Addressing uncertainty in adaptation planning for agriculture

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We present a framework for prioritizing adaptation approaches at a range of timeframes. The framework is illustrated by four case studies from developing countries, each with associated characterization of uncertainty. Two cases on near-term adaptation planning in Sri Lanka and on stakeholder scenario exercises in East Africa show how the relative utility of capacity vs. impact approaches to adaptation planning differ with level of uncertainty and associated lead time. An additional two cases demonstrate that it is possible to identify uncertainties that are relevant to decision making in specific timeframes and circumstances. The case on coffee in Latin America identifies altitudinal thresholds at which incremental vs. transformative adaptation pathways are robust options. The final case uses three crop–climate simulation studies to demonstrate how uncertainty can be characterized at different time horizons to discriminate where robust adaptation options are possible. We find that impact approaches, which use predictive models, are increasingly useful over longer lead times and at higher levels of greenhouse gas emissions. We also find that extreme events are important in determining predictability across a broad range of timescales. The results demonstrate the potential for robust knowledge and actions in the face of uncertainty.

climate change | food security | vulnerability | future scenarios | policy

Achieving food security under climate change is a complex public policy issue, a so-called "wicked problem." The magnitude of plausible impacts, and costs of inaction or delayed action, mean that individuals and societies must undertake adaptation actions despite uncertainty. Policymakers are accustomed to making decisions under considerable uncertainty and do not necessarily need systematic reductions in uncertainty to act on climate change (1). Nonetheless, science can make a major contribution by elucidating or prioritizing uncertainties in ways that are helpful to the decision-making processes of national policymakers and other stakeholders (2–4). The purpose of this article is to demonstrate how science can provide practical approaches to addressing uncertainty that can assist adaptation planning for agriculture in developing countries over multiple lead times. We achieve this goal by presenting four case studies linked by a framework that combines a simple uncertainty analysis with a characterization of different approaches to adaptation planning.

Impact and Capacity Approaches to Adaptation Planning

Adaptation planning can incorporate scientific information both from projections of climatic impacts and assessments of adaptive capacity (Fig. 1). Impact approaches (5, 6) use statistical or mechanistic models to attach probabilities to possible outcomes under a range of scenarios; they arrive at adaptation options for agriculture and food security via analyses that start with climate forcings and global circulation models, and from these project progressive impacts on local climates, crop physiology, crop yields, food prices, and, finally, outcomes for human welfare and nutrition. Capacity approaches (7, 8) start by assessing the existing capacities and vulnerabilities of socioeconomic groups such as communities, industries, or countries. From this base, they develop sets of "no regrets" options that are considered politically and economically feasible over a range of possible climatic futures. Overall, capacity approaches to analysis and planning are more compatible with stakeholder-driven processes (7, 9).

The two approaches also have different implications for uncertainty. Impact approaches have been criticized on technical grounds for the accumulation of uncertainties along the cascade of impact, and exclusion of potentially important factors about which little is known (10, 11). Global change researchers have put considerable emphasis on quantifying imprecision in projections—e.g, through the use of ensemble modeling techniques (5). A key concern is that models are more conducive to an emphasis on precision (measurable uncertainty, or known unknowns) than on ambiguity (nondescribed uncertainties, or unknown unknowns) (3). Some critics have gone further to argue that systematic reductions in uncertainty have little or no relevance to policy-making on climate change; worse still, the "uncertainty fallacy" hinders urgently needed action by providing a rationale for delay (1). Furthermore, complexities in economic and social systems may outweigh climatic uncertainties in determining possible and desirable suites of adaptation actions, thus favoring a capacity approach (12, 13). However, capacity approaches, though increasingly used in national planning, have received less scrutiny than impact approaches. The treatment of uncertainty in vulnerability assessments is relatively immature (13), with little explicit treatment of either imprecision or ambiguity.

The need to integrate impact approaches with capacity approaches is increasingly recognized (9, 14). For example, the Intergovernmental Panel on Climate Change's (IPCC) method for vulnerability analysis integrates an impact assessment of exposure with assessments of sensitivity and adaptive capacity. Arguably, the main challenge is not the technical task of bridging impact and capacity analyses, but rather the effort needed to bridge science and policy. There is a considerable literature on

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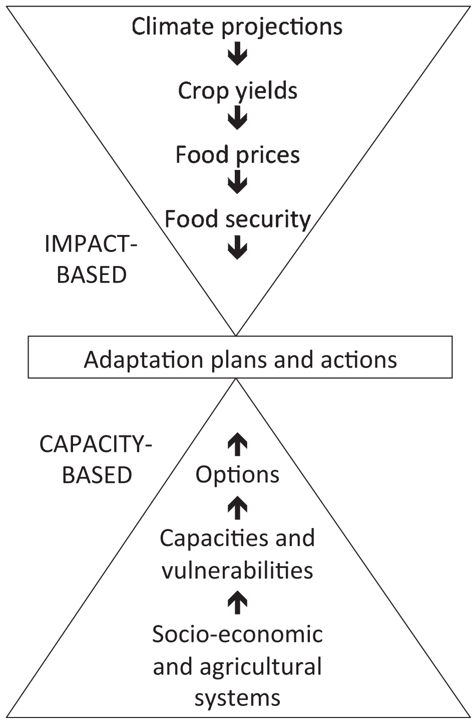

Fig. 1. Impact and capacity approaches to adaptation planning.

this topic. Recommended strategies include specific go-between roles for boundary organizations (15) or decision scientists (4). Emerging principles of "consensus beats reality" and "good enough is best" suggest that stakeholder trust and agreement may be more important to effective evidence-based decision making for wicked problems than high levels of scientific rigor and certainty (15, 16).

Uncertainty in Nearer-Term and Longer-Term Adaptation

The uncertainties pertinent to longer-term vs. nearer-term adaptation planning are likely to differ. At low levels of climate change, the climate signal may be indistinguishable from climate variability, and thus improving precision and managing known risks may be more important than identifying completely new (and ambiguous) possibilities. Farmers and societies can adjust by making incremental adaptations and innovations based on long experience in dealing with a highly variable climate. Thus, the key investment in incremental adaptation is likely to be institutional support to farmers to enlarge their portfolio of strategies, both old and new, to manage increasing climatic risks (17). There are rich historical antecedents for innovation systems for agricultural risk management that share learning among farmers, businesses, scientists, and other stakeholders (18).

At higher levels of climate change, systemic or even transformative adaptation may be needed: wholesale reconfigurations of livelihoods, diets, and the geography of farming and food systems (19, 20), as has happened historically in response to market changes, for example. These adaptations require different understandings of uncertainty. For example, assessments of seasonal predictability have the potential to improve risk management, such as by informing the financial efficiency, and hence affordability, of index-based crop and livestock insurance. However, at some particular magnitude of climate change, risk insurance will become significantly less effective, and a change in herd size or crop variety (systemic change), or a switch entirely from crop systems to livestock (transformative change) may be needed. Systemic and transformative adaptation will benefit from large-scale, anticipatory investments in infrastructure, livelihoods diversification, and possibly migration. These innovations carry major costs, and in some cases disruptive social changes that are not evenly distributed, and thus can lead to massive misallocations of resources if misjudged (21). Shared learning among stakeholders is arguably even more critical to successful adaptation over decadal timeframes than to near-term innovation. The ability of stakeholders at all levels to make long-term no-regrets decisions will be limited by their capacity to envisage and prepare for unknown unknowns. Adaptation planning based purely on stakeholder consensus may lead to maladaptation (22, 23), particularly where there is future likelihood of entirely novel climates or crossing thresholds in productivity of crops, rangelands, livestock, or fisheries.

Results and Discussion

Here we present a framework for prioritizing adaptation approaches at a range of uncertainty levels linked to lead times. The framework draws on methods to calculate when a climate change signal emerges from the "noise" of climate variability (24). We develop and illustrate the framework using four case studies. Fig. 2 presents the framework for linking uncertainty analysis with adaptation planning, including impact vs. capacity analytic approaches (9), and three types of adaptation: incremental, systemic, and transformative (19). The x axis is a signal-to-noise ratio (the ratio of the mean trend to the imprecision around that mean) for an observable and, at least to some extent, predictable variable. This variable measures the extent to which climate change is detectable, using a climatic or impact variable (case 4). We place time on the y axis (24) because it is the dependent variable—i.e., our analysis assesses when a transition between types of adaptation occurs, rather than the range of possible conditions and associated adaptations at a fixed point in time. For example, a transformative adaptation may happen in Fig. 2 at some time between t1 and t4. For a known emissions trajectory, this time window is narrowed (e.g., t3–t4 for the low-emissions pathway). Similarly, a narrower uncertainty in the response of the system to climate change (lower signal-to-noise ratio) results in a narrower uncertainty in the time of transformation (t1–t3).

Near-term adaption planning can be effective using capacity analytic approaches alone. Case 1 on Sri Lankan national adaptation planning shows the utility of capacity approaches for near-term planning where there is not yet a strong climate change signal, and adaptation options derive from existing good development practice. However, limitations to this approach are likely to emerge over longer timeframes, as climatic impacts and possible responses move beyond collective historical experience. Case 2 on East African scenarios documents a stakeholder-led approach to planning for longer time horizons that addresses ambiguity about the future (unknown unknowns) and tests capacity solutions against impact projections.

Sources of uncertainty in adaptation studies vary depending on the climate change challenge or policy response in question (e.g., between different time horizons, localities, or agricultural systems). Quantification of uncertainty can assist policy by identifying those uncertainties that are irrelevant to specific policy decisions and those for which further characterization of uncertainty would be most helpful to decision making. Case 3 on coffee in Central America provides an example of altitudinal thresholds providing the basis for robust and differentiated adaptation pathways for different localities, despite wide disagreement among model projections. Case 4, which presents three sets of crop–climate simulations, demonstrates how uncertainty can vary in identifiable ways across time and with different adaptation options, providing opportunities for robust decision making.

Taking our four case studies together, we offer the generalization that capacity analyses are most important for near-term adaptation planning, but impact predictive tools, though useful

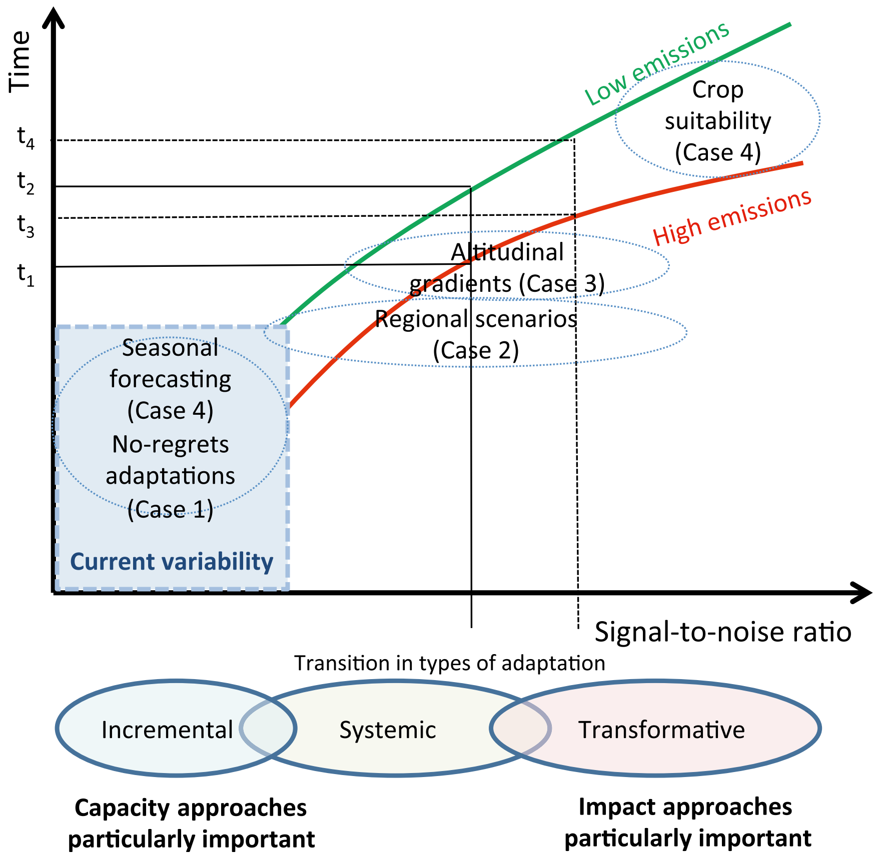

Fig. 2. Schematic framework of the relationship between signal-to-noise ratio for a climate impact and the period during which progressive levels of adaptation occur. The relationship varies according to greenhouse gas emissions. The shaded box shows current climate variability, where the signal-to-noise ratio is less than 1.

even in the near term, generally become increasingly important over longer-term planning horizons, which contain increasingly novel climates (Fig. 2). Building analytic approaches into iterative stakeholder processes is crucial whatever the timeframe and whatever the combination of impact and capacity analyses (1, 9, 15, 25). Stakeholder processes for near-term planning may emphasize consensus-building around current knowledge, but over longer time horizons this may shift toward scenarios-based dialogue and priority-setting, as climate change surpasses human experience and major transformations are required.

Case 1: Adaptation Planning Under Climatic Uncertainty in Sri Lanka. The National Climate Change Adaptation Strategy for Sri Lanka 2011–2016 (26) provides an example of national priority-setting in the face of ambiguous climate projections. In particular, projections of precipitation do not provide a reliable basis for planning. The majority of models project higher mean annual precipitation under a range of emissions scenarios (27–31), but with considerable discrepancies in the distribution of precipitation between the two monsoons, whereas others project lower mean annual precipitation (32, *). Projections of the future spatial pattern of rainfall display similar contradictions. Given this uncertainty, the Government of Sri Lanka took a pragmatic approach of basing its adaptation plan on an integrated vulnerability analysis across five key sectors, including agriculture and water, coupled with a multistakeholder analysis of intervention options that show a high degree of policy and technical feasibility (i.e., capacity rather than impact). Sri Lanka's vulnerability index (33) uses the IPCC framework of exposure, sensitivity, and adaptive capacity (34), but is designed to minimize the dependence of the analysis on ambiguous model-based projections. The Sri Lankan exposure index uses frequency of historical exposure to climate hazards (droughts, floods, cyclones, and multihazards) as a proxy for future climate hazard exposure. The sensitivity index uses rural population density, degree of employment in agriculture, availability of irrigation water to paddy areas, and agricultural diversity as proxies for sensitivity to climatic changes. The adaptive capacity index uses the availability of infrastructural assets and socioeconomic assets as proxies for adaptive capacity. This information is readily available, meaning that the index is simple to calculate.

The Government of Sri Lanka then used this analysis of district-level vulnerability to identify feasible, cost-effective, low-risk responses in high-vulnerability districts. Through stakeholder consultation (involving government, nongovernment, private and research organizations, and the general public), the 5-y adaptation strategy adopted multiple-benefit adaptation interventions that simultaneously deliver climate resilience and address current development needs. These types of common-sense interventions are able to maximize current benefit-cost ratios while also providing robustness to climatic uncertainty (25). The best example of such an intervention in Sri Lanka is the restoration of the ancient tank storage system in the country, to provide "insurance" against climate variability in the most vulnerable districts (primary agricultural). Other no-regrets interventions for water and agriculture, currently practiced at a low level, but warranting wider adoption, are rainwater harvesting (30), development of sustainable groundwater, adoption of microirrigation technologies, and wastewater reuse (33). Quantitative decision tools can help when choosing among options. The Sri Lankan case illustrates how "good enough" knowledge assists decision making under climatic and socioeconomic uncertainty.

*Basnayake BRSB, Rathnasiri J, Vithanage JC, Paper presented at the Second Assessments of Impacts and Adaptations to Climate Change (AIACC) Regional Workshop for Asia and the Pacific, November 2–5, 2004, Manila, Philippines.

Case 2: Scenarios of Societal and Climatic Uncertainty in East Africa. Multistakeholder processes to derive regional socioeconomic scenarios have been organized by the Research Program on Climate Change, Agriculture and Food Security (CCAFS), and they provide an example of how capacity and impact approaches can be combined. In East Africa, CCAFS brought together national policy advisors and representatives from regional economic bodies, academia, media, civil society, farmers' associations, and the private sector working in the agriculture and food, environment, and planning sectors. These stakeholders explored key regional socioeconomic uncertainties as they might affect future food security, environments, and rural livelihoods, and the capacity of the region to adapt to climate change (35). These uncertainties were structured to produce four socioeconomic scenarios up to 2030, designed to provide multiple plausible, future contexts for decision makers to use in regional, national, and local planning (36). Rather than attempting to forecast, these multistakeholder processes seek to combine societal perspectives and explore unknown unknowns to challenge assumptions about the future, and foster collaborative, adaptive decision making (37).

As in the current IPCC-related Shared Socioeconomic Pathways (38), CCAFS socioeconomic scenarios are produced as complementary to climate projections, allowing for combinations of both sets. In East Africa, the stakeholder-driven socioeconomic scenarios were themselves quantified through two global agricultural economic models: International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT) (39) and Global Biosphere Management Model (GLOBIOM) (40), with regional stakeholders providing iterative feedback. These models explore long-term consequences of stakeholder-generated futures, such as market dynamics and food prices, land use change, and greenhouse gas emissions. The models also allow stakeholder assumptions about regional socioeconomic change to be compared against long-term global socioeconomic projections, such as future global food demand. Additionally, the models allow for the application of the impacts of climate scenarios, through crop model outputs, on the socioeconomic scenarios (39, 40).

To link scenarios to decision making, workshops were coorganized with the East African Community and partners, inviting state and nonstate participants to develop and test adaptive planning actions across the different scenarios by planning backward from desired outcomes while navigating the challenges and opportunities in the different scenarios (36). This exercise yielded both no-regrets adaptations expected to work under any scenario with appropriate adjustment, as well as scenario-specific options. For example, combining regionally coordinated food reserves with an early warning system for food crises was deemed unfeasible in a scenario that was characterized by strong regional political instability and fragmentation, but feasible in other scenarios.

Other policy objectives, such as increased participation of farmers' associations in policy development for more effective links between farmers' needs and policy decisions and the fostering of community-led experiments with climate-resilient indigenous crops, were seen as generally feasible across all scenarios, but the pathways and actors needed to achieve them varied strongly between the scenarios. Decision makers attested that the scenario exercise equipped them with a diverse set of strategies to achieve those objectives, while also establishing the need for strategic rather than linear planning.

Participants from the East African Community countries and Ethiopia said they appreciated this open approach; they thought the model outputs were "tangible and practical" and helpful for policy makers wanting "legitimate information before making choices." CCAFS is facilitating a regional learning partnership in 10 African countries, in which representatives of national governments are using the scenarios, together with evidence from case studies of agricultural adaptation, for adaptation planning where such decisions were previously based entirely on projections from climate models. This partnership has resulted in African negotiators, for the first time, making submissions on agriculture to the United Nations Framework Convention on Climate Change Subsidiary Body for Scientific and Technological Advice.

Case 3: Robust Elevation-Based Adaptation Options in Coffee-Growing Regions of Central America. This case study shows how high scientific uncertainty can be irrelevant at the time and spatial scale of the decision required to address the problem. In the mountainous regions of Latin America, Arabica coffee is a mainstay source of income for smallholder farmers, and a commodity that generates significant economic benefits for rural service providers and global supply chains. In Nicaragua, 14% of agricultural gross domestic product is derived from coffee (41). *Coffea arabica* is grown in a very narrow climatic niche, requiring mean temperatures of 19–22 °C with little intraannual variation and ample rainfall. Furthermore, coffee is a perennial crop, planted either in exposed full-sun conditions or under shade, with significant upfront investments and a desired cropping cycle of 15 y or more. Thus, the crop must be grown across specific altitudinal bands of suitable temperature, and changes in growing areas are multiyear investments. In Nicaragua, the altitudinal band is 400–1,400 meters above sea level (masl) (42), and in Colombia 1,200–1,800 masl. Temperature in Colombia reduces by 0.5 °C for every 100 m elevation, so this altitudinal range corresponds to ~3 °C. If global temperature rises stay, optimistically, within 2 °C, this would mean a 400-m change in the elevation range of the crop or, in other words, a loss of two-thirds of the current altitudinal band, which makes high-value coffee production particularly vulnerable to climate change. An evaluation of the impacts of climate change on suitability to grow coffee using general circulation model (GCM) scenarios for 2030 and 2050 in Nicaragua (42) reported a very significant decrease in suitability of 80% of potential area for coffee production by 2050, as the zones suitable for the crop move up the altitudinal gradient, and in many important coffee-growing regions simply run out of mountain to climb.

The most important finding of this work is that despite differences among 19 GCM projections, they show absolute agreement with regard to shifts in crop suitability across the altitudinal gradient. Between 400 and 1,200 masl, covering over 90% of the land currently suitable for coffee, there is full agreement among models that suitability will reduce, and a threshold at which coffee will be profitable can be identified. Likewise, above 1,600 masl (covering only the tops of mountains) there is full agreement between all GCMs that suitability will increase. This finding has significant implications for climate change adaptation planning. Even when the significant uncertainty is fully quantified through impact analyses (from climate models through to impacts then adaptation actions), there are robust no-regrets actions for specific farming altitudes.

The altitudinal bands correspond to progressive levels of incremental, systemic, and transformative adaptation (19). Policy derived from impact analyses could enable crop substitution in low elevations under a no-regret basis, and start the transformation from one high-value perennial cropping system to another (e.g., cocoa). In high elevations, where natural ecosystems commonly provide water and other environmental services for downstream urban populations, policies may look to control the expansion of coffee farming, or to ensure that any high-elevation expansion of the crop is achieved without detriment to the environment. At mid-elevation, incremental adaptation through greater shading and other management practices will suffice in areas higher than the threshold for profitable coffee production, but nearer the threshold altitude, system-level adaptation such as diversification will be the more appropriate response. Thus, tradeoffs exist that require sophisticated policy, but the inherent uncertainty from climate is not a major concern in defining that policy.

Case 4: Informing Adaptation Using Crop and Climate Models. The ongoing focus on quantifying uncertainty in impact analyses serves to avoid overconfidence in projections. However, this focus can also lead to the impression that nothing is known for certain. We conducted an extensive analysis of yields on a range of timeframes using multiple models for one crop in one location, and found a relatively small number of climatic uncertainties (*SI Appendix*, *Text S1*). This small study therefore demonstrates that not all uncertainties are equally important, which in turn begs the question: For what time horizons is uncertainty sufficiently small to enable meaningful predictions? The results from case 3 suggest that the answer to this question will vary according to the location and type of agricultural system studied. Two further studies, for crop yield in two locations, elucidate this point and in doing so provide the underpinning numerical analysis for the framework presented above.

First, a decomposition of the uncertainty was conducted to assess the predictive capacity of decadal mean wheat yield simulations in Northeast China for the period 1980–2099, as influenced by climate variability and change. Four separate GCM ensembles were used, corresponding to no change in crop variety, use of variety tolerant to heat stress during flowering, and two other adaptations. Each ensemble comprised 136 equally likely yield projections that quantify uncertainty in climate and crop simulation for a given scenario [IPCC Special Report on Emission Scenarios A2 (SRES A2)]. The uncertainty decomposition method used (*SI Appendix*, *Text S2*) permits the total uncertainty in simulation of decadal mean yields (noise) to be compared with the change in decadal mean yield (signal). It also identifies the individual contributions to total uncertainty of the crop model, the climate model, and interannual variability in crop yield. The results, presented in Fig. 3, demonstrate that decadal mean yields are predictable (i.e., the signal is greater than the total uncertainty) for a more heat-tolerant crop, but not for a crop that is susceptible to heat stress. This difference is due to increases in extreme heat stress increasing the interannual variability of yield.

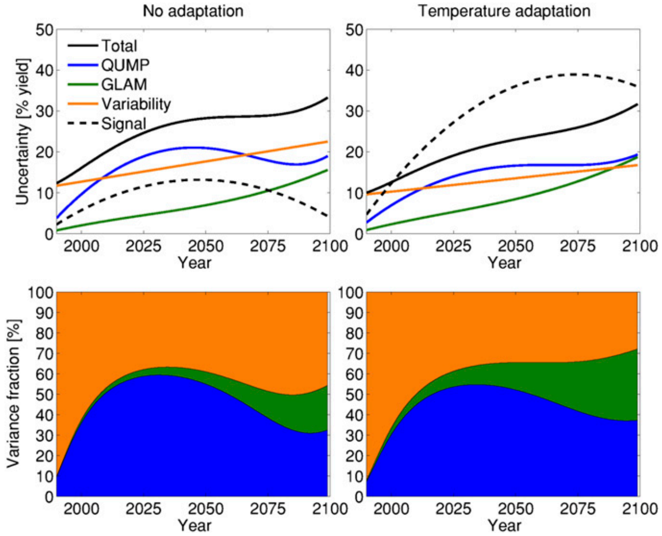

Fig. 3. Uncertainty in decadal mean wheat yield in China, decomposed by source (*Upper*): climate ensemble (QUMP, blue), crop ensemble (GLAM, green), and natural variability in decadal mean yield (orange). The total uncertainty (black) and change in decadal mean yield normalized to the baseline (signal, dashed black) are also shown. The signal in decadal crop yields is detectable when it exceeds the total uncertainty. (*Lower*) Fraction of total variance explained by the three separate components of uncertainty. These metrics are shown assuming no adaptation (*Left*) and temperature adaptation (*Right*). Details of calculations are given in *SI Appendix*, *Text S2*.

The second example in this case study demonstrates that the impact of extreme events on water stress is predictable on seasonal timescales. We found significant seasonal predictability of high and low yields of groundnut in West Africa (*SI Appendix*, *Text S3*). In contrast, less extreme departures from average yields are less predictable: root mean square errors are commonly in the range 15–40% of mean yield. Thus, at long lead times, extreme events limit the predictability of mean yields, whereas at short lead times the impact of the extremes themselves may be predictable. This finding demonstrates the importance of extreme events across a range of timescales and suggests that there is scope for near-term forecasting of impacts of extreme events to support incremental or systemic adaptation strategies.

What about adaptive planning at longer timescales? The behavior of a hypothetical perfectly heat-tolerant crop provides an upper limit to the benefit of heat tolerance. By removing the impact of heat stress and then decomposing uncertainty, we demonstrate the effect that heat stress has on the predictability of mean yield, a result that could not be derived from knowledge of crop physiology alone. Fig. 3 *Upper Right* shows that decadal mean yields of this heat-tolerant crop are predictable. The maximum predictability occurs ∼2050–2070, with the subsequent decline being largely due to crop, rather than climate, uncertainty (Fig. 3, *Lower Right*; see also *SI Appendix*, *Text S2*). Significant changes in decadal mean yields may themselves suggest a change in crop suitability, indicating the need for systemic or transformative adaptation. However, in this case mean yields increase due to elevated CO_2. Adaptation to these new conditions might include the use of additional fertilizer to obtain greater gains from the change in atmospheric composition. Thus, for this heat-tolerant crop, climate information can be used to inform adaptation over long time periods. In this example, the adaptation maximizes yield gain, rather than minimizing or mitigating yield loss. This numerical illustration of a method to determine when a climate change signal emerges from the noise of current climate variability provides some of the theoretical basis for the framework outlined in Fig. 2.

Analysis of uncertainty is important not only for the development of robust statements based on existing knowledge and models, but also for identifying where efforts to reduce uncertainty would result in the most significant gains. All three examples presented in this case study confirm previous findings (43) that increased efforts to collect and maintain crop yield datasets may result in improved predictive ability at a range of timeframes (*SI Appendix*).

Conclusions

We provide a framework for considering adaptation options for different time frames. We have presented two case studies in which quantitative tools have assisted decision making under uncertainty in adaptation planning processes over shorter (Sri Lanka) and longer (East Africa) time horizons. Stakeholder processes, crucial to wicked problems, can incorporate useful information from analyses of capacity and of impacts. A further two case studies provide evidence on how predictive models can identify uncertainties that are more or less relevant to decision making in specific timeframes and circumstances. We find that uncertainty does not preclude robust decisions on adaptation actions, and that exploring uncertainty can assist with decision making.

Materials and Methods

Case 1. The Sri Lankan National Climate Change Action Strategy was developed through a three-stage process: (*i*) preparation of sector vulnerability profiles (SVPs) for five key sectors, using an iterative participatory process to refine content of the SVPs and to identify and prioritize areas for future investment, (*ii*) synthesizing these sector-based analyses into one cohesive national adaptation strategy, which includes a program for priority action and investment, and (*iii*) targeting of priority districts based on the vulnerability profiles.

Case 2. Approximately 40 multisectoral policymakers and technical professionals convened over 12 mo to define scenario parameters, describe and systematically assess developments per scenario for each key food security determinant, and plot and compare each assessment of food security outcomes. The four scenario narratives were then quantified using the IMPACT and GLOBIOM models of global food supply, demand, trade, prices, and food security, and land use competition.

Case 3. Historical climate data were obtained from the WorldClim database (www.worldclim.org). Statistical downscaling of 18 GCMs was done to provide projections of future climates at 10-, 5-, and 1-km resolution surfaces. In all cases, we used the IPCC scenario SRES A2a ("business as usual"). The method assumes that the current mesodistribution of climate will remain the same, but that regionally there will be a change in the baseline. Though in some specific cases this assumption may not hold true, for the great majority of sites it is unlikely that there will be a fundamental change in mesoscale climate variability. Suitability was estimated using MAXENT, a general-purpose method to estimate a target probability distribution based on maximum entropy, subject to a set of constraints that represent incomplete information.

Case 4. Full methods are given in *SI Appendix*. GCM ensembles were used with single models of crop growth or suitability [General Large-Area Model for annual crops (GLAM), EcoCrop, CROPGRO]. For the signal-to-noise analysis, the signal (s) in yield for each projection is defined by fitting a second-order polynomial to the yield data; the residuals from this fit represent the variability in yield (v): $Y_{q,c}(t) = s_{q,c}(t) + v_{q,c}(t)$, where the subscripts refer to the QUMP (q) or crop (c)models used. The uncertainty in yield due to the choice of climate model and crop model are defined as $U_q = \sigma(\overline{S}_q)$ and $U_c = \sigma(\overline{S}_c)$, respectively, where $\overline{S}_q$ represents the mean across the crop ensemble for each QUMP member, and $\overline{S}_c$ represents the mean across the QUMP ensemble for each GLAM member. Finally, the variability component of uncertainty is defined as a best-fit linear trend to $\sigma(v_{q,c})$, using all members.

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