Regionalization of IHACRES Model Parameters for Integrated Assessment across the Lake Erie, northern Ohio USA basin

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Abstract: The IHACRES model is being applied in a regionalization approach to develop streamflow predictions within the region of Northern Ohio, U.S.A. that drains into Lake Erie, located on the border between the U.S. and Canada. The approach to-date is based on independent univariate regressions of model parameters on watershed attributes for a collection of 11 watersheds. Anderson et al. (2005) used one of these regression relationships to represent possible effects of declining forest cover on streamflow, but did not obtain regional models for the parameters of the routing model of IHACRES. Here we apply and "validate" a regionalization approach to estimating the full set of parameters of the IHACRES hydrologic model for integrated assessment across the Lake Erie, northern Ohio USA basin. We also propose that future research should focus on (1) increasing the quality of rainfall estimates as an important way to potentially improve simulation performance; (2) developing joint probability distributions over the full set of IHACRES model parameters to improve estimates of predictive uncertainty; and (3) developing estimates of actual forest cover trends to obtain more useful predictions of future trends in streamflow.

Keywords: IHACRES, regionalization, Lake Erie, integrated assessment, hydrologic modelling, least squares

1. INTRODUCTION

In the Lake Erie northern Ohio, USA basin, reductions in forest cover implied by ongoing rates of urbanization are likely to lead to changes in hydrologic regime (Anderson et al. 2005). To link land use and river discharge, the parameters of the loss module of the IHACRES hydrologic model were statistically related to catchment landscape attributes, including forest cover. This regionalization approach was based on a set of 11 catchments related hydrologically by their common location within the Lake Erie drainage basin. Two catchments are of particular interest for predictive purposes, the Chagrin (637.1 km^2) and the Grand (1774.1 km^2). Both are located toward the east within the more urbanized portion of the region. Our previous analysis did not report regional relationships with the parameters of the routing model of IHACRES and thus was unable to sufficiently test predictive ability within the catchments of interest.

The top-down approach to hydrologic model development is one that begins with an analysis of catchment scale data and features and from these attempts to infer smaller-scale processes (e.g., Sivapalan et al. 2003). Previous authors have categorized the use of the hydrologic model IHACRES in a regionalization approach as an example of the top-down method (e.g., Kokkonen et al. 2003). IHACRES is desirable for use in regionalization analysis because of its simple structure and parsimonious parameterization (Jakeman and Hornberger 1993). The goal of this paper is to assess the usability of the IHACRES model within an overall integrated assessment framework under development for application within the Lake Erie, northern Ohio USA basin. First, we discuss the development of statistical relationships between landscape attributes and IHACRES model parameters, highlighting the difficulties encountered and how they were addressed. Second, we attempt to "validate" these relationships for the Chagrin and Grand by re-deriving the regional relationships based on sets of catchments from which the Chagrin and Grand are successively excluded. We evaluate the predictive ability of the "validated" regional relationships based on comparing their streamflow simulation performance to that based on calibrated parameters.

2. METHODOLOGY

2.1 IHACRES Model Description and Calibration.

Detailed description of the IHACRES model and several applications can be obtained from a number of sources (e.g., Jakeman et al. 1990, Kokkonen et al. 2003). IHACRES applies a transfer function/unit hydrograph approach to relate total rainfall to total discharge in two stages. In the first (Table 1a), a nonlinear loss module calculates the amount of rainfall that is not delivered to the stream (e.g., lost due to evapotranspiration or held within the soil), producing an effective rainfall, which, in the second stage module (Table 1b) is linearly routed to the catchment outlet. Routing takes place via two parallel flow paths, one a quick flow path to the catchment outlet with a short response time, and the other a slow flow path with a long response time.

Table 1a: IHACRES Loss Model

Equations	
$s_k = c \cdot r_k + \left[1 - \frac{1}{\tau_w(T_k)}\right] s_{k-1}$ $\tau_w(T_k) = \tau_w \exp[(20 - T_k) f]$ $u_k = r_k s_k$	
Variables	
k	Time step = 1 day
s_k [unitless]	Index of Soil Moisture Storage
T_k [°C]	Temperature
r_k [mm/day]	Incident rainfall
u_k [mm]	Rainfall excess
Parameters	
τ_w [days]	Time constant of wetness decline at 20 °C
f [1/°C]	Temperature modulation parameter
c [1/mm]	Index of catchment wetness capacity

We calibrated IHACRES for each of 11 catchments and chose the models, one per catchment that best simulated observed streamflow for water years spanning the period October 1989 – September 1999. Thus a model consists of a calibrated set of six parameters τ_w, c, f, τ_q, τ_s, v_s, which can be viewed as attempting an efficient and unique characterization of key hydrologic processes of the catchment.

2.2 Development of Regional Landscape-Hydrologic Parameter Relationships.

Regression approaches that have been applied to cross-sectional data to relate catchment characteristics to model parameters typically apply the following general steps (e.g., Kokkonen et al. 2003, Wagener and Wheater 2005):

(1) Establish an expectation of which landscape or climate variables could yield strong statistical relationships with each calibrated model parameter.

(2) Use linear regressions to formulate and assess these relationships.

(3) Validate linear regressions by predicting model parameters for each catchment based on a regression assessed without including the particular catchment.

Here we follow these steps, highlighting the particular problems encountered in the Lake Erie context. We focus on step (3) for the Chagrin and Grand. Table 2 lists calibrated parameters and a subset of attributes for the 11 catchments. Landscape attribute and hydrometerological data sources are described in Anderson et al. (2005). While there are many additional candidate landscape attributes, we had a high prior probability that many of these might be suitable based on previous reported studies with IHACRES (e.g., Sefton and Howarth 1998, Post and Jakeman 1999).

Table 1b: IHACRES Routing Model

Variables	
Δ	Sampling interval = 1 day
α , β	Polynomial transfer function coefficients
Parameters	
$\tau_q = -\Delta / \ln(-\alpha_q)$ [days]	Quick response time constant
$\tau_s = -\Delta / \ln(-\alpha_s)$ [days]	Slow response time constant
$v_q = \beta_q / (1 + \alpha_q)$ [unitless]	Quick volumetric throughput
$v_s = \beta_s / (1 + \alpha_s)$ [unitless]	Slow volumetric throughput

3. RESULTS AND DISCUSSION

3.1 Temperature Modulation Parameter.

Factors affecting seasonal variation of evapotranspiration, such as climate and land use/land cover, should drive variations in the temperature modulation parameter f. Climate variables do not vary much across our 11 catchments and thus will not explain much of the variation in f. A relationship was found with the percentage of each catchment with forested land cover, *Forested* (Table 3).

Table 2a: Calibrated IHACRES Model parameters. Listing order corresponds to the gradient from predominantly agricultural in the west to large proportions of forest in the east.

Catchment	Calibrated Parameters					
	f	τ_w	$1/c$	τ_q	τ_s	v_s
Tymochtee	2.7	3.4	148	1.95	80	0.21
Rock Creek	2.4	5.5	178	0.80	426	0.11
Honey Creek	2.8	1.8	132	2.59	40	0.12
Bucyrus	4.0	3.0	186	1.43	511	0.08
Huron	3.4	3.0	200	1.36	191	0.15
Black	3.1	2.7	200	2.08	251	0.07
Rocky	2.3	8.1	222	1.05	718	0.11
Yellow Creek	1.7	14.6	351	1.54	110	0.32
Tinkers Creek	1.5	10.1	153	1.6	158	0.22
Chagrin	2.0	5.2	180	0.96	352	0.35
Grand	1.6	6.6	176	2.65	123	0.02

Larger values of f in IHACRES mean that soil drying times (a parameterization of the evapotranspiration process) decrease more rapidly as temperatures increases. The negative relationship with *Forested* says that drying times decrease more slowly (smaller values of f) as *Forested* increases, which takes place as you move eastward in this region. So, for example, as temperatures rise in the early spring, forests experience lower rates of increase in photosynthesis and transpiration relative to agricultural fields. Leaf-out of agricultural fields (typically planted in corn and soybeans) may take place earlier in the spring due to crop rotation schedules and/or may be enhanced by fertilization. The hypothesized relationship suggested by this statistical finding was further investigated by examining the annual water balance across the region by calculating the annual average fraction of evapotranspiration based on available discharge and rainfall data within the ten-year study period (ETFrac, Table 2b). We found consistency with our regional model used to predict f in that ETFrac increases towards the west where there is more agriculture. This result is also consistent with previous bottom-up approaches that have confirmed the importance of the link between land use and evapotranspiration on catchment hydrology (e.g., Dunn and Mackay 1995). This result has the potential for fruitful interaction between top-down and bottom-up research perspectives.

3.2 Time Constant of Wetness Decline.

Land use/land cover, soil drainage and infiltration rates, or some aspect of hydrogeology (e.g., soil or aquifer depths) should drive variations in the time constant of wetness decline τ_w. Anderson et al. (2005) reported a relationship with *g100* (R^2 = 0.64), the extent of drift thicknesses greater than 100 ft in depth (Table 3). The prevalence of very deep soils and/or associated aquifers leads to longer soil drying times, which would produce more runoff. Incidence of drift thicknesses greater than 100 ft. increases as you move eastward (Table 2b). Thus this statistical finding is consistent with the fact that eastward catchments within the region have higher runoff proportions.

Table 2b: Subset of attributes for the 11 catchments (corresponding to rows of Table 2a).

Catchment Attributes				%ARPE^{-1}
Area [km^2]	*Forested* [%]	*g100* [%]	*ETFrac*	
593.1	10.8	1.2	0.66	11.11
89.6	16.2	0.0	0.67	8.33
385.9	12.5	6.5	0.68	6.67
230.0	12.6	0.5	0.56	11.11
960.9	15.1	5.7	0.65	12.5
1025.6	26.5	14.5	0.67	10
691.5	42.7	17.8	0.55	12.5
79.5	60.3	35.2	0.61	6.67
217.3	38.1	36.9	0.42	14.29
637.1	62.5	24.8	0.53	9.09
1774.1	45.2	12.2	0.54	1.79

3.3 Catchment Wetness Capacity Index.

The larger the value of $1/c$ [mm], the greater the catchment storage capacity, and the lower the streamflow. Thus $1/c$ should vary directly with landscape attributes that slow flow delivery to stream channels. Post et al. (1996) found a dramatic reduction in $1/c$ as a result of the reduction in transpiration following clearfelling (85% removal of tree cover). However, our relationship with Forested was not very strong (R^2 = 0.30; Table 3). Wagener and Wheater (2005) suggest that a better fit could be derived from attributes that measure physical characteristics of soil such as porosity.

3.4 Quick Response Time Constant.

Post and Jakeman (1999) assumed that surface and shallow subsurface flow delivery times, such as characterized by τ_q, are likely to be related to size and shape of the catchment and stream network densities. Here a positive relationship with catchment area was identified; though weak statistically (R^2 = 0.25), it shows the right physical trend (Table 3). Littlewood (2003), who also carried out a regionalization analysis using IHACRES, comments that calibrated values of τ_q that are close to or less than 1 day indicate that sub-daily data (unavailable in this case) would be required to establish the quickflow dynamic. Rock Creek, Rocky, and Chagrin fall into this category (Table 2), which may explain the weak statistical performance obtained in this study.

Table 3a: Regional models relating catchment attributes to IHACRES model parameters

Model Parameter	Regional Model
f	− 0.03 · *Forested* + 3.43
τ_w	0.23 · *g100* + 2.56
$1/c$	1.64 · *Forested* + 142.10
τ_q	0.002 · *Area* + 1.27
v_s	0.003 · *Forested* + 0.07
τ_s	190.64 (median)

3.5 Slow Volumetric Throughput Fraction.

Soil depths or geology would control the split v_s between shallow and deeper flow pathways. Sefton and Howarth (1998) identified a strong relationship (R^2 = 0.59) between v_s and percent catchment containing a groundwater or aquifer component. Our initial attempts produced only weak relationships. Wagener and Wheater (2005) suggested that improvement over the traditional approach of seeking correlations between model parameters and landscape attributes could be obtained by weighted regression in which more weight is given to parameters that are better identified in the calibration process. They used a heuristic measure of identifiability that functions as an indicator of posterior parameter uncertainty, using the identifiability measures themselves as weights. The calibration/estimation algorithm used by IHACRES to identify routing model parameters produces an average relative parameter error, %ARPE (Jakeman et al. 1990), the reciprocal of which was used here as weights in a weighted regression (Table 2). This resulted in a stronger (R^2 = 0.40) and physically sensible relationship between v_s and *Forested* (Table 3).

Table 3b: CL indicates 95% confidence limits for the parameters corresponding to the rows of Table 3a.

Lower CL	Regional Parameter	Upper CL	R^2
− 0.05 2.68	− 0.03 3.43	− 0.01 4.18	0.54
0.10 0.05	0.23 2.56	0.36 5.07	0.64
− 0.23 74.01	1.64 142.10	3.52 210.20	0.30
− 0.001 0.64	0.002 1.27	0.004 1.90	0.25
0.002 0.04	0.003 0.07	0.004 0.10	0.40
–	–	–	–

3.6 Slow Response Time Constant.

Wagener and Wheater (2005) argue that calibrations to identify the slow response time constant τ_s based on the entire hydrograph will tend to be unsuccessful because this parameter is related to the low flow periods. This is a possible reason for the weak relationship obtained by Sefton and Howarth (1998) (R^2 = 0.14) and in our study as well. IHACRES estimates the parameters of the routing model (τ_q, v_s, and τ_s) together, limiting the possibility of estimating τ_s by comparison to low flows alone. Littlewood (2003) proposed an augmented calibration scheme to readjust the temperature modulation parameter f after initial calibration in order to improve the fit at low flows, but did not obtain stronger statistical relationships between τ_s and catchment attributes. Following Seibert (1999), we choose the median value as a regional model for the parameter. Weighted regression did not lead to useful relationshps in estimating τ_q or τ_s.

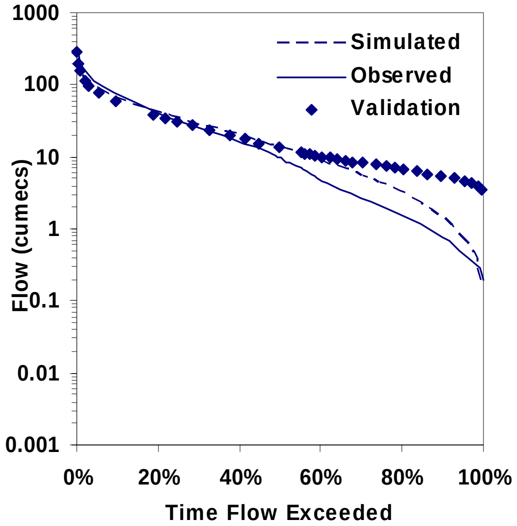

Figure 1a: Flow Duration Curves for observed, simulation, and validation streamflows for the Grand catchment.

3.7 Validations for Grand and Chagrin Catchments.

Figure 1 shows for the Grand and Chagrin flow duration curves for observed flows, as well as for simulations based on calibrated model parameters and on validation runs from which the Grand and Chagrin have been successively excluded. Observed flows show more variability for the Grand than for the Chagrin, where flows are sustained in between rainfall events by a relatively substantial baseflow component. This difference in flow behaviour is captured in the simulations (Table 2, column v_s). However, the simulations also show departure from observed flows, particularly at the low flow end of the spectrum, where flows are overestimated. Poor estimates of rainfall available for runoff are likely to be an important reason, since the region is one of significant snowfall and IHACRES has no mechanism to account for frozen precipitation. A simple degree-day approach was taken to improve initial Thiessen polygon-based estimates of available precipitation (Anderson et al. 2005). However, further research is necessary to explore additional gains that might be obtained via methods based, for example, on more appropriate rainfall interpolation schemes. Littlewood (2003) also obtained low flow simulation errors after initial calibration, but does not attribute it to quality of rainfall estimates.

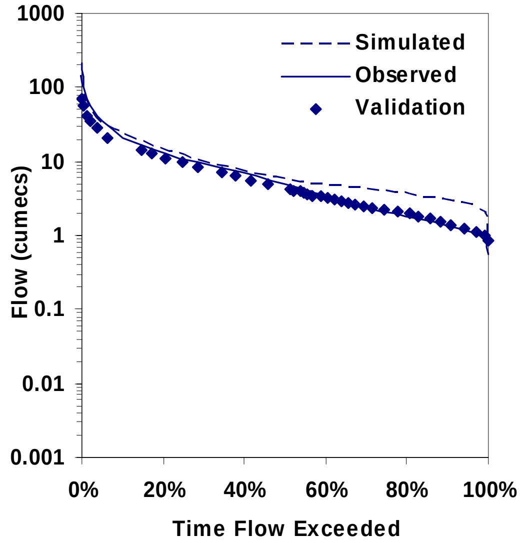

Figure 1b: Flow Duration Curves for observed, simulation, and validation streamflows for the Chagrin catchment

Figure 1 also compares model performance for the Grand and Chagrin for simulations based on the original calibrated parameters (Table 2) with validation runs. Validation runs result in greater overestimation of low flows for the Grand, but, unexpectedly, low flows decline and low flow fit improves for the Chagrin. This is not explained by the accompanying changes in v_s, which increases from the calibrated value of 0.02 (Table 2c) to 0.23 for the Grand, but decreases from 0.35 to 0.22 for the Chagrin. Such unintuitive results are likely to be an effect of our small sample size.

Table 4 gives another perspective on the performance obtained in validation runs. The declines in R^2 and standard error for the Grand are mostly due to deviations at the low flow end, while for the Chagrin they are due mostly to deviations at the high flow end. Given the modest overall degradation in performance, future research will focus on improving the performance of original simulations.

Table 4: Model Performance of calibrated parameters vs. parameters predicted by regional regressions from which Chagrin and Grand have been successively excluded ("validation").

Catchment	Calibrated Parameters		
	R^2	Standard Error	Avg. Bias (m^3/s)
Chagrin	0.63	10.0	-1.65
Grand	0.66	25.3	-0.58
	"Validation Parameters"		
	R^2	Standard Error	Avg. Bias (m^3/s)
Chagrin	0.59	10.5	2.33
Grand	0.64	26.1	1.81

3.8 Effects of Forest Cover Reduction on Streamflow

Under assumptions of normality, one can take the standard errors of regression and propagate these into streamflow predictions to obtain an estimate of predictive uncertainty, which could in turn be expressed as a function of different levels of forest cover. This was demonstrated by Anderson et al. (2005) under the simplifying assumption that changes in streamflow can be usefully predicted by a single regression between forest cover and the temperature modulation parameter f (Table 3a). However, as this analysis shows, there are relationships between forest cover and other parameters of the IHACRES model (Table 3a), so this interaction is likely to be more complex. Future research should focus on developing joint probability distributions over IHACRES model parameters to be combined with actual estimates of forest cover trends to develop more useful predictions of future trends in streamflow in the region.

4. CONCLUSION

The IHACRES model is being applied in a regionalization approach to develop streamflow predictions for integrated assessment within the region of Northern Ohio, U.S.A. that drains into Lake Erie. The methodology is applied and "validated" for the full set of IHACRES model parameters. Given the modest overall degradation in performance, we conclude that ongoing development of IHACRES in this context could be fruitful. Future research should focus on (1) increasing the quality of rainfall estimates as an important way to potentially improve simulation performance; (2) developing joint probability distributions over the full set of IHACRES model parameters to improve estimates of predictive uncertainty; and (3) developing estimates of actual forest cover trends to obtain more useful predictions of future trends in streamflow.

5. REFERENCES

Anderson, RM, B.F. Hobbs, and J.F. Koonce. Modeling effects of forest cover reduction on larval walleye survival in Lake Erie Tributary spawning basins. To appear in *Ecosystems*, 2006.

Dunn, SM., and R. Mackay. Spatial variation in evapotranspiration and the influence of land-use on catchment hydrology. *J. of Hydrology* 171: 49-73, 1995.

Jakeman AJ, Littlewood IG, Whitehead PG. Computation of the instantaneous unit hydrograph and identifiable component flows with application to two small upland catchments. *J. of Hydrology* 117: 275-300, 1990.

Jakeman AJ, Hornberger GM. How much complexity is warranted in a rainfall-runoff model? *Water Resour. Res.* 29: 2637-2649, 1993.

Kokkonen, T.S., A.J. Jakeman, P.C. Young, and H.J. Koivusalo. *Hydrol. Proc.* 17: 2219-2238, 2003.

Littlewood, IG. Improved unit hydrograph identification for seven Welsh rivers: implications for estimating continuous streamflow at ungauged sites. *Hydrol. Sci. J.* 48: 743-762, 2003.

Post DA, Jakeman AJ. Predicting the daily streamflow of ungauged catchments in S.E. Australia by regionalising the parameters of a lumped conceptual rainfall-runoff model. *Ecol. Model.* 123: 91-104, 1999.

Post DA, Jakeman AJ, Littlewood IG, Whitehead PG, Jayasuriya MDA. Modelling land-cover induced variations in hydrologic response: Picaninny Creek, Victoria. *Ecol. Model.* 86: 177-182, 1996.

Sivapalan, M., G. Bloschl, L. Zhang, and R. Vertessy. Downward approach to hydrological prediction. *Hydrol. Proc.* 17: 2101-2111, 2003.

Sefton CEM, Howarth SM. Relationships between dynamic response characteristics and physical descriptors of catchments in England and Wales. *J. of Hydrology* 211: 1-16, 1998.

Seibert, J. Regionalisation of parameters for a conceptual rainfall-runoff model. *Agric. Forest. Meteor.* 98-99:279-293, 1999.

Wagener, T., and H.S. Wheater. Parameter estimation and regionalization for continuous rainfall-runoff models including uncertainty. To appear in *J. of Hydrology*, in press.