A Macro Analysis of Illegal Hunting and Fishing Across Texas Counties:

Using an Economic Structural Approach

by

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ABSTRACT

The purpose of this disseration is to examine the distribution of illegal hunting and fishing violations across Texas counties in respect to the economic structure. Illegal hunting plays a part in the extraction of resources that are overly withdrawn, and criminologists have ignored this form of deviancy that has large ramifications for the environment. To view this criminal phenomenon, the study uses the Treadmill of Production theory to determine economic structural factors and whether those factors explain the distribution of illegal hunting and fishing. Using regression analyses and SatScan, the findings suggested that while there are significant factors related to the distribution of illegal hunting, these factors do not explain the distribution completely when a spatial component is included. Thus, while the economic structure does explain the distribution when comparing illegal hunting and fishing across counties, it does not explain individual county's illegal hunting and fishing activity within them. Texas state and county governments should not form a uniform policy across Texas, but have policy situated for each county in order to address this issue.

CHAPTER 1:

INTRODUCTION

This dissertation examined whether variables from two theoretical fields (e.g., green criminology and environmental sociology) employed to explain environmental destruction and disorganization, and situational-opportunity and social structural variables that have been used to predict the geographic distribution of crime, are relevant for understanding the geographic distribution of hunting and fishing violations across counties in Texas. To explore this possibility, political economic green criminological (PEG-C) explanations of environmental crimes will serve as the primary theoretical background for this research. The key theoretical variables that will be explored are drawn from treadmill of production theory in regards to environmental disorganization. Control variables representing another green criminological subfield, conservation criminology, and those representing relevant social structural research on crime will also be included. Additionally, separate tests of the geographic explanations of crime will be examined. The significant variables from initial tests of each approach will be included in a "combined" model to determine which factors appear to be significant predictors of hunting and fishing violations (IH&F). Predictor variables were employed to draw hot and cold spot maps of hunting and fishing violations in Texas counties.

Criminologists have not widely examined IH&F. Illegal hunting and fishing can potentially produce numerous ecological impacts for wildlife and ecosystems (Sollund, 2017; Petrossian, 2015; Petrossian and Clarke, 2014). For example, hunting keystone wildlife species like tigers, elephants, and wolves contributes to the decline of some species, and may also have adverse ecological system impacts (Beschta and Ripple, 2016; Breuer, Maisels, and Fishlock, 2016; Painter et al., 2015; Ripple et al., 2015; Marshall et al., 2014; O'Brien, Kinnaird, and Wibisono, 2006). In other words, illegal hunting and fishing can have wide ranging ecological effects criminologist often overlook. In addition, IH&F are violations of law which therefore make those acts fall into the categories that behaviors criminologists have traditionally examined. At the same time, while IH&F are criminal activities, criminologist have ignored understanding the causes of these crimes and their distribution. With a growing awareness of environmental issues, there is importance that criminologist join in expanding environmental protection and contribute efforts to impact environmental policies and criminal acts against those policies. In recent years, this situation has begun to change and some criminologists have taken up the study of IH&F. The following section reviews some of what is known about illegal hunting and fishing.

What is Known about Illegal Hunting and Fishing

Illegal hunting is an important criminal behavior to explore due to the cultural importance of hunting activity in the United States of America (USA). Animals have long been hunted (Eliason, 2020; Jacoby, 2003), and a hunting and fishing culture is well established in the United States of America (Williams, 2015; Herman, 2014; Fine, 2000). In the late 19th and early 20th centuries, threats to the vitality of wildlife populations such as mass hunting for both big game (e.g., bears, cougars, and wolves) and birds stimulated concern for wildlife preservation, particularly among economically advantaged outdoorsmen (Beschta and Ripple, 2016; Ripple, Beschta, and Painter, 2015; Jacoby, 2003). The desire to reserve the traditions of hunting and fishing and access to wild game provided a foundation for the support of public land (Eliason, 2020; Walberg, Cornicelli, and Fulton, 2018; Newman, 2017; Herman, 2014). Public land gives everyone the right to access fauna for their own personal benefits (Eliason, 2020), but the privatization of land has restricted access to fauna for the public (Eliason, 2020; Jacoby, 2003). Hunt Talk Radio is a podcast hosted by Randy Newman who interviews scholars around hunting, public lands, and conservation. On this podcast, Dr. Greg Blascovish, founder of Keep It Public, and Dr. Randall Williams, employee of the Theodore Roosevelt Conservation Partnership, argued that the USA was founded on the idea that anyone can be a gentleman which coincided with being a sportsman (Newman, 2017); in contrast to the UK where the idea of hunting was restricted to the elite (Herman, 2014). Keeping the land public protects the environment or common collective (i.e. the public) from privatization and business exploitation. Research has also found that private land has encouraged the decline in hunting participation for the common man, and increased hunting for a subgroup of wealthier individuals (Walberg et al., 2018; Eliason, 2017; Williams, 2015), causing conflict resulting in illegal hunting activity (Eliason, 2020; Jacoby, 2003; Forsyth, Gramling, and Wooddell, 1998). The wilderness and fauna in the USA are seen as a right for the public, not just for the elite, but there is little research on how the public acts within a political economy that encourages privatization and business.

This conflict between business and the public has been expressed throughout the history of conservation within the USA with known relationships to IH&F (Sawyer, 2013; Jacoby, 2003); however, IH&F, their extent and distribution, have not been well studied within criminology. Moreover, little is known about the extent and distribution of wildlife crime in general particularly in the USA. Much of the available wildlife crime data and research come from other countries, and similarly tends to show rising rates of IH&F over time, though these trends vary by species (Brisman and South, 2018). Yet, only a handful of studies have examined trends and patterns of wildlife crimes in the USA (Kurland, Pires, and Marteache, 2018; Fischer, Naiman, Lowassa, Randall, and Rentsch, 2014; Crow, Shelley, and Stretesky, 2013; Haines et al., 2012).

The purpose of this dissertation is to address the distribution of IH&F activity by analyzing official records from law enforcement in Texas. Here, the focus is on IH&F across counties in Texas assessed whether county characteristics affected the distribution of IH&F. For Texas, IH&F is a violation of hunting and fishing regulations overseen by the Texas Parks and Wildlife codes (https://tpwd.texas.gov/regulations/outdoor-annual/). While these violations are defined as crimes by the law, criminologist have paid little attention to these crimes, and have not explored their distribution, or factors that may affect the distribution of those crimes geographically. There is a rich tradition of geographic or spatial analysis within the field of criminology which has been applied to a variety of subjects, and in particular the urban geography of crime. In recent years, however, this approach has been increasingly applied to rural crime (Kaylen and Pridemore 2013), but has not been applied to hunting and fishing violations.

Prior criminological research around wildlife crimes suggests that characteristics of places or situations can affect the volume of IH&F found in a location (Moreto and Pires, 2018). These studies have been derived from PEG-C and conservation criminology, which suggest that social and economic structural variables might potentially affect the geographic distribution of IH&F. The primary theoretical argument for this association can be drawn from PEG-C and environmental sociology, through the use of treadmill of production (ToP) theory. Control variables useful for assessing the geography of wildlife crime can, however, also be gleaned from the conservation criminology literature, which primarily address situational context and opportunity structures for crime. Alternatively, a small subgroup of research on IH&F, departing from both fields, suggest that certain social factors may also play a role in explaining.

The Scope and Focus of the Dissertation

IH&F is defined differently across the USA, by both state and federal authorities. The current study focused attention on one state in an effort to determine whether the structural characteristics of counties play a role in understanding the distribution of IH&F violations across counties in Texas. Texas, with its 254 counties, provided a unique opportunity to examine the distribution of IH&F given the large number of counties. The IH&F data were collected from the Texas Parks and Wildlife Department which included hunting and fishing violations across the counties in Texas for the year 2015. Macro-level, county specific explanatory variables representing arguments from green criminology and conservation criminology research were drawn from several sources described later in this dissertation. The year 2015 was selected for two primary reasons. The first involved data availability and efforts to match data across datasets. Second, the data were limited to 2015 given expenses associated with obtaining hunting and fishing violations from the Texas Parks and Wildlife Department, which charges a fee to obtain each year of data. Further details and relevance about the data can be found in the methods section. Given that the data only address the year 2015, the dissertation is considered with the structural associations with the distribution of IH&F.

The focus on Texas also reflected this strong interest and history in conservation and hunting (Sawyer, 2013). Research has found struggles between private landowners and the economic cost of hunting on private property, and how the rights of the public to hunt conflict with the rights of private property landowner (Bean, 1997; Thomas et al., 1994). Landowners were also split on whether or not their land should be used for conservation and animal repopulation such as the black bear (Rice et al., 2007). Williams et al. (2011) found that land stakeholders saw black bears as a means to increase the appeal of residency and tourism; however, stakeholders or landowners did not want government interference with the black bear population.

Research on IH&F, or wildlife crimes in general, does not exhibit a uniform theoretical or methodological approach. The majority of researcher addresses IH&F crimes, however, theoretically employs what can be described as structural analysis. Current PEG-C research addresses animals by referring to the economic context in which action are treated and regulated, which can has also included research on the historical origins of attitudes towards animals and their treatment in the law (Beirne 2009; Sinclair, Fryer, and Phillips, 2019; Martilli, 2009). Not all wildlife research, however, takes a PEG-C approach. Similar to traditional criminological studies, researchers also take a micro-level approach focused on offender characteristics and also on micro-sociological (e.g. strain or subcultural) explanations to explain IH&F (Forsyth and Forsyth, 2018; Agnew, 2012; Eliason, 2012; Enticott, 2011; Eliason, 2004: Muth and Bowe, 1998). While PEG-C has been applied to the analyses of a wide variety of green crimes (Lynch et al, 2017), it has not been applied to IH&F, leaving open the explanation of how the economic structure influences the distribution of wildlife harm.

An alternative to PEG-C is conservation criminology, which examines how the structure of opportunity and enforcement in a particular context influences the decision of an offender to engage in environmental crimes, including wildlife crime. Conservation criminologists refer to a wide variety of situational or contextual factors that they suggest affect opportunity for environmental crimes (Moreto and Pires, 2018; Gibbs, Gore, Hamm, Rivers, and Zwickle, 2017). These contextual factors focus on available markets, geographical opportunities, product demand, and risk factors (Moreto and Pires, 2018: Moreto, 2018). It would be intuitive to control for these alternative explanations to obtain a clearer effect of how or whether political economic measures affect the distribution of IH&F.

Drawing on observations made in prior research, this dissertation examines structural factors that may help explain the distribution of wildlife enforcement in Texas, using PEG-C as the main theoretical explanation. In doing so, this dissertation addressed the following: (1) the content of extant of wildlife crime research that has examined IH&F in the USA; (2) how political economic studies have explained harms against wildlife and IH&F; (3) whether variables from the treadmill of production processes widely referred to in the PEG-C literature are useful for explaining and understanding the distribution of IH&F in Texas; and, (4) discussed whether finding of the study have implications for theory and policy and future research.

Dissertation Outline

The remainder of this dissertation continues in the following manner:

Chapter 2 discussed the literature relevant from the both criminological categories along with a subgroup of small series of studies. Frist, green criminological research on wildlife harm and biodiversity loss was reviewed. Next, conservation criminology research was reviewed as a competing explanation, and analyzed for relevant control variables. Lastly, a small subgroup of USA-based illegal hunting research that has not drawn on the two approaches above was reviewed to determine which factors should be considered controls for analysis. The chapter concluded by summarizing the theoretically important concepts from green criminology and control variables.

Chapter 3 examined treadmill of production (ToP) theory to provide further context to analyze concepts related to the economic factors found within the literature review. The discussion examined how each concept would explain illegal hunting. Some subfields of criminology, such as radical and structural criminology, have explored the importance of economic structural factors to explain crime. These approaches have also been explored in the sociological and economic literature (Wallerstein, 1974; Bunker, 1985; O'Connor, 1973). Economic structure literature looked at not just the composition business but the composition of business growth and processes. For green criminology, the literature argues that along with business growth, the ecological consequences of this composition provided a structural framework in which society operates. The chapter concluded with a summary of the theoretical understanding of the economic structure.

Chapter 4 discussed the data, operationalization of variables, and an analytic plan to assess the variables. The chapter first examines research questions and hypotheses of the study. Next, the relevancy and details of IH&F data are discussed. After that, the operationalization of variables of interest and control variables are presented Lastly, the chapter covers an analytical plan to assess the data using regression analyses and spatial analyses to test the hypotheses of the study. The chapter concluded with how this methodology builds on the current knowledge of IH&F and how the results are presented in the next chapters.

The remaining chapters examined the findings of the study with interpretations and implications. Accordingly, chapter 5 reported the linear analyses results. Descriptive statistics and bivariate results are also reported in the chapter. Chapter 6 reported the spatial analyses results, controlling for significant variables found in the linear analyses. Maps of clustering are also provided. Lastly, Chapter 7 concluded the dissertation by discussing the results, theoretical implications, policy implications, and limitations.

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CHAPTER 2:

LITERATURE REVIEW ON ILLEGAL HUNTING AND FISHING

The focus of this chapter is to review the current literature around the political economic green criminology (PEG-C), to describe how that approach applies to understanding wildlife harms, and to identify factors for exploring a structural explanation of illegal hunting and fishing (IH&F) in Texas. Additionally, research on alternative explanations is explored to identify control variables for the current study. The existing literature on hunting and fishing in Texas is primarily located in the wildlife management literature, and does not discuss criminological factors that may help explain the distribution of IH&F. It also should be noted that the criminological literature contains a limited number of relevant studies to IH&F. For example, much of the conservation criminological research that explains wildlife crimes fails to examine IH&F in developed nations, and has largely drawn attention to providing a theoretical understanding of poaching behaviors in less developed nations. Furthermore, the limited IH&F literature that does exists, does not provide substantial material applicable at the structural level. Thus, the literature review focuses on areas that examine wildlife crimes and harms to determine factors that could be used to extend the research on IH&F in the United States of America (USA). The following sections cover, in order, PEG-C, conservation criminology, and the social literature around IH&F in the USA. The chapter concludes with a summary of factors the current dissertation uses for analysis.

Political Economic Green Criminology Research

Green criminology draws from multiple fields to compile evidence to support a theoretical framework for criminological applications that explains various outcomes such as environmental injustices, the structure of environmental law, or green crimes that involve large scale harmful activities including biodiversity loss, pollution and other forms of illegal and legal ecological destruction that have extensive ecological impacts (e.g., mining and timber-clear cutting). The ultimate goal of green criminology is to challenge the traditional social construct of crime by recognizing who had the power to influence the construction and application of relevant laws (Sollund, 2017). One way in which green criminology addresses these power relationships is through the theoretical lens of the political economy, which forms the basis of political economic green criminology (PEG-C).

Several varieties of green criminology have emerged such as nonspeciesist criminology (Beirne 1999), green-cultural criminology (Brisman and South, 2013), dark green criminology (McClanahan 2019), and visual green criminology (Natali 2016). Of these variations that have examined animal harms, the political economic green criminology (PEG-C) focuses on how the economic structure produces outcome that harm fauna. PEG-C research borrows from related research in environmental sociology, emphasizing the exploration of biodiversity loss that can be explained as a consequence of the organization and structure of capitalism. As several studies note (Lynch and Pires, 2019; Lynch, Stretesky, Long, and Barrett, 2019; Lynch, Barrett, Stretesky, and Long, 2017; Eliason, 1999), non-PEG-C research has tended to overlook empirical studies of explanations for green crimes, especially macro-structural analyses. Thus, the review below explores and draws primarily from the PEG-C literature.

PEG-C criminology has been most often associated in recent years with treadmill of production theory (ToP), introduced into criminology by Long et al. (2012), Lynch et al. (2013) and Stretesky, Long and Lynch (2013a, 2013b). In the ToP view, the production of commodities for consumption causes ecological destruction and disorganization through a continually need to extract natural resources for expanded production and consumption associated with the expansion of capitalism (Lynch, Long, and Stretesky, 2019). In other words, this economic structure is argued to encourage an expanding process of producing and consuming goods and services that require a continuous acceleration of natural resources extraction, that facilitates the depletion of the ecosystem (Lynch, Long and Stretesky, 2019; Lynch et al., 2017). While the perspective examines the consequence of human actions on an economic level (Brisman and South, 2018), PEG-C research also focuses on business and government agencies due to the applied theoretical framework. Within the USA, farms, business factories, and industrial factories are the main offenders of EPA regulations (Jarrell, Ozymy, and Sanders. 2017). There have been studies examining environmental crime in the production of coal (Lynch and Barrett, 2015; Long, Stretesky, Lynch, and Fenwick, 2012; Stretesky and Lynch, 2011) and refining industries (Ozymy and Jarrell, 2011; Jarrell, 2007) which led to destroyed and polluted lands, ultimately limiting habitats for wildlife (Lynch et al., 2019).

The research around this political economic orientation emphasizes the larger structure of operations in production, trade, and class relationships (Pires and Moreto, 2018). PEG-C has used a variety of methods to demonstrate this issue through the use of descriptive statistics, inferential statistics, mix-methods of quantitative and qualitative analyses, and spatial analyses (Lynch, Long, Stretesky, and Barrett, 2017); however, spatial analyses are more concentrated within conservation criminology (see below). PEG-C criminological research mainly focuses on the effects of manufacturing growth on the environment through ecological destruction, and how the legal system has failed to enforce regulation compliance to protect the environment (Lynch et al., 2017).

Borrowing from environmental sociology, Lynch et al. (2017) argue that the political economy is structured to promote or accept the over usage of natural resources. Within a free market, good and services are not protected by government agencies and are subjected to market demands. For the market to sustain itself, more production, while lowering labor cost, is needed to generate more wealth and value for the market (O'Connor, 1973). Continual extraction of natural resources is needed to maintain production. Thus, the PEG-C school of green criminology is centered around the structure of the economy. While green criminology addresses crimes against wildlife, it has not translated green criminological theories into explanations for IH&F.

Qualitative green criminological literature offer some discussion of how a political economic perspective could be used for green criminological research (Eliason, 2020; Peterson, Von Essen, Hansen, and Peterson, 2017; Sollund, 2016). The literature observes that access to wildlife is desired by different classes, and this can cause a conflict between the ruling class and the public. Eliason (2020) argued the ruling class can maintain control over wildlife through land ownership. In some views, natural resources (e.g. wildlife and land) are considered a public trust or a resource held in common by the public, not by individuals, leading to conflicts over the rights to own land and the right to use undeveloped land for purposes such as hunting and fishing (Eliason, 2020). As society expands, undeveloped land is threatened, limiting the resources that were once held in common by the public. As a result, one can argue that individuals hunt illegally (i.e., are defined as hunting illegally) as a result of how access to land and wildlife is distributed legally. At the individual level, Eliason (2020) also argued that some hunt illegally to exercise what they view as their right to natural resources. Alternatively, Peterson et al. (2017) argued that government and colonialism establish rules to protect wildlife and criminalize people who are not environmentally conscience. There are arguments that the political economy motivates competition within the market to illegally hunt (Eliason, 1999), however, PEG-C is more concerned with power relationships and the impact of economic structures, rather than explanations of the motivations of individual hunters.

Sollund (2017), taking a qualitative approach to explore the PEG-C perspective, examined the value of wildlife itself in relation to government protection in Norway. She focused on the differences in value of animals within government. After analyzing different types of legislation related to protecting animals, she concluded that domestic animals seem to have a higher value to society than wildlife, and thus receive more extensive legal protection (Sollund, 2017). This also seemed to be the case when examining a court case of illegal wolf killings (Sollund 2017). The Supreme Court rejected a lower court's interpretation that the legal killing of wolves keeps the population on the brink of extinction and in violation of a pervious establish law to protect wildlife. While the offenders still were sentenced to prison, the point was the court's perception on the value of wildlife was influenced by the hunting and farming lobby to encourage protection for agriculture. While, Sollund's research focuses on the micro-aspects of the political economy, the majority of PEG-C research focuses on macro-patterns of the economic structure.

Due to trends in globalization and nationalization of economic relationships, most green criminological studies examine the depletion of biodiversity at the cross-national level (Lynch et al., 2017). Relevant research has explored different measures of economic structure to determine how those structure leads to animal biodiversity loss. Of all the levels of the economic structure, research has found that cross-national or global relationships best explain animal biodiversity loss (Hoffman 2004). McKinney, Fulkerson, and Kick (2009) focused on measures of country's world system position (WSP) as a predictor of biodiversity loss. Countries were either core or periphery to the global economy; some were coded as semiperiphery or in between countries. Controlling for other explanations, WSP (i.e., being a peripheral nation) had the largest effect among competing variables, indicating that the dynamics of the global economy plays a larger part in determining the percent threatened bird populations across nations (McKinney et al., 2009). McKinney et al. (2010) expanded on the previous study by incorporating measures of non-governmental organizations (NGOs), arguing that these groups can mitigate factors against biodiversity loss. Using structural equation modeling, the study found NGOs to be ineffective, reinforcing the finding that the WSP or country's relevance to the global economy is still the dominate explanation for biodiversity loss.

Shandra et al. (2009, 2010) took a different approach to explore how cross-national relationships relate to biodiversity loss. Focusing on the commodity exports and import of nations, these studies controlled for government spending, economic activity, economic development, environmental NGOs, and urban-rural population growth. Shandra et al. (2009) found that only a few variables were significant. Primary export flows, NGOs, and GDP; however, export measures had the strongest effect, indicating that countries that export more raw materials experience higher losses of threatened mammals. This result is consistent with those from McKinney's studies, since peripheral nations in the world system are exploited for their resources. Shandra et al. (2010) expanded on the previous study by including measures of country foreign debt, capturing the economic dependency of countries. Debt measures were positively related to bird and mammal loss, and in addition, the effects of exports increased (Shandra et al., 2010).

These pieces of research suggest that biodiversity loss is dependent on the economic power relationship across nations in the world system. That is, locations with lower debt and with a higher WSP in the global economy are environmentally benefiting from trades with lower class countries or trade partners. Stretesky, McKie, Lynch, Long, and Barrett (2018) expanded on these studies by including measures that represent the effect of the treadmill of production. They specific analyzed whether GDP, ecological footprints, and level of export activity of nations affected the trade in Saker falcons, Stretesky et al. (2018) found that ecological footprints had no relation to the frequency of falcon exports. More importantly, the level of general export activity had the strongest effect on falcon export, followed by a nation's GDP. Thus, it is possible these measures can explain one form of animal biodiversity loss related to global trade patterns' effects on a national level.

The Take Away from Green Criminology Research

The application of PEG-C is limited to explanations of how economic structures affect outcomes such as biodiversity loss and international wildlife trade. This approach has not, however, been applied to efforts to explain illegal hunting and fishing violations. More recently, some studies have drawn on concepts relevant to PEG-C analysis to explain the relationship between the geography of pollution, inequality and crime (Muller, Sampson, and Winter, 2018; Sampson and Winter, 2018; Winter and Sampson, 2017; Barrett, 2017; Sampson and Winter, 2016). In these studies, the economic structure is interpreted as affecting the criminal behavior of people primarily in urban areas. This style of argument and analysis has not, however, been applied to understanding or analyzing the distribution of hunting and fishing violations.

Some factors can be taken from the PEG-C research that may help explain the geographic distribution of IH&F. First, the economic development of underdeveloped nations led to biodiversity loss (Shandra et al., 2010; McKinney et al., 2010; Shandra et al., 2009; McKinney et al., 2010). Factors such as the volume of agricultural land would grow to compensate the demand for food export relationships (Shandra et al., 2010). This suggests that the physical change of the land to support international economic growth would lead to biodiversity loss. Following Sollund (2017), this growth could lower the value of wildlife to protect crops and land. Second, the withdrawal of land from wilderness ecosystems could lead to wildlife loss. Lynch et al. (2019) argued that the research around resource mining destroys land in order to extract raw materials for the economy. This behavior, according to Jacoby's (2003) historical documents of early IH&F in the USA, restricts hunters from land that was supposed to be set aside for the public. For these reasons, the behaviors and consequences of the economy influences the location and displacement of behaviors.

Conservation Criminology

Conservation criminology seeks to integrate principles of opportunity theory (i.e., how do opportunities contribute to crime), mapping, and situational crime explanations to tailor policies and enforcement to address specific causes of the business of illegal wildlife trade (Brisman and South, 2018; Pires and Moreto, 2018). This area of criminology heavily focuses on the rationale for wildlife trading, bushmeat hunting, and illegal commercial fishing in relation to the situational context of opportunities for these crimes (Moreto and Pires, 2018). This school employing methods of analysis that examine the situational context using spatial analyses and linear analyses (Moreto and Pires, 2018), with a growing interest in crime scripts (Viollaz, Graham, and Lantsman, 2018), to explain crimes against wildlife. The methodological approach in this perspective has brought a spatial and temporal understanding to understanding the risk assessment of wildlife offenders. Typically, conservation criminology examines how the behaviors of certain groups leads to decreases in animal biodiversity and density, and to illegal wildlife trading behaviors. This school of criminology, however, does not necessarily provide an appropriate perspective for the current dissertation. Three central limitations related to actors, areas of study, and situational factors typically employed within conservation criminology demonstrate why this perspective is inappropriate on its own for a study drawing attention to a structural explanation of wildlife crimes in the USA.

Conservation criminology is focused on four main actors: (1) bushmeat hunters (Greengrass, 2016; Moreto and Lemieux, 2015); (2) commercial fishing violators (Petrossian, 2015; Petrossian and Clarke, 2014); (3) transnational illegal trade organizations (Pires and Moreto, 2018; Kurland and Pires, 2017; Lemieux and Clarke, 2009); (4) and law enforcement agencies (Pires and Moreto, 2018; Weekers, Zahnow, and Mazerolle, 2019; Adams, Mustin, Possingham, and Fuller, 2016; Gibbs, Gore, McGarrell, and Rivers, 2010). Gibbs et al. (2010) argued that the implications of conservation criminology is for conservation enforcement to be organized or structured around the risk assessment of offenders, and as a result, this perspective does not necessarily explain the entire situational structure in which these offenders operate. Thus, conservation studies ultimately examine the effectiveness of enforcement in regards to a specific wildlife crime situation (e.g., the trade in parrots in Mexico, Pires and Clarke 2012).

The primary focus of conservation criminology is to identify the situational factors that can be used to explain the commission of wildlife crime. Conservation criminology studies largely examine situational context, arguing that an offender's rationale to commit a crime is based on an array of situational factors (Pires and Moreto, 2018). Given that these explanatory factors are situational, they are likely to vary significantly depending on the particular wildlife crime being examined, where those crimes occur, and other factors related to how the situational context of a crime is defined (for discussion see, Lynch, Stretesky and Long, 2018).

Pires and Moreto (2011) described the main premises of conservation criminology as involving a person-situation nexus. Exploring that nexus involves employing a case-by-case methodology that focuses on contextual factors within one area of wildlife crime (e.g., what factors produce parrot poaching?), and then combining the results from numerous, independent studies to yield a larger understanding of the situational context behind a given kind of crime. Thus, conservation crime studies use a variety of factors based on the current structure of the location and crime type being examined. This can mean that the structural factors identified as a "cause" of any given crime change from study to study and from one location to the next. As has been noted in the literature, in this approach, the "causes" of a crime may be related to specific situational factors that are not generalizable (Lynch, Stretesky and Long, 2018). These causes are structural to the extent that they identify the structure of a context, but are not structural in the same, more general sense, as variables associated with PEG-C theory.

Though there are multiple iterations of the theoretical model used to conceptualize decision-making, the majority of these models target concepts expressed within the CRAVED model (Moreto and Pires, 2018). This model is used to understand "hot products" or why certain fauna are illegally handled (CRAVED) over others. CRAVED is comprised of six concepts which capture the essence of the situation around the opportunity to illegally handle an animal. The concepts are: concealable, removable, available, valuable, enjoyable, and disposable. Each concept in the CRAVED model reflects the structure of the situation, especially how wildlife products are targetable for crime in relationship to the structure of enforcement.

It has been suggested that while these factors explain why certain wildlife species are illegally acquired and traded, the factors do not target the driving force of the structure that allows for opportunity (Lynch, Stretesky, and Long, 2018). Lynch et al. (2018) argued that situational explanations do not ultimately prevent wildlife crime; the approach only provides information for building more efficient enforcement and compliance strategies, and is based on an assumption that doing so will deter environmental offenders (on the limits of environmental crime deterrence see, Lynch et al., 2016). With the focus on the structure of the situation, the literature around CRAVED or decision making does not have a universal means to measure factors pertaining to the theoretical model. This is because the information is contextual, and changes based on the situation in question. This is the point of conservation criminology; conservation criminology argues that no situation is the same and has unique social and economic relationships between people that have to be considered when understanding wildlife crime. Research reflects on the chain of behaviors of criminal actors and how enforcement can address those behaviors; thus, the purpose of conservation criminology is not to explain the structure of wildlife crime in general, but rather to understand how rational actors behave in different situational contexts.

As a result, there is a wide variety of research on various forms of wildlife crime within the field of conservation criminology. Adams et al. (2016), for instance, examined migratory bird populations in relation to the cost of wildlife enforcement and patrol efforts. They found that offenses did not differ between low cost-low patrol areas and high-cost-high patrol areas, suggesting that enforcement should focus less on patrols and more on other forms of protection. In contrast, Moreto and Lemieux (2015) focused on illegal wildlife trades within a local town's market-place, and found that the ability to move an animal through the stages of trade without detection made it more suitable to be traded (i.e., the animal was easily concealed). Given the six CRAVED factors, and the inconsistent results across studies that examine different kinds of poached animals, and the various contexts in which animals are poached, there are no consistent outcomes related to CRAVED models that can be neatly summarized. Moreover, the majority of these studies occur outside the US, and consequently involve situational factors that are not relevant to the US, making an effort to attempt to understand any potential similarities across these studies tangential to the focus of the current study on wildlife crime in the US. There is, however, a handful of conservation criminology studies that have relevance to the US.

The research in conservation criminology that specifically focuses on the USA addresses the context of the wildlife trade business (Kurland and Pires, 2017; Petrossian, Pires, and van Uhm, 2016), with two exceptions -- Haines et al. (2012) which focuses on specifically illegal hunting in Iowa, and Crow, Shelley, and Stretesky (2013), which focuses on the geographical differences of IH&F in the state of Florida. As of now, there is no study within conservation criminology that has tied IH&F within the USA to the wildlife trade business. In fact, Kurland and Pires (2017) argued that the United States is more likely to import wildlife than to export wildlife. Though most factors within conservation criminology would not relate to IH&F for the USA, especially measuring on a county level, some findings do warrant some attention. Factors that may be relevant to the IH&F in the USA is the spatial and temporal context of hunting. Kurland and Pires (2017) spatially and temporally observed 40,113 incidents of illegal wildlife trade seizures across USA ports. The study found that holidays where enforcement was lower had more seizures of illegal wildlife, indicating that the amount of enforcement may influence the decision on when to ship illegal wildlife products (Kurland and Pires, 2017). Extending that finding, one could argue that different times of the year might relate to the quantity of hunting and fishing violations on particular days of the year. Given that the current study has annually aggregated data for a one-year period, this possibility cannot be assessed.

Haines et al. (2012) used a geo-spatiotemporal approach to explain the physical patterns of offenders killing White-tailed deer in Fayette County, Iowa. Using 67 reported events over a ten-year period (2000-2009), the study examined the space of the events in respect to the landscape (valleys, roads, etc.). Cases typically occurred at night, and on Thursdays during the late fall- to early winter months. The majority of cases occurred along the forest line, valleys, or road side with variable topography to provide as cover from detection (Haines et al., 2012). This study, however, has several limitations similar to qualitative studies, including a small sample size. The small sample size itself is not the only factor that limits the generalizability of the study, especially since all events occur on private land that has limited access to majority of the hunting community (Eliason, 2019; Haines et al., 2012). Additionally, the study only examines physical landscape. No information is applicable when studying how other structures (e.g. economic structure) impacts the distribution of IH&F.

Crow et al. (2013) is one study that expands IH&F outside of qualitative approaches and applies a quantitative analysis. The analysis focuses on descriptive statistics and logistic regressions to find which Florida offenders commit hunting and fishing offenses, and where those offenses occurred. Results revealed that about half (49.5%) of cases were coded as improper permitting; around 81% of offenders were white; and 92% of offenders were male.

Logistic regression showed that when compared to whites, blacks were more likely to receive violations related to illegal possession of fish and improper permitting. Apart from whites, Hispanics were more likely to be cited for illegal fishing methods in additions to the same violations for blacks. The issue with this study is the geographical categorization of cases. Crow et al. (2013) sectioned the state of Florida into five large sections, but these sections can be further broken down into counties with different environments which may hide more differences between offenses, offenders, and locations. Moreover, county-level analysis would allow other factors to be assessed, and allow the inclusion of, for example, county level geographic features (e.g., number of rivers and streams, acres of farm lands or hunting preserves) and economic characteristics from the census to be assessed.

These studies indicate that wildlife crimes do not happen uniformly across time or space, suggesting that spatial and temporal analyses are needed to understand the context of IH&F. Spatial analysis has been used for multiple forms of wildlife crimes (Marteache and Pires, 2020; Kurland, Pires, and Marteache, 2018; Petrossian, Pires, and van Uhm, 2016; Petrossian, 2015), with each study suggesting that wildlife crime happens in specific locations at specific times – a finding that replicates result from traditional criminological studies of street crime (i.e., that crime has time and space correlates). The time and space correlates related to street crime, however, are necessarily relevant to the explanation of IH&F crimes. To know, for example, that more crimes occur in location A compare to locations B, C or D does not tell us how A differs from other areas in terms of factors that may contribute to criminogenic activity.

Additionally, the cross-cultural findings from conservation criminology suggests that the availability of markets and product should relate to illegal markets in the USA. Petrossian, Pires, and van Uhm (2016), for instance, established that illegal wildlife products in the USA have a marketable purpose in relation to their availability (e.g. leather products, jewelry, hunting trophies, etc.), but there has not been a study examining the markets themselves when it comes to illegal wildlife activity within the USA. A few studies can be drawn upon to understand how these factors might impact IH&F. Petrossian and Clarke (2014) examined the location of illegal fish products and ports across numerous countries and found that all CRAVED factors significantly correlated with illegal fish products, but abundance, a newly added variable, had the highest correlation (r = .39). Whether "market place" variable would have a relationship to IH&F in the US is an unknown. Petrossian (2015) found that the centration of illegal fishing internationally occurred in areas where there was an available "port of convenience" or a port commonly used for illegal fishing trade, again indicating a market-place (e.g., economic) effect. Other studies have shown that the amount of product and markets available affect the amount and degree of illegal hunting focused on larger mammals and birds (Moreto and Lemieux, 2015; Pires and Clarke, 2012; Lemieux and Clarke, 2009; Schneider, 2008; Wright et al., 2001). These studies indicate that the availability of wildlife and access to markets could be common factors when analyzing the spatial concentration of IH&F within the USA.

These factors targeting markets, spatial, and temporal concepts seem to be the more common factors found within the literature when analyzing wildlife crime; however, they do not seem to be the focus of the situation – hence, the focus on contextual factors. Still, the common discussion of these factors across studies warrants some attention when discussing IH&F within the USA. It should also be mentioned that these factors are also considered within green criminology. This overlap, coupled with a lack of understanding, suggest that green criminology may be another avenue to understand IH&F within the USA; however, green criminology is not above reproach.

The Take Away from Conservation Criminology Research

For reasons noted above, conservation criminology, which comprises a major area of wildlife crime research, offers only a few studies relevant to the assessment of whether economic and social structural factors contribute to the explanation of IH&F across counties in Texas. Conservation criminology seeks to explain the decisions of offenders' link to situational context (Lynch, Stretesky, and Long, 2018; Moreto and Pires, 2018; Gibbs, Fore, McGarrell, and Rivers, 2010), and the research has been applied to a number of contextual situations. Most of the existing studies examine actors and outcomes outside the US, mainly focusing on African, Asian, or Latin countries (Weekers, Zahnow, and Mazerolle, 2019; Moreto, 2018: Moreto and Pires, 2018: Viollaz, Graham, and Lantsman, 2018; Petrossian, 2015; Lemieux and Clarke, 2009). The field has rarely been applied to the study of wildlife crimes such as IH&F within the USA (Kurland and Pires, 2017; Petrossian, Pires, and van Uhm, 2016; Haines et al., 2012). The focus on these countries is due to the types of wildlife accessible in those nations that are valued across nations, or in regard to internal hunting and trading for bushmeat. For instance, Pires and Moreto (2011) reviewed cases that covered macaws in Peru, snow leopards in Mongolia, India, and Peru, and fish populations in Benin, Senegal, and Australia. Petrossian et al. (2016) and Petrossian (2015) examined the geographical patterns of illegal commercial fishing in international and national waters. Moreto and Lemieux (2015) sought to expand situational crime models to explain illegal wildlife markets in Africa. Because these studies have varied situational contexts and focus on contexts outside of the US (for an exception see, Haines et al., 2012), they provide limited insight into the problem of IH&F within the USA (Kurland and Pires, 2017). Apart from these few studies, the school of conservation criminology has a focus that addresses poaching for larger, more economically valued animals which would typically be seen outside of the USA (Brisman and South, 2018).

It should be noted, however, that this school of research provides reason to geographically map and understand the spatial and temporal location of events, which is consistent with the current dissertation, which looks to explain how variations in the geography of the economic structure across Texas counties may impact the geographic distribution of IH&F. The conclusion concerning the utility of conservation criminology for the current study of IH&F in Texas should not be taken as rejection of this area of wildlife crime research. That is to say, this research approach can still be examined to determine how situational factors held out by conservation criminology as an explanation of wildlife crime could potentially be modified and be applied to future research of wildlife crime in the USA. The school of thought provides multiple tools to examine case studies within the USA, but first, there needs to be a better theoretical understanding that examines how the economic structure affects the distribution of IH&F, since the economic structure is part of the situational context that affects participation in and the distribution of crime. In other words, one could argue that the economic structure of different locations determines the situational context that researchers interested in IH&F should investigate further. Currently, however, conservation criminology has overlooked the importance of the superseding structure of the situations, which I argue, following the logic of Marx (1859), Foster (1999), and O'Connor (1971), is the economic structure. In general terms, the focus of conservation criminology on situational context effecting the opportunity of crime would seem to suggest that including those kinds of factors would appear relevant, given under certain economic structural organizations. Therefore, it is intuitive to include factors that address the opportunity for IH&F behaviors within any study of IH&F behaviors.

Cultural and Social Literature on Illegal Hunting and Fishing

Another explanation of IH&F comes from a small group of research focused on cultural and social relationships around the hunting culture in the USA. These studies mainly examine the perspective of poachers or game wardens to examine mainly IH&F in the USA. Eliason (1999) argued that to study these motivations, the best criminological theories were differential association and techniques of neutralization (Eliason and Dodder, 2000; Curcione, 1992). Later, Eliason (2012a) used routine activities theory to study illegal hunting. In another series of studies attempting to explain motivations for wildlife crime, Forsyth and colleagues used a subculture-conflict approach (Forsyth and Forsyth, 2018; Forsyth, Gramling, and Wooddell, 1998; Forsyth and Marckese, 1993). It should be noted that such studies use data about individuals, and attempt to discover individual correlates of hunting and fishing crimes.

Curcione (1992) interviewed 16 California anglers about a form of illegal fishing called party-boat poaching. The content of the interviewed showed commonalities associated with the theory of differential association. First, the act of party-boat poaching must be conducted in the company of others, and due to this, findings showed that these anglers shared the same values around the activity (Curcione, 1992). Second, the act of party-boat poaching was passed down from fathers or brothers (Curcione, 1992). Lastly, these individuals did not have criminal backgrounds apart from fishing violations. Curcione (1992) concluded that these offenders reflect what are called “folk crimes,” defying authorities that impose laws that negatively affect local lifestyles.

Forsyth and Marckese (1993) explored the sociological connection between pleasure and deviance culture with illegal hunting, using Walter Miller's (1965; 1958) focal concern theory. Interviewing 36 rural offenders, Forsyth and Marckese (1993) examined the focal points, toughness, excitement, smartness, toughness, autonomy, and fate. All points were found except for fate; however, not all points were found within each individual surveyed. The most common point was trouble, followed by excitement. Both points related to the idea that offenders found it fun to evade enforcement (Forsyth and Marckese, 1993). In all, the study found support that socially isolated groups segregated from normal society have a subculture value. However, one must keep in mind the very small and nonrandom samples employed to reach this conclusion.

Forsyth, Gramling, and Wooddell (1998) explored the cultural conflict of illegal hunters and enforcement in Louisiana through a conflict perceptive. Most illegal hunters were white males, young and old. Illegal hunters either hunted for food, money, tradition, and exhilaration, and enforcement varied by the perceived motivation of the offender. Forsyth, Grambling and Wooddell (1998) found that game wardens were more lenient if an individual illegally hunted for food or survival or tradition, most likely to avoid the conflict of hunting culture. Anytime a game warden confirmed alternative motives such as money or exhilaration, wardens would be stricter. This dichotomy for the wardens, however, disappeared if the animal victim was endangered, leading to stricter enforcement universally.

Eliason and Dodder (2000) hypothesized that illegal hunting has its own culture of rationalities. To study this assumption, they examined data from forty-two individuals across 1990 to 1996 who completed surveys using a Likert-type scale targeting multiple techniques of neutralization. Eliason and Dodder (2000) found that offenders use multiple forms of neutralization to justify illegal hunting. Around 59 percent would deny responsibility or intent to kill a deer illegally. About 97 percent of offenders denied injury, while 94 percent, denied the victim, or asserted that the crime was victimless. Of the offenders, 92 percent claimed entitlement to the hunt. Many offenders, 62 percent, denied the necessity of the law.

Continuing the research on techniques of neutralization, Eliason (2004) found several factors played into the motivation of illegal hunting. Typically, excuses such as ignorance, forgetfulness, and carelessness were expressed by respondents. Illegal hunters relayed either they did not know the restrictions existed, or forgot about the restrictions. Some broke the law to experience the recreational activity of hunting, which mitigated the seriousness or the restrictions (Eliason, 2004). Game wardens who were surveyed believed that people hunt illegal out of entitlement for meat, contradicting the responses from the poachers (Eliason, 2004). Game wardens would also apply techniques of neutralization to understand illegal hunting. The wardens would not pursue charges or arrest against poor rural individuals. According to Eliason (2004), wardens had sympathy for lower class citizens to illegally hunt and supply their families with food.

Trophy hunting is also argued to be harmful to the population of fauna (Nurse, 2013; Eliason, 2008a). To understand the motivations to trophy hunt, Eliason (2008a) sent out 1,000 surveys to Montana state hunters, with a return of 255 surveys for resident hunters and 281 for non-residents. Findings suggests that non-residents are more likely to pursue trophy hunting, but the appeal of trophy hunting is relevantly low. Eliason (2008a) concluded that this appeal to hunting was promoted by the general tendency toward competition engendered by the capitalistic system.

Eliason (2008b) interviewed 24 conservation officers and 29 interviews with wildlife offenders concerning the motivations of people who specifically illegally hunted. Findings suggested a few types of illegal hunting (Eliason, 2008b). The first, the back door hunter, illegally hunts on their own land away from law enforcement. The second, experienced hunter, are individuals who have the experience to outwit law enforcement. The third, the opportunist hunter, are people who only illegal kill in favorable opportunities. The fourth, the quiet hunter, are the individuals who do not talk about their illegal hunting success. And lastly, the trophy hunter are individuals who use illegal technology to kill the best specimen they could find. Eliason (2008) argued that law enforcement needs to understand why people chose one type of illegal hunting over the other to start address the behavior.

Using routine activities theory, many factors found in the historical literature were reinforced for more current times. Eliason (2012a) focused on illegal trophy hunting and the opportunities around the hunt. There are many reason Eliason (2004) offered for why people illegal trophy hunt. Explanations from wardens range from the limitation of laws targeting meat hunting, the crime is victimless, to obtaining an elite hunter status. Private lands have dual roles in illegal hunting. Since wildlife enforcement does not have jurisdiction on private land, which leaves animals without a capable guardian, making the animals suitable targets (Eliason, 2012a).

The Take Away from Social Literature on Illegal Hunting and Fishing

Research on IH&F within the USA provides multiple motivations explaining individual level factors that might be related to IH&F; however, the research fails to provide an explanation for the distribution of IH&F, especially at a structural level. The information found by the researchers above provides some contextual background for individuals who illegally hunt. Additionally, most of the literature describes the interactions between wardens and illegal hunters; in other words, the research examines how individuals perceive enforcement or rationalize justification to break hunting laws. Similar to Lynch et al. (2019) critique of conservation criminology, these studies ignore the structural factors that comprise the social environment that influences these decisions. Eliason (2008) argued that the increase in individual competition in hunting which caused in the decrease in fauna populations, but hunting is a behavior supported and regulated by how the economy and government organizes itself (e.g. policies, agencies, law, and business) around the value of nature as a public trust (Jacoby, 2003). The social literature fails to acknowledge the growing resource mining industry destroying and polluting land, limiting animal populations (Shandra et al., 2010; Shandra et al., 2009; Jacoby, 2003). The context found in this body of research is dictated by the narrative of the motivations of individuals, ignoring the organization of society around the value of wildlife.

There are several general limitations found in this literature. First, the generalizability and application of the findings are hindered by the small sample size in most studies. Eliason (2004, 2000) had a survey sample size ranging from 113 to 115 people who illegally hunted. Some of the studies brought in game wardens to add additional information (Eliason, 2012). Those sample sizes ranged from 22 to 146 game wardens. Wardens gave insight to the dangers and enforcement perspectives of offenders, but the information is only assisting in understanding the conflict between officers and offenders (Eliason, 2012; Forsyth and Forsyth, 2009; Forsyth et al., 1998). The issue of small samples exasperates other issues like relatability; however, the studies have yet to come contradicting responses from interviews and surveys.

The second issue with the studies is the discovery of location. One study found the importance of spatial factors (Eliason, 2012); however, none of the studies used this information to spatially illustrate the relevance with the different types of land and how space effected enforcement and IH&F. Location seems important since Eliason (2012a) found factors of routine activity theories when interviewing game wardens. For instance, Eliason (2020; 2012) emphasized the need to acknowledge private lands due to the lack of enforcement. Similarly, Forsyth and Forsyth (2009) discussed the hardships of game wardens, especially how dangerous natural environments threaten the life of game wardens. Unfortunately, these studies did not provide any means to analyze geographically. Geographically mapping out jurisdictions provide visual understanding with enforcing large pieces of land and how other factors can impact the concentration of IH&F. This discovery of location would warrant further scholarly investigation, but no discussion was given. Instead, conservation criminology took up this discussion but applied a different perspective.

Lastly, and the most important, there is a lack of quantitative analysis within this literature. Only two studies examining IH&F in the USA used quantitative analyses, which are conservation criminological research (Crow et al., 2013; Haines et al., 2012). With the lack of quantitative studies, there is insufficient information to fill in the gap of understanding on the trends and distribution of IH&F using social factors. This brings to question about the generalizability of understanding the behavior across the USA. In contrast to qualitative research, no theoretical framework has been quantitively applied to determine how IH&F behaves within the USA. More quantitative studies are needed to offset this gap in social research, and additional investigation is needed to determine if social factors influence IH&F in the USA, and by extension, Texas.

Though social research does not have sufficient evidence to support a social framework, it would be intuitive to include the social commonalities between the research and measure this commonality at a structural level. Specifically, the social research argues the illegal hunters are more likely to be poor (Forsyth and Forsyth, 2018; Eliason, 2012; Eliason, 2004; Forsyth, Grambling and Wooddell, 1998; Forsyth and Marckese; 1993; Curcious, 1992). This would suggest a class conflict within the ownership of nature. Second, local residents are perceived to be related to illegal hunters (Forsyth and Forsyth, 2018; Eliason, 2012; Eliason, 2004; Forsyth et al., 1998). This would suggest IH&F is not a behavior generalizable across areas where there is little resident tenure. Jacoby (2003) documented a historical trend of class conflict between lower class locals and businesses over the right to use the land over the Adirondacks park, supporting social factors play into the explanation of IH&F. Thus, measures of social factors are structural level that relate to class and local residency should be controlled.

Summary of Literature

This current dissertation seeks to explore the structural factors related to the geographical distribution of illegal hunting across Texas counties. Following PEG-C research, factors that would affect IH&F would be how economic factors affect the destruction, modification, and withdrawing of the natural ecosystems. An alternative explanation with more empirical application to wildlife crimes, conservation criminology, suggest that factors of opportunity could influence the distribution of IH&F. Therefore, in order to ensure the effects of PEG-C factors are independent from alternative explanations, control variables representing geographical features that would provide opportunity for IH&F are used. Additionally, social literature argues that social factors like socioeconomic status and residential tenure provide explanation to illegal hunting. Even though the research did not explore how these factors influence the spatial distribution of IH&F, it would be intuitive to control for these factors for a clearer effect of the PEG-C factors. To understand the how the PEG-C factors would relate to IH&F, the next chapter explored the treadmill of production theory. The theory covers factors targeting the behaviors and consequences of economic growth within a capitalistic structure. After, a methodology is discussed to determine a quantitative approach to study the effect of these factors.

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CHAPTER 3:

ECONOMIC STRUCTURE AND ILLEGAL HUTNING AND FISHING

In the previous chapter, an analysis of illegal hunting's history revealed that economic context and structures impacted how social relationships and lifestyles affect trends in illegal hunting. Building upon that observation, this chapter discusses how structural factors identified in the Treadmill of Production (ToP) theory could be employed to explain the distribution of illegal hunting. ToP theory argues there are two ecological consequences of capitalism – ecological additions and ecological withdrawals – which combine to cause ecological disorganization. While both processes are important to describing the operation of the ToP, the process of ecological withdrawals is argued to play a role in affecting the distribution of illegal hunting by altering the distribution of, and access to wildlife. Adding to the observations from ToP theory, it is also argued that other *ecological modifications* such as the building of roadways which contribute to the stability of the ToP can segment ecosystems, and affect the distribution of illegal hunting.

To establish the above, this chapter begins with a review of treadmill of production theory. That discussion includes a review of the ecological consequences of capitalism. Those discussions, I introduce the concept of ecological modifications, and argue that these modifications should be included as control variables that could affect the distribution of hunting violations across Texas counties. The chapter concludes with a summary of the theoretical models that will be examined in the empirical portion of this study.

The Treadmill of Production Theory

Political economic green criminology (PEG-C) argues that economic forces impact the types and amount of environmental crime found in society. Increasingly, PEG-C has done so through the lens of the Treadmill of Production (ToP) theory. While not all green criminological research is grounded in a political economic approach, here, I draw more heavily on the PEG-C approach. In general, the purpose of green criminology is to address how the economic organization of society (i.e. the organization of production) consumes and pollutes the natural environment and causes ecological disorganization or the dysfunctionality of nature (Lynch and Stretesky, 2011). The concept of ecological disorganization did not originate within green criminology but stems from theoretical critiques of capitalism in the economics, political science, and sociological literatures (O'Connor, 1988; Foster, 1999). Green criminology argues that the harms produced by the structural organization of capitalism produces ecological costs that can be considered crimes from the perspective of nature as a living entity (Lynch et al., 2013).

The concept of the treadmill of production (ToP) was introduced by Schnaiberg (1980) to describe the production's impact on the ecosystem, as well as social and political responses to the production (Schnaiberg, Pellow, and Weinberg, 2000). According to Schnaiberg, the ToP started after 1945 when factories needed greater material input as well as expanded fossil fuel and chemical energy technologies to increase production and profit-making. The environmental impact of the ToP originates from the dynamic relationship between laborers, the state, and capital owners. Schnaiberg et al. (2000) observed five axes of this dynamic relationship. *Economic Expansion* was the idea that as the economy grew, all parties receive an increase in a form of capital. *Increased consumption* is the axis that as goods are produced, there needs to be an increase in consumption. Thus, consumers need financial assistance to continue to consume (i.e. credit). The third axis, *solving social and ecological problems by speeding up the treadmill*, focuses on the ability of the market and technological development to “solve” problems such as poverty and environmental degradation. *Large firms,* the fourth axis, were believed to be the driving mechanism of economic expansion in treadmill capitalism; these firms provide the greatest demand for jobs, and encouraged smaller firms to supply the larger firms. Lastly, the fifth axis focused on an implicit contract with the *alliances among capital, labor, and governments,* to ensure the stability of the ToP. The alliance influences society to maintain laborers and entrepreneurs; but, following the classic theory of capitalism development by Marx, the growth of technology was seen as detrimental to the needs of the working class, since technology functions to make production efficient, leading to the elimination of labor costs and employment (Schnaiberg et al., 2000). At the same time, however, Schnaiberg argues that working class members participate in this technological restructuring in an effort to save as many jobs as possible.

In sum, Schnaiberg (1980) argued that the structure of the capitalist ToP operates to fulfill the primary function of capitalism – profit making – but does so endlessly, as if it were on a treadmill. This treadmill continually expands production. In order to continually expand production, the treadmill must increase the extraction of raw materials used in the production process. In addition, it must emit an increasingly larger volume of pollution. Accordingly, Schnaiberg et al. (2000) argued there is an ecological dimension to the ToP that negatively impacts the stability of the ecosystem, and increasingly disorganizes the ecosystem over time. According to O’Connor (1988) and Foster (1999), this relationship between capitalism and the environment is one of the central contradictions of capitalism: as capitalism grows, it continually destroys nature, and must do so. That contradiction reveals a central limitation of capitalism – as it destroys nature, it consumes the natural resources it requires for production, and, at some point, nature is no longer able to support capitalism or its expansion (Foster 1999). Drawing on these observations and those from scientific studies, green criminologists have employed these observations to note that this process promotes such extensive ecological damage and ecological disorganization that the ecosystem is faced with the possibility of collapse (Lynch and Stretesky, 2014). It is in this sense that capitalism is said to not only harm, but to commit crimes against nature (Lynch et al., 2013), with environmental sociologists specifically referring to this process as "the robbery of nature" (Foster and Clark, 2018, 2020).

According to Lynch et al. (2017a), green criminology discusses the contradiction between the ToP and the environment in terms of environmental disorganization or destruction outcomes. The ToP generates adverse ecological outcomes that hinder the ability of the environment to maintain itself, and by extension, lower the availability of natural resources for the ToP (Lynch et al., 2013). These outcomes have been supported by multiple studies in environmental sociology and natural sciences. Schnaiberg et al. (2000), and recently scholars like Jorgenson (2006: 2009); Shandra and colleagues (2010; 2009); McKinney and colleagues (2010; 2009), and Lynch and colleagues (2013), globalization has brought this uneven distribution in the ToP across nation borders, expanding the ToP beyond a nation's ability to control the ToP. Now, companies move production to nations with cheaper labor and use other nation's recourses as input into the system (Schnaiberg et al., 2000). however, only a few studies have explored theoretically and empirically how the ToP relates to the distribution of green crimes (Lynch, Long and Stretesky, 2019). Due to the limited scope of this literature, numerous topics have escaped examination. To date, for example, the PEG-C approach has not been applied to the study of illegal hunting and fishing.

While the ToP approach draws attention to how capitalism generates ecological disorganization through ecological withdrawals and additions, I argue that the ecological withdrawal dimension is the most relevant to consider when attempting to understanding the distribution of illegal hunting. The opportunity for illegal hunting, for example, is not likely to be impacted by pollution since a great deal of pollution is located in urban areas where hunting opportunities are diminished. However, illegal hunting is likely to be affected by ecological withdrawals since they restrict and change the nature of the ecosystem and landscapes in which wildlife are found. For example, during the early conservation years of the Adirondack Park, the lumber industry was growing, buying land and logging down forestry and displacing wildlife. In response, the state of New York enacted conservation regulations to preserve the remaining public land of the park, but the regulations were imposed on the public, rather than the lumber industry. As a result, hunters ignored conservation efforts and the lumber industry by continuing to hunting and poach lumber illegally to counteract the shrinking land to hunt and gather materials (Jacoby, 2003). This can also be seen within the agricultural industry, lowering the biodiversity of a nation's fauna (Shandra et al., 2010; McKinney, 2010).

Additionally, while the ToP approach provides an overarching description of a given form of capitalism, the ToP itself can be understood in more nuanced ways, and consisting of various dimensions. For example, while a major component of the ToP is the manufacturing sector, manufacturing itself is comprised of subareas. For instance, the manufacture of food also involves agricultural production, and this process of manufacturing/producing food can be described as being part of the ToP (Konefal and Mascarenhas, 2005). Drawing from ToP theory, one can suggest that large scale agricultural operations promote the withdrawal of ecological resources and facilitates the destruction of habitat for certain wildlife species. At the same time, large agribusinesses may also provide habitat for certain species (i.e., quail, pheasant) hunters desire. Thus, the distribution of the agricultural portion of the ToP may impact opportunities for illegal hunting by altering natural terrain, affecting the presence of certain species of wildlife, and affecting lands hunter can access to carry out hunting activities.

Conflicting Industries in the Treadmill of Production

According to Jacoby (2003), there are two industries in conflict with one another access to, and the preservation of nature – the hunting industry and the mining industry (e.g. mining, fracking, etc.). Posited here, there is a hunting or outdoor industry (HI) that can be considered to be part of the economic treadmill. The HI portion of the United States' (USA) ToP may come into conflict with other, and much larger, sectors of the ToP, such as the mining sector (MI). Prior studies, for instance, demonstrate that during the early years of conservation efforts, there was an increase in illegal hunting and conservation violations due the growth of the MI and HI (Jacoby, 2003). During these times, there was a growing HI that encouraged more and more individuals to invest in hunting. At the same time, the wildlife needed to satisfy the growing number of hunters was decreasing due to habitat lost from the growing lumber industry and urban sprawl, which the government endeavored to balance through increased forest conservation efforts (Eliason, 2012; Jacoby, 2003). During those times, as mining (i.e. lumber extraction), and hunting industries grew, social conflicts followed, and increased the likelihood of acts of illegal hunting (Jacobs 2003).

As the mining industry expanded, resources available to other industries become more limited. The MI is responsible for land destruction, limiting the volume of undeveloped land and resources individuals – and wildlife – can use or access. Similarly, expansion of the agricultural sector of the ToP can also have adverse ecological impacts on wildlife, and affect the opportunity for hunting and hunting violations. For instance, Shandra et al. (2010) observed a relationship between increased agricultural land use and bird and mammal biodiversity loss. This association may indicate that land losses – a specific forms of ecological disorganization -- may affect illegal hunting by changing the availability of the number of species, or the quantity of any given species.

In regards to the HI, the HI does not cause the same kinds of ecological harms as other segments of the ToP. In general terms, the HIs, themselves, do neither withdraw resources (with the exception of game animals), add pollutants, or produce large changes to ecosystems, like other industries green criminological research has explored. Hunting industries relay on available land for customers to use their products for hunting and fishing. This is an important observation to bear in mind when discussing the context behind the economic behaviors of the ToP and the distribution of illegal hunting.

Overall, the growth of certain sections of the ToP leads to ecological consequences that affect the state of the ecosystem, and the distribution of wildlife species. In this way, the ecological disorganization effects of the ToP may be shaping the distribution of illegal hunting. More specifically, the mining industry restricts the capital of nature from hunting industry consumers or individuals through ecological disorganization and privatization of land for the mining industry. The following sections further expands the discussion of these adverse ecological consequences that flow from the expansion of the ToP and how they relate to the distribution of illegal hunting.

Ecological Disorganization Outcomes

The ToP disorganizes the environment and harms the replenishment of natural habitats and resources. Thus, ecological disorganization outcomes (EDO) are an umbrella term used to describe how the economy damages the environment through ecological withdrawals and additions. These behaviors "disorganize" the current state of nature. Over the years, Lynch and other green criminologist (e.g. Nigel South, Avi Brisman, Michael Long, Melissa Jarrell, Paul B. Stretesky, and Kimberly L. Barrett) have observed how corporate behavior massively alters the environment (e.g., blowing up mountain tops, polluting waters with chemicals; Lynch, Long, and Stretesky, 2019). One of the most famous examples of adverse environmental impact was the BP oil spill in 2010. Situations like the BP oil spill have questioned the legitimacy of business behavior with respect to environmental consciousness. EDO seeks to highlight how even the mundane use of the environment as a resource, or as a sink for pollutants causes deterioration of the overall health of the environment. Additionally, research around economic structure and biodiversity loss have pointed towards a third outcome – ecological modifications – as a cause of ecological disorganization due to physically changes which support the expansion of the ToP while damaging the ecosystem.

To date, studies have not separately analyzed these outcomes, let alone the disaggregated effect of industries found in the ToP. This is because the ToP involves a complex set of relationships that it is unable to be captured within one or even several simple measurements. Typically, ToP related research focuses on the main premise of economic expansion to show how the economy is producing and using natural resources. Empirical research related to this argument has been shown to explain outcomes such as global animal biodiversity (McKinney, Kick, and Fulkerson, 2010; Shandra et al., 2010; Shandra et al., 2009; McKinney, Fulkerson, and

Kick 2009). The current dissertation, then, seeks to determine whether certain EDOs would relate to the spatial distribution of illegal hunting.

There are currently two EDO supported by green criminological research. First, there are ecological withdrawals which describe the economic behavior of extracting resource. Second, there are ecological additions which describe negative additions to the environment such as pollution. As the ToP expands, more behaviors are exhibited that facilitate disorganization of the environment. However, there are also other ecological changes that can alter ecosystems which I shall call ecological modifications. These include the construction of roadways, for example, which can cause the fragmentation of ecosystems (on ecosystem fragmentation see, Geneletti 200). The adverse ecological consequences of ecological modifications have not been examined in the green criminological literature. I will suggest that it is necessary to consider ecological modification as another way in which the ToP can adversely impact ecosystems, and consequently, to affect the distribution of outcomes such as illegal hunting.

Ecological withdrawals

As the ToP expands, the resource mining industry must extract more and more materials to keep the production process in motion (Schnaiberg et al., 2000). It should be noted that the damage associate with the ecological extractions from mining can be extensive, and may exceed the ability of nature to replace or replenish extracted materials. An obvious example is the extraction of fossil fuels, which take millions of years to form, but are currently extracted at very high rates (e.g., in 2019, more than 95 million barrels of oil were extracted daily). Ecological withdrawals are not simply the use of natural resources, but include the excessive rate at which resources are extracted. The process of ecological withdrawals can also be related to the concept of metabolic rift (Foster 1999). According to Lynch et al. (2019), “the process of metabolic rift leads to the unequal distribution of matter and energy represented in the capitalist economy by good/commodities…” (p. 153). The metabolic rift can also be related to planetary boundaries that describe the limits of natural recourses. These boundaries describe the ecological sustainability of the planet (Lynch et al., 2019; Rockstrom et al., 2009). When a planetary boundary is reached, environmental sustainability is threatened (Rockstrom et al., 2009).

There are multiple ecological withdrawals required to operate the ToP. Research has identified one form of withdrawal that lowers the diversity and density of wildlife --deforestation – which also promotes habitat destruction/loss (Lynch, Long, and Stretesky, 2015). Examining virtually every inhabited nation in the world, Hoffmann (2004) found that as percent of forest cover decreased, the number of threatened species increased. Schipper et al. (2008) found around 40% of land mammal species assessed were adversely affected by habitat loss and degradation. The destruction of habitat, in short, causes both the population of species and the number of species to decline. Within the context of hunting, it can be argued that as the ToP expanded and consumed more and more of nature, species richness declined, limited the opportunity to hunt successfully, and perhaps creates pressure to hunt illegally. It might also enhance the ability of enforcement agents to discover more hunting violations as the volume of nature that needs to be police shrinks, and access to the “deep” wilderness becomes easier.

At the same time that the ToP was consuming nature, hunting industry (HI) was promoting hunting in order to expand its profit-making capacity. The HI was very successful in this regard, and the number of registered hunters has grown substantially. In Texas alone, for instance, there are more than 1.25 million registered hunters. Overall, in the US, the number of registered hunters has grown from 34.19 million in 2004 to 36.82 million by 2017, or by about

8% (Lock, 2017). To protect the remaining wildlife from extinction while also protecting the ToP, state conservation laws are passed to limit the amount of people who can hunt (e.g., through the use of license limits or bag limits). Laws may prohibit actions such as hunting at night, or hunting without a paid permit.

It should be expected that withdrawals from resource mining would impact where illegal hunting occurs. Unfortunately, when it comes to the impact of the economic structure, little attention has been paid to how those structure affect the local or county level, and studies of economic production have mainly focused on the effects the ToP at the national and global levels (Hoffman 2004)). On a smaller scale or local level, information on these withdrawals is limited; however, following the logic of the ToP, examining the growth of employment in, the volume of output from, and the establishments of mining operations can serve as direct indictors of mining activity and growth (Lynch et al., 2017; O'Connor, 1988). Paralleling Jacoby's (2003) observation within history, wherever the resource mining industry grows, the public's access to land is restricted either by private purchase of land, or government conservation efforts designed to limit wildlife resource extraction. In certain instance, illegal hunting can occur due to a conflict between local hunting cultures/values and land ownership patterns. For example, in areas where there are no public lands to hunt due to a large concentration of resource mining, illegal hunting occurs, because there is a fundamental value that the wilderness is a public trust, not to be owned by business (Jacobs 2003).

Ecological Additions

On the opposite end of the production process is ecological additions. These additions are pollutants or waste that are not part of the natural ecosystem. According to Lynch and Stretesky

(2014), these additions are discharged into the environment as the result of production, and as a consequence of resource extraction processes. These pollutants can change ecosystems as well as the behavior of animals, and may even affect the heath of local wildlife species. One of the most well-known examples of an ecological addition is the BP Oil Spill. This spill impacted over 1,300 miles of shoreline in the Gulf of Mexico in 2010, which generated extensive pollution from a resource withdrawal method (National Oceanic and Atmospheric Administration, 2017). NOAA scientists saw environmental damage to breeding and nesting grounds for four endangered species of turtles (Kemp's ridley, loggerhead, green turtle, and hawksbill). Scientists confirmed a trend of reproductive failure and organ damage that caused the longest and largest marine mammal mortality event (NOAA, 2017). NOAA found a 50 percent reduction in the population of bottlenose dolphins after the event.

Ecological withdrawals have a direct effect on habitat destruction, while the destruction associated with ecological additions is less obvious. While the health of the wilderness is affected and contributes to the overall biodiversity loss, this does not limit the land where people are able to hunt, but may affect the availability of species, as demonstrated in the famous book by Rachel Carson, *Silent Spring*, which showed how pesticide pollution was killing bird populations. That work was so influential it ushered in the environmental era of the 1960s.

Ecological Modifications

I argue there is a third EDO that has not been discussed in the ToP literature, but has been addressed in other research that explores the ecological contradictions of capitalism. O'Connor (1988) argued that capitalism shapes "urban space", a term to describe the social organization such as family roles, education, labor, and more. The urban space helps centralizes production and distribution of capital exchange, but there is also another aspect to urban space -- its physical space or composition. In order for this urban space to development, modifications to the natural environment must occur to sustain such a setting. Deriving from the theoretical framework of Marxist geography, space and a physical infrastructure plays a large role for the urban space to sustain of the ToP. On this point, Peet (1979: 166-167) has argued that

> A mode of production generates a typical set of relations with the physical environment, and a territorial structure, which reflect the relations of production (especially the purposes of the owners of the means of production) and the level of development of the productive forces. Social formations structured by the same mode of production thus have generally similar geographies. But a given mode of production expresses itself differently under varying physical conditions or in areas of varying cultural transmission from decayed modes of production, producing variations between and within the social formations it generates. Also, a social formation develops historically in spatial interaction with other social formations, those produced by the same mode of production, those produced by previous modes, and those produced by alternative modes. Geographic relations thus play extremely important mediating roles between modes of production and the social formations which appear on the earth's surface.

This view draws attention to how the development of capitalism affects the types of and the distribution of different kinds of space. In this long history, the development of urban centers was necessary to the development and growth of capitalism (Peet 1979). Moreover, Peet (1969) argued that the development of urban space required the development of centralized agricultural. To align these spaces, transportation technology grew which assisted in creating more agricultural zones outside cities, and which moved food (metabolic materials) from rural to urban areas. As the economy grew, land and technology were transformed to produce more product to compensate for the demand of the economy, a transformed more rural and natural areas into farm lands, affecting wildlife habitat and access to wildlife. Today, this relation has become internationalized as well. On a global scale, Shandra et al. (2010; 2009) found this relationship between undeveloped nations experiencing economic growth and growing agricultural land due to the increase demand for exports to more developed nations.

This process can also be applied to the demand of labor for industries. Parks and Burgess (1921) discussed how cities were centered around a business zone and workers are centralized around that zone. According this concentric zone theory, as transportation improved and groups gain wealth, they moved further away from the business zone (Sampson, 2012). From a ToP perspective, the cost of labor (the support of people) is lower when labor lives in proximity to businesses, but as industries grew, more labor was needed and more room for the excess labor was need. Transportation was needed to improve to compensate the travel of cost of labor to the business zone. Soon after, the cost of labor to live away from the business zone was more cost effect than before. Dennis and Urry (2009) found that road development was created to assist in the innovations in transportation. In turn, Shatz (2011) saw that road developed assisted in economic factors such as productivity and worker transportation. Therefore, as the ToP lead to "urban space", the ToP also modifies the natural environment to build an infrastructure to support this urban space for the productivity of the ToP. Therefore, just like agricultural land, as the economy grows, urban areas grow outward from the business zone. Additionally, along with modifying the physical space of the natural environment, this growth also results in increase consumption of nature around the area. Queen et al. (1934) argued that urban development settled on land full of resources like water access to supply the urban setting. Therefore, as the economy grows, urban areas will transform the land to allow easier access to these natural recourses and lower the cost of labor. Moreover Peete (1979) argues that the physical urban space growth space assists in ecological contradiction and destruction of the natural environment.

In this manner, ecological modifications change the ecosystem. Ecological modifications are the products or the result of the ToP growing, laying a foundation of an ecosystem to further support the ToP. Ecological modifications are considered buildings, roads, farms, and other forms of human development that change the "nature of nature". From discussions above, ecological modifications change the physical landscape of the environment itself. Unfortunately, this concept has not been fully explored within green criminology. This is mainly due to the focus of the remaining environmental lands; however, when focusing on the health of animal wildlife, there needs to be a focus on these modifications since animal wildlife migrate from place to place. For example, a grazing ground becomes a supermarket and a parking lot. The newest suburban neighborhood was a habitat for small mammals and hunting grounds for predatory birds. McKinney (2002) found that as the physical urban development expanded, there was a downward trends of species richness, and a growth in species that benefit from human development (e.g. mice, rats, pigeons, etc.).

Some modifications are referenced within conservation criminology studies of factors that affect outcomes such as illegal fishing or hunting. Fine (2000) suggested that the expansion of roads allowed more urban dwellers to travel to parks to hunt. Haines et al. (2012) found that road development created increased opportunity to hunt within a forest ecosystem. Illegal hunters hunted near the road, because animals would graze in the open grass by the tree lines (Haines et al., 2012). For conservation criminology, these modifications affect rational decision making-factors related to engagement in illegal behaviors. In contrast, green criminologists would address environmental modifications as structural factors related the expansion and ecosystem invasion of the ToP. For instance, roads assist human transportation of natural resources for the purpose of expanding economic development (Shatz, 2011; Peet, 1969). Thus, these modifications help understand where human development invades the wilderness, leading to increased ecological withdrawal, ecological additions, and more ecological modifications.

How does ecological modification relate to hunting? Hunting is a form of ecological withdrawals, though not from an industry but from individuals. Yet, at the structural level, ecological modifications change ecosystems, essentially "causing" hunting to be limited in certain locations, to be more prevalent in others, and also affecting how wildlife species are distributed. In essence, ecological modifications limit the distribution of wildlife, increasing the value of wildlife. As a response, to restructure the capital of wildlife and lower the cost of wildlife, illegal hunting occurs around these areas. Without controlling for ecological modifications, studies on the ToP have potentially ignored an important spatial dimension of how the ToP affects ecosystems.

While ecological modification can be employed to control for some spatial relationships, they also offer a perspective on private lands, and issue that is not addressed by an ecological withdrawal or addition approach associated with ToP arguments. Privatized lands restrict access to wilderness land potentially for both the ToP and the general public. For instance, when the state was unable to monitor the wilderness effectively due to limited economic means, people bought land to preserve it, and turned those lands into private hunting clubs and businesses (Jacoby, 2003). It should also be recognized that privatized land can be used for multiple reasons, not just conservation or hunting business. Privatized land can be used for ranches, farms, mining industries, or for resale for future development. The argument here is that when you examine ecological modifications, you need to control for the remaining privatized land to determine an accurate measure of effect of the current degree of ecological modifications.

To sum up, ecological modifications effect illegal hunting in two ways. First, the modifications can interrupt animal migration and habitats, and alter the concentration and availability of animals that could be hunted. Second, ecological modifications affect the volume of and access to land usable for hunting. By controlling for ecological modifications, the effects of withdrawals become clearer, because you are controlling for the space in which withdrawals cannot occur. It must be kept in mind that privatized land is an alternative explanation to the spatial explanation of the ToP. Privatized land can limit the access of land to the ToP and hunting. Without controlling for this factor, the effect of the ecological modifications can be overestimated or underestimated.

Summary of Economic Structure and Illegal Hunting and Fishing

Ecological withdrawals from the mining industry, but not necessarily ecological additions, are key economic factors that can be employed to describe how illegal hunting is distributed (Figure 3.2). As the treadmill expands, ecological disorganization also spreads, becoming more invasive and harmful over time. Therefore, a ToP model explaining illegal hunting would propose that illegal hunting is a result of outcome effects associated with the distribution of the mining and hunting industries. Both ecological withdrawals and modifications limit the availability of hunting, thus limiting the fauna resources hunters may extract, and the lands they may access. These effects also impact hunters from different social classes in unique ways. For example, some social classes are more likely to rely on hunting to provide food, and some people are more likely to engage in sports hunting depending on their social class (Johnson, 1999; McGee, 2010) or their ethnicity (e.g., Native Americans, see Sepez, 2002).

Put simply, economic factors focus more on how the growth of certain sectors of the economy the extraction of natural resources. The mining industry extracts resources for the masses and to facilitate the growth of the ToP, while the hunting industry wants individuals to extract resources instead of the industry. Ultimately, when one industry expands within an area, the ability of the other industry struggles to maintain relevancy. According to Jacoby (2003), mining industries have more control over land, limiting the enlarging consumer base of the hunting industry to use the land. Thus, the distribution of illegal hunting is determined by how dominate the MI or HI is over the other.

The next chapter examines the data used in the analysis, variable operationalization, and methodological steps employed to assess the distribution of illegal hunting in Texas. A few things must be taken into consideration within the quantitative analysis. That chapter also explores variables that may provide alternative explanations to ToP theory. These additionally control variables include those from conservation criminology, from social disorganization theory, and other cultural factors described in prior research (Jacoby 2003; (Eliason, 2020; Eliason, 2004; Forsyth et al., 1997; Forsyth and Marckese, 1993). By controlling for these variables, the relationship between the economy and illegal hunting becomes clearer.

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CHAPTER 4:

METHODS AND DATA

The prior review of the research suggested that there is a relationship between economic organization represented by the Treadmill of Production (ToP), and illegal hunting and fishing (IH&F). While this association has been demonstrated in qualitative assessments, there has yet to be a quantitative assessment on the effect of the economy on IH&F. Unfortunately, due to limited data covering one year, the current dissertation employs a cross-sectional study using Texas data from 2015 to examine the concertation of the ToP and how the concertation of the ToP affects the distribution of illegal hunting and fishing in Texas. While this is a limitation to testing the ToP theory, it allows a basic assessment of the geographic associations between IH&F and ToP variables. The chapter focuses on the methodology employed to study these relationships. To begin, the relationships to be tested and hypotheses statements are explored. Then, the data, units of analysis, and sample are discussed. Next, the conceptualization and operationalization of the dependent, independent, and control variables is provided. Finally, methodological steps for analysis of the hypothesized associations are discussed.

Research Questions and Hypotheses

This study has specific but exploratory aims. First, the study explores the distribution of economic structures, opportunity variables, and social factors hypothesized to affect the distribution of IH&F across Texas counties. Second, it explores the relationship between the ToP and the distribution of IH&F across Texas counties. Third, this study asked whether significant, if any, discovered between ToP indicators and IH&F change after when control variables representing opportunities for crime are controlled. Spatial analyses of these associations are also conducted to identify whether high risk counties are grouped for IH&F in Texas.

Treadmill of Production Variables

PEG-C research discusses how the ToP impacts ecological withdrawals or the consumption of nature (Lynch, Long, and Stretesky, 2019). Three variables representing the ToP, according to literature, were used to capture the concertation of the ToP in the current study. First, the Gross Domestic Product (GDP) per capita was used for the concentration of the overall economic activity across counties that represented the ToP (Shandra et al., 2010). Second, an additional aspect of the ToP was assessed by measuring manufacturing concentration across counties (Lynch et al., 2019). Lastly, resource mining industries concentration was used to assess one dimension of ecological withdrawals and ecological consumption activity across counties (Jacoby, 2003). The exact definitions of these variables are found below.

The study addresses a straight forward research questions: Are variables that measure aspects of the treadmill of production related to the geographic distribution of illegal hunting and fishing violations in Texas? Regression models are employed to determine whether ToP indicators and IH&F violations across Texas counties appear to be statistically related. The more specific hypotheses tested are found below. Based upon assumption contained within ToP theory, these hypotheses posit the following.

H1: County measures of the GDP per capita are associated with illegal hunting and fishing at the county level.

H2: County measures of manufacturing industries are associated with illegal hunting and fishing at the county level.

H3: County measures of resource mining industries are associated with illegal hunting and fishing at the county level.

Schnaiberg (1980) argued that as the overall economy grew, the consumption of nature increases. As argued in Lynch et al. (2019) and Shandra et al. (2010), both the GDP per capita and manufacturing industries reflect dimensions of the ToP. Previous studies have not specifically linked the ToP to illegal hunting activities. However, following the logic of ToP theory, one would expect that even illegal resource consumption might increase with the concentration of the ToP. In the current study, therefore, I expect areas with a higher concentration of the GDP per capita (H1) and manufacturing industries (H2) to be associated with higher concentrations of illegal hunting and fishing activity. The ToP effect for MI on illegal hunting, however, would not necessarily be consistent with the effect for other indicators of the ToP. For example, following Jacoby's (2003) account of the lumber industry, the development of the MI reduced the land available for wildlife by destroying wildlife habitat, and also and by restricting access to land for public uses such as hunting. Therefore, it is expected that as MIs grow and consume larger segments of animal habitat, there would be fewer available animals, and less opportunity for wildlife crime, leading to a negative association between MI concentration and illegal hunting.

Hunting Industry Variables

As mentioned in the previous chapter, other the ToP may come into conflict with other segments of society. Conservation efforts to preserve land against the ecological destruction associated with expansion of the MI, for instance, emerged in location where efforts were made to protect the hunting industry and the rights of individuals to access nature and to hunt (Jacoby, 2003). Thus, as both the MI and HI grew, an increasing number of conservation regulation were passed into law that endeavored to preventing the loss of flora and fauna. Some of those new laws criminalized illegal hunting and fishing. This historical relationship would suggest a potential relationship between the development of the hunting industry and the distribution of illegal hunting and fishing.

Two variables were employed to measure the concentration of the HI across counties in Texas. The first variable is the number of hunting establishments. Number of hunting establishment is used to describe the presence of the industry. The second variable is the number of licenses and permits within a county. These variables are employed to address two additional research questions. First, does the HI, consisting of the count of hunting establishments and licenses, impact the distribution of illegal hunting and fishing? And second, if apparent, does HI impact the distribution of illegal hunting and fishing when controlling for the effect of ToP variables? The specific hypotheses measuring these relationships are as follows.

> H4: County measures of hunting establishments are associated with illegal hunting and fishing at the county level.
>
> H5: County measures of licenses and permits are associated with illegal hunting and fishing at the county level.

Both hypotheses posit a positive relationship between HI indicators and illegal hunting and fishing violations. In part, this empirical relationship may be driven by the unobserved impact of enhanced enforcement, which might be elevated in counties with more hunting business and licenses.

Ecological Modifications Variables

Research has shown how the physical development of human society has led to an increase in land destruction and modification (Lynch, Long and Stretesky, 2019; Lynch et al., 2017). This argument is supported in the environmental sociology, ToP and Marxist Geography literatures (Peet, 1979, 1969). As noted, however, one of the missing pieces in those literatures involves identifying empirical measures of each view.

In the current study, three measures were taken to capture the concentration of ecological modifications associated with the ToP: the amount of area of road in a county (i.e. road development), the amount of area of land dedicated to growing crops (i.e. agricultural development), and the concentration of house construction in an area (i.e. structural development). While the effect of the ToP is typically described in relationship to its broad ecological effects that occur through ecological withdrawals and additions, I argue that the social and economic systems support the ToP in other ways as well. This includes the construction of an appropriate infrastructure that supports the ToP (Curran, 2017). Related to these observations, the finally hypotheses address whether measures of ecological modification are associated with the distribution of illegal hunting and fishing activity.

H6: County measures of road development are associated with measures of illegal hunting and fishing at the county level.

H7: County measures of agricultural development are associated with measures of illegal hunting at the county level.

H8: County measures of structural development are associated with measures of illegal hunting and fishing at the county level.

For hypothesis 6, road development, measured by lane miles, is expected to be positively associate with IH&F, because roadways help provide access for the ToP to consume more nature by making transporting easier (Shatz, 2011; Dennis and Urry, 2009). Similarly, Fine (2000) argued that the development of roads made it easier for urban dwellers to travel to areas where you are able to hunt. Also, studies indicate that lane mileages is a significant predictor of travel, particularly in rural areas (Lia, Kaiser, Zekkos, and Allison, 2006). Therefore, counties with higher concentration of roads should see higher concentration of IH&F activity. For hypothesis 7 and 8, a negative association with IH&F is expected due to the species richness that is lost in areas with agricultural development (Shandra et al., 2009) and structural development (McKinney, 2002). With a smaller number of species, there should be less availability of fauna for people to illegal hunt and fish.

Spatial High-Risk Clustering of Illegal Hunting and Fishing Violations

Individual pieces of research have suggested that IH&F may be spatially grouped (Crow et al., 2013; Haines et al., 2012; Eliason, 2012; Jacoby, 2003). That is, there should be a clustering pattern of IH&F violations across Texas counties. Since the dissertation is exploratory and no prior research has discussed these factors spatially in relation to IH&F, there is no predisposition on the spatial effects of these variables. Additionally, spatial effects for all variables may not be warranted if certain variables have no statistical relationship with IH&F. No hypotheses can be drawn at this current time. Therefore, to start the discussion for future research, a post linear spatial analyses is conducted to test if counties with a high risk of IH&F violations cluster controlling for variables found to be significant in the linear analyses.

Units of Analyses

The current study examines the above hypotheses at the county level. In Texas, IH&F data are collected at the county level. A number of criminological studies have employed county level analysis (Deller and Deller, 2010; Bouffard and Muftić, 2006; Wells and Weisheit, 2004; Osgood and Chambers, 2000). One advantage of using counties as the unit of analysis is that many measures of social and economic relationships are available at the county level.

Dependent Variable Data and Measures

This study employs official measures of known violations of hunting and fishing regulations. As prior studies suggest, official statistics represent a blend of the behavior of individuals, and the behaviors of law enforcement agencies and agents (McCleary 1982). Addressing this observation, Gove, Hughes, and Geerken (1985) found that while official crime statistics do not capture all crimes, and addressing the dark figure of crime has included the use of self-report or victimization surveys, the purpose of official crime statistics are accurate for what they measure. This does not mean that official data are the best means to measure crime rates, but that those data accurately describe the crime rate. Since the dissertation is focused solely on Texas, and IH&F is investigated by the same agency in all locations, it is reasonable to assume the official data represents some dimension of the "real" crime rate combined with TPWD enforcement policies and initiatives. IH&F data from the TPWD is meant to capture the violations set forth by law, and provides a one useful indicator of the crime rate for these violations.

The data for this study was requested from the Texas Fish and Wildlife Department (TFWD). The latest available data upon request was 2015. Therefore, the data requested was the entire list of 22,141 IH&F incidences with offenders over the age of 18 within the year 2015. Following, all other variables reflected the year 2015. Data for the current dissertation were extracted from multiple sources. Most data were extracted from federal and state government census data with the closest corresponding year. No census data extracted were after 2015. Since data source is not constant across variables, the source of data is discussed within the respective variable sections. The remainder of this section discusses the 2015 IH&F data.

The data will be treated as counts by county. While county-base population adjusted IH&F rates could be used, IH&F is a rare occurrence. For example, the Uniform Crime Report for Texas reported a total of 890,966 incidences of violent and property criminal activity for 2015, or about 40 times more UCR crimes compared to IH&F crimes. The total UCR crime rate was roughly 3,244 incidences per 100,000 people. For IH&F, the rate was roughly 81 incidences per 100,000 people, or 40 times less likely. Additionally, when considering the statistical distribution of an event across large and small populations, rates tend to be misleading. Wiersema, Loftin, and McDowall (2000) and Nolan (2004) found that homicide rates were best used to compare areas with large populations, but when smaller populations are included, the rates no longer represented the population. Wiersema et al. (2000) found that the distribution favored urban areas while count data provided a more even distribution across areas. Therefore, the overall counts of IH&F are used as a measure for the dependent variable.

Within Texas, IH&F cover a wide variety of activities. Typically, these illicit activities are defined under the Texas Parks and Wildlife code, and include code violations numbered 1000 to 5799. These violations cover a variety of animal victims such as mammals, birds, exotic land and water animals, birds, salt and fresh water fish, shell fish, and alligator. See Table 1 for more information on specific species and groupings. Additionally, these violations address a multitude of activity involved around hunting and fishing activity. Activities such as illegal use (i.e. without a permit or illegal equipment) of a bow, firearm, animal call, vehicle, light, trap, net, and bait. Trespassing on restricted, private, or road along with hunting and fishing before and after hours. Lastly, these violations also cover illegal possession of animals, live, hunted, or dead.

Table 1. Groupings of Animal Victims from Hunting and Fishing Violations

TERRESTRIAL	**BIRD**
Javelina	Duck
Mule Deer	Eastern Turkey
Pronghorn	Falcon
White-tailed Deer	Geese
Squirrel	Mourning Dove
Alligator	Quail
Exotic Species*	Rio Grande Turkey
Endangered Species*	Sandhill Crane
Threatened Species*	Chachalaca
Non-game Species*	Pheasant
	White-winged Dove
	Other Migratory Birds*
AQUATIC	
Mussels	
Oysters	
Shrimp	
Crab	
Fresh-water Fish†	
Salt-water Fish†	
Aquatic Exotic Species*	

*These miscellaneous categories were grouped based on violation code and examining similar victim species around those codes. Most violations are grouped by similar species. For instance, violation codes numbered 2000 to 2507 and 5000 to 5799 cover only terrestrial species.
†The number of species under these categories is too vast to list. These categories are covered by violation codes numbered 1000 to 1899.

The eight hypotheses described earlier were tested using four different four dependent variables, using victim data, which are measures of illegal hunting and fishing: (1) the total number of illegal hunting and fishing violations (N = 22,141), (2) the number of illegal hunting violations against terrestrial species (n = 5603), (3) the number of illegal hunting violations against birds (n = 4,435), and (4) the number of illegal fishing violations against aquatic species (n = 12,103). Testing the hypotheses on four measures of the dependent variable allows assessment of the relevance of the explanations for IH&F for different IH&F measures. It is possible that some variables are useful for predicting hunting violations against birds, but not for explaining fishing violations, or hunting violations against terrestrial species. Ascertaining whether the hypotheses fit different measures of IH&F tells us something about the generalizability of the explanation for illegal hunting, and its applicability in different circumstances.

Measures of Treadmill of Production Variables

Variables relating to measuring dimensions of the ToP were the GDP per capita, the concentration of manufacturing industries, and the concentration of resource mining industries.

The GDP per capita was measured as a ratio of a county's GDP over the county's population. GDP was measured as the current dollar GDP for the 2015, extracted from the Bureau of Economic Analysis. A county's population count was extracted from the 2015 five year estimate American Community Survey. Using these two measures, a ratio was calculated with the GDP as the numerator and population count as the denominator. As indicated in hypothesis 1, GDP per capita is expected to have a positive correlation with IH&F violations.

To measure the concentration of manufacturing and resource mining industries, the location quotient from the Bureau of Labor Statistics is used for each industry. Location quotients (LQ) "compare the concentration of an industry within a specific area to the concentration of the industry nationwide" (Bureau of Labor Statistics, 2020). The calculation is conducted for employment, establishments, and other measures of industries. According to the Bureau of Labor Statistics, this quotient allows for the distribution of an industry in one area to be compared to the nation's industry distribution. Moreover, the LQ are argued to be a measure of exports or indicates locations where resources are extracted for the rest of the nation, which is a measure of economic activity consistent with ToP research While the Bureau of Labor Statistics applies the ratio to multiple measures of industry such as earnings and wages, the current study uses the number of establishments for manufacturing and resource mining industry. (Shandra et al., 2010; McKinney et al., 2009).

The LQ is a ratio that is calculated as follows: [1]

$$LQ = \frac{(county, private, industry/county, all\ ownership, all\ industry)}{(nation, private, industry/nation, all\ ownership, all\ industry}$$

The formula shows that the numerator is the proportion of a county measure of private owned industries, to the county measure of all owned industries, including government owned industries. The denominator is the proportion of a national measure of *private* owned industries, to the national measure of all owned industries, including government owned industries. Thus, the ratio is comparing the percent of establishments of an industry within a county to the percent of establishments of that industry across the nation. Using this quotient gives an understanding on the status of an industry in 2015 within a certain county.

[1] For more information visit www.bls.gov/cew/about-data/location-quotients-explained.htm.

Measures of Hunting Industry Variables

The elements that comprise the treadmill of production have not been entirely specified. To be sure, the ToP includes manufacturing, and also the extractive industries. In the view taken here, hunting can be interpreted as being part of the extractive sector of the ToP since hunting directly extracts raw materials – albeit in the form of living beings – from nature.

The study uses two variables to measure the hunting industry: hunting establishments and licenses and permits. Since hunting establishments have not been explored quantitively, multiple measures of the hunting establishments were taken. Using the NAISC code 114 for private hunting and trapping industries, data was extracted from the federal Bureau of Labor Statistics that included location quotient of hunting industry establishments, and the total number of establishments in each county in Texas. Neither of these measures has been included in prior research attempting to predict the geographic distribution of IH&F violations. To find the best fitting measure, analyses rotated each measure to determine the best predictor. Licenses and permits were measured as the total of licenses and permits sold, requested from the Texas Parks and Wildlife Department.

Ecological Modifications Variables

Three variables are proposed to capture the distribution of ecological modifications, that might impact the opportunity for IH&F: road development, agricultural development, and structural development. These variables are argued to impact fauna and the availability to hunt; however, the statistical relationship of these factors on IH&F are unknown.

To measure the structural development, a structural density quotient of the 5-year estimates of unweighted sampling of housing units from the 2015 census bureau per square mile of land was calculated. A value of 0 indicate that there are no enough housing units or people per square mile within a county. To measure agricultural development, a percent of farm land in acres to the number of acers in a county was calculated. Data on acres of farm land and total acres in a county were extracted from the 2012 Census of Agriculture of National Agriculture Statistics Service of the United States Agriculture Department. Data on farmland are only available once every 5 years, and 2012 is the closet measure to the year examined here. To measure road development, data on lane miles of road were extracted from the County Information Program in Texas. Unlike centerline miles which look at the length of roads, lane miles are a measure of the total length of a roadway, and includes an adjustment for lane counts for a given highway or road. Traditionally, this measurement takes the length of the road multiplied by the number of lanes.

Measures of Control Social Variables

Extant literature suggests two social factors influence IH&F. Prior studies have found that people who commit IH&F acts are not from out of town (i.e., they are locals), and tend to be low income or poor (Forsyth and Forsyth, 2018; Eliason and Dodder, 2000; Forsyth, Gramling, and Wooddell, 1998). Prior criminological and sociological research has examined these variables at a structural level using counties as units of analysis, but typically measures these indicators as socioeconomic status and as residential turnover rates (Lobao, Zhou, Partridge, and Betz, 2016; Bouffard and Muftic, 2006; Wells and Weisheit, 2004; Osgood and Chambers, 2000). In the current study, three indicators of socioeconomic status were extracted from the American Community Survey: the percent of people living below poverty level; the unemployment rate; and medium housing value (Lobao et al., 2016; Bouffard and Muftic, 2006).

Similarly, using the American Community Survey, residential turnover was measured as the precent of renters and the percent of residence who moved between 2010 and 2014 (Lee, 2008; Wells and Weisheit, 1994).

Measures of Control Opportunity Variables

While the economic and social structural variables are of theoretical interest, there are other potential explanations for the distribution of IH&F that needs to be controlled for in the analysis. These variables can be extracted from research in conservation criminology that address the opportunities for wildlife crime. Haines et al. (2012) and Crow at al. (2013), for example, both found that certain characteristics of the local geography provide opportunities to illegal hunt. Consistent with prior studies, the current research addressed the potential geographic opportunity for IH&F by measuring county level public hunting lands, private hunting lands, bodies of water, and a species richness indicator. Public hunting lands were measured as a percent ratio between the acres of public hunting lands and the total acres of a county. Private hunting land was also measured as a percent ratio between the acres of known private hunting land and the total acres of a county. Data on the acres measures of public and private hunting land were extracting from the Texas Parks and Wildlife Department geographical database. Bodies of water were measures as a count measure which included lakes, rivers, streams, and reservoirs by county, and were extracted from the National Water Information System of the US Geological Survey. Species richness was measured as the number of species listed as rare, threaten, and endangered within a county, extracted from the Texas Park and Wildlife Department. Theoretically, each measure of opportunity should be related to an increase in the likelihood of IH&F violations across Texas counties.

Methodological Steps

This section breaks down the analysis process employed to assess the hypotheses. First, basic statistics are used to determine how these variables vary. Second, the skewness and kurtosis statistics of independent variables are explored to determine if the natural log of a variable should be taken into consideration. The natural log is taken for any variable where the skewness statistic is lower than -1 or higher than 1 (Bulmer, 1979) and the kurtosis statistics is higher or less than 3 (Westfall, 2014). Third, a correlation matrix is used to determine which variables are highly correlated with one another, followed by an OLS regression to examine VIF factors and goodness of fit. Forth, using SPSS generalized linear modeling, Poisson regressions are used to test hypotheses 1 through 8.

A Poisson regression was used as the primary method of analysis. The assumption of the Poisson regression is that the dependent variable is a interval count measure with a Poisson distribution starting at a value of 0. As Figure 4.1 illustrates, the count data indeed follows a Poisson distribution. It is also assumed that the number of zero cases is limited. Consistent in the current study, the number of counties with zero IH&F violations was three. The model also assumes three conditions: (1) all events are independent from one another, (2) the average rate of the event is independent from other events, and (3) events cannot happen at the same exact time. As well, the regression assumes is that the mean and variance are similar. The assumption of the mean and variance can be statistically asses. To test this assumption, a deviance statistic, calculated by SPSS, is used. If the deviance statistics is near or exactly 1, there is overdispersion and violates this assumption. As a result, a negative binomial model is used to statistically handle the overdispersion.[2]

[2] Though there were concerns about the dependent variable being zero-inflated, the number of counties without any form of illegal hunting or fishing was 4. Therefore, no zero-inflated regressions were used; however, when breaking

Osgood (2000) and other scholars noted (Nolan, 2004; Wiersema, Loftin, and McDowall, 2000), when counts of the dependent variable are small and there is a comparatively small population, a one-unit change in counts can have large effect on rates and significantly impacts the estimates of the outcome. For example, in the current data, 70 percent of counties have counts below the mean (n = 176 counties). Among those counties, 130 have IH&F counts below a value of 50. This distribution implies that the data contains a large number of locations were the counts of IH&F are small enough that a one-unit change in IH&F could generate large changes in the rate of offending. Considering the above, Osgood (2000) suggests an alternative Poisson rate model, which address problem related to small counts in small populations. Thus, two Poisson regressions were used, one with count measures and one with adjusted rate measures. Most of the analysis focuses on the count results. The adjust rate measures are used for comparative purposes and to assess whether different analytic approaches significantly alter the findings.

Several regression models are used to slowly introduce and assess the effects of independent variables. This procedure was followed to assess effects for related sets of independent variables associated with one of the theoretical or research perspective as prescribe earlier (e.g. ToP variables; conservation/opportunity variables), while limiting the number of variables in a model. This was also done to minimize problems encountered with collinearity among estimators. Following estimation of the separate models, final models are estimated employing the significant variables from the prior models.

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down illegal hunting and fishing into categories, there were more counties with zero observations. Additionally, SPSS does not have an option for a zero-inflated regression. Future versions of the study will explore other statistical programs to provide zero-inflated regression options.

Lastly, SatScan is used to spatially analyze the data and provide geographical locations where IH&F is concentrated to test hypotheses 9. The program QGIS is used to map out these location outputs by SatScan. At this point of the analysis, geographical and law enforcement districts are used within the maps to show the degrees of clusters within these districts. More information on SatScan is discussed in chapter 6.

Summary of Methodology

Using data from the Texas Parks and Wildlife Department, the current study uses spatial and regression analyses to determine the distribution of IH&F across space. GDP, manufacturing industries, resource mining industries are used as variables to represent ToP theory assumptions. Hunting establishments and hunting and fishing licenses and permits are used as variables representing the expected impact of the hunting industry on IH&F. Measures of residential turnover, socioeconomic status, acres of public hunting land, acres of known private hunting land, and number of bodies of water (e.g. rivers, bays, lakes, etc.) are used as control variables. Nine hypotheses are presented in a step-by-step fashion to determine the influences behind the distribution of IH&F across Texas counties. This analysis is large due to the exploratory nature of the study. As a result, the analysis is broken down over the next two chapters. The fifth chapter covers hypotheses 1-8, discussing the basic statistics and regression outputs. The sixth chapter presents the statistics, figures, and tables on spatial analyses of significant variables found in the fifth chapter to address hypothesis 9.

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CHAPTER 5:

REGRESSION ANALYSES RESULTS

This chapter reports the results from the analyses of factors hypothesized to affect the distribution of illegal hunting violations. Mentioned in the previous chapter, observations and results are used to address hypotheses 1 through 8. In this chapter, the skewness and kurtosis are analyzed, and based on those results, variables lacking normal distributions were logged. Lastly, Poisson regressions are used to determine if variables associate while controlling for other explanations. The following chapter explores these relationships in spatial analyses.

Analyzing the Distribution of Variables

Using SPSS, descriptive statistics are reported along with skewness, kurtosis, and Shapiro-Wilk statistics (Table 2). The skewness, kurtosis, and Shapiro-Wilks statistics were used to determine the normality of the distribution of variables. These statistics help determine whether or not variables need to be logged for regression purposes. Highly skewed variables violate many assumptions of data analyses. The probability of producing inaccurate estimates may be increased when modeling variables with non-linear relationships. It is widely noted in the statistics literature that logging variables helps reduce errors in the estimates without overfitting the modeling. The transformation of variables helps make the distribution closer to a normal bell curve. In addition, highly skewed and varying distributions can yield statistical outcomes that are not easily interpretable.

Table 2. Descriptive Statistics of Variables

		N Statistic	Minimum Statistic	Maximum Statistic	Mean Statistic	Std. Deviation Statistic	Variance Statistic
1.	Total Violations	254	0.00	584.00	87.17	107.41	11,537.82
2.	Violations against Land Animals	254	0.00	149.00	22.06	23.77	565.12
3.	Violations against Birds	254	0.00	262.00	17.46	25.46	648.08
4.	Violations against Aquatic Animals	254	0.00	531.00	47.65	83.74	7,012.54
5.	GDP Per Capita	254	40,965.00	360,491,167.00	6,175,027.56	28,964,662.91	838,951,697,771,033
6.	LQ of Manufacturing Industries	254	0	3.04	0.92	0.50	0.25
7.	LQ of Mining Industry	254	0.00	45.40	9.10	7.41	54.91
8.	LQ of Hunting Industry	254	0.00	175.81	5.49	19.12	365.64
9.	# of Hunting Establishments	254	0.00	44.00	0.80	3.20	10.21
10.	# of Licenses and Permits Sold	254	0.00	386,482.00	18,367.76	47,876.76	2,292,183,959.08
11.	Road Development	254	18.85	11,861.73	1,168.88	959.18	920,025.24
12.	Agricultural Development	254	2.54	99.63	76.48	22.95	526.89
13.	Structural Density	254	0.11	1,105.05	43.51	124.08	15,396.54
14.	% of Public Hunting Land	254	0.00	22.37	0.96	2.63	6.90
15.	% of Private Hunting Land	254	0.00	1.10	0.03	0.11	0.01
16.	# of Bodies of Water	254	0.00	50.00	3.32	5.25	27.53
17.	# of Species Listed as R/T/E	254	24.00	224.00	55.12	26.09	680.51
18.	% Unemployed	254	0.00	19.80	6.74	3.00	9.02
19.	% Below Poverty	254	1.40	40.30	17.16	6.12	37.48
20.	Average Housing Value	254	32,300.00	281,200.00	97,947.24	39,031.66	1,523,470,644.55
21.	% of Rented Housing Units	254	9.80	69.90	28.41	8.08	65.27
22.	% of New Residents	254	8.20	51.10	26.97	6.08	36.99

LQ = Location Quotient
R/T/E = Rare, Threatened, or Endangered

Table 2. Descriptive Statistics of Variables (Cont.)

		Skewness Statistic	Kurtosis Statistic	Shapiro-Wilk Statistic	Shapiro-Wilk Sig.
1.	Total Violations	2.29	5.90	0.73	6.16
2.	Violations against Land Animals	2.12	6.26	0.80	1.58
3.	Violations against Birds	4.44	34.08	0.63	4.08
4.	Violations against Aquatic Animals	3.10	11.19	0.60	6.93
5.	GDP Per Capita	9.54	103.368	0.18	0.00
6.	LQ of Manufacturing Industries	0.59	1.259	0.98	0.00
7.	LQ of Mining Industry	1.26	2.02	0.90	0.00
8.	LQ of Hunting Industry	5.96	41.27	0.31	0.00
9.	# of Hunting Establishments	10.76	136.80	0.22	0.00
10.	# of Licenses and Permits Sold	5.43	33.82	0.37	0.00
11.	Road Development	6.06	62.13	0.63	0.00
12.	Agricultural Development	-1.48	1.47	0.82	0.00
13.	Structural Density	5.94	40.79	0.34	0.00
14.	% of Public Hunting Land	5.30	32.86	0.39	0.00
15.	% of Private Hunting Land	6.13	45.47	0.30	0.00
16.	# of Bodies of Water	5.13	35.39	0.53	0.00
17.	# of Species Listed as R/T/E	2.22	8.17	0.82	0.00
18.	% Unemployed	0.86	1.64	0.96	0.00
19.	% Below Poverty	0.87	2.30	0.95	0.00
20.	Average Housing Value	1.45	2.87	0.89	0.00
21.	% of Rented Housing Units	1.37	4.56	0.92	0.00
22.	% of New Residents	0.49	0.77	0.98	0.01

*Sharpiro-Wilks degrees of freedom is 254
LQ = Location Quotient
R/T/E = Rare, Threatened, or Endangered

A variable is skewed if the skewness statistics is less than -1 or greater than 1. Any kurtosis statistic below the value of 3 is suggested to have a platykurtic distribution shape, and any value above the value of 3 is suggested to have a leptokurtic distribution. Shapiro-Wilks is used to determine whether the distribution is significantly different from a normal distribution.

The Shapiro-Wilks statistics for all independent variable were significant, and the kurtosis and skewness statistics show that each measure of the dependent variable were heavily right skewed with a high peak. Of the independent variables, the percent unemployed, percent living below poverty, and percent of new residents were the only variables that did not need to be corrected. The natural log was taken from the remaining independent variables for regression analysis. Observations and discussions on the normality of variables are found below.

Illegal Hunting and Fishing Measures

All measures of hunting violations have a large range of outcomes. That is, the number of violations found across counties have a large range overall. Total variance for each measure is as follows: total violations ($\sigma 2 = 11537.817$); hunting violations ($\sigma 2 = 1429.041$); and fishing violations ($\sigma 2 = 7012.537$). Fishing violations specifically have the larger variation out of the two subtypes of violation. This is expected since bodies of water are more concentrated in certain areas of Texas compared to others (e.g., around the Southeast end of Texas). As illustrated in Table 2, the Shapiro-Wilks statistics is not significant, suggesting the distribution of the measures of illegal hunting and fishing not violating the assumption of normality, but skewness and kurtosis statistics illustrate a right skewness. Therefore, a Poisson regression remains a more appropriate approach than an ordinary least square regression.

Economic Structural Measures

According to Table 2, Shapiro-Wilks statistics for each economic variable are significant, suggesting that the distribution of all economic measures across counties are highly skewed. Measures of the treadmill of production (ToP), the Gross Domestic Product (GDP) per capita and location quotient (LQ) of manufacturing establishment, were not normally distributed. GDP per capita was rightly skewed with a high peak. The LQ of manufacturing establishments is not skewed, but is more platykurtic in shape. The difference in distribution suggest that economic growth does not reflect manufacturing establishments; however, this could suggest that certain areas benefit more from manufacturing than other area. The LQ of resource mining establishments had skewness following the pattern of a platykurtic shape, though not extreme ($K = 2.020$). With a statistic above 1, mining industry observation display a right skew. The hunting industry (HI) variables are distributed similar to the Mining Industry (MI), but the distributions are more pronounced in shape. The skewness statistics range from 5.43 to 10.76, with the kurtosis statistics ranging from 33.81 to 136.801. This suggests a right skewed distribution with an incredibly high peek. The Shapiro-Wilks statistics are significant, indicating this distribution shape is non-normal (i.e., not Bell-shaped). A high peek right-skewed distribution means that when the value of the measures deviates from the mean, the values tend to be smaller and likely to be an extreme deviation. These basic statistics argue a stark contrast of areas with high measures of the HI and areas with low measures of the HI.

The distributions of ecological modification measures appear to have similar distributions to the LQ of the mining industry. The amount of housing units ($W = .260$, $p. < .001$), the density of housing units ($W = .340$, $p. < .001$), lane miles of road ($W = .626$, $p. < .001$), and acres of farm land ($W = .562$, $p. < .001$) have Shapiro-Wilks statistics which indicate that all measures of ecological modification are not normality distribution. All variables have a skewness statistic above 1, ranging from 5.941 to 7.928, and are heavily right skewed. Additionally, the Kurtosis statistics are higher than 3, ranging from 24.129 to 75.800, indicating a leptokurtic shape. The combination of these two statistics suggests that observations are either closely associated with the mean or extremes, with little if at all between. With a right skew, the extreme or rare cases are more likely to reflect metropolis areas the while majority of counties are rural, centering around the mean.

Control Variables

The first set of control variables, geographical opportunity variables appear to be rightly skewed with a skewness value ranging from 2.22 to 6.13. Additionally, the variables have a leptokurtic shaped distribution with a kurtosis value ranging from 8.17 to 45.47. The distribution of these statistics would suggest that there is a heavy concentration of geographical opportunity variables for a few areas. Similar to economic measures, this may reflect the contrast between a few urban settings surrounded by many rule areas. Social variables, however, have different disruptions from the rest of the variables.

Measures of socioeconomic status seem to be the set of social structure variables closest to a normal distribution. All SES variables have a significant Shapiro-Wilks statistic, ranging from .894 to .980. Housing values were considered skewed with a skewness statistic over 1; however, housing values (K = 2.865) had Kurtosis statistics close to a value of 3. In contrast, poverty and unemployment were not skewed, but the distributions had Kurtosis less than 3 suggesting a platykurtic shape where extreme values are more likely to occur. It is interesting to point out that all measures of poverty and unemployment had a fairly normal distribution across counties; but measures of wealth had a right skew, suggesting that the distribution of wealth does not reflect the distribution of low socioeconomic status measures.

Examining the measures of residential turnover, percent of renters have a stark shape compared to the percent of new residents. The percent of new residents have a skewness statistic between 1 and -1. The kurtosis for new residents (K =.0.767), which suggest a platykurtic shape. The percent of renters for occupied housing has a skewness above 1, and kurtosis above 3. With a skewness statistic over 1 and a Kurtosis statistic over 3, the distribution shape suggests there is a high concentration of counties around the mean but that any deviation away from the mean is extreme, particularly towards the right of the mean. Taken all together, residential turnover does not seem to have similar observations across counties. Additionally, this indicates that there are certain levels of structure in which turnover is higher than others.

Bivariate Relationships

The next analysis tests the bivariate relationships between theoretical, control, and dependent variables. The analysis is presented in Table 3. Results suggest multiple variables are significantly associated with the total count of hunting and fishing violations, with results breaking down violations by land, air, and aquatic victims. The analysis shows significant positive relationships between the following theoretical variables and the total count of hunting and fishing violations: (1) GDP per capita ($r = .41$, $p < .01$), (2) LQ of MUI ($r = .21$, $p < .01$), (3) number of hunting establishments ($r = .45$, $p < .01$), (4) the number of hunting and fishing licenses and permits sold ($r = .61$, $p < .01$), (5) road development ($r = .40$, $p < .01$), and (6) structural density ($r = .51$. $p < .01$). Only two theoretical variables had a significant negative relationship, the LQ of MI ($r = -.45$, $p < .01$) and agricultural development ($r = -.22$, $p < .01$).

Table 3. Pearson Correlation Matrix of Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1														
2	.48**	1													
3	.64**	.18**	1												
4	.95**	.28**	.47**	1											
5	.41**	.06	.15*	.46**	1										
6	.21**	.22**	.17**	.15*	.05	1									
7	-.45**	-.33**	-.28**	-.39**	-.17**	-.52**	1								
8	.05	.04	.08	0.02	-0.04	-.13*	.17**	1							
9	.45**	.03	.30**	.47**	.22**	.00	-.10	.32**	1						
10	.61**	.10	.32**	.66**	.69**	.08	-.33**	-.06	.26**	1					
11	.40**	.20**	.19**	.40**	.60**	.22**	-.18**	-.13*	.15*	.50**	1				
12	-.22**	-.06	-.06	-.25**	-.13*	-.30**	.23**	.07	-.04	-.18**	-0.11	1			
13	.51**	.06	.26**	.56**	.89**	.10	-.32**	-.07	.21**	.74**	.44**	-.22**	1		
14	.08	.10	-.06	.10	-.02	-.01	-.16*	-.02	-.01	.00	.01	.23**	-.02	1	
15	.02	-.07	.06	.02	.02	.03	-.05	.03	.07	.05	.02	-.04	.02	.02	1
16	.44**	.19**	.21**	.44**	.71**	.14*	-.35**	-.02	.21**	.69**	.62**	-.12*	.67**	.03	.00
17	.40**	.23**	.33**	.36**	.17**	.04	-.42**	.06	.34**	.34**	.07	.24**	.26**	.41**	-.04
18	.15*	.13*	.15*	.11	.02	.16*	-.23**	.09	.09	.04	.00	.17**	.03	.06	.14*
19	.16*	.11	.24**	.10	.00	-.03	-.11	-.03	.17**	.00	-.01	.14*	-.03	.02	.14*
20	.27**	.09	.12*	.28**	.23**	.34**	-.41**	-.09	.03	.38**	.20**	-.22**	.37**	.02	-.04
21	.18**	-.03	.14*	.20**	.30**	-.04	-.17**	-.15*	.09	.34**	.11	.06	.34**	.11	0.10
22	.31**	.04	.20**	.32**	.32**	.11	-.32**	-.14*	.07	.44**	.26**	-.08	.44**	.09	.02

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Table 3. Pearson Correlation Matrix of Variables (cont.)

	16	17	18	19	20	21	22
16	1						
17	.32**	1					
18	.01	.18**	1				
19	-.10	.18**	.48**	1			
20	.40**	.30**	-.23**	-.43**	1		
21	.22**	.17**	-.02	.21**	.13*	1	
22	.37**	.16*	-.08	-.06	.39**	.60**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).
1 = Total Violations
2 = Violations against Land Animals
3 = Violations against Birds
4 = Violations against Aquatic Animals
5 = GDP Per Capita
6 = LQ of Manufacturing Industries
7 = Location Quotient of Mining Industry
8 = Location Quotient of Hunting Industry
9 = # of Hunting Establishments
10 = # of Licenses and Permits Sold
11 = Road Development
12 = Agricultural Development
13 = Structural Density
14 = % of Public Hunting Land
15 = % of Private Hunting Land
16 = # of Bodies of Water
17 = # of Species Listed as R/T/E
18 = % Unemployed
19 = % Below Poverty
20 = Average Housing Value
21 = % of Rented Housing Units
22 = % of New Residents

Only three theoretical variables were significantly associated with illegal hunting against terrestrial species: (1) LQ of MI ($r = .22, p < .01$), (2) LQ of MI ($r = -.33, p < .01$), and road development ($r = .20, p < .01$). As illustrated, the largest association with illegal hunting against terrestrial species was the LQ of MI with a negative relationship. However, the amount of illegal hunting against birds was associated with seven theoretical variables: (1) GDP per capita ($r = .15, p < .05$), (2) LQ of MUI ($r = .17, p < .01$), (3) LQ of MI ($r = -.28, p < .01$), (4) number of hunting establishments ($r =.30, p < .01$), (5) number of hunting and fishing licenses and permits sold ($r = .32, p < .01$), (6) road development ($r = .19, p < .01$), and (7) structural density ($r = .26, p < .01$). Unlike illegal hunting against terrestrial species, the largest association with illegal hunting against birds was the number of hunting and fishing licenses and permits sold with a positive relationship.

With regards to illegal fishing, the amount of illegal fishing is similar to illegal hunting of birds. Six theoretical variables were associated with the number of violations against aquatic species: (1) GDP per capita ($r = .46, p < .01$), (2) LQ of MUI ($r = .15, p < .01$), (3) number of hunting establishments ($r = .47, p < .01$), (4) the number of hunting and fishing licenses and permits sold ($r = .66, p < .01$), (5) road development ($r = .40, p < .01$), and (6) structural density ($r = .56. p < .01$). Only two theoretical variables had a significant negative relationship, the LQ of MI ($r = -.39, p < .01$) and agricultural development ($r = -.25, p < .01$). The highest association found was the positive relationship for the number of hunting and fishing licenses and permits sold.

These results indicate that unique theoretical variables affect different types of illegal hunting violations. As noted, violations against bird and aquatic species have similar relationships with theoretical variables. This relationship might also suggest that the geographic distribution of these violations would be similar as well: that is, where there is illegal hunting of bird animals, there is also illegal fishing. The analysis also suggested that different variables explained the distribution of illegal hunting of terrestrial species. The remaining sections explore these similarities and differences between IH&F in more detail.

Hypotheses Testing

Multiple research questions and hypotheses were posed concerning the relationships between IH&F and economic and other structural variables. To test these hypotheses, a Poisson regression was argued to be appropriate. (see chapter 4 for full discussion). IH&F was measured in four ways to address whether economic and structural variables are associated with the distribution of IH&F. To address these questions/hypotheses, multiple analyses were conducted using the total amount of IH&F violations, the number of illegal hunting violation against terrestrial species, the number of illegal hunting against birds, and the amount of illegal fishing as dependent variables. Before analysis were conducted, two steps were taken to address multicollinearity between independent variables and overdispersion of the dependent variables.

First, multicollinearity was assessed. While multicollinearity does not affect the underlying assumptions required for regression analyses, it would impact the slopes and standard errors (Allison, 1999). To test for multicollinearity, the variance influence factors (VIF) was examined across each theoretical and control variable using ordinary least squares regressions. Variables are argued to have serious multicollinearity if VIF are above the value of 10 (Menard, 1995; Mason, Gunst, and Hess, 1989). The mean VIF among each variable was 2.74, but two variables did approach the value of 10: GDP per capital (VIF = 8.52) and structural density (VIF = 8.50). Though this may be a problem, the natural log of the variables was taken as discussed in the section above. After logging variables to correct for normality, the mean VIF decreased to 2.71. The VIFs also decreased for GDP per capita (VIF = 1.77) and structural density (VIF = 6.84). Collinearity diagnostics are reported in Appendix A.

Second, model fit diagnostics were assessed in order to determine if Poisson modeling or negative binomial model should be employed. Intercept only Poisson models were estimated using each measure of IH&F. Presented in Table 4, the log-likelihood suggests that the models for illegal hunting against land and bird animals have a better fit; however, all measures of IH&F seem to be over dispersed. SPSS provides two statistics to show overdispersion, deviance and Pearson chi-square. These statistics are the value of the deviance and Pearson chi-square divided by the degrees of freedom (df = 253). If the result of this calculation centers around one, the data are considered to exhibit equidispersion. Values greater than 1 suggest data are overdispersed. Values less than 1 would indicate underdispersion within the data. For the intercept only models, the results suggest that negative binomial regressions are preferred.

Table 4. Goodness of Fit Test of Poisson Modeling Intercept Only[a]

Model	Deviance	Pearson Chi-Square	Log Likelihood[b]
Total Violations	101.275	132.361	-13510.890
Illegal Hunting against Land Animals	21.505	25.618	-3255.459
Illegal Hunting against Birds	24.421	37.117	-3555.022
Illegal Fishing against Aquatic Animals	94.563	147.169	-12463.121

a. Information criteria are in smaller-is-better form.
b. The full log likelihood function is displayed and used in computing information criteria.

With multicollinearity and overdispersion attended to, each analysis of illegal hunting and fishing used multiple negative regression models to introduce estimates for theoretically relevant variables, and then the removal of insignificant variable and re-estimation of equations to eliminate variables that were not contributing to the empirical explanation of IH&F[3]. This procedure allows researchers to see how relationships change or emerge when new variables are added to or removed from the analysis. To reduce a model, variables that were insignificant from a full model were removed, and the remaining variables were regressed on the dependent variable. Variables continued to be removed if variables lost significance after reducing the

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[3]Other regressions were used, as requested, to determine how the data behaved. The main reason for running two different regressions was to address the absence of a population variable in the original analysis. In the original analysis, population variables were excluded. Population and population per square mile had a large correlation with the total number of houses and the number of houses per square mile. Correlations between the four variables ranged from .93 to .99. Statistically, it would be improper to include population, and since the number of houses per square mile was more reflexive of the theory, it was retained. Thus, initially, population was removed from the analyses. Still, the critiques argued that population is a key variable in terms of spatial analyses and theory at a macro level. Therefore, two different regressions were request, an ordinary least square (OLS) with population rate measure of the dependent and an offset negative binomial with a weighted logged population variable. When rerunning the models with these regressions, outputs for the variables drastically changed. Regression models were running with all variables from the study.

Population was measured as the total amount of individuals within a county. To create a population rate of illegal hunting and fishing, the formula (crime/population)*100,000 was used. This formula reflects the crime rate per 100,000 people in a county.

Within the OLS regressions, no variables remained significant for the total of IH&F violation. However, the percent of public hunting land in acres did become significant. The variables that remained significant for the number of illegal hunting violations against terrestrial species were the number of hunting and fishing licenses sold and structural development. The new variables that became significant were road development and manufacturing industries. The variable that remained significant for the number of illegal hunting violations against birds was hunting establishments. No other variables were significant. The variable that remained significant for the number of illegal fishing violations against aquatic species was the number of hunting and fishing licenses and permits sold, and only the GDP per capita became significant.

After using the offset negative binomial regression, outputs drastically changed. The variables that remained significant for the total number of hunting and fishing violations species were the number of hunting and fishing licenses and permits sold and structural development. Additionally, road development, agricultural development, the percent of public hunting land in acres, and the percent of rented homes became significant. The variables that remained significant for the number of illegal hunting violations against terrestrial species were GDP per capita, number of hunting and fishing licenses and permits sold, agricultural development, structural development, and the number of bodies of water. No new variables were significant. The variable that remained significant for the number of illegal hunting violations against birds was manufacturing industries, the number of hunting establishments, and structural development. One other variable became significant, road development. Lastly, the variables that remained significant for the number of illegal fishing violations against aquatic species were the number of hunting and fishing licenses sold, the percent of public hunting land, and the number of bodies of water. Four new variables became significant, resource mining industries, road development, agricultural development, and the percent of houses that are rented.

From these analyses, the methodologically approach used to study illegal hunting can provide different outcomes. Therefore, when future research explores explanations for illegal hunting and fishing, the methodology should be the biggest concern to properly communicate relationships. While the OLS found significance, there are many assumption violations of the OLS analysis, because the nature of the data at county level, as discussed in the Chapter 4, can be sensitive to rate measures. While some outputs were similar to the presented results, offset negative binomial seems to be the better analyses. Though it includes population, the calculations of the formula to calculate the regression line alleviates many violations of OLS assumptions (Osgood, 2000). Thus, future versions of this study will pursue an offset negative binomial analysis instead.

model.[4] This procedure was followed because of the large number of potential variables used to explain IH&F across the models. While variables were selected in each model due to prior research or theoretical implications, variables that were statistically insignificant become, in principle, theoretically meaningless once they are shown to be devoid of any practical empirical predictive power. Most analyses had gone through a process of 10 models to find a reduced model, with the except of Table 7. A summary of hypotheses testing is presented in Table 9 at the end of the chapter.[5]

Treadmill of Production Variables

The first research question asked whether there "is there a relationship between measures of the treadmill of production (ToP) and illegal hunting and fishing?" Bivariate relationships found initial relationships between GDP per capita, manufacturing industries, and mining industries with multiple measures of illegal hunting and fishing, with illegal hunting violations against terrestrial species with the least number of associations. The following set of hypotheses answers this question by exploring the condition in which (if any) significant relationship between variables of the ToP and illegal hunting and fishing. The test of hypotheses proceeded in

[4] In Table 6, the GDP per capita and resource mining industry were included in the reduced model, because those variables were significant in a model controlling for other economic variables. Using the Akaike Information Criterion (AIC), model 7 had a value of 2027.05. Model 8 has an AIC of 2028.84. Since model 7, containing only economic variables, had a better model fit, those variables significant in model 7 but not model 8 were also retained for the reduced model, model 9.

[5] One of the concerns here is with the interpretation of the logged models. This may be particularly true for the Census variable, the Location Quotient, used to determine where industries are most concentrated using cross-county import and export data. Additional models (not shown here) were estimated without logged variables. After rerunning the models without logged variables, the significance of some variables was different, but the coefficient became substantively insignificant. For instance, in the unlogged model, GDP per capita had a significant relationship with illegal hunting violations against terrestrial animals, but the coefficient was less than .0000001, in contrast to it logged version (see Table 6). Due to the issue with interpretation of output and variables, future versions of this research based on this disseration will explore other measures that are more intuitive and interpretable.

Table 5. Negative Binomial Regression for the Total Hunting and Fishing Violations Across Counties (N = 254)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
% Unemployed						0.06 *		-0.04		
						(0.29)		(0.03)		
% Below Poverty						0.07 **		0.02		
						(0.01)		(0.02)		
Average Housing Value†						1.55 **		-0.33		
						(0.25)		(0.34)		
% of Rented Housing Units†						-0.76 *		-0.36		
						(0.38)		(0.37)		
% of New Residents						0.05 **		0.01		
						(0.02)		(0.02)		
(Intercept)	6.52 **	1.54 **	1.62 **	5.09	-2.37	-13.97	5.27 *	4.82	-1.18	-1.18
Log Likelihood[a]	-1330.1	-1311.3	-1309.0	-1313.9	-1318.0	-1338.0	-1297.2	-1286.4	-1293.4	-1295.1
Pearson Chi-square	291.11	207.88	201.54	213.20	208.34	230.06	182.22	162.54	168.18	170.36
Degrees of Freedom	250	251	251	250	249	248	245	236	249	250
AIC	2668.24	2628.68	2624.68	2635.81	2646.00	2688.00	2612.37	2608.77	2596.77	2598.25

a. The full log likelihood function is displayed and used in computing information criteria.

*p < .05

**p < .01

†the natural log was taken

LQ = location quotient

AIC = Akaike's Information Criterion

Table 5. Negative Binomial Regression for the Total Hunting and Fishing Violations Across Counties (Cont.)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
% Unemployed						0.06 *		-0.04		
						(0.29)		(0.03)		
% Below Poverty						0.07 **		0.02		
						(0.01)		(0.02)		
Average Housing Value†						1.55 **		-0.33		
						(0.25)		(0.34)		
% of Rented Housing Units†						-0.76 *		-0.36		
						(0.38)		(0.37)		
% of New Residents						0.05 **		0.01		
						(0.02)		(0.02)		
(Intercept)	6.52 **	1.54 **	1.62 **	5.09	-2.37	-13.97	5.27 *	4.82	-1.18	-1.18
Log Likelihood[a]	-1330.1	-1311.3	-1309.0	-1313.9	-1318.0	-1338.0	-1297.2	-1286.4	-1293.4	-1295.1
Pearson Chi-square	291.11	207.88	201.54	213.20	208.34	230.06	182.22	162.54	168.18	170.36
Degrees of Freedom	250	251	251	250	249	248	245	236	249	250
AIC	2668.24	2628.68	2624.68	2635.81	2646.00	2688.00	2612.37	2608.77	2596.77	2598.25

a. The full log likelihood function is displayed and used in computing information criteria.

*p < .05

**p < .01

†the natural log was taken

LQ = location quotient

AIC = Akaike's Information Criterion

Table 6. Negative Binomial Regression for Illegal Hunting Violations Against Terrestrial Species Across Texas Counties (n = 254)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
GDP Per Capita†	-0.20 *						-0.20 *	-0.13	-0.26 **	-0.28 **
	(0.09)						(0.09)	(0.11)	(0.09)	(0.09)
LQ of Manufacturing Industries†	0.47						0.16	0.38		
	(0.31)						(0.33)	(0.36)		
LQ of Mining Industries†	-0.35 **						-0.33 *	-0.12	-0.08	
	(0.11)						(0.16)	(0.18)	(0.16)	
LQ of Hunting Industry†		0.25								
		(0.05)								
# of Hunting Establishments†			-0.07				0.09	-0.10		
			(0.12)				(0.12)	(0.14)		
# of Licenses and Permits Sold†		0.23 **	0.23 **				0.23 **	0.18 **	0.20 **	0.23 **
		(0.03)	(0.29)				(0.05)	(0.09)	(0.05)	(0.04)
Road Development†				0.21			0.22	0.17		
				(0.12)			(0.12)	(0.13)		
Agricultural Development†				-0.47 **			-0.40 **	-0.34 *	-0.37 **	-0.43 **
				(0.14)			(0.14)	(0.16)	(0.14)	(0.14)
Structural Development†				0.07			0.35 **	-0.30 *	-0.28 **	-0.28 **
				(0.06)			(0.09)	(0.11)	(0.08)	(0.07)
% of Public Hunting Land†					0.23 *			0.09		
					(0.12)			(0.13)		
% of Private Hunting Land†					-0.74			-0.17		
					(0.68)			(0.73)		
# of Bodies of Water†					0.35 **			0.35 **	0.35 **	0.40 **
					(0.10)			(0.13)	(0.12)	(0.11)
# of Species Listed as R/T/E†					0.93 **			0.57 *	0.41	
					(0.22)			(0.28)	(0.24)	

Table 6. Negative Binomial Regression for Illegal Hunting Violations Against Terrestrial Species Across Texas Counties (Cont.)

	Model 1		Model 2		Model 3		Model 4		Model 5
% Unemployed									
% Below Poverty									
Average Housing Value†									
% of Rented Housing Units†									
% of New Residents									
(Intercept)	6.46	**	1.15	**	1.14	**	3.45	**	-1.14
Log Likelihood[a]	-1023.8		-1018.8		-1018.8		-1027.9		-1016.8
Pearson Chi-square	253.58		251.24		251.88		274.465		239.84
Degrees of Freedom	250		251		251		250		249
AIC	2055.65		2043.69		2043.57		2063.85		2043.59

a. The full log likelihood function is displayed and used in computing information criteria.

*p < .05

**p < .01

†the natural log was taken

LQ = location quotient

AIC = Akaike's Information Criterion

Table 6. Negative Binomial Regression for Illegal Hunting Violations Against Terrestrial Species Across Texas Counties (Cont.)

	Model 6		Model 7		Model 8		Model 9		Model 10	
% Unemployed	0.04				-0.02					
	(0.03)				(0.03)					
% Below Poverty	0.04	**			0.02					
	(0.01)				(0.02)					
Average Housing Value†	0.77	**			-0.17					
	(0.25)				(0.34)					
% of Rented Housing Units†	-0.67				-0.37					
	(0.37)				(0.39)					
% of New Residents	0.01				0.01	**				
	(0.02)				(0.02)					
(Intercept)	-4.89		5.65	**	4.78		5.73	**	7.44	**
Log Likelihood[a]	1033.7		-1004.5		-994.4		-999.9		-1002.0	
Pearson Chi-square	264.45		205.52		189.20		204.37		222.57	
Degrees of Freedom	248		245		236		246		248	
AIC	2078.69		2027.05		2028.84		2015.77		2016.06	

a. The full log likelihood function is displayed and used in computing information criteria.

*$p < .05$

**$p < .01$

†the natural log was taken

LQ = location quotient

AIC = Akaike's Information Criterion

Table 7. Negative Binomial Regression for Illegal Hunting Violations Against Birds Across Texas Counties (n = 254)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
GDP Per Capita†	-0.15						-0.19	0.01	
	(0.09)						(0.09)	(0.11)	
LQ of Manufacturing Industries†	0.40						0.58 *	1.03 *	0.63 **
	(0.30)						(0.30)	(0.35)	-0.29
LQ of Mining Industries†	-0.50 **						0.20	0.23	
	(0.10)						(0.16)	(0.19)	
LQ of Hunting Industry†		0.17 **							
		(0.06)							
# of Hunting Establishments†			0.50 **				0.61 **	0.46 **	0.59 **
			(0.13)				(0.14)	(0.15)	(0.13)
# of Licenses and Permits Sold†		0.23 **	0.21 **				0.03	0.02	
		(0.02)	(0.03)				(0.05)	(0.05)	
Road Development†				0.01			0.02	-0.03	
				(0.12)			(0.13)	(0.14)	
Agricultural Development†				0.09			0.02	-0.07	
				(0.12)			(0.12)	(0.13)	
Structural Development†				0.42 **			0.33 **	0.41 **	0.33 **
				(0.05)			(0.09)	(0.11)	(0.05)
% of Public Hunting Land†					-0.13			-0.16	
					(0.10)			(0.12)	
% of Private Hunting Land†					0.96			0.45	
					(0.79)			(0.80)	
# of Bodies of Water†					0.34 **			0.13	
					(0.09)			(0.12)	
# of Species Listed as R/T/E†					1.08 **			0.25	
					(0.19)			(0.27)	

Table 7. Negative Binomial Regression for Illegal Hunting Violations Against Birds Across Texas Counties (Cont.)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
% Unemployed						0.05		-.01	
						(0.03)		(0.03)	
% Below Poverty						0.06 **		.03	
						(0.01)		(0.02)	
Average Housing Value†						1.14 **		-.46	
						(0.24)		(0.36)	
% of Rented Housing Units†						-0.35		-0.06	
						(0.39)		(0.37)	
% of New Residents						0.04		-0.01	
						(0.02)		(0.02)	
(Intercept)	5.75 **	0.66 **	0.81 **	1.28	-1.88 **	-11.57	3.39	4.68	1.28 **
Log Likelihood[a]	-957.13	-939.58	-937.26	-936.19	-950.30	-949.76	-920.61	-909.78	-923.93
Pearson Chi-square	435.08	379.73	359.58	336.08	312.32	328.992	275.48	234.87	295.45
Degrees of Freedom	250	251	251	250	249	248	245	236	250
AIC	1922.25	1885.17	1880.52	1880.38	1910.61	1911.51	1859.21	1855.55	1855.86

a. The full log likelihood function is displayed and used in computing information criteria.

*p < .05

**p < .01

†the natural log was taken

LQ = location quotient

AIC = Akaike's Information Criterion

Table 8. Negative Binomial Regression for Illegal Fishing Violations Against Aquatic Species Across Texas Counties (n = 254)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
GDP Per Capita†	0.12						0.06	0.17		
	(0.08)						(0.09)	(0.10)		
LQ of Manufacturing Industries†	0.56						0.13	0.58		
	(0.36)						(0.36)	(0.41)		
LQ of Mining Industries†	-1.17 **						0.00	0.36		
	(0.10)						(0.16)	(0.20)		
LQ of Hunting Industry†		0.08								
		(0.05)								
# of Hunting Establishments†			0.31 **				0.31 *	0.03		
			(0.11)				(0.12)	(0.14)		
# of Licenses and Permits Sold†		0.48 **	0.45 **				0.22 **	0.12 *	0.13 **	0.14 **
		-0.03	(0.03)				(0.05)	(0.05)	(0.05)	(0.05)
Road Development†				-0.32 **			-0.19	-0.26		
				(0.11)			(0.12)	(0.14)		
Agricultural Development†				-0.42 **			-0.44 **	-0.38 *	-0.26	
				(0.15)			(0.15)	(0.16)	(0.15)	
Structural Development†				0.74 **			0.45 **	0.52 **	0.37 **	0.38 **
				(0.06)			(0.10)	(0.12)	(0.07)	(0.07)
% of Public Hunting Land†					0.35 **			0.28 *	0.21 *	0.27 **
					(0.10)			(0.12)	(0.11)	(0.10)
% of Private Hunting Land†					0.16			-0.03		
					(0.73)			(0.74)		
# of Bodies of Water†					0.78 **			0.53 **	0.41 **	0.35 **
					(0.09)			(0.13)	(0.12)	(0.11)
# of Species Listed as R/T/E†					2.08 **			0.91 **	0.95 **	1.12 **
					(0.20)			(0.28)	(0.23)	(0.22)

Table 8. Negative Binomial Regression for Illegal Fishing Violations Against Aquatic Species Across Texas Counties (Cont.)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
% Unemployed						0.09 **		-0.05		
						(0.03)		(0.03)		
% Below Poverty						0.10 **		0.05 *	0.02	
						(0.01)		(0.02)	(0.01)	
Average Housing Value†						2.30 **		0.06		
						(0.27)		(0.37)		
% of Rented Housing Units†						-1.57 **		-1.00 *	-0.26	
						(0.43)		(0.43)	(0.26)	
% of New Residents						0.12 **		0.04		
						(0.02)		(0.02)		
(Intercept)	5.20 **	-0.69 **	10.55 *	5.49 **	-5.81 **	-23.07 **	2.28	-2.72	-1.45	-3.78 **
Log Likelihood[a]	-1129.9	-1094.0	-1090.8	-1083.3	-1111.4	-1129.5	-1064.0	-1041.5	-1050.5	-1053.7
Pearson Chi-square	832.69	657.06	505.78	611.75	521.72	547.77	479.76	459.17	539.51	498.57
Degrees of Freedom	250	251	251	250	249	248	245	236	245	248
AIC	2267.80	2194.02	2187.78	2174.66	2231.74	2271.00	2146.07	2118.92	2119.04	2119.43

a. The full log likelihood function is displayed and used in computing information criteria.

*p < .05

**p < .01

†the natural log was taken

LQ = location quotient

AIC = Akaike's Information Criterion

three steps across analyses of IH&F. First, a cross sectional analysis was conducted assessing the association of all variables of the ToP regressed onto the total number of IH&F measures. Second, a cross sectional analysis was conducted exploring the associations of all ToP variables regressed onto IH&F measures while controlling for other economic variables. Third, a cross sectional analysis was conducted exploring the associations of all ToP variables regressed onto the total number of IH&F while controlling for other economic, opportunity, and social variables. These steps are presented in Model 1, 7, and 8 across Tables 5.4 to Table 8. If the variable remains significant in model 8, the variable would be included in reduced models for future analysis of effect strength.

> H1: County measures of the GDP per capita are associated with illegal hunting and fishing at the county level.

Over all tables and models, little support was found for hypothesis 1. Presented in Table 5, the GDP per capita had a negative relationship with the total number of illegal hunting, until the full model where the direction changed. This pattern was also seen in Table 7 when analyzing the relationships with illegal hunting violations against bird animals. The GDP per capita was non-significant and negative, until the full model, where the variable become very mildly (b = 0.01) positive. When assessing the illegal fishing violations against aquatic species (Table 8), the GDP per capita was not significant but positive, and significant and negative for illegal hunting violations against terrestrial species (Table 6). Surprisingly, GDP per capita lost significance in the full model; however, model 7 had a slightly lower AIC indicating a better model fit than model 8. GDP per capita was retained for the reduced form models, 9 and 10. In the reduced models (models 9 and 10), the strength of the GDP per capita increased. Basing on the model 10 in Table 6, a one unit change in the log of the concentration of the GDP per capita is significantly and negatively associated with a .28 change in the log of the number of illegal hunting violations against terrestrial species. In all, I find no support for hypothesis 1 throughout all analyzes – the results were either insignificant or in the unexpected direction.

> H2: County measures of manufacturing industries are associated with illegal hunting and fishing at the county level.

Little support was found for hypothesis 2 across equations predicting the different dependent variables. For total illegal hunting and fishing violations, manufacturing industries had no significant relationships, though the effect was in the predicted direction (Table 5). No significant results were apparently in the separate estimations for illegal hunting of terrestrial species or aquatic species (Tables 5.5 and 5.7). Manufacturing industry was significant in models 7, 8 and 9 in Table 7 predicting the number of illegal hunting violations against birds. Thus, there is support for hypotheses 2, but only when predicting illegal hunting activities focusing around birds. A unit change in the log of the concentration of manufacturing industries positively associated with a .63 unit change in the log of the number of illegal hunting violations against bird animals.

> H3: County measures of resource mining industries are associated with illegal hunting and fishing at the county level.

For resource mining industries, mixed support was found for hypothesis 3. Across all the analyses, mining industries was significant in the initial model (i.e., model 1 in Tables 5.4., 5.5., 5.6. and 5.7), but became insignificant once other structural variables and control variables were entered into the analysis. Mining was not significant in any of the reduced form models regardless of the nature of the dependent variable (i.e., total, land, bird or aquatic animal illegal hunting violations). In short, when just examining the economic structure alone, the resource mining industry does have a significant impact on the dependent variable, regardless of how it is measured. When, however, additional variables representing other explanations are added, the effect of the mining industry is removed. This suggests the need for future research to determine if certain control variables are impacted by resource mining which then impact illegal hunting violations against terrestrial species. In the end, no support for hypothesis 3 was found.

Hunting Industry Variables

The second research question asked whether there is a relationship between measures of the hunting industry and illegal hunting and fishing. The third research question asked whether hunting industry variables are associated with IH&F when variables representing ToP theory are included. Bivariate relationships have already found initial relationships between the number of hunting establishments and the number of hunting and fishing licenses and permits sold.

As noted, the location quotient of hunting establishments did not have any significant bivariate relationship with any measures of illegal hunting and fishing. The following two hypotheses address this relationship by exploring the condition in which (if any) significant relationship between hunting industry variables and illegal hunting and fishing occurs. The test of hypotheses proceeded in four steps. To determine the better measure to capture the presence of the hunting industry, the first two steps analyzed two different measure of hunting establishments separately. First, a cross sectional analysis was conducted assessing the association of the LQ of hunting establishments and the number of hunting and fishing licenses and permits sold regressed onto IH&F measures. Second, a cross sectional analysis was conducted assessing the association between the number of hunting establishments and the number of hunting and fishing licenses and permits sold regressed onto IH&F measures. Third, a cross sectional analysis was conducted exploring the association of either the LQ of hunting establishments or the number of establishments, depending on the better explanatory measure, and the number of hunting and fishing licenses and permits sold regressed onto IH&F measures with other economic variables in the model. Fourth, a cross sectional analysis was conducted exploring the association of hunting industry variables regressed onto IH&F measures while controlling for other economic, opportunity, and social variables. These steps are presented in Model 2, 3, 7, and 8 across Tables 5.4 to Table 8. If the variable remains significant in model 8, the variable would be included in reduced models for future analysis of effect strength.

> H4: County measures of hunting establishments are associated with illegal hunting and fishing at the county level.

Only one measure of hunting establishments supported hypothesis 4, but overall, little support was found for this hypothesis. Model 2 explored the effect of the LQ of hunting establishment. Model 3 explored the effect of the number of hunting establishment. For the LQ of hunting establishments, significance was only found in Table 7, while the alternative measure (i.e., number of hunting establishments) was significant more often across models. Additionally, even with a significant effect, across Tables 5.4 to 5.7, Model 2 had higher AIC compared to model 3, suggesting a worse model fit. Therefore, it is safe to assume that the number of hunting establishments is a better measure of the illegal hunting outcomes.

As illustrated in Table 5, the number of hunting establishments was significantly and positively associated with the total number of IH&F violations. The significance remained in model 7 when controlling for other economic variables, but disappears in the full model (model 8). Thus, there is some partial support concerning the effect of the number of hunting establishments on hunting violations. Table 8 displays a similar pattern between the number of hunting establishments and the number of illegal fishing violations. When examining illegal hunting against terrestrial species, no significance was found in any model. In contrast, the number of hunting establishments had a significant, positive association with illegal hunting violations against birds. The final result indicates that a unit change in the log of the in the number of hunting establishments was positively associated with a .59 unit change in the log of the number of illegal hunting violations against birds. Overall, however, support was only found in one analysis i.e., birds), indicating only partial support for the hypothesis.

> H5: County measures of licenses and permits are associated with illegal hunting and fishing at the county level.

Hypothesis 5 had more support than any of the preceding hypotheses. The the number of hunting and fishing licenses and permits sold was significant in three out of four analyses of IH&F. Starting with Table 5, the number of hunting and fishing licenses and permits sold was significant in model 2 and 3 with relatively the same coefficient. When controlling for other economic variables in model 7, the number of hunting and fishing licenses and permits sold remained significant. In model 8, while the coefficient decreased to .11, it remained significant. After reducing the models to only significant variables, a one unit change in the log of the number of hunting and fishing licenses sold was associated with a .15 unit change in the log of the total number of IH&F violations. Table 6 (predicting hunting violations against terrestrial species) displays a similar pattern. Here, a one unit change in the log of the number of hunting and fishing licenses and permits sold positively associated with a .23 unit change in the log of number of illegal hunting violations against terrestrial species. Table 7, the analysis of the number of illegal hunting violations against bird animals, showed no support for hypothesis 5. Though initially, the number of hunting and fishing licenses and permits sold were significant in model 2 and 3, when controlling for other economic variables in model 7, the coefficient is greatly reduced and the variable is no longer significant. The analysis of the number of illegal fishing violations against aquatic species presented in Table 8 showed a different pattern compared to Table 5 and 5.5. Compared to earlier analyses, the strength of the variable continued to decrease across models. However, the variable remained significant, providing support for hypothesis 5. Thus, a one unit change in the log of the number of hunting and fishing licenses and permits sold was positively associated with a .14 unit change in the number of illegal fishing violations against aquatic species. In sum, there is relative support for hypothesis 5, though this hypothesis is not fully supported for each IH&F subtype.

Ecological Modification Variables

The fourth research question asked whether there "is there a relationship between measures of ecological modifications and illegal hunting and fishing." Bivariate relationships indicated initial relationships between road development, agricultural development, and structural development and multiple measures of illegal hunting and fishing; however, there is less association with modifications and illegal hunting against terrestrial species. The follow set of hypotheses answers the fourth research question by exploring the condition in which (if any) significant relationship between variables of ecological modification and IH&F. The test of the hypotheses proceeded in three steps across analyses of IH&F. First, a cross section analysis was conducted assigning the association of all ecological modification variables regressed onto IH&F measures. Second, a cross sectional analysis was conducted exploring the association of all ToP variables regressed onto IH&F measures while control for other economic variables. Third, a cross sectional analysis was conducted assessing the association of ecological modifications variables regressed onto IH&F measures while controlling for other economic, opportunity, and social variables. These steps are presented in Model 4, 7, and 8 across Tables 5.4 to Table 8. If the variable remains significant in model 8, the variable would be included in reduced models for future analysis of effect strength.

H6: County measures of road development are associated with measures of illegal hunting and fishing at county level.

Initially, in the bivariate analysis, road development had a significant positive relationship with measures of IH&F, but in the regression models, no support was found for road development across the regression analyses. Table 5 illustrates a negative relationship between road development and the total number of IH&F violations. In Table 6, road development has a positive relationship with illegal hunting violations against terrestrial species. In Table. 5.6, the analysis of illegal hunting violations against birds, the relationship was positive. When analyzing the total illegal fishing violations against aquatic species, road development was negatively significant in model 4, but when controlling all other economic variables, the significance and strength was lost Overall, no support was found for hypothesis 6.

H7: County measures of agricultural development are associated with measures of illegal hunting at the county level.

Some support was found for hypothesis 7. Bivariate relationships showed that agricultural development did not associate with either illegal hunting violations against terrestrial species or bird, but was significantly and negatively associated with the total number of IH&F violations and illegal fishing violations against aquatic species. Looking at Table 5, partial support for hypothesis 6 was found. Agricultural development was significantly and negatively associated with the total number of IH&F violations in model 4, analyzing only ecological modification variables. After including other economic variables (model 7), the significance remained; however, when controlling for every variable (model 8), significance disappeared. In Table 7, no support was found for hypothesis 6, however, Table 8 illustrates mix support for hypothesis 7. Similar to Table 7, agricultural development was significantly and negatively associated with the total illegal fishing violations against aquatic species (models 4, 7 and 8). However, when models were reduced, agricultural development lost significance. This lost in strength suggests a conditional effect, meaning, agricultural development does not associate with illegal fishing against aquatic species by itself. Hypotheses 7 was supported when analyzing the number of illegal hunting against terrestrial species (Table 6). Across models, agricultural development was significantly and negatively associated with the number of illegal hunting against terrestrial species. Over the models, the strength of coefficient decreased as variables were added. However, in the last reduced model (model 10), mining industries were dropped and the strength of agricultural development increased from a beta of -.37 to a beta of -.43, almost back to its initiation beta in Model 4 ($b = -.47$, $p < .01$). Therefore, a one unit change in the log of agricultural development was negatively associated with .43 unit change in the log of the number of illegal hunting violations against terrestrial species. Overall, there is mixed support for hypothesis 7 when considering all analyses taken together.

H8: County measures of structural development are associated with measures of illegal hunting and fishing at the county level.

There was mixed support for hypothesis 8. Bivariate relationships showed positive associations with structural development, the opposite of the hypothesis. Further regression analyses showed a mix of associations between structural development and IH&F measures. When analyzing the total number of IH&F violations, no support for hypothesis 8 was found -- even though the variable was significant, the effect was in the opposite of the direction of the theoretical prediction. In Table 5, structural development had an interesting pattern across the models due to the significance in model 8, structural development was included in the reduced models, and remained significant. As illustrated in Table 5, model 10, a one unit change in the log of structural development in a county is positively associated with a .21 unit change in the log of the total number of IH&F violations.

Table 6 also shows support for hypothesis 8. Apart from the decrease in coefficient due to added variables, the variable was consistently significant and in the same direction throughout all the models. A one unit change in the log of structural development is negatively associated with a .28 unit change in the log of the number of illegal hunting violations against terrestrial species. Table 7 illustrates similarities with Table 5. 4. Here, the number of illegal hunting violations against birds are positive, contradicting hypothesis 8. The variable increased in coefficient from model 7 to model 8, suggesting some multicollinearity with control variables, because when the control variables were dropped in the reduced model (model 9), the beta decreased back to .33, the same value in model 7. Therefore, a one unit change in the log of structural development was positively associated a .33 unit change in the log of the number of illegal hunting violations against bird animals.

The last analysis, focusing on the number of illegal fishing violations against aquatic species, showed the same pattern of associations illustrated in Table 7. After reducing the models, the effect strength does decrease but stabilized across each reduced model 9 and 10. Therefore, a one percent increase in the concentration of structural development predicts a 38 percent change in the number of illegal fishing violations against aquatic species.

Beyond Significance

Looking at the regression outputs, the values for the statistically significant effect do not reflect the effect size of the effect, or the relevance of the effect, of the independent variables. To examine this issue further, the percent change associated with statistically significant variables was examined further. The following formula is used to change the beta coeffects into percent changes of the dependent variable to provide more clarity about the effects on the dependent variable (Lorenzo-Seva, Ferrando and Chico, 2010).

$$\%\ Change = (e^{b} - 1)100$$

Using this formula, we can convert the beta coefficients into a percent change and see whether dependent variables have a "reasonable" effect, meaning one that is possible given the measure of the variable. Additionally, after applying the formula, the data is broken down in order to examine raw differences to see how counts of IH&F violation differ across different measurements of an intendent variable. Only variables of interest that showed significance are discussed below.

The GDP per capita was only associated with illegal hunting against terrestrial species. After applying the formula, the effect of the variable was that a one percent change in the GDP per capita was associated with a 32.3 percent decrease in the number of hunting violations against terrestrial species. The counties with a GDP per capita above 100,000 dollars had a total of 410 illegal hunting violations against terrestrial species. The remaining counties had a total of 5,193 violations. Using a different criteria, the criteria, the top 100 counties in GDP per capita had a total of 1,484 violations compared to 4,119 in the remaining 134 counties. More importantly, it is perfectly reasonable for GDP to change by 1% across counties in this data. The standard deviation for GDP per capita was $591,260 across counties, and the mean was $124,512. A one percent change in the mean of GDP per capita would amount to $1,245. &&&

The manufacturing industries variable was associated only with illegal hunting against birds. The effect of the variable was that a one percent change in the location quotient of manufacturing industries was associated with an 87.8 percent change increase in the number of illegal hunting violations against birds. However, when looking at counties where the proportion of industries for manufacturing exceed the proportion of industries for manufacturing nationwide (i.e. a location quotient higher than 1), this association is brought to question. A total of 1,956 violation against birds were observed in counties with a location quotient above 1. Those counties had an average of approximately 19 violations per county. A total of 2,479 violations were observed in the remaining counties, with only around 16 violations per county. While the averages are higher for counties with a higher quotient, the mean difference across high and low LQ counties is about 20%. Given the mean and standard deviation for this variable, it is possible for manufacturing LQ to change 1%, but this would be only in extreme cases given the ratio of the standard deviation to the mean.

Looking at hunting establishments, only 78 counties had the presence of one or more hunting establishments. Those 78 counties contained 10,643 out of 22,141 total IH&F violation. About 48 percent of the total IH&F violations are accounted by 30 percent of Texas counties. Similarly, when looking at the significant relationship with illegal hunting violations against birds, counties with hunting establishments had 2303 out of 4,435 illegal hunting violations against birds. In other words, about 30 percent of counties account for 50 percent of illegal hunting violations against birds. Here, hunting established are observed to be related to a higher concentration of illegal hunting and fishing activity.

The number of hunting and fishing licenses and permits sold was one of the two variables associating with multiple measures of illegal hunting. A one percent change in the number of hunting and fishing licenses and permits sold was associated with a 16.2 percent change increase in the total number of IH&F violations, a 25.9 percent increase for illegal hunting against terrestrial species, and a 15 percent increase in illegal fishing. Counties with measures of hunting and fishing licenses and permits sold between 0 and 1,000 had a total count of IH&F violations of 793 across 49 counties with an average of 16 hunting and fishing licenses and permits sold. The counties between 1,000 and 10,000 hunting and fishing licenses and permits sold had a total count of 7,306 IH&F violations across 121 counties, with an average of 60 hunting and fishing licenses and permits sold. Counties between 10,000 to 100,000 had a total count of IH&F violations of 10,663 across 75 counties with an average of 142 hunting and fishing licenses and permits sold. Contrarily, counties with over 100,000 hunting and fishing licenses and permits sold had a lower total of IH&F violations (N = 3,379). Those violations, however, occurred in a very small number of counties, nine. Given the means and standard deviations for the number of hunting and fishing licenses sold, it is entirely possible for this effect to occur quite easily across counties.

Similar to GDP per capita, agricultural development was only associated with illegal hunting against terrestrial species. After transforming the beta, a one percent change in agricultural development was associated with a 53.7 percent decrease in illegal hunting against terrestrial species. Upon further analysis, 151 counties had 80 percent or more land dedicated to agriculture or crop harvesting. These counties also contained 2,550 observations of illegal hunting against terrestrial species with an average of 16 offenses per county. The remaining counties contained 3,053 illegal hunting offenses against terrestrial species, with an average of 30 illegal hunting violations per county.

Structural density (i.e. the number of houses per square mile) was the second variable associated with multiple measures of illegal hunting. Using the above formula, a one percent change in structural density was associated with a 23.4 percent increase in the total number of IH&F, a 32.3 percent decrease in illegal hunting against terrestrial species, a 39 percent increase in illegal hunting against birds, and a 30 percent increase in illegal fishing against aquatic species. Looking at the distribution of structural density, 233 counties which had 100 houses per square mile or below had a total of 16,207 IH&F violation. In contrast, counties which had over 100 houses per square mile had a total of 5,934 IH&F violations across 33. Though this first appeared to be in opposition from the analyses, counties with 100 houses or below per square mile, on average, had around 96 IH&F violations. For the remaining denser counties, there was an average of about 282 IH&F violation for each county. While structural development is concentrated across 21 counties, the average effect on the distribution from these counties had a much higher impact. Therefore, as the data shows, more houses built in closer proximity (i.e. towns and cities) more IH&F violations would appear, only to decrease in regards to terrestrial species victims.

For some variables, the percent change can be extreme, and whether or not the results apply to any individual county would require further examination. For instance, if a county with only one establish hunting industry obtains another establishment, the percent increase in the hunting industry would be 100 percent. Using the appropriate equation, this would, following the equation result, cause an increase of 8,039.9 percent in illegal hunting against bird animals, which is highly unlikely. The limitations of applying these results to any specific county can also be observed by focusing on the changes in the values of IH&F outcomes. For instance, there is a mean of 17 illegal hunting violations against bird violations across Texas counties, and a total of 4,4,35 illegal hunting violations against birds in Texas. The largest number of these violations in any county is 264. Thus, it is mathematically plausible that in some places, the effect size estimated by the equation would be possible, while in other specific locales, the effect size would be impossible. This occurs because the equations predict the mean rather than the outcome in a specific county.

Summary of Results

Throughout the analysis, support of economic variables related to the ToP was at best mixed. Speculating, there may be more to the relationship between economic structure and measures of social behavior than has been explored here. Of the hypotheses examined, hypothesis 5 had the most support. The number of hunting and fishing licenses and permits sold had the most consistent association with the distribution of measures of IH&F violations. In contrast, while support was not found, some variable remained significantly associated through the analyses, the number of hunting and fishing licenses and permits sold, structural development, and the number of species listed as rare, threatened, and endangered (a control variable), were consistently associated, even though the direction of the association was opposite of the hypotheses. Overall, there seems to be no association between the ToP and measures of IH&F violations. The summary of the hypotheses testing is presented in Table 9.

When examining model 7 in Tables 5.4 through Table 8, which included all economic measures, at least one measure of an economic structural concepts (Treadmill of Production, hunting industry, ecological modifications) was related to the distribution of measures of IH&F violations. With the inclusion of the control variables on geographical opportunity and social factors (model 8 across these tables), the associations of economic measures disappeared. This indicates two possibilities: (1) the association of economic structure measures is associated with geographical opportunity measures, and then, these measures influence the geographical space of social behaviors; or (2) the current economic structure measures are spurious and do not determine the linear distribution of social behaviors. Given that measures of the economic structure do initially significantly associate with the linear distribution of IH&F violations, the former seems more likely of an explanation. Additionally, significant associations with measures of ecological modification, a proposed outcome of the ToP, after considering control variables, would suggest that the outcomes of the ToP, rather than the ToP itself, may be more relevant to determining the distribution of social behavior. Therefore, there should be additional exploration of how physical ecological changes due to the ToP affects these geographical opportunities variables.

Table 9. Hypothesis Testing Summary

Hypothesis	Table 5 (Total)	Table 6 (Land)	Table 7 (Bird)	Table 8 (Aquatic)
1	×	×	×	×
2	×	×	✓	×
3	×	×	×	×
4	×	×	✓	×
5	✓	✓	×	✓
6	×	×	×	×
7	×	✓	×	×
8	×	✓	×	×

In the next chapter, an analysis of the geographical clustering of IH&F violations is undertaken. Conservation criminology (Moreto and Pires, 2018), along with historical analyses (Jacoby, 2003), found theoretical and statistical reason to believe that any form of wildlife crime is spatially distinct, and both argued that policy has ignored the fundamental differences of space to properly address crime against wildlife. Using the found linearly associated variables, the SatScan program tests whether counties with measures of IH&F violations that deviate from the mean are clustered over space.

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CHAPTER 6:

SPATIAL ANALYSES CHAPTER

In the previous chapter, Poisson linear regression analyses were used to determine which variables representing the Treadmill of Production (ToP) were linearly associated with the geographic distribution of illegal hunting and fishing (IH&F) violations. Structural density had the strongest association with IH&F violations across Texas counties. Other variables also had significant associations with the dependent variables, such as the number of rare, threatened, and endangered animals (RTE) and the number of hunting and fishing licenses and permits sold; however, linear analysis showed no support for hypotheses linking these variables to the dependent outcomes.

In this chapter, I take up a geographic analysis of IH&F clusters, controlling for these significant variables (i.e. covariates) from the linear analyses. Mapping clusters of IH&F violations can reveal the existence of geographic relationships that linear analysis cannot depict. Locating these hotspots can have policy implications, and can help direct limited resources to controlling IH&F crimes where they are the most concentrated. Accordingly, the following chapter examines the spatial concentration of IH&F violations using the program SatScan. The following sections briefly discuss the SatScan program and how data were organized. After that, the chapter covers spatial analyses of each measure of IH&F violations, each presented with three tables and two geographical figures. The tables cover information on high-risk clusters

(HRC) which include indicators of relative risk, observed outcomes, expected outcomes, cluster size information, and averages of covariate measures across counties in a given HRC.

SatScan Program

SatScan is a program that uses a spatial discrete Poisson analysis to detect spatial clusters of events, and to determine whether the relative risk within clusters is significant compared to the total population surrounding the cluster. The relative risk of an event within an area (i.e., a certain sized circular space) is calculated by dividing the observed number of events by the expected number of events, and then using a moving cluster measure to compare the results to a sample of all other results (e.g., to 999 to 999,999 other clusters). The software looks at clusters in relation to a portion of population at risk of your choosing. The null hypothesis of the software is that the observed events are comparatively proportional to the population. Therefore, the alternative hypothesis argues that there is an unexpected count of observed events for certain locations compared to the rest of the population.

SatScan uses a scan statistic to create an ellipse window (i.e. circles) across all locations, comparing the observed and expected number of events inside the widow. The statistics compared the mean of the number of cases in the window to λ, the counts outside of the window. The radius of each circle (i.e. cluster of counties) is set to increase continuously to include up to a specified percentage of the total population at risk. We did not allow windows to overlap. The program is able to determine this ellipse window to a designated population at rick. While the default for the program is 50% of a cluster's population at risk to engage in illegal activity, for more conservative measures, the population at risk is set to 5 percent to determine clusters. This would indicate that significant windows only appear if 5 percent of the population engages in IH&F not by random chance.

To determine if the windows (i.e. clusters) found in the real data set are not by random change, the software uses Monte Carlo replications to determine which clusters are by random chance. Monte Carlo is a series of algorithms that rely on repeated random samples (see Kroese, Brereton, Taimre, and Botev, 2014 for more information). The study set the count of replications to 999. A test statistic is calculated for each random replication as well as the real data set. If the real data set is statistically different among the distributions of replications, it would be ruled significant signifying confidence that the real data outputs did not appear by random chance. SatScan uses a threshold of 5% to determine if the real data set is statistically different.

This method has not been widely employed within criminology, and is more prevalent in other disciplines. Within criminology, this method has been used for homicide (Zeoli et al., 2014), general crime patterns (Leitner and Helbich, 2011), drug trafficking (Beato Filho et al., 2001), and police officer deaths (Kaminski, Jefferis, and Chanhatasilpa, 2000).

Understanding SatScan Clusters

SatScan looks for counties where the expected count is lower or higher than the observed count, using population means to weigh the expected count across locations. Thus, while certain counties have a high raw score – for example, Harris county with a total count of 544 violations – the purpose of SatScan is to find counties where activity is higher or lower than it should be, warranting attention to the characteristics of a county to determine why observations do not match an expected outcome. To determine these clusters, a two-step process was used which includes hierarchical and Gini cluster models.

SatScan gives three options to observe clusters. The first is a default option comparing the spatial windows to the surrounding counties, not considering counties that are similar to each other. The second option is the hierarchical cluster option, where the program finds clusters that are distinct from other clusters, but the counties within clusters are similar. The third option is the Gini cluster option, where the program implements the Gini coefficient to determine if there are smaller clusters hidden within hierarchical clusters. This latter option allows SatScan to find irregular shaped clusters that are not perfectly spherical and high-risk counties that are significant but are not surrounded by similar counties. If a cluster does not have smaller clusters, the Gini cluster should have the same centroid, radius, and observations as the hierarchical cluster.

When conducting the geographic cluster analyses, the default option and the hierarchical option both provide cluster results that have large radii, and do not provide enough information on the distribution of relative risks across counties. One of the uses of cluster analysis with respect to the location of high (and low) rate areas of IH&F violations is to inform hunting and fishing policy and/or the distribution of resources that address hunting and fishing violations. With respect to policy implications, the Gini cluster option has been argued to be more effective due to the ability to capture more refined non-overlapping clusters (Han et al., 2016), and according to Han et al. (2016), "it also fulfils a set of desirable theoretical properties, such as being invariant under a uniform multiplication of the population numbers by the same constant."

In order to use Gini clusters appropriately for policy related purposes, hierarchical clusters are also reported to show whether these Gini clusters form larger clusters. Therefore, for each measure of IH&F violations, two geographical cluster maps were complied. One cluster map illustrates hierarchical clusters controlling for covariates showing hierarchical clusters, while the second map shows Gini clusters, controlling for covariates. These corresponding maps for each measure of IH&F violations were demonstrate how cases are clustered, and whether these clusters are comprised of multiple clustering of IH&F activities. Additionally, high populated metropolitan cities and city headquarters for Texas Park and Wildlife law enforcement districts were marked with stars to show visual representations of human development and law enforcement. These cities were San Angelo, Houston, Fort Worth, Corpus Christi, Lubbock, Temple, Lufkin, San Antonio, Dallas, and Austin.

Including and Reporting Covariates

In the previous chapter, significant variables are found for each analysis of illegal hunting and fishing violations (see Tables 5.4 to 5.7). To include these variables in the SatScan analysis, the variables must be transformed into categorical variables. Unfortunately, SatScan is limited to analyzing categorical co-variates. There is a way to work around this for continuous co-variates, but this requires generating the predicted results of each analysis when considering all significant variables and treating the predicted values as the dependent variable in SatScan. To avoid complications within the program and interpretations, transforming the variables into z-score for the SatScan analysis is the more usual method.

Variables were transformed into z-scores to standardize the distribution and categories variables in relation to the mean of the destitution. First, the z-score of each significant variable, illustrated in the last models across Tables 5.4 to 5.7, was generated. Second, the z-scores were coded into categories. For z-scores below the mean (e.g. negative values): (1) scores more than three standard deviation of the mean was coded as 1; (2) scores coded more than two standard deviation away were coded as 2; (3) scores coded more than one standard deviation away were coded as 3; (4) scores below one standard deviation of the mean was coded as 4. The mean z-score was considered 0, and any scores transformed be a z-score of 0 was coded as 5. For z-scores that fell above the mean: (1) scores below one standard deviation of the mean was coded as 6; (2) scores coded more than one standard deviation away were coded as 7; (3) scores coded more than two standard deviations away were coded as 8; (4) scores coded more than more than three standard deviations away were coded as 9.

Using this approaching affects interpreting the z-scores with respect to the mean. For instance, the mean z-score is represented by the number 5. In this case, a county with a z-score of 8 would be +2 z-scores above the mean, while a county with a score of 2 would be -2 z-scores from the mean.

The Total Amount of Illegal Hunting and Fishing Violations High Risk Clusters

Examining the spatial analysis of total amount of IH&F violations, I found that high risk clusters (HRC) had low measures of covariates across clusters which were positively associated with IH&F violations, the number of hunting and fishing licenses and permits sold, structural development, and the amount of rare, threatened, and endangered species (RTE). I also found that initial hierarchical clusters are influenced by the proximity of smaller clusters, suggesting a spatial diffusion effect when clusters are close together, forming what seems to be large clusters; however, the covariates that significantly associated with the overall distribution did not provide an explanation to the clustering of counties with high risk of IH&F violations.

Figure 6.1 shows visual clusters of the total amount of illegal hunting and fishing violations across Texas counties, controlling for covariates. Table 10 presented details on a total of 11 hierarchical clusters. Here, only two clusters are contained within a county, while the radii of clusters extend from the centroid county ranges from 48 to 147 kilometers. Additionally, these clusters capture 13,915 observations, or roughly 65 percent of the total amount of violations. Thus, 65 percent of IH&F occur in "problematic" counties, if problematic means areas where there are high volumes of IH&F.

Figure 6.2 illustrates the Gini clusters while controlling for the covariates. Table 11 provides information on 22 Gini clusters, with clusters 9 and 10 being insignificant. The radii of Gini clusters are smaller, ranging from 0 to 98.3 kilometers, with 6 clusters contained in a single county. Noticeably, while there are more clusters, these clusters account for only 9,746 IH&F violations, or about 70% of the number of cases identified by the hierarchical cluster model. This may indicate a spatial diffusion effect from smaller clusters in close proximity to each other. Thus, when initially analyzing clusters, the hierarchical calculations capture more cases due to the proximity of these smaller clusters.

For further analysis, Table 12 present information on averages of covariate measures across counties in a given HRC. In regards to these covariates, the averages of HRC for the number of hunting and fishing licenses and permits sold ranged from 986.33 to 57,751 with an average of 8,715 hunting and fishing licenses and permits sold across all HRC. The averages of HRC for structural development ranged from .35 to 89.80 houses per square mile with an average of 16.62 of houses per square mile across HRC. Lastly, the averages of HRC for RTE ranged from 33.38 to 124 number of species with an average of 59.21 number of species across HRC. Referencing back to Table 2, in Chapter 5, HRC averages had two covariates well below the averages across counties while RTE cluster measures nearly matches the average across counties. First, the mean of NLPS across counties was 18,367, 1or 0,000 more than the mean across HRC. Second, the mean of structural development across counties was 55.12 houses per

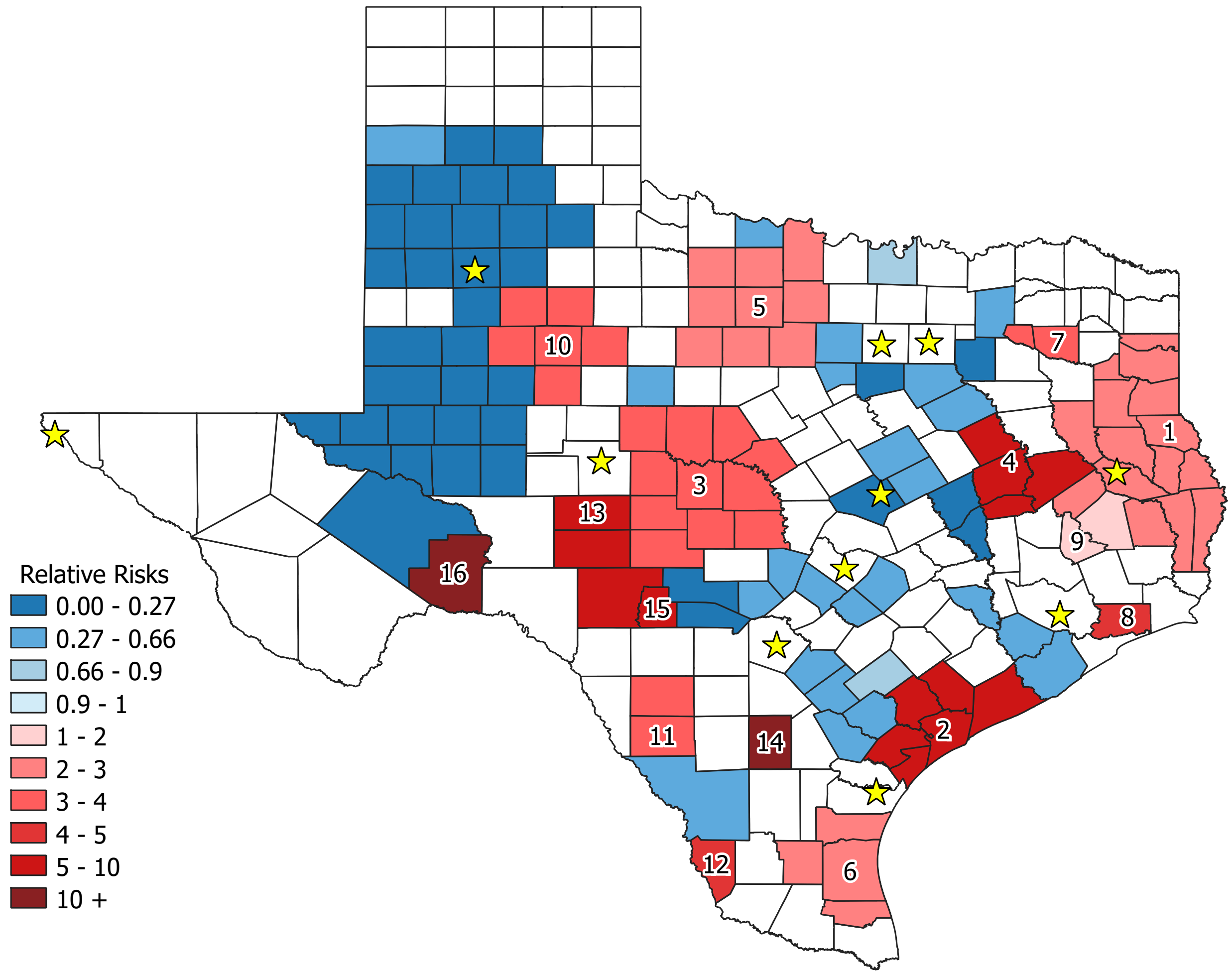

Figure 1. Relative Risk Hierarchical Clusters for the Total Amount of Hunting and Fishing Violations Controlling for Covariates

Covariates are the number of hunting and fishing licenses and permits sold, structural development, and the number of species listed as rare, threatened, and endangered.

Table 10. Hierarchal Clusters of the Total Amount of Illegal Hunting and Fishing Violations Controlling for Significant Variables

Cluster #	P-value	Centriod County FIPS	Cluster Radius (KM)	Number of Counties in Cluster	Cluster Observations	Expected Observation Count	Ratio of Observed to Expected	Relative Risk Ratio	Cluster Population
1	<0.01	48401	147.44	29	4302	1069.38	4.02	4.75	1281783
2	<0.01	48409	177.58	26	3095	800.05	3.87	4.33	958957
3	<0.01	48083	175.33	42	2520	705.40	3.57	3.90	845504
4	<0.01	48245	108.24	9	1719	739.04	2.33	2.44	885825
5	<0.01	48339	49.21	5	615	499.69	1.23	1.24	598939
6	<0.01	48337	89.35	7	523	140.35	3.73	3.79	168226
7	<0.01	48463	87.08	9	477	159.15	3.00	3.04	190755
8	<0.01	48015	61.85	5	364	128.96	2.82	2.85	154575
9	<0.01	48505	0.00	1	137	11.94	11.48	11.54	14308
10	<0.01	48305	48.14	2	93	10.16	9.16	9.19	12174
11	<0.01	48119	0.00	1	70	4.36	16.06	16.11	5223

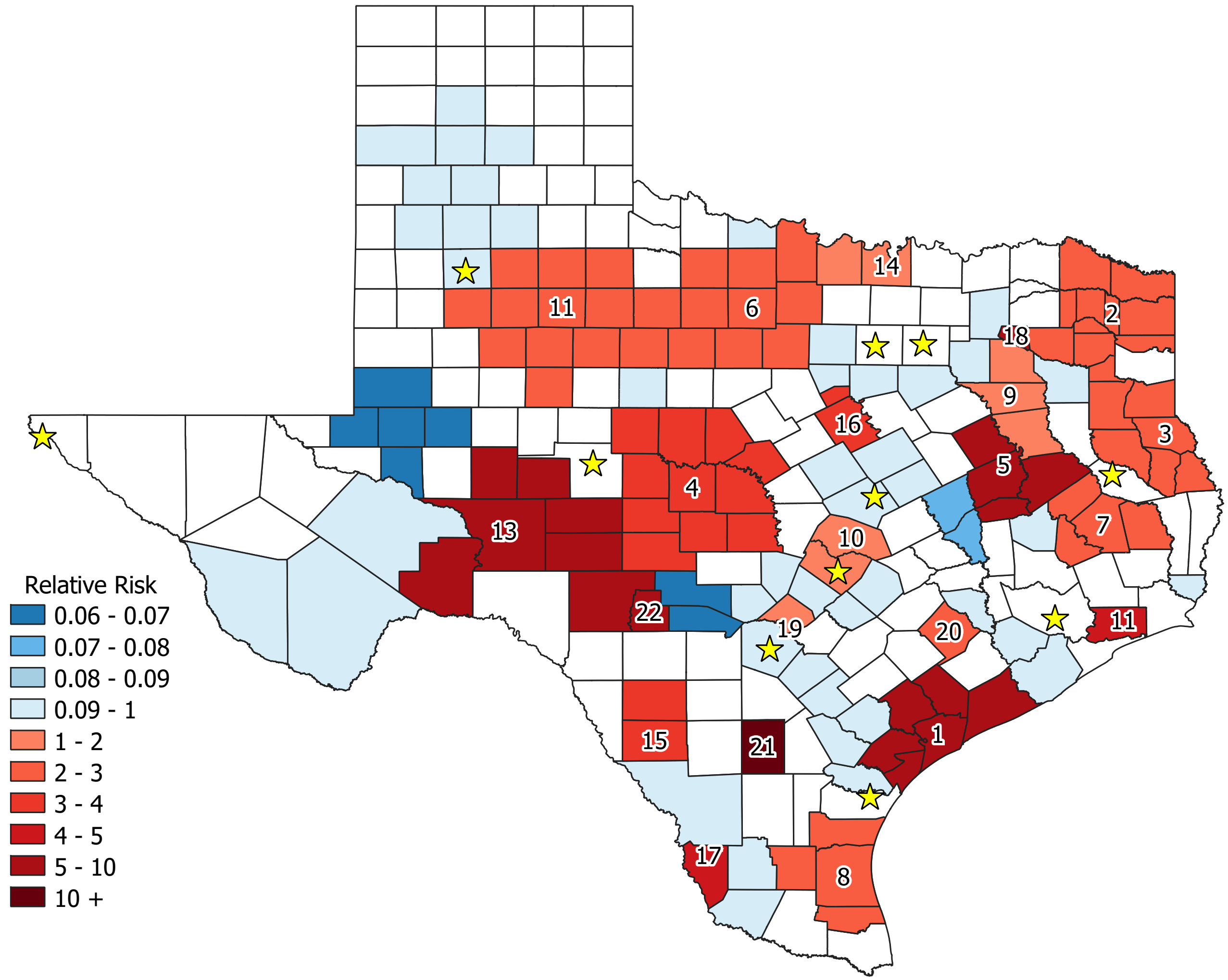

Figure 2. Relative Risk Gini Clusters for the Total Amount of Hunting and Fishing Violations Controlling for Covariates

Covariates are the number of hunting and fishing licenses and permits sold, structural development, and the number of species listed as rare, threatened, and endangered.

Table 11. Gini Clusters of the Total Amount of Illegal Hunting and Fishing Violations Controlling for Significant Variables

Cluster #	P-value	Centriod County FIPS	Cluster Radius (KM)	Number of Counties in Cluster	Cluster Observations	Expected Observation Count	Ratio of Observed to Expected	Relative Risk Ratio	Cluster Population
1	<0.01	48057	76.95	6	1396	277.95	5.02	5.29	194418
2	<0.01	48343	70.83	11	1371	619.87	2.21	2.29	420652
3	<0.01	48419	67.91	6	991	373.97	2.65	2.73	187748
4	<0.01	48307	92.09	11	846	221.11	3.83	3.94	109998
5	<0.01	48289	54.48	4	762	147.13	5.18	5.33	73192
6	<0.01	48503	80.75	9	500	185.80	2.69	2.73	92431
7	<0.01	48373	43.93	4	495	219.11	2.26	2.29	109003
8	<0.01	48261	56.72	4	464	160.10	2.90	2.94	61817
9	0.89	48213	48.18	3	442	381.26	1.16	1.16	189667
10	0.93	48491	38.97	2	424	365.67	1.16	1.16	1595237
11	<0.01	48071	98.30	13	399	160.34	2.49	2.52	79765
12	<0.01	48263	0.00	1	313	74.88	4.18	4.23	37251
13	<0.01	48105	87.23	13	195	34.88	5.59	5.63	17052
14	0.03	48097	47.55	2	167	117.07	1.43	1.43	58239
15	<0.01	48127	49.31	2	165	45.71	3.61	3.63	22742
16	<0.01	48035	38.12	2	163	53.43	3.05	3.07	26579
17	<0.01	48505	0.00	1	137	28.76	4.76	4.79	14308
18	<0.01	48379	0.00	1	124	22.19	5.59	5.61	11037
19	<0.01	48091	0.00	1	114	61.85	1.84	1.85	119632
20	<0.01	48089	0.00	1	110	41.72	2.64	2.64	20757
21	<0.01	48311	0.00	1	97	1.56	62.02	62.29	778
22	<0.01	48385	49.42	2	71	10.58	6.71	6.73	5262

Table 12. Averages of County Variable Measurements in Total Hunting and Fishing Violations Gini High Risk Clusters

Cluster #	Number of Counties in Cluster	NLPS	Structural Development	RTE
1	6	57751.00	29.86	79.33
2	11	10708.36	38.37	48.00
3	6	8786.17	17.88	55.33
4	11	5342.73	6.18	51.00
5	4	4993.75	8.42	58.25
6	9	3449.33	5.66	38.89
7	4	7258.50	25.16	61.50
8	4	8796.25	7.55	92.00
9	(not significant)			
10	(not significant)			
11	13	1215.62	2.98	33.38
12	1	6722.00	23.68	61.00
13	13	986.33	0.92	53.50
14	2	9337.50	14.97	51.00
15	2	2193.00	3.30	41.00
16	2	3652.50	14.83	49.00
17	1	4608.00	6.24	70.00
18	1	4309.00	22.97	41.00
19	1	22156.00	89.80	124.00
20	1	9399.00	10.98	58.00
21	1	1141.00	0.35	50.00
22	2	1504.00	2.36	68.00
Means		8715.50	16.62	59.21

* = found to be significant in linear analyses
NLPS = Number of Hunting and Fishing Lisences and Permits Sold
RTE = Number of Species Listed as Rare, Threatened, and Endangered

square mile, or 26.89 houses more per square mile than the mean of HRC. For the third variable, the county mean of RTE was 55.12 species, which was roughly 4 species less than the HRC mean of 59.21 species.

Measures of RTE, structural development, and NLPS all had significant positive linear relationships with all IH&F violations (Table 5). When controlling for these covariates spatially, HRC had lower measures of these covariates with one covariate measuring near the mean of counties. Linear analyses suggested that as NLPS and structural development increased, IH&F violations increased. The clusters, however, show low measures of NLPS and structural development in locations with higher-than-expected counts of IH&F violations. RTE had a positive significant linear relationship with IH&F violations, and the mean of HRC averages was near the mean of county measurements. According to linear analyses, counties with these measures would not exhibit higher than expected counts of IH&F violations. These findings suggest, that even though these covariates were associated with the overall distribution of the total amount of IH&F violations, the covariates do not explain the grouping of high-risk counties. In other words, while certain variables explain which counties had higher IH&F violations, they do not necessarily explain how counties are clustered.

Below, this analysis is repeated for IH&F violation for terrestrial species hunting violations only, and then for bird hunting violations only, and finally for fishing violations only.

Illegal Hunting Violations Against Terrestrial Species High Risk Clusters

When analyzing illegal hunting violations against terrestrial species with a spatial component, I found that HRC had a mix of low, high, and average measures of controlled covariates that had significant linearly associations; however, the measurements opposed the direction of associations found in the linear analysis (Table 6.). These covariates were GDP per capita, NLPS, agricultural development, structural development, and the number of bodies of water. Additionally, I found that initial hierarchical clusters do not capture all Gini clusters that are at high risk, suggesting that the majority of high-risk Gini clusters do not include characteristics exhibited in the hierarchical cluster analysis. Only a few counties that are high risk and close in proximity were similar to each other. Similar to the above analysis, the covariates did not provide insight to the clustering of counties with a high-risk of illegal hunting violations against terrestrial species.

Figure 3 shows six high-risk clusters while controlling for covariates with one cluster contained in a county. Paralleling Figure 6.2, high-risk clusters tend to be located away from metropolitan areas or cities (i.e., the border of the clusters are about one to two counties away from metropolitan or city counties). Table 13 presents description of high-risk counties for illegal hunting violations against terrestrial species. The radii of these hierarchical clusters ranged from 0 to 179.73 kilometers. The total amount of violations captured by the hierarchical clusters was 1,835 violations, roughly 33 percent of 5,603 total amount of illegal hunting violations against terrestrial species. This result suggested that majority of counties have, on average, observed violation numbers close to the expected amount of illegal hunting violations against terrestrial species when considering covariates. Figure 4, however, illustrates a different distribution of high-risk counties. Table 14 shows that, when examining for Gini clusters, 22 smaller high-risk clusters are found, with only clusters 14 and 16 being insignificant. The radii of these clusters similarly ranged from 0 to 179.73 kilometers, but 11 clusters were isolated within a county. Unlike the cluster descriptions for the total amount of IH&F violations, the Gini clusters captured more violations (n = 2,808), roughly 50 percent of the total cases. This reversal between hierarchical and Gini clusters suggests that there are only a small group of counties that are similar to each other in the hierarchical cluster analysis, while there are more clusters when using the Gini cluster methods, and that these clusters contain more cases than those produces by the hierarchical method.

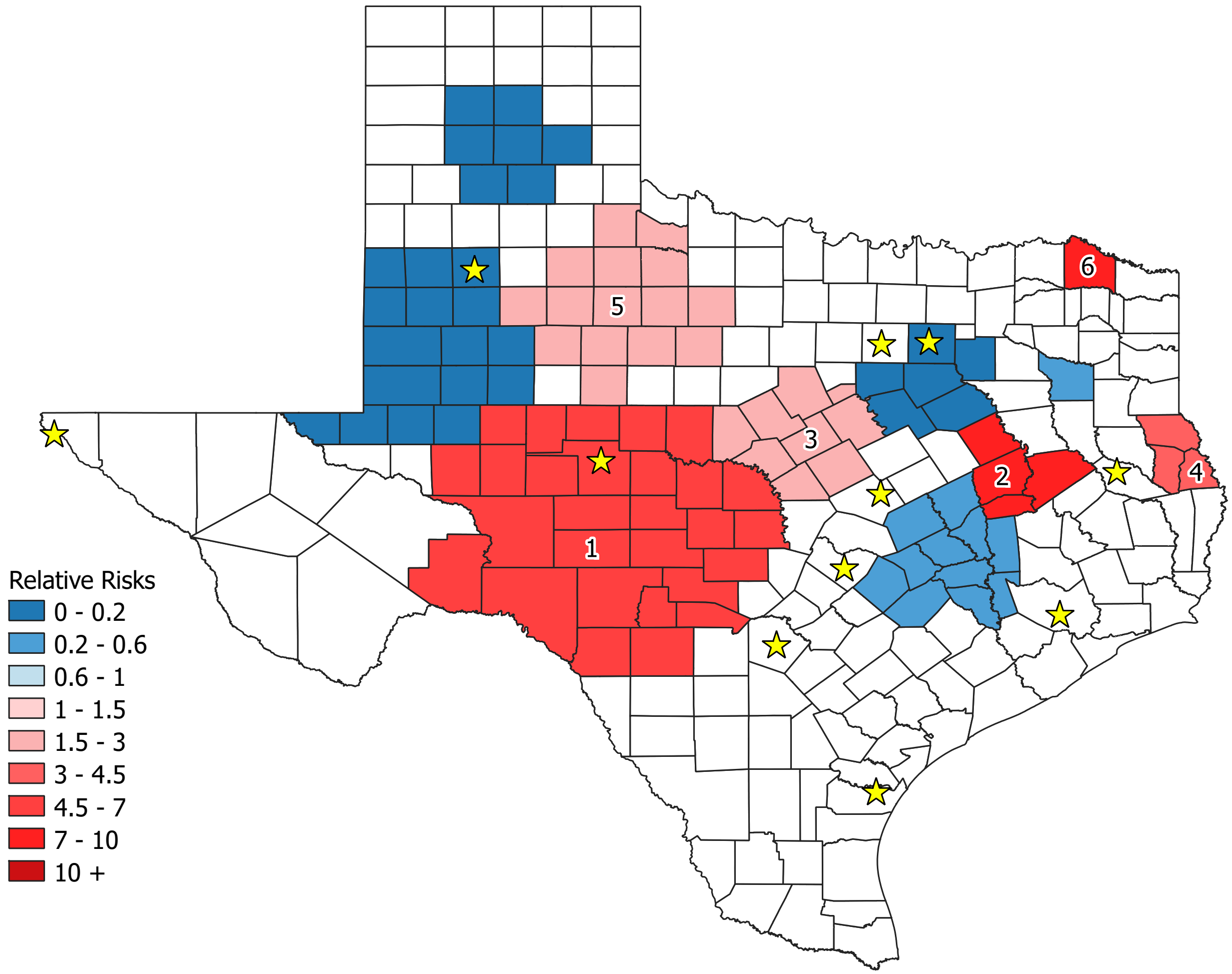

Figure 3. Relative Risk Hierarchical Clusters for Total Hunting Violations against Terrestrial Species Controlling for Covariates

Covariates are Gross Domestic Product per Capita, the number of hunting and fishing licenses and permits sold, agricultural development, structural development, and the number of bodies of water

Table 13. Hierarchal Clusters of High Risk Illegal Hunting Violations Against Terrestrial Species Controlling for Significant Variables

Cluster #	P-value	Centriod County FIPS	Cluster Radius (KM)	Number of Counties in Cluster	Cluster Observations	Expected Observation Count	Ratio of Observed to Expected	Relative Risk Ratio	Cluster Population
1	<0.01	48435	179.73	28	802	183.29	4.38	4.94	389681
2	<0.01	48289	54.48	4	329	44.99	7.31	7.71	73192
3	<0.01	48193	84.39	9	315	139.87	2.25	2.33	227562
4	<0.01	48403	57.12	3	177	50.27	3.52	3.60	44860
5	<0.01	48433	99.95	15	141	51.99	2.71	2.76	84581
6	<0.01	48387	0.00	1	71	7.72	9.19	9.30	12567

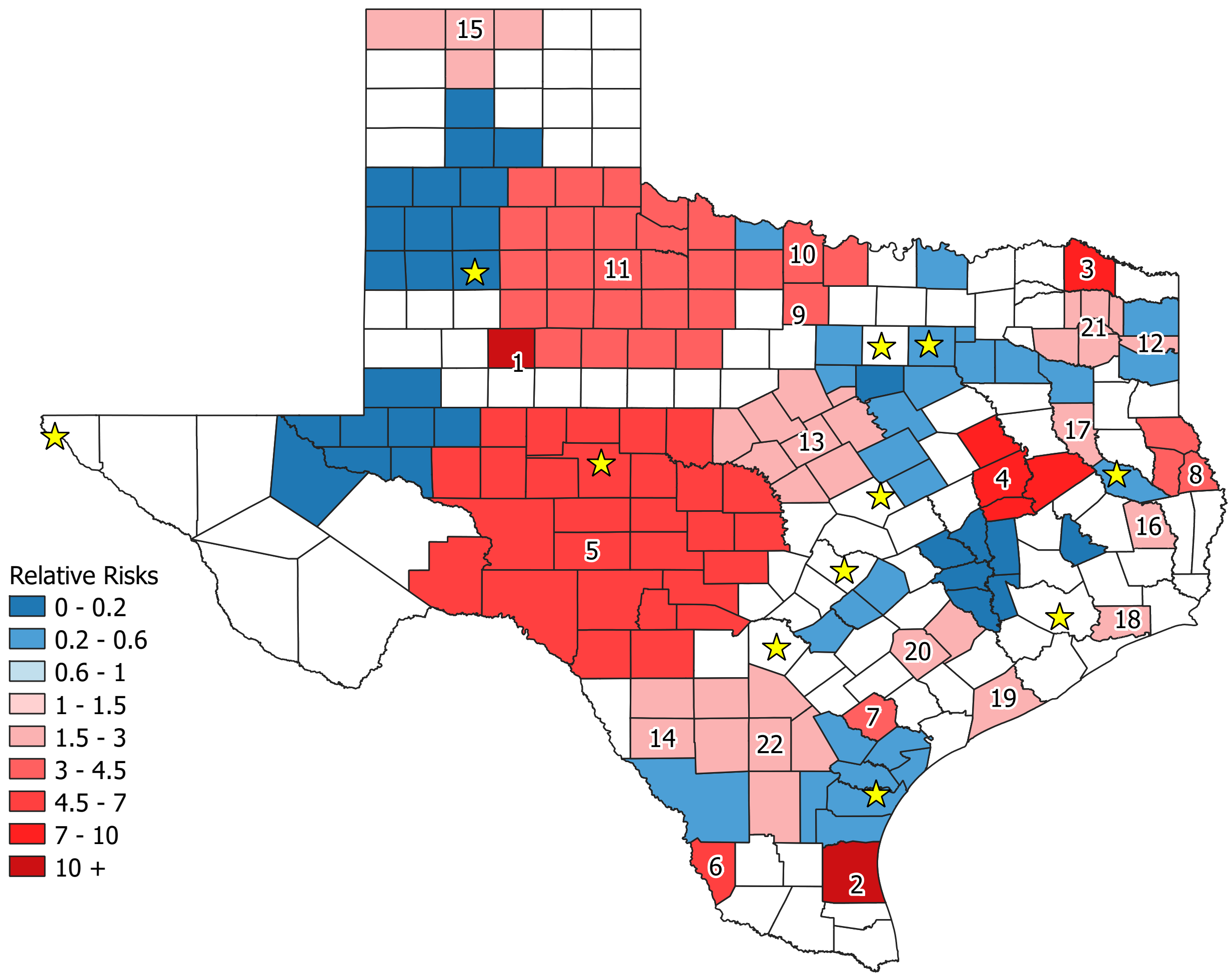

Figure 4. Relative Risk Gini Clusters for Total Hunting Violations against Terrestrial Species Controlling for Covariates

Covariates are Gross Domestic Product per Capita, the number of hunting and fishing licenses and permits sold, agricultural development, structural development, and the number of bodies of water

Table 14. Gini Clusters of High Risk Illegal Hunting Violations Against Terrestrial Species Controlling for Significant Variables

Cluster #	P-value	Centriod County	Cluster Radius (KM)	Number of Counties in Cluster	Cluster Observations	Expected Observation Count	Ratio of Observed to Expected	Relative Risk Ratio	Cluster Population
1	<0.01	48435	179.73	28	802	183.29	4.38	4.94	389681
2	<0.01	48289	54.48	4	329	44.99	7.31	7.71	73192
3	<0.01	48193	84.39	9	315	139.87	2.25	2.33	227562
4	<0.01	48269	134.19	23	202	66.98	3.02	3.09	115486
5	<0.01	48403	57.12	3	177	50.27	3.52	3.60	44860
6	<0.01	48063	43.00	6	156	92.92	1.68	1.70	151176
7	<0.01	48311	77.67	6	135	87.61	1.54	1.55	96637
8	<0.01	48073	0.00	1	91	42.35	2.15	2.17	51167
9	<0.01	48077	48.07	3	77	23.81	3.23	3.27	38736
10	<0.01	48387	0.00	1	71	7.72	9.19	9.30	12567
11	<0.01	48457	0.00	1	70	32.50	2.15	2.17	21462
12	<0.01	48421	63.50	4	51	23.31	2.19	2.20	37920
13	<0.01	48071	0.00	1	49	22.90	2.14	2.15	37251
14	0.06	48285	47.08	2	48	24.77	1.94	1.95	40306
15	0.05	48321	0.00	1	45	22.50	2.00	2.01	36598
16	0.06	48315	0.00	1	44	15.52	2.84	2.85	10248
17	<0.01	48505	0.00	1	42	8.79	4.78	4.80	14308
18	<0.02	48127	49.31	2	32	13.98	2.29	2.30	22742
19	<0.03	48033	0.00	1	20	0.43	46.15	46.32	705
20	<0.04	48175	0.00	1	20	4.55	4.39	4.40	7410
21	<0.05	48237	0.00	1	18	5.50	3.27	3.28	8946
22	<0.06	48261	0.00	1	14	0.35	40.31	40.41	565

For further analysis, Table 15 presents information on averages of covariate measures across counties in a given HRC. A number of covariates were significantly associated linearly. The HRC averages for GDP per capita ranged from $19,811.81 to $584,052.69 with a mean of $12,081,100.09 across clusters. The HRC averages for NLPS ranged from 67 to 21,747 with a

Table 15. Averages of County Variable Measurements in Illegal Hunting Violations Against Terrestrial Species Gini High Risk Clusters

Cluster #	Number of Counties in Cluster	GDP Per Capita	Agricultural Development	Structural Development	# of Bodies of Water
1	28	155,257.95	84.24	8.33	2.57
2	4	55,766.49	80.36	6.74	0.75
3	9	42,341.40	87.22	5.04	1.44
4	23	71,624.74	81.10	5.44	2.57
5	3	39,771.89	88.78	19.22	3.33
6	6	38,786.31	85.88	8.23	1.33
7	6	584,052.69	55.93	6.89	2.17
8	1	27,945.92	99.37	1.14	0.00
9	3	33,582.39	70.13	8.25	2.67
10	1	19,850.48	98.72	1.39	0.00
11	1	19,811.81	76.56	19.84	3.00
12	4	113,057.64	87.62	0.85	1.50
13	1	59,507.40	86.98	1.15	1.00
14	(not significant)				
15	1	58,020.36	15.32	11.47	2.00
16	(not significant)				
17	1	49,001.33	86.38	1.22	0.00
18	2	165,627.03	86.39	6.51	7.00
19	1	331,547.52	94.50	6.47	2.00
20	1	42,787.31	55.05	32.45	4.00
21	1	64,862.28	88.13	6.24	0.00
22	1	438,504.42	83.44	3.31	1.00
Means		120,585.37	79.60	8.01	1.92

GDP = Gross Domestic Product

mean of 4,889.38 NLPS across clusters. Agricultural development averages for HRC ranged from 15.32 to 99.37 percent of agricultural land with a mean of 79.6 percent of agricultural land. Structural development averages for HRC ranged from 0.85 to 32.45 houses per square mile with a mean of 8.01 houses per square mile. Lastly, the averages for HRC for the number of BW ranged from 0 to 7 BW with a mean of 1.92 across clusters. Comparing these results to the means of covariates across counties (see Table 2), four covariates of HRC were less than the means across counties, and one variable was near even with the mean of counties. The mean of HRC for the GDP per capita was about four thousand less than the mean of the GDP per capita across counties, $124,512.77. The mean of HRC for NLPS, was about 4 times less than the mean of NLPS for counties, 18,367.76. The mean of HRC for structural development, houses per square mile, was about 5.5 times less than the mean of structural development for counties, 43.51. Lastly, the mean of HRC for the number of BW was about 1.8 times less than the mean of BW for counties. The mean of HRC of agricultural development, was about even with the mean of agricultural development for counties (76.48 percent of agricultural land).

Measures of the GDP per capita, agricultural development, and structural development had significant negative linear relationships with illegal hunting violations against terrestrial species. When considering these covariates spatially, HRC has lower measures of structural development, average measures of agricultural development, and higher measures of GDP per Capita. Both the measures of the NLPS and the number of BW had a significant positive linear relationship with illegal hunting violations against terrestrial species. When considering NLPS and BW spatially, HRC had lower measures of both BW and NLPS. According to linear analyses (Table 6), there should be an expected high observation of illegal hunting against terrestrial species for counties with low measures of structural development, agricultural development, and

GDP per capita; however, the spatial analysis shows that counties with these characteristics have higher than expected counts. As well, the measures of NLPS and BW were opposite of the linear relationships. These findings suggest, that even though these covariates have an association with the overall distribution of illegal hunting violations against terrestrial species, the covariates do not explain the grouping of high-risk counties.

Illegal Hunting Violations Against Birds High Risk Clusters

In the spatial analysis for illegal hunting violations against birds, I found that high-risk clusters (HRC) had average measures of controlled covariates that positively and significantly associated with illegal hunting violations against birds (see Table 7), the LQ of the manufacturing industry, the number of hunting establishments, and structural development. Examining hierarchical and Gini clusters, I found that smaller clusters that were characteristically similar had a spatial diffusion effect. Just like the prior analyses, the covariates that were linearly associated with IH&F violations did not provide an explanation for the groupings of IH&F clusters.

Figure 5 illustrates the 21 hierarchical HRC of illegal hunting violations against birds, controlling for the manufacturing industry, hunting establishments, and structural development. Unlike the previous analyses, these clusters were not located near metropolitan areas. As seen in Table 16, two of the hierarchical clusters were insignificant. The radii of clusters ranged from 0 to 204.27 kilometers; 8 clusters were contained within a county. The hierarchical HRC captured 2,204 cases, or about 49.6 percent of the total number of illegal hunting violations against birds (n = 4,435).

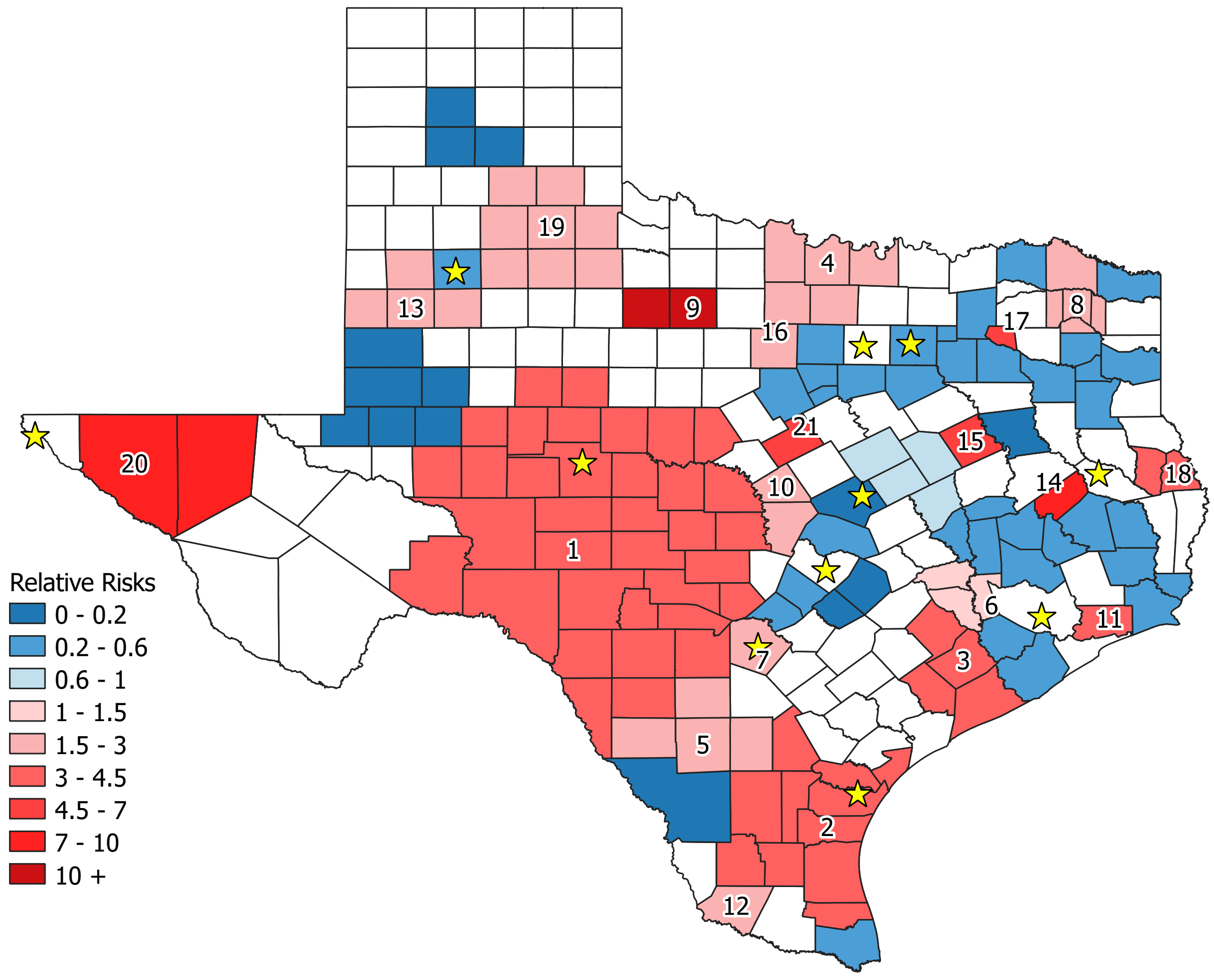

Figure 5. Relative Risk Hierarchical Clusters for Total Hunting Violations against Birds Controlling for Covariates

Covariates are the location quotient manufacturing industries, number of hunting establishments, and structural development.

Table 16. Hierarchal Clusters of High Risk Illegal Hunting Violations Against Birds Control For Significant Variables

Cluster #	P-value	Centriod County	Cluster Radius (KM)	Number of Counties in Cluster	Cluster Observations	Expected Observation Count	Ratio of Observed to Expected	Relative Risk Ratio	Cluster Population
1	<0.01	48435	204.27	35	525	185.29	2.83	3.08	605105
2	<0.01	48273	109.24	11	398	109.36	3.64	3.90	574389
3	<0.01	48481	51.10	4	190	43.87	4.33	4.48	113105
4	<0.01	48337	64.28	5	147	50.79	2.89	2.96	138907
5	<0.01	48283	64.79	4	120	61.56	1.95	1.98	36819
6	1.00	48473	45.94	3	111	85.54	1.30	1.31	108969
7	<0.01	48029	0.00	1	100	48.28	2.07	2.10	1825502
8	<0.01	48449	45.65	5	74	33.03	2.24	2.26	80935
9	<0.01	48447	48.17	2	67	2.62	25.55	25.93	7398
10	<0.01	48281	45.67	2	66	28.13	2.35	2.37	64363
11	<0.01	48071	0.00	1	63	17.69	3.56	3.60	37251
12	0.12	48427	0.00	1	50	27.01	1.85	1.86	62648
13	<0.01	48445	48.29	4	46	17.72	2.60	2.61	49986
14	<0.01	48455	0.00	1	43	5.11	8.42	8.49	14405
15	<0.01	48161	0.00	1	43	6.94	6.19	6.24	19586
16	<0.01	48363	0.00	1	37	13.26	2.79	2.81	27921
17	<0.01	48379	0.00	1	35	5.24	6.68	6.72	11037
18	<0.01	48403	30.55	2	27	6.78	3.98	4.00	19135
19	0.02	48345	70.18	8	25	8.64	2.89	2.91	22187
20	<0.01	48229	82.41	2	19	1.99	9.53	9.56	5626
21	<0.01	48193	0.00	1	18	3.93	4.59	4.60	8266

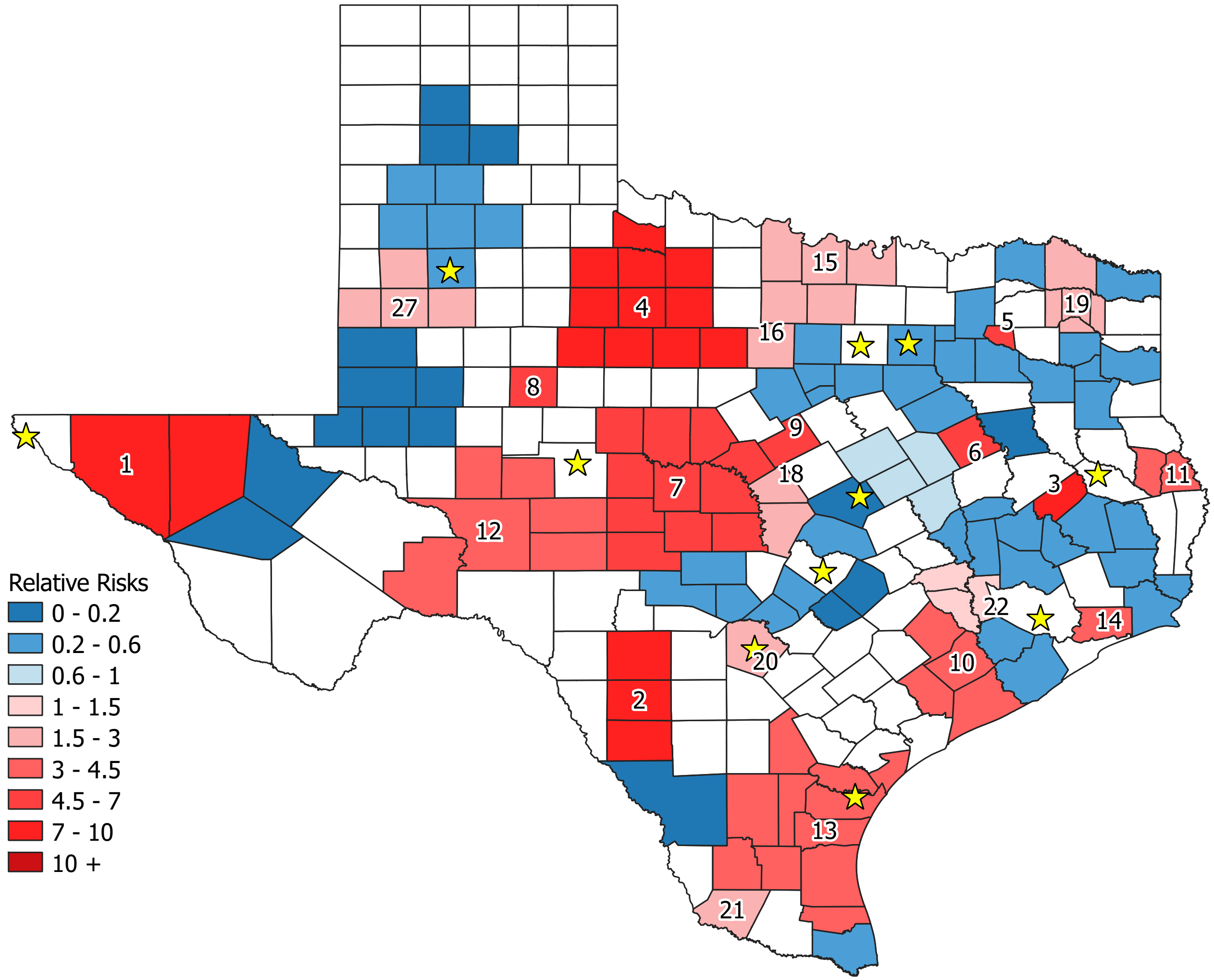

Figure 6. Relative Risk Gini Clusters for Total Hunting Violations against Birds Controlling for Covariates

Covariates are the location quotient manufacturing industries, number of hunting establishments, and structural development.

Table 17. Gini Clusters of High Risk Illegal Hunting Violations Against Birds Controlling for Significant Variables

Cluster #	P-value	Centriod County	Cluster Radius (KM)	Number of Counties in Cluster	Cluster Observations	Expected Observation Count	Ratio of Observed to Expected	Relative Risk Ratio	Cluster Population
1	<0.01	48273	109.24	11	398	109.36	3.64	3.90	574389
2	<0.01	48307	92.09	11	219	39.16	5.59	5.83	109998
3	<0.01	48481	51.10	4	190	43.87	4.33	4.48	113105
4	<0.01	48507	54.61	3	160	17.61	9.08	9.39	49694
5	<0.01	48337	64.28	5	147	50.79	2.89	2.96	138907
6	<0.01	48207	96.79	11	142	19.98	7.11	7.31	54340
7	1	48473	45.94	3	111	85.54	1.30	1.31	108969
8	<0.01	48029	0.00	1	100	48.28	2.07	2.10	1825502
9	<0.01	48449	45.65	5	74	33.03	2.24	2.26	80935
10	<0.01	48281	45.67	2	66	28.13	2.35	2.37	64363
11	<0.01	48071	0.00	1	63	17.69	3.56	3.60	37251
12	0.12	48427	0.00	1	50	27.01	1.85	1.86	62648
13	<0.01	48445	48.29	4	46	17.72	2.60	2.61	49986
14	<0.01	48455	0.00	1	43	5.11	8.42	8.49	14405
15	<0.01	48161	0.00	1	43	6.94	6.19	6.24	19586
16	<0.01	48363	0.00	1	37	13.26	2.79	2.81	27921
17	<0.01	48379	0.00	1	35	5.24	6.68	6.72	11037
18	<0.01	48403	30.55	2	27	6.78	3.98	4.00	19135
19	<0.01	48105	87.23	6	26	6.67	3.90	3.91	17052
20	<0.01	48229	82.41	2	19	1.99	9.53	9.56	5626
21	<0.01	48193	0.00	1	18	3.93	4.59	4.60	8266
22	<0.01	48335	0.00	1	17	3.25	5.23	5.25	9169

Figure 6 (see also Table 17) shows 22 Gini HRC of illegal hunting violations against birds, with clusters 6 and 12 as insignificant. The range of radii in the Gini models was close to the hierarchical clusters, 0 to 109.24 kilometers with 9 clusters contained within a county. Similar to the hierarchical clusters, the Gini clusters capture 2,031 cases – only 173 fewer cases than included within the hierarchical cluster results. These similarities between the two cluster analyses suggest that clusters are robust, but figures show that the shape and size of the clusters differ, meaning that there could be a spatial diffusion effect from these smaller clusters. Additionally, 5 county centroids are different between analyses, suggesting that the centroids of hierarchical clusters were not robust. Overall, the clusters for bird hunting violations seem more robust or reliable than the previous two analyses.

Table 18 presents information on the averages of covariate measures across counties in a given HRC for bird hunting violations. Three covariates were associated with illegal hunting and violations against birds in a linear analysis -- the location quotient of manufacturing industries, the number of hunting establishments, and structural development. The averages of HRC for the location quotient of manufacturing industries ranged from 0.40 to 1.87 with a mean ratio of 0.99. The averages of HRC for the number of hunting establishments ranged from 0 to 6 with a mean number of 0.89. Lastly, the averages of HRC for structural development ranged from 0.31 to 544.52 houses per square mile with a mean of 38.70 houses per square mile. Cross examining these means with the mean of county measures (Table 2), all covariates were similar to means of county measures. The ratio mean of HRC for manufacturing industries was only 0.07 units more than the ratio mean for all counties in the linear analysis, 0.92. The mean of the number of hunting establishments was only 0.09 units more than the mean of counties, 0.80. Lastly, the

Table 18. Averages of County Variable Measurements in Illegal Hunting Violations Against Birds Gini High Risk Clusters

Cluster #	Number of Counties in Cluster	LQ of Manufacturing Industries	# of Hunting Establishments	Structural Development
1	11	0.60	1.18	30.27
2	11	1.03	0.18	6.18
3	4	1.03	6.00	21.17
4	3	0.73	1.67	4.55
5	5	1.31	0.00	13.12
6	11	0.53	0.18	2.77
7	(not significant)			
8	1	0.72	4.00	544.52
9	5	1.28	0.20	21.89
10	2	1.52	0.00	13.72
11	1	1.67	3.00	23.68
12	(not significant)			
13	4	0.62	0.00	5.61
14	1	0.78	0.00	12.58
15	1	0.99	0.00	10.58
16	1	1.87	0.00	16.05
17	1	1.56	0.00	22.97
18	2	0.72	0.00	13.18
19	6	0.40	0.33	0.92
20	2	0.59	0.00	0.31
21	1	1.45	1.00	5.46
22	1	0.43	0.00	4.45
Means		0.99	0.89	38.70

mean of HRC for structural development was only 4.81 houses per square mile less than the mean of counties, 43.51 houses per square mile.

Measures of the LQ of manufacturing industries, number of hunting establishments, and structural density had significant positive linear relationships with illegal hunting violations against birds. When considering these covariates spatially, HRCs had average measures of these covariates. According to linear analyses (Table 7), there should be an average count of observations of illegal hunting against birds for counties; however, the spatial analysis shows that areas with these characteristics have higher than expected counts. These findings suggest, that even though these covariates are associated with the overall distribution of illegal hunting violations against birds, the covariates do not explain the grouping of high-risk counties.

Illegal Fishing Violations Against Aquatic Species High Risk Clusters

Figure 7 illustrates seventeen significant hierarchical HRC for illegal fishing violations controlling for NLPS, structural development, public hunting lands, number of BW, and RTE. Presented in Table 19, all HRC were significant. The radii of clusters ranged from 0 to 95.74 kilometers, with 9 clusters contained within a county. The hierarchical HRC captured 4,482 cases, roughly 37 percent of the total amount of illegal fishing violations against aquatic species (n = 12,103). Figure 8 illustrates nineteen significant Gini HRC for illegal fishing violations. According to Table 20, the radii of clusters ranged from 0 to 85.54 kilometers, with 10 clusters contained within a county. Similar to illegal hunting violations against terrestrial species, Gini clusters captured more cases – in this case,4,856 case, or about 8.3% more cases than identified by the hierarchical cluster analysis. This result suggests that there are smaller clusters that have similarity with other clusters, and that those clusters were not captured by hierarchical clustering.

Table 21 presented the data for the averages of covariate measures across counties in a given HRC. There was a total of five covariates: NLPS, structural development, public hunting lands, number of BW, and RTE. The averages of HRC for NLPS ranged from 2,677 to 228,580 NLPS with a mean of 2,2029.89 NLPS. The averages of HRC for structural development ranged from 5.83 to 51.81 houses per square mile with a mean of 24.30 houses per square mile. The averages of HRC for public hunting lands ranged from 0 to 4.95 percent of land for public

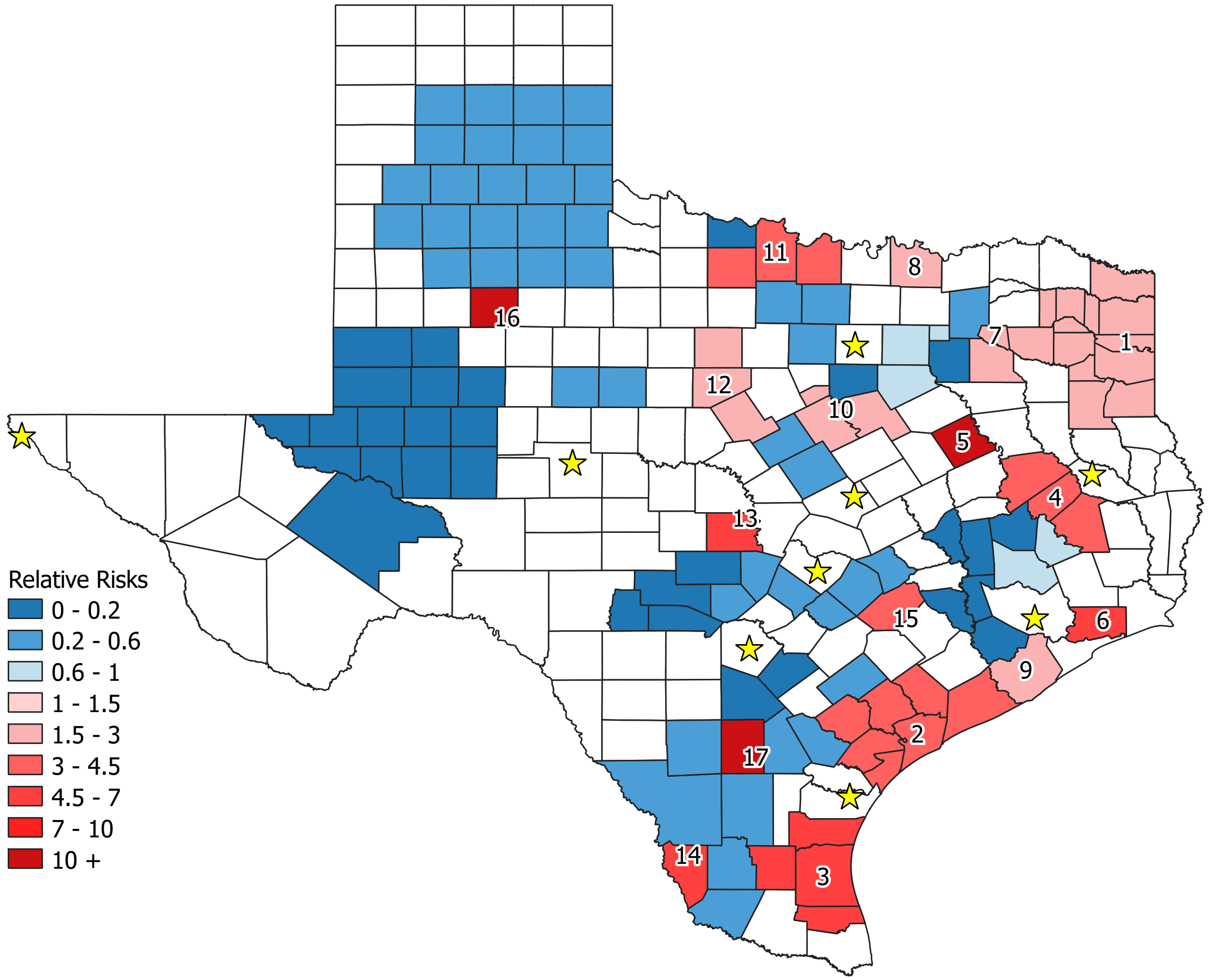

Figure 7. Relative Risk Hierarchical Clusters for Total Fishing Violations Against Aquatic Species Controlling for Covariates

Covariates are the number of hunting and fishing licenses and permits sold, structural development, percent of county that is public hunting land, percent of county that is private hunting land, number of bodies of water, and the number of species listed as rare, threatened, or endangered.

Table 19. Hierarchal Clusters of High Risk Illegal Fishing Violations Against Aquatic Species Control For Significant Variables

Cluster #	P-value	Centriod County	Cluster Radius (KM)	Number of Counties in Cluster	Cluster Observations	Expected Observation Count	Ratio of Observed to Expected	Relative Risk Ratio	Cluster Population
1	<0.01	48315	95.74	13	1109	434.44	2.55	2.71	551859
2	<0.01	48057	78.30	7	1069	285.30	3.75	4.01	201828
3	<0.01	48261	56.72	4	311	68.83	4.52	4.61	61817
4	<0.01	48455	43.93	3	255	71.21	3.58	3.64	83467
5	<0.01	48161	0.00	1	248	16.71	14.84	15.13	19586
6	<0.01	48071	0.00	1	201	31.78	6.32	6.41	37251
7	<0.01	48379	34.28	2	198	103.60	1.91	1.93	63773
8	<0.01	48181	0.00	1	190	104.75	1.81	1.83	122780
9	<0.01	48039	0.00	1	176	106.24	1.66	1.67	331741
10	<0.01	48035	48.38	3	156	52.47	2.97	3.00	61502
11	<0.01	48077	48.07	3	118	32.30	3.65	3.68	38736
12	<0.01	48133	49.33	3	103	35.32	2.92	2.93	41403
13	<0.01	48299	0.00	1	88	16.49	5.34	5.37	19323
14	<0.01	48505	0.00	1	73	12.21	5.98	6.01	14308
15	<0.01	48149	0.00	1	68	21.20	3.21	3.22	24849
16	<0.01	48169	0.00	1	66	5.47	12.07	12.13	6410
17	<0.01	48311	0.00	1	53	0.66	79.85	80.19	778

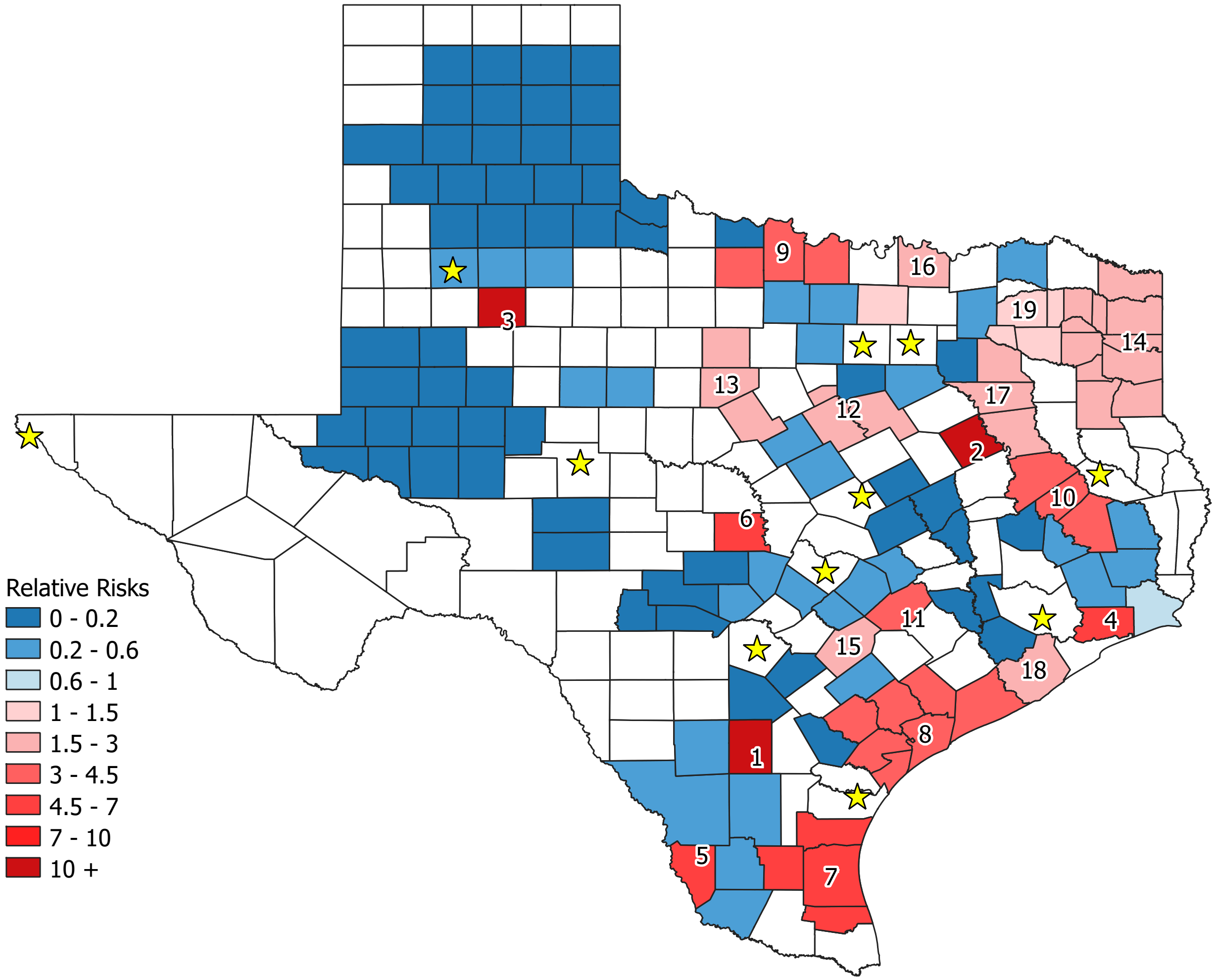

Figure 8. Relative Risk Gini Clusters for Total Fishing Violations Against Aquatic Species Controlling for Covariates

Covariates are the number of hunting and fishing licenses and permits sold, structural density, percent of county that is public hunting land, percent of county that is private hunting land, number of bodies of water, and the number of species listed as rare, threatened, or endangered

Table 20. Gini Clusters of High Risk Illegal Fishing Violations Against Aquatic Species Controlling for Significant Variables

Cluster #	P-value	Centriod County	Cluster Radius (KM)	Number of Counties in Cluster	Cluster Observations	Expected Observation Count	Ratio of Observed to Expected	Relative Risk Ratio	Cluster Population
1	<0.01	48057	78.30	7	1069	285.30	3.75	4.01	201828
2	<0.01	48315	85.54	11	867	331.80	2.61	2.74	498548
3	<0.01	48223	43.76	5	474	326.57	1.45	1.47	831844
4	<0.01	48261	56.72	4	311	68.83	4.52	4.61	61817
5	<0.01	48213	48.18	3	296	174.91	1.69	1.71	189667
6	<0.01	48455	43.93	3	255	71.21	3.58	3.64	83467
7	<0.01	48161	0.00	1	248	16.71	14.84	15.13	19586
8	<0.01	48071	0.00	1	201	31.78	6.32	6.41	37251
9	<0.01	48181	0.00	1	190	104.75	1.81	1.83	122780
10	<0.01	48039	0.00	1	176	106.24	1.66	1.67	331741
11	<0.01	48035	48.38	3	156	52.47	2.97	3.00	61502
12	<0.01	48077	48.07	3	118	32.30	3.65	3.68	38736
13	<0.01	48133	49.33	3	103	35.32	2.92	2.93	41403
14	<0.01	48299	0.00	1	88	16.49	5.34	5.37	19323
15	<0.01	48505	0.00	1	73	12.21	5.98	6.01	14308
16	<0.01	48177	0.00	1	44	17.21	2.56	2.56	20172
17	<0.01	48149	0.00	1	68	21.20	3.21	3.22	24849
18	<0.01	48169	0.00	1	66	5.47	12.07	12.13	6410
19	<0.01	48311	0.00	1	53	0.66	79.85	80.19	778

hunting with a mean of 1.18 percent of land for public hunting. The averages of HRC for the number of BW ranged from 0 to 6 BW with a mean of 3 BW. Lastly, the averages of HRC for RTE ranged from 38 to 85 species with a mean of 59.81 species. Compared to Table 2 with the means of counties, two cluster means differed from the county means while three cluster means were relatively similar to county means. The mean of HRC for NLPS did not differ significantly from the mean of counties, valuing only 3,662.13 more (22,029.89 versus 18,367.76). In contrast, structural development differed from the mean of counties, and was two times greater. The mean of HRC for public hunting lands, BW, and RTE were relatively close to the mean of counties. The mean of HRC for public hunting land was only .22 percent more than the mean of counties for public hunting land, .96 percent of land was dedicated to public hunting. The mean of HRC for the number of BW was only .28 BW less than the mean of counties, 3.32 BW. Lastly, the mean of HRC for RTE have 4.96 more species listed than the mean of counties which listed 55.12 species.

Measures of NLPS, structural development, public hunting lands, number of BW, and RTE all had positive linear associations with the overall distribution of illegal fishing violations (Table 8). When considering these covariates spatially, HRC had lower than average measures of structural development, higher than average measures of NLPS, and average measures of public hunting lands, BW, and RTE. NLPS was the only variable that differed from the mean in the expected positive direction found in linear analyses. Structural development was found to have a positive association, but the measures of HRC are low. These findings suggest, that even though these covariates were associated with the overall distribution of illegal fishing violations across counties, the covariates do not explain the grouping of high-risk counties.

Table 21. Averages of County Variable Measurements in Illegal Fishing Violations Against Aquatic Species Gini High Risk Clusters

Cluster #	Number of Counties in Cluster	NLPS	Structural Development	% Public Hunting Land	# of Bodies of Water	RTE
1	7	28350.71	33.43	0.78	4.14	67.29
2	11	11469.18	42.85	2.20	3.18	50.09
3	5	16496.80	51.81	0.47	3.80	55.00
4	4	13471.25	28.31	0.66	3.25	52.00
5	3	4562.33	5.83	0.00	2.67	76.00
6	3	8505.67	10.27	0.22	3.00	73.67
7	1	3104.00	6.01	1.67	4.00	52.00
8	1	21747.00	49.83	1.03	5.00	75.00
9	1	6395.00	10.89	0.00	4.00	47.00
10	1	2677.00	23.88	4.00	1.00	38.00
11	3	9205.00	19.61	4.95	3.00	50.67
12	3	3495.67	15.90	0.60	3.67	64.33
13	3	6343.33	15.93	1.92	3.00	44.33
14	1	6619.00	28.66	0.00	2.00	49.00
15	1	8674.00	27.16	3.77	2.00	54.00
16	1	228580.00	40.68	0.07	6.00	73.00
17	1	14131.00	12.02	0.10	0.00	85.00
18	1	20133.00	32.45	0.00	4.00	60.00
19	1	4608.00	6.24	0.00	0.00	70.00
Means		22029.89	24.30	1.18	3.04	59.81

* = found to be significant in linear analyses

NLPS = Number of Hunting and Fishing Lisences and Permits Sold

RTE = Number of Species Listed as Rare, Threatened, and Endangered

Summary of Results

Four spatial analyses were conducted for the four measures of IH&F violations (i.e., total IH&F; animal hunting violations; bird hunting violations; and fishing violations). The spatial analysis controlled for the results from the linear analysis to map the spatial locations of areas with higher-than-expected areas of violations (i.e., violation hotspots). Multiple clusters were found to be significantly different than the county means, suggesting that counties with higher-than-average IH&F violations, when controlling for covariates, are not grouped by random chance. Clusters were compared using hierarchical and Gini clustering methods. These results indicated that the two methods did not produce the same outcomes. In most cases, the Gini derived clusters were smaller and more refined but contained fewer cases. The hierarchical methods, therefore, appears better suited for discovering a larger number of violations but does so by including more geographic area within the cluster scope. Thus, with respect to implementation of "rational" policies that are more target focused and potentially less resource intensive, the Gini models would appear to provide a preferred outcome.

CHAPTER 7:

DISCUSSION AND CONCLUSION

The goal of this disseration was to examine whether concepts and variables drawn from Treadmill of Production (ToP) theory could help explain the distribution of illegal hunting and fishing (IH&F) violations across Texas. The current chapter begins with a summary and discussion of the findings. These are also explored in sections that focus attention on the two primary analyses, the linear analysis and the spatial analysis. This chapter also addresses the policy implications of these findings, and the limitations of the current study.

Discussion of Results

Findings in the analyses suggest that the economic structure does affect with IH&F in Texas, supporting ToP arguments. It should be noted, however, that the results are not persistent or consistent across all hypotheses tests, and vary depending on how the dependent variable was measures (see Table 9). These inconsistencies make it difficult to provide a clear and convincing conclusion concerning the utility of ToP theory with respect to attempts to use this theory to explain IH&F crimes. Moreover, results from the linear analysis and the geographic analysis, while related, provided unique insights into the use of ToP analysis in Texas. Accordingly, results from the linear and geographic analysis are discussed separately below.

Linear Analyses

First, in the linear analyses, the majority of the results supported only Hypothesis 5, and showed that the number of hunting and fishing licenses and permits sold (NLPS) was positively associated with IH&F violations across counties in Texas. This finding supported the observation in ToP theory which argued that the state can operate in ways that facilitates the expansion of economic activity. In this case, the state may be contributing to the expansion of the hunting and fishing portions of the economy by licensing hunters to engage in those activities.

All other analyses found that NLPS significantly associated with other forms of IH&F. Surprisingly, NLPS had a larger effect than traditional ToP measures. It would be reasonable to suggest that the increase of consumerism in the hunting industry would lead to an increase in IH&F; however, the issue of causality was not addressed. Instead, this finding could be interpreted relative to the cultural setting of the economic structure surrounding a given hunting and fishing location, as, perhaps, was evident in the geographic analysis. The problem of illegal hunting and fishing persists in areas where the is more consumption of the commodities or resources supplied by the hunting industry. This is consistent with Jacoby's (2003) historical analysis of illegal hunting in the United States of America (USA) reviewed in chapter 3. Recall that Jacoby (2003) argued that illegal hunting occurred in areas where hunting and fishing was prevalent before the growth of conservation efforts in response to the growing MI.

Second, the results also estimated the impact of the hunting industry on IH&F violations. In a previous chapter, it was argued that the hunting industry could be interpreted as being a dimension of economic activity in conflict with other industries of the ToP when analyzing IH&F. With respect to the ToP-hunting establishment IH&F connection, the results indicated that the number of hunting establishments in a county were associated only to illegal hunting violations against birds. While this finding provides some support for a modified ToP theory that includes hunting establishment effects with respect to one form of IH&F, it does not rule out the possibility that other economic measures of hunting or fishing consumerism may be useful for describing the effect of the treadmill of hunting industries on IH&F.

Third, traditional measures of the ToP were not found to relate consistently to measures of illegal hunting or fishing violations. Instead, measures of the resource mining industry (MI) and measures of ecological modification had more persistent associations on the dependent variables. This would follow historical accounts of MI and urbanization slowly encroaching on undeveloped land used for hunting and fishing (Jacoby, 2003). Consistent with that argument, the analysis found a negative relationship between MI and IH&F, so that as the volume of land associated with mining increased, the number of IH&F violations decreased. Related to this finding, Eliason (2020) and Jacoby (2003), however, have argued that the privatization of land for businesses and industry hurt the ability of the general public to hunt freely, and that this would be expected to increase illegal hunting and fishing. Interestingly, the association between IH&F and the MI disappeared when other economic or geographical factors were included. While this would suggest the association was spurious, other factors included in the model could be mediating the association. It could be that the association of MI is conditional upon the presence of other variables and vice versa. In other words, both the mediating factors and MI may need to be present to express the association between the economic structure and IH&F. Finally, since the analysis examined a specific timeframe, temporal order was not established. The lack of temporal ordering is important to understand the analysis. Areas with a higher concentration of MI establishments exhibit lower counts of illegal hunting and fishing, but this does not contradict Jacoby (2003). Jacoby (2003) and Eliason (2020) did not determine illegal hunting directly occurred in areas where MI industries were established. No spatial analyses were implemented.

In regards to the Gross Domestic Product (GDP) per capita and manufacturing industries, associations were significant only in regards to violations against land and bird animals. Traditional ToP variables do not seem to have uniform associations. The GDP per capita only associated with illegal hunting against land animals, and opposite of the hypothesized direction. Manufacturing industries were only positively associated with illegal hunting against birds, supporting Hypothesis 2. Though the GDP per capita did not support the intended direction, this association does reflect some literature finding a negative relationship between the relative economic size of areas on environmental health, particularly with respect to mammal and bird species richness on a global level (Shandra et al., 2010; Shandra et al., 2009). It could be assumed that overall economic growth is positively associated with IH&F in general, but when focusing on the locations of IH&F, particularly against land animals, these forms of environmental harm occur away from wealthier areas. Lynch et al. (2019) described this relationship between urban and rural areas where resources are extracted from poorer areas to supply the wealthier areas. Future research should determine who is hunting in different areas, and should examine if those hunters reside in urban areas. This may explain other aspects of illegal hunting against land animals.

Manufacturing industries seem to only be associated with illegal hunting against birds. This finding parallels McKinney et al. (2009) research, which found support of the ToP relating the bird species richness; however, McKinney et al. (2009) examined the GDP of countries instead of manufacturing industries within counties. As discussed above, different measures of the ToP may associate differently on different levels of analyses. These findings would suggest that smaller levels of analyses need more refined measures of the ToP, because the ToP is not distributed evenly across space as discussed in Lynch et al. (2019) in their discussion of metabolic rift, which argued that resources are unevenly extracted and processed across ecosystems causing certain ecosystem to lose the ability to replenish themselves. Supporting this concept of the metabolic rift, basic statistics (Table 2) showed that the manufacturing industries and MI have a large variation and abnormal distribution. Therefore, using overarching measures of the ToP at smaller levels are not necessarily appropriate when examining the location of environmental harms, and better, more localized indicators of the ToP may need to be developed for more disaggregated analyses.

The association between IH&F and ecological modifications, mainly the measure of structural development, were resilient through the analyses, even though the direction of the association occasionally changed directions. This change in directions would indicate that ecological modifications have different contextual effects depending on the type of illegal hunting or fishing violations examined. For instance, structural development and agricultural development had a negative association with violations against land animals. It is reasonable to conclude that modifying the environment for humans decreases the volume of habitat for animals, perhaps decreasing the opportunity to hunt illegally. In contrast, in regards to violations against bird and fish, structural development had a positive association. Though speculative, it could be argued that unlike land animals, bird and fish can easily migrate through urban counties, exposing these animals to illegal hunting in more locations.

Lastly, the more prevalent effects for control variables in the study were found for the number of species listed as rare, threatened, or endangered (RTE), the number of bodies of water

(BW), and the percentage of county land dedicated for public hunting. The only time these variables did not explain the linear distribution of IH&F violations was the analyses of illegal hunting against birds (Table 7). To further support the idea of a mediating effect of economic variables, both RTE and BW were significant in the full model (model 8) for the total violations and for violations against land animal analyses, but lost significance in the reduced models (model 9). Thus, the significance of these variable appeared only when certain variables are present in the analysis. The only exception is illegal fishing against aquatic species when all three geographic-opportunity variables were significant in the reduce models. Thus, it appears that geographic opportunities only mediate the association of the economic structure for certain measures and approaches to IH&F.

The varying associations with geographical opportunity variables and different IH&F violations, intuitively makes sense. If you compare the victims examined in each analysis, certain geographical variables must be present in order for illegal activity to occur. With land animals, this would not be the case, because land animals migrate through different ecosystems; however, access to water ways and bodies are the only means to encounter aquatic species. The Texas Park and Wildlife Department website has a list of public hunting land, all showing some access to a body of water. Thus, it should be expected that public hunting land would associate with illegal fishing. Still, more research is needed to determine the extent of these mediating variables.

Spatial Analyses

When considering the linear associations spatially, spatial analysis indicated that counties with low-risk ratios focused around metropolitan and law enforcement headquarter cities, while high-risk counties were located away from cities (see Table 5). This may indicate a metabolic rift Foster (1999) discussed as an outcome from the ToP. The metabolic rift assumes that nature is geographically distributed in specific ways, and is extracted unevenly in distant areas (i.e., rural locations) to support larger, populated areas (i.e., urban areas). The top nine counties in terms of the number of hunting and fishing licenses and permits sold (NLPS) included Harris, Travis, Galveston, Victoria, and Bexar, Tarrant, Nueces, Jefferson, and Cameron county. With the expectation of Jefferson, most of these counties contain a metropolitan or micropolitan city. The remaining 9 counties contain 45 percent of NLPS, with the remaining 55 percent of licenses spread across the other 245 counties. Thus, it can be assumed, in conjunction with ecological modifications limiting species richness in urban counties**,** these 9 counties are hunting and fishing animals at a much higher rate, limiting the opportunity for residents in other counties to legally hunt. This finding is consistent with following Fine's (2000) discussion of the automobile mobilizing urban dwellers access hunting opportunities. Unfortunately, travel data for this activity is not available to confirm.

The most apparent concern with the spatial analyses was lack of explanation of high-risk clusters (HRC) from variables found to be significantly associated with IH&F in the linear analyses. Examining the characteristics of the high-risk clusters (Tables 12, 15., 18, and 21), cluster co-variates had signs in the opposite direction of those found in the linear regression analysis. While it could be argued that high-risk counties cluster around these variables in the opposed direction, these measures do not explain why the observed count is higher than expected. Insignificant variables were not reported, but further analyses should examine these insignificant variables from the linear analyses and determine if these variables explain the clustering of the high-risk clusters. Here, Jacoby's (2003) historical account of MI industries may provide some insight. During the height of the lumber industry in the late 19th century, conservation efforts were made to compensate the loss of natural resources by the industry, particularly around mining areas. As conservation efforts increased, the opportunity to legally hunt and fish decreased around these areas. Examining linear analyses again, MI industries were significant, only to lose significance when other variables were added. It could be that the variable initially related to the distribution of IH&F due to the clustering of these violations. Further analyses are needed to determine the reason why high-risk counties are clusters together.

The last detail was the visual spatial distribution of different IH&F activity. Many high-risk clusters (HRC) and clusters for illegal hunting against land animals were heavily concentrated in mid to west Texas with some areas throughout east Texas. HRCs and counties for illegal hunting against birds at first seemed similar to the spatial distribution of illegal hunting against land animals, but the clusters were not as large. Additionally, these clusters expanded all the way to the western and southern tip of Texas. The HRC and counties for illegal fishing aquatic species deviated from the others, with these clusters concentrated along the Texas coastal bend and east Texas. This should not be unexpected, as the opportunity for illegal fishing would be more prevalent in areas where there are high concentrations of water. Overall, these results are similar to those found by Crow et al. (2013), who also found that levels of IH&F activity are not uniform across geographical locations.

Theoretical Implications

The findings have two main implications for the economic structure, particularly around the ToP theory and the environment. First, not all measures of the ToP explain harmful behaviors to environmental. Both the GDP per capita and manufacturing industries associated differently with IH&F, and their effects varied depending on the measure of IH&F employed. This would indicate that the different parts of the economic structure contribute differently to specific types of IH&F. This differential effect may occur through the ways in which the ToP and geography interact and relate to the formation of social space. Though geographical Marxist have discussed how the ToP creates social space to support the ToP (see Peet, 1966), the economic structure is not commonly discussed as affecting the social space for green crimes within criminology.

One could argue that MI industries should be considered a measure of ecological withdrawals, as has been argued in PEG-C research (Lynch et al., 2019; 2017), and that, in that view, MI should diminish the opportunity for IH&F through adverse ecological impacts such as destruction of ecosystems or their destabilization and segmentation. MI was found to have initial significant relationships with all measures of IH&F. Though the study found the initial association of MI industries with IH&F to be spurious or perhaps mediated by other ecological outcomes, manufacturing industries did not have consistent support as a measure of ecological withdrawals. It is also important to understand that the environmental harm captured by this study was not pollution or quality of an ecosystem, which are often the focus of green criminological studies drawing on political economic and ToP theory, but rather focused on crimes affecting animals. Calls for green criminological research mainly focuses around environmental harms which threaten ecosystem health more generally (e.g., land, water, air pollution). As noted earlier in this dissertation, green criminologists have not widely studied crimes against wildlife, nor have they, in particular, applied ToP theory to efforts to neither explain nor empirically model wildlife crime. As this dissertation's results illustrate, the associations of the ToP on IF&H violations were inconsistent. This suggests that ToP theory may not be the best way to explain IH&F violations, and that IH&F violations may be quite different that the kinds of environmental crime that ToP theory has been used to explain.

With respect to the above, it is also important to consider that there is perhaps dimension of the treadmill of production that are important to explaining IH&F violations that are not normally incorporated into ToP explanations. One of the concepts that demonstrated a persistent effect on IH&F was ecological modifications – which included measures such as miles of roadways, physical building construction, and agricultural land. As argued in an earlier chapter, these kinds of ecological modification can be seen as important to expanding the treadmill of production, and supporting economic activity. Roadways, for example, provide the means to move commodities and raw materials. Often, the building of roadways to support economic activity outweighs the effect of that activity on ecosystems or wildlife, and those roadways can segment ecosystems, diminish wildlife habitat, and affect the opportunity for hunting and fishing, including illegal hunting and fishing.

Previous ToP relevant PEG-C theory and research has overlooked modifications to ecosystem as an extension of the influence of the ToP, and as a central component of how the ToP develops, and perhaps also developed differentially across geographic locations. Though PEG-C research has discussed habitat destruction for development, (Lynch, Long, and Stretesky, 2015), the discussion has yet to connect development as a variable to be used in discussions of ecological disorganization in PEG-C research. The present analyses found that illegal hunting against terrestrial species occur away from ecological modifications, which one could argue tend to replaces natural habitats with a human friendly ecosystem. Illegal hunting against birds and illegal fishing aquatic species increased in areas with ecological modifications, perhaps by increasing access to those areas. In addition, it is also likely that the ecosystems for birds, aquatic species, and humans overlap more so than does the space occupied by land species that are hunted, meaning that there is more interaction among the human population with birds and aquatic species, and more opportunities to illegally acquire fish and birds. The context of ecological modifications, in other words, may help explain human-animal conflict in a spatial dimension. That is an important consideration given that the spatial analyses indicated that IH&F was distributed in specific ecological ways. Additional research is needed to determine the proper measurements of ecological modifications, relevant to the environmental harm in question.

Policy Implications

Since the current disseration is exploratory, policy implications are rudimentary, especially since the study is cross-sectional and lacking temporal ordering. Though the economic structure is argued to create social spaces, changing the economic structure with the goal of changing individual behavior is often seen as involving an ecological fallacy, and one can argue, that in such an approach, human agency would be ignored. Many social theorists, from Marx through more contemporary analysts such as C. Wright Mills, address the effects of social structure on human behavior. Mills is well recognized for arguing that history (i.e., social structure) and biography (i.e., the life course of the acting individual) intersect. Other contemporary theorists such as Anthony Giddens (e.g., in his theory of structuration, Giddens, 1984), and Pierre Bourdieu (e.g., in his theory, praxeology, Bourdieu, 1984), address the interaction of social structure and agency. Thus, many social theorists would disagree that adopting a structural view requires abandoning efforts to consider agency. How exactly one would translate the implications of ToP theory into a perspective that considers agency is challenging, but has been addressed in various works (e.g. Bunker, 2005; Gould, 2004). Given the complex nature of such arguments, it is beyond the scope of this brief analysis on policy implications to extract a theory of ToP-agency interaction.

On the policy front, it can be argued that the most important implications of this dissertation come from the spatial analyses (chapter 6). While the linear analyses suggest that certain aspects of the economic structure should be the target of policies because they are the best empirical predictors, controlling for those effects, the spatial analysis indicated the existence of high-risk clusters. Cluster maps indicate places where IH&F is elevated geographically, and the count of IH&F crimes in the extracted areas exceed the mean. Since the maps indicate places where IH&F exceed the mean, one can argue that the maps can be used to inform the use of targeted policies designed to control IH&F. That is to say, rather than create IH&F control policies and then apply them statewide, the cluster maps suggest that IH&F crimes are concentrated in certain locations, and that, therefore, targeting those locations with IH&F control polices makes the greatest sense or might have the greatest impact. In addition, the clusters maps can be used to address whether separate IH&F polices are needed for different species, because IH&F violation maps vary for mammals, birds, and fish. This result is easily demonstrated in the cluster maps, and may suggest that different IH&F polices would be more or less useful in different locations depending on which particular IH&F violation is more prevalent in a cluster.

The cluster maps draw attention to locations where there is an excessive concentration of IH&F crimes in Texas, and may, in this way, also be drawing attention to the fact that in some locations there are "contextual" factors affecting effecting the distribution and concentration of IH&F crimes. That finding is consistent with the approach taken within conservation criminology, which attempts to identify how a content affects environmental crime (Moreto and

Pires, 2018). Thus, PEG-C research should have follow-up case studies of "troubled areas" for policy implications after geographically analyzing the distribution of the economic structure.

Two policies at enforcement and legislative levels can be pursued to address illegal hunting and fishing across Texas. First, law enforcement should be concentrated around areas with higher risk of illegal hunting or fishing; however, allocation should be based on the type of illegal hunting enforcement wants to target. For example, if there is a concern of overhunting of white-tail deer and other terrestrial species, law enforcement agencies should focus manpower and resources for patrols or operations based on the means of illegal hunting such as tools used, time illegal hunting occurs, and more, while other areas have average enforcement operations; however, while increasing resources to high-risk areas can be done, the policies do not target the problem contributing to the problem with illegal hunting. Second and therefore, the state governor should work with county government to enact policies to either regulate to change the economic structure around hunting. From discussions above, the economic structure can create social space for illegal hunting when an economic hunting culture is present. As well, illegal hunting seems to occur in areas where there is less species richness. Policies could focus on allocating more land for hunting and encouraging conservation to push back against industries restricting land and destroying habitats through development. Following Eliason (2020) and Jacoby (2003), government buying land for the public trust helps alleviate the economic control of industries in conflict with hunting and conservation. Unfortunately, conservation is expensive for the government and could be privatized to independent land buyers when finances are low (Jacoby, 2003). Thus, the state and county governments must consider the economic upkeep of conservation and make it profitable for private land owners and government operations.

Limitations

As with all studies, this study is not without its limitations. Those limitations could affect the results of this study, which would affect the finding, conclusions and policy implications that can be drawn from this research. As with all criminological research, care should be taken not to generalize these results, since they are based on studying IH&F crimes across counties in Texas.

The first and major limitation of the dissertation is the cross-sectional nature of the study. Cross sectional studies are useful for capturing snapshots of associations between dependent and independent variables and easier to conduct than longitudinal studies (Menard, 2002). Some scholars argue that longitudinal studies may not be needed to study structure, since structure does not drastically change over time (Brush, 2007; Butchart & Engrom, 2002). The theoretical framework of the Treadmill of Production (ToP), however, does suggest the need for a longitudinal study, since within criminology, this approach argues that economic change and trends explains the rise of or distribution of environmental crimes and harms (Lynch et al., 2017). For example, Long, Lynch and Stretesky (2018) employed time-series production and pollution output data to assess the relationship between the expansion and contraction of the US economy before, during and after the "Great Recession" on the emission of pollutants. The results show that the recession, which slowed the treadmill of production, lead to reduced pollution emission during the recession, follow by a return of rising levels of pollution following the recession and a return to expanded ToP economic activity. Given the cross-sectional nature of the data used in this dissertation, this time effect was not able to be assessed. It is possible that the relationships examined here may not produce the same results if assessed over time.

Another limitation would be the measures of the ToP. Unlike traditional measures, such as accounts of pollution or habitat destruction (e.g. Lynch, 2019; Barrett, 2017; and Stretesky and Lynch, 2011), the current study examines the presence of industries related to the ToP. In general, the ToP is described theoretically, as a structure, and direct measures of the ToP have not been offered in the literature. In those approaches, the ToP is described as a national and international structure that emerged following WWII. In the current study, the focus was at the county level. To date, there have been no empirical studies that attempt, to my knowledge, to employ measures of the ToP at the county level. Thus, in the current study, county level measures of the ToP were inferred from the theoretical work describing the components of the ToP (see Chapter 3, section ecological withdrawals for details). To be sure, these measurements can be seen as proxy measures of the behavior of the economic structure described in ToP theory. It would therefore be improper to conclude that the behavior of the economic structure at the county level is perfectly reflected by the measures employed in this study. Thus, the results may reflect the nature of the measures used in this study to measure the various dimensions of the ToP.

In addition, though it is assumed the method appropriately models the outcome, there is no guarantee that the empirical results from the linear analyses reflect the behavior of the economic structure, nor that they constitute the best empirical model for predicting the outcome, IH&F. It is likely, for example, that there were omitted variables, and that their inclusion could impact the results. Also, again because the ToP measure does not occur over time, the cross-sectional method does not necessarily describe the behavior of the economic structure as it might unfold if time were included in the analysis. Finally, it is also possible that within counties, the ToP behaves differently overtime, and that this change in county-specific economic change has not been captured in the current study.

It should also be noted that the data and analysis is limited to Texas, and thus cannot be generalized to other states. Additional research in other states or across states is needed before any generalized implications of the current study could be made. Additionally, only linear associations were examined in the current analyses. It is possible that there are curvilinear relationships that should be explored. There are some theoretical indications that would support the need for additional exploration of these data using other procedures. For instance, PEG-C suggests that mass production creates an exponential use of natural resources (Lynch et al., 2019; Lynch et al., 2017; Stretesky, Long, and Lynch, 2013). If this description is accurate, it may suggest that the ToP models should be assessed using some kind of growth modeling.

With these limitations in mind, the discussion of the results presented above below should be taken as constituting an initial contribution to assessing the applicability of PEG-C to the potential explanation of IH&F, but not as the final word on this matter. As noted in this research, prior studies in PEG-C criminology have not addressed IH&F crimes, nor have they attempted to predict these crimes using either linear or spatial analysis. Thus, while these results have limitation, they mark a unique step in the application of PEG-C theory and research.

Future Research

In addition to the limitations of the study, there are some other means that can be proposed to explore these data for future research. First, political factors may also be involved with the distribution of illegal hunting and fishing. For instance, factors such as the politics of law enforcement, jurisdiction, or community political affiliation and beliefs may play into the distribution of illegal hunting and fishing. For example, it is possible that county-level party affiliation might be associated with either the enforcement of IH&F violations, or the propensity to engage in IH&F. Given that these data represent reports from the enforcement of Texas Parks and Wildlife laws by state officers, variations in the counts of state police are not expected to be associated with the outcome. It is possible, however, that these outcomes might be the result of the distribution of State wildlife enforcement officers across counties. Second, longitudinal studies should be pursued to further assess the potential casual relationships between variables. It is possible that the results of the cross-county models would different from results obtained by tracing those counties across time and space, or by tracking a particular county over time. In addition, Treadmill of Production theory implies the existence of structural processes that develop and change over time. Thus, a more approximate test of ToP theory would require a longitudinal study of illegal hunting and fishing to determine whether the change in the economy changes the distribution of illegal hunting and fishing over time. Third, the methodology of the study should also be conducted in other states to determine whether the economy behaves similarly for other forms and definitions of illegal hunting and fishing by the state. As discussed in Lynch et al. (2018), states have jurisdiction over most wildlife conservation and law enforcement. Therefore, applying studying other locations may produce different results. Moreover, testing for differences in these results across states would also discover whether there appear to be any situational characteristics or structures within states that affect IH&F. Such results would be consistent with the results found in the conservation criminology literature. Fourthly, future research should explore whether other structural correlates such as those associated with street crime also explain the distribution of IH&F across locations. These studies are needed to determine whether the factors affecting IH&F are different from those affecting street crimes. In doing so, these studies should explore more traditional criminological theories that have been argued to explain crimes against the environment. Agnew (2012) argued that strained pressure people into harming the environment, given certain situations. These studies are needed to determine whether general theories of crime can explain any form of crime or challenge our knowledge on the correlates of crime.

Conclusion

Building on political economic green criminology, treadmill of production theory, and drawing also from conservation criminology, this dissertation argued that the economic structure might be useful for understand IH&F violations. In chapter 2, previous literature discussed three approaches that explain wildlife crimes, conservation criminology, PEG-C, and social factors. The vast majority of research to date addressing wildlife crime has been derived from conservation criminology, which focuses attention on examining the context surrounding those crimes, and includes discussions of the structural opportunity for those crimes. In contrast to the kind of situational approach taken in conservation criminology, PEG-C argues that any form of environmental harm or criminal act can be explained by the organization and impact of the larger economic structure. Unfortunately, studies focusing on illegal hunting in the USA mainly employed social factors as an explanation. Here again, however, little quantitative analyses have been applied to determine the extent of the effect of social factors as the correlates of IH&F. The current disseration examines these approaches to analyses IH&F violation across space (i.e. counties), focusing on an economic structural explanation (i.e. ToP theory) while controlling for other explanations noted above.

The study found that the economic structure is associated with some kinds of IH&F violations, but that the associations vary depending on the victim (i.e., the kind of wildlife being illegally taken) of IH&F violations. Additionally, geographical opportunity factors also were also found to be relevant to the distribution of IH&F violations; however, these factors were argued to mediate the association of the economic structure. More research is needed to address these findings. Lastly, no significant associations were found for the association between social factors and IH&F in this study.

Drawing on these findings, a few points were highlighted to further theory and policy. First, ecological modifications (e.g., roadway volume and physical development of buildings) should be included in ToP theoretical framework as a variable that affects local ecosystem. These modifications may improve access to certain locations, increasing the ability to hunt or fish illegally, or they may also reduce the opportunity for IH&F by segmenting or destroying ecosystems through forms of ecological disorganization induced by the needs of the ToP to, for example, ship products. Second, ToP research should explore other measure of the means of production such as measures of the MI which may better capture ecological withdrawals. Third, the spatial analysis indicated that policy needs to consider the varying associations of the economic structure across geographic locations, and avoid the use of uniform policies to protect wildlife from IH&F.

In sum, this research indicates that some IH&F violations have an association with indicators measuring economic structure. This is an area of research that has largely been overlooked within criminology generally, but within the illegal hunting literature in particular. Thus, these results suggest that future illegal hunting research should focus on attention on economic explanations and the effect of economic variables on IH&F in order to develop a more complete understanding of the covariates of illegal hunting and fishing.

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