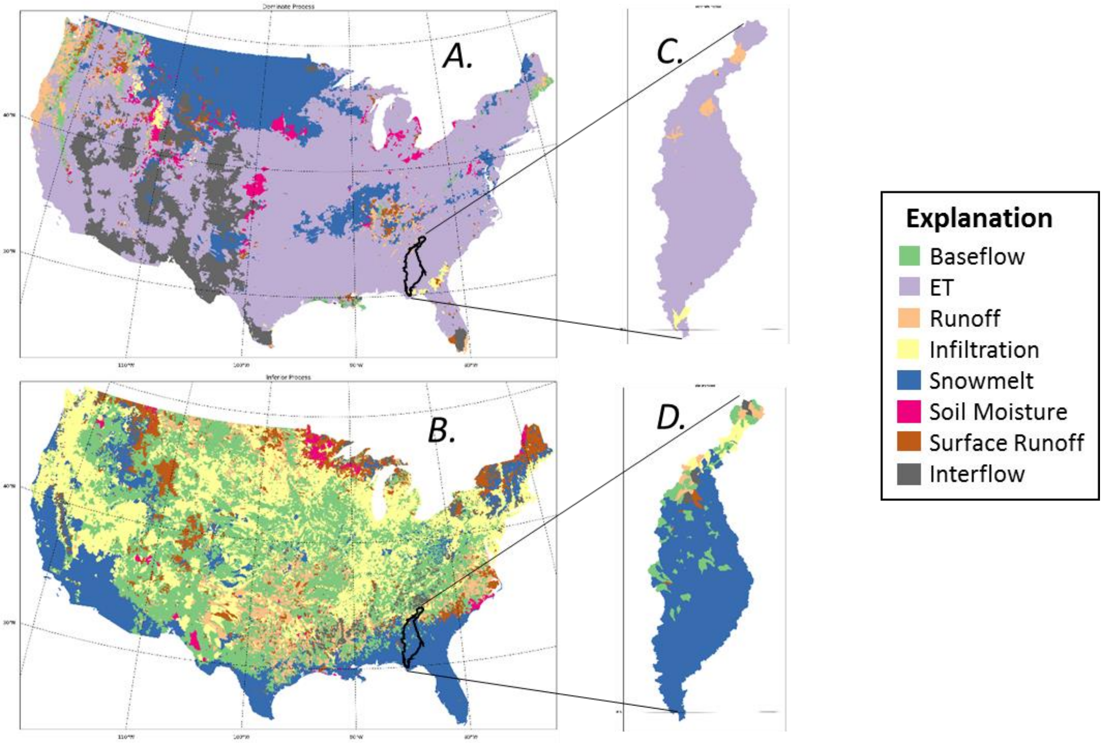

Figure 6. Precipitation-Runoff Modeling System parameter sensitivity organized by process have been ranked for each hydrologic response unit for the entire conterminous United States (maps A and B) and for the Apalachicola – Chattahoochee – Flint River basin (maps C and D). The maps on the top (A and C) show the most dominate process, while the maps on the bottom (B and D) show the most inferior process.