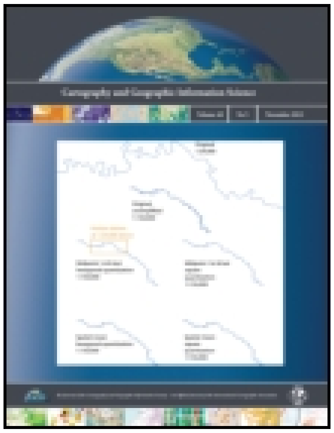

Cartography and Geographic Information Science
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/tcag20

Illegal drug cultivation in Mexico: an examination of the environmental and human factors

Monica Medel[a] & Yongmei Lu[a]
[a] Department of Geography, Texas State University, San Marcos, TX 78666, USA
Published online: 26 Nov 2014.

Cartography and Geographic Information Science, 2015
Vol. 42, No. 2, 190–204, http://dx.doi.org/10.1080/15230406.2014.985716

Illegal drug cultivation in Mexico: an examination of the environmental and human factors

Monica Medel and Yongmei Lu*

Department of Geography, Texas State University, San Marcos, TX 78666, USA

(*Received 15 April 2014; accepted 16 October 2014*)

Patterns of illicit narcotics cultivation are among the understudied topics. Some studies estimate the prevalence of illegal crops using imagery and remote sensing data. These studies rely heavily on the availability and quality of the related images, which is often an issue for many countries known as major drug producers. Using official drug crop eradication data, this study examines the patterns of illegal drug cultivation in Mexico at the municipality level. Species distribution models of ecology were used to guide the selection of environmental variables. A number of sociodemographic variables were incorporated into the model to describe human factors. Global and local models were compared to discern the determinants of marijuana and opium cultivation. Geographically weighted regression was proved overall more effective than global ordinary least square regression despite the spatial variation of its explanation power. The models explained the spatial patterns of opium poppy cultivation are better than those of marijuana cultivation, suggesting the possible presence of more complicated local factors for growing illicit marijuana crops. A number of human factors such as law enforcement, gang activities, and transportation accessibility were found significant for illicit cultivation.

Keywords: drug cultivation; geographically weighted regression; species distribution models; environmental factors; human factors

Introduction

The patterns of illegal narcotics cultivation in Mexico are among the understudied topics about drug activities. There are many studies on Mexican antinarcotics policies and law (e.g., Reuter 1988; Toro 1995; Dominguez and Fernandez de Castro 2001), the history of drug smuggling (e.g., Astorga 2005; Youngers and Rosin 2005), the relationship between drugs and economy (e.g., Resa Nestares 2003; Thoumi 2003), and the socioeconomic impact of drug cultivation on communities where different types of drug crops are grown (e.g., De la Herrán 1980; Marín 2002; Lizarraga and Lizarraga 2006). Studies can also be found on illicit cultivation activities in other countries, including Colombia and Peru, the chief producers of cocaine in South America, and Afghanistan and Myanmar, the largest producers of opium and heroin in Asia. Many of these studies were led by the United Nations Office on Drugs and Crime (UNODC), which conducts periodic surveys on illegal crops, especially the cultivation of opium, coca, and marijuana (UNODC 2000–2012). These studies incorporated remote sensing data and techniques with fieldwork and surveys to determine drug production. Preharvest images with high spatial resolution, such as GeoEye, WorldView2, Quickbird, and Ikonos data of 1.65- to 4-meter resolution, were often used (UNODC 2011). They cover a number of countries including Afghanistan, Bolivia, Colombia, Ecuador, Peru, Morocco, Myanmar, and Laos, but not Mexico, which is a main opium and marijuana producer in the Americas (INCSR 2008, 2009).

Marijuana (*Cannabis sativa*) is endemic to the state of Sinaloa, located in the northwest region of the country (Figure 1). Its presence was noted in books as early as the end of the nineteenth century (Ortega and Lopez Manon 1987). But its cultivation did not begin to boom until the advent of the twentieth century when narcotics became prohibited in the United States and the rest of the world (Astorga 2005). By 1920, Mexico too had banned the cultivation and sale of marijuana. As early as a decade later, the first Mexican drug traffickers began being mentioned in the national press as operating in the border region with the United States and producing their crops in state of Sinaloa and the neighboring states of Durango and Chihuahua – an area that has been dubbed “the Golden Triangle” of drug production in Mexico (Astorga 2005). In the subsequent decades, the cultivation of marijuana spread to other, more distant regions, following valleys in the Sierra Madre Mountains. Crops began being detected far from Sinaloa, in areas ranging from the southernmost Chiapas state to the Gulf Coast Veracruz state and the deserts of the Baja California peninsula (Astorga 2005). The vast quantities of marijuana crops in so many varied areas across Mexico make it a good drug specimen to study in order to understand the effects of both environment factors and human actions.

*Corresponding author. Email: YL10@txstate.edu

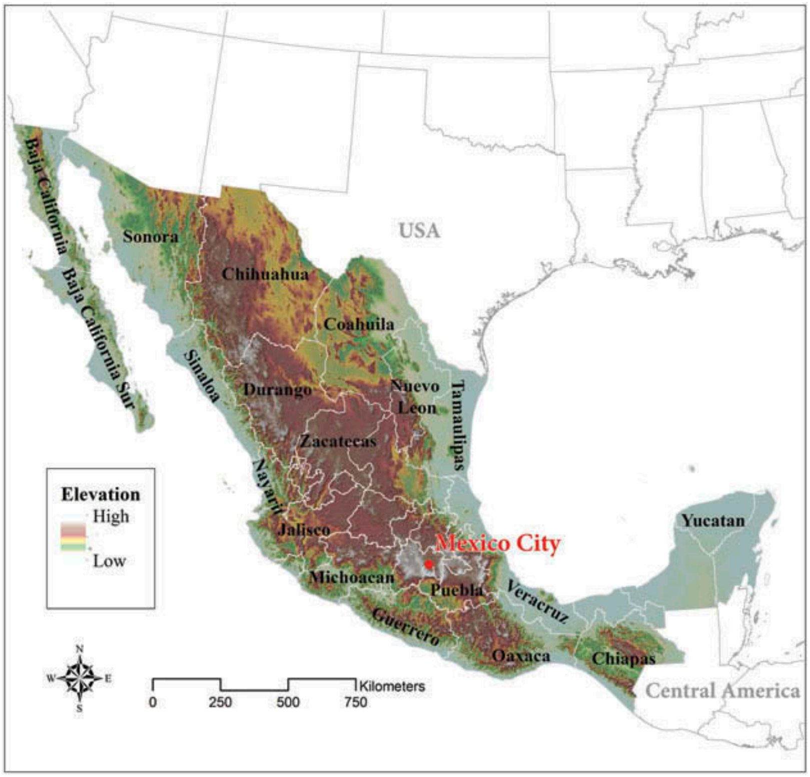

Figure 1. Mexico – the study area.

Opium poppy (*Papaver somniferum*) is not native to Mexico but is believed to have been introduced in the late 1800s by Chinese immigrants who arrived in the country to work in mines and on railroad construction (Astorga 2005). The result was the spread of a plant that the locals dubbed *Adormidera blanca* but was none other than opium. It began to spring up in Sinaloa shortly after the arrival of the Chinese. Opium crops then spread rapidly to neighboring states, including Sonora and Chihuahua as mining developed in the area (Toro 1995). By the 1960s, it was being cultivated even in the southern states of Oaxaca and Chiapas and in the Pacific coast states of Nayarit and Guerrero (Astorga 2005).

Understanding the factors that are favored by the illicit crop cultivation could help authorities better pinpoint where such illicit production is likely to occur, and thus act to eradicate it. This perspective has guided a number of studies on marijuana in the United States and Canada (Walthall et al. 2003; Thomas et al. 2004; Partelow 2008; Hurley, West, and Ehleringer 2010; Bouchard, Beauregard, and Kalacska 2013), but none in Mexico. This study investigates the factors impacting the cultivation of marijuana and opium poppy in Mexico. The goal is to examine the relationship between the illicit cultivation and the environmental and human conditions tied to the cultivation activities. By adapting the species distribution models (SDMs) from ecology, both global and local models are employed to investigate the illicit cultivation of marijuana and opium poppy in Mexico.

Species distribution model: a framework for illicit cultivation study

SDM relates observation of species presence or their abundance with environmental factors (Elith and Leathwick 2009). It is frequently used as a framework to study spatial patterns of species. Environmental factors impacting species distribution can be classified into indirect, direct, and resource variables (Guisan and Zimmerman 2000). Resource variables describe matter and energy consumed by the plant (like nutrients or water). Direct variables are linked to environmental conditions that affect plants but cannot be consumed by them (e.g., temperature or PH). Indirect variables do not have a physiological impact on plants but are well correlated with species distribution (such as slope, elevation, geology, and aspect).

In the case of crops, however, their distribution does not depend solely on environmental factors. Because seeding, cultivation, and harvest do not occur naturally, but rely heavily on human factors, certain variables can be controlled to create the optimal environmental conditions for the plants to grow. For example, water can be dispensed using top-notch irrigation systems that allow crops to thrive in natural conditions that otherwise could be adverse (Fortes, Platonov, and Pereira 2005; Liu 2009). For outdoor cultivation of illegal drugs, human factors can play a significant role. Aside from certain environment requirements for temperature, slope, aspect, and soil characteristics, proximity to roads and highways is important to make drug smuggling easier, while hiding away from urban centers can help minimize police surveillance (Partelow 2008). Moreover, availability of rainfall can be supplemented using irrigation technologies. Therefore, growing drug crops is not fully restricted by environmental factors.

The distribution of environmental variables may introduce spatial autocorrelation (Václavík and Meentemeyer 2009; Václavík, Kupfer, and Meentemeyer 2012) and nonstationarity (Osborne and Suárez-Seoane 2002; Austin 2007) to species distribution. Dispersal process, or the behaviors that lead to the propagation and aggregation of illicit crop cultivation, may also cause nonstationarity. But general SDMs do not account for these properties because either data to measure these processes are unavailable or the factors that lead to the formation of certain specific spatial patterns in the species distribution are unknown (Václavík, Kupfer, and Meentemeyer 2012).

Spatial autocorrelation and nonstationarity must be accounted for when modeling the relationship between illicit crops and their environment. Otherwise, models predicting species distribution may be misspecified, and the coefficient estimation may be incorrect (Lennon 2000; Keitt et al. 2002). The inclusion of environmental variables for a habitat modeling is not enough as spatial autocorrelation and nonstationarity may be introduced to species distribution by nonresource or nonenvironmental conditions (Bahn, O'Connor, and Krohn 2006; Diniz-Filho, Bini, and Hawkins 2003). For illicit cultivation, human factors such as crop growers' measures to minimize the possibility of being captured play an important role in the dispersal process of the crops, and so does the effectiveness of law enforcement's antidrug actions. Adopting a wider definition of dispersal conditions as Lidicker et al. (1975), this study includes a number of human factors that are important for understanding the distribution of marijuana and opium cultivation in Mexico.

Data and methods

Data on illicit cultivation in Mexico

Traditionally, areas along the Sierra Madre Mountains have been most coveted by drug gangs looking to establish their territories and corridors for moving narcotics into the United States. These regions have low population density, are usually well connected by road network, and are clustered with low-income population with limited access to basic services (CONEVAL 2010). The states with major drug production sites are mostly marketed by their beach resorts along the Pacific Ocean, while the drug fields remain in the mountains and valleys in the rural areas.

Data on Mexican marijuana and opium cultivation are scarce. Records of eradication of marijuana and opium poppy plants for 2009 and 2010 were obtained from the Mexican Secretary of Defense (SEDENA) through a Freedom of Information Act Request. The data were reported at municipality level, the administrative unit below state. There were 2456 municipalities in Mexico in 2010, among which 552 municipalities (22.5%) had marijuana crops eradicated and 274 municipalities (11.5%) had opium poppy plantations eradicated according to SEDENA (Figure 2).

The data on eradication were used as a proxy for the presence and quantity of marijuana and opium crops cultivation. The total amount of hectares eradicated was used in the study as a quantitative description of the illegal cultivation in a municipality. The municipalities with no eradication in 2010 were excluded from further analyses to avoid model bias. As Bahn, O'Connor, and Krohn (2006) suggest, a model including all municipalities, including those with no eradications, would have modeled the presence and absence rather than abundance. Using abundance information makes it possible to model the magnitude of illicit cultivation rather than only the presence/absence as commonly done by SDMs (Iverson et al. 2011). Moreover, most statistical models developed to deal with data sets with excess zeroes, such as zero-inflated models, assume that part of the zero group has no probability of having a count greater than zero (Barry and Welsh 2002; Lee et al. 2006). This is not the case for this study in which eradication data are used to approximate the scope of illicit drug cultivation. Treating the 80–90% of Mexico municipalities with zero eradications during the study period as having no illicit cultivation is likely to be very risky; using a zero-inflated model will likely introduce excessive errors. This study chose to focus on the municipalities with eradications to investigate the quantitative relationships between the independent and the dependent variables (Bahn, O'Connor, and Krohn 2006; Dormann et al. 2008; Iverson et al. 2011).

Data on marijuana and opium eradication in hectares were standardized by municipality areal size. Furthermore, because the standardized eradication data for both the crops were highly positively skewed (with very few municipalities having relatively large amount of eradication per square kilometer), the variables were transformed by using logistic transformation.

Independent variables

Environmental variables

Following SDMs, two environmental variables (temperature and precipitation) and two topographical variables

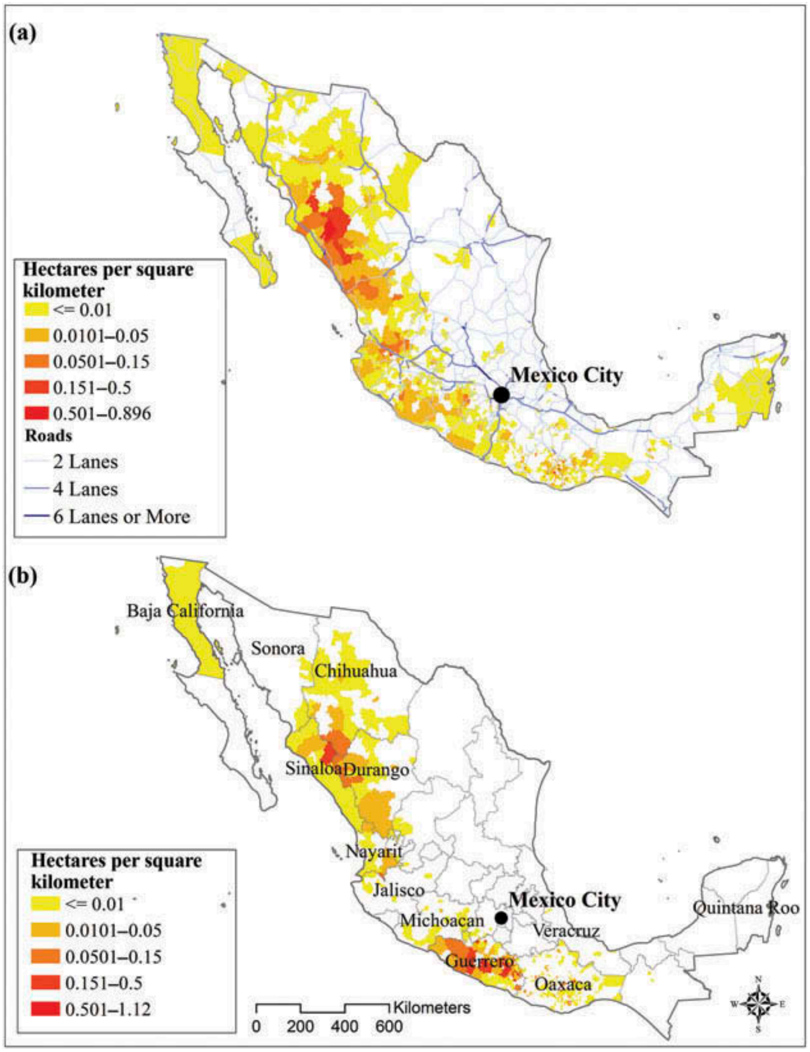

Figure 2. Eradications of illicit crops of (a) marijuana and (b) opium poppy.

(elevation and slope) are considered. Temperature – a direct variable – and precipitation – a resource variable – are fundamental for the development of plants. An appropriate temperature range for day and night allows plants to perform its metabolic processes and grow, while a proper level of humidity and soil pH guarantee its ability to acquire all the necessary nutrients (Hough et al. 2003). The optimal day temperature range for marijuana is 14–27°C (57.2–86°F). Even though they can resist light frosts (−5°C) (Small, Pocock, and Cavers 2003), extended cold weather may stop crop maturation. In comparison, day/night temperature for opium poppy is steady at 28°C/15°C, but leaf development increases at 19.5°C (Acock, Pausch, and Acock 1997). This study uses precipitation level as an indicator for humidity condition. Tetrahydrocannabinol (THC) strains, the primary psychoactive ingredient in marijuana, grow best in humid conditions, but it also grows well in areas with a dry atmosphere during the plant maturation period (Clarke 1981). Opium poppies grow best in temperate and warm climates with low humidity and not too much rainfall during early growth period (Booth 1999).

Elevation and slope are indirect variables. Elevation is closely related to temperature, while slope can be linked to soil moisture or texture. Slope may also help hiding illegal crops from the public eye by increasing access difficulty. A report on illicit crop management by the Canadian Police Research Centre (CPRC) identified those locations under 1219 meters of elevation and south-facing as being suitable for marijuana cultivation (Howell 2002).

Both the plants have specific needs for sunshine. Marijuana cultivation requires at least 10 hours of sunlight and between 11 and 12 hours of continuous darkness to flower and get close to its optimal THC production (Clarke 1981). Opium poppy needs direct sunlight for at least 12 hours daily while maturing. Unfortunately, this study does not account for sunshine as a factor for crop growing as the eradication data do not have information about specific growing sites.

Temperature, precipitation, and elevation data were obtained from the Institute of Statistics and Geography (INEGI 2005) in Mexico. The data for temperature and precipitation were polyline shapefiles and were converted to raster format using ArcGIS. Digital elevation model (DEM) data have a resolution of 1 arc second (about 31 meters) and were used to extract slope. The GIS files were projected into North America Lambert Conformal Conic Projection, and the datum was ITRF 1992. The three raster layers were resampled and registered for further analyses.

Considering the nonlinear effects of environment parameters on species abundance (Austin 2002; Dormann et al. 2008), mean annual precipitation was included in the model in quadratic form. Temperature was included in the model as a dummy variable where 1 indicated that the average annual temperature of a municipality falls in the proper range for the growth of the crops and 0 otherwise. Elevation and slope were used to describe the variation in topography, knowing that marijuana in Mexico is preferably cultivated in flatter surfaces, while opium is grown in the mountains. The environmental variables and their expected relationship with illicit cultivation are explained in Table 1.

Human variables

Human actions can greatly contribute to fragmenting the distribution landscape of species (Wiens et al. 2009). Further, they may work together with environmental conditions and push the species to isolated patches of terrain. Fung and Welch (1994) identified proximity to transportation network and water sources, as well as forest cover and distance from population center as human factors that impact marijuana cultivation. Howell's study in Canada found that forest clear-cuts with irrigation nearby and wetlands, mainly in park lands, are suitable for cultivation of marijuana (Howell 2002). Thomas et al. (2004) examined certain topographic characteristics that could facilitate cultivation or transportation of illicit crops; they further suggested unemployment rates as potentially being related to illicit cultivation. More recently, in a study of marijuana cultivation in California National Parks, Partelow (2008) mentioned variables such as vegetation and canopy coverage, and the effectiveness of law enforcement, for identifying potential places for marijuana cultivation. Still other studies suggested that, for drug cultivation, the impact of human factors may be measured by considering distance from urban centers, population density, and police presence (Partelow 2008; Bouchard, Beauregard, and Kalacska 2013). Bouchard, Beauregard, and Kalacska (2013) proposed that an index of corruption or propensity for illegal behavior in an area can help determine the variation in illicit activity dispersal. In a most recent study, Dube, Garcia-Ponce, and Thon (2014) found that, in addition to the impacts of drug cartel operations and drug killings, the illicit cultivation of both marijuana and opium in Mexico is negatively related to rural wages. Finally, opium poppy cultivation and marijuana cultivation are known to show spatial and temporal continuity – they tend to be close to each other spatially and tend to be grown 1 year after another if without interruption.

The data on roads, police forces, and land cover were obtained from INEGI (2013). Road data were polyline shapefiles, while the number of police officers for each municipality came as statistical data. Land cover data were polygon shapefile and were resampled to municipality level to reflect the dominant type of land cover for each municipality. Those municipalities where forest was the majority were coded as ForestLandCover = 1, while the rest were assigned a zero. Population data for each municipality in 2010 were also obtained from INEGI, while drug-related killing data on municipality level in 2010 were obtained from Mexico's Presidency. Lastly, illicit cultivation at a location tends to show spatial and temporal continuity, meaning that it is likely to be related to the illicit cultivation in the past as well as the illicit cultivation of other crops nearby. Therefore, eradication data of the same type of crop in 2009 and that of a different crop in 2010 were included in the models. All variables were standardized by the areal size of municipalities. Table 2 explains the human variables. The distributions of both environmental and human factors were heavily positively skewed and therefore were log-transformed before being included in the model.

Table 1. Environmental and topographic variables.

Variable name	Explanation	Expected relationship
TemperatureRange	Dummy variable for temperature in suitable range for cultivation (1 = in range, 0 = out of range)	+
MinimumPrecipitation	Minimum precipitation	−
MaximumPrecipitation	Maximum precipitation	−
MinimumPrecipitationSq	Minimum precipitation squared	−
SlopeVariation	Slope variation range	+ (opium) − (marijuana)
ElevationVariation	Elevation variation range	+ (opium) − (marijuana)

Notes: The symbols + and − indicate positive and negative, respectively.

Table 2. "Human" variables.

Variable name	Explanation	Expected relationship
MarijuanaEradication09	Marijuana crops eradication in hectares in 2009 (weighted by municipality area)	+
MarijuanaEradication10	Marijuana crops eradication in hectares in 2010 (weighted by municipality area)	+
OpiumEradication09	Opium crops eradication in hectares in 2009 (weighted by municipality area)	+
OpiumEradication10	Opium crops eradication in hectares in 2010 (weighted by municipality area)	+
DrugKillings	Drug-related killings in 2010 (weighted by population in each municipality)	−
HighwayDensity	Length of federal administration or at least four-lane roads by municipality (weighted by the municipality area)	+
PopulationDensity	Population density by municipality	−
PolicePresence	Police force in 2010 (weighted by population in each municipality)	−
ForestLandCover	Dummy variable for majority land cover type (1 = forest; 0 = everything else)	+

Notes: The symbols + and – indicate positive and negative, respectively.

Road data and police forces data were not available for some municipalities. This missing data problem resulted in a small number of municipalities with illicit drug eradications being excluded from modeling. These include 18 municipalities with marijuana eradications and six municipalities with opium eradications in 2010, leaving a sample size of 534 municipalities for marijuana cultivation prediction and 268 municipalities for opium illicit cultivation prediction. It is important to point out that these dropped observations are not among the municipalities with the largest eradications. Rather, most of them are in the state of Oaxaca (southern Mexico), which has a large number of small and isolated communities. Moreover, despite that some studies suggested a connection between economy and drug activities (e.g., Thomas et al. 2004; Dube, Garcia-Ponce, and Thon 2014), the analyses reported in this article were not able to examine this dimension due to the data unavailability at the time of the study.

Models

Ordinary least square (OLS) regression and geographically weighted regression (GWR) were employed to examine illicit cultivation at municipality level. Separate models were created to analyze how the cultivations of marijuana and opium poppy may be related to the environmental and human variables. Moreover, the cultivation of the same crop in the previous year and the cultivation of the other crop in the same year are included in the models as they may impact the illicit cultivation of a certain crop. The models can be described in general as follows:

$$\begin{aligned}\text{MarijuanaEradication10} = f(&\text{environment variables},\\ &\text{human variables},\\ &\text{OpiumEradication10},\\ &\text{MarijuanaEradication09})\\ &+\text{error}\end{aligned} \tag{1}$$

$$\begin{aligned}\text{OpiumEradication10} = f(&\text{environment variables},\\ &\text{human variables},\\ &\text{MarijuanEradication10},\\ &\text{OpiumEradication09}) + \text{error}\end{aligned} \tag{2}$$

OLS is a global linear model that does not allow modeling parameters to vary in space (Austin 2007). Global models assume that the relationships being studied are spatially stationary and that the parameters derived from the regression are valid for the whole data (Foody 2004). Global models cannot account for spatial nonstationarity between the dependent variable and the predictors. The presence of spatial autocorrelation among the residuals of an OSL model commonly indicates the ineffectiveness of the model. When the dependent variable responds differently to the predictors across the study area, a local model should be a better choice (Fotheringham, Brunsdon, and Charlton 2002; Osborne and Suárez-Seoane 2002; Foody 2004).

GWR is an extension of the regression baseline (Brunsdon, Fotheringham, and Charlton 1996; Kupfer and Farris 2007); it allows the parameters to vary across the study area. GWR was chosen over spatial autoregression (SAR) for this study because it can reveal the spatial variation of the relationship between the dependent and independent variables (Brunsdon, Fotheringham, and Charlton 1998; Fotheringham, Brunsdon, and Charlton 2002; Foody 2004). SAR models this relationship at the global level; it accounts for the effect of spatial autocorrelation but fails to reveal the nonstationarity of the relationship among variables (Anselin 2005). For an ecosystem, the spatial heterogeneity can result from systematical environmental, physical, and biological processes (Legendre and Legendre 1998). Because both the environmental factors and the human factors may relate to the dependent variables (i.e., illicit cultivation in 2010) differently across the municipalities in Mexico, this study opted to compare OLS global model with GWR local model.

$$\text{MarijuanaEradication10}_i = f(\text{environment variables at } i \text{ municipality, human variables at } i \text{ municipality, OpiumEradication10}_i, \text{MarijuanaEradication09}_i) + \text{error}_i \quad (3)$$

$$\text{OpiumEradication10}_i = f(\text{Environment Variables at } i \text{ municipality, HumanVariables at } i \text{ municipality, MarijuanEradication10}_i, \text{OpiumEradication09}_i) + \text{error}_i \quad (4)$$

Results

A preliminary correlation analysis among the independent variables revealed no significant collinearity issue. For OLS, the exploratory regression tool in ArcGIS10.1 was used to evaluate all possible combinations of the explanatory variables to predict the dependent variables. Various models were tested with between three and nine explanatory variables, an acceptable adjusted R^2 of 0.5 and a maximum p-value of 0.05 for explanatory variables. ArcGIS exploratory regression tool takes these parameter settings and the given dependent and independent variables to examine all the possible regression models; the return from this tool is a report on the performance of the best models, a summary of the significant explanatory variables, and statistics of the relationship between each explanatory variable and the dependent variable.

Examining opium cultivation

A total of 268 municipalities with eradications in 2010 were included in the analyses. Among the many models that passed the cut-off criterion of an adjusted R^2 of 0.50 (Table 3), a five-variable model revealed the greatest explanatory power with an adjusted R^2 of 0.692 and an Akaike information criterion (AIC) of −846.408 (Model (5)).

$$\begin{aligned}\text{OpiumEradication10} = \beta 0 &+ \beta 1^{*}\text{MarijuanaEradication10} \\ &+ \beta 2^{*}\text{OpiumEradication09} \\ &- \beta 3^{*}\text{DrugKillings} \\ &+ \beta 4^{*}\text{PopulationDensity} \\ &+ \beta 5^{*}\text{HighwayDensity} + \text{error}\end{aligned} \quad (5)$$

Table 3. Summary exploratory regression for opium poppy.

Variable	Percentage of the tested models where the variable was significant	Percentage of the models where the coefficient was positive	Percentage of the models where the coefficient was negative
OpiumEradication09	100	100	0
PopulationDensity	89.44	100	0
SlopeVariation	69.73	7.67	92.33
DrugKillings	59.83	50.89	49.11
ElevationVariation	52.72	82.53	17.47
ForestLandCover	50.89	98.12	1.88
MaximumPrecipitation	36.72	98.83	1.17
MarijuanaEradication10	20.21	100	0
HighwaysDensity	9.55	100	0
MinimumPrecipitation	9.34	40.17	59.83
TemperatureRange	1.47	0.51	99.49
PolicePresence	1.42	51.60	48.40

Three variables in this model were significant (OpiumEradication09, DrugKillings, and Population Density). The joint F-statistic and the joint Wald statistic were 121.08 and 124.19 at a significant level of 0.001, showing a good fit of the model. However, the Koenker's studentized Breusch-Pagan (BP) statistic was significant ($p < 0.001$), suggesting a nonstationarity problem. The Jarque–Bera statistic revealed that the residuals are not from a normal distribution ($p < 0.001$), a warning for possible spatial autocorrelation (Figure 3). Moran's I value for the residuals is 0.028 with a Z-score of 2.061, suggesting that the residuals are spatially clustered at 95% confidence level.

Being a local model to account for nonstationarity, GWR was applied to examine the variation of the relationship between the explanatory variables and the opium eradication. The best five-variable OLS model was adapted for the local model.

$$\begin{aligned}\text{OpiumEradication10}_i = \beta 0_i &+ \beta 1_i\text{MarijuanaEradication10}_i \\ &+ \beta 2_i\text{OpiumEradication09}_i \\ &+ \beta 3_i\text{DrugKillings}_i \\ &+ \beta 4_i\text{PopulationDensity}_i \\ &+ \beta 5_i\text{HighwayDensity}_i + \text{error}_i\end{aligned} \quad (6)$$

where "i" denotes a measurement for municipality i. The local variable coefficients in GWR are a function of the spatial kernel surrounding municipality i (Foody 2004; Kupfer and Farris 2007). That means that close observations have a greater influence than distant ones on the resulting coefficients. Because the data for this study are embedded in

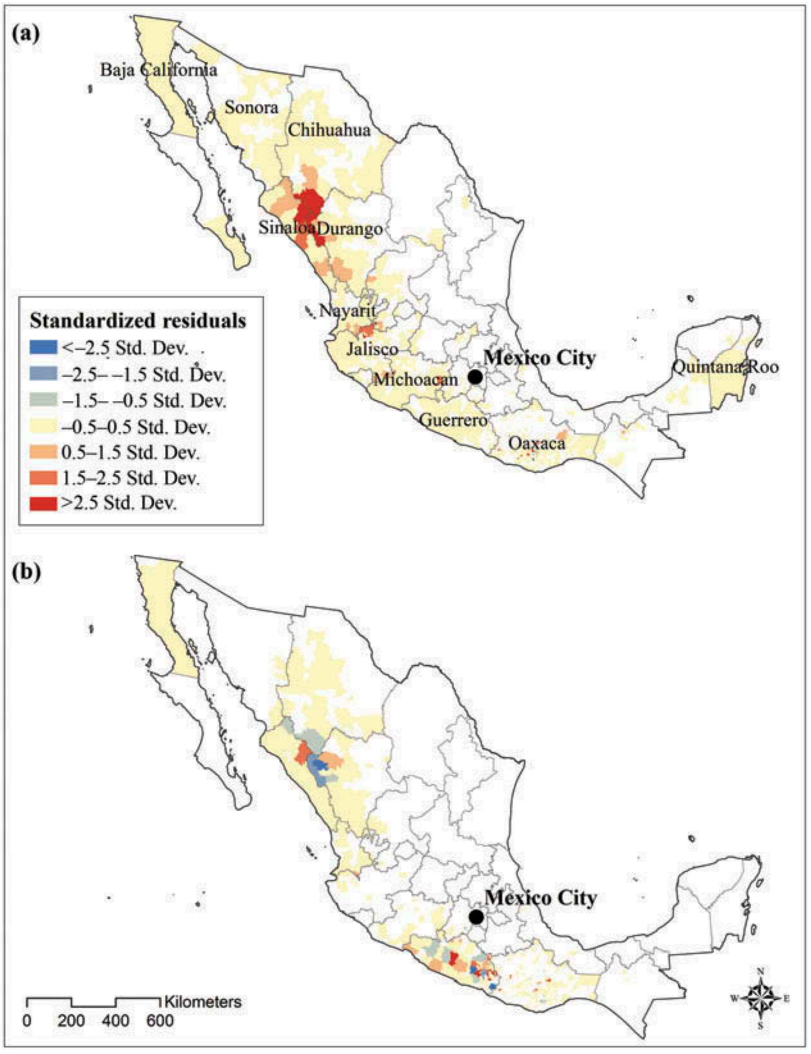

Figure 3. Residuals of the OLS regression model for (a) marijuana and (b) opium poppy.

irregular, asymmetrical polygons, adaptive kernel was used to make local estimation for the parameters.

The GWR model showed improvement compared with the OLS model when the residuals and AIC are concerned (Figures 3 and 4 and Table 4). The condition number, which evaluates local collinearity, remained much lower than the threshold of 30, suggesting that the model has reliable, stable results (Table 4). The values of local R^2 (Figure 5) ranged between 0.42 and 0.88, and their spatial distribution suggested that the GWR model explains opium cultivation better for central Pacific coast and the north regions of Mexico than the southern region.

Examining marijuana cultivation

A total of 534 municipalities were included in the modeling of marijuana cultivation. But the overall performance of the OLS models for marijuana cultivation was not as good as that for opium. The best OLS model has an adjusted R^2 value of 0.16, accounting for only 16% of the variance in marijuana eradication in 2010. MarijuanaEradication09 was revealed by multiple top models as significant predicting variable and with the largest coefficient; the variable is significant in more than half of all the possible models, and it is always positively related to the dependent variable (Table 5). Other common variables across the different models are MaximumPrecipitation and PolicePresence, being significant for around 25% of all possible models. However, MaximumPrecipitation is always negatively related to marijuana eradication, while PolicePresence is always positive.

The OLS model with the highest adjusted R^2 and the lowest AIC to predict marijuana eradication is a nine-variable model with explanatory variables including ForestLandCover, MarijuanaEradication09, Opium Eradication10, DrugKillings, PolicePresence, Elevation

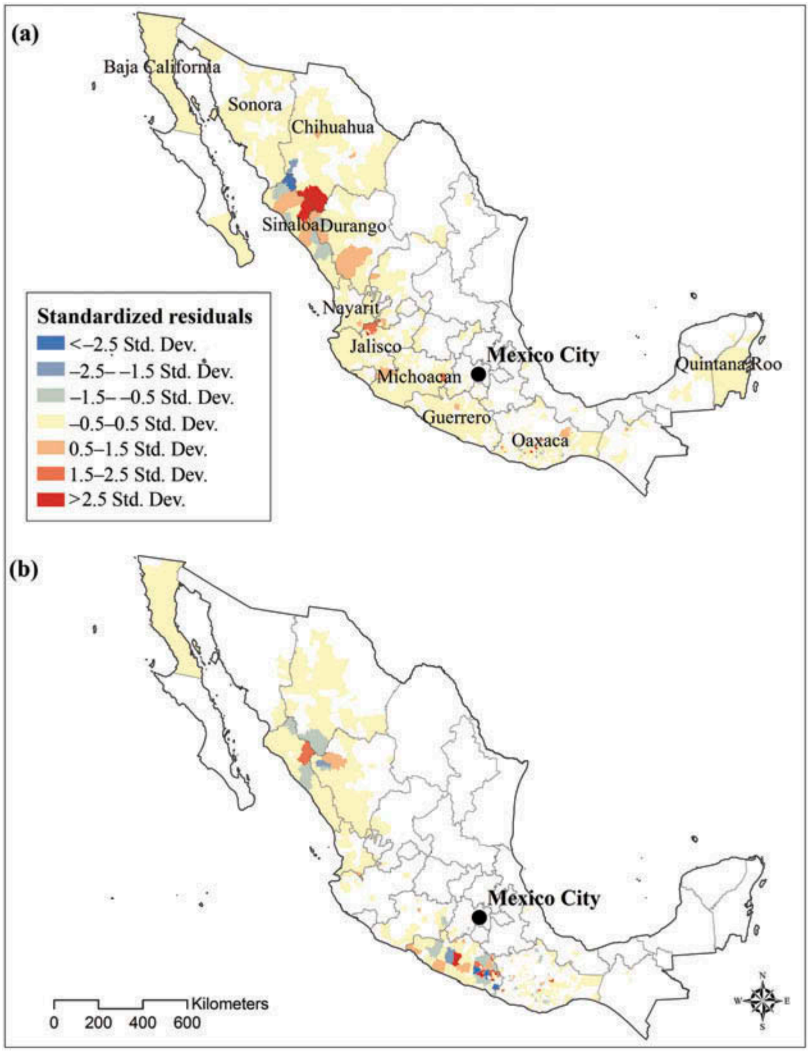

Figure 4. Residuals of the GWR model for (a) marijuana and (b) opium poppy.

Variation, MinimumPrecipitation, MaximumPrecipitation, and SlopeVariation. The last two variables are negatively related to the dependent variable, while other variables are positively related, and only MarijuanaEradication09 and MaximumPrecipitation are significant. However, the Jarque–Bera statistic, which tests for normality of residuals, and the Koenker (BP) statistic both pointed to autocorrelation among the residuals, indicating possible nonstationarity in the relationship between the dependent and independent variables (Table 6).

Since GWR does not allow for dummy variables, an OLS model without the ForestLandCover variable must be selected in order to compare with GWR model. Furthermore, GWR model requests that the independent variables are free from global and local multicollinearity. To prevent global multicollinearity, variance inflation factor (VIF) was forced to remain below 7.5. To preclude local collinearity, the independent variables were analyzed via thematic mapping and those with low spatial variability, particularly SlopeVariation, ElevationVariation, and MaximumPrecipitation, were excluded from the model. The best OLS model that is free from collinearity problem was used for comparison with GWR model. As a result, a four-variable model was selected through ArcGIS OLS exploratory regression analysis:

$$\begin{aligned}\text{MarijuanaEradication10} = \beta 0 + \beta 1^{*}\text{MarijuanaEradication09} \\ + \beta 2^{*}\text{DrugKillings} \\ + \beta 3^{*}\text{PolicePresence} \\ + \beta 4^{*}\text{HighwayDensity} + \text{error}\end{aligned} \tag{7}$$

This four-variable model, measured by F-statistic and joint Wald statistic, was significant at 0.01 level. MarijuanaEradication09 was the only significant

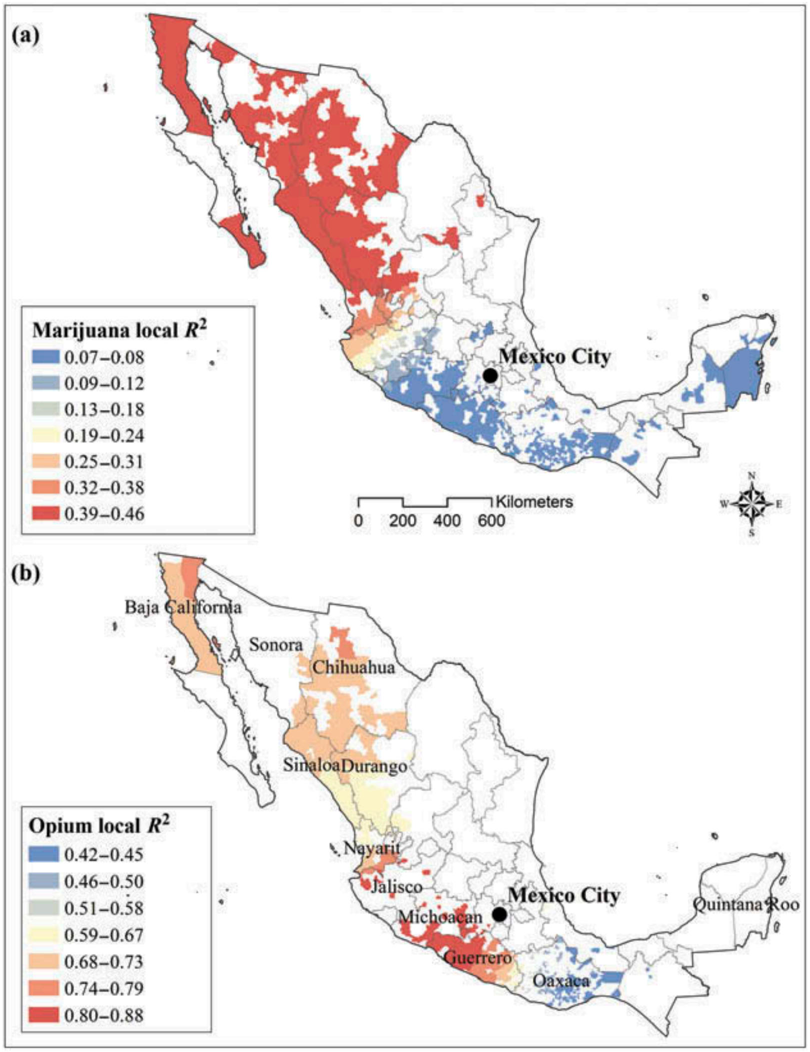

Figure 5. Local R^2 of the GWR models for (a) marijuana and (b) opium poppy.

Table 4. OLS and GWR models predicting opium.

Variable	Coefficient
Best OLS model	
Adjusted R^2 = 0.692; AIC = −846.408; maximum VIF = 1.262; JB = 0; K (BP) = 0	
MarijuanaEradication10	0.1173
Killings	−0.0027**
OpiumEradication09	0.8128*
PopulationDensity	0.0052**
HighwayDensity	0.0017
Comparing GWR model	
Adjusted R^2 = 0.734; AIC = −873.079; condition number < 13.392	
MarijuanaEradication10	−0.0765 ~ 0.4407
DrugKillings	−0.0065 ~ −0.0008
OpiumEradication09	0.2322 ~ 0.9284
PopulationDensity	−0.0011 ~ 0.0103
HighwayDensity	−0.0019 ~ 0.0073

Notes: *p < 0.001; **p < 0.05. VIF, variance inflation factor; JB, Jarque–Bera; K (BP), Koenker (BP).

Table 5. Summary on exploratory regressions for marijuana eradications in 2010.

Variable	Percentage of the tested models where the variable was significant	Percentage of the models where the coefficient was positive	Percentage of the models where the coefficient was negative
MarijuanaEradication09	50.89	100	0
MaximumPrecipitation	25.34	0	100
PolicePresence	24.89	100	0
MinimumPrecipitation	8.18	49.21	50.79
DrugKillings	5.89	96.39	3.61
OpiumEradication10	3.71	100	0
ForestLandCover	0.86	92.08	7.92
PopulationDensity	0.05	63.59	36.41
TemperatureRange	0	99.75	0.25
HighwaysDensity	0	98.32	1.68
SlopeVariation	0	0	100
ElevationVariation	0	49.11	50.89

Table 6. OLS and GWR models predicting marijuana.

Variable	Coefficient
Best OLS model (nine-variable)	
Adjusted R^2 = 0.16; AIC = −1694.91; maximum VIF = 5.26; JB = 0; K (BP) = 0	
ForestLandCover	0.0044
MarijuanaEradication09	0.2141***
OpiumEradication10	0.0975
DrugKillings	0.0015
PolicePresence	0.0013
ElevationVariation	0.0110
MinimumPrecipitation	0.0064
MaximumPrecipitation	−0.0127**
SlopeVariation	−0.0559
Comparing OLS model (four-variable)	
Adjusted R^2 = 0.094; AIC = −1662.05; maximum VIF = 1.12; JB = 0; K (BP) = 0.01	
MarijuanaEradication09	0.2360**
DrugKillings	0.0006
PolicePresence	0.0039
HighwayDensity	0.0007
Comparing GWR model	
Adjusted R^2 = 0.174; AIC = −1708.04; condition number < 5.089	
MarijuanaEradication09	0.1377 ~ 0.8186
DrugKillings	−0.0016 ~ 0.0004
PopulationDensity	−0.0011 ~ 0.0061
HighwayDensity	−0.0028 ~ 0.0027

Notes: ** p < 0.05; *** p < 0.1. VIF, variance inflation factor; JB, Jarque–Bera; K (BP), Koenker (BP).

(p < 0.05) predicting variable. However, the adjusted R^2 was 0.094, indicating that only 9.4% of the variation in the cultivation of marijuana was explained by the model. The VIF was lower than 7.5, indicating no concerns about multicollinearity. But a significant (p < 0.01) Jarque–Bera statistic indicates that the residuals are not from a normal distribution (Figure 3). Further investigation of the residuals revealed a Moran's I value of 0.074 with Z-score as 6.462, suggesting spatial clustered residuals at a 99% confidence level (Table 4).

A GWR model was run in comparison with the four-variable OLS model (Model (7)). The model detail is as follows:

$$\begin{aligned}\text{MarijuanaEradication10}i = {} & \beta 0_i + \beta 1_i \text{MarijuanaEradication09}_i \\ & + \beta 2_i \text{DrugKillings}_i \\ & + \beta 3_i \text{PolicePresence}_i \\ & + \beta 4_i \text{HighwayDensity}_i + \text{error}_i\end{aligned} \tag{8}$$

Overall, the GWR model showed an improved performance (Figures 3 and 4). The AIC for the GWR model was −1708.04, compared to AIC of −1662.05 for the four-variable OLS model. The GWR analyses revealed that the relationships between marijuana cultivation and the environmental and human variables were nonstationary. With the exception of MarijuanaEradication09, the coefficients for all the other variables changed the sign in the GWR model compared with the OLS model (Table 6). The local R^2 showed that the model explains marijuana cultivation better in the north areas of Mexico than in the south and central regions (Figure 5). The condition number, which evaluates local collinearity, remained below 5.1, suggesting reliable, stable results.

Findings and discussion

GWR models performed better than OLS models for explaining the patterns of opium and marijuana cultivation. As a global model, OLS parameters are estimated averages of the processes that may potentially exhibit great variation (Fotheringham, Martin, and Brunsdon 2001). The spatial variation of the coefficient values for GWR independent variables illustrates clearly the nonstationary nature of the relationship between the independent variables (i.e., the examined environmental and human variables) and the dependent variables (i.e., illicit cultivation of marijuana or opium). Moreover, the local R^2 of GWR models varies across municipalities. Higher explanation power of the GWR models, as indicated by larger local R^2 in Figure 5, can be found in the areas where the largest drug producers are and where drug cultivation has been a tradition for decades.

The GWR model for opium poppy cultivation appeared to perform much better compared to that for marijuana cultivation. The GWR model for opium cultivation explained between 59% and 88% of the variance in the major drug-producing regions. The best results ranging from 74% to 88% of local R^2 were found in the states of Guerrero, Michoacán, Jalisco, and Nayarit. These were not the early drug cultivation regions in the late 1800s, but they are among the top producers of opium and heroin in Mexico nowadays, particularly Guerrero (Bucardo et al. 2005). The explanation power of the GWR model decreased to about 50% for the areas that are new for opium cultivation, such as some municipalities in Oaxaca, Veracruz, and Chiapas, in the southern parts of the country. Most of these regions are not among the top opium producers.

The local R^2 varies from 7% to about 50% for the marijuana GWR model. The lowest explanation power explains between 7% and 18% of the variance in marijuana cultivation, similar to the best OLS models. These fall in areas that are relatively new for marijuana cultivation, including Puebla, Quintana Roo, and Veracruz, which are in the heart of central Mexico and the Gulf Coast. The GWR model did not perform well for marijuana cultivation in the municipalities in Guerrero and Oaxaca states, which are heavy producers of opium poppies and have produced marijuana for decades, though in less quantity. On the contrary, the local models showed apparent improvement in explaining marijuana cultivation in the states where the drug has been harvested for decades, including Sinaloa, Chihuahua, Durango, and Sonora. The GWR model explained more than a third of the variance for these areas.

It is interesting to note that the GWR models clearly separate the regions that are traditional and larger drug producers from the newer and less active areas for drug cultivation, including both opium poppy and marijuana. Overall, the GWR models show stronger explanation power (with larger local R^2 values) for the traditional and larger drug-producing areas. Chihuahua, Durango, and especially Sinaloa all are big for drug production and trafficking, which is intertwined with a history of local corruption and lawlessness (Astorga 2005), a characteristic that makes producing marijuana easier than in other states (Bouchard, Beauregard, and Kalacska 2013). This suggests that, different from ordinary plants, the illicit cultivation in these areas is closely related to the human factors that are included in the models. In other words, the social, cultural, and policing factors are significant for the distribution of illicit cultivation. Nevertheless, the fact that the models perform not as well for the relatively new drug-producing regions indicates they failed to capture certain factors for illicit drug growth in these areas. It could be that these newly developed drug cultivation areas have incorporated more adaptive measures and new technologies, making illicit cultivation less dependent on the traditional factors.

There are clear differences in the performance of the OLS models for explaining marijuana and opium cultivation. For opium poppy eradication, the overestimated regions are about the same across the OLS and GWR models, so are the underestimated regions, suggesting the similarity in goodness of fit for both the models. However, the OLS model for marijuana underestimates almost all the major and traditional drug-producing regions, while the GWR model exhibits both overestimation and underestimation. The systematic error by the OLS model for marijuana cultivation seems to confirm its limitation in accounting for the spatial variations based on the particular idiosyncrasy of certain regions in Mexico. These variations may not follow administrative boundaries, but they play a significant role in defining the patterns of illicit cultivations. One such example is the gang influence in the "golden triangle", laying northwest of Mexico between the states of Sinaloa, Chihuahua, and Durango (Astorga 2005). Increased gang activities may make it harder for illicit crops being detected, leading to model underestimation. Moreover, the fact that the OLS model for opium cultivation performed better than that for marijuana cultivation may suggest that the model failed to capture the more complicated local factors impacting marijuana cultivation. In recent years, the Mexican Army has found several marijuana fields with complex irrigation systems, materials that provide protection from the sun, and even genetically modified plants that are resistant to pesticides and that can be cut and removed without fully pulling out the roots (Llana 2006; Reuters 2011). On the contrary, the conditions required for growing opium poppy are relatively straightforward and call for little modification. Opium poppies develop best in regions featuring warm temperature and moderate moisture, and they do not require special irrigation, which makes the Sierra Madre Mountains a perfect area for the crop to grow. Opium poppy tends to perform poorly in the other areas of Mexico where more tropical climates prevail (Duke 1983).

Overall, both human variables and environmental factors were revealed to be associated with the illicit cultivation activities at municipality level. Factors that are related to the easiness of starting illicit cultivation, the presence and effectiveness of law enforcement, and the magnitude of drug activities are significantly related to the illicit crop cultivation. Some environmental variables may affect drug cultivation through impacting human factors. Slope variation was a consistent predictor for opium poppy cultivation in OLS models, being significant at about 70% of the times. In addition to ensuring necessary climate conditions for the crops, increased slope variation may help hiding the crops from being found by law enforcement. Population density was significant at almost 90% of the times for the opium cultivation OLS models, but it showed spatial variation in the GWR models. Population may positively contribute to illicit cultivation as it provides a pool of labor; it may be a negative factor, however, because more people would increase the risk of cultivation being detected and cracked down by police force. The latter may explain the negative coefficients for population density in GWR for some northern municipalities. It is very important to note the spatial and temporal continuity of illicit cultivation activities. As can be seen in Tables 5 and 7, the cultivation eradication was found to be significantly related to that in the previous year in all of the OLS models for opium poppy cultivation and more than half of the models for marijuana cultivation. Furthermore, more than 20% of the OLS models revealed that opium cultivation is positively related to the cultivation of marijuana in the same year.

The limitations of this study warrant some discussions here. First, the fact that the eradication data were available only at municipality level created limits to the study. *GWR* model has proved that nonstationarity is embedded in the relationship between illicit cultivation and the independent variables. Because the data were set at a certain spatial structure, it is impossible to test for the local variation across different scales. Second, the environmental data from INEGI were the mean annual minimum and maximum temperature in degree Celsius and the mean annual precipitation in millimeters. These data do not reflect the real extremes of temperature or precipitation, which can be critical for the survival and development of plants. Moreover, the environmental variables were aggregated to and recorded at municipality level. This process may introduce errors. Future research is warranted to examine illicit crop cultivation using site-specific data. Last, by only including those municipalities with illicit drug eradications into the models, the spatial continuity of the study area is interrupted at some places (although not in the major drug production areas). Although adaptive bands were used for the GWR models, there may still be potential impact for the modeling results, which should be investigated by future studies.

Summary

Cultivation of marijuana and opium poppy in Mexico is related to the distribution of favorable climate and geographical conditions – the physical environment required to grow the crops. But drug production is also a narrative of decades of social and political processes, lately seasoned by increasing access to high-tech means to help plants grow faster and produce more of the raw materials that make illicit drugs. The human factors have actually begun to play an increasing role, sometimes making the environmental factors more or less secondary while the diversity of drug production and the easiness of managing and sustaining the producing process are being more important.

In fact, human factors that account for ineffective law enforcement, the corruption in social and management processes, and the easiness of the setup process for crop growing are the most influential when trying to explain the opium and marijuana cultivation in Mexico. Traditional environmental variables like temperature and precipitation cannot explain drug production by themselves; rather, to a great extent, they may be significant for explaining the patterns of illicit drug cultivation when they are examined as part of the easiness of the setup process.

The drug cultivation in Mexico, however, shows a notable spatial variation, reflecting differences in not only climate and topography but also governance styles and drug gang activity, among other factors. Furthermore, more marijuana plantations are starting to appear in the middle of the Mexican desert, supported by complex water irrigation systems, and light, net-like covers to provide protection from the sun and hiding from police surveillance (Reuters 2011). All these add up to spatial variation in the illicit crop growing process. Human actions are making the crop cultivation respond differently to the traditional explanatory variables across different growing locations, thereby making researching outdoor drug cultivation an even more challenging task.

References

Acock, M. C., R. C. Pausch, and B. Acock. 1997. "Growth and Development of Opium Poppy (*Papaver somniferum* L.) as a Function of Temperature." *Biotronics* 26: 47–57.

Anselin, L. 2005. *Exploring Spatial Data with GeoDaTM: A Workbook*. Urbana: Center for Spatially Integrated Social Science, Department of Geography, University of Illinois. https://geodacenter.asu.edu/system/files/geodaworkbook.pdf

Astorga, L. 2005. *El Siglo de las Drogas: el Narcotrafico, del Porfiriato al Nuevo Milenio*. Mexico: Random House Mondadori.

Austin, M. 2002. "Spatial Prediction of Species Distribution: An Interface between Ecological Theory and Statistical Modelling." *Ecological Modelling* 157 (2–3): 101–118. doi:10.1016/S0304-3800(02)00205-3.

Austin, M. 2007. "Species Distribution Models and Ecological Theory: A Critical Assessment and Some Possible New Approaches." *Ecological Modelling* 200 (1–2): 1–19. doi:10.1016/j.ecolmodel.2006.07.005.

Bahn, V., R. J. O'Connor, and W. Krohn. 2006. "Importance of Spatial Autocorrelation in Modeling Bird Distributions at a Continental Scale." *Ecography* 29 (6): 835–844. doi:10.1111/j.2006.0906-7590.04621.x.

Barry, S. C., and A. H. Welsh. 2002. "Generalized Additive Modelling and Zero-Inflated Count Data." *Ecological Modelling* 157: 179–188. doi:10.1016/S0304-3800(02)00194-1.

Booth, M. 1999. *Opium: A History*. New York: St. Martin's Griffin.

Bouchard, M., E. Beauregard, and M. Kalacska. 2013. "Journey to Grow: Linking Process to Outcome in Target Site Selection for Cannabis Cultivation." *Journal of Research in Crime and Delinquency* 50 (1): 33–52. doi:10.1177/0022427811418001.

Brunsdon, C., S. Fotheringham, and M. Charlton. 1996. "Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity." *Geographical Analysis* 28 (4): 281–298. doi:10.1111/j.1538-4632.1996.tb00936.x.

Brunsdon, C., S. Fotheringham, and M. Charlton. 1998. "Geographically Weighted Regression – Modelling Spatial Non-Stationarity." *Journal of the Royal Statistical Society: Series D (The Statistician)* 47 (3): 431–443. doi:10.1111/1467-9884.00145.

Bucardo, J., K. C. Brouwer, C. Magis-Rodriguez, R. Ramos, M. Fraga, S. G. Perez, T. L. Patterson, and S. A. Strathdee. 2005. "Historical Trends in the Production and Consumption of Illicit Drugs in Mexico: Implications for the Prevention of Blood Borne Infections." *Drug and Alcohol Dependence* 79 (3): 281–293. doi:10.1016/j.drugalcdep.2005.02.003.

Clarke, R. C. 1981. *Marijuana Botany: An Advanced Study: The Propagation and Breeding of Distinctive Cannabis*, 109–110. Berkeley, CA: RONIN.

Consejo Nacional de Evaluación de la Política de Desarrollo Social (CONEVAL). 2010. *La Pobreza Por Ingresos En México*. Mexico, DF: CONEVAL.

De la Herrán, J. 1980. "La migración campesina en Sinaloa." *Ciencia y Universidad* 13: 77–102.

Diniz-Filho, A. F., L. M. Bini, and B. A. Hawkins. 2003. "Spatial Autocorrelation and Red Herrings in Geographical Ecology." *Global Ecology and Biogeography* 12 (1): 53–64. doi:10.1046/j.1466-822X.2003.00322.x.

Dominguez, J., and R. Fernandez de Castro. 2001. *The United States and Mexico: Between Partnership and Conflict*. New York: Routledge.

Dormann, C. F., O. Purschke, J. R. García Márquez, S. Lautenbach, and B. Schröder. 2008. "Components of Uncertainty in Species Distribution Analysis: A Case Study of the Great Grey Shrike." *Ecology* 89 (12): 3371–3386. doi:10.1890/07-1772.1.

Dube, O., O. Garcia-Ponce, and K. Thon. 2014. *From Maize to Haze: Agricultural Shocks and the Growth of the Mexican Drug Sector*. Working Paper 355. Washington, DC: Center for Global Development. Accessed October 10. http://www.cgdev.org/sites/default/files/maize-haize-agricultural-shocks-growth-mexican-drug-sector_0.pdf.

Duke, J. A. 1983. "*Papaver somniferum* L." Handbook of Energy Crops, unpublished. http://www.hort.purdue.edu/newcrop/duke_energy/papaver_somniferum.html.

Elith, J., and J. R. Leathwick. 2009. "Species Distribution Models: Ecological Explanation and Prediction Across Space and Time." *Annual Review of Ecology, Evolution, and Systematics* 40: 677–697. doi:10.1146/annurev.ecolsys.110308.120159.

Foody, G. 2004. "Spatial Nonstationarity and Scale Dependency in the Relationship between Species Richness and Environmental Determinants for the Sub-Saharan Endemic Avifauna." *Global Ecology and Biogeography* 13 (4): 315–320. doi:10.1111/j.1466-822X.2004.00097.x.

Fortes, P. S., A. Platonov, and L. S. Pereira. 2005. "GISAREG–A GIS Based Irrigation Scheduling Simulation Model to Support Improved Water Use." *Agricultural Water Management* 77 (1–3): 159–179. doi:10.1016/j.agwat.2004.09.042.

Fotheringham, S., C. Brunsdon, and M. Charlton. 2002. *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*. Chichester: Wiley.

Fotheringham, S., C. Martin, and C. Brunsdon. 2001. "Spatial Variations in School Performance: A Local Analysis Using Geographically Weighted Regression." *Geographical & Environmental Modelling* 5 (1): 43–66. doi:10.1080/13615930120032617.

Fung, D. S., and R. Welch. 1994. *Modeling Canabis Cultivation in North Georgia*. Technical Paper, ASPRS/ACSM Annual Convention & Exposition: Reno, Nevada, 217–220. Bethesda, MD: American Society for Photogrammetry and Remote Sensing-American Congress on Surveying and Mapping.

Guisan, A., and N. E. Zimmerman. 2000. "Predictive Habitat Distribution Models in Ecology." *Ecological Modelling* 135 (2–3): 147–186. doi:10.1016/S0304-3800(00)00354-9.

Hough, M., H. Warburton, B. Few, T. May, L. Man, J. Witton, and P. J. Turnbull. 2003. *A Growing Market: The Domestic Cultivation of Cannabis*. York: Joseph Rowntree Foundation.

Howell, T. 2002. "TR-03-01, Operation SABOT and Illicit Crop Information Management Using Satellite Imagery." Canadian Police Research Centre (CPRC). Accessed March 31, 2014. http://publications.gc.ca/collections/collection_2008/ps-sp/PS63-2-2001-3E.pdf

Hurley, J., J. West, and J. Ehleringer. 2010. "Tracing Retail Cannabis in the United States: Geographic Origin and Cultivation Patterns." *International Journal of Drug Policy* 21 (3): 222–228. doi:10.1016/j.drugpo.2009.08.001.

Instituto Nacional de Estadísticas y Geografía (INEGI). 2005. "Guía Para la Interpretación de Cartografía Climatológica." Mexico. Accessed October 26, 2013. http://www.inegi.org.mx/.

Instituto Nacional de Estadísticas y Geografía (INEGI). 2013. "Catálogo de Municipios Nacionales." Accessed October 26. http://geoweb.inegi.org.mx/mgn2k/catalogo.jsp.

International Narcotics Control Strategy Report (INCSR). 2008, 2009. "Drug and Chemical Control." Vol. I, Mexico Chapter. Accessed October 24, 2013. http://www.state.gov/p/inl/rls/nrcrpt/2009/vol1/116522.htm.

Iverson, L. R., A. Prasad, S. Matthews, and M. P. Peters. 2011. "Lessons Learned While Integrating Habitat, Dispersal, Disturbance, and Life-History Traits into Species Habitat Models Under Climate Change." *Ecosystems* 14 (6): 1005–1020. doi:10.1007/s10021-011-9456-4.

Keitt, T. H., O. N. Bjørnstad, P. M. Dixon, and S. Citron-Pousty. 2002. "Accounting for Spatial Pattern When Modeling Organism-Environment Interactions." *Ecography* 25 (5): 616–625. doi:10.1034/j.1600-0587.2002.250509.x.

Kupfer, J., and C. Farris. 2007. "Incorporating Spatial Non-Stationarity of Regression Coefficients into Predictive Vegetation Models." *Landscape Ecology* 22 (6): 837–852. doi:10.1007/s10980-006-9058-2.

Lee, A. H., K. Wang, J. A. Scott, K. K. W. Yau, and G. J. Mclachlan. 2006. "Multi-Level Zero-Inflated Poisson Regression Modelling of Correlated Count Data with Excess Zeros." *Statistical Methods in Medical Research* 15 (1): 47–61. doi:10.1191/0962280206sm429oa.

Legendre, P., and L. Legendre. 1998. *Numerical Ecology*. Amsterdam: Elsevier Science.

Lennon, J. J. 2000. "Red-Shifts and Red Herrings in Geographical Ecology." *Ecography* 23 (1): 101–113. doi:10.1111/j.1600-0587.2000.tb00265.x.

Lidicker, W. Z. 1975. "The Role of Dispersal in the Demography of Small Mammals." In *Small Mammals: Their Productivity and Population Dynamics*, edited by F. B. Golley, et al., 103–128. London: Cambridge University Press.

Liu, J. 2009. "A GIS-Based Tool for Modelling Large-Scale Crop-Water Relations." *Environmental Modelling & Software* 24 (3): 411–422. doi:10.1016/j.envsoft.2008.08.004.

Lizarraga, A., and O. Lizarraga. 2006. *Narcotráfico, Violencia y Emigración Femenina. Estudio de Caso*. Mexico: Universidad Autónoma de Sinaloa. Accessed March 31, 2014. http://estudiosdeldesarrollo.net/coloquio2006/docs2006/11772.pdf

Llana, M S. 2006. "Mexican Army Invades Pot Plantations." *USA Today*, December 21. Accessed February 10, 2014.

http://usatoday30.usatoday.com/news/world/2006-12-21-mexico-drug-effort_x.htm

Marín, A. 2002. “Cambios en el financiamiento de las labores del campo Mexicano desde las reformas estructurales de 1983 hasta la fecha. El caso de los municipios serranos de sinaloa”. *Revista de Antropología Experimental* 2: 1–12.

Ortega, S., and E. Lopez Manon. 1987. *Sinaloa, Textos de su Historia*. Vol. 2. Mexico: Instituto de Investigaciones Jose María Luis Mora.

Osborne, P., and S. Suárez-Seoane. 2002. “Should Data Be Partitioned Spatially before Building Large-Scale Distribution Models?” *Ecological Modelling* 157 (2–3): 249–259. doi:10.1016/S0304-3800(02)00198-9.

Partelow, C. 2008. “Using GIS to Depict Resource Risk from Probable Cannabis Cultivation Sites.” Master thesis, San Jose State University. http://scholarworks.sjsu.edu/cgi/viewcontent.cgi?article=4584&context=etd_theses&sei-redir=1&referer=http%3A%2F%2Fscholar.google.com%2Fscholar%3Fq%3DGis%2Bcannabis%2Bcultivation%2Bpolygon%2Bfile%26hl%3Den%26btnG%3DSearch%26as_sdt%3D1%252C44%26as_sdtp%3Don#search=%22Gis%20cannabis%20cultivation%20polygon%20file%22.

Resa Nestares, C. 2003. El Valor de las Exportaciones Mexicanas de Drogas Ilegales 1961–2000. Colección Documentos, Universidad Autónoma de Madrid.

Reuter, P. 1988. “Quantity Illusions and Paradoxes of Drug Interdiction: Federal Intervention into Vice Policy.” *Law and Contemporary Problems* 51 (1). doi:10.2307/1191721.

Reuters. 2011. “Mexico Marijuana Plantation Reportedly Biggest Ever.” 14 July. Accessed May 1, 2012. http://www.huffingtonpost.com/2011/07/14/mexico-marijuana-plantation-_n_898630.html#s309904.

Small, E., T. Pocock, and P. B. Cavers. 2003. “The Biology of Canadian Weeds. 119. *Cannabis sativa L.*” *Canadian Journal of Plant Science* 83: 217–237. doi:10.4141/P02-021.

Thomas, M., S. Hallman, M. Plaisent, and P. Bernard. 2004. “Using IT and GIS to Improve Crop Assessments.” Proceedings of the 15th Annual Conference of the IIMA (International Information Management Association): Technology Twenty Years After Orwell. Chicago, IL. Accessed February 6, 2012. http://psugeo.org/Publications/MJ%20Paper%20Rev%204%20IIMA.doc.

Thoumi, F. 2003. *Illegal Drugs, Economy, and Society in the Andes*. Washington, DC: Woodrow Wilson Center Press.

Toro, M. C. 1995. *Mexico's War on Drugs*. Boulder, CO: Lynne Rienner.

UNODC. 2000–2012. “Illicit Crop Monitoring.” Accessed February 6, 2012. http://www.unodc.org/unodc/en/crop-monitoring/index.html.

UNODC. 2011. “South-East Asia Opium Survey 2011. Lao PDR, Myanmar.” Accessed February 8, 2012. http://www.unodc.org/documents/crop-monitoring/sea/SouthEastAsia_2011_web.pdf.

Václavík, T., J. A. Kupfer, and R. Meentemeyer. 2012. “Accounting for Multi-Scale Spatial Autocorrelation Improves Performance of Invasive Species Distribution Modelling (ISDM).” *Journal of Biogeography* 39 (1): 42–55. doi:10.1111/j.1365-2699.2011.02589.x.

Václavík, T., and R. Meentemeyer. 2009. “Invasive Species Distribution Modeling (Isdm): Are Absence Data and Dispersal Constraints Needed to Predict Actual Distributions?” *Ecological Modelling* 220 (23): 3248–3258. doi:10.1016/j.ecolmodel.2009.08.013.

Walthall, C., C. Daughtry, V. Vanderbilt, M. Higgins, T. Bobbe, J. Lydon, and M. Kaul. 2003. “What Do We Know about the Spectral Signatures of Illegal Cannabis Cultivation?” Paper Presented at the 2003 ONDCP International Technology Symposium, San Diego, CA, July 8–11. Accessed March 31, 2014. http://psugeo.org/Interagency%20MJ%20Study%20Project/AppendixB03.doc.

Wiens, J. A., D. Stralberg, D. Jongsomjit, C. Howell, and M. Snyder. 2009. “Colloquium Papers: Niches, Models, and Climate Change: Assessing the Assumptions and Uncertainties.” *Proceedings of the National Academy of Sciences* 106 (Supplement 2): 19729–19736. doi:10.1073/pnas.0901639106.

Youngers, C., and E. Rosin. 2005. *Drugs and Democracy in Latin America: The Impact of U.S. Policy*. Boulder, CO: Lynne Rienner.