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# Predicting the Effects of Decentralization on the Reliability, Resilience, and Stability of Wastewater Treatment Systems Using Generalized Linear Models

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*Predicting the Effects of Decentralization on the Reliability, Resilience, and Stability of Wastewater Treatment Systems Using Generalized Linear Models*

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## Abstract

Weirich, Scott Reily (Ph.D., Civil, Environmental, and Architectural Engineering)

*Predicting the Effects of Decentralization on the Reliability, Resilience, and Stability of Wastewater Treatment Systems Using Generalized Linear Models*

Thesis directed by Professor JoAnn Silverstein

There is growing interest in decentralized and cluster-scale wastewater treatment, but knowledge of the effects of decentralization on treatment performance and by extension surface water quality is limited. This research demonstrates a method for using Generalized Linear Models to quantify the effects of facility size and capacity utilization on effluent BOD, TSS, and ammonia discharges from individual facilities as well as the aggregate of networks of facilities. Small and overloaded facilities have more frequent and longer permit violations. However, by dispersing the risk of violations across many facilities, decentralized networks have less variability than centralized networks of equivalent capacity and thus have fewer extreme events. By providing a method for prediction of typical treatment performance as well as the frequency and magnitude of variations, this research provides a valuable tool for wastewater managers considering decentralized treatment.

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# Chapter 1. Introduction

## Problem Description

The modern industry of wastewater collection, treatment, and disposal began with an effort to protect public health in cities and to mitigate nuisance conditions brought about through lack of disposal locations for the waste. The high population density in large urban centers in the late nineteenth century meant sufficient land area for disposal of the untreated waste was not available, prompting early treatment methods (Tchobanoglous & Burton, 1991). These early efforts often included minimal treatment such as sand filtration, settling, or disinfection before the sewage was disposed of away from the city. In the USA, the need for wastewater treatment was codified in the Federal Water Pollution Control Act of 1948, amended in 1966 when it became known as the Clean Water Act. The FWPCA amendments of 1972 brought sweeping changes to wastewater treatment with surface water quality standards as foundation. Approximately $50 billion in Federal investments through the construction grants program resulted primarily in the construction of centralized wastewater treatment plants using the sewer infrastructure which had been built over the previous 75 years. Furthermore, the fixed costs of following FWPCA requirements for NPDES permits and extensive monitoring in order to discharge wastewater to surface water probably favor larger facilities supported by fees from residential, commercial and industrial users. Decentralized systems consisted mostly of on-site systems in rural areas (U.S. Environmental Protection Agency [USEPA], 1997). However, recently development of suburban and exurban areas and the need to serve communities too dense for on-site systems has brought new interest in small decentralized wastewater treatment plants (Tchobanoglous & Burton, 1991). Factors such as the cost of building out collection systems and pumping wastewater, improvements in small system technology, and automated operation have led organizations such as National Decentralized Wastewater Resources Capacity Development Project and the Centre for

Alternative Wastewater Treatment and the EPA-sponsored National Environmental Services Center to advocate for decentralized systems and small satellite plants (National Decentralized Water Resources Capacity Development Project; Centre for Alternative Wastewater Treatment, 2009; National Environmental Services Center, 2008).

Decentralized treatment systems are defined as “systems that collect, treat, and reuse or dispose of wastewater at or near its point of generation (Crites & Tchbanoglous, 1998).” This is commonly taken to mean on-site and cluster systems serving at most a few hundred homes (Pinkham, et. al., 2004a; USEPA, 1997), or more generally any system that is not centralized (Fane, Ashbolt, & White, 2002; Wang et. al., 2008). This research studied wastewater treatment systems of cluster scale and larger. As such, it is a study of decentralized systems in that it promotes consideration of wastewater treatment systems at scales less than whole community or municipality. This study specifically addresses the effect of system scale and fraction of design capacity used effluent water quality and reliability, resilience, and stability of treatment. These criteria were chosen due to their importance to wastewater decision makers, especially those in areas experiencing rapid growth in wastewater treatment coverage. This includes new developments as well as redevelopments such as rural areas experiencing more dense development. Additionally, though the study is based in the United States the methods described here should also apply in other countries such as those like India which are expanding wastewater treatment coverage. These criteria clear implications for meeting regulatory requirements and protecting receiving water quality (Crites & Tchobanoglous, 1998). While much research has focused on average or typical contaminant removal, it is frequently deviations from the mean that cause problems. Reliability, resilience, and stability are all measures of negative extremes and constitute a valuable contribution to knowledge of wastewater treatment.

**Incentives for Decentralization**

Since the 1950s, suburbanization has been a major geographical trend in the United States. With increased incomes, the population increasingly moved from dense urban city-centers to suburban areas typically featuring more single family homes and decreased population densities. From 1950 to 1990 the urban population grew by 92.3 percent while urban land use grew by 245.2 percent, indicating lower density development (Kahn, 2000). For similar household income, suburban dwellings typically have approximately 50 percent larger lots despite similar dwelling square footage. The 1995 American Housing Survey indicates that a suburban dweller earning $50,000 annually lived on a 1.1 acre lot, while an average city dweller lived on a 0.7 acre lot (Kahn, 2000). Similarly, between 1960 and 2000 development in one third of US counties became less dense, “particularly in high-amenity areas such as the mountain counties of the Rocky Mountain states (Theobald, 2001).”

This decrease in housing density affects the economies of scale derived from large centralized wastewater treatment through increased collection system costs. As cities expand, sewer systems must be expanded over longer distances, reaching relatively fewer people (Carruthers & Ulfarsson, 2003). This is especially true in cities such as San Francisco which have high degrees of clustering, often described as a desirable development pattern (Galster, 2001). The long wastewater transportation distances require significant capital expenditure in the form of piping and excavation. Though there are economies of scale in treatment, the diseconomies of scale in collection become increasingly significant as development density decreases (Clark, 1997 cited in Pinkham et al., 2004a), driving increasing interest in decentralized treatment. Furthermore, collection systems represent a sizable fraction of wastewater utility assets. In fact, for smaller communities, the capital cost of conventional gravity sewers on average was found to be four times the cost of treatment with a similar relation for operation and maintenance costs. This is due to both the longer piping distances in lower density developments and the increased need for lift stations (Water Environment Foundation [WEF], 2008). In addition to serving populations in growth areas, many US cities with centralized plants expect to replace aging sewers in the coming decades, and there is the potential for considerable economic benefits from smaller collection systems served by satellite wastewater treatment.

Increasing interest in water reuse provides further incentive to reduce wastewater transport distances. Because gravity flow sewers are the primary means of wastewater conveyance, wastewater treatment facilities are typically located at or near the lowest elevation in the service area, so recycled water often must be pumped back to higher elevations. In Denver, for example, pumping constitutes 50% of the costs of reuse water in a separate distribution system. Reducing the service area of the facility would reduce the pumping requirements provided there were local opportunities for reuse, leading to savings in capital costs and operations costs, especially energy. Reduced flows in small service areas will result in smaller but more numerous treatment plants which will also have impacts on receiving water quality, unit costs, and system reliability.

Financing presents additional incentive for decentralized systems. Decentralization allows development of wastewater infrastructure as needed, as opposed to well in advance as with centralized systems. This distributes capital outlays rather than concentrating them in time, reducing debt financing costs, operations and maintenance costs when a centralized facility would be under loaded, and risks due to uncertainty of growth predictions (Pinkham, Magliaro, & Kinsley, 2004b). However, smaller systems have difficulties financing growth and capital investments though these could problems be avoided by integration into a larger management scheme (Garvin, 2003).

There is additional demand for small treatment plants due to communities increasing their wastewater treatment standards. The EPA's 2004 Clean Watersheds Needs Survey (CWNS) estimates that if current documented needs are met there will be 1552 new treatment plants of which 53 percent will serve small communities, defined as those with less that 10,000 people or 1 MGD wastewater flow. These facilities will serve an estimated 680,000 people at a cost of $2.0 billion. Many of these facilities are expected to replace failing onsite treatment systems. Total small community needs are $17 billion, 9 percent of the total wastewater need monetary need (USEPA, 2008a). The demand for small treatment facilities is amplified in Colorado which reported needs of $408 million, an increase of $158 million in needs for small communities compared to the 2000 CWNS. Small communities account for 19 percent of the total needs in the state despite only serving 10 percent of the population, and combined with the increasing needs indicates increasing investment in small community wastewater infrastructure relative to larger communities (USEPA, 2008a).

**Treatment Options for Small or Satellite Systems**

To meet this growing demand for decentralized and small community wastewater treatment, a number of technologies have been developed or adapted from conventional processes to provide primary, secondary, and advanced or tertiary treatment. These include a number of activated sludge processes, trickling filters, wetlands, anaerobic digestion, and lagoons and can achieve a variety of treatment levels (Crites & Tchobanoglous, 1998).

Activated sludge processes typically have been used in large treatment plants, though the processes can be effectively scaled down for smaller plants using extended aeration, oxidation ditches, and sequencing batch reactors and, more recently (microfiltration) membrane bioreactors. These processes are desirable for small communities because they can produce high quality effluent including nutrient removal while being relatively easy to operate and energy efficient (Crites & Tchobanoglous, 1998). A study of facilities serving between 1,600 and 20,000 population equivalents found that biological denitrification and aerobic-anoxic secondary treatment were more efficient than extended air processes due to reduced energy use (Gallego, Hospido, Moreira, & Feijoo, 2008). Attached growth processes such as trickling filters are less common than they once were since they are less consistent in meeting stricter discharge standards, especially for nitrogen compounds (Tchobanoglous & Burton, 1991; Beavers & Tully, 2005). A number of attached growth processes such as recirculating sand filters and biofilters are being developed to effectively remove nitrogen in small facilities (Beavers & Tully, 2005). Anaerobic processes implemented in small plants are similar to septic tanks and are well suited to individual households and small treatment facilities.

Considerable research has been done to characterize the performance and reliability of these processes. Research in Belgium has shown activated sludge processes serving less than 2200 people can reliably achieve BOD levels of less than 30 mg/L and suspended solids under 40 mg/L, similar to large facilities (Geenens & Thoeye, 2000). A study of 356 small treatment facilities in Norway shows activated sludge and biofilm processes achieved average BOD removal efficiencies of 81% and suspended solids removal of 91%. Variation in effluent quality between facilities was higher than that for large facilities, indicating biological processes may be unstable on a small scale (Odegaard & Skrovseth, 1997). A comparison of treatment reliability was performed on 166 plants in Brazil using methodology developed by Niku et al. (1979, 1981a), which verified the lognormal distribution of effluent concentrations for several constituents. This study found that activated sludge processes and upflow aerated sludge blanket reactors achieved the highest reliability while septic tanks had the lowest reliability (Oliveira & Von Sperling, 2008). Several models for predicting effluent variability have been developed for specific treatment processes, including aerated lagoons (Ouldali, Leduc, & Nguyen, 1989), an activated sludge plant in Israel (Weber & Juanico, 1990), and anaerobic reactors (Leitao, van Haandel, Zeeman, & Lettinga, 2006). No studies have been found relating reliability or performance variability to facility size.

**Wastewater Planning**

Despite the wide range of treatment facility scales and processes available, there has been little comprehensive research to determine the relationships between facility size and a number of factors important to wastewater engineers and decision makers, particularly for small systems. As the number of processes and decentralization options increases, coupled with the trend toward multi-objective design including life cycle costs, energy use, and various environmental concerns, knowledge of the overall effect of treatment system size and organization become more important. "Important research questions for decentralized and centralized wastewater treatment in the United States revolve around how to incorporate these technologies to the present infrastructure and institutions (Etnier, 2007)."

Several studies have been performed to determine economies of scale for wastewater treatment plants. In an analysis of 172 facilities in Britain, a strong economy of scale for operations and maintenance was found for plants smaller than 5 MGD; larger facilities, however, showed very little decrease in cost as size increased (Knapp, 1978). A similar result was found for O and M costs among facilities in Italy serving 10,000 people or more (Fraquelli & Giandrone, 2003), and for O and M and construction costs for facilities in the US with flows 0.6 MGD and larger (USEPA, 1978a, 1978b). The studies in Britain and Italy also found that removal of BOD and COD, respectively, were significantly positively correlated with O and M costs. In contrast, a study in Adelaide, Australia found diseconomies of scale for collection system costs and that the overall economy or diseconomy of scale for collection and treatment was dependent on population density (Pinkham et al., 2004a). In all cases, data on smaller systems was not considered.

To date, there is substantial case study literature demonstrating the potential advantages of decentralized and clustered systems. The EPA considered two hypothetical communities: a small rural community with 135 homes on 1 acre or larger lots, and a suburban community with 220 homes on half acre lots expected to grow to 443 homes. Both communities have existing onsite treatment systems, some of which are failing. In both cases, the study found that new onsite treatment systems and cluster systems with small diameter gravity sewers had similar costs, with cluster systems having higher capital costs but lower operating costs. Centralized treatment (for the rural community) and connection to the nearby city (for the suburb) were found to be more expensive in both cases. The capital cost of collection systems were the determining factor because the study cost estimates showed conventional gravity flow sewers were considerably more expensive per connection than septic tanks or the small diameter gravity sewers used in cluster systems. The cost for collection was more than three times the cost for treatment (USEPA, 1997).

The Rocky Mountain Institute conducted case studies of eight communities considering decentralized wastewater infrastructure. These studies included various sized communities from small Coaldale, Pennsylvania to Boston, Massachusetts and Mobile, Alabama. Key findings included: the hydrologic importance of incidental interbasin transfers in the Boston area resulting from wastewater discharging to different watersheds than the drinking water sources, the potential for integration of centralized and decentralized treatment in Mobile, and how the negative perception of onsite treatment performance affects decision making (Pinkham et al., 2004b).

These studies highlight many factors involved in decision making for wastewater management, including: land use planning, public perception, financing costs and options, hydrologic impacts, reuse considerations, and system reliability. Combined with increasingly strict discharge requirements for nutrient levels and concern over emerging contaminants such as pharmaceuticals, these many factors complicate wastewater planning, but a variety of methods have been developed to aid decision makers.

Asset management aims to increase system reliability while decreasing costs through the use of specific tools (Allbee, 2005). Life cycle costing, organizational structures, and information systems are used to optimize operations and maintenance procedures, for example reliability analysis of pumps to determine the optimal life span and replacement schedule (Fane et al., 2004). By contrast, environmental impact assessment (EIA) and life-cycle assessment (LCA) are decision making tools which use detailed accounting procedures to identify and quantify a variety of noneconomic effects of a project. EIA primarily focuses on predicting and mitigating environmental and social effects of projects, while LCA is a specific methodology designed to account for environmental impacts such as greenhouse gas emissions over the whole life of a product, including embodied emissions or energy of materials, construction effects, operational emissions, and disposal (Kirk, 2005). LCA has been used to compare alternatives for specific wastewater treatment facilities using criteria such as nitrogen and phosphorus recycling, water reuse, and treatment performance (Lundin & Morrison, 2002), and energy use and global warming potential (Peters & Lundie, 2008; Zhang & Wilson, 2007).

Though these methodologies are helpful in deciding between specific alternatives, they are not very helpful for regional wastewater planning decisions such as location of treatment facilities, sewer service area, and treatment levels for each facility. Mathematical models have been developed for this problem, but the complexity requires significant simplifications. Cunha, Pinheiro, Zeferino, Antunes, & Afonso (2009) developed a method to optimize treatment locations and sewer connections to meet surface water quality standards in a stream, but simplifications include limiting the model to only two treatment facility sizes. Similarly, Wang & Jamieson (2002) optimize treatment for a region treating communities as discrete point sources. Voutchkov & Boulos (1993) use a heuristic method with simplified cost equations to screen infeasible treatment options. These methods all assume regionalizing treatment will result in cost savings through economies of scale. Furthermore, these methods do not account for variations in treatment performance or likelihood and aggregate affect of simultaneous poor treatment at several facilities.

In contrast to the optimization methods, regional agencies such as the Denver Regional Council of Governments [DRCOG] must manage wastewater treatment for a largely continuous urban area and DRCOG delineates treatment system service areas through a combination of municipal, hydrologic, and legal boundaries (Denver Regional Council of Governments, 1998). Assuming one treatment facility for each service area precludes consideration of decentralized treatment, and does not account for the differences in treatment performance and reliability that the degree of centralization affects.

There is a large body of anecdotal evidence that small treatment facilities often perform poorly compared to large facilities. Reasons for this poor performance include limited operator presence or training, poor growth forecasting leading to over or underloading and lack of regulatory oversight. However, previous studies have not produced a systematic comparison of treatment performance of large (centralized) and small (decentralized) treatment facilities as well as resulting differences in risk to receiving waters. To address that need, a statistical study was designed to test whether a relationship exists between treatment plant capacity and effluent quality. Through analysis of a national database of operating facilities using Generalized Linear Models, this research guides planners, regulators, and utility managers in defining service areas and system-scale which will provide adequate treatment and reliability to meet water quality goals.

**Generalized Linear Models**

Generalized Linear Models are an advanced regression technique that solves several of the issues ordinary linear regression can have. Ordinary linear regression models attempt to quantify the relationship between a response variable and one or more predictor variables with the following form:

$$\boldsymbol{Y} = \boldsymbol{X\beta} + \boldsymbol{\varepsilon} \qquad (1\text{-}1)$$

***Y*** is a vector of observations of the response variable. $\boldsymbol{X\beta}$ is the linear predictor and accounts for the systematic variability of the predictor variables. More specifically, ***X*** is a matrix of observations of the predictor variables and $\boldsymbol{\beta}$ is a vector of the parameters to be estimated. Finally, $\boldsymbol{\varepsilon}$ is the vector of random errors. The parameters $\boldsymbol{\beta}$ are most commonly fit using ordinary least squares though other procedures exist.

For this modeling method to be valid, a number of assumptions must be made. Two important assumptions are linearity and constant variance. Linearity occurs when the mean of the response variable changes linearly with the predictor variables. Constant variance means that the variability of the random errors is the same regardless of the magnitude of the response variable, which often implies a normal distribution of the random error or other distribution with an unbounded range. For wastewater treatment, neither of these assumptions hold true. Even when the predictor variables are transformed with logarithms or other ways, there is no reason to believe that effluent concentrations vary linearly with flow and capacity utilization (the predictor variables in this study). Constant variance is even more problematic, because effluent variability is clearly related to the magnitude of the effluent discharge. At low effluent concentrations, there is also low variability while at high concentrations the variability is large.

To deal with this issue, the observations of the response variable ***Y*** can be transformed and the transformed data is fit to the predictor variables ***X***. Common transformations for nonnegative data include the logarithm and square root. Because the transformation is performed on the observed data, it is possible to achieve linearity or constant variance, but it is often not possible to achieve both simultaneously. Fitting to the transformed data still relies on the assumption that the transformed data comes from a normal distribution. This assumption is particularly inappropriate for modeling the probability of occurrence of an event such as an effluent violation (chapter 2). In this case the response variable has both a lower of 0 and an upper bound of 1. In this situation, variance is not constant nor does it vary proportionally to the response variable. For this case, specialized regression techniques have been developed for data which fits a binomial distribution.

Though other regression techniques cannot overcome these issues, Generalized Linear Modeling (GLM), developed by Nelder and Wedderburn (1972), is able to accomplish this. By separating the random aspect of the model from the systematic part, GLMs accommodate data with random errors from any distribution in the exponential family including normal, Gamma, binomial, Poisson, and other distributions. In GLM, linearity is achieved by transforming the *expected value* of the response variable, but not the observed data itself, with a link function *g*. This results in the following equation:

$$E(\boldsymbol{Y}) = g^{-1}(\boldsymbol{X\beta}) \qquad \text{(1-2)}$$

By using maximum likelihood to fit the model parameters, the need for constant variance is dispensed with. Maximum likelihood is an iterative method in which the likelihood of generating each observation is calculated for a given set of parameters and the selected distribution. In effect, the likelihood of a given value of ***Y*** can be calculated from the expected value for a given set of parameters and predictor variables ***X*** and the chosen error distribution. The parameters are then adjusted and the likelihoods recalculated until the set of parameters which produce the greatest likelihood are found. The Newton-Raphson method and the Fisher's scoring method are common algorithms used in this calculation. See McCullagh and Nelder (1989) for more information.

With the choice of an appropriate link function to achieve linearity and a distribution which effectively models the random variation, GLMs can model a wide variety of data. In this study, a binomial distribution with the logit link function is used to model the probability of a violation (chapter 2), and a Gamma distribution with the inverse link function is used to model the effluent concentration (chapters 3 and 4). To choose the proper link function as well as the best combination of predictor variables, the Akaike Information Criterion (Akaike, 1974), calculated as:

$$AIC = 2k - 2L \tag{1-3}$$

where k is the number of model parameters (terms in $\boldsymbol{\beta}$) and L is the logarithm of the likelihood. The model with the lowest value of AIC is considered the best model. This means the model with the highest likelihood and the fewest parameters is chosen for further analysis. Obviously the model with the highest likelihood fits the data best. The penalty for number of parameters protects against overfitting.

In addition to the use of GLM, the effluent concentration models developed in chapter 3 and used for simulation in chapter 4 includes a lag 1 autoregressive term. This means that the predictor variables at a given time step include the response variable from the previous time step in addition to other quantities. The inclusion of prior performance means the model contains time-dependent information which allows for analysis of sequential performance and time series simulation.

GLMs have been used in many fields. Examples include Furrer and Katz (2007), who used autoregressive GLMs to model and simulate daily weather data, including rainfall occurrence and intensity as well as minimum and maximum temperature. GLMs have also been used to analyze the resilience of bird populations to temperature changes (Jiguet et. al, 2006), the distribution of parasites (Wilson and Grenfell, 1997), and dose-response toxicity relationships for water contaminants (Kerr and Meador, 1995).

# Chapter 2. Effect of Average Flow and Capacity Utilization on Effluent Water Quality

## Background

Effluent concentration of a constituent and relative concentration, normalized to permit limits, will have both systematic variability, represented as its relationship to factors like facility size and capacity utilization, and random variability arising from changes in effluent water quality within a single facility over time and inherent differences between facilities including influent characteristics, facility age and process type. Factors which may be associated with plant size such as equipment, maintenance levels, labor quality and hours could lead to variation in treatment performance (Niku and Schroeder, 1981b).

Since the work of Niku et al., the generalized linear model (GLM) has been developed as a flexible statistical method of accurately modeling a wide variety of data including non-normal distributions and discrete variables. As described in detail in chapter 1, in a GLM the response or the dependent variable *Y* can be assumed to be a realization from any distribution in the exponential family with a set of parameters (McCullagh and Nelder, 1989). Thus positively-skewed, nonnegative data such as effluent concentrations of constituents can be modeled with a gamma or lognormal distribution and violation probability can be directly modeled with a binomial distribution using the same statistical method. The GLM enables simultaneous consideration of more than one independent variable without the assumption of linear relationships between independent and dependent variables.

In GLM, a smooth and invertible link function transforms the conditional expectation of *Y* to a set of predictors.

$$G(\mathrm{E}(Y)) = \eta = f(\boldsymbol{X}) + \varepsilon = \boldsymbol{X\beta}^{T} + \varepsilon \qquad (2\text{-}1)$$

$\boldsymbol{\beta}^T$ is the transposed vector of model parameters, $\boldsymbol{X}$ is the set of predictors or independent variables, E($Y$) is the expected value of the response variable, ε is the error, and $G$(.) is the link function.

After choosing a distribution and link function, the model parameters are estimated using an iterated weighted least squares (IWLS) method that maximizes the likelihood function as opposed to an ordinary least squares method used in linear modeling. The best model is chosen based on the Akaike Information Criteria (AIC, Akaike, 1974) by comparing models fit using all possible subsets of predictors. This criterion rewards models with a close fit and penalizes models with more parameters. The model with the lowest AIC is taken to be the 'best model'. Models can also be tested for significance against a null model or an appropriate subset model using a chi-squared test.

## Methods

To analyze the effect of treatment facility size and capacity utilization on effluent quality and violation history, data from the Environmental Protection Agency's Integrated Compliance Information System (ICIS) was used. ICIS contains enforcement and compliance information for over 10,000 wastewater facilities with NPDES permits in 28 states and US territories (USEPA, 20089b). The ICIS database is gradually replacing the older Permit Compliance System (PCS); hence it does not have data for facilities in the 22 states that have not yet switched their reporting to the newer system. For those states with data, however, the most recent 2 to 5 years of discharge monthly reports (DMR) are available for most facilities. The data include all required reporting for each facility, including effluent concentrations for permitted constituents, influent measurements, flow through the plant, and the permitted discharge limits each month.

To reduce data processing time and storage requirements, a systematic sample consisting of 5% of the ICIS database (629 facilities) was used for analysis. The data set was further reduced by filtering out facilities with insufficient data for analysis of each of the four constituents, BOD, TSS, ammonia, and fecal coliforms, resulting in four separate data sets. The data set for BOD contains 209 facilities, TSS has 211, ammonia has 110, and fecal coliforms has 109 with an average of 41 months of data per facility.

## Prediction of Effluent Constituent Levels

An important criterion related to treatment performance is effluent concentration, but permit standards vary considerably between plants due to factors such as receiving water quality, dilution factor, location, and season. Plants may be designed to meet current permit levels or anticipated future permit levels. As a result of these local differences, the absolute concentration of a constituent in the effluent is expected to differ between treatment facilities of equivalent treatment performance and reliability. To account for this the relative concentration was selected to be the dependent variable for regression, where relative concentration is the reported average monthly discharge concentration for a given constituent divided by the discharge permit standard.

Relative concentration is greater than zero and positively-skewed so the gamma function and its associated canonical link function, the inverse, was selected for GLM modeling of effluent constituent levels resulting in the following equation.

$$\frac{1}{E(R)} = \boldsymbol{X\beta^T} + \varepsilon \qquad (2\text{-}2)$$

where E(R) > 0 is the predicted effluent concentration of the constituent (BOD, TSS, ammonia or fecal coliforms), $\boldsymbol{X}$ is the matrix of independent variables, ε is the error, and $\boldsymbol{\beta^T}$ is the transposed vector of model parameters which are estimated following the methods described above.

To determine the effect of facility size on treatment performance two independent variables have been chosen. First is the logarithm of the average monthly flow rate, *A*. Flow rates of facilities in the data sets vary from 1 to 335,000 m^3/d. It was hypothesized that plant performance could also be influenced by over- or under-loading, so the second independent variable is capacity utilization, *C*, defined as the reported monthly average flow rate divided by the design flow rate. The product of these two variables, *AC*, is also included as an independent variable, and all combinations of independent variables are compared using AIC. Process type was explicitly ignored as an independent variable due to lack of data and a desire to quantify performance explicitly as related to decentralization. Analysis was performed using R, a free software package for statistical computing and graphics.

**Probability of Violation**

To quantify risk the frequency and magnitude of permit violations were modeled. Permit standards are based on scientific water quality criteria adopted to protect aquatic life and other uses of receiving waters, and therefore the probability of violations are a reasonable indicator of risk of significant adverse effects to the receiving water. The probability of a violation also can be considered a second indicator of treatment plant reliability. Permit violations subject the plant owner/operator to regulatory penalties, including fines.

To model violation frequency the response variable, effluent concentration, was converted to a binomial variable where *1* represented a permit violation and *0* represented no violation. The GLM is fitted using a binomial distribution with the logit link function as follows:

$$\ln\left(\frac{E(V)}{1-E(V)}\right) = \boldsymbol{X\beta^T} \qquad (2\text{-}3)$$

where $E(V)$ is the probability of a violation that ranges between 0 and 1, and other terms are as described for equation 3. With the fitted best model the risk of violations can be estimated.

**Violation Magnitude**

A second component of risk is the magnitude of violations. Large exceedances of discharge standards could have a significant effect on receiving water quality, especially in cases where there is little dilution, sensitive aquatic habitat, or proximate human use. The relative discharge values exceeding the threshold are obtained from the data and best GLM model based on the three independent variables is fitted using the Gamma distribution and the inverse link function using the same procedure described above.

**Results and Discussion**

Results of GLM analysis for prediction of effluent BOD as a function of plant flow and capacity utilization are presented in detail. Since the same procedure was followed for TSS, ammonia and fecal coliforms, results for these constituents have been summarized to allow discussion of differences in effluent trends among the four constituents.

**Effluent Concentration Model – BOD**

Flow rates of the 209 facilities used for BOD analysis ranged from 1 $m^3$/d (0.001 MGD) to 335,000 $m^3$/d (100 MGD) and capacity utilization rates ranged from 5% to 180%. Interestingly, 13% of those facilities average flow rates above their permitted capacity. Because EPA regulations require a plant to begin the re-design phase when a facility averages more than 85% of its design capacity, these facilities are in violation of that portion of their permit. Exceeding the hydraulic capacity of plants turns out to be a significant factor in effluent quality for smaller plants, as will be discussed below.

Using these 209 facilities, GLM to predict relative BOD concentration were fit for all possible combinations of the independent variables (logarithm of average flow and capacity utilization), as described in section 2.1. The AIC values of each model were compared, as shown in Table 2-1, and $Cond_{A+C+AC}$ was identified as the best model. This model uses both independent variables as well as the nonlinear product and was significantly better at fitting effluent data than the unconditional model and $Cond_A$ and $Cond_{A+C}$ at alpha = 0.05. This model is used for subsequent analysis.

Table 2-1: GLM functions, parameters, $\beta^T$, and associated AIC values for prediction of relative effluent BOD. R = predicted monthly average BOD (mg/l); A = log(average monthly flow) $m^3/d$; C = fraction of hydraulic capacity utilized; se = standard error

| | Uncond | $Cond_A$ | $Cond_C$ | $Cond_{AC}$ | $Cond_{A+C}$ | $Cond_{A+AC}$ | $Cond_{C+AC}$ | $Cond_{A+C+AC}$ |
|---|---|---|---|---|---|---|---|---|
| 1/R = | $\beta_0$ | $\beta_0+\beta_1 A$ | $\beta_0+\beta_2 C$ | $\beta_0+\beta_3 AC$ | $\beta_0+\beta_1 A+\beta_2 C$ | $\beta_0+\beta_1 A+\beta_3 AC$ | $\beta_0+\beta_2 C+\beta_3 AC$ | $\beta_0+\beta_1 A+\beta_2 C+\beta_3 AC$ |
| $\beta_0$ (se) | 2.62 (0.0332) | 2.79 (0.0405) | 2.83 (0.0714) | 2.79 (0.0377) | 3.26 (0.0829) | 2.79 (0.0406) | 2.89 (0.0678) | 3.03 (0.0989) |
| $\beta_1$ (se) | - | 0.143 (0.0160) | - | - | 0.182 (0.0177) | 0.00744 (0.0254) [a] | - | 0.0691 (0.0343) |
| $\beta_2$ (se) | - | - | -0.299 (0.0869) | - | -0.588 (0.0870) | - | -0.155 (0.0849) [a] | -0.308 (0.114) |
| $\beta_3$ (se) | - | - | - | 0.266 (0.0217) | - | 0.259 (0.0332) | 0.254 (0.0222) | 0.176 (0.0450) |
| *AIC* | -3 | -175 | -26 | -290 | -269 | -288 | -295 | -302 |

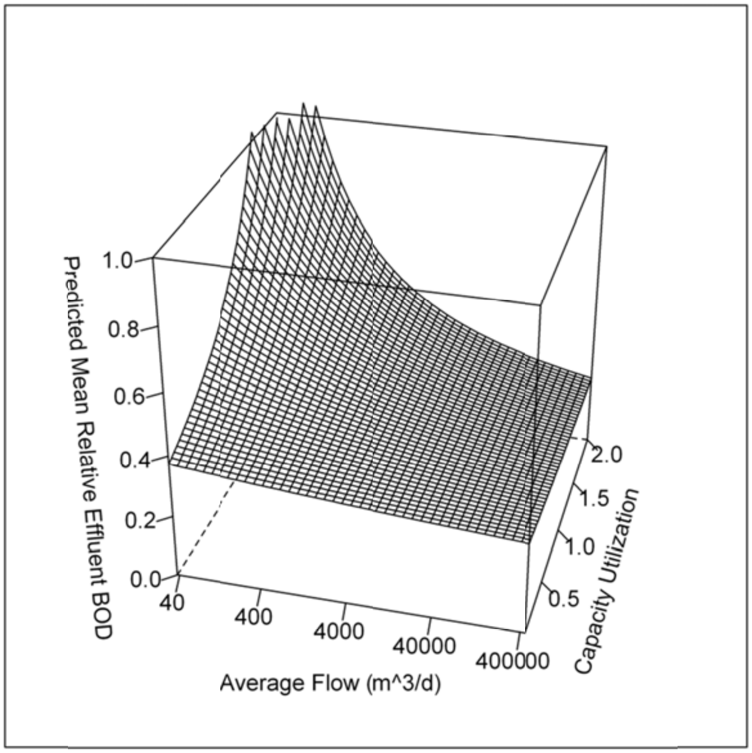
[a] Term not significant at $\alpha = 0.05$

A generalized linear model from the gamma family was fit to the data using the inverse link function. Thus, the expected value of the relative effluent BOD, *E(R)*, is modeled as:

$$1 / E(R_{BOD}) = 3.03 + 0.0691A + -0.308C + 0.176AC \qquad (2\text{-}4)$$

In the equation above, positive coefficients indicate a negative correlation between the independent variable and response variable so large and highly utilized facilities have lower expected effluent BOD than small facilities operating close to or over their permitted capacity, as shown in Figure 2-1. More specifically, small facilities (40 $m^3/d$) are predicted to discharge BOD that averages 40% or more of permit limits while predicted effluent BOD from large facilities (400,000 $m^3/d$) is consistently 33% of permit limits. Furthermore, for facilities 40,000 $m^3/d$ and larger, capacity utilization has almost no effect on the effluent BOD while for smaller facilities increasing capacity utilization is associated with increasing relative effluent BOD.

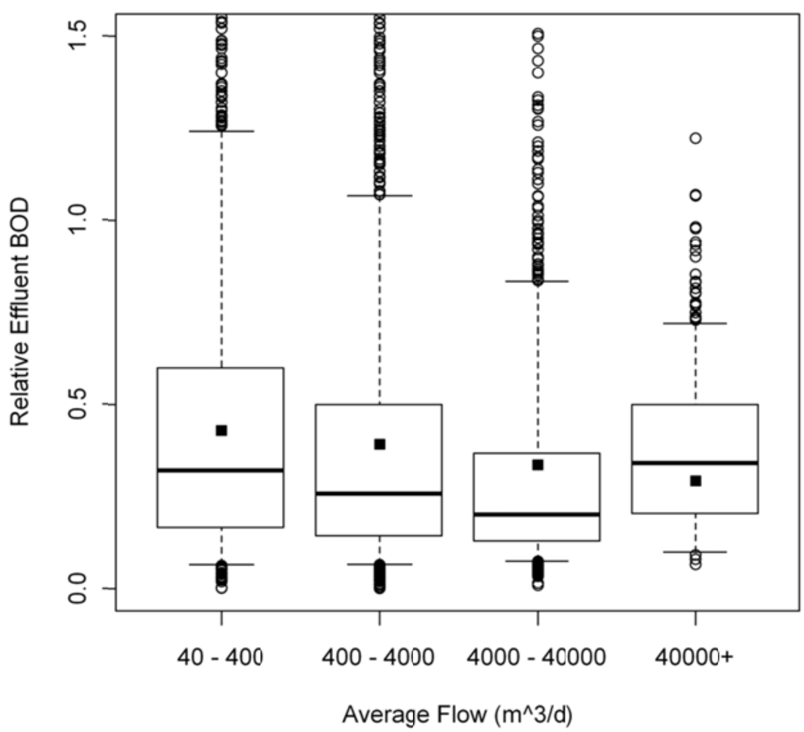
Figure 2-1: Predicted relative effluent BOD concentration versus average flow and capacity utilization




**Comparison of model and actual data**

A boxplot shows actual effluent data sorted by facility flow rate (Figure 2-2). The whiskers of the boxplot indicate the 5$^{th}$ and 95$^{th}$ percentiles, and not the interquartile range (IQR) times 1.5 as is common for boxplots, and the black squares show the predicted effluent level for the average flow rate and capacity utilization in that size range. The predicted values consistently fall between the first and third quartiles and also follow the trend shown in the median values up to 40,000 m$^3$/d, specifically that there is a decrease in average BOD discharged as plants increase in size. Above 40,000 $m^3/d$, however, there is a significant increase in median effluent BOD not predicted by the model.

Figure 2-2: Boxplot showing variation of BOD discharges by facility size where whiskers show 5% and 95% percentiles and black square is the model prediction using the average flow and capacity utilization for facilities in the size range.




Both the IQR and the whisker length decrease as facilities get larger, and it is especially notable that the 95th percentile effluent BOD is above the permit limit for the two smallest size categories. By contrast, the largest facilities have the highest median discharge but the 95th percentile is furthest below the permit limit, showing that median discharge is not related to permit violations in the same way for larger facilities as it is for smaller plants. The latter result suggests that large facilities discharge closer to their permit limits on average but also have fewer violations, possibly due to more consistent treatment.

The large variation in BOD discharges, both for facilities of a given size range as shown but also within individual facilities, indicates that flow and capacity utilization are not sufficient to predict a facility's performance in any given month; however, for comparison of the BOD removal among the entire data set or prediction for a single facility over a long period of time, the GLM does provide a good estimate of effluent BOD.

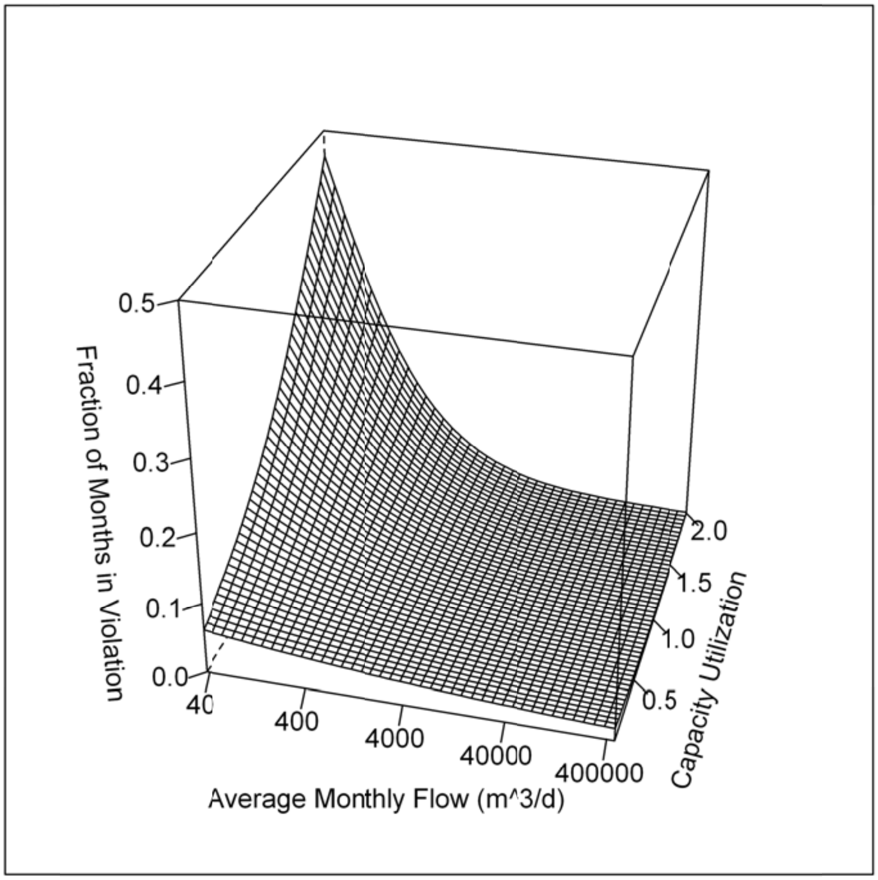
**BOD Permit Limit Violations**

While average effluent levels provide one measure of treatment performance, permit violations may be a better measure of the risk of significant BOD release to receiving waters. As Figure 2-2 shows, though the largest facilities have the highest median relative effluent BOD they have the fewest discharges above their permitted values. To directly model probability of permit violations the data for effluent BOD are transformed into a *1* for effluent BOD exceeding the permit limit - a violation, or a *0* indicating no violation. A binomial GLM was fit to the data using the logit link function. The model with the best set of predictors (lowest AIC) is:

$$\ln\left(\frac{E(V_{BOD})}{1-E(V_{BOD})}\right) = -3.35 + -0.128A + -0.284AC \qquad (2\text{-}5)$$

The negative coefficients indicate a negative correlation for average flow and for the combined term, meaning larger facilities and more highly utilized facilities have lower violation rates as shown in Figure 2-3.

Figure 2-3: Model prediction of BOD violations versus average flow and capacity utilization

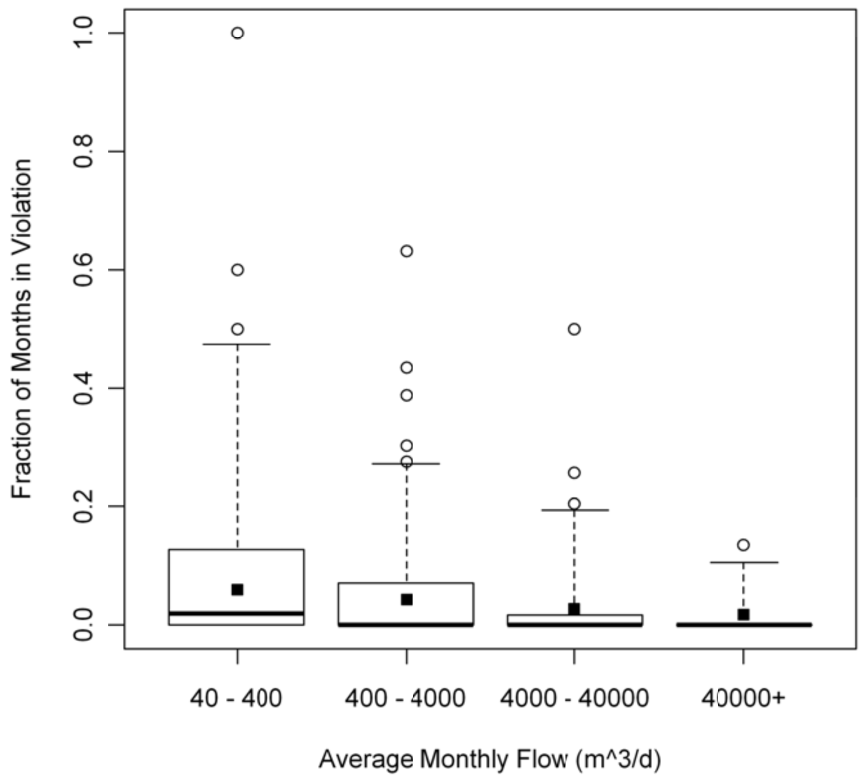



Consistent with the average effluent BOD data, as facility size increases the predicted fraction of months in violation decreased, with small facilities (40 $m^3$/d) violating their BOD permits in more than 6.6% of months while large facilities (400,000 $m^3$/d) violate BOD limits less than 2.2% of the time. Second, capacity utilization has a large positive relationship with violation frequency for facilities 4,000 $m^3$/d and smaller, while for large facilities capacity utilization has almost no relationship to violation frequency.

**Comparison of model and actual violation data**

Actual violation data are grouped by plant size and shown in a boxplot (Figure 2-4) of the fraction of months in violation. As before, the whiskers indicate the $5^{th}$ and $95^{th}$ percentiles. The lower whisker and first quartile fall at zero violations for all facility size ranges, and even the median is zero for all except the smallest size range indicating most of the facilities had zero violations in the database and are performing reliably. The upper whisker and third quartile do show trends among the worst 5% and 25% of facilities, however. The model predictions and actual data show that increasing facility size is associated with fewer BOD violations. The worst 5% of plants smaller than 400 $m^3$/d violate their BOD permit limits nearly half of the time, while the worst 5% of plants larger than 40,000 $m^3$/d have violations only 11% of the time. Additionally, for the smallest facilities one quarter violated limits at least 12% of months, or 1.4 BOD violations per year. While most facilities are reliable and have no violations, significantly more small plants violate their BOD permits more frequently than larger ones and the GLM captures this trend.

Figure 2-4: Boxplot showing variation of violation fractions grouped by facility size where whiskers show 5% and 95% percentiles of BOD violation frequency and square is the model prediction calculated using the average flow and capacity utilization for facilities




**Violation Magnitude and Risk**

To model violation magnitude, the BOD data are filtered to include only those data points in which a violation occurred. Of the 209 facilities in the original data set, there were 454 violations at 84 unique facilities with flow rates from 4 $m^3/d$ to 40,000 $m^3/d$. A comparison of models showed that neither average flow rate nor capacity utilization were significant with respect to violation magnitude. The intercept indicates that BOD limit violations for facilities of all sizes average 1.6 times the permitted value. While the mean violation magnitude is 1.6 times the permit, the median is only 1.3 and 95% of the violations are less than 2.8. 15% of violations are serious violations, defined as effluent discharges more than double the permitted value for BOD, and there are a small number of extreme violations up to 20 times the permit.

Risk is considered as the violation frequency multiplied by the relative magnitude, but because violation magnitude does not vary with facility flow rate or capacity utilization, risk is characterized by the violation frequency alone. Modeled violation probabilities translate to a violation every 8 months for the smallest facilities (40 m^3/d), every 2.5 years for the medium facilities (4,000 m^3/d), and every 10 years at the largest facilities (400,000 m^3/d). Because 15% of these violations are serious, the expected return period for serious BOD permit violations is 4.3 years at small facilities, 16 years at medium-sized facilities, and 70 years at the largest. Wastewater treatment facilities are operated for many decades so it is likely that all but the largest facilities will have several serious BOD violations during its lifetime. This is especially true for smaller facilities.

**Predicted Effluent TSS, ammonia, and fecal coliforms**

Using the same methods as presented previously for BOD, average relative effluent values for TSS, ammonia, and fecal coliforms were predicted using GLMs with the gamma distribution and inverse link function.

$$1 / E(R_{TSS}) = 3.41 + 0.233A + -0.626C \qquad (2\text{-}6)$$

$$1 / E(R_{NH4}) = 3.91 + 0.329A + 0.423AC \qquad (2\text{-}7)$$

$$1 / E(R_{FC}) = 7.28 \qquad (2\text{-}8)$$

The best GLMs for each constituent differ somewhat: the product *AC* was not significant for TSS, and capacity utilization, *C*, was not significant for ammonia except as the product AC. However, both TSS and ammonia show similar trends as BOD. Specifically, small and highly utilized facilities are predicted to discharge higher average relative levels of these two constituents. None of the flow or capacity variables produced better prediction of fecal coliforms than the unconditional model. The difference is not surprising because disinfection is carried out in a separate process from the biological treatment processes that determine the effluent BOD, total suspended solids, and ammonia.

**Risk of TSS, NH4, and FC Permit Violations**

Violation frequency and risk models for TSS, ammonia, and fecal coliforms using a binomial GLM are as follows:

$$\ln\left(\frac{E(V_{TSS})}{1-E(V_{TSS})}\right) = -3.37 + -0.167A + -0.275AC \qquad (2\text{-}9)$$

$$\ln\left(\frac{E(V_{NH4})}{1-E(V_{NH4})}\right) = -3.95 + -0.483A + 0.658C \qquad (2\text{-}10)$$

$$\ln\left(\frac{E(V_{FC})}{1-E(V_{FC})}\right) = -4.30 + -0.212A \qquad (2\text{-}11)$$

The coefficients for average flow are negative for all four constituents, meaning that larger facilities violate their permits less frequently than smaller facilities. This trend is especially strong for ammonia while BOD actually shows the weakest trend. Like for BOD, small and highly utilized facilities have higher rates of TSS violations; however under-utilized facilities are predicted to have more frequent ammonia violations than highly utilized ones. Interestingly the GLM for expected frequency of violations of fecal coliform standards is associated only with plant average flow, with higher risk at smaller plants.

Average flow rate is a statistically significant predictor in more of the best-fit models than capacity utilization. Therefore, model predictions of violation rate are presented in Table 2-2 with capacity utilization fixed at the observed mean value of 0.69 and three flow rates: 40, 4,000, and 400,000 $m^3/d$ . The smallest facilities (40 $m^3/d$) are estimated to violate BOD and TSS permits about 15 times more frequently than the largest facilities (400,000 $m^3/d$), ammonia permits 75 times more frequently, and fecal coliform permits 7 times more often. Because BOD and TSS are closely related in treatment processes, it is not surprising that the models of those two constituents have very similar violation rates and magnitudes. By contrast, there are fewer fecal coliform violations for facilities of all sizes, but the magnitude of violations is much greater relative to permits levels. While disinfection processes are more reliable generally, the failures that do happen appear to be more significant.

Table 2-2: Summary of GLM-predicted violation rates and magnitudes based on average monthly flow rate with capacity utilization fixed at 0.69. Serious violations are those where the discharge concentration was twice the permit limit.

| | BOD | TSS | $NH_4$ | FC |
|---|---|---|---|---|
| Violation Rate (40 $m^3/d$ flow) | 13% | 15% | 22% | 3.5% |
| Violation Rate (4,000 $m^3/d$ flow | 3.4% | 3.3% | 3.0% | 1.3% |
| Violation Rate (400,000 $m^3/d$ flow) | 0.8% | 0.7% | 0.3% | 0.5% |
| Mean Violation Magnitude (effluent / permitted) | 1.63 | 1.75 | 2.59 | 2.34 |
| Serious violations (% of total violations) | 15% | 20% | 40% | 37% |

As a constituent of increasing concern (State-EPA Nutrient Innovation Task Group, 2009), the risk for ammonia violations stands out both for the predicted frequency of violationsfor small facilities as well as the severity of the violations. Modeled violation probabilities translate to a violation every 4.5 months for the smallest facilities (40 m^3/d) and every 2.8 years for the medium facilities (4,000 m^3/d). 40% of these violations are double the permitted value, so the expected return period for serious ammonia permit violations is 11 months at small facilities and 7 years at medium facilities while larger facilities have significantly fewer violations. This finding indicates that care should be taken when implementing a decentralized wastewater infrastructure in watersheds sensitive to excess ammonia such as the Chesapeake Bay.

**Conclusion**

Small facilities often have fewer resources for upgrading or expansion of their treatment facilities which may be an explanation for the number of plants reporting flow rates over the design capacity that in turn affects performance. Many small wastewater facilities also may have fewer hours of attended operation than centralized plants. While large facilities can afford to have full time certified operators and engineers, small facilities can often only afford part-time contract operators. One possible result of limited oversight is that management is less responsive to process changes or upsets, resulting in increased effluent variability and a higher violation frequency. Coupled with the reduced regulatory oversight for small facilities, there is little incentive to improve their operation.

Statistical evaluation of discharge monthly report (DMR) data for 211 wastewater treatment plants in the EPA ICIS-NPDES database using a generalized linear model (GLM) indicated significantly increased frequency of permit violations for BOD, TSS, ammonia, and fecal coliforms as plant capacity decreased. This trend was consistent over the entire range of plant capacities sampled: 1 to 335,000 $m^3$/d. For facilities smaller than 40,000 $m^3$/d, there is also a trend that increasing facility size correlates with decreasing effluent constituent concentrations relative to permitted values for BOD, TSS, and ammonia. The trend toward increasing risk of discharges for smaller facilities exceeding permit limits was strongest for ammonia. Facilities larger than 40,000 $m^3$/d have predicted effluent levels of constituents that are closer to permit limits but reduced violation rates, suggesting that larger plants can operate more efficiently than smaller facilities by not over-treating wastewater. For facilities smaller than 4,000 $m^3$/d, exceeding the plant design hydraulic capacity was a significant factor in decreased treatment reliability. Small facilities near or over their design flow rates had significantly more permit violations and higher relative effluent levels for BOD, TSS, and ammonia than those operating under their hydraulic capacity.

The GLM approach developed in this research offers a flexible framework for modeling a suite of variables with different characteristics (skewed, binary, discrete etc.) unlike the more commonly used linear modeling methods. As demonstrated above, we obtained insights into reliability and risk associated with facility size which may guide effective management and planning of treatment plants.

If networks of decentralized small facilities are to become a larger part of the wastewater treatment infrastructure in the US, planners and regulators should consider the GLM results that suggest the possibility of increased aggregate risk to surface water quality and public health from multiple small plants.

# Chapter 3. Resilience of Secondary Wastewater Treatment

## Background

The introduction of wastewater treatment in the early 19th century and widespread construction of secondary treatment facilities after the 1972 Federal Water Pollution Control Act (FWPCA) amendments to the Clean Water Act resulted in reduced risks to human health and aquatic environments from untreated human waste; however, impaired surface water continues to be an issue in the United States. The National Water Quality Inventory (USEPA, 2009a) reports that the water quality of 44% of a sample of US rivers and streams and 64% of a sample of lakes and reservoirs were inadequate to support their designated uses. Municipal discharges and sewage contain toxic organics, pathogens, and nutrients and can cause organic enrichment and oxygen depletion. These discharges account for approximately 15% of the impairment (6th ranked source) for rivers and streams, 6% (7th ranked source) for lakes and reservoirs, and are the 2nd ranked source of impairment for the Great Lakes behind historical pollution. Currently the EPA and state regulatory agencies are considering more stringent standards for nutrients in part due to recognition of the impacts of high nitrogen loads from both point and non-point sources on water bodies as large as the Gulf of Mexico and the Chesapeake Bay (USEPA, 2008b). However, retrospective studies on wastewater treatment have focused primarily on receiving water quality, with less attention paid to performance of treatment plants themselves. This is a missed opportunity. In addition to its role in enforcement, monitoring and reporting required under the NPDES system provides an opportunity to assess treatment plant performance as a function of both design and operation factors and predict impacts on water quality in effluent-influenced receiving waters.

Recently there has been growing interest in decentralized wastewater infrastructure, since decentralized wastewater systems may offer significant savings particularly in collection system construction, operation and maintenance (O&M), and pumping costs. This interest is timely in light of the recognized need for significant repair or even replacement of aging centralized collection and treatment facilities. The EPA estimated capital needs for wastewater systems in the US between 2000 and 2019 to be $331 to $450 billion with an associated gap between current capital spending and needs ranging from $73 to $122 billion over that period (USEPA, 2008a). Repair and replacement of existing sanitary sewers, new interceptors and combined sewer overflow represent nearly 50% of anticipated needs of clean water systems, which could be reduced with smaller decentralized systems (USEPA, 2008a). However, Fane et al. (2004) described concerns arising from decentralized wastewater systems, including plant siting in residential areas, general lack of effluent data from many smaller treatment plants, and complex risks of failure.

Another concern with decentralized wastewater systems is treatment performance. Implicit in the operation of many traditional isolated small wastewater systems is reliance on high dilution of treated effluent in receiving waters. Accordingly, small systems may operate with smaller staffs, less redundancy and fewer monitoring requirements. However, replacing a centralized system with a network of small collection and treatment facilities with multiple discharge points effectively eliminates the dilution factor. In chapter 2, I investigated the relationship between plant size and performance. A statistical model to predict effluent water quality was developed using data from 210 treatment plants ranging in size from 1 to 335,000 $m^3$/d from the EPA's Integrated Compliance Information System (ICIS). I found that the size (capacity) and hydraulic loading influenced a treatment plant's ability to meet discharge permit levels of BOD, suspended solids, and ammonia, regardless of treatment process type. Furthermore, the risk of permit violations for these contaminants was larger for smaller plants, especially those operating at a higher percent of their rated capacity. The frequency of permit violations for ammonia, for example, ranged from less than 1% for larger plants to nearly 20% for small plants.

A second concern in considering the sustainability of decentralized wastewater systems is resilience. Historically, infrastructure resilience has been considered primarily in the context of disaster response – the capability of a system exposed to natural or man-made hazards either to resist failure, recover within an acceptable time period, or adapt to changed conditions and continue to function. Resilience is a function of physical properties of infrastructure system components, interactions between components, and even societal factors. If recovery sequences consisting of activity or performance values are generated, the cumulative difference from expected normal performance represents costs or losses during recovery, an indicator of resilience (Corotis, 2011). The ability to learn from past events or failures is also a factor in infrastructure resilience, related to adaptation (McDaniels et al., 2008). To date, there have been no efforts to define, much less quantify, resilience of wastewater treatment systems. Yet because wastewater discharges will continue to be a significant potential source of contamination of natural waters, achieving more sustainable wastewater systems will depend to some degree on increasing the resilience of treatment plants with a related reduction in degradation of receiving water quality. Resilience of wastewater infrastructure may have a number of components including the ability to maintain treatment performance and discharge water quality during extreme events or hazards, the ability to adapt to changing discharge standards, and the ability to recover from process upsets or failures. In this study, it is assumed that factors that affect treatment system resilience may not be related to traditional design and operations practices, which tend to be based on normed values for inputs and performance requirements. A statistical definition of treatment plant resilience is proposed along with a methodology for quantifying this property to provide guidance for planning and regulatory agencies, utilities and individual plant operators.

Resilience of treatment plants is quantified as the time required to restore discharged constituent levels to those allowed by permit. Lack of resilience makes treatment facilities and receiving waters vulnerable to continued excess contaminant discharge even after the initial cause has ended. Lack of resilience and longer recovery after a transient may magnify the impact of the initial stressor on receiving water quality by many times due to higher chronic exposure to harmful substances.

We have developed a statistical approach based on Generalized Linear Models (GLM) for predictive modeling of wastewater treatment plant performance that can be used to quantify treatment plant reliability and risk of contaminant discharge in excess of permit limits. The current study applies a statistical modeling approach that includes simulating a time series of effluent concentrations, normalized to permitted levels, discharged from wastewater treatment facilities as a function of average monthly flow and fraction of design capacity used, and applies this method to an analysis of the resiliency of treatment facilities and aggregate reliability of networks of facilities with varying degrees of decentralization. The model incorporates a first-order non-homogeneous Markov chain, and it allows for simulation of representative time series of permit violations by including the previous month's violation status in the estimate of the relative effluent concentration in the current month.

This approach is not meant to duplicate or replace existing wastewater process modeling software programs, such as BIOWIN and AQUASIM, which are valuable tools for predicting the effluent of treatment facilities with fixed design inputs and operating conditions. Our method tests the hypothesis that facility performance is to some degree determined by general system characteristics like capacity and actual loading. The predictive value of these general characteristics could be of great interest in identifying unique attributes of decentralized wastewater systems. Additionally, our method focuses not on fixed operating conditions but instead on predicting the frequency and length of deviations from design performance, i.e., permit violations, with the potential of improving estimates of risks to human health and aquatic life associated with wastewater system organization.

**Data**

To analyze the effect of treatment facility size and capacity utilization on process resiliency and stability, data from the Environmental Protection Agency's Integrated Compliance Information System (ICIS) was systematically sampled. ICIS contains enforcement and compliance information for over 10,000 wastewater facilities with NPDES permits in 28 states and US territories (USEPA, 2009b). First, data for 5% of the facilities in the ICIS database (629 facilities) was collected. This data set was further reduced by filtering out facilities with insufficient data for analysis of each of the four constituents, BOD, TSS, ammonia, and fecal coliforms, resulting in four separate data sets. The data set for BOD contains 209 facilities; TSS, 211; ammonia, 110; and fecal coliforms, 109, with an average of 41 months of data per facility. Average monthly flow rates of facilities in the data set range from 4 $m^3$/d to 355,000 $m^3$/d and capacity utilization, defined as the average monthly flowrate divided by permit capacity, ranges from 5% to 180%.

**Modeling Procedure**

A two-part procedure was developed to analyze the resiliency and stability of wastewater treatment facilities. First, a GLM of the relative effluent concentration for each of the constituents is generated, and that model is subsequently used to simulate a 10-year long discharge sequence, which is then used to evaluate a characteristic recovery time following a violation (**resilience**) and frequency of a sequence of repeated violations (**stability**). The GLM, described below, is fitted to the relative effluent concentration $R_t$ at current time *t* as a function of the combination of the logarithm of average monthly flow $A_t$ in $m^3$/d, capacity utilization $C_t$, previous month's relative effluent concentration $R_{t-1}$, and previous month's violation status $V_{t-1}$. Relative effluent concentration is the ratio of constituent effluent concentration to the permit limit, capacity utilization is the ratio of average monthly flow to permitted flow. Relative concentrations, average flow, and capacity utilization are continuous non-negative numbers; violation status is a discrete binary variable with *1* indicating a violation and *0* indicating no violation. The GLM framework is chosen for its ability to consider data with a variety of types (discrete, binary, continuous, etc.) and distributions (Normal, skewed, exponential, etc.), unlike traditional linear regression.

In GLM, a smooth and invertible link function transforms the conditional expectation of the independent variable to be linearly related to a set of predictors (McCullagh and Nelder, 1989). For modeling relative effluent concentration, the gamma distribution with the inverse link function is appropriate, resulting in the following equation:

$$\frac{1}{R_t} = \boldsymbol{X\beta^T} + \varepsilon \qquad (3\text{-}1)$$

where $\boldsymbol{\beta^T}$ is the transposed set of model parameters, $\boldsymbol{X}$ is the vector of possible combinations of the predictor variables ($A_t$, $C_t$, $\mathrm{R_{t-1}}$, and $\mathrm{V_{t-1}}$), and ε is the error assumed to be Normally distributed. The independent variable here is the effluent concentration $R_t$, which is a positive and skewed variable, for which the assumption of Gamma distribution and its canonical link function of inverse is most appropriate. The model parameters are estimated using an iterated weighted least squares (IWLS) method that maximizes the likelihood function. The best model is chosen based on the Akaike Information Criteria (AIC, Akaike, 1974) by comparing models fit using all possible subsets of predictors. For each model, the AIC is computed as:

$$AIC = 2k - 2L \qquad (3\text{-}2)$$

where L is the logarithm of the likelihood function of the model and *k* is the number of parameters to be estimated in this model. The model with the lowest AIC is used for subsequent analysis and simulation.

**Modeling Results**

The best model for the relative BOD concentration is:

$$\frac{1}{R_t} = 5.49 - 2.41\mathrm{C_t} - 5.16\mathrm{R_{t-1}} - 3.81\mathrm{V_{t-1}} + 0.224\mathrm{A_t C_t} - 0.120\mathrm{A_t V_{t-1}} + 3.05\mathrm{C_t R_{t-1}} + 1.02\mathrm{C_t V_{t-1}} + 4.88\mathrm{R_{t-1} V_{t-1}} - 0.284\mathrm{A_t C_t R_{t-1}} + 0.0372\mathrm{A_t R_{t-1} V_{t-1}} - 2.71\mathrm{C_t R_{t-1} V_{t-1}} + 0.233\mathrm{A_t C_t R_{t-1} V_{t-1}} \quad (3\text{-}3)$$

This model can be thought of as an Autoregressive model of lag-1 with external covariates in the context of time series modeling because $R_t$ is modeled as a function of its past value and other predictors and the lag-1 provides a Markovian dependence structure. This form of GLM has been used in models for stochastic weather generators (Furrer and Katz, 2007).

Similar models were fitted to TSS and ammonia data. To validate their performance scatterplots of observed and modeled estimates of relative effluent concentration, averaged for each treatment facility, along with the 1:1 line are shown for BOD, TSS, and ammonia in Figure 3-1. It can be seen that the models perform quite well for all three constituents studied.

Figure 3-1: Modeled versus actual average effluent concentrations for each facility.

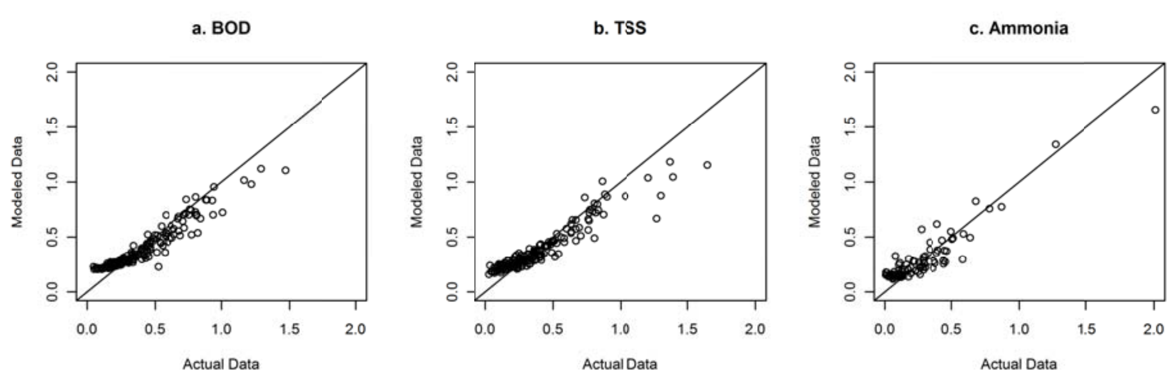
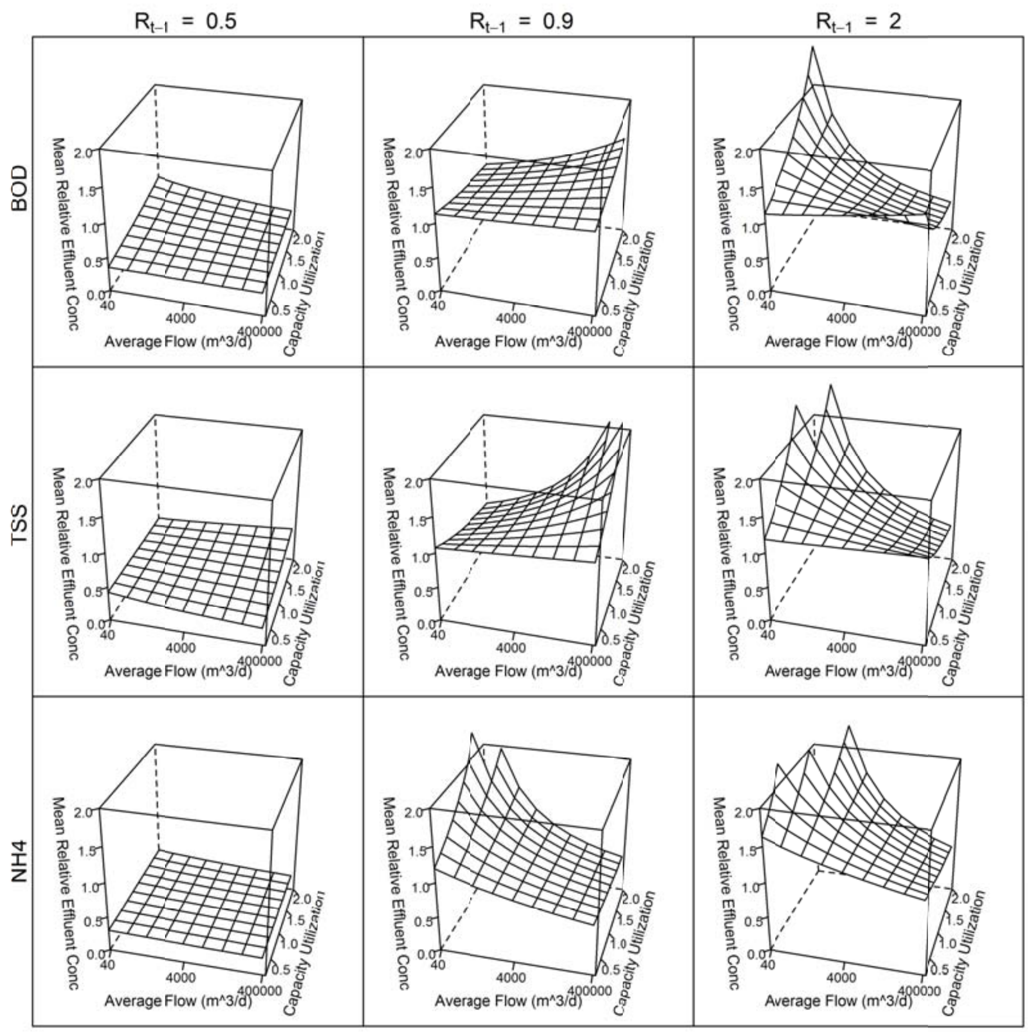


Figure 3-2 shows the expected relative effluent concentration for three constituents for months following three representative relative effluent concentrations, $R_{t-1}$ = 0.5, 0.9, and 2.0 for prior discharge concentrations well under, close to and far exceeding the permit limits, respectively. Expected effluent concentration is clearly correlated with the effluent level of the previous month. Furthermore, the models for BOD and TSS indicate large and overloaded facilities can expect the highest effluent concentrations in the month following relative effluent concentrations of 0.9 (non-violations); however, in the month following permit violations ($R_{t-1} > 1$) small, overloaded facilities and large, underloaded facilities are expected to have the highest effluent constituent concentrations. This trend is more pronounced for effluent TSS than for BOD. In contrast, small facilities in general have the highest expected effluent ammonia concentration in months following violations as well as months where the effluent ammonia was close to but below the permit level ($R_{t-1}$ = 0.9). That lower resilience of ammonia removal is predicted for small plants is not surprising given the extra demands of biological nitrification processes.

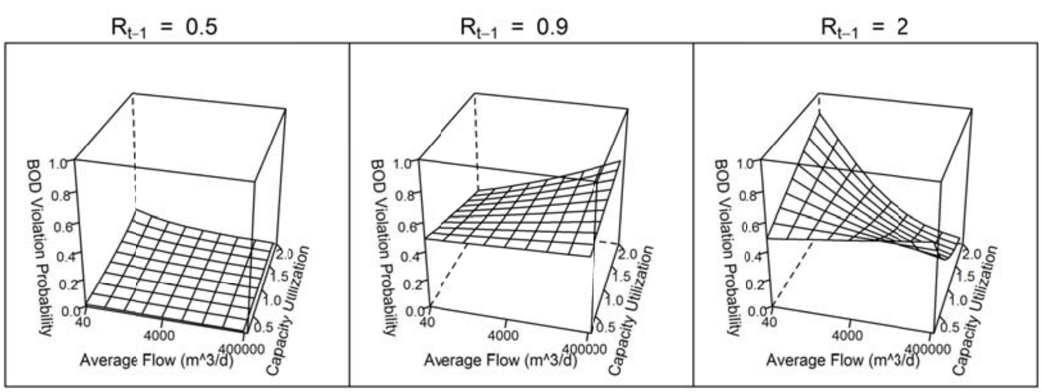
Figure 3-2: Expected value of the relative effluent concentration for BOD, TSS, and ammonia from the GLM as a function of three values of the previous month's relative effluent concentration. $R_{t-1} = 2$ indicates significant violation of permit value in the previous




The model predicts the expected effluent concentration under a Gamma distribution. The expected effluent concentration and the associated standard errors are used to obtain the parameters of the appropriate Gamma distribution. With the obtained Gamma distribution, the probability of an effluent concentration greater than 1 can be calculated as the value of the cumulative distribution function evaluated at 1. The resulting probability for a BOD violation is obtained for all the observations and is shown as surfaces in Figure 3-3, and mirrors the trends for effluent concentration shown in Figure

3-1. Following a month with an effluent concentration half of the permitted level ($R_{t-1} = 0.5$), the probability of a violation for BOD in the next month is low. In this situation, small and overloaded facilities had the highest probability of a subsequent violation, 12%. In contrast, following a month with relative effluent levels of 90% of the permitted level or an actual violation, facilities of any size and capacity utilization can expect concentrations close to or greater than the permitted level with a 50% probability of a violation the next month. Small and overloaded facilities actually were predicted to perform best. Finally, in the month following a large permit exceedence ($R_{t-1} = 2$), all facilities have at least a 50% probability of a violation the next month. In this situation, small facilities operating at over their permit capacity perform the worst with the probability of a permit violation for BOD, TSS or ammonia between 60% and 100%. Violation probability for TSS and ammonia, not shown, also follow the same patterns evident in predicted effluent concentration. Specifically, TSS violation probability for small plants is more dependent on capacity utilization, and small overloaded facilities have a higher probability of an ammonia violation than other facilities for all values of $R_{t-1}$.

Figure 3-3: Probability of a permit violation for effluent BOD as a function of average flow and capacity utilization given three relative effluent concentrations in the previous month, where Rt-1 = 2 indicates a significant violation – effluent BOD of twice the permit limit



Attempts to model the dependence of effluent fecal coliform concentration on prior month's performance using the GLM method were not successful. Previous research has shown that facility capacity and loading were not good predictors of either relative effluent coliform density or violations, possibly due to the fact that disinfection is a different process than BOD, TSS and ammonia removal. Lack of dependence of relatively simple disinfection processes on prior performance may be explained by the fact that process failures can be quickly detected and easily corrected.

**Time Series Simulation**

The fitted GLM models from the previous section were used to simulate a long synthetic time series of effluent concentrations for a given average flow (i.e. facility size) and capacity utilization or sequence of flow values. The average effluent concentration is assumed for the first month ($t = 0$). For each subsequent month ($t = 1,2,\ldots,n$), the expected relative effluent level is simulated from the GLM model (Equation 3) using flow data at time $t$, and effluent level and violation status at time $t-1$. We generated 100 sequences, each 10 years long. The simulations can be viewed under the assumption of representativeness of the observed flow variability. With the expected value and the standard error the associated Gamma distribution parameters are obtained and a random deviate from this distribution is generated, thus, obtaining a sequence of relative effluent levels of a selected length. The same methodology is applied for a range of average flows and capacity utilization values. All relative effluent concentrations greater than 1 are considered a violation. Finally, a suite of statistics is calculated from the simulated sequences, including:

a. L = average length of violation sequence, in months

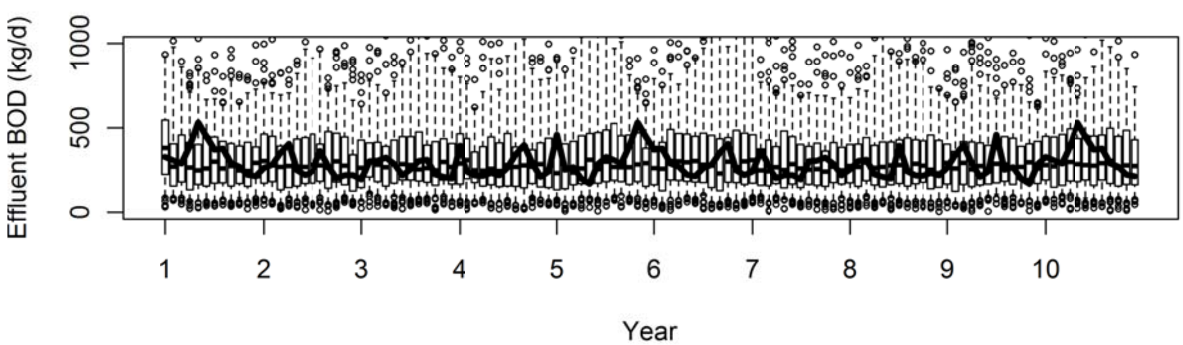
b. N = number of independent violation sequences, where a sequence consists of all consecutive violations separated by a month without a violation

c. M = mean relative effluent level for a constituent

d. F = fraction of months in violation

This time series procedure was used to simulate overall facility resilience, measured as length of monthly violation sequences (L), and stability, measured as both number of independent violation sequences (N) and fraction of months in violation (F). These statistics from the simulations were compared to BOD, TSS and ammonia effluent data from a second independent ICIS data set to verify model predictions. For the model verification procedure, the time series length was the same as the original data set for that facility. Figure 3-4 shows the 100 ensembles of 10-year long simulations of BOD for an example facility, the City of Boulder, Colorado wastewater treatment plant, with a capacity of 80,000 $m^3$/d during the study period. The simulations are shown as boxplots with the observed BOD a solid line. It can be seen that the simulations capture the historic variability quite well.

Figure 3-4: Simulated effluent BOD (boxplots) and actual effluent concentration (solid line) for a 80,000 m3/day facility.



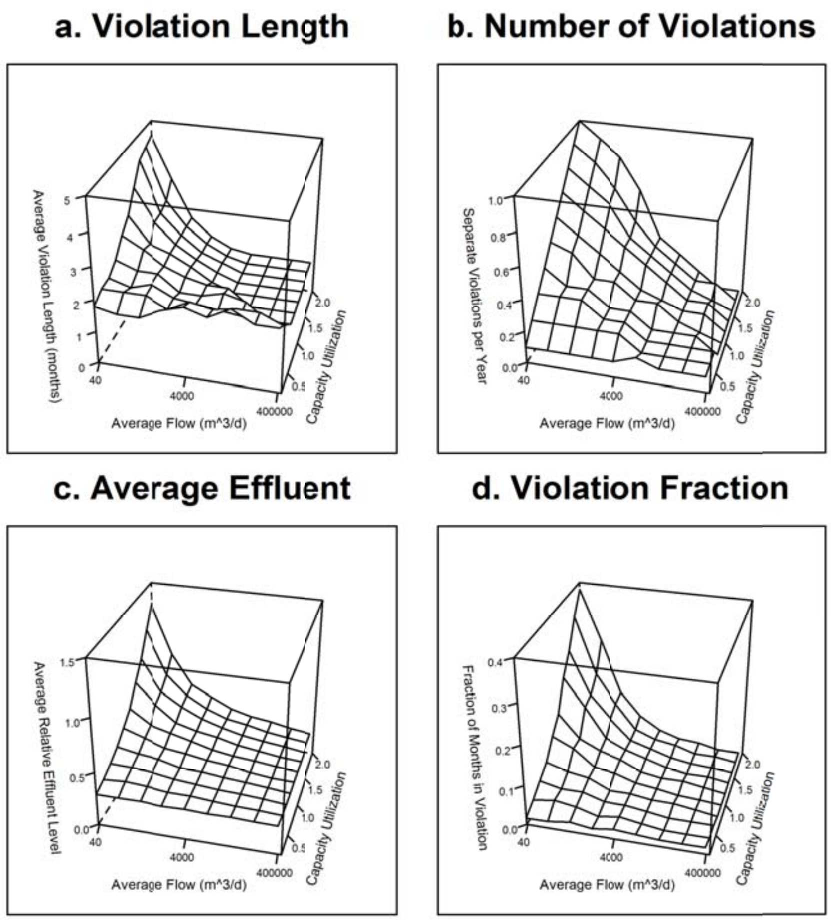
**Resilience and Stability Modeling**

**BOD**

Figure 3-5a shows average violation length (L); 5b, the number of separate violation sequences (N); 5c, the average relative effluent (M); and 5d, the fraction of months in violation (F), all for BOD. The model predicts that small and overloaded facilities have the highest average effluent levels, which coincide with large numbers of violation sequences per year. Specifically, facilities 40,000 $m^3/d$ (10.5 MGD) and larger can expect 0.1 violation per year, while facilities 400 $m^3/d$ (0.105 MGD) and smaller should expect violations proportional to their capacity utilization ranging from 0.1 per year for those significantly underloaded to 0.8 per year or more for those receiving flows significantly higher than their rated capacity. As expected, these results are consistent with those from the expected estimates of the fitted GLM shown in Figure 3-3. Thus instability, measured as total number of violations over the ten-year simulation period (N), corresponds strongly with violation probability following good treatment performance ($R_{t-1} = 0.5$).

Average violation length (L) has a similar trend: small and overloaded facilities are the least resilient. BOD violation length was greater than four months for these facilities, compared with approximately 3 months for large and underutilized facilities. For facilities receiving flows of 50% of their rated capacity ($C_t = 0.5$) the expected average violation length ranged from 2 months for $A_t < 400$ $m^3/d$ to1.2 months for $A_t > 40,000$ $m^3/d$. Thus resiliency, measured as the average length of violations, most closely follows the trend seen for violation probability following a significant violation ($R_{t-1} = 2$). Small overloaded facilities have the highest average relative effluent BOD concentration (M) and the highest fraction of months in violation (F) over the ten-year simulation, which is consistent with previous findings.

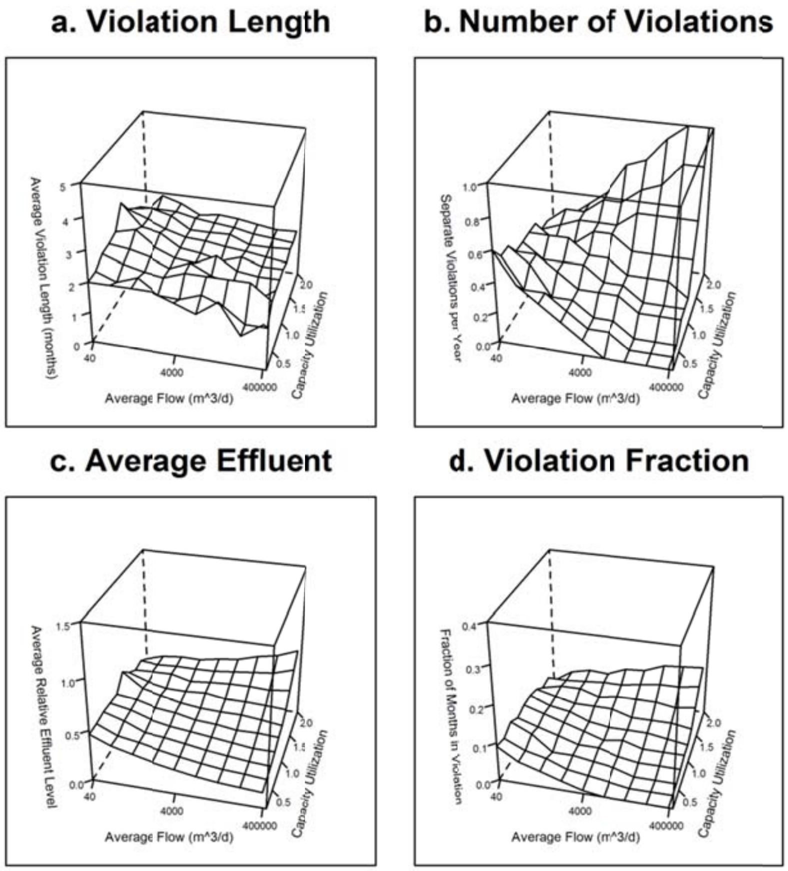
Figure 3-5: Long-term resilience and stability of BOD removal for wastewater treatment facilities as determined by capacity and capacity utilization. Plots are median values of simulated average violation length (a), number of independent violations per year (b), average relative effluent concentration (c), and fraction of months in violation (d) over the ten-year time series.




**TSS**

Results from simulations of effluent TSS (Figure 3-6) show different trends from those of BOD. First, average length of violation is 2 months for all facilities and does not vary significantly with flow rate or capacity utilization. Second, there are distinct trends in the number of separate violation sequences, as seen in Figure 3-6c. Most striking is the large number of violation sequences for large and over-utilized facilities. However, the significance of this prediction is minimal since all facilities larger than 10,000 $m^3$/d had capacity utilization under 1.3, though smaller facilities had capacity utilization up to 1.8. Thus, underloaded large facilities can expect nearly 0 violations per year, while those with capacity utilization of near 1.3 can expect 0.3 separate violations per year. It is expected that TSS removal, dependent on secondary clarifier performance, would be sensitive to overloading regardless of facility size. Also, higher flows are associated with increased BOD loading and higher mixed liquor suspended solids, resulting in increased solids as well as hydraulic loading to the secondary clarifiers. However, capacity utilization is less of a factor for smaller facilities, such that 400 $m^3$/d facilities can expect 0.3 violations per year regardless of utilization. Other factors than loading may particularly affect solids discharge at small facilities, including algae growth in polishing ponds and excessive solids accumulation in the clarifiers due to infrequent sludge disposal. Predicted average relative effluent concentrations (M) and violation fraction (F) follow the same trends as the number of violations (N). Small underloaded and large overloaded facilities average 0.5 times their permitted discharge with violations 10% of months while other facilities average as low as 0.2 times their permit level and 1% violations.

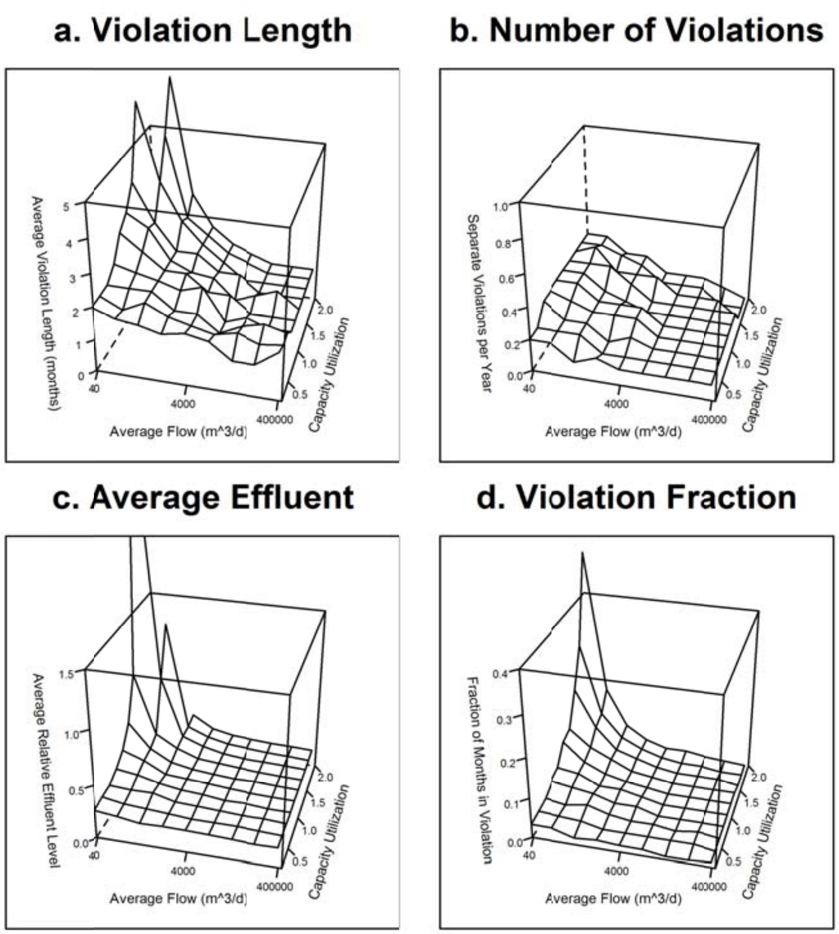
Figure 3-6: Long-term resilience and stability of TSS removal for wastewater treatment facilities as determined by capacity and capacity utilization. Plots are median values of simulated average violation length (a), number of independent violations per year (b), average relative effluent concentration (c) and fraction of months in violation (d) over the ten-year time series.




**Ammonia**

Simulation results for effluent ammonia are shown in Figure 3-7. The model predicts that on average most facilities discharge approximately 30% of their permitted limit, but there is a sharp increase in predicted discharge concentration for facilities smaller than 400 $m^3/d$ treating flows over their design capacity. Violation fraction and average length of violation follow roughly the same pattern. Over the ten-year simulation, it is expected that ammonia discharged from most facilities would exceed their permit 5% of the time and the average violation duration is two months, but both increase dramatically for small, overloaded facilities. The simulated number of separate ammonia violations decreases as facility size increases. Facilities with an average flow of 400 $m^3$/d average 0.2 separate violations per year, while those with a flow of 40,000 $m^3$/d average only 0.1 violations per year. Unlike an earlier study on the probability of excess ammonia releases over a short duration, capacity utilization is a factor the overall fraction of months in violation over the ten-year time frame; however the relationship is seen in the length of violations (L) and not the frequency of occurrence (F). Although the violation frequency of smaller plants is relatively low, predicted duration is two months or larger, suggesting that nitrification is more difficult to restore once lost, than BOD or TSS removal.

Figure 3-7: Long-term resilience and stability of ammonia removal for wastewater treatment facilities as determined by capacity and capacity utilization. Plots are median values of simulated average violation length (a), number of independent violations per year (b), average relative effluent concentration (c) and fraction of months in violation (d) over the ten-year time series.



**Conclusion**

Resilience and stability of wastewater treatment plants are important aspects of sustainability, and both are time dependent properties. Thus, models used to predict these properties must also be time dependent. Resilience is the ability for a system to recover from a perturbation or failure and quantified in this study as the length of successive monthly violations of discharge standards. Stability is measured by the predicted frequency of violations over a time period. A statistical model has been developed to quantify resilience and stability by evaluating plant performance as a continuum with dependence on prior performance rather than as independent discharge events, while still incorporating non-time-dependent factors, namely average flow rate and capacity utilization.

The likelihood of a permit violation is significantly increased by a prior month's violation for BOD, TSS and ammonia, across all plant capacities and hydraulic loading values. Moreover, given a BOD discharge violation in one month, the expected duration of subsequent violations varied from two to five months and small plants receiving higher than capacity flows (flow $\leq$ 400 m^3/day, and capacity utilization > 1) are predicted to have the longest duration of monthly violations. A similar trend was found for ammonia.

Another finding of this study is that small and overloaded plants are least stable when considering BOD and ammonia removal. These facilities average up to one expected violation per year over a ten-year simulation period, several times more frequent than larger or under-loaded facilities. Overloading can lead to reduced treatment performance through inadequate hydraulic residence times and increased loss of solids, both of which should affect plants of all sizes. The fact that small facilities are more sensitive to overloading suggests that these facilities share underlying characteristics that affect their resilience and stability including the inability to learn from past performance or adapt to failures. In contrast, average flow and capacity utilization are unrelated to the time for plants to recover from TSS violations, and facilities across the range of capacity average approximately two month-long TSS violation sequences. TSS violations at large overloaded facilities are expected more frequently than for smaller facilities. Together, these differences show that factors that affect TSS removal may be different than those determining BOD and ammonia removal. Smaller facilities may have proportionally larger clarifiers or off-line storage for solids in ponds. The prevalence of extended air processes at smaller facilities may also provide more volume so that flows in excess of rated capacity are less significant than at larger plants. Also longer aeration times may lead to decreased solids production.

An important potential application of the time series approach developed for this study is prediction of cumulative pollution risk to a receiving water or watershed. Continuous discharge of excessive BOD, ammonia and other constituents over a period of months may have a greater impact on aquatic life or other designated uses than intermittent and isolated releases of these constituents at higher than permit values.

# Chapter 4. Decentralization vs. Centralization of Wastewater Treatment in the St. Vrain Watershed

## Background

Decentralized wastewater treatment, usually classified as on-site and cluster systems, is gaining popularity in the United States due to factors such as increased exurban development, expansion of treatment to many small communities, and its advantages over centralized treatment. Approximately 25% of American homes are served by decentralized systems (Nelson & Shephard, 1998), and wastewater treatment needs for small communities total $17 billion (USEPA, 2004). Decentralized systems have several advantages (National Decentralized Water Resources Capacity Development Project) including reduced upfront capital costs for sewers and large treatment works. As-needed implementation can be desirable for communities with limited resources or uncertain finances, especially in the face of uncertain growth projections. Decentralized treatment also allows for more local control of land use and zoning, desirable for many periurban communities. Increasing pressure for water reuse also encourages decentralization by reducing the pumping distances required in “purple pipe” systems, reducing energy costs leading to economic savings. Finally, decentralized systems may have a reduced hyrological impact than centralized systems which may transfer large amounts of water between distant intake and outlet points, and even between watersheds.

There are also several disadvantages and concerns about decentralized wastewater treatment systems. Reliability and treatment performance are frequently troublesome. In Boulder County, Colorado, USA approximately one third of the 14,000 on-site systems are unpermitted and believed to be failing. Poor accountability due to the difficulty of regulating and enforcing action for many small systems can lead to lack of proper operation and maintenance (Nelson & Shephard, 1998). Nutrient removal is also a common difficulty leading to nitrogen and phosphorus concerns in many surface waters. Removal of nitrogen and phosphorus are more complex processes than removal of BOD, requiring more sophisticated treatment and operation.

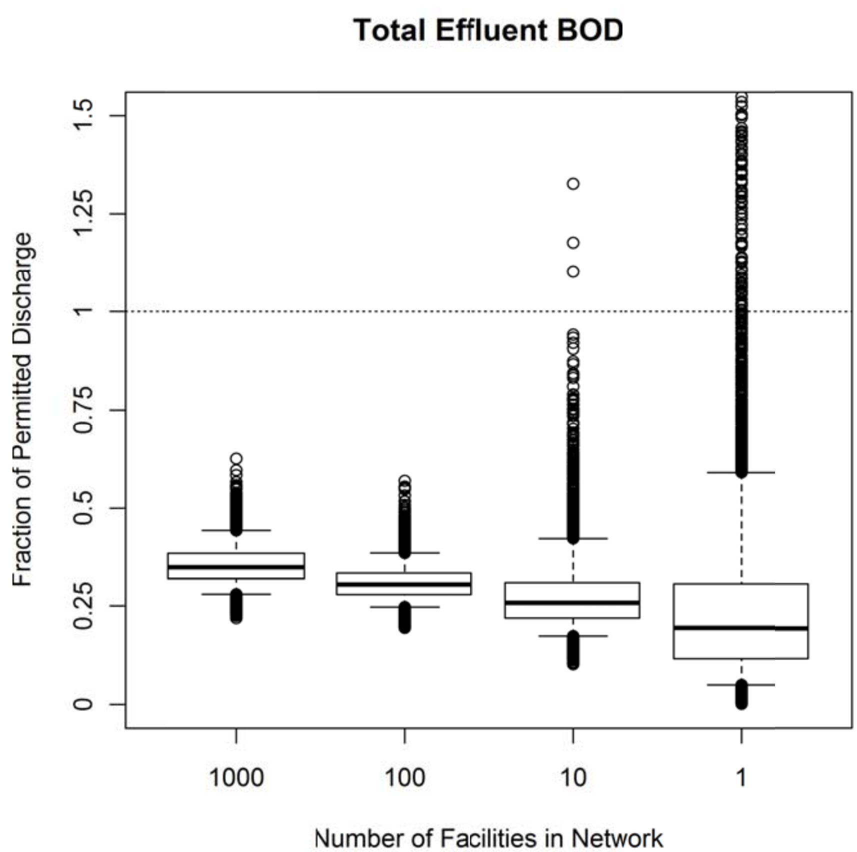
Though most research on decentralization has focused on on-site and cluster systems, these advantages and disadvantages also apply small centralized wastewater treatment systems, especially when many are implemented in a watershed. This paper examines the network wide effects of varying levels of centralization of wastewater treatment on the total discharge of wastewater constituents to a watershed. Generalized Linear Models of wastewater treatment performance based of average flow and the fraction of design capacity utilized was used to simulate effluent BOD levels for a hypothetical treatment network, followed by analysis of the effect of ammonia discharged to the St. Vrain watershed located near Denver, USA. In particular, this simulation method allows for comparison of the likelihood and magnitude of deviations from the expected effluent levels, events which are often of particular interest because excessive discharge of constituents like BOD and ammonia can influence water quality and damage the surface water ecosystems. These GLMs are useful as a decision support tool to facilitate comparison the environmental impacts of alternative wastewater collection and treatment systems on a watershed, a component of the "triple bottom line" associated with infrastructure sustainability.

**Network Simulations of BOD Discharge**

To explore the environmental impacts of decentralized wastewater collection and treatment on a watershed, simulations of several hypothetical networks of varying complexity were performed. Four networks consisting of 1, 10, 100, and 1000 equally sized treatment facilities were simulated assuming a total wastewater flow of 400,000 m^3/d split evenly among them. This could represent, for example, the total wastewater flow for an urban watershed. For purposes of the simulation, it was assumed that all facilities had a capacity utilization of 0.69, the average for all facilities in the database. Using a previously developed procedure for simulating effluent values, 100 simulations were performed for each facility, each 120 months long. For each month, the sum of relative effluent concentration for all facilities was compared to the total permitted effluent. Because all facilities in the network have the same flow rate, this is equivalent to comparing the total mass flow rate of ammonia to the permitted mass flow rate. These total effluent ammonia discharges are presented for each network in Figure 4-1. Two trends become clear as the network is decentralized:

- The median total effluent increases
- The upper extremes for effluent BOD decrease

Figure 4-1: Boxplot of simulated relative effluent BOD concentrations for increasingly centralized networks.



Smaller facilities discharge higher average effluent concentrations of BOD than large facilities. This causes networks of small facilities to discharge higher median levels of BOD. However, the distribution of treatment reduces the magnitude of extreme events by distributing the risk. While a single large facility violates its permit less frequently than an individual small facility, the likelihood that many small facilities will simultaneously perform poorly is low. Thus, a more network of 100 facilities each treating 400 m^3/d will almost never discharge more than the total permitted mass of BOD, but a single facility will exceed that permit approximately 1.1% of the time. Decentralization increases the chronic BOD load to a watershed but decreases the magnitude of extreme acute events, but there is a limit. As the facilities become very small, the poorer treatment overshadows the benefits of distribution of the risk, resulting in higher median and acute discharges meaning there is an optimum degree of decentralization to minimize risk.

It is important to note that this simulation assumes the probability of a violation at each facility in a network is independent, though this may not be the case. Certain events, such as infiltration from stormflow, unusual temperatures, etc., could cause simultaneous violations at many facilities in a small geographic area. This would reduce the ability of decentralized networks to meet permitted levels. Despite this caveat, it is clear that networks of small facilities have a different risk profile than more centralized systems. In addition, the risk profile for networks should be considered along with the receiving water characteristics. Watersheds susceptible to chronically high levels, such as those with chronic eutrophication issues, would benefit from the better removal given by centralization. If the main concern is instead acute events, decentralization would reduce the risk.

**St Vrain Watershed**

Boulder Creek, St. Vrain Creek, and numerous tributaries form the St. Vrain watershed. These 627,082 acres are located primarily in Boulder County, Colorado at the eastern edge of the Front Range mountains. The streams flow from high mountains and valleys to plains before emptying into the South Platte River. Approximately 280,000 people live in several small cities and towns, primarily in the plains region. Besides urban areas, other major land uses include forest (42% of total area), rangeland (29%), and cropland (18%). Several of the water bodies are classed as impaired by the EPA. Leading causes of impairment are metals from abandoned mines and ammonia, E. Coli, and heightened water temperature from wastewater treatment facilities (USDA, 2010). Though non-point sources of ammonia contribute significantly to the impairment, the difficulties of regulating and controlling non-point sources may lead to stricter discharge limits for point sources such as wastewater treatment facilities. The ability to and cost of meeting lower discharge limits is a major concern of treatment facilities in this watershed.

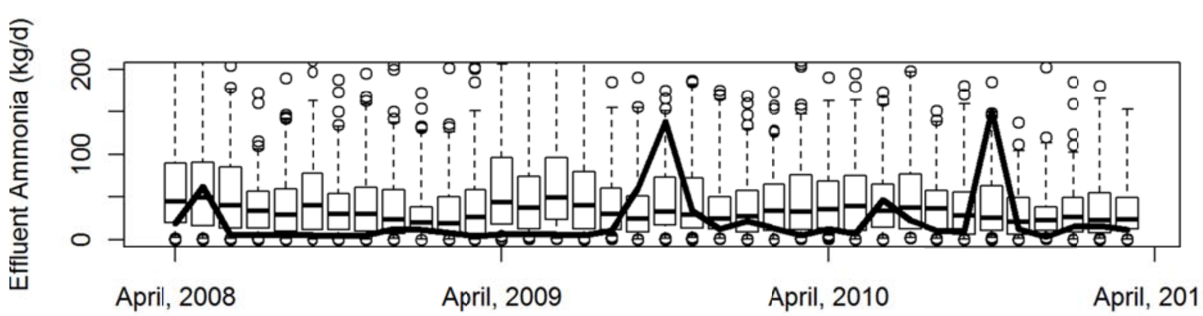
Within the watershed, there are 21 NDPES permitted wastewater treatment facilities ranging from an average flow of 6 $m^3/d$ to 49,000 $m^3/d$, of which 18 have ammonia permit limits and are included in this study. The types of treatment include conventional large activated sludge plants, lagoons, smaller extended air plants, package plants, and a commercial septic system (USEPA, 2009b). Many of the facilities are quite small, and only 8 of the 18 facilities have average flow rates greater than 1000 $m^3/d$.

**St. Vrain Watershed: WWTP Simulation**

To analyze the effects of decentralization of wastewater treatment the St. Vrain watershed, simulations of three separate levels of centralization were performed. First, simulations of the network of existing treatment facilities were compared to the actual treatment to determine the model accuracy. Then, a hypothetical decentralized case was created in which all facilities with an average flows greater than 4000 $m^3/d$ were replaced with an appropriate number of facilities such that each has a flow lower than that limit. Finally, a hypothetical more centralized case was simulated. For this last case, wastewater flows from nearby facilities were combined creating six larger facilities.

For the existing case, simulations of each facility are conducted using actual average flow and capacity utilization values for each plant over a three year period (April, 2008 – March 2011). For facilities with missing data, the sequence of flow values was repeated as necessary. Finally, ammonia concentration permits vary seasonally in Colorado, with the loosest limits often three times higher than the strictest. Effluent data from the individual facilities shows that they do not adjust their operations seasonally, and instead seek to meet the strictest permit standards year round. To match this, the simulations were performed assuming the strictest ammonia standard was in effect year round. The results of 100 simulations of the City of Boulder WWTP are shown as boxplots in Figure 4-2, with the actual ammonia discharged indicated as a solid line.

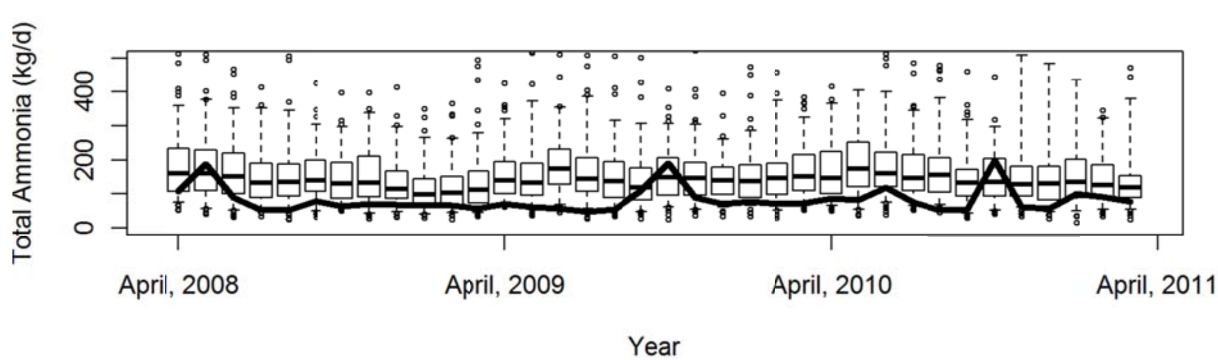
Figure 4-2: Simulated and actual effluent ammonia discharged from the Boulder WWTP



The total simulated ammonia discharged to the St. Vrain watershed is shown with the actual discharged amount in Figure 4-3. Actual ammonia discharge into the St. Vrain watershed from wastewater treatment plants is generally between 50 kg/d and 100 kg/d. There are three major excursions from this trend in May, 2008, October, 2009, and October, 2010 in which the amount discharged triples to about 200 kg/d. These unusually high (though within permitted limits) effluent concentrations can be traced primarily to the City of Boulder WWTP (Figure 4-2), which is the largest WWTP in the watershed and comprises 46% of the total wastewater flow and 27% of the ammonia discharged to the St. Vrain. An increased discharge of ammonia by the City of Longmont WWTP (26% of total flow, 39% of total ammonia) also contributed to the high levels in May of 2008. While the other facilities have variations in effluent concentration, they have very little effect on the overall ammonia discharge due to comparatively low flow rates, reinforcing the finding that treatment performance variation at large, centralized facilities can have a significant impact on a watershed while variations at small facilities have minimal effect on the watershed as a whole, though the small facilities may still affect the stream to which they discharge.

Median simulated ammonia discharge for the watershed varies between 100 and 175 kg/d, approximately double the typical actual discharge but less than the three peak discharges mentioned before. The average actual ammonia discharge for the watershed commonly falls between the $5^{th}$ and $25^{th}$ percentiles of the simulations. The facilities in the St. Vrain watershed are performing better than the model predicts, especially the largest facilities, reflecting better removal of ammonia compared to the facilities in the national database from which the model was developed. This is consistent for all three contaminants studied: BOD, TSS, and ammonia. Relative effluent values of ammonia are 47% less in the St. Vrain watershed than nationally, 60% less for BOD, and 38% less for TSS. Both the Boulder and Longmont treatment facilities have undergone major upgrades in the last 10 years to improve nitrification specifically. Also, in anticipation of stricter ammonia discharge standards beginning around 2017, many local treatment facilities closely monitor their treatment processes, likely resulting in better than average performance. A closer look at the data shows that smaller facilities in the St. Vrain watershed discharge higher relative levels of ammonia, as is predicted by the model. Effluent variability is of concern in this method, so it is important that the simulations accurately capture the variability of effluent discharge. To verify this, I compared the range between the 5th and 95th percentile of the simulations as well as the actual data. A direct comparison shows that the simulation range is slightly more than double the range of the actual data; however, this is expected given the improved performance in the watershed compared to nationally. Because the model uses a gamma distribution with a constant shape parameter, the effluent variability is proportional to the effluent concentration. A comparison of the data ranges normalized by median effluent discharge shows that the simulation range is only 12% larger than that of the actual data. Thus, the variability and trends evident in the model still apply to the watershed, and the simulations are a valid method of analyzing the effects of decentralization and centralization.

Figure 4-3: Simulation of existing wastewater treatment in the St. Vrain watershed compared to actual data (solid line)



**Decentralization and Centralization**

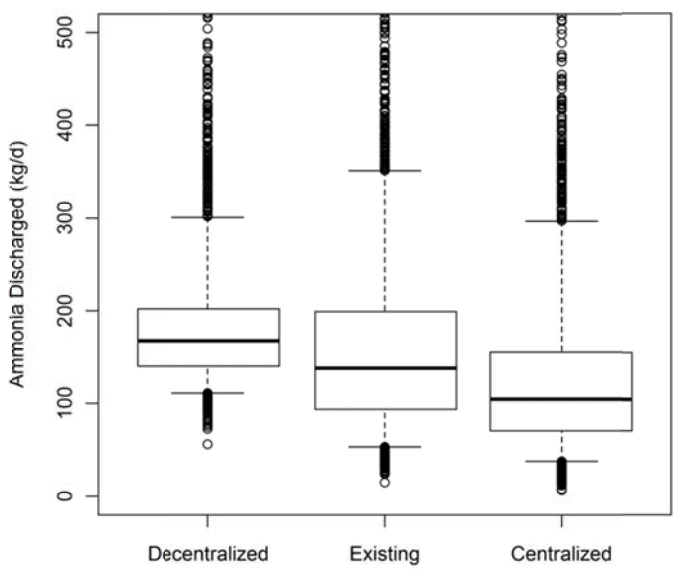
To compare with the existing system, two hypothetical treatment scenarios were constructed and simulations performed. For the decentralized system, all facilities with an average flows greater than 4000 $m^3$/d will be replaced with an appropriate number of facilities such that each has a design flow lower than that limit. This resulted in the 7 largest facilities being split into a total of 55 separate small treatment facilities, resulting in a total network of 66 facilities. For these hypothetical facilities, the monthly flow of the original was divided evenly between its replacements, and the permitted effluent concentration was kept the same so the decentralized network has the same permitted mass flow rate of ammonia as the existing system.

For the centralized system, clusters of nearby facilities were combined resulting in six centralized facilities. Five of these facilities have flow rates larger than 4000 $m^3$/d, and the last is a combination of two small facilities separated from others in the watershed by approximately 15 miles of rugged terrain. The average flow and design flows of these facilities were added together, and the permitted effluent concentration of ammonia was a weighted average (based on the design flow) of the original facilities, once again maintaining the same permitted mass flow rate of ammonia.

Treatment simulations of these hypothetical scenarios were performed using the same procedure as for the existing system. Figure 4-4 shows box-whisker plots of the monthly total mass flow rate of effluent ammonia for each of the three scenarios. Clearly, median ammonia discharge decreases for more centralized systems, consistent with the finding that larger facilities discharge lower effluent concentrations. The discharge of the decentralized is 167 kg/d, higher than both the existing system (138 kg/d) and the centralized system (105 kg/d). However, if we look at extreme events a different story emerges. The 95$^{th}$ percentile of discharges (upper whisker) from the decentralized and centralized system are both approximately 300 kg/d, lower than that of the existing system (351 kg/d). For the centralized system, the increased reliability and decreased variability of large treatment facilities also reduces the magnitude of extreme events. But for the decentralized system a different effect dominates. To significantly affect the network-wide ammonia discharge, a sizable portion of the facilities in the network must simultaneously perform poorly. As the number of facilities increases the likelihood of this event decreases, except in the case where a few facilities comprise most of the wastewater flow for the network as is true for the existing system. The existing network comprised of 18 treatment facilities of varying sizes takes advantage of neither the improved treatment performance of large facilities nor the dispersion of risk of decentralized networks.

The total permitted discharge for the watershed was calculated as sum of the permitted concentration times the design flow for each treatment facility, and is 1411 kg/d. Of this, 95% comes from the seven largest facilities. Water quality modeling of those seven largest facilities performed in preparation for the creation of new standards for ammonia discharge indicates that a reduction of 42% of the total permitted discharge of ammonia is needed to achieve the desired water quality in the watershed. Assuming a 42% reduction for all facilities, the total permitted discharge under the new standard will be 821 kg/d. For all three scenarios simulated, the discharge of ammonia even in extreme cases is well below both the current total permitted discharge for the watershed and the anticipated stricter standards.

Figure 4-4: Boxplot showing the simulated mass flow rate of ammonia discharged to the St. Vrain watershed for three wastewater treatment scenarios: decentralized, existing, and centralized




**Conclusion**

The potential environmental impacts of decentralization of wastewater treatment will grow as it becomes more popular throughout the United States. One aspect of understanding these impacts is knowledge of the variability and reliability of treatment plant performance and the aggregate performance of a network of treatment plants. In particular, deviations from normal plant performance are of interest because high levels of BOD and ammonia released into surface waters can have significant negative effects on water quality. The simulation method demonstrated in this paper can serve as a decision support tool for agencies considering decentralization.

Using a Generalized Linear Model of relative effluent concentration based on average flow, capacity utilization, and previous treatment performance, simulations of BOD discharge for a hypothetical network of wastewater treatment plants were performed. These simulations show that as a network becomes more decentralized, the median effluent discharge of BOD increases due to poorer treatment performance of small facilities. However, the magnitude of variation decreases due to dispersal of the risk across many facilities. Thus, while centralized wastewater networks will have better BOD removal on average, they will also have worse extreme events possibly resulting in a more negative impact on water quality.

Simulations of the St. Vrain watershed reveal the same trend for the median ammonia discharge—decentralization results in higher median ammonia levels. However, concerning extreme events the existing system was the worst of the three scenarios considered. Simulations of the decentralized and centralized scenarios indicate that the total effluent ammonia would exceed 300 kg/d only 5% of the time, while simulations of the existing system show it would exceed 350 kg/d 5% of the time. The existing systems mix of large and small plants fails to take full advantage of the increased treatment performance of centralized facilities or the reduction in effluent variation of decentralized networks.

# Chapter 5. Conclusion

This research makes two significant contributions to the field of wastewater treatment: the methodology and the subsequent analysis of decentralization. The method of analysis using Generalized Linear Models to model wastewater treatment facility effluent concentrations is an effective and flexible way to measure trends present in large datasets. Chapter 2 demonstrates its use to quantify the relationship of facility size and capacity utilization with relative effluent concentration and the probability of a permit violation for four constituents of wastewater: BOD, TSS, ammonia, and fecal coliforms. Violation probability was directly modeled using a binomial distribution. Modeling the effluent concentration using a Gamma distribution allows for prediction of secondary statistics, such as the total mass flow rate of discharged contaminants or the probability of the effluent concentration exceeding any threshold of concern. In chapter 3, the analysis was expanded by including an autoregressive term and using the resulting model to simulate time sequences of effluent quality. By adding an autoregressive term (prior month's effluent concentration) to the independent variables, the model becomes time dependent. This allows for the simulation of effluent time sequences and prediction of time dependent like recovery time and length of a violation.

Because this method is not dependent on process modeling or specific influent characteristics but instead on data from operating facilities, it can be used for long term forecasting or high level planning. Other wastewater simulation methods, such as BIOWIN, effectively model individual plant processes but require detailed input. BIOWIN also does not account for outside factors, like operator error, that can play a significant role in treatment performance. By duplicating simulations, the methodology developed here also provides an estimate of the variability of treatment. It can estimate the best and worst case scenarios or tell the probability of a given deviation from the median.

A number of extensions to this methodology are possible. First, the relationships between additional variables could be tested for significance and measured. Obviously the effluent concentration or violation probability of other wastewater constituents could be modeled, but further efforts could include direct modeling of the number of violations per year using a Poisson distribution, for example. It is also possible to include additional or different independent variables in order to better predict effluent concentration. This could include process type, influent concentrations, labor hours, operator training, or fee structure. Some, like influent concentration, would be simple to include in the model. Others, like operator training level, would first need to be codified numerically. Another independent variable of interest would be current and past effluent concentrations of other constituents to determine the covariance between treatment of BOD and emerging contaminants, for instance.

Furthermore, this method of simulating effluent sequences presents numerous opportunities. Chapter 4 presents one application in which time sequence simulations for all wastewater treatment facilities in the St. Vrain watershed are used to predict the total mass flow rate of discharged ammonia to surface waters for different levels of decentralization. By changing the input sequence of average flow values to the simulation, treatment performance under different growth projections or climate change could be predicted. Finally, coupled models and simulations could be used for more complex relationships, such as first simulating a sequence of flow values and using that to predict effluent BOD.

This use of Generalized Linear Models shows that facility size and capacity utilization are significant factors affecting wastewater treatment performance, which has several implications for decentralization. Smaller facilities experience more violations and higher effluent concentrations of effluent BOD, TSS, and ammonia. They can expect several times more violations than larger or underloaded facilities. Time dependent analysis in chapter 3 also shows that the probability of a violation goes up considerably following a violation the previous month, indicating that the processes vary over a monthly time scale or longer. In fact, simulations show that the median violation length for large facilities is approximately 1 month for all three constituents, but increases to 2 months or more for small facilities. Small and overloaded facilities should expect BOD violations to last 4 months or more. This indicates that treatment at small facilities is less resilient, defined as the ability for a system to recover from a perturbation or failure and quantified in this study as the length of successive monthly violations of discharge standards. Similar trends are evident for stability, measured as the number of separate violations per year.

It is clear from these trends that small facilities and overloaded facilities perform more poorly than others despite often having less strict permit standards due to high dilution factors. Technical characteristics such as flow equalization at large facilities due to larger volumes and collection systems could cause this trend. Another possible cause is differences in operations or regulation. Small facilities have less income leading to part time staff with less education and training than at large facilities. They may also have a harder time paying relatively fixed costs like redesign and permitting, which inhibits timely process updates leading to equipment staying in service longer than expected. More research is needed to identify and mitigate the reasons for the differences in performance of large and small facilities.

Despite the poor performance of individual small facilities, network wide simulation (chapter 4) reveals a different story. The median discharge for the St. Vrain watershed follows the expected trend. Decentralized treatment, with large numbers of small facilities, has higher median discharge of ammonia than centralized treatment. However, if we are concerned with the upper limit of expected discharges, decentralized and centralized treatment are very similar. In both cases, ammonia discharges of 300 kg/d or greater will only happen 5% of the time. Though the effluent from small, decentralized facilities typically contains higher concentrations of ammonia than from centralized facilities, the likelihood of a sizable portion of the decentralized network simultaneously having a month of poor treatment is low. No single facility, or even a few facilities, treat a high enough portion of the total flow to significantly influence the watershed wide performance. It is important to note that they can affect the stream at the discharge point, though. In the centralized scenario, one facility makes up nearly half of the network's flow. Poor treatment at that one facility strongly influences the overall ammonia discharged to the watershed. As a result, the variability of centralized treatment is higher despite better average performance. The existing network actually had a higher 95$^{th}$ percentile discharge (350 kg/d) than either decentralized or centralized. With a wide variety of facility sizes, a few facilities still dominate the overall flow, so does not get the benefits of dispersal of risk from decentralization or the improved treatment of centralization.

Whether average discharge or worst case discharge is more important depends on the watershed and the constituent in question. Nitrogen stays in the water for a long time, causing eutrophication problems for areas like the Chesapeake Bay or the hypoxic zone of the Gulf of Mexico. For these situations, the average discharge is of greater concern indicating centralized treatment may be a better option. For small, fast flowing watersheds or rapidly degraded contaminants, acute extreme discharges would be of greater concern than chronic levels. Decentralization could be preferable in this scenario. In either case, the simulations show that trends on the scale of a single facility do not directly translate to the watershed scale. Those considering decentralization should weigh the tradeoff between poor performance of small facilities and dispersal of risk.

The methods and results of this study provide a valuable tool for analyzing the effects of decentralization on the scale of an individual facility and for a whole watershed. It is flexible and requires minimal specific data input, enabling engineers, government officials, and utility managers to make more informed decisions about wastewater infrastructure.

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