Ecological Economics 142 (2017) 70–80

Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon

Analysis

Inside the Emerald Triangle: Modeling the Placement and Size of Cannabis Production in Humboldt County, CA USA

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ARTICLE INFO

Article history:
Received 9 January 2017
Received in revised form 16 May 2017
Accepted 12 June 2017
Available online xxxx

Keywords:
Marijuana
Heckman Models
GIS
Spatial Modeling
Illegal Drugs

ABSTRACT

Cannabis agriculture is a multi-billion dollar industry, yet the factors driving the spatial location of cannabis production are not well understood. That knowledge gap is troubling, as there is evidence that outdoor production takes place in ecologically sensitive areas. Policy aimed at mitigating the impacts of current and future cultivation should be based on an understanding of what drives cultivation siting. Using parcel level data and a Heckman sample selection model, we estimate where cannabis cultivation is likely to take place and the number of plants in each site using biophysical, historical, and network variables. We use this model to estimate drivers of greenhouse and outdoor cultivation siting. We find strong implied network effects – parcels are far more likely to have cultivation sites if there are cannabis plants nearby. However, the proximity of other cannabis sites does not impact the size of a parcel's own cultivation. Similarly, a history of timber harvest increases the likelihood of outdoor cultivation, but is linked to cultivation sites with fewer plants. Biophysical properties such as slope, aspect, and distance to water did not statistically impact the likelihood of a parcel to be cultivated. Our results are a first step toward understanding the emergence of an agricultural activity likely to grow in other locales in the future.

1. Introduction

Land-use conversions from forested and natural lands to agricultural landscapes are a leading cause of biodiversity decline worldwide (Gibson et al., 2011; Laurance et al., 2014). Agricultural conversions also release large amounts of carbon and contribute significantly to climate change (Mendelsohn and Dinar, 2009). Economic models of agricultural land-use change have proved helpful in understanding the ecological consequences of land conversion across multiple scales and for many commodities (Lubowski et al., 2008). These models can also be used to predict the environmental impact of changes in agricultural policy or prices (Lawler et al., 2014; Polasky et al., 2008).

Cannabis represents an emerging agricultural crop of economic and ecological significance (Carah et al., 2015; Decorte et al., 2011). Cannabis is now legal, either as a medicine or for recreational use, in over half the United States and the federal government has signaled potential shifts in its classification of cannabis as well (National Conference of State Legislatures, 2016). The market for legal cannabis is already estimated to reach $22.8 billion nationwide by 2020, approximately double the value of wheat production (Arcview Market Research, 2014). The growth of this industry may lead to clearing of new land for agriculture or the intensification of already established sites.

While many facets of cannabis production are not well documented, there is ample evidence that cannabis production can have negative ecological impacts (Carah et al., 2015). For instance, illegal cannabis cultivation sites have been linked to rodenticide poisoning throughout Northern California (Gabriel et al., 2012; Thompson et al., 2014), and to dewatering of streams due to irrigation practices (Bauer et al., 2015). Many grows are located in areas of potential ecological impact, such as on steep slopes, far from developed road networks, and near habitat for threatened and endangered fish species (Butsic and Brenner, 2016).

Given its high economic value and potential impact on the environment, surprisingly little is known about the most basic spatial dimensions of this emerging agricultural activity. Even less is known about how cannabis farmers choose the location and size of their operations. Unlike most agricultural crops in the United States, which are mapped and recorded by various government departments, the presence of cannabis agriculture has gone widely undocumented, with the exception of police reports during the era of strong prohibition. Recent advances in the availability of high resolution satellite imagery have made it possible to map cannabis farms at some times of the year across fairly broad spatial scales (Bauer et al., 2015). One recent study (Butsic and Brenner, 2016) produced baseline data that could be used to model land-use

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http://dx.doi.org/10.1016/j.ecolecon.2017.06.013
0921-8009/

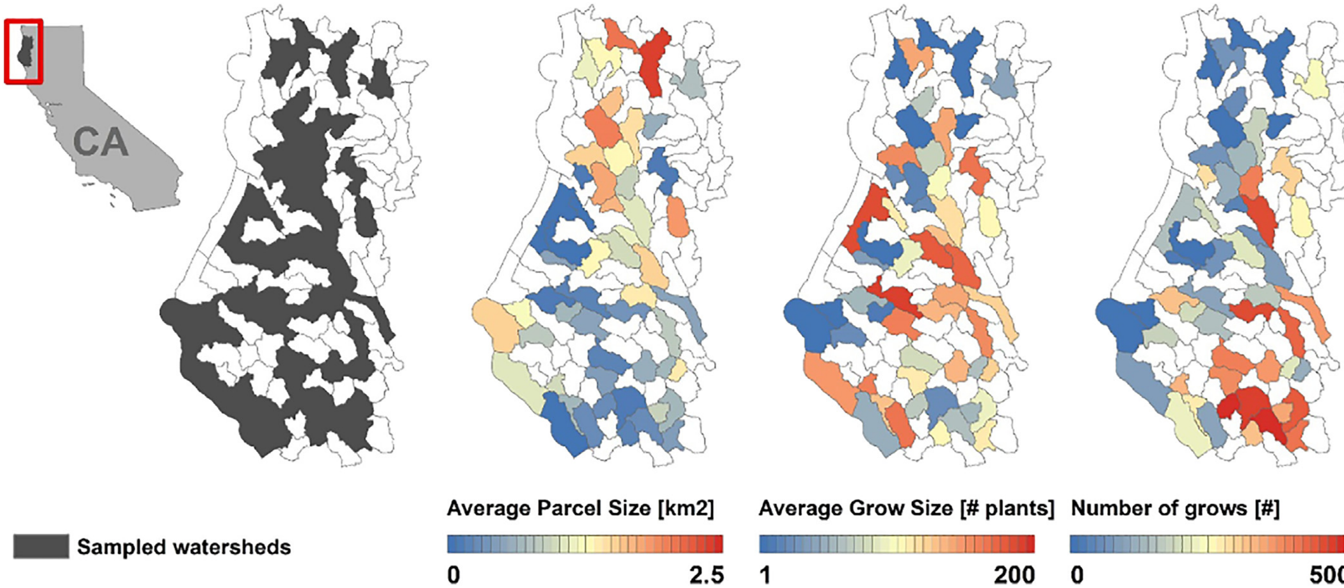

Fig. 1. Map of study area, and summary statistics.

decisions on cultivation location and size. With these insights, policymakers, planners, and others charged with governing this emerging land-use activity might better prepare to mitigate anticipated environmental impacts.

We use a dataset consisting of 1341 documented cannabis cultivation sites on private land in Humboldt County, California to model the spatial location and production decisions of cannabis farmers. We evaluate the impact of biophysical variables (slope, distance from ocean, distance to water, vegetation cover, and aspect), network variables (number of plants on nearby parcels), local regulations (zoning), and historical variables (whether or not a timber harvest has taken place in the last 15 years) on producer decisions. In addition, we test to see if the impact of these variables differs for alternative production methods (outdoor cultivation vs. greenhouse cultivation).

2. Methods

2.1. Study Area

Our study area consists of 54 randomly selected watersheds in Humboldt County, CA which are representative of the county as a whole (Butsic and Brenner, 2016). Humboldt County is located in northern California (Fig. 1) along the Pacific coast and is considered the leading cannabis producing county in the United States, if the not world. The county is a mix of coniferous and hardwood forest with pockets of open rangeland. The study area is home to numerous threatened and endangered species, including: Chinook and Coho salmon, steelhead trout, and the northern spotted owl (California Department of Fish and Wildlife, 2015).

Due to the steep terrain and poor soils, agriculture is limited to a relatively small area of the county. Livestock, dairy, and nursery production are the largest agricultural sectors ($76, $61, $41 million dollars in sales in 2014) and make up over 95% of all agricultural production by value. Timber production contributes another $72 million in direct sales (Humboldt County, 2015). In comparison, the wholesale value of cannabis production is likely over $300 million, although no official figures exist (Butsic and Brenner, 2016).

2.2. Cannabis Production in Humboldt County

Cannabis can be legally cultivated in California for medicinal purposes, although the federal government still considers cannabis an illegal Schedule I drug (McGreevy, 2015). Medical producers (recreational marijuana will not be legal in California until 2018) must be documented care givers and can supply their crop either to individuals who have physician approval to use cannabis or to dispensaries, which can sell cannabis to patients. During the time period of our study, there was virtually no chain of custody in the cannabis industry, and the supply chain from growers to consumers was undocumented. Under the Obama administration, federal law enforcement agencies did not strongly enforce federal cannabis laws nationally, although there is precedent for federal actions on dispensaries and growers (Zilversimt, 2016). Federal law typically enforces a 5-year prison sentence for cultivation sites larger than 99 plants, hence anecdotal evidence suggests that many farmers stay under that number in case of federal intervention (California Normal, 2016). Currently there is no organized program in California to track cannabis cultivation siting, production, or sales, even in the legal market. New laws passed in 2015 aim to establish such a system by 2018 (McGreevy, 2015). The details of such laws are still under formation in California, with the California Department of Food and Agriculture (CDFA) releasing their first proposed regulations on medical cannabis cultivation on April 28, 2017. From a land use perspective individual counties will be able to create land use ordinances that limit production beyond state standards.[1]

There is little documentation of actual practices of cannabis production in the scientific literature (Carah et al., 2015). The lack of research stems in part from federal restrictions on interacting with cannabis, which have prevented researchers from observing and studying production systems (Sides, 2015). Nevertheless, researchers have anecdotally observed several tendencies of cannabis production that are relevant to our modeling exercise. First, production takes place both outdoors and in greenhouses. Outdoor production is reliant on natural sunlight and plants are typically grown in groups or individually in raised beds. Greenhouse production allows for light to be diminished

[1] Humboldt County passed the only such land use ordinance in California in 2016, after the period from which our data are drawn.

with shades or enhanced with artificial light. The manipulation of light allows growers to precisely control flowering, which gives greater control over production in terms of both the schedule and the amount produced.

Cannabis requires water throughout its growing season, which takes place during Humboldt County's dry season and can last up to 150 days.[2] Given Humboldt County's dry summers and falls, irrigation of cannabis plants is needed on a nearly daily basis, with some estimates suggesting up to 22 l per day per plant (Humboldt Growers Association, 2010). Although not documented, it is likely that cannabis produced in greenhouse settings may need less irrigation.

Finally, for most agricultural crops, soil quality is a driver of crop choice. In Humboldt County, poor-quality agricultural soil covers nearly 90% of the county. Therefore, many growers import soil for both outdoor and greenhouse grows. While there is no documentation of how much soil is imported, various local businesses exist to supply soil in large quantities (e.g. www.humboldtnutrients.com, www.royalgoldcoco.com).

2.3. Data

We use a number of spatial datasets to parametrize our model. The main cannabis dataset is a reduced version of the dataset used in Butsic and Brenner (2016). The dataset used in this study includes only cultivation sites in Humboldt County to control for any policy or enforcement differences across county boundaries. Our dataset documents cannabis cultivation sites on 1341 parcels (out of 14,462 parcels larger than one acre), with the majority of cultivation sites recorded in 2012 and the remainder in 2013. Of these 1341 parcels, 726 have greenhouse operations, 478 have outdoor grow operations, and 137 have both. The average production of each parcel is 180 plants, while the parcel with the most cannabis plants has 2794 plants (Table 1).

We joined the cannabis dataset with several other spatial datasets. Parcel boundaries and zoning designations were provided by Humboldt County. We used the CalVeg (http://www.fs.fed.us/r5/rsl/projects/mapping/accuracy.shtml) vegetation layer to quantify the percent of each parcel in different vegetation types. The percent of each parcel with over 30% slope was estimated using a digital elevation model (DEM) provided by Humboldt County.

A number of variables which describe the spatial location of a parcel were created. For each parcel we calculated the distance to the Pacific Ocean and the meters north. Humboldt County receives dense fog near the Pacific Ocean, so growers might hypothetically locate farther from the ocean to obtain more sunlight. Also provided by Humboldt County was a map of maintained roads. We used the dataset to calculate the distance from a parcel edge to a developed road. We calculated the distance of each parcel to the nearest water source, based on data provided by the California Department of Fish and Wildlife (https://www.wildlife.ca.gov/Data/GIS/Clearinghouse). For each parcel we also calculated the number of plants within 100 m and 500 m of its boundary in order to identify parcels that were located in clusters of cultivation sites.

Finally, we were interested in the historical land use of each parcel, especially whether or not a parcel had been logged in the last 15 years. A common narrative is that areas where timber was produced in the past are often converted into cannabis cultivation sites. In California, Timber Harvest Plans (THP) are required for the harvest of merchantable timber on private lands. Landowners, either individuals or firms, apply for plan approval and once approval is granted, timber harvest can commence. Once timber is cut, it is usually replanted. However, it may be the case that some landowners are not replanting but converting to cannabis. This may be economically efficient as the land cleared by timber harvest may be less expensive to convert to cannabis since trees are already removed from this area. We used the Timber Harvest Plan database provided by the State of California to document for each parcel the percent of land that was permitted to be harvested since 1997 (Table 2).

2.4. Intuition Behind Spatial Location and Size of Cultivation Sites

Our goal was to estimate what factors influenced two decisions on the part of cannabis growers. First we wanted to know where cannabis cultivation sites were most likely to be located. Typical economic models of land use focus on the expected net returns to different crops to model the decision of where cropland will expand. Much of the intuition from these models may hold true in our case as well. We expect that parcels with better growing conditions – more sunlight, less slope, nearer to sources of irrigation – would produce higher returns, and thus we would expect these to be more likely to support cannabis production.

Cannabis differs from other crops in important ways, particularly the ambiguous nature of its legal status: production is licit and socially accepted, but federally illegal (Short Gianotti et al., 2017). Therefore, we anticipate that producers likely cultivate in areas where the risk of law enforcement activities is relatively low. In years past, when strict enforcement was in place, legal considerations incentivized growers to locate far from developed properties on lands that would be hard for law enforcement personnel to visit (Corva, 2014). Thus, we hypothesized cultivation sites to be in remote locations, even though these sites may actually be less suitable physically for growing cannabis.

While the illegality of cannabis provides incentives for remoteness in the location of cultivation sites, several factors could give rise to spatial clustering. One such factor is information flows. A distinction between cannabis production and other agricultural commodities is the lack of formal training and educational resources available to cultivators. Cannabis producers cannot avail themselves of university courses or cooperative extension services. Therefore, producers have traditionally been left to develop their own techniques and networks to disseminate information. For this reason, we expected that strong returns from network effects would give rise to spatial patterns of cannabis production, where clustered growers could share knowledge and technologies with each other.

Further, the clandestine nature of cannabis marketing could promote the formation of geographically clustered distribution networks. While standard models of agricultural marketing emphasize transportation costs, high search costs stemming from the illegality of the industry likely induce significant frictions in the matching of cannabis producers and distributors. As a result, spatial clustering of growers may be of first-order importance in the development of efficient post-harvest cannabis markets. Similar search frictions might also arise in the labor market—cannabis harvest is labor intensive, often requiring large numbers of 'trimmers'—which also might provide incentives for spatial clustering.[3] We therefore model the extent to which nearby cultivation predicts the likelihood and extent of cannabis production.

Finally, in densely forested areas of the county, we may expect that cleared forest provide relatively low-cost areas for cultivating cannabis, since a producer will not have to pay for land clearing. This may be especially true after recent timber harvest. Therefore, timber harvest in the previous 15 years may predict areas where new cannabis cultivation sites are located. We chose the 15 year mark because digitized THP records exist back to 1997. Likewise, after 15 years we would expect vegetation to have regrown to the point where gains from past clearings are

[2] Though cannabis has been labeled a "thirsty" crop, precise data on water use are scarce.

[3] Indeed, anecdotal reports suggest a strong preference for local (known) labor, suggesting a further incentive for clustering. Trimming is a large part of total labor cost and can cost producers up to $250 a pound (http://www.marijuanaventure.com/trimming-crews-harvest-hire/)

Table 1
Types of cultivation sites, number of cultivation sites, and number of plants.

	Number of parcels with grows	Average number of plants	Std. dev	Minimum number of plants	Maximum number of plants
All production sites	1341	180.8	209.614	4	2794
Outdoor production sites	478	68.5	72.5091	4	635
Greenhouse production sites	726	251.0	238.289	10	2794
Production sites that have outdoor and greenhouses	137	200.1	201.853	14	1423

Total number of parcels in the data: 14,462.

Table 2
Variable names, definitions, data sources and summary statistics.

Variable	Definition	Data source	Mean	Std. dev	Min	Max
Plants (the natural log of this is used in regressions)	Number of plants per parcel	Butsic and Brenner, 2016	180.763	209.614	4	2794
Parcel size	Size of parcel in hundreds of acres	Humboldt County parcel layers (http://www.humboldtgov.org/201/Maps-GIS-Data)	72.169	137.300	1	865.811
Slope 30	Percent of parcel with slope >30%	Humboldt County parcel layers (http://www.humboldtgov.org/201/Maps-GIS-Data)	0.141	0.226	0	1.024
Percent mixed forest	Percent of parcel in mixed forest	CalVeg (http://www.fs.usda.gov/detail/r5/landmanagement/resourcemanagement/?cid=stelprdb5347192)	0.275	0.336	0	1.013
Percent hardwood	Percent of parcel in hardwood forest		0.127	0.233	0	1.015
Percent shurb	Percent of parcel in shrub land		0.013	0.075	0	1.004
Percent coniferous	Percent of parcel in coniferous forest		0.264	0.360	0	1.024
Percent barren	Percent of parcel barren		0.039	0.148	0	1.025
lnnp100	Natural log of number of plants within 100 m of a parcel boundary	Derived from Butsic and Brenner, 2016	0.683	1.680	0	8.3577
lnroaddist	Distance of parcel to road in km	Derived from road layer from Humboldt GIS (http://www.humboldtgov.org/201/Maps-GIS-Data)	0.214	0.437	0	3.087
Distance to stream	Distance to nearest stream or waterbody	California Department of Fish and Wildlife (https://www.wildlife.ca.gov/Data/GIS/Clearinghouse)	538.949	828.984	0	9831
Aspect	% of parcel with South, Southeast or Southwest aspect	Derived from DEM provided by Humboldt County GIS	0.212	0.279	0	1
THP	Equal to 1 if a Timber Harvest Plan was on the parcel at any time between 1997 and 2012	CALFIRE http://calfire.ca.gov/resource_mgt/resource_mgt_forestpractice_gis	0.209	0.406	0	1
Distance to ocean	Distance to ocean in hundred KMs	California Department of Fish and Wildlife (https://www.wildlife.ca.gov/Data/GIS/Clearinghouse)	0.116	0.126	0.0008	0.60622
Northness	Y coordinate in meters	Calculated in ArcGIS	143,095	38,993.71	75,652	237,906
Distance to city	Distance to city in in hundred of KMs	Humboldt County parcel layers (http://www.humboldtgov.org/201/Maps-GIS-Data)	0.963	0.73	0	2.638

lost. We measure this using the existence of an approved timber harvest plan (THP).[4]

2.5. Statistical Model

Our goal is to model the results for two joint decisions (1) Whether or not to use a parcel for cannabis cultivation and (2) The number of plants to cultivate. Given that the outcome (the number of plants are on a cultivation site) is conditional on selection (whether cannabis is cultivated on the parcel or not) a model that does not account for sample selection may be biased. The Heckman (1979) two-step sample selection estimator (i.e. Heckit) is one way to account for this issue and has been previously used in land-use change settings (Lewis et al., 2009).

We assume an underlying regression relationship between the number of plants on parcel j, y_j and a set of covariates

$$y_j = x_j B + u_{1j}$$

In our case, the dependent variable y_j is greater than zero only in the case where cannabis is gown (1341 out of 14911 parcels over 1 acre). We can estimate the likelihood of a parcel growing cannabis (i.e. $y_j>0$) as the selection equation.

$$y_j = \left\{ \begin{matrix} 1 & \text{if } z_j G + u_{2j} > 0 \\ 0 & \text{otherwise} \end{matrix} \right\}$$

where z_j is a vector of variables that influence whether or not a parcel produces cannabis and G, the coefficients. We assume the following error structure.

$$\mathrm{u}_1 \sim \mathrm{N}(0, \sigma)$$

$$\mathrm{u}_2 \sim \mathrm{N}(0, 1)$$

$$\mathrm{corr}(\mathrm{u}_1, \mathrm{u}_2) = \rho$$

Correlation in the error terms of the equations reflect the degree to which the unobserved factors that determine first stage selection (i.e. the decision to grow) are linked with the second stage (i.e. grow size) residual. When $\rho = 0$, standard regression techniques will provide unbiased results. If this is not the case, the outcome equation will be biased due to the omission of a key regressor. The Heckman model, which recovers an estimate of the missing regressor using the Inverse Mills Ratio (IMR) from the first stage Probit estimate of the selection equation, provides consistent asymptotical efficient estimates for model parameters when the errors of the two equations are correlated.

We applied the Heckman model to our suite of variables. The dependent variable of the selection equation is whether or not a parcel has a cultivation site. The dependent variable of the outcome equation is the log of the number of plants grown.

There is a long debate regarding the importance of exclusion restrictions (i.e. variables that influence the selection equation but not the outcome equation) when estimating Heckman models. In the absence of such restrictions (i.e. $x_j = z_j$), the non-linearity of the IMR from the first stage equation is the source of identification. In the presence of high collinearity between the IMR and the regressors, however, sole reliance on such a functional form assumption results in unreliable estimates of the outcome equation (Leung and Yu, 1996; Madden, 2008).

In our data, we indeed found quite high collinearity between the IMR and the regressors (Cameron and Trivedi, 2005).[5] As a result, we utilized the zoning status of parcels as a further source of identification in the outcome equation. We ran the model where zoning variables are included in the selection equation but not the outcome equation. We justify these exclusion restrictions by noting that the zoned status of the parcel may influence the suitability of a site for any cultivation; for instance if a parcel is zoned for commercial use it is unlikely to be a good site for outdoor cannabis production. However, if a person decides to produce on a site, zoning is unlikely to impact the size of the cultivation site, as zoning did not legally limit cannabis production on any parcels at the time of data collection.

To estimate the model, we used a suite of independent variables that include biophysical properties of a parcel (slope, nearness to a water source, southward facing), vegetation type (% in shrub, herbaceous, barren, coniferous forest, hardwood forest, and mixed forest), spatial location (distance from road, distance from nearest city, distance from ocean, m north) administrative (zoning), historical (had there been a THP on the property in the last 15 years), and network (the log of the number of plants within 100 m of a parcel).

In order to focus on parcels with potential production, we restrict our sample to parcels greater than one acre and parcels that were not protected (i.e., public parks, National Forest, Nature Conservancy lands, etc.).[6,7] In addition to the main specification, we also run separate regressions for outdoor and greenhouse production. These models allow us to determine the extent to which site selection and production intensity decisions differ by production methods with respect to our explanatory variables. Because an important variable of interest, the number of grows on neighboring parcels, may be endogenous, we also examine the robustness of the results using a control function approach.

Finally, we also face potential concerns stemming from the possibility that spatially autocorrelated errors exist in our data. There are limited applications of Heckman models that correct for spatially autocorrelated errors and empirical results from these models show little bias reduction (Flores-Lagunes and Schnier, 2012). Therefore, we apply a sampling procedure where we create 300 samples from the full dataset. In each sample, parcels are at a minimum 200 m from each other. We run our models over these 300 datasets, and then average the coefficients and standard errors. This procedure should limit spatial autocorrelation resulting from parcels located <200 m away from each other. The results of these averaged models were very similar to the models run over the full dataset, but with larger standard errors. This is to be expected as the spatial sample limits the size of the dataset for each model run to <4000 parcels.

3. Results

3.1. The Spatial Location of Cultivation Sites

Many biophysical variables that typically impact the spatial location of agriculture had weak, yet statistically significant, impacts on cannabis grow location. Both the percent of the property facing south and steep slope reduced the likelihood of a cultivation site, at the 10% significance level. The distance of a parcel to a water source did not impact the likelihood of a parcel's use for cannabis cultivation. All else being equal, forested parcels overall were more likely to have cultivation sites than non-forested parcels regardless of forest type (Table 3).

The size of the parcel was an important predictor of the spatial location of cultivation sites, although the relationship between parcel size and the likelihood of a cultivation site is likely non-linear. Larger parcels are more likely to have cultivation sites, but the negative sign of the quadratic term suggests that this positive association does not hold for very large parcels (Fig. 2).

[4] A THP approved by the California Department of Forestry and Fire Protection (CDF) is legally required for any parcel on which timber is harvested in Humboldt County.

[5] Following Cameron and Trivedi (2005), we measure collinearity of the IMR and explanatory variables by comparing the condition number of the second stage regressors with and without the inclusion of the IMR.

[6] We used the California Protected areas Data Portal to identify protected properties (http://www.calands.org/).

[7] <1% of parcels under one acre in size have grows.

Table 3
Heckit estimation results for the full sample.

	Outcome equation (# of cannabis plants)	Selection
Distance to stream	−0.077	−0.001
	(0.055)	(0.003)
Slope 30	0.3982	0.0168
	(0.1362)***	(0.0094)*
% of parcel facing S, SW, or SE	0.0149	0.0130
	(0.0999)	(0.0072)*
% of parcel mixed forest	0.183	0.044
	(0.126)	(0.008)***
% of parcel hardwood forest	0.199	0.046
	(0.163)	(0.011)***
% of parcel shrub	−1.662	−0.002
	(0.647)**	(0.037)
% of parcel coniferous	−0.157	0.022
	(0.145)	(0.009)**
% of parcel barrren	0.292	−0.089
	(0.618)	(0.032)***
Parcel size	0.363	0.022
	(0.087)***	(0.006)***
Parcel size squared	−0.047	−0.006
	(0.018)***	(0.001)***
Northness	−0.002	−2.2E−04
	(0.001)	(7.2E−05)***
Distance to road (log)	−0.001	0.027
	(0.067)	(0.004)***
Distance to an ocean	0.907	0.074
	(0.295)***	(0.018)***
Distance to a city	−0.181	0.022
	(0.078)**	(0.005)***
THP	−0.113	0.003
	(0.083)	(0.006)
# of plants within 100 m (log)	−0.002	0.028
	(0.033)	(0.001)***
Ag exclusive zone		0.018
		(0.010)*
Ag zone		0.022
		(0.011)**
Timber production zone (TPZ)		0.008
		(0.011)
Residential suburban		−0.005
		(0.015)
Forest recreational		0.091
		(0.011)***
City land		−0.012
		(0.018)
Unzoned		0.034
		(0.010)***
Rho	−0.22	
N	14,462	

Marginal effects reported for the selection equation. Standard errors in parentheses. Constant term not reported.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

A parcel's location within the county significantly impacts the likelihood of cultivation. Parcels that are further to the north are less likely to have cultivation sites, as are parcels closer to cities and farther from the ocean. Proximity to roads also significantly reduces the likelihood of cultivation, with a 1% increase in distance to a road increasing the probability of a cultivation site by 2.3%. The impact of a parcel having had a timber harvest plan associated with it in the last 15 years did not appear economically or statistically significant.

Current zoning appears more precisely correlated with farm location. The coefficients of forest recreational, agriculture (exclusive) and unzoned land were all positive and significant relative to the omitted zone of “other”, which includes all zones that have <1% of parcels in cultivation.

Finally, proximity to other cultivation site also positively and significantly increases the likelihood that a parcel will have a cultivation site. A 1% increase in the number of plants within 100 m of a parcel boarder raises the probability of cannabis production on a parcel by 2.8%. To better illustrate the impact of network effects, we predicted the probability of a parcel having a cultivation site for plant numbers (within 100 m) from 0 to 4600. When there are no plants within 100 m of a cultivation site, the probability of a parcel having a cultivation site is 4.5%. When there are 200 plants within 100 m of a parcel, the predicted probability jumps to 35.7%, this effect steadily increases through 4600 plants, for which the predicted probability of a parcel having a cultivation site is 66.5% (Fig. 2).

3.2. Size of Cultivation Sites

In contrast to its impact on the selection equation, a parcel's slope is a strong predictor of cultivation site size. The amount of slope over 30% has a positive relationship with the number of plants cultivated on a parcel. However, distance to streams and the proportion of the parcel facing south, which both theoretically influence the favorability of growing conditions, do not appear to have a strong or precisely estimated impact on cultivation site size.

However, the spatial location of a cultivation site does impact its size. Distance to ocean increases size in a statistically significant manner, likely indicating that growers have larger farms where there is less fog. At the same time cultivation sites that are closer to a city are likely to be smaller. Zoning and northness have no impact on cultivation site size.

The size of a parcel always has a statistically significant and positive impact on the outcome model.[8] As in the first stage selection equation, the negative sign on the quadratic term indicates diminishing returns to size for very large parcels. The role of vegetation cover in predicting the number of cannabis plants grown on a given site is more ambiguous; forested parcels had slightly larger cultivation sites than non-forested parcels, but the estimated coefficients are imprecisely estimated. However, a higher degree of shrub land is strongly negatively associated with cultivation site size. The impact of a parcel ever having a THP was also negative, but imprecisely estimated.

Finally, we find that, in contrast to the selection equation estimates, ‘network effects’ do not appear to be a strong predictor of cultivation site size. The coefficient estimate for number of plants within 100 m is close to zero and not statistically significant by any measure.

3.2.1. Differences between outdoor and greenhouse cultivation sites

Running separate regressions for outdoor and greenhouse plants reveals largely similar results with respect to site selection and production intensity, but with a few important deviations (Table 4). Notable differences emerge with respect to forestry history and zoning. THP significantly increases the likelihood of outdoor cultivation, but not of greenhouse cultivation.[9] Agriculture exclusive zoning and “unzoned” designation increase the likelihood of greenhouse cultivation sites, but not of outdoor cultivation sites.

There are differences in predictors of the size of cultivation sites as well. The relationship between high percentages of slope over 30% and greater numbers of plants in the overall estimates is clearly driven by greenhouse cultivation sites, not outdoor sites. The same holds true for parcels farther from the ocean. Outdoor cultivation sites located farther north are predicted to be significantly smaller than cultivation sites in the southern part of the country, but the model shows an opposite, though imprecisely estimated, relationship for greenhouses.

3.2.1.1. Spatial Sample. Finally, models built on the spatial sampling routine provide similar average estimates, but the coefficients were less precisely estimated. For example, in the spatial model parcel size is

[8] The positive relationship also holds when the data set is restricted to parcels larger than 5 acres.
[9] The differences in the coefficients between the regressions are themselves significant, as well.

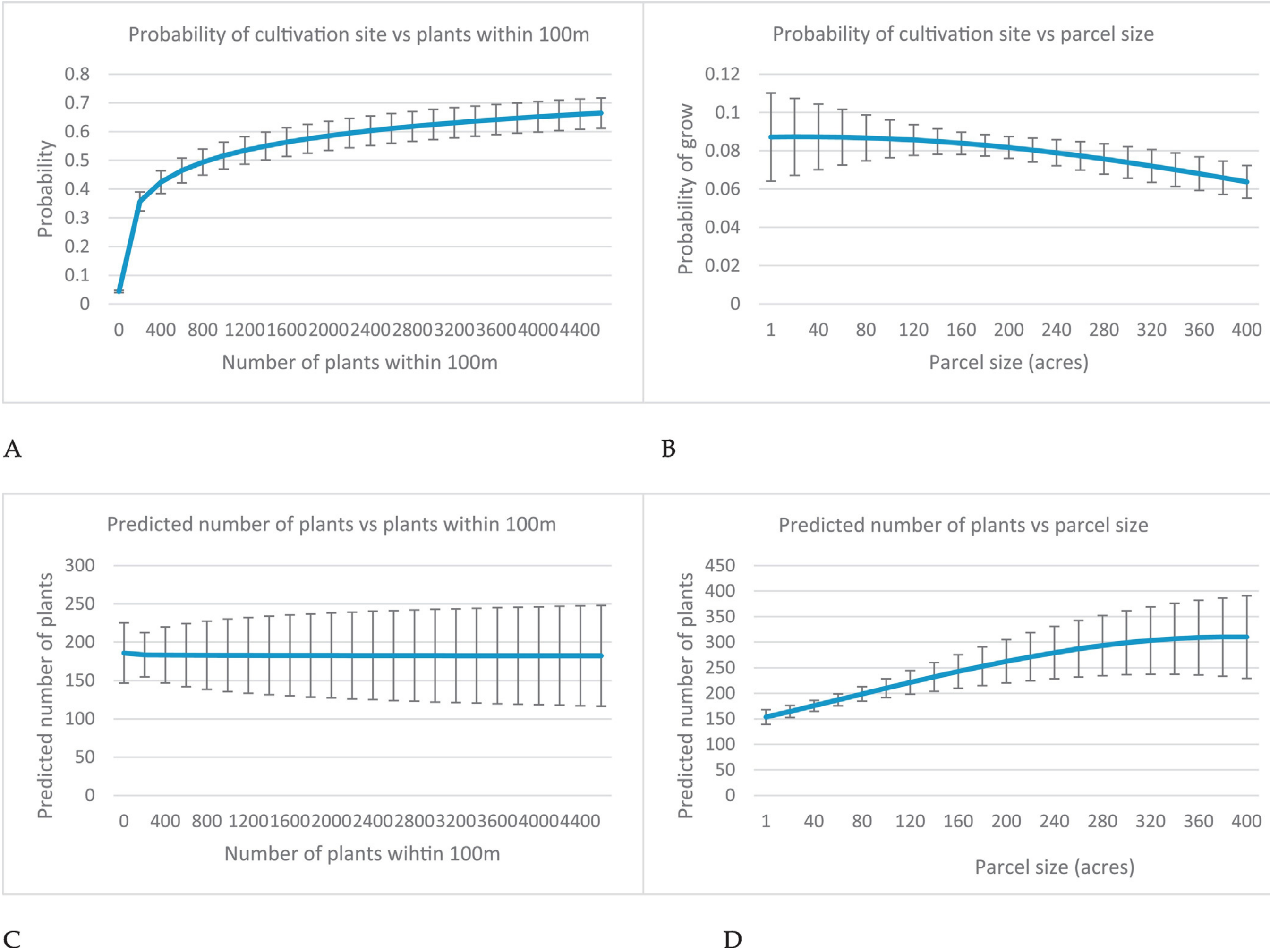

Fig. 2. (A) relationship between the predicted probability of a cultivation site and parcel size; (B) relationship between the probability of a cultivation site and the number of plants within 100 m of a parcel; (C) relationship between the predicted number of plants and parcel size; (D) relationship between the predicted number of plants and the number of plants within 100 m of a parcel.

significant and positive in the outcome equation, but the squared term is not significantly different from zero. Both terms are significant in the non-spatial model. Such results may be expected as the sampling procedure greatly reduces sample size. Importantly, perhaps the most interesting result – the impacts of networks on siting – are still detected in this model in a statistically significant manner (Table 5).

3.2.1.2. Control Function. The estimation of both the main model and the spatial sample suggest that the number of cannabis plants on neighboring parcels strongly increases the probability a given parcel will itself host cannabis cultivation. However, if there are factors unaccounted for in our model that make cannabis production attractive on neighboring parcels, such as a favorable microclimate, the measured effect may be biased upwards. In particular, the endogeneity problem would suggest that the previously estimated positive coefficient on the number of plants grown on neighboring parcels cannot be interpreted as a direct effect of neighboring cultivation sites, rather a result of this unobserved feature favoring cannabis cultivation on multiple neighboring parcels. An unobserved variable that is unfavorable between clusters – such as if clustered farms suffer from unfavorable pest or wind conditions – could actually bias our estimates downward.

To correct for the potential endogeneity problem, we employed a control function approach (Lewis and Alig, 2014). Our strategy relies on the fact that observed physical characteristics of neighboring parcel *j* should only affect cannabis production on parcel *j*, and not on adjacent parcel *i*. Therefore, the physical characteristics of a parcel *j* should serve as valid instrument for the log of the number of plants on parcel *j*, as they should not directly affect the existence of cannabis production on parcel *i*. To implement this strategy, we defined an instrument that aggregates each biophysical and zoning variable used in the main estimate across the neighboring parcels from which the network variable is derived.[10] As in Wooldridge (2015), we recovered unbiased estimates of the network variable, *lnnp100*, using a two-step procedure: we estimate a first-stage OLS of *lnnp100* on the instruments, and then a second stage probit of the main equation (i.e. the first stage selection equation of the Heckman model) that includes functions of the residuals from the first stage. As in Wooldridge (2015), we use several different specifications of the control function to check the robustness of the results to various functional forms. Standard errors are obtained by bootstrapping both steps.

The results (Table 6) suggest that correcting for the endogeneity of *lnnp100* slightly increases the estimate of the effect on the probability of cannabis production on a given parcel. In all specifications, neighboring parcel characteristics appear to be ‘strong’ instruments for neighboring cannabis plants ($F > 100$). Under the assumption that *lnnp100* is exogenous (i.e. Table 3), our estimated marginal effect is 0.028.

[10] The instruments used are neighbor's slope, forest type (mixed, hardwood, shrub, barren), zoning classification, and existence of a THP. All variables are aggregates of values within 100 m of a given parcel.

Table 4
Heckit estimation results by cultivation site location (greenhouse or outdoor).

	Greenhouse		Outdoor	
	Outcome equation (# of cannabis plants)	Selection	Outcome equation (# of cannabis plants)	Selection
Distance to stream	−0.068	−0.002	−0.041	0.001
	(0.056)	(0.003)	(0.074)	(0.003)
Slope 30	0.5022	0.0111	0.2023	0.0102
	(0.1379)***	(0.0081)	(0.1874)	(0.0071)
% of parcel facing S, SW, or SE	0.0015	0.0092	0.0083	0.0059
	(0.1036)	(0.0063)	(0.1311)	(0.0053)
% of parcel mixed forest	0.149	0.037	−0.099	0.012
	(0.134)	(0.007)***	(0.155)	(0.006)**
% of parcel hardwood forest	0.032	0.039	−0.006	0.013
	(0.173)	(0.009)***	(0.205)	(0.008)
% of parcel shrub	−0.438	−0.010	−2.170	−0.002
	(0.758)	(0.034)	(0.780)***	(0.027)
% of parcel coniferous	−0.307	0.022	−0.215	0.003
	(0.151)**	(0.008)***	(0.191)	(0.007)
% of parcel barrren	−0.924	−0.089	1.516	−0.049
	(0.730)	(0.034)***	(0.777)*	(0.024)**
Parcel size	0.186	0.028	0.352	0.004
	(0.097)*	(0.006)***	(0.115)***	(0.005)
Parcel size squared	−0.012	−0.007	−0.037	−0.001
	(0.022)	(0.001)***	(0.021)*	(0.001)*
Northness	0.002	−2.6E-04	−0.003	−8.1E−05
	(0.002)	(6.7E-5)***	(0.001)*	(5.2E−05)
Distance to road (log)	−0.019	0.021	0.021	0.015
	(0.068)	(0.004)***	(0.093)	(0.003)***
Distance to an ocean	1.404	0.033	0.083	0.045
	(0.296)***	(0.016)**	(0.411)	(0.014)***
Distance to a city	0.077	0.005	−0.091	0.026
	(0.089)	(0.004)	(0.123)	(0.004)***
THP	0.041	−0.007	−0.038	0.010
	(0.088)	(0.005)	(0.113)	(0.004)**
# of plants within 100 m (log)	0.017	0.020	−0.046	0.013
	(0.031)	(0.001)***	(0.046)	(0.001)***
Ag exclusive zone		0.015		2.6E−04
		(0.009)*		(0.007)
Ag zone		0.013		0.013
		(0.010)		(0.008)
Timber production zone (TPZ)		0.011		−0.007
		(0.010)		(0.008)
Residential suburban		0.001		−0.018
		(0.014)		(0.012)
Forest recreational		0.073		0.032
		(0.010)***		(0.008)***
City land		−0.019		0.001
		(0.017)		(0.014)
Unzoned		0.031		0.008
		(0.009)***		(0.007)
Rho	−0.16		−0.39	
N	13,988		14,152	

Marginal effects reported for the selection equation. Standard errors in parentheses. Constant term not reported.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Estimating *lnnp100* without assuming exogeneity, increases the estimate to between 0.041 and 0.045, depending on the exact specification of the control function. The coefficients remain significant at the 5% level.

These findings do not support the idea that unobserved factors common to neighboring parcels are the primary driver of the observed positive influence of nearby cultivation sites on the probability of cannabis cultivation. In fact, given the higher estimated control function coefficients, and the fact that the control function terms are significant in the second stage probit, these results indicate that the original estimates

Table 5
Estimation results from spatial sample models.

	Outcome equation (# of cannabis plants)	Selection
Distance to stream	−0.071	0.001
	(0.11)	(0.005)
Slope 30	0.394	0.009
	(0.272)	(0.151)
% of parcel facing S, SW, or SE	0.049	0.083
	(0.202)	(0.118)
% of parcel mixed forest	0.187	0.395
	(0.255)	(0.134)**
% of parcel hardwood forest	0.216	0.425
	(0.333)	(0.172)**
% of parcel shrub	−1.067	−0.222
	(1.374)	(0.628)
% of parcel coniferous	−0.156	0.112
	(0.289)	(0.143)
% of parcel barrren	−0.280	−0.868
	(1.265)	(0.533)
Parcel size	0.004	0.001
	(0.002)**	(0.001)**
Parcel size squared	−5.2E−06	−5.5E−06
	(4.48E−06)	(2.08E−06)*
Northness	0.002	−0.002
	(0.003)	(0.002)
Distance to road (log)	−0.033	0.219
	(0.133)	(0.068)**
Distance to an ocean	0.006	0.006
	(0.006)	0.003**
Distance to a city	0.001	0.001*
	(0.002)	(0.000)
THP	−0.128	0.073
	(0.168)	(0.096)
# of plants within 100 m (log)	−0.014	0.239
	(0.067)	(0.015)**
Ag exclusive zone		0.142
		(0.153)
Ag zone		0.116
		(0.176)
Timber production zone (TPZ)		0.042
		(0.166)
Residential suburban		−0.189
		(31.467)
Forest recreational		0.707**
		(0.171)
City land		−0.513
		(856.039)
Unzoned		0.201***
		(0.146)

Marginal effects reported for the selection equation. Standard errors in parentheses. Constant term not reported.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 6
Control function estimation results.

lnnp (log of # of plants within 100 m)	0.045	0.041	0.043	0.043
	(0.007)**	(0.006)**	(0.007)**	(0.007)**
v (first stage residual)	−0.0169	−0.0186	−0.0201	−0.0041
	(0.0066)*	(0.0064)**	(0.0069)**	(0.0074)***
v^2		0.0021		0.007
		(0.0005)**		(0.001)**
lnnp v			0.0014	−0.0080
			(0.0008)	(0.0018)**
N	13,244	13,244	13,244	13,244

Dependent variable is a dummy equal to one if a cannabis plant is observed on a parcel. Marginal effects are reported from a probit regression of the dependent variable on all independent variables in Table 3 (not shown), as well as residuals from a first stage estimate of *lnnp* on neighboring parcel characteristics. Standard errors in parentheses based on 1000 bootstrap replications.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

may have suffered from downward bias. Correcting for the fact that unobserved factors common to neighboring parcels may actually be unfavorable to cannabis production, proximity to neighboring cultivation sites is an even stronger predictor of the location of cannabis cultivation.

4. Discussion

Cannabis agriculture is an emerging crop in many parts of the world (Potter et al., 2011), and a force for landscape change in the United States. While other forms of agricultural change have been well documented with established theoretical and modeling frameworks, these insights are lacking for cannabis agriculture. As such, advances in the understanding of decisions surrounding cannabis cultivation have potentially broad relevance. We believe that our case has particular relevance to other situations—at least in the U.S.—because California has historically played a leading role in the US cannabis industry and often serves as a bellwether of policy changes anticipated in other states (Weisheit, 2011).

In this study, we quantified how a few selected physical and policy variables drive cannabis producers' decisions regarding farm location and size. Our main findings show that biophysical drivers are less important to location choice for cannabis farmers than for other farmers, and that network effects are strong. Both findings suggest that social relations between farmers and other actors are important and research – qualitative or quantitative – that addresses farmers directly is an important next step in understanding the broader impacts of this new crop.

The locational choice of cannabis production is influenced most strikingly through the impact of the number of plants grown in a given parcel's neighborhood. This result holds for both outdoor and greenhouse cultivation sites. The mean probability of a cultivation site being located on a parcel jumps from <5% for a cultivation site without any neighboring cannabis plants within 100 m to over 30% when 200 plants are located in the neighboring 100 m perimeter. Controlling for potential endogeneity of the placement of neighboring cultivation sites via a control function approach does not diminish the estimated effect of neighboring plants.

The large positive impact of neighboring sites on predicting cultivation within a parcel suggests strong network effects among producers. Given the lack of formal training and fractured input and markets, it is likely that producer networks have been essential factors in the development of the industry, a conclusion supported by some of the historical ethnographic work done in the area (Raphael, 1985). Further, we believe that these network effects have played a role in determining landscape pattern and impacts.

However, despite the evidence of clear spatial clustering of cannabis production operations, the sizes of neighboring cultivation sites are not strongly correlated. These results suggest heterogeneity in farm types at the time of our study that also seem to be consistent with the documented history of cannabis cultivation in the region (Raphael, 1985). Such mixing of small-scale cultivation sites with larger operations may not hold in the future, as increased policy liberalization and a general formalization and mainstreaming of the industry could facilitate consolidation among producers by reducing disincentives for growth.

Many biophysical variables that commonly feature in crop choice models are not important in the case of cannabis. Our model predicts that areas with steep slopes, poor irrigation access, and location far from roads are just as likely places for cannabis cultivation as areas more suited to conventional agriculture.[11] Likewise, we found that cultivation sites that did take place on steep slopes were likely to be larger than cultivation sites that took place on flat land for both the full dataset and for greenhouse cultivation sites. This suggests that producers increased the size of their operations on account of factors different from those affecting conventional agriculture. (For example, steep slopes would disadvantage large-scale conventional crop production.) We speculate that after decades of law enforcement, producers on steep slopes, that are difficult to access and navigate, perceive lower risk of raids, and therefore enjoyed opportunities to grow their operations.

There are clear negative environmental consequences of such placement. As has been documented elsewhere, this placement can lead to excessive private road building, which is often associated with erosion and stream sedimentation. The unofficial road-building and forest clearing that often accompany expanded cannabis production can also result in significant fragmentation of natural habitat. We would hypothesize that as liberalization continues, steep locations will be chosen less frequently for cannabis cultivation, and the location of large cultivation sites will shift to less remote, more physically suitable locations. Then again, some local growers assert that Humboldt growing conditions, typified by steep, remote mountain slopes, add to their product a certain "terroir" value. Future research could benefit from directly interviewing farmers about their decisions and applying either qualitative or quantitate methods to analyze such data.

The clustering we note in our data may have positive or negative implications for the environment. On one hand, clustering may diminish the spread of cannabis into further remote areas of the County. That is, cannabis impacts may be localized by virtue of clustering. On the other hand, clustering may actually magnify the effects of these grow operations, thereby intensifying local environmental impacts. Clustering thus presents a classic trade-off involving localized but relatively severe impacts versus widespread but relatively modest impacts. Resolving this dilemma will require continued ecological research.

Our results lend only modest support for the common story of cannabis production on cut-over timber land. The overall estimate reflects significant heterogeneity with respect to production type (outdoor versus greenhouse). Statistically, parcels that have had a THP in the last 15 years are only 1% more likely to have an outdoor cannabis cultivation site than parcels that did not have a THP. No similar effect exists for greenhouse sites. These results suggest that some outdoor producers are perhaps more opportunistic, taking advantage of canopy openings for outdoor crops which take less capital investment than greenhouses.

While our models are relatively robust to changes in the underlying dataset as well as alternative exclusion restrictions there are still caveats to consider. First, given the one-time nature of our observations and a relatively homogenous policy landscape, we would caution against causal claims from our data. Second, while we are able to successfully bring together multiple spatial datasets, there remain some weaknesses in the measurement of some specific characteristics. In particular, we have some concerns about the robustness of our water access variable. While we use the highest resolution dataset possible, we have had many conversations with hydrologists who say there are numerous undocumented springs in Humboldt County, and that these springs could provide adequate flow to irrigate cannabis. The lack of significance in our water access variable may simply be a case in which we are unable to measure this variable at a fine enough resolution.

Overall, our results suggest that the factors influencing cannabis farm location and size may be quite different from those affecting other agricultural crops. This is likely due to the still unresolved legal landscape in which cannabis producers operate, as well as factors that likely prevailed during the prohibition era: a desire for remoteness and a reliance on informal networks. Future research would do well to illuminate more clearly the coevolution of sophisticated cannabis production and the social institutions that facilitated that growth.

Our findings suggest intriguing prospects for future land-use patterns under a further liberalized cannabis regime. On one hand, land-

[11] Here it seems important to acknowledge that our population of cultivation sites excluded so-called "trespass grows" on public land. These are amply, if not systematically, documented elsewhere, primarily as a result of the law enforcement activities of federal and state agencies. Our past work has shown that the vast majority of cultivation in this region takes place on small, private land holdings, so we focused our study on these parcels.

use decisions underlying cannabis production activities seem to reflect lingering fears of legal sanction under the era of strict prohibition. The November 2016 ballot initiative legalizing recreational use state-wide would hypothetically result in larger, more homogenous farms located on flatter, less remote terrain in the years to come—perhaps in the Central Valley where cannabis would compete with other high-value crops. On the other hand, a thriving clandestine production regime arose under strict prohibition, in spite of an extremely challenging agro-ecological environment. Farmers' ability to overcome these limits probably hinged on the development of specialized human capital and institutions, which remain in place today. In an environment of legal ambiguity stemming from continued federal restrictions, a rapid reorientation of cannabis production to more traditional farming areas is not a foregone conclusion. If factors driving the network effects we identify remain relevant, further state and local liberalization may simply intensify current practices.

Our findings are valuable for documenting the emergence of cannabis agriculture as a mainstream activity and for guiding agricultural and land-use policy. Future ecological and economic sustainability in cannabis agriculture depends on proactive policy design informed by a sound empirical knowledge of (a) the forces that have historically driven production decisions, and (b) the ways farmers are likely to modify production practices under increasing liberalization. While this study cannot directly address how the present-day emergence of cannabis agriculture (amidst a sociopolitical climate of liberalization) will impact land-use in other contexts, lessons from our analysis of Humboldt County's experience can be pertinent. In particular, our results suggest that despite two decades of legalization at the state level, cannabis agriculture production patterns remain strongly influenced by the priorities of growers during the strong prohibition era. This path-dependence suggests that states and localities transitioning to a liberalized regime would be well-served to provide a clear regulatory framework around production that addresses potential environmental concerns before potentially harmful practices take root.

There is a clear and urgent need for research that integrates social and ecological perspectives—using both qualitative and quantitative approaches. Such integrated research can allow policymakers to better understand why cannabis farmers do what they do—in response to both the biophysical conditions of a challenging environment and the social conditions surrounding an emergence from the shadows. The emerging changes in local and state laws across the country provide several opportunities for fruitful research. In particular, state and county level differences in supply chain regulation should provide an excellent source of variation to identify the influence of policy on the pattern of production (and the environmental consequences). Changes in real estate patterns represent another area of exploration.

Our analysis examines outdoor cannabis cultivation on private lands, and does not directly address indoor growth in urban areas and "trespass grows" on public lands. Thus, our conclusions are limited to more mainstream outdoor production. The specific factors associated with the spatial distribution of indoor and trespass producers, and the environmental consequences they entail, may differ from the growers in our sample along several dimensions. Indoor producers, in particular, face large energy requirements. However, despite the increased attention to indoor production, outdoor cultivation (including greenhouse production) is likely to remain a major element of cannabis supply due to its significant cost advantage (Caulkins, 2010; Hawkins, 2013).

Acknowledgements

We thank the Sponsored Projects Office for Undergraduate Research for assistance with this project as well as undergraduate researcher J. Nguyen. We also thank the helpful discussion of members of the AAG Panel "Geographies of Marijuana Production," including A. Short Gianotti, J. Carah, M. Polson, J. Rose, and S. Keene.

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