Características de los vecindarios y la distribución espacial de problemas sociales en la ciudad de Valencia

TESIS DOCTORAL

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Índice

Abstract

The aim of this doctoral thesis is to explore the influence of neighborhood-level variables on the spatial and spatio-temporal distribution of different social problems in the city of Valencia. In **Study 1**, we present data on the development and validation of an observational instrument to assess neighborhood disorder. Results supported a three-factor model (physical disorder, social disorder and physical deterioration), and they showed good reliability and validity evidences. In **Study 2**, we assess the psychometric properties of a neighborhood disorder scale using Google Street View. Results supported a bifactorial solution with a general factor (general neighborhood disorder) and two specific factors (physical disorder and physical decay), and also showed good indicators of reliability and validity. In **Study 3**, we analyze the spatial distribution of drug-related police interventions and the neighborhood characteristics influencing these spatial patterns. Results indicated that high physical decay, low socioeconomic status, and high immigrant concentration were associated with high levels of drug-related police interventions. In **Study 4**, we analyze the spatio-temporal distribution of alcohol outlet density and its relationship with neighborhood characteristics. Results showed that off-premise density was higher in areas with lower economic status, higher immigrant concentration, and lower residential instability; restaurant and cafe density was higher in areas with higher spatially-lagged economic status, and bar density was higher in areas with higher economic status and higher spatially-lagged economic status. Furthermore, restaurant and cafe density was negatively associated with alcohol-related police calls-for-service, while bar density was positively associated with alcohol-related calls-for-service. In **Study 5**, we analyze the spatio-temporal distribution of suicide-related emergency calls. Results showed the importance of using a spatio-temporal modeling that also includes a seasonality effect. In **Study 6**, we

analyze the relationship of suicide-related calls with neighborhood-level variables. Results showed that neighborhoods with lower levels of education level and population density, and higher levels of residential instability, percentage of one-person households and aging population had higher levels of suicide-related calls for service. Finally, in **Study 7**, we analyze the influence of university campuses on intimate partner violence against women risk. Results showed that the distance to the university campuses was associated with an increased risk of intimate partner violence against women, once controlled for other types of neighborhood-level variables. This doctoral thesis contributes to the understanding of the neighborhood-level characteristics associated with different social problems. These results are useful when planning and implementing community-level prevention and intervention strategies.

1. Marco teórico

1.1 La influencia de las características del vecindario en los problemas sociales

1.1.1 La Escuela de Chicago

Los orígenes del estudio de los vecindarios como elemento sociológico relevante se pueden situar en la Escuela de Chicago. Esta escuela hace referencia a las investigaciones realizadas en el ámbito de las ciencias sociales llevadas a cabo por diversos autores de la Universidad de Chicago a principios del siglo XX (Abbot, 1997). Durante ese periodo, la ciudad de Chicago vivía inmersa en un proceso de expansión de gran magnitud, fruto de la llegada de inmigrantes europeos y de población rural que empezaba a dirigirse a las ciudades (Shaw y McKay, 1969; Sozzo, 2008). Este crecimiento en un corto periodo de tiempo supuso un proceso de transformación profunda de la ciudad, y la aparición de diversos problemas sociales como el auge de la delincuencia y de los conflictos sociales. Así, se creó el ambiente perfecto para el desarrollo de una nueva línea de estudios basados en la ciudad y en los cambios sociales que estaban ocurriendo en la misma (Bulmer, 1984).

Los investigadores de la época desarrollaron una serie de teorías sociológicas centrados en su interés por analizar el fenómeno social urbano desde un punto de vista científico (Abbot, 1999; Bellair, 2017; Sampson, 2012), dando pie al surgimiento del campo de la Sociología Urbana (Shaw y McKay, 1969). Las ideas iniciales de esta nueva rama de la sociología se basaban en que la ciudad se comportaba de la misma forma que ocurría con los seres vivos, tal como explicaba la teoría de la evolución darwinista; es decir, los residentes de las ciudades debían adaptarse al medio urbano y sus características para poder sobrevivir. La ciudad adquiría características totalmente diferenciadas de los entornos rurales, y en la primera las relaciones sociales se muestran de forma muy diferente y más impersonal. La formación y crecimiento de la ciudad de Chicago fue un ambiente óptimo para el estudio, asemejando las condiciones de un experimento natural, de las comunidades y sociedades humanas y de las relaciones que tienen entre los ciudadanos (Shaw y McKay, 1969).

La base del pensamiento de la Escuela de Chicago y su vinculación con la ciudad y los problemas urbanos tiene sus orígenes en los estudios clásicos de Park y Burgess (1925). Su investigación se centraba principalmente en estudiar la interacción entre los procesos de la naturaleza humana y la geografía física de la ciudad (Sampson, 2012).

Robert Park, considerado el fundador de la Escuela de Chicago y padre de la Sociología Urbana, sugirió en sus trabajos esa visión de la ciudad desde el punto de vista de una Ecología Humana (Park y Burgess, 1921; Sampson, 2012). Park consideraba que la ciudad estaba formada por una construcción física pero también por una construcción social, basada en tradiciones, costumbres, y actitudes sociales. Para este autor, el concepto de "comunidad" tendría gran relevancia, la cual definió como las relaciones que se desarrollan entre las diferentes especies de un mismo hábitat, que a través de mecanismos de cooperación y competición van formando comunidades más amplias con el objetivo de preservar el equilibrio (Brantingham y Brantingham, 1984). De este modo, una comunidad estaría formada por una población con una organización territorial clara, basada en individuos en constante relación, que tienen cierto arraigo con el área o suelo que ocupan. Los aspectos culturales, las tradiciones y las normas sociales posibilitarían la supervivencia de la comunidad (Park y Burgess, 1925).

Park defiende que la ciudad está formada por una serie de áreas naturales, con diferentes funciones y características poblacionales (Lindner, 1996). Estas áreas se agrupan de forma ordenada después de un proceso de competición entre comunidades para habitar cierto espacio urbano, creando un tejido social con sus propias características culturales y unas funciones definidas para la sociedad (Park y Burgess, 1925). De esta idea surgirían de una forma natural, sin realizar ninguna planificación consciente, las áreas tradicionales de la ciudad como son el centro donde se aglutina el comercio, las áreas más residenciales o las áreas industriales (Bulmer, 1984; Park, 1915).

Por otro lado, Ernest Burgess, trabajando en la misma línea que Park, propuso un modelo según el cual los entornos urbanos no evolucionan al azar, sino que se van desarrollando en forma de anillos concéntricos (Brantingham y Brantingham, 1984). Burgess consideró cinco tipos de anillos (Park y Burgess, 1925): El más interno sería el centro, origen de la ciudad y zona más comercial; a continuación, un área de transición, constituída por zonas industriales, que se caracteriza por ser un área con construcciones deterioradas y una alta desorganización social; seguidamente se situaría el área de la clase obrera, donde conviven aquellos trabajadores que han de acudir a trabajar a las industrias del nivel anterior, y por lo tanto les interesa vivir cerca de sus lugares de trabajo; a continuación encontraríamos un área residencial, donde vive el resto de la población, constituída por barrios privilegiados con más recursos; y por último, las áreas suburbanas (Figura 1).

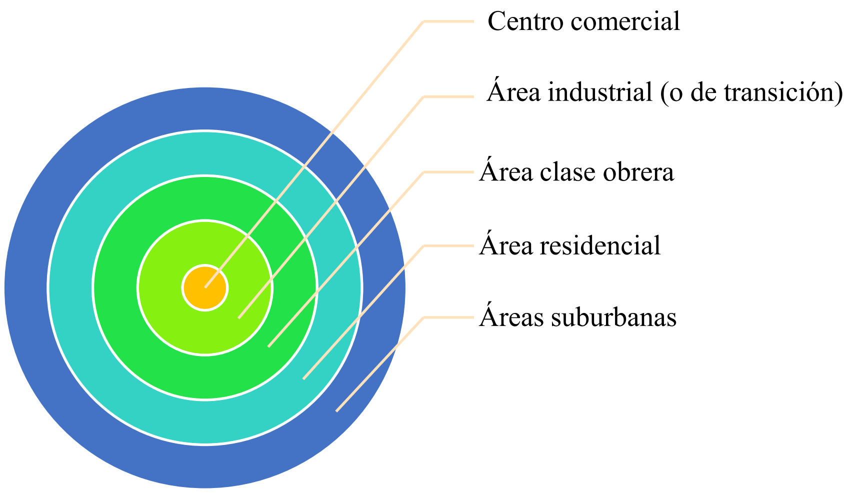

Figura 1. Distribución de la ciudad según el Modelo de Áreas Concéntricas de Burgess (Park y Burgess, 1925).

Estos anillos muestran diferentes características físicas y culturales: los más internos son incapaces de resistir el conflicto, y exhiben mayores niveles de deterioro físico y desorganizació social. En concreto, el área de transición sería la que mayor desorganización social mostraría, y presentaría características de desorden social del vecindario tales como prostitución, personas sin hogar, o niveles elevados de delincuencia y criminalidad. En cambio, los anillos más externos se acomodan, y permanecen ajenos a la desorganización y la delincuencia (Cullen y Agnew, 2011; Park y Burgess, 1925).

Las teorías y estudios aportados por Park y Burgess se complementan con el trabajo de Roderick McKenzie. Este autor se centró en la metrópolis y en la organización social de los espacios urbanos (McKenzie, 1933). McKenzie propuso que la comunidad y la ciudad se desarrollan de forma cíclica, empezando con un proceso de expansión que termina cuando se alcanza un equilibrio. Así, es importante estudiar las relaciones temporales y espaciales que se producen en el seno de la ciudad. Estas relaciones se ven afectadas por factores geográficos, como pueden ser los recursos territoriales de cada una de las zonas, factores económicos y factores culturales (McKenzie, 1924).

Los autores de la Escuela de Chicago dieron una especial importancia al vecindario, que surge como elemento de solidaridad social, y nace de la vinculación entre los ciudadanos de una forma más directa. Para entender la organización urbana general, es necesario a su vez estudiar cada una de las comunidades locales. Según el modelo de ciudad establecido por estas corrientes, la vida en el vecindario residiría en las áreas más periféricas, áreas que contarían con una población más estable, y una serie de costumbres y tradiciones esenciales para mantener el orden de la sociedad (Park y Burgess, 1925).

1.1.2 La teoría de la desorganización social

Más adelante, Shaw y McKay (1942) propusieron la teoría de la desorganización social extendiendo los trabajos de Park y Burgess e incorporando las características del vecindario y los factores sociales que median entre ellos. La teoría de la desorganización social apunta a que los vecindarios que muestran rasgos de desorganización social (es decir, una mayor privación económica, mayor movilidad residencial, y mayores niveles de heterogeneidad étnica), muestran a su vez niveles más altos de criminalidad (Sampson y Groves, 1989; Veysey y Messner, 1999; Law y Quick, 2013). Shaw y McKay centraron sus estudios en explicar la distribución espacial de la delincuencia juvenil en Chicago. Sus estudios mostraron que en el centro de la ciudad, donde había más desorganización social, había más delincuencia juvenil, y ésta se distribuía espacialmente de manera no aleatoria (Shaw y McKay, 1942).

Inicialmente, la teoría de la desorganización social se basaba en tres factores estructurales del vecindario: la privación económica, o bajo nivel económico, la alta movilidad residencial, y la heterogeneidad étnica (Shaw y McKay, 1942). La privación económica, medida con variables como la pobreza, el desempleo, o los bajos ingresos, supondría una falta de recursos por parte de los residentes que conduciría a un mayor aislamiento social. Por su parte, la inestabilidad residencial actuaría como barrera para el desarrollo de redes sociales positivas en la comunidad. Por último, la heterogeneidad étnica marcaría una segmentación del orden social del vecindario, y estaría causalmente relacionada con la delincuencia ya que genera conflictos entre los residentes, lo que impide la organización comunitaria (Bursik y Grasmick, 1993; Cullen y Agnew, 2011). Todos estos aspectos influirían de forma decisiva en el aumento de los problemas del vecindario, la criminalidad o el desorden (Sampson y Groves, 1989).

Estos autores propusieron que un entorno social organizado y estable es más proclive a la aparición de actitudes prosociales, de solidaridad y cohesión social, donde los residentes tienen una mayor capacidad para colaborar en la resolución de problemas sociales que surgen a nivel local (Bursik y Grasmick, 1993). Estos valores prosociales se ven reforzados por las instituciones sociales (escuelas, iglesias y otras organizaciones comunitarias). En cambio, en entornos sociales inestables, es más difícil la aparición de estas actitudes compartidas de apoyo y cohesión social, dando lugar a una menor socialización de los residentes y un aumento de la probabilidad de delincuencia y violencia (Browning, Feinberg y Dietz, 2004).

Las comunidades urbanas, afirman estos autores, tienen menos capacidad de control social en comparación con las comunidades suburbanas y rurales porque las características urbanas de la ciudad debilitarían las redes sociales y limitarían la participación social en los asuntos locales (Jacob, 2006; Sampson y Groves, 1989). Además, estas características urbanas afectarían a la oportunidad de que las personas participen en organizaciones comunitarias e impediría el fortalecimiento de vínculos sociales formales e informales entre los vecinos (Veysey y Messner, 1999). De esta forma, los vecinos se verían incapaces de formar una estructura comunitaria que trabaje de forma activa por proteger los valores comunes de los residentes y mantener un control social efectivo (Bursik, 1984).

Shaw y McKay utilizaron una gran cantidad de datos sobre la delincuencia juvenil, y realizaron mapas que mostraban cómo las áreas con mayores tasas de delincuencia juvenil se caracterizaban por una mayor presencia industrial, edificios deteriorados, gran movilidad residencial y una mayor concentración de inmigrantes y de afroamericanos. Con estos datos, concluyeron que la relación entre las características del vecindario y el crimen y la delincuencia estaba mediada por la desorganización social (Shaw y McKay, 1942).

Desde entonces, son muy diversos los estudios que se han realizado partiendo de las ideas de Shaw y McKay, y muchas las temáticas exploradas. Esto incluye, por ejemplo, la delincuencia juvenil (Browning et al., 2010; Jacob, 2006; Law and Quick, 2013; Oberwittler, 2004; Wikström y Loeber, 2000), la victimización (Browning y Erickson, 2009; Graif y Sampson, 2009; Sampson, Raudenbush y Earls, 1997; Veysey and Messner, 1999), el homicidio (Morenoff, Sampson y Raudenbush, 2001; Sampson et al., 1997; Thompson y Gartner, 2013), los delitos violentos (Andresen, 2006; Hipp. 2007) o la violencia familiar (Beyer, Wallis y Hamberger, 2015; Caetano, Ramisetty-Mikler y Harris, 2010; Coulton, Korbin y Su, 1999; Gracia, López-Quílez, Marco, Lladosa y Lila, 2014, 2015; Gracia, López-Quílez, Marco y Lila, 2017, 2018; Freisthler, Bruce y Needell, 2007; Freisthler, Gruenewald, Ring y LaScala, 2008; Frye y O'Campo, 2011).

Estos estudios han mostrado cómo los barrios desfavorecidos socioeconómicamente son aquellos que se relacionan en mayor medida con la criminalidad y otros problemas sociales, incluso después de tener en cuenta características individuales (Sampson et al., 1997; Thompson y Gartner, 2013). La inmigración también se ha relacionado con las tasas de criminalidad, y la investigación previa ha demostrado que los niveles más altos de heterogeneidad étnica se relacionan con niveles más altos de delincuencia (Sampson et al., 1997). De la misma forma, los estudios han encontrado que una baja estabilidad residencial se relacionaría con más problemas sociales, y los vecindarios con poblaciones más estables mostrarían tasas de criminalidad menores que los vecindarios caracterizados por una población transitoria y cambiante (Bursik y Webb, 1982).

1.1.3 La teoría de las ventanas rotas de Wilson y Kelling

Desde la teoría de las ventanas rotas (Broken Windows Theory, en inglés) se ha hecho hincapié en el concepto de desorden en el vecindario como elemento clave para entender los procesos de deterioro y mantenimiento de la decadencia de los vecindarios en las ciudades (Gracia, 2014; Sampson y Raudenbush, 1999; Skogan, 1990; Taylor, 1997, 2005; Toet y van Schaik, 2012; York Cornwell y Cagney, 2014; Wilson y Kelling, 1982).

Esta teoría, propuesta por Wilson y Kelling (1982), postula que las formas menores de desorden público conducen a un nivel de criminalidad superior y una espiral ascendente de decadencia urbana (Kelling y Coles, 1996). El nombre de la teoría proviene de la siguiente idea: si una ventana rota (o cualquier signo físico de desorden) situada en un vecindario no es reparada, habrá más probabilidad de que el resto de ventanas del vecindario acaben de la misma forma. Esto es así porque la ventana rota es señal de que los residentes no se preocupan por el buen funcionamiento de su vecindario, con lo cual alentan a los delincuentes a llevar a cabo futuros actos de vandalismo y violencia.

Según esta teoría, las señales físicas y sociales de desorden en el vecindario son una muestra de la falta de control social formal e informal. Por un lado, los agentes sociales (la policía o los administradores locales) no proveen de recursos al vecindario para la mejora de sus instalaciones; por otro lado, los vecinos no realizan ninguna vigilancia sobre su propio barrio. De esta forma, los delincuentes de la zona se ven alentados a realizar actos delictivos en esa área, a la vez que otros infractores de otras áreas se vean tentados a acudir a estas áreas. Todo ello puede producir un mayor desorden y criminalidad, creando una espiral de decadencia (Gracia, 2014; Sampson y Raudenbush, 1999; Skogan, 1990; Taylor, 1997, 2005; Toet y van Schaik, 2012; Wei, Hipwell, Pardini, Beyers, y Loeber, 2005; York Cornwell y Cagney, 2014).

De esta forma, la teoría de las ventanas rotas vincula el desorden y la criminalidad. De acuerdo con Gracia (2014), cuando ni los vecinos ni los agentes externos, como son la policía u otras autoridades, son capaces de intervenir y mantener el orden social, se produce un efecto de facilitación de más desorden, que conduce a mayores tasas de delincuencia.

El desorden en el vecindario, además, desencadenaría una sería de procesos negativos en la comunidad, como son el miedo, la inseguridad, la impotencia o la desconfianza, que lleva a los vecinos a no formar parte de la vida comunitaria, lo que aumenta a su vez la desorganización social y el deterioro del vecindario (Geis y Ross, 1998; Kim y Conley, 2011; Ross, Mirowsky, y Pribesh, 2001; Skogan, 1986, 1990).

Por último, el desorden en el vecindario se ha relacionado con el deterioro urbano, la concentración de problemas sociales, la segregación racial, la desintegración social, la desconfianza en la policía, u otras estrategias de control público como la denuncia del delito (Gracia, Garcia, y Musitu, 1995; Gracia y Herrero, 2007; Ross y Mirowsky, 1999; Skogan, 1990; Toet y van Schaik, 2012).

1.1.4 Wilson y "los verdaderos desfavorecidos"

A finales de la década de los 60, se empezaron a producir una serie de cambios macroeconómicos en Estados Unidos que promovieron el cuestionamiento de las teorías de la desorganización social (Bursik, 1988). Como resultado de estos cambios macroeconómicos, en la década de los 80 el desempleo y la pobreza en Estados Unidos llegaron a niveles no conocidos hasta entonces. William Julius Wilson, desde la Universidad de Chicago, se interesó por estos fenómenos y realizó un análisis del vecindario y de los problemas sociales relacionados con la pobreza de los ciudadanos, reorientando la investigación existente respecto a la influencia de los vecindarios en los problemas sociales (Sampson, 2012).

Este autor estudió cómo las profundas transformaciones sociales sufridas en el centro de las ciudades habían dado lugar a un incremento de la concentración de población más desfavorecida. Estas transformaciones se debieron a que la población afroamericana había abandonado las zonas rurales para dirigirse a zonas urbanas más industrializadas (Wilson, 1987). Sin embargo, a medida que las ciudades fueron cediendo estos trabajos en la industria a otros negocios relacionados con el sector terciario, los jóvenes afroamericanos que anteriormente tenían un trabajo de poca cualificación en las fábricas dejaron de ser útiles para el sistema económico, teniendo que competir por nuevos empleos con una exigencia educativa superior. Esto posicionó a la población afroamericana con mayores niveles educativos y más favorecidos en una clase media creciente, pero aquellos jóvenes afroamericanos con menores capacidades se vieron rechazados por el sistema (Sampson, 2012; Wilson, 1991). Las familias afroamericanas de clase media se movieron a zonas más externas de la ciudad, mientras que los guetos del centro de las ciudades se quedaron únicamente poblados por afroamericanos desempleados, familias monoparentales y personas con graves problemas económicos, aumentando la concentración de la pobreza en estas zonas urbanas deprimidas (Wilson, 1987). Estos movimientos de esta nueva clase media a las zonas más externas de la ciudad, supuso, a su vez, la eliminación de modelos positivos para los jóvenes más pobres y la desaparición de las instituciones comunitarias anteriormente formadas por familias afroamericanas de clase media y trabajadora (Sampson, 2012).

La investigación anterior sobre las clases sociales se había centrado en las características individuales de aquellos más desfavorecidos, a los que tendían a culparles de sus propios problemas, defendiendo argumentos como la falta de motivación o una actitud negativa hacia el trabajo, en lo que englobaría una cultura de la pobreza. Las clases sociales más bajas se mostraban compuestas mayoritariamente de población afroamericana, lo cual tendía a incrementar los estereotipos raciales desde un punto de vista individual (Wilson, 1987). Sin embargo, Wilson se desvió de esta corriente, y sugirió que existen otras causas más comunitarias que explican estos fenómenos, como el aislamiento social, las características culturales y las oportunidades sociales y económicas. Es decir, él propuso que no se trata de que las características individuales creen diferencias entre la población, sino que la pobreza urbana, mayoritariamente afroamericana, tiene un origen cultural y estructural (Wilson, 1987, 1991, 1996).

De esta forma, características como la pobreza y la segregación social fueron elementos clave para este autor en el estudio de los contextos comunitarios. Así, propuso el concepto de “los verdaderos desfavorecidos”, del inglés, *The truly disadvantaged* (Wilson, 1987). Wilson define a la clase social que se situaría en el peldaño más bajo de la pirámide de la organización social como aquella en la que sus individuos carecen de habilidades de trabajo, están fuera del mercado laboral o sufren un desempleo de larga duración, y además están inmersos en un proceso de pobreza, que les hace involucrarse en delitos callejeros y depender de los sistemas de seguridad social (Wilson, 1987).

Wilson realizó un análisis de diferentes ciudades de Estados Unidos, centrándose especialmente en la población afroamericana (y en menor medida en la población latina), y vio cómo esta comunidad se había deteriorado rápidamente por la falta de acceso a los puestos de mayor privilegio e influencia. En concreto, en los años 80 la comunidad afroamericana experimentó un aumento en el número de familias disfuncionales y familias monoparentales, las tasas de criminalidad, especialmente en delitos violentos, y el desempleo, en parte debido a un aumento del empobrecimiento y la marginalidad de las clases trabajadoras (Wilson, 1987). Mediante investigaciones exhaustivas exploró la tasa de desempleo entre los ciudadanos afroamericanos y los ciudadanos blancos, así como los ingresos anuales. Wilson demostró que la desigualdad en los ingresos y en el desempleo era mayor entre las familias afroamericanas que entre las familias blancas. Estas altas tasas de desempleo entre los jóvenes negros en las ciudades tienen un gran impacto en la estructura familiar. Wilson estableció una conexión entre los problemas económicos de la población joven afroamericana y el crecimiento desproporcionado del número de familias monoparentales afroamericanas, formadas por una madre y sus hijos (Wilson, 1987).

Para hablar de la pobreza urbana desde el punto de vista de los vecindarios y explicar los procesos sociales que hay detrás de este fenómeno, Wilson utiliza dos conceptos esenciales (Young, 2003). En primer lugar, habla de los *efectos de concentración* (del término *concentration effects*, en inglés). Estos efectos de concentración hacen referencia a las limitaciones en cuanto a igualdad de oportunidades en las que viven aquellos residentes de los vecindarios que presentan más desventajas sociales, es decir, se produce cuando un gran número de personas en situaciones de pobreza viven en áreas próximas (Wilson, 1987). La pobreza urbana, por lo tanto, no se basa sólo en ser pobre o residir en un vecindario con residentes pobres, sino en que el contexto social esté estructuralmente basado en personas con el mismo estado de pobreza. Wilson se refirió a los barrios desfavorecidos socioeconómicamente como aquellas áreas con una concentración de afroamericanos pobres, sin trabajo, con un alto nivel de delincuencia, y con dificultades de movilidad residencial (Young, 2003). Sostuvo que los efectos negativos en la vida de sus residentes se ven agravados por la estabilidad residencial entre los residentes pobres, que no pueden acceder a otro tipo de vida y moverse a áreas más prósperas de la ciudad, a diferencia de la clase media. Es decir, aunque estas áreas, como apuntaban Shaw y McKay, continuaban experimentando movilidad residencial, una parte de la población (los residentes más pobres y desfavorecidos) sí mostraban estabilidad residencial debido a su incapacidad para moverse a áreas más prósperas (Wilson, 1987).

El otro concepto importante que propone Wilson es el del aislamiento social como elemento clave para explicar la pobreza urbana (Young, 2003). El aislamiento social sería resultado de la distancia, tanto geográfica como social, entre los residentes de las ciudades de clase social baja y otro tipo de residentes, así como de las instituciones y recursos a los que sí pueden acceder los residentes con mayor estabilidad económica. La fuga de la clase media afroamericana de estas zonas desfavorecidas provoca el aislamiento social y cultural entre los residentes más pobres y desfavorecidos, ya que éstos se quedan sin modelos de aprendizaje de comportamientos más adecuados, propios de la clase media (Wilson, 1987), tal y como se ha apuntado anteriormente.

A su vez, el aislamiento social incrementa los efectos negativos de la concentración de la pobreza (Sampson y Wilson, 1995). Los residentes de estas áreas empobrecidas no pueden acceder a las instituciones sociales de sus comunidades, tales como escuelas, asociaciones comunitarias, iglesias, etc., puesto que estos se desplazan con la ausencia de la clase media y trabajadora, lo que da lugar a que el desempleo se convierte en una forma de vida validado socialmente y pierda su estigma negativo (Young, 2003). El aislamiento social que propone, por tanto, no es tanto a nivel individual, sino una característica comunitaria, es decir, supone que las comunidades urbanas empobrecidas están desconectadas tanto geográfica como socialmente de otro tipo de comunidades que son las que tienen a su disposición los recursos municipales y sociales necesarios para la mejora de la calidad de vida de los ciudadanos (centros de salud, organizaciones comunitarias, servicios sociales, etc.)

Los vecindarios que están sujetos a una mayor concentración de problemas sociales y al aislamiento social muestran en consecuencia una incapacidad de desarrollar y mantener vínculos con las redes sociales y las instituciones que son claves para conectar con el mundo del trabajo y las oportunidades laborales (Wilson, 1987;

Young, 2003). Formar parte de vecindarios con estas condiciones de vida reduce la capacidad de desarrollar patrones de comportamiento positivos para el desarrollo de una vida laboral más sólida. Todo ello separa radicalmente a la sociedad general de los residentes en este tipo de vecindarios.

Wilson sugirió que los programas sociales contra la discriminación racial no estaban actuando correctamente (Wilson, 1987). Estos programas eran de gran ayuda para las personas afroamericanas con un mayor nivel educativo y capacidad de empleo, sin embargo no estaban funcionando para la comunidad afroamericana más empobrecida, con escaso acceso al mercado de trabajo, por lo que las políticas antidiscriminación y antirracismo de la época no eran útiles para la clase más baja. Wilson centró la crítica en que los responsables de las políticas públicas debían centrarse no sólo en los individuos, sino en encontrar una solución comunitaria a los problemas de los vecindarios del centro de las ciudades (Wilson, 1987).

Los estudios de Wilson, por lo tanto, suponían ciertos cambios respecto a las teorías de Shaw y McKay (1942). Ahora, los vecindarios que mostraban mayores problemas sociales, como procesos de delincuencia o criminalidad, serían aquellos más desfavorecidos socioeconómicamente, pero con homogeneidad étnica (compuesta por afroamericanos), y con menor inestabilidad residencial (debido a la incapacidad de estos residentes de salir de estas áreas). Estos resultados no son congruentes con lo esperado por las teorías de la desorganización social, que apuntan a que la pobreza, la heterogeneidad étnica y la inestabilidad residencial son claves para explicar las altas tasas de delincuencia en los vecindarios, y apuntan a que las ciudades que estudiaron en su día Shaw y McKay (1942) habían evolucionado a otro tipo de ciudades más modernas. Así, en las ciudades de los años 80, los barrios más desfavorecidos socioeconómicamente se caracterizarían por una mayor estabilidad residencial, que puede causar frustración y aislamiento en la población, y una mayor homogeneidad racial, que conduciría a mayor aislamiento social.

Una de las aportaciones fundamentales de las teorías de Wilson en la investigación actual es el uso del concepto de barrios desfavorecidos socioeconómicamente (en inglés, *concentrated disadvantage),* en lugar de utilizar únicamente el concepto de pobreza o estatus económico, con el fin de explicar la desorganización social y las tasas de delincuencia en el vecindario (Bellair, 2000; Browning, 2002; Gracia, López-Quílez, Marco, Lladosa y Lila, 2014, 2015; Kubrin y Weitzer, 2003; Morenoff et al., 2001; Peterson y Krivo, 1996; Sampson et al., 1997; Sampson y Raudenbush, 1999; Thompson y Gartner, 2013; Warner, 2003; Wright y Benson, 2010). La investigación actual ha apuntado que estos barrios desfavorecidos socioeconómicamente serían clave a la hora de analizar las características de los vecindarios donde la criminalidad y la violencia es mayor, y un gran número de publicaciones ha encontrado esta variable como la más relevante a la hora de explicar procesos violentos en el vecindario (Benson, Fox, DeMaris y Van Wyk, 2003; Gracia et al., 2014, 2015; Sampson et al., 1997; Thompson y Gartner, 2013; Wright y Benson, 2011).

De la misma forma, en vez de utilizar la heterogeneidad racial, muchos investigadores posteriores se han centrado en analizar la concentración de inmigrantes en el vecindario, puesto que los barrios más desfavorecidos suelen presentar una gran homogeneidad racial (Browning et al., 2004; Morenoff et al., 2001; Sampson et al., 1997; Sampson y Raudenbush, 1999).

1.1.5 Nuevas aportaciones a la Teoría de la Desorganización social

A partir de los estudios clásicos de la desorganización social han sido muchos los autores que han realizado aportaciones y actualizaciones a esta teoria. Las propuestas más actuales derivan del enfoque sistémico, según el cual la organización social de las comunidades es vista como un sistema complejo de redes sociales. Una buena organización comunitaria aumenta la capacidad de control social informal, es decir, la capacidad de los residentes del vecindario para mantener una vigilancia informal de los espacios mediante la observación activa de las actividades que ocurren en las calles del vecindario, desarrollar reglas que rijan el comportamiento dentro de este e intervenir directamente cuando se dan lugar problemas en el vecindario o comportamientos que se consideran inaceptables en la comunidad (Bursik, 1988).

En los barrios en los que el rechazo a la violencia es un valor compartido, ejercer la violencia supondría altos costos sociales para los perpetradores (Bursik, 1999; Gracia y Tomás, 2014). La desaprobación comunitaria del uso de la violencia, por lo tanto, puede ser inhibidor de los actos violentos debido al temor a sanciones públicas informales, como la pérdida de respeto (Emery, Jolley y Wu, 2011; Fox y Benson, 2006; Gracia, 2014; Wright y Benson, 2011) o a la preocupación de que los vecinos llamen a la policía (Emery et al., 2011). Estos vecindarios jugarían un papel protector, y se esperaría que las tasas de violencia fueran más bajas en comparación con otros vecindarios cuyas normas sociales son más tolerantes con respecto a la violencia como forma de resolución de problemas. Siguiendo estas ideas, los vecindarios con altos niveles de desorganización social y socialmente desfavorecidos mostrarían bajos niveles de control social. Por otra parte, la falta de recursos, las pobres condiciones socioeconómicas, o los altos niveles de exposición al desorden y a la violencia en estas comunidades puede incrementar los niveles de estrés en los residentes y el nivel de tolerancia hacia la violencia, a su vez que reducirían los niveles de control social, lo cual facilita la incidencia de criminalidad (Caetano et al., 2010; Lila, Gracia y Murgui, 2013; Raghavan, Mennerich, Sexton y James, 2006).

En las últimas décadas, Robert Sampson y colaboradores han realizado una importante aportación en este sentido, examinando los procesos sociales que pueden estar detrás de la relación entre las características del vecindario y los problemas sociales. Estos autores proponen que algunos vecindarios pueden dar forma a un particular "paisaje cognitivo" con respecto a la violencia (Sampson y Lauritsen, 1994). Este concepto hace referencia a las normas culturales sobre los estándares de conducta apropiados, incluyendo actitudes hacia la violencia. Este paisaje cognitivo podría caracterizarse por normas sociales basadas en el respeto, la igualdad y la intolerancia a la violencia que inhibirían los procesos de violencia en la comunidad o, por el contrario, por normas sociales basadas en la tolerancia hacia la violencia como una vía aceptable para resolver problemas (Bursik, 1999; Fox y Benson, 2006; Sampson y Wilson, 1995).

Sampson y colaboradores (1997) han proporcionado además un nuevo empuje a la teoría de la desorganización social por su uso de una metodología más exhaustiva en el análisis de los procesos sociales involucrados en la relación entre las características del vecindario y los problemas sociales, la delincuencia y la criminalidad (Raudenbush y Sampson, 1999). En este sentido, y siguiendo los razonamientos sobre el control social informal, propusieron el concepto de eficacia colectiva como elemento fundamental para explicar estos procesos en el vecindario. La eficacia colectiva se define como el proceso de activar los lazos sociales entre los residentes del barrio para alcanzar objetivos colectivos, como el orden público o el control del delito (Sampson, 2010). De este modo, la eficacia colectiva está caracterizada por dos elementos: la cohesión social entre los vecinos (su confianza entre ellos y cooperación para conseguir objetivos comunitarios), y la voluntad para intervenir activamente para lograr el bien común (Sampson et al., 1997). La falta de eficacia colectiva se asocia con una mayor desconfianza entre los vecinos, lo que crea un entorno peligroso e impide el control social efectivo, lo que conduce a un aumento de los conflictos y de la criminalidad (Kubrin y Weitzer, 2003; Sampson y Groves, 1989; Sampson et al., 1997).

Estos autores han encontrado resultados que evidencian la importancia de la eficacia colectiva como mediador de la relación entre las características del vecindario y la criminalidad y la violencia en diferentes contextos y países (Morenoff et al., 2001; Sampson et al., 1997; Sampson, 2012). Un reciente metaanálisis sobre la criminalidad desde un punto de vista comunitario refuerza este apoyo a la eficacia colectiva como elemento fundamental (Pratt y Cullen, 2005).

1.1.6 Influencia de las características del vecindario en las relaciones familiares

Como hemos visto hasta ahora, el estudio de la influencia del vecindario en los problemas sociales se ha centrado en analizar aquellos problemas que ocurren en espacios públicos, es decir, la criminalidad, la violencia callejera, el desorden en el vecindario, o los delitos relacionados con drogas entre otros. Sin embargo, otra línea de estudios se ha centrado en analizar otro tipo de problemática en los que la influencia del vecindario no parece tan evidente, puesto que se desarrollan en la intimidad de los hogares, donde en principio puede parecer que el vecindario es poco determinante. Nos referimos a la violencia en el ámbito familiar, donde destacan el maltrato infantil y la violencia de género.

Algunos estudios consideran que los malos tratos y la desprotección de los menores necesitan comprenderse más allá de los factores individuales y relacionales, para incluir factores del contexto social más amplio (Garbarino, 1977; Belsky, 1980; NRC-National Research Council, 1993; IOM y NRC, 2014), Entre los factores del contexto social que mayor atención han recibido en la investigación se encuentran los vecindarios donde residen las familias. La investigación de las relaciones entre las características de los vecindarios y el riesgo de malos tratos y la probabilidad de ingresar en los sistemas de protección de la infancia cuenta ya con una larga tradición que se remonta a los estudio pioneros realizados por Garbarino y sus colegas (e.g., Coulton, Korbin, Su y Chow, 1995; Coulton, Korbin y Su, 1996, 1999; Drake y Pandey, 1996; Ernst, 2001; Freisthler et al., 2007, 2008; Garbarino y Crouter, 1978; Garbarino y Sherman, 1980; Klein, 2011; Klein y Merritt, 2014; Lery, 2009; Merritt, 2009; Molnar, Buka, Brennan, Holton y Earls, 2003).

La investigación desarrollada desde entonces ha vinculado características estructurales y demográficas de los vecindarios como los niveles de pobreza y otros indicadores socioeconómicos, la inestabilidad residencial, la violencia en la comunidad, el acceso a drogas y alcohol, la concentración de familias monoparentales, la densidad poblacional, la disponibilidad de recursos para el cuidado y educación de los menores, o la composición étnica con las tasas de incidencia de malos tratos en la infancia y la probabilidad de los menores de entrar en los sistemas de protección (Coulton, Crampton, Irwin, Spilsbury y Korbin, 2007; Freisthler, Merritt y LaScala, 2006; Maguire-Jack, 2014).

En su conjunto, este cuerpo de literatura apoya la idea de que ‘el lugar’ importa, y que determinadas características de los vecindarios, como el empobrecimiento y la desorganización social, constituyen factores contextuales significativos en las variaciones del riesgo de malos tratos y desprotección de menores. Este vínculo se ha interpretado generalmente en términos de la teoría de la desorganización social (Shaw y McKay, 1942; Sampson et al., 1997), proponiendo que estas características de los barrios debilitarían la capacidad de la comunidad para ejercer el control social sobre los miembros de la misma, y regular la conducta también en el ámbito familiar mediante la supervisión del cuidado de los menores (Coulton et al., 1999; Garbarino y Kostelny, 1992; Gracia y Herrero, 2006).

Asimismo, se ha considerado que las familias residentes en vecindarios desfavorecidos y socialmente desorganizados experimentan mayores niveles de estrés, reduciendo la calidad de la conducta parental (Franco, Pottick y Huang, 2010; Garbarino y Sherman, 1980; Gracia, Fuentes, García y Lila, 2012; Guterman, Lee, Taylor y Rathouz, 2010; Leventhal y Brooks-Gunn, 2000). Finalmente, en estos vecindarios también se puede producir un proceso de aislamiento de los valores sociales mayoritarios con respecto a lo que es aceptable en las relaciones padres-hijos, formándose un sistema de actitudes y valores sobre los estándares y expectativas de la conducta parental más tolerante con respecto a comportamientos que, al no reconocerse como 'desviantes', pueden poner a los menores en riesgo de desprotección, incrementando su incidencia (Gracia y Herrero, 2008; Sampson y Lauritsen, 1994).

En general, la investigación desarrollada en este ámbito de estudio sugiere que, más allá de los factores individuales de riesgo, la distribución desigual de factores de riesgo del vecindario podría estar asociada a una distribución desigual del riesgo de malos tratos y desprotección del menor en esos vecindarios. En el Anexo 2 y el Anexo 3 se muestran dos trabajos sobre el riesgo de maltrato infantil en los vecindarios realizados por nuestro equipo de investigación, trabajos en relación directa con esta tesis doctoral, y cuyos resultados van en línea con esta hipótesis (Gracia, López-Quílez, Marco y Lila, 2017, 2018). Según estos trabajos, el riesgo de maltrato infantil no se distribuye aleatoriamente en el espacio y en el tiempo, sino que sigue ciertos patrones espacio-temporales que se relacionan con ciertas características del vecindario, como son un menor estatus económico, un menor nivel educativo, y mayores tasas de actividad policial y de inmigración (Gracia et al., 2017, 2018).

Por otro lado, recientemente estas ideas se han extendido también al estudio de la violencia contra la mujer en las relaciones de pareja. Un creciente número de investigadores, basándose principalmente en la teoría de la desorganización social y en las aproximaciones ecológicas (ver Apartado 1.1.2), ha impulsado el reconocimiento de la importancia de los factores de riesgo más allá de los niveles individual y relacional. De esta forma, son muchos los autores que han empezado a explorar en mayor medida el rol de los factores contextuales en la explicación de la violencia de género (Browning, 2002; Pinchevsky y Wright, 2012).

La violencia de género es un tipo de delito de características especiales, ya que ocurre dentro del ámbito familiar, donde es difícil acceder. Así, ha sido conceptualizado como un tipo de violencia que ocurre *behind closed doors*, o "detrás de puertas cerradas" (Strauss, Gelles y Steinmetz, 1980; Wright y Benson, 2011). Sin embargo, cada vez más estudios sugieren que este tipo de violencia, como ocurre con otros tipos de delitos, no solo se relaciona con las características individuales y los procesos relacionales, sino que también estaría asociada con las características del barrio (Burke, O'Campo y Peak, 2006; Caetano et al., 2010; Cunradi, Mair, Ponicki, y Remer, 2011; Frye y O'Campo, 2011; Kirst, Lazgare, Zhang y O'Campo, 2015; Li et al., 2010).

En concreto, algunos estudios han comprobado que las mujeres que residen en barrios desfavorecidos (con altos niveles de pobreza, desempleo, desorden social y violencia en general) suelen presentar un mayor riesgo de sufrir violencia de género

(Benson et al., 2003; Cunradi, 2010; Cunradi et al.,, 2011; Fox y Benson, 2006; Gracia et al., 2014, 2015). Tal y como apunta la teoría de la desorganización social, son aquellas características relacionadas con la pobreza, el desempleo o el desorden físico o social, y que se pueden definir como condiciones negativas del vecindario, las que aparecen como uno de los predictores más consistentes de las tasas de violencia de pareja contra la mujer, incluso cuando se controlan los niveles individuales (Beyer et al., 2013; Cunradi, Caetano, Clark, y Schafer, 2000; O'Campo, Burke, Peak, McDonnell, y Gielen, 2005; Pinchevsky y Wright, 2012). Otros factores demográficos como inestabilidad residencial, heterogeneidad étnica o mujeres solteras con hijos también han sido analizados, con resultados mixtos (Benson et al., 2003; Browning, 2002; Waller et al., 2011).

En esta línea, se han publicado dos revisiones sistemáticas que muestran la influencia de los vecindarios en la violencia de pareja, señal del interés científico que están suscitando los factores comunitarios. Ambas revisiones sugieren que los factores del vecindario más comúnmente asociados con la violencia de género son las que tienen que ver con las desventajas socioeconómicas del barrio (Beyer, Wallis y Hamberger, 2013; Pinchevsky y Wright, 2012). Estas revisiones sistemáticas, sin embargo, también muestran que las evidencias que vinculan la violencia de pareja con otras características del vecindario, como son la concentración de inmigrantes, la inestabilidad residencial, los problemas en el barrio o la delincuencia, son menos concluyentes.

Para explicar la relación entre las condiciones negativas del barrio y la violencia de pareja contra la mujer, se ha sugerido que las comunidades con mayor privación social serían menos capaces de ejercer control social sobre sus vecinos, puesto que la violencia es considerada una conducta tolerada y aceptada (Taylor, 1997). Por otra parte, la falta de recursos, las pobres condiciones socioeconómicas, y los altos niveles de exposición al desorden y la violencia en estas comunidades puede incrementar los niveles de estrés en los residentes y el nivel de tolerancia hacia la violencia, y reducir los niveles de control social, facilitando la incidencia de violencia contra la mujer en las relaciones de pareja (Caetano et al., 2010; Lila et al., 2013; Raghavan et al., 2006). Los estudios disponibles sugieren que el mantenimiento de normas sociales compartidas de aceptación de la violencia como forma de relación social puede incrementar las tasas de violencia de pareja en estos vecindarios (Browning, 2002; Pinchevsky y Wright, 2012; Wright y Benson, 2011). Algunas investigaciones también han estudiado la influencia de procesos como la eficacia colectiva en la violencia contra la mujer en las relaciones de pareja (Browning, 2002; Jackson, 2016; Showalter, Maguire-Jack y Barnhart, 2017; Wright y Benson, 2011).

Los Anexos 1 y 3 muestran dos estudios de nuestro equipo de investigación sobre las características del vecindario relacionadas con un mayor riesgo de la violencia de género, estudios que complementan los trabajos de esta tesis doctoral. En ellos se comprueba que la violencia contra la mujer en las relaciones de pareja no se distribuye al azar en las ciudades, sino que existen ciertas características de los vecindarios, como el estatus socioeconómico, la concentración de inmigrantes, el desorden en el vecindario, o la criminalidad, que hacen que el riesgo de este tipo de violencia “behind closed doors” sea mayor (Gracia et al., 2014, 2015, 2018). Estos procesos espaciales, además, serían comunes entre el maltrato infantil y la violencia de género (Gracia et al., 2018): estos dos problemas sociales mostrarían un riesgo alto en las mismas áreas de la ciudad (ver Anexo 3).

2. Problemas sociales estudiados en la tesis

2.1 El desorden en el vecindario (Estudios 1 y 2)

El concepto de desorden en el vecindario ha sido muy estudiado desde diferentes disciplinas científicas como son la sociología, la criminología, la psicología social o la epidemiología. El desorden en el vecindario se puede definir como las características físicas y sociales observadas o percibidas de los vecindarios, que son señal de una ruptura del orden y el control social, y que pueden deteriorar la calidad de vida del vecindario (Gracia, 2014). Así, características del vecindario como pueden ser la prostitución, la venta de drogas, las peleas en la calle, la presencia de coches abandonados, viviendas tapiadas o quemadas, o la basura en las calles, serían ejemplos del desorden en el vecindario (Sampson y Raudenbush, 1999; Skogan, 1990; Taylor, 2001; Wilson y Kelling, 1982).

El desorden en el vecindario tradicionalmente se ha ligado a las teorías de la desorganización social (ver Apartado 1.2.1), y su premisa de que las características estructurales de los vecindarios, como la privación social, pueden producir una falta de control social y aumentar a su vez los niveles de violencia, criminalidad, y otros procesos del vecindario (Gracia, 2014; Kingston, Huiziga, y Elliot, 2009; Kubrin y Weitzer, 2003; Park, Burgess, y McKenzie, 1925; Sampson et al., 1997; Shaw y McKay, 1942; Wilson, 1987).

Tradicionalmente, el desorden en el vecindario se ha estudiado en relación a otros problemas que ocurren en la calle, como son la criminalidad y la violencia (Law, Quick y Chan, 2014; Toet y van Schaik, 2012; Skogan, 1990). En los últimos años, su estudio se ha extendido también a otros ámbitos, donde destacan las investigaciones que han relacionado el desorden en el vecindario con procesos sociales que ocurren "behind closed doors" (ver Apartado 1.1.6). Entre ellos encontramos estudios que han analizado la relación entre el desorden en el vecindario y las prácticas parentales (Gracia et al., 2012; Lila y Gracia, 2005; McDonell, 2007), el maltrato infantil (Coulton et al., 1999, 2007; Freisthler et al., 2006, 2007; Garbarino y Sherman, 1980; Gracia y Musitu, 2003; Lila y Gracia, 2005), o la violencia de género (Cunradi, 2007, 2009; Gracia, Herrero, Lila, y Fuente, 2009; Kirst et al., 2015).

Los estudios que han analizado el desorden en el vecindario han sugerido diferentes clasificaciones del mismo. La mayoría de estudios ha defendido la clasificación del desorden en el vecindario en dos tipos: el desorden físico y el desorden social (Brunton-Smith, Sindall, y Tarling, 2010; LaGrange, Ferraro, y Supancic, 1992; Robinson, Lawton, Taylor, y Perkins, 2003; Sampson y Raudenbush, 2004; Skogan y Maxfield, 1981). El desorden físico hace referencia a características de deterioro como son las casas abandonadas, los grafitis, la basura en la calle, coches abandonados, preservativos usados en las calles, o locales abandonados solares (Brunton-Smith, 2011; Garvin, Cannuscio y Branas, 2013; Robinson et al., 2003; Sampson y Raudenbush, 1999; Skogan, 1990; Taylor, 2001, Toet y van Schaik, 2012). Por otro lado, el desorden social hace referencia a eventos que ocurren en lugares públicos y que son percibidos por los ciudadanos como potencialmente amenazantes, como pueden ser personas consumiendo alcohol y drogas en la calle, la protitución callejera, la venta de drogas, las peleas callejeras, la presencia de personas sin hogar, o elevados niveles de actividad policial (Gracia, 2014; Ross y Mirowsky, 2001; Sampson, 2009; Sampson y Raudenbush, 2004).

Otra línea de investigación ha considerado no sólo estas dos categorías, sino que, además, ha distinguido entre desorden físico y deterioro físico, dando lugar a tres categorías. Así, el desorden físico se centraría en manifestaciones del comportamiento humano como pueden ser basura en las calles (ya sea botellas, desperdicios, o preservativos), grafitis, coches abandonados, etc., mientras que el deterioro físico se referiría a características más estructurales que se producen por una falta de inversión institucional y tienen efectos a largo plazo, como son viviendas abandonadas, casas quemadas o tapiadas, zonas recreativas deterioradas, etc. (Sampson, 2009; Sampson y Raudenbush, 2004).

Por ultimo, un grupo de estudios sugiere que no existiría tal tipificación, sino que el desorden físico y el desorden social se solaparían, y formarían parte de un único continuo entre el orden y el desorden (Ross y Mirowsky, 1999; Xu, Fiedler, y Flaming, 2005).

Más allá del análisis teórico del concepto de desorden en el vecindario, el interés de los investigadores radica en desarrollar herramientas adecuadas para evaluarlo. Esto no carece de dificultad, y uno de los problemas que surgen en el estudio del desorden en el vecindario ha sido establecer de qué manera evaluarlo de una forma eficaz. Sobre esta base se asientan los Estudios 1 y 2 de esta tesis (ver Apartados 5.1 y 5.2), donde se realiza una validación de dos instrumentos para evaluar el desorden en el vecindario.

Los investigadores han utilizado tres aproximaciones diferentes a la hora de evaluar el desorden en el vecindario (McDonell y Waters, 2011; Mooney, Bader, Lovasi, Neckerman, Teitler y Rundle, 2014). En primer lugar, algunos autores que parten de una visión más objetiva, se han basado en información procedente de fuentes de información gubernamentales o comerciales (Cerdá, Tracy, Messner, Vlahov, Tardiff y Gelea., 2009; McDonell, 2007; Mooney et al., 2014). Este tipo de información suele recogerse con fines administrativos, y a pesar de estar libres de la subjetividad que supone otras medidas que se basan en percepciones subjetivas del desorden (Kubrin, 2008), algunos autores sugieren que no capturan totalmente el constructo de interés (Money et al., 2014).

En segundo lugar, otros autores se han centrado en las percepciones de los vecinos sobre las características de desorden social y físico de sus propios vecindarios. Esta forma de medir el desorden ha sido utilizada por un gran número de investigaciones; sin embargo, presentan una gran cantidad de limitaciones, donde destacan la confusión con otros constructos psicológicos (como el miedo al crimen), o la influencia de los estereotipos y los prejuicios (como la composición racial o socioeconómica del vecindario) en la percepción del desorden (Caughy, O'Campo, y Patterson, 2001; Duncan y Raudenbush, 1999; Gómez, Johnson, Selva, y Sallis, 2004; Mooney et al., 2014; Sampson, 2009; Sampson y Raudenbush, 1999, 2004; Schaefer-McDaniel, Caughy, O' Campo, y Gearey, 2010).

Por último, un tercer grupo de autores han desarrollado herramientas para solucionar los problemas de las otras dos aproximaciones. En concreto, han diseñado instrumentos observacionales sistemáticos directos que se realizan mediante por observadores entrenados (Franzini, Caughy, Nettles, y O'Campo, 2008; McDonell, 2007; McDonell y Waters, 2011; O'Neil, Parke, y McDowell, 2001; Raudenbush y Sampson, 1999; Sampson y Raudenbush, 1999). El objetivo de estas herramientas es obtener medidas con las que capturar aspectos que no están disponibles de otra forma, y permitir su replicación en otros contextos (Caughy et al., 2001; Cohen, Spear, Scribner, Kissinger, Mason y Wildgen, 2000; Franzini et al., 2008; McDonell y Waters, 2011; Sampson y Raudenbush, 2004; Taylor, 2001). El Estudio 1 se centra en esta tercera posibilidad, y en él se desarrolló un instrumento basando en observaciones sistemáticas y se presentaron los resultados del estudio psicométrico del mismo (ver Apartado 5.1).

Sin embargo, esta última perspectiva también tiene algunas desventajas importantes, como son el gran costo en recursos humanos y en desplazamiento, ya que en ocasiones los observadores deben moverse por un área de estudio grande (Bader et al., 2015; Mooney et al., 2014). Además, algunas áreas pueden ser conflictivas y poner en peligro la integridad del equipo de observación (Griew, Hillsdon, Foster, Coombes, Jones y Wilkinson, 2013; Rundle, Bader, Richards, Neckerman y Teitler, 2011; Wilson et al., 2012). Así, los últimos desarrollos en este sentido han propuesto nuevas herramientas para evaluar las características del vecindario utilizando las nuevas tecnologías. Una de las alternativas más utilizadas ha sido Google Street View (Badland, Opit, Witten, Kearns y Mavoa, 2010; Griew et al., 2013; Kelly, Wilson, Baker, Miller y Schootman, 2013; Odgers, Caspi, Bates, Sampson y Moffitt, 2012), herramienta que permite visitar los vecindario de manera virtual con una alta resolución e imágenes en 360 grados, y supone un avance en las limitaciones de las observaciones directas.

De esta forma, el Estudio 2 de esta tesis propone una herramienta de evaluación del desorden en el vecindario mediante el uso de Google Street View (ver Apartado 5.2).

2.2 Características de los vecindarios y problemas relacionados con la venta de bebidas alcohólicas y las intervenciones policiales por drogas (Estudios 3 y 4)

Desde el campo de la criminología, se ha producido un incremento del número de estudios que se han centrado en la dimensión espacial del delito. En este sentido, algunos estudios clásicos identifican cuatro dimensiones en el delito (Brantingham y Brantingham, 1981): 1. la dimensión legal (se debe incumplir una ley); 2. la víctima (alguien o algo es objeto del delito); 3. el infractor (alguien tiene que cometer el delito); 4. la dimensión espacial (el delito tiene que ocurrir en algún lugar). Esta última dimensión del delito no sólo hace referencia a que el delito tiene inherentemente una cualidad geográfica, sino que éste puede ser además comprendido y explicado mejor cuando se exploran sus componentes geográficos y las variables que los determnan (Chainey y Ratcliffe, 2005).

Desde este punto de vista, el crimen, el delito y la violencia, no se distribuye al azar en las ciudades, sino que tiende a concentrarse espacialmente en lo que se denomina 'clusters' o puntos calientes ('hot spots'). Esta concentración espacial del crimen y el delito ocurre, además, en un número relativamente pequeño de lugares y, por esa razón, a este fenómeno se le ha denominado en el ámbito de la criminología como la 'ley de la concentración del crimen' (Weisburd, 2015), una idea básica en la denominada criminología del lugar (Sherman, Gartin y Buerger, 1989; Weisburd, Groff y Yang, 2012). Desde esta perspectiva se pone el acento en el análisis de los puntos calientes de los delitos y la criminalidad, utilizando como unidad de análisis áreas geográficas pequeñas de las ciudades.

La relación entre el delito y el lugar donde se produce es un tema de estudio que cuenta con una larga trayectoria. La mayoría de las investigaciones, sin embargo, se han centrado en delitos concretos, como son los robos en viviendas (Johnson y Bowers, 2005; Johnson et al., 2007; Townsley, Homel, Chaseling y 2000), la delincuencia juvenil (Browning et al., 2010; Law y Quick, 2013), los homicidios (Capowich, 2003; Sampson y Raudenbush, 1999; Sampson et al., 1997) o los robos y asaltos (Capowich, 2003; Sampson y Raudenbush, 1999).

Un menor número de estudios se ha centrado en la relación entre las características del vecindario y los delitos relacionados con las drogas (Hibdon y Groff, 2014; Martínez, Rosenfeld y Mares, 2008; Dunlap, 1992). Este tipo de delitos son un grave problema en nuestras sociedades, debido a las repercusiones negativas que tienen las drogas: suponen un importante problema de salud pública, crean conflictos personales y sociales a corto y largo plazo, y pueden perpetuar el deterioro de nuestras comunidades convirtiéndose en un problema endémico (Dunlap, 1992; Johnson, Williams, Dei y Sanabria, 1990). De esta forma, algunos estudios han encontrado relación entre la venta y consumo de drogas y otro tipo de actos delictivos (Lum, 2008). Sin embargo, el estudio de los delitos relacionados con las drogas desde un punto de vista comunitario se ha centrado principalmente en los mercados de venta de droga (Taniguchi, Ratcliffe y Tayler, 2011), mientars que otros problemas relacionados con las drogas han sido menos estudiados.

En el Estudio 3 se ha tenido en cuenta esta carencia y se ha explorado la distribución espacial de las intervenciones policiales relacionadas con las drogas, así como las características del vecindario que influyen en esa distribución espacial (ver Apartado 5.3).

Por otro lado, el consumo abusivo de alcohol es una problemática que afecta en gran medida a los ciudadanos. En concreto, en el año 2012 el consumo de alcohol fue el responsable del 5.9% de las muertes globales, lo que se traduce en más de 3.3 millones de muertes relacionadas con el alcohol a nivel mundial (OMS, 2014).

En el caso del alcohol, la disponibilidad de alcohol se ha convertido en un importante campo de estudio. Concretamente, se ha puesto gran interés en la densidad de establecimientos donde se vende y se consumen bebidas alcohólicas, y su asociación con problemas sociales tan dispares como los delitos violentos (Britt, Carlin, Toomey y Wagenaar, 2005; Cameron, Cochrane, Gordon y Livingston, 2016; Furr-Holden et al., 2016; Gorman, Speer, Gruenewald y Labouvie, 2001; Gruenewald y Remer, 2006), los accidentes de tráfico (LaScala, Johnson y Gruenewald, 2001; Popova, Giesbrecht, Bekmuradov y Patra, 2009; Treno, Johnson, Remer y Gruenewald, 2007), el consumo abusivo de alcohol (Azar et al., 2015; Foster, Trapp, Hooper, Oddy, Wood y Knuiman, 2017; McKinney, Chartier, Caetano y Harris, 2012), el maltrato infantil (Freisthler, Gruenewald, Treno y Lee, 2003; Freisthler, Kepple y Holmes, 2012; Freisthler y Weiss, 2008) o la violencia de pareja (Cunradi et al., 2011; Snowden, 2016).

Estudios previos han analizado la relación entre las características del vecindario y la distribución espacial y temporal de los establecimientos donde se vende y se consumen bebidas alcohólicas, o 'alcohol outlets' en su término inglés, en diferentes ciudades (Angus, Holmes, Maheswaran, Green, Meier y Brennan, 2017; Ellaway, Macdonald, Forsyth y Macintyre, 2010). Estos estudios han mostrado que los establecimientos de venta y consumo de bebidas alcohólicas no están distribuidos al azar en el espacio y en el tiempo, sino que están relacionados con diferentes características del vecindario.

Partiendo de nuevo de las teorías de la desorganización social (ver Apartado 1.1.2), estos estudios han encontrado una relación entre la densidad de bares, restaurantes y tiendas que venden alcohol y los barrios desfavorecidos socioecononómicamente, la inestabilidad residencial y la composición étnica. Los barrios desfavorecidos socioeconómicamente, al igual que ocurría en el caso de otros problemas sociales, han sido los más estudiados, y los resultados de las investigaciones muestran que aquellas áreas más desfavorecidas socioeconómicamente tienden a mostrar mayores tasas de establecimientos de venta de alcohol (Bluethenthal et al., 2008; Ellaway et al., 2010; Hay, Whigham, Kypri y Langley, 2009; McKinney et al., 2012). Otros estudios también han mostrado una relación positiva con la inestabilidad residencial, de forma que aquellos vecindarios con más movimientos migratorios son los que muestran mayor densidad de puntos de venta de alcohol (Nielsen, Hill, French y Hernandez, 2010). Respecto a la heterogeneidad étnica, los resultados han sido inconclusos, y algunas investigaciones apuntan a una asociación positiva (LaVeist y Wallace, 2000; Snowden, 2016), mientras que otros estudios no han encontrado relación entre estas dos variables (Bluethenthal et al., 2008; Nielsen et al., 2010).

La mayoría de los estudios que han analizado los bares, restaurantes y tiendas que venden alcohol se han llevado a cabo en Estados Unidos o en países del norte de Europa (Angus et al., 2017; Ellaway et al., 2010; Gorman y Speer, 1997; Nielsen et al, 2010; Zhang et al., 2015). Estos países generalmente se definen como "países secos", clasificación que se basa en la cantidad media de alcohol consumido per cápita, y distingue entre culturas "consumidoras" y "no consumidoras" (Rahav, Wilskack, Bloomfield, Gmel y Kuntsche, 2006; Room y Mitchell, 1972). Estados Unidos, así como el norte de Europa, serían ejemplo de países secos dentro de esta clasificación, y estarían caracterizados por bajos niveles de consumo de alcohol, un gran número de ciudadanos abstemios, controles restrictivos para beber y vender alcohol, y menos tradición de consumir alcohol en contextos sociales. Por otro lado, los países mediterráneos (Francia, Italia, Portugal, Grecia o España) se encontrarían en el extremo 'húmedo' de esta clasificación, y se caracterizan por mayores tasas de consumo de alcohol y un control menos restrictivo del comportamiento relacionado con el mismo (Room y Mitchell, 1972; Room y Mäkela, 2000).

En los 'países húmedos', entre los que se encuentra España, el alcohol es parte de la vida social y suele estar presente en las reuniones sociales (Allamani, Voller, Kubicka y Bloomfield, 2000; Mäkela et al., 2006). Además, las personas beben más frecuentemente durante el día a día, a diferencia de lo que ocurre en los países secos (Bloomfield, Stockwell, Gmel y Rehn, 2003; José, O'Leary, Graña Gómez y Foran, 2014). A pesar de estas diferencias relevantes en el consumo de alcohol y la cultura del beber, los estudios sugieren que las personas de los 'países húmedos' llegan con menor frecuencia a la intoxicación que las de los países secos (Bloomfield et al., 2003).

Estas diferencias culturales en los patrones de bebida también se reflejan en la disponibilidad y el acceso a los establecimientos de bebidas alcohólicas. Por ejemplo, según datos de 2014, Nueva York tenía una densidad de 88 bares por cada 100.000 habitantes, mientras que Madrid disponía de 186 bares por cada 100.000 habitantes, lo que supone más del doble (BOP Consulting, 2014). Por otro lado, en los 'países húmedos' la aceptación social del consumo de alcohol se traduce en una mayor permisividad en la venta de bebidas alcohólicas. Esto también se refleja en las diferencias en la edad legal para el consumo de alcohol, que es de 21 años para Estados Unidos y de 18 años para la mayoría de los países europeos, incluído España.

Estas diferencias culturales también pueden verse reflejadas en la distribución de los establecimientos de venta y consumo de bebidas alcohólicas en las zonas urbanas, así como en la relación entre los puntos de venta y los problemas sociales. Por lo tanto, la distribución espacio-temporal de los establecimientos de venta y consumo de bebidas alcohólicas, las variables de vecindario que pueden influir en esta distribución espacio-temporal, y la relación entre la densidad de estos establecimientos y los problemas sociales relacionados con el consumo de alcohol, pueden diferir entre países donde la cultura relacionada con el consumo es diferente. Sin embargo, hasta ahora, ningún estudio ha analizado estos problemas desde una perspectiva espacio-temporal en los 'países húmedos'.

Entender cómo se distribuyen espacial y temporalmente los establecimientos donde se vende y se consumen bebidas alcohólicas y cómo se relacionan con el consumo del mismo podría contribuir a prevenir este tipo de problemática y sus consecuencias negativas en la comunidad. De este modo, en el Estudio 5 se exploran las características del vecindario que influyen en la distribución espacio-temporal de los establecimientos de venta y consumo de bebidas alcohólicas y se analiza la relación entre estos establecimientos y las llamadas policiales relacionadas con el consumo de alcohol (ver Apartado 5.4)

2.3 La influencia de las características del vecindario en las llamadas policiales relacionadas con el suicidio (Estudios 5 y 6)

La conducta suicida es un problema social y de salud pública de gran relevancia (Hawton y van Heeringen, 2009). En 2012 hubo más de 800.000 muertes por suicidio en todo el mundo (OMS, 2016). En concreto, Europa es la región de la Organización Mundial de la Salud con las tasas más altas de suicidio a nivel mundial, con 14,1 suicidios por cada 100.000 habitantes, seguida de la Unión Europea, donde las tasas son de alrededor de 11 casos por cada 100.000 habitantes (Unión Europea, 2017).

En España, y según datos de 2015, el suicidio fue la primera causa externa de muerte, 1,9 veces por encima de las lesiones causadas por el tráfico y 12,6 veces más que los casos de homicidio (Fundación Salud Mental España, 2017). En ese año, 3.602 personas murieron debido a conductas autolíticas, número que representa casi 10 suicidios al día (Instituto Nacional de Estadística, 2017), y supone que esta problemática, lejos de tratarse de casos aislados, es un problema social de gran envergadura.

El problema es aún mayor si tenemos en cuenta el parasuicidio (es decir, los casos de intentos de suicidio que no llegan a causar la muerte de la víctima), casos que no se pueden medir fácilmente y en ocasiones pasan desapercibidos o son tratados como otras tipologías o causas de fallecimiento, como accidentes o accidentes de tráfico. Sin embargo, y a pesar de los grandes costos sociales y económicos del suicidio en nuestras sociedades, todavía hay una carencia de programas y estrategias de prevención que puedan analizar adecuadamente este fenómeno (Fundación Salud Mental España, 2016; OMS, 2014).

Recientemente, un creciente número de estudios ha vinculado las variables del vecindario con el riesgo de suicidio más allá de los factores individuales (Burnley, 1995; Congdon, 2011; Hawton, Harris, Hodder, Sinkin y Gunnell, 2001; Rehkoff y Buka, 2006). Especialmente relevante es la investigación de Peter Congdon, cuyos estudios han demostrado la relación entre el riesgo de suicidio y tres conjuntos de factores: la privación social, la fragmentación social y la ruralidad (Burnley, 1995; Congdon, 1996; Congdon, 2011; Johnson, Woodside, Johnson y Pollack, 2016).

La privación social del vecindario, en línea con las teorías de la desorganización social (ver Apartado 1.1.2), hace referencia a aquellas características negativas del vecindario de tipo socioeconómico. Para evaluarla, se han utilizado diferentes indicadores como son la tasa de pobreza, la tasa de desempleo, la clase social ocupacional del vecindario, o el nivel educativo medio de la zona. Todas estas variables se han encontrado relacionadas positivamente con el suicidio en una serie de estudios (Congdon, 2011; Congdon, 2013a; Helbich, Plener, Hartung y Blüml, 2017; Yoon, Han, Jung-Choi y Khang, 2015).

Por otro lado, Congdon ha estudiado ampliamente la relación de la fragmentación social del vecindario con el riesgo de suicidio. Dicha fragmentación social hace referencia a una baja integración comunitaria o mayores niveles de aislamiento de los residentes respecto a su propio barrio. Para medir esta variable se han utilizado indicadores como la inestabilidad residencial, el número de personas que viven solas o las altas tasas de divorcio o de personas no casadas. La fragmentación social del vecindario también ha demostrado una relación positiva con el riesgo de suicidio (Congdon, 2011; Congdon, 2013a). Aquellos vecindarios con mayores niveles de inestabilidad residencial, un alto porcentaje de hogares con personas solas, y tasas de divorcio elevadas se han relacionado con un mayor riesgo de conducta suicida incluso después de tener en cuenta los elementos de la privación social (Hawton et al., 2001; Evans, Middleton y Gunnell, 2004). Este vínculo estaría relacionado con el aislamiento social y la falta de apoyo social (Congdon, 2011).

Por último, este autor ha propuesto un tercer elemento importante en el estudio del suicidio a nivel comunitario: la ruralidad. Este concepto serviría para diferenciar entre las áreas urbanas de las zonas rurales, ya que diversos estudios han sugerido que el riesgo de suicidio es mayor en las zonas rurales que en zonas urbanas (Knipe, Padmanathan, Muthuwatta, Metcalfe y Gunnell, 2017; McCarthy, Blow, Ignacio, Ilgen, Austin y Valenstein, 2012). Como explicación a estos resultados se ha propuesto que los aspectos relacionados con la economía y el acceso al sistema de salud pueden ser clave para explicar las diferencias en cuanto a la conducta suicida. Así, las zonas rurales mostrarían un mayor empobrecimiento y menores oportunidades de empleo, así como un acceso más limitado al sistema de salud o a servicios psiquiátricos (Congdon, 2010).

En ocasiones, cuando se estudian las zonas urbanas exclusivamente (por ejemplo, cuando se trabaja con grandes ciudades) no es posible realizar esta comparativa rural-urbano. Sin embargo, diversos estudios han utilizado como variable que se acerca al concepto de ruralidad la densidad de población. Estos estudios han demostrado que las áreas con menor densidad de población (zonas más despobladas, con un menor número de vecinos cercanos) también muestran mayor riesgo de suicidio (Congdon, 2011; Stark, Hopkins, Gibbs, Belbin y Hay, 2007).

Más allá de la relevante aportación realizada por Congdon, otros estudios también han explorado otros indicadores del vecindario como predictores del riesgo de suicidio en el vecindario. Por ejemplo, algunas investigaciones se han centrado en la relación entre la composición étnica de los vecindarios y las tasas de suicidio (Johansson, Sundquist, Johansson, Wvist y Bergman, 1997; Knipe et al., 2017; Neeleman, Weessely y Lewis, 1998). Esta relación, sin embargo, aún no es concluyente. Si bien algunos resultados sugieren que existe una relación positiva entre las tasas de suicidio y el porcentaje de minorías étnicas (Johansson et al., 1997; Neeleman et al., 1998) otros estudios no han encontrado una relación significativa entre ambas variables (Knipe et al., 2017).

Otra variable que puede ser de gran interés para el estudio del riesgo de suicidio en el vecindario es el envejecimiento poblacional. A nivel individual, diversos estudios han relacionado positivamente la edad con el riesgo de suicidio; es decir, se han encontrado mayores tasas de suicidio entre las personas mayores que entre personas más jóvenes (Fundación Salud Mental España, 2016; Burnley, 1995; Santurtún, Santurtún y Zarrabeitia, 2017). Sin embargo, esta variable no ha sido muy estudiada desde un punto de vista comunitario. La poca investigación que hay al respecto sugiere que los vecindarios con niveles más altos de envejecimiento de la población (es decir, mayor proporción de personas mayores respecto a personas jóvenes) tienden a mostrar tasas de suicidio más altas (Yoon et al., 2015).

El estudio de los patrones espacio-temporales del suicidio, así como los factores de riesgo del vecindario que pueden estar influyendo en que ocurran más casos de suicidio en el mismo, tiene gran interés práctico de cara a desarrollar estrategias de prevención comunitarias más específicas, y pueda ser de utilidad para los agentes de protección ciudadana como son la policía, las asociaciones comunitarias o los ayuntamientos. De esta forma, los Estudios 5 y 6 de esta tesis analizan las características del vecindario que influyen en los patrones espacio-temporales de las llamadas policiales relacionadas con el suicidio en la ciudad de Valencia (ver Apartados 5.5 y 5.6).

2.4 Los campus universitarios como factor protector de la violencia contra la mujer en las relaciones de pareja en el vecindario (Estudio 7)

Como se ha señalado en el Apartado 1.1.6, el interés por el estudio de la violencia contra la mujer en las relaciones de pareja y su relación con las características del vecindario ha aumentado en los últimos años. Desde nuestro grupo de investigación se analizó la epidemiología espacial de la violencia de género en dos estudios previos (Gracia et al., 2014, 2015). En ellos se analizaba la influencia de diferentes variables del vecindario en la explicación de este tipo de violencia (ver Anexo 1). Sin embargo, otras variables mediadoras no fueron analizadas en estos estudios.

Algunos estudios han propuesto la eficacia colectiva como una variable relevante a la hora de explicar la distribución espacial de la violencia contra la mujer en el ámbito de la pareja (ver Apartado 1.1.6). Sin embargo, si bien la eficacia colectiva es una de las variables mediadoras más analizadas, otras variables del vecindario, como las normas sociales han recibido una menor atención científica. A nivel individual, la aceptabilidad de la violencia de pareja se ha relacionado con la perpetración de este tipo de violencia (Archer y Graham-Kevan, 2003; Capaldi, Knoble, Shortt y Kim, 2012; Gracia, Rodriguez y Lila, 2015; Martín-Fernández, Gracia, Marco, Vargas, Santirso y Lila, 2018; Stith, Smith, Penn, Ward y Tritt, 2004). A nivel comunitario, estas actitudes pueden crear un clima social de aceptabilidad de la violencia de pareja en las relaciones íntimas de forma que se fomente y legitime el uso de este tipo de violencia.

Evaluar las actitudes y normas sociales que están detrás del fenómeno de la violencia de pareja a nivel comunitario no es una tarea fácil. Un enfoque sería identificar entornos comunitarios que, dada su ubicación, composición y actividad, se podría esperar una menor aceptación y tolerancia de la violencia contra la mujer. Por ejemplo, los entornos cercanos a los campus universitarios, donde residen personas jóvenes y de altos niveles educativos, especialmente estudiantes y personas relacionadas con la comunidad académica, podrían ser uno de estos entornos protectores (Brockliss, 2000; Bruning, McGrew, y Cooper, 2006; Russo, y Tatjer, 2007).

Las normas sociales que estos residentes comparten probablemente sean menos tolerantes a la violencia contra las mujeres y más sensibles a la igualdad de género. Por lo tanto, los vecinos que viven a menor distancia de los campus universitarios pueden compartir normas sociales basadas en la noción de violencia como una forma inapropiada de resolver conflictos, lo que puede conducir a un mayor control social informal que reduciría el riesgo de violencia contra la mujer en las relaciones de pareja (Abbot, 2010; Cortes, 2004).

Algunos autores sostienen, sin embargo, que los procesos de control social informal y la eficacia colectiva no sería aplicable al problema de la violencia contra la pareja (Frye et al., 2012). Tal y como se apuntaba en el Apartado 1.1.6, estos resultados van en línea con los autores autores que plantean que el hecho de que sea un delito que se produce mayoritariamente en entornos privados hace que sea menos probable que las características del vecindario influyan en el mismo (Block y Skogan, 2001).

Por tanto, este es un tema que sigue generando cierta controversia. Aunque la evidencia empírica tiende a respaldar la aplicación de la teoría de la desorganización social, también en cuanto a las variables relacionadas con las normas sociales y el control social, en el ámbito de la violencia contra la pareja, no existe todavía un consenso generalizado (Pinchevsky y Wright, 2012). Esto hace que sea necesario realizar nuevos estudios que analicen la cuestión desde una perspectiva diferente, utilizando métodos de análisis más complejos.

En el Estudio 7 se va un paso más allá respecto a los estudios anteriores realizados en la ciudad de Valencia por nuestro grupo de investigación (Gracia et al., 2015, Anexo 1), incorporando la influencia de los campus universitarios a la hora de explicar la distribución espacial del riesgo de violencia de pareja contra la mujer (ver Apartado 5.7), variable que no ha sido explorada anteriormente por la literatura científica.

3. Metodología

3.1 Área de estudio

El primer paso para llevar a cabo los diferentes trabajos de investigación fue trabajar con la cartografía del área de estudio. En este caso, nos centramos en la ciudad de Valencia. El Ayuntamiento de Valencia proporcionó los archivos cartográficos de toda la ciudad dividida por barrios y por sectores censales. Una vez estudiado el mapeado de la ciudad, se decidió eliminar las diferentes pedanías, correspondientes a los distritos de Poblados del Norte, Poblados del Oeste y Poblados del Sur. Esta decisión se ha tomado puesto que las pedanías se hallan separadas de la zona urbana y muestran unas características diferentes al resto de la ciudad, con una mayor proporción de zonas rurales y unos vecindarios que se asemejan más a los propios de poblaciones más pequeñas como pueblos o pequeñas ciudades que a la población de una ciudad grande como es Valencia.

Se utilizó como unidad de medida el sector censal, que es la unidad más pequeña de la que se dispone información proporcionada por el censo del Ayuntamiento de Valencia. Trabajar con el barrio como unidad de análisis ofrece poca información respecto a las características reales del vecindario, puesto que son áreas muy grandes que comprenden diferente tipo de población y pueden albergar subsecciones muy diferenciadas entre sí. Por ello, el nivel de sector censal es el más adecuado para este tipo de estudio, donde la agregación de datos es menor y se ajusta más a la realidad de la zona. Las áreas centrales de la ciudad tienen una distribución censal más similar, con sectores pequeños y en su mayoría ocupados por viviendas. En cambio, las áreas más periféricas constan de sectores censales más grandes donde gran parte está sin edificar o constituye zona de huerta. Debido a las diferencias entre los sectores centrales y los sectores más periféricos, se decidió eliminar aquellos sectores censales donde más del 50% de su área constituía zonas sin viviendas, por ser área de huerta, campos, descampados, etc. De esta manera, el mapa de Valencia con el que se trabajó finalmente queda reflejado en la Figura 2.

Figura 2. Representación espacial de la ciudad de Valencia (izquierda) y del área de estudio final eliminando los sectores censales mayoritariamente despoblados (derecha).

En total, el área de trabajo final comprende 552 sectores censales, con una población total de 736.580 habitantes, según el censo de 2013, donde la media de población es de 1.334 personas por sector censal. El sector más pequeño tiene una población de 630 personas y el más grande, de 2.845 personas.

3.2 Variables de estudio

Para capturar las variables del vecindario de interés para este estudio, se utilizaron diferentes fuentes de información. Al tratarse de datos a nivel municipal, se utilizó información de diferentes recursos de la ciudad de Valencia. En concreto, se accedió a información de la Oficina de Estadística del Ayuntamiento de Valencia y de la Policía Local de Valencia. Además, se recogió información observacional de los diferentes vecindarios de la ciudad. A continuación, se presenta cada una de las variables con las que se ha trabajado.

3.2.1 Variables procedentes de la Oficina estadística del Ayuntamiento de Valencia

La Oficina de Estadística del Ayuntamiento de Valencia proporcionó una serie de variables de gran interés para el estudio. Para todas ellas, se proporcionó la información de cada sector censal en cada uno de los años desde 2004 hasta 2016.

Variables económicas

Se utilizaron diferentes variables altamente correlacionadas como indicadores económicos:

- Valor catastral total medio de las viviendas posteriores a 1800.
- Porcentaje de vehículos de alta gama (> 16 CVF, caballos de vapor fiscales) respecto al total de vehículos.
- Porcentaje de actividades comerciales respecto al total de actividades económicas.
- Porcentaje de actividades financieras respecto al total de actividades económicas.

Nivel educativo

Se utilizó el nivel medio de educación de cada uno de los sectores censales. Para ello, se utilizó el porcentaje de personas en cada uno de los siguientes niveles educativos:

- 1 personas analfabetas.
- 2 personas con titulación inferior a graduado escolar.
- 3 personas con graduado escolar o equivalente.
- 4 personas con estudios superiores.

Mediante estos porcentajes, se calculó el nivel medio del sector censal, dando lugar a una escala de 1 a 4, siendo 1 el nivel educativo más bajo, y 4 el nivel educativo más alto.

Población extranjera

Porcentaje de concentración de población extranjera (%100).

Inestabilidad residencial

Hace referencia a los movimientos migratorios medidos como la tasa media de movimientos de inmigración y emigración inter e intraurbanos. Es decir, es el cociente resultante de dividir el número de altas y bajas por inmigración y emigración en cada sector censal en un año por la población total calculada a mitad del mismo expresada en tasa por mil habitantes. Esta tasa es calculada por la Oficina de Estadística para conocer los movimientos migratorios de la ciudad.

Superficie de solares

Porcentaje de superficie de solares respecto a la superficie total.

Familias uniparentales formadas por una mujer con hijos

La Oficina de Estadística dispone de información pormenorizada de las unidades familiares por sector censal para cuestiones electorales y poblacionales. Se dispuso del procentaje de unidades familiares con sólo un adulto mujer y uno o más menores de 16 años respecto al total de hojas familiares.

Unidades familiares formadas por una sola persona

Porcentaje de unidades familiares constituidas por una única persona respecto al total de unidades familiares.

Densidad de población

Se consideró la población total por kilómetro cuadrado por 1.000. La Oficina de Estadística proporcionó información de la población de cada uno de los sectores censales por año. Mediante el software R y la cartografía de la ciudad, se calculó el área de cada sector censal en kilómetro cuadrado, y se dividió la población por el área y se multiplicó por 1.000 para extraer la densidad de población.

Índice de envejecimiento

Hace referencia a la ratio entre la población envejecida respecto a la población joven. Se calcula como el cociente resultante de dividir el número de personas de 65 años y más entre las personas menores de 15 años, en tanto por 100.

Densidad de bares, restaurantes y puntos de venta de bebidas alcohólicas

La Oficina de Estadística del Ayuntamiento de Valencia proporcionó una medida agregada por sector censal de los diferentes establecimientos donde legalmente se vende o consumen bebidas alcohólicas. Con este valor, se calculó la densidad de estos establecimientos por km cuadrado. Siguiendo estudios internacionales, se consideraron tres categorías diferentes de establecimientos:

(1) **Puntos de venta de bebidas alcohólicas:** Variable compuesta por establecimientos que venden alcohol para consumir en el exterior y contempla tanto supermercados, como venta al por menor de alimentos y bebidas, o venta al por menor de bebidas.

(2) **Restaurantes y cafeterías:** Hace referencia a servicios en restaurantes y cafeterías, con o sin servicio de comidas, donde se consumen bebidas alcohólicas en el interior del establecimiento.

(3) **Bares:** En este caso, son establecimientos donde el principal producto de venta son las bebidas alcohólicas, a pesar de que también pueden servir comida.

3.2.2 Variables procedentes de las bases de datos de la Policía Local de Valencia

Además de las variables objetivas procedentes del Ayuntamiento de Valencia, se ha contado con el apoyo de la Policía Local con el fin de obtener diferentes variables relacionadas con sus intervenciones policiales. En concreto, se recogió toda la información de las órdenes de protección por violencia de género, así como los datos de las llamadas al servicio 092 relacionadas con intervenciones por alcohol, y aquellas relacionadas con conductas suicidas. Todas estas variables fueron recogidas para cada sector censal, pero cada una de ellas se recogió en diferentes periodos temporales, según la disponibilidad de los datos.

Violencia de género

Las órdenes de protección por violencia de género son coordinadas por el grupo GAMA (Grupo de Actuación contra los Malos Tratos) de la Policía Local y se abren cuando se considera que existe un peligro potencial para la integridad física de la víctima. Por ello, se lleva a cabo una protección especial de la misma, proporcionada por agentes de la policía pertenecientes a esta unidad especializada en materia de violencia de género. Se ha centrado el estudio en este tipo de casos por ser los de mayor relevancia.

Para recoger los datos de las órdenes de protección, se acudió a los diferentes retenes de Policía Local de Valencia. En total, se dispuso de la información de los 7 distritos policiales de la ciudad: Tránsitos, Patraix, Ciutat Vella, Marítim, Exposición, Russafa y Abastos. En cada uno de ellos, se puso en contacto con el grupo GAMA y los miembros del equipo permitieron acceder a los expedientes de todos los casos abiertos por violencia contra la mujer y recabar la información necesaria. En todos los casos, un Policía Local del grupo participó completando la información necesaria.

Solamente se consideraron los casos donde la víctima era una mujer puesto que los casos donde la víctima era un varón eran prácticamente inexistentes. Los pocos casos en los que existía una orden de protección contra una mujer, se trataba de una denuncia cruzada, es decir, tanto el hombre como la mujer habían denunciado por malos tratos en ambas direcciones. Esto hace pensar que, al menos en el caso de las órdenes de protección, la incidencia es mucho más alta cuando la víctima es una mujer que cuando lo es un hombre, y se consideró que era más conveniente estudiar esta problemática por separado para comprender las posibles causas de la violencia contra la mujer.

Se recogió la información de las órdenes de protección ocurridas desde 2011 (año en que se sistematizó la recogida de información por parte de la policía) hasta marzo de 2013 inclusive, puesto que la recogida de datos comenzó a principios de abril del mismo año. La variable sobre la que se trabajó principalmente fue la localización o dirección donde ocurrieron los hechos conducentes a la orden de protección. Para mantener el anonimato, se evitó recoger datos personales que pudieran identificar a la víctima.

Llamadas policiales al servicio 092 relacionadas con alcohol

Además, la Policía Local de Valencia proporcionó datos sobre todas las llamadas ciudadanas al teléfono 092 relacionadas con problemas por consumo de alcohol. La Policía contempla bajo la categoría de «Servicios Humanitarios-Persona en mal estado por consumo de alcohol» aquellas llamadas en las que se refieren casos como pueden ser un menor alcoholizado, personas indigentes bajo los efectos del alcohol, comas etílicos, u otro tipo de problemas de salud o sociales relacionados con el consumo abusivo de alcohol. En todos los casos, la policía ha de ser requerida por un ciudadano telefónicamente. Otros tipos de problemas sociales relacionados con el alcohol, donde la policía no interviene, o lo hace directamente sin mediación de una llamada previa, no fueron incluidos.

Se geolocalizó la dirección desde donde fue realizada la llamada, y se hizo un conteo de todas las llamadas ocurridas en cada uno de los sectores censales. Esta información fue recogida para los años entre 2010 y 2016.

Llamadas policiales al servicio 092 relacionadas con conductas suicidas

Por otro lado, también se recogieron las llamadas policiales relacionadas con conductas suicidias. En concreto, se recogió aquellas llamadas donde un ciudadano informaba de una muerte por suicidio o bien de un intento de suicidio. La Policía contempla estas llamadas bajo las categorías de «Servicios Humanitarios-Riesgos. Muerte. Suicidio» y «Servicios Humanitarios-Riesgos. Persona en mal estado. Intento de suicidio»

Igual que en el caso anterior, se geolocalizó la dirección desde fue realizada la llamada por un ciudadano y se realizó el conteo de llamadas por sector censal. Las llamadas se recogieron para el periodo entre 2010 y 2016. Además, cada año fue dividido en periodos de 3 meses, siendo el periodo 1 entre Enero y Marzo, el periodo 2 entre Abril y Junio, el periodo 3 de Julio a Septiembre, y el periodo 4 de Octubre a Diciembre. De esta forma, se obtuvo un total de 28 periodos, para permitir la exploración de un posible efecto de la estacionalidad en el suicidio.

3.2.3 Variables observacionales

En ocasiones, las variables estadísticas no pueden recoger toda la información necesaria para comprender fenómenos del vecindario complejos. Por lo tanto, además de las anteriores, se dispuso a su vez de dos variables observacionales, una realizada por miembros de la Policía Local y otra por miembros del equipo de investigación.

Actividad Policial

Policías Locales de barrio con amplia experiencia en su zona proporcionaron un índice de actividad policial indicativo del nivel de desorden público y el crimen en cada sector censal. Este índice incluye intervenciones en delitos relacionados con drogas y armas, vandalismo, servicios humanitarios por ingesta de alcohol, personas sin hogar, ruidos, peleas, etc. El índice se baremó desde 0 (muy bajo) hasta 4 (muy alto) en cinco tipos de intervenciones policiales, dando lugar a un máximo total de 20 puntos.

Desorden físico

Dos investigadores entrenados realizaron una observación de cada sector censal y completaron una escala de 13 ítems tipo Likert con 5 puntos de respuesta (de 0 = no presencia, hasta 4 = muy presente), que incluye ítems como basura en las calles, grafitis, casas o locales abandonados, zonas residenciales o de ocio muy deterioradas, etc. Las observaciones se realizaron durante el horario de actividad comercial. Usando la misma escala, se evaluó de nuevo el desorden físico del vecindario utilizando Google Street View.

3.2.4 Otras variables

Distancia a la comisaría de policía

Con el fin de tener en cuenta un posible efecto disuasorio, se calculó la distancia euclidea en kilómetros entre el centroide de cada sector censal y la comisaría o retén de Policía (tanto Nacional como Local) más cercana. Valores más bajos de esta variable indican una mayor proximidad a una comisaría/retén, y valores más elevados indican una mayor distancia a una comisaría/retén.

Distancia a las universidades

De la misma forma que en el caso anterior, se calculó la distancia euclídea en kilómetros desde el centroide de cada sector censal hasta el campus universitario más cercano. La ciudad de Valencia posee tres grandes campus universitarios que pertenecen al sistema público universitario. Valores más bajos de esta variable indican una mayor proximidad a un campus universitario, y valores más elevados indican una mayor distancia al campus universitario.

3.3 Análisis estadísticos

Para realizar los diferentes estudios que conforman esta tesis doctoral, se ha utilizado una metodología común. En concreto, se ha trabajo con una perspectiva espacial o espacio-temporal dependiendo del objeto de estudio, y para ello se ha seguido una aproximación Bayesiana.

El enfoque Bayesiano, basado en el Teorema de Bayes, combina la construcción de modelos complejos con la inclusión, en los mismos, de información previa conocida sobre los parámetros (Banerjee, Carlin y Gelfand, 2004). Es decir, para realizar los análisis no sólo se utilizan los datos, sino que los resultados se basan también en fuentes de información "a priori", conocidas antes del muestreo de los datos (Lindley, 1972). Esta información previa se transforma en probabilidades "a posteriori", y estas probabilidades son las que se utilizan para realizar la inferencia.

Esta aproximación metodológica está siendo cada vez más utilizada desde campos muy diferentes, debido principalmente a las ventajas que supone la inclusión de esta información previa, que la estadística frecuentista no puede incluir en sus modelos, los cuales están muy limitados a los datos. Asimismo, las técnicas de inferencia Bayesiana se basan en métodos de simulación, que permiten calcular las distribuciones a posteriori de los parámetros cuando no es posible muestrear directamente, lo cual es una de las ventajas importantes que nos hace decantarnos por este tipo de análisis (Gilks, Richardson y Spiegelhalter, 1996)

En concreto, se ha trabajado con modelos jerárquicos espacio-temporales Bayesianos (Bernardinelli, Clayton, Pascutto, Montomoli, Ghislandi y Songini, 1995). Estos modelos son muy eficaces para modelar la información a priori descomponiéndola en distintos niveles o capas, lo cual permite diferenciar entre elementos propios de la estructura del modelo y elementos relacionados con información externa (Lawson, 2009). Los modelos jerárquicos permiten la inclusión de efectos aleatorios en alguna de sus capas, como por ejemplo, y en nuestro caso particular, la estructura espacial y temporal (Law et al., 2014). La primera capa modeliza los datos condicionados por el vector aleatorio de los parámetros, que tienen asociada una distribución a priori definida en la segunda capa. En el caso de que los parámetros del modelo dependan, a su vez, de otros parámetros (conocidos como hiperparámetros), las distribuciones a priori de éstos se definen en la tercera capa.

El efecto espacial se tiene en cuenta mediante la adición de un efecto aleatorio de autocorrelación espacial. Debido a que todos los datos de los que disponemos contienen unas coordenadas geográficas que se pueden geolocalizar en un mapa cartográfico, se puede trabajar con la relación entre áreas. La autocorrelación espacial hace referencia a que las tasas de riesgo que encontramos en áreas cercanas están más relacionadas que aquellas áreas más distantes. Detectar esta dependencia espacial puede ser de gran utilidad para proporcionar información acerca de la estructura espacial no observada de los datos, que puede deberse a que las áreas vecinas tienen características más similares, bien sean a nivel social, económico o cultural (Banerjee et al., 2004; Bernardinelli et al., 1995; Matthews, Yang, Hayslett y Ruback, 2010; Waller y Gotway, 2004; Zhu, Gorman y Horel, 2006).

Además, los modelos espaciales con los que trabajamos incluyen otro efecto aleatorio, conocido como heterogeneidad o sobredispersión. Este efecto aleatorio hace referencia a la diferenciación espacial de las unidades geográficas. Cuando se trabaja con unidades espaciales (en nuestro caso, sectores censales dentro de una ciudad), suele ocurrir que el fenómeno de estudio se distribuya de forma distinta en el espacio, es decir, los datos no son homogéneos. Sin embargo, debido a los pequeños valores que toman nuestros datos (en ocasiones, hay una gran presencia de ceros, puesto que se trata de áreas muy pequeñas) es importante corregir y suavizar las diferencias que pueden aparecer entre áreas, que no se deberían a una diferencia real sino a un efecto de sobredispersión (Haining, Law y Griffith, 2009).

Además de los efectos aleatorios relacionados con el factor espacial, también resulta de gran interés la introducción de un efecto aleatorio temporal. De la misma forma que en el efecto espacial, éste puede ser introducido en el modelo para detectar la dependencia temporal de los datos. Por tanto, las tasas de riesgo de una variable estarán relacionadas con las de los años previos. A su vez, también podemos introducir un efecto de heterogeneidad temporal, donde las diferencias temporales son suavizadas por un efecto de sobredispersión.

Los métodos Bayesianos de análisis espacio-temporal son particularmente apropiados para el estudio de las influencias de los vecindarios en las variaciones del riesgo en áreas pequeñas y a lo largo del tiempo. Como los factores de riesgo en los vecindarios tienden a agruparse en el espacio, los modelos jerárquicos Bayesianos son de gran utilidad en los estudios que incorporan información geográfica para hacer mapas de los componentes espaciales y temporales que expresen la variación del riesgo (Congdon, 2013b; Law et al., 2014).

Aunque este tipo de aproximación metodológica se ha utilizado frecuentemente en el ámbito de la epidemiología y en el desarrollo de mapas de riesgo de enfermedades (Best, Richardson y Thomson, 2005; Congdon, 2013b; Lawson, 2009; Waller y Gotway, 2004), su uso en las ciencias sociales es todavía muy escaso.

Sin embargo, un pequeño número de estudiosos ha comenzado a reconocer las ventajas de los modelos espacio-temporales Bayesianos frente a la investigación desarrollada en el pasado en la que se utilizaban métodos analíticos no espaciales u otros métodos espaciales no Bayesianos. Así, un pequeño número de investigadores han comenzado a aplicar métodos Bayesianos en el estudio de la criminalidad y de diferentes procesos de violencia urbana (Cunradi et al., 2011; Groff, Weisburd y Morris, 2009; Grubesic y Mack, 2008; Haining et al., 2009; Law y Quick, 2013; Law et al., 2014; Matthews et al., 2010; Sparks, 2011; Zhu et al., 2006).

Este tipo de análisis permite identificar patrones significativos y distribuciones desiguales del riesgo de diferentes problemas sociales, es decir, puntos con altas tasas de incidencia, lo cual puede contribuir a evaluar las estrategias existentes de prevención e intervención, y dotar de información novedosa para el diseño de estrategias tanto de intervención, teniendo en cuenta las zonas y perfiles de riesgo y de esta forma destinar mayores recursos tanto sociales y policiales como de prevención, puesto que si se encuentran patrones significativos, se pueden identificar zonas donde sea más probable la aparición de nuevos casos.

4. Objetivos

El objetivo general de esta tesis doctoral es analizar las características de los vecindarios relacionadas con diferentes problemas sociales, y la distribución espacial o espacio-temporal de los mismos. Los objetivos específicos de este trabajo son los siguientes:

Objetivo 1. Realizar una evaluación de las características psicométricas de dos escalas sistemáticas observacionales de desorden físico y social del vecindario, una mediante observaciones in situ (Estudio 1), y otra mediante Google Street View (Estudio 2).

Objetivo 2. Analizar las características del vecindario relacionadas con la distribución espacial de las intervenciones policiales relacionadas con drogas (Estudio 3).

Objetivo 3. Estudiar las características del vecindario relacionadas con la distribución espacio-temporal de los establecimientos de venta y consumo de bebidas alcohólicas, así como su influencia en las llamadas policiales por problemas relacionados con el consumo de alcohol (Estudio 4).

Objetivo 4. Analizar las características del vecindario y su influencia en la distribución espacio-temporal de las llamadas policiales relacionadas con la conducta suicida (Estudios 5 y 6).

Objetivo 5. Explorar la influencia de los campus universitarios en la distribución espacial del riesgo de violencia de género (Estudio 7).

En esta tesis doctoral se muestran siete trabajos de investigación, publicados en revistas científicas indexadas en el Journal Citation Reports (JCR), que se organizan alrededor de estos objetivos.

Objetivo 1:

- **Artículo 1**: Marco, M., Gracia, E., Tomás, J. M. y López-Quílez, A. (2015). Assessing neighborhood disorder: Validation of a three-factor observational scale. *The European Journal of Psychology Applied to Legal Context, 7*, 81-89.
- **Artículo 2:** Marco, M., Gracia, E., Martín-Fernández, M., & López-Quílez, A. (2017). Validation of a Google Street View-based neighborhood disorder observational scale. *Journal of Urban Health, 94*, 190-198.

Objetivo 2:

- **Artículo 3:** Marco, M., Gracia, E. y López-Quílez, A. (2017). Linking neighborhood characteristics and drug-related police interventions: A Bayesian spatial analysis. *International Journal of Geo-Information, 6*, 65.

Objetivo 3:

- **Artículo 4:** Marco, M., Gracia, E., López-Quílez, A. y Lila, M. (2017). Neighborhood alcohol outlet density and alcohol-related calls-for-service: A spatio-temporal analysis in a wet drinking country. *International Journal of Geo-Information, 6*, 380.

Objetivo 4:

- **Artículo 5:** Marco, M., López-Quílez, A., Conesa, D., Gracia, E. y Lila, M. (2017). Spatio-temporal analysis of suicide-related emergency calls. *International Journal of Environmental Research and Public Health, 14*, 735.
- **Artículo 6:** Marco, M., Gracia, E., López-Quílez, A. y Lila, M. (2018). What calls for service tell us about suicide: A 7-year spatio-temporal analysis of neighborhood correlates of suicide-related calls. *Scientific Reports, 8.*

Objetivo 5:

- **Artículo 7:** Marco, M., Gracia, E. y López-Quílez, A. (2018). The university campus environment as a protective factor for intimate partner violence against women: An exploratory study. *Journal of Community Psychology. 46,* 903-916.

Además, en Anexos se incluyen otros tres estudios realizados por nuestro equipo de investigación que utilizan también una perspectiva espacio-temporal para analizar el riesgo de la violencia de pareja contra la mujer y del maltrato infantil. Estos trabajos, si bien no forman parte directa de esta tesis doctoral, están estrechamente vinculados con ella.

En el primer estudio (Gracia, López-Quílez, Marco, Lladosa y Lila, 2015), se analizan las características del vecindario relacionadas con la distribución espacial del riesgo de violencia de pareja contra la mujer en la ciudad de Valencia (ver Anexo 1).

En el segundo estudio (Gracia, López-Quílez, Marco y Lila, 2017), se realiza un análisis espacio-temporal de las características del vecindario relacionadas con el riesgo de maltrato infantil a lo largo de 12 años de estudio (2004-2015), y se analizan los patrones espaciales existentes a lo largo del tiempo, así como los cambios ocurridos temporalmente (ver Anexo 2).

En el tercer estudio (Gracia, López-Quílez, Marco y Lila, 2018), se estudian los patrones espaciales comunes entre el maltrato infantil y la violencia de pareja contra la mujer, ambos problemas que ocurren de puertas hacia adentro, y se analiza si ambos tipos de violencia están influenciados por las mismas características del vecindario (ver Anexo 3).

5. Studies

Study 1.

Assessing neighborhood disorder: Validation of a three-factor observational scale

Assessing neighborhood disorder: Validation of a three-factor observational scale[1]

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Abstract

This study presents data on the development and preliminary validation of an observational scale assessing neighborhood disorder. Independent observations by trained raters of neighborhood disorder were conducted in 552 census block groups in the city of Valencia (Spain). Intraclass correlation coefficients assessing inter-rater reliability indicated fair to substantial levels of agreement among raters. Confirmatory Factor Analyses supported a final three-factor model scale measuring physical disorder, social disorder, and physical decay. Results for the internal consistency showed large Composite Reliability Indices indicating good reliability for all neighborhood disorder factors. Evidence of criterion-related validity was found by exploring associations between neighborhood disorder factors and three neighborhood characteristics: neighborhood socioeconomic status, immigrant concentration, and residential instability. Also for criterion-related validity, Moran's I test results for spatial correlation showed that the three types of neighborhood disorder tend to cluster in space, and are not randomly distributed across the city. In general, this paper provides evidence of a reliable and valid observational measure to assess neighborhood disorder.

Keywords: Confirmatory factor analysis, Neighborhood disorder, Observational scale, Physical decay, Physical disorder, Spatial clustering, Social disorder, Social disorganization

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[1] Marco, M., Gracia, E., Tomás, J. M., & López-Quílez, A. (2015). Assessing neighborhood disorder: Validation of a three-factor observational scale. *The European Journal of Psychology Applied to Legal Context, 7*, 81-89. doi: 10.1016/j.ejpal.2015.05.001

Introduction

In recent decades, a large body of literature has examined the influence of neighborhood characteristics on a wide range of outcomes, including health, violence, or crime (Diez-Roux & Mair, 2010; Kawachi & Berkman, 2003; O'Campo et al., 2015; Sampson, 2012; Sampson, Raudenbush, & Earls, 1997). Among these neighborhood characteristics, the concept of neighborhood disorder has played a central role, and has received the attention of scholars from different disciplines like sociology, criminology, social psychology or epidemiology. Neighborhood disorder can be defined as "observed or perceived physical and social features of neighborhoods that may signal the breakdown of order and social control, and that can undermine the quality of life" (Gracia, 2014, p. 4325). Examples of neighborhood disorder may include behaviors such as prostitution, drug dealing, and fighting in the streets, or physical characteristics such as abandoned cars, vandalized buildings, or litter in the streets (Sampson & Raudenbush, 1999; Skogan, 1990; Taylor, 2001; Wilson & Kelling, 1982).

The concept of neighborhood disorder can be linked to social disorganization theories and their idea that structural characteristics of neighorhoods, like concentrated disadvantage, can undermine social control and increase levels of violence, crime, and other negative outcomes (Gracia, 2014; Kingston, Huiziga, & Elliot, 2009; Kubrin & Weitzer, 2003; Maimon & Browning, 2010; Park, Burgess, & McKenzie, 1925; Sampson et al., 1997; Shaw & McKay, 1942; Wilson, 1987). Also, the Broken Windows Theory of urban decay has been of particular relevance for the wide appeal of the concept of neighborhood disorder (Wilson & Kelling, 1982). According to this perspective, physical and social cues of neighborhood disorder signal the breakdown of formal and informal social controls leading to further disorder and crime (Gracia, 2014; York Cornwell & Cagney, 2014; Perkins, Meeks, & Taylor, 1992; Sampson & Raudenbush, 1999; Skogan, 1990; Taylor, 1997; 2005; Toet & van Schaik, 2012; Wei, Hipwell, Pardini, Beyers, & Loeber, 2005). According to Gracia "as neither residents nor external agencies (e.g., police and other authorities) are able or willing to intervene and maintain social order, more disorder is facilitated, and criminal activity is attracted" (2014, p. 4325). Neighborhood disorder would also trigger a number of community processes like fear, insecurity, powerlessness, or mistrust that lead residents to disinvest in and withdraw from community life, increasing social disorganization and neighborhood decline (Geis & Ross, 1998; Kawachi, Kennedy, & Wilkinson, 1999; Kim & Conley, 2011; Ross, Mirowsky, & Pribesh, 2001; Skogan, 1986, 1990). In this regard, neighborhood disorder has been linked to urban decay, concentration of social problems, racial or ethnic segregation, social integration, confidence in the police, or public social control strategies like reporting crime (Gracia, Garcia, & Musitu, 1995; Gracia & Herrrero, 2006a,b, 2007; Perkins et al., 1992; Perkins & Taylor, 1996; Ross & Mirowsky, 1999; Skogan, 1990; Taylor, 1997; Toet & van Schaik, 2012).

Although neighborhood disorder has traditionally been studied in relation to street-level outcomes, an increasing body of literature has also examined its influence on processes and outcomes that occur "behind closed doors" (Wright & Benson, 2011), such as parental socialization practices (Gracia, Fuentes, García, & Lila 2012; Lila & Gracia, 2005; McDonell, 2007; Roosa et al. 2005; Tendulkar, Buka, Dunn, Subramanian, & Koenen, 2010; White, Roosa, Weaver, & Nair, 2009; Worton et al., 2014), child maltreatment (Coulton, Korbin, & Su, 1999; Coulton, Crampton, Irwin, Spilsbury, & Korbin, 2007; Freisthler, Bruce, & Needell, 2007; Freisthler, Merritt, & LaScala, 2006; Garbarino & Sherman, 1980; Gracia & Musitu, 2003; Lila & Gracia, 2005; Martin-Storey et al., 2012), or intimate partner violence (Cunradi, 2007, 2009; Gracia, Herrero, Lila, & Fuente, 2009; Gracia, López-Quílez, Marco, Lladosa, & Lila, 2014, 2015; Kirst, Lazgare, Zhang, & O'Campo, 2015; see Pinchevsky & Wright, 2012; Beyer, Wallis, & Hamberger, 2015, for reviews).

More recently, research on social disorder has also examined its influences on individual well-being indicators like subjective well-being, psychological distress, anxiety, or depression (García-Ramírez, Balcázar, & de Freitas, 2014; Herrero, Gracia, Fuente, & Lila, 2012; Hill & Angel, 2005; Hombrados-Mendieta & López-Espigares, 2014; Latkin & Curry, 2003; Latkin, German, Hua, & Curry, 2009; O'Campo et al. 2015; Ross & Mirowsky, 2009), and how this may affect negative health behaviors such as low physical activity, heavy drinking, smoking, or obesity (O'Campo et al. 2015 ; Burdette & Hill, 2008; Echeverría, Diez-Roux, Shea, Borrell, & Jackson, 2008; Hill, Ross, & Angel, 2005; Keyes et al, 2012; Ross & Mirowsky, 2001). Research has also examined the association between neighborhood disorder and different public health issues such as health service usage, low body weight at birth in children, injuries, sexually transmitted diseases, loss of physical function in older adults, and mortality risk (Balfour & Kaplan, 2002; Cohen et al., 2000, 2003; Martin-Storey et al., 2012; Pearl, Braveman, & Abrams, 2001; Winkleby & Cubbin, 2003).

Assessing neighborhood disorder

Assessment of neighborhood disorder tipycally considers two types of disorder, physical and social (Skogan & Maxfield, 1981; Robinson, Lawton, Taylor, & Perkins, 2003; Taylor & Shumaker, 1990). Physical disorder refers to urban landscapes with high levels of decay and deterioration. For example, abandoned houses, graffiti, trash on the streets, abandoned cars, used needles and vacant lots would exemplify physical disorder (Brunton-Smith, 2011; Garvin, Cannuscio & Branas, 2013; Robinson et al., 2003; Sampson & Raudenbush, 1999; Skogan, 1990; Taylor, 2001, Toet & van Schaik, 2012). Some scholars, however, make a further distinction between physical disorder and physical decay: physical disorder would refer to features like dirt in the streets (litter, bottles, condoms), graffiti, abandoned cars, etc. (i.e., behavioral manifestations), whereas physical decay would refer to structural characteristics that can arise from lack of institutional investments and have long term effects, such as abandoned buildings, burn-out houses, badly deteriorated recreational facilities, etc. (Sampson, 2009; Sampson & Raudenbush, 2004). As Sampson and Raudenbush argue, it is important to make this distinction because physical disorder is “limited to behavioral manifestations (e. g. graffiti, garbage in the streets) that can be conceptually decoupled from structural resources” (2004, p. 326). Social disorder refers, on the other hand, to events in public places seen as potentially threatening, and can be exemplified by the presence of people taking drugs or alcohol in the street, drug dealing, fights and arguments, presence of homeless people, public drunkeness, street prostitution, high levels of police activity and other criminal or not criminal activities that create a sense of danger (Gracia, 2014; Gracia & Herrero, 2007; Robinson et al., 2003; Ross & Mirowsky, 2001; Sampson, 2009; Sampson & Raudenbush, 2004). Despite some studies suggesting that physical and social disorder may overlap, being order and disorder two ends of a single continuum (Xu, Fielder, & Flaming, 2005; Ross & Mirowsky, 1999), most studies support the distinction between physical and social disorder (Brunton-Smith, Sindall, & Tarling, 2010; LaGrange, Ferraro, & Supancic, 1992; Sampson & Raudenbush, 2004; Taylor & Shumaker, 1990).

In order to assess neighborhood disorder, researchers generally use three different approaches (McDonell & Waters, 2011; Mooney et al., 2014). One approach, based on a more objective perspective, draws from neighborhood information from governmental or comercial data sources (Cerdá et al., 2009; McDonell, 2007; Mooney et al., 2014). Althoug these data is freer from the variability and subjectivity of subjective perceptions of disorder (Kubrin, 2008), however, this information is “often collected for administrative purposes, may not fully capture the construct of research interest, and may be collected at a spatial resolution that is not optimal for research purposes” (Mooney et al, 2014, p. 626-627). A second, and widely used, approach is based on resident’s perceptions of their neighborhood physical or social characteristics. A number of limitations have been noted, however, regarding this approach, including "same source bias" (e.g., same source reporting perceived neighborhood disorder and related outcomes), confusion with other psychological constructs (e.g., fear of crime), or the influence of stereotypes, and neighborhood prejudices (e.g., racial, ethnic, or socioeconomic composition) in perceptions of disorder (Caughy, O’Campo, & Patterson, 2001; Duncan & Raudenbush, 1999; Gómez, Johnson, Selva, & Sallis, 2004; Mooney et al., 2014; Sampson, 2009; Sampson & Raudenbush, 1999, 2004; Schaefer-McDaniel, Caughy, O’ Campo, & Gearey, 2010). Finally, a third approach, that aims to overcome the above limitations, emphasizes the importance of using direct and systematic observations of neighborhood characteristics by trained researchers (Franzini, Caughy, Nettles, & O’Campo, 2008; McDonell, 2007; McDonell & Waters, 2011; O'Neil, Parke, & McDowell, 2001; Reiss, 1971; Raudenbush & Sampson, 1999; Sampson & Raudenbush, 1999). This approach aims to obtain objective measures of neighborhood conditions, to capture a wide range of factors, which are not always available otherwise, and to allow its replication in other contexts (Caughy et al., 2001; Cohen et al., 2000; Franzini et al., 2008; McDonell & Waters, 2011; Sampson & Raudenbush, 2004; Taylor, 2001).

The present study

This study aims to add to this body of research by validating an observational measure of neighborhood disorder in the context of a European city, that may differ from the culture and structure of anglosaxon cities where most of this type of measures have been developed and validated (Le Galès & Zagrodzki, 2006; Summers, Cheshire, & Senn, 1999). The availability of a reliable and valid measure of neighborhood disorder in this context, may be an important addition to the growing body of literature exploring neighborhood effects (Sampson, 2012). To this end, independent observations by trained raters of neighborhood disorder will be conducted using small-areas of the city as the ecological units (i.e., census block groups, which are the smallest administrative sections of the city available). By using the smallest posible geographical units of the city we expect greater homogeneity of neighborhood characteristics (Ocaña et al., 2008). Also, by using all census block groups of the city we will obtain greater variability and, as neighborhood characteristics tend to cluster in space, this will provide the possibility to explore the clustering of these characteristics for validation purposes (Gracia et al., 2014).

This study presents data on the development and preliminary validation of an observational instrument to assess neighborhood disorder. The specific objectives of the study are: (1) To test the inter-rater reliability of the scale. (2) To test the factorial validity of the scale using Confirmatory Factor Analysis. We expect a factorial structure reflecting three theoretically a priori factors: physical disorder, social disorder and physical decay (Sampson & Raudenbush, 2004). (3) To test the reliability of the scale by means of the composite reliability index. (4) To test the criterion-related validity of the scale also employing structural equations. Drawing from social disorganization theory we expect associations between neighborhood disorder and three neighborhood structural characteristics, central in this theoretical perspective: neighborhood socioeconomic status, immigrant concentration, and residential instability (Caughy et al., 2001; Jones, Pebley, & Sastry, 2011; Kubrin & Weitzer, 2003; McDonell, 2011; Mooney et al., 2014; Sampson et al., 1997; Sampson & Raudenbush, 1999). Also, for validation purposes, a spatial perspective will be applied. As we expect that disordered neighborhoods will cluster in space, rather than be randomly distributed in the city, spatial correlation analyses will be conducted to test whether neighborhood disorder shows a significant spatial pattern (Bruinsma, Pauwels, Weerman, & Bernasco, 2013; Gracia et al. 2015; Quick, 2013; Veysey & Messner, 1999).

Method

Sample

This study was conducted in the city of Valencia, the third largest city of Spain. As proxy of neighborhood units, we used census block groups that were the smallest administrative unit of the city available. Census block groups can be defined as walkable areas within a few number of city blocks, and as they are smaller than census tracks are particularly appropriate for neighborhood studies (Gracia et al., 2014; Sampson & Raudenbush, 2004). Observations by trained raters were conducted in each of the 552 census block groups in which the city is divided. The total population for these census block groups was 736,580 inhabitants (2013 data), with an average of 1,334 inhabitants per census block group (ranging from 630 to 2,845).

Measures

Neighborhood disorder observation scale. A neighborhood disorder scale was initially constructed with a total of 20 items based on three dimensions of neighborhood disorder proposed by Sampson and Raudenbush (Sampson & Raudenbush, 2004). Thus, the scale included three theoretically motivated subscales measuring physical disorder, social disorder, and physical decay. *Physical disorder* was defined by 8 items: cigarettes in the street, trash in the street, empty bottles in the street, graffiti, abandoned cars, used condoms and syringes in the street, and political or protest message graffiti. *Social disorder* was defined by 7 items: adults or young people loitering, people drinking alcohol in public, gangs, public intoxication, adults fighting or arguing, selling drugs and street prostitution. *Physical decay* was defined by 5 items: vacant or abandoned houses, abandoned commercial buildings, vandalized and run-down buildings, deteriorated residential units and deteriorated recreation places. The observations are rated on a 5-point response scale (from 0 = no presence, to 4 = highly present). Two trained raters walked each census block group in order to complete the observational scale. All observations were made during business hours.

Criterion-related validity measures. Drawing form social disorganization theory, to test criterion-related validity we will explore relationships between neighborhood disorder and three neighborhood characteristics measured at census block group level: neighborhood socioeconomic status, immigrant concentration, and residential instability. The City of Valencia Statistics Office provided these data for each census block group. Neighborhood socioeconomic status was measured with an indicator created through factor analysis (this factor included educational level, property value, percentage of high-end cars, and financial and commercial activities). Immigrant concentration was the percentage of immigrant population in each census block, and residential instability was the proportion of the population who had moved into or out of each census block group during the previous year (rate per 1,000 inhabitants).

Statistical analysis

To measure inter-rater reliability, two pairs of trained undergraduate students walked a random sample of the census block groups. They observed a subset of 15% of them approximately (N= 86). Inter-rater reliability scores were computed per each of the three scales by calculating intraclass correlation coefficients (ICC) due to the quantitative nature of data. This analysis was performed with SPSS 22 for Windows.

Several competing Confirmatory Factor Analyses (CFA) were specified, estimated and tested in Mplus 7.3. According to the ordinal nature of the data and its non-normality WLSMV (Weighted Least Squares Mean and Variance corrected) estimation was used, the one recommended in the literature (Finney & DiStefano, 2006). Several criteria were used to asses goodness-of-fit: (a) the chi-square statistic; (b) the comparative fit index (CFI); and (c) the root mean squared error of approximation (RMSEA). A model with a CFI of .95 or larger and a RMSEA of .08 or lower would be indicative of very good fit between the hypothesized model and the data (Hu & Bentler, 1999). Nevertheless, overall fit must be accompanied by a careful diagnostic of the analytical fit (parameter estimates) in the model in order to not blindly use the aforementioned thresholds (Kline, 2011). For model comparison a modeling approach that uses practical fit indices to determine the overall adequacy of a fitted model has been used as recommended by Cheung and Rensvold (2002) or Little (1997). From this point of view, if a parsimonious model evidences adequate levels of practical fit, then it is preferred over the more complex model. Usually, CFI differences (ΔCFI) are used to evaluate measurement invariance. CFI differences lower than .01 (Cheung & Rensvold, 2002) or .05 (Little, 1997) are usually employed as cut-off criteria.

Additionally, internal consistency of the dimensions in the scale has been estimated with the Composite Reliability Index (CRI). Although Cronbach's coefficient alpha is the most widely used estimator of internal consistency, it has been criticized as being only completely appropriate with essentially tau-equivalent items (and tests), and also by being a lower bound for the true reliability (Raykov, 2004). More explicitly, a tau-equivalent test assumes all items measure the same latent variable, on the same scale, with the same degree of precision, with all true scores being equal (Graham, 2006). When tau-equivalence does not hold, alpha will over- or under-estimate (more often the latter) the population value. An alternative to the coefficient alpha is the CRI, which is usually calculated using estimates from confirmatory factor analyses (Graham, 2006). Accordingly, the more adequate CRI, was employed.

Criterion-related validity was established by correlating neighborhood disorder factors with other neighborhood constructs theorically linked in the literature (Gracia, 2014; Gracia et al., in press; Kubrin & Weitzer, 2003, Sampson & Raudenbush, 1999; Sampson et al., 1997; Shaw & McKay, 1942). This correlation was obtained within the context of a structural equation modeling, in order to prevent as much as possible the correlation attenuation due to measurement error. Specifically, neighborhood disorder was correlated to neighborhood socioeconomic status, immigrant concentration, and residential instability (see Measures section).

To test criterion-related validity we also used a spatial methodology approach. To assess spatial autocorrelation, we computed Moran's I (Moran, 1950) per each of the three subscales or factors, considering as the observation the midpoint of each of the census block groups. We expected a significant spatial distribution of neighborhood disorder, rather than a random distribution, because we expect that disorder, as other neighborhood characteristics, will show a tendency towards spatial clustering (Bruinsma et al., 2013; DiMaggio, 2015; Quick, 2013; Veysey & Messner, 1999).

Results

Inter-rater reliability

Intraclass correlation coefficients were computed to assess inter-rater agreement for the three subscales (see Odgers, Caspi, Bates, Sampson, & Moffit, 2012, for a similar approach). Intraclass correlations ranged from .25 to .71 (See Table 1). Landis and Koch (1977) criteria was used to interpret results regarding inter-rater agreements: < .20 slight, .21 – .40 fair, .41 – .60 moderate, .61 – .80 substantial, and .81 – 1 almost perfect agreement. Our results indicated fair to substantial levels of agreement between raters (Landis & Koch, 1977). Social disorder obtained the lowest value, and physical disorder and physical decay showed similar results.

Table 1. Inter-rater agreement. Intra-class correlations coefficients (ICC)

Scales	No. of items	M (SD)	ICC_1	ICC_2
Physical disorder	8	5.97 (3.54)	.55***	.71***
Social disorder	7	0.57 (0.79)	.25***	.40***
Physical decay	5	2.64 (2.82)	.46***	.63***

* < .05, ** < .01, *** < .001
ICC_1= index of reliability for a single rater.
ICC_2 = index of reliability for multiple raters averaged together.

Confirmatory Factor Analysis

Three a priori competing models were specified. The theoretical model that supports the content validity of the scale a priori hypothesizes three dimensions; physical disorder, social disorder and physical decay. Indicators were developed to tap these three theoretical dimensions. However, there was doubt about weather two of these dimensions could be too overlapped to have discriminant validity: physical disorder and physical decay. Accordingly, another a priori model was specified with two dimensions: social disorder and all the indicators of physical disorder and physical decay specified to load onto a single dimension. Finally, the most parsimonious latent structure, a one-factor model underlying all the indicators, was also specified. Goodness-of-fit indices for these three a priori models are shown in Table 2. Model fit for the three models was extremely poor, and none of them can be retained as a good approximation to the observed data. Nevertheless, the three factor model shown a *relative* better fit compared to the other two models: ΔCFI = .06 compared to the one-factor model, and ΔCFI = .04 compared to the two-factor model. Taking this information into account, plus the fact that the theoretical model that supports the scale was three-dimensional, this model was retained for further psychometric scrutiny.

Table 2. Goodness of fit indices for the tested models

	χ^2	**df**	***p***	**CFI**	**RMSEA**	**90% CI**
One-factor model	1471.75	152	< .001	.643	.12	.12-.13
Two-factor model	1407.56	151	< .001	.660	.12	.11-.12
Three-factor model	1272.59	70	< .001	.700	.11	.11-.12
Modified three-factor model	278.61	87	< .001	.940	.06	.05-.07

A careful look at the factor loadings, together with the lack of variability in some indicators, allows to remove some of them. Those removed lacked variability and/or had poor consistency with their dimension. The final version of the questionnaire was presumed to measure three factors (physical disorder, social disorder and physical decay) with 5, 6 and 4 indicators each (see Appendix). This depurated version of the original scale was tested and its goodness-of-fit indices are shown in Table 2. There was a huge improvement in model fit, and it can be said that the model seems to adequately represent the observed data. Factor loadings are shown in Figure 1. They were all statistically significant ($p < .01$) and, in general, pretty large. These results are indicative of good analytical fit.

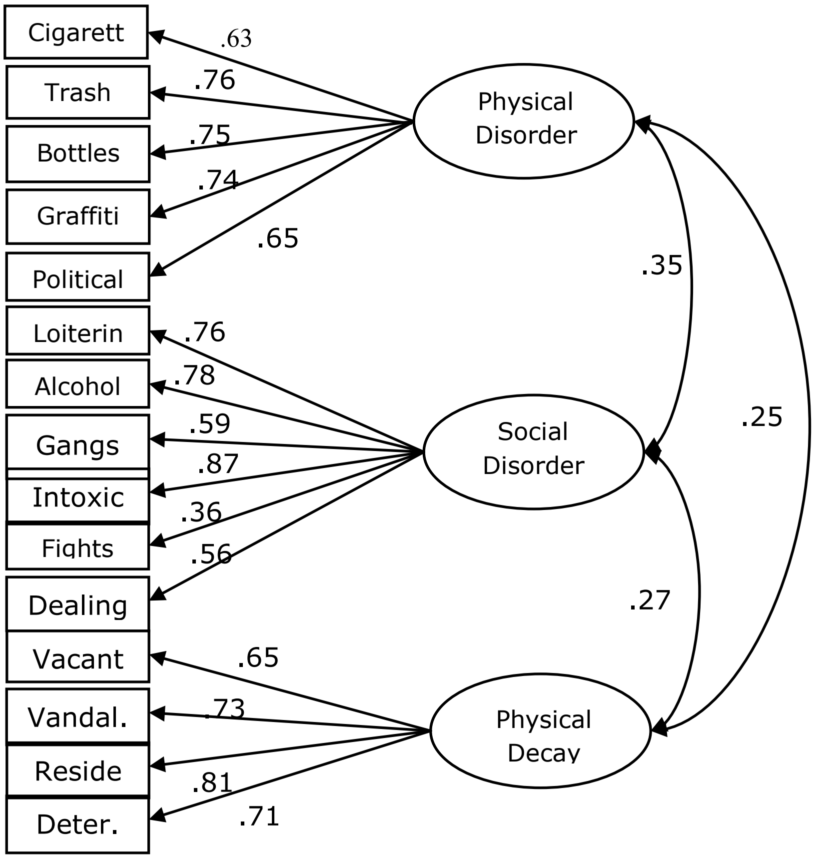

Figure 1. Standardized factor loadings and correlations for the Confirmatory factor analyses of the Neighborhood Disorder Observational Scale.

Notes: all coefficients statistically significant ($p < .01$); Intoxicat = Intoxication; Dealing = Drug dealing; Vacant = Vacant houses; Vandal. = Vandalized buildings; Residen. = Residential deterioration; Deter. = Deteriorated facilities.

Internal consistency

Reliability (internal consistency) estimates were calculated for each dimension or factor in the scale. The calculated reliability estimates were Composite Reliability Indices (CRI), as already mention in the method section. All the CRI were large, indicating a good reliability for all the dimensions. Specifically, CRI for physical disorder was .83, .82 was the estimate for social disorder, and .82 the internal consistency estimated for physical decay.

Criterion-related validity

Finally, evidence of criterion-related validity has also been found. Three criteria were used (neighborhood socioeconomical status, immigrant concentration and residential instability). The relationship between the criteria and the latent variables were calculated at the latent level, not the observed one. A first structural model included the measurement model found to fit well to the data, plus the first criterion (neighborhood socioeconomical status). Again, this structural model fitted the data well ($\chi^2(99)$ = 339.78, $p < .001$; CFI = .93, RMSEA = .066 [.059 - .074]). The correlations between neighborhood socioeconomic status and the criteria and the factors were: $\rho = -.13$, $p < .01$ with physical disorder; $\rho = .04$, $p > .05$ with social disorder; and $\rho = -.29$, $p < .01$ with physical decay. With respect to immigrant concentration, the structural model also adequately fitted the data ($\chi^2(99)$ = 309.38, $p < .001$; CFI = .93, RMSEA = .062 [.054 - .070]). The correlations among the criterion and the factors were: $\rho = .044$, $p > .05$ with physical disorder; $\rho = .13$, $p < .05$ with social disorder; and $\rho = .21$, $p < .01$ with physical decay. Finally, a third structural model was specified and tested to relate the three factors with residential instability. Again the model fitted the data well ($\chi^2(99)$ = 333.54, $p < .001$; CFI = .92, RMSEA = .066 [.058 - .073]), and its correlations with the factors were: $\rho = .05$, $p > .05$ with physical disorder; $\rho = .15$, $p < .05$ with social disorder; and $\rho = .22$, $p < .01$ with physical decay.

Also, for criterion-related validity purposes, tests for spatial correlation were conducted for the three dimensions. Results showed spatial autocorrelation in the three scales as all Moran's I values were positive and significant (p < .001). Moran's I values for the three measures were .20 for social disorder, .39 for physical decay and .49 for physical disorder, indicating a stronger spatial pattern for physical disorder and physical decay than for social disorder. These results indicate a positive non-random distribution of all types of neighborhood disorder in the city (i.e., rather than being randomly distributed across the city, they tend to cluster in space).

Discussion

In this paper we described the development and the psychometric properties of a preliminary validation of an observational scale assessing neighborhood disorder. This scale was implemented in the city of Valencia (Spain), using independent observations of all census block groups of the city conducted by trained raters. In general, results showed that this scale is a psychometrically sound and valid instrument to assess three neighborhood disorder dimensions: Physical disorder, social disorder, and physical decay.

Results regarding inter-rater reliability showed fair to substantial levels of agreement (Landis & Koch, 1977), with stronger agreements for physical disorder and physical decay factors, and lower inter-rater reliability for social disorder. Although these results are slightly lower than in other studies (e.g., Caughy et al., 2001; Franzini et al., 2008; Jones et al., 2011), they are, however, comparable to others (e.g., Mooney et al., 2014; Wei et al., 2005). As to why social disorder showed lower levels of agreement, one possibility is that social disorder cues such as fights or public intoxication tend to be less stable over time (e.g., depending on the time of the day), than other physical features of neighborhoods, like those indicating physical decay and disorder, that are more temporally stable (Jones et al., 2011).

With respect to the factorial structure of the observational scale, our analyses aimed to validate a three theoretically-based neighborhood disorder dimensions (Sampson & Raudenbush, 2004). To this end, several competing confirmatory factor analyses were first estimated and discarded, yielding a final and depurated version of the scale with good analytical fit. This final scale supported a three-factor model measuring physical disorder, social disorder, and physical decay, as theorized by Sampson and Raudenbush (2004).

This final three-factor model was obtained after removing some items for their low variability or poor consistency with their dimension. Although these items are usually present in other scales measuring neighborhood disorder, however, indicators such as abandoned cars, used condoms and syringes (physical disorder), prostitution (social disorder), or abandoned commercial buildings (physical decay) were discarded in the final model. The presence of these items was very low and, in the case of syringes, there was no presence at all in any of the census block groups observed. Although the time of the observation may have influenced the low presence of some of these indicators (e.g., prostitution), another possible explanation is that, given the characteristics of cities like Valencia, with high density in a relative small area (Le Galès & Zagrodzki, 2006; Summers et al., 1999), some of these indicators could be more present in the outskirts of the city, and therefore outside of the boundaries were the observations were made. This also suggests that differences between the present scale, and others developed elsewhere, may reflect context-specific features of the cities. Given that these results may be context-dependent, we do not favour the uncritical use of the short-version of the originally proposed scale destilled for this particular study. On the contrary, careful theoretical considerations previous to the use of this scale in other cities should consider whether some (or all) of the removed items could have enough variability and importance as to be included in the instrument. Clearly, a posterior depuration of the scale according to its psychometric properties is always possible. On the other hand, results for internal consistency of the final three-factor scale by confirmatory analyses also supported its reliability, with CRI values between .82 and .83 for the three scales.

Two different criterion-related validity tests of this observational measure of neighborhood disorder were conducted. For the first one, and drawing from social disorganization theory, we explored associations with three criteria tapping neighborhood characteristics central to this theoretical perspective: neighborhood socioeconomic status, immigrant concentration, and residential instability, measured at the census block group level. As expected, correlations between measures of neighborhood disorder and these structural characteristics of neighborhoods were mostly in the expected direction (Kubrin & Weitzer, 2003; Sampson et al., 1997; Sampson & Raudenbush, 1999), although with stronger associations for physical decay. For example, high levels of physical decay were significantly associated with lower neighborhood socioeconomic status, higher rates of immigrant concentration, and higher residential instability. Social disorder was positively related to levels of immigrant concentration, and residential instability, but its association with neighborhood socioeconomic status was not statistically significant. Physical disorder was also negatively related to neighborhood socioeconomic status, however, associations with immigrant concentration and residential instability did not reach significance. These results partly support previous research were significant associations between disorder and a number of neighborhood characteristics were also found, especially those regarding the relationship between physical disorder and decay and neighborhood socioeconomic indicators (Caughy et al., 2001; Jones et al., 2011; McDonell, 2011; Mooney et al., 2014; Sampson & Raudenbush, 1999). Also, some of our results support studies that fail to find a significant relationship between physical disorder and residential instability (Sampson & Raudenbush, 1999), or between physical disorder and immigrant concentration (Jones et al., 2011). It is interesting to note that physical decay was associated with all neighborhood characteristics (socieconomic status, immigrant concentration, and residential instability), suggesting that differentiating between physical disorder and physical decay is an important theoretical distinction that may provide a more detailed analysis when assessing neighborhood disorder, and exploring its relationships with different outcomes and processess (Sampson, 2009; Sampson & Raudenbush, 2004).

As we expected that disordered neighborhoods would tend to cluster together in space (Bruinsma et al., 2013; DiMaggio, 2015; Quick, 2013; Veysey & Messner, 1999), for the second criterion-related validity test we used a spatial analytical approach to assess the spatial distribution of the different types of neighborhood disorder across all census block groups observed. Results showed that the three types of disorder (physical disorder, social disorder and physical decay) were spatially clustered, confirming that they were not randomly distributed in the city. This reflects the existence of different areas of the cities were neighborhood disorder tends to concentrate, and shows that this neighborhood risk factor tends to cluster in space. These results support the idea that different manifestations of neighborhood disorder, as other characteristics of the cities, are not randomly distributed in space. As illustrated by a growing body of literature linking neighborhood disorder with a wide array of outcomes, including crime, violence, or health, the spatially patterned nature of this risk factor makes more likely that related outcomes will also be spatially patterned (Cunradi, Mair, Ponicki, & Remer, 2011; Freisthler et al., 2007; Diez-Roux & Mair, 2010; Kawachi & Berkman, 2003; Law, Quick, & Chan, 2014; O'Campo et al., 2015; Gracia et al., 2015; Sampson, 2012).

Finally, this study has both strengths and limitations. Among the strenghts, the use of independent observations of neighborhood conditions, rather than residents' subjective perceptions, allows to overcome some of the limitations noted in the literature regarding this later approach (Caughy et al., 2001; Mooney et al., 2014; Sampson & Raudenbush, 1999; Schaefer-McDaniel, et al., 2010). Relatedly, for the observation of neighborhood disorder at the level of ecological units (rather than the personal level), we also use a high-resolution approach. We used the smallest administrative units available (i.e., census block groups) that allow greater homogeneity and precision than lower resolutions such as census tracks or postal codes, commonly used in other neighborhood studies (Beyer, Wallis, & Hamberger, 2013; Bursik et al., 1990; Kaufman, Dole, Savitz, & Herring, 2003; O'Campo, Xue, Wang, & Caughy, 1997). By using small-area units, we also reduced potential ecological bias, as this resolution is closer to the individual level (Gracia et al., 2015; Lawson, 2006, Ocaña-Riola et al., 2008). We used census block groups in our study, which substantially reduced this potential bias. Finally, we used all census block groups of the city, rather than selecting only a sample of them, which provided greater variablity and the possibility to explore potential significant spatial patterns in the distribution of neighborhood disorder across the city (Caughy et al., 2001; Mooney et al., 2014). In this regard, the use of spatial methods to complement the criterion-related validity of our observational scale is an important addition to the existing literature, as neighborhoods, from this perspective, are not treated as independent units (Gorman, Gruenewald, & Waller, 2011; Morenoff, Sampson, & Raudenbush, 2001; Mooney et al., 2014). Although widely used in epidemiological studies (Lawson, 2009), and despite its advantages, this methodological approach is still uncommon in neighborhood studies, and future research would clearly benefit from incorporating a spatial perspective (Cunradi, et al., 2011; Gracia et al., 2014, 2015; Law & Quick, 2013; Law et al., 2014; Sparks, 2011). As for limitations, as noted above, some measures of neighborhood disorder may have been affected by the time of the day they were observed. Our observations were limited to business hours, and the same places may have shown different characteristics at night (Caughy et al., 2001). Future research would benefit from including different observations during the day, and revisiting the same areas during night hours. Also, other neighborhood indicators such as trash in the streets may be present only at specific moments, and repeated observations of the same area would be advisable, although clearly more costly (Wei et al., 2013). In this regard, recently new technologies, such as virtual environments, or Google Street View, provide powerful and easy accessible tools that may help to advance neighborhood research (Toet & van Schaik, 2012, Odgers et al., 2012).

In conclusion, this paper provides evidence of a reliable and valid observational measure to assess neighborhood disorder. Adequate measures to assess neighborhood characteristics are important research and intervention tools, as they are key to better understand neighborhood processes, as well as to evaluate related outcomes, and monitor changes after grass-roots efforts or official initiatives to reduce neighborhood inequalities.

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Appendix

Neighborhood disorder observation scale

Item no.	Scale	Item content*
1	Physical disorder	Colillas en la calle / Cigarettes in the street
2	Physical disorder	Basura en la calle o acera / Trash in the street
3	Physical disorder	Botellas o latas vacías de cerveza u otras bebidas en la calle / Empty bottles or cans in the street
4	Physical disorder	Graffitis / Graffiti
5	Physical disorder	Pintadas de carácter político o reivindicativo / Political or protest message graffiti
1	Social disorder	Jóvenes o adultos merodeando por el barrio / Adults or young people loitering
2	Social disorder	Gente bebiendo alcohol en la vía pública / People drinking alcohol in public
3	Social disorder	Bandas / Gangs
4	Social disorder	Gente borracha o drogada por la calle / Public intoxication
5	Social disorder	Peleas o discusiones agresivas entre jóvenes o adultos / Adultos or young people fighting or arguing
6	Social disorder	Venta de droga / Selling drugs
1	Physical decay	Casas vacías / Vacant houses
2	Physical decay	Viviendas abandonadas, quemadas o tapiadas / Abandoned, vandalized and run-down buildings
3	Physical decay	Zonas residenciales muy deterioradas / Deteriorated residential units
4	Physical decay	Zonas recreativas muy deterioradas / Deteriorated recreation places

*Items in Spanish in the original scale, item translation for information purposes

Study 2

Validation of a Google Street View-based neighborhood disorder observational scale

Validation of a Google Street View-based neighborhood disorder observational scale[2]

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Abstract

Recently, there has been a growing interest in developing new tools to measure neighborhood features using the benefits of emerging technologies. This study aimed to assess the psychometric properties of a neighborhood disorder observational scale using Google Street View (GSV). Two groups of raters conducted virtual audits of neighborhood disorder on all census block groups (N = 92) in a district of the city of Valencia (Spain). Four different analyses were conducted to validate the instrument. First, inter-rater reliability was assessed through intraclass correlation coefficients, indicating moderated levels of agreement among raters. Second, confirmatory factor analyses were performed to test the latent structure of the scale. A bifactor solution was proposed, comprising a general factor (general neighborhood disorder) and two specific factors (physical disorder and physical decay). Third, the virtual audit scores were assessed with the physical audit scores, showing a positive relationship between both audit methods. In addition, correlations between the factor scores and socioeconomic and criminality indicators were assessed. Finally, we analyzed the spatial autocorrelation of the scale factors, and two fully Bayesian spatial regression models were run to study the influence of these factors on drug-related police interventions and interventions with young offenders. All these indicators showed an association with the general neighborhood disorder. Taking together, results suggest that the GSV-based neighborhood disorder scale is a reliable, concise and valid instrument to assess neighborhood disorder using new technologies.

Keywords: Google Street View; Neighborhood disorder; Physical decay; Physical disorder; Virtual audits

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[2] Marco, M., Gracia, E., Martín-Fernández, M., & López-Quílez, A. (2017). Validation of a Google Street View-based neighborhood disorder observational scale. *Journal of Urban Health, 94*, 190-198. doi: 10.1007/s11524-017-0134-5

Introduction

Neighborhood disorder has been related to a wide number of health outcomes such as obesity, chronic diseases, mortality, and sexually transmitted diseases,[1-4] as well as to mental and behavioral disorders such as depression, anxiety, well-being, and binge drinking.[5,6] Research has also found an association between neighborhood disorder and crimes such as juvenile delinquency, child maltreatment, and intimate partner violence.[7-12]

To assess neighborhood disorder and related outcomes, researchers have traditionally used self-report measures [13-15] or physical systematic social observation.[16-18] Regarding the first, residents provide information about their own neighborhoods, which provide subjective data that it is difficult to obtain otherwise such as feelings of mistrust or fear, perceived safety or social disorder. [14-15] However, these data collection have some drawbacks, including that perceived neighborhood disorder may not match with the realities of the ecological context, [19-20] and neighbors may be influenced by stereotypes, personal characteristics or the tendency to offer socially desirable responses. [20] Regarding the later, it overcomes some of these concerns, but this method has some major disadvantages: raters have to move to the study area (a very large area in some cases), and human resources and travel costs can be considerable.[21-25] In addition, conducting physical audits in some highly conflictive areas that are difficult to access may pose dangers to research staff. [24,26]

These limitations have led to the development in recent years of innovative instruments to evaluate neighborhood characteristics using new technologies. One of the main alternatives is Google Street View, which has been used in a growing number of studies to assess neighborhood features.[26-29] Google Street View is freely available from the Google Maps website, and its database has images of almost all areas of western countries. Raters can visit neighborhoods and streets virtually, and due to its powerful zoom and high resolution, they can capture neighborhood characteristics in 360º images (Figure 1). Google Street View is user-friendly and it does not require any special computer skills.

The general aim of this study is to assess the psychometric properties of a neighborhood disorder observational scale using Google Street View in a Spanish city. The secondary objectives of the study are: (1) to assess the inter-rater reliability; (2) to test the latent structure of the scale through confirmatory factor analysis; (3) to assess the relationship between the virtual and the physical audit scores; and (4) to assess the relation between the scale and some socioeconomic and criminality indicators.

Figure 1. Google Street View image (above) vs. real photograph (below) of a boarded-up, vandalized house

Methods

Sample

The study area was the Maritime district of the city of Valencia, the third largest city in Spain. The city covers an area of 134.65 km^2, and has a population of 786,189 inhabitants (2015 data).[30] The Maritime district is located in the east of the city, near the Mediterranean coast, and comprises very different neighborhoods in sociodemographic and physical terms. This district has a population of 57,710 inhabitants (2015 data),[30] and is divided into 92 census block groups, the smallest administrative unit available. We used census block groups as the neighborhood proxies. The virtual audits were conducted by two groups of raters using Google Street View imagery. Each group assessed the 92 census block groups.

Instrument

Google Street View (GSV)-based neighborhood disorder observational scale. We used a neighborhood disorder observational scale previously validated in the same city. [31] The original scale has 20 items and measures three factors: physical disorder, social disorder and physical decay. The social disorder factor includes items such as people drinking alcohol or arguing in the street, and therefore could not be assessed with Google Street View imagery, which does not capture social interactions. This factor was therefore removed from the scale, leaving the two factors of physical disorder and physical decay. The physical disorder factor evaluated the presence of cigarette butts, trash and empty bottles in the street as well as graffiti, including political and protest graffiti. Indicators of abandoned cars, used condoms and syringes were removed from the scale because of their extremely low frequency. The physical decay factor assessed the presence of vacant or abandoned houses, abandoned commercial buildings, vandalized and run-down buildings, deteriorated residential units and deteriorated recreation places. The final scale was composed of 10 Likert-type items ranging from 0 (no presence of the item) to 4 (high presence of the item) (see Appendix 1). The data were collected in 2015. All Google Street View images assessed were from 2014 and 2015.

Criterion-related validity measures

Physical audits of neighborhood disorder in the same area were obtained to study criterion-related validity. We used physical audits conducted in a previous study in the same city area. [31] These audits were collected in 2014 by trained raters walking each census block group.

Two neighborhood characteristics frequently associated with neighborhood disorder were also assessed. Firstly, socioeconomic status was assessed by two indicators provided by the city's Statistics Office: education level (measured as the mean education level in the census block group on a 4-point scale, where 1 = less than primary education, 2 = primary education, 3 = secondary education, and 4 = college education) and cadastral property value (average value of housing per square meter).

Secondly, criminality indicators were used. To this end, police officers provided information about two types of police interventions: drugs-related interventions (police interventions related to possession, misuse or distribution of drugs), and interventions with young offenders (police interventions where minors participate in illegal or disruptive behavior). Police officers' perceptions of the level of policing activity in each census block group was measured on two 5-point scales evaluating the level of police intervention involving drugs or minors, respectively, where 0 = very low level of intervention, and 4 = very high level of intervention.

Procedure

Two groups of two research assistants not directly involved in the project conducted virtual audits of neighborhood disorder in all the census block groups. In an initial training session led by the research staff, raters were introduced and instructed how to complete the GSV-based neighborhood disorder observational scale, and several examples were performed. Raters virtually walked around the whole census block group, and they assessed all the streets within. If the boundary divided a street or avenue into two, only the side corresponding to the census block group was assessed. Virtual audits were collected in 2015.

Data Analysis

Several analyses were performed to assess the psychometric properties of the scale. Inter-rater reliability was evaluated first using the intraclass correlation coefficients (ICC), computing the raw scores of each of the originally proposed factors of the GSV-based neighborhood disorder observational scale. Descriptive analyses were obtained for all items, as well as item-total corrected correlations.

To examine the latent structure of the scale a confirmatory factor analysis was performed; various models were tested to achieve the best fit for the data. Three models were specified: a one-dimensional model, grouping all items into a general measure of neighborhood disorder; a two-dimensional model, based on the model proposed by Marco et al.,[31] where social disorder items were removed, and only two correlated factors were specified (physical disorder and physical decay); and finally, a bifactor solution was specified, considering the previous two specific dimensions and also one general factor (i.e. general neighborhood disorder). Factors in this model are orthogonal, thus the general factor captured all the variance shared by the specific factors; each item loaded on one specific dimension and also on the general one. Given the categorical nature of the data, the WLSMV estimator was used to estimate the model parameters. [32] The fit of the models was assessed with the CFI and the TLI indices, following the criteria proposed by Hu and Bentler (CFI/TLI > 0.95).[33] The RMSEA was also used to evaluate the residuals of the models. Values of the RMSEA less than 0.06 and 0.08 indicate good and mediocre fit, respectively. [34] Composite reliability index (CRI) also assessed reliability in conditions of non tau-equivalence.[35]

To assess criterion-related validity, factor scores of the GSV-based neighborhood disorder observational scale were correlated with the criterion-related measures (physical audits, socioeconomic indicators and criminality indicators). In addition, a spatial analysis was performed. Some studies have shown that neighborhood disorder tends to cluster spatially.[36,37] We tested the presence of spatial autocorrelation using exploratory spatial data analysis with Moran's I index.[38] This statistic is commonly used to measure spatial autocorrelation, where positive values indicate the dataset exhibits a clustered pattern, negative values indicate the dataset displays a dispersed pattern, and zero indicates that there is no spatial clustering.

Finally, Bayesian spatial regression models were tested to analyze the influence of GSV-based neighborhood disorder observational scale factors in explaining drug-related police interventions and interventions with young offenders. We ran two spatial regression models using GSV-based neighborhood disorder observational scale scores as covariates to explain drug-related police interventions and interventions with young offenders, respectively. To measure the spatial component, we introduced two random effects: a structured spatial effect *S,* and an unstructured spatial effect *U* to assess heterogeneity. All analyses were performed with the statistical software *R* except the confirmatory factor analyses, which were performed with *MPlus* 7.[39-40]

Results

Descriptive statistics and inter-rater reliability

The mean, standard deviation and range of each item are displayed in Table 1. Descriptive analysis showed that the items are slightly displaced to the left (mean range 0.43-2.53 with a mean standard deviation around 1), indicating, on average, a low presence of the observed indicators of physical disorder and decay. The item-total corrected correlations were moderately high, ranging from .40 to .73, which suggests that the items were related to the measured construct. Intraclass correlation coefficients for random raters (ICC_2) and average intraclass correlation coefficients (ICC_{2_k}) were between the standard cut-offs, indicating a fair agreement if all the items are taken into account (between .21-.40), and moderate agreement if only the mean of each subscale is considered (between .41-.60).[41]

Table 1. Item descriptive statistics and inter-rater reliability for each item assessed on the 92 census block groups

Item	*M*	*SD*	*Max*	*Min*	r_{drop}	
Cigarettes	1.30	1.27	0	4	0.45	
Trash	1.55	1.27	0	4	0.63	
Bottles	0.55	0.94	0	4	0.72	
Graffiti	2.53	1.06	0	4	0.40	
Political graffiti	0.29	0.66	0	3	0.43	
Vacant houses	0.88	1.11	0	4	0.68	
Deteriorated commercial buildings	1.04	1.13	0	4	0.64	
Vandalized buildings	0.85	1.08	0	4	0.63	
Residential deterioration	1.16	1.28	0	4	0.70	
Deteriorated facilities	0.43	0.79	0	4	0.73	
Subscale	***M***	***SD***	***Max***	***Min***	**ICC_2**	**ICC_{2_k}**
Physical disorder	3.82	2.85	0	15	0.28	0.43
Physical decay	6.24	3.67	0	16	0.38	0.55

Factor structure and scale reliability

Three models were fitted and compared to evaluate the latent structure of the scale.

Table 2. CFA fit indices

Model	χ^2	*df*	CFI	TLI	RMSEA	$RMSEA_{05}$	$RMSEA_{95}$
One Factor	86.412	35	.950	.936	.126	.093	.160
Two Factor	74.656	34	.961	.948	.114	.079	.149
Bifactor	33.430	59	.992	.985	.061	.000	.110

As shown in Table 2, the three models yielded adequate relative goodness-of-fit indices. Though the relative fit indices were fair for the one-dimensional and the two-dimensional models, the residuals for both models indicated a poor fit to the data.

The bifactor solution had an excellent fit in both indices, however, and the third model was therefore retained.

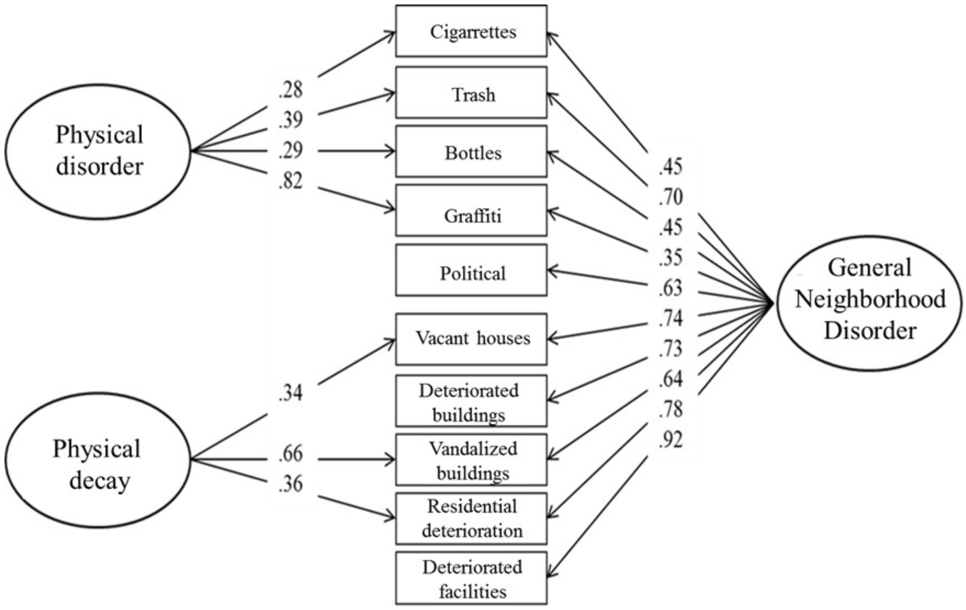

Figure 2. CFA Bifactor Model. Factors and factor loadings of each item

Figure 2 includes the model diagram with the standardized parameter estimates. All items loaded significantly on the general factor, whereas loadings for some of them were not significant on their specific factors. Specifically, indicators of political or protest graffiti, abandoned commercial buildings and deteriorated recreation places loaded only on the general dimension. Taking the bifactor model as the latent structure of the scale, the Composite reliability index (CRI) was obtained. The CRI for the general neighborhood disorder dimension was very high (CRI = .93), although the reliability was lower for the specific dimensions of physical disorder (CRI = .57) and physical decay (CRI = .61).

Criterion-related validity

GSV-based neighborhood disorder observational scale scores were related to the criterion measures (see Table 3). First, the factor scores of the physical and virtual audits were correlated. Note that the physical audit scores followed the original model proposed by Marco et al.,[31] whereas the virtual audits followed the bifactor model. Scores obtained with the GSV-based neighborhood disorder observational scale were positively related to the physical audit scores. The general neighborhood disorder factor of the virtual audits showed an extremely high relation between the physical audit factors (physical disorder, r_{xy} = .95, $t(90)$ = 27.97, p < .001, and physical decay, r_{xy} = .97, $t(90)$ = 38.27, p < .001), meaning that the virtual audit scores ordered the census blocks groups in a similar way to the physical audit scores. Regarding the specific factors of the virtual audits, both physical disorder and physical decay scores were positively related with the physical audits of disorder, r_{xy} = .39, $t(90)$ = 3.98, p < .001, and decay, r_{xy} = .37, $t(90)$ = 3.74, p < .001.

On the other hand, the general neighborhood disorder factor was highly correlated with socioeconomic indicators: higher scores in the general factor were related to lower neighborhood education level, r_{xy} = -.33, $t(90)$ = -3.48, p < .001, and lower cadastral property value, r_{xy} = -.34, $t(90)$ = -3.37, p < .001. In addition, the general neighborhood disorder factor was strongly correlated with police interventions, especially those involving young offenders, r_{xy} = .40, $t(90)$ = 4.15, p < .001, but also drug-related interventions, r_{xy} = .33, $t(90)$ = 3.27, p < .001. The specific factors, however, showed no significant association with criminality indicators, and only the physical decay factor was negatively related to cadastral property value, r_{xy} = -.28, $t(90)$ = -2.80, p = .006, and education level, r_{xy} = -.28, $t(90)$ = -2.81, p = .006. Therefore, high scores in the physical decay factor tended to co-occur with lower cadastral property values and lower education level.

Table 3. Criterion-related validity correlations

	General Neighborhood Disorder	**Physical Disorder**	**Physical Decay**
Physical audits			
Physical disorder	0.95	0.39	0.12
Physical decay	0.97	0.14	0.37
Socioeconomic indicators			
Cadastral property value	-.33	-.11	-.28
Education level	-.34	-.14	-.28
Criminality indicators			
Drug-related police interventions	.33	.09	.17
Young offenders police interventions	.40	-.09	.19

In the spatial analysis, the three factors showed significant positive spatial autocorrelation (general neighborhood disorder: I = .41, p < .001; physical disorder: I = .20, p < .001; physical decay: I = .30, p < .001), indicating a tendency to cluster together geographically, rather than being randomly distributed in space. In addition, in the two spatial Bayesian regression models general neighborhood disorder and physical decay showed more than 95% posterior probability of being higher than zero. These results indicated a higher prevalence of drug-related police interventions and interventions with young offenders in areas with higher general neighborhood disorder and physical decay. Physical disorder showed no relevant relationship with drug-related interventions nor with interventions with young offenders. Table 4 summarizes the models.

Table 4. Bayesian regression models with dependent variable: drug-related police interventions and police interventions with young offenders

Explanatory variables	**Drug-related police interventions**			**Police interventions with young offenders**		
	Mean	**Std. Error**	**95% CrI**	**Mean**	**Std. Error**	**95% CrI**
Intercept	.401	.061	.275, .513	.398	.061	.272, .511
General neighborhood disorder	.210	.091	.034, .395	.209	.088	.025, .375
Physical disorder	.061	.083	-.097, .222	.061	.085	-.094, .232
Physical decay	.173	.100	-.030, .370	.172	.098	-.015, .364
σ_s	.201	.126	.017, .427	.197	.126	.014, .446
σ_u	.312	.175	.028, .660	.310	.178	.013, .681

Discussion

The aim of this study was to develop and analyze the psychometric properties of a neighborhood observational scale using Google Street View. In light of the results obtained, we can conclude that the GSV-based neighborhood disorder observational scale provides an accurate, concise and valid measure of neighborhood disorder, comparable to measures obtained with traditional observational instruments. The strong relation between physical and virtual audits suggests it is feasible to conduct neighborhood disorder assessments using Google Street View.

We found that the bifactor model was the latent structure that best fitted the data of the models compared for the virtual audit of neigborhood disorder. This model yielded two specific dimensions that covered the unique aspects of physical disorder and physical decay. The model revealed also a general neighborhood disorder dimension that explained all the shared variance not captured by the specific dimensions. [42] Thus, the common elements of the specific factors originally proposed by Marco et al. [31] could be unified into one general neighborhood disorder dimension in the virtual neighborhood disorder audits.

The internal consistency of the general neighborhood disorder factor was very high, indicating a good overall reliability of the GSV-based neighborhood disorder observational scale.

Several variables were used to study criterion-related validity. On the one hand, the strong relationship between the virtually audited general neighborhood disorder factor and the two physically audited factors indicated that the factor scores of the two methods ordered the census block groups almost identically. This result is not entirely unexpected if we take into account that the bifactor solution modeled the common elements (i.e., the relation) of the physical disorder and decay factors into one general factor. Therefore, a strong correlation would be expected between the physically audited factors —which followed a two correlated factor model— and a non-specific measure of the shared variance of the same factors in the virtual audit. Likewise, the correlations between the virtually audited specific factors (i.e. physical disorder and decay) and their physically audited counterparts reflected that the core and non-shared elements of both specific factors —those accounted for by the bifactor solution— were positively related with the factors found in the original scale. [31] These results suggest that, in general, virtual and physical audits of the characteristics of disorder tend to be very similar.

On the other hand, we found an association between the GSV-based neighborhood disorder observational scale and drug-related interventions and those involving young offenders. These results support previous research findings that neighborhoods with higher levels of disorder are likely to show higher crime rates. [11,12,43] Similarly, the relationship between neighborhood disorder and socioeconomic indicators are in line with previous studies linking neighborhood disorder and socioeconomic neighborhood characteristics. [16,22,44,45] The association found between neighborhood disorder and criminality indicators suggests that this instrument may be useful for studying neighborhood criminality

The spatial analyses showed that the three disorder factors (general neighborhood disorder, physical disorder and physical decay) were spatially clustered as expected.[36,37] We then conducted two spatial Bayesian regressions to study the two criminality indicators. We found that general neighborhood disorder and physical decay were related to both types of police interventions, but there was no such association with physical disorder. These results might be due to the fact that the general neighborhood disorder captures part of the variability of physical disorder, and this part would explain the relationship between policing activity and disorder.

In recent years there has been growing interest in the use of computer applications to assess neighborhood characteristics. Some research has shown the advantages of using this kind of instrument. [21,22,25,27] Specifically, previous research has shown Google Street View can be a useful research instrument. [22,28,29] Our results provide new evidence of the benefits of using Google Street View in applications such as neighborhood disorder assessment. [21,22,29] This measurement approach avoids researchers having to move around the city and face the risks of visiting potentially hazardous areas, [26] and reduces observation time. [27] Nevertheless, some studies found that virtual audits were faster than physical audits [27,46], while others showed opposite results. [47] Future studies would benefit from including observation times measures to assess the differences between physical and virtual audits. Also, most of the studies assessing neighborhood characteristics using Google Street View have been conducted in Anglo-Saxon cities, [48,49] and only few studies have been conducted in the context of European countries. [47] This study provides new evidence about virtual audits in a European city.

Among the limitations, the GSV-based neighborhood disorder scale can only obtain static observations, and generally Google images are of neighborhoods in the same or the previous year. Although Google Street View is constantly being updated, unlike traditional physical audits it can be more difficult to use for longitudinal studies. Some urban areas are assessed from Google Street View less frequently than others; also, Google Street View does not capture time periods shorter than a year. However, the virtual data has the potential to facilitate longitudinal studies if archived imagery is available. Another limitation is that some characteristics often studied in the neighborhood context cannot be assessed with this instrument because it is not accurate enough to observe small items, [22,24,29] such as syringes and condoms in the street, which we had to remove from the final analysis. Likewise, social disorder, which has typically been considered as another relevant dimension of neighborhood disorder, [18,50] cannot be observed through Google Street View because it refers to potentially threatening social interactions such as street fights, the presence of homeless and drunk people, street prostitution, etc. [18,50] However, Google Street View could be used in conjunction with other measures such as resident surveys and physical audits to address these limitations.

In conclusion, this study provides evidence of a reliable and valid instrument to evaluate neighborhood disorder using new technologies. Google Street View can be a useful tool to avoid the problems of physical audits, and it can contribute to the study of various social and health outcomes.

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Appendix

GSV-based Neighborhood Disorder Observational Scale items

1. Cigarettes in the street
2. Trash in the street
3. Empty bottles in the street
4. Graffiti
5. Political or protest message graffiti
6. Vacant or abandoned houses
7. Abandoned commercial buildings
8. Vandalized and run-down buildings
9. Deteriorated residential units
10. Deteriorated recreation places

Study 3

Linking neighborhood characteristics and drug-related police interventions: A Bayesian spatial analysis

Linking neighborhood characteristics and drug-related police interventions: A Bayesian spatial analysis[3]

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Abstract

This paper aimed to analyze the spatial distribution of drug-related police interventions and the neighborhood characteristics influencing these spatial patterns. To this end, police officers ranked each census block group in Valencia, Spain (N = 552), providing an index of drug-related police interventions. Data from the City Statistics Office and observational variables were used to analyze neighborhood characteristics. Distance to the police station was used as the control variable. A Bayesian ecological analysis was performed with a spatial beta regression model. Results indicated that high physical decay, low socioeconomic status, and high immigrant concentration were associated with high levels of drug-related police interventions after adjustment for distance to the police station. Results illustrate the importance of a spatial approach to understanding crime.

Keywords: Drug-related police interventions, neighborhoods, Bayesian spatial modeling, small-area variations, risk maps

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Introduction

The association between crime and place is one of the long-standing topics in the study of crime. From a social disorganization framework, neighborhoods characterized by poverty, ethnic heterogeneity, and residential instability are expected to have higher crime rates [1–3]. From this perspective, crime is not randomly distributed in the city; rather, people living in poor and deteriorated neighborhoods are more likely to be the victims of crime [2,4].

Studies based on the social disorganization perspective have largely shown the association of neighborhood concentrated disadvantage, immigration, and residential instability with crime and violence. Concentrated disadvantage reflects the negative socioeconomic features of a neighborhood, such as poverty, unemployment, low income, family disruption, or physical and social disorder [5–7]. Research has found that concentrated disadvantage is the factor most strongly associated with crime, even after controlling for individual characteristics [1,8]. Immigration has also been related to crime rates, and previous research has shown that higher levels of ethnic heterogeneity are related to higher levels of crime [1,9,10]. Residential instability is also a relevant factor in social disorganization theory. Studies have found that low residential stability would be related to crime, and neighborhoods with more stable populations should have lower crime rates than those characterized by transitory and changing neighbors [3,11].

It has been suggested that the link between neighborhood characteristics and crime may be mediated by underlying social processes. High levels of social disorganization and concentrated disadvantage in communities would be linked to low levels of social control and collective efficacy. Collective efficacy is defined as 'the process of activating or converting social ties among neighborhood residents in order to achieve collective goals, such as public order or the control of crime' [12] (p. 802). A lack of collective efficacy is associated with increased mistrust between neighbors, which creates a dangerous environment and impedes effective social control, thus leading to increased conflict and crime [1,2,5].

The relationship between crime and place has been studied for different types of crime. Most research has focused on residential burglary [13–15], juvenile delinquency [16,17], homicides [1,18,19], and robbery and assaults [18,19]. Interest is also growing in studying this relationship in other crimes that tends to occur 'behind closed doors' [20] such as intimate partner violence [9,10] or child maltreatment [21].

Drug-related crime has also been linked to neighborhood characteristics [22–24]. Drug-related crime is a major problem in our society; it has negative repercussions on health, creates personal and social conflicts, and can perpetuate community deterioration [24,25]. Moreover, some studies have found a relationship between drug dealing and consumption and other types of criminal acts [26]. However, the study of drug-related crime has focused mainly on drug markets [27], and other perspectives and research approaches have received little research attention.

In this study, we aimed to analyze the relationship between neighborhood characteristics and drug-related police interventions from a Bayesian spatial perspective. Clearly, understanding how drug-related police interventions are spatially distributed across a city's neighborhoods and how they relate to neighborhood characteristics may contribute to preventing this type of crime and related negative outcomes in the community.

Recently, research linking crime and neighborhood characteristics has relied more heavily on spatial analysis [9,10,28,29]. The majority of these studies use the frequentist or classical paradigm [30]. However, recent research is showing the advantages of using spatial methods from a Bayesian perspective [9,10,29]. These types of models come from disease mapping [31] and are increasingly being incorporated into social studies [9,10,29]. The frequentist approach treats parameters as fixed unknown values, while the Bayesian approach uses probability distributions to represent the uncertainty of the parameters [32]. Researchers may base their interpretation of this probability on their knowledge about the parameters, and it allows random effects to be included. Including random effects reduces the biases of spatial autocorrelation and overdispersion common in spatial analysis [33]. In addition, Bayesian models provide risk estimations and analyze the effect of unobserved spatially structured influences [34,35]. The use of a Bayesian spatial random-effects modeling approach in this study (almost nonexistent in current research) may provide new knowledge and a new perspective to research on drug-related crime [36,37]. Most studies focusing on drug crime and place have been conducted in Anglo-Saxon cities (predominantly in the US, UK, or Australia). However, there are fewer studies from other European areas such as Southern European cities. Analyzing drug-related crimes in cities from different countries would add new valuable data to the existing literature.

Study area and data

In this study, we conduct a Bayesian ecological analysis to understand the influence of neighborhood characteristics on the spatial distribution of drug-related police interventions. Ecological studies are based on populations that are defined geographically. Following a social disorganization perspective, we analyze the influence of four neighborhood-level variables; two different measures of concentrated disadvantage (socioeconomic status and physical decay), immigrant concentration, and residential instability. We also consider that the proximity of the police station could also have a deterrent effect, and therefore we include the distance to the nearest police station as a control variable.

Study area

This study was conducted in Valencia, the third largest city in Spain, which has a population of 736,580 inhabitants and covers an area of 134 km^2 approximately. Its fairly large size allows us to study the spatial distribution with adequate variability.

We used the census block group as a proxy for neighborhood. Census block groups were the smallest administrative units available, and they are defined as walkable areas with a low number of city blocks and are smaller than a census tract [9,10,38]. The sample had 552 census block groups with an average of 1,334 residents (a maximum of 2845 and a minimum of 630).

Dependent variable

To study drug-related crimes, we used the police perception of the level of drug interventions conducted in each census block group. Police records have been used extensively to study crime [9,10,30] but they were not available for this study. However, previous research suggests that police perception and police records are correlated for some types of crime [39]. In the present study, we use police perceptions of police interventions. With this measure, we can distinguish between areas where the police intervene more frequently from those with a low level of interventions. In this way, we capture all the police's valuable experience and information [39,40]. Police perceptions could be especially useful to study under-reported crime, and they could help to plan law enforcement policies or urban planning strategies.

Senior police officers with a thorough knowledge of the area were selected to provide an index of policing activity, indicative of the level of drug-related crime in each census block group (i.e. they evaluated the level of police interventions where drugs are involved). This index was based on police officers' perceptions and experience. Police officers placed each census block group on a 5-interval scale, in which the first interval represented a very low level of drug-related interventions and the fifth interval, a very high level of drug-related interventions.

Independent variables

In this study we used data provided by the City Statistics Office and observation data gathered by trained raters; all data corresponded to 2013.

Socioeconomic Status (SES): We constructed an index using several socioeconomic indicators, as in previous research [10]. These indicators showed a high correlation, and a scale was created through factor analysis to avoid collinearity. The scale consisted of the following variables: (a) cadastral value, an administrative value of a property calculated by the city council and used as a reference for fiscal and other administrative purposes; (b) percentage of high-end cars; (c) percentage of financial businesses (percentage of financial institutions and insurance companies out of total activities); (d) percentage of commercial businesses (percentage of trade, hostelry, or repairs business out of total activities); and (e) education level, measured on a 4-point scale, where 1 = less than primary education, 2 = primary education, 3 = secondary education, and 4 = college education. We selected the first principal component of the factor analysis in which the five variables had a relevant factorial weight (i.e. each variable was properly represented in the scale).

Observed Physical Decay: Trained raters assessed the level of observable physical decay in each census block group. A 4-item scale was used including the following items: vacant houses; abandoned, vandalized and run-down buildings; deteriorated residential units; and deteriorated recreation places [38]. Each item was rated from 0 to 4, where 0 indicates no presence and 4 indicates high presence. Observations were made during business hours.

Immigrant Concentration: Percentage of immigrant population in each census block group.

Residential Instability: We used an index of residential mobility, measured as the proportion of the population who had moved into or out of each census block group during the previous year (rate per 1000 inhabitants).

Distance to Police Station: Euclidean distance to police stations was measured to control for the deterrent effect they may have on drug crime. Distance was measured as the kilometers between the centroid of each census block group and the nearest police station.

Table 1 summarizes the descriptive statistics for all the variables.

Table 1. Variables (mean, standard deviation, minimum and maximum values) at the census block group level.

Variable	Mean	SD	Minimum	Maximum
Socioeconomic status	0	0.98	−1.69	4.22
Cadastral value	250.10	74.61	111.50	590.70
High-end cars (%)	5.75	3.62	1.30	24.80
Financial business (%)	18.15	7.77	0	43.20
Commercial business (%)	34.03	9.21	7.50	66.40
Education level	3.15	0.33	2.39	3.86
Immigrant concentration (%)	13.45	6.53	1.90	40.20
Physical decay (0–20)	5.83	3.61	0	20
Residential instability (per 1000)	268	87.98	91.10	649.80
Distance to police station (km)	0.75	0.38	0	2.10
Drug-related police interventions (0–1)	0.34	0.32	0	1

Design and analysis

We assumed the dependent variable (an index of the level of drug-related police interventions) as a proportion based on police perception between 0 and 1 on a continuum, where 0 was the minimum perceived level of drug-related police interventions and 1, the maximum perceived level. A value of 0.5 therefore would be the intermediate level of perceived police interventions. We considered that a beta distribution (a continuous positive distribution used with variables bounded between a minimum and a maximum) best reflects the nature of this variable, which is commonly used for modeling proportions [41,42]. Five intervals were established, and we took the average value of each interval. Specifically, if Y_i represents the level of interventions, we assumed that $Y_i \sim Be(\mu_i,\phi)$, where μ_i is the mean level of interventions in each of the i census block groups and ϕ is a secondary parameter to regulate the variability of the distribution.

We performed regression modeling using Generalized Linear Models with a logit link function. The model assessed included the five explanatory variables; socioeconomic status, immigrant concentration, physical decay, residential instability, and distance to the police station.

A random effect to determine spatial autocorrelation was introduced to account for the spatial effect. Spatial autocorrelation occurs because nearby areas are more related to each other than more distant areas [43]. In social research, this effect may occur because the surrounding areas have similar social, economic, and cultural characteristics [44]. Detecting spatial dependence may be useful to provide information about the spatial structure of the data.

Moreover, an unstructured random effect was included to account for the heterogeneity, overdispersion, and the arbitrariness of spatial unit choice. This effect is related to the spatial differentiation of geographic units, (i.e. when the data are not homogeneous throughout the data set). In these cases, there may be greater variability than expected under the assumed distribution [45]. An unstructured random effect would correct and smooth the distribution [34].

Therefore, the complete model is as follows:

$$Logit(\mu) = \alpha + X_i\beta + S_i + U_i \qquad 1)$$

where α is the total mean (intercept), β represents the vector of the regression coefficients, X_i is the matrix of covariates in the census block group i $(i = 1, \dots, n)$, and S_i and U_i are two random effects terms, which explore spatial autocorrelation and overdispersion respectively.

The component S_i is the spatially correlated heterogeneity, and it was specified by a conditional spatial model (CAR). [45]:

$$S_i|S_{-i} \sim N(\frac{1}{n_i}\sum_{j\sim i} S_J, \frac{\sigma_S^2}{n_i}) \qquad 2)$$

We used contiguity as neighborhood criterion. Contiguity is one of the most common criteria for urban contexts where areas are connected. Thus, adjacent areas were considered neighbors.

The random unstructured heterogeneity (U_i) was specified as a normal distribution centered at zero with standard deviation σ_u. The standard deviations of S and U were defined as a prior uniform distribution $U(0,1)$.

Generalized linear models may be analyzed following a frequentist methodology. However, Bayesian methods introduce random effects and are more flexible. Taking a Bayesian approach, the parameters are treated as random variables, and we need to incorporate prior distributions to assess prior knowledge [45]. In our study, we used vague Gaussian distributions $N(0, 100000)$ for the fixed effects β and an improper uniform distribution for α. Finally, we used a Gamma distribution $Ga(0.1,0.1)$ to define the prior distribution of ϕ. A sensitivity analysis on these prior distributions was performed to select the most suitable possible prior distributions, repeating the study with different prior distributions values. Specially, we focus on the prior distribution of the variability parameters (σ_s, σ_u, and ϕ). The results did not change using different prior distributions. Figure 1 shows the complete model and the hierarchical structure.

LEVEL 1

$$Y_i \sim Be(\mu_i, \phi)$$
$$Logit(\mu) = \alpha + X_i\beta + S_i + U_i$$

LEVEL 2

$$S_i|S_{-i} \sim N(\tfrac{1}{n_i}\textstyle\sum_{j\sim i} S_j, \tfrac{\sigma_S^2}{n_i})$$
$$U \sim N(0, \sigma_U^2)$$

PRIORS

$$\propto \sim U(0,1)$$
$$\beta \sim N(0, 10^5)$$
$$\phi \sim Ga(.1,.1)$$

HYPER-PRIORS

$$\sigma_s \sim U(0,1)$$
$$\sigma_u \sim U(0,1)$$

Figure 1. Illustration of the model.

To perform estimations, we generated simulations of the parameters with Markov Chain Monte Carlo (MCMC) using the software R and WinBUGS (see Appendix 1 for the WinBUGS code for the model). A total of 1,000,000 iterations were carried out (the first 10,000 were discarded as burn-in).

Convergence of the simulated samples was measured using the convergence diagnostic $\hat{R}$ [46], which was close to 1.0 for all parameters. The posterior distributions showed consistent results. To select the final model, we ranked the deviance information criterion (DIC), and the model with the lowest DIC was chosen because it shows a better fit.

Results

A Bayesian beta regression model was conducted with the five explanatory variables (socioeconomic status, immigrant concentration, residential instability, physical decay, and distance to the police station) and two random variables were introduced (unstructured U and structured spatial S effect). The DIC of this model was −1431.8. We ran a second model without these two random variables, and the model fit was clearly the worst (DIC = −190.7). The complete model represented the best fit and was therefore selected as the final model. Table 2 summarizes the results of the final regression model.

Table 2. Beta Regression Model with Dependent Variable: drug-related police interventions.

Explanatory Variables	Mean	Std. Error	95% CrI
Intercept	−1.285	0.217	−1.712, −0.893
Socioeconomic status	−0.127 *	0.074	−0.279, 0.020
Physical decay	0.038 *	0.018	0.005, 0.072
Immigrant concentration	0.015 *	0.013	−0.012, 0.043
Residential instability	0.000	0.001	−0.002, 0.002
Distance to police stations	0.403 *	0.178	0.059, 0.730
σs	0.776	0.037	0.901, 0.999
σu	0.973	0.026	0.703, 0.844

* Posterior probability of positive or negative association higher than 80%; CrI: Credible Interval; σ_s Standard deviation spatially structured term; σ_u Standard deviation unstructured term.

The posterior distribution of fixed effects (Figure 2) shows the probability of having a negative or positive association between independent variables and the outcome variable, and it allows us to assess the relevance of the variables in the model. Variables with a posterior probability of being different from zero above 80% were considered relevant to the outcome variable. Specifically, socioeconomic status has a 96% probability of having a negative association, and immigrant concentration, physical decay and distance to the police stations have a high probability of having a positive association (87.3%, 98.8% and 99.4% respectively). Residential instability did not have a clear association with drug-related police interventions (only a 53.6% probability of having a positive association). Thus, areas with lower socioeconomic status, high levels of immigrant concentration, and high physical decay and that are further from police stations showed higher mean levels of drug-related police interventions.

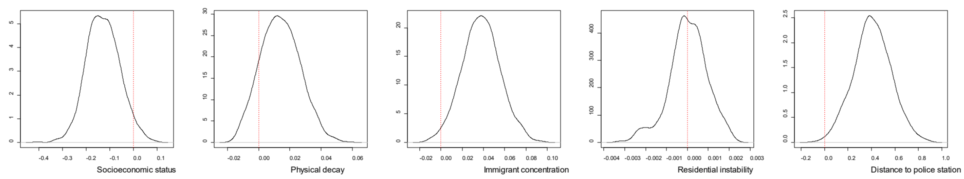

Figure 2. Posterior distribution of fixed effects in the model.

Beyond the effect of the variables, the results showed the influence of spatial dependency and unstructured heterogeneity. A Bayesian approach reveals the spatial effect through illustrative maps. Figure 3 shows the posterior mean value for the spatial component. There is a clear geographic pattern: northern areas of the city have higher mean values than southern areas. This indicates the existence of a significant underlying spatial process that is not explained by the variables we have explored.

Figure 4 shows the mean level of drug-related police interventions in each census block group once we incorporated explanatory variables and random effects (heterogeneity and spatial autocorrelation). Some areas have high levels of interventions, and others have very low levels. Specifically, there is a higher probability of drug-related interventions in the northern and eastern zones; some areas have a level of intervention higher than 80%. This map shows the areas with higher mean levels of drug-related police interventions, which is useful when planning and implementing prevention and intervention strategies. Also, to map the uncertainty associated with the posterior means, Figure 5 represents the map of the first and the third quartile for the posterior mean level of drug-related police interventions.

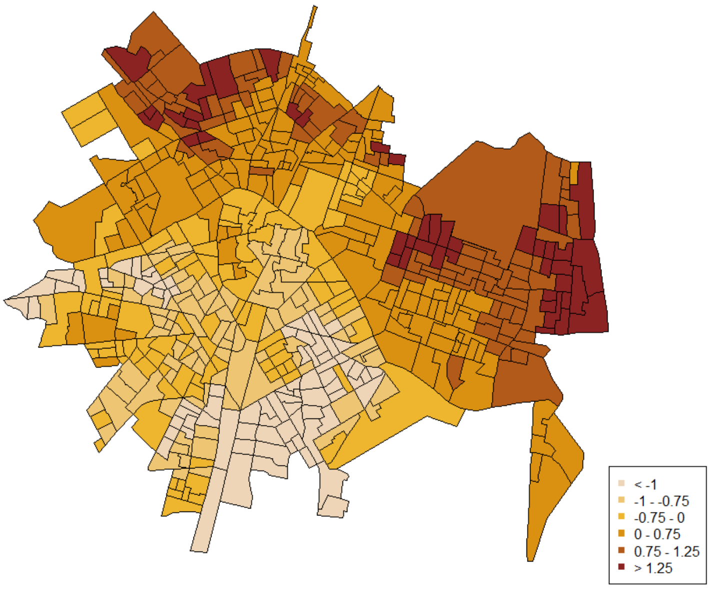

Figure 3. Posterior mean values for the spatial component (census block group) of the estimated prevalence of drug-related police interventions.

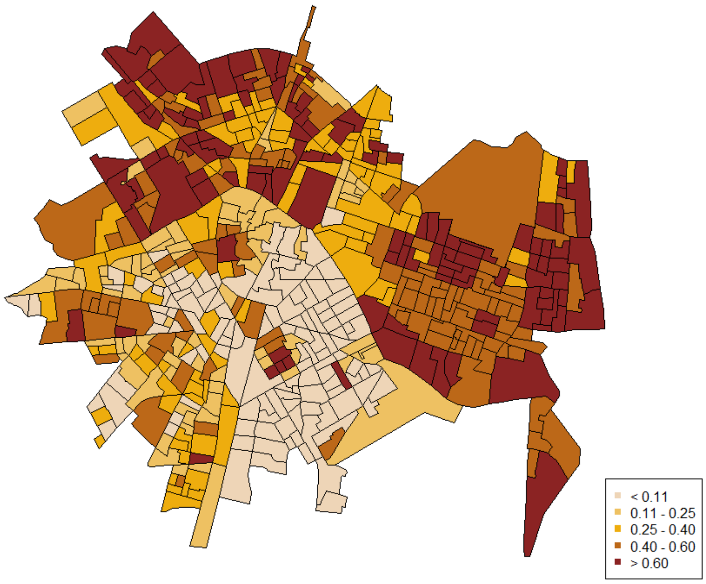

Figure 4. Posterior mean level of drug-related police interventions in each census block group.

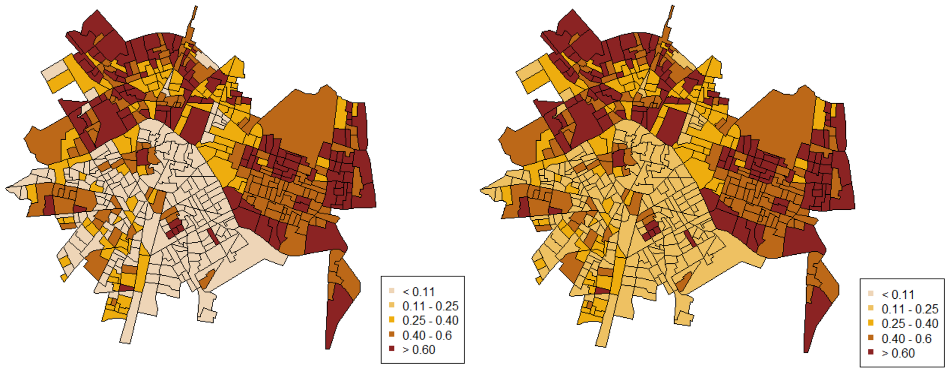

Figure 5. Map of the first (**left**) and the third (**right**) quartile of the posterior mean level of drug-related police interventions.

Discussion

In this study, we conducted a spatial analysis of drug-related police interventions exploring the influence of neighborhood characteristics. A Bayesian spatial modeling approach was used, which is common in health and epidemiology studies [34] and is especially appropriate to study small-area variations [47]. We used census block groups (the smallest unit available), and, drawing from social disorganization theory, we explored the influence of four neighborhood characteristics; socioeconomic status, physical decay, immigrant concentration, and residential instability. We incorporated distance to the police station in each census block group as a control variable to avoid the confounding effect that it could have on drug-related crime.

Our results showed a significant spatial distribution, according to which the areas with lower levels of socioeconomic status and higher levels of physical decay, higher immigrant concentration, and greater distance to a police station were those which had higher levels of drug-related police interventions. Residential instability, however, was not clearly associated with the distribution of drug-related interventions.

These results are in line with previous research. Social disorganization theory suggests that areas with higher concentrated disadvantage, higher ethnic heterogeneity, and higher residential mobility should show higher levels of disorder and crime [1,3,17]. In order to measure concentrated disadvantage, two indicators were used, both leading to the same results. On the one hand, we measured socioeconomic status, and we observed a negative relationship with drug-related police interventions, as expected from previous literature [48]. The second indicator used was physical decay, which measured the level of structural disorder in the neighborhood. Our results showed that physical decay was positively related to drug-related police interventions, also in line with previous research [26].

With respect to immigrant concentration, we found a positive association with drug-related police interventions. Some studies have shown similar results with other types of crime [1,9,10,49]. However, other studies showed a negative or null association between immigrant concentration and crime when socioeconomic characteristics are controlled for [50,51]. As regards drug-related crime, our results are similar to those found in other studies [52]. It is important to note, however, that most of these studies come from the US, and most of them focus on black residents and the black sub-culture of drugs and violence [11,53]. In Spain, most immigrants are from South American (34.3%) and European (34%) countries. These differences should be taken into account to properly analyze the effect of immigration on drug-related interventions.

Residential instability, however, did not have a significant influence on the spatial distribution of drug-related police interventions. The research is inconclusive on this question; some studies found a positive association between residential instability and crime [8,11], while others found no correlation [9,10,54]. Our study aligns with the second group.

Finally, because we considered that distance to the police station could also have a deterrent effect, we included it as a control variable. We found evidence to support our hypothesis that the places closest to a police station are less likely to be the scene of drug-related crimes. The introduction of this control variable increases the model fit, and without it there could be a confounding effect that is unaccounted for. The distance method available for the study was Euclidean distances. Due to the street distribution of Valencia (a round city, with no important architectural or natural barriers), this type of distance was considered appropriate. However, future research would benefit from taking into account distance-based relationships, which could be a more accurate measure for distances in the context of a city.

Taking these explanatory variables together and analyzing the distribution of the mean level of drug-related police interventions, we can appreciate some important differences among census block groups. Specifically, some areas in the north and the east of the city present higher drug-related police interventions, indicating that police officers perceived that more drug-related police interventions are needed in such areas. These results suggest that police strategy should point to those city areas that show higher perceived drug-related police interventions.

Bayesian statistics have the advantage of incorporating a random effect beyond those explained by the variables considered in the study to explore the underlying spatial distribution in the variable of interest [10,34]. In our study, we found a spatial distribution unexplained by the specific covariates. The drug-related police interventions showed a clear spatial distribution, wherein the estimated prevalence was higher in the north of the city and lower in the south. Future research should consider other variables when attempting to explain this gradient. One possible explanation is that these neighborhoods placed in the north and east of the city may carry the burden of stigma (i.e. deprived neighborhoods historically related to crime and disorder) [55]. The police perceptions on drug-related crime could be influenced by such stigmatization. This hypothesis could be further explored in future studies comparing police calls or police reports data with police perceptions.

This study had both strengths and limitations. One of the strengths is that few studies focus on crime from an epidemiological perspective using Bayesian regression analysis, and there has been little research on drug-related crime [36]. Thus, this study contributes by adding a new approach to the existing literature. Furthermore, Bayesian models allow controlling for biases such as overdispersion and spatial autocorrelation and allow underlying spatial patterns to be analyzed [10,34,35]. Finally, explanatory variables were collected from two different sources, census data and systematic observations, which make the study more complete and provide more information about the neighborhood characteristics.

Among the limitations, the use of a subjective measure of the police perceptions on drug-related crime is a potential shortcoming since there is no numerical value of police interventions on drug-related crimes in small areas. This could be a handicap due to the nature of subjective data. However, previous research suggests that police perception correlates to census data [39,40], and using a subjective police measure could provide additional information to objective data when detecting risk areas [28,39]. Police perceptions, moreover, could be especially adequate to study under-reported crime, and some authors highlight the importance of social perceptions for law enforcement policies or urban planning [55].

Furthermore, some variables that may be relevant to the study of crime [18] were not used in this study. For example, data on collective efficacy and neighborhood processes were not available, as well as variables related to routine activities or crime pattern theory [56,57], which would help to better understand the spatial distribution of drug-related crime. Future research could be enriched by the addition of these variables. Moreover, ecological studies present some biases due to the aggregation of data (e.g. ecological fallacy or the modifiable areal unit problem) [10]. However, this study was conducted with high spatial resolution (census block groups), reducing the ecological biases from aggregation effects.

Lastly, it should be taken into account that this study was conducted in a European city with specific characteristics and its own culture. As noted, most studies are conducted in US cities [58] and there are fewer studies from Europe [30,59]. The differences in the culture and structure of European cities may lead to different results than those from studies conducted in US cities [10,60,61]. However, since our study was conducted in a European city, our results offer a valuable addition to the existing literature, bearing in mind that an understanding of these cultural variables is important to reliably analyze the results.

Conclusions

The results of this study illustrate the importance of a spatial and contextual approach to understanding drug-related crimes. A spatial perspective provides a new approach in the study of crime in neighborhoods and could help to improve and design new crime prevention policies at more localized level (e.g. allocating more human and economic resources to those high risk areas, or conducting studies over time to assess the effectiveness of new policies in reducing crime).

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Appendix

WinBUGS Code

```
model{
for(i in 1:n) {
y[i] ~ dbeta(a[i], b[i])
a[i] <- mu[i] * phi
b[i] <- (1-mu[i]) * phi
logit(mu[i]) <- alpha + beta[1]*X1[i] + beta[2]*X2[i] + beta[3]*X3[i] +
beta[4]*X4[i]+ beta[5]*X5[i] + S[i] + U[i]
U[i] ~ dnorm(0,prec.u)
}
phi ~ dgamma(.1,.1)
S[1:n] ~ car.normal(adj[], weights[], num[],prec.s)
prec.s <- pow(sigma.s,-2)
sigma.s ~ dunif(0,1)
prec.u <- pow(sigma.u,-2)
sigma.u ~ dunif(0,1)
alpha ~ dflat()
for(i in 1:5){
beta[i] ~ dnorm(0, 0.00001)
}
}
```

Study 4

Neighborhood alcohol outlet density and alcohol-related calls-for-service: A spatio-temporal analysis in a wet drinking country

Neighborhood alcohol outlet density and alcohol-related calls-for-service: A spatio-temporal analysis in a wet drinking country [4]

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Abstract

Alcohol outlets have been associated with different social problems, such as crime, violence, intimate partner violence, and child maltreatment. The spatial analysis of neighborhood availability of alcohol outlets is key for better understanding of these influences. Most studies on the spatial distribution of alcohol outlets in the community have been conducted in U.S. cities, but few studies have assessed this spatial distribution in other countries where the drinking culture may differ. The aim of this study was to analyze the spatiotemporal distribution of alcohol outlets in the city of Valencia, Spain, and its relationship with neighborhood-level characteristics, as well as to examine the influence of alcohol outlet density on alcohol-related police calls-for-service. Spain is characterized by having a "wet" drinking culture and greater social acceptance of drinking compared to the U.S. Data on alcohol outlets between 2010–2015 in three categories (off-premise, restaurants and cafes, and bars) were used for the analysis. We used the 552 census block groups allocated within the city as neighborhood unit. Data were analyzed using Bayesian spatiotemporal regression models. Results showed different associations between alcohol outlets categories and neighborhood variables: off-premise density was higher in areas with lower economic status, higher immigrant concentration, and lower residential instability; restaurant and cafe density was higher in areas with higher spatially-lagged economic status, and bar density was higher in areas with higher economic status and higher spatially-lagged economic status. Furthermore, restaurant and cafe density was negatively associated with alcohol-related police calls-for-service, while bar density was positively associated with alcohol-related calls-for-service. These results can be used to inform preventive strategies for alcohol-related problems at the neighborhood-level in Spain or other countries with a wet drinking culture. Future research would benefit from

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[4] Marco, M., Gracia, E., López-Quílez, A., & Lila, M. (2017). Neighborhood alcohol outlet density and alcohol-related calls-for-service: A spatio-temporal analysis in a wet drinking country. *International Journal of Geo-Information, 6*, 380. doi: 10.3390/ijgi6120380

exploring the relationship between alcohol availability and different social problems in cities outside the U.S.

Keywords: alcohol outlets, neighborhood-level characteristics, spatiotemporal analysis, Bayesian modeling approach, calls-for-service

Introduction

The relationship between alcohol abuse and different public health problems has been well established [1,2]. Alcohol consumption was the responsible for 5.9% of global deaths in 2012, which translates to about 3.3 million alcohol-related deaths, and it is a public health priority for the World Health Organization (WHO) [2].

Alcohol availability has become an important field of study because it is the major point of access for alcohol consumption [3]. Variation in price and density of alcohol outlets are the most commonly used measures of alcohol availability [4]. Alcohol outlet density, specifically, has been associated with different social problems, such as a violent crime [1,5–8], traffic incidents [9–11], alcohol-related problems [12–15], child maltreatment [16–18], and intimate partner violence [19,20].

In order to assess alcohol outlet influences, some studies have analyzed the link between neighborhood-level characteristics and the spatial and temporal distribution of alcohol outlets in different cities [21–23]. These studies have shown that alcohol outlets (usually represented as off-premise and on-premise establishments) are not randomly distributed in space and time, but they differ by neighborhood characteristics. Drawing from the social disorganization theory [24–26], these studies have found associations between alcohol outlet density and a number of neighborhood characteristics such as neighborhood deprivation, residential instability and ethnic composition. In this body of research, most studies have focused on neighborhood deprivation, showing that areas with higher socioeconomic disadvantage tend to have higher alcohol outlet density [12,22,27–29]. Residential instability has also shown a positive relationship with alcohol outlet density [30]. However, the study of the influence of ethnic composition on alcohol outlet density, has yielded mixed results, with some studies supporting this link [31,32], while other studies showing no association [29,30].

Most of these studies have been conducted in the U.S. and north European countries [21,22,30,33,34]. These countries are usually defined as “dry countries”, as opposed to “wet countries”. This classification is based on the average amount of alcohol consumed per capita in order to distinguish between “drinking” and “not drinking” cultures [35,36]. United States, as well as northern Europe, would exemplify the “dry” end of this classification, which is characterized by low levels of alcohol consumption, many people who abstain, restrictive controls on drinking and selling alcohol, as well as less of a tradition of alcohol consumption in social contexts. On the other hand, Mediterranean countries (France, Italy, Portugal, Greece, or Spain) would be at the “wet” end of this classification, as they are characterized by higher rates of alcohol consumption and less restrictive control of alcohol-related behavior [36,37]. In these countries, alcohol is part of the social life and it is usually present in social meetings [38,39]. Also, in wet countries people drink more frequently during daily life (e.g., it is consumed at meals), unlike dry countries [40,41]. Despite these relevant differences in alcohol consumption and drinking culture, research suggests that people from wet countries are less likely to drink to intoxication than people from dry countries [41].

These cultural differences in drinking patterns are also reflected in the availability of and access to alcohol establishments. For example, according to 2014 data, New York had a density of 88 bars per 100,000 people, while Madrid, Spain, had 186 bars per 100,000, which is almost double [42]. On the other hand, in wet countries, the social acceptance of alcohol consumption behavior translates to a higher permissiveness in the sale of alcohol. This is also reflected in differences in the legal drinking age, which is 21 years old for the U.S. and 18 for the most European countries.

These differences in drinking culture may also be reflected on the distribution of alcohol outlets across city areas, as well as on the relationship between alcohol outlets and social problems. Thus, the space-time trajectories of alcohol outlets, the neighborhood variables that can influence this spatiotemporal distribution, and the relationship between alcohol outlet density and alcohol-related social problems, may differ between countries where the drinking behavior and culture is different. However, so far, no studies have analyzed these issues from a spatiotemporal perspective in wet countries.

The present study was conducted in the city of Valencia, Spain, which has been defined as a wet country [41]. The aim of the study was to analyze the influence of neighborhood-level characteristics on the spatiotemporal distribution of alcohol outlets, and to examine the influence of alcohol-outlet density on alcohol-related police calls-for-service. To this end, we consider three categories of alcohol outlets (i.e., off-premise, restaurants/cafes, and bars), three neighborhood-level characteristics (i.e., socioeconomic status, residential instability, and immigrant population), and all alcohol-related police calls-for-service in the city of Valencia during a six-year period.

Materials and methods

Study area

This study was conducted in the city of Valencia, Spain. Valencia is the third largest city in Spain, with a population of 790,201 (2016 data). We used census block groups as proxies for neighborhood. They are the smallest administrative units available in the city. Census block groups had an average of 1338 inhabitants, with a minimum of 625 and a maximum of 3202. We used 552 census block groups that cover the entire geography of the city.

Alcohol outlets data

Data for alcohol outlets were collected from the Statistics Office of the Valencia City Hall. They provided an aggregated measure for each census block group of different licensed alcohol establishments. Alcohol outlet refers to any establishment that legally sells alcohol. It is important to note that, in Spain, a special license is not needed to sell alcohol, but this permit is included in the license of selling products for human consumption. Thus, all establishments of food and beverages can sell alcohol legally. We considered three different categories of alcohol outlets based on previous research [7,43–45]: off-premise outlets (composed of retail sale of wines and beverages, and retail sale of food and beverages), restaurants/cafes (services in restaurants and coffee shops), and bars. Data from 2010 to 2015 were available for this study. The data correspond to the number of alcohol outlets at the end of the year. Table 1 shows the temporal distribution of alcohol outlet establishments in the different years of the study.

Table 1. Descriptive statistics of alcohol outlets during the 6-year period of the study

	Off-premises				**Restaurants-cafes**				**Bars**			
	Mean	**Min**	**Max**	**Total**	**Mean**	**Min**	**Max**	**Total**	**Mean**	**Min**	**Max**	**Total**
2010	2.02	0	43	1,113	2.51	0	33	1,385	6.44	0	38	3,553
2011	1.81	0	15	998	2.41	0	30	1,328	6.17	0	39	3,405
2012	2.05	0	31	1,129	2.46	0	29	1,357	6.29	0	42	3,472
2013	2.21	0	54	1,219	2.41	0	28	1,331	6.48	0	44	3,576
2014	2.35	0	52	1,298	2.29	0	30	1,265	6.65	0	39	3,671
2015	2.44	0	53	1,344	2.36	0	32	1,301	6.71	0	42	3,706

Alcohol-related calls-for-service

The Valencia Police Department provided data from all calls where police were required to intervene because of alcohol-related problems. These problems refer to drunk minors, drunk homeless people, people with an ethyl coma, or other alcohol-related health issues, etc. “Alcohol-related calls” is the category under which police officers who attend the call classify these problems. In all cases, the police have to be required by a citizen’s call. Other types of alcohol-related social problems, where the police do not intervene, or direct interventions without a previous call-for service, are not included. All alcohol-related police calls-for-service in the city of Valencia from 2010 to 2015 were collected and aggregated at the census block group level. There were 11,789 alcohol-related calls-for-service in this period. Calls-for-service in census block groups varied from 0 to 115 in a year. Table 2 shows the temporal distribution of alcohol-related calls-for-service in the different years of the study.

Table 2. Descriptive statistics of alcohol-related calls-for-service during the 6-year period of the study

	Min	1st quartile	Median	Mean	3rd quartile	Max	Total
2010	0	0	2	2.62	4	34	1,444
2011	0	1	2	3.54	4.25	40	1,952
2012	0	1	2	3.40	4.25	40	1,876
2013	0	1	2	3.53	4	43	1,949
2014	0	1	2	3.74	5	39	2,067
2015	0	1	3	4.53	6	115	2,501

Independent variables

Different neighborhood-level variables provided by the City Statistics Office were used for each census block group and each year of the study. Economic status:

The average cadastral property value (in €) was used as a proxy of economic status. This value is set by City Hall in order to establish city taxes, and it is based on the combination of the land and construction value.

Spatially-lagged economic status: Spatially-lagged variables are useful to capture the effect of neighboring areas, and it is calculated as the weighted sum of values for neighborhood i by using its neighboring areas as weights [46,47]. We used this spatially-lagged variable in order to assess not only the influence of economic status in alcohol outlet density, but also to analyze the influence of the nearby neighborhoods' economic statuses [48].

Immigrant concentration: Percentage of immigrant population in each census block group. The mean level of immigrant concentration was about 12% of the population.

Residential instability: Proportion of the population who had moved into or out of each census block group during the previous year: for example, residential instability value for 2015 captures all movements into or out of the census block groups during 2014. This measure was rated per 1000 inhabitants.

In addition, population density was included as a control variable. This variable refers to the population of each census block group per square kilometer. Table 3 summarizes the descriptive statistics for all variables.

Table 3. Variables (mean, standard deviation, minimum and maximum values) at the census block group and year level.

Variable	Mean	Median	SD	Min	Max
Cadastral property value (€)	24,204	21,324	10,107	10,686	84,208
Spatially lagged cadastral value	24,269	24,026	9,076	11,278	78,541
Immigrant concentration (%)	12.25	11.45	5.96	1.89	42.62
Residential instability (per 1,000 inhabitants)	256.00	259.2	52.48	119.6	411.8
Population density (per km^2)	3,379.0	3,306.1	1,767.87	104.80	13,480.80
Off-premise density (per km^2)	45.14	61.52	8.50	0	1,042.25
Restaurants-cafes density (per km^2)	49.62	21.13	88.08	0	1,038.55
Bars density (per km^2)	134.38	94.43	138.49	0	1,631.96
Off-premise (total count)	2.14	2	2.64	0	54
Restaurants-cafes (total count)	2.41	1	3.94	0	33
Bars (total count)	6.46	5	5.50	0	44
Alcohol-related calls	3.56	2	5.19	0	115

Data analysis

First, we assessed the spatio-temporal distribution of alcohol outlets and the neighborhood-level characteristics related to this distribution. A conditionally independent Poisson distribution was used to model the number of alcohol outlets in each census block group and each year:

$$O_{it} \sim Po(E_{it} \exp(\eta_{it})), \qquad i = 1, \dots, 552, \qquad t = 1, \dots, 6 \tag{1}$$

where O_{it} is the number of alcohol outlet establishments in each census block group i during year t, E_{it} accounts for the expected number of alcohol outlets in census block group i and year t in proportion to the area density, and η_{it} is the log relative risk for every area and year.

A space-time model was used including two spatial random effects (unstructured and structured spatial effect) as well as incorporating a linear temporal trend parameter. In addition, we introduced the different neighborhood-level covariates to the model (economic status, spatially lagged economic status, immigrant concentration, and residential instability), and the control variable, population density.

The log-relative risk of the spatio-temporal model was defined as follows:

$$\eta_{it} = \mu + X_{it}\beta + \varphi_i + \theta_i + \gamma * t + \delta_i * t \quad (2)$$

where μ is the intercept, X_i is the vector of covariates per area over time, and β is the vector of regression coefficients, φ_i refers to the structured spatial random effect, θ_i is the unstructured spatial random effect, $\gamma * t$ is a fixed linear time trend for t years, and $\delta_i * t$ is a random spatio-temporal interaction [49, 50]. This model was used for the three alcohol outlet categories (off-premise establishments, restaurants-cafes, and bars).

We decided to use a linear time trend to detect changes during the period of study. Non-linear temporal structures would be also appropriate [51, 52]. We also conducted a spatio-temporal autoregressive model [52] which incorporates more complex and flexible interactions. However, it showed a similar fit and we decided to keep the linear trend according to the criterion of parsimony.

In addition, to check the influence of this temporal trend, and the need to introduce a temporal effect, previously a spatial model including only the two spatial random effects as well as the covariates was assessed. The Deviance Information Criterion (DIC) was used for comparison purposes. The model with smaller DIC values indicates the better fit [53].

After analyzing the spatio-temporal distribution of the different categories of alcohol outlets, they were used as explanatory variables for alcohol-related calls-for-service. To this end, the same space-time models were used following the equations 1 and 2. In this case, O_{it} represents the alcohol-related calls-for-service in each census block group i during year t, and E_{it} accounts for the expected number of alcohol-related calls in census block group i and year t in proportion to the population. We used the population as denominator following previous research on police calls [19, 54, 55]. The three alcohol outlet categories (off-premise establishments, restaurants-cafes, and bars) were introduced as covariates using the posterior probability for alcohol outlet density from the previous models and controlled by the same neighborhood-level characteristics used in the previous models. The spatio-temporal smoothing of alcohol outlet density provides that the estimates of police calls risks have already taken into account the influence of the neighboring alcohol outlets.

We followed a Bayesian approach for all models, and we assigned prior distributions for the parameters. Specifically, vague Gaussian distributions were assigned for the fixed effects β and the time-trend coefficient γ; μ was specified as an improper uniform distribution. The unstructured spatial effect θ was modeled by independent identically distributed Gaussian random variables $N(0, \sigma_\theta^2)$, and the structured spatial effect φ was modelled as a conditional spatial autoregressive (CAR) model [56]:

$$\varphi_i|\varphi_{-i} \sim N(\frac{1}{n_i}\sum_{j\sim i}\varphi_J, \frac{\sigma_\varphi^2}{n_i}) \tag{3}$$

where n_i is the number of neighboring areas following the queen's criterion of each census block group i, φ_{-i} represents the values of the φ vector except the component i, σ_φ assesses the standard deviation parameter, and $j \sim i$ indicates the units j neighbors of census block group i.

The spatio-temporal term δ_i was also modeled as a CAR model following the same distribution. The spatial CAR prior on the space-time interaction term assumes that nearby areas exhibit similar linear time trends. Finally, uniform distributions were used for the three hyperparameters following the structure of the hierarchical Bayesian models, $\sigma_\theta, \sigma_\delta, \sim U(0{,}1)$ and $\sigma_\varphi \sim U(0{,}3)$. A sensitivity analysis on these prior distributions was performed to select the most suitable ones. Specifically, different upper ends were used for Uniform distributions, and the precisions parameters were also assessed as Gamma distributions. The results remained stable.

To implement the models, the software R and the R2WinBUGS package were used. Bayesian models were performed using Markov Chain Monte Carlo (MCMC) techniques; three chains with 50,000 iterations were generated, being the first 10,000 part of the burn-in period. Convergence was checked by visually examining the plots of simulated chains as well as using the convergence diagnostic $\hat{R}$ [53]. The Supplementary Material 1 shows the WinBUGS code for the final models.

Results

Spatio-temporal ecological Bayesian regression models of alcohol outlets

The same spatio-temporal models were conducted for the three alcohol outlet categories in order to compare the results. The four explanatory variables (economic status, spatially lagged economic status, immigrant concentration, and residential instability) were included in the models. In addition, population density was incorporated as control variable. Following the Bayesian approach, the credible interval was interpreted in probability terms. The variables with a more-than-80% posterior probability of being over or under zero were considered relevant to the model.

Previously, each of these models was compared to a spatial one in terms of DIC. In the case of off-premise and bars density, the spatio-temporal model showed the better fit compared to the spatial model. Specifically, the spatial model for off-premise had a DIC value of 11,224.9, which decreased to 11,216.4 in the spatio-temporal model. The spatial model for bars showed a DIC value of 15,779.8, while the spatio-temporal model had a clear decrease in this value (DIC = 15,697.8). For restaurants-cafes density, the spatial model showed a better fit (DIC = 10,112.6) than the space-time model (DIC = 10,123.7). However, the parameter coefficients were stable in both models. Thus, we present the results of the spatio-temporal models for all alcohol outlets categories for comparison purposes. Table 4 summarizes the results of the spatio-temporal models.

The three models showed a relevant spatial structure (both spatial unstructured and structured effect), and space-time trends. Regarding the spatial structure, this indicates that the three categories of alcohol outlet density showed a spatial distribution, with some areas presenting higher levels of alcohol outlet density. Regarding the space-time trends, this indicates that neighboring areas are experiencing similar changes in alcohol outlet density over time (i.e., nearby areas exhibit similar linear time trends). The time trend was positive for off-premises and restaurants-cafes, but there were no changes for bars. All models showed good convergence diagnosis and parameter stability.

The results also indicate different relationships between the categories of alcohol outlets and neighborhood characteristics. Specifically, economic status was negatively related to off-premises, while for bars this relationship was positive. In addition, restaurants-cafes and bars showed a positive association with spatially lagged economic status. Immigrant concentration and residential instability only showed a relevant association with off-premises, indicating that areas with higher immigrant concentration and lower residential instability had higher levels of off-premise density. Table 5 indicates the odds ratios for covariates of the alcohol outlet models.

Figure 1 shows the estimated time trend $E[\exp(\gamma + \delta_i)|Y]$ across each of the census block groups for alcohol outlet density. In these maps, areas with a time trend value over one represent those census block groups with increasing alcohol outlet density, while areas with a time trend value lower than one represent census block groups with decreasing alcohol outlet density.

Table 4. Spatio-temporal Bayesian model estimates of alcohol outlets establishments.

Variable	**Model 1. Off-premises**		**Model 2. Restaurants-cafes**		**Model 3. Bars**	
	Mean (CrI 95%)	**SD**	**Mean (CrI 95%)**	**SD**	**Mean (CrI 95%)**	**SD**
Intercept (μ)	-0.617	0.199*	-0.603	0.133*	-0.640	0.097 *
	(-1.004, -0.2222)		(-0.868, -0.370)		(-0.839, -0.441)	
Economic status[1]	-0.003	0.003*	-0.001	0.002	0.002	0.002*
	(-0.009, 0.002)		(-0.005, 0.003)		(-0.002, 0.005)	
Spatially lagged economic status[1]	0.002	0.005	0.004	0.001*	0.004	0.003*
	(-0.009, 0.011)		(-0.002, 0.008)		(-0.001, 0.019)	
Immigrant concentration	0.012	0.004*	0.001	0.003	-0.001	0.002
	(0.004, 0.019)		(-0.005, 0.007)		(-0.006, 0.004)	
Residential instability	-0.001	0.001*	-0.001	0.001	-0.001	0.001
	(-0.001, 0.000)		(-0.001, 0.001)		(-0.001, 0.000)	
Spatial heterogeneity (σ_θ)	0.721	0.049	0.506	0.035	0.633	0.036
	(0.627, 0.822)		(0.439, 0.575)		(0.560, 0.700)	
Spatial structure (σ_φ)	0.960	0.146	0.727	0.097	0.903	0.099
	(0.644, 1.238)		(0.543, 0.927)		(0.718, 1.095)	
Year (γ)	0.008	0.008*	0.010	0.007*	-0.001	0.005
	(-0.007, 0.023)		(-0.004, 0.023)		(-0.009, 0.009)	
Spatial x Year (σ_δ)	0.090	0.026	0.006	0.006	0.118	0.015
	(0.038, 0.132)		(0.001, 0.018)		(0.091, 0.146)	

* Posterior probability of being over or under zero > 0.80.

[1] This variable was included as the cadastral value divided by 1,000 to solve computational problems with the prior distributions assigned to fixed effects

Models controlled for population density.

Table 5. Odds ratios for variables of the alcohol outlet models

Variable	Off-premises (CrI 95%)	Restaurants-cafes (CrI 95%)	Bars (CrI 95%)
Economic status[1]	0.997 (0.991, 1.002)	0.999 (0.995, 1.003)	1.002 (0.998, 1.005)
Spatially lagged economic status[1]	1.002 (0.991, 1.011)	1.004 (0.998, 1.008)	1.004 (0.999, 1.019)
Immigrant concentration	1.012 (1.004, 1.019)	1.002 (0.995, 1.007)	0.999 (0.994, 1.004)
Residential instability	0.999 (0.999, 1.000)	0.999 (0.999, 1.001)	0.999 (0.999, 1.001)

[1] This variable was included as the cadastral value divided by 1,000 to solve computational problems with the prior distributions assigned to fixed effects

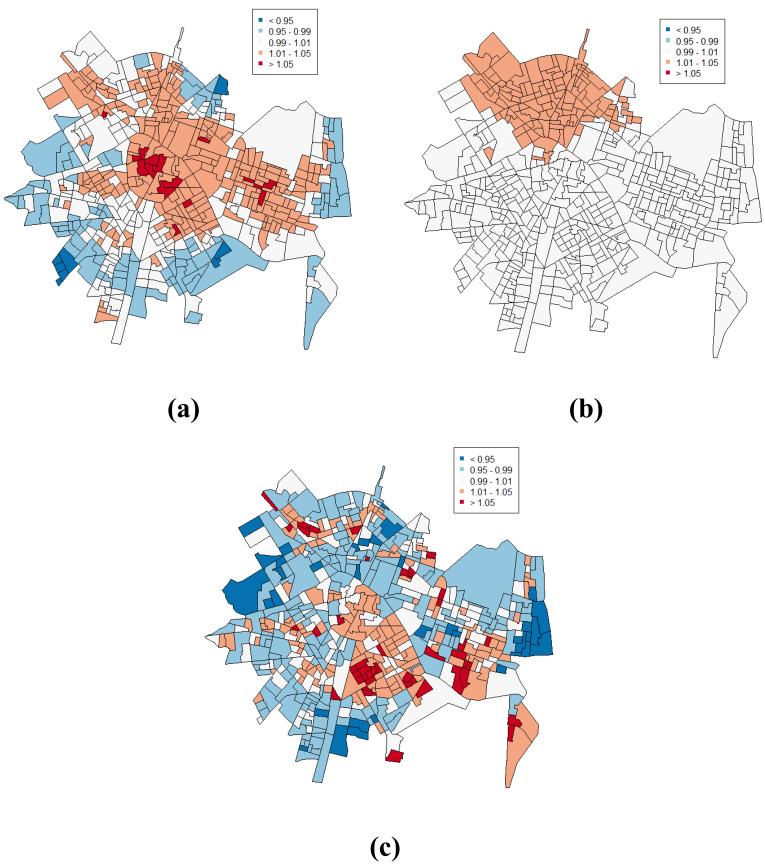
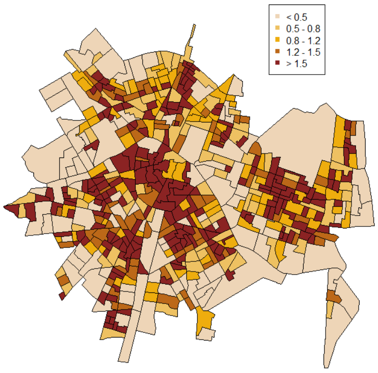


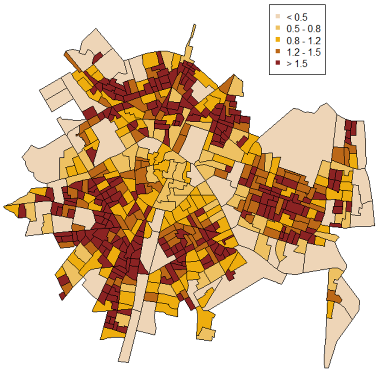
Figure 1. (a) Change in off-premise density from 2010 to 2015 **(b)** Change in restaurants-cafes density from 2010 to 2015 **(c)** Change in bars density from 2010 to 2015

Regarding off-premise density (Figure 1a), center-east and north-west areas of the city have showed a relevant increase, while south and east areas showed a decrease. Restaurants-cafes (Figure 1b) showed a small increase in the north. However, these changes over time were very small, as indicated by the small effect of the spatio-temporal interaction. Restaurants-cafes density, thus, was practically stable in the same areas over the years. Bars density (Figure 1c) showed a different trend, with an increase of bars density in the central-southern parts of the city, and a decrease in the peripheral areas.

Figure 2 shows the density of alcohol outlets in the last year of the study period, 2015. The density was calculated from equation 2 as $\exp(\eta_{it})$. Areas with a value over one indicate an above-average density.



(a)



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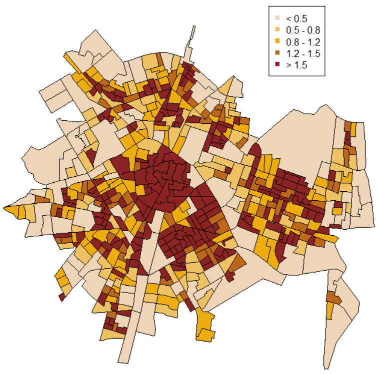


(c)

Figure 2. (a) Off-premise density in 2015 **(b)** Restaurants-cafes density in 2015 **(c)** Bars density in 2015

In these maps, we can examine areas with higher alcohol outlets density in 2015. They show that, despite some areas having high alcohol outlets density for all categories, other areas presented different spatial patterns. Specifically, off-premise density (Figure 2a) was higher in the central part of the city, restaurants-cafes density (Figure 2b) was higher in the peripheral areas, and bars density (Figure 2c) was especially concentrated in the center of the city. In Supplementary Material 2 we show the posterior probabilities of being greater than 1 for each model.

Spatio-temporal ecological Bayesian regression models of alcohol-related calls-for-service

After analyzing the spatio-temporal distribution of alcohol outlets density for each category, a spatio-temporal model was assessed for alcohol-related calls-for-service to analyze the influence of alcohol outlets in neighborhood alcohol-related problems. In this model, the three alcohol outlet categories were introduced as covariates controlled for the other neighborhood characteristics. First we also assessed a spatial model, which showed a DIC value of 13,699.9. The spatio-temporal model presented a clear improvement (DIC = 13,146.6), and thus this last model was selected as final one. Table 6 shows the results of the model (see Supplementary Material 3 for the complete table).

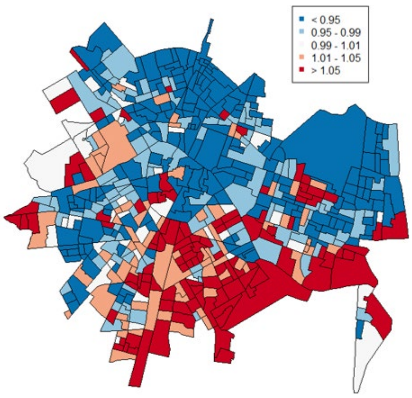
Table 6. Spatial-temporal Bayesian model estimates of alcohol-related calls-for-service controlled for neighborhood-level covariates

Variable	Mean	SD	95% CrI	Odds ratio
Intercept (μ)	0.461 *	0.110	(0.242, 0.672)	
Off-premise density	-0.008	0.016	(-0.023, 0.040)	0.992 (0.941, 1.029)
Restaurants-cafe density	-0.036 *	0.003	(-0.041, -0.031)	0.965 (0.960, 0.970)
Bars density	0.010 *	0.009	(-0.008, 0.026)	1.010 (0.992, 1.023)
Spatial structure (σ_{φ})	1.281	0.372	(0.750, 2.040)	
Year (γ)	-0.025 *	0.007	(-0.038, -0.013)	
Spatial x Year (σ_{δ})	0.244	0.017	(0.212, 0.278)	

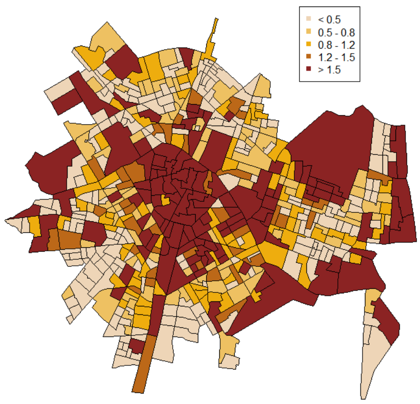
* Posterior probability of being over or under zero > 0.80.
Model controlled for economic status, spatially lagged economic status, immigrant concentration, residential instability, and population density.

Off-premise and restaurants-cafes density show a negative relationship with alcohol-related calls-for-service, while bars density shows a positive association, controlled for economic status, spatially lagged economic status, immigrant concentration, residential instability, and population. These results suggest a different influence of alcohol outlets in neighborhood alcohol-related problems, being bars density the alcohol outlet category that is positively related to alcohol-related calls-for-service.

Figure 3a shows the estimated time trend across each of the census block groups for alcohol-related calls-for-service. In this map, we can observe that the northern and the western part of the city have experienced a decrease in the number of calls-for-service, while the southern part has experienced a clear increase. Figure 3b shows the relative risk of alcohol-related calls-for-service in 2015. We can observe that the relative risk for alcohol-related calls-for-service was higher in the center of the city, as well as all in the easternmost part. In Supplementary Material 2 we show the posterior probabilities of being greater than 1.



(a)



(b)

Figure 3. (a) Change in alcohol-related calls-for-service from 2010 to 2015 **(b)** Relative risk of alcohol-related calls-for-service in 2015

Discussion

This study used a spatial-temporal approach to assess the distribution of alcohol outlet density in the city of Valencia (Spain) from 2010 to 2015. Spain has been characterized as a wet drinking country, where alcohol consumption is less problematized. We used three different categories of alcohol outlet density (off-premise, restaurants-cafes, and bars) [43–45] and we analyzed the spatial patterns and the temporal trends of each category, as well as the neighborhood-level variables influencing these patterns. After analyzing the spatiotemporal distribution of alcohol outlets, we used these categories to study their relationship with alcohol-related calls-for-service.

The results indicated different relationships between the categories of alcohol outlets and neighborhood characteristics. Specifically, off-premise density was higher in areas with lower economic status, higher rates of immigrant population, and lower residential instability. Restaurant/cafe density was higher in areas with lower economic status, and higher spatially lagged economic status. Bar density, however, was higher in areas with higher levels of economic status, and higher spatially lagged economic status.

Previous studies conducted in U.S. cities have shown that socioeconomic disadvantage and lower economic status were positively related to alcohol outlet density [12,22,24–26,30]. Our results suggest that, in Valencia, off-premise outlets are located in lower economic status neighborhoods, restaurants/cafes are located in areas with lower local economic status but higher lagged economic status, while bars appear to have a different spatial signature (i.e., in local and lagged areas with higher economic status). Particularly interesting are the results for restaurants-cafes, which suggest that neighborhoods with higher density of restaurants/cafes are more likely to have lower economic status, but their neighboring areas are more likely to have higher economic status. Future studies would benefit from exploring the mechanisms involved in this relationship between local and lagged economic status and the restaurant and cafe distribution.

On the other hand, the location of the bars presents clear differences compared to the U.S., where alcohol outlet density tends to be associated to lower economic status areas. In our study, bar density was higher in local and lagged areas with higher economic status. These differences may reflect the characteristics of those who frequent bars and the reasons why people go to bars. In Valencia (and other Spanish cities), areas with a high number of bars are often frequented by young people who have a job or are studying at the university, and going to bars is culturally seen as a social activity. In this regard, bars would be more a meeting space than just a place for alcohol consumption. These areas with a higher density of bars often become popular areas and the cost of alcohol consumption at bars in these trendy areas tend to be higher, attracting a more wealthy type of clientele. These differences in the use of bars could lead to the different spatial association with neighborhood characteristics that we found in our study.

In regard to immigrant concentration, areas with higher immigrant concentration showed higher off-premise density. However, immigrant concentration was not associated with restaurants/cafes or bar density. Previous studies have also shown mixed results regarding the influence of immigrant concentration on alcohol outlet density [26–29]. Similarly, residential instability was only relevant in the off-premise density model, however, in contrast to previous studies [27], our results showed a negative relationship between residential instability and off-premise density. In other words, those areas with higher residential stability showed higher off-premise density. These results suggest that off-premise establishments in Valencia are more frequent in stable neighborhoods, with families that tend to live in the same areas for a long time.

Taken together, these results suggest that research on the spatial distribution of alcohol outlets and the neighborhood characteristics influencing this distribution conducted in “dry” countries cannot be directly extrapolated to “wet” drinking countries, where the drinking patterns and culture are different. Clearly, further cross-cultural research is needed to better understand the different spatial distribution of alcohol outlets in countries with different drinking cultures.

Our study also showed the spatiotemporal trends of alcohol outlets from 2010 to 2015. Off-premises and bars models showed a clear improvement in fit when introducing a spatiotemporal structure, and only restaurants/cafes showed a better fit using only a spatial model, suggesting different space-time patterns depending on the alcohol outlet category. For example, during this time period, off-premise density increased in the central and eastern part of the city, and decreased in the peripheral areas. On the other hand, bar density increased in the south-central part of the city. This area corresponds to one of the traditional neighborhoods of Valencia, which has become a trendy district for the city’s nightlife after a process of gentrification [56], which may explain the significant increase in bars in the area. Restaurant/cafe density, however, did not show important changes over the years, suggesting stable density levels.

To examine whether alcohol outlets were associated with alcohol-related problems in the neighborhoods, we also analyzed the influence of alcohol outlet density on alcohol-related calls-for-service. Results showed that bar density was the only alcohol outlet category with a positive association with alcohol-related calls-for-service risks. Restaurant/cafe density showed a negative relationship. Off-premise establishments showed no association with alcohol-related calls-for-service. When comparing the spatial distribution of alcohol-related calls-for-service and alcohol outlets, we can observe that the spatial pattern of alcohol-related calls-for-service is similar to the spatial distribution of bars. Specifically, the centre of the city showed higher relative risk of alcohol-related calls-for-service, as well as higher bar density. In addition, the temporal trend for calls-for-service (increasing in the south areas and decreasing in the north areas) is more coincident with the temporal trend for bars, which shows the same change patterns.

These findings show that police alcohol-related interventions are more common in neighborhoods with a higher density of bars. Despite the fact that these high bar-density areas are located in higher-income areas, police interventions are requested more often in these areas due to alcohol-related problems. This is similar to the context in the U.S., where bars are related to a variety of crimes [6,19]; although those studies did not measure only alcohol-related crimes. However, off-premise density was not related to alcohol-related calls-for-service. In the U.S., off-premise establishments are seen as an indicator of a "spiral of decay" that leads to more social problems, such as violent crime or injuries [8,57–59]. These differences between Spain and U.S. cities could be explained by the different meaning of off-premise establishments in Spain. In a wet country like Spain, the sale of alcohol does not require strict conditions, and alcohol is easily available in many establishments, including supermarkets, grocery stores, petrol stations, or small stores, where they are usually displayed along with nonalcoholic beverages. Spain, and by extension, wet drinking countries, would have the off-premise sale of alcohol more integrated into social life. These differences regarding off-premises may also be due to the fact that our study only assessed alcohol-related crimes. The U.S. studies tend to focus on all crimes within a specified area. As off-premise outlets do not allow alcohol use on premise, the number of alcohol-related crimes may actually be unaffected. In addition, wealthy neighborhoods may be more likely to call the police, because they may show greater trust in the police system, or because the police could be more likely to respond promptly in this type of neighborhoods than in deprived neighborhoods. However, we do not have available data to assess these possible relationships. Cross-cultural studies are needed to further analyze these differences and the implications of alcohol outlets in social problems.

This study has both strengths and limitations. Among the strengths, to the best of our knowledge, this is the first study on the spatial-temporal distribution of alcohol outlets in a city from a "wet" country. Most of the research in this field has been conducted in U.S. or northern European countries. Our results show that the influence of neighborhood-level variables on the distribution of alcohol outlets could be different in southern European cities, and that it is important to take into account the country's drinking culture to make appropriate conclusions. In addition, this study uses a spatiotemporal perspective. This type of analysis presents major advantages because it reflects not only the spatial distribution, but it also accounts for changes over time. Studies that only consider spatial trends could bias the results and mask any relationship between variables [49]. In addition, we use a Bayesian perspective, and we introduced different random-effects accounting for both spatial and temporal influences. Bayesian modelling has the advantage of addressing issues such as spatial autocorrelation or overdispersion, which can bias estimates if not taken into account

[60–62]. Finally, this study provides information about alcohol outlet distribution in small areas. Some studies have focused on larger areas such as zip codes, census tracks, or counties [7,26,63]; we used census block groups, which were the smallest spatial unit available. This high-spatial resolution approach addressed potential issues in ecological studies due to aggregation effects [62].

This study has also limitations. First, some traditional variables used for characterizing neighborhoods were not available for this study; for example, other socioeconomic indicators used in previous research that may reflect the better economic status of the census block groups (e.g., income, unemployment, or poverty indicators [19,25,28,29]), or variables related to neighborhood disorder [64,65]. In addition, we cannot discard that some endogeneity may exist in the relationship between bars, crime, and property values. For example, property values may be a product of overall crime rates in the area. Future research should address the possible nonrecursive relationship between these variables, and study the causality processes that would be explaining the results found in this study.

Regarding methodological aspects, a potential issue is the modifiable areal unit problem [66]. In addition, our analysis may also be subjected to edge effect, where spillovers into surrounding rural areas around Valencia are not included in our model [5,67]. Another possible limitation is that, due to the short number of years available, we have used a linear time trend. However, other alternative and more complex models may be more appropriate and reveal more information about the problem when using longer time periods, such as an autoregressive structure or other nonlinear space-time models [51,52,68].

In addition, it is important to note that alcohol-related calls refer only to those cases where police are required to intervene for alcohol-related problems, and they do not reflect other outcomes, such as hospital admissions, where the police do not intervene, or traffic crashes where alcohol is involved, which were not available for this study. Future research would benefit from focusing on other alcohol-related outcomes and explore their relationships with alcohol outlet density. In addition, more research is needed in the context of wet drinking countries, in order to analyze if they show the same sociospatial patterns, which differ from those found in dry drinking countries.

Conclusions

This is the first study focused on the spatiotemporal distribution of alcohol outlets in a city from a wet drinking country, and its relationship with alcohol-related calls-for-service. After analyzing the different categories of alcohol outlets, we can conclude that they present different space-time distributions, as well as different associations with neighborhood-level characteristics. This suggests that an aggregated measure of total alcohol outlet density would not be appropriate, and future studies that use alcohol outlets to study social outcomes in a wet country should take into account each category separately. Our results regarding alcohol-related calls-for-service could be of help for planning and evaluating prevention policies for alcohol-related police interventions, focusing on those places with high density of bars, which show more alcohol-related problems that require police intervention. Future studies should focus on using these alcohol outlets categories to explain different social problems (i.e., intimate partner violence or child maltreatment) after controlling for social disorganization traditional variables (e.g., socioeconomic status, immigrant concentration, or residential instability). In addition, future studies should focus on analyzing whether the influence of alcohol outlet density in neighborhood social problems in wet countries follow the same patterns as those found in previous studies conducted in dry drinking countries.

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Study 5

Spatio-temporal analysis of suicide-related emergency calls

Spatio-temporal analysis of suicide-related emergency calls [5]

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Abstract

Considerable effort has been devoted to incorporate temporal trends in disease mapping. In this line, this work describes the importance of including the effect of the seasonality in a particular setting related with suicides. In particular, the number of suicide-related emergency calls is modeled by means of an autoregressive approach to spatio-temporal disease mapping that allows for incorporating the possible interaction between both temporal and spatial effects. Results show the importance of including seasonality effect, as there are differences between the number of suicide-related emergency calls between the four seasons of each year.

Keywords: Bayesian modelling, disease mapping, police calls-for-service, seasonality, social epidemiology

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Introduction

Suicide is a global health problem that is receiving increasing interest worldwide [1]. According to the World Health Organization (WHO), in 2012, there were over 800,000 suicide deaths in the world, and suicide was the second leading cause of death after road traffic injuries in young adults [2]. In Spain, where this study was conducted, 3602 people died by suicide in 2015, which corresponds to the 24% of deaths by external causes [3]. The numbers would even increase if we take into account the suicide attempts where the victim finally survives. These data highlight the necessity of further analyzing the different mechanisms that may be involved in this problem.

Although previous research has mainly focused on individual and familiar characteristics of suicide, an increasing number of studies have suggested that spatial patterns would also have an impact in suicide risk, in other words, that suicide would not be randomly distributed across the space, but subjected to underlying spatial patterns [4–13]. In addition, other studies have shown the seasonality of suicide: previous research suggests that the prevalence of suicide deaths are not constant, but varies during the year [14–18]. Specifically, these studies have shown that there is a peak of suicide cases in spring and summer, and the findings are similar independently of the study country. Indeed, linking both ideas of area patterns and seasonality would result in the most appropriate approach to conduct an ecologic study of suicides [4,10].

The Bayesian approach has turned into an appropriate choice when dealing with spatio-temporal disease mapping models in the public health context [19–22], although its use for the analysis of suicide-deaths is more recent but already productive [4,5,8,12,13,23–28]. A good comparison of the most relevant spatio-temporal disease mapping approaches can be found in this special issue [29].

The focus of this work is to model the spatio-temporal distribution of suicide-related emergency calls (including suicide deaths and suicide attempts) in the city of Valencia (Spain), in particular by means of an autoregressive approach to spatio-temporal disease mapping that brings together ideas from autoregressive time series in order to link information in time and from the spatial modeling context to link information in space [30]. Although other studies have also used calls to analyze different crime and police intervention outcomes [31–33], the main focus here is in showing that the inclusion of the effect of seasonality can help to understand the temporal pattern of suicide risks.

Materials and methods

Emergency police calls in Valencia City

This study was conducted in Valencia (Spain), which is the third largest city in the country with a population of 736,580 inhabitants. The census block group, the smallest administrative unit available, was used as a proxy of neighborhood. In particular, the city of Valencia is divided into 552 census block groups. The population of the census block groups ranges from 630 to 2845, with an average of 1334 residents.

The outcome variable of interest was the number of suicide-related emergency calls. Valencia Police Department and its call service (number 092 in Spain) provided information about all the calls they received requiring police intervention in the city of Valencia. From the entire database, we selected the calls informing of a death by suicide (142 calls) and those informing of a suicide attempt (6395 calls), 6537 being the total number of suicide-related calls. The address where the call was made was geocoded in order to keep track of the census block group where it was produced.

All the suicide-related calls analyzed had been obtained during a seven-year period (from 2010 to 2016), providing the possibility of capturing any possible temporal trends. Each year was also divided into 3-month periods, where period 1 starts in January and lasts until the end of March, period 2 comprises from April to June, period 3 from July to September, and period 4 from October to December. The outcome variable was described in those 28 periods allowing the exploration of the possible effect of seasonality.

Table 1 presents summary statistics for the counts of suicide-related emergency calls aggregated both at global and annual scales.

Table 1. Summary statistics for counts of suicide-related emergency calls by Valencia census block groups, for globally and annually aggregated data, 2010–2016.

Statistic	**Global (2010-2016)**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
			Counts of Suicide-Related Emergency Calls					
Total	6537	709	824	781	968	1082	1126	1047
Min.	0	0	0	0	0	0	0	0
Max.	70	11	18	12	14	15	19	15
Mean	11.84	1.24	1.46	1.37	1.72	1.91	2.02	1.85
			Standardized Suicide-Related Emergency Calls Ratio					
Min.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max.	7.38	10.46	17.72	10.95	10.90	10.50	8.85	10.62

As it can be appreciated, an aggregated total of 6537 calls was reported and geocoded, being the range of the number of calls for each census block group from 0 up to 70. The standardized suicide-related emergency calls ratio (calculated as the received calls divided by the expected calls by census block group) for all census block group ranges from a minimum of 0.00 to a maximum of 7.38. Note that, as usual in the context of small area disease mapping, there are census block groups for which standardized incidence ratios are zero, the reason underneath being that there are census block groups with zero number of calls. The percentage of census block groups with zero frequency was 0.5% for the whole study period. This percentage increased to 33% when taking into account yearly periods and up to 70.4% when taking into account the 28 quarterly periods. The map of the standardized suicide-related emergency calls ratio can be seen in Figure 1. It is worth noting that the cut-offs in all the figures were selected to provide symmetric intervals and a balanced number of units per interval rounded to one decimal.

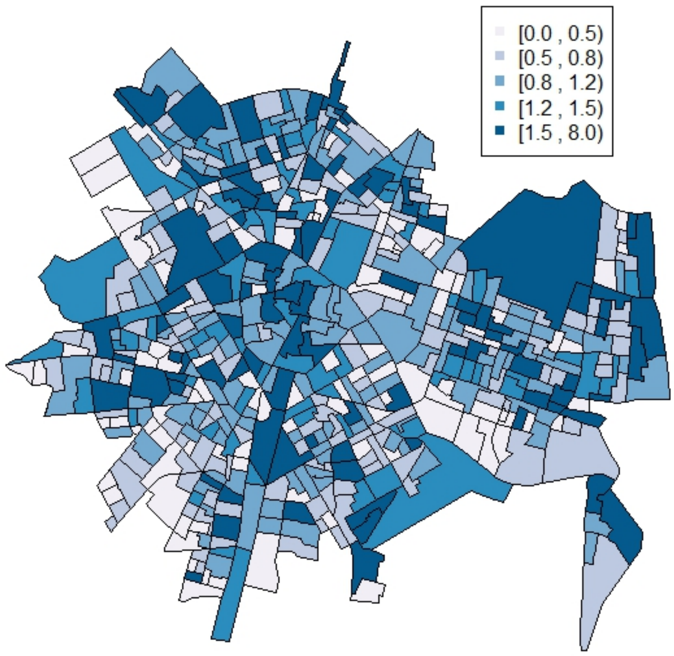


Figure 1. Map of the standardized suicide-related emergency calls ratios in Valencia census block groups during the whole period analyzed (2010–2016).

Spatial Disease Mapping

A first approach to describe this dataset was to conduct a purely spatial model in line with [5,23,25,34,35]. The most popular one was due to [36], and it is based on considering the observed number of calls as conditionally independent Poisson variables and then linking them via a Poisson regression with two random effects. In particular, if Oi represents the observed number of suicide-related emergency calls at the census block group i, then:

$$O_i \sim Poisson(E_i \exp(\eta_i)), \quad i = 1, \dots, 552 \qquad (1)$$

where E_ii is a quantity that accounts for the expected number of calls in census block group i, that is

$$E_i = \text{Population living at census block group i} \times \frac{\text{Total number of calls}}{\text{Total population in Valencia}},$$

and η_i is the log relative risk that takes into account the spatial effects as

$$\eta_i = \mu + \phi_i + \theta_i \qquad (2)$$

μ being the intercept, ϕ a spatially structured random effect, and θ the unstructured random effect.

As stated in [36], the unstructured spatial effect θ is modeled by means of independent identically distributed Gaussian random variables $N(0, {\sigma_\theta}^2)$, while the structured spatial effect ϕ is considered to be a conditional spatial autoregressive model [36] in order to reflect the spatial neighborhood relationships:

$$\phi_i | \phi_{-i} \sim N(\tfrac{1}{n_i} \textstyle\sum_{j \sim i} \phi_j, \tfrac{\sigma_\phi^2}{n_i}) \qquad (3)$$

where n_i is the number of neighboring areas of census block group i, ϕ_{-i} indicates the values of the ϕ vector except for the ith component, the expression $j \sim i$ denotes all units j that are neighbors of census block group i, and σ_ϕ is the standard deviation parameter.

To finally set up the model, and taking into account that in this work the inferential approach was made under the Bayesian paradigm, any information about the unknown parameters was expressed in probabilistic terms via the so-called prior distributions. In particular, an improper uniform distribution was assigned for μ, while for the hyperparameters of σ_θ and σ_ϕ, prior distributions of standard deviations were uniform distributions $\sigma_\phi, \sigma_\theta \sim \mathrm{U}(0, 1)$.

Spatio-Temporal Disease Mapping: Annual Data

Incorporating the temporal effect in the context of disease mapping has been a matter of interest for researchers lately. Anderson and colleagues [29] have compared many of them looking for good behaviors in terms of ability to fit and computational effort. In this work, based on [29], comments about its good behavior in terms of fitting, the model proposed by [30] was used. Indeed, previous studies have shown that this approach can provide a very good fit in many complex situations, in particular those involving relevant epidemiological outcomes [29,37,38].

In particular, the number of suicide-related police calls-for-service in each census block group in the seven years of the study, Oit, were modeled as conditionally independent Poisson distributions

$$O_{it} \sim Poisson(E_{it} \exp(\eta_{it})), \quad i = 1, \dots, 552, \quad t = 1, \dots, 7, \qquad (4)$$

where E_{it} is the expected number of calls in census block group i during yeart and η_{it} is the log relative risk.

The spatio-temporal effect is included in the model via the η_{it}. The proposed approach of [30] cleverly combines autoregressive time series and spatial modeling by means of a spatio-temporal structure in which the relative risks are both spatially and temporally dependent. For the first annual period, the relationship is:

$$\eta_{i1} = \mu + \alpha_1 + (1 - \rho^2)^{-1/2} \cdot (\phi_{i1} + \theta_{i1}), \qquad (5)$$

while for the remaining periods is

$$\eta_{it} = \mu + \alpha_t + \beta_{q(t)} + \rho\big(\eta_{i(t-1)} - \mu - \alpha_{t-1}\big) + \phi_{it} + \theta_{it}. \qquad (6)$$

It is worth noting that, in both equations, αt represents the mean deviation of the risk in year t, ρ represents the temporal correlation between years (that is, the temporal correlation between the spatial effects of each year), and ϕ_{it} and θ_{it} refer to the structured and unstructured spatial random effects of each year, respectively. With respect to the structure for α_t , the choice was a conditional autoregressive temporal model depending on the parameter σ_α, while the unstructured spatial effect is also modeled by means of independent identically distributed Gaussian random variables and the structured spatial effect is considered to be a conditional spatial autoregressive model.

As previously commented, the final set up of the model consists of assigning the priors. In this case, the selection was an improper uniform distribution for μ, uniform over the whole space for the autoregressive term $\rho \sim \mathrm{U}(-1, 1)$, and uniform distributions for the three standard deviations involved $\sigma_\alpha, \sigma_\phi, \sigma_\theta \sim U(0,1)$.

Spatio-Temporal Disease Mapping: Quarterly Data

As the number of observed suicides could also be seasonal, a spatio-temporal model similar to the previous one but using trimesters as time units was also considered. During the analyzed period, there were 28 trimesters, and for each one, the number of suicide-related police calls-for-service in each census block group was also expressed as

$$O_{it} \sim Poisson(E_{it}\exp(\eta_{it})), \qquad i = 1, \ldots, 552, \qquad t = 1, \ldots, 28, \quad (7)$$

In the same manner as before, the spatio-temporal effect is included in the model via the ηit by means of [30], but including an additional quarterly effect. Indeed, for the first trimester of 2010, the relationship is now expressed as:

$$\eta_{i1} = \mu + \alpha_1 + (1 - \rho^2)^{-1/2} \cdot (\phi_{i1} + \theta_{i1}), \quad (8)$$

while for the remaining periods is

$$\eta_{it} = \mu + \alpha_t + \beta_{q(t)} + \rho\big(\eta_{i(t-1)} - \mu - \alpha_{t-1}\big) + \phi_{it} + \theta_{it}. \quad (9)$$

Note that, similarly to the previous model, in both equations, αt represents the mean deviation of the risk in trimester t, ρ represents the temporal correlation between periods, and φit and θit refer to structured and unstructured spatial random effects of each trimester, respectively. In addition, and in order to express the effect of the four seasons of each year, $\beta_{q(t)}$ represents now the mean deviation of the risk at season $q(t)$. The fourth trimester was selected as the reference one, and the remaining three were compared to it.

Again, assigning the priors is the last step to complete the models. The selection here was an improper uniform distribution for μ, uniform over the whole space for the autoregressive term $\rho \sim \mathrm{U}(-1, 1)$, , uniform distributions for the three standard deviations involved $\sigma_\alpha, \sigma_\phi, \sigma_\theta \sim U(0,1)$.and Gaussian distributions with large variance for the parameters of the fixed effect $\beta_1, \beta_2, \beta_3 \sim \mathrm{N}(0, 10{,}000)$.

A simplified version of this model in which the correlation between periods, ρ, is zero (and so, there is no autoregressive term explaining interactions between space and time) was also considered. This model was analyzed to validate that the extra complexity added by including the interaction between space and time is really worthwhile.

Statistical Inference

As usual in this context, the resulting hierarchical Bayesian model containing all the information about the suicides has no closed expression for the posterior distribution of all the parameters, and so numerical approximations are needed. Computation of posterior probability distributions is not always easy to deal with. For many years, the computational challenge of obtaining posterior distributions has been one of the main issues for not using Bayesian statistics. However, nowadays, this task has been simplified by the increasing capacity of computers together with the development of simulation methodologies based on Monte Carlo sampling and Markov Chain Monte Carlo (MCMC) methods (see, for instance, [39] for a good review on the subject).

MCMC methods can be implemented in many statistical packages. In this paper, MCMC was performed through WinBUGS [40], a statistical software that provides a simple implementation of a great number of complex statistical models. The WinBUGS code of the final model can be found in the Supplementary Materials Section S1. In particular, three chains with 50,000 iterations for each chain were generated, and the first 10,000 for each chain were discarded as burn-in. Convergence of all the chains was assessed by visual inspection of simulated chains and by means of the Brooks–Gelman–Rubin statistic and the effective sample size [41].

Most of the above presented methods are not comparable in terms of useful model selection criteria. For those cases in which there were different comparable models, the Deviance Information Criterion (DIC) [42] was used to compare among them. As other similar criteria, it weighs up the goodness-of-fit and the complexity of the selected model, but, more importantly, it has good behavior when comparing models whose posterior distribution has been approximated by MCMC. The smaller the DIC, the better the fit.

Results

Table 2 shows the summary statistics along with the credible intervals of the posterior distributions of the parameters of the pure spatial model in Section 2.2, while Figure 2 shows its corresponding spatial effect ϕ and the relative risk for each census block group. Note that the spatial effect is not as important as the heterogeneity effect (σ_ϕ = 0.355 and σ_θ = 0.478, respectively). However, more importantly, although this spatial effect is relevant and the relative risk for each census block group shows a smoother version of the standardized incidence ratios presented in Figure 1, it is worth mentioning that this pure spatial model does not incorporate any information about any possible time trend.

Table 2. Mean and standard deviation of the posterior distribution along with the 95% credible interval of the parameters of the pure spatial model.

Parameter	Mean	SD	Quantile 0.025	Quantile 0.975
μ	-0.126	0.032	-0.191	-0.070
σ_ϕ	0.355	0.093	0.181	0.534
σ_θ	0.478	0.028	0.424	0.532

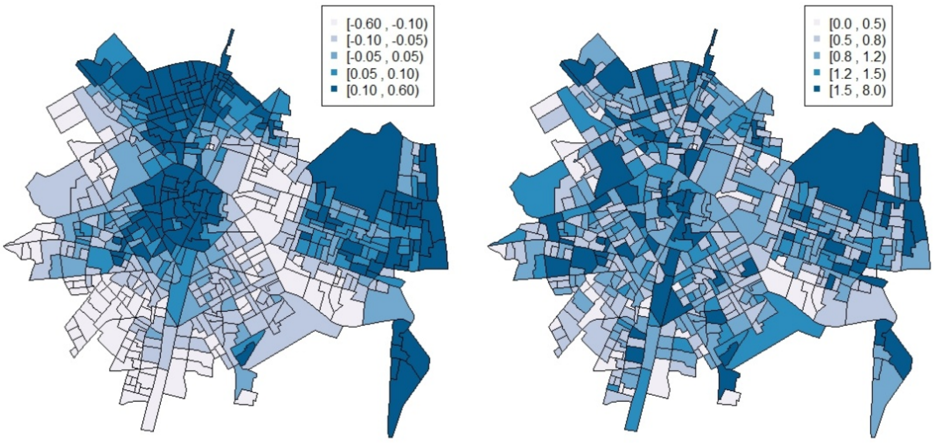


Figure 2. (a) spatial effect; and **(b)** relative risks of the pure spatial model.

In order to reflect the possible year effect on the number of calls for each census block group, Table 3 resumes the posterior distributions of the parameters of the spatio-temporal model with annual data introduced in Section 2.3. In the same way as the pure spatial model, the heterogeneity effect (σ_ϕ = 0.512) has a greater weight than the spatial effect (σ_θ = 0.272). In addition, there are two important things to be noted here, namely, the strong relevance of the autoregressive term (ρ is nearly 0.7), and also the importance of the year term. Nevertheless, this temporal effect (α) can be more clearly appreciated when observing Figure 3d, where an increasing trend of the number of calls for each census block group is clearly marked. This can also be observed in Table 1, where the number of calls increase over the years. Figure 3 also shows the spatial effect (φ) for three particular years 2010, 2013, and 2016, showing different patterns for the three years.

Table 3. Mean and standard deviation of the posterior distribution along with the 95% credible interval of the parameters of the spatio-temporal model.

Parameter	Mean	SD	Quantile 0.025	Quantile 0.975
μ	-0.269	0.032	-0.334	-0.208
σ_ϕ	0.272	0.058	0.159	0.384
σ_θ	0.623	0.025	0.462	0.564
σ_α	0.034	0.029	0.002	0.105
ρ	0.692	0.024	0.644	0.739

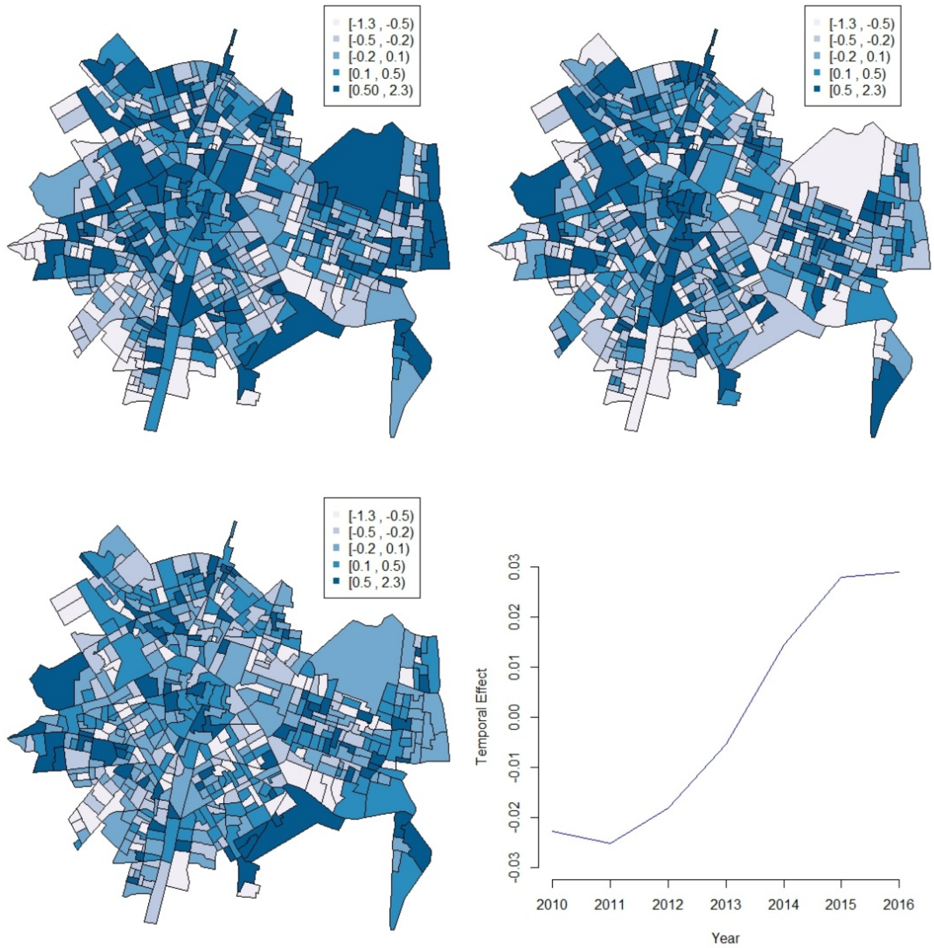


Figure 3. (a–c): spatial effect for the years 2010, 2013 and 2016, respectively; **(d):** temporal effect during the period (2010–2016).

Anyhow, taking into account that the temporal effect has resulted in being relevant, a model incorporating the possible seasonality inside years was also analyzed. In particular, Table 4 resumes the posterior distributions of the parameters of the spatio-temporal model with quarterly data introduced in Section 2.4. The convergence of the parameters of the model was properly good, as showed in the Supplementary Materials Section S2. Posterior distributions of the parameters describing the fixed quarterly effect show that the number of calls is larger in the second and third trimester.

Again, results in Table 4 show a higher effect of the heterogeneity parameter (σθ = 0.359) compared to the spatial structured term (σ_ϕ = 0.160), as well as a strong relevance of the autoregressive term (ρ is around 0.9). However, more importantly, the temporal term (without the quarterly effect) now becomes more relevant, shown by a higher value of the autoregressive standard deviation σ_α. The resulting temporal effect (α) presented at Figure 4 clearly shows a different behavior (increasing trend but with more ups and downs) than the one observed at Figure 3d.

Table 4. Mean and standard deviation of the posterior distribution along with the 95% credible interval of the parameters of the spatio-temporal quarterly model.

Parameter	Mean	SD	Quantile 0.025	Quantile 0.975
μ	-0.362	0.045	-0.450	-0.275
β_1	-0.122	0.057	-0.230	-0.008
β_2	0.093	0.059	-0.024	0.208
β_3	0.118	0.053	0.016	0.227
σ_ϕ	0.160	0.030	0.102	0.220
σ_θ	0.359	0.019	0.323	0.398
σ_α	0.106	0.032	0.051	0.178
ρ	0.903	0.003	0.885	0.919

Figure 4. Temporal effect for each trimester during the whole 2010–2016 period analyzed.

An added bonus when analyzing this kind of spatio-temporal model is the possibility of describing the temporal trend of each census block group along the whole period. Figure 5 shows the relative risks for three kinds of census block groups (in orange those with an increasing trend, in green those with a decrease in the tendency, and in red those where the relative risk was always high) and their relative position in the city of Valencia.

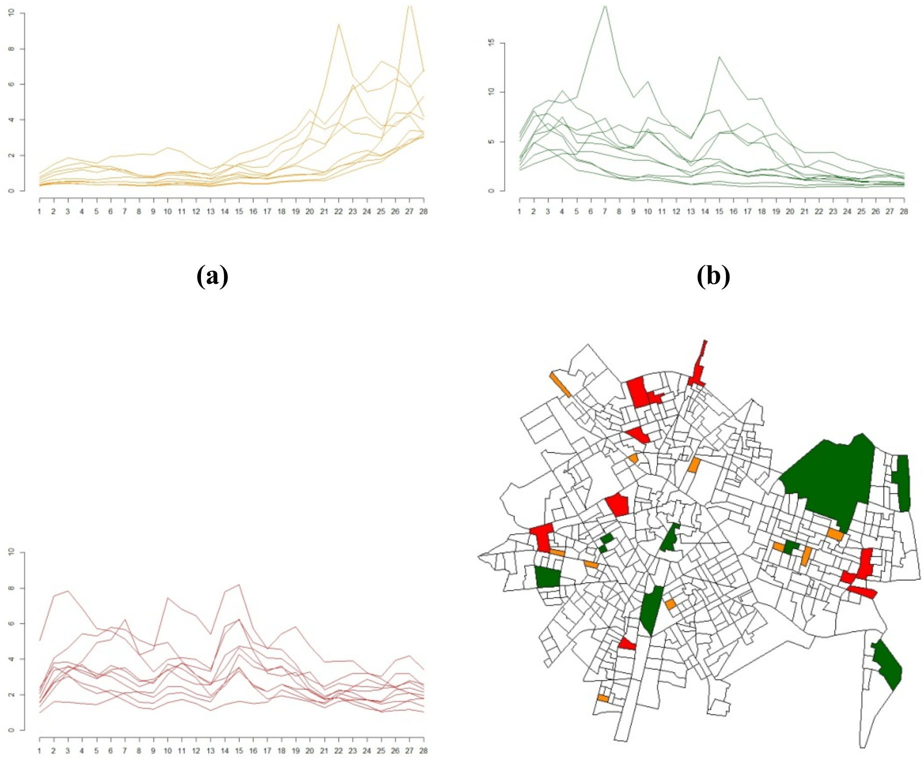
Finally, and in order to validate that the extra complexity added by including the interaction between space and time is really worthwhile, this autoregressive spatio-temporal model with quarterly data was compared with a simplified version of this model in which the correlation between periods, ρ, is zero. DICs [42] obtained in each case (25,752 in the latter and 24,577 in the former) show that the autoregressive part must be considered.

Discussion

This study has explored the importance of including possible trends in the context of suicide-related emergency calls. After describing in Section 2 an autoregressive approach to spatio-temporal disease mapping that links information in time and in space, this work has presented how different non-comparable models can show different features from the same dataset when time is considered.

Results have showed that suicide-related emergency calls are spatially patterned. This is in line with previous research that also suggested the unequal distribution of suicide across areas [4–13]. However, more interestingly, results also indicate that suicide-related emergency calls have a quarterly effect, with a peak of calls in the second (April to June) and in the third trimester (July to September), and a decrease in the other trimesters. These results are in line with previous research that has found higher suicide rates in spring and summer [14–18]. It is important to note that we split the annual data into four quarterlies for practical reasons. Due to the high number of geographical units with zero frequency, more partitions would have been inconvenient. Notwithstanding, studies with higher samples could benefit from conducting a monthly or even higher resolution analysis.

This study has both strengths and limitations. On the one hand and regarding the strengths, this study has provided relevant findings about the spatio-temporal distribution of suicide-related emergency calls in a South European city. To the best of our knowledge, there are no studies available in these countries in which suicide risk has been analyzed using a small-area approach. The Southern Europe cities may show different characteristics from Northern Europe, and focusing on these cities, one could provide new evidence about the suicide behavior at the community level. In addition, a complex modeling has been used in order to improve the model fit. Previous studies have shown that the autoregressive model used here provided better results than other spatio-temporal models [29]. This model, however, is still infrequent, and this study has also provided new evidence about its possible benefits when applied to a public and social health problem compared to other spatial and spatio-temporal modeling approaches. Other alternative models could also be appropriate—for example, negative binomial models. The zero-inflated models can also be used to treat with an excess of zeros, but not in this situation, as it can not be assumed that there are some census block groups where the population are not exposed to the suicide behavior.



(a) **(b)** **(c)** **(d)**

Figure 5. Changes in relative risks for three kind of census block groups in the city of Valencia. **(a):** Relative risks of census block groups with an increasing trend; **(b):** Relative risks of census block groups with a decreasing trend; **(c):** Relative risks of census block groups with permanent high risk; **(d):** Changes in relative risk: location of the selected census block groups in the city of Valencia (in orange those with an increasing trend, in green those with a decrease in the tendency, and in red those where the relative risk was always high).

On the other hand, this study also has some limitations. First, results show a general landscape about the spatio-temporal distribution of suicide-related emergency calls; nevertheless, a further analysis is needed to understand the underlying processes and the covariates that could explain these patterns. Previous studies have shown that age of suicide victim, as well as gender, could be important individual characteristics. Prevalence of suicide behavior among men has also been found to be higher than the prevalence among women. Moreover, the age cohort could also affect the risk of suicide [7]. These data, however, were not available for the study. Neighborhood-level characteristics could also be included in order to understand the ecological suicide risks. Some studies have supported the relationship between neighborhood variables and different social outcomes such as family violence or crime [43–48]. Likewise, previous research has suggested that areas with lower levels of socioeconomic status, higher rates of rurality, and highly fragmented areas would show higher risks of suicide behavior in their population [9,13,25,35,49–51]. Future studies would benefit from analyzing these neighborhood-level covariates and their influence in the spatial variations of suicide risks. In addition, despite the benefits of autoregressive modeling, it is important to take into account the computational complexity of this kind of models, which causes a high computation time [29]. We are now exploring new possibilities and developing tools to decrease the computation time without losing complexity.

Conclusions

This study has shown the presence of small-area variations in suicide-related emergency calls and the need of including temporal terms in the analysis. A 7-year study divided into 28 trimesters has provided the insights of clear differences in the spatio-temporal effects, and also that there is a seasonal pattern. It should be noticed that the growing amount of yearly (quarterly, weekly, daily and even hourly) data available is moving researchers to use spatio-temporal models that could bring more insights about the temporal behavior and not only about the aggregated (in terms of time) spatial data. Models that incorporate these temporal components (like the one used here) are needed and should be used by researchers.

To conclude, our results may contribute to implementing strategies to prevent suicide in the community, as well as possibly being a useful tool in the suicide-related police interventions. Despite the social and economic costs of suicide in our societies, and the clear need of developing preventive actions, there is still a lack of prevention strategies and plans that could adequately face this social problem. The hotspot areas found in this study could guide police action to effectively manage its resources and develop preventive strategies to these neighborhoods with higher risks of suicide. Moreover, analyzing those neighborhoods where the risk has increased or decreased in the last years and exploring the covariates that could be explaining these changes over time could provide helpful information about suicide behavior risks in order to assess the impact of preventive policies.

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Study 6

What calls for service tell us about suicide: A 7-year spatio-temporal analysis of neighborhood correlates of suicide-related calls

What calls for service tell us about suicide: A 7-year spatio-temporal analysis of neighborhood correlates of suicide-related calls[6]

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Abstract

Previous research has shown that neighborhood-level variables such as social deprivation, social fragmentation or rurality are related to suicide risk, but most of these studies have been conducted in the U.S. or northern European countries. The aim of this study was to analyze the spatio-temporal distribution of suicide in a southern European city (Valencia, Spain), and determine whether this distribution was related to a set of neighborhood-level characteristics. We used suicide-related calls for service as an indicator of suicide cases (n=6,537), and analyzed the relationship of the outcome variable with several neighborhood-level variables: economic status, education level, population density, residential instability, one-person households, immigrant concentration, and population aging. A Bayesian autoregressive model was used to study the spatio-temporal distribution at the census block group level for a 7-year period (2010–2016). Results showed that neighborhoods with lower levels of education and population density, and higher levels of residential instability, one-person households, and an aging population had higher levels of suicide-related calls for service. Immigrant concentration and economic status did not make a relevant contribution to the model. These results could help to develop better-targeted community-level suicide prevention strategies.

[6] Marco, M., Gracia, E., López-Quílez, A., & Lila, M. (2018). What calls for service tell us about suicide: A 7-year spatio-temporal analysis of neighborhood correlates of suicide-related calls. *Scientific Reports, 8.* doi: 10.1038/s41598-018-25268-0

Introduction

Suicide is a major social and public health problem worldwide[1]. In 2012, there were over 800,000 suicide deaths around the world[2]. Europe is the WHO region with the highest rates of suicide worldwide, with 14.1 per 100,000 inhabitants, followed by the European Union, where the rates are around 11 per 100,000[3]. In Spain, where this study was conducted, and according to 2015 data, suicide was the first leading external cause of death, 1.9 times more than road traffic injuries, and 12.6 times more than homicides[4]. In the same year, 3,602 people died by suicide, which represents almost 10 suicides a day[5]. The problem is even greater if we take into account parasuicide (i.e., suicide attempts), which cannot be easily measured. Despite the social and economic costs of suicide in our societies, there is still a lack of prevention strategies that can adequately deal with this phenomenon[6, 7]. Focusing on the range of variables that could explain suicidal behavior from different levels of analysis may help to design better-informed preventive actions.

Recently, a growing number of studies have suggested that neighborhood-level variables have an impact on suicide risk beyond individual-level factors[8-11]. Starting from the research of Congdon[12], these studies point to the link between suicide risk and three sets of factors: social deprivation, social fragmentation, and rurality[8, 9, 13, 14]. Neighborhood social deprivation, measured by different indicators such as poverty rate, unemployment, occupational social class, and education level, has been positively linked with suicide in a number of studies[9, 14-16]. Neighborhood social fragmentation also has shown a positive relationship with suicide risk[9, 14]. Indicators such as high levels of residential instability, high percentage of one-person households, and high divorce rates have been related to higher risks of suicide behavior, even after controlling for social deprivation[10, 17]. Another stream of research studies has compared rural and urban areas in suicide risk, suggesting that the risk of suicide is higher in rural areas[18, 19]. Research using population density as a proxy of rurality has also shown that areas with higher population density have lower risks of suicide[9, 20].

In addition to these variables, other neighborhood-level indicators have also been explored as predictors of suicide risk. For example, some research has focused on the relationship between ethnic density and suicide rates[18, 21, 22]. This relationship, however, is still inconclusive. Although some studies have found higher suicide rates in areas with high density of ethnic minorities[21-23], other found no such significant relationship[18].

Finally, although age has been positively linked to suicide risk at the individual level—i.e., higher suicide rates among older people[6, 8, 24]—the influence of this variable at the neighborhood-level has received less research attention. Some research suggests, however, that neighborhoods with higher levels of population aging (i.e., the ratio of elderly to young populations), tend to show higher suicide rates[15].

Present study

The aim of this study was to analyze the spatio-temporal distribution of suicide-related calls for service in a southern European city (Valencia, Spain), and whether this distribution was related to a set of neighborhood-level characteristics: economic status, education level, residential instability, one-person households, population density, immigrant concentration, and population aging. We used suicide-related calls for service as an indicator of suicidal behavior. This measure captures all calls for service received by the police related to suicide and parasuicide interventions, and has previously been considered as an indicator of suicidal behavior[25].

A Bayesian spatio-temporal approach was used to deal with the methodological biases usually present in ecological studies such as overdispersion or spatial autocorrelation[26, 27]. This methodological approach is common in public health analysis[26-28] and is increasingly being used in the geographical study of suicide[14, 15, 29-36].

Previous research has shown that high-resolution studies taking a small-area approach are more appropriate than other levels of aggregation with lower resolution (such as districts, counties or cities) for assessing spatial variations and neighborhood influences on suicide risk[14, 37]. Similarly, they have shown the importance of taking into account a temporal approach when analyzing social problems in the neighborhood. More specifically, studies on suicide have shown the relevance of a temporal perspective, which could improve our knowledge of this outcome[37]. A previous study analyzed the baseline distribution of suicide-related calls comparing different spatial and spatio-temporal models and it showed that using a spatio-temporal approach improved the results obtained with a purely spatial model[37]. Research has also shown that yearly studies could mask the effect of seasonality found in suicide events[1, 37, 38], and therefore using shorter temporal periods, such as seasons, is more appropriate[37]. Thus, we chose a spatio-temporal approach for this study.

This study therefore analyzes the influence of a set of neighborhood-level characteristics on the spatio-temporal distribution of suicide calls for service using census block groups (the smallest area available), and trimesters as the temporal unit in a Southern European city. To the best of our knowledge, this is the first study that has used a Bayesian spatio-temporal modeling approach to analyze neighborhood influences on the spatio-temporal distribution of suicide-related calls in a Southern European city.

Methods

Study area and time

Valencia is the third largest city in Spain, with a population of 790,201 inhabitants (2016 data) [39]. The census block group—the smallest administrative unit available—was used as the proxy for the neighborhood. The city of Valencia has 552 census block groups (population range 630–2,845).

The number of suicide-related calls for service was used as the outcome variable. Valencia Police Department provided data of all suicide-related calls requiring police intervention in the city of Valencia from 2010 to 2016. There were 6,537 calls in this period, of which 142 were related to suicide deaths, and 6,395 to suicide attempts. The address where the incident leading to a police intervention occurred was geocoded and located on the map of Valencia. Each year count was divided in 3-month periods to assess seasonality (period 1 = January to March, period 2 = April to June, period 3 = July to September, and period 4 = October to December). Thus, the outcome variable was divided into 28 periods.

Covariates

Several indicators were collected for each census block group. In line with previous studies, indicators of social deprivation, social fragmentation and population density were assessed[9, 14], as well as the variables population aging and immigrant concentration. Data was collected from the official records of the statistics office of Valencia City Hall corresponding to the year 2013. These indicators did not present significant differences across the years of the study, so the central year was selected.

Social deprivation indicators. Two variables were used as social deprivation indicators: economic status and education level. For economic status an index was constructed through an unrotated factor analysis using several highly correlated economic indicators, including cadastral value, percentage of high-end cars, percentage of financial businesses (number of businesses related to finances and insurances activities by the total of businesses), and percentage of commercial businesses (number of businesses related to commercial activities by the total of businesses). For the second variable, the average education level of neighborhood residents was measured on a 4-point scale, where 1 = less than primary education, 2 = primary education, 3 = secondary education, and 4 = college education.

Social fragmentation. We used two indicators to measure social fragmentation: residential instability and one-person households. The residential instability variable was calculated as the proportion of the population that had moved into or out of each census block group during the previous year (rate per 1,000 inhabitants). One-person households were measured as the number of households with only one person per total number of households.

Population density. Population density per square kilometer was used as a proxy of rurality.

Population aging index. An index of the population aging (i.e., the ratio of elderly to youth populations) was measured as the number of people aged 65 years or over per hundred people under the age of 15 years old.

Immigrant concentration: This was measured as the percentage of immigrant population in each census block group.

Seasonality: To explore the effect of seasonality, a dummy variable was introduced creating three binary variables that account for the first three trimesters; the fourth trimester was selected as the reference.

Table 1 shows the descriptive statistics for all the variables.

Table 1. Variables (Mean, Standard Deviation, Minimum and Maximum Values) at the Census Block Group and Year Level (2013 data).

Variable	**Mean (SD)**	**Min**	**Max**
Deprivation			
Economic status			
Property values (€)	260.10 (74.61)	111.50	590.70
High-end cars (%)	5.75 (3.62)	1.30	24.80
Commercial businesses (%)	34.03 (9.21)	7.50	66.40
Financial businesses (%)	18.15 (7.77)	0	43.20
Education level	3.15 (.33)	2.39	3.86
Population Density	3,346 (1,736.94)	107	13,112
Fragmentation			
Residential instability	268.00 (87.98)	91.10	649.80
One-person households	32.72 (6.58)	15.46	54.78
Aging index	151.2 (60)	16.20	501.10
Immigrant concentration (%)	13.28 (6.53)	1.90	40.20
Suicide-related calls	.26 (.57)	0	7

Abbreviations: SD, standard deviation; Min, minimum; Max, maximum

Data analysis

A conditionally independent Poisson distribution was used to model the number of suicide-related calls for service. Specifically, the outcome in each census block group and each period was expressed as follows:

$$O_{it} \sim Po(E_{it} \exp(\eta_{it})), \qquad i = 1, \dots, 552, \qquad t = 1, \dots, 28 \qquad (1)$$

where E_{it} is a fixed quantity representing the expected number of calls in census block group i during period t in proportion to the population in Valencia in this census block group. η_{it} is the log relative risk for every area and period.

Two different models were used. Both models included a spatio-temporal effect via the η_{it}. We followed an autoregressive approach, which combines autoregressive time series and spatial modeling using a spatio-temporal structure where relative risks are both spatially and temporally dependent[40]. The log relative risk for the first period was defined as:

$$\eta_{i1} = \mu + \alpha_1 + (1 - \rho^2)^{-1/2} \cdot (\phi_{i1} + \theta_{i1}) \qquad (2)$$

while the relative risks for the following periods were defined as:

$$\eta_{it} = \mu + \alpha_t + \beta_{q(t)} + \rho\big(\eta_{i(t-1)} - \mu - \alpha_{t-1}\big) + \phi_{it} + \theta_{it}) \qquad (3)$$

where μ is the intercept, α is the mean deviation of the risk in the period t, ρ represents the temporal correlation between the spatial effects of each period, and ϕ_{it} and θ_{it} refer to structured and unstructured spatial random effects, respectively.

We incorporated a $\beta_{q(t)}$, which represents the mean deviation of the risk in trimester $q(t)$. The fourth trimester was selected as the reference, and the other three trimesters were compared to it.

The first model only accounted for this spatial-temporal effect and included seasonality as a covariate, while the second model incorporated different covariates to analyze the influence of neighborhood-level characteristics in the outcome. Seven covariates were introduced to this second model: economic status, education level, residential instability, one-person households, population density, population aging index, and immigrant concentration. The final model was as follows:

$$\eta_{it} = \mu + \alpha_t + X_i\beta + \rho\big(\eta_{i(t-1)} - \mu - \alpha_{t-1}\big) + \phi_{it} + \theta_{it}) \qquad (4)$$

where X_i is the vector of covariates, and β is the vector of regression coefficients.

A Bayesian approach was followed for both models. Accordingly, appropriate prior distributions were assigned for the parameters, namely, vague Gaussian distributions for the fixed effects β; μ was specified as an improper uniform distribution; the autoregressive term ρ was modeled as a uniform over the whole space

$U(-1,1)$; and the structured effect was specified by a conditional spatial autoregressive (CAR) model[41]:

$$\phi_i|\phi_{-i} \sim N(\frac{1}{n_i}\sum_{j\sim i}\phi_j, \frac{\sigma_\phi^2}{n_i}) \quad (5)$$

where n_i represents the number of neighboring areas of each census block group i, ϕ_{-i} indicates the values of the ϕ vector except the component i, σ_ϕ is the standard deviation parameter, and $j\sim i$ is the units j neighbors of census block group i. The unstructured spatial effect θ was modeled by means of independent identically distributed Gaussian random variables $N(0, {\sigma_\theta}^2)$. Finally, uniform distributions were used for the three hyperparameters $\sigma_\alpha, \sigma_\phi, \sigma_\theta \sim U(0,1)$, following the structure of the hierarchical Bayesian models.

In order to test the robustness, a sensitivity analysis was conducted using different prior distributions for the hyperparameters. The posterior distributions showed consistent results (see Supplementary Material 1).

To implement the models, simulation techniques based on Markov Chain Monte Carlo (MCMC) were used with the software R and the R2WinBUGS package. Three chains with 50,000 iterations were generated, and the first 10,000 were discarded as burn-in. The deviance information criterion (DIC) was used to compare models and select the best fit: the smaller the DIC, the better the fit[42].

Results

The results of the two Bayesian autoregressive models are presented in Table 2.

Model 1 represents the autoregressive model without covariates, while Model 2 incorporates the effect of the covariates of the study. Note that Model 2 showed a relevant decrease in the DIC (30.3 units of decrease), and was therefore selected as the final model.

In this final model, indicators of social deprivation (education level), social fragmentation (residential instability and one-person households), and population density were associated with higher levels of suicide-related calls for service. Population aging was also relevant to the model. All these variables showed a posterior probability of being over or under zero higher than 95% (i.e., their 95% credible intervals did not include zero). Economic status and immigrant concentration, however, did not show a relevant relationship with the outcome, including zero in the 95% credible interval. These results indicate that areas with lower education level, lower levels of population density, higher residential instability and concentration of one-person households, and higher population aging have higher levels of suicide-related calls for service.

Table 2. Mean, standard deviation and 95% credible interval of the parameters of the autoregressive models

	Model 1 (Autoregressive model without covariates)				Model 2 (Autoregressive model with covariates)			
	Mean	**SD**	**95% CrI**		**Mean**	**SD**	**95% CrI**	
Intercept	-.362	.045	-.450	-.275	-0.136	.528	-1.265	.767
Economic status					-.029	.057	-.141	.082
Education level					-.269	.160	-.645	-.021
Density					-.015	.018	-.018	-.012
Residential instability					.001	.001	.000	.002
One-person households					.002	.000	.002	.003
Aging					.002	.000	.001	.002
Immigrant concentration					-.007	.008	-.024	.009
Trimester 1	-.122	.057	-.230	-.008	-.119	.053	-.220	-.014
Trimester 2	.093	.059	-.024	.208	.093	.058	-.019	.206
Trimester 3	.118	.053	.016	.227	.119	.054	.011	.222
σ_θ	.359	.019	.323	.398	.377	.021	.337	.416
σ_ϕ	.160	.030	.102	.220	.144	.080	.011	.256
$\sigma_\propto$	.106	.032	.051	.178	.106	.030	.055	.166
ρ	.903	.009	.885	.919	.881	.011	.859	.900
DIC	24,577				24,546.7			

Abbreviations: SD, standard deviation; CrI, credible interval; σ_θ, standard deviation spatially unstructured term; $\sigma_\phi$standard deviation structured term; $\sigma_\propto$, standard mean deviation of the risk; ρ temporal correlation

The seasonality effect was also relevant. Specifically, results show that the estimated number of suicide-related calls increases in the second and the third trimesters (i.e., from April and September), with a higher increase in the third trimester. In contrast, in the first trimester the estimated number of suicide-related calls is lower. The first and third trimesters had a 95% credible interval where zero was not included. For the second trimester, although its 95% credible interval includes zero, the posterior probability of being positive was .948, so we considered its effect relevant.

The Bayesian autoregressive model used allows us to analyze both spatial and temporal trends. Figure 1 shows the relative risk for a sample of the periods: the four trimesters of 2010, 2013 and 2016 (see Supplementary Material 2 for all maps). This figure reflects the differences between census block groups in each year, where areas with relative risks greater than 1 indicate an above-average probability. The general pattern shows that the highest risks are concentrated in some areas of the center, the north-west and the east of the city. These risks are higher in the second and the third trimester than in the first and the fourth.

Regarding the temporal pattern, the parameter ρ had a value of .88, indicating a high temporal correlation between a particular trimester and its predecessor. Figure 2 shows the temporal effect for each trimester. Despite the increasing trend over the years (there is no evidence of stabilization), this increase was not constant, but we found some clear peaks within the year as a result of the seasonality effect. Therefore, it is important to take into account seasonality to better capture the temporal trend of suicide-related calls for service.

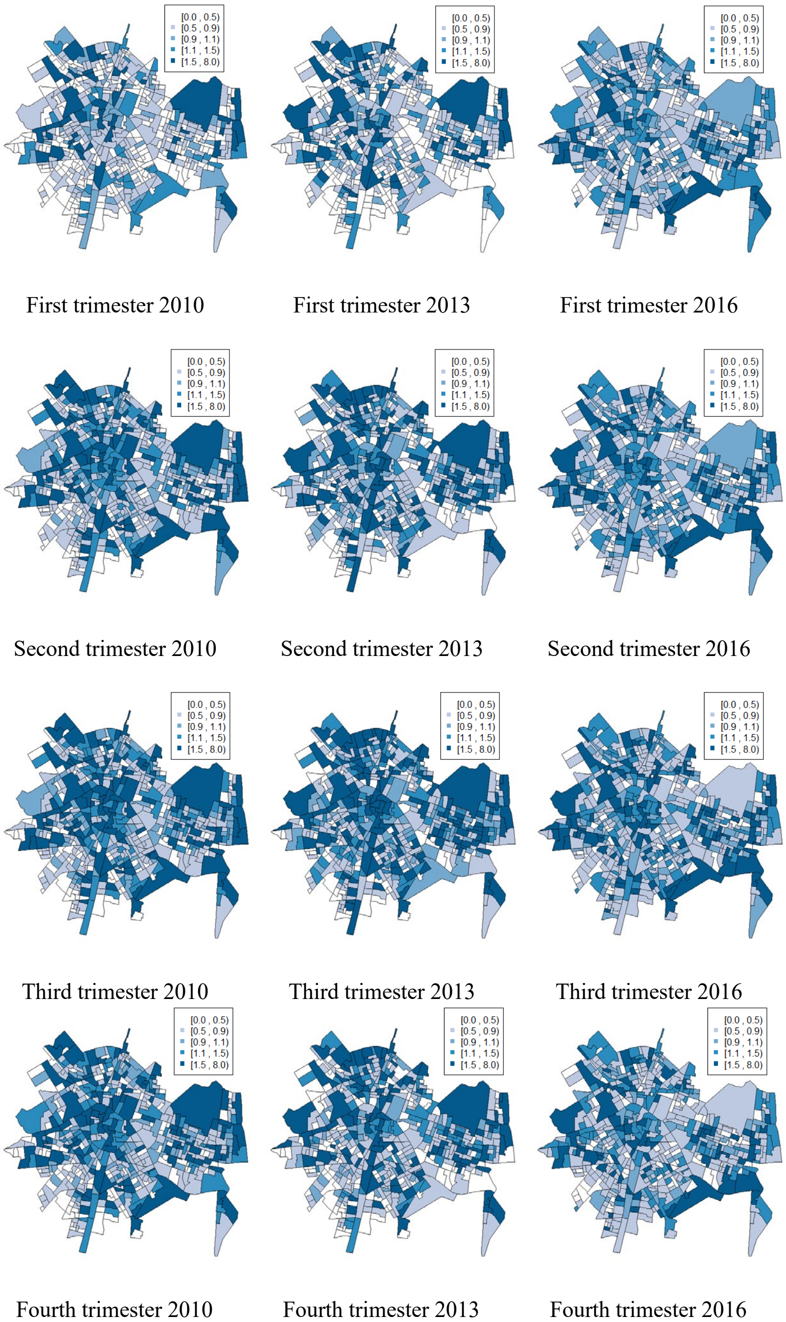

Figure 1. Relative risk for the four trimesters of 2010, 2013 and 2016 (maps created with the software R version 3.4.2., available in https://www.r-project.org/)

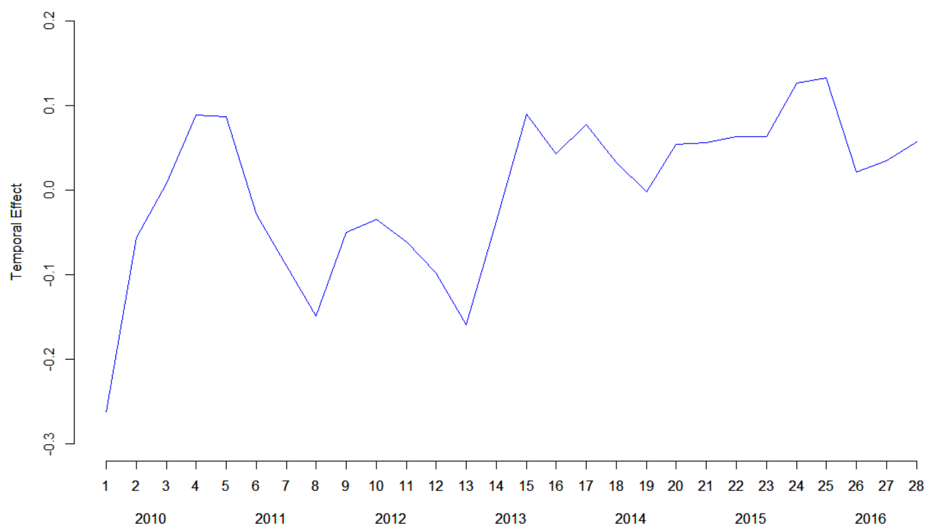

Figure 2. Temporal effect during the period (2010-2016)

Discussion

This study explored the influence of neighborhood-level characteristics on the spatio-temporal distribution of suicide-related calls for service in Valencia, Spain. An autoregressive model following a Bayesian approach was conducted to assess both spatial and temporal effects. Although previous studies have shown the relationship between ecological variables and the risk of suicide[11, 14, 30, 33], to the best of our knowledge there are no studies assessing the geography of suicide in South European countries using a small area approach[43].

Our results showed that neighborhoods with lower levels of education and population density, and higher levels of residential instability, higher concentration of one-person households, and higher population aging had higher levels of suicide-related calls for service. These results are in line with previous research suggesting that social deprivation, social fragmentation, and low population density are closely related to suicide risk at the community level[8-11, 13, 15, 44].

Economic status and immigrant population did not make a relevant contribution to the model. Previous studies have found a negative relationship between economic status and suicide-related outcomes[9, 10, 14, 30]. The use of different measures of economic status may explain these differences, as these studies usually included variables such as income and unemployment, which were not available for the present study. In our case, education level was the deprivation variable with the greatest contribution to the model.

Regarding the results for immigrant concentration, it is important to take into account differences Spain has from other countries. Previous studies were mostly conducted in English-speaking and northern European countries, and usually focused on ethnic differences or indigenous people, where they found a positive association between suicide rates and percentage of ethnic minorities[9, 21, 23, 45]. However, some cultural factors may influence the relationship between immigration and suicide rates. In Valencia, the largest immigrant group is from Latin American countries (34%). A shared dominant language in Spain and Latin America could facilitate social integration in the community more than in English speaking countries, and may be a protective factor against suicidal behavior. Future research would benefit from cross-cultural studies to analyze the differences among countries in the relationship between suicide and immigration rates.

Furthermore, we found a seasonality effect, with a peak of calls in the second (April to June) and third (July to September) trimesters, and a decrease in the other two. These results are similar to previous research suggesting that suicide rates increase in spring and summer[24, 38, 46, 47]. These results indicate the importance of taking seasonality into account when conducting a temporal analysis of suicide trends. Our results also showed an important increase in the number of suicide-related calls for service from 2010. The results suggest that suicide-related calls for service increased over the study period (2010 – 2016), and that there was no stabilization by the end of 2016. Future studies would benefit from incorporating long-term data, including the following years, to further analyze the evolution of suicide trends.

This study has both strengths and limitations. Its strengths include its location in in a southern European city, as noted above, where there is a lack of studies on suicide at the neighborhood level[37]. Our results suggest that, despite the differences between countries, some neighborhood-level characteristics associated with suicide in the U.S. and northern European cities can also explain suicide variations in a southern European city. This paper, thus, provides new evidence about the spatio-temporal distribution of suicide calls in southern European cities and the neighborhood-level characteristics that may be related to this distribution. However, it is important to be cautious as this study was conducted in one specific city. Future research would benefit from conducting studies with a similar approach in other South-Europe cities.

This study used census block groups, which is more appropriate for addressing bias associated to aggregate data[48]. Moreover, we used an autoregressive model following a Bayesian approach. The Bayesian autoregressive model has been found to perform better than other spatio-temporal models, and some studies have showed that it provides a slightly better fit in terms of DIC[49]. The Bayesian approach also has some advantages over the frequentist perspective. Bayesian models let researchers incorporate prior information, and also address issues such as overdispersion and spatial autocorrelation[26, 27, 31]. The Bayesian approach is increasingly being used to analyze social outcomes such as crime or violence[48, 50-57], and also to study suicide[31, 32, 37].

Among the limitations, as we noted before, some commonly used variables such as income levels or unemployment were not available at the census block group level. Individual characteristics (such as the person's gender or age) were also unavailable. Future research would benefit from analyzing the possible different spatial patterns according to the sex or the age of the person making the suicide-related call for service in Valencia. Furthermore, this study is based on calls for service, and other commonly used measures of suicidal behavior (such as hospitalizations or medical records) were not analyzed. In addition, although our results suggest an increase in suicide-related calls for service, the study period was limited and does not allow us to draw strong conclusions. Clearly, future studies need to incorporate longer periods of time in order to further analyze the temporal trend of suicide-related calls for service. Finally, despite the autoregressive model having a better performance than other models, it requires a high computation time due to the complexity of the model and the considerable time periods covered by this study[37, 49].

In conclusion, this study illustrates the relevance of a number of ecological variables in explaining suicide-related calls for service. Addressing these neighborhood risk factors and focusing on the high-risk areas with a higher increase in suicide-related calls for service could help to develop better targeted community-level suicide prevention strategies.

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Study 7

The university campus environment as a protective factor for intimate partner violence against women

The university campus environment as a protective factor for intimate partner violence against women: An exploratory study[7]

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Abstract

Some neighborhood characteristics linked to social disorganization theory have been related to intimate partner violence against women (IPVAW). The study of other neighborhood-level factors that may influence IPVAW risk, however, has received less attention. The aim of this paper is to analyze the influence of university campuses on IPVAW risk. To conduct the study, IPVAW cases from 2011 to 2013 in the city of Valencia, Spain, were geocoded (n = 1,623). Census block groups were used as the neighborhood analysis unit. Distance between each census block group and the nearest university campus was measured. A Bayesian spatial model adjusted for census block group-level characteristics was performed. Results showed that the distance from a university campus was associated with an approximate 7% increase in IPVAW risk per kilometer. These results suggest that university campuses integrated in the city are related to IPVAW risk. Further research is needed to explain the mechanisms involved.

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Introduction

Intimate partner violence against women (IPVAW) is a major public health and social problem (WHO, 2013). Estimated global prevalence suggests that 30% of women have experienced at least one episode of physical or sexual violence by a partner in their lifetime (WHO, 2013). In Europe, 22% of women over 15 years old reported having been victims of physical or sexual violence by a partner or ex-partner in their lifetime (European Union Agency for Fundamental Rights, 2014). In Spain, where this study was conducted, data from a 2015 survey revealed that 12.5% of women over 16 have experienced violence by a current or a former partner in their lifetime (Government Office against Gender-based Violence, 2015).

IPVAW has been conceptualized as a type of violence “behind closed doors” (Strauss, Gelles, & Steinmetz, 1980; Wright & Benson, 2011). However, a growing number of studies suggest that place also matters in IPVAW. These studies have illustrated that violence “behind closed doors”, as with other types of crime, is not only related to individual characteristics and relational processes, but it is also associated with neighborhood-level characteristics (Burke, O’Campo, & Peak, 2006; Caetano, Ramisetty-Mikler, & Harris, 2010; Cunradi, Mair, Ponicki, & Remer, 2011; Frye & O’Campo, 2011; Freisthler, 2004; Freisthler, Kepple, & Holmes, 2012; Gracia, López-Quílez, Marco, Lladosa, & Lila, 2014; 2015; Gracia, López-Quílez, Marco, & Lila, 2017; Kirst, Lazgare, Zhang, & O’Campo, 2015; Li, Kirby, Sigler, Hwang, LaGory, & Goldenberg, 2010; Wright & Benson, 2011).

Specifically for IPVAW, some variables linked to social disorganization theory have been widely studied: neighborhoods with higher levels of concentrated disadvantage, characterized by poverty, unemployment, low education and income levels in households, and physical and social disorder, are associated with higher risk of IPVAW (Beyer, Wallis, & Hamberger, 2015; Cunradi, Caetano, Clark, & Schafer, 2000; Gracia et al., 2014; 2015; O’Campo, Burke, Peak, McDonnell, & Gielen, 2005; Pinchevsky & Wright, 2012). Demographic factors such as residential instability, ethnic heterogeneity, or single women with children have also been analyzed, with mixed results (Benson, Fox, DeMaris, & Van Wyk, 2003; Browning, 2002; Gracia et al., 2014; 2015; Waller et al., 2011). In addition, some research has also studied the influence of neighborhood processes such as collective efficacy on IPVAW (Browning, 2002; Jackson, 2016; Showalter, Maguire-Jack, & Barnhart, 2017; Wright & Benson, 2011). Although available research suggest a link between collective efficacy and IPVAW rates, some questions regarding this link remain open, and clearly more research is needed (Block & Skogan, 2001; Frye et al., 2012; Pinchevsky & Wright, 2012). While collective efficacy is one of the intervening variable most analyzed, other neighborhood-level variables such as social norms, often unmeasured in this type of research, have received little research attention. From this perspective, neighborhood social norms regarding what is or is not acceptable regarding the use of violence in intimate relationships can be an important variable to better understand the unequal distribution of IPVAW risk.

At the individual level, the acceptability of IPVAW has been linked to the perpetration of this type of violence (e.g., Archer & Graham-Kevan, 2003; Capaldi, Knoble, Shortt, & Kim, 2012; Gracia, Rodríguez, & Lila, 2015; Martín-Fernández et al., 2018; Stith, Smith, Penn, Ward, & Tritt, 2004). At the aggregated level, these attitudes can shape a social climate of acceptability of IPVAW that can foster and legitimize this violence. In this regard, there is growing evidence that social norms condoning IPVAW are important predictors of increased risk of IPVAW at the neighborhood, community and country level (see Heise, 2011; Heise & Fulu, 2014 for reviews). For example, in an analysis of 66 surveys from 44 countries, Heise and Kotsadam (2015) found that norms justifying wife beating were especially predictive of the geographical distribution of IPVAW. These add to a growing body of research suggesting that neighborhood social norms regarding violence in intimate relationships are associated with the unequal distribution of IPVAW risk across neighborhoods (e.g., Frye, 2007; Frye & O'Campo, 2011; McDonnell, Burke, Gielen, O'Campo, & Weidl, 2011; Wright & Benson, 2011; see also Beyer et al, 2015; Pinchevsky & Wright, 2012; Voith, 2017, for reviews).

Following Sampson and Lauritsen (1994) argument, some neighborhoods may shape a particular "cognitive landscape" regarding violence against women (i.e., normative ecologies or cultural structured norms about appropriate standards of conduct, including attitudes toward violence). This cognitive landscape could be characterized by social norms based on respect, equality, and intolerance to violence that may inhibit IPVAW in the community or, on the contrary, by social norms based on tolerance towards violence as an acceptable way to solve problems (Bursik, 1999; Fox & Benson, 2006; Gracia & Herrero, 2007; Sampson & Wilson, 1995). Neighborhoods were the rejection of violence in intimate relationships is a shared value, may act as deterrent factor for IPVAW as it increases the social costs for perpetrators (Bursik, 1999; Gracia & Tomás, 2014). Community disapproval of IPVAW, thus, may inhibit acts of violence because of the fear of informal public sanctions such as the loss of respect (Emery, Jolley, & Wu, 2011; Fox & Benson, 2006; Gracia, 2014; Wright & Benson, 2011), and the concern that neighbors will call the police (Emery et al., 2011). These neighborhoods would play, therefore, a protective role, and rates of IPVAW would be expected to be lower as compared to other neighborhoods with social norms more tolerant regarding violence in intimate relationships.

Assessing attitudes and social norms regarding IPVAW at the neighborhood-level is clearly a difficult task. However, an indirect approach is to identify community environments that given its location, expected composition, and activities, a lower acceptance and tolerance of IPVAW could be expected. One of such environments are neighborhoods near to university campuses were young, highly educated residents, especially students and people related to the academic community, typify the composition of these neighborhoods (Brockliss, 2000; Bruning, McGrew, & Cooper, 2006; Russo, & Tatjer, 2007). The social norms these residents share are likely to be less tolerant of violence against women, and more sensitive to gender equality. Thus, neighbors living close to university campuses may share social norms based on the notion of violence as an inappropriate way to resolve social and relationship conflicts, which may lead to a social control that would reduce the risk of IPVAW. In addition, these neighborhoods usually attract businesses, resulting in high levels of activity in the community that could create a sense of safety among residents (Abbot, 2010; Cortes, 2004). The close vicinity of a university campus, with the above-mentioned characteristics, may create a deterrent effect and be a protective factor for IPVAW.

In this regard, some research has suggested that the presence of university campuses in the city may influence neighborhood social norms that, in turn, affect the risk of IPVAW. In their study on neighborhood influences on the spatial epidemiology of IPVAW in a Spanish city, Gracia et al. (2015) found an unexplained spatial effect on the relative risk variations of IPVAW in different parts of the city (i.e., unobserved spatially structured influences that revealed remaining variability not explained be the covariates used in the study). As a lower risk (around 10%) was observed in the north part of the city, where the university campuses are concentrated, these authors hypothesized that the population linked to the universities living in that part of the city may have different social norms regarding IPVAW, and therefore may have an influence on the risk variations observed. However, this hypothesis could not be tested empirically.

Following this idea, in this study we aim to conduct an exploratory study to analyze whether the presence of a university campus would be a protective factor for IPVAW in nearby neighborhoods, that is, whether the risk of IPVAW is lower in neighborhoods near university campuses. We conduct this study in the context of a European University City, which is relevant to study this type of influences. Although in some cities university campuses are located on the outskirts (mainly in North-American universities), others, particularly in Europe, are established in the city, and are fully integrated into the urban context. To the best of our knowledge, there are no spatial studies that analyze the proximity of university campuses as a factor related to IPVAW risk in the community. In addition, most of the studies that link place and IPVAW have not been conducted following a spatial epidemiologic approach and using appropriate spatial statistical techniques (see Cunradi et al., 2011; Gracia et al., 2014, 2015, for exceptions). In this study, we used Bayesian spatial analysis, which allows us to assess the underlying spatial distribution of risk and to propose and test new predictor variables that could explain this distribution (Bernardinelli, Clayton, Pascutto, Montomoli, Ghislandi, & Songini, 1995; Gracia et al., 2015; Law & Chan, 2012; Lawson, 2009). In addition, Bayesian spatial modeling has the major advantage of addressing important issues in this type of research such as overdispersion and spatial autocorrelation (Gracia et al., 2015, 2017; Haining, Law, & Griffith, 2009; Lawson, 2009; Sparks, 2011). This study aims to add to previous research by exploring the influence of a new predictor variable explaining the link between neighborhoods and IPVAW.

Methods

Sample

The study was conducted in the city of Valencia (Spain). Valencia is located on the Mediterranean coast, and is Spain's third largest city with a population of 736,580 inhabitants (Statistics Office, 2014). We used census block groups as neighborhood proxies, which is the smallest administrative unit available and is especially appropriate to reduce ecological bias (Gracia et al., 2014; Sampson & Raudenbush, 2004). Valencia is divided in a total of 552 census block groups. The census block groups have an average number of residents of 1,334, ranging from 630 to 2,845. The mean area for the census block groups was 0.04 square kilometer.

Variables

*IPVAW protection orders***.** Cases of IPVAW in the city of Valencia were selected from protection order records filed between January 2011 and March 2013. Protection orders were provided by the Valencia Police Department; these orders represent severe cases of IPVAW and are issued by a court of law and enforced by the police (approximately 15% of all reported IPVAW cases). The address where the IPVAW incident leading to the protection order occurred was geocoded, and each address was situated on the map of Valencia to establish the count number of IPVAW cases in each of the 552 census block groups. A total of 1,623 protection orders were geocoded.

Neighborhood-level control variables. We used different variables based on social disorganization theory. These were provided by the city's Statistics Office for each census block group and included education level (calculated as the average level of education based on the percentage of the population in each education level category, where 1 = less than primary education, 2 = primary education, 3 = secondary education, 4 = college education. Individual data was no available for the study); economic status (measured as the factorial combination through an unrotated principal component analysis of 4 highly correlated economic indicators: cadastral property values, percentage of high-end cars, percentage of financial businesses, and percentage of commercial businesses); percentage of immigrants in the population, and percentage of vacant lots. Physical disorder was also assessed by trained raters using a 5-point Likert scale with 9 items including variables such as cigarette butts in the street, empty bottles in the street, graffiti, vacant houses, abandoned, vandalized and run-down buildings, and deteriorated recreation places. On this scale, 0 indicated *no presence of the item* and 4 indicated *high presence of the item*. Two trained raters walked each census block group during business hours and completed the observational scale. The scale showed good psychometric characteristics (CRI = .83; ICC = .63) (Marco, Gracia, Tomás, & López-Quílez, 2015). Lastly, policing activity was assessed as an indicator of public disorder and crime levels using an index completed by police officers based on their perceptions and experience (objective records were not available). This index was composed of 5 items on a 5-interval scale (where 0 = very low, and 4 = very high) including interventions such as drug-related crimes, public drunkenness and fights, vandalism, homeless people and truancy. Senior police officers with a thorough knowledge of the area were selected to score each item in each census block group (Marco, Gracia, & López-Quílez, 2017). Cronbach's alpha was .74. In addition, this measure showed adequate validity properties, as it was associated with neighborhood-level variables related to concentrated disadvantage and disorder (Marco, Gracia, & López-Quílez, 2017; Marco, Gracia, Martín-Fernández, & López-Quílez, 2017).

Distance from university campuses. The Euclidean distance from the university campuses was measured as the kilometers between the centroid of each census block group and the nearest university campus. The average distance to the three university campuses was previously assessed, with similar results. The city has three university campuses belonging to the two public universities located in the city. Lower values indicated closer proximity to university campuses, and higher values, greater distances.

Table 1 shows the descriptive statistics for the outcome and the covariates.

Data analysis

IPVAW protection orders referred to counts for the 552 census block groups. Therefore, a Poisson distribution was assumed to model the dependent variable:

$$y_i|\eta_i \sim Poisson(E_i\lambda_i), \quad i = 1, \ldots, 552$$

where E_i represents the expected number of cases of IPVAW in the i −census block group, and λ_i is the specific risk in area i.

Following this distribution, a Poisson hierarchical regression modeling was performed. The control variables included in the model were: education level, economic status, immigrant concentration, vacant lots, physical disorder, and policing activity. In addition, distance from the university campuses was included to assess the importance of this variable in the explanation of IPVAW. All variables were centered subtracting the mean for greater stability. The model was defined by the following form:

$$\log(\lambda_i) = \mu + X_i\beta + S_i + U_i$$

where μ is the intercept or total mean; vector β represents the regression coefficients that are multiplied by the matrix of covariates X; and S and U are the random effects terms (spatially structured term and unstructured term respectively) to account for non-observed variability (autocorrelation and overdispersion).

Table 1. Variables (Mean, Standard Deviation, Minimum and Maximum Values) at the Census Block Group Level.

Variable	Mean (SD)	Min	Max
Education level	3.15 (0.33)	2.39	3.86
Economic status	0.00 (0.96)	-1.60	4.60
Property value	260.10 (74.61)	111.50	590.70
High-end cars	5.75 (3.62)	1.30	24.80
Commercial activities	34.03 (9.21)	7.50	66.40
Financial activities	18.15 (7.77)	0	43.20
Immigrant concentration (%)	13.45 (6.53)	1.90	40.20
Vacant lots (%)	1.03 (3.11)	0	63.71
Physical disorder	9.00 (5.24)	0	28
Policing activity	7.16 (3.99)	0	19
Distance from university campus	2.31 (1.03)	0	4.79
IPVAW cases	2.94 (2.31)	0	14
IPVAW incidence rates (per 1000)	4.96 (3.84)	0	25.07

Abbreviations: SD, standard deviation; Min, minimum; Max, maximum, IPVAW, intimate partner violence against women

We used a Bayesian perspective to model the outcome; we therefore assigned different prior distributions and treated parameters as random variables. Specifically, we used vague Gaussian distributions for the fixed effects β and an improper uniform distribution for μ. The unstructured term U was specified as a normal distribution $N(0,\sigma_U^2)$, where $\sigma_U \sim U(0,1)$. The structured spatial term S was defined as a conditional spatial autoregressive model (Besag, York, & Mollié, 1991) reflecting spatial neighborhood relationships:

$$S_i|S_{-i} \sim N(\frac{1}{n_i}\sum_{j\sim i} S_j, \frac{\sigma_S^2}{n_i})$$

where n_i is the number of neighborhoods of the i -census block group, S_{-i} indicates the values of the S vector except the i-th component, $j\sim i$ expresses all units j that are neighbors of area i, and σ_S is the standard deviation parameter. We specified a uniform distribution $\sigma_S \sim U(0,1)$ for the prior distribution of the standard deviation σ_S.

Bayesian regression modeling was performed using R (R Core Team, 2015) and WinBUGS software (Lunn, Thomas, Best, & Spiegelhalter, 2000) through Markov Chain Monte Carlo (MCMC) simulations. We generated 100,000 iterations and discarded the first 10,000 as a burn-in period. Convergence was checked using the convergence diagnostic $\hat{R}$ (Gelman, Carlin, Stern, Dunson, Vehtari, & Rubin, 2013), and was near to 1.0 for all parameters. A sensitivity analysis on prior distributions of hyperparameters was performed, where different distributions were selected and results were compared. Specifically, different upper ends were used for Uniform distributions, and the precisions parameters were also assessed as Gamma distributions. The results remained stable, indicating that the results were robust.

In order to select the best model, the deviance information criterion (DIC, Spiegelhalter et al., 2002) was used; the model with the lowest DIC value showed the better fit and was chosen as the final model. In addition, following the Bayesian approach, the credible interval was interpreted in probability terms. By contrast with the frequentist perspective, the Bayesian approach to hypothesis testing is not based on a p-value criterion, but it is reasonable to consider that the variables are relevant when they reach a high probability of a positive or negative association (Carlin & Louis, 2008; Gelman et al., 2013). We considered that the variables with more-than-80% posterior probability of being different from zero were relevant (Gracia et al., 2015).

Results

Figure 1 shows the map of the study area and the spatial distribution of IPVAW rates per 1,000 women.

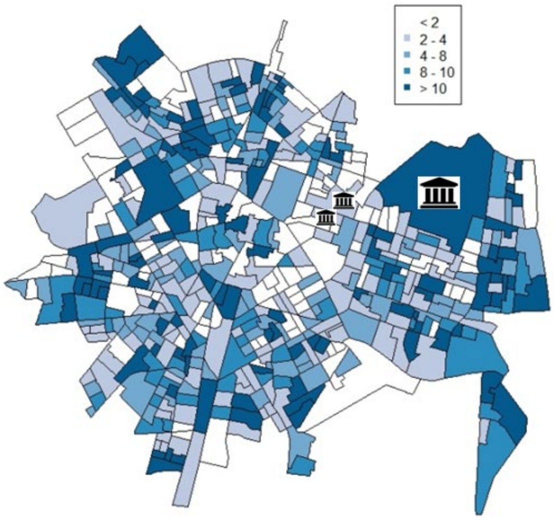

Figure 1. Spatial distribution of IPVAW rates per 1,000 women

Table 2 shows the results of the Bayesian models. Model 1 includes the control variables (education level, economic status, immigrant concentration, vacant lots, physical disorder, and policing activity), the unstructured heterogeneity and the spatial effect, and Model 2 also incorporates the effect of distance from university campuses.

Table 2. Results of Spatial Bayesian Poisson Regression Model for IPVAW Risk

	Model 1 Posterior mean; SD (95% CrI)	**Model 2 Posterior mean; SD (95% CrI)**	**Model 2 Relative Risk**
Intercept	-0.263; 0.084 (-1.840, -0.730)	-0.252; 0.080 (-0.410; -0.101)	
Education	-0.414; 0.173 (-0.756, -0.085)	-0.304; 0.181 (-0.662; 0.054)	0.74 (0.52, 1.06)
Economic status	-0.083; 0.069 (-0.220, 0.051)	-0.086; 0.067 (-0.220; 0.038)	0.92 (0.80, 1.04)
Immigrant concentration	0.033; 0.005 (0.023; 0.043)	0.036; 0.005 (0.026; 0.045)	1.04 (1.03, 1.05)
Vacant lots	0.010; 0.009 (-0.008, 0.026)	0.010; 0.008 (-0.016; 0.026)	1.01 (0.98, 1.03)
Physical disorder	0.007; 0.005 (-0.003; 0.016)	0.005; 0.005 (-0.004; 0.014)	1.01 (1.00, 1.02)
Policing activity	0.013; 0.08 (-0.003, 0.029)	0.013; 0.008 (-0.001; 0.028)	1.01 (1.00, 1.03)
Distance from university campuses		0.063; 0.039 (-0.016; 0.138)	1.07 (0.98, 1.15)
σ_s	0.149; 0.097 (0.008, 0.346)	0.121; 0.077 (0.009; 0.291)	
σ_u	0.232; 0.061 (0.091, 0.332)	0.237; 0.058 (0.117; 0.341)	
DIC	2,135.7	2,133.9	

Abbreviations: SD, standard deviation; CrI, credible interval; σ_s, standard deviation spatially structured term, $\sigma_{u,}$ standard deviation unstructured term, DIC, deviance information criterion

Model 1 had a DIC value of 2,135.7, while Model 2 showed a DIC value of 2,133.9. The complete model, therefore, showed a fair fit improvement. Results indicated, as expected, that lower levels of education and economic status, higher immigrant concentration, higher percentage of vacant lots, and higher levels of physical disorder and policing activity were related to higher IPVAW risks. All covariates showed a posterior probability greater than 80%. Moreover, once these covariates were controlled for, the influence of the distance from university campuses slightly improved the model fit. Specifically, the distance from university campuses was related to higher risk of IPVAW with a credible interval clearly shifted to the right (posterior probability = 94%). The mean of the parameter was 0.063, which corresponded to a relative risk of 1.07. These data suggest that each additional kilometer of distance from the nearest university campus is associated with an approximate 7% increase in IPVAW cases. For example, a distance of 4.79 kilometers from the nearest university campus (the longest distance in the city) would increase IPVAW by approximately 33.5%.

Although the DIC value did not present a large difference (1.8 units), taking into account also the other criteria (the high posterior probability of the distance from university campuses, the high relative risk associated to this variable, as well as the convergence diagnostics which were very good), we selected the model 2 as the more accurate one. Figure 2 shows the posterior distributions of fixed effects for the final Bayesian regression model.

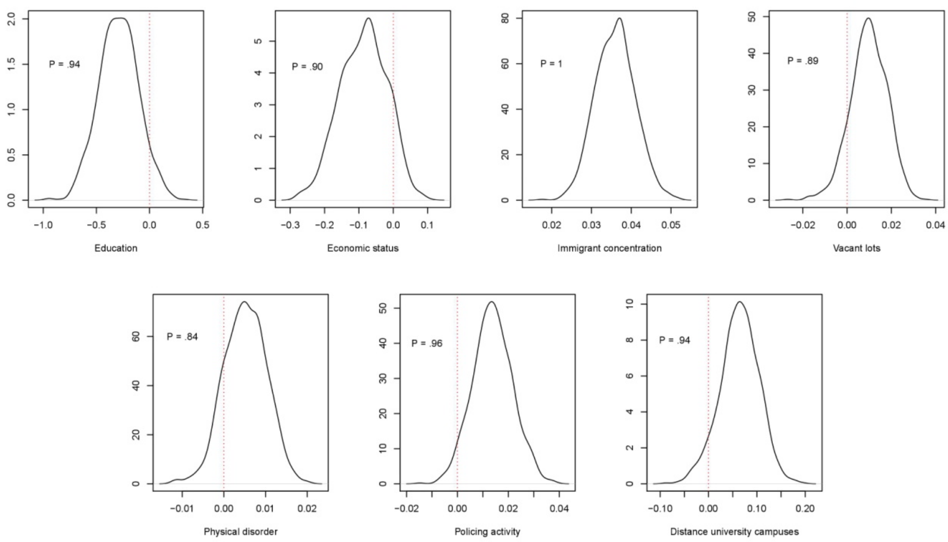

Figure 2. Posterior distribution of fixed effect in the final model (Model 2)

Figure 3 illustrates the comparison in the spatial component between the two models, one including the distance from university campuses and the other without. Mapping the spatial component (i.e., the structured spatial term S_i) helps us to analyze the underlying spatial distribution once the covariates of the model are controlled for, and it is useful to detect patterns that could be explained by other variables that we do not take into account. In these maps we observe a clear smoothing: once we introduced the distance from university campuses in the model the effect of the spatial component is smaller, and although an underlying pattern unexplained by covariates still remains, the distance from university campuses has captured part of this variability.

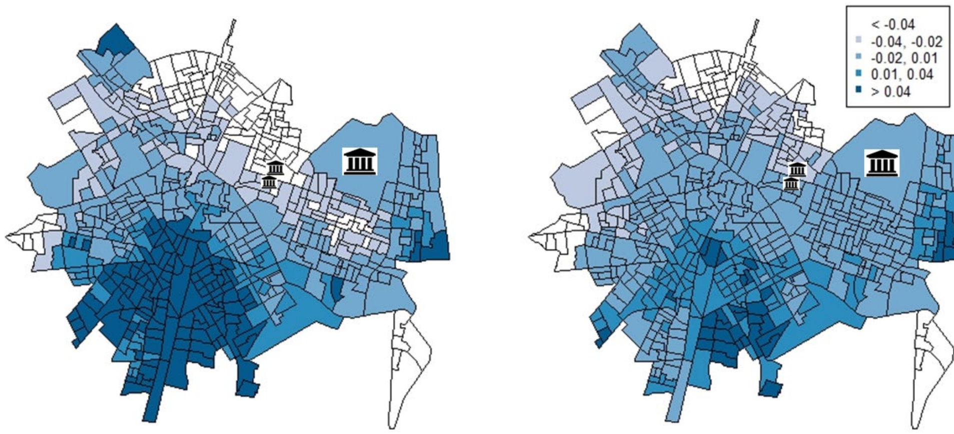

Figure 3. Comparison between spatial components in the model with control variables (left) and the model including distance from university campus (right)

Discussion

In this study we analyzed the relationship between IPVAW risk and distance from university campuses using a Bayesian spatial approach. Previous studies have analyzed the influence of other neighborhood-level characteristics in IPVAW risk. In this research we hypothesized that distance from university campuses may also be related to higher risk of IPVAW.

Results suggest that the distance from university campuses is associated with higher risks of IPVAW, after controlling for variables typically studied in research linking neighborhood-level variables and IPVAW (i.e., education level, economic status, vacant lots, physical disorder, policing activity, and immigrant concentration). The distance from the nearest university campus was associated with an approximate 7% increase in IPVAW risk per kilometer. In addition, the structured spatial effect was smoothed. This suggests that although a part of variability is still unexplained, distance from university campuses may be a relevant variable that should be taken into account.

These results are consistent with the hypothesis of the study, suggesting that the presence of university campuses in the neighborhood is a protective factor for IPVAW. This effect may be due to the characteristics related to the university environment: neighborhoods around the university usually have younger and highly educated populations, and these residents may share similar social norms regarding

IPVAW. These neighborhoods may shape a particular cognitive landscape regarding violence against women based on intolerance to violence that may inhibit IPVAW in the community (Bursik, 1999; Fox & Benson, 2006; Gracia & Herrero, 2007; Sampson & Wilson, 1995). These intervening mechanisms should be further analyzed in order to interpret consistently the results.

This study has both strengths and limitations. One of its strengths is that it goes one step further in explaining the variability among neighborhoods in the risk of IPVAW. To the best of our knowledge, this is the first study analyzing the relationship between IPVAW and university campuses in the neighborhood from an ecological perspective. Although some studies have analyzed the prevalence of IPVAW or other types of violence against women such as dating violence or sexual abuse in university campuses (Branch, Richards, & Dretsch, 2013; Fass, Benson, & Leggett, 2008; Porter & Williams, 2011; Sylaska & Edwards, 2015; Sutherland, Fantasia, & Hutchinson, 2015; Tsui & Santamaria, 2015; Witte & Mulla, 2013), these studies have focused on individual and relational characteristics, or other processes such as the fraternity subculture. In our case, we analyzed the spillover effect that university campuses may have in nearby neighborhoods.

A further strength of this study is the use of a Bayesian random-effects modeling approach, which is especially appropriate for the study of neighborhood-level influences, and addresses important issues such as overdispersion and spatial autocorrelation (Bernardinelli et al., 1995; Gracia et al., 2017; Haining et al., 2009; Lawson, 2009; Rezaeian, Dunn, Leger, & Appleby, 2007). Using Bayesian spatial analysis also has the advantage of allowing us to assess underlying spatial distribution of risk, which is a useful tool to advance explanations of the variable of interest as well as to propose and test new hypothesis (Bernardinelli et al., 1995; Gracia et al., 2015; Law & Chan, 2012; Lawson, 2009).

Among the limitations, this study is an exploratory approach of the relationship between university campus and IPVAW at the neighborhood level. Although results revealed a positive relationship between the distance from university campuses and IPVAW risk, our analysis did not show a strong evidence (i.e., the DIC difference was not large), and future studies are needed. Moreover, the relationship we found could be influenced by other possible variables that we did not take into account. For example, neighborhoods close to university campuses tend to have high street activity both diurnal and nocturnal (Abbot, 2010; Cortes, 2004), which may lead to a greater informal control and safety in these areas, working as a protective factor for violence in general, and IPVAW in particular. Relatedly, in residential areas close to university campuses, the level of collective efficacy may be higher, leading to a greater informal social control, which could explain the lower risk of IPVAW in these neighborhoods (Browning, 2002; Jackson, 2016; Showalter, Maguire-Jack, & Barnhart, 2017; Wright & Benson, 2011). Finally, another possibility is that in these neighborhoods the levels of officially reported IPVAW (the type of data we use in this study) are lower compared to other neighborhoods, as alternative ways to deal with this type of violence (not involving the law enforcement system that can be more stigmatizing) may be preferred. However, there were no data available to assess the possible influence of these factors and processes. This study opens a new avenue for research, and future studies are needed to better understand this relationship.

Our study suggests preliminarily that these social processes could be explaining this relationship. However, more evidence is needed to draw more accurate conclusions about the social processes we proposed and other potential mediators of the relation between the university environment and IPVAW risk. For example, a potential line of inquiry would be to further analyze attitudes toward violence against women among residents in these neighborhoods.

Also, to assess the influence of university campuses we used Euclidean distance. Recent studies are applying network distances instead of Euclidean distances in the study of the spatial influences on neighborhood outcomes such as violence or crime (Furr-Holden et al., 2016; Lu & Chen, 2007; Xu & Griffiths, 2017). However, network distances were not available for this study. Further research is needed in order to explore network distances between university campuses and neighborhoods, and compare our results with those obtain with the network distances.

As we noted before, this study was conducted in Europe, where many universities are integrated in cities, and the results may differ from other cities with different structural characteristics and different integration in the urban network. For example, US university campuses are usually located in peripheral areas with a large number of university buildings in an independent environment, while many European university campuses are integrated in the city and form part of the social and cultural fabric (Brockliss, 2000; Bruning et al., 2006; Chatterton, 2000; Palavecinos, Amérigo, Ulloa, & Muñoz, 2016; Russo, & Tatjer, 2007; Stachowiak, Pinheiro, Sedini, & Vaattovaara, 2013). Future research would benefit from cross-cultural studies analyzing the differences between cities and the varied neighborhood characteristics and social norms with regard to IPVAW associated with the university campus environment.

In conclusion, this study provides new evidence in the research of neighborhood characteristics related to IPVAW, and specifically provides new data regarding university campuses as a potential protective factor for IPVAW risk. Future studies of the influence of university campuses and the social norms operating in nearby areas would provide further evidence to advance our understanding of the mechanisms linking IPVAW risk and neighborhood characteristics.

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6. Conclusiones

6.1 Conclusiones relacionadas con la validación de escalas de desorden en el vecindario

En relación a las herramientas diseñadas para evaluar el desorden en el vecindario, los trabajos realizados en los Estudios 1 y 2 nos aportan evidencias de que las dos escalas utilizadas son herramientas válidas y fiables para medir el vecindario desde un punto de vista observacional.

En el Estudio 1, los resultados muestran una estructura factorial basada en tres dimensiones: el desorden físico, el desorden social, y el deterioro social. Estos resultados van en línea con las investigaciones de Sampson y colaboradores (Sampson, 2009; Sampson y Raudenbush, 2004). La consistencia interna para los tres factores también fue adecuada, así como los niveles de fiabilidad interjueces. Sin embargo, para el caso del desorden social esta fiabilidad interjueces fue menor. Esto puede deberse a la dificultad de observar adecuadamente elementos del entorno social, como pueden ser las peleas callejeras, la prostitución o el consumo de alcohol y/o drogas en la calle, puesto que estos ítems son muy dependientes de la hora y el momento del día en que se realice la observación. En cambio, los elementos del entorno físico que se utilizan para evaluar el desorden y el deterioro físico son más estables a lo largo del tiempo (Jones, Pebley y Sastry, 2011).

En este estudio también se encontró una adecuada validez de criterio, medida mediante la correlación entre las diferentes dimensiones del desorden y tres variables de la desorganización social: el estatus socioeconómico, la concentración de población inmigrante y la inestabilidad residencial. Las correlaciones encontradas siguen la dirección esperada (Kubrin y Weitzer, 2003; Sampson et al., 1997; Sampson y

Raudenbush, 1999), siendo las más altas las encontradas para el deterioro físico del vecindario. En concreto, aquellas áreas con altos niveles de deterioro físico mostraban a su vez bajos niveles de estatus socioeconómico, altas tasas de población inmigrante, y mayor inestabilidad residencial. Respecto al desorden social, éste se relacionó positivamente con la concentración de inmigrantes y la inestabilidad residencial. Por último, el desorden físico se relacionó negativamente con el estatus socioeoconómico del vecindario.

Estos resultados van en línea con los estudios que han mostrado que el desorden se relaciona con diferentes indicadores socioeconómicos del vecindario (Caughy et al., 2001; Jones et al., 2011; Mooney et al., 2014; Sampson y Raudenbush, 1999). Es interesante señalar que el deterioro físico mostró una correlación significativa con las tres características del vecindario, lo que sugiere que la diferenciación entre el desorden físico y el deterioro físico es una distinción teórica importante que puede proporcionar un análisis más detallado del desorden en el vecindario y explorar su relación con diferentes procesos sociales (Sampson, 2009; Sampson y Raudenbush, 2004).

Además, los resultados muestran que los barrios con mayor desorden y deterioro tienden a agruparse en el espacio (Bruinsma, Pauwels, Weerman y Bernasco, 2013; DiMaggio, 2015; Quick, 2013; Veysey y Messner, 1999), tanto para el desorden físico, como para el desorden social y el deterioro físico. Estos resultados respaldan la idea de que las diferentes manifestaciones del desorden en el vecindario, como otras características de las ciudades, no se distribuyen aleatoriamente en el espacio. La naturaleza espacial de este factor de riesgo hace más probable que los problemas del vecindario relacionados con el mismo también sigan un patrón espacial (Cunradi et al., 2011; Freisthler et al., 2007; Diez-Roux y Mair, 2010; Kawachi y Berkman, 2003; Law et al., 2014; Gracia et al., 2015; Sampson, 2012).

En cuanto al Estudio 2, debido a las dificultades que supone realizar una observación directa de un área tan grande como la de la ciudad de Valencia (con 552 sectores censales o áreas de estudio), se llevó a cabo el diseño y validación de una herramienta de desorden basada en el estudio anterior, pero utilizando Google Street View para realizar observaciones virtuales. En este caso, sólo se tuvieron en cuenta dos dimensiones, el desorden físico y el deterioro físico, puesto que el desorden social no es posible observarlo de forma virtual.

Los resultados muestran que la herramienta diseñada presenta buenas características psicométricas. En concreto, se encontró una estructura factorial de tres factores, el desorden físico, el deterioro físico, y una dimensión general de desorden en el vecindario. La consistencia interna de la escala fue muy elevada y con evidencias de fiabilidad. El factor de desorden general del vecindario correlacionaba positivamente con los factores de desorden y deterioro físico del Estudio 1. Estos resultados sugieren que, en general, las observaciones virtuales y las observaciones físicas del desorden en el vecindario tienden a ser muy similares.

Por otro lado, se encontró una correlación negativa entre la escala de desorden en el vecindario mediante Google Street View y las características socioeconómicas del vecindario, en línea con el Estudio 1 y con la investigación previa (Caughy et al., 2001; Mooney et al., 2014; Sampson et al., 1997). Asimismo, los factores de desorden medidos con Google Street View estaban correlacionados positivamente con las intervenciones policiales relacionadas con drogas y con las intervenciones policiales con jóvenes infractores. Estos resultados respaldan los hallazgos de investigaciones previas que muestran que los vecindarios con niveles más altos de desorden muestran tasas de criminalidad más altas (Gracia et al., 2014; 2015; Lum, 2011). La asociación encontrada entre el desorden en el vecindario y los indicadores de criminalidad sugiere que este instrumento puede ser útil para estudiar la criminalidad del vecindario.

De nuevo, se exploró la distribución espacial del desorden en el vecindario, y los resultados mostraron que los tres factores de desorden estaban espacialmente agrupados. De la misma forma, se llevaron a cabo dos regresiones espaciales Bayesianas, y se encontró que el desorden general del vecindario y el deterioro físico estaban relacionados tanto con las intervenciones policiales relacionadas con drogas, como las intervenciones policiales con jóvenes infractores.

Estos resultados proporcionan evidencias de dos medidas de observación fiables y válidas para evaluar el desorden en el vecindario. Por un lado, la escala de desorden diseñada mediante observaciones directas nos permite evaluar tanto el desorden y el deterioro físico como el desorden social, el cual no es posible capturar mediante otros procedimientos. Por otro lado, la escala de desorden diseñada mediante observaciones virtuales permite superar aquellas limitaciones encontradas en las herramientas directas y supone ciertas ventajas importantes, entre las que cabe destacar la sencillez y el menor uso de recursos personales y económicos.

Contar con estas medidas validadas de evaluación de las características del vecindario es de gran importancia como herramientas de investigación e intervención, ya que son clave para comprender mejor los procesos del vecindario, así como para evaluar los problemas sociales relacionados.

6.2 Conclusiones sobre las intervenciones policiales relacionadas con las drogas

En el Estudio 3 se realizó un análisis de la influencia de las características de los vecindarios en la distribución espacial de las intervenciones policiales relacionadas con drogas. Los resultados muestran la existencia de una distribución espacial según la cual las áreas con menores niveles de estatus socioeconómico y mayores niveles de deterioro físico, concentración de inmigrantes, y mayor distancia a las comisarías de policía muestran mayores niveles de intervenciones policiales relacionados con drogas.

La inestabilidad residencial no mostró una relación con la distribución de estas intervenciones policiales.

Estos resultados están en línea con las investigaciones previas basadas en la teoría de la desorganización social (Browning et al., 2010; Sampson et al., 1997; Shaw y McKay, 1942). Estudios anteriores mostraron una relación negativa entre las variables socioeconómicas del vecindario y los delitos relacionados con drogas (Lum, 2011), así como entre la violencia en el vecindario y la venta de drogas (Lum, 2008). Respecto a la concentración de población inmigrante, algunos estudios han mostrado resultados similares a los de otros tipos de delitos (Freisthler et al., 2005; Gracia et al., 2014; 2015; Gruenewald, Freisthler, Remer, LaScala y Treno, 2006; Sampson et al., 1997), mientras que otros trabajos han mostrado una asociación negativa o nula una vez se han controlado otras variables económicas del vecindario (Graif y Sampson, 2009; Sampson, Morenoff y Raudenbush, 2005). Sin embargo, es importante señalar que la mayoría de estos estudios provienen de los Estados Unidos, y una gran parte de ellos se centran en analizar la relación entre los delitos relacionados con drogas y la población afroamericana (Anderson, 1999; Bursik y Webb, 1982). En España, la mayoría de los inmigrantes provienen de países sudamericanos (34.3%), seguidos de países europeos (34%). Estas diferencias deben tenerse en cuenta para analizar adecuadamente el efecto de la inmigración en las intervenciones relacionadas con las drogas.

La inestabilidad residencial, sin embargo, no tuvo una influencia relevante en la distribución espacial de las intervenciones policiales relacionadas con las drogas. La investigación no es concluyente sobre esta cuestión; algunos estudios han encontrado una asociación positiva entre la inestabilidad residencial y la delincuencia (Bursik y Webb, 1982; Thompson y Gartner, 2013), mientras que otros estudios no han apreciado una correlación significativa entre ambas (Gracia et al., 2014; 2015; Pìnchevsky y Wright, 2012). Nuestro estudio se alinea con el segundo grupo de estudios.

Finalmente, como consideramos que la distancia a la estación de policía también podría tener un efecto disuasorio, la incluimos como variable control. Los resultados apoyan nuestra hipótesis de que los lugares más cercanos a una comisaría de policía son menos propensos a ser el escenario de delitos relacionados con las drogas. La introducción de esta variable control aumenta el ajuste del modelo, por lo que es importante tenerla en cuenta cuando analizamos las intervenciones policiales relacionadas con drogas.

Tomando estas variables explicativas en su conjunto y analizando la distribución del nivel medio de las intervenciones policiales relacionadas con las drogas, podemos apreciar algunas diferencias importantes entre los sectores censales. Específicamente, algunas áreas en el norte y el este de la ciudad presentan mayores intervenciones policiales relacionadas con las drogas, lo que indica que los agentes de policía perciben que es necesaria una mayor intervención policial relacionada con las drogas en dichas áreas. Estos resultados sugieren que la estrategia policial debería ser especialmente sensible a aquellas áreas de la ciudad que muestran una mayor percepción de las intervenciones policiales relacionadas con las drogas.

Además, en nuestro estudio encontramos una distribución espacial no explicada por las covariables analizadas, donde la prevalencia estimada es más alta en el norte de la ciudad y más baja en el sur. Una posible explicación de esta distribución es que los barrios ubicados al norte y al este de la ciudad son barrios más estigmatizados, es decir, barrios desfavorecidos históricamente relacionados con la delincuencia y el desorden (Sampson, 2009). Las percepciones de la policía sobre los delitos relacionados con las drogas podrían verse influidas por esa estigmatización. Esta hipótesis podría explorarse más a fondo en estudios futuros que comparen dichas percepciones policiales con otras medidas más objetivas como las llamadas a la policía o los informes policiales.

6.3 Conclusiones relacionadas con la distribución espacio-temporal de los bares, restaurantes y puntos de venta de bebidas alcohólicas

En el Estudio 4 se realizó un análisis espacio-temporal de la distribución de lo bares, restaurantes y puntos de venta de bebidas alcohólicas. Los resultados indican diferentes relaciones entre las tres categorías de establecimientos donde se vende y consumen bebidas alcohólicas y las características del vecindario. Específicamente, los barrios con mayor densidad de puntos de venta de alcohol se situaban en áreas con un estatus económico más bajo, mayores tasas de población inmigrante y una menor inestabilidad residencial; los barrios con mayor densidad de restaurantes y cafeterías mostraban un estatus económico más bajo en el propio sector censal, y mayor estatus económico en los sectores censales vecinos. Por último, los barrios con mayor densidad de bares se caracterizaban por ser áreas con niveles más altos de estatus económico en el sector censal y en los sectores censales vecinos.

Estos resultados difieren de los encontrados en estudios realizados en ciudades estadounidenses, que sugieren que los barrios desfavorecidos socioeconómicamente presentan mayor densidad de puntos de venta de bebidas alcohólicas (McKinney et al., 2012; Nielsen et al., 2010; Samspon et al., 1997). Nuestros resultados sugieren que, en Valencia, los puntos de venta de bebidas alcohólicas se ubican en vecindarios de menor estatus económico, los restaurantes y cafeterías están ubicados en áreas con menor estatus económico local pero con un estatus económico más alto en sus áreas vecinas, mientras que los bares parecen tener una distribución espacial diferente (es decir, estarían situados en áreas con mayor estatus económico). Particularmente interesantes son los resultados para los restaurantes-cafeterías, que sugieren que los barrios con una mayor densidad de restaurantes y cafeterías muestran un estatus económico más bajo, pero sus áreas vecinas muestran un estatus económico más alto. En investigaciones futuras se podrán explorar los mecanismos involucrados en esta relación entre el estatus económico y la distribución de restaurantes y cafeterías.

Además, la ubicación de los bares en Valencia presenta claras diferencias en comparación con las ciudades de Estados Unidos, donde tienden a situarse en áreas con menor estatus económico. En nuestro estudio, los vecindarios con mayor densidad de bares presentaban un estatus económico más alto. Estas diferencias pueden reflejar las características de quienes frecuentan los bares y las razones por las que lo hacen. En Valencia (y en otras ciudades españolas), las áreas con un alto número de bares suelen estar frecuentadas por jóvenes trabajadores o estudiantes, puesto que ir a bares se considera culturalmente como una actividad social, más allá de un mero recurso para consumir alcohol. Estas áreas con una mayor densidad de bares a menudo se convierten en áreas populares donde el coste del consumo de alcohol tiende a ser mayor, atrayendo a un tipo de clientela con más posibilidades económicas. Estas diferencias en el uso de bares podrían conducir a la diferente asociación espacial con las características del vecindario que encontramos en nuestro estudio.

Con respecto a la concentración de inmigrantes, las áreas con mayor concentración de inmigrantes mostraron una mayor densidad de puntos de venta de bebidas alcohólicas. Sin embargo, esta variable no estaba asociada con la densidad de restaurantes y cafeterías o con la densidad de bares. La investigación previa también ha mostrado resultados mixtos con respecto a la influencia de la concentración de inmigrantes en la densidad de tiendas que venden alcohol (Bluethenthal et al., 2008; Hay et al., 2009).

De manera similar, la inestabilidad residencial solo fue relevante en el caso de los puntos de venta de bebidas alcohólicas, sin embargo, en contraste con estudios previos (Hay et al., 2009), nuestros resultados mostraron una relación negativa. Estos resultados sugieren que estos establecimientos son más frecuentes en los barrios estables, con familias que tienden a vivir en las mismas áreas durante un largo periodo de tiempo.

Todos estos resultados sugieren que la investigación sobre la distribución espacial de los establecimientos de venta y consumo de bebidas alcohólicas y las características del vecindario que influyen en esa distribución realizada en 'países secos’ no puede extrapolarse directamente a los 'países húmedos’, donde los patrones de consumo y la cultura son diferentes. Claramente, se necesita más investigación intercultural para entender mejor la diferente distribución espacial de los establecimientos de venta y consumo de alcohol en países con diferentes culturas de consumo.

Nuestro estudio también mostró las tendencias espacio-temporales de los establecimientos de venta y consumo de bebidas alcohólicas de 2010 a 2015. Durante este período, la densidad de puntos de venta de bebidas alcohólicas aumentó en la parte central y oriental de la ciudad, y disminuyó en las áreas periféricas. Por otro lado, la densidad de bares aumentó en la parte sur y central de la ciudad. Esta área corresponde a uno de los barrios tradicionales de Valencia (Ruzafa), que se ha convertido en un distrito de moda para la vida nocturna de la ciudad después de un proceso de gentrificación (del Romero y Lara, 2015), lo que puede explicar el aumento significativo de bares en la zona. La densidad de restaurantes y cafeterías, sin embargo, no mostró cambios importantes a lo largo de los años.

También se analizó la influencia de la densidad de los establecimientos de venta y consumo de bebidas alcohólicas en las llamadas policiales relacionadas con el consumo de alcohol. Los resultados mostraron que la densidad de bares era la única categoría con una asociación positiva con las llamadas relacionadas con el alcohol. La densidad de restaurantes y cafeterías mostró una relación negativa, mientras que las tiendas que venden alcohol no mostraron ninguna asociación con las llamadas policiales relacionadas con el consumo de alcohol.

Al comparar la distribución espacial de las llamadas relacionadas con el alcohol, podemos observar que el patrón espacial y temporal es similar a la distribución espacial de la densidad de bares. Específicamente, en el centro de la ciudad se aglutinan tanto un mayor número de llamadas policiales relacionadas con el alcohol, como una mayor densidad de bares, y la tendencia temporal de llamadas (que aumenta en las áreas del sur y disminuye en las áreas del norte) es más coincidente con la distribución temporal de los bares, mostrando los mismos patrones de cambio.

Estos hallazgos muestran que las intervenciones policiales relacionadas con el alcohol son más comunes en vecindarios con una mayor densidad de bares. A pesar de que estas áreas con alta densidad de bares están ubicadas en áreas con mayores niveles económicos, las intervenciones policiales debido a problemas relacionados con el alcohol se solicitan con mayor frecuencia en esta zona. Esto es similar a lo que ocurre en las ciudades norteamericanas, donde la densidad de bares está relacionada con una variedad de delitos (Cunradi et al., 2011; Gorman et al., 2001).

La densidad de puntos de venta de bebidas alcohólicas, en cambio, no se mostró relacionada con las llamadas policiales relacionadas con el consumo de alcohol. En Estados Unidos, estos establecimientos se consideran un indicador de una "espiral de deterioro" que conduce a más problemas sociales, como delitos violentos o lesiones (Fone et al., 2012; Furr-Holden et al., Zhu et al., 2006). Estas diferencias entre España y las ciudades de Estados Unidos podrían explicarse por el diferente significado de los puntos de venta de bebidas alcohólicas en España. En un 'país húmedo' como España, el alcohol está disponible en cualquier tipo de establecimiento, como supermercados, tiendas de alimentación o gasolineras, puesto que el consumo de alcohol se considera parte integrada de la vida social. Por otro lado, es más probable que los barrios con mayores capacidades socioeconómicas sean los que llamen más a la policía, bien porque muestren una mayor confianza en el sistema policial, o porque sea más probable que la policía responda con mayor rapidez en este tipo de vecindarios que en los barrios desfavorecidos. Sin embargo, no tenemos datos disponibles para evaluar estas posibles relaciones; futuras investigaciones podrían ir en esta línea.

6.4 Conclusiones relacionadas con la distribución espacio-temporal de las llamadas policiales relacionadas con el suicidio

También se ha analizado la distribución espacio-temporal de las llamadas a la policía relacionadas con el suicidio, así como la influencia de las características del vecindario en dicha distribución espacio-temporal. En el Estudio 5 se analizó la distribución espacio-temporal de las llamadas policiales relacionadas con el suicidio utilizando diferentes modelos para comprobar qué estructura espacio-temporal era la más adecuada para este tipo de datos. Los resultados muestran, en línea con investigaciones previas, que las llamadas policiales relacionadas con el suicidio siguen un patrón espacial (Carcach, 2017; Congdon, 2009; Hempstead, 2006; Hsu, Chang, Lee y Yip, 2015; Johnson et al., 2017; Lam, Kinney y Bell, 2017).

Se analizaron diferentes tipos de modelos: un modelo únicamente espacial, otro modelo espacio-temporal con datos anuales, y un modelo espacio-temporal con datos trimestrales. Los resultados evidencian que este último es el que mostraba un mejor ajuste. Además, las llamadas policiales relacionadas con el suicidio mostraron una distribución diferencial según el trimestre del año, con un pico de llamadas en el segundo (abril a junio) y en el tercer trimestre (julio a septiembre) y una disminución en los otros trimestres. Estos resultados están en línea con la investigación previa que ha encontrado mayores tasas de suicidio en primavera y verano (Woo, Okusaga y Postolache, 2012; Santurtún et al., 2017; Silveira et al., 2016; Christodoulou et al., 2011; Yip, Chao y Chiu, 2000), e indican la importancia de tener en cuenta la estacionalidad al realizar un análisis temporal de las tendencias suicidas, ya que considerar solamente el efecto anual puede conducir a error en la interpretación de los resultados.

Nuestros resultados también mostraron un aumento importante en el número de llamadas policiales relacionadas con el suicidio a partir de 2010. En concreto, los resultados sugieren que las llamadas policiales relacionadas con el suicidio aumentaron durante el período de estudio (2010 - 2016), y que no hubo estabilización al menos hasta 2016, último año analizado. Es necesario incorporar datos más a largo plazo en futuros estudios, con más periodos anuales, con el fin de analizar más a fondo la evolución de las llamadas policiales relacionadas con el suicidio.

En el Estudio 6 se parte de los resultados obtenidos en el Estudio 5 para ir un paso más allá e incorporar diferentes variables del vecindario en la explicación de los patrones espacio-temporales encontrados. Los resultados muestran que los barrios con niveles más bajos de educación, menor densidad de población, una mayor inestabilidad residencial, mayor concentración de hogares compuestos por una persona sola, y un mayor envejecimiento de la población, son aquellos que muestran a su vez mayores niveles de llamadas policiales relacionadas con el suicidio. Estos resultados están en línea con la literatura previa, que sugiere que el aislamiento social, la fragmentación social y la baja densidad de población están estrechamente relacionadas con el riesgo de suicidio a nivel comunitario (Congdon, 2011; Hawton et al., 2001; Helbich, Blüml, Jong, Plener, Kwan y Kapusta, 2017; Rehkoff y Buka, 2006; Yoon et al., 2015)

El estatus económico y la población inmigrante no fueron relevantes para explicar las llamadas relacionadas con el suicidio. Sin embargo, estudios previos encontraron una relación negativa entre el estatus económico y el suicidio (Congdon, 2011; 2013; Chang, Sterne, Wheeler, Lu, Lin y Gunnell, 2011; Hawton et al., 2001). El uso de diferentes medidas que reflejen el estatus económico puede explicar estas diferencias, ya que los estudios generalmente incluyen variables como el nivel de ingresos y el desempleo, variables no disponibles en nuestro trabajo. En nuestro caso, el nivel educativo fue la variable de privación con la mayor contribución al modelo.

Es importante tener en cuenta las diferencias que muestra España respecto a otros países en cuanto al tipo de inmigración. Los estudios existentes se han realizado principalmente en países anglosajones, y generalmente se han centrado en las diferencias étnicas o en la conducta autolítica de los pueblos indígenas, estudios que han mostrado una asociación positiva entre las tasas de suicidio y el porcentaje de minorías étnicas (Congdon, 2011; Johansson et al., 1997; Neeleman et al., 1998; Philip, Ford, Henry, Rasmus y Allen, 2016). Sin embargo, algunos factores culturales pueden influir en la relación entre la inmigración y las tasas de suicidio. En Valencia, como hemos apuntado anteriormente, el mayor grupo de inmigrantes proviene de países latinoamericanos. El uso del mismo idioma de este grupo de población podría facilitar la integración social en la comunidad, cosa que no ocurre en los países de habla inglesa, y esto puede ser un factor de protección del comportamiento suicida. Para un mejor análisis de esta cuestión, es fundamental realizar estudios interculturales que permitan analizar las diferencias entre los países en relación a la asociación entre el suicidio y las tasas de población inmigrante.

Por último, la incorporación de las variables del vecindario relacionadas con las llamadas policiales por suicidio nos permite visualizar los mapas del riesgo relativo para los diferentes años del estudio. En estos mapas se observa cómo algunos sectores censales cambian a lo largo de los años, con un aumento o descenso del número de llamadas, pero existe cierto patrón espacial que apunta a que algunas áreas del centro-oeste y del noreste presentan un mayor número de llamadas constantemente a lo largo de los años. De gran interés resulta el análisis exhaustivo de estas áreas para los agentes políticos y sociales a nivel local: tanto las áreas que mantienen un alto número de llamadas a lo largo de los años, como aquellas que han ido aumentando o disminuyendo, pueden aportar información fundamental para la implementación y evaluación de medidas para el tratamiento del problema del suicidio a nivel comunitario.

6.5 Conclusiones relacionadas con la influencia de la proximidad de los campus universitarios en la distribución espacial de la violencia de género

Por último, en el Estudio 7 se analizó la distribución espacial de la violencia contra la mujer en las relaciones de pareja, yendo un paso más respecto a las variables clásicas de la desorganización social. En él, se propone que la proximidad de los vecindarios a los campus universitarios puede ser un elemento importante para explicar el riesgo de violencia de pareja contra la mujer en el vecindario. Los estudios que analizan las variables del vecindario relacionadas con la violencia de pareja están recibiendo cada vez más atención científica (Burke et al., 2006; Caetano et al., 2010; Cunradi et al., 2011; Frye y O'Campo, 2011; Kirst et al. 2015; Li et al., 2010). Sin embargo, estos estudios se han centrado sobre todo en analizar las variables tradicionales, como son los barrios desfavorecidos socioeconómicamente, la concentración de inmigrantes y la movilidad residencial. En un estudio previo realizado por nuestro equipo de investigación (ver Anexo 1), se comprobó que variables como el nivel educativo, el estatus económico, el desorden en el vecindario, o el porcentaje de población inmigrante estaban relacionadas con un aumento en el riesgo de la violencia de género en el vecindario (Gracia et al., 2015).

Otras variables, no obstante, han sido mucho menos exploradas. En este sentido, los vecindarios cercanos a los campus universitarios, donde residen personas jóvenes y con alto nivel educativo, podrían funcionar como un entorno protector, debido a que los vecinos que viven más próximos a los campus universitarios compartirían normas sociales donde la violencia se perciba como una forma inapropiada de resolver conflictos, conduciendo a un mayor control social informal y reduciendo así el riesgo de violencia contra la mujer en las relaciones de pareja (Abbot, 2010; Cortes, 2004). Nos planteamos, de esta forma, que una mayor distancia de los vecindarios a los campus universitarios podría ser un factor que explique parte de la variabilidad en el riesgo de violencia contra la mujer, variabilidad que las otras variables no podían explicar.

Los resultados de este estudio sugieren que la proximidad de los vecindarios a los campus universitarios se asocia con un menor riesgo de violencia de género, una vez controlado por algunas variables tradicionales desde la teoría de la desorganización social (el nivel educativo, el estatus económico, la superficie de solares, el desorden físico, la actividad policial y la concentración de inmigrantes). En concreto, cada kilómetro adicional que aumentamos la distancia del vecindario a un campus universitario, aumenta el riesgo de violencia de pareja contra la mujer aproximadamente en un 7%. Además, cuando se introduce esta variable en el modelo, el efecto espacial se suaviza: si sólo tenemos en cuenta las variables contextuales clásicas, el efecto espacial apunta de forma clara que existe un mayor riesgo en el sur que en el norte de la ciudad, patrón que no estaría explicado por esas covariables, sino que indicaría que hay algo más allá de ellas que establece ese patrón. Sin embargo, al introducir la variable de la distancia a las universidades, el patrón sigue siendo norte-sur, pero ya no es tan pronunciado, debido a que esta variable explica una parte importante de la variabilidad existente. Esto sugiere que, aunque aún queda una parte de la variabilidad por explicar, y deben establecerse nuevas hipótesis en este sentido, la proximidad de los vecindarios a los campus universitarios es una variable relevante que debe tenerse en cuenta.

Estos resultados son consistentes con la hipótesis del estudio, lo que sugiere que la presencia de campus universitarios en el vecindario es un factor de protección para la violencia de género. Este efecto puede deberse a las características relacionadas con el entorno universitario: como se ha apuntado, los barrios alrededor de la universidad suelen tener poblaciones más jóvenes y con mayor nivel educativo, y estos residentes pueden compartir normas sociales similares con respecto a la violencia de género, de forma que ésta sea vista como un comportamiento no tolerable desde el punto de vista social. Estas normas compartidas de intolerancia a la violencia podrían dar lugar a la inhibición de comportamientos violentos contra las mujeres en la comunidad (Bursik, 1999; Fox y Benson, 2006; Sampson y Wilson, 1995).

Algunos estudios previos han analizado la prevalencia de la violencia contra las mujeres (por ejemplo, en el caso de parejas jóvenes o de abuso sexual) en los campus universitarios, encontrando por el contrario una presencia muy elevada de violencia en los campus (Branch, Richards y Dretsch, 2013; Fass, Benson y Leggett, 2008; Porter y Williams, 2011; Sutherland, Fantasia y Hutchinson, 2015; Sylaska y Edwards, 2015; Tsui y Santamaria, 2015). Sin embargo, estos estudios se han centrado en un enfoque individual o relacional, haciendo hincapié sobre todo en la subcultura de las fraternidades, muy presente en Estados Unidos. En el caso de España, como en muchas ciudades Europeas, las universidades están integradas dentro de las ciudades y son parte del entramado social y cultural de la ciudad, a diferencia del caso estadounidense, donde los campus suelen estar situados en áreas periféricas, fuera de las ciudades, en un entorno independiente (Brockliss, 2000; Bruning, McGrew y Cooper, 2006; Chatterton, 2000).

Nuestro estudio es un primer acercamiento a la idea de que estos procesos sociales podrían estar explicando la relación entre un menor riesgo de violencia de género y la proximidad de los vecindarios a los campus universitarios. Son necesarios nuevos estudios para analizar los procesos sociales que están detrás y evaluar otros posibles mediadores de la relación entre el entorno universitario y el riesgo de violencia contra la mujer en las relaciones de pareja. Además, la relación que encontramos podría verse influenciada por otras posibles variables que no se han tenido en cuenta. Por ejemplo, los vecindarios cercanos a los campus universitarios tienden a mostrar una gran cantidad de actividades en la calle tanto diurnas como nocturnas (Abbot, 2010; Cortes, 2004), lo que puede conducir a un mayor control informal y un mayor sentimiento de seguridad en estas áreas, trabajando como un factor de protección para la violencia en general, y para la violencia contra la mujer en particular.

Relacionado con esto último, en las áreas residenciales cercanas a los campus universitarios el nivel de eficacia colectiva puede ser mayor, lo que lleva a un mayor control social informal, y a su vez podría explicar el menor riesgo de violencia de pareja contra las mujeres en estos barrios (Browning, 2002; Jackson, 2016; Showalter et al., 2017; Wright y Benson, 2011).

Finalmente, otra posibilidad es que en estos vecindarios los niveles de violencia de género según los informes oficiales (el tipo de datos que usamos en este estudio) sean más bajos en comparación con otros vecindarios. En estos vecindarios, los residentes pueden elegir otras formas alternativas de intervenir ante este tipo de violencia (sin involucrar al sistema legal, ya que hacerlo puede ser más estigmatizador). Sin embargo, no hay datos suficientes para evaluar la posible influencia de estos factores y procesos. Este estudio abre una nueva vía para la investigación, y se necesitan estudios futuros para comprender mejor esta relación.

6.6 Conclusiones generales

Los resultados de los estudios realizados en el marco de esta tesis doctoral han demostrado que, independientemente del tipo de problemática social analizada, tanto en el caso de fenómenos que ocurren en la calle, como son los delitos relacionados con drogas, o el desorden en el vecindario, como en problemáticas que ocurren de puertas para adentro, como son la violencia de género o incluso podríamos considerar el suicidio, todas ellas siguen una distribución espacial, es decir, no están distribuidas aleatoriamente en la ciudad, sino que hay áreas con mayor riesgo que otras, y esta distribución espacial está relacionada con ciertas características del vecindario que explicarían el riesgo desigual en las diferentes áreas de la ciudad.

Con los resultados obtenidos, podemos decir que los barrios desfavorecidos socioeconómicamente son aquellos que muestran un mayor riesgo de presentar diferentes problemas sociales. Hemos observado una relación entre la distribución desigual de las características del vecindario indicativas de la desorganización social y la desigual distribución espacial del riesgo de problemas sociales. Desde las formulaciones recientes de la teoría de la desorganización social se ha propuesto que existen diferentes procesos del vecindario, principalmente la eficacia colectiva, los vínculos sociales y las normas sociales y culturales que explicarían por qué estas características del vecindario crean un “entorno de riesgo” (Beyer et al., 2013; Pinchevsky y Wright, 2012). Una baja eficacia colectiva y unos limitados vínculos sociales entre los vecinos pueden disminuir el control social informal en los casos de violencia, y reducir la conducta de ayuda hacia las víctimas. De la misma forma, los vecindarios cuyos residentes se encuentran aislados socialmente de otro tipo de personas que comparten valores considerados positivos (como una desaprobación hacia la violencia) pueden presentar un clima de tolerancia y aceptación de la violencia, lo cual reduce el control social informal de la misma (Browning, 2002; Gracia y Tomás, 2014). Además, las condiciones negativas del barrio pueden ser un factor estresante para los residentes que puede disminuir sustancialmente la calidad de vida y desencadenar la violencia (Hill, Ross y Angel, 2005; Ross y Mirowsky, 2009).

De la misma forma, la concentración de inmigrantes y la movilidad residencial se han mostrado relacionados con algunos de los problemas analizados, si bien no en todos los casos. Estas variables han mostrado tradicionalmente resultados contradictorios, con algunos estudios que muestran una relación positiva (Bursik y Webb, 1982; Gracia et al., 2014; 2015; Gruenewald et al., 2006; Sampson et al., 1997; Thompson y Gartner, 2013), mientras que otros no han encontrado relación con estas variables (Gracia et al., 2014; 2015; Graif y Sampson, 2009; Pinchevsky y Wright, 2012; Sampson et al., 2005).

Es importante resaltar que en nuestros estudios, más allá de los tres factores clásicos de las teorías de la desorganización social, como son los barrios desfavorecidos socioeconómicamente, la concentración de inmigrantes y la inestabilidad residencial, también se han analizado otras características del vecindario que han recibido menor atención científica. En concreto, se han analizado los bares, restaurantes y puntos de venta de bebidas alcohólicas, y la distancia a los campus universitarios como factores de gran interés para explicar diferentes problemas sociales.

Los estudios realizados en esta tesis doctoral suponen importantes aportaciones a la literatura previa que cabe destacar. En primer lugar, el área de estudio elegida para cada uno de los estudios (una ciudad del Sur de Europa) aporta nuevas evidencias al estudio de los problemas sociales y los vecindarios. Apenas existe investigación centrada en las características del vecindario relacionadas con la distribución espacio-temporal de los diferentes problemas sociales en países del sur de Europa, sino que en su mayoría procede de Estados Unidos. Los estudios realizados en esta tesis doctoral son pioneros en este sentido, y dentro del marco español son los primeros estudios que analizan las diferentes problemáticas sociales utilizando análisis espaciales adecuados. Las ciudades del sur de Europa pueden mostrar diferentes características culturales respecto a otros países. Así apuntan algunos de los resultados de nuestros estudios, que muestran una discrepancia con los resultados obtenidos en estudios realizados en Estados Unidos. Contar con nuevas evidencias desde otros países diferentes a Estados Unidos es de gran utilidad, ya que parte de los resultados puede estar influida por el tipo de cultura predominante.

Por otro lado, los estudios están realizados con una unidad de medida muy pequeña, lo que supone una mayor precisión: se han utilizado sectores censales como unidad de análisis, que es la unidad administrativa disponible más pequeña. Otros estudios se han basado en unidades más grandes como son los barrios, los distritos, los códigos postales o el término municipal. Sin embargo, estas áreas tan grandes pueden mostrar una gran heterogeneidad dentro de sus límites, y trabajar con una resolución mayor como los sectores censales supone conseguir un grado de precisión que puede ser de gran utilidad para el diseño de políticas de intervención y prevención específicas en áreas concretas. Además, al usar unidades de área pequeña, también se reduce el potencial sesgo ecológico, ya que esta resolución está más cerca del nivel individual (Gracia et al., 2015; Lawson, 2009; Ocaña-Riola et al., 2008).

Los trabajos realizados siguen una perspectiva espacial, y en los casos en los que se contaba con suficientes datos, una perspectiva espacio-temporal. Este último tipo de análisis presenta ventajas importantes porque refleja no sólo la distribución espacial, sino que también explica los cambios a lo largo del tiempo. Los estudios que sólo consideran las tendencias espaciales podrían sesgar los resultados y enmascarar cualquier relación entre variables (Lawson, Brown y Vidal Rodeiero, 2003), de ahí la importancia de tener en cuenta una perspectiva longitudinal siempre que sea posible.

Otra importante aportación de este trabajo es la utilización de una modelización Bayesiana para explorar la conexión entre las variables del vecindario y los problemas sociales. Este tipo de modelos son todavía muy novedosos en este área, y permite establecer conclusiones estadísticas sobre la influencia del vecindario en una gran variedad de fenómenos incluidos la salud y el crimen (Congdon, 2000; Kawachi y Berkman, 2003; Sampson, 2012). Los modelos Bayesianos espaciales permiten controlar posibles sesgos que surgen con otro tipo de aproximaciones, como son la sobredispersión y la autocorrelación espacial (Bernardinelli et al., 1995; Haining et al., 2009; Lawson, 2009). El uso del análisis espacial Bayesiano también tiene la ventaja de permitirnos evaluar la distribución espacial subyacente al riesgo, lo cual es una herramienta útil para avanzar en las explicaciones de la variable de interés, así como para proponer y probar nuevas hipótesis (Bernardinelli et al., 1995; Gracia et al., 2015; Lawson, 2009), como se ha podido comprobar en el Estudio 7.

Además, para analizar las características del vecindario relacionadas con los diferentes problemas sociales se han integrado datos de diferente naturaleza (composición de la población y estructura de la misma), y de diferentes fuentes (datos del Ayuntamiento, obtenidos de observadores entrenados y de la policía), lo cual aporta una mayor riqueza a los análisis realizados.

6.7 Limitaciones de los estudios y líneas futuras

A pesar de las ventajas de las técnicas utilizadas en este trabajo de tesis, también encontramos ciertas limitaciones generales que cabe destacar. En primer lugar, en cuanto a las covariables con las que se ha trabajado, en otros estudios se han usado frecuentemente indicadores socioeconómicos tales como los ingresos, el porcentaje de personas que viven por debajo del nivel de pobreza, o las tasas de desempleo. Sin embargo, este tipo de indicadores no estuvieron disponibles para cada sector censal para nuestro tipo de muestra. Además, no se pudieron explorar algunas variables teóricas relevantes que podrían estar explicando las relaciones entre las características estructurales del vecindario y algunos de los problemas sociales analizados, como la eficacia colectiva, los vínculos sociales o las normas sociales y culturales.

Estos elementos pueden ser de gran importancia, especialmente para estudiar el riesgo de la violencia de género a nivel comunitario. Futuras investigaciones se beneficiarían de la inclusión de estas variables en el análisis de la influencia de las características del vecindario en la distribución espacio-temporal de los fenómenos sociales. Así, una futura línea de investigación consiste en el desarrollo y validación de instrumentos de medida de las normas sociales percibidas en cada sector censal, para poder introducir estas normas sociales como variable explicativa en el estudio de problemas sociales como la violencia de pareja.

La forma en que se ha medido los problemas sociales también puede suponer algunas limitaciones. En algunos casos se ha trabajado con variables subjetivas como la percepción policial de las intervenciones que realizan, o la percepción subjetiva de desorden en el vecindario; en otros casos se ha optado por medidas del delito basadas en las llamadas policiales. No se ha podido disponer de otro tipo de medidas, como expedientes policiales o datos estadísticos oficiales debido a que este tipo de medidas generalmente no se recoge para cada sector censal. Sin embargo, las medidas estudiadas en esta tesis pueden proveer información adicional y ser un proxy adecuado para estudiar el delito y los problemas sociales en la ciudad.

Por otro lado, la decisión sobre el tipo de unidad de medida a utilizar para trabajar a nivel espacial siempre tiene sus ventajas e inconvenientes, problema intrínseco para cualquier tipo de dato agregado. No obstante, el uso como unidad de medida del sector censal, la unidad más pequeña disponible, reduce sustancialmente este potencial sesgo.

Como se ha comentado anteriormente, se ha trabajado con una ciudad del sur de Europa, donde hasta el momento ha habido una falta de estudios que analicen las características del vecindario y su influencia en la distribución espacio-temporal de los problemas sociales. Sin embargo, y a pesar de que ello es una importante aportación de esta tesis, hay que ser cauto cuando se establecen conclusiones o se hacen inferencias, puesto que sólo se ha utilizado una ciudad específica. Es esencial llevar a cabo nuevos estudios utilizando una perspectiva similar en otras ciudades del sur de Europa, con el fin de poder comparar los resultados obtenidos y poder realizar conclusiones sobre las características del vecindario que influyen a los problemas sociales en este tipo de países. Una línea de investigación futura de gran relevancia sería realizar estudios interculturales que permitan establecer conclusiones sólidas sobre lo que ocurre en diferentes culturas con los mismos problemas sociales. Es fundamental contar con estudios que analicen lo que ocurre en diferentes países utilizando las mismas técnicas, de forma que pueda realizarse una comparación de los resultados.

Los resultados obtenidos pueden ser de gran utilidad para la planificación y evaluación de estrategias de prevención de los agentes locales como pueden ser los Servicios Sociales, el Ayuntamiento, o la Policía Local. A pesar de los costes sociales y económicos que suponen los problemas sociales analizados en nuestras sociedades, y la clara necesidad de desarrollar acciones preventivas, aún faltan estrategias y planes de prevención que puedan hacer frente adecuadamente estos problemas. El conocimiento de las áreas donde se encuentra un riesgo mayor de ocurrencia de estos problemas sociales puede ser muy útil para guiar las acciones locales, administrar de manera efectiva sus recursos y desarrollar estrategias preventivas para los vecindarios con mayores riesgos. Para ello, se pueden estudiar las áreas donde el riesgo es mayor, centrándose en aquellos lugares donde haya mayor presencia de las características del vecindario relacionadas con ese alto riesgo. Trabajar con los factores de riesgo del vecindario e intervenir sobre ellos puede ser una forma indirecta de prevenir los problemas sociales relacionados.

La realización de estudios longitudinales, además, ha mostrado ser de relevancia para estudiar los problemas sociales. Analizar los barrios donde el riesgo ha aumentado o disminuido en los últimos años y explorar las covariables que podrían explicar estos cambios a lo largo del tiempo podría proporcionar información útil sobre la incidencia de los problemas sociales y ser una herramienta efectiva para evaluar el impacto de las políticas preventivas. Estos estudios pueden ayudar a detectar si aquellas áreas donde hay más presencia de problemas vecinales reducen su riesgo una vez planteadas diferentes políticas de prevención e intervención. Realizar mapas del riesgo tanto en los años anteriores como en los posteriores de la puesta en marcha de cualquier tipo de medida preventiva puede ser una herramienta muy valiosa de evaluación de los cambios ocurridos en la incidencia de los problemas sociales. Futuros estudios se centrarán en explorar estas posibilidades.

En conclusión, es necesario seguir profundizando en la compresión de los factores de riesgo del vecindario asociados a los problemas sociales, y es importante trabajar desde una perspectiva espacial y temporal, que puede ser clave para conocer en mayor profundidad las relaciones entre las características de vecindario y el riesgo de los problemas sociales. Estas aportaciones a nivel comunitario van más allá de los factores de riesgo individuales, y pueden ser de gran utilidad para mejorar la calidad de vida en nuestras ciudades.

Sin duda, queda mucho por explorar, y es importante seguir avanzando e investigando desde el nivel del vecindario para poder aportar más información de los factores de riesgo de los problemas sociales desde un punto de vista comunitario y cómo intervenir sobre ellos.

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ANEXOS.
Otros estudios

1. The spatial epidemiology of intimate partner violence: Do neighborhoods matter?

The spatial epidemiology of intimate partner violence: Do neighborhoods matter?[8]

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Abstract

We examined whether neighborhood-level characteristics influence spatial variations in the risk of intimate partner violence (IPV). Geocoded data on IPV cases with associated protection orders (n = 1,623) in the city of Valencia, Spain (2011–2013), were used for the analyses. Neighborhood units were 552 census block groups. Drawing from social disorganization theory, we explored 3 types of contextual influences: concentrated disadvantage, concentration of immigrants, and residential instability. A Bayesian spatial random-effects modeling approach was used to analyze influences of neighborhood-level characteristics on small-area variations in IPV risk. Disease mapping methods were also used to visualize areas of excess IPV risk. Results indicated that IPV risk was higher in physically disordered and decaying neighborhoods and in neighborhoods with loweducational and economic status levels, high levels of public disorder and crime, and high concentrations of immigrants. Results also revealed spatially structured remaining variability in IPV risk that was not explained by the covariates. In this study, neighborhood concentrated disadvantage and immigrant concentration emerged as significant ecological risk factors explaining IPV. Addressing neighborhood-level risk factors should be considered for better targeting of IPV prevention.

Keywords: Bayesian spatial modeling; concentrated disadvantage; disease mapping; intimate partner violence; neighborhoods; risk probability; small-area variation; spatial epidemiology

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Introduction

A 2013 World Health Organization report defined violence against women as a "public health problem of epidemic proportions, requiring urgent action" (1, p. 3). This report estimated a global lifetime prevalence of intimate partner violence (IPV) of 30% for women. In Europe, where the present study was conducted, a 2014 survey with data from the 28 European Union member states estimated that 22% of women had experienced physical and/or sexual violence since the age of 15 years by actual or former intimate partners (43% when psychological violence was included) (2). The magnitude of this problem and the serious health and social consequences for women, their children, and the wider community make it an urgent public health priority (3–5). A better understanding of the factors explaining the increased risk of IPV is key for better-informed intervention and prevention initiatives.

Recently, a growing body of research, mainly informed by social disorganization theory and ecological approaches (6–9), is recognizing the importance of IPV risk factors beyond the individual and relational levels and has begun to explore the role of contextual factors in explaining IPV (10–28). The recent publication of 2 systematic reviews on the influence of neighborhoods on IPV illustrates this growing interest in contextual explanatory factors (29, 30). Both reviews suggested that, in line with social disorganization predictions, the most common neighborhood-level factors associated with IPV in the available research are those characterizing neighborhood socioeconomic disadvantage.

These systematic reviews, however, also showed that the evidence base regarding the link between other neighborhood-level characteristics and processes (e.g., concentration of immigrants, residential instability, neighborhood disorder and crime, collective efficacy, social ties, and cultural norms) and IPV is either less conclusive or mixed (29, 30). Differences in sample sizes, modeling techniques, study settings, the definition of a neighborhood, the measurements and proxies used to analyze neighborhood-level factors, and the measurement, type, and severity of IPV may explain why some results are not consistent and are sometimes conflicting (29, 30).

This is still a relatively new area of study, and clearly more research is needed to build a more consistent evidence base. For example, it is surprising that despite the growing body of research examining neighborhood influences on IPV, there has been practically no use of spatial analysis techniques and disease mapping methods to analyze spatial patterns in IPV risk and their associations with neighborhood-level explanatory variables. However, a spatial epidemiologic approach seems especially appropriate for the study of neighborhood influences on area variations in IPV risk (28). Because neighborhood risk factors are usually clustered in space, spatial epidemiologic methods allow a more detailed examination of their influence on geographical variations in IPV risk. The analysis of spatial patterns of IPV risk with Bayesian spatial models is particularly suitable for small-area data analysis, as it allows us to incorporate geographical information and map the spatial components that reflect area variations in risk (31–33). Important issues that arise when using small-area counts, such as spatial autocorrelation, overdispersion, and the small-numbers problem, can also be addressed with this approach. Another advantage is that it takes into account unobserved spatially structured influences on risk variations (34–39).

We are aware of only 2 instances of the use of this approach to study neighborhood-level influences on IPV risk. One study was conducted in the United States and showed associations between the density of alcohol outlets (liquor stores, etc.) and IPV (26). The other, an exploratory analysis conducted in Europe, found that IPV cases were more likely to be found in areas with higher levels of immigrant concentration, disorder, and crime (28). However, that study was limited by the small number of neighborhood units (only 1 area of the city was explored), the small size of the IPVcase sample, and the definitions of covariates used to capture some relevant neighborhood-level factors such as economic disadvantage.

In this study, we aimed to add to this growing body of literature by using spatial data on IPV cases and a Bayesian random-effectsmodeling approach to analyze the influence of neighborhood-level characteristics on small-area variations in IPV risk. Drawing from social disorganization theory, we analyzed whether any of 3 types of contextual influences explained spatial patterns in IPV risk: concentrated disadvantage, concentration of immigrants, and residential instability. Because concentrated disadvantage has been measured in a variety of ways in the literature (29), we included multiple neighborhood-level indicators, both compositional and structural, to capture the construct (i.e., education, economic status, female-headed families with children, vacant lots, physical disorder, and public disorder and crime). To the best of our knowledge, this is the first study that has used a Bayesian random-effects modeling approach to analyze neighborhood influences on the spatial epidemiology of IPV in a European city.

Methods

The study was conducted in the city of Valencia, the third largest city in Spain. We used the census block group, which was the smallest administrative unit available, as a proxy for neighborhood. The city of Valencia is divided into 552 census block groups, with a total population of 736,580 (2013 data (40)). The populations of the census block groups range from 630 to 2,845, with an average of 1,334 residents (40).

All IPV cases in this study had an associated legal protection order. We used all protection orders issued in the city of Valencia between January 2011 and March 2013 (n = 1,623). Protection orders are issued by a court of lawand enforced by the police. Datawere provided by the Valencia Police Department. These IPV cases represent the severe end of the IPV spectrum, as they are issued when the court believes there is an objective risk of harm to the victim. They represent approximately

15% of all reported IPV cases. All protection orders in this study were for male-against-female IPV. To geocode the data, we used the geographical coordinates of the place where the IPV incident leading to the protection order occurred.

Covariates

Data on neighborhood concentrated disadvantage, concentration of immigrants, and residential instability were obtained from 3 different types of sources—the Spanish census, trained raters, and the police department—and corresponded to the year 2013.

Census data. Data on the following variables were provided by the city's Statistics Office for each census block: education, economic status, percentage of female-headed families with children, percentage of vacant lots, percentage of immigrants in the population, and residential instability. Education was measured on a 4-point scale (1 = less than primary education, 2 = primary education, 3 = secondary education, 4 = college education). Economic status was measured with a scale created through factor analysis which included 4 highly correlated economic indicators (cadastral property values, percentage of high-end cars, percentage of financial businesses, and percentage of commercial businesses). Residential instability was measured as the proportion of the population who had moved into or out of each census block group during the previous year (rate per 1,000 inhabitants).

Observed physical disorder. Trained raters assessed the level of observable physical disorder in each census block group. They used a 13-itemscalewith a 5-point response (ranging from 0 for not present to 4 for highly present) that included items such as trash in the street, graffiti, vacant or abandoned houses, and vandalized and run-down buildings (28). Observations were made during business hours ($\alpha = 0.70$).

Policing activity. Senior police officers provided an index of policing activity, indicative of the level of public disorder and crime in each census block. This policing activity index was based on police officers' perceptions and experience (no recorded objective information was available) and included interventions in violent and drug-related crimes, public drunkenness and fights, vandalism, homeless people, truancy, and other forms of public disorder. The index was based on a 5-item scale with a 5-point response (0 = very low, 4 = very high).

Descriptive statistics for all variables are shown in Table 1. The spatial distribution of all covariates is reported in Web Figure 1, available at http://aje.oxfordjournals.org/.

Table 1. Distributions of Neighborhood Sociodemographic Variables Evaluated for a Relationship with Intimate Partner Violence at the Census Block Group Level, Valencia, Spain, 2011–2013

Variable	**Distribution**		
	Minimum	**Mean (SD)**	**Maximum**
Education[a] (possible range: 1–4)	2.39	3.15 (0.33)	3.86
Property values, €/m^2	111.50	260.10 (74.61)	590.70
High-end cars, %	1.30	5.75 (3.62)	24.80
Commercial businesses, %	7.50	34.03 (9.21)	66.40
Financial businesses, %	0	18.15 (7.77)	43.20
Female-headed families with children, %	1.00	15.75 (8.21)	52.00
Vacant lots, %	0	1.03 (3.11)	63.71
Physical disorder[b] (possible range: 0–52)	0	10.22 (5.79)	30
Policing activity[c] (possible range: 0–20)	0	7.16 (3.99)	19
Immigrant concentration, %	1.90	13.45 (6.53)	40.20
Residential instability[d], rate/1,000 inhabitants	91.10	268.00 (87.98)	649.80
IPV incidence rate, cases/1,000 inhabitants	0	4.96 (3.84)	25.07

Abbreviations: IPV, intimate partner violence; SD, standard deviation.
[a] 1 = less than primary school, 2 = primary school, 3 = secondary school, 4 = college or more.
[b] Score on a 13-item scale with a 5-point response. Higher scores indicate greater physical disorder.
[c] Policing activity index based on a 5-item scale with a 5-point response. Higher scores indicate more policing activity.
[d] Proportion of the population who had moved into or out of each census block group during the previous year.

Statistical analysis

The dependent variable was number of IPV cases for the 552 census block groups. Therefore, we assumed that the data were conditionally independent Poisson (Po) random variables:

$$y_i|\eta_i \sim Po(E_i \exp(\eta_i)), \quad i = 1, \dots, 552$$

where E_i is a quantity which accounts for the expected number of IPV cases (calculated in proportion to the female population aged ≥16 years) in census block group i and η_i is the log relative risk. The model for η_i takes the form

$$\eta_i = \mu + X_i\beta + S_i + U_i$$

where μ is the intercept, β is the regression coefficients vector, X represents the matrix of covariates, S is a spatially structured term, and U is the unstructured term, both (S and U) accounting for nonobserved variability.

In a Bayesian approach, all parameters are considered random variables and must be supplemented with appropriate prior assumptions via prior distributions. We assigned vague Gaussian distributions for the fixed effects β and an improper uniform distribution for μ. The unstructured spatial effect U was modeled by means of independent identically distributed Gaussian random variables $N(0, \sigma_U^2)$, and for the structured spatial effect S we considered a conditional spatial autoregressive model (41), which reflects spatial neighborhood relationships. This model is defined as

$$S_i|S_{-i} \sim N(\frac{1}{n_i}\sum\nolimits_{j\sim i} S_j, \frac{\sigma_S^2}{n_i})$$

where n_i is the number of neighboring areas of census block group i, S_{-i} indicates the values of the S vector except for the i th component, the expression $j\sim i$ denotes all units j that are neighbors of census block group i, and σ_S is the standard deviation parameter.

Following the structure of the hierarchical Bayesian models, it was necessary to assign prior distributions (or hyperpriors) to the hyperparameters σ_U and σ_S. Specifically, we considered as prior distributions of standard deviations a uniform distribution: $\sigma_S, \sigma_U \sim U(0,1)$.

Inference with this method is fully Bayesian and was performed using Markov chain Monte Carlo simulation techniques with WinBUGS software (MRC Biostatistics Unit, Cambridge Institute of Public Health, Cambridge, United Kingdom). A total of 100,000 iterations were generated, and the first 10,000 were discarded as the Markov chain Monte Carlo burn-in period.

Convergence was inspected by visually examining the plots of the samples for each chain and also using the convergence diagnostic $\hat{R}$ (R Foundation for Statistical Computing, Vienna, Austria) (42), which was near 1.0 for all parameters. Finally, as a measure of model fit and identification of the final model, we used the Deviance

Information Criterion (DIC) (43). Models with smaller DICs are considered better-fitting.

Results

Different Bayesian Poisson regression models were examined. In a first step, a model without random variables was fitted (DIC = 2,156.4) and then both unstructured (*U*) and structured spatial (*S*) effects were introduced. Table 2 summarizes the results derived from 2 Bayesian regression models (both were specified with the *U* + *S* components).

Model 1 included all covariates, the unstructured heterogeneity, and the spatial effect. The DIC value obtained was 2,137.6, which improved on the DIC of the initial model (2,156.4). Variables with a less-than-80% posterior probability of being different from zero (single female-headed families and residential instability) were discarded.

Model 2 was specified with both random effects and variables that were considered relevant in model 1 (the Supplementary Data shows the WinBUGS code for the final model). When the models' DICs were compared, model 2 (DIC = 2,135.2) showed a small improvement in fit. Thus, model 2 was chosen as the final model, following the DIC criteria. As Table 2 shows, model 2 included neighborhood education and economic status, physical disorder, percentage of vacant lots, policing activity, and concentrated immigration as relevant explanatory variables (Supplementary Data shows posterior probabilities). Results indicated that the risk of IPV was higher in areas with lower educational and economic status, greater physical disorder, a higher percentage of vacant lots, higher levels of policing activity (which indicates public disorder and crime), and a higher percentage of immigrants. These results can be interpreted in terms of odds ratios (e.g., a 10% increase in immigrant concentration increases the relative risk of IPV by 65%).

By estimating a structured random effect and an unstructured random effect, we aimed to assess separately the influences of spatial dependency and independent heterogeneity in the data. Figure 1 (which depicts the posterior mean of the spatial random effect) shows a clear north-south gradient. This suggests a spatial effect that can increase or reduce IPV risk by up to 10%. In the southern part of the city, for example, there was a higher relative risk of IPV.

Table 2. Results from spatial Bayesian Poisson regression models of the risk of intimate partner violence, Valencia, Spain, 2011–2013

	Model 1		Model 2	
	PM (SD)	**95% CrI**	**PM (SD)**	**95% CrI**
Intercept	0.460 (0.570)	−0.641, 1.648	0.547 (0.582)	−0.569, 1.684
Education[a]	−0.398 (0.172)	−0.746, −0.077	−0.401 (0.179)	−0.757, −0.062
Economic status[b]	−0.089 (0.065)	−0.218, 0.036	−0.085 (0.068)	−0.217, 0.053
Female-headed families with children, %	0.002 (0.003)	−0.004, 0.009		
Vacant lots, %	0.010 (0.008)	−0.008, 0.026	0.010 (0.008)	−0.007, 0.025
Physical disorder[c] (possible range: 0–52)	0.007 (0.005)	−0.003, 0.016	0.006 (0.005)	−0.004, 0.016
Policing activity[d] (possible range: 0–20)	0.013 (0.008)	−0.004, 0.029	0.013 (0.009)	−0.004, 0.029
Immigrant concentration, %	0.030 (0.009)	−0.004, 0.046	0.033 (0.005)	0.024, 0.043
Residential instability[e], rate/1,000 inhabitants	0.000 (0.001)	−0.001, 0.002		
σ_S[f]	0.145 (0.081)	0.012, 0.322	0.146 (0.082)	0.008, 0.316
σ_U[g]	0.239 (0.059)	0.096, 0.340	0.237 (0.059)	0.108, 0.335
DIC	2,137.6		2,135.2	

Abbreviations: CrI, credible interval; DIC, Deviance Information Criterion; PM, posterior mean; SD, standard deviation.

[a] 1 = less than primary school, 2 = primary school, 3 = secondary school, 4 = college or more.

[b] Scale created through factor analysis which included 4 highly correlated economic indicators (cadastral property values, percentage of high-end cars, percentage of financial businesses, and percentage of commercial businesses).

[c] Score on a 13-item scale with a 5-point response. Higher scores indicate greater physical disorder.

[d] Policing activity index based on a 5-item scale with a 5-point response. Higher scores indicate more policing activity.

[e] Proportion of the population who had moved into or out of each census block group during the previous year.
[f] Standard deviation spatially structured term.
[g] Standard deviation unstructured term.

Figure 1. Posterior mean values for the spatial component (census block group) of the relative risk of intimate partner violence, Valencia, Spain, 2011–2013.

Figure 2 maps the relative IPV risk in each census block group. The risk values were calculated from equation 1 as exp (η_i), where the impacts of both random effects and the explanatory variables are included. By mapping these values, one can visualize where the excess risk among observations lies. Risks greater than 1 indicate an above-average probability. For example, Figure 2 shows some census block groups with relative risks exceeding 1.5, indicating an increase in risk of over 50%. In some areas, this relative increase reaches 100%.

Figure 2. Relative risk of intimate partner violence by census block group, Valencia, Spain, 2011–2013.

Discussion

In this study, we used a spatial epidemiologic approach to analyze the influence of neighborhood-level characteristics on small-area variations in IPV risk in Valencia, Spain. Results showed that IPV risk was spatially patterned (i.e., it was not randomly distributed across the city's areas) and that neighborhood-level characteristics matter in explaining spatial variations in IPV risk. The use of Bayesian spatial modeling to explore this link is a relevant addition to a compelling evidence base documenting neighborhood influences on a wide variety of outcomes, including health and crime (8, 32, 38, 39, 44–48). More importantly, this methodological approach, seldom used in the ecological study of IPV, adds further evidence to the more recent body of research documenting neighborhood influences on IPV (10–30), illustrating that neighborhood influences also extend to a crime that tends to occur "behind closed doors" (25).

The picture that emerges from our study is that IPV risk is particularly high in neighborhoods that are physically disordered and have low educational and economic status levels, a high percentage of vacant lots (also an indicator of physical disorder and decay in neighborhoods (49, 50)), high levels of public disorder and crime (as indicated by high policing activity), and high concentrations of immigrants. When we mapped area-specific levels of excess risk, these variables explained substantial spatial variations in IPV risk, identifying some areas with a relative risk 100% above the average. From these results, concentrated disadvantage and immigrant concentration emerge as significant ecological risk factors explaining IPV, illustrating how the unequal spatial distribution of these neighborhood characteristics is linked with the unequal spatial distribution of IPV risk.

Our study used a variety of indicators to reflect concentrated disadvantage, and our results support a possible effect not only of neighborhood socioeconomic indicators (education and economic status)—in line with other studies (29, 30)—but also of other neighborhood characteristics indicative of neighborhood disadvantage that in those studies showed less conclusive evidence of an influence on IPV. Thus, high levels of both physical (high percentage of vacant lots, observed disorder) and social (public disorder and crime) neighborhood disorder are clear influences on increased IPV risk. Interestingly, these results are in line with those of other studies linking perceived neighborhood disorder to residents' willingness to intervene on behalf of victims of frequently hidden violence (such as IPV and child maltreatment) (19, 51), suggesting that neighborhood disorder and crime are associated with reduced levels of informal social control that may increase rates of violence, including IPV.

Our results regarding immigrant concentration, however, are not in line with those of other studies, which found either no association or a negative one (29, 30). In our study, concentration of immigrants was a clear predictor of higher IPV risk and did not support the so-called "immigrant paradox," according to which immigrant concentration may protect against IPV (contrary to traditional social disorganization expectations). Although the available body of research on this issue is still small, most studies have used US samples, and some cultural factors may be involved in explaining these differences (21, 28). Official records and surveys show that the prevalence of IPV in Spain is disproportionally higher among immigrants (52–54). Of all officially reported IPV cases in Spain, one-third pertain to immigrants, despite this group's accounting for only 10% of the total population (52). Risk of death from IPV is also higher among immigrant women (55). The main countries immigrants in Valencia come from are South American countries (34.3%) and European Union countries (34%) (40). Some research suggests attitudes of greater acceptability and tolerance of IPV among Latin-American immigrants as compared with the Spanish population, which may explain a greater incidence in this group (21, 56); however, prevalences of IPV among immigrants in Spain appear to be similar regardless of their country of origin (57). Thus, it is not surprising that in our study IPV risk was higher in neighborhoods with high immigrant concentrations, especially when other risk factors were present at the neighborhood level. Spanish cultural influences might also be relevant to explaining why the "immigrant paradox" may not apply in Spain, since the prevalence of IPV among the Spanish population is the lowest in the European Union (2, 58). Clearly, this is an issue that deserves further cross-cultural research.

With regard to other covariates explored in this study, residential instability did not make a clear contribution to the model, which is in line with available research that also provides inconclusive evidence (29). Although the presence of female-headed families with children has been an indicator of neighborhood socioeconomic disadvantage linked to IPV in a number of studies, in our research this variable was not clearly associated with IPV risk. Again, cultural differences may be involved. Notwithstanding the need for further cross-cultural research, our results suggest that the link between neighborhood and IPV observed in US cities (where most of this type of research has been conducted) also matters in the context of a European city, despite differences in urban structures and culture (59, 60).

Several processes may help to explain why neighborhood concentrated disadvantage and immigrant concentration create a “risk environment” for IPV (29, 30). Reduced collective efficacy and social ties among neighbors may diminish informal social control in IPV cases. Social isolation from mainstream values (such as those disapproving of IPV) may also lead to the emergence in these neighborhoods of social and cultural norms that create a climate of tolerance for and acceptance of violence, including IPV (12, 13, 61–64). Furthermore, these neighborhood conditions may be highly stressful, and they can substantially reduce quality of life and trigger violence among partners (25, 29, 30, 65–67). Unfortunately, the nature of our data did not allow us to test hypotheses regarding these processes.

This study also revealed spatially structured remaining variability in IPV risk that was not explained by our covariates. Although this variability was not particularly large (up to 10% increased or reduced risk), it does suggest that future research should take into account other variables that might explain this geographical pattern. One possibility is that unmeasured neighborhood processes, like neighborhood social norms regarding IPV, may explain this pattern (24, 68). For example, we hypothesize that the presence of 2 universities in the northern part of the city, with a large population of students renting apartments in the area, might have an influence, since they may hold different social norms regarding IPV.

Taken together, the influences of both the explanatory variables and the spatially structured random effects point to areas of excess IPV risk deserving of special attention. Our results suggest that addressing neighborhood-level risk factors is an important avenue for better-targeted intervention and prevention strategies designed to reduce the high incidence of IPV in our communities.

This study had both strengths and limitations. Among its strengths was the fact that this was the first study to have data from all neighborhood units of a European city. It was also conducted with high spatial resolution using census block groups, which is more appropriate for addressing limitations such as the small-numbers problem and can reduce ecological bias due to aggregation effects. The use of a

Bayesian random-effects modeling approach was also a major advance for addressing issues such as overdispersion, spatial autocorrelation, and unobserved spatially structured influences on risk (31–39). In addition, we integrated information of different natures (compositional and structural) and from different sources (census data, trained raters, and police).

The type of IPV we examined adds to the existing body of literature analyzing other types of IPV data. However, it also represents a limitation, since our results applied only to the severe end of the IPV spectrum, and we cannot be sure whether they would also apply to other types of IPV, such as less severe cases, self-reported IPV, police calls, or what has been termed “common couple violence” (69). Moreover, no cases of female-to-male or same-sex IPV were available, and thus we cannot generalize our results to those types of IPV (22, 70). Regarding the covariates, we did not have access to other socioeconomic indicators that are often used in this type of research (e.g., income, people living below the poverty line, or rates of unemployment), the above-mentioned neighborhood processes (e.g., collective efficacy, social ties among neighbors, social isolation from mainstream values, neighborhood social norms), or variables that have been previously linked to IPV, such as density of alcohol outlets (26, 71–73). Finally, the modifiable areal unit problem is always an issue in spatial analysis, since other areas of aggregation could have been used. However, we are confident that using census block groups substantially reduced this potential bias.

Future research should address rural-urban differences in the spatial epidemiology of IPV. It would also benefit from studies including the temporal dimension in the analysis of small-area variations in IPV, which would further our understanding of risk factors and trends resulting from planned or unplanned neighborhood changes (e.g., neighborhood-level intervention strategies).

In conclusion, in this study of a European city, neighborhood concentrated disadvantage and immigrant concentration emerged as significant ecological risk factors explaining IPV. Addressing neighborhood-level risk factors should be considered for better targeting of IPV prevention.

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2. Mapping child maltreatment risk: a 12-year spatio-temporal analysis of neighborhood influences

Mapping child maltreatment risk: a 12-year spatio-temporal analysis of neighborhood influences[9]

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Abstract

Background

'Place' matters in understanding prevalence variations and inequalities in child maltreatment risk. However, most studies examining ecological variations in child maltreatment risk fail to take into account the implications of the spatial and temporal dimensions of neighborhoods. In this study, we conduct a high-resolution small-area study to analyze the influence of neighborhood characteristics on the spatio-temporal epidemiology of child maltreatment risk.

Methods

We conducted a 12-year (2004–2015) small-area Bayesian spatio-temporal epidemiological study with all families with child maltreatment protection measures in the city of Valencia, Spain. As neighborhood units, we used 552 census block groups. Cases were geocoded using the family address. Neighborhood-level characteristics analyzed included three indicators of neighborhood disadvantage—neighborhood economic status, neighborhood education level, and levels of policing activity—, immigrant concentration, and residential instability. Bayesian spatio-temporal modelling and disease mapping methods were used to provide area-specific risk estimations.

Results

Results from a spatio-temporal autoregressive model showed that neighborhoods with low levels of economic and educational status, with high levels of policing activity, and high immigrant concentration had higher levels of substantiated child maltreatment

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risk. Disease mapping methods were used to analyze areas of excess risk. Results showed chronic spatial patterns of high child maltreatment risk during the years analyzed, as well as stability over time in areas of low risk. Areas with increased or decreased child maltreatment risk over the years were also observed.

Conclusions

A spatio-temporal epidemiological approach to study the geographical patterns, trends over time, and the contextual determinants of child maltreatment risk can provide a useful method to inform policy and action. This method can offer a more accurate description of the problem, and help to inform more localized prevention and intervention strategies. This new approach can also contribute to an improved epidemiological surveillance system to detect ecological variations in risk, and to assess the effectiveness of the initiatives to reduce this risk.

Keywords: Child maltreatment, Neighborhood influences, Bayesian spatio-temporal modeling, Disease mapping, Spatial inequality, Small-area study, Area-specific risk estimation

Introduction

Child maltreatment is a major social, public health, and human rights problem, with severe, far-reaching, and long-lasting consequences. Its impact on victims' physical, mental, and reproductive health, behavioral problems, or education attainment; its role in the intergenerational transmission of violence; and its elevated costs for the criminal, health, and social welfare systems, poses a high burden on society [1-4]. Child maltreatment is a global phenomenon, and its prevalence in high-income countries remains high and is considered a leading cause of health inequality and social injustice [4-7]. From a public health perspective, child maltreatment is, however, a preventable problem as potentially risk-modifying factors can be identified and targeted in preventive interventions.

Child maltreatment research has typically focused on individual or family risk factors, but 'place' also matters in understanding prevalence variations and inequalities in child maltreatment risk [8-12]. A growing body of research is increasingly recognizing the importance of the context in which families live, linking neighborhood characteristics and processes—such as poverty, disorder and crime, immigrant concentration, social impoverishment, or diminished social control—to child maltreatment [13-32]. However, studying neighborhood influences on child maltreatment presents important challenges, and there are still some shortcomings in the available literature, which we address in the present study.

Child maltreatment and neighborhood risk factors are not equally distributed spatially, and it is to some extent surprising that the use of spatial analysis techniques and disease mapping methods to analyze geographical patterns of child maltreatment risk, and whether these patterns are associated with neighborhood-level explanatory variables, has been almost non-existing. In this regard, and despite the substantial body of research showing an association between neighborhood characteristics and child maltreatment, most studies examining neighborhood influences fail to take into account the implications of the spatial dynamics of neighborhoods. For example, important issues such as the similarity and influence between neighboring areas, are not appropriately addressed in most studies analyzing neighborhood influences on child maltreatment [10, 11, 25]. Neighborhood risk factors that have been associated with child maltreatment are usually clustered in space, and therefore a spatial analytical approach is particularly appropriate for the study of their influences on the spatial variations of child maltreatment. Furthermore, when analyzing neighborhood influences on ecological variations in child maltreatment risk, the temporal dimension must also be taken into account. Neighborhoods characteristics may change over time and, therefore, their influence on child maltreatment risk can also change over time [10]. In this regard, adding the temporal dimension is a key in identifying and tracking trends in child maltreatment risk—for example, stable high or low risk areas, or areas of increasing or decreasing risk over time. Finally, most studies exploring neighborhood influences on child maltreatment do not provide small-area-specific risk estimations, which limits their relevance to inform more localized intervention and prevention strategies. A new generation of ecological studies needs to take into account the spatial and temporal dimensions to better understand small-area variations in child maltreatment risk.

Bayesian spatio-temporal modeling provides an adequate methodological framework to overcome the above limitations in studying neighborhood influences on child maltreatment risk variations. This analytical approach, allows to incorporate geographical and temporal information to provide more reliable area-specific risk estimates than other non-Bayesian methods, by addressing important methodological issues such as modeling small area counts, spatial auto-correlation, or overdispersion, that can bias estimates if ignored [33- 39]. Although Bayesian spatio-temporal disease mapping is common in other public health and epidemiological areas, this approach is relatively new in the area of family violence [40-44]. So far, only a handful of studies conducted in the US have addressed the spatial and temporal dimensions to study neighborhood influences on child maltreatment with appropriate methodologies [40, 42, 44]. However, these studies are usually low-resolution ones, using larger geographical areas, such as counties, zip codes, or census track, which somehow limits their potential to inform more localized interventions. On the other hand, high-resolution studies using small-area geographical units offer a finer neighborhood characterization, and provide specific risk estimations for small areas, which increases their potential to inform highly localized policies targeting high-risk areas [36, 38, 39].

Based on a social disorganization theoretical framework [43, 45-48] in this study we analyze the influence of a set of neighborhood characteristics on local patterns of substantiated child maltreatment over a 12-year period at the small-area level. Neighborhood-level characteristics analyzed include three indicators of neighborhood concentrated disadvantage—neighborhood economic status, neighborhood education level, and levels of policing activity—, immigrant concentration, and residential instability. As far as we are aware, the present study is the first to conduct a high-resolution small-area study on the spatio-temporal epidemiology of child maltreatment risk using Bayesian spatio-temporal modeling and disease mapping methods. Our study is conducted in a European city which also provides a ground for comparison to US cities where most of the research on neighborhood influences on child maltreatment has been conducted.

Methods

Variables

The study was conducted in the city of Valencia, the third largest city of Spain with a population of 736,580. As neighborhood proxies, we used the 552 census block groups into which the city is divided. This was the minimum administrative unit available, with an average of 1334 residents, and ranging from 630 to 2845. To capture temporal trends, data for 12 years were used, from 2004 to 2015. Data for cases of substantiated child maltreatment were provided by Valencia Child Protection Services. Covariates for each census block group were provided by the Valencia Statistics Office and the Valencia Police Department.

Outcome variable

Number of families with child maltreatment protection measures. Data of all families with child protection measures from 2004 to 2015 were collected—no computerized and systematized data were available before 2004. The data we used correspond to all official cases of substantiated child maltreatment in the city of Valencia during the period of the study, to which a child protection measure is associated after the maltreatment and the risk for the child is established. Child maltreatment refer to any type of child maltreatment, including physical, psychological, or sexual abuse, as well as neglect. Perpetrators were parents or legal tutors–child abuse by other parties, such as non-related adults, are dealt by other agencies and are not considered in this study. The data provided by the Child Protection Services did not allow to distinguish between child maltreatment types or perpetrators. Protection measures are issued by the Child Protection Services for all substantiated cases of child maltreatment, and may include a range of measures such as home visiting, family support programs, family or residential foster care, or adoption. Data for this study were 1799 families with child maltreatment protection measures. To avoid data dependency, cases were ‘unique’ families, meaning that a family was only included the first time they received a child maltreatment protection measure. Data were geocoded using the family address, and we counted the cases in each census block group for each of the 12 years in the study period.

Covariates

Neighborhood concentrated disadvantage. Economic status: Neighborhood economic status was measured using the average cadastral property value. This value is set by the City Hall and is used to establish local taxes. *Education level*: The average education level of neighborhood residents in each census block group was measured on a 4-point scale, where 1 = less than primary education, 2 = primary education, 3 = secondary education, 4 = college education. *Policing activity*: An indirect measure of public disorder and crime was measured through police officers’ assessments of their policing activity. Senior police officers provided an index of policing activity that included interventions in drug-related crime, public disorder such as drunkenness and fights, vandalism, homeless people and truancy. The index was structured as a 5-item scale, and each item ranged from 0—very low level of interventions—to 4—very high level of interventions. This measure of policing activity has been associated in previous studies with other types of family violence such as intimate partner violence [43], as well as with a number of neighborhood-level characteristics, such as neighborhood disorder, low socioeconomic status, and high immigrant concentration [49, 50]. Cronbach’s alpha was .74.

Immigrant concentration: Using census data, immigrant concentration was measured as the percentage of immigrant population in each census block group.

Residential instability: An index of residential mobility, based on census data, was used as the proportion—rate per 1000 inhabitants—of the population who had moved into or out of each census block group during the previous year—for example, residential instability for 2015 captures all population movements occurred in 2014.

Statistical analysis

The outcome variable was the number of families with child maltreatment protection measures, corresponding to all substantiated cases of child maltreatment in the city during the period of the study. We use, therefore, a conditionally independent Poisson distribution based on the count of families in each census block group in the 12 years of the study:

$$y_{it}|\eta_{it} \sim Po(E_{it}\exp(\eta_{it})), \qquad i = 1, \ldots, 552, \qquad t = 1, \ldots, 12$$

where E_{it} is a fixed quantity that accounts for the expected number of families with child maltreatment protection measures, in proportion to the total number of families, in census block group ii in year *t*; ηitηit is the log-relative risk for every area and year.

We used different models for ηitηit with an increasing level of complexity, from a Poisson regression model to a spatio-temporal autoregressive model. First, model 1 only included all covariates—that is, economic status, education level, policing activity, residential instability, and immigrant concentration.

$$\eta_{it} = \mu + X_{it}\beta$$

where μ is the intercept, X_{it} is the vector of covariates, and β is a vector of regression coefficients.

Model 2 was specified as a spatial model; it included all covariates and added unstructured and structured random effects. The unstructured random effect accounted for spatial heterogeneity or overdispersion, while the structured random effect accounted for the spatial effect:

$$\eta_{it} = \mu + X_i\beta + \phi_i + \theta_i$$

where ϕ_i represents the spatially structured term, and θ_i the spatially unstructured term.

Model 3 included the previous terms and incorporated an unstructured temporal effect:

$$\eta_{it} = \mu + X_i\beta + \phi_i + \theta_i + \alpha_t$$

where α_t accounts for the temporal heterogeneity. This model, however, does not account for past cases of child maltreatment —that is, temporal dependency.

Finally, model 4 included a spatio-temporal effect. To this end, we followed an autoregressive approach [51], combining autoregressive time series and spatial modeling. We defined a spatio-temporal structure in which the relative risks are both spatially and temporally dependent.

$$\eta_{i1} = \mu + X_i\beta + \alpha_1 + (1-\rho^2)^{-1/2} \cdot (\phi_{i1} + \theta_{i1})$$

$$\eta_{it} = \mu + \alpha_t + X_i\beta + \rho\big(\eta_{i(t-1)} - \mu - \alpha_{t-1}\big) + \phi_{it} + \theta_{it})$$

The first equation defines the log-relative risk for the first year observed (2004) and the second equation defines the log-relative risk for the following years. In both, α_t is the mean deviation of the risk in the year *t*, ρ represents the temporal correlation between years, and ϕit and θit refer to structured and unstructured spatial random effects, respectively.

Models were specified following a Bayesian approach. Therefore, we assigned appropriate prior distributions for all parameters. We assigned vague Gaussian distributions for the fixed effects β; μ was specified as an improper uniform distribution; unstructured effects were modeled as a normal distribution $N(0, \sigma^2)$,)in the different models (θ and α). Structured effects (ϕ) were specified by a conditional spatial autoregressive (CAR) model [52] defined as follows:

$$\phi_i|\phi_{-i} \sim N(\frac{1}{n_i}\sum_{j\sim i}\phi_j, \frac{\sigma_\phi^2}{n_i})$$

where n_i is the number of neighboring areas of each census block group *i*, ϕ_{-i} represents the values of the ϕ vector except the component *i*, σ_ϕ is the standard deviation parameter, and $j \sim i$ indicates all units *j* that are neighboring areas of census block group *i*. Finally, and following the structure of the hierarchical Bayesian models, hyperparameters σ were specified by uniform distributions $U(0,1)$ in the models.

Bayesian estimations were performed using Markov Chain Monte Carlo simulation techniques with the software R and the WinBUGS package. 100,000 iterations were generated, discarding the first 10,000 as a burn-in period. Models were compared by the Deviance Information Criterion (DIC) [53]. This measure of fit assumes that models with smaller DIC should be preferred to models with larger DIC. Following this criterion, the model with smaller DIC was chosen. Differences in DIC between 5 and 10 are considered substantial; whereas differences of more than 10 units clearly indicate that the model with the higher DIC should be ruled out.

To ensure robustness of the results, we checked convergence with the convergence diagnosis $\widehat{R}$ [54] which was near to 1.0 for all parameters. A sensitivity analysis was also performed on prior distributions of hyperparameters, with consistent results.

Results

Table 1 summarizes the descriptive statistics of the variables in the study. The neighborhood-level economic status, based on the average cadastral property value, had a mean of 26,320 € [standard deviation (SD) = 13,046], with wide variation across neighborhoods, ranging from 7943€ to 98,560€. The average neighborhood education level, corresponded to secondary education (Mean = 3; SD = .33). Policing activity had a mean of 7.16 (SD = 3.99), again with wide variations across neighborhoods ranging from 0 to 19. The mean of neighborhood residential instability was 200 (SD = 65.96) meaning that, in average, 200 people moved into or out of a census block group in a specific year. Neighborhood immigrant concentration had a mean of 13.3%, ranging from just 1 to 51%, which means that in some neighborhoods over half of the population were immigrant. Finally, the outcome variable, families with child protection measures, ranged from 0 cases of substantiated child maltreatment in some neighborhoods to a maximum of 7 families per census block group in a single year with child protection measures after child maltreatment was substantiated.

Table 1. Variables (mean, standard deviation, minimum and maximum values) at the census block group and year level

Variable	**Mean (SD)**	**Min**	**Max**
Economic status (€)	26,320 (13,046)	7943	98,560
Education level	3.155 (.33)	2.39	3.86
Policing activity	7.16 (3.99)	0	19
Residential instability	200 (65.96)	4.2	771.3
Immigrant concentration (%)	13.28 (6.92)	1.03	51.47
Child protection records	0.26 (.57)	0	7

After conducting the four Bayesian Poisson regression models, we analyzed the DIC values (Table 2). Model 1, which included only the covariates, showed the worst fit (DIC = 8517.9). Once we introduced both structured and unstructured spatial random effects in model 2, the DIC decreased significantly (DIC = 8164.9). In model 3, which included an unstructured temporal effect, the DIC slightly increased to 8166.8. Finally, model 4, an autoregressive model, despite being the most complex had the lowest DIC value (8126.1), 38 units lower than model 2, and was therefore chosen as the final model. The sign of the covariate estimations (positive or negative) remains invariant in the different models, ensuring the stability of the effects.

Table 2. Results of different spatial and spatio-temporal regression Bayesian models for child maltreatment risk. Posterior mean, standard deviation (SD) and the 95% credible interval (CI) of all parameters

	Model 1 (β)			**Model 2 (β + spatial heterogeneity + spatial effect)**		
	Mean	**SD**	**95% CI**	**Mean**	**SD**	**95% CI**
Intercept	4.055	.289	3.500, 4.615	4.335	.516	3.320, 5.328
Economic status[a]	−.021	.003	−.027, −.015	−.016	.004	−.024, −.009
Education level	−1.261	.091	−1.431, −1.083	−1.464	.161	−1.745, −1.123
Policing activity	.026	.006	.014, .038	.036	.011	.012, .053
Residential instability	.000	.001	−.001, .001	.000	.001	−.001, .001
Immigrant concentration	.003	.005	−.006, .013	.005	.006	−.005, .016
σ_θ				.329	.084	.136, .468
σ_ϕ				.781	.115	.541, .979
σ_α						
ρ						
DIC	8517.9			8164.9		

Table 2. (Cont.)

	Model 3 (β + spatial heterogeneity + spatial effect + temporal heterogeneity)			Model 4 (spatio-temporal autoregressive model)		
	Mean	**SD**	**95% CI**	**Mean**	**SD**	**95% CI**
Intercept	4.284	.520	3.916, 5.304	4.135	.500	3.274, 5.127
Economic status[a]	−.016	.004	−.023, −.009	−.016	.004	−.023, −.008
Education level	−1.418	.164	−1.746, −1.096	−1.391	.157	−1.690, −1.122
Policing activity	.035	.012	.012, .057	.031	.011	.009, .053
Residential instability	.000	.001	−.001, .001	.000	.001	−.001, .001
Immigrant concentration	.005	.005	−.005, .016	.009	.006	−.003, .020
σ_θ	.320	.095	.063, .456	.234	.045	.162, .333
σ_ϕ	.787	.118	.552, .976	.257	.062	.149, .391
σ_α	.023	.019	.001, .070	.021	.019	.001, .070
ρ				.903	.031	.827, .946
DIC	8166.8			8126.1		

SD standard deviation, *CrI* credible interval, *DIC* deviance information criterion
σ_θ standard deviation unstructured term
σ_ϕ standard deviation spatially structured term
σ_α Standard deviation temporally unstructured term
[a]This variable was included as the cadastral value divided by 1000 to solve computational problems with the prior distributions assigned to fixed effects

For model relevance, we consider posterior probability distributions of the regression coefficients (β) of being different from zero. The probability of being positive was higher than 90% for policing activity and immigrant concentration. The probability of being negative was higher than 90% for economic status and education level. These results indicate that the risk of substantiated child maltreatment was particularly high in neighborhoods with low economic status and education level, and with high levels of policing activity and immigrant concentration. Residential instability, however, did not show a relevant association with substantiated child maltreatment.

To know the relative influence of the four neighborhood variables that were relevant for the final model, our results can be interpreted in terms of odds ratios expressed as exp $(\beta\Delta X)$. For example a 10,000€ increase in economic status decreases the relative risk of substantiated child maltreatment by 17%; a 0.1 increase in education level decreases the relative risk by 15%; a 5 unit increase in policing activity increases the relative risk by 17%; finally, a 10% increase in immigrant concentration increases the relative risk by 9%.

Bayesian spatio-temporal modeling allows area-specific risks of substantiated child maltreatment to be mapped and differences analyzed over the years. Figure 1 shows the relative risk for each year of the study. These maps show areas with higher (> 1) or lower (< 1) than average risk. In some areas, the relative risk is more than twice the average, which reflects very high-risk levels of substantiated child maltreatment.

These maps also reveal common patterns over the years, showing areas with higher levels of relative risk at the periphery, especially in the eastern part of the city. The parameter ρ ($\rho = .90$) indicated a high temporal correlation between a particular year and the previous one.

Autoregressive models can be used to represent temporal paths of relative risk in different census block groups, thus identifying areas with stable risks and areas with changes in risk over time. Figure 2 shows the most stable areas. Results showed both chronic spatial patterns of high risk of substantiated child maltreatment during the years analyzed, as well as stability over time in areas of low risk. The most stable low risks are located in the city center, while peripheral areas present more stable high risks. Figure 3 shows areas with increased or decreased substantiated child maltreatment risk over the years.

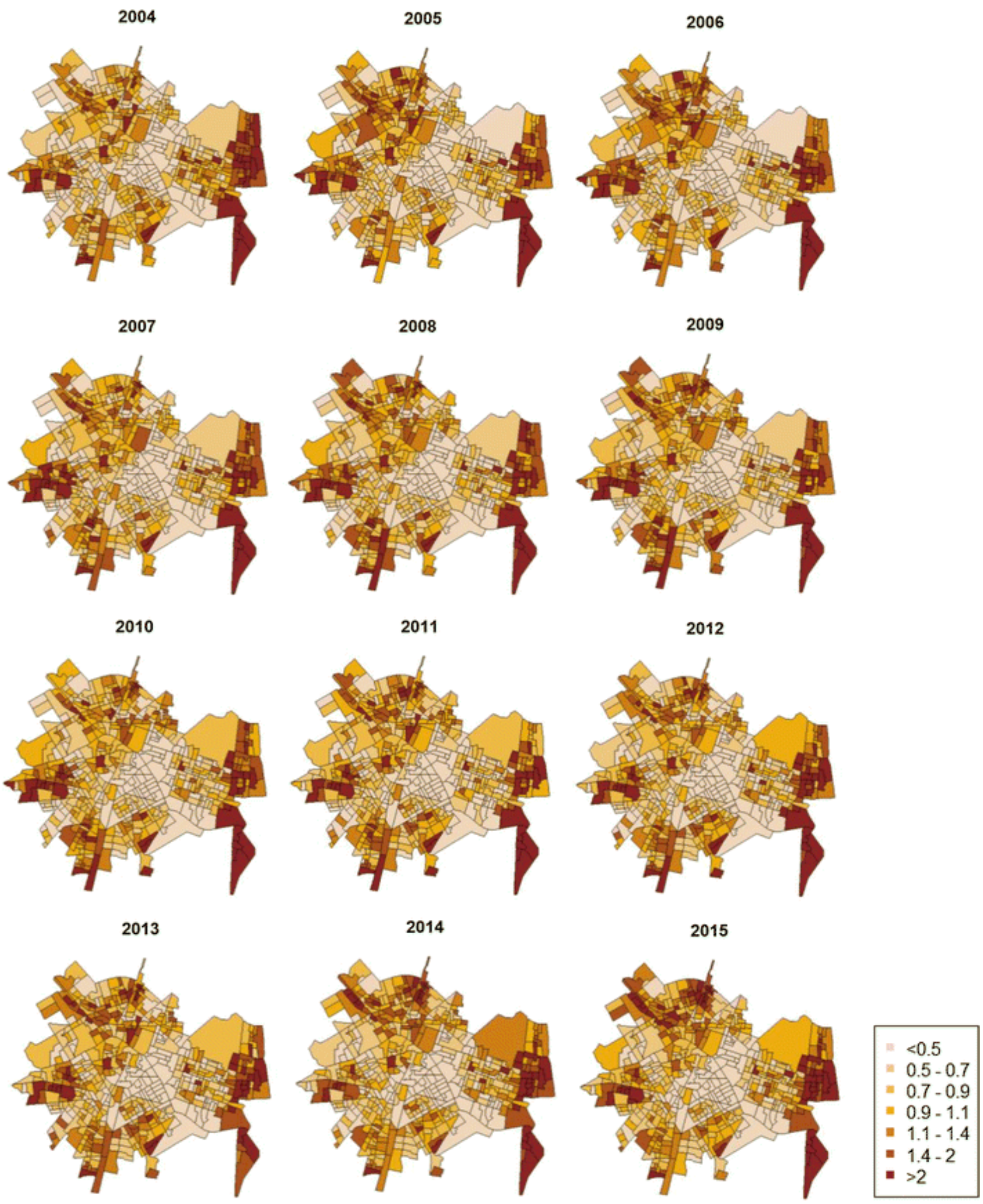

Figure 1. Maps of relative risks of child maltreatment by census block group in each year of study, Valencia, Spain, 2004–2015

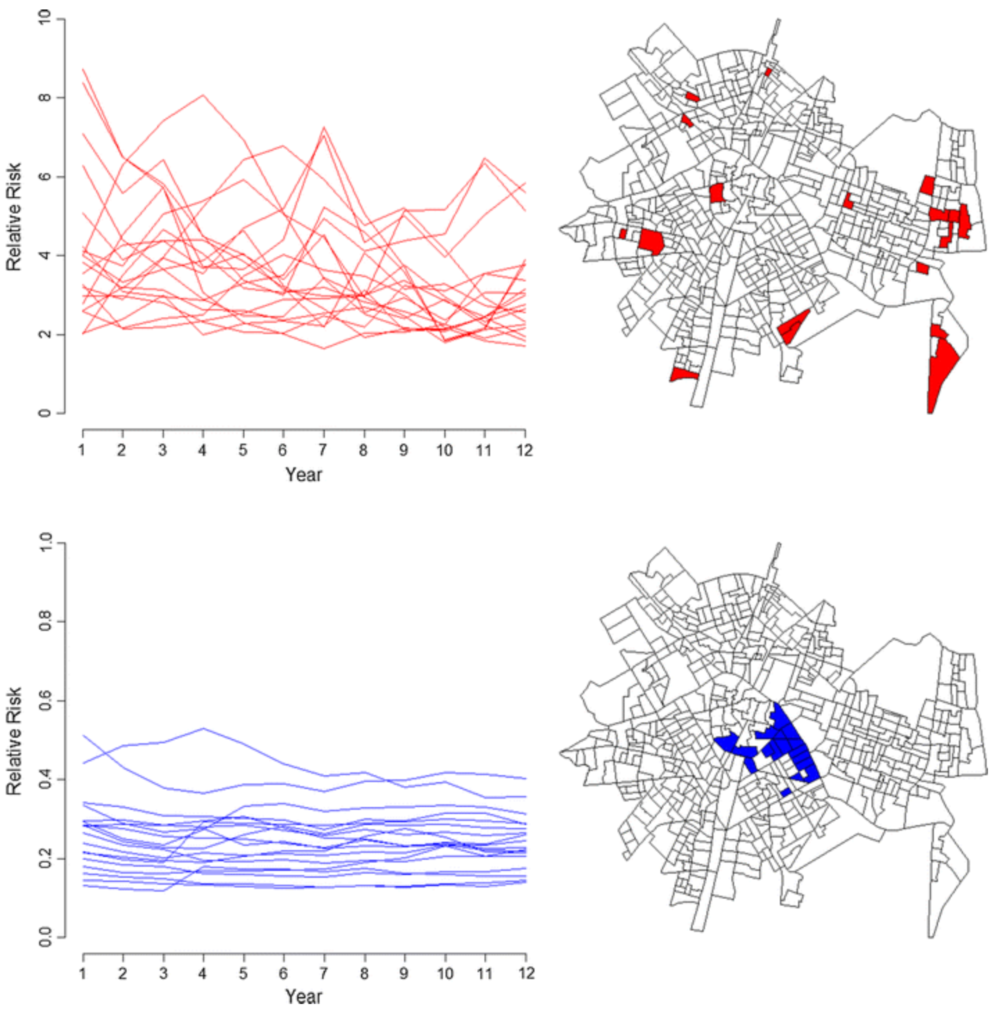

Figure 2. Temporal paths of relative risk in areas with stable high risk (above), and stable low risk (below). Relative risk values greater than 1 indicate higher risk than the city average. Relative risk values lower than 1 indicate lower risk than the city average

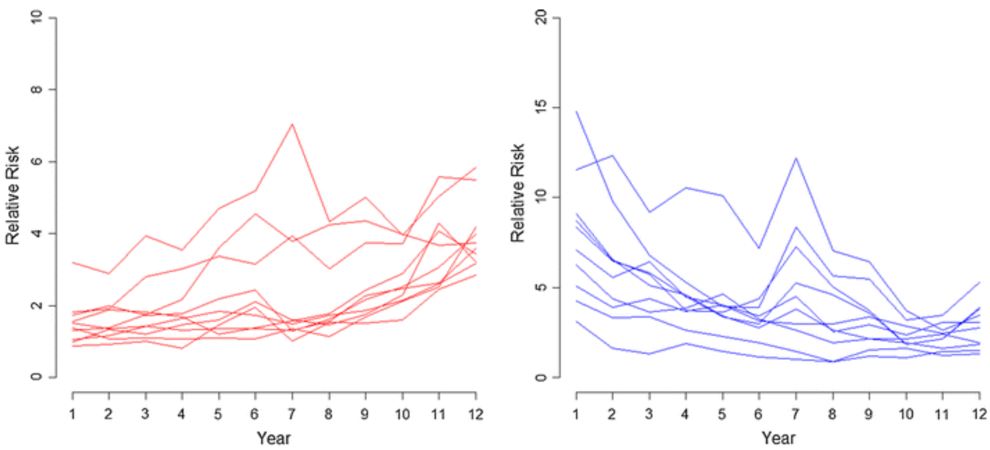

Figure 3. Temporal paths of relative risk in areas with increasing and decreasing child maltreatment risk, respectively

Discussion

This study showed that the neighborhoods where the families live matter in understanding spatial and temporal variations in child maltreatment risk [8-12]. Our results showed that neighborhoods with low levels of economic and educational status, with high levels of policing activity, and high immigrant concentration had higher risk of substantiated child maltreatment. This study illustrates how the unequal distribution of neighborhood risk factors in an urban area is linked to the unequal spatial distribution of substantiated child maltreatment risk in the city. These results support the view that 'place' matters in relation to child maltreatment, as these ecological variations reflect important inequalities in substantiated child maltreatment risk [10-12]. Among the explanatory mechanisms that have been proposed to explain this link are: social impoverishment—that is, lack of trust and support networks in the neighborhood—, and diminished social control; social isolation from mainstream values regarding what is acceptable in parent–child relationships; and high levels of parental stress [8, 10-12, 19, 27].

Previous studies have linked these neighborhoods characteristics—that is, neighborhood socioeconomic disadvantage, disorder and crime, and immigrant concentration—indicative of social disorganization to child maltreatment rates [10, 11, 27, 29]. However, the present study is, as far as we are aware, the first to analyze this link using a high-resolution Bayesian spatio-temporal approach to study the influence of neighborhood characteristics on small-area variations in substantiated child maltreatment risk. Using this approach, we were able to analyze small-area variations in substantiated child maltreatment risk over a 12-year period, which provided the possibility to identify and track risk trends. Our results, in addition, show that 'time' is also a key element to analyze variations in child maltreatment risk. Studies that do not take into account the temporal dimension may misinterpret risk estimations due to data aggregation—for example increasing or decreasing risks in certain neighborhoods would not be detected. In our study, introducing a spatio-temporal autoregressive structure clearly improved the model fit, and provided more reliable area-specific risk estimates. Thus, our results showed chronic spatial patterns of high risk of substantiated child maltreatment during the years analyzed. We found areas where risks were over five-times higher than the city average, and this high risk was stable over the years. Results suggest that in certain city areas substantiated child maltreatment risk can become 'endemic'. On the other hand, risks in other areas were between two and four times lower than the city average, and these lower risks were also stable over the years. In this regard, low-risk city areas could be considered to be providing a more protective social environment for the well-being of children, as opposed to the very high-risk ones—for example, differences in risk between some of the low risk areas and some of the high-risk ones are nearly tenfold. Finally, spatio-temporal analyses allowed us to identify areas where substantiated child maltreatment risk increased or decreased over the years analyzed.

Detecting and tracking these inequalities in substantiated child maltreatment risk is important for better-informed prevention and intervention strategies. One of the advantages of the high-resolution approach used in the present study is that it provides small-area-specific risk estimates pointing to areas of stable excess risk, as well as to areas of increasing or decreasing substantiated child maltreatment risk. Identifying and tracking these risk trends at the small-area level can provide a more useful method to inform policy and action, as compared to other low-resolution approaches—for example, counties or large census tracks. Interventions targeting areas of excess risk of child maltreatment—for example, increasing or chronic high-risk areas—can have an important preventive potential. Neighborhood-level interventions, as opposed to a person-centered approach, can reach a larger number of families, providing a more cost-effective strategy, as not only the individuals are the subject of the intervention, but also the context where these families live [10, 55, 56]. The spatio-temporal epidemiological approach used in this study not only provides a powerful method to map and track variations in risk, but it can also contribute to a surveillance system to assess the effectiveness of intervention and prevention strategies by monitoring changes in risk over time across different city areas [6, 12].

Limitations to our study include the type of data used, namely, only officially reported and substantiated cases of child maltreatment under the supervision of Child Protection Services. Child maltreatment is, however, still largely underreported and underestimated, as many cases do not come to the attention of these services, or are unsubstantiated after reporting [4, 44]. On the other hand, it is important to note that families living in high risk neighborhoods may be more visible to authorities and therefore can be more susceptible to be reported and substantiated, as these residential areas may lead to a higher surveillance by social welfare or law enforcement agencies, as compared to other residential areas [10, 11, 42, 44]. A related issue is the potential problem of neighborhood selection bias, whereby families with higher risk of being investigated by child protection services, either choose or are forced to live in these high-risk neighborhoods [10]. The question here is to which extent the higher risk of substantiated child maltreatment is the result of the influence of neighborhood-level factors or the self-selection of families with certain characteristics in certain neighborhoods. Although this line of criticism tends to give more preeminence to individual-based explanations, than to other higher-order explanations such as neighborhood mechanisms, a substantial body of research supports the link between neighborhood concentrated disadvantage and the spatial inequality in a wide variety of outcomes, including violence, crime, or health. This body of literature led Sampson to conclude that "spatially inscribed social differences, …, constitute a family of neighborhood effects that are pervasive, strong, cross-cutting, and paradoxically stable even as they are changing in manifest form" [55, p. 6].

Regarding the covariates used in our study, the measurement of policing activity could be biased by self-report. However, this measure has adequate psychometric characteristics [49, 50] and previous studies have shown that police perceptions capture their valuable experience, are correlated with police records, and can provide important information to identify high crime areas [50, 57, 58, 59]. Nevertheless, clearly, future studies would benefit from using more objective crime reports. Another limitation in our study is that a number of potentially relevant neighborhood-level measures were not available for a 12-year spatio-temporal analysis. For example, socioeconomic measures such as people living below the poverty line, rates of unemployment, or income, or other covariates tapping potentially relevant neighborhood processes—such as collective efficacy, social networks, neighborhood disorder, neighborhood social norms, or alcohol outlets—, were not available [29, 30, 31, 60-66]. The modifiable areal unit problem is also a potential limitation. We are confident, however, that the high-resolution approach in this study, using the smallest geographical administrative unit available—census block groups are walkable areas with a small number of city blocks—, was particularly adequate to capture neighborhood influences on small-area variations in risk [7].

Regarding the implications for policy and action, the neighborhood conditions linked to substantiated child maltreatment in the present study are risk factors that cluster in space and, therefore, can be targeted in more focused preventive interventions. Although potentially modifiable, some of these factors, such as poor housing, or high levels of crime, or high levels of immigrant concentration are clearly difficult to change. However, other type of focused neighborhood-level interventions can address indirectly these factors. For example, urban planning and environmental approaches such as urban redevelopment and revitalization—for instance, providing new infrastructures, greening vacant lots, improving access to services, or increasing community programs—, have been shown to improve the quality of life of residents, and reduce crime, drug use, and violence in disadvantage communities [67-70].

Finally, this study was conducted in a medium-sized European city. Although similar neighborhood effects in relation to other type of offenses have been observed in European and American cities despite their differences in culture and organization [43, 55, 71, 72], future cross-national research with a similar approach would help to strengthen and generalize our results.

Conclusion

Our 12-year study showed that there are important spatial inequalities in substantiated child maltreatment risk across the city areas and over the years. Our study illustrates that a spatio-temporal epidemiological approach to study the geographical patterns, trends over time, and the contextual determinants of substantiated child maltreatment risk, can provide a useful method that can be of help to better inform policy and action. This methodological approach—that uses data that can be routinely collected—, can offer a more accurate description of the problem, and help to design new local prevention and intervention strategies. A spatio-temporal approach can also contribute to an improved epidemiological surveillance system to detect ecological variations in risk, and to assess the effectiveness of the initiatives to reduce this risk.

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3. Neighborhood characteristics and violence behind closed doors: The spatial overlap of child maltreatment and intimate partner violence

Neighborhood characteristics and violence behind closed doors: The spatial overlap of child maltreatment and intimate partner violence[10]

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Abstract

In this study, we analyze first whether there is a common spatial distribution of child maltreatment (CM) and intimate partner violence (IPV), and second, whether the risks of CM and IPV are influenced by the same neighborhood characteristics, and if these risks spatially overlap. To this end we used geocoded data of CM referrals (N= 588) and IPV incidents (N= 1450) in the city of Valencia (Spain). As neighborhood proxies, we used 552 census block groups. Neighborhood characteristics analyzed at the aggregated level (census block groups) were: Neighborhood concentrated disadvantage (neighborhood economic status, neighborhood education level, and policing activity), immigrant concentration, and residential instability. A Bayesian joint modeling approach was used to examine the spatial distribution of CM and IPV, and a Bayesian random-effects modeling approach was used to analyze the influence of neighborhood-level characteristics on small-area variations of CM and IPV risks. For CM, 98% of the total between-area variation in risk was captured by a shared spatial component, while for IPV the shared component was 77%. The risks of CM and IPV were higher in neighborhoods characterized by lower levels of economic status and education, and higher levels of policing activity, immigrant concentration, and residential instability. The correlation between the log relative risk of CM and IPV was .85. Most census block groups had either low or high risks in both outcomes (with only 10.5% of the areas with mismatched risks). These results show that certain neighborhood characteristics are associated with an increase in the risk of family violence, regardless of whether this violence is against children or against intimate partners. Identifying these high-risk areas can inform a more integrated community-level response to both types of family violence. Future research should consider a community-level approach to address

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both types of family violence, as opposed to individual-level intervention addressing each type of violence separately.

Introduction

Child maltreatment (CM) and intimate partner violence (IPV) are both major social, public health, and human rights problems, highly prevalent globally, and with severe and far-reaching consequences not only for victims but also for the wider society [1-13]. CM and IPV are two forms of family violence (the umbrella concept under which these two types of violence among intimates are often included) with common characteristics and risk factors [14-17]. Both forms of violence are considered risk factors for the other [18-22], and as the high rates of co-occurrence of CM and IPV reported in the literature illustrates, they tend to overlap in the same families [15,16,23-25]. Although existing research has examined the co-occurrence of these two types of violence in the same families, no research has examined whether the risk of CM and IPV also overlap in the same neighborhoods. This is a relevant research question, because if the interconnection of CM and IPV also occurs at the community-level, neighborhood-level interventions targeting high-risk areas would emerge as a cost-effective and integrative public health approach to reduce both types of family violence within the same policy agenda.

CM and IPV have both been considered as types of crime that tend to occur 'behind closed doors' [26,27]. However, and despite the often-hidden nature of these offenses, a substantial body of research supports the idea that, beyond individual and relational factors, 'place' also matters for both CM and IPV. Research based on social disorganization and ecological perspectives points to the importance of community characteristics (e.g., neighborhood concentrated disadvantage) in explaining rates of both CM and IPV [28-32]. As similar neighborhood risk factors have been linked to these two types of family violence, it is likely that they will both tend to occur more often in neighborhoods that are characterized by those risk factors. In this study we hypothesize that the risk of CM and IPV will overlap spatially in the same neighborhoods.

Previous research has showed that CM and IPV, respectively, tend to spatially concentrate in certain city areas [33-39]; however, no studies have yet examined both types of family violence simultaneously, using appropriate spatial techniques to analyze whether the risks of CM and IPV are influenced by the same neighborhood characteristics, and tend to spatially overlap.

Material and Methods

Outcome variables

The study was conducted in the city of Valencia (Spain). Valencia is the third largest city in Spain with a population of 736,580 (2013 data). For this study, census block groups were used as the neighborhood proxy, and were the unit of analysis. Valencia is divided into 552 census block groups (with populations ranging from 630 to 2,845).

Two different outcomes were collected for this study. First, addresses for all IPV cases with an associated protection order issued between 2011 and 2012 were provided by the Valencia Police Department. Protection orders represent severe cases of IPV, as they are issued by a court of law to provide special protection for the victim. In this study, we consider only male-against-female IPV. The number of protection orders in this period was 1,450. Second, addresses for all child maltreatment referrals investigated by the city's Child Protection Services during the same years (2011 to 2012) were provided by this agency. To avoid data dependency, child maltreatment referrals were per family unit (i.e., each family investigated is included only once), as a family can have more than one child with protection measures. This did not apply to IPV protection orders, as only one protection order was associated with each case. The total number of family units with child maltreatment referrals was 588. Data for IPV cases and CM referrals were geocoded using the address where the incidents occurred.

This research was conducted under two Joint Research Agreements signed between the University of Valencia and the Valencia Police Department, and the Social Welfare Department of the Valencia City Hall, respectively. Both agencies, the Valencia Police Department, and the Valencia Social Welfare Department through its Child Protection Services, participated actively in this research project by facilitating the data required. Permissions to access police records regarding address of IPV incidents were granted by the Head of the Valencia Police Department. This research was approved and funded by the Spanish Institute for Women (Instituto de la Mujer, Ministerio de Sanidad, Servicios Sociales e Igualdad) and the European Social Fund as part of project MUJER2012-PI-154, and by the Spanish Ministry of Economy and Competitiveness as part of project PSI2014-54561-P. For this observational study, both the Ethics and Data Protection Committees of the University of Valencia were consulted to address potential confidentiality issues. All data used for this study was completely anonymized, and did not include any identifying information about individuals or families. Also for further anonymization, for analyses, all geographical coordinates corresponding to cases of IPV and CM were aggregated at the census block group level, so no individual addresses can be identified.

Covariates

Different neighborhood-level characteristics were used as covariates based on a classic social disorganization theory approach [28,29,30,32,37]. We used three indicators to assess concentrated neighborhood disadvantage (neighborhood economic status, neighborhood education level, and policing activity, as a proxy of neighborhood public disorder and crime) one indicator of ethnic heterogeneity (immigrant concentration), and an indicator of residential instability.

Economic status: A factor analysis derived scale was used to measure neighborhood-level economic status; the scale contained 4 indicators: cadastral property value, percentage of high-end cars, percentage of financial business, and percentage of commercial business.

Education level: The value of this covariate was calculated as the average level of education in each census block group based on the percentage of the population in each education level category measured on a 4-point scale where 1 = less than primary education, 2 = primary education, 3 = secondary education, 4 = college education.

Policing activity: An index for each census block group was provided by senior police officers composed of 5 items measured on a 5-point Likert scale (0= very low level of interventions, and 4=very high level of interventions), which included police interventions such as drug-related crime, drunkenness and fights, vandalism, homeless people and truancy.

Immigrant concentration: Percentage of immigrant population in each census block group.

Residential instability: Proportion of the population who had moved into or out of each census block group during the previous year (rate per 1,000 inhabitants).

Table 1 summarizes the descriptive statistics for all variables.

Table 1. Variables (mean, standard deviation, minimum and maximum values) at the census block group level

Variable	Mean (SD)	Min	Max
Economic Status			
Property value (€/m^2)	260.10 (74.61)	111.50	590.70
High-end cars (%)	5.75 (3.62)	1.30	24.80
Financial activities (%)	18.15 (7.77)	0	43.20
Commercial activities (%)	34.03 (9.21)	7.50	66.40
Education level	3.15 (.33)	2.39	3.86
Policing activity	7.16 (3.99)	0	19
Immigrant concentration (%)	13.45 (6.53)	1.90	40.20
Residential instability	288.00 (87.98)	91.10	649.80

Abbreviations: SD, standard deviation; Min, minimum; Max, maximum €/ m^2, euros per square meter

Statistical analysis

Two different analytic approaches were used. First, a Bayesian joint modeling analysis was conducted to examine the spatial distribution of IPV and CM cases [40]. We assumed that the outcomes followed a conditional independent Poisson distribution, and a shared component was introduced in the model:

$$Y_{ik} \sim Po(\mu_{ik})$$

$$\log \mu_{i1} = \log E_{i1} + \alpha_1 + \phi_i * \delta + \psi_{i1}$$

$$\log \mu_{i2} = \log E_{i2} + \alpha_2 + \phi_i / \delta + \psi_{i2}$$

where Y_{ik} are the observed counts for the outcome k (1 for IPV, and 2 for CM cases) in census block group i, μ_{ik} is the unknown mean, E_{ik} are the expected counts for the outcome k in i-census block group (in proportion to the number of female population over 16 years old for IPV, and in proportion to the number of family units for CM); α_k is the intercept, δ represents the scaling factor which allows the risk gradient for the shared component to be different for each outcome; ϕ is the shared component, and ψ_{i1} and ψ_{i2} are the two specific components. ϕ and ψ were composed of unstructured and structured spatial components [41]. We used the logarithmic transformation of the shared component proposed by Knorr-Held and Best [40]. The unstructured term was modeled by means of independent identically distributed Gaussian random variables, and the spatially structured term was modeled as a conditional spatial autoregressive (CAR) model [41]. Additionally, an improper uniform distribution was used for α_1 and α_2.We obtained the proportion of shared variance for each outcome (η_k).

Second, after examining the common spatial distribution of IPV and CM, a Bayesian Poisson spatial regression modeling was conducted for each outcome. The five variables (economic status, education level, policing activity, immigrant concentration, and residential instability) were introduced in the models, and two spatial effects were assessed (structured and unstructured terms). The models were defined as follows:

$$\log \mu_{ik} = \log E_{ik} + \alpha + X_i\beta + S_{ik} + U_{ik}$$

where $\propto$ is the intercept, β represents the regression coefficients vector, X is the matrix of covariates, and S and U are the structured and unstructured terms, respectively. Thus, the log relative risk was modeled as $\alpha + X_i\beta + S_{ik} + U_{ik}$.

Vague Gaussian distributions were used for the fixed effects β, while α was considered as an improper uniform distribution. U was modeled by means of independent identically distributed Gaussian random variables, and S was modeled as a CAR model [41].

Markov Chain Monte Carlo (MCMC) simulation techniques were applied to perform the Bayesian models [42], using software R and the WinBUGS package. 100,000 iterations were generated in each of the models assessed, and the first 10,000 were discarded as a burn-in period. The $\hat{R}$ parameter (the convergence diagnosis) showed a suitable convergence for all parameters.

Results

Joint modeling results were firstly assessed (Table 2). For IPV cases, about 77% of the total between-area variation in risk was captured by the shared component. For CM referrals, about 98% of the total between-area variation in risk was captured by the shared component. Both outcomes, therefore, showed a common spatial pattern. Figure 1 illustrates this shared spatial component.

Table 2. Results from Bayesian Joint Modeling of the shared spatial component between intimate partner violence and child maltreatment risks

	Mean	**SD**	**CrI 95%**
α_1	-.096	.040	-.174, -.018
α_2	-1.828	.082	-1.973, -1.670
δ	.703	.052	.606, .813
η_1	.768	.162	.459, .995
η_2	.978	.046	.832, .999

Abbreviations: SD, standard deviation, CrI, credible interval
[1] Intimate partner violence
[2] Child maltreatment

Secondly, a Bayesian Poisson spatial regression was conducted for each outcome. In both models, the covariates presented the same relationship with the outcome (see Table 3). Specifically, results indicate that IPV and CM risks were higher in disadvantage neighborhoods, with lower levels of economic status and education, and higher levels of policing activity, immigrant concentration, and residential instability.

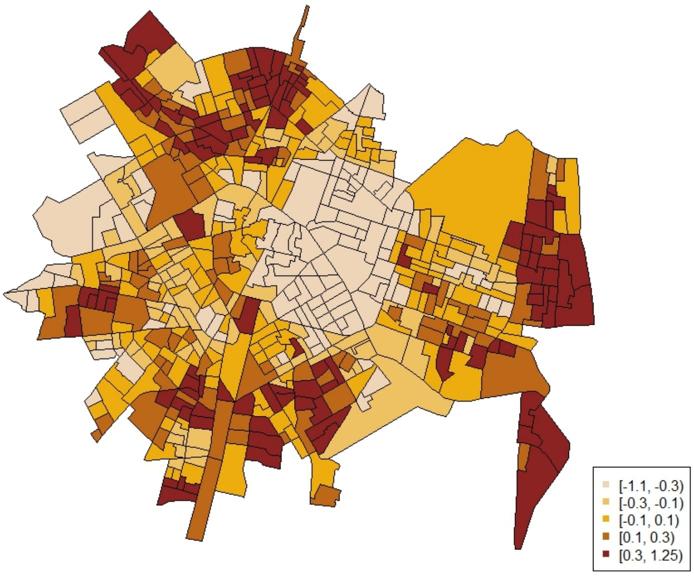

Figure 1. Shared spatial component from the joint modeling between child maltreatment and intimate partner violence risks.

Table 3. Results from Bayesian Poisson spatial regression models of intimate partner violence and child maltreatment risks

	Intimate partner violence			**Child maltreatment**		
	Mean	**SD**	**95% CrI**	**Mean**	**SD**	**95% CrI**
Intercept	.182	.617	-.982, 1.403	2.498	1.127	.222, 4.586
Economic status	-.131	.070	-.263, .004	-.145	.135	-.414, .117
Education level	-.287	.184	-.644, .060	-1.121	.341	-1.760, -.418
Policing activity	.016	.009	-.001, .033	.032	.015	.004, .060
Immigrant concentration	.030	.008	.013, .146	.018	.014	-.009, .044
Residential instability	.001	.009	-.001, .002	.001	.001	-.001, .003

Abbreviations: SD, standard deviation, CrI, credible interval

The relative risks of each model were correlated using Pearson's correlation coefficient and a scatter plot. Figure 2 shows a high correlation between the log relative risks for IPV and CM (r = .85, CrI = [.81, .88]). In addition, Figure 3 displays the census block groups where the log relative risks for each outcome overlap (above-average and below-average risk levels). Most of the census block groups have low or high risks in both outcomes: only 10.5% of the areas have mismatched risks.

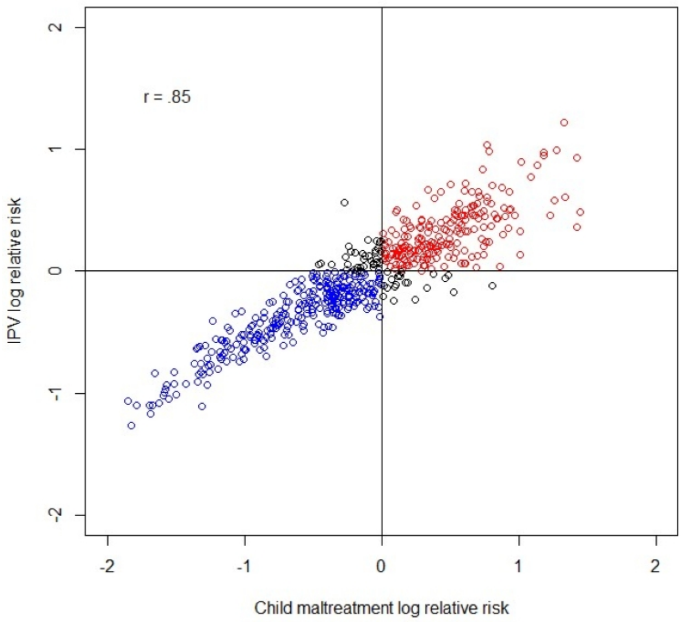

Figure 2. Scatter plot of the correlation between child maltreatment and intimate partner violence log relative risks.

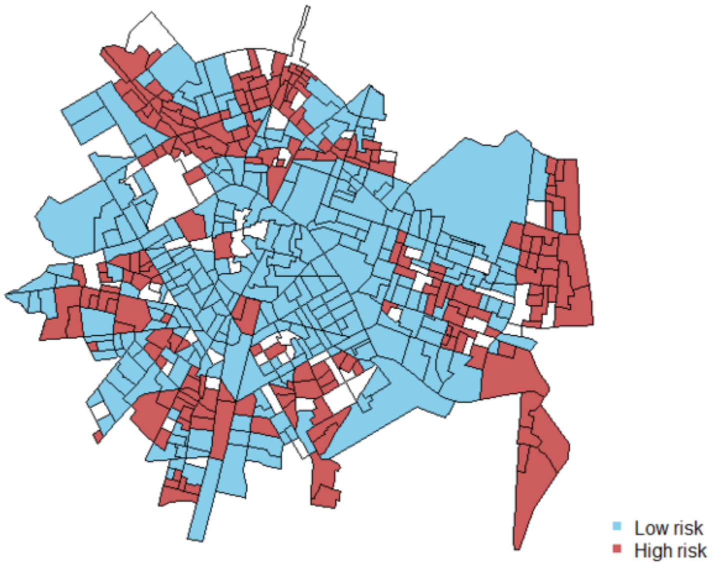

Figure 3. Map of the census block group with coincident low (blue) and high (red) relative risks for child maltreatment and intimate partner violence.

Discussion

In this study, we analyzed first whether there was a common spatial distribution of IPV and CM in the city of Valencia and, second, whether the risks of IPV and CM were influenced by the same neighborhood characteristics, and if these risks spatially overlap. As hypothesized, results showed a common spatial distribution of CM and IPV, as a large percentage of the variation in both types of family violence across city areas was explained by a common spatial component (98% of the between-area variation for CM, and 77% for IPV). Results also showed that the same neighborhood characteristics (i.e., neighborhood economic status, neighborhood education status, policing activity, immigrant concentration, and residential instability) explained the risk of CM and IPV, and that these risks were higher in city areas with low economic and education status and with high levels of policing activity, immigrant concentration, and residential instability. Finally, our study clearly illustrated the spatial overlap of CM and IPV risks, as the correlation of the relative risks for the two types of family violence was .85, with only 10.5% of the city areas having mismatched risks (most areas of the city had coincident lower or higher risks than the city average in both outcomes).

The co-occurrence of CM and IPV in the same families is a well-established finding in the literature [15,16, 23-25]. What the present study highlights is that the overlap of these two types of family violence occurs not only at the individual (e.g., having been victim of CM and perpetrator of IPV later in life) or family levels (families in which both CM and IPV occur), but that the overlap between CM and IPV also occurs at the neighborhood level. In this regard, our results extend the common ground connecting these two types of family violence to the social context in which the families live, acknowledging the importance of neighborhood characteristics as common risk factors for both CM and IPV. This study not only supports previous research showing that 'place' matters for CM and IPV [28-32], independently, but provides evidence that the risks for both types of violence are simultaneously high or low in the same places. Our study illustrated that certain neighborhood characteristics indicative of social disorganization (i.e., low economic and education status, high levels of policing activity indicative of public disorder and high criminality, immigrant concentration, and residential instability) increases the risk of family violence, regardless of whether this violence is against children or against intimate partners.

Various psychosocial processes can be called upon to explain why neighborhoods where these characteristics concentrate are associated with family violence, increasing the risk of both CM and IPV [27-32]. First, from a social disorganization perspective, neighborhood concentrated disadvantage has been linked with reduced social control, and this diminished social control would be responsible for the relationship between these neighborhood characteristics and family violence. In disadvantaged neighborhoods, mistrust and a lack of social cohesion among residents may inhibit prosocial behavior and social control, reducing willingness to become involved in other residents' lives (e.g., challenging other residents' behavior toward their children or partners, or reporting known cases of CM or IPV), thus explaining the link between neighborhood disadvantage and family violence [43-50]. Second, isolation from mainstream values of what is acceptable in intimate relationships may also explain the higher risk of family violence in disadvantaged neighborhoods. Some behaviors involving the use of violence in intimate partner and parent-child relationships may be more tolerated and accepted in these neighborhoods, compared to mainstream norms or values regarding family violence (e.g., not disapproving of violent behaviors toward intimates in certain circumstances, or approving violence as an accepted way of settling family conflicts). These social norms have been defined as "cognitive landscapes or ecologically structured norms (normative ecologies) regarding appropriate standards and expectations of conduct" [51,p. 63] that would provide the bases for a social climate of greater tolerance of family violence, whereby violence among intimates is not recognized or condemned as deviant but considered as a tolerated and accepted strategy that in these contexts, increases the risk of CM and IPV. From this perspective, disadvantaged neighborhoods can become fertile grounds for socialization that fosters attitudes accepting violence in intimate relationships, and internalizing these attitudes as acceptable violence becomes an appropriate strategy to resolve relationship conflicts, and either CM or IPV are not considered as important social problems deserving the mobilization of informal social control [44,52-58]. Finally, another possible explanation of the link between concentrated neighborhood disadvantage and risk of family violence is that these residential/social contexts can be highly stressful, reducing the quality of family life, and triggering violence in both parent-child and intimate partner relationships [27,30,32,59-62]. However, these variables were not available for this study, and we cannot test hypotheses on these alternative or complementary explanations.

This study also has several implications for advancing our understanding of and responses to family violence. Calls have been made for a greater integration of research addressing CM and IPV [15-17,63-68]. The interconnection between CM and IPV at the community level illustrated in this study not only advances our understanding of the causes of family violence by identifying common risk/protective factors at the community level, but also supports the need for a more integrative and broader approach in the prevention of family violence. Neighborhood conditions linked to both CM and IPV are modifiable risk factors, and identifying high-risk areas for both of them can potentially have an important preventive effect by targeting these two types of family violence within a same preventative/policy agenda. The high-resolution approach used in this study provides information that is more significant for policy relevance, as area-specific risk estimations are provided to inform a more localized intervention strategy. Furthermore, this community-level approach to address both types of family violence, as opposed to individual-level intervention addressing each type of violence separately, can reach a larger number of families in a more integrative and cost-effective way [28,31,65-71].

Finally, this study has both strengths and limitations. Examining for the first time the spatial overlap of CM and IPV within the same research framework, using appropriate analytical techniques and high-resolution disease mapping methods, thus providing greater policy relevance, are clearly among the study's strengths. As for its limitations, this study uses only official cases of CM and IPV, and we cannot generalize our results regarding the overlap of CM and IPV to underreported cases, which is a common issue in both types of family violence [12,13]. Regarding the covariates used in this study, other socioeconomic measures such as rates of unemployment or income, other neighborhood variables linked in other studies to both types of family violence, such as alcohol outlets, and neighborhood processes such as those mentioned above were not available for this study [33,34,72-76]. Finally, the results correspond to a European city, and future research should examine the overlap of CM and IPV in other cities that may differ in structure and organization, as well as in other cultural contexts.

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