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The Impact of Climate Change on Agriculture in the Southwestern United States: the Ricardian Approach Revisited

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Abstract: This paper estimates a Ricardian model of farmland value across the counties of the semiarid Southwestern United States. Compared to previous contributions, we focus on one climate zone and include the presence of extreme weather events and of farm subsidies in our analysis. We also control for heterogeneity and for various types of spillover effects. Once calibrated, the model is used to project changes due to future climate conditions. We find that the probability of a loss is great in highland counties while gains and losses are relatively equally probable in lowland counties where climate impacts farmland value less.

Keywords: farmland, climate change, spillovers, spatial econometrics

JEL: Q1, R14,R15

1. Introduction

A recent report by Garfin *et al*. (2013) highlights how the Southwestern U.S. is likely to be challenged by future climate conditions. In addition to being the hottest (based on July maximum temperatures) and driest region of the country, the Southwest is warming and is experiencing more drought than in the past century and a reduction in streamflows from its four major drainage basins. The projected climate conditions compiled in this report offer a future with more frequent heat waves in summer, decreasing precipitation, more frequent precipitation extremes in winter, a decline in river flows and soil moisture and more severe extremes (droughts and/or floods) in parts of the Southwest.

Among the different sectors of the southwestern economy that could be affected by new climate conditions, agriculture is one of the most obvious due to the high sensitivity of its output to temperature and precipitation. Yet, in spite of its current climate, the Southwest is an area that displays an astonishing amount of agricultural activity. Farmland represents 35% of Arizona's territory, 47% of Colorado's, 20% of Utahs' and 55% of New Mexico's. In addition to cattle and dairy activities which are present in the four states, the top crops represent a wide range of products going from lettuce, cotton, alfalfa, hay (AZ), barley, wheat, beans, potatoes, onions, corn, tomatoes (UT), proso millet, potatoes, onions, sunflower, fruits (CO), chile, corn, wheat, onions, peanuts, hay, cotton, beans (NM). Grazing is also very lucrative in UT.

All these activities are supported by a well-developed irrigation system that imposes huge water demands on the ecological system of the Southwest. Large-scale water projects, such as dams, reservoirs, canals, pumping stations and the Central Arizona Project, help to fulfill some of this demand through water storage and transfer. However, irrigated water availability is still sensitive to weather conditions and their changes at the source; and projections reported in

Garfin *et al.* (2013) indicate a reduction in late winter-spring mountain snowpack. As a result, agriculture in Arizona relies heavily on the Colorado River, consumes 80% of the water used in the state and is highly sensitive to future climate conditions in the Colorado Rockies (U.S. Bureau of Reclamation, 2007).

Measuring the impact of future climate conditions on agriculture has attracted a lot of attention among academic scholars over the last two decades. In the U.S., it is anticipated that some regions will be winners and others losers, but it is still unclear whether climate change will bring a net gain or a net loss for the US agriculture as a whole (Mendelsohn *et al*., 1994; Deschênes and Greenstone, 2007), as production currently spans a variety of climate zones over all the lower 48 states and occupies up to 42% of US territory. In addition, the results are sensitive to whether adaptation is part of the conceptual framework used for the analysis. Crop growth simulation models and econometric models focusing on one type of crop only rely on the assumption that farmers do not adapt their choice of inputs and crops to changing climate conditions. On the other hand, the Ricardian approach initiated by the work of Mendelsohn *et al.* (1994) relies on the assumption that landowners adapt to changing local weather conditions and allocate their land to the most rewarding use. In spite of its criticisms (e.g. Kelly *et al*., 2005), this framework has attracted much attention when analyzing the U.S. agricultural sector (Schlenker *et al*., 2005, 2006; Deschênes and Greenstone, 2007, Polsky, 2004) in large part because empirical evidence clearly demonstrates that adaptation at the farm level is already taking place in the U.S. (Reilly and Schimmelpfennig, 1996) and in its Southwest.

While we also adopt a Ricardian framework in this paper, our work departs from previous contributions on a number of important points. First, we limit our analysis to the counties of the Southwestern United States (Colorado, New Mexico, Arizona, Nevada) because they belong to the same climate zone. Previous contributions have overlooked the fact that the role of climate conditions on agriculture is expected to vary across climate zones, which raises concerns on the accuracy of coefficient estimates measured on the entire sample of U.S. counties. Even in a limited sample like ours, the large variety of the Southwest's landscapes - mountains, valleys, plateaus, canyons, and plains – and associated elevation (Pinal, AZ, is 713 meters above sea level while Hinsdale, CO, is 3311 meters high) leads to diverse climates, a form of spatial heterogeneity that we will define based on altitude.

Secondly, we include extreme events (heat and cold waves as well as heavy precipitation) because several global and regional climate models suggest that they will occur more often in the future (Tebaldi *et al.,* 2006, Dominguez *et al*. 2012). Unlike work using global climate models (GCMs) data or statistically downscaled GCMs, we use dynamically downscaled data that allow us to explicitly account for changes in the intensity and frequency of extreme events at the local scale (a spatial resolution of 35-50km while GCMs used in Schlenker *et al. (*2006) have a spatial resolution of about 200-300km). This level of detail is applied to future climate projections, which in our case come from seven regional climate model (RCM) simulations. Such a variety of projections allow us to account for model uncertainty for future climate projections and will allow us to provide an envelope of likely future farmland values. This approach improves upon the usual projections based on a single climate model.

Third, we pay special attention to the role of government-funded projects on agriculture. Polsky (2004) and Massetti and Mendelsohn (2011) have explored this issue but used only one type of support. Here, we rely on a unique database from the Census Bureau that allows us to consider up to 7 types of federally-funded farm programs. While previous contributions have found agricultural subsidies to increase the value of the land (e.g. Goodwin *et al*., 2003; Roberts *et al*., 2003), the work of Lewandrowski and Brazee (1993) and Barnard *et al.* (1997) indicates that the government's creation of economic disincentives through subsidies could counterbalance the process of farmers' adaptation to climate change. In addition, because increasing climate variability could result in an increasing occurrence of very good or very bad harvests, government programs could slow down farmers' consideration of crop failures (Reilly and Schimmelpfennig, 1996).

Finally, while it is largely accepted that counties that are located nearby tend to share similar climatic conditions, soil characteristics and irrigation practices, spatial autocorrelation has often been treated as a second-order issue in Ricardian studies. The phenomenon has either been ignored (Mendelsohn *et al*., 1994), treated with Conley's (1999) non-parametric approach (as in Deschênes and Greenstone, 2007; Le, 2009; Schlenker and Roberts, 2009) or in the frame of a model with spatially autocorrelated omitted variables (as in Schlenker *et al.*, 2005, 2006). All of these methods fail to model explicit, empirically verified, spillover effects. They come from the knowledge spillovers farmers experience when in contact with their peers (Rogers, 1995), which leads them to adopt similar farming practices (Polsky, 2004) and they may also come from public spending in agricultural R&D that spills over neighboring states (McCunn and Huffman, 2000). They may also originate from the complex cycle of water (Dominguez *et al.*, 2009). For instance, the irrigated water that is so crucial to Arizona's and New Mexico's agriculture actually originates hundreds of miles away in the Colorado Rockies. The reliable water reservoir it provides is principally due to winter precipitation in this area. Negative externalities happen too when, for instance, intense precipitation due to summer thunderstorms leads to floods, property damages and casualties across several nearby counties (Garfin *et al*., 2013).

Accounting for spillovers allows us to deal with the omitted variable bias that plagues the

Ricardian literature. Deschênes and Greenstone (2007) have raised similar concerns about estimates' bias although they list other factors than spatial externalities as the source of it. To our knowledge, only two spatial econometric contributions have measured spillovers in a Ricardian setting. They are Polsky (2004) and Seo (2008). This paper improves upon the spatial econometrics used in these contributions by, first, testing whether local (first-order only) or global spillovers fit our data better. Second, we report the direct and indirect effects à la LeSage and Pace (2009) so that the coefficient estimates can be readily interpreted as marginal effects.

The structure of this paper is as follows: section 2 reviews the Ricardian framework and provides details about the way spatial autocorrelation has been dealt with so far and should be treated. Section 3 describes our sample, data and weight matrix while section 4 provides the estimation results. Section 5 builds on the estimated coefficients and seven combinations of RCM-GCMs to project climate conditions and future farmland values over the 2038-2070 period. Finally, the conclusions are reported in section 6.

2. The Ricardian setting, model specification and spatial autocorrelation

The traditional Ricardian setting is that of a single farmer putting his land to its most profitable use given a set of conditions. In the absence of data at the individual farm level, a Ricardian model is estimated on a sample of geographical units and its reduced form is as follows:

$$y = \alpha\iota_n + X\beta + \varepsilon \quad with\ \varepsilon \sim N(0, \sigma^2 I_n) \tag{1}$$

where the dependent variable, farmland value per acre, is a function of a matrix X which stands for a set of climate, land and human variables that will be described further in section 3.

One caveat of equation (1) is that it does not consider spatial autocorrelation. This phenomenon comes from a true interaction between places, such as when farmers exchange ideas about the production process (Polsky, 2004), or from a mismatch between the scale and spatial extent of the units of observations and the scale and spatial extent of the studied process (the ecological fallacy highlighted in Anselin and Cho, 2000). For instance, precipitation does not stop at the county boundaries and nearby counties share similar soil conditions (Ezcuerra *et al.*, 2008). These elements explain why nearby counties tend to rely on similar production practices, including the use of irrigation and fertilizers. While this problem has been recognized in the Ricardian literature, it has not been properly treated. Some contributions disregard the phenomenon entirely (Mendelsohn *et al.*, 1994), which is a problem as it is now well known that Ordinary Least Squares (OLS) estimates are biased and inconsistent and/or inefficient in the presence of spatial autocorrelation (Anselin, 1988). As such, later contributions such as Deschênes and Greenstone (2007), Le (2009) and Schlenker and Roberts (2009) decided to account for it, but they chose Conley's (1999) non-parametric approach that provide consistent standard errors calculated on spatially autocorrelated error terms or they adopt a spatial error model where the errors are spatially autocorrelated (Schlenker *et al.*, 2005, 2006; Lippert *et al.*, 2009) as follows: $\varepsilon = \lambda W\varepsilon + u \;\; and \; u \sim N(0, \sigma^2 I_n)$ where W is the spatial weight matrix.

Both approaches provide consistent estimates (OLS does not) but they are also biased when the true data generating process calls for actual spillover effects. Their parameter estimate equals the average marginal effect of the rth variable on the dependent variable y as if there is no marginal effect of the cross-partial derivatives, i.e. no spillover effects (LeSage and Pace, 2009). Formally:

$$\partial y_i / \partial x_{ri} = \beta_r \tag{2}$$

$$\partial y_j / \partial x_{ri} = 0 \quad (3)$$

This assumption is impossible to match with reality. Consider a simple example: if no precipitation were to take place in the Rocky Mountain region of the Colorado River Basin, there would be no snowpack, no Colorado river and no water for irrigation in Arizona. As such, agriculture in AZ is highly sensitive to climate changes in Colorado. Other spillovers due to precipitation include the floods due to the frequent summer thunderstorms in the Southwest. In addition, McCunn and Huffman (2000) show that public spending in agricultural R&D spills over neighboring states and Polsky (2004) demonstrates that interactions between neighboring farmers lead them to share similar production practices. We could also argue that the absence of spillovers implies all agricultural goods produced in location *i* serve the local demand only. Yet, empirical evidence proves this assumption is not sustainable. For instance, only 30% of AZ-produced agricultural goods are consumed locally while the rest is sold to other US states (60%) or abroad (10%) according to IMPLAN (2010). Econometrically, the omission of spillover effects lead to an omitted variable bias that plagues the Ricardian literature as noted by Deschênes and Greenstone (2007). However, for them the source of the bias lies in the researcher's incapacity to account for characteristics such as "soil quality and the option value to convert [land] to a new use" (p. 355) that are fully contained within the county of interest. In this paper, we put to the fore the bias due to the omission of externalities that influence the dependent variable.

The most difficult question then becomes: "What is the appropriate spatial model specification?". The first option, not implemented in any Ricardian study to our knowledge, would consist in adopting a spatial lag of the explanatory variables that are spatially dependent.

If we adopt the idea that only the climate conditions are spatially autocorrelated, such as model can be written as follows:

$$y = \alpha\iota_n + X_1\beta_1 + X_2\beta_2 + WX_2\theta + u \quad with\, u = \lambda Wu + \varepsilon \;\; and\; \varepsilon \sim N(0, \sigma^2 I_n) \qquad (4)$$

where X_1 is a matrix of all conditioning variables but the weather variables, X_2 captures the weather conditions and WX_2 measures them in the neighbors of each location. We add here the assumption that the errors may be spatially autocorrelated.

Note that the spatial lag of the other regressors could also be considered. For instance, the work of McCunn and Huffman (2000) and Polsky (2004) suggest that production processes (e.g. use of irrigation or fertilizer) developed elsewhere can be adopted locally and influence the local farmland value. However, we believe that the neighbors' soil characteristics should not appear as regressors as the spatial association they display is only due to a problem of ecological fallacy (Anselin and Cho, 2000) that is traditionally dealt with through spatial error autocorrelation (Anselin, 1988).

The advantage of a model specified as (4) relatively to model (1) is that

$$\partial y / \partial x_r = (\beta_r + W\theta_r) \qquad (5)$$

where β reflects the direct effects (as in 2) while □ captures local spillover effects, i.e. the role of the weather experienced in the immediate, first-order, neighboring observations only.

However, model (5) does not consider higher-order effects and feedback effects, i.e. indirect effects. Traditionally the spatial hedonic literature pinpoints their origin in the set of "comparables" that have been sold in the past and are located in the same vicinity. They have been used to assess the value of a property in the frame of a spatial autoregressive model, also called spatial lag model or SAL (e.g. Can and Megbolugbe, 1997). At the spatial scale we use here, we believe that the farmland value is comparable across neighboring counties because they generally display similar topographic, soil and climate characteristics as well as access to similar amenities (road or city, for instance). We can also argue that the cycle of water is so that evapotranspiration from region *i* can lead to rain in neighboring region *j* (first-order effect) which, in turn, will evaporate and fall in region *k* (higher-order effect) or even feedback to region *i* (Dominguez *et al.*, 2009). Since our data are measured on a 5-year average, it could leave enough time for several cycles of rain-evapotranspiration to take place. Direct effects and all the successive rounds of evapotranspiration-rainfall can be modeled in the frame of a SAL specified as follows:

$$y = \alpha \iota_n + X\beta + \rho W y + \varepsilon \quad with\ \varepsilon \sim N(0, \sigma^2 I_n) \qquad (6)$$

where $\partial y / \partial x_r = (I_n - \rho W)^{-1} I_n \beta_r = (I_n + \rho W + \rho^2 W^2 + \cdots + \rho^n W^n) I_n \beta_r$ (7)

Such a model accounts for direct effects (I_n) plus neighborhood effects (ρW) and higher-order effects including feedback effects ($\rho^2 W^2 + \cdots + \rho^n W^n$). They are called global spillovers. Theoretically, it means that all counties are linked with each other while empirical evidence indicates that higher-order effects tend to zero after a few rounds of spillovers as $\rho < 1$ and the elements w_{ij} of W are also below 1 in a standardized weight matrix.

3. Data and weight matrix

Our analysis is applied to the counties of Arizona, New Mexico, Colorado and Utah. Among the 138 counties that compose these four states, we remove five counties for which there is no or very little agricultural activity as defined by the absence of any employment in this sector over 2001-2010[i]. We also omit all the urban counties because urbanization biases farmland value due to the option of developing land for further urban uses (Plantinga *et al.*, 2002). Following Schlenker *et al*. (2006), we define urban counties as those where the density of population is above 400 inhabitant per square mile[ii]. Finally, we also remove Yuma, AZ, because its net profits per acre are 52 times the average of the sample (it is the world's winter lettuce capital), which leads to farmland values about 4 times the sample average. As a result, our sample is composed of 124 counties.

Our dependent variable is the (log of) average value of land and buildings per acre. Data come from the 2007 census of USDA that has not yet been used in any Ricardian study. Our independent variables capture a set of climate conditions, land conditions and socio-economic characteristics. The North American Regional Reanalysis (NARR) (Mesinger *et al.*, 2006) is used as the proxy for observations of past climate data as it assimilates observed precipitation and temperature. NARR data are available for the conterminous US and are at a 32-km spatial resolution, 3-hourly temporal resolution for the period 1979-present. Hence, we used a spatial interpolation method to calculate a county's values[iii]. We prefer the NARR data over the well-published PRISM data used in several other Ricardian studies because the latter is a monthly dataset that will not provide information on extreme events of which relevance to our dataset is described further below. Our climate variables capture the average value over 5 years prior to the dependent variable (2003-2007) as we hypothesize that 5 years is long enough to allow farmers to adapt to climate change while it is still short enough to have an influence on production in 2007.

Because of high levels of multicollinearity across seasons, we cannot use all the climate variables our dataset could provide. As such, we choose the summer temperatures because most crops (corn, cotton, sorghum, beans, potatoes, sunflower, alfalfa (in AZ and UT), barley and wheat (in UT and CO) grow during that season in the Southwest (USDA, 2010). We also choose the winter and summer precipitation knowing that, in the Southwest, most of the yearly amount of precipitation takes place during these seasons. We do not use the squared term of the above variables as it would lead to perfect collinearity with their original values and we disregard the product of summer precipitation and temperature for similar reasons. On the other hand, we can use the maximum daily precipitation for each season. The latter variable captures, first, the seasonal changes in precipitation that are common in the Southwest. Indeed, a pronounced peak in precipitation in later summer due to the monsoon is observed in most of Arizona, western New Mexico, southern Utah and southwest Colorado. On the other hand, the high plains and plateaus of New Mexico and Colorado observe frequent storms in the spring and less wintertime precipitation. The second motivation behind precipitation extremes is that their frequency and intensity is expected to increase in the future (Trenberth, 1999). The Southwest is also a place that experiences frequent cold and heat waves that affect the agriculture of the region. Southwest Utah and the southern parts of Arizona and New Mexico are prone to hard freezes when the storm track plunges far to the south of its average position. At the same time, the Southwest is experiencing more regular episodes of extreme high temperatures than in the past. We calculate them based on Perkins and Alexander (2013) which consists, for each day, in defining a moving window of 15 days (7 before and 7 after) and counting the number events above the upper 90^{th} percentile of the entire distribution[iv]. We do the same with the lower 90^{th} percentile for the definition of extreme cold events. We do not include the intensity of extremes events as it leads to multicollinearity. We believe this approach corresponds to a more appropriate definition of a local extreme than counting the number of days above/below a specific thresholds (Ritchie and NeSmith, 1991). The basic statistics of our climate data are reported in table 1 below. They indicate the level of heterogeneity that is present between high- and low-elevated counties.

<< Insert table 1 here >>

Including variables that reflect the quality and topography of the land (matrix "*land*") is standard in the Ricardian literature. Soil characteristics data do not vary with time and are available from USDA's General Soil Map (STATSGO2) National Resource Inventory. We do not include them all due to problems of perfect collinearity. We select the soil erodibility factor (K-factor in the Universal Soil Loss Equation), permeability, moisture capacity and clay content. Erosion is a measure of the loss of fertile topsoil. It is a problem in the arid or semi-arid parts of the Southwest because the soils are shallow and with an inadequate vegetative cover due to low annual precipitation and soil water storage capacity. Permeability refers to the ease with which pores in a saturated soil transmit water. In the Southwest, the soil is less permeable than in other parts of the country. Poor levels of permeability in the soil layers close to the surface can hinder root development and restrict water movement. The soil moisture capacity refers to the quantity of water that the soil is capable of storing for use by plants. Its volume is a function of the difference between precipitation that infiltrates the soil and evapotranspiration that removes moisture from the soil. In the Southwest, the difference between these two processes varies by region and by season. Finally, the level of clay content is inversely related to the quality of the soil. Our soil data are transformed like the climate data above to match county boundaries.

We also include elevation measurements provided by the USGS National Elevation Dataset. However, its role is not measured through a regressor but as the variable used to split our sample into sub-groups. More precisely, we use the median value of elevation (1890.583 meters)[v] to differentiate the marginal effect of the above regressors on the mountains, high plains and plateaus of Colorado, northern New Mexico, northern Arizona and the Northeastern part of

Utah from the marginal effect in the less elevated counties of southern Arizona, southern New Mexico and the eastern part of Colorado. This form of spatial heterogeneity will be tested econometrically and confirmed by a significant Chow test across all our specifications.

The variables capturing human intervention are all measured in 2007. They include population density, which acts as a proxy for demand and for the potential effect of development upon farmland value as well as per capita income. They come from the Regional Economic Accounts developed by the Bureau of Economic Analysis. We also use two variables that directly affect the production process, i.e. irrigation quantified as the share of irrigated farmland and fertilizer per acre. Last but not least, we investigate the role of the federal government through 7 types of agricultural subsidies[vi]. The latter variable is measured as the sum over 2003-2007 per acre of farmland and comes from the US Census Bureau Consolidated Federal Fund Report.

Before closing this section, it is important to provide a few words about the specification of the spatial weight matrix we use. It aims at capturing the capacity of farmers to integrate in their production process the knowledge/information generated elsewhere. Farmers are sensitive to information brought by their peers whether it is in the frame of their personal (Cochrane, 1979; Rogers, 1995) or business-related network (Berger, 2001; Polsky, 2004). However, much heterogeneity exists in the capacity or desire of farmers to adopt new information. For instance, Berger (2001) demonstrates that there are thresholds to innovation adoption based on each farmer's financial and personal situation. Farmers with a high net benefits from adoption and low information, planning and psychological adjustment costs innovate first while others will follow when their higher costs decrease with information spillovers. Another example is Munshi (2004) who shows that social learning is more restricted among rice growers than among wheat growers in India, probably because the former have a less strong social network. Education plays a key role too as it has been found empirically to positively affect a farmer's decision to adopt a new seed (Lin, 1991). Other sources of heterogeneity such as bandwagon behavior and forced adoption (by the government) of technically inefficient technology have been highlighted by Snedon *et al.* (2011) and challenge the usual assumption that the choice to adopt or reject new agricultural technologies is based on an economically rational choice.

The above studies rely on farm level information that is not available for our sample. As a result, we proxy for the capacity of farmers to adopt new technology and information developed elsewhere by relying on the (per acre) agricultural output ratio between county i and county j : GDP_i/GDP_j. It implies that for any pair *i*-*j* of counties the spillovers W_{ij} and W_{ji} are asymmetric and the leading region (say *i*) benefits from its economic advantage to absorb information from *j* better than *j* absorbs information from *i* ($W_{ij} > W_{ji}$).

In addition, we limit the spatial extent of spillovers as the literature has shown that the process of knowledge diffusion is restricted spatially due to the face-to-face contacts it relies on (Jaffe, 1986). We choose a cut-off of 240 kilometers as it corresponds to the minimum distance necessary to connect every county to at least two neighbors. We prefer a great-circle distance approach than one based on neighborhood contiguity as the latter does not account for the continuous nature of the physical landscape and climate conditions. We then globally standardize the elements of the matrix for the reasons described in Kelejian and Prucha (2010).

4. Estimation results

Table 2 starts with an OLS estimation of the basic model (1). The results indicate that irrigation plays a significantly positive role in the Southwest. It confirms our expectation that controlling water supplies leads to higher yield and land values. As noted by Plantinga *et al*. (2002), denser counties have a greater propensity to buy farmland for higher-valued activities, which explains the positive coefficient associated to density. While per capita income is generally assumed to increase farmland values, in the Southwest the need for land to be converted to urban purposes is largely limited to the few existing urban centers. As a result, it is not surprising that income does not have a significant role on farmland values. Among the soil characteristics, our results confirm the negative role of erosion on productivity and hence on farm values. The other soil characteristics do not display a significant role.

While it seems intuitive that more precipitation would benefit agriculture in a dry area like the Southwest, we find a negative impact of winter precipitation on agriculture. It could be due to the bulk of the water (60%) being delivered in the form of snow in the highland counties and/or the heavy rainfall that follows winter storms – both in highland and the lowland of the Southwest interior - and lead to floods (Garfin *et al.*, 2013). Yet, the effect is not linear as reflected by the positive impact of maximum winter precipitation. We believe it is because beyond some threshold winter precipitation contributes to building a snowpack that provides a natural and reliable water reservoir for the region throughout the rest of the year. Maximum fall precipitation is also found to act positively on agriculture. Not surprisingly, extreme heat events hurt agriculture. Several heat waves lasting several days take place every year in the Southwest with a greater frequency in the lowland counties. In addition to agriculture, they also affect the ecosystems, hydrology and human health. For instance, the 2013 heat wave reached a record 49 °C in Arizona and led to a wildfire that cost the lives of 19 firefighters. Extreme cold events are not found to significantly impact agriculture probably because they are less frequent than heat waves (see table 1).

Several econometric aspects deserve additional attention in this specification. First, we need to deal with the potential simultaneity issue of the average 2003-2007 farm subsidies on the 2007 farmland values. We choose as instrument the farm subsidies allocated in 2003 only. We use a past value in order to guarantee its exogeneity. In addition, we decided to select a year posterior to the 2002 farm bill as the decoupling principles governing the allocation of fixed income support payments, i.e. their independence from farm prices, production and planting decisions, started with the 1996 Federal Agriculture Improvement and Reform Act but took full effect in 2002 only. As a result, we believe that subsidies allocated past 2002 are less correlated with farm values than in prior years. A Wu-Hausman test indicates that the 2003-2007 farm subsidies are an endogenous regressor at the 10% level of significance. The OLS estimates are thus biased and inconsistent and a two-stage-least-square approach is necessary.

Second, the entire sample can be split into highland vs. lowland counties (n=62 in each sub-sample) because, as noted previously, elevation leads to differences in climate and ecosystems. In addition, the work of Zhang *et al*. (2013) indicates that the degree of sensitivity of agriculture to extreme weather events varies across ecosystems and the seasonality of precipitation varies across regions of the Southwest due to their altitude (Garfin *et al*., 2013). The presence of these two sub-groups is confirmed by a significant Chow test (p-value < 0.000) for all models. It can also be at the origin of the significant heteroskedasticity the Breusch-Pagan test result indicates. Finally, we detect the significant presence of spatial error autocorrelation (Moran's I statistics has a p-value =0.001), which could be due to the lack of consideration for spatial externalities in this model as described in section 2.

Before we focus on this hypothesis, we first re-estimate model (1) by two-stage-least-square, control for the presence of heterogeneity across lowland and highland counties and we report robust standard errors (BP test is significant in each group at 10%). The first stage regression indicates that the 2003 farm subsidies are not a weak instrument. Indeed, the associated Wald-F statistics are 99 and 388 for the highland and lowland counties respectively, i.e. well above the Staiger and Stock (1997) rule-of-thumb of 10. Their associated p-value is below 0.000. The coefficient estimates presented in column 2 confirm the role of irrigation. Its elasticity is greater in the lowland counties where water is scarcer. Fertilizer is found to have a positive and significant role on farm value, although in lowland counties only. Highland counties experience better soil quality, hence they are less dependent on fertilizer. Population density is still a significant factor with little to no difference in its return by elevation. Agricultural subsidies are found to act positively on farm value, a result that has already been highlighted in the literature (Goodwin *et al*., 2003; Roberts *et al*., 2003), although it is significant among highland counties only. We also find a significant harmful effect of summer temperature on agriculture, but only in the highland counties. The rest of the climate variables acts similarly in highland counties as in model (1) while the extreme heat events are the only variable impacting agriculture in lowland counties. Not surprisingly, the effect is negative.

<< Insert table 2 here >>

As spatial error autocorrelation is still present among highland counties at 10% and the spillovers have been ignored in the previous two specifications, we now turn to estimating model (4) with two combinations of spatial lags: only the climate variables and the climate plus socio-economic variables. The results are reported in columns 3 and 4 of table 3. For each group, the direct effects are robust across specifications and are consistent with those found in model 2 where spillovers are not included. The spillover effects are also robust across specifications in the highland counties. We find that the maximum winter precipitation falling in neighboring counties act in a similar way as their direct effect and contribute to the formation of a natural water reservoir for the rest of the year. Maximum spring precipitation falling in the neighbors acts negatively on a county's agriculture. It is mostly abundant in the Western parts of Colorado and Utah and takes the form of intense but short-lived rainfall that can lead to increased streamflow and floods damaging local production in less elevated regions. In the lowland counties, the spillovers are found to be somewhat sensitive to the specification under study although the externalities of population density, summer temperature and winter precipitation are consistent across models. Model specification 4 also reports that irrigation taking place across neighbors is found to harm local agriculture. Several contributions have already highlighted that this process comes from local stream or groundwater depletion intensive irrigation leads to (Kuwayama and Brozovic, 2013; Kang and Dall'erba, 2014) [1].

The theoretical, empirical and statistical results indicate that spillover effects need to be accounted for to match our model to the actual data generating process of farmland values. Their presence indicates that the estimates of the a-spatial model are biased and inconsistent. Yet, we have explored the role of the first-order neighborhood spillovers so far. If they are global in nature, i.e. they rely on several orders of neighborhood and include feedback effects, then the estimates of specifications 3 and 4 are biased and inconsistent. We report in specification 5 the spatial 2SLS results of the spatial lag model (6). As usual in the spatial econometric literature (e.g. Kelejian and Prucha, 1998; Robalino and Pfaff, 2012), the instruments used for the spatial lag of the dependent variable are WX (the neighbors' characteristics) and WWX (the neighbors' neighbors'characteristics). In addition, we use the same instrument as above for the agricultural

[1] A specification with the spatial lag of all the regressors leads to direct and indirect effects that are robust to previous specifications for both subgroups, although the indirect effect of irrigation is not significant anymore. Since, as expected, the spillovers of the soil characteristics are not statistically significant (ecological fallacy) and the fit of such a model does not outperform the one of model 4, we do not display its results.

subsidies. We follow the decomposition method of Le Sage and Pace (2009) in order to dissociate the direct effects from the indirect effects. Their significance level is based on simulated values (10,000 random draws) for the parameters from the estimated variance-covariance matrix. In addition, we control for heteroskedasticity as the spatial BP test is significant. Estimation results confirm the direct effects found in previous specifications. However, only two types of spillovers are found significant among highland counties (one is close to the 10% threshold) and none in the lowland counties, which leads us to conclude that the relevant spillovers are not global in nature.

5. Projected global climate change and its impact on agriculture

This section calculates future farmland values based on dynamically downscaled climate conditions simulated for the period 2038-2070 and the estimates of specification 4 as an F-test indicates that it significantly outperforms the a-spatial model (specification 2) at the 5% level for the highland counties, although both models perform equally for the lowland counties. Previous Ricardian studies on the US counties have also aimed at estimating the impact of future climate conditions on agriculture and their results tend to differ. Some estimate an annual gain in the future (+4% inDeschenes and Greenstone, 2007; +0.7-1.2% in Mendelsohn *et al*., 1994; + 1.5% in Massetti and Mendelsohn, 2011) while others do not (-10 to -25% in Schlenker *et al*., 2006). The differences in their results come from the dependent variable used (profits vs. land value), differences in the specifications of the temperature and precipitation data, in the sample, concerns for irrigated vs. dryland counties, the use of cross-section vs. panel data and the time periods (past and future) under study. Eventually, our analysis is closer to the one of Polsky (2004) because he focuses on only one area of the United States, namely the Great Plains, and concludes to an estimated gain between 0.5-6% depending on the reference year.

In this paper, we use state of the art future climate projections that rely on GCMs driven by different greenhouse gas emission scenarios. The driving GCMs use the SRES A2 emission scenario for future greenhouse gas emissions as described in the IPCC 4th Assessment Report (IPCC, 2007). The A2 scenario describes a world with a continuously increasing population, an emphasis on economic growth and regionally oriented economic development (heterogeneous world) (Nakicenvoic *et al.*, 2000). The projected CO_2 concentrations based on this scenario are about 575ppm and 870ppm by the middle and end of the 21st century, respectively, which corresponds to a global temperature rise of around 3.5°C between 2000-2100. However, GCMs generally do not realistically represent precipitation due to their coarse spatial resolution and physical parameterizations, especially in complex terrain. Consequently, the models must be downscaled using either statistical or dynamical downscaling (see Fowler *et al.*, 2007, for details on the two methods). In this work we rely on dynamical downscaling because it provides a physically based method to bring the global scale projections to the regional scale using RCMs, it can simulate changes that have never been observed in the historical period, addressing the issue of non-stationarity (Fowler *et al*. 2007), and it better captures mean and extreme precipitation at the regional scale as stated by Leung and Qian (2009). In the end, it permits us to create a dataset of climate indicators at the same scale as the economic indicators and is thus more appropriate for estimating the impact at the local scale. To our knowledge, this is the first time that dynamically downscaled data are used to drive a Ricardian model.

Instead of relying on one model of future climate projections like previous contributions, this study uses seven NARCCAP (North American Regional Climate Change Assessment Program) simulations based on different GCM-RCM combinations. It is also important to note that

NARCCAP uses the A2 scenario because it is at the higher end of the emissions scenarios in the Fourth Assessment Report (but not the highest), making it particularly useful for adaptation work because it gives an upper bound on projected changes. The global climate models used in NARCCAP are: the Community Climate System Model; the Third Generation Coupled Global Climate Model; the Geophysical Fluid Dynamics Laboratory; the Hadley Centre Coupled Model (v.3) and the regional climate models are the Canadian Regional Climate Model (v.4); the Pen. State University NCAR Mesoscale Model; the International Centre for Theoretical Physics Regional Climate; the NCAR Weather Research and Forecasting Model. Table 3 shows the sample average change of the simulated climate variables between 2038-2070 and 1968-2000 while the last column provides the average and standard deviation. These statistics reflect that there is some discrepancy on the magnitude and, sometimes, the direction of the change. It is due to the set of assumptions each model relies on and of which description is beyond the scope of this paper. Overall, the models predict a future that will be hotter with more winter precipitation but less monsoon precipitation in summer. Mean winter precipitation is projected to increase over northern Colorado and Utah, while southern Arizona and New Mexico show decreased winter precipitation (Dominguez et al. 2012) – however, averaged over the region, winter precipitation is expected to increase. Maximum precipitation is assumed to increase every season. The frequency of heat and cold waves is projected to increased too, although to a lower extent. All these results are in tune with the projections reported in Garfin *et al.* (2013).

<< Insert table 3 here >>

Based on these seven models, we project future average farmland values for the highland and lowland counties and report their minimum (and 95% lower bound), maximum (and 95%

upper bound), standard deviation and mean in figure 1. All the results are based on a 5% discount rate as in Mendelsohn et al. (1994), Deschenes and Greenstone (2009). Using a lower value (2.9% as in Schlenker et al., 2005) does not change our conclusions. We find that all models predict an average loss (the *overall* average is -128.59%) in the highland counties, although the likelihood of a gain is still within the 95% confidence interval of each model (see figure 1). For the lowland counties, the *overall* average of the predictions is also a loss (-2.33%). However, the distribution of the predictions reported in figure 1 indicates a relatively equal probability of gain or loss once the 95% confidence interval is accounted for[vii]. While it is difficult to pinpoint with certainty the reasons for the difference across sub-samples, we note that land value in highland counties is negatively affected by heat waves (table 2) of which frequency will increase in the future (table 3). In addition, land productivity in lowland counties is less sensitive to climate conditions (see table 2) as it relies more than the highland counties on irrigated water of which extent is not assumed to change in these simulations.

<< Insert figure 1 here >>

6. Conclusion

In addition to being the hottest and driest region of the country, the Southwest of the U.S. is expected to meet increasingly challenging climate conditions in the future. Yet, there is very little expertise with regards to how agriculture, a sector that consumes a large share of its land, will be affected. This paper fills this gap by offering a Ricardian model that estimates the sensitivity of farmland value to climate and by treating some of the usual caveats of the Ricardian literature. First, we limit our analysis to counties that belong to the same climate zone. The role of various climate zones has been overlooked in the literature, even though this form of spatial heterogeneity can lead to unreliable estimates if not accounted for. Even in a limited sample like ours, we find out that the variety of climate conditions obliges us to treat heterogeneity in the form of two clusters (high- vs. low-elevated counties) which are consistent across all specifications. Secondly, we use a dataset and dynamically downscaled projections that allow us to explicitly account for changes in the frequency of heat and cold waves as well as very heavy precipitation at the local scale. Several global climate models suggest that such events will likely become more frequent and more intense in the future (Tebaldi *et al.*, 2006, Dominguez *et al*. 2012), hence their role needs to be investigated as well. Another contribution consists in paying attention to the role and endogeneity of government-funded farm subsidies. Finally, this work offers various ways of controlling for spillovers effects which come from similarity in farming practices across nearby counties (Ezcuerra *et al*., 2008), social and professional interaction between farmers (Rogers, 1995; Polsky, 2004), their capacity to absorb knowledge developed elsewhere (Berger, 2001) and water run-offs or floods that makes each location depends to various degrees on weather events, information and technology that originate from a different location. We also test the nature of these spillovers and find that the model that is closer to the actual data generating process needs to include the first-order spillovers of the climate and socio-economic factors only. Global spillovers and their feedback effects prove non-significant.

In such a model, the coefficient estimates confirm the expected positive role of irrigation and population density. Agricultural subsidies are found to support farmland values but only among highland counties. While the soil conditions play a negligible role, the results highlight the non-linear, seasonal and heterogeneous role of climate on agriculture. As expected, heat waves are found to hurt productivity. Our estimates also indicate that land values in one location are significantly influenced by irrigation and climate conditions in neighboring locations. We believe their effect takes place through water depletion (irrigation), steady water run-offs and/or sudden floods that follow intense rainfall.

Future climate conditions are expected to lead to decreasing (summer) precipitation, hotter summers, and more frequent and intense extreme events in the Southwest. As a result, we rely on seven combinations of regional-global climate models to project future climate conditions and forecast future farmland values. While previous contributions rely on only one model, our approach allows us to account for model uncertainty in projections and to generate an interval of future farmland values. We find that the probability of a loss is greater than the alternative in the highland counties whereas gains and losses are relatively equally probable in lowland counties. The latter are less sensitive to climate conditions as they rely more on irrigation than the highland counties. In addition, more frequent heat waves are expected to hurt the future land productivity in the highland counties.

It is important to note our projection efforts are constrained by the usual set of limitations inherent to the Ricardian literature, namely the controversial assumptions of constant technology, market structure, input and output quantities and prices in the future (Schlenker *et al*., 2006). For instance, an increase in population in the Southwest could escalate the water demand stress on the local ecological and agricultural systems. We have also assumed that irrigation will continue at its current rate in the future when, in reality, irrigation depends on the availability of water from the Colorado River. If climate change dramatically affects water resources in the Colorado, then the effects on the southwestern agriculture would be dramatic. In the absence of appropriate remedy to the above limitations, we think that future work should focus on identifying the sectors and places that are the most likely to lack the capacity to adapt to a future with more scarce water but more frequent and intense extreme precipitation and temperature events.

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[i] San Juan, Gilpin, Clear Creek and Lake in Colorado as well as Los Alamos in New Mexico.

[ii] Davis, Salt Lake in Utah; Maricopa in Arizona; Bernalillo in New Mexico; Boulder, Jefferson, Denver and Arapahoe in Colorado.

[iii] Point climate values are transformed to continuous variation over the conterminous US using an inverse distance weighting interpolation method. Based on these continuous values, we performed a zonal sum analysis to calculate each county's average climate values. ArcGIS 10 was used for this task.

[iv] We thank an anonymous referee for suggesting this definition.

[v] The median value guarantees equal number of observations across groups and, in our case, is relatively close to the average level of elevation (1934.089 meters).

[vi] Crop insurance, production flexibility payments, grants for agricultural research, conservation reserve program, environmental quality incentives program, crop disaster program, emergency conservation program.

[vii] Since a F test cannot distinguish statistically the fit of models 2 and 4 for the lowland counties, we performed the projection exercise for model 2 also. All models indicate a clear loss, even including the 95% confidence interval.

Table 1- Summary statistics

	High elevation counties (≥1.89 km)				Low elevation counties (<1.89 km)			
Variable	$\overline{\square}$	$\square$	**Min**	**Max**	$\overline{\square}$	$\square$	**Min**	**Max**
summer Temperature (° C)	18.140	2.909	12.276	22.949	24.534	1.544	21.678	30.156
summer precipitation (mm/day)	1.495	0.406	0.777	2.220	1.513	0.410	0.471	2.232
winter precipitation (mm/day)	1.142	0.382	0.492	2.021	0.698	0.275	0.374	1.617
Max. spring precipitation (mm/day)	12.380	2.918	7.000	21.679	13.898	5.852	3.978	25.388
Max. summer precipitation (mm/day)	15.992	4.885	8.449	27.296	16.061	4.070	6.363	23.992
Max. fall precipitation (mm/day)	13.845	3.041	9.000	20.510	13.666	3.785	6.775	21.710
Max. winter precipitation (mm/day)	10.731	1.886	6.978	16.687	11.646	3.258	6.465	21.810
Extreme heat event (frequency)	4.456	0.986	3.113	7.067	5.904	0.964	3.933	7.868
Extreme cold event (frequency)	2.775	0.579	2.019	4.219	2.818	0.423	1.817	3.767

Table 2- Estimation results - Dependent variable: ln(farm value/acre). Number in parenthesis are p-values.

	1 - OLS	2- No spillover - 2SLS		3- SLX model (climate) - 2SLS				4- SLX model (eco & climate) - 2SLS				4- SAL model – 2 SLS			
				High		Low		High		Low		High*		Low*	
		High*	Low*	Direct effect	Indirect effect	Direct effect	Indirect effect	Direct effect	Indirect effect	Direct effect	Indirect effect	Direct effect	Indirect effect	Direct effect	Indirect effect
Intercept	6.540	7.762	8.919	7.732		7.912		7.081		9.179					
	(0.000)	(0.000)	(0.000)	(0.000)		(0.005)		(0.000)		(0.002)					
Irrigation	**0.014**	**0.009**	**0.015**	**0.004**		**0.015**		**0.005**	**-0.031**	**0.018**	**-0.057**	**0.009**	0.004	**0.016**	0.008
	(0.000)	**(0.000)**	**(0.000)**	**(0.088)**		**(0.010)**		**(0.055)**	**(0.048)**	**(0.002)**	**(0.054)**	**(0.000)**	(0.147)	**(0.000)**	(0.149)
Fertilizer	0.014	-0.018	**0.057**	-0.016		0.036		-0.014	0.228	0.014	0.301	**-0.018**	-0.009	**0.045**	0.023
	(0.123)	(0.141)	**(0.003)**	(0.423)		(0.221)		(0.561)	(0.200)	(0.741)	(0.116)	**(0.035)**	(0.247)	**(0.025)**	(0.150)
Per capita income	0.004	0.002	0.003	0.008		0.009		0.012	0.036	-9.10^{-4}	-0.111	0.004	0.002	0.004	0.002
	(0.383)	(0.521)	(0.771)	(0.210)		(0.609)		(0.116)	(0.380)	(0.961)	(0.283)	(0.244)	(0.415)	(0.725)	(0.771)
Pop. density	**0.004**	**0.004**	**0.002**	**0.003**		**0.003**		0.001	0.008	**0.007**	**0.043**	**0.004**	**0.002**	**0.002**	0.001
	(0.000)	**(0.000)**	**(0.010)**	**(0.014)**		**(0.102)**		(0.424)	(0.581)	**(0.021)**	**(0.011)**	**(0.000)**	**(0.107)**	**(0.007)**	(0.206)
Ag. subsidies	9.10^{-4}	**0.008**	-2.10^{-4}	**0.013**		0.001		**0.012**	0.010	0.002	0.001	**0.007**	0.003	-5.10^{-4}	-2.10^{-4}
	(0.555)	**(0.064)**	(0.892)	**(0.028)**		(0.638)		**(0.034)**	(0.724)	(0.481)	(0.934)	**(0.003)**	(0.183)	(0.820)	(0.829)
Erosion	**-2.889**	-0.635	**-4.501**	1.054		-3.883		1.185		-2.285		-0.241	-0.122	**-2.988**	-1.513
	(0.025)	(0.643)	**(0.035)**	(0.575)		(0.136)		(0.553)		(0.443)		(0.849)	(0.836)	**(0.092)**	(0.260)
Perm.	4.10^{-4}	-0.003	-0.015	-0.006		-0.005		**-0.006**		-0.018		**-0.004**	-0.002	-0.014	-0.007
	(0.890)	(0.113)	(0.188)	(0.104)		(0.749)		**(0.088)**		(0.283)		**(0.036)**	(0.256)	(0.144)	(0.312)
Moisture capacity	3.604	-2.658	4.955	-3.927		3.771		-4.968		4.957		-3.019	-1.528	3.173	1.607
	(0.337)	(0.479)	(0.444)	(0.504)		(0.629)		(0.414)		(0.491)		(0.416)	(0.520)	(0.585)	(0.641)
Clay content	0.012	0.020	-0.011	0.007		-0.019		0.001		-0.049		0.011	0.005	-0.015	-0.007
	(0.473)	(0.300)	(0.646)	(0.767)		(0.570)		(0.953)		(0.191)		(0.510)	(0.610)	(0.489)	(0.558)
Temp. summer	0.018	**-0.113**	-0.034	**-0.112**	0.116	-0.078	0.227	-0.091	0.049	-0.055	**0.526**	-0.057	-0.029	0.038	0.019
	(0.499)	**(0.041)**	(0.448)	**(0.070)**	(0.595)	(0.351)	(0.172)	(0.149)	(0.852)	(0.494)	**(0.010)**	(0.250)	(0.412)	(0.378)	(0.482)
Precip. winter	**-0.533**	**-1.085**	-0.371	**-0.770**	-2.759	-0.162	0.963	-0.543	-2.620	-1.235	**4.843**	**-0.877**	**-0.444**	-0.122	-0.061
	(0.043)	**(0.000)**	(0.466)	**(0.074)**	(0.222)	(0.860)	(0.238)	(0.248)	(0.261)	(0.205)	**(0.061)**	**(0.000)**	**(0.081)**	(0.790)	(0.880)
Precip. summer	-0.222	-0.329	-0.268	-0.250	0.595	-0.072	-0.080	0.090	-0.699	0.185	-1.833	0.127	0.064	0.110	0.055
	(0.238)	(0.352)	(0.374)	(0.514)	(0.579)	(0.872)	(0.929)	(0.831)	(0.638)	(0.702)	(0.265)	(0.715)	(0.642)	(0.733)	(0.667)
Max. winter precip.	**0.081**	**0.092**	0.066	**0.106**	**0.717**	0.059	-0.065	**0.126**	**0.734**	**0.094**	**-0.433**	**0.075**	0.038	**0.066**	0.033
	(0.007)	**(0.018)**	(0.126)	**(0.056)**	**(0.066)**	(0.239)	(0.658)	**(0.033)**	**(0.068)**	**(0.063)**	**(0.091)**	**(0.032)**	(0.168)	**(0.013)**	(0.186)
Max. spring precip.	**-0.032**	0.015	-0.032	**0.058**	**-0.399**	-0.040	0.089	0.033	**-0.392**	-0.028	**0.245**	-0.002	-0.001	-0.036	-0.018
	(0.048)	(0.528)	(0.188)	**(0.098)**	**(0.012)**	(0.229)	(0.160)	(0.352)	**(0.022)**	(0.408)	**(0.004)**	(0.922)	(0.819)	(0.150)	(0.355)
Max. summer precip.	0.016	0.019	0.040	0.002	0.006	-0.007	0.091	-0.013	0.043	-0.007	0.022	8.10^{-4}	4.10^{-4}	0.025	0.012
	(0.350)	(0.393)	(0.161)	(0.929)	(0.937)	(0.895)	(0.500)	(0.666)	(0.660)	(0.878)	(0.900)	(0.965)	(0.923)	(0.426)	(0.550)
Max. fall precip.	**0.034**	**0.111**	0.010	**0.100**	-0.007	1.10^{-4}	-0.034	**0.095**	-0.039	0.050	-0.248	**0.108**	**0.054**	0.010	0.005
	(0.032)	**(0.000)**	(0.631)	**(0.003)**	(0.953)	(0.996)	(0.740)	**(0.015)**	(0.840)	(0.225)	(0.116)	**(0.000)**	**(0.090)**	(0.652)	(0.764)
Ext. heat events	**-0.301**	**-0.207**	**-0.309**	**-0.213**	-0.525	-0.073	-0.695	**-0.247**	-0.028	-0.420	-0.384	**-0.211**	-0.107	**-0.257**	-0.130
	(0.000)	**(0.041)**	**(0.009)**	**(0.075)**	(0.316)	(0.777)	(0.227)	**(0.059)**	(0.964)	(0.141)	(0.548)	**(0.015)**	(0.160)	**(0.020)**	(0.182)
Ext. cold events	-0.015	0.104	-0.040	-0.124	-0.068	0.333	-1.189	-0.106	0.065	0.265	-0.806	0.089	0.045	-0.147	-0.074
	(0.909)	(0.382)	(0.852)	(0.457)	(0.868)	(0.323)	(0.125)	(0.541)	(0.891)	(0.412)	(0.332)	(0.426)	(0.529)	(0.479)	(0.571)
Adj-R2	0.684	0.737	0.626	0.805		0.595		0.814		0.665					

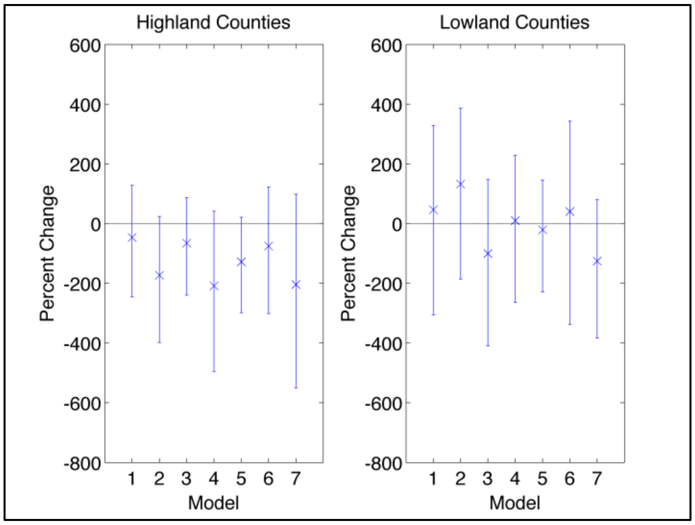
Moran's I	0.091 (0.024)	0.067 (0.098)	0.036 (0.216)	-0.018 (0.966)	0.053 (0.188)	-0.073 (0.843)	-0.067 (0.750)	-0.075 (0.919)
(Spatial) BP test	40.726 (0.001)	26.614 (0.086)	32.265 (0.020)	25.311 (0.557)	36.182 (0.111)	29.314 (0.603)	36.169 (0.280)	62.624 (0.003)

*: Huber-White robust standard errors.

Table 3- Climate change for each RCM-GCM model (2038-2070 vs. 1968-2000)

	(1) CRCM + ccsm	(2) CRCM + cgcm3	(3) MM5I + ccsm	(4) RCM3 + cgcm3	(5) RCM3 + gfdl	(6) WRF + ccsm	(7) WRF + hadcm3	**Average And St. dev.**
Temp. summer (° C)	3.318	3.173	2.245	0	2.668	2.858	2.734	2.428 1.126
Precip. winter (mm/day)	-1.063	6.523	-0.867	7.268	1.944	2.795	2.774	2.768 3.238
Precip. summer (mm/day)	-12.30	-9.373	-0.753	1.205	-0.951	-9.397	6.078	-3.642 6.764
Max. winter precip. (mm/day)	1.593	11.519	5.030	10.315	2.277	8.195	8.547	6.782 3.880
Max. spring precip. (mm/day)	3.283	11.051	7.614	17.58	7.654	8.182	7.184	8.935 4.438
Max. precip. summer (mm/day)	-2.006	-3.663	4.081	11.637	13.52	4.716	5.317	4.800 6.345
Max. fall precip. (mm/day)	5.081	14.44	14.828	17.136	5.576	10.660	8.827	10.935 4.715
Ext. heat events (frequency)	0.087	-0.023	0.122	0.021	0.219	-0.211	7.209	1.061 2.715
Ext. cold events (frequency)	0.170	0.231	-0.041	0.005	-0.218	0.037	-0.025	0.023 0.147

Figure 1 – Percent change compared to 2003-2007 fitted values (upper bound, average, lower bound)



Models: (1) CRCM + ccsm; (2) CRCM + cgcm3; (3) MM5I + ccsm; (4) RCM3 + cgcm3; (5) RCM3 + gfdl; (6) WRF+ ccsm; (7) WRF + hadcm3