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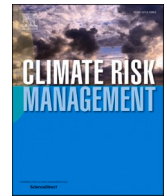
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# The role of smartphone-based weather information acquisition on climate change perception accuracy: Cross-country evidence from Kyrgyzstan, Mongolia and Uzbekistan

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## ABSTRACT

Individual perception about climate risks is critical for adopting mitigation and adaptation measures, yet international experience shows that individual perception might fundamentally deviate from objective changes. So far, little attention has been paid in the literature to understanding the role of ICTs in improving the accuracy of farmers' perceptions of actual drought occurrence. Therefore, this study aims to fill this gap by analyzing the discrepancy between farmers' subjective perceptions and actual drought occurrence. Furthermore, the study investigates the role of smartphone-based weather information on accurate perception of drought.

Subjective drought assessment was obtained by a cross-sectional dataset of 2830 farm-level observations collected in Kyrgyzstan, Mongolia and Uzbekistan in 2021. For measuring objective meteorological drought occurrence, this study employs a standardized precipitation evapotranspiration index (SPEI) based on satellite imagery. The role of smartphone-based weather information acquisition on drought perception accuracy was measured by Propensity score matching. The comparison of objective and subjective assessment showed that 67 percent of farmers in Kyrgyzstan, 32 percent in Mongolia and 46 percent in Uzbekistan perceived meteorological drought inaccurately. The PSM estimates indicate that smartphone-based weather information acquisition significantly influences accurate meteorological drought perception. With these results, we advocate for higher attention to improving internet speed in rural areas and providing online weather information also to farmers with low digital literacy and low incomes.

## 1. Introduction

Drought is one of the major natural hazards causing significant damage to agriculture, the economy and the environment (Mishra and Singh, 2010; Wilhite, 1993). As climate change due to human activities and environmental changes accelerates, both the intensity and frequency of droughts are increasing (Trenberth et al., 2014; Dai, 2013). Droughts are classified as meteorological, agricultural, hydrological, and socioeconomic (Mishra and Singh, 2010). Among them, meteorological drought resulting from a deficiency in precipitation over an area for some particular period of time (Palmer, 1965; WMO, 2016) is the most important form of drought that has a devastating impact on the agricultural sector in dryland areas. Central Asia and Mongolia, due to their geographic location and

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topography, are highly sensitive and vulnerable to drought (de Beurs et al., 2018; Parry et al., 2007). This region has experienced complex changes in precipitation and temperature as a result of climate change associated with greenhouse gas emissions, hydrological fluctuations and land use/cover changes (de Beurs et al., 2018; Lioubimtseva, 2015). It has been proven that in recent decades there has been a significant increase in temperature and a slight decrease in precipitation in Central Asia (Bobojonov et al., 2016; Xu et al., 2016; Hu et al., 2014; Lioubimtseva and Henebry, 2009). As a result, the frequency and severity of droughts has intensified in the region. Drought has been linked to the decline in biomass and agricultural productivity in the last few decades (Ray et al., 2019; Xu et al., 2018); for example, severe drought events between 2003 and 2015 (Guo et al., 2018) have had a significant impact on croplands in Central Asia. Agriculture remains an economically important and main source of livelihood in rural Kyrgyzstan, Mongolia and Uzbekistan.

Worldwide, climate risk perception is a precondition for adaptation measures. Howden et al. (2007) emphasize that farmers are unlikely to take adaptation measures if they do not perceive climate risks. In effect, systematic misperception or under-estimation of flood risks are considered to be the primary reason for not taking out insurance (Kunreuther, 2006). Mase et al. (2017) found that farmers' climate risk perception significantly influences new technology adoption and in-field conservation adoption strategies in Uganda. So far, rarely any study has looked into the perception of meteorological drought and compared it with actual occurrence. Access to reliable, timely and relevant information can help to reduce farmers' risk and uncertainty (Mittal and Mehar, 2012), but can also help bridge the gap between subjective risk perception and objective risk, as found for consumers in a food safety risk study (Santeramo and Lamonaca, 2021). For several decades, traditional channels like television, radio, newspapers, other farmers or extension services have been important sources for information on climate risk. The rapid growth of the Internet and ICT-based technologies could provide farmers with faster and more region-specific information (Mittal and Mehar, 2012; Sørensen and Bochtis, 2010). As the diffusion of mobile ICTs continues, their importance for agricultural and rural development is receiving increasing attention by researchers. A growing body of literature has been analyzing the impacts of information acquisition/access via the Internet, computers, mobile phones, and smartphones on smallholder farm performance worldwide (Min et al., 2020; Ogutu et al., 2014; Aker, 2011). Several studies also show that ICT-based climate information and agro-advisory services can help farmers make better decisions concerning seasonal crop management, choice of technologies, and marketing strategies (Gangopadhyay et al., 2019; Mittal and Hariharan, 2018). However, empirical evidence on the role of smartphone-based weather information on accurate climate risk perception is lacking. The existing literature on determinants of farmers' climate risk perception focuses on a variety of socio-economic, individual and risk characteristics (Finger and Möhring, 2022; Gebrehiwot and van der Veen, 2021; Madhuri and Sharma, 2020; Meraner and Finger, 2019; Cullen and Anderson, 2017; Bahta et al., 2016; Duinen et al., 2015;). While many studies have scrutinized determinants of climate change and risk perceptions of farmers in particular (Gebrehiwot and van der Veen, 2021; Madhuri and Sharma, 2020; Cullen and Anderson, 2017; Bahta et al., 2016; Duinen et al., 2015), the communication of climate data among farmers has so far not found special attention. Therefore, the first objective of this study is to check the consistency of farmers' perception of meteorological drought with actual drought events. Second, we analyze the role of smartphone-based weather information explaining perception accuracy, also considering the determinants of smartphone-based weather information acquisition. With this study, we go beyond general climate change recognition and instead provide new evidence on discrepancies between perception and reality of local meteorological drought risk, based on a combination of farm-level and satellite data. The contributions of this study are: (a) linking the accuracy of farmers perceptions with smartphone-based weather information, whereas previous literature has been limited to individual determinants of climate risk perception accuracy. This is of high practical implication too, as interventions in this direction might be of critical influence; (b) providing practical suggestions for app developers and policymakers, explaining how smartphone applications could improve the preparedness of farmers for natural hazards, in particular drought events. This study has the following research questions: (1) Is the perception of farmers of meteorological drought in Central Asia in line with actual drought? (2) What is the role of smartphone-based weather information access in drought perception?

The remainder of this manuscript is structured as follows: Section 2 presents a review of the literature. Sections 3 and 4 describe the data, descriptive statistics, and the econometric approach. Discrepancy results and empirical results are presented in section 5. Discussion and conclusions are presented in section 6.

## 2. Literature review

### 2.1. Risk perception

The term "probability" refers to how often the given outcome is likely to occur, while impact refers to the size of the potential loss (Hardaker and Lien, 2010). Based on probability assessment, risk can be viewed from two perspectives (Hardaker and Lien, 2010): objective risk, also called the degree of risk, refers to the relative deviation of actual losses from expected losses. Subjective risk, called perceived risk, refers to the personal expectation of loss (Rejda and McNamara, 2014). Expected utility (EU) theory (Von Neumann and Morgenstern, 1947) assumes that the decision maker has complete information about the likelihood of risk and damage, meaning that their perception of risk is identical to the actual risk. Subjective expected theory (Savage, 1954), on the other hand, assumes that the decision maker makes statements based on personal judgments, a theory which allows for deviation between objective and subjective risk perception. This theory purports that an individual's optimal decision in a risky setting is determined by their subjective belief regarding the probability of an uncertain outcome occurring. Hardaker et al., 2015 suggests that SEU-based decision theory is equally applicable explaining people's behaviour and advising how people should make choices. Therefore, subjective risk perception can be a good reflection of an individual's overall perception of risk, which will be influenced by different components of risk. Such kind of risk perception influenced by diverse factors, such as characteristics of risk (Slovic et al., 1979), personal variables, and cultural and

socioeconomic background (Douglas and Wildavsky, 1983).

Following the political instrumentalization of climate change and increasing societal disagreement over its existence and extent, numerous studies on subjective climate risk perception have emerged in comparison to actual climate risk. For instance, Hasan and Kumar (2019) have found that household level perception about drought and flood did not match well with meteorological data. A correlation with climate accuracy of climate perception was found for income, indicating the need for targeted weather information. Falaki et al. (2013) assessed farmers' perception of temperature and rainfall with meteorological records and found that the majority of farmers' perception corroborated with meteorological changes. Similarly, Roco et al. (2015) assessed subjective and objective climate change trends in Chile over 24 years and found that the majority of respondents recognize climate change. Access to meteorological weather information through the media (press, radio, television and the Internet) correlates with perceptions of climate change. This indicates that weather information is an important tool for raising awareness among farmers. Simelton et al. (2013) studied the variability in precipitation perception using meteorological data; they found a discrepancy between farmers' perceptions of changes in rainfall and meteorological data, with farmers reporting earlier on a change of rainfall than meteorological data suggest. Khan et al. (2020) have stated that farmers perceive weather hazards differently at farm households in different regions, with several factors age, education, and income influencing perceptions. Furthermore, Van der Linden (2015) argues that risk perception is shaped by a variety of personal and social, cultural and socio-demographic factors. Deressa et al. (2011) have determined that age, wealth, knowledge of climate change, social capital, and agroecological conditions influence risk perception.

However, the majority of these studies are focusing mainly on meteorological risks that can occur repeatedly rather than the perception of local climate events like catastrophic risk or the occurrence of catastrophic risks, which are very much subject to regional or even farm-level variations: a catastrophic risk can be defined as event with low probability of occurrence leading to large and usually irreversible losses (Chichilnisky, 2000). Thus, studying subjective risk assessment requires an a-priori assessment of objective risks in order to determine the accuracy of subjective assessment.

In particular for drought, awareness is typically low and delayed among the public, due to its slow onset, spatiotemporal variation and delayed impact on harvests (Shao et al., 2022; Wens et al., 2019). Until now, much effort has been made to understand the physical characteristics and the mechanism of drought (Hoerling et al., 2013). Thus, understanding farmers' perceptions of drought and its actual changes, together with the factors influencing those perceptions, is important for developing adequate policies. Moreover, in order to influence public knowledge, there is a need to understand individual perceptions of drought. Several studies have investigated the determinants of farmers' perception of drought risk in developing countries and highlight the significance of personal, socio-demographic, and economic factors. van Duinen et al. (2015) have studied subjective and objective variables that can influence farmers' perceptions of drought risk in the Netherlands. Their results show that the occurrence of salinity, the cultivation of drought or salt-sensitive crops, farm incomes, and experience of droughts were important factors in farmers' perceptions of drought risk. Hughes et al. (2022) found that the main drivers of drought risk perception were regional differences, cultural factors, higher off-farm incomes, age, and education. Akerlof et al. (2013) state that perceived personal experience of global warming appears to reinforce people's perceptions of risk, likely through some combination of direct experience, indirect experience such as media reports, and social interaction. Bloodhart et al. (2015) note that attention to television weather forecasts is associated with a belief that extreme weather events are becoming more frequent, which in turn is associated with stronger beliefs and fears about climate change. These findings suggest that information communication technologies can affect farmers' perception of drought. Gamble et al. (2010) have found that Jamaican farmers' perceptions of worsening drought conditions have been confirmed by satellite assessments indicating that severe droughts are becoming more frequent. In addition, farmers' perception was determined by the magnitude and frequency of dry months, and the difference between growing seasons. Salam et al. (2021) have found that expert views on drought risk were similar to the individual household level perceived risk. These results indicate that information on individual farmers' perceptions of drought with actual changes is still limited and therefore needs to be studied more thoroughly.

## 2.2. Determinants of ICT use

Various case studies have suggested that information and communication technology (ICT) could play an important role in agricultural development. Qiang et al. (2012) pointed out that the application of ICTs in agriculture can stimulate the rapid development of the agricultural sector and rural areas, primarily because ICTs can provide millions of farmers with access to information, markets and services. Several studies have found that the adoption of ICT has a significant positive impact on agricultural productivity (Issahaku et al. 2018; Ma et al. 2018; Lio and Liu, 2006), increase of income (Min et al. 2020), and climate-sensitive decision-making (Kumar et al., 2021). The most fundamental theory behind technology adoption in agriculture is the diffusion of innovation theory by Rogers et al. (2008). According to this theory, socio-economic characteristics and farm characteristic could influence ICT adoption. Empirical studies provide insight into the factors that determine the use of ICTs. ICT tools are often influenced by socio-economic factors such as educational background, age, gender, income, farm experience (Giua et al., 2022; Michels, et al., 2020; Michels et al., 2019; Mittal and Mehar, 2016; Meso et al., 2005). Older farmers are less likely to use modern information technology because they trust their own experience and skills much more (Tamirat et al., 2018; Tiffin and Balcombe, 2011). The younger generation, on the other hand, is more interested in using ICT tools and receiving updates. Gender plays an important role in the decision process in ICT use (Venkatesh and Morris, 2000). A study of Australian graziers found women livestock producers were more likely to use most ICT components than man (Hay and Pearce, 2014). Education allows farmers to better understand the benefits of obtaining information and to use modern information technologies without hindrance (Krell et al., 2021; Rose et al., 2016). Higher education helps farmers with the analytical skills they need to access agricultural data using ICTs (Paustian and Theuvsen, 2017), and to make better decisions (Carrer et al., 2017). For instance, Mwombe et al., 2014, found that a low level of education and distance to internet services were found to be the

most constraining to the use of ICT tools, including lack of finance to buy internet services. Farm economic dimensions like income have a positive influence on ICT adoption (Kolady et al., 2021). Income, for once, is one of the main determining factors for Internet access at home, smartphone ownership, and access to ICT-based information (Gutiérrez and Gamboa, 2010). For instance, farmers in Ghana indicated network failure and the high price of mobile phones were the largest hindrances to mobile phone use (Folitse et al., 2019). The location of a farm also plays an important role in ICT usage due to differences in climatic, soil and topographic conditions (Michels et al., 2019; Paxton et al., 2011), and due to digital infrastructure (Srinuan et al., 2012). Extension services are assumed to influence the digital agricultural tools adoption with different types of innovation (Caffaro et al., 2020; Fecke et al., 2018); farmers during such events may get suggestions on usage of smartphone-based applications. Farmer's attitudes towards the information are assumed to influence digital technology adoption. Koshy and Kumar (2016) state that farmers' attitudes to information will reflect their positive or negative feelings about mobile-based advisory services. Moreover, trust in the usefulness of the provided information via smartphones determines the usage of ICT tools. For instance, Bonke et al. (2018) have shown that German farmers are more likely to have a general willingness-to-pay for crop protection smartphone apps if they perceive them as useful for reducing externalities in crop protection and for decreasing production costs. Also in other studies, ICT usefulness and usability and trustfulness were the key indicators for adoption of climate sensitive decision-making ICT tools (Kumar et al., 2021).

With these literature findings in mind, we propose following hypotheses:

H1: Farmers' subjective perceptions deviate from the actual drought occurrence.

H2: Smartphone-based weather information access improves the accurate perception of meteorological drought.

H3: Farmers' higher reliance on smartphone applications influence weather information access.

### 3. Data and measures

#### 3.1. Farm level data and sampling

This study is based on a cross-sectional dataset of 2830 grain farmers in Kyrgyzstan, Uzbekistan and Mongolia. The data was collected in a CAPI survey (Survey Solutions Platform<sup>1</sup>) within the scope of the project KlimALEZ. The questionnaire was developed in English, then translated into four languages and tested with random farmers in three countries. Due to travel restrictions during the period, the data collections were implemented by local universities or companies, all of which were trained on data collection and the usage of the Survey Solution application.

The target population of the study were grain farming households in Central Asia (see Fig. 1). The survey regions were selected following a multi-stage cluster sampling procedure. First, study provinces in each country were selected based on their characteristics as the largest grain producers in the respective country. After that, districts were selected based on the same criterion. Within districts, samples were obtained from a sampling frame provided by the local state administrations using a simple random sampling approach. This produced a total sample size of 1200 in Kyrgyzstan, 1088 in Uzbekistan and 542 in Mongolia. The reason for the smaller sample size in Mongolia is that Covid-19 travel restrictions applied within the country at the time of data collection. According to power calculations suggested by (Israel, 1992), the minimum sample size for our study was 385 observations per country with a 95 percent confidence interval and a 5 percent error margin. Our sample size is therefore considered sufficiently large for our research question. In addition, the representativeness of the sample was cross-checked with the statistics of the National Statistics Committee in terms of average grain yield per hectare in each country. Based on the sampling procedure and comparison of key production statistics, the sample can be considered representative for each of the study countries in terms of production of grain crops.

Kyrgyzstan is located in eastern Central Asia and covers 199,951 km<sup>2</sup>. The country is highly mountainous and lies at on average 2750 m above sea level. The total agricultural area of the country is 1.4 million ha, of which approximately 870 thousand ha is irrigated (NSC, 2021). The average annual precipitation is approximately 533 mm, and most of it is concentrated during the winter season (between October and April) (Frenken, 2013). The absolute temperature greatly varies (from -18 to -28 °C in winter to 43 °C in summer) depending on the location. For this study, the regions Chui, Issyk-Kul, Osh, Batken, and Jalal-Abad were purposely selected based on cereal and grain growing areas (NSC, 2021). Agro-ecologically, these regions are located in sub-humid and semiarid zones (Bobojonov and Aw-Hassan, 2014). Kyrgyzstan belongs to the countries in the world which are strongly affected by climate change (Fay et al., 2010) and may worsen further in the future. According to the World Bank Group and Bank, (2021a) the ensemble predicts 5.6 °C of warming by the 2090 s at the highest emission path (RCP 8.5), well above the expected global average increase of 3.7 °C.

Mongolia is located between Russia to the north and China to the south and lies at an average of 1580 m above sea level. Almost 113 million ha is pasture and less than 651 thousand ha is considered arable land (WBG and ADB, 2021b). About 1.3 million ha of total land is suitable for agricultural production. The climate in Mongolia is characterized by long and cold winters with -52.9 °C in January and hot, dry and short summers that can reach 43.1 °C in July (Batima and Dagvadorj, 2000). Annual precipitation is about 227 mm, and about two-thirds of its annual precipitation falls between June and August (WBG and ADB, 2021b). Eleven main grain-producing regions, namely Arkhangay, Bulgan, Darkhan-Uul, Dornod, Khentii, Kuvsgul, Orkhon, Selenge, Tuv, Uvurkhangay and Zavkhan, were selected. These regions are located in semi-arid and arid agro-ecological zones (Fischer et al., 2021). Similar to Kyrgyzstan, Mongolia also faces rates of warming far higher than the global average. On the highest future emissions pathway (RCP 8.5) average warming would exceed 5 °C by the end of the century (WBG and ADB, 2021b).

<sup>1</sup> Survey Solution.

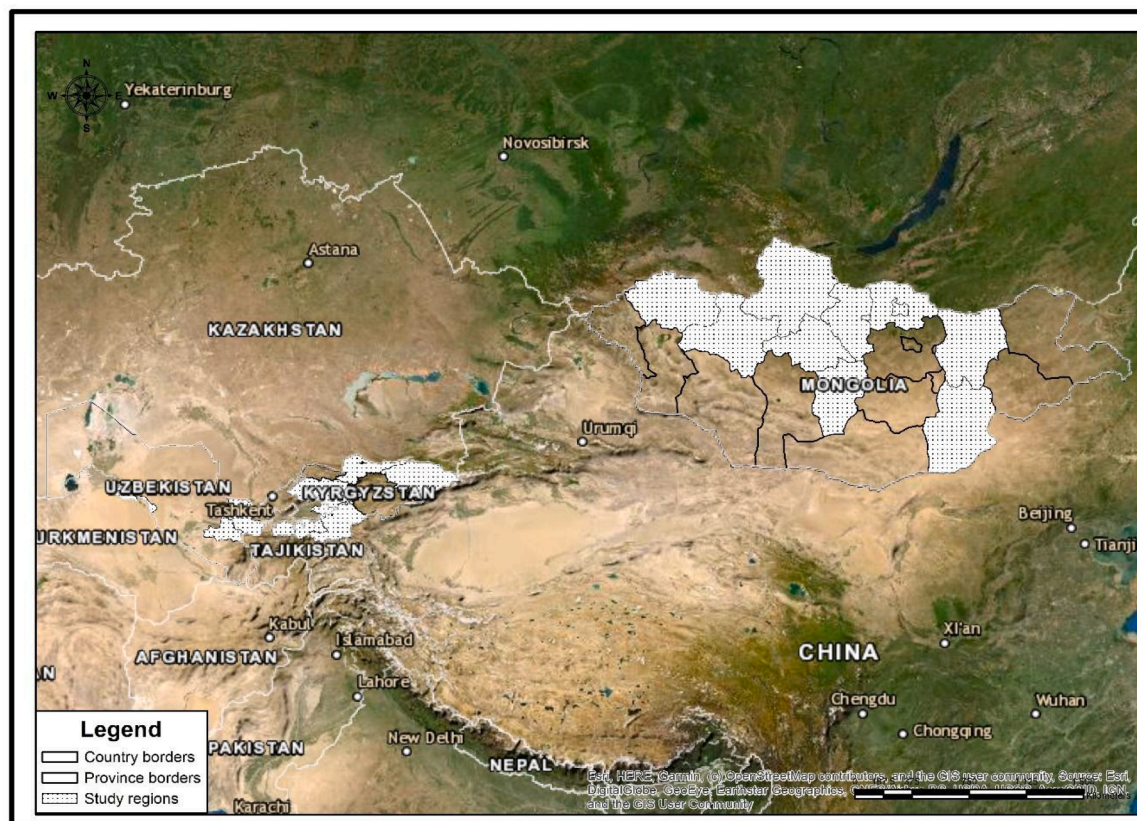


Fig. 1. Physical map of the study area: Kyrgyzstan, Uzbekistan and Mongolia.

Uzbekistan is bordered by Kazakhstan in the west and north, Afghanistan and Turkmenistan in the south, Kyrgyzstan and Tajikistan in the east. Uzbekistan lies at an average of 450 m above sea level. It covers an area of 44.8 million ha, of which 4.5 million ha is irrigated arable land, and almost 80 percent of the total irrigated area is occupied by winter wheat and cotton (Nurbekov et al., 2006). The average annual precipitation is approximately 200 mm and the average annual temperature varies from 29 – 42 °C.

Four main grain-producing regions, Jizzakh, Samarkand, Khorezm and Andijan, were selected. These regions are located in semi-arid and arid agro-ecological zones (Bobojonov and Aw-Hassan, 2014). Similar to Kyrgyzstan, Uzbekistan is also suffering from climate change, and a temperature increase of 4.8 °C is expected by the end of this century under the highest emission pathway (RCP 8.5).

### 3.2. Subjective weather risk perception

As we are assuming that farmers are not in full knowledge of risks and probabilities of climatic events, our study rests on subjective utility theory. To elicit subjective probability there are direct and indirect methods. Direct techniques involve the direct questioning of assessors regarding their perceptions of the probability of an event or outcome. Indirect methods involve individual techniques, and probabilities are inferred from preferences or choices between possible bets, decisions, or alternatives (Norris and Kramer, 1990). In our study we used direct techniques to elucidate climate risk perception.

To elucidate farmers' main concern about climate related risks, the following multiple-choice question was asked: "Which of these events did you experience at least once in the last 10 years?" The responses contained seven weather risks such as high summer temperature, lack of rainfall during vegetation period, seasonal heavy rainfall, very cold winters, mudslide, strong winds drying out soil and intensification of meteorological drought. Responses were collected by providing binary "yes" or "no" answer options to clearly distinguish between farmers who had a clear recall perception of particular climate risk in the list and those who did not. There might be some recall errors but since the farmers had to recall "any" event in ten years and not the number of extend the events, we assume that potential recall errors are minimal.

### 3.3. Meteorological data

Ground-based weather stations are sparse and unevenly distributed in CA and Mongolia (Eltazarov et al., 2021; Hu et al., 2014). Furthermore, many of them are outdated and have limited observation data. Therefore, this study uses meteorological data from CHIRPS and GLDAS, which covers each study district from 2010 to 2020 at a weekly frequency. In detail, the study uses daily

precipitation (CHIRPS), and maximum and minimum air temperature (GLDAS). The CHIRPS rainfall dataset generates gridded rainfall time series data using three different sources of information: 1) global precipitation climatology, 2) 0.5-degree resolution satellite imagery, and 3) in-situ station observation. The CHIRPS precipitation dataset combines more station data than other products and uses high-resolution background climatology to provide more accurate estimates of mean and variation in precipitation, resulting in a better hydrological status (Shukla et al., 2014). The GLDAS is a global offline terrestrial modelling system (Rodell et al., 2004), developed jointly by the National Aeronautics and Space Administration (NASA), Goddard Space Flight Center (GSFC) and the National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Prediction (NCEP). GLDAS-2.1 has a spatial resolution of 0.25 arc degrees, which corresponds to approximately  $28 \times 24$  km at the latitude of the study area. We used temperature data from the Global Land Data Assimilation System version 2.1 (GLDAS-2.1). The accuracy of these dataset was tested in the past by Eltazarov et al. (2021) and found suitable for conditions in Central Asia.

### 3.4. SPEI index

A variety of indices are available to identify meteorological drought, for instance Evaporative Demand Drought Index (EDDI) (Hobbins et al., 2016), Evaporative Stress Index (ESI) (Anderson et al., 2016), Standardized Precipitation Evaporation Index (SPEI) (Vicente-Serrano et al., 2010), and Standardized Precipitation Index (SPI) (McKee et al., 1993). In our study we focus on the intensification of drought events using the SPEI index at a weekly frequency over the past 11 years, between 2010 and 2020. The SPEI index has been used in a large number of drought monitoring studies in many countries, including Central Asia and Mongolia (Pyarali et al., 2022; Xu et al., 2016). In comparison to SPI and PDSI, SPEI has a very good performance in drought monitoring in the context of global warming (Vicente-Serrano et al., 2010). The SPEI can apply different time scales, such as weekly, 1-, 3-, 6-, and 12- month scales, and it is capable of analyzing both short term and long-term drought. The drought at these time scales is relevant for agriculture (1, 3, and 6 months), hydrology (12 months), and socioeconomic impact (24 months). We calculated drought occurrence on the basis of frequency distribution of the SPEI values from  $-1$  to  $-1.49$  (moderate dryness),  $-1.5$  to  $-1.99$  (severe dryness) and  $< -2$  (extreme dryness) on a weekly scale from 2010 to 2020 (see Table 1). For this study, we compared severe and extreme dryness events during vegetation season with subjective drought perception due to its high impact on crop production as compared to moderate dryness. The dates for calculating the index were chosen based on a crop growing calendar suggested by the FAO, 2018 (see Table A1 in the Appendix A).

## 4. Estimation strategy

### 4.1. Dependent variable

The motivation behind comparing subjective meteorological drought perception and objective meteorological changes in this study originates from studies that have compared subjective and objective rainfall changes, e.g. Kosmowski et al., 2016; Simelton et al., 2013. These studies have focused on average rainfall changes and farmers' perception of rainfall changes. We follow this approach, only slightly adjusting the measures. As described above, objective drought is defined as severe dryness measured along a SPEI index, while subjective perception was measured directly by a binary variable on drought experience in the last ten years. Based on this information, we divided farmers into a binary variable of accurate drought risk perception. Farmers were labelled "false perceivers" when their statement about meteorological severe drought was not in line with the SPEI values, and "accurate perceivers" when their perceptions coincided with the SPEI values.

### 4.2. Propensity score matching (PSM)

To estimate the effect of smartphone-based weather information acquisition on accurate drought risk perception, we must consider endogeneity issues. Farmers who own smartphones and choose to use them to check weather information may systematically differ from other farmers, also influencing their subjective drought perception. To control for possible latent selection bias, most empirical studies use a two-stage Heckman estimation method and Instrumental variable (IV) methods. The advantage of Heckman models is that they can model differences in both observed and unobserved characteristics between treatment and control groups by including the inverse Mills coefficient as an additional explanatory variable in the outcome model. However, Heckman selection estimators are based on strong assumptions that unobserved variables are normally distributed, and their robustness has been questioned in a growing literature using both simulated and actual data (Kiiza and Pederson, 2012). The instrumental variable (IV) method reduces the causal estimates and introduces new uncertainty due to its reliance on additional untestable assumptions (Kiiza and Pederson, 2012; DiPrete and Gangl, 2004). Moreover, finding valid instruments is a challenge for many empirical studies (Angrist and Krueger, 2001).

**Table 1**  
Classification of Standardized Precipitation Evapotranspiration Index (SPEI).

SPEI value	Class	Possible impacts
$-1$ to $-1.49$	Moderate dryness	Some damage to crops (Venkatappa et al., 2021; Wang et al., 2020)
$-1.5$ to $-1.99$	Severe dryness	Major reduction in yields (Madadgar et al., 2017)
$< -2$	Extreme dryness	Exceptional and widespread crop yield loss; severe water crisis (Yu et al., 2018; Zhang et al., 2018).

Source: McKee et al., 1993.

In contrast to the Heckman and IV methods, matching models assume that conditioning on observable variables eliminates sample selection bias (Heckman and Navarro-Lozano, 2004). The PSM technique (Rosenbaum and Rubin, 1983) provides unbiased estimation of treatment effects and can be used to draw causal-effect inference in non-experimental settings. It does this in our study by constructing a counterfactual of the outcome of the farmers who obtain smartphone-based weather information conditional on non-obtained ones (Ogutu et al., 2014). This method also allows to properly control for differences between farmers who obtain and don't obtain weather information using a smartphone, which is the average treatment effect on the treated (ATT) after controlling for differences among them (Mendola, 2007; Rosenbaum and Rubin, 1983). Our analysis is based on the idea that farmers who obtain smartphone-based weather information represent the treatment group, while the non-obtained group represent the counterfactual group (control group).

The average treatment effect on the treated (ATT) can be calculated as follows:

$$ATT_{(x)} = E[Y_1 | D = 1, X = x] - E[Y_0 | D = 0, X = x] \quad (1)$$

Where  $x$  is set of relevant confounding characteristics,  $E[Y_1 | D = 1, X = x]$  is the expected outcome for the units that received treatment, and  $E[Y_0 | D = 0, X = x]$  is the expected outcome for the treated units' best matches. For the purpose of comparison, PSM uses balancing scores to extract the observed mean outcome of the non-obtained farmers who are the most similar in observed characteristics to the obtained ones. In order for the true parameter to be estimated, it requires that:

$$E(D = 1, X = x) - E(D = 0, X = x) = 0 \quad (2)$$

which ensures that the ATT is free from self-selection bias.

There are different approaches to implementing PSM, including Nearest neighbor matching (NNM), Caliper or Radius matching, Stratification or Interval matching, and Kernel and Local Linear matching (Smith and Todd, 2005; Heckman et al., 1998). In this study, Nearest neighbor matching (NNM) and Kernel matching (KM) estimates were used. NNM matches each farmer from the obtained weather-information with the farmers from the control group having the closest propensity score. In case of large distance to the nearest neighbors, NNM might however yield imprecise results. Kernel matching uses a weighted average of all farmers in the adopted group to construct a counterfactual. The reason behind using these two approaches is to be sure of the robustness of the model.

Propensity score method relies on two assumptions often made in estimating treatment effects, first the conditional independence assumption (the independent and identically distributed observations), and second overlap assumptions (Rosenbaum and Rubin, 1983). Conditional independence assumption states that no unobservable variable affects both the likelihood of treatment and the outcome of interest after conditioning covariates. The overlap assumption in our case requires that each farmer has a strictly positive probability of obtaining weather information via smartphones after conditioning on a set of covariates.

The main purpose of the propensity score estimation is to balance the observed distribution of covariates across the two groups (Lee, 2013). The balance test is usually required after matching to establish whether differences in covariates between the two groups in the matched sample have been eliminated, in which case the matched comparison group can be considered a plausible counterfactual (Kassie et al., 2011). According to Caliendo and Kopeinig, (2008), a standardized bias of less than 5 percent is considered acceptable. If there are unobserved covariates that simultaneously influence the smartphone-based weather information and outcome variable, then there is a possibility of a hidden bias to which matching estimators may not be robust (Becker and Caliendo, 2007; Rosenbaum, 2002). This study used the Rosenbaum bounding approach to determine the extent of the influence of unobserved factors and their implications on our matching analysis; in particular, we used Mantel and Haenszel test statistics (1959).

#### 4.3. Demographic and farm characteristics of study participants

The average age of respondents was 47 years in three countries. The share of female farm heads and respondents was higher in the overall sample (30 percent) than in Uzbekistan (only 5 percent), which can be explained by regional differences in culture and labor migration. The number of farmers with agricultural education was higher in Uzbekistan and Mongolia (46.3 percent and 34.1 percent respectively), while in Kyrgyzstan, only 9.7 percent of farmers had an agricultural education. Farmer attendance to extension services was also low in Kyrgyzstan, at 16.2 percent, compared to Mongolia (56.8 percent) and Uzbekistan (50.7 percent). The average annual income of farmers was lower in Kyrgyzstan (2.3) compared to Mongolia (4.0) and Uzbekistan (5.6) (see footnote 2 for details). Also, the distribution of farmers across agro-ecological zones differed considerably across countries: while Kyrgyz farmers were mostly located in the semi-humid zones, farmers in Uzbekistan were rather located in arid zones, and Mongolian farmers nearly completely in arid zones. The perceived reliability of online weather information on a five-point Likert scale was highest among Kyrgyz famers (3.4). Smartphone adoption was high in Mongolia (96.9 percent) and Uzbekistan (93.6 percent), and a bit lower in Kyrgyzstan (87.6 percent). Similarly, smartphone access to weather information was high in Mongolia and Uzbekistan (81.5 percent and 79.2 percent, respectively), but significantly lower in Kyrgyzstan (33.2) (see Table 2).

#### 4.4. Factors affecting smartphone-based weather information acquisition

The PSM estimator for ATT is based on a logit model presented in Table 3. Results show that age of household, education in

<sup>2</sup> Farm survey, 2021: e.g. irrigated land accounted for 12.36%, and rain fed land for 98.71%.



agriculture, annual farm income, agro-ecological zones, attitude to online weather information reliability, smartphone ownership variables have a significant influence on smartphone-based weather information acquisition. Household age was found to be a determinant of smartphone-based weather information access. The younger the head of the household, the more likely it is that they obtain smartphone-based weather information. A unit increase in education in agriculture will increase obtaining weather information via smartphone by 18 percent. The results imply that when it comes to smartphone-based weather information acquisition, people with an education in agriculture tend to obtain weather information on their smartphones. A unit increase in farm annual income will increase the access to weather information via smartphone by 5.6 percent. Farmers in semi-arid and arid regions are likely to obtain weather information on their smartphones. The results also suggest that farmers' attitude to the reliability of the weather information significantly promote smartphone weather information acquisition; farmers who rely on online weather information are likely to acquire smartphone-based weather information. Gender, attendance in extension services and country variables did not significantly influence smartphone-based weather information access.

## 5. Results

### 5.1. Farmers subjective climate risk perception

Fig. 2 indicates major extreme phenomena that respondents perceived in the last 10 years. The major climate risk in three countries was meteorological drought. 34 percent of study participants in Kyrgyzstan perceived meteorological drought as a major risk source; 68 percent in Mongolia and 55 percent in Uzbekistan, respectively. Following this, high summer temperatures and a lack of rainfall were the second and third major extreme phenomena in all study areas.

### 5.2. Actual meteorological drought occurrence calculated from climate data

Table 4 shows the total average extreme, severe and moderate drought events that occurred in all study countries during the crop growing season per year. Over the past 10 years, there have been 12 incidences of severe and extreme droughts in all studied districts in Kyrgyzstan during the crop growing season, while the maximum severe and extreme droughts have occurred 27 times. Mongolia experienced an average of 27 incidences of severe and extreme drought and a maximum of 95 incidences in all study districts. At the same time, there have been on average 12 incidences of severe and extreme droughts in all study districts in Uzbekistan, and they have reached up to 51. In contrast, there were 47 incidences of moderate drought in Kyrgyz districts, 113 in Mongolian districts and 66 in Uzbek districts per crop growing season.

**Table 2**  
Summary statistics of household characteristics and outcome variable.

Variables	Value	Kyrgyzstan	Mongolia	Uzbekistan
		Mean Std. Dev; Percentage (N = 1200)	Mean Std. Dev; Percentage (N = 542)	Mean Std. Dev; Percentage (N = 1088)
Age of head of household	Mean (years)	48.57 (13.28)	47.94 (11.19)	45.55 (8.89)
Gender	Male	73.33	70.11	94.94
	Female	26.67	29.89	5.06
Education in agriculture	Yes	9.67	34.13	46.32
	No	90.33	65.87	53.68
Farmers extension service attendance	Yes	16.17	56.83	50.74
	No	83.83	43.17	49.26
Annual farm income in US dollar	Mean (1–6)	2.33 (0.90)	4.03 (1.66)	5.55 (0.88)
Farm location <sup>3</sup>	Sub -humid	68.75	–	–
	Semi – arid	31.25	8.67	32.08
	Arid	–	91.33	67.92
Attitude to the online weather information reliability	(1 strongly agree – 5 strongly disagree)	3.34 (0.99)	1.75 (0.67)	2.18 (0.65)
Smartphone adoption	Yes	87.58	96.86	93.57
	No	12.42	3.14	6.43
<i>Outcome variable</i>				
Accurate drought perception	Yes	33.92	68.27	54.96
	No	66.08	31.73	45.04
<i>Dependent/Treatment variable</i>				
Smartphone - weather access	Yes	33.17	81.55	79.23
	No	66.83	18.45	20.77

<sup>3</sup>Annual farm income categories in US dollar: 1 = KG < 707; MN < 1753; UZ < 467.

2 = KG 707.1 – 1769; MN 1753.1 – 8772; UZ 467.1 – 2341.

3 = KG 1769.1 – 2948; MN 8772.1 – 17545; UZ 2341.1 – 4680.

4 = KG 2948.1 – 4717; MN 17545.1–26316; UZ 4680.1 – 7017.

5 = KG 4717.1 – 7076; MN 26316.1–35088; UZ 7017.1–9.357.

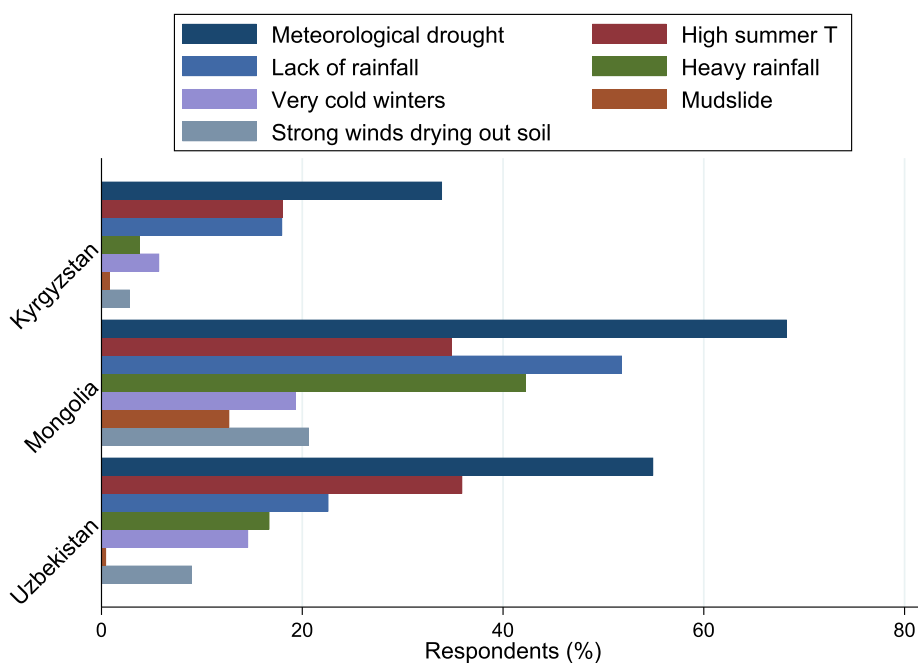
6 = KG \$ >7076.1; MN \$ > 35088.1; UZ \$ > 9.357.1.

**Table 3**  
Determinants of smartphone-based weather information acquisition: logit model estimates.

Variable	Logit	Marginal effect
Age of the head of household	-0.009 (0.00) ***	-0.002 (0.00) ***
Gender of the head of household	-0.057 (0.12)	0.014 (0.02)
Education in agriculture	0.791 (0.12) ***	0.188 (0.02) ***
Attendance in extension services	0.089 (0.10)	0.021 (0.03)
Annual farm income	0.235 (0.04) ***	0.056 (0.01) ***
Agroecological zones	0.340 (0.07) ***	0.081 (0.02) ***
Attitude to online weather information reliability	-0.311 (0.05) ***	-0.068 (0.01) ***
Smartphone ownership	3.214 (0.28) ***	0.765 (0.1) ***
Country	-0.060 (0.08)	-0.014 (0.02)
constant	-2.959 (0.48)	
Number of observations	2830	
Pseudo R2	0.2271	

Standard errors in parentheses.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .



**Fig. 2.** Direct personal experience of extreme weather events in Kyrgyzstan, Mongolia and Uzbekistan.

**Table 4**  
Total average extreme, severe and moderate drought events calculated from climate data within 10 years.

Country	Types of drought incidences	Mean	Min	Max
Kyrgyzstan	Severe and extreme	11.82 (8.98)	0	27
	Moderate	47.82 (11.32)	36	72
Mongolia	Severe and extreme	27.64 (28.01)	0	95
	Moderate	112.09 (66.76)	14	222
Uzbekistan	Severe and extreme	11.18 (14.89)	0	51
	Moderate	66.45 (12.70)	45	85

Fig. 3 shows that the number of incidences of severe drought, calculated from climate data, shows an increase in Kyrgyzstan, while in Mongolia and Uzbekistan a decreasing trend can be observed. It can be seen that the incidences of severe drought have increased in Kyrgyzstan (see Table A2 in the Appendix).

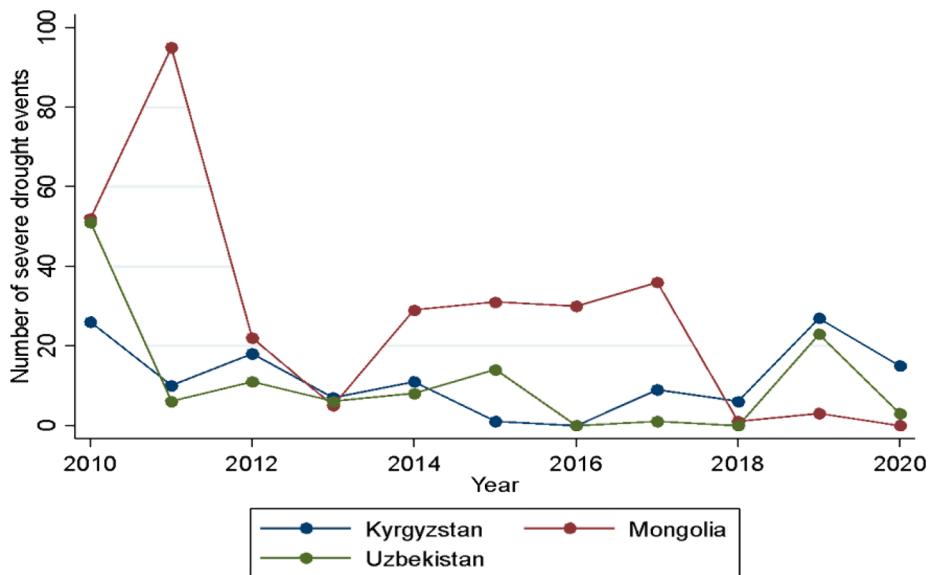


Fig. 3. Total severe and extreme drought events in study districts during the growing season calculated from climate data.

5.3. Discrepancies between subjective and objective drought changes

The average SPEI values during vegetation crop season and the percentage of accurate meteorological drought occurrence perceivers show discrepancies after comparison with the SPEI values in a given district. According to the calculation, 33 percent farmers in Kyrgyzstan perceived meteorological drought accurately, compared with around 54 percent farmers in Uzbekistan and 68 percent in Mongolia (also see in Table 2).

5.4. Impact of smartphone-based weather information acquisition on accurate drought perception

To analyze the impact of smartphone-based weather information acquisition on accurate meteorological drought perception, we first generated the density distribution of propensity score for the treated (farmers who obtained smartphone-based weather

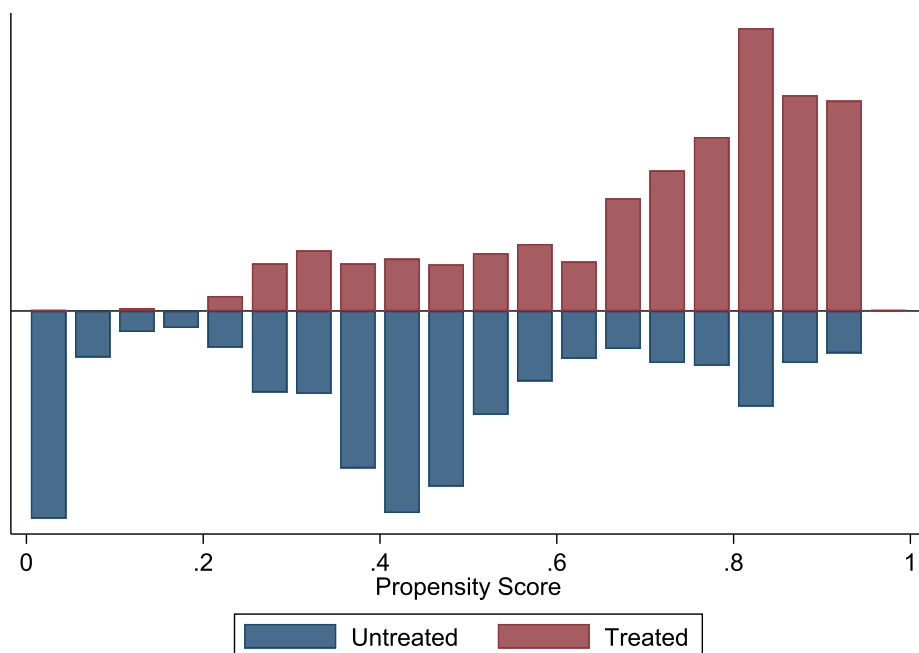


Fig. 4. Household propensity score distribution for treated and control households with an area of common support.

information) and non-treated (non-obtained) households. Meanwhile, differences in the distribution of treated and control households confirmed the use of the PSM method to ensure comparability. Therefore, only treated households and control households with the same propensity scores were included in the analysis. Fig. 4 shows, before matching and after matching, the density distribution of propensity scores for the treated overlap that of the non-treated; therefore, the common support criterion of the propensity score matching technique has been met (see country specific results in the Appendix).

The validity of the use of propensity score matching requires that the treated (farmers who obtained smartphone-based weather information) and control (non-obtained) groups have either the same or similar characteristics. Therefore, we also check for balancing tests before matching and after matching, as can be seen in Table 5. From Table 5, differences between weather information-obtained farmers and non-obtained farmers are found to be insignificant regarding age, education in agriculture, annual farm income, agro-ecological zones, attitude to online weather information reliability, smartphone ownership and country after matching.

Table 6 lists values of indicators before and after matching. Rosenbaum and Rubin (1985) recommended standardized bias (SB) to check the matching quality. Before matching, the average standardized bias was 50.2 percent; after matching, the standardized mean difference of covariates reduced to 3.7 percent using for Nearest neighbor matching (NNM) and 5.1 for Kernel matching. This gives a total bias reduction of about 16.3 and 19.6 percent of both matching algorithms. The *Pseudo R*<sup>2</sup> is considerably reduced after matching. The decreasing trend indicates that the matching procedures produce a better balance.

The impact of smartphone-based weather information acquisition on accurate agricultural drought risk perception is reported in Table 7. This was estimated using nearest neighbor matching (NNM) and kernel matching (KM) algorithms used in propensity score matching. The NNM and Kernel matching results revealed that smartphone-based weather information acquisition significantly affects accurate meteorological drought risk perception 8–7 percent, respectively.

### 5.5. Country-specific results

The country-specific results of NNM and Kernel matching in Table 8 show that farmers who check weather information via smartphone exhibit a higher accuracy of meteorological drought perception in Kyrgyzstan (15 and 14 percent for Nearest neighbor and Kernel matching). In the Mongolian sample, farmers who access smartphone-based weather information have higher accurate meteorological drought perception by 16 and 17 percent, respectively. Only in the Uzbek sub-sample, access to smartphone-based weather information did not significantly influence meteorological drought perception.

### 5.6. Sensitivity of ATT to hidden biases

To check whether the PSM results are sensitive to hidden bias as a result of unobserved factors, we applied the bounding approach proposed by Rosenbaum (2002), which determines how strongly an unobserved factor may influence the selection process in order to invalidate the results of PSM analysis. Such an analysis is carried out by calculating upper and lower bounds for different values of unobserved selection bias for the test-statistics under the null hypothesis of no training effect. The Mantel and Haenszel test statistics shows that the causal effects of the smartphone-based weather information acquisition on accurate meteorological drought perception in the study area would change at the bound statistics,  $\Gamma = 1.5$  (i.e., the upper critical gamma cut-off value). This indicates that, for two farmers of the same characteristics, the probability of receiving the treatment can differ by up to 7 percent without altering the inference of the treatment effects (see Table A3 in the Appendix). Following Kiiza and Pederson (2012), who applied the same test statistic when studying the ICT-based market information on intensity of adoption of improved seed, we hence conclude that our estimates indicate relative robustness to hidden bias.

## 6. Discussion

This article aimed at assessing the impact of smartphone weather information on climate risk perception accuracy of farmers in our sample regions. To measure climate risk perception accuracy, we compare an objective measure for meteorological drought (SPEI index) with subjective perception of drought incidence. In a sample of 2830 grain farmers in Kyrgyzstan, Uzbekistan and Mongolia, overall accuracy of perception was only 48 percent. Furthermore, our sample countries exhibited distinct differences in the accuracy of meteorological drought perception, namely 33 percent in the Kyrgyz sample, 68 percent in Mongolia and 54 percent in Uzbekistan.

Considering the progressive development and spreading of information and communication technology (ICT), our study reveals that farmers' smartphone-based weather information acquisition have a substantial effect on accurate meteorological drought risk perception in general. Herein, we confirm previous studies that link the use of ICT-based information services to a stronger perception of climate hazards (Hasibuan et al., 2020). However, country-specific results showed that smartphone-based weather information acquisition positively influenced accurate meteorological drought risk perception in the Kyrgyz and Mongolian sample, but was insignificant in the Uzbek sample. The reason for the lacking association in the Uzbek sample could be that, even though the mobile Internet coverage is high among sample farmers (90 percent according to our survey), mobile internet traffic is relatively slow (13.67 Mbps) compared to Kyrgyzstan (23.68 Mbps) and Mongolia (16.53 Mbps) (Digital, 2022).

Our findings on the impact of online weather information on risk perception accuracy have some important implications for a more efficient distribution of climate and weather information. As indicated above, slow internet speed may have hindered people effectively using smartphones for weather information. Therefore, policy makers need to pay special attention to enable good internet speed also in rural areas, considering its potential usage for climate risk adaptation measures. A growing of multifunctional mobile apps are available also for agricultural producers, most of them certain requirements of internet connectivity and speed. For example,

**Table 5**  
Test of equality of means of each variable before and after matching.

	Unmatched samples			Nearest-neighbor matching			Kernel matching		
	Treated	Control	Diff.	Treated	Control	Diff.	Treated	Control	Diff.
	N =	N =	P-value	N =	N =	P-value	N =	N =	P-value
	1702	1128		1700	1128		1700	1128	
Age	45.99	49.25	-7.49 ***	46.00	46.97	0.10	46.00	46.15	-0.41
Gender	1.16	1.23	-4.42 ***	1.16	1.16	1.59	1.16	1.15	0.82
Education in agriculture	0.37	0.16	12.67 ***	0.37	0.36	0.30	0.37	0.36	0.71
Extension service attendance	0.45	0.26	10.11 ***	0.45	0.50	-3.07***	0.45	0.49	-2.88*
Annual farm income	4.42	3.09	20.59 ***	4.42	4.49	-1.15	4.42	4.47	-0.77
Agroecological zones	2.40	1.77	20.96 ***	2.39	2.35	1.70	2.39	2.36	-1.43
Attitude to reliability of online weather information	2.30	3.03	-19.40 ***	2.30	2.34	-1.32	2.30	2.34	-1.21
Smartphone-ownership	0.99	0.80	18.35 ***	0.99	0.99	-1.35	0.99	0.99	-0.71
Country	2.25	2.11	4.81 ***	2.25	2.27	-0.77	2.25	2.28	-1.10

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0$ .

**Table 6**  
Overall matching quality indicators before and after matching.

Quality indicators	Pseudo R <sup>2</sup>	LR chi <sup>2</sup>	Mean standardized bias	Total bias reduction %
Matching algorithms				
Before matching	0.227	864.30	50.2	116.7*
Nearest neighbor matching	0.005	22.60	3.7	16.3
Kernel matching	0.007	32.42	5.1	19.6

**Table 7**  
ATT results for the impact of smartphone-based weather information on accurate drought perception.

Outcome variable	Treated households (N = 1700)	Control households (N = 1128)	ATT nearest neighbor	ATT kernel
Accurate meteorological drought perception	0.56 (0.50)	0.37 (0.48)	0.08 (0.02) *	0.07 (0.03) **

Standard errors in parentheses.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Table 8**  
ATT results for the impact of smartphone-based weather information on accurate drought perception.

Accurate meteorological drought perception	Treated households	Control households	ATT nearest neighbour	ATT kernel
Kyrgyzstan	0.45 (0.02)	0.31 (0.03)	0.15 (0.04) ***	0.14 (0.03) ***
Mongolia	0.71 (0.02)	0.54 (0.05)	0.16 (0.06) ***	0.17 (0.06) ***
Uzbekistan	0.54 (0.02)	0.58 (0.03)	-0.04 (0.05)	-0.04 (0.04)

Standard errors in parentheses.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

the Android app FarmPulse, which was introduced in the scope of the KlimALEZ project, provides weather information, opportunities for financial risk management and satellite-based plant growth data for crop monitoring. Like similar software, this app relies on real time satellite data and requires a stable and fast internet connection. Our findings also have implications on design of potential agricultural software and mobile applications: (a) the important role of farmers' age and higher education suggest that smartphone applications should be simple and easily accessible for older farmers and farmers with low digital literacy in general; (b) the important role of income means that the services need to be free of charge to give access also to low-income farms, who also tend to be the most vulnerable to drought risk.

Beyond internet speed, also other geospatial differences in risk proximity and reliance on rainfall for agriculture may have influenced our results. For instance, this concerns the spatial heterogeneity of the farms in the three countries (Bobojonov and Aw-Hassan, 2014), socio-economic attributes of farmers (Hughes et al., 2022) and hazard proximity (Lujala et al., 2015). In terms of geographical context, some regions of Kyrgyzstan and most regions of Uzbekistan are heavily dependent on irrigation and not direct precipitation. In contrast, Mongolia is dominated by rainfed agriculture<sup>2</sup>; Mongolian farmers therefore heavily rely on precipitation and thus might be more informed about related changes in rainfall. In Kyrgyzstan, where many farmers partially irrigate their fields with meltwater from mountain glaciers, farmers are to a certain degree independent from rainfall and thus might be less sensitive to drought events caused by lack of precipitation. In addition, water reservoirs could also alleviate the impact of meteorological drought

in Kyrgyzstan and Uzbekistan, resulting in the observed discrepancies. Another explanation for these strong country-level differences might be risk-proximity. Wachinger et al. (2013) stated that people located in risk-prone areas perceive themselves closer to danger and are thus more aware of potential risks connected to the economic activity. About 91 percent of our sample farmers in Mongolia and 67 percent of the sample farmers in Uzbekistan were located in arid zones, which could have made them more alert to climate risk and climate events, hence resulted in higher accuracy of drought incidence perception. Our results are consistent with the findings of other studies highlighting individual differences in risk perceptions (see also chapter 2.1) (van Winsen et al., 2016; Weber et al., 2002).

For future research, our results thus suggest to take a closer look on the interaction between precipitation dependence and risk proximity with (digital) climate risk information. A dedicated measurement of these variables was unfortunately not within the scope of this study. For instance, general areas of rainfed and irrigated agriculture are in theory well discernable, yet we observed that the differences between both systems are blurred within our target regions, as outdated irrigation systems may not be functional under regional drought events. Similarly, risk proximity may be dependent on a number of individual factors, for instance farming history, and would require a more in-depth study. On a more detailed level, this study is limited by the fact that it focused on meteorological drought instead of agricultural drought due to data requirements. In future research, we would like to test the robustness of our result to a change in drought definition. Furthermore, higher resolution of weather data from satellites could help to reduce potential bias risk in terms of the chosen weather index. Future research should focus more in-depth on subjective drought perception along a smaller in-depth sample. Finally, panel data could provide the opportunity to test farmers' perception changes over time.

## 7. Conclusion

Overall, we showed that farmers' in our study region are mostly not aware of objective drought risk in their region. This is problematic because lacking knowledge of climatic risks may inhibit appropriate climate risk adaptation measures, making farmers in the region highly vulnerable to future weather extremes under progressing climate change. While many farmers today can still rely on irrigation, their dependency on rainfall may in future increase, when surface and groundwater reservoirs are depleted and glacier melting peaked. Our findings suggest that smartphone-based weather information access could be a tool in promoting awareness for farmers to weather changes in the scope of climate change. Policy makers should create an enabling environment to accelerate the adoption and use of applications to access weather information and support risk management. Moreover, our results show that software solutions and policy interventions should also target marginalized farmers with low incomes, low education and low digital literacy, who might otherwise not be able to make full use of ICT potential. One example for a targeted software solution is the Farm Pulse App developed in the scope of project KlimALEZ, which is available in all regional languages and provides easy access to users even with low digital literacy.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

## Acknowledgements

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## Appendix A

**Table A1**

Crop growing calendar based on FAO, 2018.

Country	Crop type	Sowing months	Growing months	Harvesting months
Kyrgyzstan	Spring wheat, barley	A, M	J, J, A	S, O
Uzbekistan	Cotton, summer wheat	A, M	J, J, A	S
Mongolia	Spring wheat, barley	A, M	J, J, A	S

**Table A2**  
SPEI values and their trends in Kyrgyz, Mongolian and Uzbek districts.

	Region	District	Average severe drought events	Coefficient	
Kyrgyzstan	Chuy	Jayil	1.09	1.945	
		Panfilov	1.45	0.534	
		Sokuluk	1.27	1.226	
	Issyk-Kul	Ak suu	0.82	-1.727	
		Tup	1.73	-0.185	
	Batken	Batken	0.64	-1.917	
		Kadamjy	1.45	-1.618	
	Osh	Kara-Suu	0.91	1.007	
		Nookat	1.18	-0.959	
	Jalal-Abad	Bazar Korgon	0.73	0.917	
		Suzak	0.55	-1.290	
	Mongolia	Arkhangai	Khotont	0.3	-1.375
			Tuvshruulekh	0.3	-2.750
		Bulgan	Bayan Agt	0.6	-1.833
Bugat			0.5	-1.784	
Bugerkhangai			0.5	-1.864	
Khangel			0.6	-2.903	
Khisih-Undur			0.5	-1.338	
Khutag Ondor			0.7	-1.410	
Orkhon 1			0.5	-2.420	
Selenge			0.6	-3.270	
Teshig			0.7	-1.100	
Darkhan-Uul		Khongor	0.5	-1.635	
		Khalkhgol	0.7	-0.971	
Dornod		Tsagan Ovoo	0.6	0.000	
		Bayan Adarga	0.6	-0.936	
Khentii		Binder	1.0	-2.200	
		Dadal	1.0	-1.438	
		Kherlen	0.5	-1.338	
		Unmnudelger	1.0	-2.600	
Khuvsgul		Erdenebulgan	0.8	-2.357	
		Rashant	0.6	-1.328	
		Tarialan	0.8	-2.357	
Orkhon		Bayan-Undur	0.5	-1.338	
		Jargalant1	0.6	-3.3	
Selenge		Altanbulag	0.6	-1.053	
		Baruunburen	0.5	-1.904	
		Bayangol	0.5	-1.338	
		Eroo	0.7	-2.357	
		Javkhilant	0.5	-2.115	
		Khuder	0.6	-1.043	
		Khushaat	0.5	-3.173	
		Mandal	0.7	-1.410	
		Orkhon	0.6	-2.221	
		Orkhontuul	0.2	-5.500	
		Saikhan	0.6	-3.270	
		Sant	0.5	-3.270	
		Tsaganuur	0.6	-3.080	
		Zuunburen	0.4	-4.321	
		Tuv	Argalant	0.5	-2.538
			Bayankhangai	0.3	-3.109
Bayantsogt			0.5	-2.538	
Ceel			0.2	-5.500	
Erdenesant			0.5	-2.567	
Jargalant			0.4	-3.3	
Sumber			0.2	-5.500	
Ugtaaltsaidam			0.5	-1.948	
Baruunturuun			0.6	-0.936	
Sagil			1.0	-1.100	
Ulaangom			0.4	-2.420	
Uvurkhangai			Kharkhorin	0.1	-5.500
			Asgat	0.5	-1.481
Zavkhan			Tes	0.4	-0.880
Uzbekistan		Andijan	Altinkul	0.6	-0.660
	Khadjaabad		0.5	1.058	
	Pakhtaabad		0.6	0.550	
	Ulugnar		0.6	-1.069	

(continued on next page)

**Table A2** (continued)

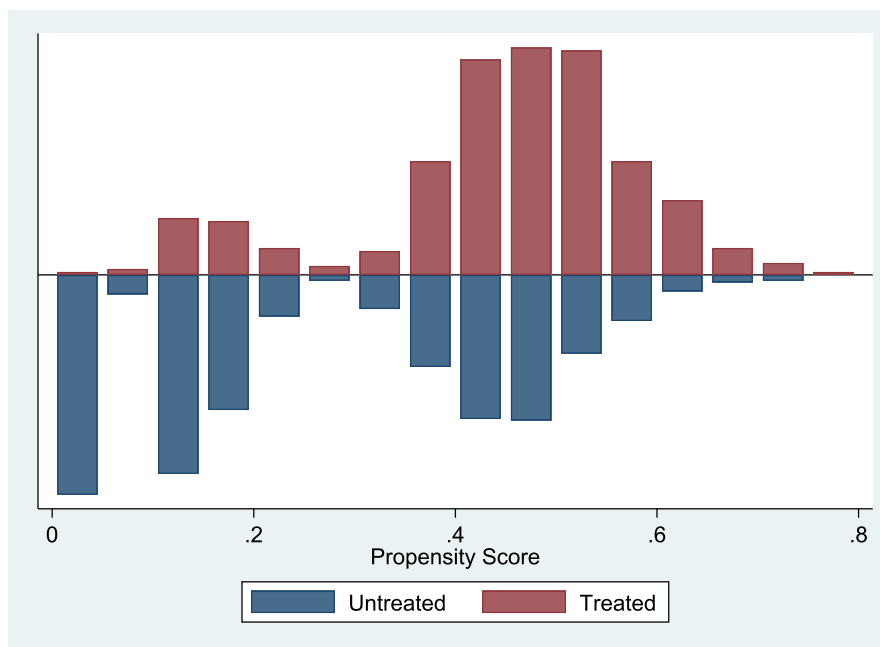
Region	District	Average severe drought events	Coefficient
Khorezm	Yangiarik	1.1	-1.185
	Yangibazar	1.1	-1.100
	Khiva	1.0	-1.188
	Koshkupir	1.1	-1.294
	Shavat	1.0	-1.188
Samarkand	Pakhtachi	0.6	-0.907
	Pastargom	0.7	0.000
	Payarik	0.5	-0.839
	Narpay	0.7	0.282
	Zamin	0.8	-1.764

**Table A3**

Test of Sensitivity to hidden biases Mantel and Haenszel, (1959), test statistics.

Gamma	Q_mh+	Q_mh-	p_mh+	p_mh-
1	2.613	2.613	0.004	0.004
1.1	2.190	3.045	0.014	0.001
1.2	1.805	3.440	0.036	0.000
1.3	1.451	3.808	0.073	0.000
1.4	1.126	4.151	0.130	0.000
1.5	0.823	4.475	0.205	0.000
1.6	0.540	4.780	0.294	0.000
1.7	0.275	5.071	0.392	0.000
1.8	0.025	5.348	0.490	0.000
1.9	-0.017	5.612	0.507	0.000
2	0.207	5.866	0.418	0.000

Country-specific results of Propensity score matching.



**Fig. A1.** Propensity score distribution and common support for Kyrgyz sample.

**Table A4**

Test of equality of means of each variable before and after matching, Kyrgyz sample.

Unmatched Sample	Nearest Neighbour Matching	Kernel Matching
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Table A4 (continued)

Variable	Unmatched Sample			Nearest Neighbour Matching			Kernel Matching		
	Treated	Control	Diff. P-value	Treated	Control	Diff. P-value	Treated	Control	Diff. P-value
Age	46.01	49.83	-4.74 ***	46.10	45.82	0.3	46.10	46.07	0.04
Gender	1.25	1.27	-0.71	1.26	1.27	-0.54	1.26	1.27	-0.43
Education in agriculture	0.14	0.07	4.08 ***	0.14	0.15	-0.53	0.14	0.14	0.04
Extension service attendance	0.17	0.15	0.61	0.17	0.18	-0.40	0.17	0.19	-0.60
Annual farm income	2.37	2.3	1.27	2.37	2.35	0.34	2.37	2.37	0.02
Agroecological zones	0.87	0.59	10.40 ***	1.12	1.13	-0.07	1.12	1.13	-0.18
Attitude to reliability of online weather information	3.24	3.39	-2.47 ***	3.25	3.27	-0.29	3.25	3.26	-0.10
Smartphone ownership	1.00	0.82	9.31 ***	1.00	1.00	0	1.00	1.00	0.04

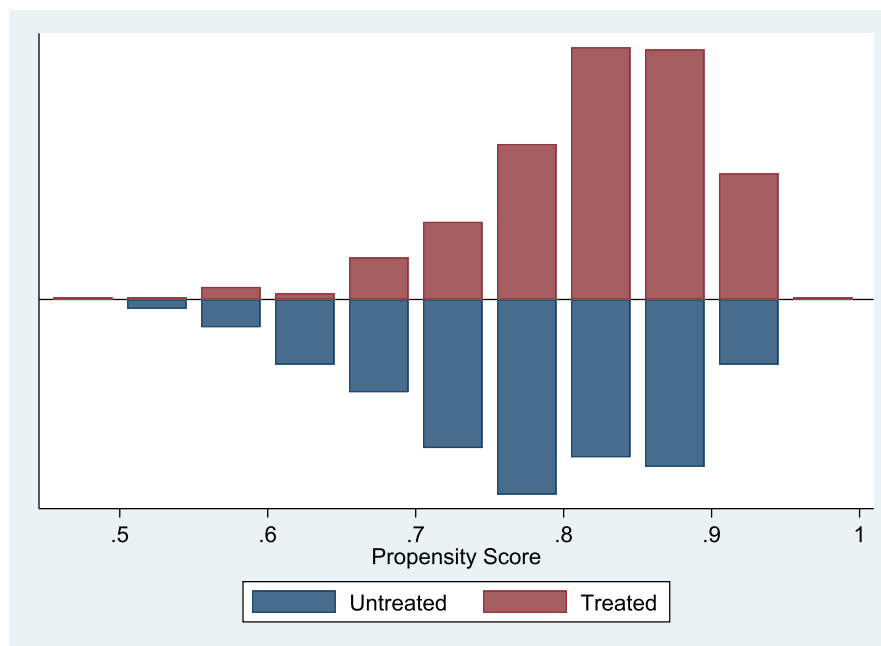


Fig. A2. Propensity score distribution and common support for Mongolian sample.

Table A5

Test of equality of means of each variable before and after matching, Mongolian sample.

Variable	Unmatched Sample			Nearest Neighbour Matching			Kernel Matching		
	Treated	Control	Diff. P-value	Treated	Control	Diff. P-value	Treated	Control	Diff. P-value
Age	47.52	49.77	-1.82 *	47.84	47.74	0.12	47.84	47.83	0
Gender	1.3	1.28	0.46	1.30	1.30	-0.20	1.30	1.30	-0.14
Education in agriculture	0.33	0.38	-0.9	0.33	0.29	1.21	0.33	0.33	-0.06
Extension service attendance	0.59	0.46	2.43 ***	0.58	0.62	-0.98	0.58	0.57	0.23
Annual farm income	4.15	3.52	3.45 ***	4.10	4.08	0.21	4.10	4.10	0.03
Agroecological zones	0.9	0.94	-1.05	2.92	2.90	1.05	2.92	2.92	0.15
Attitude to reliability of online weather information	1.73	1.83	-1.25	1.73	1.84	-2.46	1.73	1.81	-1.76*
Smartphone-ownership (omitted from the regression)	-	-	-	-	-	-	-	-	-

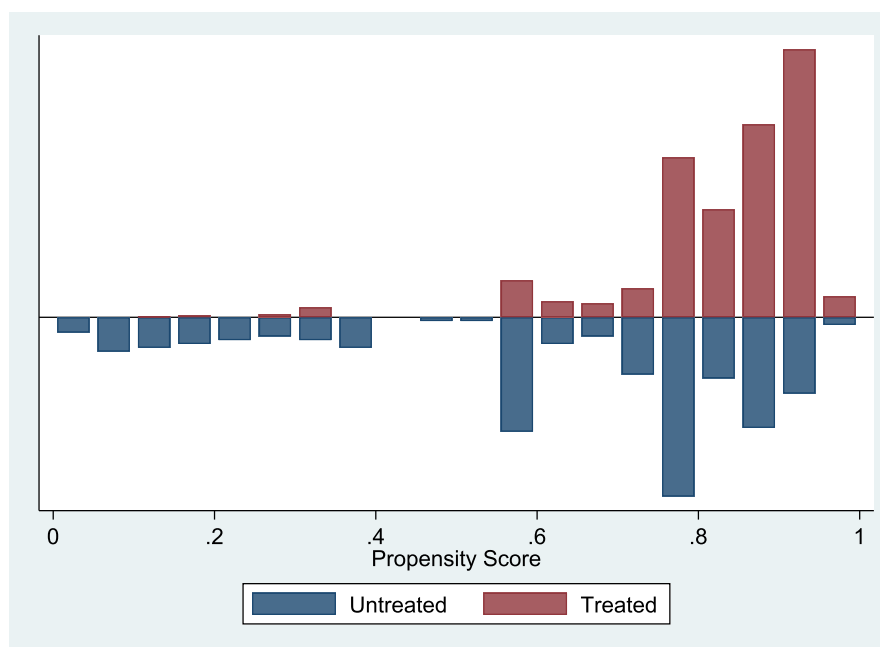


Fig. A3. Propensity score distribution and common support for Uzbek sample.

Table A6

Test of equality of means of each variable before and after matching, Uzbek sample.

Variable	Unmatched Sample			Nearest Neighbour Matching			Kernel Matching		
	Treated	Control	Diff. P-value	Treated	Control	Diff. P-value	Treated	Control	Diff. P-value
Age	45.19	46.92	-2.61***	45.20	44.10	2.81***	45.20	44.43	1.92*
Gender	1.05	1.05	-0.2	1.05	1.07	-1.35	1.05	1.05	0.25
Education in agriculture	0.49	0.35	3.72***	0.49	0.48	0.48	0.49	0.48	0.58
Extension service attendance	0.49	0.54	-1.25	0.49	0.47	1.16	0.49	0.51	-0.79
Annual farm income	5.5	5.68	-2.70***	5.53	5.54	-0.3	5.53	5.59	-1.30
Agroecological zones	0.27	0.47	-5.77***	2.72	2.72	-0.05	2.72	2.73	-0.65
Attitude to reliability of online weather information	2.14	2.28	-2.79***	2.15	2.14	0.41	2.15	2.08	2.4***
Smartphone ownership	0.98	0.76	12.89***	0.98	0.98	0	0.98	0.98	0

## References

- Aker, J.C., 2011. Dial "A" for agriculture: a review of information and communication technologies for agricultural extension in developing countries. *Agric. Econ.* 42, 631–647. <https://doi.org/10.1111/j.1574-0862.2011.00545.x>.
- Akerlof, K., Maibach, E.W., Fitzgerald, D., Cedeno, A.Y., Neuman, A., 2013. Do people "personally experience" global warming, and if so how, and does it matter? *Glob. Environ. Change* 23, 81–91. <https://doi.org/10.1016/j.gloenvcha.2012.07.006>.
- Anderson, M.C., Zolin, C.A., Sentelhas, P.C., Hain, C.R., Semmens, K., Tugrul Yilmaz, M., Gao, F., Otkin, J.A., Tetrault, R., 2016. The Evaporative Stress Index as an indicator of agricultural drought in Brazil: An assessment based on crop yield impacts. *Remote Sens. Environ.* 174, 82–99. <https://doi.org/10.1016/j.rse.2015.11.034>.
- Angrist, J.D., Krueger, A.B., 2001. Instrumental Variables and the Search for Identification: From Supply and Demand to Natural Experiments. *J. Econ. Perspect.* 15, 69–85. <https://doi.org/10.1257/jep.15.4.69>.
- Bahta, Y.T., Jordaan, A., Muyambo, F., 2016. Communal farmers' perception of drought in South Africa: Policy implication for drought risk reduction. *Int. J. Disaster Risk Reduct.* 20, 39–50. <https://doi.org/10.1016/j.ijdrr.2016.10.007>.
- Batima, P., Dagvadorj, D. (Eds.), 2000. *Climate Change and Its Impacts in Mongolia*. JEMR Publishing, Ulaanbaatar.
- Becker, S.O., Caliendo, M., 2017. Mhbounds - Sensitivity Analysis for Average Treatment Effects. SSRN Electronic J. <https://doi.org/10.2139/ssrn.958699>.
- Bloodhart, B., Maibach, E., Myers, T., Zhao, X., 2015. Local Climate Experts: The Influence of Local TV Weather Information on Climate Change Perceptions. *PLOS ONE* 10, e0141526.
- Bobojonov, I., Aw-Hassan, A., 2014. Impacts of climate change on farm income security in Central Asia: An integrated modeling approach. *Agric. Ecosyst. Environ.* 188, 245–255. <https://doi.org/10.1016/j.agee.2014.02.033>.
- Bobojonov, I., Berg, E., Franz-Vasdeki, J., Martius, M., Lamers, J.P., 2016. Income and Irrigation Water Use Efficiency under Climate Change: An Application of Spatial Stochastic Crop and Water Allocation Model to Western Uzbekistan. *Climate Risk Management* 13, 19–30. <https://doi.org/10.1016/j.crm.2016.05.004>.

- Bonke, V., Fecke, W., Michels, M., Musshoff, O., 2018. Willingness to pay for smartphone apps facilitating sustainable crop protection. *Agron. Sustain. Dev.* 38, 51. <https://doi.org/10.1007/s13593-018-0532-4>.
- Caffaro, F., Micheletti Cremasco, M., Rocca, M., Cavallo, E., 2020. Drivers of farmers' intention to adopt technological innovations in Italy: The role of information sources, perceived usefulness, and perceived ease of use. *J. Rural Stud.* 76, 264–271. <https://doi.org/10.1016/j.jrurstud.2020.04.028>.
- Caliendo, M., Kopeinig, S., 2008. Some Practical Guidance for the Implementation of Propensity Score Matching. *J. Econ. Surv.* 22, 31–72. <https://doi.org/10.1111/j.1467-6419.2007.00527.x>.
- Carrer, M.J., de Souza Filho, H.M., Batalha, M.O., 2017. Factors influencing the adoption of Farm Management Information Systems (FMIS) by Brazilian citrus farmers. *Comput. Electron. Agric.* 138, 11–19. <https://doi.org/10.1016/j.compag.2017.04.004>.
- Chichilnisky, G., 2000. An axiomatic approach to choice under uncertainty with catastrophic risks. *Resour. Energy Econ.* 22, 221–231. [https://doi.org/10.1016/S0928-7655\(00\)00032-4](https://doi.org/10.1016/S0928-7655(00)00032-4).
- Cullen, A.C., Anderson, C.L., 2017. Perception of Climate Risk among Rural Farmers in Vietnam: Consistency within Households and with the Empirical Record. *Risk Analysis* 37 (3), 531–545. <https://doi.org/10.1111/risa.12631>.
- Dai, A., 2013. Increasing drought under global warming in observations and models. *Nat. Clim. Change* 3, 52–58. <https://doi.org/10.1038/nclimate1633>.
- de Beurs, K.M., Henebry, G.M., Owsley, B.C., Sokolik, I.N., 2018. Large scale climate oscillation impacts on temperature, precipitation and land surface phenology in Central Asia. *Environ. Res. Lett.* 13, 065018 <https://doi.org/10.1088/1748-9326/aac4d0>.
- Deressa, T.T., Hassan, R.M., Ringle, C., 2011. Perception of and adaptation to climate change by farmers in the Nile basin of Ethiopia. *J. Agric. Sci.* 149, 23–31. <https://doi.org/10.1017/S0021859610000687>.
- Digital, 2022. Global Overview Report [WWW Document], n.d. accessed 9.28.22 DataReportal – Glob. Digit. Insights. <https://datareportal.com/reports/digital-2022-global-overview-report>.
- DiPrete, T.A., Gangl, M., 2004. 7. Assessing Bias in the Estimation of Causal Effects: Rosenbaum Bounds on Matching Estimators and Instrumental Variables Estimation with Imperfect Instruments. *Sociol. Methodol.* 34, 271–310. <https://doi.org/10.1111/j.0081-1750.2004.00154.x>.
- Douglas, M., Wildavsky, A., 1983. *Risk and Culture: An Essay on the Selection of Technological and Environmental Dangers*. University of California Press.
- Eltazarov, S., Bobojonov, I., Kuhn, L., Glaben, T., 2021. Mapping weather risk – A multi-indicator analysis of satellite-based weather data for agricultural index insurance development in semi-arid and arid zones of Central Asia. *Clim. Serv.* 23, 100251 <https://doi.org/10.1016/j.cliser.2021.100251>.
- Falaki, A.A., Akangbe, J.A., Ayinde, O.E., 2013. Analysis of Climate Change and Rural Farmers' Perception in North Central Nigeria. *J. Hum. Ecol.* 43, 133–140. <https://doi.org/10.1080/09709274.2013.11906619>.
- Fay, M., Block, R., Ebinger, J., 2010. *Adapting to Climate Change in Eastern Europe and Central Asia*. World Bank Publications.
- Fecke, W., Michels, M., von Hobe, C.F., Musshoff, O., 2018. How do farmers communicate in times of digitisation? *Berichte Über Landwirtschaft*. 96.
- Finger, R., Möhring, N., 2022. The adoption of pesticide-free wheat production and farmers' perceptions of its environmental and health effects. *Ecological Economics* 198, 107463. <https://doi.org/10.1016/j.ecolecon.2022.107463>.
- Fischer, G., Nachtergaele, F.O., van Velthuisen, H.T., Chiozza, F., Franceschini, G., Henry, M., Muchoney, D., Tramberend, S., 2021. *Global Agro-Ecological Zones v4 – Model documentation*. Food & Agriculture Org.
- B.Y. Folitse S.A. Manteau L.P. Dzandu G.O. Koranteng S. Bekoe "The Determinants of Mobile-Phone Usage among Small-Scale Poultry Farmers in Ghana - 2019 2019 <https://journals.sagepub.com/doi/abs/10.1177/0266666918772005>.
- Frenken, K. 2013. Irrigation in Southern and Eastern Asia in figures. AQUASTAT Survey - 2012. FAO Water Rep. FAO.
- Gamble, D.W., Campbell, D., Allen, T.L., Barker, D., Curtis, S., McGregor, D., Popke, J., 2010. Climate Change, Drought, and Jamaican Agriculture: Local Knowledge and the Climate Record. *Ann. Assoc. Am. Geogr.* 100, 880–893. <https://doi.org/10.1080/00045608.2010.497122>.
- Gangopadhyay, P.K., Khatri-Chhetri, A., Shirsath, P.B., Aggarwal, P.K., 2019. Spatial targeting of ICT-based weather and agro-advisory services for climate risk management in agriculture. *Clim. Change* 154, 241–256. <https://doi.org/10.1007/s10584-019-02426-5>.
- Gebrehiwet, T., van der Veen, A., 2021. Farmers' drought experience, risk perceptions, and behavioural intentions for adaptation: evidence from Ethiopia. *Climate Devel.* 13 (6), 493–502. <https://doi.org/10.1080/17565529.2020.1806776>.
- Giua, C., Matera, V.C., Camanzi, L., 2022. Smart farming technologies adoption: Which factors play a role in the digital transition? *Technol. Soc.* 68, 101869 <https://doi.org/10.1016/j.techsoc.2022.101869>.
- Guo, H., Bao, A., Liu, T., Jiapaer, G., Ndayisaba, F., Jiang, L., Kurban, A., De Maeyer, P., 2018. Spatial and temporal characteristics of droughts in Central Asia during 1966–2015. *Sci. Total Environ.* 624, 1523–1538. <https://doi.org/10.1016/j.scitotenv.2017.12.120>.
- Gutiérrez, L.H., Gamboa, L.F., 2010. Determinants of ICT Usage among Low-Income Groups in Colombia, Mexico, and Peru. *The Information Society* 26 (5), 346–363. <https://doi.org/10.1080/01972243.2010.511559>.
- Hardaker, J.B., Lien, G., 2010. Probabilities for decision analysis in agriculture and rural resource economics: The need for a paradigm change. *Agric. Syst.* 103, 345–350. <https://doi.org/10.1016/j.agsy.2010.01.001>.
- Hardaker, J.B., Lien, G., Anderson, J.R., Huirne, R.B.M., 2015. *Coping with Risk in Agriculture, 3rd Edition: Applied Decision Analysis*.
- Hasan, M.K., Kumar, L., 2019. Comparison between meteorological data and farmer perceptions of climate change and vulnerability in relation to adaptation. *J. Environ. Manage.* 237, 54–62. <https://doi.org/10.1016/j.jenvman.2019.02.028>.
- Hasibuan, A.M., Gregg, D., Stringer, R., 2020. Accounting for Diverse Risk Attitudes in Measures of Risk Perceptions: A Case Study of Climate Change Risk for Small-Scale Citrus Farmers in Indonesia. *Land Use Policy* 95, 104252. <https://doi.org/10.1016/j.landusepol.2019.104252>.
- Hay, R., Pearce, P., 2014. Technology adoption by rural women in Queensland, Australia: Women driving technology from the homestead for the paddock. *J. Rural Stud.* 36, 318–327. <https://doi.org/10.1016/j.jrurstud.2014.10.002>.
- Heckman, J.J., Ichimura, H., Todd, P., 1998. Matching As An Econometric Evaluation Estimator. *Rev. Econ. Stud.* 65, 261–294. <https://doi.org/10.1111/1467-937X.00044>.
- Heckman, J., Navarro-Lozano, S., 2004. Using Matching, Instrumental Variables, and Control Functions to Estimate Economic Choice Models. *Rev. Econ. Stat.* 86, 30–57. <https://doi.org/10.1162/003465304323023660>.
- Hobbins, M.T., Wood, A., McEvoy, D.J., Huntington, J.L., Morton, C., Anderson, M., Hain, C., 2016. The Evaporative Demand Drought Index. Part I: Linking Drought Evolution to Variations in Evaporative Demand. *J. Hydrometeorol.* 17, 1745–1761. <https://doi.org/10.1175/JHM-D-15-0121.1>.
- Hoerling, M., Kumar, A., Dole, R., Nielsen-Gammon, J.W., Eischeid, J., Perlwitz, J., Quan, X.-W., Zhang, T., Pegion, P., Chen, M., 2013. Anatomy of an Extreme Event. *J. Clim.* 26, 2811–2832. <https://doi.org/10.1175/JCLI-D-12-00270.1>.
- Howden, S.M., Soussana, J.-F., Tubiello, F.N., Chhetri, N., Dunlop, M., Meinke, H., 2007. Adapting agriculture to climate change. *Proc. Natl. Acad. Sci.* 104, 19691–19696. <https://doi.org/10.1073/pnas.0701890104>.
- Hu, Z., Zhang, C., Hu, Q., Tian, H., 2014. Temperature Changes in Central Asia from 1979 to 2011 Based on Multiple Datasets\*. *J. Clim.* 27, 1143–1167. <https://doi.org/10.1175/JCLI-D-13-00064.1>.
- Hughes, N., Soh, W.Y., Boulc, C., Lawson, K., 2022. Defining drought from the perspective of Australian farmers. *Clim. Risk Manag.* 35, 100420 <https://doi.org/10.1016/j.crm.2022.100420>.
- Israel, G.D. 1992. Determining sample size.
- Issahaku, H., Abu, B.M., Nkegbe, P.K., 2018. Does the Use of Mobile Phones by Smallholder Maize Farmers Affect Productivity in Ghana? *Journal of African Business* 19 (3), 302–322. <https://doi.org/10.1080/15228916.2017.1416215>.
- Kassie, M., Shiferaw, B., Muricho, G., 2011. Agricultural Technology, Crop Income, and Poverty Alleviation in Uganda. *World Dev.* 39, 1784–1795. <https://doi.org/10.1016/j.worlddev.2011.04.023>.
- Khan, I., Lei, H., Shah, I.A., Ali, I., Khan, I., Muhammad, I., Huo, X., Javed, T., 2020. Farm households' risk perception, attitude and adaptation strategies in dealing with climate change: Promise and perils from rural Pakistan. *Land Use Policy* 91, 104395. <https://doi.org/10.1016/j.landusepol.2019.104395>.
- Kiiza, B., Pederson, G., 2012. ICT-based market information and adoption of agricultural seed technologies: Insights from Uganda. *Telecommun. Policy* 36, 253–259. <https://doi.org/10.1016/j.telpol.2012.01.001>.

- Kolady, D.E., Van der Sluis, E., Uddin, M.M., Deutz, A.P., 2021. Determinants of adoption and adoption intensity of precision agriculture technologies: evidence from South Dakota. *Precis. Agric.* 22, 689–710. <https://doi.org/10.1007/s11119-020-09750-2>.
- Koshy, S.M., Kumar, N.K., 2016. Attitude of Farmers towards Kisan Call Centres. *J. Ext. Educ.* 28. <https://doi.org/10.26725/JEE.2016.4.28.5753-5759>.
- Kosmowski, F., Leblouis, A., Sultan, B., 2016. Perceptions of recent rainfall changes in Niger: a comparison between climate-sensitive and non-climate sensitive households. *Clim. Change* 135, 227–241. <https://doi.org/10.1007/s10584-015-1562-4>.
- Krell, N.T., Giroux, S.A., Guido, Z., Hannah, C., Lopus, S.E., Caylor, K.K., Evans, T.P., 2021. Smallholder farmers' use of mobile phone services in central Kenya. *Clim. Dev.* 13, 215–227. <https://doi.org/10.1080/17565529.2020.1748847>.
- Kumar, U., Saska, E.W., Paparrizos, S., Datta, D.K., Ludwig, F., 2021. Co-Producing Climate Information Services with Smallholder Farmers in the Lower Bengal Delta: How Forecast Visualization and Communication Support Farmers' Decision-Making. *Climate Risk Manage.* 33, 100346 <https://doi.org/10.1016/j.crm.2021.100346>.
- Kunreuther, H., 2006. Disaster Mitigation and Insurance: Learning from Katrina. *Ann. Am. Acad. Pol. Soc. Sci.* 604, 208–227. <https://doi.org/10.1177/0002716205285685>.
- Lee, W.S., 2013. Propensity score matching and variations on the balancing test. *Empir. Econ.* 44, 47–80. <https://doi.org/10.1007/s00181-011-0481-0>.
- Lio, M., Liu, M.C., 2006. ICT and Agricultural Productivity: Evidence from Cross-Country Data. *Agricultural Economics* 34 (3), 221–228. <https://doi.org/10.1111/j.1574-0864.2006.00120.x>.
- Lioubimtseva, E., 2015. A multi-scale assessment of human vulnerability to climate change in the Aral Sea basin. *Environ. Earth Sci.* 73, 719–729. <https://doi.org/10.1007/s12665-014-3104-1>.
- Lioubimtseva, E., Henebry, G.M., 2009. Climate and environmental change in arid Central Asia: Impacts, vulnerability, and adaptations. *J. Arid Environ.* 73, 963–977. <https://doi.org/10.1016/j.jaridenv.2009.04.022>.
- Lujala, P., Lein, H., Rod, K.J., 2015. Climate Change, Natural Hazards, and Risk Perception: The Role of Proximity and Personal Experience. *Local Environment* 20 (4), 489–509. <https://doi.org/10.1080/13549839.2014.887666>.
- Ma, W., Renwick, A., Nie, P., Tang, J., Cai, R., 2018. Off-farm work, smartphone use and household income: Evidence from rural China. *China Econ. Rev.* 52, 80–94. <https://doi.org/10.1016/j.chieco.2018.06.002>.
- Madadgar, S., AghaKouchak, A., Farahmand, A., Davis, S.J., 2017. Probabilistic estimates of drought impacts on agricultural production. *Geophys. Res. Lett.* 44, 7799–7807. <https://doi.org/10.1002/2017GL073606>.
- Madhuri, Sharma, U., 2020. How do farmers perceive climate change? A systematic review. *Climatic Change* 162 (3), 991–1010. <https://doi.org/10.1007/s10584-020-02814-2>.
- Mantel, N., Haenszel, W., 1959. Statistical Aspects of the Analysis of Data From Retrospective Studies of Disease. *JNCI: J. Natl. Cancer Institute* 22 (4), 719–748. <https://doi.org/10.1093/jnci/22.4.719>.
- Mase, A.S., Gramig, B.M., Prokopy, L.S., 2017. Climate change beliefs, risk perceptions, and adaptation behavior among Midwestern U.S. crop farmers. *Clim. Risk Manag Useful to Usable: Developing Usable Climate Science for Agriculture* 15, 8–17. <https://doi.org/10.1016/j.crm.2016.11.004>.
- McKee, T.B., Doesken, N.J., Kleist, J., 1993. The relationship of drought frequency and duration to time scales 6.
- Mendola, M., 2007. Agricultural technology adoption and poverty reduction: A propensity-score matching analysis for rural Bangladesh. *Food Policy* 32, 372–393. <https://doi.org/10.1016/j.foodpol.2006.07.003>.
- Meraner, M., Finger, R., 2019. Risk perceptions, preferences and management strategies: evidence from a case study using German livestock farmers. *Journal of Risk Research* 22 (1), 110–135. <https://doi.org/10.1080/13669877.2017.1351476>.
- Meso, P., Musa, P., Mbarika, V., 2005. Towards a model of consumer use of mobile information and communication technology in LDCs: the case of sub-Saharan Africa. *Inf. Syst. J.* 15, 119–146.
- Michels, M., Bonke, V., Musshoff, O., 2019. Understanding the adoption of smartphone apps in dairy herd management. *J. Dairy Sci.* 102, 9422–9434. <https://doi.org/10.3168/jds.2019-16489>.
- Michels, M., Fecke, W., Feil, J.-H., Musshoff, O., Pigisch, J., Krone, S., 2020. Smartphone adoption and use in agriculture: empirical evidence from Germany. *Precis. Agric.* 21, 403–425. <https://doi.org/10.1007/s11119-019-09675-5>.
- Min, S., Liu, M., Huang, J., 2020. Does the application of ICTs facilitate rural economic transformation in China? Empirical evidence from the use of smartphones among farmers. *J. Asian Econ.* 70, 101219 <https://doi.org/10.1016/j.asieco.2020.101219>.
- Mishra, A.K., Singh, V.P., 2010. A review of drought concepts. *J. Hydrol.* 391, 202–216. <https://doi.org/10.1016/j.jhydrol.2010.07.012>.
- Mittal, S., Hariharan, V.K., 2018. Mobile-based climate services impact on farmers risk management ability in India. *Clim. Risk Manag Scaling Up Climate Services for Smallholder Farmers: Learning from Practice* 22, 42–51. <https://doi.org/10.1016/j.crm.2018.08.003>.
- Mittal, S., Mehar, M., 2012. How Mobile Phones Contribute to Growth of Small Farmers? Evidence from India 19.
- Mittal, S., Mehar, M., 2016. Socio-economic Factors Affecting Adoption of Modern Information and Communication Technology by Farmers in India: Analysis Using Multivariate Probit Model. *J. Agric. Educ. Ext.* 22, 199–212. <https://doi.org/10.1080/1389224X.2014.997255>.
- Mwombe, S.O.L., Mugivane, F.I., Adolwa, I.S., Nderitu, J.H., 2014. Evaluation of Information and Communication Technology Utilization by Small Holder Banana Farmers in Gatanga District, Kenya. *J. Agric. Educat. Extension* 20 (2), 247–261. <https://doi.org/10.1080/1389224X.2013.788454>.
- National Statistical Committee of the Kyrgyz Republic - Statistics of the Kyrgyz Republic [WWW Document], n.d. URL <http://www.stat.kg/en/> (accessed 9.28.22).
- Norris, P.E., Kramer, R.A., 1990. The Elicitation of Subjective Probabilities with Applications in Agricultural Economics. *Rev. Mark. Agric. Econ* <https://doi.org/10.22004/ag.econ.12253>.
- Nurbekov, A., Paroda, R., Box, P.O., 2006. The Uzbekistan Seed Industry 16.
- Ogutu, S.O., Okello, J.J., Otieno, D.J., 2014. Impact of Information and Communication Technology-Based Market Information Services on Smallholder Farm Input Use and Productivity: The Case of Kenya. *World Dev.* 64, 311–321. <https://doi.org/10.1016/j.worlddev.2014.06.011>.
- Palmer, W.C., 1965. Meteorological Drought. U.S. Department of Commerce, Weather Bureau.
- Parry, M.L., Canziani, O., Palutikof, J., Van der Linden, P., Hanson, C., 2007. Climate change 2007-impacts, adaptation and vulnerability: Working group II contribution to the fourth assessment report of the IPCC. Cambridge University Press.
- Paustian, M., Theuvsen, L., 2017. Adoption of precision agriculture technologies by German crop farmers. *Precis. Agric.* 18, 701–716. <https://doi.org/10.1007/s11119-016-9482-5>.
- Paxton, K.W., Mishra, A.K., Chintawar, S., Roberts, R.K., Larson, J.A., English, B.C., Lambert, D.M., Marra, M.C., Larkin, S.L., Reeves, J.M., Martin, S.W., 2011. Intensity of Precision Agriculture Technology Adoption by Cotton Producers. *Agric. Resour. Econ. Rev.* 40, 133–144. <https://doi.org/10.1017/S1068280500004561>.
- Pyarali, K., Peng, J., Disse, M., Tuo, Y., 2022. Development and application of high resolution SPEI drought dataset for Central Asia. *Sci. Data* 9, 172. <https://doi.org/10.1038/s41597-022-01279-5>.
- Qiang, C.Z., Kuek, S.C., Dymond, A., Esselaar, S., 2012. "Mobile Applications for Agriculture and Rural Development. DC, World Bank <https://openknowledge.worldbank.org>.
- Ray, D.K., West, P.C., Clark, M., Gerber, J.S., Prishchepov, A.V., Chatterjee, S., 2019. Climate change has likely already affected global food production. *PLOS ONE* 14, e0217148.
- Rejda, G.E., McNamara, M.J., 2014. Principles of risk management and insurance, Twelfth edition. Pearson Education Limited, New York.
- Roco, L., Engler, A., Bravo-Ureta, B.E., Jara-Rojas, R., 2015. Farmers' perception of climate change in mediterranean Chile. *Reg. Environ. Change* 15, 867–879. <https://doi.org/10.1007/s10113-014-0669-x>.
- Rodell, M., Houser, P.R., Jambor, U., Gottschalck, J., Mitchell, K., Meng, C.-J., Arsenault, K., Cosgrove, B., Radakovich, J., Bosilovich, M., Entin, J.K., Walker, J.P., Lohmann, D., Toll, D., 2004. The Global Land Data Assimilation System. *Bull. Am. Meteorol. Soc.* 85, 381–394. <https://doi.org/10.1175/BAMS-85-3-381>.
- Rogers, E.M., Singhal, A., Quinlan, M.M., 2008. Diffusion of Innovations. An Integrated Approach to Communication Theory and Research. Routledge.

- Rose, D.C., Sutherland, W.J., Parker, C., Lobley, M., Winter, M., Morris, C., Twining, S., Ffolkes, C., Amano, T., Dicks, L.V., 2016. Decision support tools for agriculture: Towards effective design and delivery. *Agric. Syst.* 149, 165–174. <https://doi.org/10.1016/j.agsy.2016.09.009>.
- Rosenbaum, P.R., 2002. Overt Bias in Observational Studies. In: Rosenbaum, P.R. (Ed.), *Observational Studies*, Springer Series in Statistics. Springer, New York, NY, pp. 71–104. [https://doi.org/10.1007/978-1-4757-3692-2\\_3](https://doi.org/10.1007/978-1-4757-3692-2_3).
- Rosenbaum, P.R., Rubin, D.B., 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika* 70, 41–55. <https://doi.org/10.1093/biomet/70.1.41>.
- Rosenbaum, P.R., Rubin, D.B., 1985. Constructing a Control Group Using Multivariate Matched Sampling Methods That Incorporate the Propensity Score. *Am. Stat.* 39, 33–38. <https://doi.org/10.1080/00031305.1985.10479383>.
- Salam, R., Ghose, B., Shill, B.K., Islam, M.A., Islam, A.R.M.T., Sattar, M.A., Alam, G.M.M., Ahmed, B., 2021. Perceived and actual risks of drought: household and expert views from the lower Teesta River Basin of northern Bangladesh. *Nat. Hazards* 108, 2569–2587. <https://doi.org/10.1007/s11069-021-04789-4>.
- Santeramo, F.G., Lamonaca, E., 2021. Objective Risk and Subjective Risk: The Role of Information in Food Supply Chains. *Food Research International* 139, 109962. <https://doi.org/10.1016/j.foodres.2020.109962>.
- Savage, L.J., 1954. *The Foundations of Statistics*. John Wiley, New York.
- Shao, W., Kam, J., Cass, E., 2022. Public awareness and perceptions of drought: A case study of two cities of Alabama. *Risk Hazards Crisis Public Policy* rhc3.12248. <https://doi.org/10.1002/rhc3.12248>.
- Shukla, S., Funk, C., Hoell, A., 2014. Using constructed analogs to improve the skill of National Multi-Model Ensemble March–April–May precipitation forecasts in equatorial East Africa. *Environ. Res. Lett.* 9, 094009. <https://doi.org/10.1088/1748-9326/9/9/094009>.
- Simelton, E., Quinn, C.H., Batisani, N., Dougill, A.J., Dyer, J.C., Fraser, E.D.G., Mkwambisi, D., Sallu, S., Stringer, L.C., 2013. Is rainfall really changing? Farmers' perceptions, meteorological data, and policy implications. *Clim. Dev.* 5, 123–138. <https://doi.org/10.1080/17565529.2012.751893>.
- Slovic, P., Lichtenstein, S., Fischhoff, B., 1979. Perception and Acceptance of Risks from Nuclear Power. [https://scholarsbank.uoregon.edu/xmlui/bitstream/handle/1794/22516/slovic\\_120.pdf?sequence=1](https://scholarsbank.uoregon.edu/xmlui/bitstream/handle/1794/22516/slovic_120.pdf?sequence=1). Accessed June 30, 2023.
- Smith, J., Todd, P., 2005. Does matching overcome LaLonde's critique of nonexperimental estimators? *J. Econom. Experimental Non-Experiment. Eval. Econ. Policy Models* 125, 305–353. <https://doi.org/10.1016/j.jeconom.2004.04.011>.
- Sørensen, C.G., Bochtis, D.D., 2010. Conceptual model of fleet management in agriculture. *Biosyst. Eng.* 105, 41–50. <https://doi.org/10.1016/j.biosystemseng.2009.09.009>.
- Srinuan, C., Srinuan, P., Bohlin, E., 2012. An analysis of mobile Internet access in Thailand: Implications for bridging the digital divide. *Telemat. Inform.* 29, 254–262. <https://doi.org/10.1016/j.tele.2011.10.003>.
- Tamirat, T.W., Pedersen, S.M., Lind, K.M., 2018. Farm and operator characteristics affecting adoption of precision agriculture in Denmark and Germany. *Acta Agric. Scand. Sect. B — Soil Plant Sci.* 68, 349–357. <https://doi.org/10.1080/09064710.2017.1402949>.
- Tiffin, R., Balcombe, K., 2011. The determinants of technology adoption by UK farmers using Bayesian model averaging: the cases of organic production and computer usage. *Aust. J. Agric. Resour. Econ.* 55, 579–598. <https://doi.org/10.1111/j.1467-8489.2011.00549.x>.
- Trenberth, K.E., Dai, A., van der Schrier, G., Jones, P.D., Barichivich, J., Briffa, K.R., Sheffield, J., 2014. Global warming and changes in drought. *Nat. Clim. Change* 4, 17–22. <https://doi.org/10.1038/nclimate2067>.
- van der Linden, S., 2015. The social-psychological determinants of climate change risk perceptions: Towards a comprehensive model. *J. Environ. Psychol.* 41, 112–124. <https://doi.org/10.1016/j.jenvp.2014.11.012>.
- van Duinen, R., Filatova, T., Geurts, P., van der Veer, A., 2015. Empirical Analysis of Farmers' Drought Risk Perception: Objective Factors, Personal Circumstances, and Social Influence: Empirical Analysis of Farmers' Drought Risk Perception. *Risk Anal.* 35, 741–755. <https://doi.org/10.1111/risa.12299>.
- van Winsen, F., de Mey, Y., Lauwers, L., van Passel, S., Vancauteren, M., Wauters, E., 2016. Determinants of Risk Behaviour: Effects of Perceived Risks and Risk Attitude on Farmer's Adoption of Risk Management Strategies. *J. Risk Res.* 19 (1), 56–78. <https://doi.org/10.1080/13669877.2014.940597>.
- Venkatappa, M., Sasaki, N., Han, P., Abe, I., 2021. Impacts of droughts and floods on croplands and crop production in Southeast Asia – An application of Google Earth Engine. *Sci. Total Environ.* 795, 148829. <https://doi.org/10.1016/j.scitotenv.2021.148829>.
- Venkatesh, V., Morris, M.G., 2000. Why Don't Men Ever Stop to Ask for Directions? Gender, Social Influence, and Their Role in Technology Acceptance and Usage Behavior. *MIS Q.* 24, 115–139. <https://doi.org/10.2307/3250981>.
- Vicente-Serrano, S.M., Beguería, S., López-Moreno, J.I., 2010. A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index. *J. Clim.* 23, 1696–1718. <https://doi.org/10.1175/2009JCLI2909.1>.
- Von Neumann, J., Morgenstern, O., 1947. *Theory of games and economic behavior*, 2nd rev. ed., Theory of games and economic behavior, 2nd rev. ed. Princeton University Press, Princeton, NJ, US.
- Wachinger, G., Renn, O., Begg, C., Kuhlicke, C., 2013. The Risk Perception Paradox—Implications for Governance and Communication of Natural Hazards: The Risk Perception Paradox. *Risk Analysis* 33 (6), 1049–1065. <https://doi.org/10.1111/j.1539-6924.2012.01942.x>.
- Wang, C., Linderholm, H.W., Song, Y., Wang, F., Liu, Y., Tian, J., Xu, J., Song, Y., Ren, G., 2020. Impacts of Drought on Maize and Soybean Production in Northeast China During the Past Five Decades. *Int. J. Environ. Res. Public Health* 17, 2459. <https://doi.org/10.3390/ijerph17072459>.
- E.U. Weber A.R. Blais N.E. Betz A Domain-Specific Risk-Attitude Scale: Measuring Risk Perceptions and Risk Behaviors *Journal of Behavioral Decision Making* 15 4 2002 263290 <https://doi.org/https://doi.org/10.1002/bdm.414>.
- Wens, M., Johnson, J.M., Zagaria, C., Veldkamp, T.I.E., 2019. Integrating human behavior dynamics into drought risk assessment—A sociohydrologic, agent-based approach. *WIREs Water* 6, e1345.
- Wilhite, D.A., 1993. The Enigma of Drought. In: Wilhite, D.A. (Ed.), *Drought Assessment, Management, and Planning: Theory and Case Studies*, Natural Resource Management and Policy. Springer, US, Boston, MA, pp. 3–15. [https://doi.org/10.1007/978-1-4615-3224-8\\_1](https://doi.org/10.1007/978-1-4615-3224-8_1).
- World Bank Group, Bank, A.D., 2021a. Climate Risk Country Profile: Kyrgyz Republic. World Bank. <https://doi.org/10.1596/36377>.
- World Bank Group, Bank, A.D., 2021b. Climate Risk Country Profile: Mongolia. World Bank. <https://doi.org/10.1596/36375>.
- World Meteorological Organization Drought monitoring and early warning: concepts, progress and future challenges 2016 <https://public.wmo.int>.
- Xu, H., Wang, X., Zhang, X., 2016. Decreased vegetation growth in response to summer drought in Central Asia from 2000 to 2012. *Int. J. Appl. Earth Obs. Geoinformation* 52, 390–402. <https://doi.org/10.1016/j.jag.2016.07.010>.
- Xu, M., Wu, H., Kang, S., 2018. Impacts of climate change on the discharge and glacier mass balance of the different glacierized watersheds in the Tianshan Mountains, Central Asia. *Hydrol. Process.* 32, 126–145. <https://doi.org/10.1002/hyp.11409>.
- Yu, C., Huang, X., Chen, H., Huang, G., Ni, S., Wright, J.S., Hall, J., Clais, P., Zhang, J., Xiao, Y., Sun, Z., Wang, X., Yu, L., 2018. Assessing the Impacts of Extreme Agricultural Droughts in China Under Climate and Socioeconomic Changes. *Earths Future* 6, 689–703. <https://doi.org/10.1002/2017EF000768>.
- Zhang, J., Zhang, S., Cheng, M., Jiang, H., Zhang, X., Peng, C., Lu, X., Zhang, M., Jin, J., 2018. Effect of Drought on Agronomic Traits of Rice and Wheat: A Meta-Analysis. *Int. J. Environ. Res. Public Health* 15, 839. <https://doi.org/10.3390/ijerph15050839>.