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Research article

Incorporating uncertainty and risk into decision making to reduce nitrogen inputs to impaired waters

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ABSTRACT

This article aims to understand decision making under uncertainty and risk, with a case study on Cape Cod, Massachusetts. Decision makers need to consider imperfect information on the cost and effectiveness of advanced nitrogen-removing on-site wastewater treatment systems as options to mitigate water quality degradation. Research included modeling nitrogen load reduction to impaired coastal waters from seven treatment system technologies and eliciting expert knowledge on their costs. Predictions of nitrogen load removal and cost for each technology incorporated variation in effectiveness and uncertainty in household water use, costs, and expert confidence in costs. The predictions were evaluated using the Pareto efficiency concept to reveal tradeoffs between cost and effectiveness. The stochastic dominance index was used to identify preferred technologies for risk-averse decision making, assuming no further learning is possible. Lastly, the predictions were combined into a cost-effectiveness metric to estimate the expected payoff of implementing the best treatment system in the face of uncertainty and the expected payoff of learning which treatment systems are most cost-effective over time. The expected value of perfect information was calculated as the difference between the expected payoffs. Three technologies revealed Pareto efficient tradeoffs between cost and effectiveness, whereas one technology was the preferred risk-averse option in the absence of future learning. There was a high expected value of perfect information, which could motivate adaptive management on Cape Cod. This research demonstrated decision analysis methods to guide future research and decision making toward meeting water quality objectives and reducing uncertainty.

1. Introduction

The structure and function of coastal ecosystems are degraded in part by point and nonpoint sources of nitrogen (Boesch, 2002). Excessive amounts of nitrogen are linked to eutrophication, hypoxia, food web alteration, and harmful algal blooms in coastal waters (Howarth et al., 2000). Anthropogenic sources of nitrogen, particularly wastewater disposal, are a significant cause of these degrading effects (USEPA, 1993; Bowen and Valiela, 2004; Williamson et al., 2017). Excessive nitrogen, among other chemical pollutants, contributes to water quality characteristics that exceed state mandates for designated industrial, agricultural, wildlife, and recreational uses. In the United States, impaired waters that do not meet these standards are listed in the Environmental Protection Agency's Clean Water Act Section 303(d) program, and a management plan must develop total maximum daily loads (TMDL), or the allowable nitrogen load that meets state mandates. For these reasons, industrial and household wastewater treatment systems are areas of concern to reduce inputs of nitrogen to impaired waters.

Household septic tanks are the most common form of on-site wastewater treatment systems (OWTS) in the world (Withers et al., 2014) and a significant contributor of local and regional nitrogen pollution (Bunnell et al., 1999). Standard septic tanks are not effective at removing nitrogen to levels that mitigate water quality degradation, and there is little to no regulatory control over these systems for removing nitrogen in environmentally-sensitive areas (USEPA, 2002). Since the 1980s, however, advanced nitrogen-removing OWTS have been designed to facilitate denitrification processes that reduce the amount of nitrogen that enters coastal waters (Ritter and Eastburn, 1988).

The likelihood that advanced OWTS are affordable and effective at removing nitrogen inputs to impaired waters are determining factors in decisions to meet water quality mandates, such as a TMDL (Martin

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et al., 2019). The focus of this research is to formalize a basis from which to implement advanced OWTS as environmental management options that achieve cost and effectiveness objectives. The methodological approaches of decision analysis aid in critical thinking, collecting information, evaluating alternative courses of action, prioritizing actions, and enhancing decision making (Keeney and Raiffa, 1976). Decision analysis is a well-established analytical framework based on concepts from decision theory, systems analysis, statistical theory, and behavioral psychology (von Winterfeldt and Edwards, 1986; Edwards et al., 2007). Acknowledging uncertainty and risk about the consequences of management actions is a key feature of decision analysis because it helps decision makers make better decisions (Williams et al., 2009). Decision analysis also allows decision makers to understand how to implement actions where learning is a desirable component of the decision-making process. With these features, we can ask: What advanced OWTS are better options in the face of uncertainty? What do decision makers sacrifice if they start implementing advanced OWTS and fail to identify the most appropriate option(s)? Methods for decision analysis can inform these inquiries and aid decision makers in implementing advanced OWTS and meeting water quality standards.

In the remainder of this article, we employ decision analysis methods and evaluate advanced OWTS as options to mitigate water quality degradation on Cape Cod, Barnstable County, Massachusetts (MA). The research provides a general understanding of (i) which advanced OWTS options trade off achievements in cost and effectiveness objectives, (ii) which advanced OWTS are better options under different risk attitudes, and (iii) the value of learning that could improve the cost-effectiveness of advanced OWTS. Expert elicitation and Monte Carlo sampling incorporated uncertainty in several cost and nitrogen-removing effectiveness parameters of seven advanced OWTS technologies. The concept of Pareto efficiency and the stochastic dominance index (Levy, 2016) revealed tradeoffs between the options and ordered them relative to decision maker risk preferences, respectively. Lastly, value of information analysis (Raiffa and Schlaifer, 1961) estimated the value of reducing uncertainty in cost and effectiveness through learning. The planning implications of each method are described in the context of adaptive management.

1.1. Case study

Over 70% of the nitrogen that enters coastal waters on Cape Cod is from household septic systems (Cape Cod Commission, 2015). This characteristic of wastewater disposal, combined with shallow groundwater and sandy soils, represents a significant vulnerability to nitrogen pollution. Possible sources of uncertainty include nitrogen effluent measurement errors, operational inaccuracies, system location and variation in performance, human cognitive and behavioral biases, and irreducible randomness of system cost and effectiveness (Regan et al., 2002).

There are currently over 2,900 advanced OWTS on Cape Cod.[1] The relationship between advanced OWTS and water quality has been investigated, particularly in coastal areas of the northeastern United States (Valiela et al., 2016; Lancellotti et al., 2017; Amador et al., 2018). However, few studies incorporate uncertainty and risk into a decision-making process. Wood et al. (2015) estimated costs and nitrogen-removing performance of four OWTS available for the town of Falmouth, MA, on Cape Cod. That analysis incorporated variation in the ranges of cost and nitrogen removal rate estimates to determine how much nitrogen can be removed from the watershed. The assessment in Wood et al. (2015) did not address risk, however, and was not performed to determine how effectively the OWTS meet water quality standards. The New Jersey Pinelands Commission (2018) reported point estimates for cost and nitrogen-removing performance of several OWTS to meet water quality standards in New Jersey, but variations in performance or uncertainties in costs were not documented. Martin et al. (2019) researched numerous possible combinations of management strategies to meet a TMDL, minimize cost, and provide environmental benefit for a watershed in Barnstable, MA, on Cape Cod. That and a similar analysis by AECOM (2014) incorporated variation in the ranges of nitrogen removal rates and costs for two OWTS options, but no formal risk assessment for decision making was performed.

Decision makers on Cape Cod are tasked with evaluating options to mitigate water quality degradation and implement TMDLs in impaired watersheds. Upgrading standard septic systems to advanced OWTS at the household level are an area of concern (Adler et al., 2014). With guidance from decision makers at the Massachusetts Department of Environmental Protection, Barnstable County Department of Health and Environment, Cape Cod Commission, and Barnstable Clean Water Coalition, this research investigated seven advanced OWTS technology types that are currently permitted for use in MA, pursuant to Title 5 of the State Environmental Code (310 CMR 15.000). This research was performed so that decision makers could prioritize and finance the technologies for installation at households in nitrogen-sensitive areas. These technologies were coded Alpha, Beta, Gamma, Delta, Epsilon, Zeta, and Eta to avoid the appearance of endorsing a technology. All seven technologies are currently installed in numerous environmentally-sensitive areas across Cape Cod with varying effectiveness. Technologies that are in piloting and testing phases of development on Cape Cod were not included, although they will be included in future iterations of these research methods.

The currently permitted advanced OWTS technologies include secondary treatment units with separate aerobic and anaerobic chambers for nitrification and denitrification, respectively. They vary by method to promote bacteria for nitrification (e.g., timers, trickling filters, air blowers, surface area-to-volume ratio of media) and denitrification (e.g., artificial organic carbon media, wood-based carbon media, microbial film media). Most of the systems recirculate wastewater through the system for nitrification and denitrification and are retrofitted to a Title 5 septic system, whereas few systems evenly apply wastewater over media in a linear process and can be submerged inside a Title 5 septic system. All system types are controlled by an electronic panel and require routine operation, maintenance, and monitoring.[2]

2. Materials and methods

2.1. Estimating nitrogen removal rates

With the assistance of the Barnstable County Department of Health and Environment, we obtained total nitrogen (sum of total kjeldahl nitrogen, nitrite, nitrate) effluent data for the seven advanced OWTS installations for the years 2000–2018. This investigation was limited to single-family household installations with less than 2,000 gallons per day of water flow and effluent data from the years 2014–2018 to control for design improvements in the technologies. To calculate how much nitrogen has been removed per installation per technology, all total nitrogen effluent samples taken in a year at an installation were averaged to yield an average annual total nitrogen effluent sample per installation (for an explanation of our use of average annual concentrations, see Supplementary material). If there were no total nitrogen effluent samples taken in a year, we treated the year as missing data. This gave us a dataset based on 66 installations of Alpha (159 samples), 8 installations of Beta (18 samples), 52 installations of Gamma (166 samples), 386 installations of Delta (914 samples), 2 installations of Epsilon (5 samples), 12 installations of Zeta (37 samples), and 120 installations of Eta (259 samples). Our colleagues at the MA

[1] https://septic.barnstablecountyhealth.org/.

[2] More information can be found at: https://www.mass.gov/guides/title-5-innovativealternative-technology-approval-letters.

Department of Environmental Protection accepted the low sample size for Epsilon installations because it is a permitted technology in terms of its nitrogen-removing effectiveness. Other sources of Epsilon data exist (e.g., MA controlled testing facility; multi-family and non-residential installations). However, those data revealed the same trend observed at the single-family household level regarding the mean and standard deviation and therefore were not used in this analysis.

Next, the average annual total nitrogen effluent concentration was subtracted from a baseline target of 26.25 mg/L (Supplementary material) to obtain an annual nitrogen removal concentration n per technology i (n_i) per sample. To obtain a mass load (kg/yr), total nitrogen effluent concentrations are multiplied by household water use under average water flow rate conditions (Adler et al., 2014). However, these data are not typically collected in practice because many OWTS are not equipped with a flow monitoring device (Adler et al., 2014). Rather, household water use is assumed to be the product of household size p and per capita water use w. In addition, Cape Cod is a tourist destination with year-round occupancy y_T and seasonal occupancy $(1 - y_T)$ that varies significantly by town T. To incorporate these uncertainties, two different removal rates were modeled, $N.\,1_i$ and $N.\,2_i$, for each average annual nitrogen removal concentration based on different assumptions for household water use.

$$N.\,1_i = n_{iT} p_T uw \tag{1}$$

$$N.\,2_i = n_i\{(p_T y_T) + (2p_T(1 - y_T))\}uw \tag{2}$$

where n_i is average annual total nitrogen removal concentration per technology (mg/L); is average household size per town; y_T is percent of seasonal households per town; u is per capita water use flows into the treatment system ($u = 0.9$; the remaining 10% is discharged as greywater; MA Estuary Program); w is per capita water use (gal/day; $w = 55$; MA Estuary Program). Data sources for average household size and percent of seasonal households are given in the Supplementary material. In Eq. (2), we assumed that the occupancy of seasonal homes doubled in each town. All estimates were converted to kg/yr values.

Uncertainty in total nitrogen removal rate estimates (quantity and variability of total nitrogen effluent concentrations and removal rates, unknown household water use) can be characterized as probabilistic predictions. To do this and control for the limited quantity of data among the technologies, we used the means and standard deviations of all nitrogen removal rate samples from Eq. (1) and Eq. (2) and sampled 10,000 removal rate predictions s (kg/yr) from a normal distribution. We multiplied these removal rate predictions by 20 years, the assumed life cycle, to achieve total nitrogen removed predictions E_{is}. These predictions represent competing hypotheses about the potential effectiveness of each technology.

2.2. Estimating economic costs

Data availability for estimating economic costs of advanced OWTS is poor. Many studies provide point estimates of economic costs, but extrapolations from point estimates are not useful due to uncertainties associated with predicting the ranges of costs of future household installations. Eliciting probabilities directly from experts runs the risk of linguistic uncertainties and conflicts of interest, among other cognitive and contextual biases (Hemming et al., 2018; O'Hagan et al., 2006).

To overcome these limitations, a four-step elicitation procedure was implemented to obtain expert judgments of several types of fixed and variable costs (Table 1; Speirs-Bridge et al., 2010). We met in-person with 12 experts for the advanced OWTS, including private vendors and distributors, as well as developers of the technologies and contractors for site installation. We asked three questions to elicit upper bound, lower bound, and most likely cost estimates for relevant fixed and variable cost parameters. The four-step elicitation procedure also asks one question to obtain expert confidence levels for each cost estimate. To avoid possible confusion of experts providing probabilities, sensitivity analysis was performed with varying confidence levels for the cost estimates. We specifically asked for interval judgements to incorporate information that is not provided by point estimates. We performed one follow-up communication with each expert to confirm their initial set of judgments. The four-step elicitation procedure tends to incorporate uncertainty and reduce overconfidence in expert judgements (Speirs-Bridge et al., 2010).

The upper bound, lower bound, and most likely cost estimates and the confidence levels can be used as parameters of a probability distribution (McBride et al., 2012; O'Hagan et al., 2006). The fixed and variable cost estimates were combined, and we fit a lognormal distribution to them via quantile matching. To match quantiles and analyze the sensitivity of the results, we developed credible intervals[3] (Speirs-Bridge et al., 2010), sometimes referred to as subjective confidence intervals (McBride et al., 2012), based on four different expert confidence levels: 70% confidence level (15 and 85 percentile credible interval), 80% confidence level (10 and 90 percentile credible interval), 90% confidence level (5 and 95 percentile credible interval), and 95% confidence level (2.5 and 97.5 percentile credible interval). In a similar manner to estimating nitrogen removal rate predictions, fixed and variable costs of the corresponding lognormal distribution were obtained, and we sampled 10,000 predictions s from the credible intervals per technology i. These predictions incorporate uncertainty in the fixed and variable cost estimates and expert confidence in cost estimates.

We investigated three financing scenarios based on whether Cape Cod decision makers can obtain state or federal grants to distribute to homeowners for upgrading existing Title 5 septic systems to advanced OWTS. Scenario 1 assumed a \$10,000 grant for combined fixed costs, and we calculated an annual loan schedule with reduced fixed cost predictions and a 0% interest rate over a 20-year life cycle. Scenario 2 assumed a \$10,000 grant for combined fixed costs, and we calculated an annual loan schedule with reduced fixed cost predictions and a 2% interest rate over a 20-year life cycle. Scenario 3 assumed no grant, and we calculated an annual loan schedule with fixed cost predictions and a 5% interest rate over a 20-year life cycle. These different annual fixed costs, obtained under the three financing scenarios, were combined with the annual variable costs and converted into 10,000 total life cycle cost predictions (Table 1) per scenario per technology C_{is}. The total nitrogen removed calculations were performed using Microsoft Excel and the cost calculations were performed using the open-source computing language R Version 3.5.0 (R Core Team, 2016).

2.3. Pareto efficiency

The concept of Pareto efficiency assumes that a known set of alternative management options are Pareto efficient if they trade off improvements in at least one objective for declines in others. To exemplify, let two options A and B represent viable alternative investments. Let two objectives for the investments be minimize cost in dollar values (\$) and maximize performance or satisfaction in utility values (0–1). A Pareto efficient pair of outcomes for the options could be |\$2,1| for option A and |\$1,0.5| for option B, whereas an inefficient pair

[3] Credible intervals are different than confidence intervals. Confidence intervals represent a range of plausible values for the true cost value, whereas credible intervals represent a range of plausible cost values that matches an expert's subjective opinion that the true value is within that range. For example, a 95% confidence interval for treatment system costs is the interval that is expected to contain the true cost in 95 out of 100 household installations. In contrast, if an expert is 95% confident in an upper and lower cost judgement, then we can expect that the true cost will fall within that interval in 95 out of 100 household installations. In this conception, a credible interval derived from a 70% confidence level is wider than a credible interval derived from a 95% confidence level due to the greater probability that a cost will fall outside of the interval (30% probability for a 70% confidence level vs. 5% probability for a 95% confidence level).

Table 1
Method for calculating total life cycle costs for advanced on-site wastewater treatment systems.

Total life cycle cost per technology C_i = *total annual cost* (\$/*yr*) *x* 20 *year life cycle*
Where:
Total annual cost (\$/*yr*) = (*monthly fixed costs x* 12 *months*) + *annual variable costs*
Monthly fixed costs (\$/*month*) = *f* (*fixed costs*, *annual interest rate*, 12 *payments* /*yr*, 20 *year life cycle*)
Annual variable costs (\$/*yr*) = $\sum$ *variable costs*
Using the following values[a]:

Fixed (\$)	*Brief description*
Capital/materials	Cost of treatment system unit + replacement equipment over 20-year life cycle
Installation	Design (perk test, soils test), permitting, and excavation costs to upgrade existing residential Title 5 septic system
Recording	One-time cost for notice of advanced OWTS on property deed
Variable (\$/yr)	
Operation	Average annual electrical usage (kilowatt-hour), multiplied by local provider (\$/kilowatt-hour) cost estimates
Maintenance	Certified treatment system operator time and number of services per year
Management	User fee for annual management of treatment system data
Monitoring (years 3–20)[b]	Sampling protocol; price per sampling event, assuming two events per year + operator time

[a] See Table S1 in the Supplementary material for expert cost estimates for these parameters.
[b] Assumed monitoring would be performed for the first two years after installation at no expense to the homeowner.

of outcomes for the options could be |\$2,0.5| for option A and |\$1,1| for option B. In the Pareto efficient context, option A maximizes satisfaction but at a higher cost, whereas option B is less satisfying but provides a better cost. This outcome is Pareto efficient because we cannot objectively distinguish between the two options to determine which one is better unless decision maker preferences are placed on the objectives. In the inefficient context, there is no need for an investor to choose option A because option B dominates option A over both objectives. This outcome is inefficient, meaning that there are no tradeoffs, which provides decision makers with an objective ranking of the options to make decisions.

The concept of Pareto efficiency was used to distinguish between efficient and inefficient OWTS options, independent of decision maker preferences. We took the mean of the cost and effectiveness values obtained by the Monte Carlo sampling method and visualized the options in two-dimensional coordinate space. Visualizing options in coordinate space can be an effective way at eliminating inefficient options and identifying Pareto efficient ones.

2.4. Stochastic dominance

The stochastic dominance risk index (Levy, 2016) was used to understand which advanced OWTS option(s) are the most attractive to decision makers, assuming no further learning is possible. The index is seldom employed in the environmental sciences, although there have been recent advances in wildlife management (Canessa et al., 2016; Johnson et al., 2017).

First order stochastic dominance assumes that efficient options can be distinguished from inefficient options under the monotonicity assumption of expected utility, namely that decision makers are satisfied with more of something rather than less (e.g., more income; Levy, 2016). In this study, we assumed that decision makers prefer options that are lower in cost and provide the highest nitrogen removal. The cost and effectiveness predictions were normalized onto a 0–1 scale (highest cost = 0; lowest effectiveness = 0) and aggregated into utility values using equal weights for the objectives. Objective weights should only be used if there is explicit preference information from decision makers. This preference-neutral analysis was based on stakeholder input. However, sensitivity analysis on weights is an option for stakeholders (e.g., Martin et al., 2015) and could reveal how changing preferences lead to different results. First order stochastic dominance exists if the cumulative distribution function of one option is less than that of another option. In other words, for every utility value the cumulative probability of achieving a lower utility value is lower for one option compared to other option(s). This can occur if the cumulative distribution function of the utilities of the OWTS do not overlap (but they can tangent each other; Levy, 2016).

Second order stochastic dominance assumes that if the cumulative distribution functions of the options cross, the general risk attitude of the decision maker must be known to identify a preferred option. Risk-seeking behavior can be accommodated (Wong and Li, 1999), but we assume a risk-averse decision-making attitude for this research. Second order stochastic dominance exists if the difference between the net integral under the cumulative distribution function of any two options is positive (Levy, 2016). Graphically, the area enclosed between the probability functions of two options should be non-negative up to any increasing utility value for one option to be considered better than another (Levy, 2016). In other words, the utilities of one option are higher than another across all levels of uncertainty and there is less of a probability of getting worse utility values of the preferred option. This can occur if the area under the cumulative distribution function of the utilities of the OWTS do not overlap (but they can tangent each other; Levy, 2016).

2.5. Expected value of perfect information

Value of information analysis (Raiffa and Schlaifer, 1961) is a method to evaluate the differences in value that would result if decision makers monitored and learned about the OWTS as a result of their implementation. The 10,000 cost C_{is} and effectiveness E_{is} predictions were combined into a single cost-effectiveness metric $V(i, s)$ in kg/\$ per scenario. Each cost-effectiveness prediction represents a decision point or payoff for implementing technology i under prediction s (Canessa et al., 2015).

$$V(i, s) = E_{is}/C_{is} \tag{1a}$$

for all technologies $i = 1, \ldots 7$, predictions $s = 1, \ldots 10{,}000$.

The concept of expected value is a common strategy in decision making under risk (von Winterfeldt and Edwards, 1986). Expected value was used to aggregate the cost-effectiveness predictions into a single metric. The scaling factor for this metric is a credibility measure p_s, regarded as the relative degree of belief in a prediction, warranted by evidence. Because we specified probability distributions for cost and effectiveness and randomly sampled from them, the samples are inherently weighted by their probability of occurrence, which are equal and sum to unity (1) in this study. The expected value of a single OWTS E_i is found by multiplying the payoff of each cost-effectiveness prediction by its credibility measure and summing across all possible predictions (Canessa et al., 2015).

$$E_i = \sum p_s V(i, s) \quad (2a)$$

for all technologies $i = 1, \ldots 7$, predictions $s = 1, \ldots 10{,}000$, where $\sum p_s = 1$.

Value of information is the net payoff of making a decision with near-complete information versus making a decision with incomplete information. The expected value under uncertainty $EV_{uncertainty}$ was calculated as the expected payoff of choosing the best OWTS over all predictions. In this calculation, decision makers don't know which OWTS is the best but choose a single option anyway. Knowing what we know with the given predictions and uncertainty surrounding them, the decision maker retains the best expected payoff (i.e., maximize cost-effectiveness) over all predictions.

$$EV_{uncertainty} = max_i E_s = max_i \sum p_s V(i, s) \quad (3)$$

where max_i indicates that the OWTS with the best cost-effectiveness calculation is chosen over all predictions (Canessa et al., 2015).

By weighting each cost-effectiveness prediction equally, the expected value under certainty $EV_{certainty}$ is estimated as the expected payoff of getting the best cost-effectiveness outcome considering all predictions. In this calculation, decision makers seek to spread the allocation of OWTS and allow each the opportunity to yield the best cost-effectiveness outcome possible. The payoff is *expected* to be equivalent to choosing the best OWTS per prediction, conditional on the prediction being credible and true (Canessa et al., 2015).

$$EV_{certainty} = E_s[max_i V(i, s)] = \sum p_s [max_i V(i, s)] \quad (4)$$

The expected value of perfect information (EVPI) is the difference between the expected payoff of choosing the best OWTS before and after new information has been collected via monitoring.

$$EVPI = EV_{certainty} - EV_{uncertainty} \quad (5)$$

The EVPI allows decision makers the ability to draw conclusions on the differences in payoffs attributed to acquiring more information on multiple parameter sets of uncertainties through monitoring and adjusting decisions over time (Runge et al., 2011). EVPI calculations were performed per scenario per confidence level in costs using Microsoft Excel spreadsheets.

3. Results

In this section, we present a subset of results. Results were based on the 70% confidence level in costs because it is more conservative than results based on the other confidence levels (see footnote 3). The inverse of the EVPI results were calculated to present a metric in dollars per kilogram nitrogen removed ($/kg), which is the common currency of communicating water quality management actions on Cape Cod (Cape Cod Commission, 2015). A summary of all iterations of the methods is in the Supplementary material.

3.1. Cost and effectiveness predictions

The nitrogen load removal rate predictions ranged from 0.25 kg/yr (Delta) to 2.99 kg/yr (Epsilon) on average. The mean and quartile ranges of OWTS effectiveness were graphed in Fig. 1 as total nitrogen removed over 20-year life cycle. It is important to note that many predictions were calculated below zero. Negative removal rates do not necessarily mean that nitrogen is being added to Cape Cod waters. Advanced OWTS should do no worse than conventional septic systems. Although a baseline total nitrogen concentration must be set to earn credit towards a nitrogen TMDL in watersheds, the assumptions on setting baseline concentrations are subject to discretion (Supplementary material).

Financing Scenario 1 was the most generous in terms of support for

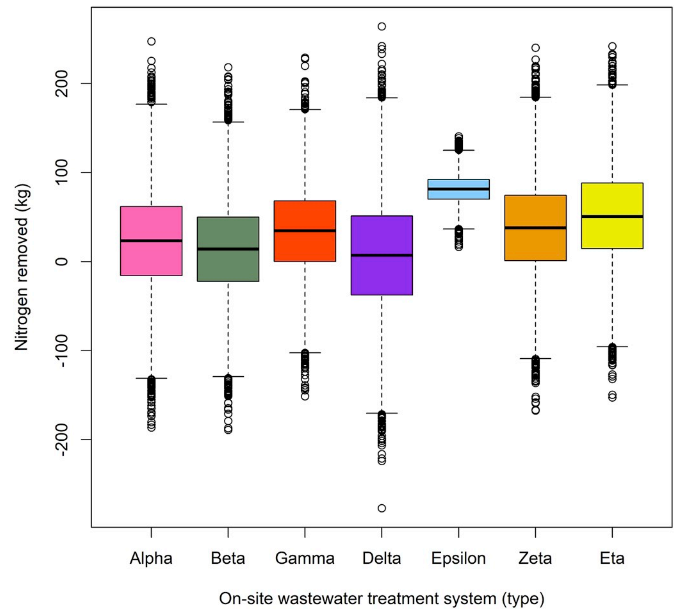

Fig. 1. Summary box and whisker plot of sample of nitrogen removal rates, converted to total nitrogen removed over 20 years. Each box contains the 50% interquartile range, separated by the median line. The whiskers contain the 90% interquartile range with outlier points extending from the range.

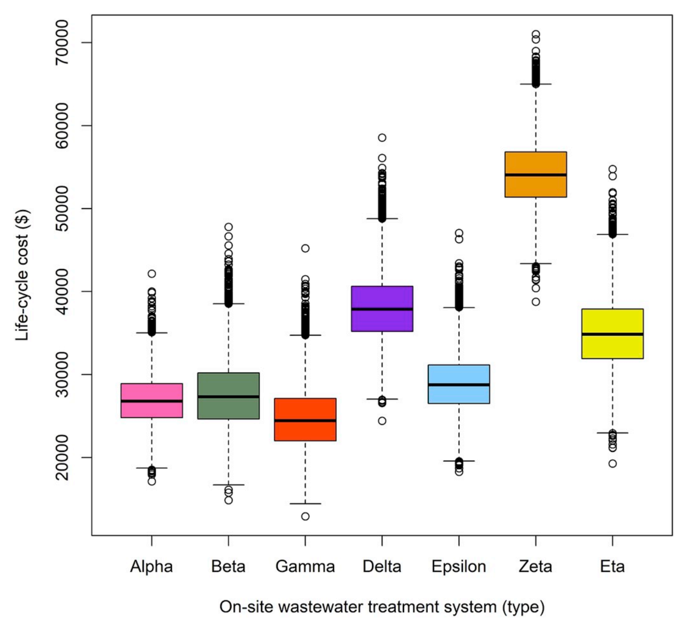

Fig. 2. Summary box and whisker plot of total life cycle cost predictions under financing Scenario 2, derived from sample of fixed and annual variable costs at 70% confidence level. Each box contains the 50% interquartile range, separated by the median line. The whiskers contain the 90% interquartile range with outlier points extending from the range.

homeowners, which returned life cycle cost predictions that ranged $24,714 (Gamma) to $54,194 (Zeta) on average (Fig. S1), rounded to nearest dollar. Subsequent scenario predictions estimated life cycle costs that ranged much higher (e.g., Scenario 2 predictions in Fig. 2).

3.2. Pareto efficiency

The concept of Pareto efficiency was used to distinguish between efficient and inefficient OWTS and understand tradeoffs. The mean and quartile ranges of life cycle cost and effectiveness were graphed in two-

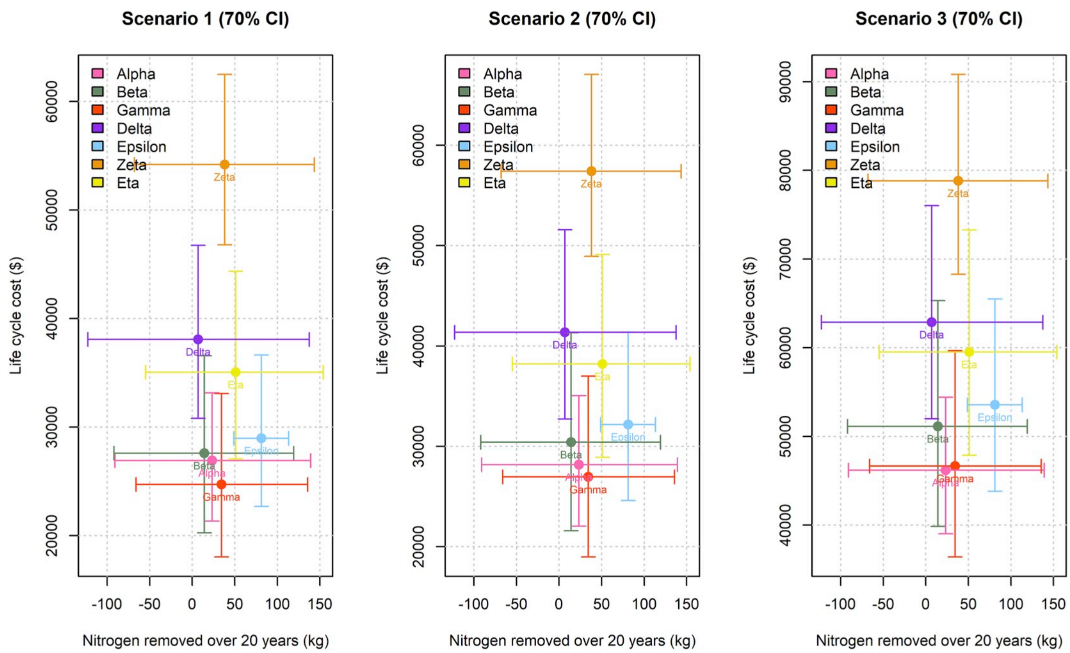

Fig. 3. Visualization of means (points) and 0.25–0.975 quartile range (lines) of cost and effectiveness under all scenarios at the 70% confidence level. Scenario 1 assumes a $10,000 homeowner grant for combined fixed costs and a loan schedule with 0% interest rate, Scenario 2 assumes a $10,000 homeowner grant for combined fixed costs and a loan schedule with 2% interest rate, and Scenario 3 assumes no grant and a loan schedule with 5% interest rate.

dimensional coordinate space (Fig. 3). The ideal but non-feasible point is in the lower right corner, which specifies the lowest cost and highest nitrogen removed values on the graph. According to Scenario 1 and 2 predictions (Fig. 3, left and middle panels), Alpha, Beta, Delta, Zeta, and Eta are inefficient and Gamma and Epsilon are Pareto efficient. This can be visualized by picking one OWTS and seeking another that does better in both objectives. Gamma has better mean cost and effectiveness values than Alpha, Beta, and Delta, whereas Epsilon has better cost and effectiveness values than Zeta and Eta. There is little reason for decision makers to choose the inefficient OWTS because both objectives can be improved, on *average*, by choosing either Gamma or Epsilon. However, Gamma and Epsilon are Pareto efficient because neither one is better than the other over both objectives. According to these results, decision makers could consider Gamma and Epsilon as viable options for implementation. Implementing Epsilon instead of Gamma could remove around 40 kg of nitrogen loading per installation but at higher costs of around $4,000 per installation.

This result was consistent for each iteration of confidence level for Scenarios 1 and 2 (Supplementary material). However, if homeowners do not receive financial support under Scenario 3, Alpha also becomes a viable technology alongside Gamma and Epsilon (Fig. 3, right panel; Supplementary material). This occurs in part because the variable costs of Gamma are more expensive than Alpha (Supplementary material).

3.3. Stochastic dominance

The stochastic dominance index explicitly deals with uncertainty and decision maker preferences to identify preferred options. First order stochastic dominance revealed one inefficient OWTS, visualized as the cumulative distribution function (Fig. 4, left panel). Eta and Gamma dominate Delta because their distributions do not intercept as utility increases. In other words, for each utility value, the cumulative probability of achieving an even higher utility value is higher for Eta and Gamma than for Delta. All other cumulative distribution functions cross each other as utility increases, meaning that additional preference information is needed to distinguish between Alpha, Beta, Gamma, Epsilon, Zeta, and Eta.

Applying the second order stochastic dominance rule resulted in Epsilon as the preferred OWTS (Fig. 4, right panel). A risk averse decision maker could choose Epsilon over all other OWTS because there is less of a probability of achieving unsatisfactory utility values. For each utility value, the area under the cumulative distribution function is smaller for Epsilon versus all other options.

3.4. Expected value of perfect information

Each of the value of information calculations showed high EVPI (Table 2; Supplementary material). Epsilon is the best option under uncertainty, with $EV_{uncertainty}$ values ranging between $351/kg and $655/kg, rounded to nearest dollar (Supplementary material). However, monitoring and reducing uncertainty in the cost and nitrogen removal parameters is expected to improve overall cost-effectiveness by between 22% and 25% (Table 2). These are among the highest EVPI values we've encountered.

The EVPI calculations did not change significantly among confidence level iterations within each scenario, meaning that expert confidence in cost estimates did not contribute to a significant variation in result. The EVPI tended to increase significantly among the finance scenarios, meaning that the value of reducing uncertainty is greater when homeowners are not provided financial support for implementing advanced OWTS, but the percent change in the EVPI remained consistent among all iterations. Therefore, significant increases in amortized loan costs among the scenarios is a determining factor to EVPI.

4. Discussion

The results have various implications for decision making. If decision makers want to consider tradeoffs between cost and effectiveness, some but not all of the advanced OWTS technologies can be eliminated from additional investigation. Gamma and Epsilon, and in some instances Alpha, are Pareto efficient (Fig. 3). If decision makers accept the monotonicity assumption of expected utility, some but not all of the technologies can be eliminated from additional investigation (Fig. 4, left panel). Further, if decision makers are risk averse and no future learning is possible, then Epsilon could be a preferred option (Fig. 4, right panel).

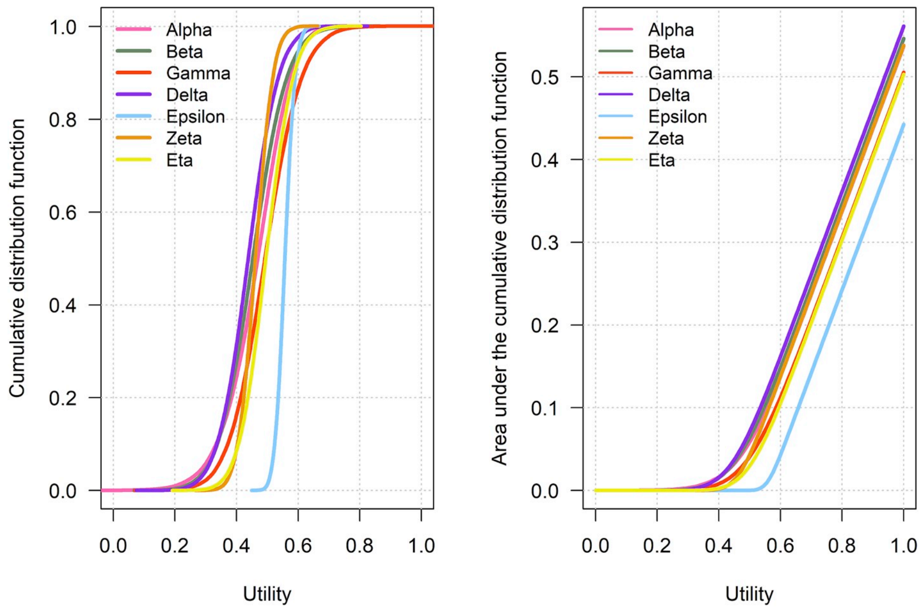

Fig. 4. Cumulative distribution function (left panel) and area under the cumulative distribution function (right panel) of the utilities of each advanced on-site wastewater treatment system at the 70% confidence level.

The Pareto efficiency and stochastic dominance results clarify decision making under specific planning contexts. The Pareto efficiency results inform that more preference information is needed to distinguish between some of the OWTS. This type of analysis is worthwhile because decision makers can think about and discuss tradeoffs without explicitly making tradeoffs. The stochastic dominance results inform that Epsilon can be a risk-averse option in the absence of future learning. This type of analysis is worthwhile because it provides decision makers with a single option that is least likely to yield unsatisfactory objective values.

The value of information results inform that experimentation with multiple technologies is a smart decision in a future learning context, and therefore moving forward with a single option is risky. Although implementing a single advanced OWTS technology has been proposed for mitigating water quality degradation elsewhere (Lancellotti et al., 2017), implementing a single technology over time is analogous to putting 100% of a portfolio into one investment. The findings point to Epsilon as a risk-averse option if no further learning is possible, but it is also a risk-seeking option if learning is desirable. For these reasons, analysts and their stakeholder constituents should be aware that Pareto efficiency, stochastic dominance, and value of information methods assume different planning contexts and associated risk attitudes. These assumptions should be reported in future publications using these methods.

For decision makers who are comfortable with relying on existing information and its attendant uncertainty, the choice of a single option could be considered risk-seeking behavior when the EVPI is high. This is due in part to the possibility that learning over time may result in better OWTS cost and effectiveness. However, in cases where the EVPI is low, decision making and expected payoffs may not improve because of learning; in such cases, it is unlikely that learning will change the decision or outcome over time (Yokota and Thompson, 2004) and the Pareto efficiency and stochastic dominance methods could prove valuable. The high EVPI results from this analysis (Table 2), however, show that there are advantages to learning.

4.1. Adaptive management

A high EVPI is a sufficient condition for motivating adaptive management, an iterative decision-making process to set goals and objectives for achieving environmental management policies while at the same time monitoring options and re-adjusting decisions in the face of uncertainty (Williams et al., 2009). Under adaptive management, data availability and the uncertainties surrounding data are less of an impediment to decision making. A significant advantage of adaptive management is the flexibility to change decisions in response to monitoring and obtaining new information, assuming that there are tradeoffs in the consequences of management options. This flexibility addresses some of the limitations of Pareto efficiency and stochastic dominance in a learning context and separates adaptive management from ad hoc scientific investigation and trial and error (Gregory et al., 2006; Williams and Brown, 2012).

Adaptive management requires a monitoring protocol and significant institutional and stakeholder engagement and support (Gregory et al., 2006). One approach to passive adaptive management (Walters and Hilborn, 1978; Williams, 2011) assumes that decision makers put all of their resources into the best option at every decision point in time (e.g., review period), whichever option decision makers thought was the best one at that time. For example, decision makers could choose to implement multiple installations of a single OWTS technology in one time period. If monitoring data on total nitrogen effluent, household water use, and economic costs yields satisfactory information, then decision makers could implement more of the same technology in the next time period. If performance is unsatisfactory, then decision makers could choose to implement a different OWTS technology in the next time period. Learning can be extremely slow in this context, particularly if only one type of OWTS was monitored at a time.

Under an active adaptive management approach (Johnson and Williams, 2015), parallel implementation of multiple OWTS in the short term could balance exploitation with learning. Decision makers aren't sure in the end which technology is going to be the most cost-effective, but the idea is that monitoring, maintaining, and adjusting implementations of multiple technologies over time can assure the best possible conditions for cost and nitrogen removal. This process can include substantial maintenance and consistent monitoring visits per year, voluntary household water use documentation, assuring properly-timed effluent dosing and recirculation within the OWTS, installing nitrogen sensors to assure proper operation, and adjusting system components to assure compliance to design specifications (Lancellotti et al., 2017). Likewise, learning and technical adjustments can assure

Table 2
Results of value of information analysis, presented as $/kg (inverse of expected value calculations).

	Alpha	Beta	Gamma	Delta	Epsilon	Zeta	Eta	EVPI	Change between *EV.certainty* and *EV.uncertainty*
Scenario 1 cost-effectiveness	$1,400.79/kg	$1,928.14/kg	$700.34/kg	$5,407.33/kg	$353.73/kg	$1,421.40/kg	$675.11/kg	$78.63/kg	22%
Scenario 2 cost-effectiveness	$1,520.91/kg	$2,116.65/kg	$759.80/kg	$5,856.53/kg	$391.69/kg	$1,504.70/kg	$734.44/kg	$92.42/kg	24%
Scenario 3 cost-effectiveness	$2,371.57/kg	$3,594.40/kg	$1,334.10/kg	$8,976.12/kg	$654.87/kg	$2,067.45/kg	$1,151.79/kg	$157.31/kg	24%

Notes: estimates are based on the 70% confidence level; see Supplementary material for all results.

that fixed and variable costs are minimized, such as installing energy-efficient pumping and assuring efficient system run times, developing multi-system maintenance schedules or programs, developing management programs similar to centralized wastewater treatment, and improving internet connectivity to electrical equipment to reduce operational costs. Learning under active adaptive management could change decisions toward the most cost-effective option(s) over time at a faster rate. The expected payoffs of these decisions could trend toward $EV_{certainty}$, in which case risk aversion may become irrelevant (von Winterfeldt and Edwards, 1986).

We have determined that adaptive management could give decision makers the opportunity to reduce uncertainty in the case study context. Moving forward, we ask: How much better or worse is an active approach versus a passive approach? Which approach provides greater payoffs toward meeting a TMDL or other possible objectives on Cape Cod? Decision makers may prefer passive adaptive management because they favor short-term gains over potential short-term "losses" when allocating multiple technologies (Tversky and Kahneman, 1991). These biases are perfectly understandable but may lead to errors in judgement and decision making that may be sub-optimal in terms of meeting environmental management objectives over time. To the best of our knowledge, these approaches have never been tested and compared for water quality management.

5. Conclusions

Decision makers are often tasked with complicated problems that have multiple objectives and uncertainties. Decision analysis is an analytical framework with methods to overcome these challenges and allow decision making to be informative and effective. The Pareto efficiency, stochastic dominance, and value of information methods provided valuable insights into choices among OWTS options but also assume different planning contexts that should be communicated with decision makers.

It is important to note that environmental benefit can be incorporated into future iterations of these methods. However, limited information is currently available on quantitative non-market (e.g., Bellver-Domingo and Hernández-Sancho, 2018á) or qualitative non-monetary (Martin et al., 2018) valuation methods across Cape Cod. Likewise, less information is available to trace environmental outcomes to OWTS performance (Bowen and Valiela, 2004).

Our approach and results depend on decision maker preferences, planning context, the availability of data, and methodological assumptions. Results may vary with new information that changes the predictability of OWTS cost and effectiveness. Although sensitivity analysis on model inputs might be useful to forecast changes in results, the Monte Carlo sampling design incorporates variability in model inputs. Likewise, adaptive management could control for variability and uncertainty in model inputs as OWTS are implemented in real time. Nevertheless, the methods presented herein are necessary first steps to experimental design and provide a trial context for decision analysis that could extend beyond Cape Cod to water quality management contexts and other impaired waters worldwide. Although the approach and findings may add more steps and research to the decision-making process, decision analysis is a sensible and tractable framework for analyzing uncertainty and risk while considering multiple planning contexts and maintaining transparency.

It is often at the decision maker's discretion whether there is sufficient value in learning to reduce uncertainty. There are no hard rules about which results warrant adaptive management. However, there are several approaches and contexts for analyzing uncertainty and risk attitudes depending on planning context. More research and engagement are needed to decide how to manage advanced OWTS to mitigate water quality degradation and reduce uncertainty. This article provides context for these next steps and implementing adaptive management.

6. Disclaimer

The authors declare no conflicts of interest. The views expressed in this article are those of the senior author and do not necessarily represent the views or policies of the U.S. Environmental Protection Agency. Mention of trade names or commercial products does not constitute endorsement or recommendation for use. This contribution is identified by tracking number ORD-029255 of the Atlantic Ecology Division, Office of Research and Development, National Health and Environmental Effects Research Laboratory, U.S. Environmental Protection Agency.

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Appendix A. Supplementary data

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