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OPINION

On the use and misuse of climate change projections in international development

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Climate resilience is increasingly prioritized by international development agencies and national governments. However, current approaches to informing communities of future climate risk are problematic. The predominant focus on end-of-century projections neglects more pressing development concerns, which relate to the management of shorter-term risks and climate variability, and constitutes a substantial opportunity cost for the limited financial and human resources available to tackle development challenges. When a long-term view genuinely is relevant to decision-making, much of the information available is not fit for purpose. Climate model projections are able to capture many aspects of the climate system and so can be relied upon to guide mitigation plans and broad adaptation strategies, but the use of these models to guide local, practical adaptation actions is unwarranted. Climate models are unable to represent future conditions at the degree of spatial, temporal, and probabilistic precision with which projections are often provided, which gives a false impression of confidence to users of climate change information. In this article, we outline these issues, review their history, and provide a set of practical steps for both the development and climate scientist communities to consider. Solutions to mobilize the best available science include a focus on decision-relevant timescales, an increased role for model evaluation and expert judgment and the integration of climate variability into climate change services.

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KEYWORDS
climate change adaptation, climate change projections, climate resilience, climate services, international development

1 | INTRODUCTION

As evidence of anthropogenic climate change mounts, so too does concern over the impacts of associated changes in local weather and climate. Once viewed as an independent problem, climate change is now seen as a confounding threat that can interact with other social and environmental pressures to moderate development outcomes. Consequently, recent years have seen an escalating demand for information about the local impacts of future climate change to guide climate resilience efforts in development practice (Frankel-Reed, Fröde-Thierfelder, Porsché, Eberhardt, & Svendsen, 2011; Mitchell & Maxwell, 2010; The White House, 2015; UNDP-UNEP, 2011). Prompted by the emergent focus on adaptation following the IPCC's Third Assessment Report (Burton, 2002; Parry, Arnell, Hulme, Nicholls, & Livermore, 1998), climate change projections that were originally developed to guide policy-makers regarding greenhouse gas mitigation strategies are now in demand to inform highly localized and detailed adaptation decisions (Villanueva & Sword-Daniels, 2017; Vincent et al., 2014).

Most decisions in both the public and private sectors involve responding to immediate challenges or planning for the short-term future, often from days to months or a few years ahead (Baethgen & Goddard, 2013; Jones et al., 2015; Nyamwanza, New, Fujisawa, Johnston, & Hajat, 2017; Singh et al., 2018; Vaughan, Buja, Kruczkiewicz, & Goddard, 2016; Vincent et al., 2014; Watkiss, 2014) (Figure 1). This emphasis on short-term risk management is particularly relevant in developing countries because of typically lower adaptive capacities and a higher dependence on rain-fed agriculture, leading to greater impacts from climate and weather shocks (Dessai, Lu, & Risbey, 2005; Munday, Reason, Todd, & Washington, 2016; Ranger & Garbett-Shiels, 2012; Singh et al., 2018). Significant improvements in climate resilience therefore must include improved management of variability across these timescales (Baethgen, Berterretche, & Gimenez, 2016), and climate and weather forecasts can assist with climate-sensitive decisions when provided on an appropriate timescale for the problem in question.

There are, of course, situations where a longer-term view is needed. In addition to energy policy, examples include infrastructure projects, such as irrigation reservoirs, coastal developments and flood defenses, and other long-term investment and planning (Jones et al., 2015). Research on longer-term climate change also helps shape policy priorities by influencing the discourse around climate resilience and change (Nissan & Conway, 2018) and can cast shorter-term decisions in the context of underlying trends to ensure resilience (Dessai et al., 2005). Time horizons for most longer-term decisions range from several years to two or three decades (Figure 1). However, the demand and supply of climate information to support adaptation thus far has focused on projections of the climate several decades, even up to a century, into the future. The prioritization of multi-decadal (i.e., more than 30 years ahead) information is incongruous with developmental needs in lower- and middle-income countries and constitutes a substantial opportunity cost for the limited human and financial resources available for climate adaptation and resilience. At best, this long-term focus is irrelevant to practitioners. At worst, we argue, it could even lead to maladaptation (Hall, 2007; Hewitson, Waagsaether, Wohland, Kloppers, & Kara, 2017). For example, Figure 2 illustrates the potential pitfalls of conflating decadal signals with longer-term trends. Even without concrete examples, strategies with a high opportunity cost can themselves be considered maladaptive (Barnett & O'Neill, 2010).

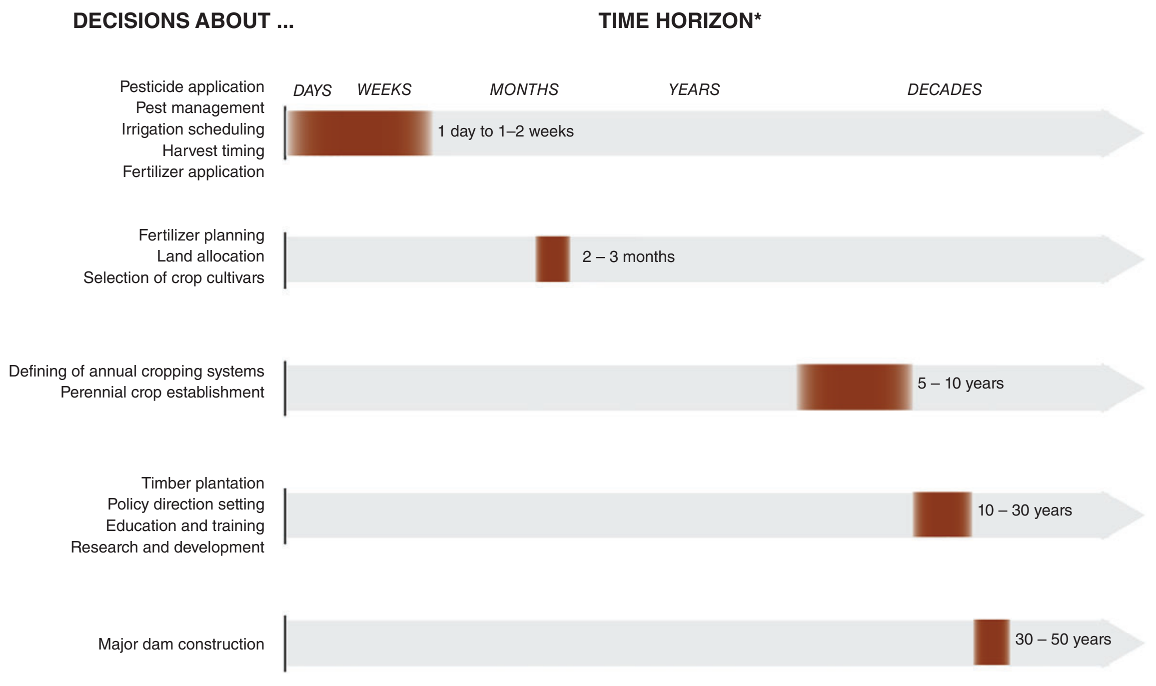

FIGURE 1 Approximate time horizons of decision-making in the agricultural sector. The time horizons relate to the period of time between when a decision is taken and when the implications of that decision have expired. For example, the top entry describes a variety of field operations, which are planned around expected weather and other logistical factors over the coming days to 1–2 weeks. Crop cultivars are selected before planting according to expected yields for the coming 2–3 months. Overall, the majority of practical decisions are taken with a view to managing the coming days up to a few years ahead, with fewer issues requiring a longer-term view. Policy direction setting, education and training, and research and development decisions are usually made at governmental level in order to prepare for the coming 10–30 years. Very few decisions in agriculture have a time horizon longer than about 30 years. Note the approximate logarithmic time scale on the horizontal axis

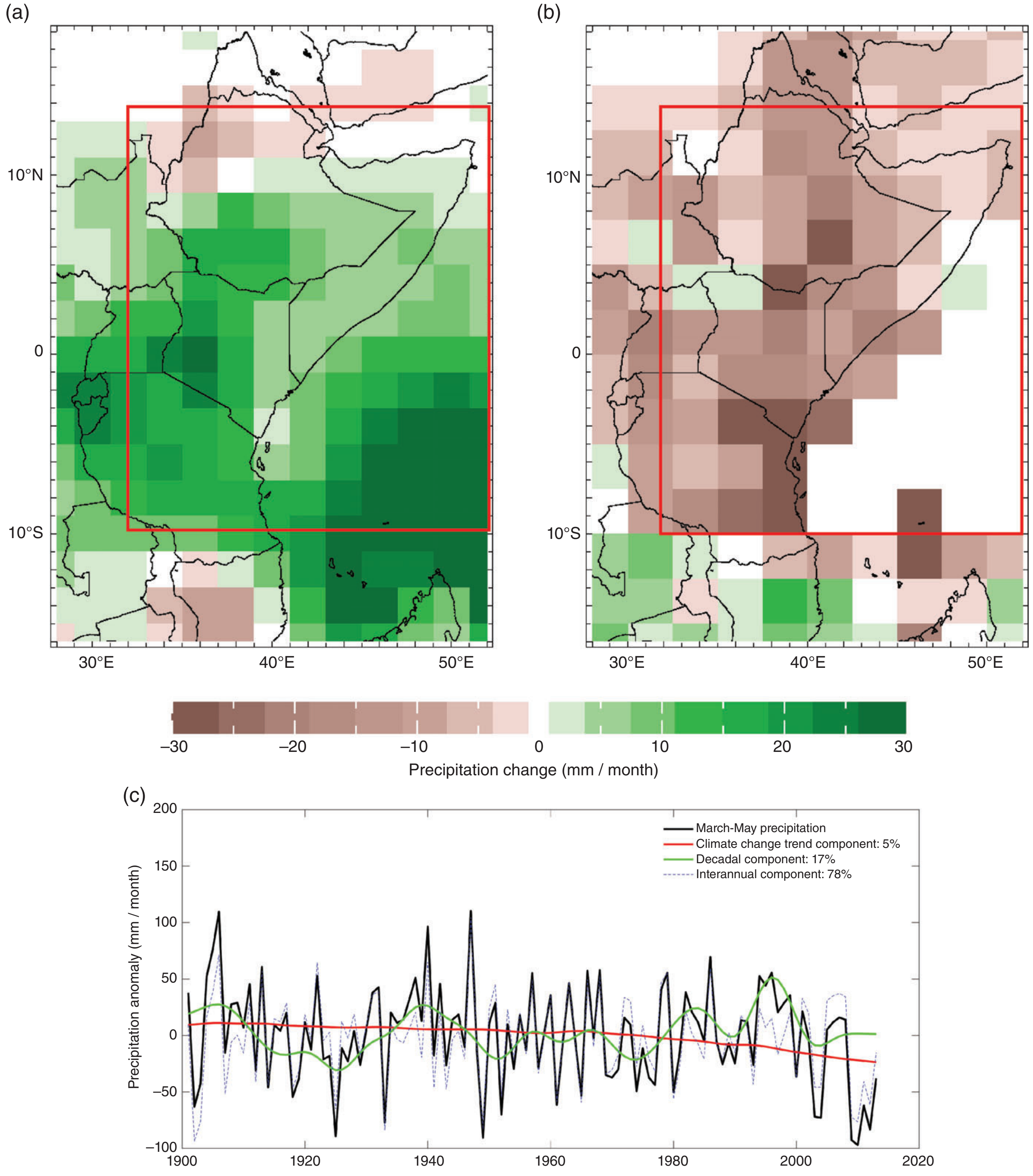

FIGURE 2 (a) Multimodel mean projected change in March–May rainfall (mm/month) over East Africa between 1970–2000 and 2035–2050 (b) Difference in March–May rainfall (mm/month) between 1977–1998 and 1999–2010. The difference between (a) and (b) demonstrates that multidecadal projections may not be representative of decadal changes, either because the projections are inaccurate (climate model error) or because of natural decadal variability around the long-term trend. (c) Timescales of variability for March–May rainfall over the red box shown in (a) and (b): Average March–May precipitation anomalies are shown in black, the long-term trend in red, fitted decadal cycles in green and the residual interannual fluctuations in dashed blue (see Greene, Goddard, and Cousin (2011) for methodology). The legend indicates the percentage of total variance in March–May precipitation explained by the trend (5%), decadal (17%) and interannual variability (77%), illustrating the prominence of year to year fluctuations compared with longer timescales of variability. Observations in (a) and (c) were taken from the Global Precipitation Climatology Center (GPCC) version 7. For (b) the multimodel mean was calculated across 39 models in the CMIP5 ensemble. (a) and (b) were reproduced from Lyon and Vigaud (2017)

An informed user community is imperative to navigate the rapidly growing market of climate change information products, and to enable development practitioners to make more informed demands of climate information suppliers. In Section 2, we review the evidence on the suitability of climate change projections for use in decision-making, including those products developed with the explicit goal of informing adaptation. We explore why, even when long-term information would be relevant for decision-making, the use of climate change projections for detailed planning stretches the models beyond their capabilities. In Section 3, we chart the history of the problem and propose that both an inflated demand for and supply of such detailed projections is leading to a proliferation of poor-quality information and a waste of valuable resources. However, climate services can facilitate robust adaptation, and there is a growing roster of examples of the effective use of climate information in development (Petrik & Ashburner, 2018). Addressing two communities of practice: development practitioners and scientists providing climate change information for adaptation, Section 4 proposes practical solutions that aim to redirect both the demand for and supply of climate change information where it is most reliable and can usefully be applied. We conclude with a summary of our key arguments, in Section 5.

2 | ARE CLIMATE CHANGE PROJECTIONS FIT FOR PURPOSE?

Where climate information on longer timescales would be relevant for decision-making, it is imperative to ask whether the information available is fit for purpose. In general, a failure to acknowledge the limitations of climate change projections for informing policy and decision-making has resulted in a proliferation of suboptimal information that could lead to maladaptation (Adams et al., 2015; Hall, 2007; Hewitson, Daron, Crane, Zermoglio, & Jack, 2014) and a questionable use of resources that are needed to address more pressing climate-sensitive problems in developing countries. Although the limitations of climate change projections are well-documented (Harris et al., 2014; Hazeleger et al., 2015; Smith, 2002; Solomon et al., 2007), the consequences of these limitations for practical decision-making in development practice have not been clearly laid out for the nonspecialist.

2.1 | Limitations of climate change projections

The scientific community can ascribe high confidence to some aspects of climate change projections, which justifies action to mitigate further changes. These include temperature trends, melting glaciers, and an enhanced hydrological cycle. However, climate change projections also suffer from several well-documented fundamental problems that limit their utility in practical decision-making:

2.1.1 | Climate model errors

Models are capable of reproducing many key aspects of the large-scale climate system and of observed climate change, and can provide useful information on appropriate spatial and temporal scales. However, major errors persist. Differences between model-simulated and observed climate trends are prevalent in large-scale patterns of temperature and rainfall (Shin & Sardeshmukh, 2011), which of course lead to errors in simulation of the direction and magnitude of local trends (Gonzalez, Polvani, Seager, & Correa, 2014). Models are unable to capture the seasonal cycle for some locations (Yang et al., 2014) and have a poor representation of daily rainfall characteristics, particularly on local scales (Stephens et al., 2010) and for extremes (Kharin, Zwiers, Zhang, & Wehner, 2013), which are most relevant for risk assessments. For example, low soil moisture is a key physical driver of heat waves in Bangladesh (Nissan, Burkart, Coughlan De Perez, van Aalst, & Mason, 2017), but annual average soil moisture over the country differs from observations by over 50% in three of the most widely used climate models, and by over 250% in one model (Figure 3). Furthermore, the seasonality of soil moisture is delayed in all five models examined. A simple bias correction of the multiyear average soil moisture or temperature will not eliminate this problem. Therefore, these models cannot immediately be used to infer changes in heat wave seasonality in Bangladesh without a more thorough analysis; yet even elementary assessments such as this are not routinely carried out before providing climate change information to stakeholders.

2.1.2 | Regional downscaling

High resolution dynamical (physics-based) regional models and statistical downscaling are often seen as a valuable fix for the coarse-resolution output from global climate models, as they deliver information at higher spatial and temporal resolutions. Regional models, which have a better representation of the spatial features of the climate in regions with complex topography, for weather extremes and mesoscale features (Kendon, Roberts, Senior, & Roberts, 2012; Roberts & Lean, 2008) are widely used for weather prediction, because on those lead times the uncertainties can be quantified and the forecasts calibrated. However, these methods do not apply to climate change projections. Furthermore, regional models inherit the problems of global

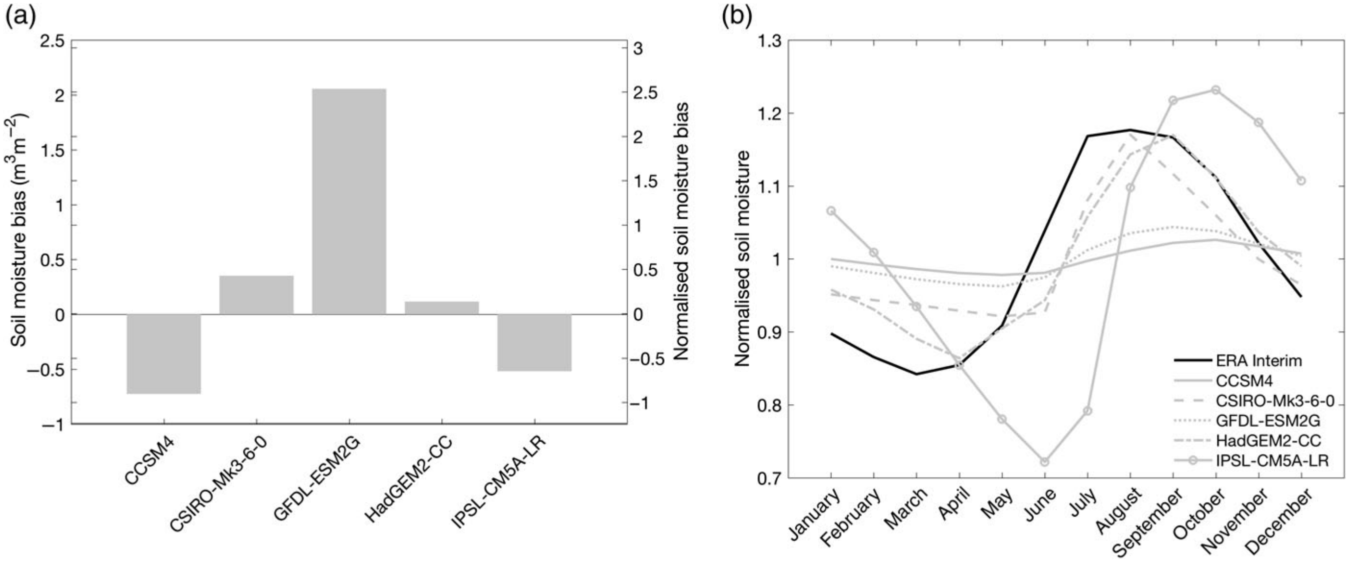

FIGURE 3 Evaluation of soil moisture in five widely-used climate models from the CMIP5 ensemble compared with ERA Interim/Land reanalysis over the period 1979–2005. (a) Annual mean soil moisture bias over Bangladesh (left axis: Raw bias in $m^3\ m^{-2}$; right axis: Bias normalized by observed annual mean); (b) seasonal cycles of soil moisture in ERA Interim/Land and in each of the five climate models (CCSM4, CSIRO-Mk3.6.0, GFDL-ESM2G, HadGEM2-CC and IPSL-CM5A-LR), normalized by the annual mean for comparison on a common scale. ERA Interim/Land reanalysis provides a continuous dataset of soil moisture over a sufficiently long historical period to evaluate the climate models; other products do not span the full study period. Soil moisture is computed using near-surface meteorological fields from the ERA Interim analysis and the HTESSEL land-surface model

models and add additional assumptions and approximations with each step of processing (Barsugli et al., 2013; Endris et al., 2016; Hewitson et al., 2014; Laprise et al., 2008; Trzaska & Schnarr, 2014). Statistical approaches are an alternative to dynamical models, but depend on long, historical records at the desired high resolution, which are unavailable for much of the world. They also assume that statistical relationships seen in the historical record will hold in the future. Whether dynamical or statistical, downscaling therefore cannot be considered a panacea for the problem of inadequate resolution.

2.1.3 | Deep uncertainty

The reliability of probabilistic climate change projections is unknown. Unlike weather forecasts, for which we have many past test cases, climate change projections cannot be calibrated (Knutti et al., 2010; Stainforth, Allen, Tredger, & Smith, 2007; Tebaldi & Knutti, 2007). Instead, probabilities are estimated from the relative frequencies with which different outcomes occur within an ensemble of several models and simulations. However, given that this method of deriving probabilities is unreliable over most of the globe even at seasonal timescales (Weisheimer & Palmer, 2014), the collection of models that contribute to the IPCC's future climate projections should not be expected to represent the true range of uncertainty in a meaningful or quantitative way. Rather, this "ensemble of opportunity" (Stainforth et al., 2007) is simply the cross section of models and simulations available. Each model run represents a "best guess" of the future climate, so the spread of a multimodel ensemble cannot, and was never intended to, capture the true breadth of uncertainty (Allen & Ingram, 2002; Hazeleger et al., 2015; Mote, Brekke, Duffy, & Maurer, 2011; Tang, Dessai, Tang, & Dessai, 2012). The probability of outcomes that fall outside the ensemble spread cannot be estimated. Moreover, models share many components and cannot be considered mutually independent (Stainforth et al., 2007). As a result, model agreement should not impart confidence unless supported by an understanding of the scientific reasons for a particular outcome (Frigg, Smith, & Stainforth, 2015; Hewitson et al., 2014; Palmer, Doblas-Reyes, Weisheimer, & Rodwell, 2008).

2.1.4 | Natural variability

The climate varies naturally on multiple timescales, from the daily weather and seasons to interannual and decadal fluctuations. This variability is superimposed onto any trends driven by anthropogenic changes to the atmosphere and land surface (Figure 2c). Accurate prediction of the near- and long-term climate therefore requires models to capture both manmade trends and natural variability, as the observations contain both. However, while the models do simulate variability, the timing of fluctuations in the models rarely aligns with their timing in the real world, or in other models[1] (Baethgen & Goddard, 2013; Conway, 2011; Lyon & Vigaud, 2017). Thus, an average is often calculated across several models to smooth out natural variability and cancel random errors, so that only the trend remains. Natural variability is therefore a crucial additional source of uncertainty, which should be, but rarely is, factored into long-term climate information provided to decision-makers.

Decadal variability represents a particular trap, as recent decadal cycles can be mistaken for longer-term trends. For example, East Africa has seen a decline in rainfall over recent decades, opposing the long-term wetting trend projected by climate models (Figure 2). Focusing on projected trends without accounting for decadal variations could thus leave communities more vulnerable to climate shocks and stressors.

2.2 | The illusion of precision

Although the above limitations have been documented (Harris et al., 2014; Hazeleger et al., 2015; Smith, 2002; Solomon et al., 2007), climate model errors and projection uncertainties are rarely considered explicitly in the production of future outlooks. As a result, the representation of climate projections for decision-makers tends to be overconfident (Hewitson et al., 2014, 2017; Stainforth et al., 2007). Examples of products explicitly intended to inform local decision-making include the World Bank Climate Change Knowledge Portal,[2] the United Kingdom Climate Projections[3] (Frigg et al., 2015), the NASA NEX Global Daily Downscaled Climate Projections, the U.S. National Climate Assessment,[4] the E.U. Climate4Impact initiative,[5] the WorldClim Global Climate Data portal,[6] the Partnership for Reilience and Preparedness (PREP),[7] the TNC Climate Wizard[8] and the Climate Change, Agriculture and Food Security (CCAFS) climate portal,[9] among others (Hewitson et al., 2017).

2.2.1 | Spatial precision

High-resolution maps of projected climate change convey a false sense of precision. Although seductive, these maps can be misleading to would-be users of climate information (Hewitson et al., 2017). The demand for projections at such fine spatial and temporal resolutions belies an ignorance of the inherent and practical limits of information at local scales noted above (Daron, Sutherland, Jack, & Hewitson, 2015; Hewitson et al., 2014) and encourages an excessive emphasis on regional downscaling techniques (Weaver et al., 2013). While useful information can be gleaned from the models on larger space and timescales, model output should not be equated with useful information.

2.2.2 | Temporal precision

Projections are often provided over short-term (e.g., 1- or 5-year) windows 10–30 years ahead. It is easy to extract model output over such short windows, but this practice neglects the fact that the timing of modelled decadal and interannual variations, which may be substantial, are not in sync with observed variability (Figure 2 and Section 2.1). This practice is common in the impact-modeling community (Harris et al., 2014; Martens et al., 1999) and in climate risk assessments for development (Simpson, 2014).

2.2.3 | Probabilistic precision

Despite the deep uncertainties involved in projecting future climate change (Section 2.1), it has become standard practice to interpret the range of climate model projections as the range of possible outcomes and the relative frequencies of different outcomes within the model ensemble as their probability of occurrence in the real world, sometimes with some statistical postprocessing (Frigg et al., 2015). The possibility of outcomes outside the range of model simulations is rarely addressed (Stainforth et al., 2007; Wade et al., 2015). In practice, outliers are often treated as extreme and are jettisoned, so that projections are essentially forced to converge, artificially inflating confidence in the ensemble (Wood & Moriniere, 2013).

3 | HOW DID WE GET HERE?

Businesses and governments are used to dealing with uncertainty in future planning (Huntjens et al., 2012; Kiem, Verdon-Kidd, & Austin, 2014; Nyamwanza et al., 2017). Foresight about future exchange rates, oil prices, geopolitical disruptions, or epidemics of new diseases would be invaluable, but there is little expectation that such things can accurately be forecast beyond the short term. Despite high confidence in many aspects of present and future climate change, localized projections are highly unreliable. Where then does the unrealistic expectation come from that the future climate, among the most complex of known systems, should be predictable to the degree of precision often demanded? The responsibility lies with both the demand and supply sides of climate information.

Major international development agencies, national governments, and non-governmental organisations (NGOs) have become a hungry audience for high-resolution, long-term projections to inform development planning (Hewitson et al., 2014; Jones et al., 2015; Villanueva & Sword-Daniels, 2017). Funding from development donors is often contingent on incorporating projections. Climate scientists also bear responsibility for the proliferation of unjustifiably-precise climate change projections, given the uncertainty considerations described above (Spiegelhalter & Riesch, 2011). As with development funding, climate research grants are often conditional on the provision of user-relevant climate change projections, yet project resources are usually insufficient to enable the type of in-depth scientific analyses needed to develop these projections reliably (see Section 4.2).

The original climate change projections developed for the IPCC were used to weigh the evidence for human impact on the climate, in order to guide policy makers regarding the mitigation of greenhouse gas emissions. However, the same projections, run at higher resolution, are now employed to answer much more spatially and temporally precise questions relating to national- or even local-level adaptation planning. A willingness to produce and proliferate high-resolution climate change projections, without careful consideration for how they may be interpreted by user communities, reinforces the demand. A common dilemma for climate information providers is that, even if they themselves refrain, there is always someone willing to meet this demand with detailed projections, despite their questionable quality.

These systemic problems are fuelled by a lack of accountability on both sides. Demonstration of successful and unsuccessful adaptation to long-term climate change, and the role that climate information plays in those choices, is extremely challenging (Barnett & O'Neill, 2010; Eriksen et al., 2011; Kiem & Austin, 2013; Vaughan & Dessai, 2014). Until examples are found, and publicized, there is little incentive to pursue alternatives to the status quo. The inability to verify climate projections against observations at long lead times similarly shields scientists from accountability for the information provided. In practice, long-term projections are rarely used directly to influence operational decisions (Berrang-Ford, Ford, & Paterson, 2011; Dilling & Lemos, 2011; Jones et al., 2015; Kiem & Austin, 2013; Singh et al., 2018; Villanueva & Sword-Daniels, 2017), though there are many examples of their use to assess future risks (Dessai et al., 2005; Mittal et al., 2017; Singh et al., 2018). More often, they are employed to advocate for mitigation and adaptation efforts (Nissan & Conway, 2018), to set priorities and guide long-term strategy, and to write reports and comply with funding requirements (Mittal et al., 2017; Sherman et al., 2016).

4 | COMMUNITY-SPECIFIC SOLUTIONS

Concrete measures, tailored for the development and climate science communities, are offered below to improve the provision and use of climate information for adaptation in the face of uncertainty. Proper implementation of these measures calls for intermediary experts with the skills needed to help stakeholders articulate their demands, and to negotiate a compromise between these demands and what the available science is able to provide. This team should comprise multiple disciplines from both social and physical sciences, stakeholder groups and climate information providers, as well as a range of cultural, geographical, and institutional views as appropriate (Vincent, Steynor, Waagsaether, & Cull, 2018). Capacity building for these actors is a vital element of the solution space (Kandlikar, Zerriffi, & Ho Lem, 2011), as is the involvement of developing country practitioners with knowledge of the local context, to ensure solutions are salient and sustainable.

4.1 | Development agencies and practitioners

The commonly held notion that high-resolution, quantitative, and probabilistic climate change projections are necessary to take action today is ill-founded (Dessai & Hulme, 2004; Hallegatte, 2009); the literature on decision-making under deep uncertainty is extensive (Hallegatte, 2009; Hallegatte, Shah, Lempert, Brown, & Gill, 2012; Ranger et al., 2010). While some methods may be prohibitively costly in developing country settings, there are low-cost alternatives to facilitate robust decision-making (Ranger & Garbett-Shiels, 2012). For example, scenario planning is used effectively in many areas, such as military strategy, urban planning and situations where exchange rates, research outcomes or energy costs are deeply uncertain (Hallegatte, 2009).

Exploring adaptation options before commissioning a full climate change risk analysis, not after, can identify low-risk, robust adaptation options (Lempert, Groves, Popper, & Bankes, 2006; Steynor, Padgham, Jack, Hewitson, & Lennard, 2016). The goal of this process should be to avoid an overreliance on climate change projections, particularly at local or regional scales and focused on specific future dates. Many of the problems discussed here can be avoided by addressing a few key questions through coexploration with stakeholders:

- *Identify the relevant timescales of stakeholder decisions*

Often, decisions are taken on short (daily to seasonal) timescales, in which case long-term projections need not be prioritized. In these cases, improved resilience to climate variability, supported by climate services based on historical data, real-time monitoring, and shorter-term forecasts, can be the most effective way to build resilience to future changes in climate risk.

Identifying the timescales of relevant stakeholder decisions (for example, as demonstrated in Figure 1 for the agricultural sector) can assist in selecting appropriate climate information.

- *Assess the will for action*

In the absence of feasible alternative adaptation options, a full climate change analysis is unnecessary and a waste of resources, even if some decisions do pertain to longer timescales. An unwillingness to consider long-term adaptations could arise for a number of reasons, such as shorter-term priorities, budget constraints, lack of infrastructure, or cultural values (Dilling & Lemos, 2011; Glantz, 1977; Ingram, Roncoli, & Kirshen, 2002; Lemos, Finan, Fox, Nelson, & Tucker, 2002; Nielsen & Reenberg, 2010; Tarhule, Lamb, Tarhule, & Lamb, 2003).

- *Reframe long-term problems where possible*

Identify long-term decisions that could be recast onto shorter timeframes. Some decisions can be managed iteratively through regular reviews or postponed until a later time when uncertainties in relevant aspects of the problem have been reduced through monitoring (Conway & Schipper, 2010; Michel-Kerjan et al., 2013). For example, city planners wishing to adapt a heat action plan for a warmer future could incorporate iterative updates every 5 to 10 years (Hess & Ebi, 2016). In these reviews, observed changes in relevant aspects of heat waves could be incorporated without the need for a full evaluation of climate change projections. Remaining flexible carries other advantages too, such as the ability to consider emerging vulnerable groups and to evaluate and refine intervention strategies. Even for large infrastructure developments, opportunities to retrofit at a later date can be incorporated (Huntjens et al., 2012; Ranger, Reeder, & Lowe, 2013).

- *Aim for an appropriate level of precision*

Some sectors (e.g., hydroelectricity) have formal decision frameworks to consider the effects of changes in inputs and uncertainties from a range of sources, including price, regulations, or weather (Baethgen et al., 2016). However, other sectors do not and so would not be able to make use of quantitative predictions even if such information was trustworthy. Qualitative projections and uncertainty qualifications may often be sufficient (EFSA, 2006).

- *Identify flexible adaptation options*

Guidance on flexible adaptation strategies abound in the literature (Hallegatte, 2009; Hallegatte et al., 2012; Lempert & Collins, 2007; Ranger & Garbett-Shiels, 2012). In particular, the adaptation deficit in many developing countries means that potential gains from improving the capacity to cope with climate shocks and variability are high. These benefits can be felt today so may be more justifiable for policy-makers. There may also be low-regret options available; for example, improving transport networks enables the redistribution of produce to mitigate food insecurity while also facilitating broader economic development. Decisions which can be reversed when new information becomes available, or safety margins that can be incorporated (Aggett, 2007; National Research Council, 2009), are not zero cost but allow flexibility (Hallegatte, 2009). The expense of these options must be weighed against the costs of undertaking the in-depth analyses needed to produce more reliable tailor-made scientific information.

- *Stress test the system*

It can be helpful to stress-test systems to potential, hypothetical, changes in weather and climate (e.g., an increase in the number of rainstorms or the frequency of delayed-onset monsoons) (Lempert et al., 2006; Weaver et al., 2013). Identifying high sensitivities to small changes in weather can guide adaptation decisions without the need for projections (Baethgen et al., 2016; Dessai et al., 2005). Stress tests can also clarify any critical thresholds to guide the climate analyses proposed in Section 4.2, if deemed necessary.

4.2 | Considerations for climate scientists

Examples of climate services developed through coexploration with stakeholders are rapidly accumulating (Petrik & Ashburner, 2018). Such methods challenge the model of climate services as an information chain, whereby climate information is fed linearly from producer to decision-maker, instead favoring a network approach that allows for information exchange among diverse actors with a range of values and criteria (Hewitson et al., 2017; Vincent et al., 2018). However, such tailored climate information is challenging and resource intensive to develop. Often the priorities of universities and research centers emphasize model improvement (Di Luca, de Elía, & Laprise, 2015) and, while the development of "user-relevant" climate change information is increasingly valued, the connections between scientists and stakeholders that are needed to make that information truly actionable are not incentivized or facilitated. Most climatologists lack the expertise and training required to engage effectively with decision-makers, and for many in the field such activities are not their focus (nor should they be). However, delivering climate services requires climate scientists who are focused on bringing the best science into decision-making, and who can participate in intermediary teams to work with stakeholders to develop and translate the science (Kiem et al., 2014). Without these interactions, scientists are often unaware of the type of information that could aid or hinder effective adaptation (Adams et al., 2015; Hewitson et al., 2017; Jones et al., 2015; Kiem et al., 2014; Steynor et al., 2016).

Nonetheless, a number of practices could substantially improve the quality and effectiveness of climate information provided, while working within existing institutional and funding constraints:

- *Understand observed variability and trends*

Given the adaptation deficit in many less-developed countries, climate services can focus on local climate variability, which drives most climate-related risk, and on observed trends to assess whether recent events are within the range of natural variability or symptomatic of longer-term shifts (Dessai et al., 2005). Historical analogues can be a powerful tool, by highlighting where vulnerability can be reduced (Ford et al., 2010; Klinenberg, 2015). Observational analyses are constrained by poor data quality and coverage in many places, but, without sufficient data for model evaluation in these regions, the utility of climate model projections is also seriously compromised (Di Luca et al., 2015) and, we assert, dangerously ignored. National meteorological departments working to restore national data are critical to overcoming these barriers (Dinku et al., 2014). Where rainfall is concerned, observations and shorter-term forecasts, in conjunction with flexible adaptation choices, will often be sufficient, since trends in monthly precipitation are either undetectable or small in many regions.[10] Temperature trends are more significant and confidence in projections is higher, but observational analyses remain critical for adapting to temperature variability.

- *Incorporate climate variability into climate change projections*

Climate is not experienced as a long-term average or trend, but as weather and climate variability on a range of timescales. Setting long-term trends in the context of climate variability can help stakeholders to assess how climate change may affect them (Kiem et al., 2014). To date, we have seen trends in daily weather variability (Alexander et al., 2006; Donat et al., 2013a, 2013b), but substantial trends in interannual and longer-term variability have not been detected (see Table 2.14 in Haartman et al., 2013). Potential changes in climate variability are thus poorly understood, but projected trends can be combined with historical analyses and with a range of plausible changes in future variability to illuminate the vulnerabilities of decision-systems. Statistical models can be used to incorporate realistic spatial and temporal variability into projected trends based on observed data. In Uruguay, for example, future climate variability was stochastically simulated around projected trends to estimate agricultural risks (Greene, Goddard, Gonzalez, Ines, & Chryssanthacopoulos, 2015). Such methods suffer from stationarity problems but are preferable to the use of unverified model output, particularly when observed trends in variability are undetectable or small (Greene, Hellmuth, & Lumsden, 2012; Greene, Robertson, Smyth, Triglia, & Greene, 2011).

Projections with 10- to 30-year lead times have a particularly high potential to mislead decision-makers because climate change projections do not capture the timing of interannual and decadal cycles (see Section 2) (Baethgen & Goddard, 2013; Lyon & Vigaud, 2017). Initialized decadal predictions could rectify this problem but are currently experimental,[11] and show very little additional skill over most land areas, especially for precipitation (Goddard et al., 2013). Projections should only be provided as statistics calculated over periods of more than 30 years, and over multiple model simulations that contain different phases of decadal variability (Harris et al., 2014).

- *Provide climate information at an appropriate level of precision and no more*

At present, there is inadequate distinction among methodologies suitable for broad, horizon-scanning assessments of climate change risks or mitigation options, and those that can inform practical decision-making. Guidance on the use of model projections for specific applications must be tailor-made; it is not adequately served from open platforms (Hewitson et al., 2017). Nevertheless, generic information provided on open platforms (e.g., data portals), or climate risk assessments without a target application, can be useful for identifying hazard categories that may become problematic. Such information should be in the form of scenarios, without probabilities attached, provided on coarse spatial scales, and accompanied by clear statements about the limitations for direct use in decision-making.[12] Anything more is irresponsible (Adams et al., 2015; Daron, Sutherland, et al., 2015; Hewitson et al., 2017; Steynor et al., 2016).

Facing the demand for increasingly precise information, there is an ethical responsibility on scientists to provide only information that can be substantiated by evidence (Spiegelhalter & Riesch, 2011). Raw model output does not necessarily provide useful information, and can be misleading. Thus, one role of a climate service provider is to identify the area of overlap between what practitioners want and what is scientifically reliable and achievable. Robust adaptation plans can be made based on information at relatively coarse spatial resolution (Coughlan de Perez & Mason, 2014) and on analyses of observed variability and trends. Often, qualitative statements about the likely direction of change are sufficient (Stainforth et al., 2007). Quantitative predictions should only be given when (a) scientifically reliable and (b) directly relevant for the decision at hand, to avoid overoptimization to uncertain projections (Hassenzahl, 2006; Steynor et al., 2016). Instead of probabilistic information, output can be presented as plausible scenarios, emphasizing the unquantifiable uncertainties involved (Dessai et al., 2005). Where probabilities are deemed essential, their subjectivity should be clearly identified (Spiegelhalter & Riesch, 2011).

- *Choose decision-relevant metrics and communication strategies*

Average temperature or precipitation is rarely a relevant metric. Decision points in most systems are concerned with specific thresholds, which may not be well captured by models, especially in the tails of distributions. Climate change information should be coproduced with stakeholders to find metrics that balance their needs with model capabilities (Coughlan de Perez, Monasso, van Aalst, & Suarez, 2014; Singh et al., 2018).

Although intended as mere scenarios of the future, climate change projections are often presented, and interpreted, as quantitatively meaningful forecasts. The prevailing emphasis on quantifying and reducing uncertainty in future climate change does not address this problem. Much more could be achieved through investigation of new methods to visualize and communicate projections in a way that emphasizes the deep uncertainties involved, while highlighting aspects about which we have more confidence (Adams et al., 2015; Daron, Lorenz, Wolski, Blamey, & Jack, 2015; EFSA, 2006; Hassenzahl, 2006; Hewitson et al., 2017; Risbey & Kandlikar, 2007; Spiegelhalter & Riesch, 2011).

- *Emphasize model evaluation*

The development of climate change information to inform practical adaptation requires thorough model evaluation and expert judgment, and cannot be streamlined into a one-size-fits-all methodology (Adams et al., 2015; Gleckler, Taylor, & Doutriaux, 2008; James et al., 2018; Knutson et al., 2010; Knutti et al., 2010; Spiegelhalter & Riesch, 2011; Steynor et al., 2016). The purpose of such model evaluation is not necessarily to reduce uncertainty about future climate change; instead, it can be applied to judge the level of confidence in future projections from a perspective of scientific understanding (James et al., 2018; Pinto, Jack, & Hewitson, 2018). In a nonstationary climate, no basis exists for prediction of the future if the model physics and dynamics cannot be trusted. Process-based model evaluations are therefore a critical line of evidence in assessing confidence (Hewitson et al., 2014, 2017; James et al., 2018; Pinto et al., 2018). It is often not possible to determine definitively when a model is "good enough" to answer a particular question and when it should be rejected completely (Di Luca et al., 2015; Knutti et al., 2010) so, for now, subjective judgment is an essential component of this process (Di Luca et al., 2015; Spiegelhalter & Riesch, 2011).

To facilitate robust decision-making, information is needed about the range of plausible outcomes, not just the best guess given by climate models, which do not represent the true prediction uncertainty (and were never intended to) (Hallegatte, 2009). Stochastic simulations and statistical models trained on past data can be used to estimate uncertainty in future projections (Greene, Goddard, & Lall, 2006). However, the possibility of outcomes outside the range of model projections can only be assessed subjectively with information about where the models fail to perform well, and why they fail in those situations (Lyon & Vigaud, 2017; Stainforth et al., 2007). If evaluations reveal that little about the long-term future can be determined with confidence or that the data are inadequate to enable a proper assessment, climate services should focus on observed variability and trends (Dessai et al., 2005) and on shorter-term forecasts.

We propose a minimum set of evaluation procedures that should be undertaken to develop information on climate change risks for decision-makers, noting the role of expert judgment in interpreting the results of these evaluations:

1. *Basic statistics of underlying climate variables: mean, trend and variability on decision-relevant timescales*

To place any confidence in a particular model's projections of, for example, a change in heat wave frequency in a given region it should, at the very least, broadly capture the mean, trend, and seasonality of temperature. A model that cannot capture the basics cannot responsibly be used to assess how an extreme weather event may change decades in the future (see Endris et al., 2013; Gleckler et al., 2008; Kalognomou et al., 2013; Muñoz, Yang, Vecchi, Robertson, and Cooke, 2017).

2. *Basic statistics of the climate event of interest: mean, trend, and variability on decision-relevant timescales*

Practitioners are often interested in potential changes in the variability of extreme weather and climate hazards (Coughlan de Perez et al., 2014). Such events are usually triggered by particular patterns of circulation in the atmosphere, which may alter with climate change in nonobvious ways that differ from the average. To infer anything about plausible changes in the variability of a hazard, we should be confident that its variability on relevant timescales is well represented in the climate model we intend to use (e.g., Knutson et al., 2010).

3. *Physical drivers of the climate event of interest on decision-relevant timescales*

Correctly capturing the drivers of the climate hazard of interest on appropriate timescales should be considered a necessary, though not a sufficient, criterion for trusting a model's predictions (Endris et al., 2013, 2016; Fernandes, Giannini, Verchot, Baethgen, & Pinedo-Vasquez, 2015; James et al., 2018; Kalognomou et al., 2013; Knutti et al., 2010). One might ask if heat waves in a model are caused by the same physical mechanisms that drive heat waves in the observed climate system, or if the model has its own way to generate temperature extremes differently from the real world. These physical “drivers” of local climate impacts differ across the timescales of variability that may be of interest to decision-makers. For instance, a particular seasonal weather pattern may be responsible for precipitation at an important stage in the agricultural calendar, but the amount of rain falling from year to year may be driven by other phenomena, such as the El Niño Southern Oscillation.

4.3 | The demand for quick-and-easy solutions

A common criticism of the more tailored approach proposed here is that it is resource-intensive. In-depth scientific analysis takes time, funding, and human capacity, posing a particular challenge in developing countries. When many in the field are willing to provide quick, off-the-shelf answers, a tailored approach may seem expensive and unnecessary. However, in most cases, readily available projections are not fit for purpose. Numbers may be easily generated by models, but their reliability cannot be assumed. A forecast for oil prices in 2043 can be made simply enough, but how many would invest their savings in the outcome? The potential costs of optimizing adaptation choices to overconfident projections are hidden for now but could be significant. Moreover, a process of stakeholder engagement can reduce the burden of a full analysis by avoiding unrealistic demands and targeting resources where they can deliver actionable and reliable information (Steynor et al., 2016).

5 | CONCLUSIONS AND KEY ARGUMENTS

Multidecadal climate change projections, while essential for informing mitigation policy, do not target the appropriate timescale needed for the majority of adaptation decisions in developing countries. Resources could be better spent building resilience to climate variability, which drives the majority of climate-related risk, supported by climate services focused on observations of local variability and trends and on shorter-term forecasts.

When a long-term view is relevant, the adaptation community should be aware that widely available climate change projections are overconfident, and are advised to avoid seductive promises of information about future climate conditions at local scales and particular future dates. Methods used routinely in climate risk assessments invariably attempt to streamline complex scientific questions into off-the-shelf algorithms. A thorough scoping process would help avoid an overreliance on projections and maximize the efficient use of limited resources for climate adaptation and resilience. Often this process reveals that detailed planning is possible without detailed climate change projections.

Climate scientists, meanwhile, are engaged in a major effort to provide precise, quantified, probabilistic climate change projections at high-resolution. This information is inappropriate for direct use in operational decision-making as it encourages an inflated impression of confidence in future changes. Effective climate change services can still be delivered by incorporating information about past climate variability and trends, and by investing in new methods to communicate areas of confidence and uncertainty in future changes that facilitate robust decision-making (Dessai et al., 2005; Hassenzahl, 2006; Risbey & Kandlikar, 2007). Scalable solutions are needed, as the breadth of users and applications far exceeds the capacity to develop tailored solutions for all, but innovation is required to ensure that the fundamental limitations of long-term projections are adequately and transparently represented (Adams et al., 2015; Hewitson et al., 2017). Such innovation will require us to develop new ways to assess confidence through expert judgment (Kandlikar, Risbey, & Dessai, 2005; Mastrandrea et al., 2010; Thangaratinam & Redman, 2005), supported by thorough model evaluation and scientific understanding (Hewitson et al., 2014, 2017; James et al., 2018). Methods to distil the consequences of these evaluations for decision-makers are lacking but should be prioritized.

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CONFLICT OF INTEREST

The authors have declared no conflicts of interest for this article.

ENDNOTES

[1]One exception is climate fluctuations driven by volcanic eruptions.

[2]http://sdwebx.worldbank.org/climateportal/ (accessed December 30, 2018).

[3]https://ukclimateprojections-ui.metoffice.gov.uk/ (accessed December 30, 2018).

[4]http://scenarios.globalchange.gov/scenarios/climate (accessed December 30, 2018).

[5]https://climate4impact.eu/impactportal/general/index.jsp (accessed December 30, 2018).

[6]http://www.worldclim.org/ (accessed December 30, 2018).

[7]https://www.prepdata.org/ (accessed December 30, 2018).

[8]http://www.climatewizard.org/ (accessed December 30, 2018).

[9]http://ccafs-climate.org/ (accessed December 30, 2018).

[10]The relative contribution of long-term trends, decadal and interannual variability to the total variance in precipitation and temperature over the 21st century can be visualized easily using the IRI's Timescales Maproom, accessible at http://iridl.ldeo.columbia.edu/maproom/Global/Time_Scales/.

[11]https://www.wcrp-climate.org/dcp-activities/dcp-cmip5 (accessed December 30, 2018).

[12]http://tool.globalcalculator.org/globcalc.html?levers=22rfoe2e13be1111c2c2c1n31hfjdcef222hp233f211111fn2211111111/dashboard/en (accessed December 30, 2018).

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