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# Web-based visualization of uncertain spatio-temporal data



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## **Abstract**

Numerical ensemble models are commonly used in the analysis and forecasting of a wide range of environmental processes. Use cases include assessing the consequences of nuclear accidents, pollution releases into the ocean or atmosphere, forest fires, volcanic eruptions, or identifying areas at risk from such hazards. In addition to the increased use of scenario analyses and model forecasts, the availability of supplementary data describing errors and model uncertainties is increasingly commonplace. Unfortunately most current visualization routines are not capable of properly representing uncertain information. As a result, uncertainty information is not provided at all, not readily accessible, or it is not communicated effectively to model users such as domain experts, decision makers, policy makers, or even novice users.

In this research the state of the art of uncertainty visualization is reviewed. Building upon the literature review, a conceptual framework is developed for visualizing uncertainty information in an interactive web-based mapping environment. Attribute uncertainty in ensemble datasets is quantified using various uncertainty metrics, such as the standard deviation, inter-quartile range, or interval probabilities derived from a cumulative probability density function. The metrics are well defined and mapped to a representation which uses dynamic circular glyphs to represent uncertainty. The application was developed in line with the data state model and makes the uncertainty visualizations available in an online mapping and visualization environment (UVIS). The visualization routines incorporate aggregation (upscaling) techniques to adjust the uncertainty information to the zooming level, resulting in a new and visually pleasing bivariate display in which both attribute value and uncertainty are embedded.

The web-application was presented to groups of test users of varying degrees of expertise. The interface and the visualizations were usable even for non-expert users, and the dynamic circular glyphs were found to be an effective way to identify areas of uncertainty, quantify uncertainties, and to estimate probabilities of attribute value intervals occurring.

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# Table of Contents

<b>1</b>	<b>Introduction .....</b>	<b>5</b>
1.1	The Bigger Picture .....	5
1.2	Problem Statement .....	6
1.3	Research Objectives .....	8
1.3.1	Research Questions .....	8
1.3.2	Deliverables .....	9
1.4	Research Methodology .....	9
1.5	Document Outline .....	10
<b>2</b>	<b>Uncertainty in Geospatial Data .....</b>	<b>12</b>
2.1	Defining Uncertainty .....	12
2.2	Sources of Uncertainty .....	13
2.3	Towards a Framework for Uncertainty .....	14
2.4	Properties of Geospatial Data .....	15
2.5	Quantifying Uncertainty .....	16
<b>3</b>	<b>Visualizing Uncertainty .....</b>	<b>19</b>
3.1	Users and Tasks .....	19
3.2	Scale .....	21
3.3	Cartographic Concepts for Uncertainty Representation .....	22
3.4	Cartographic Representation Methods .....	23
3.4.1	Utilization of Graphical Variables .....	24
3.4.2	Adding Glyphs .....	24
3.4.3	Adding or Modifying Geometry .....	25
3.4.4	Animation .....	25
3.4.5	Interactivity and Information Control .....	26
3.4.6	Others .....	26
3.5	Representations of Uncertain Data .....	26
3.6	Integrated Applications for Visualizing Uncertainty .....	28
3.7	Evaluating Uncertainty Visualizations .....	30
3.7.1	Usability of representation methods and manipulable interfaces .....	30
3.7.2	Use of information uncertainty .....	31
<b>4</b>	<b>Improving Uncertainty Visualizations for the Web .....</b>	<b>33</b>
4.1	Design Guidelines .....	33

4.2	Requirements .....	34
4.2.1	Models and Data Types .....	34
4.2.2	Technical Requirements .....	34
4.2.3	Users and Tasks .....	35
4.3	Uncertainty Metrics .....	36
4.4	Upscaling .....	41
4.5	Uncertainty Representation Using Glyphs .....	42
4.5.1	Circular Glyphs.....	44
4.5.2	Placement .....	44
4.5.3	Interactivity.....	45
4.6	Uncertainty Representation Using Graphical Summaries .....	45
4.6.1	Spatial dimension.....	46
4.6.2	Time dimension.....	46
<b>5</b>	<b>Visualizing Uncertainty on the Web .....</b>	<b>48</b>
5.1	Implementation of the Data State Model.....	48
5.2	Analytical and Visualization Abstraction (UVIS-App) .....	50
5.3	Web-based Visualization (UVIS-Web) .....	52
5.4	View Stage Operators.....	55
<b>6</b>	<b>A Web Application for Visualizing Uncertainty in Numerical Ensemble Models .....</b>	<b>57</b>
6.1	Models and Datasets .....	57
6.1.1	Snow .....	57
6.1.2	NPK-Puff .....	57
6.2	Navigation and Control Panes .....	59
6.3	Uncertainty Visualizations.....	60
6.4	Region Summary .....	62
6.5	Change of Support.....	62
<b>7</b>	<b>Uncertainty Visualization User Study .....</b>	<b>64</b>
7.1	Objectives .....	64
7.2	Methods .....	64
7.3	Results.....	67
<b>8</b>	<b>Discussion.....</b>	<b>72</b>
<b>9</b>	<b>Conclusion .....</b>	<b>78</b>
<b>10</b>	<b>References .....</b>	<b>82</b>
<b>11</b>	<b>Appendix A – Survey Questionnaire .....</b>	<b>87</b>
<b>12</b>	<b>Appendix B – Survey Results (Unprocessed).....</b>	<b>100</b>







# 1 Introduction

## 1.1 The Bigger Picture

In 1998 former U.S. Vice President Al Gore conveyed a vision of a Digital Earth which could be questioned by a young girl about the planet and its resources. Components of this Digital Earth are being developed across various scientific disciplines, and modeling and visualization are two of its important use cases (Goodchild 2008). Models can help us analyze and forecast the consequences of nuclear accidents, pollution releases into the ocean or atmosphere, forest fires, volcanic eruptions, or they can identify areas at risk from such hazards. Not only is spatial data produced by these models, but supplementary data concerning errors, model uncertainties, occurrence probabilities, chances of exceeding thresholds, timelines, scenarios, and other multi-dimensional data is also at our fingertips.

Web-based visualization platforms offer great potential to make model results available to an audience: the general public, specialists, scientists, decision makers, or even the girl mentioned in Gore's speech. The current state of web-based model visualizations is progressing fast, but limitations in visualization techniques means that much work remains to be done. Established applications such as Google Maps<sup>1</sup>, Google Earth, but also smaller startups such as MapBox<sup>2</sup>, are facilitating the publication of geodata in an online environment, but as these applications are not designed specifically for complex model visualizations, the information which is communicated is often limited to simple

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<sup>1</sup> <http://maps.google.com/>

<sup>2</sup> <http://www.mapbox.com/>

attribute maps, choropleth maps, or data points supported by metadata in the form of tables, graphs, or popups. Some reasons for these limitations are that complex visualizations can potentially lead to a cognitive overload, and that the choice of a web-platform comes with a specific set of restrictions and rules. As a consequence, both the complexity and the limitations of offline environmental models are not well represented in their online counterparts. This research attempts to bridge that gap by making clear and concise web-based uncertainty visualizations available to spatio-temporal environmental models developed in the PCRaster-Python modeling framework (Karssenberget al. 2009).

## **1.2 Problem Statement**

Digital visualization of geodata is built upon concepts which find their origin in cartography. As such, the visualization of continuous, ordinal, or nominal data using Bertin's (1985) graphic variables (location, size, value, texture, colour, orientation, and shape) is well defined and comprehensible for map users. For such data types there are also various methods and online services which can provide standardized visualizations such as choropleth or raster maps. This is not so for uncertain data. Both the visualization of uncertainty (MacEachren 1992; Pang et al. 1997; MacEachren et al. 2005; Pang 2008) and the ability of users to understand, explore, and make decisions based upon uncertain data (Drecki 2002; Aerts et al. 2003; Deitrick 2006; Riveiro 2007; Sanyal et al. 2009) is riddled with complexity and alternating conclusions. Spiegelhalter et al. (2011) acknowledge these concerns by stating that there are "still few reproducible experimental findings for assessing best practice in visualizing uncertainty."

As early as 1994 the lack of innovative graphical display techniques was noted by Goodchild et al. (1994) and he subsequently warned for "the potential for cognitive overload in displays where data and data validity are embedded." Various innovative display techniques for uncertainty have since been developed. Amongst these are visual metaphors such as fog (Beard et al. 1991), texture overlays (MacEachren 1992), tessellation trees (Kardos et al. 2008), using sound to represent uncertainty (Fisher 1991), many others using glyphs

(Wittenbrink et al. 1996), animation, or psychovisual approaches (Pang et al. 1997), and interactive desktop applications for exploring ensemble data sets in which uncertainty information is embedded in the form of probability density functions (Pebesma et al. 2007; Potter et al. 2009; Sanyal et al. 2010). Even though visualization methods are now plentiful, the risk of cognitive overload and the lack of a visualization framework mean that the development of new uncertainty visualization techniques is still a key research challenge (Johnson and Sanderson 2003).

Risks of cognitive overload and the effectiveness and usability of uncertainty visualizations also remain to be addressed. The effectiveness of several uncertainty visualizations has been investigated previously (Riveiro 2007; Aerts et al. 2003; Deitrick 2006), but none of these include interactive visualizations in a web-based environment. Deitrick and Edsall (2008) suggest that customizing visualizations based on whether the user is an expert or novice may help in the communication of uncertainty data. In this regard a web-based approach which is accessible and interactive, providing advanced features for advanced users, and simple features for novice users, may also offer opportunities that other visualization platforms do not.

Research into the scientific concepts underlying uncertainty visualization is ongoing, and over time various uncertainty frameworks have been proposed in order to formalize the concept of uncertainty visualization and its applications (Buttenfield and Weibel 1988; MacEachren 1992; Pang et al. 1997; Thomson et al. 2005; MacEachren et al. 2005). In spite of these developments there is still no consensus as to which methods are most suitable for visualizing uncertainty across a range of environmental models. The lack of a visualization framework is noted by Johnson and Sanderson (2003):

“We see the need to create a formal, theoretical error and uncertainty visualization framework and to investigate and explore new visual representations for characterizing error and uncertainty.”

Pang (2008) acknowledges this in a research challenge by concluding that a new framework is needed which is “cognizant of the users needs and tasks as well as the properties of the data that they are dealing with.” We live in a digital era which is greatly impacting and transforming the two factors mentioned by Pang (2008): tasks and needs of model users, as well as the properties of the data being visualized. The onset of affordable computing power has led to a new generation of models which can produce ensemble datasets which – assuming visualizations can keep up – will offer unprecedented possibilities for modeling, analyzing, and visualizing environmental processes. Simultaneously, the advancement of web-based technologies and global access to the internet has opened the door to uncertainty visualizations which have the potential to be universally accessible and understandable, regardless of where the user is or whether they are experts, policy or decision makers, operational users, or simply casual users that may just be interested in what the chances are of a hurricane reaching their backyard in the coming days. Realizing this potential is a challenge that this research will attempt to address.

### **1.3 Research Objectives**

#### **1.3.1 Research Questions**

The main research question is:

“How can uncertainty information in higher-dimensional datasets produced by spatio-temporal environmental models be represented and visualized effectively in a modern web-based environment?”

In order to answer this question four sub-questions are defined. The first two review and explore the current state and methods in uncertainty visualization and web-based mapping. Building upon these insights, the last two questions focus on future perspectives: bringing uncertainty visualizations to the web and evaluating their effectiveness in communicating uncertainty information to both experts and non-expert model users such as decision makers, policy makers, and casual users. The sub-questions (RQ) and objectives (OBJ) are:

- RQ I. What type of uncertainty information is produced by spatio-temporal environmental models, and what methods and frameworks exist for quantifying and visualizing these uncertainties?
- RQ II. What methods, tools, or services can be used to produce interactive online maps suitable for a selection of uncertainty visualizations?
- RQ III. How can the technical requirements and challenges (with regard to infrastructure, operations, transformations, rendering algorithms, and data flows) be met so that uncertainty information can be explored in an interactive web application?
- OBJ I. To develop an intuitive and usable web application prototype which can visualize, using a selection of suitable methods and visualizations, spatio-temporal data and its uncertainties.
- RQ IV. How effective and how usable are the web-based uncertainty visualizations in communicating uncertainty information present in spatio-temporal datasets to users with varying degrees of expertise?

### **1.3.2 Deliverables**

This project has two deliverables:

- An operational web application prototype for visualizing uncertainty in spatio-temporal datasets.
- A scientific report which provides an extensive review of the current state of uncertainty visualization, documents the development of a conceptual framework, the implementation of the web application, and the user survey used in the evaluation of the uncertainty visualization methods.

## **1.4 Research Methodology**

A literature study will be completed in order to review past developments and the current state of uncertainty visualization. The literature study will address the first two research questions. The literature review and its findings will subsequently be used and built upon to create a conceptual framework for improving

uncertainty visualization on the web. These improvements, together with a selection of established methods and visualizations, will be implemented in a web-based visualization application. To test the effectiveness and whether the objectives of the web application were achieved a user survey is conducted in which users of varying levels of expertise are asked to answer various questions using the web application.

## **1.5 Document Outline**

Chapter two encompasses a high level overview of uncertainty in environmental models. It defines uncertainty and its sources, different data types, and provides a review of past attempts at developing a unified framework for working with uncertainty in geospatial data.

Chapter three provides a review of applied aspects of uncertainty visualization. It describes common problems with visualizing uncertainty, cartographic concepts and methods which can be used to visualize uncertainty, and various representations which have been developed and modified over time by others in the geovisualization community. Several existing web and desktop applications for uncertainty visualization are reviewed which implement uncertainty visualizations. The chapter ends with a brief review of how the visualization community has evaluated the effectiveness of uncertainty visualizations.

Chapter four builds on the literature review and describes a conceptual framework which lays the groundwork for the development of the web application. It describes the prior motivation and objectives for the web application, as well as the desired technical and user requirements. With this vision in mind a selection of existing methods and representations is refined and improved upon to form, together with new insights and techniques, a solid foundation for a newly developed web application prototype.

Chapter five describes the technical implementation of the web application, outlining the data model, implementation details, data and visualization

abstractions, the web based visualization layer, and the front-end interaction design.

Chapter six showcases the results of this project: a web application for visualizing uncertainty in numerical ensemble models. Using an air dispersion model as a sample dataset, the features of the web application (navigation, map and uncertainty layers, and regional summaries) are displayed and reviewed.

Chapter seven describes the uncertainty visualization user study which was completed using the web application. It outlines the procedures and objectives, and presents the results of the user survey.

Chapters eight and nine contain respectively the discussion which has arisen as a result of the research as well as any final conclusions.

## 2 Uncertainty in Geospatial Data

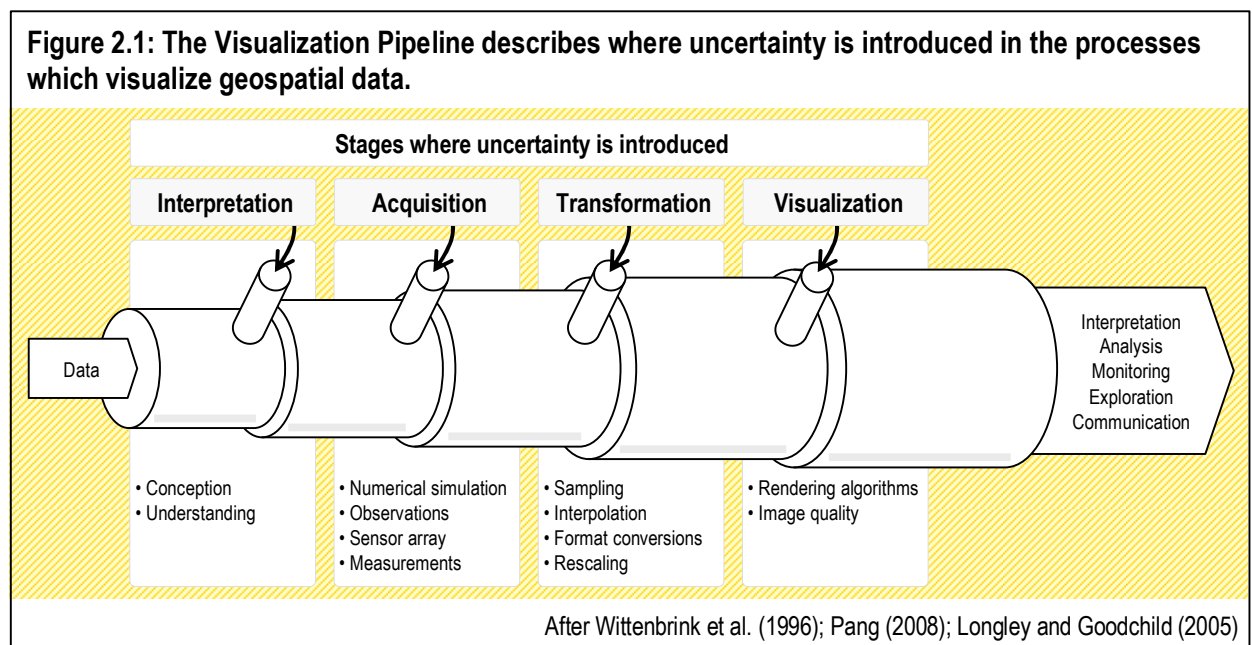
### 2.1 Defining Uncertainty

MacEachren et al. (2005) state that “information uncertainty is a complex concept with many interpretations across knowledge domains and application contexts.” Uncertainty encompasses an accumulation of other data quality concepts such as imprecision, inaccuracy, inconsistency, noise, ambiguity, and lack of reliability (Pang 2008). As such, there is no universally applicable definition of uncertainty, but in the context of this research, uncertainty visualization for spatio-temporal data, such a definition is easier to formulate. Wittenbrink et al. (1995) define uncertainty as “statistical variation or spread, error, and minimum-maximum ranges.” The definition by Wittenbrink et al. (1995) does not differentiate between uncertainty and error though, an important distinction as errors in environmental models (especially those predicting the future) are rarely known objectively. MacEachren et al. (2005) address this by defining uncertainty as inaccuracies in data which are not known objectively, for otherwise they would be considered error. Other authors use similar but more explicit approaches by requiring uncertainty to be quantifiable. Mowrer (2000) states that “uncertainty implies a quantifiable inexactness in a point estimate.” In a similar definition, Foody and Atkinson (2002) define uncertainty as a “quantitative statement about the probability of error.” From a visualization standpoint it is especially important that uncertainty can be quantified in a meaningful manner, therefore the latter definitions of uncertainty will be used in this research.



## 2.2 Sources of Uncertainty

Wittenbrink et al. (1995), Pang et al. (1997), and Pang (2008) use an uncertainty visualization pipeline which describes the processes and stages involved in the visualization of geographic data and its associated uncertainty. Along the pipeline uncertainty is introduced during various stages (acquisition, transformation, and visualization), and it is then propagated towards the end of the pipeline where visualization and analysis takes place. Longley and Goodchild (2005) added interpretation to the beginning of the pipeline, resulting in a visualization pipeline (Figure 2.1) which describes four stages at which uncertainty can be introduced:



- *Interpretation.* The first step in the visualization pipeline is interpretation of the natural phenomenon. Often our understanding of natural processes is not complete, and misunderstanding or lack of knowledge at this stage can introduce uncertainty.
- *Acquisition.* In the measurement of data there is an experimental variability. Therefore measured data, or data produced as a result of numerical modeling, may not accurately represent the observed phenomenon. Additional measurements or model runs can result in more confidence in the results, and thereby reduce the introduction of uncertainty.

- *Transformation.* Transformations occur when data is interpolated, resampled, rescaled, during format conversions, or when deriving new data using algorithms (Pang et al. 1997). Transformations can take place at the acquisition stage, but also as far back as the visualization stage (Pang et al. 1997).
- *Visualization.* Uncertainty can also be introduced at the visualization stage. Rendering algorithms, limitations of visual cues, or image quality can introduce uncertainty at the visualization stage.

The introduction of uncertainty throughout the visualization pipeline is compounded by the problem that uncertainty may propagate and influence succeeding stages in the pipeline (Wittenbrink et al. 1996). In furthering our understanding of uncertainty and to formalize the concepts that underlie it, an uncertainty framework is needed. Over the past decades various uncertainty frameworks have been developed which can help us navigate, discuss, and understand what happens in the later stages of the visualization pipeline.

### **2.3 Towards a Framework for Uncertainty**

Buttenfield and Weibel (1988) were among the first to construct an uncertainty framework that focused on the cartographic representation of uncertainty (MacEachren et al. 2005). They constructed a matrix of data types (discrete, categorical, continuous) and certain aspects of data quality (positional and attribute accuracy, logical consistency, completeness, and lineage) and suggested some general forms of cartographic representation in each of the resulting fields of the matrix. Thomson et al. (2005), in the context of intelligence analysis, expanded on these data quality concepts by adding currency, credibility, subjectivity, and interrelatedness. While the frameworks by Buttenfield and Weibel (1988) and additions by Thomson et al. (2005) demonstrate the range of data quality concepts we are dealing with, their approaches are arguably too broad for the visualization of spatio-temporal data which finds its origin in environmental modeling. Abstract data quality concepts such as logical consistency, completeness, and subjectivity are difficult to quantify and represent graphically and as such may be better represented using a lexical syntax.

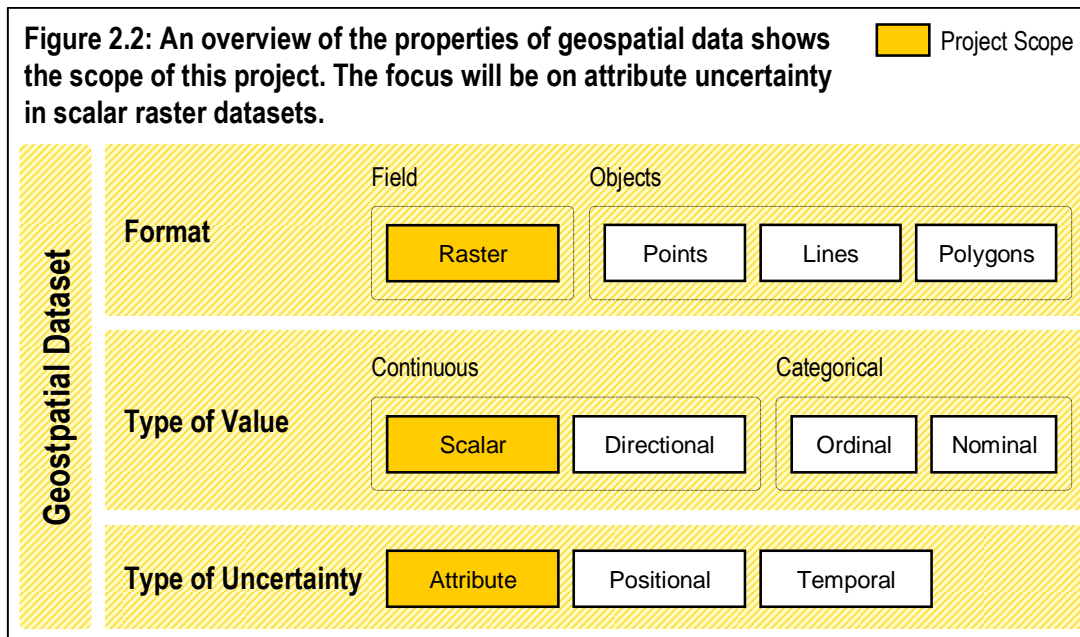
Pang et al. (1997) produced a classification matrix which matches data type or value (scalar, multivariate, vector, and tensor) to a visualization form or extent (discrete and continuous). Their full classification also used other characteristics such as location (0D – 4D and time), data extent, and axis mapping (Pang et al. 1997). Pang et al. (1997) focus less on the abstract aspects of uncertainty, but their technical approach therefore means that the visualizations presented are more applicable in the field of scientific or information visualization, rather than in the visualization of spatio-temporal data.

Pang (2008), in a fresh look at uncertainty visualization, emphasizes uncertainty visualization in datasets used in geospatial applications such natural hazards assessments. Rather than expanding further on different concepts of uncertainty Pang (2008), much like MacEachren (1992), focuses on how these uncertainties can ultimately be represented numerically. Various methods and visualizations are presented according to whether uncertainty is represented as scalar, vector, or multi-value data. Several shortcomings of the current state of uncertainty visualization are also touched upon by Pang (2008). Of particular interest is the lack of a framework for uncertainty visualization which is “cognizant of the users needs and tasks as well as the properties of the data they are dealing with” (Pang 2008). This concern was also expressed by Pham et al. (2009). It begs the question of whether current uncertainty frameworks are still up to their task, and with the onset of ensemble datasets, affordable computing, and with web-based technologies at our fingertips, is there a paradigm shift taking place which requires a new type of uncertainty visualization framework which, as Pang (2008) and Pham et al. (2009) suggested, focuses on the users, tasks, and objectives rather than just on the properties of the data?

## **2.4 Properties of Geospatial Data**

The frameworks discussed in the previous chapter show that uncertainty in geospatial datasets is defined across a range of data formats, data types, and various aspects of data quality. The scope of this research project has been limited to include only a selection of these properties. As is shown in Figure 2.2,

only datasets in a raster format with scalar attribute values will be included. Datasets based on object features (points, lines, polygons) or those which use categorical attribute values fall outside of the scope of this research. The range of data quality concepts has also been limited to only include attribute uncertainty; therefore positional, temporal, or other abstract data quality concepts fall outside of the scope of this research. The reason for this is that the visualizations required for other data types and data formats are likely to be significantly different from those for scalar raster data. Especially in the development of new visualizations it may lead to visualizations which are diluted compromises rather than effective and usable solutions to a specific visualization problem.

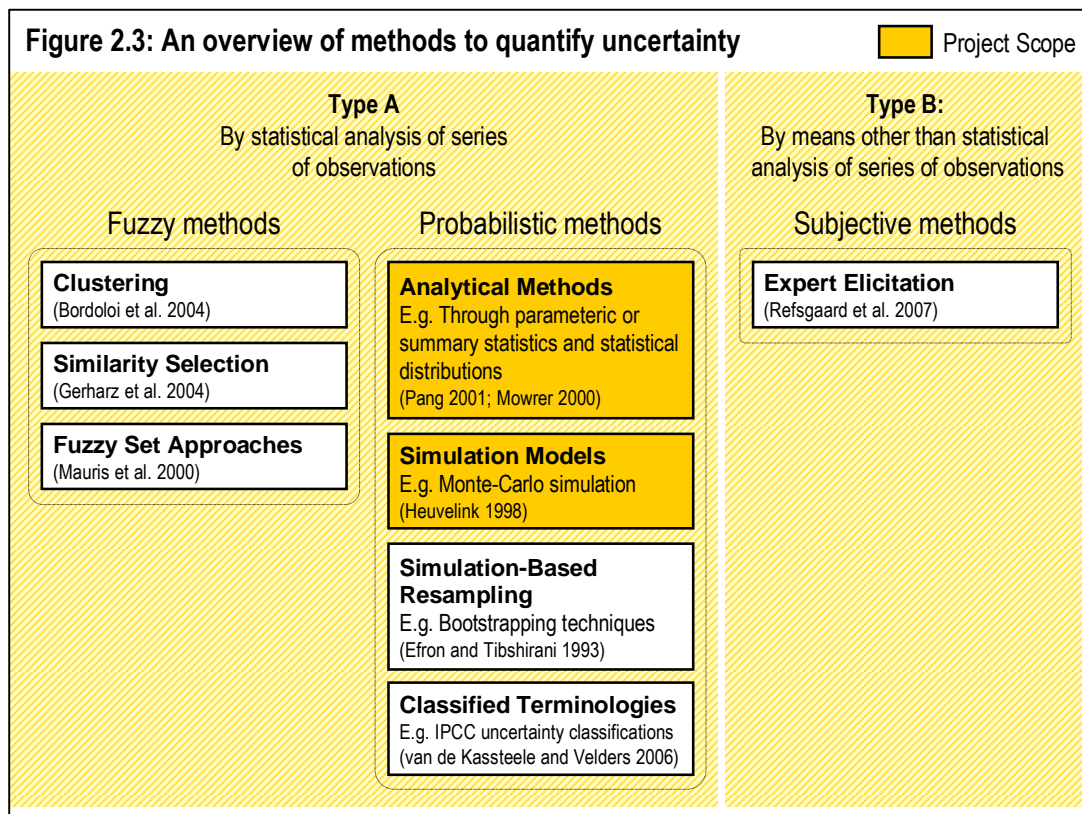


## 2.5 Quantifying Uncertainty

The International Bureau of Weights and Measures (BIPM 2008) defines two types of methods evaluating uncertainty. The first (Type A evaluation) is “by the statistical analysis of series or observations” and the second (Type B evaluation) is by “means other than the statistical analysis of series of observations.” Type B methods apply to abstract data quality concepts which are evaluated by the use

of judgment or expert elicitation. Figure 2.3 shows the range of different approaches which can be used to evaluate uncertainty in a geospatial dataset.

This research encompasses the computational visualization of attribute uncertainty and therefore a quantitative statement about the uncertainty is a requirement. As fuzzy methods are experimental and difficult to implement in a cartographic application, only probabilistic Type A methods are considered further.



The focus will be on the accentuated boxes in Figure 2.3: the analytical methods and on numerical simulation models which quantify uncertainty through the use of Monte Carlo simulation. Monte Carlo simulation is an increasingly common method in environmental sciences to emulate systems which are too complicated to analyze analytically. The geospatial datasets produced through Monte Carlo simulation are called *ensemble datasets*. An ensemble dataset is a multi-value dataset which can be viewed mathematically as a stochastic function where each variable (an attribute value) is a function of a specific location (the support) and a

specific time (the model timestep). Each variable is defined by a probability density function which can be estimated numerically by sampling all the ensembles at a specific location and time (Bierkens et al. 2000). The estimated probability density function and the values from which it is sampled are used as the basis for quantifying the attribute uncertainty at a particular location.

The probabilistic methods in Figure 2.3 are not mutually exclusive either. For example, it is possible to apply a simulation-based resampling technique on the results of a Monte Carlo simulation, as is classifying the results of analytical methods into an uncertainty terminology classification.

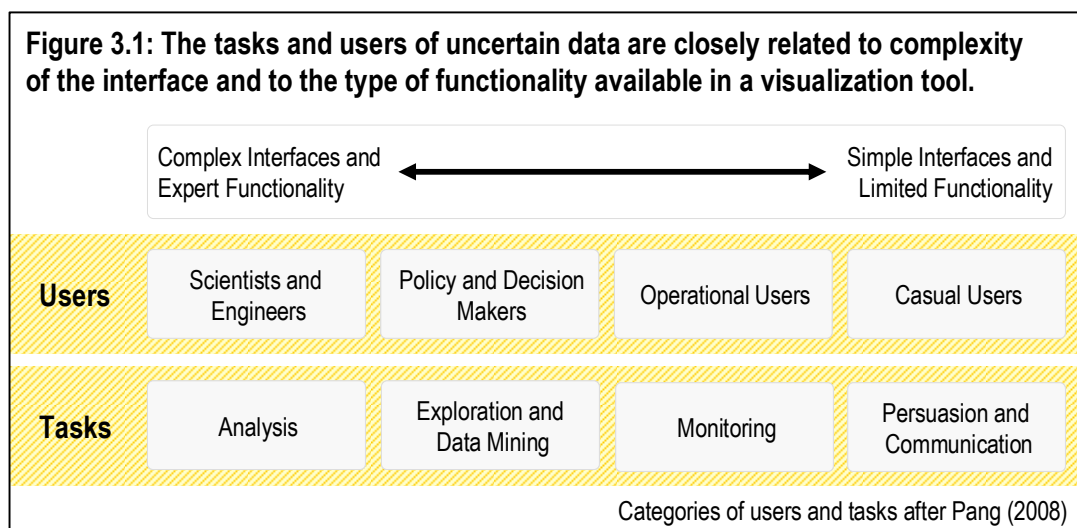
## **3 Visualizing Uncertainty**

Chapter three is a literature review of uncertainty visualization in geospatial data. Since uncertainty visualization is a broad and sometimes confusing topic it is built up incrementally, with each subchapter building upon the content of the previous one. Chapters 3.1 and 3.2 provide a review of higher level concerns such as the role of users, tasks, and scaling in the visualization of uncertainty. Chapter 3.3 moves into cartographic concepts and describes the types of maps which can be used to display uncertainty. Chapter 3.4 focuses on cartographic methods (such as adding lines or modifying colors) which can be used on maps to communicate additional information. Chapter 3.5 lists actual uncertainty representations; representations are a specific visualization which uses one of the predefined cartographic methods to visualize additional uncertainty information. Chapter 3.6 reviews integrated applications which usually implement one or more representations in order to give a complete overview of the uncertainty present in the dataset. Chapter 3.7 focuses on usability and reviews studies which have evaluated uncertainty visualizations.

### **3.1 Users and Tasks**

The needs and tasks of the users of visualizations are all different and Pang (2008) suggests that a “one-size-fits-all” approach, at least with regard to hazard visualization, may not be the right one. For example, a casual user might be more interested in whether their cabin is within a landslide hazard zone, a decision maker with a broader picture is concerned all the cabins in a municipality, whereas a scientist may focus more on improving and understanding the numerical modeling of landslides. Pang (2008) suggests a

division of users which ranges from expert users such as scientists, engineers, and doctors through decision and policy makers to novices such as casual users. Examples of the tasks which they have to perform are analysis, monitoring, exploration, or simply communicating a certain message in an effective way (Pang 2008; Pham et al. 2009). An overview of each these tasks and specific groups of users is shown in Figure 3.1. These relations help to explain why some tasks and objectives (and therefore the visualizations associated with them) are more important to non-expert users, and why advanced analysis tasks may be highly relevant for experts in the field, but that they offer fewer advantages to non-expert users.



Other important aspects of visualization systems are also closely related to users and tasks. Decisions regarding the complexity of the interface of the visualization system and the amount of functionality available are, if a system is to be effective, important to the users and the tasks which they intend to perform (Figure 3.1). Overloading casual users with complex functionality and interfaces may lead to a cognitive overload, whereas not doing so may lead to expert users not being able to fulfill their objectives. This remains a delicate balance which should be considered throughout the design and implementation of any visualization application.



Pham et al. (2009) suggest that visualization traditionally followed a data-driven approach and that visualization techniques in the past therefore naturally followed data formats. The question of whether a data-driven approach is inadequate or outdated remains unanswered. However, Pham et al. (2009) suggest that task-driven approaches to visualization may provide outcomes which are immediately useful in the context of a particular application domain, something which may be well suited to policy and decision makers and operational users within that domain. A drawback of this is that they may be difficult to transfer to other application domains, but as Pham et al. (2009) suggest, this is where user-objective-driven approaches may provide a solution. User-objective-approaches are more goal-oriented, and because objectives (as opposed to tasks) work at a more generic and abstract level, it may be possible to create a “coherent visualization framework that satisfies specific objectives” (Pham et al. 2009).

### **3.2 Scale**

Scaling of uncertainty information is often overlooked in discussions concerning uncertainty visualization. It is important to take into consideration though, especially in light of the previous discussion regarding the increasing importance of users and tasks associated with uncertain information. Bierkens et al. (2000) differentiate between three different types of scale in applied environmental research: observations scale, model scale, and policy scale. The latter two are of most interest to uncertainty visualization discussions. Bierkens et al. (2000) define the model scale as the scale “at which the model provides its output” and the policy scale as the scale “at which the results of the research project are required in order to answer the decision makers’ questions.” With a wide range of models able to produce uncertainty information and with an even broader scope of users and tasks which aim to produce some sort of results or answers using data produced by a model, a conflict is likely to occur. If the results of the analysis are to be trustworthy and representative of the model which produced them, then the model scale must match the policy scale. Overlooking this may

even may even introduce uncertainty into the transformation or visualization stages of the visualization pipeline (Figure 2.1). To resolve this conflict a scale transfer needs to occur, in practice this is often a transfer of information from a smaller to a larger scale. Approaches for the upscaling and aggregation of uncertainty information in are discussed further in Chapter 4.

### 3.3 Cartographic Concepts for Uncertainty Representation

Various authors have outlined uncertainty visualization techniques which can be applied to spatio-temporal datasets in which uncertainty can be expressed in numerical terms (MacEachren 1992; Pang 2008). Before looking into specific methods for adding additional data to a map, several forms of representation can be distinguished amongst these uncertainty visualizations. MacEachren (1992) proposed three different representation concepts, namely map pairs (univariate), sequential, and bivariate. Gershon (1998) used the terms intrinsic and extrinsic to further differentiate between methods of bivariate representation, resulting in four important cartographic concepts for representing uncertainty: univariate representation, sequential representation, intrinsic bivariate representation, and extrinsic bivariate representation.

*Univariate representation* (Figure 3.2a) means that only one variable is represented per display. In order to visualize both data and uncertainty information two displays are required, such as side-by-side maps of data and uncertainty (MacEachren 1992). It is up to the map user to spatially correlate the two variables in their interpretation.

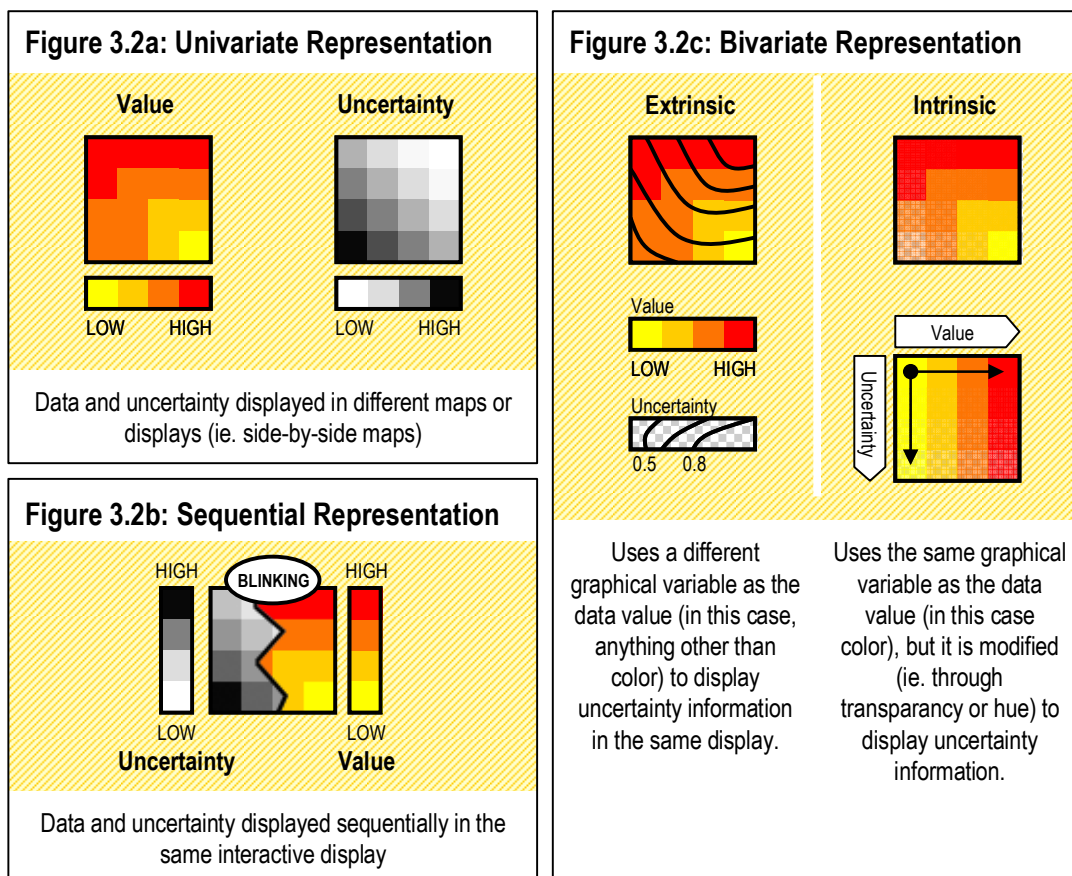
*Sequential representation* (Figure 3.2b) uses a dynamic display to show multiple univariate maps of data quality and data value in a sequential (toggling, fading, flickering, or other types of animation) fashion (Drecki 2002).

A *bivariate representation* (Figure 3.2c) is a combined representation where a attribute value and attribute uncertainty are shown on the same map (Trau and Hurni 2007). An *intrinsic* bivariate representation is one where the same visual variable which is used to display attribute value, is modified to depict attribute

uncertainty as well (Kunz 2011). Examples of this are pseudo-coloring, where value is mapped to color hue and uncertainty to color value, transparency, or saturation (Kunz 2011). An *extrinsic* bivariate representation is one where additional geometry (such as lines, icons, patterns, dials, arrows, or bars) is added to the map to represent uncertainty (Kunz 2011).

### 3.4 Cartographic Representation Methods

There are several cartographic methods which can be used to add supplementary data to a plain map. In regular maps for example, these methods are commonly used to indicate political boundaries (colored lines), elevation contours (isolines with an elevation), hillshading (coloring), mountain summits (triangular glyphs), ocean currents (arrows), or even categorizing land use into forests, swamps, or deserts (using textures).



The uncertainty visualization community has adopted these methods and instead uses them to depict supplementary information about the uncertainty within a map of attribute values. What follows is an overview of the cartographic representation methods at our disposal.

### **3.4.1 Utilization of Graphical Variables**

The most straightforward method of representing uncertainty is through the utilization of free graphical variables like those described by Bertin (1985), these include location, size, value, texture, colour, orientation, and shape. Other authors made additions to this list at later points in time (such as color saturation, transparency, crispness, and clarity). Mapping uncertainty to transparency, lightness, or color saturation are examples of pseudo-coloring and could be considered as an additional “modifying attributes” method. However, if transparency or lightness is not already used in the map it is still a free graphical variable, and therefore such representations of uncertainty are considered to be members of this category.

### **3.4.2 Adding Glyphs**

Glyphs are geometrically plotted specifiers that can encode multiple data dimensions through geometric and appearance attributes (Ward 2002; Pang et al. 1997; Potter 2006). Ward (2002) lists typical geometric attributes such as location, shape, size, and orientation, as well as appearance attributes like color, texture, or transparency. Examples of common glyphs are arrows which can be modified to represent scalar and directional uncertainty when used to represent flow direction (Wittenbrink et al. 1996). Other types of glyphs such as graduated circles can be used to represent the deviation of ensemble members and the number of outliers in an ensemble dataset (Sanyal et al. 2010). Glyphs which are designed for uncertainty visualization can provide a visually pleasing representation of data and uncertainty that is easy to decode for the user (Potter 2006). Glyphs are not without limitations though. The ability to differentiate between colors or size may vary between individuals, displaying too many glyphs

at once may lead to confusion or overlap, and encoding too many data dimensions into the glyph can make it difficult to discern between the individual dimensions (Ward 2002).

### **3.4.3 Adding or Modifying Geometry**

Geometrical objects can be added to a map in order to represent uncertainty. A grid overlay is a common example of adding geometry to represent uncertainty, in an overlaid grid the uncertainty can be represented by varying the thickness, colour, noise, or amplitude of the grid (Cedilnik and Rheingans 2000). Texture overlays (MacEachren 1992) or tessellation trees for categorical data (Kardos et al. 2008) are also geometrical additions to a map which can be used to represent uncertainty. Two recent uncertainty visualizations which can visualize data in ensemble datasets are spaghetti plots (Potter et al. 2009) and graduated uncertainty ribbons (Sanyal et al. 2010), both of which add geometric shapes to the map. Spaghetti plots can be used to examine spatial variations across the members of an ensemble (Potter et al. 2009), and graduated uncertainty ribbons can quantify uncertainty along a contour, the width of the ribbon represents the uncertainty, whereas the color graduation across the ribbon captures the variations between individual ensemble members (Sanyal et al. 2010).

It is also possible to modify geometry already present on the map to represent uncertainty. MacEachren (1992) shows examples of modifying geometry by changing resolution detail or changing the contour crispness of feature boundaries to denote uncertainty. Image discontinuity is a method which can be used as well, and when applied to geometry it means that geometry already present in the image can be translated, scaled, warped, and distorted to visualize uncertainty (Potter 2006).

### **3.4.4 Animation**

Animation can be used in a dynamic display to represent uncertainty. Animation parameters such as a speed, duration, motion blur, and the range or extent of the motion can be used to denote uncertainty (Pang et al. 1997).

### **3.4.5 Interactivity and Information Control**

Interactivity is especially suitable to dynamic displays and offers the possibility to show different levels of uncertainty information based on user requests. Examples of interactivity are a clickable map where uncertainty information can be retrieved by clicking on a particular location (van der Wel et al. 1998), or a small uncertainty inset, where a small area of the map is modified to represent only uncertainty information, depending on where the cursor is located.

### **3.4.6 Others**

Several rather more obscure methods of uncertainty visualization have also been explored in the past. These include using sound parameters such as pitch, duration, timbre, and volume (Fisher 1991) and psychovisual approaches such as stereo pairs and subliminal messages (Pang et al. 1997) to denote uncertainty. The application potential of these methods in a modern web-based environment is very limited.

## **3.5 Representations of Uncertain Data**

A representation is one of the final steps in visualizing uncertainty and it usually implements one of the representation methods discussed previously. For example, the addition of geometry is a cartographic method used in many different representations such as contouring, tessellation trees, texture overlays, or uncertainty ribbons. Table 3.1 shows an overview of various uncertainty representations which have been adopted or invented over the years by researchers in the geovisualization community, and which are suitable for spatio-temporal datasets produced by environmental models. Most of the representations are applicable only to scalar 2D datasets such as raster maps, and while glyphs technically represent point data (0D), a regular grid of many glyphs can also be used to represent 2D data. Some representations (such as “point symbols” and “squares” in Table 1) even use small glyphs which have the same size as one raster cell, thereby mimicking a single pixel and creating a

sense of two-dimensionality. Visualizations for categorical spatio-temporal data are also included.

Multi-value representations have been explicitly included in this list because they form a category of visualizations especially suitable to ensemble datasets. In an ensemble dataset the attribute value of each location is defined by multiple values rather than by a single value. This set of values is considered to be a numerical estimation of a probability density function, and several representation methods exist which are created specifically for visualizing this multi-value data. Representations for single-value data can also be used to represent information from multi-value datasets, but in such cases an additional abstraction using statistical properties of the multi-value data needs to be made first. The newly derived value (such as the standard deviation of all the values in the multi-value dataset) can then be used to visualize uncertainty using a representation for a single-value scalar data type.

A preliminary selection (the “web” column) has been made for visualizations which are suitable for implementation in a web-based environment. These include visualizations which are intuitive, implementable using web technologies, or which are particularly suitable to a particularly common task or objective.

**Table 3.1: Overview of uncertainty representations for continuous and categorical data**

		Representation Method (Ch. 3.4)	Dimensionality	Concept (Ch. 3.3)	Static or Dynamic	Web	Reference or implementation examples
<b>Data Type: Scalar</b>							
01	Pseudo-coloring	Modify Attributes	2D	Bivar Intr	Static		Hengl 2003
02	- Saturation-Intensity	Modify Attributes	2D	Bivar Intr	Static		Hengl 2003
03	- Transparency	Modify Attributes	2D	Bivar Intr	Static	✓	
04	- Fog	Modify Attributes	2D	Bivar Intr	Static	✓	MacEachren 1992
05	Static	Modify Attributes	2D	Bivar Intr	Static		
06	Texture overlay (1)	Modify Attributes	2D	Bivar Intr	Static		
07	Blurriness	Modify Attributes	2D	Bivar Intr	Static		MacEachren 1992
08	Side-by-side	Various	2D	Univar	Both		MacEachren 1992
09	Squares	Add glyphs	0D,2D	Bivar Extr	Static		Drecki 2002
10	Point symbols	Add glyphs	0D,2D	Bivar Extr	Static	✓	Kunz et al. 2011
11	Scattered dots	Add glyphs	0D,2D	Bivar Extr	Static		Kunz et al. 2011

12	Arrowheads	Add glyphs	0D	Bivar Extr	Static	✓	Wittenbrink et al. 1996
13	Circular glyph	Add glyphs	0D	Bivar Extr	Static		Sanyal et al. 2010
14	Texture overlay (2)	Add geometry	2D	Bivar Extr	Static	✓	MacEachren 1992
15	Grid overlay	Add geometry	2D	Bivar Extr	Static		Cedilnik and Reinghans 2000
16	Contour overlay	Add geometry	1D	Bivar Extr	Static	✓	Potter et al. 2009
17	Uncertainty ribbon	Add geometry	2D	Bivar Extr	Static	✓	Sanyal et al. 2010
18	Contour styling	Modify geometry	1D	Bivar Intr	Static		Pang 2008
19	Blinking/random dots	Animation	2D	Bivar Intr	Dynamic		Fisher 1994
20	Sequential pres.	Animation	2D	Sequential	Dynamic		MacEachren 1992
36	Toggling	Interactivity	2D	Sequential	Dynamic		MacEachren 1992
21	Uncertainty inset	Interactivity	2D	Univar	Dynamic	✓	
22	Trend chart	Interactivity	0D, time	Univar	Dynamic	✓	Potter et al. 2009
37	Sound	Other	2D		Dynamic		Fisher 1991
-----							
<b>Data Type: Categorical</b>							
23	Tessellation trees	Add geometry	2D	Bivar Extr	Static		Kardos et al. 2008
24	Contour crispness	Modify geometry	1D	Bivar Intr	Static		MacEachren 1992
25	Fill clarity	Modify geometry	2D	Bivar Intr	Static		MacEachren 1992
26	Resolution detail	Modify geometry	2D	Bivar Intr	Static		MacEachren 1992
27	Blinking regions	Animation	2D	Univar	Dynamic		Kardos et al. 2006
28	Blanket of error	Modify geometry	2D	Bivar Intr	Static		Buttenfield and Weibel 1988
-----							
<b>Data Type: Vector</b>							
29	Arrows	Add glyphs	0D	Bivar Extr	Static		Wittenbrink et al. 1996
-----							
<b>Data Type: Multi-Value</b>							
30	Grad. uncert. ribbon	Add geometry	2D	Bivar Extr	Static	✓	Sanyal et al. 2010
31	Spaghetti plots	Add geometry	1D	Bivar Extr	Static		Potter et al. 2009
32	Grad. circular glyphs	Add glyphs	0D	Bivar Extr	Static		Sanyal et al. 2010
33	Plume trend chart	Interactivity	0D, time	Univar Extr	Static	✓	Potter et al. 2009
34	Histogram	Interactivity	0D	Univar Extr	Static	✓	
35	Quartile trend chart	Interactivity	0D, time	Univar Extr	Static	✓	Potter et al. 2009

### 3.6 Integrated Applications for Visualizing Uncertainty

Several digital applications for visualizing uncertainty have been developed in the past. What follows is a chronological overview of a selection which have implemented one or more uncertainty representations listed in Table 3.1. Unless specifically mentioned these are not web applications but thick clients running on a dedicated system.

Cliburn et al. (2002) developed a decision support system for a water balance application in which various uncertainty visualizations are embedded. The



system is unique in that it is intended to be displayed on a 7.5m by 2m wall display. It uses both intrinsic (pseudocoloring) and extrinsic (line glyphs) visualizations of uncertainty in water balance model outputs. Their evaluation of the system deserves merit as well. By using an iterative process of usability engineering with regular feedback moments with domain experts, decision makers, and usability experts they were able to improve their own system and suggest various interface and usability guidelines which similar systems in the future could adopt.

Pebesma et al. (2007) developed *Aguila*, an interactive tool for visualizing spatio-temporal datasets which have attribute values encoded as probability density functions. The application can dynamically generate map views for quantiles, exceedance probabilities, and classified probabilities such as approximate 90% prediction interval (Pebesma et al, 2007). In addition to this the user can zoom or pan on the map, compare scenarios, change the time cursor to move through modeled timesteps, and examine at various charts and graphs (Pebesma et al, 2007). While the usability of the tool has not been reviewed extensively, it requires some time and skill to operate (Senaratne et al. 2012; Gerharz and Pebesma 2009) and therefore seems suitable mostly to expert or users with some prior experience or training.

Potter et al. (2009) developed *Ensemble-Vis*, a framework for the statistical visualization of large volumes of ensemble data. They use a broad spatial summary view and a “filmstrip” approach to let the user move through timesteps. In addition, various plume trend and quartile charts are utilized, as well as the option to execute conditional queries which let the user select ranges of attribute values; contour line representations are then used to denote the fraction of ensembles whose predictions match the user selected conditions.

Sanyal et al. (2010) developed *Noodles*, a tool for the visualization of numerical weather model ensemble uncertainty. Noteworthy about their research is the development of various novel uncertainty representations, such as graduated circular glyphs where the graduations describe characteristics of the underlying population, and graduated uncertainty ribbons which describe uncertainty along a

specific contour. They also implemented a bootstrapping algorithm and a regular grid of circular glyphs to show spatial patterns of uncertainty.

Gerharz et al. (2012) developed a web application for uncertainty visualization in the model web. It offers two view modes: side-by-side maps and a bivariate display in which uncertainty and data are embedded. In addition to these features it contains visualizations of maps, statistical plots, timeseries, and user inputs to specify uncertainty thresholds.

### **3.7 Evaluating Uncertainty Visualizations**

Compared to the development of new uncertainty representations much less empirical research has been done to evaluate whether visualizations work and how effective they are (MacEachren et al. 2005). MacEachren et al. (2005) provide two criteria which are important in the evaluation and assessment of uncertainty visualizations. The first criteria is the *usability* of uncertainty representations and the interfaces for using those representations, and the second criteria is the way in which information uncertainty is *used* and how it affects further information analysis and decision making.

#### **3.7.1 Usability of representation methods and manipulable interfaces**

The usability of uncertainty representation techniques has also been tested in various studies. An important conclusion from this review which is shared by Gerharz and Pebesma (2009) is that there are many conflicting findings depending on the users, the purpose, and the design of the study. There seem to be some indications that displaying uncertainty in bivariate extrinsic maps is relatively comprehensible, but the evidence is clearly not conclusive.

In terms of representation methods, generally positive responses were found to texture overlays (MacEachren et al. 1997; Leitner and Buttenfield 2002) and pseudocoloring using lightness (Leitner and Buttenfield 2002), and variations of circular or square symbols or glyphs (Senaratne et al. 2012; Sanyal et al. 2009; Drecki 2002; Edwards and Nelson 2001). Mixed to negative reviews were found for flickering (Monmonier and Gluck 1994; Evans 1997), intrinsic pseudocoloring

using saturation or other color combinations (Leitner and Battenfield 2002; MacEachren 1994; Schweizer and Goodchild 1992), and side-by-side maps (Senaratne et al. 2012, Edwards and Nelson, 2001). An additional concern is the lack of recent studies and the abundance of inconclusive evidence. Many of the usability studies were undertaken with primitive outdated interfaces and evaluate only qualitative rather than quantitative indicators of uncertainty.

Not many modern systems were evaluated extensively. Cliburn et al. (2002) form an exception in their evaluation of a decision support system in a water balance application. They warn for visually overloading the display and after testing sessions with domain experts they added various features to improve the manipulable interface of the application. These include orthogonal (flat) views of surfaces rather than 3D images, options for adding references such as country boundaries or coordinate grids, and interactive legends on each display. Senaratne et al. (2012) provide a recent overview of the usability of various methods, also taking into account the domain expertise of the interviewees. The survey setup seems chaotic though, conditions and maps under which the methods were tested were not identical, and videos were used to evaluate interactive methods such as desktop and web clients. Concluding that the most suitable spatio-temporal uncertainty visualization for all the tested domains of expertise is “contouring” because most interviewees in each group selected it as their favorite is premature.

### **3.7.2 Use of information uncertainty**

The *use* of information uncertainty is a topic which has not been extensively researched and it is therefore difficult to draw any definite conclusions. The way in which information uncertainty is used in making decisions or performing an analysis may be influenced by a range of factors such as experience, visualizations or interfaces. Kobus et al. (2001) investigated the effects of uncertainty and the level of experience in determining a course of action in the context of military operations. They found that after assessing uncertain information, experienced individuals needed less time to decide on a course of

action than individuals with little experience, where usage of certain information required approximately equal time for both groups. Deitrick (2007) found that uncertainty visualizations may influence decision making, but that the “degree of influence may be governed by the decision task and not solely by the visualization technique,” a conclusion with which Sanyal et al. (2009) concur. Leitner and Buttenfield (2002) concluded that the inclusion of attribute certainty modified and led to improved spatial decision making for various visualization methods. They also found that for easy tasks the response times decreased when certainty information was included in the map.

It can only be concluded that as with the visualization of uncertainty, the *evaluation* of the visualization of uncertainty is an equally complex topic for which neither best practices nor solid foundations have yet been established.

## **4 Improving Uncertainty Visualizations for the Web**

The literature review presented in the previous chapters makes it clear that despite different visualization concepts, numerous methods of representing uncertainty present in a map, and many different representation techniques, the inherent challenges and problems associated with the visualization of uncertainty are not yet addressed satisfactorily. Many of the visualizations presented are an adequate solution to a specific problem, but often leave much to be desired in other aspects of the visualization. Complex visualizations may be beautiful and superbly implemented, but they risk cluttering the display when zooming out or result in a cognitive overload and may lead to alienation of non-expert users. Simple visualizations on the other hand are understandable, but they in turn lack the complexity which is required by expert users to do any sort of useful analysis on the data. The strengths of the web as both a visualization and communication platform to a worldwide audience of experts and novices alike are also underused. To improve the visualization of uncertain information on the web a conceptual end-to-end solution is developed in this chapter. It aims to sacrifice on the breadth of visualization techniques and methods outlined in the previous chapters in favor of a narrower, dynamic, and usable end-to-end solution.

### **4.1 Design Guidelines**

Visual design guidelines for information exploration were developed well before the onset of the web. Shneiderman (1996) summarizes visual design guidelines with a “visual information seeking mantra”, repeating it to stress its importance: “overview first, zoom and filter, then details-on-demand.” While Shneiderman’s (1996) mantra was not specifically aimed at geospatial visualization, the tasks

involved apply equally well, and form not only an excellent starting point, but they also serve as a guideline for further development of visualizations, interfaces, and other features. The tasks described by Shneiderman (1996) are summarized in Table 4.1.

**Table 4.1: Visual design guidelines**

<i>Task</i>	<i>Description</i>
Overview	Gain an overview of the entire collection
Zoom	Zoom in on items of interest
Filter	Filter out uninteresting items
Details-on-demand	Select an item or group and get details when needed
Relate	View relationships among items
History	Keep a history of actions to support undo, play, and progressive refinement
Extract	Allow extraction of sub-collections and of the query parameters

Source: Shneiderman 1996

The web application should implement a similar design: a map which provides an overview and zooming functions, a way to filter the information, and functionality for getting more details which may be required by expert users.

## 4.2 Requirements

The requirements provide a more detailed outline of what the web application should be able to do, what the technical requirements are, at what type of users it is aimed at, and what tasks they may be able to perform with the application.

### 4.2.1 Models and Data Types

The web application is aimed at the visualization of numerical ensemble models which produce multi-value scalar datasets, meaning that an individual map with a scalar attribute value exists for each model attribute, for each ensemble, for each timestep.

### 4.2.2 Technical Requirements

The technical requirements of the web application are as follows:

- Be accessible through any modern browser connected to the internet

- Support various visualization techniques, as well as a framework for adding new visualization routines as plugins.
- Support various types of environmental models, as well as a framework for adding new types of model as plugins.
- Be implemented, where possible, using open-source technology.

### **4.2.3 Users and Tasks**

As a major strength of web-based applications lies in their universal accessibility, the aim remains to develop an application which is accessible and usable for users of any level of expertise. This does not mean that non-expert users should be able to perform expert tasks, as this would invariably require extra training, experience, or domain expertise not present in non-expert users. It does mean however that the interface and visualizations should be designed in a way that non-expert users can at least execute tasks which are at their level of expertise, and that more complicated aspects of the application degrade gracefully for less experienced users. Therefore features which only experts use should not clutter the interface for non-experts. The intended users of the web application are therefore broad:

- Non-experts and casual users
- Operational users
- Policy and decision makers
- Scientists, engineers, and domain experts

While initially a web application may face some functional limitations regarding expert functionality (i.e. due to bandwidth bottlenecks, restrictions in technology), there are also some specific advantages for expert users. Most prominently, they can share model results with their peers regardless of geographical location and without worrying about whether a certain application for viewing the model results is installed. In future versions, collaboration is also an option, in such a scenario other experts could comment on the model results, assist in the analysis,

propose changes, or even tweak input parameters and run the model remotely under a different scenario. It is in these aspects that a web based application shows its virtue, and any short term limitations will in the long term be outweighed by the advantages. However, for now the tasks defined in the requirements of the web application are of a simpler nature:

- To distinguish *spatially* between areas of high uncertainty and areas of low uncertainty.
- To *quantify* the uncertainty present in an area using various uncertainty metrics.
- To estimate the *probability* of categorized attribute value intervals occurring.
- To be able to tell *when in time* certain events (with regard to uncertainty or probabilities) occur.

While the aim is to have experts and non-experts be able to execute all the tasks, the extent to which this is realistic, especially for the latter group is difficult to estimate beforehand and will need to be determined by the results of the user study.

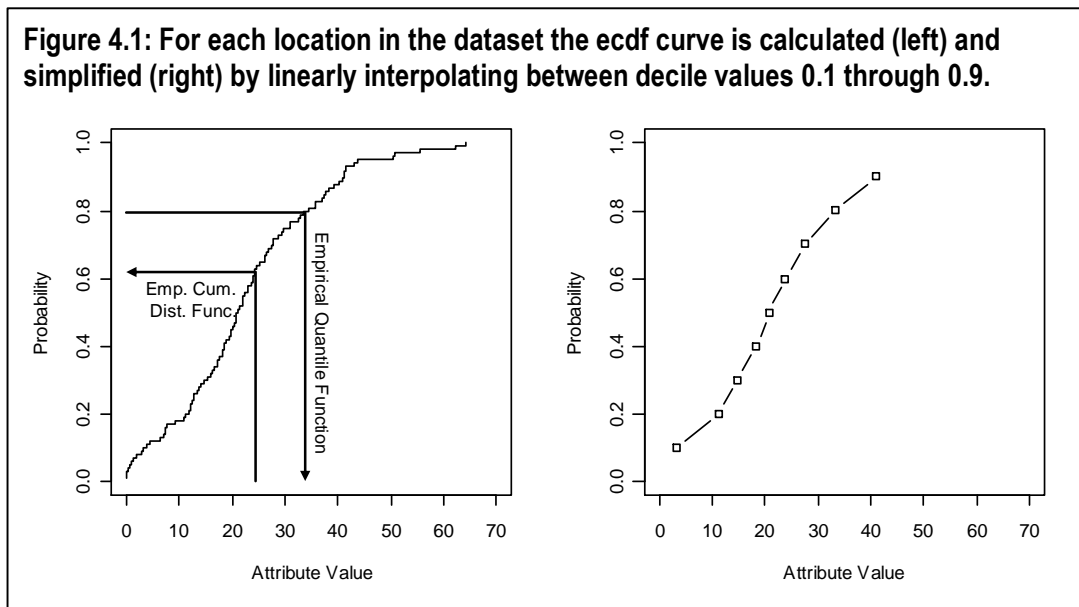
### 4.3 Uncertainty Metrics

The uncertainty in a geospatial dataset needs to be quantified in order to be visualized in an effective manner. The web application will use only a subset of possible Type A methods (Figure 2.3) to calculate various *uncertainty metrics*. These metrics are an abstraction of the original data and form a quantitative representation of the uncertainty in a particular location in the dataset. The metric, irrespective of whether it is the standard deviation, a confidence interval, a probability, or a custom metric derived especially for a particular model or dataset, can then be visualized by mapping its value to a glyph, a color, a classification, or another form of cartographic representation.

In the multi-value ensemble datasets which are the focus of this project, the  $n$  attribute values at a specific support and timestep are considered to be  $n$  samples from a continuous random variable with an unknown distribution.



Together, these sample values  $X$ , further denoted as  $X = (x_1, x_2, \dots, x_n)$  for  $n$  ensembles, are as a *group* representative of a geographic region, and they are later used in the calculation of an uncertainty metric for this region which can be integrated into the map. During the visualization processing, the ordered sample values of  $X$  are also used to calculate an *empirical cumulative distribution function* (ecdf). The ecdf is a numerical estimation of the unknown true cumulative distribution function (cdf). The ecdf is a step function calculated from the ordered samples, and gives the proportion of samples in the dataset  $X$  which are less than or equal to a specific value (Dekking et al. 2005). Figure 4.1 (left) shows a sample ecdf calculated from 100 ensembles.



The inverse of this function is the *empirical quantile function*<sup>3</sup>, which is used to calculate empirical quantiles of the samples in  $X$  using the ecdf as is shown Equation 1 (Jones 1992).

$$Q_n(p) = x_{(1)} + \sum_{i=2}^n (x_{(i)} - x_{(i-1)}) I \left[ \frac{i-1}{n} < p \right] \quad (\text{Eq. 1})$$

<sup>3</sup> In the actual visualization routine described in Chapter 5.2 the `mquantiles` function in Scipy is used (see <http://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.mstats.mquantiles.html> for more info) with values of `alpha=0` and `beta=1`, yielding the same results as Equation 1.

Where  $x_{(1)}, x_{(2)}, \dots, x_{(n)}$  are the order statistics of the original sample,  $n$  is the total number of samples, and  $p$  is a probability between 0 and 1. The function  $I$  is an indicator function which resolves to 1 if the condition within the square brackets is met and is 0 otherwise. Implementing a discretization approach similar to Pebesma et al. (2005), Equation 1 is used to further simplify the ecdf by calculating  $Q_n$  only for the deciles 0.1 through 0.9, thereby reducing the storage requirements of the ecdf curve while still preserving its shape, as shown in Figure 4.1 (right). The discretized ecdf curve is used in calculating various uncertainty metrics.

Uncertainty metrics used in this project which are used to quantify uncertainty in a specific region are the sample standard deviation (STDEV), inter-quartile range (IQR), the width of the 95% confidence interval for the mean (CI), the median of absolute deviations (MAD) (Sanyal et al. 2010; Dekking et al. 2005), interval probabilities (PROB), and an experimental metric dubbed legend uncertainty (LEGQ).

#### *Standard Deviation (STDEV)*

The sample standard deviation of the samples in  $X$  is calculated with Equation 2:

$$STDEV = s_n = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x}_n)^2} \quad (\text{Eq. 2})$$

#### *Interquartile Range (IQR)*

The IQR metric is defined by the range between the 25th and 75th percentiles. The value of the 25th and 75th percentile is calculated using Equation 1, resulting in the calculation of the IQR as per Equation 3.

$$IQR = Q_n(0.75) - Q_n(0.25) \quad (\text{Eq. 3})$$

#### *Width of the 95% Confidence Interval (CI)*

The width of the 95% confidence interval is calculated using the function described in Equation 1, and implemented as shown in Equation 4:

$$CI = Q_n(0.0.975) - Q_n(0.025) \quad (\text{Eq. 4})$$

In this case the *CI* metric denotes the width of the interval in which 95% of the samples fall, resulting in an interval with edges at the tails of the distribution. In some cases however, when information about the uncertainty of the *ensemble mean* is requested, a different method can be used. The reason for this is that the spread of the sample mean is much smaller, in such cases the 95% confidence interval *for the mean* may be calculated using large sample confidence intervals. The values in *X* are again treated as *n* random samples from an unknown distribution with an unknown mean. A variant of the central limit theorem states that as the number of samples increases, the distribution of the studentized mean approaches the standard normal distribution (Dekking et al. 2005). Therefore, if *n* is large enough, the width of the 95% confidence interval (at which  $\alpha=0.05$  and the z-score  $z_\alpha=1.96$ ) for the mean may be approximated by Equation 5 (Dekking et al. 2005).

$$CI = \left( \bar{x}_n + 1.96 \frac{s_n}{\sqrt{n}} \right) - \left( \bar{x}_n - 1.96 \frac{s_n}{\sqrt{n}} \right) \quad (\text{Eq. 5})$$

The implementation discussed in Chapter 5 and 6 uses Equation 4 to calculate the confidence interval metric.

#### *Median of Absolute Deviations (MAD)*

Using the median of absolute deviations (MAD) to quantify uncertainty is uncommon, but it provides a more robust measure of variability which is hardly affected by outliers (Dekking et al. 2005). It is obtained by first calculating the absolute deviation of all the sample values to the sample median, and then taking the median of all those absolute deviations (Dekking et al. 2005), as shown in Equation 6:

$$MAD = Med(|x_1 - Med(X)|, |x_2 - Med(X)|, \dots, |x_n - Med(X)|) \quad (\text{Eq. 6})$$

### *User-Defined Interval Probabilities (PROB)*

The user-defined interval probabilities (PROB) reflect the probability that a sample in  $X$  falls within predefined upper and lower boundaries ( $x_{upper}$  and  $x_{lower}$ ) which can be chosen arbitrarily by the user. The probability is derived by implementing Equation 1, which interpolates the simplified ecdf curve shown in Figure 4.1 to obtain a probability for an attribute value lower than  $x_{upper}$  and  $x_{lower}$ . These probabilities are then subtracted and multiplied by 100 to be represented as a percentage, as shown in Equation 7:

$$PROB = 100 \times (Q_n(X_{upper}) - Q_n(X_{lower})) \quad (\text{Eq. 7})$$

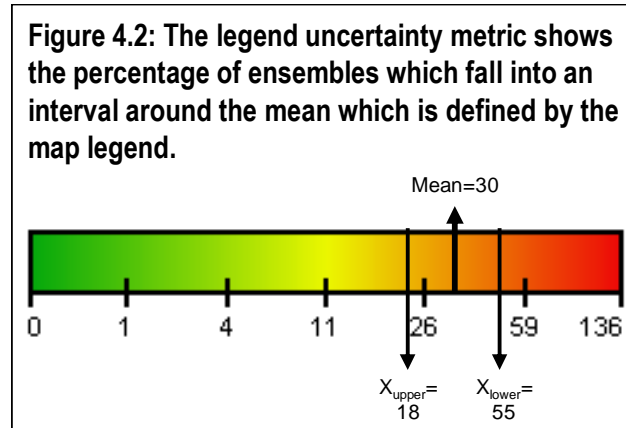
### *Legend Uncertainty (LEGQ)*

The legend uncertainty metric evaluates the percentage of samples in  $X$  which fall within a custom confidence interval around the attribute value shown in the background map, which is usually the ensemble mean. The upper and lower boundaries ( $x_{upper}$  and  $x_{lower}$ ) of this interval are determined on the basis of the map legend and the transformation used in the visual display mapping of the attribute values. The idea is that the uncertainty of contextual information which is present in the display of the map (i.e. red areas for *high* or *dangerous* levels and green for *low* or *safe*) is evaluated. For a map showing the ensemble mean, the metric answers the question “what is the probability that the map of the ensemble mean is *actually red* or *actually green* in this specific area?” The metric is implemented in the same way as the user-defined probability interval (Equation 7), but the upper ( $x_{upper}$ ) and lower ( $x_{lower}$ ) boundaries of the interval are not determined by user input, but calculated automatically using Equation 8:

$$(x_{upper}, x_{lower}) = \bar{x} \pm (T(a) \times \bar{x}) \quad (\text{Eq. 8})$$

Where  $a$  is an arbitrary factor which defines the width of the interval ( $a=0.1$  was used in the implementation discussed in Chapter 5 and 6, in which case it is loosely coupled to the number of colors in the map legend), and  $T$  is a

transformation function which depends on the transformation used in the map legend. If the legend is linear,  $T$  is 1, but it may differ for a logarithmic map, resulting in a value for  $x_{lower}$  which is (in absolute terms) closer to the mean than  $x_{upper}$ , as is shown in the example in Figure 4.2.



#### 4.4 Upscaling

Through zooming in and out, a conceptual link is made between the zoom level and the amount of detail which is desired by the user. Zooming in means the user desires detailed information at a smaller scale, and zooming out is interpreted as a request for aggregated information at a larger scale. To accommodate this, the support size used in calculating the uncertainty metrics outlined in Chapter 4.3 is linked to the zoom level. This allows both attribute value and attribute uncertainty to be explored at a range of different scales. An aggregation algorithm is applied to the individual ensembles to ensure that when the map is zoomed out the uncertainty metrics are still representative of the underlying data. Equation 9 (adapted from Bierkens et al., 2000) is used for upscaling and aggregation the data from their native support size  $s_1$  to a larger support  $s_2$ :

$$z(s_2) = \frac{1}{n} \sum_{i=1}^n z(s_1; i) \quad (\text{Eq. 9})$$

Where  $n$  is the number of support units at a support of  $s_1$  which are required for calculating the support  $s_2$ , and  $i$  represents each individual support unit at  $s_1$

which is used for calculating  $s_2$ . Essentially it is an algorithm which averages the  $s_1$  values within the newly created region represented by  $s_2$ . The aggregation algorithm is applied to the entire dataset: for every zoom level, for every attribute, for every ensemble, for every timestep.

There are two map spaces where the upscaling can be applied. The first is to apply the upscaling to the original raster *before* it is projected. In this case the support size of the data value or uncertainty metric is directly proportional to the original raster cells. If the original support  $s_1$  represents one raster cell, then the number of units  $n$  within a larger support is an exponential function of the desired support level.

The second approach is to warp the original raster data into the output projection which the map viewer requires, and to apply the upscaling algorithm *after* the reprojection. Rather than defining a support size as a number of exponentially increasing individual raster cells, it becomes a function of the map scale and zoom level and is defined instead using coordinates defined in the output projection. Whichever support units at support  $s_1$  fall within this region (completely or partially) as a result of the reprojection are then used to calculate a new aggregated value at support  $s_2$ . Each approach has advantages and disadvantages which must be weighed by the map user. The upscaling in this project is applied to the original dataset, resulting in an upscaled grid which looks slightly warped in the map viewer as a result of the reprojection.

#### **4.5 Uncertainty Representation Using Glyphs**

Various authors (Wittenbrink et al. 1996, Sanyal et al. 2010, Kunz 2011, Drecki 2002) have used glyphs to represent uncertainty in geospatial data. Further evaluation studies have also confirmed that glyphs are an effective method for communicating uncertainty (Sanyal et al. 2009). This has led to the decision to incorporate and use glyphs in improving uncertainty visualizations for the web. Several characteristics of glyphs-based visualizations support this decision:

- Glyphs allow for an extrinsic bivariate display where data value and uncertainty are clearly recognizable in a single map. This lets map users of different levels of expertise to differentiate between data value and uncertainty.
- Glyphs allow more than one data dimension to be encoded. For example, a mean value could be mapped to the glyphs size and the standard deviation could be mapped to the color.
- Glyphs are easily understood and their meaning degrades gracefully for less experienced users. An expert can recognize all of the attributes in a glyph and thereby interpret all of its dimensions. However, the meaning of the glyph is not entirely lost on a novice as he may still be able recognize at least the size or color of the glyph, and thereby interpret at least one of its underlying data dimensions.
- Careful placement of glyphs in a 2D space can preserve spatial patterns in the uncertainty data which would be difficult to discern when intrinsic visualization methods are used.
- A grid of glyphs representing aggregated raster information requires a relatively low number of glyphs to fill the map screen. This results in a smaller amount of bandwidth than it would take for raster images to fill the same space. It is therefore easier for the glyphs to be updated instantaneously, or trigger events as a response to a user action such as filtering, queries, requesting more information, or interactions like mouse clicks or hovering.

There are also some potential pitfalls and weaknesses that have been considered in using a glyph-based uncertainty display. In addition to the limitations addressed in the literature review several others have also surfaced during this research. First, the values of one data dimension in the glyph may compromise legibility of another data dimension. This occurs most noticeably with size; when a glyph becomes very small because size is mapped to a particular variable then the color, transparency, or any other attribute becomes difficult to differentiate. The second risk is that a glyph is technically always a point specifier. As a result, when a glyph is positioned in the design in a way that

suggests that it represents anything other than a single point or cell (such as an area or region on the map) a transfer of scale problem occurs. Subsequently, to be able to use glyphs to represent spatial patterns and values in a map which supports different zoom levels it is nearly always required to perform an upscaling or aggregation algorithm before mapping a data value to a glyph.

#### **4.5.1 Circular Glyphs**

Circular glyphs which map a previously discussed uncertainty metric to the size attribute of the glyph have been chosen for further development in the web application. Their simplicity allows less experienced users to work with them, positioning in a grid preserves spatial patterns, and because the glyph is relatively simple there is still potential for adding other data dimensions to unused attributes such as color or transparency at a later stage. Nearly identical solutions of mapping uncertainty to the size of a simple glyph have been explored by Sanyal et al. (2010) (filled or graduated circles), Kunz (2011) (filled circles or scattered dots), and Drecki (2002) (small squares instead of circles). The approaches by Kunz (2011) and Drecki (2002) map the glyph to a single cell, thus restricting usage to cases where individual raster cells are so large that it is possible to render a glyph in it, unfortunately analysis at a larger scale is therefore difficult. The solution by Sanyal (2010) shows the circular glyphs in a grid on a larger scale, but the glyphs seem to represent only a single point or cell at the geographic location where the glyph is rendered. Visually, the glyph looks to represent an area or region, but the value mapped to the size attribute is that of a single cell, resulting in a mismatch between the model scale and the scale the glyph represents in visual terms. The implementation of circular glyphs as proposed in this chapter attempts to subvert these problems by applying the previously discussed upscaling algorithm.

#### **4.5.2 Placement**

The placement of the glyphs will be in the center of the support which the glyph represents. A gridded surface with the size of the support will also be overlaid on



the map so that it is clear what area the support of the glyph covers. Due to reprojection which may need to take place between the original projection in which the model was run, and the pseudomercator projection used by web mapping clients, the grid may be warped or distorted slightly in the final map view.

### 4.5.3 Interactivity

Because glyphs have low bandwidth requirements and are usually rendered as vector objects (therefore their graphical attributes can be manipulated easily) they are especially suitable to user interaction. Table 4.2 shows three proposed interaction types for the uncertainty glyphs.

**Table 4.2: An overview of the glyph interactions proposed for the web application**

Interaction	Result
Hovering (mouse)	Hovering the mouse over the glyph will show a <i>popover</i> , a small box which disappears again when the mouse leaves the glyph. The popover shows the exact value and the metric to which the size of the glyph is currently mapped. This prevents users from having to compare glyph sizes with a size in the legend.
Clicking (mouse)	Clicking the glyph will open a <i>popup</i> which displays a region summary showing all the metrics calculated for the region that the glyph represents. The region summary will also allow the user to explore graphical summaries of the data.
Filtering (user selection)	Filtering takes place in the map legends where the user can select which uncertainty metric he wishes the glyphs to represent. Selecting a different metric will instantaneously update all the glyphs (and associated interactions) within the map screen. Interval probabilities can also be selected using sliders, after which the glyphs once again update themselves to represent the interval probability the user selected.

## 4.6 Uncertainty Representation Using Graphical Summaries

Graphical summaries are commonly used when condensing a dimension in a dataset to a single uncertainty metric is not the most viable option. They are often a visual representation of larger volumes of data corresponding to a slice of data, visualized through a specific dimension like time or location. In the web application graphical summaries are seen as uncertainty representations aimed mostly at experts in the “details-on-demand” phase of Shneiderman’s (1996)

visual information seeking guidelines, the graphical summaries can be shown through interaction (clicking) on the uncertainty glyph.

#### 4.6.1 Spatial dimension

Table 4.3 shows two graphical summaries which represent data in the spatial dimension, meaning that variability in time is not shown. To view the summary at a different time, the user must first select a different timestep.

**Table 4.3: Overview of suitable graphical summaries through space**

Name	Description
Histogram	A histogram is a bar chart which shows the number of ensembles in specific intervals (bins), and it gives an approximation of the distribution of the ensemble values at a specific location. There are various methods of choosing bin widths (Dekking et al. 2005) but in the web application a fixed number of 25 bins are chosen between the maximum and minimum ensemble values.
Cumulative Probability Density Function	By linearly interpolating between the ordered ensemble values a cumulative probability density function can be constructed. Experts can use the CPDF to estimate the probability of certain threshold values occurring. The shape of the curve can also be indicative of uncertainty.

#### 4.6.2 Time dimension

Where spatial summaries present a large amount of data about a certain point in time, it is also possible to explore how this data (or its derived metrics) change in the time dimension. Several graphical summaries are proposed in Table 4.4.

**Table 4.4: Overview of suitable graphical summaries through time**

Name	Description
Quartile trend chart	A quartile trend chart (Potter et al. 2009) shows the quartile range of the ensembles through time for the region represented by the glyph. The minimum and maximum value are shown, and the regions between the 5th and 95th percentile, and the 25th and 75th percentile are shaded. It thus gives an indication of uncertainty through time and can help answer questions regarding <i>when</i> certain attribute values occur.
Probability interval timeseries	When a certain probability interval or class (i.e. “dangerous” or “safe”) is selected by the user, a chart can be created of the probability of this class occurring through time. It can help experts to answer questions about <i>when</i> the probability of a certain interval occurring changes or passes through a certain threshold.

Plume trend chart	<p>A plume trend chart (Potter et al. 2009) shows a single parameter (most commonly the mean) of each ensemble through time. The dispersion of each of the lines indicates uncertainty, and expert users can also use a plume trend chart to differentiate groups of ensembles which show similar behavior.</p>
Parallel coordinates	<p>Parallel coordinates (McDonnell and Mueller, 2008) are a technique to visualize multidimensional data which could potentially be applied to plume trend charts. Using an interactive parallel coordinates display experts could identify clusters of ensembles and interactively trace them through time to identify certain patterns.</p>

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## 5 Visualizing Uncertainty on the Web

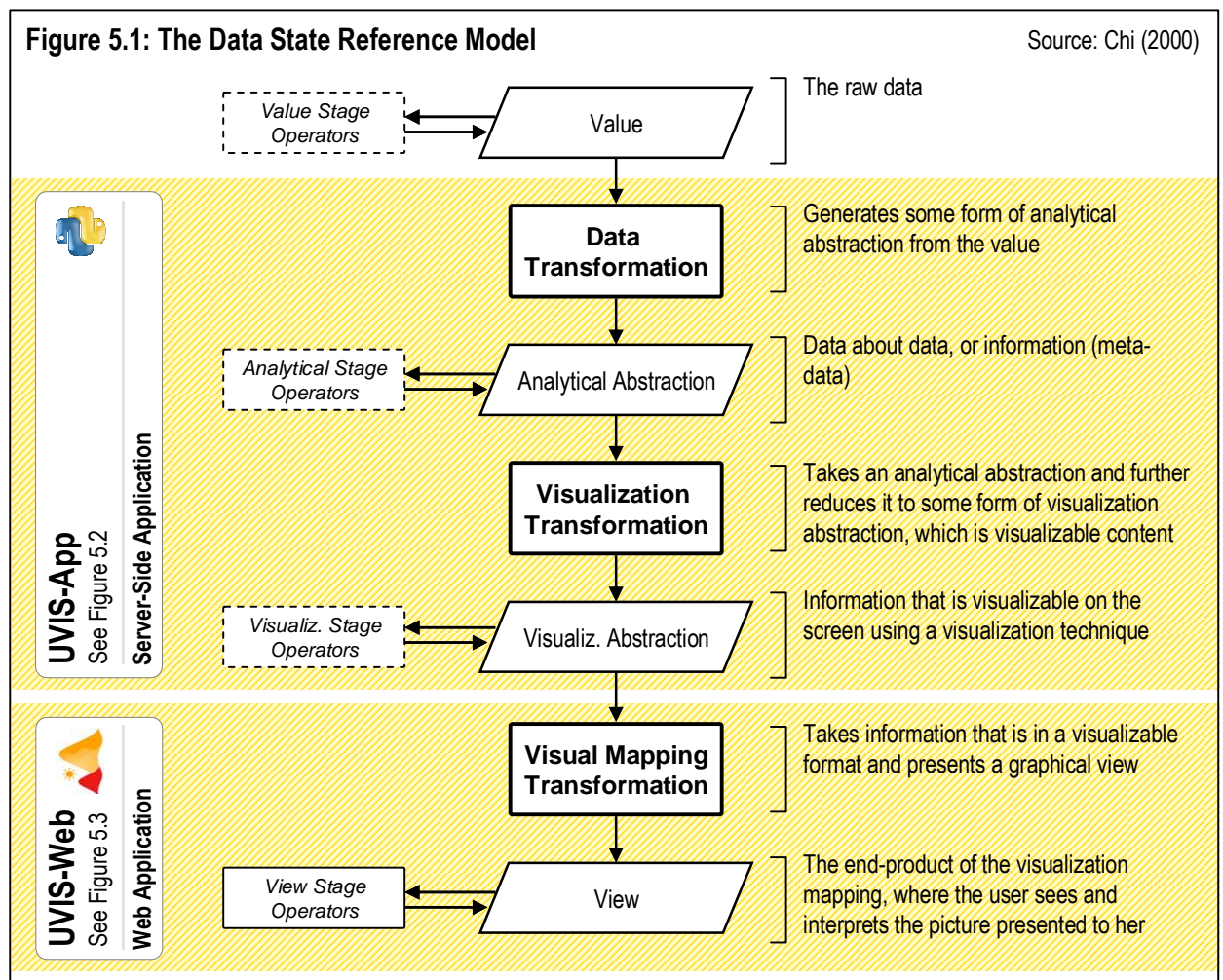
This chapter details the technical implementation of a web application prototype (UVIS) using a selection of techniques and methods described in the previous chapter *Improving Uncertainty Visualization for the Web*. The UVIS processing and visualization routines are implemented after an information visualization model called the *Data State Model*.

### 5.1 Implementation of the Data State Model

The *Data State Model* (Chi and Riedl 1998; Chi 2000) is a taxonomy of information visualization techniques which breaks the techniques down into data stages, data transformations, and within-stage operators. In the context of this research it is used to define how a geospatial dataset passes through different sections of the processing chain and to clearly establish where, and using what programming code and methods, each operation is carried out. Figure 5.1 shows the information visualization data state reference model as defined by Chi (2000). The individual stages are denoted by a parallelogram whereas the transformation operators which allow data to be transformed from one stage into another are denoted in bold by the rounded rectangles. There are also within-stage operators which do not alter the data structure or data stage, but can perform operations such as filtering or normalization which may be required within a particular data stage (Chi 2000).

The technical implementation of the web application is split into two parts as is shown in Figure 5.1. The first is a server side application (UVIS-App) written in

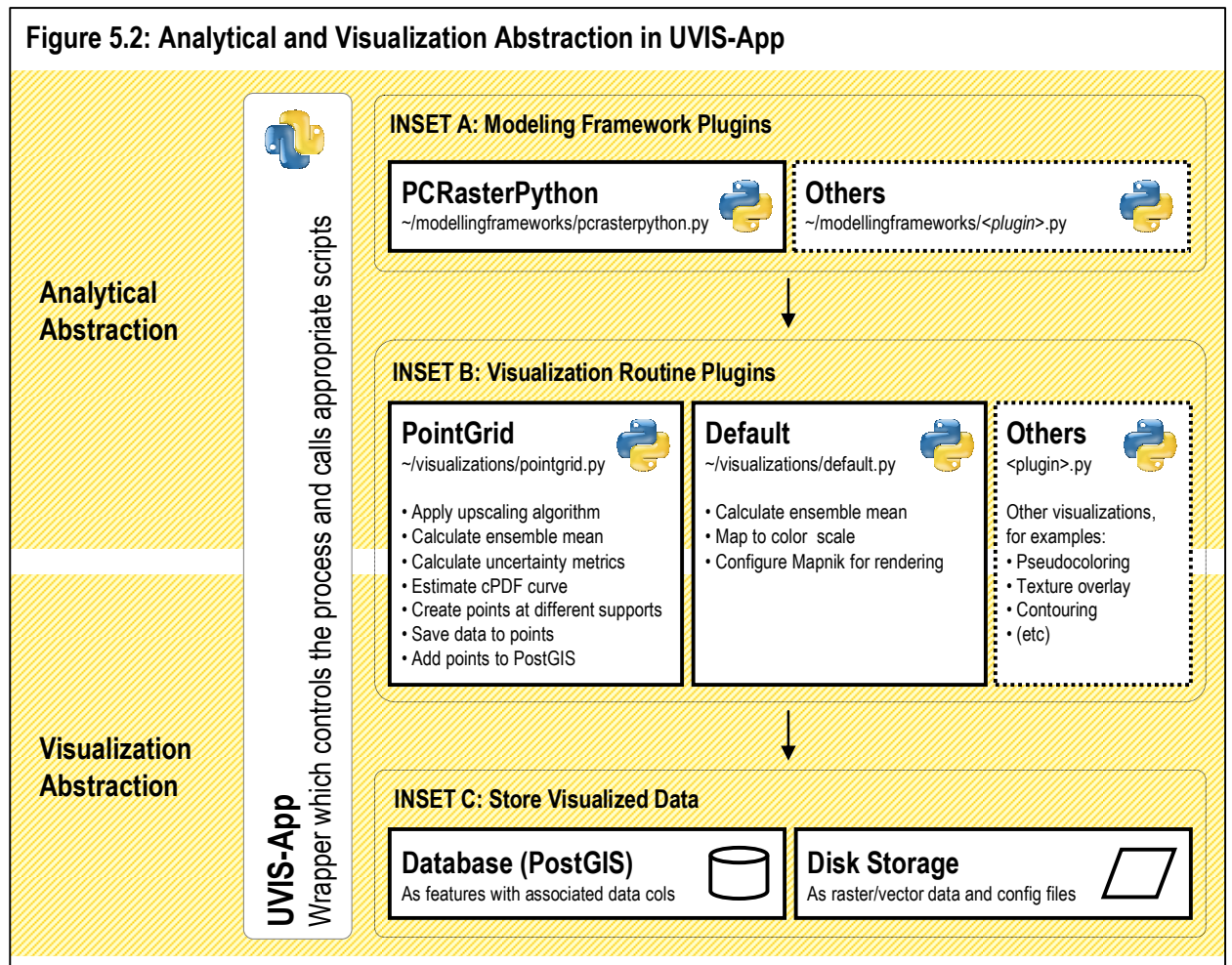
the Python programming language<sup>4</sup> which is responsible for transforming the geospatial dataset from raw data through an *analytical abstraction stage* to a *visualization abstraction stage*, where the output data is directly visualizable on the screen using a visualization technique. The second part is a web application (UVIS-Web) which takes information which is in the *visualization abstraction stage* (as produced by UVIS-App) and transforms it through the *visual mapping transformation stage* to an end-product in the browser which the user can see and interpret. The *within view stage operators* are client-side operations which allow for dynamic view filtering, selection of model attributes or uncertainty metrics, and for other user interaction within the web application.



<sup>4</sup> <http://www.python.org>

## 5.2 Analytical and Visualization Abstraction (UVIS-App)

The *Data State Reference Model* (Figure 5.1) shows a high level overview of the processing chain. The specific objectives of the server-side UVIS-App application are to transform data into the analytical and visualization abstraction stages shown in Figure 5.1. A detailed view of UVIS-App is shown in Figure 5.2.



To make these transformations UVIS-App acts as a wrapper which performs the following functions:

- Import a geospatial dataset using an importer for a particular data format (Figure 5.2 inset A), for example a dataset generated by the PCRaster Python Modelling Framework (Karssenberget al. 2009).

- Extract and store metadata about the model (Figure 5.2 inset A), such as the model name, data types, the different attributes and scenarios, the extent, the number of timesteps, and stores these in a database for later display in the web application.
- Run a visualization routine plugin on a particular model (Figure 5.2 inset B). For example, the “pointgrid” visualization routine outputs a regular grid of circular glyphs which represent uncertainty whereas the “default” visualization routine prepares a simple map of the ensemble mean.

Running a visualization routine is the most computationally intensive task. After defining an input model, output visualization, and the requested timesteps and attributes to be visualized, UVIS-App runs the requested visualization routine, which in turn completes the following tasks internally within the routine:

- Perform an analytical abstraction to obtain the required data. This can include an upscaling algorithm, calculating the ensemble mean, summary statistics, or estimating various uncertainty metrics.
- Perform a visualization abstraction to map the outputs of the analytical abstraction to a format which can be directly visualized on the screen. This may include: creating a set of points at different supports, calculating the location of the point in the output projection, or scaling the value of a particular uncertainty metric so that it can be applied as a glyph size.
- Write the visualization data to a storage location such as a database or disk storage.
- Write configuration files for applications that will be used in the visualization. This includes creating the color mapping for the map renderer and creating predefined SQL queries by which visualization data can be easily requested.

The visualization routines overlap both the analytical and visualization abstraction stages. This is a design decision based on the fact that different visualizations require different types of data, and therefore the analytical abstraction occurs as part of the visualization routine. In the future this may be

improved by the use of analytical abstraction scripts which can perform these functions, and having the visualizations request a dataset containing the particular type of data which the visualization requires from them instead. The visualization output in the data store is in such a state that is directly visualizable on screen using a visualization technique. The UVIS-App application is written in Python and extensively uses the SciPy and NumPy libraries<sup>5</sup>. As of yet there is no functionality for letting model creators upload their own dataset and configure and run visualizations through a web interface.

### 5.3 Web-based Visualization (UVIS-Web)

UVIS-Web takes information which is in a visualizable format and presents it in a graphical view. In the *Data State Reference Model* (Figure 5.1) it is responsible for the *visual mapping transformation* and for the *view state* and its associated operators. Because the *view state* is contained within a web application rather than in a traditional desktop application, the transfer and display of geospatial data requires a more complicated architecture. To streamline the display of geospatial data in an online environment an architecture called the *Web-Mapping Stack* has been developed (Smith 2008). The web mapping stack is a system traditionally based on image tiles which are generated from geospatial data on an application server, cut into small image tiles and cached on a tile server, and the image tiles are then sent to the browser and arranged in a slippy-map interface<sup>6</sup> such as Google Maps. UVIS-Web uses a similar architecture and the information flow from the data store, through the application server, to the web server is outlined in Figure 5.3. While it resembles a traditional web mapping stack, several additions have been made:

- In addition to image tiles, vector tiles (which have geographic features encoded in GeoJSON format<sup>7</sup>) are also supported. Vector tiles have a lower bandwidth

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<sup>5</sup> SciPy and NumPy are open source libraries used for scientific computing with Python. For more information see: <http://www.scipy.org>.

<sup>6</sup> For more information on tile-based geospatial information systems refer to Sample and Ioup (2010)

<sup>7</sup> GeoJSON is a format for encoding a variety of geographic data structures. More information at <http://www.geojson.org/>.



overhead, can be rendered dynamically in the map interface, and are cached in the same way as image tiles. In the web application vector tiles are used to dynamically load the glyphs (and the associated data values) visible in the uncertainty visualization.

- Python CGI scripts are used to request supplementary information from the data store, such as data for timeseries plots or plume charts of a particular location. The script queries the database and returns data to the web application in JSON format<sup>8</sup> through a common gateway interface (CGI).
- The web mapping library used in UVIS-Web is Leaflet<sup>9</sup>, a lightweight open-source Javascript library for interactive maps. Additional Javascript libraries (specifically jQuery<sup>10</sup> and Flot<sup>11</sup>) have been used to add controls for changing timesteps, selecting model attributes, and visualizing uncertainty glyphs on top of the map display.

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<sup>8</sup> JSON is a lightweight data exchange format. More information at <http://www.json.org/>.

<sup>9</sup> More information about Leaflet can be found at <http://www.leafletjs.com/>.

<sup>10</sup> More information about jQuery can be found at <http://www.jquery.com/>.

<sup>11</sup> More information about Flot can be found at <http://www.flotcharts.org/>.

Figure 5.3: Web Mapping Stack Implementation for UVIS-Web

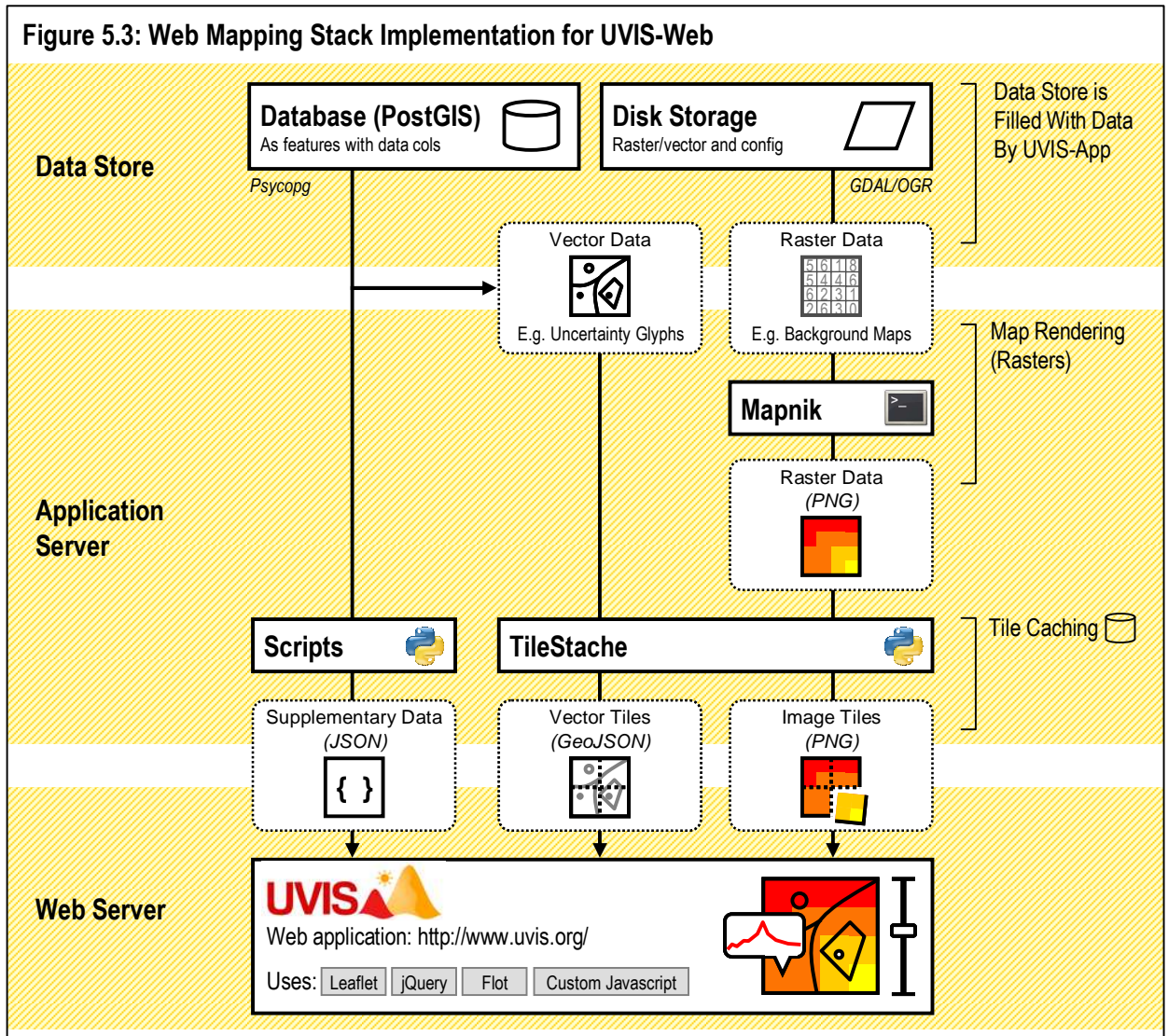


Table 5.1 contains a complete list of all the external applications, libraries, and bindings, as well as their purpose, which were used in the implementation of the web mapping stack.

Table 5.1: External applications, libraries and bindings used in UVIS-Web

<i>Description</i>		<i>Purpose</i>
Data Store	PostgreSQL postgresql.org	PostgreSQL is a powerful, open source object-relational database system.
	PostGIS postgis.refrations.net	PostGIS adds support for geographic objects to the PostgreSQL database system.
	Psycop initd.org/psycop/	Psycop is a PostgreSQL adapter for the Python programming language.

	GDAL/OGR www.gdal.org	GDAL and OGR are open-source abstraction libraries for reading and writing various raster and feature formats.
Application Server	Mapnik www.mapnik.org	Mapnik is a free toolkit for developing mapping applications. It is written in C++ but provides Python bindings.
	TileStache www.tilestache.org	TileStache is a Python-based server application that can cache and serve image and vector map tiles. Supports tiles rendered with Mapnik as well as vector geometries from PostGIS.
Web Server	Leaflet www.leafletjs.com	Leaflet is a lightweight open-source mapping library.
	jQuery www.jquery.com	jQuery is a small and feature-rich Javascript library used for document traversal and for simplifying client-side scripting.
	Flot www.flotcharts.org	Flot is a Javascript plotting library for use with jQuery.

## 5.4 View Stage Operators

The *within view stage operators* are client-side operators which do not change underlying data structures, but they are used in the *view stage* to add interactivity and extra functionality which help users to interpret the visualization image. The view-stage operators are client-side operators programmed in Javascript, they either fetch and display data themselves (such as the charts using Flot) or instruct the Leaflet mapping library to show a specific combination of layers, zoom in or out, show the layers corresponding to a specific timestep, or request Leaflet to render the uncertainty glyphs again using another parameter. The implemented *within view stage operators* in UVIS-Web are shown in Table 5.2.

**Table 5.2: The within view stage operators implemented in UVIS-Web**

<i>Name</i>	<i>Description</i>	<i>Screenshot</i>
Zoom	The zoom operator facilitates zooming in and out in the map pane in order to view information in a user-specified amount of detail.	Fig 6.2 inset C
Pan	The pan operator lets the user click and drag on the map to select a different viewport in order to see information in a different geographic location.	Fig 6.2 inset D
Select Timestep	The select time step operator lets the user navigate through the timesteps in the dataset.	Fig 6.2 inset E
Select Attribute	The select attribute operator lets users choose which model attribute they wish to visualize.	Fig 6.2 inset A
Select Visualization	The select visualization operator lets users choose which visualization technique the application should show.	Fig 6.2 inset B

Dynamic view filtering	The dynamic view filtering operator is a flexible operator which allows users to specify parameters for a particular visualization which is currently selected. This includes selection of uncertainty metrics or defining custom value intervals.	Fig 6.3 inset B
Glyph Interaction	Glyph interaction operators allow for user interaction with the uncertainty glyphs. By hovering the mouse over them it will show the value of the selected metric, and by clicking on a glyph it will open a popup with additional information.	Fig 6.3 inset C Fig 6.3 inset D

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## **6 A Web Application for Visualizing Uncertainty in Numerical Ensemble Models**

This chapter describes the results of this research. The end product is a web application for visualizing uncertainty in numerical ensemble models. The user interface and functionality are demonstrated using a sample model and screen captures from the web application.

### **6.1 Models and Datasets**

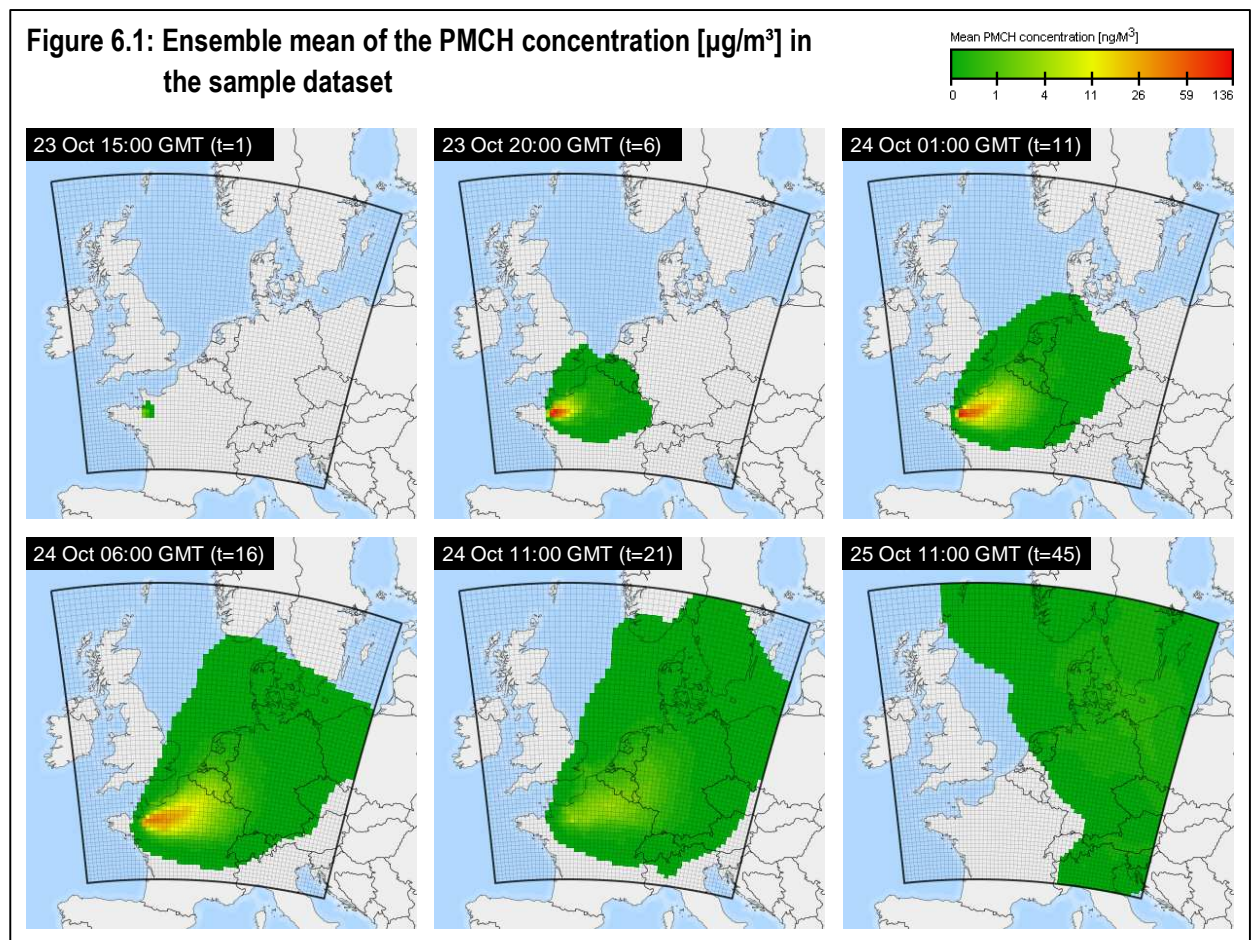
#### **6.1.1 Snow**

Snow is a simple snowmelt model developed by Karssenberget al. (2009) for illustrative purposes in the PCRaster Python modeling framework. It uses stochastic inputs for the temperature lapse rate and a Monte Carlo simulation was performed on an SRTM elevation model extract in Switzerland. The snow model was used in developing proof-of-concepts and mockups, development and testing of the web application, but was not used in the actual user tests upon completion of the web application.

#### **6.1.2 NPK-Puff**

A dataset by Hiemstra et al. (2002) which was created by the NPK-Puff (Verver and De Leeuw 1992) model has been chosen as a test case for implementation in the web application. The reason for switching to a dataset created by an atmospheric dispersion model was twofold. First, the idea of a pollution cloud traveling across a continent can be conceptualized by non-expert users without having to understand the underlying physical processes. Even realizing that uncertainties in wind speed and direction may lead to uncertainties in the

eventual forecast is not as difficult to understand as in other domains of environmental modeling. Second, in light of events such as the Chernobyl disaster and the Eyjafjallajökull ash cloud which disrupted much of the European air space in 2010, there is general interest for atmospheric dispersion models, and therefore it may be less difficult for users to imagine making decisions based on levels of pollution, or estimating what the chances are of certain events happening.



NPK-Puff was used by Hiemstra et al. (2011) in a case study to assimilate observations of radiation levels into model forecasts and nowcasts using a particle filter technique. Hiemstra et al. (2011) used stochastic representations of input parameters such as wind speed and direction to model the atmospheric dispersion of a non-reactive tracer across Western Europe. The release of the

tracer was part of the ETEX tracer experiments<sup>12</sup> which released, on 23 October 1994 at 15:00 GMT over a period of 12 hours, a total of 340 kg perfluoromethylcyclohexane (PMCH) from the western part of France into westerly-south-westerly air flows dispersing across northern Europe (van Dop et al. 1998). Hiemstra et al. (2011) performed three ensemble runs, of which one was a Monte Carlo forecast. The forecast did not assimilate any observations and is used as a demo dataset for the UVIS application. The dataset contains raster files of 64 by 64 cells in a 60 degree shifted-pole projection, 61 timesteps of one hour, and has been limited to 100 ensembles per timestep. The spread of the tracer at several timesteps is displayed in Figure 6.1 and gives an indication of the modeling results. The upscaling of the uncertainty information in the model was performed on the unprojected dataset, resulting in the distorted raster grid visible in Figure 6.1.

## 6.2 Navigation and Control Panes

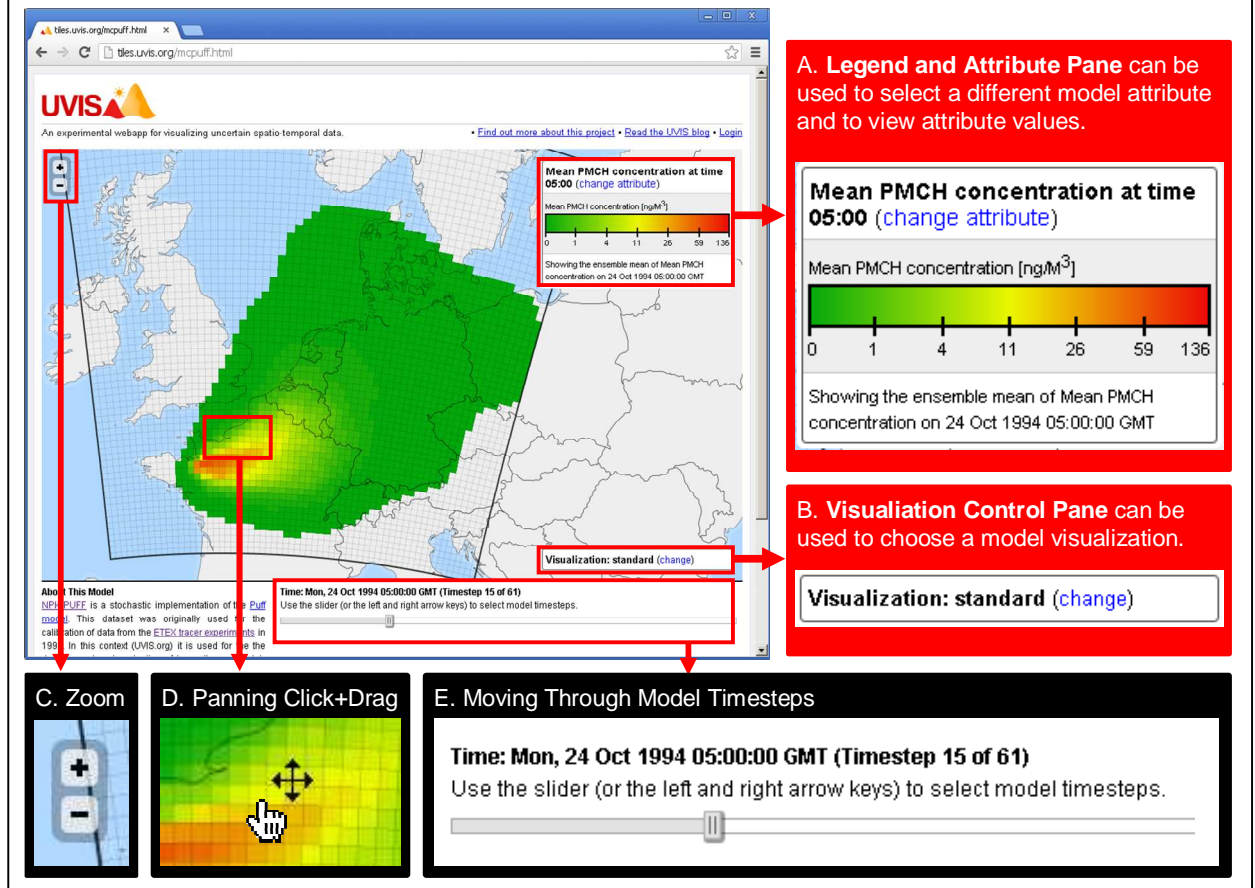
The UVIS application (accessible via <http://www.uvis.org> using recent versions of the Firefox or Chrome browser) is not set up as a full-screen web application but instead contains a map pane below the website header and above supplementary information. This is a design decision because future versions of the website may contain links to other sections of the website, different types of models, or text or user comments further describing what is happening in the map pane. Reserving space for this functionality outside of the map pane leaves the map pane itself clear and uncluttered, with only functionality contained within it which allows the user to directly interact with the map. Figure 6.2 shows the navigation options (Fig. 6.2 inset C, D, E) and control panes (Fig. 6.2 inset A, B) which are visible for the standard visualization. The standard visualization shows a colored map of the ensemble mean. The control panes can be used to select a different model attribute (Fig. 6.2 inset A) or to select a different visualization (Fig. 6.2 inset B). Navigation through the dataset is possible by using the timestep slider (Fig. 6.2 inset E), panning by clicking and dragging (Fig. 6.2 inset

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<sup>12</sup> For more information about the ETEX experiments refer to: <http://rem.jrc.ec.europa.eu/etex/>

D), or zooming in or out using the controls (Fig. 6.2 inset C, and explained in detail in Chapter 6.5).

**Figure 6.2: The UVIS entry screen shows the *Navigation and Control Panes*. Default no uncertainty information is shown, using the *Visualization Control Pane* (B) a visualization can be selected.**



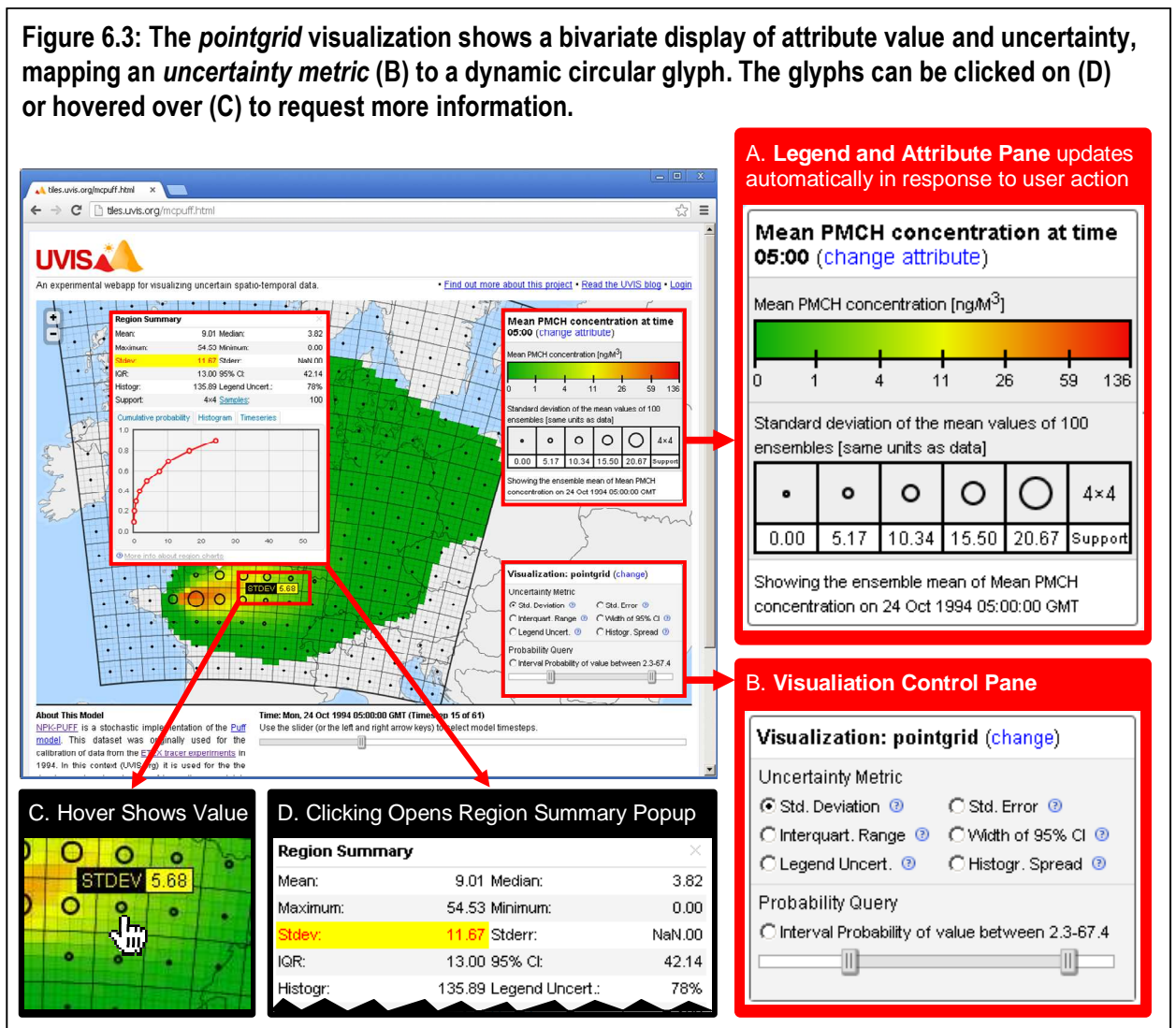
### 6.3 Uncertainty Visualizations

The visualization in Figure 6.2 does not show any uncertainty information yet. By clicking on the “change” link within the visualization control pane (Fig 6.2 inset B) a popup appears which lets the user select different visualizations which have been processed for this dataset. Selecting the “pointgrid” visualization loads a grid with circular glyphs, as specified in Chapter 4, which are overlaid over the map of the ensemble mean. The resulting changes in the interface are shown in Figure 6.3. The legend and the visualization control pane automatically expand to match the options available within the map view, and the user can interact with



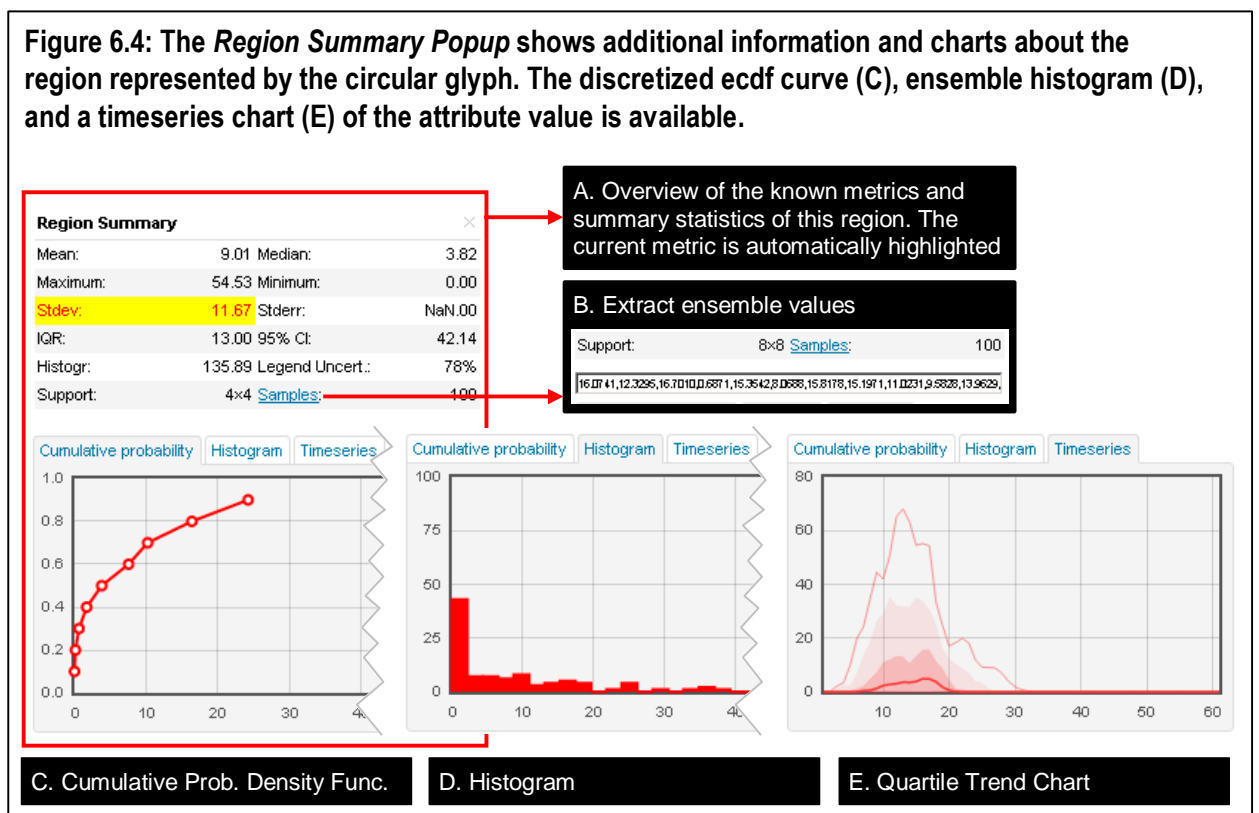
the uncertainty glyphs by hovering over them with the mouse (Fig. 6.3 inset C), clicking on them to open a popup with more information (Fig. 6.3 inset D, and explained in detail in Chapter 6.4), or by selecting a different uncertainty metric or value interval from the visualization control pane (Fig. 6.3 inset B). The part of the legend which maps the size of the uncertainty glyph to the value of the uncertainty metric (Fig. 6.3 inset A) also updates automatically when the user zooms in or out or selects a different metric.

**Figure 6.3: The *pointgrid* visualization shows a bivariate display of attribute value and uncertainty, mapping an *uncertainty metric* (B) to a dynamic circular glyph. The glyphs can be clicked on (D) or hovered over (C) to request more information.**



## 6.4 Region Summary

To allow users to request details on demand it is possible to click on any circular glyph. A popup called the *Region Summary* opens above the location of the glyph (Figure 6.4) and shows more details about the region represented by the uncertainty glyph. In the summary the mean, median, minimum, maximum, and the other available uncertainty metrics are listed (Fig. 6.4 inset A). The individual values of the ensembles can be requested for further analysis or for testing purposes (Fig 6.4 inset B). Charts are available which show the cumulative probability density function (Fig 6.4 inset C), the histogram (Fig. 6.4 inset D), and a quartile trend chart which shows the minimum, maximum, median, and the 5th-95th and 25th-75th quartile values through time (Fig 6.4 inset E).

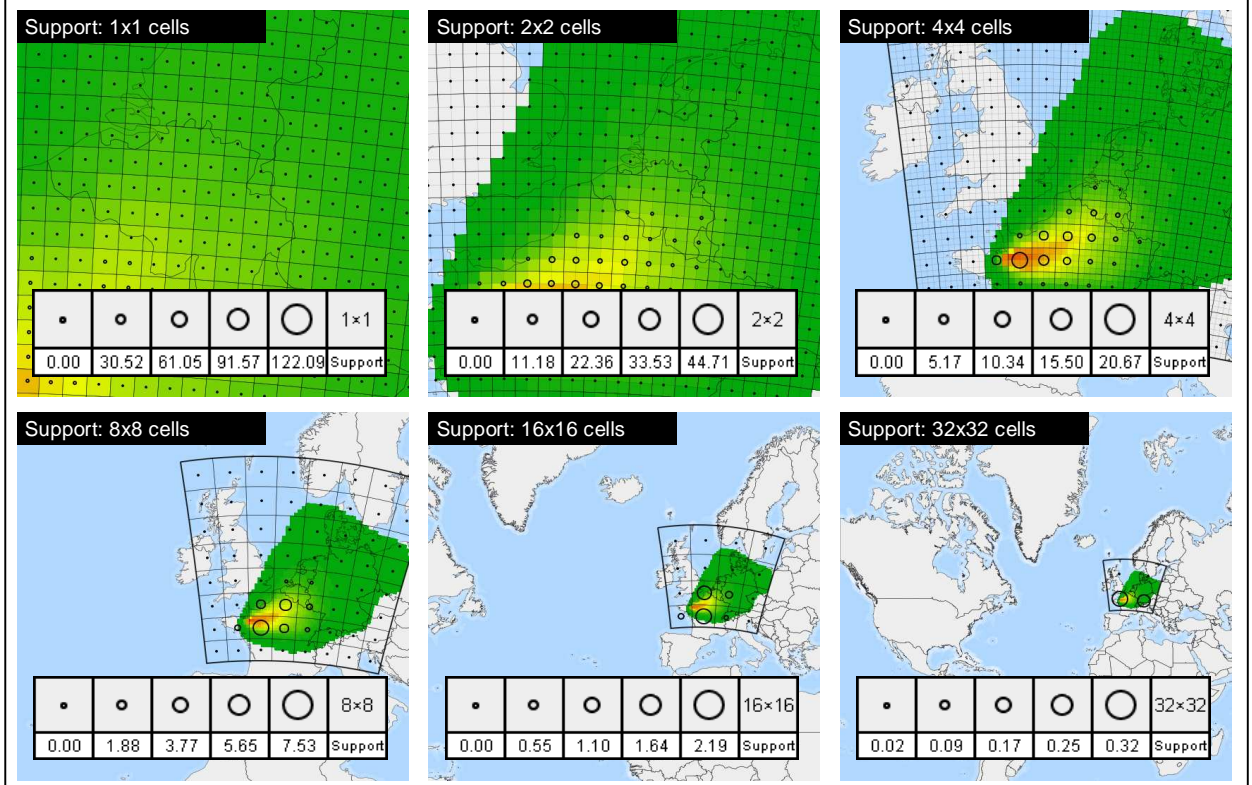


## 6.5 Change of Support

Figure 6.5 shows the results of the upscaling algorithm described in Chapter 4.4. By linking the zoom level to the support size UVIS ensures that the display does

not become overcrowded, while still being able to show accurate indications of uncertainty over regions which are larger than the original cell size. The map legend updates automatically after each zoom change and also shows the support level the user is currently viewing the uncertainty information at.

**Figure 6.5: Zooming in or out is interpreted as a request for information at a different scale. To provide this and to avoid cluttering an upscaling algorithm is applied. The circular glyphs represent the standard deviation, which decreases as the user zooms out. The cell size is approximately 25x25km.**



## 7 Uncertainty Visualization User Study

Chapter seven describes a user study which evaluates the usability of the UVIS application and the effectiveness of dynamic circular uncertainty glyphs. A copy of the full survey and the unprocessed results is included in Appendix A.

### 7.1 Objectives

Because the research objectives envisioned an application which was usable for both expert and non-expert users, a user survey was desired upon completion of the prototype to evaluate to what extent these objectives have been met. The objectives of the user study are twofold:

- To test *how effective* uncertainty visualizations based on dynamic circular glyphs are in communicating uncertainty information present in an ensemble dataset.
- To test the *usability* of the UVIS web application by assessing whether the interfaces and functionality were intuitive and versatile enough to allow both expert and non-expert users to explore the uncertainty information present in an ensemble dataset.

### 7.2 Methods

The user survey was set up and analyzed in a similar fashion to uncertainty visualization surveys undertaken by Evans (1997) and Aerts et al. (2003). The surveys were taken under the following conditions:

- All the users had access to the same web application and the same paper questionnaires.

- All users read a short (three page) introduction to environmental modeling with ensemble datasets. This introduction was written to introduce the application and the model so that even users without any prior experience could imagine what the purpose of the model was, and how the spread between the individual ensembles can be used as an indication of the uncertainty in the dataset.
- The questions (see Appendix A) were posed as 1) statements to which users could agree or disagree to a certain extent, 2) multiple choice questions and 3) open questions where users were asked to make a quantification, for example to estimate the standard deviation of a particular area.

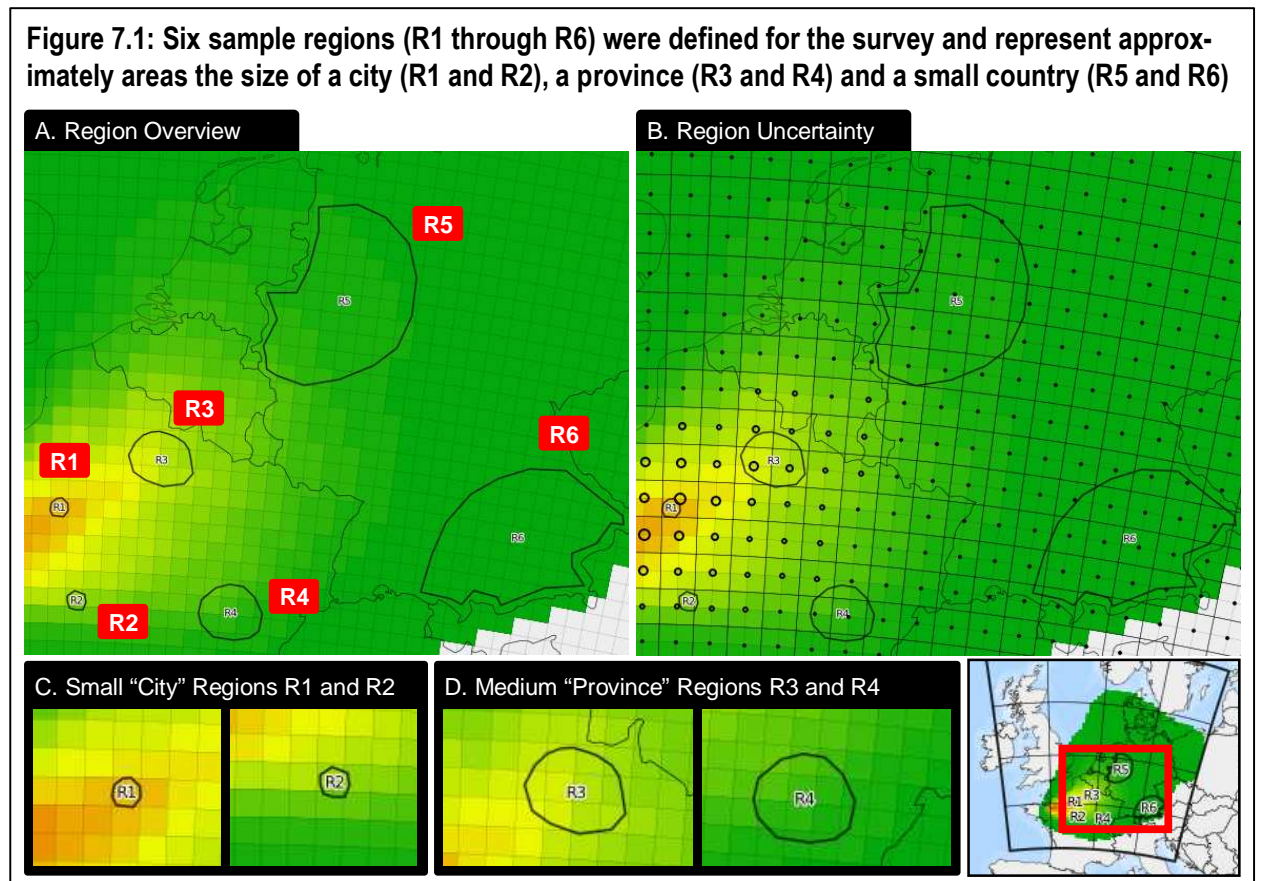
The surveys were presented in a printed form to users seated in front of a computer with an internet connection. Printed surveys were used instead of digital ones as it would prevent users from having to switch between windows and thereby lose focus or track of the progress in the survey. The survey took approximately 30-40 minutes and was split into five sections, each of which had a different purpose, as outlined in Table 7.1.

**Table 7.1: Different sections of the user survey and their purpose**

<i>Section</i>	<i>Description</i>
1. Introduction (Q1-Q2)	Determine the level of experience of the user and if they could understand the map without any uncertainty information present.
2. Spatial (Q3)	Distinguish <i>spatially</i> between areas of high uncertainty and areas of low uncertainty.
3. Quantification (Q4)	<i>Quantify</i> the uncertainty present in an area using various uncertainty metrics.
4. Probabilities (Q5)	Estimate the <i>probability</i> of categorized attribute value intervals occurring, and estimate <i>when</i> this would occur.
5. Evaluation (Q6)	Evaluate the experience and the opinions of users towards the interface and the use of circular glyphs to depict uncertainty.

The NPK-PUFF dataset by Hiemstra et al. (2011) described in Chapter 6.1.2 was used as a demo dataset for answering all the questions. Six regions (R1 through R6) of three different sizes were defined as sample regions about which either

decisions or a statement about the uncertainty of the prediction of that region needed to be made. The regions as they were defined in the survey are shown in Figure 7.1 (inset A), which shows a demo uncertainty overlay as well (inset B). The small regions R1 and R2 (Figure 7.1 inset C) correspond in size roughly to a large city, the medium regions R3 and R4 (Figure 7.1 inset D) to a province, and R5 and R6 (Figure 7.1 inset A) to a country or region within a country. The different sizes were chosen to investigate the zoom level (and corresponding support) users would decide to use in order to make an estimation or a decision about a region. Note that the red labels in Figure 7.1 have been added manually to clarify the figure, the map interface showed only the smaller label text within the region.



### 7.3 Results

In total 12 users have completed the survey. Due to the small sample size it is not possible to statistically differentiate amongst different groups of users (for example between experts and non-experts). The results are therefore based on lumped outcomes of the survey and serve as an indication of the experiences of the respondents. The actual questions and responses are included in Appendix A. The actual survey questions from which statements in this chapter have been derived are denoted in square brackets and can also be viewed in Appendix A.

#### *Types of users*

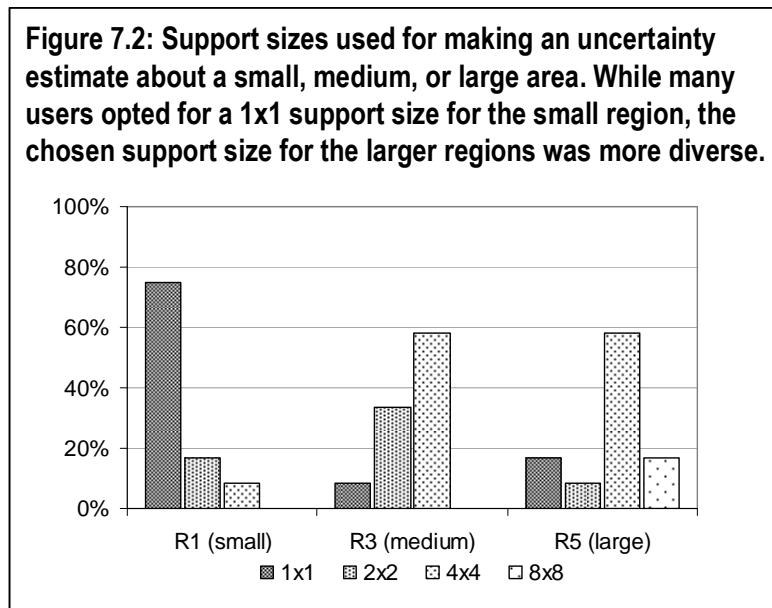
In total 7 test users indicated that they had prior experience (above a “beginner” level) working with geospatial data [Q1a] and had at least worked regularly with geospatial data for at least one year [Q1b]. These users with prior experience were MSc level students in geography or hydrology and several others who are currently employed in the geomatics field. The other 5 test users had not worked with any environmental models or geospatial data before, with the exception of casual use of Google Maps. All the users performed well at simple map reading tasks on a plain forecast map without any uncertainty information [Q1c, Q1d, Q1e] (similar to Figure 7.1 inset A).

#### *Spatially identifying areas of uncertainty*

Users performed well when asked to identify areas of uncertainty in the map. After the survey instructed users to select a particular visualization and a model timestep, 92% of the respondents thought they could “almost completely” or “completely” differentiate between areas of high and low uncertainty as they were shown (in absolute terms using the standard deviation as a metric) in the map legend [Q3a]. The three subsequent questions which were used to test whether the respondents *actually could* compare and identify the regions with the highest and lowest uncertainty were also answered overwhelmingly correct [Q3b, Q3c, Q3d, Q3e].

#### *Quantifying uncertainty*

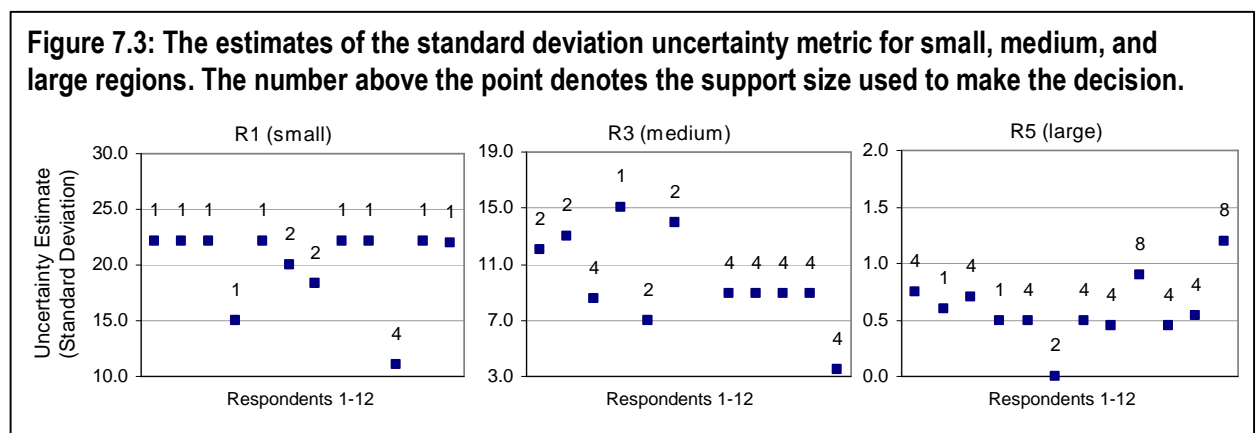
The quantification of uncertainty in this survey is complicated because there are no right answers; the value of the uncertainty metric for a region depends on the zoom level and the support at which the map is viewed. The zoom level used by the respondent to answer the questions was at his or her digression, and the link between zoom level and a change in uncertainty was, due to its complicated nature, not discussed or explained in the introductory text. In the survey only 58% of the respondents even realized that the uncertainty changed when zooming in or out [Q4a, Q4b], and only 53% of the users thought they could “almost completely” or “completely” give an indication of the value of various uncertainty metrics [Q4c]. To test this, the users were asked to estimate the standard deviation of the prediction of a small (R1), medium (R3) and large (R5) region and to note the support size they had used to come to their decision. As is shown in Figure 7.2, users tended to zoom in and use a small support size for determining the uncertainty in the small region.



The chosen support size seems to get larger when estimating uncertainty of the medium and large areas, but it is difficult to tell by how much, or whether there is a specific support size which is most appropriate for an area which does not closely match the location and positioning of the uncertainty glyphs [Q4d]. The magnitude of the standard deviation that the users estimated for each region was



most consistent for the small area, as shown in Figure 7.3. Figure 7.3 also shows the spread of the estimates for the three regions as well as the support size used when making the estimate. The spread in both the estimated value and chosen support size for the medium and large regions suggests that the uncertainty estimates for larger regions are still subject to user interpretation, and that the estimated values are therefore inconsistent across different respondents. There was possibly some ambiguity in the question formulation as well, which is included in the discussion of the results.



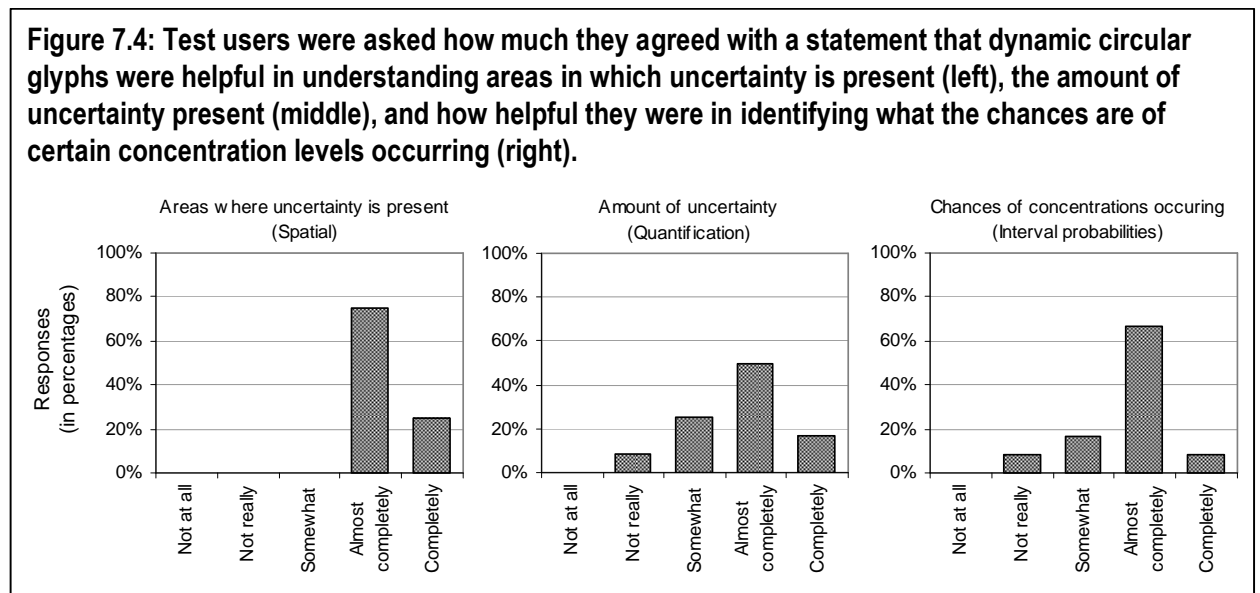
### Estimating interval probabilities

In this section the survey asked users to make decisions and answer questions only regarding the two small regions R1 and R2, and to use a 1x1 support size so that the area represented by the uncertainty glyph corresponded with the area of the region in question. The reason for this was to eliminate any confusion caused when having to make decisions or estimates about areas which overlap multiple uncertainty glyphs, as was the case in the results of the medium and large areas shown in Figure 7.3. Users were asked questions about how likely (in terms of percentages) they thought it was that certain *danger classifications* would occur (which were attribute value intervals corresponding to imaginary “safe”, “dangerous”, or “sound the alarm” levels of pollutant). Users generally performed well on estimating interval probabilities. Over 90% of the respondents answered correctly about what the probability was that “dangerous” levels of pollutant would occur in Region 1 and 2 [Q5a, Q5b], and over 80% answered

correctly to a question about what the probability was that “alarm” would have to be sounded at a specific time [Q5c]. Respondents were also instructed to use the time slider to estimate *when* concentrations were unlikely (i.e. a less than 25% chance) to be dangerous anymore, a multiple choice question which proved to be slightly more difficult, but was still answered correctly by 67% of the respondents [Q5d].

### Evaluation

The evaluation section of the survey asked the respondents to what extent they agreed that the circular uncertainty glyphs had helped them in understanding the areas, the amount, and the probabilities involved in the forecasted pollution cloud. The responses were generally positive. As is shown in Figure 7.4 (left), all the respondents (100%) indicated that they agreed “almost completely” or “completely” with the statement that the glyphs were helpful in identifying areas where uncertainty was present [Q6aa]. This agreement was lower (See Fig. 7.4 middle and right) for the questions regarding quantification (67%) and identifying probability classes (75%) using the circular uncertainty glyphs [Q6ab,Q6c].



A positive note is that 83% of test users indicated that the interface was adequate for questioning the data and its uncertainties, and that the uncertainty information did not make the display of information too difficult or complex to use

[Q6d,Q6f]. The web application is therefore successful in avoiding a cognitive overload for its users.

## 8 Discussion

This research resulted in a usable and integrated uncertainty visualization web application. The results were obtained by developing innovative visualization methods and by selectively improving upon snippets of work by others in the geovisualization community. While the initial results look promising, this chapter discusses various assumptions and addresses the shortcomings that have surfaced during this research.

### *On the representation method of dynamic circular glyphs*

The use of dynamic circular glyphs was found to be an effective way of visualizing spatial, quantitative, and probabilistic aspects of uncertainty in spatio-temporal datasets. While the effectiveness of the glyphs in these three aspects looks promising, its use as an all-round solution nevertheless remains a compromise which is important to acknowledge. In itself, spatial aspects of uncertainty could possibly be visualized more effectively or in more detail using only contouring or texture overlays as a representation method. Furthermore the use of glyphs limits the spatial resolution of the data, as only a limited number of glyphs can be added to the map pane without overloading the display. Mapping quantitative uncertainty values to the size attribute of a circular glyph also works satisfactorily, but unfortunately the mental mapping of a glyph size to an accurate quantified value of uncertainty remains difficult and inaccurate for the map reader without the use of additional interactions, such as hovering the mouse over the glyph or clicking it to request the exact value. This limitation is also an issue for uncertainty which is represented as a probability of a value interval occurring.

Perhaps interval probabilities may be represented more intuitively by small pie charts outlining the probable outcome categories, or by using the color attribute of the glyph rather than its size attribute to represent the likelihood of certain intervals occurring. Within the scope of this research, the dynamic circular glyph is an effective representation, but its application as an all-round solution remains a golden mean whose weaker aspects can still be improved upon.

*On issues of scale and support*

While the upscaling of uncertainty information in the manner shown in the web application is a new and visually pleasing technique, it could potentially introduce uncertainty and confusion into the map. When the upscaling takes place in the projected output raster, as opposed to the original unprojected input raster, resampling and warping of the original data needs to occur. This changes the underlying support of the uncertainty data more in some areas (especially on the edges of the map extent and in regions which are stretched due to different input and output projections) than in others. Together with the resampling, this results in a distorted uncertainty display which uses different underlying supports in a single map view. On the other hand, when the upscaling takes place in the original projection then the output uncertainty grid is transformed and no longer regular, making it impossible to compare uncertainty in that specific map with maps that originally had another input projection or cell size, as the locations of the uncertainty glyphs will no longer match up across different datasets.

Another risk is that map users do not understand or anticipate that uncertainty can change depending on the support size which is used to calculate it. In the user study many non-expert users realized upon being asked about it that the uncertainty was changing as they zoomed in or out but, lacking the experience, they were unlikely to understand why this occurred. Even expert users had difficulties with this; several interviewees indicated on the survey that uncertainty did not change according to the zoom level. Whether this is due to the glyph sizing or simply an incorrect assumption (i.e. “uncertainty does not change with zoom level because that makes no sense”) is unknown. One user in the survey

even skeptically asked whether it was a trick question and subsequently stated that it did not change. The questioning (see Appendix A, Q4a and Q4b) also left room for ambiguity, as some users may have interpreted “uncertainty” as the uncertainty in the original dataset (which did not change), whereas others could interpret “uncertainty” as the uncertainty “at a specific glyph (with its associated support)” something which did increase or decrease with a change of support.

Choosing an appropriate support size for areas which covered multiple glyphs was also difficult for users. The spread of the chosen support size which is observed in Figure 7.3 could be due to ambiguity in the questioning. The survey was intentionally vague and asked users to estimate the “standard deviation” of a small, medium, and large region. This could be interpreted as the “standard deviation of individual pixels/cells in the region” or as “an average of the standard deviation in the region.” Perhaps if the survey had asked explicitly for an average value of the entire region, users would be more inclined to zoom out to attempt and match the support size of the glyph to the size of the region, but it is difficult to capture the user’s exact train of thought without making the questions leading. These issues could possibly be resolved within the visualization by calculating uncertainty metrics for predefined areas such as countries or provinces. However, that solution would in turn introduce other problems: the grid would be irregular and comparing between countries would be difficult, as their size, support, and therefore uncertainty are all different once again. Finding a suitable method which allows users to objectively compare areas of different sizes or proportions which do not match the grid of the circular uncertainty glyphs is a research challenge for the future. It is clear that best practices are still lacking, and finding a usable and consistent solution for these problems is a priority if the visualization is to be used in an operational setting.

#### *On the use of metrics to quantify uncertainty*

The calculation of various uncertainty metrics which define the spread of the individual ensembles is relatively simple and straightforward. However, statistics such as the mean or standard deviation require the data to be normally

distributed in order to be accurate estimators. This was not the case in the demo data set (and may not be the case either in other datasets) as the actual distribution in many locations was unknown and unlikely to be normal. The presence of outliers in the data also had a significant effect on metrics such as the standard deviation, resulting in uncertainty values which seemed to be strongly correlated to the attribute value. Using robust metrics which are less sensitive to outliers or which are not dependent on the assumed normality of the underlying distribution would be a possible solution. For example, the implementation of a bootstrapping algorithm, as was also done in other integrated visualization applications (Sanyal et al. 2010), could be used to overcome the normality constraint.

#### *On the UVIS web application*

The UVIS web application has shown that it can visualize and communicate various aspects of uncertainty in spatio-temporal datasets. Due to time and scope constraints the functionality is limited to a basic set of features. Improvements to the application can still be made by:

- Further separating the analytical and visualization abstraction stages in the UVIS-App backend. Various metrics would have to be calculated only once and could be used by all the visualizations, whereas currently each visualization routine has to perform its own analytical abstraction. This will also aid in the development of new visualization abstractions, as the abstractions will become plug-ins of the application rather than be integrated into a specific visualization.
- Determine best practices for whether the analytical and visualization abstraction should take place before or after the data is projected to the output projection used in the web application.
- Integrate the comparison of multiple scenarios in the application and in the visualizations. Having the possibility to add the data of another scenario to the histogram, cumulative density function, and the timeseries charts would allow users to compare uncertainty across datasets.

- Add other interactive chart types such as the parallel coordinates chart proposed in Table 4.4. This would allow expert users to isolate clusters of ensembles and track the corresponding attribute values through time.
- Investigate alternative positioning or arrangement of uncertainty glyphs. Rather than in a grid, uncertainty glyphs can be positioned along line features, within predefined regions such as countries, centered in areas where high uncertainty is predicted, or in a tessellated manner mimicking a pattern overlay. No best practice for positioning uncertainty glyphs is yet defined.
- Develop a web-based interface where model creators can upload and annotate their model, select appropriate color scales, and define contextual input for the visualizations. For example, specific value intervals which correspond to levels of danger could be predefined by model experts. The visualization could interpret these and allow users to select the predefined intervals using radio buttons and immediately see the corresponding probability, rather than having to define the intervals manually.

#### *On evaluating uncertainty visualizations*

The evaluation of uncertainty visualizations remains an inexact science for which it is also difficult to establish best practices or common conventions. Developing some guidelines would allow researchers in the geovisualization community to better compare their work and the effectiveness of their visualizations. Perhaps further development of common use cases of uncertain geospatial data would allow researchers to test in a unified manner how adept their visualizations are for completing a certain case study. In the future it would then be easier for developers of visualization applications to reject underperforming visualizations for their use case in favor of those with an established track record.

The survey and visualizations presented in this work are unique because they also evaluated quantitative aspects of uncertainty by having users estimate metrics and probabilities of certain events occurring. This is a significant step forward from other visualization evaluation studies. While the results of the quantification questions showed that users still found it difficult and were unable



to come up with completely consistent answers, the fact that most respondents estimated similar ballpark figures indicates that the circular glyphs were nevertheless effective. Furthermore, it is likely that visualizations which do not have a built-in upscaling algorithm would perform even worse as there is literally no possibility for users to quantitatively estimate aspects of uncertainty over larger areas.

Unfortunately the response was too limited for statistical analysis of the results, and it was difficult to define how much information to give the respondents without making the questions leading. Increasing the sample size would also allow testing for differences between expert and non-expert groups. Finding out whether expert and non-experts interact differently with the web application would be useful in determining what changes could still be made to the interface. It would also be helpful to try the survey on a different type of dataset where the magnitude of the uncertainty did not correspond so closely with the magnitude of data values in the background map. The survey also did not include the graphical summaries in the region popup (Figure 6.4) in any questions. This was done to avoid alienating non-expert users, but as these summaries show information which may be important to expert users they should be included in future work.

## 9 Conclusion

### *The smaller picture: conclusions of this research*

This research has presented a functional end-to-end solution for visualizing uncertainty in a web based environment. A literature review has mapped the current state of uncertainty visualization and found it to be a complex environment with implications across many disciplines. The science underlying uncertainty visualization forms a divide. It is an exact science when numerical quantification of uncertainty and visualization or upscaling routines are concerned, and inexact when it comes to cartographic conventions, developing new visualizations, evaluating user experiences, or assessing the risks of cognitive overload of maps in which data value and uncertainty are embedded. Best practices and undisputable conclusions have, despite the efforts of the geovisualization community over the years, not yet been established.

Building upon ample literature, a conceptual framework of a web application which visualizes uncertainty in spatio-temporal datasets has been developed. While various approaches to visualizing uncertainty have been covered, a bivariate display based on dynamic circular glyphs was found, especially in combination with an upscaling algorithm, to have the most potential for displaying spatial, quantitative, and probabilistic aspects of uncertainty in numerical ensemble datasets. The legibility and ease-of-use of the circular glyphs for both expert and non-expert users played an important role in this.

In the implementation of the UVIS web application prototype, the *Data State Model* was found to be an excellent framework on which to base the design and the data flows of the visualization application. It allowed for conceptual

separation of the visualization processes, and some of the individual stages are implemented separately in the visualization application as plug-ins. The UVIS application also uses modern open-source programming and web technologies to create an interactive, accessible, and intuitive web application. The use of open source software in this implementation (such as Leaflet, jQuery, Flot, Numpy, Scipy) was paramount, and is highly recommended for future work involving web mapping and uncertainty visualization.

Finally, a user survey was conducted to evaluate the usability and the effectiveness of the web application. A group of test users comprising of both experts and non-experts were asked to complete several tasks, which included identifying areas of uncertainty, quantifying it, and estimating probabilities of attribute value intervals occurring. The users generally performed well, but found it difficult to quantify uncertainty in irregularly shaped areas which did not closely match the support size of the glyph display. User feedback to the web application was also positive. Users found dynamic circular glyphs helpful in order to understand the uncertainty present in the dataset, and there was no evidence to suggest that the interface or dynamic uncertainty glyphs contributed to a cognitive overload on the users' part.

#### *The bigger picture: progressing the state of uncertainty visualization*

The implementation details and visualization routines described in this research provide a starting point towards further web-based uncertainty visualizations which can eventually be used operationally. Both the visualizations and the methods by which uncertainty is quantified look promising, but despite years of innovation a research issue posted in 1994 by Encarnaç o et al. (1994) is still as relevant today as it was nearly twenty years ago:

“[...] it is clear that the current techniques aren't sufficient in all cases. We need a three-pronged approach: technology-driven (what we can do), perception driven (what makes sense), and task-driven (what users want)”

As advances in web technology trickle down into the domain of geovisualization we are increasingly without limits as to what we can accomplish on web-based

platforms. Even the tasks and needs which define what model users want to do with uncertain information are crystallizing. Use cases are increasingly common and there is a real-world need for uncertainty information.

Nowadays we are critically dependent on environmental models for forecasting, emergency response, planning, decision making, policy making, and scientific research. We use these models at various scales: from predictions about our backyard to analyzing the impact of humankind on our global climate, and everything in between. In fact, the stakes are sufficiently high that it can be argued that uncertainty about the data is as important as the data itself, for without the first, the latter lacks both momentum and credibility. Unfortunately in the visualization of uncertainty one prong is lagging behind: we still do not know *what makes sense*. It is a problem of perception, as Nielson et al. (1994) stated:

“Consider that a visualization tool’s purpose is to produce not an image but rather a perception. How can we possibly put a metric on perceptions?”

It is still a problem that current visualization tools do just that, they produce images with metric inputs and outputs, but not yet perceptions. The challenge in the coming years is to develop uncertainty quantifications for multi-value datasets which dive deeper into the data and can explore, interact with, and visualize uncertainty in ways beyond simple derivations of a probability density function. To turn images into perceptions, the interfaces which render them need to be intuitively interactive, usable, degrade gracefully for less experienced users, evolve iteratively on the basis of user feedback, and they need to be based on solid foundations and best practices which are widely supported in the geovisualization community. Only when perceptions are produced by visualization applications can we fully utilize the strengths of web based technologies to share, collaborate, discuss, analyze, and build forth upon the increasingly complex datasets produced by modern environmental models.

\* \* \*



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## 11 Appendix A – Survey Questionnaire

### USER EXPERIENCE SURVEY

#### UVIS WEB APPLICATION

This is a user experience survey related to mapping and cartography and is part of the MSc research of Koko Alberti at the Department of Physical Geography at Utrecht University. Please read the survey carefully and fill out the questions without reservation and to the best of your ability. It is not a test but rather a survey to see how well the web application works for users with different levels of experience and what can be done to improve on this. The survey consists of 7 questions, please try and fill in all the answers and do not go back and change any answers if you have changed your mind about something or learned something new as the survey progresses.

The results will be used to improve the web application and to further the understanding of how users interact with online mapping applications.

Please circle your answers, or enter an answer in the highlighted area. In case that the application freezes or does not respond, please write down what happened and press “reload” in your browser.

<b>Starting time:</b>	__ : __
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### **Question 1**

**Q1a.** What is your level of expertise in working with geospatial data such as digital maps, geographical information systems, or environmental models?

No Experience	Beginner		Intermediate		Expert
0	1	2	3	4	5

**Q1b.** For how long have you worked regularly with digital geospatial data?

Not at all	1-2 years	3-4 years	4-6 years	Longer than 6
1	2	3	4	5

Please open the following website in the browser in front of you in a recent browser such as *Mozilla Firefox* or *Google Chrome*. Unfortunately Internet Explorer is not supported at the moment.

<http://tiles.uvis.org/mcpuff.html>

Displayed is a forecast which predicts the spreading of an airborne pollutant from the west of France across Europe. The release occurred at 15:00 GMT on the and stopped approximately 12 hours later. The model uses timesteps of one hour. Use the time slider at the bottom of the screen to go to Timestep 5 (19:00 GMT) and observe the dispersion of the cloud. Now use the slider to go to Timestep 10 (Midnight) and observe the further dispersion. Finally go to Timestep 15 at 05:00 GMT the following morning. There are six regions shown on the map which will be used for the questions, they are labeled R1 through R6. The map shows the average forecasted concentration of the pollutant in the air. Judging from the map:

**Q1c.** Can you differentiate between relatively high and low concentrations in different areas using the legend?

Not at all	Not really	Somewhat	Almost completely	Completely
1	2	3	4	5

**Q1d.** To what extend do you agree that Region 4 has the highest average forecasted concentration of all the regions?

Not at all	Not really	Somewhat	Almost completely	Completely
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1	2	3	4	5
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**Q1e.** To what extent do you agree that Region 2 has an average predicted concentration of somewhere between 3-8 $\mu\text{g}/\text{m}^3$ ?

Not at all	Not really	Somewhat	Almost completely	Completely
1	2	3	4	5

**Question 2**

**Q2.** Generally speaking, how uncertain (with regard to the predicted concentration, the shape of the cloud, the direction in which it travels...) do you think this forecast/prediction is?

Not at all	Not really	Somewhat	Quite uncertain	Very uncertain
1	2	3	4	5

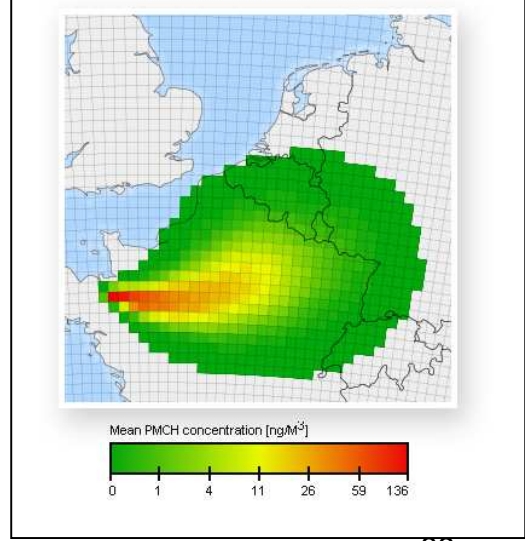
**Question 3**

The following pages will contain some text which explains how an environmental model works, and how a forecast like the one you've seen is constructed. Even if you are familiar with environmental modeling, please read it carefully and then continue with the rest of the questions.

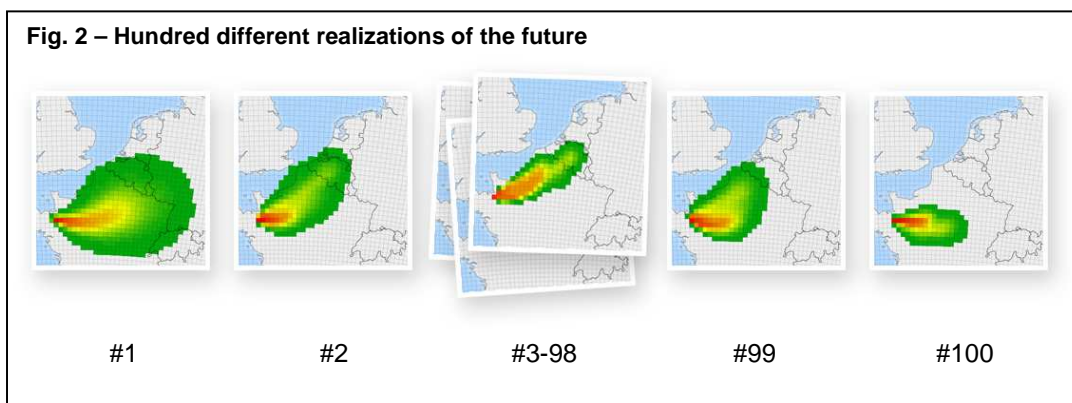
**A quick introduction to uncertainty in environmental models**

Numerical models are commonly used in predicting the consequences or impacts of environmental processes which occur at the surface of the Earth. They can simulate anything from flood risk, weather forecasts, erosion processes, pollution, or predict the path and concentration of an ash plume or a cloud of radioactive dust. However, the future is inherently uncertain and environmental models can only hope to simulate it as best as they can. The example model you have just looked at forecasts the spread of a cloud of pollutant across Western Europe, something that could be the result of for example an industrial accident. If we run the model just once it may make a prediction like in Figure 1 of the concentration (in micrograms) of pollution per cubic meter of air [ $\mu\text{g}/\text{m}^3$ ] at a certain time, let's say at midnight, 10 hours after the release.

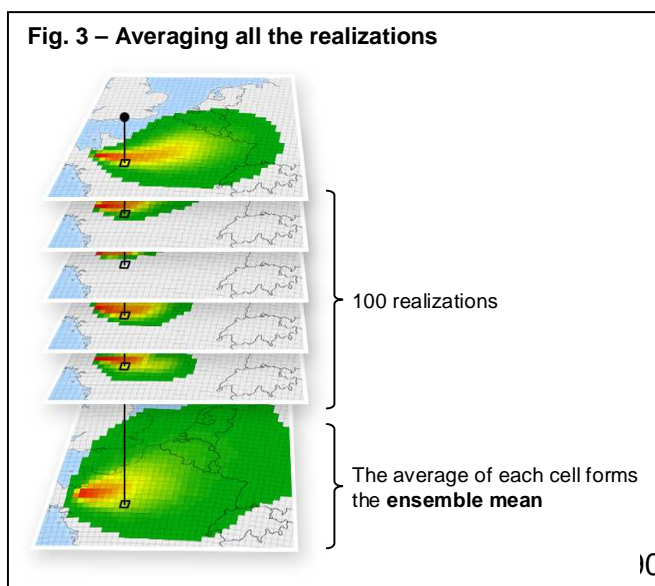
**Fig. 1 – One realization of the future**



To make this prediction the model uses probabilistic inputs such as wind direction, the type of pollutant, and how much is thought to have been released. The problem is that any model is only an approximation of reality, and if it is a good model it is likely that the cloud looks *something* like this, but at the same time it is also highly unlikely that the actual real life cloud looks *exactly* like this. The wind speed or direction may be a little off, the amount of pollutant may be a little different, and we may not understand exactly how a pollutant travels through the air. We call one such forecast of the future **one realization** of the future. To make sure we don't make rash decisions (such as evacuating a city or shutting down an airport) based on just this one realization, we can run this prediction model 99 more times to see what 99 other possible versions of tomorrow look like (Figure 2).



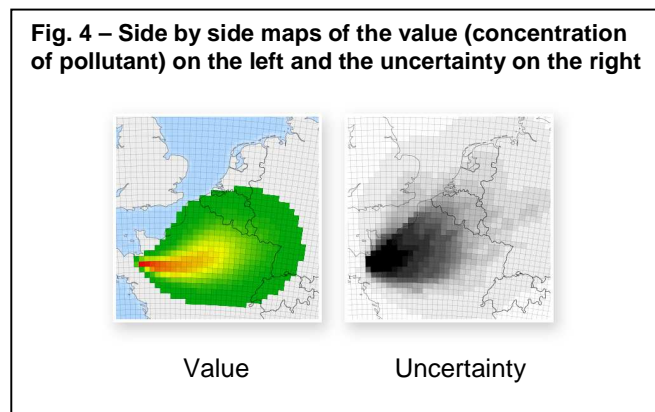
We now have 100 realizations of the future which are all a little bit different and are equally likely to occur. Sometimes at a certain location a predicted value of 140-160 is just as likely to occur as a value between 240-260. Imagine at a certain location, an airport for example, where 40 realizations predict a value of between 140-160, another 40 realizations predict a value 240-260, and 20 other even a different concentration of the pollutant. What do we do when we have to make a decision based on this information, especially an important decision like closing an airport for traffic or issuing an alarm? We can't be sure whether the actual value tomorrow morning will be between 140-160, or whether it will be between 240-260. They are equally likely outcomes, and this is where **uncertainty** about the forecast rears its head. It would be much easier to make a decision if 95 of 100 ensembles predicted a value of below 140 because then we could state confidently, for example "we are 95% sure that the pollution level will be below 140, so we don't need to



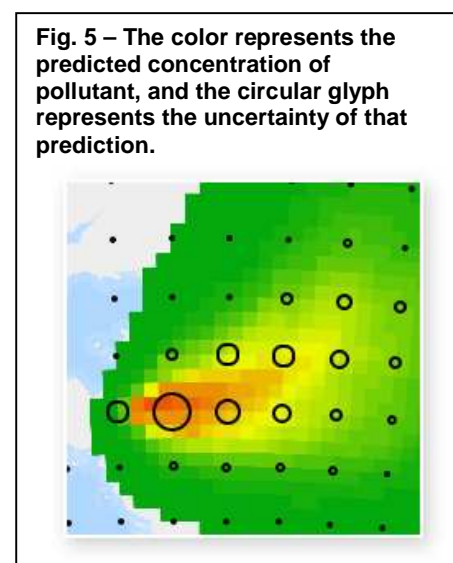
close the airport or issue an alarm.”

The colored map that you’re seeing in the web application is the average of all 100 realizations. We calculate for every position in the map the average of all the realizations and save this in a new map, we call this new map the **ensemble mean**. Figure 3 above shows how this map is constructed.

The ensemble mean shows the average in every location of all the 100 realizations. In addition to the average we can also calculate the standard deviation (an indication of how spread out the individual realizations are) in exactly the same manner and show that in a map next to the ensemble mean. We then have a basic indication of the average value (ensemble mean) and a map which says something about the uncertainty or spread of the individual realizations (standard deviation). Traditionally these can be shown side by side to give the map user an idea of the uncertainty involved in the forecast which the model has produced (Figure 4).



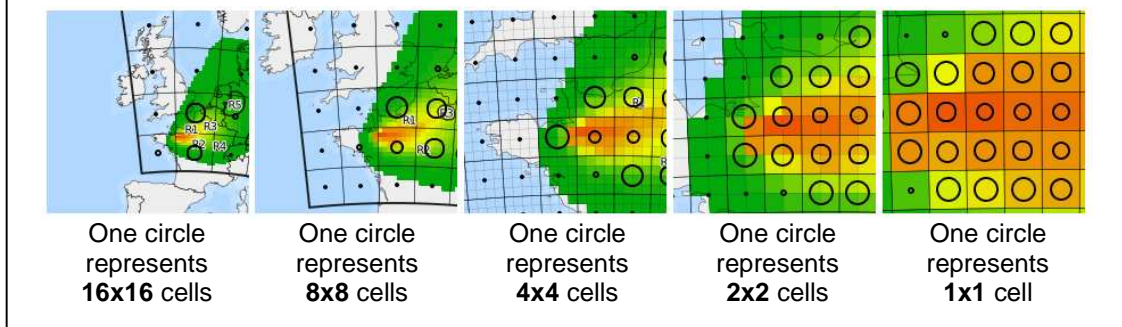
However, if there are two side-by-side maps then it is left up to the map user to look back and forth between the maps and correlate areas of uncertainty with the areas of a specific value. The web application uses a map display which shows both variables in the same map, linking *value* (in this case the concentration of the pollutant) to color, and the *uncertainty* (the spread or indecisiveness amongst the 100 different realizations) to circular glyphs. The larger the circle, the more uncertain the prediction is at that point, as shown in Figure 5 on the right:



The web application also shows uncertainty at different supports. As you can see, the real-world area covered by a single circle becomes larger if you zoom out, and smaller if you zoom in (See Figure 6). The underlying cells which are used for making estimations of the

average value and of the uncertainty associated with it are called the **support** of the data. It can be viewed as the actual data which supports us in making an estimation such as the average or the uncertainty about a specific area.

**Fig. 5 – Different support sizes of the circular glyph**



Make sure you are still viewing timestep 15 of the model. On the right bottom the current visualization is the “standard” visualization. Click “change” and select the “pointgrid” visualization. You will see a regular grid of black circles (circular glyphs) which represent the uncertainty of the underlying color map. In the legend the support size is visible:

•	◦	◌	○	⊙	4x4
0.00	5.17	10.34	15.50	20.67	Support

Make sure “standard deviation” is selected and zoom in or out so that the support size of the circles is “4x4”. Note that there are many sizes of circles, not just the five shown in the legend as they are scaled to a certain value.

Feel free to zoom in or out to answer the following questions.

**Q3a.** Can you differentiate between areas of high uncertainty and areas of low uncertainty?

I can't tell from the map	Not at all	Not really	Somewhat	Almost completely	Completely
<b>0</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>



**Q3b.** To what extent do you agree that the predicted values in Region 5 have a smaller uncertainty than those in Region 3?

I can't tell from the map	Not at all	Not really	Somewhat	Almost completely	Completely
0	1	2	3	4	5

**Q3c.** To what extent do you agree that the predicted values in Region 4 have a smaller uncertainty than those in Region 3?

I can't tell from the map	Not at all	Not really	Somewhat	Almost completely	Completely
0	1	2	3	4	5

**Q3d.** Compare the forecast of the cloud in Region 1 and Region 2. Which of the values in the two regions is the most uncertain?

I can't tell from the map	The prediction of Region 1 is most uncertain	The predictions are about equally uncertain	The prediction of Region 2 is most uncertain
0	1	2	3

Use the timestep slider to move forward to timestep 35 (01:00AM on 25 Oct)

**Q3e.** Compare the uncertainty in the forecast of the cloud in all the different regions. Which region's prediction contains the most uncertainty?

I can't tell from the map	Region 1	Region 2	Region 3	Region 4	Region 5
0	1	2	3	4	5

**Question 4**

Use the timestep slider to move back to timestep 15.

There are various ways to quantify uncertainty. Right now in the menu "standard deviation" is selected, which is one of several uncertainty metrics.

Select a few different uncertainty metrics, such as “*interquartile range*,” “*legend uncertainty*,” “*histogram spread*,” or “*width of the 95% confidence interval*”. These are various ways of describing the uncertainty in a specific place with just a single number. Don’t worry about their exact meaning at the moment! This number is then linked to the size of the black circle. To find the value of the standard deviation you can:

- Compare the size of the circle to the legend
- Move the mouse over the circle
- Click on the circle to view all the values as well as other charts and graphs.

Try clicking moving the mouse over a black circle as well as clicking it to find the exact value of the standard deviation.

Make sure “standard deviation” is selected and zoom in or out so that the support size of the circles is “4x4” to start with. Again, you can see the support size in the legend. Feel free to zoom in or out to answer the following questions.

•	◦	◌	○	⊙	4x4
0.00	5.17	10.34	15.50	20.67	Support

**Q4a.** What happens to the standard deviation/uncertainty when you zoom in (i.e. use a smaller support?)

I can't tell from the map	The uncertainty gets smaller	The uncertainty remains about the same	The uncertainty gets larger
<b>0</b>	<b>1</b>	<b>2</b>	<b>3</b>

**Q4b.** What happens to the standard deviation/uncertainty when you zoom out (i.e. use a larger support?)

I can't tell from the map	The uncertainty gets smaller	The uncertainty remains about the same	The uncertainty gets larger
<b>0</b>	<b>1</b>	<b>2</b>	<b>3</b>

**Q4c.** Using the map and the legend, can you give an indication of the value of various uncertainty metrics, such as the standard deviation or the interquartile range?

I can't tell from the map	Not at all	Not really	Somewhat	Almost completely	Completely
<b>0</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>

**Q4d.** This question asks you to quantify the uncertainty present in some of the regions. Please fill out the table below (only the highlighted boxes) to the best of your ability. There is no right answer for these values, just enter your **estimate** as best as you can and the **support size** you used to make your estimation. If you are unable to make an estimate or you can't use the map to do so, please check the box in the 3rd column instead.

Metric	Region		Approximation	Support
Whether you are asked to give the value of the standard deviation, interquartile range, or some other metric.	The region for which you are asked to make an estimate	Check the box below if you can't/are unable use the map to make an estimation.	Enter your estimate in this column	Enter the support size/zoom level that you used to make your estimation. It is always visible in the legend (i.e. 4x4)
Standard deviation	Region 1	<input type="checkbox"/>		___ x ___
Interquartile range	Region 1	<input type="checkbox"/>		___ x ___
Standard deviation	Region 3	<input type="checkbox"/>		___ x ___
Width of 95% CI	Region 3	<input type="checkbox"/>		___ x ___
Standard deviation	Region 5	<input type="checkbox"/>		___ x ___
Legend uncertainty	Region 5	<input type="checkbox"/>		___ x ___

### Question 5

Zoom in to Region 2 until the support size is 1x1, and then select "Interval Probability" from the visualization options. Drag the map so that Region 1 is also still visible.

The black circles now no longer represent standard deviation or some other uncertainty metric, but they represent a **probability** between 0% and 100% that the forecasted value is within a specified interval. A small circle means 0% chance, and a big circle means 100% chance. Again you can use the legend or move your mouse over the circle to see the exact chance.

Below the label for “Interval Probability” is a slider which you can use to specify a maximum and minimum value. Adjust the slider so that the black circles will represent the probability of a value between 4.1 and 135.0. Please ask for help if you can’t find it or if it doesn’t work.

Imagine a simplistic assumption that certain concentrations of the pollutant can be classed into levels of danger, these are the classes:

Lower Limit	Upper Limit	Classification
0.0	4.1	SAFE
4.1	135.0	DANGEROUS
7.3	135.0	ALARM

As you can see a value between 0.0 and 4.1 is classified as a “safe” amount of pollutant in the sense that it will not endanger the general public, and a value of above 4.1 (i.e. between 4.1 and 135.0) is classified as “dangerous”. When the prediction is above 7.1 an alarm needs to be sounded.

**Q5x.** Can you identify which areas are likely (i.e. there is a more than 75% chance) to be “dangerous” at 05:00 in the morning?

I can't tell from the map	Not at all	Not really	Somewhat	Almost completely	Completely
<b>0</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>

**Q5a.** How likely do you think is it that the pollution concentration in Region 2 reaches a “dangerous” level of above 4.1 at 05:00 in the morning?

I can't tell from the map	Closest to 0%	Closest to 25%	Closest to 50%	Closest to 75%	Closest to 100%
<b>0</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>

**Q5b.** How likely do you think is it that the pollution concentration in Region 1 reaches a “dangerous” level of above 4.1 at 05:00 in the morning?

I can't tell from the map	Closest to 0%	Closest to 25%	Closest to 50%	Closest to 75%	Closest to 100%
<b>0</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>

**Q5c.** Imagine you are the decision maker tasked with public safety of a city in Region 1. When the pollution level is predicted to be above 7.3 an alarm needs to sound that everyone must keep their windows closed. What do you estimate the probability to be that the alarm has to be sounded at 5:00AM?

I can't tell from the map	Closest to 0%	Closest to 25%	Closest to 50%	Closest to 75%	Closest to 100%
<b>0</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>

**Q5d.** You are still the decision maker tasked with the public safety of a city in Region 1. It still seems the cloud will pass over your city early in the morning. What is the earliest time at which you think the chance of “dangerous” levels of pollutant (i.e. a concentration above 4.1) will have dropped below 25%? (Hint: use the timestep slider to move forward in time)

I can't tell from the map	By 6AM	By 8AM	By 10AM	By Noon	By 2PM	By 4PM
<b>0</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>	<b>6</b>

**Question 6**

You have by now experienced a few aspects of uncertainty and decision making under uncertainty using a forecast or prediction from an environmental model. Question 6 looks back on your experiences and asks you some questions about you feel about whether adding uncertainty information to a forecast has added value.

**Q6a.** Generally speaking, how uncertain (with regard to the predicted concentration, the shape of the cloud, the direction in which it travels...) do you think this forecast/prediction is?

Not at all	Not really	Somewhat	Quite uncertain	Very uncertain
<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>

**Q6b.** Using circular glyphs to represent uncertainty indicators/metrics such as standard deviation has helped me understand the **areas in which uncertainty is present** in the forecast of the pollution cloud while it spreads across Europe. Do you agree with this statement?

Not at all	Not really	Somewhat	Almost completely	Completely
<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>

**Q6b.** Using circular glyphs to represent uncertainty indicators/metrics such as standard deviation has helped me understand the **amount of uncertainty** in the forecast of the pollution cloud while it spreads across Europe. Do you agree with this statement?

Not at all	Not really	Somewhat	Almost completely	Completely
1	2	3	4	5

**Q6c.** Using circular glyphs to represent probabilities has helped me understand what the **chances are of certain concentration levels occurring** (i.e. “dangerous” or “safe”) in the forecast of the pollution cloud while it spreads across Europe. Do you agree with this statement?

Not at all	Not really	Somewhat	Almost completely	Completely
1	2	3	4	5

**Q6d.** Using circular glyphs to depict various aspects of uncertainty makes the display of information about the cloud of pollution too difficult and complex to use. Do you agree?

Not at all	Not really	Somewhat	Almost completely	Completely
1	2	3	4	5

**Q6e.** Visualizing uncertainty using circular glyphs would improve the accuracy of decision makers’ views, analyses and predictions. Do you agree?

Not at all	Not really	Somewhat	Almost completely	Completely
1	2	3	4	5

**Q6f.** The interface (locations of buttons and links, design, look and feel) of the web application is adequate for allowing me to question the dataset and the uncertainty present in the dataset. Do you agree?

Not at all	Not really	Somewhat	Almost completely	Completely
1	2	3	4	5

*(please fill in the end time on the next page)*

<b>End time:</b>	__ : __
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**Exit Questions (Optional):**

Are there any other comments or feedback you would like to share?

Given your professional background, are you interested in keeping up to date with this research and web-based uncertainty visualization applications? If so, please leave your e-mail address below:

Name:	
E-mail:	
Institute:	

## 12 Appendix B – Survey Results (Unprocessed)

Nr	Start	End	Diff	Q1a_Lvl_Exp	Q1b_Exp_Yrs	Q1c_HiLow_Value	Q1d_Reg4Highest	Q1e_Reg2Betw3_8	Q2_Prior	Q6a_Posterior	Q3a_HiLow_Uncert	Q3b_Reg5_smlr_Reg3	Q3c_Re4_smlr_Reg3	Q3d_MostUncert_Reg1_Reg2	Q3e_WhichRegMostUncert	Q4a_ZoomIn	Q4b_ZoomOut	Q4c_GiveVal_Metrics
1	12:55	13:25	0:30	4	4	5	1	4	3	3	5	5	5	2	5	1	2	5
2	12:55	13:27	0:32	3	3	3	1	5	3	3	4	5	5	1	5	2	2	3
3	12:59	13:31	0:32	3	2	3	1	4	3	4	5	5	5	1	5	2	2	3
4	10:45	11:15	0:30	3	2	5	2	4	4	4	4	2	5	1	5	3	1	5
5	17:16	17:55	0:39	4	4	5	1	4	3	3	4	5	5	1	5	2	2	3
6	13:48	14:38	0:50	5	5	5	1	5	4	4	5	5	5	1	5	3	1	4
7	18:13	18:54	0:41	1	1	4	1	4	2	2	5	5	5	1	5	1	3	4
8	18:58	19:38	0:40	0	1	4	2	4	3	2	4	5	5	1	5	3	1	4
9	18:41	19:23	0:42	1	2	4	1	4	2	2	5	5	5	1	5	3	1	5
10	19:29	20:13	0:44	0	1	4	1	4	3	3	3	5	5	1	5	3	1	3
11	18:51	19:25	0:34	0	1	5	1	5	2	2	5	5	5	1	5	3	1	4
12	9:55	10:24	0:29	4	5	5	1	5	4	4	4	5	5	1	5	3	1	3



