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Data Visualization as a Tool for Groundwater Management: Bridging Science and Policy

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Data Visualization as a Tool for Groundwater Management: Bridging Science and Policy

by

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Thesis

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Dedication

to people who appreciate the beauty and potential of elegant graphic design,

to data gurus who understand the power of harnessing and analyzing big data,

and

to the inspirational people in this changing world who strive to solve complex social and environmental problems with innovative solutions founded on research and design.

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Abstract

Data Visualization as a Tool for Groundwater Management: Bridging Science and Policy

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The University of Texas at Austin, 2015

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Groundwater resources in Texas are a contentious topic in social and political arenas. As ongoing drought and growing populations put stress on surface water supplies, more water users turn to groundwater to meet increased water demands. It is critical to manage groundwater supplies to meet current and future water demands from agriculture, industry, growing urban centers, and the environment. Data visualizations can serve as an effective tool to make informed policy decisions for groundwater resource management. Incorporating uncertainty into groundwater models and into the visualizations used to convey scientific information can aid in making well-informed decisions. Groundwater availability models and scientific information are used as guides for creating policy, but data from scientific sources and tools, displayed in maps, graphs, charts, etc., are often difficult to understand without a background in hydrology or a water resource management. Water management is not restricted to the scientists who produce data; it

reaches into a broader arena of stakeholders and policy makers. What is lacking are approaches to present groundwater information such that visualizations create a base level of understanding among all actors involved in decision-making processes while retaining key elements to convey scientific uncertainty in the data. This research presents statistical analyses of uncertainty interpretations for a large dataset in the Barton Springs segment of the Edwards Aquifer in Central Texas. Results explore visualization approaches for groundwater information that are based on graphic design principles. Visualizations are presented that display results of uncertainty analysis as a means to support science-based discussions among stakeholders about future water plans and policies.

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Chapter 1: Introduction

Groundwater resources in Texas are a contentious topic in social and political arenas. As ongoing drought and growing populations put stress on surface water supplies, more water users turn to groundwater to meet increased water demands. It is critical to manage groundwater supplies to meet current and future water demands from agriculture, industry, growing urban centers, and the environment. Groundwater management decisions in Texas are required to use the best available scientific information and are recommended to consider stakeholder input (Pierce et al., 2013; Mace et al., 2008).

Data visualizations serve as an effective tool to make informed policy decisions for groundwater resource management. Incorporating uncertainty into both groundwater models and visualizations used to convey scientific information aids in making well-informed decisions. Effective visualizations can serve as a means to communicate complexities in groundwater systems to decision-makers and stakeholders when determining sustainable aquifer yield. This research presents a systematic assessment of operational aquifer yield using a large dataset for the Barton Springs segment of the Edwards Aquifer in Central Texas. Results explore visualization approaches for groundwater information, using graphic design principles. Visualizations display results of uncertainty analysis as a means to support science-based discussions among stakeholders about future water plans and policies related to sustainable aquifer yield.

SUSTAINABLE YIELD FOR GROUNDWATER MANAGEMENT

The research presented here uses the concept of an aquifer-yield continuum as proposed by Pierce et al. (2013). The continuum serves as a systems approach to groundwater management. One of the key ideas behind the aquifer-yield continuum is that determination of sustainable yield for groundwater systems needs to integrate consensus yield (community preferences of management goals) and operational yield (scientific information) (Figure 1.1).

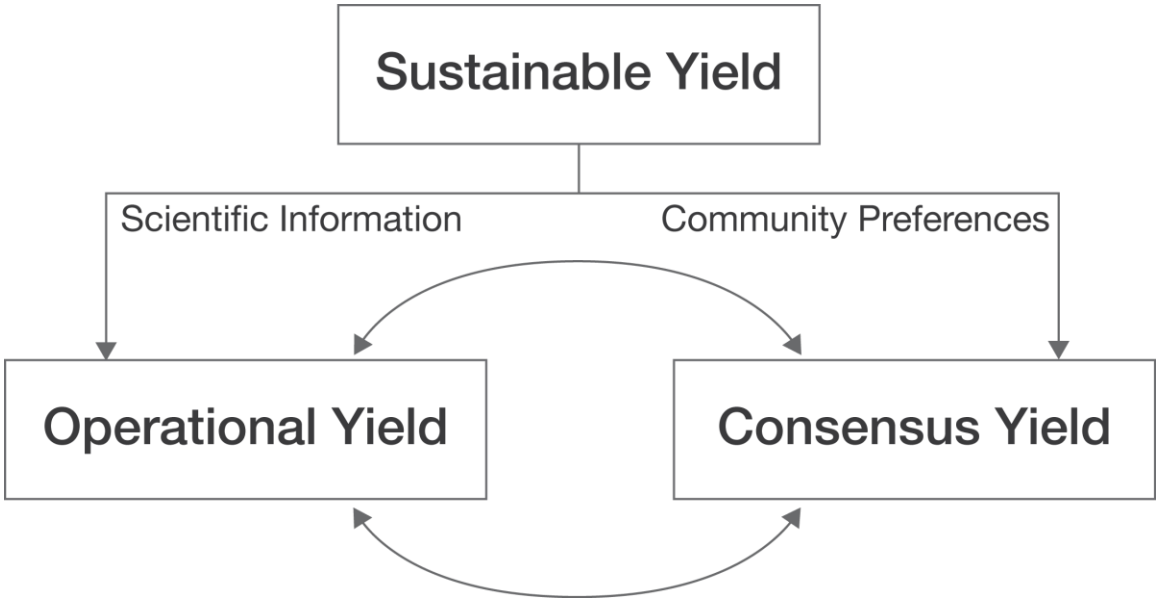

Figure 1.1 The relationships between sustainable, operational, and consensus yields (from Pierce et al., 2013).

Consensus yield is a stakeholder-defined range of desired extraction volumes that exist in a negotiation space within the physical constraints of an aquifer system. (Pierce et al, 2013; Pierce, 2006). Operational yield is defined as the "dynamic range of water volumes that can be extracted from an aquifer under a given set of operating conditions,

or within a management regime, while meeting consensus and sustained-yield metrics throughout a planning horizon" (Pierce et al., 2013, p. 336). Elements of operational yield include decision variables, like pumping rates and drought restriction triggers, objective functions, and constraints (Pierce et al., 2013).

Operational aquifer-yield needs a foundation in quality scientific information, however, the physical behavior of aquifers and the models used to simulate groundwater flow contain inherent uncertainties. Groundwater decision-makers and stakeholders depend on science-based operational yield to develop potential management regimes, but need a way to understand uncertainty within a system without being overwhelmed. This study uses groundwater availability model scenarios that refine scientific inputs to reduce uncertainty in model outputs, and analyzes modeled outputs to evaluate different policy and management options within the context of operational uncertainty. A case study of the Barton Springs segment of the Edwards Aquifer in Central Texas shows that alternative recharge interpretations may provide significant insight to management alternatives, and can influence the consensus yield and, thus, the sustainable yield, for this region.

Chapter 2: Data Visualization

Data visualization is a graphical means of displaying information. The purposes of visualization are to communicate complex ideas and to analyze trends in data such that qualitative conclusions can be drawn from quantitative information. Effective data visualizations are an important tool used in interdisciplinary decision-making processes. With the advent of "big data" and more complex interactions between types of data, simple spreadsheets no longer suffice to communicate concerns or conclusions. Framing issues and evidence with a strong link to data is extremely valuable in supporting fact-based decision-making. Environments where there is a synergy among academia, industry require data visualizations that welcome exploration, are scientifically accurate, and are easy to understand.

The field of energy and earth resources (EER) has a vast landscape of data that lends itself well to visualization. From crude oil spot prices to stratigraphic columns and groundwater management scenarios, analysis of data and systems requires a keen eye and a grasp of the basics of visualization theory. This chapter covers several concepts from various authors in visualization techniques, as well as foundational principles and guidelines for best data visualization practices.

WHY USE DATA VISUALIZATION?

The visual display of information is not a new idea. Hieroglyphics and cave drawings are among the first examples, packing descriptions, stories, and knowledge into simple, easily understood drawings. In 1972, astronomers Carl Sagan and Frank Drake

designed a graphic with the intention of being able to communicate across all forms of intelligent life. This image was attached to the Pioneer 10 spacecraft (Figure 2.1). While it is unknown whether other forms of life would understand the graphic, the design elements used to create it are simple, using line, proportion, and proximity to describe the layout of the solar system, relative size of the spacecraft to a human being, and the hydrogen atom.

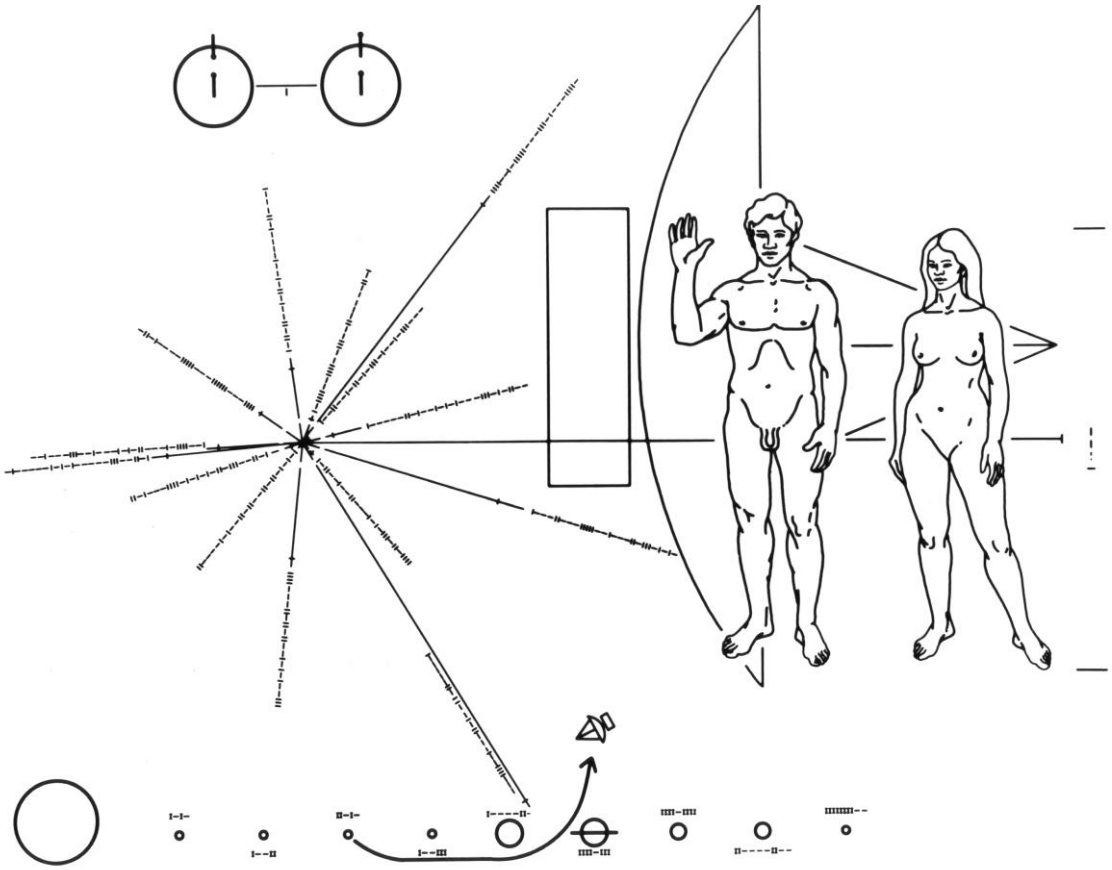

Figure 2.1 Line rendering of the engraved aluminum plate on the Pioneer 10 spacecraft, designed to communicate with all intelligent life. It contains information about human bodies, dimensional units, and the hydrogen atom, and shows the position and origin of the spacecraft (from Sagan, Sagan, and Drake, 1972).

An effective informational display can combine multiple levels of information into a single graphical representation that is easier to understand than spreadsheets of data or long strings of words. As Galileo stated in 1610, "…the disputes which for so many generations have vexed…are destroyed by visible certainty, and we are liberated from wordy arguments" (Tufte, 2006). Advanced computing power and the exponential expansion of data collection makes the idea of "visible certainty" a much more powerful concept than "wordy arguments". An observation unaccompanied by visual evidence is not readily welcomed in today's information driven environment, so the ability to harness data and turn it into a tangible piece of information has great strength in communicating concerns and ideas.

DATA AND THE BRAIN

To begin thinking about data and its connection to EER fields, the following two quotes illustrate how data can be thought of as a natural element in today's world.

> *Information gently but relentlessly drizzles down on us in an invisible, impalpable electric rain.*
>
> *–Hans Christian von Baeyer, Information: The New Language of Science*

> *Today we live invested with an electric information environment that is quite as imperceptible to us as water is to a fish.*
>
> *–Marshall McLuhan, Counterblast*

The above quotes (Lima, 2011) spark thinking on the ubiquitous nature of data and the necessity and importance of data visualization.

Data is integrated into aspects of everyday life. Humans are constantly gathering a wealth of new information from social interactions, nature, the surrounding environment, and technology. The ability to sort through a large amount of data, provide a conduit for the information to pass through, and to frame and anchor an argument to a logical conclusion at the end of the conduit is an emerging necessity.

Colin Ware, the Director of the Data Visualization Research Lab at the Center for Coastal and Ocean Mapping at the University of New Hampshire, specializes in advanced data visualization and has a special interest in applications of visualization for ocean mapping. Ware describes visualization in his book *Information Visualization* as an "external artifact which supports decision-making" (Ware, 2011). Visualizations can provide an ability to comprehend huge amounts of data, allow for the perception of emergent properties that were not anticipated, facilitate hypothesis formulation, and reveal qualities not only about the data itself, but also about the way it was collected (Ware, 2012). However, poorly designed visualizations can distract from the benefits of a well-executed visualization. Details on how to avoid the downfalls commonly seen in visualization will be discussed later.

Simply, visualizations turn raw data into visual elements; the effectiveness of visual elements is determined by the dataset, and the physical and social contexts of the data set (Yau, 2011). Part of what makes a good visualization is to understand how the brain processes received information. Information that can deliver substantiated data for policy decisions is most useful when integrated into a process that factors in the ability of the human optic and neural systems to quickly transfer large amounts of information to

the brain (Ware, 2012). Figure 2.2 shows human-data interaction flows from raw data to human information-processing systems.

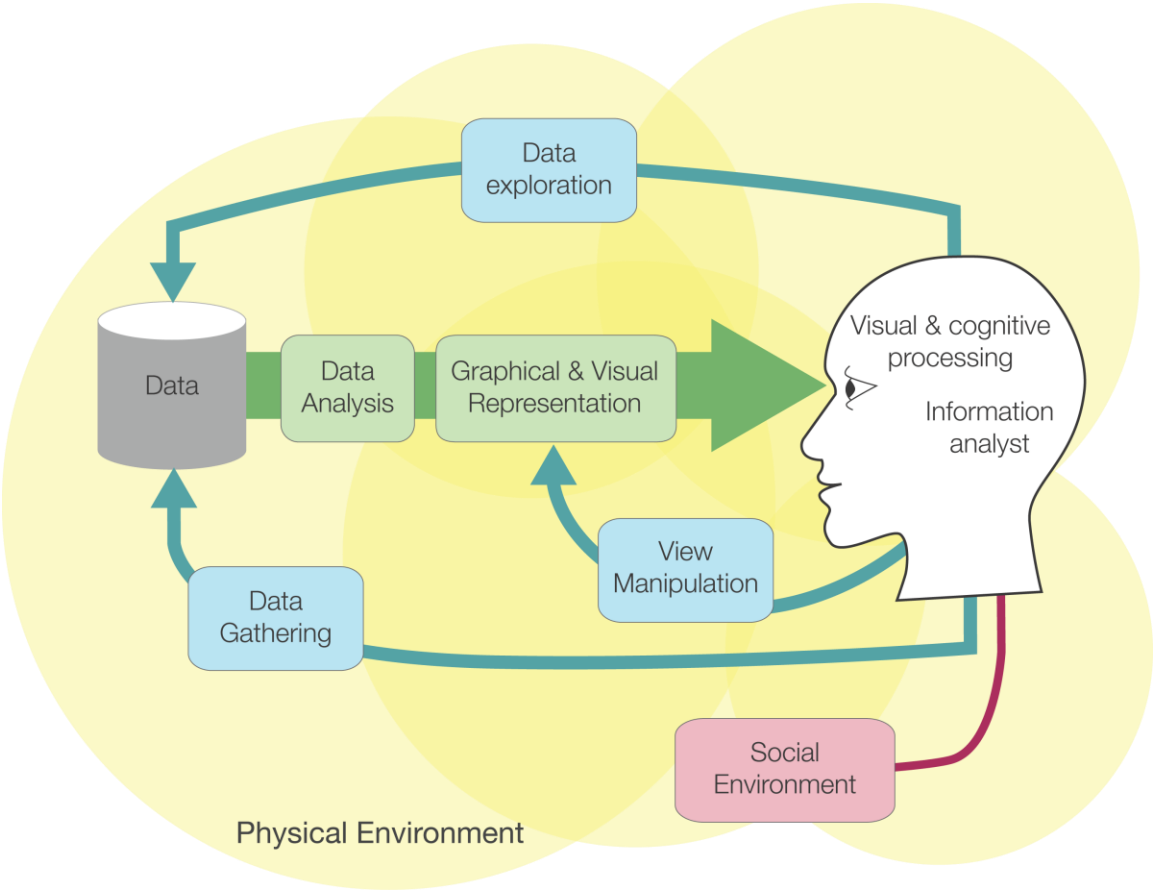

Figure 2.2 The visualization process (modified from Ware, 2012). Data undergoes a transformation process through analysis and visual representation and is then further refined as the information analyst manipulates the visual representation, explores the data, and gathers additional data. The information analyst operates within the context of the physical and social environment.

As shown in Figure 2.2, the movement of information from its abstract data form into the brain's visual processing unit undergoes a transformation process. A visual display of data is shaped to allow information to move from point A (abstract and raw data) to point B (the brain) in an explanatory framework (Illinksy, 2011). The best

visualizations incorporate methods of good design (an art-intensive angle) and solid scientific, statistical, and mathematical methods (a science-intensive angle). Taking strong points from each angle creates a feedback loop that takes raw data and transforms or manipulates it to create a tangible map of patterns, connections, and structures out of intangible evidence (Ware, 2012; Lima, 2011). Effectively combining the art and science aspects of visualization creates a clear and strong path for data exploration, manipulation, and broader context and application. Making data easy to understand with direct causality and comparison delivers high-quality returns for the concept and evidence; this should be offered quickly and accurately to decision makers.

The fine line between science and art within data visualization is becoming thinner as computer processing power progresses ad infinitum and delivers tools able to analyze multivariate problems in a more approachable form. Understanding the methods and theories to translate raw data into decision-making tools can prove ineffective and even disastrous without holding up to a quality standard of basic design principles and guidelines associated with making visual displays of information.

A VISUALIZATION WORKFLOW: CONCEPTS, PRINCIPLES, AND GUIDELINES

In sync with the recent prevalence of large amounts of complex data, or "big data", there has been an explosion of literature on data visualization and best practices. A grasp of these best practices, applied when using available software tools, facilitates creating the best display of data. Most of visualization literature is derived from the work of Edward Tufte, who has written a series of books on data presentation (Tufte, 1983; Tufte, 1991; Tufte, 2006). In the book *The Visual Display of Quantitative Information*

(1983), Tufte describes what characteristics determine graphical excellence, and these principles are incorporated into the workflow presented in Figure 2.3.

Common Types of Data Visualizations

Before delving into design elements and principles and guidelines to achieve graphical excellence, it is useful to know what types of visualizations are available, and how to choose the graphic, or combination of graphics, to create an informative narrative from abstract data. It is important to remember that combinations of visualization types elicit more data exploration as long as they are appropriate to the narrative of the graphic and to the physical and social environment in which the visualization is used. Following is a list of commonly used data visualizations (modified from Hardin et al., 2015), though there are many more options that may be more appropriate for a particular dataset and narrative.

- **Bar Chart**: show categorical data. Use when data can be divided into independent categories
- **Line Chart**: visualize a sequence of values. Use when viewing data trends over time.
- **Pie Chart**: show relative proportions or percentages. Use *only* when visualizing proportions, or parts of a whole.
- **Map**: view spatial data. Use when dataset contains geographical reference points.

- **Scatterplot**: display independent variable information. Best used to explore data and identify trends, concentrations, and outliers.
- **Histogram**: view distribution of data or frequency of values of a variable. Use to group data into categories based on the distribution.
- **Heat map**: show intensity of the relationship between variables. Use when showing a relationship between two variables.
- **Box-and-whisker plot**: show statistical distributions of a dataset. Use to show medians and quartile ranges or value ranges for a dataset.

Graphics should be presented in a simple yet multi-dimensional manner so that the viewer can focus on the data and what emerges from the data, rather than focus on how a graphic is created or the downfalls of a graphic. The first step to achieving graphical excellence is to adhere to the basic design elements and principles. Design elements relevant to scientific data visualization are listed in Table 2.1. These elements should be used as a foundation to achieve the design functions, principles, and guidelines presented in Figure 2.3.

Design Elements	
Element	**Description**
Line	Graphic features such as axes, gridlines, tick marks, etc. should be minimized to let the data and important information shine through in any graphic.
Color	Our minds may associate colors of the rainbow to signify intensity, though which colors we associate may be different than another person's association; it is more effective to use shades of a color when depicting magnitudes or importance. Harsh or vibrant colors can distract the eye from important information in the data, unless used to highlight that important information. Colors found in nature are often more pleasing. An important point of consideration is that some viewers may have a limited perception of certain colors.
Shape	Overly caricatured images representing data can distract from the data itself. Simple shapes that serve multiple purposes—like labels and data points—are effective.
Texture	Texture can be used to add information within shapes, but should be minimized and used in a subtle manner.
Space	Space is very important to visualizations. A large amount of information in a small area can allow the viewer to compare data more readily and can promote connections among data; however, information that is too tightly fit can be difficult to read.
Form	Form is a three-dimensional aspect that should be considered when making three-dimensional interactive visualizations. When making two-dimensional visualizations, it is also important to consider how a three-dimensional object will be translated onto a two-dimensional plane.
Typography	Typography is not a traditional art element, but is often present in scientific data visualizations that require some explanation. Typography combines the line and shape elements. Clean sans serif fonts, such as Arial and Helvetica, are recommended.

Table 2.1 Basic design elements and descriptions relevant to scientific data visualization.

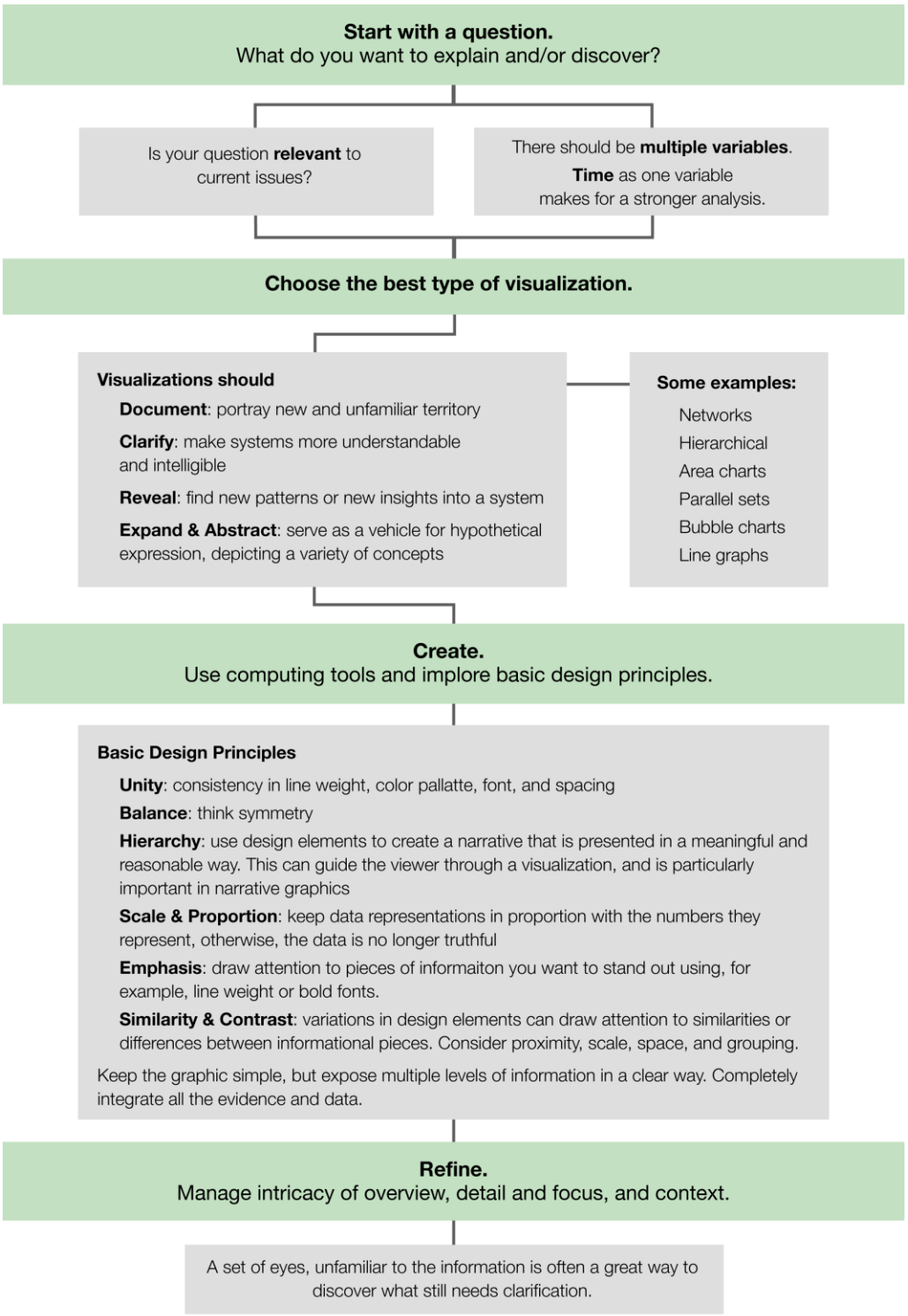

Figure 2.3 Visualization workflow and suggestions. This workflow should be used after raw data gathering and can be used to explore the data and to create final graphics.

One of the most important aspects of data behind a graphic is the presence of more than two variables. Multivariate displays have more depth and room for expansion than displays with two variables alone. These displays include familiar graphics: maps, bar charts, scatterplots, line graphs, etc. Even more effective displays include narrative and relational graphics; an aspect of storytelling can prove an effective way for a viewer to make sense of a multitude of data. Narrative graphics show data moving over space and time and is a great way to incorporate a larger number of variables. Tufte uses the Charles Joesph Minard graphic of Napoleon's 1812 Russia campaign as an example of a narrative graphic (Figure 2.4).

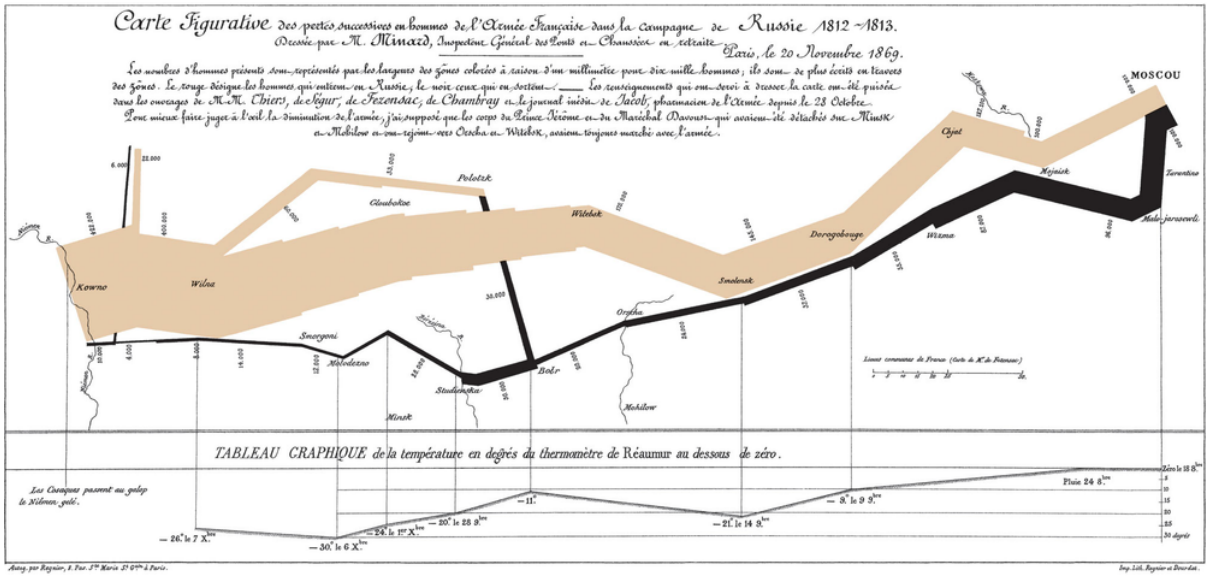

Figure 2.4 Minard's chart of Napoleon's 1812 Russia campaign (from Tufte, 1983).

This chart tells the story of Napoleons troops' journey to Russia and back. This chart subtly incorporates complexity using six variables, including time, geographical location, army size, and temperature. It tells a story rather than just giving the data. This

chart not only achieves the six design principles, but also fulfills the basic principles of graphical excellence, giving the viewer the most amount of information using the least amount of ink (Tufte, 1983). Narrative graphics present both quantitative and qualitative information, and guide the viewer to deduct a conclusion and explore further potential implications of the topic presented.

A basic understanding of graphic design principles allows for full attention to be directed to data manipulation and to mastering available processing tools. It is ideal to be able to process a large amount of data and present it in a way that is easy to digest so that further discussion on what story the data is telling can be pursued. It is important to an EER professional to have skills for designing effective graphics and visualizations because much of the information in the EER field covers complex topics, such as water, finance, energy, and commodities, that are defined by multiple attributes. Reigning over interdisciplinary data requires knowledge of the best way to display the data. The final purpose and audience should also be considered when selecting the methods for visualization.

A small selection of the vast amount of information that exists in regards to data visualization has been presented thus far. There is a multitude of ways to design and craft data visualization through best practices and following data visualization guidelines. The connection between data, design, and viewer has been represented by Illinsky and Steele (2011; Figure 2.5) and can aid in how our understanding of how design for complex problems can be approached from a broader perspective.

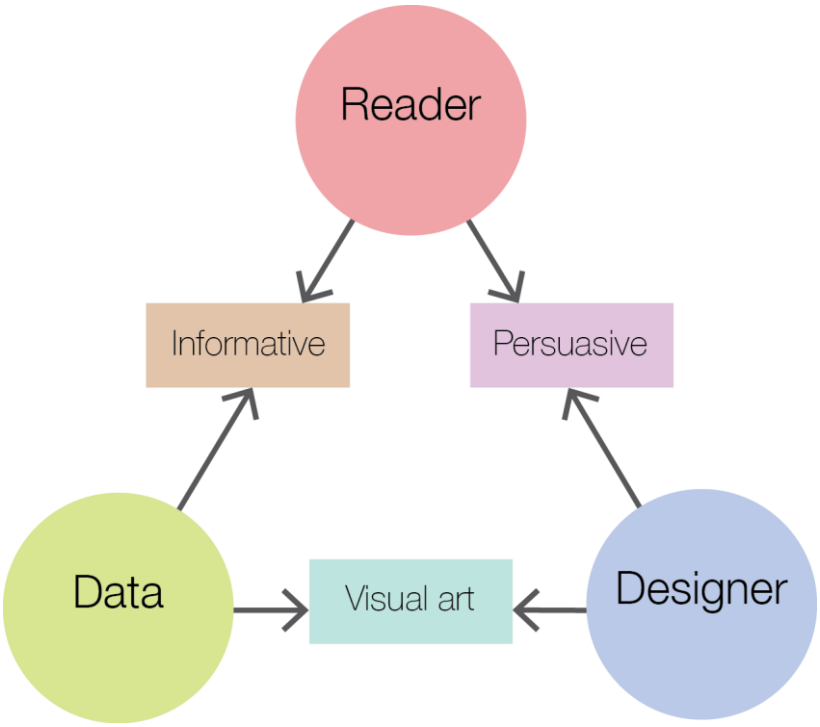

Figure 2.5 The Designer-Reader-Data Trinity representation of interactive considerations for designing visual elements for complex problems. Dominant relationships determine the nature of the visualization (modified from Illinsky and Steele, 2011).

Figure 2.5 shows how the three participants of the visualization process—reader, data, and designer—interact and how each should be considered when designing a visualization. The interactions between the reader and designer and between reader and data are the two most relevant roles to focus on within an EER context. One of the functions of a graphical representation is to make a point to the reader—the data-reader interaction. If the visualization is trying to demonstrate positive judgment, then strategies should be used in a way that will *inform* the reader and will "…[aim] for a neutral presentation of the facts in such a way that will educate the reader…" (Illinksy and Steele, 2011). Understanding the role of each participant and the interactions among the

participants can equip the average person with the critical information pertaining to the intention of a visualization so the reader can remove the data dimensions seeking to convince her of a particular perspective or view. In this sense, the designer is not inserting herself into the visualization to make an editorial judgment with the data. This is a more formal role for visualizations in an academic or information-providing role.

The second and perhaps more important relationship in the Designer-Reader-Data Trinity is the reader-designer relationship. This is where the designer introduces a normative point of view to the visualization and clearly advocates a position using the design elements they have chosen. This is a way for the designer to *persuade* the reader of the information. In this situation, the designer is taking data that has been manipulated and transformed within the context of a specific viewpoint, and that preference in view is applied to the visualization. This intention is especially important to understand if the visualization is in a policy or consulting setting.

IMPROVING POORLY DESIGNED GRAPHICS

This section shows how graphics can be refined with the visualization workflow using two graphics relevant to the groundwater management problem case study presented in Chapter 4. Figure 2.6 (Pierce, 2006) is a conceptual graphic of aquifer response over a period of time within a particular governance structure that ranges from no aquifer use to maximum aquifer mining (i.e. no pumping to maximum pumping). Figure 2.7 (Pierce, 2006) overlays a negotiation space based on hypothetical stakeholder input. These graphics have the potential to be used in a decision-making setting, though the design principles and elements used can be improved upon.

The motivation behind these two graphics is strong, but improving the execution of the graphics can make their messages stronger and clearer. There are three immediate issues:

1. **Axis orientation**: Axis depicting total aquifer goes from zero at the top of the image to maximum at the bottom of the image. This is opposite of how viewers generally read values on a chart. Reversing the axis is more consistent with cognitive processing of values and is also consistent with representing the concept of a full aquifer compared to an aquifer with significant drawdown.
2. **Color**: The gradient behind the graph distracts from the content of the graph.
3. **Labeling**: Font styles are inconsistent (both serif and sans serif fonts). The distance of each label from the chart element it describes makes it difficult to discern exactly which element it is describing. The purpose and description of the labels "sum of all non-consumptive flow", "annual recharge", and "ideal condition response to pumping" are not clear.

Figure 2.8 and Figure 2.9 are improved versions of Figure 2.6 and Figure 2.7. In these improved versions, the axes are reversed, the color schemes are simplified, and fonts are normalized to minimize confusion and to allow the important information to dominate the images.

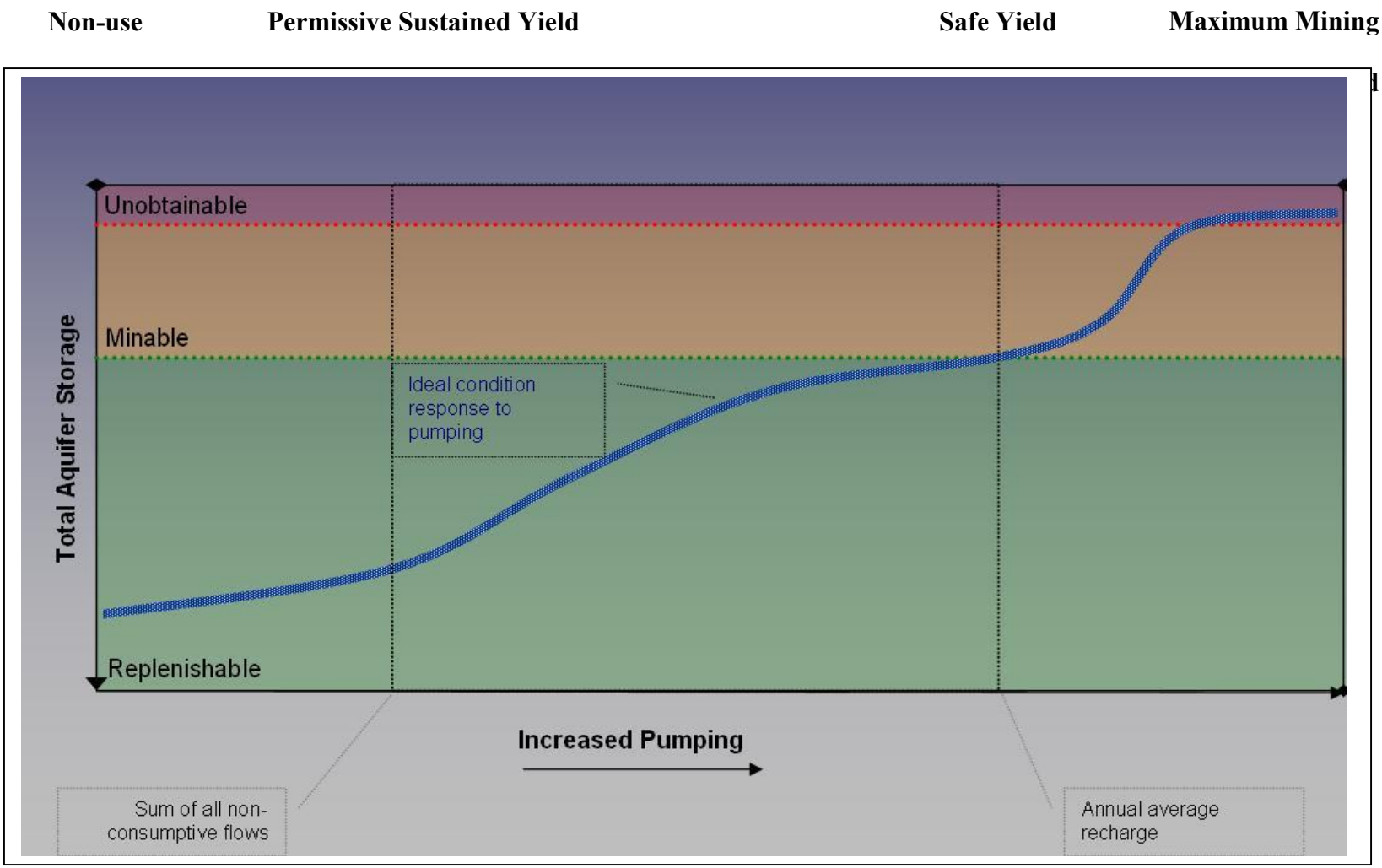

Figure 2.6 Available yield of the continuum for a given planning horizon (from Pierce, 2006).

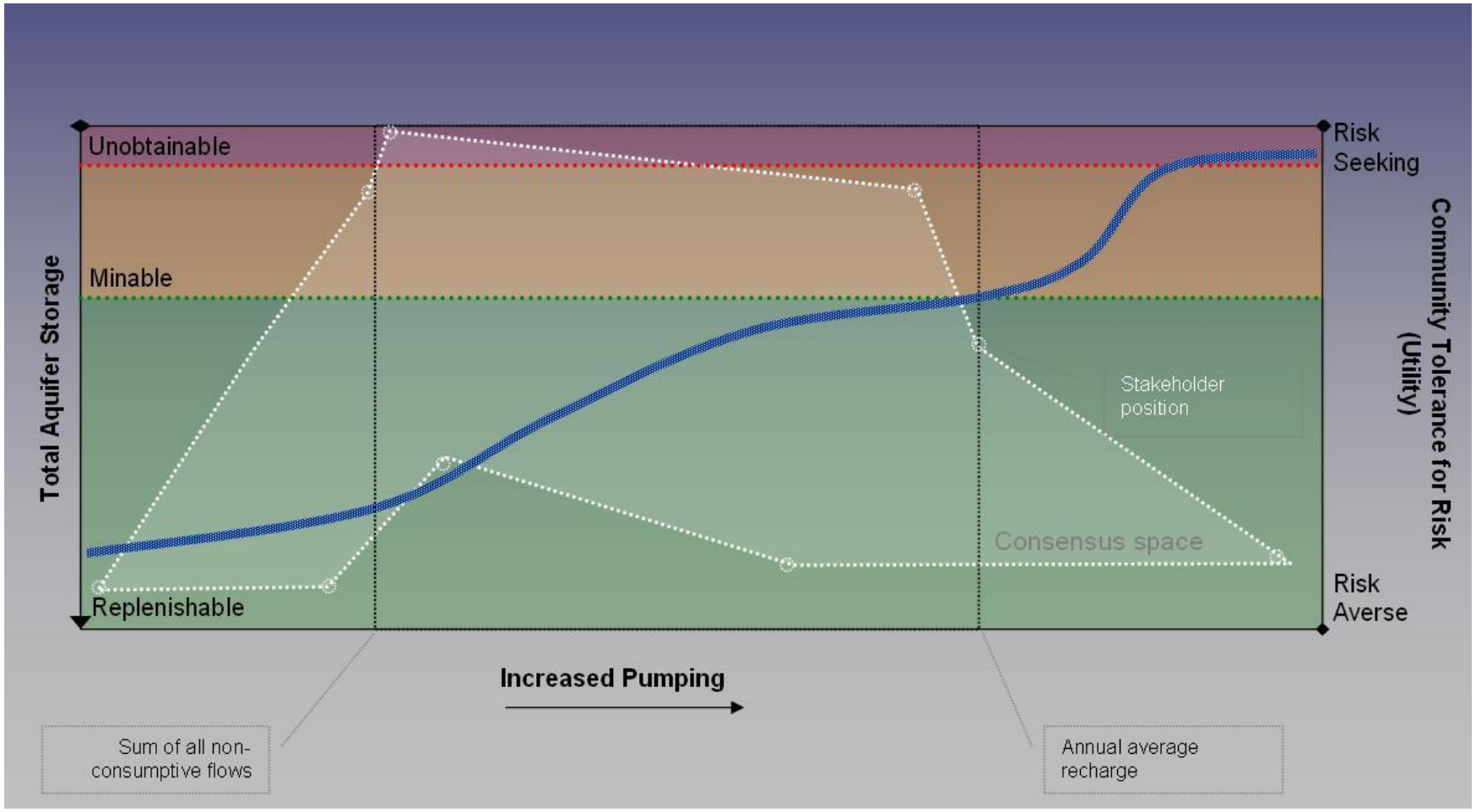

Figure 2.7 Available yield continuum with overlay of feasible negotiation space for determining an available yield, as determined by stakeholder positions (from Pierce, 2006).

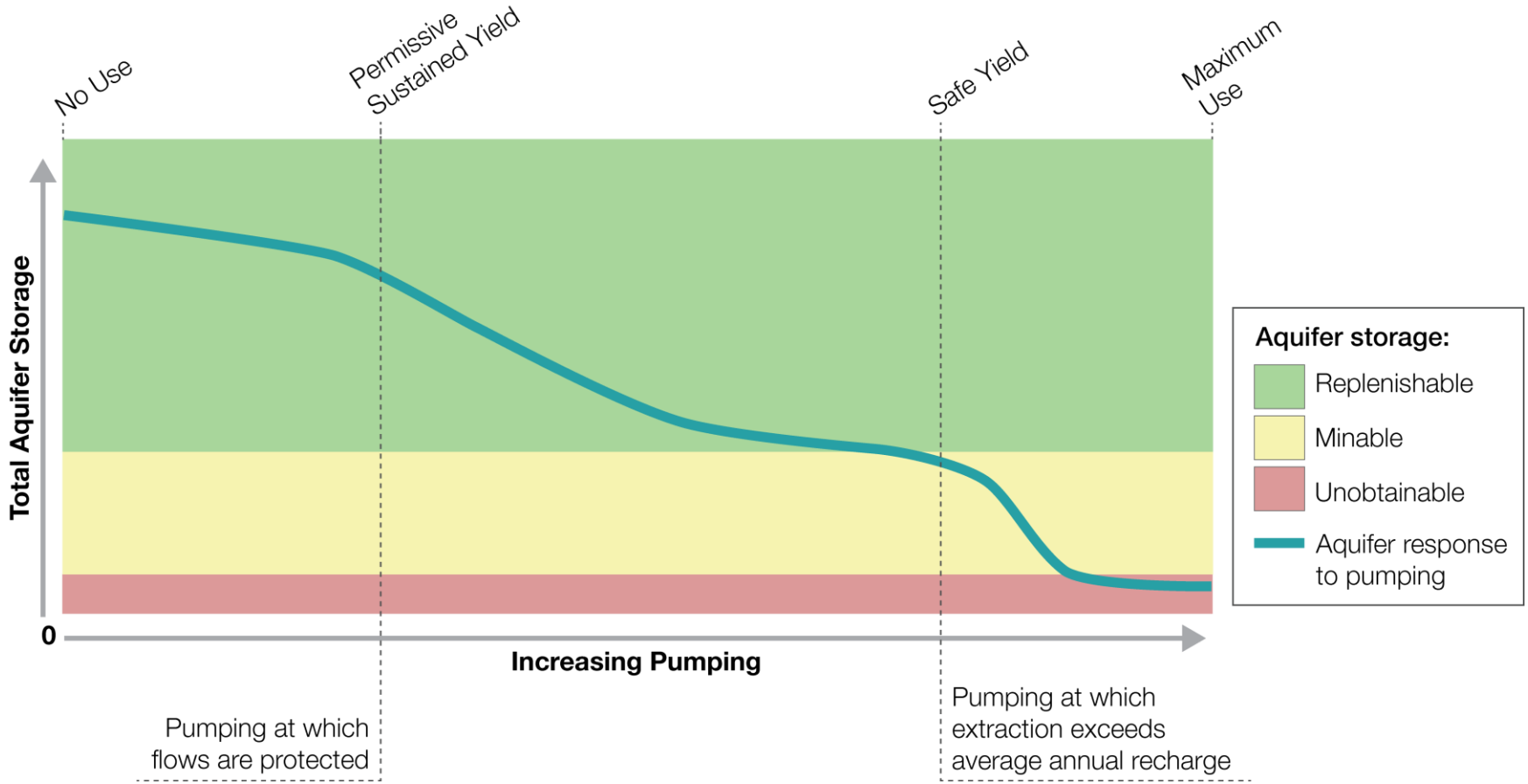

Figure 2.8 Improved version of available yield of the continuum for a given planning horizon (modified from Pierce, 2006).

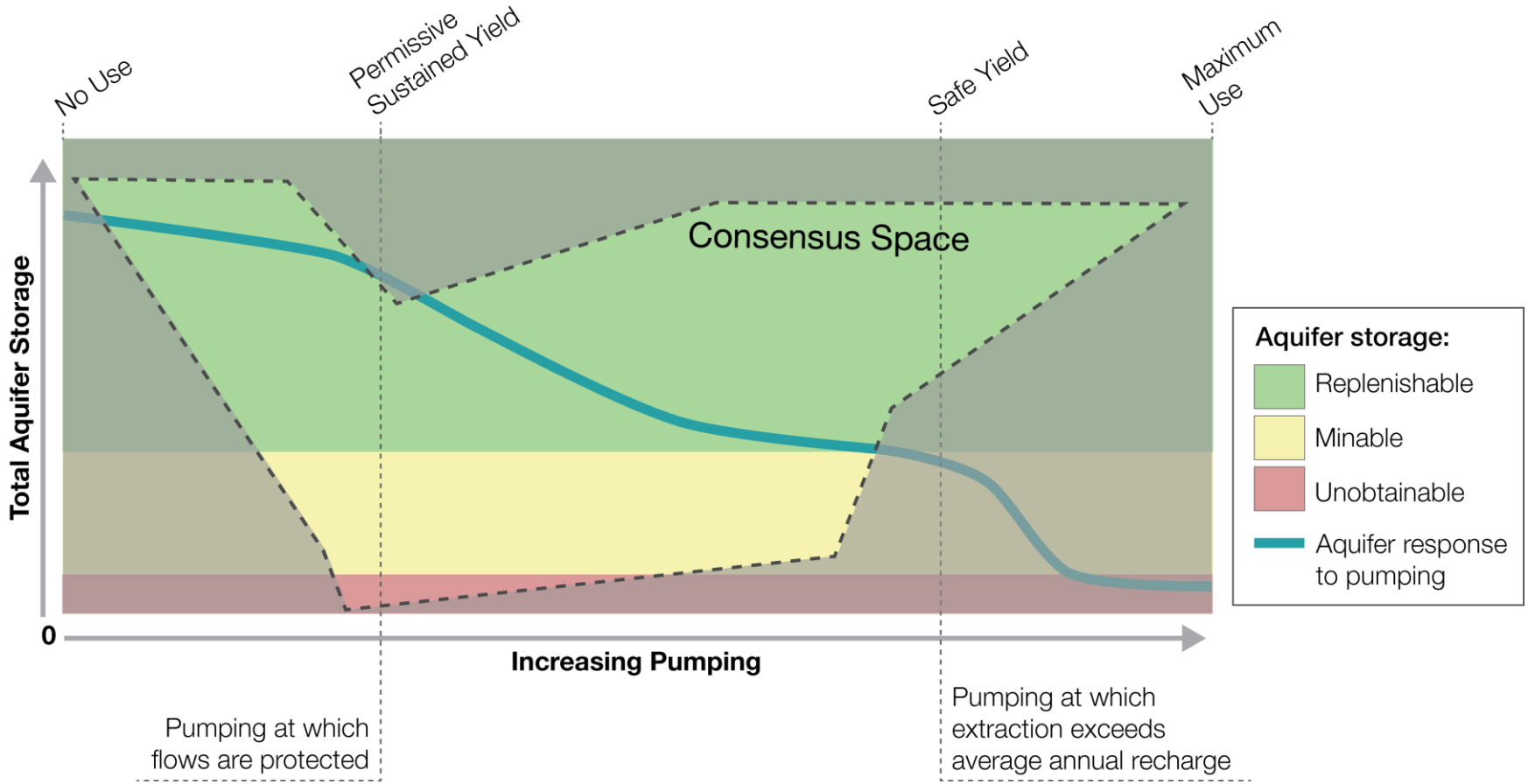

Figure 2.9 Improved version of available yield continuum with overlay of feasible negotiation space for determining an available yield, as determined by stakeholder positions (modified from Pierce, 2006).

Chapter 3: Visualizations and Uncertainty for Groundwater Policy and Management

Groundwater management decisions frequently must be based on both scientific models and input from stakeholders with differing objectives. Water managers use models as tools to assess potential impacts and identify best management practices for groundwater resources. Models are simplified representations of the way complex physical and natural systems work. In the case of integrated modeling, groundwater models can be coupled with other representative elements to reflect how these natural systems interact with socio-economic systems. Models are made to represent these real systems as closely as possible, minimizing unknowns through real values, historical values, or assumptions. However, it is difficult to fully represent complexity in dynamic systems, introducing a level of uncertainty in a model.

While it is important to know what models can represent, it is also important to understand what models are missing. Recognizing knowledge and information gaps can significantly improve the way decisions are made. If modelers do not acknowledge the level of uncertainty in their model, it will likely be perceived as less credible and managers and policy makers may be reluctant to use outputs in decision-making. When visualizations of model results are used to inform decision-making, it is important to explicitly address risk and uncertainty that is inherent in the natural system, the technical representation, and in the decisions made based on model scenarios.

Based on a study done by Brugnach et al. (2007), policy and decision makers tend to avoid using highly uncertain information and avoid addressing issues with a large

amount of uncertainty. Uncertainty for decision makers translates to risk in the decisions they make. Often, models are used to make important decisions that can be expensive or have extensive social ramifications. Ideally, decisions would have no risk and no uncertainty, but this is not how the world operates. By addressing uncertainty in a model, the risk of using a model is explicitly recognized and modeled outcomes or recommendations that are generated from modeled outputs may be considered in the context of representative and relevant uncertainty. All decisions have some level of risk associated with them, so addressing risk as uncertainty is a crucial component of using models to inform decisions. Similarly, models can often be discredited if uncertainty is not addressed, thus by explicitly laying out all unknown information, and the degree to which it is unknown, the perceived legitimacy of the model is likely to be greater.

GROUNDWATER MODELS AND UNCERTAINTY

Groundwater models are most often used to understand the physical and chemical behaviors of aquifer systems. Some groundwater models may inform decisions for groundwater resource management. These models provide the fundamental scientific information of aquifer characteristics, a baseline from which to begin to make decisions, and indications of how water in an aquifer system may respond under varying scenarios. Natural systems are not autonomous; they are connected to social, political, and economic systems in which resources are used differently among interested parties, or stakeholders. The scientific information is only one attribute that informs decision-making. The use of groundwater differs between interested parties, ranging from urban development to environmental health. The goals and objectives of the various

stakeholders also need to inform decision-making. These goals and objectives produce a level of uncertainty in the process, as will be discussed later (Pierce et al., 2013).

A constantly evolving and challenging part of science is how to best communicate and present scientific information to the public and interested parties. Communicating hydrogeological concepts in groundwater systems to both technical and non-technical audiences is a challenging task because of the complexity involved. Communicating these complex groundwater concepts to the general public is an especially difficult task because groundwater resources cannot be observed and explored in the same way as surface water resources can. Effects of groundwater use cannot be seen, compared to the effects of surface water use, like declining lake levels or low streamflow. Consensus is difficult to achieve in both groundwater and surface water management, but the inability to observe groundwater introduces a different type of difficulty in reaching consensus.

Types of Uncertainty

There has been fair amount of research and thinking about the types of uncertainty that exist within models and within the contexts that complex system models are used (Zimmermann, 2000; Aerts, Clarke, and Keuper, 2003; Brugnach et al., 2007; Brugnach, et al., 2008). While the names and groupings of these uncertainties vary in the literature, they all represent the same fundamental elements. The three areas of uncertainty are in the natural system itself, the model created for the natural system, and the socio-economic context in which the system functions. Dewulf et al. (2005) define a set of language to use when considering uncertainty that folds in these three areas:

indeterminacy, *uncertainty*, and *ambiguity*. These are each described and discussed below and depicted in Figure 3.1.

Types of Uncertainty		
Indeterminacy	Uncertainty	Ambiguity
temporal variability spatial variability	model uncertainty parameter uncertainty	goals & objectives values & preferences

Figure 3.1 Three ways to classify uncertainty (modified from Dewulf et al, 2005).

Indeterminacy it is the inherent chaotic and variable nature of a system that can change unpredictably; it is the uncertainty within the system that is unknown and can never be fully known. In the context of groundwater, indeterminacy would include weather patterns and precipitation. Some aquifers, like the Barton Springs segment of the Edwards Aquifer (Chapter 4), are located in regions where precipitation is highly variable and is largely unknown, particularly in the long run. In these situations with highly variable future conditions historical data is used to simulate future aquifer behavior. Using multiple model iterations or instances and simulation runs is one methodological approach for addressing the indeterminacy within natural systems.

Uncertainty is the lack of knowledge or information about a natural system. Often, making assumptions or collecting more data addresses this uncertainty. Most modelers are comfortable with this type of uncertainty because it can be reduced and addressed in a straightforward, quantitative manner.

Ambiguity is the presence of multiple social frames of reference through which to view a system. Ambiguity is the result of stakeholders framing a situation in different ways, without understanding the differences between each framing. Incongruent goals and objectives among stakeholders can lead to conflict and impasse when making decisions. Different framing lends itself to creating multiple scenarios; decision support systems that use visualizations function as a starting point to connect various stakeholder perspectives and explore a range of possible outcomes. Unlike parameter and model uncertainty, the addition of more information during stakeholder phases of modeling is likely to increase ambiguity. When another stakeholder enters the discussion, for example, the new stakeholder needs to tune in with the frames of all other stakeholders, and vice versa.

Dewulf et al. (2005) make the claim that scientists and researchers jump straight to reducing uncertainty as ambiguity by including stakeholders only after a certain point, presenting them with predefined parameters. In reality, ambiguity that could arise at that particular point and could be minimized if stakeholders were involved earlier in the process, having input in the parameters that should be defined.

Loucks and van Beek (2005) similarly recognize these three areas of uncertainty. Indeterminacy is described as natural variability; uncertainty is described as knowledge uncertainty, and ambiguity is described as decision uncertainty. The authors also comment on the use of not only multiple scenario testing, but also sensitivity analyses to estimate the impacts of uncertainty.

To ignore uncertainty is to ignore reality. Uncertainty should be addressed at every stage of decision making, from model development, to defining goals, to predicting future scenarios. By both recognizing uncertainty at every stage and engaging stakeholders early on in the process, there can be an improved understanding of the state of natural systems. The following section describes a framework developed to deal with uncertainty.

Frameworks for Dealing with Uncertainty

Guillaume, Pierce, and Jakeman (2010) developed a framework for uncertainty management (Figure 3.2). In this framework, uncertainties are identified, prioritized, reduced, described, propagated throughout the model, and communicated to decision makers. Uncertainties are categorized in *nature, level,* and *source. Nature* is concerned with whether the uncertainty can be reduced. It can be classified as variable (similar to *indeterminacy*), limited knowledge (similar to *uncertainty*), or contradiction (similar to *ambiguity*). *Level* describes the amount of detail that is known about an uncertainty. *Source* is where the uncertainty originates.

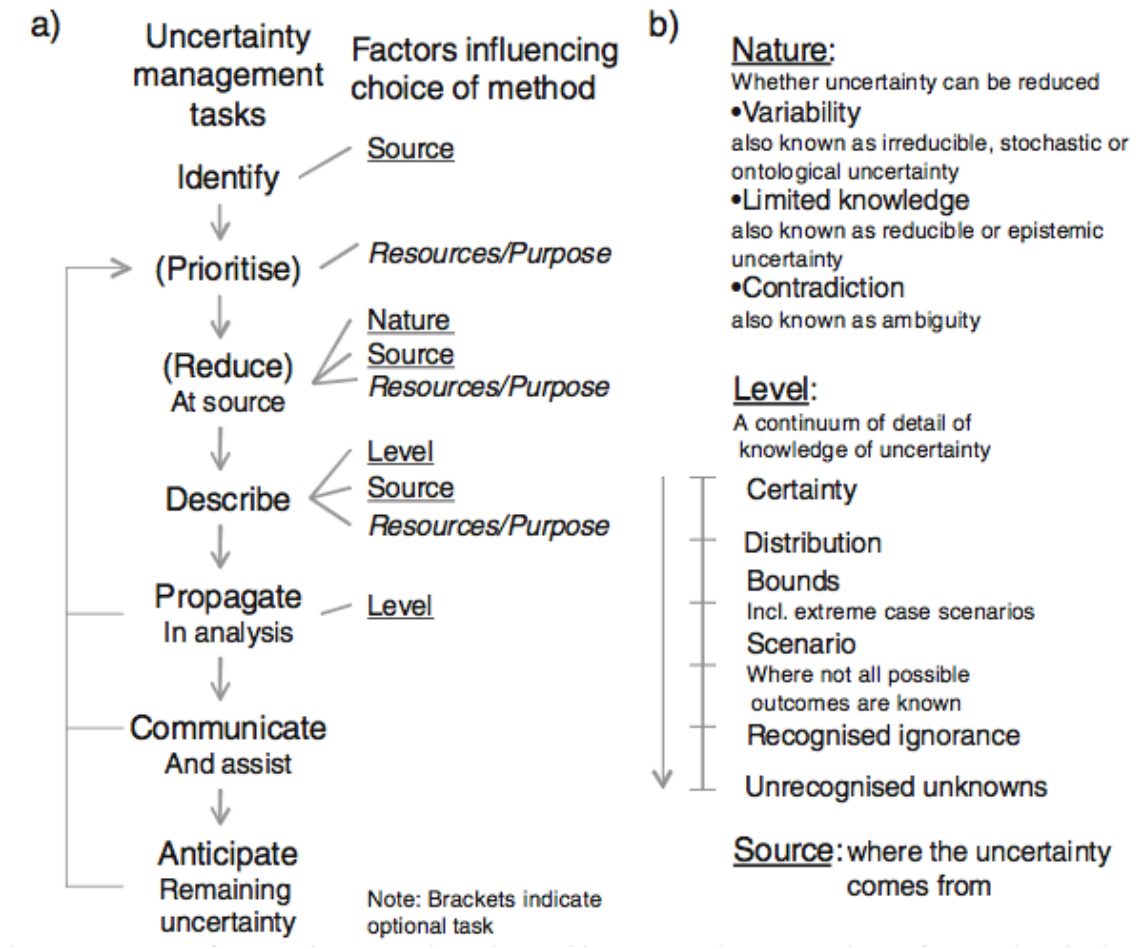

Figure 3.2 Uncertainty Management Framework a) how to address uncertainty, b) language to define uncertainty (from Guillaume et al., 2010).

To summarize Figure 3.2, the following are more detailed steps for uncertainty management (Guillame et al., 2010; Guillame, Qureshi, and Jakeman, 2012):

1. **Identify all sources of uncertainty** within the model and throughout the modeling process. Sources of uncertainty can range from defining initial variables and methodologies to uncertainties in model parameters, and inputs

to framing and using the model. It is possible to miss some uncertainties in this process.

2. **Prioritize resources to address uncertainty**. Some uncertainties will be more important than others for the purpose of model use.
3. **Reduce the prioritized uncertainties**. If an uncertainty is stochastic, it cannot be reduced because it is unknown (e.g., precipitation). As mentioned previously, acquiring more data can reduce knowledge and information gaps, but adding more information may not necessarily reduce ambiguity. Sometimes, adding complexity to a simplified model, reflecting a more realistic state of the system, can reduce uncertainty.
4. **Describe uncertainty** in such a way that it can be carried through the entire modeling process. Unless the implications of uncertainty are addressed explicitly, uncertain information is treated as a certain fact or known aspect of a model. Incorporating probability or confidence intervals are two ways to describe uncertainty.
5. **Propagate uncertainty** through the analysis. Uncertainty propogation can be done with processes such as Monte Carlo simulations[1] or modeling all possible combinations of model parameters to get a distribution of outcomes.

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[1] A Monte Carlo simulation is often use in a decision-making environment to assess risk by assessing all possible outcomes and their occurrence probabilities. See Saltelli (2000), Refsgaard et al. (2005), and Refsgaard et al. (2007) for more general overviews of methods to address uncertainty in computational modeling.

There are many different sampling methods and error propagation methods that could be used in this task.

6. **Communicate uncertainty**. The task of communicating uncertainty is the most delicate task of the process because it is important to communicate the appropriate uncertainties to a specific group of decision makers. Frequently, visualizations provide a strong, robust mechanism for communicating key considerations to stakeholders, particularly non-technical stakeholders. By creating an environment to explore information about uncertainty, decision makers can better understand different policy scenarios and the risk associated with decisions, leading to a well-informed final decision.
7. **Anticipate and manage residual uncertainty**. The nature of knowledge and uncertainty is dynamic. Over time information and knowledge about a problem shifts. Designing and anticipating an iterative learning process throughout model development is a useful way to approach uncertainty. One method to accomplish this task would be to run sensitivity analysis at this point in the process, then do further fine-tuning of uncertainties.

Visualizing Uncertainty

Multiple techniques have been proposed to expand the sixth step of the uncertainty management framework with the goal of visually communicating uncertainty to viewers. In a broad sense, these methods are used in decision support systems that create a synergistic environment, connecting scientific data with stakeholders. In a more

detailed sense, these methods reflect exactly how uncertainty is incorporated in the tools used in decision support systems.

Hearnshaw and Unwin (1994), as well as Pang, Wittenbrink, and Lodha (1997), suggest design methods to subtly convey data and model uncertainty to viewers. These expand upon the basics outlined in Chapter 2 and Bertin's (1983) set of visual variables used to display information in cartography. As an example of these methods, Figure 3.3 below shows a 3D geologic model of stratigraphic horizons. The clear-cut boundaries of the horizons and well locations in image A do not show uncertainty, while image B blurs the boundaries to reflect model uncertainty.

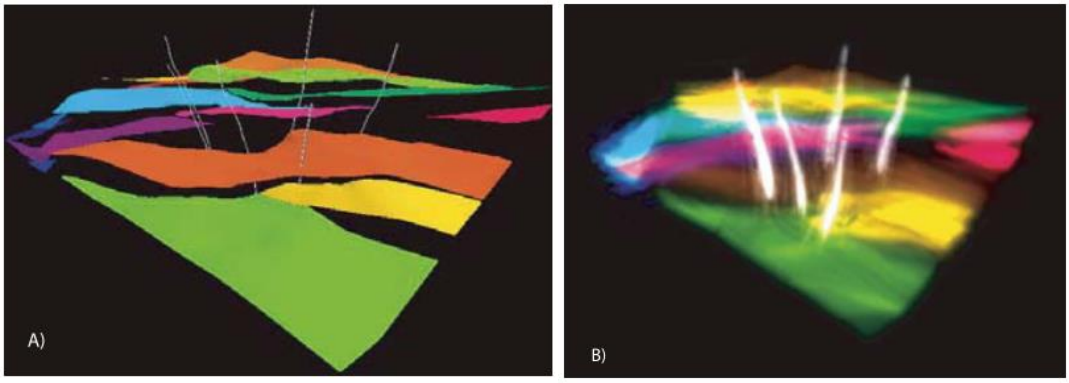

Figure 3.3 A 3D model of geologic strata and well locations. (A) shows the model without uncertainty. (B) shows the model with an added level of fuzziness to convey uncertain boundaries (from Bond, 2007).

Other methods suggested by Bond (2007) are to use various colors and transparencies, glyphs of different size and shape, or toggling methods, which show data in one panel and uncertainty in another. A survey conducted by Aerts et al. (2003) tested uncertainty visualization methods on internet users. They found that techniques using

changing colors and embedded uncertainty proved more effective than techniques where users had to toggle between multiple images.

GROUNDWATER VISUALIZATIONS

Visualizations of groundwater have typically been related to groundwater quality and the transport of contaminants. For example, Stiff diagrams, like the one in Figure 3.4, show the proportions of various chemical compounds in the water. Stiff diagrams can be combined on a map to show the locations of each sample. Piper plots, like the one in Figure 3.5, also represent geochemical data. Although these can display information from multiple samples on one diagram they do not necessarily give the physical coordinates of the sample.

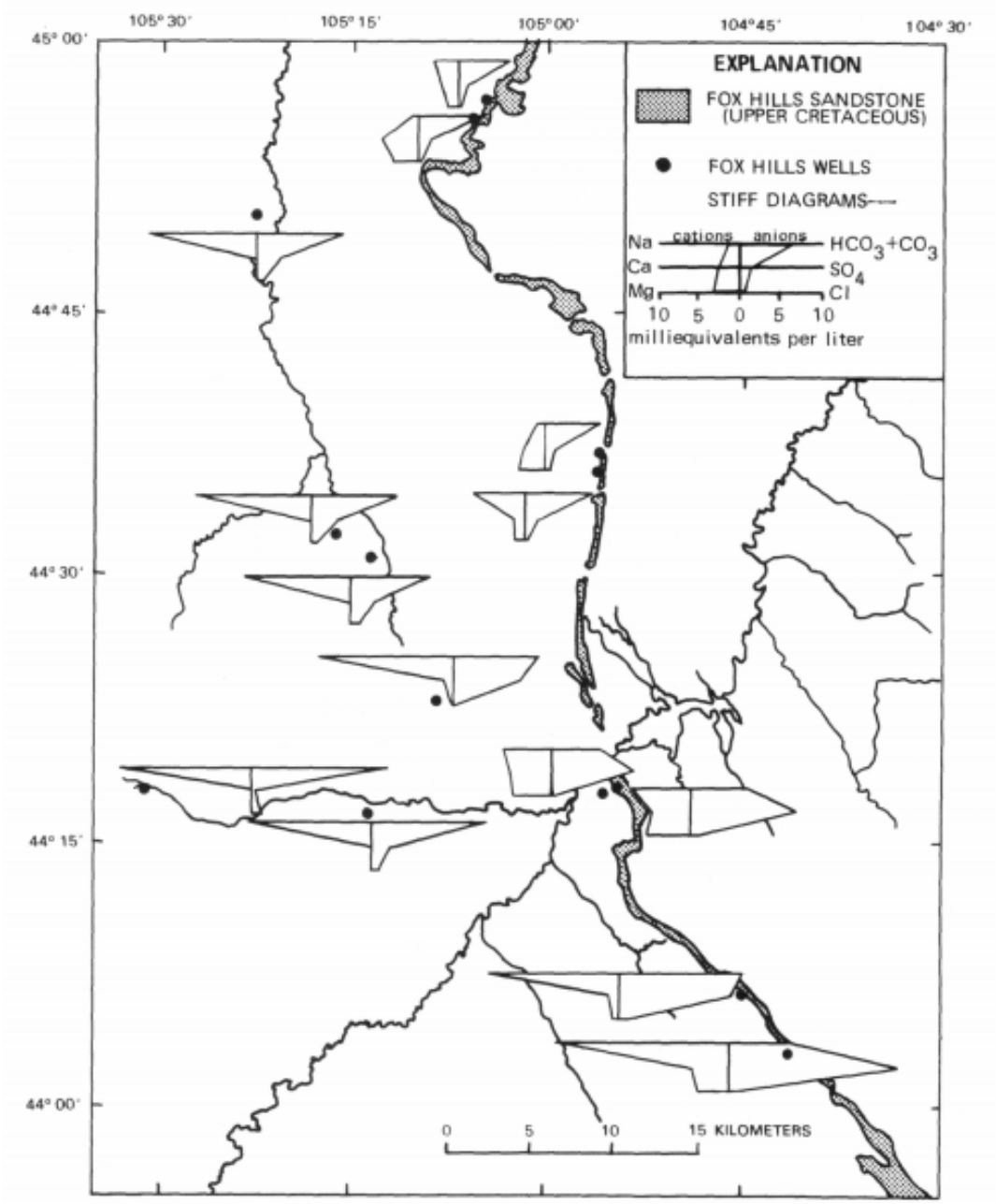

Figure 3.4 Stiff diagrams to show spatial variability of water quality in along a river. (from Helsel and Hirsch, 2002).

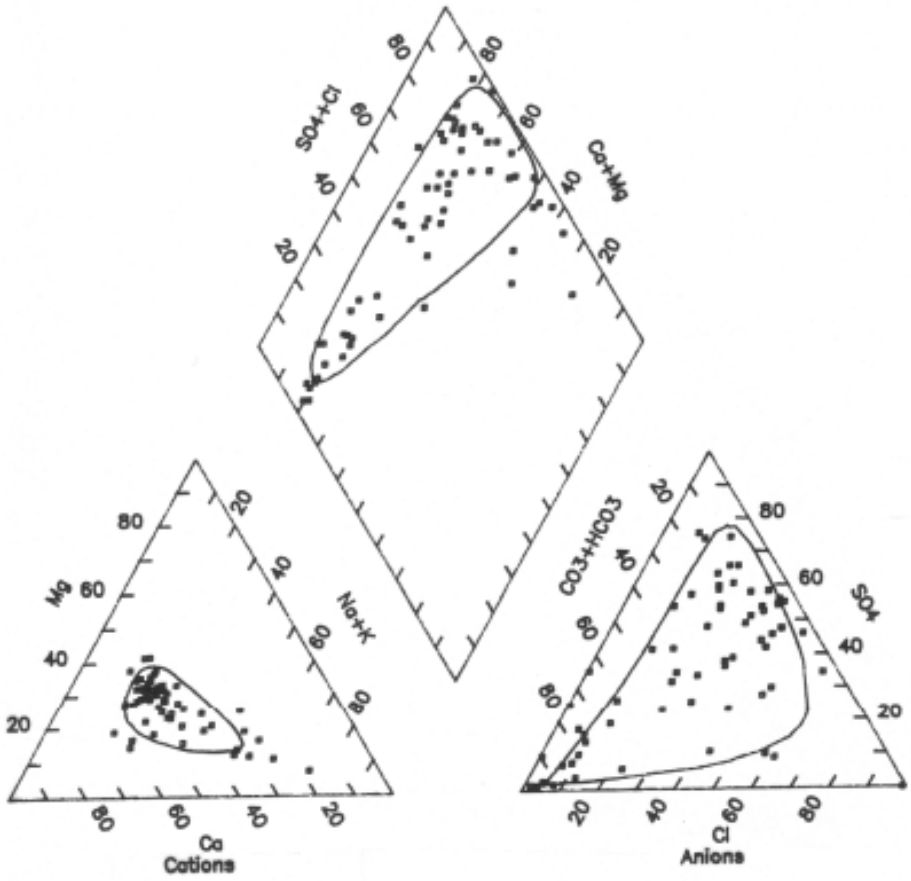

Figure 3.5 Example of a Piper diagram depicting groundwater chemistry in an aquifer (from Helsel and Hirsch, 2002).

Only fairly recently have visualizations been used to show groundwater supply for use in decision-making. These visualizations are typically GIS-based (Geographic Information System) maps that show the effects of decisions on groundwater levels or springflow. An increasing interest in the costs and benefits of groundwater pumping have resulted in visuals that show marginal utility or overall results of a benefit-cost analysis, such that a stakeholder can see the financial and welfare impacts of a decision.

Chapter 4: Visualizing Uncertainty: A Case Study of the Barton Springs segment of the Edwards Aquifer

The Barton Springs segment of the Edwards Aquifer in Central Texas carries cultural, environmental, and economic significance in the region. Recent drought periods and an increasing population draw attention to the significance of efficient and equitable groundwater management. The implications of increasing water demand and uncertain climatic conditions, which have significant impacts on water levels and aquifer springflow, require management strategies that support urban and economic growth while protecting environmental features. The Barton Springs/Edwards Aquifer Conservation District (BSEACD) is charged with conserving, protecting, and enhancing groundwater in this segment of the Edwards Aquifer (BSEACD, 2014). The BSEACD creates rules and policies to manage the limited and often stressed water supplies in the aquifer. Management decisions are made using observed and modeled groundwater information. This case study explores how the uncertainties inherent in models used for planning can be visualized to better inform decision-making for drought management and pumping allocation.

THE BARTON SPRINGS SEGMENT OF THE EDWARDS AQUIFER

The Barton Springs segment of the Edwards Aquifer (BSEA) is a karst aquifer that is part of the larger Edwards Aquifer system spanning Central Texas (Figure 4.1). It is located in Travis and Hays counties, bounded in the north by the Colorado River, in the south by a groundwater divide near the City of Kyle, in the east by a saline section, and in the west by the Balcones Fault (BSEACD, 2004; BSEACD, 2014). Figure 4.2 shows the

extent of the BSEA. Including the contributing, recharge, and artesian zones, the area of the system is 916.87 km^2 (354.39 mi^2) (Scanlon et al, 2001). Water use occurs in the recharge and artesian zones, but processes that occur in the contributing zone are important to consider when determining water budgets for this segment of the Edwards Aquifer.

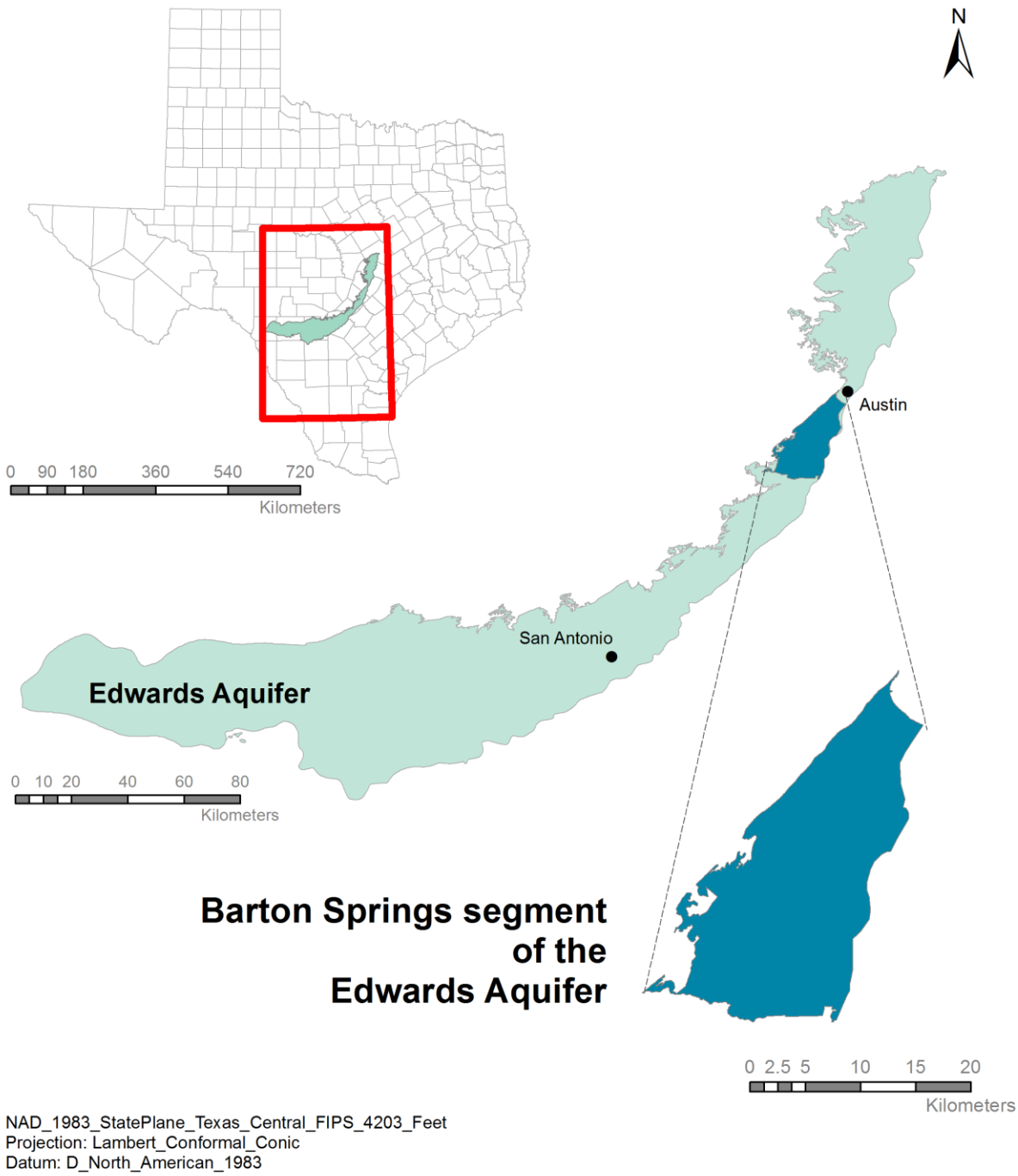

Figure 4.1 Location of the Edwards Aquifer and the Barton Springs segment in Central Texas.

Figure 4.2 Areal extent Barton Springs segment of the Edwards Aquifer. The artesian and recharge zones are part of the aquifer. The contributing zone is the watershed containing streams that contribute to the aquifer when they pass the recharge zone.

The BSEA discharges at many spring locations, but Barton Springs is the primary point of discharge, averaging 1.56 $m^3 s^{-1}$ (55 cfs) (Winterle, Painter, and Green, 2009). The lowest recorded discharge was 0.31 $m^3 s^{-1}$ (11 cfs) during the 1950s, or during what is often referred to as the drought of record. In September 2011, a period of extreme drought, Barton Springs experienced daily fluctuations of up to 30% of flow as springflow approached 0.57 $m^3 s^{-1}$ (20 cfs). (Hunt, Smith, and Hauwert, 2012). The drought in 2011 was the most intense Texas drought in recorded history. Flow during this time did not reach or drop below the value recorded in the 1950s potentially due to conservation strategies and to contributions from urban recharge (Passarello, Pierce, and

Sharp, 2014; Garcia-Fresca and Sharp, 2005). Springflow and water levels in wells serve as indicators of aquifer health. Pumping restrictions put in place given certain levels of discharge or water levels attempt to provide a solution to stressed supply and consistent demand.

Springflow, water level, and storage in the aquifer vary in response to pumping and precipitation. Some springs and wells respond rapidly to fluctuations in pumping or recharge as a result of faults, fractures, and conduits that allow water to easily flow through the limestone system. Significant efforts have been made to refine the conceptual and geological models used to characterize groundwater flow through the system. These models, and the differences between them, become especially important when creating policies for aquifer management.

AQUIFER MANAGEMENT USING THE BARTON SPRINGS GROUNDWATER AVAILABILITY MODEL (BS GAM)

The Barton Springs/Edwards Aquifer Conservation District implements a drought management program using water levels in the Lovelady monitoring well (State Well No. 58-50-301) and discharge from Barton Springs (Smith, Hunt, and Holland, 2013). Measurements at these two locations trigger drought stages during which mandatory and voluntary water conservation policies are initiated. The values that trigger drought stages are depicted in Figure 4.3. The BSEACD defines desired future conditions (DFCs)[2] for the aquifer based on a numerical groundwater flow model, called a groundwater

[2] Texas Administrative Code. Title 31, § 356.2(8) states that desired future conditions are "the desired, quantified condition of groundwater resources (such as water levels, water quality, spring flows, or volumes) for a specified aquifer within a management area at a specified time or times in the future." See Mace et al., 2008 for a discussion about desired future conditions.

availability model, and implements pumping and drought restrictions in an attempt to meet established DFCs[3]. The original groundwater availability model developed for the BSEA (BS GAM) has been updated in efforts to refine underlying assumptions and better understand groundwater behavior. However, the model replicates the 1950s drought of record and indicates that a repeat of that drought combined with increased water demand has potential for significant negative impacts on water levels and springflow (Smith and Hunt, 2004). Drought conditions from 2011 to the present are redefining may redefine drought-of-record levels, thus increasing concerns from a management standpoint.

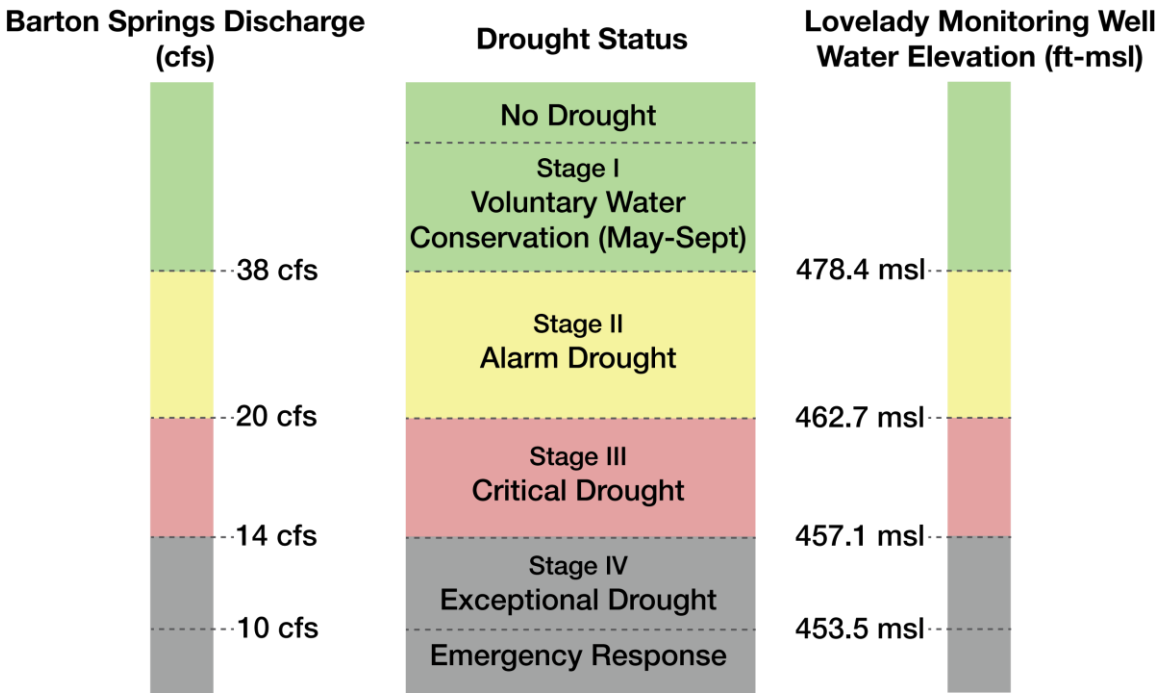

Figure 4.3 Barton Springs/Edwards Aquifer Conservation District drought triggers using springflow from Barton Springs and water level in the Lovelady Monitoring Well (modified from BSEACD, 2015).

[3] Texas State Water Code, Section 36.1071 (h) requires that a groundwater conservation district use groundwater availability modeling information provided by the Executive Administrator of the Texas Water Development Board in in developing its groundwater management plan.

Population growth and urbanization in central Texas is increasing the demand for water. Multiple stakeholders have an interest in how the BSEA is managed, including urban developers, environmentalists, and other water users (private well owners, irrigators, etc.). The question is whether the uncertainties in the BS GAM are important when making management decisions in light of multiple users and ongoing drought conditions, and how all of these factors can be incorporated to communicate the state of the BSEA in a way that can be used effectively to make management decisions. In creating policies that trigger drought conditions and conservation requirements, the establishing benchmark values that trigger drought condition water restrictions, the BSEACD recognizes that uncertainties like climate change, recharge sources, endangered species habitat requirements, and accurate data collection influence the water budget and will change how the aquifer needs to be managed (Smith et al., 2013). The following case study aims to visualize the uncertainty of recharge for use in decision-making situations.

RECHARGE VISUALIZATION CASE STUDY

In this case study, pumping levels in the BSEA control primary management and policy decisions made by the BSEACD. Threshold levels for key aquifer health indicators, like springflow and water levels, are used to determine what water restrictions are enacted.

Recharge to the Barton Springs segment of the Edwards Aquifer is a critical component for understanding the water budget, yet it is difficult to quantify with precision. Changes in precipitation and land use, stream loss, leaky water infrastructure,

and alternative water supplies can influence recharge rates and distribution in a rapid response aquifer like the BSEA (Smith and Hunt, 2010; Passarello, 2011).

Previous Work

Prior research into the nature of model inputs in the BSEA created a set of recharge interpretations (Passarello, 2011; Passarello, Sharp, and Pierce, 2012; Passarello et al., 2014), as well as a rich dataset from simulations (Pierce, 2006; Pierce et al., 2006) to assess aquifer response in the BSEA to alternative management strategies and pumping scenarios. The information used here is data resulting from the work of Pierce (2006) and Passarello (2011). The dataset is based on the BS GAM as reported by Scanlon et al. (2001). The model is a two-dimensional groundwater flow MODFLOW96 model calibrated using observed data from a ten-year period. The BS GAM is a tool used as a part the BSEACD's water planning process to evaluate groundwater availability and to predict future water level and springflow response to increasing demand and future drought periods. The BS GAM information used here is based on data from 1999–2009 (Passarello, 2011).

The model area of the BS GAM is shown in Figure 4.4. The model consists of 7,043 active cells within the hydrogeological boundary of the aquifer. The model zones overlap the recharge zone and the artesian zone. To better visualize how each cell responds to decision parameters in the model, and to better evaluate management

decisions, Pierce (2006) uses the Groundwater Decision Support System (GWDSS)[4] to create simulations based on management decisions and scenarios. In the GWDSS architecture, the BS GAM is grouped into 11 zones of hydraulic conductivity (Pierce et al., 2006); these zones also represent pumping zones used for management decision variables.

[4] The Groundwater Decision Support System (GWDSS) is an integrated assessment tool that links MODFLOW-based groundwater models to stakeholder values to improve aquifer management (Pierce, 2006).

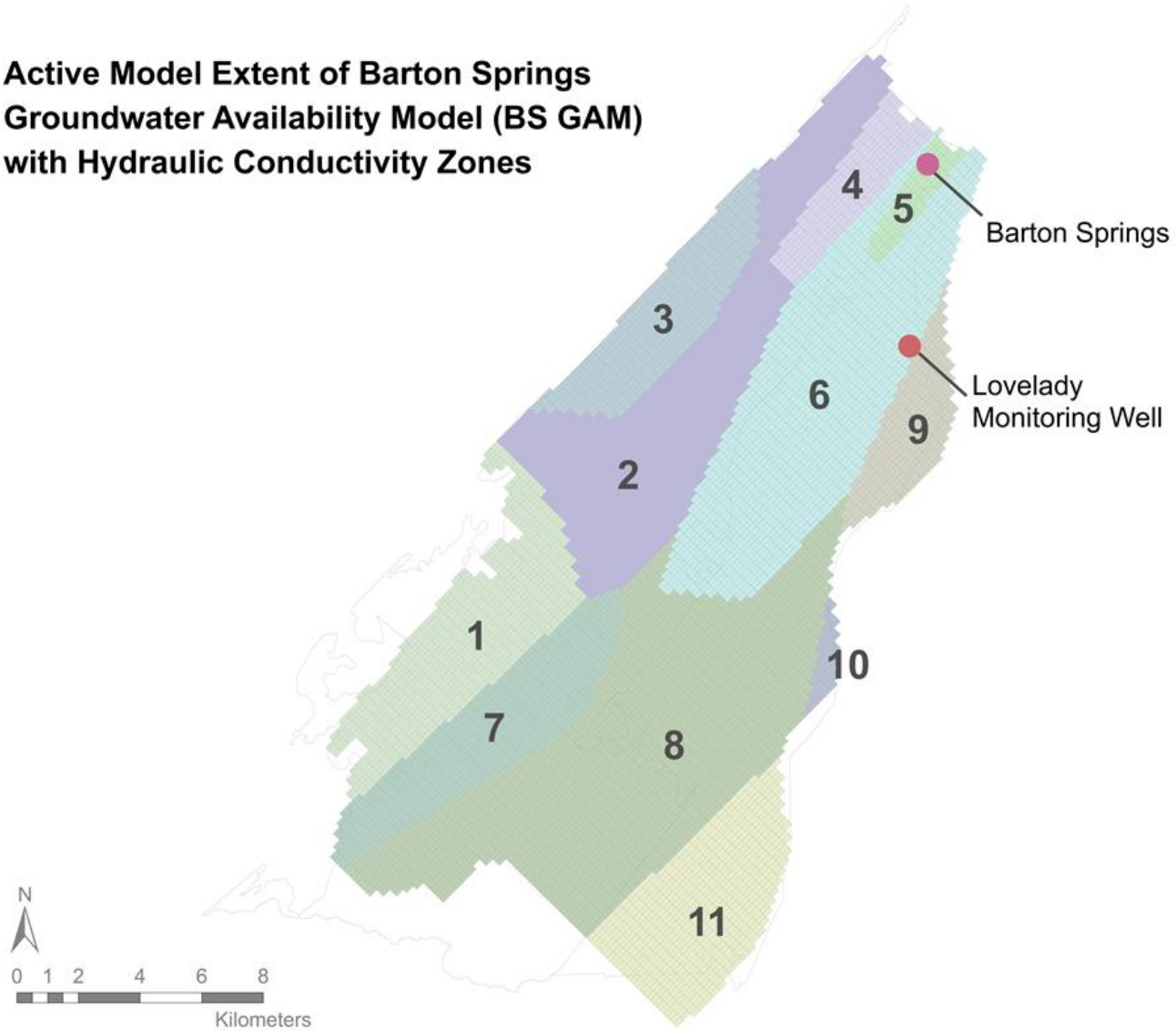

Figure 4.4 Extent of MODFLOW model divided into eleven zones based on hydraulic conductivity. Barton Springs and the Lovelady monitoring well are located in two different zones out of the eleven (modified from Pierce, 2006; Pierce et al, 2006).

Four different recharge scenarios were used to create revised inputs for the BS GAM. The GWDSS simulation-optimization platform generated a set of output results based on these scenarios. The modified interpretation of recharge sources (Passarello, 2011), which includes natural recharge (precipitation, diffuse, and stream recharge) and artificial recharge (human recharge), reflects uncertainties in the scientific understanding of this aquifer system. Modeling results show that the scenario with natural recharge and artificial recharge (Altered Natural + Artificial Recharge) best reflects observed Barton Springs discharge and Lovelady monitoring well water levels (Figure 4.5). Figure 4.6 shows the spatial variability of recharge in the baseline scenario compared to the best-fit recharge interpretation. Model runs that use the best-fit recharge interpretation (i.e. Altered Natural + Artificial Recharge) reduce uncertainty within the simulation model and are expected to provide more accurate outputs; the Altered + Natural Recharge Scenario is used in the following study. While the uncertainty related to artificial recharge was quantified in Passarello's work, still more research can be done to quantify diffuse recharge.

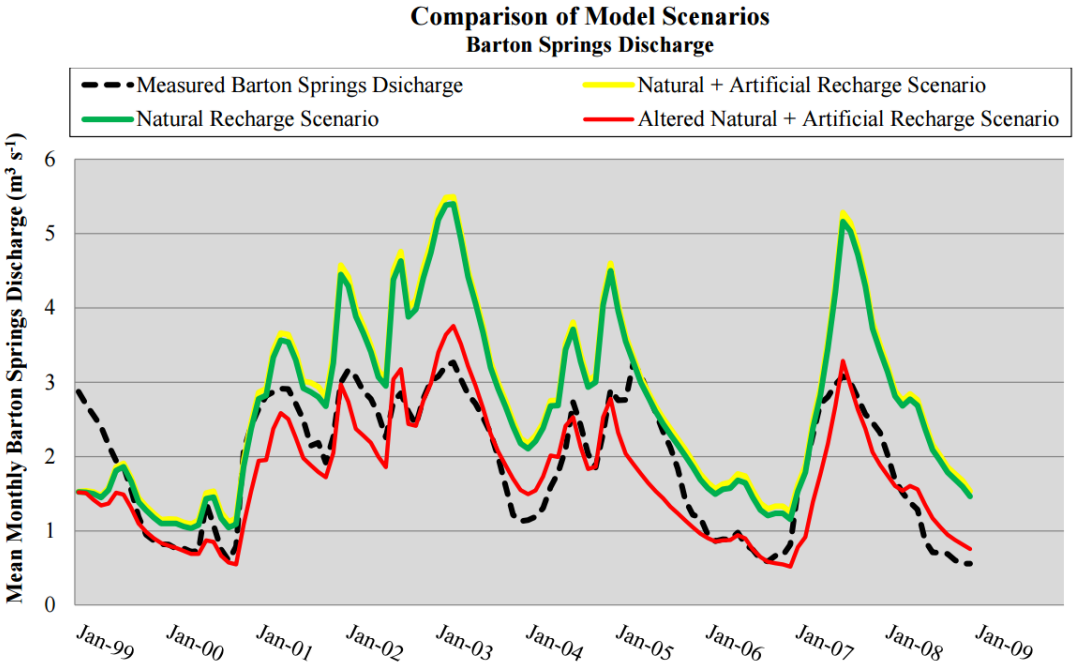

Figure 4.5 Results comparing outputs from BS GAM simulations using a set of modified recharge inputs to measured Barton Springs discharge (Passarello, Pierce, and Sharp, 2014; Passarello, Sharp, and Pierce, 2012 from Passarello, 2011).

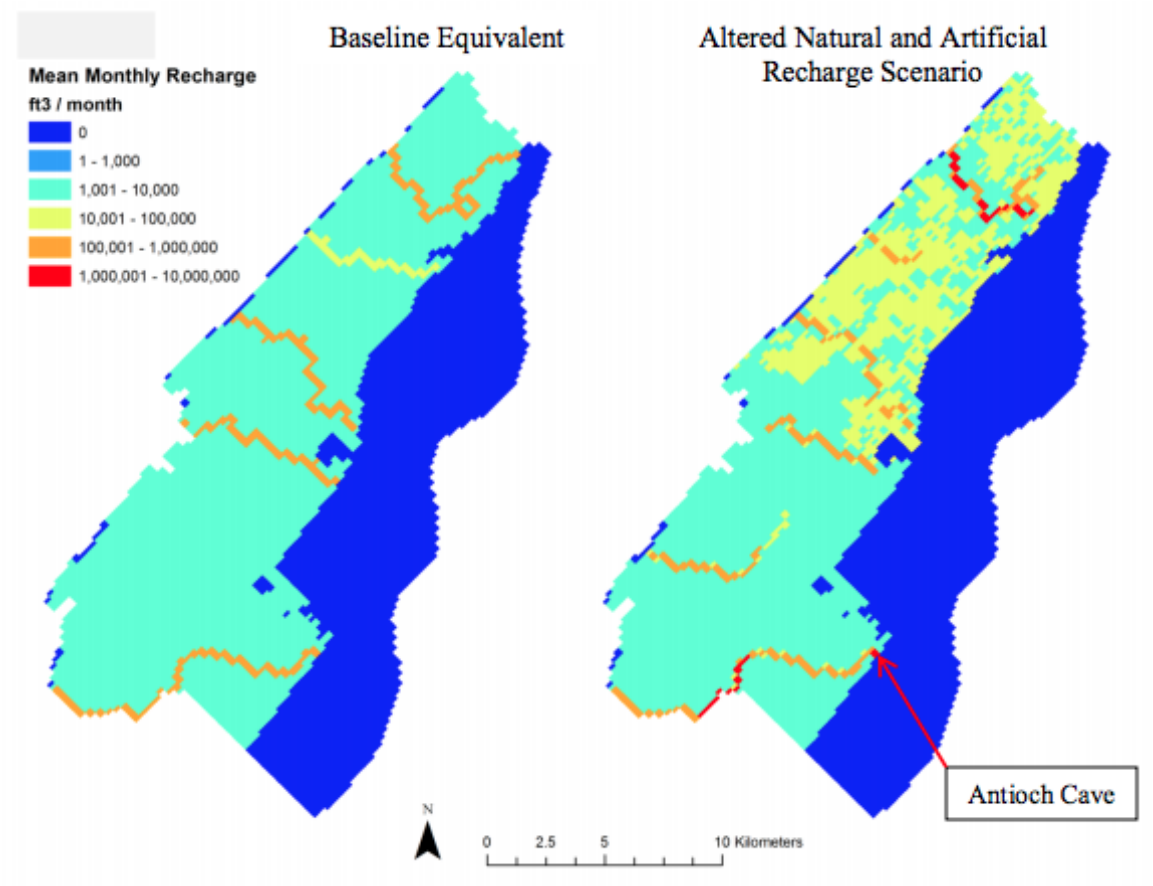

Figure 4.6 Monthly mean recharge distributions of the baseline (Original) recharge scenario and the Altered Natural + Artificial Recharge (Modified) scenario. (Passarello et al, 2014; Passarello, 2011).

The following uncertainty analysis examines springflow and water level response to variations in pumping between hydraulic conductivity zones in the baseline scenario (Original)[5] and the Altered Natural + Artificial Recharge scenario (Modified) as a way to evaluate the impact of scientific uncertainty on groundwater management. Examining

[5] The baseline GAM scenario was formerly used for management decisions in the BSEACD. The BS GAM has since been updated twice (Smith and Hunt, 2004; Painter, Sun, and Green, 2007). These updated models should be used in future studies on how different model interpretations and assumptions influence management decisions.

differences in the simulations graphically and spatially can better inform management strategies and policies related to pumping during drought conditions.

Uncertainty Analysis of Original and Modified Recharge Scenarios

This section outlines the conceptual workflow and methodology used for data exploration to assess the significance of scientific uncertainty between modeled interpretations used in relation to groundwater management. The knowledge discovery process was completed through data manipulation and visualization. A number of commercial software packages for post processing and visualization were used to complete steps in the analysis, in particular Microsoft Excel, Tableau, and Geographic Information Systems (GIS) were used to explore the datasets of the original and modified simulation runs. The intent of this analysis is to understand how uncertainty in recharge interpretations can influence primary management and policy decisions, particularly in determining what management restrictions are enacted by specific aquifer metrics.

Pumping volumes used in this study were calculated by Passarello for 1999-2009. Average monthly pumping for this time period is shown in Figure 4.7. Note that the majority of pumping occurs in the southeastern portion of the there is no reported pumping in zones 1, 5, or 9. The BSEACD permits for pumping water from the BSEA to meet the sustainable yield goals outlined in their DFCs. This creates permitting limitations for the district. Currently, the amount of water the district can permit is 11,528 acre-feet per year (16 cfs) in average conditions, and 3,765 acre-feet per year (5.2 cfs) in drought conditions. Threshold drought restriction triggers are depicted in Figure 4.3.

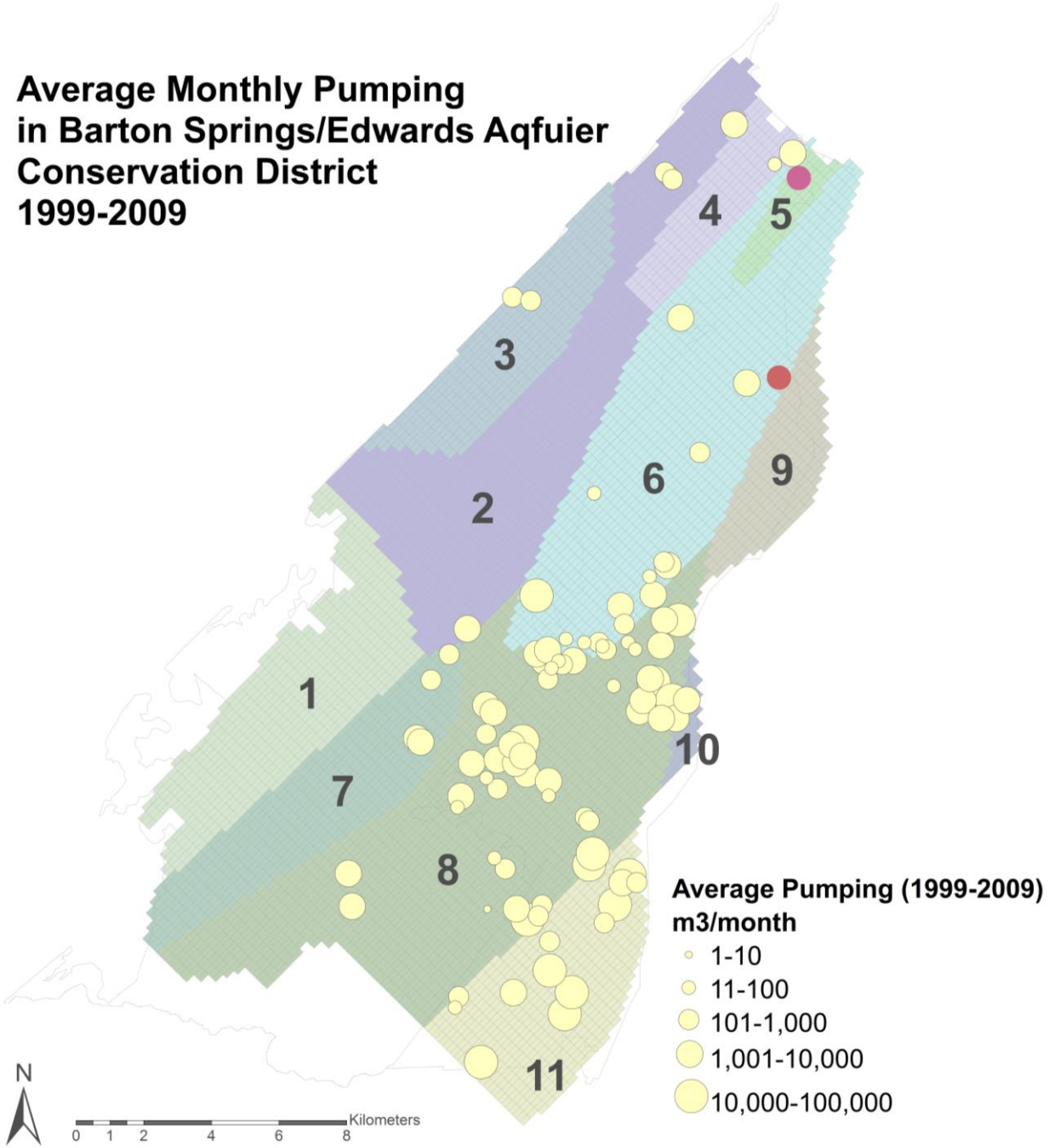

Figure 4.7 Site map of pumping wells and average pumping volumes within the BS GAM. Locations and discharges are based on Hunt and Smith (2006) (modified from Passarello, 2011).

Dataset and methods

The dataset reflects outputs from GWDSS. It includes Original simulation runs and Modified simulation runs, which include the natural and artificial recharge estimates determined by Passarello (2011). The original dataset includes 10,256 simulation runs and the modified data set includes 9,382 simulation runs that completed to convergence. The correlating 9,382 simulation runs in the original and modified datasets were used in this analysis.

Each simulation run includes aquifer metrics of springflow, water level, and total storage based on pumping scalars from 0.0-2.0 in each zone—a scalar below 1 representing a decrease in pumping and a scalar greater than 1 representing an increase in pumping. Each simulation run for each of the scenarios includes a 10-year horizon from 1999-2009 with monthly time steps.

Attributes from each simulation run were processed using a high-performance computing system. This process streamlined data compilation, making it easier to explore the vast amount of data than it would be on a typical computing platform with limited processing power.

The analysis presented here is a simple uncertainty analysis to quantify the differences between the Original and Modified scenario simulation runs and to relate the differences in response metrics to spatial variations in pumping over the area extent of the model.

Initial analysis of key response variables

Metrics of interest for this analysis are minimum discharge values from Barton Springs, average monthly water level for the aquifer, and total storage of the aquifer. Table 4.1 shows the statistical distribution of all 9,382 simulation runs for key aquifer metrics. The Original scenario consistently simulates metric values greater than the Modified scenario.

Minimum Barton Springs Discharge (cfs)				
	Average	*Minimum*	*Maximum*	*Standard Deviation*
Original	18.181469	15.036542	19.909279	0.517824
Modified	15.418322	9.351716	20.620870	1.215050

Average Monthly Water Level over entire Model Area (feet)				
	Average	*Minimum*	*Maximum*	*Standard Deviation*
Original	781.983604	773.156800	790.238700	1.894588
Modified	570.231778	560.194300	581.164860	2.369292

Storage (million feet^3 for the entire model)				
	Average	*Minimum*	*Maximum*	*Standard Deviation*
Original	3187	1650	4950	356
Modified	2093	1310	3150	196

Table 4.1 Statistics of aquifer metrics for all simulation runs.

Overall, springflow in the Modified scenario runs is less than springflow in the Original scenario runs. This difference is important because the modified interpretation of recharge incorporates more complete and accurate scientific information. There may be implications for less springflow than modeled originally and, therefore, current policies based on the original interpretation may overestimate groundwater availability. This difference in scenario runs will be further explored in this section.

The resulting average minimum discharge from Barton Springs and average monthly water level in all active model cells over the modeling time period are shown in

Figure 4.8, along with observed precipitation from 1999-2009. Over the 10-year model period, springflow values at Barton Springs in both the Original and Modified scenarios reach BSEACD threshold limits that trigger drought restrictions. In this time period both scenarios simulate springflow values that drop below 38 cfs (1.08 $m^3 s^{-1}$), trigging Stage II Alarm Drought restrictions, and below 20 cfs (0.56 $m^3 s^{-1}$), triggering Stage III Critical Drought restrictions. While the trends of springflow and water level are relatively similar over the model time period, there are key points of divergence mid-way through the modeling period, between months 36 and 50, and towards the end of the model, between months 59 and 79 and from month 108 to the end of the model period.

Figure 4.9 shows the average minimum springflow values for all simulation runs in each scenario. As observed in the statistics calculated in Table 4.1, the Original scenario simulates greater springflow values than the Modified scenario. This difference demonstrates that changes in recharge interpretation may result in lower springflow values and could have implications for drought management policies. A further look into how the differences in the model runs vary spatially can give more insight to aquifer response to pumping and drought conditions.

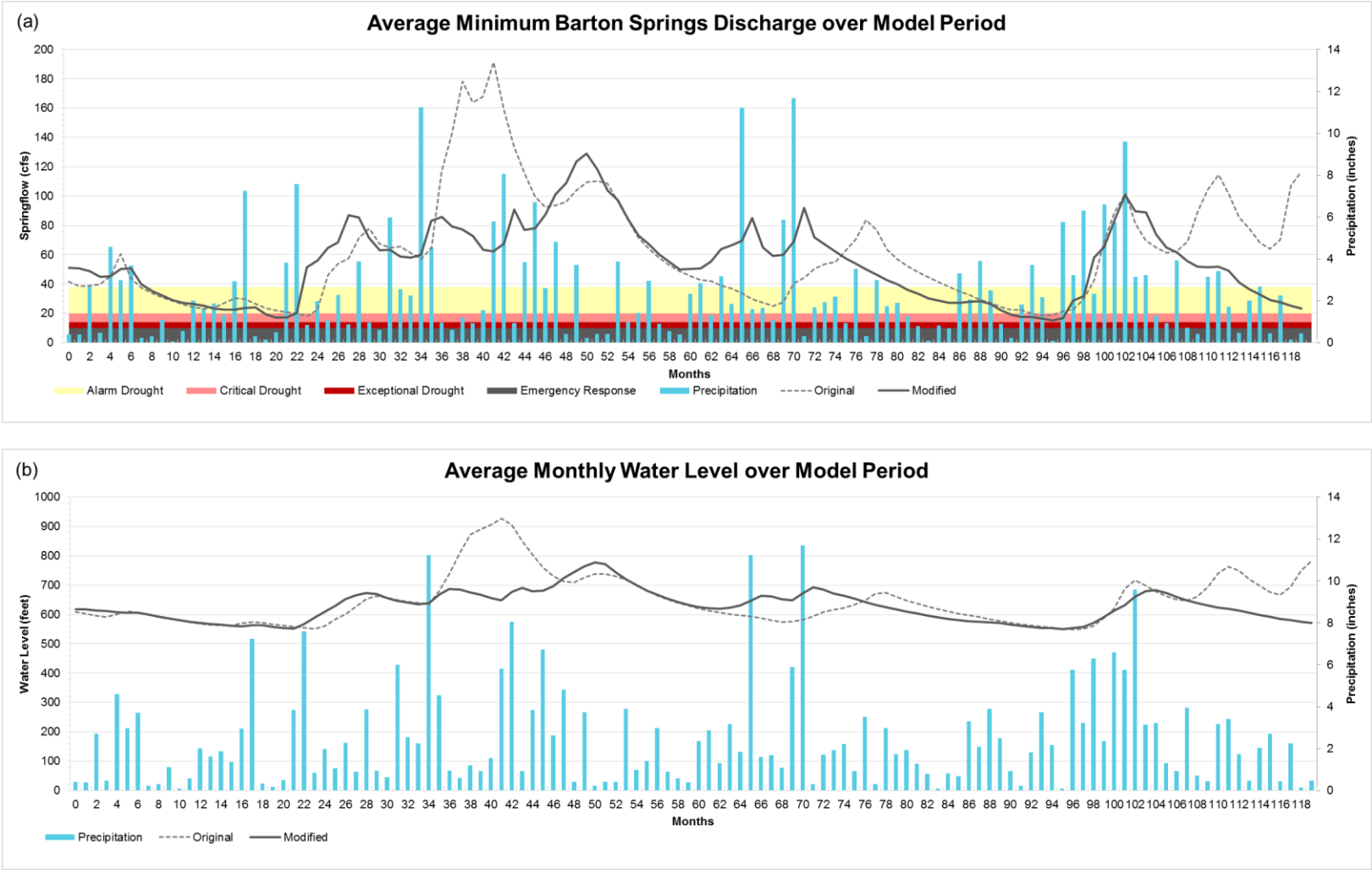

Figure 4.8 (a) Average monthly springflow at Barton Springs (cfs) and (b) average monthly water level (feet) in all active cells in the model over the model period. BSEACD drought triggers based on Barton Springs measurements are depicted along with the graph showing springflow values (a).

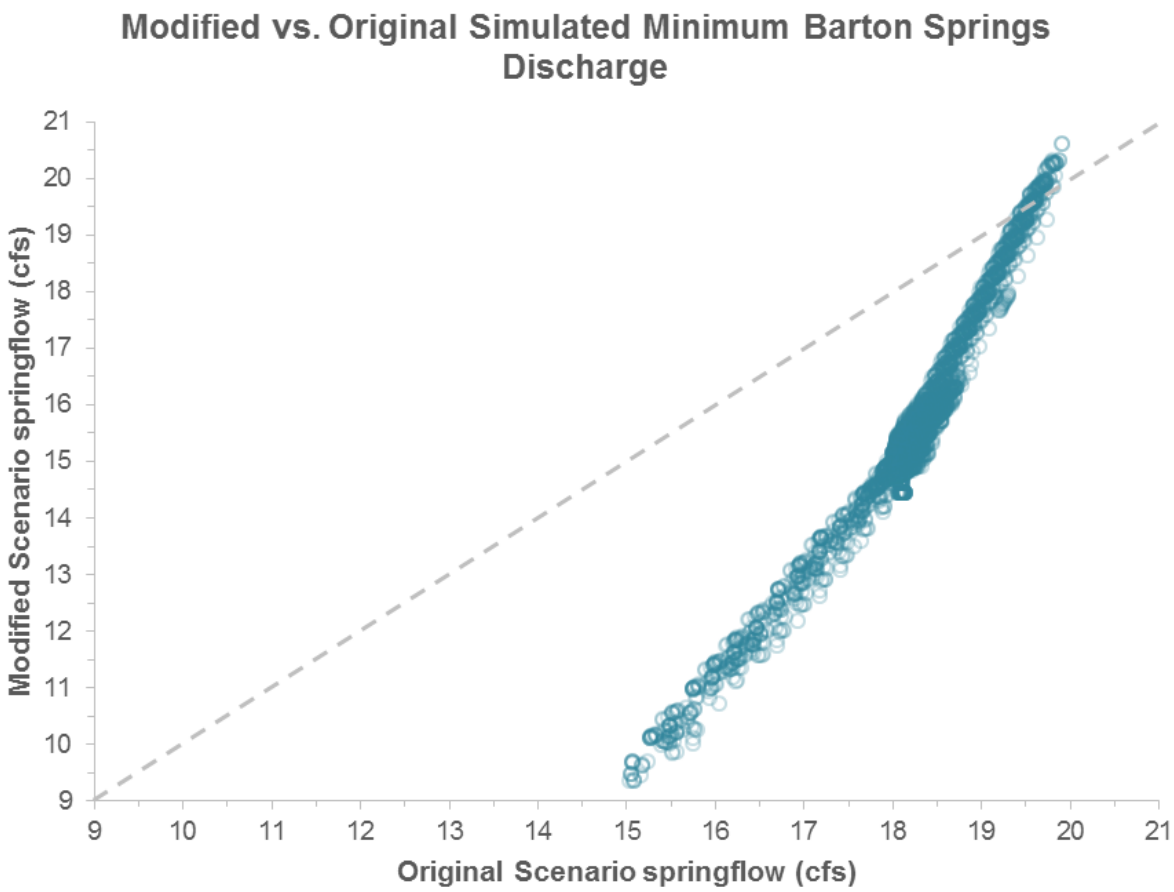

Figure 4.9 Modified vs. Original simulated minimum Barton Springs discharge for each simulation run. The gray dotted line indicates the values where there would be no difference between the values in each scenario. Original scenario springflow values are generally greater than springflow values simulated in the Modified scenario. This difference demonstrates that changes in recharge interpretation may result in lower springflow levels with modified interpretation.

Evaluating the relationship of response to decision variables

To begin to learn how pumping decision variables relate to these variations between simulation runs, the difference between simulated Original and Modified values of springflow, water level, and aquifer storage were calculated for all simulation runs (Original value minus Modified value). Figure 4.10 shows the results from the calculation, displaying that the majority of runs have relatively similar differences but there are some runs that deviate.

Springflow was the primary metric of interest for this study because it is one of the most important factors influencing management strategies due to federal mandates to protect endangered species habitats. To organize the data in some manner, the differences in springflow values for all simulation runs were ranked from smallest to largest (-0.71 to 5.72 respectively). Figure 4.11 shows the relationship between springflow difference, water level difference, and volume difference when ranked by values for increasing springflow difference. Differences in simulated water levels and aquifer storage similarly track increasing differences in springflow. The water levels shown here are averages over the entire model extent, and it would be more useful to query for and analyze simulated water levels in the Lovelady Monitoring Well since this is the other indicator of drought conditions.

The intent of the comparative method is to determine through a visual representation of data if there is a trend in the differences for each run for later correlation to pumping decisions for runs with a greater difference. By ranking the difference values, ranges of runs can be selected to analyze pumping trends within those ranges. Breaks in

springflow response occur with differences roughly between 2 and 3 and between 3 and 4 (Figure 4.12).

Groups of similar springflow differences were created using a distribution of the difference frequencies within the dataset (Figure 4.13). Three bins, delineated in Table 4.2, were created that reflect the two major breaks in the springflow difference values. The average minimum springflow difference for each bin is 1.04, 2.83, and 4.21.

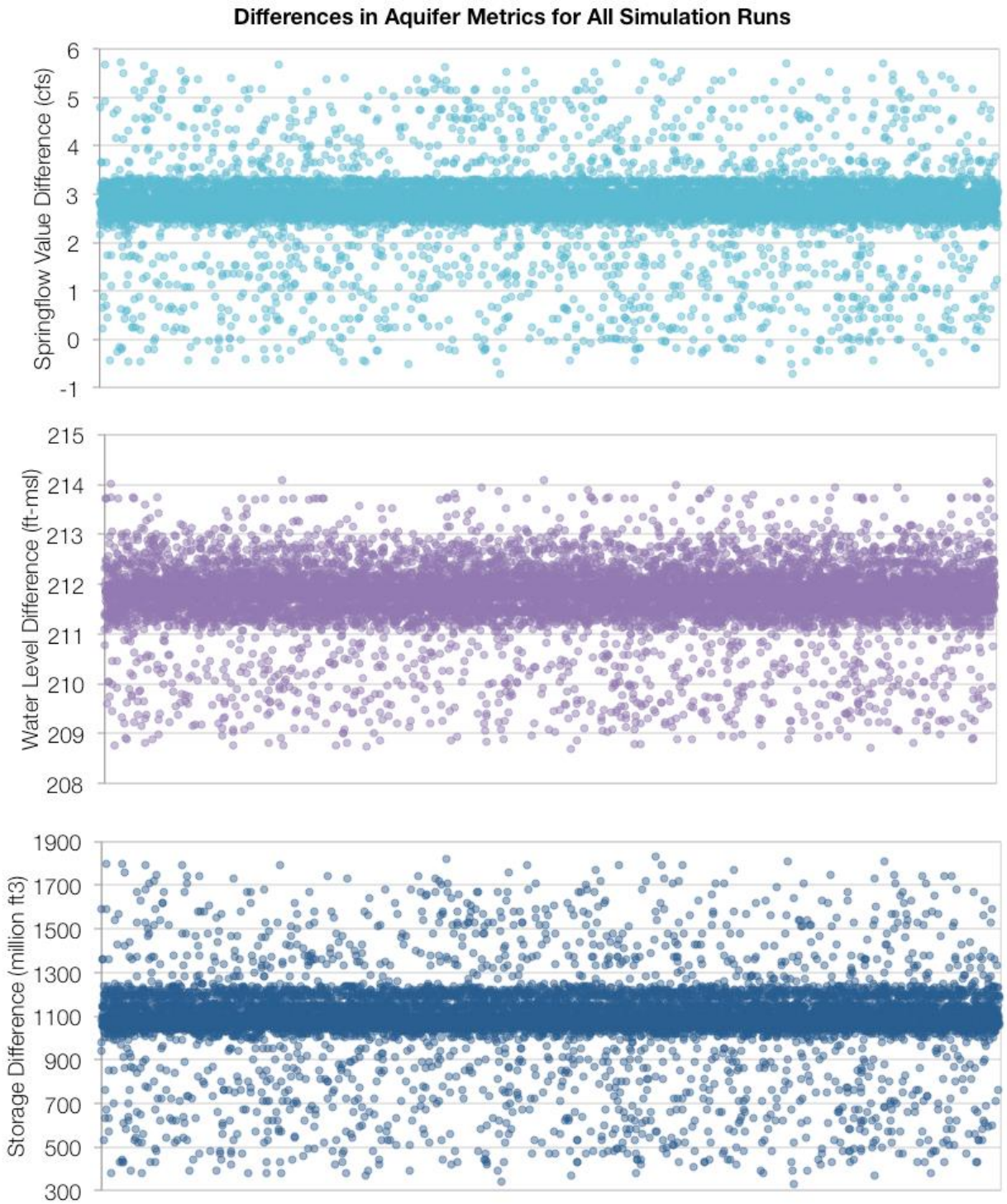

Figure 4.10 Differences in springflow, water level, and aquifer storage volume values for Original and Modified simulations. Each model run is indicated by a circular mark.

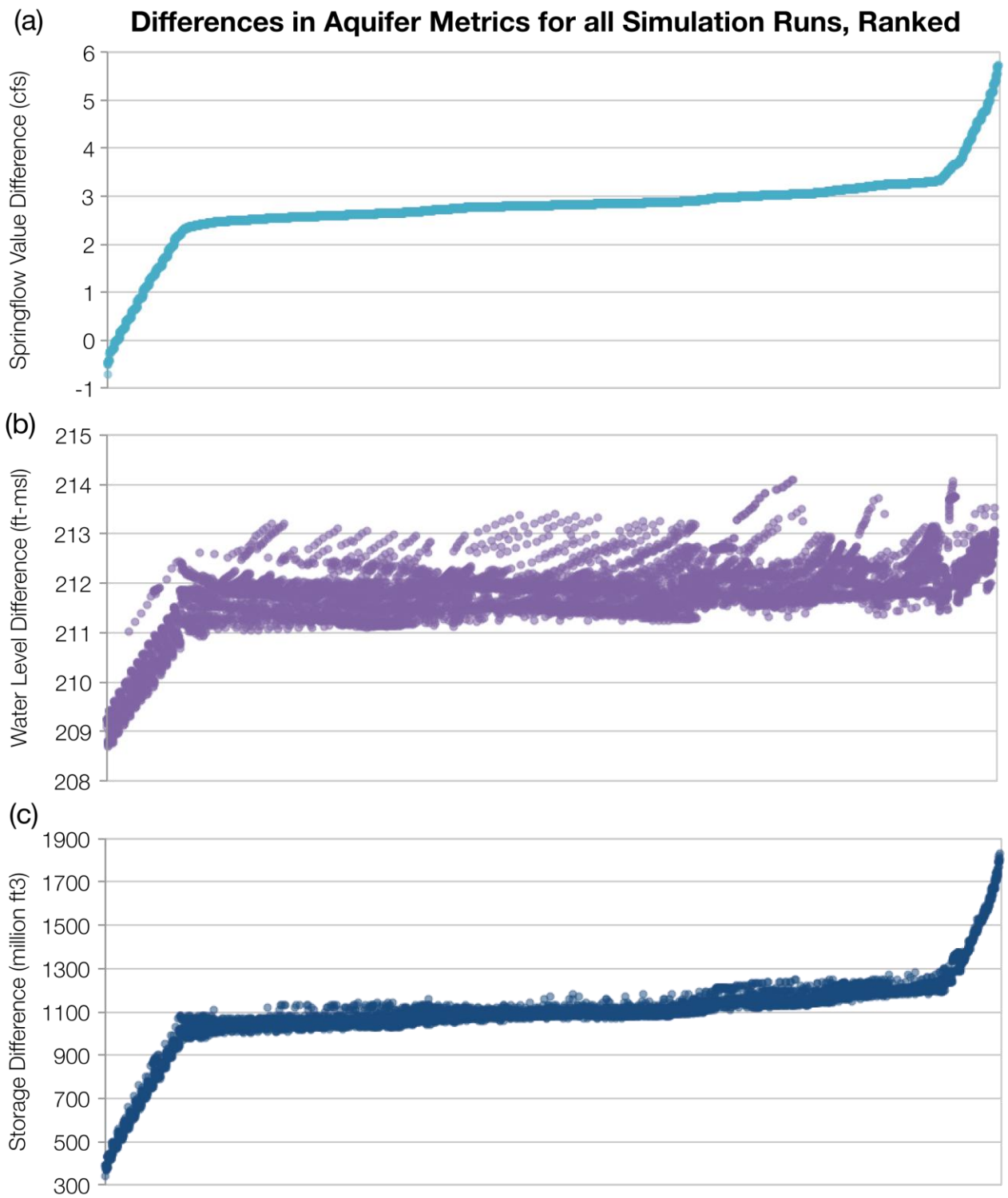

Figure 4.11 Difference in metrics between original and modified simulations for all runs, ranked by ascending springflow difference. (a) Shows springflow differences ranked from smallest to largest. (b) and (c) Show the runs with the corresponding differences in water level and storage.

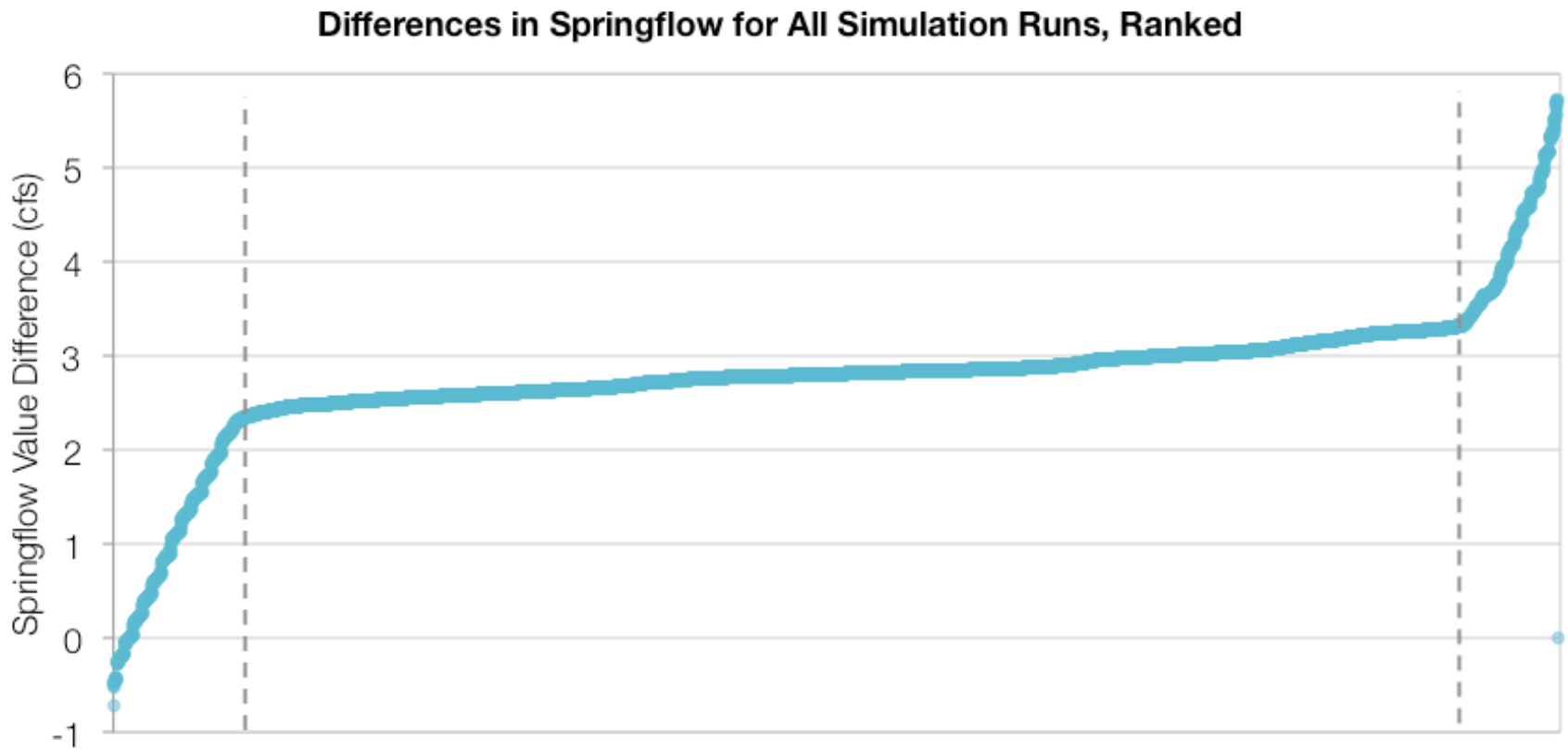

Figure 4.12 Springflow difference between original and modified scenarios for all runs. Dotted gray lines show the breaks used in frequency analysis.

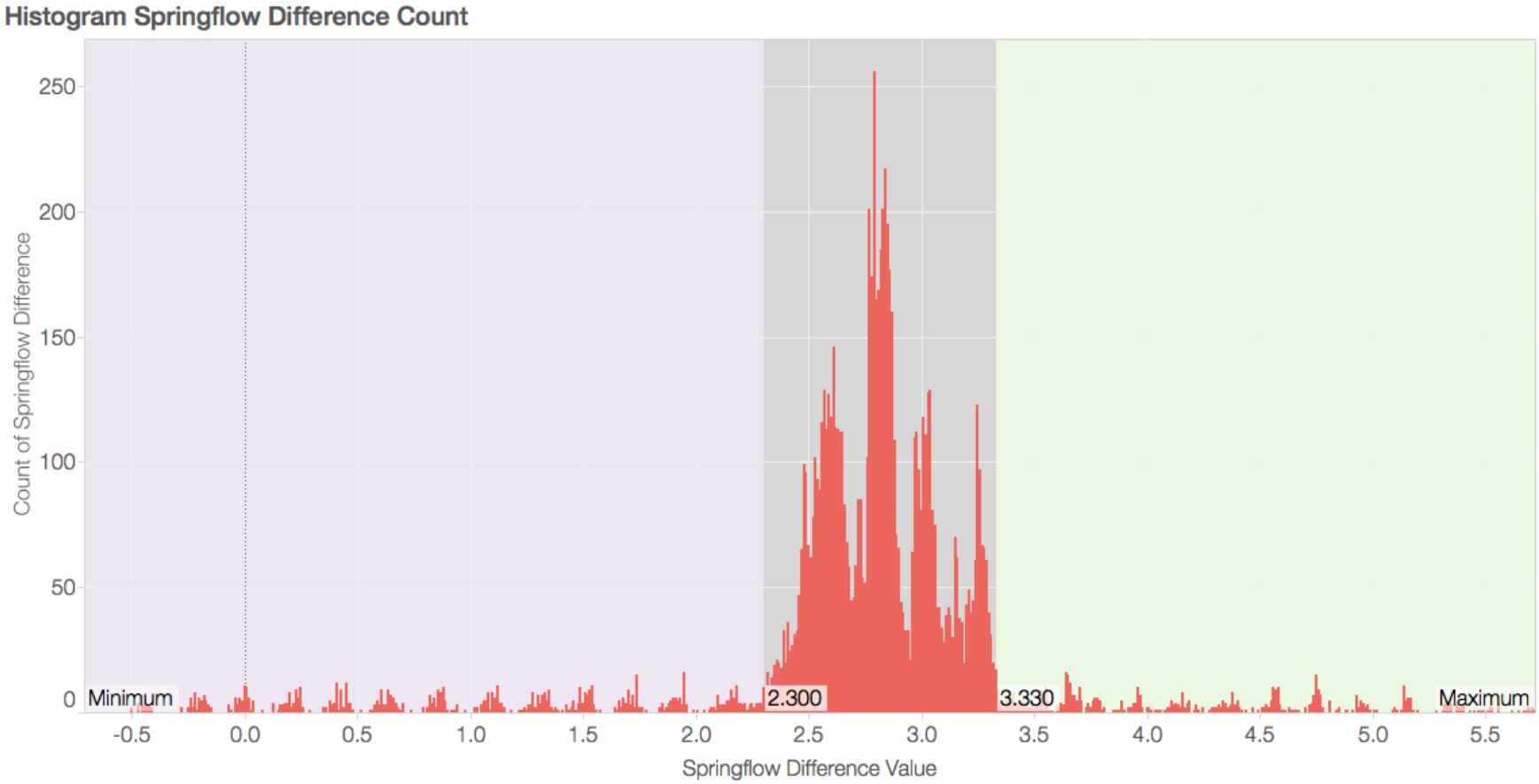

Figure 4.13 Springflow difference value frequency grouped into bins.

Bin	Original Average Min. Springflow (cfs)	Modified Average Min. Springflow (cfs)	Average Springflow Difference	Springflow Difference Range
1	19.07	18.04	1.04	-0.71 - 2.30
2	18.19	15.37	2.83	2.30 - 3.33
3	16.86	12.65	4.21	3.33 - 5.72

Table 4.2 Bin divisions for springflow difference value frequencies.

Simulation runs with smaller differences between the Original and Modified scenarios indicate that recharge and pumping decisions for those simulation runs are less likely to be critical to springflow requirements. Simulation runs with larger differences are the more interesting aspect showing that the modified recharge values were significant in changing the model behavior. A visual comparison of simulated springflow values in each scenario with the differences between scenarios (Figure 4.14) supports the hypothesis that smaller differences between the models occur with higher springflow rates This invites further exploration of how pumping scenarios change between the simulation runs with smaller differences and the runs with greater differences.

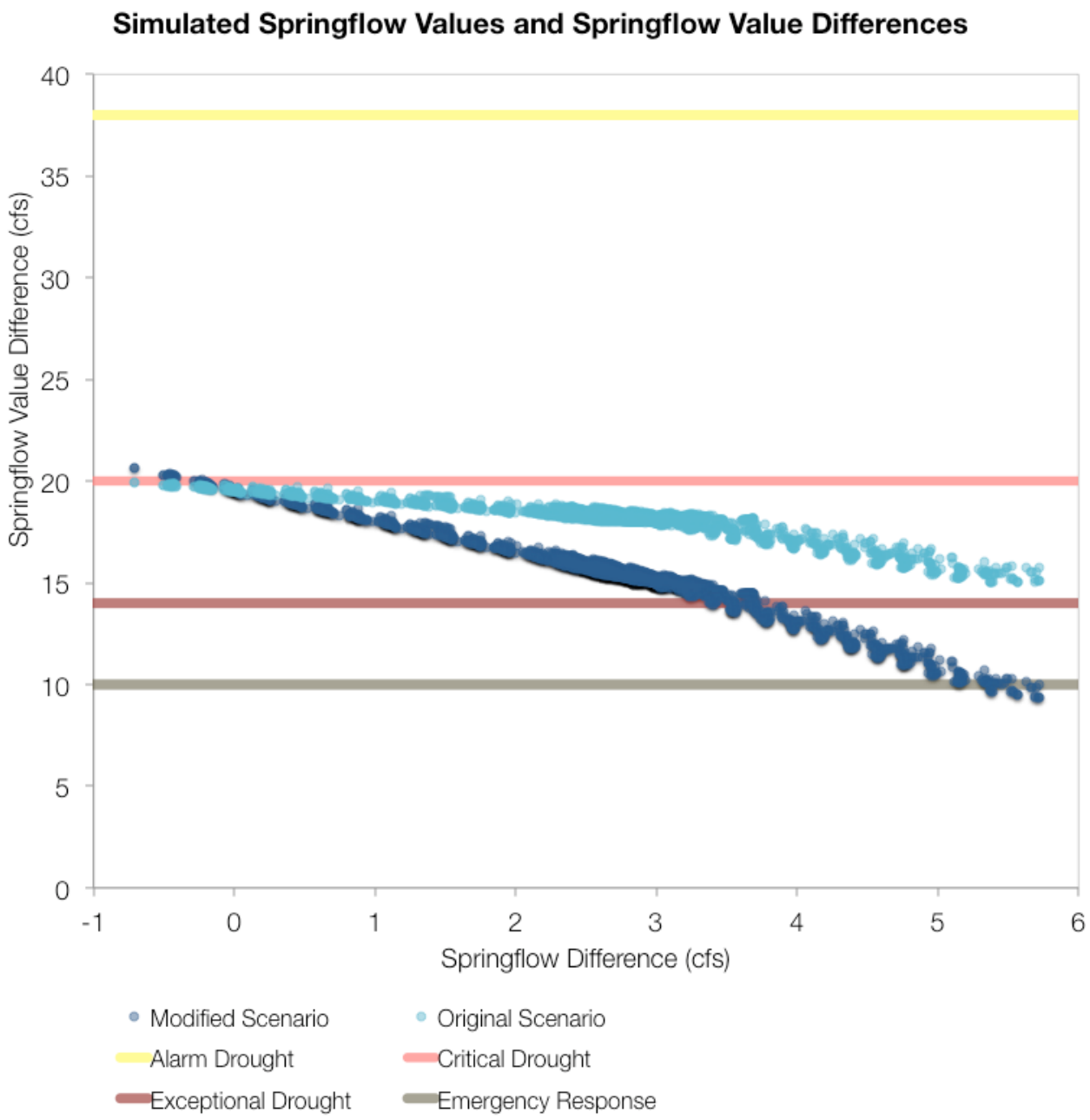

Figure 4.14 Simulated minimum springflow values for the Original (light blue) and Modified (darker blue) scenario runs compared to differences in the values. BSEACD drought triggers are indicated by the colored horizontal lines.

The spatial variability of changes in pumping in all hydraulic conductivity zones can be visualized in GIS. Using the groups created from the natural breaks in data from the comparative ranking of springflow values, average pumping multipliers in the 11 pumping zones were calculated for each bin. Figure 4.15 shows the average pumping decisions in each zone for each of the data bins. As a first step in data exploration, the minimum and maximum pumping multipliers for each bin are displayed to see if any information surfaces from the dataset. This exercise produced an interesting, but confusing and ineffective graphic. There are only a few pieces of information revealed and more questions raised in this image:

1. A pumping increase in Zone 8 results in a greater difference in springflow values.
2. Pumping rates in Zones 1, 7, and 9 do not appear to have a significant impact on springflow differences.
3. There is some kind of relationship between pumping in Zones 3, 4, 5, 10, and 11, but the nature of the relationship cannot be discerned from the graphic.
4. Pumping decisions in zones without displayed average pumping multipliers could influence the indiscernible relationships and answer the questions raised by this image.

Further refining this image and reconnecting with the dataset and model input values resolves some of the issues in Figure 4.15. Figure 4.16 incorporates more details and information to further refine Figure 4.15.

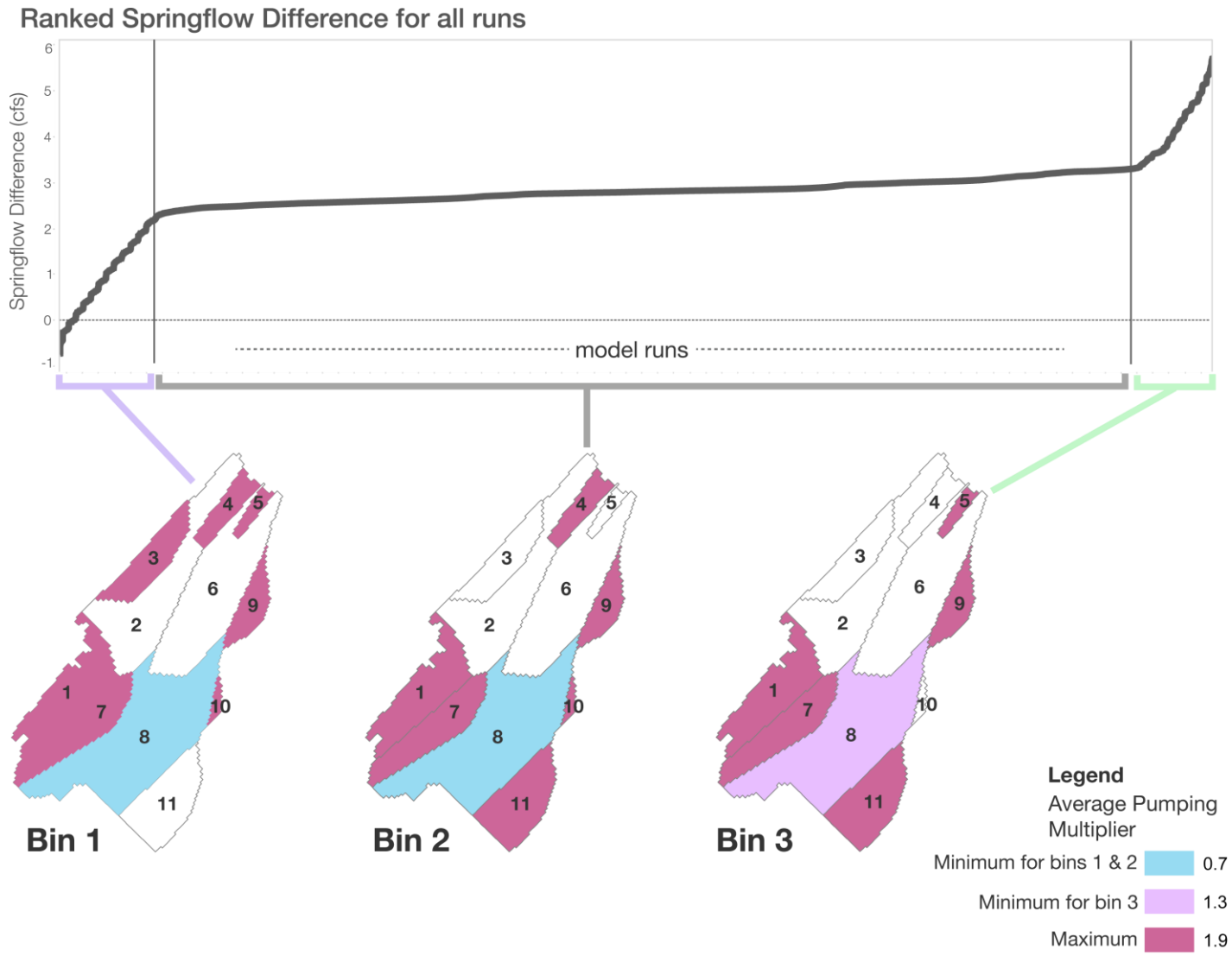

Figure 4.15 Spatial comparison of pumping decisions by zone to springflow difference.

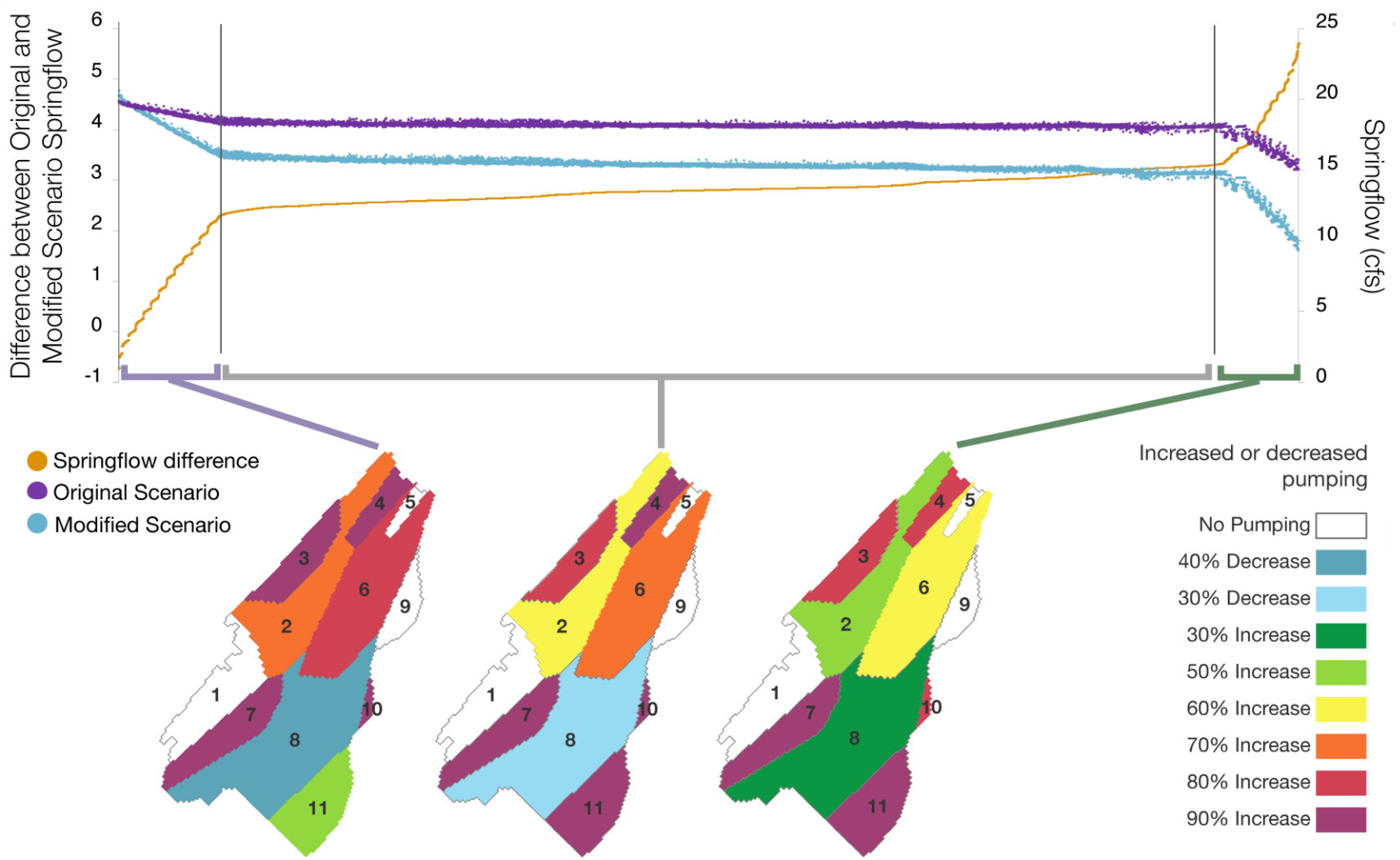

Figure 4.16 Refined spatial comparison of pumping decisions by zone to simulated springflow values.

Returning to the dataset and examining the inputs used in the model simulation and optimization scenarios revealed that while the GWDSS assigned pumping decisions to Zones 1, 5, and 9, there are no reported pumping volumes in these zones, so their actual values are zero and decisions in these zones are inconsequential to springflow response. In future studies with this dataset and with the GWDSS, reported pumping values should be updated relevant to the modeling planning period and pumping decisions variable in GWDSS should be updated accordingly.

In addition to differences in springflow values, simulated values for the Original and Modified scenarios are included in Figure 4.16. Increases or decreases in pumping are shown for all pumping zones for greater spatial detail. These refinements clarify questions from Figure 4.15 and provide further insight, though each of the observations below should not be considered singularly when attempting to explain aquifer response to recharge interpretations and pumping decisions:

1. It is expected that higher percentage increases in pumping zones would result in lower simulated springflow values; this is observed for each of the data groups in both the Original and Modified scenario outputs. The Zone 7 average pumping increase value remains the same as springflow values decrease, possibly indicating that this zone could be a good candidate to increase pumping in drought conditions to meet social needs.
2. There is less divergence in springflow values when the simulated outputs are greater; there is greater divergence when simulated outputs are lower. This becomes an important consideration in endangered species habitat conservation decisions.

3. Average pumping multipliers in Zones 2, 3, 4, 6, and 10 decrease in each of the data groups as springflow values decrease. Average pumping multipliers in Zones 8 and 11 increase in the data groups as springflow values decrease and as there is greater divergence between the Original and Modified scenarios.
4. Zones in the northern extent of the segment correspond to the location of higher recharge values (Figure 4.6) estimated by Passarello (2011). This correspondence welcomes a more detailed analysis of actual pumping volumes in these zones in conjunction with recharge estimates.

How pumping decisions in each zone influence springflow response should not be considered singularly, rather, they should be considered in conjunction with the pumping decisions throughout the aquifer extent. Spatial and graphical comparison is a useful way to begin to explore how new scientific information influences management and policy decisions. Higher resolution analysis of pumping rates temporally over the model period, and in relation to the actual volume of pumping, rather than a multiplier, would be more useful management tool.

Figure 4.17 shows average minimum springflow and average water level values for the Modified scenario with an overall increase in pumping over the entire model zone. Significant springflow decrease occurs around an 80% average increase in pumping. Depending on management goals and projected increases in water demands, a policy maker may want to use the information in this image to define a desired minimum springflow value and an associated range of pumping increases, and then select the model

outputs that meet those criteria. The policy maker could then graphically explore the actual pumping volumes by zone and the effects on springflow values to craft a drought condition policy based on a reduced-uncertainty modeling scenario.

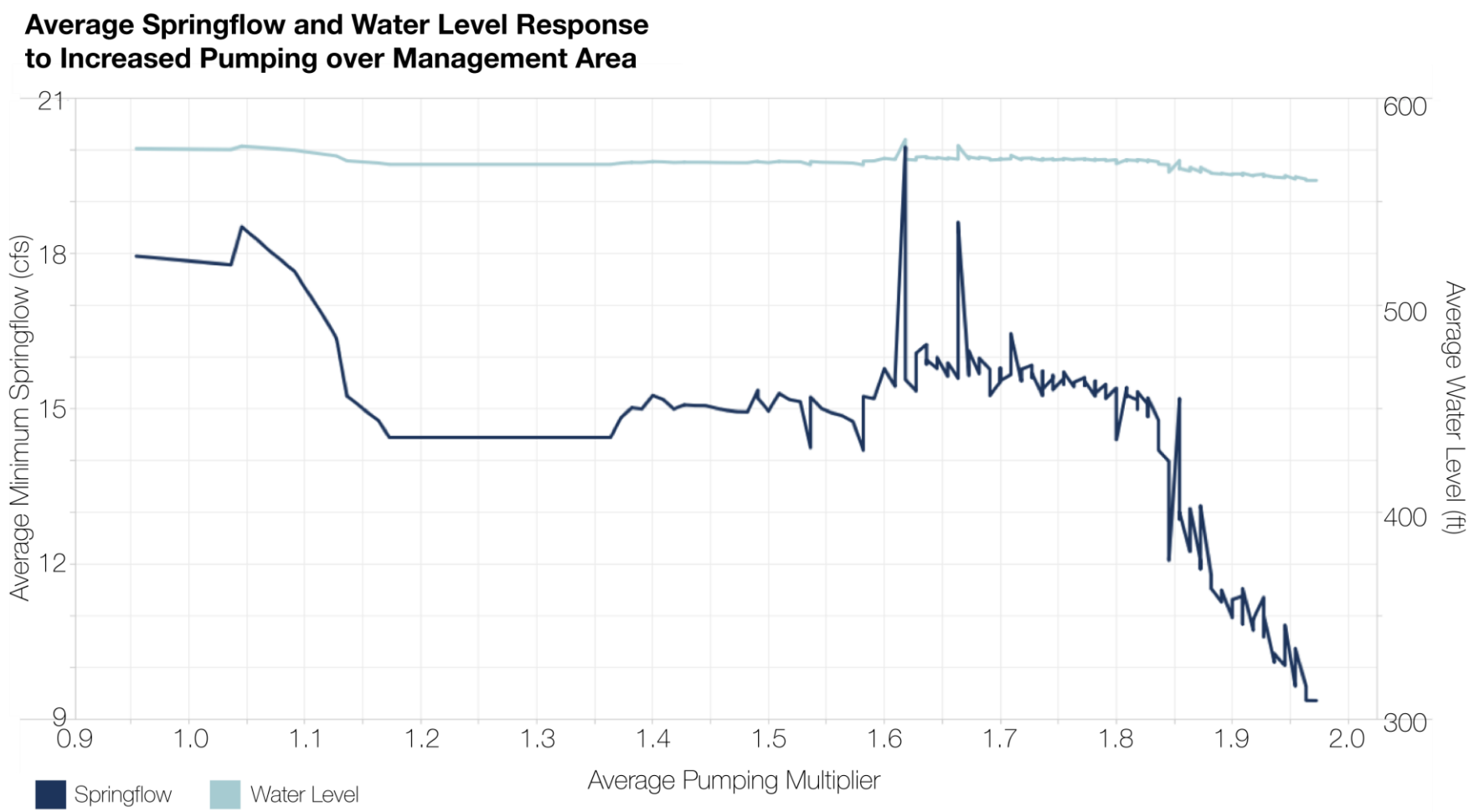

Figure 4.17 Average minimum springflow and average water levels with increasing pumping in the recharge scenario.

Implications of analysis for management decisions

With reduced recharge uncertainty, better decisions can be made about best aquifer management. Using the modified recharge inputs in a reallocation model, and running a Monte Carlo simulation to evaluate the probabilities of pumping in certain zones to produce minimum aquifer metrics could provide useful information for creating drought policies. This simple analysis of the uncertainty between the original and modified recharge scenarios should be expanded to a more in depth look at the simulation runs that have the greatest difference in aquifer metrics. Locations with a greater difference could indicate possible areas where diffuse recharge can be estimated.

Pumping in zones where springflow response under the Modified scenario is greater than springflow response in the Original scenario indicates that urban recharge serves as an inflow to the BSEA during drought conditions. This new interpretation of recharge should be used to predict how often drought restrictions would be imposed with the current drought trigger methodology used by the BSEACD, and could influence permit allocations in certain regions of the aquifer. There is, however, greater variation in Modified scenario springflow outputs than in Original scenario springflow outputs as pumping increases, as shown in Figure 4.18. Further statistical analysis should be conducted to quantify the variations in these outputs and how they are related to recharge characteristics.

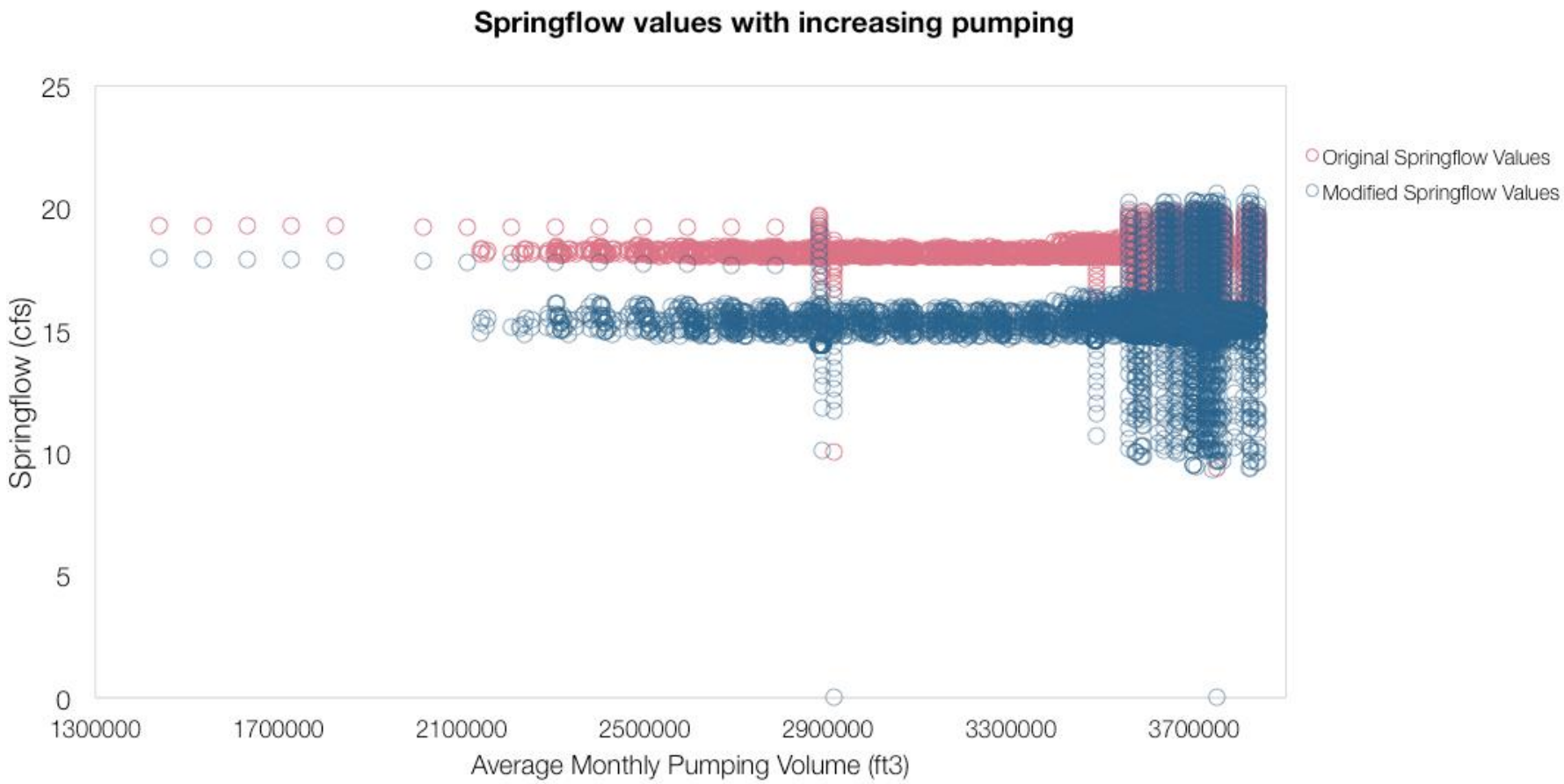

Figure 4.18 Simulated springflow values for all simulation runs in the Original (pink color) scenario and the Modified (blue color) scenario. Note that the Modified scenario produces greater variation in springflow response with increased pumping.

Future Work

The work presented here shows that the recharge interpretations estimated by Passarello (2011) more closely represent actual aquifer responses than the baseline interpretation that is used in water planning today. There is also a significant difference in pumping regime effects on springflow and water levels between the two model scenarios. To test how the Modified recharge scenario would influence current allocation, it would be useful to input these interpretations into the Groundwater Management (GWM) software developed by the USGS to allocate groundwater using desired constraints and outcomes. Additionally, this research dataset was generated using the original Groundwater Availability Models designed for the Texas Water Development Board. Revised, refined, and alternative simulation models, such as those evaluated by the BSEACD, should be run using the same recharge and pumping settings to assess and compare response. Comparative and multi-model evaluation of aquifer response to various uncertainties in the models, operational yield, and management or policy settings could provide improved understanding about the resilience of the system and robustness of decisions under uncertainty.

One of the contentions discussions, currently in the greater Central Texas region, is how to supply growing urban and suburban populations with reliable water supplies. Many urban centers are turning to smaller communities to purchase groundwater, or are looking for other alternative water supplies, like desalination or aquifer storage and recovery (ASR). In the BSEACD, there are several large water users that depend on the BSEA to meet the needs of their communities and are looking in to ASR or desalination

projects. Having the best knowledge of a groundwater systems is critical to effectively conduct a benefit-cost analysis of these projects; using aquifer response based on this Modified recharge scenario could mean the difference between secured water supplies and unmet demands with sunk costs.

Chapter 5: Conclusions

Groundwater management decisions involve scientific information and stakeholder concerns or desires that have complex interactions. Data visualizations can serve as a means of communicating complex systems and information to technical and non-technical audiences. The work presented in this thesis has shown how scientific uncertainty can be incorporated into groundwater data visualization to better inform management decisions about sustainable aquifer yield. This research presented a systematic assessment of operational aquifer yield using a large dataset for the Barton Springs segment of the Edwards Aquifer in Central Texas. Results explored visualization approaches for groundwater information and relied on the concept of knowledge discovery through data interaction.

This case study used a very large set of data that would have been impossible to interpret without a scientific knowledge of which pieces of data could be of interest and without a graphic knowledge of the means which to display the data. Drawing from scientific and artistic angles facilitated the transformation of abstract data from hazy evidence to clear delineations of patterns and connections. The process of building knowledge through visual representation is a iterative and layered process.

Data visualization techniques and applications present significant opportunities to improve and aid future groundwater management. Better understanding of physical systems reduces uncertainty and more accurately represents aquifer behavior. High power computer performance capabilities create a way to analyze and process results of physical

system models and simulations in a relatively short time period. Widely available access to internet and a general increasing trend in the use of electronic devices can encourage non-technical audiences to interact with visualizations. However, without holding onto the fundamentals of design considerations, visualizations will be ineffective and could even be detrimental to communicating complex scientific concepts. The process of building knowledge through visual representation is a iterative and layered process. Creating effective visual displays of scientific information takes time, discussion, and attention to detail, but if the final product answers scientific questions, and challenges the way policies are currently made, the work is well worth it.

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