Climate Risk Management 40 (2023) 100512

Contents lists available at ScienceDirect

Climate Risk Management

journal homepage: www.elsevier.com/locate/crm

Climate learning scenarios for adaptation decision analyses: Review and classification

Vanessa Völz [a,b,*], Jochen Hinkel [a,b]

[a] Humboldt-Universität zu Berlin, Albrecht Daniel Thaer-Institut für Agrar- und Gartenbauwissenschaften, Unter den Linden 6, 10099 Berlin, Deutschland
[b] Global Climate Forum, Neue Promenade 6, Berlin, 10178 Berlin, Germany

ARTICLE INFO

Keywords:
Decision making
Adaptation
Learning scenarios
Climate uncertainty
Real-option analysis

ABSTRACT

Economic decision analysis is an important tool for developing cost-efficient adaptation pathways in sectors that involve costly adaptation options, such as flood risk management. Standard economic approaches, however, do not consider learning about future changes in climate variables even though a large literature on adaptive planning emphasises the key role of learning over time, because uncertainties about climate change are substantial. An emerging, diverse and fragmented set of economic adaptive decision making approaches, coming under labels such as real-option analysis or optimal control, have started to address this challenge by including the economic valuation of learning in the economic appraisal of adaptation options through making use of so-called climate learning scenarios. We synthesise this literature and classify the climate learning scenarios applied with respect to which climate variable is learned about, which learning sources are employed, how the learning is modelled, which climate data is used for calibrating learning scenarios, which goodness of fit information is provided and how deep uncertainty is handled. Our results show that publications consider learning through observations or do not explicitly state the source of learning. Most authors generate climate learning scenarios through stochastic processes or Bayesian approaches and use climate model output from the IPCC or the UK Met Office to calibrate the learning scenarios. The reviewed literature rarely provides information on the goodness of fit of learning scenarios to the underlying climate data. We conclude that most of the methods used to generate climate learning scenarios are not well-grounded in climate science and are inadequate to represent climate uncertainty. One avenue to improve climate learning scenarios would be to combine a Bayesian approach with emulators that mimic climate model runs based on observations from future moments in time.

1. Introduction

According to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2021), global warming will lead to a range of impacts and associated risks to humans and nature, for instance through heat waves, heavy precipitation, droughts, sea level rise, loss of species, increased water stress and reduced crop yields. Adaptation measures can reduce these risks and a wide range of diverse adaptation measures are available for different sectors and contexts. For example, sea level rise risks can be reduced through upgrading coastal dikes and seawalls, or through nature-based solutions such as planting mangroves or sand

* Corresponding author.
E-mail addresses: vanessa.voelz@globalclimateforum.org (V. Völz), hinkel@globalclimateforum.org (J. Hinkel).

https://doi.org/10.1016/j.crm.2023.100512
Received 11 November 2022; Received in revised form 24 March 2023; Accepted 16 April 2023
Available online 21 April 2023

nourishment.

The decision process to plan and implement adaptation measures is not straightforward as it is faced with large and deep uncertainties in future projections of climate variables (i.e., probabilities cannot be agreed upon due to ambiguity among experts), long lead times (i.e., time for planning and implementing) and lifetimes of some adaptation measures and high investment costs. Traditional planning methods, based on the idea to design once and build immediately, are incapable of confronting these challenges. Instead, *adaptive decision making* (ADM) approaches have been suggested to enable decision makers to plan adaptation measures that are robust against a wide range of futures and flexible to allow adjustments over time once future information about climate change emerges (New et al., 2022; Marchau et al., 2019). Hence, adaptation decisions are not taken as a single shot decision today, but as sequences of decisions at many different points in time.

Similarly to other areas of decision support, adaptive decision making generally requires the combined application of both participatory and analytical methods, which fulfil complementary roles in supporting adaptation decisions. Participatory methods (also called transdisciplinary, co-development or co-creation methods) target the social processes of learning and cooperating among researchers and stakeholders (Anderson and McLachlan, 2016; Cornwall and Jewkes, 1995; Funtowicz and Ravetz, 1993; Watson, 2014). Examples of such approaches include *climate risk narratives* (Jack et al., 2020) or *resilience thinking* and *action learning* (Tschakert and Dietrich, 2010), which foster *anticipatory learning* through iterative and reflective learning-by-doing cycles. Analytical methods, in turn, support the identification of suitable adaptation pathways given the stakeholders' values, goals and aspirations in those situations in which it is not obvious what to do. In the application of both types of methods, it is important to adapt a system's perspective in that stakeholder engagement is inclusive, indigenous knowledge is incorporated and complex, interdependent and cascading risks are considered (Cavallo and Ireland, 2014).

This paper focuses on analytical methods for adaptive decision making. By doing so we don't want to suggest that these methods are more important than participatory ones. Rather both kinds of methods are important and each constitutes a large literature, which is too extensive to treat in a single review. Furthermore, the literature on the analytical methods, specifically economic ones, for adaptive decision making is underdeveloped even though there is a great potential for their application to climate adaptation (Wreford et al., 2020), as we will elaborate further below.

Broadly, two categories of analytical ADM approaches exist. The first category consists of *economic ADM approaches* that use probabilistic information about current and future climatic conditions to identify optimal adaptation decision rules with respect to information about future development of climate variables, as found in real-option analysis (Wreford et al., 2020) and optimal control studies (Herman et al., 2020). The second category of analytical adaptive decision making approaches consists of approaches that we will call *adaptive planning* (Walker et al., 2001) in the following. These start with a set of pre-defined adaptation options and then analyse under which future climatic developments desired objectives can be achieved through following some of the pre-defined adaptation options. Prominent examples of such adaptive planning approaches are adaptation pathway analysis (Haasnoot et al., 2012) and dynamic adaptive policy pathways (Haasnoot et al., 2013).

The key benefit of economic ADM approaches is that they provide information on cost-efficient strategies given the flexibility of options and future learning about climate change. In many contexts decision makers have to ensure accountability and provide economic justification for large adaptation investments funded by public money. For instance, decision makers have to justify if they decide to implement more costly, but flexible adaptation options (which can be adjusted once more is known about climate change in the future) instead of cheaper inflexible ones. Economic ADM approaches are able to quantify the value of future learning in adaptive adaptation decisions and provide decision makers with economic arguments for the trade-off between flexible and inflexible adaption options (Wreford et al., 2020).

Economic ADM approaches require special kinds of probabilistic information about climate variables, which we will call here *learning scenarios* (Hinkel et al., 2019). Learning scenarios can be seen as a generalisation of the "normal" climate scenarios made available by the IPCC and similar sources. These scenarios will be called *static scenarios* here. Static scenarios provide (probabilistic) projections of climate variables relative to a single past moment in time. For example, the IPCC global mean sea level rise scenarios project that under RCP8.5 there is a 83% chance that global mean sea level will be lower than 1.01 m in 2100 relative to 1995–2014. Learning scenarios extend this by also providing probabilities of sea level rise as seen from other future moments in time, such as for 2050, or 2080. Comparing the magnitude of climate change in a given year seen from two different moments in time illustrates the magnitude of learning. For example, the probability of a climate variable exceeding a given threshold in 2100 would be different seen from 2050 as compared to seen from today. Up to now, however, learning scenarios are not readily available from authoritative sources such as the IPCC and virtually all assessments of climate impacts and adaptation use static climate scenarios.

Due to the unavailability of learning scenarios from authoritative sources, decision scientists generate their own climate learning scenarios using a variety of different methods in order to apply economic ADM approaches to climate adaptation. To complicate matters, similar or even identical economic ADM problems are being addressed in different communities under a range of different names such as real-option analysis, optimal control theory and Markov Decision Processes. So far no review has brought together this fragmented literature on generating learning scenarios for climate adaptation across communities and methods. Two available reviews have looked at the real-option (Ginbo et al., 2020) and optimal control (Herman et al., 2020) literature separately, with the latter only considering adaption in the water resource sector. Furthermore, both reviews have not focused on the generation of learning scenarios, which is the focal point of this paper.

Here, we address this gap and review climate learning scenarios for adaptation decision analyses across diverse research domains such as real-option analysis, optimal control theory and Markov Decision Processes. We compare characteristics and generation methods of climate learning scenarios and discuss how well climate learning scenarios are grounded in climate science. We construct categories to classify learning scenarios by means of learning sources, modelling techniques and forms of learning scenarios to synthesise current state-of-the-art climate learning scenarios. We go beyond the studies of Ginbo et al. (2020) and Herman et al. (2020) by reviewing learning sources and data foundations, validation information and handling of deep uncertainty. Finally, we identify research gaps and propose avenues forward to improve climate learning scenarios.

2. Learning scenarios

2.1. Definition of learning scenarios

Most scenarios of uncertain variables are static in the sense that they provide information about future values as seen from today (or a moment in the recent past) without considering that these estimations will change as time progresses and one learns more about the future through new observations being made or other scientific progress. Hence, static scenarios consist of time series with relevant climate variables as points, intervals or probability distributions (see Fig. 1a). Well-known examples of static scenarios are the temperature and sea level rise projections of the IPCC (IPCC, 2021).

In opposition to static scenarios, we define learning scenarios as scenarios that provide information about future values of an uncertain variable seen not only from today (or a moment in the recent past), but also from future moments in time (Hinkel et al., 2019). The information on future values seen from future moments in time is based on information that becomes available as one progresses towards these future moments in time, e.g. through new observations made until then.

In mathematical terms, the difference between static scenarios and learning scenarios can be expressed in terms of unconditional versus conditional probabilities. A static scenario contains information about the *unconditional* probabilities of an uncertain variable X_t for different values x_t at different moments in time, $t_1, t_2, \ldots, t_T$:

$$P(X_{t_1} \leqslant x_1), P(X_{t_2} \leqslant x_2), \ldots, P(X_{t_T} \leqslant x_{t_T}). \tag{1}$$

A learning scenario contains the same information as the static scenario plus additional information in the form of *conditional* probabilities of the uncertain variable X_t, seen from future moments in time, t_f, with possible observations made until t_f:

$$P(X_t \leqslant x_t | X_{t_f} \leqslant x_{t_f}), \quad t_f < t. \tag{2}$$

Fig. 1b visualises a discrete learning scenario in the form of a directed graph. The nodes of the graph represent climate variable values at different moments in time. The edges of the graph represent possible transitions over time from one node to another. In this example, the projection of the climate variable at time t_5 seen from today is represented by the whole graph, starting at the first node in t_1. The projection of the climate variable at t_5 seen from a future moment in time, e.g. t_3, is represented by a subset of the graph, starting from one of the three nodes in t_3.

It is important to note that the values and probabilities of climate variables seen from future moments in time can be grounded on today's scientific knowledge. For example, sea level rise is a steady process without rapid changes and thus projections seen from future high end observations should exclude transitions to subsequent low end values.

2.2. Improving adaptation decisions with learning scenarios: A simple example

To demonstrate how learning scenarios can support the planning and justification of flexible and adaptive adaptation decisions, we

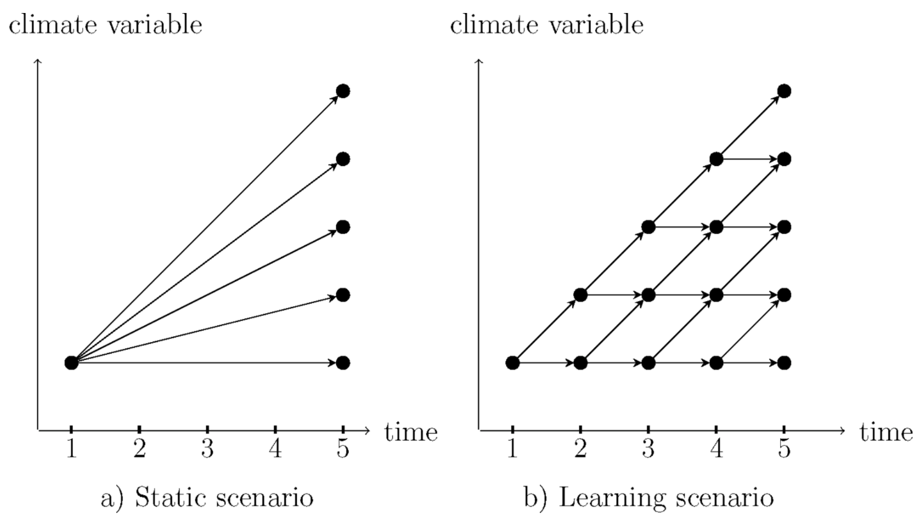

Fig. 1. Visualisations of a static scenario (a) and a learning scenario in the form of a binomial tree (b). The nodes represent climate variable values at different moments in time and the edges between nodes represent a possible transition from one node to another.

provide a simple economic ADM example. We consider a coastal adaptation decision maker who has three dike adaptation options to adapt to rising sea levels. Either non-flexible dikes with a height of 0.5 or 1 m ($1 M or $2 M), or a flexible dike with a height of 0.5 m and a wider foundation ($1.2 M) can be implemented. It is cheaper to upgrade the flexible dike with the wider foundation to the height of 1 m ($1 M) than to upgrade the non-flexible 0.5 m dike to 1 m ($2 M).

Together with the sea level rise learning scenario in Fig. 2 we can now estimate the average adaptation costs occurring in 2050 and 2070, depending on the action we implement today. If we implement the non-flexible 0.5 m dike, there is a likelihood of 50 % that we will observe low sea level rise in 2050 and then know that the 0.5 m dike will be effective until 2070. However, with a likelihood of 50 % there is also the chance that we observe high sea level rise in 2050 and the 0.5 m dike might be insufficient in 2070. A risk-avers decision maker would then decide in 2050 to upgrade the non-flexible dike to a height of one meter. Thus, the average adaptation costs when implementing the non-flexible 0.5 m dike today are: $0.5 \times 1\$ + 0.5 \times (1\$ + 2\$) = 2\$$. Analogously, implementing the non-flexible 1 m dike today leads to average costs of 2$ and the flexible 0.5 m dike to 1.7$.

The optimal decision is to implement the flexible 0.5 m dike, observe future sea level rise and to upgrade the dike in case high sea level rise above 25 cm is observed in 2050. Thus, the learning scenario based economic ADM justifies the additional implementation costs for the flexible adaptation option and provides trigger thresholds that specify when further actions are needed.

We assume several simplifications in this adaptation example for the purpose of illustration. We note that sea level rise is an accelerating process (not uniformly increasing) that will be ongoing for centuries, and thus, adaptation beyond 2070 is indispensable (IPCC, 2021). Further, adaptation to sea level rise should consider other potential impacts, such as the increase in frequency of storm surge events, coastal erosion or salt water intrusion, and therefore, dike upgrades are only one part of comprehensive coastal adaptation decisions (Oppenheimer et al., 2019).

3. Methodology

3.1. Literature selection

To review publications using climate learning scenarios within adaptation decisions we build upon existing literature overviews from diverse research fields. We consider all adaptation decision publications in literature overviews of Ginbo et al. (2020), Herman et al. (2020), Kind et al. (2018) and Wreford et al. (2020). We exclude papers that focus on economic uncertainties (e.g. Guo and Costello (2013), Regan et al. (2017), Sanderson et al. (2015)). We further exclude papers that address climate uncertainties in the absence of any learning, such as Abadie et al. (2018), Deng et al. (2013), Heumesser et al. (2012), Kim et al. (2019), Manocha and Babovic (2018a), Manocha and Babovic (2018), Mortazavi-Naeini et al. (2015), van der Pol et al. (2021), Woodward et al. (2011). For instance, Kim et al. (2019) assume fixed time series as sea level rise projections and add stochastic extreme events in each scenario. This results in stochastic but static scenarios about (extreme) sea level developments without considering learning. Similar, Mortazavi-Naeini et al. (2015) use regional general circulation model (GCM) projections as static scenarios to account for climate uncertainty. Applying all previously stated exclusion criteria to the references of Ginbo et al. (2020), Kind et al. (2018), Wreford et al. (2020) and Herman et al. (2020) results in 23 remaining papers. We add the publications of Dittes et al. (2018), Espada et al. (2014), Fletcher et al. (2019b), Webster et al. (2008), Guillerminet and Tol (2008), Guthrie (2019), Shuvo et al. (2020), Špačková and Straub (2017) and van der Pol et al. (2013) to this list and remain with a total of 32 papers relevant for our review and classification.

3.2. Classification

In order to compare characteristics of generation methods, and to answer the question of how well learning scenarios are grounded in climate science, we classify the literature and the methods applied therein as follows:

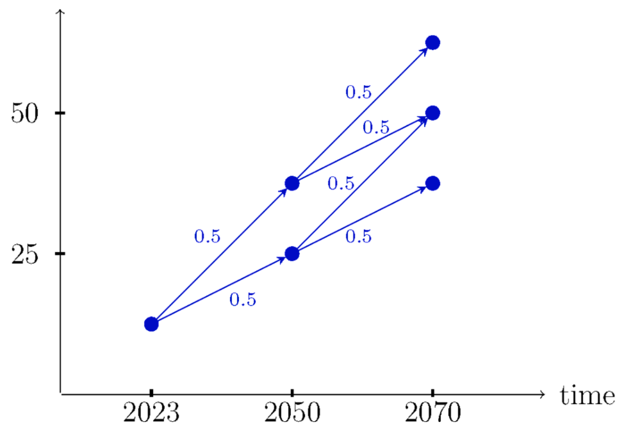

Fig. 2. A simplified learning scenario for sea level rise in the form of a binomial tree. The nodes represent climate variable values at different moments in time and the edges between nodes represent a possible transition from one node to another with a probability of 50%.

Sector: We classify the papers according to the sectors of application, e.g. coastal adaptation, river flood management or water resources, to overview which learning scenarios are used within the different fields of application.

Learning variable: We identify which climate learning variables are considered within the learning scenarios, e.g. precipitation or sea level rise.

Learning source: Learning about climate variables can emerge from different learning sources that we categorise as follows:

1. **Observations:** Observing actual developments of climate variables over time leads to a gain of knowledge by updating climate projections with the new observations. For example, parameters of an extreme value distribution can be updated in the future based on additional observations.
2. **Scientific knowledge gain:** New or improved scientific knowledge evolving over time is a source for learning. For example, additional knowledge about physical processes may be incorporated into climate, ocean and land ice models, to adjust future projections about future variable development.
3. **Unspecified:** Some authors assume learning, e.g. revealing mitigation pathways or statistical parameters, without explaining the learning source. We classify undefined learning sources as unspecified learning sources.

Scenario method: Researchers make use of different modelling techniques to generate learning scenarios. We classify these methods according to the following categories:

1. **Stochastic process:** A stochastic process can be fitted to historic or future climate variable developments. The parameters of the stochastic process can be used to estimate the transition behaviour of the stochastic process between time steps and to generate a learning scenario (see Section 4.3).
2. **Direct fit:** This method generates a learning scenario by directly fitting the learning scenario form onto a probability distribution function (PDF) or cumulative distribution function that describes future variable development.

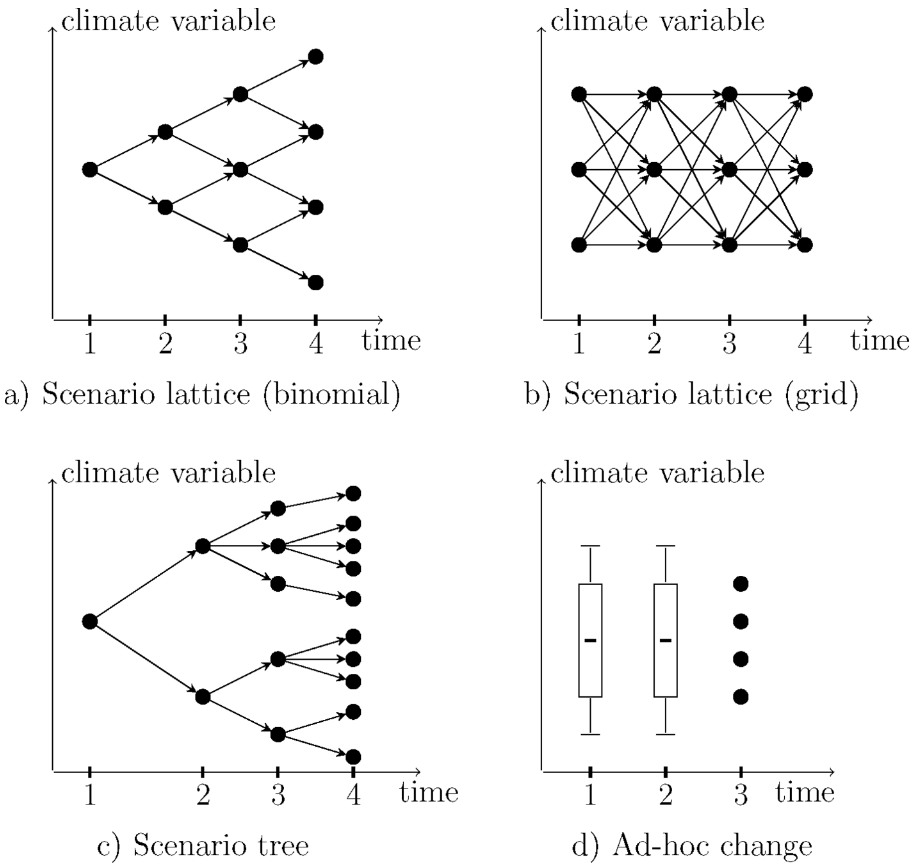

Fig. 3. Visualisation of different scenario forms: (a) binomial scenario lattice, (b) grid scenario lattice, (c) scenario tree and (d) ad hoc change. The nodes represent climate variable values at different moments in time and the edges between nodes represent a possible transition from one node to another. In subfigure d) (ad hoc change) the boxplots represent probability distribution functions of climate variables and the nodes represent four different climate variable values that could be revealed.

3. **Bayesian approach:** This method is based on Bayesian updating. A model is used to generate projections and can be rerun with a sample of future observations to generate projections seen from future moments in time based on these sampled observations. For example, future projections based on extrapolation can be updated by rerunning the extrapolation with additional future observations as data points.
4. **Revelation:** The revelation technique consists of the unconditional assumption that after a specific point in time, additional knowledge is available for the decision maker. For example, the evolving mitigation pathway or a trend parameter can be revealed.
5. **Other:** A few publications use modelling techniques that cannot be categorised in one of the previously defined classes and are pooled in the category other.

Scenario form: We define the general mathematical structure of a learning scenario as the form of a learning scenario and categorise these according to:

1. **Scenario tree:** A scenario tree is a directed graph that represents variable states via nodes and time-dependent evolution from one state to another via edges and probabilities. Over time and space, scenario trees may have different numbers of evolving nodes. As the graph is a tree, two nodes never merge into the same node in the next time step. Seen from a variable state in the future, only a subset of future states can evolve thereafter, representing more precise projections seen from that future moment in time (see Fig. 3).
2. **Scenario lattice:** A scenario lattice is a directed and homogeneously structured graph without the tree characteristics, meaning different nodes merge into the same node in the following time step. The number of nodes merging into the same node in the following time step defines the lattice structure, e.g. two merging nodes create a binomial lattice and the same number of nodes in each time step create a grid (see Fig. 3).
3. **Ad-hoc change:** Ad-hoc knowledge gain occurring at one moment in time is represented by an ex-ante uncertainty representation abruptly changing to an ex-post uncertainty representation. The uncertainty representation itself can have different forms such as probability distribution functions or single values (see Fig. 3).

Data: We classify the data used for calibrating the learning scenarios and distinguish between climate model output and historic data.

Validation: In order to analyse the goodness of fit of learning scenarios to the underlying climate data we review the validation information provided within the literature. This can be information on the goodness of fit of assumptions or the fit of final learning scenarios to underlying climate data.

Discretisation: We provide information on the discretisation used within the decision analysis to inform about the granularity of the learning scenarios.

Handling of deep uncertainty: A downside of economic ADM approaches is that they can only be applied to settings with known probabilities of different states of the world. Hence, without further extensions they can only be applied within one emission scenario, as crisp probabilities cannot be assigned to different socioeconomic pathways in an unambiguous way, i.e. large disagreement amongst experts (Hinkel et al., 2019). We summarise how publications handle this.

4. Results: review and classification of climate learning scenarios

The classification of relevant publications according to the categories defined in Section 3 is provided in Table 1.

4.1. Learning variables

The majority of publications can be found in the coastal adaptation, urban or river flood management and water resources sectors. The most commonly used learning variables are sea level rise and precipitation (Dawson et al., 2018; Dittrich et al., 2019; Fletcher et al., 2019a; Gersonius et al., 2013; Gersonius et al., 2012; Hino and Hall, 2017; Jeuland and Whittington, 2014; Kim et al., 2017; Kim and Kim, 2018; Linquiti and Vonortas, 2012; Liu et al., 2018; Oh et al., 2018; Park et al., 2013; Ryu et al., 2018; Špačková and Straub, 2017; Steinschneider and Brown, 2012; van der Pol et al., 2013; Webster et al., 2008; Woodward et al., 2014; Deng et al., 2013). Less commonly used learning variables include flood damage, flood risk or river flow (Abadie et al., 2017; Bruin and Ansink, 2011; Dittes et al., 2018; Espada et al., 2014; Hui et al., 2018; Park et al., 2013; Oh et al., 2018; Steinschneider and Brown, 2012; Hino and Hall, 2017; Schou et al., 2015; Kind et al., 2018; van der Pol et al., 2016).

Some of these publications consider learning about extreme event developments, for instance Linquiti and Vonortas (2012) approach increasing extreme flood events by increasing a fixed occurrence probability in a static scenario by an arbitrary value. Abadie et al. (2017) consider increasing extreme flood events by learning about more frequent flood damages caused by precipitation. Dittes et al. (2018) update future flood projections based on incoming extreme river discharge observations. van der Pol et al. (2016) learn about river peak flows that increase over time with respect to predefined distributions. Guillerminet and Tol (2008) update a simplified physical coastal catastrophe model to learn about extreme flood events under a collapsing West-antarctic ice sheet. Hui et al. (2018) learn about river peak flows by adjusting the probabilities for different fixed scenarios of streamflow distributions based on observations. Guthrie (2019) develops a general model to predict all different kinds of extreme events and updates the predictions once new observations are available.

Table 1
Literature classification of climate learning scenarios.

Paper	Sector	Learning variable	Learning source	Scenario method	Scenario form	Data	Validation	Discretisation		Handling of deep uncertainty
								Time horizon (yr.)	Time steps (yr.)	
Woodward et al. (2014)	coastal adaptation	sea level rise	observations	other: draw realisations from PDF, predefine thresholds in iterative alg.	ad hoc change	climate model output: UKCP09	-	100	2010, 2060	equal prob.
Espada et al. (2014)	river flood management	flood risk	observations	other: model with four risk states	scenario lattice (grid)	-	-	one decision point		separate analysis
Abadie et al. (2017)	urban flood management	extreme flood damage	observation	stochastic process (GBM)	scenario lattice (binomial)	literature, government report	-	50–100	$\frac{1}{50}$–1	one scenario
Gersonius et al. (2012)	coastal adaptation	sea level rise	observations	stochastic process (GBM)	scenario lattice (binomial)	expert opinion	-	90	15	distr. valid for all scenarios
Gersonius et al. (2013)	urban flood management	precipitation	observations	stochastic process (GBM)	scenario lattice (trinomial)	climate model output: UKCP09	assumption: test verifies normal distr.	90	30	equal prob.
Kim et al. (2017)	urban flood management	precipitation damage	observations	stochastic process (GBM)	scenario lattice (binomial)	climate model output: IPCC AR4, historic data	-	50	1	separate analysis
Kim and Kim (2018)	river flood management	precipitation damage	observations	stochastic process (GBM)	scenario lattice (binomial)	climate model output: IPCC AR4, historic data	-	83	1	separate analysis
Kontogianni et al. (2014)	coastal adaptation	adaptation benefits	observations	stochastic process (GBM)	scenario lattice (binomial)	model output: NPV from CBA	-	90	30	two fixed sea level rise values
Liu et al. (2018)	urban flood management	precipitation	observations	stochastic process (GBM)	scenario lattice (trinomial)	climate model output: UKCP09	assumption: visualise normal distr.	60	30	one scenario
Park et al. (2013)	urban flood management	flood damage	observations	stochastic process (GBM)	scenario lattice (binomial)	climate observation: historic data	-	50	2012, 2019	-
Ryu et al. (2018)	river flood management	precipitation exceedance probability	observations	stochastic process (GBM)	scenario lattice (binomial)	climate model output: IPCC AR4	-	30	1	fit binomial lattice to max. and min. scenario
Oh et al. (2018)	coastal adaptation	flood damage	observations	stochastic process (GBM)	scenario lattice (quadrinomial)	climate observation: historic data	-	3	3	-
Erfani et al. (2018)	water resources	urban development water supply	observations	direct fit to quantile values	scenario tree	climate model output: UKCP09	learning scenario: 5% information loss from CDF to lattice	50	5	assign prob.
Kind et al. (2018)	river flood management	river discharge	observations	direct fit to 500 end scenarios	scenario tree	literature	-	120	20	subjective prob.

(*continued on next page*)

Table 1 (*continued*)

Paper	Sector	Learning variable	Learning source	Scenario method	Scenario form	Data	Validation	Discretisation		Handling of deep uncertainty
								Time horizon (yr.)	Time steps (yr.)	
Dittrich et al. (2019)	river flood management	precipitation	observations	direct fit to quantile values	scenario lattice (grid)	UKCP09	-	64	2016, 2040	one scenario
Steinschneider and Brown (2012)	water resources	streamflow	observations	other: algorithm creating water supply rule curve	ad hoc change	model output: General circulation models	-	58	1	separate analysis, sampling method
Dittes et al. (2018)	river flood management	extreme discharge	observations	Bayesian approach (update distr. parameters)	ad hoc change	climate observation: historic data	learning scenario: visualisation	80	20	-
Linquiti and Vonortas (2012)	coastal adaptation	sea level rise	observations	Bayesian approach (update distr. parameters)	ad hoc change	climate model output: IPCC AR4	assumption: mean based on data, deviation random	100	20	separate analysis
		population growth				model output: UN projections				
Webster et al. (2008)	mitigation policy	temperature, sea level rise	observations	Bayesian approach (update distr. parameter)	ad hoc change	-	-	100	10	dist. valid for all scenarios
Guillerminet and Tol (2008)	mitigation policy	extreme floods	observations	Bayesian approach (simple model)	scenario tree	hypothetical & literature	-	100	1	-
Guthrie (2019)	universal	general extremes	observations	Bayesian approach (simple model)	scenario lattice (binomial)	-	-	100	1	combine two scenarios
Fletcher et al. (2019b)	water resources	groundwater level	observations	Bayesian approach (neural network model)	scenario lattice (grid)	literature	-	30	1	-
Špačková and Straub (2017)	river flood management	max. precipitation	observations	Bayesian approach (update scenario prob.)	scenario lattice (grid)	-	-	90	30	combine three scenarios
Hui et al. (2018)	river flood management	river peak flow	observations	Bayesian approach (update scenario prob.)	scenario lattice (grid)	hypothetical	-	200	1–200	separate analysis
Fletcher et al. (2019a)	water resources	precipitation	observations	Bayesian approach (combine GCMs)	scenario lattice (grid)	model output: GCMs	cross validation for Bayesian approach	100	20	one scenario
Dawson et al. (2018)	coastal adaptation	sea level rise	scientific knowledge gain	other: analyse ex-post knowledge gain from two historic reports	ad hoc change	climate model output: UKCIP02, UKCP09	-	60	2002, 2010	subjective prob.
		rail demand				model output: UKCIP 2001, Network Rail 2010				
van der Pol et al. (2016)	river flood management	peak flow distr.	observations, unspecified	revelation: scenarios contain diff. information sets, composed of diff. distr.	ad hoc change	literature	-	90	2050	regret criterion
van der Pol et al. (2013)	coastal adaptation	sea level rise	unspecified	revelation (perfect information)	ad hoc change	literature	-	250–1500	0.5	-
Bruin and Ansink (2011)	river flood management	flood damage	unspecified	revelation	ad hoc change	-	-	-	2	-

(*continued on next page*)

Table 1 (*continued*)

Paper	Sector	Learning variable	Learning source	Scenario method	Scenario form	Data	Validation	Discretisation		Handling of deep uncertainty
								Time horizon (yr.)	Time steps (yr.)	
Hino and Hall (2017)	river flood management	river flow	unspecified	revelation	ad hoc change after 15 yr.	climate model output: UKCP09, rainfall runoff models	-	90	10	assign probabilities
		asset value growth				-				
Jeuland and Whittington (2014)	water resources	hydrological conditions	unspecified	revelation	ad hoc change after 5–8 yr.	literature: Strzepek & McCluskey 2007	-	30	10, 20	separate analysis
		water consumption				country master plans				
Schou et al. (2015)	forest management	soil expectation	unspecified	revelation	ad hoc change after x yr.	literature: Seidl 2008, Lohmander & Helles 1987	-	100	10	subjective prob.

Abbreviations: distr. = distribution, lin. = linear, GBM = Geometric Brownian Motion, log. = logarithm, CDF = Cumulative Density Function, PDF = Probability Density Function, EVA = Extreme Value Analysis, GCM = General Circulation Models, diff. = different, prob. = probability.

4.2. Learning sources

In most cases, learning stems from observations. Dawson et al. (2018) are the only authors that account for learning based on scientific knowledge gain in an ex-post analysis. Six papers base learning on unspecified learning sources (Bruin and Ansink, 2011; Jeuland and Whittington, 2014; Hino and Hall, 2017; Schou et al., 2015; van der Pol et al., 2013; van der Pol et al., 2016).

4.3. Scenario methods and forms

Two scenario methods are most commonly used to generate learning scenarios based on observations. The first one is to fit a stochastic process (Geometric Brownian motion) to underlying climate data and is often used by real-option analysis. A stochastic process S_t follows a Geometric Brownian Motion (GBM) if it satisfies the stochastic differential equation:

$$dS_t = \mu S_t dt + \sigma S_t dW_t \tag{3}$$

with a constant drift μ, a constant volatility σ and a Wiener process W_t (also called Brownian Motion) (London, 2005). Mostly the papers use the parameters of the stochastic process to generate a binomial scenario lattice. The most frequently used method to design a binomial scenario lattice from the parameters μ and σ is to apply formulas developed by Cox et al. (1979) (Ryu et al., 2018; Abadie et al., 2017; Kim et al., 2017; Kim and Kim, 2018; Oh et al., 2018; Park et al., 2013; Kontogianni et al., 2014). This method defines the scenario lattice parameters p (likelihood for moving upwards in the tree) and u, d (multiplication factor for up or down movements) by:

$$u = e^{\sigma\sqrt{\Delta t}}, \tag{4}$$

$$d = e^{-\sigma\sqrt{\Delta t}}, \tag{5}$$

$$p = \frac{e^{\mu\Delta t} - d}{u - d}. \tag{6}$$

Fig. 4 visualises how the above defined parameters build the binomial scenario lattice. Some papers use other methods to calibrate the lattice based on the Geometric Brownian motion's parameters. For example, Gersonius et al. (2012) use the formula proposed by Jarrow and Rudd (1983) that is based on a binomial lattice with $p = 0.5$ and Gersonius et al. (2013) and Liu et al. (2018) use the formula from Zaboronski and Zhang (2008) to create a trinomial lattice.

The second most commonly used scenario method is the Bayesian approach based on the idea to rerun models with future incoming observations. These approaches use future observations within realistic boundaries as future incoming observations and rerun models with these additional information to generate projections seen from future moments in time. Dittes et al. (2018),Linquiti and Vonortas (2012) and Webster et al. (2008) apply this method by considering additional input data in their extrapolation model and update distribution parameters. Guthrie (2019) and Guillerminet and Tol (2008) generate simplified physical models for predicting climatic variables and rerun these models with new observations. Fletcher et al. (2019b) use an artificial neural network as a model to update projections about groundwater levels. Hui et al. (2018) update probabilities for different fixed scenarios of streamflow distributions. Fletcher et al. (2019a) extend a Bayesian approach to project precipitation based on the time-dependent behaviour of precipitation trajectories, stemming from general circulation models, and future incoming observations. These approaches make use of all three different scenario forms (scenario tree, scenario lattice and ad hoc change).

Three papers apply a direct fit method to design flexible scenario tree structures. Erfani et al. (2018) construct a scenario tree by first defining 100 scenarios in the final time step according to the cumulative density function (CDF) based on 100 equal intervals. An iterative greedy algorithm based on Growe-Kuska et al. (2003) then constructs a discrete scenario tree that results in 100 end nodes for each interval under the constraint that only 5 % of the CDF information is lost after reduction. Kind et al. (2018) generate a scenario

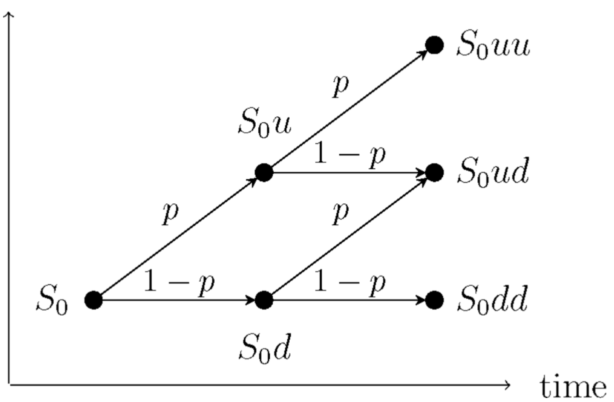

Fig. 4. Visualisation of a binomial recombining scenario lattice defined by parameters of Cox, Ross and Rubinstein.

tree which incorporates several uncertainties, e.g. uncertainties stemming from extrapolation, scenarios, erosion etc., and afterwards reduce the tree size with a reduction technique. Dittrich et al. (2019) directly fit a small scenario tree onto quantile values of the UKCP09 precipitation data. They define the transition probabilities between consecutive nodes according to the time-dependent behaviour of single precipitation time-series, which is a rather simple method in comparison to Erfani et al. (2018) and Kind et al. (2018). These three scenario trees differ from scenario lattices in the literature, because they are not recombining and have different numbers of nodes, transition steps and transition probabilities in each time step (see Fig. 3).

Five papers use revelation and assume that mean variables, scenarios or climate change effects on damages are revealed after some time (Bruin and Ansink, 2011; Hino and Hall, 2017; Jeuland and Whittington, 2014; Schou et al., 2015; van der Pol et al., 2013). Similar, van der Pol et al. (2016) use revelation to reveal one of several possible future distributions of climate variable development.

The following authors use scenario methods grouped in the category "Other". Steinschneider and Brown (2012) apply an algorithm that creates water supply rule curves to update river flow projections. Woodward et al. (2014) draw sea level rise realisations from a normal distribution and predefine thresholds for adaptation options. Dawson et al. (2018) consider learning based on scientific knowledge gain by means of an ex-post analysis based on future projections from two consecutive climate reports in 2002 and 2010. Hence, no learning scenario needs to be generated for this ex-post analysis.

4.4. Data used for calibrating learning scenarios

A third of the publications use official climate model output from the IPCC (AR4, AR5) or the Met Office of the UK (UKCP09, UKCIP02) to calibrate their learning scenarios. Some authors calibrate their learning scenarios to other simulation or model results, for instance rainfall circulation models or cost-benefit analyses. Other data sources to calibrate learning scenarios are local or regional historic data, related literature or official government reports.

4.5. Validation

Three papers provide information on the goodness of fit of their assumptions. Liu et al. (2018) assume that the change in rainfall intensity is normally distributed and backup this assumption with a visualisation of a normal distribution fitted to the UKCP09 data. Linquiti and Vonortas (2012) assume a normal distribution and base their assumption of 3 mm mean sea level rise on AR4 results, while choosing a standard deviation of 2 mm based on speculative judgement. Gersonius et al. (2013) assume that the change in precipitation intensity is normally distributed and verify this assumption with a Shapiro Wilk W test at a 5 % significance level. Only two papers report on the goodness of fit of their learning scenarios to the original data used for deriving the learning scenarios. Erfani et al. (2018) construct a lattice by use of an algorithm that minimises the relative probability distance to a given CDF, also known as information loss. This ensures a maximum of 5 % information loss during the transformation from a probability distribution to the scenario tree. Dittes et al. (2018) plot the river discharge estimate, resulting from rerunning the extrapolation model, with the underlying historic data record and show that longer data records improve their estimation results.

4.6. Discretisation

The considered time horizon ranges from 3 to 1500 years, whereas most papers consider a time horizon of 50 to 100 years. The number of time steps considered for decisions ranges from only one point in time to yearly (and even more frequent) assessments. Bruin and Ansink (2011); Dawson et al. (2018); Dittrich et al. (2019); Espada et al. (2014); Park et al. (2013); van der Pol et al. (2016) and Woodward et al. (2014) only consider one or two fixed years as decision moments. One third of the publications analyse the adaptation decision every year, while the rest use one or several decades as time steps.

4.7. Handling of deep uncertainty

Some papers ignore the issue of deep uncertainty and analyse adaptation decisions within each future emission scenario separately (Espada et al., 2014; Hui et al., 2018; Kim and Kim, 2018; Steinschneider and Brown, 2012; Jeuland and Whittington, 2014; Kim et al., 2017; Linquiti and Vonortas, 2012). Others apply only one scenario (Abadie et al., 2017; Dittrich et al., 2019; Fletcher et al., 2019a; Liu et al., 2018) or assume that they can represent full climate uncertainty within one learning scenario (Ryu et al., 2018; Gersonius et al., 2012; Webster et al., 2008). Others combine multiple scenarios into a single one by assuming equal probabilities across emission scenarios (Woodward et al., 2014; Gersonius et al., 2013). Learning scenarios that rely on historic data do not account for different climate scenarios (Dittes et al., 2018; Oh et al., 2018; Park et al., 2013). A few authors consider a combination of different emission scenarios without assuming equal probabilities, for example by use of robust-decision making and subjective probability assumptions (Dawson et al., 2018; Schou et al., 2015; Kind et al., 2018). Hino and Hall (2017) determine the likelihood for each river flow scenario by weighting the scenarios to reproduce one future flow PDF.

5. Discussion

5.1. Considerations for choosing the right method for generating learning scenarios

The revelation scenario method is a simple and straightforward way to incorporate learning in decision frameworks and is a convenient choice if no learning variable projections are available. Most of the time this method is combined with unspecified learning sources and sometimes with learning based on observations. This method often represents learning in the form of ad hoc perfect knowledge. Neither unspecified learning sources, nor perfect knowledge assumptions are based on climate science.

Stationary stochastic processes offer an easy way to model gradual learning over time with constant growth rates and no computational restrictions, but a relative weak fit of learning scenarios to climate projections can be expected and it does not surprise that relatively few papers report, let alone rigorously analyse, the goodness of fit. This scenario method originates from financial economics and was originally designed to model stock price developments under the assumption of constant, or in other words stationary, growth rates within real-option analysis (Cox et al., 1979). This assumption is indefensible when modelling climatic variables, for example climate model output does not exhibit constant growth rates. A stationary stochastic process fails to model global temperature change predicted under low emission scenarios, because the temperature first exhibits positive, later negative growth rates (IPCC, 2021).

Bayesian approaches enable a more precise representation of the uncertainty dynamics of climate variables, because they do not assume constant growth rates as stochastic processes do. The output of Bayesian approaches is sensitive to the choice of the underlying model, which determines how well the learning scenario is grounded in climate science. However, a disadvantage of the Bayesian approach is that running models several times is often accompanied with computational restrictions and only fast models are suitable for this approach. One example for a Bayesian approach learning scenario well grounded in climate science is Fletcher et al. (2019a). They develop a Bayesian approach that is based on time-dependent behaviour of different climate model output and consider how well each climate model represents historic and future scenarios.

The direct fit method is based on climate projections and enables an equally precise representation of the uncertainty dynamics of climate variables as the Bayesian approach. The method is suitable if detailed climate projections in the form of a probability distribution function or ensemble trajectories are available, but rerunning the underlying model multiple times, as needed for a Bayesian approach, would be too time consuming. For example, Dittrich et al. (2019) incorporate time-dependent behaviour of climate model output trajectories through the direct fit method and generate a direct fit learning scenario well grounded in climate science.

5.2. Combination of climatic and socioeconomic variables

While some papers apply the stochastic process scenario method by Cox et al. (1979) on pure climate variables to generate learning scenarios (Gersonius et al., 2012), others apply it on climate change induced damages (Abadie et al., 2017; Park et al., 2013). Learning scenarios representing climate change induced damages consider the damage occurring from the combined development of climate and socioeconomic variables. While the goodness of fit of the method by Cox et al. (1979) is expected to be better for climate change induced damages than pure climate variables, as socioeconomic variables usually exhibit exponential growth and outweigh the non-exponential behaviour of climate variables (Hinkel et al., 2021), this procedure has several disadvantages. First, modelling the combination of two or more uncertainties stemming from different variables is less precise than modelling each uncertainty individually to account for specific characteristics. Second, using one variable to represent the combination of a climate variable and a socioeconomic variable cannot model divergent developments (e.g. accelerating high sea level rise combined with decelerating socioeconomic development). These combinations can occur within regional case studies where regional shared socioeconomic pathways can differ from global ones. Third, the resulting adaptation decision rule depends on the development of climate change induced damages, which is hard to observe in reality, for example, damages of extreme events may not occur on an annual basis. Instead, it is easier to observe climate variables such as sea level rise and socioeconomic development separately, and represent their respective uncertainties by two learning variables.

Several publications consider climatic and socioeconomic variables separately as independent learning variables within learning scenario development (Dawson et al., 2018; Hino and Hall, 2017; Jeuland and Whittington, 2014; Linquiti and Vonortas, 2012; Oh et al., 2018; Webster et al., 2008). All of these publications, however, use relatively simple methods for generating learning scenarios (e.g. revelation) and often consider very few time steps. This indicates that computational restrictions prevent the application of more advanced learning scenario generation methods to multiple learning variables.

5.3. Research gaps and avenues forward

One avenue for improving economic decision making in the context of climate change would be the development of learning scenarios that capture scientific knowledge gain, e.g. through the improvement of physical models. This seems particularly relevant for sea level rise, as its major uncertainty stems from potential rapid melting of the ice sheets of Greenland and Antarctica by processes that are currently not or only insufficiently captured by physical models. For instance, the understanding of ice sheet processes were not considered in the IPCC fourth assessment report in 2007, but improved remarkably until the special report in 2019 and led to corrections in the sea level rise projections (Oppenheimer et al., 2019). Furthermore, a review of global coastal impact studies by Hinkel et al. (2021), for example, shows that sea level rise uncertainty until the 21st century is equally caused by uncertainty arising from diverse emission pathways and uncertainty arising from climate models. This emphasises the importance of learning based on improved physical models. The absent literature application could be explained by a lack of appropriate methodologies, for instance it is difficult to fit a stochastic process to qualitative scientific knowledge gain. Instead, using expert elicitation methods could be a way forward to incorporate learning based on scientific knowledge gain.

One particular way for improving climate learning scenarios would be to apply the Bayesian approach with climate models. This would imply to rerun climate models with new calibrations based on possible future global warming observations at future moments in time. Until today, no attempt of rerunning climate models seen from future moments in time with calibrations based on future observations has been made. This finding is unsurprising, as simulations from climate models are computationally expensive and rerunning climate models is too time-consuming.

An innovative alternative to obtain results from climate models is the generation of fast statistical approximation models, called emulators. For instance, Edwards et al. (2021) recently developed emulators for the land ice contribution to sea level rise projections based on climate model output. These emulators use Gaussian process emulations to mimic land ice models. Such emulators would be a well-grounded source to apply the Bayesian approach to consider future projections based on future observations. Until today, no attempt in the literature exists to use emulators with future observations to generate learning scenarios.

Another avenue to improve economic ADM methods is to improve the handling of deep uncertainties. So far, only a few approach extend economic ADM with robust decision making methods to address deep uncertainty (Dawson et al., 2018; Kind et al., 2018; Schou et al., 2015). One novel approach of Stroombergen and Lawrence (2022) applies real-option analysis combined with dynamic adaptive pathways planning to real world applications in New Zealand. This novel combination does not use probabilistic climate learning scenarios, but so-called "cut-off probabilities" for specific events, which define until which threshold adaptation options are effective. Combinations of economic ADM and adaptive planning seem to be a way forward as they can combine advantages of both methods and offer diverse perspectives for decision makers. Further, combining analytical methods and participatory approaches could enable decision makers to consider compound and cascading risks.

6. Conclusion

With this paper we synthesised the current state-of-the-art of climate learning scenarios development within adaptation decision analyses across different research domains.

We conclude that even though the importance of anticipating future learning about the climate system has been recognised since a long time (O'Neill, 2008), the representation of future learning in climate learning scenarios is still in the early stages of development, and that the majority of existing learning scenarios is not well-grounded in climate science. For example, prominent methods to generate learning scenarios are of rather simple nature such as revelation of ad hoc assumptions (e.g. Hino and Hall (2017); Schou et al. (2015)), highly simplified models (e.g. Guthrie (2019); Hui et al. (2018); Linquiti and Vonortas (2012); Webster et al. (2008)) or stationary stochastic processes with time-independent parameters (e.g. Abadie et al. (2017); Gersonius et al. (2013); Ryu et al. (2018)). In fact, using stochastic processes originates from financial economics and is inadequate to represent climate uncertainty. Furthermore, most papers consider learning through observations only or do not explicitly state the source of learning. Learning scenarios based on scientific knowledge gain do not exist.

We identify only two papers (Dittrich et al., 2019; Fletcher et al., 2019a) that use state-of-the-art climate model trajectories to generate climate learning scenarios for precipitation well grounded in climate science. However, these analyses are only based on climate simulations from today onwards. The generation of learning scenarios could be improved by running climate models from future moments in time onwards, using possible future observations as input.

Another gap is that the majority of authors do not provide any information on the goodness of fit of their learning scenarios to underlying climate projections or historic data. Thus, we concur with what Ginbo et al. (2020) found specifically for the literature on real-options, that the complex nature of climate uncertainty is only superficially taken into account, for almost all climate learning scenarios across diverse research domains.

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

No data was used for the research described in the article.

Acknowledgments

Vanessa Völz has been funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) within the Special Priority Program SPP-1889 SeaLevel - project SEASCApe II. Jochen Hinkel has been supported by funding from the European Union's Horizon 2020 research and innovation program under the PROTECT project (grant agreement No. 869304). There are no conflicts of interests to declare. The article processing charge was funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – 491192747 and the Open Access Publication Fund of Humboldt-Universität zu Berlin.

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