Software for Scientists facing Wicked Problems—

Lessons from the VISTAS Project

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ABSTRACT

The *Visualization for Terrestrial and Aquatic Systems* project (VISTAS) aims to help environmental scientists produce visualizations for themselves and for a range of stakeholders including other scientists and decision makers. The need for better visualization tools for scientists is well-documented, but little prior work determines what kinds of visualizations work with different audiences and different kinds of problems. The VISTAS project applied social science research methods to this question and identified issues relevant to visualization software development, particularly where the domain involves wicked problems such as climate change. This paper presents visualization issues confronted by VISTAS collaborators who used visualization to enhance their own inquiry and to communicate complex concepts, present results, and include decision makers in data exploration and hypothesis formation. Case study findings suggest that scientists use visualization to communicate concepts, validate findings to skeptics, and include stakeholders in data exploration; they decide which visualizations to present based on their impressions of audiences when including visualizations in decision-making. The primary lesson learned is that extending the scope of the software problem domain beyond the explicit functionality of creating visualizations, to include the reactions or enhanced participation of decision makers, will likely provide scientists with more effective software.

Keywords: Scientific Visualization, Visual Analytics, Wicked Problems, Climate Change, Post-Normal Science, Software Development

1. INTRODUCTION

Current ecological problems such as environmental change drive researchers to look outside their normal, discipline-oriented boundaries to understand how their particular model, process or system might interact with other models and systems. Technology innovations from computer science and engineering research provide not only hardware (e.g., sensor tools, processing capability of computers), but also software, for dealing with ecological problems [1]. Using these new technologies, researchers learn, observe, and might come to conclusions differently than they had before. New practices usually emerge with technical innovation, and the relatively recent deluge of data now available for analysis is no exception. Some observers have suggested the data deluge might lead to the end of theory, where data mining will be just as important as experimental hypothesis testing [2]. Whether that comes to pass or not, the amount of data collected by sensors and models is clearly outpacing the ability of scientists to process and analyze data, and many scientists ask how they can increase their understanding and use of data, and whether technology innovations can lead to new insights into contemporary problems. Clearly, the nearly overwhelming amount of data increasingly available to scientists necessitates looking beyond current disciplinary practices for new approaches.

Responding to the above issues, in 2011 computer scientists, social scientists and environmental scientists at The Evergreen State College, Oregon State University, Willamette University, the Environmental Protection Agency, and the Conservation Biology Institute launched the *Visualization for Terrestrial and Aquatic Systems* project (VISTAS). The project had three initial objectives, each with explicit expected outcomes:

1) Conduct ecology informatics and computing research to enable the visual analytics of environmental science models and data—in order to develop a visualization tool that would be used by our collaborators and visualization research transferable to other visualization efforts.
2) Jointly with three close science collaborators, conduct environmental science research using the VISTAS software and study VISTAS' extensibility to other applications—in order to create visualizations applied to climate change problems and publish environmental science research that use those visualizations.
3) Use social science methods to study VISTAS' co-development process, visual analytics, and usability—in order to:

a) conduct social science research into understanding which visual analytics work, for whom, and why;

b) publish best practices for engineering complex scientific systems;

c) determine prerequisite knowledge and skills for co-developers and articulate a process for studying co-development of scientific visualizations and software.

This paper focuses on the third aspect of these objectives; we began with the research question "which visualizations work for which audiences and which problems". Social scientists partnered with VISTAS conducted a qualitative case study to better understand how and why scientists in VISTAS intended to use visualization and what the benefits and limitations are to visualization use for informing the design and development process. Analytical generalizations, then, might be made for how to incorporate into the design and development process the needs of primary users (scientists) for communicating with secondary users in public policy settings. VISTAS investigators originally had assumed that their environmental scientist collaborators primarily used visualizations to enhance their own scientific inquiry, sorting out reams of sensed and modeled data to arrive at new insights into the underlying physical phenomena, or at least to conduct their own research more efficiently. We also believed that scientists would use visualization to present results to other scientists. Within a year, however, it became clear that two of our three collaborating teams, those studying the impacts of climate change, were using visualizations to explain complex environmental science phenomena to non-scientist audiences, and needed to create visualizations we had not anticipated. Non-scientists with whom the scientists were interacting were typically local, state, or national government decision makers involved in defining policy for environmental science problems.

That our scientist collaborators presented different kinds of visualizations to non-scientists prodded us to modify both software specifications and development priorities. While we had expected changes during the development process, these new requirements involved more extensive review and revision of the underlying scientific and social problem than expected, and in fact altered some underlying technical assumptions that had driven initial software design and implementation. We also refined our research question(s) to also focus on the role of visualization in communicating scientific results involving wicked problems to decision makers:

1) Do visualizations that scientists develop for their own use or to show to other scientists differ from those developed for communicating with decision makers in the context of wicked problems? If so, how and why?

2) Do best practices for co-developing visualization software used in this context differ from those developed for a purely scientific use? If so, how?

3) Do prerequisite knowledge and skills for co-developers for this kind of software and visualizations also differ, and if so how?

Thus, we realized that, even if visualization and other innovations were successful in providing scientific insight and solving scientific problems, the challenge of addressing pressing environmental societal problems—especially those classified as "wicked"—would remain [3].

In this paper, we present findings that suggest that designing visualizations and developing software for scientists who work with decision makers in the context of wicked problems differ from developing software that does not involve wicked problems or where decision makers are not involved. Scientists, software engineers and systems analysts who co-design and co-develop such artifacts should thus be cognizant of the type of problems to which those artifacts will be applied; this implies that the co-developers should understand the characteristics of wicked problems in order to recognize them and act accordingly. Sections 2 and 3 provide background information, explaining first the changing roles for science in the context of wicked problems and post-normal science, and then the case study methodology employed in our study of VISTAS' co-development process, visual analytics, and usability. Section 4 describes the case study participants, the context of their work, and the design process for VISTAS' visualization and software. Section 5 presents findings and analysis, and in Section 6 we discuss how visualization and visual analytics strategies might affect outcomes of problem solving in a public policy setting and how our work relates to other digital government studies. We then go on to discuss strengths and limitations of this work and summarize conclusions.

We believe our results are relevant to the digital government community as they develop or select software to study complex scientific problems in which the public holds considerable interest. The primary contribution lays in our contention that understanding the nature of so-called wicked problems is critical to developers and procurers of software products that convey scientific results to decision makers and the public. While the Association for Computing Machinery (ACM) engineering code of ethics contends that "…software engineers…[should] consider broadly who is affected by their work," stakeholders are typically thought of not only as developers and users, but also those who have to support, deploy, or pay for the software; secondary users are at best thought of as those whose information is ingested into software systems [4]. In our case, the software and visualizations are shown by scientists to decision makers, and most scientists, designers and developers would contend that it is the primary user's responsibility to design effective visualization and relate to software developers what they need for that. Further, while engineers have traditionally been taught to eschew policy matters [2, 5], recent social science research suggests that technology inevitably has policy implications [6] despite best efforts of scientists and engineers to divorce themselves from policy decisions [7]. We now believe developers will produce more effective software if they explicitly recognize the role their artifacts play in decision making, and hence in policy. In light of recent studies in public policy and philosophy of science that suggest that policy and government decision making are not greatly influenced by scientific research results and, conversely, that nonscientists rarely influence the formulation of science problems [6], it seems critical to extend both the scientists and software engineers' understanding of both primary and secondary users of their science and technology, given the global-scale nature of current issues and the likely failure of straightforward technological solutions to solve those problems [8, 9]. We do not advocate that scientists and engineers practice normative science, but that they become more aware of the information, technology, or science needs of those who set policy and make decisions.

2. WICKED PROBLEMS AND POST-NORMAL SCIENCE: CHANGING ROLES FOR SCIENCE

The late 20th century brought a host of grand challenges to the discipline of ecology, including the concept of coupled human and natural systems (e.g., Liu et al [10]), which present as complex, dynamic, and adaptive systems. When managers or policy makers deal with problems in these complex systems, they often exhibit features of what have come to be known as wicked problems (Table 1). Wicked problems are characterized as difficult or impossible to resolve because of the fluid and often contradictory requirements for any effective or acceptable solution [11]. For example, the complex interdependencies of the issues usually result in the creation of new problems even as we think we're making progress with the original problem [12]. For the most part, traditional "normal science" [13] is unprepared to answer questions posed by policy makers responsible for managing the complex systems that generate wicked problems. New approaches, what have come to be known as post-normal science, are emerging as ways to generate the information needed to make intentional and collective choices to resolve wicked problems.

There are three key, interconnected, components of the post-normal science model that make it different from other approaches and more appropriate for dealing with wicked problems: (1) Uncertainty is considered more than a technical or methodological issue; uncertainty is accepted as the state of affairs within which decisions must be made. (2) Different approaches are recognized and leveraged rather than assuming a scientific or policy consensus can be found. (3) The group of individuals considered capable of assessing the quality of the results is extended beyond the normal disciplinary peer community to a wider range of experts and knowledge; this new group is then better able to consider the array of risks, benefits, and implications for multiple stakeholders [3].

This relatively new approach to developing science, especially in the face of wicked problems, is in contrast to normal science. In normal science, peer communities are typically limited to those experts who can judge the quality of the science; for the most part, these are disciplinarily-trained peers (e.g., environmental scientists, biologists, physicists, geologists). When uncertainty and decision stakes increase, the post-normal approach suggests that the peer community can and should be extended to non-disciplinary experts, those with experiential, context, or local expertise. This is because a single scientific discipline and strictly scientific knowledge are, by definition, incapable of capturing the full complexity of such problem settings. In post-normal approaches, the peer community is extended to include not only producers of information but potential users as well. Non-experts can contribute to knowledge production in a variety of ways including co-framing problems, providing non-scientific information or data, acting as critical reviewers of the output, helping interpret data in the local context, and acting as critical reviewers of the output.

Multiple approaches have been created to bring non-experts into both the production and evaluation of knowledge including consensus conferences, which have been used to bring together competing perspectives and values around topics like bioremediation of hazardous wastes [14]; citizen juries, which have been organized to assess the quality of biomedical research [15]; or the introduction of uncertainty guidance to the Netherlands Environmental Assessment Agency that includes ways to consider both quantitative and qualitative metrics of uncertainty in risk assessments [16]. Another approach is creation or use of a knowledge to action network (KTAN) [17] that brings together a dynamically evolving group of participants who work together to pose and answer questions collaboratively and iteratively, with the goal of creating usable information (or knowledge). One highly visible and credible example that integrates the idea of an extended peer community is the Intergovernmental Panel on Climate Change (IPPC) [18], which can best be described as an interdisciplinary assessment of scientific research to integrate available knowledge for use by policy makers [19]. This extended peer group is not only an interdisciplinary group of scientists studying the problem, but an interdisciplinary group of scientists <u>and</u> policy experts working together to interpret and understand the consequences of the data.

Two of VISTAS scientist collaborators work with non-scientist decision makers on wicked problems related to the impact of climate change on local and regional landscapes. In these cases, even as the decision stakes rise for policy makers and citizens due to climate impacts, the level of uncertainty increases as global models are downscaled to regional areas and as forecasts are stretched into an unknowable future. This combination of high systems uncertainty and high decision stakes suggests the situations these teams find themselves in have evolved such that a new problem solving strategy grounded in post-normal science may be appropriate for developing the information needed to move forward on local and regional decisions. What makes these cases unique is that our collaborators—and subsequently the VISTAS team—are part of a larger team that includes non-scientists working together to co-develop a sophisticated model to explore together the impact of climate change in the local context. Not only was the choice of technology co-selected, but the scientists and the community also co-developed the inputs and assumptions of the model, working together as a knowledge to action network. VISTAS developers were brought in to develop the software tools and help the team create visualizations to explain results generated by the complicated model to answer questions about the impact of climate change.

3. CASE STUDY METHODS FOR DESIGN AND ANALYSIS

A single case study approach [20] was chosen for this project as a way to test the propositions the VISTAS research team (n=21) set out to explore, and in a way that might be beneficial to other researchers considering similar problems in scientific visualization meant for both exploration and for broader communication of complex datasets. The case study approach is often used when a research question is unveiling concepts and discoveries in a relatively new or unexplored topic, such as in this study about innovation and a new technology like VISTAS. Case study is also a useful method for uncovering deep insight into a topic or group of people over time. A current gap in the visualization community is studies that incorporate real users, with real problems, using real data [21]. Studies in the wild, such as VISTAS, are valuable because they explore phenomena within real settings, rather than using contrived settings such as a lab with controls.

The approach included working with key informants to test the use of visualization as a way to analyze and communicate research output. Each key informant—ecologists and computer scientists—was formally interviewed at least once with a semi-structured interview. Instruments and protocols were crafted both early in the VISTAS case study and developed over time. Interview questions were based on a number of propositions, including the hypothesis that visualization would help scientists understand their data and come to insight more easily. Developing questions and analyzing responses based on initial propositions are common techniques for framing a single case study [20].

In addition to the transcripts from interviews with key informants, data in the form of (1) field notes from emails and informal conversations with members of the group; (2) weekly project meetings; and (3) audio recordings of annual all-hands meetings (n=21 participants, including the seven key informants) were also analyzed. General e-mails and the project website, though not used in the analysis, became an archive of the timeline of events and project highlights. Project meetings varied topically to include both high-level ecology problems and technical detail. All data from interviews, conversations, meetings, and memos were transcribed for an analysis that used themes built from the project's propositions, interviews with the key informants, and models and frameworks for understanding the facets of the VISTAS case study.

Data analysis from the case study provides insight into both the visualization software design process and the greater ongoing conversation about how visualization contributes to problem solving in an era of wicked problems and big data. Initial themes and topics for analyzing communication of big data using visualization were based on the framework of post-normal science (e.g., for analyzing communication with stakeholders and the extended peer community) and were created over the course of the project as new topics emerged (e.g., audience analysis practices of the case study scientists). Table 2 describes what VISTAS primary users consider to be important issues related to developing data visualizations for ecological science. The themes suggest that the design team consider not only the primary users, but also the secondary users of VISTAS visualizations. It should be noted that the VISTAS software development project did not include stakeholders directly in any of the project data or content at the time of this analysis, so the results presented here about the relationship between the key informants and their stakeholders is based on the key informants' perceptions about those needs. Other similar development projects also base development on assumptions made about secondary users in a similar way during their first round of development (e.g., QuestVis [22]). Codebook definitions in Table 2 were developed through iterative analysis of transcripts.

4. CASE STUDY PARTICIPANTS AND THE CONTEXT OF THEIR WORK

During the VISTAS software design process, which was tracked and analyzed as the case study described above, scientists with real data who were dealing with real scientific problems determined development directions. We thus assert that the co-development process fit the description of a problem-driven design project. Software developers considered the types of visualization that science collaborators requested, and VISTAS collaborators communicated how they wanted to visualize results for different audiences.

The first and primary visualization design objective for VISTAS involved recreating the collaborators' visualizations of physical terrain from flat two dimensions (2D) to incorporate topography. While scientists have always suspected that the ecology of a region varies with topography, only recently have innovations in data acquisition enabled them to collect data, conduct experiments, and validate models in topographically complex areas. Our collaborators came to us with an overarching problem: with their current visualization tools, they could not see topographic differences that might drive the physical processes under study. They wanted to enhance current two-dimensional visualizations with digital elevation models so that the landscape's topography would stand out in three-dimensions. They were convinced (and this has been confirmed) that the third dimension would allow them to intuit more readily where environmental variables respond to changes in drivers and assumptions. Thus the primary visualization problem we aimed to address was (and remains): visualize landscape processes where topography likely plays a role.

We found during the VISTAS project, however, that topography generally serves a different purpose for non-scientist audiences. This theme emerged over the course of the project in both the interview and meeting data when VISTAS scientists highlighted the distinction between the different audiences to whom they present visualizations, and described how they would design visualizations with a particular audience in mind. Rather than illuminate the science problem of determining the effect of topography on ecological response variables, topography helps non-scientists recognize and relate to familiar landscapes; the third dimension allows secondary users to more easily recognize features on the landscape. Other primary visualization needs were to produce animations, i.e., include in visualizations a fourth dimension (time), and to display changes in landscape via fly-throughs that highlight particular areas. A third initial goal, not yet accomplished, was to be able to view data at different geographic extents (spatial scales) in the same window. To make developing the new system tractable, we focused on three environmental scientist collaborators; all would benefit from viewing data topographically but each focused at different spatial scales. They all also wanted to use animation to visualize space displacement or the fourth dimension time, and to view different variables or scenarios simultaneously. The following three sections describe our collaborators' projects and resulting VISTAS visualizations.

4.1 Alternative Land Use Scenarios

VISTAS collaborator John Bolte and his team at Oregon State University worked with VISTAS developers to embed VISTAS into ENVISION, Bolte's open-source GIS-based multi-agent model for scenario-based community and regional integrated planning and environmental assessments [23]. ENVISION integrates spatially explicit models of landscape change processes and production for alternative futures analyses, and currently produces 2D maps that illustrate changes over time of modelled attributes such as species habitat, ecosystem type, and disturbance. Bolte believes that 3D maps and animations will help both scientists and stakeholders better understand alternative futures. He also wants to view side by side camera-position-coordinated fly-throughs at specific points in time for different attributes or scenarios.

Bolte's team wanted to generate fly-throughs for a stakeholder decision process focusing on better understanding how biophysical systems, management actions, and socio-economic influences interact to affect sustainability in fire-prone landscapes under climate change. Figure 1 shows a still-view of a VISTAS animation, designed to show how land use affects vegetative cover, which in turn will determine fire hazards. Bolte's team was also tasked with modeling the impact of climate change on water availability in the Big Wood basin of south central Idaho. This project involved a group of community members and potential information users engaged with scientists and computer modelers. Initial meetings included state and federal agency staff, non-governmental organization members, local and county officials, university extension agents, canal company representatives, and area residents interested in thinking about the future of the region. Back-casting was used to start people thinking about the future and characterizing conditions that might lead to desired futures [24]. Later, the group developed a concept map (Figure 2) and a system dynamics model of the hydrological system [25], both of which the group found too static to help in decision-making in the face of multiple uncertainties including, but not limited to, climate change.

The above activities deepened all participants' knowledge of relationships among natural and human systems, and others' perspectives and values around those systems. The concept map exercise moved the group forward in identifying variables they wanted to consider, data they would need to support those variables, and what probably could not be included in the model due to limitations in data or research methods, and brought about two impacts critical to the VISTAS visualization effort: (1) Non-scientist participants realized that a complex model was critical to understanding and mitigating the problem, and (2) scientist participants tasked with developing that model were provided with assumptions and variables that the community viewed as important and that would drive the model. In other words, the process identified gaps in knowledge for both non-scientists and scientists.

As a result of this exercise, Bolte and his team were tasked with co-developing a complex model that would allow the joint exploration of the impact of climate change in the local context. In this case, not only the choice of technology but the inputs to and assumptions of the model were co-developed by scientists and the community, working together as a knowledge to action network. VISTAS developers were then tasked to help Bolte create visualizations that could help explain the results generated by the complicated model to answer questions about the impact of climate change in this western basin. Thus visualization challenges not anticipated for VISTAS/ENVISION's use with non-scientist stakeholders were expanded to showing model assumptions and levels of uncertainty and aggregating variable types to simplify visualizations, as well as increasing audience attentiveness with 3D maps, animations, and fly-throughs.

4.2 Hydrological-Biogeochemical Processes

VISTAS collaborators Bob McKane and Allen Brookes of the U.S. Environmental Protection Agency (EPA) use VISTAS to demonstrate results from their ecohydrological model VELMA [26]. Given a set of drivers (e.g., temperature, precipitation) and disturbance (e.g., fire, harvest, fertilization), VELMA models the interaction of stream flow and biogeochemical processes, and carbon and nitrogen dynamics in plants and soils. Running on a daily time step across thousands of pixels, VELMA generates multiple gigabytes of output for multi-century simulations of large landscapes. VELMA results are difficult to tune, interpret and communicate without visualization. The EPA currently studies nitrogen deposits, a critical problem near croplands and in wetlands because agricultural pollutants and eutrophication are critical water quality problems, and many bays, estuaries, and tributaries exhibit high nitrate levels. VELMA was run to investigate the feasibility of using an ecohydrological model to help bound uncertainties in difficult-to-measure nitrogen fluxes. VISTAS visualizations (Figure 3) were generated from VELMA by McKane for an EPA webinar in July 2014, in which decision makers participated.

Unanticipated specifications for VELMA arose as McKane presented the results of VELMA visualizations to non-scientist stakeholders. For example, McKane found it easy when refining his science model to view one image with land use (Figure 4, Left) then to imagine in his mind's eye the land use boundaries on VISTAS visualizations of nitrate flux (Figure 3), but his new audience wanted to see the land use boundaries explicitly. This issue was critical enough for McKane that he reprioritized his wish list for visual analytics within VISTAS and put as top priority the overlay of land use boundaries. While this seems like a simple change in the visualization, for technical reasons it required re-thinking how to render the overlay in VISTAS. See Figure 4 (right) for an initial effort at this visualization; achieving this feature will involve a re-implementation of the underlying graphical rendering technique, a non-trivial undertaking.

4.3 Creating Visualizations with VISTAS

VISTAS grew out of prior scientific visualization work [27] implemented in Java and the Visualization Toolkit VTK; that initial expertise guided VISTAS' modular, scalable design implemented in C++ and OpenGL. We aimed to create a scalable and extensible visualization tool for environmental scientists that allowed viewing landscapes in 3D and animating landscape changes over time and space—all with a response time that would allow for exploratory analysis. A plug-in design made adding new data and visualization types straightforward, and clear architectural separation between the visualization core and user-interface components rendered practical embedding the visualization engine in other scientific applications such as ENVISION [28]. Throughout the software design process, we have emphasized close collaboration with users to solve their problems, interpreted generally as viewing data in the context of topographically complex terrain..

We knew that visualization can help non-scientists better understand complex scientific results [1] and VISTAS scientist collaborators specified this as their primary objective. As VISTAS matured and our collaborators wanted to also use visualization in problem solving (analysis) sessions with stakeholders, both scientist and developers began to think about how to enhance the visual interest of the images (e.g., improving the aesthetics or providing animation) to create visualizations more accessible to secondary non-scientist users [29]. To address this problem, we chose a design model for visualization.

4.4 Using a Design Model for Visualization

Munzner's nested blocks and guidelines model is often used for conceptualizing design and evaluation criteria by visualization design researchers [30]. The nested design model defines four levels; analysis in the highest level (problem characterization) cascades to affect design criteria at lower levels, ideally aligning with the problem at hand (Figure 5). For example, to solve a problem within a certain domain, scientists might rely on datasets that they analyze using statistics or with a simulation; these datasets constitute the data or task abstraction block, where researchers choose which phenomena to measure [31]. Once scientists collect datasets and perform necessary manipulations, transformations, or simulations, a technique for visualizing the data or model is chosen. The domain problem characterization thus affects all design decisions about the resulting visualization. We used our own refinement to Munzner's model to characterize the outermost level of the nested model—the domain problem—and postulated that for wicked problems the domain problem is dynamic and difficult to problematize [32].

4.5 Design for Wicked Problems

VISTAS end users are scientists and stakeholders working together to understand the short- and long-term effects of decisions on the landscape, and problems vary in size and complexity from solvable puzzles to wicked problems. The wicked problem paradigm applies to the VISTAS case study, where the environmental domain problem is tightly coupled with sociological and political domains [32]. Wicked problems, such as what to do about climate change, move beyond the ability of science to determine clear causal relationships, to predict the future, to control or overcome unpredictable outcomes, or to establish the best outcome [33]; these factors make them not only challenging to solve but also controversial. VISTAS scientist collaborators distinguish among activities to address research problems, but they do not necessarily frame their research activities by referring to them as wicked problems, nor do they talk about the distinction between complicated problems and simpler puzzles when they devise models or analyze data. Even so, understanding that science will be conducted within the context of wicked problems could help characterize and design software for visualization use. This context includes not only technically challenging problems, but also problems where there might be low consensus and skepticism within the extended community.

5. Findings and Analysis

The VISTAS research group began the project with the proposition that data visualization tools could help scientists better understand and communicate their own data, as well as increase their ability to integrate their research with others and overcome challenges associated with big data [34]. VISTAS science collaborators had used visualization prior to the project, but their processes, tools, and output varied. They also vary in their workaday tasks, not only because of the ecological processes they study, the scale at which they study, or the part of the visualization process they work on, but because they use technology and modeling in different ways, and produce results for different audiences.

As discussed above, one visualization design objective for VISTAS involved moving the collaborators' visualizations of physical terrain from flat 2D to incorporate topography so they could observe the topographic difference in landscape that drove the physical processes under study. In constrast, visualizing topography helped non-scientist audiences recognize and relate to familiar landscapes. This difference scientist and non-scientist emerged over the course of the project in both the interview and meeting data when VISTAS scientists highlighted distinctions between different audiences to whom they present visualizations, and described how they would design visualizations with a particular audience, such as non-scientists, in mind. Visualizations created by VISTAS scientists become artifacts viewed by secondary users, who for the most part are not scientists. As described in the post-normal science paradigm, the extended peer community often requires the scientist to design visual output to enable others' understanding. Key to designing both the tool and the visualization is the realization that the scientist is most likely to use the visualization in telling a story about the results of his or her scientific research. Consider the dialogue between a VISTAS computer scientist and a VISTAS scientist at a development meeting in April, 2013:

> ***Project Lead:*** *Does [the scientist] ever see his role diminishing as the [translator of the model results]? Could someone naïve understand without him being the [translator]?*

Computer Scientist: *Look at this as part of the set of tools to make an end product that someone views. The Public is not going to sit down and use these tools…these are all tools that scientists use to produce a final product…final material is accompanied by metadata or the person who explains…*

Visualization research studies often focus on tasks, techniques, and algorithms, or lower-level software design considerations in order to boost automation of tasks and the power of machine learning [35]. However, the contribution of the case study presented here is aimed at broader issues in public policy, ecological management, and understanding scientific research practices. Our collaborators are aware that visualization might affect their communication practices and have dedicated their time to developing better software tools for such a purpose:

. . . standing back, and being able to see how different the landscape looks in these four different views, looking forward in time under different scenarios is really an eye opener. Often when I've shown this to people, just this frame here [points to visualization], they need some explanation of what they're looking at, naturally, but that doesn't take very long, and it's proven. (VISTAS Scientist, Interview 2011)

When the decision stakes are high, other factors in addition to information access, such as values and trust, are likely to sway public opinion [36]. According to case study interview and meeting data, stakeholder audiences are characterized as trusting of visualizations that are relatively familiar or intuitive to what they hold in their minds. In other words, for certain audiences, matching what they have in their minds to what they see in the visualization is often proof of truth or fact. This finding might show a problem of confirmation bias in certain visualization viewers. Within the academic institution, scientists are trained to ward against confirmation bias; however, other stakeholders may not be so trained. On the other hand, stakeholders might become more critical of results if they encounter a visualization counter to what they expect or intuit. One scientist alluded to this problem when discussing the concept of mental models during a discussion of data exploration practices. He commented on instances when scientists used visualization to validate their data, only to find out that something was wrong with the data. In such instances, the visualization does not match the viewer's mental model of how the data should look. When a relatively uninformed audience has the same experience of not seeing what is expected, they might also question the data, methods, or visualization, uncovering problems that escaped the trained viewer. More research on best practices for communicating via visualization seems merited based on this analysis.

5.1 Designing Visualizations with VISTAS

Throughout the software design process, traditional methods were used that emphasize close user collaboration and designing a tool to solve users' primary problems. The problem was interpreted, generally, as viewing data in the context of topographically complex terrain. While the ecological problems had been the primary focus for developing visualizations, we found that in settings such as the Big Wood Basin, that the ecological problems were considerably more complex than originally anticipated. Computer scientists and scientists involved in design and implementation of both visualization tools and visualizations for wicked problems must take particular care to fully characterize the domain problems early in the design process, and throughout the subsequent implementation, deployment and maintenance. The VISTAS case study highlights that both software developers and scientist users should recognize wicked problems and better understand how to characterize them and design visualizations for them.

In traditional scientific visualization projects, computer scientists often suggest and prototype technological innovations to enhance the scientific content of the visualization. However, few computer scientists are trained in which scientific visualizations work for non-scientists in a wicked problem context. Social and environmental science research conducted by the VISTAS team found that even the scientists themselves don't always know how to design visualizations accessible to non-science audiences. These findings are consistent with the literature, which highlights the difficulty of matching the best visualization technique with the way the data is abstracted [12].

6. Discussion

During the VISTAS experience, the scientists were characterized as primary users of the visualization tool and the non-scientist audience as secondary. We extend the traditional concept of software system stakeholder, which is limited to those with a stake in the software per se [4], to includeas software system stakeholders to include stakeholders in the overall ecological problem of climate change.   One implication of this characterization is that, even if a scientist has a good scientific visualization tool, he or she might not know how to present data visually in a way non-scientists will understand and the tool will not then serve the non-scientist stakeholder. How one views, experiences, and transposes the data—how one designs visualization—affects understanding of the data. This problem is not widely addressed by the visualization research community, and as Desnoyers points out, "Most scientists were scarcely exposed to formal training in the use of visuals and it is our experience that students resort to learning by doing and imitating what they read and see, for better or for worse" [37]. He goes on to describe the need for more systematic training in visualization creation and use, especially due to the problem of polysemy, or the diversity of perceived meanings. In addition to training scientists, software design and development might take into account the context in which visualization might be used and characteristics of the various types of visualization users [32].

6.1 Relevance to Public Policy and e-Government

Visualization and visual analytics strategies may affect outcomes of problem solving in a public policy setting. As mentioned earlier, VISTAS case study scientists are using visualization for communication both in and outside of the research institution. They see the need for and potential of visualization as part of good communication practice. Also, they are using visualization currently with various audiences, deciding how to present findings based on assumptions about those audiences, and designing visualizations with different audiences in mind. These scientists are engaged in research that affects management and decision-making processes, in which case considering best practices for visualization in various settings becomes a public policy concern. For example, more research on this topic seems necessary for developing best practices to explore how scientists increase non-scientists' accessibility to scientific findings while communicating complex data transformations, uncertainty, or model calculations. To address this problem, one VISTAS scientist mentioned that when he uses visualization outside of the academic institution—such as with stakeholder groups or in any type of policy process—he endeavors to explain the related model behind the image in a way that overcomes disciplinary boundaries.

It is difficult to tell with visualization what might lead to inaccurate conclusions when used in stakeholder engagement settings where the scientist or primary user is not available to provide an explanation. Strict methodology reporting and overcoming bias is an important part of scientific practice during hypothesis formulation, data collection, and statistical transformations; and one might apply that same caution to visualization design that transforms scientific data for the purpose of increasing understanding or communication. That said, methodology for visualization production does not necessarily address the caveat that visualization—which allows for accelerated understanding—might also lead to unexamined conclusions. Educating not just scientists, but stakeholders and the interested public on how to interpret scientific visualization seems necessary. This problem becomes even more important when decision stakes are high.

Other research in the e-government field suggests that software tools are increasingly used within government agencies to enable collaboration between scientists with non-scientists—for example, tools for supporting lay stakeholders in the framework of the democratic paradigm of environmental decision making [38], decision support systems that bridge science and values [39], or information systems in a mediating role for tackling climate change adaptation [40]. These studies complement an increasing interest within e-government research of using open data and visualization not only to improve government efficiency but also to make closer connections between citizens and government [41] and to enable stakeholders themselves to make sense of the data [42]. We believe that scientists' use of effective visualizations to both explain complex results to stakeholders and to engage them in knowledge to action networks could increase trust between government-employed or -funded scientists and decision makers; whether this would pave the way for higher utilization of e-government services remains, for us, an open question [43]. In any case, government agencies and policy researchers are increasingly considering information technology as a topic meriting serious consideration.

6.2 Strengths and Limitations

Delivering science into policy and managerial processes can challenge scientists; our study sought to understand how visualization tools might equip them to better communicate and explore new findings both in their own work and in broader policy settings. In reporting distinction between exploring and communicating among scientists, we highlighted how visualization use might change depending on the audience and the purpose, i.e., whether a visualization was used for exploration in a scientific setting or communication in a broader decision-making process [32]. The visualizations created by VISTAS scientists become artifacts viewed by secondary users, and the success of the software itself hinges on whether visualizations enhance scientific insight not only for scientists but also for these stakeholders and enable scientist and non-scientist collaboration in decision making. Evidence for this contention emerged during interviews and field observations, where scientists described the need both for a flexible visualization tool and for training using the tool to create visualizations for non-scientists. Increasing the extended peer community as in the post-normal science paradigm often requires the scientist to design good visualizations as cues for others' understanding. Key to designing both the tool and the visualization is the realization that scientists are most likely to use visualization when telling a story about the results of their scientific research.

One strength of the VISTAS visualization case study presented here is the variety of science collaborators who range in their level of experience with visualization, in the types of relationships they have with the development team, in their relationships with other software developers, in the types of models they produce, in their various collaborations, and in the scales at which they work. Such strong collaboration is typically an indicator of software development success [44, 45]. The intention of these scientists to use visualization for exploring big data and addressing wicked problems shows the need for development of better tools, but it also highlights the potential problem of confounding factors in using visualization for communicating results to a wide variety of audiences. Considering options to support visualization, such as providing the data, models, or a verbal explanation of what the visualization is demonstrating, might help overcome these problems; such support where appropriate could be viewed as a criteria of successful software. More empirical work, directly observing stakeholders or secondary users interacting with visualization, seems merited in order to understand how the visual and verbal work together in a decision-making process.

Problem-driven design studies for software design (e.g., [46]), and for visualization range from referencing specific users and situations, such as the intelligence community in Kang & Stasko [47], to casual users in Sprague & Tory [48]. Our study, however, is unique in seeking to understand how visualization might be used in a public policy and decision making setting where scientists are presenting data or models to stakeholders. Users find that certain visualizations serve better than others for certain tasks; however, pinning down what matters into a conceptual model and measuring effectiveness still challenges visualization researchers and designers.

6.3 Conclusions

The primary lesson thus far from our experience working with scientists who present research results exploring wicked problems to non-scientist stakeholders is that the problem domain affecting the design of the visualization is likely much broader than originally conceived. Additionally, developers and scientists should be prepared to recognize when they are working with wicked problems and be cognizant of the range of audiences interacting with visualizations produced via a software tool. Finally, while these considerations will help improve design decisions made at the beginning of the project, it is unlikely that all decisions will be correct as the project matures, and it might become necessary to revisit software design decisions as they emerge. Developers and users need to be prepared for the time and cost of revising assumptions that drove initial technology decisions. We believe that the lessons learned over the course of the VISTAS project apply to other similar software design and development projects where scientific data is to be visualized and used in decision-making processes and public policy settings.

The VISTAS project findings drive new research questions that distinguish those (scientists) who create data stories or narratives through visualization, and the audiences of these data stories. VISTAS problem-driven design method highlights the importance of creating software that serves both the primary users, the scientists who create models and visualize their output, and secondary non-scientist users, the stakeholders and decision makers who experience the data stories told by the scientists. Future research for the VISTAS project includes testing the visualization output of the VISTAS tool with various audiences in different settings. Additionally, researchers might track and measure the role of visualization in a problem-solving process, especially the extent to which the audience can use the visualization to provide insight into a problem, and where visualization might fall short of that goal.

More generally, research on group interaction with visualization, rather than single-user interaction, would provide insight into the contribution of visualization to the process of communicating results, or of telling a data story. And, finally research into how to create visualizations for non-scientists—which visualizations work and why—is needed. Training for both computer scientists and scientists on designing such visualizations for diverse audiences seems merited based on the findings presented here.

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Table 1.An overview of wicked problems (adapted from Rittel & Webber [11])

Scientific or technical solution?	Consensus of general agreement about the problem?	
	YES	**NO**
YES	***Tame Problem*** Problem is isolated Agreement on Solution Examples: fire suppression, municipal trash collection	***Mess or Complex Problem*** Science provides solution No agreement on how to proceed Examples: population control, traffic congestion
NO	***Puzzle or Mystery*** Agreement on solution Lack technical/scientific capability for solution Examples: disease treatments, flood control	***Wicked Problem*** No agreement on solution Lack technical/scientific capability for full solution Examples: climate change; middle east war; waste cleanup

Table 2: Initial themes related to communication using visualization**.**

Topics	Definitions
Communication with non-science audiences	Communication with various audiences in general needed *Visual communication* simplifies concepts for general audiences *Visual communication* is used with audiences who are hard to convince Verbal explaining, in addition to visualization, is a communication strategy used with non-science audiences
Communication with scientists	Communication occurs within the institution and is with others who are trained in a specific discipline.
Audience Analysis: Appeal	Has intuitive feel Creates a narrative Grabs attention
Audience Analysis: Reasons Behind the Appeal	Appeals to sense of home (audiences recognize familiar places in the visualization) Helps users understand and simplify complex concepts and findings Shows planning outcomes Design: making connections between variables Visualization shows future scenarios (Allows audience to ask what if…?) Visualization shows relationships between variables Combines visuals with graphs
Designing with an audience in mind	Pre-processed movies or animations Variety of variables Design/aesthetics Less abstract Photorealistic (also a challenge) Added key to design Showing "what if?" Helps prove findings/convince
Meta-design	Scientists expressed perceiving a strong demand for visualizations Scientists guide design, rather than the development team At times, visualization has limited effect Visualization useful for gaining funding

Fig. 1. ENVISION alternative land use futures scenario—Central Oregon alternative futures:

Left: Vegetative cover (giant trees to seedling, shrub, meadow, barren, developed),

Right: Land use (homeowner, tribal, private or public industrial, state or federal).

Fig. 2. Big Wood Basin stakeholder problem solving and concept mapping.

Fig. 3. VELMA model of Chesapeake Bay nitrate: Left 2000, right 2003.

Fig. 4. Land use boundaries for VELMA Chesapeake nitrate study:
Left: Land use boundaries annotated hand, by the scientist,
Right: Initial VISTAS land use overlay onto Fig. 3 visualization.

Fig. 5. Munzner's *Nested Model* [30].

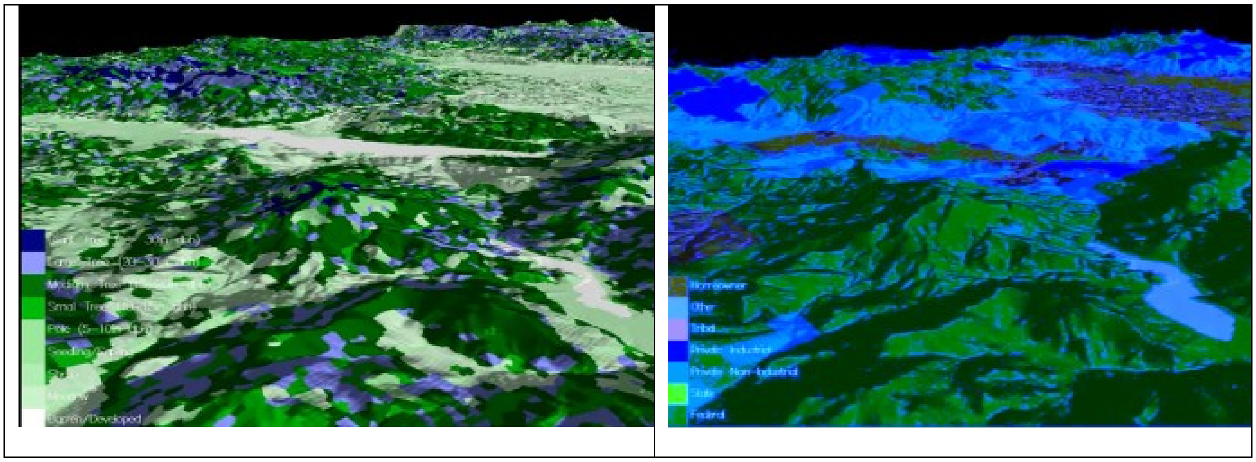
Barren/Developed
Homeowner
Other
Tribal
Private Industrial
Private Non-Industrial
State
Federal

Fig. 1.

Fig. 2.

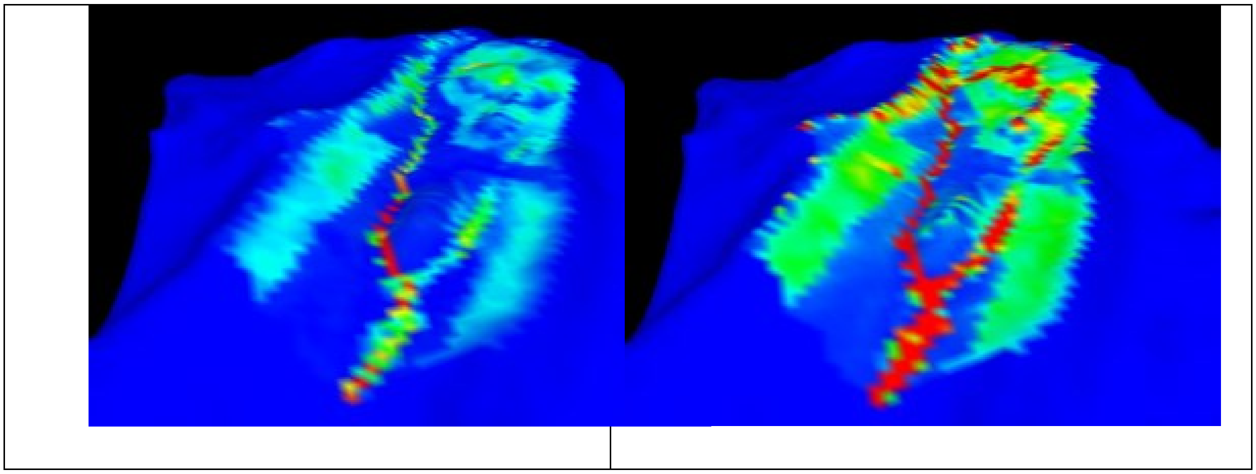

Fig. 3.

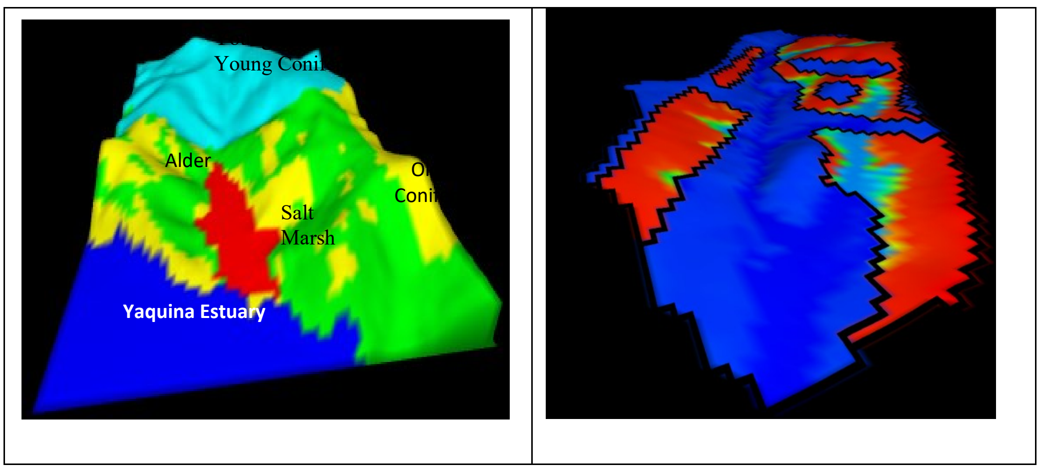

Fig. 4.

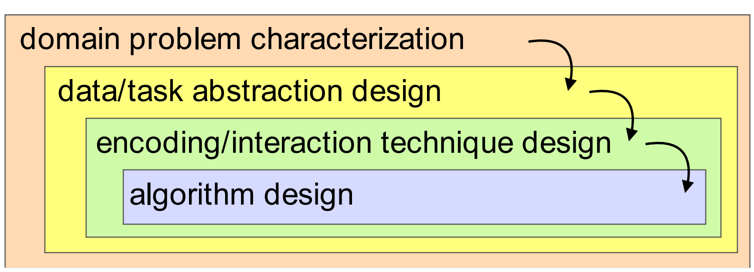

Fig. 5.