Modelling the risk of robbery in the city of Tshwane, South Africa

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Abstract

In this study we model the risk of robbery in the City of Tshwane in South Africa. We use the collective knowledge of two prominent spatial theories of crime (social disorganization theory, and crime pattern theory) to guide the selection of data and employ rudimentary geospatial techniques to create a crude model that identifies the risk of future robbery incidents in the city. The model is validated using actual robbery incidences recorded for the city. Overall the model performs reasonably well with approximately 70% of future robbery incidences accurately identified within a small subset of the overall model. Developing countries such as South Africa are in dire need of crime risk intensity models that are simple, and not data intensive in order to allocate scarce crime prevention resources in a more optimal fashion. It is anticipated that this model is a first step in this regard.

Keywords: robbery, social disorganization, South Africa, risk intensity, model

Introduction

Examining the association between crime and its spatial location is not new. Indeed, early crime mapping efforts date back to the 19th century when Guerry (1833) mapped personal and property crime occurrences throughout France. A few years prior Guerry and Balbi (1829) used shaded maps as a display for crime rate intensity with the researchers being the first to combine multiple variables to compare personal and property crimes. Their results indicated that both personal and property crime were higher in urban areas and that areas where residents were more educated were more often prone to property crime. While theoretical advancements were made throughout the early 20th century in the 'geography of crime' literature it was the development and proliferation of geographical information systems (GIS) in the 1990s that truly opened up the discipline of criminology and offered new insights on the importance of crime linked to place. In fact, GIS lies at the vanguard of new explorations of crime. Although displaying and visualizing crime data were previously the rudimentary outcome of a GIS, increased computing power has allowed the technology to integrate new and different datasets into crime analysis and allowed more sophisticated geospatial techniques to be employed in order to better understand the spatial dimension of crime. Rather predictably a plethora of studies have been undertaken over the past thirty years using GIS to examine and investigate different aspects of criminal activity. These include studies investigating crime concentrations (Braga, Hureau, & Papachristos, 2010; Breetzke & Edelstein, 2019; Weisburd, Groff, & Yang, 2012), crime clustering (Drawve, Walker, & Felson, 2015; Polończyk & Leśniak, 2020), repeat and near-repeat victimisation (de Melo, Andresen, & Matias, 2018; Johnson, 2008), and journey-to-crime modelling (Block & Bernasco, 2009; Wheeler, 2015), among numerous others. Although inherently different the general aim of these studies are the same in that they attempt to spatially link offenders with crime opportunities. Relatedly, a vast array of geospatial techniques have been developed and employed by researchers to identify what increases the risk of crime and/or criminal victimisation at a particular location. These range from geographically-weighted regression (Breetzke, 2012), to geographic profiling (Canter, Coffey, Huntley, & Missen, 2000; Rossmo, 2000) and, more recently, to risk terrain modelling (Caplan, Kennedy, & Miller, 2011). The vast majority of these studies, and associated methods, have however been undertaken and employed in the United States or Europe with little known about crime and its causation in less developed context, particularly in Africa. Moreover, the ability of GIS to aid in the development of crime risk models in developing countries is largely unknown.

In the present study we aim to fill this gap by using GIS to develop a simple robbery risk model for the city of Tshwane in South Africa. The city of Tshwane (population three million;

6,500 square kilometres) is located in the central Gauteng province of South Africa and is one of six major metropolitan areas in the country. The present study attempts to contribute to the extant literature in a number of ways. First, crime data has rarely been analyzed in South Africa and certainly never, to our knowledge, been used in a modelling capacity. Indeed, the region-specific monitoring of crime began only after the African National Congress (ANC) came to power in 1994 (Blackmore, 2003), whilst the spatial recording of crime incident locations has only been conducted by the South African Police Services (SAPS) from 2001 (Breetzke, 2006). Identifying the possible future location of crime therefore represents a new step in analysis in a developing context. Second, the current study develops a risk intensity model of robbery based on two international spatial crime theories, namely the social disorganization theory (Shaw & McKay, 1942), and crime pattern theory (Brantingham & Brantingham, 1991). Classic spatial theories of crime such as those listed above have rarely been empirically employed to describe or ascribe risk to crime distributions in the country. While these and other theories and their propositions have been universally applied and tested (see, e.g., Chaix, Leyland, Sabel, Chauvin, Rástam, Kristersson, & Merlo, 2006; Lanier & Huff-Corzine, 2006; McCulloch, 2003) their applicability within an African context is largely unknown. Finally, post-apartheid South Africa holds a unique position in terms of its previous and current crime situation. Indeed, the country is one of the most dangerous in the world with rates of crime among the highest in any country outside a warzone (Luthy-Kaplan, 2015). Findings could potentially reveal interesting insights related to macrostructural risk factors for robbery in an increasingly desegregating and racially diverse post-apartheid city.

The rest of the manuscript proceeds as follows. First, we provide a brief overview of the spatial theories of crime that informed the selection of data and methods used in the development of the risk intensity model. We then outline the data used to build the model and chronicle its geospatial development. Finally we provide a short validation of the model using actual robbery incidences recorded by the SAPS before we discuss our results and outline a number of theoretical and practical implications

Theoretical framework

A number of theories have been used to identify when and where crime is most likely to occur. From a spatial perspective, these theories are generally housed within the school of environmental criminology. Proponents of environmental criminology suggest that any crime comprises of four dimensions: the law, the offenders, the target, and the place (Brantingham & Brantingham, 1981). Importantly, the place is not simply a spatial location but is a setting in space and time at which the other three dimensions of crime intersect and a criminal event occurs. Two major theoretical perspectives are housed within the school of environmental criminology and both form the theoretical basis for this study: social disorganization theory, and crime pattern theory. The social disorganization theory is synonymous with Chicago researchers Shaw and McKay (1942) who developed their social disorganization theory through mapping thousands of incidents of delinquency and analyzing the relationships between delinquency and various social conditions. They argued that social disorganization and hence crime and delinquency depended on a neighborhoods level of socioeconomic deprivation, residential mobility, and ethnic heterogeneity. For social order to exist, a sense of community or community cohesion should prevail which allowed the community to uphold common goals and regulate itself through formal and informal measures. Sampson (1986) expanded on the work of Shaw and McKay (1942) by adding social control as a community characteristic. According to the researcher, one of the most fundamental limitations to the social disorganization theory was the negligence of social control at the macro-level. Social control refers to a community's ability to reach consensus on mutual principles and values. Sampson introduced family disruption as a structural variable while exploring the effect male joblessness and disrupted family values have on violent crimes in black urban communities. He argued that the way families function within a society impacts how informal and formal control are applied on a macro-level.

Crime pattern theory explores the distribution and interaction of targets, offenders, and opportunities across time and space (Brantingham & Brantingham, 1991). According to crime pattern theory offences are most likely to occur where opportunity spaces - places perceived by the offender to contain attractive targets - intersect with awareness spaces – places about which an offender has specific environmental knowledge, for example the surroundings of his or her home. Importantly, an individuals' awareness spaces do not exist in isolation but are made up of different structures which provide opportunities to commit crime depending on the environmental backcloth – the social, psychological, physical, and temporal mosaic of the offender passing through space (Chainey & Ratcliffe, 2005). One central concept related to crime pattern theory is the notion of crime generators. These are places to which strongly motivated, intending criminal offenders migrate to because of increased opportunities for crime (Brantingham & Brantingham, 2000). Numerous types of facilities such as shopping malls, schools, and parks as well as their surrounding environs present opportunities as they are easily accessible to the public and attract large numbers of people providing an increased opportunity for motivated offenders. One specific type of facility that has received considerable attention as a crime generator are transport commuter nodes (see Brantingham & Brantingham, 1993; Brantingham & Brantingham, 1995; Badiora et al., 2015; Natarajan et al., 2015; Newton, 2014). The notion is that commuter nodes such as bus, taxi or train stops bring together in space and time a number of individuals who have a legitimate association with the facility (commuter users) but potentially also intending offenders who are knowledgeable enough to know the personal and physical landscape and for whom legitimate users make easy targets. Public transport networks also provide a number of other unique settings (such as large interchanges) across which crime and disorder can occur and brings increased accessibility to places, and this creates distinctive patterns and risks of offending around these locations.

The creation of the robbery risk intensity model in this study is loosely informed by these two crime theories although we emphasize that this study is not a test of these frameworks. Rather the emphasis here is on developing a simple yet effective risk model informed by theories which have universally been used to explain the increased risk of crime occurring in space.

Data and methods

Facility data

According to crime pattern theory, certain types of facilities may increase the risk of crime in their surrounding areas (i.e., crime generators). Examples of these types of facilities include schools (Hewitt, Beauregard, Andresen, & Brantingham, 2018), alcohol outlets (Conrow, Aldstadt, & Mendoza, 2015), shopping centers (Kinney, Brantingham, Wuschke, Kirk, & Brantingham, 2008), sexually orientated businesses (McCord & Tewksbury, 2013), and parks (Groff & McCord, 2012) among a plethora of others. In South Africa a limited number of studies have similarly identified so-called crime generators within cities including schools (Breetzke, Fabris-Rotelli, Modiba, & Edelstein, 2019), gated communities (Breetzke, Landman & Cohn, 2014) as well as shopping centres, major roads, retail and industrial nodes (Hiropoulos & Porter, 2014). In the current study we obtained and mapped data pertaining to the location of 3500 facilities across the city across 11 different types for 2006. This date was selected as it most closely aligns with the crime data available for the validation of the model. The list of facilities in Tshwane by sub-place is shown in Table 1.

Table 1. List of facilities in Tshwane by sub-place (*n* = 455)

Facility	Count	Min	Max	Mean	SD
Parks	1,748	0	193	5.81	14,21
Clothing Stores	143	0	23	0.48	1.91
Convenience stores	84	0	4	0.28	0.71
Schools	365	0	28	1.21	2.52
Fast food outlets	123	0	19	0.41	1.39
Filling/petrol stations	260	0	18	0.86	1.70
Office park/blocks	85	0	9	0.28	1.03
Restaurants	244	0	33	0.81	2.92
Shopping centers	163	0	7	0.54	1.14
Supermarkets	147	0	9	0.49	1.03
Other stores	138	0	21	0.46	1.66

Commuter node data

According to crime pattern theory, the locations at and/or immediately surrounding public transport interchanges may also increase the risk of crime in that they bring a large number of individuals together including commuters as well as informal traders. In this study we mapped the location of 4778 commuter nodes as of 2006 (including highway/main road intersections, as well as public transport stations) throughout Tshwane and used them in the development of the robbery risk model. The reason for including these commuter data separately in the study were twofold. First, offenders become aware of potential targets while commuting to and from transport nodes. Individuals at or surrounding these nodes are therefore at an increased risk of criminal victimisation. Second, previous research in a variety of contexts has most often found a positive spatial association between the presence of public transport facilities and a range of different crime types (see Badiora, Ojewale & Okunola, 2015; Irvin-Erickson & La Vigne, 2015, Newton, Partridge, & Gill, 2014). Commuter nodes were included in the analysis based on the theoretical notion that potential offenders spend an increased time at these nodes increasing their awareness of robbery opportunities.

Census data

A total of nine sociodemographic variables were drawn from Statistics South Africa's (SSA) 2001 census dataset and used to create a social disorganization index at the sup-place (suburb) level of spatial aggregation of Tshwane. The smallest unit area of the census geography frame for the census of 2001 in South Africa was the enumeration area (EA). These areas are of approximate equal population size and are so designed that an enumerator can visit and interview members of households within a specified time period. Census data in South Africa is not, however disseminated at this level of aggregation to the general public due to privacy concerns. Sub-places are one aggregation level up from EAs and represent the finest spatial unit of analysis at which Statistics South Africa has legally provided census information. It is, therefore, at this spatial level of aggregation at which the social disorganization index was created. The city of Tshwane has 455 sub-places with each sub-place consisting of between 150 – 300 households.

The census data obtained from Statistics South Africa was used to operationalize the four main tenets of social disorganization theory: socio-economic deprivation, residential mobility, family disruption, and ethnic/heterogeneity. *Socio-economic deprivation* was measured using five variables: the percentage of the population that have no access to electricity, the percentage of the population that have no running water in their household, the percentage of the population with no toilet and the percentage of the population that are unemployed. The first four variables are noted by Noble and Wright (2013) as a means of describing deprivation within an administrative area. The percent unemployed is a universal indicator of neighborhood level affluence previously shown to be associated with crime rates in a variety of contexts (see Poutvaara & Priks, 2007; Raphael & Winter-Ebmer, 2011). The percentage of people who have moved in the last five years was used to represent *residential mobility*. To represent *family disruption* in Tshwane, the percentage of individuals divorced or separated was utilised. It is expected that an increase in the number of separations or divorces will signal declining informal social control. Our measure of *ethnic heterogeneity* was the percentage of individuals that are foreign born. This measure has previously been shown to be positively associated with crime in South Africa (see Breetzke, 2010). Finally, the *percentage of males aged between 15 and 34 years* was also included. Young males are a subpopulation that have been identified in previous literature as associated with an increase in crime in neighborhoods (see Gruenewald & Remer, 2006; Hirschi & Gottfredson, 1983).

Crime data

Crime data for this research was obtained from the South African Police Service. The information provided included the geographic location, date and time of day, and type of crime committed in Tshwane for 2007. From the dataset we extracted six subcategories including:

aggravated robbery, attempted aggravated robbery, common robbery, attempted common robbery, robbery with a firearm, and robbery with a weapon other than firearm. A total of 9684 robberies were recorded for the time period under investigation. The 2007 robbery dataset obtained from the SAPS was used to validate the risk intensity model.

Development of a robbery risk intensity model

The first step in the development of the robbery risk intensity model was to construct a *facility density map* for Tshwane. This was done using the 3500 facilities as points of interest. A facility density map (using Kernel Density Estimation (KDE)) was constructed for each of the eleven types of facilities used in the study and combined to create a composite facility map indicating the density of facilities throughout the city at a 100 meter spatial resolution. According to crime pattern theory public facilities may act as crime generators as they are freely accessible, leading to an increased risk for offending and/or victimisation among people. The raster output (density map) from the facility density map was normalised (rescaled from zero to one) with higher scores indicating greater density. Second, a *commuter density map* was constructed for Tshwane using the 4778 commuter nodes as points of interest, also at a 100 meter spatial resolution. These commuter nodes included major highway and main road intersections as well public transport stations. Again, the raster output (density map) was normalised (rescaled from zero to one) with higher scores indicating greater commuter zone density.

We created a separate density map for commuter nodes due to the increasing evidence that the areas immediately surrounding these types of facilities in South Africa are extremely prone to crime (Page, 2001; Dordley, 2018; Anciano and Piper, 2019). Taxi ranks, in particular, are known locations of violence between rival taxi associations clashing over taxi routes between the outlying township areas and the Central Business Districts of South African cities. In fact, a number of commuter nodes and routes have been closed, albeit temporarily, over the past two years across the country due to crime (Dordley, 2018). Crime surrounding train stations is also prevalent with numerous instances of robbery reported in and around train stations over the past decade (Daniel, 2018; Payne, 2019). Recent research indicates that 43% of former passengers have stopped riding trains in South Africa over the past four years due mainly to fears of safety and security (#UnitedBehind, 2019). The researchers note that women and children are particularly vulnerable to crime at train stations, and that Metrorail – the state-run surface rail network – is bankrupt and simply unable to provide protection for commuters. It is for this reason that we created a separate density map for commuter nodes and, by the additive design of the model, weighted it more than the other combined facilities data.

Third, a *social disorganization index* was constructed for Tshwane using variables extracted from the 2001 census. According to social disorganization theory, crime is more prominent in neighborhoods with low-economic status, high ethnic heterogeneity, high residential migration, and high family disruption. As previously mentioned, a total of nine variables were extracted from the census and used to represent social disorganization theory. All nine variables were recorded as percentage measures for each sub-place (i.e., the percentage unemployed, the percentage that had moved in the last five years). Each variable was then normalised between zero and one. An index value was then created per sub-place by adding each of the nine variables' normalized scores together. As a result each sub-place was ascribed a social disorganization index value between zero (least disorganised) and nine (most disorganised). The resultant vector layer of sub-places for Tshwane (n = 455) was converted into a raster grid (100 meter spatial resolution) with each sub-place given a uniform social disorganization index value. Alternative multivariate statistical techniques, such as exploratory factor analysis and principal component analysis were considered in the construction of the index but a simple summation of the selected variables, with equal weighting, was applied.

This was done for two main reasons. First, there is a dearth of local research to inform the weighting that could be applied to each variable in the creation of index. The varying impact that each individual variable could play on robbery causation is therefore largely unknown which led us to apply equal weightings. Second, the model that is being developed is a global model and does not take local variability into account. As a first iteration of a model we therefore applied equal weightings to all variables.

The final stage in the development of the robbery risk intensity model was to combine the two density maps (facility and the commuter node) with the rasterised social disorganization index into a robbery risk intensity model using map algebra. Both density maps and the disorganization index were constructed using identical raster dimensions and resolutions. Moreover all final grids were normalised and rescaled between zero and one which allowed them to be overlaid and summed to produce the final robbery risk raster. The resultant risk intensity model has grid cells ranging from zero to three with higher scores indicating greater robbery risk based on the three inputted grids.

Similar to above, no weightings were applied to either density map or the disorganization index in the creation of the final robbery risk intensity model as it was assumed that each plays an equal role in the occurrence of robbery in the city. It could be that facilities play a bigger role than social disorganization in the risk of robbery or that commuter nodes are more important but that is an avenue for future research and the possible next iteration of the model.

As described above, we employed an additive normalization approach - with no weightings - throughout in the creation of our robbery risk intensity model rather than a multiplicative and/or reductionist approach. It is true that in many applications an additive model is not adequate for describing the combined influence of more than one risk factor (see Lisner et al., 2011). However in this instance we assert that the contribution of each individual model (facility, commuter, social disorganization) to overall robbery risk is high, restricting the use of a more reductionist approach. Moreover an additive approach is favourable when it is assumed that each robbery risk factor adds a different element of risk to the overall composite risk intensity model. Adding up differential contributions is not unreasonable, as robbery risk factors can be additive. For example, living near a transport commuter node can represent one form of risk (the movement of commuters to and from commuter nodes increases opportunities), while living in a socially disorganized neighborhood is another (individuals are less likely to know their neighbor and/or report suspicious activity). These two factors are related, but they relate to different underlying causes of robbery risk. Importantly, all factors do not necessarily need to be present to increase the risk of robbery. Moreover, the additive approach does not distort influences of single factors in the overall robbery risk intensity model. It is therefore easier to comprehend and to communicate to stakeholders, which increases the application potential. Indeed, there is some evidence that stakeholders favour the additive approach (see Reckien, 2018) whilst an additive normalisation approach - without the use of weightings - have previously been successfully applied in a range of other contexts assessing risk (see Abson et al., 2012; Yoon, 2012; Tate, 2012).

Results

Figure 1 shows the facility density map for the city of Tshwane. Rather predictably facilities in the city tend to cluster in the central business district (CBD) as well as in the more affluent south-eastern region of the city. Smaller clusters of facilities are notable in peri-urban enclaves towards the east of the city. There is notable dearth of facilities in the outlying former black African township areas in the northern region of the city – this is largely due to the historical socio-spatial design of apartheid cities in which the former whites-only neighborhoods in the central city received the bulk of the infrastructure whilst the outlying townships in the urban periphery were most often under-serviced and under-resourced, a spatial pattern that continues

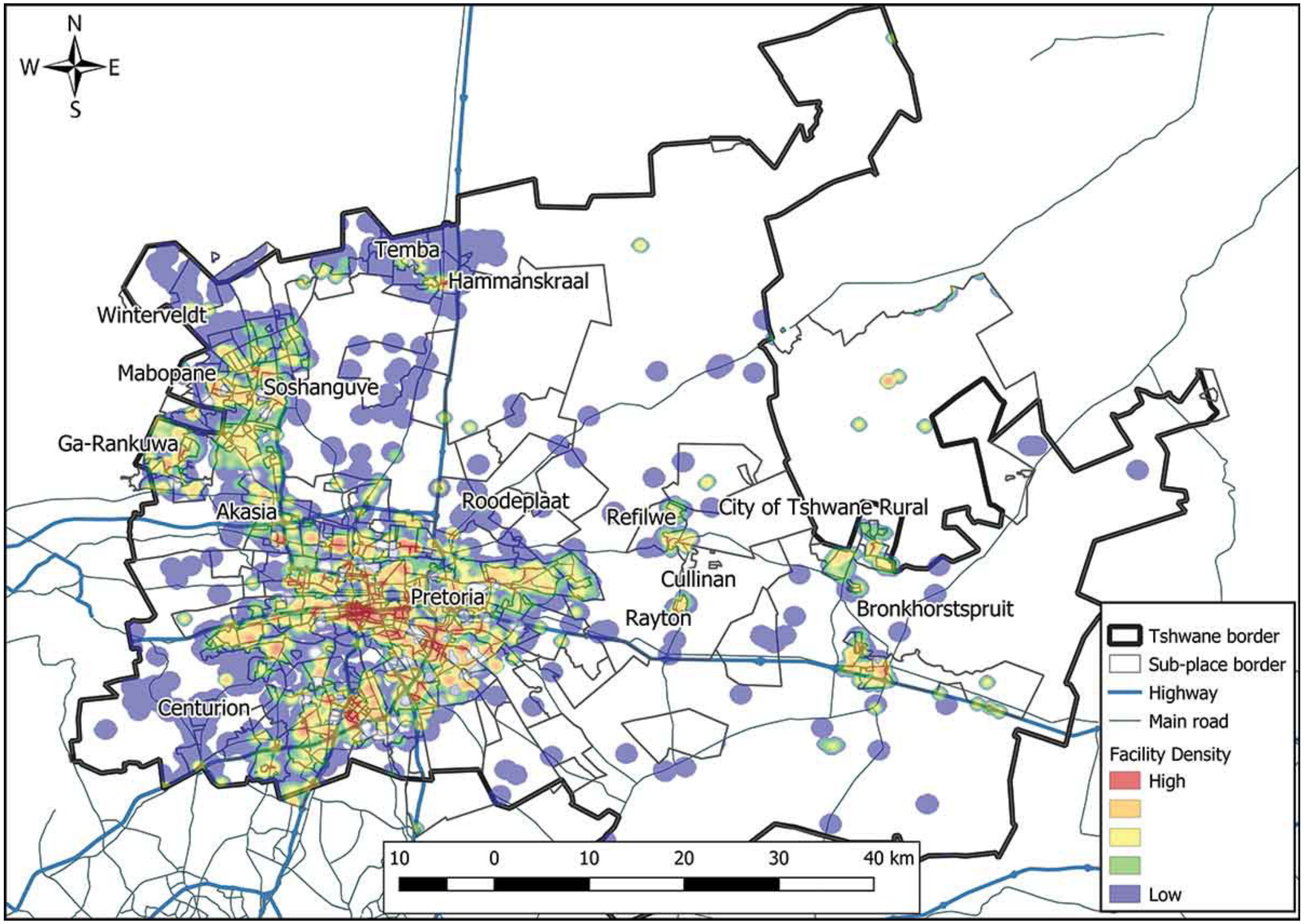

Figure 1: Facility density map for the city of Tshwane (a quintile classification technique was used with the actual data ranges of 0 to 1 converted to the ordinal presentation)

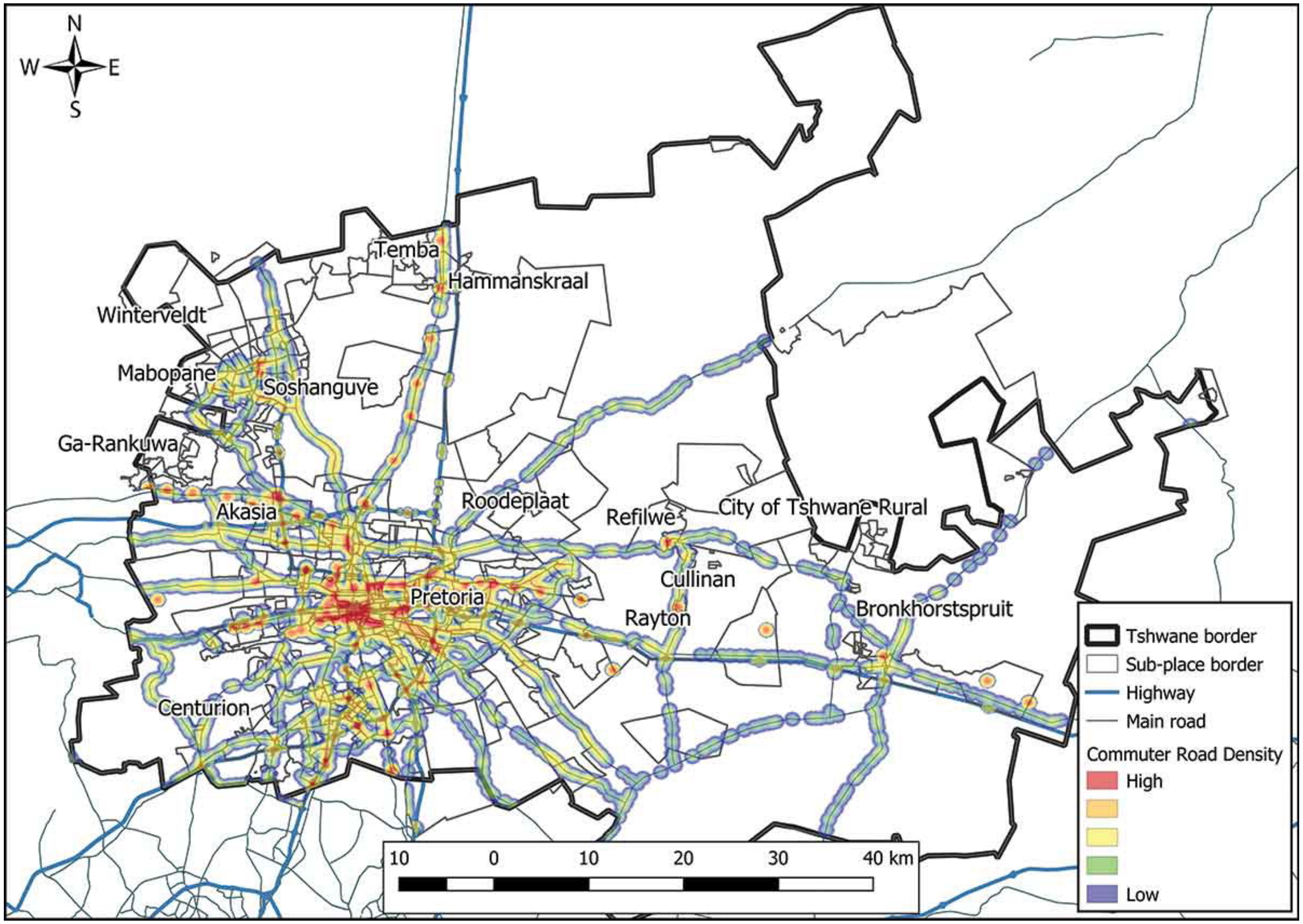

Figure 2: Commuter node density map for the city of Tshwane (a quintile classification technique was used with the actual data ranges of 0 to 1 converted to the ordinal presentation)

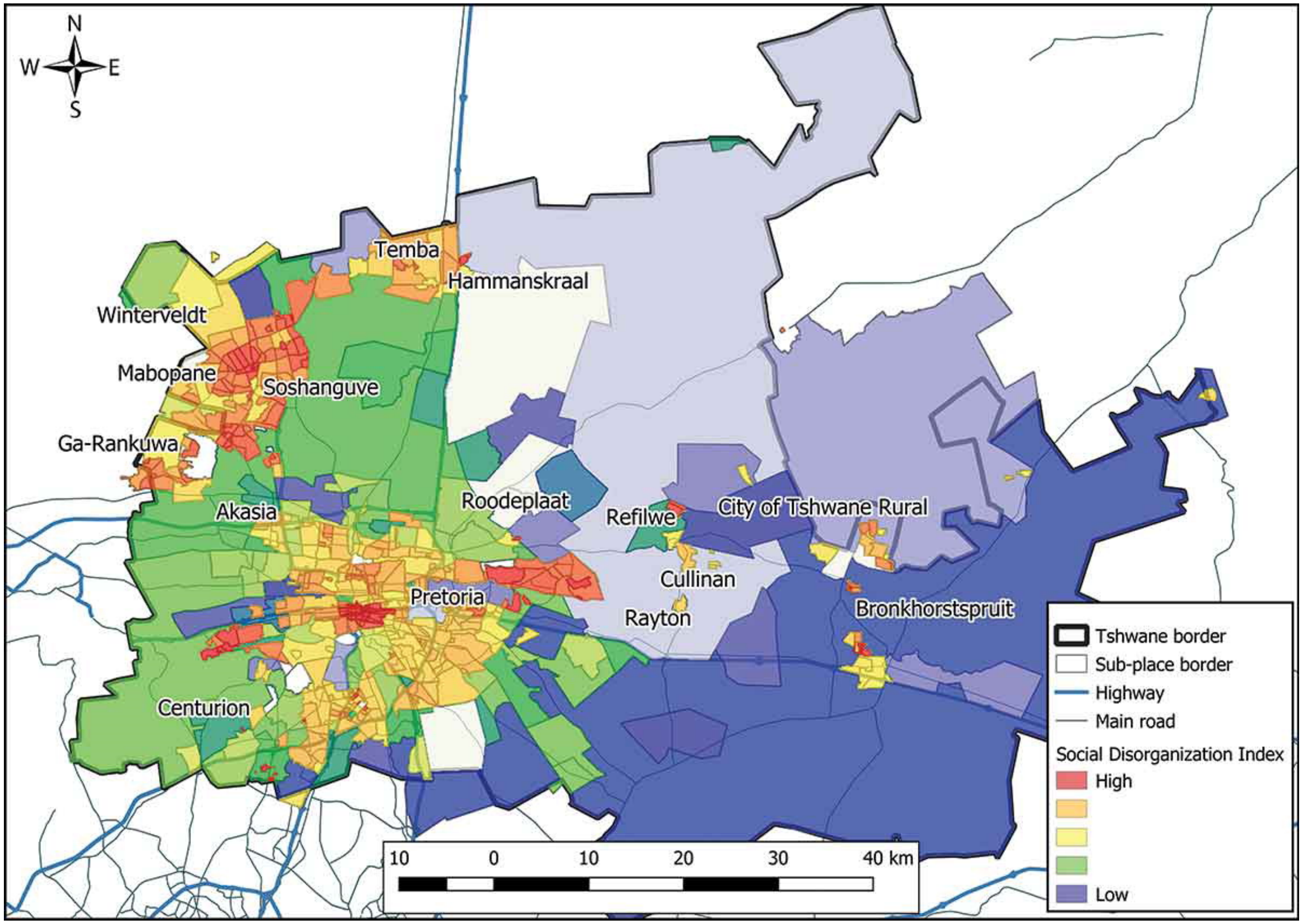

Figure 3: Rasterized social disorganization index for the city of Tshwane (a quintile classification technique was used with the actual data ranges of 0 to 9 converted to the ordinal presentation)

more than 25 years into democracy. Figure 2 shows the commuter node density map. Understandably the areas with the greatest density of commuter nodes lie along major transport routes leading into Tshwane from the south and existing the city to the north. Similar to above, commuter nodes in Tshwane tend to cluster in the CBD with main arterial routes leading from the CBD towards the townships on the northern and eastern periphery of the city also dominating. These routes tend to have sporadic public transport nodes in addition to major route intersections. Finally the rasterized social disorganization index is shown in Figure 3. Suburbs that are the most socially disorganized in Tshwane, based on the central tenets of social disorganization theory, are mainly located in the township areas on the northern urban periphery of the city. Interestingly, the CBD is also characterised as being socially disorganized as well as areas immediately adjacent to the CBD.

The final robbery risk intensity model is shown in Figure 4. This model combines the two density maps as well as the social disorganization index into a composite robbery risk intensity model. The quintile classification scheme was employed to create the range values shown in the legend for all figures. For figures 1, 2 and 3 the classification scheme is applied to pixels, so the area in each class is identical. For the figure 4 the classification scheme is applied to the sub-place units themselves, which vary in size and shape.

The highest risk of robbery in the city is in the CBD with robbery risk spatially diffusing towards the east and south-eastern suburbs of the city. High risk clusters of robbery are also observable in the far east and in a number of townships in the northern periphery of the city. The robbery risk intensity model was validated using actual robbery incidences from 2007 recorded for the city of Tshwane. To do this we first extracted the top five percent, 10%, 15% and 20% percent of raster cells from the robbery risk intensity model for the city boundary of

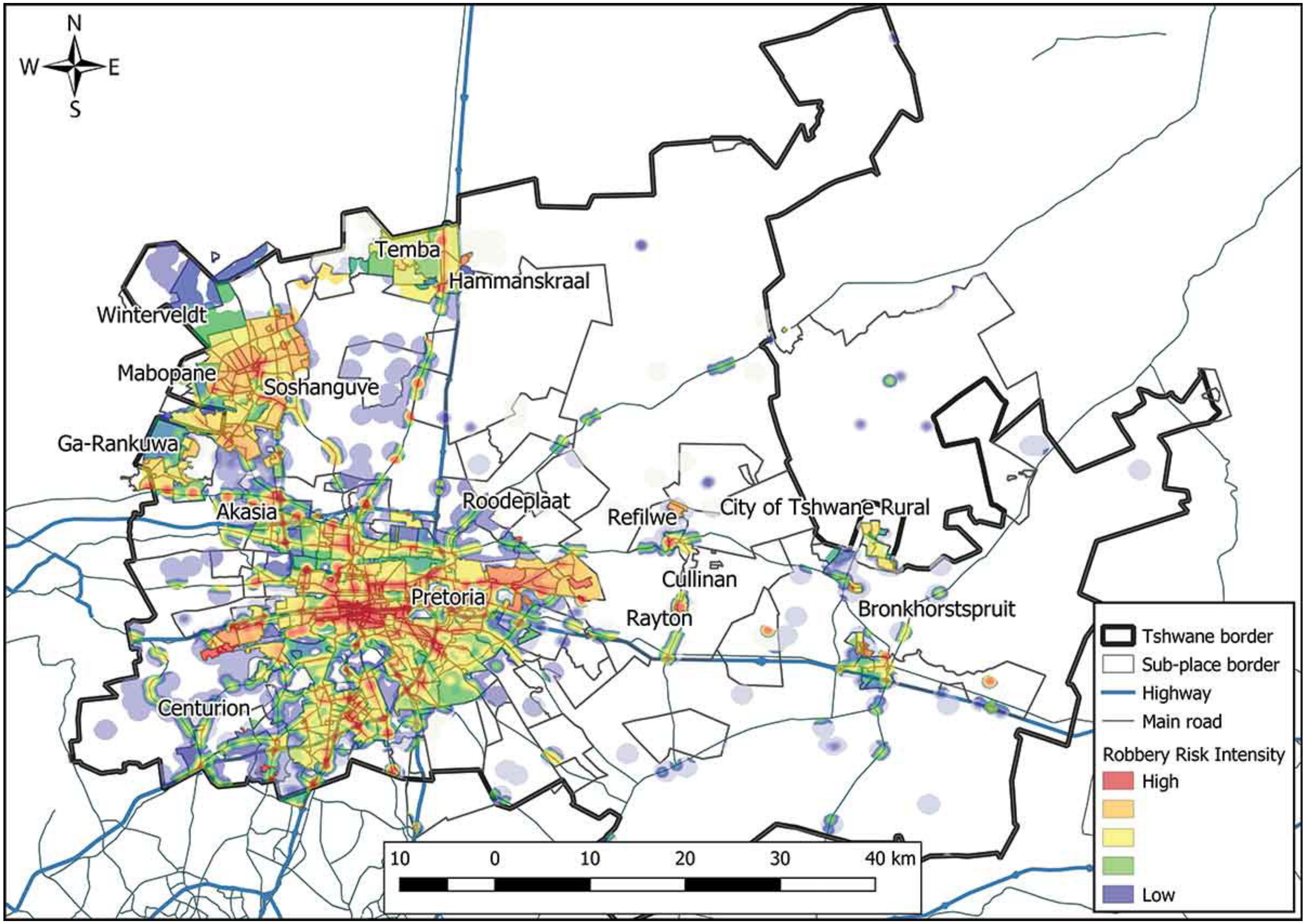

Figure 4: Robbery risk intensity model for the city of Tshwane (a quintile classification technique was used with the actual data ranges of 0 to 1 converted to the ordinal presentation)

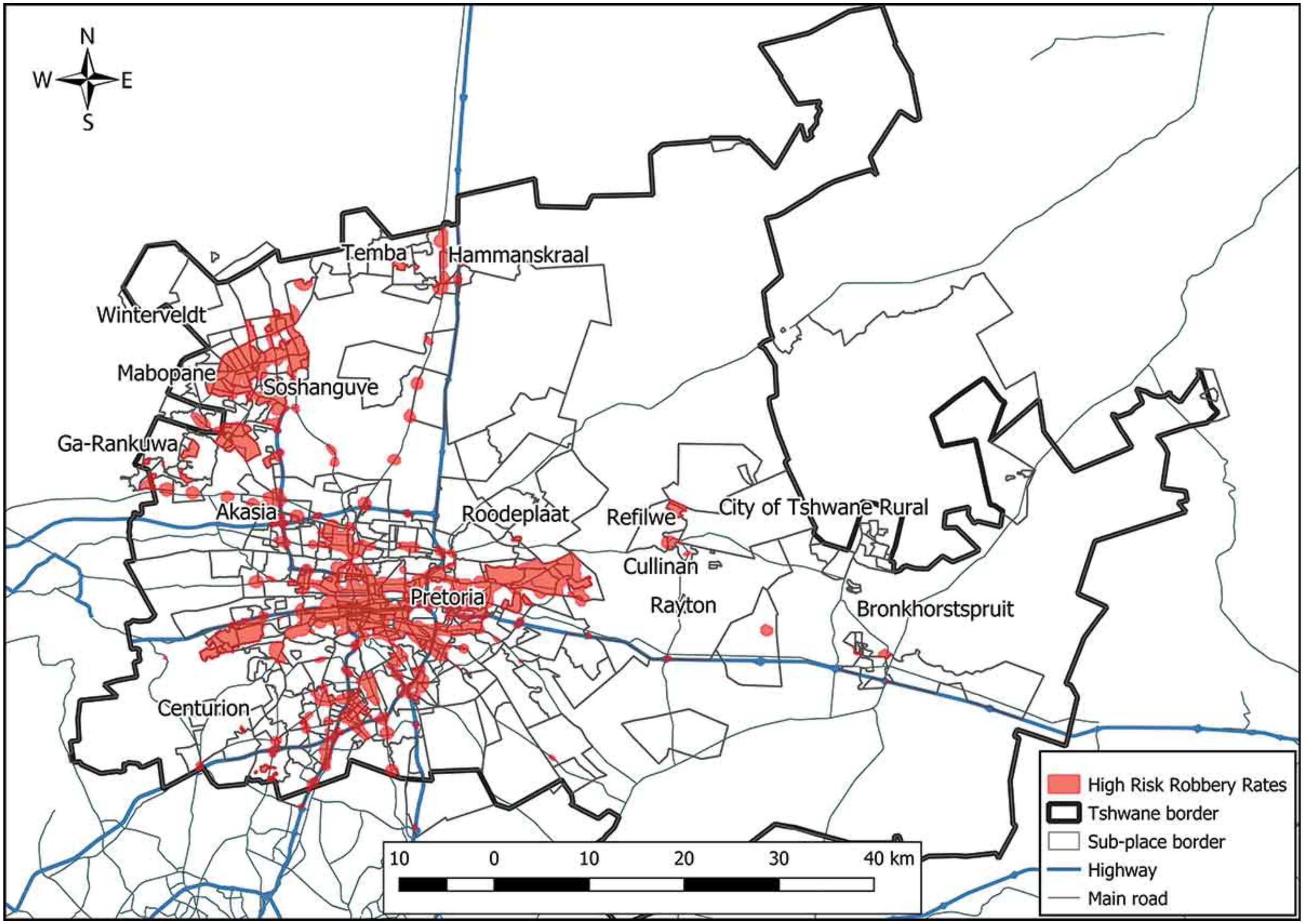

Figure 5: Top five percent of robbery hot spot areas in the city of Tshwane (a quintile classification technique was used with the actual data ranges of 0 to 3 converted to the ordinal presentation)

Tshwane which exhibited the highest risk for robbery based on the models' output. We then overlaid the 2007 robbery incidences (n = 4852) over these subsets of the model in order to generate a graduated 'hit-rate'. Table 2 indicates the 'hit rate' of robberies per percentage model extraction while Figure 5 shows the map with the top five percent of raster cells from the robbery risk intensity model.

Table 2: Graduated 'hit-rate' of the robbery risk intensity model

Percentage coverage	Number of pixels	Number of robberies	Hit-rate
5%	34,739	3,391	69.89
10%	69,479	4,175	86.05
15%	104,218	4,426	91.22
20%	138,958	4,586	94.52

We did this extraction for two main reasons. First, we wanted to determine whether our model accurately identifies the 'hottest' robbery densities in the future. The more accurately the model can identify highest-risk locations, the more certain we are of its efficacy and development for future use. Second, from a practical perspective, selecting a narrower subset of the full risk intensity model allows for the disproportional spatial distribution of robbery to be identified and potentially addressed. Police in South Africa are extremely limited in terms of time and resources. Selecting a series of narrower areas allowed for our model to identify areas most in need of police intervention. The city of Tshwane covers an area of just under 6950km^2 whereas the 'hottest' five percent covers an area of roughly 350km^2. The validation of the model in this smaller subset would allow for the geographically targeting of resources into these areas potentially having a greater effect. Based on our analysis just under 70% of 2007 robberies (n = 3391) fell within the top five percent of our robbery risk intensity model while almost 95% of 2007 robberies (n = 4586) fell within the top twenty percent of our model, an extremely encouraging result which indicates that facilities, commuter nodes and neighborhood-level social disorganization collectively do have power in identifying the vast majority of crimes in the validation dataset. Future research can attempt to revalidate this model in a time-series mode not available in this model due to data constraints.

Discussion

Research on crime pattern theory has most often found positive associations between facilities and different types of crime (Conrow et al., 2015; Groff & McCord, 2012; Hewitt et al., 2018; Kinney et al., 2008; McCord & Tewksbury, 2013). Likewise studies have highlighted the importance of commuter nodes in predicting future criminal victimisation (Badiora et al., 2015; Irvin-Erickson & La Vigne, 2015, Newton et al., 2014). In terms of the social disorganization theory, previous studies both in South Africa and internationally have found positive associations between a number of measures of social disorganization and crime (see Cahill & Mulligan, 2003; Freisthler, 2004; Jacob, 2006; Ouimet, 2000). The current study uses and collates this collective knowledge to build a robbery risk intensity model for the city of Tshwane.

The results of this research has a number of theoretical and practical implications. From a theoretical perspective, the results of our model suggest that a number of prominent international spatial theories of crime such as the crime pattern theory, and social disorganization theory can, to some extent, be used to identify the future spatial distribution of robbery in the country. The fact that the results of South African spatial crime research are largely supported by international crime theory is important as it allows relevant stakeholders that deal with crime prevention in the country to prescribe policies to reduce crime using a theoretical framework with relevance to South Africa. Moreover, the use and testing of these international spatial crime theories in South Africa gives the country and its researchers some measure of credibility internationally. The vast majority of existing research in the geographic risk modelling of crime has been carried out in the United States, with studies in other parts of the globe extremely rare, especially in Africa. Incorporating South African content also allows for a greater understanding of the generalisability of international spatial crime theories to less developed areas and to areas with markedly different cultural perspectives and ethnocentricities.

From a practical perspective the development of a risk intensity model for robbery in Tshwane can assist in the prescribing of prevention policies that work to reduce crime. Indeed, the identification of future robbery risk areas can inform crime prevention policy in a number of ways. Operationally, the SAPS could implement policing interventions in the areas at greatest risk for robbery. This can be done through the use of route and foot patrols; roadblocks, and cordon-and-search and stop-and-search operations. Importantly, these interventions do not necessarily have to take place in areas which exhibit the most robbery but in areas where the *risk* of robbery occurring is highest based on the risk intensity model. Such an intervention would ideally allow the majority of existing law-abiding residents of these communities greater safety; whilst potentially leading to the arrest of perpetrators of crime.

Strategically, key stakeholders can implement much needed early crime prevention programmes to areas of greatest concern. One such intervention to deterring criminal behaviour in ‘high-risk’ robbery areas is using crime prevention through environmental design (CPTED) techniques. This refers to the notion that physical space can be designed to maximise the crime prevention potential of an area. It then involves the development of physical designs that reduce the opportunity for crime to occur. Various CPTED initiatives have been undertaken in a South African context with reasonable success (see Coetzer, 2009; Landman & Kruger, 2009). Importantly, these potential CPTED initiatives would be geographically-targeted. That is, the areas with the highest risk of robbery would be known and targeted for certain CPTED intervention initiatives. The results of our model suggests that this task would not be too onerous since the areas identified as being at a greater risk for future robbery incidents in Tshwane are significantly spatially skewed meaning primary interventions would only need to occur in a relatively low number of areas to have an effect. It was demonstrated earlier how almost 70% of future robberies in Tshwane occur in an extremely low percentage of the city. This implies that prevention initiatives could be manageably and suitably implemented in a relatively low number of locations with the greatest effect. In this sense, the strong spatially skewed pattern of crime in cities such as Tshwane could be used as an advantage in the fight against crime in the city.

Of course, the limitations of this study need to be considered. First, the robbery risk intensity model developed is based on the assumption that the datasets used in its construction are complete and accurate. Indeed, data is the single most important factor in any risk intensity model as the accuracy of the identified risk is only as good as the input data. The robbery data we obtained from the SAPS has admitted shortcomings. Most notably the under-reporting of robbery particularly in less affluent areas of the city. According to Mistry (2004) only 29% of robbery cases in South Africa are reported to the police. It can therefore be assumed that the robbery counts used in the current study are an under-representation of its true magnitude. This limitation is almost impossible to overcome as the data we obtained to validate the model is the most official and spatially replete robbery dataset available. Additional ways to conduct crime analysis using other crime data sources – recently outlined by Faull (2019) – could be used in the future when applying, or improving upon, the model developed here. Second, it is likely that there are a large number of facilities in Tshwane that are not included in the creation of our facility density map. These are likely to be 'informal' and undocumented facilities that are most often located in township settings. This is especially the case in the outlying areas of Tshwane where are there are a disproportionate number of informal dwellings and where the informal economy thrives. These informal areas contain facilities known to the community but are not officially listed and are therefore not captured in this study. In truth it is impossible to know this ‘dark number’ and it is futile to attempt to capture this information digitally when often there is no permanent spatial footprint of these facilities. We also did not capture other types of facilities such as alcohol outlets, nightclubs, parking lots, ATM locations, which may also act as generators of crime in the city. Despite these limitations, we are nevertheless reasonably satisfied that the facility data that we did use, namely the 3500 facilities, is a relatively accurate representation of the true magnitude and location of the vast majority of facilities in the city. Third, the use of density measures in the creation of the robbery risk intensity model is problematic due to the fact that the underlying population is not taken into account when assessing risk. It could, therefore, be that the robbery risk is higher in areas in Tshwane simply because there is a higher percentage of the population residing in these areas. Kernel density methods do however have the advantage of deriving crime density estimates based on calculations performed at all locations (Levine, 2002). The methods also have visual appeal and do consider concentrations of crime at all event levels, rather than cluster grouping some and discounting others. If an alternative methodology were however employed that did take the underlying population into account, such as using rate maps, the densities generated would still suffer from the problems inherent when using geographic boundary thematic maps such as the modifiable areal unit problem (MAUP). Results may also potentially mislead focused crime prevention targeting because of failing to reveal patterns within and across the geographic division of boundary areas (Chainey, 2005). Moreover, the most suitable denominator for calculating robbery rates in this study would be pedestrian counts for an area, was not available to us. Using ‘simple’ population counts as denominators for calculating robbery rates would merely create density mapping output that exaggerates the crime problem in areas that have few residents but a high concentration of robbery. By using kernel density estimation also allowed us to be more flexible with our output and subsequent map design.

Finally, the robbery risk intensity model is cross-sectional and did not take time into account. Robbery is known to have temporal variability with increased risk by hour of the day, day of the week, and month of the year (Breetzke, 2018; Felson & Poulsen, 2003) while spatial crime models assessing risk most often taken a temporal component into account (see Helbich & Arsanjani, 2015; Leitner & Helbich, 2011). It is therefore quite likely that the risk intensity model output for day-time robbery would differ to night-time robbery and/or robbery on weekends would differ to the robbery risk during weekdays. Robbery risk could also differ year-on-year. In our study we were however totally dependent on the availability and accuracy of our data suppliers (i.e., the SAPS). The data available to us precluded any form of temporal component to be added to the study as they were available at one point in time only. This also limits its generalizability to other contexts. Indeed, it could be that the risk we identify in this study do not hold true in other cities in South Africa or in similar contexts, internationally. Conversely, it could also be that stronger risk patterns are observed in other contexts. Future research should aim to replicate this model in cities in other countries and/or within South Africa that are distant and distinct from Tshwane, taking the other limitations into account as well. The strength of this study is that we managed to accumulate and map data for a large number of facilities, commuter nodes and robbery incidences and build, for the first time in a developing context, a robbery risk intensity model. By doing so we believe this study demonstrates that GIS can play an important role in identifying risk factors for robbery incidences in less developed contexts. While the model may be rather rudimentary, the fact that it is the first of its kind in South Africa, and indeed anywhere in Africa, makes it highly significant. Developing countries are most often constrained in the availability and accessibility of data pertaining to crime risk. A simple yet effective model of crime causation we felt is more prudent to develop than an overly complex data-intensive model that can rarely, if ever, be tested and applied in contexts outside South Africa. Future iterations of the model can also consider applying a suitable weighting mechanism in the construction of the social disorganization index as well as in the formulation of the final model. Geospatial techniques are becoming increasingly used and developed in the spatial analysis of crime. This study hopefully represents a small but important step in the future development and identification of crime risk in contexts outside the West.

Data availability statement

The facility and commuter node data that support the findings of this study are available from AfriGIS (Pty) Ltd. Data are available from the authors with the permission of AfriGIS (Pty) Ltd. The crime data that validate the findings of this study are available on request from the corresponding author. The data are not publicly available due to their containing information that could compromise the privacy of victims of crime.

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