Taylor & Francis
Taylor & Francis Group

International Journal of Digital Earth

ISSN: 1753-8947 (Print) 1753-8955 (Online) Journal homepage: http://www.tandfonline.com/loi/tjde20

Challenges and strategies for the visual exploration of complex environmental data

Carolin Helbig, Doris Dransch, Michael Böttinger, Colin Devey, Antonie Haas, Mario Hlawitschka, Claudia Kuenzer, Karsten Rink, Christian Schäfer-Neth, Gerik Scheuermann, Tom Kwasnitschka & Andrea Unger

To cite this article: Carolin Helbig, Doris Dransch, Michael Böttinger, Colin Devey, Antonie Haas, Mario Hlawitschka, Claudia Kuenzer, Karsten Rink, Christian Schäfer-Neth, Gerik Scheuermann, Tom Kwasnitschka & Andrea Unger (2017): Challenges and strategies for the visual exploration of complex environmental data, International Journal of Digital Earth, DOI: 10.1080/17538947.2017.1327618

To link to this article: http://dx.doi.org/10.1080/17538947.2017.1327618

Published online: 13 May 2017.

INTERNATIONAL JOURNAL OF DIGITAL EARTH, 2017
https://doi.org/10.1080/17538947.2017.1327618

Check for updates

Challenges and strategies for the visual exploration of complex environmental data

Carolin Helbig [a], Doris Dransch[b], Michael Böttinger[c], Colin Devey[d], Antonie Haas[e], Mario Hlawitschka[f], Claudia Kuenzer[g], Karsten Rink[a], Christian Schäfer-Neth[e], Gerik Scheuermann[h], Tom Kwasnitschka[d] and Andrea Unger[b]

[a]Helmholtz Centre for Environmental Research (UFZ), Leipzig, Germany; [b]German Research Centre for Geosciences (GFZ), Potsdam, Germany; [c]German Climate Computing Centre (DKRZ), Hamburg, Germany; [d]Helmholtz Centre for Ocean Research Kiel (GEOMAR), Kiel, Germany; [e]Helmholtz Centre for Polar and Marine Research (AWI), Bremerhaven, Germany; [f]Faculty of Computer Science, Mathematics and Natural Sciences, Leipzig University of Applied Sciences (HTWK), Leipzig, Germany; [g]German Aerospace Centre (DLR), Oberpfaffenhofen, Germany; [h]Institute of Computer Science, Leipzig University, Leipzig, Germany

ABSTRACT

In this opinion paper, we, a group of scientists from environmental-, geo-, ocean- and information science, argue visual data exploration should become a common analytics approach in Earth system science due to its potential for analysis and interpretation of large and complex spatio-temporal data. We discuss the challenges that appear such as synthesis of heterogeneous data from various sources, reducing the amount of information and facilitating multidisciplinary, collaborative research. We argue that to fully exploit the potential of visual data exploration, several bottlenecks and challenges have to be addressed: providing an efficient data management and an integrated modular workflow, developing and applying suitable visual exploration concepts and methods with the help of effective and tailored tools as well as generating and raising the awareness of visual data exploration and education. We are convinced visual data exploration is worth the effort since it significantly facilitates insight into environmental data and derivation of knowledge from it.

ARTICLE HISTORY
Received 19 December 2016
Accepted 3 May 2017

KEYWORDS
Digital Earth; geoinformatics; geospatial data integration; visualization

1. Introduction

We, a group of scientists from environmental-, geo-, ocean- and information science, argue visual data exploration should become a common analytics approach in Earth system science due to its potential for analysis and interpretation of large and complex spatio-temporal data. Visual data exploration describes the process where researchers analyze complex and large observation and simulation data by employing their perceptual abilities in combination with adequate visualization methods to interactively extract relevant information and discover patterns and correlations. Intuitive and effective visual exploration techniques enable humans to formulate and test scientific hypotheses, draw conclusions and interact with the data (Keim et al. 2003).

The understanding of the Earth system with its short- and long-term processes is fundamental for challenging tasks such as the prediction and management of land-, water-, energy- and resource scarcity or of natural disasters and their impact (e.g. earthquakes, volcanic eruptions, floods). Permanent and long-term observation of the Earth system is essential to understand

CONTACT Carolin Helbig carolin.helbig@ufz.de

and model these processes. Furthermore, computer simulations with coupled Earth system models will result in a better understanding of the various processes and interactions that govern this system.

An immense and quickly growing amount of data has been collected in the last decades. In addition, the amount of data continuously produced by a variety of environmental simulations on high-performance computers (HPC) as well as high-resolution monitoring and remote sensing methods is growing more quickly than ever.

Several ongoing activities worldwide (e.g. Earth Cube 2016; EPOS 2016) engage in the management of these big data sets in terms of storing, archiving and processing. But there is also a growing demand for enhanced analysis tools capable to handle and interpret the large, complex and heterogeneous data. We anticipate that visual data exploration will have a huge influence on understanding the increasingly large and complex environmental data in the future. Visualization has been applied in Earth system sciences for decades. However, traditional visualizations are mostly static pictures presenting data from one perspective, and even 3D and rotatable GIS applications usually only allow for the analyses of a small subset of data sets within the environmental sciences. However, in our experience it is often necessary to assess and correlate data from very different sources (maps, remote sensing, subsurface exploration, modeling software, etc.). Visual data exploration allows for interactive visualization that enables scientists to interact with the data, for instance to filter or modify data adaptively according to characteristics, thresholds or other data, or to create different perspectives on the data. We argue that visual methods perfectly complement automated data analysis methods to detect and interpret patterns and correlations in the complex environmental data.

2. Challenges regarding data analysis that benefit from visual data exploration

2.1. Synthesize heterogeneous data from various sources

For many research questions in Earth system sciences, interactions among different subsystems or environmental compartments have to be taken into account. Examples include processes taking place at interfaces between subsystems, such as, evaporation that originate in the oceans but will influence the atmosphere, or precipitation that will have an effect on soil or sediments by changing parameters such as conductivity or the concentration of chemical compounds. Data from different sources have to be examined in combination to get a deeper understanding of the processes in question. Investigating the Earth system across subsystems requires dealing with a wide range of data sets with varying characteristics. These data sets differ in dimensionality, spatial and temporal resolution and scale, reference system, data quality and uncertainty (Rink, Bilke, and Kolditz 2014). A multitude of different variables (multivariate data) representing the Earth system have to be handled, too. The analysis of such heterogeneous data is an ongoing challenge. New approaches are required to jointly visualize and analyze heterogeneous data from various sensors, to compare simulation results with observation values of a certain area (multimodal data), to cross-compare simulation results with slightly varying parameters (multi-run data, ensemble simulations) or with data from different models (multi model ensembles). We also need approaches to analyze simulation data of coupled models. For instance, distinct subsystem models of the atmosphere, ocean and land need to be coupled in order to represent the whole climate system and simulate the interactions and feedback between its components (Kehrer and Hauser 2013). Here, we have to analyze processes and feedbacks taking place on heterogeneous model discretization of different subsystems (Taylor, Stouffer, and Meehl 2012).

Another aspect concerning the various data sources is the different quality of data that has to be documented for further processing of the data. Data quality differences arise from varying data sources and varying pre-processing routines. Data from observations and models require an assessment of precision and accuracy. For instance, proxy data derived from geo-archives such as climate data inferred from ice or sediment cores is characterized by low and often varying accuracy. Results from multi-run simulations have a bandwidth of accuracy representing the feasible result space. Making data quality apparent is important to assess the data's relevance with respect to the focused question, and to guide further processing of the data.

Visual data exploration enables the analyst to create synopses of different, heterogeneous data. It allows data integration and synthesis to generate a complete picture. Multiple views can relate data sets, e.g. putting temporal and spatial dimensions or different variables of the Earth system into relation. Providing different perspectives of the data by interaction options, such as moving through the data space and filtering subsets, supports researchers in creating a holistic view of the data and in detecting patterns and relationships in temporal and spatial dimension, as well as relationships between different variables (Helbig et al. 2015; Unger et al. 2012). Visualizing meta data about data quality enables researchers to examine and simultaneously validate the data, for instance by considering their uncertainty (Köthur et al. 2015). The combined visual analysis of data and related uncertainty information is still a challenging task, being actively discussed in the visualization community (Böttinger et al. 2015).

2.2. Reduce the amount of information

Besides the increase in data complexity, the amount of data collected or generated is rapidly growing as well. Observation systems nowadays continuously measure more and more parameters of increasing spatial and temporal resolution instead of just punctual data. In addition, the variety of sensors that collect environmental data is also growing very fast (Kolditz et al. 2012). Models, which are getting more and more complex, are another aspect that leads to growing data amounts. There is a high demand for methods and applications being able to handle these large data sets and the information contained within.

It is obvious that the information density of environmental data is often very high, pushing the demand for methods that are able to handle this density and ultimately display the relevant information hidden in complex data in an understandable, well-arranged way. This is not only true for single data sets but also for data repositories. To get an understanding of which data sets are contained in a data repository and how particular data sets are related regarding space, time and variables is a prerequisite for exploiting the existing data bases.

Scientific visualization and visual analytics allow reducing the amount of information by making only relevant parameters and features visible. One approach is the use of interactive visualization that is based on the information seeking mantra 'overview first, details on demand'. It allows researchers to filter their data during exploration. Feature-based visualization is another approach for exploring large data sets, where features in the data are extracted by automated analysis steps and then stored to disk to allow for interactive visualization (Köthur et al. 2014a, 2014b; Manten, Vetter, and Olbrich 2011). For the exploration of simulation data that is too large to store in a timely manner, *in situ* visualization is a promising approach. Here, the data computed remains in the HPC memory while being interactively visualized (Bethel, Childs, and Hansen 2012).

2.3. Facilitate multidisciplinary, collaborative research

In environmental sciences, multidisciplinary research is increasing to understand the Earth system as a whole beyond single subsystems. Therefore, it is common to have geographically separated, but collaborating research groups from different disciplines (Anderson et al. 2011; MacEachren 2001). Observation data and analysis results of single groups have to be linked, discussed and presented. To this end, multidisciplinary research groups have to face the challenge not only to bridge geographic distance but also to bridge knowledge space by aligning different scientific concepts and languages. In addition, the need for professional data presentation is growing in all scientific disciplines, because of the increasing importance of communicating scientific results to the public.

Visual data exploration can facilitate multidisciplinary, collaborative research and scientific communication in the following way: it allows integrating the various data into a synoptic view, as already mentioned. Additionally, it can operate as boundary object that enables sharing and discussing concepts, ideas and results. Boundary objects were introduced as a concept to facilitate cross-disciplinary collaboration by contextualizing foreign knowledge in the own thought world (Star and Griesemer 1989). Visual data exploration designed as a boundary object supports scientists in talking about findings, developing, clarifying and structuring arguments, and in coordinating different domain specific perspectives. Vivid and appealing visualizations also enable stakeholders from outside the subject area to get quick insight into complex concepts. An interactive character of the visual exploration enables and encourages researchers and stakeholders to investigate the data.

3. What do we need to enable visual data exploration in Earth system science?

To fully exploit the potential of visual data exploration, several bottlenecks and challenges have to be addressed.

3.1. Efficient data management

First, some preconditions have to be satisfied regarding the quality of data acquisition and an adequate data management to enable a directed quick data search. The heterogeneous, large data has to be categorized by taking into account the existing analogies of data from various fields. In addition, generalized metadata standards, which are giving information about quality of data and uncertainty, have to be implemented for all data types discussed (ECJRC 2009; Maidment et al. 2011; OGC 2016). An adequate data management system (DMS) should collect, host and supply data and corresponding meta data in a standardized and permanent way. Availability and transparency of the DMS will raise the motivation to supply data and data products (Haas et al. 2016). Several frameworks have already been developed for this purpose (Gerchow 2014; Koppe et al. 2015) and they need to be integrated in a DMS that provides solutions across institutes and thereby covers multiple project partners (Kunkel et al. 2013; Nebert 2005; Tomasicm and Simon 1997). An adequate solution here would help to synthesize large collections of heterogeneous data (Challenge 2.1) and it would form a useful basis for collaborative research (Challenge 2.3).

3.2. Integrated workflows

The use of a common, generalized visual data exploration workflow with efficient, configurable, modular methods could bring together currently isolated applications, where every project and task has its own customized solution. Therefore, interfaces for transforming heterogeneous input data to standardized data types have to be used (Rew and Davis 1990; Schroeder, Martin, and Lorensen 2006) or developed. These interfaces have to fill the gap between the software commonly used in the various research disciplines and the software used for visual data exploration. As before, this would help mainly with Challenges (2.1) and (2.3) as such workflows would support working with previously unknown data formats and give guidance to collaboration partners.

3.3. Suitable visual exploration concepts and methods

Visual concepts and methods that are able to display and explore the complexity of the data in Earth system sciences need to be developed. Depending on the character of the data and the goal of the analysis, these can be methods from scientific visualization, information visualization or visual analytics. Scientific and information visualization investigate how to represent more-dimensional, multivariate data, e.g. four-dimensional environmental data sets (Helbig et al. 2014); visual analytics focuses on the combination of automated data analysis and human judgment facilitated by interactive visualization (Keim et al. 2010). In addition, concepts for interacting with complex, large data need to be developed supporting researchers to analyze their environmental data. Existing standard methods are rarely satisfying for the complex purposes of scientific research. As a variety of users should be involved, visual data exploration has to be feasible with various devices such as PC, web and virtual reality environments (Bilke et al. 2014; Chen et al. 2015; Rink et al. 2016). The visualization process should be documented in order to be reproducible. This includes the methods and algorithms chosen as well as their parameterization (Van Wijk 2005). Since a suitable concept is the basis for any exploration effort, all of the suggested challenges would benefit from progress in this domain.

3.4. Effective and tailored tools

The best visual exploration tools would not be used very often, if they were not applicable for daily work or need to address issues that have not been covered by existing solutions (Van Wijk 2005). Thus, usability aspects are of great importance in a visual data exploration workflow. Tools have to be intuitive and provide adequate interaction methods. They have to efficiently facilitate the users' analytical tasks and goals and complement their set of analytical methods. An appropriate balance between usability and flexibility has to be worked out. Development of successful visual data exploration tools requires a close cooperation between visualization experts and environmental researchers (Dransch et al. 2010; Jänicke et al. 2008). While everyone will benefit from working with suitable tools, these are of particular interest for collaborative work (Challenge 2.3) so project partners can reproduce results and have no need to re-implement already existing functionality to participate in collaborations.

3.5. Awareness of visual data exploration/education

The method of visual data exploration has not yet been introduced to environmental science to its full potential. Visualization is mostly regarded as means for result presentation; exploring data by interactive visual interfaces is widely unknown. Also, visual exploration is often not yet regarded as suitable method for data analysis and interpretation since many domain scientists are not familiar with the advantages of interactive visualization. A change in attitude and perspective is necessary. We need compelling examples showing the benefit of visual data exploration in environmental science (Billen et al. 2008; Helbig et al. 2015; Köthur et al. 2014a, 2014b, 2015; Sips et al. 2012; Unger et al. 2012). A wider awareness of the possibilities for exploration would benefit every researcher in environmental sciences but is especially helpful in collaborative projects (Challenge 2.3). Education and training in novel data analysis approaches such as visual data exploration and visual analytics will provide advantages and support all disciplines handling large and complex data.

Summary

Visual data exploration has much potential to meet recent challenges regarding data analysis and interpretation in Earth system science. It facilitates synthesis of heterogeneous data from various sources, reduces the amount of information by making only the relevant information visible and supports multidisciplinary collaborative research. To exploit this potential, a broad effort is required concerning efficient data management, integrated workflows, suitable visual exploration concepts and methods, effective and tailored tools, as well as education to increase awareness of visual data exploration. We are convinced visual data exploration is worth the effort since it significantly facilitates insight into environmental data and derivation of knowledge from it.

Acknowledgements

This work was supported by the German Federal Ministry of Education and Research within the project Competence Center for Scalable Data Services and Solutions (ScaDS) Dresden/Leipzig (BMBF 01IS14014B).

Disclosure statement

No potential conflict of interest was reported by the authors.

ORCID

Carolin Helbig http://orcid.org/0000-0001-8508-2751

References

Anderson, J. C., M. Davis, K. Fujiwara, T. Fang, J. Andres, and M. Nedbal. 2011. "Web-Based Scientific Visualization Software for Geospatial Displays and Collaborative Applications." OCEANS'11 MTS/IEEE KONA, Waikoloa, HI, 1–7.

Bethel, E. W., H. Childs, and C. Hansen, eds. 2012. *High Performance Visualization—Enabling Extreme-Scale Scientific Insight*. Boca Raton, FL: Chapman & Hall, CRC Computational Science. CRC Press/Francis–Taylor Group.

Bilke, L., T. Fischer, C. Helbig, C. Krawczyk, T. Nagel, D. Naumov, S. Paulick, et al. 2014. "TESSIN VISLab – Laboratory for Scientific Visualization." *Environmental Earth Sciences* 72 (10): 3881–3899. doi:10.1007/s12665-014-3785-5.

Billen, M. I., O. Kreylos, B. Hamann, M. A. Jadamec, L. H. Kellogg, O. Staadt, and D. Y. Sumner. 2008. "A Geoscience Perspective on Immersive 3D Gridded Data Visualization." *Computers & Geosciences* 34 (9): 1056–1072. doi:10.1016/j.cageo.2007.11.009.

Böttinger, M., H. Pohlmann, N. Röber, K. Meier-Fleischer, and D. Spickermann. 2015. "Visualization of 2D Uncertainty in Decadal Climate Predictions." EuroVis Workshop on Visualisation in Environmental Sciences (EnvirVis), Cagliari. doi:10.2312/envirvis.20151083.

Chen, M., H. Lin, O. Kolditz, and C. Chen. 2015. "Developing Dynamic Virtual Geographic Environments (VGEs) for Geographic Research." *Environmental Earth Sciences* 74 (10): 6975–6980.

Dransch, D., P. Köthur, S. Schulte, V. Klemann, and H. Dobslaw. 2010. "Assessing the Quality of Geoscientific Simulation Models with Visual Analytics Methods – A Design Study." *International Journal of Geographical Information Science* 24 (10): 1459–1479.

Earth Cube. 2016. https://www.earthcube.org.

ECJRC. 2009. *INSPIRE Metadata Implementing Rules: Technical Guidelines Based on EN ISO 19115 and EN ISO 19119*. Ispra: European Commission Joint Research Centre.

EPOS (European Plate Observing System). 2016. https://www.epos-ip.org.

Gerchow, P. 2014. "RDIF@AWI: Raw Data Ingestion Framework at Alfred Wegener Institute, Helmholtz Centre for Polar and Marine Research". Third EUDAT Conference, Amsterdam, hdl:10013/epic.44298.

Haas, A., B. Heim, S. Zubrzycki, K. Elger, C. Schäfer-Neth, A. Morgenstern, and I. Fedorova. 2016. "Assembly of the CarboPerm WebGIS for the Laptev Sea Region, Arctic Siberia – Data Visualisation as a WebGIS Service." *Polarforschung, Bremerhaven, Alfred Wegener Institute for Polar and Marine Research & German Society of Polar Research* 85 (2): 135–141. doi:10.2312/polfor.2016.010. hdl:10013/epic.48082.

Helbig, C., H.-S. Bauer, K. Rink, V. Wulfmeyer, M. Frank, and O. Kolditz. 2014. "Concept and Workflow for 3D Visualization of Atmospheric Data in a Virtual Reality Environment for Analytical Approaches." *Environmental Earth Sciences* 72 (10): 3767–3780. doi:10.1007/s12665-014-3136-6.

Helbig, C., L. Bilke, H.-S. Bauer, M. Böttinger, O. Kolditz, and G. Bohrer. 2015. "MEVA – An Interactive Visualization Application for Validation of Multifaceted Meteorological Data with Multiple 3D Devices." *PLoS One* 10 (4): e0123811. doi:10.1371/journal.pone.0123811.

Jänicke, H., M. Böttinger, X. Tricoche, and G. Scheuermann. 2008. "Automatic Detection and Visualization of Distinctive Structures in 3D Unsteady Multi-Fields"." *Computer Graphics Forum* 27 (3): 767–774.

Kehrer, J., and H. Hauser. 2013. "Visualization and Visual Analysis of Multifaceted Scientific Data: A Survey." *Visualization and Computer Graphics* 19 (3): 495–513.

Keim, D., J. Kohlhammer, G. Ellis, and F. Mansmann, eds. 2010. *Mastering the Information Age. Solving Problems with Visual Analytics*. Bad Langensalza: Springer Berlin.

Keim D. A., C. Panse, J. Schneidewind, M. Sips, M. C. Hao, and U. Dayal. 2003. "Pushing the Limit in Visual Data Exploration: Techniques and Applications." In *KI 2003: Advances in Artificial Intelligence*, edited by A. Günter, R. Kruse, and B. Neumann. Lecture Notes in Computer Science, Vol. 2821. Heidelberg: Springer Berlin, doi:10.1007/978-3-540-39451-8_4.

Kolditz, O., K. Rink, H. Shao, T. Kalbacher, R. Kunkel, S. Zacharias, and P. Dietrich. 2012. "International Viewpoint and News: Data and Modelling Platforms in Environmental Earth Sciences." *Environmental Earth Sciences* 66 (4): 1279–1284.

Koppe, R., P. Gerchow, A. Macario, A. Haas, C. Schäfer-Neth, and H. Pfeiffenberger. 2015. "O2A: A Generic Framework for Enabling the Flow of Sensor Observations to Archives and Publications." OCEANS 2015, Genova. doi:10.1109/OCEANS-Genova.2015.7271657. hdl:10013/epic.46020.

Köthur, P., M. Sips, H. Dobslaw, and D. Dransch. 2014a. "Visual Analytics for Comparison of Ocean Model Output with Reference Data: Detecting and Analyzing Geophysical Processes Using Clustering Ensembles." *IEEE Transactions on Visualization and Computer Graphics* 20 (12): 1893–1902.

Köthur, P., M. Sips, A. Unger, J. Kuhlmann, and D. Dransch. 2014b. "Interactive Visual Summaries for Detection and Assessment of Spatiotemporal Patterns in Geospatial Time Series." *Information Visualization* 13 (3): 283–298.

Köthur, P., C. Witt, M. Sips, N. Marwan, S. Schinkel, and D. Dransch. 2015. "Visual Analytics for Correlation-Based Comparison of Time Series Ensembles." *Computer Graphics Forum* 34 (3): 411–420.

Kunkel, R., J. Sorg, R. Eckardt, O. Kolditz, K. Rink, and H. Vereecken. 2013. "TEODOOR: A Distributed Geodata Infrastructure for Terrestrial Observation Data." *Environmental Earth Sciences* 69 (2): 507–521.

MacEachren, A. M. 2001. "Progress Reports – Cartography and GIS: Extending Collaborative Tools to Support Virtual Teams." *Progress in Human Geography* 25 (3): 431–444. doi:10.1191/030913201680191763.

Maidment, D., B. Domenico, A. Gemmell, K. Lehnert, D. Tarboton, and I. Zaslavsky. 2011. "The Open Geospatial Consortium and EarthCube." An EarthCube Technology Paper, OGC Document, 11–159.

Manten, S., M. Vetter, and S. Olbrich. 2011. "Evaluation of a Scalable In-Situ Visualization System Approach in a Parallelized Computational Fluid Dynamics Application." In *Virtual Realities*, edited by G. Brunnett, S. Coquillart, and G. Welch, 225–238. Vienna: Springer.

Nebert, D. D. 2004. "Developing Spatial Data Infrastructures: The SDI Cookbook." Global Spatial Data Infrastructure (GSDI), version 20.0, GSDI Association.

OGC (Open Geospatial Consortium). 2016. http://www.opengeospatial.org.

Rew, R., and G. Davis. 1990. "NetCDF: an Interface for Scientific Data Access." *IEEE Computer Graphics and Applications* 10 (4): 76–82.

Rink, K., L. Bilke, and O. Kolditz. 2014. "Visualisation Strategies for Environmental Modelling Data." *Environmental Earth Sciences* 72 (10): 3857–3868.

Rink, K., C. Chen, L. Bilke, Z. Liao, K. Rinke, M. Frassl, T. Yue, and O. Kolditz 2016. "Virtual Geographic Environments (VGEs) for Water Pollution Control." *International Journal of Digital Earth*. doi:10.1080/17538947.2016.1265016.

Schroeder, W., K. Martin, and B. Lorensen. 2006. *Visualization Toolkit: An Object-Oriented Approach to 3D Graphics*. New Jersey: Kitware.

Sips, M., P. Köthur, A. Unger, H.-C. Hege, and D. Dransch. 2012. "A Visual Analytics Approach to Multiscale Exploration of Environmental Time Series." *IEEE Transactions on Visualization and Computer Graphics* 18 (12): 2899–2907.

Star, S. L., and J. R. Griesemer. 1989. "Institutional Ecology, 'Translations' and Boundary Objects: Amateurs and Professionals in Berkeley's Museum of Vertebrate Zoology." *Social Studies of Science* 19 (4): 387–420. doi:10.1177/030631289019003001.

Taylor, K. E., R. J. Stouffer, and G. A. Meehl. 2012. "An Overview of CMIP5 and the Experiment Design." *Bulletin of the American Meteorological Society* 93 (4): 485–498. doi:10.1175/BAMS-D-11-00094.1.

Tomasicm, A., and E. Simon. 1997. "Improving Access to Environmental Data Using Context Information." *ACM SIGMOD Record* 26 (1): 11–15. doi:10.1145/248603.248606.

Unger, A., S. Schulte, V. Klemann, and D. Dransch. 2012. "A Visual Analytics Concept for the Validation of Geoscientific Simulation Models." *IEEE Transactions on Visualization and Computer Graphics* 18 (12): 2216–2225.

Van Wijk, J. J. 2005. "The Value of Visualization." Proceedings VIS 05 – IEEE Visualization 2005, 79–86.