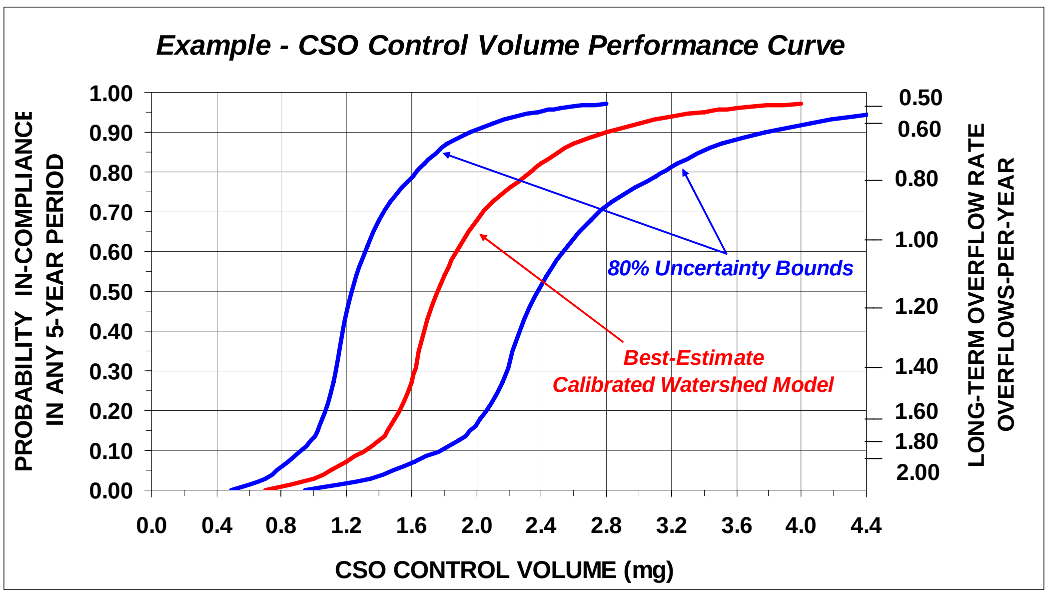
METHODS FOR ESTIMATING CONTROL VOLUMES FOR CSO REDUCTION

Technical Guidance Manual



Seattle Public Utilities

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GUIDANCE MANUAL

TECHNICAL METHODS FOR ESTIMATING CONTROL VOLUMES FOR CSO REDUCTION

February 2009

1.0 INTRODUCTION

This User's Manual is intended to provide technical information about the application of probabilistic and risk-based methods for estimating the Control Volume needed for reducing the frequency of Combined Sewer Overflows (CSOs).

The CSO Control Volume is the volume that must be created within the CSO basin to reduce the frequency of sewer overflows to meet SPU performance targets for CSO reduction. The Control Volume can be created by a variety of approaches including: storage vaults; separation of storm and sanitary sewers; implementation of low-impact development features; land use changes; changes to operation of the sewer system; inter-basin transfers, etc. It is anticipated that a combination of approaches will be used in most CSO basins to meet CSO reduction targets.

Analysis of the operation of combined sewer systems and estimating the Control Volume for CSO reduction are difficult technical challenges. The difficulty in estimating the Control Volume occurs for two primary reasons. First, water quality compliance targets are performance based. The State water quality regulations require reducing sewer overflows at each NPDES site to an average overflow rate of once per year, five overflows in a 5-year NPDES permit period. Federal regulations utilize an alternative frequency threshold for the number of overflows from the collection of NPDES sites in a sewer system. These regulations translate into the estimate of the CSO Control Volume being subject to the chance occurrence of the number of significant storms that occur in a given 5-year permit period. Storms over the past 60-years in the Seattle area have shown very high variability with regard to the number, magnitude and temporal characteristics in any given 5-year period.

Second, it is common that there are sizable uncertainties associated with the various analyses and computer modeling of combined sewer systems. Uncertainties arise from a variety of sources including:

- representativeness of precipitation measured at the nearest precipitation gage for describing precipitation over the CSO basin;
- imperfect information on the connection of rooftops, yard drainage, driveway and roadway drainage into the combined sewer system;
- imperfect information on the configuration of pipes in the combined sewer network;
- imperfect computer models with regard to mimicking the hydrologic response of CSO basins and the hydraulic operation of complex sewer systems;
- uncertainties in the actual discharge characteristics for hydraulic structures, hydrobrakes and pump stations;
- uncertainties regarding the accuracy of flow measurements in the sewer system that are used for calibrating computer models; and
- uncertainties regarding the hydraulic operation and accuracy of measured overflow depths and volumes at overflow structures.

This diverse collection of uncertainties lessens the reliability of projections from analyses and the projections of conventional best-estimate calibrated computer models. In this situation, methods of analysis are needed that are capable of determining the best-estimate projections and are also capable of characterizing how uncertainties affect the accuracy of projections of sewer overflow volumes.

As another consideration, the construction costs associated with CSO reduction are expected to be very high. An overly conservative design approach could result in wasting of many millions of dollars. Conversely, trying to sharpen the design too fine could result in under-sizing of CSO Control Volumes and not meeting water quality regulations. Methods of analysis are needed that will allow decision-makers to make tradeoffs between the excess costs due to over-design and the risk of under-design.

In considering the factors listed above, a risk-based approach was developed to provide information to SPU decision-makers for evaluating options for sizing of Control Volumes for meeting compliance targets for CSO reduction. A risk-based approach is particularly well-suited to the CSO reduction problem because many of the factors to consider have elements of chance and uncertainty, and there can be significant environmental, economic and social consequences for not complying with State and Federal water quality regulations.

The primary purpose of this manual is to provide detailed information on the methods of analysis for computing the probability of being in-compliance for a given CSO Control Volume. This includes assessment of the magnitude of uncertainties and the affect of uncertainties in estimating the probability of being in-compliance. A short introduction on risk concepts and the technical and management roles are presented to provide context for the technical information provided for the risk-based approach to CSO reduction.

1.1 RISK CONCEPTS FOR SIZING OF CONTROL VOLUMES FOR CSO REDUCTION

Risk can generally be defined as *a measure of the likelihood and severity of adverse consequences* (NRC[9]). Application of risk concepts starts with clarifying the meaning of adverse consequences, which usually requires defining what is meant by failure of a project or system. SPU managers have discussed the issue of adverse consequences and have defined failure as:

Failure occurs when the long-term rate of combined sewer overflows exceeds a frequency of once-per-year at a CSO basin outfall for those overflows that are attributable to under-sizing of the CSO Control Volume, or when operation of the redesigned combined sewer system for a CSO basin causes unmitigatable adverse impacts to other portions of the CSO system.

It should be noted that the performance criterion is based on the long-term overflow rate of once-per-year rather than the overflow rate in any given 5-year period. Using the definitions above, risk can be computed as the product of the likelihood of failure and the consequences of failure (Equation 1.1).

$$Risk = Likelihood\ of\ Failure \bullet Consequences\ of\ Failure \qquad (1.1)$$

Risk can be expressed in a qualitative manner with likelihoods and consequences being described in qualitative terms such as low, moderate or high. Risk can also be expressed in a quantitative manner, where economic risk, for example, can be expressed on an annualized basis in terms of the risk-cost of failure in dollars per-year.

Balanced Risk

SPU managers have chosen to use qualitative measures of risk and to use a balanced risk approach in managing the risk of combined sewer overflows. The balanced risk approach identifies a tolerable level of risk and applies it to all CSO basins within the city. This may be viewed as balancing the likelihood of failure and the consequences of failure at a given project (Equation 1.1) to achieve a tolerable level of risk. In particular, this requires reducing the likelihood of failure (increasing the probability of being in-compliance) for those projects where the consequences of failure are more severe.

Management Role in Risk-Based Approach for CSO Storage Facilities

The role of SPU managers in the risk-based approach for a given CSO basin is to evaluate the site-specific characteristics of alternative projects for CSO reduction and to select a project configuration. There are two main tasks in evaluating alternative projects. The first task is to assess the characteristics of a give project and to evaluate the consequences if the project fails to meet water quality regulations - based on the definition of failure above. This includes evaluation of all pertinent environmental, economic and social consequences. The second task is to utilize the information provided by technical staff on the likelihood of meeting the compliance targets and consider how uncertainties in the technical information may affect whether the project meets the compliance targets.

Evaluation of the Consequences of Failure

Evaluation of the consequences of failure requires assessing a wide range of project-specific factors. These factors have been grouped into categories of environmental, economic and social consequences. Table 1.1 provides an overview of the type of project characteristics that are considered by SPU decision-makers in assessing the consequences of failure.

Table 1.1 – Factors Considered in Evaluating the Consequences of a CSO Reduction Project Failing to Meet Compliance Targets

CATEGORY	FACTOR
ECONOMIC	Life-Cycle Project Costs analysis, design, construction, operation and maintenance
	Magnitude of regulatory fines and mitigation costs
	Magnitude of clean-up costs for receiving water bodies
	Other Costs – emergency response, lost opportunity costs
ENVIRONMENTAL	Magnitude of potential impacts to human health from overflows
	Seasonal timing of future overflows
	Magnitude of potential impacts to flora and fauna
	Increased concern due to constituents of overflow
	Overflows discharge to previously contaminated area
SOCIAL	Potential for loss of credibility with regulatory agencies and public
	Likelihood for intervention by special interest groups and the potential for lawsuits potentially making problem solution more difficult and costly
	Likelihood of adverse media coverage potentially making problem solution more difficult and costly
OTHER	Other site-specific project characteristics that warrant consideration

Role of Technical Staff in Risk-Based Approach for CSO Reduction

The technical role in the risk-based approach is to provide information to SPU managers about the probability of being in-compliance for alternative sizes of CSO Control Volumes. This includes characterizing uncertainties in the predicted performance of a redesigned CSO system that are attributable to uncertainties in the data, analyses, and computer models that are used to develop the probability estimates for alternative sizes of the Control Volume.

The primary purpose of this manual is to provide detailed information on the methods of analysis for computing the probability of being in-compliance for a given CSO Control Volume. This includes assessment of the magnitude of uncertainties and the resultant affect on the estimate of the probability of being in-compliance that are attributable to a given analysis or prediction from a computer model. That balance of this manual will address those topics.

Flowchart of Tasks for CSO Reduction Project

In discussing the various technical tasks required for estimating the CSO Control Volume, it is helpful to have an understanding of the typical sequencing of tasks within an overall project plan. There are four technical tasks which are the subject of this manual and include:

- analysis of CSO volumes for estimation of once-per-year overflow volume;
- automated calibration of InfoWorks watershed model;
- uncertainty analysis; and
- development of a CSO Control Volume Performance Curve and uncertainty bounds.

The sequencing of the four technical tasks is depicted in Figure 1.1 along with the related planning and management tasks that are part of a CSO reduction project. The four technical tasks are highlighted in yellow.

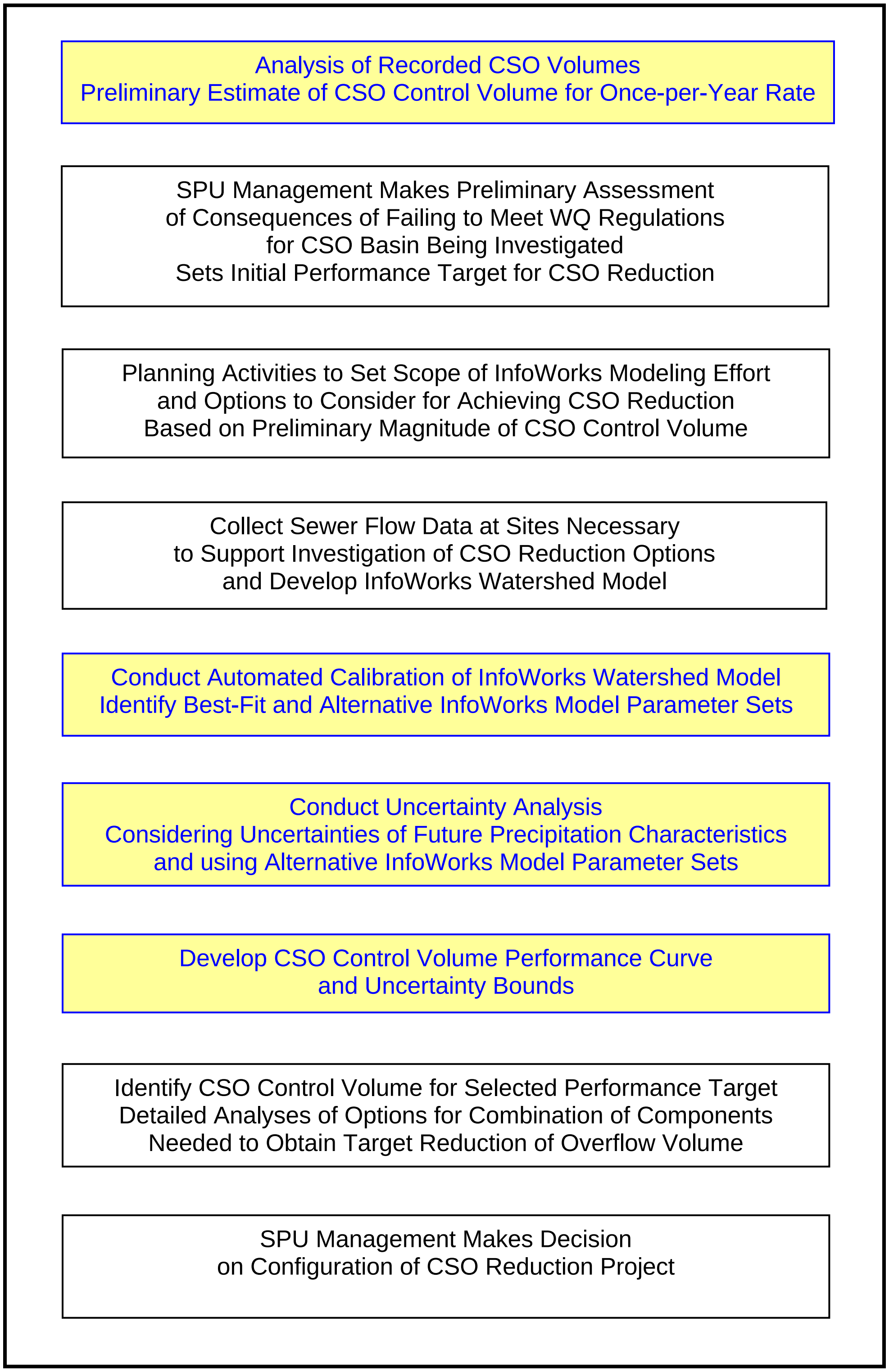


Figure 1.1 – Typical Flowchart of Technical Tasks and Related Planning and Management Tasks for CSO Reduction Project

2.0 PERFORMANCE MEASURE FOR SIZING OF CSO CONTROL VOLUME

In applying a risk-based approach to the sizing of control volumes for CSO reduction, a measure is needed for describing the level of performance for a given project configuration. For the case of a CSO Control Volume, it is useful to express project performance in terms of the probability of being in-compliance in any 5-year period. The term *in-compliance* refers to meeting State water quality regulations of 5 sewer overflows or less in any given 5-year NPDES permit period based on the once-per-year rate of sewer overflows.

Use of the probability of being in-compliance as the performance measure leads to development of Figure 2.1, which depicts the basic format of the performance curve used for sizing of a CSO Control Volume. The primary vertical axis depicts the probability of being in-compliance in any given 5-year period. Prior studies (Schaefer[14,15]) have identified that a 65% probability of being in-compliance during any given 5-year period generally corresponds to meeting the long-term average rate of one CSO per year. The secondary vertical axis on the right margin provides a cross-reference between long-term overflow rates and the probability of being in-compliance in any 5-year period. Thus, the primary axis depicts short-term behavior for 5-year periods and the secondary axis reflects long-term behavior for the long-term average rate of sewer overflows.

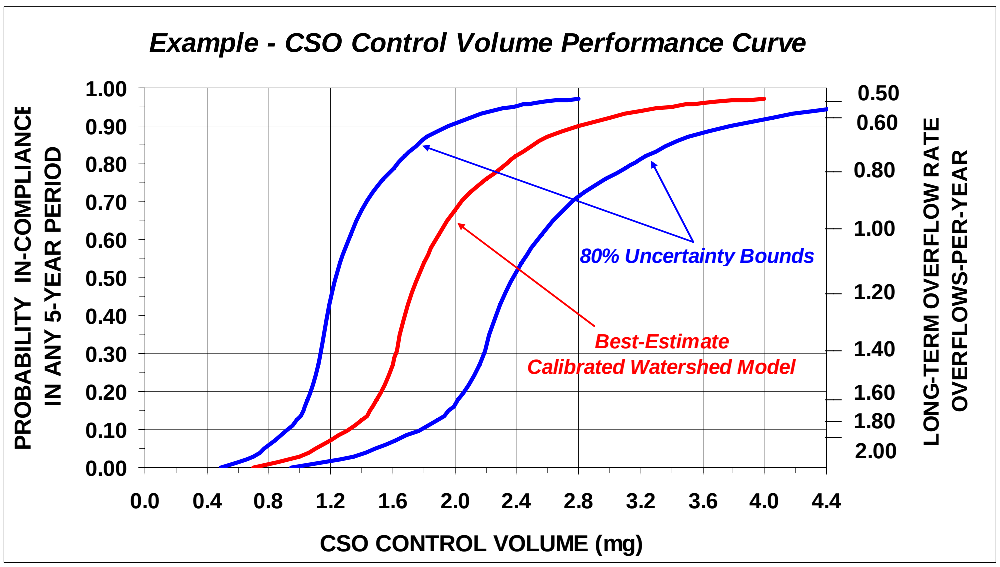


Figure 2.1 – Example of Combined Sewer Overflow (CSO) Control Volume Performance Curve and 80% Uncertainty Bounds

The "S" shape of the CSO Control Volume performance curve arises from the chronological sequencing of storms that produce sewer overflows. Examination of precipitation characteristics over many decades shows benign periods with few noteworthy storms; active periods with clustering of many noteworthy storms, and other periods that are generally more balanced with regard to the frequency of storms. This behavior can be seen from the collection of 67 largest storms at SeaTac Airport for the 24-hour duration for the period from 1940 through 2006 (Figure 2.2). This corresponds to 67 storms in 67 years, an average rate of 1 storm per year. A review of Figure 2.2 shows that the distribution of storms is not uniform. Some 5-year periods are benign with few large storms, other 5-year periods are quite active with many storms, and many 5-year periods are relatively "typical" with 4 to 6 storms.

If the sequence of storms from Figure 2.2 is used as a surrogate for the sequence of sewer overflows, it is seen that it is possible to be in-compliance for the long-term average of one overflow per year and out-of-compliance for some 5-year periods. The performance curve shown in Figure 2.1 is used to describe this behavior that results from the sequencing of storms in a given 5-year period. As stated earlier, a probability of being in-compliance of 65% in any given 5-year period generally corresponds to a sewer overflow rate of once-per-year as a long-term average.

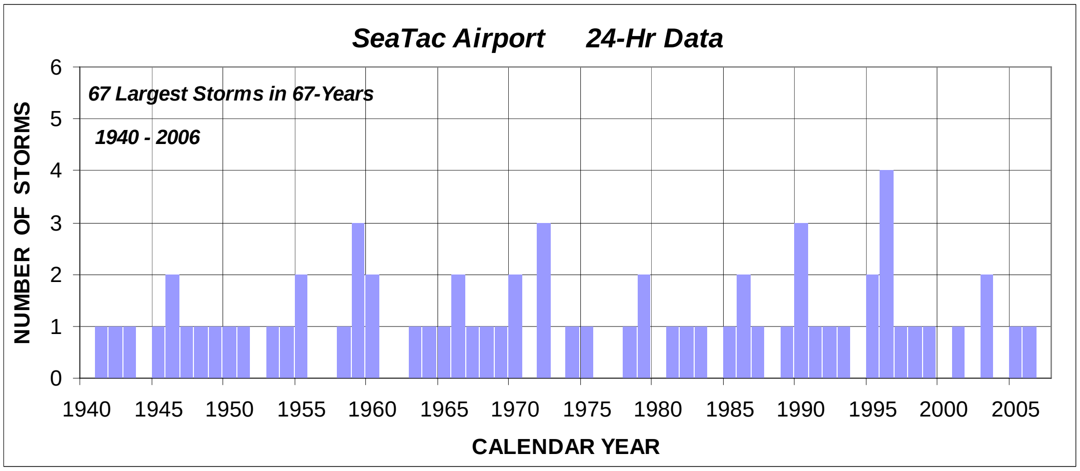


Figure 2.2 – Sequence of 67 Largest 24-Hour Precipitation Events at SeaTac Airport 1940-2006

2.1 Uncertainties in Development of the CSO Control Volume Performance Curve

It is standard engineering practice to provide a factor of safety in engineering analyses to account for uncertainties and factors that are beyond the control of the designer. For the case of sizing a CSO Control Volume, the factor of safety would take the form of an upsizing factor to increase the storage of the CSO Control Volume. The magnitude of the upsizing factor would be based on prior experience and the level of uncertainties in the engineering analyses. However, the conventional factor of safety approach is not practical for CSO Control Volumes because of the number of sources of uncertainty and limited experience in sizing of CSO Control Volumes.

In particular, there are sizable uncertainties in analysis and prediction of CSO volumes and in development of the CSO Control Volume performance curve. These uncertainties arise from several sources including those listed in the Introduction as well as the characteristics of storms that may occur in future NPDES permit periods. Recognizing that the magnitude of uncertainty from any particular source varies from project to project, it is important that project-specific analyses are conducted to examine how uncertainties affect the sizing of the CSO Control Volume at a particular CSO basin.

The findings of the uncertainty analysis replace the use of a factor of safety for upsizing the CSO Control Volume. The results of the uncertainty analyses take the form of uncertainty bounds and are depicted in Figure 2.1. Uncertainty bounds have the distinct advantage of allowing decision-makers to consider the magnitude and effect of uncertainties when deciding on the size of a CSO Control Volume needed for meeting CSO reduction targets.

3.0 ANALYSIS OF COMBINED SEWER OVERFLOW VOLUMES FOR ESTIMATION OF ONCE-PER-YEAR OVERFLOW VOLUME

Installation of equipment for measuring sewer overflow volumes began in 1998 at NPDES sites throughout the City and most sites were on-line in the year 2000. The record of sewer overflow volumes for the period from 1998 to present provides data for estimating the CSO Control Volume.

3.1 Methods of Analysis of CSO Volumes

There are two methods of analysis for estimating the once-per-year sewer overflow rate using recorded overflow data. The first method is a direct analysis of the overflow record from 1998 to present. This method is intended for application at the beginning of the CSO reduction project to get a preliminary estimate of the magnitude of the CSO Control Volume. This preliminary estimate is useful in the early planning stages for CSO reduction at a given CSO basin and provides a ballpark estimate of the magnitude of the problem. This information can then be used in planning the scope of investigations for various options for CSO reduction including details of the configuration of the InfoWorks watershed model and identification of sites where flow measurement data are needed.

The second method utilizes a precipitation-based overflow volume predictor equation based on regression analyses of the relationship between precipitation from significant storms and recorded overflow volumes. This method provides an alternative to watershed modeling and may be of use in situations where lack of flow measurement and basin data render watershed modeling unreliable. This alternative method is described in Chapter 8 of this manual.

3.2 Key Considerations in Computing CSO Volumes

Data on CSO volumes have been recorded at most NPDES sites within the City since about 1998. The data were collected as stage hydrographs for overflow weirs at NPDES outfalls. Sewer overflow volumes were estimated by converting stage hydrographs to discharge hydrographs using standard weir equations. The discharge hydrographs were then integrated over time to estimate the volume of sewer overflow. All of these computations were done using automated procedures based on weir measurements at the outfall. Unfortunately, record keeping on weir invert elevation, weir geometry, weir length and any unusual aspects of the weir hydraulics often did not keep pace with instrument changes and modifications to the outfall structures. As such, many of the CSO volumes that have been reported in various documents have inaccuracies or are invalid.

All CSO volumes used in these analyses must be verified by obtaining the original overflow stage hydrographs (Figure 3.1) and re-computing the overflow volumes. This requires a field visit by the analyst to personally inspect the outfall structure to confirm the geometry of the overflow weir with regard to weir height, weir length and crest geometry and to confirm the elevation at which overflow occurs. A document search should also be undertaken to determine if instrument changes and/or changes to the weir structure have occurred in the past that would result in different stage-discharge relationships for the overflow weir. Inspection of as-built drawings is not sufficient to confirm the weir geometry because it is has been common to find either insufficient detail or discrepancies in the details between as-built drawings and actual constructed geometry.

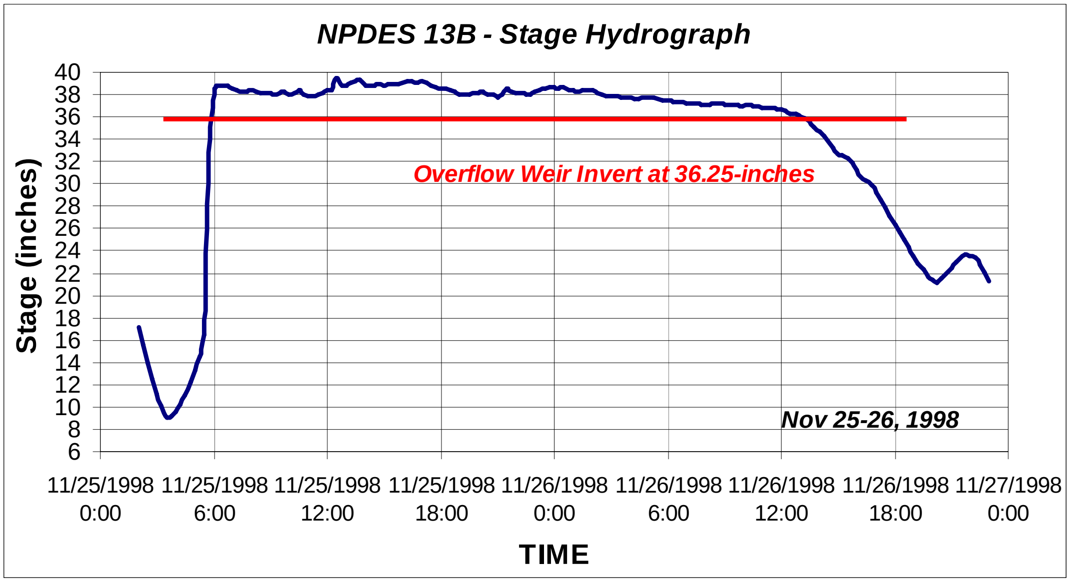


Figure 3.1 – Example Stage Hydrograph at NPDES Site 13B
for Sewer Overflow Event of November 25-26, 1998

A second check on the accuracy of the reported elevation of the overflow weir crest can be made by examining the shape of stage hydrographs. For example, inspection of the crest section and recession limb of the stage hydrograph in Figure 3.1 shows a marked change in the shape of the stage trace as the stage falls below the overflow weir crest after nearly 30-hours of overtopping. Accurate data on the weir crest elevation is critical to obtaining accurate estimates of sewer overflow volumes.

3.3 Direct Analysis of Recorded Overflow Volumes

The end product of the analysis of recorded overflow volumes is the production of a probability-plot of the sewer overflow volumes (Figure 3.2). The estimate of the overflow volume for the once-per-year rate of overflows can be obtained directly from the analysis as depicted on the probability-plot. The analysis proceeds as follows:

<u>Step 1 - Assemble Listing of CSO Overflow Volumes and Dates</u>
Assemble list of sewer overflow volumes, durations, and dates from CSO reports presented to the Washington State Department of Ecology for period from 1998 to present. Rank the overflow volumes in descending order of magnitude.

<u>Step 2 – Compute Overflow Volumes from Stage Hydrographs for Largest Overflow Events</u>
Conduct field visit to overflow structure to confirm geometry and invert elevation of overflow weir crest, and to determine flow patterns within the overflow structure. Use the weir geometry to develop a stage-discharge relationship for each weir configuration that was in-place during the recording period.

Obtain stage hydrographs of weir overflow for N largest overflow volumes,

where: $N=3m$ and m is the years of record. (3.1)

This approach focuses on the largest overflow volumes and avoids computation of smaller overflow volumes that are not of interest.

Compute the overflow volume for the *N* largest overflow volumes using the stage hydrographs and the stage-discharge relationship for the overflow weir. Where multiple overflow events occur in close proximity, a non-overflow period of 24-hours is used as criterion for separation into two overflow events. The 24-hour period is a prescriptive measure of inter-event time set by the Department of Ecology.

<u>Step 3 – Compute Probability-Plot and Estimate Overflow Volume for Once-per-Year Rate</u>
Rank the *N* largest overflow volumes from largest to smallest and compute the estimated Recurrence Interval (*T*) for each overflow volume using the Cunnane[3] plotting position:

$$T = (m+1-2\theta)/(i-\theta) \quad (3.2)$$

where: *T* is the recurrence interval in years; *m* is the years of record; *i* is the rank of the overflow volume ordered from 1 to *N*; and θ is a weighting factor equal to 0.40.

An example of this computation is shown in Table 3.1 and depicted in Figure 3.2. The overflow volume for the once-per-year overflow rate can be taken as the *m* largest overflow volume, which equates to about 2.88 million gallons for this example (Table 3.1).

Table 3.1 – Example Computation of Recurrence Intervals for Overflow Volumes in 1998-2006 Period.

RANK	OVERFLOW VOLUME (million gallons)	DATE	RECURRENCE INTERVAL (Years)
1	10,995,700	10/21/2003	15.33
2	5,240,400	1/29/2006	5.75
3	5,093,500	11/26/1998	3.54
4	4,538,700	11/18/2003	2.56
5	4,054,300	12/26/2006	2.00
6	3,967,400	12/14/2006	1.64
7	3,621,500	12/24/2005	1.39
8	3,408,200	1/9/2006	1.21
9	2,879,700	11/13/2001	1.07
10	2,522,500	11/11/1999	0.96
11	2,400,000	1/29/2004	0.87
12	1,778,800	11/4/2006	0.79
13	1,723,000	12/16/2001	0.73
14	1,567,300	12/12/1998	0.68
15	1,381,800	1/5/2006	0.63
16	1,302,200	2/23/1999	0.59
17	1,272,900	12/9/2004	0.55
18	1,265,000	2/21/2002	0.52
19	1,260,900	1/17/2005	0.49
20	1,204,000	1/7/2002	0.47
21	900,300	6/24/1999	0.45
22	590,300	11/20/2006	0.43
23	586,400	1/14/1998	0.41
24	493,700	12/30/2005	0.39
25	458,100	11/22/2001	0.37
26	352,400	3/27/2005	0.36
27	284,200	1/17/1999	0.35

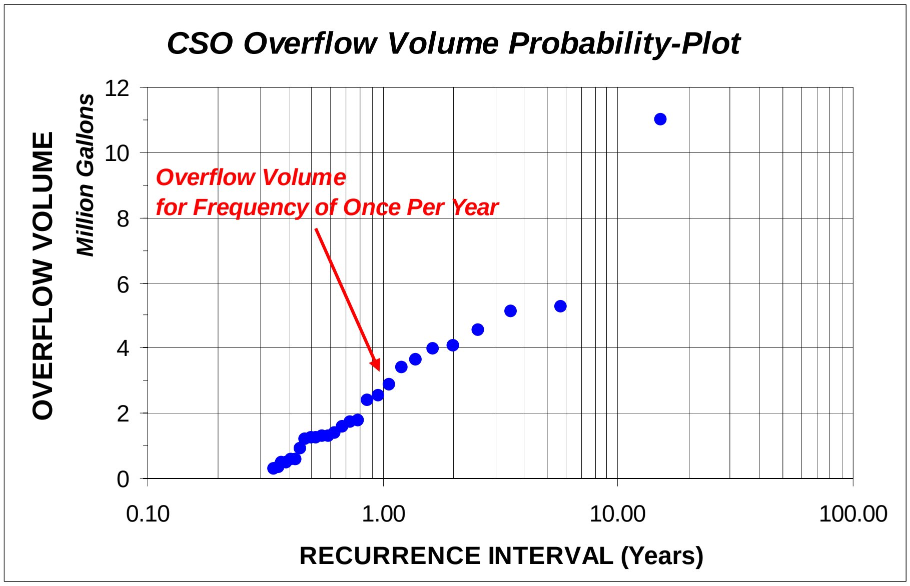


Figure 3.2 – Example Probability-Plot of Sewer Overflow Volumes for Period from 1998-2006

Commentary

The direct analysis of overflow volumes provides a straightforward approach to estimating the overflow volume for a once-per-year overflow rate. It is only suitable as a preliminary estimate of the CSO Control Volume because the estimate of the once-per-year overflow volume is based on a relatively short record. The storm characteristics that caused overflows during the short record may, or may not be, representative of the storm characteristics expected over a long period in the future.

3.4 Storm Characteristics for 1998-2007 Period as Indicator of Once-per-Year CSO Volume

Storm characteristics in three periods, 1998-2007, 1999-2007 and 2000-2007, were recently analyzed (Schaefer[16]) to provide a comparison between storms in these periods relative to storms over the longer, more representative period from 1978-2007. This analysis of precipitation was conducted as a surrogate for the behavior of CSOs for the same periods. This information is important because the analysis of CSO volumes described in this chapter utilize the frequency and volume of sewer overflows for the short 1998-2007 period as an estimate of the long-term once-per-year volume of sewer overflow. Evidence suggesting that the estimate produced by the methods above is likely an under-estimate, a good estimate, or an over-estimate would be helpful in the planning stages of the CSO reduction project.

Findings from Schaefer[14,16] indicate that storms in the recent period were characterized by above-average precipitation magnitudes. This includes the noteworthy storms of October 2003, August 2004, December 2006 and December 2007. Conversely, while magnitudes were generally above-average for this recent period, the number of storms exceeding the once-per-year magnitude threshold was somewhat below-average at durations ranging from 30-minutes through 48-hours. Since the method of analysis of CSO volumes described in this chapter is a frequency-based approach that utilizes ranking of overflows, the estimate of CSO volumes are likely to be under-estimated slightly relative to the long-term magnitude. This situation should be kept in mind as CSO volume estimates are computed and utilized in the early stages of a CSO reduction project.

3.5 STORMSCAN Computer Program

The *StormScan* computer program was developed to provide insights into the storm characteristics that have produced sewer overflows. Inputs to the model include the date, duration and volume of sewer overflows. The dates are then used to examine the storm characteristics that caused each of the overflows. Graphical and tabular outputs include:

- seasonality plot of the months when overflows occurred;
- histogram of the total volume of overflow for each month;
- probability-plot of overflow volume (as described in prior section);
- three dimensional plot of storm recurrence interval, overflow duration and volume;
- storm recurrence interval and storm duration;
- storm duration and overflow duration;
- listing of recurrence intervals for precipitation maxima at the 5-min, 10-min, 15-min, 20-min, 30-min, 45-min, 60-min, 2-hr, 3-hr, 6-hr, 12-hr, 24-hr, 48-hr and 72-hr durations for the storm that produced the overflow; and
- hyetographs can also be plotted to allow viewing of individual storms that caused a sewer overflow.

It is intended that *StormScan* be executed in the planning and scoping phases for CSO reduction. The analyses conducted by this program should provide a greater understanding of the behavior of the CSO basin and assist in the planning the scope of investigations for options for CSO reduction. Examples of the *StormScan* output are depicted in Figures 3.3a,b,c,d,e,f,g. Table 3.2 contains an abbreviated listing of the output of storm characteristics. It should be noted that occasionally precipitation data are wholly or partially missing at a given rain gage for a given date. In these situations, the program will return invalid results of either zero precipitation or values that are clearly too small to have generated sewer overflows. In these cases, a nearby precipitation gage may be used as an alternative measure of storm characteristics.

The *StormScan* program can be executed before the overflow volumes have been recomputed as discussed in Section 3.2. This provides insight into the storm characteristics that have caused sewer overflows. This is accomplished by simply inputting the dates of sewer overflows into *StormScan* and executing the program. The program can be rerun after all the data on sewer overflow volumes and overflow durations have been compiled.

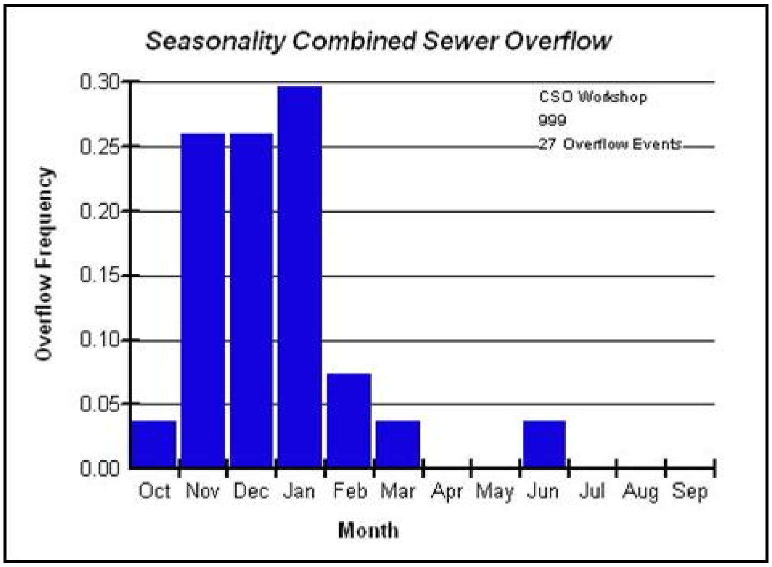


Figure 3.3a – Example Seasonality Histogram of Combined Sewer Overflows based on Number of Sewer Overflows

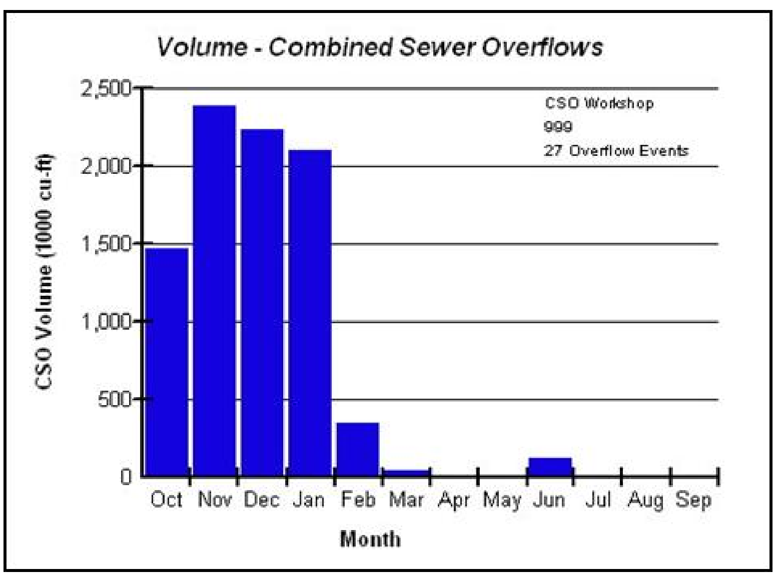


Figure 3.3b – Seasonal Histogram of Combined Sewer Overflows based on Monthly Volume of Sewer Overflows

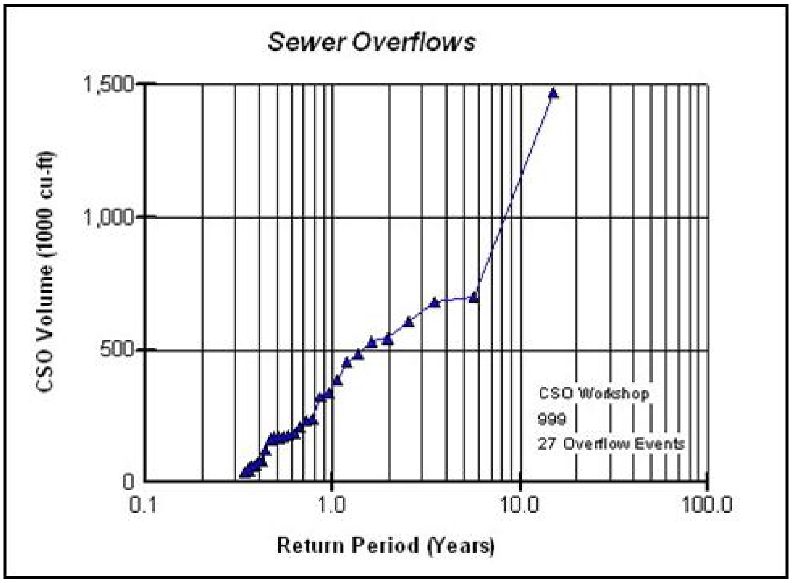


Figure 3.3c – Probability-Plot of Volume of Sewer Overflows
(Same Procedure as Described in Section 3.3 above)

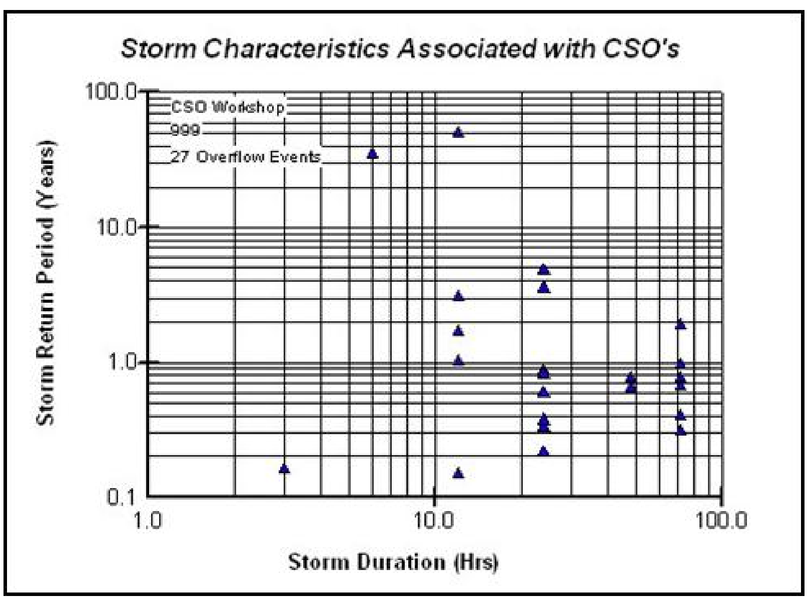


Figure 3.4d – Plot of Maximum Return Period of Precipitation
for Range of Durations (5-min to 72-hrs) Versus Storm Duration
for Storms that Caused Combined Sewer Overflows

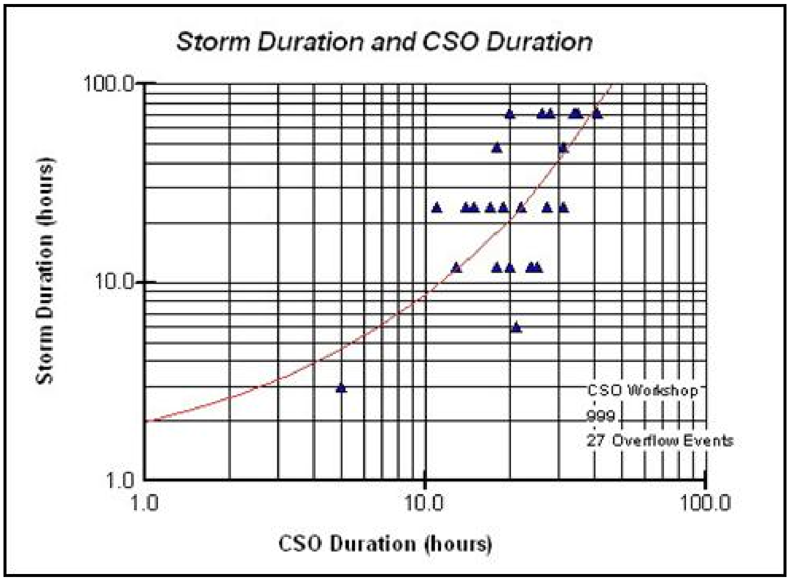


Figure 3.4e – Plot of Storm Duration for Duration where Precipitation was Rarest
Versus Duration of Sewer Overflow
for Storms that Caused Combined Sewer Overflows

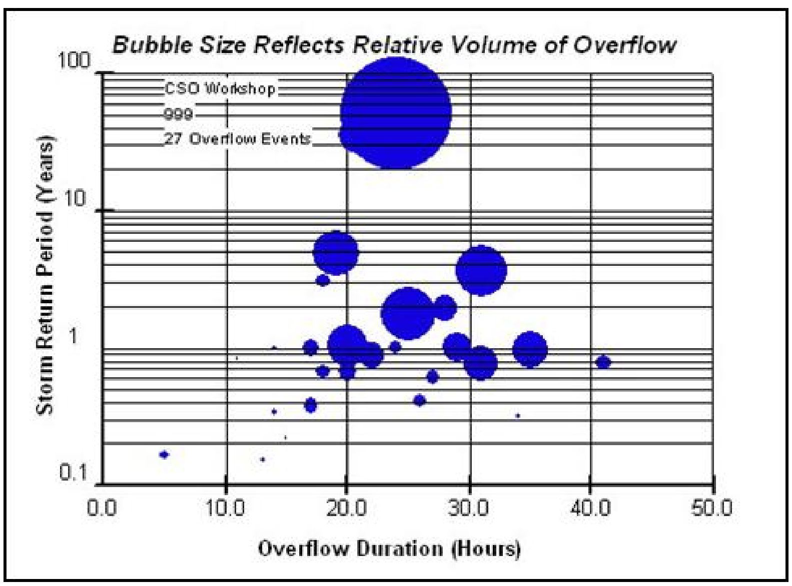


Figure 3.4f – Plot of Maximum Return Period of Precipitation
for Range of Durations (5-min to 72-hrs) Versus Duration of Sewer Overflow
and Bubble Plot of Relative Volume of Sewer Overflow

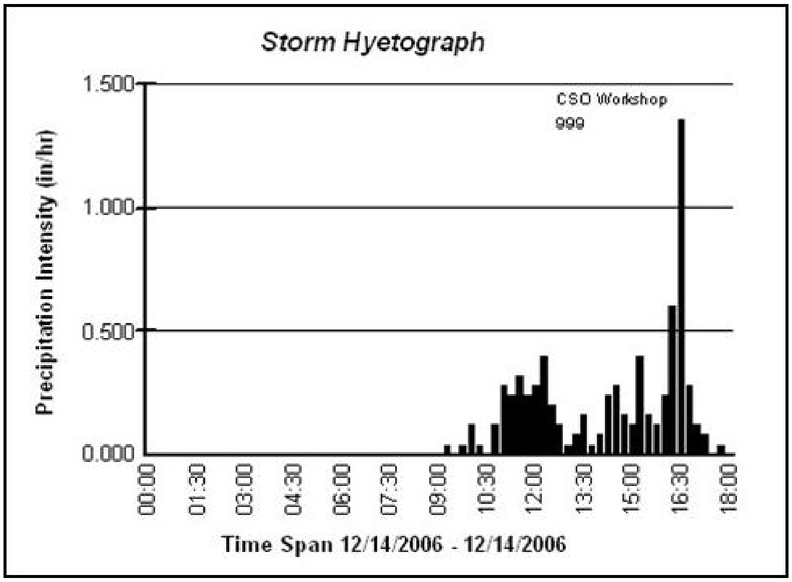


Figure 3.3g – Example Hyetograph for Storm that Caused a Sewer Overflow

Table 3.2 – Example Output from *StormScan* Computer Program Listing Precipitation Maxima and Associated Return Periods for Range of Durations from 5-Minutes through 72-Hours

				Return Periods for Precipitation at Various Durations within Storms										
CSO Basin:		**Example**						**Precip Station:**		**3 UW Hydraulics Lab**				
NPDES No:		**999**										**5/11/2007**		
Note: Recurrence Interval of -0.10 indicates precipitation has a frequency more common than 10 times per year														
			5-min	**10-min**	**15-min**	**20-min**	**30-min**	**45-min**	**60-min**	**2-hr**	**3-hr**	**6-hr**	**12-hr**	**24-hr**
		11/26/1998	**CSO Overflow**		**624,600**	**cubic feet**	Rarest Storm	Duration:	24 hr	Recurrence Interval (years):		3.6		
Return Period (Yrs)			0.11	0.11	-0.10	0.11	0.12	0.20	0.23	0.37	0.44	1.09	2.65	3.64
Precipitation (in)			0.04	0.06	0.07	0.09	0.12	0.18	0.22	0.37	0.50	0.91	1.57	2.21
		11/11/1999	**CSO Overflow**		**312,200**	**cubic feet**	Rarest Storm	Duration:	72 hr	Recurrence Interval (years):		1.9		
Return Period (Yrs)			0.16	0.14	0.23	0.21	0.30	0.27	0.30	0.21	0.23	0.27	0.66	1.18
Precipitation (in)			0.05	0.07	0.11	0.12	0.17	0.20	0.24	0.31	0.41	0.64	1.14	1.71
		10/21/2003	**CSO Overflow**		**1,084,900**	**cubic feet**	Rarest Storm	Duration:	12 hr	Recurrence Interval (years):		50.9		
Return Period (Yrs)			0.16	0.24	0.36	0.44	0.77	1.34	2.33	7.50	21.18	34.29	50.91	38.02
Precipitation (in)			0.05	0.09	0.13	0.16	0.23	0.32	0.42	0.75	1.10	1.61	2.52	3.30
		11/18/2003	**CSO Overflow**		**433,400**	**cubic feet**	Rarest Storm	Duration:	24 hr	Recurrence Interval (years):		4.9		
Return Period (Yrs)			-0.10	-0.10	-0.10	-0.10	0.12	0.17	0.23	0.48	0.90	2.34	1.49	4.85
Precipitation (in)			0.03	0.05	0.06	0.08	0.12	0.17	0.22	0.40	0.60	1.06	1.39	2.34
		1/17/2005	**CSO Overflow**		**313,800**	**cubic feet**	Rarest Storm	Duration:	12 hr	Recurrence Interval (years):		3.1		
Return Period (Yrs)			0.11	0.14	0.15	0.21	0.18	0.24	0.34	0.41	0.73	2.11	3.10	2.23
Precipitation (in)			0.04	0.07	0.09	0.12	0.14	0.19	0.25	0.38	0.57	1.04	1.62	1.99
		12/24/2005	**CSO Overflow**		**780,100**	**cubic feet**	Rarest Storm	Duration:	72 hr	Recurrence Interval (years):		1.0		
Return Period (Yrs)			0.23	0.24	0.29	0.37	0.49	0.48	0.49	0.81	0.84	0.59	0.48	0.50
Precipitation (in)			0.06	0.09	0.12	0.15	0.20	0.24	0.28	0.46	0.59	0.79	1.04	1.34
		1/9/2006	**CSO Overflow**		**763,200**	**cubic feet**	Rarest Storm	Duration:	48 hr	Recurrence Interval (years):		0.8		
Return Period (Yrs)			0.11	0.18	0.19	0.21	0.25	0.20	0.20	0.16	0.21	0.16	0.31	0.46
Precipitation (in)			0.04	0.08	0.10	0.12	0.16	0.18	0.21	0.28	0.40	0.55	0.91	1.30
		1/29/2006	**CSO Overflow**		**1,017,900**	**cubic feet**	Rarest Storm	Duration:	12 hr	Recurrence Interval (years):		1.7		
Return Period (Yrs)			-0.10	-0.10	-0.10	-0.10	-0.10	0.13	0.15	0.21	0.28	0.62	1.75	1.66
Precipitation (in)			0.03	0.05	0.06	0.07	0.10	0.15	0.19	0.31	0.44	0.80	1.44	1.86
		11/4/2006	**CSO Overflow**		**404,500**	**cubic feet**	Rarest Storm	Duration:	72 hr	Recurrence Interval (years):		0.7		
Return Period (Yrs)			0.16	0.11	0.12	0.17	0.12	0.17	0.18	0.21	0.17	0.14	0.25	0.45
Precipitation (in)			0.05	0.06	0.08	0.11	0.12	0.17	0.20	0.31	0.37	0.52	0.84	1.29
		12/14/2006	**CSO Overflow**		**737,600**	**cubic feet**	Rarest Storm	Duration:	6 hr	Recurrence Interval (years):		36.0		
Return Period (Yrs)			2.85	10.00	11.15	14.30	18.03	20.02	17.66	13.04	13.29	35.95	5.15	1.48
Precipitation (in)			0.15	0.28	0.34	0.40	0.49	0.58	0.64	0.83	1.02	1.62	1.78	1.81
		12/26/2006	**CSO Overflow**		**763,000**	**cubic feet**	Rarest Storm	Duration:	12 hr	Recurrence Interval (years):		1.0		
Return Period (Yrs)			0.11	-0.10	-0.10	-0.10	-0.10	0.11	0.15	0.24	0.38	0.65	1.04	0.63
Precipitation (in)			0.04	0.05	0.06	0.08	0.10	0.14	0.19	0.32	0.48	0.81	1.28	1.44

4.0 DEVELOPMENT OF A CSO CONTROL VOLUME PERFORMANCE CURVE

The CSO Control Volume Performance Curve (Figure 2.1) describes the relationship between the Probability of Being In-Compliance in any given 5-year period versus the size of the Control Volume. The performance curve is used by SPU management in decision-making to assist in the selection of the configuration of a CSO reduction project. The CSO Control Volume performance curve is computed after the Uncertainty Analysis (Chapter7) is completed based on computer simulations of overflow volumes.

4.1 Procedures for Developing a CSO Control Volume Performance Curve

Construction of a CSO Control Volume Performance Curve is a relatively straightforward accounting procedure. The basic approach is to examine the number of overflows above a user specified threshold of overflow volume in a moving 5-year window of time. The number of 5-year periods where there are 5 overflows or less are tallied and the probability of in-compliance is computed as the ratio of the 5-years periods in compliance divided by the total number of 5-year periods. This process is repeated for various trial values of the Control Volume until the entire performance curve is generated. Details of this process are described in the following steps.

<u>Step 1 – Assemble List of Overflow Volumes and Dates and Rank in Descending Order</u>
Rank the N largest overflow volumes from largest to smallest along with the associated dates of occurrence. As in the prior analyses, $N=3m$, where m is the record length in years.

<u>Step 2 – Compute Probability-Plot and Estimate Overflow Volume for Once-per-Year Rate</u>
Compute a probability-plot of the overflow volumes in the same manner as described in Chapter 3 on direct estimation of control volumes from recorded overflows. Determine the estimate of the once-per-year overflow volume from the probability-plot.

<u>Step 3 – Compute Probability of In-Compliance for Range of Trial Control Volumes</u>
Select the overflow volume for the once-per-year overflow rate (Step 2 above) as the initial trial value of the Control Volume. Scan the list of N largest overflow volumes and remove all volumes (and associated dates) less than or equal to the trial value of the Control Volume.
An example of this process is shown in Table 4.1.

Tally the number of overflow events in each calendar year from the list of overflow events that exceeded the trial value of the Control Volume. Using a sliding 5-year window of time, compute the total number of overflows in a given 5-year period (Table 4.1, Figure 4.1). Mark those 5-year periods where there are 5 overflows or less as being in-compliance.

Compute the probability of being in-compliance for the trial value of the CSO Control Volume as the number of 5-year periods that were in-compliance divided by the total number of 5-year periods (Table 4.1).

Repeat this process for a range of trial values of the CSO Control Volume to generate the entire performance curve (Figure 4.2).

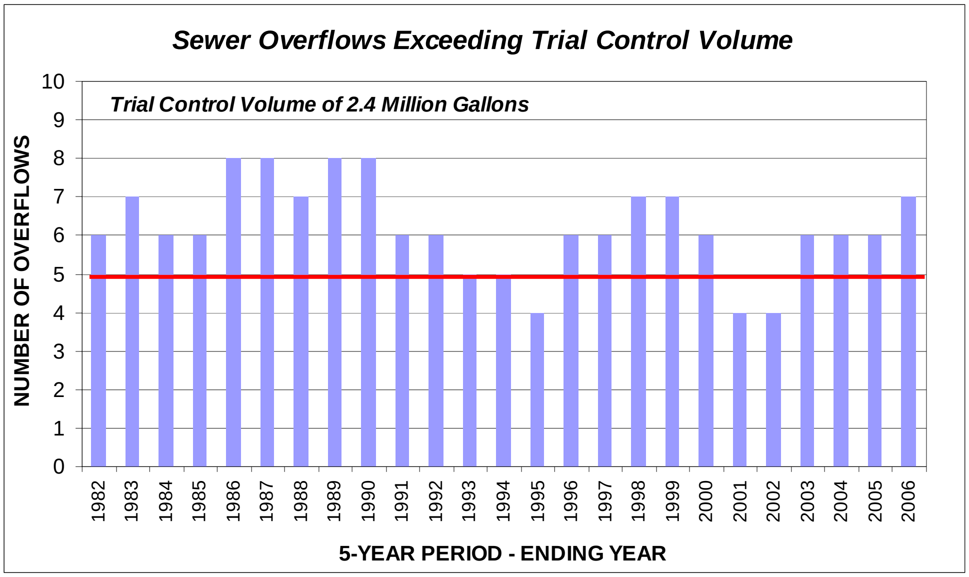


Figure 4.1 – Histogram of the Number of Overflows in 5-Year Periods for Trial CSO Control Volume of 2.4 Million Gallons

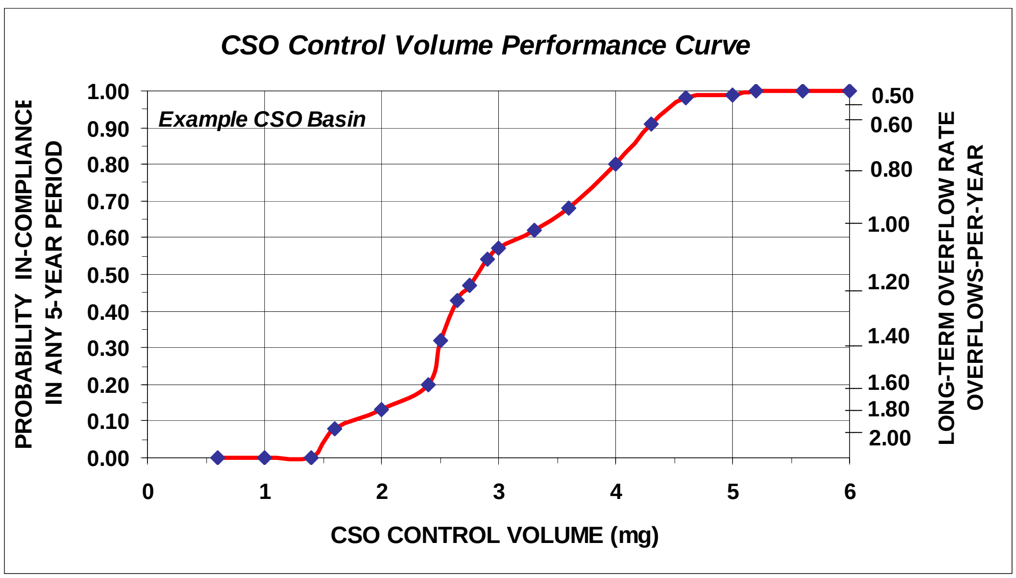


Figure 4.2 – Example CSO Control Volume Performance Curve

Table 4.1 – Computation of Probability of Being In-Compliance in Any 5-Year Period for a Trial Value of 2.4 Million Gallons for the CSO Control Volume

OVERFLOW VOLUMES EXCEEDING 2.4 MG	DATE		CALENDAR YEAR	NUMBER OVERFLOWS CALENDAR YEAR	NUMBER OVERFLOWS PRIOR 5-YEARS	TALLY OF 5-YEAR PERIODS IN-COMPLIANCE
4,099,695	11/3/1978		1978	1		
8,768,379	12/16/1979		1979	1		
2,908,471	1/11/1980		1980	2		
2,882,352	12/25/1980		1981	1		
9,066,656	10/5/1981		1982	1	6	0
4,613,744	12/3/1982		1983	2	7	0
4,866,579	1/4/1983		1984	0	6	0
3,776,703	11/19/1983		1985	2	6	0
5,287,511	6/6/1985		1986	3	8	0
4,030,132	10/26/1985		1987	1	8	0
10,694,923	1/17/1986		1988	1	7	0
4,830,185	10/26/1986		1989	1	8	0
4,676,521	11/23/1986		1990	2	8	0
3,988,384	3/2/1987		1991	1	6	0
3,356,869	1/14/1988		1992	1	6	0
4,392,549	12/3/1989		1993	0	5	1
4,732,820	1/9/1990		1994	1	5	1
4,945,422	11/23/1990		1995	1	4	1
6,894,867	4/3/1991		1996	3	6	0
2,541,203	1/27/1992		1997	1	6	0
4,725,576	12/19/1994		1998	1	7	0
2,401,912	11/7/1995		1999	1	7	0
7,139,011	2/8/1996		2000	0	6	0
3,913,891	4/22/1996		2001	1	4	1
15,217,758	12/29/1996		2002	1	4	1
7,995,187	3/18/1997		2003	3	6	0
6,789,687	11/24/1998		2004	1	6	0
4,055,911	11/11/1999		2005	0	6	0
6,184,155	11/13/2001		2006	2	7	0
2,698,449	2/21/2002		**Number of 5-Year Periods In-Compliance**			**5**
2,411,419	3/12/2003					
11,607,744	10/20/2003		**Total Number of 5-Year Periods**			**25**
7,776,819	11/18/2003					
2,656,295	1/29/2004		**Probability of Being In-Compliance**			**0.200**
3,668,474	1/29/2006		**in any 5-Year Period**			
3,365,940	11/5/2006					

5.0 AUTOMATED CALIBRATION PROCEDURES AND GLUE CONCEPTS FOR DETERMINING A BEST-FIT MODEL PARAMETER SET

A computer model is developed for the hydrologic response of a CSO basin and the hydraulic operation of a combined sewer system because there is interest in the predictive power of the model for assessing performance of the system in the future. Calibration of the computer model is the mechanism by which confidence is gained that sewer flows and overflow volumes predicted by the computer model will be acceptably close to actual sewer flows and overflow volumes.

There are two primary considerations in determining the manner in which calibration is to be accomplished for a computer model of a combined sewer system. First, it must be recognized that there are sizable uncertainties in the models inputs, and measurements of sewer flows and overflow discharges used for calibration of the model. Like all computer models, there are also imperfections in the model structure and algorithms that are used for computation of sewer flows and overflow discharges. The existence of these uncertainties and imperfections destines to failure any search for a unique "true" calibrated model parameter set. In contrast, multiple model parameter sets can usually be found that reproduce measured sewer hydrographs within some error tolerance. Furthermore, the existence of these uncertainties and imperfections results in the propagation of uncertainties through the model to the model outputs. This situation requires that the calibration process be conducted in a manner that allows assessment of the uncertainties in the predictions of sewer flows and overflow volumes when using the calibrated model.

The second consideration in CSO model calibration is the recognition that calibration of the computer model can be a very time-consuming task because of the extensive computer run-times required to conduct the large number of simulations of sewer flows and sewer overflow volumes. This situation requires that the computer model be run in a batch mode without inter-action from the analyst. This was addressed by creating a windows-based control program *ACU-SWMM* that allows continuous operation of the SWMM watershed model in an automated batch mode. Automation of the calibration process allows a more thorough examination of the model parameter space and identification of parameter sets that can reasonably reproduce measured sewer flow hydrographs. The details for application of *ACU-SWMM* will be described later in this chapter.

5.1 Overview of Issues in Calibrating Watershed Models

At the most basic level, model calibration is simply a mathematical exercise to find model parameter values that produce model outputs that acceptably match measured outputs within some error tolerances (Figure 5.1). If the model inputs accurately represent field conditions, and if the model structure, governing equations and algorithms are physically-based and accurate depictions of field conditions and the phenomenon being modeled, and if the model outputs can be compared against corresponding outputs that have been measured in the field with high accuracy – then it is possible to search for a "true" calibrated model parameter set. However, this is rarely the case in watershed modeling, particularly for CSO modeling where it is common to have sizeable uncertainties in all aspects of the modeling process.

In calibrating a computer model, all of the errors and uncertainties are absorbed in the model parameters, because they are the variables being used to obtain a match between computer outputs and measured outputs. The effect of uncertainties in obtaining a "calibrated" model parameter set can be inferred from consideration of uncertainties in the measurement of sewer flows. It is not uncommon to have uncertainties on the order of $\pm$15% in sewer flow measurements as depicted by the hydrographs shown in Figure 5.2. In examining the hydrographs in Figure 5.2, a model parameter set that can reasonably replicate the 115% hydrograph, would clearly be different from the parameter set that can replicate the 100% or 85% hydrographs. This simple example only considered uncertainties in sewer flow measurements. Additional uncertainties in model inputs, and model structure and algorithms, produces compensating errors in the parameter values which results in many combinations of model parameter values that can replicate the measured hydrographs within some error tolerance.

The following generalizations can be made about calibration of watershed computer models:

- as uncertainties increase in model inputs and measured outputs and the model structure becomes more complex, the potential increases for compensating errors in the model parameter values of the “calibrated” model parameter set;

- when uncertainties in the modeling process are considered, a number of model parameter sets can be found that produce outputs that reproduce measured outputs within some error tolerance;

- while modelers tend to place importance on the physical meaning of model parameters, the larger the uncertainties in inputs and observed outputs and the greater the imperfections in model structure, the weaker the correspondence between model parameters and the physical elements they are intended to represent.

In recognizing that sizable uncertainties are inherent in computer modeling of CSO basins, procedures must be utilized in model calibration that allow analysis of the effect of uncertainties on the predicted outputs from the model. It is the predicted model outputs and the reliability of those predictions that are of interest in assessing options for CSO reduction.

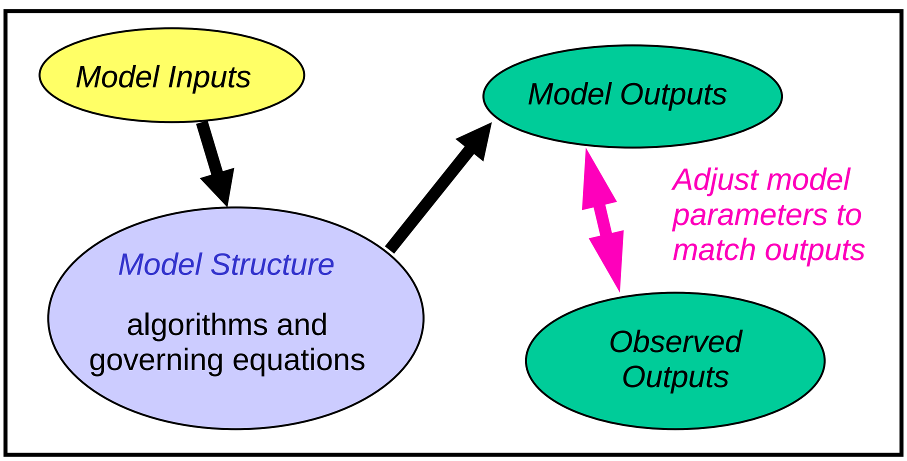


Figure 5.1 – Overview of Conventional Model Calibration Process

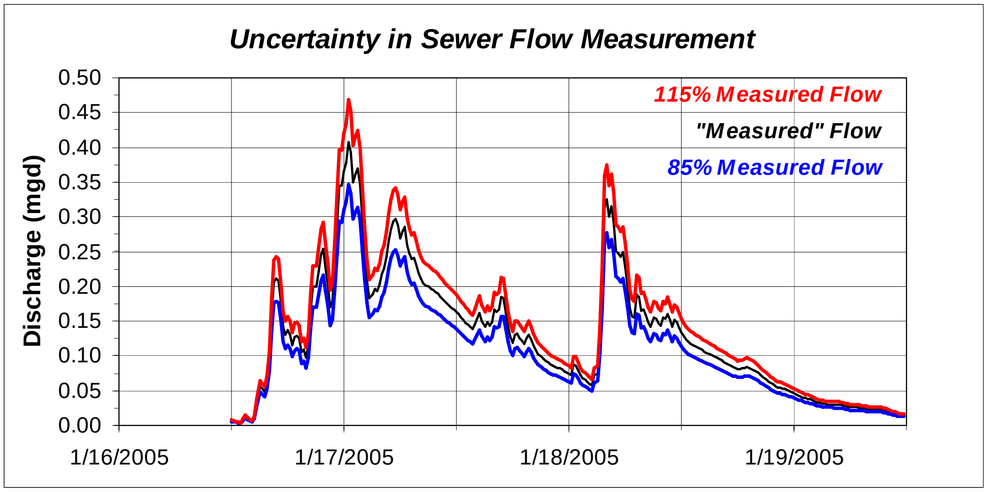


Figure 5.2 – Comparison of Sewer Flow Hydrographs
with Uncertainties in Flow Measurement of ±15%

5.2 GLUE Concepts

The issues of automated calibration and modeling uncertainties can be addressed by adapting concepts from the Generalized Likelihood Uncertainty Estimation (GLUE) procedures developed by Beven and Binley[1]. The GLUE methodology explicitly recognizes that the search for the "true" parameter set via calibration is obstructed by the inaccuracies and uncertainties that exist in the hydrometeorological inputs, sewer flow measurements, and the limitations of the structure and algorithms of the computer model. Recognizing these limitations, the GLUE approach seeks to identify those combinations of model parameter values (model parameter sets) that can reasonably replicate the observed sewer flow hydrographs based on an objective measure of the goodness-of-fit between simulated and recorded hydrographs. The GLUE calibration process utilizes Monte Carlo sampling techniques as shown schematically in Figure 5.3.

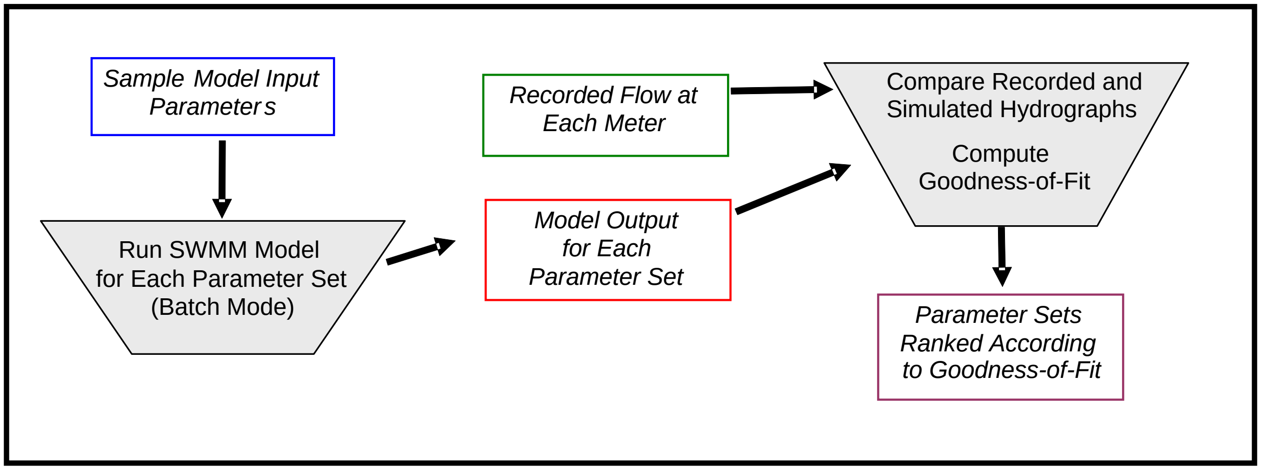


Figure 5.3 – Overview of GLUE Monte Carlo Sampling Approach to Model Calibration Process

The GLUE approach proceeds by assembly of numerous trial parameter sets based on Monte Carlo sampling over the plausible range of values for the various model parameters. The watershed model is then executed using each of the sampled parameter sets and the simulated flow rates are saved at each sewer flow measurement site. A post-processor routine within *ACU-SWMM* then computes goodness-of-fit measures using the recorded and simulated hydrographs for each of the parameter sets.

The parameter set that yields the closest match of the simulated and recorded hydrographs based on numeric goodness-of-fit measures is termed the "best-fit" model parameter set. The best-fit parameter set is then used in conducting an uncertainty analysis (Chapter 6) and developing uncertainty bounds for the CSO Control Volume (Chapters 4,6). This approach is discussed in more detail in Section 5.5.

5.3 Goodness-of-Fit Measures for a Single Storm/Sewer Flow Event at a Specific Site

There are several goodness-of-fit measures that will be used for characterizing how well a simulated hydrograph of sewer flows matches a recorded sewer flow hydrograph at a flow measurement site (Figure 5.4).

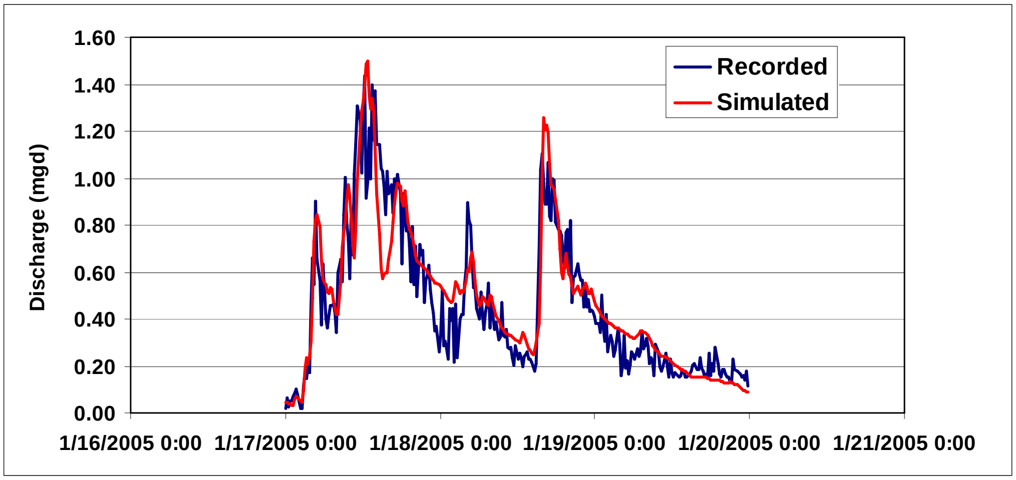


Figure 5.4 – Example of Simulated and Recorded Sewer Flow Hydrographs

Two coarse measures are used for characterizing the similarity of elements of simulated and recorded hydrographs. GOF_{Peak} is used for comparing peak discharges (Equation 5.1a). GOF_{Volume} is used for comparing volumes for simulated and recorded hydrographs (Equation 5.1b), where the volume is computed for those time increments where the flow exceeds a user-specified threshold. Both measures are expressed as a percentage.

$$GOF_{Peak} = 100 * (Peak\ Discharge_{simulated} \,/\, Peak\ Discharge_{recorded}) \qquad (5.1a)$$

$$GOF_{Volume} = 100 * (Volume_{simulated} \,/\, Volume_{recorded}) \qquad (5.1b)$$

These two measures provide quick, intuitive measures of goodness-of-fit. The volume comparison is particularly useful for CSO projects because overflow volumes are an item of particular interest.

Two additional goodness-of-fit measures are used to provide a finer measure of the similarity of simulated and recorded hydrographs. Both measures are based on the behavior of the residuals (Equation 5.2), where a residual is the difference between a recorded and simulated flow at a given point of time. The residuals may be viewed graphically in Figure 5.5 as the scatter about the blue *y=x* line. Numerically:

$$residual_i = Qsim_i - Qrec_i \qquad (5.2)$$

where: $Qrec_i$ is the recorded flow at time *i*, $Qsim_i$ is the computer simulated flow at time *i*, for the time interval of interest *(i=1 to n).* All computations are conducted for those time increments when the recorded flow exceeds a user-specified threshold. The threshold for the example shown in Figure 5.5 is 0.15-mgd for the recorded flow.

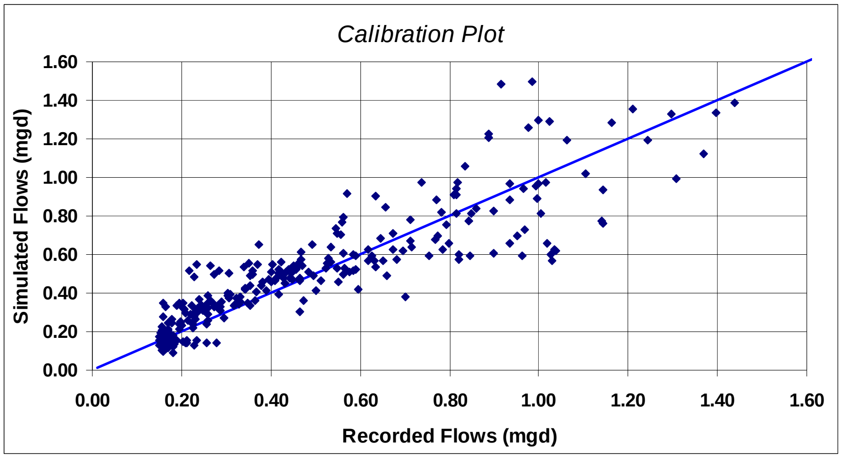


Figure 5.5 – Comparison of Simulated and Recorded Sewer Flows for Hydrographs in Figure 5.4

Standardized Bias is a standardized measure of the average amount of under-simulation or over-simulation, expressed as a percentage (Equation 5.3b).

$$Bias = \frac{1}{n}\sum_{i=1}^{n}\left(residual_i\right) \qquad (5.3a)$$

$$Standardized\ Bias = 100 * \frac{Bias}{\overline{Qrec}} \qquad (5.3b)$$

where: $\overline{Qrec}$ is the average recorded flow, for time increments where the recorded flows exceed the user-specified threshold.

Standardized RMSE is a standardized measure of the root mean square error of the residuals, expressed as a percentage (Equation 5.4b). For cases where the bias is small, the Standardized RMSE can be viewed as essentially a standardized measure of the standard deviation of the residuals (Figure 5.5).

$$RMSE = SQRT\left[\sum_{i=1}^{n}\left(\frac{residual_i^{\,2}}{n}\right)\right] \qquad (5.4a)$$

$$Standardized\ RMSE = 100 * \frac{RMSE}{\overline{Qrec}} \qquad (5.4b)$$

The four goodness-of-fit measures were computed (Table 5.1) for the recorded and simulated hydrographs depicted in Figure 5.4 and Figure 5.5 using a threshold of 0.15 mgd. The GOF measures for peak discharge and hydrograph volume show good performance of the computer model for these two hydrograph characteristics. This is seen graphically in Figure 5.4 by the similarity of hydrograph shapes. The standardized bias measure of 4.4% indicates a tendency for the computer model to slightly over-simulate flows. The standardized RMSE measure of 29.8% indicates moderate levels of variability in the difference between simulated and recorded flows.

Table 5.1 – Goodness-of-Fit Measures for Simulated and Recorded Hydrographs Shown in Figure 5.4 for Recorded Flows that Exceed 0.15 mgd

GOODNESS-OF-FIT MEASURES	
$Peak_{GOF}$	96.7%
$Volume_{GOF}$	104.4%
Standardized Bias	4.4%
Standardized RMSE	29.8%

5.4 Global Goodness-of-Fit Measures for Multiple Flow Measurement Sites and Multiple Storm/Sewer Flow Events

A goodness-of-fit measure is needed for ranking of watershed model parameter sets to determine the parameter set that provides the best-fit of computer simulated hydrographs to the hydrographs that have been recorded at various sites throughout the CSO basin. This computation is somewhat complicated because it must consider the goodness-of-fit measure at each flow measurement site for all storm/sewer flow events while considering the relative importance of each site. For a model calibration with 4 storm/sewer flow events and 6 flow measurement sites, there are 24 recorded and simulated hydrographs and associated goodness-of-fit measures that must be considered. While numerically a little cumbersome, this approach has the distinct advantage of incorporating the sewer flow information at numerous sites, thus reducing the effect of uncertainties in flow measurements and improving the identification of the best-fit model parameter set.

A weighted averaging procedure is utilized for computing global goodness-of-fit measures for each model parameter set and is computed in two steps. First, a goodness-of-fit measure is obtained for each storm/sewer flow event ($GOFevent_m$) as a weighted average of the goodness-of-fit measures from the various flow measurement sites as:

$$GOFevent_m = \sum_{k=1}^{KK} \left(GOFevent_{k,m} * SiteWeight_{k,m} \right) \qquad (5.5a)$$

where: $GOFevent_{k,m}$ is any goodness-of-fit measure for flow measurement site k of KK total sites and storm/sewer flow event m of MM total events. $SiteWeight_{k,m}$ is the weighting for flow measurement site k and storm/sewer flow event m. For each storm/sewer flow event m, the site weights, k=1 to KK, sum to unity.

The second step is to compute the global goodness-of-fit measure (GOF_{global}) for the collection of storm/sewer flow events as a weighted average of the goodness-of-fit measures for the individual storm/sewer flow events. Numerically:

$$GOF_{global} = \sum_{m=1}^{MM} \left(GOFevent_m * EventWeight_m \right) \qquad (5.5b)$$

where: $EventWeight_m$ is the weighting for storm/sewer flow event m of MM total events, and the individual event weights sum to unity.

In some cases, the analyst may choose to weight the storm/sewer flow events equally. In other cases, the analyst may choose to give storm/sewer flow events that cause sewer overflows greater weight. Similarly, greater weight may be given to those events where there is greater confidence in the precipitation inputs and flow measurements. Selection of site and event weightings will be discussed further in Step 10 below.

Global Goodness-of-Fit Measures for Volume

The global goodness-of-fit measure for volume ($GOFvolume_{global}$) is computed as a weighted mean as:

$$GOFvolume_{global} = \sum_{m=1}^{MM} EventWeight_m \sum_{k=1}^{KK} \left(GOF_{Volume_{k,m}} * SiteWeight_{k,m} \right) \tag{5.6a}$$

where: $GOFVolume_{k,m}$ is the standardized measure of volume (Equation 5.1b) for sewer flow event m and flow measurement site k. This computation is numerically equal to application of Equations 5.5a,b.

The global goodness-of-fit measure of the standard deviation of volume ($GOFvolumeStDev_{global}$) is useful for identifying candidate model parameter sets. It provides a measure of the variability in prediction of sewer flow volumes across all sites and sewer flow events. It is computed as:

$$Variance_{global} = \sum_{m=1}^{MM} EventWeight_m \sum_{k=1}^{KK} \left(\left(GOF_{Volume_{k,m}} - GOFvolume_{global} \right)^2 * SiteWeight_{k,m} \right) \tag{5.6b}$$

$$GOFvolumeStDev_{global} = \sqrt{Variance_{global}} \tag{5.6c}$$

Global Goodness-of-Fit Measure for RMSE

The goodness-of-fit measure for standardized root mean square error is computed as a weighted average obtained from the Standardized RMSE values for each measurement site for a specific storm event. This computation follows the format of Equations 5a,b above where the event goodness-of-event measure is first computed as:

$$GOFevent_m = \sum_{k=1}^{KK} \left(Standardized\ RMSE_{k,m} * SiteWeight_{k,m} \right) \tag{5.7a}$$

The global goodness-of-fit measure for the collection of storm/sewer flow events ($GOFrmse_{global}$) is then computed as a weighted average of the goodness-of-fit measures for the individual storm/sewer flow events. Numerically:

$$GOFrmse_{global} = \sum_{m=1}^{MM} \left(GOFevent_m * EventWeight_m \right) \tag{5.7b}$$

Goodness-of-Fit Measures for Sites

A goodness-of-fit measure can also be computed for a specific flow measurement site ($GOFsite_k$) as a weighted average obtained from the goodness-of-fit measures values for each storm/sewer flow event for a given flow measurement site. This site-specific goodness-of-fit measure may be useful for identifying a flow measurement site where the watershed model is performing poorly relative to other sites. This may be an indicator of lower quality flow measurements or the watershed model may need refinement for the sub-area tributary to the flow measurement site.

$$GOFsite_k = \sum_{m=1}^{MM} \left(GOFevent_{k,m} * EventWeight_m \right) \tag{5.8}$$

Initial Estimate of Site Weights

Site weights are needed in the weighted averaging scheme for computing goodness-of-fit measures. In practice, site weights are usually set by judgment considering the relative magnitude of flow at a given site, the reliability and accuracy of the flow measurements at the site, the relative importance of a given storm/sewer flow event and the level of uncertainties imparted to the site by hydraulic elements such as hydrobrakes, storage vaults, weirs and other control structures.

An initial estimate of site weights can be made by assessing the magnitude of flow at a given site relative to that at other sites. This approach yields the following initial estimates of site weights, where the $SiteWeight_k$ is computed as:

$$SiteWeight_{k,m} = \frac{\overline{Qrec_{k,m}}}{\sum_{k=1}^{KK} \overline{Qrec_{k,m}}} \tag{5.9a}$$

and

$$\overline{Qrec_{k,m}} = \frac{1}{KK} \sum_{k=1}^{KK} \overline{Qrec_{k,m}} \qquad \textit{(average flow for all sites for event m)} \tag{5.9b}$$

where: $SiteWeight_{k,m}$ is the weighting for flow measurement site k of KK total sites, and event m of MM total events. $\overline{Qrec_{k,m}}$ is the average flow at site k for sewer flow event m for those time increments where the sewer flow exceeds the user-specified threshold, and sewer flow events are numbered *m=1 to MM*. As indicated above, for a given storm/sewer flow event, the weighting factors for the collection of flow measurement sites sum to unity. Likewise, the weighting factors for the sewer flow events sum to unity.

Choice of Global Goodness-of-Fit Measure for Automated Calibration

A global goodness-of-fit measure(s) is needed for ranking of model parameter sets to identify candidate model parameter sets that best replicate the recorded sewer flow hydrographs. Visual comparisons of recorded and simulated hydrographs for the candidate model parameter sets are then used to select the "calibrated" best-fit parameter set from amongst the candidate model parameter sets.

In general, the global goodness-of-fit measures for *standardized RMSE* (Equations 5.7a,b) are preferred for the ranking process to identify candidate model parameter sets. However, data quality problems can sometimes render the RMSE measures ineffective. Specifically, time-stamp inaccuracies for flow meter measurements and other instrument-related errors can distort the RMSE measures, particularly for sewer flows that can change significantly on a short 5-minute time-step (see section below). When this situation occurs, global goodness-of-fit measures for volume and standard deviation of volume (Equations 5.6a,c) are the preferred choice for ranking and selecting candidate model parameter sets. All of the global goodness-of-fit computations are conducted within the *ACU-SWMM* software provided for automated model calibration.

Examples of Limitations of RMSE Goodness-of-Fit Measure

Two situations occasionally arise that reduce the usefulness of the RMSE GOF measure. The analyst should be aware of these potential situations to assure that appropriate global GOF measures are used in the selection of candidate parameter sets. The first situation results from time-stamp problems or other instrument-related problems that result in a false lag in the timing of the simulated and recorded sewer flow hydrographs. Figure 5.6a depicts an example where the simulated and recorded hydrographs are identical except for a time-lag. In this example, the standardized bias is 0.9% and the standardized RMSE is 60% as indicated by the wide scatter in simulated and recorded flows shown in Figure 5.6b. Thus, visual comparison indicates the watershed model is replicating the behavior of the recorded sewer flow hydrograph (except for timing), whereas the numerical RMSE GOF measure indicates a very poor replication.

A second example is due to a problem termed “hyperactivity”. Sewer flow measurements are obtained as the product of a depth measurement and an average velocity which is an integration of sonic velocities taken within the conduit. The flow measurement that is sent to the data logger is an instantaneous value taken on a fixed time-interval (5-minutes). However, review of the continuous output of integrated flows from the flow measurement instrument shows the instantaneous flows to fluctuate about a mean value. This occurs due to a combination of minor depth fluctuations, minor transients in the hydraulics of flow that alter the velocity profile in the conduit and other site-specific and instrument-related issues. This situation results in a recorded hydrograph with a “hyperactive” appearance (Figure 5.6c), that artificially increases the RMSE measure because of the distortion of the magnitude of residuals (Equations 5.2, 5.4a,b).

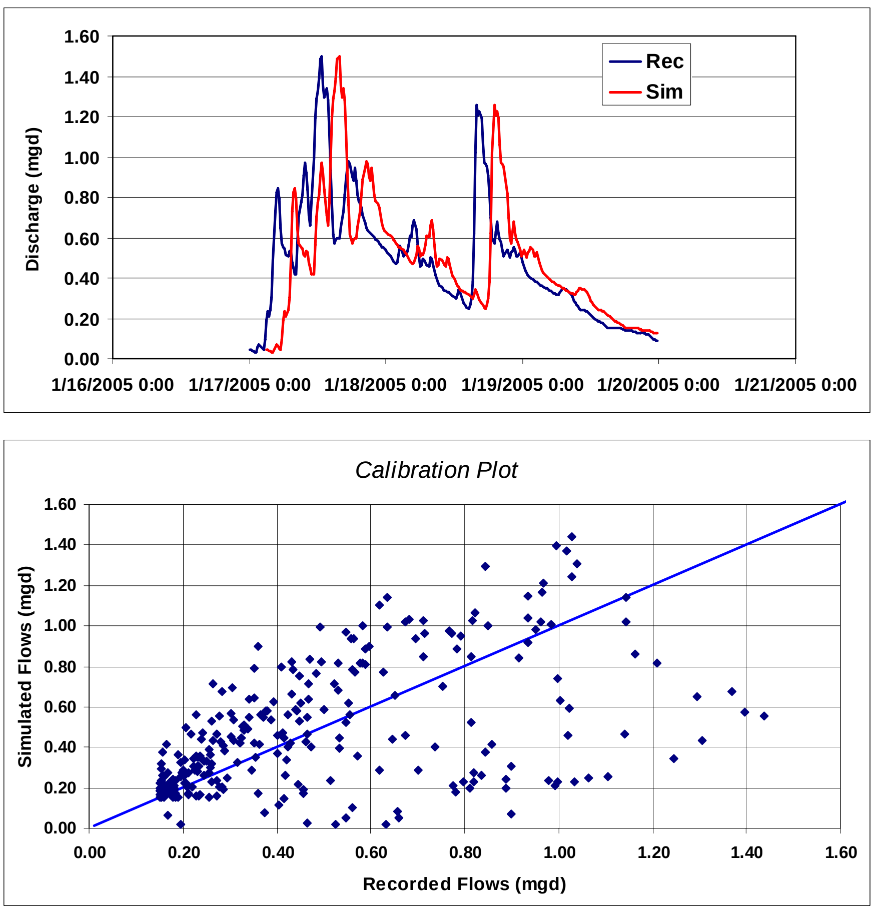


Figure 5.6a,b – Comparison of Simulated and Recorded Sewer Flows
for Case of Identical Hydrographs Lagged by a Fixed Amount of Time

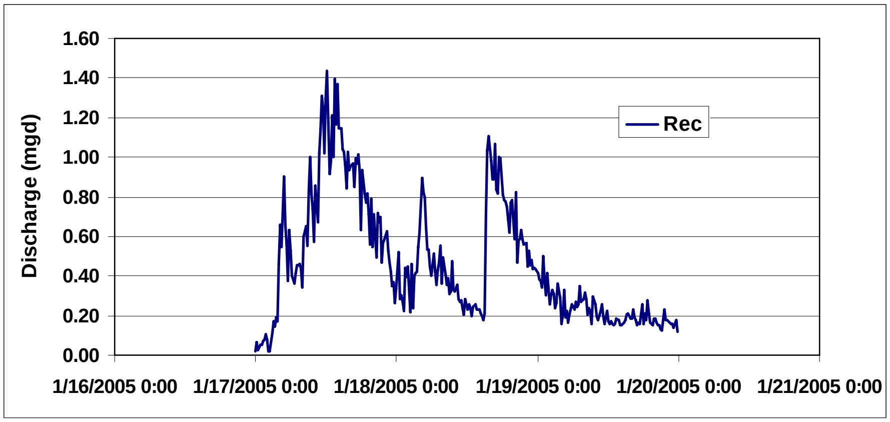


Figure 5.6c – Example of "Hyperactive" Recorded Sewer Flow Hydrograph with Short-Term Fluctuations in Sewer Flows Due to Site-Specific and Instrument-Related Issues

5.5 Procedures for Automated Calibration

The following procedures for automated calibration are applicable to the case of sewer flow hydrographs recorded at multiple sites for multiple storm/sewer flow events.

Setting Up the Watershed Model for Calibration

Step 1 – Assemble Watershed Model

Assemble the watershed model for the CSO basin of interest. Model setup is performed using conventional methods. There is no difference in the model setup used in the GLUE automated calibration approach versus the setup used in a conventional trial-and-error manual calibration approach. The *CSO Modeling QA/QC Checklist for Model Development, Calibration and Validation* should be used to provide a check that all model components have been adequately addressed. The watershed model should be executed sufficiently to confirm that it is acceptably mimicking the hydrologic and hydraulic operation of the combined sewer system. Final model checkout can be done in Step 5 after storm/sewer flow events have been selected for use in calibration.

Step 2 – Identify Storms and Sewer Flow Hydrographs to be used for Calibration

Scan the time-series records of precipitation and sewer flows to identify noteworthy storms and sewer flow events to be used in the calibration process. Particular attention should be given to include storm events where sewer overflows occurred and storm events of a magnitude near the regulatory target of the once-per-year frequency of occurrence.

Precipitation Data – In conducting model calibration, the underlying assumption is that the precipitation recorded at a nearby gage(s) is representative of the precipitation that actually occurred on the watershed. Particular attention should be given to confirming this assumption. This can be accomplished by examining precipitation temporal patterns (Figure 5.7a) at other gages in the area and making an assessment of the spatial and temporal variability and the representativeness of the rain gage record to be used for calibration. This may be done using precipitation data from other SPU rain gages, rain gages operated by King County and the National Weather Service, and private weather stations with records obtained from the weather underground website (http://wunderground.com).

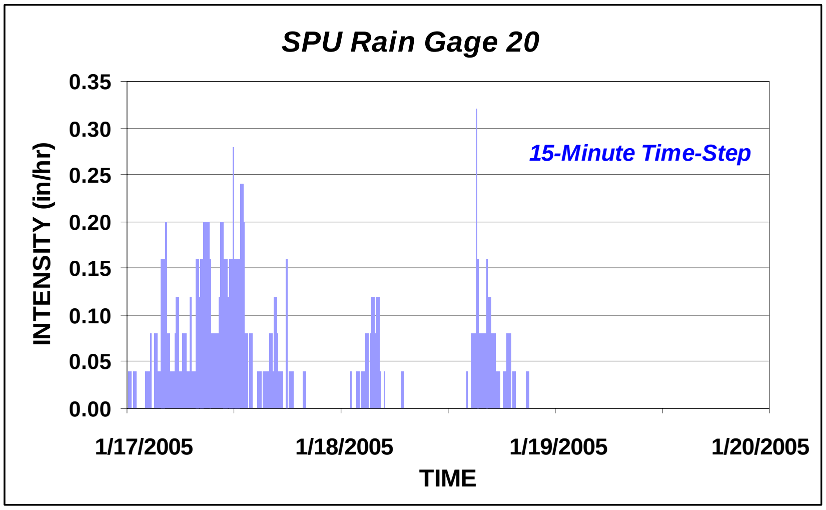


Figure 5.7a – Hyetograph for SPU Rain Gage 20 near Montlake 20 CSO Basin

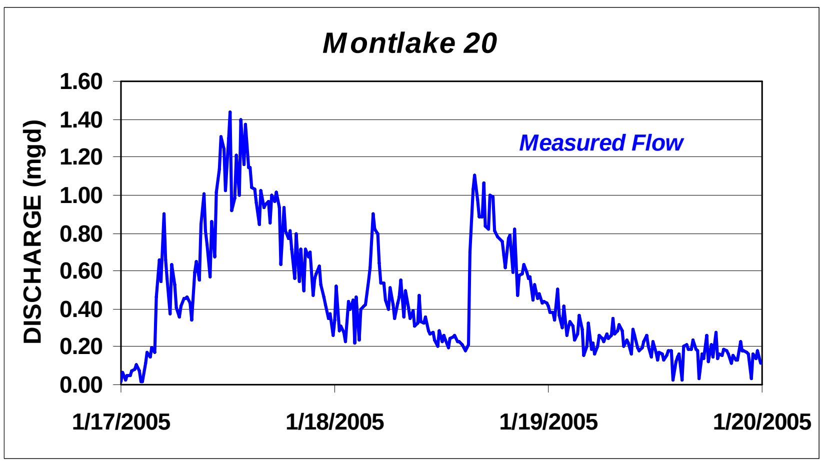


Figure 5.7b – Sewer Flow Hydrograph for Selected Site in Montlake 20 CSO Basin

A time-step of 15-minutes has been found to be useful for smoothing some of the high-intensity bursts and providing a more representative comparison with the record from other rain gages. Similarly, the 15-minute time-step has been found to be suitable for comparison of the temporal pattern of precipitation (Figure 5.7a) with the shape of sewer flow hydrographs (Figure 5.7b).

<u>Sewer Flow Hydrographs</u> – Sewer flow hydrographs should be assembled for all the metered sites of interest within the CSO basin for all the storm/flow events that were identified. Whenever possible, include the hydrographs for sewer overflow sites for these are the locations of greatest importance for accuracy in estimation of the CSO Control Volume. If there are data dropouts or missing data, fill-in the missing segments of the hydrographs to the extent practical by smoothing or other case-specific methods to provide more continuous hydrographs. Continuous hydrographs are preferred for computation of the goodness-of-fit measures.

Each hydrograph of recorded flows should be quality-checked to confirm its suitability for use in calibration. It is critically important that sewer flow hydrographs be checked to verify that measured flows are representative of reality. Discussions should be held with SPU field personnel and contractors familiar with the installation and operation of each metered site to confirm the accuracy and quality of measured sewer flows. Some metering sites may need to be dropped from the calibration process if the measured flows are found to be inaccurate or inconsistent with measured flows at all other sites.

A decision can also be made to include or reject a flow measurement site(s) based on goodness-of-fit measures for flow volume (GOF_{volume}) and peak flow rate (GOF_{Peak}). That decision can be made after goodness-of-fit measures have been calculated at all flow measurement sites. Sites that consistently exhibit poor matching between recorded hydrographs and simulated hydrographs ($GOFsite_k$) while the majority of other sites are obtaining acceptable matches between hydrographs would warrant consideration for rejection of a site or sites.

Step 3 – Set the Flow Threshold for Computation of Goodness-of-Fit Measures

For each flow measurement site, set the flow threshold for computation of the goodness-of-fit measures. Flows for the time increments when the flow exceeds the user-specified threshold will be used in the goodness-of-fit calculations. The flow threshold should be set in the general range well above the base level of sanitary flows and below the flow magnitude associated with sewer overflows at the outfall of the CSO basin (Figure 5.8). The flow threshold that is chosen should result in the goodness-of-fit measure being computed on flows of a magnitude in the general range both below and above that associated with sewer overflows. This approach places emphasis on simulation of the flows of interest and avoids over-emphasizing the simulation of long series of smaller flows that are not relevant to modeling of the sewer overflow events.

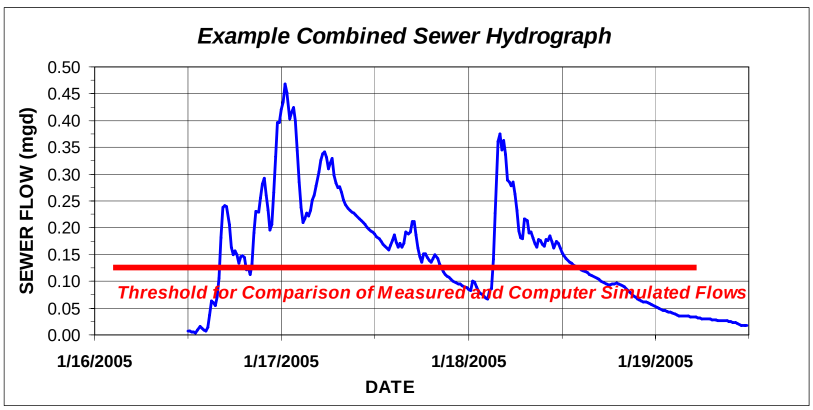


Figure 5.8 – Example of Flow Threshold Used in Computation of Goodness-of-Fit Measure

Step 4 – Select the Watershed Model Parameters to Be Used in the Calibration Process

Selection of the specific model parameters to be used in model calibration is an important task in the automated calibration approach. The general case is that there are many more model parameters than can be explored because of the computational constraints posed by the long computer simulation time. This situation requires parsimony in the selection of a limited number of model parameters for calibration. Sensitivity analyses and analyst experience and judgment should be used to identify those model parameters that have the greatest effect on the watershed model outputs of sewer flows and overflow volumes.

The recommended approach is to first sort the list of model parameters into groups representing the major hydrological processes. Then for each of the major hydrological processes, identify the dominant parameters with regard to model sensitivity. Also identify where overlap exists in the effect that model parameters have on the resultant sewer flows. Then select the minimum number of parameters for model calibration while providing at least one calibration parameter for each of the major hydrological processes. Confirm that there is minimum overlap/redundancy in the chosen parameters.

The terms model parameter set and model parameter space are used to describe the Monte Carlo process and are defined here for clarity.

Model Parameter Set – A specific collection of model parameter values for the model parameters that are selected for model calibration. One parameter value for each model parameter.

Model Parameter Space – The mathematical space encompassing the full range of model parameter values for each of the model parameters used for model calibration.

<u>Step 5 – Conduct Trial-and-Error Manual Calibration and Final Model Checkout</u>
It is suggested that the analyst use conventional trial-and-error manual calibration procedures to obtain a first approximation of the "best-fit" calibrated model parameter set. This conventional calibration effort would be helpful in gaining a better understanding of the operation of hydrologic response of the CSO basin and the hydraulic operation of the combined sewer system. This would also be a practical way to thoroughly test the computer model as indicated in Step 1 to confirm that it is acceptably mimicking the hydrologic and hydraulic operation of the combined sewer system. The trial-and-error manual calibration would provide a baseline for comparison of the goodness-of-fit measures with the best-fit model parameter set that will be obtained from the Monte Carlo GLUE approach.

Iterative Approach to Automated Model Calibration

Automated calibration can often be conducted more efficiently using an iterative approach. This can be described as follows. Monte Carlo sampling of the model parameter space is used for assembling trial model parameter sets for calibration. This is done by initially setting the sampling range for each model parameter quite wide and then performing several hundred simulations of the SWMM watershed model. Global goodness-of-fit (GOF) measures are calculated for each simulation based on the similarity between predicted and recorded sewer flow hydrographs. Candidate model parameter sets are identified that yield predicted sewer flow hydrographs that are acceptably similar to recorded hydrographs based on the GOF measures.

Sensitivity plots are then prepared and the findings used to narrow the sampling range for each of the model parameters used for model calibration. Additional iterations are then conducted in the manner described above until the sampling ranges are judged suitable for the final calibration runs. After the final round of computer simulations are completed, the collection of predicted sewer flow hydrographs for the candidate parameter sets are visually examined and a best-fit calibration parameter set is selected.

This process is described in detail in Steps 6-13 below.

Step 6 – Set the Minimum and Maximum Values to be Considered for Each Model Parameter

Automated sampling procedures are used for selecting the values of model parameters. It is therefore necessary to set minimum and maximum values of each model parameter that is used in the automated calibration process. The minimum and maximum values should be selected based on any physical limits for the model parameter as well as recognizing that compensating errors in the calibration process may yield suitable parameter values outside of the range typically associated with the physical character of the parameter.

A probability model is also needed for sampling of parameter values for each model parameter. Choices of probability models include the Uniform distribution for selection of equally likely parameter values and the Normal and Log-Normal distributions where the analyst judges greater likelihood in the central portions of the range between the minimum and maximum values. Table 5.3 depicts an example of the ranges of some model parameters that were used in the automated calibration procedure for a CSO basin in eastern Seattle.

Model parameters that are not used in the automated calibration procedure should be set at fixed values. The fixed value of each model parameter should be selected based on experience and judgment of the analyst while considering the specific features of the CSO basin being investigated. Where practical, sensitivity analyses should be conducted and the findings used to assist in setting of fixed values of those model parameters that are not varied in the calibration process.

Table 5.3 – Example of SWMM Model Parameters Used in Automated Calibration Procedure

MODEL PARAMETER	PROBABILITY MODEL FOR SAMPLING	SAMPLING RANGE OF PARAMETER VALUES	
		Minimum	Maximum
Percent Imperviousness – Roofs (includes connectivity factor)	Uniform	5%	90%
Percent Imperviousness – Roadways (includes connectivity factor)	Uniform	5%	90%
Saturated Hydraulic Conductivity for Pervious Runoff	Uniform	0.05 in/hr	0.50 in/hr
Saturated Hydraulic Conductivity for Groundwater Movement	Uniform	0.001 in/hr	0.25 in/hr

Step 7 – Sample the Values for Each Model Parameter and Assemble Model Parameter Sets

Candidate parameter sets are assembled by Latin Hypercube sampling procedures (McKay et al[8], Wyss and Jorgenson[19]) wherein a value is selected for each of the model parameters to create a parameter set. This task is done automatically by the *ACU-SWMM* program after the minimum and maximum parameter values and probability model are specified for each model parameter by the analyst.

Step 8 – Set the Number of Computer Simulations to be Executed

The number of computer simulations executed in each round of iterations should be set as high as practical considering available time and budget. The goal is to thoroughly examine the model parameter space in searching for the best-fit model parameter set. As a rough guide, about 300 to 1,000 simulations have previously been used in each iterative round for the Genesee and Henderson CSO projects.

Step 9 – Execute the SWMM Model and Compute Single Site-Event Goodness-of-Fit Measures
Automated calibration is accomplished by execution of the SWMM model via the *ACU-SWMM* program whereby the basin model is executed in a batch mode. Outputs from the SWMM model, specifically sewer flow hydrographs and overflow volumes, are saved and single site-event goodness-of-fit measures are computed for similarity of hydrograph volume (GOF_{Volume}) and peak discharge (GOF_{Peak}) for the computer simulated and measured hydrographs. Numerical single site-event goodness-of-fit measures are also computed that characterizes the bias (*Standardized Bias*) and magnitude of variability (*Standardized RMSE*) in the differences between simulated and recorded flows (Equations 5.3b and 5.4b, respectively). All single site-event goodness-of-fit measures are computed via the *ACU-SWMM* program.

Step 10 – Set Weighting Factors for Multiple Flow Measurement Sites and Sewer Flow Events
The global goodness-of-fit measures for a given model parameter set are computed as a weighted average of the goodness-of-fit measures for the flow measurement sites and storm/sewer flow events. The weighting factor for each of the sewer flow measurement sites is based on the relative flow contribution and quality of each measurement site. Judgment is used to adjust these weightings based on site specific considerations to emphasize or de-emphasize a particular site or sites. The weighting factors for the flow measurement sites must sum to unity as described in the discussion of Equations 5.5a,b.

The weighting factors for storm/sewer flow events are initially given equal weightings but may be adjusted by the analyst. For example, an analyst may choose to place greater weight on sewer flow events of a magnitude near the once-per-year overflow frequency. Conversely, lesser weights may be given to the smallest sewer flow events or very large sewer flow events. The weighting factors for the storm/sewer flow events must sum to unity.

Step 11 – Compute Global Goodness-of-Fit Measures and Identify Best-Fit Model Parameter Set
Global goodness-of-fit measures ($GOFvolume_{global}$, $GOFvolumeStDev_{global}$, $GOFpeak_{global}$, $GOFrmse_{global}$) are computed for each storm/sewer flow event based on the single site-event goodness-of-fit measures at all flow measurement sites and storm sewer flow events. Model parameter sets can then be ranked by the analyst based on the magnitude of the user-selected global goodness-of-fit measure(s).

For example, lower and upper limits such as:

$95\% < GOFvolume_{global} < 105\%$ and

$80\% < GOFpeak_{global} < 120\%$

may be used to identify candidate model parameter sets along with a global GOF measure of variability for volume predictions ($GOFvolumeStDev_{global}$). Graphical comparisons of the simulated and recorded sewer flow hydrographs may then be used to select the best-fit model parameter set from amongst the candidate parameter sets.

The best-fit parameter set is chosen from amongst the candidate parameter sets based on a visual comparison of simulated and recorded hydrographs. The chosen best-fit parameter set would ideally have a global GOF measure for volume near 100%, a global GOF for standard deviation of volume that is small (near 10%), a global GOF measure for peak flow near 100%, and if the RMSE measure is valid, a global GOF for standardized RMSE that is also small (say less than 20%).

Step 12 – Sensitivity Plots

Sensitivity plots are used in a variety of ways in the automated calibration process. This includes:

- examining the behavior/sensitivity of GOF measures in response to model parameters
- adjusting the sampling range for each model parameter in successive iterative rounds
- confirming the model parameter space has been adequately sampled

Sensitivity plots should be prepared (Figures 5.9a,b,c) and the findings used to narrow the sampling range for each of the calibration parameters for the next round of computer simulations. Figure 9a shows an example of a sensitivity plot for a dominant model parameter with a strong relationship to the GOF measure. The sampling range could be narrowed to perhaps 0.03-m to 0.06-m for the next round of iterations. Figure 5.9b depicts the sensitivity for a model parameter where the sampling range was too narrow to yield a sufficient number of samples near a GOF measure near 100%. The sampling range should be adjusted to have a range of say 0.0 to 0.70 for this model parameter.

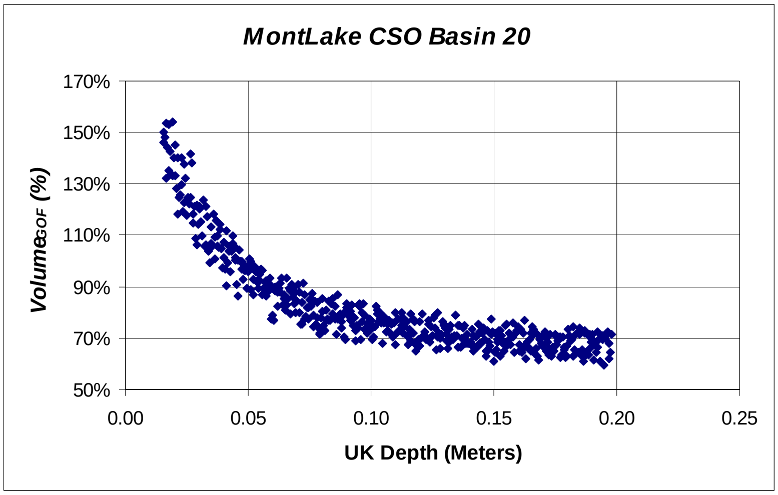


Figure 5.9a – Example, Sensitivity of Hydrograph Volume to Changes in UK Depth for InfoWorks Watershed Model

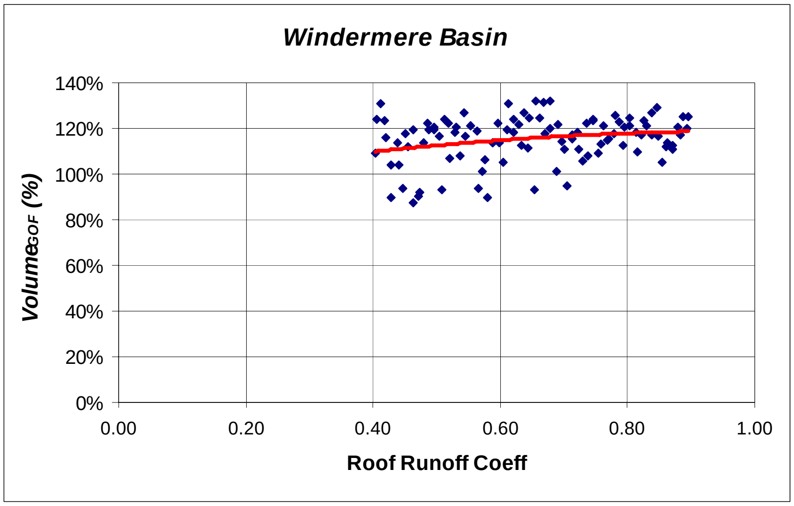


Figure 5.9b – Example, Sensitivity of Hydrograph Volume to Changes in Roof Runoff Coefficient for InfoWorks Watershed Model

Figure 5.9c depicts the sensitivity of a GOF measure to the deep percolation rate for one soil type in a large forested watershed. Review of the sensitivity plot indicates better replication of recorded hydrographs at small values near zero. However, the large variability of the scatterplot indicates that the deep percolation rate in this soil is not a dominant parameter and other model parameters are responsible for changes in the GOF measure.

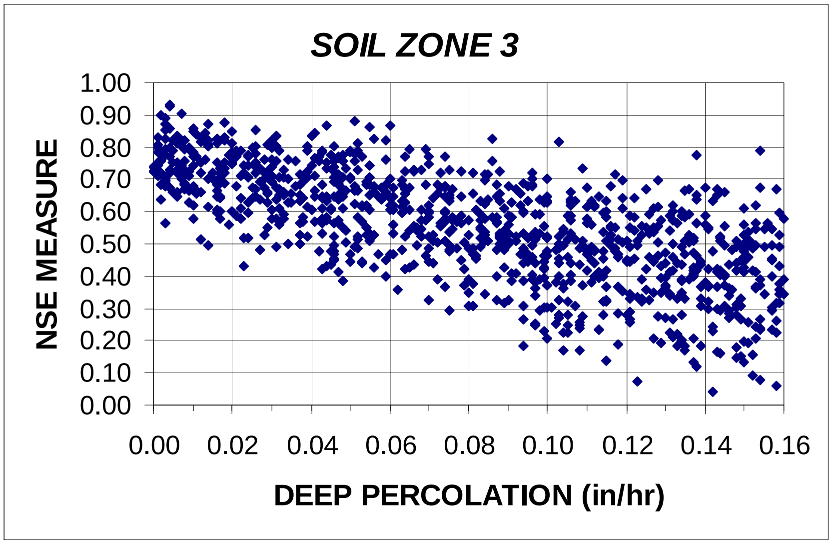


Figure 5.9c – Example, Sensitivity of a GOF Measure to the Deep Percolation Rate of a Soil for a Large Watershed in Central California

<u>Step 13 – Next Round of Iterations</u>

The process described in Steps 6 through 12 is repeated for each iterative round of simulations. In each iterative round, the sampling ranges for the model parameters are narrowed and additional simulations are conducted with the watershed model. The process concludes when only minimal improvement can be made in the global GOF measures with additional sampling and simulations. The best-fit model parameter set is then selected from amongst the candidate parameter sets.

6.0 ANALYSIS OF UNCERTAINTIES AND DEVELOPMENT OF UNCERTAINTY BOUNDS FOR CSO CONTROL VOLUME PERFORMANCE CURVES

The purpose of the uncertainty analysis is to determine the effects of uncertainties on the magnitude of sewer flows and overflow volumes predicted by the computer model. The findings of the uncertainty analysis are depicted as uncertainty bounds on the CSO Control Volume and provide a measure of the uncertainty/reliability of model predictions (Figure 2.1, Figure 6.9, Table 4). The graphics for the CSO Control Volume Performance Curve and Uncertainty Bounds for the CSO Control Volume are the cornerstone products for characterizing the magnitude of the sewer overflow volume that must be accommodated by CSO reduction measures.

6.1 Non-Linear Effects of Uncertainties in Predicted Sewer Flows

Uncertainties in predicted sewer flows generally have a non-linear effect that acts to amplify uncertainties in the estimation of overflow volumes and widen the uncertainty bounds for the CSO Control Volume (Figure 6.9). This non-linearity occurs because of the existence of the overflow weir at the outfall which diverts a portion of the sewer flows. This situation can be best explained by examining a sewer flow hydrograph and considering the effect of uncertainties in sewer flow magnitudes. Figure 6.1 shows two sewer flow hydrographs. The smaller hydrograph represents the sewer flow predicted by the computer model and the larger hydrograph represents the sewer flow hydrograph if the flows were actually 15% greater than that predicted by the model. Comparison of the volume of overflow over the outfall weir shows amplification of the overflow volume relative to the 15% difference in sewer flow. In this example, there is a 30% increase in overflow volume for a 15% increase in sewer flow magnitude. The converse is also true. If the actual sewer flows are smaller than predicted, there is a non-linear effect that acts to decrease sewer overflow volumes relative to that predicted by the model. In some cases, over-estimation of the actual sewer flows results in the model prediction of an overflow volume when no overflow actually occurs. This non-linearity of response acts to significantly widen the uncertainty bounds for the CSO Control Volume.

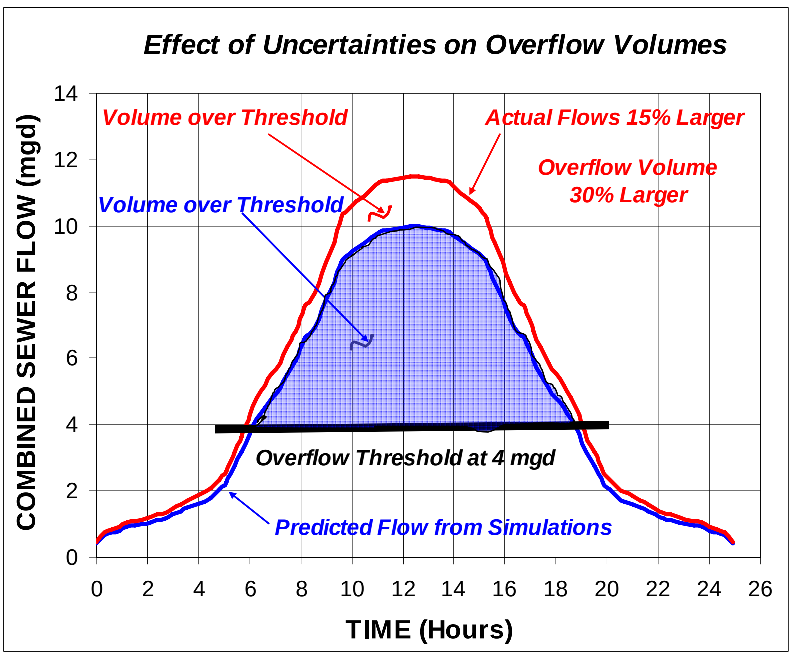


Figure 6.1 – Example of Non-Linear Effect of Uncertainties in Sewer Flows on Predicted Sewer Overflow Volumes

6.2 Overview of Uncertainty Analysis

The uncertainty analysis is conducted by examining the range of model predictions that could be produced considering the uncertainties in model inputs and uncertainties in model operations. This process can be envisioned from a conceptual starting point for the case where future precipitation is known and the "true" watershed model parameter set is known and yields highly accurate predictions of future sewer flows. For this hypothetical case, the future performance of the combined sewer system for the CSO basin would be determined with high accuracy by execution of the watershed model as driven by precipitation in the future period.

In reality, of course, precipitation in the future is not known, nor do we know the parameter set for the watershed model that yields predictions nearest to true field conditions. However, we do have 30-years of historical precipitation that provides a good estimate of future precipitation characteristics. We also have a best-fit model parameter set that is capable of reasonably replicating observed sewer flows and overflow volumes. The range of model predictions for the future, that includes the "true" future, can be examined by considering various scenarios of future precipitation and accounting for uncertainties that were observed in model predictions of historical sewer flows.

As described above, uncertainties in the future performance of the CSO system occur as the result of contributions of uncertainties from several sources. Three general sources of uncertainty are listed below and will be examined in detail in the following sections:

- uncertainties in precipitation inputs for the future period, including climate change;
- uncertainties in predicted sewer flows from the watershed model of the CSO basin; and
- residual uncertainties (catch-all for uncertainties not captured by prior two components).

The uncertainty analysis proceeds by examining the model predictions for various plausible models of future conditions. Plausible future models are assembled by selecting plausible values of future conditions for the various components that contribute uncertainty to the model predictions. Ideally, uncertainty in a given component in the CSO system would be addressed in the uncertainty analysis by sampling from the probability distribution for uncertainties for that component. This can readily be done for the uncertainty components associated with future precipitation by use of a precipitation scaling factor applied to the 32-year historical precipitation time-series. The precipitation scaling factor acts to increase or decrease precipitation observed in the historical 32-year period as a plausible representation of future conditions.

Mimicking uncertainties in model predictions and residual uncertainties is not as straightforward because there is not a practical approach to altering computed sewer flows at all the computational nodes within the watershed model. However, sewer flows can be modified to mimic the effect of model uncertainties by application of a precipitation scaling factor. The underlying concept is that the magnitude of precipitation directly affects the magnitude of sewer flows. Therefore, precipitation scaling factors may be used as a surrogate mechanism to mimic the effect of uncertainties in the predicted sewer flows.

As discussed previously, plausible future models are assembled by selecting plausible values of future conditions for the various components that contribute uncertainty to the model predictions. Latin-Hypercube sampling methods (McKay et al[8] and Wyss and Jorgenson[19]) are used to assemble plausible future models comprised of combinations of future precipitation with the best-fit calibrated watershed model. These plausible future models are executed and outputs of sewer flows and overflow volumes are produced. The outputs from these plausible models of the future provide a sample-set of possible future performance of the CSO system that can be analyzed to produce both a best-estimate CSO Control Volume and uncertainty bounds. All of these tasks and execution of the plausible future models are performed within the *ACU-SWMM* computer program.

6.3 Uncertainties in Precipitation Inputs

For purposes of conducting the uncertainty analysis, uncertainties in precipitation inputs are considered to be associated with uncertainties in storm characteristics in the future period where model predictions are needed. Uncertainties in future storms characteristics can be viewed as having two components. First, uncertainties arise in using the precipitation record from 1978 to 2009 (rain gages in SPU network) to represent storm characteristics in the future period. These uncertainties can be evaluated from standard sampling theory for a 32-year record assuming a stationary climate. The second component considers the possible effects of climate change and that the climate may not be stationary over the future period of CSO system operation.

6.3.1 Uncertainties in Future Precipitation (Stationary Climate)

Sampling variability associated with the 32-year record of precipitation can be simulated by rescaling of the precipitation time-series by a scaling factor whose magnitude reflects uncertainty in the magnitude of future storms. This may be envisioned as scaling the *n*-largest storms that cause sewer overflows such as depicted in Figure 2.2. The uncertainty in the magnitude of the precipitation scaling factor can be modeled with a Normal probability distribution with a mean of unity and a standard deviation equal to Cv/sqrt(32), where Cv is the coefficient of variation for the precipitation duration(s) most responsible for causing the largest sewer overflows. Experience to date indicates that large sewer overflows are predominately associated with precipitation durations in the range of 6-hours through 48-hours. Coefficients of variation for precipitation annual maxima series for these durations are in the range of 0.26 to 0.29 for the Seattle area (Schaefer et al[10,11,12,13]). Application of these values equates to a standard deviation of about 0.05 (5%) for the precipitation scaling factor. Figure 6.2 depicts the uncertainty in the precipitation scaling factor in using the 1978-2009 period to represent storm characteristics in the future.

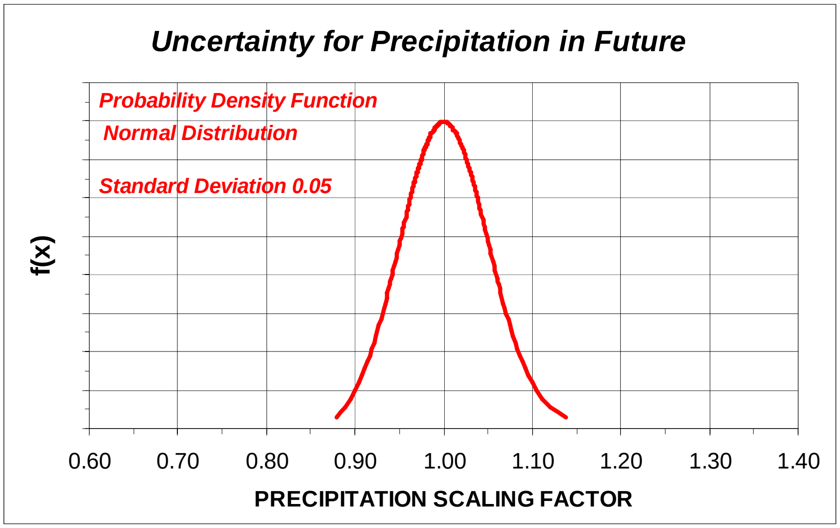


Figure 6.2 – Uncertainty in Precipitation Scaling Factor for Precipitation in Future Periods

6.3.2 Uncertainties in Future Precipitation Due to Climate Change

The subject of climate change is fraught with uncertainty. Consensus in the scientific community suggests that the effects of climate change have been ongoing for some time. If that is the case, then the storm characteristics contained in the precipitation record from 1978 to present already reflect influences of climate change. The issue of interest for CSO modeling is - what additional increase in storm frequency and/or storm magnitude may occur in the next planning/operational period?

This is a very difficult question to answer quantitatively. The question was addressed by considering the effect of increases in sea-surface temperature on levels of atmospheric moisture. For example, an increase of sea-surface temperature and dewpoint of 1°F results in a potential increase in atmospheric moisture of 5% for sea-surface dewpoints in the general range of 50°F, which are common in our fall-winter storm season. This is based on consideration of precipitable water and a saturated pseudo-adiabatic atmosphere. Consideration of a range of no change in sea-surface temperature to a maximum increase of 3°F for storms originating over the Pacific Ocean, suggests potential increases in storm magnitude of from zero to 15%.

An empirical likelihood function was constructed (Figure 6.3) reflecting the simple concepts outlined above with a mode representing a 5% increase in storm magnitude (1°F) and a maximum increase of 15% (3°F). Sampling from this likelihood function yields a mean value of the precipitation scaling factor of 1.06 and a standard deviation of 0.034. This empirical likelihood function will be used as the default selection for uncertainties due to climate change until something more rigorous can be developed.

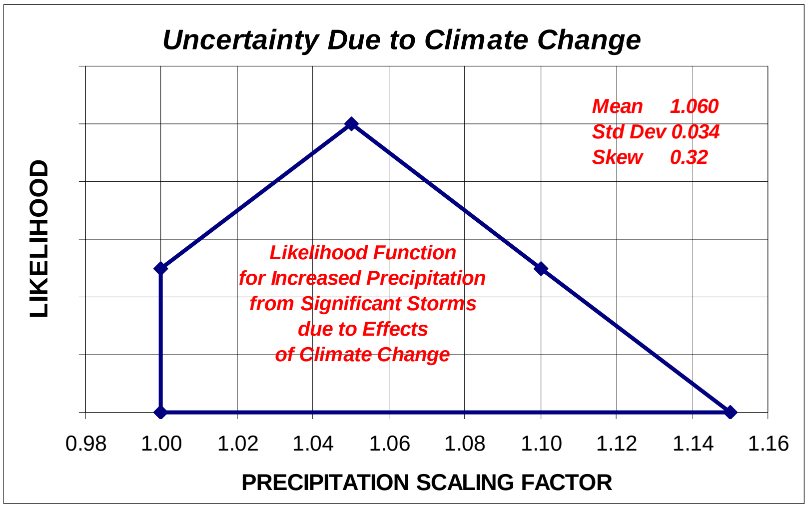


Figure 6.3 – Uncertainty in Precipitation Scaling Factor Due to Climate Change

6.4 Uncertainties in Predictions from Watershed Modeling of CSO Basin

Uncertainties associated with prediction of sewer flows from the watershed model of the CSO basin arise from several sources including:

- differences in the actual spatial and temporal distribution of precipitation for the CSO Basin relative to that measured at the nearby precipitation gage(s);
- imperfect information on the connection of rooftops, yard drainage, driveway and roadway drainage into the combined sewer system;
- imperfect algorithms in the watershed model with regard to computing the hydrologic response of CSO basins and the hydraulic operation of complex sewer systems;
- uncertainties in the actual discharge characteristics and operation of hydraulic structures, hydrobrakes, pump stations and overflow weirs; and
- uncertainties in the accuracy of flow measurements at the various flow measurement sites that are used for calibrating the watershed model.

Ideally, uncertainties in watershed model predictions would be mimicked by adjusting the runoff predictions at each computational node in the watershed model. This approach is impractical or impossible for most watershed models. As an alternative, a precipitation scaling factor is applied to the 32-year historical precipitation time-series to mimic uncertainties in the prediction of sewer flows from the best-fit calibrated watershed model. The underlying assumption in the use of precipitation scaling factors is that a given increase (decrease) in precipitation magnitude causes a near-linear increase (decrease) in sewer flows for highly urbanized areas in response to storms of a magnitude of once-per-year or greater. The magnitude of the precipitation scaling factor appropriate for mimicking uncertainties in sewer flow predictions is determined from global goodness-of-fit measures that are computed during automated calibration of the watershed model. These goodness-of-fit measures are a subset of the global goodness-of-fit measure (GOF_{global}) described in Chapter 5.

With regard to the uncertainty analysis, the accuracy of prediction of sewer flow volumes is of primary interest. The first goodness-of-fit statistic is a standardized measure of the difference between recorded and simulated volumes for all sewer flows events and all flow measurement sites. This is measured by a global standardized mean ($Mean_{global}$). The second goodness-of-fit statistic is a standardized measure of the variability of the difference in recorded and simulated sewer flow volumes for all events and flow metering sites. This is measured by a global standardized standard deviation ($StDev_{global}$). Both measures are weighted statistics that allow different weights (importance) to be placed on each sewer flow event and each flow measurement site (see Chapter 5).

Experience to date (Nov 2009) is to assign the weights by judgment based on a combination of factors. In some cases, the analyst may choose to weight the storm/sewer flow events equally. In other cases, the analyst may choose to give greater weight to storm/sewer flow events that are nearest to the once-per-year frequency. Conversely, less weight may be given to those events where there is lower confidence in the precipitation inputs and flow measurements. The decisions on weightings are made during the automated model calibration process described in Chapter 5. Thus, for the individual storm/sewer flow events:

$$1 = \sum_{m=1}^{MM} EventWeight_m \tag{6.1}$$

where: $Event\ Weight_m$ is the weighting for storm/sewer flow event m of MM total events, and the individual event weights sum to unity.

The global standardized measure of the mean of the flow volume is computed as:

$$Mean_{global} = \sum_{m=1}^{MM} EventWeight_m \sum_{k=1}^{KK} \left(Volume_{GOF\ k,m} * SiteWeight_{k,m} \right) \tag{6.2}$$

where: $Volume_{GOF\ k,m}$ is the standardized measure of volume (Equation 5.1b) for sewer flow event m and flow measurement site k.

The global standardized measure of the standard deviation of flow volume is computed as:

$$Variance_{global} = \sum_{m=1}^{MM} EventWeight_m \sum_{k=1}^{KK} \left(\left(Volume_{GOF\ k,m} - Mean_{global} \right)^2 * SiteWeight_{k,m} \right) \tag{6.3a}$$

$$StDev_{global} = \sqrt{Variance_{global}} \tag{6.3b}$$

The Normal probability distribution is used to describe uncertainties in sewer flow model predictions using precipitation scaling factors as a surrogate to produce larger or smaller sewer flows. Two examples of the distribution of model uncertainties are shown in Figures 6.4a,b. The first case (Figure 6.4a) is where the model predictions are unbiased (*MEANglobal* = 1.00) and the mean of the uncertainty distribution ($Mean_{ModelUncertainty}$) equals 1.00. The second case (Figure 6.4b) is for the situation where the model predictions were over-simulating the recorded sewer flows by 3% (*MeanGlobal*=1.03) and thus the mean of the uncertainty distribution is adjusted downward to compensate for the over-simulation by the model to yield unbiased predictions. For this example, the mean of the uncertainty distribution for precipitation scaling is adjusted such that $Mean_{ModelUncertainty}$ = 0.97. This procedure is described in Step 3 in the following section.

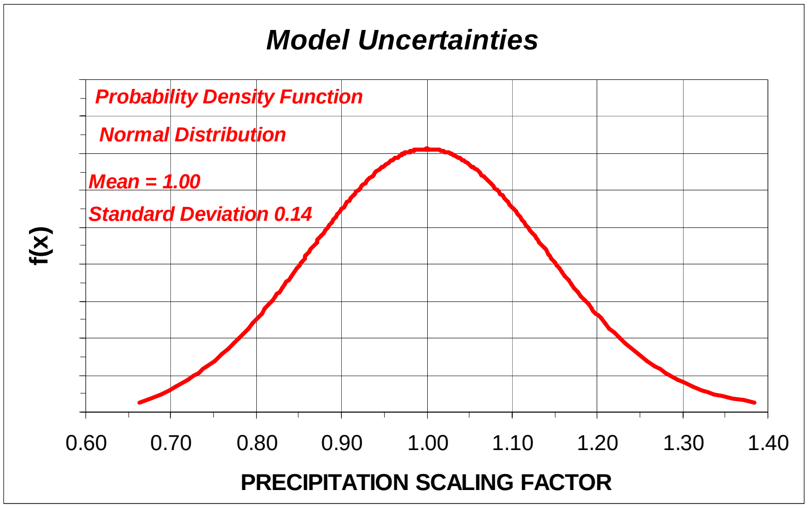


Figure 6.4a – Use of Precipitation Scaling Factors as a Surrogate for Uncertainties in Model Sewer Flow Predictions, Case of Unbiased Model Predictions

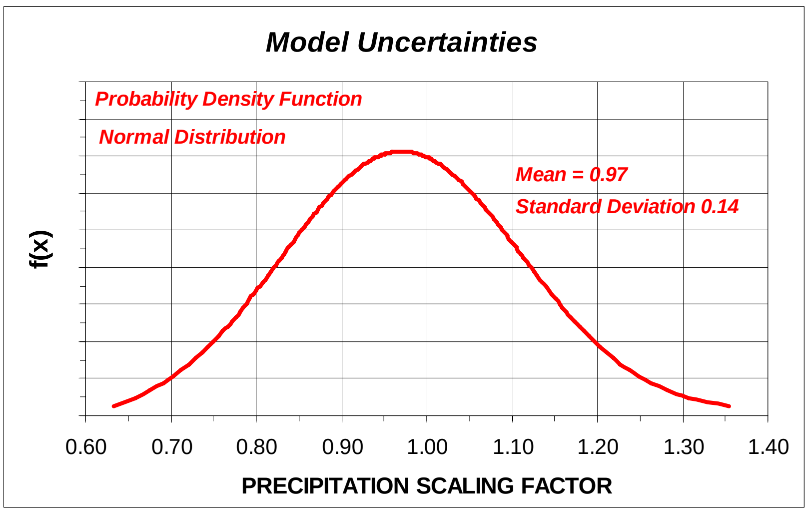


Figure 6.4b – Use of Precipitation Scaling Factors as a Surrogate for Uncertainties in Model Sewer Flow Predictions, Adjusted to Correct Biased Model Predictions

Application of the two measures of uncertainty in prediction of sewer flows will be discussed in Step 3 of Section 6.6. All of the computations described above are made within the *ACU-SWMM* computer program during the automated model calibration process described in Chapter 5.

6.5 Residual Uncertainties

In conducting an uncertainty analysis, it is difficult to characterize all of the uncertainties from multiple sources. Use of a residual uncertainty component is an attempt to capture uncertainty from several sources that are not readily amenable to being characterized directly. Examples of uncertainty that could be covered by the residual uncertainty component would include:

- spatial precipitation characteristics in the 1978-2009 precipitation record from the nearby gage(s) that were not represented in the short record used for watershed model calibration;
- runoff conditions in the CSO basin in the 1978-2009 period that were not represented in the short record used for watershed model calibration;
- sewer flow conditions in the combined sewer system in the 1978-2009 simulation of sewer flows and overflow volumes that were not represented in the short record used for watershed model calibration;
- uncertainties in the accuracy of flow measurements for the various flow measurement sites used for calibration of the watershed model that are not addressed by the measure of model uncertainties;
- uncertainties in the hydraulics of the outfall structure and overflow weir that are not addressed by the measure of model uncertainties; and
- other basin-specific and CSO system-specific sources.

Ideally, uncertainty in a given component in the CSO system would be addressed in the uncertainty analysis by sampling from the probability distribution for uncertainties for that component. This approach is impractical considering the number of sources of uncertainty and the difficulty of quantifying the magnitude of each uncertainty. For the case of residual uncertainties from multiple sources, a precipitation scaling factor may be used, similar to that used for the uncertainties in precipitation inputs. Figure 6.6 depicts an example of the uncertainty distribution for the precipitation scaling factor as a surrogate for residual uncertainties.

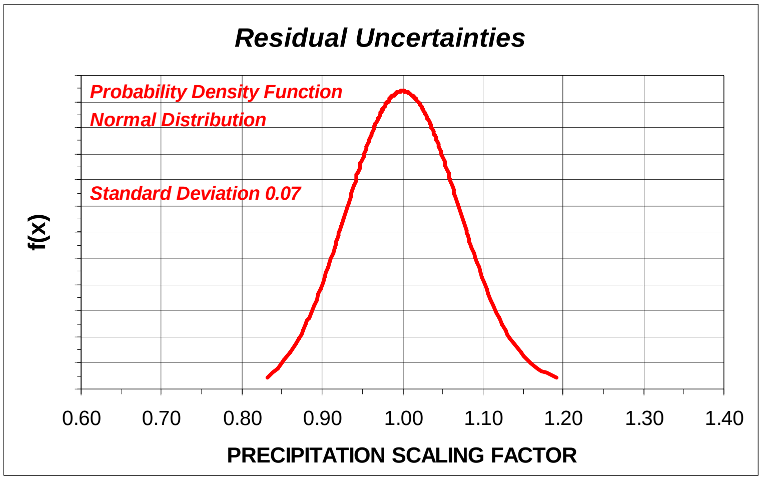


Figure 6.6 – Use of Precipitation Scaling Factor as a Surrogate for Residual Uncertainties from Multiple Sources

The example shown in Figure 6.6 has a standard deviation of 0.07 (7%) for the precipitation scaling factor. It is the responsibility of the analyst to select the magnitude of the standard deviation for the precipitation scaling factor based on consideration of the basin-specific components of the CSO system under investigation. Table 6.2 is provided as a general guide to assist in the selection of the precipitation scaling factor representing residual uncertainty.

Based on the current level of experience with the operation of various CSO basins, residual uncertainties have been considered to be in the range of about 4% to 15%. To date (Nov 2009), residual uncertainties have typically been rated in the 4% to 8% range. Ratings exceeding these values have been due to one or more major uncertainties associated with hydraulic operation of the system (pumps, hydrobrakes and overflow structures).

6.5.1 Rating of Residual Uncertainties

The following three questions may provide some assistance in assessing the magnitude of residual uncertainties through discussion by the CSO Modeling Team.

1. What is the level of adequacy of the collection of storms in the calibration period for providing a representative sample of storm magnitudes? Ideally, there would be some storms with a magnitude below, near, and greater than the once-per-year frequency storm. Similarly, what is the level of adequacy of the collection of sewer overflow volumes in the calibration period for providing a representative sample of sewer overflow magnitudes similar to the once-per-year frequency?

    If the sample set of recorded storms and sewer overflow volumes provide a good range of magnitudes that bracket the once-per-year frequency storm and sewer overflow volume, there would be minimal or no residual uncertainty.

2. What is the level of adequacy of the number and location of sewer flow meters to characterize the hydrologic response of the basin and hydraulic operation of the system and produce representative Goodness-of-Fit measures for model uncertainty?

    If there are many meters well-distributed throughout the basin, then there is minimal residual uncertainty. Conversely, if there is only one meter or the spatial distribution of meters is insufficient to be representative of the basin, there would be greater residual uncertainty.

    A framework for characterizing uncertainties associated with the adequacy of the storm sample (Question 1) and the adequacy of the number and location of sewer flow meters (Question 2) is needed to provide consistent rating across CSO Basins. Table 6.1 is provided for rating purposes.

Table 6.1 – Categories for Rating of Adequacy of Storms and Meters Used for Model Calibration

CATEGORIES FOR RATING OF ADEQUACY OF STORMS AND METERS			
Poor	Adequate	Good	Excellent

3. What uncertainties remain about elements of the watershed model that result in uncertainties in computation of sewer overflow volumes? What is the level of confidence in the watershed model to mimic operation of the sewer system for generating sewer overflow volumes?

    If uncertainties about CSO system operation remain that contribute to uncertainties in estimation of overflow volumes and the CSO Control Volume, these uncertainties would be contributors to the residual uncertainty. A list of uncertainties (unknowns) should be created and each source of uncertainty should be rated as *minor*, *moderate* or *major*.

The following Table is provided as a general guide in assessing the magnitude of residual uncertainties after the preceding three questions have been thoroughly discussed by the CSO modeling team. The level of residual uncertainties identified for CSO Basins in the Windermere, Genesee and Henderson projects can also provide guidance in the selection of residual uncertainties.

Table 6.2 – Guidance in Selecting Magnitude of Residual Uncertainties for Uncertainty Analysis

JUDGMENT OF RELATIVE MAGNITUDE OF RESIDUAL UNCERTAINTIES ASSOCIATED WITH WATERSHED MODELING OF CSO BASIN AND COMBINED SEWER SYSTEM	STANDARD DEVIATION OF PRECIPITATION SCALING FACTOR
Minor Level of Residual Uncertainties Large Portion of Uncertainties Captured by Model Uncertainties Component	4%
Moderate Level of Residual Uncertainties	7%
High Level of Residual Uncertainties	10%
Very High Level of Residual Uncertainties (Example - Sewer Overflow Volumes Cannot Be Measured Directly and were not Used in the Automated Calibration Process)	15%

6.6 Procedures for Conducting Uncertainty Analysis to Determine Best-Estimate CSO Control Volume and Uncertainty Bounds

The uncertainty analysis has been automated to simplify application and to reduce the computational effort. The following list describes the sequence of steps that are taken to determine the best-estimate CSO Control Volume and uncertainty bounds. These procedures may be modified from time-to-time as experienced is gained about uncertainties in watershed modeling of CSO basins.

The following procedures are executed for each CSO Basin where a CSO Control Volume is required.

Step 1 – Select the mean and standard deviation of the precipitation scaling factor for describing uncertainties associated with precipitation in the future period. See Section 6.3.1 for details. Enter a mean value of 1.00 and a standard deviation of 0.050 for the Normal Probability Distribution on the data entry form of the *ACU-SWMM* computer program (Screen Shot 6.1a).

Step 2 – Select the default Trapezoidal Probability Distribution for the precipitation scaling factor for describing uncertainties associated with precipitation due to climate change in the future period. The minimum, mode, and maximum precipitation scaling factors and the associated likelihoods for uncertainties due to climate change are preset (Screen Shot 6.1a). See Section 6.3.2 for details.

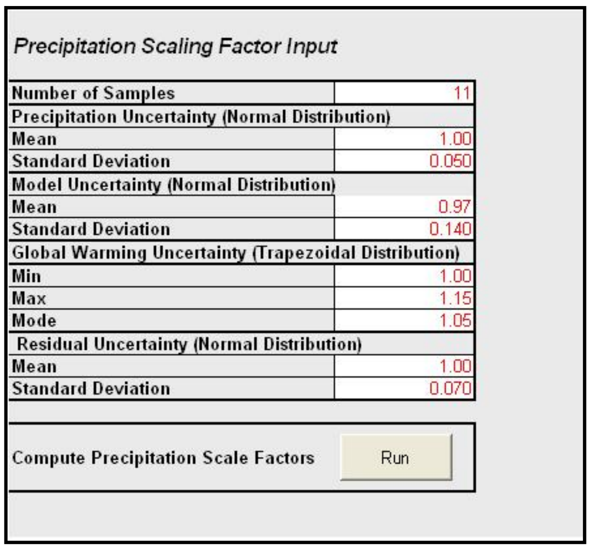
Step 3 – Select the mean and standard deviation of the precipitation scaling factor for describing uncertainties associated with predictions of sewer flows from the watershed model. See Section 6.4 for details. The value of the mean includes an adjustment to correct for bias in the sewer flow predictions from the watershed model. For the case of zero bias (volume simulated equals volume recorded), the mean value would be unity. The value of the mean of the precipitation scaling factor ($Mean_{ModelUncertainty}$) to account for model uncertainties is computed as:

$$Mean_{ModelUncertainty} = 2 - Mean_{global} \tag{6.4}$$

where: $Mean_{ModelUncertainty}$ and $Mean_{global}$ are expressed as decimal values, not percentages.

The value of the standard deviation for the precipitation scaling factor for mimicking model uncertainties is determined from the $StDev_{global}$ value computed in the automated model calibration phase (Equation 6.3b) and the number and weighting of storms. Enter the values of $Mean_{ModelUncertainty}$ and $StDev_{global}$ for the Normal Probability Distribution on the data entry form of the *ACU-SWMM* computer program (Screen Shot 6.1a). Also enter the non-zero storm weights used in computing the goodness-of-fit measures for model uncertainty (Screen Shot 6.1b).

Step 4 – Select the mean and standard deviation of the precipitation scaling factor for describing residual uncertainties. See Section 6.5 for details. Enter a mean value of 1.00 and the selected standard deviation value for the Normal Probability Distribution on the data entry form of the *ACU-SWMM* computer program (Screen Shot 6.1a).



Precipitation Scaling Factor Input

Number of Samples	11
Precipitation Uncertainty (Normal Distribution)	
Mean	1.00
Standard Deviation	0.050
Model Uncertainty (Normal Distribution)	
Mean	0.97
Standard Deviation	0.140
Global Warming Uncertainty (Trapezoidal Distribution)	
Min	1.00
Max	1.15
Mode	1.05
Residual Uncertainty (Normal Distribution)	
Mean	1.00
Standard Deviation	0.070
Compute Precipitation Scale Factors	Run

Screen Shot 6.1a – (Placeholder) Data Entry Format for Precipitation Scaling Factors for Use in Uncertainty Analysis

(Awaiting Graphic)

Screen Shot 6.1b – Data Entry Format for Storm Weights Used in Uncertainty Analysis

Computation of Composite Precipitation Scaling Factors
Latin-Hypercube sampling methods are used within the *ACU-SWMM* computer program to assemble a sample-set of 500 composite precipitation scaling factors for the four sources of uncertainty - future precipitation, climate change, prediction of sewer flows from the watershed model and residual uncertainty. For each sample of the sample set of 500, the four precipitation scaling factors are combined by addition to produce a composite precipitation scaling factor. An empirical cumulative distribution function is developed using non-parametric ranking methods for the 500 composite precipitation scaling factors. Examples of the outcome of this process are shown in Figures 6.6a,b,c.

Figure 6.6a depicts a histogram of the composite precipitation scaling factor for uncertainties in future precipitation including climate change. Figure 6.6b shows a histogram with an increase in the composite precipitation scaling factor due to the addition of uncertainties for prediction of sewer flows from the watershed model and residual uncertainties. Lastly, Figure 6.6c depicts a probability-plot of the composite precipitation scaling factor for the data in Figure 6.6b, which shows the data are well described by a Normal Distribution.

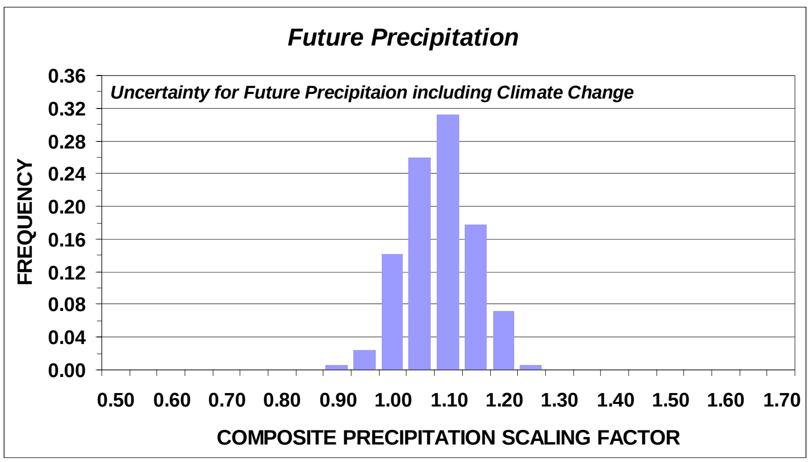


Figure 6.6a – Example Histogram of Composite Precipitation Scaling Factors for Uncertainties in Future Precipitation including Climate Change

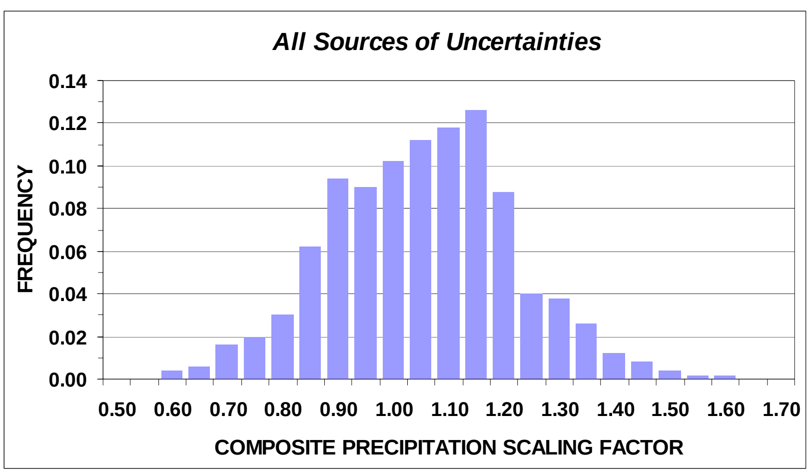


Figure 6.6b – Example Histogram of Composite Precipitation Scaling Factors for Uncertainties in Future Precipitation including Climate Change, Prediction of Sewer Flows from the Watershed Model and Residual Uncertainties

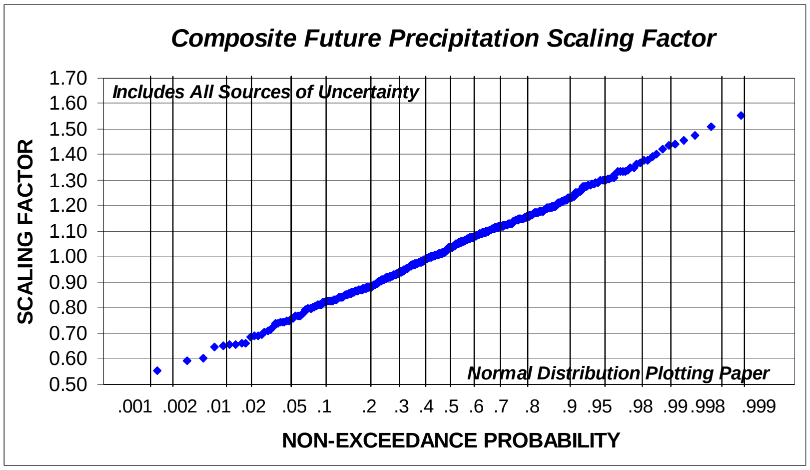


Figure 6.6c – Example Probability-Plot of Composite Precipitation Scaling Factors for Uncertainties in Future Precipitation including Climate Change, Prediction of Sewer Flows from the Watershed Model and Residual Uncertainties

Latin-Hypercube sampling procedures are then used to select 11 composite precipitation scaling factors (Table 6.2) from the empirical cumulative distribution function (Figure 6.6c) that in conjunction with the best-fit calibrated model parameter set constitute the 11 Plausible Future Models. This task is accomplished within *ACU-SWMM*.

Table 6.2 – Example Latin-Hypercube Sample of Composite Precipitation Scaling Factors

PLAUSIBLE FUTURE MODEL	COMPOSITE PRECIPITATION SCALING FACTOR
1	0.747
2	0.847
3	0.897
4	0.947
5	0.994
6	1.035
7	1.075
8	1.113
9	1.148
10	1.197
11	1.308

Computation of CSO Control Volume for 11 Plausible Future Models
Overflow volumes and CSO Control Volumes for the 11 Plausible Future Models are computed as follows.

Step 5 – Long term simulations are conducted for the watershed model for each of the 11 Plausible Future Models. Each execution of an Plausible Future Model consists of scaling the 1978-2009 precipitation time-series at the nearby representative gage(s) by one of the composite precipitation scaling factors (Table 6.2) and utilizing the best-fit calibrated model parameter set.

Step 6 – Overflow volumes are computed for each of the 11 Plausible Future Models which are then used to compute the once-per-year CSO Control Volume for each Plausible Future Model. The CSO Control Volume is computed for each Plausible Future Model as the *m* largest overflow volume for the *m* years of generated sewer flows from the long-term simulations. Table 6.3 lists an example of the results from the long-term simulations. CSO Control Volume Performance Curves may also be generated for each Plausible Future Model and would look similar to that depicted in Figure 6.7. The range of performance curves in Figure 6.7 provides a good indication of the effects of uncertainties on estimating the required CSO Control Volume.

Table 6.3 – Example CSO Control Volumes Estimated For Plausible Future Models

PLAUSIBLE FUTURE MODEL	COMPOSITE PRECIPITATION SCALING FACTOR	CSO CONTROL VOLUME (mg)
1	0.747	1.50
2	0.847	1.97
3	0.897	2.45
4	0.947	2.70
5	0.994	2.95
6	1.035	3.10
7	1.075	3.35
8	1.113	3.70
9	1.148	4.00
10	1.197	4.50
11	1.308	5.30

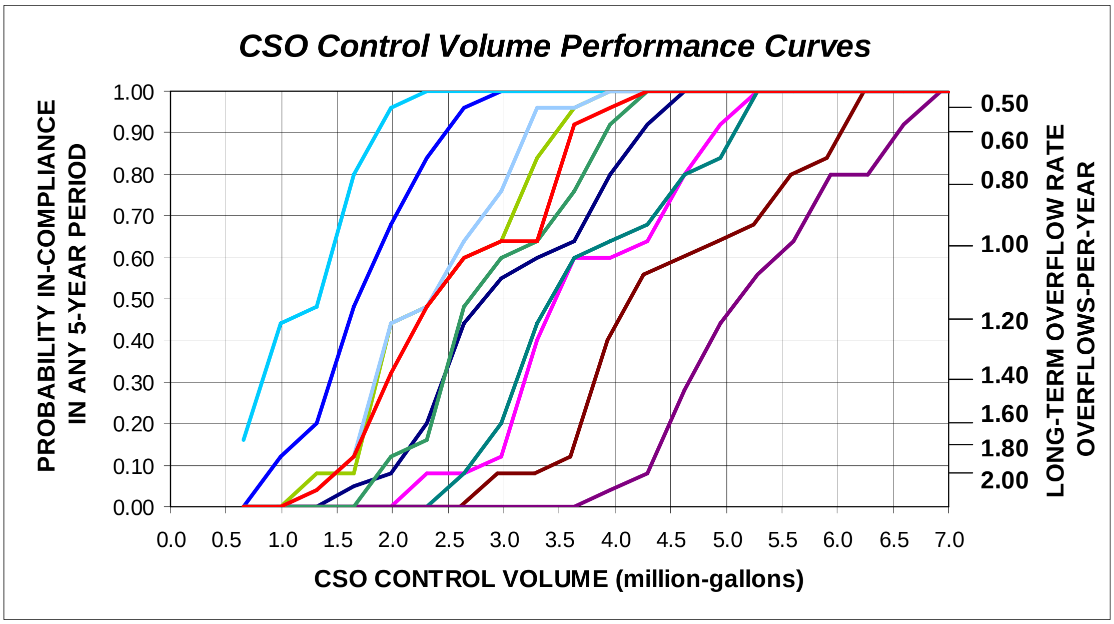


Figure 6.7 – Example CSO Control Volume Performance Curves for Plausible Future Models

Computation of Best-Estimate CSO Control Volume and Uncertainty Bounds

Step 7 – The best-estimate CSO Control Volume Curve is computed as the arithmetic mean (average) of the sample set of 11 CSO Control Volumes (Table 6.3). Uncertainty Bounds are computed for the best-estimate CSO Control Volume by fitting a 3-parameter Gamma Distribution (Hosking and Wallis[xx]) to the sample set of 11 CSO Control Volumes (Figure 6.8). These computations are done within *ACU-SWMM* and are output as shown in Screen Shot 6.2. An example of the results from this process is displayed in Figure 6.9 and Table 6.4. It is intended that the results of the uncertainty analysis would be presented to decision-makers in the form shown in Figure 6.9 and Table 6.4.

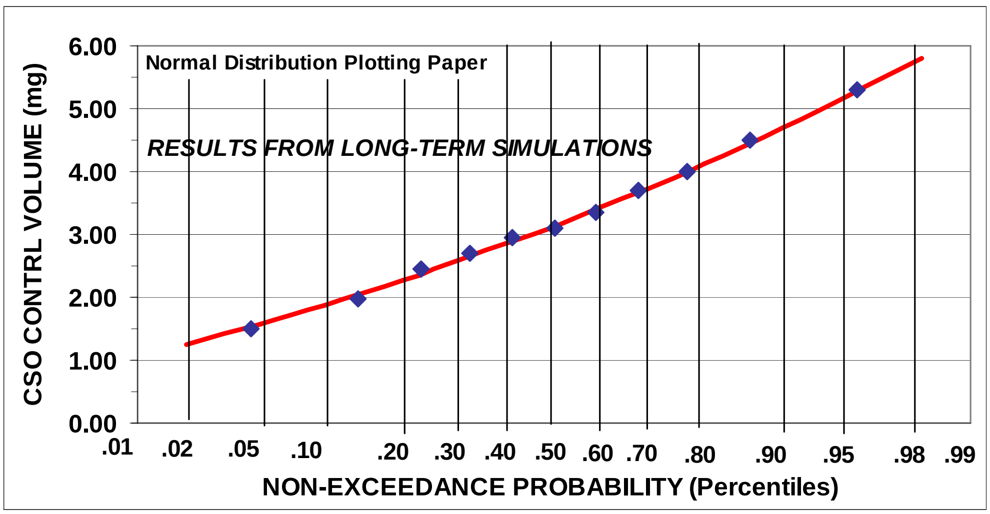


Figure 6.8 – Example Distribution of CSO Control Volumes from Uncertainty Analysis

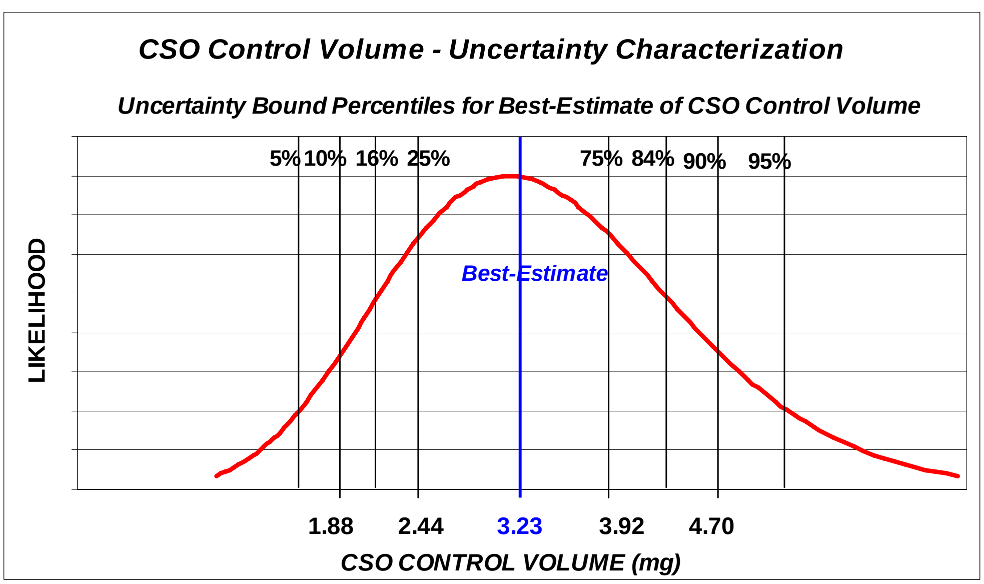


Figure 6-9 – Example Uncertainty Bounds for Best-Estimate CSO Control Volume

Table 6.4 – Uncertainty Bound Percentiles for Best-Estimate of CSO Control Volume

UNCERTAINTY BOUNDS FOR BEST-ESTIMATE OF CSO CONTROL VOLUME (Million Gallons)									
CSO BASIN	**UNCERTAINTY BOUND PERCENTILES**								
	5%	**10%**	**16%**	**25%**	**Best Estimate**	**75%**	**84%**	**90%**	**95%**
Example	1.58	1.88	2.14	2.44	3.23 mg	3.92	4.32	4.70	5.20

(Awaiting Graphic)

Screen Shot 6.2 – Output for Best-Estimate CSO Control Volume and Uncertainty Bounds

Computation of Sewer Overflow Amplification Factor

<u>Step 8</u> – As described in Section 6.1, amplification of overflow volumes commonly occurs due to the existence of the overflow weir at the outfall structure. The magnitude of amplification can be estimated by constructing a plot (Figure 6.10) depicting the once-per-year overflow volumes for the 11 Plausible Future Models and the corresponding composite precipitation scaling factors.

The procedure is to use the slope of the curve shown in Figure 6.10 in the vicinity of a precipitation scaling factor of 1.0 to determine how changes in the magnitude of sewer flows relates to changes in the precipitation scaling factor. Sewer overflow volume amplification is computed as:

$$Amplification = \left(\frac{\Delta\, CSO\, Control\, Volume}{\Delta\, Composite\, Precipitation\, Scaling\, Factor\ *\ CVOL_{1.0}} \right) \tag{6.5}$$

where: $CVOL_{1.0}$ is the once-per-year Control Volume generated by a precipitation scaling factor of 1.0 in Figure 6.10; *ΔCSO ControlVolume* is the change in the CSO Control Volume for a corresponding change in the precipitation scaling factor *ΔCompositePrecipitationScalingFactor* as obtained from the data used to develop Figure 6.10, both measures are centered about a precipitation scaling factor of 1.00.

This procedure can best be explained by an example. Using Figure 6.10, the change in the CSO Control Volume for a change in the composite precipitation scaling factor of from 0.90 to 1.10 corresponds to approximately 1.31 million-gallons. The value of $CVOL_{1.0}$ from Figure 6.10 is 2.97 million-gallons. Equation 6.5 yields a value of 2.21 for the amplification factor.

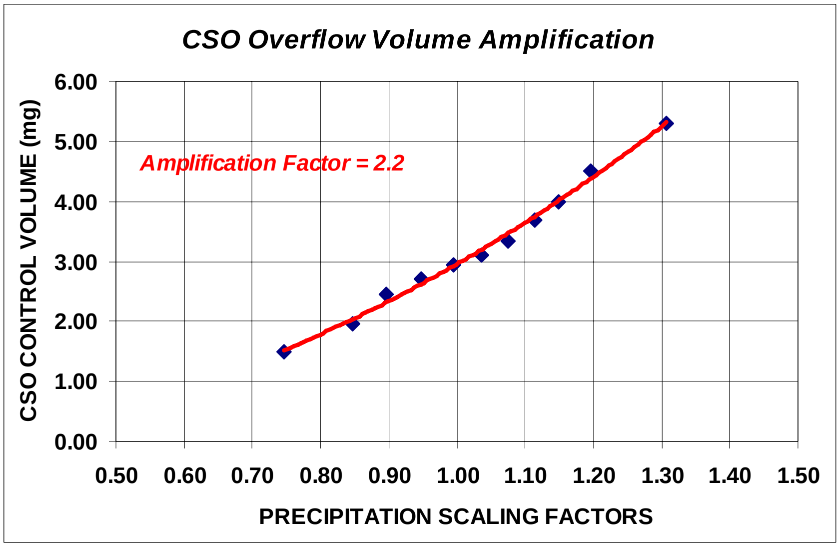


Figure 6.10 – Example Plot of Composite Precipitation Scaling Factors and Resultant Once-Per-Year CSO Control Volume for 11 Plausible Future Models for Computing CSO Overflow Volume Amplification Factor

6.7 Procedures for Conducting Uncertainty Analysis when a Watershed Model Contains Multiple CSO Basins

In assembling a watershed model for a portion of the city, it is common that multiple CSO basins are grouped together as part of the watershed model. In conducting the uncertainty analysis for a CSO Control Volume, it is also common that a different suite of 11 precipitation scaling factors are needed for each CSO Basin. This occurs because different magnitudes of model uncertainties and residual uncertainties are applicable for the various CSO Basins.

Considering the time and cost of conducting the long-term 32-year simulations, a procedure is needed to reduce the number of long-term simulations that would otherwise be needed for the group of CSO Basins. This can be accomplished by revising Steps 5 and 6 that were presented earlier. The revised procedure for multiple CSO Basins is described below.

<u>Step 5 for Multiple CSO Basins</u> – Assemble the collection of 11 precipitation scaling factors generated in Step 4 for each of the CSO basins. Identify the maximum and minimum precipitation scaling factors for the entire collection. Enter these values into the data entry screen in *ACU-SWMM* shown in Screen Shot 6.3. A sample set of 15 precipitation scaling factors will be generated to span the range encompassed by the collection of scaling factors for the multiple CSO Basins.

Long term simulations are then conducted for the watershed model for each of the 15 precipitation scaling factors. Each execution of the watershed model consists of scaling the 1978-2009 precipitation time-series at the nearby representative gage(s) by one of the 15 precipitation scaling factors (Screen Shot 6.3) and utilizing the best-fit calibrated model parameter set for each CSO Basin.

SAMPLE SET	SAMPLING PERCENTILE	PRECIPITATION SCALING FACTOR
1	0.033	Minimum Value
2	0.100	**Generated Values**
3	0.167	**From ACU-SWMM**
4	0.233	
5	0.300	
6	0.367	
7	0.433	
8	0.500	
9	0.567	
10	0.633	
11	0.700	
12	0.767	
13	0.833	**Generated Values**
14	0.900	**From ACU-SWMM**
15	0.967	Maximum Value

(Awaiting Graphic)

Screen Shot 6.3 – Data Entry and Output Format for Computing Sample Set of 15 Precipitation Scaling Factors to be Used for Conducting Uncertainty Analyses for Multiple CSO Basins

Step 6 for Multiple CSO Basins – For each CSO basin, overflow volumes are computed from the long-term simulations for each of the 15 long-term simulations. The overflow volumes for each long-term simulation are then used to compute the once-per-year CSO Control Volume for each of the 15 long-term simulations for each CSO Basin. As before, the CSO Control Volume is computed for each long-term simulation as the *m* largest overflow volume for the *m* years of generated sewer flows.

For each CSO Basin, a plot is then made of the 15 precipitation scaling factors and the resultant CSO Control Volumes, similar to that shown in Figure 6.10. A regression equation is then fitted to the data, such as a 2^{nd} order polynomial. The 11 CSO Control Volumes for the Plausible Futures can then be obtained from the regression equation for each of the 11 precipitation scaling factors (Step 4) that are applicable to a given CSO Basin. This yields the sample set of 11 CSO Controls Volumes applicable to a given CSO Basin to be used for computing the best-estimate CSO Control Volume and uncertainty bounds.

The remaining tasks in the uncertainty analysis for computation of the best-estimate CSO Control Volume and uncertainty bounds for a given CSO Basin proceeds as described in Steps 7 and 8 above.

7.0 APPLICATION OF WATERSHED MODEL FOR DESIGN OF CSO REDUCTION

After the CSO Control Volume Performance Curve is completed, the information provided by the curve will be used by SPU management to assist in selecting the performance target for CSO reduction. The performance target will typically be specified as a given probability of being in-compliance value at a given uncertainty bound. For example, the performance target could be specified as 65% probability of being in-compliance in any-5-year period and an upper uncertainty bound of 80% (Figure 7.1).

For design usage, the watershed model will need to be modified to include all of the elements that are proposed for CSO reduction. The logical question is what version of the watershed model should be used, since there are multiple alternative models of future conditions? The choice of alternative future model should be made by examination of the performance curves for the alternative future models (Figure 7.2) and selecting the alternative future model whose performance curve best meets the performance target. This selection is shown in Figure 7.2 for the various alternative future models for the example performance target presented here.

The chosen alternative future model would then be modified to include all of the chosen elements for CSO reduction. That model would be executed using the composite precipitation scaling factor applicable to that model (Chapter 6) and the precipitation time-series for the period from 1978-present. Iterations will likely be needed to examine various combinations of CSO reduction elements to meet the performance goals.

7.1 Confirmation of Adequacy of Proposed CSO Reduction Elements

An acceptable CSO reduction solution is confirmed by examination of the rate of sewer overflows and confirmation that the long-term rate of sewer overflows is once-per-year or less based on the predicted sewer overflows for the full period from 1978-present.

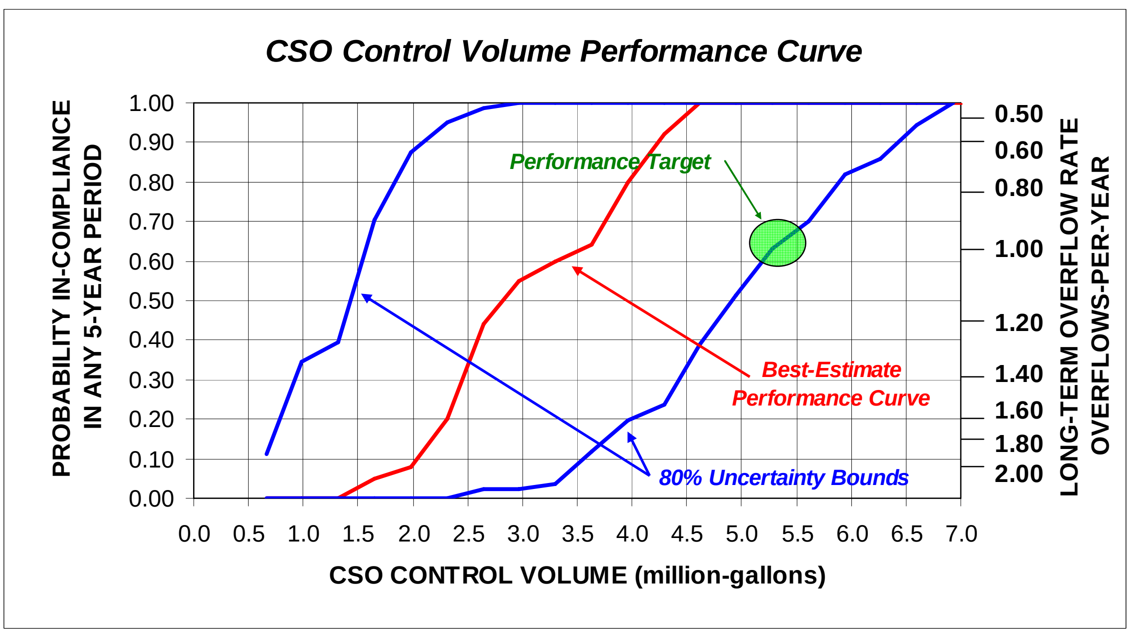


Figure 7.1 – Example of Adopted Performance Target for CSO Control Volume

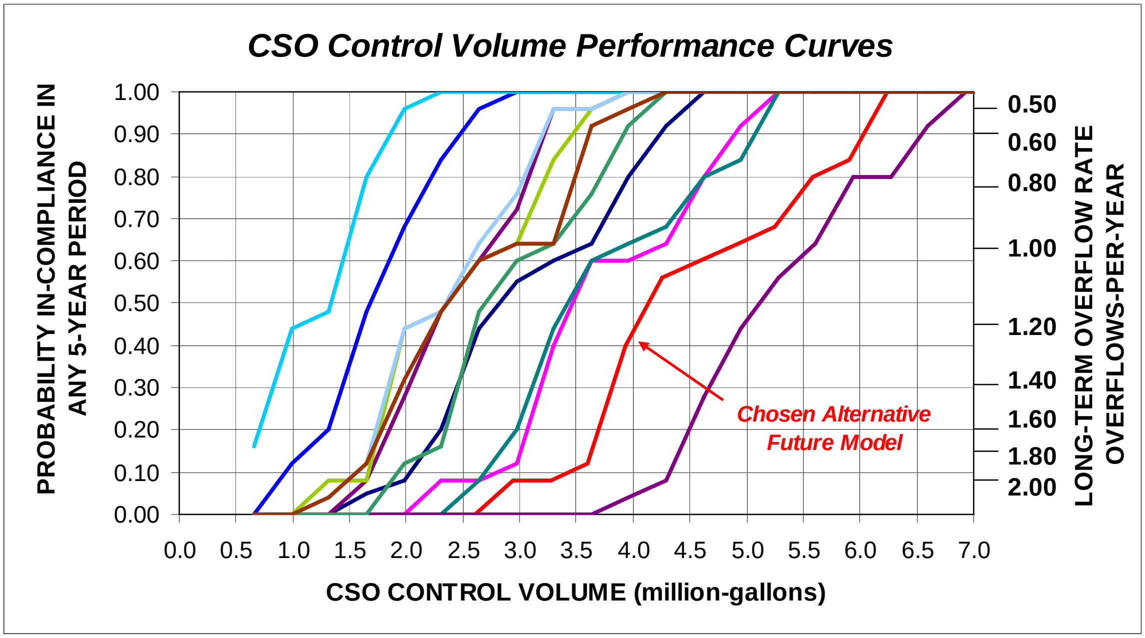


Figure 7.2 – Example CSO Control Volume Performance Curves
for 12 Alternative Future Models and Selection of Alternative Future Model

8.0 ALTERNATIVE METHOD FOR ESTIMATING CSO CONTROL VOLUME

PRECIPITATION-BASED PREDICTOR EQUATION OF OVERFLOW VOLUMES

Situations may arise where an alternative method to watershed modeling is needed for developing a CSO Control Volume Performance Curve. Direct analysis of measured overflow volumes provides such an alternative. The shortcoming of the direct analysis method discussed previously in Chapter 3 is the dependency on the representativeness of a relatively short record of sewer overflows. This shortcoming can be overcome somewhat by developing a precipitation-based predictor equation of sewer overflow volumes. This approach is applicable if a suitable relationship can be developed between precipitation and the resultant sewer overflow volumes. The predictor equation can then use the precipitation record from 1978 to present for estimation of overflow volumes in that same period. This longer record of sewer overflow volumes will generally provide a more stable estimate of the once-per-year overflow volume and a CSO Control Volume performance curve.

8.1 Method of Analysis and Development of CSO Control Volume Performance Curve

As indicated above, the basic approach is to find a relationship between precipitation and sewer overflow volume that has sufficient predictive capability to be used for predicting sewer overflows in the period from 1978-1998 before sewer overflows were measured. The following sections describe procedures for developing a CSO Control Volume performance curve using predictions from a precipitation-based predictor model. The start of data collection for sewer overflow volumes is assumed to begin in 1998 for simplifying the description of the following procedures.

<u>Step 1 – Conduct Regression Analyses Between Sewer Overflow Volumes and Precipitation</u>

Use the precipitation maxima for selected durations output by the *StormScan* program for conducting regression analyses. Precipitation at a given duration would be the explanatory variable and overflow volume would be the response variable.

Conduct regression analyses and compute the correlation coefficient for several durations. Identify the duration which yields the greatest predictive power. Experience has shown that the greatest correlation is often achieved for precipitation durations of 12-hours and 24-hours. and Many statistical textbooks (Helsel and Hirsch[5], Freund and Walpole[7]) provide guidance on conducting regression analyses and selecting a suitable mathematical form for conducting the regression analyses. Figure 8.1 depicts an example of a regression relationship using precipitation maxima at the 12-hour duration for estimation of overflow volumes. The standard error of estimate for the regression was 50% for the example shown in Figure 8.1.

If an acceptable level of correlation can be obtained, then the regression relationship may be used as a predictor of overflow volumes for the period from 1978 to 1998. If an acceptable level of correlation cannot be obtained, then this approach should not be used.

<u>Step 2 – Generate Overflow Volumes Using Predictor Equation for Period from 1978 to 1998</u>

Scan the record of the precipitation gage most representative of precipitation for the CSO basin for the *N* largest precipitation maxima at the duration identified in Step 1 for the period from 1978 to present. As in the prior analyses, $N=3m$, where m is the record length in years. Alternatively, this dataset of precipitation maxima may be obtained from SPU staff. Use the precipitation maxima and the predictor equation from Step 1for generating overflow volumes for the period from 1978 to 1998.

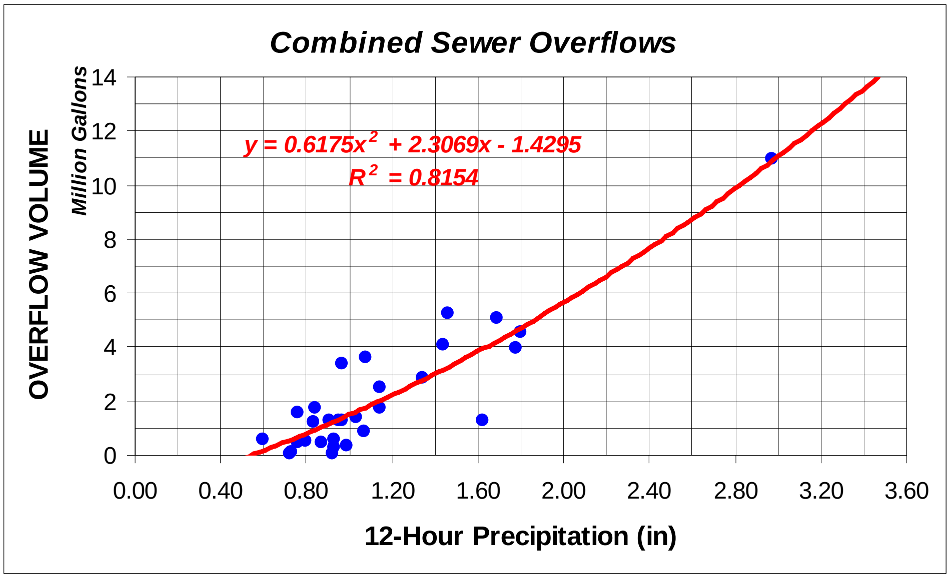


Figure 8.1 – Example Precipitation-Based Predictor Equation
for Sewer Overflow Volume for Period from 1998-2006

Step 3 – Compute Probability-Plot and Estimate Overflow Volume for Once-per-Year Rate

Compute a probability-plot for the sewer overflow volumes generated in Step 2 in the same manner as described in Chapter 3. Use the results from Step 2 above for the years from 1978-1998 (years prior to collection of overflow data). Use the measured values of overflow volumes for the most recent period (1998-present) rather than the estimates from the predictor model. Create a probability-plot and determine the once-per-year overflow rate for the period from 1978-present. This new probability-plot is useful for comparing the estimated overflow rates for the long-period from 1978-present with the more recent period (1998-present). An example probability-plot using the precipitation-based predictor model is shown in Figure 8.2.

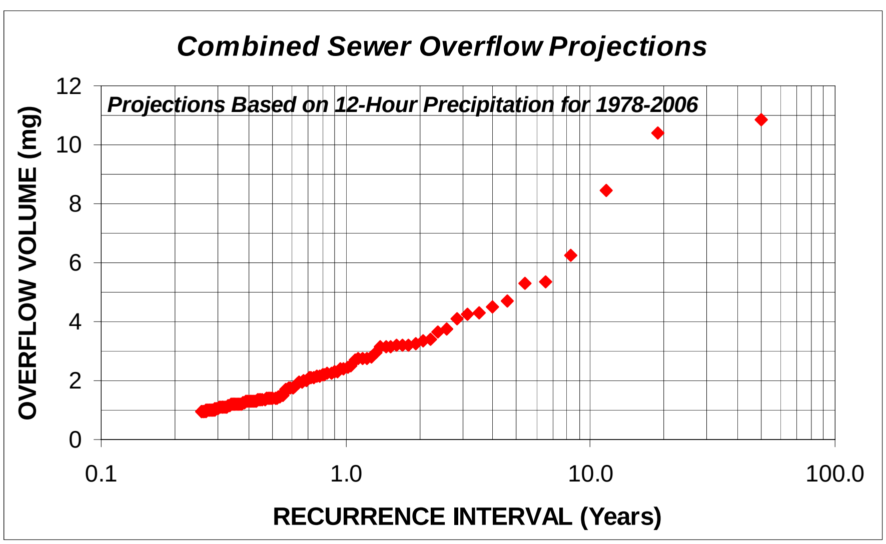


Figure 8.2 – Example Probability-Plot of Sewer Overflow Volumes for Period from 1978-2006
Based on Precipitation-Based Predictor Equation

Step 4 – Develop CSO Control Volume Performance Curve for Period from 1978-Present
Develop the CSO Control Volume Performance Curve for past conditions (1978-present) the procedures described in Chapter 4. Use the overflow volumes generated in Step 2 for 1978-1998 and the measured overflow volumes for 1998-present. An example CSO performance curve is shown in Figure 8.3.

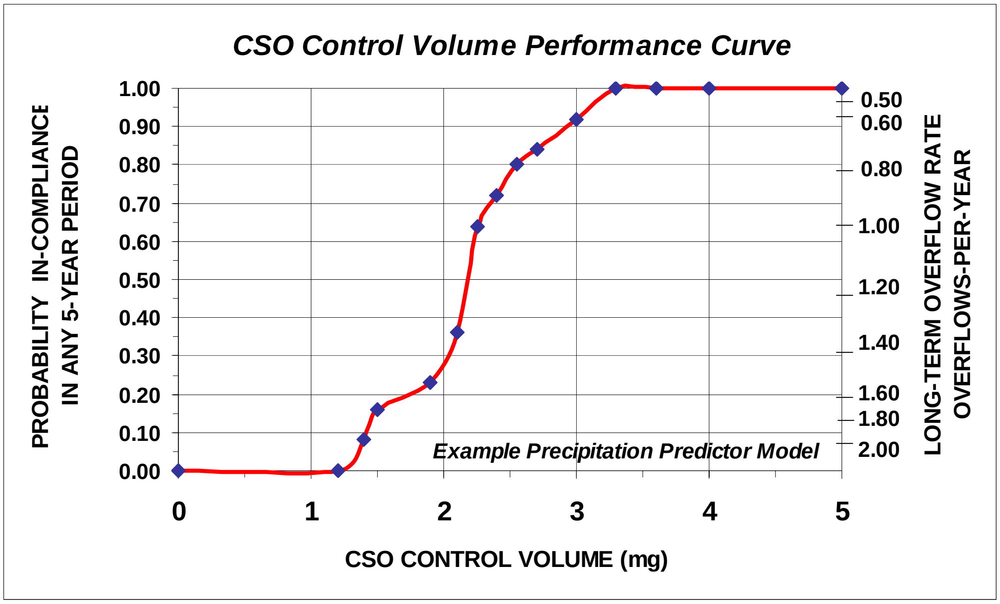


Figure 8.3 – Example CSO Control Volume Performance Curve
Generated from Precipitation-Based Predictor Model for Period from 1978-Present

8.2 Incorporation of Uncertainty Bounds on Performance Curve

Uncertainty bounds for the CSO Control Volume Performance Curve can be developed using concepts similar to that described in Chapter 6 for developing uncertainty bounds using the sewer overflow volumes output from watershed modeling. Specifically, scaling factors are applied to the sewer overflow volumes produced by the precipitation predictor model. Numerically, this is equivalent to applying the scaling factors to the CSO Performance Curve produced by the precipitation predictor model.

Production of the best-estimate CSO performance curve and uncertainty bounds for future operation of the combined sewer system would proceed as follows:

Step 5 – Compute Best-Estimate CSO Control Volume Performance Curve for Future Period
The best-estimate CSO performance curve for future operation of the combined sewer system is obtained from the best estimate values of uncertainties for future precipitation including climate change and residual uncertainties. This corresponds to mean values for the three factors and equates to a scaling factor of 1.06. The sewer overflow volumes for the CSO performance curve (Figure 8.3) are multiplied by 1.06 to produce the best-estimate CSO performance curve shown in Figure 8.4.

Step 6 – Compute Uncertainty Bounds for CSO Control Volume Performance Curve

Uncertainty bounds for the CSO performance curve are estimated by applying scaling factors to the CSO Control Volume Performance Curve obtained from the predictor model. Estimation of the uncertainty bounds is accomplished in a manner similar to that described for computing the composite precipitation scaling factors described in Chapter 6. This requires an assessment of the magnitude of the residual uncertainties associated with application of the precipitation predictor model. The magnitude of the standard error of estimate of regression for the precipitation predictor model can be used as the measure of residual uncertainties. Tables 8.1a,b,c depict composite scaling factors for sewer overflow volumes for residual uncertainties for a standard error of estimate of 30%, 40% and 50%, respectively, for the precipitation regression relationship.

Use of the standard error of estimate of 50% for sewer overflow volumes and scaling factors in Table 8.1c and the CSO performance curve shown in Figure 8.3 results in the 80% uncertainty bounds shown in Figure 8.4.

Table 8.1a – Scaling Factors to be Applied to CSO Control Volume Performance Curve
to Produce Uncertainty Bounds for Future Conditions
for Case of 30% Standard Error of Estimate for Residual Uncertainties

SCALING FACTORS FOR COMBINED SEWER OVERFLOW VOLUME		
UNCERTAINTY BOUNDS	LOWER	UPPER
50%	0.86	1.26
60%	0.81	1.31
70%	0.73	1.35
80%	0.63	1.45
90%	0.56	1.57

Table 8.1b – Scaling Factors to be Applied to CSO Control Volume Performance Curve
to Produce Uncertainty Bounds for Future Conditions
for Case of 40% Standard Error of Estimate for Residual Uncertainties

SCALING FACTORS FOR COMBINED SEWER OVERFLOW VOLUME		
UNCERTAINTY BOUNDS	LOWER	UPPER
50%	0.80	1.32
60%	0.73	1.39
70%	0.64	1.45
80%	0.50	1.58
90%	0.41	1.73

Table 8.1c – Scaling Factors to be Applied to CSO Control Volume Performance Curve
to Produce Uncertainty Bounds for Future Conditions
for Case of 50% Standard Error of Estimate for Residual Uncertainties

SCALING FACTORS FOR COMBINED SEWER OVERFLOW VOLUME		
UNCERTAINTY BOUNDS	LOWER	UPPER
50%	0.73	1.38
60%	0.65	1.47
70%	0.54	1.54
80%	0.39	1.71
90%	0.22	1.90

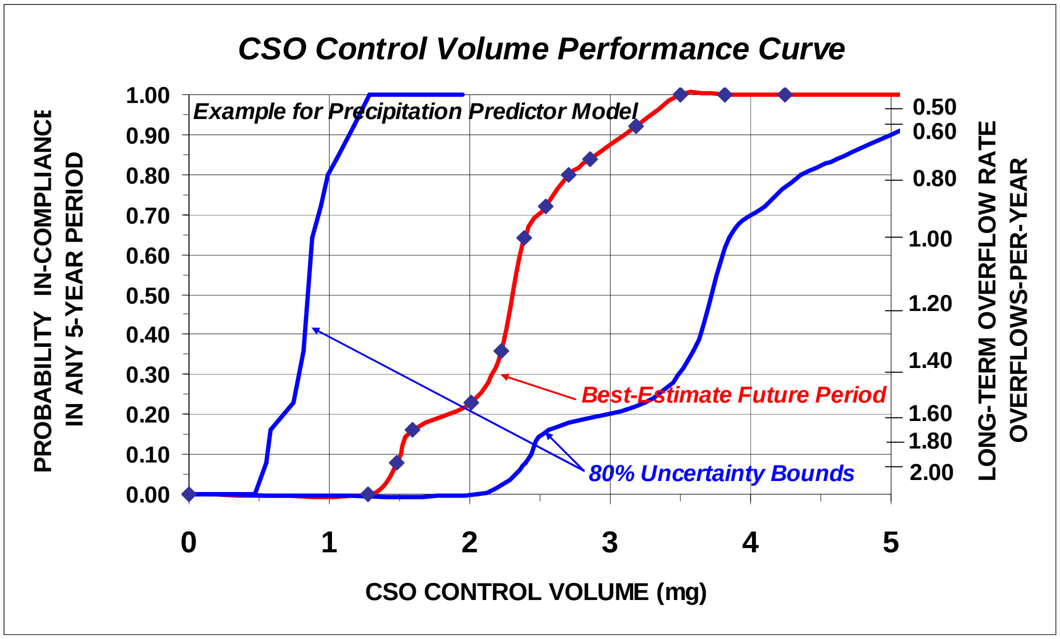


Figure 8.4 – Example CSO Control Volume Performance Curve and 80% Uncertainty Bounds Generated from Precipitation-Based Predictor Model Applicable to Future Period

SELECTED DEFINITIONS FOR TERMINOLGY USED IN THIS MANUAL

Alternative Watershed Model – for a given watershed model (InfoWorks), each model parameter set that is capable of replicating measured flows within some error tolerance is considered an alternative watershed model.

Alternative Future Watershed Model – each alternative watershed model in combination with a precipitation time-series that is scaled by a composite precipitation scaling factor for prediction of future performance of a combined sewer system is termed an alternative future watershed model.

Combined Sewer System – is a sewer system that conveys both sanitary flows and stormwater flows. Sanitary flows are conveyed during dry periods and a combination of sanitary flows and stormwater are conveyed during rainy periods.

Combined Sewer Overflow (CSO) – a combined sewer overflow occurs when stormwater additions to the combined sewer system exceed the discharge capacity of the sewer system and the overflow is redirected to a nearby receiving water body. In Seattle, combined sewer overflows are directed to Puget Sound, Elliot Bay, the Washington Ship Canal and Lake Washington.

CSO Control Volume – for an existing CSO basin, the control volume is the volume that must be created within the sewer system and/or CSO basin to reduce the frequency of sewer overflows to meet SPU performance targets for CSO reduction. The additional volume can be created by a variety of approaches including: storage vaults; separation of storm and sanitary sewers; implementation of low impact development features; land use changes; changes to operation of the sewer system; inter-basin transfers; etc. Also see CSO Reduction below.

CSO Control Volume Performance Curve (CSO Performance Curve) – the measure of performance for a CSO Control Volume depicted as a graphic with *Control Volume* (million gallons) displayed on the independent axis and the *Probability of Being In-Compliance with water quality regulations in any 5-year period* displayed on the primary dependent axis. The long-term overflow rate expressed as an annual rate is displayed on the secondary vertical axis.

CSO Reduction – is a generic term associated with methods used to reduce the frequency and volume of combined sewer overflows. This includes a wide range of methods including: construction of storage vaults; implementation of low impact development components in the CSO basin to reduce stormwater inflows; construction of stormwater sewers in portions of the CSO basin; reducing the stormwater inflow into the combined sewer by disconnecting roof drains and other surface drains; redirecting flows from a portion of one CSO basin to another CSO basin with excess capacity; changing the operation of the sanitary sewer system; etc.

Likelihood – as used in this manual, a qualitative generic term to describe the relative chance of an event occurring (not occurring) or being equaled or exceeded (not exceeded).

Model Calibration – the process of identifying values of computer model parameters that when used in execution of the computer model produces model outputs that suitably reproduce observed/measured outputs within some error tolerance.

Model Parameter Set – the collection of values for a selected group of model parameters. A trial model parameter set is the collection of values for those model parameters selected for use in model calibration.

Probability – a numerical value between zero and unity describing the chance of an event occurring (not occurring) or being equaled or exceeded (not exceeded).

Probability of Being In-Compliance – the probability of having 5 combined sewer overflows or less in any given 5-year period.

Risk – a measure of the likelihood and severity of adverse consequences (NRC[9]).

Risk-Based Approach – a generic term referring to a variety of methods of analysis and/or decision-making that employ risk concepts applied in either a qualitative or quantitative manner.

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