Do forests relieve crop thirst in the face of drought? Empirical evidence from South China

Y. Wang[1]; J. Huang[2]

1: Central South University, Business School, China, 2: Peking University, , China

Corresponding author email: yangjie.wang@csu.edu.cn

Abstract:

Although the importance of forests in climate change mitigation has been widely recognized, there has been a lack of empirical research regarding the role of forests in agricultural adaptation to climate change. This paper uses a careful designed household survey in South China that considers an exogenous shock of drought, to determine whether the presence of natural and planted forests near rice-producing villages can reduce the adverse effects of drought on rice yield. After controlling for local climate and water infrastructure, we find robust evidence that natural forests and not planted forests have significant positive effects on rice yield, due to their influence on the availability of water for irrigation. Although drought hinders farmers' access to irrigation, which negatively affects rice yield, forests near villages provide protection for rice against drought. These findings support the adoption of forest ecosystem-based adaptation (EBA) to cope with climate change and enhance food security.

Acknowledegment:

JEL Codes: Q01, C13

#306

Do forests relieve crop thirst in the face of drought? Empirical evidence from South China

Abstract

Although the importance of forests in climate change mitigation has been widely recognized, there has been a lack of empirical research regarding the role of forests in agricultural adaptation to climate change. This paper uses a careful designed household survey in South China that considers an exogenous shock of drought, to determine whether the presence of natural and planted forests near rice-producing villages can reduce the adverse effects of drought on rice yield. After controlling for local climate and water infrastructure, we find robust evidence that natural forests and not planted forests have significant positive effects on rice yield, due to their influence on the availability of water for irrigation. Although drought hinders farmers' access to irrigation, which negatively affects rice yield, forests near villages provide protection for rice against drought. These findings support the adoption of forest ecosystem-based adaptation (EBA) to cope with climate change and enhance food security.

Keywords: forest, drought, ecosystem-based adaptation, crop production, irrigation

1. Introduction

Climate change will affect human well-being in many parts of the world, and effective adaptation is needed even under the most stringent mitigation scenarios (Adger and Barnett 2009; IPCC 2014). In particular, climate change is expected to increase the frequency and intensity of extreme weather events (Dai 2013). As a type of extreme weather event, the occurrence of droughts is projected to become more frequent with global climate change (Jentsch et al. 2007). It is predicted that the total global area that suffers from drought will expand by 15-44% from now until the end of the 21st century (IPCC 2012). These changes will have a direct effect not only on rain fed crops but also on water storages and will cause increased stress on water availability for irrigation (Verchot et al. 2007). The UN's Intergovernmental Panel on Climate Change (IPCC 2014) has specifically emphasized the vulnerability of the agricultural sector to extreme events and the need for society to be proactive in adapting to them.

In the face of severe climatic variability, the role of forest ecosystem services in societal adaptation has received renewed recognition (Millennium Ecosystem Assessment 2005; World Bank 2010; Doswald et al. 2014; Locatelli 2016). Ecosystem-based adaptation (EBA) is an anthropocentric approach (Pramova et al. 2012a). The idea behind this approach is that the ecosystem services that are provided by forests have the potential to enhance the adaptive capacity of society to climate change across sectors and scales (Locatelli et al. 2008; Chong 2014). Therefore, several international and nongovernmental conservation and development organizations have promoted EBA by stressing its effectiveness in reducing the vulnerability of the people who face extreme weather threats (Vignola et al. 2009; Lukasiewicz et al. 2016). The extreme drought that occurred in Yunnan, China during 2009-2010, for example, emphasizes the need to understand the key ecological effects that may allow forests to overcome severe drought stress (Wang and Meng 2013).

However, the current level of knowledge is insufficient to support the implementation of EBA. The major problem is that forests have mostly been considered in the framework of climate change mitigation solely in the context of carbon storage and sequestration and of reducing emissions from degradation and deforestation (Sheeran 2006; Canadell and Raupach 2008; Soares-Filho and Defries 2010; Alemu 2014). These studies have largely ignored forest ecosystem services concerning adaptation to climate change (IUFRO 2009; Pramova et al. 2012a; Pasquini and Cowling 2015). Although there exists a large amount of literature that investigates the ecosystem services of forests (Martínez et al. 2009; Klemick 2011), the hydrological role of forests remains a subject of debate (IUFRO 2007; van Dijk and Keenan 2007; FAO 2008). In addition, most of the previous work on valuing watershed ecosystem services has focused on the relation between forests and water (Rosenqvist et al. 2010; Ellison et al. 2012, 2017; Brogna et al. 2017) and seldom considers the role of forests in adapting local farmers' agricultural production to climate variability. As indicated in the UNFCCC (2011), EBA should never be implemented in an isolated manner but rather, should be complemented by integrating local people's livelihood strategies. Thus, despite the rich information provided by hydrological analysis, it is difficult to provide robust evidence to support the implementation of forest EBA policies.

With the increasing significance of drought from climate change, several questions need to be answered to expand the implementation of EBA. How do drought events affect farmers' crop production? Can forests help to alleviate the pressure of drought? If so, how can farmers benefit from forests to adapt to drought? Answering these questions is critical not only to better understand the role of forests in adaptation to climate change but also to provide empirical evidence for policy makers to help them to formulate EBA policies.

In order to address these questions, the overall goal of this study is to examine the role of forests in adapting farmers' crop production to drought. In particular, we focus on the impact of forests on farmers' rice yields. Because rice production is heavily dependent on water resources and is especially sensitive to drought events (Pandey and Shukla 2015), studying rice crops enables us to better understand the role of forests in adapting to water stresses that coincide with drought.

To achieve this objective, the authors conducted a household and community survey in 86 villages from 23 counties across five provinces in South China. Our design is unique because it exploits an exogenous variation in drought events through a careful design of the field survey and then addresses how forests impact rice yield under an exogenous drought shock. In the field survey, all the selected counties in our sample experienced the most severe drought shock in one of the three years that preceded the survey (2010-2012) and a relatively normal year in one of the same three years. This sampling approach allows us to investigate the extent to which the differential effects of drought on rice yield in a county are contributed to by the forests that are near a community (within a 5-km radius).

Another core innovation relates to the measurement of forests, which previous studies have measured primarily via land cover and land use data (e.g., Fiquepron et al. 2013; Vincent et al. 2015). The key land-use variables in this approach is mostly measured in the macroscale area and modeled at larger spatial scales, lack of enough spatial variation in small scale, as well as the detailed ecological knowledge held by rural households (Gray and Mueller 2012). Instead, we draw on household self-reports of forests status in the field survey, and satellite measure of forest cover rate to build two alternative measures of forests near a village and to test the robustness of our findings. Unlike the satellite-based forest cover information, the field survey can distinguish the natural forests from the planted forests, enabling us to investigate the roles of different types of forests. This study thus adds to a small number of previous studies of EBA which have drawn on both survey and spatial measures of forests.

Our identification strategy entails two major challenges. First, in addition to forests, many other factors can confound the identification of this effect; therefore, isolating the impacts of forests on rice yield is a perennial challenge. To circumvent this problem, we use a rich dataset on forests and rice production from a survey in South China. The detailed and large coverage of information from this survey enables us to control for many potentially confounding factors. Moreover, we use plot-level fixed effects to control for much of the unobserved heterogeneity that may affect rice yield. Second, changes in land use may result in selective sorting, that is, farmers with better education or more farming experience may plant rice plots closer to forests, and these farmers may be more likely to obtain good harvests. To account for the probability of bias from selective sorting, we test for it by using information on land transfers and demographic characteristics. We do not observe increased land lease activity near forest land. We also conduct robustness checks where we exclude the samples with land transfers, and the conclusions of this study do not change.

We find robust evidence that rice yields that are in close proximity to forests suffer less damage from drought events than rice yields that are further away from forests. We also find that natural forests, rather than planted forests, have a positive effect on farmers' irrigation applications, even when the local climate and water infrastructure conditions are both controlled. This result is consistent with the findings in the hydrological science literature that emphasize that the conservation of dry season stream flows is essential for agricultural irrigation systems in drought conditions (Aylward 2005). These findings suggest that forests' regulating services can be enhanced and deliberately chosen as options for climate change adaptation in the agricultural sector. Mainstreaming forest EBA into the National Adaptation Programme of Action to address extreme drought should be emphasized in developing countries.

This paper contributes to the literature in two important ways. First, to the best of our knowledge, our study constitutes the first attempt to rigorously assess forest ecological productivity effects on adapting farmland production to drought stress in the developing world. Most existing studies on forest ecosystem services are usually based on hydrological analysis. Our study, however, is an econometric analysis based on field survey data that empirically examines the role of forests in alleviating droughts that affect farmers' crop production. Second, our study goes beyond identifying the forest effect; despite the existing literature that emphasizes that forest EBA is critical for preserving human well-being in response to climate change, the complex relations between forests and water continue to be a matter of debate (IUFRO 2007; Ellison et al. 2012; van der Ent et al. 2012). In this paper, we use information on forests and exploit farmers' irrigation behavior under an exogenous drought event to identify the connection between forests and the availability of irrigation. This study attempts to broaden the understanding of EBA, which could provide us with more insights and evidence concerning the role of forests in climate change adaptation.

2. Integrated assessment of forest-water interactions

Hydrological services or the water-related services provided by forests are considered crucial for human well-being (MEA, 2005). As defined by Brauman et al. (2007), hydrological services encompass the benefits to people derived from the regulation of water flows by forests. Water supply is one of the key services that might impact the irrigation water availability of crop yields, especially in the face of drought (Carvalho-Santos 2014). However, the potentially beneficial relation between forest cover and water yield is hotly contested (Andréassian 2004; van der Ent et al. 2012).

A large body of literature has provided evidence of the controversial effect of forests on water availability. As Ellison et al. (2012), the forest-water debate was divided into two schools of thought: the 'demand-side' and the 'supply-side' schools. The 'demand-side' of the forest–water debate see forests as consumers of available water and competitors for other downstream water uses (agriculture, energy, industry, and households). For example, according to a number of small-scale studies, the demand-side school findings suggest that forests may reduce available water supply due to the increased evapotranspiration (e.g., Zhang et al., 2001; Brown et al., 2005; Farley et al., 2005; Bredemeier 2011). In these empirical studies, the presence of forest vegetation typically removes water from the local hydrologic cycle, reducing local water supply.

Conversely, the supply-side school findings support the beneficial impact of forests on the hydrologic cycle, emphasizing that forests raise water yield. The climate regulatory function of forests has a beneficial impact on the water regime and the availability of water resources. For example, forests promote infiltration, increasing soil moisture content and groundwater recharge, contributing to the gradual release of water (Sheil and Murdiyarso 2009; Brogna et al. 2017). Many previous studies have pointed out the importance of local forest benefits such as supporting the water supply for households and communities (e.g., Schaafsma et al. 2012, 2014; Fiquepron et al. 2013; Sisak et al. 2016).

Other literature points to more ambiguous findings. D'Almeida et al. (2007) note, for example, that while a large number of large-scale modeling predictions suggest deforestation leads to reduced runoff, many local-scale observations find reduced evapotranspiration and increased runoff. This means that the magnitude of forests influencing hydrological service provision is very site/scale dependent and varies as a function of local and regional biophysical conditions (Calder 2002; Carvalho-Santos et al. 2014).

Overall, forests may or may not reduce water flow depending on their relative effects on water demand versus water supply (FAO 2009; Ellison et al. 2012). Based on the literature, it's not clear which direction the effect of forest goes with respect to yields. The offsetting effects imply that the overall impact of forests on crop yields is an empirical question. In this paper, we estimate a net forest effect and do not disentangle demand from supply.

China is of particular interest in the study of the role of forests in agricultural adaptation to climate change because of its deep reliance on agriculture and long history of forest deterioration. Our research builds on three previous studies which have examined local adaptation in China in context of climate change. Chen et al. (2014) used a large-scale household and village survey data to show that, adaptation measures applied by farmers and communities increased during periods of drought shocks but were more likely to be affected by government policy. Wang et al. (2014) used a similar approach to show that irrigation infrastructure significantly increased farmers' adaptation capacity against drought. Finally, Huang et al. (2015) used retrospective adaptation data for the period 2010-2012 described below to investigate the relation between farmers' adaptation measures and rice yield and risks.

3. Data

This study employs the following three datasets: (1) a field survey that was conducted from late 2012 to early 2013 in rice planting areas in the southern part of China; (2) a meteorological record dataset at the village level in five provinces; and (3) the land use and land cover change (LUCC) database in five provinces. The survey shows the forests and irrigation infrastructure statuses of the community and rice production under extreme weather events such as drought, while the meteorological data and the LUCC data are used to measure the weather (e.g., temperature and precipitation) and forest coverage, respectively. Merging the two datasets allows us to identify the impacts of forests on rice yield in times of drought.

3.1 Survey areas and data

The data that are used in this study are part of a large-scale household and community survey on the impacts of and adaptation to climate change on agriculture in China. Based on regional crop production systems and climate conditions, the survey included nine provinces: Jilin in northeast China, Hebei in northern China, Henan in central China, Shandong and Jiangsu in the coastal area of eastern China, Anhui and Jiangxi in the inland area of eastern China, Yunnan in southwest China, and Guangdong in southern China. Previous studies using this dataset have investigated farmers' adaptation to extreme weather events (e.g., Huang et al. 2015), perceptions of climate change (e.g., Hou et al. 2015), and the risk management in agriculture (e.g., Huang et al. 2014), among other topics. Our analysis, described below, draws on the data collected in five provinces in south China, because forest resources are mainly distributed in the southern regions of China (NBSC 2012).

The five surveyed provinces have households that produced rice during 2010-2012. Rice is typically planted in humid regions where the availability of irrigation water is more certain. Although these five provinces may not fully represent China's subtropical forest resources, the characteristic vegetation of most of these regions consists of seasonally humid, evergreen and deciduous broadleaf mixed forests. Specifically, Jiangxi, Yunnan, and Guangdong are located in the subtropical humid monsoon climate regions with richer forest resources. For example, the forest coverage in Jiangxi, Guangdong and Yunnan reaches 63.1%, 51.3%, and 50.0%, respectively. In Henan and Jiangsu, the forest coverage is lower and is 21.5% and 15.8%, respectively (NBSC 2015).

In each province, we followed three steps to select counties to analyze the effects of extreme weather events. First, in each province, we selected all counties that had experienced the most severe category of drought or flood in any of the past three years (2010-2012). According to China's national standard for natural disasters, the severity of a drought or flood has four categories: most severe, severe, moderate, and small (CMA 2007). Second, from the counties that were identified in the first step, we kept only the counties that also experienced a "normal year" in any of the past three years. Because crop production often faces various weather shocks during any growing season, the term "normal year" is relative and describes an average year with no more than moderate weather shocks. Finally, from the list of counties that were identified in step two, three counties in each province except for Jiangxi (10 counties) and Guangdong (6 counties) were randomly selected for the study. This sampling approach allowed us to examine the differences in the two distinct years (a severe disaster year and a normal year) and returned a sample of 25 counties.

Townships and villages (communities) were further selected before we interviewed households. In each of the 25 selected counties, all townships were divided into three groups based on the condition of the agricultural production infrastructure, and one township was randomly selected from each group. The same approach was used to select three villages from each township. Finally, we randomly selected 10 households for face-to-face interviews in each sampled village. A total of 2,250 households were identified in the five studied provinces. In each household, two plots with grain production were randomly selected, which resulted in 4,500 plots. However, because some households either did not plant rice or only planted one rice plot, the total sample includes 1,653 households with rice production and 2,571 plots from 185 villages in the 63 townships of 23 counties in five provinces.

In this study, we only refer to a subsample of the locations that experienced drought. In the total sample, 12 counties reported extreme drought events, and the other 11 counties reported extreme flood events. As a result, a subsample with drought used in our analysis includes 693 households, 1,449 plots from 86 villages in the 30 townships of 12 counties. Because some farmers in our samples also planted double-season rice (early- and late-season rice), we analyzed the data by the type of rice, specifically early-, middle- (single-season rice), and late-season rice. For each observation in each plot, we collected the data for two time periods during 2010-2012, namely, the severe drought year and the normal year, because the time (or year) differs across counties. We thus arrive at the final number of 2,898 observations.

One of the survey instruments was specifically designed to capture the status of forests that were in proximity to the studied villages. Questions were included to investigate whether there were forests near the villages, what type of forest they were (natural or planted) and the distance from the nearest forest to the village.[1] Based on this information, we defined a sampled village as a forested village when there were forests located within a 5-km radius of the village. We set the indicator variable *forest* equal to 1 if the sampled village belonged to a forested village and set it to 0 if it did not belong to a forested village. Note that the field survey enables us to further explore the effects of different types of forests, namely, natural (undisturbed) forests and planted forests, on yields. In our study areas, planted forests are mainly economic plantations. It is necessary to note that during our short-term survey period of 2011-2013, there were nearly no changes in forest status, which means that the *forest* variable was invariable across the survey years.

To confirm the robustness of the effects of forests and address the potential limitations of reported forest status, we also developed a second measure of forests. We draw on satellite measures of forest cover from a 1-km raster LUCC dataset in 2010 in China (Liu et al. 2014). These data were then linked to the study villages using Global Positioning System (GPS) points collected in the field. We measured the average forest cover within 5-km of the village, which we refer to as the village-specific forest cover. The mean value of this measure is 0.14, and can be interpreted as representing 14% forest coverage surrounding our sampling villages. This measure is positively correlated with reported forests at $r = 0.21$ with $p < 0.001$. In the robustness checks, we also measured the village-specific forest cover separately within 3-km and 7-km of the village.

Furthermore, the survey covers a wide range of other information. Given the research objectives of this article, in addition to the forest information, our analysis uses only the

[1] For more than one forest, we asked the nearest distance. If there were both natural forests and planted forests near a village, we recoded it as natural forests.

following data: 1) characteristics of the village (e.g., number of households, wealth, market condition, the concentration and continuity of the residential area, land area, land terrain and soil quality); 2) detailed plot-level rice production data in both the severe drought year and the normal year (e.g., rice yield and yield loss); 3) irrigation measures that may relate to adaptations to extreme drought at the plot level (e.g., the number of irrigation applications per season and the source of irrigation water); and 4) irrigation infrastructure conditions in villages.

3.2 Geographic data

Meteorological information was obtained from the National Meteorological Information Center. The dataset contained daily minimum, maximum, and average temperatures and precipitation measurements from 1960-2012 from national ground-based meteorological stations. We use village specific rainfall and temperature data generated by a spatial interpolation method proposed by Thornton et al. (1997). Their method has been widely used and is based on the spatial convolution of a truncated Gaussian weighting filter with a set of station locations (Zhang et al. 2013; Hou et al. 2015). The required inputs include digital elevation data and observations of maximum temperature, minimum temperature, and precipitation. The elevation data for each analyzed village were collected by GPS device when we surveyed the village. The LUCC data set is provided by Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (http://www.resdc.cn). We then merged these geographic data with the survey data to identify the effects of forests on rice yield. The basic descriptive statistics are presented in Table A1 of the appendix.

4. Descriptive analysis of drought, forests, and rice irrigation

4.1 Drought trends

The severity of drought in the studied provinces has increased. Historical records document that from the 1980s to the beginning of this century, the annual average crop area that suffered from drought has expanded from 2.8 million hectares to 3.4 million hectares, which is an increase of 22%. Over the same period, the proportion of crop area hit by drought increased from 36% to 66% (NBSC 2012). Moreover, the share of seriously damaged areas (a yield loss of at least 30%) to drought-hit areas (a yield loss of at least 10%) increased from 11% in the 1980s to 23% in the first ten years of the 21st century (NBSC 2012).

The household surveys also demonstrate the severity of drought that is reported by the farmers in the study areas. As shown in Table 1, the percentage of sampling plots affected by drought reached 47% when the farmers were faced with a severe drought. However, the percentage of sampling plots greatly declined to 19% in the relatively normal year. The difference is statistically significant at the 1% level (row 1). Furthermore, we find a negative relation between average rice yield and the severity of drought. For instance, the actual average yield was 6,927 kg/ha in slight drought conditions. However, in severe drought conditions, the actual average yield decreased to 6,454 kg/ha, which is a significant reduction of 6.8% (row 2). Likewise, the yield losses caused by drought also increased from 16% in the normal year to 24% in the severe drought year, which represents a significant 50% reduction (row 3). Because these results were reported by farmers, the values that are presented in Table 1 have obviously already accounted for the farmers' response to drought.

4.2 Forest status and irrigation in forested villages

The survey results demonstrate that forest cover differs among villages, which provides good empirical data for us to examine the relation between forests and the availability of water for crop irrigation under drought conditions. Among the studied villages, approximately 12% of the villages belong to forested villages as we define them (row 1, Table 2). This information suggests that in our sampling areas, the land use that surrounds most villages is non-forest cover.

Was farmers' availability of irrigation water related to the nearby forest cover? The number of irrigation applications during the rice growing season is used to measure the availability of irrigation water. More irrigation instances may imply that farmers are more likely to access water for irrigation. According to the hydrological literature (e.g., Aylward 2005; Sheil and Murdiyarso 2009), ecosystems provide watershed services that regulate the quantity of water that is available for human activities. We propose that forests may increase rice yield by enhancing farmers' access to irrigation water. Therefore, relating the forest cover near villages to the farmers' access to irrigation water could test this theory. For each household, we collected detailed, plot-level irrigation water information including both irrigation frequency and water sources.

The descriptive analysis provides evidence that there is a positive relation between farmers' access to irrigation and the forest cover nearby. As shown in the second row in Table 2, the farmers in forested villages are more likely to increase irrigation frequency. For example, in the non-forested villages, the average irrigation frequency was approximately 5.6 times per season, which was significantly lower than the average irrigation frequency of 6.4 times per season in the forested villages.

The analysis of irrigation water sources for rice plots provides further evidence for the positive association between forests and irrigation. As presented in Table 2, there are considerable differences in irrigation water sources between the forested and non-forested villages. We find that compared with the farmers in non-forested villages, the farmers in forested villages were more dependent on irrigation water from creeks or streams (57.1%) and mountain springs (5.3%) (rows 3 and 4). However, the inverse is true for irrigation facilities such as ponds and lateral canals; water from these sources was used less (38.2%) in forested villages than in non-forested villages (44.3%) (row 5). These differences are statistically significant at the 5% level. In rural China, irrigation facilities are generally created through investments by villages and/or local governments (Boyle et al. 2014). Given their ecosystem service function in regulating water flow, forests may supplement the role of irrigation infrastructure in enhancing the availability of irrigation water, which reduces the impact of droughts on crop yield.

Because the descriptive statistics do not account for other factors that may also determine irrigation and crop yield, it is still difficult for us to isolate the impact of forests on irrigation and the subsequent influence on rice yield. In the next section, we quantitatively explore this effect.

5. Empirical framework

5.1 Reduced-form model

To formally investigate the impacts of forests on rice yield, we begin with a reduced-form model that is expressed as follows:

$$y_{ikt} = \alpha_0 + \alpha_1 D_{ct} + \alpha_2 D_{ct} \times F_{vc} + \alpha_3 X_{vct} + \gamma_t + a_{ik} + e_{ikt} \quad (1)$$

where the subscripts k and i represent the k^{th} plot in the i^{th} household, v and c represent village and county, respectively, and t represents the year (2010-2012). The dependent variable, y_{ikt}, represents the log-transformed rice yield, and D_{ct} is a drought dummy variable measured at the county level. This dummy variable equals 1 if the county experienced a severe drought year and equals 0 if the county experienced a relatively normal year. F_{vc} represents the *forest* indicator variable that we previously defined, which equals 1 if there were forests located within a 5-km radius of the sample village and is 0 otherwise. As mentioned before, another measure of forests is forest cover rate within 5-km of the village. Because F_{vc} is invariable across years (2010-2012), in the estimation of the fixed effects model, it will be dropped as a time-invariant variable. To capture the impact of forests, we incorporate an interaction term between D_{ct} and F_{vt} in Eq. (1), which is the most frequently employed approach in the relevant literature. X_{vct} is a set of the exogenous determinants of rice yield (which are presented in the next section).

Furthermore, Eq. (1) includes a full set of plot fixed effects, a_{ik}, and year fixed effects, γ_t. The plot fixed effects (a_{ik}) capture time-invariant unobserved plot characteristics, such as local water resource volume, watershed size, topography, soils, and geology, as well as the forest tree species, location, age, and many more.[2] For example, there are important distinctions between the likely impact of conifers and broadleaf trees in the uplands and lowlands due to their different ecosystem service functions (Brauman et al. 2007). All of these forest characteristics vary geographically across the provinces but not over time in the short term, which can be controlled by fixed effects in Eq. (1). The ability to control for these characteristics is crucial because natural forests tend to form in areas where water resources are generally abundant, and any omitted variables could bias the estimation of the true forest effects. The year fixed effects (γ_t) control for the plot-invariant annual characteristics in the dependent variable that are common across plots, including climate trends, changes in state and national environmental and natural resource policies. e_{ikt} is the error term. α_j (j = 0, 1, 2, 3) is a parameter vector to be estimated. The key parameters of interest are α_1 and α_2, which capture the differential drought effects in villages with forest land versus other villages where the land use is non-forest cover.

Thus, by using plot and year fixed effects, the adaptation parameters are identified from the plot-specific deviations in adaptation decisions after we control for the drought shock that is common to all farms in a county. That is, the estimates are identified by comparing the plots that are located in forested villages with the plots that are not located in forested villages after we control for similar experiences of drought shock. If forests near the village help to

[2] As a robustness check, in a separate set of regressions (which are not reported here for purposes of brevity), household-level fixed effects, instead of plot-level fixed effects, are also used. The signs, levels of statistical significance and magnitudes of the estimates' coefficients are largely consistent between the plot-level fixed effects models and the household-level fixed effects models.

reduce exposure to drought and enhance the farmers' rice production, we expect the coefficient of $D_{ct} \times F_{vt}$ (that is, α_2) to be positive. Here, we implicitly assumed that α_2 is the same for all types of forests. In section IV, we relax this assumption and allow the effects of drought to differ across natural (undisturbed) forests and planted forests.

5.2 Structural-form model

The reduced-form estimates from Eq. (1) provide the total effects of forests on rice yield and set aside the farmers' adaptation to drought. The estimated total marginal effects of forests on rice yield can be interpreted as the sum of the direct effects of forests on yield (through forests' effects on crop physiology) and the indirect effects of forests on yield (through forests' influence on farmers' climate adaptation actions such as irrigation) (Welch et al. 2010). Controlling for farmers' adaptation strategies in the regression model may absorb some of the overall effects of the impacts of forests on rice yield.

Here, we are also interested in examining whether and how rice yield responds to the changes in farmers' adaptive irrigation practices in addition to the crops' proximity to forests. Accordingly, we draw on the recent work by Di Falco et al. (2011) and Huang et al. (2015) and estimate a production function by controlling for farmers' irrigation frequency as follows:

$$y_{ikt} = \beta_0 + \beta_1 D_{ct} + \beta_2 D_{ct} \times F_{vc} + \beta_3 X_{vct} + \beta_4 I_{ikt} + \gamma_t + a_{ik} + u_{ikt} \qquad (2)$$

where I_{ikt}, as we defined earlier, denotes the number of irrigation applications (times) during the rice growing season. The remaining variables in Eq. (2) are the same as in Eq. (1). A consistent estimation of β_4 requires that $E[I_{ikt} \bullet u_{ikt} \mid D_{ct}, F_{vc}, X_{vct}, a_{ik}, \gamma_t]=0$. The inclusion of plot fixed effects implicitly controls for any time-invariant determinants of yield that also covary with irrigation application frequency. However, the least squares estimation of β_4 will be biased if there are time-varying influences on both rice yield and irrigation (e.g., farmers' farming skill) and/or if there is measurement error in I_{ikt}. Because we use the number of irrigation applications in a plot during a given year as a proxy for the availability of irrigation water, measurement error may be substantial (i.e., farmers' actual access to irrigation water may differ from the access that is self-reported).

Instrumental variables (IVs) provide a convenient solution to the bias from the omitted variables and the bias introduced from the measurement error in the independent variable (Huang et al. 2017). We use village-level irrigation infrastructure as an instrument variable for irrigation applications in the following first-stage regression equation:

$$I_{ikt} = \theta_0 + \theta_1 D_{ct} + \theta_2 D_{ct} \times F_{vc} + \theta_3 D_{ct} \times Z_{vt} + \theta_4 X_{vct} + \gamma_t + a_{ik} + \varepsilon_{ikt} \qquad (3)$$

where the actual number of irrigation applications, I_{ikt}, is jointly predicted by drought, interactions with forests (F_{vt}) and irrigation infrastructure (Z_{vt}), and other control variables (X_{vct}). Similar to Eq. (1), the interaction $D_{ct} \times F_{vt}$ is used to identify the role of the surrounding forests in drought events. Infrastructure, Z_{vt}, is the vector of the instruments for irrigation that includes 1) the water storage capacity of the ponds per hectare of cultivated land in villages (cubic meters/ha) and 2) the number of lateral canals per hectare of cultivated land in villages. Logically, the irrigation infrastructure satisfies the exclusion restriction of appropriate instruments; it affects the endogenous variable, irrigation, but not rice yield, except through its impact on irrigation. The interaction terms, $D_{ct} \times Z_{vt}$, can measure the role of infrastructure in determining the farmers' irrigation practices during drought. ε_{ikt} is the error term.

One concern about the IVs is that there might be some other connections between rice yield and nature of a village's irrigation infrastructure in our sample. For example, the water storage capacity of the ponds in a village could reflect the landscape and geography of that village, which could be related to the robustness of the rice to a drought. Similarly, the number of lateral canals in a village could reflect the water resource in that village; thus, a village with more canals has better water resource so it is less impacted by a drought. To address this, as mentioned earlier, we have included the fixed effects into the model, which can control for all of these village characteristics that vary geographically across villages but not over time during the short term period of three years (e.g., water resource endowment, landscape and geography of villages, and other fixed characteristics). Importantly, as we illustrate below, the validity of the instruments was also scrutinized by statistical tests.

The first-stage regression in Eq. (3) estimates the degree to which infrastructure predicts farmers' irrigation applications. The second stage in Eq. (2) uses the predicted values from the first stage to estimate the impact of forests on rice yield in nearby villages. The estimations of Eqs. (1) and (2) provide a way to test the extent to which irrigation can account for the positive indirect effects of drought in forested villages. If the relation between drought and rice yield is different for forested villages only because of irrigation, once we control for the effect of irrigation on yield in Eq. (2), there should no longer be a differential effect of drought.

A final econometric issue concerns the standard errors of the coefficients. Conventional robust standard error estimations can underestimate the true standard errors and exaggerate significance when an explanatory variable varies at a higher level than the dependent variable varies (Moulton 1986). To address potential heteroscedasticities, we report the robust standard errors and cluster the standard errors at the household level.

6. The differential effect of drought

As a first step in our empirical analysis, the baseline estimates of Eq. (1) are given in Table 3 where the control variables are plot fixed effects and year fixed effects. By looking first at column 1, when we estimate Eq. (1) by regressing rice yield against drought while allowing for a differential effect in the forested villages, we find that the coefficient for drought is negative and statistically significant. On average, in the non-forested villages, drought events led to an average decrease in rice yield of 9.4%, which is significant at the 1% level. This finding is consistent with our descriptive statistics that demonstrate that the severity of drought impacts crop production. However, the positive and statistically significant coefficient estimate for drought interacted with the forest variable, means that rice yield in the forested villages increases sharply compared with the rice yield in the non-forested villages. This result confirms the significance of having forests near communities in adapting farmland to drought.

6.1 Do other forest or geographic characteristics explain the differential effect of drought?

When interpreting our primary results regarding the role of forests in adapting rice crops to drought, a possible source of concern is that the estimated differential effect of drought is not really a forest effect. Perhaps the effect occurs because the impacts of drought on crop yield differ for the villages with some unidentified geographic characteristics that are prevalent in forested areas. For instance, in areas where a large fraction of the territory experiences warm climates, forested areas may tend to be cooler and wetter. If warm climates are particularly prevalent in forested areas, perhaps the interaction between drought and the forest indicator is a proxy for the interaction between drought and local climates. Similarly, in some areas, a large portion of the territory could be covered by infertile soils, including saline soils. If villages with fertile soils are particularly prevalent in forested areas, perhaps the interaction between drought and the forest indicator is a proxy for the interaction between drought and high soil quality.

We consider these possibilities in columns 2 and 3 of Table 3, where we add the interactions of the climate variables and the soil variables with the drought indicator variable to our baseline estimating equation. We use the average temperature and total precipitation over the rice growing season at the village level to measure the local changes in climate.[3] To

[3] We used the season between March 1 and October 31, which covered all the three growing seasons of early-, middle-, and late-season rice in our sampling.

capture the effects of soil quality, we use soil types that are measured at the village level, which are either high fertile soil (yes=1, no=0) or medium fertile soil (yes=1, no=0) compared with poor quality soil. The coefficients of interest, which measure the differential effects for the forested villages, change little and remain statistically significant (the effects are statistically significant even when we include the sets of interactions together with other controls as shown in column 6).

We next rule out the possible confounding geographic effect by including directly interactions of forests with elevation and terrain, respectively. As discussed in Saulnier et al. (2015), the environmental conditions at mid-high altitudes are usually beneficial for the establishment of forests for long periods as pre-climax ecosystems. Moreover, the forests in areas with a rugged landscape tend to perform better with fewer disturbances than forests in flatter landscapes (Deng et al. 2011).[4] The differential effect of drought in forested areas may be biased by a differential effect of drought in villages that are located at high altitudes or on rugged terrain. We control for this possibility in columns 4 and 5 of Table 3. In column 4, we include the interaction of the elevation of the village with the drought indicator. Our results remain robust. Column 5 adds a terrain indicator variable (measured at the village, where flat land equals 1 and is 0 otherwise) interacted with drought. The differential effect of drought in the forested villages remains positive and statistically significant. Finally, in column 6, we include all of the above interaction terms. We again find that our baseline results from column 1 are robust when controlling for other geographic characteristics that could confound the true forest effect.

In Table 4, to test the robustness of these findings, we present alternative specifications of the forest effects on crop yield. The estimation pattern here is indistinguishable from that in Table 3, excluding the *forest* variable replaced with the village-specific forest cover rate.

[4] In our studied areas, all the forested villages were located in rugged terrain. Among the non-forested villages, approximately 47% of them were located in rugged terrain.

We see, as we did with the reported forest data, that forests still significantly mitigate the negative impact of drought on crop yields. Moreover, the choice of 5-km might be arbitrary for the definition of the *forest* variable. To address this, we also estimate Eq. (1) using alternative measures based on 3-km and 7-km, respectively. The results are reported in Table A2 of the appendix, and the effects of forests remain unaffected. Overall, the results indicate the forest effects described above are quite robust to alternative specifications and measures of forests.

6.2 Robustness regarding self-selection

A second concern when estimating these effects is that land transfer activities in rural China may result in selective sorting. For example, forests may have influenced migration patterns into the forested areas that had improvements in rice yield. Specifically, more educated or experienced farmers may have chosen to move to forested areas for rice production by renting cultivated land from other famers; these experienced farmers would be more likely to obtain good harvests. The presence of this self-selection close to forests could cause us to overestimate the forest effect. This upward bias would be large if the farmers who moved composed a large share of our sampling households.

To account for the probability of bias from self-selection, we test whether there were more changes in the farmers' land tenure in forested areas than in non-forested areas. In our survey, we collected the status of each plot that was cultivated by a given farmer. Specifically, we asked the farmer "whether the plot is your own or rented from others". The plots owned by farmers are allocated to households by the villages based on the number of family members (not for a fee but rather, given to a farmer because of the farmer's residency in the village), and they are cultivated by the farmer himself/herself (Gao et al. 2012). This information enables us to classify all the sampling plots as one of two types, namely, self-owned plots and rented plots. However, we find that self-owned plots accounted for nearly 89% of the total cultivated plots in the sample. In forested villages, only 14% of the plots were rented from others, while this percentage was 20% in non-forested areas. This result may imply that self-selection is not a serious problem in our sample.

In addition, we further restrict our regressions to a subsample in which we exclude the samples with land transfer activities during 2010-2012. We re-estimated Eq. (1) with the full set of controls—the specification in column 6 in Table 3— using reported forests and forest coverage separately, and results are presented in columns 1 and 2 of Table 5, respectively. The estimate on the interaction term of drought and forests is positive and statistically significant in both columns. Thus, we are confident that selective movement is not leading us to overestimate the forest effect.

6.3 Robustness concerning influential observations and collinearity

Next, we first check whether the results from Table 3 are driven by particularly influential outliers. In the first two columns of Table 6, we present the corresponding results using a sample that removes observations with large (and implausibly high) values of rice yield. For the purposes here, we estimate our baseline specification, with our full set of control variables, after we drop the top 5% of rice yield observations from our sample. The results suggest that the previous results are somewhat influenced by outliers. Relative to the full sample, the drought effects in non-forested areas here are insignificant though negative (column 1). However, as before, the coefficient estimates for drought interacted with each measure of forests are both statistically significant positive.

Second, there is concern regarding the potential collinearity between the year dummy and the drought variables. As we explained earlier, our drought indicator variable is actually designed as a year dummy variable that is equal to 1 if the year was a severe drought year and is 0 otherwise. To test this probable impact on the estimation results, as shown in columns 3 and 4, we exclude all the year fixed effects and re-estimate Eq. (1). The estimated results show that the differential effect of drought remains positive and statistically significant (row 2). Therefore, it is unlikely that our results are confounded by a collinearity issue.

6.4 Differential effects of drought across the types of forests

After we have determined that the differential effect of drought is specific to the forested villages, we examine whether the strength of this effect differs across the types of forests. As mentioned earlier, we mainly examine two types of forests, namely, natural forests and planted forests.

We construct an indicator variable for each forest type and then include each indicator variable and its interaction with drought in Eq. (1). The estimates are reported in Table 7. In columns 1 and 2, we include each of the two sets of variables one at a time with the control variables. The estimates show that the coefficient of the interaction between drought and natural forests is significantly positive. The coefficient of the interaction between drought and planted forests, however, is not significant. In column 3, we include these forest variables together and obtain a very similar pattern when we repeat the estimations. The results demonstrate that only natural forests, rather than planted forests, have ecological productivity effects in adaptation to drought. Compared with natural forests, planted forests generally have less capacity to regulate and conserve water and subsequently fail to resist the impacts of drought shock. In their analyses on the role of ecosystems, Locatelli and Vignola (2009) found significantly lower total flows or base flows under planted forests than under even non-forest land uses.

Our finding that the magnitudes of the differential effects of drought align closely with forest type provides evidence to suggest that the differential effect of drought in forested areas is intimately linked to water provision. In the following sections, we examine this link directly and provide additional evidence that this is in fact the case.

7. Does irrigation provision account for the forest effect?

7.1 Determinants of rice irrigation

We now examine whether access to irrigation water can account for the differential effect of drought in forested areas. Our first step is to check for direct evidence that drought increased the farmers' adaptation by adjusting their irrigation application frequency. Using the survey data on the farmers' irrigation information, we estimate Eqs. (2) and (3) from section 5.

The first stage estimate is reported in column 2 of Table 8. The estimate shows that drought was negatively related to farmers' irrigation frequency. However, the positive and statistically significant relation between the number of irrigation times and the interaction of drought and forest indicates that forests enabled farmers to enhance irrigation when they were faced with drought conditions. Moreover, consistent with our expectations, irrigation infrastructure also contributed to farmers' irrigation capacity under drought stress even after accounting for the differences in local climate and terrain characteristics. In column 4, when we used the alternative measure of forests, we obtained a similar result as we had done with the measure of reported forests.

We also checked the validity of the IVs (two infrastructure variables interacted with drought variable) by conducting the following tests. First, we made a balance test on the pre-treatment characteristics of villages that have different scale of irrigation infrastructure. We explore variables on village demographic characteristics (e.g., number of households, land area, the concentration and continuity of the residential area, and wealth), proxies for topography and climate (e.g., land terrain, elevation, rice growing season temperature and precipitation), and market condition (e.g. distance to the nearest county road, distance to the county government, distance to the nearest farmers market). The results are presented in Table A3. Out of the 22 coefficients we estimate, 2 (or 9%) are statistically significant, which is consistent with chance. This would help to convince us that these villages are similar in most other pathways.

Second, similar to Di Falco et al. (2011), we establish the admissibility of these instrumental variables by performing a simple falsification test: if a variable is a valid instrument, it will affect the irrigation decision, but it will not affect the rice yield among the farmers who did not irrigate. As indicated in the second column of Table 8, the IVs are jointly statistically significant drivers of the irrigation frequency under drought (Chi^2 =8.38, p = 0.000). We also rejected the null hypothesis of weak instruments (the Wald test statistic is 19.9 and exceeds the critical value even if we are willing to tolerate a relative bias of 5%). However, these instrument variables are not statistically significant drivers of the rice yield by the farmers who did not irrigate (Table A4, Chi^2 =1.54, p = 0.218). We conclude from Tables A3 and A4 that the infrastructure variables can be considered to be valid instruments.

7.2 Impact of irrigation on rice yield

After we have established that forests contributed to the farmers' irrigation frequency, we now show that irrigation is positively related to rice yield and that this relation largely accounts for the differential effect of drought in forested villages.

In column 1 of Table 8, we estimate Eq. (2). This equation is identical to Eq. (1) (for which we reported the estimates in column 6 of Table 3), except that irrigation times are also included in the estimating equation. With the full set of controls, farmers' irrigation applications led to a positive effect on rice yield, which was significant at the 5% level. More importantly, when irrigation frequency is controlled, the differential effect of drought in forested villages disappears. The estimated coefficient of Drought×Forest is close to 0 and is no longer statistically significant. In column 3, while the coefficient of the interaction is statistically significant when the measure of forest coverage is used, its magnitude has reduced largely compared with that in column 6 of Table 4. This result provides support for the explanation that the role of forests in drought conditions arises because of the increase of irrigation water availability. Overall, the effects of the satellite-based measure of forests are qualitatively similar to those of reported forests, with a few notable differences.

We also run the IV analysis for the natural and planted forests separately to see if there are differential effects. The estimated results are presented in Table 9. The results for the first stage in column 2 show that only natural forests, rather than planted forests, have significantly positive impact on rice irrigation frequency. The results are again consistent with the underlying suggestion that in small catchments, newly established forests will demand more water and reduce water flow (Brown et al. 2005). Column 1 reports the second stage results showing that both natural forests and planted forests have no impact on rice yield when irrigation frequency has been controlled.

7.3 The economic magnitude of the effects

Up to this point, we have focused on the statistical significance of our estimated coefficients and have ignored the economic magnitude of their effects. By using the estimates from Table 8, we now undertake many counterfactual calculations to show that the economic magnitudes of the impact of forests, which are operated by increasing the access to irrigation water, are substantial.

We first consider the estimated magnitude of the impact of increased irrigation frequency on rice yield. According to the estimates from columns 1 and 3 of Table 8, an increase of 1 in the frequency of irrigation is associated with an average increase of 11.2-12.6% in rice yield. As shown in Table A1, the average frequency of irrigation application was 5.72 per growing season in the five studied provinces. In 2013, the planting area for rice was approximately 9,391,773 hectares with a total output of 62,024,250 tons, which resulted in an average yield of 6,604.11 kg/ha in these provinces. Holding the total rice yield constant, this finding would suggest that there was an increase of approximately 6.9-7.8 million tons of rice output in these provinces in 2013 in response to an increase of 1 in the frequency of irrigation.

We next consider the magnitude of the benefit of forests, which occurs largely through the increased availability of irrigation. According to the estimates from column 2 (or column 4) of Table 8, when they suffered from severe drought, the farmers in forested villages increased their irrigation frequency by 0.93 (or 0.30), which is a 69.7% (or 27.9%) increase compared with the irrigation frequency in non-forested villages. This increase in irrigation frequency, in turn, increased rice output by 2.3-6.4 million tons in these five provinces. If we extrapolate this impact to the national level, it implies that China could increase its rice output by 7.7-21.2 million tons, which is equivalent to 2.8-7.7 billion USD. These effects are substantial, particularly given that we are considering the impact of one very specific ecosystem, forests, that work mainly through one channel, the increased availability of irrigation water.

8. Conclusions

Based on unique field surveys conducted in five provinces in South China, this study provides evidence that shows that forests can have important effects on farmland productivity through their interactions with drought events. By focusing on a single dimension of forest status, whether forests were present near a community, which varies throughout communities, and on an exogenous drought event, we can investigate how the presence of forests affects crop yield when there is a drought shock and to identify the role of forest ecosystem services in adaptation to climate change. We find that the drought event significantly reduces rice yield. However, the negative impacts of drought can be significantly mitigated by surrounding forests. Forests protect the water supply for crop irrigation, a resource that is seriously hindered by drought stress under non-forest land uses. We also find that this differential effect of drought is found in natural forests only, not in planted forests. Overall, the results provide one example of the importance of forests, in particular, natural forests, and

EBA to climate change.

These results are particularly important for designing effective adaptation polices to manage the impacts of climate variability. First, in addition to climate change mitigation, the natural forest management provides an important adaptation option to enhance food production in responding to drought events. Forest EBA should therefore be mainstreamed into the national development plan on climate change adaptation. Forests are usually not a priority in the current National Adaptation Programme of Action (Pramova et al. 2012b). For example, agricultural adaptation plans mostly focus on yield-related adaptation strategies in the sector, with little consideration of the associated systems such as forests. Forests provide not only general ecosystem regulating services but also significant ecological productivity through these services, especially when there are severe drought shocks. The government should consider these forest ecosystem services when it plans adaptation policies and practices in the areas of the economy beyond the forest sector. Moreover, the government could build infrastructure to take water from natural forested watersheds uphill and move it to non-forested watersheds downhill (e.g., California) to deal with droughts.

Second, China may need to continue to expand its policy that implements the Natural Forest Protection Project. In many places in China (e.g., Yunnan and Guangxi provinces), the vast bulk of the forests that lie outside of the reserves, which are far from being protected, are often felled. For example, in our study area, in recent years, most of the villages (approximately 88%) were located in non-forest lands. With the nation's dramatic economic growth, agricultural encroachment and deforestation have cleared most forests and have replaced them with the cultivation of high-value crops or plantations of fast-growing tree species. Compared with natural forests, however, these artificial plantations cannot generally resist extreme weather events.

Third, we believe that developing a better understanding of the role of forests in climate change adaptation is especially important in other developing countries. The rate of deforestation and forest degradation, and thus the threats to human well-being and increased social vulnerability, in many developing countries are still much higher than in developed countries (FAO 2009). Given the increasing challenges posed by climate change and extreme events and the significant contribution of forests to reduce negative impacts on food production and improve local adaptive capacities, forest EBA practices in developing countries should be explored in more detail.

Fourth, our results also suggest pathways for future research. First, one could employ our methodology that compares crop yield in areas suffering from drought shocks using both field survey data and LUCC data to shed light on the forest–water debate; examining, for example, how the large-scale afforestation affect water resources due to potential 'demand effects', and how this in turn affects the water availability and local adaptive capacity. Second, due to issues of data availability, our reduced-form model only documents a net effect of nearby forests on crop yield. A more meaningful model of water supply and demand and its interaction with forests could lead to a more clear understanding of the role of forest EBA. Moreover, subsequent works could build on our analysis regarding the declining impact of drought in areas with natural forests and explore the effect of other geographic, physical, or community-specific features that may attenuate or strengthen the impact of climate change on local development. Finally, our analysis suggests that research on the role of forests on agricultural adaptation to climate change should move beyond average effects and examine the delicate interplay between forests of different tree species, climate, and adaptive capacity.

References:

Adger, W. N., and Barnett, J. 2009. Four reasons for concern about adaptation to climate change. *Environment Plan A*, 41(12), 2800–2805.

Alemu, B. 2014. The Role of Forest and Soil Carbon Sequestrations on Climate Change Mitigation. *Journal of Environment and Earth Science*, 4(13), 98-111.

Andréassian, V. 2004. Waters and forests: from historical controversy to scientific debate. *Journal of Hydrology*, 291, 1–27.

Aylward, B. 2005. Land use, hydrological function and economic valuation. In Bonell M., and Bruijnzeel, L.A. (Eds.), Forests, Water, and People in the Humid Tropics: Past, Present, and Future. Cambridge, UK: Cambridge University Press (pp.99-120).

Boyle, C. E., Huang, Q., and Wang, J. 2014. Assessing the impacts of fiscal reforms on investment in village-level irrigation infrastructure, *Water Resources Research*, 50(8), 6428–6446.

Brauman, K.A., Daily, G.C., Duarte, T.K., Mooney, H.A. 2007. The nature and value of ecosystem services: an overview highlighting hydrologic services. *Annual Review of Environment and Resources*, 32, 67-98.

Bredemeier, M. 2011. Forest: climate and water issues in Europe. *Ecohydrology*, 4, 159-167.

Brogna, D., Vincke, C., Brostaux, Y., Soyeurt, H., Dufrêne, M., Dendoncker, N. 2017. How does forest cover impact water flows and ecosystem services? Insights from “real-life” catchments in Wallonia (Belgium). *Ecological Indicators*, 72, 675-685.

Brown, A.E., Zhang, L., MacMahon, T.A., Western, A.W., Vertessy, R.A. 2005. A review of paired catchment studies for determining changes in water yield resulting from alterations in vegetation. *Journal of Hydrology*, 310, 28–61.

Calder, I.R. 2002. Forests and hydrological services: reconciling public and science perceptions. *Land Use and Water Resources Research*, 2, 1–12.

Canadell, J. G., and Raupach, M. R. 2008. Managing forests for climate change mitigation. *Science*, 320, 1456–1457.

Carvalho-Santos, C., Honrado, J., and Hein, L. 2014. Hydrological services and the role of forests: Conceptualization and indicator-based analysis with an illustration at a regional scale. *Ecological Complexity*, 20, 69-80.

Chen, H., Wang, J. and Huang, J. (2014). Policy support, social capital, and farmers’ adaptation to drought in China, *Global Environmental Change*, 24, 193–202.

China Meteorological Administration (CMA). 2007. Trial Procedures for the Early warning Signal Issuance of Unexpected Meteorological Disasters. China Meteorological

Administration, Beijing. Available at: http://www.gov.cn/gongbao/content/2008/content_912553.htm.

Chong, J. 2014. Ecosystem-based approaches to climate change adaptation: progress and challenges. *International Environmental Agreements: Politics, Law and Economics*, 14(4), 391–405.

D'Almeida, C., Vörösmarty, C.J., Hurtt, G.C., Marengo, J.A., Dingman, S.L., Keim, B.D. 2007. The effects of deforestation on the hydrological cycle in Amazonia: a review on scale and resolution. *International Journal of Climatology*, 27, 633–647.

Dai, A. G. 2013. Increasing drought under global warming in observations and models. *Nature Climate Change*, 3(1), 52–58.

Deng, X. Huang, J., Uchida, E., Rozelle, S., and Gibson, J. 2011. Pressure cookers or pressure valves: Do roads lead to deforestation in China? *Journal of Environmental Economics & Management*, 61(1), 79-94.

Di Falco, S., Veronesi, M., and Yesuf, M. 2011. Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics*, 93(3), 825-842.

Doswald, N., Munroe, R., Roe, D., et al. 2014. Effectiveness of ecosystem‐based approaches for adaptation: review of the evidence - base. *Climate and Development*, 6(2), 185–201.

Ellison, D., Futter, M., and Bishop, K. 2012. On the forest cover–water yield debate: from demand- to supply-side thinking. *Global Change Biology*, 18(3), 806–820.

Ellison, D., Morris, C., Locatelli, B., Sheil, D., Cohen, J., Murdiyarso, D., Gutierrez, V., van Noordwijk, M., Creed, I., Pokorny, J., Gaveau, D., Spracklen, D., Tobella, A., Ilstedt, U., Teuling, A., Gebrehiwot, S., Sands, D., Muys, B., Verbist, B., Springgay, E., Sugandi, Y., and Sullivan, C. 2017. Trees, forests and water: Cool insights for a hot world, *Global Environmental Change*, 43, 51-61.

Farley, K.A., Jobbágy, E.B., Jackson, R.B. 2005. Effects of afforestation on water yield: a global synthesis with implications for policy. *Global Change Biology*, 11, 1565–1576.

Fiquepron, J., Garcia, S., and Stenger, A. 2013. Land use impact on water quality: Valuing forest services in terms of the water supply sector. *Journal of Environmental Management*, 126, 113-121.

Food and Agriculture Organization of the United Nations (FAO). 2008. Forest and water - A thematic study prepared in the framework of the Global Forest Resources Assessment

2005. FAO, Rome.

Food and Agriculture Organization of the United Nations (FAO). 2009. *Adapting to climate change*. Unasylva No. 60(231/232). FAO, Rome.

Gao, L., Huang, J., and Rozelle, S. 2012. Rental markets for cultivated land and agricultural investments in China. *Agricultural Economics*, 43, 391–403.

Gray, C., and Mueller, V. 2012. Drought and Population Mobility in Rural Ethiopia. *World Development*, 40(1), 134-145.

Hou, L., Huang, J., and Wang, J. 2015. Farmers' perceptions of climate change in China: the influence of social networks and farm assets. *Climate Research*, 63(3),1670-1677.

Huang J., Wang, Y. and Wang, J. 2015. Farmer's adaptation to extreme weather events through farm management and its impacts on the mean and risk of rice yield in China, *American Journal of Agricultural Economics*, 97, 602–617.

Huang, J., Jiang, J., Wang, J., and Hou, L. 2014. Crop Diversification in Coping with Extreme Weather Events in China. *Journal of Integrative Agriculture,* 13, 677-686.

Huang, J., Wang, Y., and Wang, J. 2015. Farmer's adaptation to extreme weather events through farm management and its impacts on the mean and risk of rice yield in China. *American Journal of Agricultural Economics*, 97(2), 602–617.

Huang, Q., Wang, J., and Li, Y. 2017. Do water saving technologies save water? Empirical evidence from North China. *Journal of Environmental Economics and Management*, 82, 1–16.

Intergovernmental Panel on Climate Change (IPCC). 2012. Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. Special Report of the Intergovernmental Panel on Climate Change. Cambridge, UK: Cambridge University Press.

Intergovernmental Panel on Climate Change (IPCC). 2014. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, UK: Cambridge University Press.

International Union of Forest Research Organizations (IUFRO). 2009. Adaptation of Forests and People to Climate Change: A Global Assessment Report. IUFRO World Series Volume 22. Helsinki, Finland. http://www.iufro.org/science/gfep/adaptaion-panel/the-report/

International Union of Forest Research Organizations (IUFRO). 2007. Research spotlight: how do forests influence water? IUFRO Fact Sheet No. 2. Vienna, Austria.

Jentsch, A., Kreyling, J., Beierkuhnlein, C. 2007. A new generation of climate-change experiments: events, not trends. *Frontiers in Ecology and Environment*, 5(7), 365–374.

Klemick, H. 2011. Shifting cultivation, forest fallow, and externalities in ecosystem services: Evidence from the Eastern Amazon. *Journal of Environmental Economics and Management*, 61(1), 95-106.

Liu, J., Kuang, W., Zhang, Z., Xu, X. 2014. Spatiotemporal characteristics, patterns and causes of land-use changes in China since the late 1980s. *Journal of Geographical Sciences*, 24(2), 195-210.

Locatelli, B., 2016. Ecosystem Services and Climate Change. In: Routledge Handbook of Ecosystem Services. Fish, R., and Turner, R. K. (eds). Routledge, London and New York, pp. 481-490. https://www. routledge.com/products/9781138025080.

Locatelli, B., and Vignola, R., 2009. Managing watershed services of tropical forests and plantations: Can meta-analyses help? *Forest Ecology and Management*, 258(9), 1864-1870.

Locatelli, B., Kanninen, M., Brockhaus, M., Colfer, C. J. P., Murdiyarso, D., and Santoso, H. 2008. *Facing an Uncertain Future: How Forest and People Can Adapt to Climate Change*. Bogor, Indonesia: Center for International Forestry Research.

Lukasiewicz, A., Pittock, J., and Finlayson, M. 2016. Institutional challenges of adopting ecosystem-based adaptation to climate change, *Regional Environmental Change*, 16(2), 487-499.

Martínez, M. L., Pérez-Maqueo, O., Vázquez, G., Castillo-Campos, G., García-Franco, J., Mehltreter, K., Equihua, M., and Landgrave, R. 2009. Effects of land use change on biodiversity and ecosystem services in tropical montane cloud forests of Mexico. *Forest Ecology & Management*, 258(9), 1856-1863.

Millennium Ecosystem Assessment (MEA). 2005. Ecosystems and human well-being: the assessment series (four volumes and summary). Island Press, Washington, DC.

Moulton, B. R. 1986. Random Group Effects and the Precision of Regression Estimates. *Journal of Econometrics*, 32(3), 385-397.

National Bureau of Statistics of China (NBSC). 2012. China Statistical Yearbook 2011. China Statistical Press, Beijing.

National Bureau of Statistics of China (NBSC). 2015. China Statistical Yearbook 2014. China Statistical Press, Beijing.

Pandey, V., and Shukla, A. 2015. Acclimation and Tolerance Strategies of Rice under Drought Stress. *Rice Science*, 22(4), 147-161.

Pasquini, L., and Cowling, R. 2015. Opportunities and challenges for mainstreaming ecosystem-based adaptation in local government: evidence from the Western Cape, South Africa, *Environment, Development and Sustainability*, 17(5), 1121-1140.

Pramova, E., Locatelli, B., Brockhaus, M., and Fohlmeister, S. 2012b. Ecosystem services in the national adaptation programmes of action. *Climate Policy*, 12(4), 393-409.

Pramova, E., Locatelli, B., Djoudi, H., and Somorin, O. 2012a. Forests and trees for social adaptation to climate variability and change. *Wiley Interdisciplinary Reviews Climate Change*, 3(6), 581–596.

Rosenqvist, L., Hansen, K., Vesterdal, L., van der Salm, C. 2010. Water balance in afforestation chronosequences of common oak and Norway spruce on former arable land in Denmark and southern Sweden. *Agricultural and Forest Meteorology*, 150, 196–207.

Saulnier, M., Talon, B., and Edouard, J. 2015. New pedoanthracological data for the long-term history of forest species at mid-high altitudes in the Queyras Valley (Inner Alps). *Quaternary International*, 366(24), 15–24.

Schaafsma, M., Morse-Jones, S., Posen P., Swetnam, R.D., Balmford, A., Bateman, J., Burgess, N.D., Chamshama, S.A.O., Fisher, B., Green, R.E., Hepelwa, A.S., Hernández-Sirvent, A., Kajembe, G.C., Kulindwa, K., Lund, J.F., Mbwambo, L., Meilby, H., Ngaga, Y.M., Turner, R.K. 2012. Towards transferable functions for extraction of Non-timber Forest Products: A case study on charcoal production in Tanzania. *Ecological Economics*, 80, 48-62.

Schaafsma, M., Morse-Jones, S., Posen P., Swetnam, R.D., Balmford, A., Bateman, J., Burgess, N.D., Chamshama, S.A.O., Fisher, B., Freeman, T., Geofrey, V., Green, R.E., Hepelwa, A.S., Hernández-Sirvent, A., Hess, S., Kajembe, G.C., Kayharara, G., Kilonzo, M., Kulindwa, K., Lund, J.F., Madoffe, S.S., Mbwambo, L., Meilby, H., Ngaga, Y.M., Theilade, I., Treue., T., van Beukering, P., Vyamana, V.G., Turner, R.K. 2014. The importance of local forest benefits: Economic valuation of Non-Timber Forest Products in the Eastern Arc Mountains in Tanzania. *Global Environmental Change*, 24, 295-305.

Sheeran, K. A. 2006. Forest conservation in the Philippines: A cost-effective approach to mitigating climate change. *Ecological Economics*, 58(2), 338–349.

Sheil, D., and Murdiyarso, D. 2009. How forests attract rain: an examination of a new hypothesis. *BioScience*, 59(4), 341-347.

Sisak, L., Riedl, M., Dudik, R. 2016. Non-market non-timber forest products in the Czech Republic—Their socio-economic effects and trends in forest land use. *Land Use Policy*, 50, 390-398.

Soares-Filho, B., Moutinho, P., Nepstad, D., Anderson, A., Rodrigues, H., Garcia, R., Dietzsch, L. Merry, F., Bowman, M., Hissa, L., Silvestrini, R., Maretti C., and DeFries, R. S. 2010. Role of Brazilian Amazon protected areas in climate change mitigation, *Proceedings of the National Academy of Science of the United States of America*, 107(24), 10821-10826.

Thornton, P. E., Running, S. W., White, M. A. 1997. Generating surfaces of daily meteorological variables over large regions of complex terrain. *Journal of Hydrology*, 190(3-4), 214-251.

UN Framework Convention on Climate Change (UNFCCC). 2011. Ecosystem-based approaches to adaptation: compilation of information. Subsidiary Body for Scientific and Technological Advice Thirty-fifth session, Durban. http://unfccc.int/resource/docs/2011/sbsta/eng/inf08.pdf

van der Ent, R., Coenders-Gerrits, A., Nikoli,R., and Savenije, H. 2012. The importance of proper hydrology in the forest cover-water yield debate: commentary on Ellison et al. *Global Change Biology*, 18, 806–820.

van Dijk, A., and Keenan, R. 2007. Planted Forests and Water in Perspective. *Forest Ecology and Management*, 251(1-2), 1-9.

Verchot, L.V., Van Noordwijk, M., Kandji, S., Tomich, T., Ong, C., Albrecht, A., Mackensen, J., Bantilan, C., Anupama, K., and Palm, C. 2007. Climate change: linking adaptation and mitigation through agroforestry. *Mitigation and Adaptation Strategies for Global Change*, 12(5), 901–918.

Vignola, R., Locatelli, B., Martinez, C., and Imbach, P. 2009. Ecosystem-based adaptation to climate change: what role for policy-makers, society and scientists? *Mitigation and Adaptation Strategies for Global Change*, 14(8), 691–696.

Vincent, J., Ahmad, I., Adnan, N., Burwell, W., Pattanayak, S., Tan-Soo, J., Thomas, K. 2016. Valuing Water Purification by Forests: An Analysis of Malaysian Panel Data. *Environmental and Resource Economic*s, 64 (1), 59-80.

Wang, J., and Meng, Y. 2013. An analysis of the drought in Yunnan, China, from a perspective of society drought severity. *Natural Hazards*, 67(2), 431–458.

Wang, Y., Huang, J. and Wang, J. (2014). Household and community assets and farmers' adaptation to extreme weather event: the case of drought in China, *Journal of Integrative Agriculture*, 13, 687–697.

Welch, J., Vincent, J., Auffhammer, M., Moya, P., Dobermann, A., and Daweg, D. 2010. Rice yields in tropical/subtropical Asia exhibit large but opposing sensitivities to minimum and maximum temperatures. *Proceedings of the National Academy of Sciences*, 107(33), 14562.

World Bank. 2010. Convenient Solutions to an Inconvenient Truth: Ecosystem-Based Approaches to Climate Change. The World Bank, Washington, DC.

Zhang, L., Dawes, W.R., and Walker, G.R. 2001. Response of mean annual evapotranspiration to vegetation changes at catchment scale. *Water Resources Research*, 37, 701–708.

Zhang, T., Huang, Y., and Yang, X. 2013. Climate warming over the past three decades has shortened rice growth duration in China and cultivar shifts have further accelerated the process for late rice. *Global Change Biology*, 19(2), 563−570.

Table 1. Rice Plots Affected by Extreme Drought, Actual Average Rice Yield and Yield Loss Reported by Farmers, 2010-2012

	Drought year (1)	Normal year (2)	Difference [(1)-(2)]/(2)*100
Plots affected by drought (%)	47	19	147***
Actual average yield (kg/ha)	6,456	6,927	-6.8***
Yield loss when suffered from drought (%)	24	16	50***

Source: Authors' survey.

Note: Sample includes 1,449 observations in both normal and drought years. *** denotes statistical significance at the 1% level.

Table 2. Relationship between Forests in Villages and Farmer's Irrigations, 2010-2012

	All samples (%)	Non-forested villages (%)	Forested villages (%)
Share of villages	100	88	12
Irrigation applications (times)	5.72	5.63	6.42***
Irrigation water directly from			
Creeks or streams	50.9	50.1	57.1***
Mountain springs	3.9	3.7	5.3*
Facilities	43.6	44.3	38.2**
Others	6.4	6.3	7.4

Source: Authors' survey.

Note: The sampling villages are defined as forested villages when they were forests located within a 5-km radius of the village, defined as non-forested villages otherwise. In our survey, the average, minimum, and maximum distance of forests from the community was 0.79 km, 0 km, and 5 km, respectively. The comparing base is column 2 (non-forested villages). ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 3. The Differential Effect of Drought in Villages with Forests

	Dependent Variable: Log Rice Yield					
	(1)	(2)	(3)	(4)	(5)	(6)
Drought	-0.094***	-0.433**	-0.082**	-0.089***	-0.088*	-0.329**
	(0.024)	(0.178)	(0.037)	(0.024)	(0.046)	(0.139)
Drought × Forest	0.055**	0.066**	0.056**	0.059**	0.055**	0.067**
	(0.026)	(0.027)	(0.027)	(0.028)	(0.026)	(0.028)
Drought × Temperature		0.015**				0.013**
		(0.007)				(0.006)
Drought × Precipitation		0.003				0.000
		(0.007)				(0.006)
Drought × High fertile soil			-0.024			-0.022
			(0.041)			(0.040)
Drought × Medium fertile soil			-0.011			-0.006
			(0.035)			(0.034)
Drought × Elevation				-0.073		-0.047
				(0.084)		(0.086)
Drought × Flat terrain					-0.007	-0.008
					(0.042)	(0.041)
Plot fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.051	0.054	0.051	0.053	0.051	0.055
Observations	2,898	2,898	2,898	2,898	2,898	2,898

Note: Robust standard errors clustered by households are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 4. The Differential Effect of Drought in Villages with Alternative Measure of Forests

	Dependent Variable: Log Rice Yield					
	(1)	(2)	(3)	(4)	(5)	(6)
Drought	-0.151***	-0.465***	-0.140***	-0.147***	-0.153***	-0.361***
	(0.030)	(0.174)	(0.041)	(0.030)	(0.050)	(0.137)
Drought × Forest	0.353***	0.365***	0.358***	0.354***	0.353***	0.373***
	(0.059)	(0.062)	(0.060)	(0.060)	(0.060)	(0.063)
Drought × Temperature		0.017**				0.014**
		(0.007)				(0.006)
Drought × Precipitation		-0.001				-0.004
		(0.007)				(0.006)
Drought × High fertile soil			-0.031			-0.030
			(0.041)			(0.039)
Drought × Medium fertile soil			-0.007			-0.004
			(0.035)			(0.034)
Drought × Elevation				-0.072		-0.052
				(0.083)		(0.086)
Drought × Flat terrain					0.002	-0.002
					(0.042)	(0.041)
Plot fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.067	0.071	0.068	0.069	0.067	0.072
Observations	2,898	2,898	2,898	2,898	2,898	2,898

Note: Robust standard errors clustered by households are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 5. Robustness with Respect to the Potential Self-selection Effect

	Dependent Variable: Log Rice Yield	
	(1)	(2)
Drought	-0.315**	-0.338**
	(0.148)	(0.146)
Drought × Forest	0.066**	0.419***
	(0.030)	(0.065)
Temperature × Forest	0.011*	0.012*
	(0.006)	(0.006)
Precipitation × Forest	-0.001	-0.006
	(0.007)	(0.007)
High fertile soil × Forest	-0.025	-0.036
	(0.047)	(0.046)
Medium fertile soil ×Forest	-0.014	-0.015
	(0.038)	(0.038)
Elevation × Forest	-0.054	-0.059
	(0.088)	(0.088)
Flat terrain × Forest	-0.011	0.000
	(0.049)	(0.048)
Plot fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
R-squared	0.078	0.100
Observations	2,344	2,344

Note: In column 1, forest variable is measured as the reported forests, which is a dummy variable. In column 2 it is a continuous measure of forest coverage instead of forest dummy. Robust standard errors clustered by households are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 6. Robustness with Respect to Influential Observations and Colinearity

	Dependent Variable: Log Rice Yield			
	Omit 5% highest yield		Excluding year dummies	
	(1)	(2)	(3)	(4)
Drought	-0.241	-0.305**	-0.232*	-0.162
	(0.155)	(0.151)	(0.133)	(0.133)
Drought × Forest	0.074***	0.371***	0.069**	0.356***
	(0.029)	(0.063)	(0.030)	(0.061)
Temperature × Forest	0.010	0.013**	0.010	0.008
	(0.006)	(0.006)	(0.007)	(0.006)
Precipitation × Forest	-0.003	-0.007	-0.002	-0.009
	(0.007)	(0.007)	(0.006)	(0.007)
High fertile soil × Forest	-0.022	-0.029	-0.023	-0.030
	(0.039)	(0.039)	(0.040)	(0.039)
Medium fertile soil × Forest	-0.004	-0.002	-0.009	-0.009
	(0.034)	(0.034)	(0.034)	(0.034)
Elevation × Forest	-0.061	-0.060	-0.052	-0.054
	(0.087)	(0.086)	(0.068)	(0.067)
Flat terrain × Forest	-0.003	0.001	-0.008	-0.002
	(0.042)	(0.041)	(0.041)	(0.041)
Plot fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	No	No
R-squared	0.056	0.073	0.055	0.070
Observations	2,728	2,728	2,898	2,898

Note: In columns 1 and 3, forest variable is measured as the reported forests, which is a dummy variable. In columns 2 and 4 it is a continuous measure of forest coverage instead of forest dummy. Robust standard errors clustered by households are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 7. Differential Effects of Natural Forests and Planted Forests

	(1)	(2)	(3)
Drought	-0.352**	-0.287**	-0.348**
	(0.138)	(0.138)	(0.136)
Drought × Natural forest	0.178***		0.177***
	(0.032)		(0.033)
Drought × Planted forest		-0.028	-0.018
		(0.033)	(0.033)
All controls	Yes	Yes	Yes
Plot fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
R-squared	0.061	0.053	0.061
Observations	2,898	2,898	2,898

Note: Robust standard errors clustered by households are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 8. The Impact and Determinants of Farmer's Irrigation

	(1)	(2)	(3)	(4)
	Log rice yield	Irrigation applications (times)	Log rice yield	Irrigation applications (times)
Irrigation applications	0.112**		0.126**	
	(0.046)		(0.049)	
Drought	-0.188	-1.328	-0.231	-1.082
	(0.163)	(1.245)	(0.171)	(1.228)
Drought × Forest	-0.033	0.925***	0.204**	1.412***
	(0.053)	(0.277)	(0.095)	(0.504)
Storage capacity of ponds in village × Drought		0.003***		0.003***
		(0.001)		(0.001)
Number of lateral canals per hectare of cultivated land in village × Drought		0.767***		0.739***
		(0.251)		(0.256)
All controls	Yes	Yes	Yes	Yes
Plot fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2,898	2,898	2,898	2,898

Note: In columns 1 and 2, forest variable is measured as the reported forests, which is a dummy variable. In columns 3 and 4 it is a continuous measure of forest coverage instead of forest dummy. Robust standard errors clustered by households are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 9. The Impact and Determinants of Farmer's Irrigation - by forest type		
	(1)	(2)
	Log rice yield	Irrigation applications (times)
Irrigation applications	0.108**	
	(0.049)	
Drought	-0.199	-1.432
	(0.163)	(1.231)
Drought × Natural forest	0.010	1.534***
	(0.088)	(0.407)
Drought × Planted forest	-0.060	0.453
	(0.047)	(0.348)
Storage capacity of ponds in village × Drought		0.003***
		(0.001)
Number of lateral canals per hectare of cultivated land in village × Drought		0.667***
		(0.258)
All controls	Yes	Yes
Plot fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	2,898	2,898

Note: Robust standard errors clustered by households are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Appendix

Table A1. Descriptive Statistics of Variables

Variables	Mean	SD
Rice yield (km/ha)	6,691.63	2,683.60
Reported forests (yes = 1, no = 0)	0.12	0.32
Forest coverage	0.14	0.16
Natural forests (yes = 1, no = 0)	0.05	0.22
Planted forests (yes = 1, no = 0)	0.07	0.25
Irrigation applications (times)	5.72	4.31
Drought (yes = 1, no = 0)	0.50	0.50
Growing season average temperature (℃)	18.27	2.05
Growing season total precipitation (100 mm)	15.35	5.04
High soil quality (yes = 1, no = 0)	0.25	0.43
Medium soil quality (yes = 1, no = 0)	0.59	0.49
Elevation of the village (km)	0.10	0.33
Plain land (yes = 1, no = 0)	0.50	0.50
Water storage capacity of the ponds per hectare of cultivated land in villages (cubic meters/ha)	34.99	188.66
Number of lateral canals per hectare of cultivated land in villages	0.08	0.17
Middle-season rice (yes = 1, no = 0)	0.27	0.45
Late-season rice (yes = 1, no = 0)	0.36	0.48

Note: The total observations are 2,898.

Table A2. Estimates with alternate measures of forest coverage

	Dependent Variable: Log Rice Yield	
	(1)	(2)
Drought	-0.333**	-0.385***
	(0.137)	(0.137)
Drought × Forest	0.323***	0.415***
	(0.073)	(0.063)
Temperature × Forest	0.015**	0.013**
	(0.006)	(0.006)
Precipitation × Forest	-0.006	-0.003
	(0.007)	(0.006)
High fertile soil × Forest	-0.030	-0.033
	(0.039)	(0.039)
Medium fertile soil ×Forest	-0.004	-0.005
	(0.034)	(0.034)
Elevation × Forest	-0.056	-0.052
	(0.086)	(0.086)
Flat terrain × Forest	-0.005	0.002
	(0.041)	(0.041)
Plot fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
R-squared	0.065	0.077
Observations	2,898	2,898

Note: In columns 1 and 2, forest variable is measured as the forest coverage within 3-km and 7-km of the village, respectively. Robust standard errors clustered by households are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table A3. Balance Test on the Pre-treatment Characteristics of Villages

	Number of households	Land area (100 ha)	Whether residential areas are concentrated and continued (yes=1, no=0)	Wealth (10,000 yuan)	Plain land (yes = 1, no = 0)	Elevation (km)
	(1)	(2)	(3)	(4)	(5)	(6)
Storage capacity of ponds in village	-0.148 (0.154)	-0.004 (0.002)	-0.0001 (0.0001)	-0.0005 (0.002)	0.0001 (0.0001)	-0.0003 (0.0002)
Number of lateral canals per hectare of cultivated land in village	-180.731 (149.831)	-5.520 (3.820)	0.189 (0.112)	0.746 (3.680)	0.325 (0.164)	-0.133 (0.161)
Joint test	0.97	2.46	1.51	0.05	2.77	1.57
P-value	0.389	0.131	0.238	0.949	0.176	0.251

	Growing season average temperature (℃)	Growing season total precipitation (100 mm)	Distance to the nearest county road (km)	Distance to the county government (km)	Distance to the nearest farmers market (km)
	(7)	(8)	(9)	(10)	(11)
Storage capacity of ponds in village	0.0003 (0.001)	0.007*** (0.001)	-0.0003 (0.001)	0.005 (0.010)	-0.0001 (0.001)
Number of lateral canals per hectare of cultivated land in village	0.059 (0.470)	1.646 (3.510)	-0.335 (0.330)	-11.046 (11.276)	-9.489** (4.092)
Joint test	0.30	13.04	0.62	0.32	2.18
P-value	0.741	0.000	0.546	0.731	0.120

Note: Each cell in columns 1 to 11 corresponds to an estimate from a separate regression, where each of the village characteristics is regressed on an infrastructure variable. The joint test and accordingly *P*-value are test results for the joint estimation of both infrastructure variables. All regressions are estimated using OLS. Robust standard errors clustered by townships are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level. The total observations are 172.

Table A4. Test on the Validity of the Instrumental Variables

	Log rice yield by households that did not irrigate	
	(1)	(2)
Drought	1.378	0.148
	(1.223)	(0.747)
Drought × Forest	0.166	0.819***
	(0.109)	(0.294)
Storage capacity of ponds in village × Drought	5.567	6.102
	(3.805)	(3.752)
Number of lateral canals per ha of cultivated land in village × Drought	0.163	0.189
	(0.144)	(0.135)
All controls	Yes	Yes
Plot fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Wald test on instrumental variables	$\text{Chi}^2 = 1.54$	$\text{Chi}^2 = 2.05$
	(p = 0.218)	(p = 0.133)
R-squared	0.166	0.193
Observations	305	305

Note: In column 1, forest variable is measured as the reported forests, which is a dummy variable. In column 2 it is a continuous measure of forest coverage instead of forest dummy. Robust standard errors clustered by households are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level.