

“Integrating Citizen Survey Data” Improving the Prediction of Risk Terrain Models

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What is Risk Terrain Modeling?

Risk Terrain Modeling (RTM) is a relatively new procedure being used to forecast high crime locations through the creation of a composite risk layer map (Caplan & Kennedy, 2009). The goal is to improve predictive accuracy for specific crimes beyond what can be achieved using prior criminal incidents alone. The first step in RTM is to identify geographically-based risk factors through either direct empirical testing or through literature reviews. For example, “shots fired” locations in Irvington NJ were predicted using the home addresses of known gang members, retail business locations, and the location of drug arrests in prior years (Kennedy, Caplan, & Miller, 2009). Once these individual risk factors are identified and mapped, a composite risk layer is then created combining all of the factors. The end result is a single map that depicts a broader range of geographic risk levels for the given crime. These maps can then be used to direct prevention and intervention activities.

Limitations of RTM

One of the limiting factors in recent applications of RTM is that many, if not most, of the risk factors incorporated into the predictive models are largely static. Retail business locations, zoning, and proximity to schools, police stations, public transport, and liquor establishments (Baughman & Caplan, 2010, Piza et al., 2010), all of which have been used in prior studies, are not subject to considerable change from year-to-year. If these factors do not change their utility in predicting future offenses beyond prior offenses will be limited. Similar challenges have been observed in risk assessment focusing on recidivism among criminal offenders. Static risk factors, like age at first arrest and prior felony conviction are useful in predicting new offenses although their utility diminishes with time. This has led to the identification of dynamic risk factors that are subject to change like alcohol and drug use, attitudes, peer associations, employment, and family conflict. The incorporation of dynamic factors not only improves predictive accuracy (Andrews, Bonta & Wormith, 2006), but also provides guidance for intervention efforts (e.g., alcohol and drug treatment, cognitive-behavioral therapy, job skills training).

Another limitation of RTM is that researchers often rely solely on crimes reported to the police for use as risk factors. A better reflection of criminal activity in geographic areas is the combination of reported and unreported offenses.

Current Study

The primary objective of the present study was to explore a new source of data for RTM. As suggested above, both the predictive accuracy and practical utility of RTM may be enhanced by incorporating dynamic geographic risk factors. The data we used for this purpose came from a city-wide survey of residents in Portland Oregon. Resident’s ratings of perceived neighborhood safety, social disorganization, and street traffic were aggregated at the neighborhood level (N = 75) and used to predict car prowls. These factors speak to criminal opportunity and a lack of guardianship in distinct geographic areas of the city. Other risk factors considered included the location of the prior year’s residential burglaries and car prowls that were reported to the police, car prowls (reported and unreported) documented in the aforementioned neighborhood survey, proximity to high schools & colleges, and distance from liquor establishments.

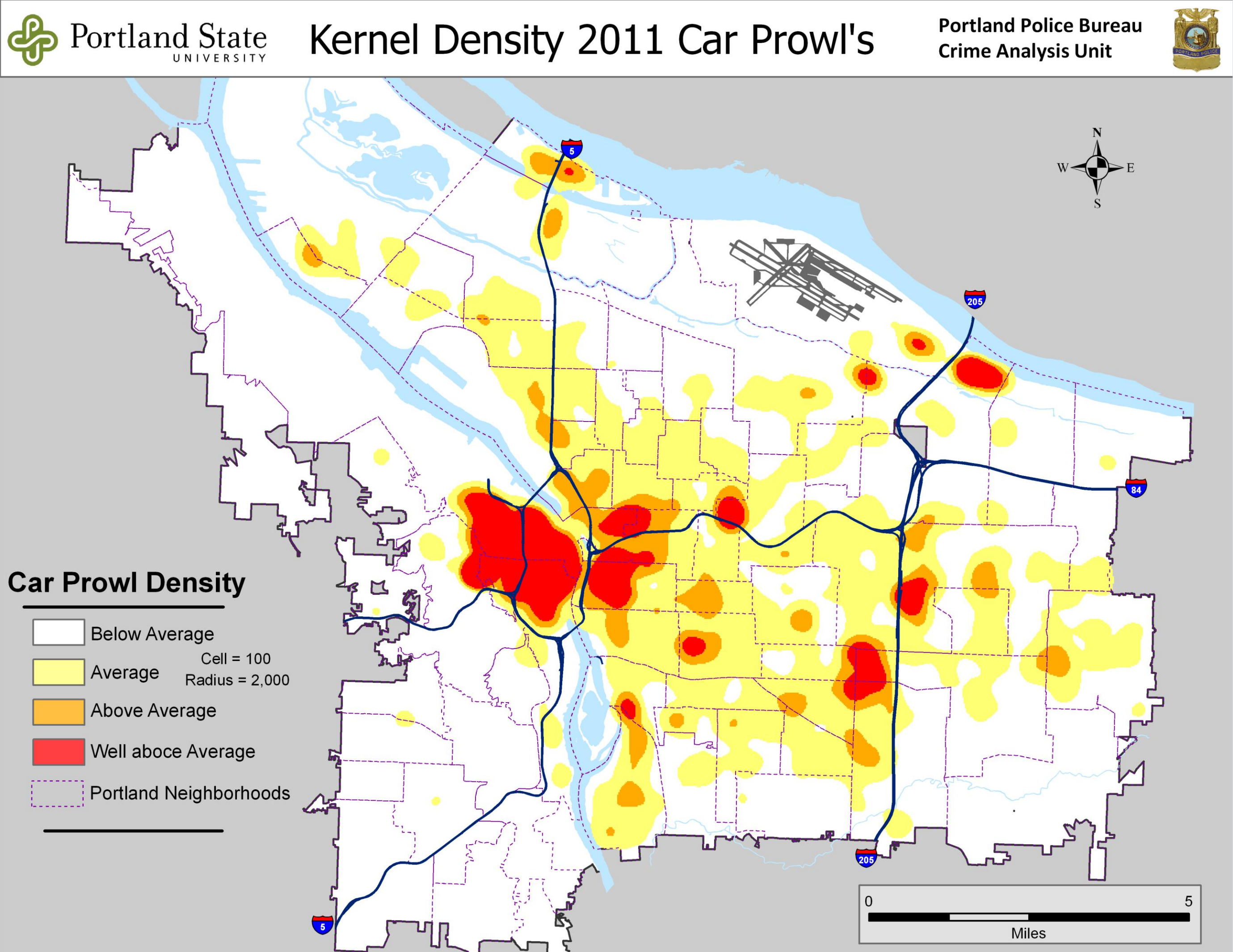
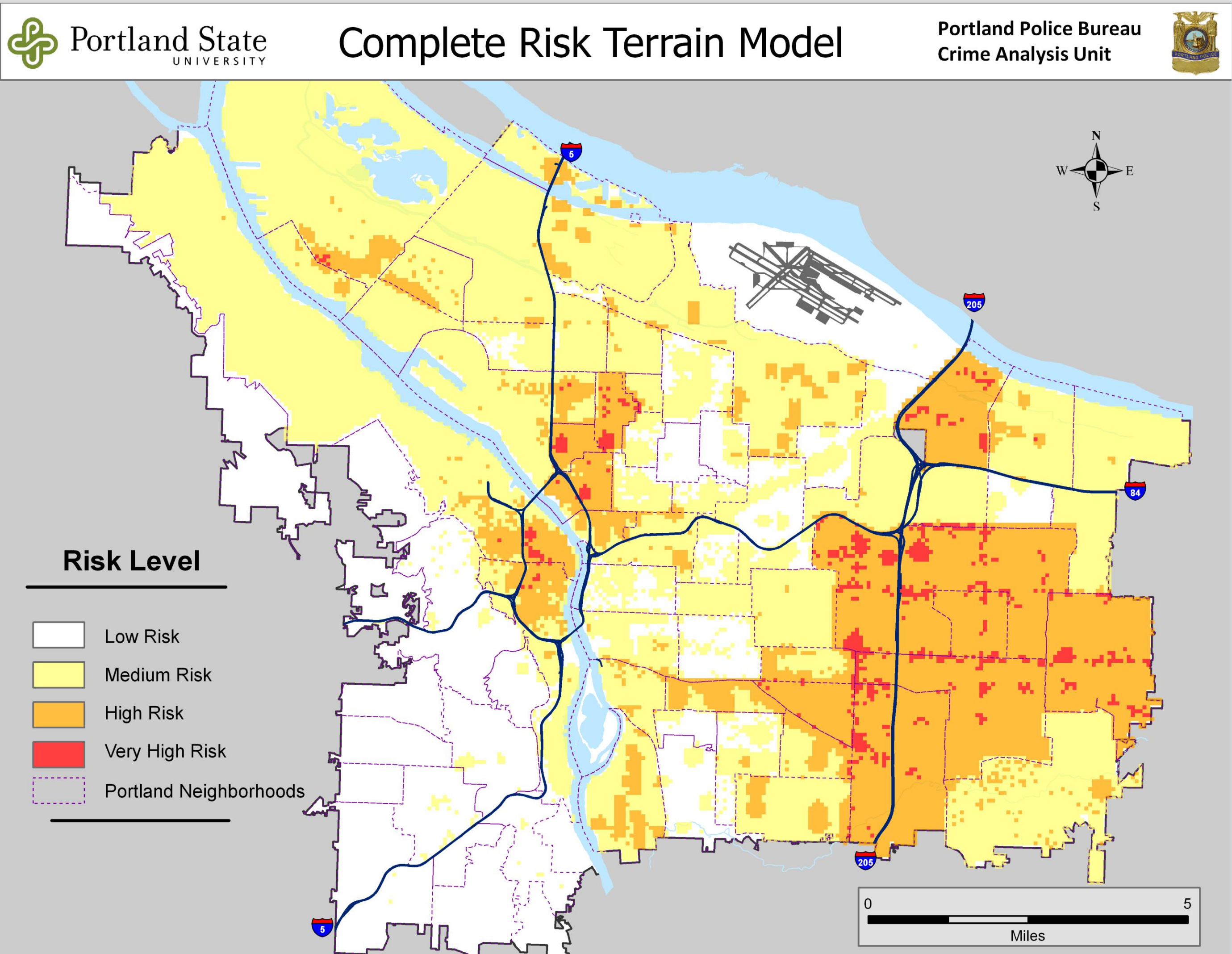
Hypothesis

We predicted that regression model adding residents’ neighborhood ratings (i.e., dynamic factors) would have greater predictive accuracy than the model based solely on burglaries, prior car prowls, and proximity to high schools, colleges, and drinking establishments.

Methods

A detailed methodology for RTM is available from (Caplan & Kennedy, 2010) . The key steps in developing the composite risk map and testing the map’s predictive accuracy are summarized below.

- Individual “dot maps” were created with four of the presumed risk factors (schools, liquor establishments, residential burglaries for 2010, car prowls for 2010).
- Presumed risk factors derived from survey data were mapped into neighborhood polygons (e.g., perceived safety, social disorganization, traffic flow, and % residents who were victims of a car prowl in prior year).
- A 250 x 250 foot grid reflecting the typical size of a city block in Portland (Rabiega, Lin, & Robinson, 1984) was overlaid on the eight maps from above.
- The eight risk factors from above were then aggregated into the 250 x 250 cells. Grid cells that spanned two or more neighborhoods were assigned neighborhood data based on the cell’s centroid.
- For the dot maps each grid cell was coded range 0 to 4 based if the centroid was within 1,000’ of a school, liquor establishment, burglary, or prior car prowl.
- Car prowls for 2011, the DV, were then mapped and grid cells were coded as positive if at least one car prowl fell into that area.



Results

The binary logistic regression used on the traditional RTM variables resulted in a Nagelkerke pseudo R² of 0.120. The Full model which incorporated the dynamic factors resulted Nagelkerke pseudo R² of .149 suggesting that it is a modestly better fitting model. After conducting both a forward and backward stepwise binary logistic regression the static variables of proximity to school and liquor establishments were first to be excluded from the analysis. We then examined the percent of incidents captured within each risk categories of both models. Table one illustrates the categorization of risk within each model as well as the percent of 2011 car prowls incidents captured. The highest risk level in the traditional model captured 1.6% of incidents while the full model captured 4.1%. When examining the amount of incidents captured within the highest two categories in both models, the inclusion of dynamic risk factors allowed for capturing roughly 4.2 times more incidents of car prowls in 2011.

Table 1. Traditional / Full Model			
Traditional Model			
Composite Risk Score		% of Incidents	% of area
Low Risk	0 to 2	42.9%	63.7%
Medium Risk	3 & 4	29.6%	30.9%
High Risk	5 & 6	7.7%	5.0%
Very High Risk	7 to 9	1.6%	0.5%
Full Model			
Composite Risk Score		% of Incidents	% of area
Low Risk	0 to 5	15.0%	25.2%
Medium Risk	6 to 10	45.8%	43.9%
High Risk	11 to 15	34.8%	28.9%
Very High Risk	16 to 21	4.1%	2.0%

Discussion

The findings of this study support the utility of citizen survey data as a new source of risk factors for use in RTM. Residents have “street-level” information regarding criminal activity that may not be reported to the police, crime attractors, crime generators, accessibility, and guardianship, all of which speak to the area’s risk for future victimization. Unlike many of the risk factors used in prior RTM efforts, these measures are subject to change through community actions and other broad movements like real estate development, employment opportunities, or gentrification. Finally, the identification of dynamic risk factors may lead to greater direction with crime prevention and intervention efforts. Static factors like proximity to a police station or school cannot easily be changed, whereas things like social disorganization can be tackled through efforts to enhance community cohesion. In summary, the present findings argue for additional research to identify the most salient predictive factors that could be obtained through residential surveys.

Data Sources

- Geographic coordinates for car prowls (2010 & 2011) and residential burglaries (2010) were obtained from the Portland Police Bureau (PPB)
- The location of 1,943 active liquor licenses in 2011 came from the Oregon Liquor Control Commission (OLCC)
- City Auditor’s 2007 Portland Neighborhood Survey
- Base maps and locations of schools were obtained from RLIS