Measuring the effectiveness of performance-based training

William Bowman, Michael Messner, Stig Regli and Jon Bender

ABSTRACT

This article describes a statistical analysis of small water systems' turbidity data within the framework of a logic model for the USEPA's Performance-Based Training (PBT) program. The logic model shows the theoretical linkages between optimization training for small system operators; operator application of optimization techniques; improvements in plant filtration performance; and public health protection. The analysis comprised two phases. For the first phase, the authors used Bayesian analysis of turbidity data to test the statistical significance of changes in finished water quality resulting from training for small water system operators. For the second phase, the authors estimated the potential health benefits resulting from measured improvements in filtration performance. Considering only the improved removal of the pathogen *Cryptosporidium*, the expected annual health benefit of PBT is about ten fewer cases of infection per thousand persons served (within a 95% credible interval 0 to 18 fewer infections), though there may be benefits associated with the removal of other pathogens. The article also describes factors contributing to uncertainty in the estimated potential health benefits. The proposed two-phase approach supports the USEPA's development of drinking water program indicators which are meaningful, measurable, broadly applicable and change-sensitive.

Key words | operator training, risk assessment, water quality, water quality indicators, water treatment

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INTRODUCTION

With the advent of the Government Performance and Results Act (GPRA) of 1993, and more recently, the Office of Management and Budget (OMB's) Program Assessment Rating Tool (PART) in 2002, identifying measures which demonstrate program results has become increasingly important to federal agencies such as the U.S. Environmental Protection Agency (USEPA). Widely accepted private-sector indicators such as profits and earnings serve as clearly defined and observable performance signals, but developing equivalent indicators for government programs is far more challenging. In response, the USEPA's national safe drinking water program should develop performance indicators which are meaningful, measurable, broadly applicable and change-sensitive (Raucher *et al.* 2006). Meaningful indicators communicate clearly the public health objectives of the Safe Drinking Water Act (SDWA) programs in terms which can be understood by the public, such as public health risk reduction. Measurable indicators are supported by observable data, and for purposes of the GPRA and the PART, must be nationally representative. Broadly applicable indicators can be used for different contaminants or categories of contaminants. And change-sensitive indicators show the effects of program implementation on the desired outcome, such as public health protection.

This article describes a two-phase approach to developing drinking water program indicators which are meaningful, measurable, broadly applicable and change-sensitive. A logic model for the USEPA's Performance-Based Training

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(PBT) program for small drinking water systems serves as the framework for the analysis (small public water systems are defined as those serving 10,000 or fewer consumers). For the first phase, the authors used Bayesian statistical analysis of small water systems' finished water turbidity to test theoretical linkages between PBT training, operator application of the training, and changes in treatment plant performance. For the second phase, the authors utilized the economic analyses for the U.S. Environmental Protection Agency's (USEPA's) Long-Term 1 and 2 Enhanced Surface Water Treatment Rules to estimate the potential health benefits of improvements in filtration performance (USEPA 2002, 2006). As a result, the national safe drinking water program could utilize this approach as the conceptual basis for improving its program performance indicators.

Purposes and goals of the analysis

In July 2003, the Office of Ground Water and Drinking Water (OGWDW) initiated a statistical analysis of its Area-Wide Optimization Program (AWOP, or optimization program) for small drinking water systems. The overall goal of this program is to improve water quality at the individual plant level by strengthening the knowledge and skills of water system operators. To achieve these goals, EPA collaborates with state drinking water programs and operators to optimize the effectiveness of their water filtration technology. OGWDW initiated the analysis to improve its understanding of the effectiveness of the optimization program, in terms of both improved compliance and the estimated risk reduction.

Under the federal drinking water regulations, turbidity (the cloudiness caused by particles in drinking water) acts as a surrogate measure for removal of microbial contaminants, including protozoa, such as *Cryptosporidium* and *Giardia*, bacteria and viruses. As described extensively in the economic analyses for two recent drinking water regulations (USEPA 1998*a*, 2002), reducing turbidity has both quantifiable and non-quantifiable benefits. Quantifiable benefits are based on several studies of the relationship between filtered-water turbidity levels and the likelihood of removal of *Cryptosporidium* oocysts from drinking water supplies (LeChevallier & Norton 1995; Patania *et al.* 1995; Regli *et al.* 1998; Emelko *et al.* 1999; Dugan *et al.* 2001; USEPA 2003). Consuming these oocysts may cause cryptosporidiosis and result in mild to severe cases of gastrointestinal illness. USEPA estimates that full implementation of the Long-Term 1 Enhanced Surface Water Treatment (LT1) regulations will prevent between 12,000–41,000 cases of endemic illness per year (USEPA 2002) (the quantified benefits reflect only the reduction in endemic cryptosporidiosis and not reductions in waterborne disease outbreaks, other types of disease, or mortalities). Filtration is particularly important to protect public health because *Cryptosporidium* is highly resistant to standard disinfection practices (Korich *et al.* 1990; Ransome *et al.* 1993; Finch *et al.* 1997). Significant non-quantifiable public health benefits from turbidity reductions include the removal of other pathogens such as *Giardia*, bacteria and viruses, as well as the avoided costs of mitigating and responding to an outbreak resulting from microbial contamination (USEPA 1998*a*).

The optimization program is well suited to benefit analysis for a couple of reasons. First, public drinking water systems with surface water sources must report turbidity readings to regulatory agencies as a standardized measure of compliance. Second, participation in the optimization program is voluntary, so one can distinguish the filtration performance of systems which participate from those that do not. Unpublished USEPA case studies have shown that systems which participate in AWOP often meet or exceed federal regulatory standards for filtration performance. OGWDW's analysis was designed to build on these promising case study results by one, exploring the statistical significance of the assumed relationships between participation and turbidity reductions; and two, quantifying estimated waterborne illnesses avoided in systems which reduce turbidity. If successful using this new approach, OGWDW could begin to move beyond measures based on compliance data alone, to those based on operational data which estimate the health benefits of reduced exposure risk.

The performance-based training (PBT) program

For purposes of a preliminary analysis of systems in the optimization program, we defined a performance improvement as a decrease in a plant's highest monthly 95% percentile turbidity level, based on 12 months of turbidity data before, and 12 months after, joining the optimization program, from a higher to a lower risk category, measured in terms of log reduction. Turbidity levels were proxies for risk, given the correlation between turbidity removal and likelihood of *Cryptosporidium* removal discussed above. Our study focused on plants using conventional or direct filtration because their mechanisms for removing protozoa are more closely related to turbidity removal than other treatment technologies (e.g., slow sand or diatomaceous earth filtration) (USEPA 1998*a*,*b*). A preliminary analysis of performance data from a simple random sample of small systems in the optimization program indicated that those only partially involved in the optimization program did not necessarily improve performance. Systems in the optimization program, however, participate to varying degrees; for example, some may agree to an assessment of plant performance, or commit to the goals of the optimization program, but not all systems in the program receive intensive training and technical assistance. As a result, the authors hypothesized that systems in the PBT program, which represents the most *extensive* degree of AWOP participation, would be most likely to improve performance consistently. In brief, the objectives of the PBT program for turbidity are to: overcome performance-limiting factors using proven optimization concepts and process control; improve finished water quality through optimization to protect customers from pathogenic organisms such as *Giardia* and *Cryptosporidium*; and, promote peer-to-peer networking among system operators on the technical and managerial aspects of water treatment optimization. Through PBT, system operators participate in a series of five intensive training sessions over several months to optimize the performance of their water filters. Trainers and operators assess plant performance through the periodic review of operational data. The goal of PBT is to reduce turbidity in filtered drinking water to 0.1 NTU (Nephelometric Turbidity Units) 95% of the time (for plants using conventional or direct filtration), which exceeds the federal performance standard of 0.3 NTU 95% of the time. This goal is based on research that found achieving 0.1 NTU, 95th percentile turbidity was most effective for removal of *Cryptosproridium* and *Giardia* from drinking water (see Executive Summary of Patania *et al.* 1995, page xx. The researchers found that the effluent goal of 0.1 NTU was most effective at *Cryptosporidium* cyst and oocyst removal).

METHODS

Overview: PBT logic model as analytical framework for two-phase analysis

A logic model is a graphical representation of the sequential relationships between resources, program activities such as training and technical assistance, and program objectives. The PBT logic model in Figure 1 shows the assumed relationships between optimization training and technical assistance for small system operators; improvements in plant filtration performance (in terms of turbidity); the estimated risk reduction; and, estimated illnesses avoided. The logic model shows that, in theory, as PBT program managers teach system operators techniques to optimize their filters, and assist them with implementation, operators receive needed training and technical assistance to improve performance. The model then shows how providing these services leads to two important outcomes: first, operators improve their understanding of how optimization techniques can help them meet rule requirements and maintain drinking water turbidity levels which meet or exceed federal turbidity requirements. Second, as turbidity is reduced, consumer risks of exposure to *Cryptosporidium* and other pathogens decrease, and fewer cases of illness occur.

The PBT logic model served as a framework for our statistical analysis to test the program theory and the underlying assumptions of the logic model. We implemented our analysis in two phases. The purpose of Phase I was to determine whether PBT leads to statistically significant reductions in plant turbidity levels. In this phase, we identified a "treatment" group comprising a stratified random sample of 18 treatment plants from Alabama, Arkansas, Kentucky, Louisiana and Texas which had completed PBT during the 1998-2004 study period, along with a similar "control" group sample of 18 non-PBT plants. We selected these states because their optimization programs are among the most mature of the participating programs, which helped ensure an adequate number of plants for our analysis. Once we had identified the plants for the study, the five state agencies generously provided electronic or hard copy files of the daily 4-hour Combined Filter Effluent (CFE) turbidity readings for two 12-month periods, one before and one after training. From these data, we calculated monthly 95th

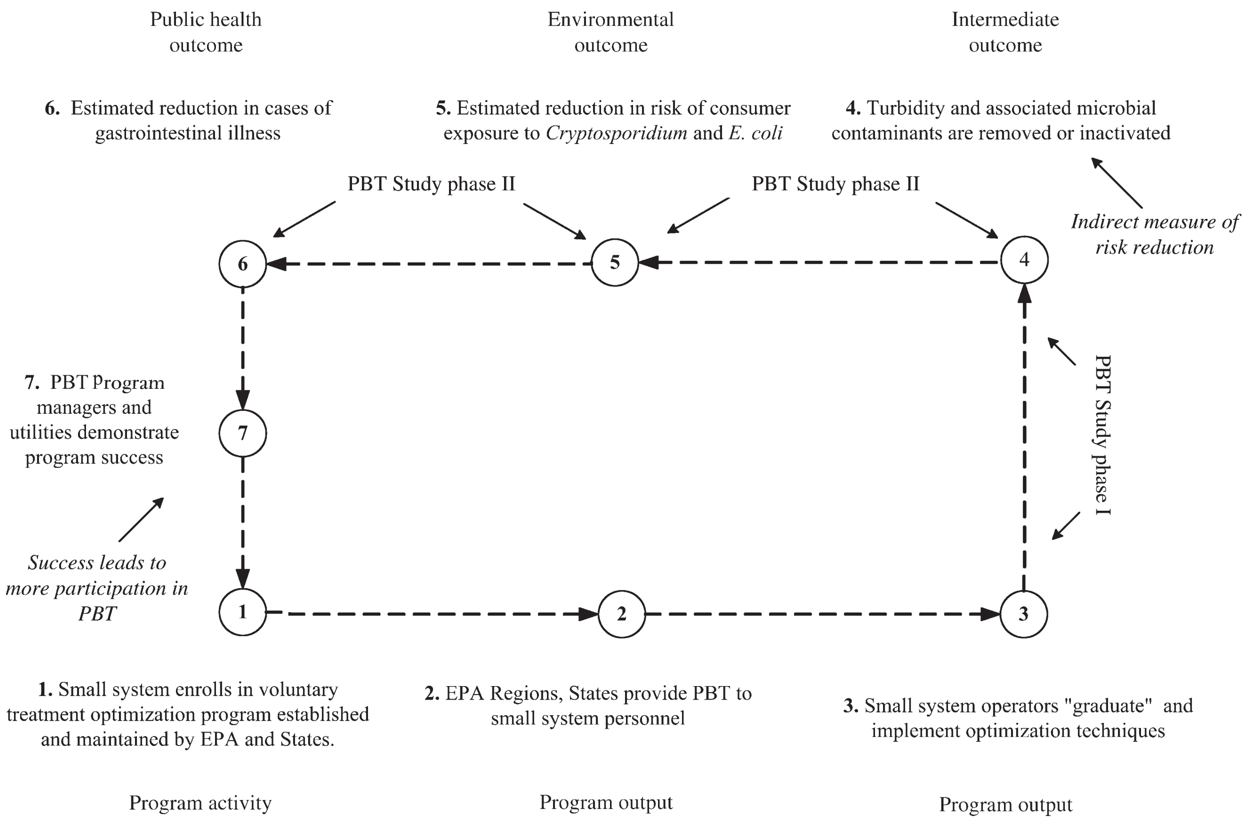

Figure 1 | Performance-based training (PBT) logic model.

percentiles for all 36 plants and the geometric mean for each 12-month period. We also assumed, after consulting with PBT program coordinators, that a six-month period after the training was a reasonable amount of time for program "graduates" to adjust operations as a result of the training. The null hypothesis for the first phase was that there would be no difference in turbidity reductions between PBT and non-PBT plants over the total 42-month timeframe for each plant: 12 months before training, 12 months to complete the training, a six-month adjustment to optimization techniques, and 12 months after training. In terms of the PBT logic model, in Figure 1, the first study phase corresponds to movement from Stage 3 (implementation of optimization techniques) to Stage 4 (turbidity reduction).

The purpose of Phase II was to estimate reductions in exposure to *Cryptosporidium* and associated illness avoided during the study period. In this phase, the authors used changes in finished water turbidity levels as a proxy for risk reduction. In Figure 1, the second phase corresponds to movement from Stage 4 to Stages 5 (reduced exposure) and 6 (estimated illnesses avoided). Because it is impossible to measure directly illnesses which do not occur, these estimates were based on the risk assessment models for the LT1 (USEPA 2002) and the Long Term 2 Enhanced Surface Water Treatment Rule (LT2) (USEPA 2006).

In implementing the study design, we attempted to account for several potential factors which could have confounded the results. One factor was the presence of the LT1 regulation itself: the treatment technique requirements of LT1 became enforceable in January 2005 and at that time would apply to all small surface water systems. Therefore, it is plausible that, during the 1998–2004 study period, both system types (i.e., participating and nonparticipating) had the incentive to reduce turbidity in anticipation of LT1 treatment requirements. We partially accounted for this factor by ensuring that we used data from both the participating and nonparticipating systems during the same time frame (all data from the 36 plants in our study were collected through November 2004, just prior to January 2005, when the LT1 regulation became enforceable against small public water systems. As a result, the study did not include operational data from small surface-water systems that may have attempted to improve performance to ensure compliance with LT1 after January 2005). A second potential confounding factor was seasonal variation in source water quality which may have affected turbidity removal due to periods of drought or intense rain events that normally occur across seasons. To reduce this concern we used a full 24 months of turbidity data (12 months before and 12 months after the training). In addition, the effects of annual variability were accounted for geographically and temporally: geographically because the sample included 36 plants from five different states and temporally because participating plants joined the PBT program in different years (1999 and 2002). Finally, the sample of plants from five different states helped account for potential variability in state oversight of the surface water regulations and in PBT program administration.

PHASE I IMPLEMENTATION

Data sources

To conduct the analysis, the authors requested 4-hour turbidity readings from treatment plants in small systems in five states (Alabama, Kentucky, Louisiana, Arkansas and Texas). For plants which participated in the PBT program, these data covered a one-year period prior to training and a second one-year period beginning six months after training was completed. The authors paired participating plants with nonparticipating plants randomly selected from the same state and size category. Data for these nonparticipating plants were obtained for the same 42-month time periods as their paired participating plants.

4-hour turbidity readings were then reduced to a single 95th percentile value for each month. Thus, each plant produced 24 observations: 12 monthly 95th percentiles for one year prior to training and another 12 monthly 95th percentiles for one year after training. These data are the basis for the analysis that follows.

Assumptions in model design

We reviewed and examined the data to identify an appropriate statistical model. We found that the 95th percentiles were log-normally distributed within the one-year monitoring periods. Figure 2 shows the data for one of the plants in our sample, together with best-fitting lognormal density functions. Shown with a logarithmic X-axis, the density functions have the familiar "bell" shape. This particular plant appeared to have reduced turbidity, represented in Figure 2 by the position of the top bell-shaped curve to the *left* of the bottom bell-shaped curve.

These lognormal distributions are defined by two parameters, μ_i and σ, where i is the plant number ($i = 1, 2, \ldots 36$). The first parameter (μ_i) is the geometric mean of the plant's 95th percentile turbidities, while the second (σ) describes the degree of month-to-month variability in turbidity. Collectively, the μ_is in the first year appear to be normally distributed. Figure 3 shows the 36 μ_is and their best-fitting normal distribution function. The mean of the 36 μs is one parameter and the standard deviation of the μs is the other parameter of the fitted curve.

We wanted to test a number of hypotheses about these plants. Having paired participating and non-participating plants allowed us to test for selection bias: whether the systems that chose to participate were fundamentally different from nonparticipating plants, before PBT training. We also wanted to see whether nonparticipating systems took actions to reduce their turbidity levels, perhaps in anticipation of LT1 requirements, or in response to state or EPA regulatory oversight. If nonparticipating systems plants reduced their levels as much as plants that enrolled in PBT, then it would have been inappropriate to attribute any

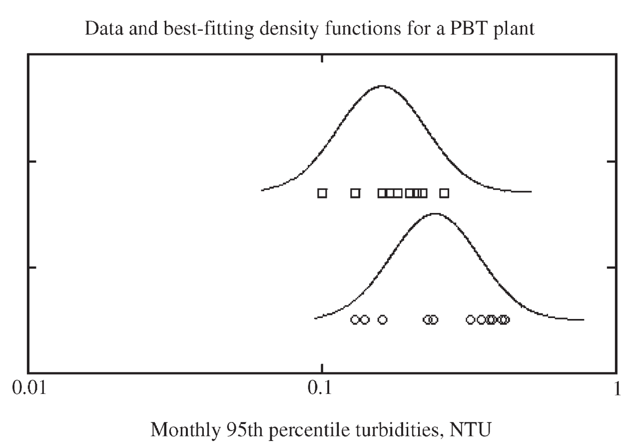

Figure 2 | Data and best-fitting density functions for a PBT plant.

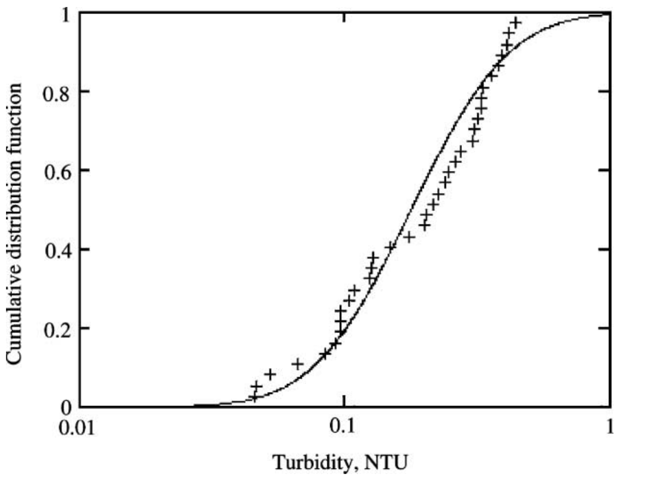

Figure 3 | Distribution of means for the 36 plants during the first monitoring year (Year 0).

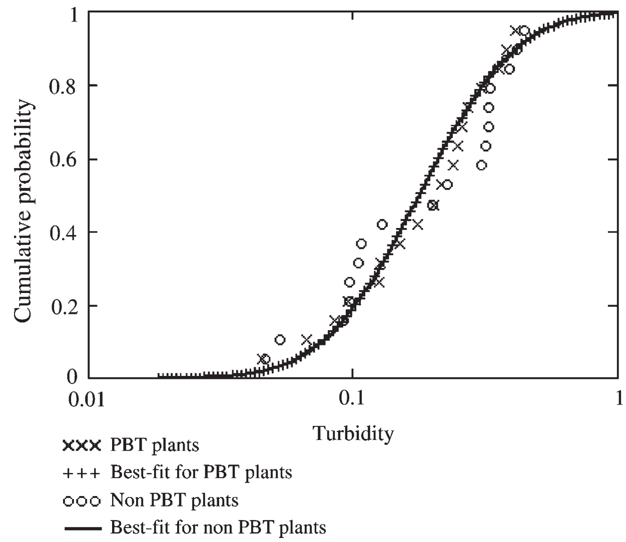

Figure 4 | Data and best-fitting distributions for Year 0.

reduction to PBT participation.

$$\ln(\mathrm{Turb}_{ij}) = \mu + \alpha_i + j{*}\beta + (\text{Plant } i \in \text{PBT?}){*}(\gamma + j{*}\delta) + \varepsilon_{ij} \quad (1)$$

The equation above describes our statistical model for Phase I. Parameter μ defines the overall turbidity level for non-PBT plants during Year 0, or the first 12-month period. Parameter β is the "Rule effect", and describes the overall turbidity reduction between both PBT and non-PBT plants that is due to anticipating upcoming rules or other influences. Parameter γ is the "PBT bias" that reflects an overall difference between non-PBT and PBT plants during Year 0. α_i is an effect for plant i. These effects allow different plants to have different initial turbidity levels. We assumed these effects were normally distributed with variance V_{plant}. ϵ_{ij} is an error term for system i during year j ($j = 0, 1$). We assumed these errors were normally distributed with error variance V_{error}. Finally, parameter δ is the desired effect of the PBT program. This is the key parameter for estimating the success of the training.

Initial findings

Figure 4 displays Year 0 data for both participating and non-participating plants and their best-fitting lognormal distribution functions; Figure 5 displays the same information for Year 1, or the second 12-month period. For PBT plants, this second period is after training. Data were first analyzed using conventional linear regression methods; then Bayesian Markov Chain Monte Carlo (MCMC) Methods were used to inform a probabilistic risk analysis (Siu & Kelly 1998). Broad, uniform priors were used so as to have negligible influence on the estimates. To gauge the influence of the priors, new estimates were obtained using priors with much larger ranges. For example, the prior on delta was broadened from Uniform (-2.3,2.3) to Uniform (-3.3,3.3). Differences between the new and

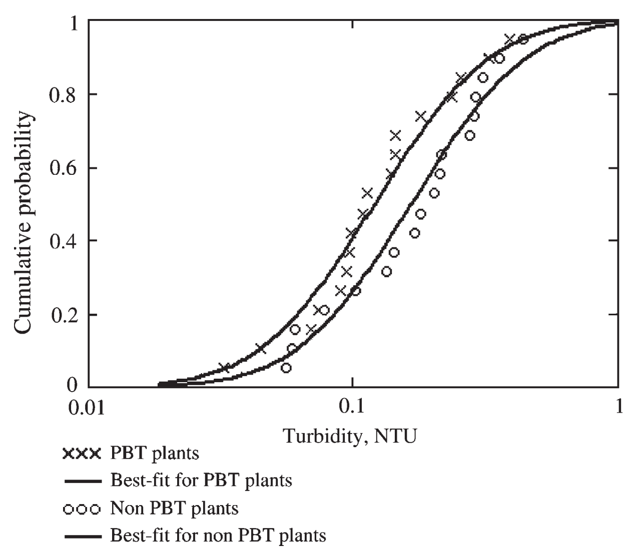

Figure 5 | Data and best-fitting distributions for Year 1 (post training for PBT plants).

original mean estimates were within the range of Monte Carlo error (due to having MCMC samples of only size 10,000) and on a relative basis were generally less than 0.2%. Table 1 provides the priors and MCMC statistics for the parameters of interest.

The regression and Bayesian results agreed, specifically:

- Non-participating plants tended to have turbidity levels centered about $e^{\mu} = e^{-1.72} = 0.178$. This is an estimate of the overall median (50th percentile) value of the monthly 95th percentile turbidities among non-participants.
- The selection bias (γ) was small (-0.003) and statistically insignificant. A real bias of this size would mean that systems choosing to participate already had lower initial turbidity levels (by about 0.3%). Based on the central value for non-participants (0.178, from above), this would mean that participating systems had central values of 0.177 prior to training.
- The rule effect (β) was also small (-0.071) and statistically insignificant. If this effect were truly -0.071, then central turbidity levels were reduced by nearly 3% per year over the 30 months that separated the two monitoring periods. Although statistically insignificant, it may be that reductions of this magnitude are of practical importance. Better estimation of this effect would require data from many more plants than we utilized for this study.
- The training effect (δ) is significantly *less* than zero–meaning we can reject the hypothesis of no real difference in performance between PBT and non-PBT plants–at the 1% level. In other words, we are 99% confident that the effect of PBT is to reduce finished water turbidity levels more than would have been achieved otherwise. A central estimate of this effect is -0.32, suggesting that median turbidity levels are reduced by approximately $1 - e^{-0.32} = 29\%$.

This last finding is important: it indicates that PBT made a highly statistically significant–and meaningful - difference in plant performance.

Limitations of phase I

The data represent a relatively small number of treatment plants in five states; training may have had a greater or lesser effect in other states with PBT programs. The authors know of no reasons why training would *reduce* the effectiveness of a plant's filtration. In some cases, turbidity increased overall after the training. Those increases were very small, however–less than 5% relative change in median turbidity–and appeared to be the result of random error. These increases may have been caused by year-to-year variability in source water quality, or by our utilization of data for a small number of months.

Another limitation is that during the study period (1998–2004) small public water systems were not yet subject to treatment requirements under the LT1 and Filter Backwash Recycling Rules. The authors estimate the overall effect of these rule requirements will be a continued reduction in finished water turbidity levels, even in systems that do not take advantage of PBT. Therefore, in the future nonparticipating systems could perform significantly better than observed in this study.

Finally, for this analysis four-hour turbidity monitoring data were reduced to monthly 95th percentiles. Turbidity data for more frequent time periods (e.g., 15-minute or hourly readings) may have revealed other differences between participating and nonparticipating plants, and

Table 1 | Summary statistics from two Markov Chain Monte Carlo (MCMC) samples (size 10,000)

Parameter	Original Prior	MCMC Median (95% interval)	Broadened Prior	MCMC Median (95% interval)
μ	U(−3, −0.6)	−1.72 (−2.05, −1.39)	U(−4, −0.1)	−1.73 (−2.05, −1.40)
β	U(−2.3, 2.3)	−0.068 (−0.286, 0.147)	U(−3.3, 3.3)	−0.068 (−0.289, 0.149)
δ	U(−2.3, 2.3)	−0.319 (−0.630, −0.017)	U(−3.3, −3.3)	−0.320 (−0.627, −0.017)
γ	U(−2.3, 2.3)	−0.005 (−0.464, 0.449)	U(−3.3, −3.3)	−0.004 (−0.452, 0.450)

may have supported a more complex model of how PBT affects variability in turbidity levels.

PHASE II IMPLEMENTATION

In both the Interim Enhance Surface Water Treatment Rule (IESWTR) and LT1, USEPA focused on turbidity reduction as a means of addressing the risk posed by *Cryptosporidium* in source waters. In its assessment of the benefits of these rules, USEPA used research data to model a relationship between turbidity and *Cryptosporidium* removal as shown in Table 2 (Regli *et al.* 1998). Table 2 is not meant to be used to estimate *Cryptosporidium* removal for any particular plant, because removals can be significantly affected by site-specific conditions, e.g. very low or very high turbidity in the source water. Rather, the values in Table 2 are used to estimate removal among plants as an aggregate. In the context of an aggregate analysis, we assume that the effects of site-specific conditions, which can result in higher or lower removal than indicated in the table, will tend to cancel each other out. Recognizing the assumptions within an aggregate analysis, Table 2 shows that, for example, a turbidity reduction from 0.25 NTU (in the range $0.2 \le \text{NTU} < 0.3$) to 0.15 NTU (in the range $0.1 \le \text{NTU} < 0.2$) would result in an improvement of 0.25 logs, which is a removal factor of $10^{0.25}$ or about 1.8. In other words, nearly twice as many *Cryptosporidium* oocysts would pass through the filter while operating at 0.25 NTU than would pass while operating at 0.15 NTU. Health risk to consumers would be reduced by the same factor.

To model the benefits of smaller reductions and also reductions within the ranges of the table, we fit a linear model to the tabled values, shown in Table 2 in parentheses. The following best-fitting linear model was the result:

$$\text{Reduction} = 2.881*(From - To) \tag{2}$$

where "*From*" is the initial 95th percentile turbidity level and "*To*" is the final 95th percentile turbidity level. For example, if turbidity is reduced from 0.25 to 0.15, then "*From*" = 0.25 and "*To*" = 0.15, and the log reduction is:

$$\begin{aligned} 2.881*(From - To) &= 2.881*(0.25 - 0.15) = 2.881*0.10 \\ &= 0.2881 \end{aligned} \tag{3}$$

This 0.2881 improvement in log removal is equivalent to a factor of $10^{0.2881} = 1.9$, or nearly a factor of 2. This is slightly more than shown in the table ($10^{0.25} = 1.8$). In general, the PBT study linear model agrees well with the modeled relationships in the IESWTR and LT1.

The linear function only provides an estimate of the relative change in log removal (e.g. a factor of two reduction). In order to model the actual log removal, we needed to assign a log removal to a particular 95th percentile turbidity value. Consistent with the assumptions underlying the LT1, we assume that three-log (99.9%) removal is achieved when the monthly 95th percentile turbidity value is 0.2 NTU. This assumption, together with the linear function described above, allows us to predict the effective log removal for any month, based on its 95th percentile turbidity value. A plant whose 95th percentile turbidity value is "*NTU*" would have the following log

Table 2 | Assumed change in log removal of *Cryptosporidium* as a function of change in turbidity (NTU)* and changes in log removal based on PBT study linear model (in parentheses)

	NTU < 0.1	0.1 ≤ NTU < 0.2	0.2 ≤ NTU < 0.3	0.3 ≤ NTU < 0.4	0.4 ≤ NTU
NTU < 0.1	0 (0)	−0.5 (−0.288)	−0.75 (−0.576)	−1 (−0.863)	−1.25 (−1.15)
0.1 ≤ NTU < 0.2	0.5 (0.288)	0 (0)	−0.25 (−0.288)	−0.5 (−0.576)	−0.75 (−0.864)
0.2 ≤ NTU < 0.3	0.75 (0.576)	0.25 (0.288)	0 (0)	−0.25 (−0.288)	−0.5 (−0.576)
0.3 ≤ NTU < 0.4	1 (0.864)	0.5 (0.576)	0.25 (0.288)	0 (0)	−0.25 (−0.288)
0.4 ≤ NTU	1.25 (1.15)	0.75 (0.864)	0.5 (0.576)	0.25 (0.288)	0 (0)

NTU–nephelometric turbidity units. Positive values indicate an improvement in log removal. Top row indicates ending values; first column indicates starting values.
*Table values based on assumptions used in: 1) Regulatory Impact Analysis for IESWTR, USEPA 1998; 2) Middle values used as described in Table 3, and elaborated on page 154 (Regli *et al.* 1998); and 3) Preambles of proposed and final LT2 rules for providing additional credit for *Crytosporidium* removal in filtered water turbidity levels less than 0.3 NTU (USEPA 2003, 2006) based on research studies by Patania *et al.* (1995), Emelko *et al.* (1999) and Dugan *et al.* (2001).

removal:

$$3 + 2.881*(0.2 - \mathrm{NTU}) \quad (4)$$

For example, a month in which the 95th percentile turbidity is 0.35 is assumed to have only $3 + 2.881 * (0.2 - 0.35) = 2.57$ log removal. A month in which the 95th percentile turbidity is 0.15 would have $3 + 2.881 * (0.2 - 0.15) = 3.14$ log removal.

Five additional pieces of information are needed in order to translate finished water turbidity levels to risk of illness. These are (a) the concentration of *Cryptosporidium* in the source water; (b) the average amount of water ingested per person each day; (c) the dose-response relationship for predicting *Cryptosporidium* infection; (d) the likelihood of people initially infected infecting other people by secondary transmission; and (e) morbidity rates for predicting illness from infection. We utilized information on these five factors from the economic analysis for the LT2 regulation. For simplicity, we use only the central estimates for these factors. A more complete analysis would incorporate uncertainty as described in the economic analysis. For occurrence, we assumed an Information Collection Rule survey-based mean estimate of 0.157 oocysts per liter. For ingestion, we assumed 1.2 litres per person-day (USEPA 2005). For dose-response, we assumed each oocyst ingested leads to infection with probability 0.09 (USEPA 2005; additional details of the dose-response analysis can be found in Appendix N of the Economic Analysis for the LT2 regulation, available on the EPA's website at: http://www.epa.gov/safewater/disinfection/lt2/pdfs/anaylis_lt2_economic_appendix2.pdf)

The solid curve in Figure 6 displays the distribution of monthly illness risk for consumers served by plants before the plants participate in PBT. The median value before training is 0.00028, meaning that about five persons would be infected and two to three of them would become ill each month in a community of 10,000 persons served by a "typical" small water system. The dashed curve displays the distribution that would result following PBT. The median value for the post-Training distribution is 0.00018, about one-third less than the median value from the pre-PBT distribution.

In both cases (pre-and post-PBT), the mean monthly risk is considerably greater than the median. The mean of the

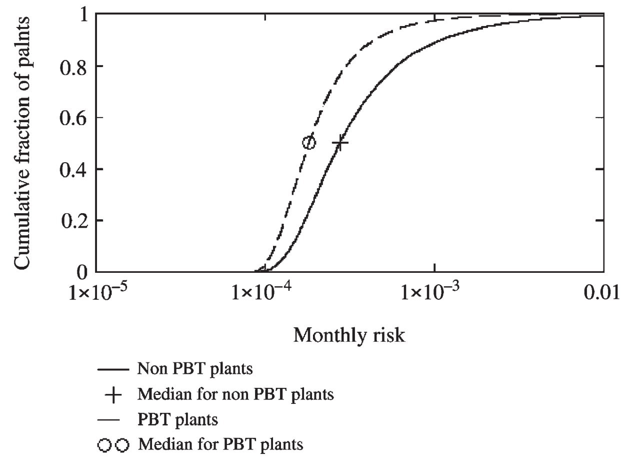

Figure 6 | Distribution of monthly illness risk with and without performance-based training (PBT).

pre-PBT distribution is 0.7 cases per thousand and the mean of the post-PBT distribution is 0.3 per thousand. As a result, PBT appears to reduce the overall risk by a factor of 2. On average, about ten cases of infection can be avoided each year for every thousand persons served by systems that take advantage of PBT, within a range of 0 to 18 fewer infections.

Uncertainty characterization

Because the risk analysis described above draws information from the LT2 economic analysis, it shares many of the same uncertainties. Table 3 lists the key uncertainty factors for this analysis. Given the lack of robust data in key areas, more research into the magnitude of uncertainty for each of these factors is needed to increase confidence in the study findings. Of these, *Cryptosporidium* occurrence and infectivity appear to be the largest contributors to overall uncertainty. While new information on occurrence should be available through the source water sampling provisions of the LT2, new information on infectivity is not expected.

Information to reduce the uncertainties regarding treatment effectiveness (baseline effectiveness of conventional treatment and any improvement realized through turbidity reduction) could be obtained through research. Continuous turbidity monitoring data from participating and nonparticipating plants could then be used to improve the PBT program's benefit assessment.

We emphasize that the predicted performance improvements indicated from the statistical models in this study

Table 3 | Factors contributing to uncertainty in estimating the PBT program's health benefit

Source of Uncertainty*	Remarks
Cryptosporidium occurrence in surface water sources	Overall level is based on the 1997–1998 ICR survey for IESWTR. Other surveys indicated somewhat lower occurrence.
	Levels may have changed significantly since the surveys were conducted.
	New data will be obtained through monitoring under LT2 that is specific to small surface water systems.
Cryptosporidium infectivity (dose-response)	Unknown how well *Cryptosporidium* isolates used in human challenge studies represent environmental oocysts.
Overall effectiveness of conventional water treatment	Need additional bench and pilot scale studies to assess relationship for a variety of source waters and conditions.
Relationship between turbidity and *Cryptosporidium* removal	Need additional bench and pilot scale studies to assess this relationship under a variety of source water types and conditions.
Overall turbidity improvement due to participation in PBT	Based on sample of 36 paired participating and non-participating systems.

*These factors vary from location to location, so individual systems may realize benefits that differ markedly from the average.

cannot reliably be applied to a specific plant. For example, mean *Cryptosporidium* source water concentrations can vary widely across systems. Also, a plant's level of turbidity and type of particulate matter, treatment processes prior to filtration, and effectiveness of its coagulation/flocculation processes, can significantly influence removal efficiencies for *Cryptosporidium* as this relates to turbidity reduction. Nevertheless, the authors conclude that the proposed approach has merit when trying to evaluate the benefits of a PBT program to a group of potential PBT systems.

IMPLICATIONS OF THE STUDY: RESULTS AND DISCUSSION

There are several important implications of the study results outlined below.

Study confirms program theory of PBT logic model

Both phases of the PBT study confirmed the assumed relationships between optimization training and technical assistance, statistically significant improvements in plant performance and reduced risk. As shown in the PBT logic model, if small system operators fully participate in the program, they can acquire the knowledge and skills to optimize their filters. If operators of plants with similar source water conditions and initial finished water turbidity can effectively optimize their filters, they also are likely to achieve meaningful reductions in turbidity. As a result of these reductions, *Cryptosporidium* is more likely to be removed from raw water, reducing consumer risk of exposure to pathogens in finished water. Most importantly, consumers of finished water served by systems that have participated in PBT are less likely to become ill.

Participation in the PBT program should be strongly encouraged

As noted above, preliminary analysis of performance data indicated that small water systems minimally or partially committed to the optimization program's goals did not achieve statistically significant performance improvements. Further analysis revealed, however, that systems fully participating in the PBT program achieved a statistically significant, median turbidity reduction of 29 percent. This result suggests that, to the extent EPA and state resources permit, any small system interested in the goals of the optimization program should be encouraged to participate fully by enrolling in the PBT program. Additionally, EPA and state program managers should engage in periodic monitoring of "graduates" to ensure that PBT plants are able to maintain their strong performance over time. Graduates with moderate performance, i.e. in the range of 0.2 to 0.3 95th percentile NTU, could benefit from

Pre PBT : **only 1 of 12** months **not** in violation of LT1 monthly 95th percentile requirement

Plant #5	
Pre-PBT monthly 95th percentile NTU	Post-PBT monthly 95th percentile NTU
0.43	0.13
0.51	0.20
0.50	0.16
0.50	**0.35**
0.28	0.23
0.38	**0.59**
0.40	0.18
0.33	0.25
0.42	0.16
0.41	0.28
0.40	0.25
0.42	0.28

Post PBT : **only 2 of 12** months **in** violation of LT1 monthly 95th percentile requirement

Figure 7 | Compliance improvements in individual plant, pre and post-PBT.

follow-up site visits and additional training to achieve the optimization program goal of 0.1 NTU.

PBT improves small system compliance and reduces risk to consumers

One of the systems in our sample of PBT plants exemplifies the dual benefits of the program: improved compliance with federal requirements *and* significant risk reduction. Figure 7 shows the change in monthly 95th percentile turbidity values before and after participation in the PBT program for one of the PBT plants in the study. Had the treatment technique requirements of LT1 been enforceable during the study period, this system would have incurred 11 violations in the 12 months prior to training, but only *two* LT1 violations in the 12 months following the training and adjustment period. More importantly, Figure 8 shows that this particular plant also achieved a five-fold reduction in risk as a result of participation in the PBT program (positive values indicate improvements). Figure 9 shows that the majority of the PBT plants improved their filtration performance in the second 12-month period (Year 1), represented by all points below the diagonal line.

Potential avoided treatment costs to meet LT2 requirements

Further benefits of the PBT program could be realized through avoidance of additional capital costs that might otherwise be incurred. Under the LT2, systems with high concentrations of *Cryptosporidium* oocysts in their source water will be required to provide additional control measures compared to those systems with low concentrations. Systems that achieve low turbidity levels in their filtered water may be able to achieve 0.5 to 1.0-log additional treatment credit for *Cryptosporidium* removal. And depending upon other control measures that might be necessary to meet the additional removal required under LT2, these systems could realize significant cost savings through PBT participation.

PBT plant	Estimated monthly risk of infection per thousand person year		Average monthly reduction of increase in risk (factor)	Relative change in monthly 95th percentile turbidity, post PBT
	Pre-PBT	Post-PBT		
PBT plant #5	0.0017	0.00033	5.2	43%

Figure 8 | Risk reduction in PBT system, EPA study.

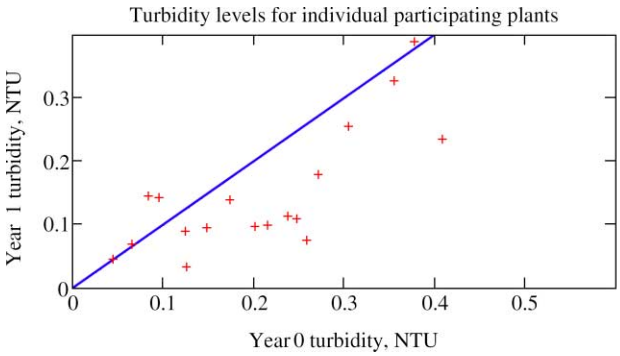

Figure 9 | Turbidity levels for individual PBT plants, pre-and post-training.

Operational data are critical to improving SDWA performance measures

The approach described above could serve as the basis for improving measures of the effectiveness of SDWA programs at protecting public health. As our analysis demonstrates, water systems' operational data (i.e. turbidity readings) are essential to improving indicators of program performance, because these data serve as a necessary link between compliance (in this case, with treatment technique requirements) and the estimated risk reduction and illnesses avoided due to plant performance. Further refinements to our models which address areas of uncertainty listed above could enhance our understanding of the relationship between turbidity reductions and public health protection.

CONCLUSION

This article describes a statistical analysis of small water systems' turbidity data within the framework of a logic model for the PBT program. The logic model shows the theoretical linkages between optimization training for small system operators; operator application of optimization techniques; improvements in plant filtration performance; and public health protection. This approach supports the development of program performance indicators which are meaningful, measurable, broadly applicable and change-oriented. It supports development of meaningful indicators because it provides estimates of risk reduction and illnesses avoided as a direct result of system performance. It supports measurable indicators because it does not attempt to measure directly illnesses which do *not* occur and it builds on the requirement that all surface water-based systems report turbidity data to the state primacy agency each month. It is broadly applicable because logic and statistical models that utilize parametric data and assumptions from previous studies could be developed for similar programs or for other contaminants. And it is change-oriented because it confirms the significant relationships between PBT participation and turbidity reductions and then quantifies the estimated waterborne illnesses avoided as a result. The approach is not without important limitations, however. One limitation is the uncertainty due to having no direct measurements of source water quality, treatment effectiveness and pathogen potency. Second, the analysis is limited to *Cryptosporidium*, though exposures to other pathogens are probably reduced due to improved water treatment and so the health benefits of the PBT program may be understated. Finally, the analysis is limited by the relatively small number and geographic range of participating plants. Other treatment plants from other regions of the United States could have different outcomes, so their actual health benefits could be significantly greater or less than estimated. Additional work in these areas of uncertainty would need to be conducted before the national drinking water program could utilize this approach to develop robust indicators of: (1) the estimated benefits of reduced exposure risk due to compliance, and (2) in the case of turbidity reductions, the estimated benefits of additional removal for systems already meeting the federal standard. Such indicators would assist the USEPA in meeting its requirements under the Government Performance and Results Act and the OMB Program Assessment Rating Tool (PART).

DISCLAIMER

The contents of this article are solely the responsibility of the authors and do not necessarily represent the views of the U.S. Environmental Protection Agency.

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