Issue a Boil-Water Advisory or Wait for Definitive Information? A Decision Analysis
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Abstract
Objective: Study the decision to issue a boil-water advisory in response to a spike in sales of antidiarrheal medications or wait 72 hours for the results of testing

Methods: Decision analysis

Results: In the base case analysis, the optimal decision is testing and waiting. If the cost of issuing a boil-water advisory is less than 13 cents per person per day, the optimal decision is to issue the boil-water advisory immediately

Conclusions: This decision analysis illustrates a common decision problem in biosurveillance

Introduction
The problem of making high-stakes decisions under uncertainty has received considerable attention in clinical medicine in the areas of diagnosis or patient treatment decisions. There is a literature on psychology of decision making (1), methodology (2), and expert systems that provide decision support to clinicians (3).

Although there are also high-stakes decisions in the domain of public health and decisions that must be made under uncertainty, there has been little work on decision making in this field.

The need for explicit modeling and analysis of decisions faced by officials responsible for the public’s health is becoming more acute as new surveillance systems capable of providing an early but non-specific warning come on line throughout the world.

The types of decisions that arise routinely in the practice of public health include decisions about how to allocate resources, decisions about what actions to take in response to an epidemic, and decisions about what actions to take in response to surveillance data.

For most policy decisions, there is little or no time pressure. At the other end of the spectrum, however, there are high-stakes decisions that are made under extreme time pressure. For example, the decision whether to mobilize the national pharmaceutical stockpile in response to surveillance data that is consistent but not conclusive about the existence of an aerosol release of B. anthracis over a large city. In this situation, delays of just hours in making a decision can translate in hundreds of lives lost (4, 5)

Tversky and Kahneman (1) have demonstrated biases that human decision makers exhibit under these circumstances that are of concern in these situations.

Examples of decisions raised by anomalies in surveillance data include:

- Should we collect more data?
- Should we mobilize resources such as the national pharmaceutical stockpile?
- Should we issue a public advisory?
- Should we quarantine (and if so whom?)
- Should we vaccinate (and if so whom?)
- Should we prophylactically treat (and if so, whom?)

To investigate the issues of constructing decision models in this domain, we developed a model of the decision whether to issue a boil-water advisory or test and wait for results when contamination of the water system is suspected.

For concreteness, we assume that the suspicion is raised by appearance of a spike of sales of antidiarrheal medications confined to a region served by a water treatment plant (Fig. 1). We assume that the differential diagnosis of this spike is increased sales due to contamination with cryptosporidium, vs. some other phenomenon that does not require public health actions.

![Figure 1: Spike in sales of diarrhea remedies](image-url)
Methods

BASE ANALYSIS

Model Structure

When faced with evidence of contamination of the water system by cryptosporidium, public health authorities face a choice between alerting the public to boil water immediately or to collect more data by testing of sick individuals and water. For a base case analysis, we assume that testing of the water or sick individuals will produce a definitive answer in 3 days based on interviews with pathologists and water experts, so the decision faced by public health authorities is to issue an alert now or wait 3 days for definitive information.

Fig. 2 is the structure of the base decision model for this decision analysis. The base model consists of a decision node Act now with two possible actions: Yes/No that correspond to issue a boil-water advisory now, or wait 72 hours for confirmatory testing; and a chance node Crypto outbreak. Probability \( p \) represents the probability that there is an ongoing cryptosporidium outbreak. We represent the costs incurred for each combination of action and chance event by \( c_1, c_2, c_3, c_4 \).

Detection System

For this analysis, we created a surveillance system that monitors the area supplied by a single water treatment plant for a spike in OTC sales of antidiarrheal medications. We use the Chicago metropolitan area, whose drinking water is treated by two water treatment plants. We therefore assume that each treatment plant serves half of the city, and we are able to aggregate sales for the region served by a single plant.

The surveillance data for this system was constructed as follows: We used published data about sales of OTC medications during the North Battleford cryptosporidium outbreak, the published epidemic curve from that outbreak (6, 7), and a method for extracting outbreak effect from the North Battleford outbreak and injecting that effect into OTC data for Chicago. This method, called HiFIDE, accounts for the population difference between Chicago and North Battleford as well as differences in OTC data quality due to retailer market share (8). This process enables us to parameterize the known outbreak effect on OTC sales in North Battleford in a way that we can vary the size of the outbreak (to enable sensitivity analyses on the effect of outbreak size on the decision).

The detection system uses as a detector the CUSUM algorithm using an exponentially-weighted moving average and weight 0.05 (9). Cusum algorithms are used to detect outbreaks that arise gradually over several days or weeks (10, 11). The moving average component enables the algorithm to adapt to changes in the baseline data.

False Alarm Rate

We measured the false alarm rate of the detection system by running its detection algorithm on OTC sales in Chicago for the period May 1, 2004 through September 30, 2004. We assume that there was no crypto outbreak during that period.

Probabilities

We use Bayesian inversion to obtain the posterior probability that there is an outbreak of cryptosporidium given that the algorithm generated a signal: \( P(\text{crypto outbreak} | \text{signal}) = k \cdot P(\text{signal} | \text{crypto outbreak}) \cdot P(\text{crypto outbreak}) \). We obtain the conditional probability of the signal given that there is a cryptosporidium outbreak, \( P(\text{signal} | \text{crypto outbreak}) \), by running the detection algorithm on multiple outbreak data sets that were generated using the HiFIDE methodology. We set the relative size of the crypto outbreak to one that would affect 35.8% of the population. This is the percentage of the population of North Battleford that was affected by that cryptosporidium outbreak. We use a prior probability of a crypto outbreak, \( P(\text{crypto outbreak}) = 0.0001 \), or about 1 outbreak every 27 years.
**Date of the Alert**
The date during the outbreak that the detection algorithm alerted, we ran the detection algorithm on the time series set at an alarm threshold that produces 1 false alarm per year. This date would be the expected date that such a detection system would actually present an alarm to decision makers.

**Efficacy of a Boil-water advisory**
For the base case, we assume that a boil-water advisory is heeded by every person in the city; thus there are no further infections, other than those in individuals already incubating the disease. We realize this is an unrealistic efficacy and explore other efficacies in the sensitivity analyses.

**Incubation period of the disease**
After the issuance of a boil-water advisory, cases will continue to develop in individuals that were infected prior to the advisory. The average incubation period is often stated to be seven days, which is the incubation period we used in the base case...

**Costs**
In this simple decision model, there are four possible outcomes.

We set the cost for the outcome that no boil-water advisory was issued and the alarm was a false alarm (there was no cryptosporidium found on testing) to zero. For this case, the communities’ health is at baseline and no cost is incurred because no boil-water advisory was issued.

We assume that the cost of a boil-water advisory is the cost of additional bottled water consumed. For the base case, we made an assumption that biased the decision against issuing a boil-water advisory without confirmatory testing. By assuming the advisory motivates half the population of Chicago to consume 1 extra liter of bottled water at $1 per bottle per day for 3 days (in the case that the boil water advisory was a false alarm), and for five days in the case of a true alarm and that the problem in the water supply is resolved in five days and the boiled water advisory is lifted. The population of Chicago is 5.35 million, so the cost of a boil water advisory for half of the city is 2.675 million dollars per day.

We base the cost of sickness due to the outbreak on number of sick individuals in the population caused by the outbreak. In Figure 3, the area under the epidemic curve marked A is the number of sick individuals in the case that the boil-water advisory is issued immediately, and the area A+B is the number of sick individuals in the case that the boil-water advisory is issued 72 hours later.

![Figure 3: An epidemic curve for diarrheal outbreak as a function of days](image)

To convert number of sick individuals into dollars, we use the average cost developed by Corso et al per case for the Milwaukee 1993 cryptosporidium outbreak of $239 (12), adjusted from 1993 dollars to 2005 dollars.

**SENSITIVITY ANALYSIS**
We explored the effect of changing the cost of the boil water advisory over the range of $0 dollars per person per day to the base model level of $1 per person per day.

**Results**
For the base model, the posterior probability of an outbreak based on the statistical properties of the spike in sales on the day that the detection algorithm fired is 0.0352. The cost of issuing an immediate boil-water advisory is $12,538,678, while the cost of waiting for confirmation is $5,805,708. Hence, the optimal decision is to wait until laboratory confirmation of the outbreak before issuing a boil water advisory. This decision is likely to be the decision that a public health authority would take when faced with an early signal of this type.

Figure 4 shows the effect of varying the cost of the boil water advisory over the range of $0 dollars per person per day to the base model level of $1 per person per day.

The cost per person per day of boiling water at which the expected cost of issuing a boil-water advisory equals the expected cost of waiting three days for
laboratory confirmation is 13.04 cents. At this cost, the expected cost of each action is $5,396,000. If the true cost of a boil-water advisory is less than 13.04 cents per person per day, then the decision to issue a water advisory while waiting for definitive test results is the optimal decision.

Cryptosporidium is a mild disease that in many cases does not require a patient to seek medical attention. If a similar analysis were to be conducted on a disease with a high mortality rate, and a three day delay to confirmation, the set of circumstances in which waiting for confirmation by testing before acting to control the disease is the best policy might be far narrower.

This approach can be applied to any surveillance system, whether based on automatic analysis or manual analysis of data, provided that diagnostic accuracy of the system can be quantified, the set of actions appropriate to the disease in question can be articulated, and the economic and health effects of the actions and the disease can also be quantified.

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References