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Loss-Rate Functions for Selected Texas Watersheds

David B. Thompson, Theodore G. Cleveland, D.B. Copula, and Xing Fang

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16. Abstract:

The purpose of this report is to present a set of results from research into loss-rates functions applicable to selected Texas watersheds. The results reported herein comprise the culmination of a set of research components for application of the unit hydrograph method for development of drainage design discharges for Texas transportation projects. A number of loss-rate methods were explored by the research teams represented by members from U.S. Geological Survey, Texas Tech University, Lamar University, and University of Houston. A variety of approaches are documented in the report, although it is left to the analyst to determine the most appropriate approach for a particular design problem.

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by
David B. Thompson
Theodore G. Cleveland
D.B. Copula
Xing Fang

Research Report Number 0–4193–6
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Regional Characteristics of Unit Hydrographs

Sponsored by the Texas Department of Transportation
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Center for Multidisciplinary Research in Transportation
Department of Civil and Environmental Engineering
Texas Tech University
P.O. Box 41023
Lubbock, Texas 79409–1023

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ENGINEERING DISCLAIMER

This report is not intended for construction, bidding, or permit purposes. The research supervisor was David B. Thompson, Ph.D., P.E., C.F.M., Texas P.E. 97852 with major assistance from Theodore G. Cleveland, Ph.D., P.E., Texas P.E. 86653.

TRADE NAMES AND MANUFACTURERS NAMES

The United States Government and the State of Texas do not endorse products or manufacturers. Trade or manufacturers' names appear herein solely because they are considered essential to the object of this report.

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A project of the magnitude of TxDOT Project 0–4193 cannot be completed without the contributions of a large number of individuals beyond the principal investigators. Texas Tech University graduate students George "Rudy" Herrmann, Cindy Jones, Amit Karki, and Jared Lujan all contributed significant efforts to the research (and earned their Master of Science degrees in the process). The service of TxDOT engineers David Stolpa and George "Rudy" Herrmann began early in the conceptual stages of the project before a problem statement was even developed. Their contributions were supplemented by other TxDOT advisors, including Amy Ronnfeldt.

The contributions of my co-researchers, William H. Asquith and Meghan C. Roussel of the U.S. Geological Survey were substantial. Xing Fang and his graduate students at Lamar University executed many model runs and carried forward their component of the regionalization effort. Ted Cleveland and his crew at University of Houston did a significant amount of watershed-characteristic development. Ted Cleveland deserves special credit for his able assistance in generating this report.

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Chapter 1

Background

1.0.1 History of the Project

Texas Department of Transportation (TxDOT) hydraulic engineers use a variety of hydrologic technologies to produce peak discharge estimates that are then used to size storm drainage facilities. Of available methods for estimating design discharges, TxDOT analysts use the rational method most frequently and regional regression equations are the next most-frequently used method. However, the principal rainfall-runoff method, and the only method used for time-distributed modeling, is the unit hydrograph method[1]. The principal method used by TxDOT analysts for rainfall-runoff modeling is the Natural Resources Conservation Service (NRCS) dimensionless unit hydrograph method[2]. The NRCS dimensionless unit hydrograph was developed by a federal agency to meet the technical needs of that agency. It is possible that the method may or may not be entirely appropriate for a specific state or region. Therefore, TxDOT Project 0–4193, *Regional Characteristics of Unit Hydrographs*, began in fiscal year 2000 in response to TxDOT hydraulic engineers' questions about the applicability of NRCS unit hydrograph procedures to Texas watersheds in the context of highway design.

A substantial database of rainfall-runoff events was constructed as part of Project 0–4193 and other TxDOT hydrologic research projects (Asquith et al., 2004a; Thompson, 2005, for example). This database is documented in Asquith et al. (2004b) and comprises more than 1,600 events recorded as part of the U.S. Geological Survey (USGS) small-watershed and urban-runoff program that was active during the period from about 1960 through about 1980. The database is unique and an important product of this project. The database was used for a suite of TxDOT research projects that were conducted in parallel.

[1] A *unit hydrograph* is the hydrograph of runoff produced by a unit depth of effective precipitation that occurs over a specific duration. *Effective precipitation* is runoff, that is the depth of precipitation left after abstractions are subtracted. The temporal duration of the effective precipitation is the duration of the unit hydrograph.

[2] The NRCS dimensionless unit hydrograph method is documented in most hydrologic textbooks used for training civil engineers (Viessman and Lewis, 2003, for example). The curve number method is also documented in an NRCS publication (U.S. Department of Agriculture, Natural Resources Conservation Service, 1997). The curve number method is currently the only approach commonly used by TxDOT designers for time-distributed modeling.

The primary project team comprised faculty from Texas Tech University (D. Thompson), University of Houston (T. Cleveland), Lamar University (X. Fang), and hydrologists from USGS (W. Asquith and M. Roussel). This team brought a diverse set of skills to bear on the problem and developed four independent research approaches to the problem. These approaches are developed in subsequent chapters.

During the course of Project 0–4193 TxDOT Project 0–2104 (*Climatic Adjustment of NRCS Curve Numbers*) terminated with production of a final project report (Thompson, 2003). One of the results of Project 0–2104 was that standard (or tabulated) values of the NRCS curve number were not necessarily appropriate for Texas watersheds, particularly those in the semi-arid western region of Texas. As a result, Project 0–4193 project advisors determined it appropriate for Project 0–4193 researchers to focus additional effort on hydrologic abstractions and determine whether information about loss-rate models[3] appropriate for Texas watersheds could be extracted from the project database. Therefore, Project 0–4193 was modified in FY 2005 and again in FY 2006 to amend the original workplan and provide resources for examining loss-rate functions in the context of unit hydrograph applications.

The original unit hydrograph research was completed in FY 2005 and results published in Asquith et al. (2006). With that work complete, the four research teams turned their attention to loss-rate models, completing a literature review (Thompson, 2005), and then proceeded to analyze the database to extract information about loss-rate functions for TxDOT applications.

1.0.2 Related Projects

Beginning in the late 1990's, TxDOT began a systematic review of hydrologic procedure used by the agency for design purposes. A group of TxDOT hydraulic engineers recognized that little applied research of the technologies deployed by their agency had been comprehensively studied for decades. In addition, the applicability to Texas watersheds of a number of approaches in-use was unknown. Because a large component[4] of the construction budget is associated with drainage-related structures, expenditure of research funds to examine the basic technologies in use was appropriate. Therefore, a research program covering engineering applications of hydrologic science was undertaken that was to last nearly ten years.

The process began with Project 0–2104, *Climatic Adjustment of NRCS Curve Numbers* (Thompson, 2000, 2003). This project was developed because climatic adjustment of NRCS curve numbers by TxDOT designers was based on a design aid known only as "Figure 4"[5]; the source of the aid was unknown. As a result, an examination of the applicability of the NRCS curve number method began and culminated in both a design aid for adjusting standard or table values of NRCS curve number for location and a reduction in confidence in use of the NRCS curve number method for

[3]Loss-rate models and runoff generation models represent two different approaches to estimating rainfall excess. The difference is elaborated in a subsequent section of this report.

[4]According to George "Rudy" Herrmann, approximately 40 percent of the construction budget is associated with drainage-related construction.

[5]It was determined that the source of the design aid was Hailey and McGill (1983).

the arid portions of Texas.

Similarly, the NRCS Type II rainfall hyetograph was commonly used by TxDOT design engineers. The opinion of TxDOT hydraulic engineers was that the central portion of the Type II distribution was so steep (indicating high-intensity rainfall) that results from its application were overly conservative, resulting in designs that far surpassed the risk level assumed for the design. As a result, an examination of the hyetographs of runoff-producing rainfall events was undertaken in TxDOT Project 0–4194, *Regional Characteristics of Storm Hyetographs* (Thompson, 2002; Asquith et al., 2004b; Williams-Sether et al., 2004). Project 0–4194 resulted in new design hyetographs appropriate for Texas hydrology. The hyetographs produced in Project 0–4194 were less steep than the NRCS Type II distribution and were similar to hyetographs produced by other researchers involved in hyetograph research in the U.S.

In parallel with hydrograph research, curve number research, and hyetograph research, a project was undertaken to determine appropriate timing parameters for characterizing watershed response. The opinion of TxDOT hydraulic engineers was that the NRCS travel-time approach resulted in times of concentration less than appropriate for the watersheds it was applied to. A reduction in time of concentration for a particular watershed inflates the peak discharge derived by either the rational method or the unit hydrograph method. Therefore, TxDOT Project 0–4696 *Timing Parameter Estimate for Applicable Texas Watersheds* (Roussel et al., 2005; Cleveland et al., 2006) was developed and completed. The result of this project was that methods such as Kirpich (1940) and Kerby (1959) produced time of concentration estimates more appropriate for Texas watersheds[6].

As these projects developed, mostly in parallel, it became apparent that an alternative technology for estimation of hydrologic abstractions would be useful for Texas applications. Given that the database of known runoff-producing events (Asquith et al., 2004b) was already developed and that technology for interacting with the database was already in place, Project 0–4193 was modified to include an assessment of alternative methods for estimating hydrologic abstractions to incoming rainfall on Texas watersheds. This report is the culmination of that research.

1.0.3 Purpose

This report represents the results of the additional two years spent working with the unit hydrograph procedure, incorporating results of research on loss-rate functions. The purpose of this report is to present results and recommendations from research on loss-rate functions for Texas watersheds.

1.0.4 Presentation

Because four distinct teams conducted essentially independent research of loss-rate functions, the results and writing styles of four different authors are represented in this report. The result is

[6] Detailed results from Project 0–4696 are presented in Roussel et al. (2005) and are too numerous to repeat in this report. The reader is directed to Roussel et al. (2005) for timing parameter estimate methods and appropriate limitations on their application.

generally expected differences in the presentation of results and graphics. This is a natural consequence of a team approach. Although effort was made to smooth the presentation, differences will be apparent to any serious reader.

Furthermore, portions of the "USGS" sections were written by non-USGS authors. In the USGS sections, non-USGS comments are *emphasized* to identify portions of the report written by non-USGS authors. These portions are included to improve clarity in the context of this final report. The core USGS results are formally available in Asquith and Roussel (2007).

Chapter 2

Procedure

In the problem statement and proposal for this project, the following tasks are listed:

1. Literature review
2. Other departments of transportation
3. Regionalization of Texas
4. Identification of applicable modeling techniques
5. Documentation

A substantial amount of work was completed during this project. Hundreds of hours of effort were expended developing a rainfall-runoff database from Texas watersheds, quality checking/quality assuring those data, and then analyzing data from the database to develop and refine technology for application by Texas Department of Transportation (TxDOT) analysts when approaching hydraulic design problems.

The initial product of this research project was a unit hydrograph (unitgraph) specifically developed for application to Texas watersheds, which is primarily documented by Asquith et al. (2006).

As the unitgraph work was brought to closure, there was a need for review of loss-rate functions used to convert precipitation to excess precipitation (or runoff). The project advisory panel determined that such a review was a natural extension to the work already in progress. As a result, the project was modified to include a review and analysis of loss-rate functions. The objective was to determine what loss-rate function or functions work best for the Texas watersheds represented in the database.

As stated in Chapter 1 of this report, four teams of researchers participated in the effort. These teams were lead by William H. Asquith and Meghan C. Roussel from U.S. Geological Survey, Ted Cleveland from University of Houston, Xing Fang from Lamar University, and David Thompson from Texas Tech University. Each team used tools developed either as part of their previous research on unitgraphs or developed additional mechanics or extension of mechanics to approach the problem.

The approach used by each team and results from each team are elucidated in subsequent chapters of this report.

2.1 Literature Review

As part of the initial research, a literature review was undertaken (Thompson, 2005). A portion of the literature review is presented in this section of the report.

2.1.1 Hydrologic Abstractions

The principal input to a watershed is precipitation (rainfall). Unless the watershed is a completely impervious surface, not all rainfall is converted to runoff at the watershed outlet. *Hydrologic abstractions* are the sum of losses to rainfall in the process of converting incoming rainfall to runoff[1]. In fact runoff is the difference between rainfall and hydrologic abstractions.

In a traditional textbook treating hydrology (Viessman and Lewis, 2003, for example), abstractions are listed as interception, depression storage, and infiltration. *Interception* is the abstraction of incoming rainfall to surfaces between the atmosphere and the ground — typically vegetation. Interception does not usually exceed a tenth of an inch or two. *Depression storage* refers to the temporary storage of incoming rainfall in small depressions on the ground surface — something typically much smaller than a pond. Water stored in depressions is either evaporated, becomes runoff, or is infiltrated into the soil profile. *Infiltration* is the portion of incoming rainfall that passes through the soil surface into the soil matrix and is lost to runoff.

Most hydrologists lump interception and depression storage into a general term called the *initial abstraction.* This represents the amount of rainfall lost to the system before the infiltration and runoff processes begin.

2.1.2 Runoff Generation Models

Philosophically, a number of approaches exist for estimating runoff from a given precipitation event. One of the classic approaches is application of a loss model to quantify losses (abstractions) from incoming precipitation. Whatever remains of precipitation after losses are accounted for is runoff. Almost all of the process models used in standard hydrologic models are loss models.

A second alternative is the *runoff generation* approach. These methods do not directly approach hydrologic abstractions; abstractions are only implied. Instead, runoff is computed directly from

[1] In some texts, evapotranspiration also is termed an abstraction. However,in the context of a storm event, evapotranspiration is generally thought to be quite small.

incoming precipitation. The University of Houston *fractional loss model* (Section 2.3.2) and the NRCS curve number method are examples of runoff generation models[2]. To compute the losses (abstractions) implied by application of a runoff generation model the difference between incoming precipitation and runoff is computed.

2.1.3 Loss-Rate Functions

Loss-rate functions are used to convert precipitation (expressed as a rate) into excess precipitation (or runoff) also expressed as a rate by subtracting values that are conceptually related to processes in the loss model. The term "excess" implies that it is the fraction of precipitation that does not become sequestered in other hydrologic compartments or fluxes (storage, infiltration, evaporation, and others.).

A loss-rate function is implicitly defined in the extraction of unit hydrographs from measured rainfall-runoff responses. For example, the process defined by Linsley, Jr. et al. (1958) uses a constant loss-rate, termed the ϕ*-index*, to achieve a mass balance between the measured rainfall hyetograph and the direct runoff hydrograph[3]. The rate, ϕ, is the average rate at which water is lost from the incoming precipitation. The ϕ-index method uses a gross loss-rate (ϕ) to represent *all* elements of the hydrologic abstractions.

A loss-rate function similar to the ϕ-index method is implemented in HEC-HMS (U.S. Army Corps of Engineers, 2006). This process is termed the initial-loss/constant loss-rate method and basically constitutes the ϕ-index method with the addition of an initial abstraction (Scharffenberg, 2001). Before the ϕ-index is applied, a specific depth of rainfall must be abstracted (subtracted).

The NRCS curve number procedure (U.S. Department of Agriculture, Natural Resources Conservation Service, 1997) is not truly a loss-rate function but is a runoff generation model. It is an empirical approach developed by NRCS in the 1940's (then the Soil Conservation Service) for use in developing design discharges for small agricultural projects. The NRCS curve number procedure[4] is widely documented in standard hydrologic texts, such as Viessman and Lewis (2003) and others. The method is based on specifying a curve number derived from soil textural classification and land use/land cover. Tabulated values were (ostensibly) derived from analysis of rainfall-runoff data measured by NRCS researchers, but little of this work was ever published in the refereed literature. Thompson (2003) developed a procedure to adjust standard or table curve numbers based on geographic location in Texas.

The NRCS curve number procedure is implemented in standard software for hydrologic computations, such as U.S. Army Corps of Engineers (2006). The method has seen wide application in the profession.

[2]Other runoff generation models also are available but are not treated in this report.

[3]This process assumes the measured hyetograph is representative of the entire watershed drainage area and that baseflow is successfully extracted from the measured runoff hydrograph.

[4]Because the curve number procedure is a runoff generation model, losses are implicit to the method — watershed storage is a component of the curve number method.

Infiltration Equations

The researchers assumed that infiltration-type losses are an important component of the loss model. However, the researchers thought that evaporation losses over the duration of a storm event would be either insignificant or indiscernible from other losses and that infiltration (or a loss model reflecting an infiltration-type process) had the greatest possibility of correlation to measurable watershed properties such as soil texture, permeability, and others. Of particular importance in this work is that infiltration-type losses do not explicitly account for on-watershed storage and are fundamentally different from the NRCS curve-number approach or the initial-abstraction/constant loss-rate type model.

The authors acknowledge that infiltration-type losses may not capture the entire set of processes that actually operate on a watershed. In fact, the runoff generation models in current HEC-HMS and SWMM software are infiltration-excess models — another entire type of runoff generation process, saturation excess, is also dominant in the literature and whereas the resulting equations look similar they are philosophically quite different in origin.

The literature is rich with research on the infiltration process. *Infiltration* is the process by which incoming rainfall passes through the soil surface to enter the soil matrix. Another term (in fact, the term used for this research project) is the *loss-rate function*, which represents more than infiltration only — loss functions comprise other components of hydrologic abstractions.

Green and Ampt (1911) developed a physics-based infiltration function. In general, it was not widely used because the function is implicit and therefore numerical methods are required to generate a solution. The Green-Ampt equation is given by

$$f(t) = K\left(1 + \frac{\psi\Delta\theta}{F(t)}\right), \tag{2.1}$$

where f represents infiltration capacity[5], t is time, K is the saturated hydraulic conductivity of the soil, ψ is the soil suction at the wetting front, and $\Delta\theta$ is the soil-moisture deficit, and F is cumulative infiltration[6]. When integrated with respect to time, Equation 2.1 becomes

$$F(t) = Kt + \psi\Delta\theta \ln\left(1 + \frac{F(t)}{\psi\Delta\theta}\right). \tag{2.2}$$

Kostiakov (1932) developed a function for infiltration capacity,

$$f(t) = \frac{\alpha A}{t^{(\alpha-1)}}, \tag{2.3}$$

where α and A are parameters. The cumulative infiltration is

$$F(t) = At^{\alpha}. \tag{2.4}$$

[5] *Infiltration capacity* refers to the rate at which water can enter the soil matrix if supply is not limiting. This is the *capacity* rate. If incoming water is less than capacity, then the infiltration rate will be less than the capacity.

[6] *Cumulative infiltration* often is termed *mass infiltration*. The two terms are synonymous.

Although present in the literature, the Kostiakov equation does not appear to be in widespread use.

Horton (1940) studied a wide variety of hydrologic processes and published his infiltration capacity equation,

$$f(t) = f_c + (f_o - f_c)e^{-kt}, \tag{2.5}$$

where f_c is the final infiltration capacity, f_o is the initial infiltration capacity, and k is the decay constant. Cumulative infiltration is given by

$$F(t) = f_c t + \frac{f_o - f_c}{k}(1 - e^{-kt}). \tag{2.6}$$

The three parameters for Horton's infiltration function are determined based on field measurements and fitted, either graphically or numerically. Although the Horton function was widely used, it is not currently available in common hydrograph modeling software.

Philip (1957) solved the more general Richards (1931) formulation of capillary-driven porous matrix flow for the specific problem of surface infiltration. The Philip equation is

$$f(t) = \frac{S}{2\sqrt{t}} + A, \tag{2.7}$$

where S is the soil sorptivity and A is the soil infiltration capacity for large time[7]. The cumulative infiltration is given by

$$F(t) = S\sqrt{t} + At. \tag{2.8}$$

Again, while the Philip equation is important, it is not generally implemented in current computational software.

2.1.4 Linear and Non-linear Programming

Mays and Coles (1980) developed a linear programming approach to solve the unitgraph deconvolution problem. Mays and Taur (1982) extended this approach to a non-linear programming model that included ϕ-index estimation of rainfall abstractions. They concluded that, whereas the non-linear programming model offered some benefits in estimates of the unitgraph, the linear programming model was able to simultaneously process a larger number of events.

Unver and Mays (1984) revisited the non-linear programming model of Mays and Taur (1982). Unver and Mays reprogrammed the optimization to search for solutions to the Horton, Philip, and Kostiakov equations. Unver and Mays were able to obtain estimates of loss-rate function parameters and the underlying unitgraph from events in their dataset, but reported that local optima may be the best solution available. Unver and Mays attribute this result to errors in the rainfall-runoff observations and because some watersheds may not respond according to the linear assumptions of the infiltration and unitgraph models.

[7] Final infiltration capacity, or soil infiltration rate for large time, is generally considered to be equivalent to the saturated hydraulic conductivity of the soil.

Prasad et al. (1999) formulated another linear programming model for extracting unit hydrographs and loss parameters from measured rainfall-runoff sequences. Their analysis included the Kostiakov, Philip, and Green-Ampt infiltration equations. By bounding the infiltration capacity between the estimate of the ϕ-index and zero, Prasad et al. obtained optimal solutions without preparing trial solutions in contrast to the work of Unver and Mays (1984).

2.2 U.S. Geological Survey

For TxDOT Project 0–4193, USGS personnel developed a specific time-distributed, watershed-loss model known as an initial-abstraction, constant-loss model. The authoritative and comprehensive report documenting USGS research efforts on unit hydrographs and loss rates is Asquith and Roussel (2007). The discussion that follows is an adaptation of the summary from that report.

2.2.1 Initial Abstraction/Constant Loss-Rate Model

The initial-abstraction constant-loss model conceptualized by USGS researchers has the capacity to store or abstract an absolute depth of rainfall at or near the beginning of a storm. Depths of rainfall less than this initial abstraction do not produce runoff. The watershed also is conceptualized to have the capacity to remove rainfall at a constant rate after the initial abstraction is satisfied. Additional rainfall inputs after the initial abstraction is satisfied contribute to runoff if the rainfall rate (intensity) is larger than the constant loss rate. Therefore, the model is a two-parameter model of watershed losses. This approach was developed through detailed computational and statistical analysis of observed rainfall and runoff data for 92 USGS streamflow-gaging stations (watersheds) in Texas with contributing drainage areas from 0.26 to 166 square miles.

For the development of the initial-abstraction constant-loss model, the unit hydrograph is limited to a previously described, watershed-specific, gamma-distribution, unit-hydrograph (GUH) model developed by the USGS (Asquith et al., 2006). The GUH has two unique parameters, which can be variously expressed, but are considered in terms of watershed-depth peak streamflow (q_p) and time to peak (T_p). The third parameter is a shape parameter (K) that is dependent on q_p and T_p.

2.2.2 Gamma Unit Hydrograph

The equations to estimate K and T_p of GUH for applicable Texas watersheds are collectively referred to as the $K : T_p$ equations and the GUH set by these equations is referred to as $K : T_p$-GUH. The $K : T_p$-GUH is deemed appropriate for development of the initial-abstraction constant-loss model.

These parameter values, $K : T_p$-GUH, are obtained by methods reported in Asquith et al. (2006) and are not re-computed in the loss-rate work. This approach is distinct from the approach of University of Houston researchers and Lamar University researchers who chose to simultaneously recompute loss rate and hydrograph parameters in their work.

2.2.3 Implementation of Computational Algorithm

To initiate initial-abstraction constant-loss model development, a complex computational analysis of the database of observed rainfall and runoff for the 92 watersheds was done using custom-built software. The computations used a 5-minute time step; rainfall and runoff values were linearly interpolated to 5-minute increments as needed. The purpose of the software was to compute optimal (storm-specific) parameter values ($\hat{I}_A$ and $\hat{C}_L$) for each suitable storm in the database. The GUH was estimated for each watershed by the $K : T_p$ equations. This "watershed-specific GUH" was considered a representative unit hydrograph for the watershed. The analysis successfully processed 1,620 out of approximately 1,660 storms and provided $\hat{I}_A$ and $\hat{C}_L$ values used in statistical analyses.

The assumption that the GUH set by the $K : T_p$ equations is representative for each watershed for the analysis of $\hat{I}_A$ and $\hat{C}_L$ is important. Although the "correctness" of $K : T_p$-GUH is not ensured, the assumption implies that the initial-abstraction constant-loss model is "tuned" against observed rainfall and runoff and $K : T_p$-GUH. Therefore, the initial-abstraction constant-loss model is linked to $K : T_p$-GUH, and in practice the two techniques are to be used together.

Values for $\hat{I}_A$ and $\hat{C}_L$ were computed by the software. Those values, which generated an excess rainfall hyetograph (time series of rainfall intensity) and when convolved with the GUH, produced a modeled runoff hydrograph that has the same volume as the observed runoff hydrograph and a minimized residual sum of squares between the observed and modeled runoff hydrographs. The means of $\hat{I}_A$ and $\hat{C}_L$ for each watershed were computed; the means ($\overline{I_A}$ and $\overline{C_L}$) are referred to as watershed-specific. $\overline{I_A}$ and $\overline{C_L}$ for each watershed are considered the most representative.

2.3 University of Houston

Figure 2.1 is a schematic of the modeling approach used by University of Houston researchers. In the figure, the watershed of interest is the elongated ellipse just above the outflow hydrograph. Above this watershed are two ovals that represent, in a signal processing context, two filters.

From the top of the diagram in the downward direction, the filters are the loss model and the unit hydrograph model. The loss model accounts for the proportion of the rainfall that is lost and the proportion that becomes available for runoff (excess rainfall hyetograph). The unit hydrograph model accounts for the temporal distribution of rainfall that is available for runoff. The resulting excess rainfall hyetograph computed from the loss model is "convolved" with the unit hydrograph to compute a runoff hydrograph for the particular storm and watershed.

The selection of candidate loss models by the University of Houston researchers was based on the principle that the watershed-loss model should be mathematically consistent in structure or general form with hypothesized processes, and it should also be at about the same level of complexity as the unit hydrograph model.

The unit hydrograph model used by the University of Houston researchers, the candidate loss

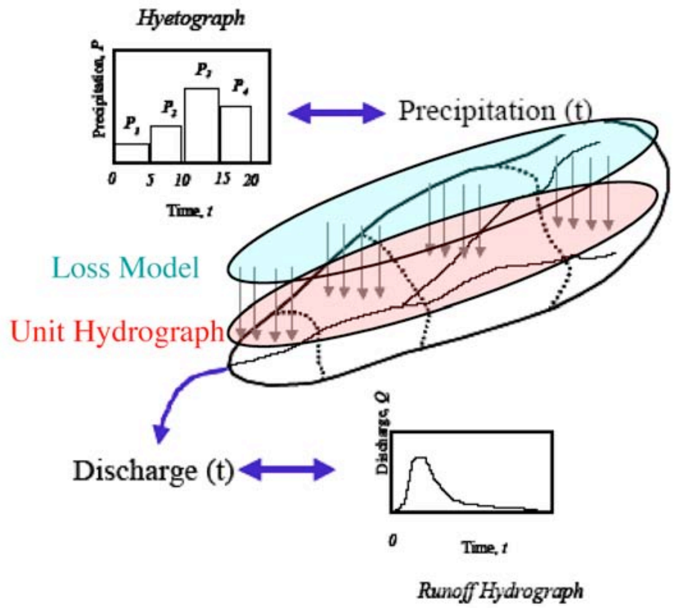


Figure 2.1: University of Houston conceptual rainfall-runoff model.

models, and the parameter identification procedure[8] are briefly described in this section of the report.

2.3.1 Lienhard Unit Hydrograph

The unit hydrograph model selected for this research is a generalized gamma distribution (Lienhard, 1964; Lienhard and Meyer, 1967) and is expressed as

$$f(t) = \frac{\beta}{\Gamma(N/\beta)} \left(\frac{N}{\beta}\right)^{n/\beta} \frac{1}{t_{rm\beta}} \left(\frac{t}{t_{rm\beta}}\right)^{N-1} \exp\left[-\frac{N}{\beta}\left(\frac{t}{t_{rm\beta}}\right)^{\beta}\right]. \tag{2.9}$$

The distribution parameters n and $t_{rm\beta}$ have physical significance in that $t_{rm\beta}$ is a mean residence time of an excess raindrop on the watershed, and n is an accessibility number, roughly proportional to the exponent on the distance-area relationship (a shape parameter). β is the degree of the moment of the residence time. $\beta = 1$ would be an arithmetic mean[9], while for $\beta = 2$ the residence time is a root-mean-square time. $\beta = 2$ is used throughout this work, in part to be faithful to Leinhard's original derivation. Equation 2.9 can also be expressed as a dimensionless hydrograph

[8] In the University of Houston work, parameter identification is a data analysis process where parameters that explain observed behavior are determined. The concept is distinct from and different than parameter estimation, which is a procedure where parameters are specified according to statistical models and explanatory variables.

[9] The gamma unit hydrograph in Asquith et al. (2006) is a special case of the distribution with $\beta = 1$.

using the following transformations (Lienhard, 1972) to express the distribution in conventional dimensionless form where Q_p and T_p are the peak rate factor and time to peak of the hydrograph,

$$t_{rm\beta} = \left(\frac{N}{N-1}\right)^{1/\beta} T_p, \text{ and} \tag{2.10}$$

$$Q_p = f(T_p). \tag{2.11}$$

Expressed as a dimensionless hydrograph distribution, Equation 2.9 becomes

$$\frac{Q}{Q_p} = \left(\frac{t}{T_p}\right)^{N-1} \exp\left[-\frac{N-1}{\beta}\left(\left(\frac{t}{T_p}\right)^{\beta} - 1\right)\right]. \tag{2.12}$$

The hydrograph distribution (Equation 2.9) is "fit" to observed hydrographs using a least-squares error minimization criterion. Once the distribution parameters, n and $t_{rm\beta}$, are recovered, they are then converted into conventional hydrograph parameters using Equations 2.10 and 2.11.

2.3.2 Loss-Rate Functions and Runoff Generation

The physical loss processes include evaporation (as well as evapotranspiration) and infiltration into the soil. The physical storage processes include storage in a thin layer of water covering a watershed (that eventually evaporates) as well as water sequestered in ponds, lakes, reservoirs, potholes, and other depressions. In the regulating structures (ponds, detention basins, reservoirs) changes in storage can be measured and quantified — pothole storage and similar mechanisms are at best a guess. For hydrologic response prediction at the storm-length temporal scale, these components are often lumped into a single loss term. This aggregation is a simplification to make data management simpler in the context of design. However, the loss term is significant because the storage process is the term in the volume balance that actually governs (mathematically) the runoff component.

The loss models included in this study are a fractional loss model, an initial-abstraction constant-loss model, and a simplified Green-Ampt infiltration model. These three are selected because of their relative simplicity — these models are at about the same conceptual complexity as the unit hydrograph model. Use of a loss model that is conceptually more complex than the corresponding time redistribution model (the unit hydrograph) is unjustified[10].

Fractional Loss Model (FRAC)

The fractional loss model (FRAC) assumes that the watershed immediately converts a constant fraction (proportion) of each rainfall input into an excess rainfall fraction that subsequently contributes to runoff (McCuen, 1998). The constant runoff fraction is a runoff coefficient. The FRAC

[10] An interpretation of Occam's razor or the principle of parsimony as applied to this study.

model is attractive for automated processing because of its simplicity and because it preserves the correct runoff volume without iteration[11]. The FRAC loss model is

$$l(t) = (1 - C_r)p(t), \text{ if } \int_0^t p(\tau)d\tau > I_a, \tag{2.13}$$

where $l(t)$ is the loss rate as a function of time, $p(t)$ is the observed rainfall rate as a function of time, and C_r is a runoff coefficient (proportion of rainfall that becomes runoff).

This model implicitly assumes that rainfall loss is a watershed property and is independent of storm history. Additional details of the data preparation, separation techniques, and rainfall loss models are reported in He (2004). The relevant portions of the FORTRAN source code that implements this model are presented in Figure A.1[12].

Initial-Abstraction/Constant Loss-Rate Model (IACL)

The initial-abstraction, constant-loss model (IACL) assumes that after rainfall begins a certain portion is initially stored, infiltrated, or otherwise removed from the system and never appears as runoff[13]. After the initial abstraction is satisfied, the loss rate is the smaller of some constant value or of the incoming rainfall rate. When the incoming rainfall exceeds the constant loss rate, the difference between input rainfall rate and this constant loss rate is the excess rainfall rate. The IACL loss model is expressed in Equations 2.14 and 2.15 as

$$l(t) = p(t) \qquad \text{if } \int_0^t p(\tau)d\tau < I_a, \text{ or} \tag{2.14}$$

$$l(t) = \min[p(t), C] \qquad \text{if } \int_0^t p(\tau)d\tau > I_a. \tag{2.15}$$

The relevant portions of the FORTRAN source code that implements this model are presented in Figure A.2.

Green-Ampt Infiltration (GAIN) Loss Model

The Green-Ampt Infiltration (GAIN) model used in the University of Houston study is a simplification of the Green-Ampt infiltration model presented in an earlier section of this report. The GAIN model assumes that the watershed has some capacity to absorb rainfall and runoff occurs only when the rainfall input rate exceeds the absorption rate. The model is developed using the

[11] As compared to the ϕ-index method.

[12] Elements with numbers preceded by a capitalized letter indicate reference to one of the appendices attached to this report.

[13] At the time scales of a storm event — this initial portion may appear much later as baseflow, well after the storm event.

infiltration theory of Polubarinova-Kochina (1962), but the model is structurally identical to the independently developed Green-Ampt model with some minor conceptual differences.

The GAIN assumes that an infiltration front propagates into the watershed soils according to Darcy's law and the water content change across the front is equal to the soil porosity. The front propagates into the soil without moisture redistribution; excess rainfall is the difference between the actual rainfall and the loss as the event progresses.

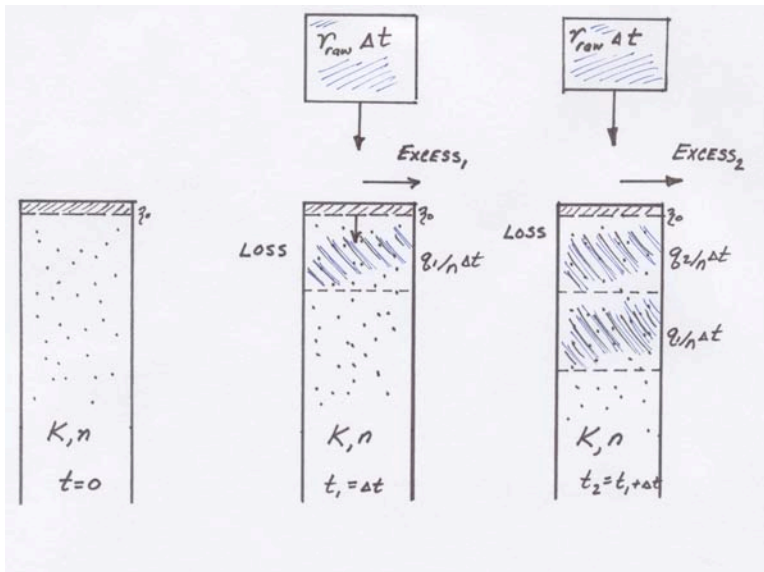


Figure 2.2: University of Houston infiltration process schematic.

Figure 2.2 is a schematic of the infiltration model. The three soil profiles represent the infiltration at different times, the left-most profile is before the event begins. In that profile, the initial wetting position should be at the land surface, but a small depth is assumed into the soil to prevent an infinite gradient when computing the flux. The middle profile is after a pulse of rainfall occurs. The rainfall volume input is represented by the block above the soil column. After the infiltration for that time interval is calculated, this portion, and possibly all the rainfall, infiltrates into the soil; any remainder is labeled excess and becomes runoff. The right-most profile is one time interval later. How infiltration depths are stacked into the soil, sequentially advancing the wetting front, is depicted in this profile.

The wetting front velocity depicted in the figure (the right two soil profiles) is expressed in Equation 2.16; q, n, and z are the potential infiltration rate, the soil porosity, and the infiltration front position at time t, such that

$$\frac{\partial z}{\partial t} = \frac{q}{n}. \tag{2.16}$$

Equation 2.17 is an expression of Darcy's law relating the potential rate to the front position as,

$$q = K\frac{H + h_c + z}{z}. \tag{2.17}$$

In Equation 2.17, the variables H and h_c are the ponding depth and suction potential, respectively. Substitution of Equation 2.17 into Equation 2.16 provides a model for infiltration and hence a tool to estimate rainfall losses as

$$n\frac{\partial z}{\partial t} = K\frac{H + h_c + z}{z}. \tag{2.18}$$

The computation proceeds in light of the following additional simplifications: H is taken to be zero, consistent with other authors (Charbeneau, 2000, e.g.). The suction potential reflects current soil moisture conditions — for a dry clay soil it could be quite large but would reduce to some minimum value rather quickly. For this work we assumed a fixed value because the time scale of our problems is large enough that this term becomes irrelevant quickly after the initial absorption of rainfall — the system behaves as nearly unit-gradient throughout each event. The initial gradient into a dry soil would be quite large because the depth to the wetting front also is zero, so a small nonzero value was also assumed. The resulting model is then

$$n\frac{\partial z}{\partial t} = K\frac{h_c + z + \zeta_0}{z + \zeta_0}, \tag{2.19}$$

where, $h_c = 0.10$, $\zeta_0 = 0.01$, and K and n are adjustable parameters both of which can be related to soil descriptions. The numerical values for suction potential and initial wetting position are strictly ad-hoc and no systematic approach was used in their specification. For most geologic media where infiltration may occur the value of n will range from 10% to 50% with 35% probably being a typical value. K can range over several orders of magnitude for different materials but is restricted in this study to range between literature values for sand to silty-clay.

The algorithm to compute loss and the excess precipitation is:

1. Time-difference computations are used to extract rainfall rates from the observed cumulative rainfall depths. These rates are the raw rainfall rates, $P(t)$.

2. $q_t = K\frac{h_c+z_t}{z_t}$ is used to compute the potential infiltration rate for the time increment.

3. If the potential rate is greater than or equal to the raw rate, all the rainfall infiltrates ($L(t) = P(t)$), and the net infiltration depth for that time increment is computed from $z_{t+\Delta t} = z_t + P(t)/n$.

4. If the potential rate is smaller than the raw rate, the excess rainfall is the difference of the raw rate and the potential infiltration ($L(t) = q_t$), and the net infiltration for that time increment is $z_{t+\Delta t} = z_t + q_t/n$.

5. All time indices are incremented by one and the procedure returns to Item 2.

The relevant portions of the FORTRAN source code that implements this model are presented in Figure A.3.

Computation of Unit Hydrograph and Loss Parameters

Using each of the three loss models, the excess rainfall hyetograph was computed from the storms in the database. The excess rainfall hyetograph is convolved using a FORTRAN program to generate simulated streamflow hydrographs in the database for each watershed. A time series of residuals (differences between the observed and simulated hydrographs) is computed.

Using a second FORTRAN program, the hydrograph parameters for each storm are systematically adjusted until the sum-of-squared residuals is minimized. The formal identification procedure is expressed mathematically as

$$\begin{aligned} \min[SSE(\bar{\alpha})] &= (Q(t)_o - Q(t:\bar{\alpha})_m)^2 \\ &\ni \bar{\alpha} \in \text{search range set}, \end{aligned} \tag{2.20}$$

where Q is the discharge (cubic length per time) and the subscripts m and o represent model and observed discharge, respectively. The term $\bar{\alpha}$ represents the vector of hydrologic variables used in the model and is a concatenation of the loss model variables and the unit hydrograph variables. The term *search range set* is a grid of possible parameter values constructed according to the values specified in Table 2.1.

Table 2.1: Grid search values (*search range set*) for Texas watersheds study.

		FRAC Loss Model		
Parameter	Low Value	High Value	Increment	Units
C_r	$\frac{\int Q(t)dt}{\int P(t)dt}$	–	–	none
t_{rms}	1.0	720.0	1.0	minutes
N	1.0	12.0	0.01	none

		IACL Loss Model		
Parameter	Low Value	High Value	Increment	Units
I_a	0.0	2.0	0.005	inches
C_l	0.0	0.036	0.0001	inches per minute
t_{rms}	1.0	720.0	1.0	minutes
N	1.0	12.0	0.01	none

		GAIN Loss Model		
Parameter	Low Value	High Value	Increment	Units
n	0.1	0.8	0.001	none
K	0.0	0.036	0.0001	inches per minute
t_{rms}	1.0	720.0	1.0	minutes
N	1.0	12.0	0.01	none

The $SSE(\bar{\alpha})$ merit function is designed to favor matching as much of the shape of the hydrograph as possible, while preserving the location of the peak discharge. An alternate merit function used earlier in the research that favored peak matching was not used for the following reasons:

1. The differences in the timing values were negligible regardless of merit function choice.
2. The sensitivity to the adjustable shape parameter of the unit hydrograph, which is an important research question, was greater using the $SSE(\bar{\alpha})$ merit function.

There is no guarantee that results from the grid-search are optimal in the Kuhn-Tucker sense (Gill et al., 1981), but the procedure allows parameter-estimation progress monitoring, limited adaptive control of the *search range set* during the computations, and is robust.

The computational effort is not trivial and a purpose-built cluster computer[14] was used to increase computational throughput. The search procedure produces an $\bar{\alpha}$ for each storm[15] that contains the loss parameters and the unit hydrograph parameters. These results are called "storm optimal" values. The mean values for $\bar{\alpha}$ for each watershed are computed from the storm optimal values and these mean values provide the basis to generate statistical (regression) models to estimate hydrologic parameters for similar Texas watersheds.

To conclude this section, several observations on the approach are useful. First, the approach reported herein was designed to be entirely automated. Once the data are prepared, computations are executed without analyst intervention, in contrast to other approaches on the same database (the USGS approach reported in Asquith and Roussel (2007)). Second, some of the storms were pathologically unsuitable. However, because of algorithm robustness, the program still produces a result. The pathological events were removed manually when detected through graphical data analysis. Third, each storm was analyzed in its entirety; multiple peaks in a storm that could potentially serve as sub-set storms and analyzed independently were not used. Fourth, the entire set of watersheds was re-examined in its entirety as opposed to using the prior work to estimate unit hydrograph parameters independently of the loss parameters[16].

[14] Efforts documenting the construction of this cluster computer were documented at `http://cleveland1.cive.uh.edu/computing/darkstar/index.html` at the time of this writing.

[15] A set of four parameters (three for FRAC).

[16] University of Houston researchers thought that coupled analysis was needed because of the formulation of their theoretical model. They found, and report later, that the processes can be decoupled and the models run with little difference in outcome.

2.4 Lamar University

Researchers at Lamar University developed and used a non-linear programming algorithm to optimize rainfall loss and unit hydrograph parameters from more than 1,600 observed rainfall-runoff events. The analysis procedure follows:

1. Data acquisition, analysis, and processing (rainfall-runoff time series and watershed characteristics).
2. Non-linear programming model development in Excel[17]
   - Define objective function for optimization.
   - Develop gamma unit hydrograph using estimated Q_p and T_p in Equation 2.21.
   - Develop VBA program to estimate constant loss from given initial loss and DRH match.
   - Develop VBA program to get runoff hydrograph using GUH and estimated rainfall excess.
3. Optimization of parameters (initial loss, Q_p, and T_p of GUH) by minimization of errors using the solver in Excel.
4. Average rainfall-loss and GUH parameters for each watershed.
5. Develop multi-parameter regression equations for average GUH parameters.

2.4.1 Gamma Unit Hydrograph

A gamma unit hydrograph (GUH) was adopted as the regional unit hydrograph model for Texas watersheds. GUH ordinates are

$$U(t) = Q_p(t/T_p)^{\alpha} e^{(1-t/T_p)\alpha}, \tag{2.21}$$

where $U(t)$ is the ordinate of the GUH at time t (hours), Q_p is the peak discharge (cubic feet per second, cfs), T_p is the time to peak discharge (hours), and α is the shape parameter. The GUH parameters are not independent and the shape factor can be estimated from Q_p and T_p using Aron and White (1982),

$$\alpha = 0.045 + 0.5\phi + 5.6\phi^2 + 0.3\phi^3, \tag{2.22}$$

where

$$\phi = \frac{Q_p T_p}{A}, \tag{2.23}$$

for drainage area, A, of the watershed (acres).

[17]Use of specific commercial software does not constitute endoresement.

2.4.2 Rainfall Loss-Model

The rainfall loss-model used for non-linear programming is an initial-loss/constant loss-rate method (similar to the ϕ-index method). There are three parameters for optimization that include initial loss (in inches), peak discharge (in cubic feet per second), and time to peak (in hours) for the GUH. The optimization algorithm forces a volume match between observed and estimated direct runoff hydrographs for all events. The constant loss-rate (inches/hour) is determined from optimized initial loss and the volume match.

2.4.3 Non-Linear Programming Algorithm

The non-linear programming model to determine the rainfall loss and GUH parameters follows that presented in Chow et al. (1988, pp. 216, 222, and 223). With unitgraph duration is D hours, the objective equations are

$$\begin{aligned} \sum_{m=1}^{n\leq M}(P_m - L_m)U_{n-m+1} + Z_n - V_n &= \hat{Q}_n + Z_n - V_n \\ &= Q_{bn}, \end{aligned} \tag{2.24}$$

where N is the number of ordinates in the observed runoff hydrograph ($n = 1, 2 \ldots N$), M is the number of ordinates in the observed rainfall hyetograph, P_m is the gross incremental rainfall depth (inches) over the time interval m (time $t = mD$ and $m = 1, 2 \ldots M$), L_m is the rainfall loss determined from the initial and constant loss model at the time interval m, U_{n-m+1} is the ordinate of the GUH given in Equation 2.21 at time $t = (n - m + 1)D$, Z_n is the deviation of the derived (predicted) direct runoff hydrograph (DRH) ordinate below the observed DRH ordinate Q_{bn}, and V_n is the deviation of the derived (predicted) direct runoff hydrograph (DRH) ordinate above the observed DRH ordinate Q_{bn}. $\hat{Q}_n$ is the derived (predicted) DRH ordinate determined from the discrete convolution equation (Chow et al., 1988) from the rainfall excess hyetograph and unit hydrograph as given in the first term in Equation 2.24, and $\epsilon_n = Q_{bn} - \hat{Q}_n$ is the deviation between observed and derived DRH ordinates. When $\epsilon_n > 0$, $Z_n = \epsilon_n$ and $V_n = 0$, and when $\epsilon_n < 0$, $Z_n = 0$ and $V_n = -\epsilon_n$. The optimization of non-linear programming used in this study determined the initial loss and the GUH parameters (Q_p, T_p) to minimize deviations between the observed and predicted DRH ordinates. For example, the sum of absolute deviation and the range of deviation (Zhao and Tung, 1994) were used as objective functions to measure the deviations (differences) between observed and predicted DRH ordinates.

The non-linear programming algorithm is implemented under Microsoft Excel using Solver function and several Visual Basic (VBA) programs developed by researchers. The non-linear programming optimization typically requires providing some constraints and initial estimates for parameters optimized. The initial guess or estimate for the initial loss is set as 10 percent of total rain depth. The constant loss is automatically calculated by a VBA module *TOTAL* based on the volume match between observed and predicted DRH. The initial guess of the time to peak T_p is calculated for a GUH based on an estimate of time of concentration as the square root of drainage area (Fang et al., 2007). The initial guess for the peak discharge Q_p is calculated from the NRCS dimensionless UH method,

$$T_c = A^{0.5}, \tag{2.25}$$

$$T_p = \frac{T_c + D}{1 + \frac{1}{\sqrt{\alpha}}}, \text{ and} \tag{2.26}$$

$$Q_p = \frac{484A}{T_p}, \tag{2.27}$$

where A is drainage area in square miles, D is the duration of the unit hydrograph (in this case five minutes), and α is 3.7 for the NRCS dimensionless unit hydrograph. When these initial estimates of T_p and Q_p could not develop an optimum solution for some events, alternative estimates of T_p and Q_p are estimated by the traditional unit hydrograph method (Chow et al., 1988; Viessman and Lewis, 2003), for example, the peak unitgraph discharge is observed Q_p of DRH divided by total rainfall excess (integrated DRH depth). The constraints used in this study are:

1. Initial loss is less than or equal to 30 percent of total gross rain (this constraint was not used for the final analysis using the objective function as minimizing the range of deviation),
2. Non-negativity constraints (initial loss, constant loss-rate, Q_p, and T_p are greater than or equal to zero),
3. $0.5\hat{T}_p \leq T_p \leq 1.5\hat{T}_p$ where $\hat{T}_p$ is the estimate of T_p computed using Equation 2.26,
4. $Q_p \leq 1.5 \max(Q_p$ from NRCS formula, Q_p by traditional unitgraph), and
5. $Q_p \geq 0.5 \min(Q_p$ by NRCS formula, Q_p by traditional unitgraph).

2.4.4 Implementation of Computational Algorithm

The rainfall-runoff and watershed attribute data of 88 selected Texas watersheds are presented in Asquith et al. (2006). The period of record for those data are from about 1959 to 1986. The rainfall and runoff data are processed using a FORTRAN program to arrange them in 5-minute intervals in required units starting from the beginning of recorded rainfall. To obtain rainfall and runoff data at an appropriate time interval linear interpolation was used. The semi-automated model is developed using Microsoft Excel with VBA as the backend to implement non-linear optimization. The direct output of the computational tool is optimized values of initial loss, Q_p and T_p of the GUH, unitgraph duration, and event-wise time series rainfall-runoff data. The computational tool selects decision variables (initial loss, Q_p, and T_p of the GUH) for each event by minimizing a set of objective functions (sum of absolute deviation, weighted sum of absolute deviation, largest absolute deviation, range of deviation, root mean square error, and overall relative bias of direct runoff hydrograph). Different constraints or limits were used in the optimization procedure so that a solution is determined faster or iteration converges to an optimal solution in a feasible part of the parameter space.

For each event, the model is run six times with six different optimization objectives. The event-wise values of each watershed are then used to obtain regionalized value for that watershed using mean and median as the statistical tools. Watershed average parameters were analyzed and regional regression equations were developed to correlate rainfall loss and unit hydrograph parameters to watershed characteristics.

2.5 Texas Tech University

The focus of Texas Tech researchers originated with an examination of the database to extract unit hydrographs using the traditional approach (Linsley, Jr. et al., 1958; Viessman and Lewis, 2003). This approach uses the direct runoff hydrograph to extract ordinates of the unit hydrograph. The duration of the resulting unit hydrograph is determined by applying a ϕ-index to the associated rainfall hyetograph to determine the duration of the unit hydrograph. If a duration other than this value is desired, then either lagging or S-hydrograph methods can be used to effect a change of unit hydrograph duration.

Because the direct runoff hydrograph is divided by the depth of runoff (determined by integrating the area under the direct runoff hydrograph) to create a unit hydrograph, the depth of runoff should be approximately one inch. Otherwise, the leverage implied by the divisor results in large changes to the ordinates of the direct runoff hydrograph. Jones (2006) learned that it was necessary to censor the project database to leave only those rainfall-runoff events with direct runoff of at least 0.1 inch[18] to achieve reasonable unit hydrographs.

As a result, a total of 455 events from 82 watersheds[19] were subjected to analysis using HEC-HMS (U.S. Army Corps of Engineers, 2006). The objective of this analysis was to extract unit hydrograph and loss-rate function parameters from the study watersheds using the Green and Ampt (1911) and initial loss/constant loss-rate functions.

2.5.1 Computational Tools

HEC-HMS (U.S. Army Corps of Engineers, 2006) was used as the computational tool for extraction of loss-function parameters from 455 events for 82 watersheds. Although the exact procedure used depended on which loss-function was being analyzed, Texas Tech researchers used the SCS (NRCS) dimensionless unit hydrograph as the transform, regardless of which loss function was being analyzed. Therefore, SCS lag time is required for generation of the unit hydrograph. In addition, baseflow was modeled for some watersheds using the HEC-HMS approach that requires a recession constant and a recession threshold to estimate baseflow components, if any.

[18] A depth of direct runoff of 0.1 inch results in a leverage of ten times to the direct runoff hydrograph ordinates. Leverage values exceeding ten were determined to result in unrealistic unit hydrograph ordinates and shapes. Therefore, the dataset was censored to use only rainfall-runoff events with direct runoff exceeding 0.1 inch.

[19] These watersheds and events were the result of Jones (2006) earlier work footnoted previously.

2.5.2 Initial Loss/Constant Loss-Rate

One of the simplest approaches to hydrologic abstractions is the the U.S. Army Corps of Engineers' initial loss/constant loss-rate method. This method for hydrologic abstractions was also present in the earlier Corps generalized flood hydrograph model, HEC-1 (Hydrologic Engineering Center, 1998). Functionally, the method is comprised of two components — the first component is an initial abstraction, specified as a depth of incoming precipitation. Before runoff can occur, this depth or loss must be satisfied. The second component is a constant loss-rate. Subsequent to satisfying the initial abstraction, further incoming rainfall is subjected to a constant loss-rate (analagous to the *phi*-index), with runoff being the difference between incoming precipitation rate and loss-rate. If the loss-rate exceeds the precipitation rate for the period, no runoff occurs during that period.

2.5.3 Green-Ampt Loss Function

As defined in HEC-HMS (U.S. Army Corps of Engineers, 2006), the Green-Ampt loss function is expressed with four parameters: hydraulic conductivity, initial loss, soil moisture deficit, and wetting front suction. The form of the Green-Ampt loss-rate function is given by Equation 2.1. The cumulative infiltration is given by Equation 2.2. Because an initial loss parameter is added to the basic Green-Ampt approach, no infiltration occurs until the initial loss is satisfied.

2.5.4 Implementation of Computational Approach

Each event in the study dataset[20] was subjected to optimization to extract model parameters. The objective function to measure the difference between the observed hydrograph and the generated hydrograph was the sum of squared errors. Conservation of mass was preferred to matching of peak discharge. The univariate gradient search algorithm was used to seek minimization of the objective function.

During the optimization process, some parameters were easily extracted from observations. In contrast, the generated hydrograph was not sensitive to some parameters. A variety of seed values for optimized parameters was used to assure that minima derived from the optimization process were not local minima but represented global minimum values of the objective function.

[20]The study dataset used by Texas Tech researchers was different than that used by the other research teams. This is explained in the Chapter 3, Results.

Chapter 3

Results

3.1 U.S. Geological Survey

Statistical analyses of $\overline{I_A}$ and $\overline{C_L}$ (watershed-specific initial abstraction and constant loss) were done with the objectives of (1) documenting the parameter distribution and (2) developing predictive procedures of each parameter for ungaged watersheds. The statistical analyses of $\overline{I_A}$ and $\overline{C_L}$ document the distribution for each parameter. The four-parameter generalized lambda distribution (GLD) was used as a parametric model, which was fit by the method of L-moments. The L-moments and corresponding GLD parameters for both $\overline{I_A}$ and $\overline{C_L}$ are tabulated. The analyses show that watershed development has **substantial** influence on I_A and limited influence on C_L.

The effect of development on $\overline{I_A}$ is illustrated in Figure 3.1. Likewise the effect of development on $\overline{C_L}$ is illustrated in Figure 3.2. Both figures are quantile diagrams of the initial abstraction and constant loss rate computed by the USGS researchers for the 92 study watersheds. The solid markers are the undeveloped watersheds and the open markers are the developed watersheds. A similar set of figures is presented in the University of Houston results (Figure 3.7). Whereas the two sets of figures differ, they depict similar findings, and provide mutually-reinforcing support.

The mean and median watershed-specific values are tabulated with respect to watershed development. Although considerable variability exists, these values are used in later analyses that develop procedures for I_A and C_L estimation for ungaged watersheds.

The statistical analyses reported by Asquith and Roussel (2007) also document predictive procedures for estimation of $\overline{I_A}$ and $\overline{C_L}$ for ungaged watersheds with respect to watershed development. Both regression equations and regression trees for estimation of I_A and C_L are provided by those authors. The watershed characteristics included in the regressions are main-channel length (L), watershed development (a binary factor $D = 0 \mid 1$), abundance of rocky terrain with thin soils and limestone and karst features (a binary factor $R = 0 \mid 1$), and curve number (CN). Other characteristics assessed were dimensionless main-channel slope, soil types and textures, and percentage impervious cover.

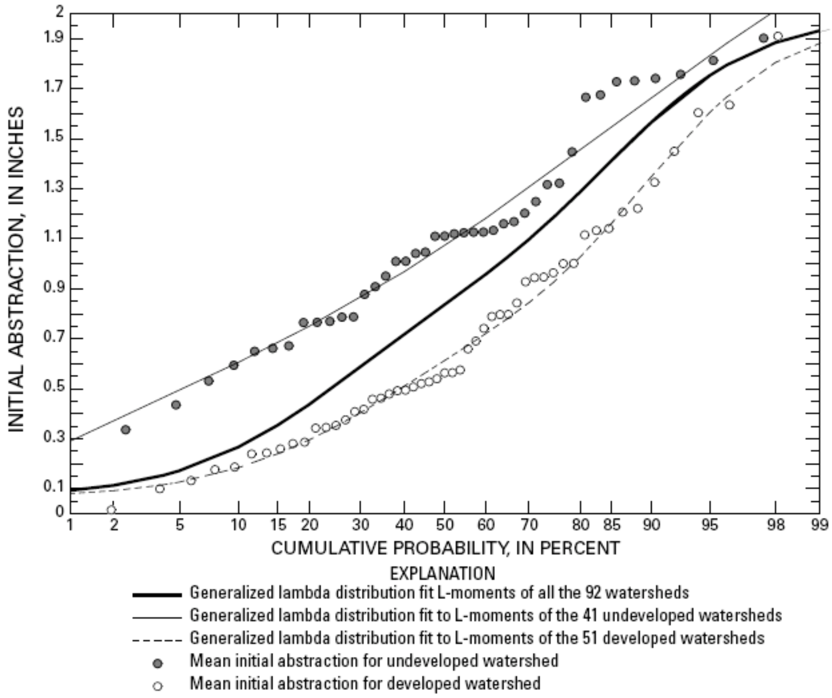


Figure 3.1: Distribution of initial abstraction and fitted general lambda distribution models for the 92 study watersheds. Figure 3.1 is identical to Figure 4 in Asquith and Roussel (2007, used with permission).

These "other" characteristics are reported as Watershed Land-Use-Type Characteristics used by the University of Houston researchers in Table A.1. These characteristics were supplied to the Houston researchers by the USGS researchers for this study. In addition, the Watershed Dimensional Characteristics reported in Table A.2 used by the University of Houston researchers were also prepared in cooperation with the USGS researchers.

The regression equations for I_A and C_L ($I_A : C_L$ equations) are accompanied by mathematical results to assess equation applicability and prediction limits. Physical interpretations of the regression coefficients are made. In summary, for the I_A equation, the coefficient on D implies that developed watersheds generally have about 1/5-inch less initial rainfall storage than undeveloped watersheds. The coefficients on R imply that rock-dominated, thin-soiled watersheds as represented by some of the 92 watersheds have about 1/4-inch larger I_A and about 1/4-inch per hour larger C_L than other watersheds. The coefficients on CN are consistent with the broadly understood definition of CN. An increase of 10 units of CN represents about $-1/7$-inch of I_A and represents about $-1/6$-inch per hour of C_L. Description and interpretation of the influence of L on I_A and C_L is more complex than for D, R, and CN.

Asquith and Roussel (2007) present regression trees to augment the regression equations. Regression trees result from an alternative method of regression (sometimes termed recursive partitioning)

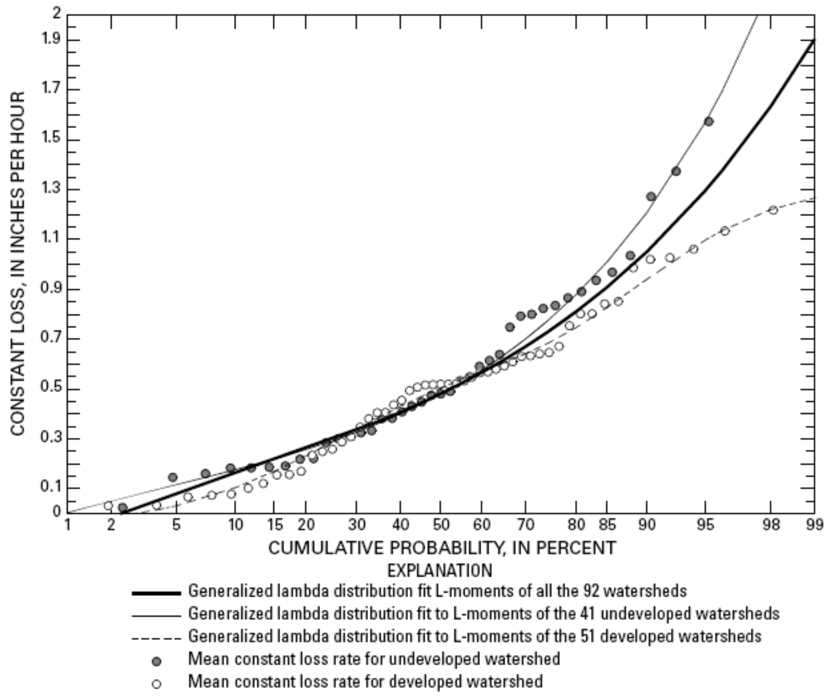


Figure 3.2: Distribution of initial abstraction and fitted general lambda distribution models for the 92 study watersheds. Figure 3.2 is identical to Figure 4 in Asquith and Roussel (2007, used with permission).

when compared to regression that produces equations. A tree is constructed such that partitions (branches) are determined by an algorithm that seeks to split and minimize residual sum of squares. A tree lists at each terminal branch the value for I_A or C_L, the number of samples, and residual standard error. Unlike for the I_A equation, D apparently does not have substantial predictive properties for I_A in a regression-tree context. Therefore, conclusions based on which parameters are important can be influenced by model structure; the I_A equation and I_A tree ($I_A : C_L$ trees) are structurally distinct.

Figures 3.3 and 3.4 are the regression trees from Asquith and Roussel (2007). They convey similar information to Figures 3.8 and 3.9 in the University of Houston results, although the regression trees convey the information in a different fashion, and more importantly provide error estimates as part of the tree. The University of Houston results present estimates for an example watershed. The example in that section is also executed using the USGS regression trees combined with Q_p and T_p equations.

Subsequent to the regression analyses, an initial-abstraction constant-loss model for watershed-loss estimation for applicable watersheds in Texas is evaluated by Asquith and Roussel (2007). The $I_A : C_L$ equations with statistically significant variables explain about 30–34 percent of the variation in the $\overline{I_A}$ and $\overline{C_L}$ values. The $I_A : C_L$ trees explain a similar amount. Therefore, the

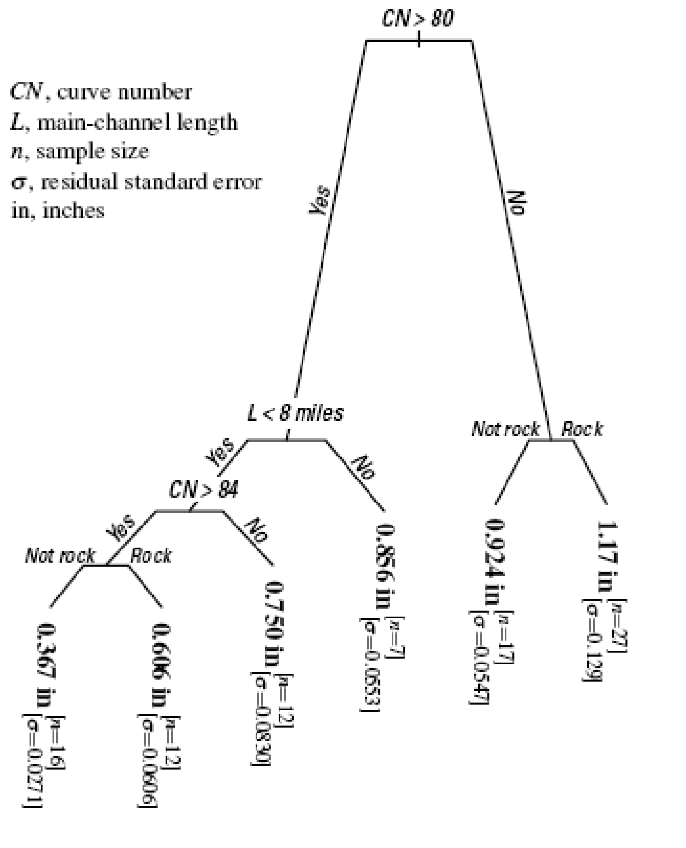


Figure 7. Regression tree of $\overline{I_A}$ for estimation of I_A.

Figure 3.3: Regression tree for I_a. From Asquith and Roussel (2007, used with permission).

mean or median of $\overline{I_A}$ and $\overline{C_L}$ ($\check{I}_A : \check{C}_L$, median; $\overline{I_A : C_L}$, mean), with consideration of watershed development, also could be reasonable estimates for a watershed. Four techniques are identified for general estimation for ungaged watersheds. The four techniques are abbreviated as $\overline{I_A : C_L}$, $\check{I}_A : \check{C}_L$, $I_A : C_L$ equations, and $I_A : C_L$ trees. The units on I_A and C_L are watershed inches and watershed inches per hour, respectively.

Custom software was developed to implement the four techniques for the 92 watersheds. As a result, all storms in the database for each of the 92 watersheds were reprocessed four separate times. With each reprocessing, the (1) Q_p error, (2) runoff volume error, and (3) time difference of Q_p were computed for each suitable storm. Analysis of the three error types is provided. The analysis of the Q_p error indicates that nearly unbiased estimates of Q_p result from each of the four techniques. The variations of the Q_p errors for each technique are about 2.5 times larger than the Q_p variation, which shows the results of optimal $\hat{I}_A$ and $\hat{C}_L$ values. The analysis of the runoff

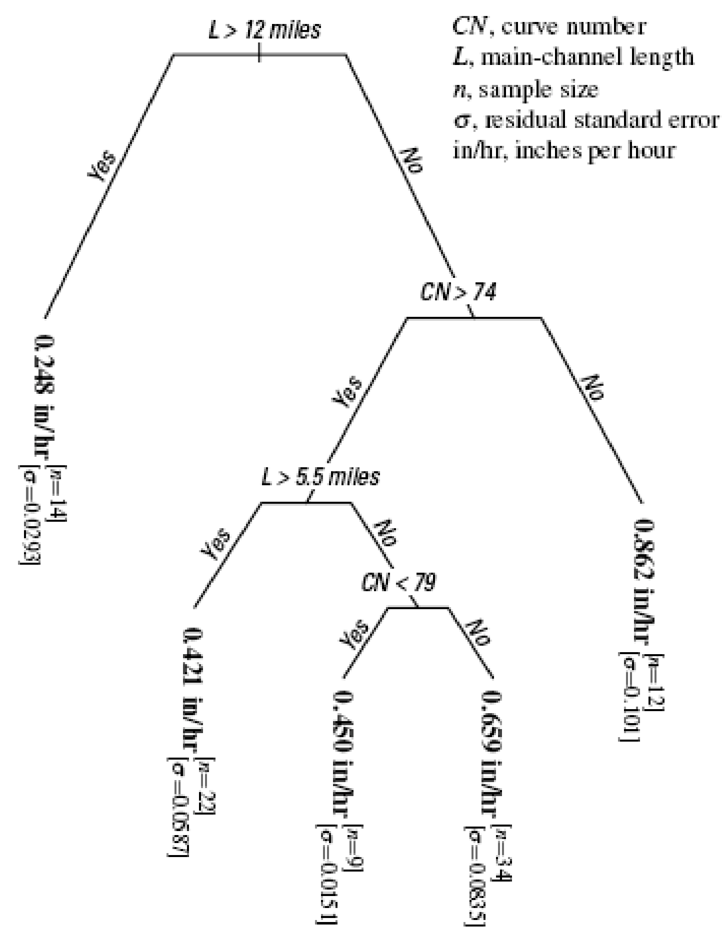


Figure 8. Regression tree of $\overline{C_L}$ for estimation of C_L.

Figure 3.4: Regression tree for C_l. From Asquith and Roussel (2007, used with permission).

volume error indicates that generally biased estimates result from each of the four techniques. The bias is between about 0.1 and 0.3 inch. The positive values indicate that runoff volume is being underestimated. A method to compensate for the underestimation is suggested. The analysis of the time difference of Q_p indicates that generally unbiased estimates result. However, specific interpretation indicates that time of Q_p occurrence is overestimated by about 15 minutes.

The analyses of the three error types shows that there is ambiguity as to which single technique is preferable for watershed-loss estimation. In particular for Q_p, the results indicate that each of the four techniques has similar bias and approximately equal standard deviations of error. Therefore, a judgement was made to combine all four techniques—the combined initial-abstraction constant-loss model. The results in terms of Q_p for the combined model are shown in Figure 3.5.

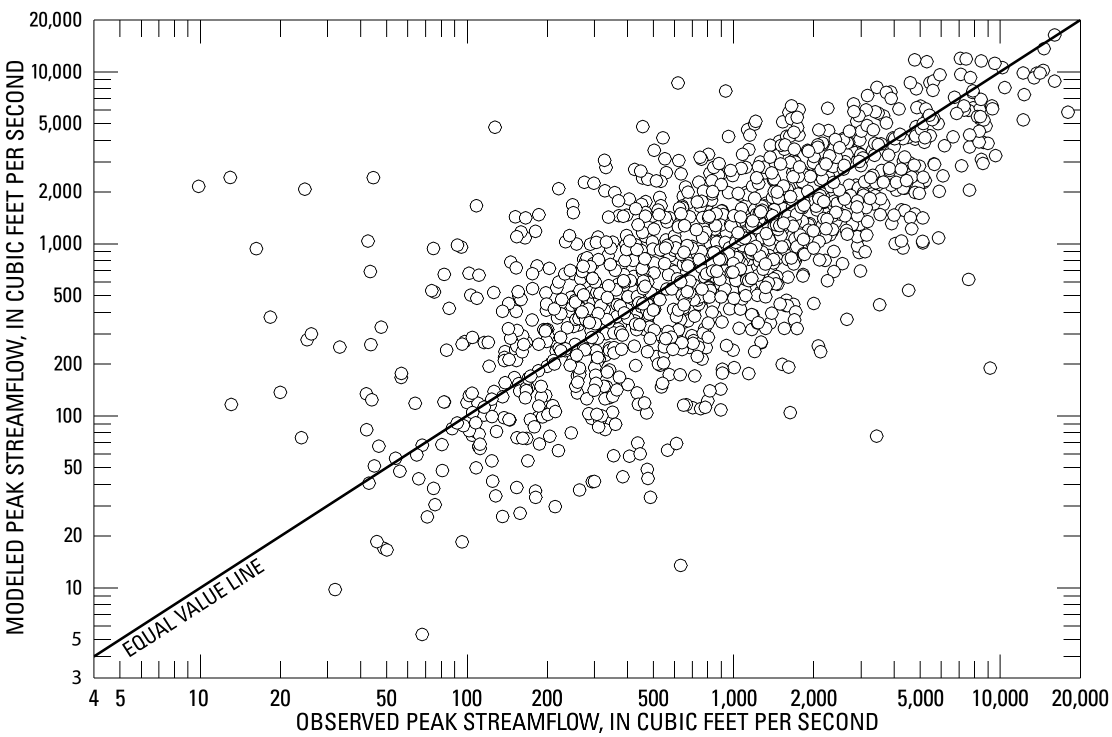


Figure 3.5: Comparison of observed and model peak streamflows from the combined $I_A : C_L$ and $K : T_p$-GUH modeled for the 92 watersheds

The combined initial-abstraction constant-loss model uses the arithmetic average of Q_p, volume, and time of Q_p occurrence. These averages provide better estimates: in particular the Q_p estimation clearly is unbiased in Figure 3.5, and the standard deviation reported by Asquith and Roussel (2007) is reduced substantially. Specifically, the mean Q_p error for the combined model is closer to zero, and the standard deviation is smaller than the corresponding statistics for the four techniques. The approximate $0.41 \log_{10}$(cubic foot per second) standard deviation of the Q_p error is about 105 percent larger than the $0.20 \log_{10}$(cubic foot per second) for optimal $\hat{I}_A$ and $\hat{C}_L$. The bias and standard deviations of the volume and time difference of Q_p for the combined model remain similar to those from the four techniques.

The combined initial-abstraction constant-loss model and $K : T_p$-GUH are based on paired rainfall and runoff data. Therefore storms for which no runoff occurred are not represented in the database. At times some storms with a given depth and duration produce no runoff; however, at other times an apparently similar storm will produce runoff. The difference in watershed response can be attributed in part to temporal differences in antecedent moisture condition. The combined initial-abstraction constant-loss model is conservative, which means that, from an overall perspective of runoff potential watershed losses are underestimated. The underestimation occurs because the computational analysis is biased by the fact that only runoff-producing storms were analyzed, or were able to be analyzed. An algorithm to compensate for subtle mathematical characteristics of the unit hydrograph method in regard to the influence of modeling time step is suggested for general application of the combined initial-abstraction constant-loss model and $K : T_p$-GUH.

3.2 University of Houston

This section presents the University of Houston analysis results and the approach to regionalization for the three loss models as applied to the study watersheds. This section is organized into two main parts:

1. Part 1 presents a summary of the parameter identification procedure described in the University of Houston theoretical development part of the report.
2. Part 2 presents regionalization analysis for the three loss models.

The identification results summary presents qualitative and selected quantitative results of application of the three models using the rainfall-runoff database of Asquith and others (2004). Houston data were available for this research but are intentionally omitted to maintain consistency with prior efforts and Asquith and Roussel (2007). These results are presented in a storm summary analysis, which presents results based on all storms, and in a station summary where the station average values for all the paired storms for each particular station are presented.

The regionalization approach was to postulate explanatory variables based on available data and researchers judgment, and then through regression analysis select regression equations that could be used for estimating values of the hydrologic variables used in each model from the watershed characteristics available for each watershed.

3.2.1 University of Houston, Storm Summary Analysis

A summary analysis for all storms studied for each of the three loss models is presented on Figure 3.6. The figure contains six panels organized from top to bottom as the total runoff volume[1],

[1] Runoff volumes and discharges are normalized by watershed area, hence dimensions are length and length per time, units are inches and inches per minute.

the peak discharge, and the time of the peak discharge. The left panels are scatterplots of these measures with an equal value line to indicate the ideal performance, the right panels are boxplots of the distributions of the various measures. Table 3.1 tabulates the essential information displayed in the boxplots.

The scatterplot of the observed runoff volume and the model runoff volume for about 1,500 storms (upper left panel) in the database using the three different loss models illustrates that there are differences in results between the three models.

The FRAC model is the only model that explicitly should match volume (by virtue of how the runoff coefficient is specified) and agrees well with the equal volume line in the volume plot. The other two models, GAIN and IACL, do not explicitly match volume and thus have an additional degree of freedom. This additional degree of freedom is a consequence of a need to keep the grid-search selection algorithm unchanged for different loss models. This panel illustrates that the unconstrained loss models (GAIN and IACL) exhibit more variability, which is an anticipated result.

The boxplots of observed runoff volume and model runoff volume for the same results (upper right panel) further illustrates differences. The FRAC model distribution is essentially identical to the observed distribution, which is an anticipated result. The two other models are biased low, which means the computed runoff depth is less than observed runoff.

The difference in medians between the FRAC and other two loss models are significant, but the differences between the GAIN and IACL model are not significant. This result is interpreted as either of these models are equivalent when computing total runoff volume. The researchers speculate that further refinement to improve the volume match might produce performance comparable to the FRAC model.

Table 3.1: Storm summary statistics for three loss models.

Runoff Depth Distribution	1st - Quartile	Median	3rd - Quartile	Units
Observed	0.277	0.603	1.140	inches
FRAC	0.276	0.595	1.130	inches
GAIN	0.244	0.496	0.982	inches
IACL	0.220	0.478	0.950	inches
Peak Flow Distribution	1st - Quartile	Median	3rd - Quartile	Units
Observed	1.4×10^{-3}	3.8×10^{-3}	8.2×10^{-3}	inches/min.
FRAC	8.7×10^{-4}	2.4×10^{-3}	5.6×10^{-3}	inches/min.
GAIN	9.8×10^{-4}	2.7×10^{-3}	6.4×10^{-3}	inches/min.
IACL	9.3×10^{-4}	2.6×10^{-3}	5.0×10^{-3}	inches/min.
Time of Peak Flow Distribution	1st - Quartile	Median	3rd - Quartile	Units
Observed	646	1140	1460	minutes
FRAC	641	1120	1460	minutes
GAIN	636	1120	1450	minutes
IACL	654	1150	1490	minutes

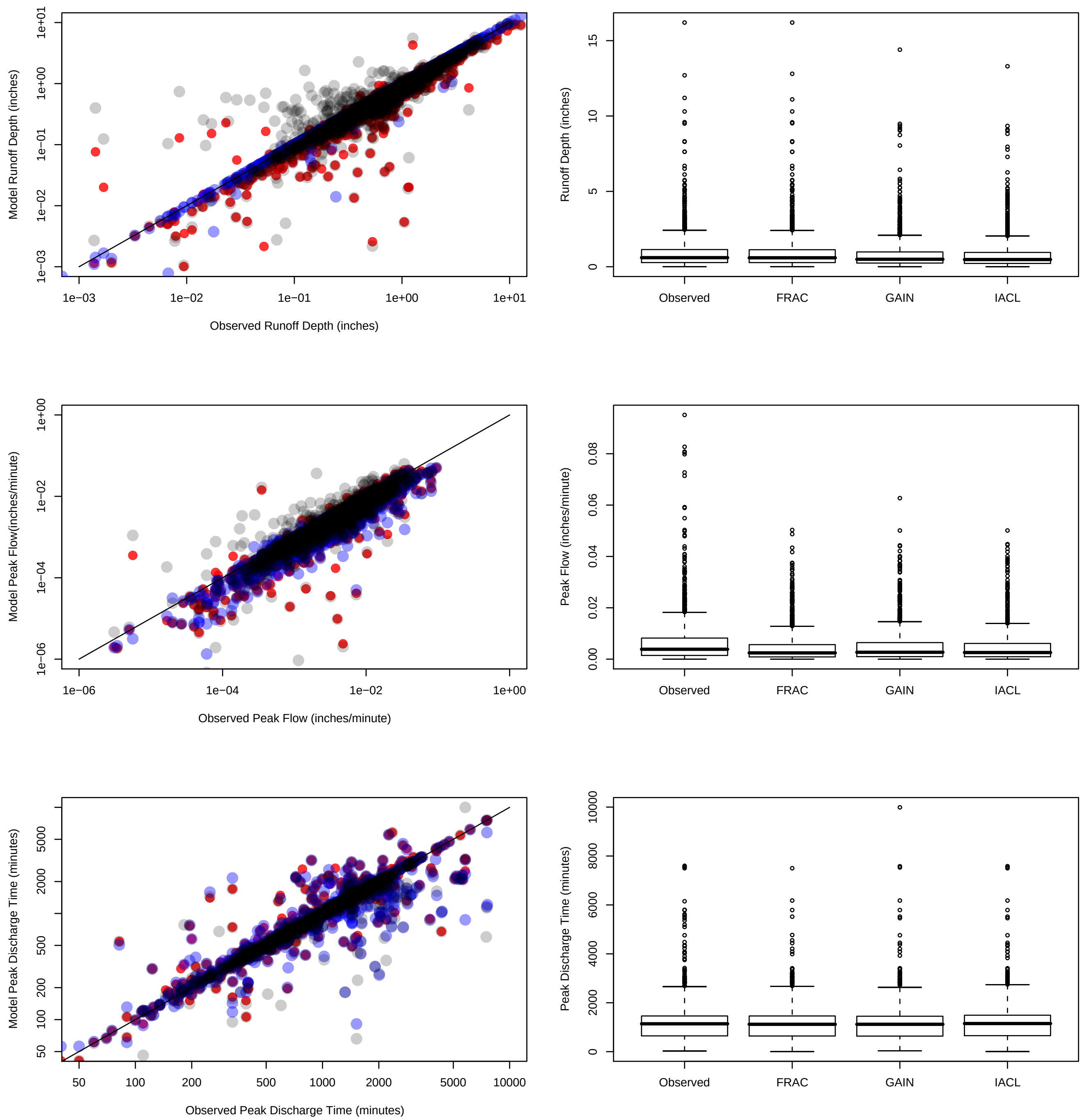


Figure 3.6: Qualitative storm summary relationships for three simple loss models. Left Panels: Red markers: IACL model; Blue markers: FRAC model; Black(Grey) markers: GAIN model.

The scatterplot of the observed peak discharge and the model peak discharge (left middle panel) illustrates that all the model results exhibit a low bias relative to the equal value line. The bias is attributed to the nature of the merit function selected in the grid search algorithm that de-emphasizes peak value in an attempt to match the hydrograph shape. The associated boxplot of the distribution of the peak discharges for the different loss models illustrates this bias. More importantly the differences in the medians are significant in comparison with the observed results. The difference in medians between the models is not significant, this result is interpreted to mean that any of the loss models perform roughly the same with respect to the computation of peak discharge.

The scatterplot of the observed time of the observed peak discharge and the model time of the model peak discharge (left lower panel) illustrates that all three loss models qualitatively perform the same. The associated boxplot as well as non-parametric tests (Wilcox) indicate that the three distributions have no statistically significant differences. This result is interpreted as meaning that the loss models have little impact on the computed response time of the study watersheds. This particular finding is important in that it supports the concept that the timing estimates can be de-coupled from the loss estimates with little impact on the resulting unit hydrograph. Such decoupling is a principal feature in the Asquith and Roussel (2007) approach.

3.2.2 University of Houston, Station Summary for IACL Model

This section presents station summary results for the IACL loss model. This particular loss model also was considered by the USGS researchers. Therefore, results are readily compared. This section presents the University of Houston findings as a comparability check with the USGS results. Such checks are important to detect substantial conceptual modeling errors. In general, because the underlying databases are the same, two different teams, operating relatively independently and exclusively, developing their own software, should produce similar results in terms of the scale of the results[2].

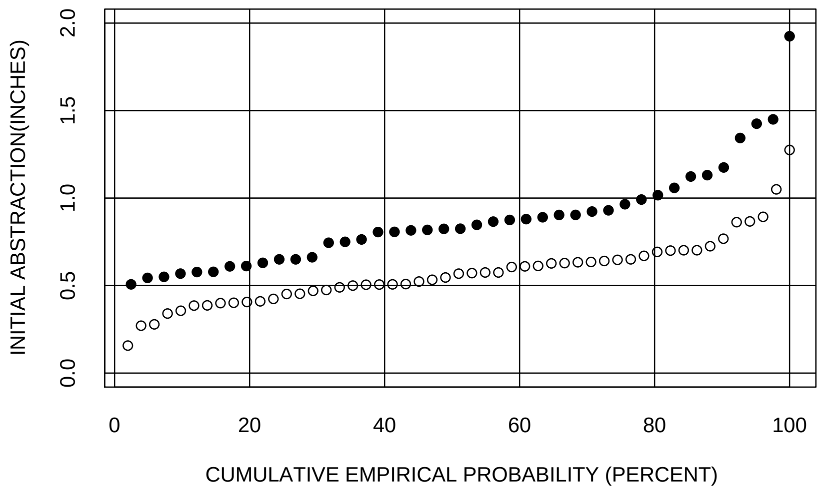
Figure 3.7 is a two-panel plot of the relationship of the initial abstraction depth I_a and cumulative empirical probability[3], and the constant loss rate C_l and cumulative empirical probability for the study watersheds.

This plot is intended to convey similar information as Figures 4 and 5 in Asquith and Roussel (2007). The upper panel is the initial abstraction relationship. The median value of I_a is 0.56 inches for an undeveloped watershed and 0.82 inches for a developed watershed and the difference is significant. Interpreting the initial abstraction as a surrogate for storage, the undeveloped watersheds in the study typically store almost fifty percent more depth as a developed watershed. This result is consistent with the independent modeling by Asquith and Roussel (2007).

The lower panel is the constant loss relation. The median values of C_l for undeveloped and developed

[2]Within say 1/3 of a log-cycle.

[3]Actually a cumulative relative frequency, but the axis label is selected for consistency with Asquith and Roussel (2007).



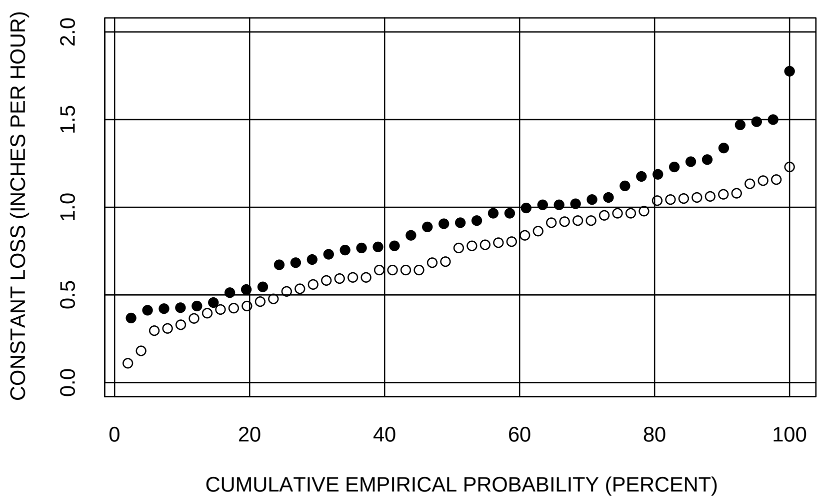


Figure 3.7: Relation between initial abstraction (I_a) and constant loss-rate (C_l) station mean values and cumulative probability segregated by development factor.
Upper panel : Initial abstraction (I_a) station mean values for undeveloped(filled markers) and developed(open markers) watersheds.
Lower panel : Constant loss rate (C_l) station mean values for undeveloped(filled markers) and developed(open markers) watersheds.

study watersheds are 0.91 inches per hour and 0.76 inches per hour, and the difference in these values is substantial. Undeveloped watersheds exhibit a loss rate about fifteen percent greater on average as does a developed watershed. This result differs from the results of Asquith and Roussel (2007), who concluded that development did not have a substantial affect. However, the magnitude of the loss rates is consistent with Asquith and Roussel.

In the Asquith and Roussel (2007) study they conclude that the effect of urbanization on the loss rate was only slight and that a useful upper limit of loss rate was on the order of $C_l = 1.3$ inches per hour. In the University of Houston results a similar upper limit is observed. However, its value is about $C_l = 1.5$ inches per hour. The numerical values are different but are of the same order of magnitude. The University of Houston team concludes that both teams are producing comparable results that increase the collective confidence in the estimation procedure described in Asquith and Roussel (2007).

3.2.3 Regression Process, Hydrologic, and Explanatory Variables

Stepwise linear regression using the **R** environment (R Development Core Team, 2006) was used to identify possible regression models, then manual substitution of explanatory variables and analysis of individual regressions was used to select a final model. Generally the researchers added and removed variables in attempts to increase the adjusted R^2 while decreasing the standard error estimates (if possible). An a-priori decision was not to accept regression models with adjusted R^2 less than 0.25. In cases where the researchers could not find a suitable regression model, the median value of the hydrologic variable being analyzed was used.

Table 3.2: Explanatory variables considered by University of Houston researchers.

Name	Domain	Description
$DEVF$	Binary; 0 or 1	Development factor
$ROCK$	Binary; 0 or 1	Rock cover factor
$ICOV$	Continuous; $[0, 100]$	Impervious cover in percent
CN	Continuous; $[0, 100]$	NRCS Curve Number
MCL/S	Continuous; $[0, +\infty)$	Ratio of length to slope, undefined for $S = 0$

The explanatory variables considered are listed in Table 3.2. Of these variables, only the MCL/S is related to physical properties of the watershed that are associated with watershed dimensions[4]. The other variables, whereas related to physical or descriptive characteristics and likely to change with size, are considered by the University of Houston researchers as land-use-type variables and distinctly different in character than the dimensionally related variables.

Table 3.3 is a list of the hydrologic variables used in the rainfall-runoff models that are being regionalized. These variables are partitioned into variables related to the loss model and the unit hydrograph model. The variables associated with the unit hydrograph are listed at the bottom of

[4]Lengths, widths, etc.

Table 3.3: Hydrologic variables used in University of Houston rainfall-runoff modeling.

Name	Range	Description
C_r	Continuous; $[0, 1]$	Runoff coefficient, dimensionless, FRAC model
I_a	Continuous; $[0, +\infty)$	Initial abstraction in inches, IACL model
C_l	Continuous; $[0, +\infty)$	Loss rate in inches per hour, IACL model
ϕ	Continuous; $[0, 1]$	Psuedo-porosity, dimensionless, GAIN model
K	Continuous; $[0, +\infty)$	Psuedo-conductivity, in inches per hour, GAIN model
t_{rms}	Continuous; $[0, +\infty)$	Characteristic time, in minutes, all models
N	Continuous; $[1, +\infty)$	Shape factor, dimensionless, all models
T_p	Continuous; $[0, +\infty)$	Lag time, in hours, all models
Q_p	Continuous; $[0, +\infty)$	Peak factor, in $\frac{cfs}{sq.mi.}$ per $\frac{inch}{hour}$

the table and appear in all three models[5]. The values may be different depending upon which loss model is selected.

The individual values of the land-use-type variables along with additional land-use-type variables not considered are listed, by station, in Table A.1. The individual values of the watershed dimensional characteristics are listed, by station, in Table A.2.

3.2.4 Regional Equations for FRAC Model

The FRAC model is a single-parameter loss model coupled with the two-parameter unit hydrograph model. The regression equation selected to estimate the runoff coefficient for the applicable Texas watersheds is

$$C_r = -0.094727 + 0.110872 \times DEVF - 0.143233 \times ROCK + 0.005255 \times CN, \qquad (3.1)$$

where the hydrologic and explanatory variables are those in Tables 3.2 and 3.3, respectively. Leverage analysis was not performed on any University of Houston regressions.

The 95-percent prediction limits for the regression model for C_r, approximated using a non-parametric interval approach (Helsel and Hirsch, 2002), are

$$(\hat{C}_r - 0.15599497, \hat{C}_r + 0.19226153), \qquad (3.2)$$

where -0.1559497 and 0.19226153 are the $\alpha/2$ and $1 - \alpha/2$ quantiles of the regression residuals.

The authors note that the number of significant digits of the numerical values is greater than that justified by the data. A decision to display all digits was made for documentation purposes. The authors also note that negative values of C_r are meaningless in the context of the FRAC loss model.

[5] Regression analysis is performed on the native variables t_{rms} and N. Results are then transformed into dimensionless Q_p, T_p form. If variable shape hydrographs are desired, then N is still required. If the hydrograph shape is fixed (N is a constant), then the model is exactly analogous to conventional dimensionless unit hydrograph methods.

The regression equation selected to estimate the watershed characteristic time, t_{rms}, for the applicable Texas watersheds is

$$t_{rms} = 10^{1.20137-0.36822DEVF+0.09857ROCK} \times (MCL/S)^{0.41105}. \tag{3.3}$$

The 95-percent prediction limits for the regression model for t_{rms}, approximated using a non-parametric interval, are

$$(0.5110381 \times \hat{t}_{rms}, 2.0192413 \times \hat{t}_{rms}), \tag{3.4}$$

where $\hat{t}_{rms}$ is the value of t_{rms} estimated using the regression model. In this particular case, the interval is a result of the product of the residual quantiles because of the logarithmic transformation (note the power-law relationship on the *size* variable).

Regression analysis could not identify any meaningful relationships between the explanatory variables and the hydrologic variable N for FRAC model station values. Thus for FRAC model use the mean value:

$$N = 3.585014, \text{and} \tag{3.5}$$

the non-parametric 95-percent estimation interval for N is

$$(3.229990 \leq N \leq 4.015025). \tag{3.6}$$

These two hydrologic variables are transformed into Q_p and T_p using Equations 3.7 and 3.8 and are intended for use in Equation 3.9, the Lienhard dimensionless unit hydrograph[6].

$$t_{rm\beta} = \left(\frac{n}{n-1}\right)^{1/\beta} T_p \tag{3.7}$$

$$Q_p = f(T_p) \tag{3.8}$$

$$\frac{Q}{Q_p} = \left(\frac{t}{T_p}\right)^{n-1} \exp\left[-\frac{n-1}{\beta}\left(\left(\frac{t}{T_p}\right)^{\beta} - 1\right)\right] \tag{3.9}$$

In the case of the FRAC model, N having a single value means that the unit hydrograph for the applicable watersheds is representable by a fixed shape hydrograph.

Table A.3 lists the observed station values (indicated by a subscript o) and the regression estimated station values (indicated by a subscript m) for the study watersheds.

3.2.5 Regional Equations for IACL Model

The IACL model is a two-parameter loss model coupled with the two-parameter unit hydrograph model. The regression equation selected to estimate the initial abstraction, I_a, is

$$I_a = 1.299918 - 0.217235DEVF + 0.211964ROCK - 0.007108CN, \tag{3.10}$$

[6]These equations first appear in the theoretical section as Equations 2.10, 2.11, and 2.12. They are repeated here for clarity.

where I_a is in inches and the explanatory and hydrologic variables are those in Tables 3.2 and 3.3, respectively. The approximate 95-percent prediction limits for the regression model for I_a, approximated using a non-parametric interval approach (Helsel and Hirsch, 2002), are

$$(\hat{I}_a - 0.3294470214,\ \hat{I}_a + 0.4791902641), \tag{3.11}$$

and the regression equation selected to estimate the loss rate, C_l (inches per hour), is

$$C_l = 0.8406 - 0.2035\, DEVF + 0.3349 ROCK - 0.00005(MCL/S). \tag{3.12}$$

The approximate 95-percent prediction limits for the regression model for C_l, approximated using a non-parametric interval approach (Helsel and Hirsch, 2002), are

$$(\hat{C}_l - 0.4597241365,\ \hat{C}_l + 0.4530855948), \tag{3.13}$$

and the regression equation selected to estimate the characteristic time, t_{rms} is

$$t_{rms} = 10^{1.25258 - 0.36105 DEVF + 0.10253 ROCK} \times (MCL/S)^{0.40163}. \tag{3.14}$$

The 95-percent prediction limits for the regression model for t_{rms}, approximated using a non-parametric interval (obtained from quantiles of the regression residuals)[7], are

$$(0.4182927 \times \hat{t}_{rms},\ 2.1557946 \times \hat{t}_{rms}). \tag{3.15}$$

Regression analysis could not identify any meaningful relationships between the explanatory variables and the hydrologic variable N for IACL model station values. Thus for the IACL model use the estimate of the pseudo-median determined by the Wilcox signed-rank test as implemented in **R**[8],

$$N = 3.262480. \tag{3.16}$$

The non-parametric 95-percent estimation interval for N is

$$(2.921379 \leq N \leq 3.703857). \tag{3.17}$$

Once the hydrologic variables t_{rms} and N are estimated, they can either be used directly in the Leinhard hydrograph function or converted into the more conventional T_p, Q_p form[9].

Values of observed station values (indicated by a subscript o) and the regression estimated station values (indicated by a subscript m) for the study watersheds are listed in Table A.4.

[7] Helsel and Hirsch (2002, p. 243).

[8] Dalgaard (2002, pp. 85–86), and **R** on-line help.

[9] In T_p, Q_p form, the values should still be used with the Leinhard hydrograph, but would likely function well with any Gamma-family hydrograph function.

3.2.6 Regional Equations for GAIN Model

The GAIN model is a two-parameter loss model coupled with the two-parameter unit hydrograph model. Regression analysis could not identify any meaningful relationships between the explanatory variables and the hydrologic variable ϕ (psuedo-porosity) for GAIN model station values. Thus for GAIN model use the estimate of the value of

$$\phi = 0.4969298, \text{ where} \tag{3.18}$$

$$(0.4758187 \leq \phi \leq 0.5166149). \tag{3.19}$$

The regression equation selected to estimate the pseudo-hydraulic conductivity, K (in inches per hour), for the applicable Texas watersheds is

$$K = 0.8862 - 0.2106 \times DEVF + 0.4013 \times ROCK - 0.00004 \times MCL/S. \tag{3.20}$$

The approximate 95-percent prediction limits for the regression model for K, approximated using a non-parametric interval approach (Helsel and Hirsch, 2002), are

$$(\hat{K} - 0.44966228,\ \hat{K} + 0.42399538). \tag{3.21}$$

The regression equation selected to estimate the lag time, T_p, for selected Texas watersheds is

$$t_{rms} = 10^{1.25361 - 0.36108DEVF + 0.10243ROCK} \times (MCL/S)^{0.40131}. \tag{3.22}$$

The 95-percent prediction limits for the regression model for T_p, approximated using a non-parametric interval (Helsel and Hirsch, 2002), are

$$(0.4163821 \times \hat{t}_{rms},\ 2.1641788 \times \hat{t}_{rms}). \tag{3.23}$$

Regression analysis could not identify any meaningful relationships between the explanatory variables and the hydrologic variable N for GAIN model station values. Thus for GAIN model use the estimate of the value of N

$$N = 3.261948. \tag{3.24}$$

The non-parametric 95-percent estimation interval for N is

$$(2.916751 \leq N \leq 3.700092). \tag{3.25}$$

The station optimal and regression estimated values for the study watersheds are listed in Table A.5.

3.2.7 Remarks on Regionalization

The regionalization analysis suggests that adjustable shape hydrographs are unnecessary for applicable Texas watersheds. Although this finding was reported earlier in He (2004) and Cleveland et al. (2006), the analysis here simply confirms prior findings. Asquith et al. (2006) also found fairly poor regression equations for shape.

All the loss models exhibited some dependence on CN in at least one of the hydrologic variables related to the loss. The predictive value of CN is proportionally small but statistically significant (at least at the acceptance level used in the analysis, a p-value at rejection of 5%). The authors conclude that the methodology used to specify a CN has value in understanding watershed loss, a reassuring result, but the dependence on the two classification variables, $DEVF$ and $ROCK$, is proportionately greater in this study.

The two models that incorporate loss rate in a direct sense (IACL and GAIN) exhibited proportionately less dependence on the characteristic size MCL/S, and a greater dependence on the two classification variables, $DEVF$ and $ROCK$. In general the loss rate increases for rocky watersheds and decreases for developed watersheds — a response consistent with intuition and the results of Asquith and Roussel (2007). While consistent with intuition, these two classification variables only allow four "states" to be mapped in a given size range.

In the GAIN model the average pseudo-porosity at the watershed scale is best modeled by a constant value — an unexpected finding. Some dependence of the pseudo-conductivity on the explanatory variables was observed so some regionalization is possible. The model was specifically developed with the use of point measurements of porosity and hydraulic conductivity as inputs for synthetic hydrograph generation. The independence of infiltration porosity (in terms of the explanatory variables used) in some sense reduces the model to a one-parameter model.

In addition, the regression estimated pseudo-conductivity is 0.5, which is a geologically observed value in the literature but at least twice that expected for the study region. The pseudo-conductivities are also realistic in the sense they are within the range of values reported in literature for porous media but are smaller than values reported in Table A.1. These findings are disappointing — the University of Houston researchers anticipated that the pseudo-conductivities would be more geologically realistic.

The characteristic time, regardless of model, depended on the same set of explanatory variables and had about the same regression coefficients on these variables. This finding is interpreted to mean that the loss model and hydrograph models, at the present scale of model complexity, can be decoupled. Decoupling means that the unit hydrograph behavior can be estimated independently from the loss model as was done by the USGS team. There is considerable savings in time if the loss model can be decoupled from the unitgraph model so, for at least 1-minute and 5-minute unit hydrograph application, the loss model can be treated independently from the unit hydrograph response providing considerable practical advantage.

3.2.8 Illustrative Use of the IACL Regression Model

The University of Houston researchers present this section as an example of how to use the results. The method suggested here is in addition to the methods suggested by the USGS researchers. The method presented here is based on the IACL model and the corresponding unit hydrograph model.

To estimate a runoff hydrograph for a given appropriate watershed the analyst must determine five watershed properties:

1. Watershed binary state factor *DEVF* Is the watershed generally developed or undeveloped?. *DEVF*=1 if the watershed is developed, *DEVF*=0 otherwise.
2. Watershed binary state factor *ROCK* Is the watershed generally rock dominated, with thin soil and limestone and karst features. *ROCK*=1 if rock dominated, *ROCK*=0 otherwise.
3. Watershed *CN*. This curve number is obtained by standard lookup tables and ancillary tools.
4. Watershed *MCL*. The main channel length can be measured from a map.
5. Watershed slope, S, is the slope along the main channel estimated using definitions in Brown et al. (2000) and Roussel et al. (2005). This slope is computed from the change in elevation from the headwaters (highest elevation along the main channel path) to the outlet (elevation of the main channel at the outlet) and from the main channel length. The dimensionless slope is $S = \frac{\Delta z}{MCL}$ where ΔZ is in feet and MCL is in feet.

Once these five items are determined, the analyst computes the value MCL/S to enter into either the appropriate IACL equations or, as an alternative, the following charts.

To determine the initial abstraction, I_a, the analyst uses the two binary variables to select one of the four lines on Figure 3.8, then uses the watershed curve number to obtain an estimate of the watershed initial abstraction in inches. An alternative is direct application of the I_a regression model from which Figure 3.8 was constructed.

To determine the constant loss rate, C_l, the analyst uses the two binary variables to select one of the four lines on Figure 3.9, then uses the calculated MCL/S to obtain an estimate of the constant loss rate in inches per hour. As before, the analyst could also choose to directly apply the C_l regression model from which the figure is constructed.

To determine the time to peak, T_p, the analyst uses the two binary state variables to select one of the four lines on Figure 3.10, then uses MCL/S to obtain an estimate of the T_p in hours. The corresponding Q_p value is obtained in a similar fashion from Figure 3.11.

As an illustration consider the Ash Creek watershed in Dallas, Texas, Station ID=08057320. The development factor and rock factor are 1 and 0, respectively. CN for this watershed is 86. MCL is 5.4 miles and the dimensionless slope is 0.0056. Therefore, MCL/S = 964 miles.

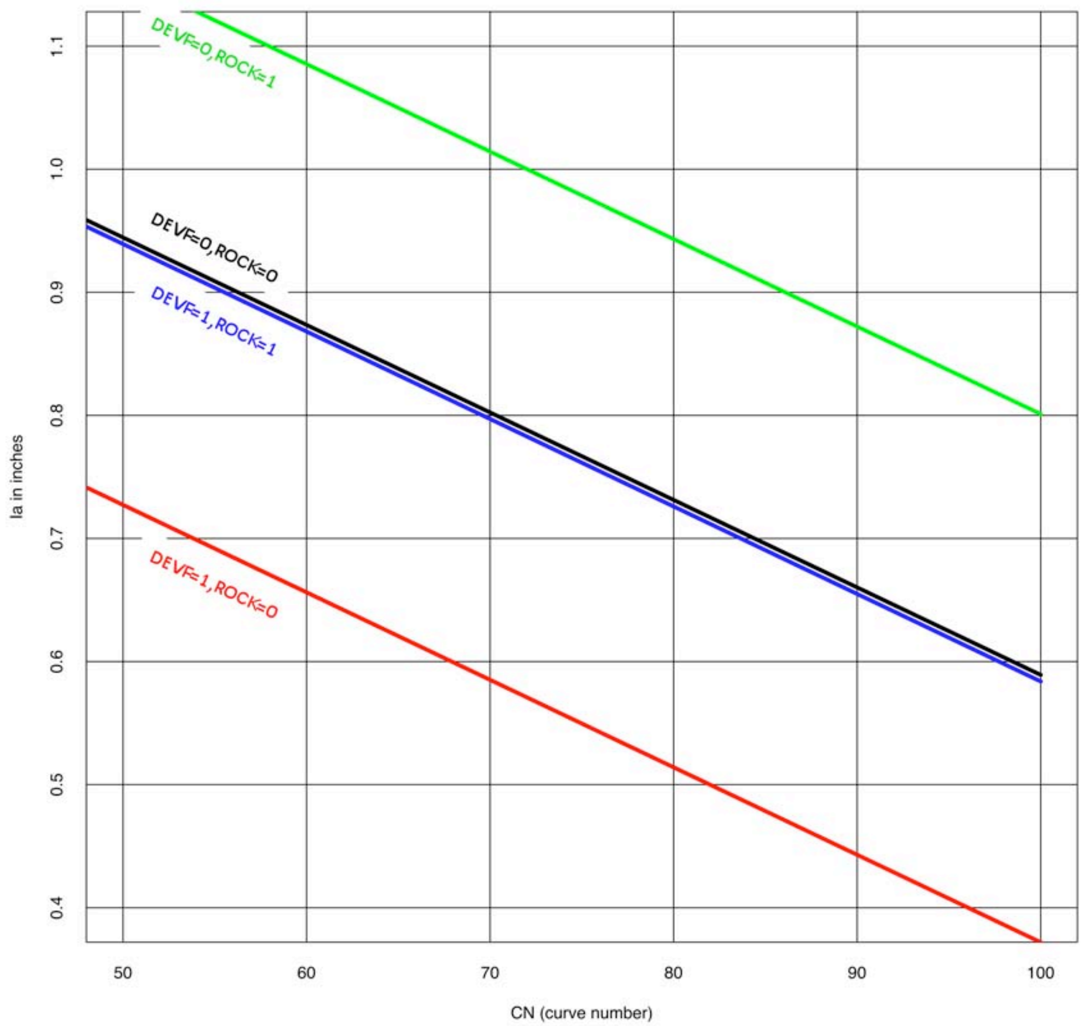


Figure 3.8: Initial abstraction versus CN for four watershed conditions. These curves are graphical representations of the I_a regression model.

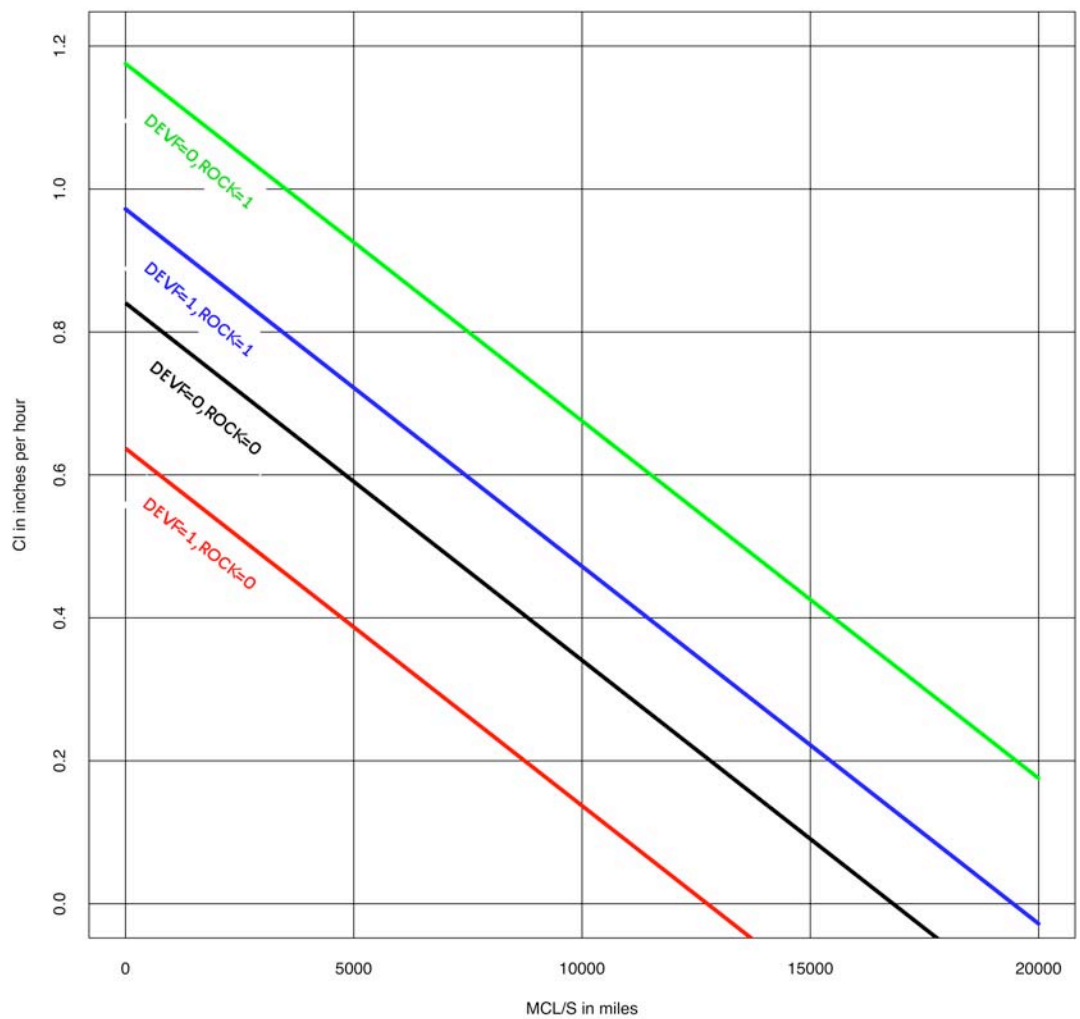


Figure 3.9: Constant loss rate versus MCL/S for four watershed conditions. These curves are graphical representations of the C_l regression model.

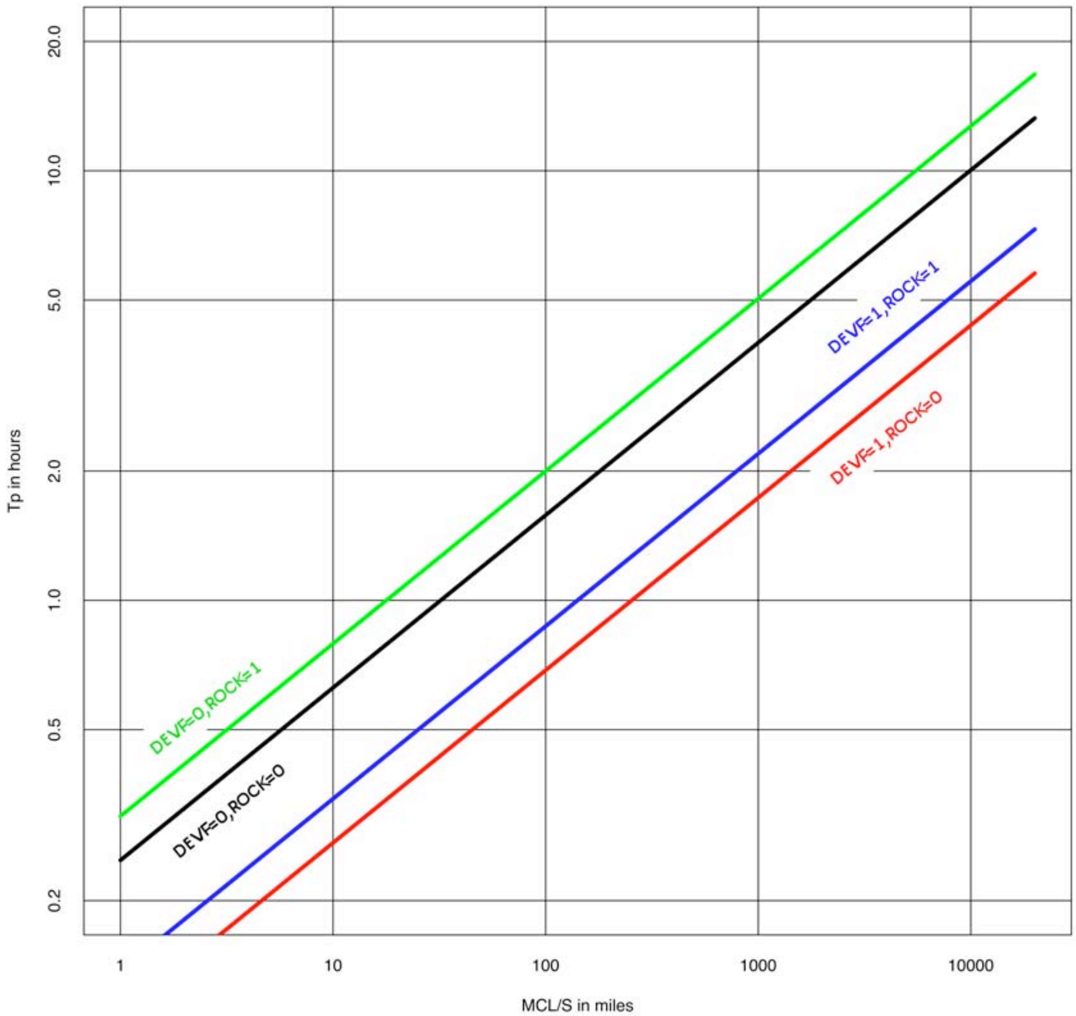


Figure 3.10: T_p, versus MCL/S for four watershed conditions. These curves are graphical representations of the T_p regression model.

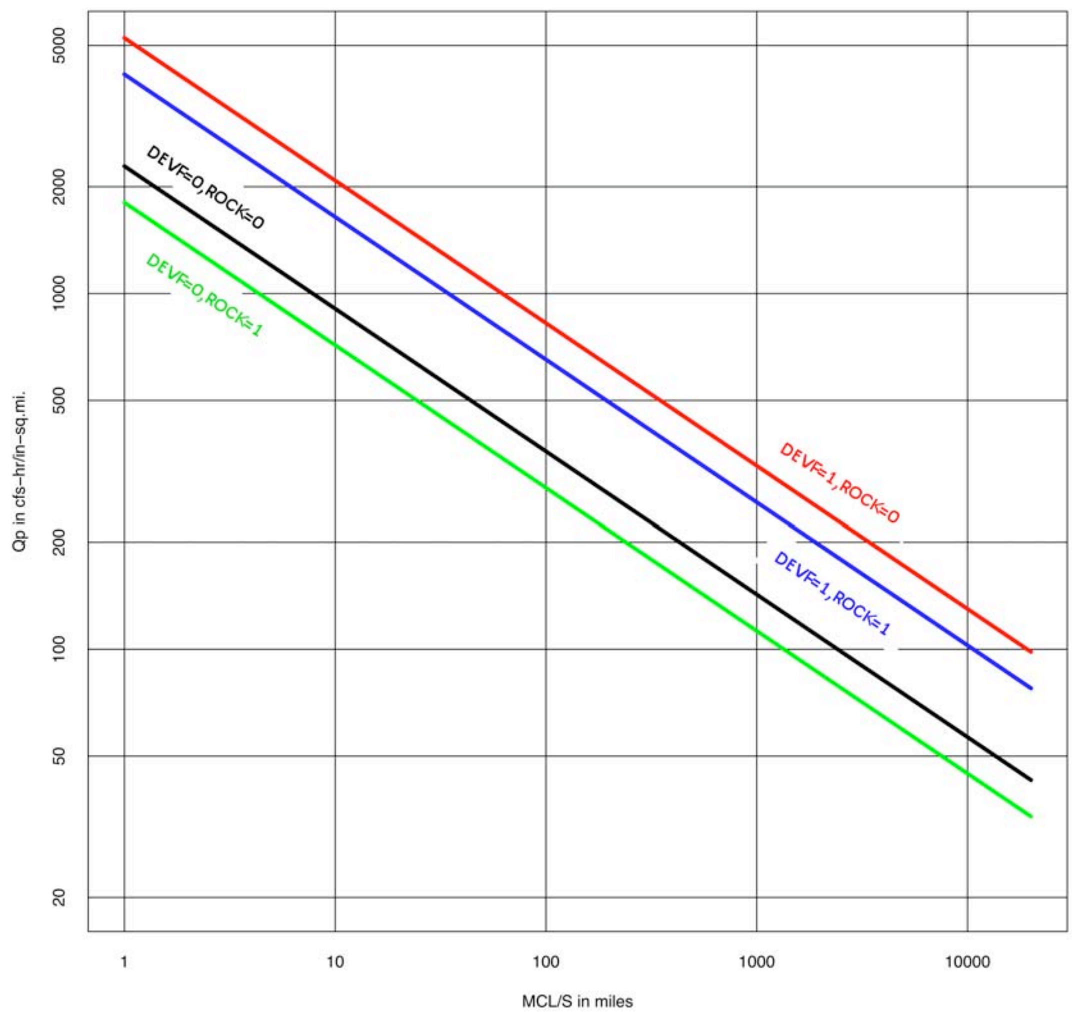


Figure 3.11: Q_p, versus MCL/S for four watershed conditions. These curves are graphical representations of the Q_p regression model.

Estimated I_a from Figure 3.8 is about 0.48 inches and the estimated C_l from Figure 3.9 is 0.59 inches per hour. Estimated T_p for the watershed is about 1.7 hours. Estimated Q_p for the watershed is about 300 cfs per square mile for each inch per hour of rainfall.

For comparison the regression tree model in Asquith and Roussel (2007)[10] is used to estimate the same parameters for this same watershed. The analyst would enter the regression tree for I_a with the same set of watershed properties. Traversing the tree results in $I_a = 0.75$ inches. From the regression tree with C_l, $C_l = 0.659$ inches per hour. Application of the regression equation for T_p using *DEVF*, *MCL*, and *SLOPE* (D, L, and S in Asquith and Roussel, 2007) results in an estimate of $T_p = 1.29$ hours. Using the regression equation with K and T_p, the peak rate factor is 311.2 cfs per square mile for each inch per hour of rainfall.

The result from the University of Houston appraoch and the USGS approach is 300 cfs/mi^2/in/hr and 311 cfs/mi^2/in/hr, respectively. Therefore, the two approaches yield substantially the same result for the peak rate factor. The initial abstraction, however, differs somewhat.

3.3 Lamar University

Researchers at Lamar University used a non-linear programming algorithm to analyze observed rainfall-runoff events from selected Texas watersheds. There are a total of 1,331 events from 88 watersheds from which Lamar University researchers were able to develop optimized rainfall loss and unit hydrograph parameters using MRNG objective function (minimizing the range of error between observed and predicted direct runoff hydrograph). Figure 3.12 shows cumulative distribution of initial rainfall loss (inches) derived from non-linear programming optimization for the study events. Figure 3.12 shows that there are 80 percent of events having initial loss less than or equal to 0.5 inches and about 5 percent of events having zero initial loss. There are less than 2 percent of events with initial rainfall loss greater than 2 inches. Figure 3.13 shows cumulative distribution of the ratio of initial rainfall loss and total rainfall depth. There are 55 percent of events with the ratio between 0.09 and 0.11 (or 0.1 ± 0.01). Therefore, a reasonable approach is to assume the initial loss is 10 percent of total rainfall depth. There are only 8.5 percent of events with initial loss greater than 30 percent of total rainfall depth. In this study, rainfall loss and unit hydrograph parameters were actually determined by five other optimization objective functions in addition to MRNG. For other optimization objective functions, there was one additional constraint used, and that is the initial loss should not be greater than 30 percent of the total rainfall depth. This constraint helps to obtain optimization solution faster.

Basin mean initial rainfall loss and constant rainfall loss were developed from optimized values for all events available for each watershed. Figures 3.14 and 3.15 show cumulative distribution of mean initial rainfall loss (inches) and mean constant rainfall loss for developed, undeveloped, and all watersheds, respectively. Figure 3.14 does not show much difference in initial loss between developed and undeveloped watersheds, but Figure 3.15 shows some difference in constant rainfall

[10] I_a and C_l are estimated using Figures 7 and 8 in Asquith and Roussel (2007). T_p is estimated using Equation 11 in Asquith and Roussel, Q_p is estimated using Equations 5, 4, and 3 in Asquith and Roussel (2007).

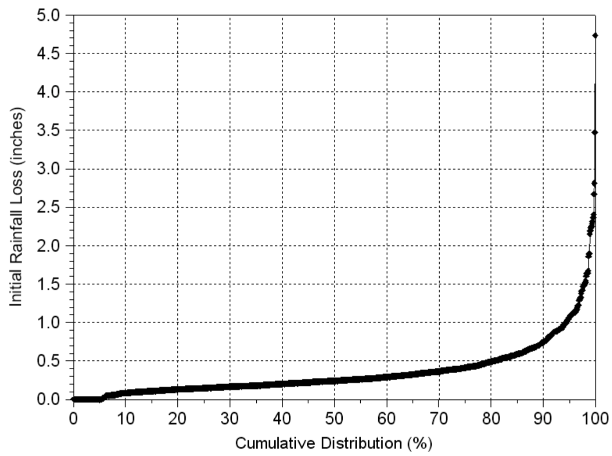


Figure 3.12: Cumulative distribution of initial rainfall loss (inches) estimated from non-linear programming optimization.

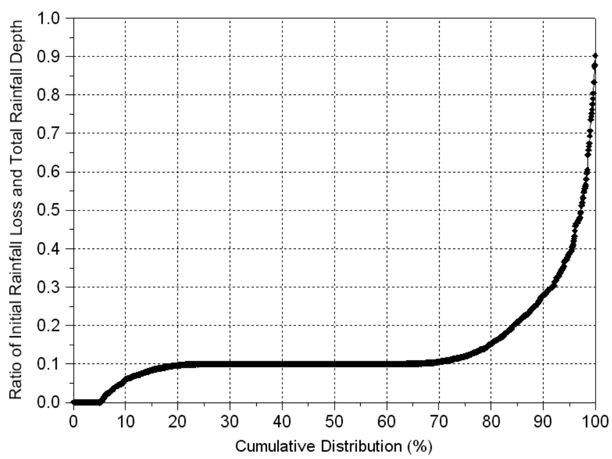


Figure 3.13: Cumulative distribution of the ratio of initial rainfall loss and total rainfall depth.

loss between developed and undeveloped watershed. Undeveloped watersheds have higher constant rainfall loss. Combined initial rainfall loss and constant rainfall loss will still give higher rainfall loss for undeveloped watersheds than for developed watersheds. Figure 3.14 shows that 80 percent of basin mean initial losses is between 0.2 and 0.6 inches, and 82 percent of basin mean initial losses is less than 0.5 inches.

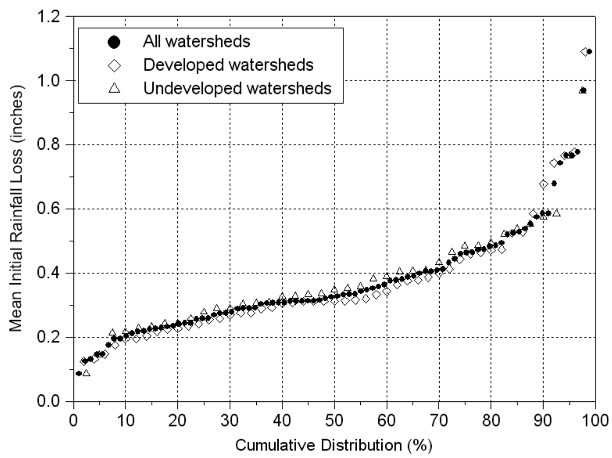


Figure 3.14: Cumulative distribution of initial rainfall loss (inches) estimated from non-linear programming optimization.

Initial rainfall loss and constant rainfall loss for any rainfall events and watersheds could highly depend on various factors, for example, rainfall characteristics, antecedent moisture conditions, type and extent of vegetal cover, and physiographic conditions in a watershed. In this study, basin mean initial loss and constant loss are correlated with basin parameters. Table 3.4 includes suggested regression equations after performing multiparameter regression analysis. There is one regression equation for mean initial loss (in), and two equations for constant rainfall loss (in/hr): one for developed watersheds and one for undeveloped watersheds. Independent variables used are channel length (L in miles) and potential maximum soil retention in inches $S_o = 1000/CN - 10$ based on land-use, hydrologic soil group, and antecedent moisture condition. Predicted curve number for each watershed is used for computing S_o and was previously determined (Thompson, 2003) assuming normal antecedent moisture condition. Standard error for initial loss regression is 0.562 (or 56.2 percent) and 0.596 (or 59.6 percent) for constant rainfall loss. Low values of adjusted R^2 indicate that these regression equations for initial and constant rainfall losses may not be useful or accurate for engineering design.

In the NRCS curve number method, the initial loss for small watersheds is assumed to be $0.2S_o$, where $S_o = 1000/CN - 10$. Correlation between initial loss estimated from NRCS CN method and from MRNG optimization is weak, as shown on Figure 3.16, which includes basin initial loss plus and minus one standard deviation from MRNG optimization. Figure 3.17 shows a sorted data with

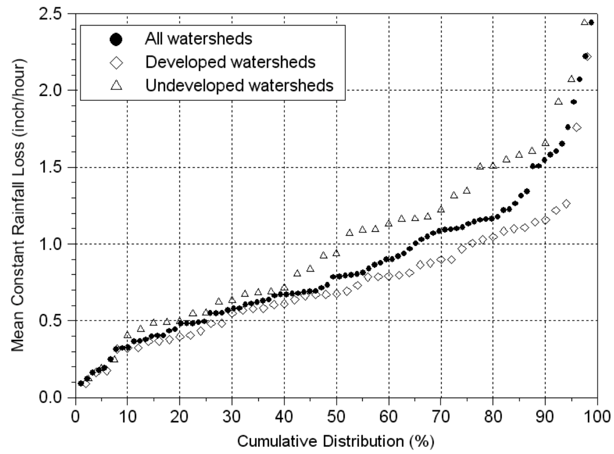


Figure 3.15: Cumulative distribution of mean constant rainfall loss (inch/hour) for developed, undeveloped, and all watersheds.

Table 3.4: Regression equations from Lamar University research results.

Regression Equation	Adjusted R^2	Standard Error
Initial loss: $I_L = 0.6928L^{-0.2240}S_o^{0.5627}$ (all watersheds)	0.116	0.562
Constant loss: $C_L = 0.7880L^{-0.2152}S_o^{0.2375}$ (developed)	0.005	0.596
Constant loss: $C_L = 0.6326L^{-0.470}S_o^{0.7403}$ (undeveloped)	0.117	0.510
Unitgraph $Q_p = 93.22A^{0.83576}L^{-0.326}S^{0.5}$	0.818	0.382
Unitgraph $T_p = 0.551A^{0.267}L^{0.426}S^{-0.06}$	0.785	0.340

a cumulative distribution plot and shows standard initial loss from NRCS CN method ($0.2S_o$) is greater than basin mean initial loss from MRNG optimization, but within one standard deviation of the mean. Figure 3.17 shows data for $0.1S_o$ and $0.15S_o$ for comparison, and the distribution of $0.15S_o$ follows well with the distribution of basin mean initial loss from MRNG optimization. This result does not mean that use of $0.15S_o$ for initial loss is recommended.

Basin mean peak discharge (Q_p, cfs) and time to peak (T_p, hr) for the GUH were developed from optimized values (MRNG objective function) for all events available for each watershed. Regression equations were developed for mean Q_p and T_p versus various combinations of watershed parameters, such as drainage area (A in square mile), main channel length (L in mile), and mean channel slope (S is ft/mile). Table 3.4 lists a set of best regression equations for Q_p and T_p of GUH including R^2, adjusted R^2, and standard errors. Values of R^2 arrange from 0.792 to 0.822 and standard errors are from 34.0 percent to 38.2 percent. These regression equations for mean Q_p and T_p are useful for engineering practices to estimate Gamma unit hydrographs for rainfall and runoff modeling and

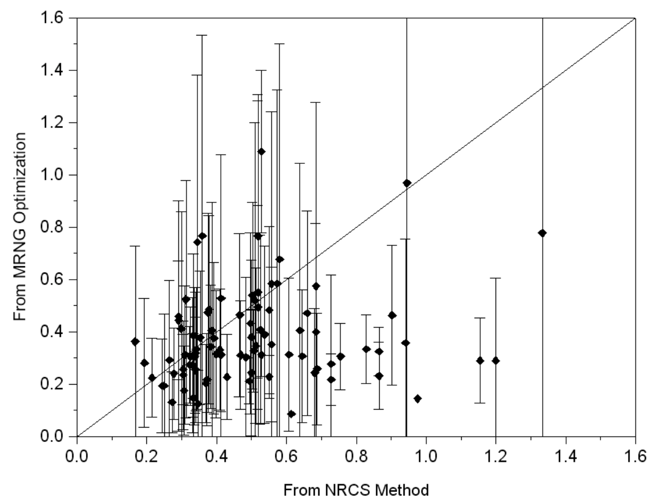


Figure 3.16: Initial loss estimated from NRCS CN method and basin mean initial loss from MRNG optimization.

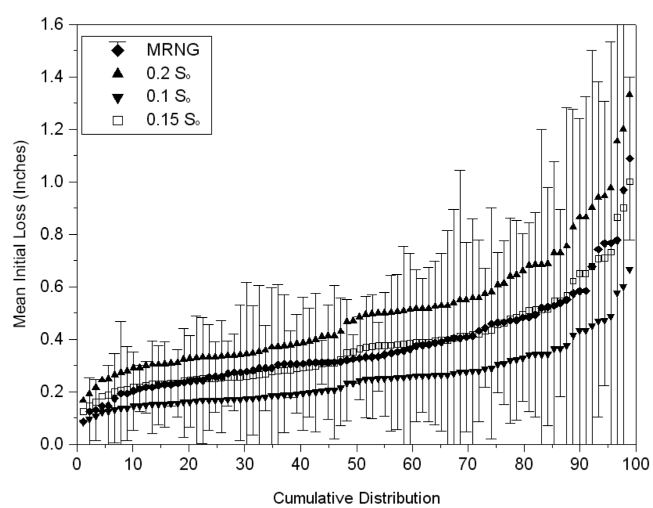


Figure 3.17: Cumulative distribution of mean initial rainfall loss (inches) from MRNG optimization and NRCS CN method ($0.2S_o$) with $0.1S_o$ and $0.15S_o$ for comparison.

prediction.

3.4 Texas Tech University

As discussed in Section 2.5, the dataset used for what was termed the *traditional approach* for developing unitgraphs was censored to only those events that produced at least 0.1 inches of runoff. Computation of a unitgraph using the traditional approach proceeds by dividing the direct runoff hydrograph by the depth of runoff. If the depth of runoff is relatively small, the leverage of the arithmetic division inflates errors in the direct runoff hydrograph and results in unitgraphs that appear to be physically unjustifiable. Therefore, to be consistent with earlier work done by Texas Tech researchers, the dataset was censored such that a total of 458 events from 82 selected Texas watersheds were analyzed. A summary of the dataset used for further analyses is presented in Table 3.5. Results from analyses are presented in subsequent sections.

Table 3.5: Events used for the Texas Tech analysis as grouped for further statistical examination. [SRWS indicates watersheds from the small rural watersheds module, a collection of 18 watersheds located in relatively rural areas and not in any specific geographic location.]

Entire Dataset					
Number of Watersheds	82				
Number of Events	458				
Development Condition					
	Developed		Undeveloped		
Number of Watersheds	49		33		
Number of Events	308		150		
Geographic Location					
	Austin	Dallas	Fort Worth	San Antonio	SRWS
Number of Watersheds	25	21	8	10	18
Number of Events	149	94	72	63	80
Development Condition and Geographic Location					
	Developed				
	Austin	Dallas	Fort Worth	San Antonio	SRWS
Number of Watersheds	15	20	8	6	–
Number of Events	97	92	72	47	–
	Undeveloped				
	Austin	Dallas	Fort Worth	San Antonio	SRWS
Number of Watersheds	10	1	–	4	18
Number of Events	52	2	–	16	80

3.4.1 Initial Loss/Constant Loss-Rate

Results from analysis of 458 observed rainfall-runoff events by Texas Tech researchers are displayed on Table B.1. The analysis, results, and conclusions of Texas Tech researchers follows.

As an example of the results of optimization of parameters from a single watershed, the results from parameter optimization for the watershed represented by USGS stream gage number 08062300 are listed in Table 3.6. Median values are presented as the last line of Table 3.6. The median value of the initial loss is 0.60 inches and the median value of the loss-rate is 0.24 inches per hour.

Table 3.6: Loss-rate parameters from optimization of rainfall-runoff events from USGS Stream Gage 08063200.

Date	Initial Loss (inches)	Loss-rate (in/hr)
10/29/1967	0.62	0.28
10/3/1959	0.64	0.44
12/15/1959	0.10	0.09
12/6/1960	0.92	0.02
2/15/1961	0.57	0.01
4/22/1966	1.02	0.20
4/26/1968	0.54	0.32
4/27/1962	0.52	0.39
6/2/1968	1.52	0.16
Median	0.60	0.24

Results similar to those listed in Table 3.6 were collected from the 82 study watersheds. Median results for all parameters are listed in Table B.1. Summary statistics from these results are listed in Table 3.7. Boxplots of results from all 82 study watersheds are displayed on Figure 3.18. For the initial loss, 50 percent of the values fall between 0.35 inches and 0.69 inches. Similarly, for the loss-rate, 50 percent of the values fall between 0.27 and 0.67 inches per hour. Although these ranges are relatively large, the greatest is only about twice the smallest, which is not such a large range that the values cannot be used for design-type activities. The analyst, however, must remain aware that substantial uncertainty exists and adjust designs derived therefrom accordingly.

Additional subdivision of the dataset was undertaken, as suggested by entries in Table 3.5. The most significant was segregating watersheds by development state. Initial loss/constant loss-rate parameters using development state as a separator are listed in Table 3.7 and displayed on Figure 3.19. What is interesting about this particular grouping is that almost no difference exists between the loss-rate from developed and undeveloped watersheds, yet some difference is observed in the initial loss. This is consistent, more or less, with USGS and UH results. The most likely reason for this is the "connectedness" of relatively impervious areas in more developed watersheds. That relatively impervious areas are connected indicates an opportunity for incoming precipitation on such surface to move without abstraction toward the watershed outlet.

Table 3.7: Results from optimization of initial loss/constant loss-rate loss function for 458 rainfall-runoff events from 82 Texas watersheds. [SRWS indicates watersheds from the small rural watersheds module, a collection of 18 watersheds located in relatively rural areas and not in any specific geographic location. IQR denotes inter-quartile range. IL denotes initial loss. CLR denotes constant loss-rate.]

Entire Dataset		
Statistic	Initial Loss (inches)	Loss-rate (in/hr)
Median	0.49	0.47
IQR	0.34	0.40

Development Condition				
	Undeveloped		Developed	
	Initial Loss	Loss-rate	Initial Loss	Loss-rate
Median	0.64	0.52	0.42	0.47
IQR	0.39	0.52	0.20	0.33

Geographic Location										
	Austin		Dallas		Fort Worth		San Antonio		SRWS	
	IL	CLR	IL	CLR	IL	CLR	IL	CLR	IL	CLR
Median	0.58	0.65	0.38	0.30	0.39	0.49	0.73	0.84	0.56	0.30
IQR	0.29	0.32	0.17	0.18	0.12	0.18	0.56	0.32	0.36	0.34

Geographic Location and Development State — Undeveloped Condition										
	Austin		Dallas		Fort Worth		San Antonio		SRWS	
	IL	CLR	IL	CLR	IL	CLR	IL	CLR	IL	CLR
Median	0.63	0.75	–	–	–	–	1.03	0.86	0.58	0.30
IQR	0.40	0.33	–	–	–	–	0.24	0.28	0.36	0.34

Developed Condition										
	Austin		Dallas		Fort Worth		San Antonio		SRWS	
	IL	CLR	IL	CLR	IL	CLR	IL	CLR	IL	CLR
Median	0.53	0.61	0.38	0.30	0.39	0.49	0.42	0.83	–	–
IQR	0.30	0.16	0.17	0.18	0.12	0.18	0.31	0.31	–	–

These results are depicted graphically on Figure 3.19. Both the median and IQR of the initial loss from undeveloped watersheds are shifted upward in comparison with values from developed watersheds. However, differences between loss-rates from developed and undeveloped watersheds are less apparent.

Results from initial loss/constant loss-rate parameter extraction were separated by geographic location. Parameter values are listed in Table 3.7 and depicted on Figures 3.20 and 3.21. From the figures, differences exist between watersheds as grouped by geographic location.

Results are further subdivided in Table 3.7, by development condition as well as geographic location. Insufficient data are available to assess differences in development condition by geographic location. However, hints exist in the dataset. For example, in the San Antonio region, the median initial loss for undeveloped watersheds is about 1 inch. However, for developed watersheds, the median initial

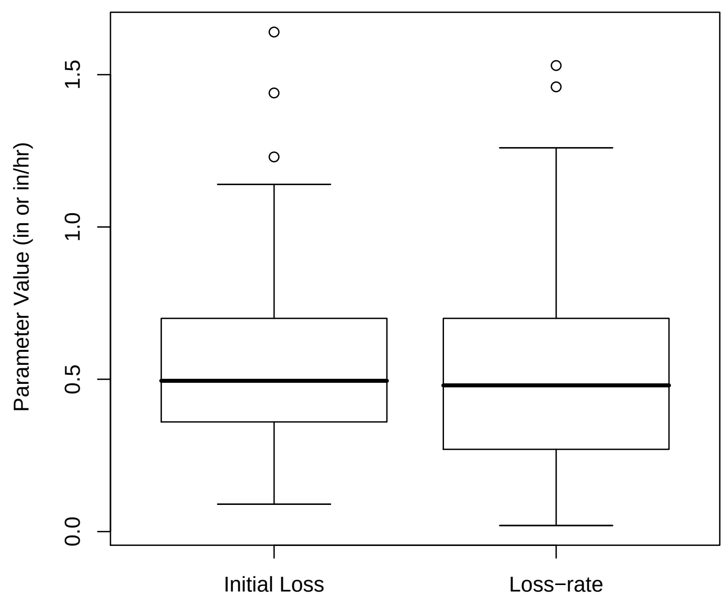


Figure 3.18: Boxplots of optimization results from all study watersheds.

loss is 0.4 inches. Such a large difference does not exist in the only other geographic region with both developed and undeveloped watersheds, Austin. The differences observed for the San Antonio watersheds could be an artifact of the particular watersheds in the dataset. Or, differences could be attributable to a physical condition. The reason for the difference is undetermined.

The empirical cumulative distributions of initial loss and constant loss-rate were computed. Three curves were computed for each parameter — all values and values segregated based on development condition. The results are displayed on Figures 3.22 and 3.23. The loss-rate parameters do not appear to be substantially different, when examined as two groups segregated on the basis of development condition. However, the initial loss parameters appear to be different. Based on this observation, further examination of the initial loss parameter as a function of development condition was warranted. Loss-rates were lumped together for additional analysis.

Thompson (2003) developed a method for adjusting NRCS curve numbers for Texas climatology. Curve numbers calculated from observations of rainfall and runoff were termed *observed curve numbers.* The study watersheds used in the project reported herein were also analyzed by Thompson. These curve numbers were used as the basis for regression analyses reported in the following text.

Observed curve numbers are denoted as C_o. Initial abstraction was regressed against C_o for all values and those segregated by development condition. Results are reported in Table 3.8.

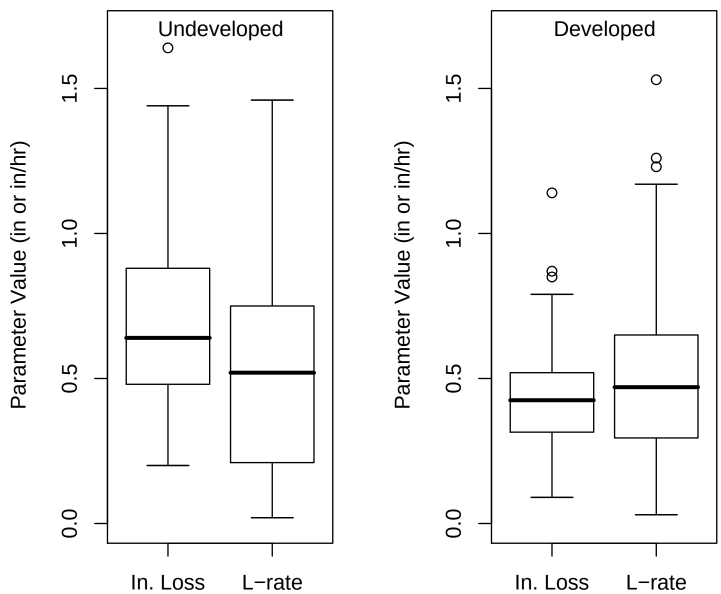


Figure 3.19: Boxplots of optimization results from study watersheds sorted by development state.

Table 3.8: Regression equations for initial loss/constant loss-rate loss model with NRCS curve number as the regressor variable.

Description	Regression Equation	Adjusted R^2
Initial Loss (undeveloped)	$I = 1.49 - 0.012C_o$	0.109
Initial Loss (developed)	$I = 1.20 - 0.010C_o$	0.202
Initial Loss (all)	$I = 1.55 - 0.014C_o$	0.245
Loss-Rate (all)	$LR = 1.38 - 0.012C_o$	0.141

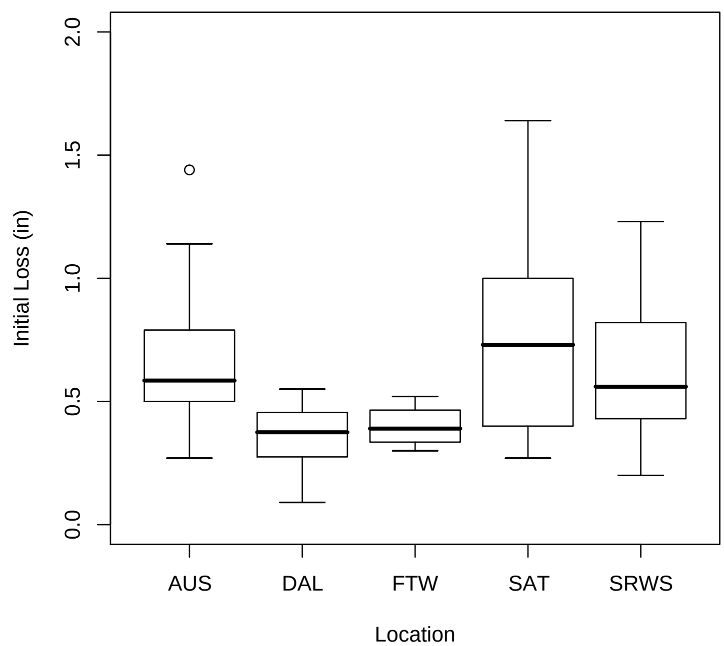


Figure 3.20: Boxplots of initial loss for study watersheds sorted by geographic location.

None of the correlation coefficients are strong; substantial variance remains unexplained by the regression equations. Therefore, use of the median values for modeling may be appropriate.

3.4.2 Green-Ampt Loss Function

USGS Station 08156750 is Shoal Creek in Austin, Texas. It is an urbanized watershed. Results from optimization of seven events are shown on Table 3.9. The values presented in Table 3.9 are typical of results from HEC-HMS optimizations to extract Green-Ampt parameters from observed hydrographs. For each watershed, similar results were retrieved. A summary of median values for Green-Ampt parameters from the watershed defined by USGS Station 08156750 are listed on Table 3.9.

Neither wetting front suction nor moisture deficit parameters were very sensitive. That is, it was difficult to detect differences in these parameters when optimizing the parameter set used for the Green-Ampt model given the data in the study dataset[11]. Furthermore, model output (the

[11]The lack of sensitivity of certain parameters when optimizing a relatively large parameter set was expected. Much work in the literature is given to addressing the issues of parameter uniqueness and identifiability. Gupta and Sorooshian (1983), and Sorooshian and Gupta (1983), and others address these issues in detail.

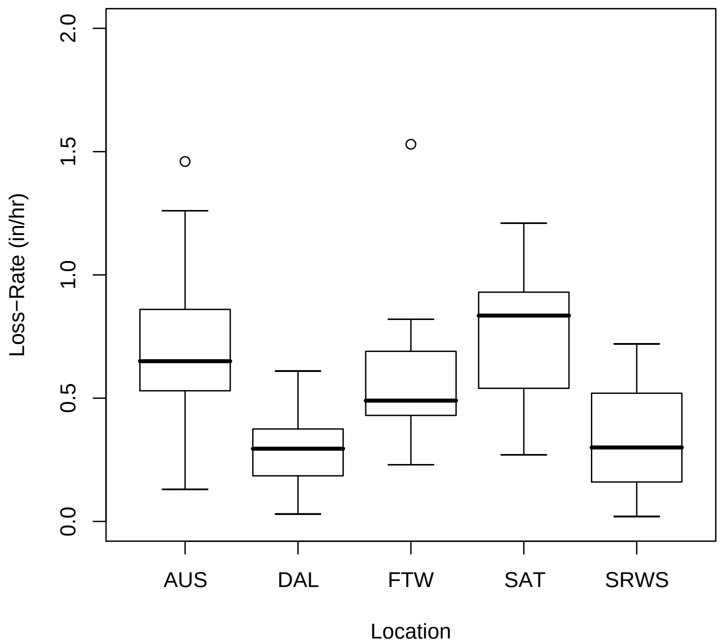


Figure 3.21: Boxplots of loss-rate for study watersheds sorted by geographic location.

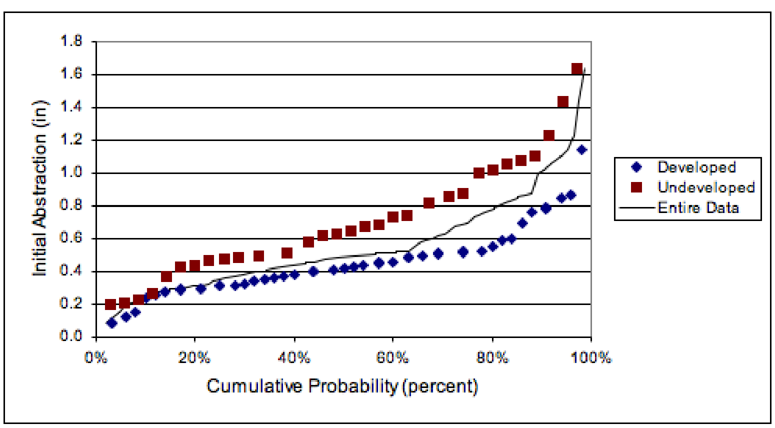


Figure 3.22: Cumulative empirical distributions of initial loss for study watersheds.

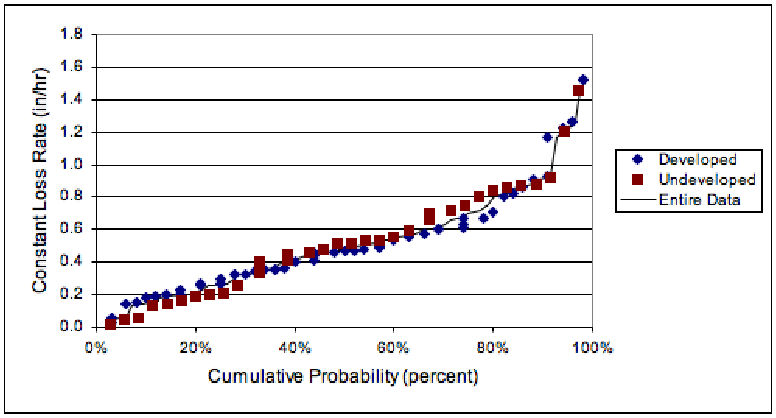


Figure 3.23: Cumulative empirical distributions of constant loss-rate for study watersheds.

Table 3.9: Green-Ampt loss parameters obtained from optimization of observed hydrographs.

Date	Hydraulic Conductivity (in/hr)	Initial Loss (inches)	Moisture Deficit	Wetting Front (inches)	Recession Threshold Ratio	SCS Lag Time (minute)
12/31/1978	0.09	0.58	0.09	12	0.34	53
04/15/1977	0.29	0.20	0.10	18	0.18	41
05/11/1978	0.09	0.43	0.18	11	0.11	41
05/12/1980	0.10	1.16	0.05	10	0.20	40
05/21/1979	0.00	0.48	0.09	11	0.20	39
05/02/1978	0.19	0.67	0.10	12	0.06	43
07/19/1979	0.12	0.31	0.18	14	0.18	46
Median	0.10	0.48	0.10	12	0.18	41

hydrograph) does not appear to be sensitive to modest changes in the value of these parameters. Therefore, further analyses focused on the initial abstraction and the hydraulic conductivity of site soils. Median values of moisture deficit and wetting-front suction were 0.12 (dimensionless) and 15 inches, respectively. Values for initial loss and hydraulic conductivity are listed in Table 3.10. Boxplots of initial loss and hydraulic conductivity are shown on Figures 3.24 and 3.25.

Table 3.10: Summary of initial loss and hydraulic conductivity from optimization of Green-Ampt loss-method parameters.

Statistic	All Watersheds		Undeveloped Watersheds		Developed Watersheds	
	Hydraulic Conductivity (in/hr)	Initial Loss (inches)	Hydraulic Conductivity (in/hr)	Initial Loss (inches)	Hydraulic Conductivity (in/hr)	Initial Loss (inches)
Median	0.13	0.20	0.18	0.24	0.10	0.16
IQR	0.16	0.15	0.18	0.24	0.19	0.16

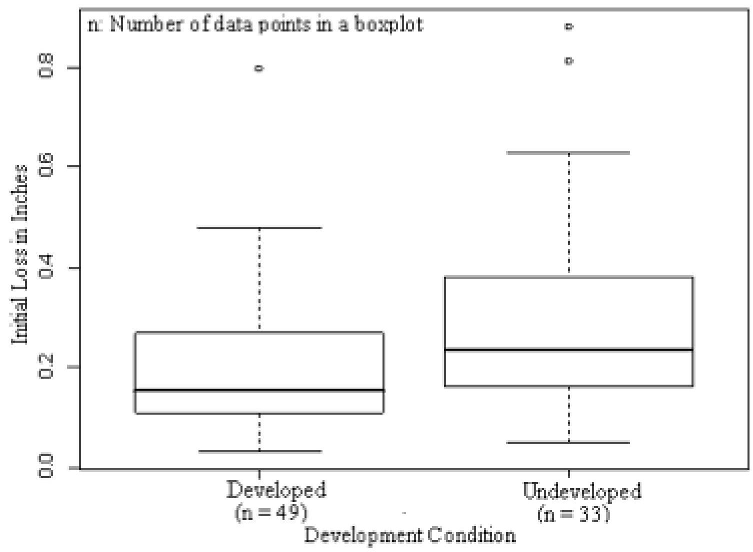


Figure 3.24: Boxplots of initial loss for the Green-Ampt loss method from TTU analysis.

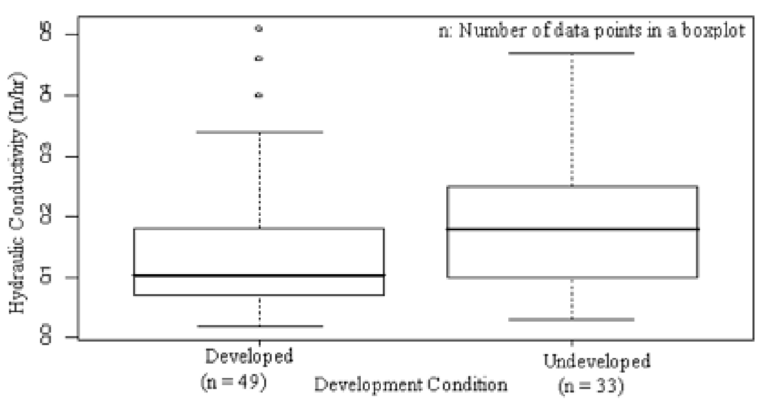


Figure 3.25: Boxplots of hydraulic conductivity for the Green-Ampt loss method from TTU analysis.

Differences between the developed and undeveloped condition are not as obvious in results from the Green-Ampt analysis. It is unclear why this should be the case. However, it may be that the additional parameters required by the Green-Ampt model *absorb* some of the variability observed in the initial-loss/constant loss-rate model. The Green-Ampt model is substantially more complex than the initial-loss/constant loss-rate model. Although correlation with watershed parameters was attempted, useful relations between watershed characteristics and model parameters were difficult to quantify. Therefore, because of the additional complexity of the Green-Ampt model and the difficulty encountered identifying appropriate parameter values, additional analyses of the Green-Ampt loss model are not presented here.

3.4.3 Suggested Application of TTU Results

Given the technical approach taken by Texas Tech University researchers, an approach to estimating a design discharge using the unit hydrograph method is proposed. The steps in such an analysis are:

1. Determine basic watershed characteristics using appropriate tools (paper maps, GIS, and so forth).
2. Apply the results of Roussel et al. (2005) to estimate the timing parameter for the study watershed.
   - A combination of Kerby (1959) and Kirpich (1940) is relatively widely-known and straightforward to apply in undeveloped settings.
   - An alternative is Morgali and Linsley (1965) for more developed settings.
   - Other estimates for the timing parameter are appropriate.
3. Use the timing parameter for the study watershed to estimate the NRCS lag time. If the time of concentration is used, then lag time is three-fifths the time of concentration.
4. The NRCS (SCS in HEC-HMS) dimensionless unit hydrograph is a reasonable approximation for the unit hydrograph for Texas watersheds[12].
5. The initial-loss/constant loss-rate model is a reasonable approach for Texas watersheds, given appropriate parameter estimates.
   - Substantial variability was observed in parameter estimates extracted from the study dataset.
   - Values for the initial loss in the range of 0.5 inches (±0.17 inches) are appropriate.
   - Values for the constant loss-rate of 0.5 inches per hour (±0.2 inches per hour) are also appropriate.

[12] Asquith et al. (2006) is the authoritative source document for unit hydrographs for Texas watersheds.

- The analyst should adjust parameter estimates for the study site based on additional available data. Such adjustments could include decreasing the initial loss for more-developed sites, increasing the initial loss for less-developed sites, increasing or decreasing the loss-rate based on soil textural classification, and so forth.

6. Determine the storm duration for analysis.
7. Determine the depth of rainfall for analysis.
8. Input the set of estimates developed in the preceding steps into a generalized hydrograph tool, such as HEC-HMS.
9. Operate the computational tool.
10. Evaluate the results[13].

The approach suggested in the algorithm presented above is only one possibility. Other methods could be substituted into the algorithm and result in reasonable estimates of discharge for design purposes. The mechanic for estimating the loss-method parameters could be adjusted to include the regression equations presented in Table 3.8 (for example). Or, estimates from the Green-Ampt results could be used.

It is suggested, however, that results from each approach not be mixed. That is, results from Texas Tech research may not (or may) be mixed with results from University of Houston, Lamar University, or USGS researchers. The results of combining the approaches from the various research teams have not been examined as part of the research reported herein.

3.5 Synthesis of Results

Four teams of researchers examined the dataset described by Asquith et al. (2004b). Each team brought a different analytical approach to the dataset. Results from each team are presented in the sections above. However, a common theme is present in the results from each team. Development condition[14] was detected to some degree by each research team. For example, median initial loss from USGS results was about 0.65 inches for developed watersheds and about 1.0 inches for undeveloped watersheds. The same parameters from Texas Tech results were about 0.42 inches and 0.64 inches, respectively[15]. University of Houston results were similar to those from Texas

[13] Checking using a variety of methods is one such check.

[14] In the case of this research, development condition was quantified by the original analysts who produced the reports that comprise the database reported by Asquith et al. (2004b). That is, development condition is represented by a binary flag — developed or undeveloped.

[15] One of the differences between USGS and TTU results is that the database used by TTU researchers is a subset of that used by USGS researchers, as stated previously in this report. Therefore, it is expected that results will be somewhat different. That does not mean that one set of parameters or the other is superior. They are simply slightly different results, depending on the database used by the respective researcher.

Tech and University of Houston researchers. Lamar University researchers were not able to detect appreciable differences.

A similar story emerges from the analysis of constant loss-rate. That is, the four teams determined similar, but different, values for the constant loss-rate parameter. The differences in results between teams were not tested for statistical significance and because of different fundamental approaches it is difficult to see how to interpret the results. However, from a practical perspective, the differences appear to be sufficiently small that the resulting differences between estimates of design discharge are likely to be less than they typical standard error of estimate from a regional regression equation.

Beyond development condition, each team detected correlation between loss-model parameters and a variety of predictor variables. These relations are presented in the results from each research team.

3.6 Interpretation

The authors (in particular the lead author) appreciate the comments of George "Rudy" Herrmann on the draft version of this report. In general, reporting by researchers in print is bereft of any material considered "opinion" or not substantiated by significant factual information. However, the complexity of this particular project deserves a little less formality. Therefore, this section of the report is offered as the lead author's opinions on the topics treated herein.

The lead author began a long career as a hydrologist in the early 1980's. While working on his Ph.D., he read Loague and Freeze (1985) in preparation for his doctoral research. One of the observations of Loague and Freeze was that the simplest approach to developing a hydrologic model was best (in very loose terms). This was during a time when hydrologic models were blossoming in complexity and distributed modeling was to revolutionize hydrologic analysis and drainage design. As a result, the lead author has a pronounced bias toward the simplest possible solution to a hydrologic or hydraulic problem[16]. That is the background.

A "ladder of technology" for development of design discharges seems appropriate. Such an approach is:

1. Use of gage data (provided one is available and the period of record is sufficient),
2. Regional regression equations (peak discharge only),
3. Rational method,
4. Unit hydrograph method, and
5. Distributed modeling.

[16] *Occam's razor* comes to mind.

All of the above should only be applied within their respective parameter spaces. That being stated, the remainder of this section treats the unit hydrograph method.

All of the technologies presented in this report should produce "reasonable" results if applied within the bounds of their respective parameter spaces. That is a truism of any hydrologic model[17]. However, that said, the lead author believes that the first choice for loss-modeling (or runoff generation modeling) in Texas should be the initial-loss/constant loss-rate approach (unless a specific technology is required by administrative requirement), given the unit hydrograph method is to be used. Parameter values can be selected from any of the results presented previously.

However, at this point engineering judgment becomes critical. Parameter values chosen must be the most representative for the watershed in question *in the analyst's best judgment*. A series of questions (not exhaustive) might be:

1. Is the watershed in question hydrologically similar to those watersheds comprising the study database?
2. Is there some component of the watershed that justifies an increase or decrease to the parameter values chosen? (Such justification might be interconnected impervious areas, slope, soil textural classification, and others.)
3. Do the results obtained after applying the parameters compare with estimates derived from other methods?
4. Are the consequences of hydraulic failure such that additional conservatism is justified?

The temptation, of course, is to always choose parameter values that result in greater estimates of design discharge. This temptation is to be avoided if good stewardship of financial resources is important.

After working on the hydrologic problems reported herein, the lead author's opinion is that the initial-loss/constant loss-rate approach to estimating hydrologic abstractions should be attempted first[18]. Parameter values can be selected based on USGS results and confirmed using results from the other research teams. If design discharges emanating from that approach seem unreasonable (judgment), then parameter values can be adjusted or a different approach used.

What is critical to understand is that we, as engineers, cannot determine the "true value" for a design discharge. We can only arrive at estimates that are subject to a substantial uncertainty. The confidence interval for most frequency distributions of hydrologic variables is at least a third of a log-cycle[19]. It should be no surprise that estimates derived using different technologies differ, sometimes substantially. These are facts that, again, are critical to understand.

[17] Beware that there are always pathological cases.

[18] To reinforce the statement, this assertion is the lead author's opinion. Other approaches to estimating runoff from rainfall are applicable and prudent and the simple appearance of the lead author's opinion in this text does not comprise a factual statement.

[19] Credit goes to Dr. William Asquith for coining the phrase "life at a third of a log-cycle."

Finally, to close this section of the report, the lead author wants to be clear. The observations and recommendations reported herein are only that – observations and recommendations. **It is the duty and responsibility of the end-user of this material to apply appropriate judgment and experience in developing designs using these technologies.**

Chapter 4

Summary and Conclusions

4.1 Summary

Four teams of researchers approached the hydrologic loss-model problem, after several years working on unit hydrographs for selected Texas watersheds. A significant product (separate from this report) is Asquith and Roussel (2007), which contains the analyses and results produced by USGS researchers. This report contains a summary of the Asquith and Roussel work as well as results of analyses by the other three teams, representing University of Houston, Lamar University, and Texas Tech University.

The objective of the research was to determine hydrologic loss methods appropriate for estimating runoff (effective precipitation or precipitation excess) from incoming precipitation for design-type analyses associated with TxDOT design problems. As a result, numerous approaches for estimating losses were examined and reported in the sections of this report above. The approaches are: a fractional loss model, the Green-Ampt loss model, and the initial-loss/constant loss-rate model. Any of these methods can be used. Parameters appropriate for each method are presented in the sections above. The simplest approach may be to use the median estimates for initial loss and constant loss-rate coupled with the unit hydrograph procedure documented in Asquith et al. (2006). The variety of parameter estimates provided in this report and in Asquith and Roussel (2007) can be used to assess uncertainty in the resulting design estimates.

4.2 Conclusions

The conclusions of this research report are:

1. Basin development is a substantial factor affecting the loss models used with the unit hydrograph procedure.

2. Several models of hydrologic losses can be used to estimate runoff from precipitation. They are
   - Initial loss/constant loss-rate,
   - A fractional loss model, and
   - Green-Ampt infiltration model (with an initial abstraction).
3. Mechanics for application of the varied analytical approaches are presented in the results from each research team.
4. Appropriate parameter values, ranges of parameter values, and uncertainties in parameter-value estimates are provided in the results sections above.

No attempts were made to determine which model is "best" in a statistical sense. The authors generally believe that the simplest tools with the fewest operational parameters are best suited to engineering analysis.

4.3 Further Work

After an effort spanning about seven years, much financial resources, and a significant amount of research-personnel and TxDOT-personnel time, work remains to be completed. A potential list of tasks/topics follows.

1. A comparison of the models developed herein with the NRCS curve number approach (perhaps the most common rainfall-runoff model) were not made. This task was not part of the original research plan and insufficient resources were available to complete such a comparison. However, given the results presented in this report, such a comparison could certainly be completed. Given the ubiquitous nature of the curve number approach, such a comparison might be useful in convincing potential end-users of this research of the utility in using locally-derived data and parameters.
2. One of the remaining uncertainties of hydrologic modeling in Texas is whether or not all of the results from the variety of hydrologic research projects executed over the preceding ten years will "fit together." That is, while much testing of the procedures developed as part of Project 0–4193 and other TxDOT research projects occurred during the course of those projects, a set of comprehensive tests and back-tests of the methods developed in those projects remains to be done.
3. As with all research projects, the availability of datasets for analysis remains an issue. While the dataset used during conduct of TxDOT Project 0–4193 is extensive and comprehensive, geographical regions of Texas remain under-represented. These areas are generally located in the arid and semi-arid portions of western Texas and in the coastal plain areas along the Gulf of Mexico. Additional datasets collected in these regions would be useful in providing

needed data points to expand analysis to landscapes and soil associations not present in the current dataset.

The project reported herein is a substantial effort and the investment of time, energy, and financial resources by TxDOT is appreciated by the research team. A research project of this magnitude has not been undertaken by other agencies in recent history and marks a substantial revisit of technologies developed over the last half-century that, while generally accepted as technically adequate, have not been evaluated in the context of such a comprehensive dataset (Asquith et al., 2004b) as that assembled under TxDOT funding. The research effort put forward by TxDOT is something TxDOT personnel can take pride in.

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Appendix A

University of Houston Results

Table A.1: Watershed land-use-type characteristics for applicable Texas watersheds used by University of Houston researchers.

[$DEVF$, Basin development factor (0=undeveloped, 1=developed); $ICOV$, Percent impervious cover; $SURFTEX$, Surface soil textural horizon; CN, NRCS Curve number ; $SOILTEX$, soil textural description; K, soil permeability (inches per second); BSC, alternate soil type code; $ROCK$, Basin rock factor (0= mimimal exposed rock, 1=exposed rock)

STATION_ID	$DEVF$	$ICOV$	$SURFTEX$	CN	$SOILTEX$	K	BSC	$ROCK$
8042650	0	0	ST-FSL	63	Sandy Loam	0.00347	B	0
8042700	0	0	ST-FSL	62	Sandy Loam	0.00347	B	0
8048520	1	26	C	82	Clay	0.000128	C	0
8048530	1	58	C	87	Clay	0.000128	C	0
8048540	1	71	C	88	Clay	0.000128	C	0
8048550	1	61	FSL	91	Sandy Loam	0.00347	B	0
8048600	1	58	FSL	84	Sandy Loam	0.00347	B	0
8048820	1	16	C	83	Clay	0.000128	C	0
8048850	1	16	C	83	Clay	0.000128	C	0
8050200	0	0	CL	80	Clay Loam	0.000245	C	0
8052630	0	0	FSL	85	Sandy Loam	0.00347	B	0
8052700	0	0	SICL	84	Silty Clay Loam	0.00017	S	0
8055580	1	74	SIC	85	Silty Clay	0.000103	S	0
8055600	1	63	C	86	Clay	0.000128	C	0
8055700	1	56	C	85	Clay	0.000128	C	0
8056500	1	65	FSL	86	Sandy Loam	0.00347	B	0
8057020	1	62	SIC	85	Silty Clay	0.000103	S	0
8057050	1	63	SIC	86	Silty Clay	0.000103	S	0
8057120	0	0	SIC	80	Silty Clay	0.000103	S	0
8057130	1	66	SIC	83	Silty Clay	0.000103	S	0
8057140	1	62	SICL	87	Silty Clay Loam	0.00017	S	0
8057160	1	62	SIC	90	Silty Clay	0.000103	S	0
8057320	1	63	C	86	Clay	0.000128	C	0
8057415	1	65	C	88	Clay	0.000128	C	0
8057418	1	34	C	79	Clay	0.000128	C	0

Continued on next page

Table A.1: Watershed Land-Use-Type Characteristics . — Continued

STATION_ID	*DEVF*	*ICOV*	*SURFTEX*	*CN*	*SOILTEX*	*K*	*BSC*	*ROCK*
8057420	1	40	C	81	Clay	0.000128	C	0
8057425	1	40	SIC	83	Silty Clay	0.000103	S	0
8057435	1	11	SIC	81	Silty Clay	0.000103	S	0
8057440	1	1	C	79	Clay	0.000128	C	0
8057445	1	49	FSL	86	Sandy Loam	0.00347	B	0
8057500	0	0	SIC	78	Silty Clay	0.000103	S	0
8058000	0	0	SIC	80	Silty Clay	0.000103	S	0
8061620	1	67	SIC	85	Silty Clay	0.000103	S	0
8061920	1	49	C	86	Clay	0.000128	C	0
8061950	1	39	C	85	Clay	0.000128	C	0
8063200	0	0	C	79	Clay	0.000128	C	0
8094000	0	0	FSL	78	Sandy Loam	0.00347	B	0
8096800	0	0	SIC	80	Silty Clay	0.000103	S	0
8098300	0	0	C	80	Clay	0.000128	C	0
8108200	0	0	C	80	Clay	0.000128	C	0
8111025	1	26	FSL	70	Sandy Loam	0.00347	B	0
8111050	0	0	FSL	70	Sandy Loam	0.00347	B	0
8136900	0	0	C	76	Clay	0.000128	C	0
8137000	0	0	FSL	74	Sandy Loam	0.00347	B	0
8137500	0	0	C	76	Clay	0.000128	C	0
8139000	0	0	FSL	75	Sandy Loam	0.00347	B	0
8140000	0	0	FSL	74	Sandy Loam	0.00347	B	0
8154700	0	18	CL	69	Clay Loam	0.000245	C	1
8155200	0	2	CL	71	Clay Loam	0.000245	C	1
8155300	0	4	CL	70	Clay Loam	0.000245	C	1
8155550	1	67	SIL	87	Silt Loam	0.00072	S	1
8156650	1	56	SIC	84	Silty Clay	0.000103	S	1
8156700	1	64	SIC	87	Silty Clay	0.000103	S	1
8156750	1	64	SIC	87	Silty Clay	0.000103	S	1
8156800	1	66	SIC	87	Silty Clay	0.000103	S	1
8157000	1	70	SIC	88	Silty Clay	0.000103	S	1
8157500	1	71	SIC	89	Silty Clay	0.000103	S	1
8158050	1	53	SIL	84	Silt Loam	0.00072	S	1
8158100	0	0	SIC	73	Silty Clay	0.000103	S	1
8158200	0	0	SIC	76	Silty Clay	0.000103	S	1
8158380	1	73	SIC	89	Silty Clay	0.000103	S	1
8158400	1	73	SIC	86	Silty Clay	0.000103	S	1
8158500	1	66	CL	77	Clay Loam	0.000245	C	1
8158600	1	34	CL	74	Clay Loam	0.000245	C	1
8158700	0	0	STX-C	73	Clay	0.000128	C	1
8158800	0	0	STX-C	70	Clay	0.000128	C	1
8158810	0	0	CL	68	Clay Loam	0.000245	C	1
8158820	0	0	STX-C	67	Clay	0.000128	C	1
8158825	0	0	STX-C	70	Clay	0.000128	C	1
8158840	0	11	CL	68	Clay Loam	0.000245	C	1
8158860	0	0	SIC	79	Silty Clay	0.000103	S	1
8158880	0	0	SIC	79	Silty Clay	0.000103	S	1
8158920	1	23	CL	77	Clay Loam	0.000245	C	1
8158930	1	27	SIC	75	Silty Clay	0.000103	S	1
8158970	1	0	C	78	Clay	0.000128	C	1

Continued on next page

Table A.1: Watershed Land-Use-Type Characteristics . — Continued

STATION_ID	*DEVF*	*ICOV*	*SURFTEX*	*CN*	*SOILTEX*	*K*	*BSC*	*ROCK*
8159150	0	35	SIC	79	Silty Clay	0.000103	S	1
8177600	1	32	STX-C	85	Clay	0.000128	C	1
8178300	1	68	C	86	Clay	0.000128	C	1
8178555	1	65	C	84	Clay	0.000128	C	1
8178600	0	1	STX-C	80	Clay	0.000128	C	1
8178620	1	28	STX-C	60	Clay	0.000128	C	1
8178640	0	16	STX-C	78	Clay	0.000128	C	1
8178645	0	0	STX-C	78	Clay	0.000128	C	1
8178690	1	72	C	84	Clay	0.000128	C	1
8178736	1	0	C	92	Clay	0.000128	C	1
8181000	0	3	STX-C	79	Clay	0.000128	C	1
8181400	0	3	CBV-C	80	Clay	0.000128	C	1
8181450	1	26	CL	87	Clay Loam	0.000245	C	1
8182400	0	0	FSL	80	Sandy Loam	0.00347	B	1
8187000	0	0	SCL	84	Sandy Clay Loam	0.00063	B	1
8187900	0	0	SCL	73	Sandy Clay Loam	0.00063	B	1

Table A.2: Watershed dimensional characteristics for applicable Texas watersheds used by University of Houston researchers.

[TDA, Drainage area in square miles; $BLENG$, Basin length in miles; MCL, Main channel length in miles; BR, Basin relief, change in elevation in feet along MCL; MCS, Main channel slope, dimensionless. The explanatory variable MCL/S is the ratio of MCL and MCS

stationID	TDA	$BLENG$	MCL	BR	MCS
8042650	6.56	3.84	4.63	338.34	0.0138
8042700	23.99	7.68	11.57	416.59	0.0068
8048520	17.63	5.95	7.53	219.56	0.0055
8048530	0.97	1.32	1.7	106.27	0.0118
8048540	1.29	1.92	2.37	140.46	0.0112
8048550	1.11	1.84	2.02	49.64	0.0047
8048600	2.57	3.67	3.85	97.71	0.0048
8048820	5.66	5.39	6.03	190.92	0.006
8048850	12.86	8.14	9.4	251.39	0.0051
8050200	0.87	2.56	2.64	148.96	0.0107
8052630	2.05	3.12	3.3	114.01	0.0065
8052700	73.1	18.74	23.23	297.46	0.0024
8055580	1.9	2.54	3	114.97	0.0073
8055600	5.69	5.97	6.74	215.1	0.006
8055700	11.04	6.63	7.77	213.23	0.0052
8056500	6.36	5.54	6.37	218.02	0.0065
8057020	4.53	4.42	5.09	261.79	0.0097
8057050	9.48	5.4	6.21	258.54	0.0079
8057120	6.57	4.68	5.19	206.05	0.0075
8057130	1.29	2.38	2.63	126.61	0.0091
8057140	8.64	6.1	7.47	230.98	0.0059
8057160	4.6	4.93	5.34	180.36	0.0064
8057320	7.17	5.44	5.42	174.94	0.0061
8057415	0.97	1.67	1.88	71.82	0.0072
8057418	8.06	5.27	5.65	235.84	0.0079
8057420	14.39	7.14	8.33	285.09	0.0065
8057425	10.33	5.07	6.16	270.16	0.0083
8057435	5.92	3.61	4.12	208.38	0.0096
8057440	2.62	3.25	3.52	159.29	0.0086
8057445	8.93	7.31	8.42	170.28	0.0038
8057500	2.09	2.31	2.07	120.61	0.011
8058000	1.21	1.95	2.09	113.26	0.0103
8061620	7.68	4.38	5.52	122.71	0.0042
8061920	12.89	6.83	7.64	156.54	0.0039
8061950	23.31	11.22	12.65	205	0.0031
8063200	18.18	7.38	8.73	192.63	0.0042
8094000	2.38	2.96	3.35	158.67	0.009
8096800	5.07	3.62	4.49	265.24	0.0112
8098300	22.98	11.68	13.73	191.58	0.0026
8108200	46.38	17.59	19.96	274.06	0.0026
8111025	1.35	2.38	2.55	95.12	0.0071
8111050	1.94	1.94	2.45	77.79	0.006
8136900	21.74	10.19	12.42	502.71	0.0077
8137000	4.09	4.02	4.4	121.69	0.0052

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Table A.2: Watershed Dimensional Characteristics. — Continued

stationID	TDA	$BLENG$	MCL	BR	MCS
8137500	69.23	16.91	19.38	568.47	0.0056
8139000	3.13	2.96	3.36	269.3	0.0152
8140000	7.32	5.39	5.91	319.7	0.0102
8154700	22.78	8.47	10.04	568.3	0.0107
8155200	89.64	18.21	28.5	752.2	0.005
8155300	116.62	26.41	45.07	982.95	0.0041
8155550	2.67	2.98	3.66	243.19	0.0126
8156650	2.71	2.11	3	183.18	0.0116
8156700	6.35	3.75	4.53	242.01	0.0101
8156750	6.84	4.22	5.13	257.89	0.0095
8156800	12.75	8.79	10.58	438.74	0.0079
8157000	2.21	3.8	4.12	212.58	0.0098
8157500	4.17	4.74	5.16	256.94	0.0094
8158050	12.63	6.01	7.36	309.76	0.008
8158100	12.74	3.75	5.67	292.89	0.0098
8158200	26.43	8	10.92	401.73	0.007
8158380	5.26	3.43	4.01	155.81	0.0074
8158400	5.71	4.05	4.48	167.07	0.0071
8158500	12.13	7.23	8.59	315.14	0.0069
8158600	53.58	14.41	19.47	528.86	0.0051
8158700	123.71	20.75	33.28	794.59	0.0045
8158800	167.29	31	48.94	1013.66	0.0039
8158810	12.3	4.96	6.29	374.07	0.0113
8158820	24.5	10.52	14.85	590.65	0.0075
8158825	21.02	8.77	12.53	443.56	0.0067
8158840	8.77	4.82	4.96	313.83	0.012
8158860	23.22	10.56	12.79	534.18	0.0079
8158880	3.57	3.82	4.4	265.7	0.0114
8158920	6.3	4.36	4.97	315.4	0.012
8158930	18.73	9.49	10.4	492.84	0.009
8158970	27.38	13.8	17.61	607.44	0.0065
8159150	4.46	2.93	3.74	169.89	0.0086
8177600	0.32	1.23	1.3	101.48	0.0147
8178300	3.27	3.15	3.58	316.32	0.0167
8178555	1.91	3.48	4.05	51.87	0.0024
8178600	9.61	6.69	7.05	489.46	0.0131
8178620	4.05	3.26	3.61	227.9	0.012
8178640	2.46	2.92	3.04	328.23	0.0204
8178645	2.46	3.36	3.96	340.17	0.0163
8178690	0.43		1.17	46.1	0.0074
8178736	0.69	1.48	1.67	82.48	0.0094
8181000	5.55	4.19	5.42	463.18	0.0162
8181400	14.9	8.46	9.82	691.44	0.0133
8181450	1.24	2.82	3.13	53.05	0.0032
8182400	7.15	4.53	4.87	146.5	0.0057
8187000	3.06	2.81	2.78	143.87	0.0098
8187900	8.78	4.35	4.87	145.18	0.0056

Table A.3: Observed and estimated hydrologic variables for FRAC model.

$C_{r,o}$, Runoff coefficient, station optimal value,; $T_{p,o}$, Lag time, station optimal value, in hours; $Q_{p,o}$, Peak discharge factor, station optimal value in $\frac{cfs-hr}{in.-sq.mi.}$; $C_{r,m}$ Runoff coefficient, regression estimated; $T_{p,o}$, Lag time, regression estimated; $Q_{p,o}$, Peak discharge factor, regression estimated value in $\frac{cfs-hr}{in.-sq.mi.}$;

STATION_ID	$C_{r,o}$	$Q_{p,o}$	$T_{p,o}$	$C_{r,m}$	$Q_{p,m}$	$T_{p,m}$
8042650	0.15	3.19	220.60	0.24	2.42	249.71
8042700	0.14	5.36	132.95	0.23	4.55	132.87
8048520	0.37	2.21	136.15	0.45	2.74	220.33
8048530	0.30	0.30	1418.55	0.47	0.68	887.69
8048540	0.39	0.32	1506.90	0.48	0.64	943.76
8048550	0.38	1.22	512.67	0.50	0.99	609.41
8048600	0.32	1.29	194.97	0.46	1.33	455.51
8048820	0.37	3.62	122.83	0.45	2.86	211.29
8048850	0.35	4.24	120.24	0.45	3.62	166.92
8050200	0.40	2.91	204.57	0.32	2.15	281.39
8052630	0.54	2.84	197.75	0.35	2.84	212.58
8052700	0.35	7.66	46.03	0.35	8.93	67.61
8055580	0.58	0.36	837.60	0.46	0.79	765.51
8055600	0.36	0.81	501.68	0.47	1.39	433.35
8055700	0.50	2.53	305.10	0.47	1.74	346.28
8056500	0.48	1.62	425.15	0.47	1.28	472.01
8057020	0.41	0.92	649.34	0.47	1.05	573.14
8057050	0.44	0.72	1370.91	0.47	1.21	497.84
8057120	0.36	1.82	376.43	0.33	3.20	188.48
8057130	0.61	0.87	533.17	0.45	0.78	771.02
8057140	0.35	1.09	387.14	0.47	1.48	407.01
8057160	0.56	1.01	575.75	0.49	1.26	478.62
8057320	0.67	0.90	644.63	0.47	1.27	474.69
8057415	0.56	0.36	1401.40	0.48	0.77	789.16
8057418	0.48	0.93	420.50	0.43	1.87	322.82
8057420	0.48	1.42	435.14	0.44	2.13	283.63
8057425	0.51	1.03	561.91	0.45	1.72	350.70
8057435	0.55	1.54	324.31	0.44	2.23	271.20
8057440	0.42	2.13	498.70	0.43	2.57	234.92
8057445	0.37	3.37	122.15	0.47	2.28	265.26
8057500	0.38	1.84	254.06	0.32	1.93	312.62
8058000	0.39	2.79	252.08	0.33	1.99	303.60
8061620	0.59	1.26	257.12	0.46	1.39	435.00
8061920	0.62	2.78	189.07	0.47	2.17	278.27
8061950	0.57	7.01	86.10	0.46	3.39	177.93
8063200	0.41	6.69	77.39	0.32	4.91	122.92
8094000	0.21	3.28	224.58	0.32	2.52	239.83
8096800	0.17	3.21	212.01	0.33	2.59	233.02
8098300	0.38	7.76	65.72	0.33	7.06	85.56
8108200	0.29	8.88	72.30	0.33	8.16	73.98
8111025	0.71	1.45	488.03	0.38	1.63	370.60
8111050	0.52	5.30	97.26	0.27	2.61	231.36
8136900	0.16	4.86	85.19	0.30	4.45	135.65
8137000	0.20	3.75	172.71	0.30	3.47	174.31
8137500	0.12	4.62	89.48	0.31	5.99	100.83
8139000	0.12	2.44	242.26	0.30	2.06	293.67

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Table A.3: Hydrologic variables for FRAC model. — Continued

STATION_ID	$C_{r,o}$	$Q_{p,o}$	$T_{p,o}$	$C_{r,m}$	$Q_{p,m}$	$T_{p,m}$
8140000	0.14	4.55	148.19	0.30	2.99	201.94
8154700	0.18	3.58	143.82	0.12	3.55	170.19
8155200	0.19	8.98	47.06	0.13	9.27	65.14
8155300	0.22	12.51	58.79	0.13	11.59	52.13
8155550	0.24	1.02	404.94	0.33	1.02	593.82
8156650	0.18	0.72	283.97	0.31	1.16	519.81
8156700	0.26	0.96	452.77	0.33	1.26	477.78
8156750	0.20	1.09	394.08	0.33	1.36	444.52
8156800	0.31	2.07	335.80	0.33	1.87	322.61
8157000	0.29	1.66	304.88	0.34	1.12	539.97
8157500	0.31	1.50	261.45	0.34	1.22	494.75
8158050	0.29	2.41	289.21	0.31	2.00	302.39
8158100	0.10	3.73	133.24	0.14	3.94	153.42
8158200	0.15	3.27	142.99	0.16	5.79	104.35
8158380	0.49	1.08	642.27	0.34	1.18	513.62
8158400	0.47	0.85	406.24	0.32	1.25	484.12
8158500	0.37	1.73	291.15	0.28	1.82	331.90
8158600	0.27	3.45	146.77	0.26	4.72	127.85
8158700	0.19	9.74	43.37	0.15	10.60	57.00
8158800	0.08	11.07	23.75	0.13	13.01	46.41
8158810	0.18	3.27	203.64	0.12	3.88	155.74
8158820	0.04	16.02	57.91	0.12	6.35	95.11
8158825	0.01	1.98	488.27	0.13	6.21	97.25
8158840	0.38	3.98	132.54	0.12	2.89	208.95
8158860	0.38	3.39	280.08	0.18	5.87	102.85
8158880	0.32	1.36	419.34	0.18	3.36	179.55
8158920	0.31	1.31	223.10	0.28	2.38	253.60
8158930	0.21	2.71	227.07	0.27	3.33	181.60
8158970	0.18	5.12	152.24	0.28	7.17	84.20
8159150	0.28	4.19	181.69	0.18	2.00	302.24
8177600	0.28	4.24	198.81	0.32	1.13	534.63
8178300	0.30	0.98	664.51	0.32	0.89	679.15
8178555	0.27	3.22	268.72	0.32	2.08	290.16
8178600	0.16	3.06	343.32	0.18	3.77	160.37
8178620	0.03	5.28	207.51	0.19	1.94	311.38
8178640	0.11	3.40	333.74	0.17	1.79	336.82
8178645	0.09	4.75	228.24	0.17	2.81	214.94
8178690	0.43	1.12	536.38	0.32	0.74	815.62
8178736	0.44	0.70	802.12	0.36	2.49	242.74
8181000	0.13	3.57	271.69	0.18	3.03	199.26
8181400	0.15	5.29	136.02	0.18	4.12	146.50
8181450	0.25	2.26	318.47	0.33	3.17	190.64
8182400	0.17	4.39	184.40	0.18	4.58	131.85
8187000	0.19	2.42	315.01	0.20	2.98	202.38
8187900	0.16	3.32	138.52	0.15	4.61	130.95
8187900	0.16	3.32	138.52	0.15	4.61	130.95

Table A.4: Observed and estimated hydrologic variables for IACL model.

[$I_{a,o}$, Initial abstraction, station optimal value, in inches; $C_{l,o}$, Constant loss rate, station optimal value, in inches per hour $T_{p,o}$, Lag time, station optimal value, in hours; $Q_{p,o}$, Peak discharge factor, station optimal value in $\frac{cfs-hr}{in.-sq.mi.}$; $I_{a,m}$, Initial abstraction, regression estimated; $C_{l,m}$, Constant loss rate, regression estimated; $T_{p,m}$,Lag time, regression estimated value, in hours; $Q_{p,m}$, Peak discharge factor, regression estimated value in $\frac{cfs-hr}{in.-sq.mi.}$; $t_{rms,m}$, root-mean-square time (natural variable) regression estimated value; N_m, shape factor regression estimated value]

STATION_ID	$I_{a,o}$	$C_{l,o}$	$T_{p,o}$	$Q_{p,o}$	$I_{a,m}$	$C_{l,m}$	$T_{p,m}$	$Q_{p,m}$
8042650	0.88	1.26	3.4	186.02	0.85	0.82	2.53	224.68
8042700	0.93	1.01	5.74	124.93	0.86	0.76	4.68	121.28
8048520	0.45	0.6	2.29	143	0.5	0.57	2.85	198.97
8048530	0.4	1.23	0.29	1240.56	0.47	0.63	0.73	777.35
8048540	0.27	1.04	0.32	1255.59	0.46	0.63	0.69	825.63
8048550	0.42	0.79	1.31	448.94	0.43	0.62	1.05	538.3
8048600	0.39	0.86	1.36	195.48	0.48	0.6	1.4	405
8048820	0.49	0.64	3.81	114.47	0.49	0.59	2.97	190.93
8048850	0.7	0.54	4.46	110.88	0.49	0.54	3.74	151.65
8050200	0.61	0.42	3.11	189.54	0.73	0.83	2.25	252.49
8052630	0.55	0.46	2.99	187.44	0.69	0.82	2.96	191.97
8052700	0.89	0.37	10.02	46.37	0.7	0.36	9.05	62.67
8055580	0.28	0.8	0.39	862.15	0.48	0.62	0.84	672.96
8055600	0.41	1.04	0.8	443.64	0.47	0.58	1.47	385.79
8055700	0.7	0.84	2.73	270.13	0.47	0.56	1.83	309.79
8056500	0.51	0.42	1.73	361.06	0.47	0.59	1.35	419.42
8057020	0.57	0.58	0.87	475.82	0.47	0.61	1.12	506.98
8057050	0.53	0.56	0.75	1302.6	0.47	0.6	1.28	441.8
8057120	0.61	0.44	1.84	291.63	0.73	0.81	3.32	170.67
8057130	0.65	0.33	0.9	460.23	0.49	0.62	0.84	677.52
8057140	0.48	0.77	1.13	383.84	0.47	0.57	1.56	362.85
8057160	0.41	0.44	0.97	454.87	0.44	0.6	1.33	425.11
8057320	0.61	0.11	0.88	576.86	0.47	0.59	1.35	421.72
8057415	0.36	0.64	0.34	1080.55	0.46	0.62	0.82	693.06
8057418	0.63	0.8	0.88	398.16	0.52	0.6	1.96	289.07
8057420	0.4	0.6	1.46	349.71	0.51	0.57	2.23	254.77
8057425	0.58	0.52	1.03	461.29	0.49	0.6	1.81	313.5
8057435	0.58	0.42	1.44	256.77	0.51	0.62	2.33	243.64
8057440	0.86	0.37	2.28	508.23	0.52	0.62	2.68	211.67
8057445	0.61	0.64	3.56	113.07	0.47	0.53	2.38	238.7
8057500	0.83	0.73	2.04	234.26	0.74	0.83	2.03	279.85
8058000	0.82	0.7	2.94	230.65	0.73	0.83	2.09	271.95
8061620	0.61	0.48	1.11	247.86	0.48	0.57	1.47	387.28
8061920	0.5	0.18	2.86	180.22	0.47	0.54	2.27	250.13
8061950	0.34	0.3	7.05	82.54	0.48	0.43	3.51	161.53
8063200	0.54	0.43	6.62	78.06	0.74	0.74	5.05	112.4
8094000	0.87	0.67	3.53	191.01	0.74	0.82	2.63	215.99
8096800	0.76	1.06	3.47	189.51	0.73	0.82	2.7	209.99
8098300	0.57	0.41	8.06	66.87	0.73	0.58	7.19	78.89
8108200	0.58	0.51	9.24	71.71	0.73	0.46	8.29	68.44
8111025	0.39	0.4	1.45	491.25	0.59	0.62	1.72	330.73
8111050	0.51	0.89	5.3	97.72	0.8	0.82	2.72	208.53
8136900	0.66	0.91	4.97	87.29	0.76	0.76	4.58	123.76

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Table A.4: Hydrologic variables for IACL model. — Continued

STATION_ID	$I_{a,o}$	$C_{l,o}$	$T_{p,o}$	$Q_{p,o}$	$I_{a,m}$	$C_{l,m}$	$T_{p,m}$	$Q_{p,m}$
8137000	0.74	0.84	3.93	162.39	0.77	0.8	3.59	158.12
8137500	0.63	0.55	5.41	99.07	0.76	0.67	6.13	92.62
8139000	0.81	1	2.59	217.33	0.77	0.83	2.16	263.25
8140000	0.97	0.91	4.94	129.51	0.77	0.81	3.11	182.58
8154700	0.9	1.18	4.18	125.79	1.02	1.13	3.72	152.33
8155200	0.99	1.01	10.5	52.01	1.01	0.89	9.53	59.57
8155300	0.75	0.68	13.52	54.97	1.02	0.63	11.84	47.92
8155550	1.28	0.98	0.91	318.59	0.67	0.96	1.1	517.37
8156650	0.63	1.13	0.83	284.35	0.7	0.96	1.25	454.12
8156700	0.65	1.05	0.98	372.26	0.68	0.95	1.36	418.3
8156750	0.51	1.06	1.14	338.55	0.68	0.95	1.46	389.83
8156800	0.7	0.97	2.15	302.95	0.68	0.91	1.99	285.01
8157000	0.55	0.92	1.85	256.27	0.67	0.95	1.2	471.52
8157500	0.51	0.91	1.69	228.23	0.66	0.94	1.31	432.91
8158050	0.51	0.92	2.6	231.02	0.7	0.93	2.12	267.43
8158100	1.12	1.47	3.8	120.94	1	1.15	4.12	137.57
8158200	0.85	0.97	3.47	117.25	0.97	1.1	6.01	94.39
8158380	1.05	0.31	1.13	524.34	0.66	0.94	1.26	449.06
8158400	0.47	0.46	0.85	369.59	0.69	0.94	1.34	423.84
8158500	0.67	0.69	1.75	251.55	0.75	0.91	1.94	293.02
8158600	0.69	0.64	3.65	128.47	0.77	0.78	4.92	115.24
8158700	0.65	0.77	10.65	46.25	0.99	0.81	10.85	52.27
8158800	1.43	0.53	11.89	29.02	1.02	0.55	13.27	42.76
8158810	1.18	1.04	3.07	219	1.03	1.15	4.06	139.6
8158820	0.65	1.02	16.79	62.93	1.03	1.08	6.58	86.22
8158825	1.93	1.78	2.29	410.81	1.02	1.08	6.44	88.11
8158840	0.82	0.77	3.76	142.41	1.03	1.15	3.05	186.11
8158860	1.45	0.76	3.36	304.5	0.95	1.09	6.1	93.07
8158880	0.9	0.92	1.33	374.33	0.95	1.16	3.54	160.43
8158920	0.89	1.16	1	240.94	0.74	0.95	2.52	224.97
8158930	0.73	0.95	2.82	189.06	0.76	0.91	3.49	162.35
8158970	0.64	0.97	5.74	140.27	0.74	0.84	7.41	76.54
8159150	0.58	0.78	4.19	178.82	0.95	1.15	2.12	267.15
8177600	0.77	1.06	4.85	181.99	0.69	0.97	1.22	466.42
8178300	0.45	1.15	1.03	597.25	0.69	0.96	0.96	589.93
8178555	0.64	0.78	3.37	262.44	0.7	0.89	2.21	256.95
8178600	0.92	1.34	3.24	368.48	0.95	1.15	3.95	143.66
8178620	0.87	1.07	5.26	251.06	0.87	0.96	2.06	274.98
8178640	1.13	1.49	3.8	378.32	0.95	1.17	1.91	296.81
8178645	1.06	1.5	5.43	229.67	0.96	1.16	2.97	191.26
8178690	0.52	1.08	1.24	478.19	0.69	0.96	0.8	705.62
8178736	0.63	0.68	0.76	679.79	0.64	0.96	2.63	215.4
8181000	0.88	1.19	4.06	243.29	0.95	1.16	3.19	177.63
8181400	1.34	1.23	5.56	121.9	0.94	1.14	4.31	131.51
8181450	0.57	0.92	2.42	293.03	0.67	0.92	3.33	170.24
8182400	0.81	0.97	4.87	171.62	0.94	1.13	4.78	118.64
8187000	0.82	1.12	2.51	290.97	0.92	1.16	3.15	180.33
8187900	1.02	1.27	3.02	132.25	0.99	1.13	4.81	117.84

Table A.5: Observed and estimated hydrologic variables for GAIN model.

[$\phi_{,o}$, Psuedo-porosity, station optimal value; $K_{,o}$, Psuedo-conductivity, station optimal value, in inches per hour; $T_{p,o}$, Lag time, station optimal value, in hours; $Q_{p,o}$, Peak discharge factor, station optimal value in $\frac{cfs-hr}{in.-sq.mi.}$; $\phi_{,m}$, Psuedo-porosity, regression estimated; $K_{,m}$, Psuedo-conductivity, regression estimated; $T_{p,m}$,Lag time, regression estimated value, in hours; $Q_{p,m}$, Peak discharge factor, regression estimated value in $\frac{cfs-hr}{in.-sq.mi.}$;]

STATION_ID	$\phi_{,o}$	$K_{,o}$	$T_{p,o}$	$Q_{p,o}$	ϕ_m	$K_{,m}$	$T_{p,m}$	$Q_{p,m}$
8042650	0.52	1.23	3.42	186.61	0.49	0.87	2.48	216.24
8042700	0.46	1.10	5.77	125.32	0.49	0.81	4.59	116.79
8048520	0.45	0.68	2.30	143.45	0.49	0.62	2.80	191.61
8048530	0.48	1.24	0.29	1244.48	0.49	0.67	0.72	748.11
8048540	0.38	1.02	0.32	1259.55	0.49	0.67	0.67	794.72
8048550	0.53	0.80	1.32	450.36	0.49	0.66	1.03	518.25
8048600	0.44	0.85	1.37	196.10	0.49	0.64	1.37	389.99
8048820	0.45	0.66	3.83	114.83	0.49	0.63	2.91	183.84
8048850	0.47	0.61	4.48	111.24	0.49	0.59	3.67	146.05
8050200	0.40	0.50	3.12	190.13	0.49	0.88	2.20	242.99
8052630	0.53	0.51	3.01	188.03	0.49	0.86	2.90	184.79
8052700	0.50	0.65	10.06	46.52	0.49	0.46	8.87	60.39
8055580	0.45	0.76	0.39	864.87	0.49	0.66	0.83	647.91
8055600	0.51	1.01	0.80	445.04	0.49	0.63	1.44	371.54
8055700	0.52	0.84	2.74	270.99	0.49	0.61	1.80	298.37
8056500	0.46	0.48	1.74	362.20	0.49	0.63	1.33	403.91
8057020	0.53	0.60	0.88	477.32	0.49	0.65	1.10	488.13
8057050	0.55	0.57	0.75	1306.71	0.49	0.64	1.26	425.44
8057120	0.22	0.47	1.85	292.55	0.49	0.86	3.26	164.30
8057130	0.62	0.45	0.91	461.68	0.49	0.66	0.82	652.21
8057140	0.41	0.80	1.13	385.05	0.49	0.62	1.53	349.47
8057160	0.61	0.43	0.98	456.31	0.49	0.64	1.31	409.37
8057320	0.62	0.32	0.89	578.68	0.49	0.64	1.32	406.12
8057415	0.64	0.61	0.34	1083.97	0.49	0.66	0.80	667.15
8057418	0.55	0.85	0.89	399.41	0.49	0.64	1.93	278.32
8057420	0.45	0.61	1.47	350.81	0.49	0.62	2.18	245.35
8057425	0.52	0.57	1.04	462.74	0.49	0.64	1.77	301.85
8057435	0.53	0.44	1.44	257.58	0.49	0.66	2.28	234.52
8057440	0.56	0.40	2.29	509.83	0.49	0.66	2.63	203.74
8057445	0.42	0.62	3.57	113.43	0.49	0.58	2.33	229.93
8057500	0.49	0.89	2.05	235.00	0.49	0.88	1.99	269.29
8058000	0.54	0.80	2.95	231.38	0.49	0.88	2.05	261.70
8061620	0.69	0.53	1.11	248.64	0.49	0.62	1.44	373.00
8061920	0.45	0.20	2.87	180.79	0.49	0.59	2.22	240.93
8061950	0.46	0.32	7.08	82.80	0.49	0.50	3.44	155.61
8063200	0.44	0.53	6.65	78.30	0.49	0.79	4.95	108.25

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Table A.5: Hydrologic variables for IACL model. — Continued

STATION_ID	$\phi_{,o}$	$K_{,o}$	$T_{p,o}$	$Q_{p,o}$	ϕ_m	$K_{,m}$	$T_{p,m}$	$Q_{p,m}$
8094000	0.56	0.83	3.54	191.62	0.49	0.87	2.58	207.89
8096800	0.50	1.15	3.48	190.10	0.49	0.87	2.65	202.11
8098300	0.32	0.47	8.10	67.08	0.49	0.65	7.05	75.99
8108200	0.33	0.56	9.28	71.94	0.49	0.55	8.13	65.94
8111025	0.27	0.22	1.46	485.67	0.49	0.66	1.68	318.35
8111050	0.35	0.62	5.39	95.01	0.49	0.87	2.67	200.71
8136900	0.43	0.95	4.90	88.88	0.49	0.81	4.50	119.18
8137000	0.39	0.91	3.95	162.90	0.49	0.85	3.52	152.23
8137500	0.43	0.95	5.43	99.38	0.49	0.73	6.01	89.21
8139000	0.44	1.07	2.60	218.02	0.49	0.88	2.11	253.33
8140000	0.49	1.22	4.96	129.92	0.49	0.86	3.05	175.75
8154700	0.55	1.25	4.20	126.19	0.49	1.25	3.65	146.71
8155200	0.47	1.04	10.55	52.17	0.49	1.04	9.33	57.40
8155300	0.32	0.73	13.58	55.14	0.49	0.80	11.60	46.18
8155550	0.71	1.49	0.91	319.60	0.49	1.06	1.08	498.17
8156650	0.57	1.36	0.83	285.25	0.49	1.07	1.23	437.23
8156700	0.53	1.18	0.98	373.43	0.49	1.06	1.33	402.83
8156750	0.54	1.11	1.14	339.62	0.49	1.05	1.43	375.43
8156800	0.48	1.04	2.16	303.91	0.49	1.02	1.95	274.57
8157000	0.57	1.06	1.85	257.07	0.49	1.06	1.18	454.08
8157500	0.57	0.95	1.69	228.95	0.49	1.05	1.28	416.94
8158050	0.57	1.05	2.61	231.75	0.49	1.04	2.08	257.59
8158100	0.63	1.67	3.82	121.32	0.49	1.26	4.04	132.46
8158200	0.48	1.27	3.48	117.62	0.49	1.22	5.89	90.92
8158380	0.71	1.09	1.14	526.00	0.49	1.05	1.24	432.50
8158400	0.55	0.52	0.85	370.76	0.49	1.05	1.31	408.23
8158500	0.61	0.77	1.76	252.35	0.49	1.02	1.90	282.28
8158600	0.52	0.84	3.67	128.88	0.49	0.91	4.82	111.05
8158700	0.32	0.87	10.70	46.40	0.49	0.96	10.64	50.38
8158800	0.46	0.82	11.95	29.11	0.49	0.73	13.00	41.22
8158810	0.23	0.53	3.09	219.69	0.49	1.26	3.99	134.42
8158820	0.40	1.00	16.86	63.13	0.49	1.20	6.45	83.05
8158825	0.66	1.79	2.30	412.10	0.49	1.20	6.31	84.87
8158840	0.42	1.01	3.78	142.86	0.49	1.27	2.99	179.19
8158860	0.71	0.77	3.38	305.46	0.49	1.22	5.98	89.64
8158880	0.50	1.17	1.34	375.51	0.49	1.27	3.47	154.45
8158920	0.58	1.30	1.00	241.70	0.49	1.06	2.47	216.61
8158930	0.59	1.00	2.83	189.65	0.49	1.03	3.43	156.38
8158970	0.37	1.06	5.76	140.71	0.49	0.96	7.27	73.74
8159150	0.43	0.82	4.21	179.39	0.49	1.27	2.08	257.24

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Table A.5: Hydrologic variables for IACL model. — Continued

STATION_ID	$\phi_{,o}$	$K_{,o}$	$T_{p,o}$	$Q_{p,o}$	ϕ_m	$K_{,m}$	$T_{p,m}$	$Q_{p,m}$
8177600	0.48	1.13	4.87	182.57	0.49	1.07	1.19	448.87
8178300	0.43	1.12	1.04	599.13	0.49	1.07	0.94	567.98
8178555	0.41	0.95	3.39	263.27	0.49	1.00	2.16	247.56
8178600	0.59	1.40	3.25	369.65	0.49	1.26	3.87	138.32
8178620	0.61	1.25	5.29	251.85	0.49	1.06	2.02	264.74
8178640	0.58	1.49	3.82	379.52	0.49	1.28	1.88	285.67
8178645	0.55	1.61	5.46	230.40	0.49	1.28	2.91	184.10
8178690	0.45	1.07	1.25	479.70	0.49	1.07	0.79	679.30
8178736	0.46	0.77	0.77	681.94	0.49	1.07	2.58	207.32
8181000	0.61	1.34	4.08	244.06	0.49	1.27	3.13	171.00
8181400	0.57	1.51	5.59	122.28	0.49	1.25	4.23	126.64
8181450	0.45	0.92	2.43	293.95	0.49	1.03	3.27	163.96
8182400	0.49	1.14	4.89	172.16	0.49	1.25	4.69	114.25
8187000	0.50	1.27	2.52	291.89	0.49	1.27	3.09	173.59
8187900	0.49	1.41	3.03	132.67	0.49	1.25	4.72	113.48

Figure A.1: FORTRAN source code for FRAC model.

```
      subroutine rainloss(acc_precip,rate_precip,acc_runoff,time,
     1                    cia,crp,irdata,maxrows)
c subroutine to implement fractional rainfall loss model
c input:
c  acc_precip = accumulated precipitation array
c  time             = elapsed time array
c  acc_runoff  = accumulated runoff array
c  cia                = initial abstraction (should be 0.0, forced in code)
c  crp                = runoff coefficient
c  irdata           = number of rows of data (integer)
c  maxrows     = array physical size (set in calling module)
c output:
c  rate_precip = excess precipitation array
c
    real*8 acc_precip(maxrows)
    real*8 acc_runoff(maxrows)
    real*8 rate_precip(maxrows)
    real*8 time(maxrows)
    real*8 cia
    real*8 crp
    real*8 temprate
c determine rate_precip (effective) from loss model
c force cia=0 in fractional loss model
      cia=0.0d0
      rate_precip(1)=0.d0
c
c calculate runoff coefficient from runoff/rainfall ratio
c
      crp=acc_runoff(irdata)/(acc_precip(irdata)-cia)
c
      do 7801 ir=2,irdata
       if( acc_precip(ir) .le. cia )then
          rate_precip(ir)=0.d0
       else
         temprate=acc_precip(ir)-acc_precip(ir-1)
         temprate=temprate/(time(ir)-time(ir-1))
         rate_precip(ir)=temprate*crp
       end if
 7801 continue
      return
end
```

Figure A.2: FORTRAN source code for IACL model.

```
      subroutine rainloss(acc_precip,rate_precip,acc_runoff,time,
     1                    cia,crp,irdata,maxrows)
c subroutine to implement IACL rainfall loss model
c input:
c  acc_precip = accumulated precipitation array
c  time             = elapsed time array
c  acc_runoff  = accumulated runoff array (not used)
c  cia                = initial abstraction
c  crp                = constant loss rate
c  irdata           = number of rows of data (integer)
c  maxrows     = array physical size (set in calling module)
c output:
c  rate_precip = excess precipitation array
c
real*8 acc_precip(maxrows)
         real*8 acc_runoff(maxrows)
real*8 rate_precip(maxrows)
real*8 time(maxrows)
real*8 cia
real*8 crp
real*8 temprate
c determine rate_precip (effective) from loss model
      rate_precip(1)=0.d0
      do 7801 ir=2,irdata
       if( acc_precip(ir) .le. cia )then
          rate_precip(ir)=0.d0
       else
        temprate=acc_precip(ir)-acc_precip(ir-1)
        temprate=temprate/(time(ir)-time(ir-1))
        if(temprate .le. crp)then
         rate_precip(ir)=0.d0
        else
         rate_precip(ir)=temprate-crp
        end if
       end if
 7801 continue
      return
end
```

Figure A.3: FORTRAN source code for GAIN model.

```
      subroutine rainloss(acc_precip,rate_precip,acc_runoff,time,
     1                    cia,crp,irdata,maxrows)
c subroutine to implement GAIN rainfall loss model
c input:
c  acc_precip = accumulated precipitation array
c  time             = elapsed time array
c  acc_runoff  = accumulated runoff array (not used)
c  cia                = psuedo porosity
c  crp                = psuedo conductivity
c  irdata           = number of rows of data (integer)
c  maxrows     = array physical size (set in calling module)
c output:
c  rate_precip = excess precipitation array
c
real*8 acc_precip(maxrows)
        real*8 acc_runoff(maxrows)
real*8 rate_precip(maxrows)
real*8 time(maxrows)
real*8 cia
real*8 crp
real*8 temprate
c internal variables
c
c q  potential infiltration rate (L/T)
c dt time step (T)
c z  cumulative infiltration depth (L)
        real*8 q
        real*8 dt
        real*8 z
        real*8 pc
c determine rate_precip (effective) from loss model
      rate_precip(1)=0.d0
      z=0.01
      pc=0.10
c
      do 7801 ir=2,irdata
c determine rainfall potential rate
        dt=time(ir)-time(ir-1)
        temprate=acc_precip(ir)-acc_precip(ir-1)
        temprate=temprate/dt
c determine potential infiltration rate
        q=crp*((pc+z)/z)
c test if all rain infiltrates or some is runoff
        if(temprate .gt. q)then
         rate_precip(ir)=temprate-q
         z=z+(q*dt)/cia
        else if(temprate .le. q)then
         rate_precip(ir)=0.d0
```

Appendix B

Texas Tech University Results

Table B.1: Results from optimization of initial loss/constant loss-rate model parameters from Texas Tech dataset. [USGS Station refers to the USGS Stream Gage identification number, Area is the drainage area of the watershed, Developed indicates whether the watershed was flagged as developed, 1 indicates yes, 0 indicates no, Initial Loss is the median optimized initial abstraction, and Loss-rate is the median optimized loss-rate.]

USGS Station	Area (mi^2)	Developed	Initial Loss (inches)	Loss-rate (in/hr)
08048520	17.70	1	0.52	0.46
08048530	0.97	1	0.36	0.82
08048540	1.35	1	0.45	0.50
08048550	1.08	1	0.42	0.56
08048600	2.15	1	0.32	0.48
08048820	5.64	1	0.35	0.23
08048850	12.30	1	0.30	1.53
08055580	1.94	1	0.15	0.46
08055600	7.51	1	0.46	0.44
08055700	10.00	1	0.55	0.35
08056500	7.98	1	0.38	0.20
08057020	4.75	1	0.50	0.40
08057050	9.42	1	0.09	0.03
08057130	1.22	1	0.31	0.61
08057140	8.50	1	0.44	0.35
08057160	4.17	1	0.30	0.33
08057320	6.92	1	0.26	0.20
08057415	1.25	1	0.13	0.15
08057418	7.65	1	0.37	0.32
08057420	13.20	1	0.29	0.19

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Table B.1: Results from optimization of initial loss/constant loss-rate model parameters from Texas Tech dataset — continued.

USGS Station	Area (mi^2)	Developed	Initial Loss (inches)	Loss-rate (in/hr)
08057425	11.50	1	0.40	0.15
08057435	5.91	1	0.51	0.27
08057440	2.53	1	0.40	0.25
08057445	9.03	1	0.24	0.34
08061620	8.05	1	0.52	0.47
08061920	13.40	1	0.33	0.06
08061950	23.00	1	0.45	0.18
08155550	3.12	1	0.60	1.26
08156650	3.19	1	0.79	0.71
08156700	7.03	1	0.31	0.57
08156750	7.56	1	0.34	1.23
08156800	12.80	1	0.85	0.49
08157000	2.31	1	0.49	0.68
08157500	4.13	1	0.49	0.67
08158050	13.10	1	0.53	0.57
08158380	5.22	1	0.79	0.42
08158400	5.57	1	0.41	0.36
08158500	12.10	1	0.87	0.61
08158600	51.30	1	0.59	0.47
08158920	6.30	1	0.51	0.91
08158930	19.00	1	0.52	0.63
08158970	27.60	1	1.14	0.60
08177600	0.33	1	0.40	0.80
08178300	3.26	1	0.43	0.93
08178555	2.43	1	0.27	0.27
08178690	0.26	1	0.29	1.17
08178736	0.45	1	0.70	0.54
08181450	1.19	1	0.76	0.86
08042650	6.82	0	0.44	0.48
08042700	21.60	0	0.68	0.66
08050200	0.77	0	0.88	0.02
08052630	2.10	0	0.65	0.26
08052700	75.50	0	0.47	0.16
08057120	6.77	0	0.48	0.40
08057500	2.14	0	0.22	0.52
08058000	1.26	0	0.21	0.14
08063200	17.60	0	0.62	0.20
08094000	3.34	0	0.82	0.59

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Table B.1: Results from optimization of initial loss/constant loss-rate model parameters from Texas Tech dataset — continued.

USGS Station	Area (mi^2)	Developed	Initial Loss (inches)	Loss-rate (in/hr)
08096800	5.25	0	1.23	0.56
08098300	22.20	0	0.37	0.21
08108200	48.60	0	0.50	0.20
08136900	21.80	0	0.20	0.72
08137000	4.02	0	0.49	0.34
08137500	70.40	0	1.02	0.05
08139000	3.42	0	0.82	0.46
08140000	5.41	0	0.43	0.45
08154700	22.30	0	0.63	0.70
08155200	89.70	0	0.27	0.75
08155300	116.00	0	0.50	0.89
08158100	12.60	0	1.44	1.46
08158200	26.20	0	1.08	0.87
08158700	124.00	0	0.51	0.86
08158810	12.20	0	0.58	0.13
08158840	8.24	0	1.10	0.84
08158860	23.10	0	0.73	0.53
08158880	3.58	0	0.51	0.52
08159150	4.61	0	0.74	0.53
08178600	9.54	0	0.85	0.81
08178645	2.33	0	1.06	0.41
08181000	5.57	0	1.00	1.21
08181400	15.00	0	1.64	0.92
08182400	7.01	0	0.69	0.06

Table B.2: Median values of results from Green-Ampt optimization.[USGS Station refers to the USGS Stream Gage identification number, Area is the drainage area of the watershed, Developed indicates whether the watershed was flagged as developed, 1 indicates yes, 0 indicates no, Initial Loss is the median optimized initial abstraction, and Loss-rate is the median optimized loss-rate.]

USGS Station	K (in/hr)	Initial Loss (in)	MD	Wetting Front Suction (in)	Recession Threshold	SCS Lag Time (min)	RC	Total Rain (in)	Total Runoff (in)	Total Loss (in)	Percent Loss	Infiltration (in)
USGS Station	K (in/hr)	Initial Loss (in)	MD	Wetting Front Suction (in)	Recession Threshold	SCS Lag Time (min)	RC	Total Rain (in)	Total Runoff (in)	Total Loss (in)	Percent Loss	Infiltration (in)
08042650	0.130	0.090	0.200	16.0	0.200	108	0.0001	2.87	0.93	1.94	67.6	1.85
08042700	0.225	0.440	0.180	13.6	0.145	191	0.0400	3.29	0.54	2.64	78.1	2.16
08048520	0.200	0.130	0.090	16.0	0.380	111	0.0001	1.71	0.40	1.29	75.7	1.08
08048530	0.116	0.074	0.171	15.6	0.090	17	0.0001	1.33	0.36	0.97	70.7	0.71
08048540	0.094	0.128	0.119	16.2	0.050	18	0.0001	1.20	0.42	0.69	62.7	0.54
08048550	0.090	0.132	0.121	16.3	0.130	35	0.0001	1.79	0.62	0.97	62.3	0.84
08048600	0.134	0.155	0.132	16.1	0.160	104	0.0001	2.30	0.84	1.53	67.8	1.44
08048820	0.118	0.301	0.065	13.3	0.585	108	0.0001	2.79	0.55	1.25	64.2	0.75
08048850	0.075	0.795	0.075	8.0	0.270	78	0.0001	2.27	0.08	2.16	96.1	1.72
08050200	0.100	0.630	0.067	8.0	0.200	68	0.0001	3.30	2.41	1.05	27.0	0.91
08052630	0.107	0.260	0.112	15.1	0.270	53	0.0001	3.57	2.34	1.58	42.1	1.29
08052700	0.098	0.099	0.045	15.1	0.300	755	0.1000	3.02	1.26	1.71	57.1	1.56
08055580	0.050	0.090	0.060	17.0	0.070	23	0.0001	2.00	1.67	0.74	34.8	0.65
08055600	0.230	0.090	0.100	15.0	0.110	48	0.0001	3.05	1.32	1.54	52.3	1.49
08055700	0.125	0.111	0.128	17.0	0.170	69	0.0001	3.04	1.24	1.28	59.7	1.17
08056500	0.073	0.061	0.100	17.2	0.200	76	0.0001	1.20	0.84	0.73	59.1	0.70
08057020	0.108	0.061	0.180	12.9	0.210	45	0.0001	2.49	0.96	1.53	61.4	1.47
08057050	0.018	0.030	0.009	15.7	0.090	54	0.0001	0.91	0.77	0.14	15.4	0.11
08057120	0.071	0.266	0.141	14.3	0.745	62	0.0001	1.61	0.51	1.10	68.3	0.83
08057130	0.158	0.137	0.142	13.4	0.330	37	0.0001	3.89	2.41	1.48	47.0	1.34
08057140	0.096	0.161	0.121	14.7	0.300	82	0.0001	1.53	0.60	0.93	58.5	0.76
08057160	0.071	0.150	0.137	15.4	0.150	60	0.0001	1.71	0.78	1.12	58.8	1.02
08057320	0.039	0.092	0.092	13.2	0.150	45	0.0001	1.91	1.45	1.14	38.4	0.87
08057415	0.033	0.120	0.055	14.9	0.040	19	0.0001	2.19	1.95	0.85	25.4	0.73
08057418	0.071	0.102	0.091	17.1	0.195	67	0.0001	3.19	1.36	1.24	56.9	1.14
08057420	0.041	0.149	0.161	14.0	0.110	88	0.0001	2.51	1.21	1.36	49.2	1.19
08057425	0.035	0.157	0.112	15.9	0.135	62	0.0001	2.54	1.20	1.24	50.6	1.15
08057435	0.060	0.183	0.170	15.2	0.070	116	0.0001	2.94	1.54	1.40	47.6	1.22
08057440	0.086	0.207	0.086	17.0	0.140	122	0.0001	3.30	1.54	1.77	54.1	1.56
08057445	0.051	0.092	0.111	14.8	0.310	192	0.0001	2.53	1.25	1.28	52.4	1.19
08057500	0.047	0.205	0.098	14.0	0.200	38	0.0001	1.67	0.76	0.71	42.5	0.64

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Table B.2: Median values of results from Green-Ampt optimization — continued.

USGS Station	K (in/hr)	Initial Loss (in)	MD	Wetting Front Suction (in)	Recession Threshold	SCS Lag Time (min)	RC	Total Rain (in)	Total Runoff (in)	Total Loss (in)	Percent Loss	Infiltration (in)
08058000	0.038	0.072	0.109	13.4	0.138	48	0.0001	2.33	1.51	0.83	36.4	0.75
08061620	0.071	0.305	0.123	16.3	0.239	68	0.0001	2.98	2.22	1.29	44.6	0.83
08061920	0.050	0.073	0.039	18.0	0.300	142	0.0001	2.93	1.83	0.95	37.5	0.88
08061950	0.104	0.271	0.040	15.0	0.200	322	0.0001	5.04	2.43	2.65	52.2	2.26
08063200	0.074	0.449	0.090	13.9	0.200	358	0.0001	3.47	1.40	1.52	53.6	1.47
08094000	0.185	0.504	0.161	15.4	0.150	96	0.0001	4.98	1.42	3.52	70.2	2.96
08096800	0.234	0.434	0.190	15.0	0.210	60	0.0001	2.66	0.47	2.33	83.0	1.92
08098300	0.075	0.240	0.086	18.5	0.200	353	0.0001	4.05	2.51	1.55	46.5	1.31
08108200	0.180	0.050	0.080	20.0	0.200	484	0.0001	2.94	1.61	1.15	45.2	1.06
08136900	0.183	0.381	0.150	15.6	0.080	209	0.0001	2.59	0.46	2.13	82.2	1.75
08137000	0.135	0.235	0.062	14.3	0.095	148	0.0001	1.76	0.81	0.96	54.6	0.72
08137500	0.053	0.057	0.030	15.1	0.100	620	0.0001	1.38	0.17	1.21	87.7	1.15
08139000	0.227	0.163	0.189	14.7	0.080	82	0.0001	3.18	1.29	1.97	63.0	1.73
08140000	0.328	0.266	0.144	15.0	0.165	90	0.0001	2.00	0.44	1.34	78.0	1.19
08154700	0.290	0.506	0.197	15.0	0.205	116	0.0001	3.82	1.00	2.82	79.8	2.53
08155200	0.147	0.200	0.166	15.5	0.250	394	0.0001	2.35	0.40	2.01	84.0	1.70
08155300	0.244	0.200	0.170	15.0	0.200	542	0.0001	2.62	0.64	1.94	75.0	1.55
08155550	0.289	0.428	0.200	15.4	0.230	58	0.0001	2.01	0.58	1.81	87.0	1.30
08156650	0.400	0.220	0.180	14.0	0.160	49	0.0001	2.50	0.56	1.94	77.7	1.79
08156700	0.130	0.150	0.100	17.0	0.300	54	0.0001	5.46	1.38	2.13	74.7	1.93
08156750	0.100	0.480	0.100	12.0	0.180	41	0.0001	2.43	0.25	2.15	86.3	1.57
08156800	0.285	0.185	0.100	15.0	0.180	82	0.0001	3.13	0.57	2.23	71.2	2.37
08157000	0.180	0.275	0.165	14.0	0.110	58	0.0001	3.90	1.03	2.25	65.6	1.98
08157500	0.160	0.170	0.120	14.0	0.180	37	0.0001	2.16	0.45	1.77	76.4	1.64
08158050	0.055	0.395	0.070	14.5	0.190	123	0.0001	3.67	1.17	2.51	69.0	2.06
08158200	0.300	0.350	0.200	15.0	0.150	111	0.0001	2.55	0.23	2.33	88.3	1.86
08158380	0.145	0.175	0.210	18.5	0.110	67	0.0001	2.62	0.97	1.66	59.6	1.48
08158400	0.090	0.150	0.060	14.0	0.100	55	0.0001	3.00	1.11	1.78	56.4	1.61
08158500	0.220	0.270	0.180	13.0	0.100	80	0.0001	3.18	0.74	2.06	76.7	1.91
08158600	0.090	0.140	0.120	14.0	0.200	236	0.0001	3.84	0.92	2.40	76.0	2.29
08158700	0.410	0.270	0.100	20.0	0.100	316	0.0001	2.70	0.57	2.13	78.9	1.86
08158810	0.090	0.060	0.050	22.0	0.100	62	0.0001	4.63	2.18	1.76	41.6	1.70
08158840	0.300	0.250	0.190	15.0	0.100	86	0.0001	3.15	0.71	2.44	73.8	2.15
08158860	0.470	0.135	0.100	21.5	0.180	182	0.0001	7.76	3.89	3.87	60.2	3.73
08158880	0.180	0.170	0.120	15.0	0.180	61	0.0001	2.71	1.24	1.47	58.4	1.35
08158920	0.285	0.365	0.160	14.5	0.185	63	0.0001	3.71	1.01	3.12	78.2	2.59
08158930	0.340	0.270	0.180	15.0	0.180	145	0.0001	4.12	1.18	2.90	70.4	2.73

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Table B.2: Median values of results from Green-Ampt optimization — continued.

USGS Station	K (in/hr)	Initial Loss (in)	MD	Wetting Front Suction (in)	Recession Threshold	SCS Lag Time (min)	RC	Total Rain (in)	Total Runoff (in)	Total Loss (in)	Percent Loss	Infiltration (in)
08158970	0.460	0.220	0.090	14.0	0.080	218	0.0001	4.50	1.16	3.34	74.2	2.46
08159150	0.100	0.210	0.100	18.0	0.183	109	0.0001	2.46	0.81	1.87	70.0	1.65
08177600	0.510	0.140	0.100	19.0	0.100	47	0.0001	4.07	1.77	2.30	59.1	2.16
08178300	0.160	0.269	0.185	15.0	0.080	23	0.0001	2.06	0.44	1.39	71.9	1.07
08178555	0.090	0.270	0.100	13.9	0.020	123	0.0001	2.51	0.81	1.91	69.7	1.45
08178600	0.267	0.451	0.170	14.3	0.060	100	0.0001	2.83	0.51	2.26	84.7	2.20
08178645	0.310	0.290	0.160	12.4	0.100	229	0.0001	2.72	0.57	2.15	79.0	1.86
08178690	0.295	0.095	0.190	15.2	0.175	16	0.0001	2.78	0.80	1.59	71.3	1.51
08178736	0.135	0.303	0.198	15.0	0.100	32	0.0001	2.60	1.21	1.54	55.7	1.34
08181000	0.230	0.230	0.180	14.3	0.100	58	0.0001	1.80	0.25	1.55	86.1	1.28
08181400	0.310	0.810	0.150	14.0	0.100	168	0.0001	4.52	0.45	3.02	90.8	1.86
08181450	0.300	0.450	0.150	14.0	0.100	103	0.0001	2.80	0.63	2.22	78.0	1.87
08182400	0.027	0.218	0.115	10.5	0.095	129	0.0001	3.09	1.92	1.18	37.6	0.96
OSSSC	0.069	0.065	0.058	12.0	0.040	17	0.0001	1.50	1.12	0.50	27.0	0.47

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P 806.742.3503 | F 806.742.4168