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A Catalogue *of* VISUALISATIONS

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ANALYSIS UNDER UNCERTAINTY *for*
DECISION MAKERS NETWORK

Prepared and edited by

Jana Kleineberg
Polina Levontin
Jo Lindsay Walton

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The **Analysis Under Uncertainty for Decision Makers Network** is a community of researchers and professionals from policy, academia, and industry, who are seeking to develop a better understanding of decision-making to build capacity and improve the way decisions are made across sectors and domains.

For further details about the network, visit **http://au4dmnetworks.co.uk/.**

Introduction

"We do not have a comprehensive understanding of the parameters that influence successful uncertainty visualization, nor is it easy to determine how close we are to achieving such an understanding." (MacEachren et al., 2005)

In this catalogue, we will briefly summarise various approaches to visualising uncertainty in the context of decision-making. We will adopt the classification of uncertainties as proposed by Simon French in the *Catalogue of Decision-Making Tools*, created earlier for the network. Although uncertainty might stem from different sources, such as observations, natural variability, or diversity of stakeholder values, the approaches to visualisation of these uncertainties might be similar.

In our increasingly visual culture, the role of visualisation in communication needs to be examined on a case-by-case basis, as our current understanding offers insufficient basis for generalisations especially for the visualisation of uncertainty. Reviewing the state of knowledge in 2005, MacEachren et al. concluded that: "[W]e do not have a comprehensive understanding of the parameters that influence successful uncertainty visualization, nor is it easy to determine how close we are to achieving such an understanding" and in a follow up to that review in 2016, Riveiro asserted that this conclusion is valid still. This is not a reflection of the paucity of studies; visualisation is a burgeoning research topic across a diversity of fields.

A sheer variety of methodological approaches and theoretical frameworks for the study of visualisation accounts for one of the difficulties in synthesising the knowledge into an applicable theory. Broadly, there are two types of investigations, subjective or objective: those that use self-reporting or those that rely on measured outcomes such as a speed of making a decision or decision accuracy. An array of methodologies have been reported for each type of observations (Kinkeldey et al., 2015).

Other problems include small sample sizes for audience testing; inappropriate subjects (students rather than decision-makers); lack of reproducibility, small effect sizes when comparing different visualisation approaches, biased self-perception (there is little correspondence between self-reported and the actual impact of visualisations); transferability issues confounded by the fact that individual, cultural, and other differences are difficult to control for. The evidence from several studies of unreliability in self-assessment is particularly problematic and it goes against the grain of a client-designer relationship. This means that client satisfaction may have little to do with the efficacy of the product: that is, people may be helped by the visualisations they don't favour or can be impaired (as decision-makers) by the visualisations they happen to prefer. As it often is with good design, the benefits may not be noticeable to users and could be received unacknowledged. Several studies noticed that the users of visualisations may become better at decision-making without realising it. Kinkeldey et al. (2015) mention a study that revealed a surprising lack of correlation between inde-

pendently measured performance and self-reported confidence in making decisions: 'decision accuracy was significantly higher with uncertainty depicted, meaning that user performance and confidence did not correspond.' The evidence pointing at people's inability to assess their own performance is broader than just research on visualisation, Hullman et al. (2008) write: 'Further, evidence from other disciplines suggests that people are not very good at making accurate judgments about their own ability to make judgments under uncertainty'.

What emerges from these various studies is a consensus that visualisation matters, and evidence abounds that visualisation of uncertainty can influence decision-making in several consequential ways, including (Kinkeldey et al., 2015):

- ***Decision outcomes***
- ***Correctness of decisions***
- ***Kinds of errors made***
- ***Decision time***
- ***Confidence in a decision***
- ***Willingness to make a decision***
- ***How much workload decision-making causes***
- ***How a decision is made.***

'Thus, even if the effects of visualizing uncertainty and its influence on reasoning are not fully understood,' write Riveiro et al. (2014), 'it has been shown that the graphical display of uncertainty has positive effects on performance...' — a review of visualisation studies indeed reveals a multiplicity of effects of visualisation on decision-making, mostly but not always positive. Negative effects of visualisation reported in the literature point to interactions with cognitive biases and human psychology more generally, resulting in delays in decision-making when extra information related to uncertainty needs to be processed; irrational attitudes to risk, such as focusing on the worst-case scenarios; or, on the contrary, focusing on the mean rather than variance; confusion between risk and uncertainty; etc..

In summary, Kinkeldey et al. (2015) observe: 'Overall, based on studies reviewed, uncertainty visualization has tended to result in a positive effect on decision accuracy. The evidence is less clear for decision speed, but it could be observed that usually, uncertainty visualization does not slow down decision-making and in one case it even decreased the decision time. The above mentioned findings on irrational decisions under uncertainty suggest that in order to use data and related uncertainty effectively, users must know how to interpret data together with related uncertainty.' Training and experience of users both play a role in determining the impact of particular visualisation on their decision-making.

However, even the expertise interacts with visualisation impacts in ways which are difficult to anticipate. For example, in some studies experience of decision-makers enabled them to make better use of visualisation than less experienced users, arriving at decisions faster and with greater accuracy. In other studies, the level of expertise was correlated with bias in the decision-making linked to uncertainty depiction; experiments 'showed that participants with a high level of

experience had the strongest bias towards selecting areas of low uncertainty' Kinkeldey et al. (2015).

What is lacking currently is the ability to predict how specific visualisation will impact a particular decision-making process. This is not to say that experience and existing research offer no guidance whatsoever—if that was the case, there would be no point in creating a visualisation catalogue—but to emphasise that any new visualisation needs to be tested and evaluated in its intended context and with the relevant audience.

Creating effective visualisations are not necessarily the guarantee of successful implementation. Uncertainty is not something people are comfortable with, no matter how well it is visualised. Widely reported in the visualisation of uncertainty literature is resistance and a general lack of acceptance towards incorporating uncertainty into decision-making that goes beyond visualisation. For example, Riveiro et al. (2014) report that 'participants' greater uncertainty awareness was associated with lower confidence.'

Kinkeldey et al. (2015) recommend that decision-makers are supported with more than just visualisations: 'Further concerns were that decision-makers needed additional information for interpreting and coping with uncertainty (e.g., when a high degree of uncertainty is a problem and when not) and that decision-makers often have little time to explore uncertainty in the data. Based on these findings, the authors contend that well-crafted visualization methods alone may not be sufficient to support decision-makers and that suitable strategies may be needed to utilize uncertainty information [...]'

Several studies explore how visualisation affects the cognitive strategies of dealing with uncertainty and find visualisations might lead to less effort being expended by the decision-maker on acquiring and processing information relevant to uncertainty, which may be undesirable. Riveiro et al. (2014) report a study where visualisation of uncertainty led to significantly fewer attempts to identify a target (in a military scenario) and also to assigning higher threat values to uncertain targets, demonstrating again the hazard of imagining the 'worst case' scenario with the visualisation (the availability heuristic exists whether or not the visualisation is there, but the visualisation invites or accommodates it).

Much of the research about visualisation of uncertainty is related to spatial reasoning and addresses the potential of visualisation to improve probabilistic spatial reasoning that is plagued (like all probabilistic reasoning) by many cognitive biases that are part of human psychology. Some researchers like Pugh et al. (2018) are optimistic: 'Visualizations have the potential to influence how people make spatial predictions in the presence of uncertainty. Properly designed and implemented visualizations may help mitigate the cognitive biases related to such prediction.'

With these caveats in mind, we will present in this catalogue some of the basic theory and practical examples of visualising uncertainty within the decision-making context.

The Framework

Before we begin discussing the foundational elements that can be called upon in the visualisation task, let's emphasise that selecting a visualisation method is not the first step. The process itself should begin with the identification of uncertainty, understanding of the various components that contribute to uncertainty and discussing the aims of visualisation. We recommend considering the framework below or a close equivalent.

Types of Uncertainty: Some Prompts

Decision-making quality is improved from understanding the uncertainty in the data and information being used. Categorising uncertainty is a preliminary step towards recognising and dealing with uncertainty in the decision-making process.

Uncertainty can come in many forms, and with many different qualities. Each uncertainty applies to different types of information, and can be quantified, and thus represented, in different ways.

French et al. (2016) list the following: Uncertainty can include **stochastic** uncertainties (i.e., physical randomness), **epistemological** uncertainties (lack of scientific knowledge), **endpoint** uncertainties (when the required endpoint is ill-defined), **judgemental** uncertainties (e.g., setting of parameter values in codes), **computational** uncertainties (i.e., inaccurate calculations), and **modelling errors** (i.e., however good the model is, it will not fit the real world perfectly).

There are further uncertainties that relate to **ambiguities** (ill-defined meaning) and partially formed value judgements; and then there are **social** and **ethical** uncertainties (i.e., how expert recommendations are formulated and implemented in society, and what their ethical implications are). Some uncertainties may be deep; i.e., within the time and data available to support the emergency management process, there is little chance of getting agreement on their evaluation or quantification.

Chung and Wark (2016) list these categories:

- **Accuracy** *the difference between observation and reality*
- **Precision** *the quality of the estimate or measurement*
- **Completeness** *the extent to which information is comprehensive*
- **Consistency** *the extent to which information elements agree*
- **Lineage** *the pathway through which information has been passed*
- **Currency** *the time span from occurrence to information presentation*
- **Credibility** *the reliability of the information source*
- **Subjectivity** *the extent to which the observer influences the observation*
- **Interrelatedness** *the dependence on other information*
- **Experimental** *the width of a random distribution of observations*
- **Geometric** *the region within which a spatial observation lies*

Cynefin

Welsh, without direct translation into English but akin to "a place to stand," "usual abode," and "habitat." It is pronounced / ˈkʌnɪvɪn / KUN-iv-in.

Excerpt from "Decision Support Tools for Complex Decisions under Uncertainty," edited by Simon French from contributions from many in the AU4DM network: Another categorisation of uncertainty called *Cynefin*—a Welsh word for habitat, and used here to describe the context for a decision—categorises our knowledge relative to a specific decision. Cynefin roughly divides decision contexts into four spaces (see *figure 1*).

In the ***Known Space***, also called *Simple*, or the *realm of Scientific Knowledge*, relationships between cause and effect are well understood, so we will know what will happen

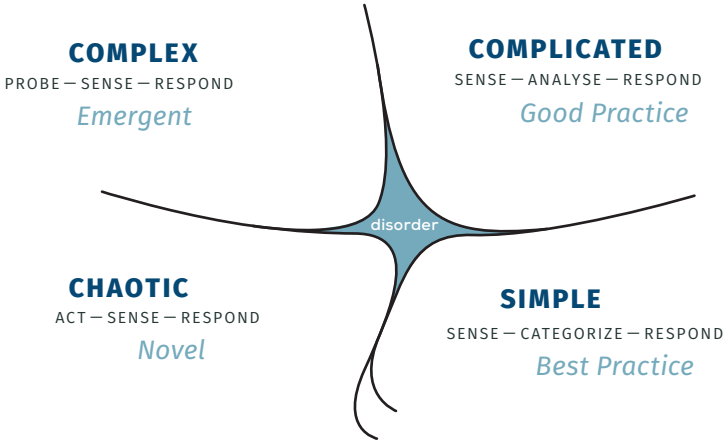

figure 1

Repeatability and increasing familiarity

SIMPLE / KNOWN SPACE:
*The realm of **Scientific Knowledge**, also called the "known knowns." Rules are in place, the situation is stable. Cause and effect relationships are understood; they are predictable and repeatable.*

COMPLICATED / KNOWABLE SPACE
*The realm of **Scientific Inquiry**, or domain of "known unknowns." Cause and effect relationships exist. They are not self-evident but can be determined with sufficient data.*

'Messy' decisions, many uncertainties are deep

COMPLEX SPACE
*The realm of **Social Systems**, or domain of "unknown unknowns." Cause and effect are only obvious in hindsight and have unpredictable, emergent outcomes.*

CHAOTIC SPACE
No cause and effect relationships can be determined.

if we take a specific action. All systems and behaviours can be fully modelled. The consequences of any course of action can be predicted with near certainty. In such contexts, decision-making tends to take the form of recognising patterns and responding to them with well-rehearsed actions, i.e., recognition-primed decision-making. Such knowledge of cause and effect will have come from familiarity. We will regularly have experienced similar situations. That means we will not only have some certainty about what will happen as a result of any action, we will also have thought through our values as they apply in this context. Thus, there will be little ambiguity or value uncertainty in such contexts.

In the ***Knowable Space***, also called *Complicated,* or the *realm of Scientific Inquiry,* cause and effect relationships are generally understood, but for any specific decision further data is needed before the consequences of any action can be predicted with certainty. The decision-makers will face epistemological uncertainties and probably stochastic and analytical ones too. Decision analysis and support will include the fitting and use of models to forecast the potential outcomes of actions with appropriate levels of uncertainty. Moreover, although the decision-makers will have experienced such situations before they may be less sure of how their values apply and will need to reflect on these in making the final decision.

In the ***Complex Space,*** also called the *realm of Social Systems,* decision-making faces many poorly understood, interacting causes and effects. Knowledge is at best qualitative: there are simply too many potential interactions to disentangle particular causes and effects. There are no precise quantitative models to predict system behaviours such as in the Known and Knowable spaces. Decision analysis is still possible, but its style will be broader, with less emphasis on details, and more focus on exploring judgement and issues, and on developing broad strategies that are flexible enough to accommodate changes as the situation evolves. Analysis may begin and, perhaps, end with much more informal qualitative models, sometimes known under the general heading of soft modelling or problem structuring methods. Decision-makers will also be less clear on their values and they will need to strive to avoid motherhood-and-apple-pie objectives, such as minimise cost, improve well-being, or maximise safety.

Contexts in the ***Chaotic Space*** involve events and behaviours beyond our current experience and there are no obvious candidates for cause and effect. Decision-making cannot be based upon analysis because there are no concepts of how to separate entities and predict their interactions. The situation is entirely novel to us. Decision-makers will need to take probing actions and see what happens, until they can make some sort of sense of the situation, gradually drawing the context back into one of the other spaces.

The central blob in *figure 1* is sometimes called the ***Disordered Space***. It simply refers to those contexts that we have not had time to categorise. The Disordered Space and the Chaotic Space are far from the same. Contexts in the former may well lie in the Known, Knowable, or Complex Spaces; we just need to recognise that they do. Those in the latter will be completely novel.

For **MORE INFORMATION** *on categories of uncertainty and Cynefin, please see the AU4DM Uncertainty catalogue "Decision Support Tools for Complex Decisions under Uncertainty;" edited by Simon French from contributions from many in the AU4DM network.*

Visualising Uncertainty

The first step, that of the identification of the nature of uncertainty, is likely to reveal that only a portion of uncertainty can be visualised. Deitrick and Wentz (2015) in their review warn that:

'It is important to note that several assumptions underlie the methods and studies discussed in this section, reflecting the way in which researchers conceptualize uncertainty. First, it is assumed that uncertainty, or at least uncertainty of interest, is both knowable and identifiable. Similarly, to be visualized, uncertainty must be quantifiable, such as through statistical estimates, quantitative ranges, or qualitative statements (e.g., less or more uncertain). Moreover, evaluations define effectiveness as an ability to identify specific uncertainty values, which assumes that identifying specific uncertainty values is useful to decision-makers and that the values of interest can be quantified. Lastly, there is an assumption that the quantification of uncertainty is beneficial, applicable to the decision task, and usable by the decision-maker, even if users do not currently work with uncertainty in that way. These assumptions pose a challenge for visualizing uncertainty to support decision-making under deep uncertainty, where quantification of uncertainty is not possible or necessarily desirable. In this way, current approaches to uncertainty visualization are more normative in nature, reflecting what researchers think decision-makers need to know about uncertainty.'

The approaches to visualising uncertainty, extrinsic versus intrinsic, should depend on the type of uncertainty, according to Kinkeldey et al. (2014): 'All in all, results on extrinsic displays discussed here highlight the potential of glyph- and grid-based techniques for uncertainty representation in maps as alternatives to intrinsic techniques. On the question

11-STEP STRATEGY *for* UNCERTAINTY VISUALIZATION DESIGN

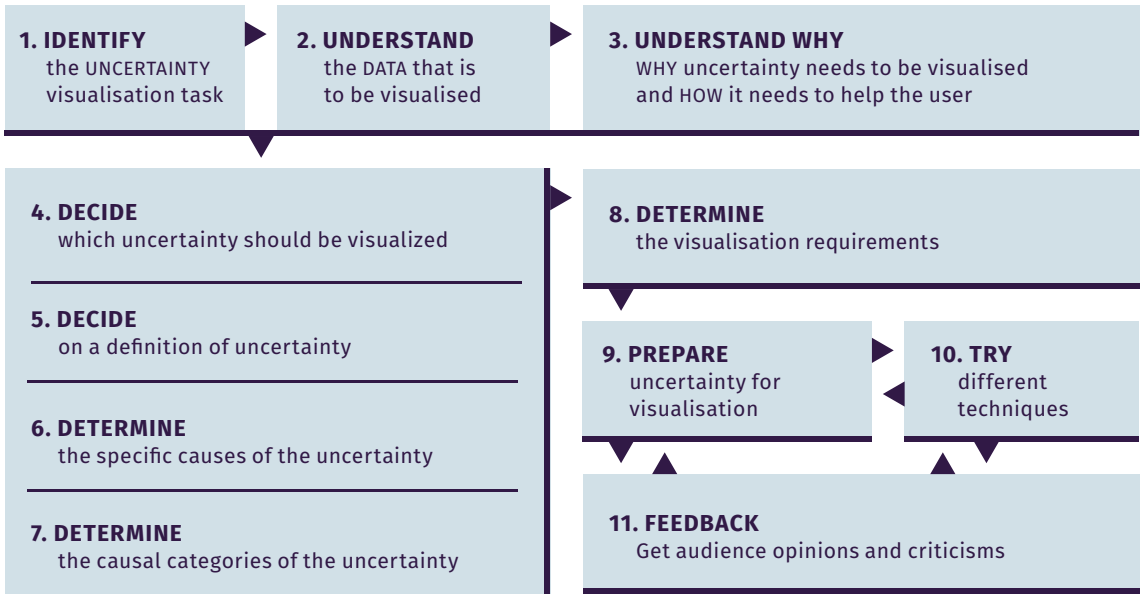

figure 2: The stepwise process for visualisation of uncertainty

of whether to choose intrinsic or extrinsic techniques, the type of uncertainty to be displayed is deemed to play a role: Kunz et al. (2011) suggested that intrinsic approaches may be more suitable for communicating quantitative and extrinsic approaches for qualitative information. This was supported by Alberti (2013) and Kinkeldey et al. (2014), who conclude that the extrinsic displays they used were especially successful for the communication of qualitative uncertainty.'

Recommendations on how to visualise uncertainty also depend on the task, so it is important to determine why uncertainty needs to be visualised: is it to explore the problem, to present results, or to analyse a situation and make decisions?

Tools

Just like there are many ways to classify uncertainties, there are many examples in the literature of the classification schemes for the visualisation techniques used in uncertainty visualisation. Kinkeldey et al. (2014), for example, reviews an array of studies in terms of how uncertainty is visualised, classifying approaches to visualisation according to three theoretical dichotomies. We follow the more pragmatic approaches by Meredith et al. (2008) and Matthews et al. (2008). In their review of the approaches to the visualisation of uncertainty, Meredith et al. (2008) mention the following:

- *adding glyphs*
- *adding geometry*
- *modifying geometry*
- *modifying attributes*
- *animation*
- *sonification*
- *fluid flow*
- *surface interpolants*
- *volumetric rendering*
- *differences in tree structures.*

This catalogue will provide examples of each of the above. However, we will begin with firstly discussing the attributes of a graphical object that can be manipulated, then how the objects can be layered, then how these can be animated and finally how interactivity can be introduced. This follows Matthews et al. (2008)'s categorisation into four nested techniques:

'1. Free graphical variables (e.g., color, size, position, focus, clarity, fuzziness, saturation, transparency and edge crispness) can be used to alter aspects of the visualizations to communicate uncertainty.

2. Additional static objects (e.g., labels, images or glyphs) can be added to the visualizations to communicate uncertainty.

3. Animation can be incorporated into the visualizations, where uncertainty is mapped to animation parameters (e.g., speed, duration, motion blur, range or extent of motion).

4. Uncertainty can be discovered by mouse interaction (e.g., mouse-over).'

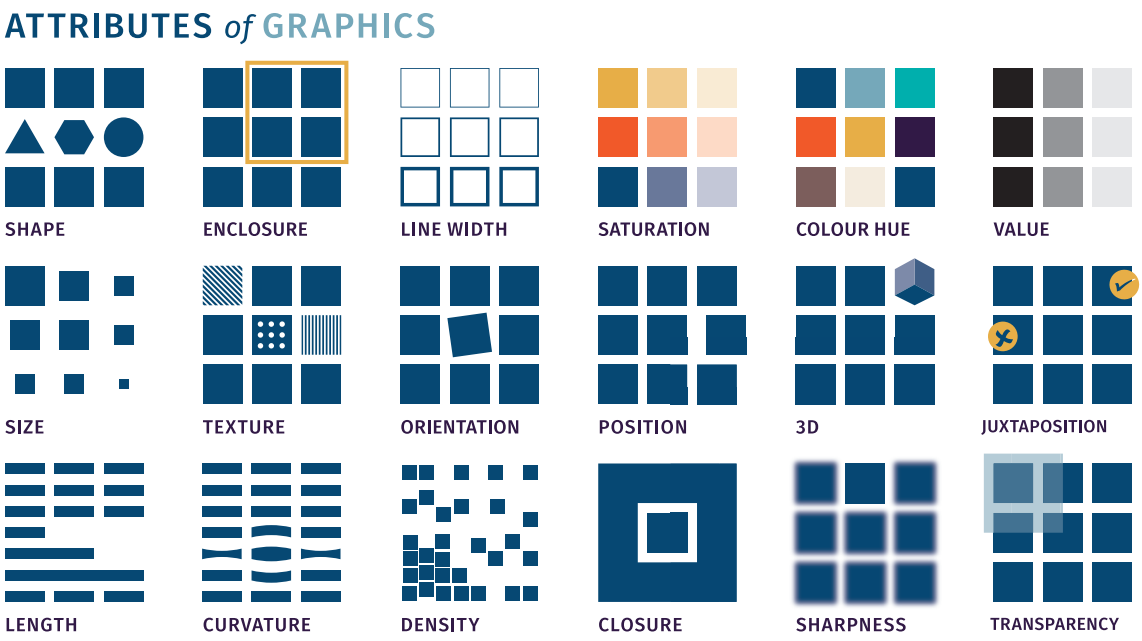

figure 3: Attributes of Graphics.

Alongside examples of visualising uncertainty, we will refer to what various studies have to say about their perspective usefulness.

There are only so many graphical attributes that can be manipulated (*figure 3* shows examples).

Various combinations involving manipulating these graphical parameters have been explored in the context of visualising uncertainty. Individual studies and reviews of existing research offer valuable insights. Seipel and Lim (2017) consider alteration to each of the three perceptual dimensions of colour, while, Kinkeldey et al. (2014) report that: 'Thus, from current knowledge, colour saturation cannot be recommended to represent uncertainty. Instead, colour hue and value as well as transparency are better alternatives.' There is another mention of saturation as unsuitable graphical parameter for the visualisation of uncertainty in Cheong's 2016 review, although the same studies are considered in both reviews, so there is a risk of double counting and drawing strong conclusions whereas there might only be weak evidence.

Value is sometimes referred to as lightness, which might also be confused with transparency, as in Aerts et al. (2003) who recommend its use: 'Color lightness as a graphical variable was found to be a powerful variable for representing uncertainty'. Cheong (2016), however, notes inconsistencies across various inquiries into the use of lightness and hue: 'For example, MacEachren (1992) explored the use of color hue for representing uncertainty, suggesting that this technique is best used for novice users. The evidence for the usability of color value (lightness) is conflicting, with some experiments indicating value is not effective (Schweizer and Goodchild 1992) and others indicating the converse (Leitner and Buttenfield 2000, Aerts et al. 2003). Where it is effective, darker values are associated with more certainty, and lighter values with more uncertainty (MacEachren 1992, Buttenfield 1993, McGranghan 1993, Van Der Wel et al. 1994).

Hue is sometimes referred to simply as colour, in another review of visualisation of uncertainty by Aerts et al. (2003) we read: 'Bertin (1983) describes an extended set of visual variables to portray information, such as position, size, value, texture, color, orientation, and shape. Among these variables, "the strongest acuity in human visual discriminatory power relates to varying size, value and color" (Buttenfield and Beard 1994).' but it is also possible that the word 'color' here refers to any combination of hue and saturation.

To understand the relationship between colour saturation, hue and value, consider *figure 4* below:

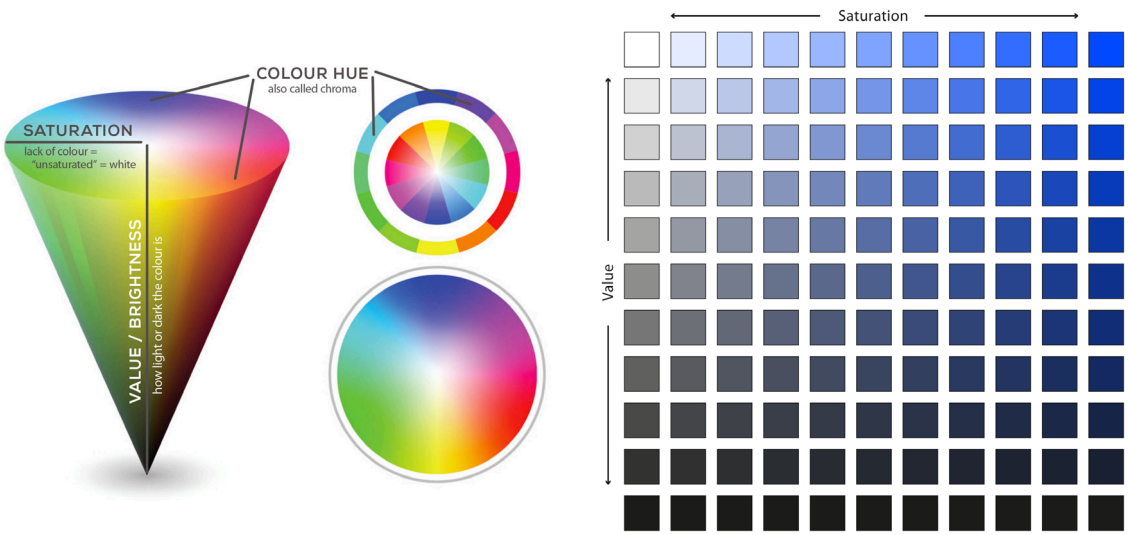

figure 4: Colour hue, saturation, value.

Effective Graphic Design Principles

Boone et al. (2018) list the following principles 'Effective graphic design takes account of

- the **specific task** at hand (Hegarty, 2011)
- **expressiveness** of the display (Kosslyn, 2006)
- data-ink **ratio** (Tufte, 2001)
- issues of **perception** (Kosslyn, 2006; Tversky, Morrison, & Betrancourt, 2002; Wickens & Hollands, 2000)
- **pragmatics** of the display, including making the most relevant information salient (Bertin, 1983; Dent, 1999; Kosslyn, 2006)

It also takes account of semantics:

- **compatibility** between the form of the graphic and its meaning (Bertin, 1983; Kosslyn, 2006; Zhang, 1996)
- **usability** of the display, such as including appropriate knowledge (Kosslyn, 2006)'

Violations of principles of effective graphics often lead to misunderstandings. An interesting example: the use of error bars to display uncertainty.

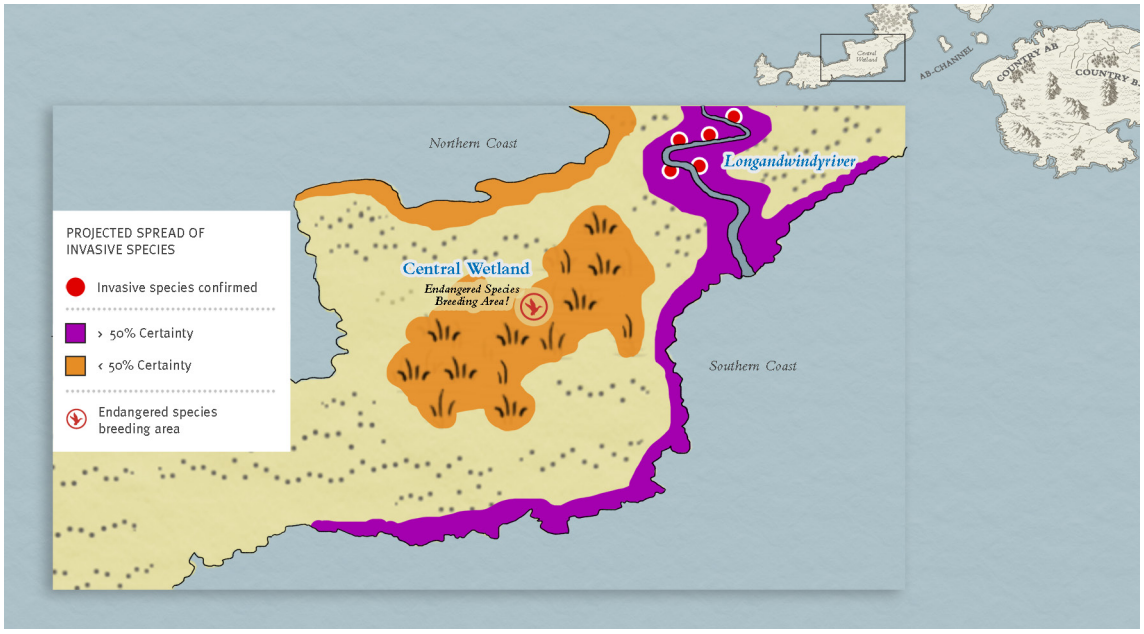

figure 5: Using hue to illustrate uncertainty (adding geometry).

Here are some examples to help illustrate techniques:

Some studies suggested using a side by side representations of uncertainty and of the variable, e.g., Deitrick and Wentz (2015).

An alternative to side by side display is interactive toggling that enables switching between representations of a variable and uncertainty. Various studies in the context of high uncertainty, time pressure and severe consequences of wrong decisions, e.g., in military battle, show that in simulations ability to toggle or switch between alternative representations of uncertainty is helpful, Riveiro et al. (2014). Finger and Bisantz (2000) explored communicating uncertainty about

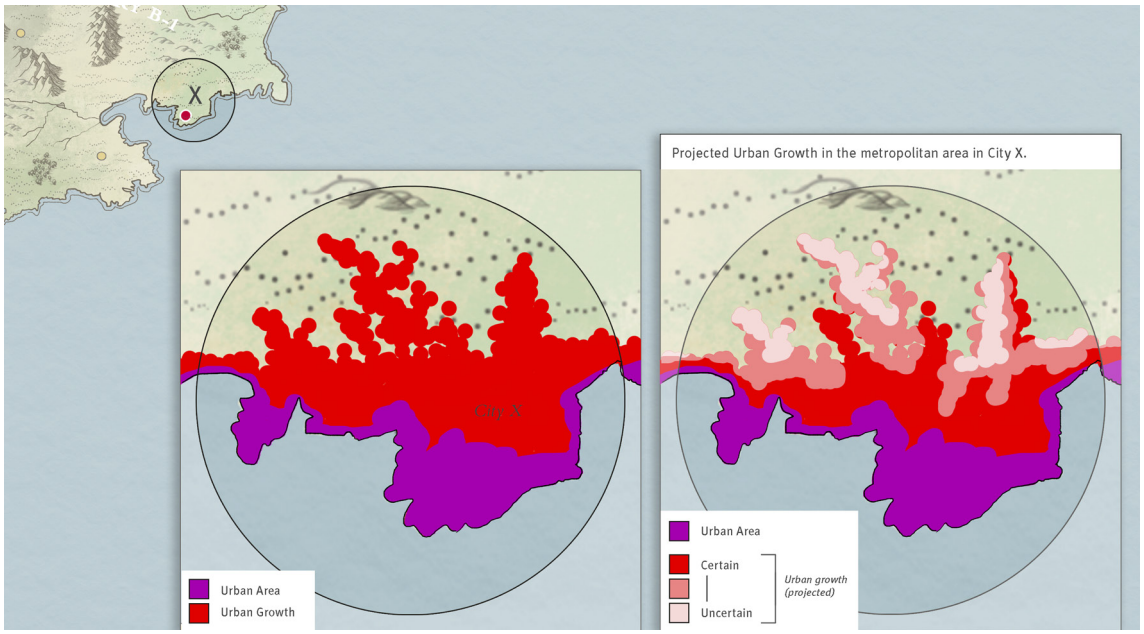

figure 6: Using hue to illustrate uncertainty (adding geometry).

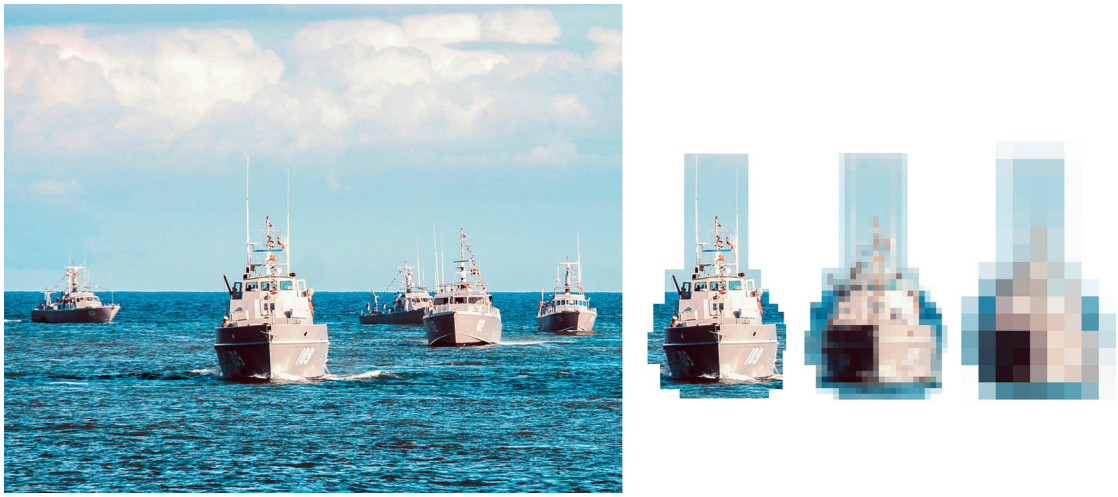

figure 7: Using degradation (here: pixelation) to illustrate uncertainty (adding geometry).

radar contacts by degrading or blurring the icons used to represent them. Bisantz et al. (2011) expanded this research, as Riveiro et al. (2014) summarise: 'several display methods were used in a missile defense game: icons represented the most likely object classification (with solid icons), the most likely object classification (with icons whose transparency represented the level of uncertainty), the probability that the icon was a missile (with transparency) and, in a fourth condition, participants could choose among the representations. Task performance was highest when participants could toggle the displays, with little effect of numeric annotations. As such, the authors once more support the use of graphical uncertainty representations, even when numerical presentations of probability are present.'

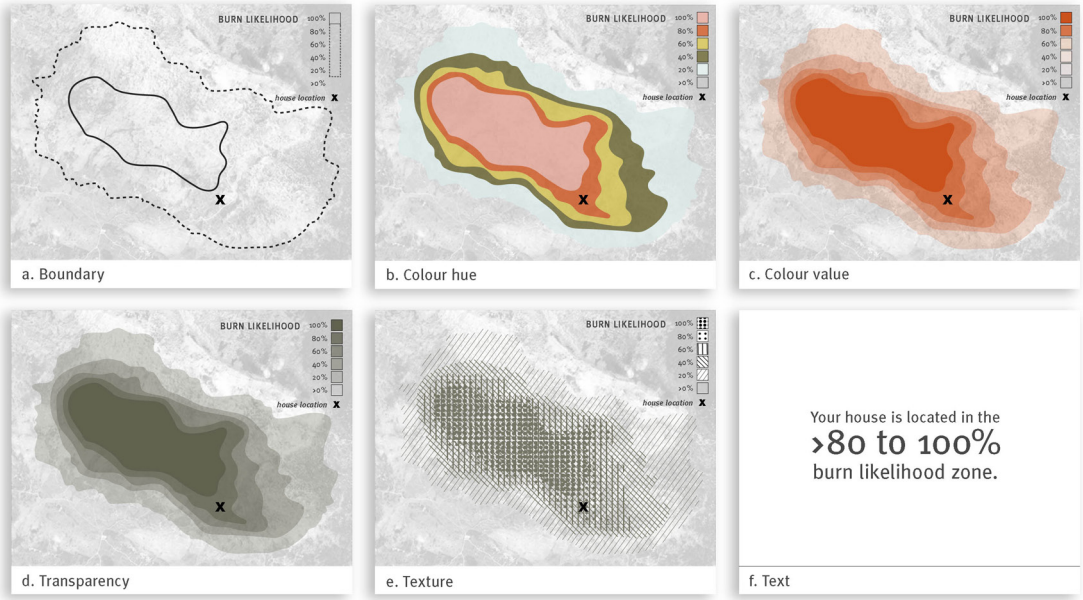

figure 8: Comparing changing different attributes to communicate uncertainty, research shows that representations involving hue(b), value(c) and transparency(d) work best.

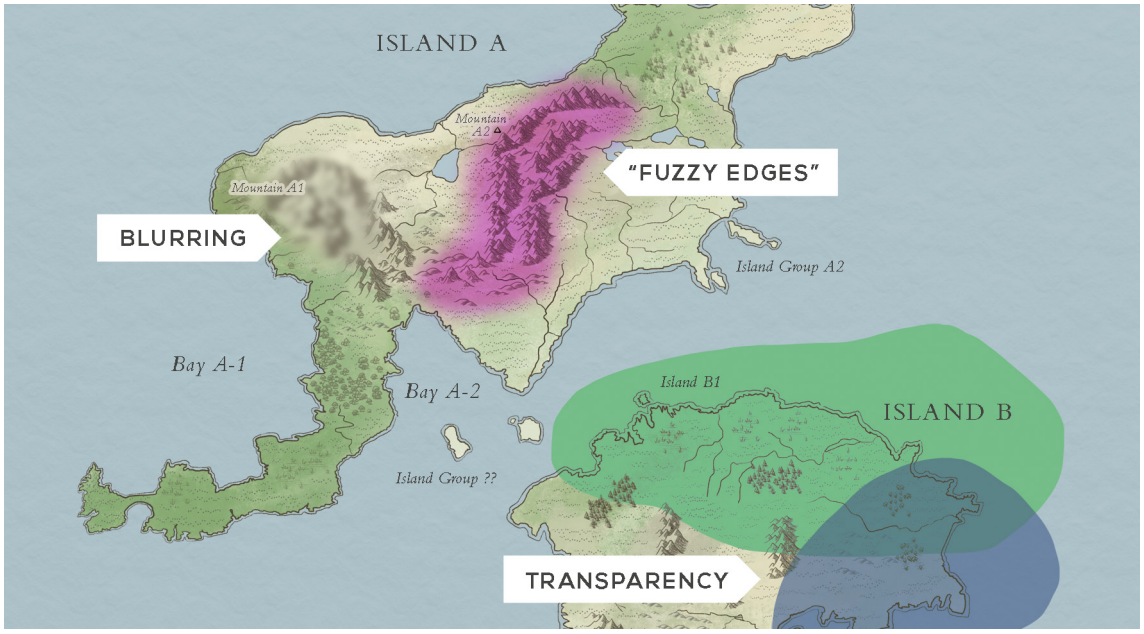

figure 9: Using blurring, fuzzy edges, and transparency to illustrate uncertainty (adding geometry).

In addition to transparency, value, and hue, graphical attributes that were found useful in representing uncertainty include resolution, fuzziness, and blurring, e.g., Kinkeldey et al. (2014).

Riveiro et al. (2014) concur, citing a couple of visualisation of uncertainty evaluations where 'fuzziness and location seem to work particularly well, and both size and transparency are potentially usable.'

These approaches make use of metaphors, Kinkeldey et al. (2014) write: 'The contention is that fog and blur are metaphors for lack of clarity or focus (as in a camera) and thus directly signify uncertainty. These metaphors have been suggested to have the potential to enable a better understanding of uncertainty (Gershon, 1998) and we make the assumption that the use of metaphors can lead to more intuitive approaches.'

Metaphors can be both useful and misleading, in a sense that particular colours carry meanings which might interfere with intended signification. For example, in discussing their guidance for climate change modelling visualisations, Harold et al. (2017) warn against the use of blue that can be misinterpreted as the colour of water, see the figure below that is reproduced from the paper.

The metaphors are not universal and associations might differ depending on the culture and experiences of users.

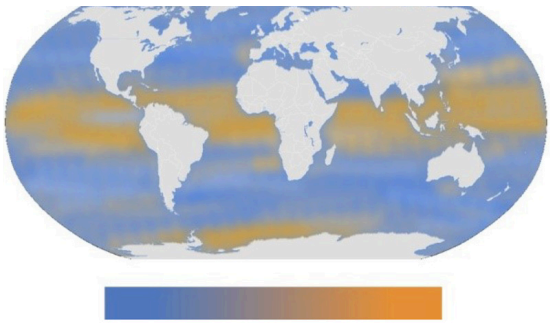

figure 10: Colour and metaphor: For maps, the colour blue is normally associated with the oceans. Hence, blue in the above example may not be automatically interpreted as representing data. Here, metaphor and inferences could mis-match. (Harold et al., 2017)

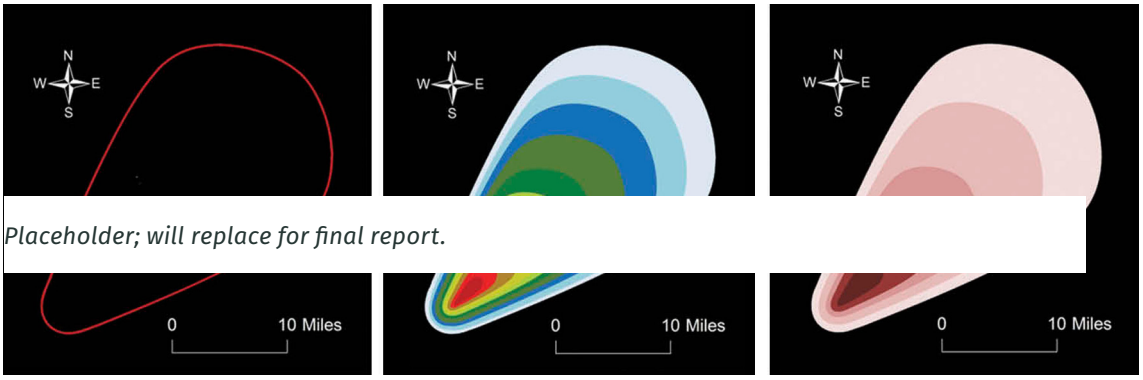

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figure 11: A study evaluating how people make decisions in response to different depictions of uncertainty.

Further, the choice of colour can have an impact on the perception of risk and hence decision-making under uncertainty such as the decision about whether or not to follow evacuation order, Kinkeldey et al. (2015). A choice of colour on a map could translate into a number of lives lost *(figure 11)*.

To understand the impact of colour we must understand the emotional significance of various colours on different users, which might be different for different users based on individual and group-linked factors.

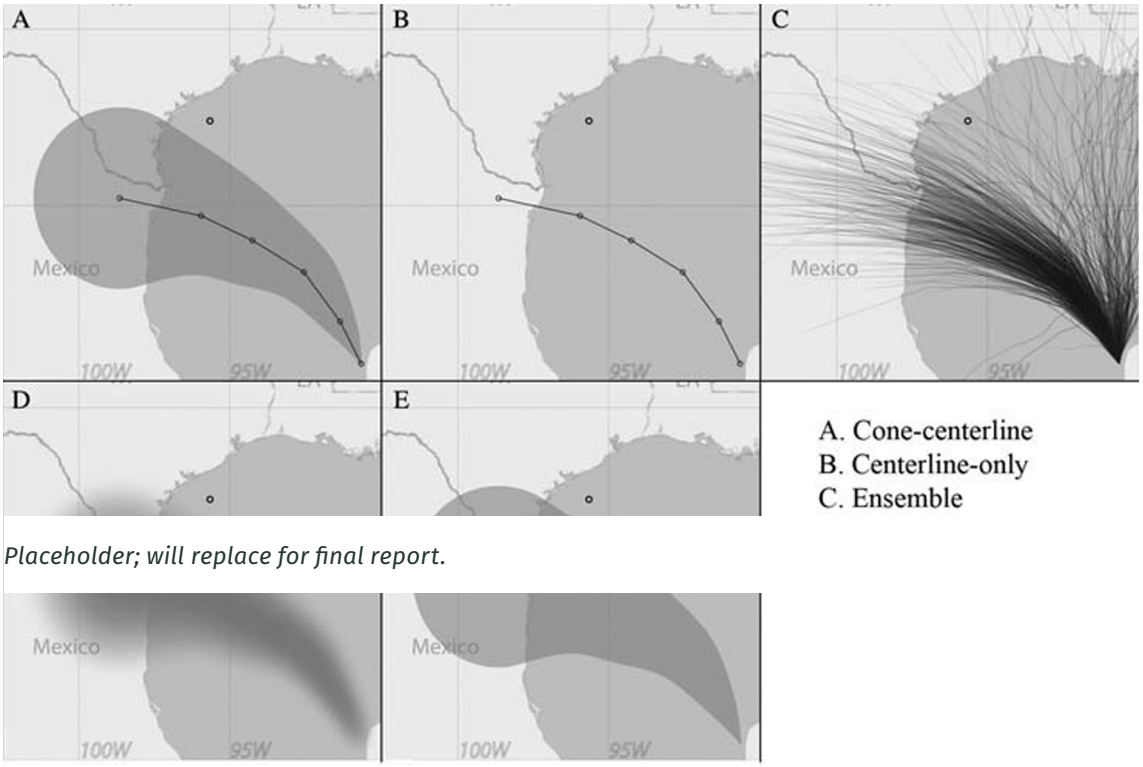
Semantic of visualisations is complex and difficult to predict, some principles however exist and are applicable. Boone et al. (2018) recommend that semantic principles be followed in visualisations of uncertainty as well: 'In the present research, we first focus on the semantic principle of natural mappings between variables in the graphic and what they represent. Examples of these natural mappings are classic metaphors such as "larger is more" and "up is good" (Tversky, 2011). The semantic principle states that the visual variables displayed should be matched according to these natural mappings (Zhang, 1996). An example of a match is using the length of a line to denote length of time. An example of a mismatch would be using higher values on a graph to show negative numbers.'

Following semantic and other design principles is not a guarantee that visualisations will be correctly interpreted. In the next couple of sections we present several lessons about misinterpretations of the visualisations that should be heeded.

Common Pitfalls

Common Pitfall: Mean vs Variance in Space and Time

Given visualisation of uncertainty, evidence suggests that it is more useful in helping with uncertainty about the mean than variance, and that reducing overconfidence is particularly hard even with visualisations. Pugh et al. (2018): 'Even when presented with an uncertainty visualization, people still exhibited greater attentional focus on the mean and overconfidence in their understanding of the variance. These results have implications for decision-makers and the consequences related to not considering alternatives to the most likely outcome.'



Placeholder; will replace for final report.

figure 12: Hurricane paths.

However, Pugh et al. (2018) note that some designs are worse than others: 'It is possible that different forms of visualizations may better enhance the understanding of variance, improve transfer effects, and reduce related overconfidence. In fact, Ruginski et al. (2016) found that the addition of a centerline, fuzzy shading, and/ or ensemble paths to a cone visualization decreased the perception of variance.'

Another common problem is the misinterpretation of increase in variance over time as increase in the mean. Here the semantic principle of larger size meaning something is bigger leads to confusion as what gets bigger is spatial uncertainty not the strength of the hurricane which is not being depicted at all.

Yet another studied misinterpretation of the cone is that it represents an area of impact rather that an area made up of possible hurricane trajectories, Ruginski et al. (2016). One solution proposed was to represent trajectories as individual lines, as a set of possible realisations, denser around the most likely path. This, however, was found to make people less afraid of the hurricane—the path ensemble visualisation reduced their estimates of risk, potentially leading some to ignore evacuation orders, as opposed to alternative visualisations based on the same predictions. Ruginski et al. (2016) note that 'the various visualizations caused participants to notice different visual properties of the displays and to base their judgments on different heuristics'; for instance they recount that, 'The fuzzy-cone and the cone-only visualizations (both without the centerline) resulted in lower damage judgments than the cone-centerline. It is possible that the presence of the salient center forecast track leads users to cognitively assess the intensity of the hurricane to be greater.'

Common Pitfall: Confidence Intervals

Misunderstanding variability is a common problem even among advanced researchers. One frequent error in using confidence intervals is interpreting all distributions as uniform. Modifying visualisations with colour gradients or violin like shapes have been recommended as these are found to ameliorate this problem in some cases.

For continuous variables, the most common representation of uncertainty using error bars violates the semantic principle, according to Boone et al. (2018), and this contributes the misinterpretation problem:

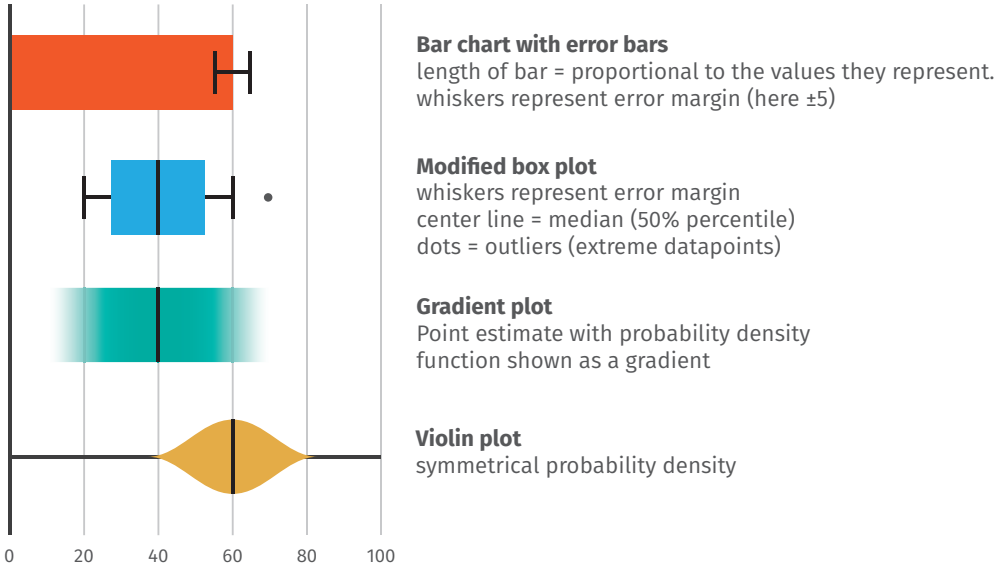


figure 13: Confidence intervals..

Common Pitfall: Anchoring and the Worst Case Scenario

Visualisation of uncertainty interacts with human psychology in ways which might also have negative consequences for decision-making, resulting in biases, especially when it comes to depictions related to safety, Kinkeldey et al. (2015): 'The most important finding was that a "worst case" map that showed the upper boundary of projected wind speeds yielded biased forecasts with higher speeds than those based on the other displays. Thus, the authors give the warning that in a real-world setting providing worst-case maps could lead to more false alarms. They explain this effect with evidence from past research that anchors (in this case the depiction of the worst case) unconsciously influence people's judgments (Chapman and Johnson 2002). Similar results were provided by Riveiro et al. (2014b) in a target identification experiment, where an expert group aided by uncertainty visualization selected higher priority values and more hostile and suspect identities. This suggests that, when safety was an issue, the experts put themselves in the "worst-case scenario" in the presence of uncertainty.'

Common Pitfall: Inappropriate Conclusions Drawn Based on What is Not Depicted

Eckert (2001) warn about another potential source of misinterpretation that stems from the fact that the viewer is drawing conclusions not just from what is shown but from a negative space, from what is not depicted: 'Understanding how much of what is not shown is fixed, and what can be varied, is as essential as understanding the explicit content of a representation. Alternative interpretations of the omitted elements of a design are made possible by uncertainty or misunderstanding about the interpretive conventions to be applied to a representation, as well as the context in which it is embedded and the assumptions the generator makes about how the gaps will be filled in. Thus it can be ambiguous by omission. In other words, what is implicit in any representation depends on the interpretive skills of the recipient and the extent of the shared understanding of context established between the sender and the recipient.'

Common Pitfall: Lack of Graphicacy

'Another factor that can greatly influence the effectiveness of a graphic is the knowledge the viewer has about the conventions of the graphic type in question. Kosslyn (2006) called this the principle of appropriate knowledge. Typically the conventions of the display are encoded in a visually represented legend expressing the correspondence between visual variables and their meaning. For instance, before using an atlas to plan a route, one might consult the legend to learn that black lines represent local roads and red lines represent interstate highways. Without appropriate knowledge of the graphic conventions, provided in a legend, one may misinterpret information presented in a graphic.' Boone et al. (2018).

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Riveiro, M., et al. (2014). *"Effects of visualizing uncertainty on decision-making in a target identification scenario."* Computers & Graphics 41: 84-98.

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Seipel, S. and N. J. Lim (2017). *"Color map design for visualization in flood risk assessment."* International Journal of Geographical Information Science 31(11): 2286-2309.

Resources
General Background:

How do you create interactive data visualisations?
Nesta Sparks lecture by Cath Sleeman
https://www.youtube.com/watch?v=ctSl8tYEEDY

Visualising the uncertainty in data by Nathan Yau (UCLA)
https://flowingdata.com/2018/01/08/visualizing-the-uncertainty-in-data/

Visualising conflict data:
https://www.acleddata.com/

Design

Free images:
https://pixabay.com/
https://unsplash.com/
https://thenounproject.com/

Catalogue of examples
http://www.rethinkingvis.com/#all
https://datavizcatalogue.com/

Tutorials
https://flowingdata.com/category/tutorials/

Platforms for Data Visualisations

Microsoft
https://powerbi.microsoft.com/en-us/

R shiny
https://shiny.rstudio.com/gallery/

Tableau
https://www.tableau.com/

D3
https://github.com/d3/d3/wiki/Gallery

Social Media on Visualising Data

Financial Times @ftdata

NYT Graphics @nytgraphics

https://twitter.com/GuardianVisuals

The Pudding @puddingviz or https://pudding.cool/

Andy Kirk @visualisingdata or http://www.visualisingdata.com/

Future collaborations

Jana Kleineberg, ***Illustration & Design***
http://www.kleineberg.co.uk/

Jo Lindsay Walton
https://www.jolindsaywalton.com/

Or contact us here:
http://www.seaplusplus.co.uk/
http://au4dmnetworks.co.uk/

Appendix A: Common Uncertainty-Representations

SIMULATIONS

Seeing various results successively to generate an overview provides intuition for the fuzziness of predictions.

Pros

Showing simulations provides a sense of build-up and a link with individual outcomes.

Cons

Too much weight might be placed on individual outcomes and obscure the overall picture.

Showing all data at once can be challenging for interpretation and lead to data overload.

OBSCURITY

Blurriness is a powerful visual metaphor for displaying uncertainty (fog).

Pros

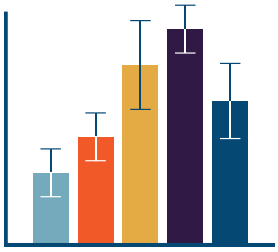
The metaphor makes sense: results that are more uncertain are displayed with a blurry (not sharp/clear) edge, which makes it less visually prominent.

Cons

How is fuzziness or obscurity perceived? Are various levels actually interpreted, and to what degree? This requires more research.

ERROR BARS

Graphical representations of the variability of data; used to indicate the error or uncertainty in a reported measurement.



Pros

Lines or bars represent a range of values, so you can see that a mean or median represents only part of an estimate. Especially useful when camparing multiple estimates.

Widely used, therefore easily understood.

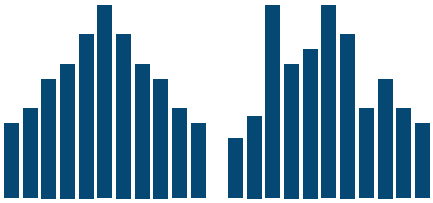
Cons

Details in the data can get lost.

“Within-the-bar bias”: viewers judge points that fall within the bar as being more likely than points equidistant from the mean, but outside the bar—as if the bar “contained” the relevant data.

DISTRIBUTIONS

Show the spread of possible values with a histogram or a variant of it. You might see something a median would never show.



Pros

By showing the variation, a reader can make a more educated judgement about the accuracy and trustworthiness a sample. It is oddly skewed? Are there multiple peaks? Or is it an expected bell curve?

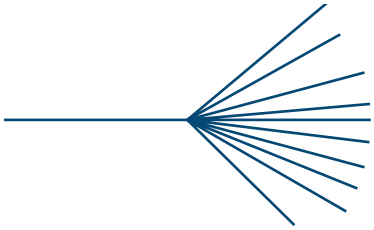
Cons

Many people don't understand distributions, so a careful explanation needs to be given in the annotations.

Sometimes variation is just noise, or the details might obscure the overall view, impression, or key point.

MULTIPLE OUTCOMES

For projections and forecasts, it can be helpful to see various outcomes of what might happen.



Pros

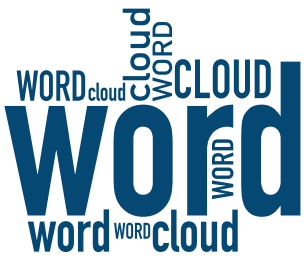
Uncertainty is displayed more explicitly; it is shown that there is not one set path, but multiple possible paths/outcomes.

Cons

The chart can become confusing if there is too much noise or too many possibilities.

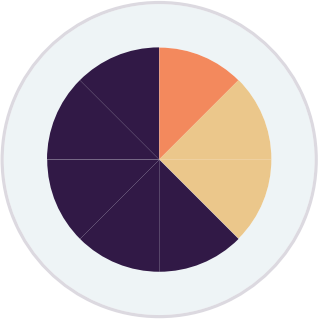
Words

Not everything has to be visualized. Sometimes words better describe uncertainty: avoid absolutes when describing numbers; treat estimates as such when you use them, and account for the uncertainty in the numbers.



Appendix B: Charts, Graphs, Symbols, Metaphors

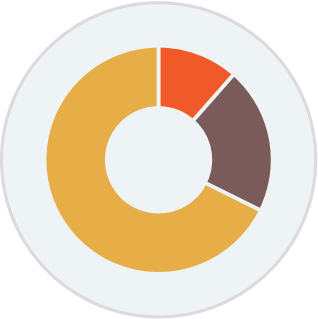
VENN DIAGRAM



PIE CHART

CONCENTRIC DIAGRAM

FAN CHART



DONUT CHART

SUNBURST DIAGRAM

CHORD DIAGRAM

RADAR CHART

CIRCULAR CHART

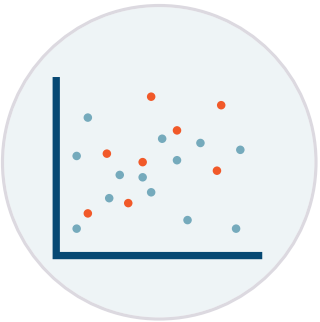
WINDROSE CHART

ARC DIAGRAM

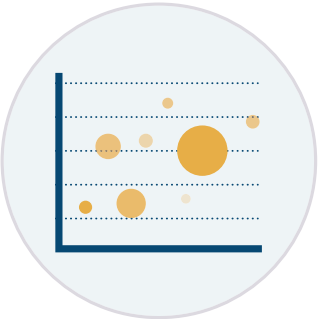
SPIRAL GRAPH

BAR CHART

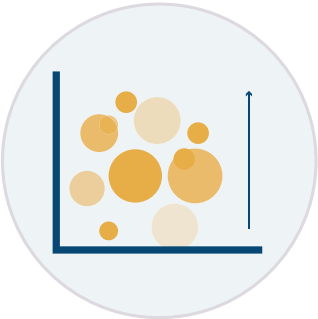
LINE CHART



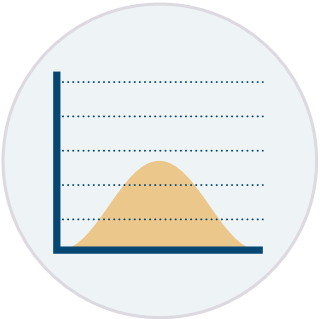
SCATTER PLOT



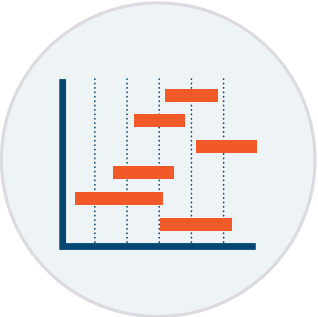
BUBBLE CHART



BUBBLE RACE CHART



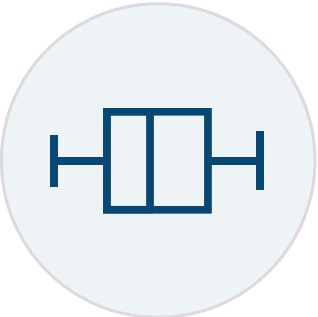
DENSITY PLOT



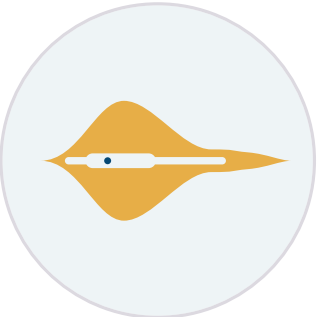
GANTT CHART

CANDLESTICK CHART

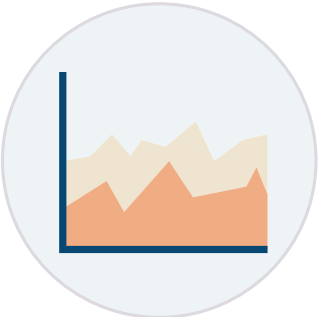
SPAN CHART



BOX & WHISKER PLOT

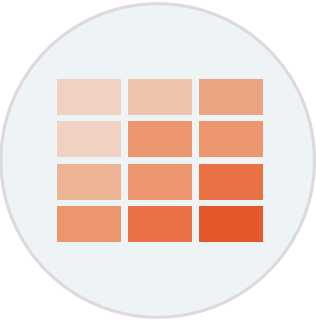


VIOLIN PLOT

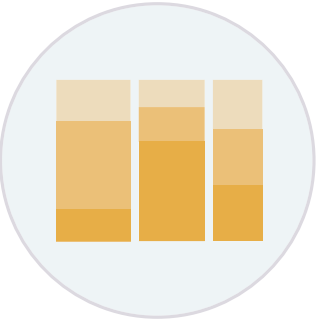


AREA CHART

TREE MAP



HEAT MAP

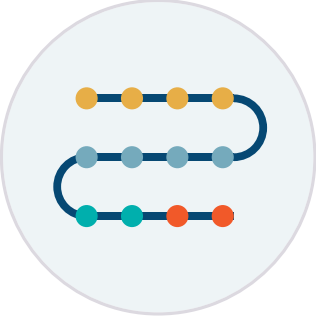


MARIMEKKO CHART

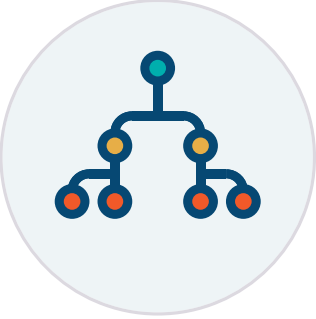
SANKEY CHART

ALLUVIAL DIAGRAM

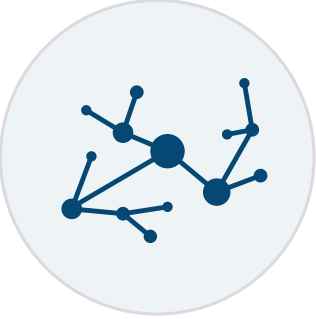
STREAM GRAPH



TIMELINE

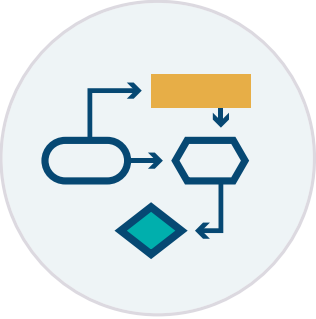


FLOW CHART 1



NETWORK DIAGRAM

WORD CLOUD

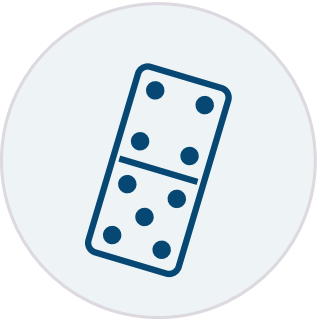


FLOW CHART 2

DOT MATRIX CHART

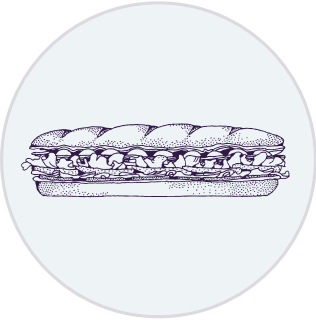
TIP OF THE ICEBERG

LAYERS OF THE ONION



DOMINO EFFECT

TIPPING THE SCALES

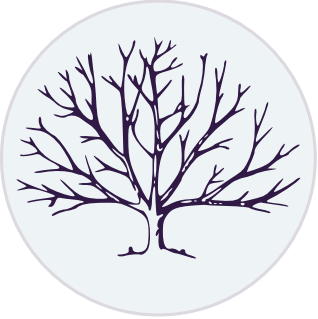


SANDWICH LAYERS

ROOTS / ORIGIN

SOLAR SYSTEM

LABYRINTH / PUZZLE



TREE / TREE OF LIFE

GEARS / WORKING / THINKING

ROLLER COASTER

CLOCK / TIME