CHALLENGES IN MULTIOBJECTIVE IDENTIFICATION AND EVALUATION OF WATERSHED MODELS FOR UNGAUGED BASINS

A Thesis in
Civil Engineering

by

Rashi Bhushan

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The thesis of Rashi Bhushan was reviewed and approved* by the following:

Patrick M Reed  
Associate Professor of Civil Engineering  
Thesis Co-advisor

Thorsten Wagener  
Assistant Professor of Civil Engineering  
Thesis Co-Advisor

Michael N. Gooseff  
Assistant Professor of Civil Engineering

William Burgos  
Associate Professor of Environmental Engineering  
Professor in Charge of Graduate Programs

*Signatures are on file in the Graduate School
ABSTRACT

Rainfall runoff models are standard tools for making hydrologic predictions. All hydrologic models require some degree of parameter calibration to achieve reliable predictions. However, a large part of the world remains ungauged and requires robust model identification and evaluation approaches to improve predictions in ungauged locations. This paper demonstrates both benefits and challenges associated with predictions in ungauged basins (PUB) framework that uses multi-objective optimization in combination with hydrologic indices regionalization to improve ensemble predictions at ungauged sites. Our objective is to assess how the quality of regionalized hydrologic constraints impacts the difficulty of identifying behavioral parameter sets using multi-objective optimization. This work characterizes the modes of failure in the optimization algorithm using random seed analysis and ensembles of hydrologic predictions obtained from high, intermediate and low quality regionalized constraints for representative watersheds in the United Kingdom. The results highlight that a slight increase in model complexity can lead to severe difficulties for the multi-objective PUB framework when the new model fails to produce simulated hydrologic indices within the feasible ranges attained from regionalization. Results also point to the issue that low quality regionalized constraints can still yield improved ensemble predictions given longer search durations for the optimization algorithm. Random seed analysis for the search dynamics of the multi-objective optimization algorithm and scatter plots showing the overall coverage of the behavioral indices space defined by regionalized hydrologic constraints provide key diagnostics of the quality and effectiveness of the predictions attained from the multi-objective PUB framework in the absence of observations.
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LIST OF NOTATIONS

\( F(c) \)  Probability of occurrence of a specific soil moisture capacity \( c \), across the catchment [mm]

\( C_{\text{max}} \)  Maximum soil moisture storage capacity of catchment [mm]

\( b \)  Degree of spatial variability of storage capacity [-]

\( PP \)  Precipitation [mm]

\( PET \)  Potential Evapotranspiration [mm/d]

\( E_{\text{adj}} \)  Vegetation adjustment factor [-]

\( ET \)  Evapotranspiration losses [mm/d]

\( S_{\text{max}} \)  Maximum combined content of all stores [mm]

\( C(t-1) \)  Initial height of the moisture tank [mm]

\( S(t-1) \)  Initial storage in tank [mm]

\( C(t) \)  Intermediate height of the storage tank [mm]

\( S(t) \)  Intermediate storage in tank [mm]

\( OV2 \)  Effective rainfall or overflow produced after filling all storages [mm]

\( P_{\text{adj}} \)  Precipitation adjustment factor

\( PP_{\text{inf}} \)  Remaining net rainfall that does not go into \( OV2 \) [mm]

\( OV1 \)  Additional effective rainfall generated by stores with capacity less than \( C_{\text{max}} \) [mm]

\( OV \)  Total effective rainfall from the soil moisture accounting module [mm]

\( \alpha \)  Flow split coefficient [-]

\( K_s \)  Time constant to linear slow flow tank (day\(^{-1}\))
\( K_q \) \quad \text{Time constant to linear quick flow tank (day}^{-1})

\( Q(t) \) \quad \text{Total flow at catchment outlet}

\( I_j \) \quad \text{\( j \)th hydrologic index calculated from simulated flow}

\( L_{ej} \) \quad \text{Center of the prediction limit of the \( j \)th hydrologic index}

\( \delta_j \) \quad \text{Spread of the prediction limit of the \( j \)th hydrologic index, that is distance of centre to the extreme}
ACKNOWLEDGEMENTS

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Chapter 1

INTRODUCTION

Hydrologic models are important tools for a broad range of water resources planning and management activities (Singh & Frevert, 2006). A major challenge to effectively predicting and managing many water resource systems around the world lies in their poor measurement networks, where missing data or lack of availability of observed data at the required scale of interest makes hydrologic predictions in these basins very difficult (Sivapalan et al., 2003). Traditionally, for basins with observed stream flow time series, parameter calibration is used to obtain estimates of parameters to enable reliable stream flow predictions (Wagener et al., 2003). However, in absence of local stream flow observations traditional parameter estimation becomes impossible in ungauged basins. Despite this challenge, all hydrological models require some degrees of parameter calibration to achieve reliable results (Beven, 2001) whether in gauged or ungauged contexts.

Beyond parameter calibration, predictions in ungauged basins (PUB) must also overcome the challenges associated with identifying appropriate model structures to predict stream flow and understand the dominant physical controls on watersheds’ responses. Model identification and selection is challenging since more than one feasible model structure can be used to describe a watershed’s behavior and a wide range of parsimonious models have been used to address the PUB problem (Cutore et al., 2007; Yu et al., 2000; Bloschl, 2005). A model abstracts the real world through a mathematical expression, which relates the model parameters to its output. These models can be of
lumped or physically distributed type. The choice of a specific model structure for a watershed becomes difficult without having local observations of stream flow to compare the models against. Moreover, the selection of different models will include different sets of parameters to describe watersheds’ characteristics.

The main approach to predictions in ungauged basins has been the regionalization of model parameters using physical characteristics of the watershed (Abdullah & Lettenmaier, 1997; Bloschl, 2004; Wagener et al., 2004; McIntyre et al., 2005; Wagener & Wheater, 2006; Bloschl, 2005). In model parameter regionalization, a suitable hydrological model is applied to a set of hydrologically similar watersheds to estimate their model parameters. Regression relationships developed between the model parameters and watershed characteristics are then used on ungauged sites to get estimates of model parameters. A major limitation of the above method is that the parameters obtained may be poorly determined or may have strong correlations. Moreover, some parameters may not be directly related to measurable watershed characteristics and hence cannot be put in a regression equation. This method also suffers from difficulties associated with how model selection can yield large estimation biases due to model structure errors.

Similarly, model applications for “similar” but gauged watersheds can help in getting parameter estimates which can be used at ungauged sites (McIntyre et al., 2005). However, as the parameters are obtained from model calibration, they are model dependent and prone to model structure errors. Also, parameter values obtained from this method may be dependent on the process or time scale foci used for model calibration (e.g. wet or dry period) limiting their relevance for other sites. Alternatively, a priori
parameter estimates from land surface characteristics such as soil texture and vegetation type have also been used to improve predictions in ungauged basins (Atkinson et al., 2003; Koren et al., 2003). However, the spatial heterogeneity of land surface characteristics yields a considerable degree of uncertainty associated with the parameters given by existing a priori procedures. Therefore, the parameter values obtained from a priori estimates vary in their scale relative to simulated area and quality for different hydro-climatic regimes which can adversely affect model performance.

This study builds on the recent work of Yadav et al. (2007) that regionalizes model independent hydrologic indices using commonly available physical characteristics of watersheds to constrain ensemble predictions of stream flow at ungauged sites. Regression equations are developed between the response characteristics and physical characteristics of watersheds at gauged sites, which can be used to predict expected stream flow indices at ungauged basins. The main advantage of this approach is its model independence, which yields the ability to constrain any model whether, lumped or physically distributed. Moreover, it limits model structural error and calibration problem biases in the regionalization. Zhang et al., (2008) extended the work by Yadav et al., (2007) by integrating the hydrologic indices regionalization approach with multi-objective optimization to increase the type and number of hydrologic indices that can be used to constrain predictions in ungauged basins.

Expanding on Zhang et al. (2008), the overall purpose of this study is to fully characterize the impact of hydrologic indices regionalization on the difficulty of using multi-objective optimization to identify behavioral parameter sets that enhance ensemble predictions in ungauged basins. This work contributes a careful analysis of the modes of
failure that can dramatically reduce the value and effectiveness of using multi-objective optimization in the PUB problem. The overall performance of our multi-objective PUB methodology is characterized in this study in terms of: (i) its potential for search failures as quantified using random seed analysis of the search dynamics for the Epsilon Dominance Nondominated Sorted Genetic Algorithm II (ε-NSGAII), (ii) the causal relationships between search failures and the quality of search constraints based on regionalized hydrologic indices, and (iii) the quality of its resultant ensemble hydrologic predictions attained using both high, intermediate and low quality regionalized hydrologic constraints. The data from 30 watersheds across United Kingdom was used to test the success of this approach.
Chapter 2

STUDY WATERSHEDS

2.1 Watershed Hydrologic Characteristics

A total of 30 humid watersheds across different locations of United Kingdom (UK) have been used in the present study. These watersheds vary in drainage area, vegetation, topography, soil type and land use. Table 2.1 enlists the general watershed characteristics. Some watersheds are predominantly clay, while others are alluvium and permeable chalk catchments. The topographic gradients vary within the watersheds ranging from a change in altitude of 75 m at Stringsde at Whitebridge to 795 m Tywi at Nantgaredig. Majority of the watersheds have natural to within 10% at the 95 percentile flow, implying that the stream flow is not impacted by human and climate induced changes. The runoff data in few watersheds is affected by effluent returns, groundwater and industrial abstractions. However, these are thought to be of minor impact and hence not considered in the study.

The source of the data for the selected watersheds was The National River Flow Archive [http://www.nwl.ac.uk/ih/nrfa]. The data was available for the forcings of Observed flow, Precipitation and Temperature at daily time steps. The stream flow was in units of mm/day and precipitation in mm. Eleven consecutive years (1980 – 1990) of data were available for 29 watersheds. Time series data for the Test at Broadlands was taken from FEH, [1999]. Data was available from 1983 – 1996. So the period of time series finally used for analysis was from 1-1-1983 – 12-31-1990.
The precipitation and stream flow time series were obtained from ‘Predictions in Ungauged Basins (PUB) – UK data downloads’ at http://www.nwl.ac.uk/ih/nrfa. Temperature data was obtained from the British Atmospheric Data Center [http://badc.nerc.ac.uk/home/index.html]. Potential evapotranspiration was calculated from temperature using Hargreaves equation (Shuttleworth, 1992).

2.2 Watershed Physical Characteristics

A detailed list of the physical characteristics of the watersheds was obtained from the National River flow archive [http://www.nwl.ac.uk/ih/nrfa] and the data CD accompanying the Flood Estimation Handbook (FEH). Watershed features like permeability, topography, land use and climate are used to obtain the physical characteristics of the watershed which are divided into six categories depending upon their functions (Wagener et al., 2004). Correlation between watershed characteristics is used to reduce the number of watershed physical characteristics and finally 13 characteristics are used in the study. This list includes watershed characteristics like area, steepness, Base flow index (BFI), woodland, grassland, built-up area, elevation, wetness index, etc. The list of physical characteristics of the watershed has been given in Table 2.2.
Table 2.1 List of General Watershed Characteristics; Source: Yadav et al., 2007

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<th>BFIHOST $^2$</th>
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$^1$ Data from [http://www.nwl.ac.uk/ih/nrfa](http://www.nwl.ac.uk/ih/nrfa)
$^2$ Data from FEH, 1999, CDROM
$^3$ 1961-1990 Average Annual Rainfall
BFIHOST: a base-flow index derived from the Hydrology of Soil Types classification;
Table 2.2 List of Physical Characteristics of Watersheds; Source: Yadav et al., 2007

<table>
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<th>Characteristic</th>
<th>Unit</th>
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<td>Base-flow index derived using Hydrology of Soil Types (HOST) classification</td>
</tr>
<tr>
<td>LDP</td>
<td>km</td>
<td>Longest drainage path</td>
</tr>
<tr>
<td>DPSBAR</td>
<td>m km$^{-1}$</td>
<td>Index of watershed steepness</td>
</tr>
<tr>
<td>DPLBAR</td>
<td>km</td>
<td>Index describing watershed size and drainage path configuration</td>
</tr>
<tr>
<td>APSBAR</td>
<td>[-]</td>
<td>Index representing the dominant aspect of watershed slopes</td>
</tr>
<tr>
<td>APSVAR</td>
<td>[-]</td>
<td>Index representing the invariability of aspect of watershed slopes</td>
</tr>
<tr>
<td>URBEXT</td>
<td>[-]</td>
<td>FEH index of fractional urban extent for 1990</td>
</tr>
<tr>
<td>LEVEL ST</td>
<td>m.o.d.*</td>
<td>Elevation of gauging station above ordinance datum</td>
</tr>
<tr>
<td>MAX ALT</td>
<td>m.o.d.</td>
<td>Elevation of point with maximum altitude above ordinance datum</td>
</tr>
<tr>
<td>ALT95</td>
<td>m.o.d.</td>
<td>95 percentile elevation (95% points in watershed above this elevation)</td>
</tr>
<tr>
<td>ALT5</td>
<td>m.o.d.</td>
<td>5 percentile elevation (5% points in watershed above this elevation)</td>
</tr>
<tr>
<td>WT. ALT</td>
<td>m.o.d.</td>
<td>Weighted average altitude of watershed</td>
</tr>
<tr>
<td>WOODLAND</td>
<td>[-]</td>
<td>Percentage woodland within watershed</td>
</tr>
<tr>
<td>ARABLE</td>
<td>[-]</td>
<td>Percentage arable land within watershed</td>
</tr>
<tr>
<td>GRASS</td>
<td>[-]</td>
<td>Percentage grasslands within watershed</td>
</tr>
<tr>
<td>MOUNTAIN</td>
<td>[-]</td>
<td>Percentage mountains within watershed</td>
</tr>
<tr>
<td>BUILTUP</td>
<td>[-]</td>
<td>Percentage built-up land within watershed</td>
</tr>
<tr>
<td>HIGH PERM</td>
<td>[-]</td>
<td>Percentage soil within watershed with high permeability</td>
</tr>
<tr>
<td>MED PERM</td>
<td>[-]</td>
<td>Percentage soil within watershed with medium/ mixed permeability</td>
</tr>
<tr>
<td>LOW PERM</td>
<td>[-]</td>
<td>Percentage soil within watershed with low permeability</td>
</tr>
<tr>
<td>SAAR</td>
<td>mm</td>
<td>1961-90 standard period average annual rainfall</td>
</tr>
<tr>
<td>RMED-1D</td>
<td>mm</td>
<td>Median annual maximum 1-day precipitation</td>
</tr>
<tr>
<td>RMED-2D</td>
<td>mm</td>
<td>Median annual maximum 2-day precipitation</td>
</tr>
<tr>
<td>RMED-1H</td>
<td>mm</td>
<td>Median annual maximum 1-hour precipitation</td>
</tr>
<tr>
<td>P/PE</td>
<td>[-]</td>
<td>Ratio of average annual precipitation and average annual evapotranspiration</td>
</tr>
<tr>
<td>PVAR</td>
<td>[-]</td>
<td>Coefficient of variation in precipitation</td>
</tr>
</tbody>
</table>

*mod: meters above ordinance datum
Fig 2.1 Map of UK showing the location of the 30 watersheds; Source: Yadav et al., 2007
Chapter 3

WATERSHED MODELS

3.1 Introduction

Two versions of the Hymod hydrological conceptual model by Moore (1985; 2007) and Lamb (1999) have been used in this study to provide a lumped representation of the watershed response behavior. The two versions of Hymod have been named according to the number of parameters used in their formulation (i.e., Hymod-5 and Hymod-7). A detailed description of both versions of the model is given in Sections 3.2 and 3.3 below.

3.2 Description of Hymod-5

Hymod-5 (Moore 1985; 2007) is a five parameter conceptual model consisting of probability distributed soil moisture accounting (SMA) component connected to two series of linear reservoirs, one for quick flow and the other for slow flow. Fig 3.1 shows the general form of the model. The Pareto distribution function for runoff generation in the watershed is expressed in equation (3.1).

\[ F(c) = 1 - \left(1 - \frac{c}{C_{\text{max}}} \right)^b, \quad 0 \leq c \leq C_{\text{max}} \]  \hspace{1cm} (3.1)

The above distribution function describes the probability of occurrence of a specific moisture capacity, \( c \) across the watershed, distributed according to the degree of spatial variability, \( b \). The working of Probability Distributed Model (PDM) has been explained with the help of the equations given below. Starting from the SMA component, the
maximum combined content of all stores can be calculated by equation (3.2). It shows that the combined storage content depends upon the maximum store capacity, $C_{\text{max}}$ and the index, $b$, describing the spatial distribution of the storage capacity.

$$S_{\text{max}} = \left[ \frac{C_{\text{max}}}{1 + b} \right]$$  \hspace{1cm} (3.2)

The initial height of the soil moisture reservoir is shown by equation (3.3) and it depends upon $C_{\text{max}}$, $S_{\text{max}}$, $b$ and the initial reservoir storage $s(t-1)$.

$$c(t - 1) = C_{\text{max}} \left[ 1 - \left( 1 - \frac{s(t - 1)}{S_{\text{max}}} \right)^{\frac{1}{1+b}} \right]$$  \hspace{1cm} (3.3)

Rainfall after filling all storages produces an effective rainfall, OV2 given in equation (3.4) and the remaining net rainfall that does not go into OV2 is given by equation (3.5)

$$OV2(t) = \max[PP(t) + c(t - 1) - C_{\text{max}}, 0]$$  \hspace{1cm} (3.4)

$$PP_{\text{inf}}(t) = PP(t) - OV2(t)$$  \hspace{1cm} (3.5)

The new capacity of SMA reservoir and the corresponding storage content are given by equation (3.6) and (3.7) respectively. The new reservoir capacity as shown in equation (3.6) depends upon the net precipitation remaining in the reservoir, $PP_{\text{inf}}$ and the initial storage capacity, $c(t-1)$. Whereas the new storage content as shown in equation (3.7) depends on $C_{\text{max}}$, $S_{\text{max}}$, $b$ and new tank capacity, $c(t)$.

$$c(t) = PP_{\text{inf}}(t) + c(t - 1)$$  \hspace{1cm} (3.6)

$$s(t) = \left[ 1 - S_{\text{max}} \left( 1 - \frac{c(t)}{C_{\text{max}}} \right)^{b+1} \right]$$  \hspace{1cm} (3.7)
The additional effective rainfall generated by stores with capacity less than OV1 is given by equation (3.8). Finally, the total effective rainfall from the soil moisture accounting module can be calculated as given in equation (3.9)

\[
OV1(t) = \max[PPinf(t) + s(t-1) - s(t), 0]
\]

\[
OV(t) = OV1(t) + OV2(t)
\]  

The evapotranspiration (ET) losses taking place from the SMA tank depend upon current storage or the potential evapotranspiration value, whichever is the minimum of the two as given in equation (3.10). The updated storage content after the ET losses and the corresponding new capacity can be calculated from equation (3.11) and (3.12) respectively.

\[
ET(t) = \min[PET(t), s(t)]
\]

\[
s(t) = s(t) - ET(t)
\]

\[
c(t) = C_{\max} \left[ \frac{1}{1 + \left( \frac{s(t)}{S_{\max}} \right)^{1+b}} \right]
\]

After the generation of runoff through the PDM model the routing component uses a constant split coefficient, \( \alpha \) to divide the runoff into a quick and slow flow. The inflow to quick flow and slow flow reservoirs is given by equation (3.13) and (3.14) respectively. The outflow from these two linear reservoirs forms the total discharge at catchment outlet.

\[
\text{Inflow to quick flow tank} = \alpha \times (OV)
\]

\[
\text{Inflow to slow flow tank} = (1 - \alpha) \times OV
\]
3.3 Description of Hymod-7

Hymod-7 is a seven parameter conceptual model. The variation of PDM in Hymod-7 is similar to the one used by Lamb (1999). Two additions have been made in this model compared to Hymod-5: (1) a precipitation adjustment factor to account for point precipitation error, and (2) a vegetation adjustment factor for improving the evapotranspiration component in the model. This results in a seven parameter lumped conceptual model consisting of a simple SMA component based on the Pareto distribution function, and a routing module, which simulates the lateral flow processes through overland flow, and groundwater flow. This model assumes that all of the effective rainfall is produced through overflow of storage reservoir. Model parameters with associated ranges shown are shown in Table 3.1 (Chow et al., 1988; Sevruk, 1982). The representation of Hymod-7 is shown in Fig. 3.1

The runoff generation is controlled by Pareto distribution function of storage capacity as in Hymod-5. Precipitation is multiplied by a correction factor, $P_{adj}$, to compensate for systematic error in point precipitation measurement (Sevruk, 1982). The adjusted precipitation $PP_{adj}(t)$ is given by equation (3.15).

$$PP_{adj}(t) = PP(t) \times P_{adj}$$  \hspace{1cm} (3.15)

The PDM of Hymod-7 works same as Hymod-5 and generates the total effective rainfall $OV$. But the ET calculation in Hymod-7 is different from Hymod-5 and is calculated by equation (3.16). Here intermediate storage content, $s(t)$, is considered as a percentage of maximum combined storage content, $S_{max}$, for calculating ET losses. A vegetation
adjustment factor, $E_{\text{adj}}$ (Chow et al., 1988) is added to take account of the variation in vegetation in the watersheds. This factor enhances the ET value, which in turn gives a better estimate of storage volume in the SMA tank. The updated storage content after ET losses is given by equation (3.17).

$$ET(t) = \left(\frac{s(t)}{S_{\text{max}}}\right) \times PET(t) \times E_{\text{adj}}, \quad s(t) \leq S_{\text{max}}$$

(3.16)

$$s(t) = \max[0, s(t) - ET(t)]$$

(3.17)

---

**Fig 3.1** Lumped Hymod-5 and Hymod-7 model structure. Parameters enclosed in circle as well as diamond belong to Hymod-7, whereas those enclosed in a circle belong only to Hymod-5. ET and PP are evapotranspiration and precipitation respectively [mm]. OV1 and OV2 are model simulated effective precipitation components [mm]. Q is model simulated stream-flow [mm]. C(t) and S(t) are Soil moisture accounting tank state contents [mm].
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Unit</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_{\text{max}}$</td>
<td>Maximum storage capacity</td>
<td>mm</td>
<td>1</td>
<td>500</td>
</tr>
<tr>
<td>$b$</td>
<td>Index describing distribution of storage capacity</td>
<td>-</td>
<td>0</td>
<td>2.5</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Flow split co-efficient</td>
<td>-</td>
<td>0.1</td>
<td>1.0</td>
</tr>
<tr>
<td>$k_q$</td>
<td>Time constant of linear quick flow reservoir</td>
<td>s$^{-1}$</td>
<td>0.1</td>
<td>1.0</td>
</tr>
<tr>
<td>$k_s$</td>
<td>Time constant of linear slow flow reservoir</td>
<td>s$^{-1}$</td>
<td>0</td>
<td>0.1</td>
</tr>
<tr>
<td>$E_{\text{adj}}$</td>
<td>Vegetation adjustment factor</td>
<td>-</td>
<td>0.2</td>
<td>1.3</td>
</tr>
<tr>
<td>$P_{\text{adj}}$</td>
<td>Correction factor for Precipitation</td>
<td>-</td>
<td>0.9</td>
<td>1.3</td>
</tr>
</tbody>
</table>

### 3.4 Differences between Hymod-5 and Hymod-7

Two additional parameters for precipitation correction ($P_{\text{adj}}$) and vegetation adjustment ($E_{\text{adj}}$) have been included in Hymod-7. Precipitation correction factor $P_{\text{adj}}$ is added to correct point precipitation, which has high probability of being underestimated. Sevruk (1982) points out that the commonly used methods of precipitation measurement underestimate actual precipitation from between 5 to 30%. This error depends upon the type of instrument and its installation, the climatology of the region and the form of precipitation (liquid or solid). The elevation of rain gauge above the ground, the direction of wind speed and angle of rainfall with the gauge can affect the amount of precipitation falling in the gauge. Similarly, splashing, wetting and evaporation can also cause the precipitation to be measured lower than the actual amount. Therefore, corrections have to
be made to the observed value to eliminate the major systematic errors to make these readings useful for hydrological calculations. $P_{\text{adj}}$ values in range of 0.9 to 1.3 have been taken in this study. Similarly, a vegetation adjustment factor $E_{\text{adj}}$ is added to take account of the varying vegetation in the watershed, which affects the ET calculation in the model. ET in the model is a function of Potential Evapotranspiration (PET) which assumes a grassy surface cover for transpiration to occur. Therefore, this adjustment factor is used to enhance calculation of ET for various vegetative covers. The rate of ET controls the volume of water storage in the soil moisture reservoir. Therefore, a more accurate ET value will give a better estimate of storage volume in the tank. $E_{\text{adj}}$ has been taken in the range of 0.2 to 1.3 based on Chow et al., 1988.

The two models differ in ET calculation as shown in equations (4.10) and (4.16). Hymod-5 calculates ET as a linear function of intermediate storage content, $s(t)$, while Hymod-7 calculates ET as a ratio of intermediate to maximum combined storage content ($s(t)/S_{\text{max}}$). This ratio is then multiplied by a vegetation adjustment factor $E_{\text{adj}}$ which enhances the value of ET calculated for diverse vegetation covers. This difference in ET calculation between two models affects the final storage volume in the tank, which is updated after ET losses. Higher ET losses will reduce the storage volume leading to less runoff production. Similarly smaller ET losses will lead to more moisture retention in the SMA storage causing more runoff generation.
Chapter 4

METHODOLOGY

The multi-objective PUB framework used in this study is drawn from the work of Zhang et al. (2008) and Yadav et al. (2007). Section 4.1 provides a detailed discussion of the physical characteristics of the UK catchments and the hydrologic indices considered in regionalization. Section 4.2 introduces the multi-objective optimization formulation used to search for behavioral stream flow ensembles at sites. Section 4.3 provides an overview of regional sensitivity analysis and its use in this study to identify the dominant model parameters controlling predictions.

4.1 Framework for Regionalization

The procedural steps of regionalization approach as suggested by Yadav et al. (2007) are explained in the flowing steps:

1. Calculate hydrological indices of interest from available stream flow observations.

2. Use linear stepwise regression to relate physical and climatic characteristics of watershed to their hydrological indices.

3. Calculate 90% Prediction limits on regression equations.

4. Run a hydrological model in a Monte Carlo framework at ungauged sites, where the model parameters are sampled from feasible ranges using independent uniform distributions.

5. Hydrologic indices are calculated for each parameter set.

6. Regionalized ranges of indices are obtained from prediction limits on regression equations. These ranges provide constraint on watershed behavior at ungauged sites.
7. Classify simulations that produce indices within the ranges as behavioral; while those that produce outside the range as non-behavioral.

8. Choose the maximum and minimum simulated flows produced using behavioral parameter sets to provide ensemble of stream flow predictions.

Regionalization involves the use of regression relationships between multiple physical characteristics of the watershed and each individual response characteristic. Thirteen physical watershed characteristics including area, steepness, base flow index (BFI), grassland, built-up area and elevation are used to establish regression equations. A list of all the physical characteristics is given in Table 2.2 in Chapter 2. The hydrological indices used in the study are derived from observed times series of precipitation, stream flow and ET. Yadav et al. (2007), considered a total of 39 hydrological indices divided into seven categories (Olden & Poff, 2003; Yadav et al., 2007) to analyze different aspects of stream flow. Key properties analyzed include-a) the magnitude of high flows, b) the magnitude of low flows, c) the magnitude of average flows, d) the duration of flows, e) flow frequencies, f) rates of change in flows, and g) the timing of flow events. The indices were pruned for redundancy using linear and Spearman rank correlation coefficients where finally, 3 out of 39 response characteristics were selected to constrain model predictions. The three response characteristics include: the high pulse count (high flows), the runoff ratio (mass balance) and the slope of the flow duration curve (median flows).
Watershed physical characteristics like watershed slope and wetness index were used as predictors of runoff ratio. BFIHOST was used as a predictor of flow duration curve slope and a combination of BFIHOST, topographic slope and wetness index formed the predictor of high pulse count. The ranges of hydrologic indices are estimated as the prediction limits of the regional regression equations for indices high pulse count, runoff ratio, and slope of flow duration. Figs 4.1 (a)-(c) shows the regionalized ranges as well as the observed values of the three indices for the 30 watersheds arranged in increasing order of their search difficulty. These figures show that most of the observed values fall within the prediction limit of regionalization, and only a few indices deviate considerably from the observed values. Ranges of indices varied considerably across 30 watersheds. Narrow constraints or ranges that did not capture the observed index posed problems for identification of behavioral parameter sets.
Fig 4.1 Regression ranges obtained by prediction limits on regression equations and observed hydrologic indices for each of the 30 watersheds (the shaded bar is the prediction limit and the circle is the corresponding observed hydrologic index): (a) high pulse count; (b) runoff ratio; and (c) slope of flow duration curve. Watersheds 13, 26, and 30 are Kirkbymills watershed, Harrowdown Old Mill watershed, and Shalford watershed, respectively. The order of watersheds is the same as the order in Table 2.1. The watersheds are sorted in descending order by the number of behavioral simulation found through ε NSGAII optimization, thus expressing the difficulty of finding behavioral simulations. The search becomes more difficult from watershed 1 to 30.
Building on Zhang et al. (2008), this study provides a detailed analysis of the predictions for the Shalford, Harrowdown Old Mills and Kirkbymills watersheds. As classified by Zhang et al. (2008) Kirkbymills represents an easy search case with high quality regionalized hydrologic indices, Harrowdown’s indices provide a lower quality representation of the watershed’s true behavior, and the Shalford case study has poorly performing regionalized hydrologic indices. For Kirkbymills all of the hydrologic indices (high pulse count, runoff ratio and slope of flow duration curve) fell within the prediction limits of regionalization, whereas for Harrowdown two out of three indices fell within the prediction limits (runoff ratio and slope of flow duration curve). For Shalford only one index (high pulse count) is captured within the prediction limits.

4.2 Multi-objective Formulation

Zhang et al. (2008) presented a novel multi-objective formulation of PUB problem that maps the behavioral model parameter sets (i.e. simulated hydrologic indices that fall within the regionalized ranges) as Pareto optimal solutions. In the formulation, the hydrological indices are normalized between -1 and 1 to provide scaling invariance across objectives (i.e., differences in indices’ magnitudes do not bias multi-objective search). The transformation of N hydrologic constraints into a multi-objective search requires N+1 Objective Functions (OF). The first N objectives minimize the distance to the centers of the prediction limits attained from regression (equation (4.1) for j = 1, 2, 3 and N),

\[
\text{Minimize } f_j = \left| \frac{I_j - I_{qj}}{\delta_j} \right|
\]  

(4.1)
where \( I_j \) is the \( j^{th} \) hydrologic index calculated from simulated flow;

\[ I_{cj} \] is the center of the prediction limit of the \( j^{th} \) hydrologic index,

\( \delta_j \) is the spread of the prediction limit of the \( j^{th} \) hydrologic index that is distance of centre to extreme.

The normalized behavioral indices fall in range of 1 and -1 and have a mean of zero. The first N objectives bias the search towards the mid-points of the hydrologic indices obtained from regionalization. The fourth objective in equation (4.2) is formulated to conflict with the first N objectives from equation (4.1) by biasing search away of the indices’ mid-points and instead seeking the outer extremes of their ranges [1,-1]. Equation (4.2) shows the fourth objective –

\[
\text{Minimize } f_4 = 1 - \left( \sum_{j=1}^{s} \left( \frac{I_j - I_{cj}}{\delta_j} \right)^2 \right)
\]  

(4.2)

Geometrically, equations (4.1) and (4.2) seek to promote the identification of behavioral model parameters over an indices space sphere using multi-objective optimization. For this study, the formulation searches and identifies only the behavioral simulations with respect to three indices. It heavily penalizes solutions which are non behavioral to ensure that all optimization yields only fully behavioral parameter ensembles.

The epsilon NSGAII (\( \varepsilon \)-NSGAII) developed by Kollat & Reed, (2006) is the optimization algorithm used to solve the multi-objective problem formulated in equations
(4.1) and (4.2). It builds on its parent algorithm the NSGAII developed by Deb et al. (2002) by adding 1) ε Dominance archiving, 2) adaptive population sizing and 3) enhanced search using time continuation (i.e., the random injection of new search solutions periodically). The addition of ε Dominance gives the user flexibility to define the precision of each objective in the given problem (Laumanns et al., 2002; Deb et al., 2002). The problem space is then searched using a user specified precision grid.

### 4.3 Regional Sensitivity Analysis

The objective of sensitivity analysis (SA) is to identify the effect of model parameters on output of the model. It helps to understand which parameters of the two models control the dominant aspects of watersheds. Regional Sensitivity analysis (RSA) is one of the methods of SA used in the present study which splits the parameters generated by Uniform random sampling into behavioral (inside the regionalized regression ranges) or non-behavioral (outside the range) according to model performance and plots the cumulative distribution function (CDF) plots of each of the behavioral and non behavioral sets (Tang et al., 2007). The marginal CDF plot of behavioral and non-behavioral parameters is a graphical method of RSA to show the difference in underlying distribution of the two solutions. Similarly, Kolmogorov-Smirnov (KS) test is a statistical method of RSA, which identifies the difference between the underlying distributions of the behavioral and non-behavioral parameter sets. The KS test uses a KS measure/statistic, which is the distance between the CDF plots of behavioral and non behavioral parameters to differentiate between sensitive (which have significant affect on model output) and insensitive parameters.
Chapter 5

RESULTS AND DISCUSSION

5.1 PUB Search Problem’s Difficulty and Failure Modes

The impacts of small increases in model complexity on the difficulty of the multi-objective PUB problem formulation given in equations (4.1) and (4.2) are characterized in Fig 5.1. The figure illustrates search difficulty using search dynamics plots for 25 random seed runs for each of the three watersheds, Kirkbymills, Harrowdown Old Mills and Shalford. In each of these plots, each line represents the progress of an independent run of the ε-NSGAII in identifying behavioral parameter sets versus the number of function evaluations (NFE) used. The NFE is a count of the number of either the Hymod-5 (gray dashed lines) or Hymod-7 (black solid lines) simulations used. The random seed analysis shown in Fig 5.1 provides a statistical evaluation of problem difficulty as has been demonstrated in prior studies (Kollat & Reed, 2006; Tang et al., 2007). As noted by Kollat & Reed (2006) successful search is represented when the independent search traces from independent random seeds show a minimum variation in their dynamics while attaining high quality results.

Comparison of Figs 5.1 (a) and (b) show that both the Kirbymills and Harrowdown cases appear to be reliably solved by the ε-NSGAII. Zhang et al. (2008) showed that Kirbymills and Harrowdown represent easy and moderately difficult search problems for behavioral parameters. Although the Harrowdown case in Fig 5.1 (b) does have a slight increase in search variation (i.e., the spread of the search traces) relative to Kirkbymills in Fig 5.1 (a), both of these cases show that Hymod-7 has little to no impact
on increasing the computational demands or reliability of the ε-NSGAII (as shown with the tightly clustered search traces after 100,000 simulations). Alternatively, Fig 5.1 (c) shows that the Shalford case has dramatically different search dynamics between the Hymod-5 and Hymod-7 cases. If we define a goal of identifying 1000 behavioral solutions for the Shalford case, than Fig 5.1 (c) shows that nearly half of the Hymod-7 runs fail to attain the goal in the 30,000 evaluations (or simulations) recommended by Zhang et al. (2008). The stark contrast in search trace dynamics between the results for the Hymod-5 and the Hymod-7 model formulations shown in Fig 5.1 (c) demonstrates a dramatic change in search failure rates and problem difficulty given a very small change in the overall model’s parameterization (adding two parameters).

A fundamental goal for this work is to characterize the mode of failure causing the highly variable search dynamics highlighted in Fig 5.1 (c) and to clarify its consequence for the PUB problem. The overall performance of our multiobjective PUB methodology is characterized in this study in terms of: (i) the computational search’s success (Fig 5.1), (ii) the impact and coverage of the behavioral indices’ ranges attained from regionalization (Figs 5.2 and 5.3), and (iii) the actual ensemble hydrologic predictions attained (Figs 5.4 and 5.5).

The parameterization changes between Hymod-5 and Hymod-7 as noted in Section 3.4 serve to scale the precipitation ($P_{adj}$) to correct for uncertainties in rain gauge estimates that tend to underestimate the volume of precipitation and to scale evapotranspiration ($E_{adj}$) to be linearly related to the volume of water in storage. Fig 5.2 shows how the addition of these parameters to yield Hymod-7 strongly changes parameter sensitivities relative to the original Hymod-5 formulation. In these figures,
visually the center line represents the uniform distribution for a parameter and the sensitivities for the Hymod parameters are represented by the degree the behavioral ensembles of each parameter deviates from the uniform (non-identifiable) distribution. Tables 5.1 and 5.2 summarize the sensitivity values of parameters where larger KS statistics represent an increased likelihood that a parameter is not uniformly distributed and therefore strongly influences Hymod predictions. For most of the cases, the value of KS statistic increases with decreasing quality of regionalization constraints across the three watersheds indicating that parameter influence on model predictions increases according to the quality of constraints. Similarly, a larger KS value across the parameters for a particular watershed indicates a stronger influence of that parameter on model predictions of the specific watershed.

Unlike traditional calibration applications, our multiobjective PUB methodology uses regionalized ranges for hydrologic flow indices (RR, SFDC, and HPC) to constrain predictions. Constraints on regionalized hydrologic indices as described in Section 4.1 are developed using commonly available sources of data without any knowledge of streamflow. Although Zhang et al. (2008) showed that our multiobjective PUB framework is quite robust as is further supported by Figs 5.1 (a) and (b), the search failures that occur for Hymod-7 in the Shalford case are of major concern. Our sensitivity results show for all of the watersheds that the modest change in model complexity does change the model identification problem’s controlling parameters. For both Kirkbymills and Harrowdown the quick flow time scale $K_q$ and $P_{adj}$ have an increased effect on model predictions. The increased influence of these parameters would have the expected effect of increasing the model’s ability to simulate higher RR
and HPC values. Conversely, the sensitivities for the Shalford case study show that $K_q$ has a diminished role whereas ET impacts on storage increase as represented by the increased sensitivity to $E_{adj}$. Interestingly, the addition of two parameters in Hymod’s formulation for the Shalford case actually reduces the range of hydrologic indices that can be simulated as shown in Figs 5.3-5.5.

**Table 5.1** Table showing Kolmogorov-Smirnov (KS) Statistic values for parameters of Hymod-5 for the three watersheds

<table>
<thead>
<tr>
<th>Name of watershed</th>
<th>$C_{\text{max}}$</th>
<th>$b$</th>
<th>$\alpha$</th>
<th>$k_s$</th>
<th>$k_q$</th>
<th>$E_{adj}$</th>
<th>$P_{adj}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kirkbymills</td>
<td>0.528</td>
<td>0.251</td>
<td>0.650</td>
<td>0.350</td>
<td>0.449</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Harrowdown old mills</td>
<td>0.308</td>
<td>0.181</td>
<td>0.615</td>
<td>0.875</td>
<td>0.488</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shalford</td>
<td>0.800</td>
<td>0.377</td>
<td>0.869</td>
<td>0.891</td>
<td>0.630</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Table 5.2** Table showing Kolmogorov-Smirnov (KS) Statistic values for parameters of Hymod-7 for the three watersheds

<table>
<thead>
<tr>
<th>Name of watershed</th>
<th>$C_{\text{max}}$</th>
<th>$b$</th>
<th>$\alpha$</th>
<th>$k_s$</th>
<th>$k_q$</th>
<th>$E_{adj}$</th>
<th>$P_{adj}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kirkbymills</td>
<td>0.195</td>
<td>0.410</td>
<td>0.442</td>
<td>0.241</td>
<td>0.744</td>
<td>0.307</td>
<td>0.582</td>
</tr>
<tr>
<td>Harrowdown old mills</td>
<td>0.343</td>
<td>0.743</td>
<td>0.739</td>
<td>0.683</td>
<td>0.835</td>
<td>0.429</td>
<td>0.835</td>
</tr>
<tr>
<td>Shalford</td>
<td>0.882</td>
<td>0.627</td>
<td>0.964</td>
<td>0.818</td>
<td>0.293</td>
<td>0.639</td>
<td>0.839</td>
</tr>
</tbody>
</table>

Fig 5.3 provides further evidence that the quality of the regionalized hydrologic indices has a significant impact on the structure of the multiobjective PUB search problem and the overall potential for search failures. Ideally, the problem formulation
given in equations (4.1) and (4.2) will yield a full three dimensional sphere of behavioral indices. In many cases this is not possible due to asymmetries in the indices ranges and feasibility limits. For example, the Shalford indices ranges are limited due to nonnegativity constraints and as shown in Fig 5.2 the Hymod-7 formulation limits the range of indices that can be simulated. Figs 5.3 (a)-(c) show two-dimensional projections for each of the pairs hydrologic indices based on runs selected to represent average or typical results for all three watershed cases. The use of two-dimensional projections allows for a clearer understanding of the distribution of the ensemble members for both the Hymod-5 and Hymod-7 versions of the problem. The Hymod-7 ensemble members are shown with black points superimposed over the gray Hymod-5 behavioral parameter sets. Additionally, the true observed indices values computed using the historical streamflow series for each watershed are plotted in the figures when they fall within the feasible indices’ ranges attained from the regionalization results.

Fig 5.3 (a) shows that the Kirkbymills case has the best performing regionalized constraints where all three observed indices fall within the feasible space defined by the multiobjective PUB formulation used in our study. Zhang et al. (2008) noted that this case is representative of the easiest search problems and the additional model complexity of Hymod-7 did not appreciably change the search problem’s difficulty as noted in Fig 5.1 (a). It should be noted that even for the easiest case the resultant ensemble members do not always perfectly fill the feasible spherical space. It is important to note that the multiobjective PUB formulation given in equations (4.1) and (4.2) is not actually optimizing “indices”, instead it is seeking to find behavioral solutions using the conflicting objectives of minimizing the their distance from the midpoints of the indices
ranges (i.e., the origin of the feasible sphere) and minimizing their distance from the outer edge of the feasible sphere. The intent of this formulation as described by Zhang et al. (2008) is to identify ensembles with a full coverage of the regionalized hydrologic indices’ ranges. As shown in Fig 5.3 the decision variables in this search problem are the Hymod-5 or Hymod-7 model parameter combinations, which in some cases may not yield simulated indices in certain portions of the feasible space.

Fig 5.3 (b) shows that for the Harrowdown case only the SFDC and RR observed indices fall within the regionalized feasible space. As expected, this does reduce the quality of the regionalized constraints used to define the behavioral ensemble and likely explains why in this study as well as Zhang et al. (2008), the Harrowdown case is classified as moderately difficult. As noted in the Fig 5.2 sensitivity results, both the Kirkbymills and Harrowdown show that $K_q$, or the quick flow residence time is sensitive for both models and has a strong impact on both versions of Hymod in terms of generating simulated HPC indices. Given that the regionalized HPC indices constraints for Harrowdown do not capture the observed values, it would be expected that this search problem should be more difficult than Kirkbymills. Overall, Figs 5.3 (a) – (c) show an increasing discrepancy between the Hymod-5 and Hymod-7 ensembles where the general trend shows that the addition of the precipitation and ET scaling factors serve to reduce the overall spread of the solution sets.

Moving from Hymod-5 to Hymod-7 generally causes preferential sampling of higher RR and HPC values. This effect can be explained simply by the fact that $P_{adj}$ will serve to increase simulated streamflow peaks and precipitation. As noted in the sensitivity results from Fig 5.2 (b) $E_{adj}$ is far less sensitive for the Kirkbymills and
Harrowdown cases versus Shalford. Shalford has a baseflow (or storage) dominated flow regime where for some ensemble members shown in Fig 5.3 (c). Hymod-7 yields significantly smaller simulated RR indices since increased evapotranspiration can reduce the overall water available from storage particularly while increasing precipitation. The overall poor indices’ coverage in Fig 5.3 (c) show the strong impacts of the poor quality regionalized hydrologic indices constraints attained for Shalford where only one of the watershed’s true indices (HPC) is captured.

To this point, we have shown how search dynamics (Fig 5.1) and their concomitant indices coverage (Fig 5.3) is impacted by the decreasing quality in the hydrologic indices constraints attained from regionalization. Figs 5.4 and 5.5 show the resultant ensemble predictions and observations for the daily hydrographs for a representative year and the overall flow duration curves for each of the watersheds, respectively. These figures provide the third criteria for judging the success or failure of our multi-objective PUB framework as noted above. Figs 5.4 (a) – (c) largely support our results and discussion in terms of the models’ sensitivities (Fig 5.2), their impacts on the simulated indices, and the overall indices space coverage attained using the regionalized hydrologic indices constraints (Fig 5.3).

The observed streamflow is well captured by the Hymod-5 and Hymod-7 ensembles for Kirbymills and Harrowdown. In general, the Kirbymills case in Fig 5.4 (a) shows minor differences between the ensembles attained by Hymod-5 and Hymod-7 with the greatest difference occurring for the lowest flow periods. This is confirmed with the Kirbymills FDC results shown in Fig 5.5 (a). Close inspection of the plots in Figs 5.4 (b) and 5.5 (b) shows that the precipitation and ET scaling factors in Hymod-7 tend to largely
affect extreme flows by increasing peak flows and decreasing low flows represented in the ensemble. Fig 5.5 (b) highlights that ensemble projections for the Harrowdown are of high quality for median and low flows, both of which are strongly impacted by the RR and SFDC regionalization constraints. It is not surprising the peak flows for Harrowdown are poorly constrained given that the regionalized HPC constraint ranges for this system failed to capture the true observed value as illustrated in Fig 5.3 (b).

For the Shalford watershed, the hydrographs and FDC results in Figs 5.4 (c) and 5.5 (c) show that the additional precipitation and ET scaling in Hymod-7 does not improve the behavioral ensembles performance. The low flow dominated hydrograph for this system shows that increase in storage dependent ET serves largely to yield lower extremes for low flow projections and that the precipitation scaling does very little to increase peak flows as demonstrated in Fig 5.5 (c). In fact, the best overall ensemble predictions for Shalford are attained for the high flow cases that are exceeded only 20-percent of the time. This is because the regionalized HPC constraint ranges for Shalford are able to capture the true observed value. The median and low flows for Shalford are not captured by the behavioral ensembles and Hymod-7 serves only to exacerbate this issue.

5.2 Advancing Ensemble Predictions in the Absence of Observations

In the general PUB context, we would not have the benefit of knowing the true or observed hydrologic indices, which gives rise to the following questions:
(1) How should we assess the quality of regionalized hydrologic constraints and their ability to improve ensemble predictions from increasingly complex models in the absence of observations?

(2) Given the regionalization errors for the Shalford case, does search with the $\varepsilon$-NSGAII matter for improving the quality of the behavioral parameter ensembles attained?

We have largely answered the first question in Figs 5.1 (c) and 5.3(c) where our changes to Hymod have actually served to reduce its ability to capture the Shalford watershed’s flow regime. Simply adding additional parameters in this case does not yield improved prediction results as is often the case for typical hydrologic calibration applications where false correlations between model parameters and observations can result as a consequence of optimization (Vogel & Sankarasubramanian, 2003). The regionalization constraints in this case cause the search problem to suffer from “deception” where regardless of search effectiveness our problem formulation is flawed. Our results highlight that there can be severe consequences for the multi-objective PUB framework with small changes in a model’s structure or formulation that do not serve to align simulated hydrologic indices with the feasible indices regions attained from regionalized constraints. In the absence of observations, the consistency of search results attained by the $\varepsilon$-NSGAII (i.e., low variation in search traces) as well as the overall coverage attained in the behavioral indices space can be used as diagnostics for our multi-objective PUB framework. Fig 5.3 shows that the coverage of the feasible hydrologic indices’ ranges is heavily limited when regionalization results are highly inaccurate.
Figs 5.6-5.7 address the second question, does search with the $\varepsilon$-NSGAII matter for cases when the regionalized indices hydrologic constraints are wrong. Fig 5.6 shows the impact of allowing the three Shalford seeds (i.e., the $\varepsilon$-NSGAII search traces) highlighted in Fig 5.1 (c) to continue to search beyond 100,000 simulations up to 500,000 evaluations. In the context of the Tang et al. (2007) classification of failure modes, it does appear that continued search allows seed 1 and 2 to reach nearly identical behavioral ensemble counts while seed 3 still struggles. To some degree, this implies that errors in formulating regionalized hydrologic constraints can result in significantly increasing the computational demands to attain comparably ensemble sizes. More importantly, Fig 5.7 demonstrates the importance of considering random seed analysis for assessing the PUB framework’s performance.

Random seed analysis itself significantly increases computational demands since each seed requires a full run of the $\varepsilon$-NSGAII. Fig 5.7 (a) shows the relative indices coverage that result from seed 2 and seed 3 after the $\varepsilon$-NSGAII searches the feasible hydrologic indices space for Shalford using 500,000 simulations. Note seed 1 and seed 2 were able to converge to similar ensemble sizes and therefore only seed 2 is shown in Fig 5.7. Although continued search served to improve seed 3, its overall coverage of the feasible hydrologic indices space is very limited relative to seed 2. This result represents a structural failure of the $\varepsilon$-NSGAII where regardless of search duration for seed 3 the algorithm was not able to identify broader regions populated by seed 2. The best overall approach in this case would likely be to build an overall set of ensemble members across all of the seeds run for an application. Fig 5.7 (b) shows that there would be a severe consequence for using solely seed 3’s ensemble for predicting the Shalford watershed’s
response. Nearly the entire observed flow regime lies outside of its prediction range. In summary, random seed analysis and increased search durations are particularly important when using the $\varepsilon$-NSGAII in cases where there are significant errors from hydrologic indices regionalization.

![Plots showing Behavioral solutions Versus Number of Functional evaluations for 25 trial seeds of Hymod-5 and Hymod-7 for the 3 test watersheds](image)

**Fig 5.1** Plots showing Behavioral solutions Versus Number of Functional evaluations for 25 trial seeds of Hymod-5 and Hymod-7 for the 3 test watersheds, (a) Kikbymills, (b) Harrowdown Oldmills and (c) Shalford. The increase in search difficulty of Hymod-7 can be seen from the increased variance of the plots from easy (a) to hard (c) cases.
Fig 5.2 Marginal cumulative distribution functions (CDF) plots of parameters of, a) Hymod-5 and b) Hymod-7, for 100,000 numbers of functional evaluations (NFE) for 3 watersheds: Kirkbymills, Harrowdown old mills and Shalford. The non behavioral parameters follow a uniform distribution shown by a straight dotted line, while the behavioral parameters are constrained according to regionalization constraints. The distance between the CDF plots of behavioral and non behavioral parameters is the Kolmorgorov-Smirov (KS) Statistic.
Fig 5.3 Scatter plot showing the coverage of behavioral indices space for the 3 indices of high pulse count (HPC), runoff ratio (RR) and slope of flow duration curve (SFDC) for a) Kirkbymills – easy case b) Harrowdown Old mills – a medium difficulty case and c) Shalford – a difficult case. The behavioral indices are normalized between 1 and -1.
Fig 5.4 Plots of observed and ensemble stream flow hydrographs for Hymod-5 and Hymod-7 for a representative year of data plotted using the Box-Cox transformation to better distinguish high flow and low flow conditions in three watersheds. The panels illustrate the resultant ensembles for (a) Kirkbymills, (b) Harrowdown Old mills and (c) Shalford. The ensembles shown correspond to representative seeds for average performance attained using 100,000 function evaluations. The stream flow data of second year has been used to plot this hydrograph.
**Fig 5.5** Plots of observed and ensemble flow duration curves for Hymod-5 and Hymod-7 for the full time series of 10 years for the 3 watersheds. The panel shows the resultant ensembles for, (a) Kirkbymills, (b) Harrowdown Old mills and (c) Shalford. The ensemble flow duration curves correspond to representative seeds for average performance attained using 100,000 function evaluations.
Fig 5.6 Plots showing Behavioral solutions Versus Number of Functional Evaluations for the 3 selected seeds of Shalford-a difficult case. The plots show the average performance of the 3 seeds attained using 500,000 function evaluations.

Fig 5.7 Plot showing (a) the three indices plots and (b) the FDC distribution for the seed2 (best) and seed3 (worst) as seen in figure 5.6 of Shalford case. The first figure, 5.7(a) shows the areal coverage of behavioral indices for Hymod-7 using the 2 seeds. The second figure shows ensemble of flow duration curve for Hymod-7 using the two seeds.
Chapter 6
CONCLUSIONS

The overall purpose of this thesis is to fully characterize the impact of hydrologic indices regionalization on the difficulty of using multi-objective optimization to identify behavioral parameters for making ensemble predictions in ungauged basins. This work contributes a careful exploration of the modes of failure that can dramatically reduce the value and effectiveness of using multi-objective optimization in the PUB problem. The overall performance of our multi-objective PUB methodology is characterized in this study in terms of: (i) its potential for search failures as quantified using random seed analysis of the search dynamics for the ε-NSGAII, (ii) the causal relationships between search failures and the quality of search constraints based on regionalized hydrologic indices, and (iii) the quality of its resultant ensemble hydrologic predictions attained using both high, intermediate and low quality regionalized hydrologic constraints.

Overall our results confirm that high quality regionalization constraints allow our PUB framework to reliably capture the full flow regimes for ungauged watersheds. As the quality of the indices decreases, the framework still performs well if the underlying hydrologic model is sufficiently parsimonious and unconstrained in simulating a range of hydrologic flow conditions. This was shown to be true even in the extreme case for Hymod-5 when two out of three hydrologic indices’ ranges attained from regionalization failed to encompass the Shalford watershed case study’s true (or observed) flow indices. Failures in our multiobjective PUB arose when we considered slight increases in our simulation model’s complexity (i.e., moving from a 5-parameter formulation to a 7-
parameter formulation). Model complexity increases had minimal impacts in cases where the regionalized hydrologic indices constraints where successful in encompassing at least a subset of the watersheds’ true flow properties. Failures arose only in the extreme case represented by Shalford where a majority (two out of three) of the hydrologic indices was not reflective of the true watershed flow properties.

Since in the general PUB context knowledge of the true or observed hydrologic indices for focus watershed systems is unavailable, our research gives rise to the following questions: (1) how should we assess the quality of regionalized hydrologic constraints and their ability to improve ensemble predictions from increasingly complex models in the absence of observations? and (2) given the regionalization errors for the Shalford case, does search with the $\varepsilon$-NSGAII matter for improving the quality of the behavioral parameter ensembles attained? Our results highlight that there can be severe consequences for the multiobjective PUB framework with small changes in model structure or formulation that do not serve to align simulated hydrologic indices with the feasible indices regions attained from regionalized constraints. In the absence of observations, the consistency of search results attained by the $\varepsilon$-NSGAII (i.e., low variation in search traces) as well as the overall coverage attained in the behavioral indices space can be used as diagnostics for our multi-objective PUB framework.

Using Tang et al. (2007)’s classification of failure modes, it does appear that continued search with $\varepsilon$-NSGAII can improve ensemble predictions in extreme cases where regionalized hydrologic indices do not reflect true watershed properties. To some degree, this implies that errors in formulating regionalized hydrologic constraints can result in significantly increasing the computational demands to attain comparable
ensemble sizes. More importantly, this study demonstrates the importance of considering random seed analysis for assessing the PUB framework’s performance. Random seed analysis itself can significantly increase computational demands since each seed requires a full run of the \( \varepsilon \)-NSGAII. This study does provide evidence that low quality regionalization results can yield premature convergence (or search stall) for the \( \varepsilon \)-NSGAII where regardless of search duration single poor runs of the algorithm are not able to improve ensemble predictions. The best overall approach in this case is to build an overall set of ensemble members across several \( \varepsilon \)-NSGAII runs (i.e., several seeds). So in summary, random seed analysis and potentially increased search durations are particularly important when using the \( \varepsilon \)-NSGAII in cases where there are significant errors in our multi-objective PUB formulation that result from low quality regionalization results.
Chapter 7

RECOMMENDATIONS FOR FUTURE RESEARCH

Several aspects of the research presented in this thesis could be advanced through additional research. The main aspects are discussed briefly below as a starting point for other students.

This study uses three hydrological indices to constrain the different flow regimes (high, medium and low flows). It might be interesting to test a more elaborative list of indices since the selection might change with watershed and climatic characteristics. The study can also be extended to better understand which combination of indices can help best in reducing predictive uncertainty for potentially different prediction objectives (e.g. flood and drought forecasting, water resource planning). The case study uses data from 30 UK watersheds to derive regression equations between watershed physical and climatic characteristics and streamflow indices. Subsequently, only 3 out of 30 watersheds are used to test differences in the optimization for the two watershed models chosen. A larger dataset with a larger variety of watersheds could help in testing the robustness of the approach for a wider range of conditions, e.g. hydroclimatic.

This study uses two lumped conceptual watershed models for testing the impact of regionalized indices constraint on predictions of flow at ungauged locations. A valuable extension to this study could be the use of more complex or even distributed hydrological models to further test the impact of complexity on calibration success.
REFERENCES


