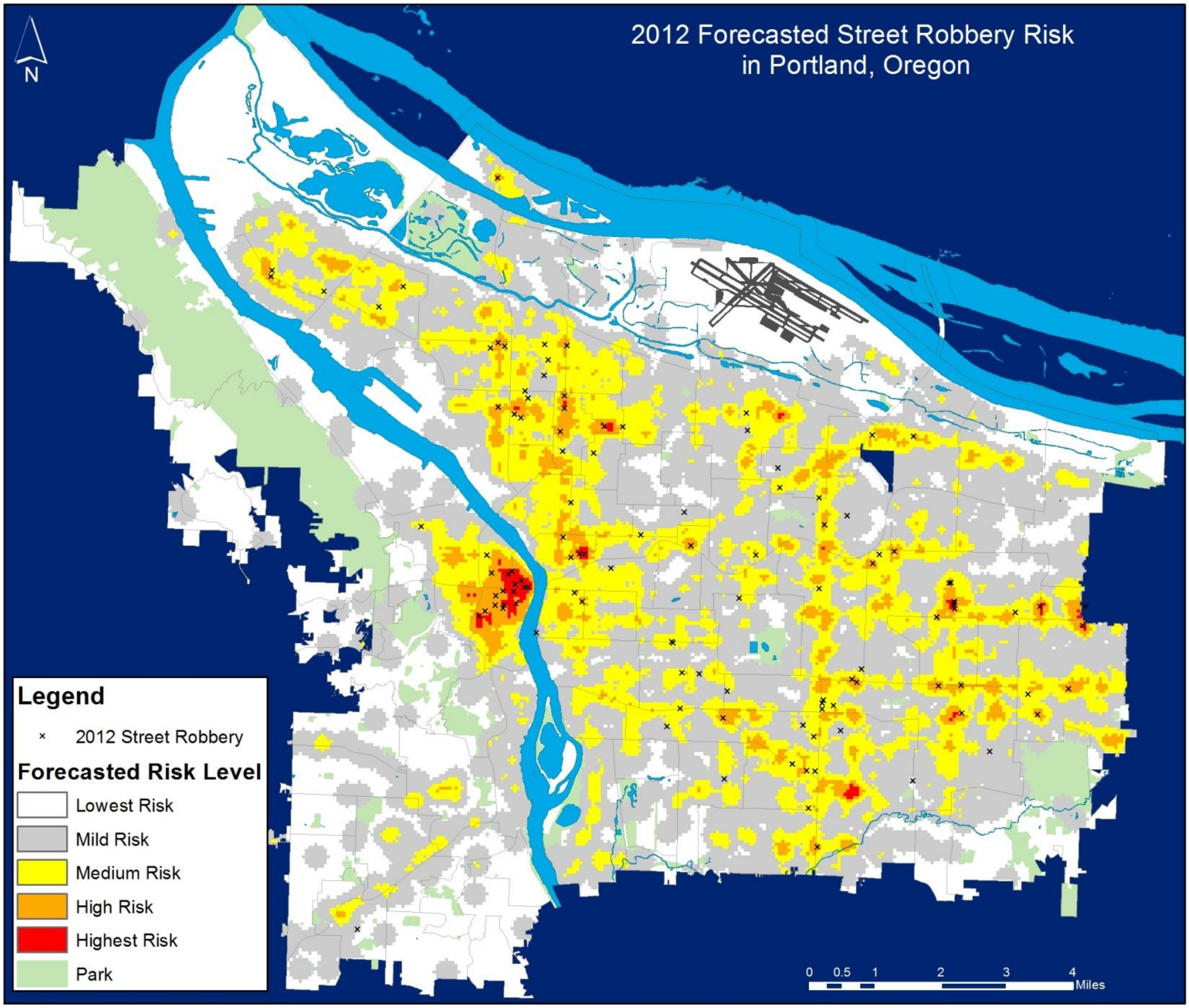
Forecasting Risk for Street Robbery in Portland, Oregon



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Executive Summary

This project applied the crime analysis procedure of risk terrain modeling to assess the likelihood of future street robbery in Portland, Oregon. Risk terrain modeling forecasts risk geographically by compositing multiple separate risk layers together. Factors contributing to the prediction of street robbery were identified through a literature review. These include prior street robbery, drug crime, prostitution, gang related incidents, vandalism, recent street robbery offender residences, alcohol serving establishments, mass transit stops and the presence of youth. These factors were then used to develop a model identifying areas of high risk for 2011 street robbery. The risk terrain model was an improvement over existing models for street robbery that use prior street robbery alone. Risk terrain modeling showed improved predictability over commonly used crime analysis techniques such as hotspot mapping and near-repeat analysis. The factors identified as important for creating the 2011 model were shown to be valid forecasters of risk for 2012 street robbery. The ability to successfully forecast areas at risk for street robbery will facilitate law enforcement efforts to reduce future crime.

Risk Terrain Modeling (RTM) was developed by Caplan and Kennedy (2010) to assess risk geographically through the creation of a composite risk map. It is the nature of crime to be concentrated over space, rather than to be evenly dispersed (Braga, 2001; P. J. Brantingham & P. K. Brantingham, 1981). The retrospective identification of areas where crime clusters has allowed for the development of strategic responses to crime (Braga, 2001). RTM goes beyond just identifying the locations of crime clusters. It identifies future locations that are conducive for a particular crime based on the changing environmental characteristics. This allows for a more proactive response to the crime. RTM builds off ideas from environmental criminology, problem-oriented policing, and hotspot mapping (Caplan & Kennedy, 2011).

Historical Introduction

RTM evolved from the field of environmental criminology introduced by Brantingham and Brantingham in 1981. Environmental criminology is the study of the spatial components of crime: where and when crime occurs. Understanding the spatial component of crime is important because it contributes to the development of policies targeted at reducing crime. Environmental criminologists have shown crime clusters at certain locations (Braga, 2001; P. J. Brantingham & P. K. Brantingham, 1981; Eck, Chainey, Cameron, Leitner & Wilson, 2005). Therefore crime rates vary over space, meaning that crime rates may be higher in downtown areas than residential areas. Additionally, crime rates vary at different levels of spatial aggregation. For example, if you look at crime rates by broad neighborhoods you may see a different spatial pattern than if you were to look at the rates by smaller city blocks. The patterns of crime can be compared to the spatial patterns of other phenomenon such as other crimes or population characteristic. This allows for the identification of factors potentially related to the occurrence of crime. RTM uses these related factors to forecast risk for future events using the assumption the factors are creating an environment conducive to criminality (Caplan & Kennedy, 2011). Understanding the spatial patterns of crime and identifying correlated factors allows for the development of predictive models which can help criminal justice practitioners develop policy recommendations aimed at preventing crime.

The research conducted by environmental criminologists has contributed to the development of targeted approaches to policing. Traditionally, a standard model of policing involving random patrols and rapid response to incidents has been used (Weisburd & Eck, 2004). The standard model of policing works under the assumption that a generalized response to crime will work universally. This model does not take into consideration the variation in the levels or nature of crime across a police jurisdiction. Criticism of the effectiveness of the standard model at preventing crime and reducing public fear of crime has led to a need for new approaches (Weisburd & Eck, 2004). One of these approaches was problem-oriented policing. This model of policing uses information gained from the analysis of crime problems to develop a directed police response (Goldstein, 1990). Law enforcement agencies have limited resources, making it important these resources are used in the most efficient manner to effectively serve the community. Problem-oriented policing was developed in an attempt to improve the effectiveness of policing (Goldstein, 1990). The goals of problem-oriented policing are preventative in nature and involve an in-depth police response. Police are more effective when given the opportunity to evaluate and respond to the conditions underlying the crime instead of acting only as responders to the crime (Goldstein, 1990). RTM can contribute to problem-oriented policing by identifying areas of high-risk for a specific crime and factors correlated with the crime. The criminogenic spatial influences of environmental risk factors could be reduced using evidence based procedures in order to deter offenders and reduce occurrences of specific crimes (Kennedy, Caplan & Piza, 2012). Risk terrain modeling has potential to contribute to the success of proactive policing by building on and improving hotspot policing; currently one of the most commonly used crime analysis procedures.

The practice of hotspot mapping identifies areas with high concentrations of crime to predict the location of future crimes (Caplan, Kennedy & Piza, 2011). The hotspot perspective suggests that crime is not evenly dispersed, but instead concentrated in small areas or hotspots. These small hotspots can represent the locations of over half the crime incidents, while other areas a relatively crime free (Braga, 2001). Hotspot policing focuses police resources to the areas where crime clusters. Hotspot mapping has been a staple of crime analysis and contributed to the success of problem-oriented policing (Braga, 2001). Hotspot mapping successfully identifies areas where crime clusters, but gives no insight into why crime clusters in these locations. Without considering the underlying causes of these hotspots, the police response to the crimes will be limited to standard practices such as directed patrols (Weisburd & Eck, 2004). The explanation of clustering is important to RTM. The environmental characteristics of a location influence the likelihood of a particular crime occurring (P. J. Brantingham & P. K. Brantingham, 1981). Many of these characteristics have been identified by criminologists as factors attracting or producing crime. To assess the risk of a crime occurring in a location, it is important to understand how the environmental characteristics of an area can be correlated with a crime (Caplan, 2011). This can involve more than just the presence of a characteristic, but a consideration of the spatial influence of the factor. Meaning risk could also increase as the density of a factor increases at a location or risk could increase as proximity to a factor increases. Understanding the spatial influence of risk factors and properly operationalizing the factors are important components of RTM (Caplan, 2011). Additionally, when multiple risk factors are present at a location it can have a compounding effect on the likelihood of crime. RTM considers the combined influence of risk factors by creating a composite risk value (Caplan & Kennedy, 2011).

Risk Terrain Modeling

Risk terrain modeling is composed of three concepts. The first concept, risk, refers to the likelihood of an event (crime) occurring based on knowledge of correlated factors (Caplan & Kennedy, 2010). RTM is used to study the risk of a specific crime. The process requires the identification of factors causing an increase or reduction in the likelihood of a crime. The second concept of RTM, terrain, refers to a map of the continuous surface of the study are where the risk is occurring (Caplan & Kennedy, 2010). Terrain represents the spatial component of RTM. The third concept of RTM is modeling. Modeling is the process of assigning real world attributes to micro-places within the terrain and then combining the terrains together to create a composite map representing the compounded criminogenic risk (Caplan & Kennedy, 2010). Through a ten step process detailed in the RTM Manual, individual risk layers are selected, operationalized to common mapping units, reclassified to meaningful risk categories, weighed against each other, and combined to create a final risk terrain map (Caplan & Kennedy, 2010). The final result is a risk terrain map which can be beneficial to law enforcement planning and resource allocation by identifying vulnerable areas in a statistically valid manner.

RTM has been applied to forecast risk for a few crimes with varying success including residential burglary, aggravated assault, shootings, and street robbery. One study suggests the Kansas City Police Department has had success utilizing RTM for violent crimes (Baughman &

Caplan, 2011). Besides a few individual cases, most the models do not appear to be in use by police yet, and therefore the value of these models for policing have yet to been tested. Instead the models are tested statistically with binary logistic regression to get an indication of predictive validity and fit. When compared to retrospective techniques such as hotspot mapping, RTM appears to be an improvement over the other techniques (Piza, Kennedy, & Caplan, 2011).

RTM was applied to residential burglary in Newark, NJ in an attempt to improve on current retrospective crime mapping techniques used for burglary. Tests of the predictive validity suggested for each unit increase in risk, there was a 15% increase in the likelihood of a burglary occurring (Moreto, 2011). There was no indication if the RTM improved over hotspot mapping. RTM was also used on aggravated assault in Newark with better predictability. The results of the tests for the predictive validity suggested that for each unit increase in risk, there was over a hundred percent increase in the likelihood of an aggravated assault (Sytsma, 2011). This study also reported a very low (0.05) pseudo-R^2 for the model which appears to be the norm for risk terrain models. The most successful fitting model appears to be for shootings in Newark. Caplan (2011) showed the likelihood of a shooting occurring more than doubling with each unit increase in risk and the reported pseudo-R^2 was once again low (0.08), but the highest reported so far.

Risk terrain modeling has also been applied to street robbery with a fair amount of success. The predictive validity of the RTM for street robbery suggested for each unit increase in risk, there was a 127% increase in the likelihood of street robbery (Kennedy & Gaziarifoglu, 2011). The model's risk factors included location of retail business venues, locations of bus stops, locations of banks, locations of drug arrests, and locations of prostitution arrests. The majority of these risk factors are static and therefore will not change much as the model is updated year to year. Rates and locations of drug and prostitution arrests may fluctuate, while it is less likely bus stops and business, especially banks, will see a lot of variation over time. Using static factors is problematic because the same areas will continue being identified as at risk, even after police responses have reduced crime in these locations. Future RTM for street robberies could be improved by focusing on risk factors with a tendency to fluctuate and respond to police reactions. The inclusion of prior street robbery as a risk factor may also capture and represent the risk associated with the static variables such as the banks. Additionally, the method for deciding which risk factors to include in this model favored risk factors that were more prevalent in the study area such bus stops and retail business venues. The risk factor of retail business venue is also very broad which makes developing targeted responses to this specific risk difficult. These businesses range from bars and exotic clubs to fast-food and leisure outlets. The problems associated with bars (such as alcohol use) which relate to street robbery are not the same as the problems associated with leisure outlets (presence of youth). The results of this RTM, including which factors were included in the final model, may have been much different if these business types were considered separately. Future RTM for street robbery should make sure risk factors are not aggregated, especially if the justification for including the risk factors are not the same. The pseudo-R^2 of the street robbery risk terrain model created by Kennedy and Gaziarifoglu (2011) was also very low (0.045), suggesting there is plenty of room for future models to improve over the current model.

The focus of the current project was to improve on the existing risk terrain model for street robbery. Street robberies by definition occur in public spaces, result in the theft of property from individuals, and include actual or implied use of force against the victim or victim's property (Gaziarifoglu, 2011). Street robbery is a dangerous crime because it can result in injury or potentially death of the victim (Monk, Heinonen & Eck, 2010). Prior studies have indicated victims are physically assaulted in approximately fifty percent of incidents. When robberies involve weapons there is an increased risk of victim injury or death (Monk et al., 2010). Street robbery is also problematic because it increases public fear of victimization (Monk et al., 2010). This can undermine both informal and organized efforts to reduce crime by causing individuals to withdraw from public interactions (Cordner, 2010). The prediction and prevention of street robberies can be difficult because it is a crime of opportunity. Opportunity theory suggests that opportunity is an important causal factor of all crimes and opportunity is specific to each crime (Felson & Clarke, 1998). RTM identifies areas that are conducive to the opportunity for a specific crime, making it a good choice for modeling street robbery risk. Additionally, there is plenty of existing research addressing factors contributing to the risk of street robbery, which is necessary in the development of a risk terrain model.

The risk terrain model in this project was developed for street robbery in Portland, Oregon. Reported street robbery rates in Portland had been decreasing since the mid-1990's, but began to stabilize after 2009 to approximately 8.3 cases per 10,000 people (Criminal Justice Policy Research Institute, n.d.). In 2011, there were 406 reported street robberies, a slight decrease from prior years. However, by April 15, 2012 there were already 122 reported street robberies in Portland, an increase over the number reported by the same time in 2011. The actual number of street robbery incidents could be higher, since street robbery victimization is correlated with victim criminal behavior which results in many crimes going unreported (Wright & Decker, 1997). The nature of street robbery, along with the prevalence of the problem in Portland, made it a good choice for risk terrain modeling.

This project aimed to assess three questions through development of a risk terrain model for street robbery. First, could a risk terrain model for 2011 street robbery in Portland be created with good predictive validity? The RTM in this project was created using 2010 data to determine the risk for 2011 street robberies. The known locations of 2011 street robberies were used in the development of the risk terrain model in order to determine which factors were important predictors of risk. Ideally the composite risk terrain model would accurately forecast areas at risk for street robbery and be an improvement over using prior street robbery locations alone to predict future occurrences. Which leads to the second question, did the risk terrain model improve on the predictive validity of using retrospective analysis of street robbery alone? The value of the model created in this project depended on whether it could continue to be a useful tool for mapping street robbery risk. This was assessed with the third research question: Could the model be updated with 2011 data to accurately forecast risk for 2012 street robbery? To support the empirical validity of the risk terrain model, cross-validation was conducted to see if the model would accurately predict 2012 street robbery. The same risk factors identified in the creation of the 2011 model were used to predict the locations of 2012 street robbery. Ideally, the RTM would be applicable to 2012 risk and therefore could potentially be a useful tool for problem oriented policing in the future.

Methods

The methods for this project involved the creation of a risk terrain model for 2011 street robbery using 2010 risk data, statistical validation of the model, and finally cross-validation of the RTM for street robbery using 2011 risk data to forecast 2012 street robbery risk. The Risk Terrain Manual (Caplan & Kennedy, 2010) outlines a ten step process for creating a final risk terrain map. These steps are described in the methods section, while detailed information on the technical processes can be found in Appendix 1. The ten steps of RTM are listed below:

1) Select an outcome event of particular interest
2) Decide upon a study area for which risk terrain maps will be created
3) Choose a time period to create risk terrain maps for
4) Obtain base maps of your study area
5) Identify aggravating and mitigating risk factors that are related to the outcome events
6) Select particular risk factors to include in the risk terrain model
7) Operationalize risk factors to risk map layers
8) Inter Risk Map Layer Weighting
9) Combine Risk Map layers to form a composite map
10) Finalize the risk terrain map to communicate meaningful information

The first four steps of RTM are focused on determining topic of interest, identifying a study area and time period of focus, and obtaining the necessary data (Caplan & Kennedy, 2011). These steps depend on the availability of the data. This study used data from the Portland Police Bureau (PPB) which helped define the study area to the city of Portland, Oregon or more specifically the areas in Portland within the PPB's jurisdiction. The choice of the study area was influenced by available resources. The entirety of the PPB's jurisdiction was used because analysis of street robbery data for the past 20 years suggests the some clusters of street robbery are shifting in the city, making it important to include all areas for the risk analysis.

Another component of identifying the study area was identifying the unit of analysis within the study area. Risk terrain modeling can be conducted at various levels of spatial aggregation depending on the aggregation of available data and the desired detail of the final model. The literature on micro-places argues most of the theoretical ideas related to spatial crime patterns apply to small units of analysis (Bernasco, 2010). Frequently, larger units of analysis such as neighborhoods or census blocks are used to study the spatial distribution of crime. Census data is available in these larger units which allows for the easy incorporation of census data into models. The size of the spatial unit also influences the model fit statistics, with larger units resulting in a better statistical fit. However, these larger units are not as appropriate when consider the influence of a factor like social disorganization. The interactions between close neighbors lead to the development of social control. The interactions between residents who live many blocks or miles apart but within the same neighborhood will not be as important or influential in the development of informal social control as interactions between residents who live within a few feet of each other (Bernasco, 2010). The spatial influence of a risk factor can be operationalized by distance from the risk factor. There is commonly a 1,000 foot cutoff for the influence a risk incident; a distance much smaller than the length of a neighborhood or some census blocks (Caplan, 2011; Bernasco, 2010). This limits the ways in which the spatial influence of risk factors can be meaningfully operationalized in the risk terrain model. Additionally, the scope of the police response to the identified risk will depend on the unit of analysis. The use of large units of analysis results in the identification of entire neighborhoods as high risk, while using smaller city blocks narrows the focus to more concise areas of risk allowing for a targeted and effective police response.

For this study, the unit of analysis was 250 foot by 250 foot blocks. The choice of this unit of analysis was based off the traditional size of a city block in Portland which is 260 feet by 260 feet (Rabiega, Lin, & Robinson, 1984). The use of micro-places, or city blocks, in this model allowed for the use of distance as means for operationalizing risk. A recent study by Caplan (2011) showed operationalizing risk with distance can lead to the production of a valid and reliable model for projecting risk.

The third step of RTM was determining a time period for which risk will be assessed (Caplan & Kennedy, 2011). This study used one year as the time period. Many of the crime incidents used in this study as risk factors for street robbery occur at low rates in Portland, and therefore aggregating a years' worth of data to model risk for future years was necessary. Low occurrence rates of risk factors influence the value of their contribution to the final model (Caplan & Kennedy, 2010). Not enough data points can cause a risk factor considered important by the literature to be irrelevant and therefore be excluded from the risk terrain model. Aggregating this data by using a year's worth helps remove some of the instability associated with the low occurrence rates. This project developed a risk terrain model using 2010 data to assess the risk for 2011 street robbery. To cross-validate the prediction model, the process was repeated with 2011 data to assess risk for 2012 street robbery. Ideally, the factors identified as significantly contributing to the risk of 2011 street robbery would also work to predict the risk for 2012 street robbery.

The fourth step of RTM modeling was to obtain base maps of the study area (Caplan & Kennedy, 2011). Base maps include things such as the boundary of the study area, locations of streets, and a grid layer for the unit of analysis. The base maps for this study were obtained from the Metro Data Resource Center – Regional Land Information System (RLIS) and the PPB.

The fifth through seventh steps of RTM are focused on the risk factors. These steps require the identification of potential risk factors, the selection of factors to be included, and the operationalization of risk factors to a map layers (Caplan & Kennedy, 2010). The identification of risk factors required a review of the current literature. After potential risk factors were identified, the quality of the available data helped narrow down the factors included in the final model. Not all risk factors for which data was available contribute to the best fitting model; statistical analysis was conducted to exclude available factors. In order to conduct the statistical analysis, data for the potential risk factors had be obtained, operationalized, and imported into SPSS.

The availability of data determined which factors could be potentially included and thus operationalized. After gathering the data, the first step in operationalizing the risk factors was to bring the data into ArcMap. Data with coordinates were easily displayed, while data with street addresses required geocoding to be displayed. After the data was displayed, the next step was to determine the distance from each map unit to the nearest risk incident. The distance from risk factors has been shown as a good way to operationalize risk (Caplan, 2011; Wright & Decker, 1997). The calculated distances were then classified into five risk levels. Prior studies have used a 1,000 foot radius to delineate areas of risk (Caplan, Kennedy, & Miller, 2011); therefore, any unit within 1,000 feet of a risk incident was assigned a positive risk level. The 1,000 foot bandwidth around risk incidents was divided into four equal intervals for risk level classification. The level of risk associated within an incident increases the closer you get to the incident (Bernasco, 2010; Caplan, 2011). Therefore, higher risk levels were assigned for units closer to a risk incident. The reclassifying scheme is presented in Table 1. Risk factors were operationalized independently and then exported to SPSS for statistical analysis.

Table 1: Risk Reclassifications

	Reclassified Risk Level	
Distance from Risk Factor (feet)	Value	Category
0 – 250	4	Highest Risk
250 – 500	3	High Risk
500 – 750	2	Medium Risk
750 – 1,000	1	Mild Risk
1,000 - Max	0	Lowest Risk

In addition to operationalizing the risk layers, the dependent variable of 2011 street robbery was also operationalized. The procedure for this variable was slightly different. A count of 2011 street robbery incidents in each 250 foot by 250 foot cell was calculated. The file containing the street robbery count information was then combined with all the operationalized risk factor to create a single file to export for statistical analysis.

Statistical analysis was used to determine which factors to include in the final model. First, the dependent variable was recoded to be dichotomous: "Yes" a street robbery occurred in the block or "No" a street robbery did not occur in the block. The dichotomization of the dependent variable was necessary for the use of certain statistical procedures. Second, binary logistic regression was conducted individually for the dichotomized dependent variable and each risk factor. The results indicated how well each variable independently forecasted 2011 street robbery risk. Finally, to create the best fitting risk terrain model for 2011 street robbery in Portland, a binary logistic regression model was run using forward selection with all nine risk factors and the dichotomized dependent variable. This process resulted in the regression model being run repeatedly, first adding only the risk factor best predicting 2011 street robbery. Then the next best predictor is added, and so on, until the addition of another variable did not significantly contribute to the predictability of the overall model. The use of an empirical method to identify the final risk factors increased the reliability and validity of the model (Caplan & Kennedy, 2010).

The eighth step of risk terrain modeling is inter risk map layer weighting. RTM employs the use of weighting multiple times. The first is during the operationalization of risk factors in step seven, when the distances were classified into risk levels. The classification of risk layers makes it so the influence of each risk factor is "weighted" about the geography (Caplan & Kennedy, 2010). The second type of weighting considers the influence of each risk factor in respect to one another based on a regression model. This way the most important risk factor will have greater influence on the model. The value of applying weights to factors in scales for the assessment of the risk has been debated in the literature. The results of a study by Grann and Långström (2007) suggested the practice of apply weights did not improve predictions and actually lead to a reduction in the statistical effects. The interpretation of the statistical effect of the final risk terrain model is easier without the use of beta weights. Therefore, the value of using beta weights in this model was assessed. The results of these analyses are presented in detail in Appendix 2 and led to the decision to not use beta weights in the final risk terrain model. The explanatory power and the pseudo R^2 of the final risk model with beta weights were not statistically different from the final model without beta weights Both models captured the same percentage of 2011 street robbery incidents within the comparable final risk levels, indicating the use of beta weights did not improve model prediction. Risk terrain models that do not include the relative importance of the individual risk factors are considered to be un-weighted (Caplan & Kennedy, 2010).

The ninth and tenth steps of RTM result in the creation of the final risk terrain map. The ninth step was to add the individual risk layers together to create a final composite risk map. IN the final step, the composite map was then symbolized in a manner in which the map clearly communicated the correct information for strategic use by law enforcement (Caplan & Kennedy, 2010). The combined risk layer map was reclassified to match the risk levels of the individual layers (lowest – highest risk).

After the risk terrain model for 2011 street robbery was created, the statistical validity was checked. First, using a logistic regression analysis, the predictive power of the model was identified. Second, to assess whether the model was an improvement over simply identifying prior hotspots for street robbery, the final model was compared to a risk model created using only 2010 street robbery locations.

The next step in testing the validity of the risk terrain model for street robbery was to repeat steps seven, nine, and ten for creating a risk terrain model using 2011 data to predict 2012 street robbery. The 2011 risk factor data was operationalized, combined to create a composite map, and then the composite map was symbolized in a meaningful manner. The same statistical analyses were conducted to test the validity of the 2012 model.

Results

Identification of Risk Factors

A review of the literature identified ten risk factors for street robbery: prior street robbery, illegal drug related activity, prostitution, gang related incidents, vandalism, recent street robbery offender residences, alcoholic establishments, mass transit stops, youth, and gambling. Only one incident of illegal gambling was recorded in Portland in 2010, so this factor was excluded.

Prior Street Robbery

Prior street robbery locations have been identified as good predictors of future street robbery locations. The relationship between the location of prior crime and future crime is well supported in the literature (Bernasco, 2010; Braga, 2001; P. J. Brantingham & P. K. Brantingham, 1981; Caplan, Kennedy & Piza, 2011). Many practices in environmental criminology are based on the relationship between prior and future crime (P. J. Brantingham & P. K. Brantingham, 1981). These practices include both hotspot mapping and near-repeat analysis. Hotspot mapping has been a staple of crime analysis and contributed to the success of problem-oriented policing (Braga, 2001). Near-repeat analysis relies on the concept that new occurrences of crime will happen within both a certain distance and time period of previous incidents (Caplan, Kennedy & Piza, 2011). The relationship between prior and future crime make the analysis of crime possible. This relationship exists because of underlying environmental and social factors that make an area conducive to crime which persist over time if actions are not taken address them. The success of using retrospective crime events to predict future events makes prior incidents of a crime an obvious risk factor for any risk terrain model.

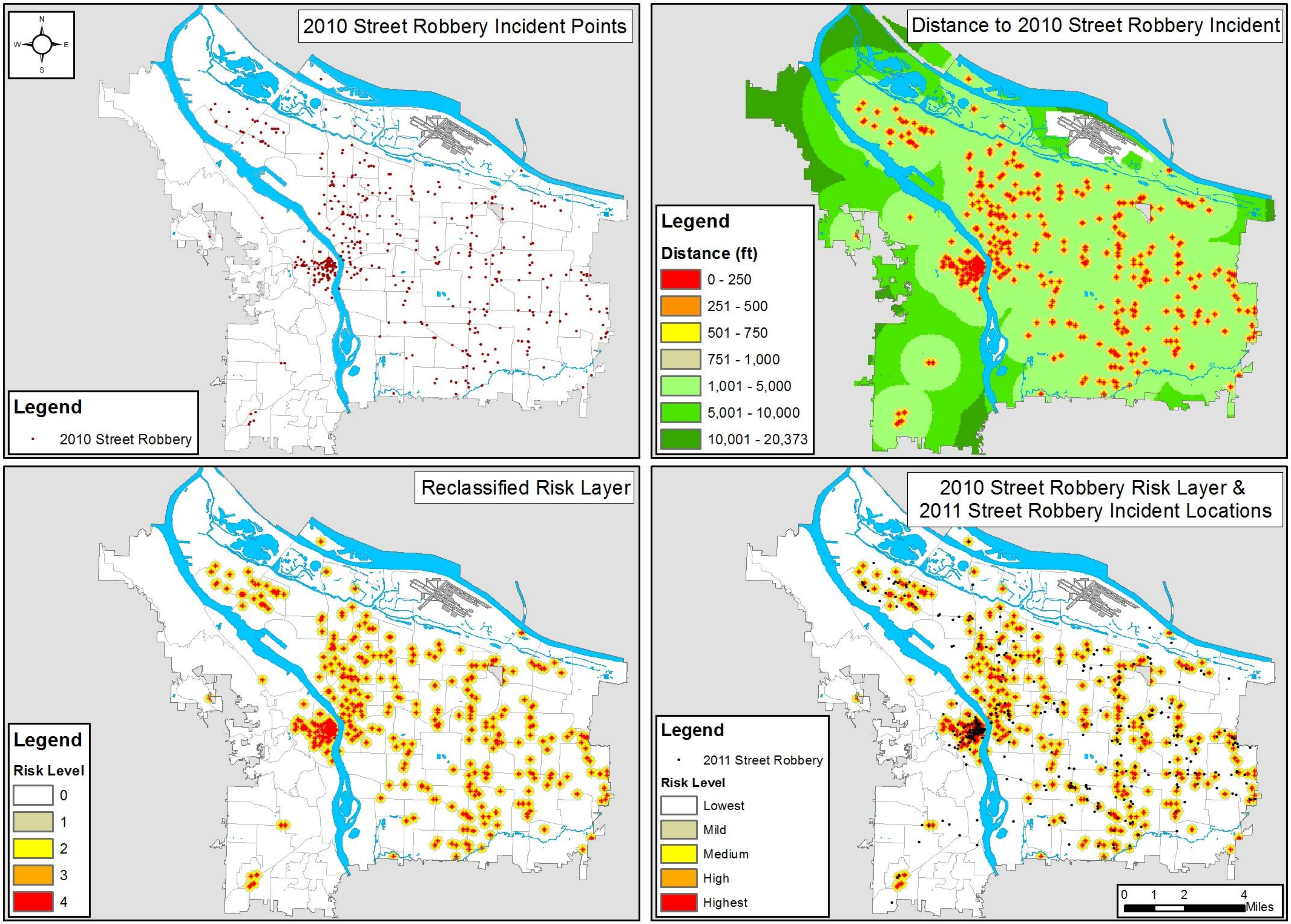
The risk associated with prior street robbery locations was modeled using the prior year's (2010) street robbery incidents. All PPB street robbery incidents with a case year of 2010 were included in this risk layer. There were a total of 473 street robbery incidents in 2010 for which incident location were available. Eighteen percent of the total study area was within 1,000 feet of a 2010 street robbery and therefore had a risk level of at least one. Seventy percent of all 2011 street robbery incidents were captured by the mild (1) to highest (4) risk levels of prior street robbery. The highest risk level captured the greatest percentage of 2011 street robbery incidents (33.9%) and only represented 2.9% of the total study area. Binary logistic regression was used to identify the predictive power of prior street robbery incidents; the results are presented in Table 2. For every unit increase in the prior robbery risk fact, there was a 124% increase in the odds that a street robbery occurred in 2011. Figure 1 displays the risk layer for prior street robbery.

Table 2: Logistic Regression for Prior Street Robbery Risk Value on Street Robberies

	B	S.E.	Wald	Exp(*B*)	95% CI for Exp(*B*)	
					Lower	Upper
Final Risk Value	0.81	0.03	619.74	2.24 *	2.10	2.39

-2LL: 3336.700; Nagelkerke R Square: 0.13,= p<0.001*

Figure 1: Risk Layer - Prior (2010) Street Robbery

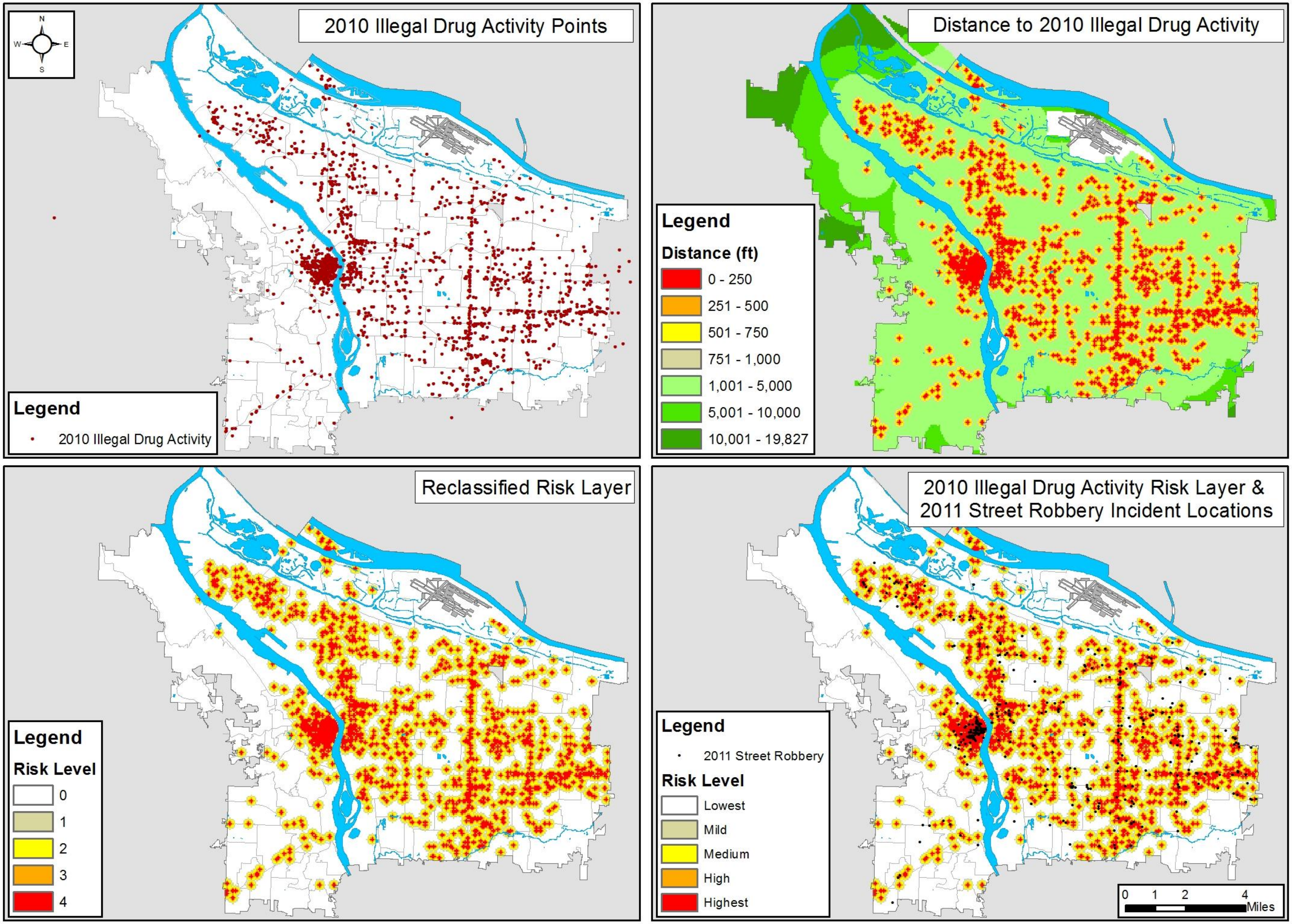


Illegal Drug Related Activity

The risk of victimization during a street robbery has been linked to criminal behavior of the victim. The main illegal activities correlated with street robbery in the literature include drug dealing, prostitution, gambling, and gang related activity (Bernasco & Block, 2010). A correlation between drug crime and street robbery has been well supported in the literature (Bernasco & Block, 2010; Bernasco, Block, & Ruiter, 2012; Gaziarifoglu, 2011; Jacobs & Wright, 2008; Lum, 2008, Sevigny & Coontz, 2008). Robbery is frequently motivated by the need to obtain cash to purchase drugs. This motivation leads to the correlation in drug crime and robbery, because drug dealing areas will have targets with both cash and drugs (Wright & Decker, 1997). Both drug dealers and customers are targeted as potential victims. The illegal nature of their activities also leads to these victims being less likely to report a robbery to the police and therefore there is less risk of punishment to the offender (Wright & Decker, 1997).

The 2010 drug crime incidents were used to model risk associated with illegal drug related activity. All PPB drug crime incidents with a case year of 2010 were included in this risk layer. There were a total of 2,587 drug law violation incidents in 2010 for which incident location was available. Thirty-eight percent of the total study area was within 1,000 feet of a 2010 drug crime incident and therefore had a risk level of at least one. Ninety percent of all 2011 street robbery incidents were captured by the mild (1) to highest (4) risk levels of illegal drug related activity. The highest risk level captured the greatest percentage of 2011 street robbery incidents (55.9%) and only represented 8.7% of the total study area. Binary logistic regression was used to identify the predictive power of illegal drug related activity; the results are presented in Table 3. For every unit increase in the illegal drug related activity risk factor,

Figure 2: Risk Layer - 2010 Illegal Drug Activity Locations



there was a 132% increase in the odds a street robbery occurred in 2011. Figure 2 displays the risk layer for illegal drug activity.

Table 3: Logistic Regression for Illegal Drug Related Activity Risk Value on Street Robberies

	B	S.E.	Wald	Exp(*B*)	95% CI for Exp(*B*)	
					Lower	Upper
Final Risk Value	0.84	0.04	460.51	2.32 *	2.15	2.50

-2LL: 3686.46; Nagelkerke R Square: 0.14,= p<0.001*

Prostitution

Similarly to drug crime, prostitution is correlated with street robbery because of the presences of cash and the reduced likelihood of the crime being reported (Tilley et al., 2004). Reports also indicate prostitutes sometimes commit street robbery, victimizing their customers (Wright & Decker, 1997). Additionally, a high correlation exists between prostitution and drugs use, which increases the risk of street robbery (Bernasco & Block, 2010; Bernasco et al., 2012; Scott & Dedel, 2006; Tilley et al., 2004).

Prostitution incident data was obtained from the PPB. Five-percent of the total study area was within 1,000 feet of a 2010 prostitution crime and therefore had a risk level of at least one. Twenty-four percent of all 2011 street robbery incidents were captured by the mild (1) to highest (4) risk levels of prostitution. The majority (76%) of the 2011 street crime incidents were not located within areas identified as risky due to the presence of prostitution. As the risk level increased, there was not an increase in the number of street robbery incidents captured. Binary logistic regression was used to identify the predictive power of prior street robbery incidents, the results are presented in Table 4. For every unit increase in the illegal drug related activity risk factor, there was an 86% increase in the odds a street robbery occurred in 2011. Figure 3 displays the risk layer for prostitution.

Figure 3: Risk Layer - Prostitution

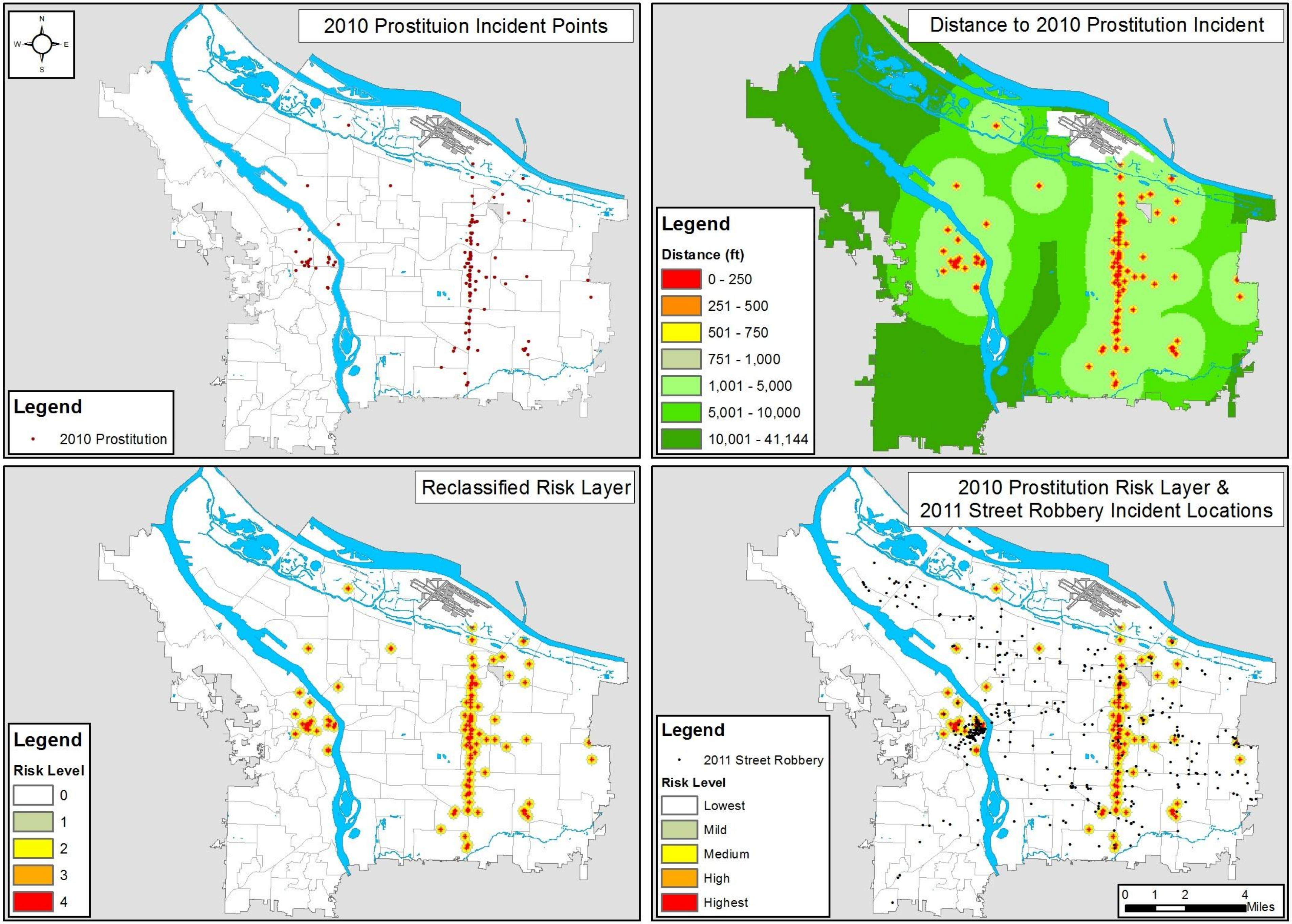


Table 4: Logistic Regression for Prostitution Risk Value on Street Robberies

	B	S.E.	Wald	Exp(*B*)	95% CI for Exp(*B*)	
					Lower	Upper
Final Risk Value	0.62	0.04	200.83	1.86 *	1.71	2.02

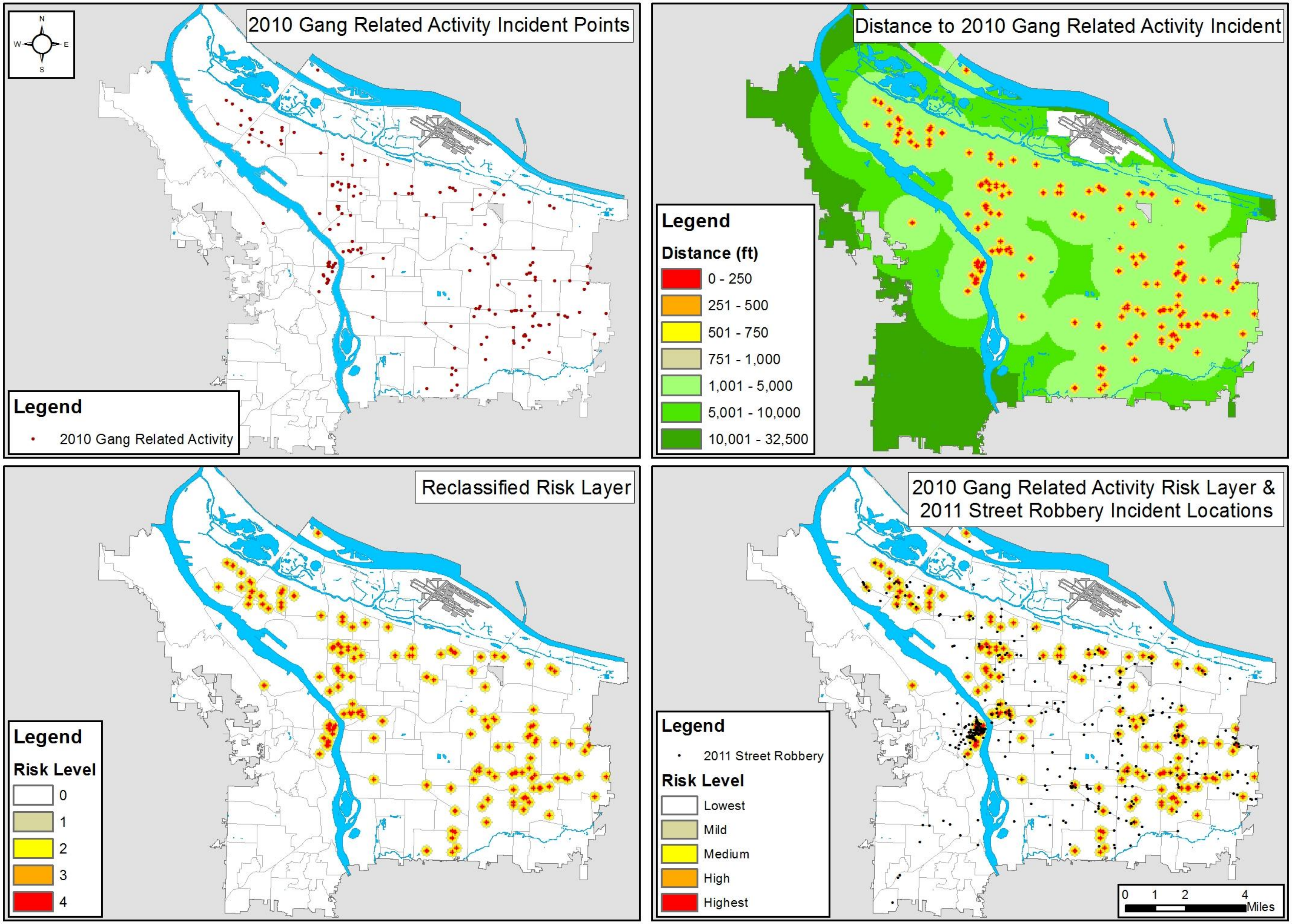
-2LL: 4134.75; Nagelkerke R Square: 0.03,= p<0.001*

Gang Related Activity

The literature shows a strong relationship between gang membership and criminal activity. Gang membership has been shown in multiple studies to increase the frequency and severity of criminal offenses (Battin, Hill, Abbott, Catalano & Hawkins, 1998; Miller & Decker, 2001). These studies also show gang members to be involved in illegal activities including street robbery and other factors associated with risk for street robbery like drug dealing or vandalism. Additionally, gang members are at an increased risk for victimization, especially violent victimization (Miller & Decker, 2001). Gang activity is associated with risk for street robbery because gang members are both offenders and victims for the crime. The spatial pattern of gang activity tends to be clustered, frequently in socially disorganized neighborhoods (Block & Block, 1993). The literature also indicates the locations of gang activity clusters are related to the locations of street robberies (Bernasco & Block, 2010).

The 2010 gang related crime incidents were used to model risk associated with gang related activity. All incidents flagged as gang related by the PPB with a case year of 2010 were included in this risk layer. There were a total of 187 gang related incidents in 2010 for which incident location was available. Nine percent of the total study area was within 1,000 feet of a 2010 gang related crime and therefore had a risk level of at least one. Forty-five percent of all 2011 street robbery incidents were captured by the mild (1) to highest (4) risk levels of gang related activity. The highest risk level captured a greater percentage of 2011 street robbery incidents (16.5%) than the other positive risk levels, but not as many incidents as the lowest risk

Figure 4: Risk Layer - 2010 Gang Related Activity



level. The highest risk level represented 1.2% of the study area while the lowest risk level represented 90.8% of the study area. Binary logistic regression was used to identify the predictive power of gang related activity; the results are presented in Table 5. For every unit increase in the gang related activity risk factor, there was a 111% increase in the odds a street robbery occurred in 2011. Figure 4 displays the risk layer for gang related activity.

Table 5: Logistic Regression for Gang Related Activity Risk Value on Street Robberies

	B	S.E.	Wald	Exp(*B*)	95% CI for Exp(*B*)	
					Lower	Upper
Final Risk Value	0.75	0.04	457.17	2.11 *	1.97	2.26

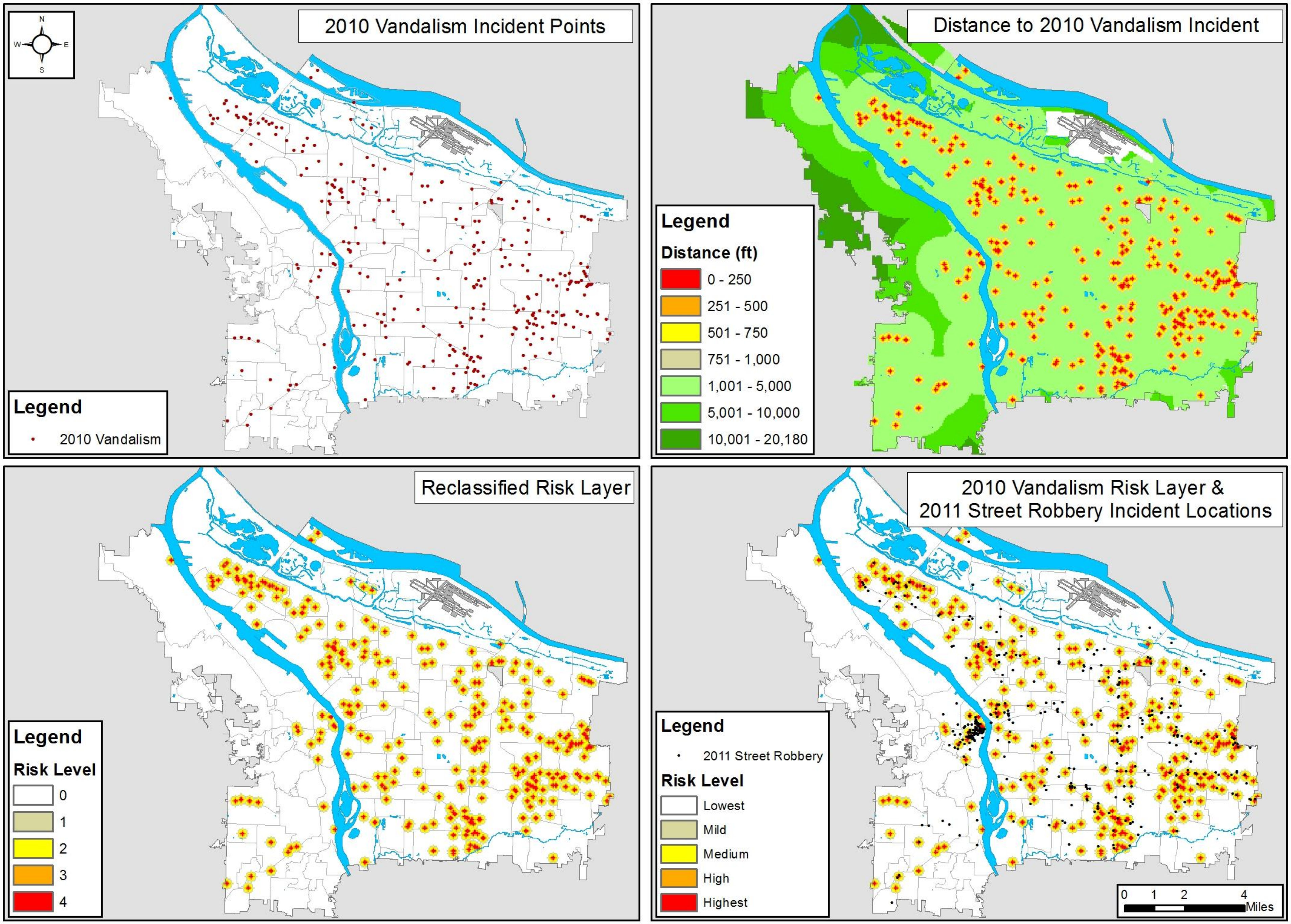
-2LL: 3951.894; Nagelkerke R Square: 0.08,= p<0.001*

Social Disorder: Vandalism

The "broken windows" theory of crime suggests that a community interprets signs of disrepair to mean that no one cares. Under this thesis when signs of physical disorder are left unchecked it, such as vandalism, further disorder and more serious crimes will occur (Wilson & Kelling, 1982). Vandalism is a sign of disorder and attracts potential offenders to the area (Doran & Lees, 2004). Studies have also indicated that signs of physical disorder such as vandalism contribute to changes in crime rates (Perkins, Wandersman, Rich, & Taylor, 1993; Taylor & Harrell, 1996). Vandalism indicates disorder which is conducive to the opportunity for committing a street robbery.

The 2010 vandalism incidents were used to model risk associated with social disorder. All PPB vandalism incidents with a case year of 2010 were included in this risk layer. There were a total of 322 vandalism incidents in 2010 for which incident location was available. Eighteen percent of the total study area was within 1,000 feet of a 2010 vandalism incident and therefore had a risk level of at least one. Fifty-one percent of all 2011 street robbery incidents were captured by the mild (1) to highest (4) risk levels of vandalism. Binary logistic regression

Figure 5: Risk Layer - Social Disorganization - Vandalism Locations



was used to identify the predictive power of vandalism; the results are presented in Table 6. For every unit increase in the vandalism risk factor, there was a 74% increase in the odds a street robbery occurred in 2011. Figure 5 displays the risk layer for vandalism.

Table 6: Logistic Regression for Vandalism Risk Value on Street Robberies

	B	S.E.	Wald	Exp(*B*)	95% CI for Exp(*B*)	
					Lower	Upper
Final Risk Value	0.56	0.04	249.77	1.74 *	1.63	1.87

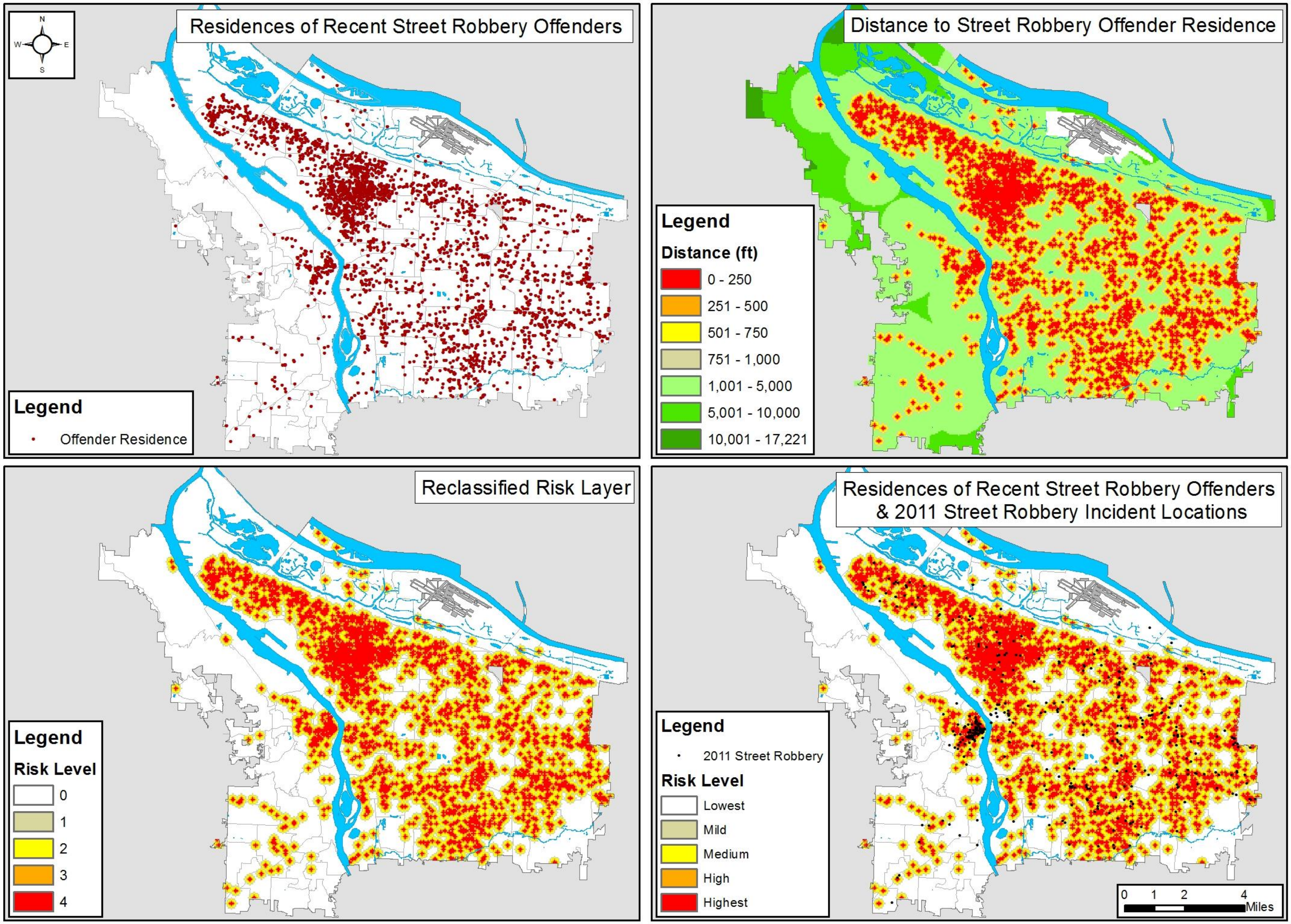
-2LL: 4068.60; Nagelkerke R Square: 0.05,= p<0.001*

Recent (2006-10) Street Robbery Offender Residences

Studies on the journey to crime have indicated some criminals have a preference for committing crime in areas they are both familiar with and comfortable (Bernasco & Block, 2010; Bernasco et al., 2012). Additionally, offenders tend to prefer shorter trips and therefore are more likely to offend near their homes (P. K. Brantingham & P. J. Brantingham, 1981). The literature has shown that locations near offender residences are more likely to experience crime (Bernasco & Block, 2010; Bernasco et al., 2012). Further, since offenders choose to offend in areas where they are comfortable, areas near former residences as well as current residence may also have the potential to see an increase in crime (Bernasco & Block, 2010; Bernasco et al., 2012). Street robbery has also been shown to be a repeat offense (Wright & Decker, 1996), making areas around offender residences at risk for future street robbery.

The addresses of recent street robbery offenders were used to model risk associated with offender residences. All known addresses within Portland (both prior and current) of anyone arrested or verified as a suspect for a street robbery in the same city between 2006-10 were included in this risk layer. This included offenders for 721 street robbery cases and 4,303 addresses. Duplicate addresses for the same case were removed. Forty-seven percent of the total study area was within 1,000 feet of a known residence of a recent (2006-10) street robbery

Figure 6: Risk Layer - Recent (2006-10) Street Robbery Offender Residences



offender and therefore had a risk level of at least one. Ninety-one percent of all 2011 street robbery incidents were captured by the mild (1) to highest (4) risk levels of offender location. The highest risk level captured the greatest percentage of 2011 street robbery incidents (46.2%) and represented 14.8% of the total study area. Binary logistic regression was used to identify the predictive power of recent street robbery offender residences, the results are presented in Table 7. For every unit increase in the recent offender risk factor, there was a 93% increase in the odds a street robbery occurred in 2011. Figure 6 displays the risk layer for recent street robbery offender residences.

Table 7: Logistic Regression for Recent Offender Residences Risk Value on Street Robberies

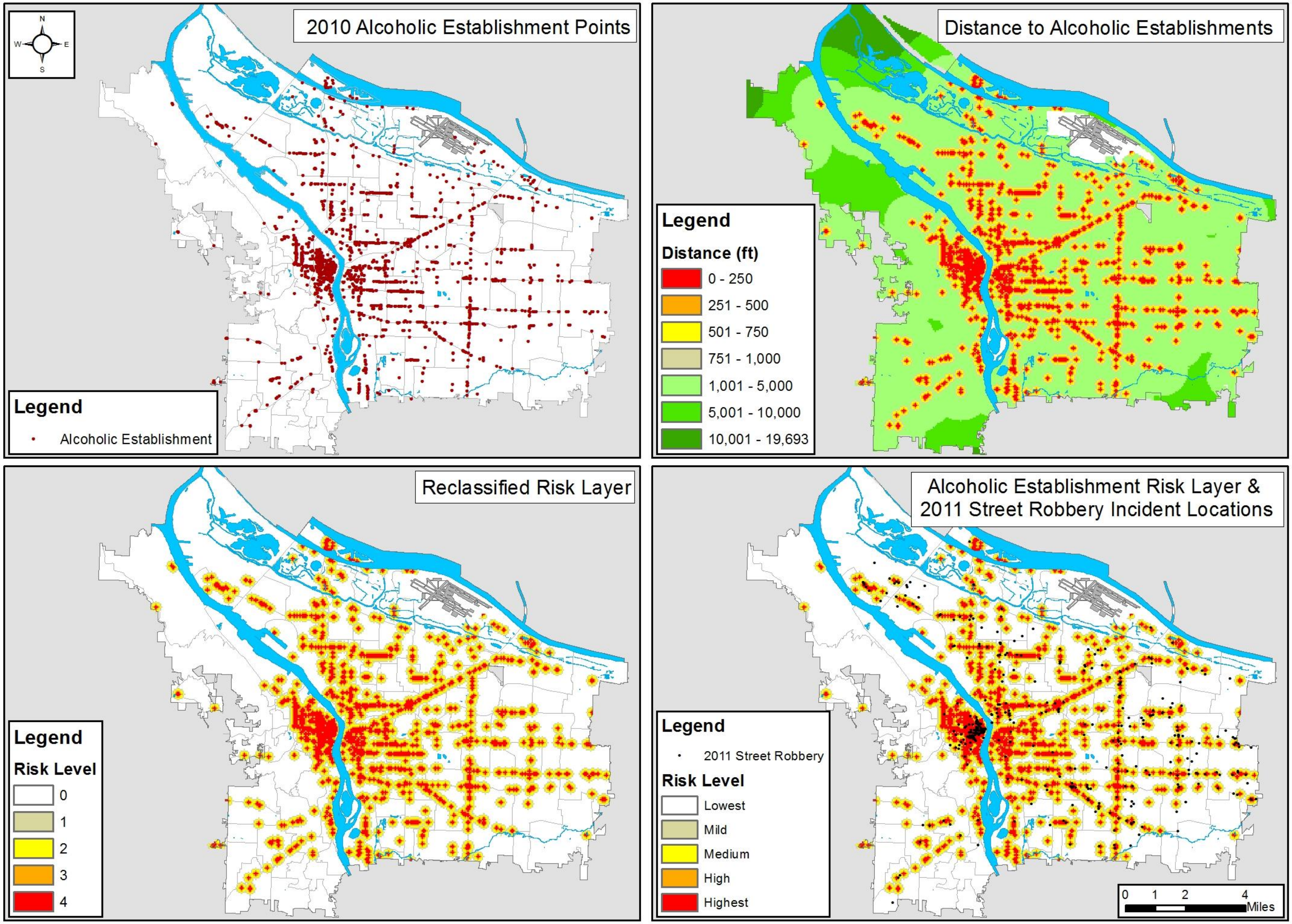
	B	S.E.	Wald	Exp(*B*)	95% CI for Exp(*B*)	
					Lower	Upper
Final Risk Value	0.66	0.04	288.59	1.93 *	1.79	2.08

-2LL: 3904.28; Nagelkerke R Square: 0.09,= p<0.001*

Alcoholic Establishments

The proximity to alcohol serving establishments has been shown to be related to street robbery (Bernasco & Block, 2010; Bernasco, Block & Ruiter, 2012; Haberman, Groff, & Taylor, 2011; Tilley et al, 2004). Intoxicated individuals are easy targets because they are less concerned about their personal safety. Alcohol also has disinhibiting effects which increases the likelihood of individuals committing illegal behavior (Deehan, 1999). Studies also indicate a link between alcohol consumption and violent behavior (Sevigny & Coontz, 2008). This is problematic because violent behavior increases the potential for serious injuries to the victim during a street robbery. Data from the Oregon Liquor Control Commission (OLCC) indicated there was an increase of 1,000 new establishments with permits for on-site service in 2010 in Portland over 2000. The risk associated with alcoholic establishments in Portland changes as more on-premise service licenses are granted to business.

Figure 7: Risk Layer - 2010 Alcoholic Establishment Locations



The addresses of businesses with alcohol permits in 2010 were obtained from the OLCC. Only addresses of business with permit types that allowed on-premise service of alcohol were used. These addresses were geocoded in ArcMap using the 10.0 US Streets Geocode Service. Addresses that were unmatched or had tied matches were rematched by hand. The 2010 data included 2,878 addresses, 85 of which were either unmatched or had a tie. Seventy of these addresses were manually matched, resulting in 2,863 matches and only 15 unmatched addresses. Out of the matched addresses, 1,943 fell within the study area, served alcohol on site, and were used in the risk modeling. Thirty-three percent of the total study area was within 1,000 feet of an establishment serving alcohol in 2010 and therefore had a risk level of at least one. Eighty-five percent of all 2011 street robbery incidents were captured by the mild (1) to highest (4) risk levels of alcohol serving establishments. The highest risk level captured the greatest percentage of 2011 street robbery incidents (49.9%) and only represented 7.4% of the total study area. Binary logistic regression was used to identify the predictive power of alcoholic establishments; the results are presented in Table 8. For every unit increase in the alcoholic establishment risk factor, there was a 127% increase in the odds a street robbery occurred in 2011. Figure 7 displays the risk layer for alcoholic establishments.

Table 8: Logistic Regression for Alcoholic Establishments Risk Value on Street Robberies

	B	S.E.	Wald	Exp(*B*)	95% CI for Exp(*B*)	
					Lower	Upper
Final Risk Value	0.82	0.04	508.87	2.27 *	2.11	2.44

-2LL: 3678.00; Nagelkerke R Square: 0.14,= p<0.001*

Mass Transit Stops

Public transportation has been linked to street robbery because offenders have been shown to travel to transit stations to commit robbery and target victims waiting at isolated stops

(Gaziarifoglu, 2011). Public transit areas are crime attractors due to the constant flux of people and common presence of illegal activities such as drug crime (Bernasco, Block, & Ruiter, 2012; Tilley et al, 2004). Block and Davis (1996) showed a clear relationship between mass transit stations and street robbery occurrence, with 39% of street robberies occurring within 1,000 feet of a transit station. Transit stations are also strategically located to serve legal business associated with risk for street robbery, such as bars and restaurants that serve alcohol (Block & Davis, 1996). The mass transit system in Portland includes light rail (MAX) and the street car.

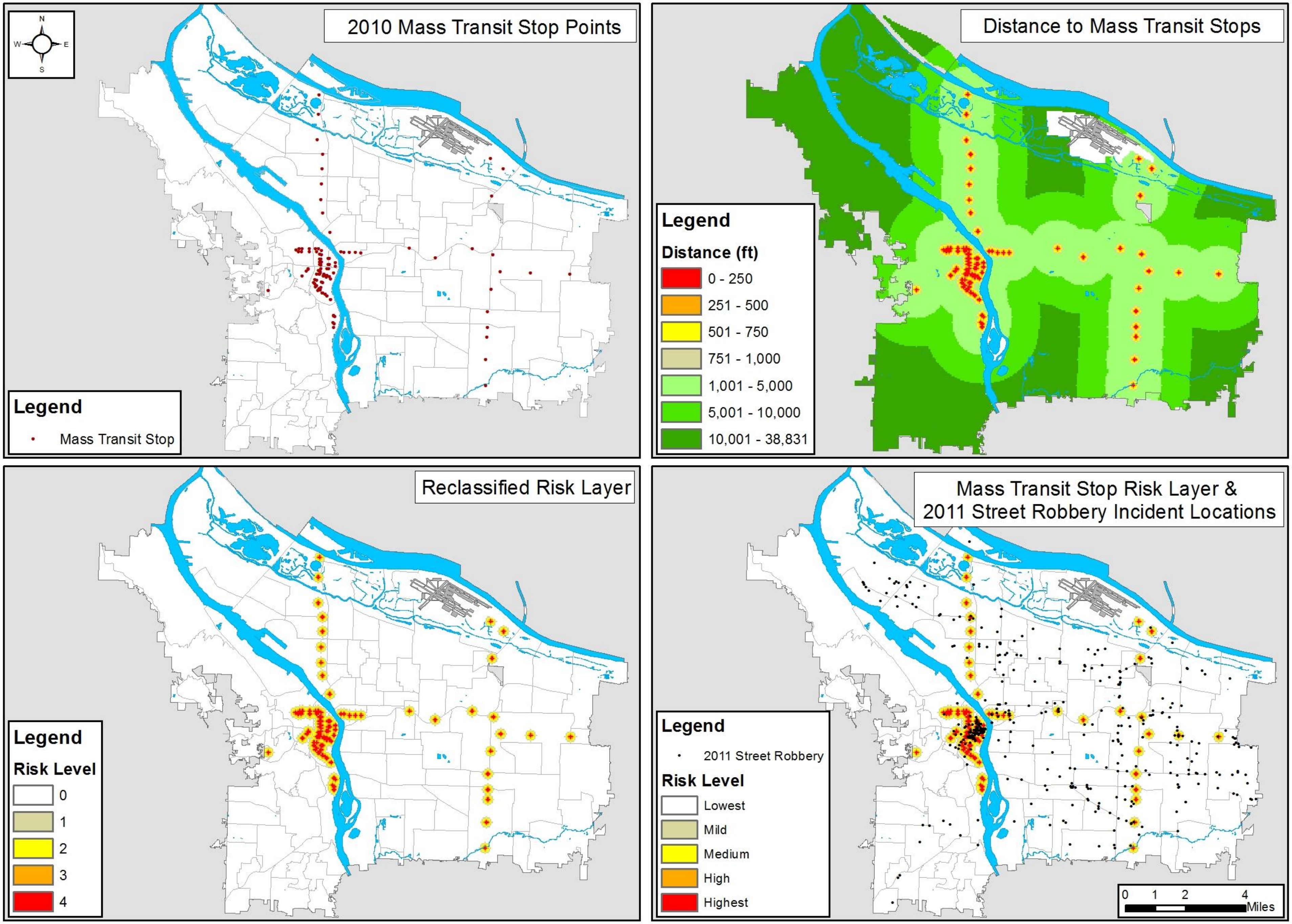
The location of mass transit stops were obtained from RLIS. The point shapefile of these stops included the locations of planned transit stops. Only transit stops existing in 2010 and located within the study area were included in the final model. There were a total of 105 transit stops used. Four percent of the total study area was within 1,000 feet of a mass transit stop and therefore had a risk level of at least one. Thirty-two percent of all 2011 street robbery incidents were captured by the mild (1) to highest (4) risk levels of mass transit stop. The highest risk level captured a greater percentage of 2011 street robbery incidents (15.7%) than the lower risk levels, but not as many incidents as the lowest risk level. The highest risk level represented 0.7% of the study area while the lowest risk level represent 96.1% of the study area. Binary logistic regression was used to identify the predictive power of mass transit stops, the results are presented in Table 9. For every unit increase in the mass transit stop risk factor, there was a 136% increase in the odds a street robbery occurred in 2011. Figure 8 displays the risk layer for mass transit stops.

Table 9: Logistic Regression for Mass Transit Stops Risk Value on Street Robberies

	B	S.E.	Wald	Exp(*B*)	95% CI for Exp(*B*)	
					Lower	Upper
Final Risk Value	0.86	0.04	544.78	2.36 *	2.19	2.53

-2LL: 3937.43; Nagelkerke R Square: 0.08,= p<0.001*

Figure 8: Risk Layer - Mass Transit Stop Locations

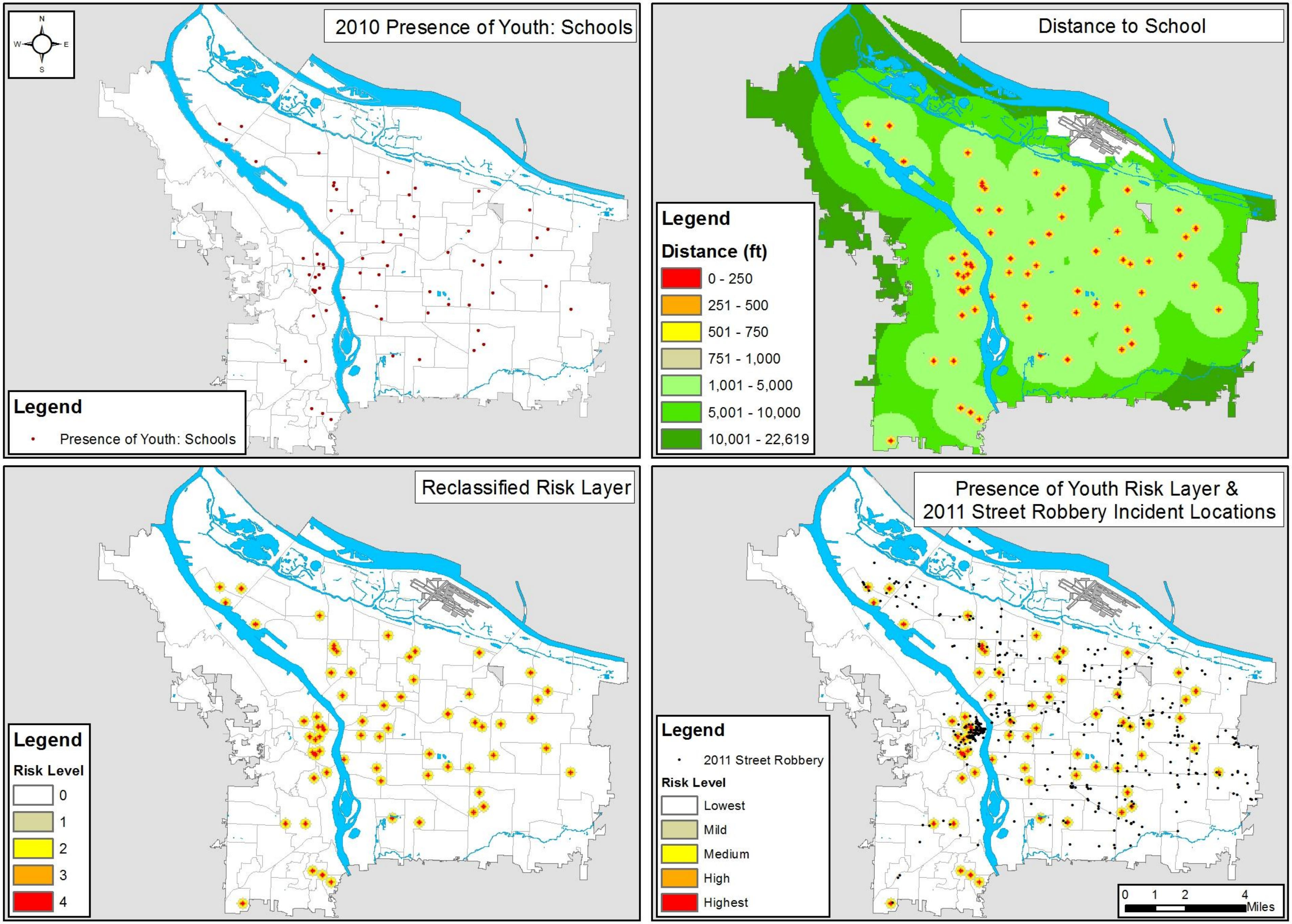


Presence of Youth

The street robbery victimization rates for youth have been shown to be significantly higher than other age groups (Monk et al., 2010). In Portland, Oregon during 2010 youth between the ages of 15-19 years old were victimized at a rate of 3.1 per 1,000 which was considerably higher than the rates for adults 30 years and older who were victimized at rates below 1 per 1,000 (Criminal Justice Policy Research Institute, n.d.). Census data can be used to model the presence of the youth population. Unfortunately, census data is aggregated to uneven sized spatial units that are much larger than the unit of analysis for the current risk model. Schools, which have been used to model the presence of youth, were used in replacement of census data. The proximity to schools catering to high-school and college age youth have been shown to be correlated with street robbery (Bernasco et al., 2012; Gaziarifoglu, 2011; Haberman, Groff, & Taylor, 2011). This is likely due to the tendency for students to carry small electronics and computers making them attractive targets (Bernasco et al., 2012). Additionally, youth are at risk for perpetuating street robbery offenses (Monk et al., 2010).

The data for the locations of schools was obtained from RLIS. There were a total of 66 schools that included students at age 15 years or older (9^{th} grade through college). Five percent of the total study area was within 1,000 feet of one of these schools and therefore had a risk level of at least one. Twenty percent of all 2011 street robbery incidents were captured by the mild (1) to highest (4) risk levels of presence of youth. The majority (80%) of the 2011 street crime incidents were not located within areas identified as risky due to the presence of youth. As the risk level increased, there was not an increase in the number of street robbery incidents captured. Binary logistic regression was used to identify the predictive power of the presence of youth; the results are presented in Table 10. For every unit increase in the youth risk factor, there was a

Figure 9: Risk Layer - Presence of Youth: Schools



78% increase in the odds a street robbery occurred in 2011. Figure 9 displays the risk layer for presence of youth.

Table 10: Logistic Regression for Presence of Youth Risk Value on Street Robberies

	B	S.E.	Wald	Exp(*B*)	95% CI for Exp(*B*)	
					Lower	Upper
Final Risk Value	0.58	0.05	127.84	1.78 *	1.61	1.97

-2LL: 4180.10; Nagelkerke R Square: 0.020,= p<0.001*

Forward selection of variables for final model

To create the best fitting risk terrain model for 2011 street robbery in Portland, a binary logistic regression model was run using forward selection with all nine risk factors and the dichotomized dependent variable. The results indicated both the risk factors for prostitution and the presence of youth did not significantly contribute to the overall model fit. This is probably due to low occurrences and poor correlation of these factors with 2011 street robbery locations. The majority of the prostitution incidents were clustered in an area of the city that did not have comparable clustering of street robbery. The location of prostitution arrests are heavily influenced by the targeted police responses to prostitution crime in specific locations within the city. Additionally, there were not many schools in the study area. The use of schools may not be the best measure for the presence of youth because it only accounts for youth attending school and is less meaningful in summer months when students do not spend time at those locations.

The final model included seven risk factors identified as significant predictors of future street robbery locations. Table 11 summarizes the individual risk factors used in the final model, including the number of 2010 incidents, addresses, or stops. Also reported is the percentage of the study area identified as at risk for street robbery due to being within 1000 feet of a risk incident. The percentage of 2011 street robberies captured in the areas identified as at risk by each individual risk factor are also reported. The equation for the final risk terrain model is presented below:

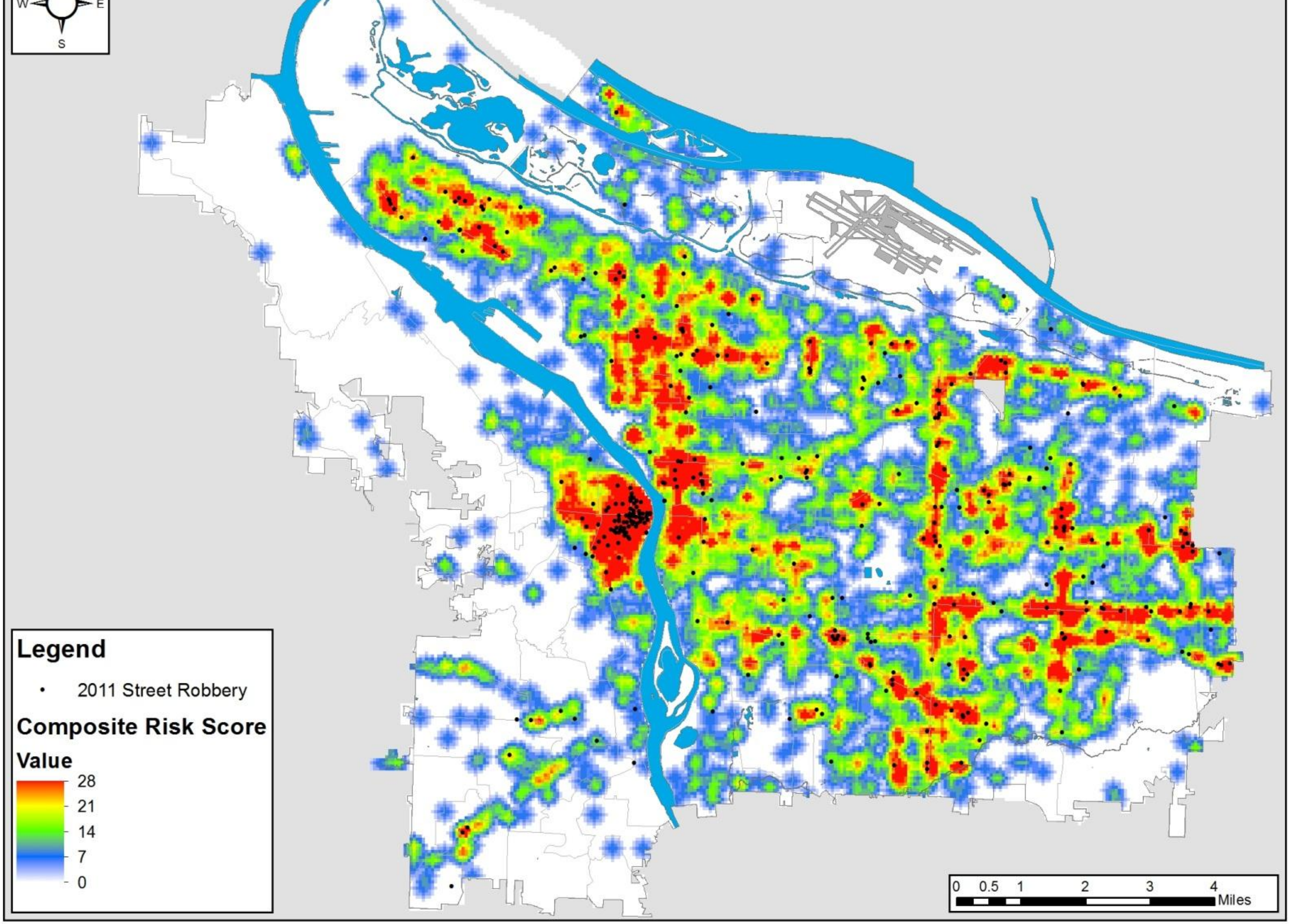
Total Risk = Prior Street Robbery + Illegal Drug Activity + Gang Related Activity + Vandalism + Recent Street Robbery Offender Residences + Alcoholic Establishments + Mass Transit Stops

Table 11: Summary of Risk Factors

Risk Factor	# of 2010 Incidents	% Study Area Identified at Risk	% 2011 Street Robbery in Risk Areas
Prior Street Robbery	473	18.2%	70.2%
Illegal Drug Activity	2,587	38.1%	90.3%
Gang Related Activity	187	9.2%	45.4%
Vandalism	322	18.1%	51.7%
Recent Street Robbery Offender Residences	4,303	47.8%	91.6%
Alcoholic Establishments	1,943	32.5%	84.9%
Mass Transit Stops	105	3.9%	31.9%

Figure 10 displays the composite risk terrain map. The risk scores on the composite map range from zero (no risk) to a high of twenty-eight, indicating a location with the highest risk value on all seven risk layers. The highest possible composite risk score is twenty-eight because there are seven risk layers and the highest possible risk value on each risk layer is four (7 * 4 = 28). Statistical analysis indicated that for every point increase in risk, there was a 30% increase in the likelihood of a 2011 street robbery occurring. Additionally, 65% of the 2011 street robberies were located in the top 10% of blocks with the highest composite risk score.

Figure 10: 2011 Composite Risk Score Map



Research Question One

The final street robbery risk terrain map was created in order to answer the first research question: Could a risk terrain model for 2011 street robbery in Portland be created with good predictive validity? The composite map was reclassified in to five risk levels to create the final risk terrain model (Figure 11). Composite scores of zero remained zero. The remaining range of composite scores (1 – 28) was divided into four equal intervals. The reclassification scheme is presented in Table 12.

Table 12: Composite Risk Reclassifications

	Reclassified Risk Level	
Composite Risk Score	Value	Category
22 - 28	4	Highest Risk
15 - 21	3	High Risk
8 – 14	2	Medium Risk
1 – 7	1	Mild Risk
0	0	Lowest Risk

The statistical validity of the risk terrain model was checked using logistic regression analysis. The results of the analysis are presented in Table 13 and indicate that for every increased final unit of risk, a street robbery is 5.3 times more likely to occur in 2011. The locations of 99.2% of 2011 street robberies fell within areas forecasted by the risk terrain model as being at risk for a future street robbery. Additionally, the majority (96.2%) of blocks where multiple street robberies occurred were forecasted as having risk levels of at least medium. The predictive validity of this risk terrain model was an improvement over the published RTM for street robbery created by Kennedy and Gaziarifoglu (2011). Both the published model and this model use comparable final risk scales of zero to four. For each unit of increased risk in the existing RTM, there was 127% increase in the likelihood of a street robbery compared to 429%

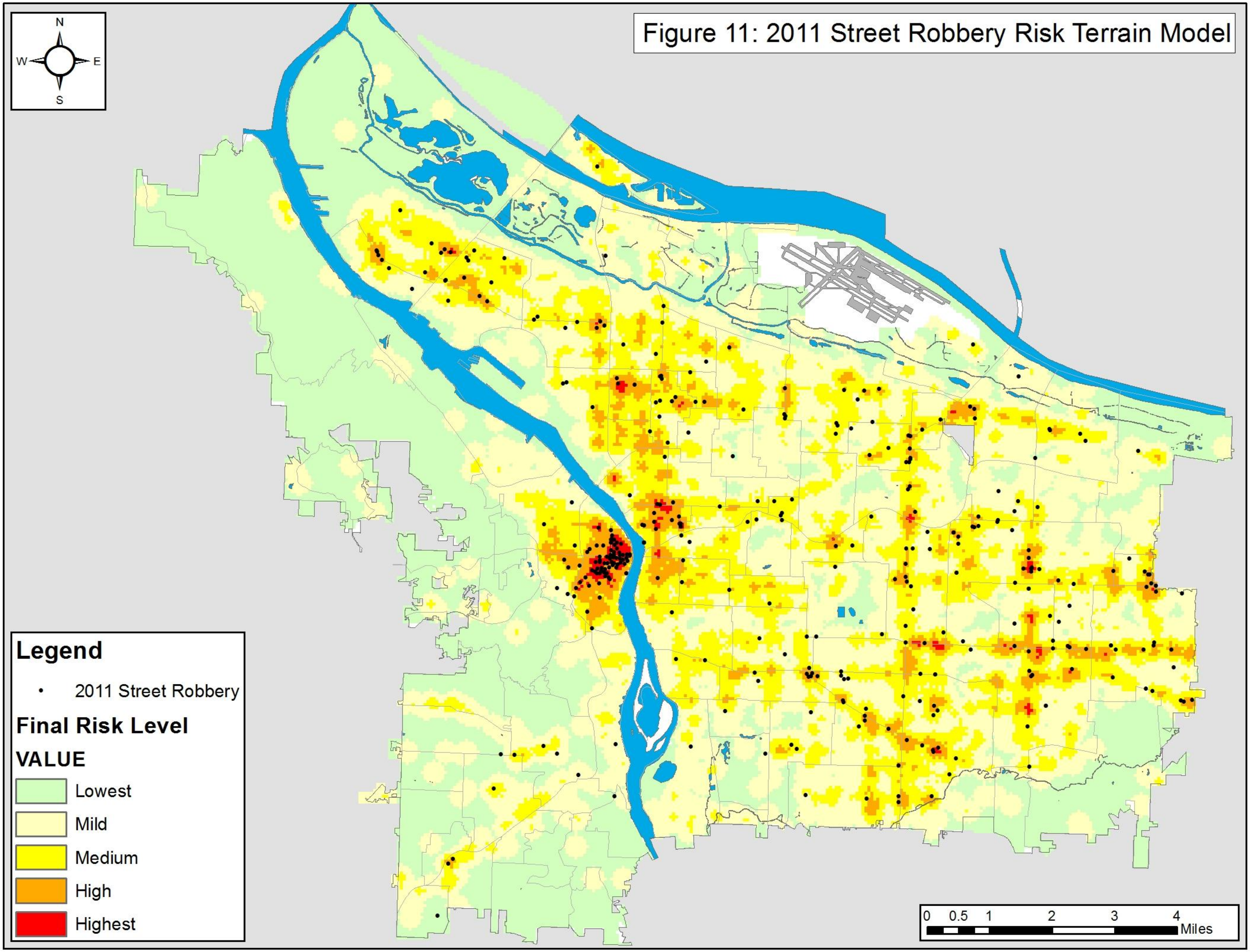


Figure 11: 2011 Street Robbery Risk Terrain Model

in this model. Additionally, the existing model had a pseudo-R^2 of only 0.045 while this model has a much larger pseudo-R^2 of 0.22 suggesting it is a better fit. The results of the statistical validity tests answer the first research question. Yes, a risk terrain model for 2011 street robbery in Portland with good predictive validity could be created

Table 13: Logistic Regression for Risk Value on Street Robberies

	B	S.E.	Wald	Exp(*B*)	95% CI for Exp(*B*)	
					Lower	Lower
Final Risk Value	1.67	0.06	828.39	5.29 *	4.72	5.93

-2LL: 3336.70; Nagelkerke R Square: 0.22,= p<0.001*

Research Question Two

The final model was compared to a risk model based on only 2010 street robbery locations to assess the second research question: Did the risk terrain model improve on the predictive validity of using retrospective analysis of street robbery alone? The areas identified as at risk for future street robberies by the risk terrain model captured all but three (or less than 1%) of the 2011 street robberies while using past street robberies alone missed 110 (or 30%) of the 2011 incidents. These results, along with a comparison of pseudo R^2 values, suggest the use of the risk terrain model (R^2=0.223) as a tool for problem-oriented policing is an improvement over using analysis of prior incidents alone (R^2=0.128).

Research Question Three

Cross-validation was conducted to assess the third research question: Could the model be updated with 2011 data to accurately forecast risk for 2012 street robbery? This was necessary because the 2011 predictive model was created based on the know locations of street robbery. The same risk factors identified during the creation of the 2011 model were used to predict the

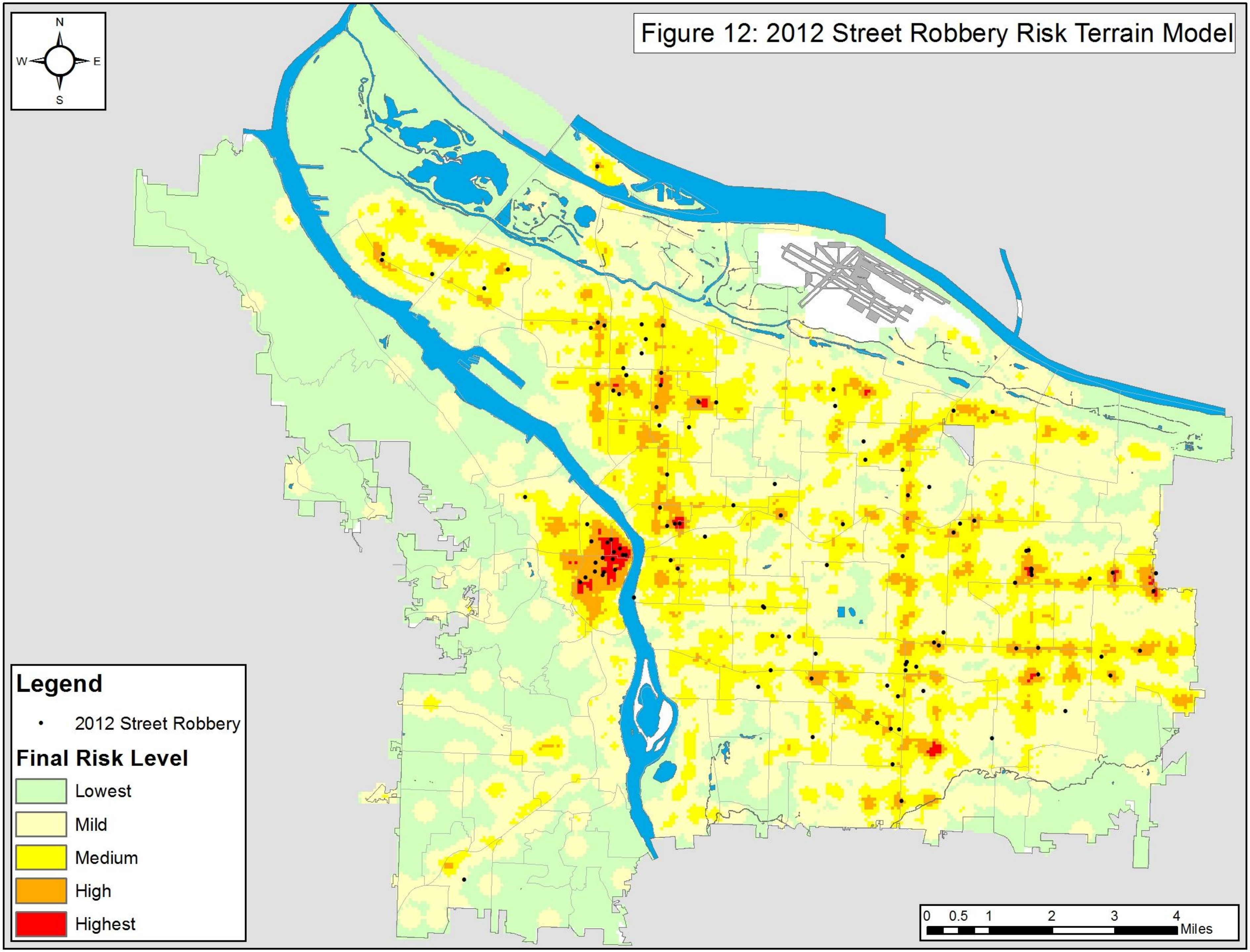


Figure 12: 2012 Street Robbery Risk Terrain Model
N
W
E
S
Legend
2012 Street Robbery
Final Risk Level
Lowest
Mild
Medium
High
Highest
0 0.5 1 2 3 4
Miles

locations of 2012 street robbery. The same data layers were used for alcoholic establishments, mass transit stops, and recent street robbery offender locations because updated data was not readily available. The risk factors of prior street robbery, illegal drug activity, gang related activity, and vandalism were all updated with 2011 data. The risk terrain model is displayed in Figure 12. The statistical validity of the risk terrain model was checked using logistic regression analysis. The results of the analysis are presented in Table 14 and indicate that for every increased final unit of risk, a street robbery is 5.3 times more likely to occur in 2012.

Table 14: Logistic Regression for Risk Value on Street Robberies

	B	S.E.	Wald	Exp(*B*)	95% CI for Exp(*B*)	
					Lower	Lower
Final Risk Value	1.66	0.10	291.08	5.28*	4.36	6.39

*-2LL: 1324.94; Nagelkerke R Square: 0.19, *= p<0.001*

The locations of 99.1% of the 2012 street robberies (that occurred between 1/1/12 and 4/15/12) fell within areas forecasted by the risk terrain model as being at risk for a future street robbery. This suggests that the risk terrain model created for this project has validity. A comparison of model fit indicates that the risk terrain model for 2012 street robbery (R^2=0.189) does not have as good a fit as the 2011 model (R^2=0.223). This could be due to not updating three of the risk factors with 2011 data.

The risk terrain model for 2012 street robbery identified less than one percent (0.3%) of the study area as highest risk. These areas were located mostly in clusters and distributed throughout different areas of the city. The largest cluster was located in the downtown/old town areas. Figure 13 shows the highest risk areas in detail. Many of the street robberies that have occurred so far in 2012 are located within these highest risk areas.

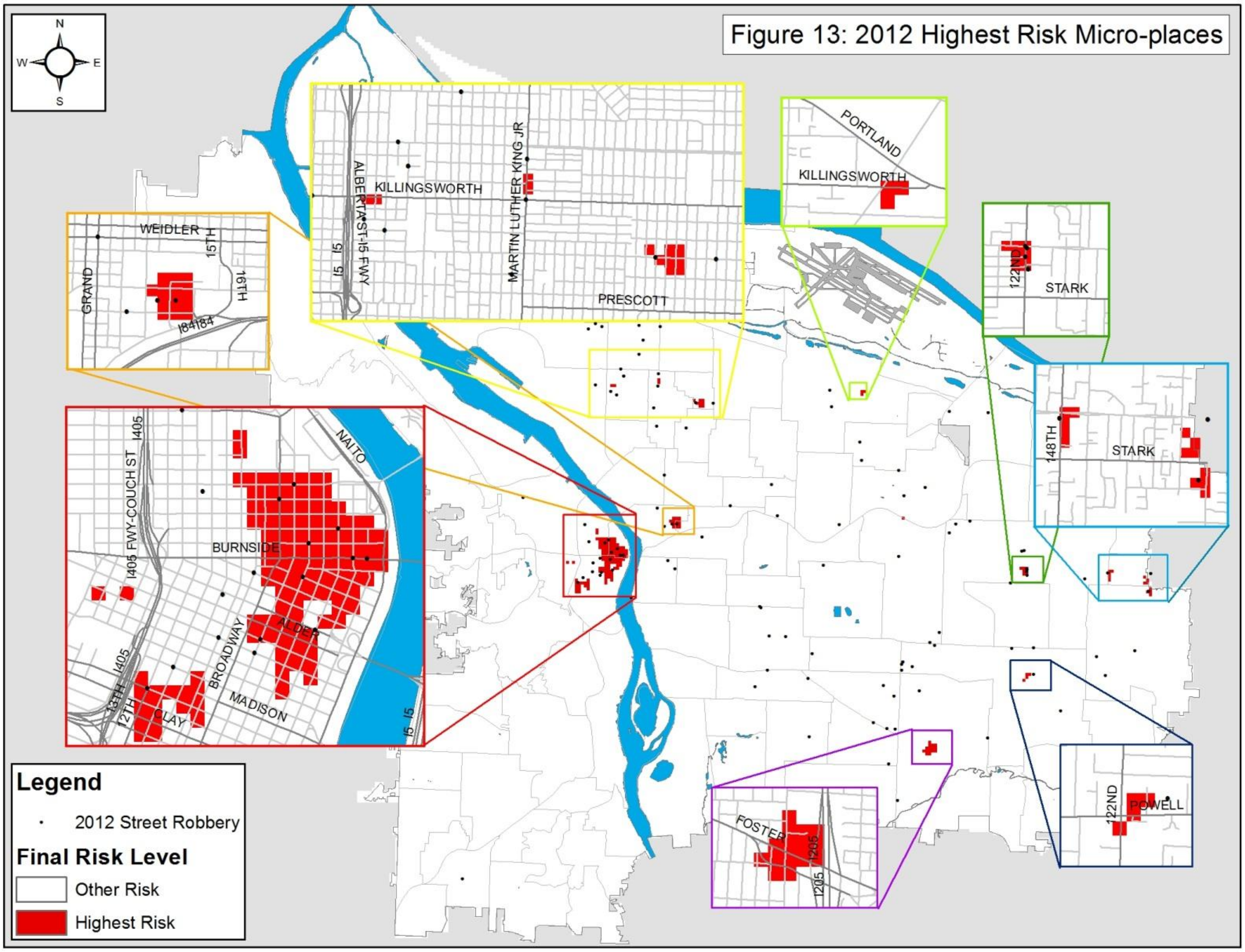


Figure 13: 2012 Highest Risk Micro-places

Discussion

Risk terrain modeling is an emerging crime analysis procedure. Risk models have successfully been created for a variety of crimes including burglary, robbery, and shootings. There is indication RTM is a statistical improvement over currently used retrospective crime analysis techniques (Piza, Kennedy, & Caplan, 2011). Though RTM has been shown to be a statistically valid procedure, there is very little indication in the literature of whether RTM has successfully been utilized for problem-oriented policing. The value of RTM to law enforcement should become clearer as more crime analyst adopt the procedure.

The risk terrain model for street robbery developed in this project proved to be a valid tool for forecasting risk. The results of this project indicate risk terrain modeling is a promising crime analysis tool with potential to help improve targeting of law enforcement responses to this crime. One potential police response could be directed police patrols in areas identified as high risk as an attempt to reduce street robbery occurrences. Another potential police response could be taking actions to reduce the opportunity for street robbery. Opportunity theory indicates that crime can be prevented by reducing opportunity, though these actions can result in the displacement of risk (Felson & Clarke, 1998). To prevent displacement, it would be necessary for risk reduction actions to be applied in more than just the highest risk areas. Police responses aimed at reducing opportunity for street robbery by addressing the identified risk factors would require careful consideration about how these factors influence opportunity. Police actions to reduce other crimes associated with risk for street robbery, such as illegal drug activity or vandalism, could potentially reduce the opportunity for street robberies. Opportunity theorists also suggest methods for reducing risk that could be applicable to street robbery risk in Portland. Improving surveillance at risky locations could increase the perceived risk of committing street robbery, thus reducing opportunity (Felson & Clarke, 1998). Surveillance can be improved though cameras, street lighting, police patrols, or neighborhood watch programs. Other responses could include community policing efforts in at risk areas to inform members of the public who frequent these areas of the potential risk and what they can do to help reduce risk while protecting themselves and others for victimization. To know the full benefit of this RTM, the PPB would have to adopt these or similar practices that utilize the model to identify areas where action needs to be taken in order to reduce the risk of future street robbery. Though this risk terrain model was statistically successful, it could still benefit from additional improvements.

Many risk factors for street robbery were identified for use in this model, but other factors not identified by the review of the literature may improve the predictability of the model. Additional research should be conducted for future models to include as many potential risk factors as possible in the selection process for the final risk model. The influence of youth would probably have been better modeled with census data, however, issues with the aggregation of the data made it difficult to include in this model. In future models, additional efforts should be made to make sure census data can be included in the risk terrain model. Other data available for the US Census Bureau could add additional variables for social disorder and concentrated disadvantage.

One way in which census data could be included would be to choose a different unit of analysis. The use of a larger unit of analysis could allow for the inclusion of data from other sources while still producing a valid risk terrain model that would be useful for law enforcement. A larger unit of analysis may also improve the predictive power of the risk terrain model. Many of the risk street robberies that occurred in 2011 or 2012 fell within a few blocks of a highest risk area. If a larger unit of analysis was used, these may have actually been captured by the highest risk area.

Another way in which this model could be improved is by operationalizing the risk factors in a different way. This study chose to use distance, how far locations were from an occurrence of a risk factor, but other methods may lead to similar or possibly better results. Future risk terrain models could assess if a different means of operationalizing the risk factors will lead to better results. One potential is to use density which considers the number of occurrences of a risk factor at a location. Additionally, a combination of density and distance could be used to potentially produce a more accurate risk assessment. It may also be that different risk factors need to be operationalized different ways.

Though there are many potential ways in which this risk terrain model could be improved. Overall the street robbery risk terrain model did a fairly good job of forecasting risk. The validity of the model was tested based on the location of reported street robbery incidents. As the literature review indicated, many street robberies go unreported. The predictive validity of this model could actually be higher than the statistics indicate. Areas identified as high risk that do not have a reported occurrence of street robbery may in fact still have future occurrence of street robbery. The RTM indicate these areas have the social and environmental characteristics conducive to street robbery. Crime prevention responses targeted in these areas may prevent future street robberies for occurring.

On top of having statistical validity, the current risk terrain model for street robbery was able to improve over prior models. The uses of risk factors that fluctuate rather than factors that remain stable (as in the prior models) lead to an improved fit in the new model. The only stable variable considered for this model was the use of schools to model the presence of youth. This variable turned out to be the weakest predictor of risk. The strongest predictors (illegal drug activity and prior street robbery) were the risk factors which fluctuate. Another benefit of the risk factors chosen for the final model is many are updated on a daily basis by the PPB. The recentness of the data can help in the assessment of current risk and early identification of problem areas.

Overall, there are a few important things to take away from this risk terrain model. First, the location of crimes of opportunity like street robbery can be fairly accurately predicted. Secondly, the identification of risk factors correlated with street robbery can help reduce the occurrence of street robbery. Reducing other crimes like illegal drug use and gang related crime, could also have in impact on the rates of street robbery. Reducing signs of disorder like vandalism can also reduce the likelihood of other crimes occurring. Risk factors like transit stops are going to be a continued feature of the study area. Steps can be taken to reduce the risk at these locations including increasing security and informing transit users of ways they can reduce their risk of victimization. Finally, the identification of areas at risk for street robbery can help reduce the occurrence of future street robbery by making law enforcement aware of potential problem areas so appropriate measures can be taken to stop street robbery before it happens.

Appendix 1: Technical Procedures

The following information describes the technical procedures for completing this risk terrain model using ArcMap 10 and SPSS. The procedures for completing steps 6 through 10 in the Risk Terrain Manual are detailed below.

After obtaining the data, the first step in operationalizing the risk factors was to bring the data into ArcMap. The data in this project was obtained in point geometry, mostly in excel file format, and required one of two methods for display. Point data that included x, y coordinates could be added to ArcMap and displayed using the display x,y coordinates function. These files could then be exported and saved as point shapefiles. Data that included addresses instead of coordinates required geocoding. These addresses were geocoded in ArcMap using the 10.0 US Streets Geocode Service. Addresses that were unmatched or had tied matches were rematched by hand. Generally, the reason a match was not automatically found was due to the use of abbreviations, the inclusion of suite or office numbers in the address, or the use of multiple address numbers for businesses that take up multiple connected storefronts. Addresses that could not be rematched by hand were left unmatched. These addresses were either incomplete, had errors such as incorrect zip codes, or as with some more recent data, they were located on new streets not yet part of the 10.0 US Streets Geocode Service.

After the data is displayed, the next step was to determine the distance for each map unit (250 foot by 250 foot block) to the nearest risk incident. The Euclidean Distance Tool located in the Distance Toolbox within the Spatial Analyst Toolset was used for this process. The point risk data was input as the feature source data. The environments were set so that the processing extent was the same as the 250 foot fishnet layer and the raster analysis was set to be masked to the 250 foot fishnet layer with a block size of 250 feet. This resulted in raster blocks of equal size, orientation, and location as their 250 foot polygon counterpart. The Euclidean distance from risk incidents was calculated for each risk factor.

The next step was to reclassify the risk layers into four risk levels. Blocks within 1,000 feet of a risk incident were assigned a risk level. The 1,000 foot bandwidth around risk incidents was divided into four equal intervals for risk level reclassification. The Reclassify tool located in the Reclass Toolbox within the Spatial Analyst Toolset was used for this procedure. Blocks located within 0-250 feet (or one block) of a risk incident were reclassified as level 4, or highest risk. Blocks located within 251-500 feet (or two blocks) of a risk incident were reclassified as level 3, or high risk. Blocks located within 501-750 feet (or three blocks) of a risk incident were reclassified as level 2, or medium risk. Blocks located within 751-1,000 feet (or four blocks) of a risk incident were reclassified as level 1, or mild risk. Blocks located over 1,000 feet from a risk incident were reclassified as level 0, or lowest risk. Each Euclidean distance raster was reclassified using these same classes.

These reclassified rasters then had to be converted back to feature shapefiles for data analysis purposes. The Raster to Polygon Tool within the From Raster Toolbox in the Conversion Toolset was used for this transformation, with simplify polygons unchecked. This processes combined neighboring blocks with the same value to create polygons of multiple 250 foot blocks. To get the polygons back into the 250 foot unit needed for analysis, the Identity Tool located in the Overlay Toolbox in the Analysis Toolset was used to assign the FID number for the 250 foot fishnet layer to the polygons in newly created raster to polygon layers. This resulted in a new shapefiles for each risk layer that included all the 250 foot polygons in the study area with the corresponding risk value.

In addition to operationalizing the risk layers, the dependent variable of 2011 street robbery also had to be operationalized. The procedure for this variable was slightly different. The first step was to get the count of incidents in each 250 foot block for each risk layer. The incident points were joined to the 250 foot fishnet layer using join data – join data to another layer based on spatial location (note: this is different than the Spatial Join Tool.) This resulted in a shapefile with polygon geometry which included the count of 2011 street robbery incidents in each 250 foot blocks. Next, the risk layer shapefiles were joined to the 2011 street robbery incident per block files to create one database with the dependent variable and all the independent variables. This was done by selecting the 2011 street robbery incident per block layer and then joining each risk layer to it based on polygon FID. Once, a file was created that included the dependent and all independent variables it could be exported to SPSS.

In SPSS, the dependent variable was recoded to be dichotomous: any block with an incident was coded as 1 and blocks with zero incidents were coded as 0. A binary logistic regression was run with forward selection the dichotomous dependent variable representing presence of 2011 street robbery and all 9 potential risk factors. The results indicated that all but two variables significantly contributed to the explanation of 2011 street robbery locations. The seven risk factors identified for use in the final risk terrain model were: prior street robbery, illegal drug activity, gang related activity, vandalism, recent street robbery offender locations, alcoholic establishments, and mass transit stops. The two variables excluded in the analysis were prostitution incidents and schools catering to high school and college-aged youth.

The ninth step of RTM is to add the individual risk layers together to create a final composite risk map. This step is completed with the use of the Raster Calculator found in the Spatial Analyst Toolbox under Map Algebra. If beta weights are used, each risk layer would be multiplied by its weight determined in Step 8 and then added to the other layers. However, since beta weights were not used in the final model, the seven risk layers just had to be added together with the raster calculator. The following equation was entered into the raster calculator: *Total Risk = Prior Street Robbery + Illegal Drug Activity + Gang Related Activity + Vandalism + Recent Street Robbery Offender Residences + Alcoholic Establishments + Mass Transit Stops*

The final step in risk terrain modeling was to symbolize the composite risk terrain map in a manner in which the map clearly communicates the information. The combined risk layer map was reclassified to match the risk levels of the individual layers. Combined scores of zero remained zeroes and were classified as lowest risk. The rest of the values were reclassified into equal intervals. Combined scores of one to seven were classified as one or mild risk. Combined scores of eight to fourteen were classified as two or medium risk. Combined scores of fifteen to twenty-one were classified as three or high risk. Combined scores of twenty-two to twenty-eight were classified as four or highest risk.

Appendix 2: Assigning weights to risk factors

The eight step of RTM is to assign weights to the risk factors. The RTM Manual (2010) suggest using logistic regression analysis to determine the relative correlations for each risk factor on the dependent variable. The process was already completed in prior steps to identify which risk factors to include in the final model. The resulting beta coefficients of the regression for the seven factors (prior street robbery, illegal drug activity, gang related activity, vandalism, recent street robbery offender locations, alcoholic establishments, and mass transit stops) were used to weight the layers. The RTM Manual (Caplan & Kennedy, 2010) suggests to use the Reclassify Tool to reclassify the old risk values for each layer by multiplying it by the beta weight. However, this step is unnecessary because the risk layers can be weighted when they are combined during Step 9 using the raster calculator.

The value of applying weights to factors in scales for the assessment of the risk of violence is debatable. Additionally, the interpretation of the statistical effect of the final risk terrain model is easier without the use of beta weights. Therefore, the value of using beta weight in this model was assessed. A comparison of the predictive power of the model with and without beta weights indicated there was statistically no difference. The explanatory power of the final risk value without using beta weights (5.292) fell within the confidence interval for the explanatory power of the model with beta weights (4.831 – 6.084). Additionally, the pseudo R^2 of the model with beta weights was only 0.003 higher than the model without. Both models captured the same percentage of 2011 street robbery incidents with in the comparable final risk levels. The results of these analyses led to the decision to not use beta weights in the final risk terrain model.

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