EPA Public Access

Author manuscript

J Hydrol Eng. Author manuscript; available in PMC 2019 October 08.

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Published in final edited form as:

J Hydrol Eng. 2018 ; 23(12): 1943–5584. doi:10.1061/(ASCE)HE.1943-5584.0001722.

Reliability-Based Water Quality Assessment with Load Resistance Factor Design: Application to TMDL

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Abstract

Effective load reduction strategies rely on an accurate Total Maximum Daily Load (TMDL) calculation, which quantifies contaminant loading from various sources. There is a wide range of methods to consider uncertainties in TMDLs: from simple, conservative assumptions regarding factors that contribute to the TMDL required margin of safety (MOS), to probability-based approaches such as Monte Carlo simulations, which explicitly quantifies TMDL uncertainty. In this paper the authors adapt the Load Resistance Factor Design (LRFD), a rigorous, reliability-based framework, to water quality assessment and the TMDL process. The LRFD replaces the lumped MOS with design factors that reflect the magnitude and distribution of uncertainty among the various contaminant loads. In addition, it produces load reduction estimates to meet management objectives with a contaminant-specific frequency-based target. The LRFD is computationally efficient and flexible in that, to compute the design factors, the procedure can utilize: measurement data, analytical solutions or model simulation results, as well as full or marginal probability distributions.

1. Introduction

Since 1972, section 303(d) of the Clean Water Act (CWA) has required that states provide lists of impaired water bodies that do not meet water quality criteria set by the Environmental Protection Agency (EPA) according to their designated uses. The Total Maximum Daily Load (TMDL) assessments characterize pollution sources and identify needed reductions in those pollutants to eventually bring water resources back into compliance with the CWA. Over the past 20 years, more than 50,000 TMDLs have been developed for different types of stressors such as water temperature, nutrients and microbial

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contaminants, and states have identified thousands more water bodies requiring analysis (USEPA 2008).

In general, the TMDL can be described by the following equation:

$$TMDL = \sum L_{PS} + \sum L_{NPS} + MOS \quad (1)$$

where L_{PS} are the allowable point-source contaminant loads, L_{NPS} are the allowable non-point source contaminant loads, and MOS is a margin of safety meant to account for uncertainties in all constituent contributors that impact water quality. Conventionally, L_{PS} are expressed as *WLA* (waste load allocation), and L_{NPS} as *LA* (load allocation). The authors use the notation as in equation (1) for mathematical clarity in derivations later in the paper.

MOS can be incorporated in TMDL implicitly or explicitly (EWRI 2017). When the MOS is incorporated implicitly, equation (1) reduces to

$$TMDL = \sum L_{PS} + \sum L_{NPS} \quad (2)$$

and conservative assumptions on contaminant loads are made to maximize safety (EWRI 2017; Hantush and Chaudhary 2014). Neither the frequency of TMDL exceedance, nor the amount by which the TMDL is likely to be exceeded, can be estimated. Thus, this approach oversimplifies the problem and does not provide a rigorously determined, quantitative measure of uncertainty, and may result in overly conservative and costly TMDL recommendations.

Most TMDL methods include the MOS explicitly. In the simplest case, the MOS is chosen arbitrarily at a fixed number, for example 10%, a method widely criticized in the literature (Dilks and Freedman 2004; Langseth and Brown 2011). This emphasizes the necessity of probability-based approaches to determine MOS . Following the 2001 National Research Council (NRC) call to improve TMDL calculations (Dilks and Freedman 2004; National Research Council 2001; Shirmohammadi et al., 2006), more advanced methods have been developed (EWRI 2017; Stow et al. 2007), including first-order error analysis (FOEA) (Zhang and Yu 2004), Monte Carlo (MC) (Hantush and Chaudhary 2014; Karamouz et al. 2015; Patil and Deng 2011), risk-based and point estimation methods (Chin 2009; Langseth and Brown 2011). However, all these methods aim to produce a lumped value of MOS . In addition, FOEA linearizes the state variables, which leads to inaccuracies with nonlinear processes; MC simulations are typically computationally expensive; and point-estimate methods do not incorporate full probabilistic information on random variables (EWRI 2017; Franceschini and Tsai 2008).

To address these issues, the authors propose the Load Resistance Factor Design (LRFD) as a consistent, flexible and computationally efficient framework for TMDL evaluation that incorporates uncertainty assessment for individual loads. It is very flexible in that it works

with measurement data, analytical solutions or model simulation results, as well as full or marginal probability distributions. In addition, the LRFD is computationally faster than MC-based methods for uncertainty analysis such as Markov Chain Monte Carlo (MCMC) or Generalized Likelihood Uncertainty Estimation (GLUE) techniques (Jia and Culver 2008; Zheng et al. 2011).

In a sense, the LRFD is a hybrid between the implicit and explicit TMDL calculation methods. Much like the implicit approach, the *MOS* term is dropped from equation (1). Instead, load and resistance factors, which reflect the uncertainty associated with the other terms of equation (1), are explicitly included. Hence, uncertainty is not lumped into a single value; rather it is distributed among individual types of loads. Sources of uncertainty typically include input variability, scale; and parameter estimation uncertainty, model algorithms and calibration – when models are used (Langseth and Brown 2011; Shirmohammadi et al. 2006). Input variability is the most relevant in our case.

LRFD, originally developed in the field of structural engineering, is a widely accepted, standard methodology for systems design, used in studies of deep foundations, geotechnical applications, wood construction and steel structures, among others (Ellingwood 1997; Fenton and Griffiths 2008; National Research Council 2007; Saka and Geem 2013). More specifically, it is based on reliability analysis that addresses uncertainty in complex engineered systems subjected to random stresses (Barker and Puckett 2013; Galambos and Ravindra 1978; McCormac and Nelson 2003; National Research Council 2007; Nowak 1995). The maximum load under which the system is able to perform satisfactorily is called the capacity, or resistance. On the basis of capacity, reliability analysis quantifies the probability of system failure, which occurs when the total stressing load ($L_{PS} + L_{NPS}$ in TMDL) exceeds system resistance (Haldar and Mahadevan 2000). LRFD provides the complex relationship between system resistance, stressing loads on the system, probability of failure and the reduction in stressing loads required to maintain probability of failure under a target value.

The overall objective of this paper is to introduce LRFD in the context of water quality assessment, with a focus on TMDL calculations. The methodology is described in detail in the following section, and its application to two watersheds in Southwestern Ohio is then demonstrated. In the first case study, the Shepherd Creek watershed, measurement data are used, and LRFD analysis for a single load is performed. In the second case study, the Upper East Fork Watershed, the modeled data were obtained from the literature, and LRFD for multiple loads is performed. Collectively, these two cases demonstrate applicability of LRFD to single and multiple loads situations.

2. Methodology

2.1. Reliability-Based Design

A basic design problem in engineering is to devise a system with sufficient resistance to withstand the stressing load. Figure 1 depicts a hypothetical example to illustrate the concept of reliability-based design. Both resistance and load are represented as random variables,

and the area of overlap is the potential failure zone where load may exceed resistance (Haldar and Mahadevan 2000).

The design problem can thus be reduced to modifying the resistance probability density function (pdf) in Figure 1 so that the overlap with the load pdf satisfies an acceptable failure probability p_f . Modifications can come in the form of shifting the position of the curve, *i.e.* the mean; changing the spread of the curve, *i.e.* the standard deviation; or the shape, *i.e.* the probability distribution type.

In water quality problems the issue is reversed, meaning that the resistance may be fixed by a regulatory standard, and loads have to be modified to meet that standard. These modifications are determined by computing the needed load reduction, which depends on load factors, and through them on all three characteristics of the load (position, spread and shape of the curve), as shown later for single and for multiple loads.

Water quality is characterized by magnitude, duration and frequency of water contamination (EWRI 2017), all of which can be analyzed using reliability theory (Maier et al. 2001; Teklitz et al. 2014). Magnitude is the actual degree of contamination; duration is the amount of time that the magnitude remains above the regulatory standard; and frequency is the probability of pollutant concentration exceeding the regulatory standard. The main focus here is on magnitude and frequency, which, translated into reliability terms, is probability of failure p_f . The acceptable level of probability of failure enters the design calculations through the reliability index β , defined in section 2.3. Hence, β is a measure of the tolerable risk of water contamination. Duration can be quantified through the concept of resilience in reliability theory; it is a subject of the authors' ongoing work and is outside the scope of this paper.

2.2. Basics of LRFD

The general form of the design equation is:

$$\gamma_R R \geq \gamma_L L \quad (3)$$

where resistance or capacity R , and stressing load L are random variables; γ_R and γ_L are the resistance and load factors, respectively. γ_R and γ_L are collectively referred to as design factors; they represent how much the resistance and load should be modified. Therefore, the design equation represents the relationship between resistance and stressing loads on the system derived from the uncertainty of involved random variables.

In the design equation (3), L can represent a single stressing load on the system, or consist of multiple loads. The corresponding design equation for multiple loads is:

$$\gamma_R R \geq \sum_i \gamma_{L_i} L_i \quad (4)$$

where L_i is the i^{th} load, and γ_{L_i} its respective load factor.

The original application of LRFD equations was in structures. The following simple example is modified from (Haldar and Mahadevan 2000) for a quick demonstration. Let us say that the design equation for a structure is $\gamma_R R \geq \gamma_{L_d} L_d + \gamma_{L_l} L_l$, where L_d and L_l are the dead and live loads, respectively. The dead load is the weight of the structure itself, while the live load includes the anticipated external stresses on the structure, such as traffic traveling over a bridge, winds and seismic forces. The resistance factor of γ_{L_d} reflects internal system characteristics such as strength and integrity of construction materials. Different loads on the structure are characterized by their respective load factors.

The reliability-based LRFD formulation (4) lends itself easily to interpretation in water quality. Capacity, or resistance, R is translated as a specific water quality standard, or TMDL; and L_i as contaminant loads from various sources in the given water body. Note that the distributed assessment of different types of loads, as opposed to a single value of MOS , could allow for adjustments in individual sources of contamination.

Depending on available information, design factors and statistics of resistance and loads can be calculated from measurement data, analytical models of contaminant fate and transport, or Monte Carlo simulations of watershed models. Note that in the case studies presented in this paper, measurement data (Shepherd Creek watershed - Section 3.1) or statistics reported in the literature (Upper East Fork watershed - Section 3.2) are used. To reduce computational time, approximation methods such as the First-Order Reliability Method (FORM) can be used instead of MC simulations.

2.3. First-Order Reliability Method (FORM)

First-order reliability method uses the first and second moments of the random variables to compute reliability index β or the probability of failure p_f . The following step-by-step algorithm is the FORM developed for reliability analysis with correlated non-normal random variables (Haldar 2008; Haldar and Mahadevan 2000). For more information about the history and theoretical background of FORM, readers are referred to Haldar and Mahadevan (2000).

Step 1. Define an appropriate performance function in the form of $g(\mathbf{X}) = g(X_1, X_2, \dots, X_n)$ where n is the number of basic random variables. The performance function represents the so-called limit state surface that serves as the boundary between satisfactory and unsatisfactory performances. When $g(\mathbf{X})$ is positive, then the system is performing satisfactorily; and when $g(\mathbf{X})$ is negative then the system is in failure. For instance, for the example shown in equation (3), the performance function will be $g = R - L$, where R is the resistance and L is the load.

Step 2. Assume an initial value for reliability index β . Initial value $\beta = 1$ is used here.

Step 3. Assume initial values for the design point $x_i^*, i = 1, 2, \dots, n$. The initial values are assumed to be equal to the mean of basic random variables X_i . The design point is defined as the most probable point of failure on the performance function (*e.g.*, the point at which the TMDL is exceeded).

Step 4. Compute equivalent normal mean and standard deviation for all non-normal random variables at the design point. For a lognormal variable X_i , it can be shown that the equivalent normal mean and standard deviation can be computed as $\mu_{X_i}^N = x_i^*(1 - \ln x_i^* + \lambda_{X_i})$ and $\sigma_{X_i}^N = \zeta_{X_i} x_i^*$, respectively. λ_{X_i} and ζ_{X_i} are the arithmetic mean and standard deviation of $\ln X_i$.

Step 5. Transform the performance function $g(X)$, that is a function of correlated non-normal random variables X_i , into $g(Y)$, that is a function of uncorrelated reduced normal variables Y_i . Equation (5) shows the relationship between X and Y :

$$X = \sigma_X^N T Y + \mu_X^N \quad (5)$$

where σ_X^N is a diagonal matrix that contains the equivalent normal standard deviations at the design point. Matrix T is an $n \times n$ orthogonal transformation matrix where its columns contain the normalized eigenvectors of the $n \times n$ correlation matrix C . Note that since normal variables Y_i are in reduced coordinates, their mean $\mu_{Y_i}^N$ is zero and their standard deviations $\sigma_{Y_i}^N$ is equal to the square root of eigenvalues of correlation matrix C .

Step 6. Find the location of the design point in reduced coordinates y_i^* using equation (5).

Since T is orthogonal, $T^{-1} = T^t$. Therefore, equation (5) can be simplified to $Y^* = T^t X'$,

$$\text{where } x_i' = \frac{x_i^* - \mu_{X_i}^N}{\sigma_{X_i}^N}.$$

Step 7. Compute the partial derivatives of performance function at the design point $\left(\frac{\partial g(Y)}{\partial Y_i}\right)^*$.

Step 8. Compute the direction cosines at the design point:

$$\alpha_{Y_i} = \frac{\left(\frac{\partial g(Y)}{\partial Y_i}\right)^* \sigma_{Y_i}^N}{\sqrt{\sum_{i=1}^n \left[\left(\frac{\partial g(Y)}{\partial Y_i}\right)^* \sigma_{Y_i}^N\right]^2}} \quad (6)$$

Step 9. Update the design point in reduced coordinates y_i^* using

$$y_i^* = \mu_{Y_i}^N - \alpha_{Y_i} \sigma_{Y_i}^N \quad (7)$$

Step 10. Find the location of the design point in the original coordinates x_i^* using equation 5.

Step 11. Repeat Steps 4–10 until the direction cosines converge. The convergence criterion of $\sqrt{\sum_{i=1}^n (\alpha_{Y_i, new} - \alpha_{Y_i, old})^2} \leq 0.001$ is used in this study.

Step 12. Keeping β as an unknown parameter, use equation 7 to find y_i^* , substitute y_i^* in $g(Y)$ and solve $g(Y) = 0$ for β .

Step 13. Repeat Steps 4–13 until reliability index β is converged. The convergence criterion of $|\beta_{new} - \beta_{old}| \leq 0.001$ is used in this study.

Step 14. Probability of failure can be computed using $p_f = 1 - \Phi(\beta)$, where Φ is the cumulative distribution function (CDF) of the standard normal variate.

2.4. Load Resistance Factor Design (LRFD)

The main objective in LRFD is to find design factors for each random variable. One of the common LRFD formulations is derived from applying the partial design factors γ_i to respective mean values μ_{X_i} (Ang and Tang 1984), in the form of

$$g(\gamma_1 \mu_{X_1}, \gamma_2 \mu_{X_2}, \dots, \gamma_n \mu_{X_n}) = 0 \quad (8)$$

From equation (8), it is clear that $\gamma_i \mu_{X_i}$ are coordinates of the design point on the limit state surface. Therefore, for a given reliability index β , if one finds the location of the limit state surface and therefore the design point, the partial design factors can be computed as

$$\gamma_i = \frac{x_i^*}{\mu_{X_i}} \quad (9)$$

In this study, we assume that the shape and coefficients of variation $\delta_{X_i} = \sigma_{X_i} / \mu_{X_i}$ do not change. This enables us to modify the position (mean) and spread (standard deviation) of random variables to meet the design requirements (Figure 1). Following Ang and Tang (1984), the following steps are taken to find the partial design factors:

Step 1. Define an appropriate performance function in the form of $g(X) = g(X_1, X_2, \dots, X_n)$.

Step 2. Assume that mean values are unknown. If the number of random variables is more than two, keep two of the mean values as unknowns and rewrite the rest as a function of the unknown mean values. For instance, in this study, if the performance function is

$$g(X) = R - L_1 - L_2 - L_3, \text{ we replace } \mu_X = [\mu_R, \mu_{L_1}, \mu_{L_2}, \mu_{L_3}] \text{ with } \mu_X = [\mu_R, \mu_{L_1}, a\mu_{L_1}, b\mu_{L_1}],$$

where a and b are constants calculated from load measurements.

Step 3. Set the target reliability index β . Given a target probability of failure of p_f , reliability index can be computed as $\beta = \Phi^{-1}(1 - p_f)$, where Φ^{-1} is the inverse of the standard normal CDF.

Step 4. Assume initial values for the design point $x_i^*, i = 1, 2, \dots, n$. The initial values are assumed to be equal to the mean of basic random variables X_i .

Step 5. Find the relationship between the unknown mean values by solving $g(X) = 0$ for x_i^* .

Step 6. Follow steps 4–10 of FORM (section 2.1) to update the design point x_i^* .

Step 7. Find the partial design factors γ_i using equation 9. If γ_i values are not numeric, use the relationship found in Step 5 to eliminate the unknowns.

Step 8. Repeat Steps 5–7 until the γ_i values converge. The convergence criterion of

$$\sqrt{\sum_{i=1}^n (\gamma_{i,new} - \gamma_{i,old})^2} \leq 0.001 \text{ is used in this study.}$$

Note that the produced design equation will be valid as long as the coefficients of variation and correlation coefficients do not change. In case of multiple loads, the relative ratio of the loads is assumed to remain constant. Otherwise, a new design equation must be produced.

2.5. Load Reduction in TMDL

As discussed in Section 2.2, the design equation for TMDL is $\gamma_R R \geq \sum_i \gamma_{L_i} L_i$ (Equation 4). It is equivalent to a performance function in the form of $g(X) = R - \sum_i L_i$. Implementing LRFD algorithm in Section 2.4, one can calculate the partial design factors for the resistance and each individual load.

Given the mean of target resistance μ_R and measured mean of individual loads $\mu_{L_i, measured}$, and assuming that all loads are to be reduced by the same fraction, we define load reduction as

$$\Delta = 1 - \frac{\gamma_R \mu_R}{\sum_i \gamma_{L_i} \mu_{L_i, measured}} \quad (10)$$

Negative reduction means that there is extra room in resistance; and positive - that the load should be reduced by Δ to meet the water quality standard.

3. Case Studies and Results

3.1. Shepherd Creek Watershed

The Shepherd Creek watershed is located in Cincinnati, Ohio. Spanning 1.85 km², it is about one-third mature deciduous forest within a city park, two-thirds residential, and the balance in livestock or horse pasture (Mayer et al. 2012). There are six stations that monitored discharge, dissolved inorganic nitrogen (DIN), and total phosphorus (TP) in the watershed (Figure 2). Samples were collected on a synoptic, monthly basis from 2005–2010, with selected rainfall events sampled at higher frequency across the storm hyetograph (Roy et al. 2014). Data at each station were pooled across the entire observation period. Assuming lognormal distributions for both load L and resistance R (Kay et al. 2008; Limpert et al. 2001), the distribution parameters were estimated by fitting lognormal distributions to the measured data. Since load and resistance are both functions of flow, their Pearson correlation coefficients were calculated and used in both FORM and LRFD analyses.

Given the safety criteria values of 1.1 mg/L for DIN and 0.1 mg/L for TP (Miltner 2010), we first present the probability of failure of the system, computed for both DIN and TP at each station using the FORM algorithm of Section 2.3. Then the reliability-based design equations are determined for the hypothetical target probability of failure of 25% using the LRFD algorithm described in Section 2.4. Finally, the load reductions are calculated using Equation (10).

LRFD for Dissolved Inorganic Nitrogen (DIN)—Given the measured streamflow (Q), DIN concentration ($C_{measured}$) and DIN safety criteria ($C_{limit} = 1.1 \text{ mg/L}$), the resistance and load is calculated as $R = QC_{limit}$ and $L = QC_{measured}$, respectively. Table 1 summarizes the DIN mean, coefficient of variation and correlation coefficient for resistance and load at each station, as well as their computed probability of failure, design equation and load reduction.

To showcase the applicability of LRFD analysis, the load duration curve analysis is performed at the outlet (Figure 3A), which is the watershed drainage point. Performing FORM analysis shows probability of failure of 56.31% at the outlet across all flow regimes. The LRFD analysis for target probability of failure of 25% results in design equation $0.19R \geq 0.16L$. This indicates that as long as the assumptions discussed in Section 2.4 remain valid, the inequality of $0.19\mu_R \geq 0.16\mu_L$ or $\mu_L \leq \frac{0.19}{0.16}\mu_R$ will guarantee probability of failure of 25%. Given the measured $\mu_R = 905.45 \text{ kg/yr}$ and $\mu_L = 6654.39 \text{ kg/yr}$, the design equation dictates DIN load reduction of 83.56% at the outlet. Figure 3B shows the load duration curve after applying the load reduction.

As shown in Table 1, high correlations between load and resistance are expected due to common dependence on streamflow. Yet, we also note that all locations require reduction in DIN to meet the water quality standard. Sub4 has the lowest required reduction among all

stations, likely due to impact of enhanced nutrient uptake (at least seasonally) in the forested portion of the watershed.

To improve water quality in a primarily urban, mixed-use watershed such as the Shepherd Creek, management options may include: nutrient management for lawns, identification and control of malfunctioning septic tanks, and managing flows. Since flow is an important contributor, its regulation would be one way to reduce the required load reduction, particularly at the Outlet. Some methods to accomplish overland flow regulation would include managing direct runoff from connected impervious areas, increasing flow paths by enhancing permeable lawns, meadows, and pastures, and adding permeable buffers to further isolate or mitigate runoff production and therefore DIN concentration reduction throughout the watershed. A more detailed analysis would involve LRFD computed for each of several distinct flow regimes identified from flow duration curves. This approach could help identify seasonal strategies to meet target failure rates.

LRFD for Total Phosphorus (TP)—Similar analysis is performed for total phosphorus (TP) in Shepherd Creek, where TP safety criteria is assumed to be 0.1 mg/L. Table 2 summarizes the TP mean, coefficient of variation and correlation coefficient for resistance and load at each station, as well as their computed probability of failure, design equation and load reduction.

The load duration curve for TP at Outlet is shown in Figure 4A. Performing FORM analysis shows probability of failure of 87.24% at the outlet across all flow regimes. The LRFD analysis for target probability of failure of 25% results in a design equation in form of $0.19R - 0.21L$. This indicates that as long as the assumptions discussed in section 2.4 remain valid, the inequality of $0.19\mu_R \geq 0.21\mu_L$ or $\mu_L \leq \frac{0.19}{0.21}\mu_R$ will guarantee probability of failure of 25%. Given the measured $\mu_R = 82.31 \text{ kg/yr}$ and $\mu_L = 2486.02 \text{ kg/yr}$, the design equation dictates DIN load reduction of 97.13% at the outlet. Figure 4B shows the load duration curve after applying the load reduction.

The LRFD results for TP in Table 2 show that reductions are needed at every location ranging from 91.84%–97.13% across the watershed. Managing flows could help reduce the required load reduction, and furthermore, better regulation of runoff will act to limit wash-off and mobilization of nutrients from fertilized residential lawns and livestock-equestrian pastures (*i.e.*, which have patchy distributions of surface-deposited animal manure), and erosion of potentially phosphorus-rich soils that comprise the landscapes in this watershed. Based on our observations, the vast majority of TP was sediment-associated forms of phosphorus, implicating soil erosion as an important contributor to TP loadings. For example, Sub1 has a large proportion of impervious area (19.9%) that contributes to direct runoff in shorter times than pervious areas, which is more or less immediately routed to streamflow. The flow in this area is routed through the catchment and concentrated in a separate storm-collection system; through Sub2, and finally to the Outlet. High flows over bare and even vegetated soils can drive inter-rill erosion processes, which makes erosion control one of the important measures that can be used to address TP transport. Runoff and erosion control strategies will reduce uncertainty in flows and in sediment loads, potentially

improving the accuracy of LRFD values. Eventually, the LRFD approach could be useful for comparing the performance of different management strategies.

During the sampling period, rain barrels and rain gardens were installed on nearly 30% of the properties in the dense residential areas that comprised Sub1 and Sub3, and as part of a retrofit, parcel-scale stormwater management project (Mayer et al. 2012; Roy et al. 2006, 2014). Over the course of this 7-year study, Shuster and Rhea (2013) found that the decentralized implementation of green infrastructures contributed to a statistically-significant, yet overall small decrease in catchment flows. This decrease was attributed to a combination of increased catchment detention capacity (*i.e.*, via rain garden) and the concomitant disconnection of directly-connected impervious areas (rooftop disconnection via rain barrels), which would serve to reduce the amount of runoff volume reaching the centralized sewer collection system. Minor changes to stream water quality were related to the green infrastructure treatments, though with no improvement in nutrient concentration, nor changes in biotic health (Roy et al. 2014). We concluded that basin health would benefit by increasing the number of management practices, especially those mitigating runoff from impervious areas. The LRFD augments these recommendations by determining the reductions required to meet management targets.

3.2. Upper East Fork Watershed

The Upper East Fork Watershed (UEFW) is a mixed-use watershed in southwest Ohio dominated by agriculture. The focus here is on a region in the headwaters of the UEFW drainage, shown in Figure 5. The drainage area is 341 km². Here we use annual predicted load values from literature and not measured data.

LRFD was performed for total nitrogen (TN) from multiple sources, for a target 25% exceedance probability. Assuming that the land cover of UEFW headwaters where we are focused is similar to the much larger Little Miami River Basin (HUC8) in which this area fall, predicted TN loads and their coefficients of variation (Table 3) were obtained from Robertson and Saad (2011). It was also assumed that 100% of predicted TN reaches the stream and eventually ends up at the outlet of the watershed. It was assumed that all load sources are lognormally distributed, and the correlation coefficient of 0.8 is used to capture the correlation between resistance and load and among different load sources. Statistics of annual flows (mean 3.8 m³/s, with standard deviation of 6.5 m³/s) were estimated from regression equations provided in Koltun and Whitehead (2001). Given safety criteria of 1.1 mg/L for TN, the mean and standard deviation of resistance was estimated to be 131,820.48 and 225,482.4 kg/yr, respectively. It should be noted that the values used in this case study may not be accurate as they are based on the HUC8 and were not validated for this particular area. Rather, the estimates are provided for the sole purpose of this case study to showcase LRFD, and don't need to have practical relevance.

Using FORM analysis, the probability of failure of the outlet is estimated to be ~80%. LRFD was performed for three cases, and for all three, design equations and load reductions were determined for a target probability of failure of 25%. First, all loads were aggregated into a total single load L , as represented in equation (2). Second, the load from point sources was separated from non-point sources:

$$\gamma_R R \geq \gamma_{L_{PS}} L_{PS} + \gamma_{L_{NPS}} L_{NPS} \quad (11)$$

Finally, each load type was included explicitly:

$$\gamma_R R \geq \gamma_{L_{PS}} L_{PS} + \gamma_{L_{Atm}} L_{Atm} + \gamma_{L_{Man}} L_{Man} + \gamma_{L_{Fert}} L_{Fert} + \gamma_{L_{Ag}} L_{Ag} \quad (12)$$

where L_{PS} is load from point sources, L_{Atm} is load attributed to atmospheric deposition, L_{Man} is load from manure, L_{Fert} is load from farm fertilizer, and L_{Ag} load from additional agriculture such as pasture, hay and range lands. Using equations (2), (11) and (12), the design equations and required reductions were calculated (Table 4).

The resistance factors vary slightly across the equations. This is due to interactions between resistance and various loads. The interactions between different loads and resistance within the watershed are elucidated in the design equations. The second design equation in Table 4, calculated in the format of equation (11), differentiates between point and non-point sources. This design equation indicates that as long as our assumptions discussed in section 2.4 remain valid, the inequality of $0.585 \mu_R \geq 0.426 \mu_{L_{PS}} + 0.553 \mu_{L_{NPS}}$ will guarantee probability of failure of 25%.

To better understand the contribution of individual non-point sources, we parse the loads even finer, and include atmospheric, manure, fertilizer and agricultural sources. The relationship among different loads and resistance can be seen in the third design equation in Table 4, calculated in the format of equation (12). It should be noted that the design equations for multiple load cases are derived based on the assumption that the ratio between mean values of different loads is constant (see Step 2 in Section 2.4). This means that if we reduce different loads with different fractions, a new equation must be produced.

4. Discussion

The LRFD methodology presented here was originally developed in structural engineering to design systems that can withstand random loads. In application to water quality, this concept is reversed; rather, the question is “given the system resistance expressed as water safety criteria, how should the loads change?”. Uncertainty evaluation is essential to answering this question. In traditional TMDL analyses, uncertainty is lumped into a single MOS. In departure from this practice, the LRFD allows for evaluation of uncertainty distributed among the loads stressing the system, as well as the system resistance. This form of attributing uncertainty can potentially help develop watershed management strategies that address a variety of contributing loads. Therefore, LRFD’s design factors serve as the primary instrument both to address the distributed uncertainty, and to determine the necessary load reductions.

Further, if loads are computed from physics-based models, better understanding of contributions from the usual suite of random parameters, such as rainfall intensity or saturated hydraulic conductivity, could guide these strategies. Finally, as part of adaptive management, to evaluate future changes in watersheds, various best management practices can be simulated and LRFD analysis implemented based on modeled results.

The relationship between design factors and uncertainty is not straightforward, and cannot be expressed in a single formula, as evidenced from complex algorithms presented in sections 2.3-2.4. In structural engineering it is typical to design resistance of the system to withstand stressing loads, with a very small probability of failure. In this situation, the relationship between uncertainty and load design factors is monotonic.

In water quality management, however, the problem is reversed. System resistance represents water quality standards, or TMDL, and stressing loads must be modified to ensure that probability of failure does not exceed a target value. Here, the probability of failure is much larger than allowed in structures, and there is no simple relationship between uncertainty and load factors. Rather, LRFD provides the complex relationship between system resistance, stressing loads on the system, probability of failure and the reduction in stressing loads required to maintain probability of failure under a target value. Future work should elucidate the relationship between input uncertainty and individual load factors in LRFD.

Water quality is assessed based on magnitude, duration and frequency of contamination. The reliability-based LRFD method presented here focuses on the frequency and magnitude of contamination. Frequency corresponds to the probability of failure, defined as the performance function of the system. Magnitude is present implicitly, as its value above or below the system resistance helps determine the probability of failure. Acceptable probability of failure is factored into the LRFD, and hence the suggested load reductions aim to achieve that value.

Furthermore, LRFD could establish a functional connection between the calculated TMDL and sustainability concepts such as reliability, vulnerability and resilience, which may facilitate the broader adoption of this method in TMDL modeling and implementation. In reliability theory, the complement of probability of failure is reliability. Magnitude of failure is referred to as vulnerability; and duration of failure is related to system resilience, defined as the probability that the system will return to the safe state in a given period of time. Reliability, vulnerability and resilience are known collectively as sustainability metrics (Hashimoto et al. 1982; Loucks 1997; Sandoval-Solis et al. 2011), and have been applied to water quality problems (Maier et al. 2001; Teklitz et al. 2014). All three can be calculated from reliability-based LRFD. Hence, posing TMDL as a LRFD problem reveals a connection to water sustainability. This is a subject of authors' ongoing work. Future work should also focus on systematic evaluation of accuracy of LRFD compared to MC-based methods, and computational efficiency compared to methods such as probabilistic collocation (Zheng et al. 2011).

5. Conclusions

LRFD was introduced as a consistent and rigorous reliability-based framework for water quality assessment. It allows for TMDL calculations, and provides a method to compute load reductions needed to attain a desired level of contamination frequency. LRFD supports data- or model-based load calculations (in this paper demonstrated with measurement data or statistics reported in the literature). Due to integration of approximation methods like FORM, it can handle a wide range of load statistics including marginal and joint probability distributions, and is computationally efficient. Collectively, these characteristics make LRFD an attractive methodology for application in water quality assessment in general, and the TMDL process in particular.

Acknowledgments and Disclaimer

The authors gratefully acknowledge the National Science Foundation for supporting this research (CBET-1351361 award). The U.S. Environmental Protection Agency (USEPA), through its Office of Research and Development, partially funded and collaborated in the research described herein. Any opinions expressed in this paper are those of the author(s) and do not reflect the views of the Agency, therefore, no official endorsement should be inferred. Any mention of trade names or commercial products does not constitute endorsement or recommendation for use by the USEPA. The authors thank Dr. A. Safwat for assistance with ArcGIS processing.

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Figure 1. The concept of reliability based design, with load and resistance expressed as random variables. The overlapping region represents the failure zone where load exceeds resistance.

Figure 2. Shepherd Creek Watershed in Cincinnati Ohio. Monitoring stations (IDs: Sub1 through Sub 5 and Outlet) are shown along with land use.

Figure 3.

Load duration curve for DIN at the Shepherd Creek Watershed outlet (A) before (B) after applying load reduction. Each point represents a sample that was taken, and the blue line represents resistance. All points above it represent loads exceeding the resistance. See USEPA (2007) for details on load duration curve calculations.

Figure 4.

Load duration curve for TP at the Shepherd Creek Watershed outlet (A) before (B) after applying load reduction. Each point represents a sample that was taken, and the blue line represents resistance. All points above it represent loads exceeding the resistance. See USEPA (2007) for details on load duration curve calculations.

Figure 5.
Upper East Fork Watershed headwaters

Table 1.

LRFD results for DIN in Shepherd Creek watershed. μ , δ and p_f represent the mean, coefficient of variation and probability of failure, respectively. The design equations and load reductions were determined to meet the target probability of failure of 25%.

Location	Correlation factor	Resistance (kg/yr) (μ, δ)	Load (kg/yr) (μ, δ)	p_f (%)	Design Equation		Load reduction (%)
Outlet	0.51	(905.45, 4.04)	(6654.39, 21.67)	56.31	0.19R	0.16L	83.56
Sub1	0.81	(173.33, 2.54)	(833.64, 5.66)	77.52	0.40R	0.40L	78.99
Sub2	0.54	(320.98, 3.12)	(3466.08, 17.67)	63.37	0.27R	0.20L	87.26
Sub3	0.54	(348.06, 3.02)	(2163.93, 14.67)	56.00	0.27R	0.22L	80.23
Sub4	0.43	(137.91, 2.30)	(500.37, 10.78)	46.60	0.33R	0.30L	69.57
Sub5	0.53	(227.38, 2.91)	(1021.23, 15.29)	47.93	0.29R	0.22L	71.10

Table 2.

LRFD results for TP in Shepherd Creek watershed. μ , δ and p_f represent the mean, coefficient of variation and probability of failure, respectively. The design equations and load reductions were determined to meet the target probability of failure of 25%.

Location	Correlation factor	Resistance (kg/yr) (μ, δ)	Load (kg/yr) (μ, δ)	p_f (%)	Design Equation		Load reduction (%)
Outlet	0.55	(82.31, 4.04)	(2486.02, 13.50)	87.24	0.19R	0.21L	97.13
Sub1	0.79	(15.76, 2.54)	(219.92, 7.01)	91.56	0.41R	0.36L	91.84
Sub2	0.70	(29.18, 3.12)	(1067.70, 10.37)	94.31	0.30R	0.27L	96.93
Sub3	0.57	(32.20, 3.06)	(747.58, 10.66)	85.85	0.26R	0.27L	95.77
Sub4	0.63	(12.54, 2.30)	(178.94, 6.13)	88.09	0.36R	0.40L	93.64
Sub5	0.48	(20.67, 2.91)	(641.66, 11.96)	84.95	0.26R	0.26L	96.75

Table 3.

Predicted TN load for UEFW headwaters, based on scaling of TN yield reported in Supplemental Material of Robertson and Saad (2011).

Load source	% Contribution	Predicted mean TN load (kg/yr)	Estimated coefficient of variation
Point sources	13.9	82924.55	3.81
Atmosphere	24.3	144968.82	2.07
Manure (confined)	4.2	25056.34	5.03
Farm fertilizers	38.0	226700.21	7.72
Additional agriculture	19.6	116929.58	12.63

Table 4.

Design equations for the UEFW headwaters for Total Nitrogen. Load reduction apply to all load sources.

Design Equation	Load reduction (%)
$0.557 R \geq 0.579 L$	78.75
$0.585 R \geq 0.426 L_{PS} + 0.553 L_{NPS}$	75.86
$0.590 R \geq 0.476 L_{PS} + 0.759 L_{Atm} + 0.365 L_{Man} + 0.308 L_{Fer} + 0.181 L_{Ag}$	68.87