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Representing storylines with causal networks to support decision making: Framework and example

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A B S T R A C T

Physical climate storylines, which are physically self-consistent unfoldings of events or pathways, have been powerful tools in understanding regional climate impacts. We show how embedding physical climate storylines into a causal network framework allows user value judgments to be incorporated into the storyline in the form of probabilistic Bayesian priors, and can support decision making through inspection of the causal network outputs.

We exemplify this through a specific storyline, namely a storyline on the impacts of tropical cyclones on the European Union Solidarity Fund. We outline how the constructed causal network can incorporate value judgments, particularly the prospects on climate change and its impact on cyclone intensity increase, and on economic growth. We also explore how the causal network responds to policy options chosen by the user. The resulting output from the network leads to individualized policy recommendations, allowing the causal network to be used as a possible interface for policy exploration in stakeholder engagements.

1. Introduction

Human-induced climate change has caused widespread impacts and losses to human society, and this is expected to increase in the near-term future (IPCC, 2022). Among the many impacts of climate change are cascading impacts, which transmit through complex physical and socioeconomic networks (e.g. trade or financial networks), propagating to regions and sectors that are remote from the original climate event location (Challinor et al., 2018). These complex transmissions of impacts abound with uncertainties: in the physical understanding of regional climate change, in its socioeconomic implications, and in the interaction between those systems. Nevertheless, tracing the transmission pathways of these climate impacts in complex systems and understanding their consequences can contribute to making informed decisions for climate adaptation. Supporting this decision-making process is one important aim of climate impacts research.

The physical climate storyline (PCS) approach has recently gained traction to tackle regional impacts from climate change in

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complex systems (Doblas-Reyes et al., 2021). PCSs are defined as a “physically self-consistent unfolding of past events, or of plausible future events or pathways” (Shepherd et al., 2018). They are represented by deterministic chains of physical events, and showcase plausible causal chains of events and impacts. In many cases, PCSs apply counterfactual reasoning, using “what-if-things-had-been-different” questions, to relate historical events (those that created significant impacts) to unprecedented but plausible future climate and socioeconomic conditions, and to present possible impacts under those conditions.

One aspect that distinguishes PCSs from the conventional probability-based approach is their conditioning nature, where certain assumptions (e.g. global warming level, prevailing atmospheric and/or oceanic conditions) related to an event or a climate condition are made. This allows some of the underlying climatological uncertainties (e.g. probability of a climate event occurring under a given climate condition) to be separated from the PCS narrative, after the selection of the storyline based on plausibility. With the uncertainties separated, the concrete narrative of the PCS allows the mechanisms underlying the processes to be directly analyzed, making them more relevant for policy decisions that require related discussions and analyses, compared to a conventional probability-based approach (Sillmann et al., 2021).

At the same time, such policy decisions often need to be made amid the balancing of conflicting interests and objectives. In the presence of severe uncertainties that may not be fully captured through deterministic PCS narratives, weighting different climate events, different underlying climate conditions, and the spectrum of possible consequences within the uncertainty range by addition of a quantified risk to the rationale, may be important for well informed decisions (Sillmann et al., 2021). The balancing of these elements is not incorporated within the language used for deterministic PCSs, and requires an additional framing to address.

Shepherd (2019) pointed out that PCSs are to be interpreted as conditional events, which can be embedded within the framework of a causal network. This provides the mathematical structure to incorporate probabilities of the PCSs, and in addition allows to explore the effect of intervention options that are subject to a decision context. Causal networks have long been used in environmental risk assessment, see for example Sperotto et al. (2017) and Kaikkonen et al. (2021). In this paper, we showcase how causal networks can play a role in handling uncertainties within the PCS approach, extended with the application of decision-making, through an explicit example.

In particular, we outline how causal networks become powerful decision support tools as they allow embedding value judgments of the user (such as decision makers) into the PCSs. These user value judgments include, as we see in the example, expectations about the future and level of risk tolerance, leading to a tailored outcome for the user’s decision making from the causal network. Moreover, these causal networks can be used as a tool to clarify assumptions and make them explicit. The user may have subjective beliefs on the propensity of an event or condition, and these beliefs may become internally inconsistent if left implicit. For example, a policy decision could be made with finite joint probabilities assigned to mutually exclusive events. With the large uncertainties and the high stakes involved in managing extreme climate impacts, it is important to ensure that one’s subjective risk assessment is at least logically self-consistent. This can be done within probability theory, as has been articulated in works by Savage (1954) and Lindley (2006) (see related discussion in Shepherd (2021)). Combining PCSs with causal networks is a tool for such realization.

The main focus of embedding PCSs in causal networks in this paper lies in the introduction of user value judgments and related uncertainties in a consistent manner, but they can also be used as a tool to formalize the storylines in a visually transparent way. We will introduce a user interface for the causal network that incorporates this functionality for the given example, designed for communicating the causal structure and parameter sensitivities of the storylines.

In the next section, we elaborate on the physical storyline approach and the causal network framework, and introduce a prototype causal network into which PCSs can be embedded. In Section 3, the main part of the paper, we showcase the causal network framework, using the storyline developed by Ciullo et al. (2021). We also outline how user value judgments enter the framework with explicit examples. In Section 4, we discuss the implications of applying causal networks to PCSs, along with a generalization of the approaches taken in Section 3. We conclude in Section 5 with a summary.

2. Combining physical climate storylines (PCSs) and causal networks

2.1. Physical climate storylines (PCSs)

The construction of PCSs is based on a range of methodological approaches with different sources of evidence and assumptions (Doblas-Reyes et al., 2021). Nevertheless, PCSs are usually constructed by analyzing observations, model output and expert judgment, and composing a causal chain of events conditioned on selected boundary conditions and (time-varying) forcings. In many cases, PCSs come in pairs: a “factual” PCS, based on observed events or patterns, and a “counterfactual” PCS, which explores “what-if-things-had-been-different” questions, usually by constructing an analogous past, present or future causal chain of the event that reflects possible changes in climatic conditions, societal characteristics, or adaptation responses (van den Hurk et al., 2023). One approach to PCS development is based on historic events experienced and remembered by community members and policymakers, with the aim of leading to higher engagement of those stakeholders, and hence higher relevance to policy making (Sillmann et al., 2021). While the approach in this paper applies to various types of PCSs, we will focus on these “event-based storylines”, as illustrated by the example in Section 3.

PCSs are typically composed of a deterministic causal chain of events, and while they are quantified using data and simulations, there are usually no probabilities assigned to the events occurring within the storyline. Probabilities can of course be assigned to these events, but there needs to be a framework where the probabilities of the conditional elements of the PCS can be formulated, together with user preferences and different intervention scenarios, in a unified, self-consistent manner.

In this paper, we showcase the approach proposed by Shepherd (2019) with an example by embedding the PCSs developed by

Ciullo et al. (2021) in a Bayesian network, or more precisely for our purpose, in a causal network, to insert probabilistic aspects into the approach.

2.2. Bayesian networks and causal networks

A Bayesian network (Pearl, 1988, 2009) is a representation of conditional probabilistic dependencies within a system, expressed in terms of a directed acyclic graph. The nodes of the graph correspond to variables/elements in the system, and their realization probabilities are conditional on their parent nodes, corresponding to another preceding variable/element within the system. Root nodes in the network do not have any parent nodes, hence are given unconditional probabilities.

The conditional and unconditional probabilities represent the uncertainties that exist within the system, and can be learned from data or assigned through expert assessment. For PCSs that will be embedded in these networks, these uncertainties can originate from aleatoric processes within the PCS, from the limitation in our knowledge about the physical and social processes, and from the uncertainties regarding future pathways and scenarios. These separate contributions to the probability distribution can be combined in a modular manner, allowing a piecewise investigation of how different assumptions alter the outcomes. This makes Bayesian networks a powerful tool in exploring the sensitivity to the assumptions made about the input probability distributions (range and shape).

We focus here on the case where each connection within the Bayesian network represents a causal relationship, i.e. focus on *causal networks*, a subcategory of Bayesian networks. Given that PCSs are typically a chain of causal connections, the causal structure of the PCS is directly mapped into a causal network. Focusing on causal networks is especially relevant when considering a non-stationary system (Pearl, 2009), for example changing climate features, or policy interventions, in which we are interested.

2.3. Embedding storylines into causal networks

The conditioning nature of causal networks allows storylines to be embedded into them, through the conditioning on corresponding storyline event nodes. If there are probabilistic processes on the path toward the outcome node, or if a probabilistic prior is set in upstream nodes, the resulting outcome from the causal network also becomes probabilistic. In this manner, probabilities are introduced into an otherwise deterministic storyline.

The causal network framework extends the scope of a single storyline to include probabilistically quantified counterfactual conditions within the same framework. It also allows those probabilistic quantities to be assigned subjectively, directly connecting the analysis to value judgments. We will explain how this is realized in an explicit example in Section 3, after which we will come back to a general discussion of these properties in Section 4.

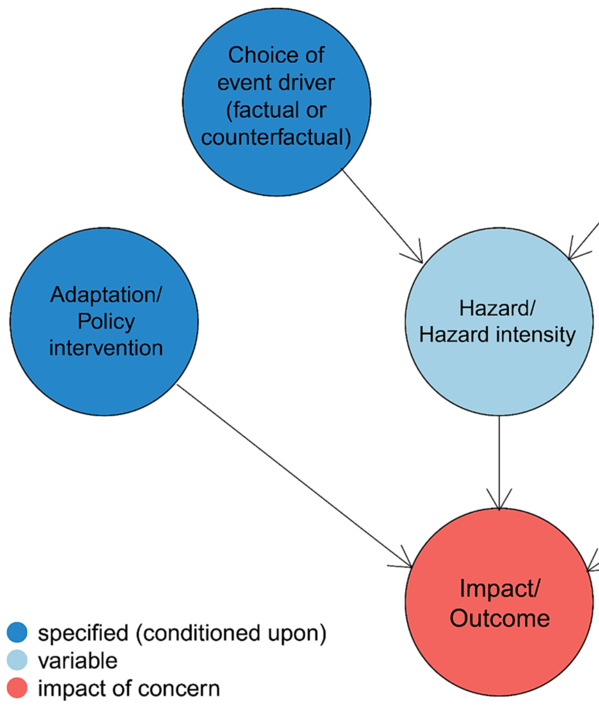

Fig. 1. Prototype causal network for embedding PCSs, following the color coding used in Doblas-Reyes et al. (2021). The event driver determining the hazard intensity typically corresponds to the main storyline specification, and has a major impact on the outcome of the PCS. Climate change, vulnerability and exposure, adaptation and policy interventions can change the trajectory and outcome of the PCS.

2.4. Procedure to embed a PCS into a causal network

Before introducing a specific example, we outline the general process of embedding a PCS into a causal network.

To embed the PCS into the causal network, we first create a network structure corresponding to the PCS. We show a prototype of the elements and structure of such a network in Fig. 1. The causal network consists of a set of nodes that together represent the causal structure of the PCS. The nodes include the drivers of the PCS and the outcome of interest (consequence). The hazard level, determined by the driver, may also depend on various climate-related assumptions that may reflect expert judgments or user choices. The shape of the outcome distribution of the hazard may change depending on socioeconomic assumptions (i.e. vulnerability and exposure) and policy interventions (or adaptation, whether intentional or not). This structure is what is represented in Fig. 1. Each connection within the network should be a causal relationship that can be expressed as a quantitative equation. Note that not every element of the storyline needs to be included, especially when there is neither related user input nor policy interventions or when the output is not sensitive to the value of the element. (These omitted elements could be intermediate processes that are not of interest to the causal network user, or background assumption settings that could not be modified by the user.) The information on such elements can be left out, or, in cases where the element is an intermediate process, be incorporated into the probability distribution of a succeeding variable. The elements of a causal network need not directly correspond to the prototype framework of Fig. 1, but the structure of the network should be made so that it enables conditioning on the physical event driving the storyline (e.g. choice of event driver).

Next, we assign conditional probabilities for the non-root nodes based on simulated counterfactuals or expert analysis. In many cases, the conditional probabilities will be based on deterministic processes governing the impact model outcomes of the PCS. The specific methods of this assignment will depend on the quantitative analysis made through the construction of the PCS, and we will outline an example of this process in Section 3. As we show in the example, the unconditional probabilities for the root nodes could be assigned as Bayesian prior distributions, where they are determined for example by user expectations of the future.

The above two steps, structurization and quantification, result in a causal network that responds to user inputs. The user can obtain different outcomes of the storyline for chosen assumptions or policy interventions.

3. Example: Causal network for storylines of tropical cyclone impacts on the European Union Solidarity Fund (EUSF)

In this section, we exemplify how user value judgments are incorporated into a storyline through the causal network framework, leading to policy recommendations tailored to policymakers. In doing so, we consider the storyline constructed in Ciullo et al. (2021) on the impacts of tropical cyclones on the European Union Solidarity Fund (EUSF).

3.1. Storylines of the impact of tropical cyclones on the EUSF

The European Union Solidarity Fund (EUSF) provides financial aid to European Union Member States affected by large disasters due to natural hazards. The EU is affected by a large variety of natural hazards, both on the continent (e.g. by earthquakes, floods, landslides, forest fires) and in the outermost regions (e.g. by tropical cyclones), which include French territories (La Reunion and Mayotte in the South-West Indian Ocean; French Guiana, Saint Martin, Guadeloupe, and Martinique in the North Atlantic Ocean) and the Macaronesian Region consisting of Portuguese (Madeira, Azores) and Spanish islands (Canary Islands). Ciullo et al. (2021) used a PCS approach to explore the possibility of EUSF impairment (i.e. capital dropping below zero) caused by increasing tropical cyclone damage to these outermost regions.

The PCSs in Ciullo et al. (2021) were built via downward counterfactual analysis, namely analyses based on imagined past events where the outcome was worse than what actually happened (Roese, 1997; Woo, 2019), by considering the impact on the EUSF of unrealized – but fully plausible – past tropical cyclones under current climate conditions. Plausibility is ensured by using past numerical weather forecast data, shown to represent physically plausible realizations of past weather events. Weather forecasts of tropical cyclones allow identifying historical near misses that could have been catastrophic. Hence, PCSs are built from downward counterfactual cyclones by identifying what kind of single events could have been detrimental for the EUSF capital.

Ciullo et al. (2021) identified 13 critical tropical cyclones, combined into four reference PCSs each with a different combination of cyclones, representing both single large events and compounding occurrences of multiple events. The four PCSs were projected into the future by evaluating climatic, socioeconomic, and policy changes. In terms of climatic changes, a change of maximum surface wind speed of tropical cyclones in the [1 %, 9 %] range is considered, in line with Knutson et al. (2020). For socioeconomic changes, a GDP increase in the [1 %, 21 %] range is considered, in accordance with past relative growth of the outermost regions compared to Europe. EUSF capitalization policy changes are modeled by increasing the EUSF capitalization in the [0 %, 150 %] range. The damage caused is calculated using the CLIMADA impact model (Aznar-Siguan and Bresch, 2019), in which the the damages are assessed as a function of weather-related hazard, exposure of people and goods to such hazards, and vulnerability of the exposed entities. Hazard from tropical cyclones is represented by wind speed information, derived from tropical cyclone tracks. The damage calculated is in turn converted to the EUSF capital level through the payout rules determined by the fund. Results show that capitalization is driving capital availability and that restoring the pre-2013 annual capitalization amount would allow coping with the highest considered climatic and socioeconomic impacts.

The analysis conducted by Ciullo et al. (2021) estimated under what plausible future scenarios the EUSF undergoes severe budget deficits, without aiming to quantify when such states may occur, nor how likely they are. The current study enhances the PCSs by adding a posteriori statements about the likelihood of different climate and socioeconomic situations within a causal network framework.

3.2. Introducing causal network and interface implementation based on the EUSF PCS

The storylines outlined in the previous section can be embedded into a causal network as illustrated in Fig. 2, following the methods in Section 2.4. The cyclone nodes are indicators of which (downward counterfactual) cyclones are included in the storyline, two of which historically led to payouts from the fund (Irma and Maria). All storylines (e.g. with different cyclone choices) embedded in this network are based on the downward counterfactual cyclones, constructed in Ciullo et al. (2021) from the forecasts in the THORPEX Interactive Grand Global Ensemble (TIGGE) program (Swinbank et al., 2016). Additionally, differing levels of climate change affect cyclone intensity, while increase in GDP affects the outcome of the storyline by altering the damage profiles. A storyline consists of one or two consecutive years (2017 and 2018), and for each year, corresponding counterfactuals are considered. The capital in a given year carries over to the next year, so we consider two consecutive years to examine how a payout will affect the capital in the following year.

The hazard level in a given year is determined by the selected set of cyclones in the storyline, and the assumed level of global warming that leads to stronger cyclones, denoted “Cyclone intensity” in Fig. 2. The damage for the specific set of cyclones and global warming level is calculated using the CLIMADA impact model with the same methods used in Ciullo et al. (2021). The payout in each year is determined by the payout rules (which depend on the GDP of the region, detailed in Ciullo et al. (2021)) and the estimated damage from the CLIMADA model. Finally, the capital level (i.e. the amount of capital remaining) for each year is determined by the payout and the chosen recapitalization (i.e. capital increase), which is a simple summation. The capital from the first year carries over to the second year, while the scenario assumptions are chosen to be similar for the two years. This is carried out for all possible combinations of cyclones, cyclone intensity, GDP increase and capital increase, and the causal network is populated by the data generated which results in a discrete network that contains all possible input combinations and their outputs.

We allow the causal network to be conditioned on a specific set of cyclones, while for the “Cyclone intensity” and “GDP increase” nodes, we allow probability distributions as inputs. The user also chooses a policy option for “Capital increase” to determine the outcome. The nodes and the values taken in the causal network are summarized in Table 1.

The outcome of the causal network can be expressed as a probability distribution of the capital level at the end of the period considered by the storyline. Comparing multiple counterfactuals with different policy options allows determination of the solution that would be most preferred according to the user’s risk tolerance.

We have developed an interactive web app using the Shiny package (Chang et al., 2022). The web app can be accessed at https://tarokuni.shinyapps.io/eusf_bn/. Outputs include both the probability distribution of the EUSF capital level in a given year and the preferred policy given the prior inputs by the user. In the following sections, we detail the user inputs, corresponding to possible user value judgments entering the storyline, after summarizing the specific user value judgments that determine those inputs.

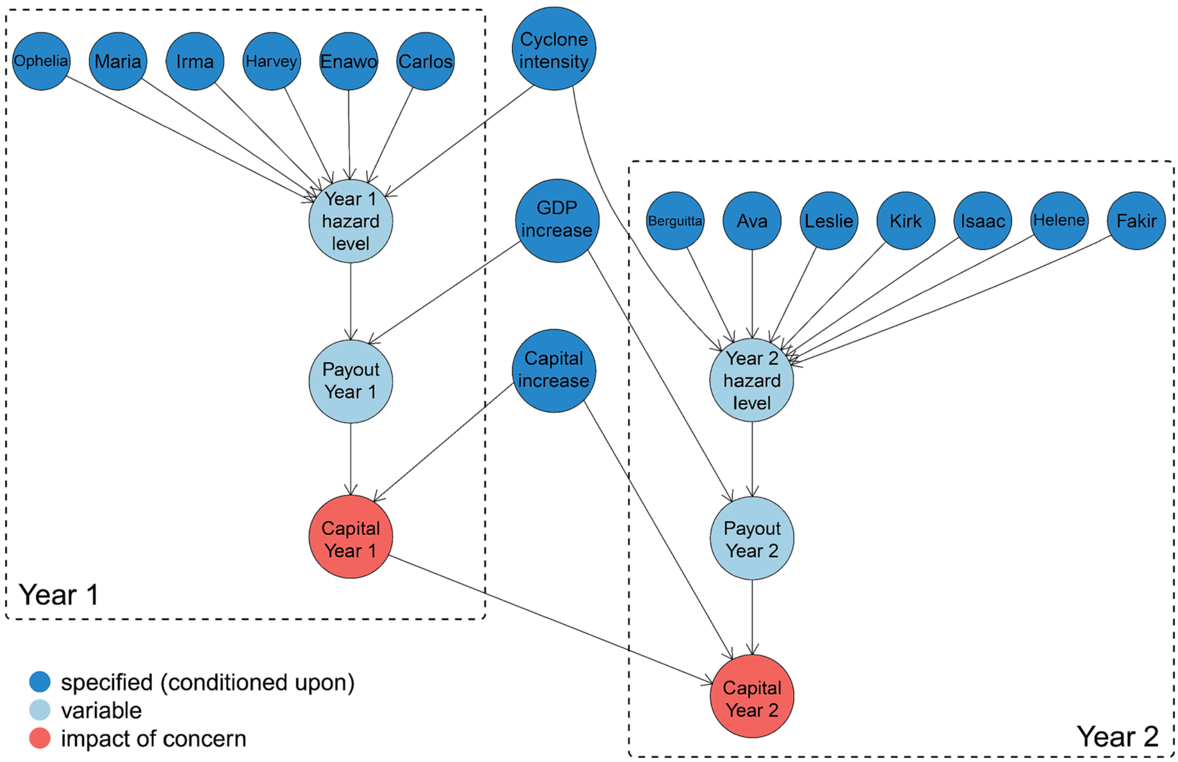

Fig. 2. Causal network for the EUSF storyline. The outcomes from the causal network are the capital remaining in the fund for the two consecutive years of cyclone impacts. The conditioned upon nodes can have value-judgment-driven inputs. See main text for descriptions of the nodes and their relationships.

Table 1
List of nodes in the causal network of the EUSF storyline and the values they take.

List of nodes	Values taken by the node
Individual cyclones	Binary value (input) on whether the cyclone exists in storyline
Cyclone intensity	Probability distribution (input) over percentage increase
GDP increase	Probability distribution (input) over percentage increase
Capital increase	Numerical value (input) of percentage increase
Hazard level	Probability distribution over possible cyclone configurations
Payout	Probability distribution over numerical values
Capital (Capital level)	Probability distribution over numerical values

3.3. On value judgments entering the construction of the storyline

While the storyline can be embedded in the causal network framework as illustrated in the previous section, there are inputs to the causal network that need to be explicitly provided. Not all of this can necessarily be drawn purely from the scientific literature or other factual information and will need to be based on the user's subjective expectations and preferences. Moreover, even when drawing from the scientific literature, scientists themselves draw from their own value judgments to drive modeling and input choices (see Elliott (2022) for an overview of how values enter scientific processes). Here we point out how value judgments are ingrained in the whole approach, and we discuss this in a more general context in Section 4.1.

Value judgments can drive the shape of the causal networks that represent possible storylines. In the current example, there are clear ways in which value judgments drive modeling choices. These manifest themselves as aspects including (but not limited to):

- *The focus on the historical years 2017/ 2018 and the selection of the 13 candidate cyclones*. Value judgments that drive this choice may be pragmatic: these are some of the most recent high impact events. Recent events may also be those for which there is most extensive data, therefore allowing for a more complete examination of the impact pathway. These events are fresh in the public's memory, which may help the communication of information about possible futures (Schacter et al., 2007), ultimately raising awareness of the impacts.
- *The decision to use downward counterfactuals as elements of the storylines*. The use of downward counterfactuals can be driven by ethical value judgments about the harm that hazards can have on local populations, with the aim of creating more resilient communities by exploring the worst possible outcomes, or promoting the study of data sparse systems (Lin et al., 2020).

While the above choices shape the setting of the causal network, the selection of a particular PCS and its outcome can additionally be shaped by value judgments of the users. These values manifest themselves as:

- *The choice of the events to consider in the storyline*. While the standard setting of the storyline is the one driven by observed events, the user can select up to 13 downward counterfactual cyclones hitting the remote region of interest. So, here, the user has the freedom to express their ethical and/or pragmatic value judgment about how much impact to include in the storyline (whether the choice is going to explore just a *slightly worse* storyline, or *the worst* storyline allowed by the causal network).
- *Expectations about the future*. User value judgments can shape the numerical values and shape of the probability distributions assigned to the unconditional and conditional nodes. Specifically, a subjective probability distribution on how the intensity of cyclones will change and how economic growth will proceed will come into the causal network as Bayesian priors.

In general, these choices embody broad non-cognitive values of the user and their subjective expectations of the future (constrained by the structure and input ranges of the causal network). For example, a pessimistic individual may favor the worst possible storyline by choosing a large number of cyclones and probability distributions that represent their worst expectations for the future. These choices will be reflected in the probabilistic outcome of the particular storyline chosen in the causal network, and will be markedly different from, for example, the choices made by an optimistic individual. In Box 1, we have outlined example narratives of different users making different input choices based on their value judgments. Underlying considerations are outlined in the following sections.

3.4. On the choice of the cyclones to include in the storyline

The choice of which cyclones to include in the storyline is the prime determinant of the obtained outcome, and will also be a crucial aspect in communicating storylines to stakeholders. Here we discuss how this selection can be motivated.

In an event-based storyline approach, the climate event under consideration is considered a given event to base the analysis upon, hence no prior probability distribution is set on the realization of the event. Nonetheless, climate change will likely have an impact on the frequency of the cyclones, although the uncertainty is large; even the sign of the change has no consensus (Knutson et al., 2020).

While it is possible to build a large variety of counterfactual storylines by varying the set of cyclones to include (within the range of scientific understanding, e.g., assumption of global warming level, plausibility), for practical reasons there may be a need for a structured approach to choosing the set of cyclones.

An option is to go through an incremental approach starting from the historical realizations. Among the 13 cyclones considered within the EUSF storyline, there are two that resulted in historical payouts from the EUSF, namely cyclones Irma and Maria. These two

Box 1
Causal network user example

In this example, the user chooses the maximum number of cyclones (13) – this might be driven by different epistemological and value theoretic considerations: they may be interested in stress testing the system to see how the EUSF holds up if all predicted storms were to make landfall, or they might just be interested in the worst case scenario driven by (social/ethical) value considerations such as the precautionary principle. In addition to the selection of the number of cyclones, the user can further specify priors of the unconditional nodes to evaluate policy options that can help inform what policy is associated with different levels of risk-aversion.

Suppose user 1 has a pessimistic outlook on the future, both regarding the impacts of climate change and about the growth of the economy. This attitude (which can reflect a variety of values) can be reflected in the choices of prior distributions in the causal network. By changing the values of the distribution assigned to the hazard increase and GDP growth of the unconditional nodes in the network, the user can specify likelihoods that skew the distribution toward a pessimistic outlook: i.e. higher likelihood of higher hazard increase and lower likelihood of higher GDP growth. A distribution skewed towards a higher hazard increase indicates that the user thinks that, within the range specified by scientists, cyclone intensity is more likely to increase by 9 % than 1 % (rather than the likelihood being uniformly distributed across all values in the range). Similar reasoning can be applied to GDP growth. This corresponds to the third column from the right in the Fig. 5 matrix.

The user then can explore the capital level under different levels of capital increase, which can represent different policy options. For example, a 0 % capital increase (which represents a lack of policy change, i.e. capitalization of the EUSF remains the same) shows that under this scenario, the EUSF will remain in the red in any (deterministic) realization of the causal network.

In order to be able to make a decision about hedging against the EUSF being in the red (and hence be able to evaluate one's risk aversion), the user will need to make some changes to policy (i.e. increase in capitalization of the EUSF). Under this (pessimistic) set-up, a 60 % increase in capitalization of the EUSF will result in being in the red 93 % of the time and positive 7 % of the time – anything below this and the fund will remain in the red. A risk seeking policy maker might deem this policy choice sufficient. A 90 % increase in capitalization of the EUSF shows that in this set-up, the fund will be in the red 43 % of the time and positive 57 % of the time. A risk neutral policy maker might choose this policy option. A very risk averse policy maker might choose to increase capitalization of the EUSF by 120 %, as this option shows that in this set-up, the EUSF never becomes red.

Suppose user 2 has an optimistic outlook on the future. This attitude may lead the user to explore policy options by selecting prior distributions which are skewed towards a low hazard increase and a high GDP increase (third column from the left in Fig. 5 matrix). In this case, the user will be able to see that under this set-up, a 60 % increase in capitalization of the EUSF fund will reflect a risk-neutral attitude – as this set up shows that under these assumptions, the fund will be in the red 57 % of the time and positive 43 % of the time. A risk averse policy maker, on the other hand, should choose to increase capitalization by at least 90 %, as this is the policy option that shows that it is overwhelmingly more likely for the EUSF to remain positive (7 % of times in the red, and 93 % of times positive).

A user (user 3) who remains neutral with respect to their outlook on the future, may choose to stick with the pre-set uniform distributions. In this case, again, they will see different options for capitalization and the respective likelihoods of the EUSF being in the red or positive under the specified set-up of the network (center column in Fig. 5 matrix). A risk-seeking policy maker may deem it adequate to only increase the capitalization of the EUSF by 60 %, as the set-up shows that in this case the fund will be positive 28 % of the time. A risk-neutral policy would need a capitalization increase between 60 % and 90 %, whereas a very risk averse policy would need a capitalization increase of 120 %.

cyclones can form a reference (or baseline) storyline, set as the default selection in the user interface. Additional cyclones can be chosen (either randomly or manually), allowing an incremental exploration and consideration of storyline implications, motivated by the user's expectations of future conditions and requirements for resilience.

In justifying this approach, we consider the probable number of cyclones that cause damage in the area (not simply the frequency of the cyclone). This is difficult to calculate, in part because each cyclone considered is a downward counterfactual, i.e. worst-case realization for which probabilities are difficult to assign. A rough estimate can nonetheless be made using simulations. Here, we use the synthetic dataset of STORM (Bloemendaal et al., 2020) to generate return periods for the damages caused in the outermost islands of interest. For the 13 possible downward counterfactual cyclones in the PCS, we assume a linear scaling of frequency according to intensity (Emanuel, 2000). Using these, we reproduce the mean damage and variance generated from the STORM dataset, which gives an average of two cyclones in two years, giving some justification. As another approach, we calculate the return period of the same level of damage caused by the two historical cyclones using the same dataset, which is estimated to be 11 years. This also justifies the method starting from two cyclones.

We note that these values of estimated cyclone number and return time have large uncertainties depending on the assumptions made, which shows that a specific number of expected cyclones cannot be determined with high confidence, and that any combination from the 13 cyclones is considered plausible.

3.5. On probabilistic user inputs to the causal network

Along with the choice of the cyclones, two prior probability distributions enter the causal network in this example, namely the increase in cyclone intensity (represented here by average wind speed) and future GDP increase. As outlined in the storyline description, higher cyclone intensity leads to larger damage caused, and hence larger payout from the EUSF, while higher GDP growth leads to more (higher value) assets destroyed, and hence changes in the payouts (depending also on changes in payout thresholds).

Here, the range of the cyclone intensity increase follows outcomes from expert assessments where a 2 °C global warming was assumed (Knutson et al., 2020). There is relatively large disagreement on the specific amount of the increase, so it is not possible to single out a likely probability distribution, let alone a single numerical value, from the current scientific understanding. In order to reflect the information provided in the scientific literature, we allow the user to choose to increase cyclone intensity within the [1 %, 9 %] range, using a probability distribution over the range. Different attitudes toward expected future cyclone intensity may be evaluated using different probability distributions within this range. For example, the impacts of a future in which a higher intensity increase is deemed more likely, or representing a future in which global warming exceeds 2 °C warming may lead to probability distributions skewed to higher values (see Fig. 3). In the narratives described in Box 1, the users use different distributions based on their future expectations of cyclone intensity.

Similarly, future GDP increase is also unknown (e.g. financial crises are unpredictable), so the expectation about the extent of this increase is inserted into the causal network as a user-determined probability distribution, assuming an increase value from the [1 %, 21 %] range, consistent with historical values. Similar to the different distributions applied for cyclone intensity (Fig. 3), a range of skewed distributions of GDP increase can be selected, which may reflect value-based expectations on the probability of the range of SSP-RCP scenarios or other drivers of GDP trends.

Finally, the capitalization of the fund is considered to be a policy option with a noticeable impact on the outcome of the causal network simulations, as shown in Fig. 4. Obviously, the higher the agreed capital increase, the larger the probability of the capital remaining positive.

In evaluating the policy choices, the effect of risk aversion[1] of the decision maker can be combined and transferred into preferred policies. Some users may want to decide on a policy aiming at a positive outcome roughly half of the time (such users are labeled as "risk-neutral" below), while "risk-averse" users may want low probability of negative outcomes, both maximizing the utility by choosing the smallest capital increase that satisfies the criteria. While this requires comparison of multiple policy options, it can easily be combined using the results obtained from the causal network.

3.6. Illustrative results from the example

For illustrative purposes, we show the outcomes for the storyline in which the maximum number of cyclones is chosen (all 13 downward counterfactual cyclones realized – hence maximum cumulative impact and sensitivity to the prior assumptions; while this is not a likely event to occur, it is still a physically plausible storyline to explore as a worst-case scenario), and how the calculated fund capital status changes depending on the user-imposed assumptions.

Fig. 5 illustrates the range of causal network outcomes for different choices of the prior assumptions of cyclone intensity and GDP increase, and for different policy options of capital increase. Some of these combinations are also illustrated in Box 1.

Using this, we calculate the policy recommendations for a risk-neutral policy maker (for which the output inferred from the probability distribution is positive half the time in the second year) and a risk-averse policy maker (for which the output inferred from the probability distribution is positive 90 % of the time in the second year). The policy recommendations are given in 30 % intervals, from 0 % to 150 %.

Fig. 6 shows the results. All prior assumptions are shown to affect the preferred decision, with a larger capital increase required when a pessimistic climate future is adopted, when an optimistic assumption on the economic future is adopted, and when the user is risk averse. For the given range of possible values, both cyclone-intensity increase and GDP increase give rise to similar impacts on the ranges of the results.

4. Discussion

As illustrated above, causal networks can be of use in communicating physical climate storylines to stakeholders, while incorporating subjective value judgments and expectations. Here we reflect on the incorporation of value judgments and probabilities, and some useful aspects of this approach.

[1] We are using "risk aversion" to refer to the user's general preference of avoiding risk, which is broader than the definition used in decision theory, but still requires the user to know (at least the direction of) the probabilistic outcome resulting from their choice. While this may be the case for choosing an expected climate future for the inputs (hence risk aversion can indeed play a role here), this is not the case in general, for example for GDP growth. We used the terms optimistic/pessimistic to refer to the expectations, which may or may not have been influenced by their risk preferences.

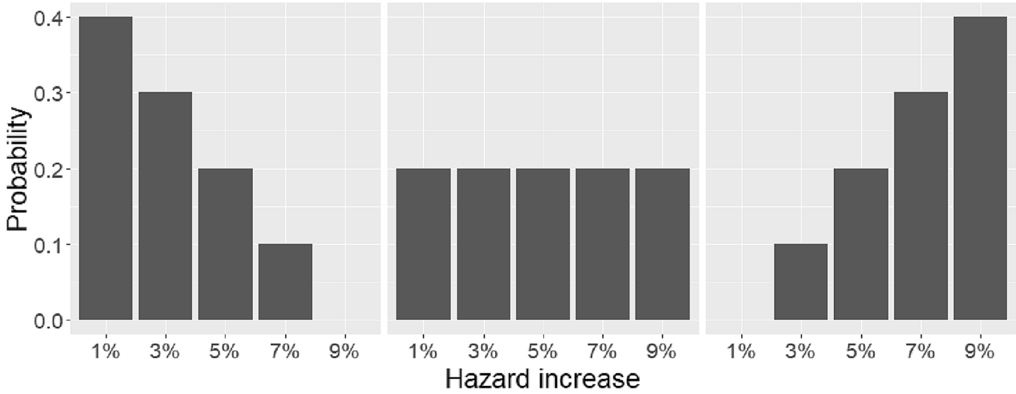

Fig. 3. For the cyclone intensity increase, we take values ranging from 1 % to 9 % at 2 % intervals, and predefine three distinct probability distributions for illustrative purposes in the results in Section 3.6 and Box 1. We also prepare a similar probability distribution for GDP increase, where the values range from 1 % to 21 % at 5 % intervals.

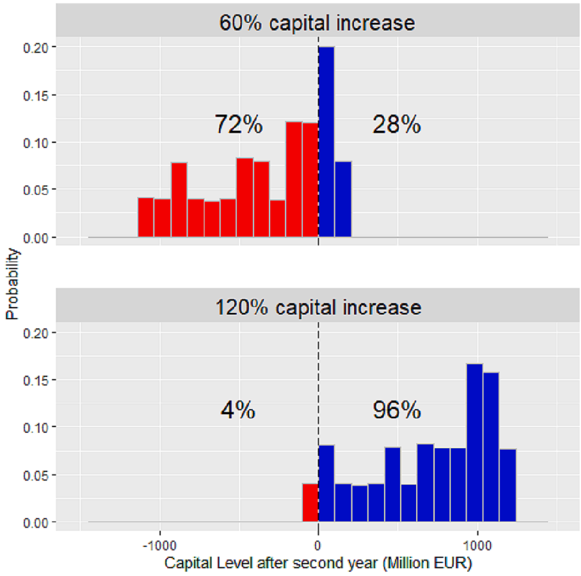

Fig. 4. Probability distribution of capital level after the second year for two different fund capitalization policies, under the same priors (uniform distribution for both hazard increase and GDP increase). The percentage values within each cell shows the proportion of the distribution that results in negative and positive values for the capital (red and blue area respectively). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4.1. On incorporating user value judgments

In the above sections, we have shown how value judgments of scientists and users of storylines can shape the causal structure of the storyline and the numerical values for independent and dependent nodes of the network. This demonstration of how value-judgments enter the construction of a particular storyline is important for two reasons. First, climate scientists agree that the role of value judgments should be more explicitly incorporated in climate science (Pulkkinen et al., 2022). Second, the aim of PCSs is to start from the decision point of the stakeholders (Shepherd et al., 2018), therefore facilitating the relevance and uptake of information derived from event-based PCSs (Sillmann et al., 2021). This point has also been long recognized in the context of environmental risk assessment (Jones, 2001).

Different cognitive and non-cognitive values may lead to different choices of model inputs, which can lead to incorporation of values into the PCS methodology (see Vezér et al. (2018) for an analysis of value trade-offs in flood risk modeling and decision making, and Undorf et al (2022) for how values enter model-based climate sensitivity assessments). The justification strategy is particularly important when PCS are used for risk assessment. As Longino (1986) argues (see also Kuhn, 1977, Wylie, 2012), the kind of interests that drive scientists and stakeholders engaged in the process will inevitably shape the results of the risk assessment process, especially when there is limited data or contested methodologies and theory available. More recently, Parker and Lusk (2019) have exemplified

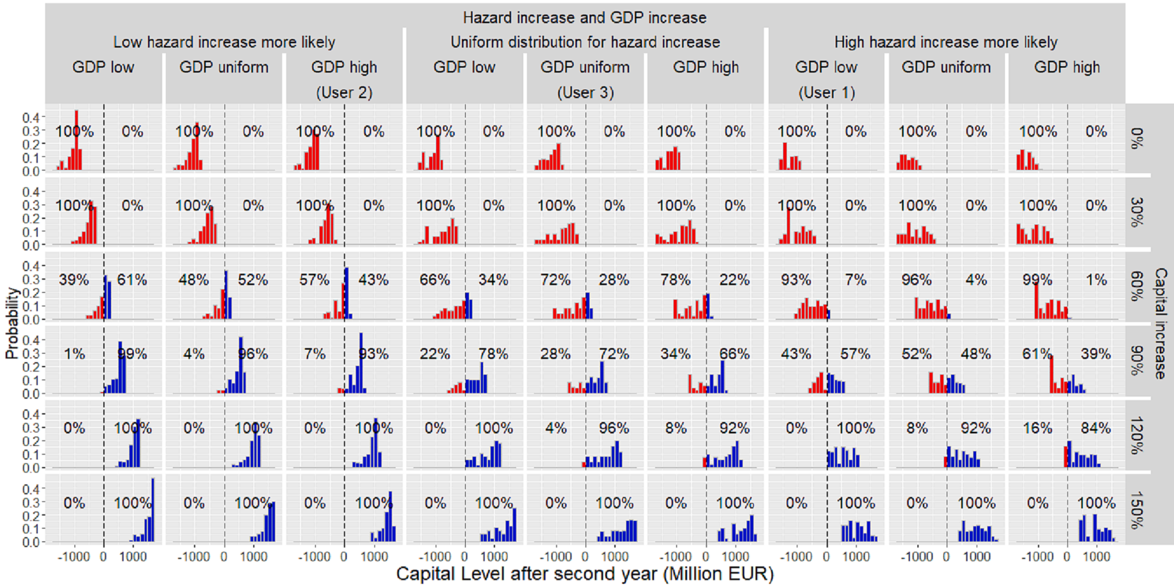

Fig. 5. As Fig. 4 for a wider range of capitalization policy options (given in 30 % intervals) and GDP and cyclone intensity ranges. The input prior distributions are of the form shown in Fig. 3. The user names correspond to the users illustrated in Box 1.

how this can occur when stakeholders and scientists co-produce climate services and have to negotiate their attitudes towards the consequences of error. This analysis is part of a broader discussion on so-called "inductive risk"; see Rudner (1953), Douglas (2009), Steele (2012), Steel and Whyte (2012), Elliott and Richards (2017), Winsberg et al. (2020) for relevant examples of this kind of philosophical analysis. As a consequence, making scientist and stakeholder interests explicit by making value judgments explicit can lead to better informed decisions based on information that is considered fit for purpose.

Making explicit the choices in the application exposes the fact that user value judgments may dominate the outcome of a particular storyline. Imposing probability distributions on the storylines allows stakeholders to be self-reflective about how their assumptions and values shape the analysis outcomes, and tailor the storylines to their interests. However, the value judgments of the scientists also shape the causal network and the bounds of numerical values and distributions of the network nodes. To maximize relevance, the construction of the storylines should preferably be carried out jointly with stakeholders and policymakers. Causal networks can be a tool in communicating and visualizing analysis results, explaining their systemic nature, and achieving further feedback to the construction of the storylines.

4.2. How causal networks are useful for storylines

Causal networks can offer several additional merits to the storyline approach. First, the probabilistic nature of causal networks allows uncertainties to be incorporated within a physical climate storyline. In the particular example demonstrated here, this was incorporated in the form of prior distributions, but this could also have been implemented as aleatoric processes within the embedded model. The resulting model uncertainty range is determined by the combined uncertainty ranges.

Second, causal networks provide an interface to communicate the storyline to multiple stakeholders. The causal structure is transparent, supporting the understanding of the cause-and-effect within the storyline. A causal network is a simple way to communicate the storyline even without the quantitative aspects. It allows one to understand what the underlying storyline conditions are, and to explore the importance of these conditions. By changing the level of conditioning within the network, it is possible to consider sub-storylines/micro storylines, or upgrade the probability assignments to drivers of upper stream nodes.

The causal network can also be viewed as an interactive sensitivity analysis interface, requiring limited expert knowledge. The causal structure emulates the analytical results from the storyline impact model (e.g. the CLIMADA model for the example in Section 3), which supports the uptake of the outcome.

Finally, the modularity of causal networks allows exploration of possible policy options that could enter and modify the storyline outcome. Since the probability distribution of each node variable is conditional on the parent node values, an intervention node that changes the value of a particular node in the network can simply be inserted without considering the effect on other parent nodes in the network. The effect of the intervention can be traced along the network structure to see how the outcome changes by the intervention.

5. Summary

In this paper, we introduced how user value judgments can be incorporated into a physical climate storyline through a causal network framework. The causal network incorporates inputs as Bayesian priors, leading to user-tailored policy analyses. We

Fig. 6. Matrix of how the policy recommendations (capital increase percentage) from the Bayesian network differ depending on the prior assumptions made about the future and the risk aversion of the user. See Fig. 3 for the values of the Bayesian prior distributions. The storyline selected here includes all 13 cyclones of the two years under consideration, and the results are based on the capital after the second year.

exemplified this through an example storyline of the EU Solidarity Fund, showing how the preferred policy changes depending on expectations of physical or socioeconomic future conditions and risk aversion. This framework allows incorporation of subjective expectations and value judgments into PCSs, and supports communicating PCS outcomes to stakeholders.

There are assumptions and distinct decisions we have made in the example. The set of possible choices of storylines, and the range of expectations the user is allowed to choose are constrained by the researcher opinions and interpretation of available evidence. Users may not agree with the assessment of the researchers, which may hinder effective communication. Communication can be fostered through a co-development process of the storyline by the researchers and users from the beginning.

Hereby, causal networks can be used as an interactive tool to communicate the storylines to stakeholders. Quantifying how effective they are in communicating a storyline will be a topic of future studies.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The source code and input data for the example can be found at https://doi.org/10.5281/zenodo.7609812.

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The Bayesian network construction and analysis was done using R 4.1.2 (R Core Team, 2021) and the bnlearn package (v4.7; Scutari, 2010). The web app interface was built using the Shiny package (v1.7.1; Chang et al., 2022).

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