THE ROLE OF CARTOGRAPHIC INTERFACE COMPLEXITY ON SPATIAL DECISION MAKING: A CASE STUDY IN THE NORTH AMERICAN HAZARDOUS WASTE TRADE

by

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One final note: Go Pack Go and On, Wisconsin!

TABLES AND FIGURES

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CHAPTER 1: INTRODUCTION AND SIGNIFICANCE

Digital interactive maps are part of our everyday lives: we use them for navigation on our smartphones, they enhance stories for online news sources, and they populate our social media timelines. The public has a favorable opinion of interactive maps and prefers them for a range of problem applications (Krygier and Reeves 1997). Interactivity is also essential for exploratory geographic visualization, where the purpose of the map is less for visual communication and more for visual thinking about complex problems (MacEachren 1994). Therefore, interactive map design is an important area of research needing increased attention, particularly for maps that support sophisticated reasoning about geographic problems (Thomas and Cook 2005). Proper interface design is essential to ensure that the *user interface* does not hinder the *user experience* (Roth 2015).

Yet, empirical evidence for effective interactive map design is limited in the literature, particularly in a context where the interactive maps support higher-level cognitive tasks, such as comprehension, reasoning, and decision making (e.g., Slocum et al. 2001, Andrienko et al. 2007, MacEachren 2015). With this research, I investigated aspects of a problem context believed to affect map-supported decision making: the complexity of the interface (Roth 2013) and the complexity of the decision (Crossland et al. 1995). Studying these topics contributes to the field of cartography and the related research thrusts of geovisualization, spatial decision support, and visual analytics, among others. Specifically, I sought answers to three research questions:

1. Does cartographic interface complexity influence the success of geographic decision making? If so, how?
2. Does geographic decision complexity influence the success of cartographic interface effectiveness for decision making? If so, how?
3. Is the influence of cartographic interface complexity and geographic decision complexity dependent upon the user's expertise with the domain topic and/or with interactive maps?

Does cartographic interface complexity influence the success of geographic decision making? If so, how?

Cartographers need guidance for balancing the complexity of their interface designs between simple, general-use systems with limited functionality and complex, expert-use systems with seemingly unbounded functionality. *Interface complexity* comprises two key components, *scope* and *freedom.* Interface scope is the number of interactive elements within the map, while interface freedom is the precision to which each map element can be adjusted (Harrower and Sheesley 2005, Cooper et al. 2007). Preliminary evidence suggests that interface complexity influences how well a user works with an interactive map, although it remains unclear if and when more or less complexity facilitates reasoning and in which decision making contexts (Davies 1998, Keehner et al. 2008). To simplify my research study design, I employed interface scope as an indicator of interface complexity to study its impact on spatial decision making. I evaluated two increasingly common design strategies for interface scope: a simple web "slippy" map including panning, zooming, and detail retrieval (see Tolochko 2016), and a more complex recommendation for information seeking adding filtering and overlay (from Shneiderman 1996).

Does geographic decision complexity influence the success of interface effectiveness for decision making? If so, how?

Map user tasks can range from simple, *benchmark tasks*, such as feature identification and comparison, to more complex spatial *decisions* requiring sophisticated reasoning to work through multiple criteria to arrive at a viable outcome. Cartographers need interface design strategies that better support the cognitive functions (i.e., learning, memory, reasoning) involved in the decision-making process for complex tasks (MacEachren 2015). As with interface complexity, *decision complexity* includes two components: the number of decision criteria and the number of potential decision outcomes (Crossland et al. 1995). While prior research has been conducted to understand the impact of the decision complexity on the decision-making process, there is limited research on the relevant effectiveness of interactive maps to facilitate this process for different decision complexities (Armstrong and Densham 1995, Crossland et al. 1995, Speier 2006). MacEachren (2015:4) identifies that empirical research is a key next step to understanding the use of maps as “cognitive artifacts”, or decision-making aids. In this research, I varied the number of decision criteria to understand the influence of decision complexity on spatial decision making using a case study of environmental justice issues in the transnational trade of hazardous waste. In North America, hazardous waste is treated as both a regulated environmental risk as well as a valuable commodity to processing and disposal facilities (Moore et al. 2017). Managing hazardous waste therefore presents a complex geographic decision that takes into account a number of criteria varying across individual sites.

Is the influence of cartographic interface complexity and geographic decision complexity dependent upon the user's expertise with the domain topic and/or with interactive maps?

Individual differences impact all map use, interactive or otherwise. *User expertise* is a combination of education (the amount of formal education the person has with the subject), experience (the amount of time the person has had with the subject), and familiarity (the self-proclaimed knowledge of the subject) (Roth 2009). Further, different kinds of expertise are needed for successfully using a complex interactive map versus successfully arriving at a complex geographic decision (Crossland et al. 1995). I recruited participants with different levels of expertise to determine the relationship of expertise to interface complexity and decision complexity.

I addressed these research questions using a mixed-methods approach. First, I conducted interviews with academic experts for insight into decision making regarding the North American hazardous waste trade. I then administered an online map survey, calibrated to results from the interviews and a preliminary pilot survey for ecological validity. The online map study followed a 2x2 factorial design with interface complexity and decision complexity as the independent variables while controlling for user expertise and other aspects of cartographic design (Montello and Sutton 2006). Due to the lack of empirical research on cartographic interface design—particularly in support of decision making—this study is both needed and timely. The results of this research contribute to both the science and practice of cartographic interaction, ultimately leading to better spatial decisions.

In Chapter 2, I review prior research about interface complexity, decision complexity, and user expertise. Then in Chapter 3, I describe my case study and research design for the online map survey. In Chapter 4, I present and discuss the results of the online map survey. Finally, in Chapter 5, I conclude with the design impacts and future directions from this research.

CHAPTER 2: LITERATURE REVIEW

The topics of cartographic interface complexity and geographic decision complexity are treated in a range of research thrusts in GIScience, including geovisualization, spatial decision support, and visual analytics, among others (e.g., Jankowski and Nyerges 2001, Thomas and Cook, 2005, Andrienko et al. 2007). In cartography, the topics of interface and decision complexity can be discussed within the context of the Cartography^3 framework outlining the complete solution space of the design and use of maps (MacEachren 1994) (Figure 1). The Cartography^3 framework centers on a continuum of map use from *visual thinking* (e.g., exploration of the problem space) to *visual communication* (e.g., final presentation of decision outcomes), exposing three dimensions or axes that express all map use contexts (DiBiase et al. 1992). These axes directly relate to my three research questions:

- Research Question #1: The amount of human-map interaction, ranging from simple to complex.
- Research Question #2: The map task, encapsulating higher-level decisions and their complexity.
- Research Question #3: The map user, primarily addressing the difference in user expertise.

Thus, the research project reported here directly addresses questions fundamental to exploratory geovisualization, and the intersections therein. Relevant themes and key gaps regarding each of the three axes are reviewed below to establish design considerations for interactive maps that support geographic decision making by a range of users.

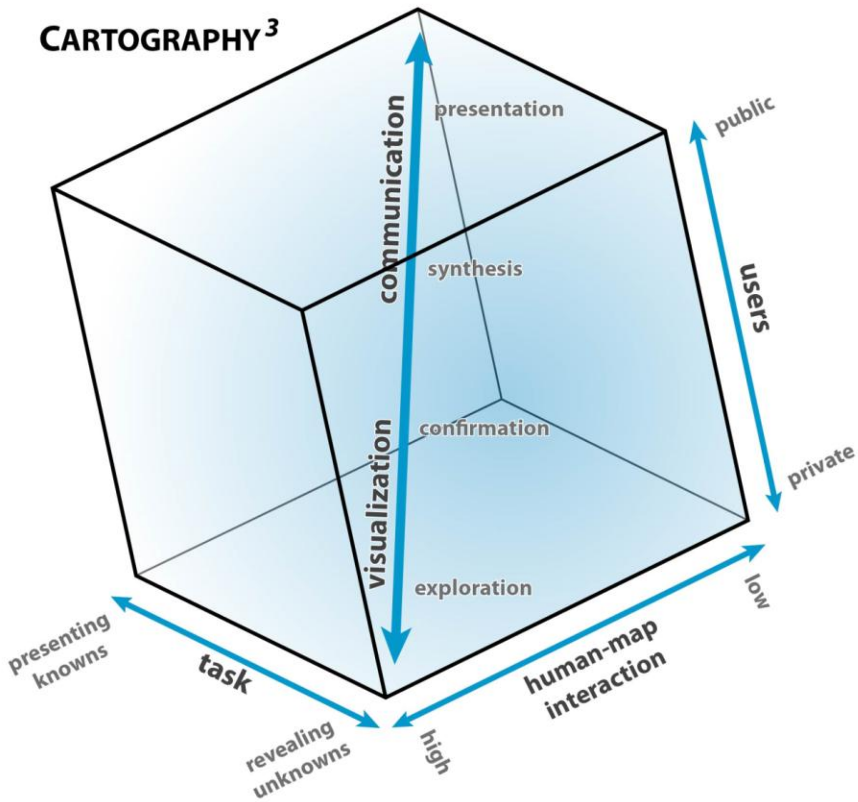


Figure 1. Cartography³ framework showing the three axes of map use (MacEachren 1994, updated in Roth 2013).

2.1: Cartographic Interaction and Cartographic Interface Complexity

Cartographic interaction describes the dialog between a human and a map mediated by a computing device (Roth 2012). MacEachren's (1994) first axis in the Cartography³ framework defines such map interactivity as a continuum from low to high based on the functional scope and freedom enabling the human and map to interact. Thus, not all interactive maps are alike, and instead vary on their level of cartographic *interface complexity* (as introduced in Chapter 1) (Harrower and Sheesley 2005, Cooper et al. 2007).

A number of scholars in cartography and related fields decomposed interactive functionality into basic *operator primitives*, or generic forms of interactive functionality, to characterize the scope of an interactive map (e.g., Becker and Cleveland 1987, Shepherd 1995, Buja et al. 1996, Chuah and Roth 1996, Shneiderman 1996, Dykes 1997, Dix and Ellis 1998, MacEachren et al. 1999, Masters and Edsall 2000, Keim 2002, Ward and Yang 2003, Edsall et al. 2008). An operator is considered as doing *work* when employed for the completion of an actual map task or decision, while an operator is considered *enabling* when employed in preparation for the task or decision (e.g., importing, exporting) (Davies 1998). Roth (2013) synthesizes these recommendations to provide a composite taxonomy of twelve work operator primitives for cartography: reexpress, arrange, sequence, resymbolize, overlay, pan, zoom, reproject, search, filter, retrieve, and calculate.

There are two emerging conventions for managing interface complexity in cartography. On the low end of interface complexity, it is now common in web cartography to implement "slippy" map operators: pan, zoom, and retrieve (Roth et al. 2014, Tolochko 2016). On the high end of interface complexity, the exploratory visualization literature has coalesced around Shneiderman's (1996) v*isual information seeking mantra* as a unifying recommendation for interactivity, which adds filtering, overlays, and other custom operators to the "slippy" pan, zoom, and retrieve to efficiently move from an overview representation of large datasets to specific details on demand. I therefore used these five work operator primitives from the Roth (2013) composite taxonomy (Table 1) to establish differences in interface complexity in the research reported here. In the following, I review existing empirical research for these five operator primitives.

Table 1. Evaluation of previous cartographic interaction studies examining operators used in this study, coded to Roth's (2013) work operator primitives. Positive indicates the respective operator was helpful for the specified task, negative means the operator was not helpful for the specified task, mixed means in some cases the operator was helpful for the task, and no discussion means that the authors did not discuss the effectiveness of the operator for the tasks. (* Indicates Decision Making Study)

Operator	Function	Interaction Study	Task	Operator Result
Zoom	Change the map scale	Crossland et al. (1995)*	Rank	No Discussion
		Davies (1998)	Classification	Positive
		Jankowski et al. (2001)*	Rank	No Discussion
		Rinner and Malczewski (2002)*	Site Selection	No Discussion
		Edsall (2003)	Recognition, Comparison, and Identification	No Discussion
		Robinson (2008)	Identify	No Discussion
		Roth and Harrower (2008)	Map Usability	No Discussion
		Zografos and Androutsopoulos (2008)*	Route Selection	No Discussion
		Jelokhani-Niaraki and Malczewski (2015)*	Site Selection	No Discussion
		Poplin (2015)	Draw and Identify	Negative
		Roth and MacEachren (2016)	Identify, Compare, Rank, Associate, and Delineate	Mixed
Pan	Move the map to view other locations	Davies (1998)	Classification	No Discussion
		MacEachren et al. (1998)	Identify and Compare	No Discussion
		Rinner and Malczewski (2002)*	Site Selection	No Discussion
		Edsall (2003)	Recognition, Comparison, and Identification	No Discussion
		Keehner et al. (2008)	Reasoning	Positive
		Roth and Harrower (2008)	Map Usability	No Discussion
		Zografos and Androutsopoulos (2008)*	Route Selection	No Discussion
		Jelokhani-Niaraki and Malczewski (2015)*	Site Selection	No Discussion
		Poplin (2015)	Draw and Identify	Mixed
		Roth and MacEachren (2016)	Identify, Compare, Rank, Associate, and Delineate	Negative
Retrieve	Obtain additional details about map features	Davies (1998)	Classification	Positive
		Andrienko et al. (2002)	Select and Identify	Positive
		Edsall (2003)	Recognition, Comparison, and Identification	No Discussion
		Roth and Harrower (2008)	Map Usability	No Discussion
		Roth and MacEachren (2016)	Identify, Compare, Rank, Associate, and Delineate	Mixed
Filter	Set the criteria by which map features are added or removed from the map	MacEachren et al. (1998)	Identify and Compare	Positive
		Frank et al. (2000)*	Route Selection	No Discussion
		Jankowski et al. (2001)*	Rank	No Discussion
		Andrienko et al. (2002)	Select and Identify	Positive
		Rinner and Malczewski (2002)*	Site Selection	No Discussion
		Roth and MacEachren (2016)	Identify, Compare, Rank, Associate, and Delineate	Mixed
Overlay	Change the layers depicted on the map	Crossland et al. (1995)*	Rank	No Discussion
		Frank et al. (2000)*	Route Selection	No Discussion
		Jankowski et al. (2001)*	Rank	No Discussion
		Edsall (2003)	Recognition, Comparison, and Identification	No Discussion
		Roth and Harrower (2008)	Map Usability	No Discussion
		Zografos and Androutsopoulos (2008)*	Route Selection	No Discussion
		Jelokhani-Niaraki and Malczewski (2015)*	Site Selection	No Discussion
		Roth and MacEachren (2016)	Identify, Compare, Rank, Associate, Delineate	Mixed

Zoom

The *zoom* operator allows the user to change the scale of the map. Multiscale zooming is now included in most web maps and most interaction studies enable zooming between multiple levels of detail (Table 1). As introduced above, zooming is also an important transition component of Shneiderman's (1996) information seeking mantra. The zoom operator has been considered both an enabling and work operator, with zooming positively used to prepare for classification (Davies 1998). Zooming also is useful for identification, comparison, ranking, association, and delineation, making it applicable to a broad range of tasks. However, zooming is not always well-received by users. For example, providing free zooming across numerous scales can cause the user to become lost in the interface and lose context within the map (Roth and MacEachren 2016).

Pan

The *pan* operator gives the user the opportunity to move the center of the map to explore off-screen locations, and typically is required to browse the map after zooming into a subset of the total map extent. Like zooming, panning also has been investigated in multiple interaction studies (e.g., Davies 1998, Rinner and Malczewski 2002, Zografos and Androutsopoulos 2008, Poplin 2015; Table 1). Panning can be helpful for completing simple recognition, identification, and comparison tasks (e.g., Edsall 2003, Poplin 2015) and can effectively offload the user's cognition to the interactive map during more complex spatial reasoning (Keehner et al. 2008). However, panning can be misapplied during interaction, negatively effecting map use. For example, while multiscale maps require the pairing of panning with zooming, maps created solely to provide an overview do not need panning capabilities (Tolochko 2016). Further, users may not be aware of every way to pan when flexibility is provided (direct manipulation of the map, panning widgets, click-and-recenter on map features, etc.; Roth and Harrower 2008), and repeated panning through direct manipulation of the map itself can be a sign that the user is lost (Roth and MacEachren 2016). Poplin (2015) reported that users had mixed reactions to panning, with some finding it straightforward and helpful, with others finding it cumbersome, particularly when employed with other map-based interactions such as annotation.

Retrieve

The *retrieve* operator lets users obtain added details, usually in an information popup or a docked panel. This operator is treated less frequently in the literature on interactive maps than zooming and panning, but is still relatively common among interaction studies (e.g., Davies 1998, Andrienko et al. 2002, Edsall 2003; Table 1). Users increasingly expect detail retrieval on simple web maps, and retrieval can be useful for completing simple identification tasks (Davies 1998, Roth et al. 2014). This operator is also essential to finding insights in large datasets, as it is detail retrieval that concludes information seeking after viewing an overview first and then zooming and filtering into a potential subset of interest (Shneiderman 1996). Research suggests that users generally are successful in employing retrieve (Andrienko et al. 2002) and will apply the retrieve functionality to confirm a classification (Davies 1998) or comparison (Roth and MacEachren 2016) task. However, repeated use of retrieve can suggest a breakdown in Shneiderman's information seeking mantra, with users blindly applying retrieve to seek desired information in a large dataset rather than using alternative operators (such as filter, see below) to first reduce the visualized complexity (Roth and MacEachren 2016).

Filter

The *filter* operator enables the user to constrain a set of features depicted on the map by choosing which features to include or exclude based on predefined criteria. As introduced above, filtering is an essential component to Shneiderman's (1996) information seeking mantra in large datasets and has been treated in a number of interaction studies (e.g., MacEachren et al. 1998, Frank et al. 2000, Jankowski et al. 2001, Rinner and Malczewski 2002; Table 1). Accordingly, many exploratory visualization tools increase interface complexity to accommodate multiple ways of filtering during open exploration (Roth and MacEachren 2016). Several studies report that filtering at first can be perceived by users as a difficult operator to learn and use, with these same studies also suggesting that users improve in their efficiency and effectiveness in applying filtering as they learn and use the interface (MacEachren et al. 1998, Andrienko et al. 2002). However, Roth and MacEachren (2016) found that users at times employ filtering excessively, particularly for tasks such as identification, comparison, and ranking, showing a default to Shneiderman's information seeking mantra when the task or dataset do not require such a sophisticated sequence of interactions.

Overlay

The *overlay* operator allows the user to add additional and remove excess layers on the map. Overlay is common in GIS-based studies (e.g., Frank et al. 2000, Jankowski et al. 2001, Zografos and Androutsopoulos 2008; Table 1), as applications built with GIS software follow a metaphor of overlapping transparent sheets that pre-date digital technology (Goodchild 2010). Overlay has been studied infrequently in the online interactive mapping literature, despite the increasingly common ability to switch basemaps (an “under”-lay) and add new vector datasets atop the basemap, a combined set of functions known as “hamburger” cartography (Roth et al. 2014). Roth and MacEachren (2016) found that users applied overlay in both successful and unsuccessful interaction strategies, with no notable patterns across different sets of tasks.

2.2: Geographic Decision Complexity

MacEachren’s (1994) second axis relates to the map task, which can vary from basic map reading and interpretation to complex reasoning and decision making. As introduced above, benchmark tasks are simple tasks that have a correct answer. After summarizing tasks used in prior cartographic studies (e.g., Wehrend and Lewis 1990, Wehrend 1993, Zhou and Feiner 1998, Blok et al. 1999, MacEachren et al. 1999, Crampton 2002, Andrienko et al. 2003), Roth (2012, 2013) presents five benchmark task types calibrated to professional practice: *identify* (studying one object on the map), *compare* (finding similarities and differences in many objects on the map), *rank* (order objects based on a given attribute), *associate* (determine the relationship between two or more objects on the map), and *delineate* (identify clusters or patterns in the mapped features).

Alternatively, *decision making* is a higher-level cognitive process through which a person evaluates all available factors to make a choice about a given problem (Payne et al. 1993). While simple decisions have a correct decision outcome, many decisions rely on *optimality*, or ranking prospective solutions by how they minimize or maximize different contextual criteria (Einhorn and Hogarth 1981). Thus, decisions differ from benchmark tasks in that there may be multiple acceptable outcomes, each having a different degree of *correctness*. Decision science is moving away from assuming a single, correct answer and towards understanding the process that decision makers take to arrive at an optimal decision using a wide range of information.

Understanding the process for determining a decision solution has been examined through many decades of research on judgment and choice (e.g., Payne 1976, Einhorn and Hogarth 1981, Payne et al. 1993). A broad, three-part decision-making strategy was introduced to explain how decisions are made (Figure 2) (Simon 1960, seen in Dillon 1998, updated with Pirolli and Card 2005). During *information seeking*—used consistently with Shneiderman's (1996) mantra—the potential problem is examined to determine if a decision solution is needed. For geographic decision making, this may include foraging through an interactive map and other information sources for interesting insights about anomalies, outliers, clusters, etc. If a problem is identified, the decision maker begins the *sensemaking* stage to capture the problem context and all available alternatives. Here, previously collected insights are used as evidence to evaluate competing scenarios. *Action* is the final stage of this model where the actual decision is made after evaluation of all prior information gained. The decision, however, will not be successful unless the right kind and amount of information is collected throughout the decision-making process (Bhattacharjya et al. 2010).

Information Seeking (Identifying the Need)	**Sensemaking** (Determining Problem Context and Alternatives)	**Action** (Identify Best Route, Given Obtained Information)

Figure 2. Simon's (1960) Decision-Making Stages (adapted from Dillon 1998, modified with Pirolli and Card 2005).

The decision-making process is not without limits, however. Due to human cognitive limits, there is a "channel capacity" of information that humans can handle before becoming confused (Miller 1956: 2). Noted above, a further limit on decision making is that not every decision has an objectively correct answer. The goal of the decision maker is to identify the best option using all available information. For geographic decision making, interactive maps enable *spatial decision support* to develop, evaluate, and select a solution to a spatial problem (Jankowski and Nyerges 2001, Andrienko et al. 2007). Here, the decision maker offloads a part of the decision-making process onto the interactive map both to improve memory during reasoning—a strategy described as *distributed cognition*—and to automate evaluation of criteria using interaction operators (Jankowski et al. 2001, MacEachren et al. 2004). *Spatial decision support systems (SDSS)* are designed for this purpose of offloading the work from the user to the computer system, with a central interactive map as the primary visual supporting distributed cognition (e.g., Crossland et al. 1995, Coutinho-Rodrigues et al. 1997, Jankowski et al. 2001).

Just as all interactive maps are not alike, all decisions also are not alike. All decisions have a different information load or level of *geographic decision complexity*, defined previously as the number of criteria and the number of outcomes involved in a decision (Crossland et al. 1995, Jelokhani-Niaraki and Malczewski 2015). All types of spatial information contribute to the overall cognitive load, including physical locations (sites), decision criteria, and attributes (Jelokhani-Niaraki and Malczewski 2015). Decision tasks require decision makers to process that information load, which affects information processing (Einhorn and Hogarth 1981). The user can work with an interactive mapping application such as desktop GIS or a web map to prioritize decision criteria (one component of decision complexity) and evaluate alternative outcomes (the second component) to arrive at an informationally-informed decision (Armstrong and Densham 1995, Jankowski et al. 2001). Table 2 below shows the correlation of provided interaction operators with the type of spatial decision the user was asked to perform and amount of decision complexity, with results marked if the combined interface and decision complexity had a positive or negative outcome on the task.

Table 2. Relationship of interaction operators to decision level and complexity. Positive: no decision inconsistency means that the task results were the same across complexity levels, negative: decision inconsistency means that the task results were different across complexity levels, and no discussion means the authors did not discuss the impact of complexity levels on task results.

Study	Operator	Task Type	Complexity	Result
Crossland et al. (1995)	Zoom Overlay	Rank	5 vs. 10 Sites 3 vs. 7 Criteria	Positive: No Decision Inconsistency
Jankowski and Nyerges (2001)	Retrieve	Site Selection	8 vs. 20 Sites 3 vs. 11 Criteria	Positive: No Decision Inconsistency
Jankowski et al. (2001)	Zoom Filter Overlay	Distribution of Funds	2 Intervals 10 Criteria	No Discussion
Rinner and Malczewski (2002)	Pan Zoom Filter	Site Selection	3 Criteria	No Discussion
Zografos and Androutsopoulos (2008)	Pan Zoom Overlay	Finding Alternative Routes	12 Customers 5 Criteria	No Discussion
Jelokhani-Niaraki and Malczewski (2015)	Pan Zoom Overlay	Site Selection	5 Alternatives, 2 Attributes 10 Alternatives, 4 Attributes 15 Alternatives, 6 Attributes 20 Alternatives, 8 Attributes	Negative: Decision Inconsistency

There is a contradiction among previous empirical studies regarding the effect of increased geographic decision complexity on decision-making outcomes. While Jelokhani-Niaraki and Malczewski (2015) found that the more complex task, in terms of decision complexity, resulted in decision inconsistency for site selection decisions, Crossland et al. (1995) and Jankowski and Nyerges (2001) did not, with most studies not varying decision complexity (decision complexity did not change throughout the study) or only discussing it as a potential issue (e.g., Jankowski et al. 2001, Rinner and Malczewski 2002, Zografos and Androutsopoulos 2008). Accordingly, additional research is needed to fully understand the influence of decision complexity on geographic outcomes.

Further, there is an incomplete body of work informing the design of interactive maps for generating knowledge about a decision problem. The operator-based synthesis in Section 2.1 was derived from a range of cartographic interaction studies using benchmark tasks rather than geographic decisions in the study procedure. When cartographic interaction studies do include a robust geographic decision, a fully-functional system is used without controlling for interface complexity or specific operator primitives, making it difficult to relate differences in decision outcomes to specific aspects of interactive map design.

Interactive functionality found in previous decision-making studies, and subsequent interface complexity variations, includes panning to explore the map (e.g., Rinner and Malczewski 2002, Zografos and Androutsopoulos 2008, Jelokhani-Niaraki and Malczewski 2015), zooming to change the map scale (e.g., Crossland et al. 1995, Jankowski et al. 2001, Rinner and Malczewski 2002, Zografos and Androutsopoulos 2008, Jelokhani-Niaraki and Malczewski 2015), filtering to remove unwanted criteria (e.g., Frank et al. 2000, Jankowski et al. 2001, Rinner and Malczewski 2002), and overlay to see multiple decision factors at once (e.g., Crossland et al. 1995, Frank et al. 2000, Jankowski et al. 2001, Zografos and Androutsopoulos 2008, Jelokhani-Niaraki and Malczewski 2015). Interestingly, the retrieve operator is commonly investigated in cartographic interaction studies (Table 1), but was not reported in any of the reviewed studies on geographic decision making. These studies focused on the decision result based on the whole interactive system, rather than the decision result based on operator usage. While many decision-making studies implemented the operators discussed in Table 1, two studies discussed the impact of interaction on the decision-making process: Crossland et al. (1995) identify that the interactive environment helped participants with spatial decision making for a site selection problem, while Mennecke et al. (2000) found that interactivity actually decreased decision success for expert users, also for a site selection problem, suggesting that the type of decision and user may matter when considering interface complexity.

2.3: User Expertise

The user is the focus of MacEachren's (1994) third axis, with an emphasis on individual user differences. MacEachren originally described this axis as a distinction between public and private map use, but later rephrased to focus on user expertise, or differences between a general and specialist map user. Expertise is a multi-faceted concept that includes education, experience, and overall familiarity (Roth 2009). Further, expertise for interactive mapping and decision making can be with either the tool (the interactive map), the domain (the decision topic), or computers (the device the user is working with) (Nielsen

1993: 43-44, seen in Slocum et al. 2001). Table 3 below examines the relationship between various types of user expertise, task type, and the results of previous studies.

Table 3. Relationship between expertise and task level for interactive tasks
(* Indicates Decision-Making Study)

Study	Task Type	Expertise Level	Result
Crossland et al. (1995)*	Rank	Non-Experts	Positive: An SDSS reduced decision time and increased decision accuracy
Mennecke et al. (2000)*	Rank	Professionals and Students	Mixed: With an SDSS, professionals were more accurate, but not as efficient as students, professionals using paper maps and SDSS had no difference in results
Jankowski and Nyerges (2001)*	Site Selection	Stakeholder Volunteers	Positive: Interface expertise did not matter in decision outcome
Jelokhani-Niaraki and Malczewski (2015)*	Site Selection	Domain Topic Students	Neutral: Information load is important to consider for a web-based system, but not the most important factor
Roth and MacEachren (2016)	Identify, Compare, Rank, Associate, Delineate	Domain Experts	Neutral: Used interface more as the objective became more complicated

As with cartographic interface complexity and geographic decision complexity, there are also contradicting results from empirical research on user expertise and interactive systems. The literature suggests that domain experts think through a decision differently than non-experts (Ericsson and Lehmann 1996), an effect that also should be observed when using an interactive map to make a decision. Domain experts are more familiar with the decision problem through experience and know which criteria are important to consider when making the domain-specific decision. Results are mixed, however, when examining user expertise for decision making supported by interactive maps. While studies on non-experts show relative success in using interactive maps to make geographic decisions (Crossland et al. 1995, Mennecke et al. 2000), studies with domain experts have shown mixed results (Mennecke et al. 2000, Jankowski and Nyerges 2001, Roth and MacEachren 2016) (Table 3). Further, it is unclear what effect *geographic* decision complexity has, coupled with expertise level, on decision makers when working in an interactive map (Crossland et al. 1995). Domain experts without training in interactive mapping technology may not correctly integrate these maps into the decision-making process because of lack of technical or map use experience (Ooms et al. 2015).

Interface and decision complexity are two factors of map design that affect the user experience with the map, and it remains unclear the effect each of these has on different user groups (Crossland et al. 1995, Davies 1998, Keehner et al. 2008). Notably, only one of the studies in Table 3 examined *both* domain experts and non-experts. In this thesis, I tested individuals with a range of expertise with the hazardous waste trade to draw conclusions about their use of an interactive system for a geographic decision. This research investigated these factors on those familiar with the hazardous waste trade and the general public, covering both ends of the continuum of MacEachren's third axis.

CHAPTER 3: METHODS

3.1: Case Study: The North American Hazardous Waste Trade

I used a case study about the North American hazardous waste trade to study the interplay of interface and decision complexity in an ecologically-valid problem context. *Hazardous waste* is defined as waste that could cause harm to humans or the environment and is also ignitable, corrosive, reactive, and/or toxic (California Department of Toxic Substances Control 2016). Hazardous waste is known as both a managed risk and a valued commodity because of the economic benefits of trading waste. This dual commodity/risk nature has led to management and policy discussions at multiple levels of government. For instance, the United States Congress signed the Resource Conservation and Recovery Act (RCRA) of 1976, with hazardous waste amendments in 1984, to manage hazardous waste (United States Congress 2002). Through this Act, the United States Environmental Protection Agency (EPA) was tasked with monitoring hazardous waste from generation to disposal. Companies are required to report waste that is imported and exported to the EPA on a yearly basis.

Further, the *transnational* trade in hazardous waste has led to considerable discussion over regulation as well. The United Nations (UN) Basel Convention in 1989 ensured proper waste trade and prevented the movement of hazardous waste from developed countries to developing countries (Alter 2000, WHO, UNEP 2000). In contrast, NAFTA (North American Free Trade Agreement) and other trade agreements have enabled freer flow of hazardous waste across North American countries (Jacott et al. 2004). The case study reported here therefore focuses on flows of hazardous waste to the United States from neighboring Canada and Mexico.

The hazardous waste trade is an appropriate case study because many management and regulation decisions are made that have multiple, often competing spatial criteria and multiple, often detrimental outcomes. Common decisions include opening and closing hazardous waste processing and storage sites, determining acceptable transportation routes between sites, and mitigating contamination of local communities. Multiple decision criteria go into making these decisions, which include environmental cost, risk, and justice (Coutinho-Rodrigues et al. 1997). To calibrate the case study to a practical task, I reviewed the hazardous waste literature to determine common decisions made using this case study, while consulting academic hazardous waste experts in a pilot study exercise. These findings informed how the map survey was designed (see Section 3.2 on preparatory research).

Data on the transnational hazardous waste trade used for this study was obtained through two Freedom of Information Act (FOIA) requests to the EPA (Nost et al. 2017, Moore et al. 2017). Scanned shipping manifests and consent forms were hand-digitized into a spreadsheet and geocoded by origin and destination address. Information recorded included: year of shipment, EPA company identification code, importing company, exporting company, receiving facility, waste type, waste amounts, waste containers, number of shipments, EPA and UN waste codes, packing group numbers, and any comments or discrepancies either mentioned on the documents or that were discovered missing from the documents (Figure 3). Digitization of manifests resulted in over 33,000 shipments from 2009-2012 with 59 United States sites importing waste and 411 United States sites exporting waste. Data on environmental risks and toxins typically are storied and visualized in a GIS environment, with GIS analysis dominating decision-making literature on hazardous waste, environmental exposure, and related environmental justice issues (e.g., Lowry et al. 1995, Lovett et al. 1997, Sheppard et al. 1999, Verter and Kara 2001, Maantay 2002, Mennis 2002, Kara and Verter 2004, Mohai and Saha 2007). Environmental justice research, with regards to the hazardous waste trade, studies the impact of hazardous waste processing facilities on the environment and people near these processing sites, and thus considers a wide range of environmental and social dimensions when arriving at an optimal outcome. This study aimed to examine the hazardous waste trade in an interactive web environment, enabling hypothetical decision makers focused on environmental justice to produce new maps interactively as they offload their reasoning and arrive at a decision.

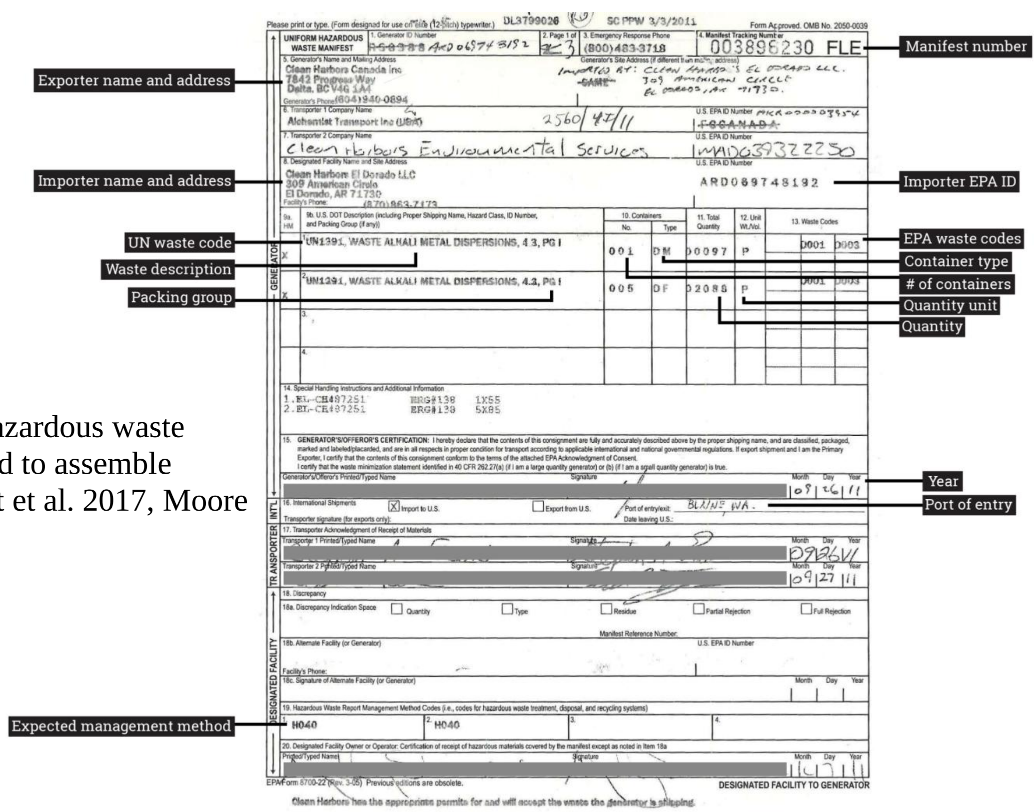


Figure 3. Hazardous waste manifest used to assemble dataset (Nost et al. 2017, Moore et al. 2017).

3.2: Preparatory Research

Before administering the experiment, I conducted three stages of preparatory research to calibrate the experimental design to the hazardous waste context and professional interactive map design practice. First, I participated in a one day mapping workshop at the University of Wisconsin-Madison—described as the Design Challenge—making use of the geocoded dataset of transnational hazardous waste transactions described above (Moore et al. 2017). Seventeen students participated either individually or in pairs, with participation split across undergraduate, post-graduate certificate, and graduate students. A total of 10 map products were created from the group, which helped build working knowledge about the regulation and management of the hazardous waste trade.

Second, I completed a set of informal interviews with domain experts to ascertain background about the transnational hazardous waste trade. The purpose of the preliminary interviews was to identify geographic decisions common to the management and regulation of hazardous waste as well as to articulate the spatial dimensions important to these decisions (i.e., decision criteria). Three (n=3) domain experts, each of whom was familiar broadly with the transnational hazardous waste trade and specifically with the hazardous waste transactions dataset used in the experiment, participated in the semi-structured interviews. The interview protocol is provided in Appendix A.

The domain experts interviewed agreed that common geographic decisions to the transnational hazardous waste trade include selecting sites to open a processing facility, close a processing facility, identifying shipping locations for hazardous waste, determining waste transportation routes, and mitigating contamination and risk for a community. The interviews further revealed regulatory compliance, facility infrastructure, level of contamination risk, toxicity of materials, and proximity to local communities as important spatial criteria to making these decisions. Finally, from the map design perspective, experts agreed that the scale of analysis should be either state or local because patterns and trends are difficult to interpret and can be misleading at the national level.

After calibrating the experimental design to expert feedback, I then conducted a pilot study with a preliminary version of the online survey to understand any confusions or problems in the experimental design. Eight (n=8) students at the University of Wisconsin-Madison Cartography Lab were recruited to identify issues and improve the map survey. Students had extensive experience in interactive map design, but limited experience with the hazardous waste trade. Revisions to the experimental design following these preparatory steps are noted in the following description of the survey materials and procedure.

3.3: Map Survey Participants

A total of 122 (n=122) participants completed the online map survey. To promote a diverse age group, educational level, and experience, n=110 participants for the map survey were recruited through Amazon Mechanical Turk and completed the survey on their own desktop or laptop computer. To complement the Mechanical Turk participants, I also recruited n=9 participants from the Design Challenge as well as n=3 experts in the hazardous waste industry, balancing the level of expertise with the transnational hazardous waste trade (Research Question #3). Despite the different exposure to the domain in Design Challenge participants and industry experts, this pair of expert groups performed consistently on the decisions. To characterize the sample, I collected biographic information and self-reported measures of expertise with the case study domain and use of interactive maps. Individuals were eligible to participate if they spoke English as a first language, resided in the United States (but not Ohio or Texas-the mapped locations), and were 18 years of age or older. Participants were required to complete the online survey using a non-mobile device.

All participant data was vetted to ensure it was acceptable for analysis (Figure 4). Two participants indicated that they started over, so their data was discarded because of learning effects. Data from two other participants was excluded because they provided false survey answers. These were identified by looking at the form fill in boxes on the exit survey, and when there were answers that were just random letters, the data was discarded because it was unusable. Data from five participants was discarded because they live in Ohio and one who lives in Texas because they did not meet the proper eligibility requirements. Removing the data from these participants left a total of 122 (n=122) valid datasets to analyze. Finally, participants ranked 50 decisions backwards (i.e., best-to-worst when instructed to rank worst-to-best), as identified through the ranking outcome. Responses with noticeable inversions around the endpoints were transposed to the intended direction before analysis.

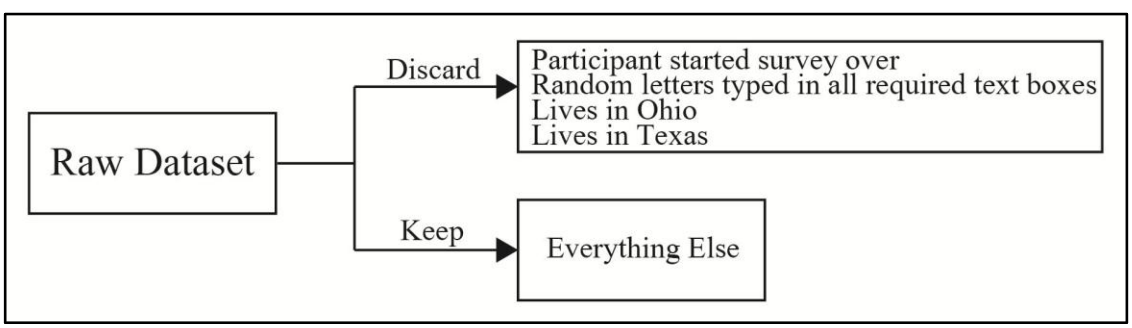


Figure 4. Data cleaning process. Participant data files were vetted to remove any unacceptable data. Reasons for removal included participants starting the survey over, false data was provided, and they currently live in Ohio or Texas.

3.4: Map Survey Materials

The materials for the online map survey were designed following a 2x2 factorial design (Montello and Sutton 2006): interface complexity (*simple*, *complex*) and decision complexity (*simple*, *complex*). The 2x2 design was replicated in two map contexts to produce a total of eight different interactive maps for the online map survey. These maps were created using the MapStudy open source library developed at the University of Wisconsin-Madison Cartography Lab (http://github.com/uwcart/mapstudy/, Sack and Roth 2016).

The interface complexity design factor included *simple* and *complex* variations (Table 4). The *simple* variation was constrained to those interaction operators common to slippy web maps after Roth et al. (2014) and Tolochko (2016): pan, zoom, and retrieve. The *complex* variation then expanded interface scope to follow Shneiderman's (1996) visual information seeking mantra and supported overlay of data (overview first), pan/zoom and filter (zoom and filter), and retrieve (details-on-demand). Thus, the interface complexity factors enabled evaluation of interface scope broadly, while also examining the impact of Shneiderman's mantra for decision making specifically. Both conditions used the same, subdued grayscale basemap tileset with limited context features and no labels to promote interaction.

The decision complexity design factor also included *simple* and *complex* variations with the *simple* condition having 3 criteria and the *complex* condition having 5 criteria (Crossland et al. 1995) (Table 4). To determine the "correct" rankings, company names were randomized from alphabetical to generate a list of best to worst for the seven companies (the most in any one state in the United States) in question. Then, values from 1-3 were assigned to all criteria for each company to generate a total score. The total score of the first company was the lowest and the total score of the last company was the highest, with every score in between evenly different than the one above and below it. The values 1-3 were converted to low-high, respectively (low=good, high=bad) and were displayed to participants on the maps (Figure 5). Companies were presented to participants in alphabetical order to remove any initial bias. Therefore, an optimal decision required consideration of all available information (i.e., decision criteria), a decision scenario illustrative of an environmental justice focus. Qualitative feedback was acquired after each decision to determine if participants followed alternative decision-making strategies that reduced the complexity of the information or focused on one attribute over others.

Table 4. 2x2 factorial design for interface and decision complexities.

	Simple	**Complex**
Interface Complexity	Basic Slippy Map Functionality • Pan • Zoom • Retrieve	Shneiderman's Mantra • Pan • Zoom • Retrieve • Filter • Overlay

	Simple	**Complex**
Decision Complexity	7 Outcomes (Sites) 3 Criteria: • Kilograms Imported • Percent Non-White Population • Air Quality Watches per Capita	7 Outcomes (Sites) 5 Criteria: • Kilograms Imported • Percent Non-White Population • Air Quality Watches per Capita • Percent in Poverty • Soil Permeability

The materials were replicated for two different geographic locations: Ohio and Texas. Replication of materials mitigated individual bias for a region, combatted learning of map patterns, and ultimately enabled users to complete two unique geographic decisions during the map survey, doubling decision responses for analysis. *Simple* and *complex* versions were created at both locations for the interface complexity and decision complexity factors, resulting in eight unique interactive maps.

A

Ohio-Simple	Kilograms	% Non-white	Air Quality	Total/Score
ENVIRITE INC.	1	1	1	3
AMG VANADIUM	1	2	1	4
SYSTECH CORP.	2	2	1	5
CLEAN HARBORS INC.	2	2	2	6
SPRING GROVE INC.	2	3	2	7
CLEVELAND CORP.	3	3	2	8
ROSS INCINERATION INC.	3	3	3	9

B

Texas-Simple	Kilograms	% Non-white	Air Quality	Total/Score
SAFETY-KLEEN	1	1	1	3
AMLON INC.	1	2	1	4
VEOLIA ENVIRONMENTAL	2	2	1	5
CLEAN HARBORS INC.	2	2	2	6
U.S. ECOLOGY	2	3	2	7
EURECAT INC.	3	3	2	8
SET INC.	3	3	3	9

C

Ohio-Complex	Kilograms	% Non-white	Poverty	Air Quality	Soil Permeability	Total/Score
CLEVELAND CORP.	1	1	1	1	1	5
SYSTECH CORP.	1	1	2	1	2	7
ENVIRITE INC.	2	1	2	1	2	8
CLEAN HARBORS INC.	2	2	2	2	2	10
ROSS INCINERATION INC.	2	2	3	2	3	12
AMG VANADIUM	3	2	3	2	3	13
SPRING GROVE INC.	3	3	3	3	3	15

D

Texas-Complex	Kilograms	% Non-white	Poverty	Air Quality	Soil Permeability	Total/Score
EURECAT INC.	1	1	1	1	1	5
VEOLIA ENVIRONMENTAL	1	1	2	1	2	7
SAFETY-KLEEN	2	1	2	1	2	8
CLEAN HARBORS INC.	2	2	2	2	2	10
SET INC.	2	2	3	2	3	12
AMLON INC.	3	2	3	2	3	13
U.S. ECOLOGY	3	3	3	3	3	15

Figure 5. Coding scheme for determining the “correct” ranking. Criteria were assigned a value of 1-3 with 1 being “low” and 3 being “high”, where “low”=good and “high”=bad. A. Ohio map with *simple* decision criteria. B. Texas with *simple* decision criteria. C. Ohio with *complex* decision criteria. D. Texas with *complex* decision criteria.

The criteria shown in Figure 5 were chosen because of their importance in environment justice, introduced in Section 3.1. These criteria (Table 5) included kilograms of waste imported, percent non-white population, percent in poverty, air quality watches per capita, and soil permeability. While not every criterion was analyzed for every decision given the differences in decision complexity, a balance was maintained between environmental and social criteria in both decision conditions (Table 5).

Table 5. Explanation of criteria used to make decisions. *Indicates criteria provided in only the *complex* decision condition.

Criteria	Description	Type
Kilograms of Waste Imported	An increased volume of hazardous waste at a processing site generally increases the potential risk to the local community and environment, all other things considered.	Environment and Social
Percent Non-White Population	Environmental justice research shows that non-white communities may be more burdened by hazardous waste facilities than white communities.	Social
Air Quality Watches per Capita	Processing hazardous waste releases emissions that can negatively impact air quality. An air quality watch is issued whenever air quality reaches unsafe levels.	Environment
Percent in Poverty*	Environmental justice research shows that poor communities may be more burdened by hazardous waste facilities than wealthy communities.	Social
Soil Permeability*	Processing hazardous waste releases toxins that can permeate the soil. The rate at which toxins penetrate into the landscape vary by soil type.	Environment

Two different scenarios were designed for the geographic decisions (Figure 6). One asked participants to assume the role of a manager of a hazardous waste firm looking to send hazardous waste to the United States for disposal. Participants were presented with the criteria in Table 5 and were asked to rank their preference for doing business with particular facilities (i.e., sites). The other scenario asked participants to assume the role of a regulator at the EPA in charge of ensuring sound waste processing practices. Participants were asked to rank the urgency of site visits to ensure companies are following government regulations. While the persona and decision scenario were different for the pair of decisions, they were determined to be comparable from the pilot study. Importantly, environmental justice was the focal point in both decision scenarios, with the scenario requiring participants consider all criteria. While it is not expected that companies make decisions in this way, the goal of this research was to learn how to design tools that enable people to take into account all of the available information before making decisions.

A

Map Task

* You are the manager of a newly opened Canadian firm looking to ship your by-product hazardous waste to processing facilities in Ohio for disposal. The transnational shipment is due to waste volume needs that cannot be met in Canada and economic benefits of Ohio facilities. You are concerned about the impact on communities near the processing facilities, given recent news coverage over disproportionate risk to marginalized populations. Further, you want to send the hazardous waste to a processing facility that will handle it properly, otherwise your business could face scrutiny about negative environmental impacts.

Given these needs and concerns, **rank your preference for doing business with** the available Ohio processing facilities using information from the interactive map **(1=most preferred, 7=least preferred)**. Again, drag the company names (seen below) above and below each other to rank your preference.

B

Map Task

* You are a regulator at the EPA responsible for ensuring that hazardous waste imported from Mexico is processed at facilities in Texas following government regulations. New information suggests that the volume of imported hazardous waste has changed, and that you will need to plan site visits to review the processing facilities. Your job is to examine recent reports to assess each company's potential for negative environmental impacts. Further, community members have come forward with concerns they are at risk of exposure to hazardous waste, and this risk disproportionately impacts marginalized populations.

Given these needs and concerns, use the interactive map to **rank the urgency you need to follow-up with site visits** to each facility **(1=most urgent, 7=least urgent)**. Again, drag the company names (seen below) above and below each other to rank the urgency.

Figure 6. Decision scenarios participants assumed to make the geographic decisions about the hazardous waste trade. A. Company manager scenario. B. EPA regulator scenario.

3.5: Map Survey Procedure

The quantitative map survey was proctored online using Amazon Mechanical Turk for non-experts and online through email recruitment for experts. The online map survey began with an opening page providing background information on project goals. After obtaining consent, participants were provided an introduction to the hazardous waste dataset with an example interactive map. The example map was accompanied with an explanation of the interactive functionality available and an example task to let participants practice interacting with the map. The participants were allotted as much time as they desired to explore the interactive map before beginning the experimental blocks (Figure 7).

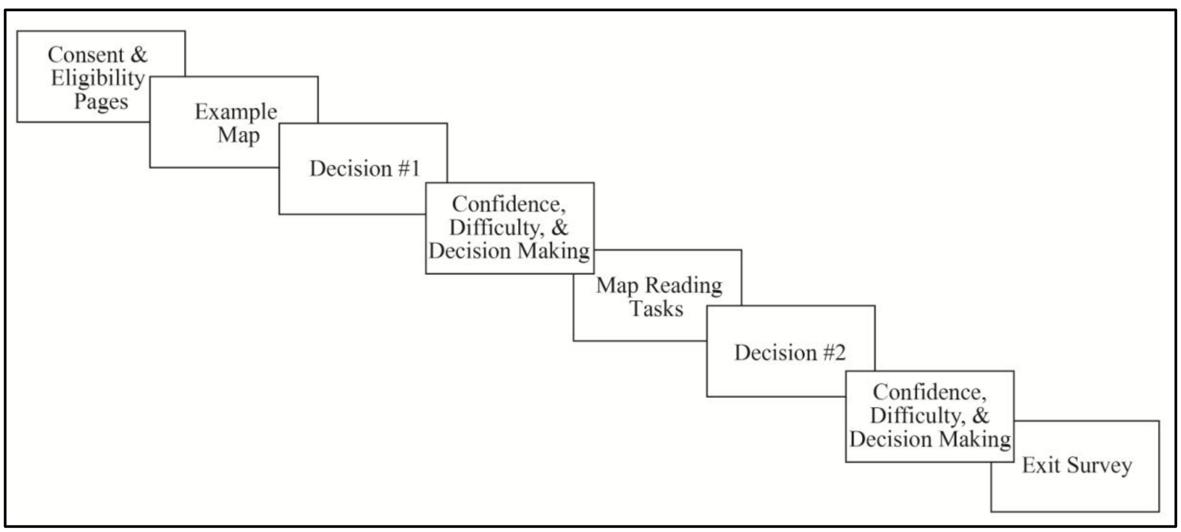


Figure 7. Map survey procedure. Participants started by completing a consent page and reviewing eligibility, then proceeded to an example map to learn functionality. They then completed one decision (balanced order), followed by decision confidence and perceived difficulty questions, and wrote a description of their decision making process. Participants completed a series of map reading tasks before proceeding to a second decision. They then completed the same confidence, difficulty, and decision making questions. The survey concluded with an exit survey.

Participants were randomly assigned between subjects into one of two groups based on interface complexity (Research Question #1): either the *simple* interface including only pan, zoom, and retrieve or the *complex* adding filter and overlay. In contrast, decision complexity (Research Question #2) was assigned within groups so that participants only learned a single set of functionality in the opening example, and thus did not try to evoke functionality that was removed in subsequent trials. Participants then completed two decisions of variable complexity using different geography: one decision with the Ohio map and one decision with the Texas map. The combination of decision complexity and geography, and the order of the two tasks within the online map survey, was randomized within the groups (Figure 8).

Interface Complexity:

A = Simple (Pan, Zoom, Retrieve)
B = Complex (Pan, Overlay, Zoom, Filter, Retrieve)

Decision Complexity:

1 = Simple (Limited Criteria (3), 7 outcomes)
2 = Complex (Expanded Criteria (5), 7 outcomes)

Assignments for Group I and Group II:*

I. $A1^{Ohio} + A2^{Texas}$ (41 participants)**
$A1^{Texas} + A2^{Ohio}$ (27 participants)

II. $B1^{Ohio} + B2^{Texas}$ (25 participants)
$B1^{Texas} + B2^{Ohio}$ (29 participants)

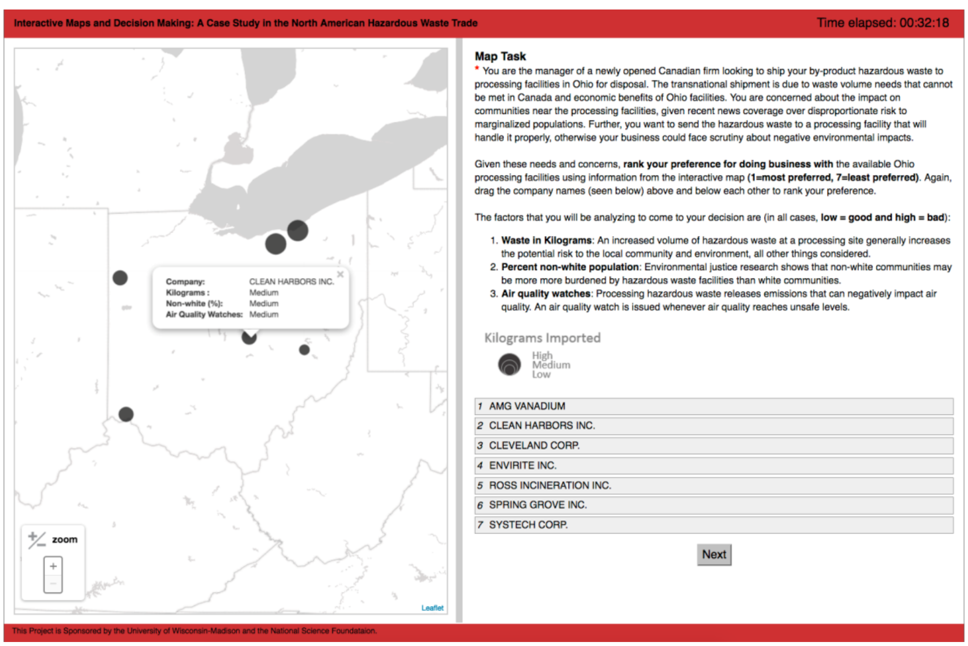
*Interface complexity varied between groups, while decision complexity varied within groups. The map the user saw first was randomized within the group.

**Note that this first assignment had many more participants than the others. This was an artifact from the randomization system used in MapStudy.

Figure 8. Participant assignments for interface and decision complexity. Participants were randomly assigned to maps with *simple* or *complex* interface complexity and *simple* or *complex* decision complexity, with interface complexity varied between groups and decision complexity varied within groups.

Both decision trials began with participants reviewing a persona and decision scenario described above (Figure 6, Figure 9). The participants then were instructed to rank the set of sites (i.e., the decision outcomes) based on the decision scenario, rather than select only a single site in order to engage a higher-level reasoning process. Between maps, the participants were required to complete a series of simple map reading tasks using additional maps of the hazardous waste trade to measure the participant's map reading ability and to combat learning effects. The online map survey completed with an exit survey capturing participant characteristics and experiences (Research Question #3), as well as insight into their decision-making process. The full map survey can be seen in Appendix B.

A



B

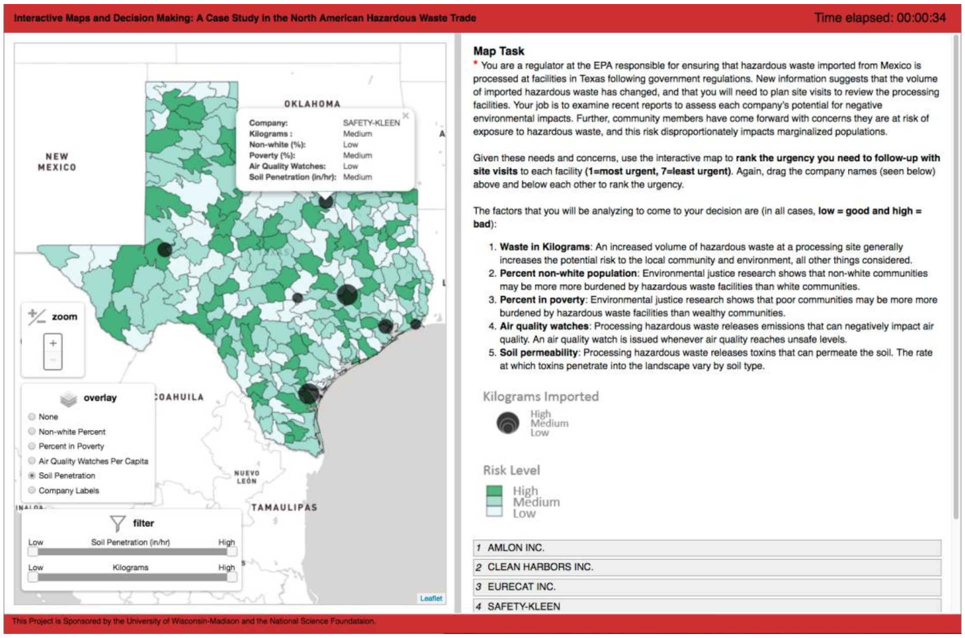


Figure 9. Two maps and scenarios tested in this research. A. Map of Ohio with *simple* interface complexity, *simple* decision complexity, and company manager scenario (popup activated [retrieve]). B. Map of Texas with *complex* interface complexity, *complex* decision complexity, and EPA regulator scenario (popup [retrieve] and overlay [soil permeability] activated).

3.6: Map Survey Analysis

The independent variables for this research study are interface complexity and decision complexity, while the dependent variables include correctness of the decision outcome, reported confidence, reported difficulty, and the interaction logs. In addition, interaction effects were assessed regarding user expertise (education, profession, and experience with the hazardous waste trade), geographic location, and order.

Quantitative analysis was used to assess decision outcomes and exit survey results. The ranking decision was assessed for correctness using the Kendall Rank Correlation Coefficient (Crossland et al. 1995, Mennecke et al. 2000, Kiker et al. 2005). Kendall analysis provides both a measure of correctness ($\bar{\tau}_b$) on a scale of -1 to 1 as well as the percentage of observations statistically correct at p=0.05. Further analysis was conducted with a z-test for differences between *simple* and *complex* interface complexity variations, and a paired two sample t-test for differences between *simple* and *complex* decision complexity variations as well as user expertise, location (Ohio vs. Texas), and order (1^{st} vs. 2^{nd}). Spearman's correlation analysis was used to determine correlations between pairings of correctness, difficulty, and confidence for all variations. Additionally, interaction logs were coded by operator (Table 1) for each decision to understand extensiveness, frequency, and type of functionality used by participants to come to their decisions (MacEachren et al. 1998, Roth and MacEachren 2016). The way I used these analyses to answer my research questions is shown in Table 6.

Table 6. Analysis techniques used to answer research questions.

Research Question-IDVs	Measures-DVs	Statistics Used
Overall: Location and Order	Location (Texas vs. Ohio) and order (1^{st} vs. 2^{nd}) correctness	Kendall's Rank Correlation Coefficient
	Location (Texas vs. Ohio) and order (1^{st} vs. 2^{nd}) significance	Paired two sample mean t-test
	Significance between Texas and Ohio (order and location) for confidence and difficulty	Paired two sample mean t-test
	Correlation between pairings of correctness, confidence, and difficulty	Spearman's correlation coefficient
	Interaction operator extensiveness	Chi-square test
	Interaction operator frequency	Chi-square test
Question #1: Interface Complexity	Decision correctness for interface complexity levels	Kendall's Rank Correlation Coefficient
	Significance between decision correctness and interface complexity levels	z-test
	Significance between complexity levels for confidence and difficulty	z-test
	Correlation between pairings of correctness, confidence, and difficulty	Spearman's correlation coefficient
	Significance in interaction operator extensiveness between complexity levels	Two sample t-test
	Significance in interaction operator frequency between complexity levels	Two sample t-test
Question #2: Decision Complexity	Decision correctness for decision complexity levels	Kendall's Rank Correlation Coefficient
	Significance between decision correctness and decision complexity levels	Paired two sample mean t-test
	Significance between complexity levels for confidence and difficulty	Paired two sample mean t-test
	Correlation between pairings of correctness, confidence, and difficulty	Spearman's correlation coefficient
	Significance in interaction operator extensiveness between complexity levels	Two sample t-test
	Significance in interaction operator frequency between complexity levels	Two sample t-test
Question #3: User Expertise	Decision correctness for expertise levels	Kendall's Rank Correlation Coefficient
	Significance between decision correctness and user expertise	Two sample mean t-test
	Significance between expertise levels for confidence and difficulty	Two sample mean t-test
	Correlation between pairings of correctness, confidence, and difficulty	Spearman's correlation coefficient
	Significance in interaction operator extensiveness between expertise levels	Two sample t-test
	Significance in interaction operator frequency between expertise levels	Two sample t-test

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Overall Results

A total of 122 (n=122) participants completed this study (68 male, 54 female). Twelve experts in the management and trade of hazardous waste participated, with the remaining 110 participants holding limited background knowledge. Regarding education level, 40 participants held a high school diploma as the highest degree earned, 15 earned an Associate's degree, 49 earned a Bachelor's degree, 4 earned a post-bachelor certificate, 12 earned a Master's degree, and 2 earned a PhD. The average age for all participants was 35.5 (min=23, max=66).

Correctness for the ranking tasks was determined using the Kendall rank correlation coefficient (Mennecke et al. 2000). The overall correctness of the ranking decisions was $\bar{\tau}_{b=}0.629$ (SD=0.449), where $\tau_{b\text{-}max=}1$, indicating a positive correlation between observed participant rankings and the expected correct rankings. 56.6% of the decision outcomes were statistically correct at p=0.05. These findings suggest that the two decisions were difficult, but not impossible, mirroring real-world problem contexts on the management and regulation of hazardous waste (Table 7).

Participants rated their perceived difficulty of the decisions and the confidence in their decision outcomes. The average difficulty for all ranking decisions was 2.3/5 (SD=1.1), where 5 is very difficult. Average participant confidence was 4.1/5 (SD=0.9), where 5 is very confident. A Spearman correlation test revealed that there was minimal association between overall correctness and overall difficulty ($\rho=-0.050$, $p=0.439$) as well as overall correctness and overall confidence ($\rho=0.082$, $p=0.204$), together indicating that self-assessed difficulty and confidence were not factors in the decision results in the aggregate. It is important to note in the following that difficulty, but not confidence, was rated on an inverse scale to improve the semantics of the question for participants, meaning that a negative Spearman association indicates that participants found the task easier as they became closer to correct in their decision outcomes.

The average correctness for Ohio decisions was $\bar{\tau}_{b=}$0.661 (SD=0.404, 57.4% statistically correct decisions), while the average correctness for Texas decisions was $\bar{\tau}_{b=}$0.597 (SD=0.489, 55.7% statistically correct decisions). A paired two sample t-test found no significant difference between the overall correctness of the Ohio and Texas decisions (paired t(121)=-1.119, p=0.265). The average difficulty was 2.3/5 (SD=1.2) for decisions supported by the Ohio map and 2.3/5 (SD=1.1) for decisions supported by the Texas map. A paired two sample t-test also found no difference in difficulty for the Texas and Ohio maps (t=-0.300, p=0.764). Spearman tests showed that there was a significant negative correlation between difficulty and correctness for the Texas (ρ=-0.237, p=0.009) maps, but no correlation for the Ohio (ρ=0.009, p=0.925) maps. Therefore, when the participants found the Texas decision easier, they were more accurate in their outcome, but this association did not hold true for the Ohio decisions. This could be because people have an overall better sense of Texas geography than Ohio geography. Further, confidence was assessed at 4.1/5 (SD=0.88) for the decisions made with the Ohio map and 4.0/5 (SD=0.99) for decisions completed with the Texas map. A paired two sample t-test found no difference in confidence for decisions made with the Ohio map and the Texas map (t=-0.657, p=0.513). Spearman tests found a significant positive correlation between confidence and correctness for the Texas maps

(ρ=0.375, p=2.08x10^{-5}), but not the Ohio maps (ρ=0.161, p=0.077), again indicating that when the participants were more confident in their Texas decision, they too, had better correctness results to show for it. Together, the significant correlations for Texas and not Ohio are curious findings, and perhaps suggest a greater geographic awareness of Texas compared to Ohio, influencing participant perception, with further testing needed to confirm this explanation. This difference in locations did not significantly influence the decision outcomes themselves and ultimately did not register in the exit survey.

Regarding order effects, the average correctness was $\bar{\tau}_{b=}$0.606 (SD=0.464, 54.1% statistically correct) for the first decision and $\bar{\tau}_{b=}$0.653 (SD=0.433, 59.0% statistically correct) for the second decision. Also using a paired two sample t-test, no significant difference was found in average correctness between the first and second decisions (paired t(121)=-0.817, p=0.415) despite the small increase in correctness from the first to second decision. The average difficulty was 2.3/5 (SD=1.1) for the first decision completed and 2.3/5 (SD=1.2) for the second decision completed. A paired two sample t-test again did not find significance between difficulty for the first and second decisions (t=-0.264, p=0.793). Spearman tests showed that there was a significant negative correlation between correctness and difficulty for the first decision (ρ=-0.222, p=0.014), but not the second decision (ρ=-0.019, p=0.835), indicating that when participants felt the first decision was easy, they tended to have better results. The average confidence was 4.1/5 (SD=0.95) for the first decision and 4.1/5 (SD=0.92) for the second decision. A paired two sample t-test found that there was no significance in confidence between the first and second decisions completed (t=0.064, p=0.949). Spearman tests showed a positive correlation between correctness and confidence for the first decision (ρ=0.399, p=5.31x10^{-6}), but not the second decision (ρ=0.154, p=0.091), indicating that when participants showed confidence in the first decision, they had better correctness results. These findings suggest that, while participants who were more comfortable with interactive maps did better on the first decision, this difference did not result in a significant order effect on decision outcomes. Table 7 provides the aforementioned results.

Table 7. Correctness results for location and order compared to overall, and difficulty and confidence results for overall decisions.

Condition	**Sample Size**	**Correctness**			**Difficulty**			**Confidence**		
Descriptive		**Average ($\bar{\tau}_b$)**	**Standard Deviation**	**% Correct**	**Average *[1=very easy]***	**Standard Deviation**	**Spearman (ρ)**	**Average *[5=very confident]***	**Standard Deviation**	**Spearman (ρ)**
Texas	122	0.597	0.489	55.7%	2.3	1.1	-0.237	4.0	0.99	0.375
Ohio	122	0.661	0.404	57.4%	2.3	1.2	0.009	4.1	0.88	0.161
First	122	0.606	0.464	54.1%	2.3	1.1	-0.222	4.1	0.95	0.399
Second	122	0.653	0.433	59.0%	2.3	1.2	-0.019	4.1	0.92	0.154
Overall	244	0.629	0.449	56.6%	2.3	1.1	-0.050	4.1	0.9	0.082
Inferential		**t statistic**	**p-value**		**t statistic**	**p-value**		**t-statistic**	**p-value**	
Location	244	-1.119	0.265		-0.300	0.764		-0.657	0.513	
Order	244	-0.817	0.415		-0.264	0.793		0.064	0.949	

Interaction logs were recorded to learn how participants used the maps when making their decisions (Table 8). Starting with extensiveness, participants interacted with the map for all but one decision (243/244, 99.6%). This was markedly higher than expected, and indicated that the training block properly introduced participants to the available interactivity. However, there was wide variation in interaction by extensiveness (whether or not an operator was used at least once) across the implemented operators. Participants retrieved details at least once during 91.4% of the decisions, changed the overlays (when implemented in the complex interface condition) at least once during 73.0%, and panned at least once during 77.5%. In contrast, participants only filtered (when implemented) during 28.7% of the decisions and only zoomed during 32.0% of the decisions. A chi-square test found that the percent of interaction extensiveness was statistically unequal across operators ($\chi 2$ (9, N=244)=362.25, $p < 2.2x10^{-16}$), meaning that the application of operators was non-random and thus intentional interaction strategies were used when making decisions. The extensive use of retrieve was expected given the simplified basemap and lack of labels. Interestingly, the uneven extensiveness of operators did not appear to follow Shneiderman's information seeking mantra—at least in the overall aggregate—in which zoom and filter are essential transitional interactions from overview to details. This finding is perhaps caused in part because of the difficult but concrete decision containing a finite set of fixed outcomes, resulting in a reduced amount of time in open exploratory mode as participants focused their attention to the specific problem at hand. Further, participants may have started in the sensemaking stage, rather than the information seeking stage because the problem was given to them; they did not have to "seek" it out (Pirolli and Card 2005). Additionally, the use of pan and not zoom may be due to reduced screen real estate for the map on smaller screens, given the 50/50 split between map and decision scenario in the MapStudy framework.

The frequency of the interactions was substantial, with 5,900 total interaction logged across the study and an average of 24.18 interactions per decision. Because the number of participants assigned to each condition of interface complexity was uneven, the average operator frequencies per decision are more meaningful than the total frequencies. By frequency, detail retrieval was by far the most commonly applied operator, used an average of 12.93 times per decision. Again, the large frequency of retrieve was expected given the simplified basemap and lack of labels. Panning was applied 5.79 times per decision and overlay (when implemented) 5.44 times. As with extensiveness, zooming (1.37 times per decision) and filtering (2.74 times per decision, when implemented) were used far less frequently. A chi-square test found that the average frequency of interactions across operators also was statistically unequal (χ^2 (9, N=244)=24.834, p=0.003), further implying a non-random use of operators that did not follow Shneiderman's mantra in the aggregate.

In the following sections, the decision outcomes and interaction logs are analyzed by interface complexity, decision complexity, and user expertise to understand the effect of each on the decision outcomes and to answer my three research questions.

Table 8. Extensiveness and frequency of operators used. *Indicates operators provided in only the *complex* interface condition; see Section 4.2 for further details. Statistical significance highlighted in red.

Operator	**Sample Size**	**Extensiveness**		**Frequency**		
Descriptive		**Total**	**Percentage**	**Total**	**Avg per Decision**	**Standard Deviation**
Retrieve	244	223 / 244	91.4%	3,156	12.93	129.38
Pan	244	189 / 244	77.5%	1,412	5.79	89.38
Overlay*	122	89 / 122	73.0%	664	5.44	55.25
Zoom	244	78 / 244	32.0%	334	1.37	23.14
Filter*	122	35 / 122	28.7%	334	2.74	39.09
Total	244	243/244	99.6%	5,900	24.18	155.45
Inferential		**chi-square**	**p-value**	**chi-square**	**p-value**	
Across Operators	244	362.25	$< 2.2\text{x}10^{-16}$	24.834	0.003	

4.2: Interface Complexity (Research Question #1)

The decision results for the *simple* and *complex* maps were compared to understand the effect of interface complexity on the decision outcomes (Research Question #1; Table 9). The average correctness for decisions supported by the *simple* interface was $\bar{\tau}_b$=0.732 (SD=0.418, 68.4% statistically correct). In contrast, the average correctness for decisions supported by the *complex* interface was only $\bar{\tau}_b$=0.500 (SD=0.454, only 41.7% statistically correct). A two sample z-test found this difference significant (z=4.102, p=4.102x10^{-5}), demonstrating that participants performed better when given a simpler interface that did not include overlay or filter.

Table 9. Correctness, difficulty, and confidence results for the *simple* and *complex* interface conditions compared to overall. Statistical significance highlighted in red.

Condition	Sample Size	Correctness			Difficulty			Confidence		
Descriptive		**Average ($\bar{\tau}_b$)**	**Standard Deviation**	**% Correct**	**Average *[1=very easy]***	**Standard Deviation**	**Spearman (ρ)**	**Average *[5=very confident]***	**Standard Deviation**	**Spearman (ρ)**
Simple Interface Complexity	136	0.732	0.418	68.4%	2.1	1.0	-0.109	4.2	0.8	0.178
Complex Interface Complexity	108	0.500	0.454	41.7%	2.5	1.2	0.014	3.9	1.0	0.306
Overall	244	0.629	0.449	56.6%	2.3	1.1	-0.050	4.1	0.9	0.082
Inferential		**z statistic**	**p-value**		**z statistic**	**p-value**		**z statistic**	**p-value**	
Simple vs. Complex	244	4.102	4.102x10^{-5}		-3.198	0.001		2.941	0.003	

A similar difference between the *simple* and *complex* conditions was observed in both difficulty and confidence. The average difficulty was 2.1/5 (SD=1.0) for decisions supported by the *simple* interface and 2.5/5 (SD=1.2) for decisions supported by the *complex* interface. A two sample z-test found this difference significant (z=-3.198, p=0.001). No significant correlation was found between correctness and difficulty in either the *simple* (ρ=-0.109, p=0.207) or *complex* conditions (ρ=0.014, p=0.884). Thus, the inclusion of additional interaction operators in the *complex* condition made the decision appear to be more difficult to participants when the decision itself was unchanged. The added interaction scope and flexibility combined with its increased perceived difficulty perhaps explains the decreased performance by correctness in the *complex* condition reported above.

Further, the average confidence for the *simple* interface condition was 4.2/5 (SD=0.8), while the average confidence for the *complex* interface condition dropped to 3.9/5 (SD=1.0). A two sample z-test found this difference significant (z=2.941, p=0.003). Thus, not only did the increased interface complexity decrease correctness while increasing perceived difficulty, it also shook participant confidence, potentially making participants less likely to act if given the interface in a real-world setting. Spearman tests found a significant positive correlation between correctness and confidence for both the *simple* interface condition (ρ=0.178, p=0.038) and the *complex* interface condition (ρ=0.306, p=0.001). This indicates that though participants using the *simple* interface overall were more confident in their decisions, participants using both the *simple* and *complex* interface exhibited an increase in decision correctness when they reported greater confidence in their answers, suggesting the potentially important role of experience.

The observed differences in correctness, difficulty, and confidence between the *simple* and *complex* are clarified by the interaction logs (Table 10). There was no difference in overall interaction extensiveness given the overwhelming number of participants that interacted at least once (t=0.619, p=0.580), although notably the one decision that was not supported by any interactions with the map was given the *complex* map condition. However, the extensiveness of interactions did vary by operator between *simple* and *complex* interfaces. Participants primarily relied on detail retrieval to make their decision when using the *simple* interface. Regarding extensiveness in the *simple* condition, all (100.0%) participants retrieved at least once, 69.9% of participants panned at least once, and only 26.5% zoomed at least once. In contrast, participants made more extensive use of operators other than retrieve to support decision making in the *complex* condition: only 80.6% retrieved details at least once, while 87.0% of participants panned at least once and 82.4% overlaid at least one layer, 38.9% zoomed at least once, and 32.4% filtered at least once.

The high extensiveness of overlay in the *complex* map is particularly notable, as toggling different visual overlays provided the same information for a single variable that could be found in the detail retrieval pop-up, but in different slices across the information. The overlay strategy more common to the *complex* condition enabled participants to see one attribute (i.e., one decision criterion) for all sites (i.e., all decision outcomes), while the retrieval strategy more common to the *simple* condition enabled participants to see all attributes (i.e., all decision criteria) for one site (i.e., one decision outcome). Further, the former strategy emphasized map reading of shaded units, while the latter emphasized interpretation of non-visual text. Given how these interaction strategies resulted in differences in correctness, difficulty, and confidence, the latter was clearly the more effective strategy for the tested decisions considering interface complexity alone.

Two sample t-tests also were used to determine if there were significance differences between complexity levels in interaction extensiveness for the pan, zoom, and retrieve operators. Pan (t=0.097, p=0.929) and zoom (t=-0.645, p=0.543) resulted in no significant difference between complexity conditions. Although the retrieve operator was used by every participant who interacted with the *simple* map, there was no significant difference in retrieve extensiveness between complexity levels (t=3.03, p=0.057), suggesting that retrieve was useful in some way for both the *simple* and *complex* map conditions.

Table 10. Extensiveness and frequency of operators used, separated by interface complexity levels. *Indicates operators provided in only the *complex* interface condition. Statistical significance between interface complexity levels highlighted in red.

Operator	**Sample Size**	**Extensiveness**		**Frequency**		
Descriptive		**Total**	**Percentage**	**Total**	**Avg per Decision**	**Standard Deviation**
Simple Interface Complexity						
Retrieve	136	136 / 136	100	1,984	14.59	104.81
Pan	136	95 / 136	69.9	494	3.63	55.62
Zoom	136	36 / 136	26.5	127	0.93	11.03
Overall	136	136 / 136	100	2,605	19.15	218.72
Complex Interface Complexity						
Retrieve	108	87 / 108	80.6	1,172	10.85	24.54
Pan	108	94 / 108	87.0	918	8.50	89.76
Overlay*	108	89 / 108	82.4	664	6.15	55.25
Zoom	108	42 / 108	38.9	207	1.92	29.34
Filter*	108	35 / 108	32.4	334	3.09	39.09
Overall	108	107 / 108	99.1	3,295	30.51	103.20
Total	244	243/244	99.6%	5,900	24.18	155.45
Inferential		**t statistic**	**p-value**	**t statistic**	**p-value**	
Simple vs. Complex	244	0.619	0.580	0.352	0.759	
Retrieve	244	3.03	0.057	3.77	0.033	
Pan	244	0.097	0.929	-2.01	0.101	
Zoom	244	-0.645	0.543	-1.28	0.271	

Differences in the interaction logs for the *simple* versus *complex* interface conditions were exacerbated when examined by frequency rather than extensiveness. By average, participants interacted more with the *complex* map (30.51, SD=103.20) than the *simple* map (19.15, SD=218.72). This is perhaps expected given the wider interface scope of the *complex* condition, but also suggests the importance of interface constraint, as the added time spent interacting did not clarify the decision, but instead complicated it, as indicated by the significant differences in correctness, difficulty, and confidence. However, a two sample t-test showed that even though participants using the *complex* map interacted more, there was no significant difference in the frequency of overall interactions due to the large amount of variation in the frequency of interactions ($t=0.352$, $p=0.759$). This finding points to the difficulty in analyzing interaction logs in an experimental setting, as the frequency of interactions during an open-ended decision does not have an upper limit, often resulting in great variability across participants.

Looking at specific operators, retrieve was the most frequently employed operator for the *simple* condition with 14.59 retrieves per decision, followed by panning 3.63 times per decision and zooming 0.93 times per decision. Retrieve was also the most frequently used operator for the *complex* condition with 10.85 detail retrievals per decision, with participants then panning 8.50 times per decision, overlaying attributes 6.15 times per decision, filtering 3.09 times per decision, and zooming 1.92 times per decision. Two sample t-tests resulted in no difference in the frequency of panning ($t=-2.01$, $p=0.101$) or zooming ($t=-1.28$, $p=0.271$) between the *simple* and *complex* maps. However, there was a difference in the *retrieve* operator frequency between the simple and complex interface conditions ($t=3.77$, $p=0.033$).

Those with *complex* interface condition retrieved less, with these interactions displaced to other operators (Figure 10).

While a direct comparison of the overlay strategy cannot be assessed given the variation in interface complexity, the significant difference in retrieve frequency does suggest that separate interaction strategies were used between the *simple* and *complex* interfaces: the former relying on retrieve and the latter integrating use of overlay (Figure 10). This difference in interaction strategy likely explained the differences in correctness, difficulty, and confidence between interface complexity conditions, and emphasizes the importance of considering the optimal interaction strategy for the targeted task when designing an interactive map supporting sophisticated geographic decision making. In the case study, participants had more success with the constrained, retrieve-focused strategy versus the more flexible, overlay-focused strategy. Further, participants improved performance viewing multiple decision criteria for one decision outcome versus viewing multiple decision outcomes for one decision criterion. From a geographic perspective, this might suggest that decision making is improved when the interactive map is designed to focus on specific sites over broad regional variation, an interesting hypothesis requiring follow-up testing.

Finally, the lack of significance in pan and zoom between the *simple* and *complex* interfaces suggests that these were used as enabling operators to support other work or did not directly influence decision making. The limited utility of pan and zoom for the decisions was supported by qualitative feedback on the decision-making process.

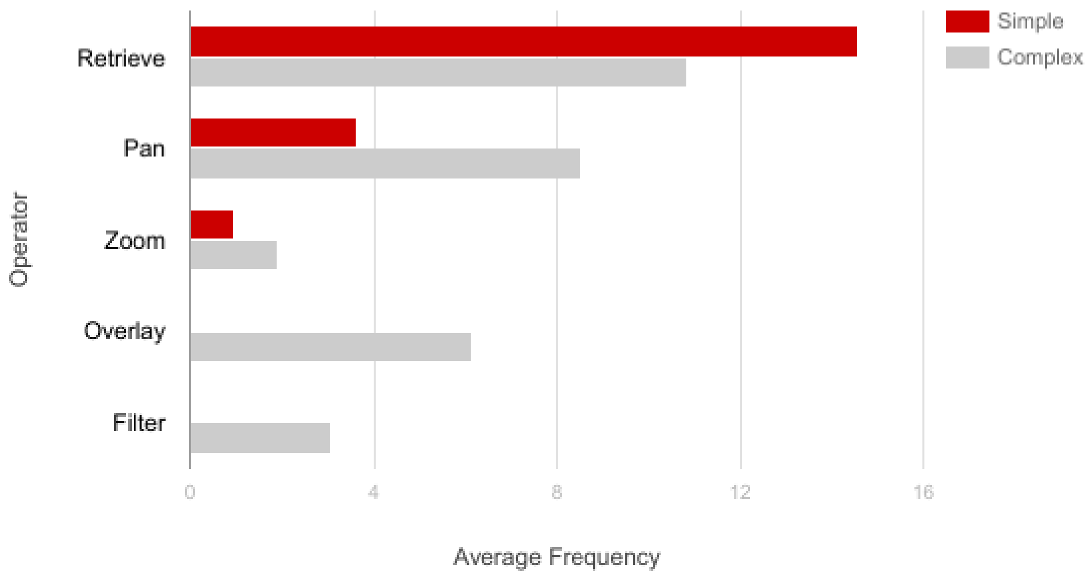


Figure 10. Average frequency of operator usage by interface complexity level.

4.3: Decision Complexity (Research Question #2)

Next, differences in correctness, difficulty, confidence, and interactions between *simple* and *complex* decisions—as defined by variation in the number of decision criteria—were evaluated to determine the effect of decision complexity on decision outcomes (Research Question #2; Table 11). The average correctness for *simple* decisions was $\bar{\tau}_{b=}0.597$ (SD=0.463, 54.1% statistically correct), while the average correctness for *complex* decisions was $\bar{\tau}_{b=}0.661$ (SD=0.433, 59.0% statistically correct). This result runs counter to expectations, as the *simple* condition had fewer criteria and therefore was expected to be an easier decision resulting in more statistically correct responses and higher confidence. One possible explanation is that the *complex* condition provided more signals to participants on how to complete the decision, and therefore modulated individual bias towards focusing on a single decision criterion versus considering all criteria. This interpretation is supported by qualitative feedback on the decision-making process, as participants focused more heavily on specific criteria when making the *simple* decision, at times even choosing a single criterion on which to base their entire decision.

A paired two sample t-test revealed that, although there was better performance on *complex* decision complexity decisions, this difference was not significant (paired t(121)=-1.352, p=0.179). Thus, the *complex* decision was not complex enough to warrant a decrease in correctness from the *simple* decision, enabling individual difference instead to account for randomness in decision responses across participants. Therefore, interface complexity, *not* decision complexity, more greatly influenced the correctness of decision outcomes for the study.

Table 11. Correctness, difficulty, and confidence results for the *simple* and *complex* decision conditions compared to overall. Statistical significance highlighted in red.

Condition	**Sample Size**	**Correctness**			**Difficulty**			**Confidence**		
Descriptive		**Average ($\bar{\tau}_b$)**	**Standard Deviation**	**% Correct**	**Average *[1=very easy]***	**Standard Deviation**	**Spearman (ρ)**	**Average *[5=very confident]***	**Standard Deviation**	**Spearman (ρ)**
Simple Decision Complexity	122	0.597	0.463	54.1%	2.3	1.1	-0.297	4.0	0.9	0.302
Complex Decision Complexity	122	0.661	0.433	59.0%	2.2	1.1	0.064	4.1	0.9	0.253
Overall	244	0.629	0.449	56.6%	2.3	1.1	-0.050	4.1	0.9	0.082
Inferential		**t statistic**	**p-value**		**t statistic**	**p-value**		**t-statistic**	**p-value**	
Simple vs. Complex	244	-1.352	0.179		0.810	0.419		-0.797	0.427	

The reported difficulty was near similar between decision complexity conditions, with an average rating of 2.3/5 (SD=1.1) for *simple* decisions and 2.2/5 (SD=1.1) for *complex* decisions. Accordingly, a paired two sample t-test identified no difference in difficulty between the *simple* and *complex* decisions (paired $t(121)=0.810$, $p=0.419$), again suggesting that the *complex* condition was not complex enough to garner significant differences in decision responses. Interestingly, however, participants reported both the *simple* and *complex* as closer to easy than difficult (5 is very difficult), despite participants overall getting only 56.6% of the decision statistically correct across conditions (as reported in Section 4.1). Spearman tests found a significant negative correlation between difficulty and correctness for the *simple* condition ($\rho=-0.297$, $p=0.0009$), but not for the *complex* condition ($\rho=0.064$, $p=0.480$), where the correlation was positive although not significant. Given the inverse scale used for difficulty, participants found the decision easier when they were closer to the correct response in the *simple* decision condition, an expected result, but not for the *complex* decision condition. In other words, participants performed the same on *complex* decisions when they believed the task to be relatively easier. This suggests that a subset of participants did not treat the *complex* decision in its full complexity, missing or ignoring dimensions of the complexity while cognitively reducing the decision. For these participants, such a complexity-reduction decision-making strategy impeded finding the optimal decision outcome for *complex* decisions. As reported above, participants still performed better overall on *complex* decisions versus *simple* decisions, so this complexity-reduction strategy did not inhibit participants from making more correct decisions compared to the *simple* decisions where this behavior was not observed. Ultimately, this suggests individual bias on *simple* decisions had a more deleterious impact on decision outcomes than complexity reduction as a decision-making strategy on *complex* decisions.

The average confidence was 4.0/5 (SD=0.9) for the *simple* decision condition and a similar 4.1/5 (SD=0.9) for the *complex* decision condition. A paired two sample t-test identified no significant difference in confidence between the *simple* and *complex* conditions (paired $t(121)=-0.797$, $p=0.427$), an unexpected result as the *simple* condition should have inspired more confidence given the anticipated ease in making the correct decision. This finding again is likely attributed to the *complex* decision condition not being difficult enough to create significant differences in correctness. Spearman tests demonstrated significant positive correlations between average correctness and average confidence in both the *simple* ($\rho=0.302$, $p=0.0007$) and *complex* ($\rho=0.253$, $p=0.005$) decision conditions. The correlation between correctness and confidence is expected, as participants who performed well on the decision should have more confidence in their response.

As with the interface complexity factor, there was no statistical difference in overall extensiveness between decision complexity conditions, as nearly all participants interacted at least once ($t=-0.127$, $p=0.902$; Table 12). Examining individual operators, there was minimal difference in complexity levels for the most extensively applied operators: 91.8% versus 91.0% retrieved details at least once for the *simple* versus *complex* decisions, 79.6% versus 85.2% overlaid additional layers at least once, and 76.2% versus 78.7% panned at least once. There also was minimal difference in the extensiveness of zooming between *simple* (30.3%) and *complex* (33.6%) conditions. There was a noticeable increase in the use of filtering as the decision increased in complexity, rising from 25.9% in the *simple* condition to 38.9% in the *complex* condition. This finding does align with Shneiderman's (1996) information seeking mantra, and it would be interesting to see if use of filtering continues to increase when increasing the decision complexity further. Ultimately, two sample t-tests found no difference between *simple* and *complex* decisions in the extensive use of retrieve ($t=0.039$, $p=0.970$), overlay ($t=-0.600$, $p=0.609$), pan ($t=-0.293$, $p=0.780$), zoom ($t=-0.422$, $p=0.695$), or filter ($t=-1.230$, $p=0.417$). Thus, the decision complexity did not significantly impact the interaction strategy used by participants to make the decisions.

Table 12. Extensiveness and frequency of operators used, separated by decision complexity levels. *Indicates operators provided in only the *complex* interface condition; see Section 4.2 for further details.

Operator	Sample Size	Extensiveness		Frequency		
Descriptive		**Total**	**Percentage**	**Total**	**Avg per Decision**	**Standard Deviation**
Simple Decision Complexity						
Retrieve	122	112 / 122	91.8	1,613	13.22	144.82
Pan	122	93 / 122	76.2	605	4.96	72.05
Overlay*	54	43 / 54	79.6	254	4.70	33.94
Zoom	122	37 / 122	30.3	134	1.10	13.63
Filter*	54	14 / 54	25.9	152	2.81	45.25
Overall	122	122 / 122	100	2,758	22.61	162.70
Complex Decision Complexity						
Retrieve	122	111 / 122	91.0	1,543	12.65	133.73
Pan	122	96 / 122	78.7	807	6.61	108.40
Overlay*	54	46 / 54	85.2	410	7.59	43.84
Zoom	122	41 / 122	33.6	200	1.64	29.70
Filter*	54	21 / 54	38.9	182	3.37	48.08
Overall	122	121 / 122	99.2	3,142	25.75	152.19
Total	244	243/244	99.6%	5,900	24.18	155.45
Inferential		**t statistic**	**p-value**	**t statistic**	**p-value**	
Simple vs. Complex	244	-0.127	0.902	-0.203	0.844	
Retrieve	244	0.039	0.970	0.178	0.865	
Pan	244	-0.293	0.780	-0.776	0.473	
Overlay*	244	-0.600	0.609	-1.990	0.185	
Zoom	244	-0.422	0.695	-1.01	0.370	
Filter*	244	-1.230	0.417	-0.321	0.778	

Interaction also was similar between decision complexity conditions when looking at frequency instead of extensiveness. By average, participants interacted with map slightly more during *complex* (25.75, SD=152.19) versus *simple* decisions (22.61, SD=162.70), as expected. However, the difference in overall frequency between complexity levels was not significant (t=-0.203, p=0.844). Retrieve (13.22 for *simple* versus 12.65 for *complex*), filter (2.81 versus 3.37), and zoom (1.10 versus 1.64) showed minimal variation in frequency between decision complexities (Figure 11). Overlay exhibited a notable increase in frequency from the *simple* (4.70) to the *complex* (7.59) decisions, perhaps indicating a tendency for some to try the overlay-focused interaction strategy in addition to the retrieve-focused strategy when completing the more *complex* decision. Pan also exhibited a slight increase from *simple* (4.96) to the *complex* (6.61) decisions, a potentially interesting result as panning can indicate that users are lost in an interactive map when completing concrete tasks (see Section 2.1). As with interaction extensiveness, two sample t-tests found no significant difference in frequency between decision conditions for retrieve (t=0.178, p=0.865), filter (t=-0.321, p=0.778), zoom (t=-1.01, p=0.370), overlay (t=-1.990, p=0.185), and pan (t=-0.776, p=0.473). Thus, it was the interface complexity, *not* decision complexity, that determined how participants developed interaction strategies to support their decisions. This finding is important from a cartographic perspective, as the interactive map design can have more influence over decision outcomes than the problem context itself.

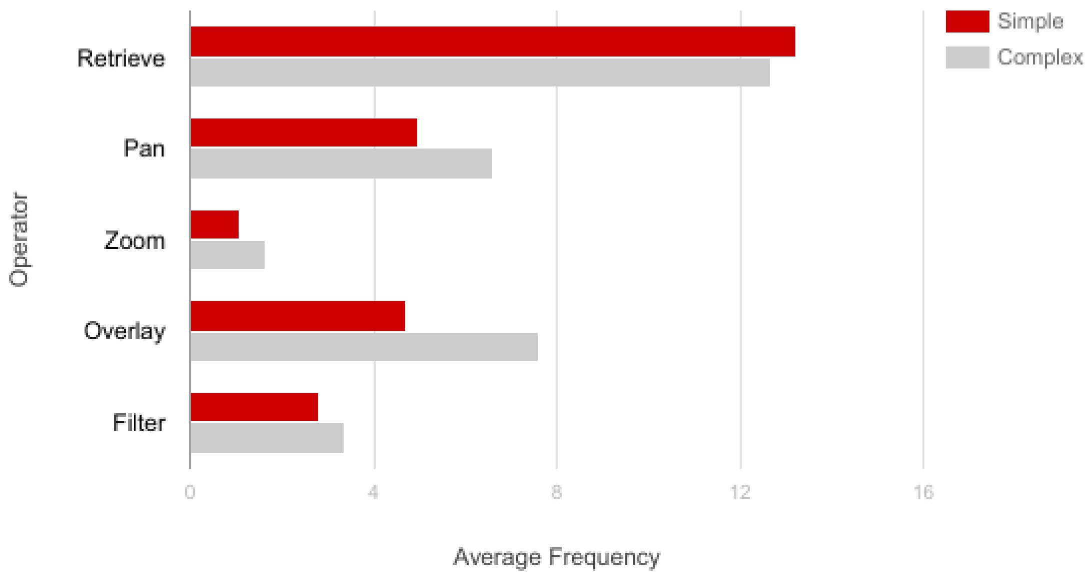


Figure 11. Average frequency of operator usage by decision complexity level.

4.4: The Role of User Expertise (Research Question #3)

Finally, differences in performance between *experts* and *non-experts* in hazardous waste were analyzed to understand the role of prior domain knowledge on decision making supported by interactive maps (Research Question #3; Table 13). A total of 12 (n=12) *experts* and 110 (n=110) *non-experts* completed this study, making comparison unbalanced. The average correctness was $\bar{\tau}_b$=0.655 (SD=0.454, 58.3% statistically correct) for *experts* and $\bar{\tau}_b$=0.626 (SD=0.449, 56.4% statistically correct) for *non-experts*. While *experts* did outperform *non-experts* on the decisions overall, a two sample t-test found no significant difference between *experts* and *non-experts* (t(242)=0.294, p=0.769). This is a plausible result given that only 10% of the sample was expert, a study limitation given the generally small and relatively inaccessible expert population. A larger *expert* sample size may lead to statistical significance, and deeper engagement with experts in an ecologically valid setting is targeted for follow-up research.

The average difficulty was 2.4/5 (SD=1.2) for *experts* and 2.3/5 (SD=1.1) for *non-experts*. Accordingly, a two sample t-test did not return significance on this small difference between the *expert* and *non-expert* difficulty ratings, indicating that both groups found the task equally difficult ($t(242)=0.467$, $p=0.641$). Spearman tests found no significant relationship between correctness and difficulty for either the *experts* ($\rho=-0.099$, $p=0.644$) or *non-experts* ($\rho=-0.121$, $p=0.072$).

Interestingly, the *non-expert* group rated their average confidence highly at 4.1/5 (SD=0.9), while the *expert* group was less confident, rating at only 3.6/5 (SD=1.1) on average. A two sample t-test found this difference significant ($t(242)=-2.723$, $p=0.007$). Thus, *non-experts* were actually more confident in their results than *experts*. While seemingly counterintuitive, this finding is consistent with prior work on geographic decision-making supported by interactive mapping (e.g. Roth 2009) and actually may be evidence that the *expert* group demonstrated their prior knowledge by properly assessing the gravity of the decision. In other words, *experts* understand the consequences of their decisions and more fully weight the costs of their decision (some of which may be uncertain) into their reported confidence. In contrast, *non-experts* had "nothing to lose" when making their decision given the lack of exposure to real consequences, leading to increased confidence. In terms of Pirolli and Card (2005), for *experts*, previous experience with "act" stages (when previously making a decision) can lead them to be more cautious in future sensemaking stages. Spearman tests found a positive correlation between correctness and confidence for *non-experts* (ρ=0.279, p=2.63x10^{-5}), but not for *experts* (ρ=0.396, p=0.056). Thus, confidence was tied to performance for *non-experts*, but other factors, such as experience and knowledge, for *experts*.

Table 13. Correctness, difficulty, and confidence for expertise level, compared to overall. Statistical significance highlighted in red.

Condition	**Sample Size**	**Correctness**			**Difficulty**			**Confidence**		
Descriptive		**Average ($\bar{\tau}_b$)**	**Standard Deviation**	**% Correct**	**Average *[1=very easy]***	**Standard Deviation**	**Spearman (ρ)**	**Average *[5=very confident]***	**Standard Deviation**	**Spearman (ρ)**
Hazardous Waste Experts	24	0.655	0.454	58.3%	2.4	1.2	-0.099	3.6	1.1	0.396
Hazardous Waste Non-Experts	220	0.626	0.449	56.4%	2.3	1.1	-0.121	4.1	0.9	0.279
Overall	244	0.629	0.449	56.6%	2.3	1.1	-0.050	4.1	0.9	0.082
Inferential		**t statistic**	**p-value**		**t statistic**	**p-value**		**t-statistic**	**p-value**	
Experts vs. Non-Experts	244	0.294	0.769		0.467	0.641		-2.723	0.007	

Experts and *non-experts* differed substantially in their interaction strategies (Table 14). There was significant difference in overall extensiveness per page as not every expert used every operator for each decision (t=-2.942, p=0.042), and there was a significant difference in the individual application of each operator: pan (t=-18.165, p=5.488x10^{-9}), zoom (t=-8.209, p=1.801x10^{-5}), retrieve (t=-8.518, p=6.094x10^{-5}), overlay (t=-19.030, p=1.361x10^{-6}), and filter (t=-4.110, p=0.015). Thus, *experts* and *non-experts* used very different interaction strategies to make their decisions.

Differences between *expert* and *non-expert* interactions clarify the relative utility of the overlay-focused and retrieve-focused interaction strategies discussed in Section 4.2. As reported above, participants using the constrained, retrieve-focused strategy performed better than participants using the flexible, overlay-focused strategy. However, *experts* more extensively made use of overlay than *non-experts* (100.0% versus 80.2%), but less extensive use of retrieve (83.3% versus 92.3%). Because there was no significant difference in correctness between conditions of expertise—with *experts* returning slightly more correct decisions—this suggests that the overlay strategy was not universally suboptimal, but rather required a degree of domain expertise to use effectively. One hypothesis is that *experts* more easily interpreted the overlay symbols, enabling them to review one criterion (attribute) across outcomes (sites), whereas non-experts relied on non-map text contained in the retrieval pop-ups, presenting information for one outcome (site) across all criteria (attributes). *Experts* also more extensively zoomed (37.5% versus 31.4%) and filtered (41.7% versus 31.3%) compared to *non-experts*, suggesting greater application of Shneiderman's (1996) information seeking mantra on which the *complex* interface design was based. Interestingly, *experts* more extensively panned compared to *non-experts* (83.3% versus 76.8%), an indication there may have been more moments of confusion on average for *experts* given the overlay-focused strategy.

Table 14. Extensiveness and frequency of operators used, separated by expertise level. *Indicates operators provided in only the *complex* interface condition; see Section 4.2 for further details. Statistical significance between expertise levels highlighted in red.

Operator	**Sample Size**	**Extensiveness**		**Frequency**		
Descriptive		**Total**	**Percentage**	**Total**	**Avg per Decision**	**Standard Deviation**
Hazardous Waste Experts						
Retrieve	24	20 / 24	83.3	346	14.42	23.51
Pan	24	20 / 24	83.3	174	7.25	15.27
Overlay*	12	12 / 12	100	114	9.50	13.10
Zoom	24	9 / 24	37.5	34	1.42	4.06
Filter*	12	5 / 12	41.7	41	3.42	8.96
Overall	24	24 / 24	100	709	29.54	20.65
Hazardous Waste Non-Experts						
Retrieve	220	203 / 220	92.3	2,810	12.77	106.26
Pan	220	169 / 220	76.8	1,238	5.63	75.77
Overlay*	96	77 / 96	80.2	550	5.73	47.19
Zoom	220	69 / 220	31.4	300	1.36	19.52
Filter*	96	30 / 96	31.3	293	3.05	31.12
Overall	220	219 / 220	99.5	5,191	23.60	136.35
Total	244	243/244	99.6%	5,900	24.18	155.45
Inferential		**t statistic**	**p-value**	**t statistic**	**p-value**	
Experts vs. Non-Experts	244	-2.942	0.042	-1.873	0.134	
Retrieve	244	-8.518	6.094×10^{-5}	8.005	4.347×10^{-5}	
Pan	244	-18.165	5.488×10^{-9}	-4.867	0.0002	
Overlay*	108	-19.030	1.361×10^{-6}	-4.451	0.021	
Zoom	244	-8.209	1.801×10^{-5}	-4.718	0.0003	
Filter*	108	-4.110	0.015	-3.891	0.030	

Analysis of interaction frequency further enriched differences in interaction strategies (Figure 12). Overall frequency between *experts* and *non-experts* was not significantly different (t=-1.873, p=0.134), but individual application of each operator differed significantly between *experts* and *non-experts*: pan ($t=-4.867$, $p=0.0002$), zoom ($t=-4.718$, $p=0.0003$), retrieve ($t=-8.005$, $p=4.347 \times 10^{-5}$), overlay ($t=-4.451$ $p=0.021$), and filter ($t=-3.891$, $p=0.030$). As with extensiveness, *experts* more frequently used overlay than *non-experts* (9.50 times on average versus 5.73 times), further suggesting that overlay required greater domain expertise for effective use. Interestingly, *experts* more frequently used both retrieve (14.42 versus 12.77 times) and pan (7.25 versus 5.63). Retrieve and pan are the two operators that either imply careful attention to or utter confusion with an interactive map (see Section 2.1), depending on the interaction context. Because *experts* applied retrieve and pan more frequently than *non-experts* without impeding decision correctness, this signal indicates a deeper, more attentive engagement with the decision by *experts* compared to their *non-expert* counterparts. It also suggests that the more extensive use of panning by *experts* reported above has more to do with being careful rather than confused. The margins between *expert* and *non-expert* were smaller for zoom (1.42 versus 1.36) and filter (3.42 versus 3.05), although still significant due to the wide variation in operator use by *non-experts*. This perhaps indicates purposeful application of zoom and filter to support Shneiderman's information seeking mantra by *experts*, but random misuse of zoom and filter by *non-experts*.

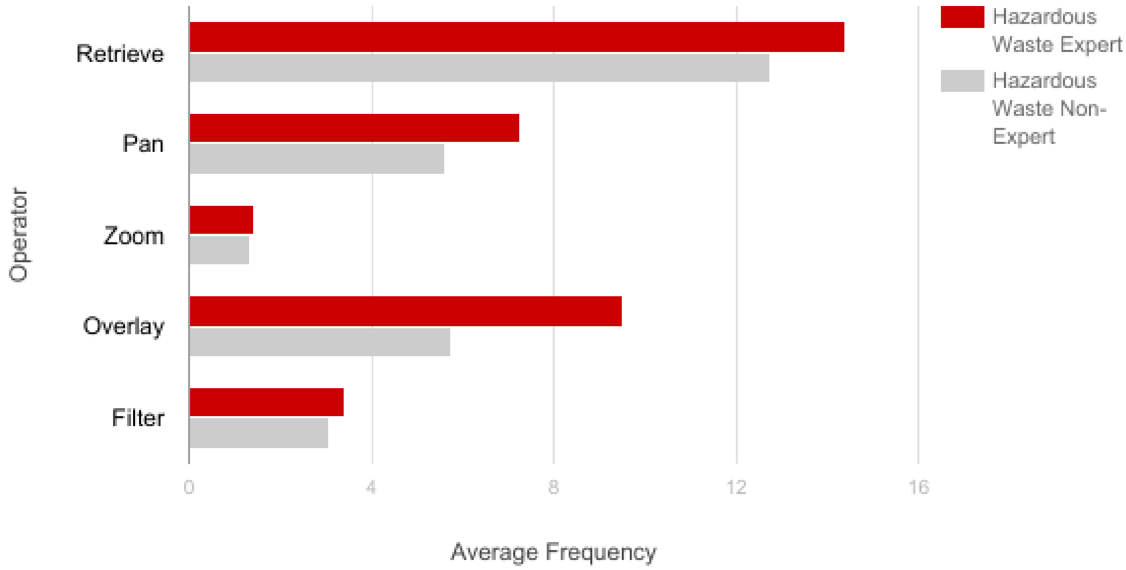


Figure 12. Average frequency of operator usage between hazardous waste *experts* and *non-experts*.

CHAPTER 5: CONCLUSION AND FUTURE DIRECTIONS

5.1 Conclusions

The goal of this research was to determine the effect of cartographic interface complexity, geographic decision complexity, and user expertise on map-based decision making to better design cartographic decision making products. This was achieved through surveying n=122 participants using a map-based survey emphasizing environmental justice issues in the North American hazardous waste trade as a case study. Overall, there was no difference in correctness between the Ohio map and the Texas map, as well as between the first decision completed and the second decision completed. There was, however, significance between difficulty and correctness and confidence and correctness for both the Texas map and the first decision completed. These results still indicate that location and order had minimal impact on the decisions. Also, 243/244 (99.6%) participants interacted with the maps, indicating that the example training map at the beginning of the survey was successful at encouraging participants to interact with the map. Participants also did not use each operator evenly, and the distribution of operators did not align with Shneiderman's information seeking mantra in which zoom and filter are necessary to transition from the initial view to the detailed view (Shneiderman 1996). Further, participants did not filter excessively, which is a sign they did not default to Shneiderman's mantra and does not align with the findings of Roth and MacEachren (2016). In particular, participants commented that pan and zoom were not helpful for the decisions, confirming the finding of uneven operator usage. Participants may have skipped the information seeking stage of decision making and went right to the sensemaking stage because they were given the problem; they did not have to find it (Pirolli and Card 2005). This explains why there was limited evidence of Shneiderman's (1996) *information seeking* mantra (i.e. unevenness) in the interaction logs.

The cartographic interface complexity results showed significance in geographic decision correctness between the *simple* and *complex* conditions. The *simple* condition resulted in higher correctness scores, which could be attributed to the fact that participants were able to view multiple decision criteria for one decision outcome with the *simple* map versus viewing multiple decision outcomes for one decision criterion for the *complex* map. This also suggests that geographic decision making may be more successful at the local level, rather than a broad overview level. Further, the participants who completed the *simple* interface condition identified that the decision was easier and had more confidence in their decisions than those who had the *complex* interface condition. Accordingly, users of interactive maps with the scope of the *complex* condition may result in an inability to act, not because the decision is untenable, but because the complexity of the interface makes the decision seem untenable. Participants who were confident in their answers tended to be more correct with both the *simple* and *complex* map. This indicates that the *complex* map appeared more difficult, although the decision was no different.

Regarding *how* users interacted, retrieve was used by all participants using the *simple* map, an expectation given the simple basemap without labels. The frequent use of retrieve, however, also indicates a deeper engagement with the range of information provided on environmental justice issues: it is clear that participants did not base their decisions solely on the circle size to come to their decision. This aligns with previous findings that retrieve can be applied successfully (Andrienko et al. 2002) and can be used to confirm findings (Davies

1998, Roth and MacEachren 2016). Retrieve was used significantly less for those with the *complex* interface complexity indicating that they used filter and overlay when provided. Because the *simple* complexity condition had greater correctness scores than the *complex* condition, filter and overlay were not helpful in decisions. The limited use of pan and zoom was explained by participant feedback. Tolochko (2016) identifies that panning and zooming are paired for multiscale maps. Since zoom was not applied often, panning was not a helpful indicator of performance, and instead may suggest the need to view offscreen features on smaller screen devices. Further, two different interaction strategies were discovered. Participants using the *simple* map used a retrieve-based strategy, while participants using the complex map used an overlay-based strategy which resulted in lower correctness. Therefore, for a general audience, toggling overlays may be ineffective. Without the necessary domain expertise (see below), participants tended to make use of text materials (as pop-ups) rather than overlays. The retrieve interaction strategy was the more successful interaction strategy in this study, so excessive retrieve did not seem like a breakdown of information seeking, as suggested by Roth and MacEachren (2016). Also, this strategy relied heavily on interpreting non-visual text, which does not align with Keehner et al. (2008) who found that relying on finding the right visual (i.e., map view) is essential for spatial tasks.

The geographic decision complexity results revealed that there was no difference in correctness between the *simple* and *complex* decision complexities, which agrees with the findings from Crossland et al. (1995) and Jankowski and Nyerges (2001), but disagrees with Jelokhani-Niaraki and Malczewski (2015), although the *complex* condition had a higher percent of correct decisions. This could be due to the *complex* criteria signaling the participants to use those criteria to answer the decision, leading to the correct decision where the *simple* condition led participants to choose a single criterion. The bias towards a single criterion in the *simple* condition was supported by the qualitative feedback. This finding goes against distributed cognition literature where the SDSS tool (i.e., the map) takes on part of the decision-making load so participants can consider all criteria (Crossland et al. 1995, Coutinho-Rodrigues et al. 1997, Jankowski et al. 2001, MacEachren et al. 2004). There was, however, significance between correctness and difficulty for the *simple* decision complexity. Those who rated the task as easier tended to be closer to the correct ranking. The same trend was true for correctness and confidence for both the *simple* and *complex* decision conditions. The more confident the participant was, the more correct they tended to be.

There was no significance in operator extensiveness and frequency between the *simple* and *complex* decision complexities overall or between individual operators, meaning decision complexity was not a factor in geographic decision correctness; the interface to the map was the influencing factor.

There were n=12 hazardous waste *experts* who took part in this study (10% of total sample). Surprisingly, the *non-experts* were more confident in their answers, which can be attributed to the fact that *non-experts* never had to act before, where *experts* have in the past, giving them a better sense of consequences (Pirolli and Card 2005). As *non-expert* confidence increased, so too did their correctness.

Expert extensiveness for pan, zoom, overlay, and filter was significantly more than *non-experts*. However, there was repeated use of operators by both *experts* and *non-experts*. Repeated panning is an indication of a lost user for *non-experts* and indication of a thorough user for *experts*, which agrees with Roth and MacEachren (2016). Also, *experts* filtered more than *non-experts*, which aligns with the previous finding that filtering is a difficult operation to perform as *non-experts* relatively avoided filtering (MacEachren et al. 1998, Andrienko et al. 2002). Filtering is also an indication of distributed cognition. *Experts* filtered with purpose, indicating that they trusted the system to offload some of the work on to the map to make their decision-making process simpler (Jankowski et al. 2001, MacEachren et al. 2004). The number of *non-experts* who retrieved was greater than the number of *experts* who retrieved. The finding that *non-experts* jumped to retrieve to find insight worked well for this dataset, a brute force interaction strategy that paid off in the evaluated decisions given the relatively small number of decision outcomes. Both overlay and filter are likely to become more important as the number of decision criteria and outcomes grow, following Shneiderman's (1996).

Experts utilized all operators with greater frequency than *non-experts*, indicating that *experts* interacted more in general. Because there was no difference in correctness between *experts* and *non-experts*, interactivity did not hinder *expert* performance. This finding does not align with Mennecke et al. (2000) who found that interactivity decreased *expert* success. The increased interactivity by *experts* is also evidence that visual information seeking (Shneiderman 1996) was more successfully applied by *experts* than *non-experts*. All *experts* who had the overlay functionality chose to use overlay, further indicating that overlay was a popular decision strategy among participants, although it was not a helpful one. Again, overall, those with the *complex* map chose to overlay more, which resulted in a worse overall correctness. *Experts* with overlay chose to overlay, which resulted in no difference in correctness between *experts* and *non-experts*. The finding that overlay showed mixed use/success results refines the finding from Roth and MacEachren (2016): expertise matters in how participants use overlay. In this study, *non-experts* used overlay minimally, and *experts* used overlay excessively. Finally, Ericsson and Lehmann (1996) found that *experts* think through a decision differently than *non-experts*, and the evidence found here in this study shows that *experts* also interact differently for the same decision problem.

Overall, these results indicate that cartographic interface complexity was the main factor in decision correctness and overall geographic decision success. The interaction logs confirm that not all participants interacted in the same way, further indicating that cartographers need to design for the target user persona and decision scenario. Below, I provide design recommendations for future decision-making tools, which were derived from this research.

5.2 Design Recommendations

Multiple design recommendations were derived from this research study, which are summarized here for cartographers developing the decision-making tools and hazardous waste decision makers requesting/using the tools:

<u>Cartographers</u>

Overall

The complexity of the decision did not matter in this study, so map design is key for developing successful decision-making tools:

- Create an interface that is easy to use. Participant confidence decreased and perceived decision difficulty increased with increased interactive scope and flexibility, so a clean interface without complicated controls is best for relatively concrete decision making.
- Include retrieve no matter the complexity level. Participants retrieved heavily and it was found to be the most successful interaction strategy. Given the reliance on retrieve, including some map labels for vector features on web maps also may be advisable, particularly for features interacted with repeatedly.
- Include pan and zoom if the decision takes place at multiple scales or if there is initial, enabling work that needs to be completed by the user. Implement pan even if zooming may not be required due to variability in screen sizes.
- Provide data on multiple criteria for each outcome (site). Participant success was greater when viewing multiple attributes for one hazardous waste facility at a time.

The geographic decisions in this research were developed using a case study of environmental justice issues in the North American hazardous waste trade. The maps showed hazardous waste facilities as proportional symbols, sized based on amount of waste imported from Canada and/or Mexico. Participants were asked to make regulation and management decisions by analyzing social and environmental criteria at the specific sites. It was found here that hazardous waste experts and non-experts interacted differently for the geographic decisions, so cartographers need to cater to user differences:

Non-Experts

- Provide non-experts with the ability to retrieve details through an information window or pop-up. This gives them the information needed to come to a decision without overwhelming them with problem details on a topic they are not domain experts on. Non-experts tend to visualize all criteria for one outcome at a time, which is possible through retrieving details from a pop-up or informational panel.
- Instead of providing non-experts shaded units to view (as was done in the overlays in this study), supply them with text for important attributes in the pop-ups (as was done in this study).
- Use a minimalist approach when designing for non-experts. Only supply the functionality needed so that they can make a decision quickly and accurately. A simple “slippy” map may be all that is needed for non-expert decision makers.

Experts

- Provide experts with the ability to filter datasets. Experts understand the importance of narrowing the data displayed for the given decision, and they know how to sift out unnecessary information. Experts will filter purposefully.
- Provide experts with the ability to overlay additional datasets. Experts find value in visualizing one criterion for multiple outcomes when assessing the scope of the decision and will apply overlays frequently.
- Use an increased interactivity approach, overall, for experts. They have the domain knowledge needed to evaluate all available factors, while using the tool to the full extent as a cognitive offload.

Decision Makers

Every geographic decision is different, with different levels of consequence if the wrong decision is made. Negative consequences for the hazardous waste trade case study include harm to the environment or people near the hazardous waste facilities. Consider the following when requesting decision-making tools from cartographers:

- Know the scale of analysis for the decision. Panning and zooming are not effective if the data is only at one scale.
- With regards to Shneiderman's information seeking mantra, "information" seeking does not equal "decision" seeking, so zoom and filter may not be necessary for every geographic decision, though they may be valuable for other applications. Consider the size of the dataset when requesting a decision-making tool. Retrieve may be ineffective for larger datasets, where filter will be helpful for narrowing the dataset. For example, filtering is typically more important for datasets larger and decisions more complex than the those used in this study.
- Decision making for environmental justice concerns were better supported by an interactive map when viewed at the site level. Consider the scope of analysis when requesting decision-making tools, as aggregated overviews may be inappropriate and even misleading.
- Finally, let the tool do the work it was designed to do. The tool is designed to offload the work from the decision maker to the system, so utilize the full extent of the tool when making decisions.

5.3 Limitations and Future Directions

There were several limitations to this research, discussed here, all with potential for future research. One limitation was that cartographic interface scope was only considered in this research, as it is known to have a greater impact on interface complexity than interface freedom. A future direction of this research would be to examine interface freedom to see if this is indeed the case for this decision-making example, as well as others. Further, geographic decision criteria were only considered in this research, not the number of outcomes (i.e., hazardous waste facility sites). A future direction of this research would be to vary the decision outcomes for this hazardous waste trade example, and other decision-making tasks. Specific future research questions involving interface and decision complexity include:

- Does cartographic interface *freedom* influence the success of geographic decision making? If so, how?
- Do geographic decision *outcomes* influence the success of cartographic interface effectiveness for decision making? If so, how?
- What is the effect of more complex decisions? When do users reach the "channel capacity" Miller (1956:2) and become confused? Do interactive maps increase the time it takes to reach that channel capacity?
- What strategies do we use for promoting learnability of general interfaces that we can apply to expert (more complex) interfaces?

Another limitation to this research was the MapStudy framework used to test the interactive maps. This study apparatus is still in development with new features currently being added. A future direction includes creating a MapStudy interface with small multiples so participants would be able to see multiple overlays at once, interaction logging that details if a participant zoomed in or out and which overlays are toggled on/off, and integrating D3 (Data Driven Documents) into the MapStudy framework to allow projection changes and dynamic labeling. Further, it is important to consider other map representations besides choropleth maps. It would be beneficial to design shaded proportional symbols, for example, to understand the effect of representation on cartographic interaction. Potential future map design and interface layout questions include:

- Does the inclusion of *small multiples* versus toggling *overlays* impact geographic decision making? If so, how?
- Does toggling overlays versus adding multiple overlays at once impact geographic decision making? If so, how?
- Does a *D3.js* map support decision making differently than a *Leaflet.js* map? If so, how?
- How does cartographic representation impact cartographic interaction for geographic decision making?
- What is the decision-making process for decisions made with interactive maps? What is the impact of the sequence of interactions performed?

Finally, future research is needed to learn more about the specific decision context—environmental justice concerns regarding the transnational trade of hazard waste. Future studies should be conducted in a realistic setting to provide deeper insight into the decision-making process, sequence of interactions performed, and influences of screen real estate and other technological constraint. However, as with this study, deeper investigation is limited by the number of experts, especially those who currently work in the hazardous waste industry. Accordingly, future research using qualitative methods is encouraged, such as participant observation or talk-aloud studies. Such research may help expose important regional, geographic variation in the management and regulation of hazardous waste. Future decision-making research questions, applicable to the hazardous waste trade include:

- Do map users have a better geographic awareness of Texas? If so, why? What about other states?
- Is decision making improved when the map is designed to focus on specific sites instead of a broad region? How so?
- What is the impact of a detailed look versus an overview look on geographic decision making? What about transitioning between scales? Is this dependent on the user's expertise with the domain topic? With interactive maps?

MacEachren (2015) identified that additional empirical research is a key next step to understanding the use of interactive maps as decision-making aids. Further, this lack of research on cartographic interface design, particularly in the decision-making context, supports the need for this research study conducted and reported here. Interface complexity and decision complexity are two factors that may hinder any geographic decision supported by a map, but they may also contribute to decision success. It is only through research, like this study, that we can understand the impact of interface and decision complexity on potential users and design interfaces that positively support decision making.

This study found that interface complexity had a greater impact on participants' success than decision complexity. It also found that experts interact differently than non-experts further demonstrating the need for cartographers to design maps for their audience and anticipated use cases. Geographic decision making is a difficult, yet necessary process with potentially negative consequences if the wrong decision is made. It is my hope that these findings stimulate continued research within the domain of decision making, so that maps can aid in the decision-making process. I further believe that the findings of this study prove to be a viable contribution to decision science and the study of cartographic interaction.

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APPENDIX A

1. How much contact have you had with professionals in the hazardous waste industry?

2. In general, in your experience talking with those people, what aspects of the hazardous waste trade seemed important to them? What do they focus on for their job? Trends?

3. Our project is very spatial. Are hazardous waste experts concerned with the geography of waste? At what scale? What time periods?

4. What decisions do you suspect hazardous waste experts have to make? What decision tasks could be made using our data?

5. What factors go into those decisions? How many factors? How many sites?

6. Which factors are most important? Please rank the importance.

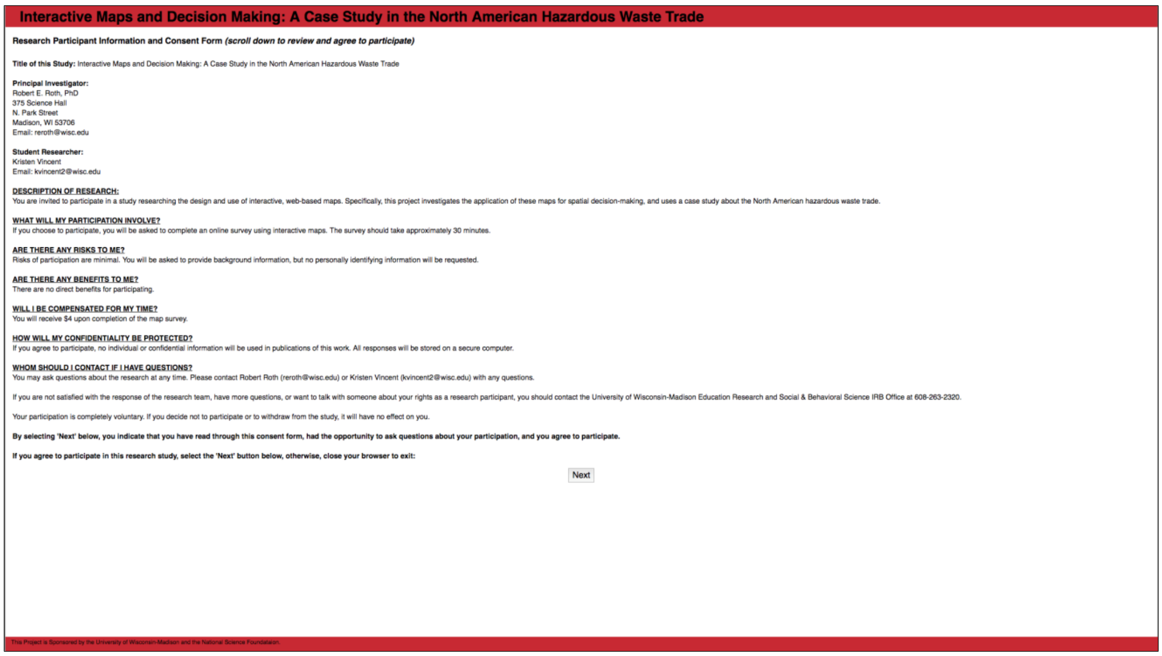
7. Do you think the following decisions are valid:

- Site Selection-where to open a new hazardous waste site in Ohio
- Site Selection-where to close a hazardous waste site in Ohio
- Transportation routes-determine acceptable transportation route
- Mitigate contamination-plan for a community

8. Anything else?

APPENDIX B

One full map survey example is shown here first, followed by the other maps tested in this study. The maps are shown at various zoom levels with various features activated.



Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade

Research Participant Information and Consent Form ***(scroll down to review and agree to participate)***

Title of this Study: Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade

Principal Investigator:
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Student Researcher:
Kristen Vincent
Email: kvincent2@wisc.edu

DESCRIPTION OF RESEARCH:
You are invited to participate in a study researching the design and use of interactive, web-based maps. Specifically, this project investigates the application of these maps for spatial decision-making, and uses a case study about the North American hazardous waste trade.

WHAT WILL MY PARTICIPATION INVOLVE?
If you choose to participate, you will be asked to complete an online survey using interactive maps. The survey should take approximately 30 minutes.

ARE THERE ANY RISKS TO ME?
Risks of participation are minimal. You will be asked to provide background information, but no personally identifying information will be requested.

ARE THERE ANY BENEFITS TO ME?
There are no direct benefits for participating.

WILL I BE COMPENSATED FOR MY TIME?
You will receive $4 upon completion of the map survey.

HOW WILL MY CONFIDENTIALITY BE PROTECTED?
If you agree to participate, no individual or confidential information will be used in publications of this work. All responses will be stored on a secure computer.

WHOM SHOULD I CONTACT IF I HAVE QUESTIONS?
You may ask questions about the research at any time. Please contact Robert Roth (reroth@wisc.edu) or Kristen Vincent (kvincent2@wisc.edu) with any questions.

If you are not satisfied with the response of the research team, have more questions, or want to talk with someone about your rights as a research participant, you should contact the University of Wisconsin-Madison Education Research and Social & Behavioral Science IRB Office at 608-263-2320.

Your participation is completely voluntary. If you decide not to participate or to withdraw from the study, it will have no effect on you.

By selecting 'Next' below, you indicate that you have read through this consent form, had the opportunity to ask questions about your participation, and you agree to participate.

If you agree to participate in this research study, select the 'Next' button below, otherwise, close your browser to exit:

Next

This Project is Sponsored by the University of Wisconsin-Madison and the National Science Foundataion.

Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade

Thank you for agreeing to participate!

Digital interactive maps are now a part of our everyday lives. This research investigates how such interactive maps can or cannot help us make choices about the management and regulation of commodities in the landscape.

Specifically, the following survey uses the North American regulation and trade of hazardous waste as a case study. Tons of hazardous waste are traded among Canada, Mexico, and the United States daily, creating many management decisions that ensure safe disposal. Such choices about how to regulate hazardous waste are complex, requiring consideration of a number of potential solutions. In this study, you will be asked to make two different decisions about the hazardous waste trade using information provided in an interactive map.

INSTRUCTIONS:

The survey proceeds in four sections:

1. First, you will be given an example map to familiarize yourself with the map symbols and map controls used in the study. You also will be given an example task to get a feel for the kinds of decisions you will need to make with the interactive maps. Use as much time as you wish to study the example map and learn how to use its controls, as these responses are not recorded.
2. You then will be presented with two different scenarios related to the regulation and trade of hazardous waste. Each scenario focuses on a different region in the United States and includes a different interactive map to support your decision. For each scenario, make use of the interactive map to arrive at a decision you feel is **optimal**. After each decision, you will be asked to assess your **confidence** in the decision solution and to rate your **difficulty** in making this choice. Please complete these questions using your **complete focus** (do not view other websites, split your attention, etc.).
3. Between the two scenarios, you will complete a set of map reading tasks with a static map showing the distribution of hazardous waste imports in the United States. Please complete these questions using your **complete focus**, as they are meant to refresh your train of thought from the prior decision.
4. After completing all map tasks, you will respond to a series of background questions about your interests and experiences. You will be compensated after you submit the background survey.

Throughout the survey, **DO NOT** use the web browser "Back" or "Forward" buttons or close your browser, as this will require you to restart the survey. Only use the "Next" buttons found at the bottom of the pages to advance the survey.

ELIGIBILITY:

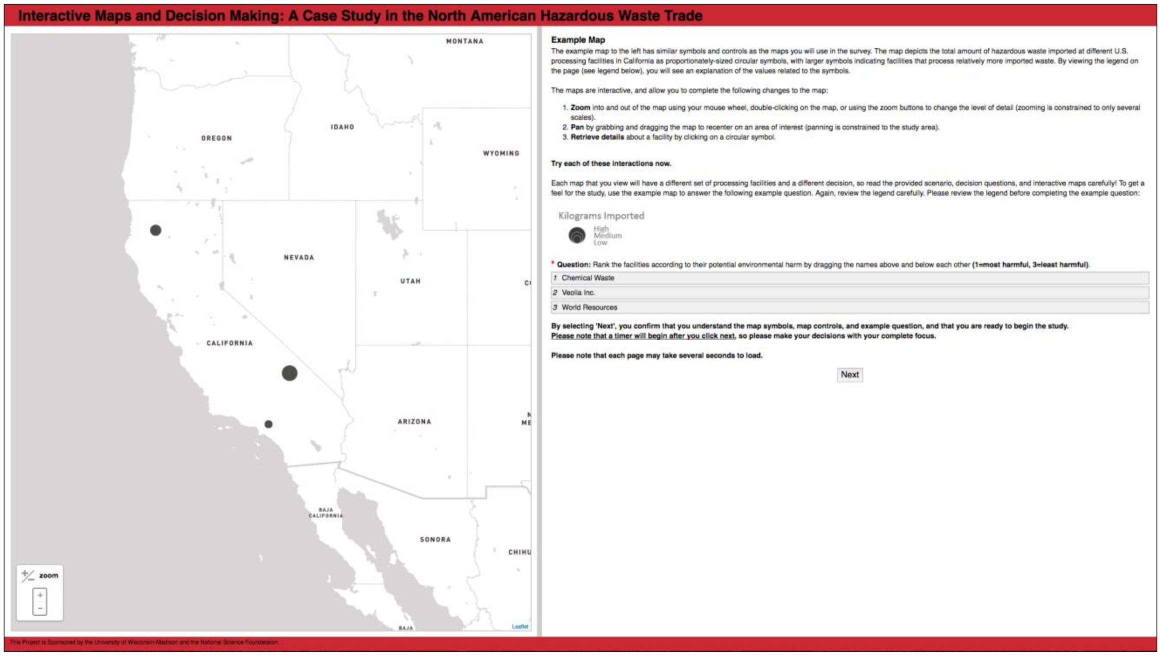
Before beginning, please once again review your eligibility for participating in the study. These restrictions greatly impact your responses:

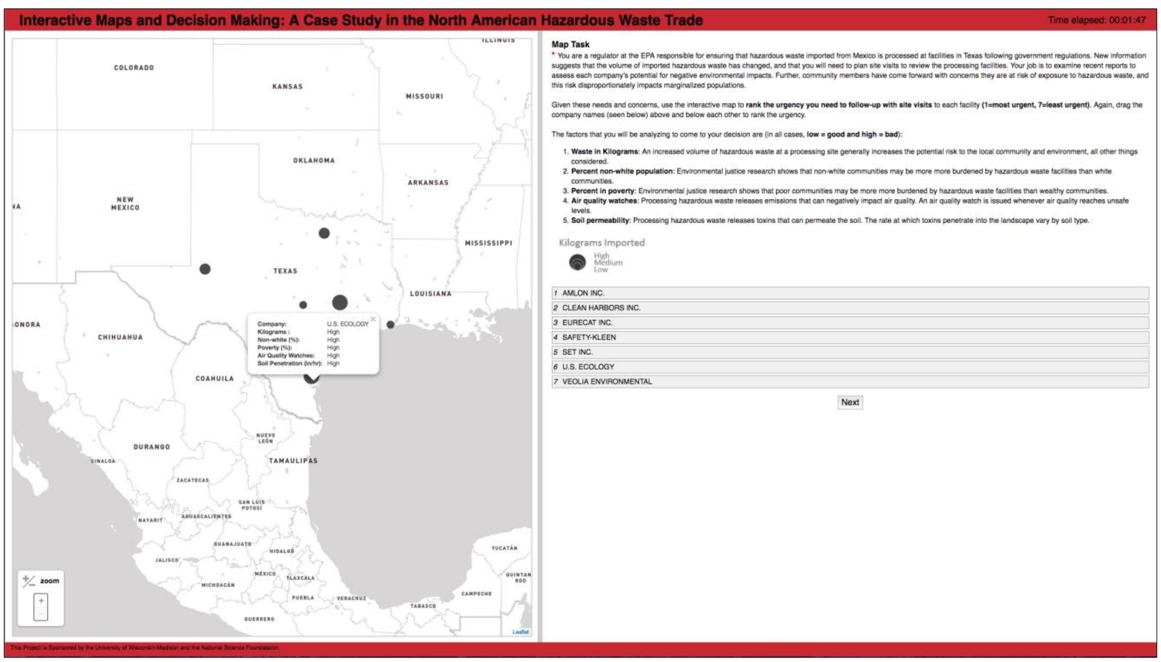
- You must be 18 years of age or older.
- English must be your first language.
- You must currently be living in the United States, but not in the states of Ohio or Texas, the location of the pair of scenarios.
- You must complete the survey on a laptop or desktop computer (i.e., **NOT** a mobile device such as a phone or tablet).

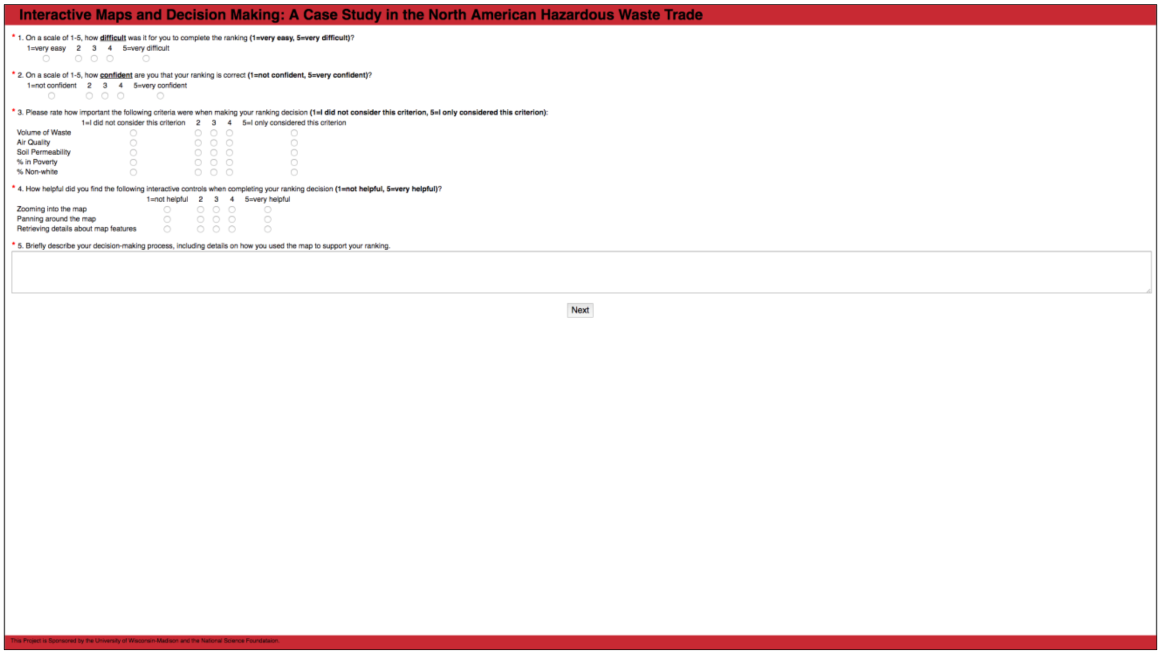
Select 'Next' to confirm that you have read the instructions and confirm that you are eligible and ready to view the example map.

Next

This Project is Sponsored by the University of Wisconsin-Madison and the National Science Foundataion.


Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade
MONTANA
IDAHO
OREGON
WYOMING
NEVADA
UTAH
CALIFORNIA
ARIZONA
BAJA CALIFORNIA
SONORA
zoom
Example Map
The example map to the left has similar symbols and controls as the maps you will use in the survey. The map depicts the total amount of hazardous waste imported at different U.S. processing facilities in California as proportionately-sized circular symbols, with larger symbols indicating facilities that process relatively more imported waste. By viewing the legend on the page (see legend below), you will see an explanation of the values related to the symbols.
The maps are interactive, and allow you to complete the following changes to the map:
1. Zoom into and out of the map using your mouse wheel, double-clicking on the map, or using the zoom buttons to change the level of detail (zooming is constrained to only several scales).
2. Pan by grabbing and dragging the map to recenter on an area of interest (panning is constrained to the study area).
3. Retrieve details about a facility by clicking on a circular symbol.
Try each of these interactions now.
Each map that you view will have a different set of processing facilities and a different decision, so read the provided scenario, decision questions, and interactive maps carefully! To get a feel for the study, use the example map to answer the following example question. Again, review the legend carefully. Please review the legend before completing the example question:
Kilograms Imported
High
Medium
Low
* Question: Rank the facilities according to their potential environmental harm by dragging the names above and below each other (1=most harmful, 3=least harmful).
1 Chemical Waste
2 Veolia Inc.
3 World Resources
By selecting 'Next', you confirm that you understand the map symbols, map controls, and example question, and that you are ready to begin the study.
Please note that a timer will begin after you click next, so please make your decisions with your complete focus.
Please note that each page may take several seconds to load.
Next
This Project is Sponsored by the University of Wisconsin-Madison and the National Science Foundation.


Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade
Time elapsed: 00:01:47
COLORADO
KANSAS
MISSOURI
OKLAHOMA
ARKANSAS
NEW MEXICO
MISSISSIPPI
TEXAS
LOUISIANA
CHIHUAHUA
COAHUILA
DURANGO
TAMAULIPAS
Company: U.S. ECOLOGY
Kilograms: High
Non-white (%): High
Poverty (%): High
Air Quality Watches: High
Soil Penetration (in/hr): High
zoom
Map Task
* You are a regulator at the EPA responsible for ensuring that hazardous waste imported from Mexico is processed at facilities in Texas following government regulations. New information suggests that the volume of imported hazardous waste has changed, and that you will need to plan site visits to review the processing facilities. Your job is to examine recent reports to assess each company's potential for negative environmental impacts. Further, community members have come forward with concerns they are at risk of exposure to hazardous waste, and this risk disproportionately impacts marginalized populations.
Given these needs and concerns, use the interactive map to rank the urgency you need to follow-up with site visits to each facility (1=most urgent, 7=least urgent). Again, drag the company names (seen below) above and below each other to rank the urgency.
The factors that you will be analyzing to come to your decision are (in all cases, low = good and high = bad):
1. Waste in Kilograms: An increased volume of hazardous waste at a processing site generally increases the potential risk to the local community and environment, all other things considered.
2. Percent non-white population: Environmental justice research shows that non-white communities may be more more burdened by hazardous waste facilities than white communities.
3. Percent in poverty: Environmental justice research shows that poor communities may be more more burdened by hazardous waste facilities than wealthy communities.
4. Air quality watches: Processing hazardous waste releases emissions that can negatively impact air quality. An air quality watch is issued whenever air quality reaches unsafe levels.
5. Soil permeability: Processing hazardous waste releases toxins that can permeate the soil. The rate at which toxins penetrate into the landscape vary by soil type.
Kilograms Imported
High
Medium
Low
1 AMLON INC.
2 CLEAN HARBORS INC.
3 EURECAT INC.
4 SAFETY-KLEEN
5 SET INC.
6 U.S. ECOLOGY
7 VEOLIA ENVIRONMENTAL
Next
This Project is Sponsored by the University of Wisconsin-Madison and the National Science Foundation.



Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade

* 1. On a scale of 1-5, how **difficult** was it for you to complete the ranking **(1=very easy, 5=very difficult)**?

1=very easy 2 3 4 5=very difficult

* 2. On a scale of 1-5, how **confident** are you that your ranking is correct **(1=not confident, 5=very confident)**?

1=not confident 2 3 4 5=very confident

* 3. Please rate how important the following criteria were when making your ranking decision **(1=I did not consider this criterion, 5=I only considered this criterion)**:

	1=I did not consider this criterion	2	3	4	5=I only considered this criterion
Volume of Waste					
Air Quality					
Soil Permeability					
% in Poverty					
% Non-white					

* 4. How helpful did you find the following interactive controls when completing your ranking decision **(1=not helpful, 5=very helpful)**?

	1=not helpful	2	3	4	5=very helpful
Zooming into the map					
Panning around the map					
Retrieving details about map features					

* 5. Briefly describe your decision-making process, including details on how you used the map to support your ranking.

Next

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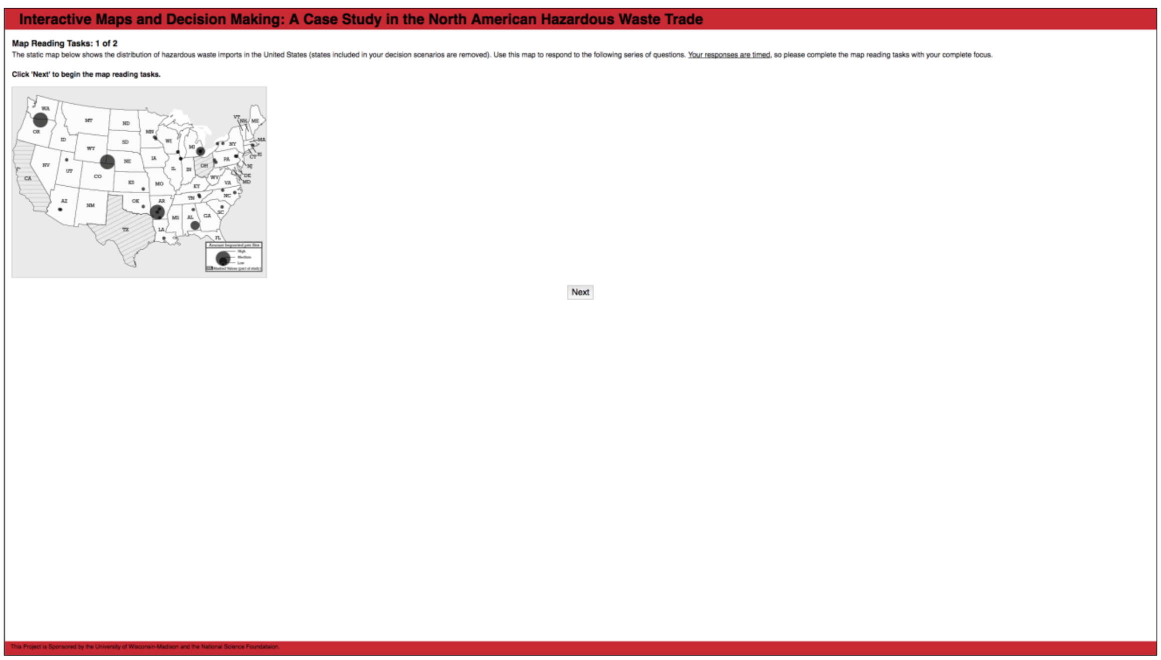

Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade

Map Reading Tasks: 1 of 2

The static map below shows the distribution of hazardous waste imports in the United States (states included in your decision scenarios are removed). Use this map to respond to the following series of questions. Your responses are timed, so please complete the map reading tasks with your complete focus.

Click 'Next' to begin the map reading tasks.

Next

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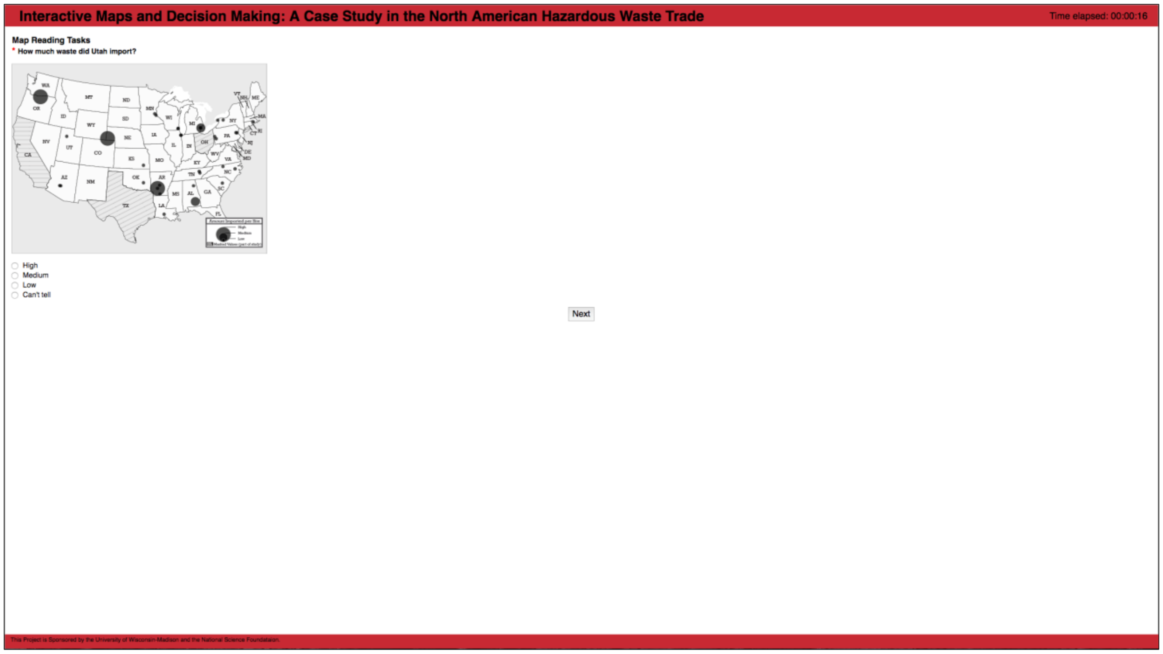
Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade
Time elapsed: 00:00:16
Map Reading Tasks
* How much waste did Utah import?
High
Medium
Low
Can't tell
Next
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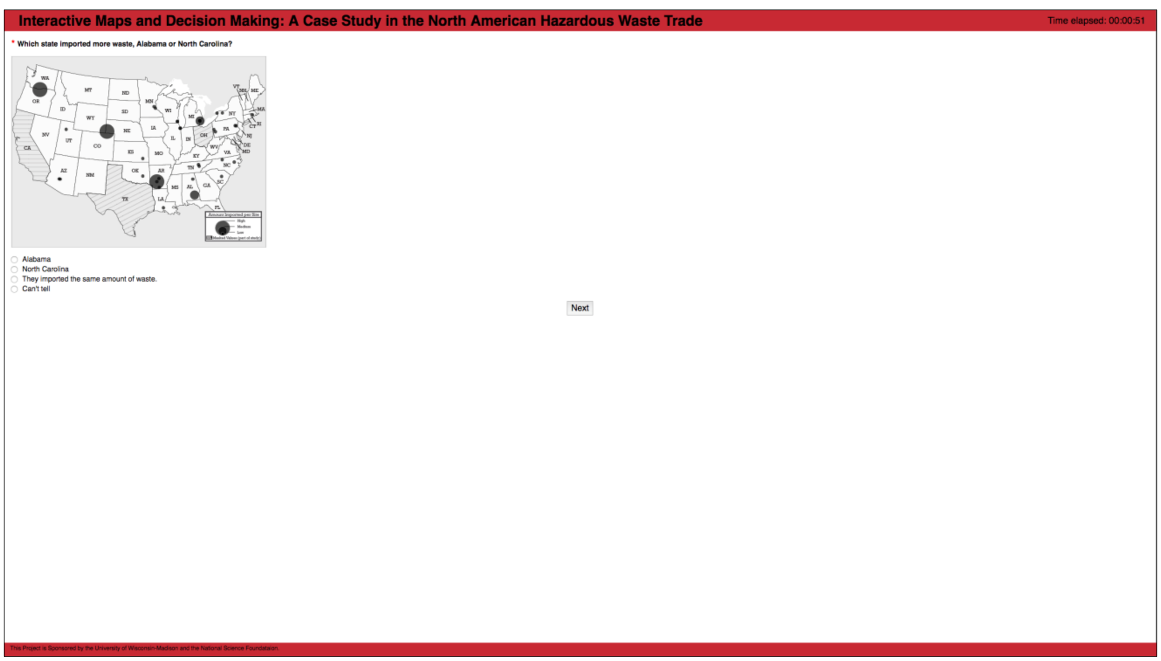
Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade
Time elapsed: 00:00:51
* Which state imported more waste, Alabama or North Carolina?
Alabama
North Carolina
They imported the same amount of waste.
Can't tell
Next
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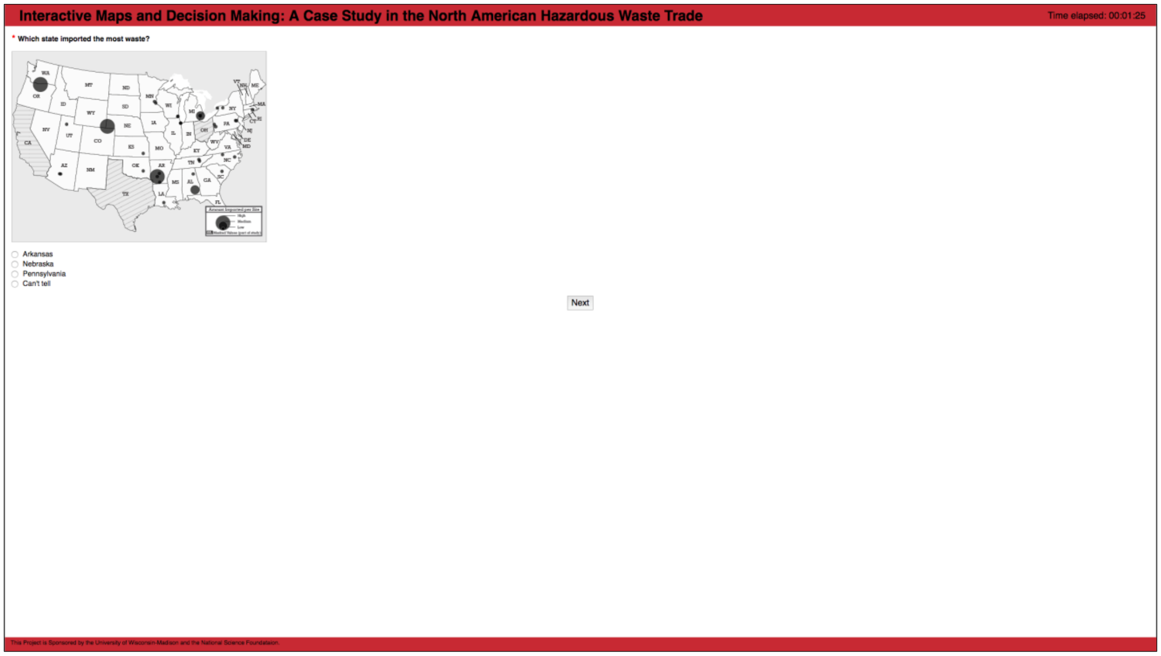
Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade
Time elapsed: 00:01:25
* Which state imported the most waste?
Arkansas
Nebraska
Pennsylvania
Can't tell
Next
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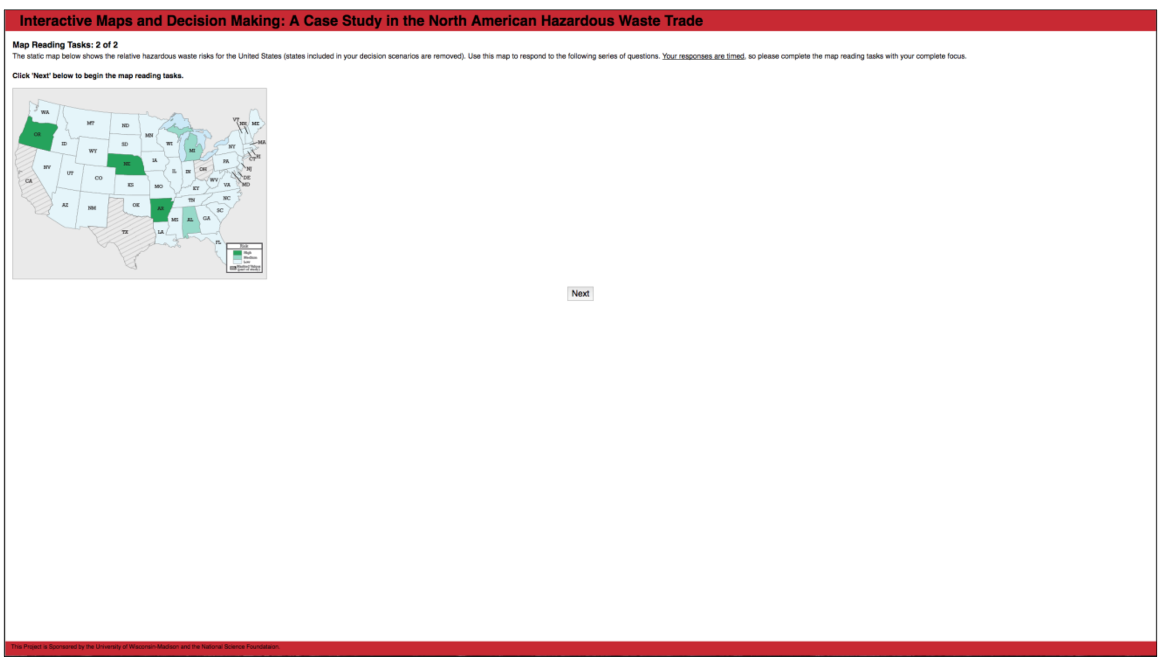
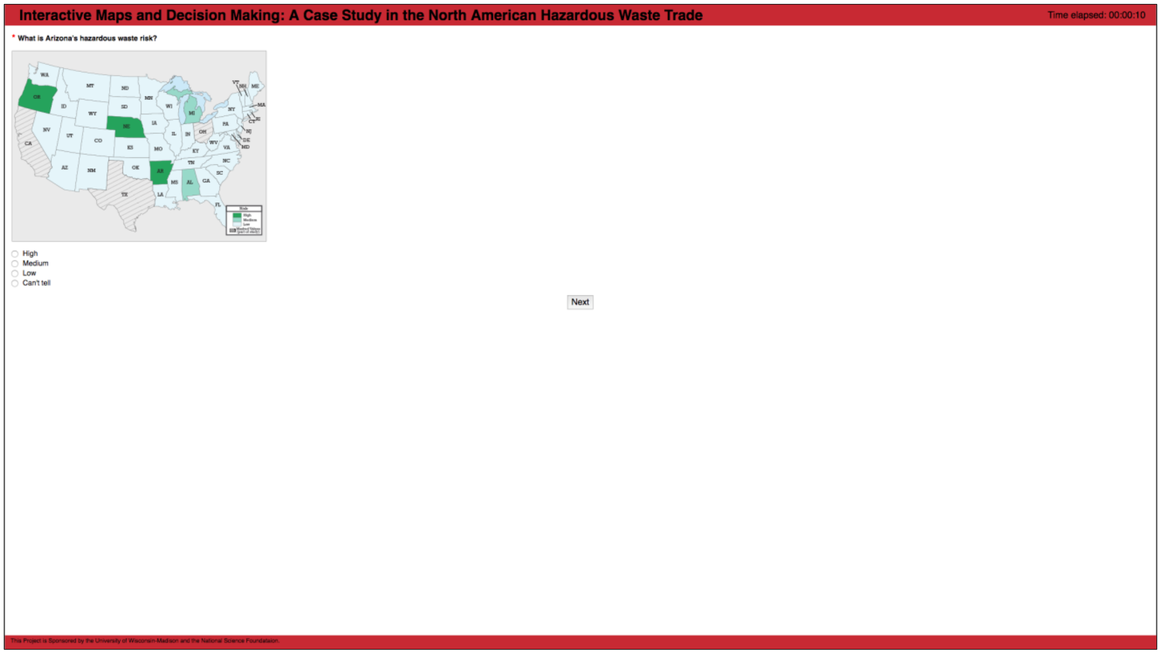

Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade
Map Reading Tasks: 2 of 2
The static map below shows the relative hazardous waste risks for the United States (states included in your decision scenarios are removed). Use this map to respond to the following series of questions. Your responses are timed, so please complete the map reading tasks with your complete focus.
Click 'Next' below to begin the map reading tasks.
Next
This Project is Sponsored by the University of Wisconsin-Madison and the National Science Foundation.


Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade
Time elapsed: 00:00:10
* What is Arizona's hazardous waste risk?
High
Medium
Low
Can't tell
Next
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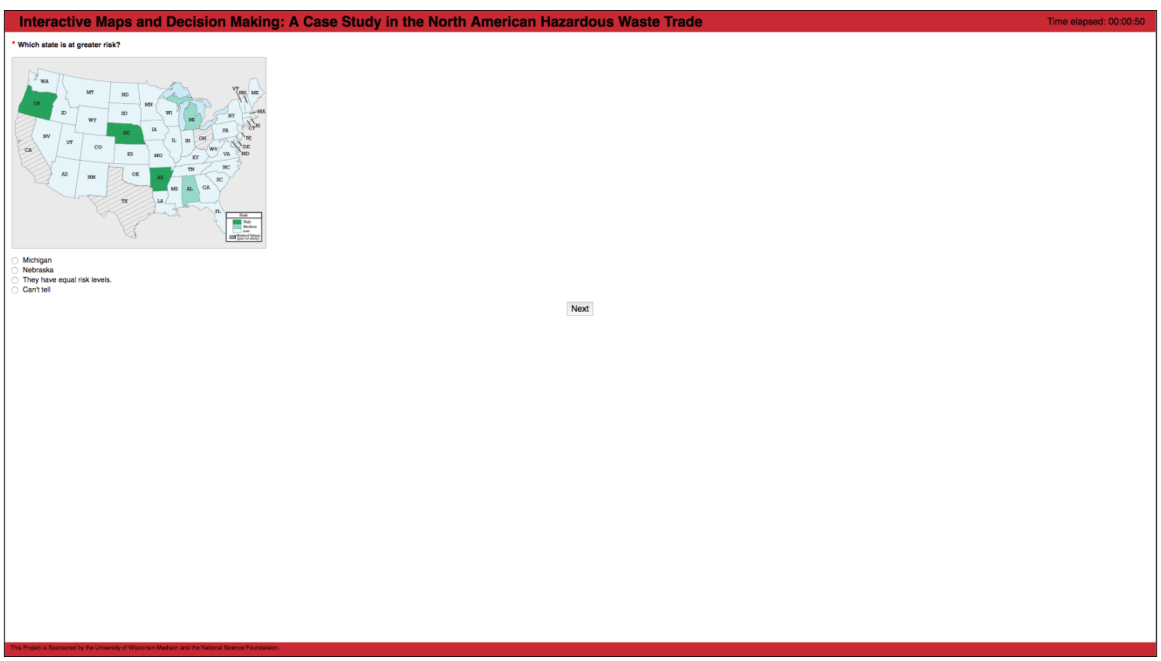
Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade
Time elapsed: 00:00:50
* Which state is at greater risk?
Michigan
Nebraska
They have equal risk levels.
Can't tell
Next
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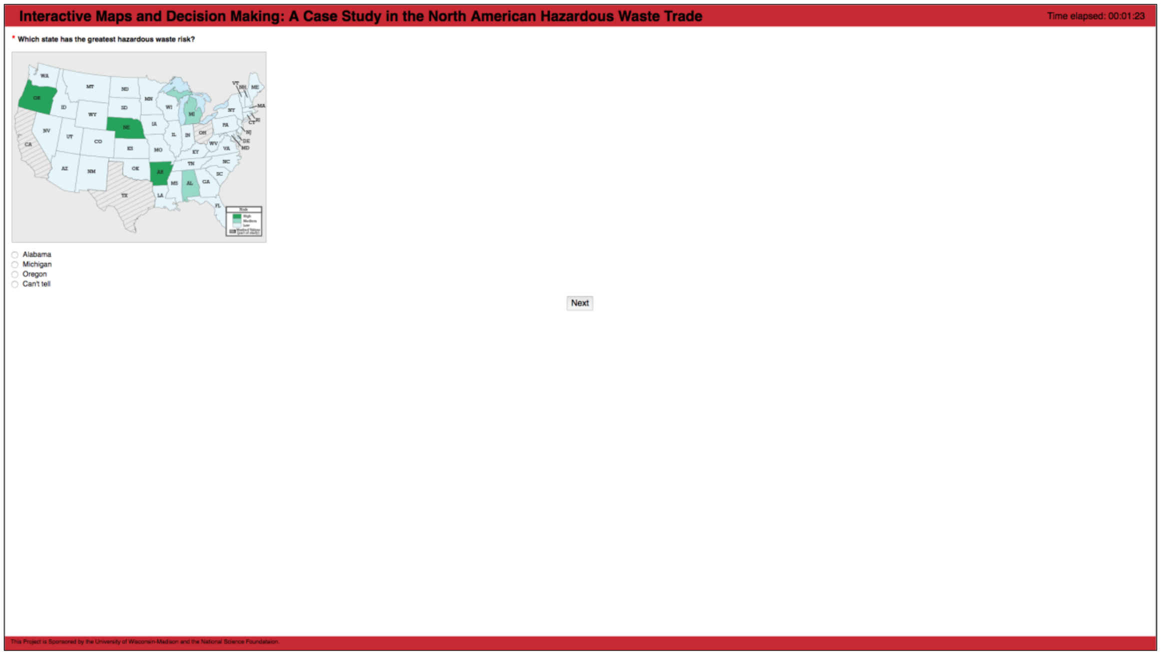
Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade
Time elapsed: 00:01:23
* Which state has the greatest hazardous waste risk?
Alabama
Michigan
Oregon
Can't tell
Next
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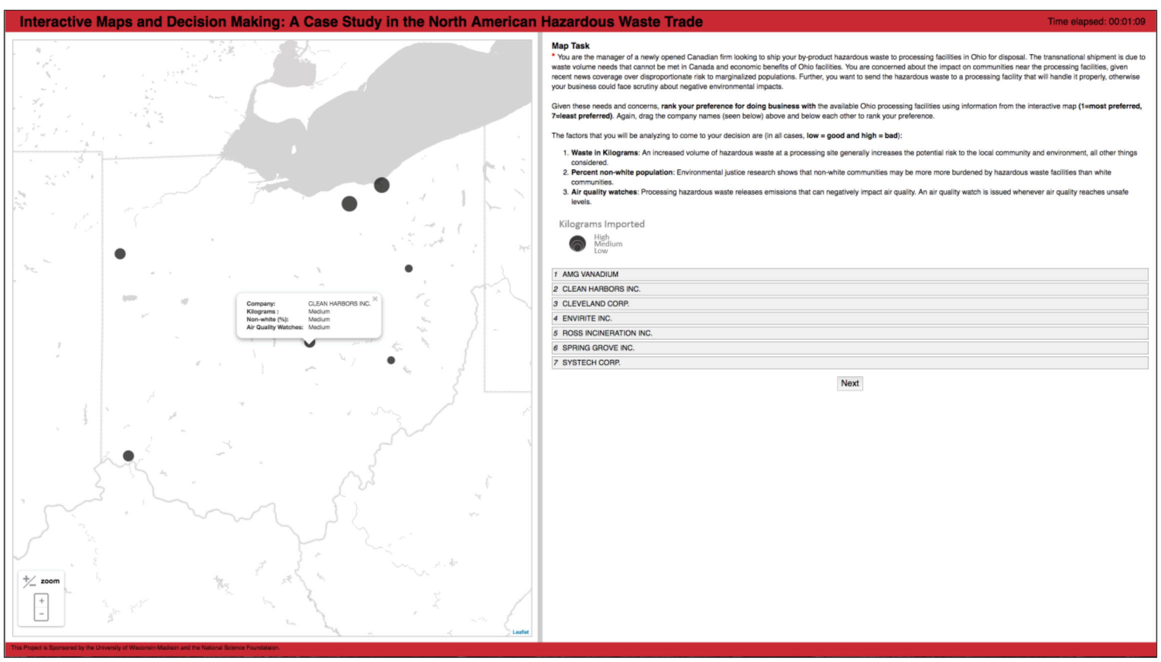
Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade
Time elapsed: 00:01:09
Company: CLEAN HARBORS INC.
Kilograms: Medium
Non-white (%): Medium
Air Quality Watches: Medium
zoom
Map Task
* You are the manager of a newly opened Canadian firm looking to ship your by-product hazardous waste to processing facilities in Ohio for disposal. The transnational shipment is due to waste volume needs that cannot be met in Canada and economic benefits of Ohio facilities. You are concerned about the impact on communities near the processing facilities, given recent news coverage over disproportionate risk to marginalized populations. Further, you want to send the hazardous waste to a processing facility that will handle it properly, otherwise your business could face scrutiny about negative environmental impacts.
Given these needs and concerns, rank your preference for doing business with the available Ohio processing facilities using information from the interactive map (1=most preferred, 7=least preferred). Again, drag the company names (seen below) above and below each other to rank your preference.
The factors that you will be analyzing to come to your decision are (in all cases, low = good and high = bad):
1. Waste in Kilograms: An increased volume of hazardous waste at a processing site generally increases the potential risk to the local community and environment, all other things considered.
2. Percent non-white population: Environmental justice research shows that non-white communities may be more more burdened by hazardous waste facilities than white communities.
3. Air quality watches: Processing hazardous waste releases emissions that can negatively impact air quality. An air quality watch is issued whenever air quality reaches unsafe levels.
Kilograms Imported
High
Medium
Low
1 AMG VANADIUM
2 CLEAN HARBORS INC.
3 CLEVELAND CORP.
4 ENVIRITE INC.
5 ROSS INCINERATION INC.
6 SPRING GROVE INC.
7 SYSTECH CORP.
Next
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Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade

* 1. On a scale of 1-5, how **difficult** was it for you to complete the ranking **(1=very easy, 5=very difficult)**?

1=very easy	2	3	4	5=very difficult
○	○	○	○	○

* 2. On a scale of 1-5, how **confident** are you that your ranking is correct **(1=not confident, 5=very confident)**?

1=not confident	2	3	4	5=very confident
○	○	○	○	○

* 3. Please rate how important the following criteria were when making your ranking decision **(1=I did not consider this criterion, 5=I only considered this criterion)**:

	1=I did not consider this criterion	2	3	4	5=I only considered this criterion
Volume of Waste	○	○	○	○	○
Air Quality	○	○	○	○	○
% Non-white	○	○	○	○	○

* 4. How helpful did you find the following interactive controls when completing your ranking decision **(1=not helpful, 5=very helpful)**?

	1=not helpful	2	3	4	5=very helpful
Zooming into the map	○	○	○	○	○
Panning around the map	○	○	○	○	○
Retrieving details about map features	○	○	○	○	○

* 5. Briefly describe your decision-making process, including details on how you used the map to support your ranking.

Next

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Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade

***The survey is no longer being timed. Thank you for completing the decision and map tasks. Before completing the survey, we would like you to answer a set of background questions to capture your interests and experiences. The following background survey is divided across 2 pages.**

Page 1 of 2: Exit Survey-Decision-Making

* Rate the degree to which you agree with the following statements **(1=strongly disagree, 5=strongly agree)**:

	1=strongly disagree	2	3	4	5=strongly agree
The U.S. should trade hazardous waste.	○	○	○	○	○
Hazardous waste poses a threat to the environment.	○	○	○	○	○
Hazardous waste poses a threat to marginalized communities.	○	○	○	○	○
Hazardous waste presents an economic opportunity.	○	○	○	○	○

* Rate the degree to which you agree with the following statements **(1=strongly disagree, 5=strongly agree)**:

	1=strongly disagree	2	3	4	5=strongly agree
People who know me would describe me as someone who generally doesn't take risks.	○	○	○	○	○
People who know me would describe me as someone who makes decisions using facts and information.	○	○	○	○	○
People who know me would describe me as someone who makes decisions using impressions and feelings.	○	○	○	○	○

* Rate the degree to which you agree with the following statements **(1=strongly disagree, 5=strongly agree)**:

	1=strongly disagree	2	3	4	5=strongly agree
I understood the map symbols.	○	○	○	○	○
I understood the map controls.	○	○	○	○	○
I understood the scenarios.	○	○	○	○	○
I understood what hazardous waste meant in the scenarios.	○	○	○	○	○
I understood what the hazardous waste trade was.	○	○	○	○	○

Was anything confusing about the survey (e.g., introduction/instructions, map symbols, map controls, scenarios, topic of hazardous waste trade, decision rankings)? Briefly describe any points of confusion.

Next

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Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade

Page 2 of 2: Exit Survey-Biographic Information

* What is your age?

* What is your gender?
- Male
- Female
- Other

* What state do you currently live in?

* Have you ever lived in Texas or Ohio?
- Lived in Texas
- Lived in Ohio
- Lived in Both
- Lived in Neither

* What is the highest degree you have received?
- PhD
- Master Degree
- Post-Bachelor Certificate
- Bachelor Degree
- Associate Degree
- High School Diploma/Equivalent

* What field is your degree(s) in?

* How much *experience* do you have with **(1=no experience, 5=use or think about everyday)**:

	1=no experience	2	3	4	5=use or think about everyday
maps					
geography					
the hazardous waste trade					
computers					
the Internet					

* How *familiar* are you with **(1=not at all familiar, 5=extremely familiar)**:

	1=not at all familiar	2	3	4	5=extremely familiar
maps					
geography					
the hazardous waste trade					
computers					
the Internet					

* Which of these best describes you?
- Professional working in the hazardous waste industry
- Graduate student studying hazardous waste
- Someone with some current or prior work with hazardous waste, including data processing or industry work
- Someone with no current or prior work with hazardous waste
- Other

* What device did you complete this survey on?
- Desktop Computer
- Laptop Computer
- Tablet or Touchscreen Device
- Smartphone
- Other

* What best describes the manner you interacted with the map and submitted your survey responses?
- Touch Screen
- Touch Pad
- Mouse
- Other

Submit

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Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade

Thank you!

Thank you for taking the time to complete this survey. Your response has been recorded. To receive your payment, please enter the following code in the submission box on Turk.

Confirmation Code: 4Pg12Cx!

We will send your payment within one week.

Please close your browser to exit.

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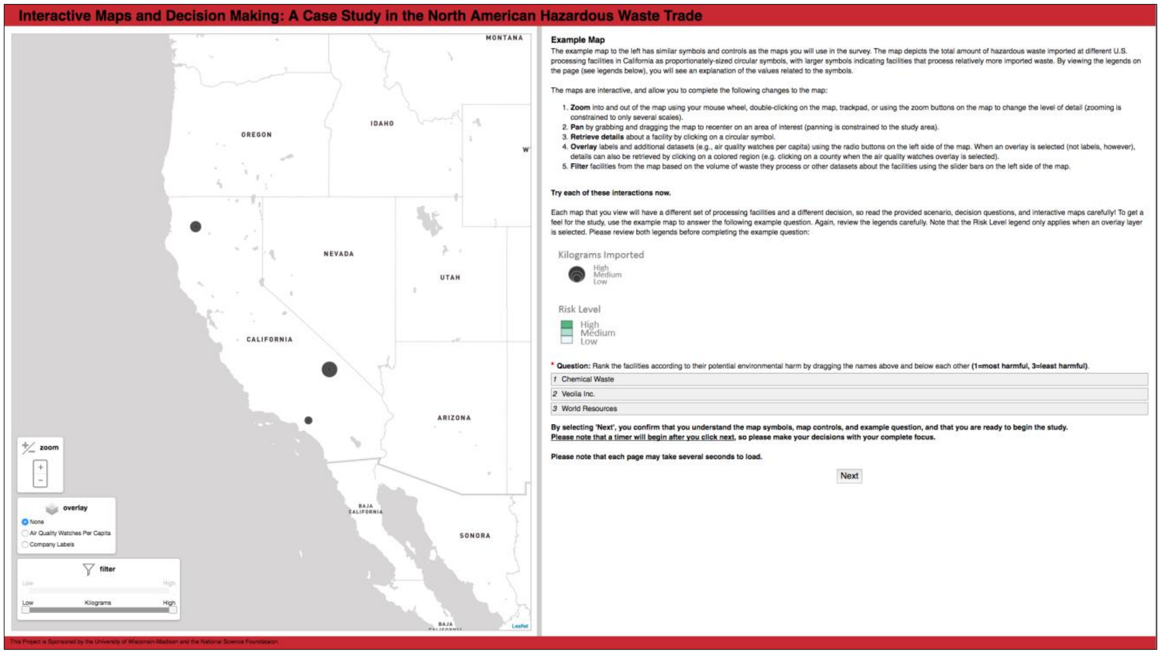
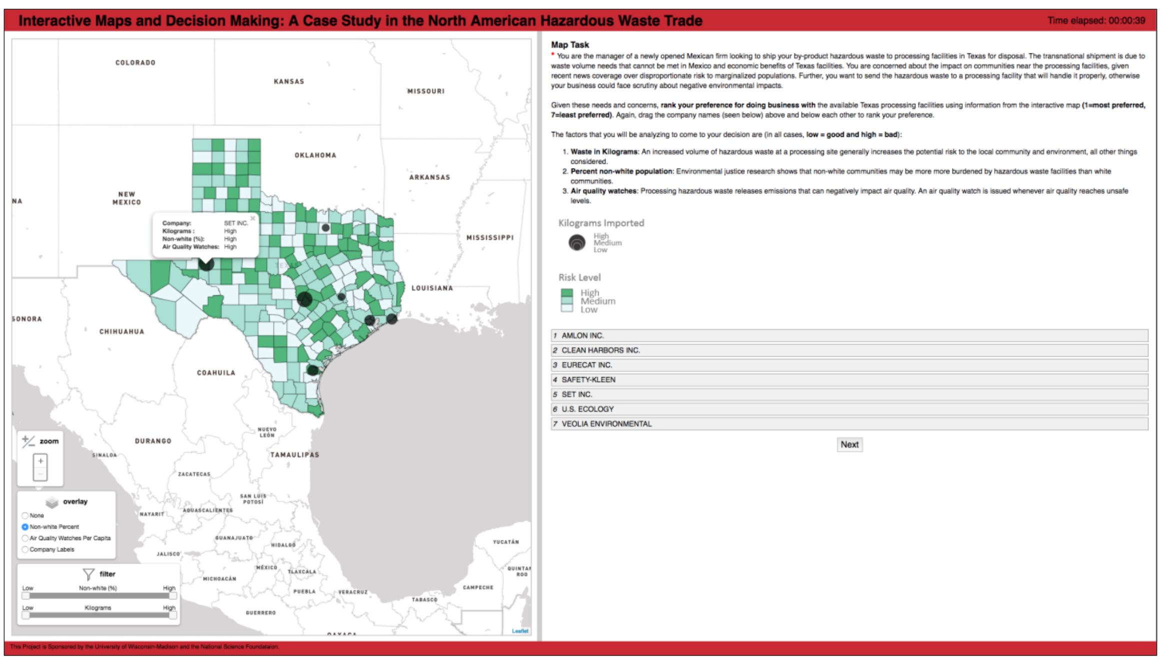
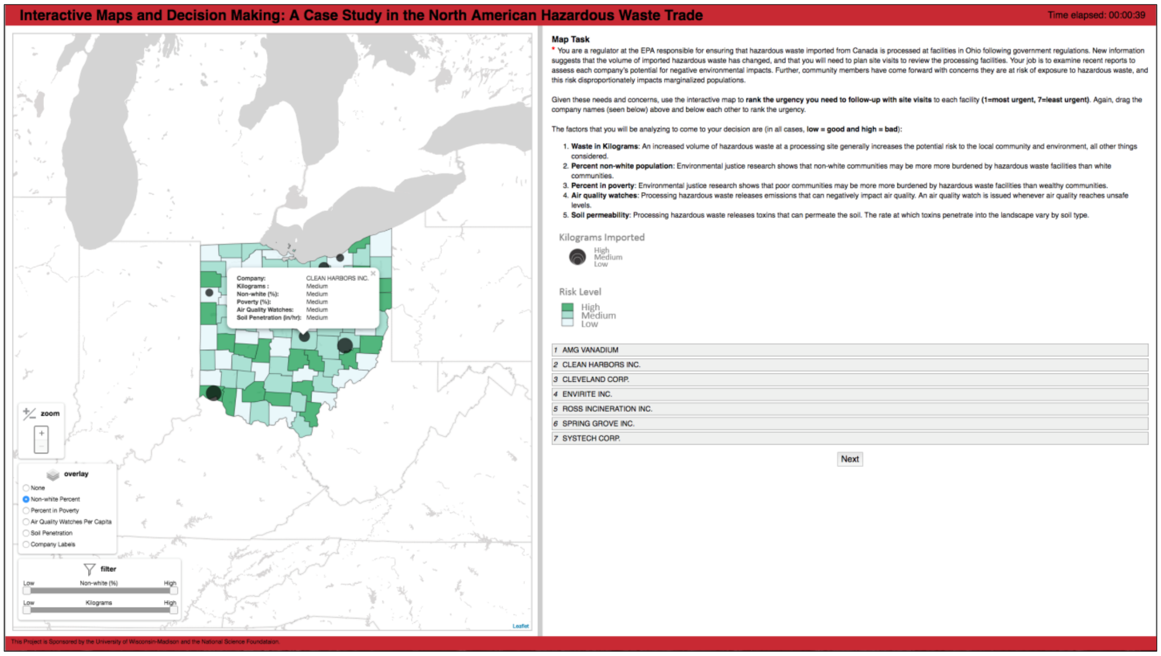

Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade
MONTANA
OREGON
IDAHO
NEVADA
UTAH
CALIFORNIA
ARIZONA
SONORA
zoom
overlay
None
Air Quality Watches Per Capita
Company Labels
filter
Low
Kilograms
High
Example Map
The example map to the left has similar symbols and controls as the maps you will use in the survey. The map depicts the total amount of hazardous waste imported at different U.S. processing facilities in California as proportionately-sized circular symbols, with larger symbols indicating facilities that process relatively more imported waste. By viewing the legends on the page (see legends below), you will see an explanation of the values related to the symbols.
The maps are interactive, and allow you to complete the following changes to the map:
1. Zoom into and out of the map using your mouse wheel, double-clicking on the map, trackpad, or using the zoom buttons on the map to change the level of detail (zooming is constrained to only several scales).
2. Pan by grabbing and dragging the map to recenter on an area of interest (panning is constrained to the study area).
3. Retrieve details about a facility by clicking on a circular symbol.
4. Overlay labels and additional datasets (e.g., air quality watches per capita) using the radio buttons on the left side of the map. When an overlay is selected (not labels, however), details can also be retrieved by clicking on a colored region (e.g. clicking on a county when the air quality watches overlay is selected).
5. Filter facilities from the map based on the volume of waste they process or other datasets about the facilities using the slider bars on the left side of the map.
Try each of these interactions now.
Each map that you view will have a different set of processing facilities and a different decision, so read the provided scenario, decision questions, and interactive maps carefully! To get a feel for the study, use the example map to answer the following example question. Again, review the legends carefully. Note that the Risk Level legend only applies when an overlay layer is selected. Please review both legends before completing the example question:
Kilograms Imported
High
Medium
Low
Risk Level
High
Medium
Low
* Question: Rank the facilities according to their potential environmental harm by dragging the names above and below each other (1=most harmful, 3=least harmful).
1 Chemical Waste
2 Veolia Inc.
3 World Resources
By selecting 'Next', you confirm that you understand the map symbols, map controls, and example question, and that you are ready to begin the study.
Please note that a timer will begin after you click next, so please make your decisions with your complete focus.
Please note that each page may take several seconds to load.
Next


Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade
Time elapsed: 00:00:39
COLORADO
KANSAS
MISSOURI
OKLAHOMA
ARKANSAS
NEW MEXICO
MISSISSIPPI
LOUISIANA
SONORA
CHIHUAHUA
COAHUILA
DURANGO
TAMAULIPAS
zoom
overlay
None
Non-white Percent
Air Quality Watches Per Capita
Company Labels
filter
Low
Non-white (%)
High
Low
Kilograms
High
Map Task
* You are the manager of a newly opened Mexican firm looking to ship your by-product hazardous waste to processing facilities in Texas for disposal. The transnational shipment is due to waste volume needs that cannot be met in Mexico and economic benefits of Texas facilities. You are concerned about the impact on communities near the processing facilities, given recent news coverage over disproportionate risk to marginalized populations. Further, you want to send the hazardous waste to a processing facility that will handle it properly, otherwise your business could face scrutiny about negative environmental impacts.
Given these needs and concerns, rank your preference for doing business with the available Texas processing facilities using information from the interactive map (1=most preferred, 7=least preferred). Again, drag the company names (seen below) above and below each other to rank your preference.
The factors that you will be analyzing to come to your decision are (in all cases, low = good and high = bad):
1. Waste in Kilograms: An increased volume of hazardous waste at a processing site generally increases the potential risk to the local community and environment, all other things considered.
2. Percent non-white population: Environmental justice research shows that non-white communities may be more more burdened by hazardous waste facilities than white communities.
3. Air quality watches: Processing hazardous waste releases emissions that can negatively impact air quality. An air quality watch is issued whenever air quality reaches unsafe levels.
Kilograms Imported
High
Medium
Low
Risk Level
High
Medium
Low
1 AMLON INC.
2 CLEAN HARBORS INC.
3 EURECAT INC.
4 SAFETY-KLEEN
5 SET INC.
6 U.S. ECOLOGY
7 VEOLIA ENVIRONMENTAL
Next


Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade
Time elapsed: 00:00:39
Map Task
* You are a regulator at the EPA responsible for ensuring that hazardous waste imported from Canada is processed at facilities in Ohio following government regulations. New information suggests that the volume of imported hazardous waste has changed, and that you will need to plan site visits to review the processing facilities. Your job is to examine recent reports to assess each company's potential for negative environmental impacts. Further, community members have come forward with concerns they are at risk of exposure to hazardous waste, and this risk disproportionately impacts marginalized populations.
Given these needs and concerns, use the interactive map to rank the urgency you need to follow-up with site visits to each facility (1=most urgent, 7=least urgent). Again, drag the company names (seen below) above and below each other to rank the urgency.
The factors that you will be analyzing to come to your decision are (in all cases, low = good and high = bad):
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2. Percent non-white population: Environmental justice research shows that non-white communities may be more more burdened by hazardous waste facilities than white communities.
3. Percent in poverty: Environmental justice research shows that poor communities may be more more burdened by hazardous waste facilities than wealthy communities.
4. Air quality watches: Processing hazardous waste releases emissions that can negatively impact air quality. An air quality watch is issued whenever air quality reaches unsafe levels.
5. Soil permeability: Processing hazardous waste releases toxins that can permeate the soil. The rate at which toxins penetrate into the landscape vary by soil type.
Kilograms Imported
High
Medium
Low
Risk Level
High
Medium
Low
1 AMG VANADIUM
2 CLEAN HARBORS INC.
3 CLEVELAND CORP.
4 ENVIRITE INC.
5 ROSS INCINERATION INC.
6 SPRING GROVE INC.
7 SYSTECH CORP.
Next
Company: CLEAN HARBORS INC.
Kilograms: Medium
Non-white (%): Medium
Poverty (%): Medium
Air Quality Watches: Medium
Soil Penetration (in/hr): Medium
zoom
overlay
None
Non-white Percent
Percent in Poverty
Air Quality Watches Per Capita
Soil Penetration
Company Labels
filter
Low
Non-white (%)
High
Low
Kilograms
High
Leaflet
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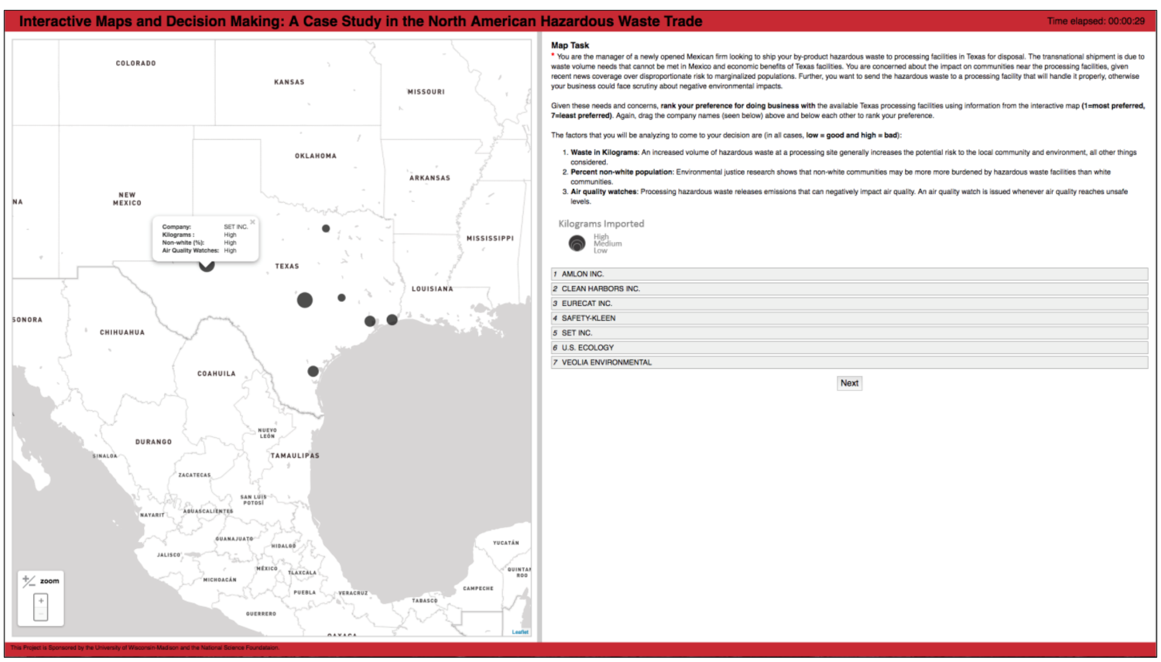
Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade
Time elapsed: 00:00:29
Map Task
* You are the manager of a newly opened Mexican firm looking to ship your by-product hazardous waste to processing facilities in Texas for disposal. The transnational shipment is due to waste volume needs that cannot be met in Mexico and economic benefits of Texas facilities. You are concerned about the impact on communities near the processing facilities, given recent news coverage over disproportionate risk to marginalized populations. Further, you want to send the hazardous waste to a processing facility that will handle it properly, otherwise your business could face scrutiny about negative environmental impacts.
Given these needs and concerns, rank your preference for doing business with the available Texas processing facilities using information from the interactive map (1=most preferred, 7=least preferred). Again, drag the company names (seen below) above and below each other to rank your preference.
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2. Percent non-white population: Environmental justice research shows that non-white communities may be more more burdened by hazardous waste facilities than white communities.
3. Air quality watches: Processing hazardous waste releases emissions that can negatively impact air quality. An air quality watch is issued whenever air quality reaches unsafe levels.
Kilograms Imported
High
Medium
Low
1 AMLON INC.
2 CLEAN HARBORS INC.
3 EURECAT INC.
4 SAFETY-KLEEN
5 SET INC.
6 U.S. ECOLOGY
7 VEOLIA ENVIRONMENTAL
Next
COLORADO
KANSAS
MISSOURI
OKLAHOMA
ARKANSAS
NEW MEXICO
MISSISSIPPI
TEXAS
LOUISIANA
Company: SET INC.
Kilograms: High
Non-white (%): High
Air Quality Watches: High
SONORA
CHIHUAHUA
COAHUILA
DURANGO
TAMAULIPAS
zoom
Leaflet
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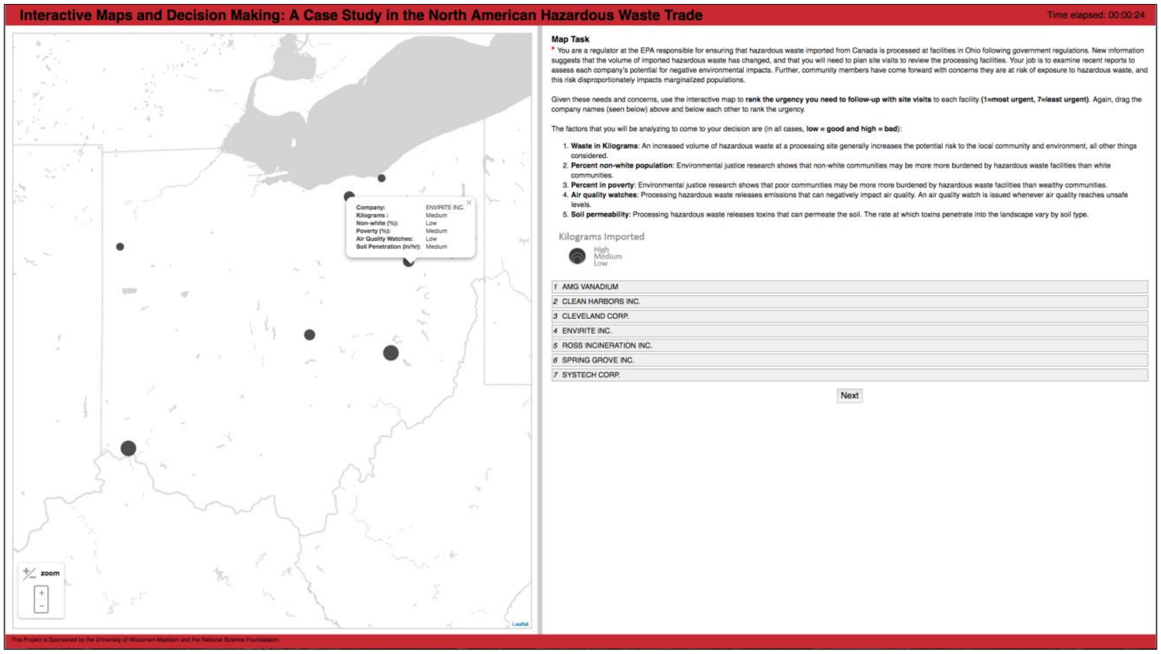

Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade
Time elapsed: 00:00:24
Company: ENVIRITE INC.
Kilograms : Medium
Non-white (%): Low
Poverty (%): Medium
Air Quality Watches: Low
Soil Penetration (in/hr): Medium
zoom
Leaflet
Map Task
* You are a regulator at the EPA responsible for ensuring that hazardous waste imported from Canada is processed at facilities in Ohio following government regulations. New information suggests that the volume of imported hazardous waste has changed, and that you will need to plan site visits to review the processing facilities. Your job is to examine recent reports to assess each company's potential for negative environmental impacts. Further, community members have come forward with concerns they are at risk of exposure to hazardous waste, and this risk disproportionately impacts marginalized populations.
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2. Percent non-white population: Environmental justice research shows that non-white communities may be more more burdened by hazardous waste facilities than white communities.
3. Percent in poverty: Environmental justice research shows that poor communities may be more more burdened by hazardous waste facilities than wealthy communities.
4. Air quality watches: Processing hazardous waste releases emissions that can negatively impact air quality. An air quality watch is issued whenever air quality reaches unsafe levels.
5. Soil permeability: Processing hazardous waste releases toxins that can permeate the soil. The rate at which toxins penetrate into the landscape vary by soil type.
Kilograms Imported
High
Medium
Low
1 AMG VANADIUM
2 CLEAN HARBORS INC.
3 CLEVELAND CORP.
4 ENVIRITE INC.
5 ROSS INCINERATION INC.
6 SPRING GROVE INC.
7 SYSTECH CORP.
Next
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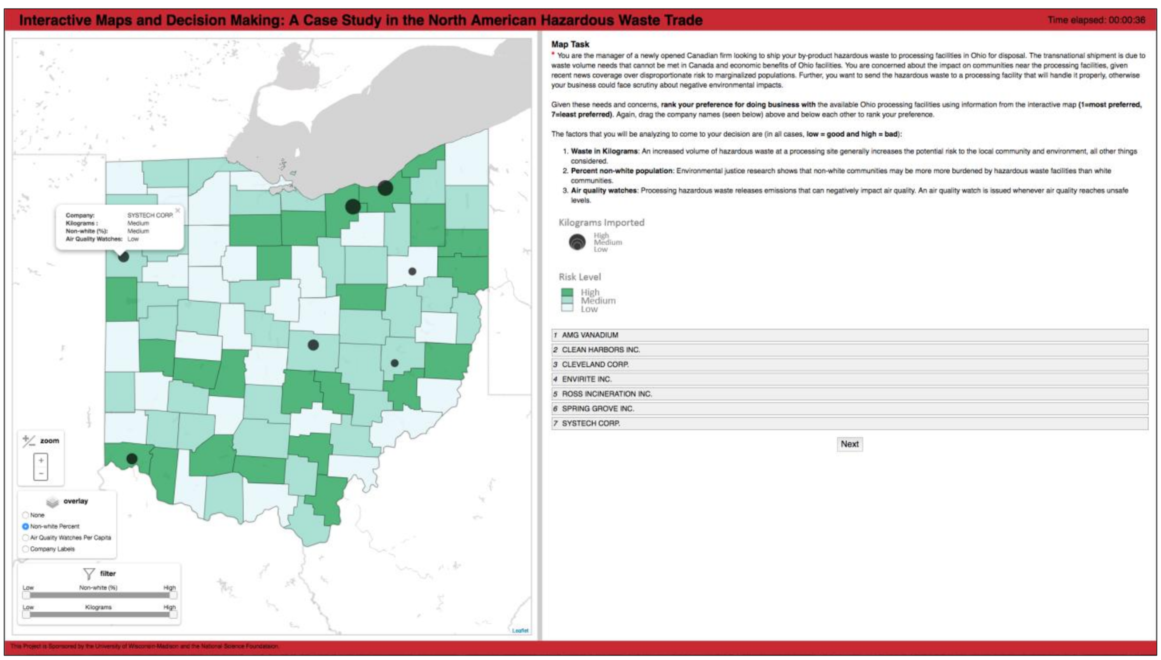

Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade
Time elapsed: 00:00:36
Company: SYSTECH CORP.
Kilograms : Medium
Non-white (%): Medium
Air Quality Watches: Low
zoom
overlay
None
Non-white Percent
Air Quality Watches Per Capita
Company Labels
filter
Low
Non-white (%)
High
Low
Kilograms
High
Leaflet
Map Task
* You are the manager of a newly opened Canadian firm looking to ship your by-product hazardous waste to processing facilities in Ohio for disposal. The transnational shipment is due to waste volume needs that cannot be met in Canada and economic benefits of Ohio facilities. You are concerned about the impact on communities near the processing facilities, given recent news coverage over disproportionate risk to marginalized populations. Further, you want to send the hazardous waste to a processing facility that will handle it properly, otherwise your business could face scrutiny about negative environmental impacts.
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The factors that you will be analyzing to come to your decision are (in all cases, low = good and high = bad):
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2. Percent non-white population: Environmental justice research shows that non-white communities may be more more burdened by hazardous waste facilities than white communities.
3. Air quality watches: Processing hazardous waste releases emissions that can negatively impact air quality. An air quality watch is issued whenever air quality reaches unsafe levels.
Kilograms Imported
High
Medium
Low
Risk Level
High
Medium
Low
1 AMG VANADIUM
2 CLEAN HARBORS INC.
3 CLEVELAND CORP.
4 ENVIRITE INC.
5 ROSS INCINERATION INC.
6 SPRING GROVE INC.
7 SYSTECH CORP.
Next
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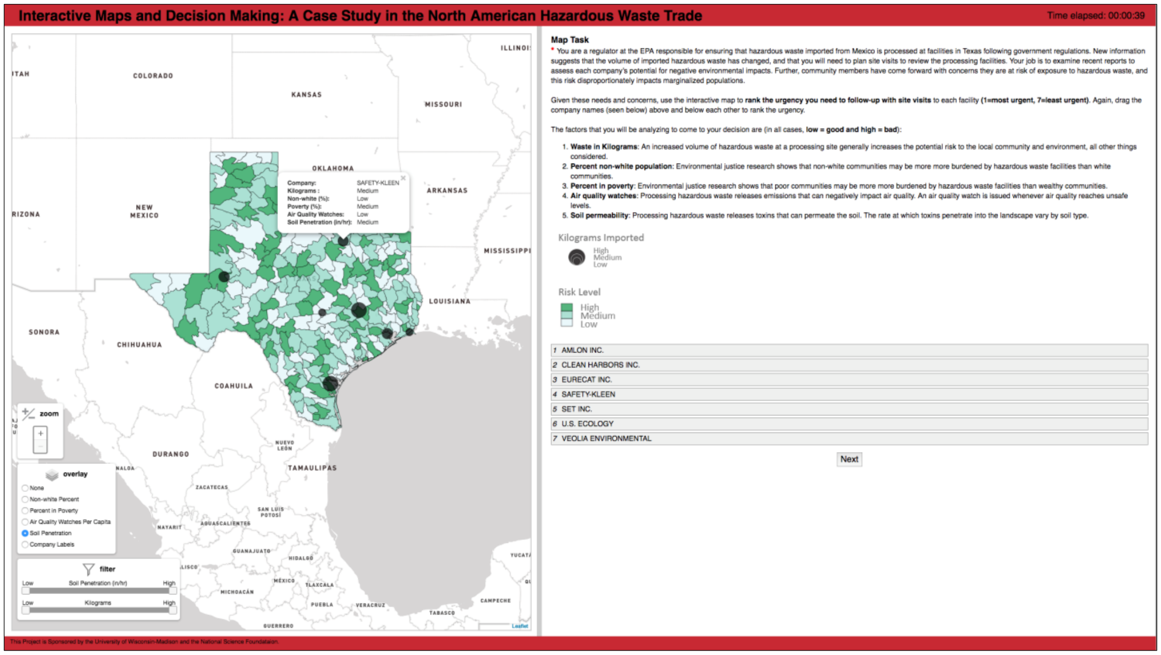
Interactive Maps and Decision Making: A Case Study in the North American Hazardous Waste Trade
Time elapsed: 00:00:39
Company:
SAFETY-KLEEN
Kilograms :
Medium
Non-white (%):
Low
Poverty (%):
Medium
Air Quality Watches:
Low
Soil Penetration (in/hr):
Medium
COLORADO
KANSAS
MISSOURI
OKLAHOMA
ARKANSAS
NEW MEXICO
MISSISSIPPI
LOUISIANA
SONORA
CHIHUAHUA
COAHUILA
DURANGO
NUEVO LEÓN
TAMAULIPAS
ZACATECAS
SAN LUIS POTOSÍ
NAYARIT
AGUASCALIENTES
GUANAJUATO
HIDALGO
MÉXICO
TLAXCALA
MICHOACÁN
PUEBLA
VERACRUZ
TABASCO
CAMPECHE
GUERRERO
zoom
overlay
None
Non-white Percent
Percent in Poverty
Air Quality Watches Per Capita
Soil Penetration
Company Labels
filter
Low Soil Penetration (in/hr) High
Low Kilograms High
Map Task
* You are a regulator at the EPA responsible for ensuring that hazardous waste imported from Mexico is processed at facilities in Texas following government regulations. New information suggests that the volume of imported hazardous waste has changed, and that you will need to plan site visits to review the processing facilities. Your job is to examine recent reports to assess each company's potential for negative environmental impacts. Further, community members have come forward with concerns they are at risk of exposure to hazardous waste, and this risk disproportionately impacts marginalized populations.
Given these needs and concerns, use the interactive map to rank the urgency you need to follow-up with site visits to each facility (1=most urgent, 7=least urgent). Again, drag the company names (seen below) above and below each other to rank the urgency.
The factors that you will be analyzing to come to your decision are (in all cases, low = good and high = bad):
1. Waste in Kilograms: An increased volume of hazardous waste at a processing site generally increases the potential risk to the local community and environment, all other things considered.
2. Percent non-white population: Environmental justice research shows that non-white communities may be more more burdened by hazardous waste facilities than white communities.
3. Percent in poverty: Environmental justice research shows that poor communities may be more more burdened by hazardous waste facilities than wealthy communities.
4. Air quality watches: Processing hazardous waste releases emissions that can negatively impact air quality. An air quality watch is issued whenever air quality reaches unsafe levels.
5. Soil permeability: Processing hazardous waste releases toxins that can permeate the soil. The rate at which toxins penetrate into the landscape vary by soil type.
Kilograms Imported
High
Medium
Low
Risk Level
High
Medium
Low
1 AMLON INC.
2 CLEAN HARBORS INC.
3 EURECAT INC.
4 SAFETY-KLEEN
5 SET INC.
6 U.S. ECOLOGY
7 VEOLIA ENVIRONMENTAL
Next
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