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Data visualisation for decision making under deep uncertainty: current challenges and opportunities

Antonia Hadjimichael[1,2,*], **Julius Schlumberger**[3,4] and **Marjolijn Haasnoot**[3,5]

[1] Department of Geosciences, The Pennsylvania State University, University Park, PA, United States of America
[2] Earth and Environmental Systems Institute (EESI), The Pennsylvania State University, University Park, PA, United States of America
[3] Deltares, Delft, The Netherlands
[4] Institute for Environmental Studies (IVM), Vrije Universiteit Amsterdam, Amsterdam, The Netherlands
[5] Department of Physical Geography, Faculty of Geosciences, Utrecht University, Utrecht, The Netherlands
[*] Author to whom any correspondence should be addressed.

E-mail: hadjimichael@psu.edu

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Abstract

This perspective article explores the role of data visualisation in decision-making under deep uncertainty (DMDU), a growing discipline tackling complex socio-environmental challenges, such as climate impacts and adaptation, natural resource management, and preparedness for extreme events. We discuss the role of visualisation for both analysis (or *exploratory*) purposes, as well as communication (or *explanatory*) purposes, including to stakeholders and the public. We identify a lack of comprehensive guidelines on how visualisations are currently used and their potential in enhancing DMDU processes. Drawing on literature and insights from a recent workshop, we identify key challenges DMDU analysts face when visualising data: managing complexity and dimensionality, effectively communicating uncertainty, and ensuring user engagement and interpretability. We propose a research agenda to address these challenges, by taxonomising and evaluating the effectiveness of different visual forms in decision-making contexts, and fostering interdisciplinary collaboration. We argue that, through these efforts, we can improve the communication and usability of DMDU analyses, ultimately aiding in more informed and adaptive decision-making in the face of deep uncertainty.

1. Introduction

We stand at the crossroads of climate change, biodiversity loss, and resource depletion, as well as tumultuous societal changes. Proactive and adaptive decision making for sustainability has never been more imperative. Understanding and planning for these challenges is confounded by deep uncertainties: conditions, especially about the future, that cannot be fully described with probabilities, because of our limited knowledge or because experts do not agree [1]. These complex problems underscore the need for multifaceted and transdisciplinary approaches to science and governance that can inform action despite (and because of) of deep uncertainty, complex dynamics, and contested interests. Such approaches typically fall under the umbrella of decision making under deep uncertainty (DMDU) [1], which aims to inform decisions in these challenging contexts. Academics and practitioners of DMDU work on methodological advancements in this field, and use these methods in real-world applications.

DMDU analysts and scientists rely on visualisations, both for analysis (or *exploratory*) purposes, as well as communication (or *explanatory*) purposes. Its use has grown in the field of DMDU, as well as in decision analysis more broadly. This is partly attributed to the rise of big data, combined with the increase in computational power, which necessitates both advanced data analytics as well as visualisation techniques to produce valuable insights [2]. In DMDU work, however, we not only deal with large datasets, but these datasets are reflective of the increasingly complex world we are trying to understand and manage [3]. Authors have recognised that in order to achieve real-world outcomes, interactions between scientists, decision makers and society need to be strengthened through co-productive processes [4].

We argue that (data) visualisation can help the DMDU community, as well as other scientific disciplines working on complex social and environmental issues, go beyond only supporting policy analysis among technical experts. Treating visualisation choices like other (often subjective) framing decisions made during 'rival decision support paths' [5] can help unveil their effects on the resulting decisions. Thoughtfully crafted exploratory and explanatory visualisations can be used to improve the communication of DMDU analysis to the wider public and stakeholders affected by the complex decisions analysed. At a time of increased politicisation of the relationship between science and the public, this becomes especially important. While review articles and perspectives have been written on the state of these methodologies and their applications (e.g., [1, 5, 6]), little attention has been placed on the important role data visualisation plays. In this perspective article, we discuss the current use of visualisation in supporting DMDU analysis and communication, and identify key challenges DMDU scholars face when engaging in visual communication. Based on literature review, our own experiences as analysts, and insights from a session organised at our Society's Annual Meeting (www.deepuncertainty.org/), we propose a research agenda.

2. How are data visualisations used?

Different approaches exist to support DMDU [1]. At their core, they all share exploratory analysis, i.e., the broad consideration of future scenarios and plausible uncertainties (often referred to as 'states of the world'), and the assessment of their implications for proposed management strategies or pathways of action to achieve objectives. Applications of these frameworks also acknowledge that, when dealing with complex socio-environmental issues, priorities, personal values and perspectives vary. So, in many examples of DMDU practitioners have to investigate and deliberate on various, typically large numbers of potential states of the world and possible strategies, each resulting in different tradeoffs. The data visualisations necessary are therefore many-dimensional. For example, when exploring possible strategies, we use visualisations that allow us to explore how alternatives perform across different objectives or scenarios. Visualisations such as scatter plots (table 1) allow us to explore performance across these goals, by displaying the values of two or more attributes for a set of candidate problem solutions or a set of states of the world. Variations of scatter plots, where the points have varying colours or sizes, are also used to incorporate additional dimensions, but interpretability quickly degrades beyond three dimensions.

When evaluating performance, tradeoffs are at the heart of complex problems, where no one solution can meet all the conflicting goals we might have for a system. An alternative visualisation which allows for emphasising tradeoffs comes in the form of parallel coordinates plots (table 1), which use vertical coordinates that reflect an attribute of interest to evaluate solutions. Each solution is then represented as a connected series of line segments, also known as a polyline, which intersects all parallel axes. Because of this layout, these plots draw the viewer's attention to where polylines intersect, i.e., on instances where performance on one metric has to be reduced to increase performance on another.

Besides tradeoffs, we often need to consider the timing of policy implementation, potential path-dependencies, and what kinds of system signals can inform the need for implementation of adaptation options. To visualise such adaptation pathways, analysts often use figures akin to transit maps (table 1, [6]). These graphics use colour-coded lines, each representing an adaptation pathway, combined with icons that indicate transitions between options and potential lock-ins. These graphics typically have a horizontal orientation, moving from left to right, and beginning with the current point in time.

Lastly, a common practice in exploratory modelling frameworks is to shift the decision-making problem from one where outcomes are assessed, to one where consequences are explored to discover what matters, i.e., on the changing conditions. To answer such questions, analysts often use plots that describe the value of a dependent outcome (e.g., reliability) with regard to how uncertain factors or actions shape it. A common visualisation of these relationships is through contour plots (table 1). Several other visual forms are used in DMDU; we highlight these four as some of the most common, but this is not an exhaustive list.

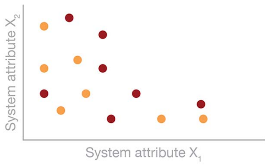
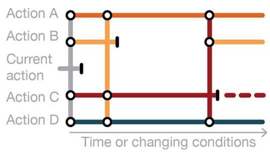
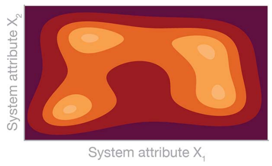
3. The challenges

To collect perspectives on how data visualisation is used and identify common challenges faced, we organised a workshop session during the Annual Meeting of the Society for DMDU (Delft, The Netherlands; October 2023). The session had approximately 50 participants, representing academic and non-academic researchers, practitioners, and students.

3.1. Complexity and dimensionality

A key challenge highlighted by workshop participants is large complexity, as outputs are often multi-dimensional with many scenarios, solutions and goals that need to be evaluated. Visualising outcomes that dynamically change over time in co-evolution with

Table 1. Common types of data visualisation in decision making under deep uncertainty and example applications.

Visualisation type			
Scatter plot	Parallel axes plot	Pathways plot	Contour plot
			
Example applications			
• Household water supply costs and reliability [7] • Damages and costs in global climate change abatement trajectories [8]	• Candidate solutions and their performance across a range of objectives [9] • Specific solutions compared against the full set of options [10]	• Interactions between pathways for multiple risks [11] • Pathways are discovered through multi-objective optimization [12]	• Vulnerability and reliability in water deliveries under different hydroclimatic conditions [13, 14]

multiple stakeholder responses further exacerbates this challenge. Even though many resources exist on how to best develop visualisations of scientific information (e.g., [15]), there is limited guidance on how to present the large and complex datasets most analysts in our community work with. This is especially important because, like other methodological choices, selecting which dimensions to show or which interactions to investigate is a central part of problem framing that can affect the ultimate decisions made [5].

3.2. Communicating and understanding uncertainty

Another common hurdle is that decision makers and other stakeholders often struggle to interpret visualisations that depict uncertainty. This relates to the inherent difficulties most humans have with probabilistic or statistical reasoning [16], but we argue that in DMDU practice this is especially important and challenging due to the many different sources of uncertainty [17]. For instance, when deciding how to adapt against sea level rise there is uncertainty in the expected sea levels, the functional life of alternative adaptation measures, societal perceptions of different measures, potential unintended impacts of these measures, among other considerations. Appropriately capturing these uncertainty sources and visualising their effects remains a major challenge and some authors choose to avoid this or focus on a single source [18, 19]. This is especially difficult in politically charged research, such as on climate mitigation, where motivated misinterpretations of uncertainty might hinder action [16].

3.3. User engagement and interpretability

Bridging between exploratory analysis and explanatory visualisation is a third challenge identified in the workshop. In other words, the need to tailor visualisations that were developed for internal analysis so that they can meet the needs of different parties to the decision making process with varying levels of technical ability, as well as different needs. For example, some are most interested in understanding what are the potential outcomes, whereas others might be most interested in how different outcomes are generated. In addition, lay audiences and decision makers often find the level of uncertainty in analysts' results too complex or time-consuming to interpret [20]. This creates a tension between ensuring explainability and usability of results, and also maintaining key nuances and important dimensions of the analysis.

4. Opportunities

Recognising some of these challenges, DMDU scholars are innovating in this space by utilising novel forms of presenting this information. For example [12], used stacked line plots to visualise thousands of candidate adaptation pathways, and [21] proposed an adapted heatmap approach to visualise attainment of many objectives under many scenarios. These alternative visualisations are concurrent to other methodological improvements made to incorporate more rich problem framings, with more dimensions and more uncertainties. While these graphic forms are important from the exploration perspective, they still struggle with meeting their explanatory goals.

But explanatory goals are central to the work of a DMDU scholar. Key aspects of what makes an analysis 'successful' relate to its ability to inform real-world decision making. In other words, unlike other types of scientific research, DMDU research and the visualisations it employs should not only be cognitively interpretable by the end user or decision maker (e.g., the user understands what error bars indicate on a chart), but also usable to make decisions (e.g., the user appropriately considers the error bars and their implications when making their decision). Scholars have distinguished these two dimensions as *visualisation of uncertainty*—or how we depict the uncertainty associated with the data—and *uncertainty of visualisation*—or how the depiction is processed and reasoned with by the viewer [17]. Studies have evaluated the effectiveness of alternative visualisations on interpretation and cognitive reasoning (e.g., [22]). However, we are not aware of systematic evaluations of visualisation forms on how they influence decision making in complex and deeply uncertain settings, with multiple stakeholders and conflicting views. This is an opportunity for the DMDU community to grow in the directions necessary to meet its end-users. In our view, the biggest opportunities for growth lie in learning from the data visualisation (e.g., [15]) and science communication (e.g., [18, 20]) communities on how to best address the interpretability and usability challenges we face. We elaborate on some of these recommendations in the following section.

Building on inputs during the workshop as well as synthesising reviews of state-of-the-art, we have identified two main promising strategies for effective user-centric visualisations. First, more engagement and collaboration to target visualisations. For example: workshop participants highlighted the importance of participatory modelling processes to ensure visualisations contain the most relevant information to end-users [4, 23] and enhance understanding, especially if regular feedback cycles are part of the process [24]. Other procedural suggestions made included building in time and budgeting specifically for visualisation development and broader knowledge dissemination during the project cycle. This will help make visualisations an intentional and integral part of the analysis. From a project management perspective, visualisation development and publishing outcomes in accessible online platforms can be prioritised during proposal and planning stages, so it is treated with equal attention as other components of the analysis. In addition, formally training students on data visualisation skills and best practices can help.

A second main strategy is to support user interaction and control, as a way of managing the cognitive load of a viewer's working memory [25]. Literature on data visualisation and user experience (UX) design suggests that allowing the viewer to manually control how data is animated may enable them to focus their working memory capacity on the right subsets of information at the right time [18]. Prominent examples of animated and interactive data visualisations are produced by data journalists in digital long-form articles, often referred to as scrollytelling [26]. Within the DMDU community, these approaches have had limited applications and primarily in an exploratory context [27, 28].

5. Future directions and broader impacts

Improving how we, DMDU analysts, as well as other scholars tackling similar problems, communicate and interact with our stakeholders will not only benefit the scholarship itself, but also the outcomes of the decisions we inform. Building on the large strides made by the data science and visualisation communities, we propose three specific directions for improvement.

A first step forward can be made by taxonomising common data visualisations as central components of DMDU analysis. Building on existing taxonomies (e.g., [5, 29]), cataloguing and assessing how various data visualisations can support both exploratory and explanatory DMDU processes could inspire and support appropriate visualisation use. The data visualisation community already has similar resources (e.g., https://datavizproject.com/). However, these need to be classified with regard to their ability and limits to represent key features relevant to decision making in complex and deeply uncertain contexts.

A second, perhaps more crucial, step is to evaluate whether the uncertainties present are appropriately communicated between analysts and decision makers and sufficiently considered in their reasoning processes. To this end, DMDU analysts could follow the lead of scholars in the cognitive sciences (e.g., [22]), and formally evaluate how different visualisations better enable decision making processes under deep uncertainty. For example [30], conducted a controlled experiment where participants were asked to answer questions about the probability of bus arrival using alternative visual forms. In a DMDU context, experiments could evaluate whether participants can effectively use alternative visuals to reason about alternative options or plausible deep uncertainties.

Lastly, DMDU scholars and others working in complex systems are typically well-versed on the ideas of transdisciplinarity and the importance of bringing in many alternative perspectives and ways of knowing. We should leverage this openness and bring in scholars from the fields of actionable knowledge [31], cognition and graphical inference [19], and visualising uncertainty and large complex data. There are also opportunities to innovate in the domains of interactive visualisation and data exploration [32], as well as the incorporation of natural language generation capabilities [33]. Such collaborations will enable research communities like that of DMDU to better bridge between exploratory and explanatory modes of visualisation, and to better inform action through their science.

Data availability statement

No new data were created or analysed in this study.

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ORCID iDs

Antonia Hadjimichael https://orcid.org/0000-0001-7330-6834
Julius Schlumberger https://orcid.org/0000-0003-1837-2390
Marjolijn Haasnoot https://orcid.org/0000-0002-9062-4698

References

[1] Marchau V A W J, Walker W E, Bloemen P J T M and Popper S W (eds) 2019 *Decision Making under Deep Uncertainty: From Theory to Practice* (Springer) (https://doi.org/10.1007/978-3-030-05252-2)

[2] Islam M and Jin S 2019 An overview of data visualization *2019 Int. Conf. on Information Science and Communications Technologies (ICISCT)* pp 1–7

[3] Kelleher C and Braswell A 2021 Introductory overview: recommendations for approaching scientific visualization with large environmental datasets *Environ. Modelling Softw.* **143** 105113

[4] Moallemi E A *et al* 2023 Knowledge co-production for decision-making in human-natural systems under uncertainty *Glob. Environ. Change* **82** 102727

[5] Moallemi E A, Zare F, Reed P M, Elsawah S, Ryan M J and Bryan B A 2020 Structuring and evaluating decision support processes to enhance the robustness of complex human–natural systems *Environ. Modelling Softw.* **123** 104551

[6] Haasnoot M, Di Fant V, Kwakkel J and Lawrence J 2024 Lessons from a decade of adaptive pathways studies for climate adaptation *Glob. Environ. Change* **88** 102907

[7] Wunderlich S, St.George Freeman S, Galindo L, Brown C and Kumpel E 2021 Optimizing household water decisions for managing intermittent water supply in Mexico city *Environ. Sci. Technol.* **55** 8371–81

[8] Lamontagne J R, Reed P M, Marangoni G, Keller K and Garner G G 2019 Robust abatement pathways to tolerable climate futures require immediate global action *Nat. Clim. Change* **9** 290–4

[9] Shi R, Hobbs B F, Quinn J D, Lempert R and Knopman D 2023 City-heat equity adaptation tool (city-HEAT): multi-objective optimization of environmental modifications and human heat exposure reductions for urban heat adaptation under uncertainty *Environ. Modelling Softw.* **160** 105607

[10] Gold D F, Reed P M, Gorelick D E and Characklis G W 2022 Power and pathways: exploring robustness, cooperative stability, and power relationships in regional infrastructure investment and water supply management portfolio pathways *Earths Future* **10** e2021EF002472

[11] Schlumberger J, Haasnoot M, Aerts J and de Ruiter M 2022 Proposing DAPP-MR as a disaster risk management pathways framework for complex, dynamic multi-risk *iScience* **25** 105219

[12] Trindade B C, Reed P M and Characklis G W 2019 Deeply uncertain pathways: integrated multi-city regional water supply infrastructure investment and portfolio management *Adv. Water Resour.* **134** 103442

[13] Ray P, Wi S, Schwarz A, Correa M, He M and Brown C 2020 Vulnerability and risk: climate change and water supply from California's Central Valley water system *Clim. Change* **161** 177–99

[14] George Freeman S S *et al* 2020 Resilience by design in Mexico city: a participatory human-hydrologic systems approach *Water Secur.* **9** 100053

[15] Schwabish J 2021 *Better Data Visualizations: A Guide for Scholars, Researchers, and Wonks* (Columbia University Press)

[16] Webster M 2003 Communicating climate change uncertainty to policy-makers and the public *Clim. Change* **61** 1–8

[17] Brodlie K, Allendes Osorio R and Lopes A 2012 A review of uncertainty in data visualization *Expanding the Frontiers of Visual Analytics and Visualization* ed J Dill, R Earnshaw, D Kasik, J Vince and P C Wong (Springer) pp 81–109

[18] Franconeri S L, Padilla L M, Shah P, Zacks J M and Hullman J 2021 The science of visual data communication: what works *Psychol. Sci. Public Interest* **22** 110–61

[19] Hullman J 2020 Why authors don't visualize uncertainty *IEEE Trans. Vis. Comput. Graph.* **26** 130–9

[20] Fischhoff B and Davis A L 2014 Communicating scientific uncertainty *Proc. Natl Acad. Sci.* **111** 13664–71

[21] Shavazipour B, López-Ibáñez M and Miettinen K 2021 Visualizations for decision support in scenario-based multiobjective optimization *Inf. Sci.* **578** 1–21

[22] Hullman J, Qiao X, Correll M, Kale A and Kay M 2019 In pursuit of error: a survey of uncertainty visualization evaluation *IEEE Trans. Vis. Comput. Graph.* **25** 903–13

[23] Hedelin B *et al* 2021 What's left before participatory modeling can fully support real-world environmental planning processes: a case study review *Environ. Modelling Softw.* **143** 105073

[24] Meyer M and Dykes J 2020 Criteria for rigor in visualization design study *IEEE Trans. Vis. Comput. Graph.* **26** 87–97

[25] Sweller J, Ayres P and Kalyuga S 2011 Emerging themes in cognitive load theory: the transient information and the collective working memory effects *Cognitive Load Theory. Explorations in the Learning Sciences, Instructional Systems and Performance Technologies* ed J Sweller, P Ayres and S Kalyuga (Springer) pp 219–33

[26] Seyser D and Zeiller M 2018 Scrollytelling—an analysis of visual storytelling in online journalism *2018 22nd Int. Conf. Information Visualisation (IV)* pp 401–6

[27] Hadka D, Herman J, Reed P and Keller K 2015 An open source framework for many-objective robust decision making *Environ. Modelling Softw.* **74** 114–29

[28] Kwakkel J H 2017 The exploratory modeling workbench: an open source toolkit for exploratory modeling, scenario discovery, and (multi-objective) robust decision making *Environ. Modelling Softw.* **96** 239–50

[29] Kwakkel J H and Haasnoot M 2019 Supporting DMDU: a taxonomy of approaches and tools *Decision Making under Deep Uncertainty* ed V A W J Marchau, W E Walker, P J T M Bloemen and S W Popper (Springer)

[30] Kay M, Kola T, Hullman J R and Munson S A 2016 When (ish) is my bus? User-centered visualizations of uncertainty in everyday, mobile predictive systems *Proc. 2016 CHI Conf.*

on Human Factors in Computing Systems, in CHI'16 (Association for Computing Machinery) pp 5092–103

[31] Jagannathan K *et al* 2023 A research agenda for the science of actionable knowledge: drawing from a review of the most misguided to the most enlightened claims in the science-policy interface literature *Environ. Sci. Policy* **144** 174–86

[32] Qin X, Luo Y, Tang N and Li G 2020 Making data visualization more efficient and effective: a survey *VLDB J.* **29** 93–117

[33] Srinivasan A, Drucker S M, Endert A and Stasko J 2019 Augmenting visualizations with interactive data facts to facilitate interpretation and communication *IEEE Trans. Vis. Comput. Graph.* **25** 672–81