Published in final edited form as:
Risk Anal. 2012 February ; 32(2): 259–280. doi:10.1111/j.1539-6924.2011.01700.x.

The influence of mapped hazards on risk beliefs: A proximity-based modeling approach

Dolores J. Severtson and **James E. Burt**

Abstract

Interview findings suggest perceived proximity to mapped hazards influences risk beliefs when people view environmental hazard maps. For dot maps, four attributes of mapped hazards influenced beliefs: hazard value, proximity, prevalence, and dot patterns. In order to quantify the collective influence of these attributes for viewers' perceived or actual map locations, we present a model to estimate proximity-based hazard or risk (*PBH*) and share study results that indicate how modeled *PBH* and map attributes influenced risk beliefs. The randomized survey study among 447 university students assessed risk beliefs for 24 dot maps that systematically varied by the four attributes. Maps depicted water test results for a fictitious hazardous substance in private residential wells and included a designated “you live here” location. Of the nine variables that assessed risk beliefs, the numerical susceptibility variable was most consistently and strongly related to map attributes and *PBH*. Hazard value, location in or out of a clustered dot pattern, and distance had the largest effects on susceptibility. Sometimes, hazard value interacted with other attributes, e.g. distance had stronger effects on susceptibility for larger than smaller hazard values. For all combined maps, *PBH* explained about the same amount of variance in susceptibility as did attributes. Modeled *PBH* may have utility for studying the influence of proximity to mapped hazards on risk beliefs, protective behavior, and other dependent variables. Further work is needed to examine these influences for more realistic maps and representative study samples.

Keywords

risk communication; visual communication; map cognition; perceived risk; hazard proximity

I. Introduction

The use of maps to communicate environmental risk to the public is rapidly expanding. These maps depict contaminant values, potential exposures, hazards, estimated health risks, and other categories of environmental risk.(1) *Risk* and *hazard* are often used generically, imprecisely, and interchangeably. Risk is the probability an adverse event will occur,(2) and hazard is an act or phenomenon that has the potential to cause harm to humans or what they value.(3) We use both terms in keeping with the literature that informed this study. Risk is used as a generic term that embodies all categories of environmental risk and hazard unless specified to mean only probability. Maps used in this study depicted an environmental health hazard, but we believe results are general and pertain to multiple types of mapped hazard and risk.

Maps illustrate the geographic distribution of risk, a key advantage over other formats of risk information. Viewers can see how the location of their home or community is

Corresponding Author: Dolores J. Severtson, Assistant Professor, UW-Madison School of Nursing, H6/236 CSC, 600 Highland Ave., Madison, WI 53792, djsevert@wisc.edu, 608-263-5311.
Second Author: James E. Burt, Professor, UW-Madison Department of Geography, Science Hall, 550 N Park St., Madison, WI 53706

configurationally related to mapped information. Severtson and Vatovec[(4)] (hereafter SV) used cognitive interviews to assess public understanding of dot and choropleth maps[1] depicting water test results for a drinking water hazard in private residential wells. Participants' beliefs about risks associated with the hazard (risk beliefs) were strongly influenced by participants' perceived map locations relative to the distribution and magnitude of mapped hazard. Dot maps illustrated site locations of well water test results. The distribution and magnitude of mapped test results relative to participants' perceived map locations are described by four attributes: the *hazard values* symbolized on the map, viewers' *distances* to hazard, and the *prevalence* and *spatial patterns* of hazards. These attributes embody the visual representation of proximity to mapped hazard. In SV, each of these attributes influenced risk beliefs,[(4)] but the nature of interview data did not allow these effects to be quantified.

Quantifying these effects would be facilitated by a model designed to estimate proximity-based hazard or risk for map locations relative to the spatial distribution of mapped hazards. Here and throughout the paper, the term “proximity-based hazard” is used to mean *the combined effect* of the four attributes mentioned above including, but not limited to, nearness. The model would provide an index of risk or hazard magnitude for a point location on the map relative to surrounding hazards, accounting for the identified attributes of hazard values, distance, prevalence, and spatial patterns. Although others have explored the influence of “on the ground” proximity to natural and manmade hazards on risk beliefs,[(5-8)] protective behavior,[(8, 9)] and social behavior,[(10, 11)] we know of no attempts to model proximity-based hazard for maps. In this paper, we develop such a model and then quantify the effects of the four attributes and modeled proximity-based hazard on selected risk beliefs. We begin with a brief summary of hazard proximity, visual cognition, how the four attributes relate to cognition, the method used to model proximity-based hazard, and evidence supporting the selection of dependent risk belief variables.

1.1 Hazard Proximity

On the ground, hazard proximity is measured in different ways including residence in a hazard area (defined by hazard magnitude or as a buffer zone surrounding a point source),[(7-9, 11)] perceived residence in a hazard area,[(8, 9)] linear distance (route or Euclidean distance),[(5, 6)] and adjusted distance using a distance decay function.[(10)] Some of these measures combine distance and hazard magnitude,[(7, 10, 11)] others use only distance.[(5-7)] Proximity to hazard or residence in a hazard area is usually related to stronger risk beliefs,[(5-7)] but sometimes related to weaker beliefs perhaps because familiar hazards are perceived as less dangerous or because polluting industries provide economic benefits.[(12)] In addition, perceived or actual residence in hurricane risk areas illustrated on maps showed no correlations with actual or intended evacuation behavior.[(8, 9)]

1.2. Visual Cognition

When people view an image, such as a map, cognition is influenced by a combination of top-down and bottom-up processes. Deliberate top-down information processing is directed by the viewer, for example to answer a question. Pre-conscious bottom-up processing occurs because our visual system is neurologically linked with cognitive centers in the brain resulting in an inherent ability to see and understand without apparent cognitive effort.[(13)] For example, seeing two points on a line conveys the magnitude of their relationship. Some work has identified “pre-attentive” features that support accurate bottom up-processing. For example, Cleveland and McGill[(14)] proposed ten pre-attentive features and ranked these by

[1]Dot maps depict the distribution of a phenomenon using small symbols. Choropleth maps depict statistical information across areal enumeration units such as a county.[(48)]

accuracy of comprehension into six categories: (1) positions along a common scale, (2) positions along nonaligned scales, (3) length, direction, angle, (4) area, (5) volume, curvature, and (6) shading, color saturation.

Visual cognition is also shaped by attention. A user-defined goal results in selective top-down attention to some visual features over others.[13] Bottom-up attention is driven by visual salience, defined as "the distinct subjective perceptual quality which makes some items in the world stand out from their neighbors and immediately grab our attention".[15] A variety of characteristics, such as color, position, texture, or motion, can make a visual stimulus stand out in a visual scene of multiple stimuli.[15]

Symbols support cognition by representing a thing or idea.[16] Color can symbolize meaning by concretely representing real-world meaning, e.g. blue to depict water on a map, or through culturally derived meaning, e.g. red to convey warning. Widely used color conventions that symbolically communicate risk include "stoplight" colors of green for safe, yellow for caution, and red for danger or warning.[17] Symbols increase comprehension because the meaning is readily accessible from long-term memory.

1.3. Map Attributes and Visual Cognition

1.3.1. Hazard Value—Brewer recommends color schemes for conveying statistical information on maps.[18] A *diverging scheme* typically consists of two colors with increasingly darker gradations (a pre-attentive feature) above and below a meaningful midpoint to depict incremental increase and decrease. A *spectral scheme* uses different colors for different values without regard to lightness gradations. SV dot maps[4] employed a modified *spectral diverging risk color scheme*[18] that uses risk colors with lightness gradations to symbolize the safety meaning and magnitude of water test results above and below the drinking water standard. Participants readily interpreted the meaning of blue and green (smaller values) as safe, yellow (values just below the standard) as caution, and red and dark red (values exceeding standard) as unsafe or warning. Some interviewees described red and yellow dots as "attention getting", suggesting visual salience. SV participants had more interest in riskier red or yellow dots compared to safer blue and green dots, perhaps due to a top-down desire to understand the location and distribution of elevated risk. Thus, the readily understood meaning of symbolic risk colors, top-down attention to larger riskier hazards, and bottom-up attention to visually salient colors appeared to explain the influence of hazard values on risk beliefs.[4]

1.3.2. Distance to Hazard—Personal relevance can focus attention through top-down processes. Personal relevance led SV participants to focus on hazards near the perceived location of their residence; "*Where I live so my eyes go right there.*"[4] Proximity influenced location-based risk beliefs; "*I would say I have a problem with rhynium in a very proximal area to where I live because two of the three wells did exceed and the one that didn't is on the border of exceeding [the standard]*".[4] The distance between two map points is a measure of *length* - the third most consistently understood pre-attentive feature.[14] Perceived and actual length are closely aligned[19] suggesting "effortless" bottom-up processing to see and understand proximity without cognitive effort. Thus, proximity to hazards appears to influence risk beliefs via top-down attention to personally relevant proximal information and bottom-up processing of length.

1.3.3. Prevalence of Hazard—In SV, the prevalence of test results was conveyed by the number of colored dots on the map. Prevalence varied by area and concern was stronger for areas where many dots were red.[4] A display of many similar symbols can decrease visual salience by distributing rather than focusing attention,[20] and lead to longer search times.[21]

These tendencies were evident in participants' description of the dot map as “busy” and needing time to process information.[4] Comments indicated attention was directed to areas with many dots and supported by theory-based claims that people notice extremes in magnitude.[13]

1.3.4. Dot Patterns—*Gestalt Laws of Perceptual Organization* describe how perceptual attributes of proximity, similarity, and continuity integrate features into a coherent entity. Proximity conveys relatedness.[22] In SV, clusters of dots drew attention. Lines of continuity among dots were sometimes noticed and interpreted as a trend. The impact of dot patterns on risk beliefs was less clear compared to the other attributes, although a cluster with many high risk dots generated substantial concern.[4] Results suggested location in or out of a hazard line or cluster impacts risk beliefs. Cluster density (tight - loose) may also influence beliefs.

1.4. Proximity-based Hazard Model (*PBH*)

In order to capture the joint and interacting effects of the factors described above, we developed a simple model of proximity-based hazard (*PBH*) that includes the number and strength of surrounding risks, their distance from a participant's location, and their spatial arrangement. This model assesses the risk associated with any map location based on the totality of mapped risks in the area. The model represents risk as a continuous field driven by risk measurements taken at discrete points in space. Given the location and numerical values of those mapped measurements, the model assigns a *PBH* value to every intervening location. Input for the specific category of risk (hazard, contaminant value, etc.) will determine the nature of the output. The most straightforward interpretation is to consider *PBH* as a hazard model, where both input and output variables are some measure of hazard intensity. However, if input values are probabilistic risk values, model output will be the same. Furthermore, assuming risk is monotonically related to hazard value, hazard measures can be translated into probabilistic risk inputs, thus the model can deliver an index of risk when driven by hazard measurements. The results section will provide some justification for this assumption and will show that linear scaling between *PBH* and risk is reasonably successful. Anticipating that, we use both “risk” and “hazard” in describing the model. Our model is based on five basic assumptions discussed below using the fictitious well contaminant (rhynium) depicted on study maps. However, the model is general and applies to other forms of hazard (e.g., air pollution point measurements, landslide potential) and risk. The five assumptions, illustrated in Figure 1, are as follows:

1. Hazard is directly proportional to the magnitude of the surrounding hazards. Thus a doubling of rhynium values in all surrounding wells would double the hazard at some interior location. Similarly, everything else being equal, a well with twice the rhynium of other wells would be twice as important as each of those other wells (Figure 1a, 1b).
2. The hazard at any location cannot exceed the largest mapped hazard value. For example, a person living in the middle of a group of wells whose largest rhynium concentration is 10 parts per billion (ppb) would not experience a threat greater than that. This assumption is obviously not valid for hazards whose effects are additive, such as windmill noise.
3. The importance of a hazard decreases with increasing distance (Figure 1c). In addition, we assume the decline is rapid for nearby hazards and falls off more slowly with increasing distance.
4. Although all mapped hazards contribute to risk, we assume tightly clustered hazard measurements contain redundant information about the risk in the cluster area. That

is, measurements very close to one another do not identify separate independent hazards. Equivalently, we assume there is positive spatial autocorrelation in the risk field. Thus hazards that are very close to one another individually contribute less to the total risk than isolated hazards (Figure 1d). Each hazard contributes to the total, but the total influence of clustered hazards is less than the sum of the clustered values.

5. Nearer hazards partially obscure the risk of hazards located in their shadow (Figure 1e). That is, we assume an intervening hazard takes precedence over a hazard located farther away in the same direction from the participant's location. Note that this is different than the distance penalty (Assumption 3). It imparts a further penalty in addition to that of increasing distance alone.

It is natural to formulate this as a problem in spatial weighting. That is, given a set of risk or hazard values H_i defined at n locations $(x_i, y_i), i = 1,2,\dots n$ we construct a set of weights W_i that are used to assign a hazard intensity value to any (x, y) location:

$$\mathrm{PBH}(x,y)=\frac{\sum_{i=1}^{n} H(x_i,y_i)\,W(x,y,x_i,y_i)}{\sum_{i=1}^{n} W(x,y,x_i,y_i)} \qquad (1)$$

Obviously, because the weights (W) vary with location, *PBH* also varies from place to place in response to the surrounding hazards. Even with a fixed set of hazards, the pattern of hazards “seen” from various locations is different, thus the hazard proximity is variable over space. Notice that because *PBH* is proportional to hazard value, Equation (1) incorporates the first assumption explicitly. The remaining four assumptions are accommodated by using modified Shepard(23, 24) weights for the W_i. Shepard weighting is widely employed as a method of spatial interpolation for mapping both social and physical phenomena[25] and is available in commercial mapping software such as Surfer[26] and ArcMap.[27] Additionally, it has wide application as a grid interpolator in computational fluid dynamics.[28, 29]

Some applications of Shepard's method include only distance, whereas we include the effects of both distance and spatial pattern. Considering distance first, we assume that the importance of an individual hazard decreases with the square of distance to the participant's location:

$$s_i^2=1/d^2(x,y,x_i,y_i)=1/[(x-x_i)^2+(y-y_i)^2]$$

We know of no theory in the hazard or risk literature behind the choice of the distance exponent and there are an infinite number of values consistent with assumption 3. Inverse square weighting is common, and has the advantage of yielding a smooth (analytic) function for *PBH.*

Assumptions 4 and 5 are combined into a single value $t_i = t(x, y, x_i, y_i)$ *that* accounts for both clustering and shadowing. Every hazard (i) has its own weight which is determined from its relationship to every other hazard. Consider, for example, two locations (x_i, y_i) and (x_j, y_j). Let α_{ij} be the angle between points i, j and (x, y) as seen in Figure 1d. The adjustment for clustering and shadowing between i and j is proportional to $1 - \cos(\alpha_{ij})$. Note that this factor ranges from zero for perfectly collinear points ($\alpha = 0$) to a maximum of 2 for $\alpha_{ij} = 180°$

(maximum angular separation). The aggregate cluster/shadow factor for point *i* is found by summing over all other points, each of which is weighted by the inverse of distance

$$t_i = \sum_{\substack{j=1 \\ j \neq i}}^{n} [1 - \cos(\alpha_{ij})] s_j$$

The combined distance and cluster/shadow weights are given by

$$W_i = s_i^2 \left(1 + \frac{t_i}{\sum\limits_{\substack{j=1 \\ j \neq 1}}^{n}} \right) = s_i^2 \left[1 + \frac{\sum\limits_{\substack{j=1 \\ j \neq 1}}^{n} \left[1+\cos(\alpha_{ij})\right] s_j}{\sum\limits_{\substack{j=1 \\ j \neq 1}}^{n} \sum\limits_{\substack{i=1 \\ i \neq j}}^{n} \left[1+\cos(\alpha_{ij})\right] s_i} \right]$$

With this implementation *PBH* is a continuous surface whose value never exceeds that of any individual H_i. Other forms of Shepard weights allow extrapolation above and below known values, but our model excludes that possibility by assumption 2. We see that W_i is infinite for d_i=0, thus *PBH* at a hazard location will equal the value of that hazard. For example, a map location with a hazard value of 40 ppb would have *a PBH* estimate of 40 ppb regardless of surrounding values. With these characteristics we believe *PBH is* a reasonable starting point for a hazard proximity model.

It is important to note that *PBH* assesses hazard or risk at map locations based on the *visual* representation of hazards. Mapped hazard values are used in the *PBH* model rather than actual hazard data. Furthermore, the *PBH* model does not account for complex factors that influence spatial variation in the distribution of various types of risk. For example, the transport of groundwater contaminants can be affected by non-uniformity and/or anisotropy in hydraulic conductivity, and a simple model like ours makes no attempt to capture such effects. Since viewers will vary widely in their knowledge and beliefs about these factors and most will lack accurate knowledge about hazard transport, a vision-based *PBH* model may function well for assessing public responses to risk maps. This approach is supported by studies that found images have a greater impact on comprehension when prior knowledge is lacking.[30]

1.5. Risk Beliefs

Of interest is an assessment of how *PBH* is related to people's beliefs about mapped risk. People prefer to derive and apply global rather than specific meaning from information.[31] In a number of behavioral theories, global risk beliefs (sometimes referred to as perceived risk) are considered to be a function of specific beliefs that include perceived *susceptibility* to a risk and the *severity* of associated consequences.[32] However, global beliefs are more predictive of behavior.[33] These tendencies were reflected in the global terms used by SV study participants', such as *a concern* or *a problem*. Susceptibility was sometimes implied, e.g. the quote in section 1.3.2 and several used susceptibility terms of *chance* or *likelihood*.[4] Although not evident in participants' comments, perceived severity of associated consequences may have identified the contaminant (described as a carcinogen) as an important health threat. In addition, the warning meaning of red may prompt stronger beliefs of severe health consequences. Maps allow the viewer to identify location-based risk, and in SV, perceived proximity to mapped hazards influenced risk beliefs.[(4)] While it is logical that nearness to large hazard values would increase beliefs of susceptibility, interviewees mostly used global risk terms. This begs the question of whether dot maps have a stronger influence on susceptibility or on global beliefs.

Since maps illustrate the geographic distribution of risk information, viewers can compare their location-based risk to the risk of others on the map, for example to compare their risk to the risk of residents in their community or county. There is a persistent and pronounced tendency for individuals to compare their risk to that of others and for social comparison to influence risk beliefs and behavioral responses to risk information.[(34)] For example, Weinstein found participants' beliefs that their radon test results were higher than “others in the community” (p. 79) was a key predictor of stronger global risk beliefs among participants living in a high radon hazard area.[(35)] Maps may facilitate what we call *locational social comparison* that may influence risk beliefs. Locational social comparison includes social[2] and locational elements. The degree to which it includes social aspects of comparison will vary based on viewers' knowledge about “others” on the map. For example, older individuals may rate their risk as less than others if they believe many children reside in their community and are more susceptible to the mapped hazard. People tend to rate their risk as less than a generic comparison group.[(34)] This tendency may be reflected in measures of locational social comparison. In summary, attributes of mapped hazard may influence specific risk beliefs of susceptibility and severity, global risk beliefs of concern and a serious problem, and locational social comparison of one's own risk to that of others on the map.

1.6 Numeracy

Numeracy, defined as the ability to understand basic probability and mathematical concepts, influences people's comprehension of risk information.[(36)] Numeracy is also related to spatial cognition.[(37)] Given the relationship between numeracy and spatial cognition, numeracy may impact risk beliefs derived from dot maps because the distribution of dots include both numerical and spatial properties.

1.7 Study Aims

Qualitative evidence indicates map attributes influence risk beliefs.[(4)] We propose the *PBH* model to estimate the combined effects of these attributes. The four primary aims of this study were to (1) select the single dependent risk belief variable most strongly and consistently related to *PBH* and map attributes, (2) examine the influences of *PBH* and map attributes on this risk belief, (3) compare the relative influences of *PBH* and map attributes on the risk belief, and (4) examine how the risk belief is aligned with *PBH* values.

2. Methods

2.1. Maps

Study maps portrayed well water test results for a fictitious hazardous substance (rhynium) as dots colored using a modified spectral diverging risk color scheme[(18)] as in SV maps[(4)] (exemplar at http://research.son.wisc.edu/wellstudy/map1a.pdf). The legend depicted rhynium test results over (red and dark red) and under (blue, green and yellow) rhynium's maximum contaminant level (MCL) of 10 ppb. MCL is a synonym for drinking water standard.[3] Our maps depicted test results for a single township using only blue (less than 2

---

[2]A variety of factors explain the influence of social comparison on responses to health risks, please see Klein and Weinstein's chapter[(34)] and other chapters from this volume.

ppb) and dark red dots (more than 20 ppb). These were the smallest and largest ranges of rhynium values depicted in the legend. An X, labeled with "You live here", indicated assigned residential location. Each 7.6 centimeter (cm) square map included a title, legend, scale, north arrow, and inset showing the location of the six mile squared township within Dane County.

2.2. Study Design and Map Variables

For this randomized trial (no control group), a full factorial 2 × 2 design was applied to create 16 attribute-defined map subsets (attribute subsets) resulting in 24 study maps (see Figure 2). For each attribute subset, dots in the lower half of the map varied by hazard value and one other attribute resulting in 4 maps, e.g. fourth row maps in Figure 2 vary by hazard value and distance.[4] To minimize simplistic mathematical interpretations of manipulated attributes, three blue dots were placed at the top of all maps to introduce controlled complexity. Some maps belong to more than one subset.[5] The 16 attribute subsets are specified in Table II column headers using map labels from Figure 2, e.g. row 4 maps in Figure 2 are 4a-d in Table II.

Independent variables for map attributes were categorically operationalized as: (1) three *hazard values* defined by the collective hazard of manipulated dots (all blue dots, even mix of blue and red, all red), (2) three *distances* from assigned residential location to the nearest manipulated dot (far = 2.5 miles, 3 map cm; medium = 1.25 miles, 1.5 map cm; near = 0.5 miles, 0.6 map cm), (3) three *prevalence* values (1, 2, 8 dots), and *dot patterns*. Dot patterns included *clusters* composed of 8 dots and patterns defined by the *angle* (narrow or wide) of assigned location to two dots (Figure 2 rows 1 and 6). Wide angle maps (160° angle) could be construed as location within a hazard line. Narrow angle maps (20° for medium distance and 45° for near) could be construed as location outside of a two dot cluster (dots were 0.55 map cm apart for both). Attribute variables for eight dot clusters (Figure 2 rows 3 and 5) included *cluster location* (medium distance outside or inside) and *cluster density* (loose, tight). Loose dots varied by nearest neighbor distances of 0.9 to 1.3 cm and tight dots by 0.3 to 0.5 cm. The 24 study maps were organized into four blocks of six maps such that within blocks there was a marked difference in manipulated dots from one map to the next (Figure 2).

2.3. Survey

Nine survey items (see appendix) were selected to assess risk beliefs: *susceptibility* (4 items, 2 with global belief terms), *severity* (1 item), *global beliefs* (2 items), and *locational social comparison* to near or community-wide residents (2 items). To assess susceptibility, we used "chance" rather than "likelihood" based on cognitive testing of survey items in SV[(4)] (unpublished results). One susceptibility item used a numerical 11 point interval response (0 – 100% chance). Other items used 5-7 ordinal word-level responses. Numeracy was measured with a slightly modified version of the subjective numeracy scale.[6],[(38)] Participants were instructed to rate their ability to use fractions and percentages (4 items) and preferences for words or numbers (3 items) using 6-point ordinal scales with mean numeracy computed from these responses. Demographic variables included age, gender, and

---

[3]The maximum contaminant level (MCL), commonly referred to as a drinking water standard, is the highest permissible level of contaminant in drinking water deemed suitable for human consumption. MCLs are enforced for public water supplies[(49)] but not private wells.[(50)]

[4]One attribute subset varied only by prevalence (1, 2, and 8 red dots - see maps 4.d, 6.b, and 3.c).

[5]For example, maps 6.a and 6.b fit with the map subset that varied by hazard amount and angle (maps 6.a-d) and the map subset that varied by hazard amount and prevalence (maps 6.a-b and 3.c-d).

[6]Among measures of numeracy, the subjective numeracy scale was found to be less time consuming, rated as less stressful,[(51)] and approached the predictability of an objective numeracy scale.[(38)]

race/ethnicity. We controlled for participants' drinking water use (unfiltered, filtered, bottled) and dominant residential experience (4 ordinal categories from rural – urban). Four survey versions were produced, one for each block of six maps. Risk belief survey items accompanied each map. The county map on the survey cover showed a distribution of dots for all ranges of hazard values.

2.4. Sample and Procedure

About 1045 undergraduate students enrolled in three courses at a large Midwestern university were verbally invited to participate in the study. Interested students picked up a survey packet (shuffled versions) as they exited class resulting in random assignment of map blocks. Students returned surveys two days later as they entered class or via mail in the provided stamped return envelope. Two reminders (verbal and e-mail) and a $5 incentive encouraged participation.

2.5. Analysis

ArcGIS 9.3[(27)] was used to create the maps and to calculate all well locations (constant and manipulated) in a Universal Transverse Mercator coordinate system (UTM). *PBH* was calculated using ArcGIS and Python computer programming language. Since points were projected in UTM, the Pythagorean theorem was used to calculate distance between wells.

Initially, the metric for mapped hazard values was blue = 1 and dark red = 5, based on the five class legend (1^{st} and 5^{th} class), thus computing an index of ordinal hazard. After the initial analysis found the 11 point susceptibility item (*% chance over MCL)* had the consistently strongest relationship with attributes and *PBH*, we changed the metric of mapped hazard values to measure the probability of having a rhynium test result exceeding the MCL (safety standard), thus computing an index of probabilistic risk. In the revised metric, blue = 0 and dark red = 100 based on the assumption that exact location at a blue or dark red dot would = 0% or 100% chance of having rhynium over the MCL. Scaling *PBH* to match the dependent variable allowed us to examine the alignment between estimated *PBH* and susceptibility. With only two hazard values, the different metrics produced nearly equal *PBH* distributions ($r = .999$). This justified the post-hoc decision to scale the independent variable to be aligned with the dependent variable.

We used PAWS Version 18[(39)] for statistical analyses. For aim 1, partial correlations (controlling for gender, numeracy, drinking water use, and dominant residence) were used to select a single dependent risk belief variable for subsequent analyses. Selection criteria were overall strongest and most consistent correlations.

For aim 2, multiple stepwise regression models were used to examine the influence of *PBH* and manipulated attributes on the risk belief variable controlling for numeracy, gender, water use, and prior residence. Regressions were conducted for each attribute subset and also for two sets of combined maps: (1) all combined maps and (2) all combined maps minus the four maps with locations inside of clusters. Regressions for combined maps examined the influence of hazard value, distance, and prevalence. To conduct a full factorial combined map analyses, inside cluster location was recoded as a very near distance for tight clusters (distance = 4) and a near distance for loose clusters (distance = 3) in keeping with the coding scale for distance. Two regressions were conducted for each attribute subset and combined map set - one using *PBH* and the other using map attributes. Step one included covariates, step two included attributes or *PBH*, and step three included the attribute interaction term. If the interaction term contributed a significant amount of variance (ΔR^2 at $p < .05$), regressions were conducted for attribute pairs stratified by hazard value to further explore interaction effects.

For aim 3 we compared the relative influences of *PBH* and attributes on the risk belief variable. Ratios of R^2 from aim 2 regressions indicated the amount of variance in the belief explained by attributes (denominator) relative to *PBH* (numerator). To examine whether *PBH* explained additional variance beyond attributes, a third step for attribute regressions included *PBH*.

For aim 4, we examined the alignment of the risk belief variable with *PBH* using color-coded maps and graphs and arithmetic differences between *PBH* (assigned location) and the mean risk belief.

3. Results

Since key findings are summarized in Section 4 prior to discussion, results are described briefly.

750 of roughly 1045 students picked up a study packet, and 447 returned a completed survey; about a 43% response rate. Sample sizes for map blocks are in Figure 2 headers. 28% were males. Mean age was 19.6 (3.03) years. Race was 92% white, 5% Asian, and 3% as other or another race. About 36% drank unfiltered, 44% filtered, and 20% bottled water. Prior residence was reported as 14% rural, 17% town, 52% suburban, and 16% urban. Mean numeracy was 4.6 (0.63) on a 6 point scale from low to high. Partial correlations between two covariates (controlling for other covariates) showed males reported more numerical ability than females (r = -.14, p < .001) and females were more likely to drink treated water (r = .06, p < .01). Drinking untreated tap water was related to prior residence in a more rural area (r = .10, p < .001) and lower numeracy (r = -.07, p < .001). No other correlations among covariates were significant.

3.1 Aim 1

Table I shows partial correlations for each risk belief with manipulated attributes or *PBH* ranked by column from left to right. *P*-values were not adjusted for multiple tests because results were used to assess general trends. Numerical *susceptibility* (%Ch>MCL) was ranked among the top three variables (first 3 columns) for all but prevalence. *Locational social comparison to township residents* (Cp TS) was ranked among the top three belief variables for all but *PBH* and hazard value. *Severity* was least correlated with map variables followed by *locational social comparison to nearby others* (Cp near). Rows show correlations ranked by *PBH* and attributes. *PBH* was more correlated than others for susceptibility and global beliefs (6 of 9 belief variables) and cluster location was more correlated for locational social comparison and severity variables (3 of 9 belief variables). Based on results, numerical susceptibility (%Ch>MCL), hereafter called susceptibility, was selected as the dependent variable for all subsequent analyses.

3.2 Aims 2 and 3

Table II shows stepwise regression results for 16 attribute subsets and Table III for both sets of combined maps. Tables provide: standardized beta coefficients (β) for the impact of *PBH* (Regression 1) and map attributes (Regression 2) on susceptibility; adjusted R^2; stepwise change in R^2; and R^2 ratios for attribute compared to *PBH* regressions. Column headers indicate maps for each regression using Figure 2 map labels. Standardized beta coefficients and R^2 ratios are bolded. Unstandardized coefficients and standard errors are available from first author.

Table II columns are ranked within attribute categories based on the amount of explained variance (R^2) for *PBH* regressions. *PBH* explained as much or more variance in susceptibility than attributes for 6 of 16 regressions, 90 - 99% variance for 5, 83% for 2, and

57% - 74% for 3. Large standardized coefficients ($\beta \geq .60$) for the influence of independent map variables on susceptibility were noted in 8 of 16 attribute subsets for *PBH*, 6 of 16 for hazard value, 1 of 3 for cluster location, and 1 of 6 for distance. Covariates explained no or small amounts of variance; Step 1 R^2 ranged from 0 - .04. Among covariates, gender had the largest influence and numeracy had smaller or no influences (see note 4 under Table II).

Interaction effects explained variance beyond that of attributes for 5 of 6 distance subsets, 2 of 3 cluster location subsets and 1 of 3 prevalence subsets. Figure 3 shows results from regressions for these subsets stratified by hazard value (standardized beta coefficients and R^2 values at http://research.son.wisc.edu/wellstudy/f3table.pdf). For distance and cluster location maps, all showed a trend of stronger effects for maps with large (all red) hazard values compared to small (all blue) or mixed values. For prevalence maps the trend was opposite; greater prevalence generated stronger effects for mixed compared to large hazard values.

For combined maps (Table III), *PBH* explained more variance than attributes (R^2 ratio = 1.07) for the regression without inside cluster location maps and nearly as much variance (0.95) for all combined maps. R^2 values with *PBH* added to the attribute regression were larger than those with *PBH* or attributes alone. R^2 values with interaction terms added to the regression show *distance by hazard value* (DxH) explained the same amount of additional variance as did *PBH* for maps with no inside cluster location but less variance than *PBH* for all combined maps.

3.3 Aim 4

Figure 4 provides isarithmic maps[7] depicting the spatial distribution of *PBH* estimates. The 11 class diverging color scheme shows incrementally higher and lower classified *PBH* values above and below the middle yellow range (45-55) that includes the *PBH* midpoint. White dots in blue and red areas show the respective locations of blue and dark red dots on study maps. The black X shows participants' assigned map location. Maps labeled as in Figure 2 are ordered from high to low in 3 rows across 8 columns based on *PBH* at the assigned location. Bar graphs of response frequencies for the 11 point susceptibility variable (*% chance over the MCL*) are color coded to match classified *PBH* (eg. 50% chance = yellow) to illustrate how susceptibility beliefs align with *PBH* values. *PBH* values (assigned location), mean beliefs with standard deviations, and mean *PBH* minus mean beliefs are below each graph.

4. Discussion

Here, we summarize and discuss results for each study aim. Figure 4 maps and graphs are referred to by column-row (C-R) numbers, e.g. 1-2 for those in C1 R2.

4.1. Aim 1: Variable Most Consistently and Strongly Influenced by Map Features

Overall, rankings showed susceptibility and locational social comparison (for township) variables as more strongly influenced, severity as least influenced, and global beliefs ranked after susceptibility. Among these, numerical susceptability[8] was ranked highest (%Ch>MCL, Table I). This variable assessed the percent chance of having a rhynium value exceeding the MCL for one's assigned map location. It is not surprising that SV interviewees spoke of risk in global terms,[(4)] but susceptibility better quantified this relationship because

[7]Isarithmic maps are used for continuously varying attributes like rainfall, air temperature, or *PBH*.[(52)]
[8]This analysis was used to select a single dependent variable for following analyses. Given the similarities among correlations for some variables, a different belief variable (likely a susceptibility variable) could consistently rank more highly for a different study sample or type of risk map.

underlying beliefs may not be directly stated in interviews.[40] The negligible to small effects of map variables on severity were appropriate because the maps did not convey the severity of health consequences. Small but significant effects on severity for cluster location, *PBH*, and hazard value may have been prompted by the strong warning meaning of red. Our proposal that spatial information on maps may facilitate locational social comparison was supported by findings that comparison at a township level was among the top three variables for all attributes except hazard value - the only attribute lacking a spatial component.[9]

4.2 Aim 2: Differential Influence of Map Attributes on Susceptibility Beliefs

All of the mapped hazard attributes identified in SV interviews as potential influences on risk beliefs[4] had quantifiable impacts on susceptibility, but effects varied substantially across and within attributes subsets (see Table II). *Hazard value*, a central component of *PBH* (substantiated by their strong correlation, see Table I, last column), had a substantial influence on participants' perceived chance of having elevated rhynium. For all attribute subsets except cluster location, hazard value had larger effects than the other manipulated attribute (see Table II). The impact of hazard value may be influenced by three factors: the strong symbolic “warning” meaning of red, top-down attention to larger and riskier hazards, and bottom-up attention to a salient color. The strong effect of color is supported by other research, summarized by McEachren,[41] that color was more influential than shape or size[42] and not overpowered by proximity.[43] Graph pairs in Figure 4 illustrate the impact of hazard value on susceptibility for near locations to one, two, or eight dots (C-R: 5-1 6-3, 4-1 1-3, 2-1 4-2).

Variance in susceptibility was substantial for maps with *mixed hazard values* in the lower half. The ambiguity of mixed hazard appeared to allow more room for personal interpretation. Nearness to mixed dots led to mean susceptibility greater than a 50% chance, suggesting a trend of more attention to red than blue dots (Figure 4, 6-2). This could result from a mix of top-down attention to personally relevant near and large values, and bottom-up attention to more visually salient red dots. As distance to mixed values increased, susceptibility beliefs decreased, likely due to the waning influence of red dots (Figure 4, 8-2, 6-2). The personal relevance of near hazards and of large compared to small hazard values were expressed by SV study participants.[4]

For combined maps, *distance* had substantial effects on susceptibility, nearly as much as hazard value. However, distance effects across attribute subsets ranged from small to large. The impact of distance on participants' perceived chance of having elevated rhynium may be explained by top-down attention to more personally relevant nearby hazards and pre-attentive (bottom-up) comprehension of distance from one's assigned location to mapped hazards. As distance to large hazards increased, beliefs grew weaker. Results are supported by findings that proximity to actual “on the ground hazard” is related to stronger perceived risk.[5-7] Participants' common sense understanding of hazards and associated risk may include the assumption that nearness to a hazard measure increases susceptibility, a tendency noted among SV participants.[4] Increased variance in susceptibility beliefs with increasing distance is consistent with the proposition that farther locations have a more uncertain risk status than near locations. For maps showing far distance from manipulated dots, susceptibility was likely weaker because location was closer to the constant blue dots at the top of the map. Maps C-R 3-1 and 6-1 show the impact of distance to large hazards controlling for distance to the upper blue dots.

---

[9]Although prevalence was measured as number of dots, prevalence indirectly includes spatial information about the distribution of dots.

Distance interacted with hazard value. The solid lines in Figure 3 show distance had a stronger influence on susceptibility for large compared to mixed or small hazard values. These interaction effects were most pronounced for single dot maps where manipulated hazard value was only small and large (gray lines in Figure 3). As expected, near distance to a blue dot resulted in a small perceived chance of having rhynium, but as distance increased perceived chance slightly increased. The resulting negative relationship between distance and susceptibility for low hazard maps may occur because participants were less certain of a small chance with increasing distance. The relationship between distance and susceptibility was weak for distance to a blue compared to red dot, likely because homogeneous blue dots decreased variance in interpolated and perceived probabilistic risk for locations between two blue dots. The influence of all blue dot maps on susceptibility is discussed further in section 4.4. Susceptibility beliefs associated with small and large hazard values that vary by distance are illustrated in Figure 4 C-R 5-1, 2-2, 5-3 (large hazard) and 6-3, 7-3, 8-3 (small hazard).

Results for attribute subsets indicated *prevalence* was weakly and positively related to susceptibility (Table II). Smaller effects for prevalence may be explained by the complexity and resulting distributed visual attention for maps with more dots.[20] Medium distance outside locations for two compared to eight dot maps indicated prevalence had substantially greater impacts on susceptibility for mixed compared to all red dots (dash-dot line in Figure 3; Figure 4, C-R: 8-1,7-1,3-3,7-2). Effects were due to substantially weaker beliefs for two mixed than two red dots, perhaps because participants found it easier to discount the influence of one red dot (of 5 on map) compared to two and because prevalence effects were stronger for less complex maps.

Participants perceived substantially more susceptibility for locations in rather than out of eight dot clusters, indeed *cluster location* had a larger impact on susceptibility than hazard value for maps with a tight cluster and the same impact for those with a loose cluster. *Gestalt Laws* of proximity, similarity, and continuity may explain how a cluster of similar dots is perceived as an area. MacEachren identified key factors that explain how “Gestalt groupings” are perceived as a figure against a visual background,[41] e.g. a cluster of dots against a background of distributed dots. Contour (a visually discriminable edge to the figure) and surroundedness (completely surrounded figures more likely to be seen as a unit) appear to explain how clustered dots could be perceived as an area. Clusters had a discriminable edge - more so for tight than loose clusters. All dot clusters were completely surrounded by white space. The unambiguous portrayal of clusters that exemplified these factors explains how they could have been perceived as a hazard area. For location within a hazard pattern, the potential visual salience of a two dimensional hazard area compared to a one dimensional line (location within a line of hazard) may further explain the substantial impact of clusters.

It is also possible that clustered hazard measures could generate a heightened sense of susceptibility independent of hazard value. Viewers may assume more testing occurs in areas with a larger potential for hazards. In addition, bottom-up processing of more dots or larger areas of testing may unconsciously promote stronger susceptibility beliefs. If so, this is problematic given that clusters reflect an increase in sampling density and may have nothing to do with hazard variations. For example in a few states, well test reports must be filed whenever a residential property changes hands. In this case, clustered measurements would reflect an active real estate market, not necessarily an area of increased hazard.

Location inside to distance outside interacted with hazard value such that locations had stronger effects for all red than mixed clusters (dashed lines in Figure 3); similar to the trend noted for distance. Location within a tight compared to loose cluster was weakly related to stronger susceptibility (Table II), and did not vary by hazard value. Stronger contour and surroundedness for tight clusters may explain the larger influence of tight than loose clusters, even though they have a smaller area.

Interaction effects between color and other attributes showed that often, attributes did not have separate, independent influences. MacEachren suggests attributes interact to influence visual perception.[41] For our study, interactions were also likely influenced by the meaning of map attributes, e.g., the meaning of hazard value interacting with the meaning of proximity.

Covariates, had only small effects, if any, on susceptibility. Females had stronger susceptibility beliefs than males for some maps - consistent with a broad body of work showing that females are more risk averse than males.[44] When present, the effects of self-rated numeracy were substantially weaker than gender. Males had higher numeracy scores than females, a tendency found in other research.[45]

4.3 Aim 3: Influence of PBH Estimates Compared to Map Attributes

Recall the R^2 ratio compares R^2 for attribute regression models (denominator) to R^2 for *PBH* regression models (numerator). Values over 1.00 indicate *PBH* explained more variance in susceptibility than attributes. Attributes may have explained more variance than *PBH* for a larger number of subsets (10 compared to 4; 2 were equivalent) because attributes were measured categorically while *PBH* was derived from continuous measures of attributes. Despite bottom-up perceptual ability to discern incremental length,[19] people tend to think and talk about proximity in terms of categories, such as near and far distances.[46] This reflects a human tendency to process complex perceptual stimuli through categorization.[41] In addition, the design of study maps to accentuate differences in map attributes, may have increased the influence of attributes over *PBH*.

In reality, the configuration of dots relative to a location could vary widely across different viewer locations and maps. The performance of *PBH* compared to attributes across a variety of dot configurations was best illustrated by the combined map analyses (see Table III). For combined maps, the interaction between hazard value and distance (Step 3 - DxH) explained significant amounts of additional variance beyond that of attributes indicating this in an important source of variance in the *PBH* model. For all combined maps, *PBH* explained almost as much variance in susceptibility as attributes (0.95) and more variance than attributes (1.07) for combined maps with no inside cluster locations. The robust performance of *PBH* across this wide variety of dot configurations suggests its potential usefulness for estimating proximity-based hazard for dot maps. It is worth noting that attributes with *PBH* explained more variance than either *PBH* or attributes alone, indicating each explained a small amount of unique variance in susceptibility. This suggests a *PBH* model that accounts for numerical and categorical aspects of mapped hazards may explain more variance in risk beliefs than a model with only one of these approaches.

4.4. Aim 4: *PBH* Compared to Susceptibility Beliefs

PBH maps in Figure 4 provide insights into the assumptions of the *PBH* model illustrated in Figure 1. The proportional relationship of *PBH* to hazard value shown in Figures 1a and 1b is illustrated in Figure 4 map 1-1 where *PBH* is close to 100 when surrounding hazards are all large and near, but about 50 for the mixed hazard cluster in map 5-2. Decreasing weight for distance shown in Figure 1c is illustrated in Figure 4 maps 3-1 and map 6-1. The impact of lower weights for clustered dots shown in Figure 1d is illustrated in maps 6-2 and 8-2 that show colored zones of red and dark blue *PBH* are smaller when dots are closer.

Differences between *PBH* and mean susceptibility in Figure 4 show susceptibility was more aligned with some *PBH* estimates than others. Overall, the perceived chance of having elevated rhynium was less than *PBH* for maps with all red dots in the lower half. This difference was larger for map locations showing less compared to more location-based risk (low prevalence or farther distance). Smaller susceptibility beliefs compared to *PBH* may have been influenced by increasing uncertainty about the chance of having elevated rhynium with increasing distance to large values and also by the uncertainty generated by viewing preceding mixed hazard maps in which small values often occurred in close proximity to large values. It might also be partially explained by the tendency for people to have optimistic responses to threat information.[47]

Conversely, the perceived chance of having elevated rhynium was greater than *PBH* for maps with mixed dots in the lower half, especially for location within a mixed dot cluster. When values are mixed and distance is near, it appears viewers focused more on large than small hazards, suggesting the role of nearness to larger hazard values on perceived susceptibility. Susceptibility grew weaker and more aligned with *PBH* with increasing distance, consistent with a persistent trend that farther distance from riskier hazard values weakens risk beliefs.

For maps with no red dots, susceptibility was substantially larger than *PBH.* Recall *PBH* can be no greater than the largest value on the map, in this case zero. Despite no elevated hazard values on the map, many participants were unwilling to assign a zero chance of having an elevated value of rhynium at their location. The presence of red dots in the first viewed map may have primed non-zero susceptibility beliefs for later maps with all blue dots. However, this finding highlights a potential shortfall of the *PBH* model. Areas which are a certain distance from hazard measures may be more appropriately represented with values that represent hazard uncertainty. This is especially important for dot maps with few and homogeneous dots resulting in homogeneous *PBH* across the map when, in fact, the hazard status of many areas is uncertain.

4.5. Limitations

The generalizability of results is limited by the contrived nature of study maps (manipulated dots and fictitious substance) and the undergraduate sample. The lack of personal relevance for private well hazards among college students together with potentially greater numerical abilities may have fostered a more analytical response to study maps compared to a target population of residents with a private well. In addition, prior knowledge and experience attenuate the influence of visual features on cognition,[30] therefore map attributes are likely to have stronger influences among college students because many lack prior knowledge and experience with private wells. A training effect over the six map sequence may have influenced beliefs for later maps. Maps varied in the degree to which un-manipulated content was held constant for different assigned locations and introduced error for comparing the influence of some map attributes. Finally, we can only speculate as to how information was processed or noticed.

4.6 Implications for Research and Practice

Although results suggest the *PBH* model may be improved by accounting for map locations with uncertain risk status and categorical aspects of map attributes, more research is needed to inform further revisions. This research should test the predictive impact of *PBH* on risk beliefs using more realistic looking maps, representative participants, and participants' perceived home location rather than assigned locations since personal relevance has a role in the interpretation of hazard proximity.[10] Research is also needed to study the potential influences of: (1) dot prevalence and dot clusters to examine how areas of intensive testing influence beliefs independent of hazard values, (2) the use of symbolic risk colors on the impact of hazard value, (3) different map scales and sizes of depicted geographic area on the

NIH-PA Author Manuscript

NIH-PA Author Manuscript

impact of proximity, (4) user characteristics such as numeracy and prior beliefs, (5) different types of risk information and maps, and (6) how risk beliefs mediate the influence of map attributes or *PBH* on protective behavior within a context of viewer characteristics.

The contrived nature of the maps and undergraduate sample constrain our ability to make recommendations for practice. Generally speaking, those who use dot maps to convey risk information to the public should be aware that viewers' perceived distance to different amounts of risk will influence derived risk beliefs, and that nearness to elevated risks and location within elevated or mixed risk clusters will be especially influential.

4.7 Conclusions

Susceptibility (a specific rather than global belief) was most strongly and consistently correlated with *PBH* and is consistent with the proposition that increasing hazard intensity increases one's beliefs of susceptibility to a hazard. Attributes interact to influence derived meaning. Notably, distance, including location inside to distance outside of a hazard cluster, had stronger effects for large than small or mixed values, perhaps due to the personal relevance of nearness to larger hazards and the use of red to symbolically convey “unsafe” hazard values. Participants' common sense assumptions that proximity to unsafe hazards increases risk would support these findings. Location within clustered hazard values had a substantial impact on risk beliefs. *Gestalt Laws* and factors that explain how a figure is visually discriminated against a background suggest how clusters may have been perceived as an area of elevated risk rather than discrete points. The perception of being surrounded by risk may heighten risk beliefs. Other map attributes (prevalence, angle, cluster density) influenced beliefs, but had substantially smaller effects.

Study results, especially those for combined maps, indicate our simple *PBH* model performed quite well compared to map attributes. *PBH* is advantageous because it combines the influence of attributes into a single estimate. We developed the *PBH* model to study how some types of risk maps influence risk beliefs and protective behavior based on viewers' perceived map locations. Further work is needed to assess the predictive value of the model in more realistic settings and for other hazards and types of maps.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

This study was supported by a grant from the UW-Madison School of Nursing *Center for Patient Centered Interventions* funded by National Institute of Health (NIH) grant P20-NR008987; a grant from the UW-Madison Graduate School; and grant 1UL1RR025011 from the Clinical and Translational Science Award (CTSA) program of the National Center for Research Resources, NIH (for editorial assistance). We also thank UW-Madison geography students Nathan Rehberg and Alvin Rentsch for assistance with maps and reviewers for helpful comments on the paper.

---

[10]This research should examine the accuracy of perceived location, factors that influence accuracy, and how accuracy impacts risk beliefs. Results from a pilot study indicated wide variance in locational accuracy and that landmarks and numeracy were related to locational accuracy.[(53)] Johnson and Monmonier recommend including landmarks to facilitate map orientation for maps designed to communicate environmental risk.[(54)] Another study found only about a third of coastal residents correctly identified their hurricane risk zone when provided with a map of these risk zones. However, accuracy of perceived risk zone was not correlated with behavioral intentions to evacuate the area.[(8, 9)]

Appendix

Appendix:

Risk Belief Variables

Belief concept	Survey Item	Response Categories
Numerical Susceptibility (%Ch >MCL) *	In your opinion, approximately what is the chance that your well has rhynium over the health-based MCL of 10 ppb?	11 (0 – 100%) “No chance” and “Certain” at each end
Susceptibility (Ch > MCL) *	What is the chance that your well has rhynium over the health-based MCL of 10 ppb?	5 (no chance – nearly certain)
Susceptibility: w/global belief (Ch problem) *	There is a good chance that my well has a rhynium problem.	6 (strongly agree-strongly disagree)
Susceptibility: w/global belief (Ch unsafe) *	There is a good chance my well has unsafe water.	6 (strongly agree-strongly disagree)
Severity (Severity) *	Rhynium-related health problems are serious.	6 (strongly agree-strongly disagree)
Global belief (S problem) *	Rhynium is a serious problem for my well.	6 (strongly agree-strongly disagree)
Global belief (Concern) *	I am concerned about the risk of having rhynium in my well.	6 (strongly agree-strongly disagree)
Locational social comparison (Cp TS) *	In your opinion, what is your risk for having rhynium in your well water compared to other people who live in Springdale township?	7 (much less - much more)
Locational social comparison (Cp near) *	In your opinion, what is your risk for having rhynium in your well water compared to people who live near you?	7 (much less - much more)

* Variable name in Table 1

References

1. Lahr J, Kooistra L. Environmental risk mapping of pollutants: State of the art and communication aspects. Science of The Total Environment. 2010; 408(18):3899–907. [PubMed: 19939435]
2. The Royal Society. Risk: Analysis, perception, management. London: Royal Society; 1992.
3. National Research Council. Understanding risk: Informing decisions in a democratic society. Washington D. C.: National Academy Press; p. 1996
4. Severtson DJ, Vatovec C. The theory-based influence of map features on risk beliefs: Self-reports of what is seen and understood for maps depicting an environmental health hazard. Journal of Health Communication. In press.
5. Brody SD, Highfield W, Alston L. Does location matter?: Measuring environmental perceptions of creeks in two San Antonio watersheds. Environment and Behavior, 2004. Mar 1; 2004 36(2):229–50.
6. Lindell MK, Hwang SN. Households' perceived personal risk and responses in a multihazard environment. Risk Analysis. 2008; 28(2):539–56. [PubMed: 18419668]
7. Poortinga W, Cox P, Pidgeon NF. The perceived health risks of indoor radon gas and overhead powerlines: A comparative multilevel approach. Risk Analysis. 2008 Feb; 28(1):235–48. [PubMed: 18304120]
8. Zhang Y, Prater CS, Lindell MK. Risk Area Accuracy and Evacuation from Hurricane Bret. Natural Hazards Review. 2004; 5(3):115–20.
9. Arlikatti S, Lindell MK, Prater CS, Zhang Y. Risk Area Accuracy and Hurricane Evacuation Expectations of Coastal Residents. Environment and Behavior. 2006 Mar 1; 38(2):226–47.
10. Downey L. Environmental racial inequality in Detroit. Social Forces. 2006; 86(2):771–96.

11. Sicotte D, Swanson S. Whose risk in Philadelphia? Proximity to unequally hazardous industrial facilities. Social Science Quarterly. 2007 Jun; 88(2):515–34.
12. Health RL, Seshadri S, Lee J. Risk communication: A two-community analyasis of proximity, dread, trust, involvement, uncertainty, openness/accessibility, and knowledge on support/opposition toward chemical companies. Journal of Public Relations Research. 1998; 10(1):35–56.
13. Pinker, S. A theory of graph comprehension. In: Freedle, R., editor. Artificial intelligence and the future of testing. Hillsdale, NJ: Lawrence Erlbaum Associates, Publishers; 1990. p. 73-126.
14. Cleveland WS, McGill R. Graphical perception: Theory, experimentation, and application to the development of graphical methods. Journal of the American Statistical Association. 1984; 79(387):531–54.
15. Itti, L. Visual salience. 2007. [updated 1/16/2010, June 4, 2010]; Available from: http://www.scholarpedia.org/article/Visual_salience
16. DeLoache JS. Early understanding and use of symbols: The model model. Current Directions in Psychological Science. 1995; 4(4):109–13.
17. Griffith LJ, Leonard SD. Association of colors with warning signal words. International Journal of Industrial Ergonomics. 1997; 20:317–25.
18. Brewer CA. Basic mapping principles for visualizing cancer data using geographic information systems (GIS). American Journal of Preventive Medicine. 2006; 30(2, Supplement 1):S25–S36. [PubMed: 16458787]
19. Baird, JC. Psychophysical analysis of visual space. New York: Pergomon Press; 1970.
20. Yantis S. How visual salience wins the battle for awareness. Nature Neuroscience. 2005; 8(8):975–7.
21. Florence D, Geiselman R. Human performance evaluation of alternative graphic display symbologies. Perceptual and Motor Skills. 1986; 63:399–406.
22. Ware, C. Information visualization: Perception for design. San Francisco: Morgan Kaufmann; 2000.
23. Shepard, D., editor. A two dimensional interpolation function for regularly spaced data; National Conference of the Association for Computing Machinery; 1968; Princeton, NJ.
24. Shepard, D. Computer mapping: The SYMAP interpolation algorithm. In: Gaile, GL.; Willmott, CJ., editors. Spatial statistics and models. Dordrecht, Holland: D Reidel; 1984. p. 133-45.
25. Willmott CJ, Rowe CM, Philpot WD. Small-scale climate maps: A sensitivity analysis of some common assumptions associated with grid-point interpolation and contouring. American Cartographer. 1985; 12:5–16.
26. Surfer. 9. Golden, CO: Golden Software, Inc; 2009. Golden Software.
27. ESRI. ArcGIS Version 9.3. Redlands, CA: 2008.
28. Shen CY, Reed HL, Foley TA. Shepard's interpolation for solution-adaptive methods. Journal of Computational Physics. 1993; 106:52–61.
29. Zuppa C. Error estimates for modified local Shepard's interpolation formula. Applied Numerical Mathematics. 2004; 49:245–59.
30. Cook MP. Visual representations in science education: The influence of prior knowledge and cognitive load theory on instructional design. Science Education. 2006; 90(6):1073–91.
31. Reyna VF, Brainerd CJ. Fuzzy-trace theory: An interim synthesis. Learning and Individual Differences. 1995; 7(1):1–75.
32. Weinstein ND. Testing four competing theories of health-protective behavior. Health Psychology. 1993; 12(4):324–33. [PubMed: 8404807]
33. Weinstein ND. The precaution adoption process. Health Psychology. 1988; 7:355–86. [PubMed: 3049068]
34. Klein, WM.; Weinstein, ND. Social comparison and unrealistic optimism about personal risk. In: Buunk, BP.; Gibbons, FX., editors. Health, coping, and well-being: Perspectives from social comparison theory. Hillsdale, NJ: Lawrence Erlbaum; 1997. p. 25-61.
35. Weinstein ND, Sandman PM. Predicting homeowners' mitigation responses to radon test data. Journal of Social Issues. 1992; 48(4):63–83.

36. Nelson W, Reyna VF, Fagerlin A, Lipkus I, Peters E. Clinical implications of numeracy: Theory and practice. Annals of Behavioral Medicine. 2008; 35:261–74. [PubMed: 18677452]

37. de Hevia MD, Vallar G, Girelli L. Visualizing numbers in the mind's eye: The role of visuo-spatial processes in numerical abilities. Neuroscience and Biobehavioral Reviews. 2008; 32:1361–72. [PubMed: 18584868]

38. Zikmund-Fisher BJ, Smith DM, Ubel PA, Fagerlin A. Validation of the subjective numeracy scale: Effects of low numeracy on comprehension of risk communications and utility elicitations. Medical Decision Making, 2007. Oct 1; 2007 27(5):663–71.

39. SPSS Inc. PASW for Windows. 18.0. Chicago, IL: 2009.

40. Cresswell, JW.; Plano, Clark VL. Designing and conducting mixed methods research. Thousand Oaks, CA: Sage Publications; 2006.

41. MacEachren, AM. How maps are seen How maps work: Representation, visualization, and design. New York: The Guilford Press; p. 1995p. 51-149.

42. Eriksen CW. Location of objects in a visual display as a function of the number of dimensions on which the objects differ. Journal of Experimental Psychology. 1952; 44(1):56–60. [PubMed: 14955591]

43. Rogers JE, Groop RE. Regional portrayal with multi-pattern color dot maps. Cartographica. 1981; 18(4):51–64.

44. Slovic P. Trust, emotion, sex, politics, and science: Surveying the risk-assessment battlefield. Risk Analysis. 1999; 19(4):689–701. [PubMed: 10765431]

45. Maier SR. Numeracy in the newsroom: A case study of mathematical competence and confidence. Journalism & Mass Communication Quarterly, 2003. Winter;2003 80(4):921–36.

46. Yao X, Thill JC. Spatial queries with qualitative locations in spatial information systems. Computers, Environment and Urban Systems. 2006; 30(4):485–502.

47. Weinstein ND. Unrealistic optimism about susceptibility to health problems: Conclusions from a community-wide sample. Journal of Behavioral Medicine. 1987; 10(5):481–500. [PubMed: 3430590]

48. Slocum, TA. Thematic cartography and geographic visualization. 3rd. Prentice Hall; 2005.

49. U.S. Environmental Protection Agency. Ground water & drinking water. 2010. [July 22, 2010]; Available from: http://www.epa.gov/safewater/index.html

50. U.S. Environmental Protection Agency. Private drinking water wells. 2010. [July 22, 2010[; Available from: http://www.epa.gov/safewater/privatewells/index2.html

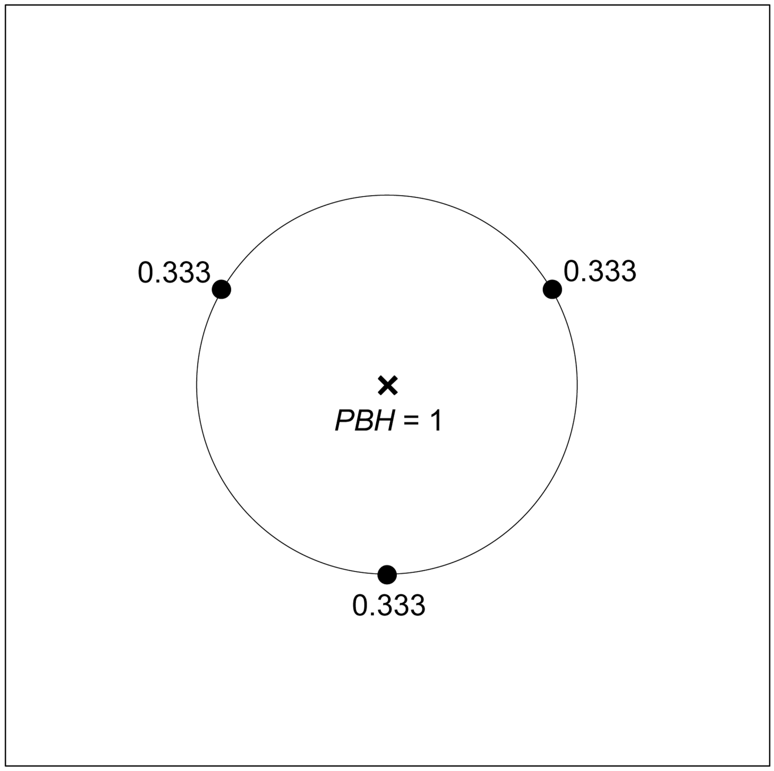
51. Fagerlin A, Zikmund-Fisher BJ, Ubel PA, Jankovic A, Derry HA, Smith DM. Measuring numeracy without a math test: Development of the subjective numeracy scale. Medical Decision Making, 2007. Oct 1; 2007 27(5):672–80.

52. Slocum, TA. Choropleth mapping Thematic cartography and geographic visualization. 2nd. Prentice Hall; p. 2005p. 250-70.

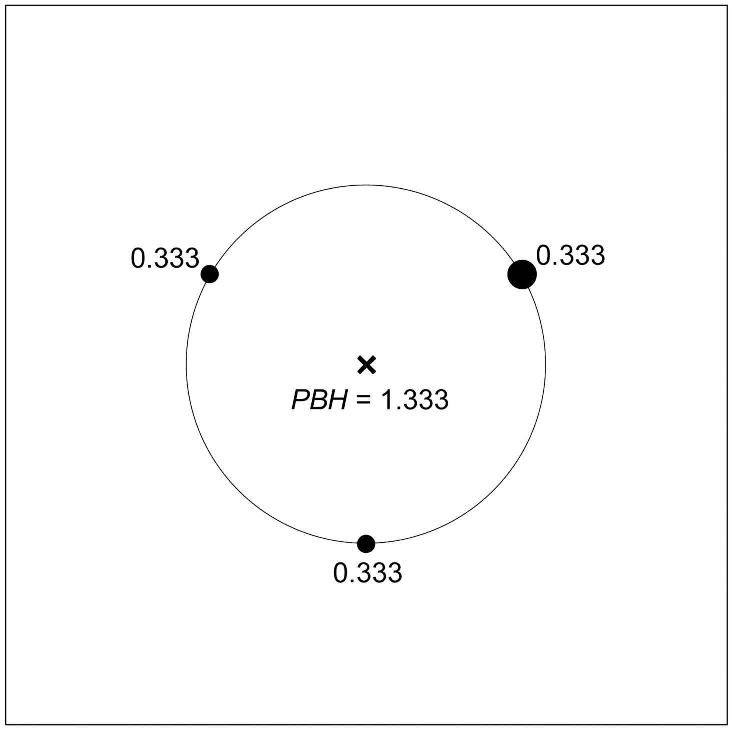
53. Severtson DJ. Predictors of locational map accuracy: Implications for designing maps that communicate environmental risk. In review.

54. Monmonier, M.; Johnson, BB. Design guide for environmental maps. 1997. Available from: http://tinyurl.com/6k2gq2k

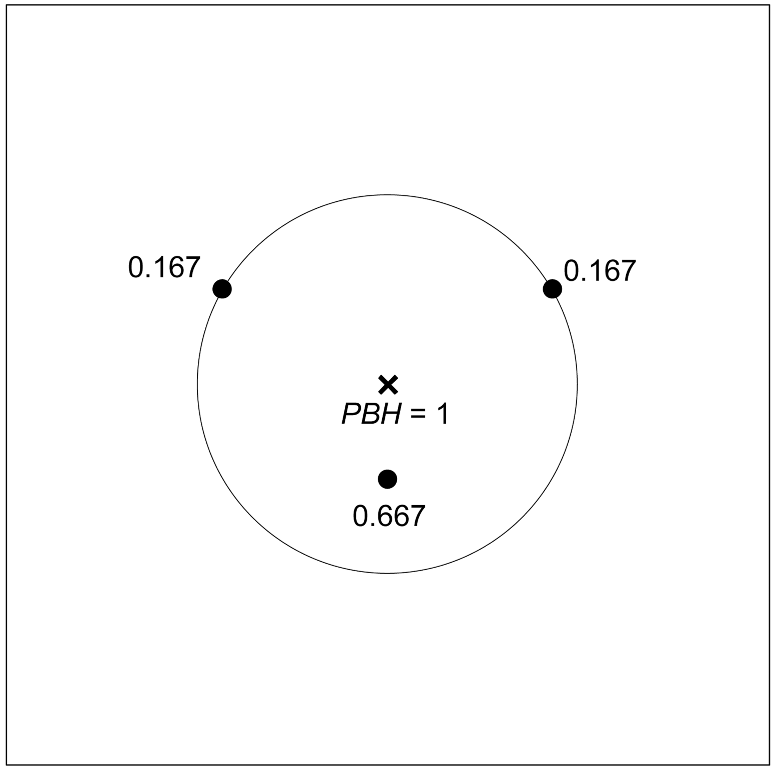
1a



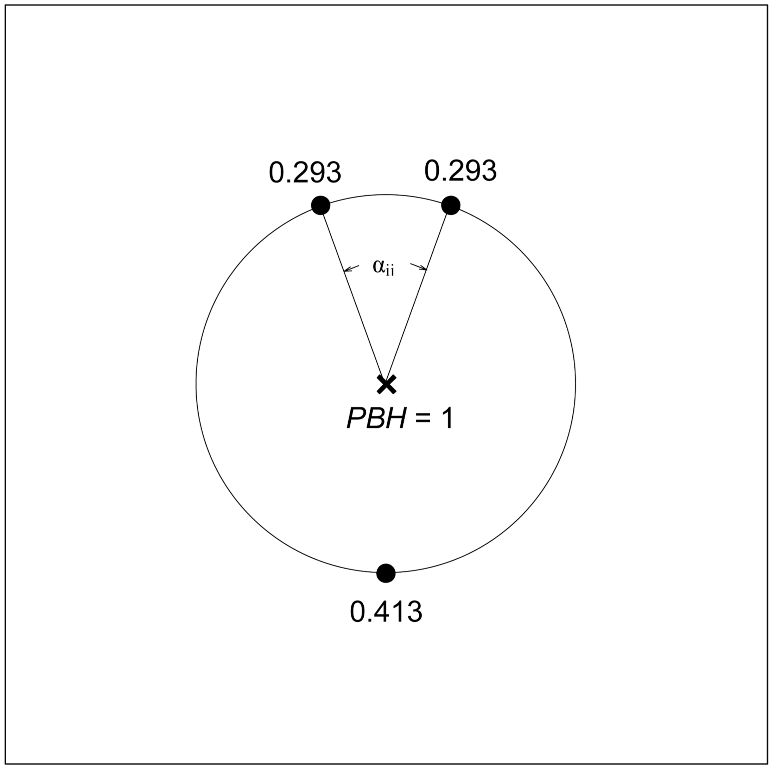
1b



1c



1d



1e

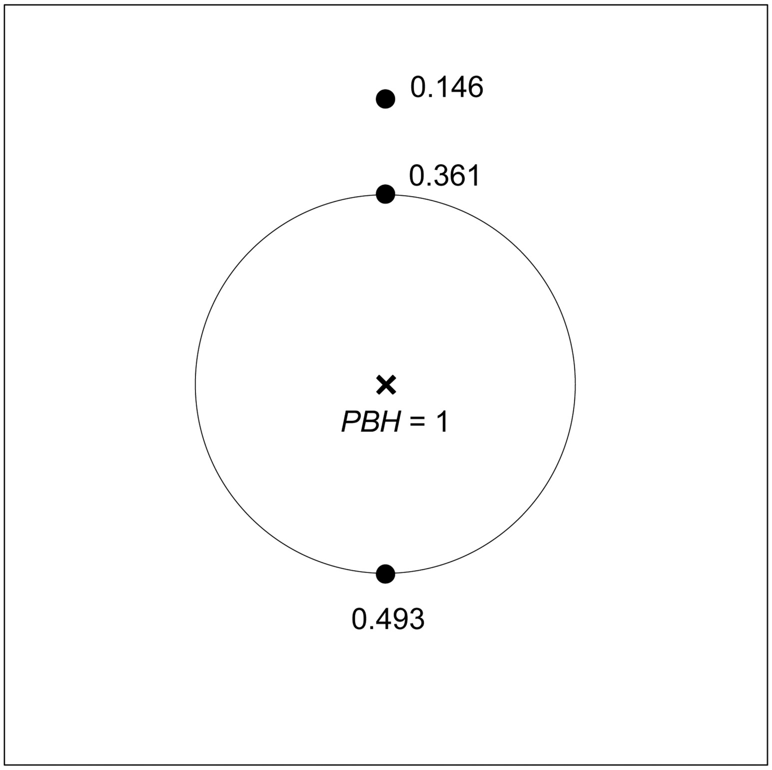


Figure 1.
Numerical weights (W_i) and computed *PBH* in hazard model. Black dots depict hazards surrounding a subject's location (black X). Hazard values H_i are indicated by dot size. All hazards have a value of 1 except in (b), where one hazard equals 2. In (a) and (b) all dots contribute equally to *PBH* because of their uniform distance and spacing. *PBH* is higher in (b) owing the larger value of one dot. In (c) the proximity of the bottom dot gives it a larger weight than the others, whereas in (d) the bottom dot has more weight because it is spatially isolated. That is, the top dots form a cluster and individually count less than the bottom dot. Diagram (e) shows how increasing distance and decreasing angle of separation capture the shadowing effect.

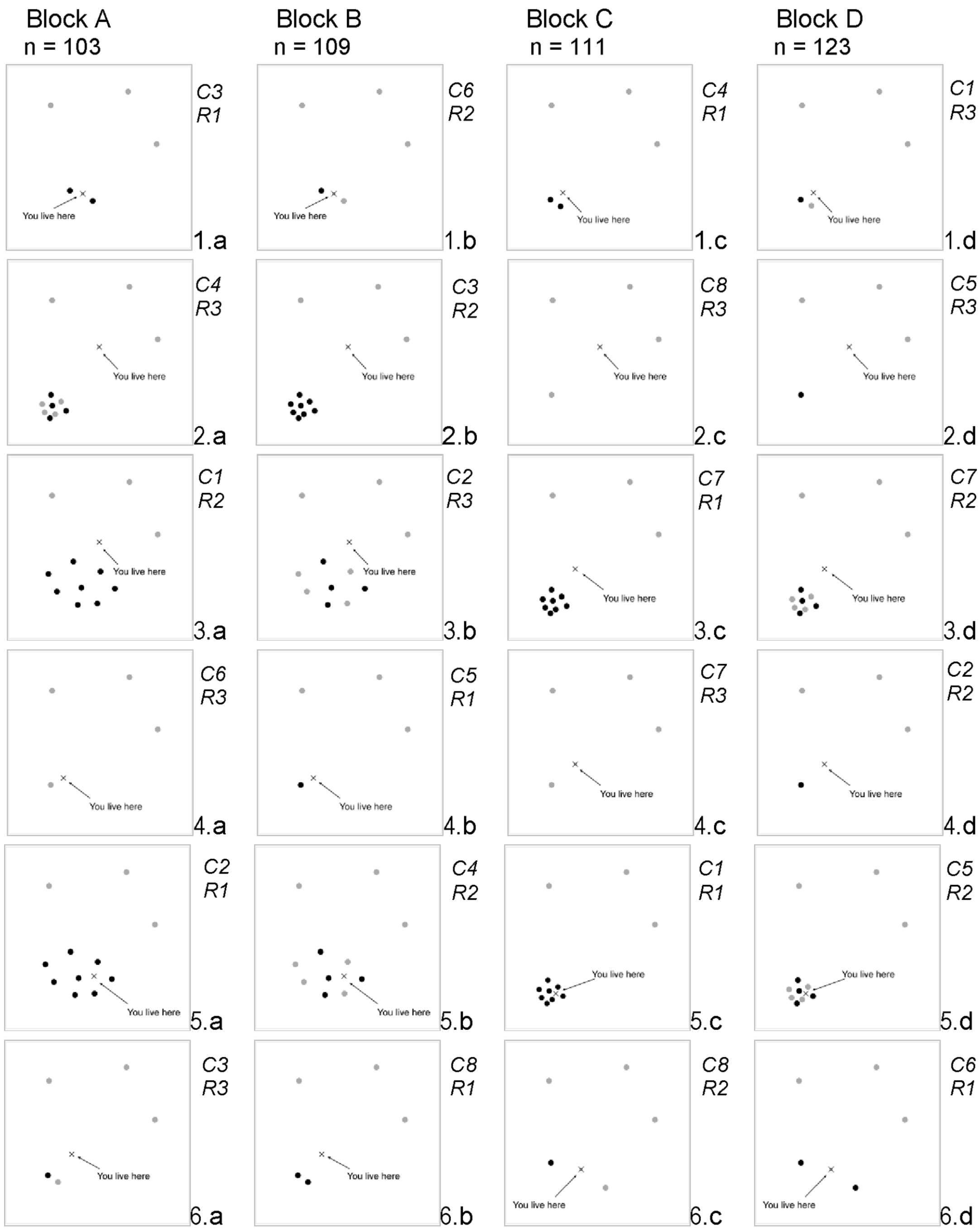


Figure 2.

Map blocks with labels (1.a – 6.d) at lower right of each map. For the study maps used in the survey the black dots were red (high arsenic value) and the light grey dots were blue (low arsenic value).

Note: *C* and *R* refer to the column and row numbers (upper right of each map) in Figure 4

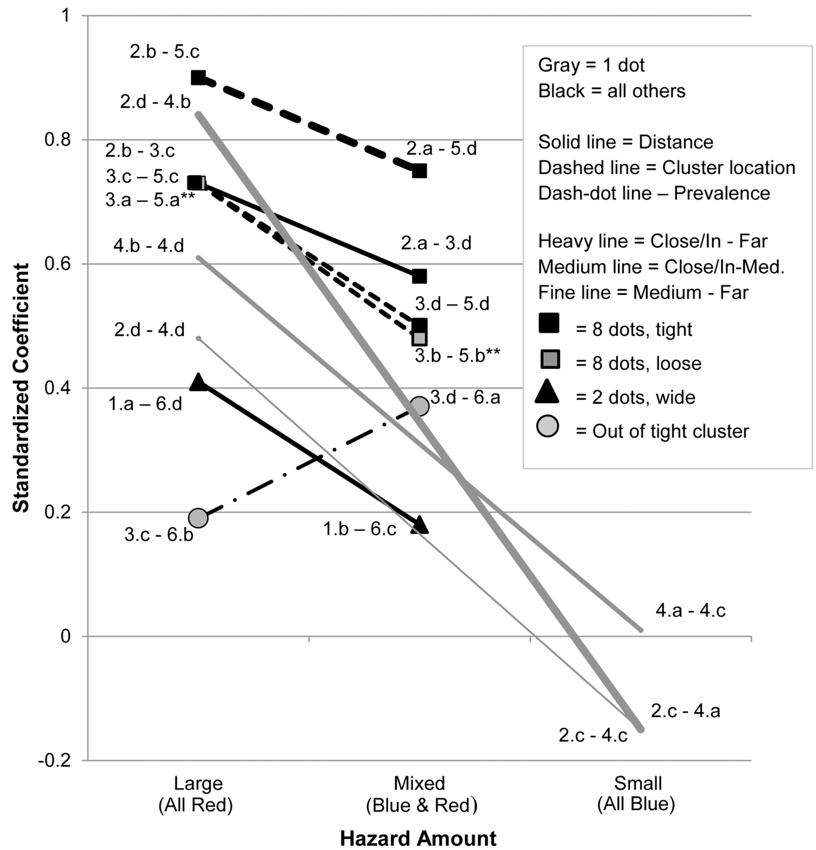
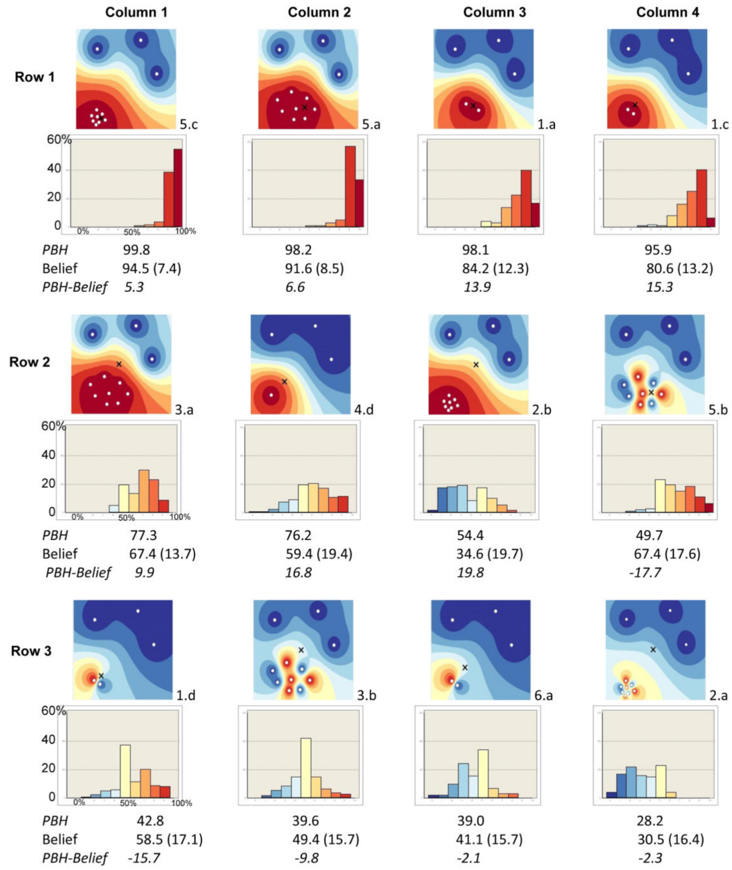


Figure 3. Standardized regression coefficients* for maps with significant interaction effects

* Maps used in each regression are labeled on the graph (map labels from Figure 2)

** The interaction between cluster location and hazard value was not significant. This pair was included to Illustrate the similarity across loose and tight clusters.



Column 1
Column 2
Column 3
Column 4
Row 1
5.c
5.a
1.a
1.c
60%
40
20
0
0%
50%
100%
PBH 99.8 98.2 98.1 95.9
Belief 94.5 (7.4) 91.6 (8.5) 84.2 (12.3) 80.6 (13.2)
PBH-Belief 5.3 6.6 13.9 15.3
Row 2
3.a
4.d
2.b
5.b
PBH 77.3 76.2 54.4 49.7
Belief 67.4 (13.7) 59.4 (19.4) 34.6 (19.7) 67.4 (17.6)
PBH-Belief 9.9 16.8 19.8 -17.7
Row 3
1.d
3.b
6.a
2.a
PBH 42.8 39.6 39.0 28.2
Belief 58.5 (17.1) 49.4 (15.7) 41.1 (15.7) 30.5 (16.4)
PBH-Belief -15.7 -9.8 -2.1 -2.3

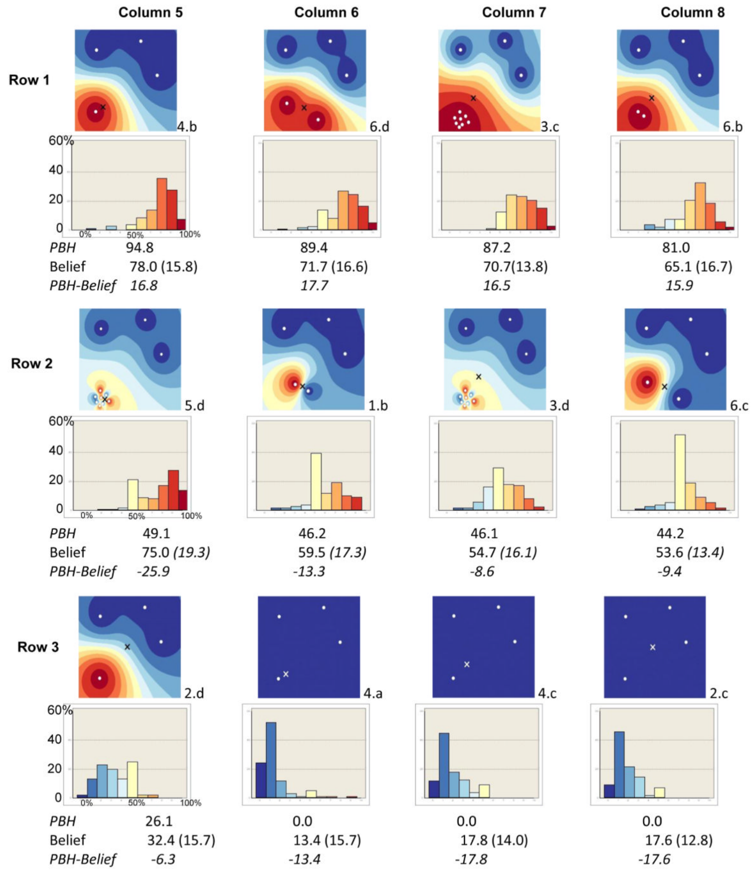


Figure 4. Maps of PBH, graphs* of susceptibility frequencies, and PBH and mean susceptibility values**

*x axis = percent chance categories (11 categories), y axis = frequencies (axis labels on 1st graph in each row)

** below each graph are: *PBH* values for the assigned map location, means (standard deviations) for susceptibility beliefs, and the difference between *PBH* and mean susceptibility (*PBH* minus mean susceptibility)

NIH-PA Author Manuscript

NIH-PA Author Manuscript

Table I

Partial Correlations[a] Between Risk Beliefs and Attributes or *PBH*: Ranked from Most[b] to Least by Risk Belief Variables[c] (columns) and by Attributes/PBH (rows)

	Partial Correlations Ranked by Belief Variables[c]									*PBH*[d]
Attributes & *PBH*	First	Second	Third	Fourth	Fifth	Sixth	Seventh	Eighth	Ninth	
PBH(*24 maps*)[e]	**%Ch >MCL .756**	**Ch > MCL .720**	**Ch problem .705**	**Ch unsafe .682**	*S problem .649*	Cp TS .592	*Concern .569*	Cp near .271	Severity .132	-
Cluster location (*10 maps*)[e]	**Ch > MCL .686**	**%Ch >MCL .683**	Cp TS .678	**Ch problem .648**	**Ch unsafe .627**	*S problem .608*	*Concern .479*	Cp near .369	Severity .149	.440
Hazard value (*24 maps*)[e]	**%Ch >MCL .571**	**Ch problem .538**	**Ch > MCL .532**	**Ch unsafe .525**	*S problem .512*	*Concern .468*	Cp TS .380	Cp near .186	Severity .092	.871
Distance (*16 maps*)[e]	Cp TS .559	**Ch > MCL .447**	**%Ch >MCL .445**	**Ch problem .422**	**Ch unsafe .397**	*S problem .370*	*Concern .285*	Cp near .226	Severity .052 *	.374
Angle (*8 maps*)[e]	Cp TS .152	**%Ch >MCL .140**	**Ch problem .139**	Cp near .134	**Ch > MCL .133**	**Ch unsafe .122**	*S problem .107***	*Concern .091***	Severity .039ns	.103 **
Cluster density (*8 maps*)[e]	Cp TS .113	**%Ch >MCL .107** **	*S problem .088***	**Ch > MCL .082** *	*Concern .066+*	**Ch unsafe .064** +	**Ch problem .060** +	Cp near .028 *	Severity .037ns	.094 **
Prevalence (*8 maps*)[e]	Cp TS -.122	Cp near -.070 **	**Ch unsafe .057** *	**Ch problem .049+**	**Ch > MCL .043ns**	**%Ch >MCL .040ns**	Severity .034ns	*Concern .023ns*	*S problem .016ns*	-.043ns

[a]Controlling for gender, numeracy, drinking water use, and prior residence. Correlations significant at $p < .001$ unless noted:

+ $p < 10$,

* $p < .05$,

** $p < .01$, ns (non-significant)

[b]Shaded variable most consistently and strongly correlated with attributes or *PBH* (underlined variable 2nd most correlated).

[c]Variables are in the appendix table; Ch = chance, S = serious, Cp = compare, TS = township, MCL = maximum contaminant level (a term for a drinking water standard). Bolded variables pertain to susceptibility beliefs, italicized variables pertain to global beliefs, underlined is compared to township (Cp TS).

[d]The last column provides Pearson correlation between *PBH* and attribute

[e]Maps included in each analysis are provided in Table 2 column headers using Figure 2 map labels

Table II

Stepwise Regression for Attribute Subsets: Standardized Beta Coefficients, Adjusted R^2, R^2 change, R^2 ratios

		Attribute Subsets and Number of Observations per Subset															
		Distance Maps[a]						Prevalence Maps[a]			Angle Maps[a]		Cluster Location Maps[a]			Cluster Density Maps[a]	
Attributes *(manipulated hazards)*		2.c,d 4.a,b	4.a-d	2.c,d[b] 4.c,d	1.c,d 6.a,b	1.a,b 6.c,d	2.a,b 3.c,d	1.a,b[b] 5.a,b	6.a,b 3.c,d	3.c,4.d 6.b	1.a-d	6.a-d	2.a,b 5.c,d	3.a,b[b] 5.a,b	3.c,d[b] 5.c,d	5.a-d	3.a-d
		n=446	n=446	n=446	n=442	n=442	n=446	n=444	n=446	n=336	n=446	n=446	n=446	n=444	n=468	n=446	n=446
Distance[c]		**C,F**	**C,M**	**M,F**	**C,M**	**C,M**	**M,F**	C	M	M	C	M	I/F	I/M	I/M	Mix	Mix
Prevalence		1	1	1	2	2	8	**2,8**	**2,8**	**1,2,8**	2	2	8	8	8	8	8
Angle, Cluster Loc.Density[c]		-	-	-	N	W	O/T	I/L	N/O/T	N/O/T	**N,W**	**N,W**	**I-O**/T	**I-O**/L	**I-O**/T	**L-T**/I	**L-T**/O
Regression 1 or 2 *Covariates* – Step 1	R^2	0	.01	.01	.03[d]	.01	.03[d]	0	.04[d]	.01	.01	.04[d]	.03[d]	.0	0	0	0
Regression 1 *PBH* - Step 2	R^2	.74	.72	.54	.38	.35	.35	.41	.33	.08	.40	.34	.48	.42	.28	.35	.26
R^2 change	ΔR^2	.74***	.71***	.53***	.35***	.34***	.32***	.41***	.30***	.08***	.40***	.30***	.45***	.42***	.28***	.35***	.26***
PBH	β	**.86*****	**.85**	**.74*****	**.60*****	**.59*****	**.57*****	**.65*****	**.55*****	**.28*****	**.63*****	**.55*****	**.67*****	**.66*****	**.53*****	**.60*****	**.52*****
Regression 2 *Attributes* – Step 2	R^2	.56***	.70	.46	.46	.38	.47	.44	.35	.07	.40	.37	.72	.51	.49	.37	.26
R^2 change	ΔR^2	.56***	.69***	.45***	.43***	.37***	.45***	.44***	.32***	.06***	.40***	.32***	.69***	.51***	.49***	.37***	.26***
Hazard value	β	**.66*****	**.83*****	**.60*****	**.55*****	**.57*****	**.23*****	**.64*****	**.52*****	-	**.62*****	**.52*****	**.20*****	**.51*****	**.45*****	**.60*****	**.51*****
Attribute[e]	β	**.37*****	**.12*****	**.31*****	**.38*****	**.26*****	**.64*****	**.20*****	**.24*****	**.25*****	**.08***	**.23*****	**.82*****	**.51*****	**.54*****	**.14*****	**.11****
Step 2 R^2 ratio *(PBH/Attribute)*		**1.32**	**1.03**	**1.17**	**0.83**	**0.92**	**0.74**	**0.93**	**0.94**	**1.14**	**1.00**	**0.92**	**0.67**	**0.83**	**0.57**	**0.95**	**1.00**
Regression 2 + *PBH* - Step 3	R^2	.74	.73	.54	.46	.38	.49	.44	.35	.08	.40	.37	.73	.52	.49	.37	.26
R^2 change	ΔR^2	.18***	.03***	.08***	0	.01**	.02***	0	.01*	.01*	0	.01+	.02***	.01*	0	0	0
Regression 2 Step 3 + *attribute interaction*	R^2	.74	.73	.54	.46	.38	.49	.44	.35	-	.40	.37	.73	.52	.49	.38	.26
R^2 change	ΔR^2	.18***	.03***	.08***	0	.01**	.02***	0	.01*	-	0	.01+	.02***	.01*	0	0	0

[a]Maps for each attribute subset are specified in the row below using map labels from Figure 2. For each subset, attributes that vary are bolded.

[b]Analysis within and across block subgroups (participants within blocks viewed both maps)

[c]C = close, M = medium, F = far, N = narrow, W = wide, I = inside, O = outside, T = tight, L = loose

[d]Step 1 β values for gender ranged from .16*** to .20***; β values for numeracy ranged from -.08^{+} to .09*

[e]The second attribute is specified in the column header (Distance, Prevalence, Line Location, Cluster Location, Density)

$^{+}$ $p < .10$,

* $p < .05$*,

** $p < .01$,

*** $p < .001$

Table III

Stepwise Regression for Combined Maps: Standardized Beta Coefficients, Adjusted R^2, R^2 change, R^2 ratios

		All Maps except 5s[a] (*no inside cluster maps*) (n=2230)	**All Maps (n = 2676)**
Regression 1 or 2 Step 1 Covariates	R^2	.01	.01
Regression 1 Step 2 - PBH	R^2	.58	.57
R^2 change	ΔR^2	*.57****	*.57****
PBH	β	**.76** ***	**.75** ***
Regression 2 Step 2 - Attributes	R^2	.54	.60
R^2 *change*	ΔR^2	*.53****	*.59****
Hazard value (H)	β	**.57** ***	**.52** ***
Distance[b] (D)	β	**.45** ***	**.50** ***
Prevalence (P)	β	**.11** ***	**.11** ***
Step 2 R^2 ratio (PBH/attribute)		**1.07**	**0.95**
Regression 2: Step 3a[c]-*PBH*	R^2	.61	.65
R^2 *change*	ΔR^2	*.07****	*.05****
Regression 2: Step 3b[c]-DxH	R^2	.61	.63
R^2 *change*	ΔR^2	.07 ***	.03 ***
Regression 2: Step 3c[c] - PxH	R^e	.55	.60
R^2 *change*[d]	ΔR^2	*.007****	*.003****
Regression 2: Step 3d[c] - DxHxP	R^2	.55	.60
R^2 *change*[d]	ΔR^2	*.011****	*.001**

[a] Map labels from Figure 2 maps

[b] Distance recoded to include cluster location

[c] For Steps 3a – 3d, only one of these variables was added at a time.

[d] More precise values to show the variation across these smaller interaction effects

+ $p < .10$,

* $p < .05$*,

** $p < .01$,

*** $p < .001$