# An Assessment and Categorisation of Quantitative Uncertainty Visualisation Methods for Geospatial Data

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## INTRODUCTION

Visualisation of uncertain geospatial data has become an intriguing part of uncertainty communication. Many methods, which vary from static to dynamic or interactive, have evolved to cater to different data and user requirements which are determined by parameters such as the measurement scale of the phenomenon, type of uncertainty bound, the data format and their spatial temporal extents (Pang et al. 1997, Heuvelink et al. 2007). Certainly, one particular method does not bear the ability to fulfil all requirements to visualise uncertain data with different combinations of the above mentioned parameters. Many researchers who have extensively discussed the use of visualisation methods with respect to different use cases and user criteria have described these methods based on a few specific parameters, which are in particular *data type*, *data format*, *uncertainty type* and *interaction type* (Pang 2001, Cliburn et al. 2002). However, so far no explicit categorisation of methods according to their supported parameters has been investigated. In order to provide an ease of selecting a best relevant visualisation method based on the data and user requirements, this paper in its first section presents an overview of standard uncertainty visualisation methods and their conformance with the identified parameters. Subsequently, we lay out the basis for a formalised model of categorisation which is capable of automatically selecting the suitable visualisation methods for specified data and user requirements. Finally, future work towards an automatic selection model and further user requirements are discussed briefly.

## OVERVIEW OF UNCERTAINTY VISUALISATION METHODS

Numerous literature exists which discusses the benefits and use cases of uncertainty visualisation methodologies. However, a limited amount of literature is available on categorisation of these methods according to a set of supported parameters (e.g. Pang et al., 1997) These invaluable contributions to this research field lack the explicit distinction of methods according to the parameters, *data type*, *data format*, *uncertainty type* and *interaction type,* which are believed to be the grounded characteristics of uncertainty visualisation methods.

Out of the plethora of existing methods, a set of standard methods which have been used and assessed intensively in the field of uncertainty visualisation for geospatial data are presented and discussed in the following.

| Name of the Method | Description |
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|---|---|
| Adjacent Maps | Value and uncertainty are presented in two separate maps. (MacEachren 1992). |
| Animation | (1) **Animation** of different realisations of the uncertain attribute to emphasise the uncertainty (Ehlschlaeger et al. 1997).<br>(2) **Blinking Regions**, where two images of data and uncertainty are overlaid on top of another and alternately displayed (Kardos et al. 2006).<br>(3) **Blinking Pixels** where the displayed data is manipulated to blink through constantly changing colour of the pixels of more uncertain data with a rate of change proportional to the uncertainty (Fisher 1993). |
| Hierarchical Spatial Data Structures | These are used as a transparent tessellated layer on top of the data. A finer tessellation indicates less uncertain areas, a coarser tessellation indicates more uncertain regions (Kardos et al. 2003). |
| Colour Models | (1) **RGB Colour Scheme,** red, green, blue represents the variables and colour intensity represents the uncertainty with higher intensity depicting lower uncertainty (Cliburn et al. 2002, MacEachren 2005).<br>(2) **Whitening**, wherethe colour hue is used to represent the data and the saturation-intensity (whiteness) is used to represent the uncertainty. (Hengl 2003). A similar result is obtained by the technique of pixel mixing (Hengl et al. 2006). |
| Glyphs | Uncertainty and the data is represented in a bivariate depiction through pictorial symbols, known as glyphs ( Pang 2001). |
| Contouring | Contour lines of different colours are used to distinguish between different variables and their uncertainties with the intensity of colour. Positional uncertainty is depicted through the gap widths in the dotted contour lines where higher uncertainty leads to wider gaps (Dutton 1992, Pang 2001). The concept of contouring can be used in an animated environment as **animated isolines** (Fauerbach et al. 1996). |
| Focus Metaphors | Uncertain data is depicted out of focus, e.g. foggy and more certain in focus, e.g. crisp boundaries. Another metaphor of this method is the Opacity method where less uncertain data is seen less opaque and more uncertain data is more opaque (MacEachren 2005). This concept can also be used in reverse where uncertain data is shown more transparently (Drecki 2002,) |
| Exceedance Probability Mapping | These maps depict the probability of exceeding a threshold in a certain pixel or area (e.g. Van de Kassteele & Velders 2006). A similar concept is giving confidence intervals. |

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|---|---|
| Statistical Dimension in a GIS | The uncertainty of the data is represented by the cumulative probability functions for each pixel or vector object. Depending on the chosen quantile or threshold value, the map colour scale shows the associated value or probability (Pebesma et al. 2007) |

***Table 1:*** Uncertainty visualisation methods

The following ***Table2*** shows the categorisation of the above described visualisation methods according to their supported parameters. The *data type* depends on the measurement scale of an attribute and is of type continuous, ordinal or categorical. *Data format* is the type of spatial data format in which the data is encoded which can be either raster or vector data. The *uncertainty type* of geospatial data refers to the attribute of the data which is uncertain. This could be classified as positional, attribute or temporal uncertainty (Longley et al. 2005). Lastly, *interaction type* describes the way the data is presented to the user with regard to the manipulability of the interface. *Interaction type* can be, static, dynamic or interactive.

<table>
<tr><th>Supported data type(s)</th><th>Supported data format(s)</th><th>Uncertainty type(s)</th><th>Interaction type</th><th>Name of the method</th></tr>
<tr><td rowspan="6">Continuous</td><td rowspan="5">Raster, vector data</td><td rowspan="3">Attribute</td><td rowspan="2">Static</td><td>Exceedance probability mapping</td></tr>
<tr><td>RGB colour scheme</td></tr>
<tr><td>Interactive</td><td>Statistical dimension</td></tr>
<tr><td rowspan="2">Attribute, positional</td><td>Dynamic</td><td>Animated isolines</td></tr>
<tr><td>Static</td><td>Contouring</td></tr>
<tr><td>Vector data</td><td>Attribute, positional</td><td>Static</td><td>Glyphs</td></tr>
<tr><td rowspan="3">Continuous, categorical</td><td>Raster data</td><td>Attribute, positional</td><td>dynamic, interactive</td><td>Blinking pixels</td></tr>
<tr><td rowspan="2">Raster, vector data</td><td>Attribute, positional</td><td>Dynamic</td><td>Animation</td></tr>
<tr><td>Attribute</td><td>Dynamic, interactive</td><td>Blinking regions</td></tr>
</table>

| | | | | |
|---|---|---|---|---|
| | | | | Whitening |
| | | | | Adjacent maps |
| | | | | Symbol focus |
| | | | Static | Opacity |
| | Vector data | Attribute | Static | Hierarchical spatial data structures |

***Table 2:*** Categorisation of quantitative uncertainty visualisation methods

## TOWARDS AN AUTOMATIC SELECTION OF VISUALISATION METHODS

Different visualisation methods have evolved to cater to different data and user requirements which are determined by parameters such as the above mentioned, and different users dealing with uncertainty data and their visualisation methods have different requirements (Davis & Keller 1997). Hence, it is not often easy to know which uncertainty visualisation method to choose for a given use case, as users can be from different domains and thus, some could lack the needed expertise. To address this problem we propose a mechanism to provide the users an ease of selecting a relevant uncertainty visualisation method. In the following we present a first version of a formalised model which is based on categorisation by the core parameters of uncertainty visualisation, *data type*, *data format*, *uncertainty type* and *interaction type*. Once the model is implemented, it bears the ability to automatically select an appropriate visualisation method based on the data and user requirements. These requirements which in our case are described by the parameters will be an input to the model to choose suitable method(s). This could be used for automated visualisation of uncertainty of results within, e.g. web-service or model chains as well as allowing non-expert users to select appropriate methods for their data.

***Figure 1*** shows the UML class diagram of the designed model. This formalised model depicts the interrelation between the uncertainty visualisation methods and their supported parameters. The abstract visualisation method type is sub-classed into three main categories based on the *interaction type*, namely static, dynamic and interactive methods, where interactive is in turn a subclass of dynamic. The other parameters which are discussed above (*uncertainty type*, *data type* and *data format*) are aggregated in the visualisation type. The concrete parameter values (e.g. positional uncertainty as uncertainty type) are modelled as subtypes.

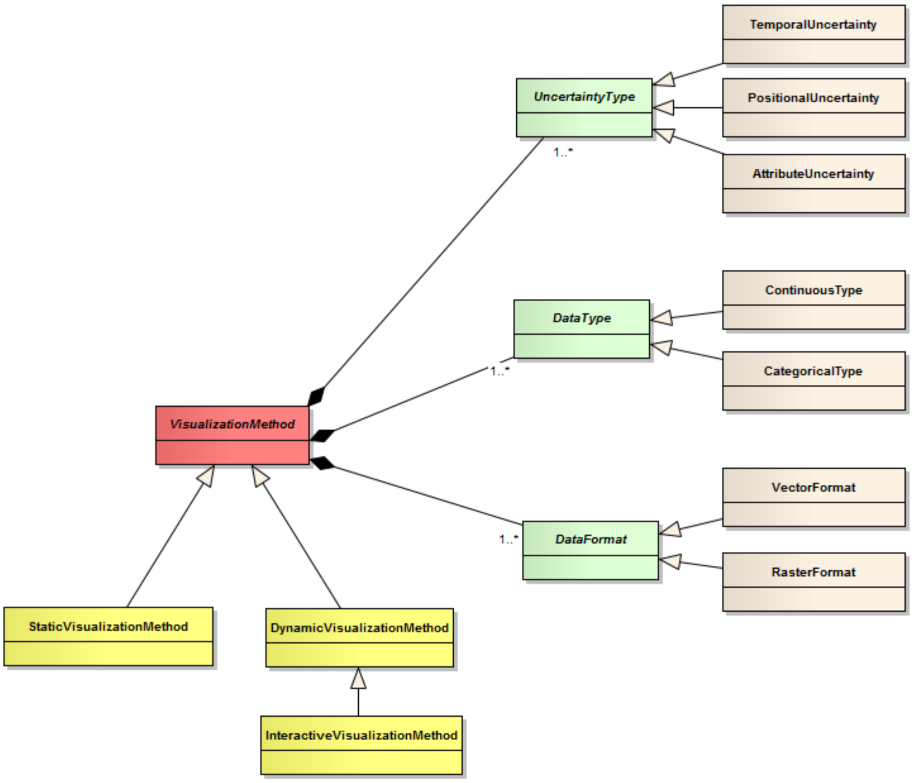


***Figure 1:*** UML Class diagram depicting the interrelation between data requirements

The following ***Figure 2*** presents a decision tree for the model which can be followed by the program to select the methods. It depicts the hierarchy of parameters. Assuming the given scenario in visualising the uncertainty of the concentration of a particular air pollutant in a given area, the user feeds in the requirements, *attribute uncertainty*, *continuous data type*, *vector data format*, and *dynamic interaction type.* Upon these requirements the decision tree ultimately leads to the consequent outcome of visualisation methods: *Animated Isolines*, *Blinking Regions* and *Animation*. The user proceeds to selecting a method. The uncertainty type, *temporal uncertainty* included in the decision tree is currently not taken into account in this first approach. However, it is a potential parameter for future advancement of the model.

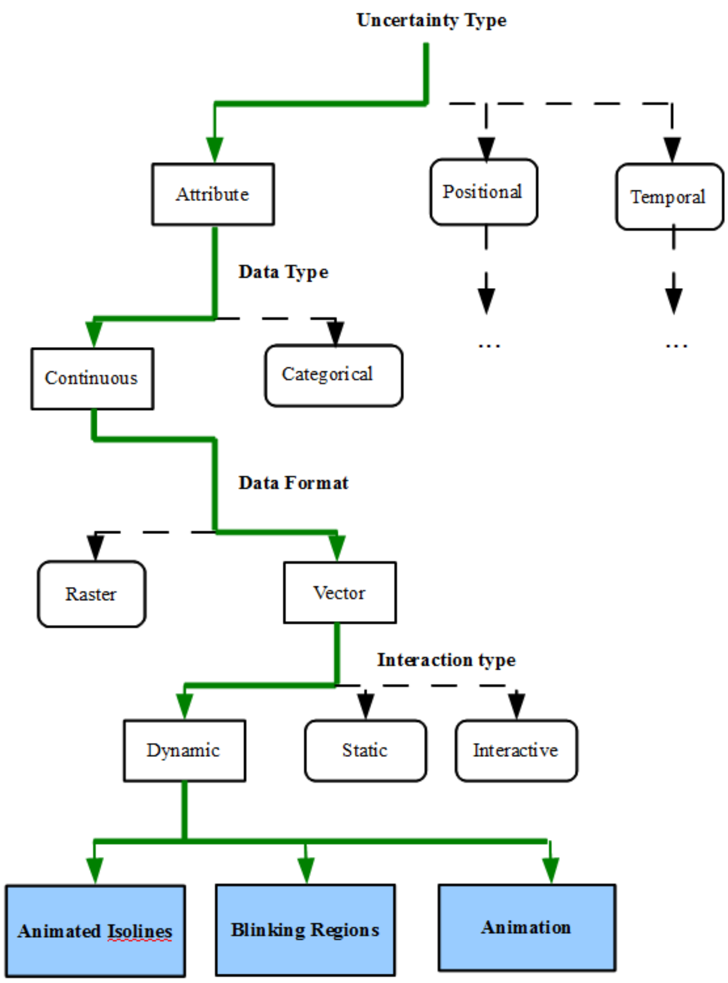


***Figure 2*:** Decision tree followed by the program to find suitable uncertainty visualisation methods

## CONCLUSION AND FUTURE WORK

This paper presents a categorisation of uncertainty visualisation methods for geospatial data and a basis for a formalised model for the automatic selection of uncertainty visualisation methods. Upon giving a brief overview of the selected uncertainty visualisation methods, we have categorised them in ***Table 2*** which provides an ease of selecting an appropriate visualisation method to the user by the chosen parameters. The basic version of the model depicts the interrelation of the parameters through a UML class diagram.

In future, the model will be implemented to integrate with a web-based visualisation tool and tested for its performance. Also, future work will be to assess the usability of these methods, at different user experience levels. Through these evaluations the assessed methods can be categorised on their relevance and usability at different user groups. This will allow novice users to choose methods according to their level of expertise. Thereupon, *usability* as another parameter for each method could be derived. This new model parameter could then be utilised to select the most "useful" method(s) which duly fulfils the data requirements for the user.

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