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Risk terrain modeling for road safety: identifying crash-related environmental factors in the province of Cádiz, Spain

Alejandro Giménez-Santana[1] (iD) · José E. Medina-Sarmiento[2] · Fernando Miró-Llinares[2]

Abstract

Environmental Criminology has developed a robust framework that provides the scientific support and necessary foundation for crime analysis through crime mapping. This theoretical approach focuses on the situational and temporal characteristics of criminal opportunity rather than on the offender's behavior for crime prevention. In the scope of road safety and traffic crashes, few studies have adopted this approach. This study used risk terrain modeling (RTM), developed by the Rutgers Center on Public Security, to determine the relative importance of varying environmental risk factors on alcohol-related crashes and traffic accidents. The independent variables consisted of a set of potential environmental risk factors, while the dependent variable comprised all DWI crashes and traffic accidents in the province of Cádiz in 2012. According to the results of the current study, restaurant locations are spatially associated with the occurrence of drunk driving crashes, while proximity restaurants and recreational lodging centers correlate with the sites of traffic accidents.

Keywords Risk terrain modeling · Environmental criminology · Road safety

✉ Alejandro Giménez-Santana
alejandro.gimenez@rutgers.edu

José E. Medina-Sarmiento
j.medina@crimina.es

Fernando Miró-Llinares
f.miro@crimina.es

[1] Rutgers Center on Public Security, Rutgers University, 123 Washington St., 5th Floor, Newark, NJ 07102, USA

[2] Centro Crímina para el Estudio y Prevención de la Delincuencia, Universidad Miguel Hernández de Elche, Alicante, Spain

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Introduction

The World Health Organization (WHO) estimates that road traffic accidents are the cause of over 1.5 million deaths with more than 50 million injured every year (WHO 2015). Only in the United States, the ratio of traffic fatalities to homicides has gradually increased since the 1990s and is nearly double the rate of homicides (Lucy 2003). In Spain, after decades of witnessing a dramatic increase in the number of traffic accidents, which in 1989 accounted for over 6000 traffic-related deaths, a series of efforts have led to a reduction in the number of fatal crashes in recent years with the implementation of new precautionary measures like higher penalties and fines (Miró and Bautista 2013). Law enforcement strategies directed at increasing drivers' awareness, in particular regarding their perceived risk of apprehension, have increased as well. An increase in a driver's perception of the risk of arrest improves norm-compliance and is well-supported by the literature (Miró and Bautista 2013). As a result, a more efficient placement of police checkpoints could contribute to a reduction of up to 17% in the number of driving while intoxicated (DWI) crashes and between 10 and 15% the number of traffic crashes (Fell et al. 2014). Thus, a common strategy to improve road safety has been the increase of traffic surveillance, considered an important factor to reduce the risk of crashes. This relationship has been addressed by different research projects like the European project ESCAPE, which conducted eight independent studies on the relationship between intense traffic surveillance, driving speed, and crashes (Elvik 2001). Similarly, project PEPPER carried out a meta-analysis study on traffic control policies (Erke et al. 2009), and project SUNflower studied the effect of surveillance on the use of seatbelts and driving under the influence (Wegman et al. 2008).

It is important to emphasize the role that road safety enforcement has as a significant component of police work (Weiss 2016). Famega (2005) found that traffic-related stops occur on average once for every police shift, while stops not linked to traffic violations take place twice every three shifts. Nonetheless, more serious crimes and calls-for-service tend to garner higher attention among analysts because of their implications for public safety (Drawve et al. 2017). As a result, most research efforts to date have focused on the study of more serious crime types (e.g., homicides, burglaries, etc.) than on the advancement of new techniques to the study of car traffic accidents (Drawve et al. 2017).

When considering that crashes are an important portion of a police department workload (see Famega 2005), a newer strategy adopted by a limited number of police departments, the Data-Driven Approaches to Crime and Traffic Safety (DDACTS), presents an example on how cooperation between different agencies can help improve road safety efficiency and overall security. DDACTS is a joint effort between the National Highway Traffic Safety Administration (NHTSA) and the U.S. Department of Justice to develop a unique strategy aimed at reducing the number of traffic crashes and crime incidents (NHTSA 2014). This approach combines the use of spatial and temporal analysis in place that present a high concentration of both crime and crash incidents. It does so by targeting crash hotspots that fall within high-crime areas with the use of high-visibility law enforcement. As a result, this approach simultaneously tackles road safety and crime problems, helping to improve overall security and reduce social harm.

One of the most critical challenges faced by police departments is where and when to implement precautionary measures to improve road safety. It is important for police (see Erdogan et al. 2008) to identify which places are more vulnerable to future traffic crashes in order to implement specific road safety strategies. Advancements in geographic information

system (GIS) technology and other crime analysis techniques have made their way into police departments throughout the world. These have led police agencies to demand access to new tools that can allow them to maximize and more efficiently use their limited resources. Government agencies are now increasingly adopting the use of more sophisticated spatial techniques to monitor and analyze the location of crash hot spots (see Prasannakumar et al. 2011; Harirforoush and Bellalite 2016; Vemulapalli et al. 2016). Research efforts have focused on a search for solutions to optimize the allocation of resources (Camacho-Collados and Liberatore 2015; Weisburd and Lum 2005), reflecting on the consideration that actions of control can be more effective if directed at a series of strategies targeting areas where events tend to cluster (Brantingham and Brantingham 1995; Sherman et al. 1989; Weisburd 2015).

The existing literature provides different explanations of how crash-prone locations can be forecasted. Levine (2017) examined the relationship between the locational influence of bars and alcohol-related crashes in the city of Houston utilizing a Poisson-Gamma-CAR spatial regression model. The results of his analysis suggest that 45% of all night DWI crashes in Houston occurred within a distance of 0.25 miles of a late-night bar. Anderson (2009) identified and compared three spatial approaches to determine the location of hot spots for traffic crashes. These methods included the use of kernel density estimation (KDE)—by far, the most common method, as well as network analysis or census output area estimation. In the same direction, Erdogan et al. (2008) employed a combination of Poisson distribution and kernel density to determine the location of hot spots using grid cells of 500-m cells. Sabel et al. (2005) created a simulated input risk surface that relies on kernel estimates to identify the location of future car accidents by using two input variables, namely, the proximity to junctions and traffic flow.

Despite the extended use of density mapping techniques, new and more sophisticated evidence-based approaches can now be used to forecast the location of future crime incidents (Caplan et al. 2011). The use of hot spot techniques has proved to be an effective tool for crime analysis (Chainey et al. 2008). However, the predictive capacity of crime mapping can be improved through the use of raster data and other multivariate methods such as risk terrain modeling (Caplan and Kennedy 2010). This approach to spatial risk analysis compares the location of past crime events against a series of features of the landscape to identify the location of risky places (Caplan and Kennedy 2016). A defining characteristic of this technique is its capacity to explain not just where but also why the clustering of crime incidents occurs at particular locations, based on the presence (or absence) of a series of aggravating factors. Risk terrain modeling (RTM) has the advantage of including other variables, not just the location of past crash incidents, to improve the general knowledge on the effect that the built environment has on traffic crashes.

Even though RTM was originally conceived to analyze crime incidents, numerous recent examples support the versatility of this technique in other fields. For example, risk terrains are now used to analyze a wide variety of situations, such as child maltreatment (Daley et al. 2016), motor vehicle theft (Piza et al. 2017), global maritime piracy (Moreto and Caplan 2010), or the various risks posed by drug markets in Colombia (Fundación Ideas para la Paz 2015). However, very few studies have addressed the environmental factors directly related to traffic accidents (Lang and Stockwell 1991; Mustaine and Tewksbury 1999). As an exception, a recent publication by Drawve et al. (2017) combined the use of RTM and conjunctive analysis of risk factor configurations (CACC) to analyze traffic accidents in Green Bay, WI (USA). Their findings suggest that the dominant behavior setting for crashes in Green Bay consists of the combined effect of retail stores, bus stops, fast-food restaurants, and religious

organizations. In the same way, the current study proposed utilizing RTM to analyze the causes of crash incidents in the province of Cádiz; a novel approach to road safety that seeks to identify the main environmental risk factors spatially correlated with the location of crashes.

This study intends to challenge existing general wisdom concerning the use of deterrence strategies as the sole solution to limit traffic accidents. As suggested by Turrisi and Jaccard (1992), perceptions on the risk of arrest due to temporary law enforcement crackdowns only persist for a short period of time. Instead, identifying the presence of environmental factors associated with the location of crash incidents could benefit the development of public health strategies aimed at reducing the number of licensed premises in areas with a high concentration of drunk driving accidents (Ewing and Dumbaugh 2009; Livingston et al. 2007; Wechsler et al. 2003). According to Stitt and Giacopassi (1992) and Watts and Rabow (1983), there is a significant correlation between places with a high concentration of licensed premises and an increased number of arrests of DWI offenders in these locations. In a more recent study, Ponicki et al. (2013) found that restaurant locations present a higher risk for overall crash accidents, whereas bars primarily affect the chances of DWI crashes. Similarly, Morrison et al. (2016) research findings indicate that areas in the vicinity of locations with a concentration of bar outlets have an impact on the likelihood of alcohol-related crashes. Thus, identifying risky locations associated with road traffic accidents can help develop a more sustainable and long-term solution to road safety.

Background

Risk terrain modeling, a new approach to analyzing road traffic crashes

Empirical evidence suggests that crime tends to concentrate in times and places, such as "hot spots" (Sherman et al. 1989). Building on these and other theories, the risk terrain modeling approach was designed to address the persistence of crime and delinquency at micro-level places. As noted by Caplan and Kennedy (2016, p. 1), "The underlying factors that increase or decrease the risk of crime are not quick to change and exert fairly consistent effects on the appearance, distribution, and persistence of crime by attracting illegal behavior." Therefore, identifying how certain factors combine to encourage crime to emerge and persist over time allows us to develop strategies to mitigate the risk of future crime events. Having this objective in mind, it is important to measure how the built environment affects human behavior. In this regard, Caplan (2011, p. 59) proposes calculating the spatial influence of criminogenic features to model the way in which "features of a landscape affect places throughout the landscape."

The theory of risky places (Kennedy and Caplan 2012) addresses how to measure risk and criminal opportunity, which is fundamental to the study of crime and places. First, this theory assumes that some places are riskier than others depending on the presence (or absence) of criminogenic features. Secondly, as noted by Kennedy et al. (2015), crime is expected to emerge at places where high vulnerability exists based on the combined spatial influence of multiple criminogenic features. Lastly, the effect of risky places on crime will be higher at places where environmental factors of vulnerability and exposure to crime collocate (Kennedy and Caplan 2012).

Since the 1990s, analysts have been investigating how the application of environmental knowledge and GIS-based techniques can apply to the study of traffic accidents (Affum and Taylor 1998; Black 1991; Medina-Sarmiento 2015; Steenberghen et al. 2004; Thomas 1996).

As a result, the combination of crime analysis pragmatism with the theoretical frameworks of environmental criminology and the theory of risky places have transformed the ways in which police departments operate. As suggested by Ratcliffe (2016), evidence-based policing strategies can benefit police departments by improving the distribution of police patrols evaluating intervention and prevention strategies, and helping to sustain efforts over time.

The adoption of these new techniques fueled an intense scientific debate regarding the search for a suitable unit of measurement, as well as an appropriate analysis technique to effectively identify intervention areas (Drawve 2016). Spatial autocorrelation techniques such as Getis-Ord Gi* have become one of the most common analytical methods used by analysts (Erdogan et al. 2008). This technique requires the use of aggregate-level data instead of a measure of individual-level locations. It can, however, lead to one of the best-known problems in geography: the modifiable areal unit problem (MAUP), which is a threat to validity (Openshaw 1984). Other researchers have opted for kernel density estimations (KDE) to calculate the density of an event based on its individual-level attributes (Anderson 2009).

Risk terrain modeling (RTM) incorporates the principles of environmental criminology (Brantingham and Tita 2008) and risk assessment (Kennedy and Van Brunschot 2009) to the study of crime outcomes. It does so by identifying the risks emanating from a series of features of the built environment and models how they collocate to create unique behavior settings for crime (Caplan and Kennedy 2016). RTM is utilized by researchers and practitioners around the globe to study a wide variety of topics and issues (see Ohyama and Amemiya 2018; Gerell 2018; Giménez-Santana et al. 2018).

Drunk driving and road traffic accidents

To date, most research studies on the causes of DWI crashes have focused on conducting macro-surveys to determine the driver's point of departure before getting intoxicated (Chang et al. 1996; Lang and Stockwell 1991; Slagle 2014; Usdan et al. 2005). These studies produced precise locational data regarding the first and last places visited by offenders before an accident. Moreover, the existing literature on road safety has extensively researched the socio-contextual characteristics of traffic accidents, including the race/ethnicity, education, or marital status of the offenders (Chang et al. 1996; Morrison et al. 2002; Lang and Stockwell 1991; Slagle 2014; Usdan et al. 2005). A number of studies have identified the location where drunk drivers tend to get intoxicated before having an accident (Lang and Stockwell 1991; Chang et al. 1996; Morrison et al. 2016; Ponicki et al. 2013), as well as the effect of socio-demographic factors on crashes (Caetano and Clark 2000; Mustaine and Tewksbury 1999).

Research efforts have focused on establishing the links between the demographic characteristics of offenders and the location where certain groups of people became intoxicated; in particular whether their preferred "points of departure" were licensed or unlicensed premises. For example, a macro-survey conducted by O'Donnell (1985) reported that 63% of all drivers arrested under DWI charges identified their "point of departure" as a licensed premise, the most frequently reported location by all respondents. The same study found that "more people may drive away from bars in an intoxicated state than from other drinking locations" (O'Donnell 1985: p. 515). Similarly, Chang et al. (1996) found that 45% of offenders reported

drinking in bars and lounges before driving. These differences can be paramount to define effective law enforcement strategies such as finding the most suitable location for a police checkpoint to increase the number of DWI arrests. As noted by Medina-Sarmiento (2014), police knowledge on known drinking locations for drunk driving offenders constitutes a pivotal element to determine the location where police patrols should be deployed. To date, the extant literature on DWI crashes has focused on the study of offenders' demographic characteristics.

Most of the existing literature on the causes of DWI crashes and other traffic accidents has relied on qualitative research based on offenders' individual-level characteristics (e.g., race/ethnicity, marital status or education). Past research has missed incorporating the locational effect that restaurants, bars, and other licensed premises have on the situational persistence of crash incidents. In this regard, the RTM technique offers a novel approach to the study of road safety by putting the focus on places and not people (Caplan and Kennedy 2016). Indeed, RTM identifies the enabling factors that attract offenders to some places rather than the people who happen to be in these locations. Therefore, and in the scope of this study, RTM is utilized to identify places at a higher risk of presenting crash incidents to help traffic safety authorities to adapt to their road strategies.

Data and methods

The study setting for this analysis is the Spanish province of Cádiz, a region extending over a total area of 7442 km^2 with a total of 2168 Kkm^2 of road networks and approximately one million registered drivers (Instituto de Estadística y Cartografía de Andalucía 2015). In the province of Cádiz, an average of 700 traffic accidents resulted in death or injuries between 2011 and 2012 with 7% (50 accidents) of all crashes reported as alcohol-related (DGT 2015). All crash data were compiled by the Guardia Civil on roads that fall within their territorial jurisdiction, including all freeways (autopistas and autovías) and arterial roads (vías convencionales) but excluding local roads. The established speed limit for motorways in Spain is 120 km/h, while secondary roads have speed limits that range from 90 to 100 km/h (depending on road characteristics).

As noted by Sánchez Ferreira (2012), in Spain, car crashes tend to concentrate on secondary road networks (e.g., arterial and collector roads) as opposed to higher capacity roads, such as freeways or expressways; a reality that suggests that freeways, where vehicles can travel at higher speeds, are not necessarily associated with an increase in crash accidents. Instead, road design and adequate infrastructure are known to be a determinant for road safety (Sánchez Ferreira 2012). In France, Martin (2002) found lighter traffic patterns to be associated with an increase in the risk of crashes due driver's loss of focus in road conditions and overcompensation in speed in detriment of safety. In a more recent study, Levine (2017, p. 156) noted that: "Since higher-capacity roads (e.g., freeways) carry much higher traffic than lower capacity roads, the likelihood of a crash is a function of the type of road." Similarly, Gruenewald and Johnson (2010), suggest that crashes are most likely to occur in areas with great road-network density and highway flow. Qin et al. (2004), however, found the relationship between crashes and traffic volume to be nonlinear and dependent on crash type, thus indicating that differences in the type of roads have a direct impact on the likelihood of crash accidents. Therefore, to control for differences arising between crashes occurring in freeways as opposed to accidents originating on secondary roads, we included all of Cádiz' road

networks[1] as part of this analysis. The inclusion of these two additional variables within our RTM models sought to bring new insights into the spatial association between the location of crashes and the varying types of roads.

The dependent variable in this analysis was the location of crash incidents in the Province of Cádiz during the calendar year 2011. As shown in Table 1, a set of potential environmental risk factors were operationalized by their spatial influence against the location of traffic accidents by utilizing the risk terrain modeling technique. All primary data on crash accidents were directly obtained through Spain's Dirección General de Tráfico (DGT), equivalent to the U.S. National Highway Traffic Safety Administration (NHTSA). This study utilized the ARENA[2] database (Accidents Data Collection and Analysis), Spain's centralized data repository, which compiles information across local, autonomic, and national police agencies. For the purpose of this analysis, all crash accidents, including fatal and nonfatal crashes, were included. Such distinctions among crash types were made by law enforcement, at the time of an accident, by conducting alcohol blood tests or breath tests to determine the causes of the crash, establishing whether or not a traffic accident resulted from driving under the influence.

Crash records were geocoded using dynamic segmentation (DynSeg) of the road networks shapefile. Cartographic data used for this analysis was directly obtained from the Andalusian Institute of Statistics and Cartography using the Projected Coordinate System ERTS89 (UTM Zone 30). Through the use of ArcGIS's linear referencing tool, road layers were converted to a linear reference system by subdividing road networks into kilometric points (KPs) and converting these layers to polyline-M shapefiles. Then, each crash incident was assigned its corresponding address for the type of network and kilometric point (KP). Through this geocoding process, we were able to spatially determine the location of 87% of all traffic accidents occurring in the province between the years 2011 and 2012.

After conducting an extensive literature review of environmental correlates of crash accidents (Chang et al. 1996; O'Donnell 1985; Usdan et al. 2005; Levine 2017; Drawve et al. 2017), we selected a set of potential risk factor measures that could spatially correlate with the location of crash incidents in our study setting, such as bars and restaurants (Chang et al. 1996; O'Donnell 1985; Usdan et al. 2005). In Spain, unlike the United States or Australia, where more restrictive rules apply to the distribution and sale of alcoholic beverages, the number of establishments allowed to sell and distribute alcohol is significantly broader. For instance, fast food restaurants, college campuses, and grocery stores are all allowed to sell alcohol, which dramatically increases the number of potential "points of departure" for drunk drivers. As a result, a larger number of locations were included as potential risk factors for DWI crashes. Additionally, we incorporated a set of major retail centers in our model like malls, shopping centers, and hypermarkets. These locations are known to attract large groups of people, thus increasing the risk of crashes near these places. A study by Abdel-Aty and Radwan (2000) found that heavy traffic environments are known to be associated with an increase in the likelihood of crashes. All environmental factors were obtained through the open-source GIS platform, OpenStreetMap (OSM), which offers access to a variety of address-level records for businesses (Moeinaddini et al. 2014), and Spain's Páginas Amarillas (Yellow Pages) with up-to-date data on businesses. Our decision to use Yellow Pages data was based on

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[1] We used line-feature shapefiles to represent all of Cádiz' road networks. These data were obtained from the Instituto de Estadística y Cartografía de Andalucía.

[2] Translated from Spanish: Accidentes, Recogida de Información y Análisis (ARENA)

Table 1 Potential risk factors

Environmental factors	N	O[a]	Spatial influence
Recreational lodging	69	P/D	Up to 4000 m
Bars	729	P/D	(500 m-increments)
Higher education campuses	24	P/D	
Shopping centers and malls	17	P/D	
Sports centers	33	P/D	
Gas stations	139	P/D	
Hypermarkets and supermarkets	53	P/D	
Entertainment venues	7	P/D	
Restaurants	885	P/D	
Highways ("autopistas" and "autovias")	10	P	
Secondary roads ("carreteras convencionales")	174	P	

[a] Operationalization: P for proximity or D for density

the need to improve the reliability of our data by being able to distinguish locations that are still open and running from those closed and no longer relevant to this study.

All variables in this analysis were analyzed using the Risk Terrain Modeling Diagnostics (RTMDx) software , a software solution developed by Drs. Leslie Kennedy and Joel Caplan at the Rutgers Center on Public Security (Caplan and Kennedy 2016). RTMDx automatizes a series of statistical analyses using the RTM technique. First, potential risk factors are operationalized as a function of their spatial influence, either by density or proximity, to the location of crashes. According to Caplan (2011), locational factors have a strong influence on explaining why crime tends to occur in some places and not others. A total of 160 potential variables[3] were tested using the RTMDx software in both models,[4] which, through cross-validation, selected 19 potentially significant variables for the RTM model on DWI crashes and 21 variables for the model on traffic accidents. In other words, for each potential risk factor, at least 16 spatial influences were tested to determine if a spatial correlation existed with the location of crashes. In the second step of the process, RMTDx used a bidirectional stepwise regression, where one model assumed a Poisson distribution, while the other calculated a negative binomial regression to build the "best model" for the remaining variables (Kennedy et al. 2015).[5] In the final step, the RTMDx software generates an output for all significant risk factors associated with crashes, their optimal operationalization, and the relative risk score (RRS).

Here, we identified the environmental risk factors that correlate with the location of road traffic accidents and DWI crashes using RTM. First, traffic accident data were disaggregated to distinguish between traffic accidents and alcohol-related crashes, allowing the control of variations between these two subgroups. As a result, two RTM analyses were produced for each type of crash incident, identifying the micro-level location of risky places along Cádiz's province geography. Then, we ran a regression analysis for each crash type to test the association between 2011 risky places and 2012 crash locations. As per the results of this analysis detailed in the results section, the predictive capacity of RTM to forecast the future location of crash events in the province of Cádiz was empirically demonstrated.

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[3] (9 factors * 2 operationalizations * 4 blocks * 2 "half increments" + 2 factors * 1 operationalization * 4 blocks * 2 "half increments") = 160 variables.

[4] The same potential risk factors were tested in both RTM models for traffic accidents and DWI crashes.

[5] The "best model" consisted of the one with the lowest Bayesian information criterion (BIC) score.

Based on previous research (see Drawve 2016; Dugato 2013; Giménez-Santana et al. 2018), we decided to compare KDE values for past crash exposure and RTM values for spatial vulnerability using PAI. Developed by Chainey et al. (2008), this technique allows for comparisons to be made between different spatial analysis techniques to predict future events. A total of three comparisons were made between hot spots for DWI crashes (KDE values[6] of +2 SD from the mean), high-risk places (RRS values of +2SD from the mean), and locations where DWI crash hot spots overlap with high-risk places. The PAI is calculated using the following formula[7].

$$PAI = \frac{\left(\dfrac{n}{N}\right) \times 100}{\left(\dfrac{a}{A}\right) \times 100}$$

Results

The current study compared two cases, the first focused on alcohol-related crashes and the second on traffic accidents occurring in the province of Cádiz during the calendar year of 2011. A total of four environmental risk factors were found to have a spatial association with the location of traffic accidents in 2011, while three risk factors were found to be correlated with the location of DWI crashes over the same year. The variations arising from these two cases offer a unique opportunity to estimate the enabling effects of the built environment on road safety while including the effect presented by variations between high and low capacity road networks. For instance, freeways presented a higher risk of victimization for drunk driving crashes, while secondary roads were riskier for overall traffic crashes. Moreover, a significant spatial correlation was found between restaurant locations in the province of Cádiz and places where drunk driving accidents occurred most frequently. In regard to the traffic crashes model, the locational effect of restaurants continued to be the most significant predictor, together with the location of recreational lodging centers (e.g., campsites and suburban hotels).

A. RTM applied to alcohol-related crashes in Cádiz

A risk terrain modeling (RTM) analysis was conducted for all drunk driving accidents that occurred in Cádiz during the year 2011. While as many as 679 car accidents took place over that year, only 42 accidents were linked to impaired driving. In other words, 6.2% of all road traffic accidents were directly caused by drivers under the influence. According to a survey conducted by the World Health Organization (WHO), approximately 1 to 3% of all European drivers (depending on the country) reported occasionally driving after consuming alcohol. These statistics are indicative of Cádiz's elevated rate of drunk driving accidents in comparison

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[6] The cell size for the analysis was 500 m, similar to RTM, and the search radius was set to 4000 m, thus assuming the maximum spatial influence used with RTM.

[7] In the PAI formula, n is the number of crashes in the high-risk places or the hot spots, N is the total number of crashes, a is the area in square kilometers of the high-risk places or the hot spots, and A is the total area for the study.

with other neighboring European countries. Moreover, based on the results obtained with RTM, the risk of DWI crashes across Cádiz's freeways was, on average, 55% higher[8] than that presented by locations across secondary roads. Therefore, these results suggest that highway road networks across Cádiz's province present a higher risk for drunk-driving crashes. These results are consistent with previous findings by Levine (2017) on the increased risk for crashes on high-capacity road networks.

Moreover, the results of this analysis suggest that proximity to restaurants significantly increased the likelihood of alcohol-related accidents. RTM was able to predict 41% (12 out of 29) of all DWI crashes that occurred in micro-level places identified as posing a higher risk for future traffic accidents. In other words, micro-places of 500 m by 500 m (324 cells or 0.39% of the study area) identified as "riskier" (see Fig. 1) allowed an effective forecast of the location of future drunk-driving crashes a year later. These results are consistent with the extant literature that supports the forecasting capacity of the RTM technique (see Kennedy et al. 2015; Dugato et al. 2017; Giménez-Santana et al. 2018).

To test the relationship between forecasted risk and the location of future DWI crashes, we decided to test the predictive accuracy of two different approaches, namely DWI crash hot spots and RTM. To conduct this comparison across methods, we used the predictive accuracy index (PAI). The interpretation of these results is simple: the higher the PAI values, the higher the predictive accuracy when comparing across techniques (Chainey et al. 2008). As shown in Table 2, PAI values of 3.3 were found for hot spots, 9.1 for RTM, and 13.3 for all places where high vulnerability and exposure to past crashes intersect. These results indicate that RTM as a solo method was overall more accurate in predicting the location of future DWI crash accidents when compared to hot spot analysis. However, it was the joint model of hot spots and RTM that emerged as the most accurate at predicting the location of future drunk-driving crashes. These results suggest that future DWI crashes are most likely to occur at places where high vulnerability and recent-past exposure to drunk-driving crashes intersect in space.

B.   RTM applied to traffic accidents in the province of Cádiz

A second RTM analysis was conducted for all traffic accidents ($n = 679$), including drunk driving incidents, in the province of Cádiz. As with the previous example, results suggest that restaurant locations are spatially associated with a higher likelihood of road traffic accidents. More specifically, locations within 2.5 km to a restaurant have an increased risk of drunk driving accidents of nearly two times[9] compared to any other location. Not only were restaurant locations significantly correlated in the two RTM analyses, but these locations were also the most significant predictors (i.e., highest risk score) for both types of car accidents. Moreover, another risk factor was found to be spatially correlated with the location of road traffic accidents, namely, recreational lodging locations. These places are known to attract large groups of people, thus increasing the volume of road traffic in the proximity of these locations. These locations commonly present crowded parking areas, thus increasing the chance for an accident to occur. As a result, the spatial influences of these risk factors could be indicative of the presence of high traffic environments in the vicinity of restaurants and

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[8] Based on the differential relative risk score (RRS) obtained with RTM for highways (RRS = 8.19) and secondary road networks (RRS = 5.23).
[9] As indicated by the RRS value of 1.82 obtained from the "Best Model Specifications" output produced by the RTMDx software.
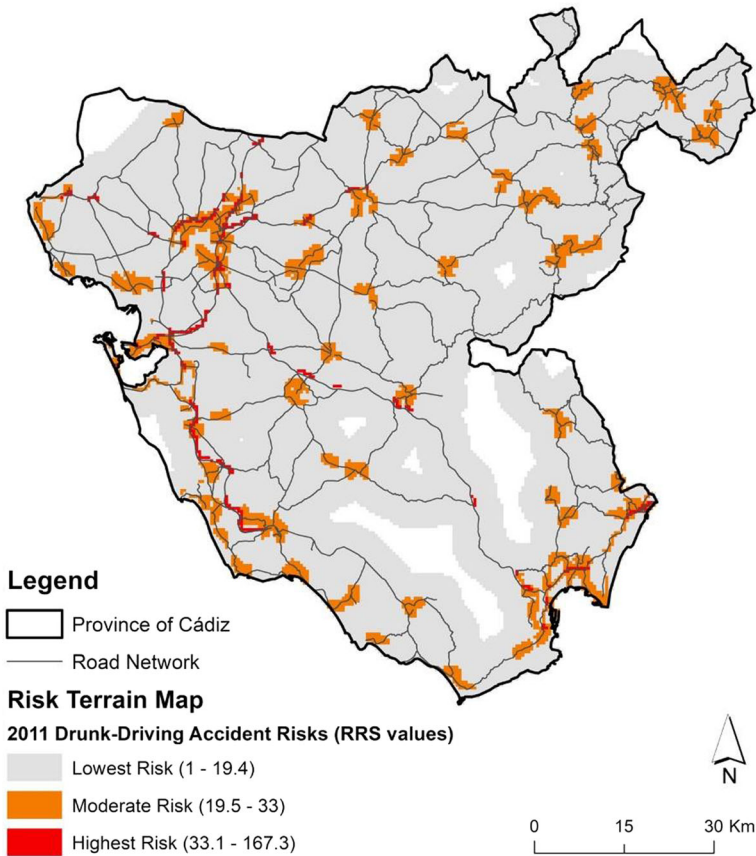
Province of Cádiz (Spain)

Fig. 1 RTM for drunk driving accidents during calendar year 2011

lodging locations. Lastly, secondary road networks emerged as presenting a higher risk for traffic crashes than those presented by freeways segments. However, the difference found between the two types of road networks was minor, with RRS values of 5.8 for conventional roads and 5.1 for freeways, therefore suggesting that the overall risk for traffic crashes is evenly distributed across varying types of roads in the province of Cádiz.

According to Fig. 2, the results presented by the risk terrain map on road traffic crashes in 2011 indicate that the highest risk of being a victim of a car accident tends to concentrate near the province's urban areas. This finding is consistent with previous research from Erdogan et al. (2008), suggesting that crossroads to cities and villages are hot spots for frequent traffic

Table 2 PAI comparison

	KDE	RTM	KDE + RTM
PAI	3.3	9.1	13.3

accidents. These results contrast with the previous model on drunk-driving accidents having a more dispersed spatial distribution throughout the study area. Such comparison illustrates the potential of crime-mapping techniques, in this particular case RTM, to improve awareness of the spatial patterns affecting traffic accidents.

Again, to compare the predictive accuracy of hot spots and RTM techniques in forecasting the location of future crash events, we measured the PAI values for each method. As shown in Table 3, the PAI value for KDE indicates that crash hot spots were more accurate at predicting the future location of traffic crashes than RTM. However, the joint utility of KDE and RTM outperformed both solo methods with a PAI value of 14.8. Therefore, these results suggest that contexts of high spatial vulnerability and exposure to past traffic crashes enhance prediction accuracy. This finding is consistent with previous research (see Caplan et al. 2013) as it demonstrates how incorporating the spatial assessment of exposure into the assessment of spatial vulnerability makes better places-based forecasts.
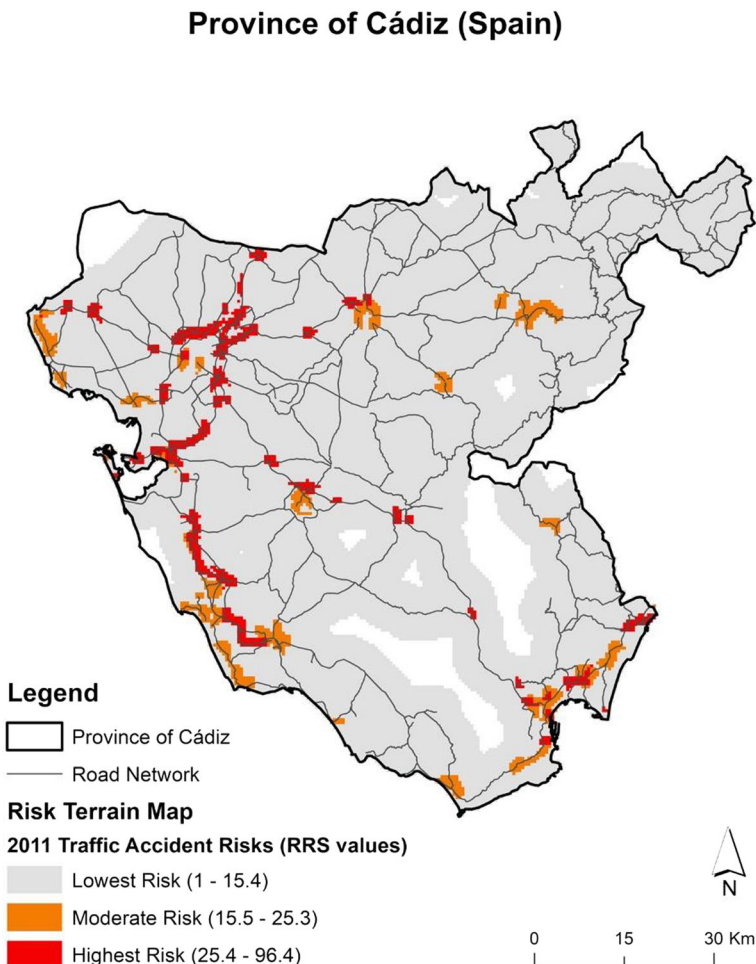

Fig. 2 RTM for overall traffic accidents during calendar year 2011

Table 3 PAI comparison

	KDE	RTM	KDE + RTM
PAI	11.9	5.5	14.8

Discussion and conclusions

The current analysis presented an overview on a number of ecological determinants of road traffic accidents and alcohol-related crashes in the Spanish province of Cádiz. The policy implications of this study are clear: the search for more effective strategies to reduce accident rates and improve road safety, a task that is not exempt from many challenges given the effect that factors like road design or heavy traffic environments pose on the increased likelihood of accident involvement. Nowadays, a considerable share of police work directly relates to an array of traffic issues (see Famega 2005); thus, the interest in advancing in the search of new tools that can help reduce accident rates and benefit police department operations. Having this objective in mind, we proposed modeling the spatial influence of the built environment using RTM to identify places posing a higher risk of future car accidents. As a result, law enforcement could benefit from better information to make strategic decisions, such as the ideal placement of police checkpoints to deter and prevent future traffic accidents and thus reduce crash rates.

The study of environmental criminology often comprises three theoretical frameworks: routine activities theory (RAT) (Cohen and Felson 1979), rational choice theory (Cornish and Clarke 1986), and crime pattern theory (Brantingham and Brantingham 1993). RAT addresses the spatial and temporal convergence of motivated offenders, suitable targets, and capable guardianship. According to Miró-Llinares and Medina-Sarmiento (2015), one of the underlying ideas from this theoretical framework is that criminal opportunity might depend on the spatial and temporal context in which crime events take place. In this regard, as noted by Mustaine and Tewksbury (1999, p. 85), "It appears that persons, in general, are more likely to drive drunk when they spend a greater proportion of their drinking time in bars, at friend's homes, and out in public." People drinking at bars are found to be at a higher risk of becoming DWI offenders than people drinking elsewhere. Similarly, people who tend to eat out present a higher risk of developing a favorable attitude towards drinking and driving (Mustaine and Tewksbury 1999). In other words, drunk driving is related to social contexts and how the combined effect of opportunities and cultural norms for driving and driving while impaired coexist. Therefore, it is in these spatial contexts that we should look for patterns that configure the risk for accidents as well as the risky behaviors that cause these events.

Access to affordable mapping software and to large data repositories offers law enforcement a unique opportunity to continue working in the development of new crime prevention strategies. Having this objective in mind, we suggested the use of RTM as an analytical tool to help diagnose the spatial influence of the built environment to at least partially explain the distribution of car accidents across Cádiz's province. As discussed in the results section, the use of the RTM technique allowed the identification of micro-level places that pose a higher risk for future crash accidents. As noted by Caplan and Kennedy (2016, p. 52), "Forecasting risky, or likely, locations for crime must incorporate spatial vulnerabilities and exposure at micro places if it is to yield the most efficient and actionable information—spatial intelligence." Hence, this signifies the importance of identifying and addressing the vulnerabilities emerging from specific environmental factors to improve road safety.

We consider that through the use of RTM, we have demonstrated how specific micro-level environmental factors are associated with a higher risk of road traffic accidents, as well as with an increased risk of DWI crashes. For instance, variations between high-capacity roads (i.e., freeways) and low-capacity road networks (i.e., secondary roads) presented a larger impact for DWI crashes than for overall traffic crashes. Therefore, these results indicate that increased speed limits across Cádiz's freeway road networks pose a higher risk for drunk-driving crashes. Moreover, the risk of traffic accidents caused by driving under the influence dramatically increased in locations within close proximity to restaurants, indicating a higher risk of victimization near these micro-level places. Similarly, we identified recreational lodging centers as places that present an increased risk for traffic accidents. This diagnosis can help law enforcement to implement the appropriate traffic safety measures to mitigate the risk posed by these micro-level places.

It is essential to have accurate and reliable databases to implement these types of strategies. In Spain, like in many other places, identifying the precise location of car accidents can be a challenging task because of the way traffic data is reported. These areas are usually reported by reference points (e.g., KPs) along with the distance to an intersection. As noted by Mammadrahimli (2015, p. 13), "Route identifiers are problematic because there is not always a single universal identifier used by all agencies within the same state." Police officers do not always have the tools to precisely measure the distance to an intersection leading to inaccurate locations of crash points. New advancements in the use of Global Positioning System (GPS) technology, are progressively being adapted to law enforcement operations to improve the location of accidents, thus improving data accuracy and reducing post-processing of location information for mapping and analysis (Mammadrahimli 2015).

We have stressed the importance of adopting evidence-based strategies to address the increase in the number of traffic crashes. This objective can be achieved by developing place-based strategies to identify where and when police resources should be placed to mitigate the risks associated with future crashes. As noted by the WHO (2015, p. 3), "A detailed understanding of the circumstances that lead to crashes is required to guide safety policy." In this way, it is essential to make the public aware of the risks derived from drunk driving behaviors. For instance, enforcement is more effective when mass media campaigns increase the public perception of the risk of being caught, thus reducing public acceptance of drinking and driving habits (Peltzer 2011).

To conclude, this study identified the micro-level environmental risk factors associated with a higher risk of traffic accidents and DWI crashes by forecasting the locations of future crash incidents during the year 2012. Moreover, this analysis proposed the use of RTM as a novel tool for the study of road safety. Through this method, police can develop targeted traffic safety strategies to mitigate the risk of future crashes, thus improving overall prevention strategies by reducing the spatial vulnerabilities created by specific features of the landscape and their enabling effect on future crash accidents.

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