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Analysis

Predicting cannabis cultivation on national forests using a rational choice framework

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ABSTRACT

Government agencies in the United States eradicated 10.3 million cannabis plants in 2010. Most (94%) of these plants were outdoor-grown, and 46% of those were discovered on federal lands, primarily on national forests in California, Oregon, and Washington. We developed models that reveal how drug markets, policies, and environmental conditions affect grow siting decisions. The models were built on a rational choice theoretical structure, and utilized data describing 2322 cannabis grow locations (2004–2012) and 9324 absence locations in the states' national forests. Predictor variables included cannabis market prices, law enforcement density, and socioeconomic, demographic, and environmental variables. We also used the models to construct regional maps of grow site likelihood. Significant predictors included marijuana street price and variables associated with grow site productivity (e.g., elevation and proximity to water), production costs, and risk of discovery. Overall, the pattern of grow site establishment on national forests is consistent with rational choice theory. In particular, growers consider cannabis prices and law enforcement when selecting sites. Ongoing adjustments in state cannabis laws could affect cultivation decisions on national forests. Any changes in cannabis policies can be reflected in our models to allow agencies to redirect interdiction resources and potentially increase discovery success.

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1. Introduction

In the United States, illegal cannabis cultivation on public lands is a major problem for land management agencies (Bouchard, 2007). In particular, national forests of the United States have experienced rising rates of illegal cultivation. The US Department of Justice's National Drug Intelligence Center (2011) reported that the rate of outdoor-grown cannabis seizures nationwide increased 150% from 2005 to 2010, fueled by apparent demand growth and profit-earning opportunities for domestic producers; of all outdoor-grown plants seized in 2010, 44% came from federal lands, primarily national forests. Large-scale producers may be motivated by the perception that domestic cultivation is less risky (i.e., in terms of detection by law enforcement) than importing cannabis across national borders (Barratt et al., 2012; Bouchard, 2007). Domestic producers also face low average costs, at $75 per pound, and can sell their output for up to $7000 per pound. Even in states such as Colorado and Oregon where cannabis possession, distribution, and production were recently legalized, illicit cultivation on national forests and other federal lands is likely to persist, either to supply states where cannabis is still prohibited (Roberts, 2014) or to avoid the taxes and regulations imposed on licensed growers.

Illegal grow operations endanger those who visit or work on national forests. They also cause extensive ecological damage and require costly clean-up (Liddick, 2010; Tynon and Chavez, 2006). Unfortunately, finding cannabis grow sites ("grows") is difficult given available enforcement resources, which must be applied to extensive areas of public land that may be suitable for grow operations (Chavez and Tynon, 2000). Therefore, law enforcement agencies need tools that can help them allocate scarce resources to improve rates of interdiction success. For example, they might employ mathematical models to predict where certain crimes – in this case, illegal cannabis cultivation – will occur in the future, a practice known as prospective hotspotting. Hotspotting techniques based on spatial patterns of historical crime occurrence data are widely used by law enforcement, but such techniques essentially assume that new crimes occur near where they happened previously (Caplan et al., 2011). This is also true of hotspotting methods (e.g., Bowers et al., 2004; Johnson and Bowers,

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2004; Ratcliffe, 2004; Rossmo, 1999) that emphasize temporal as well as spatial patterns of past criminal activity. Recently proposed approaches (e.g., risk terrain modeling) supplement historical crime occurrence data with additional data on crime-related variables to better identify hotspots (Caplan et al., 2011; Wang et al., 2013). Nevertheless, these new methods are primarily predictive in purpose, and not inferential in the sense of uncovering and understanding the roles of important drivers of crime. With respect to illegal cannabis cultivation, we believe that a more effective approach could be developed not just from knowledge of recent grow locations, but also from an understanding of grower decisions. Models structured in this way are potentially more capable of handling shifts in the decision-making environment, for example due to spatial and temporal changes in the risks and rewards of a crime. They have the additional advantage of providing inference about the importance of various factors as aspects of an underlying theoretical framework of a crime.

Illegal cultivation on national forests can be explained using rational choice theory (Becker, 1968; Cornish and Clarke, 1986, 1987). Cannabis growers, like other criminal offenders, are rational agents (e.g., Akers, 1990), and they choose locations (or victims) based on the situational status of those locations (or victims). Rational choice theory befits the analysis of criminal events, in no small part because it adopts the premise that situational (i.e., environment-describing) variables can help to explain these events (Hirschi, 1986; Weisburd and Piquero, 2008). Evidence suggests that prospective criminals often behave as if they are rational (Nagin and Paternoster, 1993), especially with respect to crimes involving monetary gains, even when emotions enter into their decision-making (Paternoster and Simpson, 1996; van Gelder and de Vries, 2014). Furthermore, drug trafficking organizations (DTOs) are thought to dominate cannabis production in West Coast national forests (Weisheit, 2011), and the decision-making by these sorts of criminal groups would seem to be well represented by a rational choice model that defines the expected costs and benefits of crime commission (e.g., Desroches, 2005).

While rational choice theory provides an overall construct of criminal decision-making, other theories from criminology help to explain how costs and benefits come together to determine decision outcomes. For instance, routine activities theory (Cohen and Felson, 1979) asserts that many crimes occur due to the convergence of three conditions: a likely offender (someone who is able and motivated to commit a crime); a suitable target (depending on the type of crime, a person or location perceived to be vulnerable or conducive to the crime); and the absence of a capable guardian (a person or thing that – as opposed to an incapable guardian – serves as a deterrent to the crime). Thus, a key aspect of the environment that a potential offender faces is the presence of factors that make the offender more or less visible to capable guardians (e.g., Jeffery, 1977), including law enforcement. Because they influence how the offender perceives the likelihood of being caught and suffering consequences, visibility factors can affect the offender's decisions significantly. These effects can be complex, non-linear, and bi-directional, as illustrated by the example of a cannabis grower selecting a new cultivation site: site preparation often requires large quantities of supplies and equipment (e.g., PVC tubing for irrigation, tools and herbicides for removing native vegetation), so locations close to a road would logically be appealing, yet locations close to a road are also more likely to be discovered by law enforcement or forest visitors.

The environment can also include factors that affect the opportunity costs of being caught, including penalties for being caught (sentences or fines) and lost wages or work opportunities related to imprisonment (e.g., Aaltonen et al., 2013; Burdett et al., 2003; Gould et al., 2002), as well as the opportunity cost of time needed to carry out the criminal activity. The environment might further be described by higher-level socioeconomic factors governing the perceived rewards from crime commission. For example, the prices that can be obtained from the sale of illicit drugs are affected by aggregate demand for and supply of such drugs, which respond to public policies directed at both producers and consumers. Finally, the reward gained by a producer physically varies across space. Ultimately, because all of these environmental factors vary over space and time, the incentives for grow establishment also vary over these dimensions.

These concepts can be used to model illegal cannabis cultivation activities on national forests in the United States, by connecting grower decisions statistically to factors affecting cannabis production risks and rewards. Although our focus is illegal cannabis cultivation, this represents just one example from a class of problems where the factors that determine the spatial pattern of a phenomenon are uncertain and resistant to simple inference. Other examples might be predicting locations where an invasive species is likely to become established or identifying hotspots of illegal wildlife poaching or plant harvesting. In such cases, human activities (e.g., travel for recreation or commerce) often strongly influence the observed pattern (Gallardo et al., 2015), but the nature and degree of that influence may be difficult to ascertain because the data available to describe the pattern (e.g., reports of crime occurrence in the field) may be incomplete or otherwise biased. Therefore, another important objective of our work was to outline a conceptual approach that could be applied to this general class of problems.

2. Methods

Predicting cannabis grow locations resembles how ecologists model the geographic distributions of species based on occurrence data. The fundamental principle behind species distribution models is that spatial variation in species occurrence can be described using environmental factors (e.g., climate or topography) that also vary across the occupied space (Elith and Leathwick, 2009). Historically, ecologists have employed regression methods (e.g., generalized linear models, especially logistic regression) to predict species distributions and to explore ecological relationships between the underlying drivers (Austin, 2007; Elith and Leathwick, 2009). In recent years, regression-based approaches have increasingly been supplanted by methods adapted from machine learning and data-mining literature, including decision trees and decision-tree ensembles (e.g., boosted regression trees, random forests), artificial neural networks, maximum entropy models, and genetic algorithms (Elith et al., 2006). While these methods have documented advantages in terms of predictive success in some empirical applications, they are complex and often opaque (Elith and Leathwick, 2009), limiting their suitability for examining interactions among explanatory variables, including endogeneity. In particular, we were concerned about the potentially endogenous relationship between grow location and cannabis price: higher price may encourage more grows, but more grows may reduce price. Consequently, we chose to use regression methods (i.e., logit and probit regression) in our analyses that allowed us to address the potential endogeneity straightforwardly. Furthermore, logit and probit regression are commonly used in analyses involving rational choice, as detailed below.

2.1. Theoretical Framework

Becker (1968) provided a formal exposition of rational choice theory in terms of expected utility:

$$EU(C) = [1-\pi(\mathbf{z})]u(B)-\pi(\mathbf{z})u(A)-c(C), \tag{1}$$

where EU denotes expected utility, C denotes a criminal action, π is the perceived (by the criminal) probability of suffering a criminal sanction, $\mathbf{z}$ is a vector of exogenous variables affecting the probability, $u(B)$ is the utility gain from committing the crime, $u(A)$ is the utility loss from being caught, and $c(C)$ are the direct costs of committing the crime. The vector $\mathbf{z}$ may also include variables describing the presence of police or other capable guardians. The benefits of committing a crime depend on the size of the reward. In the case of a crime such as cannabis cultivation