SPATIAL AND TEMPORAL DISTRIBUTION OF CUMULATIVE DISTURBANCE IMPACTS DUE TO MILITARY TRAINING ON LAND CONDITION

by

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A Thesis

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The United States Army manages land across the country for use in combat training exercises. Different training activities are causing variable levels of disturbance on the ground and hindering natural growth of vegetation and degrading land condition. This consequently creates unrealistic training environments for soldiers and impedes the readiness of the US Army. Thus, there is a strong need to develop methods that can be used to map and predict the military training-induced impacts on the land condition and monitor their dynamics for planning of military training activities and land reclamation.

For this purpose, in this study the methods were developed to map the military training-induced annual and cumulative disturbances and impacts on the land condition and further conduct spatial analysis of the maps for a time period of 13 years from 1989 to 2001 for Fort Riley installation, Kansas. Satellite Landsat Thematic Mapper ™ imagery for each of the years was used in tandem with RTLA (Range Training Land Assessment) sample plot data that measured the disturbances to create the annual and cumulative disturbance maps. A plot derived data based method was employed to generate the spatial distribution maps of the annual disturbance and a point recorded data based method was utilized to create the cumulative disturbance maps. The spatial analyses included tests of spatial autocorrelation, high-low clustering and hot spot and outliers.

The results showed that in Fort Riley i) The TM images and their various transformations were significantly correlated with the disturbances, which provided the ability to interpolate the disturbance values from the sample plot data to un-observed locations; ii) Low levels of disturbance were prominent in both annual and cumulative disturbance maps, and moderate and high disturbances were mainly located in the central and northwest regions of the study area, which was related to the use of heavy loads of military training activities in these regions; iii) Both methods well revealed the varying levels of the annual and cumulative disturbances; iv) There was a lack of consistent spatiotemporal pattern of the disturbances, implying the use of rotation of the military training activities and land reclamation in this study area reduced the degradation of the land condition. Overall, this study greatly enhanced the understanding of the military training-induced impacts on the land condition for the US Army installations and provided useful guidelines for the land managers in terms of sustaining both land condition and land military carrying capacity.

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CHAPTER 1 – INTRODUCTION

1.1. Background

The United States Army holds the responsibility of managing and maintaining over 5,500 military training sites covering more than 30 million acres of land. These training sites are used for various reasons including large combat vehicle maneuvering and other military training activities (DEPARC 2007). Military installations are commonly looked at as complex landscapes with the disturbance source mainly attributed to these large tracked vehicles (Fang 2002). The United States Army, as a standard policy, maintains training lands in a condition that is meant to closely mimic the natural conditions under which actual warfare would be conducted. Mission related resource damage compromises not only the Army's land stewardship requirements but also the importance of maintaining the element of realism in the training experience (Anderson 2005). Activities ranging from vehicle maneuvering to burning and haying consequently result in a negative change in landscape quality. The intense reduction of vegetation cover, change in soil composition and increase in overall erosion, and habitat fragmentation are all variables that affect the health of the environment as well as the Army's land carrying capacity (Wang 2009).

Military training activities began in 1985 in Fort Riley, Kansas. These activities included field maneuvers, combat vehicle operations, mortar and artillery fire, and small-arms fire. In order to spatially characterize and monitor the land conditions and cumulative military training impacts at Fort Riley, the CERL (Construction Engineering Research Laboratories) began the Land Condition Trend Analysis (LCTA) plot inventory in the summer of 1989 (Tazik 1992). The LCTA (now RTLA – Range Training Land Assessment) is a total of 154 permanent plots that were chosen through stratified random methods based on a mixture of vegetation and soil type. Each plot length is 100 meters long by six meters wide with a 100 meter transect line which spans the center of each plot length. Different attributes including ground cover and canopy cover, were recorded at every one meter interval on the transect line. Each plot was then re-measured annually in the summer season until 2001. Data would not be collected in areas where major military activities or natural factors precluded re-measurement (Diersing 1992). The center point of the transect line was used as the X and Y coordinate locations of each plot in order to link the field data with remotely sensed data (Wang 2009). This inventory data will be used to create a methodology that can be used to spatially and temporally assess cumulative disturbance impacts from large-track vehicles on the military training grounds of Fort Riley.

1.2. Research Statement and Purpose of Study

Consistent use of military training vehicles on the land in Fort Riley is causing major degradation and potential disrepair of the environment. Each year, training is conducted in different areas of the base, leading to a lack of predictors on where future disturbance may be likely to occur. Many areas are also undergoing such high training activity levels that ground disturbance is reaching staggering levels. While studies comprehensive in nature have been completed in the past, it is crucial to begin to assess the cumulative impacts that these training vehicles are causing on the land (Singer 2010). The purpose of this study is to create a methodology that can be used to both spatially and temporally evaluate cumulative disturbance impacts due to military training by reproducing spatial patterns and assessing disturbance frequencies over the designated thirteen-year period. Spatially and temporally evaluating cumulative disturbance impacts will provide a greater understanding of which areas are most commonly used for training activities and how often these activities are occurring at any given place. Frequencies will be applied to a corresponding level of disturbance. These measured levels are: low disturbance, moderate disturbance, and high disturbance. Areas that fall under the category of high disturbance would be recognized quicker and allow for more immediate measures in reclaiming the land.

1.3. Justification

It is important to consider the need of the United States Army to have easily accessible and viable training areas on which to conduct activities involving large military training vehicles. It is with the creation of cumulative disturbance maps that options for training areas will be measured. By essentially providing cumulative disturbance data in regards to land condition in Fort Riley, the military can conduct training activities on stable lands as well as begin to plan methods of land recovery and habitat restoration for both plant and animal species on lands that are considered to be highly disturbed.

1.4. Research Questions

In this study it is assumed that military training-induced cumulative impacts on land condition of Fort Riley vary spatially and temporally depending on military training intensities and their spatial and temporal frequencies and the impacts can be quantified using ground and vegetation canopy disturbance as a surrogate measure of land condition. Moreover, it is also assumed that the disturbance is spatially and temporally autocorrelated and significantly correlated with Landsat Thematic Mapper ™ imagery at Fort Riley. Thus, the spatial patterns and dynamics of the disturbance can be modeled using the remotely sensed data by combining with field observations. This study will answer the following questions:

(1) Is the correlation between the used Landsat TM images and the military training-induced ground disturbance statistically significant?

(2) Are there consistent spatial-temporal patterns for both annual ground disturbance and cumulative disturbance due to military training activities within the period of 13 years from 1989 to 2001?

(3) How do the historical military training activities impact current land condition?

(4) Is the military training-induced cumulative disturbance spatially auto-correlated?

(5) Does the land condition on Fort Riley military base become poorer over time from 1989 to 2001 and impede military training?

CHAPTER 2 – LITERATURE REVIEW

Two main topics were taken into consideration when executing the literature review: information on methodology and data collection and insight into past studies involving military training and the environment. Information on methodology and data collection included literature on the topics including LCTA and RTLA transect lines (Diersing et al. 1992, Tazik et al. 1992), Landsat TM imagery, and other remotely sensed data (Anderson et al. 2005, Wang et al. 2004, 2007, 2008). Finding literature on the use of transect lines on military bases from both the LCTA and the RTLA were vital in performing all research tasks. These plot inventory datasets were the core part of creating cumulative disturbance maps. Transect lines have been used as a method of collecting different types of ground data in numerous forts across the United States. Similar to how data were collected at Fort Riley, Fort Hood used a total of 163 permanent field transects established in a stratified random fashion based on vegetation and soil type in the spring and summer of 1989 (Diersing et al. 1992). An automated method randomly selected transect locations using satellite imagery and soil surveys. Each permanent transect is 100 meters in length and was measured annually from 1989 to 1995. Ground cover, canopy cover, and botanical composition were estimated using a modified point intercept method. Ground cover and disturbance data were collected at one meter intervals along each transect for each year. Ground categories that were considered in the classification included bare ground, rock, litter, and live basal plant cover. Disturbance categories were set into more specific categories for Fort Riley. These categories consisted of undisturbed land, single vehicle track disturbance, multiple vehicle track disturbance, and other military disturbance. Canopy cover was recorded by species at 0.1 meter intervals up to 2.0 meters (Anderson 2005). The idea of using permanent plots in military installations is useful in accurately recording disturbance and other factors. There is some literature though, that suggests otherwise. Even if the representation is initially good, the performance of a monitoring program based on permanent plots might degrade through time (Wang 2008).

Landsat TM imagery was used for the actual production of cumulative disturbance maps for plot and point-based methods. Various literature described processes in which TM imagery was used for the classification and production of maps. In the case of Wang (2004) pre-classification was performed using ground data of land use and land cover changes. This information was obtained from permanent plots in the form of transect lines. Changes in information were interpolated to unknown locations throughout the base with the aid of a differencing or ratio by bi-temporal images acquired at different times (Wang 2004). In all cases, image ratioing is performed by the use of two or more bands, or combinations of bands. Examples of popular image ratios commonly used with land cover and land use classification include the vegetation index method (ratio between near infrared and red) and normalized difference vegetation index (NDVI). Eight procedures in Wang (2004) were then used in comparison to map changes of vegetation by the use of ground sample datasets and TM imagery. These procedures included co-simulation, co-kriging, and regression modeling. The objective was to investigate the reduction of uncertainty and increase accuracy for map changes (Wang 2004).

In the case of Anderson (2005) the same bands were used in this research. Each Landsat TM image was the result of using layer stack on band 1 (0.45–0.53 lm), band 2 (0.52–0.60 lm), band 3 (0.63–0.69 lm), band 4 (0.76–0.90 lm), band 5 (1.55–1.75 lm), and band 7 (2.08–2.35 lm). In addition to the six original bands, data transformations were made using commonly used band ratios. Optimal band combinations that correlated best with vegetation cover factor derived field data were determined (Anderson 2005).

With data though, come levels of uncertainty. Levels of uncertainty may be analyzed through various methods; many of which are extending to functional models in geographic information systems (Fang 2002). During these extensions the uncertainty is applied with the assumption that attributes were independent in space. In order to simulate multiple spatial attributes, the joint sequential spatial simulation was adapted. It provides higher measures of accuracy in both a local and global scenario (Wang 2001). Methods such as these have been developed with the purpose of accounting for spatial uncertainty of attributes. The joint sequential spatial simulation can simultaneously consider the spatial autocorrelation of different attributes as well as the cross-correlation between attributes (Goovaerts 1997). When the uncertainty in predictions is assessed, both spatial and non-spatial uncertainty sources should be accounted for. Joint sequential simulation itself can provide needed data to develop a model for partitioning spatial uncertainty based on the regression approach (Gertner 2004).

All of these datasets were useful in detecting and measuring levels of ground disturbance from off-road vehicles. It is only common sense that large track vehicles used for military training would cause some level of disturbance on current habitat. Training over multiple years can begin to cause cumulative levels of disturbance. Training activities with the United States Army cause levels of disturbance to ground and vegetation cover, damage plants, increase soil erosion and change composition, degrade habitats of plants and animals, and lead to the degradation of land conditions and environments that need to be maintained. The continuous training activities are resulting in cumulative impacts to the ground and vegetation cover. The degraded land conditions and environments will in turn limit military land carrying capacity. This will make it impossible to sustain both land conditions and military land carrying capacity. Because of the issues facing ground disturbance and land carrying capacity, the installation land managers require the information on land conditions and its history for the planning of military training activities and allocation of land repair and restoration. Estimation of cumulative military training impacts has great importance for both sustainable land conditions and military training carrying capacity because the cumulative impacts not only affects allocation of land repair and restoration, but also provide the basis for predicting land conditions for the planning of future military training activities (Gertner 2002, Anderson 2005, Wang 2009). Regarding natural resources and ecological and environmental management, more and more attention has been paid to mapping and spatial uncertainty analysis of multiple variables that are spatially correlated with one another (Gertner 2002).

Soil erosion and composition changes are large factors when considering the potential alteration of the ground and soil. This alteration is even more likely to happen when the addition of large track vehicles are placed into the equation. The high frequency of off-road vehicular activities in the same areas disturbs ground and vegetation covers cumulatively and results in an increase in soil erosion over time. In other areas without such activities, soil erosion decreases due to recovery of the ground and vegetation covers (Gertner 2007).   Erosion status is regarded by the Army environmental community as a good indicator of land condition. Soil erosion in the United States is usually determined using the Revised Universal Soil Loss Equation (Renard et al. 1997). The function for the equation involves six different factors. These factors include rainfall, runoff erosivity, soil erodibility, topographic features (such as steepness, aspect, and slope length), ground and vegetation cover, and support practice.

When determining the function for more specific areas, the cover factor reflects the effect of ground and vegetation cover on the reduction of soil loss. This happens by the reduction of runoff and essentially determines the dynamics of soil erosion (Benkobi et al. 1994). This particular factor can be defined as a function of ground cover, canopy cover, and average minimum height for precipitation traveling to the ground from the lowest canopy cover layer (Wischmeier and Smith, 1978). The C factor is also an important variable in the prediction of vegetation cover and management. It is a key variable for estimation of soil loss using the Universal Soil Loss Equation (USLE). The C factor is representative of the effect of ground and vegetation cover on reducing soil loss. The higher the ground and vegetation cover, the less ultimate level of soil loss. The USLE is an important equation for measuring not only levels of soil erosion, but also the spatial information of uncertainty sources. Finding uncertainty sources reduces error and allows for improved decision-making (Gertner 2002).

Commonly at Army bases in the United States, various military training activities occur unevenly in space causing variable disturbances of ground and vegetation cover, and thus lead to spatial variation of soil erosion status. The consistent levels of training in some of these areas then create cumulative disturbance impacts on ground and vegetation cover. This consequently increases soil erosion levels over time. In areas on installations that lack such military activities, soil erosion is absent or decreases through time, allowing levels of ground and vegetation recovery. In general then, it can be said that the status of these variables varies spatially and temporally, depending on the location, intensity, and frequency of militaristic training activities. Because the Army must meet environmental standards set out by the NRCS (National Resources Conservation Service), training activities need to be more limited and should be better planned out by the use of land condition maps (Wang 2007).

While many disturbance studies have been performed, most were comprehensive in nature. Often studies would focus on a single factor for each year, but never create a unified cumulative set of maps. A number of studies have observationally quantified the impact of military land use activities on installation resources. This has commonly been done by comparing historically used areas with nonuse areas. Variables researched in these past studies have included displaced surface horizons, rut formation, increased soil density, vegetation loss, and changes in habitat composition. There has been no direct relation made between the intensity or level of military training in an area and the amount of disturbance. In standard terms, training load has been characterized in terms of the types of activities that commenced rather that the consideration of intensity. The lack of cause and effect among these variables has been due to a lack of quantitative data until the beginning of the LCTA in 1989 at Fort Riley, Kansas (Anderson 2005).

CHAPTER 3 – STUDY AREA AND DATASETS

3.1. Study Area

This study was conducted in Fort Riley, Kansas (USA). Fort Riley is located in the northeastern part of Kansas in Riley County (Figure 1). The base includes a land area of 41,154 hectares (roughly 101,693 acres). Its location is within the Blue Stem Prairie section of the Tall Grass Prairie biotic province. This area sees an annual average precipitation of 85 centimeters (Bailey 1976). The dominant vegetation cover includes approximately 80 percent grasslands and 19 percent wood and shrub lands (Althoff 2005) (Figure 1). More specifically, the eastern half of Fort Riley has a geologic makeup of limestone and shale substrate accompanied by grassland vegetation while the western half of the base consists of more deep, substantial soils accompanied by woodland forests (Quist 2002).

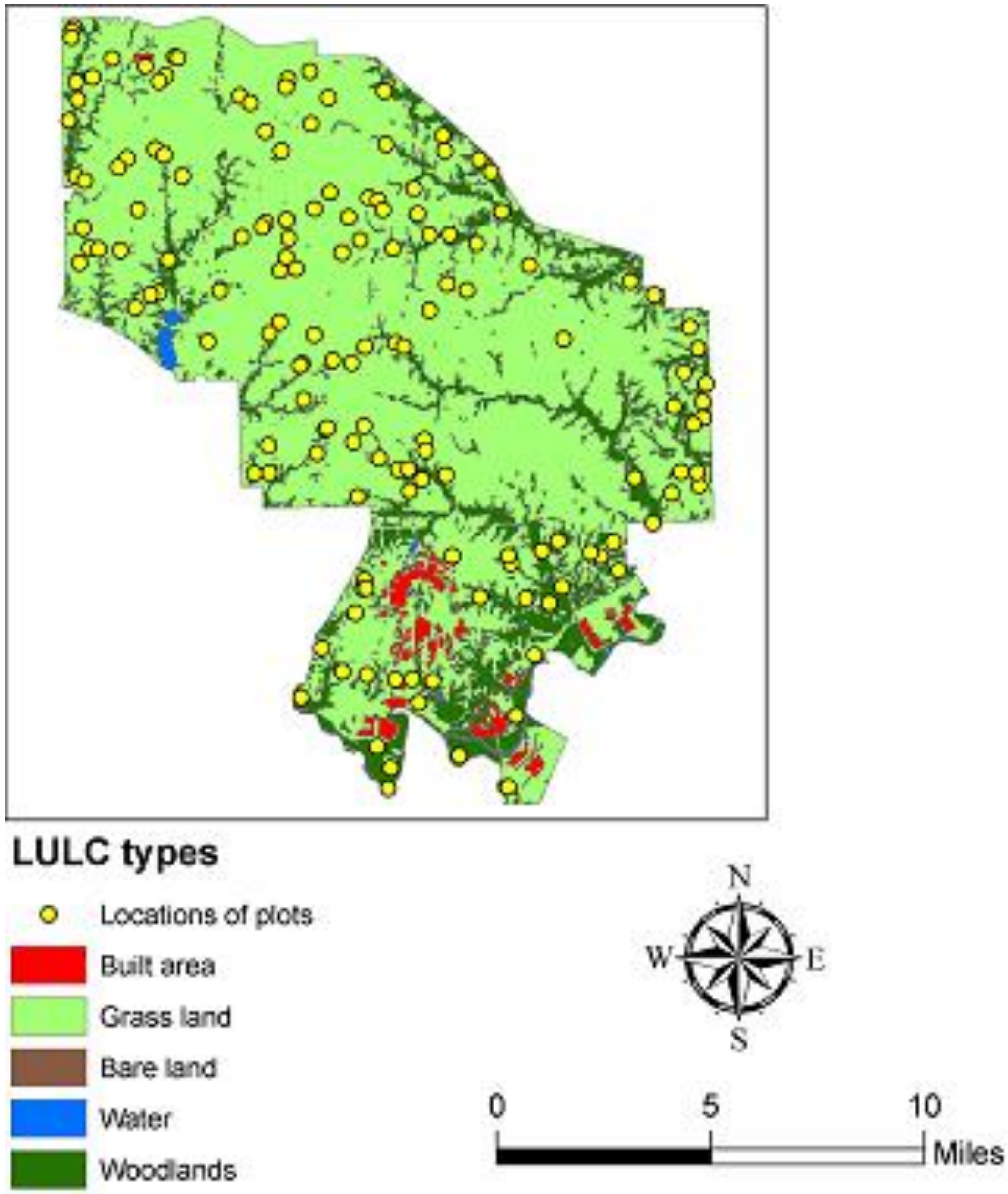


Figure 1. Study area, land use and land cover, and sample plot locations.

3.2. Datasets

The datasets needed to complete this study are all readily available. The main dataset to be used is the RTLA (previous known as LCTA) plot inventory data. These data are collected by the CERL (Construction Engineering Research Laboratories) for use in monitoring military land conditions and other environmental dynamics (Tazik et al. 1992). There have been some reports on impacts of military training on land condition and assessment of individual environmental functions for Fort Riley (Anderson et al. 2005; Gertner et al. 2002, 2004; Wang et al. 2004, 2007). For use in this study, information will be collected from the LCTA and RTLA the years ranging from 1989 to 2001. Each year has a total of 154 plots that were determined through random stratified sampling (Figure 1). Each plot is 100 meters long by six meters wide in size with a 100 meter transect line down the center of the plot and has 100 points at one meter intervals annually re-measured in the summer season.

The dataset was used for the reproduction of temporal and spatial patterns through the creation of cumulative disturbance maps. At every one meter interval, the variables such as vegetation height, ground cover, canopy cover and disturbance were measured (Diersing et al. 1992). The disturbance percentage was calculated using the number of the points, disturbed by the military training activities, divided by the total number of the points that were counted. The values of disturbance for sample plots are shown in Figure 2. The disturbance had larger values in the central parts and smaller values in the south and east parts of the study area.

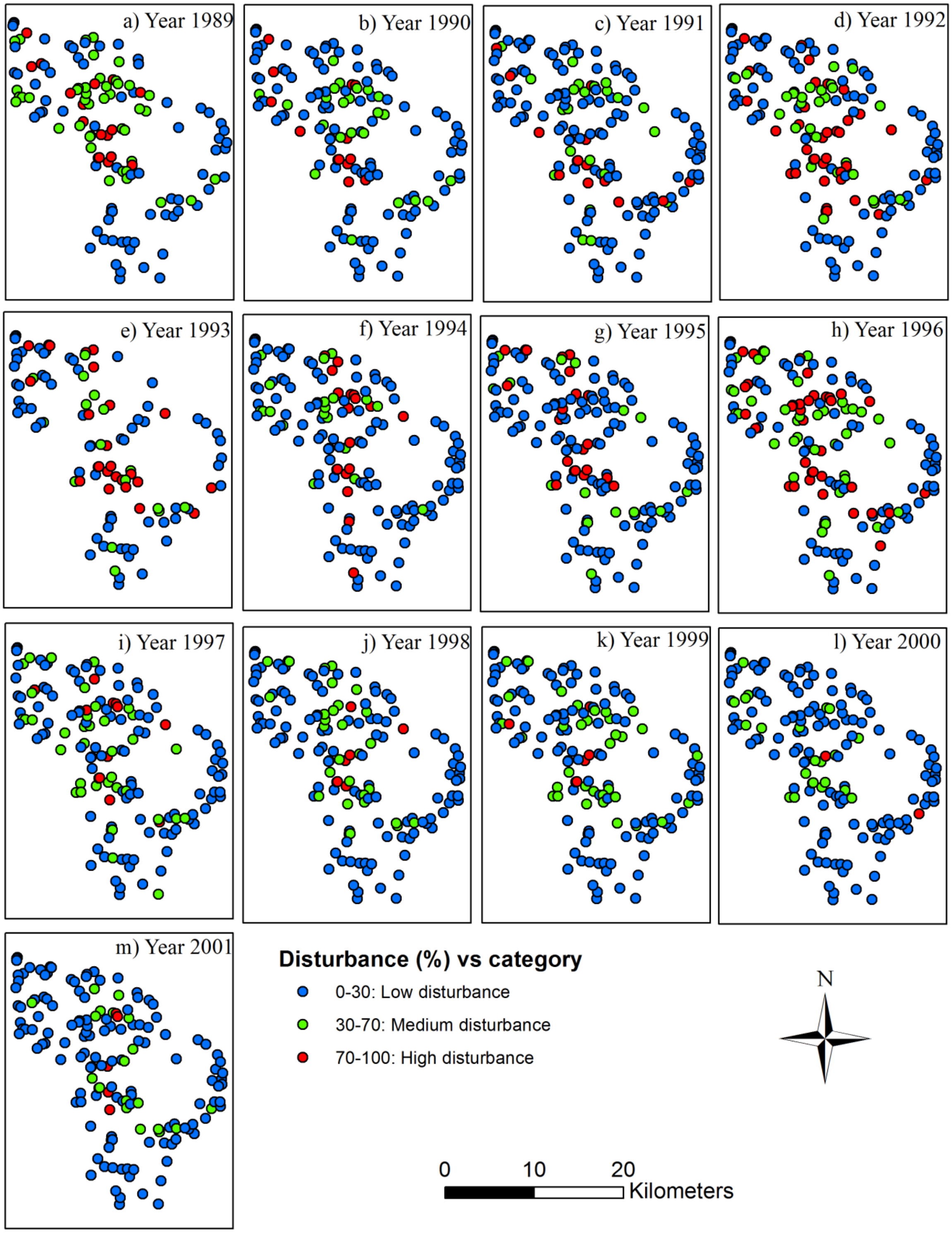


Figure 2. Plot disturbance percentages (%) due to military training vs. categories for years from a) 1989 to b) 1990, c) 1991, d) 1992, e) 1993, f) 1994, g) 1995, h) 1996, i) 1997, j) 1998, k) 1999, l) 2000, m) 2001, and n) annual average disturbance.

Figure 3 shows the relationship of military training intensity with disturbance percentage over time from year 1989 to 2001. In this study military training intensity is defined as total training day per year (TTD/year) (Howard et al. 2013). A training day is counted if any portion of a 24-hr period a training area is scheduled for soldier unit use. Training areas can be also used by multiple units and thus multiple soldier training days for a single 24-hr period can be counted. In general, the military training intensity and the disturbance percentage decreased over time from year 1989 to 2001. The lower the military training intensity is, the lower the disturbance percentage. In this study, the TTD per year was further normalized using the training area's per-unit military training intensity (Howard et al. 2013). Figure 4 shows the spatial distribution of military training intensity for three years. Overall, the normalized military training intensity had larger values at the northwest, central, and southwest parts of the study area and smaller values at the east and south parts.

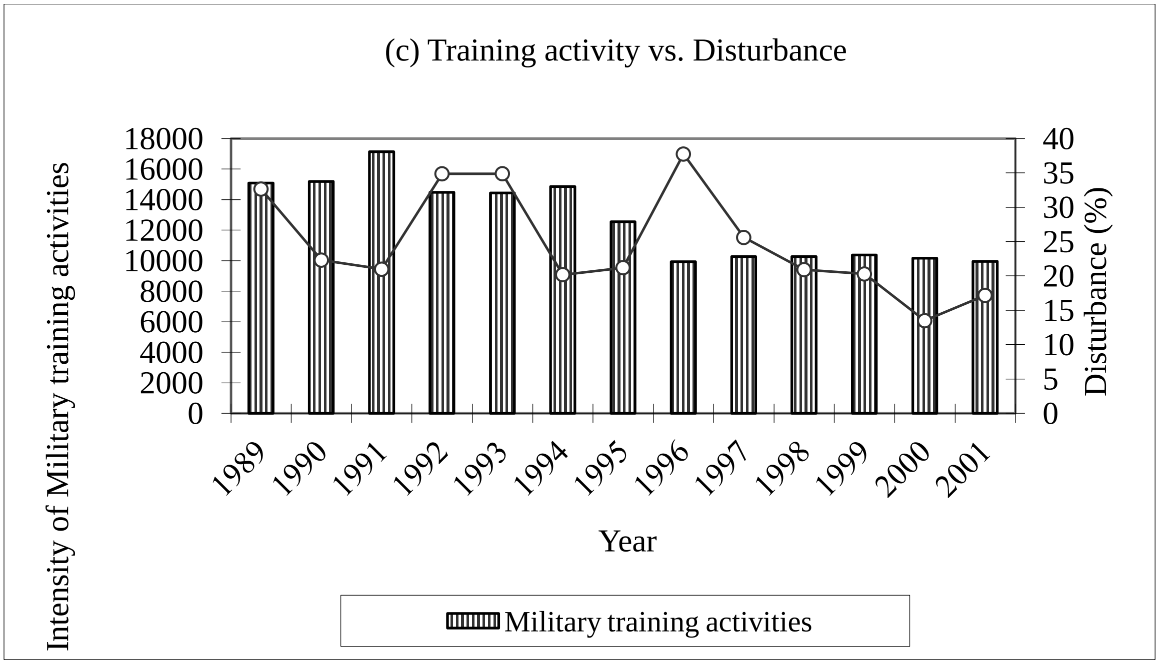


Figure 3. Relationship of military training intensity (total training days – TTD per year) with disturbance percentage over time from year 1989 to 2001.

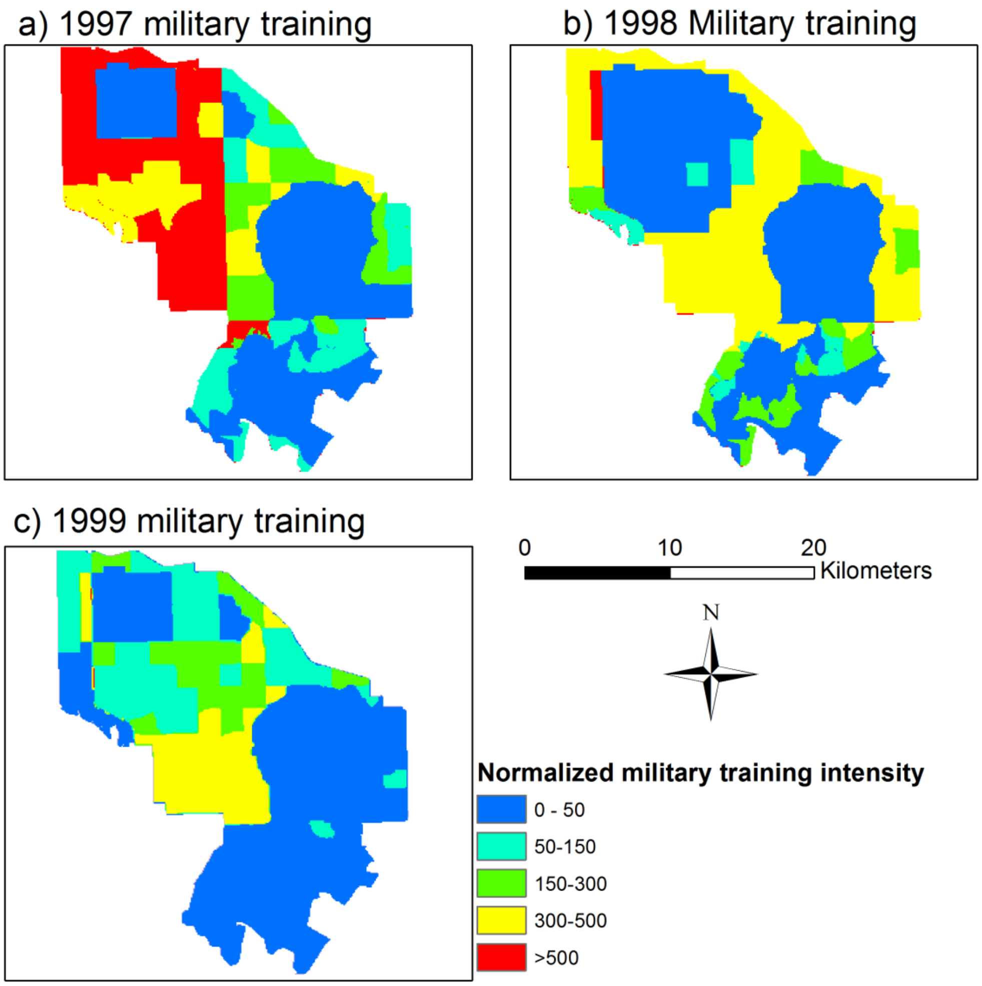


Figure 4. Normalized military training intensity (total training days – TTD per year per unit) for a) 1997, b) 1998, and c) 1999 (Howard et al. 2013).

In addition to RTLA data and military training intensity, information from digital elevation models (DEM), Landsat Thematic Mapper ™ images, and basic ground vegetation photographs were all made available. Landsat TM images were used from 1989 to 2001. The TM imagery consisted band 1, band 2, band 3, band 4, band 5, and band 7 and had a spatial resolution of 30 meter by 30 meter and was further aggregated to a spatial resolution of 90 meter by 90 meter. For the purpose of classification, the 90 meter by 90 meter spatial resolution was used (Figure 5). The purpose of the TM imagery is to create classification maps for land use and land cover and disturbance. While basic ground vegetation photographs were not used in the process of creating cumulative disturbance maps, it was still important to have them as a visual aid to create a better understanding of the conditions on the ground at Fort Riley.

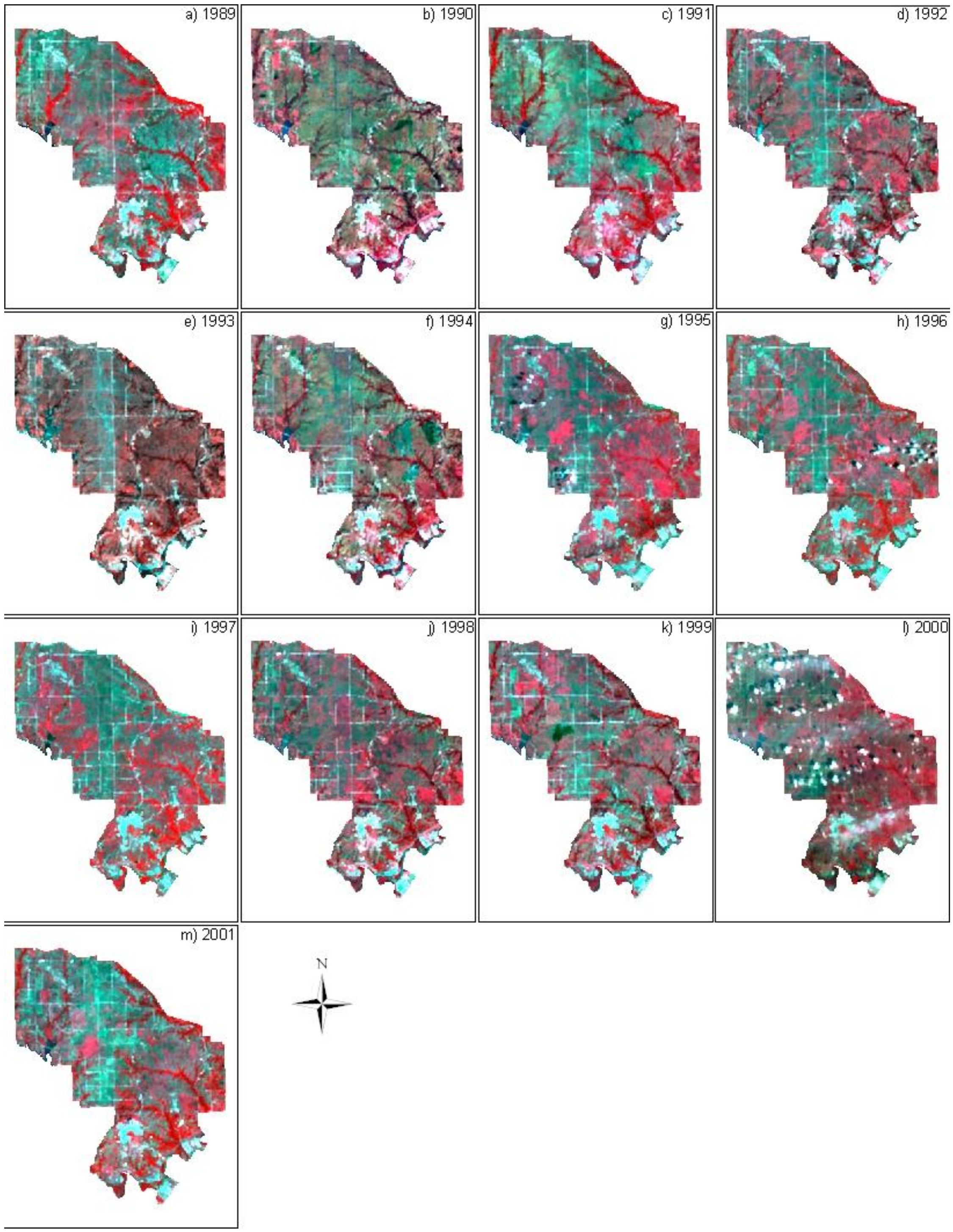


Figure 5. Color infrared composite images of the study area obtained from Landsat TM images for years 1989 through 2001.

CHAPTER 4 - METHODOLOGY

In order to assess cumulative disturbance impacts from military training vehicles on the land area within Fort Riley, a methodology was developed. Using Landsat TM imagery as well as the RTLA plot inventory data for the specified thirteen years between 1989 and 2001, cumulative disturbance maps were created through two separate processes: point-based and plot-based methods and the spatial analysis of the maps were then conducted.

Before mapping the disturbance observations, the TM images were prepared. ArcMap 10 was used to display the TM image. The cell information was exported as an image file where it was then converted to an .asc file using the conversion tool found in the arc toolbox. Then, a program was used to convert the .asc file to .gsl. This program is called avgslib. Once the TM images were created and the disturbance information checked over for missing data and inconsistencies, ArcMap 10 was used again to extract TM image values and apply them to the levels of disturbance supplied from the RTLA inventory data. The corresponding X and Y coordinate data were first added to a Microsoft Excel spreadsheet file and it was then exported into a shape file. Once this was done for all 13 years, the extractions were performed. The tool used to complete the task can be found in the arc toolbox. Under spatial analysis, the extract function was used to extract the image values to the collocated plots.

Pearson product moment correlation coefficients between the disturbance and each of the images were calculated. In addition to original TM band 1 to band 5 and band 7, various image transformations were calculated, including different ratios of Landsat TM bands and their band groups. A total of 14 different ratio combinations were tested for correlation, including band 3 / band 4, band 5 / band 4, band 7 / band 4, band 5 / band 7, band 3 / band 7, (band 4 – band 3) / (band 4 + band 3), (band 3 + band 5 + band 7) / band 4, (band 2 + band 5 + band 7) / band 4, (band 1 + band 5 + band 7) / band 4, (band 4 – band 5) / (band 4 + band 5), brightness (B), greenness (G), and wetness (W).

Equation (1)

$$B = 0.2909TM1 + 0.2493TM3 + 0.4806TM3 + 0.5568TM4 + 0.4438TM5 + 0.1706TM7$$

Equation (2)

$$G = -0.2728TM1 - 0.2174TM2 - 0.5508TM3 + 0.7221TM4 + 0.0733TM5 - 0.1648TM7$$

Equation (3)

$$W = 0.1446TM1 + 0.1761TM3 + 0.3322TM3 + 0.3396TM4 - 6210TM5 - 0.4186TM7$$

Where TM1 means TM band 1 and so on.

Moreover, variograms that account for spatial autocorrelation of military training-induced disturbance percentage were derived using the RTLA plot data for each of the years 1989 to 2001 (Wang et al. 2011). The variogram equation used is:

$$\hat{\gamma}_{zz}(h) = \frac{1}{2N(h)} \sum_{\alpha=1}^{N(h)} \left(z(u_\alpha) - z(u_\alpha + h) \right)^2 \qquad (4)$$

where N(h) is the number of all the data location pairs separated by a separation vector *h*, called lag, $z(u_\alpha)$ and $z(u_\alpha + h)$ are data values of military training-induced disturbance at spatial locations u_α and $u_\alpha + h$, respectively. The obtained variogram was then fitted using the following variance function - spherical model:

$$\gamma^{Sph}(h) = \begin{cases} c_0 + c_1\left[1.5\dfrac{h}{a} - 0.5\left(\dfrac{h}{a}\right)^3\right] & if \quad 0 < h \le a \\ c_0 + c_1 & otherwise \end{cases} \qquad (5)$$

where c_0 and c_1 are called nugget and structure parameters of the spherical model, and $c = c_0 + c_1$ is sill parameter. The nugget means micro-variability. The structure and sill parameters explain structure and total variances of the spatial variability; a is a range parameter indicating the range of spatial dependence. Beyond the range, the spatial autocorrelation of the military training-induced disturbance percentage essentially disappears.

The variograms were produced for each of the 13 years and standardized. The standardization means forcing the sill value c to be one unit. The process took three separate steps to get to the final stage of modeling using a computer software package called variowin (Pannatier 1996). First the excel file needed to be saved into a data file in the format of variowin. The Prevar2d program for data preparation was then used and the coordinates were selected and the number of pairs was determined. The information then entered the second program called Vario2DP that calculates variances of variogram at different lag h. Settings were selected to create the variogram itself and lag parameters were set in direct directional variogram. The lag spacing was set at 1,500, the lag tolerance was set to 750, and the number of lags was set to 15. Once the information was converted, the modeler could be used to find the best fit of the line through the sill, range, and nugget. The final variograms were copied as bitmap files into a word document for further examination.

Two methods including plot-based and point-based were used to military training –induced disturbance percentage by combining the sample plot data and remotely sensed images. The plot based method first calculated the disturbance percentage for each of the 154 sample plots - transect lines by dividing the number of the points that were disturbed by military training activities by the total number of the measured 100 points along the 100 m traction line. The values of the disturbance percentage at the unobserved locations were interpolated using the data of these 154 sample plots and Landsat TM images using image based sequential Gaussian cosimulation.

Because the study area is considered to consist of many square cells or pixels, this cosimulation algorithm uses the sample plot data and TM images that have the highest correlation with the military training-induced disturbance percentage and creates a predicted value of the disturbance for each pixel based on spatial autocorrelation of the disturbance mentioned previously. If the military training-induced disturbance percentage is assumed to be a random process, a predicted value is a realization of the random process and can be obtained by randomly drawing a value from a cumulative conditional distribution function. The distribution function is determined by a conditional mean and conditional variance. The conditional mean is calculated by weighting the sample plot disturbance percentage values within a given neighborhood that is determined by the range of the variogram model mentioned above. The conditional variance is computed by weighting the variances of the variogram based on the spatial configuration of the sample plot locations and the variogram model. At the same time, remotely sensed data are also used to derive the conditional mean and conditional variance. In addition, the predicted values that have been obtained can be used as conditional data for further simulations. The weights vary depending on the distances of the locations of the used data from the location to be estimated. The closer the location is, the larger the weight.

A random path was set to determine the order of visiting and predicting each of the pixels. Once each of the pixels was predicted, a map was obtained, which resulted in a realization of expectation of the military training-induced disturbance percentage. A total of 400 different random paths were created using random functions and employed to generate realizations of the disturbance percentage. This meant a total of 400 predicted values were obtained at each location. Thus, a sample mean and a sample variance were calculated from the realizations and used as the estimate and its uncertainty measure at this location. The reason of using 400 simulations was mainly because this number led to a stable variance for each location. In addition, a normal score transformation of data was conducted to meet the assumption of normal distribution for the algorithm. For the details of this algorithm, readers can refer to the study of Wang et al. (2007, 2009).

The military training-induced disturbance percentage values were classified based on 0 – 30% meaning low disturbance, 30 - 70% meaning moderate disturbance, and 70-100% meaning high disturbance. A total of 13 final maps were obtained. The maps were then used for conducting spatial analysis.

The second method used is called point-based method. For this method, cumulative disturbance frequency was directly calculated at every one meter interval along each of the 154 transect lines. The disturbance was recorded in binary form: zero meaning no disturbance and one meaning disturbance. The observations were then added up for the thirteen years resulting in a frequency of disturbance out of 13 years. The cumulative disturbance frequencies were then grouped into three classes based on 0 - 4 meaning low cumulative disturbance frequency, 5 – 8 meaning moderate cumulative disturbance frequency, and 9 – 13 meaning high cumulative disturbance frequency. The low, moderate, and high cumulative disturbance frequencies meant that out of 13 years, there were, respectively, 0 – 4 years, 5 – 8 years, and 9 – 13 years for the same point disturbed by military training activities. When it came to processing the disturbance levels in the excel files, it should be noted that some data were missing from each of the 13 years. This missing data was recorded, then factored into the ratioing of the 13 years of disturbance. For example, if plot 29 was missing from two of the 13 years, the denominator in the resulting ratio would be altered to 11 in order to reflect the present data. Therefore, instead of frequency, a ratio of disturbance was then used and further transformed into a percentage. The percentage was then classified into three groups: 0 - 30% meaning low disturbance, 30 - 70% meaning moderate disturbance, and 70 - 100% meaning high disturbance.

Moreover, Landsat TM images were used to conduct segmentation of the study area. This procedure segmented the study area into homogeneous polygons. Different parameters were set to create various segments. Unfortunately, this procedure resulted in high amounts of segments, making this process unfeasible. The method was changed to use of an unsupervised classification. That is, Landsat TM images were used to conduct stratification of pixels by an unsupervised classification (Jensen 2005), which led to homogeneous strata. Within each of the strata, the pixels are similar to each other in terms of spectral feature space, but do not have to be adjacent to each other. A total of 20 classes and 30 iterations were utilized for the unsupervised classification.

Spatial analysis of the disturbance maps obtained above was performed through the usage of several analysis programs in geographic information system ArcMap 10. The spatial analysis was conducted at both local and global levels. The purpose of performing spatial analysis on the maps was to test spatial phenomena in the study area and to enhance the understanding of military training-induced disturbances and impacts on land condition. Global Moran's Index was first conducted to test spatial autocorrelation of the disturbance, that is, clustering of high and low values, and further determine whether or not the spatial patterns of the disturbance was clustered, dispersed, or random. Each output gave a z-score, which indicated the level of significance, if any, of spatial clustering for each map. The z-score with p-value tests a null hypothesis: random distribution of feature values. If it is rejected, a positive and negative index value implies tendency toward clustering and dispersion, respectively. To help understand if the resulting z-score indicated spatial statistical significance, a confidence level of 0.05 is set. The identification of these spatial patterns helps to clearly characterize the spatial distribution of the disturbance.

Next, Getis-Ord General G was used to measure if the level of clustering was considered to be high or low. The value of the General G statistic and associated Z score for a given input feature class were output. The Z score value as a measure of statistical significance implies whether or not a null hypothesis: no spatial clustering should be rejected. The higher (or lower) the Z score, the stronger the intensity of the clustering. A

Z score near zero implies no significant clustering. A positive and negative Z score mean clustering of high and low values, respectively.

Finally, the cluster and outlier analysis was conducted using Anselin local Morans *I* statistics. This statistic outputs a Local Moran's I index value, Z score, P-value and cluster type code for each feature. The Z scores and p-values as measures of statistical significance are used to test the null hypothesis, feature by feature: the apparent similarity (or dissimilarity) in values for a feature and its neighbors is greater than one would expect in a random distribution. A high positive Z score for a feature implies that the surrounding features have similar values (either high values or low value), while a low negative Z score indicates a statistically significant spatial outlier. The results can be divided into a statistically significant cluster of high values (HH), a statistically significant cluster of low values (LL), a high value surrounded by with low values (HL), and a low value surrounded by with high values (LH).

CHAPTER 5 - RESULTS

In Table 1, the Pearson product moment correlation coefficients of the military training-induced disturbance and each of TM images and their transformations are listed. The coefficients varied from 0.04 to 0.56 and over 95% of the coefficients were significantly different from zero based on a significant value of 0.159 at a significant level of 0.05. The image that had the highest correlation with the military training-induced disturbance was TM band 5 for year 1989, (band 3 + band 5 + band 7) / band 4 for year 1990, (band 1 + band 5 + band 7) / band 4 for year 1992, B3/B7 for year 1993, B3/B4 for year 1994, B7/B4 for year 1995, MidIR for year 1996, (band 2 + band 5 + band 7) / band 4 for year 1997, B2 for year 1998, MidIR for year 1999, B7 / B4 for year 2000, and B3 for year 2001.

Table 1. Pearson product moment correlation coefficients of the military training-induced disturbance and each of TM images and their transformations for Fort Riley for years from 1989 to 2001 (note: B1 means TM band 1, etc.).

YEAR	B1	B2	B3	B4	B5	B7	B3/B4
1989	0.16434	0.232061	0.176024	-0.1099	**0.337133**	0.251917	0.143321
1990	0.292921	0.251777	0.382264	-0.18139	0.297043	0.362522	0.435649
1991	0.239608	0.21126	0.22624	-0.21245	0.235294	0.237273	0.267481
1992	0.235464	0.295822	0.343964	-0.16634	0.298391	0.334894	0.374783
1993	0.321394	0.294773	0.328282	-0.12102	0.377942	0.445912	0.357739
1994	0.313927	0.318279	0.355597	-0.30813	0.268523	0.333825	**0.455492**

Table 1. (continued)

1995	0.165201	0.214433	0.304571	-0.39856	0.434191	0.4943	0.464788
1996	0.30891	0.343765	0.345618	-0.28586	0.375675	0.412219	0.341112
1997	0.291829	0.299567	0.367278	-0.45945	0.410726	0.443121	0.448615
1998	0.206508	**0.262188**	0.227857	-0.11061	0.162903	0.187623	0.214568
1999	0.251981	0.255417	0.288472	-0.17437	0.273599	0.322868	0.281425
2000	0.049075	0.06389	0.102618	-0.13557	0.171745	0.201719	0.23332
2001	0.380317	0.392714	**0.414061**	-0.28109	0.406305	0.39094	0.409962

Year	B5/B4	B7/B4	(B4-B3)/ (B4+B3)	(B3+B5+ B7)/B4	(B2+B5+ B7)/B4	(B1+B5+ B7)/B4	B
1989	0.247702	0.205368	-0.16515	0.218719	0.226431	0.208736	0.310056
1990	0.422421	0.426937	-0.42674	**0.443733**	0.433067	0.415543	0.226724
1991	0.269922	0.261377	-0.25982	0.269217	0.270929	**0.273787**	0.201149
1992	0.335257	0.360676	-0.38083	0.356433	0.351977	0.337727	0.248429
1993	0.402283	0.458254	-0.34875	0.419966	0.422832	0.414236	0.325895
1994	0.391788	0.402916	-0.44783	0.41655	0.413935	0.416026	0.214432
1995	0.532376	**0.556303**	-0.4675	0.540537	0.54119	0.532305	0.197303
1996	0.393974	0.400411	-0.36607	0.39033	0.397935	0.384312	0.249223
1997	0.480598	0.483929	-0.45625	0.481296	**0.485718**	0.482096	0.198267
1998	0.178498	0.189784	-0.22191	0.192165	0.192714	0.18406	0.148157
1999	0.283376	0.314099	-0.29532	0.297588	0.296094	0.289627	0.235438

Table 1. (continued)

-

2000	0.295533	**0.299013**	0.23913	0.295322	0.298972	0.29538	0.084239
2001	0.404928	0.391194	-0.40274	0.404233	0.401839	0.396481	0.380375

Year	G	W	II	MidIR	SAVI	NDBI	B3/B7
1989	-0.15338	-0.29977	-0.25924	-0.15474	-0.16507	0.259244	-0.266
1990	-0.39075	-0.34941	-0.40441	-0.25207	-0.42657	0.404407	-0.20053
1991	-0.2558	-0.24358	-0.25287	-0.21064	-0.25979	0.252871	-0.21046
1992	-0.31563	-0.31496	-0.3316	**-0.38632**	-0.38056	0.331597	-0.26391
1993	-0.33322	-0.42523	-0.3855	-0.44521	-0.34857	0.385498	**-0.48464**
1994	0.214432	-0.31605	-0.38589	-0.35218	-0.44794	0.385885	-0.15423
1995	-0.45923	-0.52541	-0.51806	-0.48749	-0.46764	0.518062	-0.47745
1996	-0.35649	-0.40867	-0.41349	**-0.4511**	-0.36604	**0.413493**	-0.37573
1997	-0.45658	-0.48173	-0.48211	-0.43265	-0.45631	0.482112	-0.45462
1998	-0.19085	-0.16112	-0.19364	-0.22495	-0.22175	0.193644	-0.12937
1999	-0.27907	-0.29577	-0.29841	**-0.36564**	-0.29526	0.298413	-0.31583
2000	-0.2184	-0.25726	-0.28587	-0.28472	-0.23913	0.285874	-0.24764
2001	-0.37347	-0.39751	-0.39595	-0.33036	-0.40263	0.395955	-0.31695

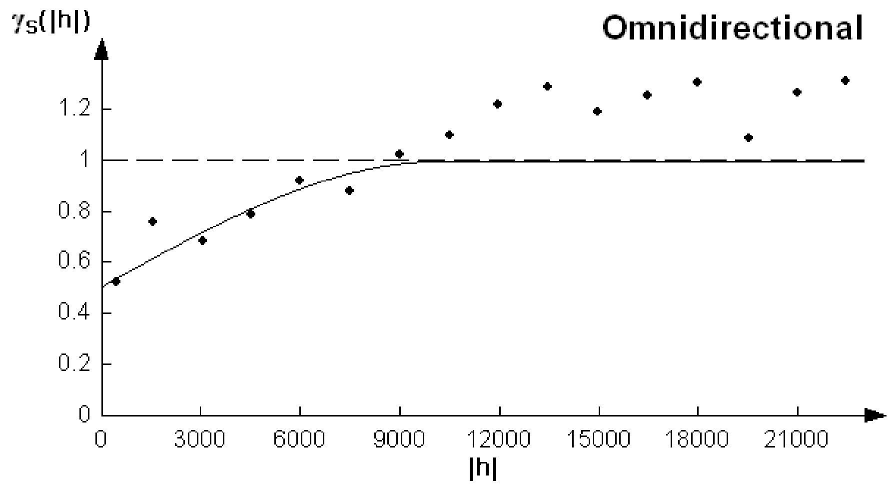
The spatial autocorrelation of the military training-induced disturbance was modeled using variogram for each of the years. A total of 13 variogram models were obtained. As examples, equations (6) and (7) show the variogram models for years 1989 and 1996. The fitting was not optimal because the standardized models that forced the sill parameter to be one unit were required in the sequential Gaussian co-simulation (Figure

6). The goodness of fit was 0.0544 for year 1989 and 0.0186 for year 1996. A value close to zero indicates a good fit.

$$\gamma_{1989}(h) = \begin{cases} 0.51 + 0.49\left[1.5\dfrac{h}{10120} - 0.5\left(\dfrac{h}{10120}\right)^3\right] & if \quad 0 < h \leq 10120m \\ 0.51 + 0.49 & otherwise \end{cases} \tag{6}$$

$$\gamma_{1989}(h) = \begin{cases} 0.61 + 0.39\left[1.5\dfrac{h}{5750} - 0.5\left(\dfrac{h}{5750}\right)^3\right] & if \quad 0 < h \leq 5750m \\ 0.61 + 0.39 & otherwise \end{cases} \tag{7}$$

a) Year 1989



b) Year 1996

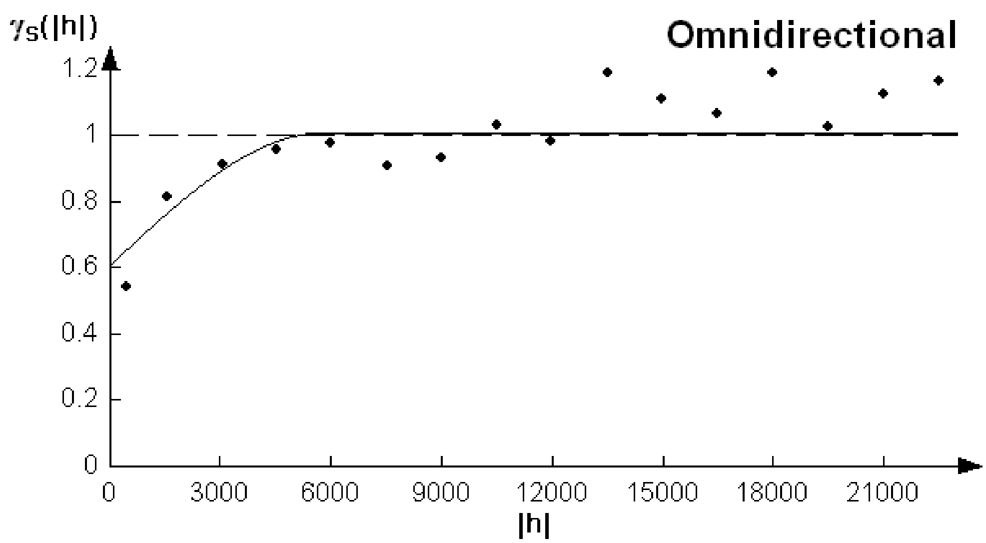


Figure 6. Standardized variogram models for years a) 1989 and b) 1996 (Note: *h* is distance in meter and $\gamma_s(h)$ is variance at distance *h*).

Plot based ground disturbance maps show all levels of disturbance periodically throughout the 13 year span (Figure 7a to 7m). It is important to note that these maps are representative of the disturbance recorded during each single year period. Low disturbance (0-30%) was most common amongst the 13 years. The areas of moderate disturbance were often found clustered in certain regions within the study area, the central northern region in particular. When there were levels of high disturbance found, these areas were generally small expanses and rather sporadic. The year 1999 resulted in the largest amount of moderate or high disturbance; where as the year 2000 resulted in the lowest levels of disturbance. The year 1993 had the largest single area of high disturbance. It is evidence that the spatial patterns and dynamics of the military training-induced disturbance in Figure 7 are similar to those obtained using the sample plot data in Figure 2 and also corresponded with the spatial distributions of the military training intensity for years 1997, 1998, and 1999 in Figure 4.

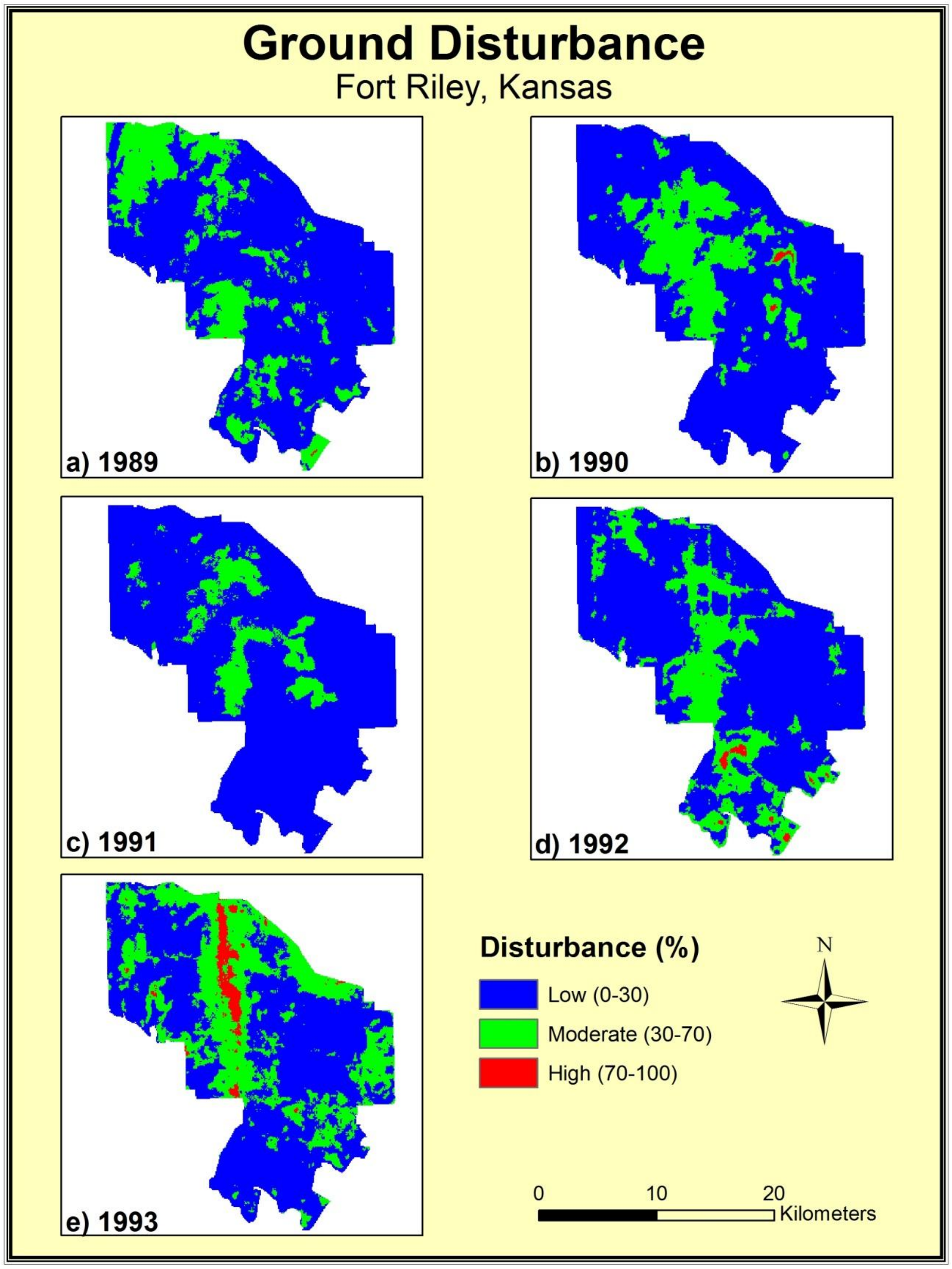


Figure 7a- 7e. The maps or spatial distributions of military training-induced disturbance obtained using plot based method for Fort Riley for years 1989 to 1993.

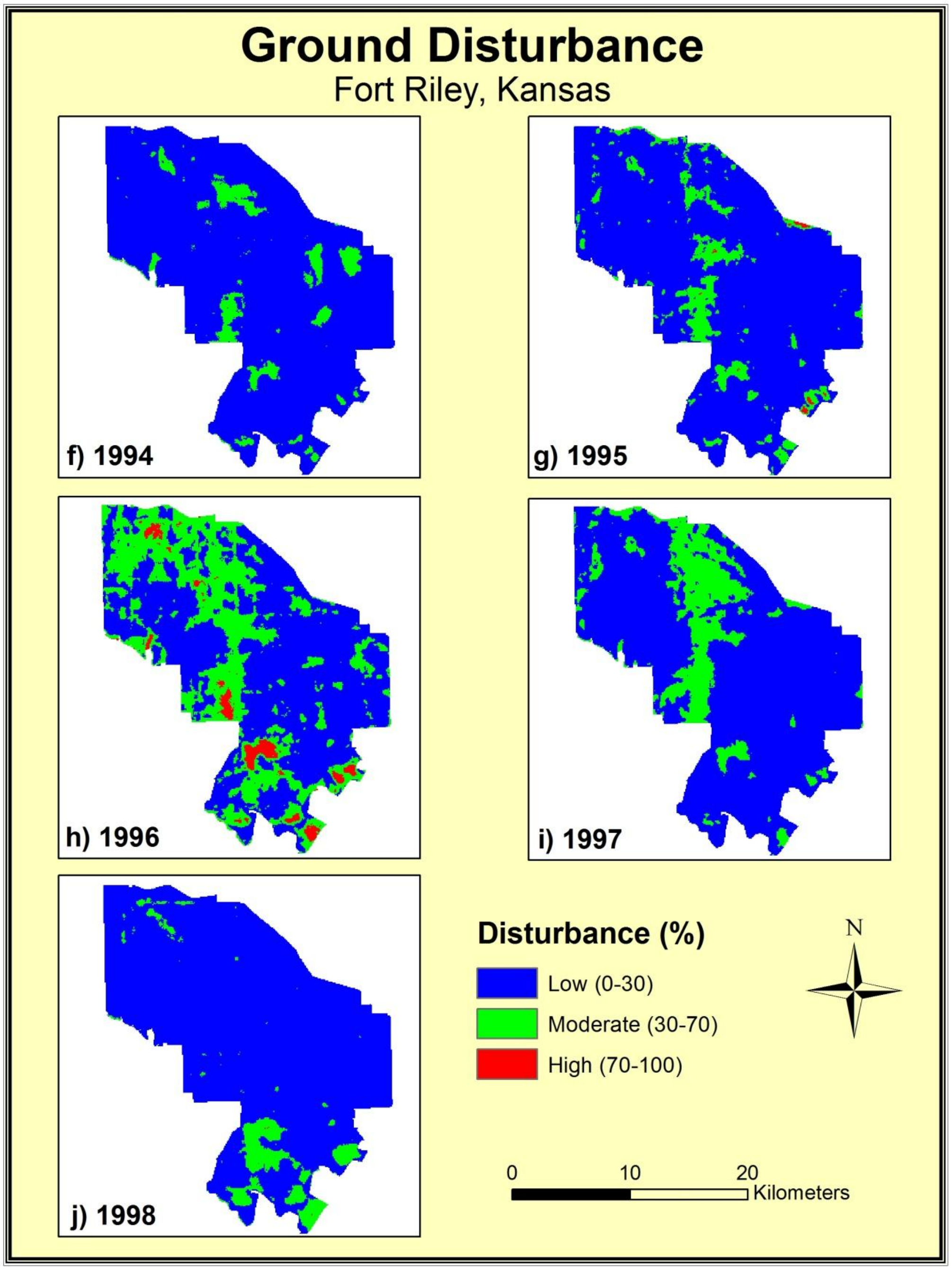


Figure 7f- 7j. The maps or spatial distributions of military training-induced disturbance obtained using plot based method for Fort Riley for years 1994 to 1998.

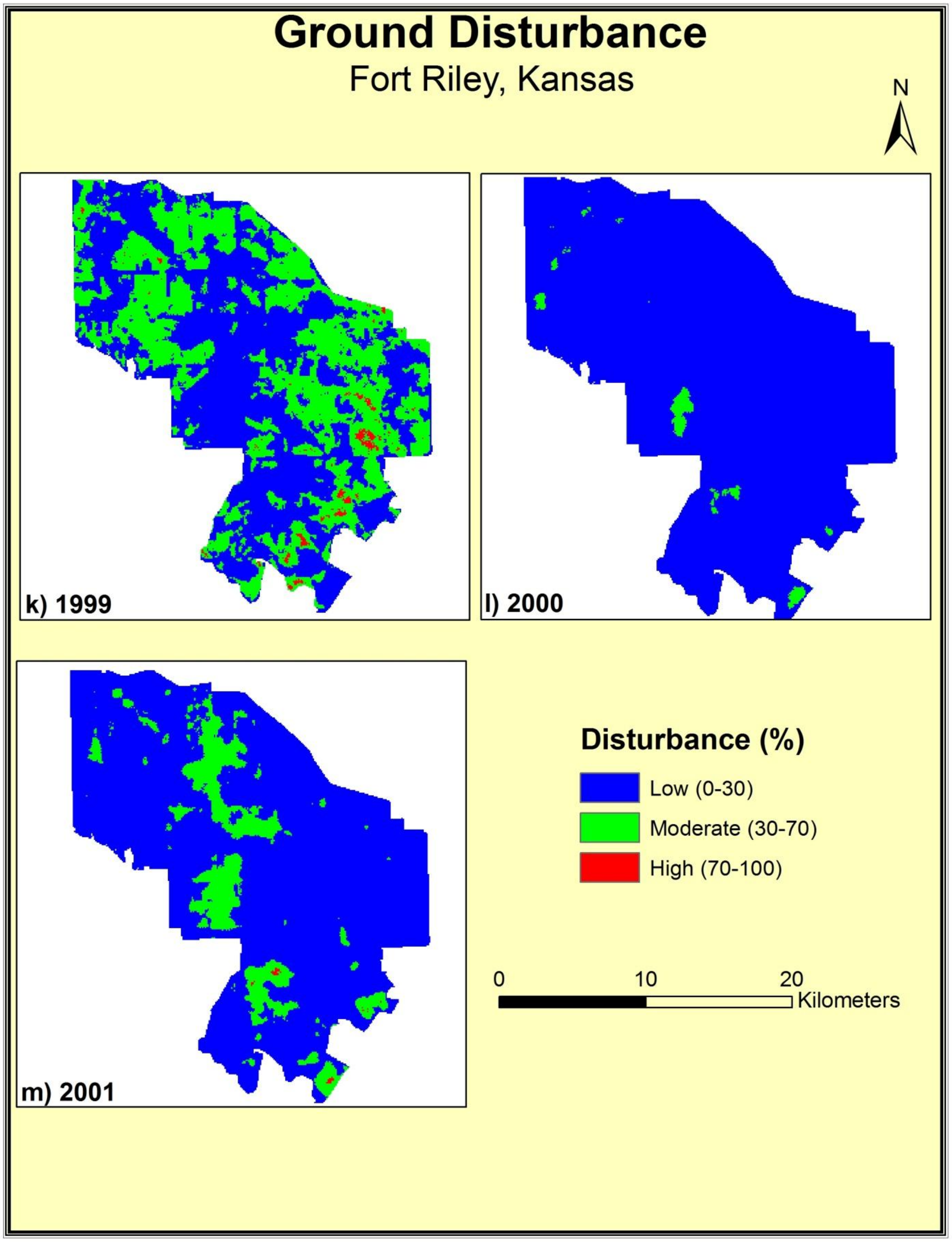


Figure 7k- 7m. The maps or spatial distributions of military training-induced disturbance obtained using plot based method for Fort Riley for years 1999 to 2001.

Point based method led to cumulative frequency maps of the military training-induced disturbance (Figure 8a-8l). Note these are not single year disturbance maps, but rather a progression of maps affected by the historical disturbance recorded previous to each year. Although the start year is the same 1989, the time periods of the maps vary depending on the end year by which the cumulative disturbances are counted. The maps show the details of spatial patterns and dynamics of the military training-induced cumulative disturbances. The cumulative disturbances vary spatially and temporally. Overall, low disturbances dominate this study area and moderate and high disturbances are mainly noticed in the central and northwest parts of the study area in which military training activities took place. These features become more obvious as the time period for calculation of the cumulative disturbances increases. However, the exceptions are 1994, 1997 and 1998 in which the levels of moderate disturbances almost appear evenly distributed among the study area. The year 1991 shows clear areas of moderate and high disturbances in the northern half of the study area. The 1995 map also shows clear areas of moderate disturbance in the northern half of the study area. The 1992 map shows only low and high levels of disturbances and lacks any levels of moderate disturbances.

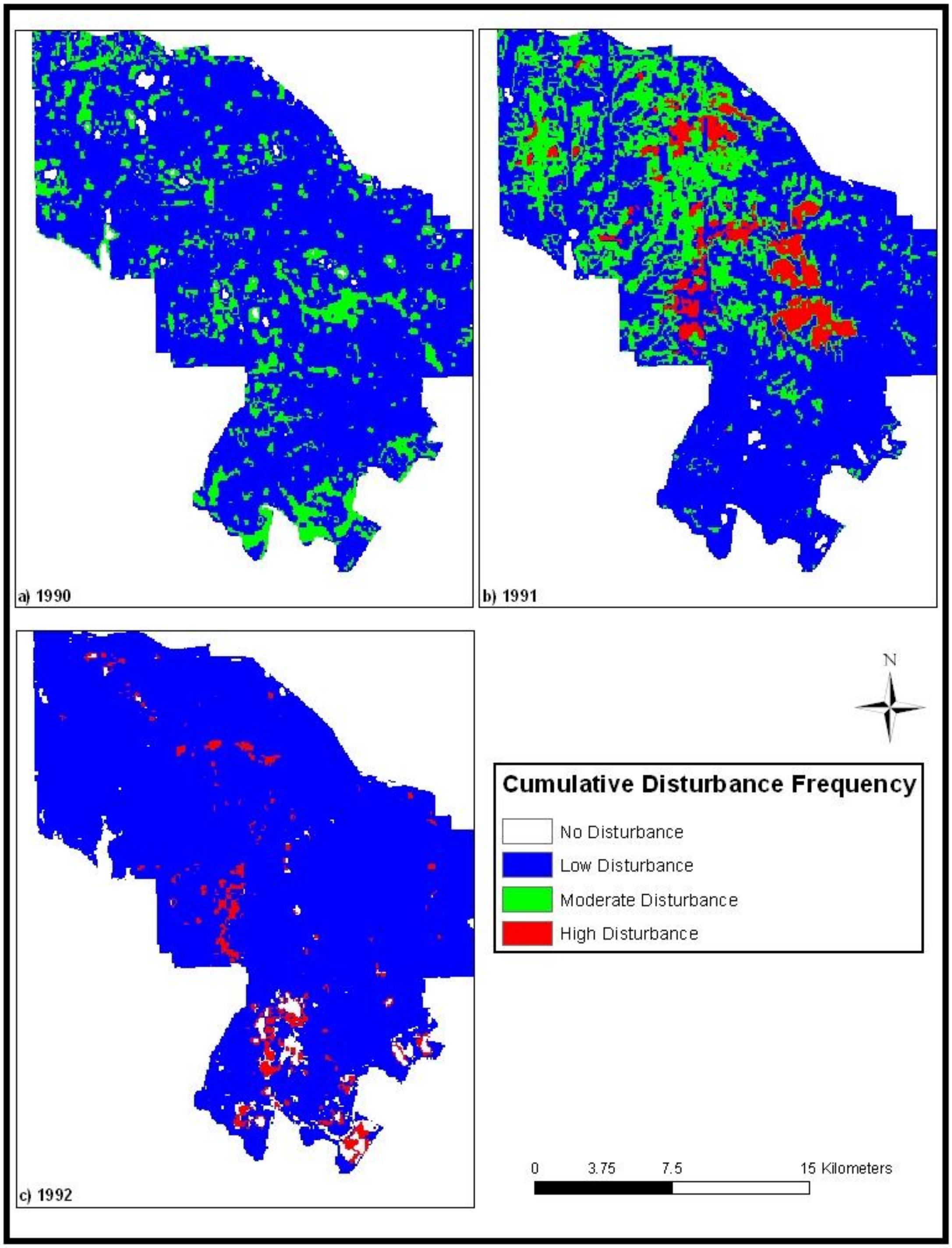


Figure 8a – 8c. Military training-induced cumulative disturbance maps of Fort Riley obtained using point based method for periods of years from 1989 to 1990, 1989 to 1991, and 1989 to 1992.

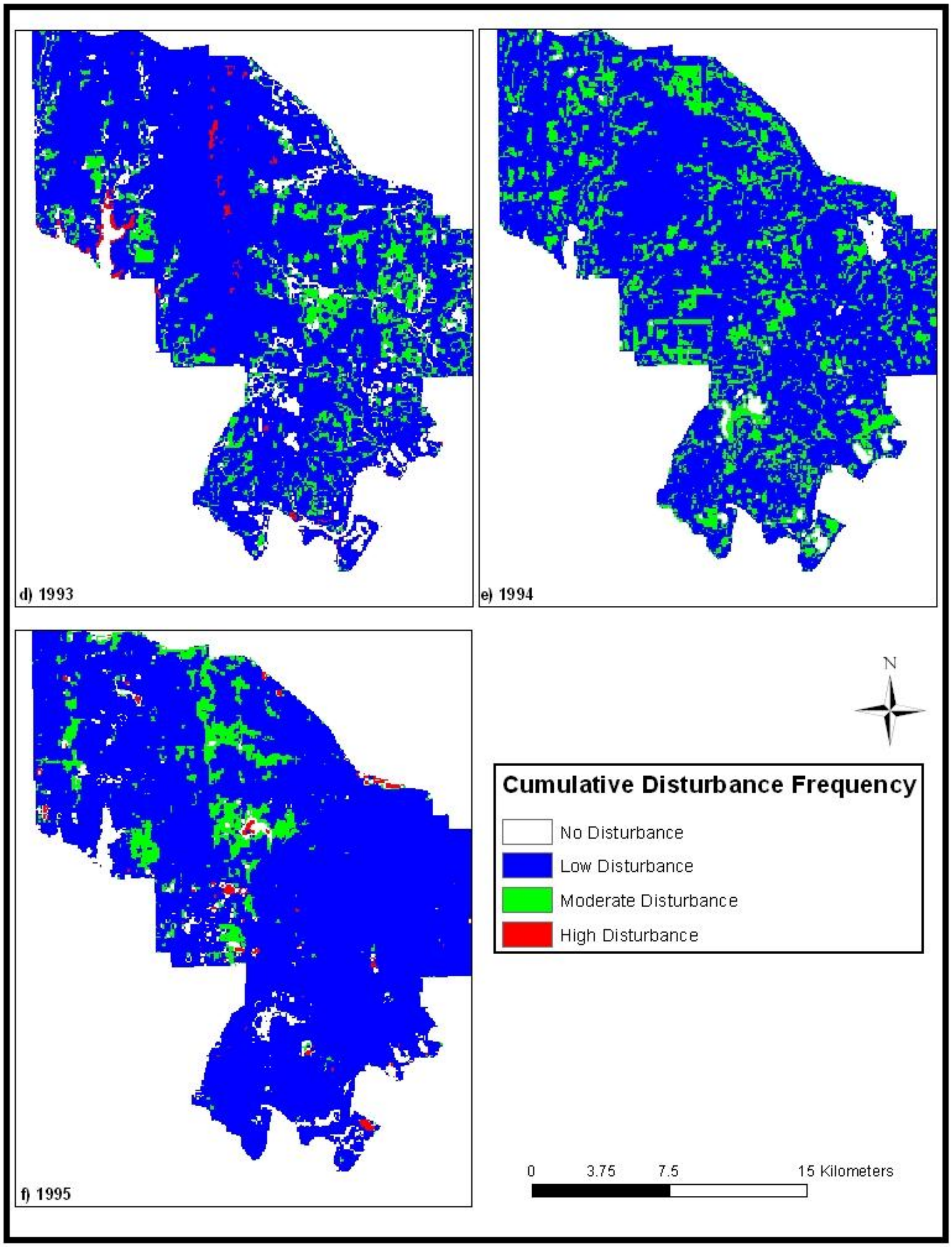


Figure 8d – 8f. Military training-induced cumulative disturbance maps of Fort Riley obtained using point based method for periods of years from 1989 to 1993, 1989 to 1994, and 1989 to 1995.

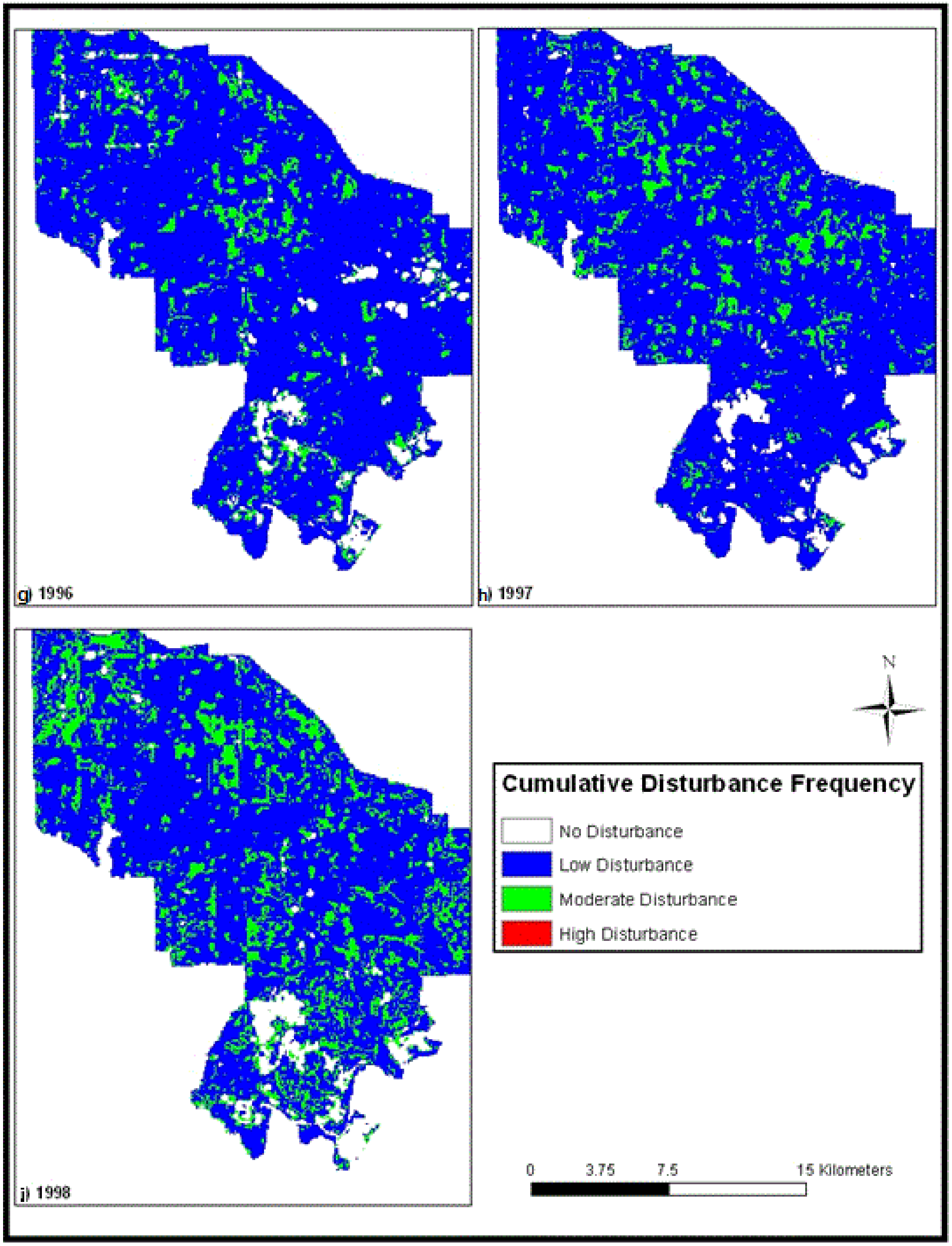


Figure 8g – 8i. Military training-induced cumulative disturbance maps of Fort Riley obtained using point based method for periods of years from 1989 to 1996, 1989 to 1997, and 1989 to 1998.

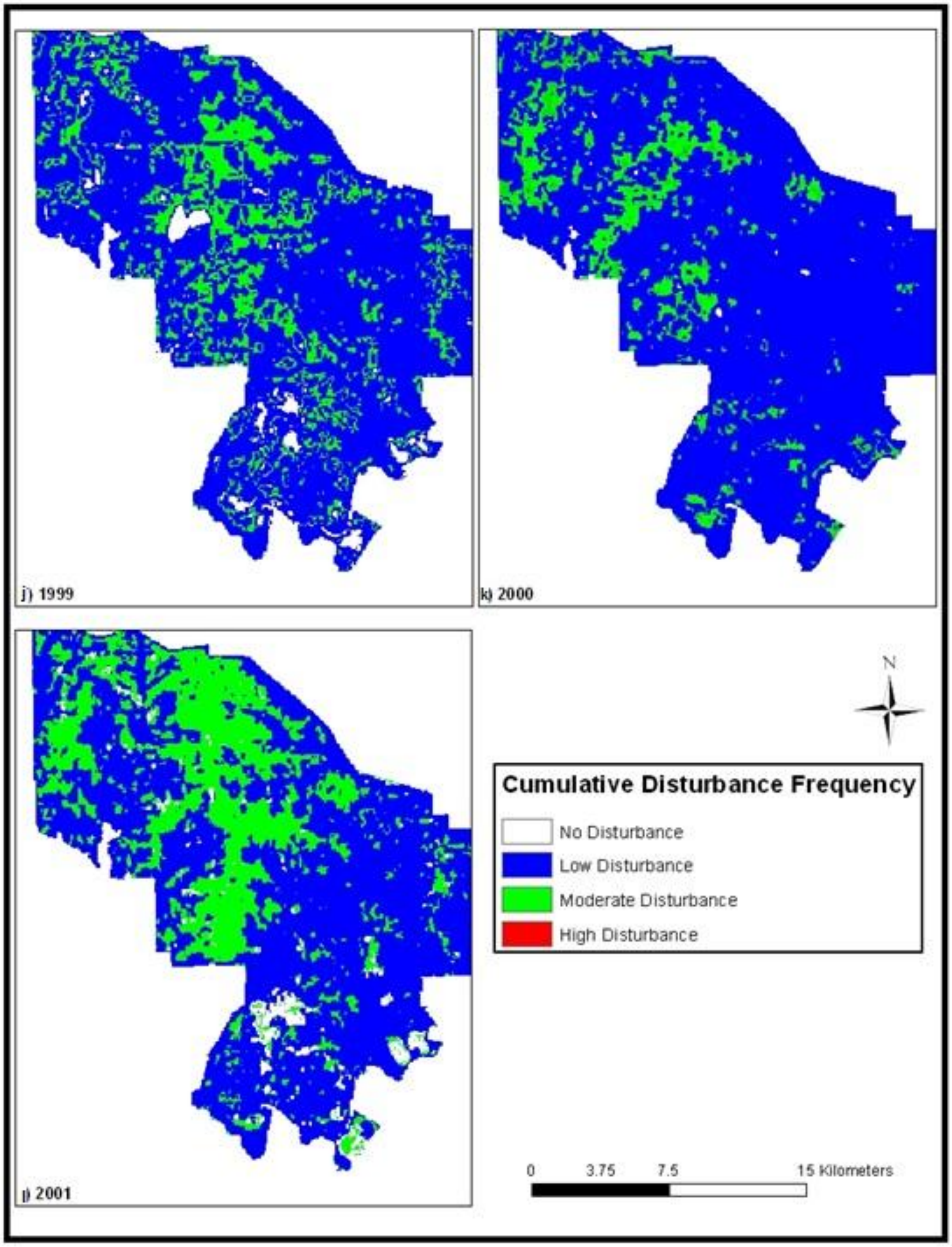
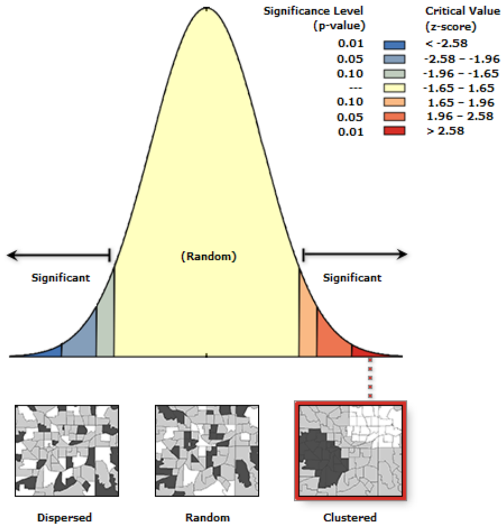
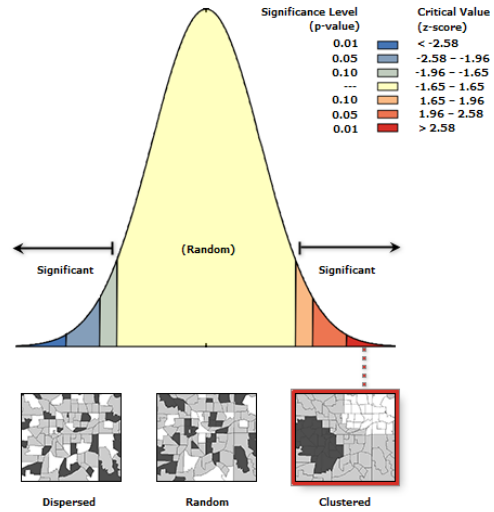


Figure 8j – 8l. Military training-induced cumulative disturbance maps of Fort Riley obtained using point based method for periods of years from 1989 to 1999, 1989 to 2000, and 1989 to 2001.

Spatial analysis was performed on the data from the cumulative disturbance maps obtained using point-based methods. High-low clustering and spatial autocorrelation reports were created for each of the years. The spatial autocorrelation report determined whether the data for each year were dispersed, clustered, or random. The high-low clustering report determined whether the data for each year had low value clusters, high value clusters, or a random distribution. As stated before, a confidence level of 0.05 was set. In Figure 9, the maps show the spatial autocorrelations of the military training-induced cumulative disturbance were statistically significant for all the years except for 1994 at a significance level of 5%. This non-significance of spatial autocorrelation for year 1994 can be noticed in Figure 8e in which the moderate disturbances are evenly distributed over the study area.

Based on Figure 10, there are a total of six years including 1990, 1991, 1995, 1997, 1999, and 2000 in which the military training-induced cumulative disturbance has a random distribution at a significant level of 5%. There are five years, including 1992, 1993, 1994, 1996, and 1998, in which the cumulative disturbance shows low value clustering. The year 2001 has a significant high value clustering of the military training-induced cumulative disturbance.

<table>
<tr><td>a) Spatial Autocorrelation - 1990</td><td>b) Spatial Autocorrelation - 1991</td></tr>
<tr><td>


</td><td>


</td></tr>
<tr><td>Given the z-score of 3.67, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.</td><td>Given the z-score of 3.50, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.</td></tr>
</table>

Figure 9a-9b. Spatial autocorrelation analysis of military training-induced cumulative disturbance maps obtained using point based method for Fort Riley for years 1990 and 1991.

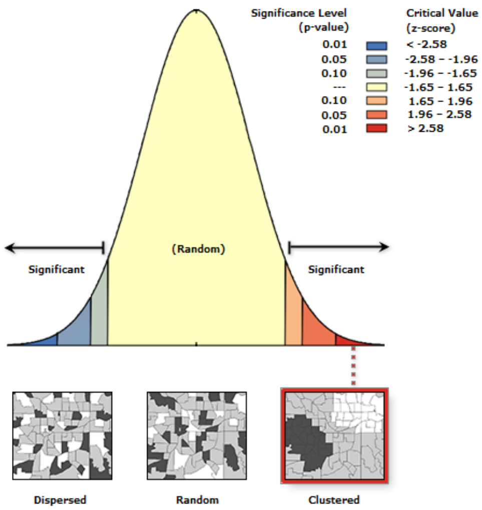
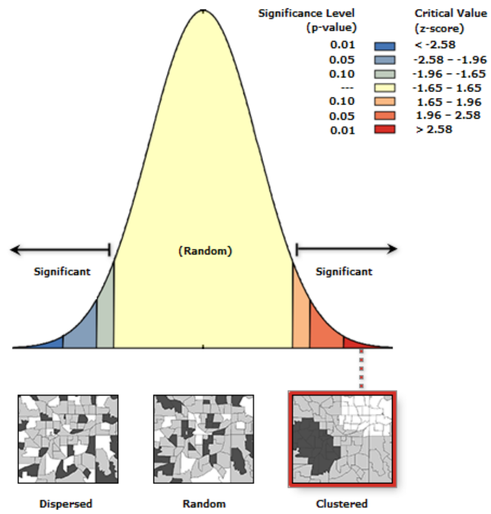
<table>
<tr><td>c) Spatial Autocorrelation - 1992</td><td>d) Spatial Autocorrelation - 1993</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Given the z-score of 13.44, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.</td><td>Given the z-score of 11.06, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.</td></tr>
</table>

Figure 9c-9d. Spatial autocorrelation analysis of military training-induced cumulative disturbance maps obtained using point based method for Fort Riley for years 1992 and 1993.

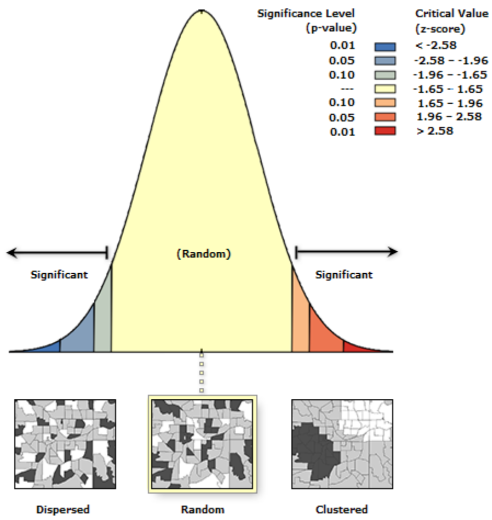
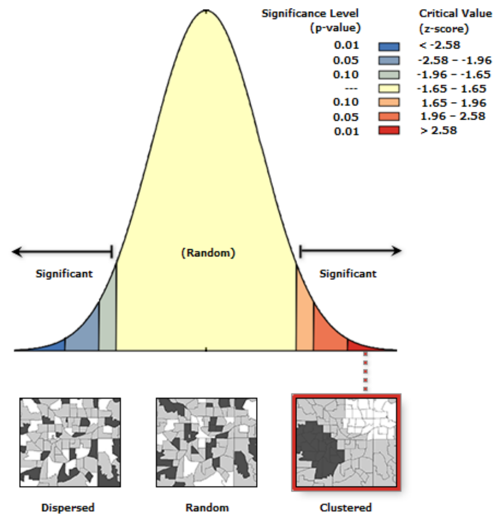
e) Spatial Autocorrelation - 1994	f) Spatial Autocorrelation - 1995
	
Given the z-score of 0.45, the pattern does not appear to be significantly different than random.	Given the z-score of 7.99, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

Figure 9e-9f. Spatial autocorrelation analysis of military training-induced cumulative disturbance maps obtained using point based method for Fort Riley for years 1994 and 1995.

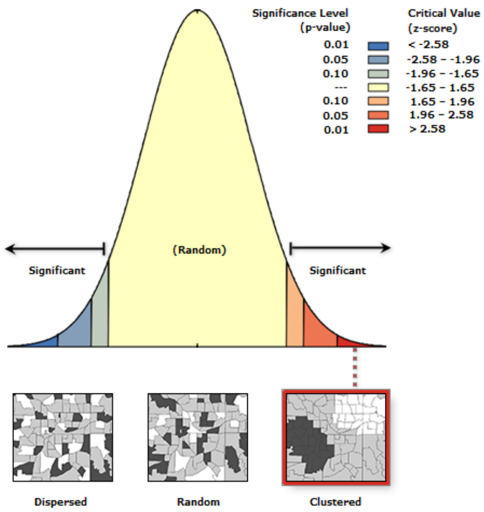
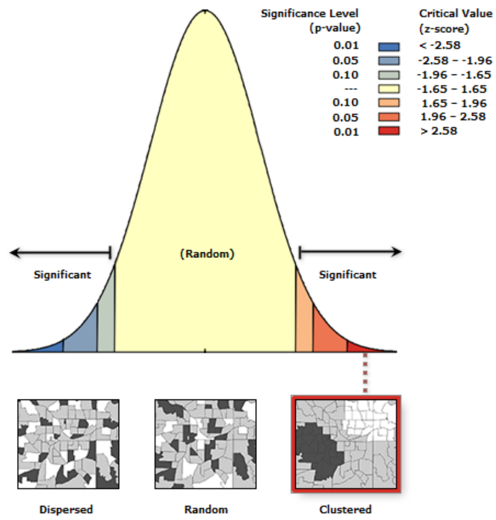
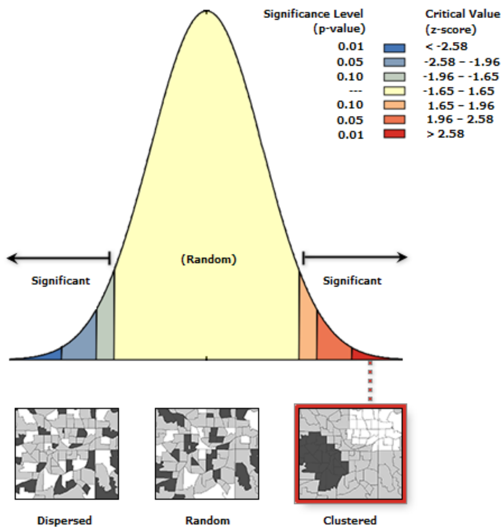
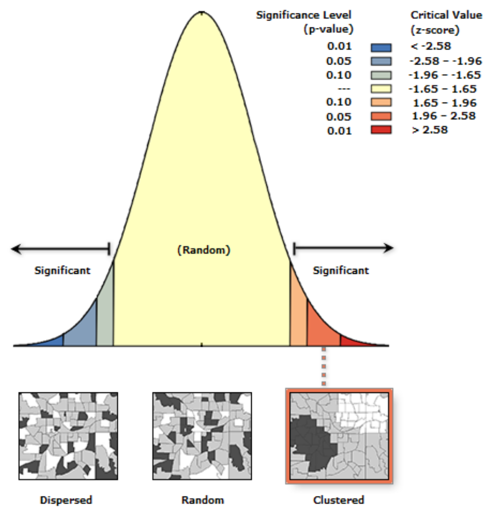
<table>
<tr><th>g) Spatial Autocorrelation - 1996</th><th>h) Spatial Autocorrelation - 1997</th></tr>
<tr><td></td><td></td></tr>
<tr><td>Given the z-score of 7.20, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.</td><td>Given the z-score of 10.56, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.</td></tr>
</table>

Figure 9g-9h. Spatial autocorrelation analysis of military training-induced cumulative disturbance maps obtained using point based method for Fort Riley for years 1996 and 1997.

<table>
<tr><td>i) Spatial Autocorrelation - 1998</td><td>j) Spatial Autocorrelation - 1999</td></tr>
<tr><td>


</td><td>


</td></tr>
<tr><td>Given the z-score of 10.41, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.</td><td>Given the z-score of 2.57, there is a less than 5% likelihood that this clustered pattern could be the result of random chance.</td></tr>
</table>

Figure 9i-9j. Spatial autocorrelation analysis of military training-induced cumulative disturbance maps obtained using point based method for Fort Riley for years 1998 and 1999.

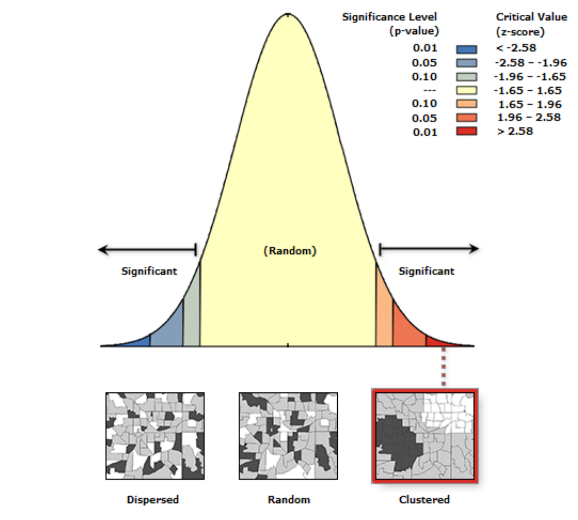
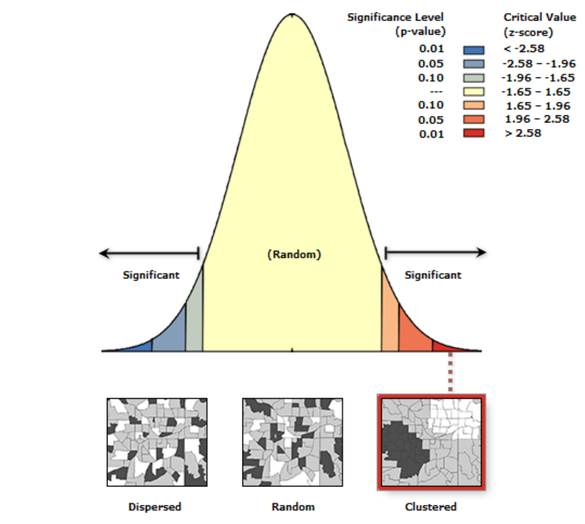
k) Spatial Autocorrelation - 2000	l) Spatial Autocorrelation - 2001
	
Given the z-score of 7.48, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.	Given the z-score of 11.45, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

Figure 9k-9l. Spatial autocorrelation analysis of military training-induced cumulative disturbance maps obtained using point based method for Fort Riley for years 2000 and 2001.

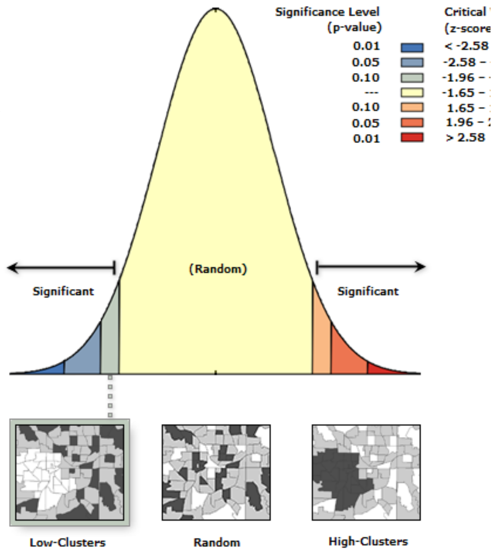
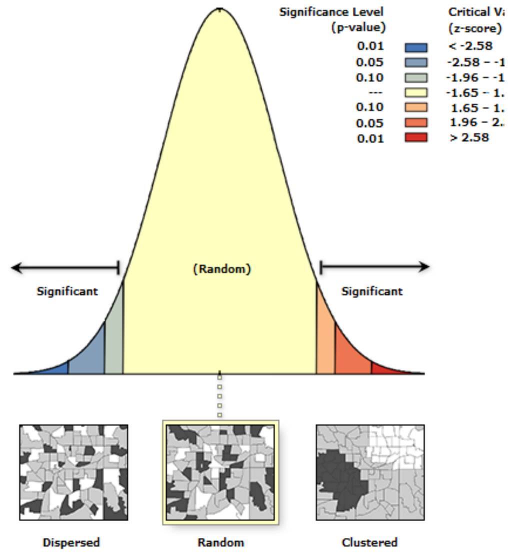
<table>
<tr><td>a) High-Low Clustering Report - 1990</td><td>b) High-Low Clustering Report - 1991</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Given the z-score of -1.80, there is a less than 10% likelihood that this low-clustered pattern could be the result of random chance.</td><td>Given the z-score of 1.53, the pattern does not appear to be significantly different than random.</td></tr>
</table>

Figure 10a-10b. High-low clustering analysis of military training-induced cumulative disturbance maps obtained using point based method for Fort Riley for years 1990 and 1991.

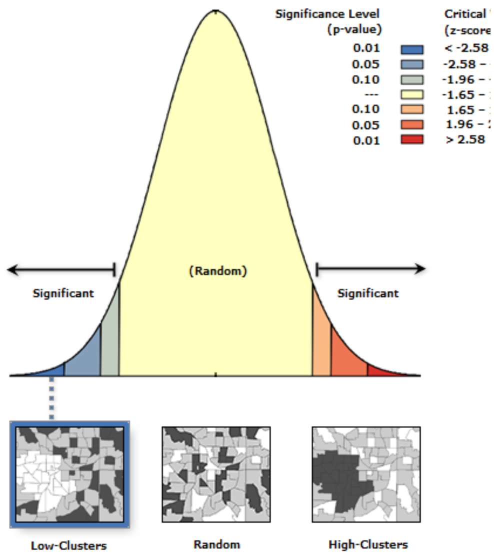
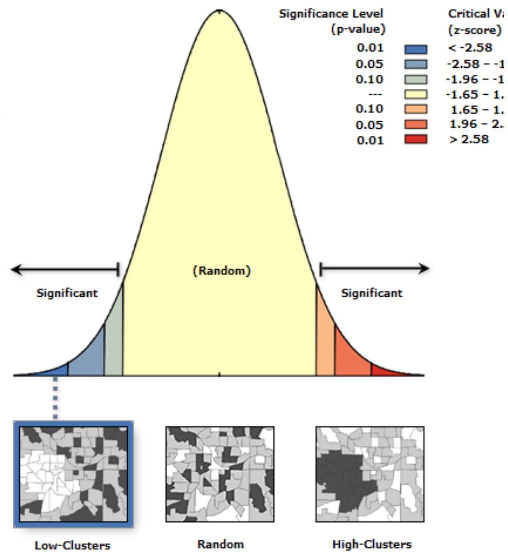
<table>
<tr><td>c) High-Low Clustering Report - 1992</td><td>d) High-Low Clustering Report - 1993</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Given the z-score of-4.61, there is a less than 1% likelihood that this low-clustered pattern could be the result of random chance.</td><td>Given the z-score of -4.31, there is a less than 1% likelihood that this low-clustered pattern could be the result of random chance.</td></tr>
</table>

Figure 10c-10d. High-low clustering analysis of military training-induced cumulative disturbance maps obtained using point based method for Fort Riley for years 1992 and 1993.

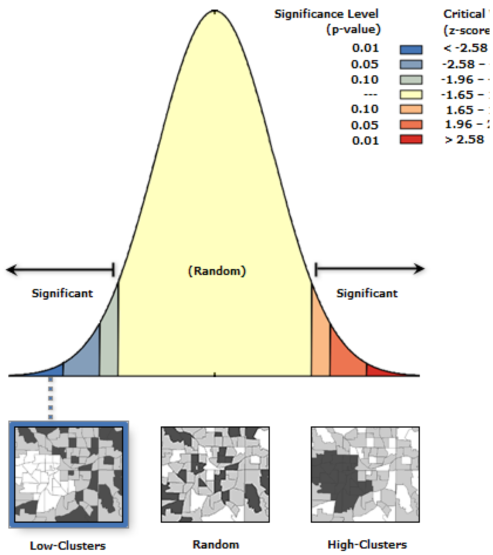
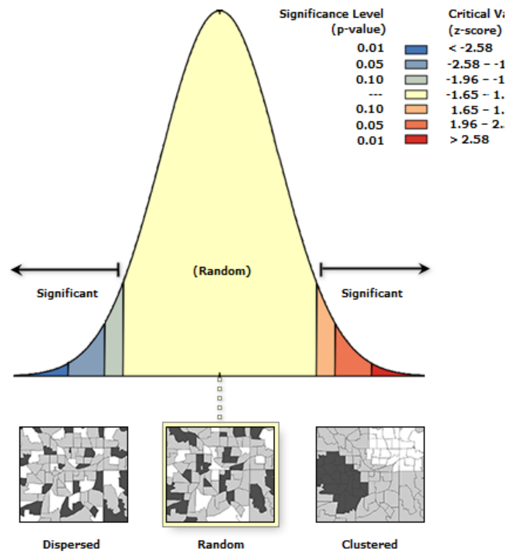
<table>
<tr><td>e) High-Low Clustering Report - 1994</td><td>f) High-Low Clustering Report - 1995</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Given the z-score of -5.49, there is a less than 1% likelihood that this low-clustered pattern could be the result of random chance.</td><td>Given the z-score of -0.11, the pattern does not appear to be significantly different than random.</td></tr>
</table>

Figure 10e-10f. High-low clustering analysis of military training-induced cumulative disturbance maps obtained using point based method for Fort Riley for years 1994 and 1995.

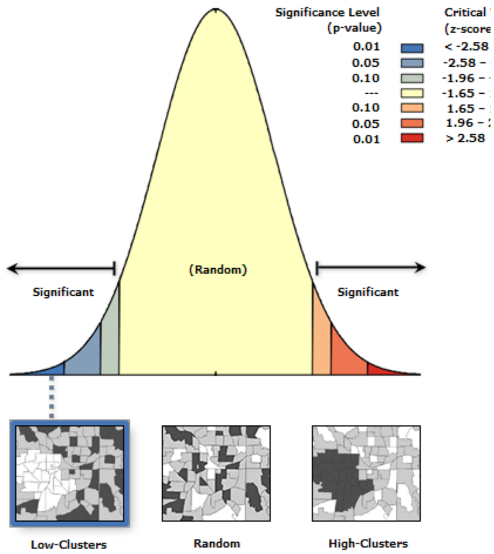
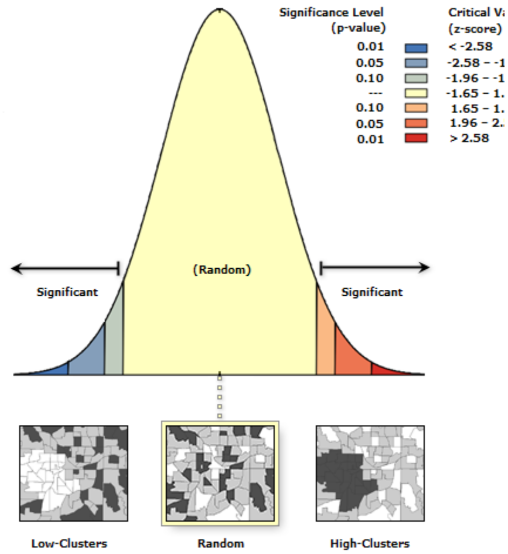
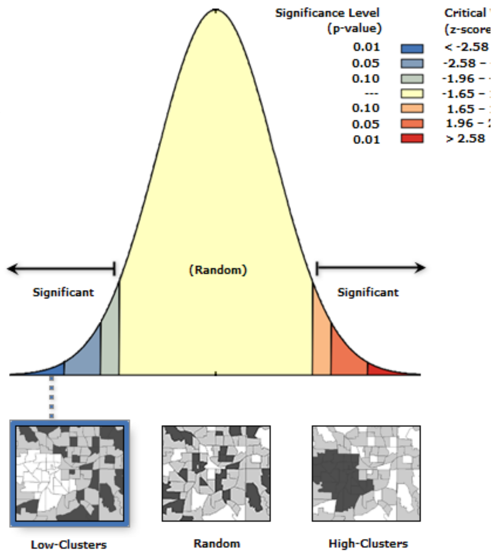
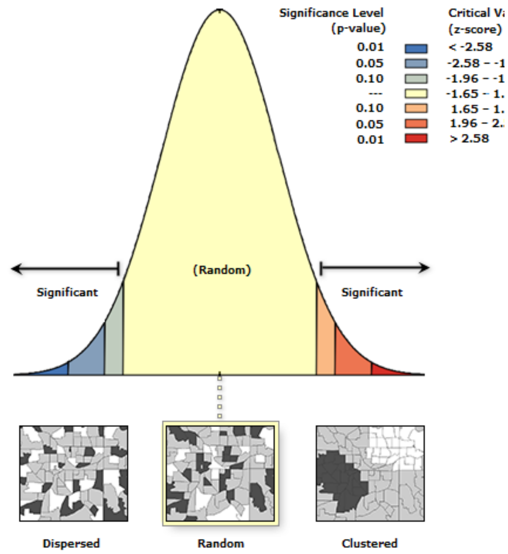
<table>
<tr><td>g) High-Low Clustering Report - 1996</td><td>h) High-Low Clustering Report - 1997</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Given the z-score of -9.46, there is a less than 1% likelihood that this low-clustered pattern could be the result of random chance.</td><td>Given the z-score of -1.48, the pattern does not appear to be significantly different than random.</td></tr>
</table>

Figure 10g-10h. High-low clustering analysis of military training-induced cumulative disturbance maps obtained using point based method for Fort Riley for years 1996 and 1997.

<table>
<tr><td>i) High-Low Clustering Report - 1998</td><td>j) High-Low Clustering Report - 1999</td></tr>
<tr><td>


</td><td>


</td></tr>
<tr><td>Given the z-score of -6.58, there is a less than 1% likelihood that this low-clustered pattern could be the result of random chance.</td><td>Given the z-score of 1.34, the pattern does not appear to be significantly different than random.</td></tr>
</table>

Figure 10i-10j. High-low clustering analysis of military training-induced cumulative disturbance maps obtained using point based method for Fort Riley for years 1998 and 1999.

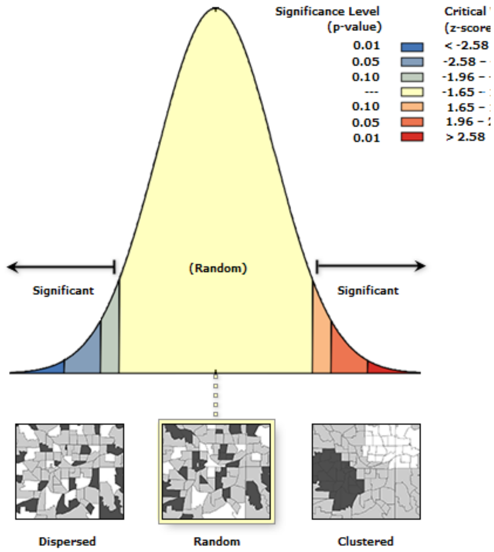
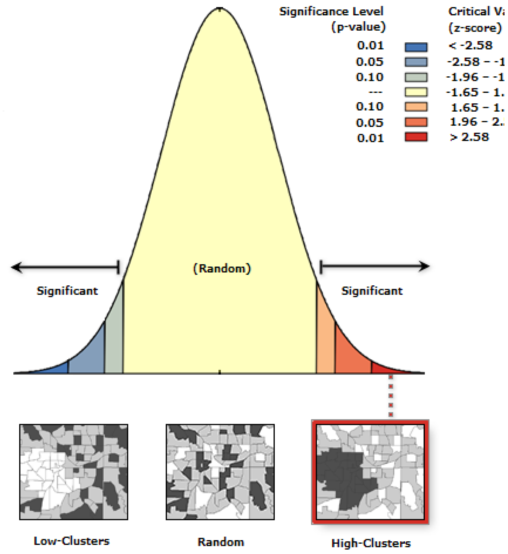
k) High-Low Clustering Report - 2000	l) High-Low Clustering Report - 2001
	
Given the z-score of 0.73, the pattern does not appear to be significantly different than random.	Given the z-score of 4.79, there is a less than 1% likelihood that this high-clustered pattern could be the result of random chance.

Figure 10k-10l. High-low clustering analysis of military training-induced cumulative disturbance maps obtained using point based method for Fort Riley for years 2000 and 2001.

Getis-Ord Gi* statistics locally identifies significant hot and cold spots with a positive z-score and a small p-value indicating a hot spot - clustering of high values, and a negative z-score and small p-value implying a cold spot - clustering of low values. The local hot and cold spot analysis was performed on the military training-induced cumulative disturbance maps using point-based method and the results are shown in Figure 11 to Figure 14. Cold spots are widely noticed in the maps of all the years. The cold spots dominated the study area in 1997. Only four years (1991, 1992, 1993, and 1995) show several small hot spots of statistical significance, and these areas did not create any pattern or relationship to surrounding years. It can also be noted that areas in white on these figures are areas that lack information for the particular year, and this varies from year to year.

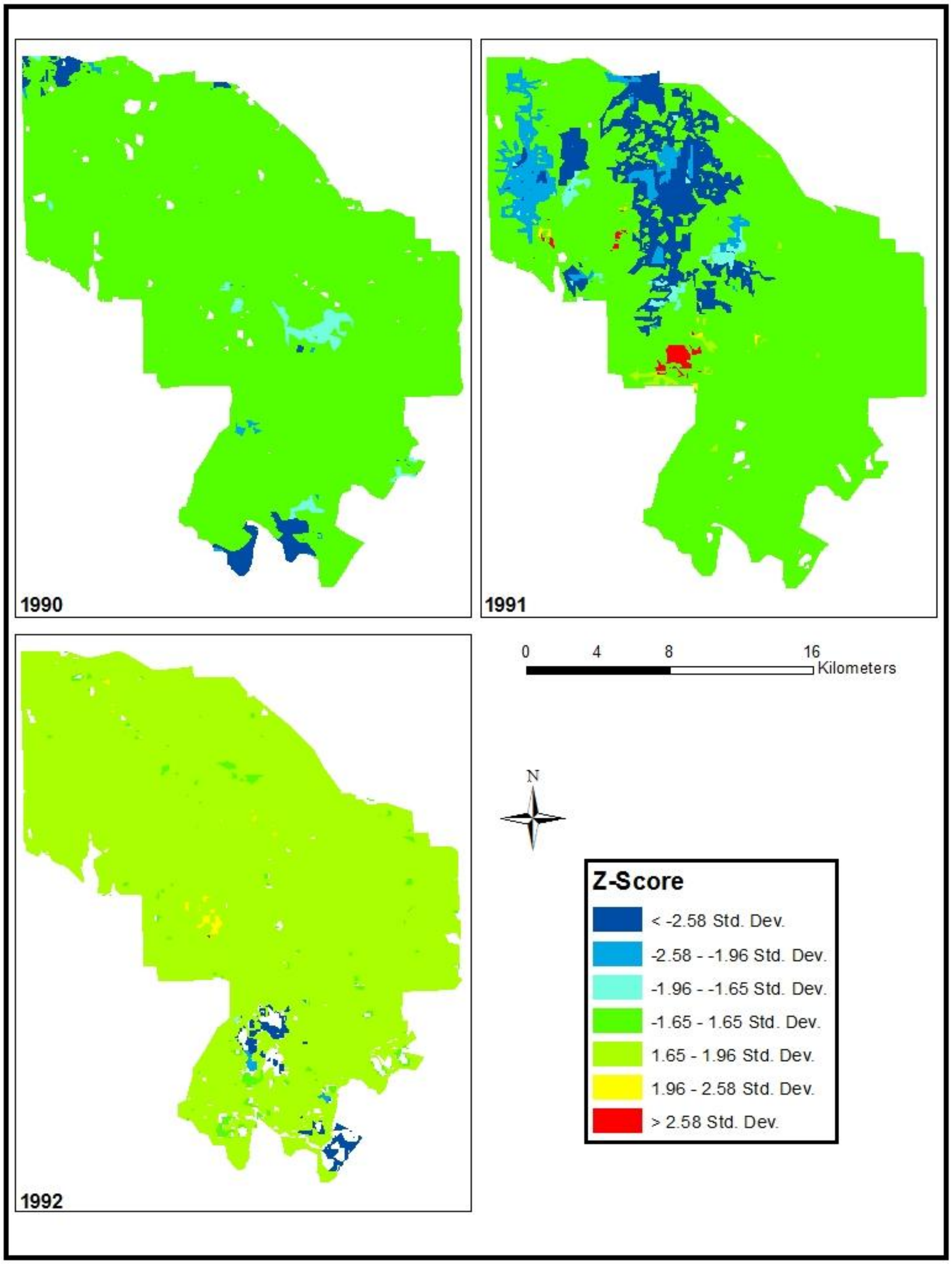


Figure 11. Hot and cold spot analysis on the military training-induced cumulative disturbance maps using point based method for periods of years 1989 to 1990, 1989 to 1991, and 1989 to 1992.

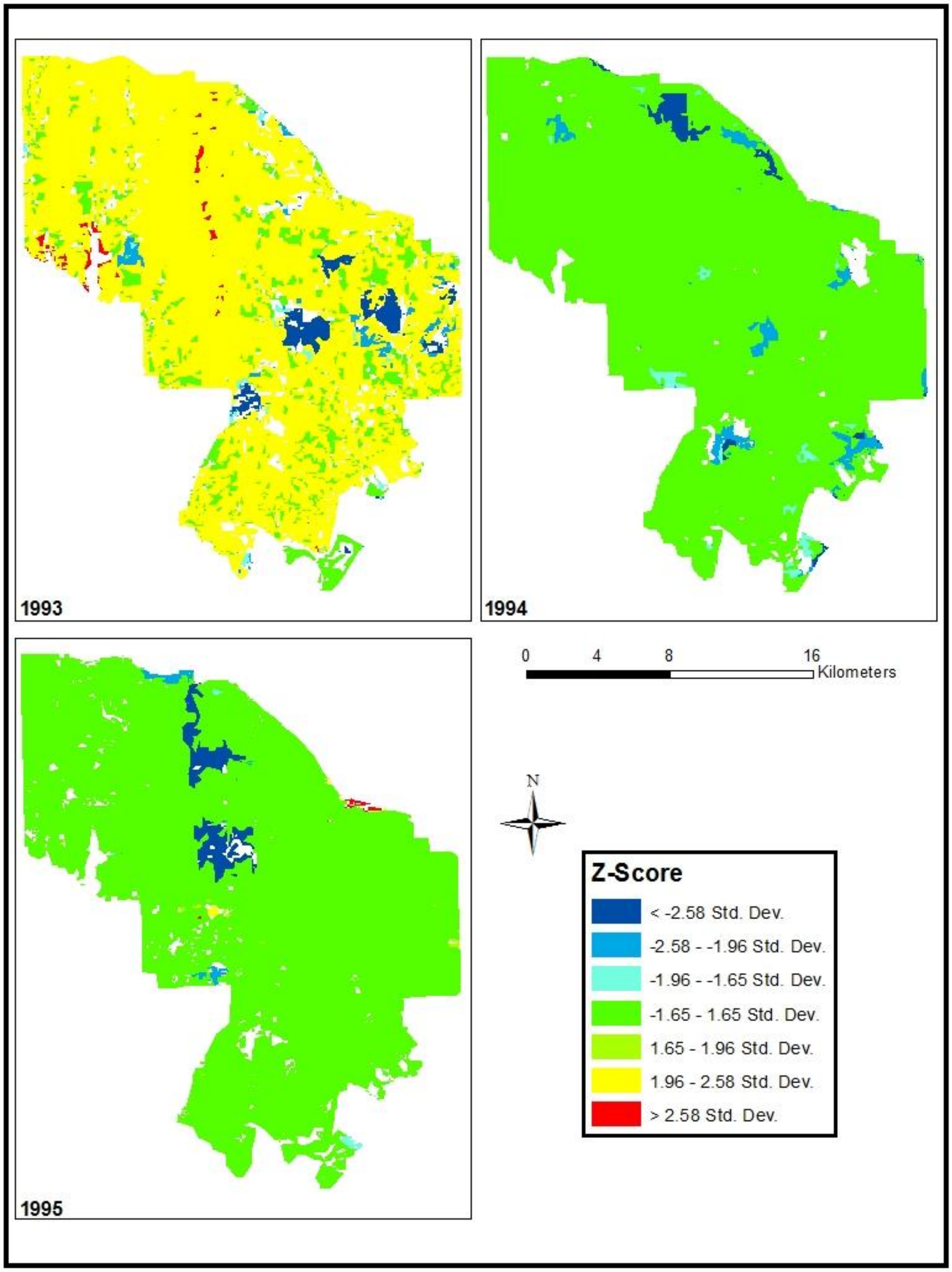


Figure 12. Hot and cold spot analysis on the military training-induced cumulative disturbance maps using point based method for periods of years 1989 to 1993, 1989 to 1994, and 1989 to 1995.

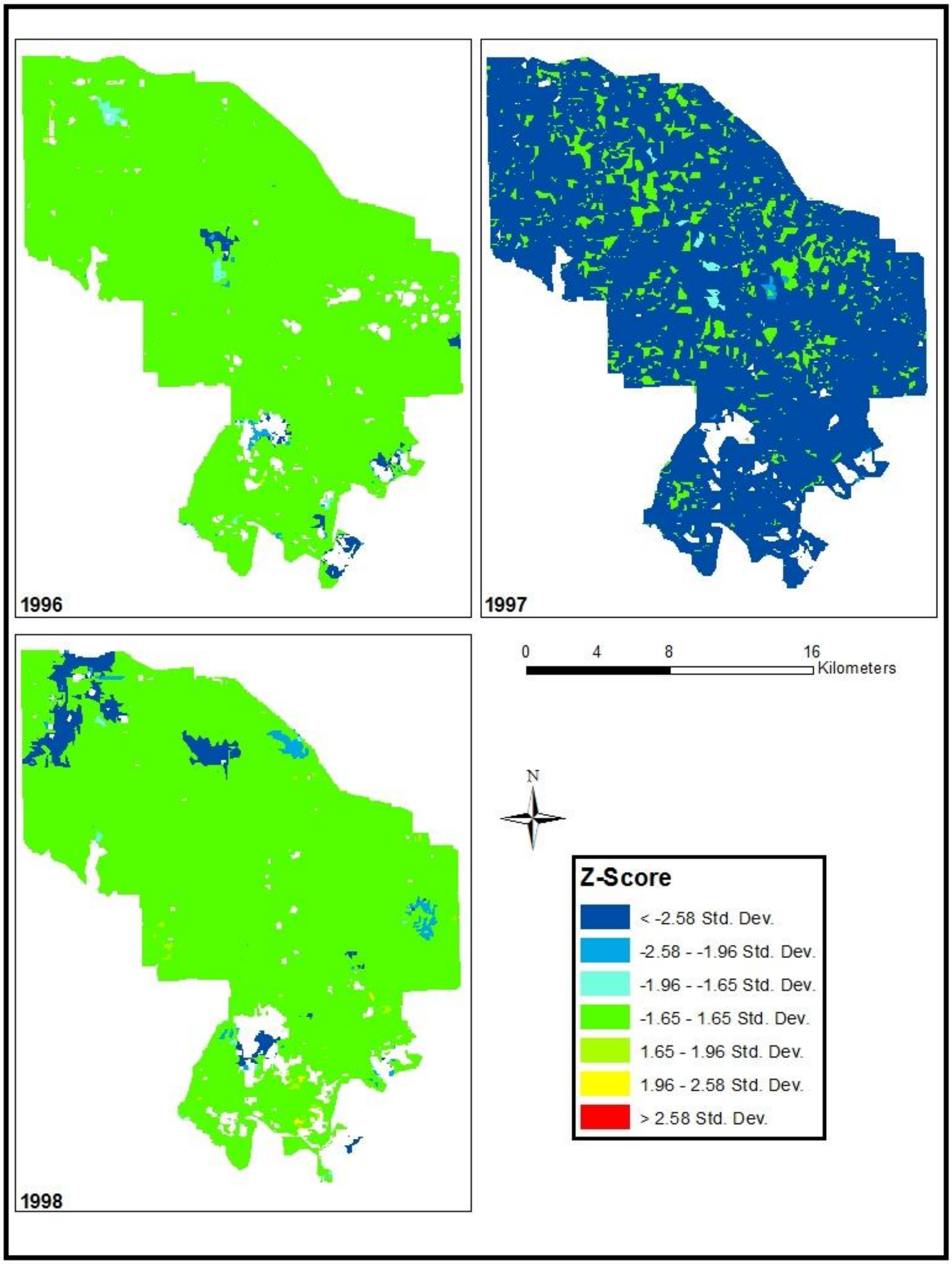


Figure 13. Hot and cold spot analysis on the military training-induced cumulative disturbance maps using point based method for periods of years 1989 to 1996, 1989 to 1997, and 1989 to 1998.

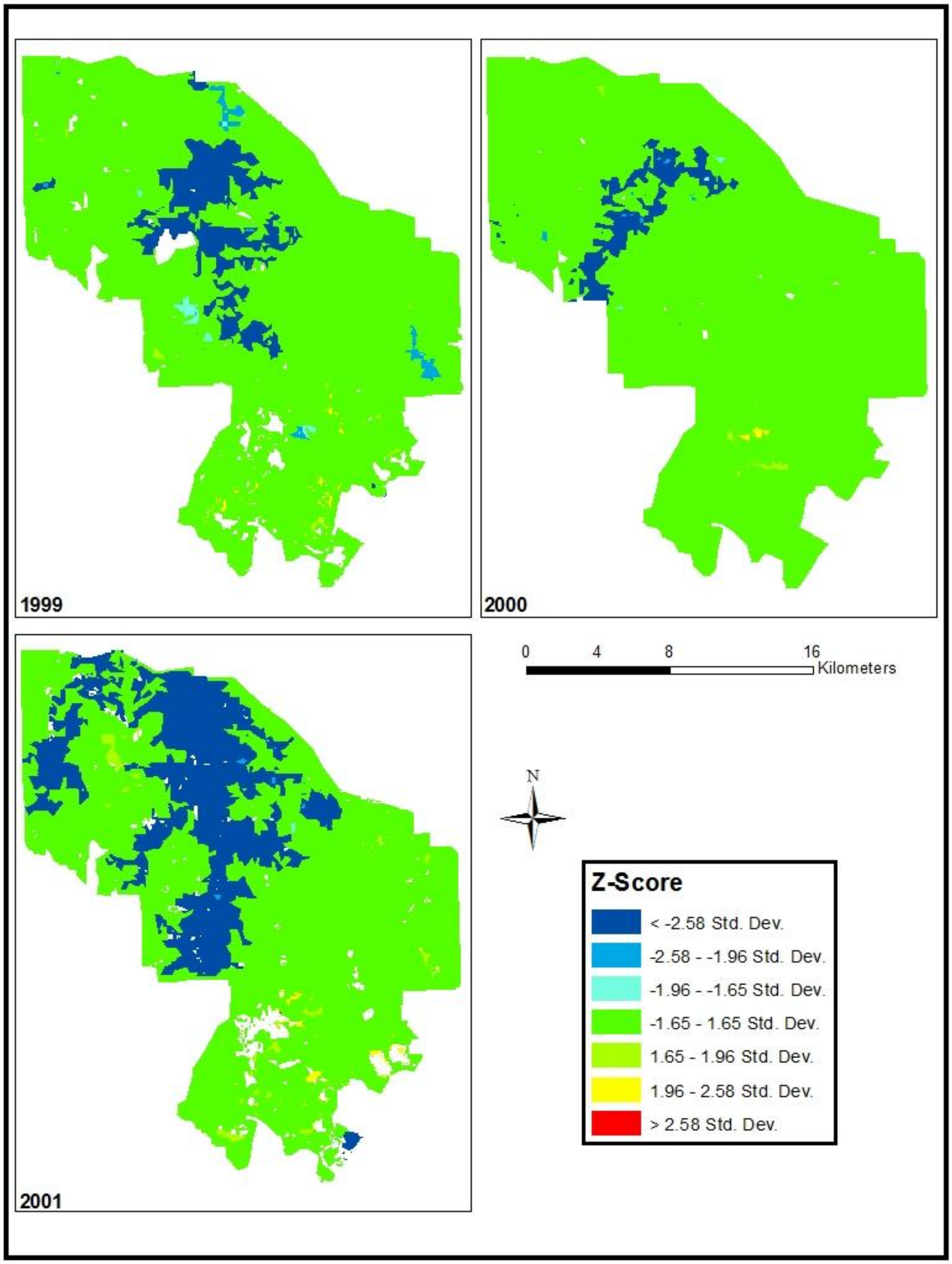


Figure 14. Hot and cold spot analysis on the military training-induced cumulative disturbance maps using point based method for periods of years 1989 to 1999, 1989 to 2000, and 1989 to 2001.

The cluster and outlier analysis was conducted using Anselin local Morans *I* statistics to create cluster-outlier maps of the cumulative disturbance (Figure 15 – Figure 18). Statistically random (not significant) values are displayed in green. Statistically significant cluster of high values (HH) is shown in red, statistically significant cluster of low values (LL) in dark blue, a high value surrounded by low values (HL) in yellow, and a low value surrounded by high values (LH) in light blue. Six years showed large areas of significance relating to low values and its relationship with the values of its neighbors, whether it is to other low values, which created an area of clustering, or high values, which resulted in areas of dispersion. In the case of the maps where the majority of the study area was not significant, areas that did have significance were often small and sporadic. The maps for years 1990, 1994, 1995, and 2000 show barely any area of significance. The maps for years 1996, 1997, and 1998 all have an overwhelming statistically significant clustering of low values. There are no years in which the maps show any large areas of statistically significant clustering of high values.

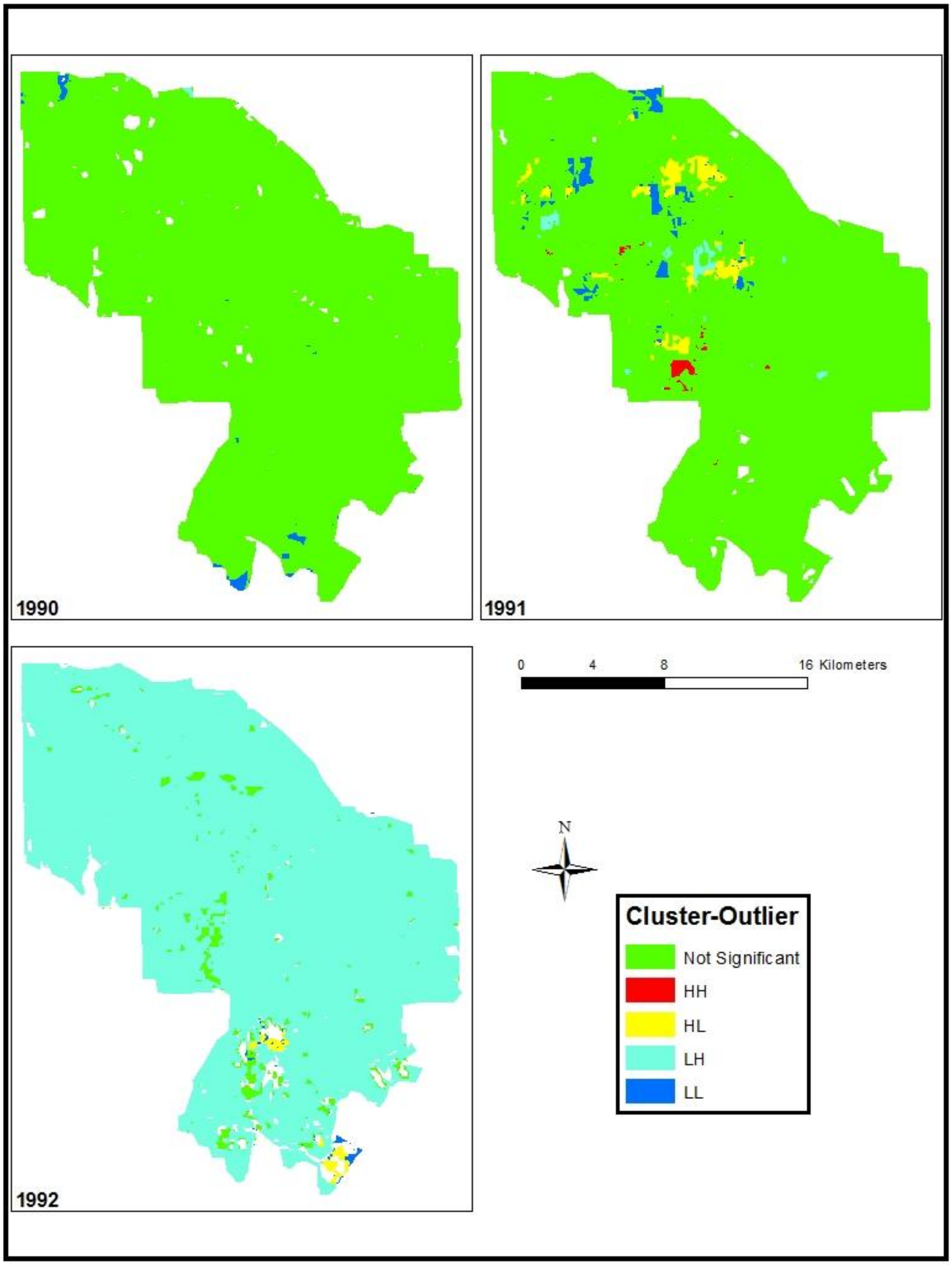


Figure 15. Cluster-outlier analysis of the military training-induced cumulative disturbance maps using point based method for periods of years 1989 to 1990, 1989 to 1991, and 1989 to 1992.

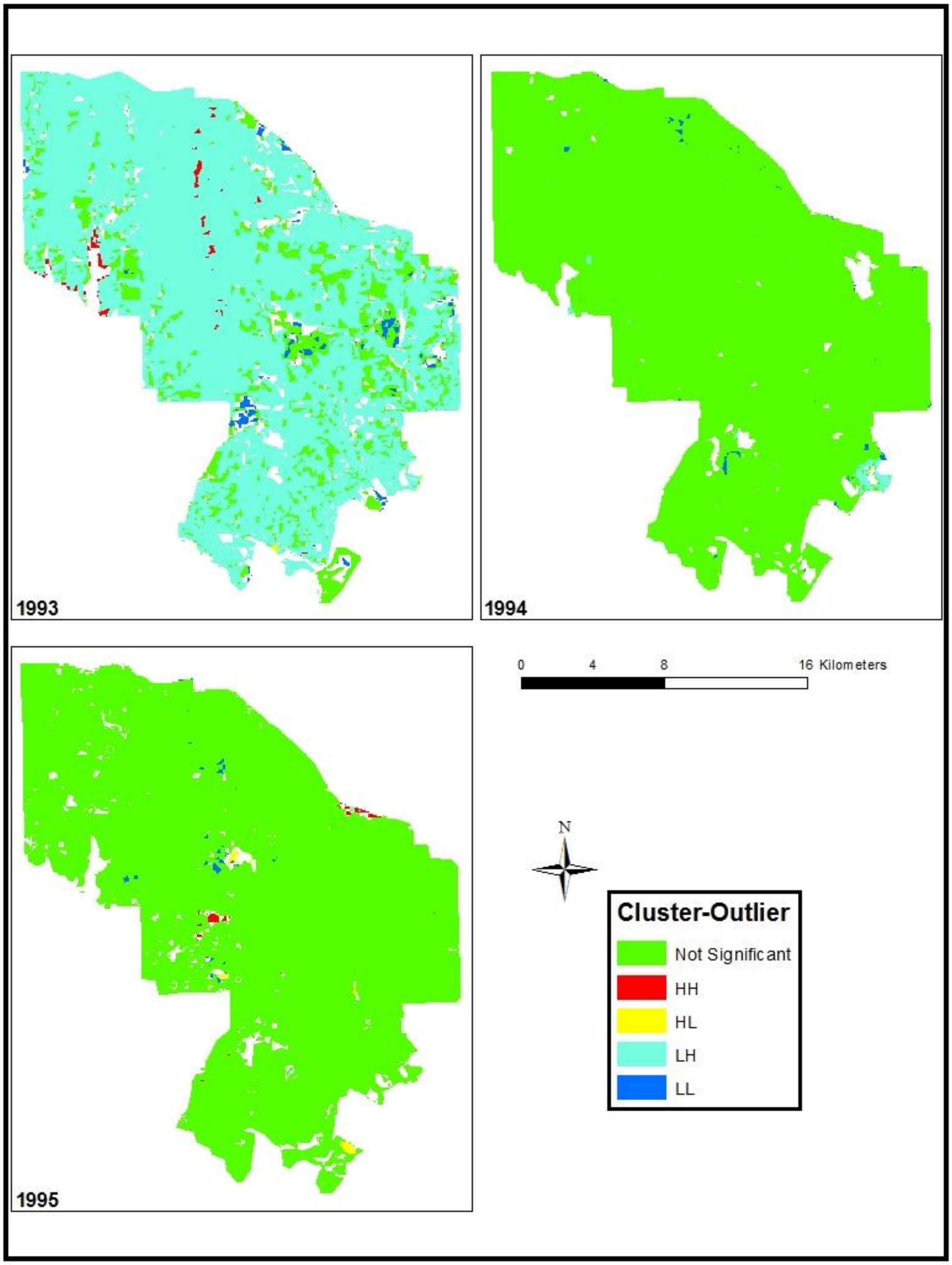


Figure 16. Cluster-outlier analysis of the military training-induced cumulative disturbance maps using point based method for periods of years 1989 to 1993, 1989 to 1994, and 1989 to 1995.

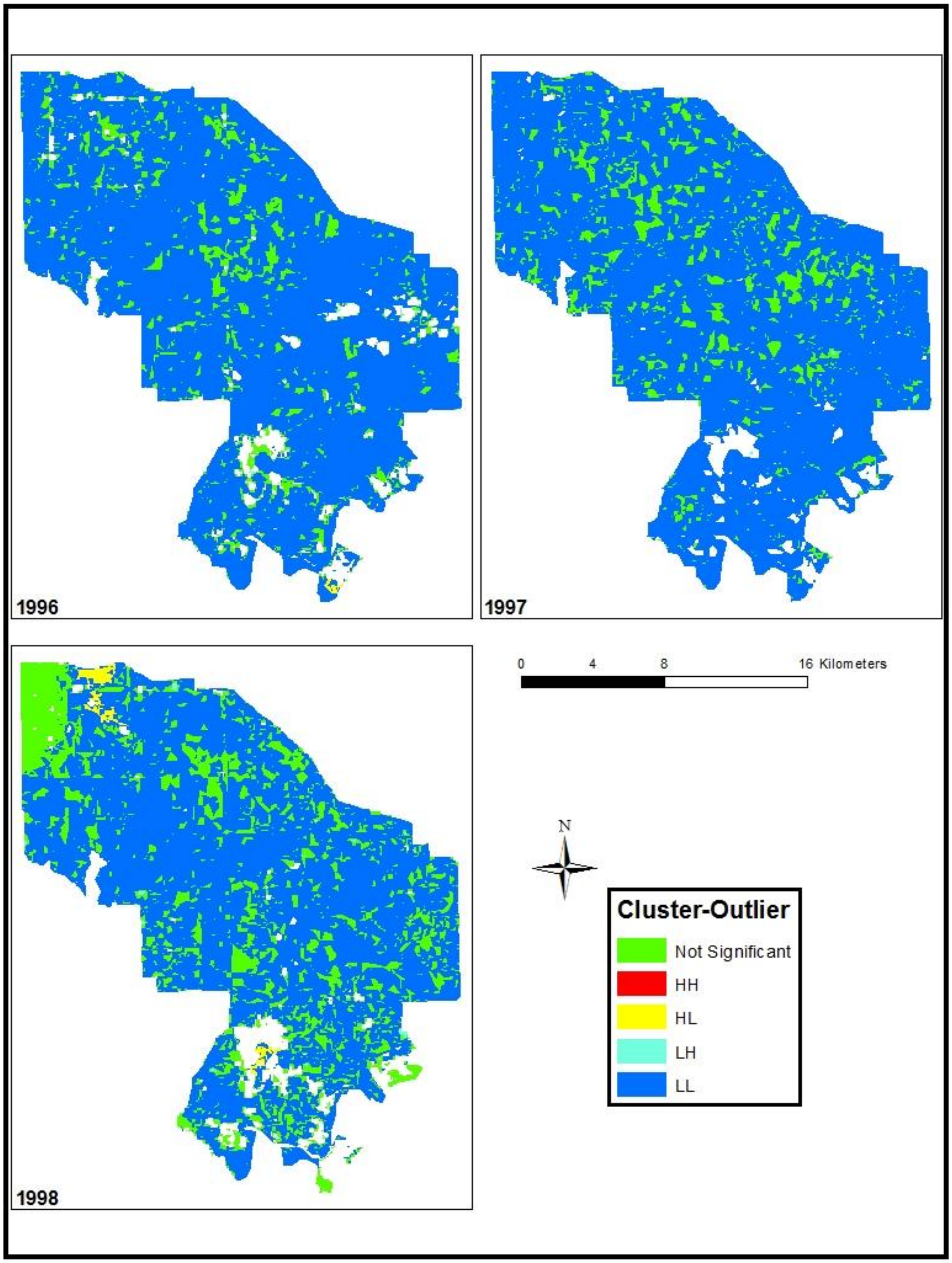


Figure 17. Cluster-outlier analysis of the military training-induced cumulative disturbance maps using point based method for periods of years 1989 to 1996, 1989 to 1997, and 1989 to 1998.

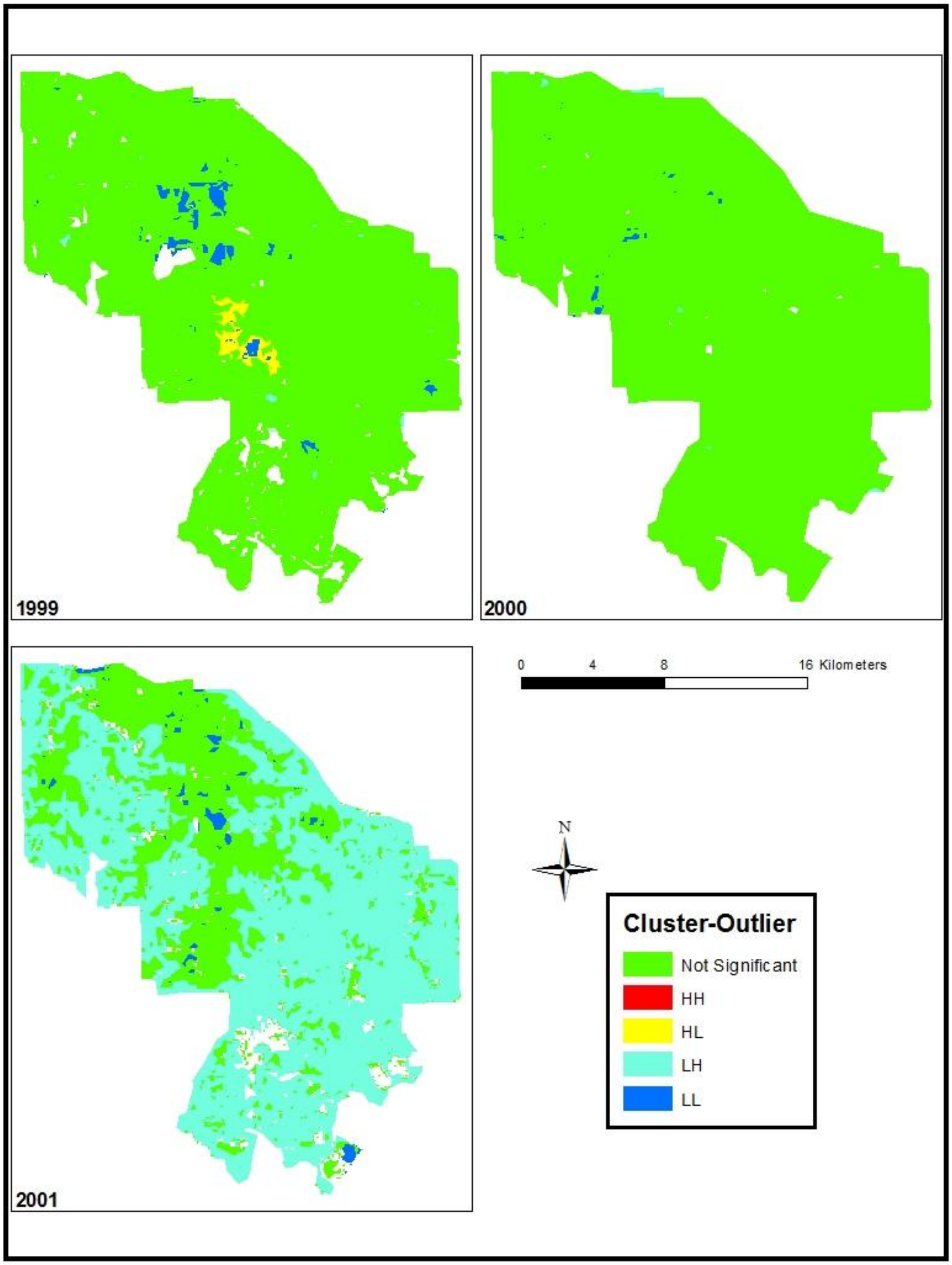


Figure 18. Cluster-outlier analysis of the military training-induced cumulative disturbance maps using point based method for periods of years 1989 to 1999, 1989 to 2000, and 1989 to 2001.

High-low clustering and spatial autocorrelation analysis was also performed on the military training-induced disturbance maps using plot-based method for three years 1995, 1998, and 2001 (Figure 19). The disturbance maps for all three years have statistically significantly spatial autocorrelation with a less than 1% likelihood of random chance. But, the spatial pattern, high-low clustering, was random for all three years.

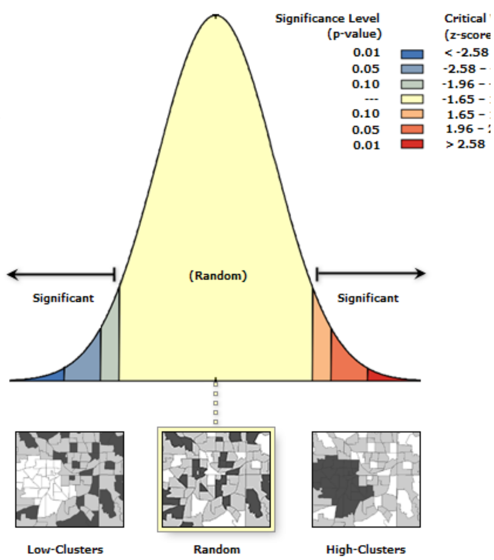
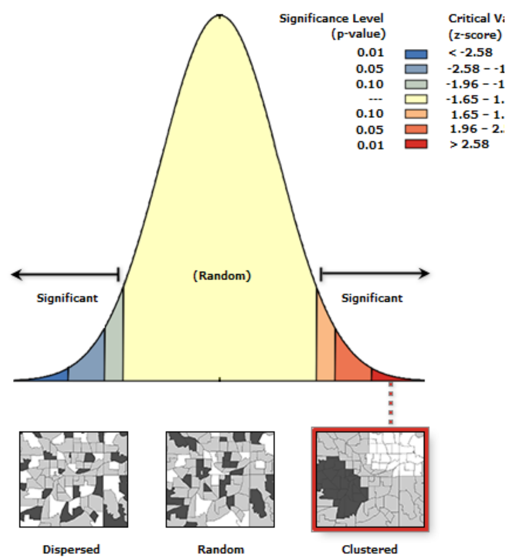
a) High-Low Clustering Report – 1995	b) Spatial Autocorrelation Report – 1995
	
Given the z-score of -1.02, the pattern does not appear to significantly different than random.	Given the z-score of 9.40, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

Figure 19a-19b. High-low clustering and spatial autocorrelation analysis of the military training-induced disturbance maps using plot based method for the year 1995.

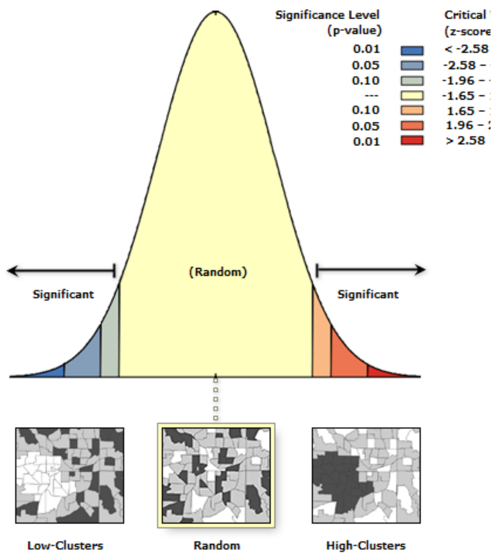
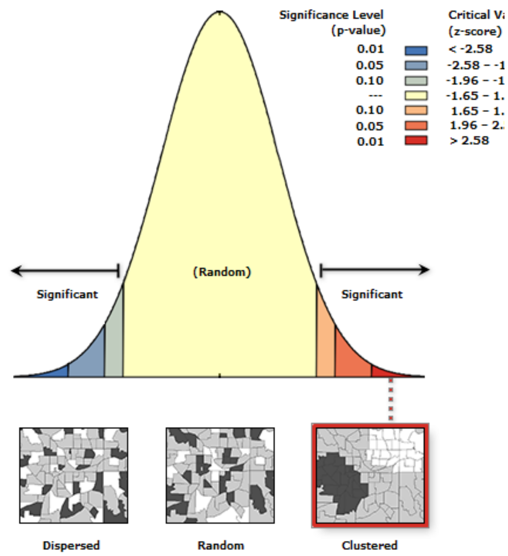
<table>
<tr><td>c) High-Low Clustering Report – 1998</td><td>d) Spatial Autocorrelation Report – 1998</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Given the z-score of -0.78, the pattern does not appear to be significantly different than random.</td><td>Given the z-score of 5.76, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.</td></tr>
</table>

Figure 19c-19d. High-low clustering and spatial autocorrelation analysis of the military training-induced disturbance maps using plot based method for the year 1998.

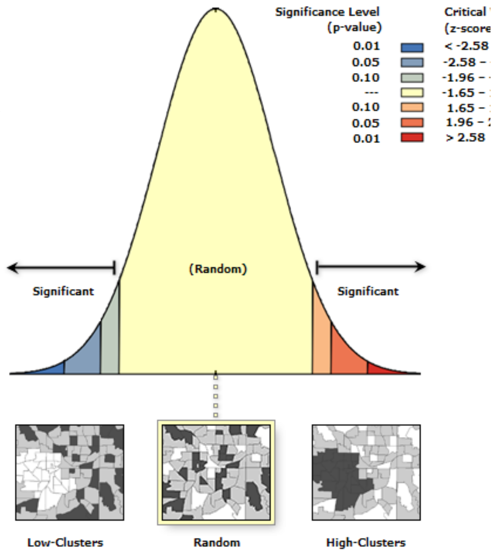
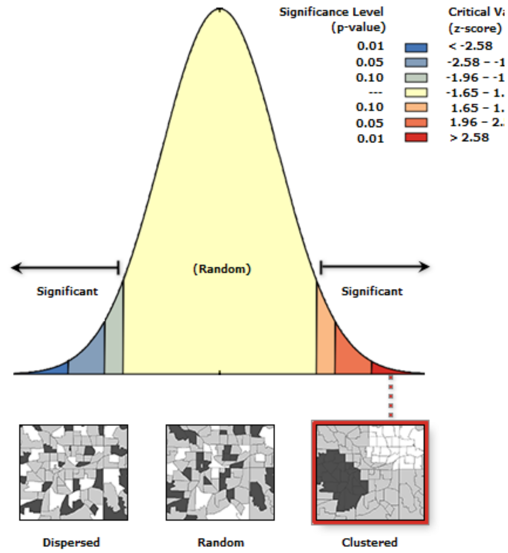
<table>
<tr><td>e) High-Low Clustering Report – 2001</td><td>f) Spatial Autocorrelation Report – 2001</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Given the z-score of -0.54, the pattern does not appear to be significantly different than random.</td><td>Given the z-score of 4.43, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.</td></tr>
</table>

Figure 19e-19f. High-low clustering and spatial autocorrelation analysis of the military training-induced disturbance maps using plot based method for the year 2001.

.

Hot spot analysis was performed on the military training-induced disturbance maps using plot based method for three years 1995, 1998, and 2001 (Figure 20). There is only one small cold spot found in 1998's map, or random distribution dominates the map.

Both 1995 and 2001 maps show several statistically significant hot spots mainly located in the south central and southeastern portion of the study area. The cold spots dominate the 2001's map.

Cluster-outlier maps for these three years 1995, 1998, and 2001 were created (Figure 21). Statistically non-significance is displayed in green. HH is displayed in red, HL in yellow, LH in light blue, and LL in dark blue. Similar to the hot spot analysis, the years 1995 and 2001 maps show statistically significant clustering of low values. The 1998 map, on the other hand, has a majority of low values being surrounded by high values.

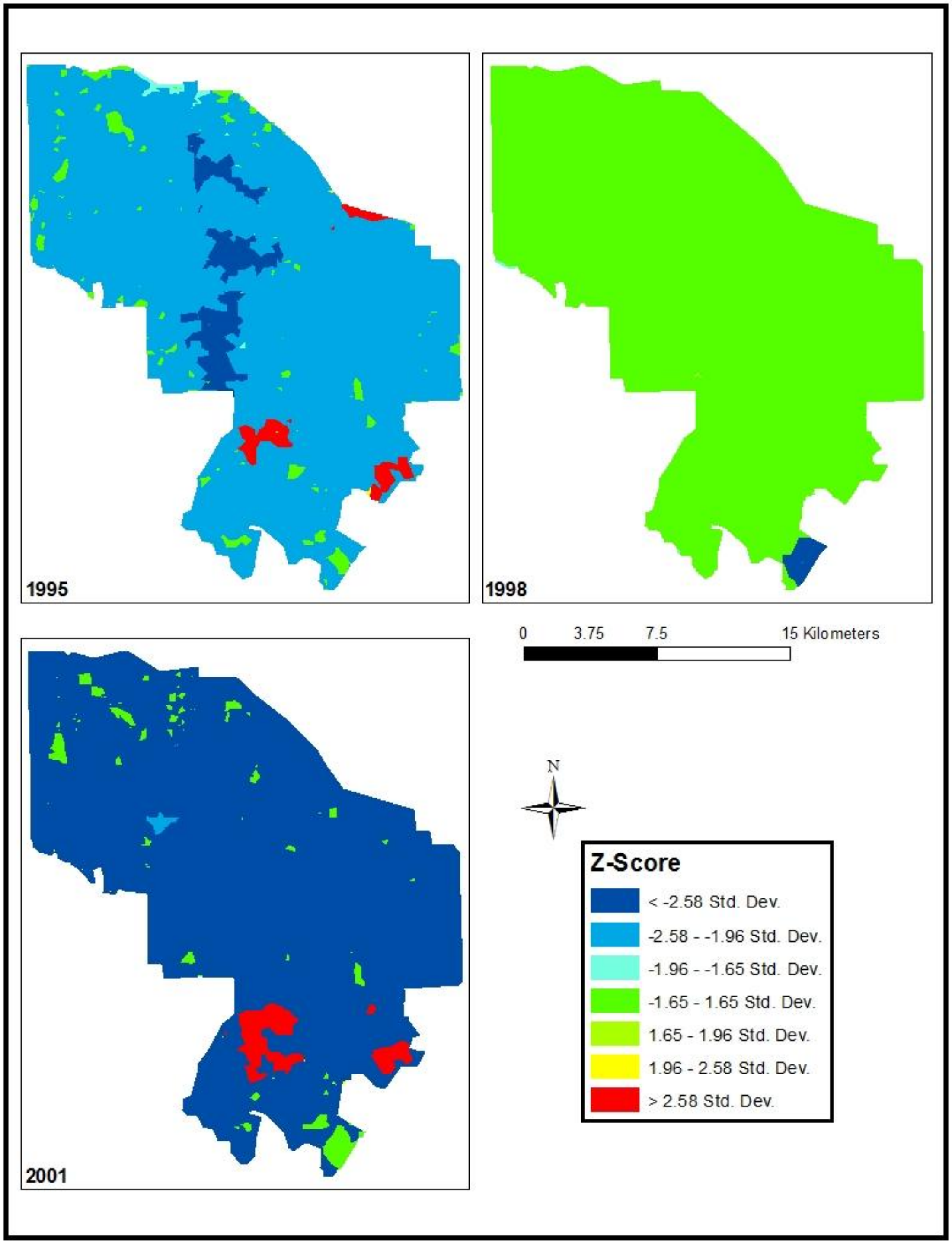


Figure 20. Hot spot analysis of the military training-induced disturbance maps using plot based method for three years 1995, 1998, and 2001.

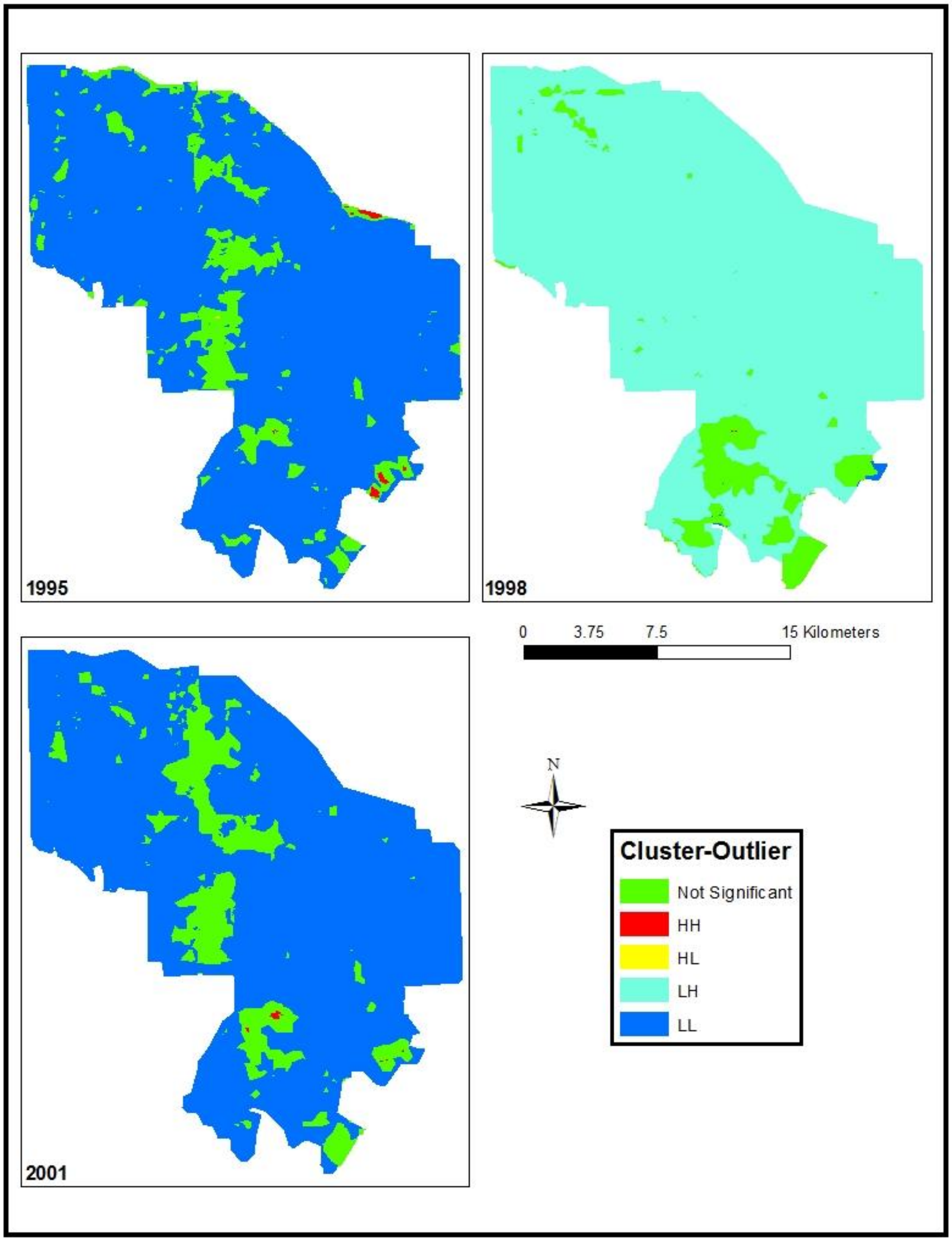


Figure 21. Cluster-outlier analysis of the military training-induced disturbance maps using plot based method for three years 1995, 1998, and 2001.

CHAPTER 6 – DISCUSSION AND CONCLUSIONS

In this study, Landsat TM imagery and the sample plot data of military training-induced disturbance were fused together in order to investigate the significance impacts of military training activities on land condition. It was found that 95% of the TM images and their transformations had a statistically significant correlation with the military training-induced disturbances. Thus, the obtained disturbance maps were reliable. However, it has to be pointed out that the results were not validated using independent sample plot data. The reason was partly because the independent sample plot data of the military training-induced cumulative disturbance were lacking and partly because the used sample size was relatively small. Moreover, any partitioning of the sample plots into calibration and validation groups could impeded the creation of the maps. Instead, cross-validation was conducted. The obtained root mean square error varied from 16.9 to 36.1 and the relative error ranged from 83.2 to 168.9%. The errors were relative large mainly because the high variation of the military training induced disturbance and relative small samples that were used in this study.

When it came to determining whether or not there were consistent spatial-temporal patterns for both the single year ground disturbance and cumulative disturbance due to military training activities, the plot and point-based methods were used. The single year ground disturbance maps were created using the plot based method (Figure 7a-7m). The legend shows the percentage of disturbance throughout Fort Riley in three separate categories including: 0-30% for low disturbance, 30-70% for moderate disturbance, and 70-100% for high disturbance. It was obvious that low disturbance dominated the study area and moderate and high disturbance mainly existed in the central and northwest parts of the study area. The features were consistent with the spatial distributions of the military training activities. However, it was found that there is no definite consistency in spatial-temporal patterns among the 13 years of the disturbance maps. That is, the spatiotemporal patterns of the military training-induced disturbance varied spatially and temporally. At the same places, the disturbance was low in some years and could change to moderate and high level in other years. In general, fewer disturbances could be seen at the southern and eastern regions of the study area.

When comparing the disturbance maps to the land use and land cover map, it could be seen that the majority of built up area lied on the southern region of the study area. This could be a possible link into why there tended to be at least a low level of disturbance in a number of years. The east regions also showed levels of low disturbance among the 13 years. The reason was because there was a sub-area at the central east part that was used as a control area in which no military training activities were scheduled within the time period. Some of the maps showed the exact opposite pattern. For example, the years of 1999 and 2000 show vastly different levels of disturbance. The 1999's map had many areas of moderate disturbance while the 2000's map, in contrast, showed basically complete levels of low disturbance. Another example was that the moderate and high disturbances dominated the central part of the study area in the 1993's map, but the features almost disappeared in the 1994's map. High disturbance was only found in seven years maps out of the 13 years.

The military training-induced cumulative disturbance maps were obtained using point based method (Figure 8a - 8l). The maps are separated into four separate classes: no disturbance, low disturbance, moderate disturbance, and high disturbance. The above description for the single year disturbance maps (Figure 7a - 7m) could also be applied to the cumulative disturbance maps (Figure 8a - 8l) except for the cumulative maps showed finer levels of details in regards to clustering and areas of disturbance. The cumulative disturbance maps also lacked consistent spatial and temporal patterns of disturbance throughout the time period. Low disturbance dominated the study area, but the moderate and high disturbance existed in the central and northwest parts, being basically confined to grassland areas in which military training activities mostly took place. Most "no disturbance areas" were found in the southern region around where built up areas were.

The above characteristics of the military training-induced disturbance were definitely dependent on the military training activities. In Fort Riley, various training exercises have been continuously executed. The training activities included field maneuvers, combat vehicle operations, mortar and artillery fire, and small-arms fire have taken place. The activities disturbed ground and vegetation canopy cover and increased soil erosion and thus degraded the land condition of military installations (Anderson et al., 2005 2006; Wang et al., 2007, 2009). Cumulative and continuous training activities accelerated the land degradation and conversely, halting, reducing or rotating the activities might help recovery of land condition (Wang and others 2007, 2009). In order to reduce the impacts and sustain the land condition, the managers who take care of military training programs often alter the positions and areas of training from year to year and keep areas from being exposed to high levels of disturbance. This sporadic nature is a possible reason that the disturbance maps lack defined and consistent spatiotemporal patterns of disturbance.

Moreover, the cumulative disturbance maps were related to the single year disturbance maps, but were not totally consistent with each other. For example, from both kinds of the disturbance maps it was found that low disturbance dominated this study area and there were moderate and high disturbances in the central and northwest parts of the study area. However, the 1993 map showed a large area of moderate and high disturbance in the central parts, while this feature disappeared in the cumulative disturbance map from 1989 to 1993. This implied the cumulative disturbance maps revealed different information from the annual disturbance maps and characterized the cumulative impacts of disturbance on the land condition. The annual disturbance maps clearly defined the level of current disturbance, while the cumulative disturbance maps had the ability to determine how the historical military training activities impact the current land condition. It was clear that the accumulation of disturbance varied spatially and temporally. For the same location, the disturbance did not always increase and thus the land condition did not become poorer through the years because the military training activities were not always done on the same pieces of land and the rotation of activities was often used. Thus, some areas that fell into the moderate disturbance in one year could become low disturbance next year. On the other hand, halting, reducing or rotating the activities could help recovery of the land condition. Past disturbance would obviously influence on the current land condition. Therefore, continuous use of heavy loads of the military training activities would definitely lead to serious impacts of cumulative disturbance on the land condition. The annual disturbance maps in general were unable to show the cumulative impacts. So, both kinds of annual and cumulative disturbance maps provide useful tools for the military land managers.

Spatial analysis was applied to both annual and cumulative disturbance maps to investigate whether the military training-induced disturbance was spatially auto-correlated or not. The results showed that both annual and cumulative disturbances were spatially auto-correlated for all the years except for 1994. Out of 13 years, moreover, there were five years in which the cumulative disturbance maps were characterized by clustering of low disturbance values and only one year (2001) by clustering of high disturbance values. Moreover, cold spots dominated the study area and several small hot spots could be seen in only four years (1991, 1992, 1993, and 1995). In addition, the hot spots did not continuously show up at the same locations over time. The features were consistent with the visual interpretation.

The nature of these findings implies that a rotation of military training activities might have been used in this installation. It is clear that the resulting levels of ground disturbances do not have a significant effect on the ability of military forces to train in the study area. The level of land condition degradation is minor in most of the training facility area and thus appears to not impede the Army's capability to effectively use the land. This means that the Army military training manager should continue to apply its current method of rotation into its training activities. This should allow to grounds to maintain a relatively low to moderate variation in disturbance.

It is to be noted that some limitations do exist within the capture of study data. The RTLA training data uses a binary format when looking for attributed such as ground disturbance along the transect lines of the sample plots. This means the data collected can only provide a measure of existence of disturbance rather than the degree of disturbance. If the RTLA training data were to include the degree of disturbance in its collection process, additional research could be done.

Overall, it can be concluded that there are indeed cumulative impacts of military training-induced disturbance on the land condition in the study area of Fort Riley Installation, Kansas, but the impacts are not serious over the study area and time. There are only few areas in which serious impacts exist. Moreover the impacts are spatially auto-correlated, but the clustering of high and low disturbance values did not have temporally auto-correlation. This may be, to a great extent, attributed to using the rotation of military training activities. In addition, the recovery of vegetation helps mitigation of the military training-induced impacts on the land condition. In a word, this study will greatly enhance the understanding of the military training-induced impacts on the land condition for the US Army installations and provide useful guidelines for the land managers in terms of sustaining both land condition and land military carrying capacity.

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