Background Paper

Human Development Report 2022
United Nations Development Program (UNDP)

Decision-making under climate uncertainty, climate information service, and climate adaptation

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June 2022

Abstract: Climate variability exerts tremendous influence on the livelihoods and well-being of people. Recent advances in climate forecasting technologies have allowed meteorological departments to produce reasonably accurate seasonal to sub-seasonal forecasts of rainfall, temperature, and extreme events (e.g., flood and drought), which has raised the prospect of developing climate information services (CISs) *customized* to local needs and conditions. This paper discusses the potential role and benefit of CISs in decision-making under climate uncertainty. More specifically, it discusses household decision-making under climate uncertainty, explores what role may CISs play in their decision-making, identifies the knowledge gaps on CISs, and highlights the main challenges in relation to their utilization, content, format, and communication. In doing so, the paper argues that provision of tailored CISs can promote adoption of climate-resilient practices for climate adaptation.

Keywords: Climate change, climate uncertainty, decision-making, CISs, climate adaptation

1. Introduction

Global surface temperatures have been rising at a historically unprecedented pace (IPCC, 2021). In addition, climate models and research also warn us for exacerbated climate and temperature variability, with increasingly erratic weather patterns (IPCC, 2021; Kotz et al., 2021; Wang et al., 2019; Bathiany et al. 2018). But these climatic patterns vary across regions of the world.

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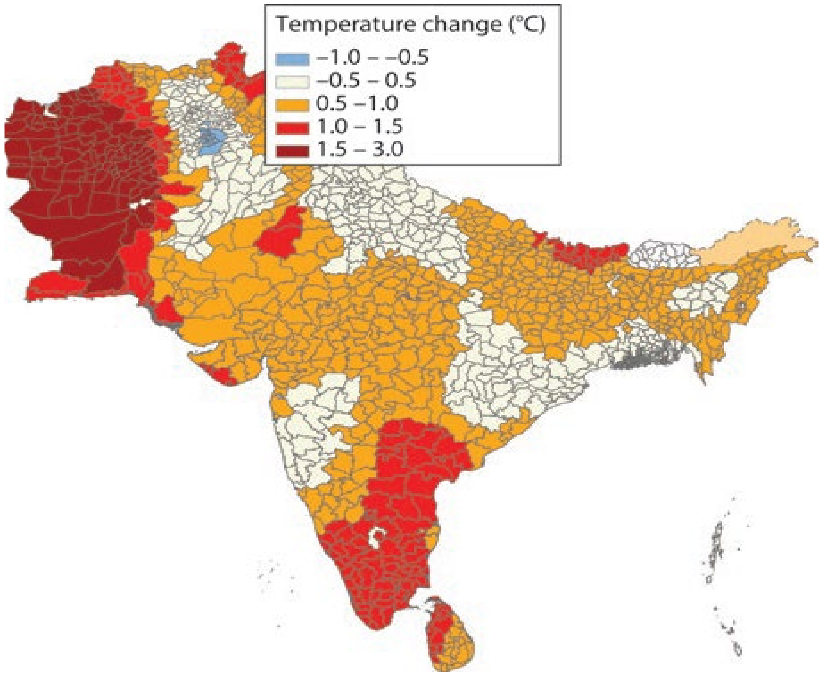
South Asia, with 1.9 billion population (approximately 24.9% of the world population), which accounts for 33.4% of the world's extreme poor, is one of the global climate hotspots (Figure 1). In some parts of South Asia, between 1950 and 2010, average annual temperatures have increased significantly, with the largest increases in western Afghanistan and southwestern Pakistan. Over the same period, southeastern India, western Sri Lanka, northern Pakistan, and eastern Nepal have all experienced average temperatures increases of 1.0°C to 1.5°C (1.8°F to 2.7°F). While the estimated temperature changes vary significantly even across South Asia, the trend is of regional warming.

Figure 1. Temperatures have been increasing in much of South Asia

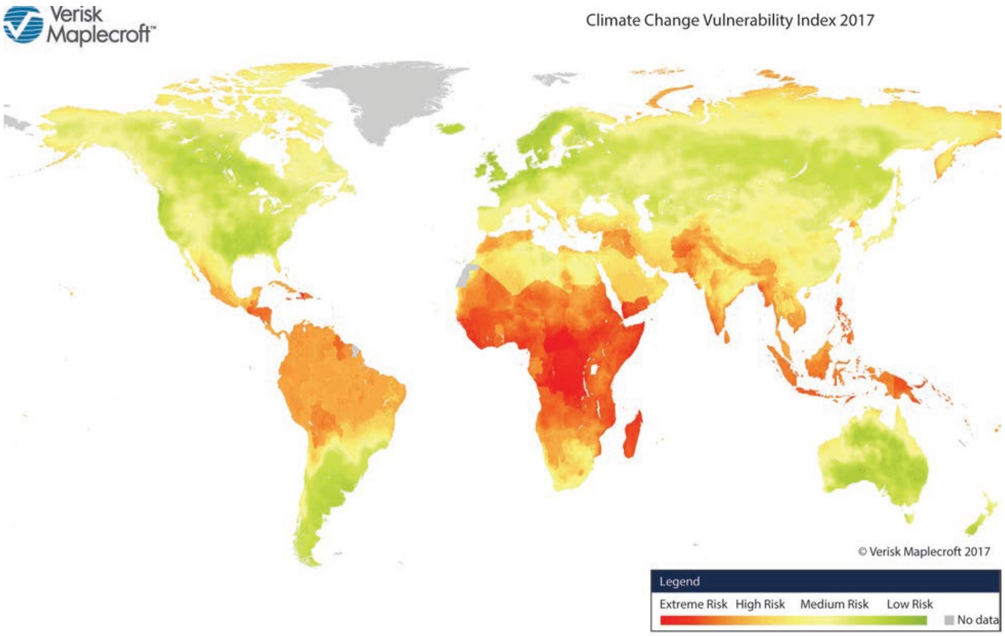


Sources: Mani et al. 2018; data from Harris et al. 2014. Changes are based on trend analysis.

The picture is similar in Sub-Saharan Africa, which also accounts for a significant share of the world's extreme poor. Consequently, the livelihoods and well-being of people are increasingly at greater risks (Figure 2). Insufficient rainfall leads to drought, with implications for energy and food security (Lobell et al., 2008). Episodic events (e.g., cyclones) portend flooding, coastal damage, and loss of human and physical capital. Especially, poor are more vulnerable to climate change and variability, given their greater reliance on agriculture and informal sectors, poor physical and human capital endowments, and limited access to formal insurance and financial institutions, among other factors.

The Intergovernmental Panel on Climate Change (IPCC) report confirms that even at the 1.1 degrees Celsius (2 degrees Fahrenheit) already observed global warming, the world is experiencing serious adverse impacts on livelihoods and ecosystems, with increasing losses of life and species projected if global warming continues. These impacts will be further exacerbated by poverty, land use change, and other changes that contribute to individual and community vulnerability (IPCC, 2022). An increasing body of empirical evidence shows a negative effect of temperature variability on economic growth. Kotz et al. (2021), using observed day-to-day temperature variability with subnational economic data for 1,537 regions of the world over 40 years, find that an extra degree of temperature variability, on average, reduces regional growth rates by 5%. In a similar vein, using data on 372 locations in 12 countries, Guo et al. (2016) find temperature variability and mortality are associated, controlling for the effects of daily mean temperature.

Figure 2. Climate vulnerability, 2017



Sources: Maplecraft climate vulnerability index, based on 42 socioeconomic and environmental factors.

The Groundswell report of the World Bank provides projection and analysis of climate-induced migration (Clement et al., 2021). Accordingly, approximately 216 million people could move within their own countries by 2050 due to slow-onset climate change impacts, migrating from areas with lower water availability and crop productivity, and from the areas affected by sea-level rise and storm surges.

Thus, climate change and variability are expected to further raise the stakes for livelihoods through diverse pathways (e.g., agriculture, productivity, health, and migration). Over centuries, while individuals and communities have adapted to climate change through various coping strategies and have been "resilient", as reflected in the changes in their livelihood practices and migration patterns (Degroot et al., 2021), in the presence of increasing climate uncertainty, the traditional coping strategies and adaptation pace are no longer sufficient and do not provide insurance against it.

Therefore, interventions for climate adaptation and climate-resilient development are necessary (Garnett et al., 2013). According to the Groundswell report (cited above), concerted action to reduce global emissions, and green, inclusive, and resilient development, can significantly reduce the projected climate-induced migration. For climate adaptation and resilience, however, at least two-pronged strategy is required: (a) helping communities understand the climate risks and impacts; and (b) equipping them to deal with climate change (IPCC, 2007, 2012, 2022).

It is in the context of the strategy# (a) that CISs, which provide climate information and knowledge to communities and decision makers, is seen as an important part of improving the management of climate-related risks (Bostrom et al., 2013; Lorenzoni et al., 2005; Bord et el., 2000). While CISs have existed for over a century, recent advances in climate forecasting technologies (White et al., 2017; Vitart, 2014; Zhang, 2013) have allowed regional meteorological departments to produce reasonably accurate seasonal climate forecast information (CFI), which has raised the prospect of developing and providing CISs, *customized* to user needs and conditions, towards improvements in their decision-making under climate uncertainty (Rahman et al., 2016). Not surprisingly, CISs have been receiving a great deal of attention in recent years, including from governments, international agencies, and private sectors (Gupta et el., 2011). The focus has been on the utilization of seasonal CFI (Hansen et al., 2011; Meza et al., 2008) and long-term climate projections (Scott et al., 2011; Ranger et al., 2010).

CISs can be developed for and provided to individuals, communities, and regional development planning authorities. They can also be tailored to suit different sectors of an economy (e.g., agriculture, infrastructure, and risks and insurance). They can also be tailored appropriately for rural and urban areas. Naturally, they are more readily applicable and relevant for some sectors than others. However, for affecting decision-making under climate uncertainty across different contexts, both at micro and macro levels, the factors that enter into the decision-making processes are the key considerations. Therefore, CISs hold the promise of improving decision-making under climate uncertainty by affecting the decision-makers' risks and time preferences, attitudes, beliefs, and perceptions about climate change and variability, and by affecting the social, cultural, and institutional norms that enter into their decision-making process. However, the decisions that are actually influenced and the degrees to which they are influenced by CISs, accounting for the roles of other factors in the decision-making, are not clearly understood. Even less is known about the effective designs of CISs. For example, some CISs impart weather information, some disseminate CFI, and others have multiple components.

This paper discusses the role of CISs in individual and household decision-making under climate uncertainty in rural areas, which are more vulnerable to climate change, given the nature of rural livelihoods (e.g., agriculture, farm and off-farm allocation of labor, seasonal migration to urban areas, saving and investment behavior) and limited access to climate information as compared to urban areas.[1] Drawing upon the interdisciplinary literature on CISs, the paper highlights their potential roles in improving rural household decision-making under climate uncertainty and their livelihoods. More specifically, it motivates rural household decision-making under climate uncertainty, discusses what roles may CISs play in supporting the decision-making, the knowledge gaps on CISs, the main challenges in relation to their utilization,

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[1] Exploring the roles of CISs in other decision-making contexts (e.g., urban areas) is equally important for generating insights for promoting climate-resilient development. However, they are beyond the scope of this paper. For the reasons including the greater vulnerability of rural areas to climate change, their relatively poor human development outcomes, and their importance in achieving the sustainable development goals (SDGs), we limit the discussion to the roles of CISs in the household decision-making and livelihoods under rural environment.

content, format, and communication, and how the development, design, and provision of CISs can be approached.

The remainder of this paper is organized as follows. To provide a broader context for thinking about CISs for rural areas, the paper briefly describes the major theories and explanations for lack adoption of improved technologies and livelihoods practices. Section 3, relying on information theory, sketches a theoretical model of household decision-making under uncertainty to illustrate the potential role of CISs. Section 4 summarizes available evidence on the benefits of CISs and identifies the knowledge gaps. Section 5 addresses important issues that must be considered in development and provision of CISs. In Section 6, some lessons for the programming of CISs for climate adaptation and climate-resilient development are provided.

2. Explanations for lack of adoption of new technologies and climate-resilient practices

In light of increasing climate vulnerability of rural areas and livelihoods, their climate adaptation is required (Garnett et al., 2013). Furthermore, it has been estimated that by 2030 the demand for agricultural products will increase by 50 percent (Bruinsma, 2003). To meet this challenge, modernization of rural livelihoods and practices are recognized as important drivers especially in developing countries. At the same time, modernization of rural livelihoods has been hindered by lack of modernization of agriculture (e.g., utilization of high level of modern inputs, adoption of improved technologies and practices), limited diversification of rural livelihoods (e.g., greater reliance on farm-based activities), and traditional migration pattern to urban areas (e.g., persistence of temporary, seasonal migration). African farmers, for example, use fertilizer at much lower rates than farmers in the rest of the world (World Bank, 2007). Similarly, farmers in eastern India use less than one-half of the fertilizer than those in other high productivity states in the country (Emerick et al., 2016).

There are several theories and explanations especially for the lack of modernization of agriculture, which at the heart of the modernization of rural livelihoods. These include procrastination and time-inconsistent preferences (Duflo et al., 2011), high transaction costs (Suri, 2011), lack of information and difficulties in learning (Hanna et el., 2014; Ashraf et al., 2009), absence of formal insurance (Karlan et al., 2014), and lack of technologies available to smallholder farmers that are well suited to their local conditions (Emerick et al., 2016).

In Duflo et al. (2011), farmers are assumed to face small fixed costs of purchasing fertilizer and some are present biased, and they are not fully sophisticated about it. This type of farmers may procrastinate and postpone fertilizer purchases until later periods, when they may be too impatient to purchase fertilizer. In such a case, farmers may fail to take advantage of profitable fertilizer investments. In other words, Duflo et al. (2011) argue that behavioral biases limit profitable investments in fertilizer by farmers in developing countries.

Suri (2011) investigates the low adoption rates of technologies (i.e., hybrid maize) that dramatically increase average farm profits and provides a simple explanation for it. That is, benefits and costs of technologies are heterogeneous. Therefore, farmers with low net returns do not adopt the technology. She tests this explanation by estimating a correlated random coefficient model of yields and the corresponding distribution of returns to hybrid maize, in which farmers with the highest estimated gross returns do not use hybrid, but their returns are correlated with high costs of acquiring the technology, among other results. Overall, she finds that adoption decisions are rational and can be explained by heterogeneous net benefits to the technology.

Hanna et al. (2014) considers a model in which learning about new technologies occurs through noticing, an environment in which people choose which input dimensions to attend to and subsequently learn about from available data. Under this setup, the authors show how people with a significant experience may persistently be off the production frontier[2], since they fail to notice important features of the data they possess, which they test, among other predictions of the model, in a field experiment with seaweed farmers in the district of Nusa Penida in Indonesia. They first document through a survey data that seaweed farmers do not attend to pod size, a particular input dimension. Then they provide experimental result that suggest that seaweed farmers are particularly far from optimizing this dimension. In addition, they find that having access to the experimental data does not induce learning. However, behavioral changes occur when the farmers are provided summaries that highlight previously unattended-to relationships in the data.

Financial consideration is a critical factor in the investment decisions of farmers, especially small-scale farmers, in developing countries. Access to credit and incomplete insurance[3] can limit investment even in activities with high expected profits. In an important study, Karlan et al. (2014) conduct experiments in northern Ghana in which they randomly assigned farmers to either receive cash grants, grants of or opportunities to purchase rainfall index insurance, or a combination of the two. They find a strong demand for index insurance[4], which leads to increase in agricultural investment and relatively riskier production choices in agriculture. In addition, uninsured risk is the binding constraint to farmer investment. However, in subsequent years, demand for insurance is strongly increasing with the farmer's own receipt of insurance payouts, with the receipt of payouts by others in the farmer's social network and with recent poor rain in the village, among other important findings.

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[2] A curve showing the varying amounts of two products that can be produced when both depend on the same finite resources (or inputs).

[3] When insurance contracts do not exist for all risks facing an individual.

[4] Index insurance is a type of insurance that pays out benefits on the basis of a predetermined index (e.g., rainfall level) for loss of assets and investments resulting from weather and catastrophic events.

Emerick et al. (2016) suggests that the technologies that reduce risk by protecting production in bad years are important factor in adoption of new technologies and modernization of agriculture. Using a randomized experiment in India, the study finds that improved technology enhances agricultural productivity by crowding in modern inputs and cultivation practices. More specifically, a new rice variety that reduces downside risk by providing flood tolerance has positive effects on adoption of a more labor-intensive planting method, area cultivated, fertilizer usage, and credit utilization.

Regarding prevalence of limited (seasonal) rural-urban migration despite higher productivity and wage in urban areas, there are different views. One view is that the rural residents are less educated (Young, 2013; Herrendorf and Schoellman, 2016) and they have less city-specific skills. Therefore, they would not necessarily replicate the higher wages that urban residents earn. An alternative view is that non-monetary disutility of rural-urban migration is substantial. Therefore, rural-urban migration, especially by poor rural residents, could be induced with subsidies (Lagakos et al., 2017).

This paper advances another plausible explanation: rural households in developing countries lack access to seasonal climate information, which in the presence of climate uncertainty hinders the modernization of their livelihoods, including lack of adoption of improved agricultural practices, limited diversification of livelihoods sources, limited rural-urban migration, and inadequate saving and investment.

3. Decision-making under climate uncertainty

Can the provision of a CIS enhance adoption of best agricultural practices and modernize rural livelihoods? This paper argues that the answer is *yes*, given the available evidence and the promise of developing and providing CISs customized to user needs and conditions.

The argument is theoretically grounded in information theory (see, e.g., Hirshleifer and Riley, 1992). Following the basics of information theory outlined in Luseno et al (2003), consider rural households who must make agricultural choices (e.g., plantation, irrigation, fertilizer use) at time *t* in the face of uncertain seasonable climate, *e(t+1)*, that affect relative productivity of different alternatives available to them. Then CFI, *I(t)*, provided by a CIS, in the form of a message has non-negative value due to its potential to resolve temporal uncertainty and improve their agricultural choices. The value of the CFI provided will depend on the following conditions: 1) *I(t)* and *e(t)* are uncorrelated (i.e., the message contains climate information, underscoring the importance of climate forecast skill); 2) the farmers receiving *I(t)* update their subjective probability distribution on *e(t)*, which underscores the importance of confidence in CFI received; and 3), their preferences and constraints are such that their optimal decisions will vary depending on their subjective probability distribution on *e(t),* with the value of information equal to the change in expected discounted welfare stream resulting from optimal decisions made with the new information. Here what matters is whether their decisions subject to climate uncertainty change.

This theoretical argument is further informed by well-established empirical results that agricultural productivity and farm profits in developing countries depend strongly on weather realizations (see, e.g., Rosenzweig and Udry, 2014).

4. The role of CISs

4.1. Evidence

There is an ongoing active debate about CISs, including where they are effective, and how they can be structured and designed (Vaughan and Dessai, 2014). For example, what kinds of information should CISs rely on, what problems they can effectively address, and what kind of institutional context and supports are required. While some aspects of this debate have received more attention, some important aspects have been largely neglected (*see* Section 4.2).

There are significant amounts of research on assessing attributes of climate information—including, for instance, the quality of the data that underlie specific CISs (Bhowmik and Costa, 2014; Girvetz et al., 2013; Brunet and Jones, 2011; Overpeck et al., 2011) and the accuracy of climate predictions (Hyvärinen et al., 2015; Goddard et al. 2013; Mason and Chidzambwa, 2009). Social science research on CISs have largely focused on their applications (Tang and Dessai, 2012; Dilling and Lemos, 2011) and identifying factors of effective communication of climate information (Joslyn and Demnitz, 2019; Bostrom et el., 2018; Lorenz et al. 2015; Taylor et al. 2015; Marx et al. 2007), which will be addressed in Section 5.

There is a large body of empirical evidence, using cross-sectional survey data, on the uses and benefits of CISs (see, e.g., Gunasekera, 2010; Gadgil et al., 2002), which can be broadly grouped in the following categories: a) increased awareness of climate change and climate-vulnerability, b) improved access to climate information, c) improved utilization of climate information, and d) improved agricultural outcomes.

It is straightforward to think that the recipients of CISs will have greater awareness about climate change and variability and the potential climate risks that the latter pose to their livelihoods (see, e.g., Birachi et al., 2020; Chiputwa et al., 2020). It seems equally straightforward to think that CISs, if provided to households, will improve households' *access* to climate information. Birachi et al (2020) finds that farmers with the awareness about climate information sources indeed access them. However, this paper argues that simply providing climate information is not sufficient for their accessibility. For the latter, climate literacy (CL) is required, especially in developing countries (see Section 5.2), primarily because of poor educational attainments of rural households and communities.

In addition to their ability to improve awareness about climate change and risks, studies show that CISs also improve the utilization of climate information in household decision-making. For example, Birachi et al. (2020) document that farmers in Rwanda use CISs in their farming decisions (e.g., crop choice, timing of planting). On the other hand, Chiputwa et al. (2020) document that the use of improved seed is positively associated with the use of seasonal climate forecast information.

However, provision of CISs does not necessarily guarantee their greater utilization in decision-making and improvement livelihoods outcomes. Consider farmer households whose main monsoon season crop is rice. Assume they receive information that there is an 80 percent chance that the seasonal rainfall will be 25 percent less than the historical average. They may not be able to act upon this information to change their crop choice from rice to another because they do not have financial resources or because rice may be their staple food. It is also possible that they may simply ignore the information because they do not trust its accuracy or the provider. It is likely that even if they use the information, their livelihoods may not improve. For instance, we may assume that climate variability is a constraint on their agricultural production, that low production is a constraint on their livelihoods. This assumption may be a valid one. But if they are faced with other challenges (e.g., access to markets), it may mean that an increase in production, helped by the information, does not lead to an improvement in their livelihoods. In this case, an analyst may *incorrectly* conclude that the CIS was ineffective. Thus, for the benefits of CISs to rural livelihoods, certain conditions must be satisfied. For example, lack of CISs must be a constraint to household decisions. Other potential constraints to the utilization of the CIS (e.g., access to credits, trust in CISs and credibility of their providers) should not be overwhelming.

In a recent study, Djibo et al. (2021) study the impacts of a CIS, which provided technical efficiency (i.e., the ratio of actual and potential output) and productivity of sorghum farming to a small sample of 200 farmers in Ghana. They find significant increase in technical efficiency and sorghum yield of the farmers.

While the preceding studies provide suggestive evidence on uses and benefits of CISs, experimental studies on CISs have been rather limited. Fafchamps and Mentin (2012) estimates the benefits of market and weather information provided to rural farming households to their mobile phones by Reuters Market Light (RML), a commercial service provider. Using a controlled randomized experiment in 100 villages in the Indian state of Maharashtra, the study finds that the treated households associated RML information with several decisions that they made, and the treatment affected spatial arbitrage[5] and crop grading. However, the study finds no significant effect of the treatment on the price received by households, crop value-added, crop losses resulting from rainstorms, or the likelihood of changing crop varieties and cultivation practices.

Pandey and Singh (2019), in a study like Fafchamps and Mentin (2012), estimates the benefits of agriculture and weather information provided to farming households on their mobile phones. Using data from a controlled randomized experiment of 20 villages in the largest state of India, Uttar Pradesh, the study finds that the treated households associated information with some of their decisions. Consistent with the findings of Fafchamps and Mentin (2012), this study

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[5] This is when an arbitrageur uses geographical factors to buy an asset from an area and sell it at a different place at a higher price.

also finds the effect of the treatment on spatial arbitrage and crop grading, in addition to significant effects on crop choice, input cost, value-added, and losses.

Camacho and Conover (2019) conduct a randomized experiment with 500 small-scale farming households in rural Colombia to estimate the impacts of 8 text messages per week containing information about prices in the main markets for crops grown in the region and customized weather forecasts. They find that the treated households were more likely to report that the treatment provided useful information for planting and selling. In addition, they find heterogeneous effects by size of farm operation. Smallholding households were more likely to use the information by planting more crops for which they received price information. Overall, this study suggests that farming households are willing to learn and use new technologies.

4.2. Knowledge gaps

From the preceding discussion, it is clear that there is a significant amount literature on uses and benefits of CISs. Also, while it is clear that counterfactual analyses of CISs are not new (Byerly et al., 2018; Di Falco & Veronesi, 2013), they are rather limited (Rahman et al., 2016; Clements et al., 2013; Vedan et al., 2012; Thornton, 2007; Hartmann et al. 2002). There are several reasons for this. Typically, CIS programs lack baseline data, include a longer time lag between intervention and measurable impact (Di Falco, and Veronesi, 2015; Ferraro, 2009; Chomitz, 2008; Hedger et al., 2008), lack an appropriate counterfactual group for attribution (Chomitz, 2008; Hedger et al., 2008), and include confounding factors and suffer from selection bias (Ferraro, 2009). In addition, CISs often include different programming activities (e.g., capacity building, climate literacy, and provision of climate forecast information). As a result, it is difficult to assess the extent to which individual CISs live up to their promise. Thus, there is significant knowledge gap on CISs.

First, rigorous impact evaluation of CISs that provide seasonal CFI, as opposed to weather and agro-advisories, has received less attention (Rahman et al., 2016; Vedan et al., 2012; Hartmann et al. 2002). What individual livelihood decisions are influenced and the degrees to which they are influenced by CISs providing seasonal CFI are not clearly understood. The goal of an impact evaluation study is to identify and estimate the causal impacts of an intervention, accounting for the contributions of other factors. This requires counterfactual analysis, involving comparisons between the targeted outcomes after the intervention and the outcomes in the absence of the intervention. However, it is not possible to know what would have been the outcomes in the absence of the intervention. Thus, researchers create a comparison (control) group, unaffected by the intervention by utilizing various statistical methods (e.g., randomization, propensity score matching, regression discontinuity design) or by identifying natural experiments. The impact evaluations of CISs providing seasonal CFI *per se* have been particularly challenging due to the lack of baseline data and control groups.

Second, even less is known about effective designs and structures of CISs (Rahman et al. 2016; Thornton 2007). For example, some CISs impart weather information, some disseminate CFI, and others provide multiple things (e.g., weather information, agro-advisories, capacity building, CFI). As a result, it is difficult to isolate the relative contributions of different components. For example, the realized impacts could be because of any single component or combination of them. While this is not a hindrance in estimating the aggregate impacts of a specific CIS, it limits our ability to apply insights into the programming of CISs in other similar contexts.

Third, causal evidence on potential mechanisms through which CISs improve decision-making and livelihoods is lacking. The motivation to use climate information may arise from a household's personal attitudes, social norms, and perceived control or ability to use the information in specific decisions (Hu et al., 2006; Artikov et al., 2006; Ajzen, 1991). CISs may influence household decisions through influencing their attitudes, perceptions, and beliefs around climate change and by shaping their risks and time preferences (Sussman and Gifford, 2019; Bernedo and Ferraro, 2018; Hu et al., 2006; Artikov, 2006; Armitage and Conner, 2001; Ajzen, 1991). Some of these potential mechanisms are expected to interact with households' educational attainment, income and wealth, and ability to understand the climate information provided, among other attributes of climate information and households (*see* Section 5.3-5.4).

Finally, the risks of droughts, floods, and coastal damage present very different challenges to livelihood decisions (Dracup and Kendal, 1990). Therefore, the lessons learned from CISs in, say, in drought-prone regions cannot be automatically applied to flood-prone or coast regions. Therefore, there is a need for the relative effectiveness of CISs across different agro-climatic zones (e.g., drought-prone, flood-prone regions).

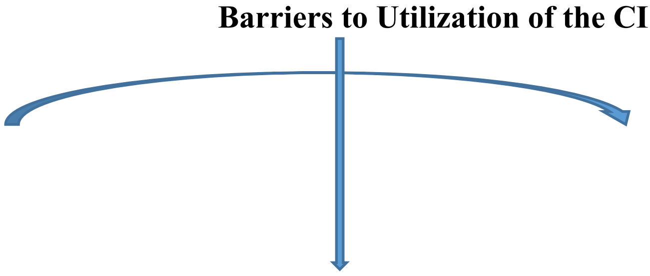
Thus, to advance the empirical bases for the future programming of CISs, beyond providing weather and agro-advisories, rigorous causal evidence on the benefits of CISs that provide climate information per se, including seasonal CFI, is needed.

4.3. Theory of Change

The idea that provision of a tailored CISs, that provide climate information per se, can improve rural household decision-making under climate uncertainty, and their livelihoods, has the theoretical foundation in information theory. Suggestive empirical support for it comes from studies on CISs that utilized cross-sectional data and experimental studies on CISs that provided weather information and agro-advisories.

Figure 2 sketches a plausible theory of change in which a CIS improves household decision-making under climate uncertainty and livelihoods. It is expected that in the absence of sustainable livelihood programs (e.g., CISs), climate change and variability will adversely impact livelihoods. However, the availability of a CIS does not imply that they will be utilized. As discussed above, there may be socioeconomic (e.g., lack of education, access to credits, lack of trust in CIS provider) barriers to the utilization of the CIS provided (Hu et al., 2016; Mase and Prokopy, 2014). For example, households may not have the credits needed for them to change decisions in response to the CIS. Therefore, to improve the likelihood of the utilization of the CIS provided, the potential barriers must be remediated.

When utilized, the CIS is expected to influence household decision-making (e.g., crop choice, use of irrigation, use of fertilizer, diversification of livelihoods, saving and investment behavior, sectoral allocation of labor) and livelihood outcomes (e.g., diversification of income sources, improved agricultural productivity, more saving and investment).



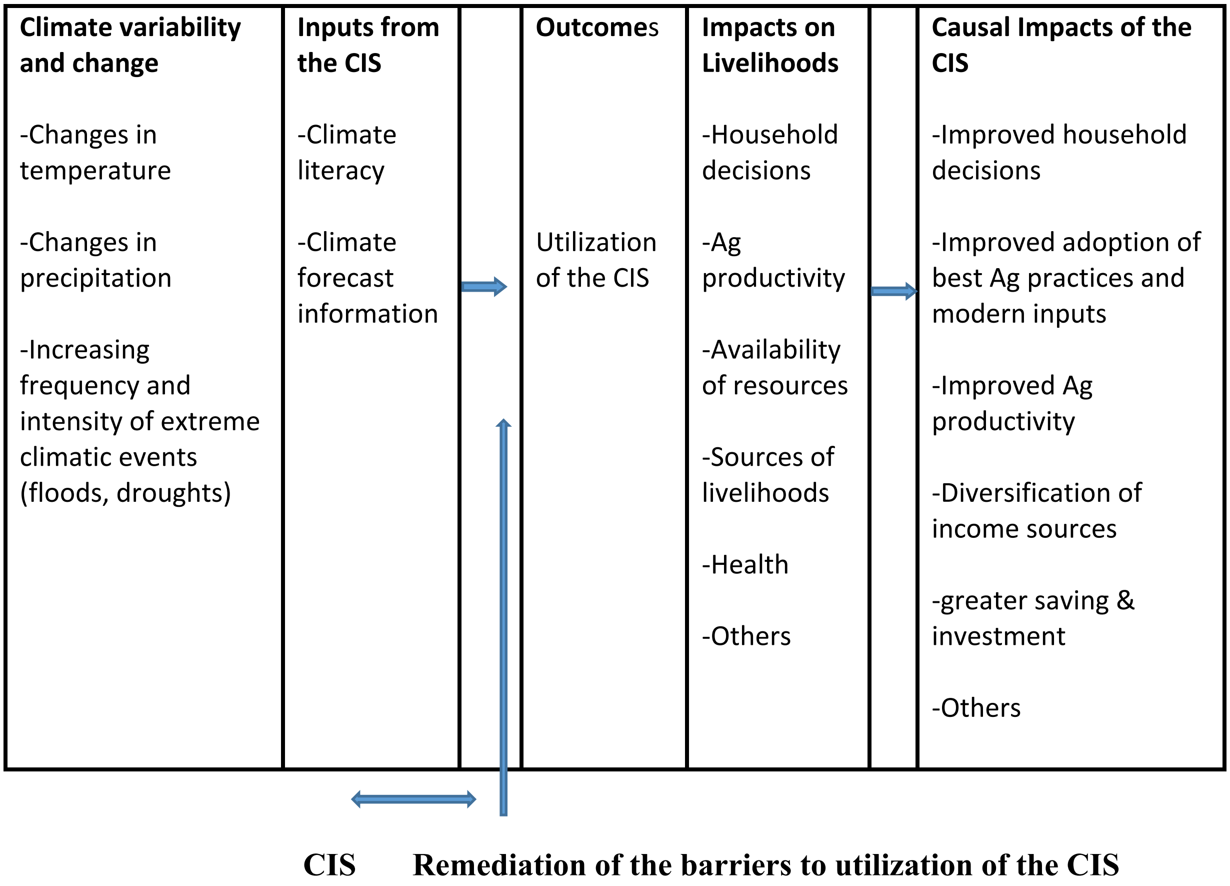


Figure 2. Theory of Change

As discussed in Section 4.2, the potential mechanisms through which the CIS may be improving decisions and livelihoods of households include influencing their attitudes, perceptions, beliefs, and values around climate change and by shaping their risks and time preferences (Meier and Sprenger, 2013). In this sense, our theory of change is related with the theory of planned behavior (see, e.g., Sussman and Gifford, 2019; Hu et al., 2006; Artikov, 2006; Armitage and Conner, 2001; Ajzen, 1991) and studies on risks and time preferences of households (see, e.g., Bernedo and Ferraro, 2018).

5. Issues in development and provision of CISs

There are several issues that need to be carefully considered in development and provision of effective CISs to rural households. They include need assessment for CISs, their designs and structures, accuracy of CFI, communication and format of CFI, content of CFI, mediums for providing CISs, and duration of CISs provision.

5.1. Need assessment

The first step is an examination of the role climate risks play in rural household decision-making—either directly experienced (e.g., drought, flood) or indirectly experienced (e.g., agricultural extension services). This step is commonly referred to as a "vulnerability assessment," which establishes for a given household the levels of exposure to climate change and variability, the sensitivity to it, and the capacity to adapt to or recover from it. Then a climate-needs matrix, indicating where corresponding climate products already exist or need to be developed. For this, engagement with the targeted rural households is needed (Acharya and Prakash, 2019), which can be conducted through focus groups (FGs). The FGs will have at least two purposes: 1) to gather the households' feedback on their exposure to and perception about climate change and usefulness of a CIS; and 2) to test and define community and household survey questionnaires for baseline data collection.

The baseline data should be collected by an independent local agency, who is unaware of the purpose of the data collection and the planned provision of CISs. The community survey should be used to collect information about community characteristics (e.g., infrastructure, public goods) by gathering a group of people in each region (e.g., village) who were knowledgeable about their community and local region. The household survey should collect data on household demographics, assets, cropping patterns, perceptions about changes in weather and climate, and coping strategies, among other information. It is important that a representative sample of households is surveyed from the area where the CIS will be provided. Then using the data from the FCs and household and community surveys, household vulnerability to climate change and variability, climate information needs, and potential dissemination channels for providing a CIS must be examined.

5.2. Developing a CIS

Given the need assessment, the next step is determining the components of the CIS that will be provided. In other words, what climate information the CIS will provide ought to be determined according to the need assessment and with the inputs from the rural households, a step that is commonly known as co-production of CISs (Acharya and Prakash, 2019).[6] For example, a CIS that provides climate information per se may have two components: provision of climate literacy (CL) and seasonal CFI.

Provision of CL may be necessary to enhance households' *capacity* to access climate information and to use them, especially if they have limited ability and capacity to understand and interpret the currently available climate information. For instance, frequently used terms in the CFI products by the Meteorological Departments (e.g., high chance, below historical average, range) fail to convey the intended meanings. On the demand-side, this is partly due to poor educational attainments of rural households. On the supply-side, the problem could be the lack of *customization* of climate information to household needs and local conditions. Thus, the provision of CL will enhance households' ability to access, process, and understand climate information. This will also constitute as a capacity enhancing investment to help people to adapt to increasing climate uncertainty. Moreover, climate adaptation is an intertemporal decision

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[6] Studies have shown that co-production of CISs critically affect their utilization. For an excellent summary of the literature on narrowing the climate information usability gap, see Lemos et al. (2012).

under risk (Bernedo & Ferraro, 2017; Bernedo, 2016). Risks and time preferences of households are expected to influence their climate adaptation decisions. Studies show that individual literacy and time preferences are linked (Meier & Sprenger, 2013). Thus, provision of CL may improve household decision-making and climate adaptation under climate uncertainty through various channels including its effects on their risks and time preferences.

Seasonal CFI refers to seasonal and sub-seasonal forecast information (e.g., rainfall, onset of the monsoon). Recent advances in climate forecasting technologies (see, e.g., Vitart and Robertson, 2018; White et al., 2017) have allowed regional meteorological departments to produce reasonably accurate seasonal CFI, which has raised the prospect of providing them to households. While the provision of CL can be an enabling factor in households' climate adaptation, provision of CFI can inform and improve their real-time decisions (e.g., choice of crop, irrigation, fertilizer uses, and allocation of labor).

5.2.1. CL Curriculum

If it is determined that provision of CL is desirable, a CL curriculum needs to be developed, which also must be informed by the need assessment. For example, a CL curriculum may have four parts. In part 1, frequently used terminologies in forecast products, figures, and coloring schema of climate maps, among others, can be explained with the help of examples collected from available climate products. In part 2, historical weather and climate patterns and observed extreme climatic events in the targeted area can be discussed. Also, households' perception about recent climate patterns (from the baseline data in Section 5.1) should be compared with the observed climate data. In part 3, the climate forecast records, and accuracy of CFI should be clearly discussed and explained. In Part 4, one can discuss adaptation strategies adopted by households in similar climatic environments.

5.2.2. CFI

Climate information needs of households can be broadly divided into (i) accurate and relevant CFI and their suitable formats, and (ii) information/training for the correct use of CFI in specific livelihood decisions (Hu et al., 2006). Not surprisingly, in climate forecasts, the attributes such as the accuracy of climate predictions (see, e.g., Hyvärinen et al., 2015; Goddard et al. 2013; Mason and Chidzambwa, 2009) and the quality of the data (Bhowmik and Costa, 2014; Girvetz et al., 2013; Brunet and Jones, 2011; Overpeck et al., 2011) have received more attention. In behavioral sciences, identification of factors that improve the communication of climate risks information (Bostrom et al., 2018; Bostrom, 2017; Lorenz et al. 2015; Taylor et al. 2015; Bostrom et al., 2013; Marx et al. 2007; Armitage and Conner, 2001) and barriers to their utilization (Sussman and Gifford, 2019; Bernedo and Ferraro, 2018; Hu et al., 2006; Artikov, 2006; Ajzen, 1991) have been extensively explored. Next, we highlight the issues of the content and format of CFI, and their communication, which are critical for their utilization.

5.3. Content of CFI

The content of CFI provided needs to be determined by considerations such as their accuracy, climate information needs of households in the targeted area, and their easy understandability, among other factors. Foremost, the forecast skill in the targeted area needs to be reasonably high (see, e.g., Chevuturi et al., 2019; Jain, Scaife, and Mitra, 2019). Otherwise, provision of CFI will be counterproductive with substantial downside risks for households. An equally important consideration is the specific content of CFI (e.g., amount of seasonal to sub-seasonal rainfall, onset and end dates of rainfall season and droughts, frequency of rainfall and droughts, cyclone, temperature, and flood). Once the content of CFI has been determined, it is advisable to pilot their understandability and usefulness with select number of households in the targeted area before their provision.

5.4. Communication and Format of CFI

Among the barriers to utilization of CFI is their uncertain nature. There is a large literature on the psychology of decision making under uncertainty and the role of heuristics (Gilovich et al., 2002; Kahneman and Tversky, 2000; Kahneman et al., 1982) in different contexts, including weather (Gigerenzer et al., 2005; Murphy, 1996; Baker, 1995; Sink, 1995). For example, overconfidence of rural households regarding their expectation about seasonable climate and their decision heuristics under climate uncertainty may hinder utilization of CFI provided. They may lead them, for example, to under- or over-estimate the probability of timely onset of rainfall by making their past rainfall experiences more "available" and easier to recall than less striking rainfall forecast information of equal or higher equality. Prospect theory also suggests important differences in how individuals may view the prospect of loss and gains from CFI use, and they may be viewed differently in flood and drought-prone regions (Kahneman and Tversky, 1979). Individual-level biases are often exacerbated by group decisions (Kerr et al., 1996; Kerr and Tindale, 2004). The limits of individual and group information processing also may prevent households from seeking or interpreting CFI (see, e.g., Vaughan, 1996; Janis, 1972). These findings must inform the communication of CFI in the targeted area.

Thus, for the effective use of CFI, it is required that the households correctly interpret them and receive them in a form that is compatible with their decisions and decision process (see, e.g., McCrea et al., 2005; Hansen, 2002). It has been widely recognized that communicating forecast uncertainty in probabilistic terms without distortion is a crucial challenge (Hammer et al., 2001; Phillips et al., 2001; Dilley, 2000; Jones et al., 2000b; Mjelde et al., 1998). While uncertainty is inherent in CFI, explicit numeric uncertainty estimates are rarely included in public forecasts for fear that they will be misunderstood (see, e.g., Grounds et al., 2018; Grounds and Joslyn, 2018; Joslyn and LeClerc, 2014; Joslyn and LeClerc, 2011). Results from lab experiments on relative benefits of different forecast formats in decision making show that forecast uncertainty information improves decision quality and increases trust in CFI (see, e.g., Joslyn and LeClerc, 2011). Also, it matters whether forecast probabilities presented are verbal or numerical (see, e.g., Gonzalez-Vallejo et el., 1994) and whether forecasts are probabilistic or deterministic (see, e.g., Joslyn and Demnitz, 2019).

Thus, guided by these finding, it is important that the alternative formats of CFI (e.g., verbal or numeric information, forecasts with/without forecast uncertainty information, predictive interval or deterministic information, probability in frequency format, single-event probability, likelihoods of deviations from normal, numeric likelihood estimates, absolute values such as minimum inches of precipitation) and the usefulness of communicating them are tested with a select number of households from the targeted area in FGs setting. Accordingly, the formats of CFI that will be provided must be determined.

Among other important considerations regarding provision of CFI is how frequently they need to be provided. Again, this must be explored with the targeted users and such data can be collected as a part of baseline survey data (see Section 5.1). In a tailored CIS, CFI should be regularly updated. It is possible that the forecasts may change for some parts of the targeted area, but not for others. In that case, the updated and unchanged CFI should be provided in the corresponding parts of the targeted area.

5.5. Dissemination of CISs

How should a CIS be disseminated to rural households? Clearly, the method of disseminating it can vary across contexts, depending on the need assessments, logistical feasibility, and the relative efficacies of the alternative methods of dissemination. Traditionally, CISs have been disseminated in FG settings, gathering of community members in rural areas, and workshops and related capacity building and training sessions. Weather and agro-advisories have been provided by agricultural extension services and through text messages to mobile phones of intended users. Seasonal to sub-seasonal CFI are published on webpages of the regional meteorological departments, which then get reported by Television channels and newspapers.

Given that people also rely on members of their social network for information, a significant amount of literature has emerged on the existence of such peer effects in different contexts (e.g., learning in schools, technology adoption). Since social networks are important, there is an active area of research on determining who in a social network should receive new information first so that it reaches to as many people in the network as possible. Such methods include mapping the full network in a community and applying diffusion models to identify optimal entry points (Beaman et al., 2020), or identifying the best individuals for spreading information with the help of community members (Banerjee et al., 2019). These methods are clearly potentially useful in dissemination of CISs.

However, it must be noted that in the context of providing CISs, the relative efficacies of the none of the methods discussed here has been evaluated against others. In fact, the methods of dissemination of CISs have been largely informed by the value-judgement of their providers and engagement with targeted users.

5.6. Mechanisms

To learn from the experience of CISs in one region for CISs other regions, a sound understanding of the channels through CISs may be affecting household decision-making and livelihood outcomes is required. That is, an addition to estimating the benefits of a CIS, its relative effectiveness, say, in drought-prone and flood-prone regions, a sound understanding of the mechanisms underlying its impacts on decision-making is needed. For example, the motivation to use a CIS arises from personal attitudes, social norms, and perceived control or ability to use the information in specific decisions (Hu et al., 2006; Artikov et al., 2006; Ajzen, 1991). A CIS may influence household decisions through influencing their attitudes, perceptions, and beliefs around climate change and by shaping their risks and time preferences (Sussman and Gifford, 2019; Bernedo and Ferraro, 2018; Hu et al., 2006; Artikov, 2006; Armitage and Conner, 2001; Ajzen, 1991). To best of our knowledge, causal evidence on mechanisms through which CISs influence decision-making is lacking.

6. Lessons for CISs and human development programs

6.1. Lessons for CISs

From preceding discussions, it is clear that CISs hold significant promise to improve household decision-making under climate uncertainty. More specifically, CISs can improve households' awareness of climate change and related risks to their livelihoods, access to climate information, the utilization of climate information in their decision-making, and their livelihoods outcomes (e.g., agricultural productivity, saving and investment, labor allocation).

However, the extent of benefits depends on several factors. First, the lack of CISs must be a constraint to household decision-making. Second, CISs must provide new information. Third, CISs must provide timely climate information. Fourth, households must be willing to update their beliefs about climate change and risks. Fifth, climate information must be relevant in the sense that the information provided must be useful in household decision-making (e.g., forecasts about amount of rainfall, onset and end dates of rainfall season, frequency of rainfall, temperature, frequency of floods and droughts). Sixth, for the effective use of climate information, it is important that households correctly interpret them and receive them in forms that are compatible with their decisions and decision process.

To further enhance the effectiveness of CISs, their provision can be enriched from the literature on the psychology of decision making under uncertainty and the role of heuristics. For instance, there are important differences in how households view the prospect of loss and gains from the use of CISs. Accordingly, climate information can be framed keeping in mind individual and household loss aversion. The risks of drought and flood present very different challenges to household decision-making and livelihoods. Therefore, CISs can be tailored differently in different agro-climatic conditions, prioritizing providing information that are contextually relevant.

6.2. Lessons for human development programs

In September 2015, the United Nations General Assembly charted out a set of seventeen Sustainable Development Goals (SDGs) designed to achieve a better and more sustainable future for all. The SDGs address issues such as poverty eradication, gender equality, quality education, good health and well-being, inequality, sustainable communities, climate action, and so forth. To achieve these goals, countries around the world have been implementing various “development” programs, ranging from anti-poverty, rural development, women’s empowerment, health, and education programs, among others.

However, to achieve the SDGs, it is not enough that these development programs are effective and successful. First, given climate change and variability, it is important that the development programs and their impacts are sustainable and climate-resilient, which is not guaranteed unless they proactively attempt to improve decision-making under climate uncertainty and promote climate adaptation. Second, the impacts of climate change and variability have strong economic, gender, social, and geographical dimensions. That is, climate impacts are exacerbated by poverty, poor health, poor education, land use change, and other changes that contribute to individual climate vulnerability (IPCC, 2022). As a result, poor, less educated, unhealthy, and rural households are more vulnerable and less resilient to climate change. Third, they also have relatively limited awareness and understanding of climate change and the risk it poses to their livelihoods. Finally, they also have less access to climate information.

Thus, in the absence of climate resilient development programming, it is expected that the gap between people with low and high level of human development (i.e., income, health, education) will further increase. In this context, tailored CISs provided to rural areas, where the majority of the global poor live, holds even greater promise and significance for promoting sustainable, inclusive development.

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