CHAPTER 4

Evaluation of NPS Return Flow to the River Using a Water Balance Model

4.1. Water Balance Model Applied to the LARV

Water Balance Model Equation.

The purpose of the water balance model is to determine the volume of unaccounted for water in each reach. We begin with a basic water balance model as describe in most hydrology texts — (Wanielista, Kersten, Eaglin, et al. 1997).

$$\text{change in storage} = \text{inputs - outputs}$$

Adding the variables, both known and unknown, present in the LARV we have the following equation:

$$\frac{\Delta S}{\Delta t} = Q_{in,US} + \sum Q_{in} + P + R + B - Q_{out,DS} - \sum Q_{out} - E - T - F \qquad (1)$$

Where:

$\frac{\Delta S}{\Delta t} =$ Stored volume change between time steps.

$Q_{in,US} =$ Flow in the river entering the study reach at the upstream end.

$\sum Q_{in} =$ Flow gained by the river from tributaries and other gauged sources.

$P =$ Volume of water gained to the river due to precipitation falling directly on the river's surface.

$R =$ Volume of water gained to the river due to precipitation runoff from adjacent land.

$B =$ Volume of water gained to the river due to subsurface flow.

$Q_{out,DS} =$ Flow in the river leaving the study reach at the downstream end.

$\sum Q_{out}$ Flow lost from the river to canals and other gauged sinks.

$E =$ Volume of water lost from the river due to direct evaporation from the water's surface.

$T =$ Volume of water lost from the river due to plant transpiration.

$F =$ Volume of water lost from the river due to infiltration into the subsurface flow.

If we combine the terms that are unknown or unmeasured, we arrive at the following equation:

$$\frac{\Delta S}{\Delta t} = Q_{in,US} + \sum Q_{in} + P - Q_{out,DS} - \sum Q_{out} - E + Q_{NPS} \qquad (2)$$

Where:

Q_{UNPS}= The sum of gains from non-point sources and losses to non-point sinks ($Q_{NPS} = R + B - T - F + Q_{U,in} - Q_{U,out}$).

There is no reasonable method for differentiating the components of Q_{UNPS}, therefore the abbreviation NPS in this thesis refers to both non-point sources and non-point sinks. Q_{UNPS}includes the non-point source gains from groundwater sources(B), non-point source losses to groundwater sinks F), transpiration losses from plants in the river channel (T), and gains from precipitation runoff from adjacent land (R). Additionally, this term includes ungauged flows leaving and entering the river. Ungauged gains to the river ($Q_{U,in}$) are suspected to be primarily in the form of irrigation drainage from adjacent farmland. Other sources could be due to errors in underestimating flows entering the river or overestimating flows leaving the river. Ungauged losses from the river ($Q_{U,out}$) are suspected to be primarily in the form of minor or unauthorized withdrawals from the river channel. Of the ungauged flows, irrigation drainage from adjacent farmlands is assumed to be the largest contributor.

The two groundwater components of $Q_{UNPS}$are suspected of being the largest components of Q_{UNPS}. Water transfer between the aquifer and river happens continually whereas $Q_{U,in}$, $Q_{U,out}$, R, and T are not continuous. $Q_{U,in}$ and $Q_{U,out}$ only occur periodically when individuals actively withdraw from the river or allow irrigation runoff to return to the river. R only occurs during rain events. Within the LARV, most rainwater is captured in irrigation canals. Only precipitation falling in the riparian zone is likely to reach the river. T only occurs during growing season. This value is also only considering the transpiration happening within the river channel and does not include the riparian zone. Any losses due to transpiration in the riparian zone are first considered river losses to the aquifer (F).

Re-arranging equation (2) 2 to solve for the unknown values produces equation 3. Due to the nearly identical method of calculating flow (Q) and it's associated error and uncertainty, these terms were associated with each other. Likewise, the precipitation (P) and evaporation (E) terms were associated with each other.

$$Q_{UNPS} = \left(Q_{out,DS} + \sum Q_{out} - Q_{in,US} - \sum Q_{in}\right) - \frac{\Delta S}{\Delta t} - (P + E) \tag{3}$$

4.2. Stochastic and Deterministic Models

Deterministic and stochastic models are used in both the unaccounted for water and mass balance models. Deterministic models are fully determined by the input parameters or variables. Randomness is not included. Stochastic models include one or more random parameters. Given the same input parameter values, a stochastic model will produce different results with each iteration.

There are many recognized methods for solving stochastic models. Solutions to these models are not definite and the term ”solve” must be taken loosely. Any solution from a stochastic model is one of a potentially infinite number of possible solutions.

The Monte Carlo (MC) simulation technique was used to obtain solutions for all stochastic models in this thesis. The MC technique is conceptually simple. The stochastic model is repetitively solved and the solution of each iteration are used to define the solution statistics of the model. The number of iterations performed is determined in one of two ways. One way is to calculate identifier statistic(s) after each run. Identifier statistic(s) are those that the modeler has determined to be of value. Usually, these statistics are monitored to identify when the change in the statistic has reached a predetermined threshold. The alternate method of determining the number of iterations to perform is more fixed. The model is run for a estimated number of iterations. A set of results for each iteration is saved. After all iterations are calculated he identifier statistic(s) are calculated for each iteration. The modeler then determines the number of iterations based on the results.

Both methods for determining the number of required iterations have their own benefits and drawbacks. The first method is more computationally intensive and is slower to solve, but the number of required iterations is never exceeded. The second method is quicker to solve, but may require more model runs if the modeler underestimated the number of required iterations. This method also has the added benefit that if, after the model is run, the modeler determines that a different identifier statistic is required, then that statistic can be calculated on the existing solution set. Due to the complexity of the models in this thesis, it was determined that the second method was the most appropriate.

It was determined that for the sake of simplicity, all of the models calculated in this thesis would use the same number of iterations. The USR mass balance model is the most complex model as it has the largest number of input variables and uncertainty terms. The identifier statistics used were the mean, variance, and skewness, which are the first, second, and third moments of the probability density. These were calculated for each iteration. The threshold between the observed iteration and the previous iteration was fixed at 0.1%. The identifier statistics reached the threshold in the following order: mean, variance, and skewness. Skewness reached its break point shortly before the 500th iteration. A judgment call was made to increase the factor of safety. Therefore, the number of stochastic model iterations was fixed at 5,000.

4.3. Error and Uncertainty.

types of uncertainty parameter uncertainty model uncertainty

Types of parameter uncertainties (Vicens et al. 1975) parameter uncertainty Model uncertainty Spatial variability Temporal variability

Parameter estimates should be strictly treated as random variables and parameters that are functions of random variables should be treated themselves as random variables (Haan 1977)

Systematic errors - introduce bias into measurements. Only reduced through proper methodology and frequency of equipment calibration and proper equipment operation.

random errors - Introduce noise into the measurements. have mean of 0 and are equally distributed on either side of 0. repeated measurements can reduce but not eliminate random error. Repeated meaurements in a dynamic system introduce temporal variability.

true value vs. measured value discussion w/ plots

Source of model uncertainty hydrologic processes cannot be conceptually or mathematically represented with total accuracy and completeness. Most hydrologic math models are emperical. This is due to the highly variable, complex, and incompletely understood processes that exist at every part of the hydrologic cycle.

While there is a much better understanding of hyraulic processes, these are also subject to uncertainty in natural channels due to the unstable nature of these channels.

Spatiotemporal uncertainty is the result of systems that vary over time and space. Spatial variability Data can be collected at given point in space, but that data may not be representative of the physical area that it is assumed to represent due to variability in physical conditions.

Temporal variability Similarly, data can be collected at a given point in time, but changes in the system over time causes the measured parameter value to change (T. K. Gates and Al-Zahrani 1996b).

The widely-accepted standard for quantifying measurement uncertainty is the ISOs Guide to Expression of Uncertainty in Measurement (GUM) (ISO 1995). GUM classifies uncertainty evaluations as either being Type A or Type B and does not differentiate errors as being random or systematic (Cox et al. 2003; Reginald W. Herschy 2009). Type A evaluations are used to estimate a value using a probability distribution that was developed from repeated measurements, and Type B evaluations use standard deviations and assumed probability distributions obtained from scientific judgment, available information, and possible variability of a measurement (Cox et al. 2003; R. W. Herschy 2004). For example, the uncertainty evaluation used for a single river discharge measurement would be Type B if the error range and probability distribution of the measurement equipment and procedure is assumed from previous studies and scientific judgment, and because a single measurement is taken at a given point in time such that a probability distribution of measurement could not be developed (i.e. due to temporal variations in flow rate). The root mean square method is widely accepted for estimating the uncertainty related to measurement of water quantity and water quality (Harmel and Smith 2007; ISO 1995; Sauer et al. 1992), as presented in ISO (1995). Harmel and Smith (2007) describe this measurement uncertainty as the probably error range, and quantify upper and lower uncertainty boundaries for measured data points as the following when attempting to specify an expected range of expected values: (1.3) and (1.4) Where: = upper uncertainty boundary = lower uncertainty boundary Oi = measured data point PERi = probable error range for measured data point Oi, (+/- This approach for describing the probable error range (Harmel and Smith 2007) is applicable for PERi that is known or assumed because no data is available to develop a probability distribution (i.e. Type B uncertainty evaluations).

— from Martin MS thesis — re-word and re-work Any water resources problem contains two fundamental types of informational uncertainties: (1) parameter uncertainty and (2) model uncertainty (Vicens et al. 1975). Parameter uncertainty is derived, in part, from measurement error or the difference between true and measured values (R.W. Herschy 2002). It is also derived from spatial and temporal variability. Even if a parameter value could be measured perfectly at a given point in space and time only a very limited number of points can be measured. Hence, the true space-time distribution of parameter values cannot be known with certainty. Due to this error and variability and the inability to know what the true values are, parameters estimates strictly should be treated as random variables (Haan 1989) and parameters that are functions of random variables should be treated themselves as random variables (Haan 1977).

Model uncertainty stems from the fact that hydrologic processes cannot be represented or approximated in a conceptual physical or mathematical form with total accuracy and completeness (Haan 1989) due to the complexities of natural systems. In relation to the mass balance equation used to estimate canal seepage loss, modeling free-water evaporation rates from the water surface of the canal is performed using an equation that does not completely account for all factors that affect evaporation rates. Evaporation is a complex process in that it is dependent upon numerous atmospheric conditions, so equations are simplified because of lack of availability of data or the inability to measure all components that affect evaporation rates. Free-water evaporation equations implement atmospheric components such as relative humidity, wind speed, solar radiation, etc. but the equations themselves provide merely an estimate of evaporation (even if every variable within the equation could be measured with complete accuracy) due to the lack of completeness of the equation. The same is true for groundwater inflows into a canal, because they cannot be measured directly or completely along the entire study reach of the canal. As such, the model has to make certain assumptions about groundwater inflows which lead to incompleteness of the model.

Standard errors cannot be easily assessed (Harmel and Smith 2007) but often are related to equipments ability to make a measurement with accuracy or with random operation errors. Measurement repetition reduces standard errors as the mean of the repeated measurements becomes closer to the true value (Bell 1999; ISO 1973), as long as the measurement error is scattered around the true mean. Systematic errors typically are either positive or negative throughout a measurement set, and likely are caused by equipment bias or user bias (Bell 1999; Harmel and Smith 2007). As opposed to standard errors, repeated measurements will not reduce the uncertainty of systematic errors since the errors are biased in a given direction (ISO 1973). As such, the only ways to reduce systematic errors are through equipment calibration and proper equipment operation.

In addition to direct measurement error, uncertainties also stem from the procedures used to perform a measurement or used to calculate a value from measurements (Harmel and Smith 2007). Model uncertainty is related to the inability to adequately represent natural systems due to their complexity, dynamic nature, and the modeler's lack of understanding of the modeled system. It is also related to the methods, equations, and procedures used to calculate given parameters. Even if random scatter errors and systematic errors did not exist (i.e. sub-parameters could be measured with 100% accuracy) there is still uncertainty related to the equations and procedures used to attempt to quantify a given parameter. For example, when estimating free-water evaporation, if temperature, relative humidity, wind speed, solar radiation, and all other required components for a given equation were all measured with 100% accuracy, the estimation of free-water evaporation still would not be equivalent to the true value due to imperfections in the equation being used.

Seepage Measurement Error and Uncertainty The inflow-outflow seepage measurement procedure was adopted for the analysis presented in this thesis. As such, literature review of the parameters associated with this method will be discussed herein, including the uncertainty of estimating parameters values. Major components of uncertainty in seepage measurement using the inflow-outflow procedure include discharge measurements, free-water evaporation estimates, water stage measurements, and measurements of canal hydraulic geometry. All physical measurements have a degree of uncertainty due to either random scatter errors (a.k.a. standard errors) or systematic errors (Harmel and Smith 2007; ISO 1973). Errors related to computational procedures and measurement techniques can be classified as random scatter errors if they create scatter around the true mean, but if they cause a unidirectional bias in estimates then they are classified as systematic errors.

Spatiotemporal uncertainty is the result of systems that vary over time and space. Data can be collected at given point in space, but that data may not be representative of the physical area that it is assumed to represent due to variability in physical conditions. Similarly, data can be collected at a given point in time, but changes in the system over time causes the measured parameter value to change (T. K. Gates and Al-Zahrani 1996b). For example, when using the velocity-area method to measure river discharge, water velocity is not measured at every location within a cross section so average velocity cannot truly be known but only estimated, which leads to spatial variability. Water velocity at a given location also changes temporally during a measurement leading to temporal variability. Discharge Measurement Error and Uncertainty The most common method for estimating stream flows is the velocity-area method (R. Herschy 1993). This method typically is conducted by summing the products of measured velocity and the corresponding flow area for a series of measurements within a channel cross-section (ISO 1979). Inflow-outflow seepage measurements can be conducted using Acoustic Doppler flow meters and other technologies that utilize the velocity-area method to measure upstream and downstream flow rates relatively quickly Kinzli et al. (2010). Additional descriptions of the velocity-area method for flow measurement with ADVs and ADCPs are provides in Section 3.1.1. Adoption of error ranges and probability distributions related to flow rate measurement with ADVs and ADCPs are discussed in Section 5.2. The sub-sections that immediately follow present a literature review of studies related to the measurement error and uncertainty of these flow measurement technologies. Acoustic Doppler Velocimeters Error and Uncertainty Rehmel (2007) compared flow rate measurements conducted using ADVs, Price AA propeller meters, and Price pygmy propeller meters. Based upon 55 measurements, the study concluded that ADV measurements are not statistically different than measurements taken by Price AA or Price pygmy meters and that ADV measurements were typically within 5Acoustic Doppler Current Profilers Error and Uncertainty Oberg and Mueller (2007) used large towing basins in a laboratory to estimate the accuracy of ADCP bottom-tracking and water-tracking velocities. They conclude that mean differences for bottom tracking velocity (pertains to area calculation) and water-tracking velocity (pertains to flow velocity) are -0.51Stage Error and Uncertainty Stage (water level) readings are necessary for all seepage measurements. For ponding tests, they are important for measuring the change in water level over a given period of time. For inflow-outflow tests, they are important for observing the stability of a canal flow and for calculating varying storage changes along the canal reach. Upon surveying channel cross-sections, relationships between stage and canal wetted perimeter and between stage and canal top width can be developed. As such, stage measurements during seepage tests can be used to estimate time-varying top width (used for evaporation calculations) and wetted perimeter (used to quantify seepage per wetted area). The accuracy of stage measurement using pressure transducers is discussed below. Technical specifications for HOBOTM pressure transducers state that the maximum stage measurement error is 0.03 ft and the average error is 0.015 ft (ONSET 2008). They also state that barometric pressure may be assumed constant across a region (within 10 miles), with the exception of a fast moving storm. This is important when using atmospheric pressure to calculate gage pressure from absolute pressure measurements. The technical specifications for the In-Situ Level Troll 300TM pressure transducer state that the accuracy for a Level Troll 300TM is 0.035 feet (In-Situ 2009). Free-Water Evaporation Error and Uncertainty In measuring seepage from animal waste lagoons, Ham (2002) found that evaporation was the most significant source of uncertainty in the volume balance using the ponding method. He concluded that evaporation could be measured within 10-20Rosenberry et al. (2007) compared 15 methods for estimating free-water evaporation. The purpose was to check 14 methods against the Bowen-ratio energy budget (BREB) method, which is stated to be the standard method for estimating evaporation. The study concludes that the PriestleyTaylor, deBruinKeijman, and Penman methods compare best with the BREB. Uncertainty analysis was not conducted as part of the study. Tanny et al. (2008) compared evaporation estimates from field measurements using an eddy covariance (EC) system with equations typically used to calculate evaporation. The study concluded that the PenmanMonteithUnsworth and PenmanBrutsaert methods result in daily evaporation rates closest to those measured by the EC system. A derivation and comparison of three simplified Penman equations was completed by Valiantzas (2006). Commonly-measured weather data used in these equations include solar radiation, air temperature, relative humidity, and wind velocity. The study then compared each of the three simplified equations to the original Penman (1948) equation using data from 535 sites in the United Nations Food and Agriculture Organization's (UN-FAO) CLIMWAT (Smith, 1993) database. The database includes long-term monthly climatic data over thirteen countries that provide a range of values. The comparison of versions of the Penman equation revealed that the least-simplified version corresponds most closely with Penman (1948). Valiantzas (2006) also revealed that neglecting wind velocity data adds variability to the results, and compares least-closely to Penman (1948). Channel Geometry Error and Uncertainty Measurement error and spatial variability of channel geometry can create significant uncertainty in open-channel hydraulic analysis (Buhman et al. 2002). Using survey data from 1600 cross-sections in the Mississippi and Red Rivers, Buhman et al. (2002) observed significant spatial variability in hydraulic geometry parameters and concluded that hydraulic-geometry patterns are not completely random but rather oscillate and display large-scale and medium-scale spatial trends. They modeled the residuals around fitted trend equations as random variables with estimated probability distributions and spatial correlation. Spatiotemporal variability creates uncertainty in predicting flow behavior including flow depth (T. K. Gates and Al-Zahrani 1996a), which affects the hydraulic geometry of a channel. Through stochastic analysis, T. Gates et al. (1992) concluded that hydraulic geometry in irrigation delivery systems varies spatiotemporally due to irrigation demands and patterns. Measurement error related to channel geometry exists on two scales. The first is at-a-station errors related to uncertainty of parameter estimation using cross-sectional surveys, and the second are longitudinal errors related to uncertainty of hydraulic geometry in channel reaches between surveyed cross-sections where no survey data were collected. Modeling Measurement Error and Uncertainty Estimates of seepage can be made with either a deterministic approach (Kinzli et al. 2010) or probabilistic approach that accounts for parameter uncertainty (Oblinger et al. 2010; Shaw and Prepas 1990). Uncertainty analysis implementing Monte Carlo simulation is more commonly being used to develop ranges of expected seepage rates from water bodies (Keery et al. 2007; Oblinger et al. 2010; Shaw and Prepas 1990). In each of these studies, probability distribution functions were assigned to sets of parameters used to calculate seepage rates from water bodies, and distributions of expected seepage rates were developed via Monte Carlo simulation. An extensive literature review was conducted, and it was found that the water balance uncertainty analysis conducted by Ham (2002) most closely reflects the method used in this thesis. Ham (2002) studied seepage rates from animal waste lagoons using the ponding method and assigned probable error ranges to measured data to consider the accuracy of the seepage measurements. Probable error ranges were assigned to atmospheric measurements (air temperature and relative humidity) used to calculate evaporation and to water depth measurements. Changes in flow depth were measured with float-based recorders and atmospheric parameters, including humidity, air temperature, and wind speed, were measured on site with weather station equipment. Ham (2002) adopted "typical" and "best" probable error ranges based upon previous studies and manufacturer specifications for these variables and calculated ranges of seepage rates accordingly. The study concluded that evaporation uncertainty had the largest impact on accuracy of the seepage results, and that seepage studies should be conducted when evaporation rates are minimal to reduce error in seepage measurement. Shaw and Prepas (1990) studied the accuracy of estimating seepage rates from lakes using seepage meters. The analysis used Monte Carlo simulation for 32 combinations of flow patterns, spatial variability of seepage flux, and placement and number of seepage meters within a transect. A total of 500 Monte Carlo simulations were performed for each combination to generate coefficients used to calculate seepage velocity. The stochastic analysis concluded that seepage meters have the ability to accurately quantify the average nearshore seepage flux and that the most important factor affecting the seepage flux measurement was spatial variability. The widely-accepted standard for quantifying measurement uncertainty is the ISOs Guide to Expression of Uncertainty in Measurement (GUM) (ISO 1995). GUM classifies uncertainty evaluations as either being

Type A or Type B and does not differentiate errors as being random or systematic (Cox et al. 2003; Reginald W. Herschy 2009). Type A evaluations are used to estimate a value using a probability distribution that was developed from repeated measurements, and Type B evaluations use standard deviations and assumed probability distributions obtained from scientific judgment, available information, and possible variability of a measurement (Cox et al. 2003; R. W. Herschy 2004). For example, the uncertainty evaluation used for a single river discharge measurement would be Type B if the error range and probability distribution of the measurement equipment and procedure is assumed from previous studies and scientific judgment, and because a single measurement is taken at a given point in time such that a probability distribution of measurement could not be developed (i.e. due to temporal variations in flow rate). The root mean square method is widely accepted for estimating the uncertainty related to measurement of water quantity and water quality (Harmel and Smith 2007; ISO 1995; Sauer et al. 1992), as presented in ISO (1995). Harmel and Smith (2007) describe this measurement uncertainty as the probably error range, and quantify upper and lower uncertainty boundaries for measured data points as the following when attempting to specify an expected range of expected values: (1.3) and (1.4) Where: = upper uncertainty boundary = lower uncertainty boundary Oi = measured data point PERi = probable error range for measured data point Oi, (+/- This approach for describing the probable error range (Harmel and Smith 2007) is applicable for PERi that is known or assumed because no data is available to develop a probability distribution (i.e. Type B uncertainty evaluations).

Error and uncertainty are two terms that appear equivalent, but are not. Error is the difference between the true value and the measured value. This variability is due to measuring instrument inaccuracy and imprecision. No instrument is perfectly accurate or precise and this variation may not be able to be captured. Error of this type is usually specified by the instrument manufacturer. Error is a combination of systemic error and random error. Measurement errors due to instrument calibration shifts and other known or unknown sources is systemic error. Random error is the that which remains even after all systemic errors are accounted for. Random error varies unpredictably and is uncorrectable. Error does not significantly impact this study. All studies that use this data or similar data will be subjected to the same error. When compared to uncertainty, error is nearly insignificant.

Uncertainty of a measured value is an interval around that value such that any repetition of the measurement will produce a new result that lies within this interval. An uncertainty estimate should address error from all possible effects (both systematic and random) and, therefore, usually is the most appropriate means of expressing the accuracy of results. This is consistent with ISO guidelines . However, in the case of this thesis, most measurements only include random error and systematic error is not address. Since, for most of the data used in this thesis, we are not the data originators, there is no reliable way to account for systemic error. In most cases, the data originators have provided uncertainty ranges which include instrument measurement random error and uncertainties due to temporal variations of the measured location. ref

Reported flow rates are an excellent example of uncertainty values. The reported value includes a range, in this case given as a percentage of the reported value. The true value lies somewhere within this range. The National Institute of Science and Technology has defined how uncertainty is to be reported. As per the Engineering Statistics Handbook (), there are four tenets for stating and combining components of uncertainty: Ref-year only

(1) Each uncertainty component is quantified by a standard deviation.

(2) All biases are assumed to be corrected and any uncertainty is the uncertainty of the correction.

(3) Zero corrections are allowed if the bias cannot be corrected and an uncertainty is assessed.

(4) All uncertainty intervals are symmetric.

In this example, the flow rate standard deviation is stated as a percentage of the reported flow. This indicates that the uncertainty increases as the flow rate increases. Biases are assumed to be corrected since none are reported.

The true value of a parameter is not directly observable and is only valid for a specific time and location. Any repeated measurements will be subjected to temporal variability. Measurements taken by two identical instruments will be subjected to temporal variability. The measured value is the value that is measured by the instrument. The difference between the two values is uncertainty. The relationship between measured value, true value, and uncertainty is described in equation 4.

$$\mathrm{mv} = \mathrm{tv} + \varepsilon \tag{4}$$

Where:

mv = measured value

tv = true value

ε = uncertainty

If the true value were known, then it would be a simple matter of algebra to determine the error from any measured value 5. This second equation shows uncertainty as a positive value when, algebraically, it should be negative. ε remains a positive term because it is assumed to be equally distributed around zero.

$$\mathrm{tv} = \mathrm{mv} + \varepsilon \tag{5}$$

Figure 4.1 is a graphical representation of a pair of possible scenarios when considering true and measured values. In all of the graphs, the uncertainty distribution is shown as the dashed black curve. The vertical black line at zero indicates the error associated with the true value. The vertical red and blue lines indicates the error for the two scenarios. The red line error value is near the black line. This indicates that the error is small and the measured value is near the true value. The blue line error value is a significant distance from the true value, but is within the uncertainty distribution. This indicates that the error is large and the measured value is significantly different than the true value. Both scenarios are plausible as the error values are within the uncertainty distribution associated with the true value. Graphs 1 and 2 show the red and blue scenarios.

The application of equation 5 can produce undesirable results. They are shown on graphs 3 and 4 of figure 4.1. In both of the scenarios, the uncertainty distribution of the true value is applied to the measured values and is depicted as dashed red and blue curves. In the red scenario where the error is small, depicted in graph 3, the overlap of the true value uncertainty distribution and the measured value uncertainty distribution is large and are almost identical. In the blue scenario, depicted in graph 4, the overlap is small. The overlap areas in graphs 3 and 4 are shaded gray. These gray areas are representative of the probability that the true value and measured value are from the same distribution.

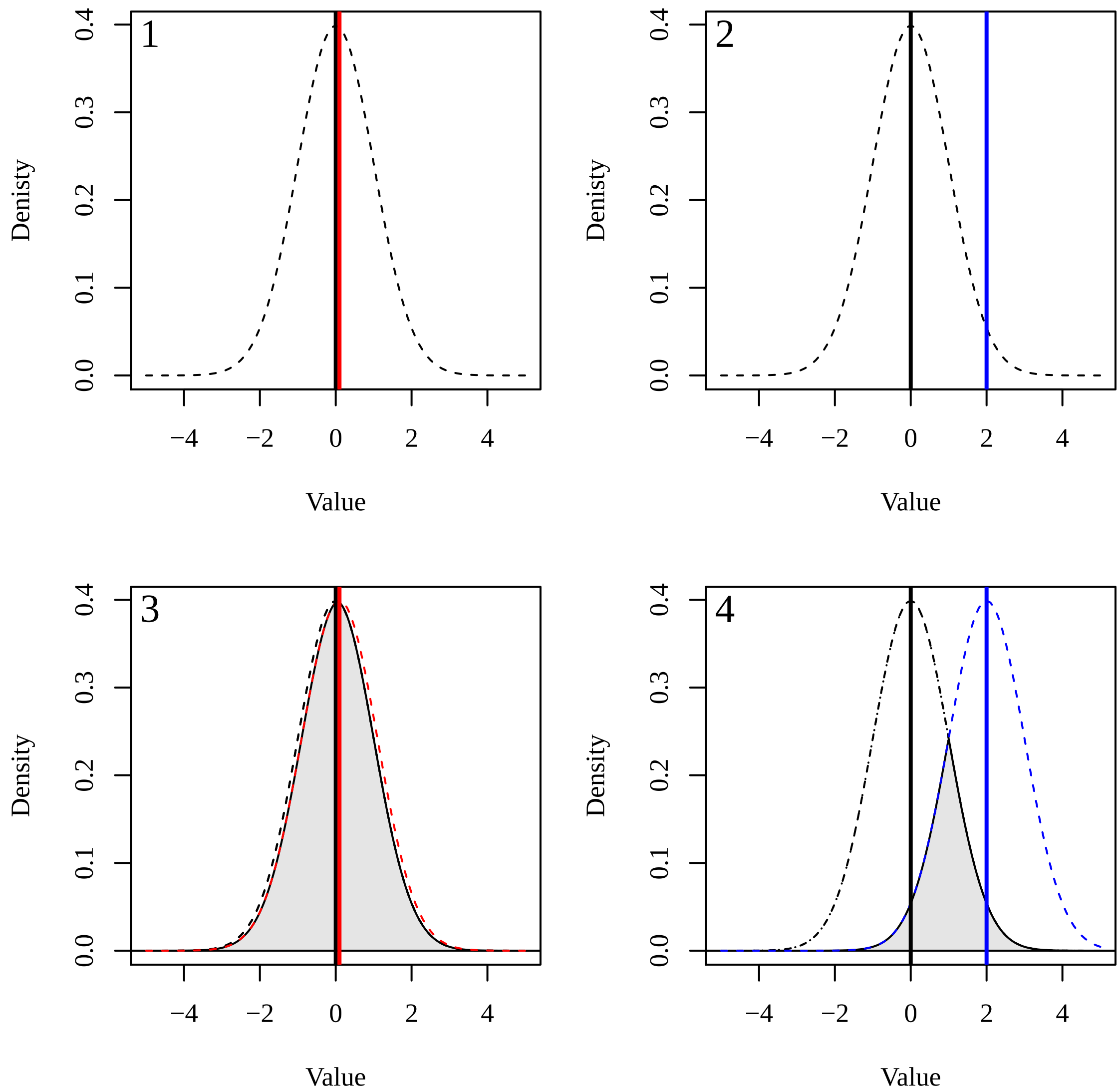

Figure 4.1. Comparison of measured value and true value. The black vertical line depicts the error associated with the true value. The black dashed line is the distribution of the uncertainty of the measured value from the true value. The red and blue vertical lines depict two measured value scenarios. The red and blue dashed curved depict the uncertainty distributions applied to the associated measured values. The gray area is representative of the probability that the true value and measured value are from the same distribution.

Ideally, the true value would be estimated based on the measured value and the relationship between the true value and the particular measured value. Since the true value is not known, the only reasonable course is to estimate the true value as in equation 5. Additional uncertainty can be attributed to this approach, but the uncertainty would be variable based on the difference between the true and measured value. Since this difference is unknown, it is unreasonable to guess.

III - define uni-variate probability distributions as estimate descriptions of an uncertainty parameter

Defining uncertainty is quite cumbersome as each variable comes with its own distinct definition of uncertainty. The definitions usually come in the form of a parametric distribution.

Distributions require as few as one factor. When a distribution had more than one definition, only standard, accepted definition was used. This thesis does not discuss the computations of the different distributions. The primary concern regarding distributions is to determine which of the well established distributions best fit the data.

References

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