

THE ILLICIT METHAMPHETAMINE LANDSCAPE OF
FRANKLIN COUNTY, MISSOURI:
APPLICATION AND ANALYSIS OF
A GIS-BASED RISK ASSESSMENT MODEL

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by
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The undersigned, appointed by the Dean of the Graduate School, have examined the thesis entitled

THE ILLICIT METHAMPHETAMINE LANDSCAPE OF
FRANKLIN COUNTY, MISSOURI:
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A GIS-BASED RISK ASSESSMENT MODEL

Presented by Lloyd E. Weber

A candidate for the degree Master of Arts

And hereby certify that in their opinion it is worthy of acceptance.

Dr. Gail Ludwig

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Dr. John Galliher

IN MEMORIAM

This work is dedicated to the memories of

My late step-father

Ned L. Freeman
1942 – 2004

&

My late grandfather

Lloyd D. (“L.D.”) Worthington
1924 - 2005

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CHAPTER 1

INTRODUCTION

Missouri has the unfortunate distinction of having led the United States in clandestine methamphetamine lab seizures each year since 2001 (DEA, 2005) in both per capita seizures and total number of labs seized. A nation-wide survey concluded that methamphetamine, often referred to as “meth”, is perceived by law enforcement agencies to be their respective counties’ greatest drug problem; greater than that of cocaine, marijuana and heroin combined (NACo, 2005). For Missouri, because of its significant nation-wide lead in manufacturing statistics (MSHP, 2004; DEA 2005), this perception is a reality.

Why would a human being intentionally ingest a potion that requires in its creation antifreeze, liquid drain cleaner, anhydrous ammonia, battery acid and other lethal materials? The answers lie in the relative ease of production and procurement of methamphetamine and the physiological addiction process that begins to take place with the first use of the drug.

Methamphetamine is a highly addictive synthetic stimulant that immediately increases the activity of the central nervous system, whether through injection, eating or inhalation (smoking). The body’s pleasure chemical, dopamine, is released *en masse* during the methamphetamine-induced stimulation. Normally an enzyme would break down and absorb excess dopamine to keep the brain in chemical balance, but methamphetamine blocks this enzyme allowing for dopamine to dominate and a “high” to be prolonged for, in some instances, hours (Murray, 1998).

The manufacturing of methamphetamine can be traced to a Japanese chemist's laboratory shortly after the turn of the 20th century (Prah, 2005). Methamphetamine production was commercialized and the drug prescribed under a variety of brand names for physical ailments that included asthma, obesity and fatigue. World War II militaries distributed methamphetamine to their soldiers in an effort to increase alertness among their fighting forces. Methamphetamine continues to be commercially produced in the United States under the trade names Desoxyn® and Methampex® and is prescribed as a treatment for attention deficit disorder. The clandestine manufacturing of meth overshadows the legitimate use of the stimulant and is a concern for many communities.

Illicit methamphetamine is often “cooked” in a house, a field or even a moving vehicle from easily available recipes with chemicals that can be found at discount stores, hardware stores and pharmacies. Meth cannot be manufactured without ephedrine or pseudoephedrine (the active ingredient in many cold and allergy medicines). It is for this reason that many states have enacted legislation controlling and limiting the distribution of this vital ingredient.

The consequences of using methamphetamine include debilitating physical, behavioral and psychological problems (Falkowski, 2004; Zweben *et al.*, 2004). Addicts of methamphetamine become prisoners of their own addiction. During long-term use and addiction, meth will no longer induce a “high” and the addict will no longer feel the euphoria that was experienced in the beginning of the addiction cycle. Paranoia and severe depression overtake the meth addict. Personal hygiene is often neglected and the results are not attractive; thinning hair, sunken cheeks, pale skin, severe degradation of

teeth structure, and body lesions are just a few outward physical maladies that are a consequence of a deep meth addiction.

The highly addictive property of meth is good news for the “cooks” of the illicit drug as it creates strong demand. Running a meth lab can be a profitable business as the meth made with \$100.00 worth of materials can be sold on the street for \$1000.00 (Kraman, 2004). This potential profit is coupled with a great risk, since the clandestine manufacturing process is a highly volatile activity. Chemical leaks and spills, inhalation of toxic fumes, explosions and fires are risks in the making of meth. Survivors of these fires may wish they had died rather than go through the painful recovery from severe burns and the psychological damage of disfigurement.

Methamphetamine use and manufacturing have negative affects that extend beyond the user or the cook. Children who live in housing units that are used for meth related activity are often neglected, abused and suffer chronic physical ailments due to exposure to chemicals used in the manufacturing of methamphetamine (Hohman *et al.*, 2004). Chemical waste produced as a by-product of meth manufacturing causes harm to the immediately surrounding physical environment of the lab (Vandeveld, 2004). Law enforcement and other emergency responders have developed upper-respiratory problems due to the inhalation of meth manufacturing-related toxic fumes (Hargreaves, 2002). The surrounding economic environment is negatively impacted as employers lose significant income due to methamphetamine use by their employees (Sam M. Walton College of Business, 2004).

Other popular drugs such as cocaine, heroin and marijuana fall behind methamphetamine as a threat to communities (NACo, 2005). Meth is a much cheaper

drug to make and buy and, according to some accounts, provides a more intense “high” giving credence to the slang term “poor man’s cocaine”. Cocaine, heroin and marijuana require a more labor intensive process in their manufacturing than meth. Cocaine and heroin are derived from plants that are not indigenous to Missouri and therefore large overhead is expended to get these drugs to a user in this state. Marijuana plants can be successfully grown in Missouri, but are not as easily concealable as the meth manufacturing process. Cultivation, processing and transporting add costs and risks to cocaine, heroin and marijuana trafficking. Methamphetamine is able to reach its market faster and cheaper due to low overhead and a streamlined process of manufacturing.

Methamphetamine manufacturing and use has geographical underpinnings. The making of methamphetamine can be tied to physical geography as the location of a clandestine meth lab is often a function of the surrounding land use/ land cover (LULC). The term “clandestine lab” is a reflection of the physical geography that is most attractive to the meth manufacturing process. Dense vegetation and non-urban areas are LULC signatures that may indicate an enticing physical landscape for the manufacturing of illicit methamphetamine. The use of illicit methamphetamine is related to human geography. The human geographic characteristics of an area afflicted with methamphetamine abuse have been established through prior research. The demographic profile generally trends towards the impoverished and undereducated (Kraman, 2004). Additional research conducted in the Midwestern region of the United States has shown the demographic profile can be expanded to include Caucasians in their mid-twenties. (Illinois State Police, 1999; NIJ, 2000; Kraman, 2004).

The physical and human geographies of rural areas are attractive for the making of methamphetamine. The sights and smells of meth manufacturing are concealed more easily in a rural landscape. The demographics of rural areas often exhibit many of the risk factors associated with meth production and use, including elevated rates of unemployment, poverty and lower levels of education (Illinois State Police, 1999; NIJ, 2000).

Spatial modeling has proven to be a useful tool in documenting and analyzing various social and environmental problems (Dahlbäck, 1998; Groff and La Vigne, 2001; Heitgerd, 2001). Since these models are only as accurate as their inputs, research should be conducted with great care to ensure that model inputs are adding to the predictive nature of the model rather than distracting from it (Dahlbäck, 1998).

Various crimes (burglary, vandalism, illicit drugs, etc) take place primarily in areas that exhibit attractive risk factors for a particular offense (Dahlbäck, 1998; Groff and La Vigne, 2001). If risk factors for a crime can be identified, it follows that a model can be created to identify areas that are most “at risk”. The Illinois State Police (ISP) identified socio-economically based methamphetamine production risk factors that may have predictive capability when combined and analyzed (Illinois State Police, 1999). These risk factors make excellent candidates for inclusion as components in a spatial model with the purpose of highlighting areas that have the potential to develop a methamphetamine production problem.

As a framework to conduct research on the creation and testing of a spatial model, a geographic information system (GIS) allows for robust data management and great flexibility (Getis *et al.*, 2000). Model variables can be added, deleted, or modified with

just a few keystrokes, as most GIS products are designed to manage demographic data with ease (Heitgerd, 2001). As many of the methamphetamine production risk factors are demographic-based data, using a GIS to research a spatial model to predict meth production areas is very feasible.

The state of Missouri has led the nation in methamphetamine lab seizures each year since the reporting of such labs became nationally uniform (DEA, 2005). Missouri's significant quantity of rural landscape may be one reason the clandestine labs seem to flourish. In spite of Missouri's position as national leader in the manufacturing of methamphetamine, very little has been accomplished with respect to analyzing and modeling the spatial distribution of clandestine meth labs within the state.

The purpose of this study is to evaluate known methamphetamine production and use risk factors by applying spatial statistics to empirical data to measure the predictive strength of the aforementioned risk factors. Because Missouri statewide methamphetamine lab address point data was not released, a smaller scale study area was chosen. The study area for this project is Franklin County, Missouri. Franklin County is located in east central Missouri and is one of Missouri's leading counties with respect to methamphetamine lab seizures (MSHP, 2004). Its land use pattern along with its demographics fit the profile of a county typically afflicted with an elevated methamphetamine production problem. The Franklin County methamphetamine empirical data used in this study ranges from 2002 – 2004 and was provided upon request by Franklin County law enforcement officials.

Methamphetamine production related activities and substance use are highly detrimental to the individual engaged in the activity. The stresses and strains

methamphetamine related activities put on families and communities have been documented to be devastating. Methamphetamine activity also has an adverse impact on the social and economic institutions of a community as well as a detrimental effect on the afflicted community's physical environment. Evaluating known risk factors to a study area will possibly allow for greater understanding and better insight into the underlying geographical relationships of methamphetamine production. Accomplishing this research within the framework of a spatial model managed by a GIS will allow the work to be conducted in an efficient manner.

CHAPTER 2

REVIEW OF LITERATURE

In applying and evaluating a spatial model that focuses on methamphetamine production a comprehensive review of literature across two broad topics needs to be accomplished to situate this study within the established body of research. This chapter will focus on defining the illicit methamphetamine landscape and reviewing how geographical information systems have been integrated into crime mapping and analysis. In addition attention will be given to a specific effort made in spatially modeling methamphetamine activity.

Defining The Illicit Methamphetamine Landscape

Crime studies often focus on metropolitan crime rather than rural crime (Bowers and Hirschfield, 1999; Groff and La Vigne, 2001; Malczewski *et al.*, 2004). This trend to focus on crime in areas of higher population density may be a function of the perception that rural areas are safer (Donnermeyer, 1994). Research conducted on the differing crime rates has shown that metropolitan crime rates decreased through the early 1980s and the early 1990s and rural crime rates increased (Donnermeyer, 1994; Stead, 2003). These studies also concluded that while urban crime rates still outpaced rural crime rates the gap between the rates closed considerably (Herz and Murray, 2003).

A partial explanation for the overall rise in rural crime is due to what has been termed “convergence” (Rephann, 1999). The primary thesis of convergence is that non-metropolitan areas are taking on the characteristics, primarily socio-economic, of

metropolitan areas through improved transportation and communication systems, improved economic opportunity and greater demographic diversity (Rephann, 1999).

Rural crime generally differs from urban crime in terms of the nature of the criminal act (Weisheit and Donnermeyer, 2000), with urban crime most often committed against persons or property. Examples of these types of crimes include vandalism, assaults, burglary and murder. Rural crime generally includes activities that are not as violent as urban crime. The majority of rural crime also tends to be clandestine with the criminal or criminals attempting to use the rural landscape to conceal their activities. Crimes that tend to occur more often in rural areas as opposed to urban areas include game poaching, crimes against the environment and illicit drug manufacturing (Weisheit and Donnermeyer, 2000; Kraman, 2004). Crimes are committed in rural areas, and although they may not be the same type or occur at the same levels as that of urban crime spatial analysis and modeling may allow for a greater understanding of rural crime patterns (Rephann, 1999).

Crime rates for offenses involving the manufacturing and sale of illicitly produced synthetic drugs are significantly higher in rural areas supporting the perception that methamphetamine production and rural areas have a positive correlation (Rephann, 1999; Weisheit and Donnermeyer, 2004). However, not all areas classified as rural exhibit a methamphetamine production problem. Other factors must then exist in rural areas in order for a methamphetamine landscape to form. The elements that comprise a methamphetamine landscape are a combination of human and physical geographic features. From a human geography perspective, these factors generally include socio-economic conditions that seem to emphasize poverty, lower levels of education, and users

or producers who are predominately white (Kraman, 2004; MIMH, 2004). The physical geography component of an area's methamphetamine landscape appears to highlight the clandestine nature of the methamphetamine manufacturing process. Land cover signatures of areas prone to the development of a methamphetamine production problem generally consist of significant areas of dense vegetation (Kraman, 2004). Other more specific components have been found to aid in the defining of an illicit methamphetamine landscape and are discussed in detail later in this chapter. How much each specific component may contribute to the formation of an area's meth landscape is an important component of this study.

Studies focused on methamphetamine production have been completed in Illinois and other states bordering Missouri. (Herz and Murray, 2003; ISP, 1999; Weisheit, 2004). Significant academic research has not been located that focuses on the methamphetamine production problem in Missouri. In the absence of formal academic research within Missouri the studies conducted in bordering states may serve as a proxy by which the methamphetamine landscape for Missouri can be defined.

Weisheit (2004) completed a methamphetamine-focused ethnography of two rural counties in Illinois discovering that they experience a higher rate of methamphetamine related activity when compared to Illinois urban counties. Bauer (2003) provided quantitative data that supports Weisheit's finding, concluding that rural counties accounted for 76% of Illinois' 2001 methamphetamine-related crime reports.

Additionally, Bauer noted that rural methamphetamine seizures tripled in Illinois between the years 1994 and 2001. Weisheit (2004) surmised that the area of interest in his study, Edgar and Clark Counties in Illinois, could serve as a "microcosm" for studying the

methamphetamine problem in the Midwest as it has become apparent that the clandestine nature of methamphetamine production is positively linked to rural landscapes (Bauer 2003; Rephann 1999).

The rural nature of illicit drug manufacturing is not exclusive to the United States. Research has been conducted examining the pattern of drug-related offenses and community structures in rural Australia (Donnermeyer *et al.*, 2002). Realizing that there are fewer people in rural areas and that the rate of use and/or production is relatively equal to that of urban areas, it was surmised that there are factors present in the rural setting that do not necessarily exist in the urban areas (Donnermeyer *et al.*, 2002). Social and economic differences between urban and rural areas appeared to have contributed significantly to the drug offense rates in the rural areas. Specifically, smaller towns with lower than average marriage rates exhibited elevated drug offense rates as compared to other rural areas lacking these characteristics (Donnermeyer *et al.*, 2002). This demographic characteristic was confirmed within the United States in 2003 by Herz and Murray in their review of methamphetamine use among Nebraska arrestees. With this finding the socio-economic component of the illicit methamphetamine landscape begins to take shape.

An examination of arrest data in various locations has shown that illicit meth production and use appears to positively correlate with several other general demographic categories (ISP, 1999; Herz and Murray, 2003; ONDCP, 2005). Illicit meth use and production has been linked overwhelmingly to whites (Herz and Murray, 2003). The general age range of meth producers and users has been found to be in the twenties (ISP, 1999; Herz and Murray, 2003). The ISP study (1999) concluded that those committing

offenses related to meth production were much more likely to be undereducated as compared to the rest of the population. Undereducated, as defined by the ISP, was having attained less than a high school education or its equivalent.

The final piece in the demographic profile as it relates to the formation of an illicit methamphetamine landscape is the poverty rate. Shaw and McKay (1942) in their seminal work on social disorganization theory stressed that areas of disadvantage are more likely to experience elevated rates of crime. Their theory was applied to other locations and was found to hold true (Barnett and Mencken, 2002; Bowers and Hirschfield, 1999; Sampson and Groves, 1989). The definition of the illicit methamphetamine landscape can be advanced by the findings of the testing of social disorganization theory as empirical data has supported that methamphetamine use and production are often found in areas experiencing elevated levels of economic disadvantage (Herz and Murray, 2003; ISP, 1999).

The other vital component of the methamphetamine landscape is the physical environment that attracts significant methamphetamine production activity. Previous research has concluded that the very nature of methamphetamine production precludes it from being manufactured in areas with rather dense populations (Kraman, 2004; O'Dea *et al.*, 1997). The smells, waste product and method of manufacturing methamphetamine make it unlikely that producers would be able to manufacture the drug in a highly populated area without being noticed (Kraman, 2004).

The wide open spaces and isolation of rural areas are attractive to the establishment of clandestine methamphetamine manufacturing laboratories (Kraman, 2004). A link has been established between a rural area's land use pattern and the access

to a methamphetamine production precursor chemical. Kraman (2004) points out that the existence of cropland within a rural landscape makes accessibility to anhydrous ammonia less of a problem than in other areas. A land cover signature that has been identified as being attractive to the methamphetamine production process is that of dense vegetation (ISP, 1999). Dense vegetation allows for the further concealment of the illicit activity and makes detection of a meth production operation more difficult. The ease of accessibility to a main production ingredient along with the ability to camouflage the production process significantly aids in the formation of a methamphetamine landscape.

Crime Mapping and Analysis Using a Geographical Information System

With the advent of geographical information systems (GIS), spatially analyzing and modeling crime has taken a large step forward with respect to accuracy and timeliness (Boba, 2001; Harries 1999). A GIS allows for the entry of recent crime data and the near instantaneous return of updated analysis. The use of GIS in the field of crime mapping and analysis is extremely important and will permit the further development of products that will aid law enforcement officials in their daily duties. As GIS technology improves so too will the subsequent crime analysis-related products (Boba, 2001; Harries, 1999).

The integration of a GIS in the field of crime analysis can be divided among two categories: descriptive and analytical (Lersch, 2004). These broad categories can be further sub-divided into more specific tasks and operations. The descriptive function of a GIS in crime analysis primarily includes the plotting of reported crimes. The analytical function of a GIS in crime analysis allows for the development and use of more sophisticated spatial analysis techniques (Lersch, 2004). These techniques include

measuring areas experiencing recurring crime and the creation of predictive spatial models (Boba, 2001).

“Push-Pin” Mapping of Crime

“Push-pin” mapping of crime entails plotting crime locations onto a map for reference purposes (Boba, 2001). This is the simplest integration of GIS into crime analysis as the output is primarily useful for “after the fact” analysis. Push-pin mapping answers the “where” question in an analysis of criminal acts.

The key to the usefulness of plotted data is in the accuracy of the data used to map the point. Getis *et al.* (2000) have noted that several sources of error may preclude the accurate plotting of crime data. These sources of error include the officer not being complete in making a report of the address and/or the reporter of a crime not being clear with respect to the location of an offense (Getis *et al.*, 2000). The address or location that is eventually plotted on the crime map, based on crime reports, may be dozens of feet from the actual location of the suspected crime. Though relatively simple, the accurate plotting of crime reports is necessary as a base from which to conduct deeper and more sophisticated crime analysis (Getis *et al.*, 2000).

Hotspot Identification

Identifying “hotspots” is emerging as one of the most important tasks in crime analysis activities (Harries, 1999; Ratcliffe and McCullagh, 1999). Hotspots are areas or specific points that have a relatively high occurrence of crime (Harries, 1999). The accurate identification of hotspots can enable law enforcement agencies, especially those operating with limited budgets, to place their resources more efficiently to maximize their effectiveness in reducing crime (Ratcliffe, 2004).

The ability to identify statistical hotspots is difficult and requires sophisticated analysis techniques (Bowers and Hirschfield, 1999, Ratcliffe and McCullagh, 1998). Spatial analysis techniques have been shown to be useful in the identification of crime hotspots (Ratcliffe and McCullagh, 1998, Weisburd, *et al.*, 2004). A GIS has the capability to manage the data of interest and apply the required spatial analysis techniques to aid in quickly and accurately recognizing areas of recurring offenses (Bowers and Hirschfield, 1999; Harries, 1999; Ratcliffe and McCullagh, 1998; Ratcliffe and McCullagh, 1999).

The research team of Ratcliffe and McCullagh built upon their 1998 work of identifying GIS as an applicable tool in the identifying of hotspots and in 1999 published work providing guidance on specific spatial analysis techniques that were proven to be useful in the identification of crime hotspots. Their study was performed using urban crime data within a relatively confined area. Ratcliffe and McCullagh (1999) called for further exploration of their utilized techniques for crime incidents of various types and at various scales.

Spatial Modeling of Crime

In their 2001 rationale for the merging of geography and criminology into a spatial analysis course, Althausen and Mieczkowski eloquently pointed out that crime is inherently spatial and that this fact has been recognized since the 19th century. They highlighted several instances where the spatial aspects of crime had been studied and indicated how spatial analysis techniques allowed for conclusions to be drawn linking crimes to specific spatial components. They also recognized that rapid advancement in geospatial technology have allowed more powerful tools and techniques to be used in the

efforts of crime analysis (Althausen and Mieczkowski, 2001). These tools and techniques include spatial modeling.

Spatial models serve as a framework within which spatial data can be manipulated and analyzed with the goal of answering complex questions. The understanding and addressing of defined spatial problems can be achieved by discovering relationships between geographic features in the processing and analyzing of spatial data. The geographic data that are inputs to a spatial model can be demographic features, physical features or a combination. Spatial models are commonly used to study the interaction and relationships between humans and the physical characteristics of the landscape. With sound design, correct inputs, and refinement spatial models can aid in the answering of these questions (Bowers and Hirschfield, 1999; Heitgerd, 1999; Best *et al.*, 2005; Bonazountas, 2005).

The utility of plotting crime locations and identifying crime hotspots can be greatly extended by spatially modeling crime. Spatial crime risk-assessment models are designed to highlight the possibility of criminal activity based on the presence of risk factors (Bowers and Hirschfield, 1999; Craglia *et al.*, 2001, Dahlbäck, 1998). Risk factors can be demographic characteristics of an area (Bowers and Hirschfield, 1999; Craglia *et al.*, 2001, Dahlbäck, 1998) or derived from an area's environmental conditions such as physical features and human constructs. (Groff and La Vigne, 2001).

Demographic based risk assessment models are popular due to the relative ease of obtaining census data and using a GIS as a framework to manage the collected data (Heitgerd, 2001). The linking of crime data to demographic data can be easily managed within a GIS if proper care is taken to design the data link (Getis *et al.*, 2000).

The accuracy of a demographic based risk assessment model is a function of the selection of appropriate risk factors (Mencken and Barnett, 1999). Some form of regression testing and analysis is often accomplished to determine the applicability and predictive power of particular demographic data. (Cunradi *et al.*, 2002; Fergusson *et al.*, 2004, Mencken and Barnett, 1999).

Conventional forms of multiple regression testing have been used to measure the explanatory value of crime-oriented spatial model components (Ceccato *et al.* 2002); however it has been recognized that these commonly used model evaluation techniques may not be immune to the problem of spatial auto-correlation (Fotheringham *et al.* 2002; Malczewski *et al.* 2004). The consequence of spatial auto-correlation is that local variations in the relationship between the criminal offense and the model components may be hidden thus weakening the value of the applied model (Malczewski *et al.* 2004).

Fotheringham *et al.* in 2002 published a volume explaining the concept of geographically weighted regression. Geographically weighted regression, or GWR, can be used to explore the possible local variations in spatial relationships. It has been concluded that GWR may be a superior tool in examining the explanatory value of spatial model components as compared to more common multiple regression schemes (Fotheringham *et al.* 2002; Malczewski *et al.* 2004).

Effort to Spatially Model Methamphetamine Production

One previous research effort has focused on spatially modeling the potential for the existence of clandestine methamphetamine labs. In 1999 the Illinois State Police made available a risk-assessment model with the purpose of highlighting potential hotspots of methamphetamine production related activity. The proposed model inputs

were based on empirical knowledge of demographic risk-factors of methamphetamine users/producers.

The model was run using the appropriate demographic data of the census tracts in Illinois. With the aid of a GIS the output was scored and scaled in a manner that census tracts with the higher scores were deemed potential hotspots. Those tracts with lower scores were classified as exhibiting low-risk in developing a methamphetamine production problem.

The physical geography of the state was taken into account in the model but only in the post-analysis phase. Empirical methamphetamine lab seizure data was plotted on a Illinois landuse/landcover (LULC) map and general conclusions were made with respect to the effect the surrounding physical landscape had on the potential for the development of methamphetamine related activity. The LULC most associated with meth lab seizures in Illinois included forested areas near plots of cropland (ISP, 1999).

The Illinois model reinforces the importance of a demographic component when attempting to define and spatially model the methamphetamine landscape by utilizing demographic data as the exclusive quantified model inputs. The purely qualitative examination of the surrounding LULC compared to meth lab seizures indicates the physical geography of an area of interest cannot be marginalized. Underlying and complex relationships between an area and its methamphetamine production activity may be missed by not quantifying the physical landscape and adding this measurement to the model as a component. A sound model with the purpose of assessing the risk of methamphetamine activity will have as its direct inputs both human and physical geographic considerations.

Conclusion

Methamphetamine production and use has gained significant national exposure over the past two years. Rarely a week goes by without a news story being printed or broadcast that focuses on illicit methamphetamine production and its devastating impact on people, communities and the environment. The attention that is being paid to the methamphetamine problem has prompted many states to pass legislation restricting the sales of meth production precursor ingredients such as pseudo-ephedrine based cold medication. Recognizing that illicit methamphetamine production is reaching epidemic proportions has become an important step in combating the grip that the problem has on many communities.

Many complex relationships may lie beyond what recognizing the problem of illicit methamphetamine production can point out. As methamphetamine addiction is a human phenomena and the manufacturing of methamphetamine often occurs in an area with a specific LULC signature, a spatial model may provide the means by which the complex human/land relationships that exist in areas afflicted with methamphetamine issues can be explored. Previous research has shown that by examining and exploring the spatial relationships within an issue more can be done in accurately explaining the genesis of and arriving at sound solutions for the problem.

The purpose of this study is to attempt to provide a sophisticated look beyond simple push pin mapping of methamphetamine lab seizures in Franklin County, Missouri. This study seeks to demonstrate that lab seizure plots combined with the geospatial data management capabilities of a GIS can be an effective tool for applying and evaluating a spatial model designed to locate areas of significant methamphetamine production

activity. This research will incorporate the majority of the model components used in the Illinois effort. The model will be advanced by defining and quantifying a LULC pattern that is consistent with reviewed literature as it relates to methamphetamine production. Model components will be tested for their explanatory powers with the aim of allowing for further refinement and improvement of the original model.

CHAPTER 3

METHODOLOGY

Overview

Clandestine methamphetamine production in a county can have devastating effects on individuals, family members and the surrounding physical and economic landscape of a community. Gaining a better understanding of the underlying spatial dynamics and relationships of an area severely afflicted with an illicit methamphetamine problem is the objective of this research. Using a quantitative approach this study will utilize a geographic information system (GIS) and employ sound spatial statistical analysis techniques to test and evaluate a methamphetamine production risk model.

The methamphetamine production model used in this study incorporates the majority of the model components as described by the Illinois State Police effort (ISP, 1999). Socio-economic data at the block group level is collected from the United States Census Bureau for the study area and used to represent the various model components. The model is enhanced in this study by quantifying a clandestine landscape that represents areas that could possibly be used for the concealment of illicit meth production activity. This landscape is represented in the model by using and manipulating spatial data in a raster format that represents various categories of landuse/landcover (LULC).

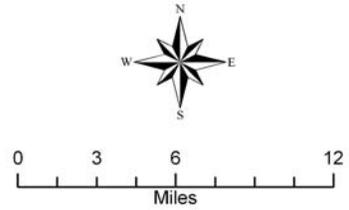
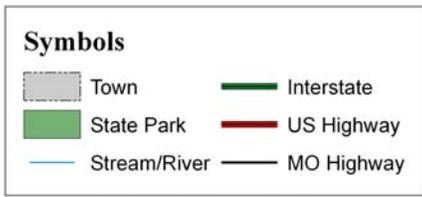
This study uses four phases to process and analyze spatial data that supports the testing and evaluation of a methamphetamine production risk assessment model. These phases are data collection, data processing, model application and model component evaluation. Various software packages support all phases of the work. Microsoft Excel is

used for various data collection and pre-processing tasks. The ArcGIS 9.0 suite on a Windows XP platform is employed for spatial data manipulation. Statistical analysis of the model components is accomplished using SPSS and the GWR 3.0 software package purchased from the National Centre for Geocomputation, National University of Ireland.

Study Area

The study area for this project is Franklin County, Missouri (map 3-1), located in the east-central part of the state approximately 40 mile west of the St. Louis major metropolitan area. Franklin County is an appropriate choice for a study area because it consistently has been a leading Missouri county with respect to total number of methamphetamine labs seized. Franklin County also is the focus of this study because of the generous data contribution provided by the Franklin County Sheriff's Department.

Franklin County



Map 3-1

The effort to obtain illicit methamphetamine lab seizure data from Franklin County was driven by the denial of state-wide seizure data. Repeated queries were made of the Missouri State Highway Patrol (MSHP) requesting access to the data representing illicit meth lab seizures in Missouri between the years 2001 and 2004. The MSHP maintained that seizure data is intelligence information and that efforts to combat illicit meth production would be hampered by the release of data that could be used to plot the seized labs on a map. The continued denials for data from the MSHP prompted requests for the same data from the Drug Enforcement Agency (DEA). Data access was denied by the DEA without a clear reason. Written requests were made of state and federal lawmakers for their assistance to obtain a state-wide data set. These requests met the same fate as the requests made to state and federal law enforcement agencies. In light of the continual denials of state-wide point data, requests were made of the leading meth producing counties in Missouri. Franklin County law enforcement was the only county to respond positively to the data request.

Year	Seizures	Rank
2001	67	9th
2002	152	2nd
2003	107	3rd
2004	138	3rd

Table 3-1: Franklin County illicit methamphetamine lab seizures and rankings within the state of Missouri

Data Collection

Point Data

The Franklin County Sheriff’s Department provided location data for the majority of the methamphetamine-related lab seizures in Franklin County for the years 2002, 2003

and 2004. This data was provided in an Excel spreadsheet and was derived from reports prepared by the Franklin County Sheriff’s Department on the National Clandestine Laboratory Seizure Report form; referred to as the El Paso Intelligence Center (EPIC) 143. The spatial aspects of the data were the street address or intersection, town and zip code. Additional information provided included the type of lab that was seized: chemical/glassware equipment, dumpsite, or traditional laboratory. Other than the year, date information of the seizure was not provided.

Census Data

Demographic data for Franklin County was collected from the United States Census Bureau via their website (U.S. Census Bureau, 2006). In an effort to make the demographic data collection process more streamlined and with less chance of data collection error the “geo within geo” functionality was utilized. This allowed for the collection of all required data from all block groups in Franklin County at once rather than having to collect data for each block group in a repetitive fashion. Figure 3-1 summarizes the tables selected. These data were chosen as they most closely resembled the components utilized in the Illinois methamphetamine production model.

Census 2000 SF-3 Tables Collected
P01: Total Population
P06: Race
P08: Sex by Age
P37: Sex by Educational Attainment
P18: Sex by Marital Status
P87: Poverty Status
P05: Urban and Rural

Figure 3-1: Census 2000 data collected for the creation of the model layers

Landuse/Landcover (LULC) Data

LULC data was collected from the Missouri Spatial Data Information Service (MSDIS, 2006) The LULC data is dated 2000 – 2004 making it the most recent data of its type. The data is in raster format and classified into fourteen distinct categories.

Study Area Census Boundaries and Roads Data

ArcGIS coverage files of the Franklin County block group boundaries and county-wide United States Census Topologically Integrated Geographic Encoding Reference (TIGER) roads were collected from the MSDIS website. Block groups are used for this study as they are the smallest geography for which census sample data is available. The TIGER road coverage is used for this study as it contains attribute data that represents address information used in the address matching and subsequent plotting of illicit meth lab seizure data in the GIS.

Data Processing

Points

The data provided by Franklin County law enforcement required two pre-processing steps due to perceived spatial inaccuracies. The first step is a visual inspection to find and correct obvious errors such as misspellings, town & zip code mismatch, etc. The second step identifies entries that are provided with a plain language description of the location rather than a more traditional street address or road intersection description. An example in the data set used for this study is the reporting of an illicit meth lab seized at ‘Red Horse River Access’. This example data, in its current form, does not allow for the accurate plotting of the data point on a map as it appears to

be a colloquial name for an area or point. Data identified during this second step are set aside for further investigation.

An identification scheme was created for the purpose of uniquely identifying the plotted points. This unique identification allows for the ability to quickly and easily locate the point using spatial queries in the event the point attribute data or its location need to be modified. The first position of the ID indicates the type of seizure: “C” for chemical/glassware equipment¹, “D” for dumpsite² and “L” for laboratory³. The second position of the ID is a unique number that is assigned based on the order of the data, and the third position is a two digit representation of the year of seizure in ‘YY’ format. In addition to unique point identification, this ID is also used as a unique column to perform desired data joins.

An attempt to have the GIS automatically address match the meth lab point data against the TIGER road coverage produced a poor performance and was attributed to two reasons. First, the addresses information provided by Franklin County law enforcement, even after corrections were made, was not completely compatible with the attribute data found in the TIGER roads spatial file. Many of the data entries were listed as having been seized at an intersection, ‘Highway 1 and Highway MM’ for example. Another incompatibility with the data occurred when colloquial or antiquated name such as ‘Old Highway 66’ were used as part of the address information. Another reason for poor

¹ The DEA defines chemical/glassware/equipment seizures as seizures “of only chemicals, glassware and/or equipment normally associated with the manufacturing of a controlled/illicit substance, but there is insufficient evidence that the items were used in the manufacture of a controlled/illicit substance.” (DEA, 2004)

² The DEA defines dumpsite seizures as locations “where discarded laboratory equipment, empty chemical containers, waste by products, pseudoephedrine containers, etc., were abandoned/dumped.” (DEA, 2004)

³ The DEA defines production lab seizures as “illicit operations consisting of a sufficient combination of apparatus and chemical that either has been or could be used in the manufacture or synthesis of controlled substance.” (DEA, 2004)

addressing performance is attributed to fact that TIGER roads did not include all valid address ranges for the county. This was a larger problem for addresses located in rural areas especially those located on county lettered routes such as ‘WW’ or ‘T’.

Because of the lack of success of the automated address matching technique, an attempt was made to manually plot the points with the assistance of third party web-based mapping services that included MapQuest, Yahoo! Maps and Rand McNally. Most of the points were successfully located within the county using these mapping services. The data point locations were manually plotted in their final position using ArcMap by matching the location provided by the web-based mapping services to the same relative position on the TIGER roads spatial data layer. Data points that could not be located through any of the web-based mapping services were noted and set aside for further investigation.

A meeting was arranged with the Franklin County Sheriff’s Department to aide in the plotting of data that could not be located and plotted. Several additional data points were plotted with their assistance and all data points that could not be located were recorded as “lost”. As a final accuracy check, a map of the successfully plotted data points was created and sent to the Franklin County Sheriff’s office for review and approval.

Quantifying Illicit Methamphetamine Activity by Census Block Group

Four weighting schemes are devised to test the methamphetamine production model components against a block group’s illicit methamphetamine activity. One of the weighting schemes treats all meth labs equally irrespective of type of seizure. The remaining schemes are structured so that each type of seizure is weighted in such a

manner that an increase of severity in the type of seizure is represented. The rationale to construct weighting schemes for the purpose of model analysis is derived from a review of the definitions of each type of seizure as published by the Drug Enforcement Agency. These definitions led to the understanding that there is a marked difference between the seizure types and the level of illicit methamphetamine production activity that each type of seizure represents. The overall purpose of implementing weighting measurements in the testing and analysis of the methamphetamine production model is to attempt to capture these differences and to more accurately quantify each block group’s illicit methamphetamine activity.

In applying each weighting scheme a block group’s meth activity score is computed by multiplying the number of seizures in a particular category by the appropriate weight. The products of these calculations are summed and assigned to the respective block group.

Scheme	Dumpsites	Chem/ Equipment	Labs
1	1	1	1
2	1	2	3
3	1	3	7
4	1	5	10

Table 3-2: Weighting schemes used to compute illicit meth activity scores for block groups

Census Data

The socio-economic data for the Franklin County block groups obtained from the U.S. Census Bureau, as summarized in figure 3-1, was in need of normalization. Normalization is the process by which data is standardized to allow for the comparison between areal units. The areal units used in this study are U.S. Census block groups and

therefore the data was required to be normalized at the block group level. An important aspect of normalization is ensuring the correct population is used in the standardizing calculation. Table 3-3 summarizes the normalization process used to compute the standardized form of each illicit methamphetamine production model component.

Included in this table is the correct population by which each component is normalized.

Raw Data	Normalizing Data	Resultant Data
Total number of whites	Total Population	% White
Total number persons aged 25 – 29	Total Population	% Population Aged 25 - 29
Total number persons aged 25 with < high school education	Total Population > 25	% Population > 25 with < high school education
Total number persons unmarried aged > 15	Total Population > 15	% Population unmarried and aged > 15
Total number persons at or below poverty	Population for which Poverty was Calculated	% Population in poverty
Total number persons classified as rural residents	Total Population	% Rural Population

Table 3-3: Summary of data normalization processing

Landuse/Landcover (LULC) Data

The LULC data collected from MSDIS consists of fourteen distinct categories. For the purpose of this study, this data is reclassified into either a clandestine landscape category or a non-clandestine landscape category. Reviewed literature points to dense vegetation as being an attractive physical geographic feature of an area prone to the formation of an illicit methamphetamine production problem. A review of the descriptions of each category shows that very few of the classifications would make good candidates for inclusion into the clandestine landscape category. Many of the LULC categories found in this data set represent land that has less than dense vegetation, urban areas, open cropland or urban areas. These types of categories represent land that is too open to conceal illicit meth production activities. Three of the classifications from the collected LULC data do make suitable candidates for inclusion into the clandestine landscape category with the rest falling into the non-clandestine landscape category. The three classifications represent land that is described as having greater than 60% forest cover with the cover coming from a variety of tree species. The details of the three classifications that were included in the clandestine landscape model component have been identified in table 3-4.

Name	Clandestine LULC	Brief Description
Impervious		Non-vegetated, impervious surfaces. Areas dominated by streets, parking lots, buildings. Little, if any, vegetation.
High Intensity Urban		Vegetated urban environments with a high density of buildings
Low Intensity Urban		Vegetated urban environments with a low density of buildings
Barren or Sparsely Vegetated		Minimally vegetated areas including bluffs, quarries, and natural expanses of rock, mud, or sand. Areas in transition.
Cropland		Predominantly cropland including row, close-grown, and forage crops
Grassland		Grasslands dominated by native warm season or non-native cool season grasses
Deciduous Forest	X	Forest with greater than 60% cover of deciduous trees
Evergreen Forest	X	Forest with greater than 60% cover of evergreen trees
Mixed Forest	X	Forest with greater than 60% cover of a mixture of deciduous and evergreen trees
Deciduous Woody/Herbaceous		Open Woodland (including young woodland) with less than 60% cover of deciduous trees
Evergreen Woody/Herbaceous		Open Woodland (including young woodland) with less than 60% cover of evergreen trees
Woody-Dominated Wetland		Forest with greater than 60% cover of trees with semi-permanent or permanent flood waters
Herbaceous-Dominated Wetland		Woody shrubland with less than 60% cover of trees with semi-permanent or permanent flood waters
Open Water		Rivers, lakes, ponds, and other open water areas

Table 3-4: Landuse/landcover (LULC) descriptions and clandestine landcover selections

The reclassification of the LULC results in a new raster file that requires additional processing to calculate the area of clandestine landscape found in each block group. ArcMap is used to compute the area of the classified clandestine landscape by block group. This data is divided by the total area of each individuals block group's areas and the resultant percentage is added to the final data table.

Block Group Centroid Computation

The GWR 3.0 statistical software package requires that data be represented by a single location. To meet this requirement centroids of the block groups are computed in ArcMap in decimal degrees and added to the data table.

Data Table Summary

The components of the final data table used in the remainder of the study are summarized in the figure below. This data table was exported to a comma separated values file for use in the required statistical analysis using the GWR 3.0 software package.

Data Table Components
Percent Rural
Percent White
Percent Unmarried > 15
Percent Aged 25 – 29
Percent Poverty
Percent > 25 with < High School Education
Percent Area Clandestine Landscape
Meth Activity Scheme 1 Total
Meth Activity Scheme 2 Total
Meth Activity Scheme 3 Total
Meth Activity Scheme 4 Total
Centroid X Coordinate
Centroid Y Coordinate

Figure 3-2: Structure of data table after normalization of required model component data and computation of meth activity scores and block group centroids

Model Application

Applying the methamphetamine production model to Franklin County for the purpose of visually displaying the results requires several steps. The data required for the application of the model is summarized and presented in figure 3-2. All data manipulations are done using ArcGIS 9.0.

The first step is to convert each of the methamphetamine production model component data layers into respective raster layers. This step allows for the ability to add values from individual layers together. Each model component is originally represented by a percentage value in decimal format. The derived raster layers are outputted in float

format in order to maintain the value of the original data. A ten meter resolution was selected for the resultant rasters to maintain smoothness in the layer.

Each of newly created rasters representing the seven model components is reclassified by equal intervals. The top interval is reclassified with a value of “5” and the bottom interval was reassigned a value of “1” with the middle three intervals classified accordingly. This allows for each model component layer to be uniformly classified for the purpose of further processing. The potential maximum score of any cell, and therefore a block group, is 35 with the minimum being 7. The reclassified layers are summed using the Spatial Analyst extension in ArcToolbox and is saved into a file that represents the composite of all of the model data layers.

The composite raster created as described above represents raw output from the application of the methamphetamine production model. Further reclassification is necessary for the purpose of assigning a risk value to the block groups. The manual interval method is used to reclassify the raster representing the raw model output. Using the manual interval method allows for the uniform application of risk assessment to each interval irrespective of study area. As there are 31 possible values that can be computed by the application of the methamphetamine risk model and there are only 5 risk ratings assigned in this study there is the necessity to slightly alter the size of the reclassified intervals as 31 is not evenly divisible by 5. The top and bottom intervals are allowed a width of eight as a means to accommodate outliers in the raw model output. The remaining intervals are divided using an equal interval method. The top interval, representing the highest risk of methamphetamine production, is assigned a value of “5” and the bottom interval, representing the lowest risk of methamphetamine production is

assigned a value of “1”. The plain language risk ratings assigned to the corresponding values are summarized in the table 3-5.

Raw Model Score	Reclassified Value	Risk Rating
28 – 35	5	High
23 – 27	4	Moderate High
19 – 22	3	Moderate
15 – 18	2	Moderate Low
7 – 14	1	Low

Table 3-5: Conversion of raw model scores to risk ratings

Model Component Evaluation

The desired statistical output used to evaluate the various components of the model is achieved by a series of ordinary least squares regression and geographically weighted regression analyses. Table 3-6 summarizes the independent variable composition of each model run. The dependent variable in each run of the model is the illicit methamphetamine activity score of the block groups. A complete cycle of model runs is accomplished for each of the block group’s four meth activity scores that were computed by applying the previously described weighting schemes.

RUN 1	RUN 2	RUN 3	RUN 4	RUN 5
% Rural % Poverty	% Rural % Poverty % Clandestine landcover	% Rural % Poverty % Undereducated	% Rural % Poverty % Undereducated % Clandestine landcover	% Rural % Poverty % Undereducated % Unmarried
RUN 6	RUN 7	RUN 8	RUN 9	RUN 10
% Rural % Poverty % Undereducated % Unmarried % Clandestine landcover	% Rural % Poverty % Undereducated % Unmarried % 25 – 29	% Rural % Poverty % Undereducated % Unmarried % 25 – 29 % Clandestine landcover	% Rural % Poverty % Undereducated % Unmarried % 25 – 29 % White	% Rural % Poverty % Undereducated % Unmarried % 25 – 29 % White % Clandestine landcover

Table 3-6: Model component permutations

The GWR 3.0 software package is used to process the data and compute the statistical output required for model testing and evaluation. Configuration of the software is required to accomplish the necessary data processing and spatial statistical computations. The Gaussian method was chosen for the model analysis type as the data set is assumed to be normally distributed. The required bandwidth entry is chosen to be computed using the fixed kernel option along with selecting minimization by the Akaike

Information Criterion. This method of computing the bandwidth in this manner is to allow the software to calculate a bandwidth that best reflects the empirical data. Output from the software is chosen to be written to a text file for further evaluation and analysis.

Conclusion

In 1999 the Illinois State Police proposed a spatial model to highlight potential risk areas for illicit methamphetamine production. This model was used as the foundation for this study. The methodology used in this study integrated components of the Illinois model into a study focused on Franklin County, Missouri. This study also attempted to advance the model by adding a landscape component that had the potential of assisting in locating clandestine methamphetamine production activity.

CHAPTER 4

RESULTS AND ANALYSIS

The purpose of this study is to apply and evaluate a spatial model that was created to indicate levels of risk in a geographic area for the potential formation of an illicit methamphetamine production problem. An analytical discussion of the results will be systematically presented in this chapter with the purpose of framing the output within the stated research objectives.

This chapter will first present a discussion of the work that was accomplished prior to the application of the spatial model. The location of the seized meth labs in Franklin County will be cartographically presented and issues about the process of plotting the labs will be discussed. Each of the model components used in this study will be graphically and statistically presented. The spatial patterns of the individual model components will be highlighted and analyzed.

Two sets of results will be presented for this study. The first set reflects the direct application of the methamphetamine production model in order to validate the model and to form a stage for the remainder of the analytical discussions of this chapter. The second set of results is the output from the ordinary least squares regression (OLS) and the results from the geographically weighted regression (GWR) diagnostics.

Seized Lab Plots

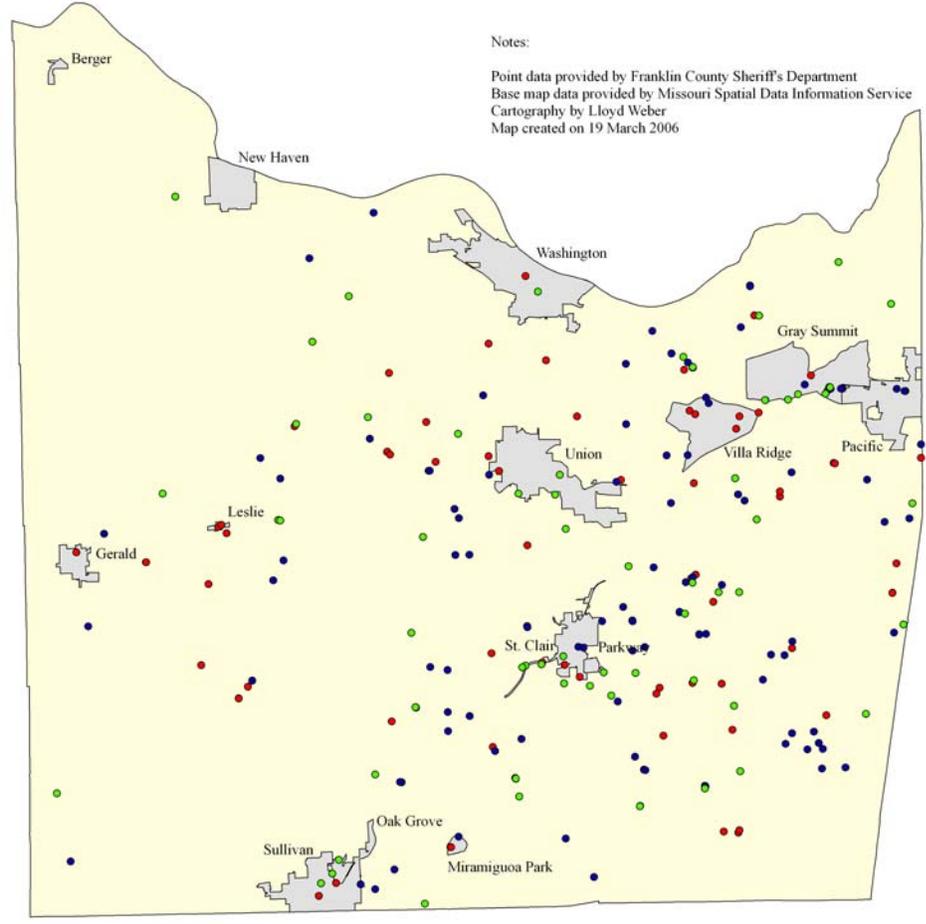
The locations of the seized illicit methamphetamine lab data is presented in map 4-1. The initial attempts to automatically geocode the address set did not produce acceptable results and various other mapping sources were used. The Franklin County

sheriff's office provided information about 302 illicit meth lab seizures for the years 2002 – 2004. Of the data provided 48 points could not be located and have been recorded as lost. The final data set that was used in this study consists of 254 seizures.

A visual inspection of the plotted seizure data (map 4-1) shows a general spatial pattern of meth lab seizures in Franklin County. There is a noticeable lack of seizures in the extreme northwest portion of the county counterbalanced by a dense cluster of lab seizures in the southeast corner of the county. A diffuse belt of lab seizures stretches from the southwest corner of the county to the northeast corner where the band becomes less diffuse and relatively more dense.

The point pattern shows a general tendency of meth lab seizures occurring away from more built-up areas. There are exceptions to this generality in the form of few towns having apparent clusters of lab seizures. The Villa Ridge – Gray Summit area located in northeastern Franklin County appears to have had a cluster of meth lab seizures as did the town of St. Clair. However, these areas contrast with the majority of the other towns in the county. An example of an urban area that did not experience many meth lab seizures is the town of Washington. Washington is the largest town in the county and during the years covered by this study and according to the dataset used had only 2 lab seizures. The overall urban/non-urban pattern appears to match that discussed in the reviewed literature.

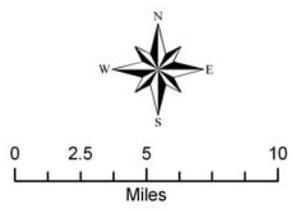
Franklin County Clandestine Meth Lab Seizures 2002 - 2004



Notes:
Point data provided by Franklin County Sheriff's Department
Base map data provided by Missouri Spatial Data Information Service
Cartography by Lloyd Weber
Map created on 19 March 2006

Legend

- Lab
- Chem/Equipment
- Dumpsite
- Towns



Map 4 - 1

Model Components

The algorithm used in applying the spatial model contains both human and physical geography components. The human geography model variables are based on socio-economic parameters and are represented by census data. The physical geography aspect of the model is the quantification of probable clandestine landcover derived from a recent Missouri landuse/landcover (LULC) spatial data product.

United States Census Bureau 2000 data was collected and processed for each of Franklin County's 64 block groups. The Missouri Spatial Data Information Service (MSDIS) hosts the most recent data set that represents a 14 category LULC classification for the state of Missouri. This LULC classification was reclassified for the purposes of this study and integrated into the model algorithm. There were no significant problems in the end to end routine of downloading, processing and integrating the census data or the LULC spatial data set.

Component	Mean	Median	SD	Skewness
Pct. Rural	0.593	0.736	0.432	-0.368
Pct. Poverty	0.072	0.054	0.048	1.141
Pct. Undereducated	0.227	0.222	0.071	0.124
Pct. Unmarried	0.384	0.374	0.085	0.665
Pct. 25 – 29	0.061	0.058	0.027	1.019
Pct. White	0.973	0.983	0.030	-2.014
Pct. Clan LULC	0.356	0.371	0.185	-0.118

Table 4-1: Model Component Descriptive Statistics

With a mean of nearly 60% (table 4-1), the population of Franklin County is solidly rural. The spatial pattern of the rural population (map 4-2) indicates the areas that the western half and the southeastern corner of the county are overwhelmingly rural and a band that runs through the center of Franklin County shows an area having less of a rural

population. This area includes Washington, Union, St. Clair and Sullivan, the larger towns of the county. The Villa Ridge – Gray Summit area in the northeast of Franklin County is also demonstrably less rural.

Franklin County does not appear to have a widespread poverty problem. The absence of deep poverty is supported by a 7% mean (table 4-1) and a significant positive skewness. The spatial pattern that emerges (map 4-3) indicates most of Franklin County's elevated levels of poverty are found in and around the urban centers of the county. There is a significant pocket of poverty outside the urban centers located in the east-central part of the county.

The undereducated population of Franklin County exhibits a slight positive skewness with a mean of nearly 23% (table 4-1). The southeast portion of the county (map 4-4) and urban centers are areas that have lower education rates as compared to the rest of the county. The northeast corner of Franklin County also shows below average education rates.

Franklin County's population over the age of 25 and unmarried (map 4-5) is primarily found in the urban areas of Washington, New Haven and Sullivan. There is a significant unmarried population pocket anchored by the urban centers of Union and St. Clair and stretching to the eastern border of the county. The mean and skewness of the unmarried population (table 4-1) indicates a positive skewness with nearly 40% of the population over the age of 25 being unmarried.

No discernible spatial pattern can be found in the percent of Franklin County's population that is aged between 25 and 29 years (map 4-6). The descriptive statistics (table 4-1) of this model component indicate a relatively small percentage of the total

population falls within the 25 – 29 age category. The greater percentages of those aged 25 – 29 are found primarily in the urban areas (map 4-6).

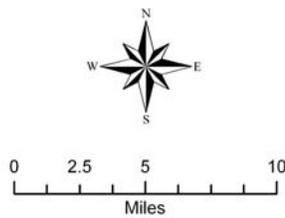
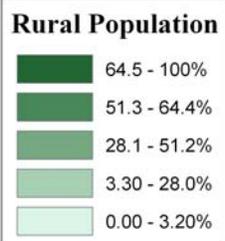
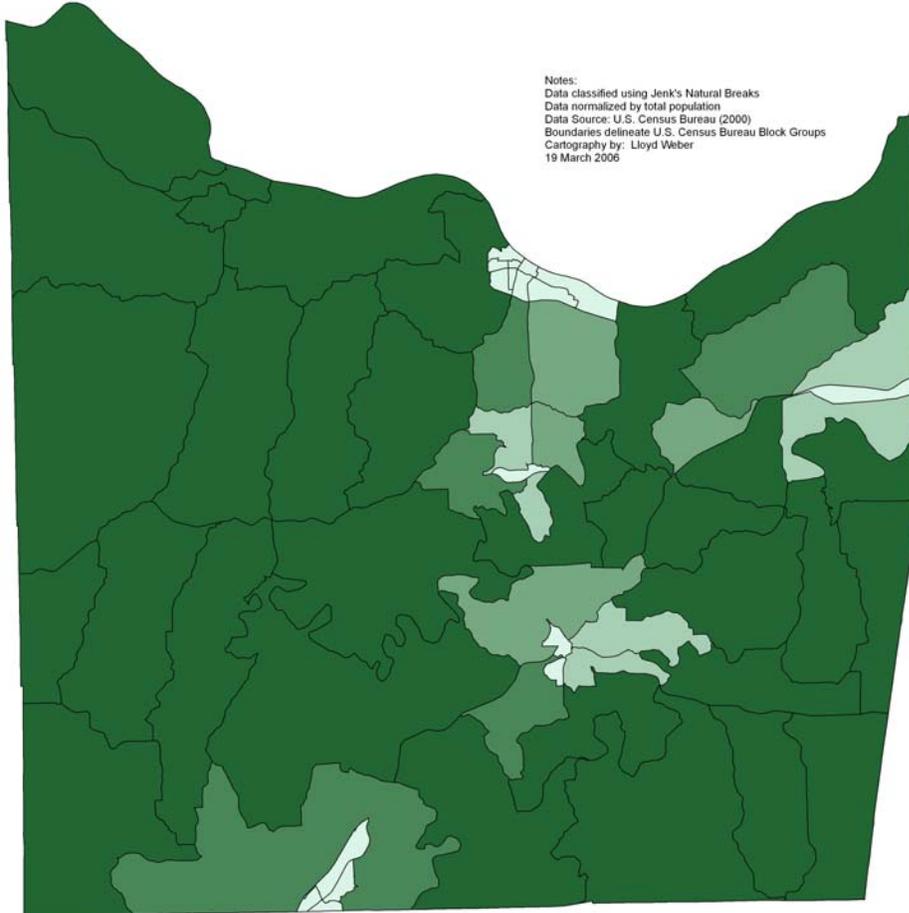
Franklin County is overwhelmingly comprised of a white population. The mean block group percent for this model component is over 97% (table 4-1). The distribution of the white population demonstrates a strong negative skewness (table 4-1). The areas where white populations are the most concentrated (map 4-7) are the north-central and south-central parts of the county. There is a relatively lower concentration of a white population in the east-central area of Franklin County.

The physical geographic component of the model was derived from raster-based LULC data. Dense vegetation allows for the concealment of illicit methamphetamine production activity and makes detection of a meth production operation more difficult (ISP, 1999). The quantification of dense vegetation for the purpose of this study was derived from the LULC categories of forest cover greater than 60%. Franklin County's clandestine landcover, as defined in this study, produces a distinct spatial pattern (map 4-8). The northwest corner of the county has less of a concentration of clandestine landcover than the Franklin County average. The concentration of clandestine landcover increases towards the southwest corner (map 4-8). There is significantly less clandestine landcover in the urban areas as compared to surrounding areas.

Missouri

Franklin County Rural Population

Notes:
Data classified using Jenk's Natural Breaks
Data normalized by total population
Data Source: U.S. Census Bureau (2000)
Boundaries delineate U.S. Census Bureau Block Groups
Cartography by: Lloyd Weber
19 March 2006

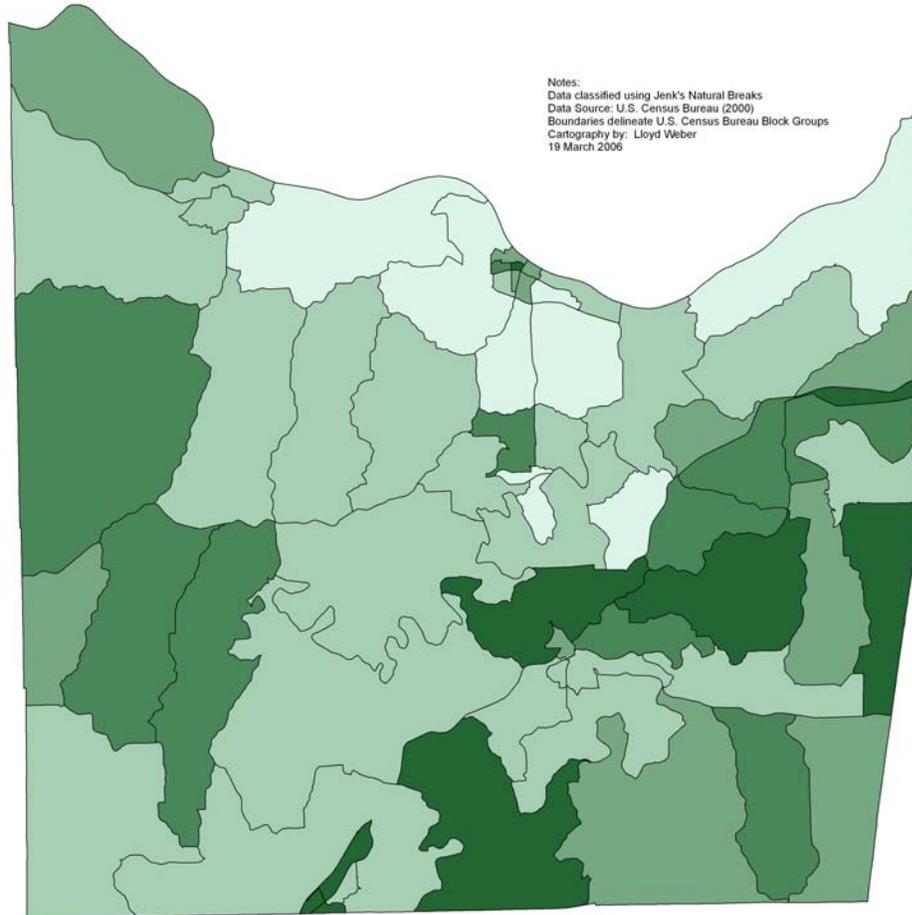


Map 4-2

Missouri

Franklin County Poverty

Notes:
Data classified using Jenk's Natural Breaks
Data Source: U.S. Census Bureau (2000)
Boundaries delineate U.S. Census Bureau Block Groups
Cartography by: Lloyd Weber
19 March 2006



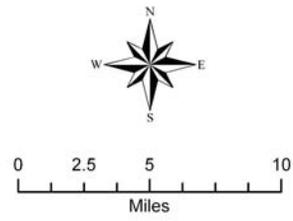
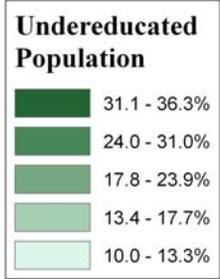
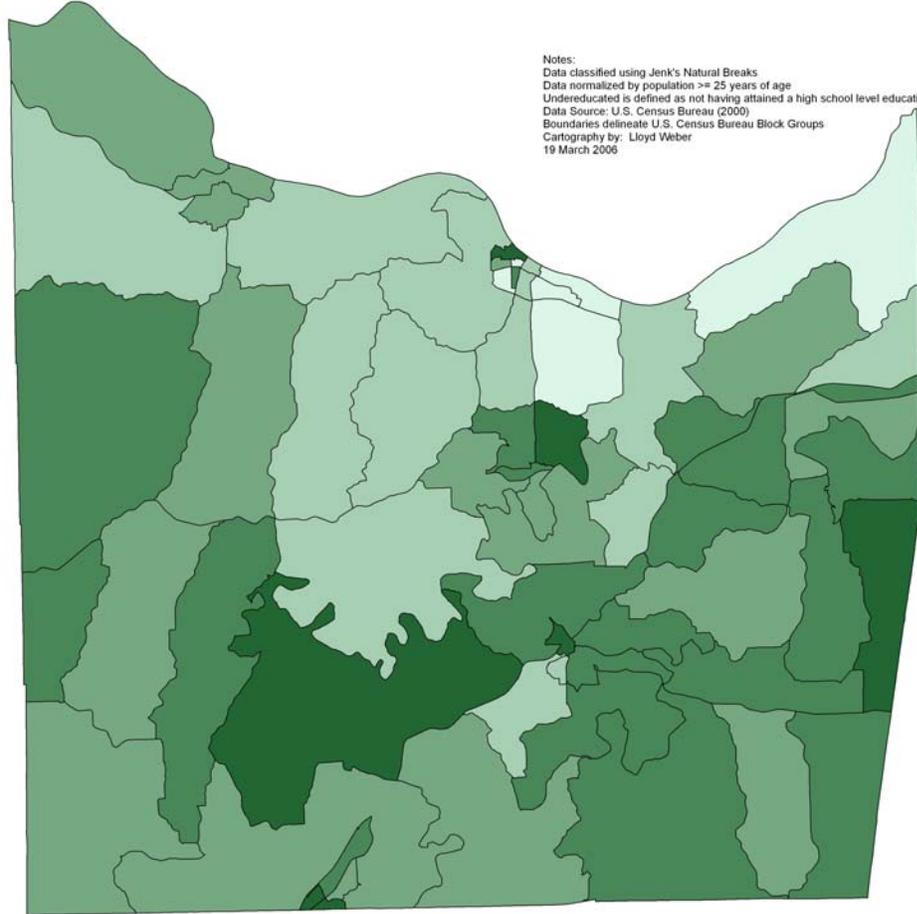
Population in Poverty



Map 4-3

Franklin County Undereducated Population

Notes:
Data classified using Jen's Natural Breaks
Data normalized by population >= 25 years of age
Undereducated is defined as not having attained a high school level education
Data Source: U.S. Census Bureau (2000)
Boundaries delineate U.S. Census Bureau Block Groups
Cartography by: Lloyd Weber
19 March 2006

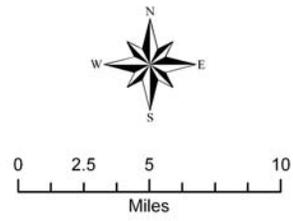
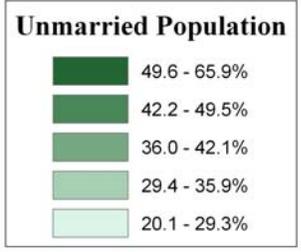
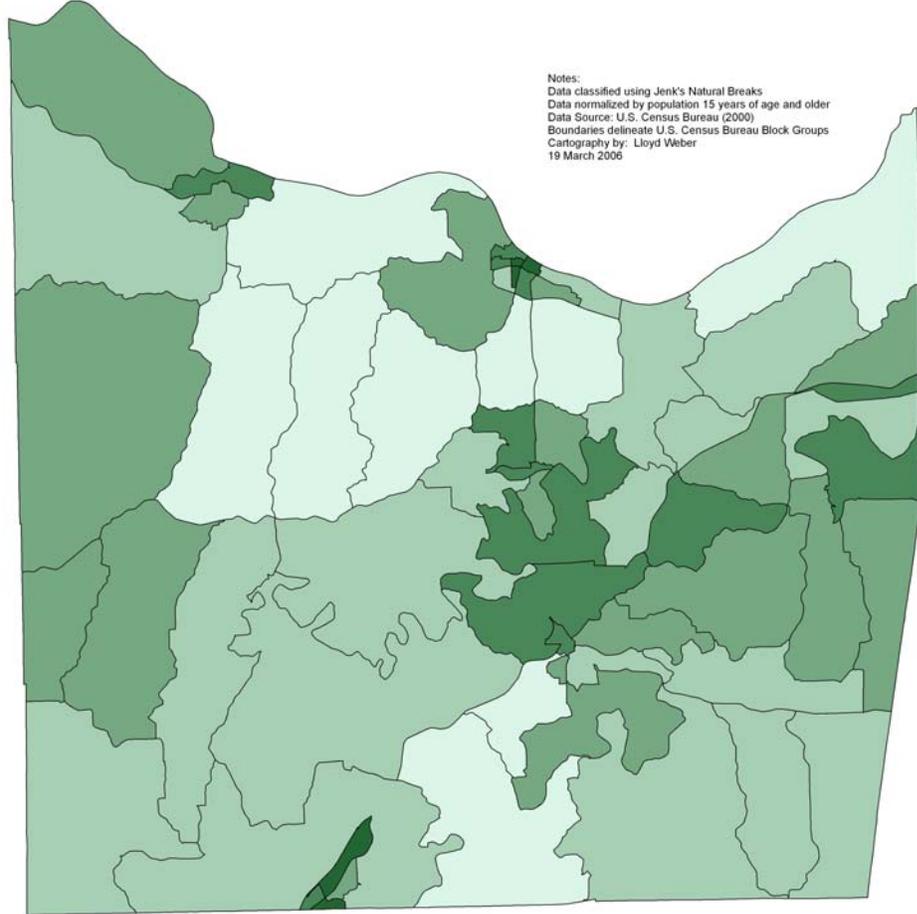


Map 4-4

Missouri

Franklin County Unmarried Population

Notes:
Data classified using Jenk's Natural Breaks
Data normalized by population 15 years of age and older
Data Source: U.S. Census Bureau (2000)
Boundaries delineate U.S. Census Bureau Block Groups
Cartography by: Lloyd Weber
19 March 2006

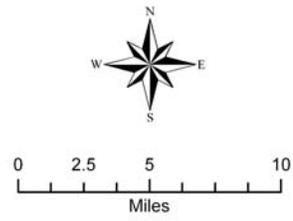
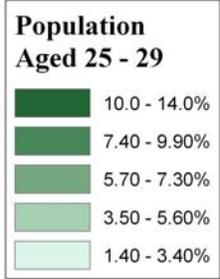
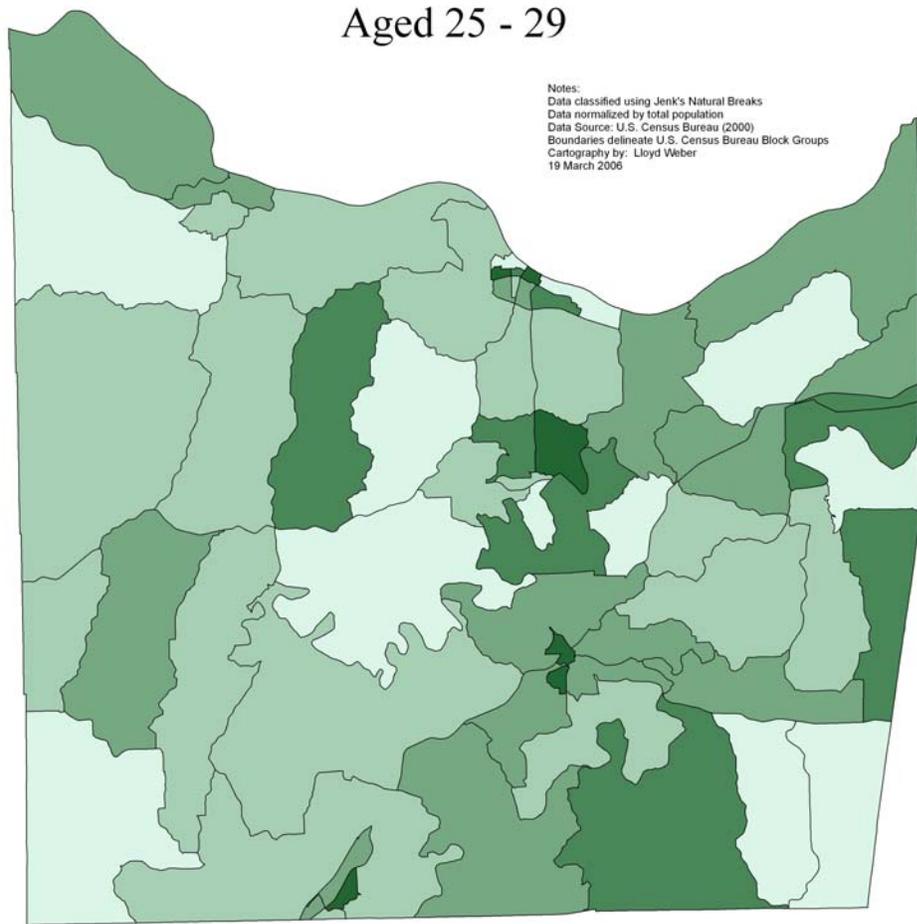


Map 4-5

Missouri

Franklin County Population Aged 25 - 29

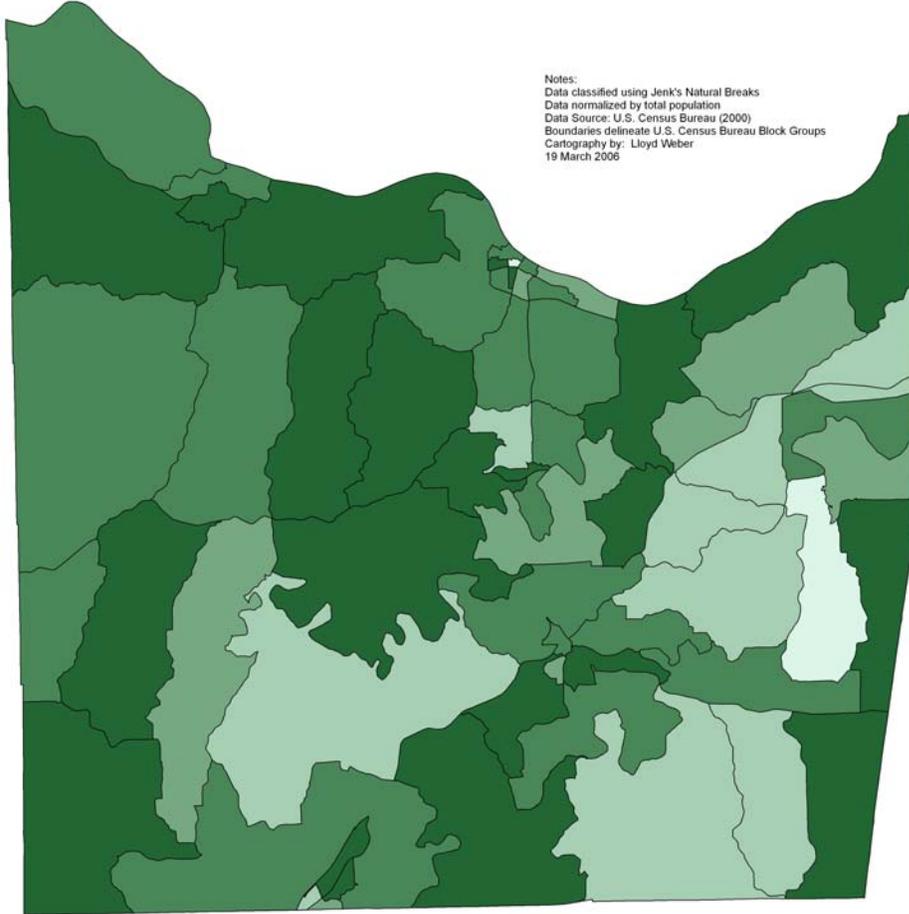
Notes:
Data classified using Jenk's Natural Breaks
Data normalized by total population
Data Source: U.S. Census Bureau (2000)
Boundaries delineate U.S. Census Bureau Block Groups
Cartography by: Lloyd Weber
19 March 2006



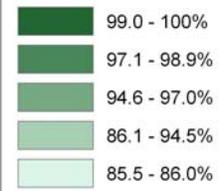
Map 4-6

Franklin County White Population

Notes:
Data classified using Jenk's Natural Breaks
Data normalized by total population
Data Source: U.S. Census Bureau (2000)
Boundaries delineate U.S. Census Bureau Block Groups
Cartography by: Lloyd Weber
19 March 2006



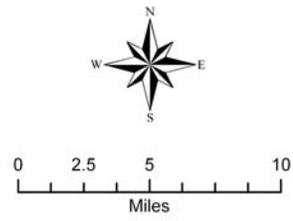
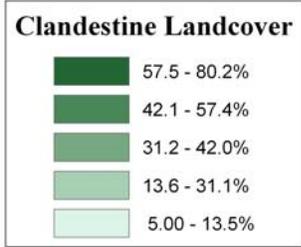
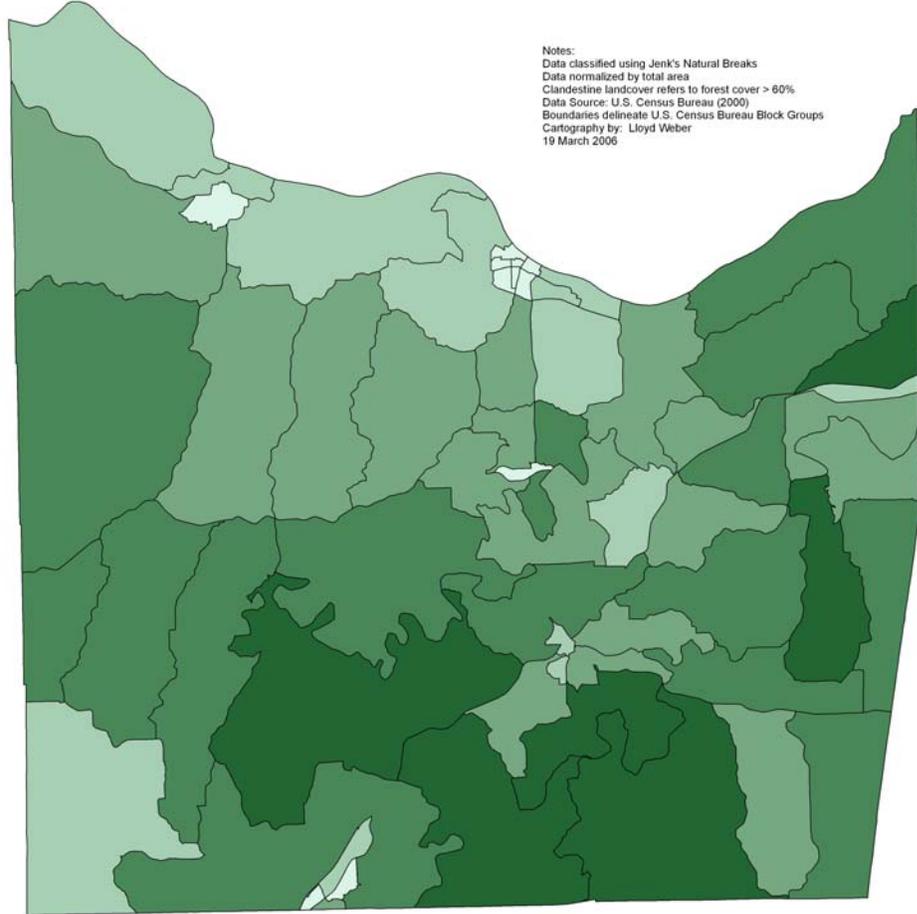
White Population



Map 4-7

Franklin County Clandestine Landcover

Notes:
Data classified using Jen's Natural Breaks
Data normalized by total area
Clandestine landcover refers to forest cover > 60%
Data Source: U.S. Census Bureau (2000)
Boundaries delineate U.S. Census Bureau Block Groups
Cartography by: Lloyd Weber
19 March 2006



Map 4-8

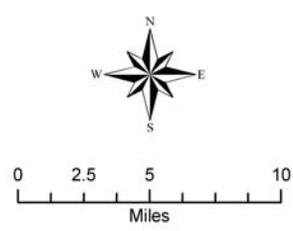
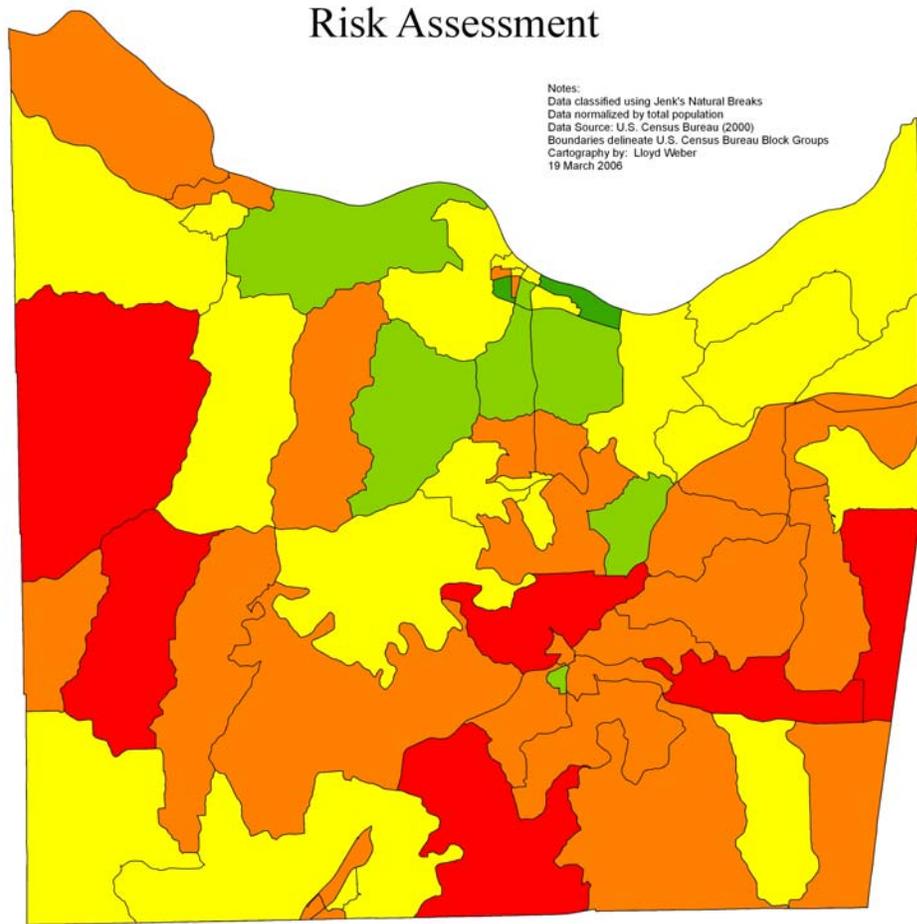
Each component of the model (table 4-1) has been reviewed and discussed above with respect to their descriptive statistics and spatial patterns. Solid conclusions cannot be drawn as to the predictive strength of any individual component. Patterns of meth lab seizures and an individual component may be coincident; however this would not lead to a well-founded conclusion that the component is predictive of illicit methamphetamine production. As reviewed literature has shown the formation and underlying dynamics of an illicit methamphetamine landscape are complicated and require deeper analysis. Therefore, the individual components were processed and combined to create model output with the intent to perform a more sophisticated analysis on the spatial relationships between the model components and the empirical meth seizure data. The presentation and analysis of the model application follows.

Model Application

The output from the model application is cartographically depicted in map 4-9. This output was created by the adding of the model component layer data. The model used contains the seven components described in table 4-1. The pattern of the results indicates the potential for an elevated risk of illicit methamphetamine production in the southeast portion of the county. There is a corridor of similar elevated risk that stretches from the west central area of the county and connects to the larger areas of higher risk. The model predicts that the north central areas of the county will experience a relatively low risk of the formation of a clandestine meth production problem. A visual inspection of the lab seizure data overlaid on the model output (map 4-10) supports the conclusion that the model has been successful in picking up the trend of illicit meth production in Franklin County, Missouri.

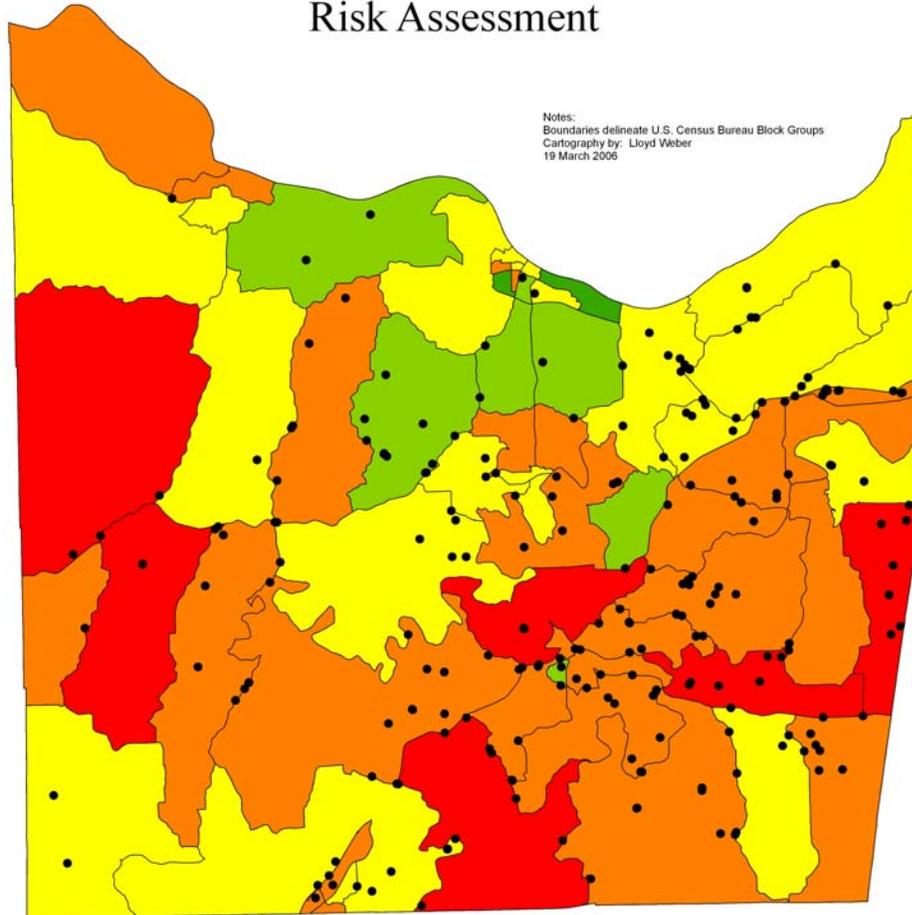
Franklin County Illicit Meth Production Risk Assessment

Notes:
Data classified using Jenk's Natural Breaks
Data normalized by total population
Data Source: U.S. Census Bureau (2000)
Boundaries delineate U.S. Census Bureau Block Groups
Cartography by: Lloyd Weber
19 March 2006



Map 4-9

Franklin County Illicit Meth Production Risk Assessment

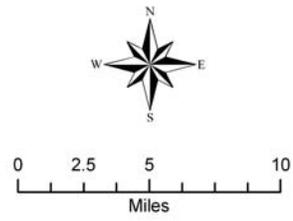


Notes:
Boundaries delineate U.S. Census Bureau Block Groups
Cartography by: Lloyd Weber
19 March 2006

Risk Rating

- High
- Moderate High
- Moderate
- Moderate Low
- Low

1 Dot Represents 1 Illicit Meth Lab Seizure



Map 4-10

A more quantitative approach to validating the model output is presented in tables 4-2 and 4-3. These statistics are based on coverage of the various risk ratings compared to the percentage of total meth activity score for the county. Table 4-2 is based on weighting scheme 1 described in table 3-2. These results confirm the visual inspection of the model output as discussed in the previous paragraph. The model is successful in identifying areas that have the potential for an elevated risk of having a meth production problem. Nearly 64% of the meth labs seized in Franklin County were located in block groups that were modeled to have a risk rating of “moderate high” or “high”. The model was also successful in its indication of areas that have a lower potential of a meth production problem. Less than 8% of the lab seizures were located in block groups that had a computed risk rating of “moderate low” or “low”.

Risk Rating	% of Meth Activity Score
High	13.0
Moderate High	50.8
Moderate	28.7
Moderate Low	7.5
Low	0

Table 4-2: Model coverage validation based on meth activity scores computed using weighting scheme 1

Table 4-3 shows results of a simple validation utilizing meth activity scores computed using weighting scheme 4 shown in table 3-2. The trend is nearly identical to that of the results presented in table 4-2. The weighting of the labs to better show the illicit meth landscape does not alter the general success of the model. Any enhancements made with the application of a weighting scheme are negligible.⁴

Risk Rating	% of Meth Activity Score
High	14.1
Moderate High	48.8
Moderate	27.7
Moderate Low	9.4
Low	0

Table 4-3: Model coverage validation based on meth activity scores computed using weighting scheme 4

Ordinary Least Squares Regression

The validation technique presented above indicates the model is picking up the trend of illicit meth seizures in Franklin County. For a deeper understanding of the underlying spatial relationships taking place between the model components a more sophisticated type of analysis is applied. This analysis is in the form of ordinary least squares (OLS) regression and is applied to several model permutations (table 3-6).⁵ In one application of OLS the dependent variable is the block group's illicit methamphetamine production score computed with a weighting scheme that treats all meth lab seizures equally (table 3-2). Another application of OLS utilizes a dependent variable that is represented by the block groups' illicit meth score computed using a

⁴ Model validation using data computed with weighting schemes 2 and 3 as described in table 3-2 were also utilized. No significant change in the validation pattern was noted.

⁵ OLS analysis was conducted using dependent variables computed using weighting schemes 2 and 3 as described in table 3-2. The results did not provide any further significant findings and will not be presented in this work.

weighting scheme that emphasizes a large difference between production labs and dumpsites (table 3-2). The structure of the model permutations is described in table 3-6.

Table 4-4 summarizes the output from the ordinary least squares regression analysis as applied to all illicit meth labs seizures in Franklin County being weighted equally. The dependent variable in this case is the total number of lab seizures irrespective of the classification. The results of the ordinary least squares regression analysis provide insight into the relationships among the model components as well as the relationships between the model components and the illicit meth lab seizure data.

There are three trends from the output that relate to the objectives of this study.⁶

Component	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8	Run 9	Run 10
Pct. Rural	4.475	1.705	4.381	1.764	2.338	0.870	2.486	0.998	1.906	0.843
Pct. Poverty	15.894	8.996	9.833	6.055	20.981	14.970	20.806	14.869	15.065	11.590
Pct. Undereducated			8.634	4.577	13.053	8.682	12.913	8.598	16.097	11.926
Pct. Unmarried					-20.542	-14.872	-20.861	-15.165	-26.494	-20.667
Pct. 25 – 29							7.797	6.254	9.472	7.860
Pct. White									-34.420	-26.716
Pct. Clan LULC		9.823		9.435		7.329		7.281		5.837
Adjusted r-squared	0.163	0.262	0.166	0.255	0.241	0.284	0.230	0.273	0.268	0.289

Bold indicates significant at $p \leq .05$

Table 4-4: OLS coefficients and adjusted r-squared values. Dependent variable was block group meth activity score computed using weighting scheme 1.

The first trend that is notable is found in the adjusted r-square values of the odd numbered model runs. These model runs focused solely on the socio-economic based model components. From the base model permutation of percent rural and percent poverty, the adjusted r-square values increase with the addition of percent undereducated and percent unmarried. The regression output indicates that percent undereducated is

⁶ Closer examination of the percent rural model component indicated the data was not normally distributed. The data exhibited a binary nature in that most block groups were either greater than 80% or less than 20% rural with very few block groups falling in the middle. The percent rural model component was reconfigured as a dummy variable and OLS regression testing was re-accomplished. This modification to data analysis was an attempt to reduce noise from the model analysis. In the end, the adjusted r-squared values varied little from the analysis accomplished using percent rural. Further results and analysis is accomplished using the results presented in table 4-4.

positively correlated with the meth production in this case study but that percent unmarried is apparently negatively correlated. The fact that percent unmarried is strongly negatively correlated is significant. Reviewed literature consistently included higher rates of unmarried populations as one of the foundations in the formation of an illicit drug production landscape. Beyond percent unmarried, adding the model component that represents the population aged between 25 and 29 reduced the adjusted r-squared value. This reduction in the predictive power of the model may indicate that the predominate age group using and producing meth has shifted. Adding percent white increased the adjusted r-square value but the analysis indicates that this model component is strongly negatively correlated to illicit meth production. The accuracy of this assessment is questionable as the descriptive statistics of the county presented in table 4-1 indicates a strong negative skewness of percent white with a mean of over 97%. The high mean combined with the small range of values indicates that the percent white model component is highly sensitive to the slightest shift in the respective block group's meth activity score.

A second significant trend that appeared in the analyzed data is that of the addition of the clandestine landcover model component. Reviewed literature referred to illicit meth landscapes as having a physical landscape that is concealing in its purpose. For this study secondary data is used that allows for the extraction of a potentially concealing landcover. Table 3-4 indicates which components from the latest Missouri LULC data are used in the derivation of this model variable. In summary, the landcover that is used consists of over 60% forest cover. When quantified and included as a model variable in the OLS regression analysis it appears to be identified as a strong positive

predictor of illicit meth production. The clandestine landcover model variable is included in the even numbered runs. This allows for focus on the added socio-economically based component before introducing the physical geographically based model component. The adjusted r-squared values increase significantly each time the clandestine landcover variable is added to the analysis. Its predictive power wanes as socio-economically based variables are added but it still continues to be measured as a positively correlated model component. These results indicate that quantifying and adding a probable clandestine landcover model component to the base model proposed by the Illinois State Police in 1999 is a significant improvement to the overall model.

The adjusted r-squared values reported in table 4-4 are relatively low in their explanatory power. The maximum value of .289 occurs when all model components are tested. There is also a noticeable trend of some variables falling in and out of statistical significance at the .05 level as various model components are added to the testing runs. The model component represented by percent rural becomes statistically insignificant at the .05 level after run 3 (table 4-4). The percent unmarried model component becomes statistically insignificant with the presence of the percent clandestine landscape model component. This pattern implies some degree of correlation between percent unmarried and percent clandestine landcover. The percent undereducated component approaches statistical significance on many occasions and does become statistically significant in the ninth model permutation (table 4-4).

There are possible explanations for the overall low explanatory power of the various tests conducted. These explanations also aid in explaining reasons model components are statistically significant in some model combination test but are not as

significant in others. Collinearity is a probable reason for the loss in overall explanatory power. It has been shown in some studies that there is a linear relationship between poverty and educational attainment (Hannon, 2003). These two components are present in eight of the tests conducted on the model components (table 4-4). The probable collinearity introduced by the presence of these two variables is a factor in keeping the overall explanatory power of the model relatively low.

The strong negative correlation measured in the percent unmarried model component is worthy of closer examination. This model component was documented in reviewed literature of having a positive correlating relationship with illicit drug production (Donnermeyer et al., 2002). Despite this finding contradicting existing research and wisdom pertaining to who produces meth, to conclude that unmarried individuals are less likely to be involved in meth production would be committing the ecological fallacy. The ecological fallacy is the inference of the nature of individuals based on aggregate data (Robinson, 1950). In the context of this study, the block groups that had higher rates of meth production may have also had a higher percentage of married population. The fact may remain that the unmarried population is more likely to be involved in meth production, but in this county they may be producing it in areas with higher rates of married adults. This model evaluates how area-wide characteristics are associated with meth production, and meth producers may have different characteristics than the areas they operate in.

Compared to the results presented based above (table 4-4), the trend of the OLS results based on data derived using weighting scheme 4 (table 3-2) remains consistent. The same components are analyzed to be either negatively or positively correlated to the

illicit meth production activity and the adjusted r-square value behaved in the same fashion. The correlation coefficients are larger due to the weighting scheme implemented for this analysis.

Component	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8	Run 9	Run 10
Pct. Rural	21.224	10.121	20.627	10.634	12.879	7.253	14.517	8.906	11.075	7.855
Pct. Poverty	57.591	29.941	19.117	4.687	61.405	38.374	59.463	37.072	25.399	14.873
Pct. Undereducated			54.801	39.308	71.565	54.820	70.012	53.743	88.905	76.270
Pct. Unmarried					-77.921	-56.198	-81.453	-59.973	-114.876	-97.225
Pct. 25 – 29							86.355	80.539	96.290	91.409
Pct. White									-204.219	-180.882
Pct. Clan LULC		39.374		36.038		28.077		27.456		17.680
Adjusted r-squared	0.134	0.191	0.147	0.191	0.183	0.201	0.179	0.263	0.236	0.235

Bold indicates significant at $p \leq .05$

Table 4-5: OLS coefficients and adjusted r-squared values. Dependent variable was block group meth activity score computed using weighting scheme 4.

A significant finding in comparing the results in table 4-4 to the results in Table 4-5 is the actual value of the adjusted r-square for each model run. The rationale behind implementing weighting schemes is to attempt to more accurately describe the severity of each block group’s illicit meth activity. Based on definitions of the three types of seizures it was concluded that certain seizures are indicative of a more severe illicit methamphetamine production problem. The results of the OLS regression tests, however, indicate that the application of the weighting schemes actually decreased the predictive power of the model components. Comparing the adjusted r-squared values for each similar model runs between weighting schemes indicates a significant decrease in the adjusted r-square value in the analysis results based on weighting scheme 4 (table 4-5). Subsequently, the adding of the clandestine landcover model component had less of an improving effect as compared to the improvements found in the analysis based on weighting scheme 1 (table 4-4). This finding indicates that an area’s illicit meth activity can be measured in terms of total number of illicit methamphetamine sites seized

regardless of the classification of the seizure sites. With the conclusion that application of a weighting scheme does not enhance the analysis of the applied model further presentation and analysis of results will be solely based on the model as applied using weighting scheme 1 (table 3-2).

Geographically Weighted Regression

The application of OLS regression as an analysis tool may not be able to provide an accurate measure of the predictive strength of a model. Ordinary least squares regression works at the global level, which in the case of this study would be Franklin County, Missouri. The model components, in an OLS analysis, are analyzed equally across space without regard for potential local variations in the model component relationships. To measure for this potential spatial variability and to produce an analysis that does account for locally significant variation geographically weighted regression is the appropriate analysis tool (Fotheringham *et al.*, 2002; Malczewski *et al.*, 2004).

Before employing geographically weighted regression as an analysis tool a determination is made if there is significant spatial variability in the data. If there is not statistically significant variability found then OLS regression would be deemed suitable as a model analysis tool. The results from the testing of spatial variability are presented in table 4-6.

Component	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8	Run 9	Run 10
Pct. Rural	0.11	0.01**	0.13	0.00	0.12	0.01**	0.15	0.02*	0.16	0.02*
Pct. Poverty	0.05*	0.00***	0.12	0.06	0.12	0.07	0.12	0.07	0.07	0.04*
Pct. Undereducated			0.43	0.61	0.36	0.45	0.39	0.47	0.68	0.72
Pct. Unmarried					0.36	0.45	0.33	0.48	0.26	0.63
Pct. 25 – 29							0.62	0.63	0.57	0.66
Pct. White									0.13	0.18
Pct. Clan LULC		0.05*		0.00***		0.02*		0.02*		0.05*

*** Significant at .001 level
 ** Significant at .01 level
 * Significant at .05 level

Table 4- 6: Monte Carlo test for spatial variability (p-values).

The results from the spatial variability test indicate statistically significant spatial variability in the model components percent rural, percent poverty and percent clandestine landcover. As has been established, the model variables represented by percent rural and percent poverty have been documented in literature as the two most common socio-economic conditions found in an illicit methamphetamine production landscape (ISP, 1999; Kraman, 2004). The significant spatial variability found in these two key model components led to the decision to commence with a set of geographically weighted regression tests.

The results of the GWR analysis are best presented and discussed in a compare and contrast fashion with that of the OLS analysis. The numeric output is presented in table 4-7. This table presents the residuals measured using OLS and compares them to the residuals measured using GWR. An F statistic is produced from this comparison on which a determination is made with respect to the statistical significance of the potential improvement in the analysis provided by GWR. The adjusted r-squared value from the GWR analysis is also provided in this table for the purpose of comparing values from the OLS regression adjusted r-squared values in table 4-4.

Parameter	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8	Run 9	Run 10
OLS Residuals DF	3.00	4.00	4.00	5.00	5.00	6.00	6.00	7.00	7.00	8.00
GWR Improvement DF	5.85	3.11	5.87	3.36	5.31	4.99	6.17	5.20	4.56	4.78
GWR Residuals DF	55.15	56.89	54.13	55.64	53.69	53.01	51.83	51.80	52.44	51.22
F Statistic	5.121	4.048	4.885	3.749	4.743	3.577	4.140	3.307	3.629	3.127
Adjusted r-squared from GWR	0.399	0.363	0.395	0.355	0.432	0.413	0.423	0.398	0.395	0.397

Table 4-7: ANOVA test and adjusted r-squared values from GWR

The improvement made by applying GWR for model analysis as measured by the F-statistic was significant at least at the .01 level. This indicates the spatial variability found in the model components discussed above was handled better by the GWR analysis as compared to the OLS regression analysis.

The comparison made between the OLS and the GWR output does indicate that the use of GWR as a model analysis tool allows for more robust investigation of the spatial dynamics found in the model components. A better way to demonstrate what GWR analysis is indicating for the methamphetamine landscape of Franklin County is to cartographically display output. The output chosen for further analysis and discussion is from the 10th model run (table 4-7). This model run included all input parameters and the results from the Monte Carlo test (table 4-6) indicates significant spatial variability in the components percent rural, percent poverty and percent clandestine landcover. The output discussed is the t-values of each model component as computed by the application of GWR. These values have been thematically map and are presented below.

Map 4-11 displays the t-values for the percent rural model component. The pattern that is shown indicates that rural population has more importance in terms of meth production in the eastern half of the county as compared to the western half of the county. This means that if increases were seen in rural populations in the eastern half of the county there is the possibility that an increase in meth production would follow.

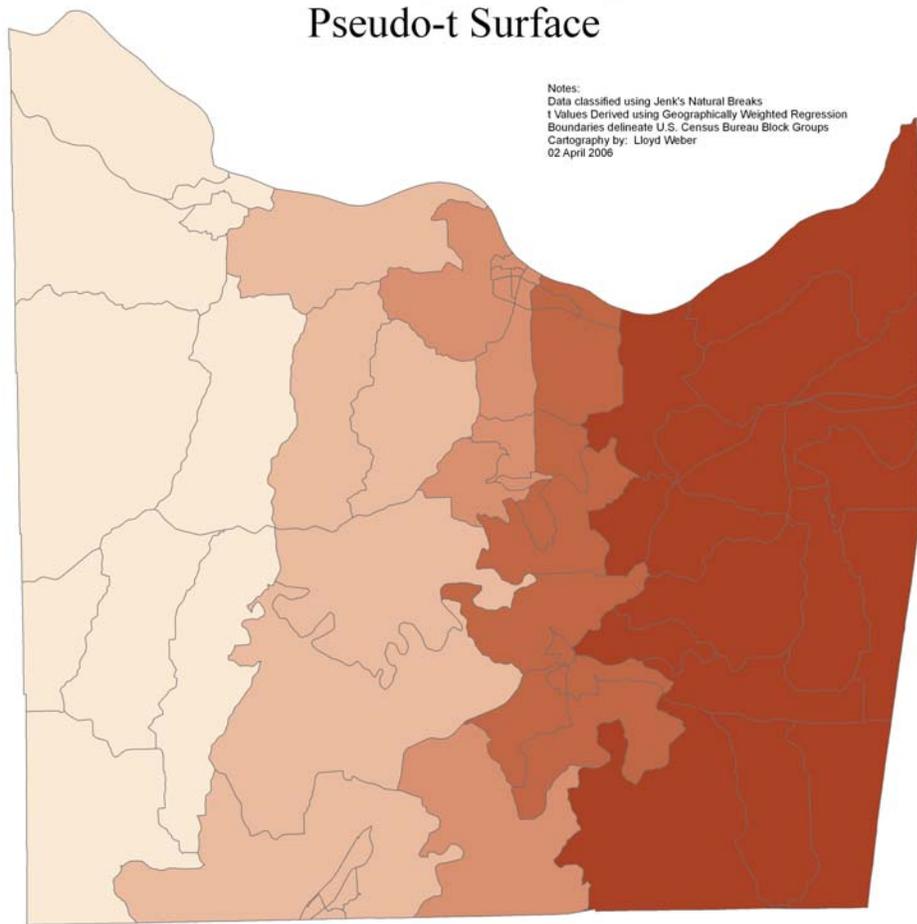
Another model component that was measured to have significant spatial variability in Franklin County is percent poverty. The t-values calculated for this model component are cartographically presented in Map 4-12. The area that percent poverty plays a strong role in the formation of a methamphetamine production problem is concentrated in the northeastern portion of the county. An increase in poverty in this area may correlate to an eventual increase in methamphetamine production in the block groups within the northeastern portion of the county.

Map 4-13 is a thematic representation of the t-values calculated for the clandestine landcover model component. The pattern that forms in the t-values for this component indicates that the clandestine landscape as defined in this study has a stronger influence in the formation of a meth production problem in the western portion of the county. This is an interesting finding as the denser clandestine landscape is found in the south central portion of the county (map 4-8) and a dense cluster of meth lab seizures are also located south central Franklin County. Map 4-13 is a good example of the type of analysis GWR allows. The global spatial pattern as well as the OLS analysis indicates that the clandestine landcover is possibly a good predictor of illicit meth production. Visual analysis of the empirical data used in this study and the reviewed literature indicate that meth production generally occurs in and around denser vegetation. The subsequent GWR analysis goes beyond both visual analysis and OLS regression analysis and indicates where, in this case, percent clandestine landcover is a stronger influence in the formation of a meth production problem.

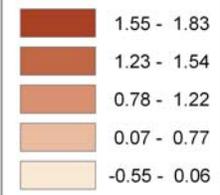
Missouri

Franklin County Rural Population Pseudo-t Surface

Notes:
Data classified using Jenk's Natural Breaks
t Values Derived using Geographically Weighted Regression
Boundaries delineate U.S. Census Bureau Block Groups
Cartography by: Lloyd Weber
02 April 2006



t Values for Rural Population

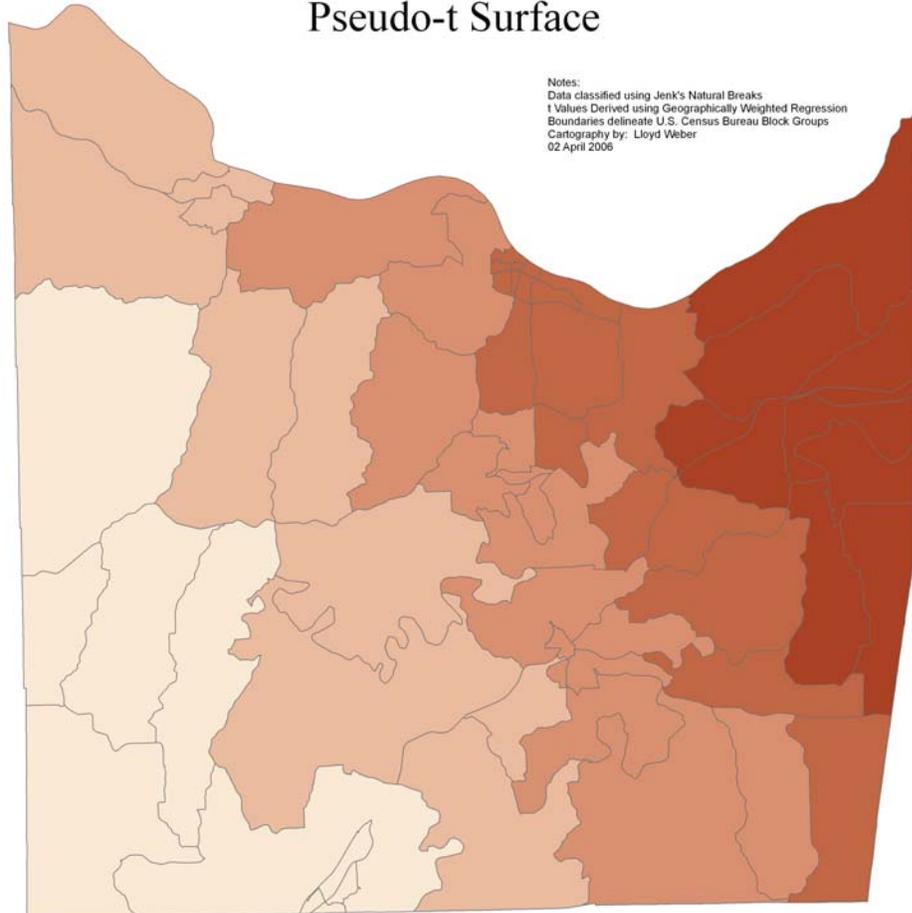


Map 4-11

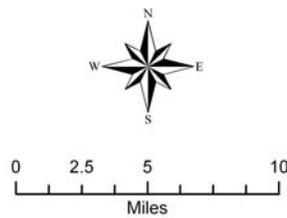
Missouri

Franklin County Population in Poverty Pseudo-t Surface

Notes:
Data classified using Jenk's Natural Breaks
t Values Derived using Geographically Weighted Regression
Boundaries delineate U.S. Census Bureau Block Groups
Cartography by: Lloyd Weber
02 April 2006



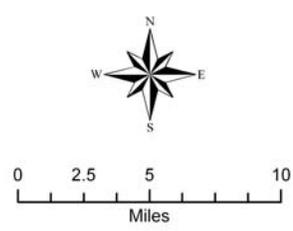
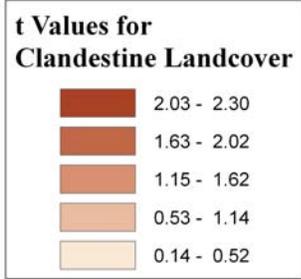
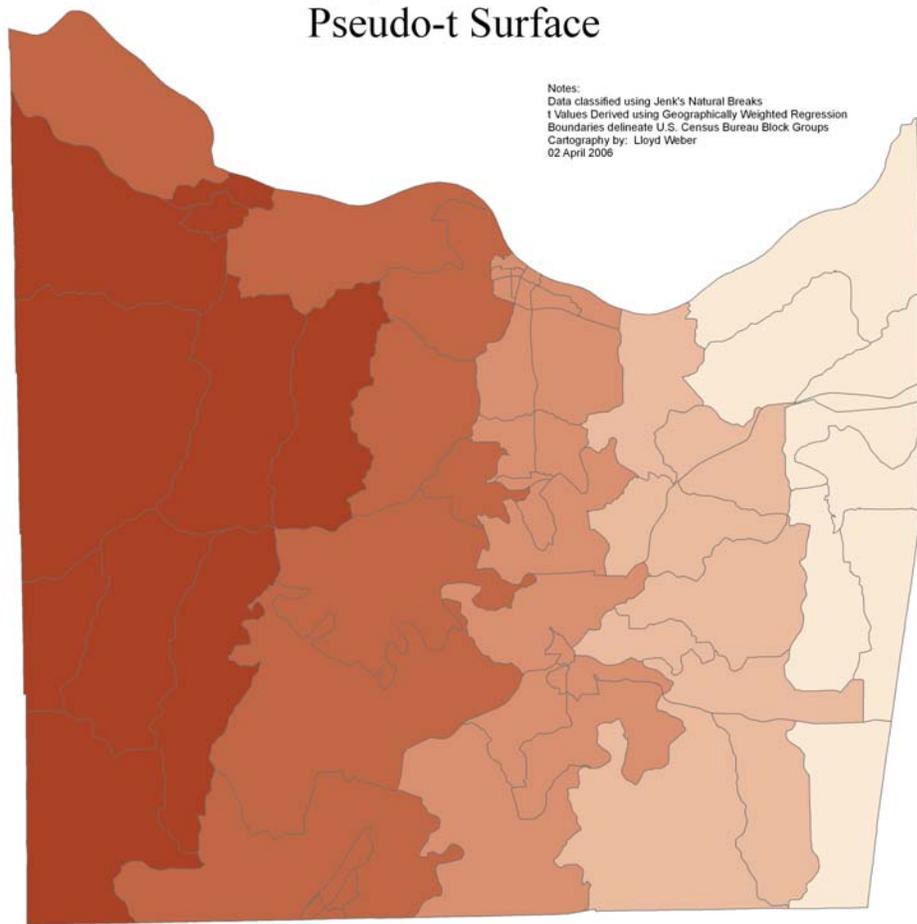
t Values for Population in Poverty



Map 4-12

Franklin County Clandestine Landcover Pseudo-t Surface

Notes:
Data classified using Jenk's Natural Breaks
t Values Derived using Geographically Weighted Regression
Boundaries delineate U.S. Census Bureau Block Groups
Cartography by: Lloyd Weber
02 April 2006



Map 4-13

Conclusion

The management of the model and empirical data along with the application of the model was greatly enhanced by the use of a GIS. Model components were easily added and analyzed as needed. The empirical data in the form of seized lab plots was also well managed by the employment of a GIS. This efficient management of critical data allowed for the deeper evaluation of the model components.

The visual analysis along with the simple form of model validation indicates that the model as created by the Illinois State Police and advanced by this study has value in identifying areas that have the potential to form methamphetamine production problems. The model, as applied in this study, was also successful in highlighting areas that are potentially at a lower risk for the development of an illicit methamphetamine problem.

A further analysis of the model components using ordinary least squares regression revealed significant trends. The addition of the clandestine landcover as a model variable enhanced the predictive ability of the model. The OLS analysis also revealed that, for this study area, percent white and percent unmarried are negatively correlated to illicit meth production. This was an unexpected result due to the findings of other studies that indicate illicit methamphetamine production is strongly correlated to meth use and production in a positive manner. The OLS regression analysis also indicated that the 25 to 29 year old age group may not be as strong a predictor of meth activity as it has been in the past.

With the possibility of locally significant variability and relationships within the data various testing was accomplished to test for this variability and to more accurately analyze the model components. The results of these additional tests indicate that the base

components of the model, percent rural and percent poverty, along with the added component of percent clandestine landcover exhibit significant spatial variability. The GWR analysis provided results that indicate this variability could be successfully accounted for and that the GWR analysis could provide model coefficients that are a significant improvement over the OLS coefficients.

CHAPTER 5

CONCLUSION

Methamphetamine use and production will always have embedded spatial elements. The meth production process will remain a function of location and meth addiction will remain a human geographic phenomenon. The illicit methamphetamine production landscape may shift in response to various controls placed upon it; however the addiction to meth is so strong that it will be met by some means.

This study has shown that geospatial tools and methods can be effective in measuring and monitoring the illicit meth landscape and should be part of any strategic plan devised to reduce illicit methamphetamine production. The use of a GIS greatly enhanced the overall management of all model components, empirical meth lab seizure data and the application of the spatial analytical tools used in this study. The ability to easily manage all aspects of the various data required for this study allowed more in depth evaluation of model components. The intricate spatial relationships found in illicit methamphetamine production makes the use of a GIS an important component of this study. Future research in the area of crime models would be severely hampered if a GIS and associated tool set is not used.

The spatial analytical techniques employed by this study allowed for the evaluation of the predictive strength of individual components that comprised the illicit meth production model. The visual analysis of the model output along with the type of model validation used in this study indicates the model as created by the Illinois State Police and advanced by this work has value in identifying problem areas that have

potential for methamphetamine production problems. The model was also successful in highlighting areas that are potentially at a lower risk for the development of an illicit methamphetamine problem. Those agencies that are responsible for monitoring an area's methamphetamine production problem would benefit greatly by integrating the use of a spatial model such as the one used in this study. The ability to accurately predict an area's illicit methamphetamine landscape would allow for more concentrated eradication efforts in the areas that are more prone to develop a meth production problem.

Data collection issues emerged as a liability during the execution of this study. The addresses provided by Franklin County law enforcement of the meth lab seizure points may not have reflected the actual location of the seized meth lab. Reviewed literature has documented that studies focused on rural crime will face this problem due to the inaccurate reporting of crime locations in wide open rural areas. Research accomplished for this study found that the form used to report illicit methamphetamine lab seizures to the federal government contains an area to record the latitude and longitude of the seized meth lab (DEA, 2003). A strong effort should be made to equip agencies responsible for the seizure and reporting of illicit methamphetamine labs with the necessary equipment to be able to record this vital spatial information. This equipment could come in the form of a relatively inexpensive global positioning system (GPS) receiver. The increase in the accuracy of the collected data points would greatly enhance efforts, such as this study, in the monitoring and modeling of areas with a meth production problem. The ability to more accurately measure the illicit meth landscape would pay dividends in the form of more quickly eradicating the problem.

Another data issue that is in need of addressing is the release of a state wide meth lab seizure data set. The methodology used and the geospatial tools and techniques employed in this study were successful in applying and evaluating the meth production model over a county. Access to the state side data set would allow researchers to apply and evaluate the meth production model over the entire state of Missouri. This ability to apply and evaluate the model state wide would provide more valuable information and further advance the knowledge of the complicated spatial relationships of meth production. More pointed conclusions could be drawn upon completion of a study that was able to use all of Missouri's meth lab seizure data. Trends and the predictive strength of model components that were discovered in this study would be better measured in a data set that had many more data points spread across a larger area. It is hoped that the success of this case study further highlights the short sightedness of the state and federal agencies that denied the request for state wide meth lab seizure point data.

Efforts to eradicate an area's methamphetamine production problem should focus on the human geographic aspect as this is where the demand for production of illicit methamphetamine is rooted. From a human geography perspective, the results from this study indicate significant predictive power by the percent rural, percent poverty and percent undereducated model components. Policies should be aggressively implemented that would address the formation of methamphetamine problems among the impoverished and undereducated. The main focus of any such policy should be educating the "at risk" population of the highly addictive properties of methamphetamine and the long term affects of methamphetamine addiction. This study has shown, by the use of geospatial

techniques, a sound way to focus efforts in identifying areas that would likely have populations at risk.

This study has demonstrated that geospatial data and tools are effective in locating and quantifying the very physical features that have been documented as being associated with the risk of forming a meth production problem. The physical geographic element incorporated into this study's model was clandestine landcover in the form of dense vegetation. The results from this study have shown that clandestine landcover is a positive predictor of illicit methamphetamine production. Polices that have an aim to reduce meth production in an area should recognize this physical feature of an area and seek to increase monitoring of these that have the ability to conceal clandestine manufacturing of methamphetamine. Awareness of the public should be increased in the form of clear and concise descriptions of areas known to be able to hide illicit meth production activity.

Illicit methamphetamine landscapes are a complicated array of human and physical geographic features. Many things are needed to accurately measure, monitor and model a spatially intricate entity such as illicit meth landscapes. Meth lab seizure point data is the most crucial piece to this process. The state of Missouri has led the nation in meth lab seizures in an overwhelming fashion for the past five years and yet when state agencies were contacted for their assistance in gaining access to a state wide meth lab seizure data set they were unwilling to provide the requested information. This may be due to simply not understanding that employing geospatial tools and techniques can be a highly effective means to combat the meth production epidemic that has gripped Missouri for the past half-decade. This study has been successful in demonstrating that

when meth seizure data is provided the power of geospatial technology can be utilized upon the data to provide deep insight into the illicit meth landscape in such a fashion that would allow for more efficient means of monitoring meth production with the goal of eradicating the problem. Sadly, the culture of Missouri state government agencies seems to treat the state's meth problem in a reactive manner rather than a proactive one. The state would be wise to follow the example of Franklin County and release its illicit methamphetamine seizure point data. The tools and techniques that could quickly be put to use in a state wide fashion have been demonstrated by this study. A small effort on the part of Missouri's agencies responsible for the maintaining of the state wide illicit meth lab seizure data would be the first step in benefiting all Missourians.

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