The Neighbor Effect: The Nature of Spatial Externalities in the Decision to Adopt Organic Production Systems

Timothy A. Delbridge* and Cristina Connolly

Agribusiness Department
California Polytechnic State University
***tdelbrid@calpoly.edu**

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The organic agriculture sector in the United States continues to expand. Total organic food sales exceeded $43 billion in 2015 (OTA, 2016) and the number of certified organic farm acres reached a record 4.3 million in 2015 (USDA-NASS, 2016). As the organic food industry becomes mainstream and the nation's largest supermarkets expand their organic offerings, food processors and retailers are increasingly concerned about the future availability of organic food products throughout the supply chain. As a result of occasional supply shortages, there is keen interest in achieving a better understanding of the organic adoption behavior of conventional farms and how that understanding can be translated into more effective extension and policy efforts aimed at supporting farms interested in pursuing organic certification.

Both agricultural economists and rural sociologists have sought to identify characteristics of farms, communities, and markets that tend to support the transition to organic production systems and those that act as barriers to further adoption. Several qualitative studies based on farmer surveys and interviews have pointed to the importance of social support and the availability of relevant technical information in the organic adoption decision (Brock & Barham, 2013; Constance & Choi, 2010; Cranfield, Henson, & Holliday, 2009). Consistent with these results are recent analyses that have highlighted the clustering behavior of organic farms in certain counties and the positive impact that outreach from organic certifiers can have on the creation of these clusters (Marasteanu & Jaenicke, 2015, 2016). However, there is still only a weak understanding of the farm-level decision to switch from conventional to organic production and the degree to which one's proximity to existing organic operations might relate to the social, informational, and market barriers to organic adoption.

This paper explores the role of externalities in the organic transition decision by estimating a spatially explicit model of organic adoption using 21 years of farm-level certification data from the Willamette Valley in Oregon. We analyze the effect that existing certified organic growers and processors have on the probability that nearby farms also achieve organic certification. By focusing on a large study area with organic processors and farms of different type and enterprise mix we are able to provide additional insight into the nature and importance of spatial externalities in the organic adoption decision.

There have been a handful of studies in recent years that have carried out quantitative analyses of spatial patterns of organic adoption in the U.S. and abroad. In the United States, Lewis, Barham, & Robinson (2011) showed that dairy farms in Wisconsin are significantly more likely to adopt organic production methods if there are existing certified organic dairy farms located nearby. However, the authors acknowledged that their analysis was unable to identify the nature of this effect. It may simply be that clustering of organic farms is encouraged by the organic dairy processor to facilitate the daily collection of milk. Wollni & Andersson (2014) explored the spatial patterns of organic adoption among small-scale farmers in Honduras and Läpple & Kelley (2015) analyzed the adoption patterns of livestock producers in Ireland. Using survey data, the authors of both studies were able to conclude that the presence of organic farms significantly increased the probability that nearby farms would also adopt organic methods. However, the degree to which these results are generalizable to the agricultural landscape in the United States is unclear and neither of these studies attempted to separately identify the effect that existing organic farms might have on farms of similar and different farm types.

A recent study on the determinants of organic adoption among farmers in West Virginia found a different result. Farmer et al. (2014) found that interaction with existing organic farmers was associated with a lower probability of organic adoption. This result, while left largely unexplained by the authors, suggests that the relationship between existing and potential organic growers might be more complicated than simply one of an early adopter paving the way for those to follow. A potential explanation for a negative spatial externality could be that existing organic growers might act as competitors for the business of a smaller pool of organic consumers.

We help to fill the gap in the understanding of organic adoption patterns in the United States with three specific contributions. First, we estimate the effect that existing organic farms and processors have on the probability that nearby farms also adopt organic methods in a geographic landscape characterized by substantial agricultural diversity. While a positive spatial externality in the organic adoption decision has been explored among producers of homogenous commodities (Läpple & Kelley, 2015; Lewis et al., 2011; Wollni & Andersson, 2014), this paper is the first to use time-series data on organic adoption to see if this relationship holds more broadly to heterogeneous groups. Second, we are the first to separately estimate the spatial spillovers on operations of differing types, which is necessary to determine the relative importance of social acceptance, technical information exchange, and organic market competition on the farm-level transition decision. Finally, we make a methodological contribution with our use of publically available spatial ground cover datasets along with tax parcel information to identify the locations of conventional farms without access to formal survey or agricultural census data.

This paper proceeds as follows: first, we develop a conceptual model of the farm-level decision to transition from conventional to organic agricultural production. The following section presents a discussion of the data that we use to estimate the model. Finally, we present the results of the spatially explicit econometric model and discuss limitations of the existing analysis and plan the next steps.

Econometric Model of Organic Adoption

The USDA's National Organic Program (NOP) sets forth all standards that must be followed by certified organic operations. Many chemical inputs that are widely used in conventional production are prohibited, and there are minimum requirements on the types of crop rotations and livestock grazing systems that are employed under organic certification. In any given time period a conventional farm has the option of initiating a transition to certified organic production practices by ceasing use of prohibited substances and farming in accordance with the NOP. In addition to the direct costs of organic certification, transitioning farmers must also incur the cost of researching the regulations and ensuring compliance of their operations. They often face production challenges, including reduced yields and increased labor expenses, before they are able to market their products as organic and receive corresponding price premiums. Finally, many organic farmers report that they have faced social costs associated with their perceived rejection of the dominant method of farming in their communities (Brock & Barham, 2013; Duram, 1999)

When deciding whether or not to exercise the option to pursue organic certification, farm managers must contend with uncertainty about the costs and availability of inputs, availability of organic marketing channels, prices of both organic and conventional crops, changes in crop and animal yield outcomes, and the optimal use of labor and machinery. The degree of uncertainty, and the costliness with which uncertainty is resolved, can be affected by the decision maker's interaction with existing certified organic farms and processors. Existing organic operations might lessen the risk in organic adoption by reducing uncertainty about how to navigate the production and regulatory considerations involved in the organic transition process. Nearby organic farms might also reduce the social costs incurred by farms that pursue an organic system within an area dominated by conventional growers. Finally, it is also possible that there are negative spatial spillovers created by existing organic farms that act as competitors in the market for certified organic crop and livestock products. This “neighbor effect” – the degree to which existing organic farms impact the probability that a nearby farm achieves organic certification - is the crux of what we are investigating in our analysis.

Since the decision to pursue organic certification involves both irreversible and uncertain costs we employ a real option investment model as our theoretical framework (Delbridge & King, 2016; Lewis et al., 2011; Musshoff & Hirschauer, 2008). This allows us to incorporate the actuality that by choosing to initiate an organic transition, an operator surrenders the option of waiting for additional technical or market information that may reduce uncertainty. Under the real options framework a profit maximizing farm manager will transition when the net present value of expected returns from organic production exceeds the cost of transition and the value of the option to delay the decision until a later date. An increase (decrease) in the expected profitability of organic farming relative to conventional farming will lower (raise) the adoption threshold and increase (decrease) the probability that a farm manager pursues organic certification. One factor that may decrease the expected profitability or organic management is the presence of competitors in local organic markets. Likewise, any reduction (increase) in the uncertainty or cost associated with transition will increase (decrease) the adoption probability. We propose that the presence of neighbors that have already transitioned to organic production might help to reduce the social costs of adopting a potentially controversial production system and reduce the costs of learning and implementing the new system. However, ex-ante it is unclear whether the potential negative externality caused by competition is outweighed by the potential positive externalities created by the assistance and support of early adopters. To distinguish between these effects we separate organic neighbors into certified organic processors and farms of similar and different farm types. We hypothesize that competitive forces and the exchange of specialized technical information would be most relevant for farms of similar type, while social support alone could come from farms of any type and organic processors.

In the vein of Lewis et al. (2011) we define the present value of organic adoption for farm n at time t as

$$NV_{nt} = V(\boldsymbol{os}_{nt}, \boldsymbol{od}_{nt}, \boldsymbol{op}_{nt}, \boldsymbol{x}_n) + \mu_n + v_{nt}$$

where V represents the portion of the farmer's value function that is observable to the researcher, $\boldsymbol{os}_{nt}$ is the number of organic neighbors that are of the same farm type, $\boldsymbol{od}_{nt}$ is the number that are of a different farm type, and $\boldsymbol{op}_{nt}$ is the number of nearby organic processors. x_n is a vector that includes all observable farm-level attributes that do not change over time, such as location, operator, or farm size. This observable portion can be formulated as a linear function with estimable parameters:

$$V\left(\boldsymbol{os}_{nt}, \boldsymbol{od}_{nt}, \boldsymbol{op}_{nt,}\right) = \delta_1 \boldsymbol{os}_{nt} + \delta_2 \boldsymbol{od}_{nt} + \delta_3 \boldsymbol{op}_{nt} + \beta x_n$$

As for the nonobservable component, μ_n represents all non-time varying farm characteristics that are known to the farmer but unobservable by the researcher, while v_{nt} is a time and farm specific error component that is distributed i.i.d. standard normal. Formally, we model the probability of a conventional farmer deciding to transition to organic production as

$$\Pr\left(y_{nt} = 1 \middle| \boldsymbol{os}_{nt}, \boldsymbol{od}_{nt}, \boldsymbol{op}_{nt,} \boldsymbol{x}_n\right) = \Phi(\delta_1 \boldsymbol{os}_{nt} + \delta_2 \boldsymbol{od}_{nt} + \delta_3 \boldsymbol{op}_{nt} + \beta x_n + \mu_n)$$

where we assume Φ is the standard normal cumulative distribution. However, one assumption of this model is that $\mu_n|\boldsymbol{o}_{nt}$~Normal(0,$\sigma_c^2$), where $\boldsymbol{o}_{nt}$ is the total number of organic neighbors ($\boldsymbol{os}_{nt} + \boldsymbol{od}_{nt} + \delta_3\boldsymbol{op}_{nt}$). While this assumes independence, it is likely that the number of organic neighbors is endogenous and spatially correlated with unobservable farm characteristics. For instance, it could be that neighboring farms all live in an area with lower priced inputs used in conversion or soil that is particularly amenable to organic practices. However, Mundlak (1978) and Chamberlin (1980) demonstrated that it is still possible to obtain consistent estimates of the model by using fully conditional maximum likelihood and assuming the particular correlation structure $\mu_n|\boldsymbol{o}_{nt}$~Normal($\psi + \overline{\boldsymbol{os}_{nt}}\zeta_1 + \overline{\boldsymbol{od}_{nt}}\zeta_2 + \overline{\boldsymbol{op}_{nt}}\zeta_3$,$\sigma_a^2$). In this expression $\overline{\boldsymbol{os}_{nt}}$ is the average number of neighbors of the same type over time, $\overline{\boldsymbol{od}_{nt}}$ is the average of a different type, $\overline{\boldsymbol{op}_{nt}}$ is the average number of organic processors nearby, and σ_a^2 is the variance of a_n in the equation $\mu_n = \psi + \overline{\boldsymbol{os}_{nt}}\zeta_1 + \overline{\boldsymbol{od}_{nt}}\zeta_2 + \overline{\boldsymbol{op}_{nt}}\zeta_3 + a_i$. This allows us to treat our binary time-series data as a random effects probit model.

Data

Estimating a model of the spatial dynamics of the organic adoption decision requires farm-level certification data and location information on the full population of potential organic farms (i.e. conventional farms) over time. To be able to identify the differences in spatial effects that might result from proximity to organic operations of varying type, information on the class of products produced by each farm is also necessary. We must additionally include contextual data that accounts for community level characteristics and the changing market dynamics that affect the profitability of an organic transition. Given the lack of publically available databases of conventional and organic farm operations, satisfying these data needs is a challenge, and requires innovative use of existing sources of spatial data.

Study Area

Oregon is an excellent setting for an analysis of the spatial patterns of organic adoption for a number of reasons. There are many organic farms and processors in the state and there has been continued growth in the number of certified operations over the past two decades (Table 1). There is also considerable diversity of farming operations in Oregon, allowing for the estimation of distinct spillover effects for farms of differing type. Moreover, most organic farms in Oregon are serviced by one of a small number of organic certifiers, making data collection feasible. Since a large majority of the state's organic farms are concentrated in the western part of the state we limit the study area to counties within the Willamette Valley. Unfortunately, there are some Oregon counties that contain a significant number of organic farms but for which we have been unable to acquire sufficient tax parcel data for inclusion in the study.

Organic Certification Data

The USDA-NOP maintains an up-to-date and publicly available database of organic certification records for operations worldwide. The data includes the name and location of the operation, as well as some information on whether the operation is an organic processor, livestock producer, crop grower, etc. However, these data are only available for years 2010 to present. There is no single source of organic certification records prior to 2010.

Since a farm's certification status is typically only reflected in USDA databases after a 3-year transition process, a longer series of data is necessary to empirically estimate the dynamics of the organic adoption decision. Through cooperation with the major organic certifiers that are active in Oregon we have obtained a 21-year series of data showing the location and certification dates of certified operations in the state. We have been able to create an Oregon-specific certification database that includes all operations certified by Oregon Tilth, California Certified Organic Farmers (CCOF), the Oregon Department of Agriculture (ODA), and the Washington State Department of Agriculture (WSDA) since 1996. While there are other smaller certifiers from which we do not have data, those represented in the dataset used in the study represent roughly 90% of the certified farms and processors in Oregon (USDA-AMS, 2016). Figure 1 shows the locations of the certified organic operations in Oregon from 1996 to 2016.

Approximating the Population of Conventional Farms

While the database of organic certification records provides information on the farms and processors that have made the decision to adopt organic production systems, it does not provide information on the farms that have declined to pursue certification. In order to estimate the impact that organic operations might have on the certification decision of nearby farms we must find a way to represent these conventional farms. As there is no accessible database of conventional farm addresses and the types of crops or livestock products that they grow, this poses a considerable challenge. In this study we use the USDA-NASS Cropland Data Layer (CDL) along with tax parcel data obtained from county governments to approximate a population of farms.

The CDL uses satellite imagery to annually map the ground cover for the entire continental United States. Many specific crops are identified as well as forestland and developed areas. We designate individual tax parcels as farmed or not farmed by overlaying the 2014 CDL on a spatial set of tax parcel data. Tax parcels that include more than 7,200 m^2 (i.e. 1.78 acres) of cropland are considered agricultural parcels. Figure 2 demonstrates how this method is used with Benton County as an example. We further categorize the agricultural parcels as "specialty crop" parcels if the CDL indicates the presence of specialty crops on the property.

Using this method, there are 34,994 tax parcels identified as farm units in the 14 county study area. According to the 2012 Agricultural Census there were 23,109 farms in these counties in that year. Therefore we can conclude that the method that we use to identify farm units overstates the true number of decision making units by roughly 50%. We would expect that the number of farmed parcels to be higher than the number of farms because many farms likely operate on multiple parcels. Since we are over representing farms that have chosen not to adopt organic management, one would rightly anticipate the estimates of adoption probability to be understated.

Other Contextual Information

We control for the distance from the farm parcel to the nearest urban area to account for differences in direct marketing opportunities that may impact certification decisions (Torres, Marshall, Alexander, & Delgado, 2016). We also include demographic data at the county level, including the median household income, percentage of the population that has earned at least a bachelor's degree, and the prevalence of liberal political beliefs as measured by the share of the vote won by the Green Party in the 2016 presidential election. Each of these demographic variables is expected to have a positive effect on the probability that a farm in the county achieves organic certification. Finally, we include a year variable that accounts for the trend of increasing organic operations as the organic market has developed over time.

The model specifications that we have just discussed do not account for the fluctuating relative profitability of organic and conventional cropping and livestock systems over time. The expected profitability that can be achieved by transitioning to an organic production system is often a primary consideration of potential organic producers and omitting any measure of profitability from the model can lead to biased estimates of included parameters. Unfortunately, there are not good time-series data on the profitability of these organic systems over time relative to their conventional counterparts.

Results

Our results suggest that there is a detectable spatial externality created by certified organic farms on the transition decision of nearby farms, though perhaps surprisingly, the net effect is negative. In our simplest model specification we first test whether or not an additional organic operation, including farms of all types and organic processors, affects the probability that a nearby farm parcel is certified as organic three years later. We estimate this model and subsequent models using a 5 mile, 10 mile, and 20 mile radius in the definition of a "nearby" operation. In table 2 we can see that the average partial effect (APE) of a single additional operation of any type within a 5 mile radius is a 0.00078% decrease in the annual probability that a given parcel certifies as organic. As we would expect, the magnitude of the effect decreases with an increase in the size of the neighbor count radius. That is, an existing organic operation that is nearly 20 miles away has a smaller impact on a given farm's organic adoption decision than an existing organic operation that is less than 5 miles away. While this is a statistically significant result it is a very small effect. However, to put this into context, the average annual probability that a farm parcel in the study area is certified as organic from 2000 to 2016 is roughly 0.0057%. A decrease of 0.00078 percentage points represents nearly a 14% decrease in the probability of organic adoption, albeit from a very low base probability.

We hypothesized that, as researchers have found in other contexts, there would be a positive spatial externality created by existing organic operations in the organic adoption decision in the Western Oregon. It seemed likely that having organic neighbors would reduce the uncertainty and transition costs thereby encouraging subsequent adoption of organic management. However, in this area characterized by large numbers of small fruit and vegetable growers that engage in direct marketing activities through road side stands, farmers markets, and restaurant sales, it appears that, on the whole, existing organic growers may actually discourage others from entering the organic market.

If there is a negative spatial externality created by the prospect of competition in local organic foods markets from existing organic operations, we would expect that effect to only hold for farms of similar type and not hold for different farm types and organic processors. For example, an organic dairy farm poses no competitive threat to a blueberry producer that is considering an organic transition. In fact, we would still expect a positive social externality to be created by farms and processors that are not in direct competition with a newly certified farm. To explore this dynamic we estimated two additional models that distinguish between farms and processors, and farms of similar and different farm type. Although there are practical data challenges encountered when attempting to make these distinctions, the results are informative.

Table 3 presents the results of a model that separates organic processors from organic farms and shows that, as in the first model, we find that an existing organic farm operation has a significant negative effect on the probability that a neighboring farm achieves organic certification. This holds for 5 and 10 mile models but significance is not achieved with the 20 mile radius model. The presence of an established organic processor is not found to have a significant impact on adoption probability. The APE in this model is estimated to be stronger than that in the first model that pooled farms and processors together. This supports the notion that existing organic farms may provide competition for new adopters while organic processors have no significant impact on a farm's adoption decision.

Table 4 presents the results of a model in which we attempt to divide the existing operations further still. We split existing organic farms into groups of like-type and different type. As explained in the methods section this is carried out based on the land cover data in the NASS CDL. If a farm parcel has 2 acres or more of specialty crops it is considered a specialty crop operation and considered not specialty crop otherwise. Unfortunately, at this point we are unable to additionally distinguish conventional livestock producers from field crop producers with the CDL method because we have no data on the type of developments that may be present on a given farm parcel. Surprisingly, the results of this third model indicate that there is a negative spatial externality created by both farms of like-type and of different type with a 5 mile radius. This is an unexpected result and runs counter to the narrative of non-competitive organic farms providing encouragement for potential organic adopters. It is only mildly comforting that the estimated effect of a dissimilar farms is less robust than like-type farms as we increase the distance by which we define "nearby" farms. Again, processors do not have a significant impact on a farm's probability of transitioning to adopt organic methods.

Conclusions

This study employs a unique dataset of organic certification decisions by Oregon farmers over the past 20 years to assess the impact of having organic neighbors on the decision of a conventional farm to adopt organic technology. We are additionally able to use USDA-NASS Cropland Data Layer to identify farm type and compare the disparate impact of having neighbors that are of similar and different farm types. We find that the presence of additional organic neighbors has a negative impact on the probability of a conventional farm converting to organic production, and that this effect decreases as the radius of a neighborhood increases from 5 miles to 20 miles. This negative result is suggestive of the competitive forces that can impact how a farm chooses to specialize in the markets. When farms and processors were separated, the magnitude of this negative result increased for neighboring farmers, with no impact from the presence of organic certifiers. These results indicate that the negative externality from increased local competition for organic consumers outweighs other potential positive interactions.

As a simplistic view of the results, one could expect that the impact of similar farm neighbors represents the effect of competition and technical information exchange, the results for different farm types and processors would represent social acceptance and in the case of processors, potential market outlets. Based on our results it would then appear that in this area of Western Oregon, the competitive externality outweighs potential benefits of information exchange among like farms and there are not significant positive social externalities created by processors and dissimilar farm types. However, there are several caveats to this interpretation. First, the impact of the share of the votes won by the Green Party was highly positive. While this variable serves as a measurement of liberal beliefs it can also be thought of as a proxy for the social acceptance of organic practices in the community, and it appears to have a large impact on the decision to convert to organic production. Of greater interest is the negative impact of having nearby organic neighbors of a different type. As noted, the non-specialty crop indicator includes both field crop and livestock producers as we are not able to distinguish conventional dairy operations from conventional field crop operations based on the ground cover data. As a result, the model specifications that separately identify the spatial spillover effects on farms of similar and different farm type must be viewed cautiously. Specifically, the result for different farm type represents two conflicting impacts when looking at the transition decision for a conventional non-specialty farm: the negative impact from competing neighbors of the same type that are erroneously included in the variable and the positive effect from increased knowledge. One solution to this problem could be to run the analysis separately for specialty and non-specialty farms.

Additionally, the negative result implies that the competition effect outweighed that of knowledge. However, we do not account for the dynamic nature of the neighbor effect over time. One could assume, for a variety of reasons, that the spatial externality produced by an early organic adopter in the 1990's might not be the same as that produced by a more recently certified organic farm. For example, early adopters might have a larger (or smaller) influence on potential organic farmers than more recent adopters, especially as organic certification has become better known. From the results it is clear that time has a significant impact, with the probability of transitioning to organic increasing annually. Moreover, if the ways in which potential organic farms access technical information are changing, with less reliance on physical proximity than in the past, we might see the magnitude of the neighbor effect decrease over time.

By modeling the relationship between pre-existing organically certified farms and the transition decision for conventional farms, we provide quantitative evidence of the importance of social support, competitive forces and knowledge transfers that has been lacking in previous organic adoption studies. However, this study is preliminary and we have not fully accounted for other factors that could impact both the adoption decision of current farms and previously transitioned neighbors. For instance, the prevalence of organic farms in a particular county has been shown to be associated with characteristics of the location such as the presence of organic certifiers that provide outreach and distance to the interstate (Marasteanu & Jaenicke, 2015; Taus et al., 2013). We intend to collect further county-level demographic data to better model this relationship. Additionally, the relative profitability of organic and conventional operations is an important factor in the decision to pursue organic certification, and will differ by type of farm. We are still determining a proper method to control for this effect. Finally, there are limitations of the current data that must be kept in mind when interpreting the reported results, as the accuracy with which we are able to identify farm type with the CDL needs to be further refined.

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Figures

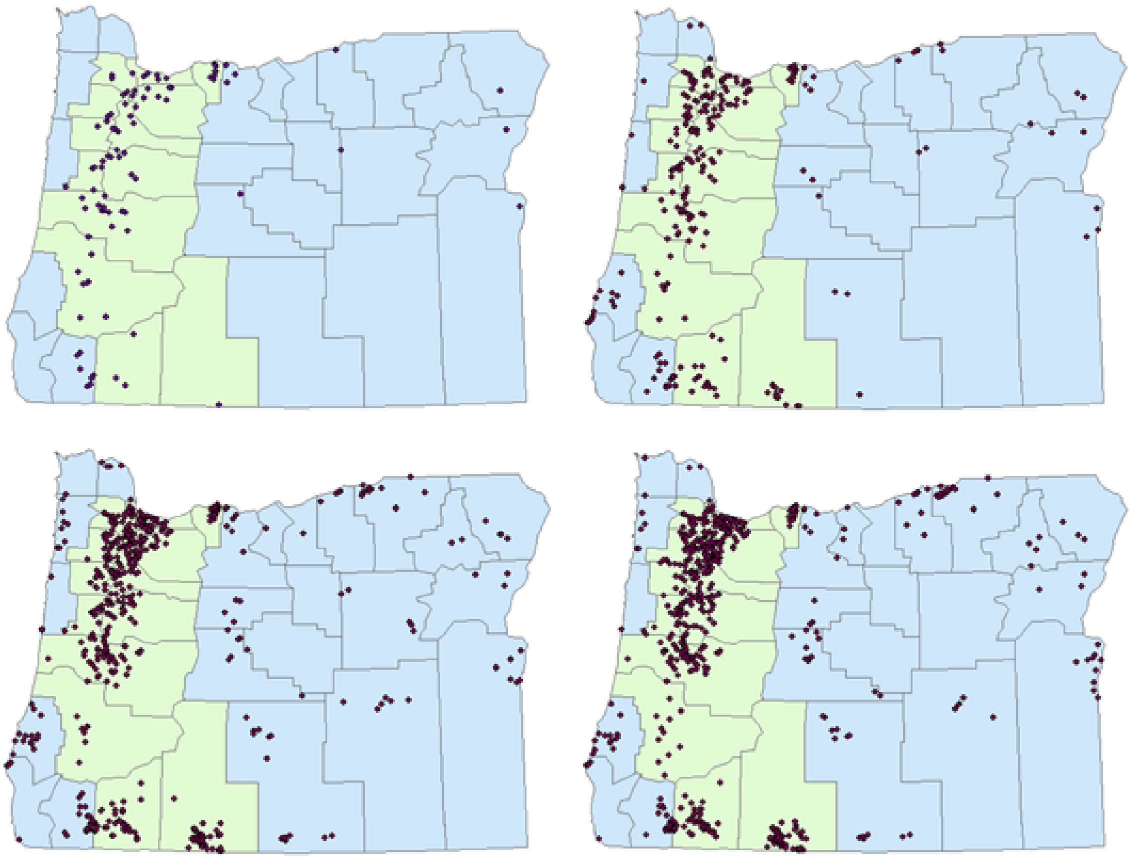

Figure 1. Certified organic operations in Oregon and study area (green shaded) from 1996 to 2014. Clockwise from top left: 1996, 2003, 2010, 2016.

Figure 2. Identification of farmed parcels using USDA-NASS Cropland Data Layer and county tax lot data. Benton County, Oregon as example.

Table 1. Numbers of certified organic farms and processors by study-area county over time.

County	Farm Parcels	Certified Operations			
		1996	2003	2010	2016
Benton	1,529	7	12	17	22
Clackamas	2,560	11	28	61	61
Deschutes	1,579	1	1	6	14
Douglas	526	10	12	9	14
Hood River	1,449	10	18	31	29
Jackson	611	3	19	49	60
Klamath	4,136	1	17	57	87
Lane	2,804	12	32	72	96
Linn	3,833	5	15	34	39
Marion	6,021	6	14	43	59
Multnomah	310	6	15	52	69
Polk	3,183	6	13	17	20
Washington	3,574	4	15	30	34
Yamhill	4,150	3	13	36	35

Table 2. Average Partial Effects on Probability of Organic Certification. All Certified Organic Operations (Including Farms and Processors) Within a 5 mile, 10 mile, and 20 Mile Radius are Counted Together.

	5 mile		10 mile		20 mile	
# of operations(t-3)	-0.0000777633	**	-0.000028281	**	-0.000007632	
	(0.00001512)		(0.00000842)		(0.00000407)	
year	0.000132818	**	0.000132582	**	0.000110131	**
	(0.00001350)		(0.00001717)		(0.00002140)	
distance to urban area	0.000000000		0.000000003	**	0.000000004	**
	(0.00000000)		(0.00000000)		(0.00000000)	
median county income	-0.000000079	**	-0.000000045	**	-0.000000050	**
	(0.00000001)		(0.00000001)		(0.00000001)	
bachelor degree %	0.000045035		-0.000024259		-0.000026434	
	(0.00003065)		(0.00003091)		(0.00003307)	
pop. density	0.000001417	**	0.000001614	**	0.000001648	**
	(0.00000016)		(0.00000016)		(0.00000017)	
Green Party vote share	0.042359550	**	0.092346610	**	0.109547011	**
	-0.0000777633	**	-0.000028281	**	-0.000007632	

Note: standard errors are in parentheses.

* significant at 5% level

** significant at 1% level

Table 3. Average Partial Effects on Probability of Organic Certification. Certified organic processors and farms within a 5 mile, 10 mile, and 20 mile radius are counted separately.

	5 mile		10 mile		20 mile	
# of processors(t-3)	-0.00002387		-0.00000913		-0.00000462	
	(0.00002196)		(0.00001243)		(0.00000826)	
# of farms(t-3)	-0.00011165	**	-0.00003609	**	-0.00000805	
	(0.00002076)		(0.00001088)		(0.00000581)	
year	0.00013246	**	0.00012823	**	0.00010634	**
	(0.00001345)		(0.00001688)		(0.00002110)	
distance to urban area	0.0000000010		0.0000000042	**	0.0000000042	**
	(.0000000006)		(.0000000007)		(.0000000008)	
median county income	-0.00000007	**	-0.00000002	*	-0.00000005	**
	(0.00000001)		(0.00000001)		(0.00000001)	
bachelor degree %	0.00005572		0.00003366		0.00003797	
	(0.00003093)		(0.00003134)		(0.00003360)	
pop. density	0.00000101	**	0.00000123	**	0.00000127	**
	(0.00000017)		(0.00000017)		(0.00000019)	
Green Party vote share	0.02537339		0.06385054	**	0.08669242	**
	(0.01340832)		(0.01392106)		(0.01658181)	

Note: standard errors are in parentheses.

* significant at 5% level

** significant at 1% level

Table 4. Average Partial Effects on Probability of Organic Certification. Certified farms of like type, different type, and organic processors within a 5 mile, 10 mile, and 20 mile radius are counted separately.

	5 mile		10 mile		20 mile	
# of same-type farms(t-3)	-0.00010224	**	-0.00003722	**	-0.00000595	
	(0.00002510)		(0.00001432)		(0.00000806)	
# of other farms(t-3)	-0.0001370	**	-0.0000341		-0.0000125	
	(0.00004143)		(0.00002136)		(0.00001099)	
# of processors(t-3)	-0.00002575		-0.00000908		-0.00000354	
	(0.00002205)		(0.00001248)		(0.00000856)	
year	0.00013427	**	0.00012803	**	0.00010702	**
	(0.00001366)		(0.00001698)		(0.00002111)	
distance to urban area	0.0000000013		0.0000000038	**	0.0000000035	**
	(.0000000007)		(.0000000008)		(.0000000009)	
median county income	-0.00000006	**	-0.00000003	*	-0.00000006	**
	(0.00000001)		(0.00000001)		(0.00000001)	
bachelor degree %	0.00005002		-0.00002691		-0.00003581	
	(0.00003201)		(0.00003188)		(0.00003354)	
pop. density	0.00000104	**	0.00000120	**	0.00000122	**
	(0.00000017)		(0.00000017)		(0.00000019)	
Green Party vote share	0.02807351	*	0.06033168	**	0.08296835	**
	(0.01398825)		(0.01420570)		(0.01652515)	

Note: standard errors are in parentheses.
* significant at 5% level
** significant at 1% level