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Spatial diffusion of efficient irrigation systems: a study of São Paulo, Brazil*

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Finding ways to stimulate the diffusion of water-saving irrigation systems is essential to mitigate the negative impacts of climate change on water supply. We analyse the spatial diffusion of more efficient irrigation strategies in São Paulo, Brazil, comparing the two most common irrigation technologies: conventional sprinkler irrigation and the localised irrigation. We use longitudinal municipal-level information for 2006 and 2017 and test different spatial panel models' specifications, representing different hypotheses about technological transfer channels. Our results highlight how the diffusion of water-saving irrigation systems (localised irrigation) in one municipality is strongly influenced by the diffusion in neighbouring municipalities. Membership in cooperatives or farmers' associations plays a significant role in this technological transfer. On the other hand, the diffusion of less efficient systems (sprinkler irrigation) depends fundamentally on the local availability of water and unobservable factors in the neighbourhood. The discussion highlights how easing knowledge transmission may contribute to the diffusion of more sustainable agriculture practices.

Key words: technological diffusion, localised irrigation, peer effects, spatial panel models.

1. Introduction

The diffusion of efficient irrigation systems in agriculture is critical to improve crop resilience to growing climate risks, such as the increased frequency of prolonged droughts (Deschênes and Greenstone 2007; Ni *et al*. 2020) and changes in the hydrological cycle that determine the water available for irrigation (Koundouri *et al*. 2006; Stern 2007; Waldman and Richardson 2018). Hence, the adaptation of agriculture to climate change would be directly dependent on the diffusion of more sustainable irrigation practices and especially those that enhance water use efficiency (Hoekstra and Chapagain 2007, 2008; Pidgeon and Fischhoff 2011; Harvey *et al*. 2017).

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Despite the potential environmental and economic benefits, the adoption of more efficient irrigation systems is still limited and the diffusion process is not yet clearly understood.

Several channels may explain how irrigation systems are diffused. One channel is by examining how the risk of water shortages in one area may accelerate individuals' water consumption in another area before the water runs out of supply (Libecap 2009). The diffusion of irrigation also depends on how quickly knowledge flows between different geographical regions (Geroski 2000), a pattern that can be understood as a process of communication and imitation (Hovardas 2016). For example, farmers facing water scarcity may learn new water-saving technologies directly from their neighbours, which is knowns as a peer effect (Sampson and Perry 2018).

We address two central questions related to the diffusion of agricultural irrigation systems in this paper. The first refers to the spatial spillover effects on the diffusion of more efficient irrigation systems, or how farmers living in one locality are influenced by irrigation and other production choices made in neighbouring localities. The second refers to the influence of environmental factors on the diffusion of less efficient (conventional sprinkler) and more efficient (localised) irrigation systems. Sprinkler irrigation systems simulate the effect of rain, while localised irrigation systems apply water directly near the plant base to minimise water loss (Brouwer *et al.* 2001; Huang *et al.* 2017). Sprinkler irrigation is less efficient than localised irrigation, resulting in greater water losses due to runoff, percolation and evaporation (Evans and Sadler 2008). Localised irrigation improves agricultural water use efficiency and saves water for neighbours, the environment and future generations (Dagnino and Ward 2012). Studies have suggested that some types of localised irrigation may increase water use efficiency by at least 50 per cent, making this technology crucial for increasing crop production under water constraints (Chartzoulakis and Bertaki 2015). We pursue these questions using spatial panel models, which allow us to evaluate how the diffusion of each irrigation system in one locality is affected by the diffusion and other characteristics in neighbouring localities.

Our study provides critical elements for understanding the diffusion of more sustainable agricultural practices, and in particular how environmental change and the transfer of technology may stimulate the diffusion of water-saving irrigation practices. Farmers make many adaptations in response to climate change, for example, choosing where and whether to irrigate (Mendelsohn 2008). Agriculture is the largest consumer of freshwater on the planet, and the diffusion of water-saving irrigation practices is critical in regions that may face increasing water stress in the short and medium term (UNESCO 2020).

We analysed a case of the state of São Paulo (SP), Brazil, between 2006 and 2017; SP is located in a region with a predominantly humid tropical climate and abundant water supply. However, SP already faced a severe water supply crisis in 2014 (Côrtes *et al.* 2015). This state is the second-largest agricultural producer in Brazil: the gross value-added of its agricultural production (R $61.6 billion, or US$1.86 billion) corresponded to 13.2 per cent of the country's total in 2017 (IBGE 2020). The main crops cultivated in SP in terms of production value are sugarcane, soy, oranges, and coffee (Silva *et al.* 2020). Moreover, SP also has the largest area of irrigation in the country—1.3 million hectares in 2015, or 18.7 per cent of the country's total (ANA 2017)—and has established itself as a forerunner in the use and diffusion of irrigation techniques. The main irrigation systems adopted in SP are the sprinkler (with a total number of 66 systems, or 748,000 ha covered) and localised irrigation systems (29 systems, or 331,600 ha) (IBGE 2020).

2. The adoption and diffusion of technologies in agriculture

The three primary factors associated with the adoption and diffusion of new technologies in agriculture are institutional constraints, risk perceptions and the transmission of information (Genius *et al.* 2014; Salazar *et al.* 2019).

Institutional constraints include any related institutions and their transactional costs and policy deficiencies—such as the availability of credit, tenure and infrastructure—that affect farmers' decisions to adopt new technologies (Salazar *et al.* 2019). Among these institutional constraints, literature has demonstrated that the diffusion of new technologies in agriculture primarily relies on policies that effectively externalise technological knowledge that is not easily internalised (de Janvry *et al.* 2016). For example, farmers may need subsidies to adopt new technologies because they otherwise cannot capture the full benefits of adoption.

Cooperatives and farmer's associations may attenuate institutional restrictions and contribute to the diffusion of new technologies (Miyata and Fujii 2007). In Brazil, cooperatives and farmers' associations are key institutions that facilitate the diffusion of technological knowledge. As many farms have little access to technical training or such information technologies as computers and Internet access, they lack traditional channels to transmit technological knowledge in agriculture (Mendes *et al.* 2014). In this context, cooperatives are key intermediaries in transmitting technological knowledge and agricultural innovation, for example, by providing public extension services or bridging the gap between research and policy systems and everyday farming practices (Yang *et al.* 2014). Nearly 21 per cent of Brazilian farmers are members of cooperatives or farmers' associations, and cooperatives are stronger among smallholders and family farmers (IBGE 2020).

The second group of factors considered in our analysis relates to water supply and climate change, and involves farmers' exposure to and perceptions of risk. Risk is a major factor affecting the diffusion of agricultural innovations (Doole *et al.* 2019). Farmers are typically uncertain about new technologies' characteristics and performance and how these factors may interact with random events that affect agriculture (Ward and Pede 2015). However, the risks and uncertainties associated with climate change may force farmers to adapt to climate-smart technologies (Falco *et al.* 2011, Gori *et al.* 2018). Although technological advances have increased the amount of information available for decision-making, climate change remains an important source of uncertainty (Seo 2011).

The risks and uncertainties caused by climate change became particularly evident in SP in the early 2010s, when the state experienced a sharp decline in precipitation during its rainy season between September and March, and overall increasing temperatures in the winter (Maia *et al.* 2018). In 2014, during the peak of the SP water crisis, the total value of temporary crop production decreased by 5 per cent in the state, while at same time it increased by 7 per cent at a national level (IBGE 2020). We posit that water scarcity and increasing climate risks may have triggered innovative approaches to improve farm irrigation systems (Connor *et al.* 2009).

The third factor considered in our analysis is the social spillover effect linked to the transmission of information in diffusing agricultural technology (Genius *et al.* 2014), as the adoption of new technologies involves information acquisition and learning (Ward and Pede 2015). The uncertainties relative to the benefits of innovation reduce as more information becomes available, knowledge increases, and innovation becomes more attractive (de Janvry *et al.* 2016). Information and learning are achieved through two main channels (Ward and Pede 2015): learning by doing (internal) and learning from others in one's network (external). The former refers to the knowledge achieved through practice and individual improvements, while the latter refers to the transmission of information through the social interaction among farmers.

The concept of learning from others involves the network structures within farmers' local neighbourhoods and the spatial spillovers that occur in using technologies (Batagelj *et al.* 2014; Pratiwi and Suzuki 2017). Farmers may consider their neighbours' experiences to guide their decisions and overcome obstacles, such as information asymmetries. In this respect, a potential adopter's geographic location is an essential factor in information spillovers (Comin *et al.* 2012; Wollni and Andersson 2014). First, spatial proximity can favour contact among agents, leading to the spread of information—and consequently, the diffusion of technology (Batagelj *et al.* 2014). Second, the spatial location influences production characteristics, such as soil type, which can then determine the farmer's choice of technology (Wright *et al.* 2013).

Spatial spillovers also reflect peer effects, or the joint influence of a reference group on individuals' behaviour or outcomes (Sampson and Perry 2018). The peer effect includes three primary categories (Tsusaka *et al.* 2015): endogenous, exogenous and correlated. The endogenous peer effect occurs when an individual's behaviour (or outcome) is influenced by their neighbours' behaviour, or when the diffusion of technology results from the knowledge spillovers generated by interactions between farmers within the same reference group (Richards 2018). The exogenous peer effect occurs when the influence comes indirectly from peers' characteristics (Ioannides and

Topa 2010), for example, when local cooperatives stimulate the diffusion of new technologies in nearby municipalities. Finally, the correlated peer effect occurs when peers behave similarly because they have similar unobserved characteristics or face similar unobserved shocks (Krishnan and Patnam 2014). For example, the quality of water management in nearby localities is an unobserved factor that may impact both the supply of water and farmers' water consumption in one locality.

Few studies have analysed spillover effects on the diffusion of irrigation, although some have tangentially examined the topic. Wright *et al.* (2013) analysed the nature of spatial spillovers in using centre-pivot irrigation (sprinklers) in the state of Texas. The authors suggested that geographical location does matter when adopting pivot irrigation, although they did not discover evidence of spatial spillovers. Sampson and Perry (2019) found strong evidence of peer effects influencing farmers' decisions to adopt groundwater irrigation in Kansas. The authors also suggest that the peer effect decreases as distance and the number of adopting neighbours increases. Peer effects are also more important in disseminating new irrigation systems because information is more restricted. For example, Genius *et al.* (2014) analysed the role of information transmission in the adoption and diffusion of drip-based irrigation systems to reveal the existence of peer effects through farmers' social learning and access to extension services. Sampson and Perry (2019) also found evidence of peer effects in the diffusion of low-energy precise application technology, which is known for its water-saving benefits.

One primary empirical challenge in estimating spillover effects is the reflection problem (Manski 1993), which arises when attempting to infer whether diffusion in one neighbourhood influences or is influenced by diffusion in another neighbourhood. The potential simultaneous diffusion of irrigation between two or more localities implies that we might have difficulty distinguishing real spillover effects (endogenous or exogenous) from the correlated effects (Bramoullé *et al.* 2009; Gibbons and Overman 2012). According to Angrist (2014), the correlation between individuals and their peers may not necessarily be interpreted as a causal relationship, and thus, the strength of identifying spillover effects remains a key issue in the literature (Goldsmith-Pinkham and Imbens 2013).

3. Materials and methods

3.1 Data source and dependent variable

We used a panel of municipal-level data for all 645 municipalities in SP for 2006 and 2017, with information sourced from the National Agricultural Census conducted by the Brazilian Institute of Geography and Statistics (IBGE) in 2006 and 2017. We also used data from the Municipal Agricultural Survey conducted by the IBGE and weather stations from the National Meteorological Institute.

We used data from the National Agricultural Census to calculate two dependent variables: the proportion of farms in the municipality that used sprinkler irrigation in the crop year and the proportion of farms that used localised irrigation. Sprinkler irrigation includes centre-pivot, travelling (self-propelled), water-reel and conventional sprinkler systems, while localised irrigation includes drip-based and micro-sprinkler systems. Sprinkler and localised irrigation systems accounted for 96 per cent of SP's total irrigated agricultural land in 2017 (IBGE 2020).[1] The average percentage of all farms (both dryland and irrigated farms) in SP municipalities that used localised irrigation increased from 2.3 per cent in 2006 to 7.7 per cent in 2017, and the average percentage of all farms that used sprinkler irrigation remained close to 7 per cent (Table 1).

Sprinkler irrigation systems were concentrated in the eastern region of SP, close to São Paulo City (Figure 1). In 2006 in some municipalities the use rate of this technology was 60-80 per cent of farms. This high concentration may relate to the prevailing crops in these municipalities, such as fruits and vegetables. This region also used mostly surface water resources—such as from rivers, springs and lagoons—which are essential for adopting sprinkler irrigation systems (DAEE and UNESP 2013). The most relevant change between 2006 and 2017 involved the expansion of localised irrigation systems, which occurred in the north-western and southern regions and was characterised by the cultivation of coffee, fruits and vegetables (ANA 2017).

3.2 Independent variables

We used two main explanatory variables related to environmental change: the aridity index and access to water resources. Using data from the National Meteorological Institute, we computed the aridity index using the logarithm of the ratio between the average temperature and total precipitation over the past 10 years in each municipality. This variable is a proxy for both climate aridity and medium- and long-term climate change (Genius *et al.* 2014). One primary advantage of this indicator is that it includes the combined effects of both temperature and precipitation; for example, the effects of high precipitation may offset those of high temperatures. We considered climate seasonality by computing the index for both the coldest and driest seasons (winter, or between April and September) and the hottest and rainiest seasons (summer, or between October and March). These seasons presented opposite dynamics between 2006 and 2017 (Table 1): summer became more arid (the index increased by 9.6 per cent) and winter became less arid (the index decreased by −12.4 per cent).

We used the National Agricultural Census data to compute a variable related to access to water resources: the share of farms in the municipality

[1] Other irrigation systems in SP include surface (2% of all irrigated land), subsurface (1%) and wet systems (1%; (IBGE 2020).

Table 1 Municipal averages and standard deviations, SP, 2006 and 2007

Variables	Source	2006		2017	
		Mean	Standard deviation	Mean	Standard deviation
Dependent variables					
Sprinkler Irrigation	CNA	6.67	0.102	7.34	0.099
Localised Irrigation	CNA	2.34	0.038	7.67	0.088
Independent (interest) variables					
Aridity index—Dry Season	INMET	0.067	0.013	0.058	0.012
Aridity index—Wet Season	INMET	0.022	0.002	0.024	0.002
Access to Water Resources	CNA	84.03	0.170	88.92	0.125
Control variables					
Types of crops					
Sugar cane	CNA	14.96	0.17	13.42	0.16
Coffee	CNA	7.08	0.13	4.92	0.12
Soy	CNA	1.84	0.07	4.16	0.11
Corn	CNA	11.84	0.11	13.18	0.13
Bean	CNA	2.44	0.06	2.29	0.06
Mango	CNA	1.13	0.04	0.93	0.04
Banana	CNA	2.79	0.09	3.62	0.11
Orange	CNA	5.60	0.12	2.56	0.06
Vegetables	CNA	8.02	0.15	14.03	0.19
Forestry	CNA	5.46	0.07	7.26	0.11
Education					
Secondary education or more	CNA	32.24	0.13	44.02	0.12
Farmers' age					
Between 25 and 45 years	CNA	25.27	0.09	16.55	0.06
Between 45 and 65 years	CNA	49.28	0.10	48.49	0.08
Over 65 years	CNA	22.07	0.07	29.60	0.08
Farmers' characteristics					
Women	CNA	8.38	0.04	11.60	0.06
Farm is managed by the farmer	CNA	72.63	0.16	73.94	0.13
Farm is managed by administrator	CNA	23.59	0.13	13.94	0.08
Farmer lives in the farm	CNA	55.97	0.21	49.82	0.18
Family farming and association					
Family farming	CNA	59.97	0.17	60.32	0.15
Farmers' association	CNA	30.49	0.20	35.47	0.20
Land tenure arrangement					
Owned by the farmers	CNA	83.04	0.18	76.84	0.17
Leased	CNA	10.87	0.08	15.65	0.10
Temporary land concession	CNA	2.23	0.08	4.39	0.13
Occupation of public land	CNA	3.15	0.07	1.41	0.04
Technical orientation					
From government	CNA	16.28	0.17	9.65	0.13
From industry	CNA	2.85	0.05	2.84	0.05
From private companies	CNA	4.35	0.07	1.15	0.02
From NGOs	CNA	0.15	0.01	0.14	0.01
Soil management					
Conventional tillage	CNA	32.94	0.18	31.78	0.17
Minimum tillage	CNA	9.66	0.10	14.97	0.12
No-tillage	CNA	3.01	0.08	7.42	0.12
Conservation practices					
Agricultural terraces	CNA	44.90	0.23	37.38	0.24
Fallow ground	CNA	4.35	0.06	15.18	0.13

Table 1 (*Continued*)

Variables	Source	2006		2017	
		Mean	Standard deviation	Mean	Standard deviation
Contour ploughing	CNA	9.16	0.11	9.43	0.11
Crop rotation	CNA	9.63	0.12	22.64	0.18
Pest control and soil correction					
Fertiliser	CNA	51.43	0.21	60.73	0.19
Pesticides	CNA	38.72	0.21	59.10	0.22
Soil pH correction	CNA	29.74	0.14	38.94	0.16
Employment, production and credit					
Number of employees	CNA	1412	1378	1455	1482
Production value—previous year	PAM	50,426	65,984	67,213	84,015
Credit for production	CNA	12.99	0.09	15.40	0.09
Machines and equipment					
Tractors	CNA	37.46	0.18	45.63	0.18
Other machines	CNA	28.44	0.21	34.81	0.26
Land size					
Between 5 and 50 hectares	CNA	25.36	0.15	50.93	0.15
Between 50 and 500 hectares	CNA	8.40	0.09	20.90	0.11
500 hectares or more	CNA	1.19	0.02	3.45	0.05

Source: Data from CNA 2006/2017, PAM 2005/2016 and INMET.

that had water sourced from springs, rivers, weirs or wells. Of the farms surveyed, 84 per cent declared access to such water sources in 2006, and 89 per cent in 2017. The primary advantage of this variable is that it avoids potential endogeneity from the explanatory water supply because irrigation and the water supply may be jointly determined. Access to water sources on the farm affects the diffusion of irrigation systems. However, irrigation diffusion does not imply changes in access to water resources, despite affecting the amount of water the farmer can pump.

Our control variables are based on primary recommendations from literature (Dridi and Khanna 2005; Koundouri *et al*. 2006; Monaco *et al*. 2014), as follows: the main crops in SP represented by the proportion of farms cultivating sugarcane, coffee, soy, corn, beans, mangos, bananas, oranges and vegetables, and forestry farming; farmers' characteristics, represented by the proportion of farmers as grouped by education, age, gender, farm management and residence in the farm; the proportion of family farms; the proportion of farms that are members of a cooperative or farmers' association; land tenure arrangement, represented by the proportion of farms that are owned by the farmers, leased, under a temporary land concession or occupy public land; technical assistance represented by the proportion of farms that received technical training from the government, industry, private companies or NGOs; soil management represented by the proportion of farms with conventional, minimum or no-tillage operations; conservation practices represented by the proportion of farms cultivating with agricultural terraces, fallow ground, contour ploughing or crop rotation; pest control and soil correction, represented by the proportion of

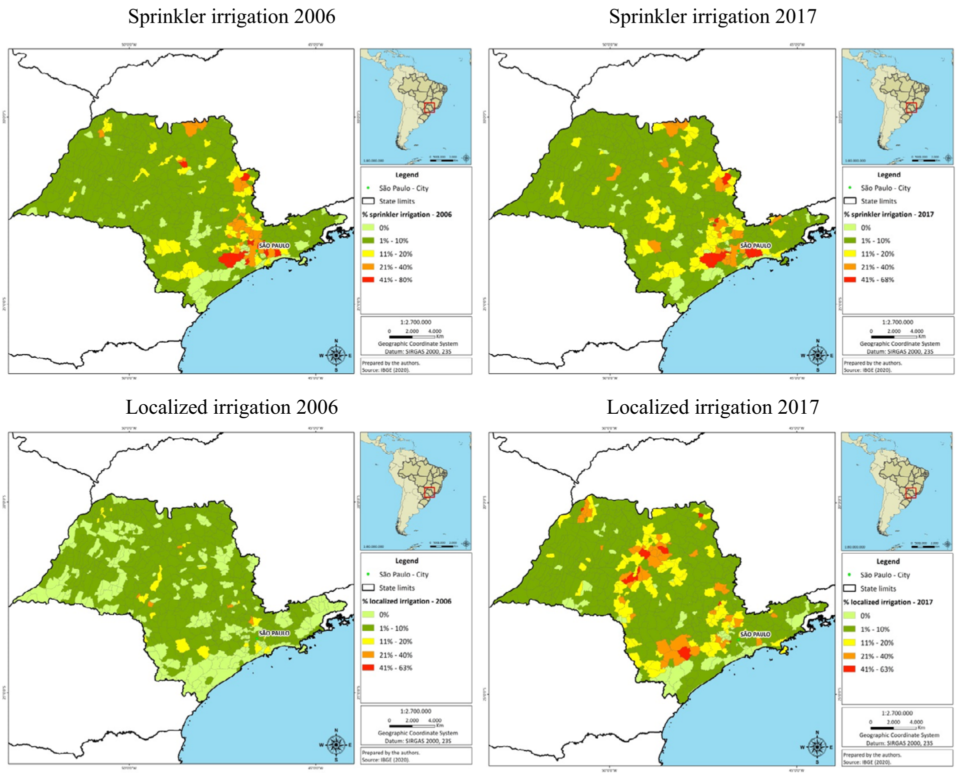

Figure 1 Percentage of farms in each municipality using sprinkler and localized irrigation systems, SP, 2006 and 2017. Source: Data from CNA 2006/2017, PAM 2005/2016 and INMET [Colour figure can be viewed at wileyonlinelibrary.com]

farms using fertiliser, pesticides and products to correct the soil's acidity; employment and production, represented by the log of the total number of employees in the municipality, log of the production value in the previous year,[2] and the proportion of farms that received credits for production; the proportion of farms that used tractors or other machines; and land size, represented by the proportion of farms with fewer than 5 hectares, as a reference; 5 to 50 hectares; 50 to 500 hectares; or 500 hectares or more.

As noted in Table 1, the main changes between 2006 and 2017 were as follows: increased educational attainment (from 32 to 44 per cent of farmers with at least a secondary education); population aging (from 22 to 30 per cent of farmers aged 65 or older); reduced access to technical assistance (from 24 to 14 per cent of farms that received some type of technical training); increased cultivation of vegetables (from 8 to 14 per cent); and increased use of minimum or no-tillage soil management (from 13 to 22 per cent), tractors or other machinery (from 66 to 80 per cent), fertilisers (from 51 to 61 per cent) and pesticides (from 39 to 59 per cent).

[2] The use of lagged production values avoids the reverse causality between the use of irrigation and the value of production.

3.3 Empirical strategy

Our benchmark model assumes that the diffusion of the jth type of irrigation (Y_j, with $j = 1$ for sprinkler irrigation and $j = 2$ for localised irrigation) is a function of environmental variables (vector **Env**, containing the aridity index and access to water sources) and a set of control variables (vector **x**):

$$Y_{j_{it}} = \alpha_{j_t} + \mathbf{Env}'_{it}\boldsymbol{\delta}_j + \mathbf{x}'_{it}\boldsymbol{\beta}_j + c_{j_i} + e_{j_{it}} \tag{1}$$

where vector $\boldsymbol{\delta}$ contains the coefficients associated with environmental variables, and vector $\boldsymbol{\beta}$ contains the coefficients of the control variables for each model ($j = 1$ or 2). The term c represents unobserved municipal heterogeneities that are time-invariant (e.g. soil type), controlled by fixed effects (*within* transformation). The term α is the time-varying intercept, which is constant across municipalities but varies from year to year (e.g. macroeconomic cycles). This term is controlled by a binary variable that assumes a value of one in the year 2017. The random error of each model j is represented as e.

Inspired by literature on peer effects, we test different specifications of the spatial models for Equation (1). The first specification evaluates the existence of endogenous (peer or spillover) effects on the diffusion of irrigation, or specifically, technological spillovers in neighbouring municipalities (Krishnan and Patnam 2014). We added the explanatory variable $\mathbf{w}'_i\mathbf{Y}_j$, which is the spatial lag of the dependent variable and represents the percentage of farms that adopted the same type of irrigation in neighbouring municipalities. This strategy is known as the spatial autoregressive (SAR) model (Anselin 2001):

$$Y_{j_{it}} = \alpha_{j_t} + \rho_j\mathbf{w}'_i\mathbf{Y}_{j_t} + \mathbf{Env}'_{it}\boldsymbol{\delta}_j + \mathbf{x}'_{it}\boldsymbol{\beta}_j + c_{j_i} + e_{j_{it}} \tag{2}$$

where the spatial weight vector $\mathbf{w}_i$ contains positive values for the five municipalities closest to the observed municipality, and zero otherwise. These positive values are equal to $\frac{1}{d^n_{ij}}$, where d^n_{iJ} is the normalised distance between municipalities i and j ($d^n_{iJ} = d_{ij}/\sum_{j=1}^{5} d_{ij}$, where d_{ij} is the distance in kilometres between municipalities i and j). The normalised distance is proportional to the spatial distance and $\sum_{j=1}^{5} d^n_{ij} = 1$. The vector $\mathbf{Y}_{j_t}$ contains the municipal percentage of irrigation adoption j in period t. The spatial autocorrelation coefficient ρ_j represents the degree of dependence between the adoption of irrigation j in municipality i and its adoption in neighbouring municipalities. This coefficient is restricted to values between -1 and 1 to avoid explosive behaviour in the spatial association (LeSage and Pace 2009).

The second specification assesses the presence of exogenous effects in the diffusion of irrigation, or the effect of changing neighbouring characteristics (Sampson and Perry 2018). We used spatially lagged X-variable (SLX) models, adding the average values of the control variables in the neighbourhood ($\mathbf{w}'_i\mathbf{x}_t$) (Autant-Bernard and Lesage 2011):

$$Y_{j_{it}} = \alpha_{j_t} + \mathbf{Env}'_{it}\boldsymbol{\delta}_j + \mathbf{x}'_{it}\boldsymbol{\beta}_j + \pi_j\mathbf{w}'_i\mathbf{x}_t + c_{j_i} + e_{j_{it}} \tag{3}$$

where coefficient π_j measures the degree of association between the neighbourhood's exogenous characteristics and the adoption of irrigation j in municipality i. Specifically, we were interested in evaluating how the neighbourhood' level of participation in cooperatives or farmers' association may affect the diffusion of irrigation systems in each municipality.

The third specification assesses the existence of correlated effects, or the influence of unobservable neighbourhood characteristics on irrigation diffusion (Tsusaka *et al.* 2015). We used the spatial error model (SEM), adding spatial lags of the error ($\mathbf{w}'_i\boldsymbol{\xi}_{j_t}$):

$$Y_{j_{it}} = \alpha_{j_t} + \mathbf{Env}'_{it}\boldsymbol{\delta}_j + \mathbf{x}'_{it}\boldsymbol{\beta}_j + c_{j_i} + \xi_{j_{it}}, \tag{4}$$

where

$$\xi_{j_{it}} = \lambda_j\mathbf{w}'_i\boldsymbol{\xi}_{j_t} + e_{jit}$$

where the coefficient λ denotes the spatial autocorrelation of the errors. Equation (4) suggests that the errors ξ are a function of the average error in the neighbourhood ($\mathbf{w}'_i\boldsymbol{\xi}_t$) plus a random error ($e$). We also impose the restriction $|\lambda| < 1$ to avoid an unstable spatial autocorrelation behaviour (Fingleton 2008).

Finally, we tested our estimates' robustness by combining different spatial model specifications. These combinations assume that spatial spillover effects may be jointly defined by combinations of endogenous, exogenous and correlated effects (Krishnan and Patnam 2014; Tsusaka *et al.* 2015):

$$Y_{j_{it}} = \alpha_{j_t} + \rho_j\mathbf{w}'_i\mathbf{Y}_{j_t} + \mathbf{Env}'_{it}\boldsymbol{\delta}_j + \mathbf{x}'_{it}\boldsymbol{\beta}_j + c_{j_i} + \xi_{j_{it}}, \xi_{j_{it}} = \lambda_j\mathbf{w}'_i\boldsymbol{\xi}_{j_t} + e_{jit} \tag{5}$$

$$Y_{j_{it}} = \alpha_{j_t} + \rho_j\mathbf{w}'_i\mathbf{Y}_{j_t} + \mathbf{Env}'_{it}\boldsymbol{\delta}_j + \mathbf{x}'_{it}\boldsymbol{\beta}_j + \pi_j\mathbf{w}'_i\mathbf{x}_t + c_{j_i} + e_{j_{it}} \tag{6}$$

$$Y_{j_{it}} = \alpha_{j_t} + \mathbf{Env}'_{it}\boldsymbol{\delta}_j + \mathbf{x}'_{it}\boldsymbol{\beta}_j + \pi_j\mathbf{w}'_i\mathbf{x}_t + c_{j_i} + \xi_{j_{it}}, \xi_{j_{it}} = \lambda_j\mathbf{w}'_i\boldsymbol{\xi}_{j_t} + e_{jit} \tag{7}$$

Equation (5) is a spatial autocorrelation (SAC) model that assumes the joint existence of endogenous ($\mathbf{w}'_i\mathbf{Y}_j$) and correlated ($\mathbf{w}'_i\boldsymbol{\xi}_t$) effects. Equation (6) represents an SDM that assumes the joint existence of endogenous ($\mathbf{w}'_i\mathbf{Y}_j$) and exogenous ($\mathbf{w}'_i\mathbf{x}_t$) effects. Finally, Equation (7) is a spatial Durbin error model (SDEM), which assumes the joint existence of exogenous ($\mathbf{w}'_i\mathbf{x}_t$) and correlated ($\mathbf{w}'_i\boldsymbol{\xi}_t$) effects.

We estimated Equation (1) using the generalised least-squares method with heteroscedasticity-consistent standard errors. Equations (2) through (7) use quasi-maximum likelihood estimates, which obtain consistent and asymptotically efficient estimators in the presence of spatial lags (Lee 2004). One main advantage of these estimators in the context of spatial spillover effect analysis involves an assumption of the simultaneity between Y_j and $\mathbf{w}_i{}'\mathbf{Y}_j$, in that the irrigation diffusion in one municipality may precede the diffusion in the neighbourhood (reflection problem). However, this strategy also assumes that we can induce exogenous changes in $\mathbf{w}_i{}'\mathbf{Y}_j$ by observing changes in other spatial lags ($\mathbf{w}_i{}'\mathbf{x}_t$ and $\mathbf{w}_i{}'\boldsymbol{\xi}_t$; (Gibbons and Overman 2012).

4. Results

4.1 Peer effects on irrigation diffusion

We initially calculated the local indicator of spatial association (LISA) clusters (Anselin 2010) to describe spatial dependence patterns in the diffusion of each irrigation system. The LISA clusters classify municipalities into four groups: high–high group, representing municipalities with a high proportion of adopters that are close to nearby municipalities with a high proportion of adopters (only for spatial association significant at 5 per cent, or $P < 0.05$); low–low, municipalities with a low proportion of adopters that are close to municipalities with low proportions of adopters (only for $P < 0.05$); high–low group, municipalities with a high proportion of adopters that are close to nearby municipalities with a low proportion of adopters (only for $P < 0.05$); and low–high, municipalities with a low proportion of adopters that are close to municipalities with high proportions of adopters (only for $P < 0.05$). In the case of sprinkler irrigation systems, most high–high clusters were located in the eastern part of SP. By contrast, the low–low clusters were concentrated in SP's western region. In the case of localised irrigation systems, high–high and low–low clusters were concentrated in SP's western and eastern regions, respectively (Figure 2).

Table 2 displays the spatial model estimates to identify the existence of endogenous (Equation 2), exogenous (Equation 3) and correlated spillover effects (Equation 4) and their combinations (Equations 5 to 7). The AIC (Akaike information criterion) statistics and LR (likelihood ratio) tests indicate that spatial lags add significant information to explain the diffusion of irrigation systems. The models for sprinkler irrigation demonstrated better goodness-of-fit statistics than the models for localised irrigation, with R-squared values ranging between 46 per cent and 48 per cent (or between 5 per cent and 8 per cent for localised irrigation). However, the estimates for the neighbouring effects (spatial lags) were more significant in the localised irrigation models (Wald's test). The AIC suggests that the best models are the SDM (Equation 6) in the case of localised irrigation and the SDEM (Equation 7) for sprinkler irrigation.

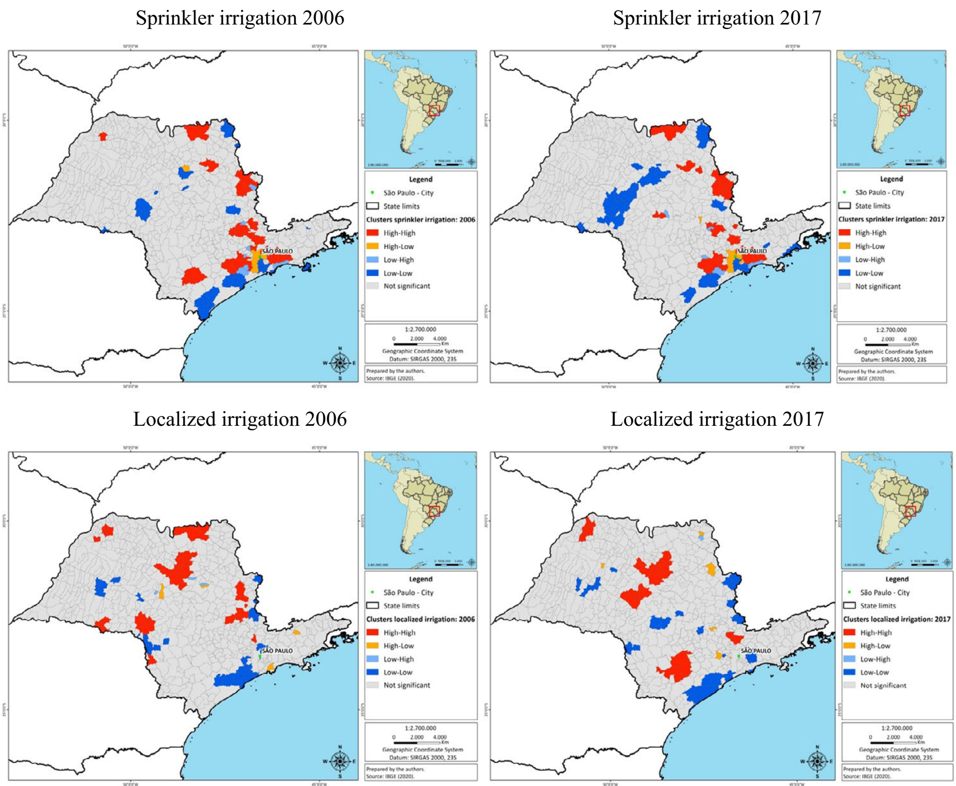

Figure 2 LISA clusters for the proportion of farms in each municipality using sprinkler and localized irrigation systems. SP, 2006 and 2017. Source: Data from CNA 2006/2017, PAM 2005/2016 and INMET. [Colour figure can be viewed at wileyonlinelibrary.com]

Our estimates indicate that the endogenous spillover effect is stronger in the case of localised irrigation; the spatial lag ($\mathbf{w}_i'\mathbf{Y}_j$) is significant at 0.1 per cent in the SAR, SAC and SDM models. The estimates are also robust to different spatial specifications, ranging from 0.424 (SDM) to 0.547 (SAC). In the sprinkler irrigation models, spatial lag was not significant at the 10 per cent level; in other words, the diffusion of irrigation technologies appears to occur only in localised irrigation.

We then tested the existence of exogenous spillover effects using spatial lags for several control characteristics. The spatial lag for the proportion of farms that were members of a cooperative or farmer's association revealed the most significant results in the SDM, SLX and SDEM models. The estimates indicate that the neighbourhood's degree of participation in associations ($\mathbf{w}_i'\mathbf{x}_t$) negatively affects the diffusion of sprinkler irrigation and positively affects the diffusion of localised irrigation. Hence, neighbourhood associations might ease the diffusion of more efficient irrigation technologies.

The sprinkler irrigation systems provided the most robust estimates for correlated spillover effects. In this case, all estimates are positive and significant at 10 per cent (estimates are also significant at 10 per cent in the SEM, SAC and SDEM models), suggesting that unobserved shocks in the neighbourhood may increase the municipality's diffusion of sprinkler systems.

Appendix S1 presents the coefficient estimates on control variables. As anticipated, the type of irrigation is depended on the crops and farm characteristics. For example, localised irrigation is more diffused in municipalities with a higher prevalence of vegetable farming, small farms, farmers with a secondary diploma and farms that received technical assistance from NGOs. By contrast, sprinkler irrigation is more diffused in municipalities with a higher prevalence of mango crops, farms receiving technical assistance from private companies, and farms using tractors and soil correction treatments.

4.2 Decomposition of spatial effects

We used LeSage and Pace's (2009) strategy to decompose the SDM estimates into direct, indirect and total spatial effects. This strategy considers that a change in the explanatory variable X_k can potentially affect the diffusion of irrigation in both municipality i (Y_j) and the neighbourhood of i ($\mathbf{w}_i'\mathbf{Y}_j$). The direct impact represents the effect of changes in X_k in municipality i on diffusion (Y_j) in municipality i. The indirect impact represents the effect that changes in X_k in neighbouring municipalities will have on the diffusion (Y_j) in municipality i. This analysis is restricted to localised irrigation models, which are the only ones that show significant estimates for the endogenous peer effect ($\mathbf{w}_i'\mathbf{Y}_j$). Table 3 shows the decomposition of the explanatory variables of primary interest: climate change and access to water sources. We also checked our estimate's robustness using two spatial-weight matrices: the inverse-distance matrix for the five nearest neighbours and the rook contiguity matrix.[3]

The net impact of changes in the aridity index was only significant in summer. Generally, the estimate for the total effect indicated that the proportion of farms using localised irrigation increased by 0.196 percentage points for each 1 per cent increase in the aridity index in the summer. The total effect as estimated by this decomposition approach (0.196) is larger than the SDM model estimates (0.115) because the former estimate measures the cumulative impact of changes in all municipalities. The indirect effect represented nearly 40 per cent of the total impact of changes in the aridity index. In other words, local climate change may have both local and regional effects on the diffusion of localised irrigation.

[3] The rook spatial-weights matrix assumes a value of one for municipalities sharing common boundaries, except in cases in which these municipalities share only a single corner point.

Table 2 Estimates of the spatial models for the dependent variables related to the diffusion of irrigation systems, SP

Independent variables		SAR		SEM		SAC		SDM		SLX		SDEM	
		Sprinkler	Localised	Sprinkler	Localised	Sprinkler	Localised	Sprinkler	Localised	Sprinkler	Localised	Sprinkler	Localised
Coefficients	**w**′**Y**	0.113	0.434^{***}			−0.099	0.547^{***}	0.112	0.424^{***}				
		(0.073)	(0.041)			(0.185)	(0.088)	(0.074)	(0.042)				
	w′**ξ**			0.189^{*}	0.513^{***}	0.281^{+}	−0.235					0.180^{*}	0.499^{***}
				(0.077)	(0.052)	(0.161)	(0.176)					(0.075)	(0.054)
	w′**x**—Association							-0.080^{*}	0.068^{*}	-0.081^{*}	0.103^{**}	-0.081^{*}	0.067^{+}
								(0.035)	(0.032)	(0.036)	(0.034)	(0.037)	(0.040)
	Water source	0.115^{**}	−0.009	0.115^{**}	−0.006	0.114^{**}	−0.006	0.111^{**}	−0.006	0.112^{**}	0.012	0.112^{**}	−0.005
		(0.035)	(0.030)	(0.036)	(0.030)	(0.035)	(0.030)	(0.034)	(0.030)	(0.035)	(0.033)	(0.035)	(0.030)
	Aridity index—Dry Season	−0.026	−0.002	−0.036	−0.028	−0.043	−0.003	−0.036	0.006	−0.035	−0.002	−0.045	−0.021
		(0.054)	(0.043)	(0.060)	(0.059)	(0.068)	(0.038)	(0.052)	(0.043)	(0.054)	(0.048)	(0.058)	(0.059)
	Aridity index—Wet Season	−0.03	0.126^{*}	−0.023	0.160^{*}	−0.02	0.114^{*}	−0.015	0.115^{*}	−0.018	0.180^{**}	−0.01	0.153^{+}
		(0.050)	(0.052)	(0.057)	(0.080)	(0.062)	(0.045)	(0.049)	(0.051)	(0.049)	(0.055)	(0.055)	(0.078)
Diagnostic Tests	Wald [ρ]	2.4	111.0^{***}			0.4	39.0^{***}	2.3	104.2^{***}				
	Wald [λ]			5.9^{*}	97.4^{***}	3.0^{+}	1.8					5.7^{*}	85.0^{***}
	Wald [**w**′**x**]							5.1^{*}	4.4^{*}	4.9^{*}	9.3^{*}	4.7^{*}	2.7^{+}
	AIC	−5390.4	−5451.4	−5398.1	−5431.5	−5397.5	−5454.3	−5400.7	−5458.9	−5395.8	−5292.5	−5407.5	−5435.4
	LR	9.1^{**}	179.6^{***}	16.7^{***}	159.6^{***}	18.1^{***}	184.4^{***}	21.3^{***}	189.1^{***}	12.4^{***}	18.6^{***}	28.1^{***}	165.6^{***}
	R^2—Overall	0.477	0.053	0.479	0.067	0.474	0.045	0.460	0.067	0.459	0.082	0.463	0.077

$^{***}P < 0.001$, $^{**}P < 0.01$, $^{*}P < 0.05$, $^{+}P < 0.1$.

All models include fixed effects for municipalities, dummy variable for year and control variables for types of crops, education, age, farmers' characteristics, family farming, land tenure arrangement, technical orientation, soil management, conservation practices, pest control and soil correction employment, production, credit, machines and equipment, and land size (see variables in Table 1).

Source: Data from CNA 2006/2017, PAM 2005/2016 and INMET.

Table 3 Decomposition of the total spatial effect of the SDM models for localised irrigation, SP

Independent variables		Main results†				Robustness‡			
		SDM	Decomposition Spatial Effects			SDM	Decomposition Spatial Effects		
			Direct	Indirect	Total		Direct	Indirect	Total
Analysis variables	**w**′**Y**	0.424***				0.475***			
		(0.042)				(0.039)			
	w′**ξ**								
	w′**x**—Association	0.068*				0.070*			
		(0.032)				(0.032)			
	Water source	−0.006	−0.003	−0.001	−0.004	−0.006	−0.003	−0.002	−0.005
		(0.030)	(0.030)	(0.021)	(0.051)	(0.030)	(0.031)	(0.026)	(0.056)
	Aridity index—Dry Season	0.006	0.008	0.006	0.014	0.009	0.011	0.010	0.021
		(0.043)	(0.046)	(0.032)	(0.077)	(0.044)	(0.047)	(0.040)	(0.086)
	Aridity index—Wet Season	0.115*	0.117*	0.079*	0.196*	0.101*	0.103+	0.084+	0.187+
		(0.051)	(0.052)	(0.037)	(0.088)	(0.051)	(0.053)	(0.044)	(0.095)

***$P < 0.001$, **$P < 0.01$, *$P < 0.05$, $^{+}P < 0.1$.
†Inverse-distance spatial weight matrix (5 nearest neighbours).
‡Rook contiguity spatial weight matrix.
All models include fixed effects for municipalities, dummy variable for year and control variables for types of crops, education, age, farmers' characteristics, family farming, land tenure arrangement, technical orientation, soil management, conservation practices, pest control and soil correction employment, production, credit, machines and equipment, and land size (see variables in Table 1.
Source: Data from CNA 2006/2017, PAM 2005/2016 and INMET.

5. Discussion

We analysed spatial spillover effects on the diffusion of more efficient irrigation strategies in SP. Spatial spillovers are linked to peer effects and can be understood in the context of agriculture as farmers' influence in a particular farmer's decision-making (Sampson and Perry 2019). The estimation of spillover effects is a topic of growing concern in economic literature, and few studies have specifically analysed irrigation in agriculture. Our fixed-effects estimators remove unobservable differences that are fixed over time (e.g. institutional rules). Another empirical challenge involves the technological changes in one municipality, which may precede changes in the neighbourhood (reflection problem). Hence, we compare different spatial econometric specifications by considering the simultaneity of irrigation that may exist between two or more municipalities. However, the spatial models' identification strategy is not without criticism, and any causal relationships must be carefully analysed (Gibbons and Overman 2012). In particular, we cannot easily disentangle whether the diffusion of irrigation in one municipality influences or is influenced by diffusion in nearby municipalities.

In SP, the share of farmers using localised irrigation increased more than threefold between 2006 and 2017. The shift to crops that are more susceptible to localised irrigation may partially explain this change in irrigation systems; for example, the share of farmers cultivating vegetables increased by 75 per cent during this period. By contrast, the share of farmers using sprinkler irrigation systems has increased by only 10 per cent. These systems are primarily associated with crops cultivated over large areas, such as sugarcane, soybeans and corn. We controlled for changes in crop type and other production characteristics to evaluate spatial spillovers' net impacts on the diffusion of localised and sprinkler irrigation across municipalities in SP.

Our results highlight that, net of changes in crop type and other production characteristics, spatial spillover effects remain key in understanding localised irrigation diffusion, (Dong *et al.* 2020). Peer effects literature indicates that spatial spillover effects on localised irrigation occur according to three main channels: endogenous, exogenous and correlated effects. Endogenous effects reflect technological spillovers in the diffusion of irrigation, for example, through the transmission of successful experiences (or imitation) of irrigation in neighbouring municipalities (Richards 2018). Similar results for irrigation technologies have been reported by Genius *et al.* (2014) and Sampson and Perry (2019).

However, we did not observe any significant evidence of endogenous effects from sprinkler irrigation. First, this result may suggest that this technology has already reached the end of its diffusion cycle in Brazil: farmers may rely more on their knowledge of this technology than on acquiring information with their peers (Wright *et al.* 2013). Second, this result may suggest that sprinkler irrigation is inefficient and may generate environmental conflicts among adopters in the same watershed (Newman 2019); further, the overuse of water supplies in neighbouring municipalities may curb water use in a given municipality. Some Brazilian regions, including SP, face water scarcity triggered by changes in the rainfall regime and water mismanagement (Garcia *et al.* 2018).

The second diffusion channel is the exogenous effect of changes in observable characteristics in the neighbourhood, which influences irrigation diffusion. We demonstrated that the neighbourhood's degree of participation in cooperatives and associations affects the diffusion of irrigation systems in a municipality. Cooperatives and farmers' associations reflect the level of social interaction in a region, which influences the transmission of information, knowledge and uncertainties regarding the adoption of new technologies (Miyata and Fujii 2007; Maertens and Barrett 2013; Genius *et al.* 2014). Moreover, our estimates indicate that neighbourhood associations negatively impact sprinkler irrigation but positively impact localised irrigation. In other words, social interaction through cooperatives and associations may favour the adoption of more efficient irrigation systems and discourage the diffusion of water-intensive systems.

The third channel is correlated effects, which represent the unobservable factors that influence the diffusion of irrigation systems (Tsusaka *et al.* 2015). Only the diffusion of the sprinkler irrigation system was significantly affected by unobservable factors in the neighbourhood. Among these unobservable factors, sustainable water management practices include on-farm water storage and wetlands, runoff control, improvements to soil quality, environmental preservation and water-pricing policies (Chartzoulakis and Bertaki 2015). Sustainable management practices may generate ecosystem benefits that transcend municipal borders, including the increased availability and quality of water for irrigation, flood control, climate regulation and soil quality maintenance (Maia *et al.* 2018). Since the early 2000s, some SP municipalities have implemented an additional tariff for water use in urban areas (bulk water pricing), which may have saved water for agriculture. However, tariffs are far from perfect and do not vary between municipalities. These tariffs have been defined at the watershed level to minimise their negative socioeconomic impacts (de Brito and de Azevedo 2020).

Our results also confirm that water supply and climatic conditions are essential factors that determine irrigation diffusion (Brouwer *et al.* 2001). One relevant result is that access to water resources affects only the diffusion of sprinkler irrigation. By contrast, the diffusion of localised irrigation seems to be more equitable because it does not relate to the share of farmers with access to water resources. One important implication is that the diffusion of localised irrigation systems may not generate conflicts over access to water resources. The primary sources of irrigation in SP are surface water, such as rivers, and natural or artificial (man made) reservoirs (ANA 2017). Among these water sources, rivers are particularly subject to tension between upstream and downstream users, which can be minimised by the diffusion of water-saving systems.

The diffusion of localised irrigation is also positively associated with summer aridification (Iglesias and Garrote 2015), while the relationship in winter is insignificant. This result may relate to crop choices and planting times, as farmers may adapt as a response to climate change by adopting irrigation, switching to more drought-resistant crops or deliberately changing their cultivation time to the following season (Mendelsohn 2008). The crop choices and planting times in SP primarily occur during the winter. As a result of their drier winters, farmers may choose more drought-resistant crops, such as sugar cane. During the growing season (summer in SP), adopting irrigation may be the only adaptation available to avoid significant losses, as variations in soil moisture can significantly compromise seedlings' development (Negri *et al*. 2005).

Decomposition of the spatial effects demonstrated that the influence of climate change on the diffusion of irrigation occurs through direct (municipality) and indirect (neighbourhood) channels. More importantly, our results indicate that climate variations in the summer may, to some extent, affect the irrigation diffusion in not only a municipality of interest (direct effect), but also neighbouring municipalities (indirect effect). The indirect effect is the result of endogenous peer effects on irrigation diffusion.

This study provides important implications for policies to encourage sustainable agricultural practices. Incentives for irrigation policies adopted by the Brazilian government have been constrained by water policy goals to restrict water scarcity and avoid conflicts with downstream users (dos Ferrarini *et al*. 2019; Multsch *et al*. 2020). Local public policies to stimulate water-saving irrigation systems may benefit farmers and other water users regionally through the spatial spillover. Potential adopters may learn from their peers the full benefits of more sustainable practices (de Janvry *et al*. 2016). Our results also suggest that policies to stimulate sustainable technologies should be integrated with cooperatives and farmer's associations, as these institutions are essential mediators for replacing less efficient (sprinklers) with more efficient (localised) irrigation systems. Generally, through peer effects or associations, collective action mechanisms can encourage adaptive strategies to respond to climate change that favour the proper use of increasingly scarce natural resources.

6. Conclusion

One primary step in proposing adaptation and mitigation policies for climate change involves understanding the determinants of the diffusion of more efficient irrigation technologies. We considered the two most widely available irrigation technologies in Brazil: sprinkler irrigation, the conventional and most popular system; and localised irrigation, which is the most efficient and readily available alternative for water use. The diffusion of localised irrigation primarily relies on the adoption of similar irrigation systems by peer farmers in a neighbourhood. The diffusion of sprinkler irrigation relies more on observable characteristics in the municipality, and on the neighbourhood's unobservable characteristics.

An important implication from our analysis is that the diffusion of more efficient irrigation systems depends on technological spillovers. Policies that stimulate interactions among farmers may ease this transmission of knowledge; however, unobservable factors are particularly important in diffusing sprinkler irrigation. Among these unobservable factors, we can highlight the proper water management practices that may affect a region's water supply and diffusion of less efficient irrigation systems.

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DATA AVAILABILITY STATEMENT

Availability of data and material: The datasets generated during the current study are publicly available and are available from the corresponding author on reasonable request. Code availability: The code generated during the current study are available from the corresponding author on reasonable request.

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