Revisiting the Spatial Analysis of Crime in National Forests

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We examined spatial patterns of crime incidents in national forests covering 112,396 km² in the northwestern United States. In this study we analyzed a database containing 40,003 spatially referenced crime incidents representing felonies, infractions, and misdemeanors during 2 calendar years (2003–2004) at several geographic scales. We applied several geospatial analytical techniques including quadrat analysis, nearest neighbor analysis (NNA), and nearest neighbor hierarchical (NNH) clustering to investigate crime incident spatial patterning. These geospatial tools were beneficial in identifying crime incident relationships contained within a large, complex spatial database. NNH clustering identified 15 regional clusters with 16,138 crime incidents, focused in the central portion of Oregon’s national forests, specifically in the Deschutes, Mount Hood, and Willamette National Forests. Subsequent NNA tests confirmed spatial patterning in all three forests. Closer examination of a confirmed hot spot in one forest revealed a recreation corridor with adjacent recreation destination amenities and a large proximate metropolitan area, a combination of circumstances not apparent at the initial regional analysis scale. Other spatial data layers, such as transportation, urban boundaries, and water bodies, augmented our ability to understand, interpret, and validate geospatial analysis results. Spatial statistical analysis of crime incidents provides managers with a better understanding of the relationships between crime patterns, natural resources, and human built environments/infrastructure. Spatial statistical analysis can contribute to natural resource law enforcement as the basis for a decision support system. Decision support efforts include identifying places where crime is prevalent and determining where crime occurs with greatest frequency.

Keywords: crime, geospatial analysis, US Forest Service

Crime research in US national forests and parks is a recent phenomenon. Crime occurrence in forests and parks, however, is not new. Chavez and Tynon (2000) investigated crime incidents in the US Forest Service and found a wide range of crimes. Examples of crimes included assaults; drug trafficking and production; and violence perpetrated by individuals, gangs, and extremist groups (Chavez et al. 2004, Tynon and Chavez 2006). Mounting evidence indicates that many types of crime occurring in metropolitan areas also occur in national forests and other public lands in the United States (Pendleton 1996, Vanderpool 2002, Wynveen 2005). Law enforcement officers who investigate crime on public lands such as the national forests often are challenged in identifying and evaluating crime incident relationships across vast landscapes (Tynon and Chavez 2006, Wing and Tynon 2006). Spatial analytical tools that examine the spatial patterning of crime incidents provide insight into how best to allocate crime mitigation efforts.

The US Forest Service developed the Law Enforcement and Investigations Attainment Reporting System (LEIMARS) to digitally encode and store crime incidents for all the national forests and grasslands that it manages (Tynon and Chavez 2006). In building on an earlier analysis (Wing and Tynon 2006), we investigated national forest crime incident magnitudes at increasing spatial resolutions. Before Wing and Tynon (2006), there were no other published studies that used LEIMARS for the spatial statistical analysis of crime in national forests and there were few examples of landscape analysis of crime patterns in rural areas.

Our primary objective was to spatially examine crime incidents and crime patterns in US Forest Service Region 6 national forests. More specifically, we wanted to determine where crime was most prevalent in Region 6, what types of crime were occurring, and whether associated landscape features offered explanations for crime patterns. We used several geospatial analytical tools to examine crime incident patterning at several spatial scales including regional and individual forest levels.

Methods

Several spatial analytical techniques are available to assist in the interpretation of...
crime incident locations. One such technique is the application of spatial statistics to analyze geographic phenomena. Spatial statistics can address whether geographic patterns exist. Spatial patterns can be described as occurring randomly, systematically, or in a clustered configuration. A random pattern indicates that there is a low probability of geographic influence on spatial distribution. A systematic pattern is one that occurs at regular intervals while a clustered pattern is a collection of features that are grouped. Systematic or clustered patterns that are statistically significant warrant closer inspection and may specify where to focus crime prevention or mitigation efforts.

Building on our earlier efforts (Wing and Tynon 2006), we used several additional geospatial analytical techniques including quadrat analysis, nearest neighbor analysis (NNA), and nearest neighbor hierarchical (NNH) clustering. We also used Kolmogorov–Smirnov (K–S) and variance–mean ratio tests to examine the statistical significance of spatial patterns in the crime incident database. We found these tools to be beneficial in identifying crime incident relationships contained within a large, complex spatial database.

We examined LEIMARS crime incident data reported by US Forest Service Region 6. Region 6 consists of approximately 112,396 km² in the states of Washington and Oregon (Figure 1), representing 14.4% of all national forestlands in the entire US Forest Service system. The Region 6 database contained 40,003 spatially referenced crime incidents representing felonies, infractions, and misdemeanors for calendar years (CYs) 2003 and 2004. LEIMARS contains not only investigative information, but also features the latitude and longitude coordinates of crime incidents, serving as a geographic information system (GIS) database for the entire 781,000 km² (193 million ac) national forest system. We also acquired spatial data layers for roads, national forest boundaries, urban boundaries, and hydrology for Region 6. We georeferenced all spatial data layers to a standard map coordinate system to ensure reliable analysis results. We used a variety of spatial statistical analysis software including ArcGIS (ESRI 2008) and CrimeStat (Levine 2007). In addition, we used geospatial analytical techniques described in Wong and Lee (2005) and Mitchell (2005). These authors provide detailed formulas and application examples for spatially based examinations of data relationships and patterns. Eck et al. (2005) provide a description of analytical approaches and software packages for analyzing spatial crime data. Anselin et al. (2000) describe methodological issues and limitations in spatial statistical analyses of crime data.

**Quadrat Analysis.** Our study area was large in geographic extent. One method for comparing change across a vast landscape is to grid the area into equal-sized portions (quadrats) and compare them. We wanted to compare crime frequencies in the quadrats. Quadrat analysis splits an area into equally sized portions and summarizes the number of crimes that occur in each portion (Eck et al. 2005). Quadrat analysis is a spatial statistical technique for quantifying density changes, as described by the proximity of features to one another, across landscapes. The identification of an appropriate quadrat size is critical to this analytical technique. Determining quadrat size requires careful consideration of the entire land area and the number of features to be analyzed. Wong and Lee (2005) suggest a general approach to identifying an initial quadrat size using the equation

\[
\text{quadrat size} = \frac{2A}{r},
\]

where \(A\) = total land area and \(r\) = the number of features.

![Figure 1. US Forest Service Region 6 national forests.](https://example.com/figure1.png)
K–S and Variance–Mean Ratio Significance Tests. Statistical significance of quadrat density distributions can be tested through several techniques. Two commonly used significance tests are K–S and variance–mean ratio. The K–S test compares observed and expected frequency distributions of features within quadrats to determine whether spatial patterns are random. A critical value is compared with a K–S statistic to determine statistical significance (Griffith and Amrhein 1991). The critical value for a single sample comparison is calculated through the equation

$$\text{critical value} = 1.36 / \sqrt{n}$$

where 1.36 is the critical value constant used at the 0.95 probability level, and \(n\) is the number of quadrats. For US Forest Service Region 6 data, we calculated a critical value of 0.13 (1.36/116).5

We needed to calculate the Poisson probability before we could address the K–S significance test. The Poisson distribution is used to describe spatially random patterns. A comparative probability for the critical value based on the Poisson distribution is calculated as follows:

$$P(x) = \left(e^{-\lambda} - \frac{\lambda^x}{x!}\right)$$

where \(P(x)\) is the probability of a given number \(x\) of features in a quadrat, \(e\) is the natural antilogarithm, \(\lambda\) is the average number of points per quadrat, \(x\) is the frequency distribution of points observed in quadrats, and \(x!\) is the factorial of the frequency distribution of points.

$$\lambda = r/n,$$

where \(\lambda\) is the average number of points per quadrat, \(r\) is the total number of points, and \(n\) is the total number of quadrats. For US Forest Service Region 6 data, we calculated \(\lambda = 344.9\) (40,003/116). Once we calculated the Poisson probability, we derived the K–S statistic by taking the largest absolute difference between a comparison of observed and expected Poisson frequencies for the frequency distribution of the number of points in each quadrat.

As with the K–S test, the variance–mean ratio significance test also compares observed and expected patterns. If the spatial distribution is truly random the mean should be equal to the variance and the variance–mean ratio is therefore expected to be near 1.0 (O’Sullivan and Unwin 2003). The variance is calculated as

$$\sigma = \frac{\sum\left[n_j(x_j - \lambda)^2\right]}{n},$$

where \(\sigma\) is the variance, \(n_j\) is the number of quadrats containing \(x_j\) points, \(\lambda\) is the average number of points per quadrat, and \(n\) is the number of quadrats.

Figure 2. Quadrat analysis results for Region 6.

The variance is compared to a theoretically random variance calculated as

$$D_{\text{avg}} = \frac{\sum d_i}{n},$$

where \(D_{\text{avg}}\) is the average distance between neighboring points, \(d_i\) is the measured distance between neighboring points, and \(n\) is the number of points. A completely clustered distri-
bution would have a mean distance of zero because all points would be at the same location. A systematic distribution is the inverse of the square root of the number of points divided by the study area size; a completely systematic distribution has a mean distance of one. A random distribution's mean distance is halfway between the mean distances for a completely clustered and a completely systematic distribution (Mitchell 2005).

The statistical significance of NNA results is determined by comparing the average distance to the distance that would result from a randomly (spatially) distributed collection of points. This comparison can confirm whether observed point distances are systematic, random, or clustered (Krebs 1999). An NNA involves calculating a nearest neighbor index (NNI). The NNI is the ratio of the observed and random distances. Where NNI < 1, features are clustered; random results have an NNI = 1; and an NNI > 1 indicates systematic patterns. A z-score test determines statistical significance.

**NNH Clustering.** In addition to examining the distance relationships between crime locations, we also wanted to see whether crimes occurred in groups. The presence of crime clusters can potentially identify hot spots or areas where crime occurs with greater frequency (Wing and Tynon 2006). Clustering techniques seek to aggregate point locations into groups of points based on spatial proximity. Clusters are created based on criteria that are repeated until all locations are grouped into clusters or the criteria can no longer be successfully evaluated. Clustering criteria can include nearest neighbor, farthest neighbor, centroid method, group averages, and minimum error (Levine 2004). The NNH clustering approach is the most commonly applied. NNH uses the distance between features to determine initial or first-order clusters and continues to group features into higher-order clusters (Mitchell 2005). In general, first-order clusters are more likely to identify crime hot spots. Input criteria include the minimum number of points needed to create a cluster and the maximum distance that a cluster can span. When the average distance between crime locations is small, fewer clusters result. Varying the minimum number of points directly impacts the number of clusters that will be formed. Selecting a larger number of minimum points will lead to fewer clusters. Clusters will only be formed that contain at least the minimum number specified.

Clustering output can be displayed in two formats: convex hulls and standard deviational ellipses (Levine 2004). The convex hull produces a very literal interpretation of the groups by creating a bounding polygon around each cluster. The output ellipses create an area shape that symbolizes collections of points that are included in clusters. This representation is not an exact approximation of a typical SD, which would include 68% of a sample’s data points; it simply serves as a visual display. Generally, a single standard deviational ellipse will encompass greater than 50% of the points within a cluster, whereas two standard deviations will encompass more than 99%. The standard deviational ellipse requires the user to input the desired number of standard deviations that define the visual appearance of the ellipse. A larger SD is typically preferred for crimes that cover entire regions (Levine 2004) such as US Forest Service Region 6. Nevertheless, despite the accepted criteria cited previously, users should experiment with a variety of input criteria values to find the best fit for their specific research needs.

**Results**

We used the general approach to quantifying quadrat size as recommended by
Wong and Lee (2005) and calculated a quadrat size of 5.6 km² ($2 \times 112,396 \text{ km}^2/40,003$) for US Forest Service Region 6. Smaller quadrat areas may not be ideal for larger land areas with many analysis features. In general, smaller quadrat sizes may lead to an excessive number of quadrats. In addition, spatial patterning may not be observable with small quadrat sizes. For US Forest Service Region 6, a 5.6-km² quadrat size results in more than 20,000 quadrats, a number too unwieldy for useful analysis.

We experimented with several quadrat sizes until we arrived at a quadrat size of 2,395 km². This quadrat area appeared to offer a better visual segmentation of US Forest Service Region 6. The larger quadrat size resulted in 116 quadrats for US Forest Service Region 6 once we eliminated quadrats located outside national forest boundaries.

We categorized and mapped the quadrats according to their crime incident density (Figure 2). Areas of higher crime incident density in US Forest Service Region 6 included the western coast of Oregon, an area already recognized for elevated crime incidents (Wing and Tynon 2006). Other areas of increased crime density included many of the national forests located in the Cascade Mountains, which extend from northern Washington to southern Oregon. In contrast, national forests in both northeastern Washington and Oregon exhibited quadrats with relatively lower crime incidents.

To test for statistical significance within the US Forest Service Region 6 data, we calculated a K–S value of 0.73, which was considerably larger than the critical K–S value of 0.13 and indicates that the point frequencies within the quadrats are not randomly distributed. We also tested statistical significance by using the variance–mean ratio test. A nonrandom pattern exists when the $t$-statistic of the variance–mean ratio is greater than the standard critical value of 1.96. Positive $t$-values are representative of clustered patterns whereas negative $t$-values indicate systematic patterns (Wong and Lee 2005). For US Forest Service Region 6 data, we calculated a variance of 433,437.6 and a variance–mean ratio of 1,257.1 (433,437.6/344.9). This high positive value indicates a statistically significant cluster patterning of crime incidents within our quadrats. These significant spatial patterning results encouraged us to apply further quantitative analyses to confirm our initial findings.

We conducted an NNA on the distribution of crime locations to draw further inferences about spatial patterning in US Forest Service Region 6. Crime incidents in US Forest Service Region 6 were significantly clustered (NNI = 0.21; $P < 0.01$; Wing and Tynon [2006]). NNA, however, does not explain where spatial patterning occurs (Chainey and Ratcliffe 2005). Using NNA with a probability level of 0.05, we identified several first-order clusters at the regional scale to identify areas of spatial patterning. This probability level offers 95% confidence that features in a cluster are not near each by chance alone (Mitchell 2005). First-order clusters occur after the first iteration of the NNA calculation. We then experimented with several different hierarchical clustering parameters and varied the search radius, the SD of the ellipse, and the minimum number of points needed to form a cluster. We compared the number and size of ellipses that resulted from the various NNA clustering parameter combinations to judge the effectiveness of this technique in identifying hot spots and how resulting clusters represented the underlying crime incident locations.

At the regional scale we identified a 10,000-m search radius with a 500-point minimum as the preferred set of criteria needed to form a cluster. In addition, we found that a 2.0 standard deviational ellipse helps us recognize hot spots more readily than smaller standard deviations. This set of parameters created 15 clusters in US Forest Service Region 6 (Figure 3). These 15 regional clusters contained a total of 16,138 crime incidents, or an average of 1,076 crime incidents per cluster. The regional clusters were focused in the central portion of Oregon’s national forests, specifically in the Deschutes, Mount Hood, and Willamette...

We used a second set of cluster parameters to investigate crime patterns at the national forest scale. Clustering parameters included a 5,000-m search radius with a 500-point minimum necessary to create a cluster. We also found the 2.0 standard deviation ellipse setting to be superior to smaller standard deviations in drawing our attention to forest scale crime incident hot spots. The forest scale approach resulted in eight clusters containing 11,865 crime incidents. These 14 clusters contained an average of 848 crime incidents. Of these eight clusters, four were located in the Deschutes National Forest and two each in the Willamette and Mount Hood National Forests (Figure 4).

Quadrat Analyses of Three National Forests. We decided to further concentrate our analysis in the Deschutes, Mount Hood, and Willamette National Forests based on the apparent crime incident clusters. We conducted quadrat analyses, calculated K–S statistics and variance–mean ratios, and performed NNAs to investigate whether spatial patterning of crime incidents occurs at finer scales (Table 1). These finer scales included analyzing each national forest separately as well as analyzing all three forests combined. For ease in visibility in our quadrat analyses, we initially targeted 30 quads per forest. We calculated the total area for all three forests and divided this sum by 90 to determine a final quadrat size of 218 km². This final quadrat size required 123 quadrats to cover the irregular area of the three national forests (Table 1). We found statistical significance of spatial patterning in each individual national forest and for all three forests combined. The K–S test results indicated significance in spatial patterning of the crime incidents; they are not randomly distributed. The high positive value for the variance–mean ratio indicates statistically significant clustering of crime incidents.

NNAs of Three National Forests. We used NNAs to confirm spatial patterning in the three national forests. The low NNI values for three national forests as well as for the combined area indicate clustered crime incidents (Table 2). The Willamette National Forest exhibited areas with the most densely clustered crime incidents, with an average mean distance between crime incidents of 98 m (Figure 5). Ellipse 8, located in the Willamette National Forest, had by far the greatest crime incident density (120.4 crime incidents/km²) of all ellipses that we identified in the three national forests. Violation levels in the LEIMARS database are organized into the following categories: administration, civil, felony, infraction, misdemeanor, noncriminal, and petty offense. Table 3 shows violation levels in CY 2003–2004 for US Forest Service Region 6, the Willamette National Forest, and ellipse 8 in the Willamette National Forest. The majority of violations in US Forest Service Region 6 were misdemeanors. Examples of misdemeanors for US Forest Service Region 6 were related to alcohol, polluting waterways, timber theft, and criminal mischief. The majority of misdemeanors in Willamette National Forest included occupancy use, alcohol, general forest products (e.g., cutting or damaging trees and removing timber), sanitation, forest roads/trails, and fire. For ellipse 8, misdemeanors were primarily occupancy use and alcohol violations.

We more closely examined spatial layers of transportation, urban boundaries, hydrography, and administrative units of the national forest area coincidental to ellipse 8. We found that ellipse 8 bordered Cougar Reservoir and Hot Springs, a popular recreation area easily accessible from a major metropolitan area. There is a recreation corridor consisting of numerous campgrounds and boat launching areas on the nearby McKenzie River and a campground and two boat ramps directly on the reservoir. McKenzie Ridge Ranger District, an administrative US Forest Service office, is also nearby. These additional layers and proximity of key landscape features helped provide an explanation for the apparent high crime incident densities in ellipse 8. Although these spatial layers may not reveal information necessary to determine crime causality, they do provide an indication of landscape, infrastructure, and the human dimensions associated with crime density. Investigation and confirmation of the underlying causes for crime hot spots within ellipse 8 should involve collaboration with on-the-ground managers of this resource area.

Table 1. Quadrat analysis results of crime incidents in three national forests (CY 2003–2004).

<table>
<thead>
<tr>
<th>Forest</th>
<th>Number of quads</th>
<th>Mean crimes per quad</th>
<th>A</th>
<th>K–S critical</th>
<th>Variance</th>
<th>Variance–mean ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deschutes</td>
<td>48</td>
<td>184</td>
<td>183.98</td>
<td>0.73*</td>
<td>0.20</td>
<td>6,219,181</td>
</tr>
<tr>
<td>Mt. Hood</td>
<td>41</td>
<td>111</td>
<td>111.46</td>
<td>0.63*</td>
<td>0.21</td>
<td>1,247,712</td>
</tr>
<tr>
<td>Willamette</td>
<td>45</td>
<td>114</td>
<td>114.00</td>
<td>0.67*</td>
<td>0.20</td>
<td>1,241,238</td>
</tr>
<tr>
<td>Three forests</td>
<td>123</td>
<td>151</td>
<td>150.66</td>
<td>0.67*</td>
<td>0.12</td>
<td>8,687,744</td>
</tr>
</tbody>
</table>

* Denotes statistical significance at 95% confidence.

Table 2. Nearest neighbor, ellipse, and density results for crime incidents (CY 2003–2004) in three national forests.

<table>
<thead>
<tr>
<th>Forest</th>
<th>Total crime incidents</th>
<th>Area (km²)</th>
<th>Crime/km²</th>
<th>Mean distance between incidents (m)</th>
<th>NNI</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deschutes</td>
<td>8,831</td>
<td>7,576</td>
<td>1.2</td>
<td>116</td>
<td>0.25</td>
<td>P &lt; 0.01</td>
</tr>
<tr>
<td>Ellipse 1</td>
<td>1,040</td>
<td>100</td>
<td>10.4</td>
<td>99</td>
<td>0.19</td>
<td>P &lt; 0.01</td>
</tr>
<tr>
<td>Ellipse 2</td>
<td>1,308</td>
<td>90</td>
<td>14.5</td>
<td>98</td>
<td>0.17</td>
<td>P &lt; 0.01</td>
</tr>
<tr>
<td>Ellipse 3</td>
<td>880</td>
<td>85</td>
<td>10.4</td>
<td>98</td>
<td>0.17</td>
<td>P &lt; 0.01</td>
</tr>
<tr>
<td>Ellipse 4</td>
<td>703</td>
<td>68</td>
<td>10.3</td>
<td>98</td>
<td>0.17</td>
<td>P &lt; 0.01</td>
</tr>
<tr>
<td>Mt. Hood</td>
<td>4,570</td>
<td>4,795</td>
<td>10.0</td>
<td>98</td>
<td>0.17</td>
<td>P &lt; 0.01</td>
</tr>
<tr>
<td>Ellipse 5</td>
<td>759</td>
<td>24</td>
<td>31.6</td>
<td>98</td>
<td>0.17</td>
<td>P &lt; 0.01</td>
</tr>
<tr>
<td>Ellipse 6</td>
<td>754</td>
<td>17</td>
<td>44.4</td>
<td>98</td>
<td>0.17</td>
<td>P &lt; 0.01</td>
</tr>
<tr>
<td>Willamette</td>
<td>5,130</td>
<td>7,268</td>
<td>0.7</td>
<td>98</td>
<td>0.17</td>
<td>P &lt; 0.01</td>
</tr>
<tr>
<td>Ellipse 7</td>
<td>597</td>
<td>58</td>
<td>10.3</td>
<td>98</td>
<td>0.17</td>
<td>P &lt; 0.01</td>
</tr>
<tr>
<td>Ellipse 8</td>
<td>843</td>
<td>7</td>
<td>120.4</td>
<td>98</td>
<td>0.17</td>
<td>P &lt; 0.01</td>
</tr>
<tr>
<td>Three Forests</td>
<td>18,531</td>
<td>19,638</td>
<td>0.9</td>
<td>107</td>
<td>0.21</td>
<td>P &lt; 0.01</td>
</tr>
</tbody>
</table>

In our earlier study (Wing and Tynon 2006), we relied on visual analyses of crime locations, crime densities, and landscape layers to determine whether patterns existed in the spatial distribution of crime on US Forest Service lands. We also visually explored the relationship of observed patterns to other geographic features using additional spatial databases. These spatial databases included transportation networks, administrative boundaries, hydrology, elevation, and digital orthophotographs.

In this study, we augmented our visual examination by using statistical significance tests to determine whether observed spatial relationships were caused by chance alone. In the current study, we also applied several geospatial analytical techniques including quadrat analysis, NNA, and NNH clustering. The combination of analytical techniques and subsequent statistical significance tests supported our examination of 40,003 crime incidents in the database at several spatial scales. Traditional investigation techniques (e.g., statistical summaries and point location mapping) are simply not as versatile or powerful. The different spatial statistical analysis techniques and scales enabled us to investigate crime density at the regional, forest, and subforest administrative levels.

The multiscale approach we applied can be used by resource managers and law enforcement officials to direct their crime prevention and mitigation efforts. These efforts can involve large landscapes or can be focused on smaller, specific areas where crime incidents or patterns appear to be concentrated. In addition, spatial statistical analysis can be used to identify the types and descriptions of crime incidents associated with a unique geospatial unit, including points, quadrats, clusters, or ellipses. Additional spatial data layers, such as transportation, urban boundaries, and water bodies, can augment the ability to understand and interpret quantitative geospatial analysis results. This augmented ability not only enhances interpretation, it can also validate quantitative results. For example, we found an ellipse in the Willamette National Forest that had a substantially larger density of crime incidents. We were able to determine potential explanations for the increased crime incident density of this ellipse by using spatial statistical analysis techniques to investigate landscape and other features within and surrounding the ellipse. Our investigation revealed that this ellipse was in a recreation corridor with many adjacent recreation destination sites including campsites and water features. There also was a large metropolitan area in close proximity. This combination of circumstances was not apparent initially at the regional scale but became obvious at the finer scale where we intensified our use of multiple spatial layers.

There is no established set of analysis...
procedures that direct the sequence of steps and techniques to analyze large spatial databases. Our spatial database was characterized by irregular administrative boundaries covering 112,396 km². In addition, the forest boundaries were not contiguous and the amorphous boundaries did not easily lend themselves to systematic analysis. For example, we found that general recommendations for quadrant area sizes were not well suited for our purposes. We chose instead to experiment with different quadrant extents so that we could visualize crime incident densities and patterns at several scales more appropriate for our analysis objectives. We also experimented with standard deviational ellipse parameters and varied clustering (NNH) parameters to maximize our ability to discern groupings of crime incidents. Our experimentation and variation of analytical parameters led us to consider additional quantitative techniques that enabled us to discover and identify spatial relationships. These spatial relationships would not have been apparent without the use of geospatial analyses.

We discussed in a previous study (Wing and Tynon 2006) several potential concerns about the consistency and quality of data within the LEIMARS database. The US Forest Service has invested significant resources in collecting and cataloguing crime incident data for the vast lands that it manages. One of our concerns was with the geographic accuracy of crime incident locations. The accuracy of recording crime incident locations depends heavily on the abilities and resources of law enforcement officers who record the geographic coordinates. This determination may come from existing maps, conversations with others, global positioning systems (GPS), or other sources. Database quality could be improved through adoption of a systematic and reliable method of recording geographic coordinates for crime incidents. One such method would be to require law enforcement officers to use GPS receivers to record the location of every incident. GPS receiver technology has evolved such that reliable GPS receivers are available for about $100 each. Wing et al. (2005) determined that such GPS receivers are capable of spatial accuracies within 10 m or less, even while operating underneath dense forest canopies. Crime incident descriptive information could potentially be entered into the GPS receiver and later downloaded to a digital database for storage and retrieval. Digital information containing spatial and descriptive information could be made available to law enforcement officers in the field, allowing them to be more effective.

The spatial cataloguing and analysis of crime incidents can provide managers with a better understanding of crime occurrence patterns. In addition, relationships with natural resources and human built environments/infrastructure also may be investigated. These attributes have the potential to provide important contributions to law enforcement in the US Forest Service and others who manage natural resource areas. As a decision support system, these contributions may help managers better direct crime prevention and mitigation resources. Decision support efforts include identifying places where crime is prevalent and determining where crime occurs with greatest frequency.

For example, a predictive spatial model could guide rural law enforcement decision-making to reduce opportunities for crime and to promote safety on rural lands. A spatially based predictive model could identify areas that have a high probability for use as marijuana cultivation and methamphetamine production sites. Existing spatial databases of eradicated drug production sites on federal, state, and other public rural lands could be used to evaluate the model. Rigorous field-based examinations could assess the effectiveness of site predictions with measured confidence. Visits to predicted sites could verify whether drug production occurs or has occurred in these areas. GPS receivers can record the spatial extent of the drug sites, significant adjacent resources, and any other notable features. Resource data collected at the predicted drug sites could confirm and help evaluate the spatial accuracy of GIS databases used in the predictive model and the model’s success rate.

A predictive spatial model can be housed within a GIS-based decision support system. An evaluative component can be to assess the decision support interface, the ease of access for law enforcement users, and the output quality. Acceptability by multiple rural law enforcement organizations could be measured through a series of trials and evaluative survey techniques. Debriefings of use trials could provide decision support system feedback opportunities. This decision support system could encourage rural law enforcement organizations to conduct their own predictive analyses to identify areas for increased crime prevention efforts. This would show how active use of GIS technology and working across jurisdictions to pool resources could lead to more effective regional law enforcement. In addition, law enforcement agencies could apply the decision support system to better understand the relationship between drug production and environmental factors—a very serious issue that affects all citizens and has practical implications for rural law enforcement across the United States (Tynon and Chavez 2006).

Literature Cited


