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OPINION

Climate storylines as a way of bridging the gap between information and decision-making in hydrological risk

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Physical climate storylines—physically self-consistent unfoldings of past events, or of plausible future events or pathways [1]—have recently emerged as a way of navigating the cascade of uncertainty that arises when considering the impacts of climate change. The Working Group I contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [2] has adopted this definition within its Glossary, and the concept is illustrated in Fig 1. Given the high levels of uncertainty concerning the climate response of remote drivers of regional change such as sea-surface temperature patterns, and of the dynamical conditions leading to extreme events, any attempt to aggregate over that uncertainty inevitably leads to general or weak statements [3]. By conditioning on those uncertain aspects of the climate response, storylines provide spatially and temporally coherent scenarios at the regional or local scale. Storylines represent the overall uncertainty in a discrete manner, and are particularly useful for exploring low-likelihood, high-impact outcomes [2].

The acid test of any science is generally understood to be successful prediction. For hydrological risk, however, the combination of deep uncertainty in the climate response at the local scale together with the non-stationarity of a changing climate challenges the kind of objective probabilistic quantification that underpins any notion of predictability [4]. But science also rests on explanation, namely the attribution of an effect (whether observed or imagined) to a set of meaningful causal factors [5]. This is quite different from prediction, but relates directly to decision-making, where the key concern is not uncertainty but rather the strength of evidence behind various competing explanations [4]—often including worst-case scenarios—and the causality of those explanations is required to inform appropriate action. Due to its deterministic representation of physical processes, physical modelling can provide explanations together with deterministic, conditional quantification in the form of storylines.

Physical modelling has long been the cornerstone of explanation in physical climate science, but as mentioned earlier, major systematic uncertainties remain. With the rapid growth in the use of Artificial Intelligence/Machine Learning (AI/ML) tools across all areas of science, there is a move away from physical modelling towards data-driven methods to assess climate risk [6]. At the same time, many climate scientists are pushing for km-scale physical modelling to overcome the systematic model errors associated with the representation of atmospheric convection [7]. Although AI/ML has definite value in detecting patterns of change, it is inherently based on statistical prediction of those patterns, rather than physically-based explanation.

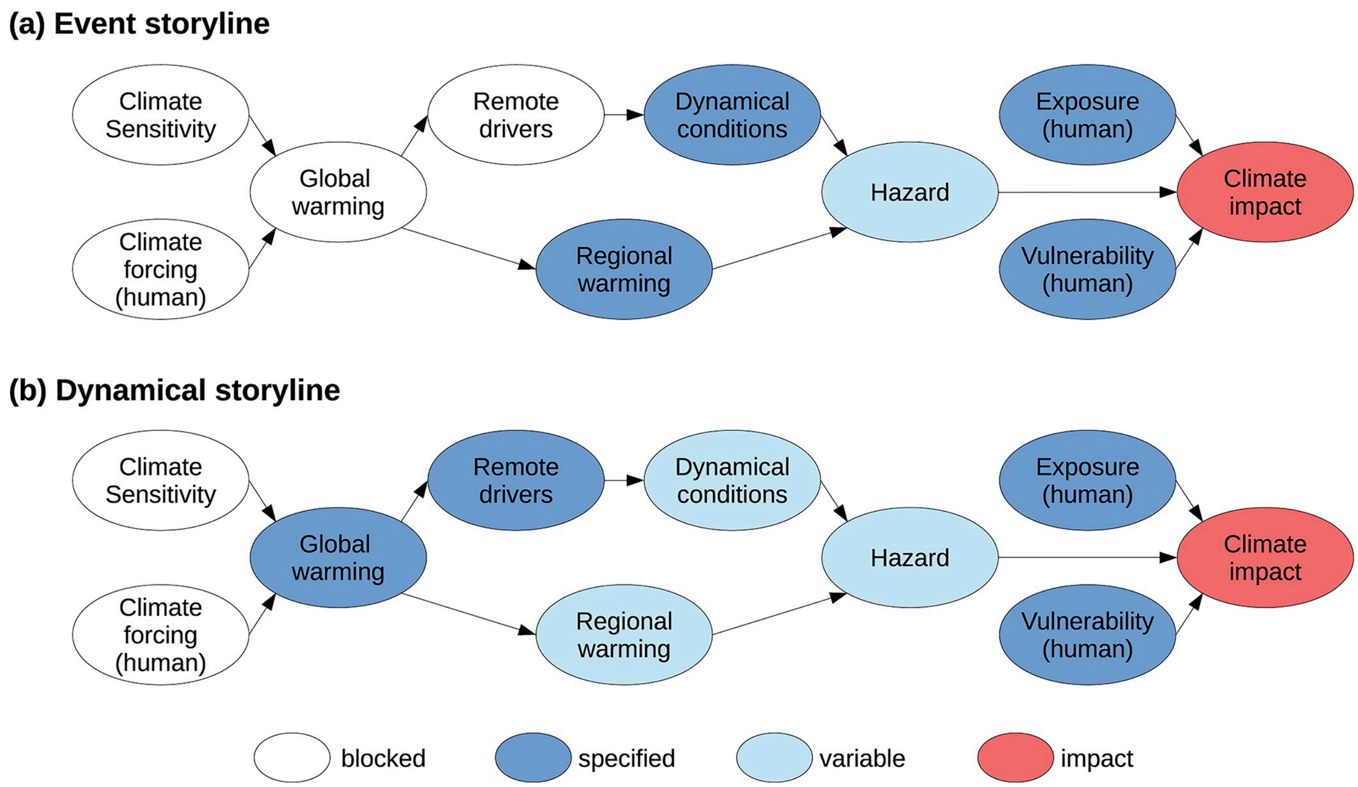

Fig 1. Schematic of two types of physical climate storylines with a particular climate impact of concern (red). The storylines are defined by specified elements (dark blue). Variable elements (light blue) are simulated conditional on the specified elements. The white elements are 'blocked' since their state does not need to be known to determine the light blue elements. Other types of storylines could be defined by specifying other elements (e.g. storylines of different climate sensitivities or different representative concentration pathways). (a) Event storyline, where the particular dynamical conditions during the event as well as the regional warming are specified and control the hazard arising from the event. (b) Dynamical storyline, where the global warming level and remote drivers are specified and control the long-term changes in atmospheric dynamics and regional warming. In both storylines, the impact is also conditioned on specified exposure and vulnerability. From Box 10.2 of [2], adapted from [3].

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And while km-scale physical modelling would be transformative, systematic uncertainties will surely remain and the simulated sample sizes will inevitably be small. Storylines could be useful in serving as a bridge between these two divergent approaches, combining the strengths of each.

In hydrological science, the classical modelling approach has been based on highly parameterised models, often conceptual and process-based, but not really physical. Historically, hydrological modelling has been concerned with quantitatively reproducing observable signatures (e.g. hydrographs) in order to support the predictive power of the models [8]. This however does not guarantee their explanatory power, fundamental for their reliability and robustness in a changing environment. Moreover, the entire approach does not allow a fine-grain process interrogation of the dynamics. Physical models are now becoming more widely used, thanks to the evolution of computing capacity and remotely sensed spatial information [9]. These models provide explicitly resolved spatio-temporal information and causal explanations. AI/ML tools have become prominent in hydrology too, e.g. to mine information to a new level out of hydrological observations [10]. As with physical climate science, storylines can be used to bridge between these different sources of information.

Storylines can also be used to bridge between climate science and hydrological science for understanding hydrological risk. IPCC Working Group I is now heavily using the concept of Climatic Impact-Drivers, which are predictors of hydrological extremes such as floods [2].

While these provide a useful first guess, storylines could be used to provide explainable and hence actionable information from deterministic physically-based hydrological models, driven with meaningful hydrometeorological events selected from counterfactual analysis, possibly based on patterns identified via conceptual and data-based models. We argue that storylines can provide a framework to adapt and prepare for extreme hydrological events, by supporting the understanding of risk causality (explanatory power) including local conditions, and contextualising (into actionable information) the plausible risks triggered by extreme events not well captured by probabilistic representations [11]. Moreover, storylines incorporating physically-based simulation can enrich the local impact assessment of rare extreme events by assimilating events which have occurred elsewhere, but for which the conditions are plausible in the place of interest due to changing climate [12].

To make scientific information useful for decision-making means crossing the science-policy boundary. Cash et al. [13] suggested three requirements for this: salience, credibility, and legitimacy of the information. They also emphasized that the difficulty primarily lies in the fact that the actors on different sides of the boundary perceive and value these three attributes quite differently. By providing conditional causal explanations of observed or imagined events at a fine-grained scale, which can be directly connected to observations and impacts and can be used to construct counter-factual events representing policy options, hydrological storylines grounded in physically-based modelling have the potential to provide a 'boundary object' that meets these requirements for both scientists and policy-makers [14]. In so doing they help make climate information meaningful at the local scale [15].

Author Contributions

Conceptualization: Daniel Caviedes-Voullième, Theodore G. Shepherd.

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