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TIME-DEPENDENT HEALTH RISK FROM CONTAMINATED GROUNDWATER INCLUDING USE OF RELIABILITY, RESILIENCE, AND VULNERABILITY AS MEASURES[1]

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ABSTRACT: Traditionally, assessment of human health risk caused by contamination of a water supply focuses on the maximum risk to an individual. Here, we introduce a time-dependent risk assessment method and adapt and explore the reliability, resilience, and vulnerability (RRV) criteria from the surface-water literature as possible tools for assessing this risk. Time-dependent risk assessment, including RRV, is applied to two synthetic examples where water quality at a well varies over time. We calculate time-dependent health risks for discrete periods of exposure to the contaminated water for a variable population. The RRV criteria provide information about time-dependent risk: probability of an acceptable risk, probability of system recovery, maximum risk, and average exceedance of a prescribed risk threshold. The results demonstrate that episodic contamination events produce fundamentally different time-dependent risks than long-term events: these differences, such as generally lower risks for the episodic contamination, can be captured via plots of the risk and the RRV criteria. Furthermore, the evaluation of time-dependent health risk and the RRV criteria demonstrates significant sensitivity to the shape of the contaminant breakthrough curve, length of exposure, and variability within the population. Overall, analysis of time-dependent health risks provides substantial insight into the structure of risk, with RRV providing a reasonable framework for the evaluation of these risks.

(KEY TERMS: groundwater hydrology; risk assessment; drinking water; public health; cancer risk; groundwater contamination.)

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INTRODUCTION

It is broadly recognized that groundwater resources are increasingly threatened, from the viewpoint of water quality, by contamination events at the ground surface related to increased urbanization (Jeong, 2001), increased agricultural production (Thomas *et al.*, 2009), and changing land use patterns (McMahon *et al.*, 2008). As a result, substantial attention has been focused on methods to both protect groundwater resources and assess or estimate the likely impact on receiving populations of contaminants in a water supply well (Harman *et al.*, 2001; de Barros *et al.*, 2011; Fadlelmawla *et al.*, 2011).

The protection of groundwater quality at a well relies, in part, on our ability to predict the movement and transformation of contaminants within the subsurface. Historically, protection methods have focused to a large degree on the concept of wellhead

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protection and wellhead capture zones. As early as 1986, the U.S. Safe Drinking Water Act was amended to require the development of wellhead protection programs for public water supplies in the United States (USEPA, 1987). Based on the recognition of the importance of preventing contaminants from entering a public water supply well, a number of authors explored both deterministic and stochastic definitions of wellhead capture zones (e.g., Cole and Silliman, 2000; Stauffer *et al.*, 2005; Paradis *et al.*, 2007). The concept of stochastic wellhead capture zones (Cole and Silliman, 2000; Stauffer *et al.*, 2005) has recently been extended to include management decision criteria focused on subsurface transport of multiple contaminants (e.g., Frind *et al.*, 2006; Enzenhoefer *et al.*, 2012). Other authors have combined mapping of land use and aquifer characteristics to provide guidance for land use zoning (Fadlelmawla *et al.*, 2011). Probabilistic and fault tree methods have also been applied to the analysis of likelihood of a contaminant reaching an extraction well (e.g., Tartakovsky, 2007; Bolster *et al.*, 2009; de Barros *et al.*, 2011; Rodak and Silliman, 2012). A major outcome of this body of work is the recognition of the need to incorporate the impact of variability and uncertainty in both the hydrologic parameters impacting the groundwater flow within an aquifer and the location, contamination history, and constituents of the contaminant event of interest.

Recognizing that analysis of contaminant history at a well opens opportunities to assess actual health risk to a population, other authors have focused efforts on the estimation of health risk resulting from exposure to contaminated groundwater (e.g., McKone and Bogen, 1991; Maxwell *et al.*, 1998; Lester *et al.*, 2007; Bolster *et al.*, 2009; Yang *et al.*, 2010; de Barros *et al.*, 2011). Specifically, both variability in critical population characteristics (e.g., variation within the population of body weight, exposure routes, etc.) and variability/uncertainty in the groundwater flow/transport have been incorporated into models involving probabilistic risk assessment (PRA) frameworks (Maxwell and Kastenberg, 1999; Maxwell *et al.* 1999, Yang *et al.*, 2010; de Barros *et al.*, 2011). This inclusion of uncertainty and variability into the calculation of health risk is in line with recent suggestions from the U.S. Environmental Protection Agency (USEPA) regarding the necessity of PRA for groundwater contamination (USEPA, 2001; Lester *et al.*, 2007).

Although health risk analysis has classically been based on estimation of maximum health risk (USEPA, 1989) during a time period of interest (e.g., the life of a well field), Siirila and Maxwell (2012) argue for a time-dependent risk assessment approach as applied to analysis of a groundwater system. The purpose of evaluating time-dependent health risk is to provide information regarding when risk will occur and how long it will persist; information lost using the traditional time-independent method focused solely on maximum risk (Siirila and Maxwell, 2012). These authors propose a method that involves sequential calculation of risk over discrete time intervals. For example, assuming an exposure duration of 30 years, the time-dependent risk would be calculated with exposure starting at times $t = 0$ years, $t = 30$ years, $t = 60$ years, and so on. By employing the time-dependent method, Siirila and Maxwell demonstrate a number of complexities not reflected in the maximum risk method such as variability in risk over time and the importance of contaminant history in estimating risk for highly sensitive members of the exposed population.

As an extension of the work of Siirila and Maxwell (2012), we are interested in the analysis of continuous time variation in health risk related to water quality at a wellhead. Specifically, we consider the application of the system criteria — reliability, resilience, and vulnerability (RRV) (derived from Hashimoto *et al.*, 1982; Maier *et al.*, 2001; Kjeldsen and Rosbjerg, 2004; Mondal *et al.*, 2010) — as a means to characterize the behavior of time-dependent risk from a contamination event. We define these criteria following the literature, resulting in estimation of:

1. the probability that a water supply based on groundwater results in an unacceptable level of health risk at any particular time due to contamination at the well,
2. the probability that a water supply will return to an acceptable level of risk following a period of unacceptable risk due to contamination,
3. the maximum risk to the population related to contamination at the well over the life of the well (equivalent to the current method of maximum risk), and
4. the average exceedance of a critical health risk limit as measured over the life of the well.

The potential utility of these criteria in groundwater assessment is discussed in the general case, but with specific consideration given to evaluating two time-dependent health risk scenarios over a range of exposure durations (ED) (1, 5, 10, and 30 years).

TRADITIONAL AND TIME-DEPENDENT HEALTH RISK

It is widely recognized that the chemical quality produced at a wellhead will vary over time (USEPA,

1987). Variation may be in response to natural changes in groundwater fluxes and geochemistry. It may also represent response to the introduction of chemical species (e.g., application of agricultural chemicals or a chemical spill) at the ground surface. The concentration of a specific chemical observed in the produced water may vary in a number of manners ranging from a long-term increase (or decrease) in concentration, to relatively short-term transients in the concentration. As examples, the four concentration histories shown in Figure 1 (U.S. Geological Survey, National Water Information System. Accessed December 13 2012, http://waterdata.usgs.gov/nwis) demonstrate significantly different behaviors relative to chemistry observed at wells. Figure 1a shows multiple spike transients in chloride concentration at a well in Hawaii. Figure 1b shows a long-term trend (decline) in concentration of chromium at a well in Idaho. Figures 1c-1d show a short-term spike and a long-term increase in chloride in wells in Georgia, respectively. We are interested in determining how such diversity in variation in chemical concentration may be reflected in analysis of health risk to a receiving population. For context, we provide a brief review of previous work on quantification of health risk.

In terms of established methods, the USEPA has suggested a mathematical relationship for estimating health risks from both acute and chronic exposure to carcinogenic and noncarcinogenic compounds (USEPA, 1989). While the discussion below could be generalized to include both acute and chronic exposure (and noncarcinogenic risk), the present discussion is limited to chronic health risk for cancer. The chronic cancer risk, $R_T(t)$, for an individual from chronic exposure to a carcinogenic compound with exposure starting at time t is defined by the USEPA (USEPA, 1989) as:

$$R_T(t) = \beta C_T(t) \tag{1}$$

where $C_T(t)$ represents the average contaminant concentration over an exposure duration (T) starting at time t, and β is a lumped parameter that quantifies behavioral and physiological response of the contaminant human system. The calculation of $C_T(t)$ for a particular start of exposure, t, is described mathematically as:

$$C_T(t) = \frac{1}{T}\int_t^{t+T} C(t')dt' \quad 0 \le t \le T^* \tag{2}$$

where $c(t)$ is the breakthrough curve of the contaminant observed at the well, and T^* is the total length of the analysis period (Figure 2). As such $C_T(t)$ varies as a function of $c(t)$, t, and T.

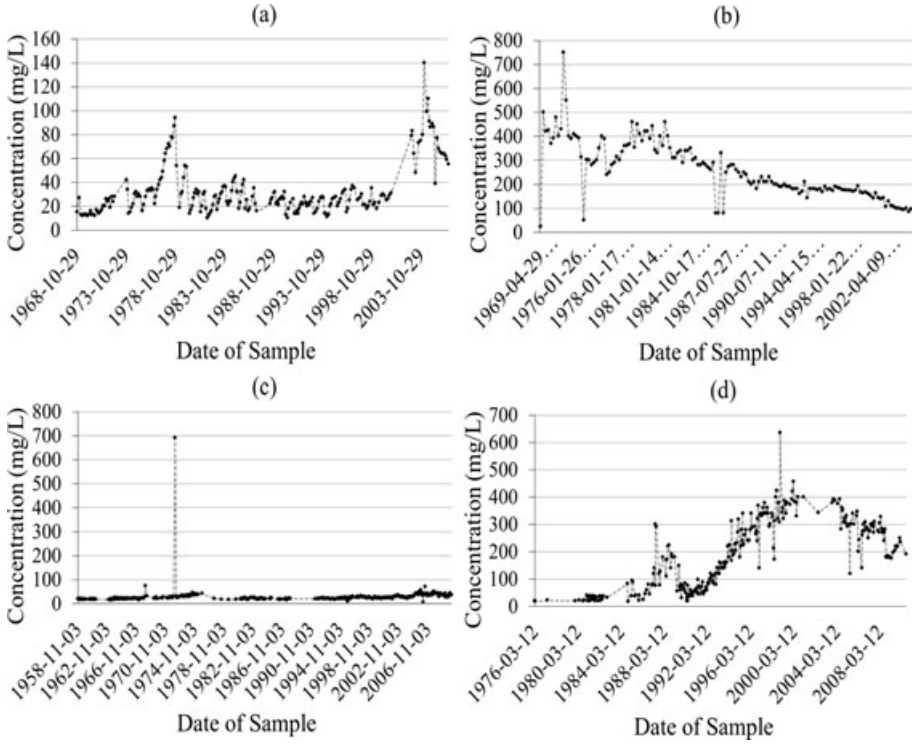

FIGURE 1. Four Example Datasets from U.S. Geological Survey (USGS), National Water Information System. Accessed December 13, 2012, http://waterdata.usgs.gov/nwis. (a) USGS 210605157012001 Kaunakakai, Molokai, Hawaii Chloride, (b) USGS 433447112574501 Butte County, Idaho Chromium, (c) USGS 311007081311401 Glynn County, Georgia Chloride, and (d) USGS 311017081285701 Glynn County, Georgia Chloride.

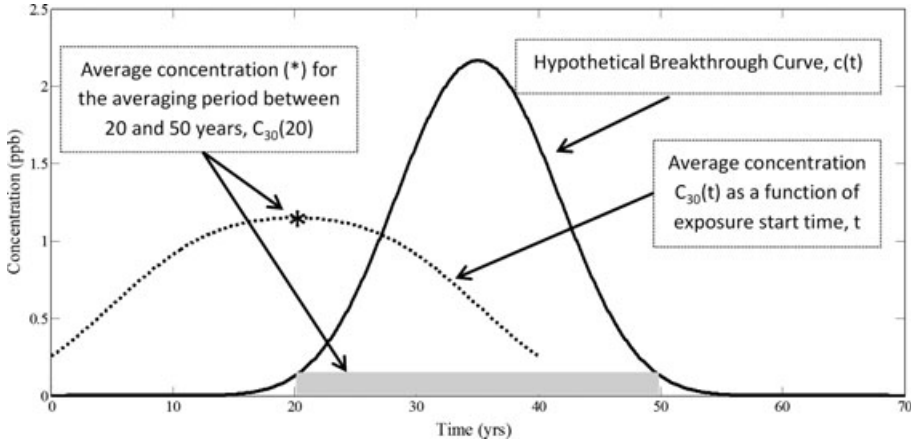

FIGURE 2. Example of Variation of $C_T(t)$ (dotted line) Using a Hypothetical $c(t)$ (solid line), an Exposure Period (T) of 30 Years, and a Total Length of Analysis (T^*) of 70 Years. The value for $C_{30}(20)$ is shown in relation to the associated averaging period for $c(t)$.

The time-dependent risk in Equation (1) can be used to calculate human health risk from different contaminated media (water, air, soil, etc.) and three primary exposure pathways: ingestion (G), inhalation (H), and dermal absorption (D) (USEPA, 1989). It is often assumed that the resulting risk from various exposure pathways is additive and is included in the calculation of β (USEPA, 1989; Maxwell *et al.*, 1998; de Barros *et al.*, 2011). Assuming health risk occurs from a contaminant originating from the water phase with exposure through the three pathways, β can be defined as:

$$\beta = \sum \mathrm{CPF}_n \left[\frac{\mathrm{IU}_n}{\mathrm{BW}_n}\right] \frac{\mathrm{ED} \times \mathrm{EF}}{\mathrm{AT}} \text{where } n = \mathrm{G, H, D} \quad (3)$$

such that β can be described as the summation of the product of the chemical and exposure route-specific cancer potency factor {CPF_n (kg-day/mg)} and the route-specific exposure parameters {IU/BW*(ED*EF/AT)} summed over the pathways. In this expression, IU/BW is the water intake rate per unit body weight (l/kg-day), ED is the exposure duration (years), EF is the daily exposure frequency (day/yr), and AT is an averaging time (days) commonly equivalent to an expected human lifetime (here we follow the example of, e.g., USEPA, 1987; McKone and Daniels, 1991; Maxwell *et al.*, 1998; and assume 70 years). The evaluation of the various parameters is discussed in the previous literature (e.g., McKone and Daniels, 1991; Maxwell *et al.*, 1998).

Within standard risk assessment as prescribed, for example, by the USEPA, the primary measure of risk of interest is based on Equation (1) using the maximum value of $C_T(t)$ over the time period of interest; for example, a 70-year lifetime of a well would be the maximum $R_T(t)$ from $0 \leq t \leq (70 - T)$ (USEPA, 1989). That is, the exposure period with the highest mean concentration of the contaminant results in the maximum estimated health risk. In the classic approach, deterministic values are assumed for $c(t)$ and β. A number of authors have advanced and modified these expressions to include human variability as well as uncertainty in $c(t)$ in what is commonly referred to as the joint uncertainty and variability process (Maxwell *et al.*, 1998; Lester *et al.*, 2007; de Barros *et al.*, 2009; Yang *et al.*, 2010; Siirila and Maxwell, 2012). Furthermore, as noted above, the work of Siirila and Maxwell (2012) suggests extension of this analysis to consideration of temporal variation in risk (including uncertainty in $c(t)$ and variability in β).

Our work, as described below, is an extension of the work of Siirila and Maxwell (2012). Specifically, we introduce a method for time-dependent chronic risk assessment in which the start of the exposure duration is continuous in time (as opposed to discrete sequential exposure durations as used in Siirila and Maxwell, 2012). We consider a simulated, deterministic $c(t)$ combined with population variability (through sampling from a random distribution of β) and consider multiple exposure durations. We justify, for this study, the use of a deterministic $c(t)$, and therefore $C_T(t)$, to focus discussion on the utility of the RRV criteria to identify risk in different portions of the population. Extension of this study to inclusion of uncertainty in $c(t)$ would not be technically difficult, but would obscure some of the results illustrated in the following sections.

RELIABILITY, RESILIENCE, AND VULNERABILITY

In characterizing time-dependent health risk, we consider the use of multiple time-sensitive criteria

previously defined in the water reservoir literature by Hashimoto *et al.* (1982): reliability, resilience, and two definitions of vulnerability (RRV). Reliability, as defined by Hashimoto *et al.* (1982), is expressed as the probability of a system being in compliance against a threshold. Resilience is the probability that a system in a state of failure will return to a non-failure state within a given time period. Vulnerability provides multiple measures of the severity of failure. The majority of the applications of the RRV criteria have focused on quantity-based failures of surface water reservoirs systems (e.g., too little or too much storage within a surface water reservoir as discussed by authors such as Hashimoto *et al.*, 1982; Kjeldsen and Rosbjerg, 2001, 2004; Fowler *et al.*, 2003; Ajami *et al.*, 2008). For example, if the management goal for a reservoir is meeting a given water demand, reliability may be expressed as the probability that the reservoir will provide the required demand for water at any particular time, resilience may be expressed as the probability that the reservoir will satisfy the required demand for water in the following cycle given that it is currently in deficit, and vulnerability may be expressed as the likely magnitude of the deficit of water given that a deficit occurs. A common analysis may include investigation of how RRV of the reservoir changes with temporal variations in precipitation patterns, changes in water demand, and, on a longer term basis, possible impacts of climate change. Some studies extended RRV to include analysis of parameter uncertainty; for example, Ajami *et al.* (2008) propagated uncertainty through several hydrologic parameters (e.g., rainfall) through prediction of the ability of a reservoir to provide an adequate quantity of water under various management scenarios. Specific to health-based management of water resources, RRV has also been used in the literature on surface water to assess quality-based failures of water systems, such as the evaluation of temporal violations of concentration standards at discharge points in a river (Maier *et al.*, 2001; Sarang *et al.*, 2008).

Application of the RRV criteria in groundwater is less common but it has been demonstrated in quantity-based failures in groundwater systems (Peters *et al.*, 2005; Mondal and Wasimi, 2007; Mondal *et al.*, 2010). For example, the impact of human- and climate-induced changes on a joint surface water/groundwater system was the focus of an application of RRV criteria in Bangladesh for the evaluation of water quantity failures (Mondal and Wasimi, 2007; Mondal *et al.*, 2010). These authors investigated the long-term behavior of the Ganges Delta (Mondal and Wasimi, 2007) and the Brahjaputra Floodplain (Mondal *et al.*, 2010), both in Bangladesh, using the RRV criteria combined with the generation of synthetic river flows and climate change scenarios to look at likely ability of these surface water/groundwater systems to meet demand through the year 2050.

In the application discussed in the present manuscript, the RRV criteria are applied to the analysis of contamination at a groundwater well, with system failure defined in terms of health risk to individuals within the receiving population. This health risk is measured for a given exposure duration commencing at a specified time, and in the presence of a known concentration history at the well, $c(t)$. As such, our analysis includes consideration of temporal variation in concentration of the contaminant at the well, variability in the receiving population, and length of population exposure (termed exposure duration or ED). As noted above, and motivated by a desire for clarity in this initial application of RRV to health risk, uncertainty in $c(t)$ is not considered in the present application. Furthermore, for clarity of presentation of results, it is assumed that the ED is uniform over all members of the population (although multiple EDs are considered): extension to variable ED would not be difficult but would, once again, obscure some of the results presented below.

Here, we define failure based on the estimated level of health risk ($R_T(t)$) for individuals within the receiving population. At a given time, t, the system is in a state of success if $R_T(t)$ for an individual is less than 10^{-6}, or in a state of failure if $R_T(t)$ is greater than or equal to 10^{-6}. We will refer to states of success as acceptable health risks and states of failure as unacceptable health risks. RRV then focus on different aspects of health risk to an individual within the population; (1) the probability that an individual has an acceptable health risk regardless of the start time, t, of their T-year exposure (reliability), (2) the probability that $R_T(t + \Delta t)$ is acceptable given that $R_T(t)$ is unacceptable — that is, that delaying the start of the exposure period by Δt results in the T-year exposure changing from an unacceptable health risk to an acceptable health risk (resilience), (3) the maximum health risk to an individual that occurs over the time period of analysis, T^* (equivalent to the current time-independent risk assessment method and herein referred to as the first measure of vulnerability), and (4) the average exceedance of the risk threshold calculated as the average difference between the risk in the current failed state and the threshold risk over the lifetime of the well (herein termed the second measure of vulnerability). Reliability (α) is represented mathematically as:

$$\alpha = \text{Prob}[R_T(t) < 10^{-6}] = 1 - \text{Prob}[R_T(t) \geq 10^{-6} \quad (4)$$

Mathematically, resilience (γ) is defined as:

$$\gamma = \text{Prob}[R_T(t + \Delta t) < 10^{-6} | R_T(t) \geq 10^{-6}] \quad (5)$$

For infinitely long sequences, the expression for resilience is equal to the inverse of the average number of consecutive $R_T(t)$ values above the threshold. Resilience, as defined here, cannot be estimated for a system with no failures or a system in constant failure due to a lack of complete information outside the 70-year window. Within the manuscript, the resilience of systems in constant failure will be represented with the maximum possible resilience given the current information. Assuming the risk is acceptable outside the 70-year time frame of interest but unacceptable during the time frame of interest, the maximum is then calculated as $\{1/[(T^* - T)/\Delta t]\}$. It is important to note that resilience, as defined here, is a measure of recovery of $C_T(t + \Delta t)$ relative to $C_T(t)$ at the wellhead for a given exposure duration, not an individual's ability to recover from risk after having been exposed to the contaminant.

The first definition of vulnerability ($v1$) is the maximum (within a T^*-year period of analysis) of health risk to an individual with a T-year exposure duration:

$$v1 = \max(R_T(t)) \quad (6)$$

This definition of vulnerability is equivalent to the classical maximum health risk over the period of analysis. The second definition of vulnerability ($v2$) we chose to explore is the average exceedance of the risk threshold and is mathematically defined as:

$$v2 = \frac{\Delta t}{T^*} \sum E_T(t)$$
$$\text{where } E_T(t) = \begin{cases} R_T(t) - 10^{-6}, R_T(t) \geq 10^{-6} \\ 0, \qquad R_T(t) < 10^{-6} \end{cases} \quad (7)$$

The purpose of the second measure of vulnerability is to provide an average estimate of the severity of the risk while also considering how frequent failure occurs (i.e., severe short-term risks *vs.* severe long-term risks). Alternatives to these definitions might also be considered and would provide somewhat different information about the probabilistic distribution of risk than presented below.

METHODOLOGY

The scenario underlying the following discussion is management of a public water supply well serving a community of 50,000 people. It is assumed that the population served has random behavioral characteristics, β, from one resident to the next. Furthermore, it is assumed for simplicity that ED is constant over the entire population but that start of exposure for an individual can occur anytime between $0 < t < T^* - T$. It is assumed here, without loss of generality, that T^*=70 years (the life of the wellhead serving the water supply is 70 years). It is noted that ED could be made random with minimal additional effort. However, as discussed above, treating ED and $c(t)$ as deterministic allows for a clearer presentation of the utility of the RRV criteria. Specifically, we have chosen to assess risk subject to two deterministic breakthrough curves with fixed exposure duration to focus on the impact of characteristics of the breakthrough curve, population variability, and mean exposure time.

With respect to the calculation of variability within the population, a distribution of β is introduced as the vector $\beta = [\beta_1, \beta_2, \ldots, \beta_{50,000}]$ representing the β parameter for each of the 50,000 individuals within the population. For this study, distributions for the general population originally proposed by McKone and Bogen (1991) are used to incorporate population variability into IU/BW in Equation (3). Each of these parameters can be considered random with a specific statistical distribution (see McKone and Bogen, 1991; Maxwell *et al.*, 1998) (Table 1). By sampling one value for each of the parameters from their respective distributions, we can construct one possible member of the model population and the respective β_i. Repeating this sampling 50,000 times, a random population containing 50,000 hypothetical individuals is generated and, thereby, a distribution of 50,000 β values for the simulated population. We then sort the β values from smallest to largest and identify fractiles within the sorted distribution.

We generate two synthetic curves (Figure 3) meant to represent two possible concentration profiles one might observe in a real system as supported by Figure 1; (1) monthly fluctuations on top of a *long-term* (~40 years) peaked baseline (we refer to this as a persistent scenario) and (2) monthly fluctuations on top of multiple *short-term* (~10 years) fluctuations with a baseline of zero (we refer to this as an episodic scenario). For both curves, we assume that the well is operational for 70 years and an equal total mass of contaminant enters the well for each of the two synthetic curves: the contaminant is assumed to be perchloroethene (PCE). The analysis is conducted for a total mass condition where the 70-year average concentration is equal to 0.5 ppb. This average concentration was chosen for two reasons: (1) approximately 50% of the population will be in a failed state assuming an exposure duration of 30 years and (2) 0.5 ppb is listed by the USEPA as the minimum detection

TABLE 1. Parameters for Risk Calculations.

Parameter	Symbol	Units	Distribution	Value
Averaging time	AT	Days	Constant	70 years (25,550 days)
Exposure duration	ED	Years	Constant	30
Exposure frequency	EF	Day/yr	Constant	350
Ingestion rate per body weight	IR/BW	l/kg-day	Lognormal	$(3.3 \times 10^{-2}, 1.3 \times 10^{-2})$
Water use rate	W_t	l/h		
Shower	W_s	l/h	Lognormal	(480, 160)
Bathroom	W_b	l/h	Lognormal	(40,15)
House	W_h	l/h	Lognormal	(40,15)
Transfer efficiency from water to air	TE_t	None		
Shower	TE_s	None	Triangular	(0.1, 0.5, 0.9)
Bathroom	TE_b	None	Triangular	(0.1, 0.43, 0.8)
House	TE_h	None	Triangular	(0.1, 0.43, 0.9)
Air exchange rate	VR_t	m^3/h		
Shower	VR_s	m^3/h	Uniform	(4-20)
Bathroom	VR_b	m^3/h	Uniform	(10-100)
House	VR_h	m^3/h	Uniform	(300-1,200)
Exposure time	ET_t	h/day		
Shower	ET_s	h/day	Lognormal	(0.13, 0.09)
Bathroom	ET_b	h/day	Lognormal	(0.32, 0.21)
House	ET_h	h/day	Uniform	(8-20)
Inhalation rate per unit body weight	HR/BW	m^3/kg-day	Lognormal	(0.39, 0.5)

Note: Lognormal and normal distributions (arithmetic mean, standard deviation), for uniform distributions (minimum-maximum) and for triangular distributions (minimum, likeliest, maximum) (Maxwell *et al.*, 1998).

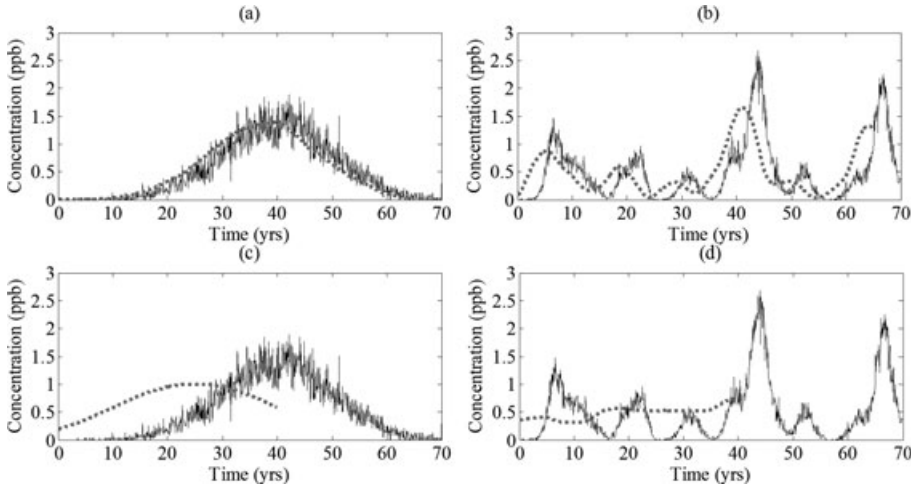

FIGURE 3. Two Synthetic Breakthrough Curves (black) and the T-Averaged Concentration Curves, $C_T(t)$ (gray dashed line) Plotted as a Function of the Time of Beginning of Each Exposure Duration. (a) Persistent scenario with T = 5 years, (b) episodic scenario with T = 5 years, (c) persistent scenario with T = 30 years, and (d) episodic scenario with T = 30 years.

limit (MDL) for PCE (i.e., analytical equipment used for monitoring must have detection limits equal to or lower than the MDL) (USEPA, 2007). We also choose to investigate four discrete exposure durations of 1, 5, 10, and 30 years (examples of the impact of exposure duration on the calculated $C_T(t)$ are illustrated by the gray dashed lines in Figure 3). Finally, we assume that no action is taken to prevent the PCE from reaching the population via the water supply well and, without loss of generality, that the concentration at the well is equal to the concentration at the point of exposure.

Returning to Equation (1) for the calculation of risk, the distribution of risk across the population can be estimated as a function of β and $c(t)$, where $c(t)$ and $C_T(t)$ are evaluated at monthly intervals (Δt = 1/12 year) for a given exposure duration (T) and a 70-year lifetime of the well (T^* = 70 years).

The RRV are then estimated for each β_i generated for the population, resulting in a distribution of RRV:

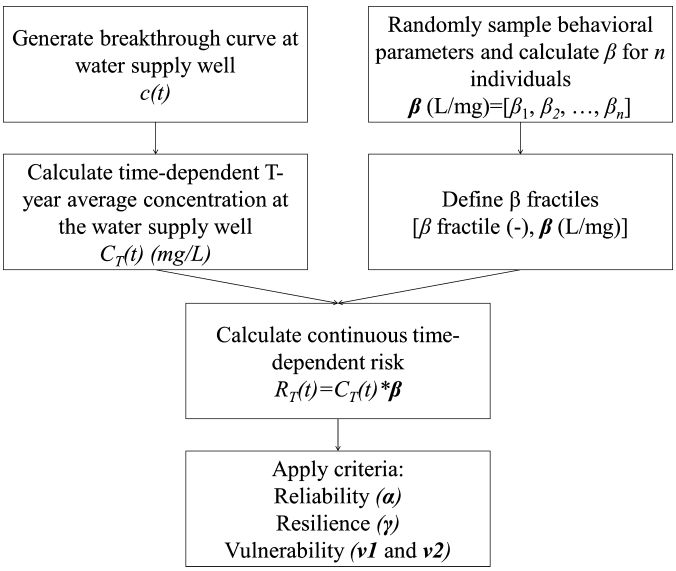

FIGURE 4. Flow chart of the Reliability, Resilience, and Vulnerability Process for the Evaluation of Time-Dependent Health Risks.

$$\alpha = [\alpha_1, \alpha_2, \ldots \alpha_{50,000}] \tag{8}$$

$$\gamma = [\gamma_1, \gamma_2, \ldots \gamma_{50,000}] \tag{9}$$

$$v1 = [v_1^1, v_2^1, \ldots v_{50,000}^1] \tag{10}$$

$$v2 = [v_1^2, v_2^2, \ldots v_{50,000}^2] \tag{11}$$

A flowchart of the methodology used within the current study is shown in Figure 4.

RESULTS

Health Risk and Population Variability

Figures 5a and 5b show the evolution of time-dependent risk for the persistent and episodic scenarios (Figure 3), respectively, using a 30-year exposure duration. Three β fractiles are represented in these curves: 25th, 50th, and 75th. In Figure 5a, the 50th fractile risk result for both breakthrough curves is shown along with the time-dependent risks for 25th and 75th fractiles using the persistent scenario. Similarly, Figure 5b shows the 50th fractiles for both breakthrough curves, along with the 25th and 75th risk percentiles for the episodic scenario. Through comparison with Figure 3, the linear relationship between $C_T(t)$ and $R_T(t)$ becomes apparent (see Equation 1); varying the β fractile has the impact of vertically shifting the risk curve. Examination of these curves (Figures 5a and 5b) results in a number of observations regarding temporal variation in risk and the relationship between the variability in concentration arriving at the well and health risk. As noted previously, the total mass arriving at the well (and therefore the 70-year average concentration at the well) is the same for both breakthrough curves (Figure 3). This allows direct comparison of multiple aspects of health risk for a persistent contamination event (i.e., concentration impacting the well over an extended period as in curve 1) *vs.* multiple, brief, higher concentration events (as in curve 2).

First, notice the importance of the breakthrough curve shape as shown in Figure 5a; the maximum risk for a 30-year exposure duration is higher even for the 25th fractile in the persistent scenario than for the 50th β fractile for the episodic scenario indicating

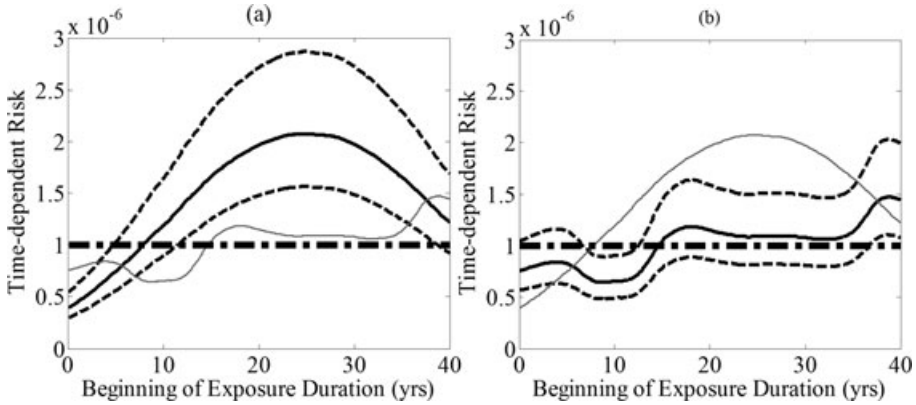

FIGURE 5. Plot of the Time-Dependent Health Risk *vs.* the Beginning of the Exposure Duration. (a) Time-dependent risk of the persistent scenario for 50th fractile (solid line) and the 25th and 75th fractile (dashed line). For reference, the 50th fractile time-dependent risk for the episodic scenario (gray solid line) and 10^{-6} risk threshold (dash dot line) are included. (b) Time-dependent risk of the episodic scenario for 50th fractile (solid line) and the 25th and 75th fractile (dashed line). For reference, the 50th fractile time-dependent risk for the persistent scenario (gray line) and the 10^{-6} risk threshold (dash dot line) are included.

a significant difference in risk based on the breakthrough curve shape despite the same total mass over 70 years. The underlying cause is that, despite the higher concentrations in the episodic scenario, the health risk is estimated based on the concentration averaged over the exposure duration. In this case, the 30-year average concentration in the episodic scenario varies only minimally with time as the averaging tends to include multiple concentration peaks with low concentration between peaks. The 30-year average concentration for the persistent scenario reaches a significantly higher peak value at approximately 25 years. As might be anticipated (and as will be shown below), the relative magnitude of the maximum average concentration (and therefore maximum health risk) reverses at shorter duration exposures.

Second, these results indicate the dependence of timing of health risk on the temporal structure of the contaminant arrival at the well (most similarly, de Barros and Rubin, 2008 show that there is value in reducing uncertainty in the temporal structure of a contaminant breakthrough curve for contamination events with temporal duration greater than the exposure duration). While seemingly an obvious statement, it is noted that first breakthrough of the contaminant as well as the first risk above the threshold occurs at an earlier time for the episodic scenario than for the persistent scenario, yet the 30-year maximum health risk for the episodic scenario occurs substantially later than for the persistent scenario. Specifically, the maximum health risk occurs when exposure begins at approximately year 25 for the persistent scenario, but at approximately 38 years for the episodic scenario. While the relative timing and peak concentrations of these two maxima are functions of the shape of the specific simulated curves utilized, these results support the argument that time may be an important factor commonly overlooked in risk assessment. The timing of the maximum concentration, and therefore maximum long-term health risk, will be dependent both on the type of contamination scenario (persistent *vs.* episodic events) and the timing of the arrival of maximum mass of the chemical (*vs.* the peak concentration) during an exposure period.

Third, the results in Figure 5 provide justification for investigation of time-dependent measures of health risk and variable βs to represent the population. For example, Figure 5a provides a situation in which there is a smooth transition, for the 50th β fractile, from low risk at early times to maximum risk, and then a decline toward low risk at late time. Other β fractiles within the population represent simple linear shifts in the risk profile *vs.* time: all sufficiently high β fractiles will provide a single, continuous period of chronic health risk above the threshold. Hence, all health risk above the threshold is associated with the same contamination event.

In contrast, the episodic scenario (Figure 5b) results in different behavior for different βs. Viewing Figure 5b, it is observed that the 75th fractile experiences two distinct periods (relative to start time to exposure) of risk consistently above the threshold — prior to approximately year 8 and after approximately year 13 with a total of three peaks in risk. In contrast, the 50th fractile experiences only one continuous period above the risk threshold (starting at approximately year 14) and two peaks in risk. Finally, risk for the 25th percentile exceeded the threshold once with an almost immediate maximum risk. While this comparison is dependent on the synthetic breakthrough curve analyzed, this result demonstrates that consideration of both time-dependent variation in health risk and population variability provides substantially different insight into a potential contamination event with respect to threshold violation than does the sole consideration of maximum risk for the average individual.

This additional insight suggests that greater understanding of health risk may be obtained through viewing the RRV criteria as functions of β. Figure 6, for example, shows the variability with β (for a 30-year exposure duration) of reliability, resilience, and our two measures of vulnerability for both synthetic breakthrough curves. While irregularity in the resilience profile is observed and is discussed below, both reliability and resilience generally decline as the β fractile increases — that is, the water system is not as reliable in terms of health risk and tends not to recover as readily (in terms of health risk) for the part of the population that is more sensitive to the contamination (higher β fractile). Similarly, the maximum risk and the average exceedance (risk above the threshold) increase at higher β fractiles indicating a greater risk of cancer for this portion of the population.

Less obvious, these curves also provide insight into the dependence of risk on the details of the mass arrival at the well. Figure 6 demonstrates significant differences in the distribution of time-dependent risks across the population despite the same total mass arriving at the well over the 70-year window. Specifically, for the majority of the β fractiles, the reliability and resilience are higher, and both definitions of vulnerability are lower, for the episodic scenario. These observations suggest that, despite equal total mass, episodic and persistent contamination events have significantly different impacts on chronic health risk impacting threshold-based management of contaminated water systems.

Considering these images in greater detail, the rate of decline in the reliability, resilience, and $v2$

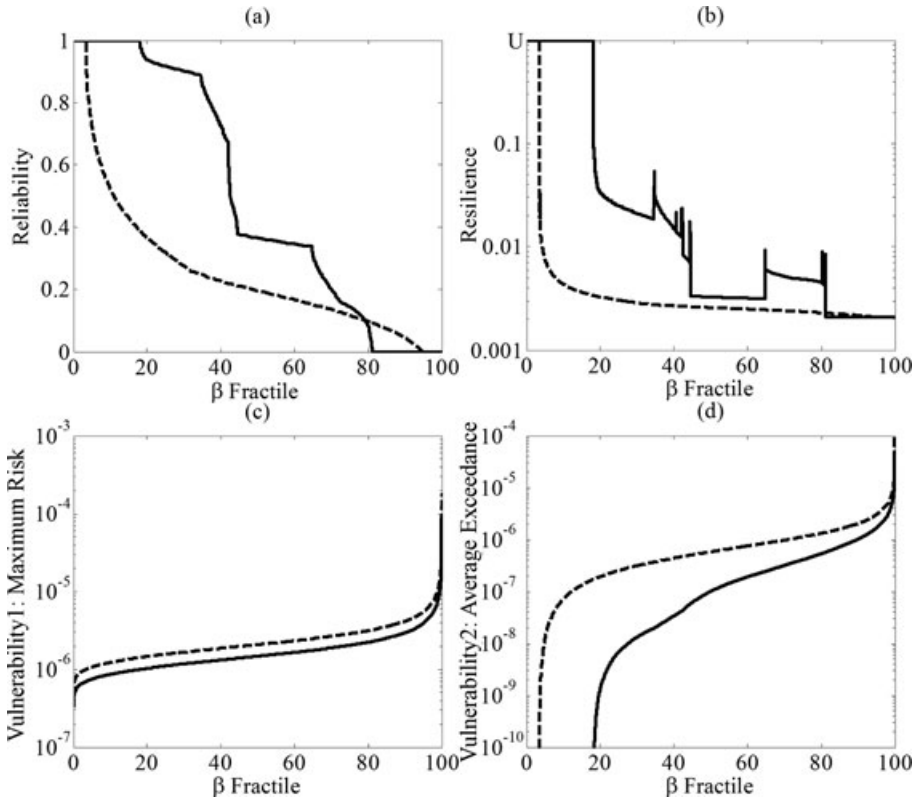

FIGURE 6. Plot of Reliability, Resilience, and Vulnerability *vs.* Fractile for Both Breakthrough Curves Assuming an Exposure Duration of 30 Years; Persistent Scenario (dashed line) Episodic Scenario (solid line). (a) Reliability, (b) resilience, (c) vulnerability1 (maximum risk), and (d) vulnerability2 (average exceedance).

vulnerability shows significant differences in the multiple-event *vs.* persistent scenarios. Specifically, these three measures demonstrate step-like transitions, nonmonotonic behavior for resilience, and inflections as functions of β fractile for the episodic scenario but smooth variation for the persistent scenario. To investigate the behavior of multievent scenario further, the reliability, resilience, and average exceedance ($v2$) for the episodic scenario have been plotted on a single graph in Figure 7.

We have confirmed that the changes in the slope for these three measures occur at identical β fractiles for all three measures (as indicated in Figure 7). This behavior indicates an important threshold-based sensitivity of the time-dependent risk to variation in β. Consider, for example, the risk curves shown in Figure 5b. At the 25th fractile, the health risk for exposure start times between approximately 23 and 33 years is nearly constant and below the risk threshold. As β increases, but before β reaches the 50th fractile, this portion of the risk curve transitions from being below the risk threshold to being entirely above the risk threshold resulting in a rapid drop in reliability and resilience (Figure 7). For systems involving variation in β and risk curves similar to the episodic scenario, these results suggest that

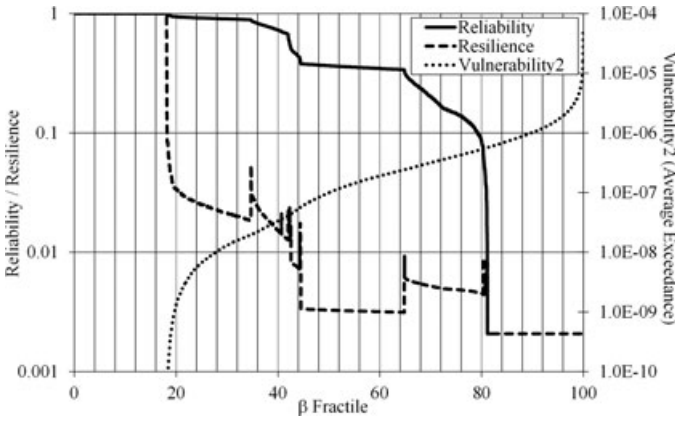

FIGURE 7. Plot of Reliability, Resilience, and Vulnerability2 (average exceedance) as a Function of β Fractile for the Episodic Scenario. Left y-axis corresponds to reliability and resilience values and the right y-axis corresponds to vulnerability2 values.

assessment of risk may be complex with minor differences in the behavior between individuals having significant impact on risk as identified in reliability, resilience, and $v2$ vulnerability. Thus, an intricate relationship exists between the population behavior, frequency, and period of fluctuations in the breakthrough curve at the well, time-dependent health

risk, and the risk threshold that would not be identified using the traditional technique focused on the maximum risk.

Time-Dependent Risk and the Impact of Exposure Duration

Figures 8a and 8b show the evolution of time-dependent risk for the persistent and episodic scenarios, respectively, using the four different exposure durations of 1, 5, 10, and 30 years. The 50th fractile is used to represent each exposure duration. As discussed previously and highlighted in Figure 3, the length of the exposure duration controls the shape of $C_T(t)$. As a result of the linear relationship between $C_T(t)$ and $R_T(t)$ for a fixed exposure duration, the variation of $R_T(t)$ with time also varies with exposure duration as shown in Figure 8. Particularly apparent in these figures, and applicable to both the persistent contaminant and multiple-event scenarios, short exposure durations result in lower risk, despite $C_T(t)$ being higher during certain time periods for a short exposure duration (as shown in Maxwell and Kastenberg, 1999). This result is consistent with the foundational assumptions of chronic cancer risk models where the chronic health risk is a function of the total contaminant mass during exposure, and not the maximum concentration (USEPA, 1987). Understanding of this assumption within the chronic cancer risk model is important from a risk assessment viewpoint as it demonstrates that shorter exposure durations may be subject to higher maximum and average concentrations but, due to the short exposure period, produce lower chronic health risks.

Beyond this general statement on the dependence of magnitude of risk on mass of exposure during a specific exposure duration, the results in Figures 8a and 8b suggest that exposure duration will impact estimated health risk in a number of other ways (as suggested by Maxwell and Kastenberg, 1999 and de Barros and Rubin, 2008). The proposed time-dependent risk method allows us to better capture these temporal features of the breakthrough curve. For example, shorter exposure duration will lead, as expressed in Equation (2), to less smoothing of the original breakthrough curve over time. Hence, risk estimated for a shorter exposure duration may reflect more of the temporal variability in the original breakthrough curve ($c(t)$), with the possibility of multiple risk peaks (for example, the five-year exposure duration in Figure 8b). This sensitivity, at short exposure durations, to short-term increases in concentration for the episodic scenario results in health risks for this scenario that, at select start times, are greater than the health risk estimated for the persistent contamination scenario as well as an overall maximum health risk that is higher for the multiple-event scenario (Figure 8b).

Finally, exposure duration may influence the relationship between the estimated chronic health risk and the risk threshold depending on the form of the breakthrough curve. Specifically, variation in exposure duration may result in variation in the number of discrete periods of chronic risk above the risk threshold for the same β fractile. For example, if we draw a hypothetical risk threshold at 2×10^{-7} in Figure 8b, visual inspection reveals that despite starting from the same breakthrough curve, the 30-year time-dependent risk is entirely above the threshold, the 10-year time-dependent risk displays four discrete windows of risk above the threshold (approximately centered around 5, 8, 38, and 58 years), the 5-year time-dependent risk has three discrete failure series above the threshold (approximately centered around 5, 41, and 62 years), and the

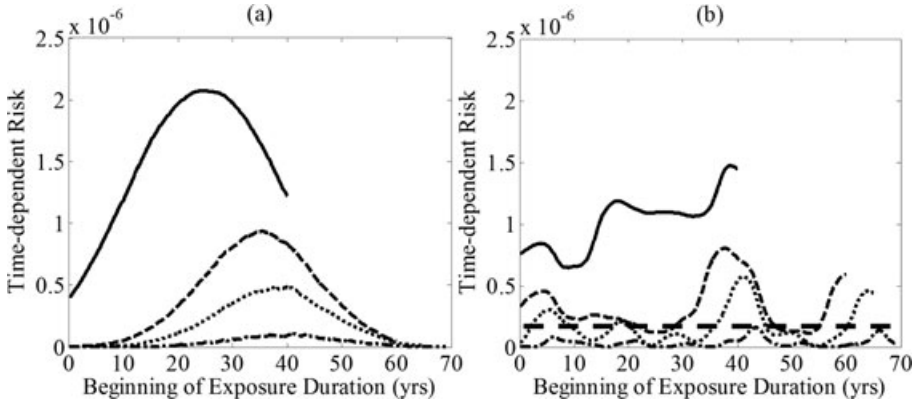

FIGURE 8. Time-Dependent Risk as a Function of the Beginning of the Exposure Duration for 30-Year (solid line), 10-Year (long dash line), 5-Year (short dash line), and 1-Year (dash dot line) Exposure Durations for the Median Individual. (a) Time-dependent risks for persistent contamination and (b) time-dependent risks for episodic contamination and hypothetical risk threshold of 2×10^{-7}.

1-year time-dependent risk is entirely below the threshold. Although beyond the scope of this manuscript, this dependence of number of risk peaks may result in very complex risk behavior/risk analysis for populations with variable exposure periods.

These findings suggest that use of the RRV criteria may provide the opportunity for greater understanding of the impact of exposure duration and β on the variation, over time, of chronic health risk. The potential utility of the RRV criteria is illustrated in Figures 9 and 10. These are plots of the variability in reliability, resilience, and our two measures of vulnerability with β fractile and exposure duration for the persistent and episodic scenarios, respectively. As would be expected, a decrease in the length of time an individual is exposed to a contaminant results in an increase in reliability and resilience and a decrease in both vulnerability measures regardless of the type of breakthrough curve analyzed. This is significant because systems serving highly mobile populations, and thereby short exposure durations, will have a higher probability of producing acceptable health risks and recovery following a period of unacceptable health risk. It is also worth noting that, although difficult to see in the Figure, the portion of the population with the highest β fractiles (most sensitive to the contaminant) continue to experience unacceptable risks even at the one-year exposure duration. Hence, the RRV criteria have the potential to provide substantial insight relative to the mobility of the population as well as chronic risk to the most sensitive portion of the population (even in situations for which the system is in a safe state for the 50th fractile).

Both of the simulated breakthrough curves demonstrate significant sensitivity in the RRV values for the majority of β values to the exposure duration (Figures 9 and 10) suggesting that consideration of transient populations could significantly impact the interpretation of the system performance. Visual inspection of the results reveals that the episodic scenario is less sensitive to changes in exposure duration than the persistent scenario; that is, the shift in the probability of compliance, the probability of recovery, the maximum risk, and the average exceedance from a 1-year exposure duration to a 30-year exposure duration is smaller. The greater sensitivity of the persistent event to the exposure duration results in a greater likelihood of compliance and recovery and a lower maximum risk and average exceedance for short exposure periods when compared to the episodic scenario — but the opposite is true for longer exposure durations (Figures 9 and 10).

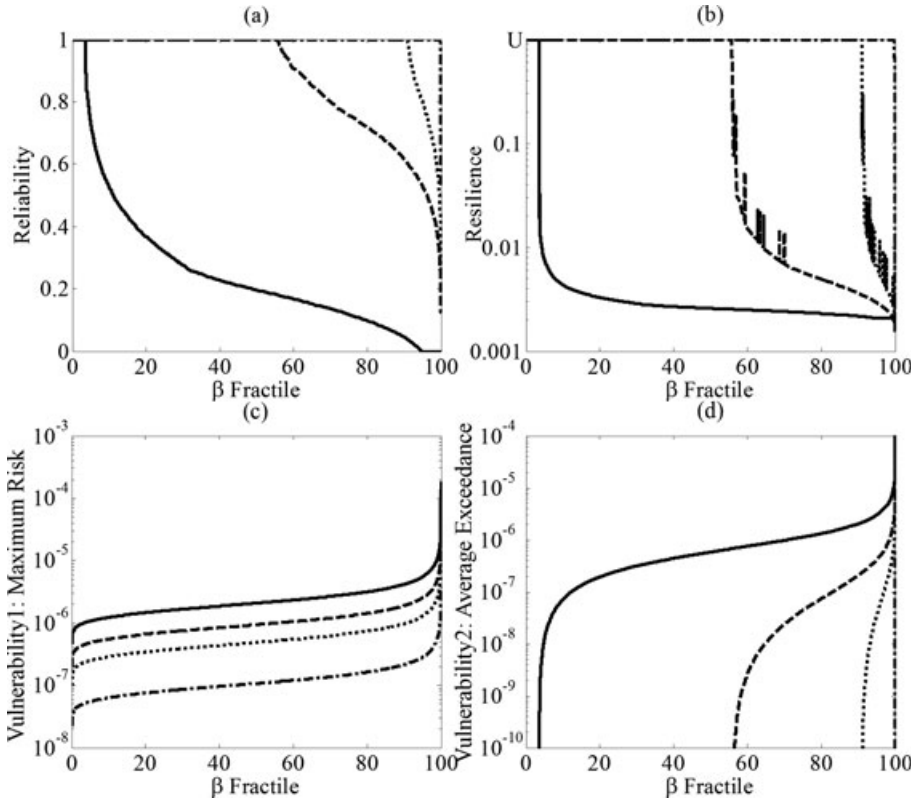

FIGURE 9. Reliability, Resilience, and Vulnerability Plots for the Persistent Scenario (a-d) Using Four Discrete Exposure Durations, T = 30 (solid line), 10 (long dash line), 5 (short dash line), and 1 (dash dot line) Years for a 70-Year Average Concentration of 0.5 ppb: (a) Reliability, (b) Resilience, (c) Vulnerability1, and (d) Vulnerability2.

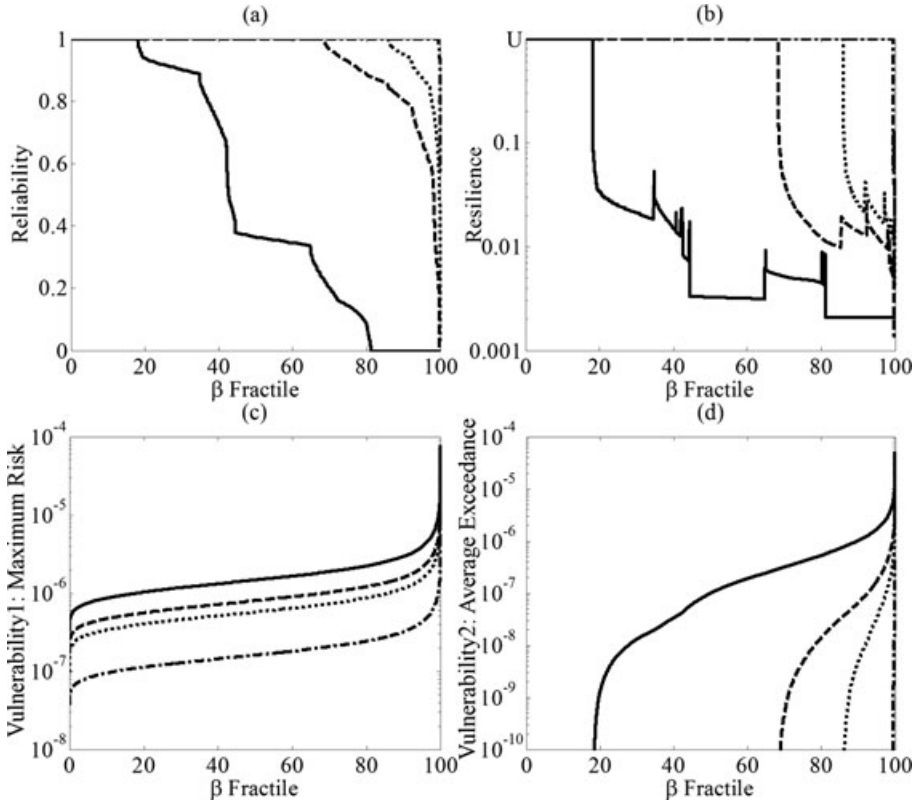

FIGURE 10. Reliability, Resilience, and Vulnerability Plots for Episodic Scenario (a-d) Using Four Discrete Exposure Durations, T = 30 (solid line), 10 (long dash line), 5 (short dash line), and 1 (dash dot line) Years for a 70-Year Average Concentration of 0.5 ppb: (a) Reliability, (b) Resilience, (c) Vulnerability1, and (d) Vulnerability2.

CONCLUSIONS

Within this manuscript, we have introduced a continuous time-dependent health risk approach for the estimation of health risks to a receiving population as derived from time-dependent contamination at a water supply well. We also proposed RRV as viable tools for the assessment of these time-dependent health risks. The results presented demonstrate that time-dependent risk and the use of the RRV criteria, in contrast to the traditional method focused on maximum health risk, can provide substantial new insight into the time and population structure of chronic health risk related to contamination at the well.

Among the observations derived from the time-dependent risk approach and application of the RRV criteria to the synthetic case studies presented include:

1. time variation in health risk is sensitive to mass arrival at the well during the exposure period, but only indirectly dependent on the maximum concentration observed during the exposure period,
2. chronic health risk evolves in a different manner for short, episodic contamination events than for persistent contamination events — this dependence is itself dependent on exposure duration (e.g., for long exposure duration, episodic events result in higher probability of acceptable health risks, higher probability of recovery, lower maximum risk, and lower average exceedance of the target concentration — the results are reversed for short exposure durations),
3. health risk derived from contaminant breakthrough curves composed of episodic events appear less sensitive to changes in exposure duration than health risks derived from the persistent contamination (for the same mean concentration), and
4. the dependence of health risk on population statistics can be extremely complex, with strong sensitivity to the temporal structure of $c(t)$, exposure duration, and regulatory risk threshold.

These observations suggest that the time-dependent health risk method, with the aid of the RRV criteria, provides insight into the complex temporal relationship among health risk, population

variability, regulatory risk threshold, and time-dependent concentration of the contaminant at the well ($c(t)$). This insight is in addition to the understanding of health risk derived from classic assessment of maximum health risk.

One shortcoming of the RRV criteria is the limited utility of resilience in assessing chronic cancer risk. Simply, the long temporal scales of common groundwater contamination events, combined with relatively long exposure durations commonly of interest in water supply analysis for chronic exposure result both in averaging over short-term episodic contamination events and a limited number of averaged events occurring within the lifetime of a water supply well (both of which effectively eliminate the opportunity for multiple recoveries from contamination events). Hence, the concept of resilience may be of limited utility for chronic health risk due to groundwater contamination events requiring transport from a source to the well. However, it is anticipated that resilience will find greater utility in assessment of acute health risk from contaminants entering a groundwater supply due to direct contamination of the well bore (related, for example, to failure of well seals, contamination introduced during maintenance, or direct contamination of wells due to the absence of well seals).

An identified area of improvement in the use of the RRV criteria for the assessment of health risks is the definition of the second measure of vulnerability, average exceedance. The definition suggested here is to divide the total exceedance by the 70-year time frame, but several other options exist. For example, dividing the total exceedance by the number of failed windows provides an estimate of the average exceedance for a failure period. It is up to the individual applying the RRV criteria to identify the appropriate definition of severity/exceedance for the system under analysis.

We acknowledge that additional research is necessary to improve the RRV criteria and further explore temporal/population variability for a larger variety of contamination profiles at the well. However, we see time-dependent risk and assessment via the RRV criteria as a promising tool to contribute to characterizing and understanding the intricacies of chronic health risk in groundwater systems and one day hope that the concepts may prove useful in promoting and improving health-based management of groundwater systems.

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