Drought, Intra-national Trade and Agricultural Profit: Theory and Evidence

Zhangliang Chen, University of Illinois Urbana-Champaign, zchen105@illinois.edu
Sandy Dall'Erba, University of Illinois Urbana-Champaign, dallerba@illinois.edu

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Zhangliang Chen

ACE and REAL,
University of Illinois

Sandy Dall'Erba

ACE and REAL,
University of Illinois

ABSTRACT:

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CONTACT INFORMATION:

Zhangliang Chen: PhD candidate in Department of Agricultural and Consumer Economics (ACE), Regional Economics Applications Laboratory (REAL), University of Illinois at Urbana-Champaign, e-mail: zchen105@illinois.edu.

Sandy Dall'Erba: Associate Professor in Department of Agricultural and Consumer Economics (ACE), Regional Economics Applications Laboratory (REAL), University of Illinois at

I. Introduction

Recent years witnessed an increase of extreme weather events due to climate change. Climate scientists predict this trend might continue for the following decades. (IPCC, 2013) Among various types of extreme events, drought is widely considered as one of the major threats to agricultural productions both in developed and developing countries. (Wilhite, 2000) This paper studies the impact of droughts on agricultural profits, and forecasts the potential damage due to the changes in future drought frequency using a dataset including continuous 48 U.S. states.

When people evaluate drought damages, one obvious but often overlooked fact is that the impact of drought would not be restricted only in the place where it happened, but also affects other places through market interactions. A Texas cattle rancher could loss a fortune when a severe drought hitting the Midwest boosts his expenses on feeding. The same Midwest drought could also enrich a corn farmer in Texas by increasing both price of and demand for his products. The domestic market of agricultural goods enables a drought has not only a local effect but also spillover effects to trade partners.

To shed light on the role of intra-national trade on drought impact evaluation, we separate the research questions into to two: (1) how do droughts affect the domestic agricultural trade flows? (2) how do droughts affect farmers' profits through agricultural trade? The gravity model is adopted for answering the first question. The gravity model, a theoretically-inspired reduced-form approach, is the workhorse model for empirically understanding trade patterns. (Anderson and van Wincoop, 2003; Arkolakis, et al. 2012; Head and Mayer, 2014) For the second question, we incorporate external demand (export demand) estimated based on the gravity model into a standard

Ricardian framework, a reduced-form regression using agricultural profit against climate variables[1]. (Mendelson et al., 1994; Schlenker et al., 2006; Deschenes and Greenstone, 2007)

Our gravity analysis finds that drought in the destination state will significantly increase the bilateral trade flow. Moreover, when droughts occur in the origin state, it reduces its export capacity and trade. Both results confirm our expectations. When we move on to the Ricardian model, our results indicate that export has a positive and significant impact on agricultural profit, hence drought events in locations j do have a significant impact on agricultural profits in i. We also note that in this specification local drought events do not display a significant impact of local agricultural profits.

This work attempts to contribute to the literature through the following four aspects. First, to our knowledge, it represents the first application of the gravity model to domestic agricultural trade flows within U.S. Even though the gravity model has been frequently used in the agricultural trade literature since Cho et al. (2002), only international trade flows have been studied (Sarker and Jayasinghe, 2007; Grant and Lambert, 2008; Sun and Reed, 2010; Jean and Bureau, 2016). The dominating research question in this area is the evaluation of the impact of free trade agreements on agricultural trade flows. As a consequence, the domestic market where up to 88% of the U.S. agricultural production are traded and 91% of the national intermediate and final demand are served (World Input-Output Database, 2016) has surprisingly received very little academic attention. This work fills this clear research gap.

[1] The list of widely used climate variables include seasonal temperatures, growing season degree days and total precipitations. Due to the high interests of modeling nonlinear climate effects, recent years witness the increasing popularity of using temperature (or precipitation) bin approach. (literature) Meanwhile, some recent authors also attempt to add a few agronomy-related climate measures, such as VPD (vapor pressure deficit), Sunshine, Evaporation, into the list. (literature)

Second, this paper contributes to answer the question: how productivity shocks affect agricultural trade flows. Our work lines up with two previous literature: Reimer and Li (2009) and Ferguson and Gars (2017). Reimer and Li construct and calibrate an Enton-Kotrum type model based on international data of agricultural trade and productivity in order to study how do trade flows and social welfare response to increasing volatility of crop yield. Ferguson and Gars, on the other hand, derive an Anderson-van-Wincoop type gravity model with perfectly inelastic supply and the presence of per unit trade cost. By applying their model to an international trade dataset, they aim to measure the impacts of short-run productivity shocks on both trade volume and price. This paper is distinct from their works by three aspects. First, we focus on drought, the major exogenous source of productivity shocks. Second, we examine the domestic trade flow between lower 48 states to minimize the impacts of the international trade barriers. Third, we further restrict ourselves to trade flow only including cereal grains, oil seed, vegetable and fruits because their productions are directly affected by drought.

Third, we offer a novel approach to model spatial spillover effect of drought in a reduced-form regression framework. The use of structural modelling approaches such as input-output (y Pérez and Barreiro-Hurlé, 2009), CGE (Horridge et al., 2005), price-endogenous regional programing (Salami et al., 2009) is necessary to model the spatial spillover effects of droughts. This paper, on the other hand, offers a spatially explicit Ricardian framework that combines two reduced-form approaches: a gravity model and the Ricardian analysis. Unlike traditional a-spatial Ricardian analyses, this new design enables drought in one place to have an indirect impact on other places through changes in trade flows, which is estimated by the gravity model.

Finally, the results of this paper could also be a useful addition to the discussion on whether trade is an efficient adaptation mechanism to global climate change. For years, many authors portrayed the free trade of agricultural goods as one of the major adjustment mechanisms to climate change, and passionately argued against trade barriers for that purpose. (Reilly and Hohmann, 1993; Rosenzweig and Parry, 1994; Julia and Duchin, 2007). However, Costinot et al., in an influential recent study (2016), challenged this traditional wisdom by using a vast new dataset containing agricultural productivity for million fields around the world. They concluded that trade only plays a minor role in mitigating the climate change compared to production reallocation based on changes in comparative advantages. Our work brings two new elements to the discussion. First, the previous works all emphasize climate change as changes in long-run temperature or precipitation, while we focus on the increasing frequency of one type of extreme event. Second, by focusing on domestic trade instead of its international counterpart, we can simulate a free trade situation and study its adaptation capacity without worrying about other cofounding factors such as manmade trade barriers, different market structures, dissimilar political systems, etc.

In next section, we provide the background information regarding agricultural trade flows between lower 48 U.S. states. Section III clarifies data sources and data transforming processes. Section IV is divided into two subsections to delineates the empirical strategies in two steps. The gravity model is specified in Section IV.A, meanwhile Section IV.B is dedicated to the Ricardian approach. Section V, the result section, is comprised of three subsections. The first two discuss the main estimation results, one for each estimation step. Multiple robustness checks are reported in the third subsection. Based on estimation results, we simulate the potential damage occurring by increasing future drought frequency. These simulation results are reported in Section VI. Finally, Section VII concludes.

II. Background

II.A Intra-National Agricultural Trade

Different parts of the U.S. continent concentrate in different agricultural activities. Corn and soybean occupies the most land in U.S. Midwest. Meanwhile, the majority of the fruit production is from a relatively small coastal region called "fruitful rim" by USDA[2]. The domestic agricultural trade enables the consumers to enjoy various fresh agricultural goods produced far away. Because of trade, a Chicago household can enjoy apples from Washington and oranges from Florida. Meanwhile, the trade between different places allow producer purchasing inputs at their lowest costs. Castle ranchers in Texas can purchase corn for feeding from cheap sources from Corn Belt states instead of relying on expensive local alternatives.

The commodity flow survey (CFS) is the primary data source for domestic freight shipment. CFS is a shipper-based survey conducted by U.S. Census Bureau (USCB) and Bureau of Transportation Statistics (BTS) together. The questionnaire asks the shipper for basic information regarding freight movement: origin, destination, size, weight, dollar value, mode of transportation, etc. Since 1997, CFS becomes a part of Economic Census, which has been (would be) conducted in years endings in "2" and "7". [3]

Despite of its widely used in previous literature (Wolf, 1997; Hillberry and Hummels, 2008; Crafts and Klein, 2014), there are two drawbacks preventing CFS giving a complete and accuracy picture of domestic commodity flows. First, not all freight shipments are covered by CFS. Second, the shipments driven by international trade are not separate from the shipments driven by domestic demand. To overcome those two shortcomings, the Oak Ridge National Laboratory, under supports from both BTS and Federal Highway Administration (FHWA), develops a new dataset

[2] see Figure 1 for the USDA's farm resource region map. Roughly speaking, the fruitful rim is comprised of west coastal states, southern Texas and Florida.

[3] There are five finished CFSs, namely 1993, 1997, 2002, 2007, 2012. CFS in 1993 is a pilot program. Many of its procedures and classification criteria have been largely revised or discontinued in the following surveys. The data of 1993 is incomparable with the latter years. Hence, we do not include 1993 in our dataset.

on freight movement within the country, called Freight Analysis Framework version 4 (FAF^4)[4] (Huwang et al., 2016)

The FAF^4 data fills the gaps of CFS in converge and final destination details by using CFS with other data sources, namely USDA agricultural census, USCB merchandise trade statistics, etc. The final data product reports how every production in a spatial unit goes to its final destinations, consumed by itself, or consumed by other place with the country, or consumed by the foreign. Take fruit as an example, in FAF^4, if one adds up fruit stay in its produced state, fruit transport to all other states, fruit export to all other countries, the quantity he gets is the total fruit production of that state.

The FAF^4 data also has fine spatial, temporal and commodity resolution compared to CFS. FAF^4 offers trade flows between three different spatial levels: state, FAF zones, MSA. We choose state level data to facilitate the merge between trade data and other datasets. For temporal resolution, FAF^4 has same five-year resolution as CFS. We include four most recent survey years, namely 1997, 2002, 2007 and 2012. In terms of commodity resolution, FAF^4 categorizes the commodities based on two-digit standard classification of transported good (SCTG). The SCTG is a commodity classification standard used by United States, similar to harmonized system (HS) in the international trade. Table 1 offers a detailed list of SCTG category related to agricultural and food commodities. We only focus on two categories: *cereal grains* (SCTG 02) and *fruits, vegetables and oil seeds* (SCTG 03) because their productions are most sensitive to the drought conditions.

[4] There are two versions of FAF available in the website of BTS, version 3 and version 4. The difference of two versions is the choice of base year, 2007 for version 3, 2012 for version 4. Therefore, version 4, which our research based on, is the most updated version for public access.

We describe the basic facts of domestic trade flows of main crops from two aspects: trade volume and trade partner. Figure 3 panel (a) illustrates the trade volumes for each state in 2012. The x axe shows the export volume in million dollars (2012 constant), while y axe reports the import volume. Two red lines, which represent the median values for export and import respectively, separate the plane into four quadrants: HH, LH, HL, LL. The HH category includes California, Illinois, Iowa, Indiana, Minnesota, Missouri, New York and Nebraska. These states are usually leading crop producers, have well-developed food-related industries, and large populations. They are the main players in the domestic market. The states in the LH category, on the other hand, are usually key livestock producers with relative small crop industries in the country, such as Texas, Wisconsin and Georgia. The HL category is comprised of two types of states: i) major producers of high-value crops such as fruit, vegetable and greenhouse nursery products and ii) main crop producers with small population density. The first type of states contains New Jersey, Florida and Michigan. Kansas, North Dakota and South Dakota are examples of the second type. Finally, the states in the LL category are usually small states in terms of population and/or land area.

Figure 3 panel (b) is a chord diagram showing the trade relationship between states in 2012. The chord diagram uses directional ribbons to represent the bilateral trade flows. The width of the ribbon shows the volume of the flow, meanwhile the arrow points from origin to destination. We group 48 contiguous states into 9 climate regions which separated by different colors. The arc length associated with each state represents the total trade volume, i.e. the sum of total export and import volume. States' export and import are separated by the fact that the endings of the links are shorter than the beginnings of the links. Two major findings from the chord diagram are: i) huge amounts of flows go from crop-producing states such as Iowa, Illinois and Kansas to livestockproducing states such as Wisconsin, Taxes and Louisiana, which verifies that the major driving force for domestic trade of crops are animal feed; ii) the primary agricultural states such as California, Illinois, and Minnesota are both largest exporter and importer of major crops. For instance, Illinois exports mainly corn and soybean to over 30 states, meanwhile it also imports various crops from the rest of the country, which can be explained by the concentration of the food manufactory industry.

II.B Drought Conditions and Climate Region

Drought is bad for crops, but how harmful a drought could be depending on its features. An ideal measure of drought conditions should reflect its four aspects: *Persistency*, how long does it last? *Extensiveness*, how large the area does it affect? *Severity*, how serious the water stress it creates and *Timing*, when does it start. Given a raw data of county-level monthly Palmer Drought Severity Index (PDSI), we construct a drought index, called cropland-weighted severe drought days.

$$\text{(1)} \qquad \text{Severe drought days}_s = \sum_{\text{c in state s}} \left\{ \underbrace{\left[\sum_{m=1}^{12} \mathbf{1}\left(\text{PDSI}_{c,m} < -3\right) \right]}_{\text{count drought month}} \underbrace{\times 30}_{\substack{\text{convert} \\ \text{months} \\ \text{to days}}} \right\} \times \underbrace{\frac{\text{cropland}_c}{\text{total cropland}_s}}_{\substack{\text{weighted by} \\ \text{county c's} \\ \text{cropland acreage}}}$$

The calculation involves two steps: first, count number of severe drought day (PDSI < -3) for each county, then weight it by the ratio of county's cropland acreage to the state total. We choose -3 as the cut-off for severe drought, according to the classification criteria used by US Drought Monitor (USDM). This drought index captures the first two aspects of a drought very well because first, itself is a measure of persistency, second the weighting scheme reflects extensiveness. On the other hand, this index is valid if two assumptions hold: (i) Only severe droughts have significant effects, (ii) Timing has a minor role compared to other aspects.

[drought maps created using our approach + discussion]

Another concept closely related is Climate Region, a grouping of lower 48 states based on long-term weather records. States with similarities in seasonal temperature and precipitation patterns are grouped together to form a region. National Oceanic and Atmospheric Administration (NOAA) identifies nine such climatically consistent regions[5] within the contiguous US based on historical weather records dated back to 1895. (Karl and Koss 1984)

II.C Changes in Trade Pattern under Drought: A Case Study of Nebraska

Before diving into the formal models, some intuitive perspectives can be reached by taking 2012 drought in Nebraska as a case study. Nebraska is selected for two reasons: first, it has one of the leading agricultural sectors in the country, ranks the fourth national wise in terms of agricultural sales. Nebraska is one of the primary producers of both cereal grains (rank 5 national wise) and livestock meat (rank 4 national wise). The agricultural sector occupies 92% of Nebraska's land area, contributes to around 30% of state's GDP in 2012. The second reason comes from the temporal variation of drought days: The year of 2007 is an almost drought-free year for Nebraska farmers. However, during the famous 2012 Midwest drought, Nebraska became one of the states suffering from most severe drought conditions. (a map of drought conditions?) Therefore, the analysis of changes in trade patterns between 2007 and 2012 offers first impression of drought's impacts on trade flows. However, without formal statistical modeling, those changes in trade flows cannot be claimed as the direct results of the 2012 drought.

Figure 4 panel (A) illustrates the trade pattern of Nebraska in 2007. It shows: i) Nebraska exported crops to 37 states, meanwhile imported crops from 32 states. The ratio of export to import is 2.3, which indicates that Nebraska is net exporter of crops in 2007; ii) among its 37 exporting

[5] See Figure 2 for a map of nine climate regions, and their member states.

partner, Texas, Colorado and California are top three destinations for Nebraska's export; iii) among its 32 importing partner, South Dakota, Kansas and Iowa are top three origins for Nebraska's import. Panel (B) displays the trade pattern under 2012 drought. Compared to the situation in 2007, it is worthy to notice that Nebraska's exporting partners reduced to 29, and the average exporting volume dropped by 33%. For instance, Nebraska stopped to export to Utah, meanwhile export to TX reduced by 80%. Its importing partners, on the other hand, drop to 28, but the average importing volume increases by 24%. For example, the trade flow from Kansas increases by over 80%. Nebraska became a net crop importer, with the ratio of export to import dropped below one.

To sum up, the case study of Nebraska hints that the drought seems to have a negative impact on outward trade flows, but a positive impact on inward trade flows. However, without a formal analysis, there is difficult to conclude that this changes in trade flow are driven by drought conditions.

III. Data Sources and Descriptions

Besides the trade flow and drought data discussed above, the remaining data sources used in the paper are summarized in Table 2. The data can be divided to two major parts, one for gravity model, the other for Ricardian analysis.

III.A Data used in gravity model

Bilateral accessibility of from importer to exporter --- Continuity, distance (or travel time), common language, and colonial ties are widely used in trade literature to measure bilateral accessibility. Based on the context of intra-national trade, we only select first two: *continuity dummy* and *travel time by road*. Continuity dummy is assigned to one if two states share a border, zero otherwise. We use R to construct it from a U.S. state shpfile. The distance between two states is defined as the travel time between their most populous cities. The travel time is calculated by Open Source Routing Machine (OSRM), which chooses the shortest path between origin and destination based on existing road networks. For instance, the distance between New York and Illinois is measured by the travel time between New York City and Chicago by road, 1270 minutes. According Hwang et al. (2016), the shipments of agricultural commodities are almost all moved by truck, therefore the travel time is more accurate measures of trade costs than the geographic distance by polygon centroids in most trade literature.

Exporter feature --- exporter features describe the capacity of a potential exporter as an agricultural supplier. We select: farm (NAICS 11) GDP, growing degree-days, growing season precipitation, severe drought days, K-ratio, Ksat-ratio and clay content into this category. farm industry GDP captures the size of farm industry in the origin state. The following three variables are weather conditions in the given states. Finally, the last three variables are soil quality variables. The farm industry GDP is collected by Bureau of Economic Analysis. The weather variables are from National Oceanic and Atmospheric Administration. The soil quality variables are reported by U.S. Geological Survey. Except industrial GDP, the other variables (weather and soil) are seldom used in traditional gravity literature. We decided to include these variables because they can reflect the physical conditions of agricultural production.

Importer feature --- importer features capture a buyer's purchasing capacity of agricultural products from all sources. We choose food manufacturing (NAICS 311) GDP reported by BEA as the proxy for the demand force, because the major buyers for raw agricultural goods, i.e. the goods included in SCTG 02 and 03 is the food industry instead of households. We purchase bread and oil from supermarkets, not wheat and oil seeds directly. Fruit and vegetable in SCTG 03 seems to be an exception. However, notice that even for fruit and vegetable, a large amount of them goes through food processing companies before into family's plates.

III.B Data used in Ricardian analysis

Agricultural Profit --- Our Ricardian analysis uses agricultural profit as the dependent variable. We define profit as the difference between value of sales by crops farm[6] and the correspondent production costs. The raw sales and costs data is from Agricultural Censuses. The Census only reports cost by expense type instead of by commodity, which leads us to estimate the production cost of crops farms. We first classify the different types of cost into three categories: crop-related, livestock-related, and universal[7]. Then, we add up all crop-related expenses plus proportion of universal expenses. The proportions used is the ratio of value of sales by crop farms to all farms. Notice that our approach is different from Deschenes and Greenstone (2007), who calculate the difference between sales and cost of all farms instead of crops farm alone.

Weather Conditions --- we choose growing degree days and total precipitation within growing season to capture the weather conditions in a given year. The growing season is defined from April 1st to September 30th, following Deschenes and Greenstone (2007). Growing degree days (GDD) is a measure of heat accumulation used by agronomists, which is critical to crop development. We first calculate county-level GDD using daily average temperature with 8 °C as the lower bound, 32 °C as the upper bound. Then, state-level GDD is attained as a weighted average of county GDDs using cropland acreage as the weight. The raw raster data of daily average temperature and precipitation is from North American Regional Reanalysis (NARR) data product (Mesinger et al. 2006). ArcGIS 10.2 is used to convert raster data to county-level.

[6] Agricultural census classifies farms into two main types based on commodity type: crops and livestock.
[7] Crop-related category includes: ; Livestock-related category includes: ; Universal category includes: ;

Socioeconomics --- population density and per-capita income are two commonly used controls in the Ricardian analysis. [literature?] The reason for adding population density is to capture the impact of potential urban development. On the other hand, previous literature to interpret per-capita income as a proxy for local demand. (?) Population density is collected by USCB. Meanwhile, per-capita income is from Bureau of Economic Analysis (BEA).

Soil Characteristics --- we collect 11 soil related variables[8] from USDA's General Soil Map (STATASGO2) National Resource Inventory. Notice that all variables in this category is time-unvarying, therefore, all of them are absorbed by the state fixed effects when the fixed effect model is estimated.

IV. Empirical Strategy

Gravity model is used for evaluating impacts of droughts on trade flows. The Ricardian analysis links the shock of external demand with agricultural profit. This section is divided into two pieces to clarify the specification issues for the two approaches, respectively.

IV.A Gravity Model for Intra-National Agricultural Trade

IV.A.1 Basic Specification

We apply a generalized structural gravity specification purposed by Head and Mayer (2014).

$$X_{ijt} = \frac{Y_{it}}{\Pi_{it}} \frac{E_{jt}}{P_{jt}} \tau_{ij} \quad (2)$$

Where X_{ij} is the bilateral trade flow from exporter i to importer j. Exporter i's features are represented by Y_i. Ideally, these features should describe state i's potential to be an agricultural

[8] They are flood frequency ratio, erosion factor, slope steepness, wetland ratio, electrical conductivity ratio, available water capacity ratio, clay content, sand content, longitude, latitude and elevation

producer. The standard practices in gravity literature is approximating this supplier potential by its GDP. We, on the other hand, also include other factors affecting agricultural productivities such soil conditions, growing degree days, precipitation and drought conditions. Eq. (3) gives the expressions for exporter's features.

$$\mathrm{Y_{it}} = \exp(\beta_1 \mathrm{GDP}_{it}^{\mathrm{farm}} + \beta_2 \mathrm{DD_{it}} + \beta_3 \mathrm{RN_{it}} + \beta_4 \mathrm{DT_{it}}) \tag{3}$$

Similarly, E_j represents importer j's features which are related to the potential demand of state j. We include not only importer's food manufacturing GDP, as the standard gravity model suggests, but also those factors affecting state j's agricultural productions. It is because the fluctuations in self-production could lead to variations in demand for external goods, i.e. in good year, demand for external goods might reduce, while bad year might require state to import more. Eq. (4) gives the expressions for importer's features.

$$\mathrm{E_{jt}} = \exp(\delta_1 \mathrm{GDP}_{\mathrm{jt}}^{\mathrm{food}} + \delta_2 \mathrm{DD_{jt}} + \delta_3 \mathrm{RN_{jt}} + \delta_4 \mathrm{DT_{jt}}) \tag{4}$$

Π_i and P_j are multilateral resistance terms (MRTs) for exporter and importer, respectively. Anderson and Van Wincoop (2003) argued that the existence of these MRTs is the key distinction between the structural gravity and the naïve gravity which can trace back to Tinbergen (1962). We approximate these multilateral resistance terms by GDP weighted distance following Wei (1996). Wei's approximation, offers an intuitive explanation of these MRTs: the remoteness of an exporter (importer) to all potential destinations (origins), therefore is called remoteness indexes by some trade literature.

Finally, τ_{ij} captures the accessibility between two states. We assume the following functional form for accessibility term τ_{ij}:

$$\tau_{ijt} = \exp(\gamma_1 T_{ij} + \gamma_2 C_{ij} + \gamma_3 H_{ij}) \tag{5}$$

Where T_{ij} is the distance between exporter and importer measured by travel time for trucks, C_{ij} is the contiguity dummy that takes one when state i and j share a border, zero otherwise. Last but not least, H_{ij} is the dummy capturing the home-state effect, which only takes one when i = j, i.e. for trade flow occurs within the state boundary. This intra-state dummy first appeared in Wolf (1997) as a measure of home-state effect in intra-national trade, has become a standard control in the following researches studying the trade between 48 continental U.S. states. (literature)

Plugging Eq. (3)-(5) into Eq. (2) results in Eq.(6), which can be estimated by Pseudo Poisson Maximum Likelihood (PPML) estimator.

$$\begin{aligned} X_{ijt} = \exp(&\beta_1 GDP_{it}^{farm} + \beta_2 DD_{it} + \beta_3 RN_{it} + \beta_4 DT_{it} + \\ &\delta_1 GDP_{jt}^{food} + \delta_2 DD_{jt} + \delta_3 RN_{jt} + \delta_4 DT_{jt} + \\ &\gamma_1 T_{ij} + \gamma_2 C_{ij} + \gamma_3 H_{ij} - \ln(\Pi_i) - \ln(P_j)) \end{aligned} \tag{6}$$

According to Silva and Tenreyro (2006, 2011), PPML estimator generates more robust results than traditional OLS when the data of bilateral trade has heteroscedasticity error terms and/or contains many zeros. Both phenomena exist in our sample: Ramsey RESET test reject null hypothesis at p-value = 0.00. And the ratio of zero flow ranges from 21% in 1997 to 25% in 2012. Therefore, PPML is the preferred estimator in this case.

IV.A.2 Predicted Directions of Coefficients

The trade theory enables us to determine the directions of coefficients in our reduced-form estimation equation, which is one of advantages for adopting a theory-based model. The predicted directions of the coefficients are summarized in Table 1 column (3).

First, the exporter's feature capturing the production capacity: GDP in the farm industry should have positive coefficients. Drought has a negative impact on productivity, therefore should also reduce the bilateral trade. The signs of GDD, precipitation and soil characteristics are undetermined because the marginal effects of these variables on agricultural productivity are not unambiguously positive or negative. Similar argument is valid for importer's feature, except for drought that reducing the importer's agricultural productivity. Poor agricultural performance weakens the state's ability of self-supply, which leads to increase in bilateral trade flow.

Second, the structural gravity theory predicts direction of remoteness indices should be positive. Krugman's (1995) offers a mental experiment to explain the intuition. Suppose we have two European countries, say France and Germany. If we clip them from the surface of earth and put on the surface of Mars. The trade flow between France and Germany will increase dramatically. But notice that everything in France does not change, same as everything in Germany. Furthermore, the accessibility between France and Germany, such as distance, tariff also remain constant. The only thing changed is the remoteness indices of France and Germany. They increase dramatically. The only reason why France and Germany trade more with each other is that there is no other trade partner near-by besides each other.

Finally, for those accessibility variables, one common rule is to verify if the variable increases or decreases the trade cost. Distance (measured by travel time) is clearly a factor that increasing the bilateral trade cost, therefore should have negative impacts. Contiguity and Intra-state dummies, on the other side, indicate the lower trade cost situation. Hence, the positive sign is predicted for coefficients associated with them.

IV.A.3 Fixed Effects in Gravity Equations

We conclude our discussion of gravity estimation by making final remarks on fixed effect choices. Fixed effect estimation, specifically using importer and exporter fixed effects to control for the multilateral resistance terms, has become a standard practice for estimating the gravity equation since it is endorsed by Robert Feenstra in his famous textbook. (Feenstra, 2004) as a simple but efficient alternative to the more complicated structural estimator purposed by Anderson and Van-wincoop's seminal paper (2003).

Despite its popularity, fixed effect estimation is not the silver bullet for every gravity estimation. One well-known limitation is the fixed effects absorb any covariates that only vary by exporter (constant across all importer) or by importer (constant across all exporter). Unfortunately, the variable of interest in our case, drought, is exporter and importer-specific, therefore would not be identifiable with importer and exporter fixed effects included. To bypass this issue, besides using Wei's approximation of remoteness indices as mentioned above, we also incorporate three different types of fixed effect structure constructed at climate zone level: (1) climate-region dyadic effect + year effect; (2) climate-region dyadic effect + importer-region by year effect + exporter-region by year effect; (3) climate-region dyadic by year effect. Eq. (7.1)-(7.3) report the three slightly different final specifications of the gravity equation.

$$\begin{aligned} \mathrm{X_{ijt}} = \exp(&\beta_1 \mathrm{GDP}_{it}^{\mathrm{farm}} + \beta_2 \mathrm{DD_{it}} + \beta_3 \mathrm{RN_{it}} + \beta_4 \mathrm{DT_{it}} + \\ &\delta_1 \mathrm{GDP}_{\mathrm{jt}}^{\mathrm{food}} + \delta_2 \mathrm{DD_{jt}} + \delta_3 \mathrm{RN_{jt}} + \delta_4 \mathrm{DT_{jt}} + \\ &\gamma_1 \mathrm{T_{ij}} + \gamma_2 \mathrm{C_{ij}} + \gamma_3 \mathrm{H_{ij}} - \ln(\Pi_\mathrm{i}) - \ln(\mathrm{P_j}) + \\ &\mu_{\mathrm{IJ}} + \theta_\mathrm{t} + \varepsilon_{\mathrm{ijt}}) \end{aligned} \tag{7.1}$$

$$\begin{aligned} \mathrm{X_{ijt}} = \exp(&\beta_1 \mathrm{GDP}_{it}^{\mathrm{farm}} + \beta_2 \mathrm{DD_{it}} + \beta_3 \mathrm{RN_{it}} + \beta_4 \mathrm{DT_{it}} + \\ &\delta_1 \mathrm{GDP}_{\mathrm{jt}}^{\mathrm{food}} + \delta_2 \mathrm{DD_{jt}} + \delta_3 \mathrm{RN_{jt}} + \delta_4 \mathrm{DT_{jt}} + \\ &\gamma_1 \mathrm{T_{ij}} + \gamma_2 \mathrm{C_{ij}} + \gamma_3 \mathrm{H_{ij}} - \ln(\Pi_\mathrm{i}) - \ln(\mathrm{P_j}) + \\ &\mu_{\mathrm{IJ}} + \theta_{\mathrm{It}} + \theta_{\mathrm{Jt}} + \varepsilon_{\mathrm{ijt}}) \end{aligned} \tag{7.2}$$

$$\begin{aligned} \mathrm{X_{ijt}} = \exp(&\beta_1 \mathrm{GDP}_{it}^{\mathrm{farm}} + \beta_2 \mathrm{DD_{it}} + \beta_3 \mathrm{RN_{it}} + \beta_4 \mathrm{DT_{it}} + \\ &\delta_1 \mathrm{GDP}_{\mathrm{jt}}^{\mathrm{food}} + \delta_2 \mathrm{DD_{jt}} + \delta_3 \mathrm{RN_{jt}} + \delta_4 \mathrm{DT_{jt}} + \\ &\gamma_1 \mathrm{T_{ij}} + \gamma_2 \mathrm{C_{ij}} + \gamma_3 \mathrm{H_{ij}} - \ln(\Pi_\mathrm{i}) - \ln(\mathrm{P_j}) + \\ &\mu_{\mathrm{IJt}} + \varepsilon_{\mathrm{ijt}}) \end{aligned} \tag{7.3}$$

IV.B Ricardian Analysis for Drought Impact

Ricardian analysis evaluates the marginal effects of changes in weather condition on agricultural section by regressing agricultural profit on weather conditions along socioeconomic and soil quality controls. We adopt the model specifications from Deschenes and Greenstone (2007) with several modifications, which leads to an estimation equation is as follows:

$$y_{it} = \hat{X}'_{i.t}\boldsymbol{\beta} + DGT'_{it}\boldsymbol{\theta} + W'_{it}\delta + C'_{it}\gamma + \nu_i + \nu_{It} + \epsilon_{it} \qquad \epsilon_{it} \sim F(0, \sigma^2_\epsilon) \tag{8}$$

Where y_{it} is the net revenue (before tax and subsidy) of crop farm at state i in year t. $\hat{X}_{i\cdot}$ represents the (log of) predicted export using the estimated gravity equations, i.e. $\hat{X}_{i\cdot t} \equiv \sum_{j \neq i} \hat{X}_{ijt}$. D_{it} is the severe drought days in state i, meanwhile $\mathbf{W}_{it}$ represents other weather variables such as GDD, total precipitations and their quadratic terms. $\mathbf{C}_{it}$ is the vector of socioeconomic controls: (log of) per capita income, population density. We also include the state fixed effects ν_i to capture the soil quality along with any time-unvarying factors at state level (examples?). Last but not least, climate-region-by-year fixed effects $\nu_{k_i t}$, where k_i stands for state i belongs to climate region k, are added to allow different time trends for different climate region. These climate-region-by-year fixed effects are necessary because during the study period (1997-2012), the bioenergy boom starting roughly at 2007 profoundly affects farmers' net revenue across the country. Furthermore, the impacts of bioenergy boom are far from homogenous: some regions gain more than others. For instance, the corn-belt states, generally speaking, are big winners because of the rocketing corn and soybean prices. The fruit-rim states, on the other hands, probably experience a much moderate impact as prices indices for fruit and vegetables only have mild increases during the same period.[9]

[9] National corn price per bushel has tripled from \$2.28 in 2006 to \$6.67 in 2012 due to the boom of bioenergy. Meanwhile, the price index for fruit and vegetable only increase by 11%, from 253 in 2006 to 282 in 2012. (fruit index in 1984 = 100)

In short, we build our Ricardian model by starting with Deschenes and Greenstone's specifications, then upscaling to state level and adding predicted exports and drought days as extra regressors. The existence of predicted exports in the Ricardian equation is critical. It enables us to link two reduced-form models together, and capture both spatial heterogeneous and spillover effect of drought on agricultural profits. To see that, let us compare two models, one without and the other with the predicted exports. In the former one, the marginal effect of drought in state i on local profit is only the direct effect, meanwhile the drought has no impact on profit beyond the state border. Formally, we have:

$$\partial \mathrm{y_i}/\partial \mathrm{DTG_i} = \boldsymbol{\beta}] \text{ and } \partial \mathrm{y_i}/\partial \mathrm{DTG_j} = \mathbf{0} \tag{9}$$

In the model with predicted export, besides the homogenous direct effect, the drought also has an indirect effect on local profit by affecting state i's external demand. Furthermore, the drought now is allowed to affect agricultural profit in other states. Specifically, the marginal effect of drought can be written as follows:

$$\partial \mathrm{y_i}/\partial \mathrm{DTG_i} = \boldsymbol{\beta} + \boldsymbol{\theta} \cdot \boldsymbol{\partial \widehat{X}_{ij}/\partial DTG_i} \text{ and } \partial \mathrm{y_i}/\partial \mathrm{DTG_j} = \boldsymbol{\theta} \cdot \boldsymbol{\partial \widehat{X}_{ij}/\partial DTG_j} \tag{10}$$

By adding the state and region-by-year fixed effects, the coefficients of interest, namely direct effect β and indirect effect θ, are identified from the plausible exogenous variations over time within states after controlling common shocks to all states in a climate region. These variations in drought and predicted export are presumed to be orthogonal to unobservable factors affecting agricultural profit. It is natural to assume that drought is exogenous. Also notice that the predicted export is a nonlinear function of presumed exogenous variables such as drought, weather conditions, etc., therefore it is exogenous as well.

V. Estimation Results and Robustness Checks

V.A Estimation Results from Gravity Equation

Table 3's columns (1)-(3) report the corresponding regression results based on Eq. (7.1)-(7.3), i.e. the gravity equations with three different fixed effect structures. From left to right, these fixed effect structure are: (1) climate-region dyadic effect + year effect; (2) climate-region dyadic effect + importer-region by year effect + exporter-region by year effect; (3) climate-region dyadic by year effect. Let us first focus on the lines named "$drought_{it}$", the severe drought days in the origin states, and "$drought_{jt}$", the severe drought days in the destination states. The directions of these coefficient are robust across different specifications, and consistent with common sense. Severe drought days in the origin have negative impacts because they reduce the state's supply capacity. While more drought days in the destination increases the state's demand for outside agricultural commodities, which explains the positive coefficient.

However, the differences between coefficients associated with origin and destination droughts become larger when we examine more theoretical-preferred specifications in the column (2) and (3). The positive effects of destination droughts outnumber the negative effects of origin drought. This founding could be explained by the two-side conjecture that: On the supply side, the farms in the origin state usually have inventories stored from previous years as an extra supply source aside with their current year production. This flexibility explained the smaller impacts. On the demand side, however, the food industry in the destination state enjoy less flexibility. It has to rely on imported raw material if the local supply is insufficient. since the locations of its food processing plants are fixed.

In terms of the rest of the covariates, they usually have theory-consistent directions and significant coefficients. The contiguity dummy has a significant and positive impact on bilateral trade. The travel time, on the other side, plays a significant negative role. The exporting state's farm industry GDP, as the proxy for the origin's supply capacity, has positive effect. The food manufacturing industry GDP, as the proxy for the destination's purchasing power, affects trade flows positively as well. The remoteness indices for both exporter and importer are positive, as the trade theory suggests. But, only the one associated with exporter is significant. Most of the weather variables are not significant, except the total rainfall in the destination.

V.B Robustness checks for gravity model

[to be continued]

V.C Estimation Results from Ricardian Analysis

Table 4's columns (1)-(2) report the corresponding Ricardian analysis results without and with the predicted export terms. Comparing column (2) to (1), we note that the coefficient associated with (log of) predicted export is 0.7, which means 1% increases in external demand leads to 0.7% increases in agricultural points, a significant strong positive effect. Including the external demand term also improves the goodness-of-fit of the model by 10%, the adjusted R-squared increases from 0.70 to 0.77. In contrast to this significant indirect impact, the direct effect of drought is not detected. The coefficient associated with severe drought days is both fairly small and insignificant in statistical sense, which once again could be explained by farmers' inventory holdings and smoothing-supply activities. These marketing strategies prevent farmers' profit from occurred by drought-induced yield drops.

The other covariates such as growing degree days, total precipitation show similar direction as previous county-level studies such as Deschene and Greenstone (2007) and Fisher et al. (2012). Both growing degree days and total precipitation have positive impacts on agriculture profit. The negative coefficients associated with the squared terms indicates the existence of some optimal ranges of both temperature and precipitation for agriculture productions. In terms of statistical significance, the rainfall effects outperform the temperature effect, which also lines up with the findings in previous researches.[10] The socioeconomic controls such as population density, per capita income also display predicted directions, positive impact on profit, even though none of them are statistical significant.

V.D Robustness checks for Ricardian analysis

We introduced a structure change that separating the sample between corn-belt and non-corn-belt states to check robustness. The column (3) reports the results. It is clear that the imposed structural difference does not alter either the direction nor magnitude of external demand. There are also lack of improvement in terms of goodness-of-fit, which indicates that the basic model is preferred according to Occam's razor.

VI. Simulation and Forecasting

[to be continued]

VII. Conclusion

This paper purposed a novel reduced-form approach for incorporating the agricultural trade information to the impact evaluation of drought days on agricultural profit. This new framework allows drought happened in different placing having different impacts on both its own profits and whole economy because of states' different position in the food supply chain, i.e. heterogeneous responses, and also because of market interactions between them, i.e. spillover effect. The previous drought impact evaluation approaches either fail to account these interregional interaction effects

[10] There is no significant impact of growing degree days on agricultural profit found in previous county-level studies. In contrast, extreme degree days is reported by many researches that has significant negative impact on crop yield. However, farmers' inventory decisions, again, make the linkage between yield and profit complicated.

or require setting up full-fledged structural general equilibrium models. Our approach reduced the barriers of considering drought impacts on agriculture in a more general equilibrium sense.

We found that droughts increase inward flows, meanwhile reduce outward flows. The responses of inward flows are more significant than outward flows. It can be explained by the fact that farmers usually have inventory left from previous year to market at drought year, which mitigate the exporting flow changes due to drought. The importing flows, by contrast, are more rigorous since the locations of food processing plants are fixed. Furthermore, our Ricardian analysis indicated that the indirect effect of drought through changing external demand has more profound impacts on agricultural profit than the direct effect of drought.

Whether trade can serve as a successful adaptation mechanism to climate change is one of heat questions debated in the climate change community. This paper contributes to this discussion by studying how does trade response to extreme weather events in an almost ideal situation, i.e. a situation with minimum possible trade barriers. However, it is worthy to note that our reduced-form method can only capture the short-run response when both beyond-production supply through inventory and fixed locations for food processing plants are valid assumptions. Future researches should focus on quantifying long-run changes in trade pattern changes due to the increasing frequency of droughts, which involves understanding how would the increasing drought frequency affect farmers' inventory decisions and food industries' allocation decisions.

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Table 1: Data Description

Variable name	Description	Expected direction
Trade flow	Interstate trade flow of major crops and fruit and vegetable (SCTG 02 and 03)	Dependent variable
Share border	If two states are share a boarder	Low trade cost (+)
Travel time	Distance between the most populous city of two states in terms of travel time. (in log)	High trade cost (-)
Farm industry (orig.)	The farm industry GDP in the orig. state	Orig. state’s supply capacity (+)
Food industry (dest.)	The food industry GDP in the dest. state	Dest. State’s crop demand for food Production (+)
Biodiesel capacity (dest.)	The biodiesel capacity in the dest. state	Dest. State’s crop demand for bioenergy production (+)
Ethanol capacity (dest.)	The ethanol capacity in the dest. state	Dest. State’s crop demand for ethanol production (+)
Origin’s accessibility	Orig. state’s remoteness index. The travel time weighted to other states by their food industry employment	The difficulty for orig. state to find another buyer for its production (+)
Destination's accessibility	Dest. state’s remoteness index. The travel time weighted to other states by their total cropland acreage.	The difficulty for dest. state to find another supplier for its need (+)
Severe drought days (orig.)	The average severe drought days in orig. state	Reduce the orig’s production capacity (-)
Severe drought days (dest.)	The average severe drought days in dest. state	Increase the dest’s demand from other sources (+)
GDD (orig. & dest.)	The total degree days in orig. (dest.) state	---
Precipitation (orig. & dest.)	The total precipitation in orig. (dest.) state	---
K-ratio (orig. & dest.)	K-factor, soil erodibility facto in orig. (dest.)	Index for poor soil quality (-)
Ksat_ratio (orig. & dest.)	K_{sat}, saturated hydraulic conductivity in orig. (dest)	---
Clay content (orig. & dest.)	clay content of soil in orig. (dest)	Index for poor soil quality (-)

Table 2: Regression Table I

Dependent variable: interstate trade flows from 1997 to 2012

PPML results	Climate zone dyadic FE and year FE	Climate zone dyadic FE and climate zone × year FE	Climate zone dyadic × year FE
Share border	1.025	1.021	1.017
	(0.226)**	(0.226)**	(0.227)**
Travel time	-0.6	-0.619	-0.623
	(0.117)***	(0.115)***	(0.116)***
Y_{it} (agricultural GDP)	0.768	0.774	0.775
	(0.091)***	(0.098)***	(0.098)***
E_{jt} (food manufacturing GDP)	0.451	0.452	0.453
	(0.052)***	(0.051)***	(0.051)***
Π_{it} (exporter's ease of market access)	1.092	1.12	1.135
	(0.462)**	(0.466)**	(0.466)**
P_{jt} (importer's ease of market access)	0.406	0.556	0.544
	(0.634)	(0.710)	(0.709)
Degree Days_{it}	0.235	0.233	0.227
	-0.346	-0.368	-0.367
Degree Days_{jt}	-0.196	-0.2	-0.203
	-0.173	-0.261	-0.261
Rainfall_{it}	0.511	0.555	0.55
	-0.356	-0.379	-0.379
Rainfall_{jt}	0.513	0.746	0.753
	(0.191)***	(0.261)***	(0.262)***
Drought_{it}	-0.054	-0.064	-0.061
	(0.025)**	(0.033)*	(0.033)*
Drought_{jt}	0.068	0.091	0.088
	(0.025)***	(0.034)***	(0.034)**
Home × year FE	Yes	Yes	Yes
Time FE	Yes	No	No
Climate zone dyadic FE	Yes	Yes	No
Climate zone × year FE (Exp and Imp)	No	Yes	No
Climate zone dyadic× year FE	No	No	Yes
N	9,216	9,216	9,216
r2	0.826	0.832	0.833

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.00$

Table 3: Regression Table II

Dependent variable: agricultural net revenue from 1997 to 2012

OLS results	Without trade	With trade	With trade and Corn Belt dummy
Per capita income	0.172	-0.079	-0.193
	(0.724)	(0.848)	(0.655)
Density	0.002	0	0
	(0.717)	(0.992)	(0.933)
Density ^2	0	0	0
	(0.247)	(0.512)	(0.505)
Log(predicted export)	/	0.710	0.742
	/	(0.000) ***	(0.000) ***
Growing degree days	0.008	0.025	0.01
	(0.852)	(0.572)	(0.878)
Growing degree days^2	0	0	0
	(0.617)	(0.819)	(0.994)
Growing season rainfall	0.07	0.08	0.054
	(0.014) ***	(0.005) ***	(0.069) *
Growing season rainfall^2	-0.001	-0.002	-0.001
	(0.089) *	(0.016) ***	(0.158)
Drought	-0.001	0	0
	(0.423)	(0.733)	(0.738)
Growing degree days × Corn Belt			0.026
			(0.805)
Growing degree days^2 × Corn Belt			0
			(0.939)
Growing season rainfall × Corn Belt			0.142
			(0.038) ***
Growing season rainfall^2 × Corn Belt			-0.004
			(0.05) **
Drought × Corn Belt			0.003
			(0.165)
State FE and Climate zone × year FE	Yes	Yes	Yes
N	192	192	192
r2	0.704	0.763	0.760

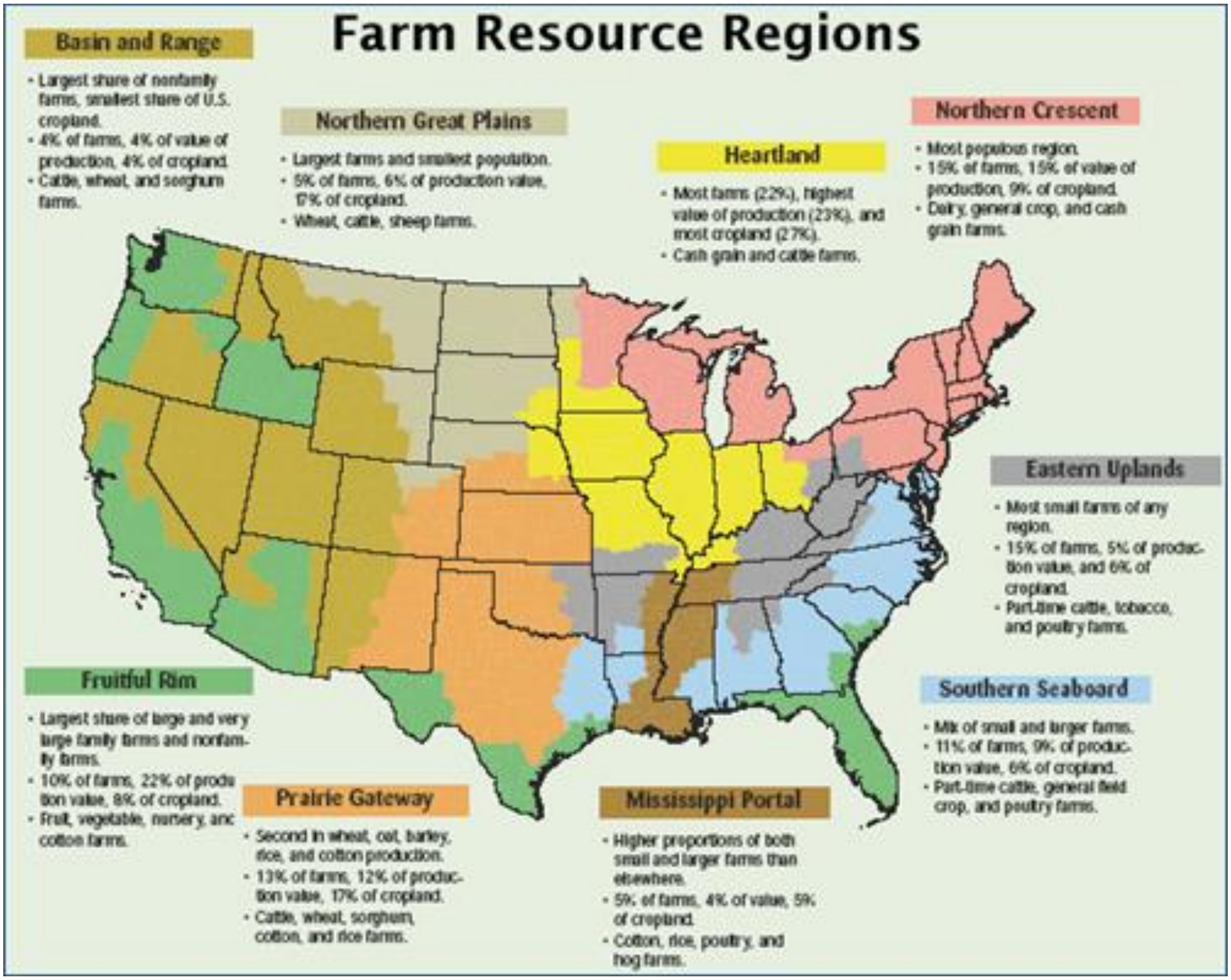


Figure 1: Farm Resource Regions

Source: USDA economic research services

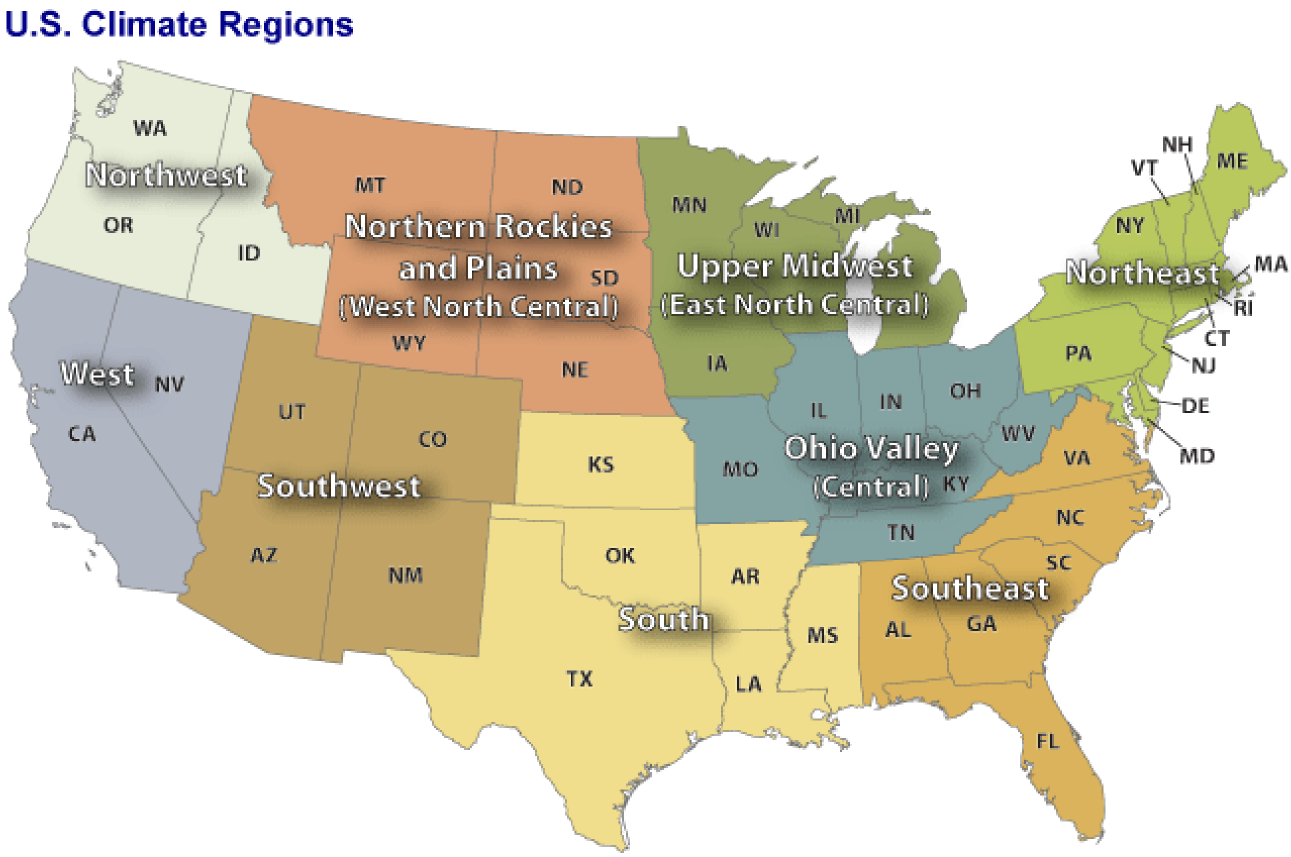
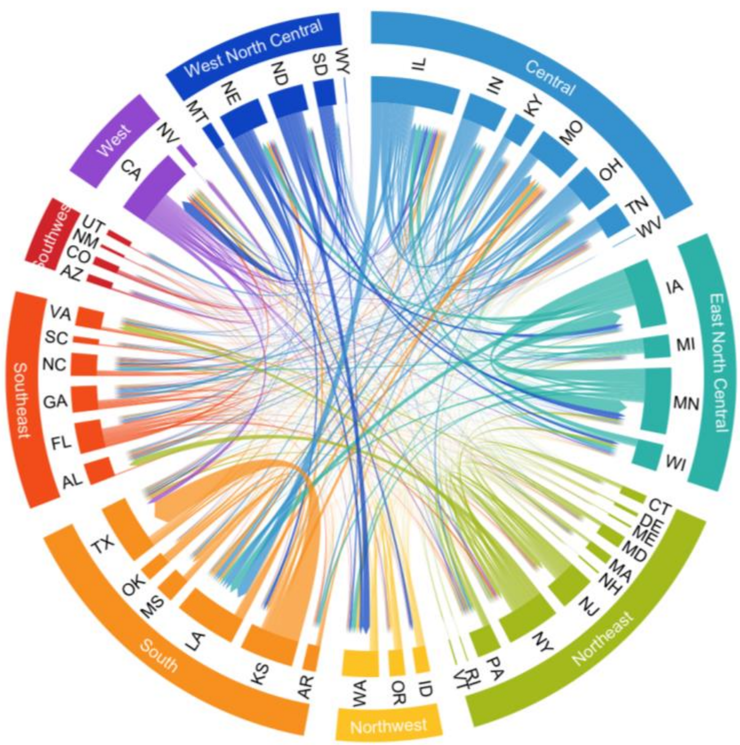


Figure 2: nine climate regions in continental U.S.

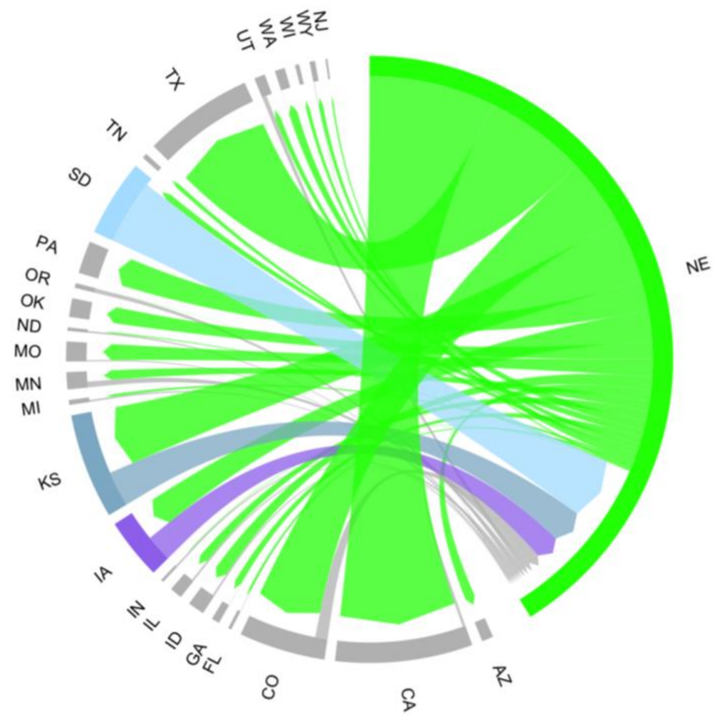
Source: NOAA

Panel (A) domestic agricultural trade volumes in 2012

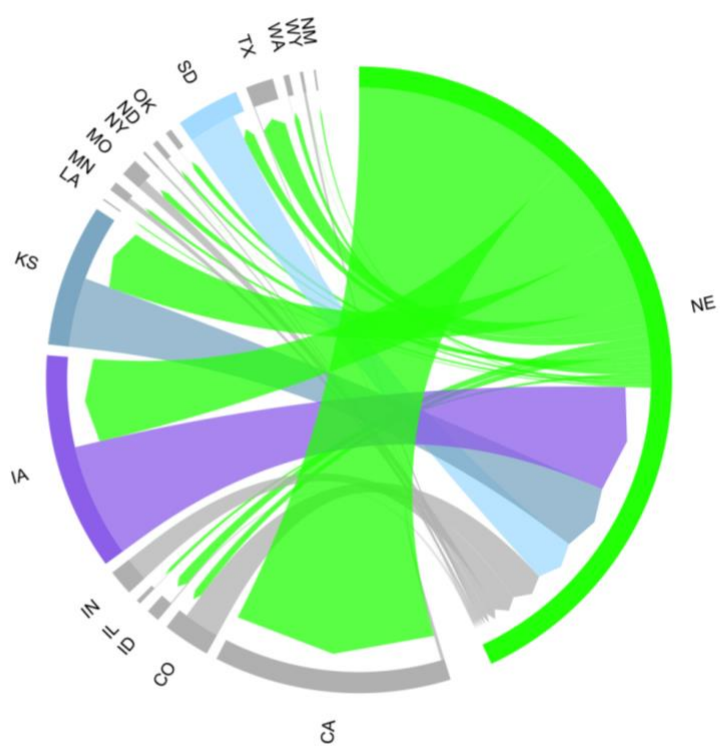


Panel (B) domestic agricultural trade partners in 2012

Figure 3: domestic agricultural trade in 2012



Panel (A) chord diagram for agricultural trade for Nebraska in 2007



Panel (B) chord diagram for agricultural trade for Nebraska in 2012

Figure 4: changes in trade pattern in Nebraska between 2007 and 2012