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Adaptation with climate uncertainty: An examination of agricultural land use in the United States

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ABSTRACT

This paper examines adaptation responses to climate change through adjustment of agricultural land use. The climate drivers we examine are changes in long-term climate normals (e.g., 10-year moving averages) and changes in inter-annual climate variability. Using US county level data over 1982 to 2012 from Census of Agriculture, we find that impacts of long-term climate normals are as important as that of inter-annual climate variability. Projecting into the future, we find projected climate change will lead to an expansion in crop land share across the northern and interior western United States with decreases in the south. We also find that grazing land share increases in southern regions and Inland Pacific Northwest and declines in the northern areas. However, the extent to which the adaptation potential would be is dependent on the climate model, emission scenario and time horizon under consideration.

1. Introduction

Farming by its very nature is adaptive to climate. Today given the rapid pace of climate change adaptation is occurring throughout the landscape. There are two types of land allocation decisions that farmers can make to cope with climate change, including short-run allocations associated with management of a particular type of system due to effects of inter-annual climate variability and long-run allocations associated with investment decisions that involve choices between different types of systems due to effects of long-term climate normals. Hsiang (2016) referred the former as the direct effect and the latter as the belief effect and the interactions between beliefs and direct impacts and belief effects themselves as adaptations.

Many studies have examined land-use with or without the consequences of climate using econometric or structure models (Adams et al., 1990; Cho and McCarl, 2017; Haim et al., 2011; Lubowski et al., 2006; Lubowski, 2008; Lubowski and Roberts, 2008; Miao et al., 2015; Mu et al., 2013, 2017; Mu et al., 2015; Reilly et al., 2003; Wu et al., 2004). In these studies, both long-term and short-term variability phenomena have been examined as potential drivers of land use change. In particular, Cho and McCarl (2017) investigated the direct effects of inter-annual climate variability on crop-mix shift and Mu et al. (2013) examined the belief effects of changes in 3-year average climate normals on land use change between crop and pasture. In addition, Mu et al. (2017) used a two-stage approach to reveal direct effect of inter-annual climate variability on land use net returns and measure adaptation as shifts of land use shares to respond to thirty-year climate characteristics.

As argued by Kelly et al. (2005), long-term shifts in regional climate characteristics determine basic crop choice and land-use patterns while actual weather (inter-annual climate variability) determines actual profits. Thus, impacts of long-term climate normals should be a fundamental driver in the choice of major enterprise characteristics and is likely more important than short run climate fluctuations (Deschenes and Kolstad, 2011; Kelly et al., 2005; Mendelsohn et al., 2007). However, inter-annual climate variability may also be very important with the incidence of droughts, heat waves etc. In this regard, it is important to consider both long-term climate normals and inter-annual climate variability when trying to understand crop mix and land-use patterns. In fact, Deschenes and Greenstone (2007) and Mendelsohn et al. (2007) both suggest that omitting these factors could lead to biased estimates of climate impacts.

Another focus in climate change assessments that has been received increasingly attentions is consideration of the full range of variability in long-term climate projections. In particular, numerous Earth System Models (ESMs) are now being used by the climate science community in

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making climate change projections.[1] The use of these many models leads to a distribution of projections with no real global basis for picking the most likely outcomes (Flato et al., 2013; Randall et al., 2007). However, virtually all land use related studies have used only a selected few projections without accounting for the full range of the existing projections (Burke et al., 2015). Burke et al. (2015) argue that estimates of climate impacts from a limited set of ESMs is likely misleading and possibly biased.

In the face of these prior studies, this study attempts to examine land-use change but in a setting where two contributions are made. First, we distinguish farmers' adaptive responses in terms of land-use to inter-annual climate variability and longer-term climate shifts in mean climate characteristics. Second, within the context of alternative climate forcing scenarios, we develop more broadly-based distributions of future land use constructed across the full set of climate model projections from the Coupled Model Intercomparison Project Phase 5 (CMIP5).

2. Methods

Theoretically, inter-annual climate variability can affect land use choices where management of farm income variability leads one to alter land use to less risky patterns, while shifts in long term climate normals lead one to choices of different enterprises that are better suited to different average climate regimes (Mu et al., 2017). Particularly, our analysis is based on the observation that farmers make two types of land allocation decisions: (1) changes in short run bio-physical or socio-economic conditions give rise to adjustments in management decisions that are low-cost and are typically made in each production period subject to the constraints imposed by a particular system; (2) changes in long run bio-physical and socio-economic conditions and changes in technology and policy may lead to more fundamental and non-marginal changes in the production system that involve substantial adjustment costs or capital investments. These two adjustments together cause shifts from cereals to other crops or pasture, or from crop to livestock production, or from dairy to meat production.

To investigate changes in land use shares as the adaptive response to inter-annual climate variability and longer-term climate normals, we will project the probability of land being used in different ways as a function of variables describing these climate phenomena. In particular, we will use a Fractional Multinomial Logit (FMLOGIT) model following the work of Mu et al. (2013) and Cho and McCarl (2017). The analysis will be done considering the uses of crop land, other cropland, grazing land and woodland as they are spread across the landscape using county-level agricultural census data for the Contiguous United States from 1982 to 2012. Here, inter-annual climate variability is the individual observation for a given year in a specific location. Long-term climate normals are expressed by taking long-term average of climate measures over a certain period, such as 10 years. The econometric form of the FMLOGIT model is:

$$E(y_{jit}\left| X, W, \overline{Z}\right.) = \frac{\exp(X_{it}\theta_j + \sum_K \beta_{jk} W_{kit} + T_{it}\gamma_j + \overline{Z_i}\varphi_j)}{\sum_J \exp(X_{it}\theta_j + \sum_K \beta_{jk} W_{kit} + T_{it}\gamma_j + \overline{Z_i}\varphi_j)} \ldots \text{for all } j \tag{1}$$

where y_{jit} is the land use share for usage type j in county i at time t and is the proportion of the land that is of total land in that county and thus falls between zero and one. The alternative land usages considered (j) include usage in cropping, other cropland use, grazing and woodland. The variables of interest are in W_{kit} and the "k" index simply denotes the various climate measures we control for. For example, ten-year average growing season degree-days and total precipitation and their squared terms, ten-year average precipitation intensity index, along annual total precipitation, degree-days and their squared terms, precipitation intensity and drought index. We use X_{it} to control for other factors, which are soil conditions, county centroid latitude, irrigation share, annualized revenue-cost ratios that we constructed for crop and livestock based on the total sales of crop and livestock products and total production expenses, amount of government payments per acre, and population density. T_{it} is the time trend, and θ, β, φ and γ are parameters to be estimated.

In Eq. (1), we also include the vector of $\overline{Z_i}$, which is a subset of the explanatory variables that is averaged over time for each county i. Specifically, we include the average of the annualized revenue-cost ratios, population density and irrigation shares that are possibly affected by land-use policies or farm management decisions.[2] There are two reasons to include $\overline{Z_i}$ in Eq. (1). First, the possible endogeneity problem may raise in the estimation with socio-economic variables.[3] For example, the annualized revenue-cost ratios based on observed revenues and costs may be biased due to unobservable effects in the error terms within the land use share equation. Also, the share of land with irrigation could be affected by unobservable factors that also affect land allocation. Second, there is a practical obstacle to incorporate panel model fixed-effects when estimating a nonlinear model, which relates to the difficulty of estimating nonlinear models with possibly thousands of dummy variable coefficients (Greene et al., 2002). To solve the possible endogeneity problem and conquer the difficulty of including fixed effects in the FMLOGIT model, we apply the correlated random effects or Chamberlain-Mundlak approach when estimating Eq. (1). This approach requires the assumption that a proportion of the explanatory variables are correlated with the unobservables. Using this approach, the fixed effects estimator can be computed as a pooled estimator using the original data, but adding the time averages of covariates as additional explanatory variables (Wooldridge, 2009).

3. Data sources and variables

Table 1 presents statistical summaries of selected items within the data set including agricultural land use shares, annualized revenue-cost ratios, inter-annual climate variability measures and long-term climate characteristics in the United States using county level data from 1982 to 2012.[4] All dollar values are adjusted to year 2007 dollars.

3.1. Agricultural land use

County-level agricultural land for cropping, grazing, other cropland use and woodland use were obtained from the Census of Agriculture for the census years 1982, 1987, 1992, 1997, 2002, 2007 and 2012 for the Contiguous United States. To avoid double counting, we reclassified land uses in the Census of Agriculture to correspond to agricultural systems defined in this paper:

(1) *Cropland:* harvested cropland;

(2) *Other Cropland:* idle cropland, land with failed crops, cover crops, summer fallow and land enrolled in conservation reserve, wetlands reserve, farmable wetlands, or conservation reserve enhancement programs;

(3) *Grazing land:* cropland for pasture, which could be used for crop production with soil improvement, and land used for permanent pasture and rangeland, and woodland for pasture, mainly for grass and other forage production;

[1] There are 20 climate models from the Coupled Model Inter-comparison Project Phase 5 (CMIP5)

[2] Although weather variables have both time and space variation, they are assumed orthogonal to the unobservables, thus are not included in $\overline{Z_i}$.

[3] The reversed causality due to the mitigation effects of agriculture for climate change is not a major concern here because we focus on farmland re-allocation among crop, other crops, grazing land and woodland. Mainly the land use change with the conversion of forests to agricultural land could involve massive greenhouse emissions and contribute to global warming (Popp et al. 2014). However, forest land is not considered in this analysis.

[4] Please note that our panel data are from Census of Agriculture with year gaps, there is no need to perform the panel unit root test because stationarity is not a concern here.

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