Calibration of a Simple Rainfall-runoff Model for Long-term Hydrological Impact Evaluation

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Abstract: *The Long-Term Hydrological Impact Assessment (L-THIA) model is widely used to study direct runoff changes with respect to different land-use conditions. L-THIA was designed to assess the long-term impacts on the hydrology of a watershed for users who want to determine the relative change in runoff from one land-use condition to another. Some users, however, are interested in results that match observed stream-flow data, which includes both direct runoff and baseflow. A simple method of calibration of the L-THIA using linear regression of L-THIA predicted direct runoff and USGS-observed direct runoff values derived from hydrograph separation was developed and tested. The calibration model has been verified using three tests in the Little Eagle Creek watershed in Indiana. Results also raise additional questions regarding the factors that control runoff production and systematic underprediction of direct runoff by L-THIA as compared to actual observed direct runoff data.*

INTRODUCTION

Continued land development and land-use changes within cities and at the urban fringe present considerable challenges for environmental management. Hydrologic changes including increased impervious area, soil compaction, and increased drainage efficiency generally lead to increased direct runoff, decreased groundwater recharge, and increased flooding, among other problems (Booth 1991).

Hydrologic models, especially simple rainfall-runoff models, are widely used in understanding and quantifying the impacts of land-use changes, and to provide information that can be used in land-use decision making. Many hydrologic models are available, varying in nature, complexity, and purpose (Shoemaker et al. 1997). One such model, Long-Term Hydrological Impact Assessment (L-THIA), a simple rainfall-runoff model based on the U.S. Department of Agriculture's Curve Number (CN) method (USDA 1986), was developed to help land-use planners and watershed managers obtain initial insight into the hydrologic impacts of different land-use scenarios, including historic, current, and future alternatives (Harbor 1994). Like other models, L-THIA is based on empirical relationships that capture the main processes and controls on runoff, but do not account for all the conditions and controls specific to particular study sites, and do not predict the baseflow component of stream flow. Where close correspondence between predicted and observed runoff values is required, rather than simply a relative measure of change, it is necessary to produce a modified (calibrated) model.

Calibration of rainfall-runoff models with respect to local observational data is used to improve model predictability. When model results match observed values from stream-flow measurement, users have greater confidence in the reliability of the model. In the present study, a simple method based on univariate linear regression has been used to calibrate L-THIA, using land-use change data, model predicted direct runoff, and direct runoff derived from stream-flow data using hydrograph separation. This calibration approach is field-verified and can be used with any simple rainfall-runoff model, if there are observational data available. Interestingly, calibration and verification test results for the Little Eagle Creek watershed in Indiana show the usefulness of this approach in general and at the same time raise new questions about the sensitivity of L-THIA model predictions to land-use changes, precipitation, and selection of CN values.

L-THIA—A SIMPLE RAINFALL-RUNOFF MODEL

Modeling rainfall-runoff relationships can be complicated and time-consuming because of the numerous variables that are involved (Bhaduri et al. 2001). Models that capture many of the factors controlling runoff typically require extensive input data and user expertise. Some types of users, such as watershed managers or urban planners, need various levels of models to support decision making, including initial assessment tools that can produce results with minimal data and user expertise. Initial assessments can be a cost-effective way to identify areas of importance that can be targeted for further analysis using a more detailed model or field-based study. Providing users with a simple assessment model can help them reach decisions more quickly and efficiently than immediately performing analysis with highly detailed hydrologic models.

The L-THIA model, developed to fill the need for a simple assessment tool, has the capability to provide relative estimates of direct runoff and nonpoint source (NPS) pollution from different land uses (Bhaduri 1998). The L-THIA model details, utility, and applicability have been demonstrated in several studies (e.g., Leitch and Harbor 1999, Harbor et al. 2000, Bhaduri et al. 2000, Grove et al. 2001), and L-THIA is now widely accessible through a Web-based version of the model (http://www.ecn.purdue.edu/runoff, Pandey et al. 2000a, Pandey et al. 2000b). Even though most studies have used L-THIA to assess the relative impacts of land-use changes, the apparently low absolute runoff values (Grove et al. 2001) predicted by the model (in comparison to "runoff" values based on local stream-flow data) has been a concern for some users. Anecdotally, in L-THIA training workshops, a frequent question from users knowledgeable about local runoff data concerns the mismatch between L-THIA estimates and "real" runoff values. On further questioning, it becomes clear that the users are referring to average annual runoff depths back-calculated from stream-flow data, i.e., including both direct runoff and baseflow. In cases where the predicted runoff is compared to the stream-flow records, the main difference is presumably caused by the fact that the stream-flow record contains both direct runoff and baseflow components, while L-THIA predicts only the direct runoff part of the flow. Additional differences between actual (observed) direct runoff and L-THIA predicted direct runoff values can result from factors such as actual antecedent moisture conditions, evapotranspiration, generalized land-cover data, surface topography, and spatial and temporal variability of rainfall. The effects of these variables should not systematically change relative comparisons of runoff associated with land-use changes using the model. However, if the objective is to compare predicted to observed runoff values, which was not the original purpose of L-THIA, then discrepancies between model predictions and observed values based on stream-flow records should be expected. To compensate for this, calibration can be used to derive values that are adjusted to local observational data.

MODEL CALIBRATION

Calibration is a process of standardizing predicted values, using deviations from observed values for a particular area to derive correction factors that can be applied to generate predicted values that are consistent with the observed values. Such empirical corrections are common in modeling, and it is understood that every hydrologic model should be tested against observed data, preferably from the watershed under study, to understand the level of reliability of the model (Linsley 1982, Melching 1995). The calibration process can provide important insight into both local conditions and model performance; if correction factors are large or inconsistent across several study areas, this suggests that some significant component of the hydrologic system or its controls is being neglected.

Several methods of calibration are available based on methods such as artificial neural networks, multiple objective methods, linear, and nonlinear regression models (Cooper et al. 1997, Madsen 2000, Yu and Yang 2000, Elshorbagy et al. 2000, Ndiritu and Daniell 2001, Madsen et al. 2002). Choosing an approach depends on the purpose of the model, the model parameters or variables involved, how they vary, and how they affect the model results. A good understanding of the particular model and sound knowledge of hydrological processes is necessary for developing a reliable calibration method (Madsen et al. 2002).

Long-term rainfall-runoff models such as L-THIA need to be calibrated based on long-term trends rather than on individual events. Even though the model generates runoff values for each rainfall event, the values are summed for each year to produce total annual runoff yield. Similarly, for calibration, observed runoff values are summed to produce total annual runoff for the study area.

Calibration is achieved in two steps, separation of observed direct runoff from stream-flow data using hydrograph separation and then comparison of predicted and observed runoff values. Numerous analytical methods for hydrograph separation have been developed (Nathan and McMahon 1990, Arnold et al. 1995, Fury and Gupta 2002). Based on the objectives and the need for comparability and reproducibility, the standard U.S. Geologic Survey (USGS) baseflow separation model HYSEP (Hydrograph Separation) (Sloto and Crouse 1996) adapted from methods developed by Pettyjohn and Henning (1979) was used here.

The accuracy of baseflow separation depends on the length of stream-gauge record data that is processed. Longer periods of data provide more reliable separation than shorter periods, and average annual or average monthly values give better results than daily predictions. Thus, the calibration period should be longer (eight years or more) and the data used to calibrate should be standardized to account for the temporal variability of runoff that is caused by changes in rainfall and land-use conditions (Linsley 1982, Yapo et al. 1996). For L-THIA to predict temporal changes that match observational data, frequent land-use data are required. Typically, only current land-use and occasional historical maps are available. If land-use data could be obtained for each year for the whole duration of the runoff studies, it would provide the most accurate calibration of the model. However, because of the unavailability of frequent land-use data, a method of land-use data generation based on interpolation between two or more existing land-use datasets is developed and used here. This ensures that the model predicted runoff actually reflects temporal variation, and thus can be compared directly with the corresponding observed data for each year.

CASE STUDY: MODEL IMPLEMENTATION ON LITTLE EAGLE CREEK WATERSHED

Little Eagle Creek (LEC) watershed with a drainage area of 58.8 km^2 (22.7 mi^2) is an urbanizing watershed, located northeast of Indianapolis in central Indiana. The spread of the city outwards has resulted in increased development within the LEC watershed, causing significant land-use change, particularly forest converted to urban uses (Figure 1). In 1991, 70 percent of the watershed was developed (built), a 40 percent increase over the previous two decades (Table 1, Grove 1997).

Category	1973		1984		1991	
	mi²	%	mi²	%	mi²	%
Developed	13.42	49.36	17.24	63.37	18.56	68.21
Undeveloped	13.77	50.64	9.96	36.63	8.65	31.79
Total	27.20	100	27.21	100	27.20	100

Table 1. Percentage of developed and undeveloped land uses in Little Eagle Creek derived from classification of Landsat satellite image from 1973, 1984, and 1991

This rapid change in land use resulted in water quality- and quantity-related concerns, which are central to the quality of life for the citizens of the community (Open House 1998, 1999). Indianapolis has been recognized as having outstanding development potential (Hedgcoth 2000), thus there are compelling reasons to study and understand the hydrologic impacts that future land development might have in this area.

Model calibration will improve L-THIA results by providing more reliable runoff predictions for future land-use conditions that can be used by urban planners and watershed managers for policy evaluations, and by decision makers in cases where zoning changes are requested. Previous studies of the LEC watershed have focused on the relative impacts of past land-use changes on direct runoff and nonpoint-source pollutants (Bhaduri et al. 2000). However, model predicted runoff values were significantly below stream-flow values (Grove et al. 2001) without calibration, and may not be sufficient for use in some decision-making cases.

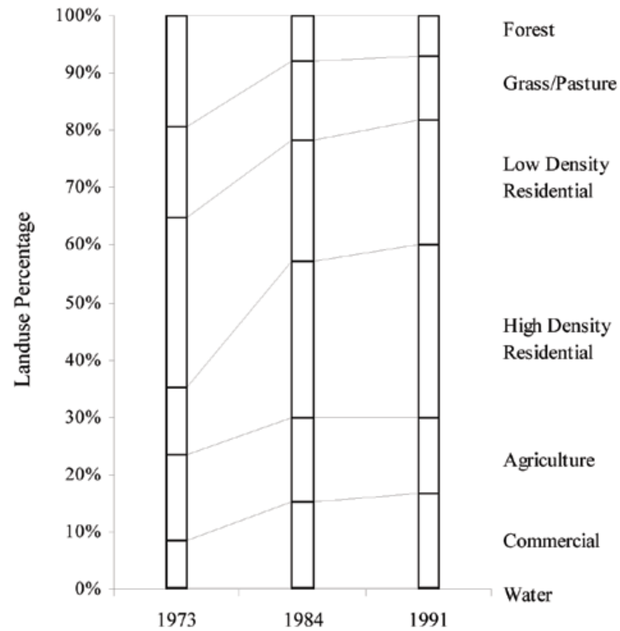

Figure 1. Land-use proportions in the LEC watershed during 1973, 1984, and 1991, derived from Landsat satellite data (after Grove 1997)

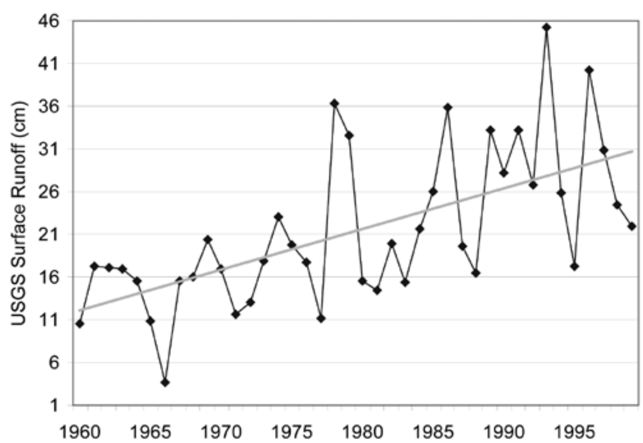

Figure 2. Long-term observed direct runoff trend in LEC watershed

CALIBRATION AND VERIFICATION OF THE L-THIA MODEL

The data used for the L-THIA analysis of the LEC watershed include land use based on remote sensing analysis for 1973, 1984, and 1991 (Grove 1997), Soil Survey Geographic (SSURGO) soil data developed by the U.S. Department of Agriculture, Soil Conservation Service (now Natural Resources Conservation Service) at 1:16,000 scale, long-term daily precipitation obtained from the National Climatic Data Center and the National Oceanic and Atmospheric Administration (NOAA 2002), and long-term daily stream flow from the national stream-flow database of the U.S. Geological Survey (USGS 2002) separated into baseflow and direct runoff. As a first step towards calibration, ArcView GIS was used to combine land-use and soil-grid data to generate curve numbers (CNs) for each land-use and soil combination. Once the area of each land-use and soil-combination classes was obtained from the three original land-use datasets (1973, 1984, and 1991), linear interpolation between 1973 to 1984 and 1984 to 1991 was used to estimate the areas of different land use and soil combinations for intervening years.

Four calibration and verification tests were designed to evaluate the model. In the first test, data from 1973 to 1982 were used for calibration and data from 1983 to 1991 were used to verify the model. In the second test, data from 1982 to 1991 were used for calibration and 1973 to 1981 were used to verify the model. In the third test, the dataset was divided into odd years and even years and odd years were used for calibration and the even years were used to verify the model. Finally, in the fourth test, calibration based on the whole dataset (1973 to 1991) was performed and compared with the other three calibration models. A comparative analysis between linear and nonlinear regression models for all four calibration tests was performed to examine which model would provide better predictions.

Once the initial data preparation was completed, a modified version of the Web-based L-THIA model was used to compute daily direct runoff values for the period 1973 to 1991. For runoff CN selection, normal antecedent moisture condition (AMC II) was assumed. Predicted daily runoff values were then summed to produce total annual runoff for each year and were used in further analysis. Observed direct runoff values were also summed to produce total annual runoff for each year.

RESULTS AND DISCUSSION

The stream-flow record is often the only practical source of information for model comparison and calibration. In the LEC watershed, the long-term observed direct runoff shows a strong increasing trend (Figure 2). From the early 1970s to early 1980s, there were significant changes in land use in the form of more urban development, as compared to the mid-1980s to late 1980s (Figure 1). Corresponding to this change in land use, one would expect to see an increase in observed direct runoff flow in streams during this time, but the stream-flow response was not immediate. It appears as though changes in land-use conditions had no immediate effect on stream flow; rather, it was a slow response that increased cumulatively. In the mid-1980s to late 1980s, even though the rate of urbanization subsided compared to the rate of the previous decades, stream flow continued to increase. Possibly, this resulted from "improvements" or changes within areas already developed, such as an increased, connected impervious area, and other drainage works that increased direct runoff through stormwater drainage pipes.

A comparison of linear and nonlinear regression models used to fit the observed and predicted data showed that a linear model was the best model, with the highest R^2 values (Table 2), suggesting more complex models are not necessary in this case. Thus, a linear regression model was adapted here. To test the calibration models developed in this study, two measures were used: Mean Absolute Error (MAE), the average value of residuals that is used as a measure of the closeness of fit of the regression model; and R^2, which measures how much of the variability in model predictions is explained by the regression model. Results from four calibration tests are summarized in Table 3. Test 1 ($R^2 = 0.85$, MAE = 0.52) produced the highest positive correlation between observed (USGS) and predicted (L-THIA) direct runoff values followed by test 4 ($R^2 = 0.68$, MAE = 0.75). Tests 2 and 3 both display a moderate correlation with relatively lower R-squared values and higher MAE values. Figures 3 to 6 show comparisons of observed, predicted, and calibrated-predicted direct runoff values for calibration tests 1 to 4, respectively. All four models perform very well in improving the predicted values for the calibration period.

The performance of the calibrated models was then assessed by comparing predicted, calibrated direct runoff values with USGS direct runoff not used in calibration. An analysis of the difference between the predicted (L-THIA) and observed (USGS) mean values of runoff, and a test of significance using t-test were used. Even though statistically the two means were found to be the same for all the calibration models, at 95 percent confidence level, analysis of Difference in Mean (DM) shows that when compared

Model	R^2			
	Test 1	Test 2	Test 3	Test 4
Linear	0.85	0.59	0.55	0.68
Square root – Y	0.84	0.58	0.54	0.67
Exponential	0.82	0.57	0.51	0.65
Square root – X	0.82	0.59	0.55	0.65
Logarithmic – X	0.77	0.58	0.55	0.62
Double reciprocal	0.74	0.54	0.47	0.55
Reciprocal – Y	0.72	0.51	0.45	0.58
Reciprocal – X	0.64	0.55	0.51	0.54

Table 2. Linear versus nonlinear models (test 1—data from 1973–1982 used to calibrate and data from 1983–1991 used to test the model; test 2—data from 1982–1991 used to calibrate and data from 1973–1982 used to test the model; test 3—data from odd years used to calibrate and data from even years used to test the model; test 4—data from 1973–1991 used to calibrate the model and tested against previous models)

Calibration		R^2	Level of Confidence (%)	Mean Absolute Error	Calibration Equation*
Name	Period				
Test 1	1973–1982	0.85	99	0.52	$Q_c = (Q_p - 0.21)/0.57$
Test 2	1983–1991	0.59	99	0.77	$Q_c = (Q_p - 0.68)/0.43$
Test 3	Odd Years (1973–1991)	0.55	95	0.88	$Q_c = (Q_p - 0.37)/0.39$
Test 4	All data (1973–1991)	0.68	99	0.75	$Q_c = (Q_p - 0.66)/0.47$

Table 3. Statistical analysis results for calibration tests
* Q_c= calibrated runoff, Q_p= predicted runoff

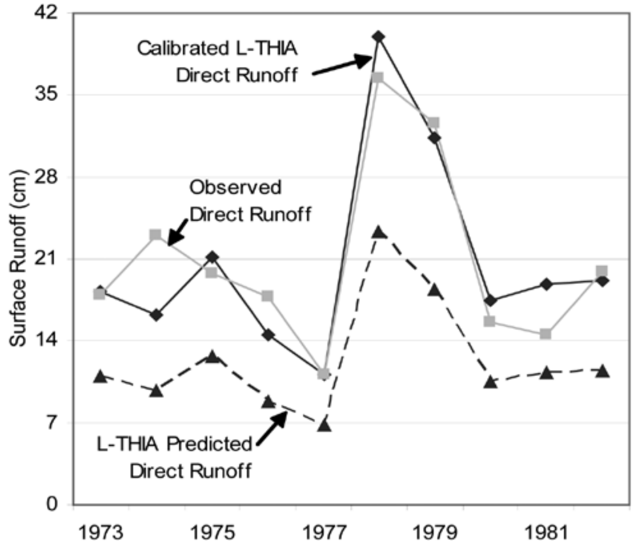

Figure 3. Comparison of predicted, observed, and calibrated runoff from test 1

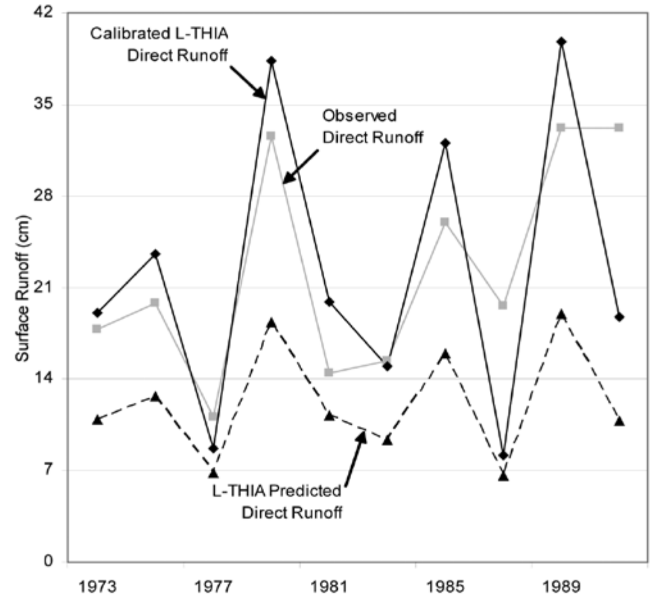

Figure 5. Comparison of predicted, observed, and calibrated runoff from test 3

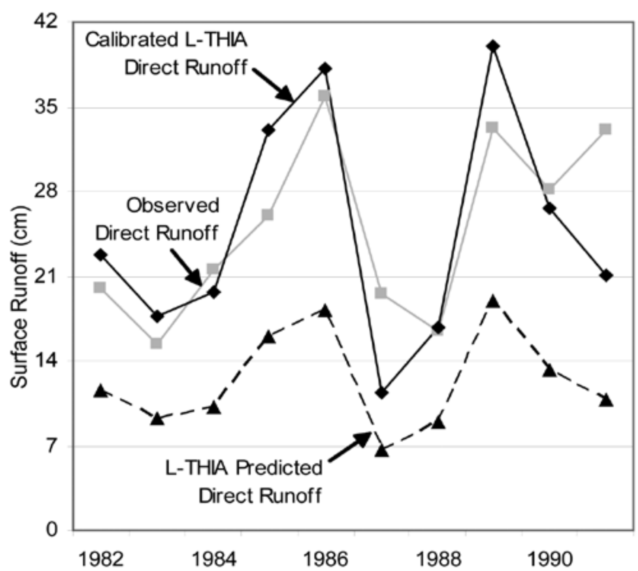

Figure 4. Comparison of predicted, observed, and calibrated runoff from test 2

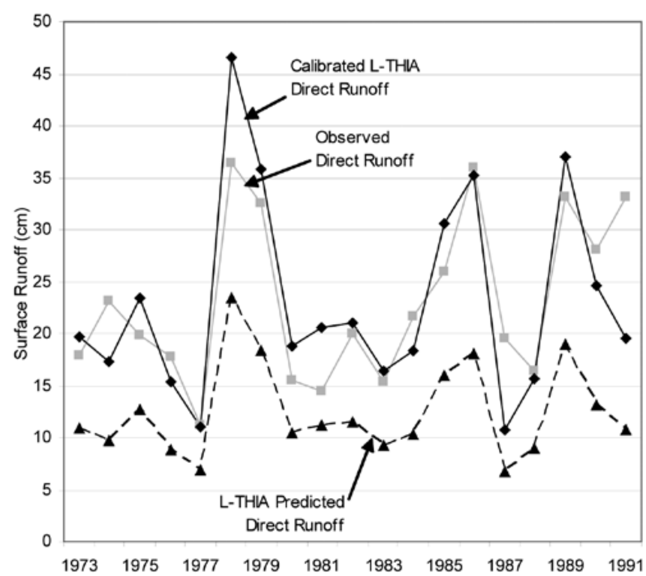

Figure 6. Comparison of predicted, observed, and calibrated runoff from test 4

with the observed runoff, test 1 underpredicts the direct runoff by 18 percent while test 2 overpredicts direct runoff by 19.5 percent (Table 4). Interestingly, test 3 predicts a runoff mean that is close to the observed runoff; however, the regression model used in test 3 does not have a very strong correlation with the observed runoff, and it also has higher MAE, suggesting that this may not be the best model to use for future land-use scenarios.

Verification		Percentage DM	t	Level of Confidence (%)
Name	Period	(Mo - Mp)*		
Test 1	1983–1991	18	-1.35	99
Test 2	1973–1981	- 19.5	1.13	99
Test 3	Even Years (1974–1990)	0.7	-0.22	95

Table 4. Statistical analysis results for verification tests
* Mo- mean of observed (USGS) direct runoff; Mp- mean of predicted (L-THIA) direct runoff after calibration

It is not surprising, however, that test 1 is underpredicting runoff for the verification period, 1983 to 1991, because the calibration model that is used for this test was developed from a period when the land-use changes were more pronounced, but the direct runoff component of stream-flow response to land-use changes was not immediate. This resulted in a smaller shift required to calibrate the model. The calibration model developed for 1982 to 1991 needed a larger shift to achieve calibration and when applied to an earlier period, it overpredicted runoff (by 19.5 percent) as compared to the observed direct runoff. To neutralize this problem, it is necessary to calibrate using the whole range of data, as was the case with the calibration test 4. Clearly, for best overall predictability, calibration using the entire dataset should be used. For the LEC watershed, the regression equation that best explains the variability in predicted runoff using the entire data set is

$Q_c = (Q_p - 0.66)/0.47$
where
Q_c = calibrated L-THIA prediction and
Q_p = predicted L-THIA values.

CONCLUSIONS

This study presents the development and testing of a simple calibration approach based on observed direct runoff values derived from readily available stream-gauge data available over the Internet; no complicated processing is required in the calibration process and, other than the stream-gauge data, no additional information is required beyond that used in an L-THIA model run. On the Web-based version of the L-THIA model, the calibration process could be automated based on the availability of stream-flow data. This will enable those users interested in results that are closer to the observed values to use calibrated L-THIA predictions. This calibration approach could be used for other rainfall-runoff models.

L-THIA model predictions are found to be approximately 50 percent lower than actual observed direct runoff for the LEC watershed. This difference could be attributed to several reasons. First, the L-THIA model is based on the CN method, which was initially developed for agricultural and natural watersheds, and extending it to "extensive" urban watersheds, for which the existing CNs are not representative, can cause the model to predict low runoff. Secondly, in the CN method, runoff is directly proportional to precipitation with an assumption that direct runoff is produced after the initial abstraction of 20 percent of the potential maximum storage. The initial abstraction represents all losses before runoff begins, and includes water retained in surface depressions, water taken up by vegetation, evaporation, and infiltration. This 20 percent was based on several studies of small watersheds, by determining the best-fit relationship between potential maximum storage and initial abstraction. However, the regression plot of this best fit shows a large scatter (Hawkins et al. 2001), reflecting a large variation because of the inherent variability of soil infiltration and land-surface characteristics. Moreover, this assumption may not be valid for urban watersheds, where even small rainfall events produce significant direct runoff because of increased efficiency of surface drainage through storm-drainage systems. The storage factor presumably becomes less and less significant as more and more surface area is paved. The same concern is addressed by Hawkins (2001), whose studies suggest that 5 percent is more representative than 20 percent for triggering runoff from rainfall events. Implementing 5 percent as the runoff triggering limit should result in L-THIA capturing the smaller, but more frequent and significant, rainfall events that produce runoff.

A final reason for underprediction of runoff may be the quality of the land-use data used. If the land-use data are not representative of actual ground conditions, runoff predictions based on this will be skewed. As annual land-use data are rarely available, there is a good chance that land-use change is not only generally represented by the data, and significant changes may occur more quickly than captured by linear interpolation. If the pace of land-use change or intensification is not captured in the available data, then L-THIA results should underpredict observations during periods of urbanization.

A thorough analysis of the causes of L-THIA underprediction is beyond the scope of this paper. Whatever the reason for the discrepancy, calibration makes L-THIA model predicted direct runoff match observed direct runoff. However, the relative impacts predicted by a calibrated L-THIA model will remain the same as those predicted by an uncalibrated L-THIA model. Four calibration tests were carried out for the LEC watershed using different datasets for calibration and verification. All four tests produced results that improved L-THIA predictions compared to actual observed runoff. Based on statistical analysis and long-term observed direct runoff trends, however, the calibration model developed with the entire dataset will best serve long-term hydrological studies and prediction of impacts of future land-use conditions. Application of this calibration equation to watersheds other than the LEC watershed, even those with similar characteristics, is not recommended at this stage. Further studies to determine the robustness of the calibration equation are needed to determine whether separate calibration is needed for each watershed. The calibrated L-THIA model can now be used to understand the impacts of future land-use conditions, so that proactive measures can be taken to control negative impacts.

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References

Arnold J. G., P. M. Allen, R. Muttiah, and G. Bernhardt. 1995. Automated base flow separation and recession analysis techniques. Ground Water 33(6): 1010-18.

Bhaduri B. 1998. A geographic information system based model for assessing long-term impact of land use change on non-point source pollution at a watershed scale. Unpublished PhD dissertation, Purdue University, West Lafayette, Indiana.

Bhaduri, B., J. Harbor, B. A. Engel, and M. Grove. 2000. Assessing watershed-scale, long-term hydrologic impacts of land-use change using a GIS-NPS model. Environmental Management 26(6): 643-58.

Bhaduri, B., M. Minner, S. Tatalovich, and J. Harbor. 2001. Long-term hydrologic impact of land use change: a tale of two models. Journal of Water Resources Planning and Management 127(1): 13-19.

Booth, D. 1991. Urbanization and the natural drainage system—impacts, solutions and prognoses. Northwest Environmental Journal 7: 93-118.

Cooper V. A., V. T. V. Nguyen, and J. A. Nicell. 1997. Evaluation of global optimization methods for conceptual rainfall-runoff model calibration. Water Science and Technology 36(5): 53-60.

Elshorbagy, A., S. P. Simonovic, and U. S. Panu. 2000. Performance evaluation of artificial neural networks for runoff prediction. Journal of Hydrologic Engineering 5(4): 424-27.

Fury, P. R., and V. K. Gupta. 2002. A physically based filter for separating base flow from stream flow time series. Water Resources Research 37(11): 2709-22.

Grove, M. 1997. Development and application of a GIS-based model for assessing the long-term hydrologic impacts of land-use change. MS thesis, Purdue University, West Lafayette, Indiana.

Grove, M., J. Harbor, and B. A. Engel. 1998. Composite versus distributed curve numbers: effects on estimates of storm runoff depths. Journal of American Water Resources Association 34(5): 1015-23.

Grove, M., J. Harbor, B. A. Engel, and S. Muthukrishnan. 2001. Impacts of urbanization on surface hydrology, Little Eagle Creek, Indiana, and analysis of L-THIA model sensitivity to data resolution. Physical Geography 22: 135-53.

Harbor, J., 1994. A practical method for estimating the impact of land use change on direct runoff, groundwater recharge, and wetland hydrology. Journal of American Planning Association, 60(1): 91-104.

Harbor, J., B. A. Engel, D. Jones, S. Pandey, K. J. Lim, and S. Muthukrishnan. 2000. A comparison of the long-term hydrological impacts of urban renewal versus urban sprawl. National Conference on Tools for Urban Water Resource Management & Protection, Environmental Protection Agency, conference proceedings.

Hawkins, R. H., R. Jiang, and D. E. Woodward. 2001. Investigation of the runoff curve number abstraction ratio. Water Resources for 21st Century: A National Hydrology and Hydraulic Engineering Workshop, Tucson, Arizona.

Hawkins, R. H. 2001. Personal communications.

Hedgcoth, R. 2000. 50 hottest cities, expansion management. A Penton Publication, http://206.183.24.47/Jan_2000/Jan00.coverstory.html, verified May 25, 2002.

Leitch, C., and J. Harbor. 1999. Impacts of land use change on freshwater runoff into the near-coastal zone, Holetown watershed, Barbados: comparisons of long-term to single-storm effects. Journal of Soil and Water Conservation 54: 584-92.

Linsley, R. L. 1982. Rainfall-runoff models—an overview. In Rainfall-runoff relationship, proceedings of the International Symposium on Rainfall-Runoff Modeling, May 18-21, 3-22.

Madsen, H. 2000. Automatic calibration of a conceptual rainfall-runoff model using multiple objectives. Journal of Hydrology 235: 276-88.

Madsen, H., G. Wilson, and H. C. Ammentorp. 2002. Comparison of different automated strategies for calibration of rainfall-runoff models. Journal of Hydrology 261: 48-59.

Melching, C. S. 1995. Reliability estimation in computer models of watershed hydrology. In Singh, V. P., ed., Reliability estimation in computer models of watershed hydrology. Water Resources, 69-118.

Nathan, R. J., and T. A. McMahon. 1990. Evaluation of automated techniques for base low and recession analyses. Water Resources Research 26(7): 1465-73.

Ndiritu, J. G., and T. M. Daniell. 2001. An improved genetic algorithm for rainfall-runoff model calibration and function optimization. Mathematical and Computer Modeling 33: 695-706.

NOAA. 2002. National Climatic Data Center, daily precipitation data, http://lwf.ncdc.noaa.gov/oa/ncdc.html.

Open house. 1998. City of Indianapolis Watershed Awareness Program. Personal communication with general public, decision makers, watershed managers, and scientists, Indianapolis, Indiana.

Open house. 1999. City of Indianapolis Watershed Awareness Program. Personal communication with general public, decision makers, watershed managers and scientists, Indianapolis, Indiana.

Pandey, S., R. Gunn, K. J. Lim, B. A. Engel, and J. Harbor. 2000a. Developing a Web-enabled tool to assess long-term hydrologic impact of land use change: information technologies issues and a case study. Urban and Regional Information Systems Journal 12(4): 5-17.

Pandey, S., J. Harbor, and B. A. Engel. 2000b. Internet-based geographic information systems and decision support tools. Urban and Regional Information Systems, Park Ridge, Illinois.

Pettyjohn, W. A., and R. Henning. 1979. Preliminary estimate of ground-water recharge rates, related stream flow and water quality in Ohio: Ohio State University Water Resources Center project completion report number 552. In Sloto, R. A., and M. Y. Crouse. 1996. Hysep: a computer program for stream flow hydrograph separation and analysis. U.S. Geological Survey, Water-Resources Investigations report 96-4040.

Shoemaker L., M. Lahlou, M. Bryer, D. Kumar, and K. Kratt. 1997. Compendium of tools for watershed assessment and TMDL development U.S. Environmental Protection Agency, EPA841-B-97-006.

Sloto R. A., and M. Y. Crouse. 1996. HYSEP: a computer program for stream flow hydrograph separation and analysis. U.S. Geological Survey, Water Resources Investigations report 96-4040.

USGS. 2002. Daily stream flow for the nation, http://waterdata.usgs.gov/nwis/discharge.

USDA, NRCS. 1986. Urban hydrology for small watersheds. U.S. Department of Agriculture, technical release 55.

Yapo P. O., H. V. Gupta, and S. Sorooshian. 1996. Automatic calibration of conceptual rainfall-runoff models: sensitivity to calibration data. Journal of Hydrology 181: 23-48.

Yu, P. S., and T. C. Yang. 2000. Fuzzy multi-objective function for rainfall-runoff model calibration. Journal of Hydrology 238: 1-14.