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The Role of the Spatial Externalities of Irrigation on the Ricardian Model of Climate Change: Application to the Southwestern U.S. Counties

Jinwon Bae*, Sandy Dall'erba**

Abstract In spite of the increasing popularity of the Ricardian model for the study of the impact of climate change on agriculture, there has been few attempts to examine the role of interregional spillovers in this framework and all of them rely on geographical proximity-based weighting schemes. We remedy to this gap by focusing on the spatial externalities of surface water flow used for irrigation purposes and demonstrate that farmland value, the usual dependent variable used in the Ricardian framework, is a function of the climate variables experienced locally and in the upstream locations. This novel approach is tested empirically on a spatial panel model estimated across the counties of the Southwest USA over 1997-2012. This region is one of the driest in the country, hence its agriculture relies heavily on irrigated surface water. The results highlight how the weather conditions in upstream counties significantly affect downstream agriculture, thus the actual impact of climate change on agriculture and subsequent adaptation policies cannot overlook the streamflow network anymore.

Keywords Ricardian model, Spatial Externality, Streamflow network, Climate change

I. Introduction

A growing number of contributions use the Ricardian framework to assess the impact of climate change on agriculture (Schlenker et al., 2005, 2006; Deschênes and Greenstone, 2007; Dall'erba and Dominguez, 2016; Cai and Dall'erba, 2021). This concept, initiated by Mendelsohn et al. in 1994, offers the advantage of accounting explicitly for farmers' adaptation to climate change.

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* Associate Research Fellow, Center for Balanced National Development, Korea Institute for Industrial Economics & Trade, Sejong, Korea; jbae@kiet.re.kr
** Corresponding author, Professor, Dept. of Agricultural and Consumer Economics, Center for Climate, Regional, Environmental and Trade Economics, University of Illinois at Urbana-Champaign., Urbana Illinois, United States: dallerba@illinois.edu

Other studies provide indirect evidence of the potential for adaptation by showing that crop yields respond to market price changes; suggesting that as crop prices increase due to adverse climatic conditions in the future, farmers are likely to respond by changing production practices and increasing yields (Miao et al., 2016). Significance evidence indicates that adaptation is already taking place among U.S. farmers and that it is not only limited to crop-producers (see, for instance, Schimmelpfennig et al., 1996). Examples of climate change adaptation mechanisms are, for instance, when farmers modify their quantity and mix of inputs and outputs, their tillage and management techniques, their crop-rotation, reduce their herd in dry years, shift to heat- and drought-resistant varieties, etc.

However, in its basic version, the model assumes that changes in climate conditions in other localities do not affect local production techniques and choices. This assumption has become impossible to defend, considering that the literature has highlighted several sources of interregional dependence by now. They are, among others, ecological fallacy (Ezcuerra et al., 2008), communication between farmers (Polsky, 2004; Munshi, 2004; Kumar 2011), technology and investment spillovers (McCunn and Huffman 2000, Chatzopoulos and Lippert 2016) and trade (Dall'erba et al., 2021a). In the latter study, the authors estimate that the impact of a drought reduces crop yield locally, which is compensated by an increase in imports from other regions or countries, hence benefiting the latter areas. For instance, in Dall'erba et al. (2021a), the authors conclude that the capacity of interstate trade to mitigate the impact of climate change in the US is worth \$14.5 billion. Several contributions concur that long-term climate changes will force the production of some agricultural products to shift to new localities, localities experiencing a new competitive advantage compared to current producers, hence indicating that the impact of climate change is not depleting of interregional externalities (Reilly and Hohmann, 1993; Costinot et al., 2016; Jones and Olken, 2010; Dallman, 2019; Dall'erba et al., 2021b).

In this manuscript, we introduce the network of surface water flows as another form of interregional externality. To our knowledge, its role has never been studied in a Ricardian framework (see Dall'erba et al., 2021c, for a meta-analysis). Surface water is well known for the spatial externalities it generates due to its common resource properties. Surface water creates both stock externalities and pumping cost externalities. The former takes place when the water pumped by a farmer in period t reduces the stock of water available in period t+1 to all the other farmers located downstream. The latter arises when pumping in one location increases the cost of pumping in any other location due to the lower level of water available, more especially during the dry seasons (Gichuki, 2004). The same phenomena have been highlighted for groundwater (Provencher and Burt, 1993). The presence and enforcement of water rights may modify the allocation of water across farmers (e.g., An and Eheart, 2006; Colby et al., 1993; Foran et al., 1995; Ghimire and Griffin, 2014; Wollmuth and Eheart, 2000), but it does not remove the presence of the above externalities.

Our contribution distinguishes itself from the previous Ricardian literature for various reasons. First, our approach provides us with more appropriate estimates and standard errors as the spatial econometric literature has now provided ample evidence that ignoring spillover effects present in a model leads to biased and inconsistent estimates (Anselin, 1988; Le Sage and Pace, 2009) even when traditional spatial fixed effects are included in the model (Baltagi et al., 2007; Kapoor et al., 2007; Anselin and Arribas-Bel, 2013). Second, while a growing number of Ricardian studies adopt a spatial econometric approach to account for interregional spillovers (Polsky, 2004; Seo, 2008; Lippert et al., 2009; Schlenker et al., 2006), all of these studies define the spatial weight matrix based on geographical proximity only. To our knowledge, the only exceptions are Dall'erba and Dominguez (2016) and Dall'erba et al. (2021a). While the latter uses a weight matrix based on the estimated value of trade flows derived from a gravity model, the former study weights spatial proximity by the origin-destination relative level of Gross Value Added in agriculture. This approach allows the authors to reflect the spatial differences in the capacity to adopt innovation generated elsewhere (Jaffe et al., 1993). Here, we push the idea further by creating a spatial weighting scheme based on actual flow data that we consider more appropriate theoretically and empirically as they change over time, they are non-symmetric, and they provide a clear idea of directionality. Spatial econometric contributions that offer weight matrices that go beyond the usual geographical proximity are, among others and in a very different context, Eliste and Fredriksson (2004), Chen and Haynes (2015), Kang and Dall'erba (2015) and Comola and Prina (2020). Third, only a handful of Ricardian studies (Deschênes and Greenstone, 2007; Fezzi and Bateman, 2012; Massetti and Mendelhson, 2011; Dall'erba et al., 2021a) use a panel approach and benefit from its advantages in terms of estimate accuracy and control of omitted variables.

Last but not least, our sample is also different from the traditional water externality literature that has often focused on a specific basin (such as Brozović et al., 2010) or a set of wells (e.g., Pfeiffer and Lin, 2012). In the current paper, we focus on the counties of the Southwestern part of the U.S. because increasing evidence indicates future climate conditions will very likely challenge their agriculture (Garfin et al., 2013; Dall'erba and Dominguez, 2016). Indeed, this region is not only the hottest and driest part of the country; it is also expected to become warmer in the future. As noted in Dall'erba and Dominguez (2016, p. 47), "the projected climate conditions […] offer a future with more frequent heatwaves 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." The sector that is the most likely to be affected by such changes is obviously agriculture because it represents a fairly large part of the land of each of the Southwestern states (35% of Arizona's land, 47% of Colorado's, 20% of Utahs' and 55% of New Mexico's) and because it is supported by a well-developed irrigation system composed of canals, reservoirs, dams and the well-known Central Arizona Project. These infrastructures allocate water across its many users, but it does not change the fact that surface water originates mainly in the Colorado Rockies and that agriculture (mostly crop production) consumes around 80% of the water available (Bae and Dall'erba, 2016). As a result, changes in the climate conditions in the Rockies is expected to impact more than the local agriculture.

In this paper, we do not use surface water flows for the purpose of highlighting negative externalities in water availability (Gichuki, 2004; Brozović et al., 2010) or for advocating for the irrigation's capacity to mitigate climate variation (Easterling, 1996; van der Velde et al., 2010; Tang et al., 2014). Instead, we use the identification, volume and directionality of these flows to demonstrate that changes in climate conditions in upstream places will affect water access, hence agriculture, downstream (Dall'erba and Dominguez, 2016). As a result, our approach has the potential to provide new insights on the magnitude and precision level of the marginal effects of the climate variables usually used in the Ricardian literature, generate new estimates on the expected impact of future climate conditions, and suggest adaptation strategies that encompass the counties that share the same streamflow.

In order to tackle these issues, the following section offers a theoretical model of the expected impact of upstream climate conditions on downstream farmland value. The model clearly separates the marginal effects in the low- and the high-irrigated counties as it is well-known irrigation acts as a substitute for the local (lack of) rainfall. The following section, section 3, starts with the description of the data and moves on to the surface water flow weighting scheme that will be used in section 4 for econometric purposes. The latter section reports and interprets the estimation results, while section 5 provides some concluding remarks.

II. Theory and reduced-form model

Following Schlenker et al. (2005), we can approximate the farmland value as the discounted sum of future profits in the equilibrium, i.e., $V = \sigma\pi^*$, where σ is the capitalization ratio and π^* is the maximized profits in the equilibrium. For a representative farmland in irrigated county i, we model profit π as a quadratic function of the inputs as in many standard agricultural economic studies, with the index i omitted for simplicity:

$$\pi = [\boldsymbol{x}' \quad \boldsymbol{z}' \quad y]\begin{pmatrix} A_{xx} & A_{xz} & A_{xy} \\ A_{zx} & A_{zz} & A_{zy} \\ A_{yx} & A_{yz} & a_{yy} \end{pmatrix}\begin{bmatrix} \boldsymbol{x} \\ \boldsymbol{z} \\ y \end{bmatrix} - \boldsymbol{p}_{\boldsymbol{z}}'\boldsymbol{z} - p_y y - C \qquad (1)$$

where $\boldsymbol{x}$ is a n × 1 vector of exogeneous inputs (say precipitation), z is a m × 1 vector of endogenous inputs (fertilizers), and y is endogenous irrigation water demand. A is a matrix of production coefficients that characterize the technology. $\boldsymbol{p}_{\boldsymbol{z}}$ is a m × 1 vector of input prices of fertilizers and p_y is the input price of irrigation water. Since the input prices of fertilizers are very similar across different areas of the country and we are interested solely in the water price, we assume that $\boldsymbol{p}_{\boldsymbol{z}}$ is given and is independent of the variation of water price. Following Mendelsohn et al. (1994) and Schlenker et al. (2005), we also assume that the price of inputs x is constant and is normalized to 1. The variables $\boldsymbol{x}$, z and y are measured in per acre unit, therefore π represents the profits per acre.

The first order condition of profit-maximization assumes that the farmer will find how much fertilizer and water is to be used as follows:

$$z^* = A_{zz}^{-1}\left(\frac{\boldsymbol{p}_{\boldsymbol{z}}}{2} - A_{zx}\boldsymbol{x} - A_{zy}y^*\right) \qquad (2)$$

$$y^* = a_{yy}^{-1}\left(\frac{p_y}{2} - A_{yx}\boldsymbol{x} - A_{yz}z^*\right) \qquad (3)$$

The second-order condition requires that the Hessian matrix of π is negative semidefinite at the optimal point, which implies:

$$a_{yy} - A_{yz}A_{zz}^{-1}A_{zy} \leq 0 \qquad (4)$$

Combining (2) and (3), we find the optimal demand of y and z as:

$$y^*(p_y, \boldsymbol{p}_{\boldsymbol{z}}, \boldsymbol{x}) = \Gamma_y^{-1}\left[\frac{p_y}{2} - \left(A_{yx} - A_{yz}A_{zz}^{-1}A_{zx}\right)\boldsymbol{x} - A_{yz}A_{zz}^{-1}\frac{\boldsymbol{p}_{\boldsymbol{z}}}{2}\right] \qquad (5)$$

$$z^*(p_y, \boldsymbol{p}_{\boldsymbol{z}}, \boldsymbol{x}) = \Gamma_z^{-1}\left[\frac{\boldsymbol{p}_{\boldsymbol{z}}}{2} - \left(A_{zx} - A_{zy}a_{yy}^{-1}A_{yx}\right)\boldsymbol{x} - A_{zy}a_{yy}^{-1}\frac{p_y}{2}\right] \qquad (6)$$

where $\Gamma_y = a_{yy} - A_{yz}A_{zz}^{-1}A_{zy}$ and $\Gamma_z = A_{zz} - A_{zy}a_{yy}^{-1}A_{yz}$.

Differentiating y^* with respect to p_y, we have: $\frac{\partial y^*(p_y, \boldsymbol{p}_z, \boldsymbol{x})}{\partial p_y} = \frac{1}{2}\Gamma_y^{-1} \leq 0$ because the second order condition in (4) implies $\Gamma_y^{-1} \leq 0$. It corresponds to the fact that π^* is convex. According to (5) and (6), we can re-write π^* as:

$$\pi^* = \boldsymbol{x}' A_{xx}\boldsymbol{x} - \boldsymbol{x}'\left(A_{xz}\Gamma_z^{-1}A_{zx} + A_{xy}\Gamma_y^{-1}A_{yx} - A_{xy}A_1A_{zx} - A_{xz}A_2A_{yx}\right)\boldsymbol{x} + \boldsymbol{p}_{\boldsymbol{z}}'\left(\Gamma_z^{-1}A_{zx} - A_2A_{yx}\right)\boldsymbol{x} + p_y\left(\Gamma_y^{-1}A_{yx} - A_1A_{zx}\right)\boldsymbol{x} - \frac{1}{4}\left(\boldsymbol{p}_{\boldsymbol{z}}'\Gamma_z^{-1}\boldsymbol{p}_{\boldsymbol{z}} + \Gamma_y^{-1}p_y^2 - p_yA_1\boldsymbol{p}_{\boldsymbol{z}} - \boldsymbol{p}_{\boldsymbol{z}}'A_2p_y\right) - C \qquad (7)$$

where $A_1 = \Gamma_y^{-1}A_{yz}A_{zz}^{-1}$; $A_2 = \Gamma_z^{-1}A_{zy}a_{yy}^{-1}$.

The Envelope Theorem implies that $\frac{\partial\pi^*}{\partial p_y} = -y^*$, which implies that the marginal effect of an increase in p_y increases the costs of agricultural production after taking the substitution effect into account, as shown by A_y, but it also influences the profits by altering the marginal effect of the climatic variables on agricultural production. For example, rainfall becomes more important to crop growth when the cost of irrigated water rises, while the lack of precipitation is less harmful to the farmers with access to cheap water.

While the water needed for agricultural production purposes in a county is rather inelastic, the supply of surface stream water varies from year to year because, for most counties, the stream originates in an upstream county and relies heavily on its local climate conditions. For instance, about 95 percent of the water needed for cotton production in California is obtained from either groundwater or from surface water of which source is more than 500 miles away (Schlenker et al., 2005). As such, we define the irrigation surface water available in county i as:

$$Y_i = g_i(q_o, q_i) \qquad (8)$$

where $q_o = q(\sum_{j\neq i}^{n} w_{ij}x_j)$ defines the surface water originating from outside county i. x_j stands for the climatic variables of counties j identified as being located upstream of county i by the interregional stream flow weight matrix w_{ij} . $q_i = q(x_i)$ stands for the surface water supply that originates from county i itself, hence it is a function of local climate conditions. Even though water is provided from the surface water system, restrictions on the quantity of water that can be pumped are often imposed on farmers (Schlenker et al., 2005), therefore a function $g_i(.)$ is used to characterize the contractual and legal water rights as well as any specific water policies that may vary across different regions. We assume that the water available in county i increases with the outside water supply:

$$q_o = \frac{\partial Y_i}{\partial q_o} > 0.$$

In the equilibrium, the input price of irrigation water is determined by equating demand and supply:

$$Ny_i^*(p_{y_i}, \boldsymbol{p_z}, x_i) = Y_i \tag{9}$$

where N stands for the quantity of farmland within county i that requires irrigation.

By solving (9), we obtain the equilibrium price of water for county i represented by $p_{y_i}^*$:

$$p_{y_i}^* = 2(\Gamma_y \frac{Y_i}{N} + \left(A_{yx} - A_{yz}A_{zz}^{-1}A_{zx}\right)\boldsymbol{x} + A_{yz}A_{zz}^{-1}\frac{\boldsymbol{p_z}}{2}) \tag{10}$$

From (10), it can be observed that $\frac{\partial p_{y_i}^*}{\partial Y_i} = \frac{\partial \Gamma_y}{N}$ <0 , indicating that the price of water rises as water availability decreases. This corresponds to the expected water pricing mechanism as a water district must raise the water price in years of short supply so that it can cover the fixed costs of operating and maintaining the irrigation system (Wichelns, 2010).

In order to illustrate the role of the spatial externalities of irrigated surface water q_o on farmland value, we investigate how a change in the former affects the equilibrium profits and thus the farmland value of county i :

$$\frac{\partial V_i}{\partial q_o} = \sigma\left(\frac{\partial \pi_i^*}{\partial p_{y_i}}\bigg|_{p_{y_i}=p_{y_i}^*} \frac{\partial p_{y_i}^*}{\partial Y_i}\frac{\partial Y_i}{\partial q_o}\right) \geq 0 \tag{11}$$

The first term of (11) results from the Envelope Theorem where $\frac{\partial \pi^*}{\partial p_{y_i}} = -y_i^*$ is negative. The second partial derivative has the form $\frac{2\Gamma_y}{N}$ that is non-positive according to (4). The last term is positive by assumption (8). Since q_o is a function of the upstream climate conditions $\sum_{j\neq i}^{n} w_{ij}x_j$, then whenever the climate variables in $j \neq i$ increase q_o in county i, the farmland value of county i rises.

III. Data and streamflow weight matrix

1. Data

We apply our approach to the 138 counties of Arizona, New Mexico, Colorado and Utah. Thirteen of the counties that compose this group need to be removed for different reasons: five of them have no or very little agricultural activity as indicated by the absence of employment in agriculture[1]. In addition, we remove eight urban counties[2] because the literature has shown that their farmland value is not necessarily driven by agricultural productivity but by the option of developing land for further urban uses (Plantinga et al., 2002; Schlenker et al., 2006). They are identified as counties where the population density is above 400 inhabitants per square mile in 2007. This sample was used by Dall'erba and Dominguez (2016) but in a cross-section setting. We revisit it in our panel data model to provide more efficient estimates, include spatial fixed-effects that control for omitted variables, and model the spatial externalities of irrigation in a structure that is closer to the actual interregional flows of surface water.

Our dependent variable is farmland value per acre from the Census of Agriculture, USDA every five years from 1993 to 2012. In general, it is evaluated that Farmland values display similar topographic, soil conditions and climate variables, hence known to be comparable across neighboring areas (Dall'erba and Dominguez, 2016).

Our independent variables are composed of three groups traditionally chosen in Ricardian studies (Mendelsohn et al., 1994; Deschênes and Greenstone, 2007; Dall'erba and Dominguez, 2016): a set of socioeconomic variables, a set of climate conditions and a couple of soil conditions. All the economic variables are converted to constant 2012 US dollars using the corresponding Consumer Price Index. Human intervention, or the level of demand, is captured through per capita income and population density. We also include elements representing the production process. Based on previous studies (e.g., Dall'erba and Dominguez, 2016), we include irrigation and fertilizers as they influence the farmland value (McCunn and Huffman, 2000; Polsky 2004). More precisely, this study will rely on the percentage of irrigated farmland from USDA's National Resources Inventory and fertilizer use of which data are also from USDA.

The climate variables are obtained from NARR (North American Regional Reanalysis), which is used as the proxy for observations as it assimilates observed precipitation and temperature. These additional variables are also available in the downscaled climate simulations. NARR data are available for the conterminous US and are at a 32-km spatial resolution. We use standard interpolation techniques and area-weighted averaging (available in, for example, ArcGIS software) to obtain unique values over each county. The high spatial resolution of these data allows us to obtain accurate estimates of climate

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

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

variables within each county for all the US counties. Because of the high degree of multicollinearity among the climate variables, we are not able to include all the seasons in our analysis. As a result, we include the summer and winter precipitation and temperature. As indicated in Dall'erba and Dominguez (2016), most of the precipitation takes place during these two seasons in the Southwest. Furthermore, most crops available in that part of the country grow during summer. We also include the squared value of precipitation as a way of testing the nonlinearity of its marginal effect. We do not do the same with temperature because of a high level of multicollinearity.

Finally, we include an index of soil erodibility (K-factor in the Universal Soil Loss Equation) and of permeability from USDA's General Soil Map (STATSGO2) National Resource Inventory as in Mendelsohn et al. (1994). These two factors have been chosen among other soil characteristics because erosion is common in the Southwest due to low annual rainfall and poor soil water storage capacity. The latter element is captured through the permeability measure.

The basic statistics associated with all these variables are reported in Table 1 below. More precisely, we report these values for the groups above and below the median elevation value (1.87 km). Following Dall'erba and Dominguez (2016), our idea is to verify if the marginal effects of the lowland counties (in southern Arizona, southern New Mexico, and the eastern part of Colorado) differ from the ones of the highland counties (in western Colorado, northern New Mexico, northern Arizona and the Northeastern part of Utah).

Table 1 Basic statistics of climate and soil variables

	High elevation counties (>1.87km)				Low elevation counties(<1.87km)			
Variable	Mean	Std. Dev	Min	Max	Mean	Std. Dev	Min	Max
Farmland value ($/acre)	1,937	1,435.7	145.8	1,1520	1,256	1,649.5	197.8	1,2680
Per capita Income ($)	29,478	11,688.5	11,859	88,163	26,337	8,433.6	12,539	63,434
Density (person/square mile)	25.238	54.456	0.455	354.049	24.365	59.155	0.329	388.594
Share of irrigated land in farm	0.654	0.267	0.045	0.9857	0.371	0.255	0.004	1
Fertilizers ($/acre)	5.072	9.829	0.006	62.778	12.255	51.8	0.005	607.176
Summer precipitation (mm/day)	1.160	0.541	0.224	2.721	1.295	0.728	0.071	3.297
Winter precipitation (mm/day)	0.832	0.525	0.069	2.384	0.571	0.400	0.031	2.022
Summer temperature(℃)	21.48	4.219	11.68	29.77	29.43	2.765	19.20	36.14
Winter temperature(℃)	-6.256	3.133	-11.533	2.492	0.626	4.513	-7.103	12.096
Squared summer precipitation	1.638	1.463	0.050	7.402	2.204	2.315	0.005	10.869
Squared winter precipitation	0.966	1.097	0.005	5.682	0.486	0.683	0.001	4.087
K-ratio (erodibility)	0.190	0.049	0.093	0.300	0.231	0.048	0.119	0.327
Awc-ratio (permeability)	0.119	0.018	0.075	0.152	0.125	0.032	0.049	0.187

2. Stream flow weight matrix using STARS toolset

We use the spatial tools for the Analysis of River Systems (STARS) ArcGIS custom toolset developed by Peterson et al. (2007) to generate the spatial weight matrix in conjunction with the linkage of river streams. In the STARs toolset, a series of geoprocessing tools are provided to build the spatial data required for spatial modeling: the Watershed attributes, the Segment PI, the Additive Function and Upstream distance (Peterson and Hoef, 2010; Peterson and Ver Hoef, 2014). Figure 1 shows the dendric system of natural stream lines and more downstream edges are expressed with thicker lines based on the Strahler's stream order. Man-made canals are also considered to build our weight matrix, as shown in Figure 1.

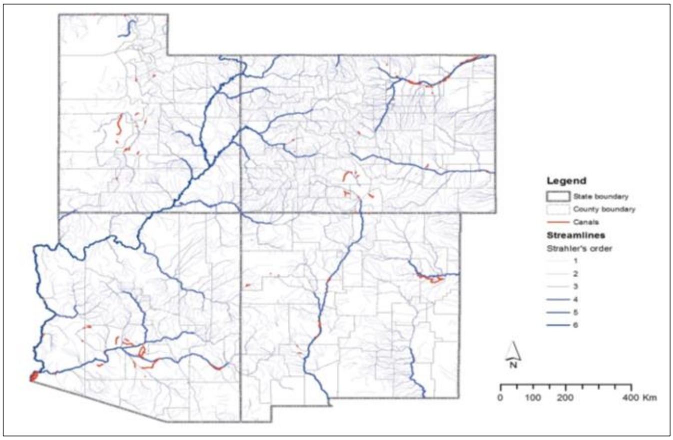


Figure 1 Stream flow connectivity in the four states in the US Southwest

Note: The stream lines are categorized by Strahler's stream order, and it increases numbers toward downstream.

Figure 2 displays the directionality of each stream edge. STARS checks the network topology for each node, and converging stream nodes should be modified before the analysis. Converging stream node error occurs at the point of the downstream node when more than two edges converge but do not flow into another downstream edge.

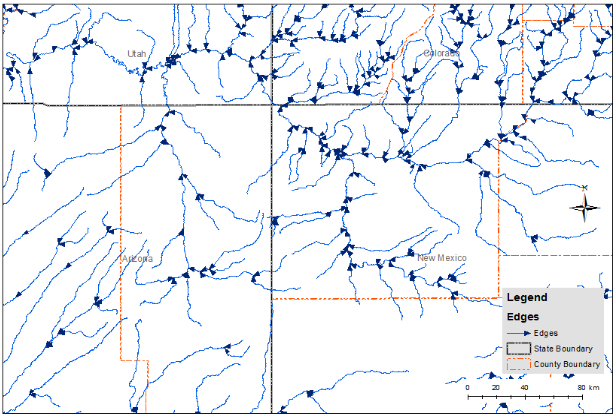


Figure 2 Flow network and directionality

Note: Regarding the stream flow direction, converging streams are manually removed before GIS analysis.

The first step to weight for the tail-up model consists in generating the PI, which is defined as the influence of an upstream location on a downstream location. To begin, each stream segment is represented as a directed line with nodes in ArcGIS. Those stream segments are identified as $j = 1, 2, 3, \ldots. n$; therefore, each location of a segment is denoted as x^j. The PI for each segment is the proportion of its cumulative watershed area for the total incoming area (Peterson et al., 2007). The watershed area of edge i is calculated by the Reach Contribution Areas (RCAs) function that builds a one-to-one relationship between edges and RCAs. The PI should range between 0 and 1 and always sum to 1 at the stream confluences. The PI is calculated by equation (12), where W_i is the watershed area of edge i, and W_j is the watershed area of edge j.

$$\omega_i = \frac{W_i}{W_i + W_j} \tag{12}$$

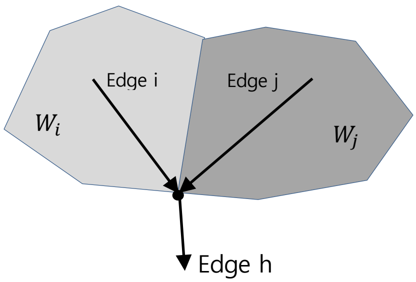
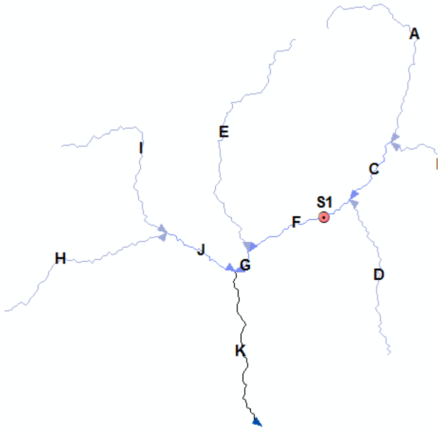


Figure 3 The segment Proportional Influence (PI) calculation

In the second step, the segment PIs are used to calculate the segment additive function value (AFV). We create the AFV for a given edge j that is defined to be equal to the value of PI of jth edge along the stream path downstream (Peterson and Ver Hoef, 2014). The most downstream segment is set as 1 in the network in the calculation of the AFV. It is considered that there exists a non-symmetric correlation between flow-connected downstream and upstream sites. An example of the calculation of the AFV for a site located on the edge is illustrated in Figure 4.

$$AFV_j = \prod_{m=1}^{n} \omega_{D_{j,m}} \tag{13}$$



If site S_1 is located on edge F,

$$\omega_i = \frac{W_i}{W_i+W_j}$$

$$\omega_F = \frac{W_F}{W_F+W_E}$$

$$D_{[F]} = [\mathrm{F}, \mathrm{G}, \mathrm{K}] = [D_{F,1}, D_{F,2}, D_{F,3}]$$

$$AFV_{S_1} = AFV_F = \prod_{m=1}^{n} \omega_{D_{F,m}} = \omega_F \times \omega_G \times \omega_K$$

Figure 4 Calculating the AFV for a site on each edge

In the final step needed to generate a valid flow-connected weight matrix, the weighted stream flow matrix is built at the county level. Along the path downstream, the downstream counties are affected by upstream counties. If an edge j is lying across the county border, we assume that upstream segment group A inside county N_i affects county N_j directly as well as N_k indirectly (see Figure 4). The indirect impact diminishes in proportion to the distance between the upstream and the downstream counties. To account for the impact of segment group A, the accumulated value of RCAs is captured in edge j. Note that the accumulated value is not the measure of stream flow quantity but the topological area that captures rainfalls. The covariance between two flow-connected counties, N_i *and* N_j, could be represented as in equation (14), where h is the hydrologic distance between two counties, and $\sum_{k=1}^{n} W_k$ represents the spatial weights based on RCAs accumulation.

$$C\ (N_i, N_j|\theta) = \begin{cases} 0 & \text{if } \mathrm{N_i} \text{ and } \mathrm{N_j} \text{ are flow} - \text{unconnected} \\ \sum_{k=1}^{n} W_k/(d|\theta) & \text{if } \mathrm{N_i} \text{ and } \mathrm{N_j} \text{ are flow} - \text{connected} \end{cases} \quad (14)$$

Because the value of RCAs accumulation on the downstream county becomes larger than on the upstream county, we input more weight toward the downstream counties by considering the topological concentration of stream flow. The distance between neighboring counties N_i *and* N_j is given the value of 1 to impose a higher connectivity weight. The final weight matrix for the 138 counties is calculated as follows:

$$\begin{bmatrix} c_{11} \times AFV_{11} & c_{12} \times AFV_{12} & c_{1n} \times AFV_{1n} \\ c_{21} \times AFV_{21} & c_{22} \times AFV_{22} & c_{2n} \times AFV_{2n} \\ \cdots & \cdots & \cdots \\ c_{n1} \times AFV_{n1} & c_{n2} \times AFV_{n2} & c_{nn} \times AFV_{nn} \end{bmatrix} \quad (15)$$

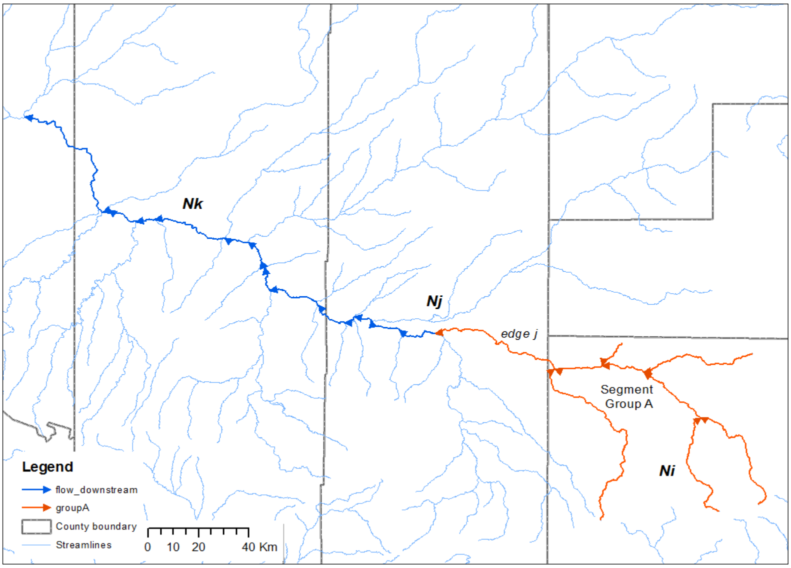


Figure 5 Flow-connectivity at a county level

IV. Estimation results

Table 2 below starts with an OLS estimation of a pooled panel data model with time- and state-fixed effects3 that can be written as follows:

$$y_{ijt} = \alpha + X'_{ijt}\beta + Z'_{ij}\delta + \mu_j + \varepsilon_t + u_{ijt} \text{ with } u_{ijt} \sim N(0, \sigma_u^2) \quad (16)$$

3 In order to avoid perfect multicollinearity with the general intercept, Utah and the year 1997 have been arbitrarily chosen as the base State and year respectively. Other pooled panel data model specifications were estimated (without fixed effect at all and with one type only), but a likelihood ratio test confirmed they led to lower log likelihood values. We also tried a county fixed effect model since a significant Hausman test (p-value=0.000) indicates it outperforms the random effect model. However, model (15) still outperforms the fixed effect model. Complete results available from the authors upon request.

where $i = 1, 2, \ldots$n stands for the counties, $j = 1, 2, 3, 4$ denotes the states, and $t = 1, 2, \ldots$T is the time index. X is a matrix of space- and time-variant socio-economic and climate controls, while Z is a matrix of space-variant soil conditions. μ_j and ε_t are state- and time-fixed effects, respectively. They control for unobservable factors that might confound the marginal effect of climate. The year fixed effect captures the time trend, such as changes in commodity prices, weather shocks, technological innovations, and policy shocks that are common to the entire sample. State-fixed effects, on the other hand, control for time-invariant elements such as soil characteristics and climate conditions. Finally, u_{ijt} denotes the error terms with the usual i.i.d. properties.

Diagnostic tests indicate the significant presence of remaining heteroscedasticity (BP test shows a p-value=0.000) and serial correlation (Breusch-Godfrey test has a p-value=0.000). On the other hand, there is no spatial error autocorrelation (Moran's I test = 0.161) probably because the state-fixed effects already control for dependence across the counties of the same state and dependence across counties of different states is limited. As a result, the standard errors presented are robust to both heteroskedasticity and serial-correlation.

The results on the socio-economic variables meet the expectations of the Ricardian literature in general and of the cross-sectional results of Dall'erba and Dominguez (2016) in particular. Indeed, per capita income (0.024, p-value = 0.076) and density (8.174, p-value < 0.000) have a significant impact on farmland values at the 10% level (Plantinga et al., 2002). Denser areas have a higher propensity to buy farmland for higher-valued activities. Moreover, irrigation (1,341.400, p-value < 0.000) and fertilizer (16.867, p-value < 0.000) are also found to act positively on farmland values, which confirms our expectations too.

When it comes to the weather conditions, the results differ by season. Summer precipitation (-919.310, p-value = 0.032) and temperature (-177.780, p-value < 0.000) act negatively on farmland value. Garfin et al. (2013) have demonstrated that intense precipitation due to summer thunderstorms leads to floods, property damages and even casualties in the Southwest. Summer is also the period when heat waves take place (e.g., the 2013 heat waves reached a record 49°C in Arizona). On the other hand, winter precipitation (1,361.2, p-value = 0.007) and temperature (129.000, p-value < 0.000) display a positive impact on farmland values. The reason could be because "winter precipitation contributes to building a snowpack that provides a natural and reliable water reservoir for the region throughout the rest of the year" (Dall'erba and Dominguez (2016, p. 58). We also find that, for both seasons, there is a non-linear effect of precipitation as indicated by the significant coefficient associated with their squared value.

Finally, we find that erodibility (-5,212.10, p=value = 0.001) reduces farmland values while permeability (3,723.700, p-value = 0.173) increases it. These results were expected as erosion and permeability act in opposite ways on productivity. Erosion is known to be a problem in the arid or semi-arid parts of the Southwest, where the vegetative cover is too thin due to low annual precipitation and poor soil water storage capacity. While, in general, the soil in the Southwest is less permeable than in the rest of the country, the level of permeability differs across its areas (see table 1). Permeability promotes root development and water movement in the soil, hence its positive impact.

One assumption that has not been tested so far is the presence of heterogeneity in the sample. As indicated in Dall'erba and Dominguez (2016) and Garfin et al. (2013), the Southwest can be split between highland and lowland counties because of the difference in climate and ecosystems that go with elevation. Furthermore, it is expected that the marginal effect of the weather variables varies with elevation. Zhang et al. (2013) show it is the case for extreme weather events. Such as model can be written as follows:

$$y_{ijt} = \alpha_L + \alpha_H + X'_{ijt}\beta_L + X'_{ijt}\beta_H + Z'_{ij}\delta_L + Z'_{ij}\delta_H + \mu_j + \varepsilon_t + u_{ijt}$$
$$\text{with } u_{ijt} \sim N(0, \sigma_u^2) \qquad (17)$$

where the subscripts L and H stand for a dummy variable for the lowland and the highland counties, respectively. The fixed effects and disturbance terms are the same as in equation (18).

The Chow test result, reported in the third column of Table 2, confirms the significant presence of two sub-groups (p-value=0.000). Furthermore, a likelihood ratio test indicates this model outperforms the previous one in terms of (log) likelihood value. Due to the significant results (p-value < 0.000) of the BP and BG tests (but not Moran's I), the standard errors are again heteroscedasticity- and serial correlation consistent.

While most of the socio-economic variables display results that are consistent with the previous model, the marginal effect of income has become non-significant. One possible reason is offered in Dall'erba and Dominguez (2016, p.55) who claim: "in the Southwest the need for land to be converted to urban purposes is largely limited to the few existing urban centers". We also note that the role of precipitation is significant in the lowland counties only. We hypothesize that it is because they are drier, and their rainfall is delivered through extreme events more often than in the highland counties. On the other hand, agricultural productivity seems sensitive to both summer (-256.73, p-value < 0.000) and winter temperature (-219.44, p-value < 0.000) in the highland counties only. The lowland counties are affected by winter temperature (103.240, p-value < 0.000) only and, not surprisingly, when the latter goes down, so does their farmland value. The non-linear effect of precipitation is confirmed.

Furthermore, we note that the influence of erodibility (-9,527.20, p-value < 0.000) and permeability (9,699.00, p-value < 0.000) is significant in the lowland counties only. They display higher mean, maximum value, and standard deviation in these variables than their highland counterparts. The pooled OLS failed to capture this heterogeneity as permeability has no significant influence on farmland value in this model.

Finally, our last model consists of testing if the weather conditions in the upstream counties affect farmland values in the downstream counties. For that purpose, we estimate the following model where the spatial lag of the weather conditions and of irrigation (noted W4) is based on the surface water irrigation flows depicted in section 3.2.

$$y_{ijt} = \alpha_L + \alpha_H + X'_{ijt}\beta_L + X'_{ijt}\beta_H + Z'_{ij}\delta_L + Z'_{ij}\delta_H + W'_{ijt}\theta_L + W'_{ijt}\theta_H + v_{ijt}$$
$$\text{with } v_{ijt} = \mu_j + \varepsilon_t + u_{ijt} \text{ and } u_{ijt} \sim N(0, \sigma_u^2) \qquad (18)$$

A significant Chow test and LR test indicate that structural instability, like in model (17), is still present but that model (18) outperforms model (17) in terms of (log) likelihood value, respectively. The direct effects in each group display a fairly similar magnitude and precision and, more importantly, the exact same sign as in model (17). However, one could claim that model (17) suffers from a missing variable bias as both the theory (see section 2) and empirical evidence indicate that the weather in upstream locations influences the availability of water for irrigation, hence farmland value, in downstream locations. Our estimation results indicate that these spillovers are significant in the lowland counties only, which makes sense since they are the downstream counties too.

Interestingly, we find that winter precipitation, summer temperature, and winter temperature in the counties upstream of the lowland counties display a significant impact on farmland value in lowland counties. As expected, we find that the marginal effect of these spillovers displays the same sign as the one of the direct effect. It also means that the overall marginal effect of any of these covariates is not $\partial y/\partial x = \beta_L$ any more but $\partial y/\partial x = \beta_L + \theta_L$. For instance, while model (17) indicates that, across lowland counties, one additional mm of rainfall per day increases farmland value by $ 1,363 per acre, model (18) indicates that the increase is actually $ 1,383. In fact, 90% of the increase ($ 1,248) comes from precipitation falling in the county itself, while the remaining 10% ($ 134.8) comes from additional rainfall in the upstream counties that combine both lowland and highland counties. Similarly, we find that the effect of one additional ℃ in winter does not increase farmland

4 The surface water flow matrix is globally standardized (ij link divided by the sum over all links) so that we do not modify the internal neighborhood structure (Kelejian and Prucha, 2010).

value/acre by \$ 103 as predicted by model (17) but by \$ 84. 72% of it is due to an increase in local temperature, while the rest comes from upstream counties. When it comes to summer temperature, the detrimental effect is only due to changes in upstream locations. In sum, our results show that ignoring such spillovers leads to erroneous conclusions about the extent and spatial origin of the marginal effects of the weather conditions.

The reported p-values are based on heteroskedasticity (White) and serial correlation-robust standard errors. For the state- and year-fixed effects, the base State is Utah and the base year is 1997.

Table 2 Estimation results of spatial models (dependent variable: farmland values per acre)

	OLS pooled model	A-spatial model		SLX model			
				High		Low	
		High	Low	Direct effect	Indirect effect	Direct effect	Indirect effect
Intercept	3,857.600 (0.000)	7,262.400 (0.000)	3,369.200 (0.049)	7,618.700 (0.000)		2,728.900 (0.110)	
Income	0.024 (0.076)	0.022 (0.181)	0.002 (0.874)	0.024 (0.144)		<0.001 (0.962)	
Density	8.174 (0.000)	9.572 (0.000)	7.221 (0.004)	9.159 (0.000)		11.004 (0.001)	
Fertilizer	16.867 (0.000)	10.848 (0.057)	15.869 (0.000)	9.188 (0.102)		16.217 (0.000)	
Irrigation	1,341.400 (0.000)	1,102.900 (0.000)	1,880.300 (0.000)	995.930 (0.006)	317.360 (0.529)	1,748.300 (0.001)	142.370 (0.387)
Summer precipitation	-919.310 (0.032)	-126.450 (0.862)	-1,275.300 (0.015)	-167.540 (0.818)	-425.520 (0.188)	-1,155.1 (0.044)	5.310 (0.899)
Winter precipitation	1,361.200 (0.007)	881.310 (0.165)	1,363.100 (0.051)	703.460 (0.289)	473.380 (0.270)	1,248.400 (0.076)	134.810 (0.099)
Summer temperature	-177.780 (0.000)	-256.73 (0.000)	-76.898 (0.191)	-257.090 (0.000)	4.652 (0.617)	-51.793 (0.383)	-8.213 (0.020)
Winter temperature	129.000 (0.000)	219.44 (0.000)	103.240 (0.000)	226.680 (0.000)	-14.728 (0.708)	61.688 (0.034)	22.532 (0.069)
Summer precipitation^2	227.740 (0.032)	-151.080 (0.548)	352.420 (0.011)	-89.121 (0.723)		317.080 (0.027)	
Winter precipitation^2	-601.310 (0.009)	-555.890 (0.059)	-400.420 (0.284)	-509.840 (0.091)		-461.770 (0.230)	
K-ratio (erodibility)	-5,212.100 (0.001)	-2,373.100 (0.309)	-9,527.200 (0.000)	-3,985.700 (0.093)		-9,393.600 (0.000)	
AWC-ratio (permeability)	3,723.700 (0.173)	733.760 (0.842)	9,699.000 (0.003)	1,204.000 (0.751)		10,210.000 (0.751)	
State dummies	Yes	Yes		Yes			
Year dummies	Yes	Yes		Yes			
N × T	500	252	248	252		248	

Adj. R2	0.640	0.830	0.837
Log Lik	-4,126.807	-4,107.910	-4,091.752
Chow test	-	5.757 (0.000)	4.154 (0.000)
Likelihood ratio test	-	37.193 (0.000)	32.316 (0.000)
BP test	75.845 (0.000)	84.395 (0.000)	81.461 (0.000)
Breusch-Godfrey test	101.300 (0.000)	89.023 (0.000)	74.229 (0.000)
Moran's I test	0.021 (0.161)	0.0175 (0.205)	-0.009 (0.601)

V. Conclusions

An increasing number of Ricardian studies have recently adopted a spatial econometric approach to highlight the role of interregional externalities in the impact of climate change on agriculture (Polsky, 2004; Seo, 2008; Lippert et al., 2009; Dall'erba and Dominguez, 2016). Yet, the large majority of these studies rely on a traditional definition of interregional linkages defined on geographical proximity. Our manuscript takes a novel approach in that dependence is based on upstream-downstream relationships of surface water flows. Moreover, it builds on the nascent panel data approach in the Ricardian framework (Deschênes and Greenstone, 2007; Fezzi and Bateman, 2012; Massetti and Mendelsohn, 2011) to uncover how weather conditions and irrigation in upstream locations affect water availability, hence agricultural productivity and ultimately farmland value in downstream locations. Our approach is applied to the counties of the four corner States because irrigation is critical for agriculture in general and for crop production in particular in that part of the country. However, this work also has strong implications for some developing countries in Asia (Mendelsohn, 2014; Wang et al., 2014) that are, in general, more vulnerable to climate variation as they are more dependent on agriculture than our sample and lack a developed irrigation system. A correct estimation of the impact of climate change on their agriculture and economy would require researchers to account for the forms of interregional spillovers depicted in our approach. Moreover, the combination of a growing urban population and of a projected increase in temperature and extreme heat events will offer new challenges to the local ecosystem (Garfin et al., 2013).

Our results indicate, first, that lowland and highland counties need to be treated separately as statistical tests and previous literature (Zhang et al., 2013; Dall'erba and Dominguez, 2016) indicate that the marginal effect of the weather variables varies with elevation. Second, while we find that local irrigation and weather conditions have the expected impact on local agriculture, we also highlight how the weather conditions in upstream counties significantly affect downstream agriculture. It allows us to provide a more accurate measurement of the marginal effect of the weather conditions and to disentangle its local amount from its interregional amount.

While our approach include interregional spillovers of surface water to a literature that has mostly ignored any form of externalities, we acknowledge that our framework suffers from the same limitations as traditional, a-spatial, Ricardian measurements. These are the assumptions of constant technology, constant market structure, and the lack of consideration for changes in input-output quantities and prices in the future (Schlenker et al., 2006). In addition, we are aware that the matrix of interregional surface water flows we rely on is exogenous because, in itself, it is not affected by changes in weather conditions. A possible way to address this issue is to adopt the recently developed instrumental variables network difference-in-differences estimator of Dall'erba et al. (2021b) and modify it to the case of continuous treatment. Future research efforts will focus on calculating the consequences of our new estimates on future farmland values. Indeed, even though our results are calibrated over historical data, it is straightforward to use them in combination with projected climate conditions to generate new predicted figures of farmland values. We anticipate that this exercise will suggest more accurate estimates of the impact of climate change and, subsequently, a set of adaptation strategies that encompass locations that share the same streamflow.

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