Expl Agric. (2011), volume 47 (2), pp. 395–410
doi:10.1017/S001447971100010X

ASSESSING AND ADDRESSING CLIMATE-INDUCED RISK IN SUB-SAHARAN RAINFED AGRICULTURE: LESSONS LEARNED

By R.COE†,‡,§ *and* R. D. STERN†

†*University of Reading, UK and* ‡*World Agroforestry Centre, PO Box 30677, 00100 Nairobi, Kenya*

(*Accepted 25 January 2011*)

SUMMARY

A defining characteristic of many rainfed tropical agricultural systems is their vulnerability to weather variability. There is now increased attention paid to climate-agriculture links as the world is focused on climate change. This has shown the need for increased understanding of current and future climate and the links to agricultural investment decisions, particularly farmers' decisions, and that integrated strategies for coping with climate change need to start with managing current climate risk. Research, largely from an Association for Strengthening Agricultural Research in Eastern and Central Africa (ASARECA) project to demonstrate the value of such increased understanding, is presented in this issue of the journal. Key lessons from this research are as follows:

1. Statistical methods of analysis of historical climate data that are relevant to agriculture need not be complex. The most critical point is to describe the climate in terms of events of direct relevance to farming (such as the date of the start of a rainy season) rather than simple standard measures (such as annual total rainfall).
2. Analysis requires access to relevant data, tools and expertise. Daily climate data, both current and historical, are primarily the responsibility of national meteorological services (NMS). Accessing such data, particularly daily data, is not always easy. Including staff from the NMS as research partners, not just data providers, can reduce this problem.
3. Farmers' perceptions of climate variation, risk and change are complex. They are keenly aware of variability, but there is evidence that they over-estimate risks of negative impacts and thereby fail to make use of good conditions when they occur. There is also evidence that multiple causes of changes are confounded, so farmers who observe decreasing crop production may not be distinguishing between rainfall change and declining soil fertility or other conditions. Hence any project working with farmers' coping and adaptation to climate must also have access to analyses of observed climate data from nearby recording stations.
4. Mechanisms for reducing and coping with risks are exemplified in pastoral systems that exist in the most variable environments. New approaches to risk transfer, such as index-based insurance, show potential for positive impact.
5. Skilful seasonal forecasts, which give a better indication of the coming season than a simple average, would help farmers take decisions for the coming cropping season. Increasing meteorological knowledge shows that such forecasting is possible for parts of Africa. There are institutional barriers to farmers accessing and using the forecast information. Furthermore, the skill of the forecasts is currently limited so that there are maybe still only a few rational choices for a farmer to make on the basis of a forecast.

With the justified current interest in climate and agriculture, all stakeholders including researchers, data providers, policy developers and extension workers will need to work together to ensure that interventions are based on a correct interpretation of a valid analysis of relevant data.

§Corresponding author. r.coe@cgiar.org

INTRODUCTION

In the preface to this issue, Cooper and Coe (2011) point out that there is increasing evidence that the quantification of climate risk and its management can greatly support risk-averse farmers' decision-making process and hence enhance the adoption of more sustainable and productive farming practices. The studies presented in this special issue illustrate a range of such tools, their effectiveness, their limitations and some of their challenges. In this paper we summarize the key lessons from them and pose further questions which they raise.

Most of the studies were initiated and supported by a project funded by the Association for Strengthening Agricultural Research in Eastern and Central Africa (ASARECA) titled 'Managing Uncertainty: Innovation Systems for Coping with Climate Variability and Change'. The project had the aim of informing agricultural decisions and investment on coping with risks and realizing opportunities associated with climate variability and change in Eastern and Central Africa. The project also aimed to identify ways of including climate-related activities in further initiatives funded through ASARECA.

There were three main components:

1. A review of the state of knowledge and availability of tools in the region (van de Steeg *et al.* 2009).
2. Linkages with, and capacity building of national meteorological services (NMSs).
3. Small projects designed as case studies that have led to this publication and other outputs.

The importance of the general topic is evident. The agricultural science community has taken seriously the task of understanding the implications of climate change and so have (maybe to a greater extent) the rural development community. Staff in one national agricultural research programme explained to us that some donors now demand a climate change component in every project proposal. Staff comply but are then unsure how their general statements can translate into well-defined project activities. We hope that the papers in this edition provide some ideas.

There is also evidence that governments, aid organizations and local people within East Africa have been so sensitized to the threat of climate change that almost any moderately extreme weather event, or even weather that does not conform to a current ideal, is labelled as being a consequence of climate change. Osbahr *et al.* (2011, this issue) state 'Scientific "truths" of global climate change may have turned into myths about environmental change at the local level.' If reactions to climate change are to be realistic and constructive they need to be based on an objective assessment of what is happening and is likely to happen to the climate, and to understand this in the context of other changes that are known to be occurring, such as increasing population pressure and soil degradation.

The weather has, of course, always been variable and that variability is a defining characteristic of agricultural environments even in the absence of any climate change. Within the tropics, the relative variability (the coefficient of variation) of rainfall is closely related to the mean, with locations of lower average rainfall experiencing greater relative year-to-year variation (Cooper *et al.*, 2009). Hence risks and uncertainties are generally larger in drier zones. Rural livelihood systems have evolved to cope with this variation to some extent, but two obvious questions are as follows:

- To what extent can formal analysis of the variability lead to increased insights and improved livelihood options?
- Can such analysis help to clarify the distinction between what is a change and what is expected anyway?

The lessons from the cases that are discussed here help answer these questions.

Jarvis *et al.* (2011, this issue) puts the ideas of climate risk analysis described in the other papers into the broader context of strategies for handling the implications of climate change for agriculture. The first of the three components of their mitigation and adaptation strategy is the management of climate risk. The case they make reinforces that provided by Cooper and Coe (2011, this issue) justifying the focus of the work reported here. The other two components of their strategy are accelerated adaptation and emissions mitigation. These two components also require an understanding of risk, because risk and variation will continue to be a determinant of agricultural investment. The usual basis for describing current risk is the analysis of the recent past. Estimating risk for evolving and future climates is, of course, more complex and the results are correspondingly less certain.

STATISTICAL ANALYSIS

Despite the ubiquity of experience and interest in climate variability, the basic concepts concerned seem to cause confusion. The IPCC's famous 'hockey stick diagram' (IPCC, 2007) was controversial in part because of different understandings of the idea of climate change and trend. The starting point is the common experience that, at any location, the weather shows some typical pattern though the year. These patterns repeat, with some variation, each year. The climate is then defined as that typical pattern, which is quantified statistically as an average. The typical or average pattern includes variation – it is typical for the weather to be different from one year to the next, within some range. Statistical summaries of climate therefore usually include quantities that describe both the average and a measure of variation. For example the total rainfall for January for a given site and set of years is summarized by giving the mean as well as the standard deviation, or another measure of variation, such as the chance or risk that the total is less that 100 mm.

Stern and Cooper (2011, this issue) show that it is simple to calculate such summaries of mean and variation or risk. If daily data are available they also demonstrate that it is possible to tune the analyses to real questions of relevance in agriculture – such as the date of the start of a rainy season. Further, the event or climate characteristic described can be as complex as needed as long as it is driven by climate data. They give the example of an estimate of risks for a measure of crop water balance, while

Dixit *et al.* (2011, this issue) do so for a crop yield simulated from climate data and Farrow *et al.* (2011, this issue) estimates disease risk. Any other agriculturally important quantities that depend on variation driven by climate, such as prices, could similarly be evaluated if a model is available that describes their connection to the climate. An intriguing example of pest dynamics is given by Cheke *et al.* (2007).

The confusion arises when we start looking at climate change. Part of the problem is that calculation of climate averages, including risks, requires multiple years. The standard set by WMO (1983; 2007) for calculating climate normals is 30 years, but there is no strong reason for selecting that time span. But if we think the climate might be changing, why average across years? The trend should first be estimated and then subtracted from the data. The second problem is that formal statistical tests of differences between periods or of smooth trends depend on assumptions that can be hard to justify. Most tests, such as those for trend used by Stern and Cooper (2011, this issue), require the assumption that, once a smooth trend has been allowed for, the remaining variation between years is random with constant variance and uncorrelated from year to year. Whether that is true is something we actually want to find out. Strictly, independent replicate series are needed to unambiguously distinguish trend from random variation, in much the same way that experimenters need replicates to distinguish real treatment effects from plot-level noise. While having data from more than one location helps, it does not solve the problem as (a) trends in different places may be different and (b) the weather at different places may not be independent. Real replicates would mean having replicate planet Earths, which we do not have. So some compromises are necessary. We assume that simple trend curves do indeed account for all the change and assess the size of that change relative to remaining year-to-year variation. Stern and Cooper (2011, this issue) then show that our problems are not over. From these and other examples in Africa it is clear that there has always been some trend or change in rainfall so that the apparent patterns depend on when you start the analysis and how smooth you assume any trend to be.

Three other important lessons from Stern and Cooper (2011, this issue) are:

1. It is as easy to look at trends in occurrence of agriculturally important weather events as it is to look at rainfall totals – but with the same problem of distinguishing annual variation from a shift in the mean.
2. Pulling apart a simple climate measure – for example looking at the number of raindays and amounts per rainday rather than rain totals, or separating El Niño from normal years, often gives a clearer picture of trends.
3. Estimates of risks for important climatic events, based on Markov chain-type modelling of the daily rainfall data, can be obtained from relatively short records of the data. Stern and Cooper (2011, this issue) give an example from just a six-year record.

One further technique that could have been included is the use of a 'sliding window' of years to show changes in a variance or risk. One prediction of global circulation models is that rainfall in East Africa might get more extreme. The extent to which that is evident could be checked by calculating a risk or variance for a moving 30-year period. Another approach to estimating climate risks in the face of change would be to consider variation around a trend rather than around a constant 'normal'. Risk estimates for the immediate future (next couple of years) derived from such a model might be more realistic than those without a built in trend. The methods based on modelling daily rainfall probabilities, described by Stern and Cooper (2011, this issue) would be one method of doing this.

One result that stands out from all the climate series presented in these papers is that any trends or changes in the mean rainfall are small compared with the random year-to-year variation. This reinforces the conclusion from Cooper *et al.* (2009) that an understanding of the farmer's options for coping better with current variation is a necessary preparation for adaptation to future climate change. For example, the response from an NMS employee to the request, during a meeting, for an estimate of climate change at a site in 2080, was (without a reference) that the mean annual rainfall is expected to be 5% less than at present. Currently the mean is about 1000 mm, so a 5% reduction would give a new mean of 950 mm. However, a 1000 mm mean implies totals in individual years that are usually between about 500 mm and 1500 mm. Hence, even if this statement of a 5% change is true, it would not imply many years with a rainfall outside the experience of recent past years. This situation does not necessarily apply to temperature changes. The effect of (say) a 2 °C rise in the maximum and minimum temperatures could be much more serious. Nor do we wish to imply that changes in rainfall climate are not important. An agricultural activity that is just viable at present may become unviable with only modest changes in rainfall risk.

The weather we experience occurs as a spatial process yet most analyses, including those referred to above, consider data from individual locations separately. This is because direct measurements of climate are collected at individual locations, there are often problems of accessing data from many stations (see section on 'Access to data and tools' below) and, until recently, repeating analysis for many places was very time-consuming. Two papers in this collection take a spatial approach. Farrow *et al.* (2011) map the risk of bean root rot and Gathenya *et al.* (2011) map hydrological processes and integrate them to estimate stream flow. These two analyses differ from each other in an important methodological way. The risk of bean root rot was estimated for each location with a separate climate record and the resulting probabilities were then mapped. This approach to analysis cannot estimate the risk that two locations both have bean root rot in the same year. Farrow *et al.* (2011) had to use simulated data due to unavailability of measured records and we do not yet have the tools to simulate rainfall fields that realistically reproduce the correlation between different stations. However, the approach with independent data at each site limits the value of the analysis, as the problem of bean root rot (or many other risky agricultural outcomes) depends on the area over which the problem is experienced at the same time. If one farmer loses her crop due to rot, it is a problem for her but will have little impact on others. If all the bean farmers in a large area lose their crop at the same time then it could have major implications for markets, consumers and food security. This idea is referred to as 'covariate risks', and its importance is described in the index-based insurance literature (e.g. Barnett *et al.* 2008).

The analyses by Gathenya *et al.* (2011, this issue) use observed daily data measured on the same day for the whole watershed, so that, for example, the flow at the outlet will depend on whether it rains everywhere in the catchment on the same day or not. The use of the real data means that the spatial correlations are automatically included. However, their analysis is still limited by data availability and so again compromises are necessary to make progress. They take the rainfall at any point in the watershed as equal to that at the nearest gauge. This might have the effect of overestimating the spatial coherence of rainfall and hence overestimating the high and low flows at the outlet. Spatial analysis of the rainfall patterns may give some insight into the scale at which rainfall tends to be coherent, but it will not suggest a way of filling the gaps if the spatial scale is found to be less than the distance between gauges, something that will probably have to be done by simulation. A lesson from this is that we need better climatological information on spatial organization of rainfall at different time scales and tools adapted for using the space-time information.

The availability of remote sensed climate data from satellite and radar imagery changes the status of spatial climate analysis as the raw data are spatial. In this special issue, only Farrow *et al.* (2011) attempted to use satellite-derived rainfall data. They show very low correlation between the estimates of three-day rainfall for the 25 km × 25 km cell produced from satellite data and that measured at a single gauge within the cell. These remote sensed data are probably better for estimating rainfall over longer periods (Coppola *et al.*, 2006) and will certainly improve over time. Estimates of rainfall from numerical weather models are also becoming available (Diro *et al.* 2009). UNEP (2011) provides an example of the results that can emerge from looking at climate trends using spatial data. When spatially interpolated rain gauge data are combined with satellite-based estimates of vegetation response to rainfall at a regional scale (West Africa), the results provide an intriguing picture of the way rainfall patterns have shifted in space over time.

ACCESS TO DATA AND TOOLS

A key message from the account of statistical analysis (above) is that an analysis of climate data to give highly useful information on averages, variability, risks and trends is not difficult, but it requires access to data and tools and also the capacity to use them. The data requirements depend on the actual question but most analyses of agricultural importance need rainfall. In addition, crop modelling requires temperature and, ideally, radiation and evaporation data. For most crop models, these are needed as daily records.

Averages can be estimated from relatively short records: 20 years will give a mean with precision equal to about 20% of the annual variation. Estimation of risks requires longer records, the length needed depending on how extreme the risks to be estimated are. Analysis of trend inevitably requires long series. There are international public archives of climate data, for example at the Global Observing Systems Information Center (http://gosic.org), the World Data Centre for Meteorology (http://www.ncdc.noaa.gov/oa/wdc/), the Intergovernmental Panel on Climate Change Data Distribution Centre (http://www.ipcc-data.org/obs/) or the Climatic Research Unit at the University of East Anglia, UK (http://www.cru.uea.ac.uk/cru/data/). However, the data available from such archives is often already summarized as monthly averages or totals, sometimes on a gridded basis. Rainfall data in these archives are sometimes estimated from satellite observations, rather than from ground stations. There remains great potential for combining information from ground stations with satellite estimates, but further work is needed on the methods. However, the primary sources of daily climate records are still the NMSs. In East Africa, as elsewhere, a substantial collection of climate data is held by NMSs, though they would always like further recording stations. Some climate projects view the NMS largely as a source of data and can be disappointed at the time and, sometimes, the cost of obtaining the observations they need. Difficulties include:

1. Poor communications within meteorology services, so that requests for data become lost in bureaucracy.
2. Metadata describing what climate records actually exist not available.
3. Some daily data, particularly for variables other than rainfall are still only in paper format.
4. A requirement that NMSs sell data as a cost recovery mechanism.

Once electronic copies of data are obtained, further common difficulties include:

5. Reformating of data to prepare it for analysis.
6. Data errors due to inadequate quality management.
7. Missing values which, for some purposes (e.g. crop modelling) require imputation.

The ASARECA project sought to engage with NMSs from the start. They were contacted at the earliest possible stage when there was a first draft concept note and they responded positively and enthusiastically. About a quarter of the funds were allocated to activities concerned with collaboration and capacity-building that involved the NMS staff directly. The aim was for the NMS staff to become full partners in the research, rather than be largely providers of the data. The challenges this poses for the NMS are considerable and are spelled out in detail in IRI (2006).

The usual responsibilities of a NMS currently include the following:

- Provision of short-term weather forecasts
- Support for aviation
- Provision of seasonal forecasts.

These responsibilities all build on the physics skills that are routine in the training of NMS staff. However, they are also custodians of the historical data they and others have collected. Building statistical capacity of NMS staff along with partners in the agricultural teams would allow them to process their own data. They could then join research teams based on their skills and be able to add value to their own data, rather than simply supply it to others. Many NMSs also have staff who collect the climate data at individual stations, often including agricultural research stations. It would be ideal if these staff had the skills to analyse the data they collect and provide products to local clients, thus decentralizing some of the NMS activities. Hence the statistical capacity-building in the ASARECA project was also for some of these staff.

Despite the collaboration, this part of the ASARECA project was not a complete success. Thus few of the papers in this issue were able to include NMS staff as authors and some, such as Dixit et al (2011), illustrated that partnership does not guarantee immunity from frustrations in being able to access and use daily climatic data. What were the main lessons learned? Discussions at the end of the ASARECA project re-enforced the view that the strategy of partnership was appropriate and should be continued in future climatic work. Where there are problems, all partners need to recognize the formidable nature of the challenges and try harder rather than change direction. This includes the NMSs themselves, who agreed that they need to become more proactive if staff are to develop the skills to the level needed to become fully involved in future agro-climatic research activities. It would also help if more information about analytical capacity and data holdings, including meta-data, were routinely available on the NMS websites. Ethiopia sets a good example at www.ethiomet.gov.et.

It was clear early in the ASARECA project that crop simulation models would play an important role in the work. These models transform climatic variability into estimated crop growth and yield variability for a wide variety of crops and crop, soil and water management practices. This enables us to phrase risk statements in terms of their impact on yields and to assess the effect of alternative cropping strategies on this risk. If crop modelling is done using say APSIM (Keating *et al.*, 2003) in Australia, it is easy to get the climatic data, see www.longpaddock.qld.gov.au/silo/. Modellers can then concentrate on the soil, crop and agronomic characteristics. In Africa the large effort currently needed to arrange for climatic data in the right form for the crop models is a serious limitation. The African NMSs could remove this limitation. Being able to provide data in relevant formats with documented quality assurance procedures and supporting expertise to use the data effectively could turn these services into sought-after partners in agricultural research and development. Without taking this step, the NMSs risk being sidelined as data acquisition and access become more international.

The practical difficulties of obtaining daily climatic data led some of the studies reported in this issue to make use of MarkSim (Jones and Thornton, 2002). This software is a tour-de-force, particularly considering that it was work mainly done more than 10 years ago. Dixit *et al.* (2011) and Farrow *et al.* (2011) demonstrate that MarkSim can generate synthetic rainfall series that accurately show patterns of variability that are important in agriculture. However such models, which are based on very simple descriptions of rainfall processes, will never be able to reproduce all important characteristics of the data. For example, real rainfall series often show much longer-term memory than assumed by the Markov chain models used in MarkSim. Moreover, given when it was developed, it would be excellent if an updated version could be produced. This could be in collaboration with the respective NMSs, as it complements what they will be able to provide in the future. A new version should use improved underlying models of the pattern of rainfall, temperatures and radiation, use a more complete database, and allow integration of observed and simulated data in various ways. It could also allow the possibility of modelling trends over time. A further enhancement would be the generation of rainfall fields with realistic spatial correlation structure. Such a development of 'MarkSim Mark 2' would be a substantial undertaking but would be a valuable addition to the climate analysis toolbox.

Climate data are not the only data needed. The crop simulation models integrate a large data-based collection of evidence and still need calibrating for particular problems using field experiments. Simpler models – for example, as used by Farrow *et al.* (2011) to relate weather to bean root rot outbreak – also require field data. The bean root rot example is based on rather weak evidence of the weather events that trigger the disease. This raises the question of how more robust data should be collected. What spatial scale is relevant – should the presence of the disease be observed at plant, plot, field or larger scale? At what distance away does meteorological data need recording? Are standard weather variables sufficient or should others (e.g. soil or leaf moisture) be observed? What covariates, such as soil texture, are needed? Modelling is not going to reduce the need for insight and skills in designing effective field data collection, but it can provide useful guidance.

Statistical software of sufficient quality and generality are freely available. The most comprehensive open source statistics software is R (R Development Core Team, 2009), but it does not currently have tools specifically developed to implement the type of analyses described by Stern and Cooper (2011). Instat (University of Reading, 2008) is much less comprehensive but has built-in facilities for analysis of events of agricultural significance in daily rainfall records and comes with a comprehensive guide to such analyses. A version of Genstat (VSN International, 2010) is freely available to researchers in developing countries and also has a guide to the analysis of climate data (Gallagher and Stern, 2009).

The value of modelling crop response to climate has been demonstrated here by Dixit *et al.* (2011) and in numerous other studies. APSIM (Keating *et al.*, 2003) and the DSSAT suite (Jones *et al.*, 2003) are standard models which have been widely used for annual crops. Researchers have developed and published numerous other models to simulate other weather-related systems (Matthews and Stephens, 2002) and to broaden the scope beyond annual crops – for example Wanulcas (van Noordwijk *et al.*, 2004) simulates tree-crop interactions in agroforestry systems. All these models have the characteristic of providing realistic descriptions of many processes, but require considerable skill and experience to use them. An alternative approach is to develop simpler models that meet specific purposes. Simple models, such as the FAO water balance model used by Stern and Cooper (2011), can be constructed without use of modelling tools. More sophisticated models become easier for non specialists to construct using modelling software such as Stella (www.iseesystems.com/softwares/Education/StellaSoftware.aspx). These tools allow modellers to concentrate on the logic and performance of a model rather than the details of computer code.

PERCEPTIONS AND ATTITUDES TO RISK AND CHANGE

Osbahr *et al.* (2011) and Rao *et al.* (2011) investigated farmers' perceptions of climate variability and change and also their attitude to climate risks. Their conclusions are similar and contain important lessons for the growing number of initiatives that include an assessment of farmer perceptions in climate change adaptation and mitigation projects. Both papers combined a survey with the analysis of climate data from nearby stations, the latter component being rare in projects that aim to help farmers take action to reduce climate risks. The results showed that farmers are well aware of climate conditions in their area, its season-to-season variability and its impact on crop performance. Farmers were also able to recollect recent seasons fairly accurately, especially the 'good' and 'poor' seasons which matched well with the meteorological records. However recollections become rather vague after more than about five seasons. Farmers classification of seasons into 'good', 'average' and 'poor' is based on criteria that include a complex mix of factors that relate to the outcome of their activities. These include rainfall, onset and cessation of the rainy season, and distribution of rainfall especially in relation to critical stages of growth. The near uniformity among the farmers in defining the criteria is a clear indication of their good understanding of the climate.

However, there were some distinct differences between farmers' assessments and researchers' conclusions based on analysis of climate data. Two factors seem to be important. First, farmers compare the weather in one season with an assumed ideal for their conditions, rather than the actual long-term pattern, mentally replacing 'rainfall expected' with 'rainfall hoped for'. Secondly, farmers over-estimate the risk of poor conditions and so reduce opportunities for benefiting from good conditions.

Both Osbahr *et al.* (2011) and Rao *et al.* (2011) elicited farmers' perceptions of climate change and compared them with the climate record. Farmer observations in these locations, that rainfall patterns are changing, agreed well with reported perceptions from other places across the African continent. They were also internally consistent between different groups of farmers, but they were generally not consistent with observed records. Whilst Osbahr *et al.* found both farmers and the climate data agreeing on increasing temperatures, there is limited evidence from these locations for the changes in rainfall amount, seasonality or extreme events that farmers report. There are some subtle rainfall patterns that do support some of the farmers' perceptions. For example, in this bi-modal rainfall region in Uganda, the risk of increased mid-season drought observed in the first season (March–May) by farmers was also suggested in the climate data, where the first season was found to have a less reliable distribution than the second season and the persistence of rain on consecutive days is now more likely in the second (October–December) season.

Both Rao *et al.* (2011) and Osbahr *et al.* (2011) hypothesize that farmers report a decline in rainfall because it is crop production that farmers recall, rather than the climate. Farmers may be reporting a decline in rainfall because their need for crop available water has changed over time and has increased demands on the rains. Rao *et al.* (2011) showed that there were clear decreasing trends in district-level maize yields at the study-locations in Kenya that could be attributed to declining soil fertility but that farmers attributed to rainfall. Other factors that might be changing and influence perceptions of climate are household economic circumstances and an increased local-level demand for water. This agrees with other studies of drought (Meze-Hausken, 2004; Slegers, 2008) that show that it is the impact on livelihood that is important in defining drought from the viewpoint of local people rather than a cause directly related to rainfall.

The two factors of confounded changes and assessment relative to ideal rather than previous weather suggest that caution is needed when interpreting results based on farmer perceptions. Two recommendations are:

1. Ensure sound methods are used when eliciting farmers' views on climate change. Such methods should not place too much emphasis on testing memory or attitudes to hypothetical situations.
2. Complement farmer knowledge with an analysis of observed climate records.

Without these there is a good chance that projects will perpetuate myths and develop interventions that fail because they are tackling the wrong problem.

A third factor that can make it hard to elicit and interpret such data is that change in climate has always happened and any description of change has to be clear about the baseline.

RISK MITIGATION AND COPING

Risk mitigation refers to actions or strategies that households pursue *ex ante* to avoid or reduce the impact of future shock or to reduce risks. Risk coping strategies are those that households pursue *ex post*, mainly to deal with the negative effects of a shock. Risk mitigation strategies may improve long-term resilience, while risk coping strategies mostly ensure survival during and after a shock. The need to address questions of risk mitigation and reducing the risks to farmers was a driver of most papers in this edition. However, only the paper on pastoral systems by Ouma *et al.* (2011) explicitly looked at current risk mitigation and coping strategies. Risk mitigation and coping are popular themes for projects motivated by global climate change. Perhaps the concepts are not so distinct, for as soon as a coping action becomes something farmers are prepared for it is then part of their system and hence something that reduces the negative consequences of a shock, and is thus part of their risk mitigation strategy. The literature on climate risk mitigation and coping is substantial. A useful overview is give by Hellmuth *et al.* (2007). Some important lessons from the collection of papers in this issue are:

1. Hansen *et al.* (2011) point out that it is not just farmers and pastoralists for whom climate risk mitigation ideas are relevant. All those along the value chain can be affected by climate risk and can probably take action to reduce those risks.

2. Dixit *et al.* (2011) show that risk and variation should not only be a concern of those operating in less favoured climates. Attention to variation in a 'breadbasket' of highland Kenya can increase productivity and profitability.
3. Current risk mitigation strategies can be complex, exemplified by the web of social and economic mechanisms found in pastoralist areas (Ouma *et al.,* 2011). Interventions to alter them will have to deal with the complexity, and hence analysis of climate data to understand the risks will need to be similarly nuanced.
4. The complexity of mitigation strategies also means that their effectiveness will be influenced by multiple changes, and they cannot be designed simply as responses to climate change. For example, Ouma *et al.* (2011) report that pastoralists see diversified livelihoods as becoming increasingly important to mitigate climate risk. Hence assessments of climate risk must include impacts on other enterprises in addition to those on livestock. Changes such as population increase and reduced options for migration must also be included in risk assessments, both current and for future scenarios.
5. An important aspect of mitigating risk is that of targeting interventions. Gathenya *et al.* (2011) predicted very different responses to interventions even in neighbouring parts of one small watershed.

Ouma *et al.* (2011) finish with the very positive message that there are new and emerging risk mitigation ideas for pastoralists that hold hope for the future. These include: (i) index-based livestock insurance, (ii) improvements in the management of food insecurity response for pastoralists (cash instead of food aid) and (iii) recasting of development interventions as risk management. It seems likely that risk mitigation for rainfed cropping farmers will need some equally innovative responses that go beyond what can be achieved by better matching of crop genotype and agronomy to climate.

SEASONAL FORECASTS

With year-to-year variation in weather being such a large component of agricultural risk, forecasts that predict the weather for the coming season would be very beneficial. Hansen *et al.* (2011) provide a comprehensive review of the methods currently being used to provide seasonal forecasts, together with steps being taken to improve the methods in the future. They state that interactions between the atmosphere and underlying oceans provides the basis for probabilistic forecasts of climate conditions at a seasonal lead-time, including during cropping seasons in parts of sub-Saharan Africa. The forecast is based on combining information from the global models with a statistical approach that relates sea-surface temperatures to the three-month rainfall totals. It is surprising that the final forecast is still produced subjectively by a consensus. We wonder what information is being brought by the participating parties that cannot be included in a quantitative data analysis process.

Hansen *et al.* (2011) accept that there remains a considerable gap between the information needed to support farm decision-making and the seasonal forecast information that is routinely available. Indeed it is often hard to see how the seasonal forecast in the format currently disseminated can be of great help to a farmer. In the absence of a forecast, the risk of the seasonal rainfall being 'below average' is, by definition, 33%. The forecast changes this, reducing it to as low as 20% or increasing it to 50%, but very rarely going outside this range. This raises the question of what decisions a farmer will change on the basis of this rather small change in probability. Hansen *et al.* (2011) propose changing from this tercile (probabilities of below average, average and above average) presentation to providing a shifted probability of any amount being exceeded. This seems correct but as the shift in probabilities is still small and as the forecast remains based on the three month rainfall totals, it still has the same problem of what actions can be taken. One limitation of forecasts of this resolution is well illustrated by the 2010 'short rains' in southeast Kenya, ongoing as this is written. The forecast was for a late start and below average rainfall. This has happened, but the rainfall distribution has matched crop requirements so crops are nevertheless performing well (K.P.C. Rao, personal communication).

Stern and Cooper (2011) and others, indicate that there is scope to work with the total number of rain days rather than only the rainfall totals. Some of the forecast skill arises because of the El Niño effect and it would be interesting to see how much skill remains after this is taken into account in describing the climatology, as in Stern and Cooper.

Hansen *et al.* (2011) report studies that show through modelling that there is useful skill in the seasonal forecasts. This is encouraging. They also claim positive results from field studies that aimed to evaluate farmers' response to forecasts. Such studies are not easy to design so that the value of the forecasts *per se* can be separated from the value of other information provided and actions taken. A well-designed experiment would require a control group of farmers that had the same level of attention as the group receiving forecasts and got all information and other inputs except the forecast itself. We have not seen results from such an experiment.

A further challenge in evaluating farmers' responses is to generate a long enough series. A probabilistic forecast that says, for example, that the chance of rain being in the lower tercile is 50% is accurate if the actual rainfall is in the lower tercile in 50% of the years that get such a forecast. In a single year, there is a 50% chance that the rain is low, and farmer's react positively to the forecast of low rain. But there is also a 50% chance that the rain is in the 'average' or 'above average' tercile, and farmers may be disappointed by the 'failure' of the forecast. Roncoli *et al.* (2009) makes the point that the positive assessment of the forecast in one season can be attributed to it actually being close to experience, but that cannot be expected to happen every year. Efforts to help farmers understand the nature of probabilistic forecasts are necessary.

The seasonal forecast is disseminated by the NMSs. There is an opportunity for NMSs to merge seasonal forecasting with their other roles of providing climate risk assessments. If questions of agricultural risk are posed long before the season, then estimates of risks can only be based on the historical data. As the season approaches, these risks could be modified, by adding the extra information that becomes available from the seasonal forecast. Then, during the season, farmers can also make use of the short-term forecast, that is routinely provided, and is usually for the subsequent five or ten days.

Hansen *et al.* (2011) describe well how constraints related to legitimacy, salience, access, understanding, capacity to respond and data scarcity have so far limited the widespread use and benefit from seasonal prediction among smallholder farmers. Constraints related to the information products and policies can be overcome, and it is probably worth doing so. However, continued effort is needed to evaluate the actual value of current forecasts to be sure we are not generating false expectations of better information than is actually possible.

Two other messages related to forecasts emerge from the papers. First, there are potential users beyond farmers, for example those responsible for co-ordinating input and credit supply, food crisis management, trade and agricultural insurance. Secondly, there is a substantial opportunity cost associated with climatic uncertainty. Forecasts can help make the most of favourable weather in the better seasons, as well as avoiding disastrous losses in the poor ones.

National Meteorological Services have achieved considerable publicity by their work on seasonal forecasting. This publicity for the service is useful, but the current seasonal products perhaps do not justify the level of publicity on their own. The seasonal products should improve over the coming years as the dynamic models of the global system continue to advance. In the interim, we suggest that the addition of further products, from the analysis of the historical data (i.e. from the sections on statistical analysis and access to data and tools of this paper) would be welcomed by users.

CONCLUSIONS

With the justified current interest in climate and agriculture, all stakeholders including researchers, data providers, policy developers and extension workers will need to work together to ensure that interventions are based on a correct interpretation of a valid analysis of relevant data. This requires capacity-building. However, many training workshops have already been held, including some within the ASARECA project, and they have had only limited impact. They have often been supply-driven rather than demand-driven and hence they have usually not been linked to proposed changes in working practices. This paper outlines the lessons we have learned from the ASARECA project, and from the other papers in this issue of the journal. Perhaps further actions, including future proposals for further capacity development, could build on the lessons that each partner has learned. One of these lessons is that, as in all scientific areas, those working on climate risk and variation need to be critical, observant, questioning and continually seeking better evidence to support assertions.

Improved methods and data sources will continue to be developed. However, the current tools and data are underused. Interventions related to climate and agriculture would be more effective if routinely linked to a thorough and insightful analysis of climate data.

Acknowledgements. We acknowledge the contribution by the African Development Bank who partially funded this work through an ASARECA Project (No. FC-1–03)

'Managing Uncertainty: Innovation Systems for Coping with Climate Variability and Change'.

REFERENCES

Barnett, B. J., Barrett, C. B. and Skees, J. R. (2008). Poverty traps and indexed-based risk transfer products. *World Development* 36: 1766–1785.

Cheke, R. A., Venn, J. F. and Jones, P. J. (2007). Forecasting suitable breeding conditions for the red-billed quelea *Quelea quelea* in southern Africa. *Journal of Applied Ecology* 44: 523–533.

Cooper, P. J. M and Coe, R. (2011). Assessing and addressing climate-induced risk in sub-Saharan rainfed agriculture. Foreword to a special issue of Experimental Agriculture *Experimental Agriculture.* 47: 179–184.

Cooper, P. J. M., Dimes, J., Rao, K. P. C., Shapiro, B. Shiferaw, B. and Twomlow, S. (2008). Coping better with current climatic variability in the rain-fed farming systems of sub-Saharan Africa: An essential first step in adapting to future climate change? *Agriculture Ecosystems and Environment.* 126: 24–35.

Coppola, E., Grimes, D. I. F., Verdecchia, M. and Visconti, G. (2006). Validation of improved TAMANN neural network for operational satellite-derived rainfall estimation in Africa. *Journal of Applied Meteorology and Climatology* 45: 1557–1572.

Diro, G. T., Grimes, D. I. F., Black, E., O'Neill, A. and Pardo-Iguzquiza, E. (2009). Evaluation of reanalysis rainfall estimates over Ethiopia. *International Journal of Climatology* 29: 67–78.

Dixit, P. N., Cooper, P. J. M., Rao, K. P. and Dimes, J. (2011). Adding value to field-based agronomic research through climate risk assessment: A case study of maize production in Kitale, Kenya. *Experimental Agriculture* 47: 317–338.

Farrow, F., Musoni, D., Cook, S. and Buruchara, R. (2011). Assessing the risk of root rots in common beans in East Africa using simulated, estimated and observed daily rainfall data *Experimental Agriculture* 47: 357–373.

Gallagher, J. and Stern, R. D. (2009). *Analysing climatic data using Genstat for Windows*. Statistical Services Centre, University of Reading, UK.

Gathenya, M., Mwangi, H., Coe, R. and Sang, J. (2011). Climate and land use-induced risks to watershed services in the Nyando river basin in Kenya. *Experimental Agriculture* 47: 339–356.

Hansen, J. W., Mason, S. J., Sun, L. and Tall, A. (2011). Review of seasonal climate forecasting for agriculture in sub-Saharan Africa. *Experimental Agriculture* 47: 205–240.

Hellmuth, M. E., Moorhead, A., Thomson, M. C. and Williams, J. (eds). (2007). *Climate Risk Management in Africa: Learning from Practice*. International Research Institute for Climate and Society (IRI), Palisades, NY.

IPCC (2007). *Fourth Assessment Report.* (www.ipcc.ch/publications_and_data/ar4/wg1/en/ch6s6–6.html).

IRI (2006). *A Gap Analysis for the Implementation of the Global Climate Observing System Programme in Africa*. International Research Institute for Climate and Society, Palisades, NY.

Jarvis, A., Lau, C., Cook, S., Bonilla, O. and Challinor, A. (2011). An integrated adaptation and mitigation framework for agricultural research development: synergies and trade-offs. *Experimental Agriculture* 47: 185–203.

Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., Wilkens, P. W., Singh, U., Gijsman, A. J. and Ritchie, J. T. (2003). The DSSAT cropping system model. *European Journal of Agronomy* 18 235–265.

Jones, P. G. and Thornton, P. K. (2000). MarkSim: Software to generate daily weather data for Latin America and Africa. *Agronomy Journal* 92: 445–453.

Keating, B. A., Carberry, P. S., Hammer, G. L., Probert, M. E., Robertson, M. J., Holzworth, D., Huth, N. I., Hargreaves, J. N. G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J. P., Silburn, M., Wang, E., Brown, S., Bristow, K. L., Asseng, S., Chapman, S., McCown, R. L., Freebairn, D. M. and Smith, C. J. (2003). An overview of APSIM, a model designed for farming systems simulation. *European Journal of Agronomy* 18: 267–288.

Matthews, R. B. and Stephens, W. (2002). *Crop-Soil Simulation Models: Applications in Developing Countries*. CABI, Wallingford.

Meze-Hausken, E. (2004). Contrasting climate variability and meteorological drought with perceived drought and climate change in northern Ethiopia. *Climate Research* 27: 19–31.

Ouma, R., Mude, A. and van de Steeg, J. (2011). Dealing with climate-related risks: some pioneering ideas for enhanced pastoral risk management in Africa. *Experimental Agriculture* 47: 375–393.

Osbahr, H., Dorward, P., Stern, R. D. and Cooper, S. J. (2011). Supporting agricultural innovation in Uganda to respond to climate risk: linking climate change and variability with farmer perceptions. *Experimental Agriculture* 47: 293–316.

R Development Core Team (2009) *R: A Language and Environment for Statistical Computing*. R Foundation, Vienna, Austria.

Rao, K. P. C., Ndegwa, W. G., Kizito, K. and Oyoo, A. (2011). Climate variability and change: Farmer perceptions and understanding of intra-seasonal variability in rainfall and associated risk in semi-arid Kenya. *Experimental Agriculture* 47: 267–291.

Roncoli, C., Jost, C., Kirshen, P., Sanon, M., Ingram, K. T., Woodin, M., Samé, L., Ouattara, F., Sanfo, B. J., Sia, C., Yaka, P. and Hoogenboom, G. (2009). From accessing to assessing forecasts: an end-to-end study of participatory climate forecast dissemination in Burkina Faso (West Africa). *Climatic Change* 92: 433–460.

Slegers, M. F. W. (2008). 'If only it would rain': Farmers' perceptions of rainfall and drought in semi-arid central Tanzania. *Journal of Arid Environments* 72: 2106–2123.

Stern, R. D. and Cooper, P. J. M. (2011). Assessing climate risk and climate change using rainfall data – a case study from Zambia. *Experimental Agriculture* 47: 241–266.

UNEP (2011). Land Health Surveillance: An evidence-based approach to land ecosystem management. illustrated with a case study in the West Africa Sahel. *Main Report. United Nations Environment Programme*, Nairobi. (In press)

University of Reading (2008). *Instat+*™ *– an Interactive Statistical Package*. Statistical Services Centre, University of Reading, UK.

van de Steeg, J. A., Herrero, M., Kinyangi, J., Thornton, PK, Rao, KPC, Stern, R. D. and Cooper, P. J. M. (2009). The influence of climate variability and climate change on the agricultural sector in East and Central Africa – Sensitizing the ASARECA strategic plan to climate change. *Research Report 22*. *International Livestock Research Institute*, Nairobi, Kenya.

van Noordwijk, M., Lusiana, B. and Khasanah, N. (2004). *WaNuLCAS Version 3.1, Background on a model of water nutrient and light capture in agroforestry systems*. International Centre for Research in Agroforestry, Bogor, Indonesia.

VSN International 2010. *GenStat for Windows 13th Edition*. VSN International, Hemel Hempstead, UK.

WMO (World Meteorological Organization) (1983). *Guide to Climatological Practices (2nd ed.)*. WMO, Geneva

WMO (World Meteorological Organization) (2007). *The Role of Climatological Normals in a Changing Climate*. World Climate Data and Monitoring Programme No 61. WMO, Geneva.