Agricultural Adaptation to Climate Variability: Farmers' Responses to a Variable Monsoon

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ABSTRACT

Social-ecological systems (SES), or systems where ecosystems and humans are inextricably linked, especially agricultural communities, are facing unpredictable pressures and shocks due to global climate change. To better understand if agricultural communities will be able to respond to future, unpredictable changes in climate, this study examines how farmers are adapting their current cropping patterns based on inter-annual variability in northwest India. This study makes the assumption that farmers who adapt to current climate variability have higher adaptive capacity and may be better able to respond to future changes in climate than those farmers who are not adapting to current climate variability. With this aim, this study examines agricultural communities in Mehsana district, Gujarat in northwest India. Using both household level surveys and regional remote sensing analyses, this study suggests that farmers are shifting the date of crop planting based on monsoon onset date, even if farmers have access to irrigation. This suggests that farmers are changing their short-term cropping patterns based on climate signals, which may suggest that farmers have some capacity to alter their cropping patterns to match with new climate patterns in the future.

INTRODUCTION

Social-ecological systems (SES), or systems where ecosystems and humans are inextricably linked, are facing unpredictable pressures and shocks due to global change and unsustainable human use of resources (Chapin *et al.* 2010). It is especially difficult to predict the consequences of climate change on SES, given that local climate projections are rare, systems may face novel climate extremes, and there are often thresholds and non-linearities in the system's response to climate shocks (Liu *et al* 2007, Williams *et al.* 2007, Burkett *et al.* 2005). This inability to predict and respond to future climate change is problematic since it may result in the irreparable loss of ecosystem functions and services, and a subsequent collapse of dependent human livelihoods (Olson 2003). Scholars and policymakers have called to make SES more *resilient* and *resistant* to change (Smit and Pilifosova 2003). One way to ensure that communities become more resilient to change is if they *adapt* livelihood strategies to match new climate patterns. This will enhance the system's capacity to respond to a wide range of climate shocks, and ensure that the system's fundamental ecological and societal functions are not compromised.

While many scholars have postulated that enhancing *adaptive capacity* increases communities' resilience to impending shocks, previous research has not comprehensively identified which factors enhance adaptive capacity and the relative importance of each factor. This is because most previous literature on adaptive capacity consists of case studies that consider only one, single-disciplinary factor at a time (Agrawal and Chhatre 2006). However, there are multiple, cross-disciplinary factors that influence adaptive capacity. The stability of smallholder agricultural systems to climate variability, for example, depends on 1) biophysical (i.e. soil fertility), 2) social (i.e. community institutions), 3) economic (i.e. market prices for crops), 4) ecological (i.e. pest control), and 5) cognitive (i.e. risk aversion) factors (Morton 2007, Howden *et al.* 2007, Brooks *et al.* 2005, Grothmann and Patt 2005, Hagmann and Chuma 2002). Thus, when studying adaptive capacity in SES, one should consider the multiple, cross-disciplinary factors associated with adaptive capacity within the same analysis (Ostrom 2009).

Given these considerations, this study aims to quantify the relative importance of various factors that have been associated with adaptive capacity in the previous literature. For example, previous studies suggest that access to capital is the most important factor identifying who can adapt, while other studies suggest that social networks may be the most important factor. By considering these various factors within the same analysis, this paper aims to identify the relative importance of various inter-disciplinary factors for adaptive capacity. In addition, given that there is little understanding of whether household level trends are more generalizeable to broader regions, this study also offers a method to examine agricultural adaptation at the district level using remote sensing analyses.

METHODS

Study Site selection

Given that climate change is predicted to most negatively impact communities that directly depend on natural resources for their livelihoods, like agricultural communities, this study focuses on how agricultural communities in India respond to and ameliorate the negative effects of climate variability. India is the ideal site for this research given that approximately sixty percent of its population depends on agriculture as a primary source of livelihood and that twenty percent of India's GDP is from agriculture. In addition, previous global studies that have estimated the impact of climate change on crop yields highlight South Asia as one of the regions that is going to be most negatively impacted worldwide (Rosenzweig and Parry 1994, Lobell et al. 2008).

Specifically, this study will consider autonomous adaptation, or strategies that farmers implement independently based on a variety of different stimuli, such as price fluctuations and inter-annual climatic variability. Understanding how farmers cope with inter-annual variability is a good short-term proxy for how farmers may adapt to long-term changes in climate. This is because current high adaptive capacity, as indicated by farmers who adapt to short-term variation in climate, may be a good proxy for future adaptive capacity and the potential for these communities to respond to future unpredictable changes in climate. I will specifically examine how farmers alter their cropping strategies based on rainfall variability because altering cropping strategies is the predominant form of agricultural adaptation in India and most of India's farmers are dependent on monsoon rains (Semwal *et al.* 2004).

This study only considers short-term agricultural adaptation to climate variability. Short-term strategies consist of altering cropping strategies, such as shifting planting date, switching crop types, and changing cropping intensity, defined as the number of times one grows crops in a single year (Lobell *et al.* 2008, Saxena *et al.* 2005). While longer-term adaptations to climate variability, such as the construction of irrigation systems, investment in children's education, and the migration of populations to urban areas (De Costa 2010, Patel 2010), are important, it was difficult to accurately account for these strategies within the time-frame of my study.

This study was conducted in Mehsana district, Gujarat, India (Figure 1). Mehsana is an ideal region to conduct this study given that it is located within a semi-arid climatic zone where water is a limiting resource. In addition, it is an area that experiences high inter-annual rainfall variability (Figure 2). Given these considerations, this area is likely to be one where farmers may alter their cropping strategies based on variable monsoon patterns from year to year.

Figure 1. Map of study region Mehsana district, Gujarat (orange) (Wikicommons, 2011)

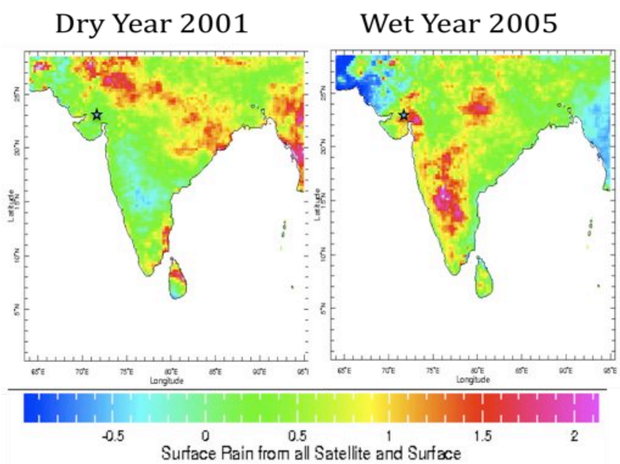

Figure 2. Rainfall anomaly map over India highlighting a dry year and wet year (IRI Data Library 2010). Mehsana district (starred region) is both drier than expected and wetter than expected in the dry and wet year respectively, highlighting the high inter-annual variability in rainfall in this region.

Remote Sensing Methods

Cropping patterns at a regional scale were detected using MODIS Enhanced Vegetation Index (EVI), which is a product that measures the amount of vegetation biomass on the ground (Huete *et al.* 2002) using the following formula:

Equation 1:
$$\mathrm{EVI} = G\frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{red}}}{\rho_{\mathrm{NIR}} + C_1 \times \rho_{\mathrm{red}} - C_2 \times \rho_{\mathrm{blue}} + L}$$

EVI is typically considered to be a better vegetation product than the Normalized Difference Vegetation Index (NDVI) because it better correct for atmospheric scattering and cloud cover. The MODIS EVI product is available at a spatial resolution of 250 m globally and at a temporal resolution of sixteen-day composites from 2000 to the present.

Previous studies have used satellite vegetation metrics, like MODIS EVI, to quantify several different measures of agricultural crop growth on the ground: 1) cropping intensity (Birander and Xiao, 2011), 2) planting date (Sakamoto et al., 2006), and 3) length of the growing season (Figure 3). This study will specifically focus on identifying cropping intensity across Mehsana district, Gujarat. Since MODIS data is available from 2000 to the present, it can be used to identify cropping intensity for each year and quantify the amount that cropping intensity changes through time.

Figure 3. One year time series for an agricultural pixel. Approximate first planting date and final harvest date are highlighted. Cropping intensity is quantified by counting the number of vegetation peaks throughout the time series (in this case there are two peaks). This suggests crops were grown during two different growing seasons throughout the year.

MODIS EVI data is first processed to remove any erroneous EVI values that may be due to cloud cover contamination. This was done by applying an algorithm that removed any EVI points that were more than 15% greater or smaller than surrounding EVI pixels. The remaining points were then smoothed and interpolated using cubic b-splines. Using training pixels from initial fieldwork and from Google Earth Quickbird images, I selected ideal spectral signatures representing urban areas, forests and plantations, single cropped areas, and double cropped areas (Figure 4). Approximately thirty pixels were used to conduct a decision-tree classification, where urban land covers were identified as having a low mean EVI value and plantation and forest pixels were identified as having a low standard deviation compared to agricultural pixels. Remaining pixels were then classified as agricultural pixels, and were separated as single or double cropping by counting the number of peaks within a given year using a local-maxima counting algorithm. All analyses were performed in ENVI Software and R statistical software (2.11).

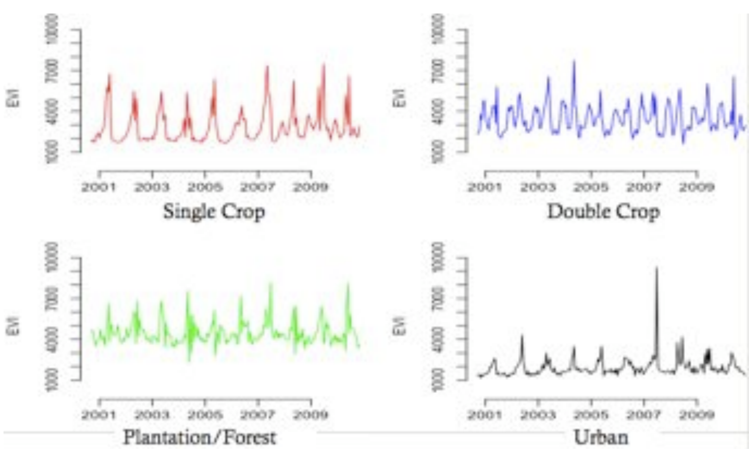

Figure 4. Ideal spectral signatures for the four main land cover classes in Mehsana district, Gujarat. Each land cover class can be separated using decision-trees of mean EVI, standard deviation of EVI, and by counting the number of local maxima for agricultural pixels.

Household-level Survey Methods

Surveys were conducted in two villages within Mehsana district, Gujarat: Kolvada and Gerita. These communities are primarily comprised of households that obtain at least a portion of their income from agriculture. Pastoralism and small businesses are the other main sources of income at the household level.

One hundred farmers were surveyed from each community (out of the approximately 800 farmers in each village), and survey sampling was stratified by access to irrigation and landholding size, since we wanted to interview farmers across a wide irrigation and income gradient. We believed that farmers who were wealthy and who had access to irrigation would have very different cropping strategies from poorer farmers who may fully rely on the monsoon rains for watering their crops.

In each survey, we asked farmers what crops they planted during the monsoon season of 2010 (the current season) and 2009 (the previous season), the date that they planted each crop in 2010, the area over which they planted each crop in both 2009 and 2010, and the inputs that were used for each crop (e.g. fertilizers, pesticides, irrigation) in 2010. We also collected a variety of demographic, economic, social, and climate perceptional data for each farmer that will be used to predict whether a farmer will adapt his cropping strategies or not to inter-annual rainfall variability. The list of each variable is explained in the following section.

Demographic, Economic, Social, and Climate Perceptional Predictor Variables
Biophysical factors: Previous studies have suggested that farmers alter their cropping strategies based on *rainfall parameters*. For example, farmers may switch to more drought-resistant crops during dry years, delay the planting of seeds to match the date of monsoon onset, and plant heat tolerant crops if there are large break periods between rainfall events (Lobell *et al.* 2008, Patel 2010, Saxena *et al.* 2005). *Soil fertility* may constrain the types of crops that farmers are able to plant in a given year (Patel 2010, Luers 2005).

Social factors: It is important to account for *networks between community members* within each village. Farmers who are well-networked may be better able to adapt to climate shocks due to knowledge transfer and the sharing of technologies (e.g. irrigation, new crop seeds) (Berkes and Jolly 2002). In addition, *demographic* factors are considered in my analysis (e.g. family size), since it is possible that demographic factors may influence planting strategies; for example, a family with more children may be more risk averse and avoid high-risk crops.

Economic factors: Farmers who have *access to irrigation* may be less likely to change their cropping strategies based on rainfall variability because they can supplement times of low rainfall with irrigation (Patel 2010). It is also important to account for the *income* of each farmer because farmers can use excess capital to buy technologies that support adaptation, such as new seed varieties that are more resistant to climate fluctuations (Patel 2010, Yohe and Tol 2002). I also considered the *selling price* of each crop since farmers will be more inclined to plant crops that are more valuable in the market (Patel 2010). To gain an understanding of the economic risk associated with each crop, I considered *price volatility* by including the variance in price for each crop since 2000.

Perceptional factors: Previous studies have also suggested that cognitive factors play an important role in farmer decision-making. It is important to include whether a farmer has *experienced past crop failures* since this may make a farmer more *risk averse* (Grothmann and Patt 2005). A farmer who is less willing to take risks may plant different crops than a risky farmer (Serra *et al.* 2008). I also considered each farmer's *goal to optimize crop yields*; some farmers may seek to maximize profit over several years regardless of inter-annual yield variability, whereas other farmers may seek to maximize stability from year to year and place less emphasis on total income.

Statistical Analyses

Maximum likelihood methods were used to identify which factors best explained cropping patterns across farmers. This study examines which factors best describe which date farmers planted a particular crop. Amir Jina (2011, unpublished report) is examining which factors best describe why farmers switch between different crops from the 2009 to the 2010 growing season, however, those results will not be discussed here.

Model selection techniques were used to identify which model best described the data. Several models were constructed that considered demographic, social, economic, biophysical, and perceptional factors in different combinations. Predictor variables were normalized by their standard deviation and mean so that the magnitude of the variables under consideration did not influence their importance within the models. Likelihood estimation techniques were then used to determine which predictor variables were included in the best model (e.g. Hilborn and Mangel, 1997). Forwards and backwards step-wise model selection was conducted considering Akaike's Information Criterion corrected for small sample size (AIC_c) values (Burnham and Anderson, 2004).

Eq. 2

$$\mathrm{AIC}_c = -2\log(\mathcal{L}(\hat{\theta})) + 2K + \frac{2K(K+1)}{n-K-1}$$

Where n = total number of observations and K = estimated number of parameters in the model

The best candidate model was the one with the lowest AIC_c values. Since AIC_c values do not account for the relative strength of the best candidate model with respect to other possible models, Akaike weights were also considered in model selection (Burnham and Anderson, 2004).

Eq. 3

$$w_i = \frac{\exp(-\Delta_i/2)}{\sum_{r=1}^{R}\exp(-\Delta_r/2)}\ .$$

Where R = the total number of models in the full model set

RESULTS

Remote Sensing

Using decision-tree classification of mean and standard deviation of EVI and by counting the local maxima of agricultural pixels, the following map over the study region in Gujarat for 2010 was produced (Figure 5). The overall accuracy of the map was 86.2%, based on thirty randomly selected pixels whose land cover class was identified using Google Earth. This suggests that this technique is fairly accurate at discerning cropping patterns at the 250 m scale.

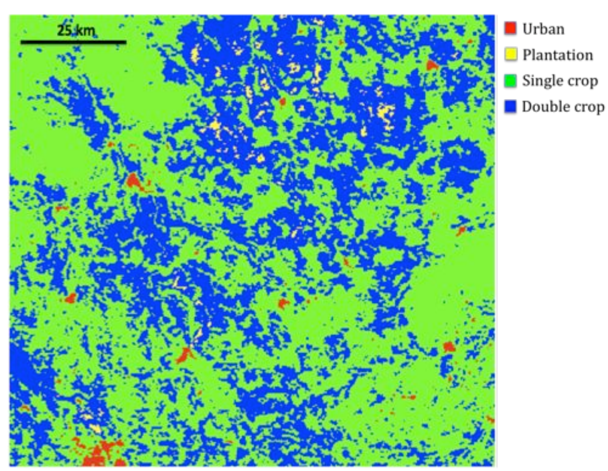

Figure 5. Map of the study region in Mehsana district, Gujarat in 2010. Map accuracy is approximately 86% using Google Earth to identify ground truth points.

Drivers of Adaptation at the household level

Crop Type Selection

Based on the two hundred surveys that were collected from the community, it appears as if cropping strategies are highly variable both between farmers (Figure 6). Figure 6 highlights the variability in crops planted across the study region between 2009 to 2010. Cotton is the most preferred crop in the region, given that it earns the highest price in the market. However, there are constraints on planting cotton given that it requires a large amount of water throughout the growing season to remain viable and provide a profitable yield. For this reason, most irrigated farmers whom we interviewed said that they planted cotton every single year regardless of the amount of monsoon rainfall, whereas farmers who either had insecure access to irrigation or had rain-fed farms were more likely to switch to other crops that did well with late or limited rainfall (e.g. sorghum, millet, castor). Factors that influence decisions on which crops to plant from year to year are highlighted in a separate paper (Jina, 2011).

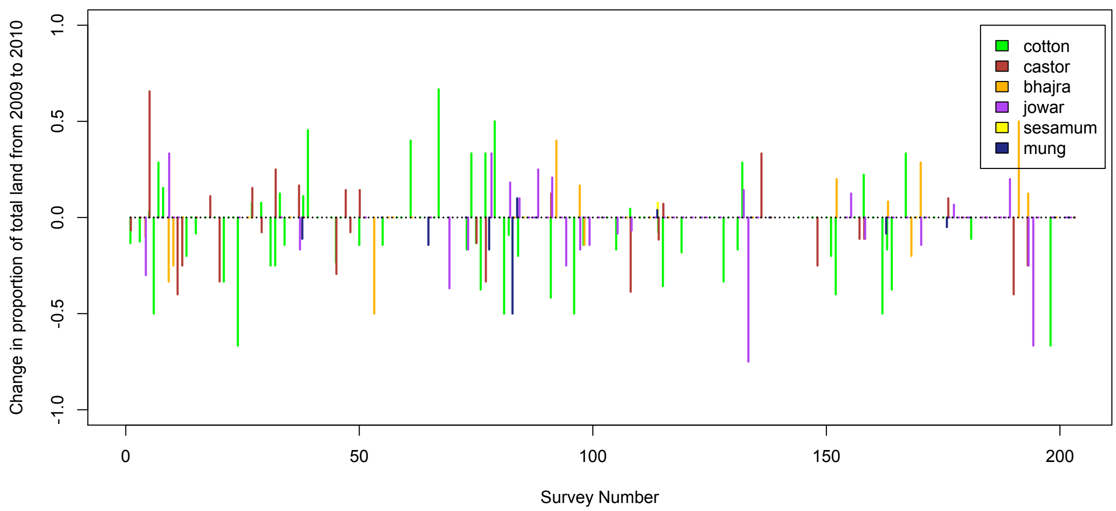

Figure 6. Graph highlighting the proportion of land that changed for each crop for each farmer from 2009 to 2010. A negative value means that farmers planted less of this crop in 2010 than they did in 2009, whereas a positive value suggests that farmers increased the amount of crop planted in 2010 compared to 2009. The six main crops grown in this region were considered for this diagram. There is a lot of heterogeneity both in what people plant from year to year and also across farmers.

Planting Date Selection

There was also high heterogeneity of planting date among farmers throughout the 2010 growing season (Figure 7). Considering only cotton, planting date ranged from late May all the way until mid-July. This is especially interesting given that the monsoon arrived approximately one month late on July 20th in 2010, though the monsoon typically arrives by June 15th in this region. Because of this, many farmers, especially those that were rain-fed or had limited access to irrigation, said that they delayed the date of planting to match the delayed monsoon onset date. Given the high heterogeneity in planting date, I used maximum likelihood analyses to identify which social, biophysical, economic, and perceptional factors most explained when farmers planted cotton, which is the main preferred crop in the region.

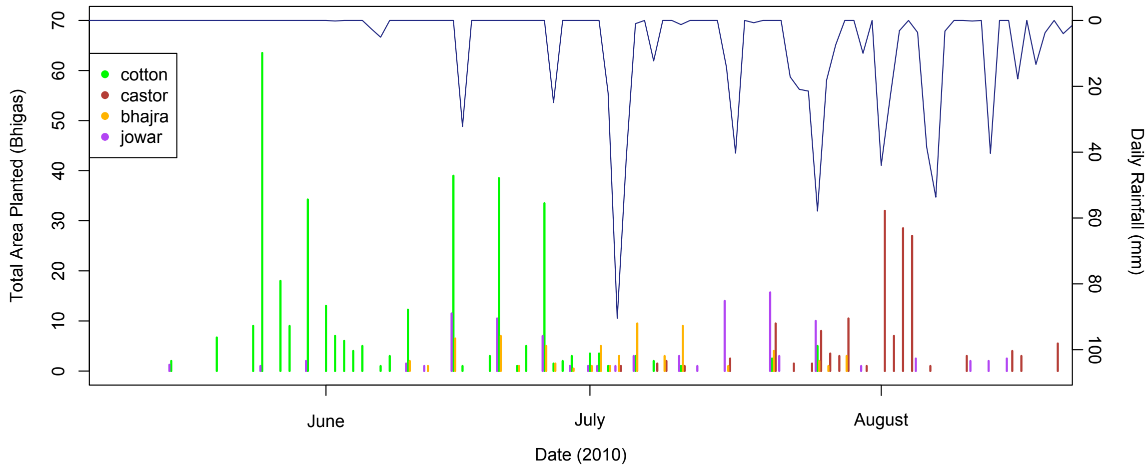

Figure 7. This figure highlights the variability in planting date across the two-hundred farmers considered in this study. The four main crops in this study region were considered. Daily rainfall as measured by the satellite TRMM was also plotted along the second y-axis. Examining only cotton, it is clear that there was high planting date variability, from some farmers planting cotton as early as mid-May and other farmes planting cotton as late as mid July.

Using model selection based on AIC_c values, the best model that predicted when farmers planted cotton consisted of the following variables, which span economic and climate perceptional factors:

Replant - Whether farmers had replanted a crop in a previous year due to crop failure (0 = no replant, 1 = replant)
Water Insecurity – A scale of 1-4 highlighting whether 1) farmers owned their own well, 2) farmers shared a well with other farmers, 3) farmers did not own a well but sometimes bought water from well owners, and 4) farmers who had no access to irrigation.
Rain Needed – The number of cm of rainfall needed for a farmer to sow his seeds.
Land Owned – The amount of land owned (bhigas) by each farmer
Asset Index – An index that was created using a PCA of different non-obtrusive wealth indicators, like the number of tractors, televisions, fans, and radios owned by each household (Howe et al. 2008).

The best model was:

Planting date of cotton ~ a + b*Replant + c*Water Insecurity + d*Rain Needed + e*Land Owned + f*Asset Index + Error (normal)

The results suggest that the more water insecure a farmer is, the later he will plant cotton, and the more rain that a farmer needs to sow his seeds, the later he will plant cotton (Figure 7).

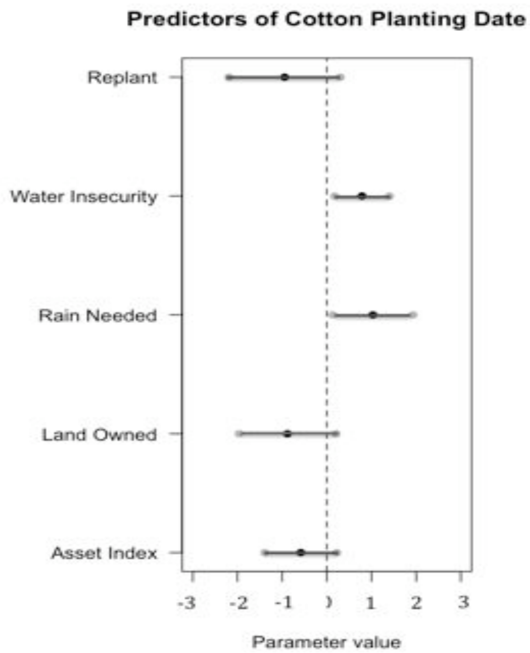

Figure 7. Parameter plot showing effect sizes with standard deviations for each variable in the best model that predicts planting date of cotton (n = 109, Adjusted $R^2 = .173$). Water insecurity and Rain Needed were significant ($p < .05$) predictors. The more water insecure a farmer was, the later he planted his cotton, and the more rain a farmer needed, the later he planted his cotton.

DISCUSSION

While the results of this study are preliminary, they suggest two things. First, farmers adjust when they plant their crops based on climate perception factors, even when controlling for access to irrigation (Figure 7). Second, they suggest that cropping patterns and changes in cropping patterns through time can be accurately assessed at the regional level using remote sensing analyses of MODIS EVI at the 250 m pixel scale (Figure 5).

Considering the first point, both farmers who had access to irrigation and farmers with rain-fed crops altered their cropping strategies based on rainfall parameters. This finding is important because it suggests that climate factors play a significant role in crop decision-making, even for those farmers who have secure access to irrigation. Though these results are only based on one-monsoon season's worth of data, they suggest that farmers are responding to climate signals in addition to various economic and social factors.

The main premise of this study was to identify if farmers alter their short-term cropping strategies based on monsoon variability. If so, this indicates that farmers have adaptive capacity with respect to current climate variability. Though it is difficult to predict future climates and future climate variability, one can make the assumption that if farmers are better able to adapt their cropping strategies to current climate variability, they may have higher adaptive capacity and the potential to respond to future climate changes than farmers who do not alter their cropping strategies based on climate variability. The preliminary results of this study suggest that farmers are responding to inter-annual rainfall variability by shifting the date of planting to match with the monsoon onset, which may suggest that farmers will respond to future changes in climate in a similar manner.

Considering the second finding, remote sensing analyses suggest that cropping patterns can be accurately identified at the 250 m scale using MODIS EVI (Figure 5). Other studies suggest that in addition to cropping intensity, similar remote sensing techniques can identify the date of planting and the length of each growing season within one week (e.g. Sakamoto et al, 2005). Future studies by this author will examine whether planting date and growing season length can be assessed accurately in India, where farm sizes are typically much smaller relative to MODIS EVI pixels than other regions where these methods have been shown to be robust (e.g. North America).

Future studies by this author will then create similar cropping maps for each year from 2000 to the present, and identify if any changes in cropping patterns from year to year are highly correlated with inter-annual rainfall variability as measured using the satellite product TRMM. Maps that highlight areas that have a high correlation between cropping pattern and rainfall will then be created to show areas that may be altering their cropping strategies based on rainfall variability.

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