Call for Papers

Data science and resilience research, from qualitative to quantitative (and back again)

June 2-3, 2022

Data science can leverage large amounts of structured and unstructured data from sensors, satellites, and online activities to provide actionable insights into shaping resilience (Roberts, 2021). Nevertheless, productive interactions between data-driven resilience research, societal concerns, and decision-making remain challenging (Lacey, Howden, Cvitanovic, & Colvin, 2018). On the one hand, selected parameters and outputs often depend on the judgment of scientists and are constrained by data availability (Janowicz, Gao, McKenzie, Hu, & Bhaduri, 2020). On another hand, assembling data and hyperparameters in algorithms can increase black-box experience, naïve extrapolation, and even practical irrelevance (Reichstein et al., 2019; Wolf, Chuang, & McGregor, 2015). In a worst-case scenario, coding biases might lead to discriminatory and pervasive decisions only justified to "this is what the model says" (Chakraborty et al., 2017). The efforts to increase the interpretability and explainability of black-box algorithms have been addressed via algorithmic amendments; however, there is a trade-off between increasing interpretability and decreasing model accuracy (Freitas, 2019). Using a second (post-hoc) model to explain the first black-box model for policymakers is problematic as they are not faithful to what the original model computes (Rudin, 2019). Overall, we need better articulation on what interpretability means and entails far data-driven resilience research (Krishnan, 2020).

We believe that perplexity around complex models and resilience can be solved by locating what renders unintelligent in the context of a new (or more refined) cognitive setting (c.f. Bhaskar, 2013). A more promising alternative is adopting data science practices leading to interpretable models in the first place (Rudin, 2019). "Qualitative to quantitative (and going back again)" aims to elaborate on the assumptions, mechanisms, and practices by which data-driven models in resilience research can turn into salient, credible, and legitimate information for public debate and decision-making (Cash et al., 2003). This conference invites resilience scholars to workshop challenges and methodological solutions for breaching the social-policy-science gap concerning data science and resilience research together. Accordingly, we propose a conference session over two days that focuses on challenges (day one) and methodological solutions (day two).

For the first day, we ask for contributions to offer philosophical insights into the challenges for making data-driven research salient, credible, and legitimate in the field of resilience. We welcome abstracts for presentations making explicit the normative and societal consequences of data-driven research practices, as well as contributions from the philosophy of science, the social sciences, engineering and design. Steering questions in this domain are:

- What are the challenges for building trust associations between machine outputs?
- What are the implicit normative commitments embodied in the modelling and research practices?
- What are the implications of reducing resilience dynamics to what we can empirically capture through data-driven research?
- What type of tensions emerge between "what works in practice" against "what the model indicates"?
- What practices jeopardize producing salient, credible, and legitimate information (e.g., policy-based evidence)?

For the second day, we ask for contributions to share their methodological practices for making models interpretable in the first place. We welcome proposals for 90 min. workshops or short presentations on enabling meaningful elaboration/interpretation of complex resilience models.

- Inter-temporal decision-making models in the context of climate stresses
- Infrastructure systems and response to disruptions models
- Digitalization of services and the emergence of public databases
- Use of technology and citizen, community, and engagement with authorities
- Leveraging data science for explainable urban resilience

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