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Original article

Rethinking the association between green space and crime using spatial quantile regression modelling: Do vegetation type, crime type, and crime rates matter?

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ABSTRACT

UN Sustainable Development Goals (e.g., Goal 16) have highlighted the importance of using policy tools (e.g., through urban planning) to prevent crimes. Existing evidence of the association between green space and crime is mixed. Some studies indicate that the inconsistencies may be due to the variance in types of vegetation and the rates of crime reported across regions and countries. This study aims to assess the conditional association between green space and crime by considering the influence of vegetation type (e.g., grassland, woodland), crime type (e.g., violence, theft) and rates of crime reported in Northern Ireland (NI), United Kingdom. Crime data were obtained from the Police Service NI and green space was determined by Land Cover Map at the Super Output Area (SOA) level provided by the UK Centre for Ecology & Hydrology. Spatial quantile regressions were used to model the adjusted association between green space and crime across areas with different rates of crime. The results showed that more grassland may be associated with lower crime rates, but only in areas with relatively low crime rates. More woodland may also be associated with lower crime rates, but only for areas with relatively high crime rates. Also, we found that associations between green space and crime varied by type of crime. In summary, policymakers and planners should consider green space as a potential crime reduction intervention, factoring in the heterogeneous effects of vegetation type, crime type and crime rate.

1. Introduction

With rapid urbanisation, crime prevention has become a key issue for researchers, policymakers and practitioners (Eisner et al., 2016). Existing evidence has documented that crime can threaten public health by reducing the sense of safety (Jackson and Stafford, 2009). High rates of crime also increase the government's financial burden and hinder the economic development of the country (Stafford et al., 2007). UN Sustainable Development Goals (e.g., Goal 16) have highlighted that it is necessary to use policy tools (e.g., through urban planning and design) to prevent crimes (Bahadure and Kotharkar, 2018; Opoku, 2019; Tate et al., 2024).

Traditional criminology studies mainly focus on potential offenders' characteristics when aiming to reduce rates of crime (Greenberg and Rohe, 1984). However, only focusing on the level of the individual neglects the important role of the environment, particularly the physical and natural environment in crime prevention (Greenberg and Rohe, 1984; Han et al., 2022; Yue and Zhu, 2021). The physical environment

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provides policymakers with a possible intervention approach that has the potential to change a criminal's environment and behaviour (Demir and Ozcan, 2023; Sohn, 2016; Stevens et al., 2024; Zhang et al., 2022; Zhou et al., 2022; Zhou et al., 2023). C. Ray Jeffery was among the first to associate crime prevention with environmental design, resulting in the field of environmental criminology (Jeffery and Zahm, 2017). There is evidence that physical environments play a significant role in people's psychological status and behaviours, which may be positively associated with their intent to commit a crime or their risk of being involved in a crime (Jefferson, 2018; Liu et al., 2022; Tulumello, 2017; Zandiatashbar and Laurito, 2022). When considering physical environments, particularly natural environments, and crime, green space has attracted attention, as they can be considered important for the prevention of crime, and also to improve physical and mental health, and mental wellbeing (Ogletree et al., 2022; Sanciangco et al., 2022; Stevens et al., 2024; Venter et al., 2022). However, previous findings on the association between green space and crime are inconsistent (Bogar and Beyer, 2016). Some studies have found that green space reduced crime (Kuo and Sullivan, 2001; Ogletree et al., 2022; Sanciangco et al., 2022; Stevens et al., 2024; Venter et al., 2022), while others have suggested that green space increased crime (Mancus and Campbell, 2018; Shepley et al., 2019). A possible explanation for the inconsistency may relate to context, such as the type and quality of green space, how green space was defined or quantified, and the type and/or rates of crime reported. Therefore, more attention should be paid to the critical appraisal of the association between green space and crime. Also, regardless of these inconsistencies, empirical evidence relating to crime and green space is still limited (Bogar and Beyer, 2016; Lorenc et al., 2013).

In addition, although there is evidence that different types of vegetation may have different impacts on mental wellbeing and overall health due to the heterogeneity of their physical features (Wang et al., 2020; Chen et al., 2023a and 2023b), little is known about the impact of vegetation types that are present specifically in urban settings and the potential associations with crime type and rates of crime. Therefore, this study aimed to 1) investigate the effects of different types of vegetation (i.e., grassland vs. woodland) on rates of crime; 2) examine the conditional green space-crime associations across different rates of crime (i.e., different quantiles); and 3) investigate the heterogeneous green space-crime associations across different types of crime. The research framework was presented in Fig. 1. It is important to note that we only focused on rates of crime reported to the police rather than fear or perception of crime or crimes not reported to the police.

2. Literature review

The link between crime and the environment has been theorised across a range of disciplines (Sampson et al., 1997). Environmental criminologists have found inconsistent evidence when investigating the association between green space and crime (Bogar and Beyer, 2016; Mancus and Campbell, 2018; Shepley et al., 2019). Some studies have found green space to be associated with reductions in crime, with several explanations (Bogar and Beyer, 2016; Mancus and Campbell, 2018;

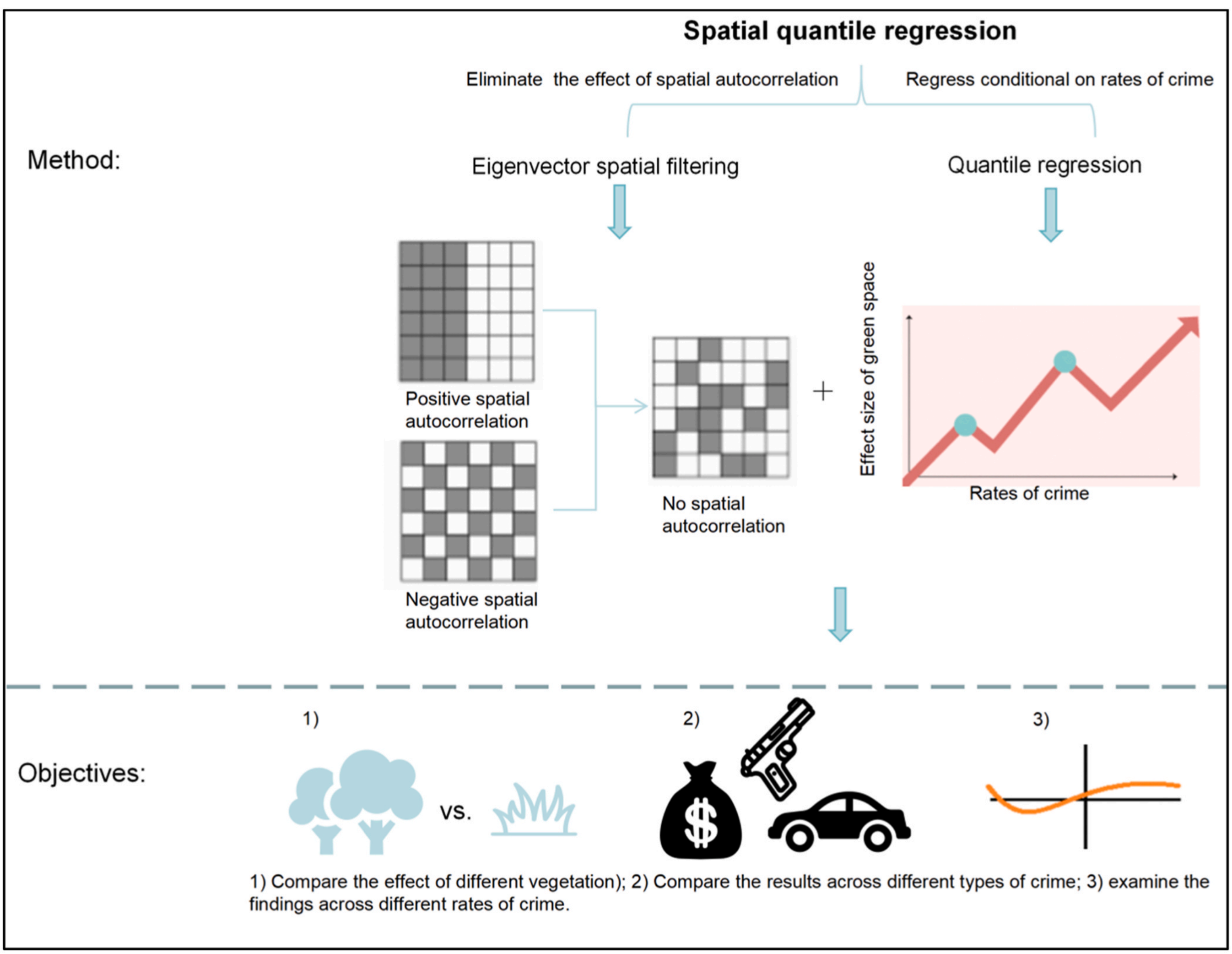

Fig. 1. The research framework.

Shepley et al., 2019) such as the positive association of green space and social contact and social cohesion (Kemperman and Timmermans, 2014; Samsudin et al., 2022). It is thought that since green space provides an open space for residents to socialise, residents may have more frequent social contact with neighbours, in turn contributing to the formation of cohesive neighbourhoods (Kemperman and Timmermans, 2014; Samsudin et al., 2022). Many criminologists have found a negative association between neighbourhood, social cohesion and crime, with cohesive neighbourhoods benefiting from collective efficacy, strengthened concern about neighbourhood issues and neighbourhood watchfulness (Cohen et al., 2008; Sampson et al., 1997), further strengthening residents' commitment to protecting their neighbours' property and discouraging criminal activity (Goudriaan et al., 2006). In addition, another benefit of green space relates to its psychological benefits, which can lower an individual's propensity for aggression and violence (Michelle C. Kondo et al., 2017). Green space encourages residents to engage more in outdoor physical activity such as walking, which is important for reducing stress (St-Jean et al., 2022; Wang et al., 2021; Wang et al., 2020). Hence, environmental psychological theories such as stress reduction theory (SRT) and attention restoration theory (ART) indicate that green space can buffer psychological stress (Jiang et al., 2015). Furthermore, green space is also associated with better public health and fewer financial burdens on healthcare systems and their services (Van Den Eeden et al., 2022), potentially freeing funding which could be invested in improving public welfare and reducing crime (Sanciangco et al., 2022). Finally, there is evidence that exposure to more green space may improve adolescents' prosocial behaviour, thus decreasing adolescents' risk of antisocial behaviour (Amoly et al., 2014).

Conversely, green space has also been found to be associated with higher rates of crime (Bogar and Beyer, 2016; Ha et al., 2024; Lee et al., 2023; Lin et al., 2021; Mancus and Campbell, 2018; Shepley et al., 2019). Routine activity theory (Miró, 2014) and defensible space theory (Reynald and Elffers, 2017) both try to build links among motivated offenders, a suitable target and a lack of a capable guardian. Green space can restrict surveillance opportunities, thus acting as a shield for gang activities (Donovan and Prestemon, 2012) and offer an ideal place for the convergence of motivated offenders, as they are less likely to be recorded when committing a crime (Bogar and Beyer, 2016). Green space can also limit people's visibility, which leads to lower levels of perceived safety and greater vulnerability to crime (Baran et al., 2018). For example, McCord and Houser (2017) found that neighbourhood parks are associated with more crimes (violent, property, and disorder crime) in their immediate surroundings in two diverse USA cities since people within the parks are of low guardianship due to the lack of visibility. Finally, the 'broken windows' theory suggests that poorly maintained green spaces such as abandoned gardens can motivate more criminal activities since it is a sign that such a place is neglected and will not be frequently visited (Branas et al., 2011; Gau and Pratt, 2010; Kondo et al., 2016; Kondo et al., 2021).

Awareness amounts that the association between green space and crime is conditional (Bogar and Beyer, 2016; Mancus and Campbell, 2018; Shepley et al., 2019). For example, evidence indicates that the association between green space and crime may be conditional on the locality's rate of crime (Venter et al., 2022). As for places with higher rates of crime, the dominant factors usually relate to governance and socio-economic factors (van Dijk et al., 2021), with physical environmental factors such as green space being considered less important. However, people's psychological stress is high in places with higher rates of crime, and existing studies suggest that the restorative effect of green space is strengthened when people are stressed (Jiang et al., 2015). Under such circumstances, green space may be more important for places with higher rates of crime. Previous studies indicate that the nature of the association between green space and crime may also be conditional on the type of crime, but most of the empirical evidence is still based on a single type of crime (Ogletree et al., 2022). Most studies focus on the association between green space and violent crimes (e.g., homicide), and such an association still varies across different violent crimes (Shepley et al., 2019). For example, Kim and Hipp (2018) pointed out that places closer to green space have higher levels of violent crimes (e.g., robbery, and aggravated assault), and Lundrigan et al. (2022) indicated that green space is a strong predictor for stranger rape (i.e., where there is no previous interaction). However, Sanciangco et al. (2022) found a negative link between green space and homicide rates across USA cities, while DeMotto and Davies (2006) found no evidence that green space is associated with gun violence. Although there is less evidence for property crime, one existing study in Vancouver, Canada, found that property crime rates had negative correlations with green space (Ye et al., 2018), and another study also found similar results in South Africa (Venter et al., 2022).

Existing literature has documented the heterogeneous effects of different types of vegetation on human behaviour (Wang et al., 2023; Wang et al., 2020). Trees may block traffic-related air pollutants and noise, so there is evidence that tree canopy cover is negatively associated with regional medical costs (Michelle C Kondo et al., 2020). This is important for crime prevention, since higher levels of air pollutants and noise may be associated with more aggressive behaviour (Herrnstadt et al., 2021). Grassland was found to provide residents with a large open space for physical activity and social contact, which may increase neighbourhood social cohesion and reduce conflicts as well as anti-social behaviour (Kemperman and Timmermans, 2014; Samsudin et al., 2022). Hence, grassland can also offer residents green views, which is associated with less stress and aggressive behaviour (Hoyle et al., 2017). For example, Venter et al. (2022) indicated that there is evidence that overall green space is negatively associated with crime, but such an association is inverse when tree cover is the predictor. Evidence has also suggested that the distribution of crimes is spatially dependent, but most existing studies examine the effect of green space on crimes using a generalised linear model or mixed effect model and thus do not control for the spatial dependency of crimes. Therefore, research using a spatial filter is needed, as it could take spatial dependency of crime into account (Kounadi et al., 2020), contributing to our understanding of the green space-crime association.

3. Data and methods

3.1. Study area

Our analysis was conducted using data from Northern Ireland (NI) (Figure S1 and Figure S2). This study focuses on Super Output Areas (SOAs), of which there are 890 in our study area (average SOA size = 16 km^2; average population = 2035 persons). Super Output Areas are the geographical units used for collecting primary demographic and socio-economic census information in NI (similar to Census Tracts which are used in the USA).

3.2. Crime data

Crime data were collected from the Police Service Northern Ireland (PSNI) and the Northern Ireland Fire and Rescue Service (NIFRS) for 2011/2012–2015/2016 due to the availability of data. In total, seven different categories of reported crime were analysed: violence (including sexual offences), robbery and public order; burglary; theft; vehicle crime; criminal damage and arson; primary and secondary fires; and anti-social behaviour. The detailed definition of each crime can be found in PSNI. (Police Service of Northern Ireland, 2017).We used the SOA crime rate as the outcome (per 1000 population). The number of crimes reported between 2011/2012 and 2015/2016 as occurring in that SOA (e.g., the total number of anti-social behaviour incidents) was treated as the numerator, while the denominator was the average population resident in that SOA (taken from the 2011 Census).

3.3. Green space

Green space was measured based on Land Cover Map 2017 (LCM2017) vector data (Morton et al., 2020). It is one of the most comprehensive land cover datasets for the UK. The LCM2017 was provided by the UK Centre for Ecology & Hydrology based on remote sensing data in 2017. We used the vector datasets of the LCM2017, which provides land cover information with 21 classes based on the UK Biodiversity Action Plan broad habitats (Morton et al., 2020). LCM data is also available for 2015 which aligns closely with the time period for the crime data. Correlation analysis indicated that the green space coverage based on LCM 2015 is highly correlated with LCM 2017 ($r > 0.90$, $p < 0.05$) at the SOA level. Green space was divided into grassland and woodland, to further distinguish the effect of different types of vegetation. Grassland includes improved grassland, neutral grassland, calcareous grassland, acid grassland, and heather grassland, while woodland includes broadleaved woodland and coniferous woodland. The proportion of grassland and woodland was calculated within each SOA.

3.4. Covariates

Based on existing literature (Ogletree et al., 2022; Venter et al., 2022), demographic, socio-economic, and police-related indicators may be important predictors of the local crime rate, consequently we collected a series of data from the 2011 Census at the SOA level. First, social disorganization theory (Jones and Pridemore, 2019) and existing studies on the association between green space and crimes (Ogletree et al., 2022; Venter et al., 2022) indicate that population demographic, socio-economic, and other characteristics are linked to local crimes. Therefore, we controlled for population density, sex, age, urbanity, income, marital status, ethnicity, religion, education, and employment status as the covariates. The proportions of the population aged below 18 years and aged 18–30 years were included since existing evidence suggests that young people are more active in criminal activity than older people (Sweeten et al., 2013). Second, since local governance plays an important role in maintaining social stability (Gilling, 2016), we also controlled for the impacts of public administration and defence workers as well as human health and social workers based on the census-based occupational classification. Public administration and defence workers can reflect the intensity of the governance, while human health and social workers can measure the quality of the governance. Third, existing literature suggested that the police are an important factor in preventing local crimes (Gilling, 2016), so we calculated the presence of a police station for each SOA. Details and the operational definition of each covariate are shown in Table 1.

3.5. Methods

3.5.1. Spatial descriptive analysis

We examined the spatial distribution and spatial autocorrelation of crime rate. Global Moran's I (Moran, 1950) can reflect the overall level of spatial autocorrelation of crime rate among all SOAs. The higher values of Global Moran's I indicate a higher level of spatial autocorrelation of crime rate. Global Moran's I only reflects the overall level of spatial autocorrelation of crime rate, but further we need to identify how the high/low crime rate clusters distribute, so we used Local Moran's I (Anselin, 1995) to reflect the spatial relevance of crime rate in each SOA to its neighbours.

3.5.2. Spatially filtered unconditional quantile regression

To investigate the cross-sectional association between green space and crime rates under different rates of crime, we used spatially filtered unconditional quantile regression (Murakami, 2017). Compared to other spatial statistical methods (e.g., geographically weighted regression and spatial lag regression), the proposed method can identify how

Table 1
Summary statistics of variables.

Variables	Definition	Proportion/ Mean (Standard Deviation)
Outcome		
All_crimes	Rate of all crimes (per 1000 population)	67.07(51.79)
Violence_robbery_and_public_order	Rate of Violence (including sexual offences), robbery, and public order (per 1000 population)	15.12(13.90)
Burglary	Rate of Burglary (per 1000 population)	3.90(2.85)
Theft	Rate of Theft (per 1000 population)	6.28(5.68)
Vehicle_crime	Rate of Vehicle Crime (per 1000 population)	2.13(2.13)
Criminal_damage_and_arson	Rate of Criminal Damage and Arson (per 1000 population)	8.96(7.93)
Primary_and_secondary_fires	Rate of Deliberate Primary and Secondary Fires (per 1000 population)	3.29(3.60)
Anti-social_behaviour	Rate of Anti-Social Behaviour Incidents (per 1000 population)	27.38(22.24)
Predictors		
Woodland	The proportion of land that is woodland (median, q25-q75)	0.03 (0.00–0.07)
Grassland	The proportion of land that is grassland (median, q25-q75)	0.18 (0.01–0.64)
Covariates		
Urban	Urbanity, which was defined by the Northern Ireland Statistics and Research Agency, (2016)(NISRA, 2016)	
	Yes	61.80
	No (rural and mixed areas)	38.20
Income	The proportion of the population living in households whose equivalised income is below 60 per cent of the NI median (%)	13.00(3.80)
Marital_status	The proportion of the adult (16+) population that is married or cohabitating (%)	47.29(11.43)
Ethnic_group	The proportion of the population that is White ethnicity (%)	98.18(1.99)
Religion	The proportion of the population that is non-religious (%)	10.39(6.67)

(continued on next page)

Table 1 (*continued*)

Variables	Definition	Proportion/ Mean (Standard Deviation)
Education	The proportion of the population with low qualifications (highest level of qualification: level 1 or 2 or no qualifications) (%)	55.95(11.03)
Unemployment	The proportion of the population that is long-term unemployed (16+) (%)	43.81(8.11)
Population_density	Population density (number of usual residents per hectare)	21.38(24.58)
Sex	The proportion of the population that is female (%)	51.10(1.95)
Age_18	The proportion of the population aged below 18 years (%)	24.88(4.73)
Age_18_30	The proportion of the population aged 18–30 years (%)	16.69(6.38)
Public_administration_and_defence_workers	The proportion of the population that is employed in the public administration and defence sectors (%)	7.97(3.77)
Human_health_and_social_workers	The proportion of the population that is employed in the human health and social sectors (%)	14.34(2.91)
Police_station	The presence of a police station	
	Yes	6.29
	No	93.71

the associations between independent and dependent variables vary across different levels of the independent variable. Variance inflation factors (VIF < 3) suggested no severity of multicollinearity among predictors. First, if spatial dependence of crime rate exists, OLS (ordinary least squares) models may cause bias. Existing studies showed that eigenvector spatial filtering (ESF) can efficiently act as a spatial process required to eliminate residuals (Murakami, 2017). ESF defines the spatial associations among different observations using the weighted sum of the Moran eigenvectors (MEs), which are spatial basis functions (Murakami, 2017). After adding the ESF to the regression model as an additional term, the effect of residual spatial dependence can be efficiently eliminated (Murakami, 2017). Second, normal OLS regression can only infer the association between predictors and the mean value of the outcome, which fails to describe the whole picture of the conditional distribution (Murakami, 2017). However, in this study, we aimed to identify the association between green space and crime rate across different rates of crime, which means such association is conditional on the outcome itself. Therefore, quantile regression was used in our analysis since it allows the final coefficients of predictors to vary with multiple quantiles of the dependent variable (Koenker and Bassett, 1978), and we can understand what the association between green space and crime rate under different quantiles of crime rate is. Spatially filtered unconditional quantile regression combines both ESF and quantile regression model, which was finally applied in our analysis.

4. Results

4.1. The spatial analysis for the crime rate in NI

Table 1 shows that the average rate of all crimes (per 1000 population) within each of the SOAs was 67.07 from 2011/2012–2015/2016, while the median proportion of woodland and grassland within each of the SOAs in 2017 was 0.03 and 0.18, respectively.

Fig. 2a shows the spatial distribution of the crime rate in NI. High values were concentrated in the major cities (e.g., Belfast) and urban areas, whereas low values were concentrated in the rural areas. The overall Moran's I of crime rate in NI is 0.451, suggesting that areas with high/low levels of crime rate were clustered. Fig. 2b displays the local Moran's I cluster for crime rate. Areas clustered with high levels of crime rate (HH) were distributed mainly in the centre of major cities, while areas clustered with low levels of crime rate (LL) were mainly in several rural areas such as Cookstown and Magherafelt.

4.2. The association between green space and crime rate (mean value)

Table 2 presents multivariate Gaussian spatial models for associations between green space and the mean value of crime rate. The results in Model 1 suggest that urban areas had higher crime rates than rural areas (Coef. = 13.71; SE = 3.62). Areas with police stations had higher crime rates than those without police stations (Coef. = 16.38; SE = 4.42). The proportion of the population living in households whose equivalised income is below 60 per cent of the NI median (Coef. = 3.23; SE = 0.49) was positively associated with the crime rate, while the proportion of the population who are: married (Coef. = −3.32; SE = 0.26), White (Coef. = −1.87; SE = 0.80), with low qualification (Coef. = −0.56; SE = 0.18), long-term unemployed (Coef. = −0.37; SE = 0.15), in higher population density areas (Coef. = −0.14; SE = 0.07), female (Coef. = −1.78; SE = 0.70), aged below 18 years (Coef. = −1.35; SE = 0.28), and 18–30 years (Coef. = −2.18; SE = 0.34) were negatively associated with the crime rate. As shown in Model 2, there is no evidence that the proportion of grassland (Coef. = −4.87; SE = 4.42) or woodland (Coef. = −1.84; SE = 1.34) was associated with the mean value of crime rate.

4.3. The association between green space and crime rate across different quantiles

Fig. 3 presents the results of spatial quantile regression on the association between green space and crime rate in different crime rate quantiles. Fig. 3(a) suggested that the proportion of grassland was negatively associated with the crime rate only when the crime rate was below 0.55 quantile. Fig. 3(b) showed that the proportion of woodland was negatively associated with the crime rate only when the crime rate was above 0.80 quantiles. These results indicated that a higher proportion of grassland may pose significant benefits to the crime rate only for areas with relatively low crime rates, while a higher proportion of woodland may pose significant benefits to the crime rate only for areas with relatively high crime rates.

4.4. The association between green space and crime rate across different types of crime

Fig. 4 presents the results of spatial quantile regression on the association between green space and crime rate in different quantiles for different types of crime. Fig. 4(a) and (b), (m) and (n) suggested that the results of violent robbery and public order, and anti-social behaviour were similar to the general crime rate.

However, Fig. 4(c) and (d), (e) and (f) showed that a higher proportion of grassland may not pose significant effects on burglary and theft, while Fig. 4(i) and (j) implied that a higher proportion of woodland may not pose significant effects on criminal damage and arson.

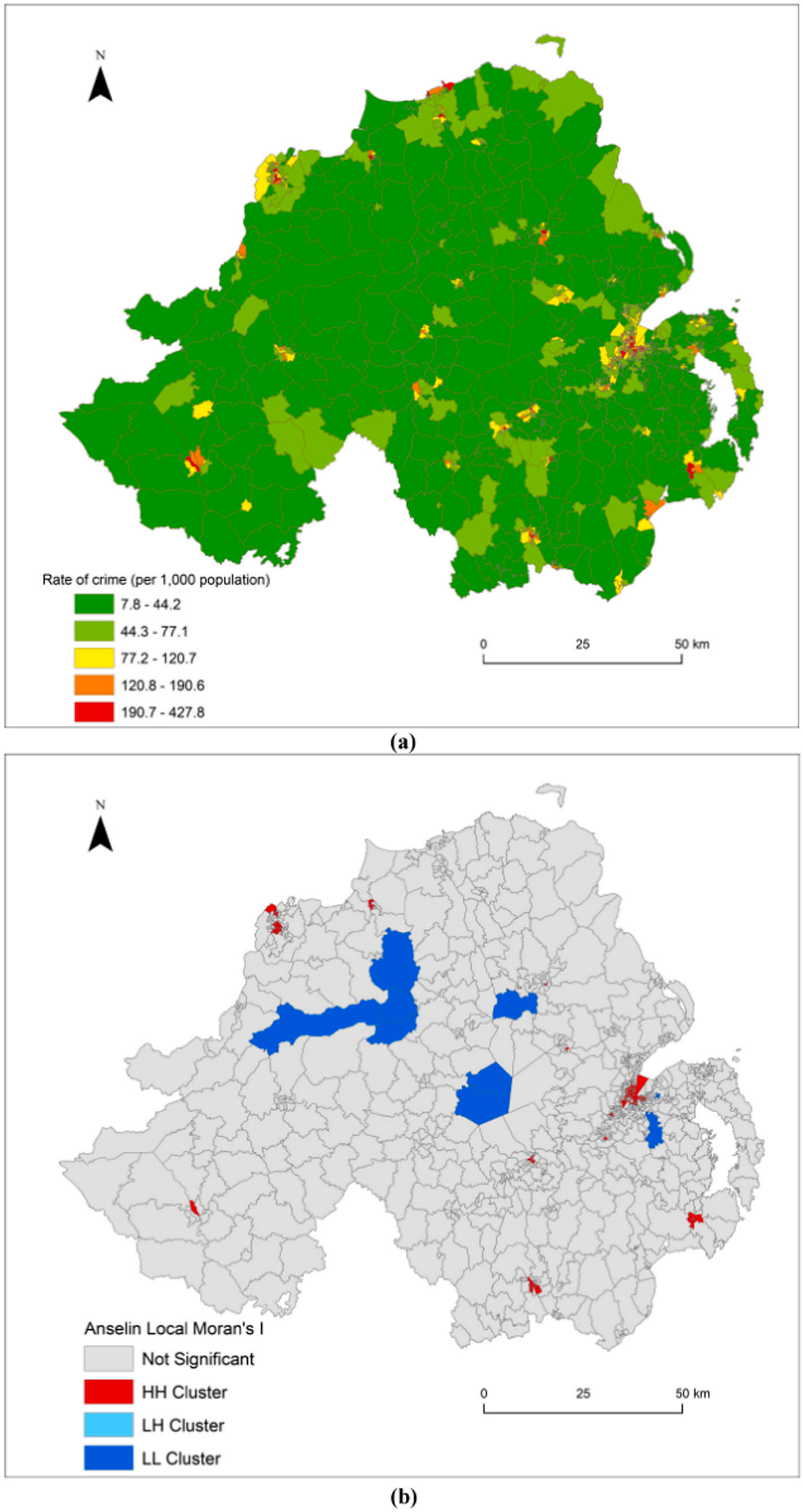

Fig. 2. (a) Distribution of rate of crime in NI SOAs; (b) Local Indicators of Spatial Association (LISA) map from Local Moran's I value showing clustering of the rate of crime. HH cluster = areas with unusually high rates of crime; LL cluster = areas with unusually low rates of crime; LH cluster = low values surrounded primarily by high values.

Table 2
Regressing crime rate on green space in NI (baseline models for the mean value of crime rate).

	Model 1	Model 2
	Coef. (SE)	Coef. (SE)
Urban	**13.71*****(3.62)	**11.47*****(3.87)
Income	**3.23*****(0.49)	**3.23*****(0.49)
Marital_status	**−3.32*****(0.26)	**−3.25*****(0.26)
Ethnic_group	**−1.87****(0.80)	**−1.83****(0.80)
Religion	−0.25(0.32)	−0.33(0.32)
Education	**−0.56*****(0.18)	**−0.53*****(0.18)
Unemployment	**−0.37****(0.15)	**−0.37****(0.15)
Population_density	**−0.14****(0.07)	**−0.17****(0.08)
Sex	**−1.78****(0.70)	**−1.89*****(0.70)
Age_18	**−1.35*****(0.28)	**−1.31*****(0.29)
Age_18_30	**−2.18*****(0.34)	**−2.06*****(0.34)
Public_administration_and_defence_workers	−0.43(0.39)	−0.53(0.39)
Human_health_and_social_workers	−0.60(0.47)	−0.50(0.47)
Police_station	**16.38*****(4.42)	**16.11*****(4.42)
Grassland		−4.87(4.11)
Woodland		−1.84(1.34)
adjR2	0.65	0.66

Coeff. = coefficient; SE = standard error,
Coefficients with statistical significance (p <.05) are shown in bold.
** p <.05,
*** p <.01.

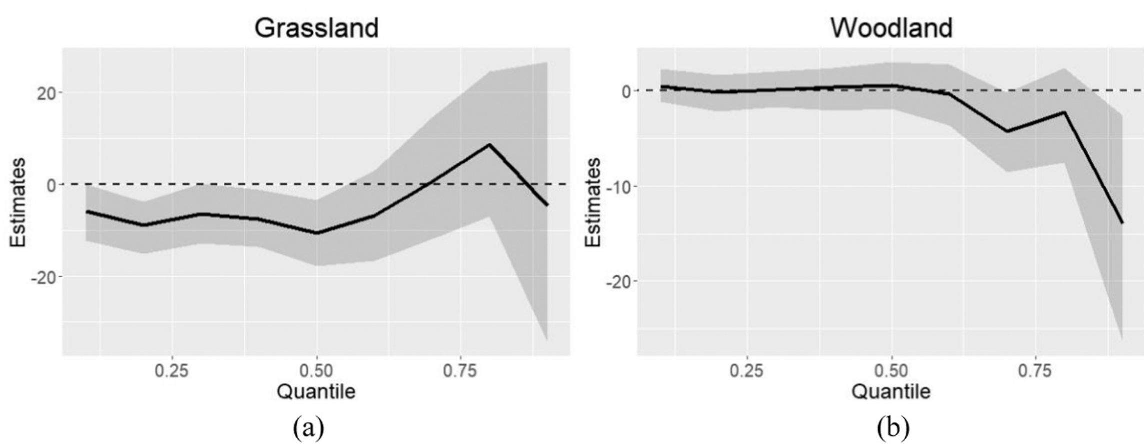

Fig. 3. Spatial quantile regression on the association between green space and crime rate. (a) Grassland; (b) Woodland. Black lines represent coefficients for different quantiles; Grey areas represent 95 % confidence intervals.

Also, Fig. 4(g) and (h) even indicated that a higher proportion of grassland may pose positive effects on vehicle crime only for areas with relatively low crime rates. Fig. 4(k) and (l) showed that a higher proportion of grassland may not pose significant effects on primary and secondary fires, while a higher proportion of woodland may pose positive effects on primary and secondary fires only for areas with relatively low crime rates.

5. Discussion

This study contributes to the understanding of the association between green space and crime in several respects. Firstly, it is among the first studies to systematically explore the association between green space and crime using a spatial quantile regression model, which enhances our understanding of how associations vary between areas with different rates of crime. Secondly, it attempts to distinguish the effect of grassland and woodland on crime, which can guide policymakers, urban planners, and practitioners in future interventions in green space. Thirdly, it further investigates the green space-crime association taking account of different types of crime, which is essential for informing crime prevention.

5.1. The association between green space and overall crimes

One of the most important findings from this study is that a higher proportion of grassland was associated with a lower rate of crime only for areas with relatively low crime rates, while a higher proportion of woodland was associated with a lower rate of crime only for areas with relatively high crime rates. There are several potential explanations for this. Firstly, areas with relatively low crime rates usually have a lower level of social conflict (Akers, 2011), and grassland may be able to provide a buffering effect by serving as an open space for social interaction and facilitating social cohesion (Samsudin et al., 2022). However, areas with relatively high crime rates may have higher levels of social conflict and are usually associated with complex and embedded socio-cultural issues, thus making it hard to solve through encouraging social contact (Akers, 2011). Under such circumstances, urban woodland may offer a solution by acting as a physical barrier (akin to a natural segregator) between residents, reducing opportunities to meet, and reducing conflict.

Secondly, the differences in the restorative effect of different types of vegetation may also partly explain our findings. Existing literature has suggested that grassland is an ideal place for outdoor physical activities,

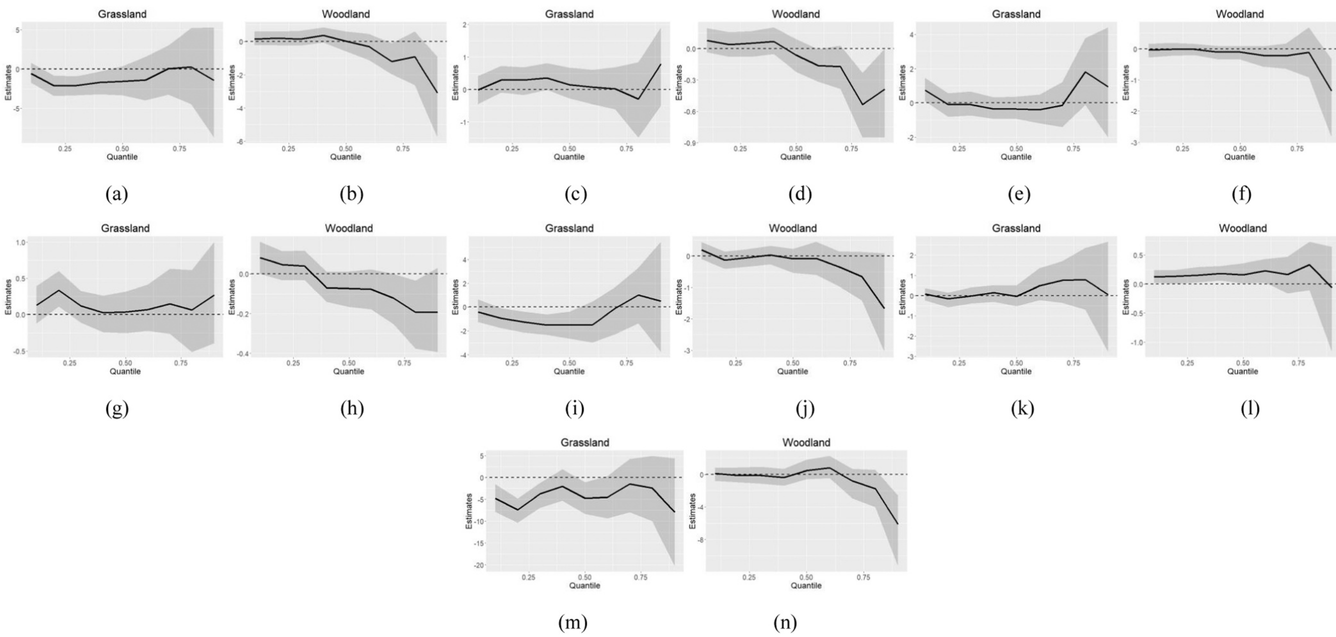

Fig. 4. Spatial quantile regression on the association between green space and crime rate. (a) and (b) Violence, robbery and public order; (c) and (d) Burglary; (e) and (f) Theft; (g) and (h) Vehicle crime; (i) and (j) Criminal damage and arson; (k) and (l) Primary and secondary fires; (m) and (n) Anti-social behaviour. Black lines represent coefficients for different quantiles; Grey areas represent 95 % confidence intervals.

mitigating typical precursors of crime such as stress and aggression (Maes et al., 2021). This may be important for the prevention of crime in areas with a relatively low crime rate because targeting stress is more efficient for the prevention of crime when the place is still under appropriate governance (Maes et al., 2021). Since woodland can serve as a habitat for more urban species than grassland, it is more associated with biodiversity and can have a stronger restorative effect for people under great mental stress (Jiang et al., 2016). Hence, residents living in areas with relatively high crime rates usually have greater mental stress (Baranyi et al., 2021) and thus can benefit more from the restorative function of urban woodland. Woodland was found to be more associated with the reduction of environmental hazards such as noise, air pollution, and extreme temperature (Wang et al., 2020). Hence, exposure to urban woodland may be associated with improved natural killer cell activity, and the immune system may benefit through contact with certain physical or chemical factors (such as phytoncides from trees) in the woodland (Li et al., 2008). As for areas with relatively high crime rates, open space may not be safe enough to encourage physical activity and social interaction, and thus the effect of grassland on crimes such as anti-social behaviour is weakened. However, the health benefits of woodland are more physical and biological as discussed above, so it may be less influential in areas with a relatively high crime rate.

Lastly, grassland is associated with adolescents' behavioural development and prosocial behaviour through the provision of attractive places for playing opportunities that encourage physical activity and social interaction and reduce screen time (Amoly et al., 2014; Putra et al., 2022). Therefore, the increase of grassland in areas with relatively low crime rates may benefit the development of adolescents and decrease their future risk of committing a crime. As for areas with relatively high crime rates, gang activities may be quite rampant around schools, so the public open space may not be safe enough for adolescents (Burdick-Will, 2013). Hence, adolescents at school are more likely to view street crime scenes in areas with relatively high crime rates (Burdick-Will, 2013), and woodland around the school is usually tall and wide enough to block these street scenes from adolescents at school and may prevent them from being negatively affected.

5.2. *The association between green space and different types of crimes*

Another important finding in this study is that although the overall results of different types of crime are similar, there are still differences to be noted. There is no evidence that grassland was associated with burglary or theft. These two types of crimes normally occur in populated and dense areas (Quick et al., 2018), so there may be only a small amount of space for street trees but not enough space for grassland to function.

Also, the association between grassland and primary and secondary fires was not significant. As discussed above, the major mechanism linking grassland to crime may be associated with the facilitation of physical activity and social contacts which can reduce social conflicts (Chen et al., 2023a and 2023b; Kemperman and Timmermans, 2014; Samsudin et al., 2022; Yang et al., 2020). However, such an effect of grassland is only effective for areas with a lower level of social conflict (Akers, 2011), where grassland can act as an open space for facilitating social contacts and thus reduce social conflicts. Crimes involving primary and secondary fires are violent and can be regarded as indictable offences (Reilly, 2001), so the increase in grassland may not be effective enough to contribute to such a conflict. We also found that woodland was positively associated with primary and secondary fires, and grassland was positively associated with vehicle crime only for areas with a relatively low crime rate. A possible explanation is that woodlands are more combustible than other outdoor areas, which makes them risky areas for fires. Hence, green space may provide a space for more interactions among gangs, and block people's view, which could exacerbate conflicts, lead to a lack of natural surveillance, and decrease the probability of being reported or even caught (Bogar and Beyer, 2016). There is no evidence that woodland was associated with criminal damage and arson. One possible explanation is that criminal damage and arson are relatively intentional, which means they are usually well-planned before the act, so they may be less influenced by the local environment (Akers, 2011). Another explanation is that criminal damage and arson occur more frequently in the indoor environment rather than in outdoor open spaces (Almanie et al., 2015), so an outdoor physical environment such as green space may be less associated with such an event. Hence, outside space is usually in public ownership, so people may be less concerned about it and report the crimes with no personal implications for them (Almanie et al., 2015). Therefore, criminal damage and arson occurring outdoors may also be less likely to be influenced by the environment.

5.3. The association between covariates and crimes

The results indicate that a series of covariates were also correlated with crime rates. First, crime rates were higher in urban areas than in rural areas, and this may be because there are more economic activities in urban areas (Jones and Pridemore, 2019). Second, areas with police stations had higher crime rates than those without police stations. A possible explanation is that police stations are more likely to be located in areas with higher crime rates. Third, the proportion of the population living in households whose equivalised income is below 60 per cent of the NI median was positively associated with the crime rates. This may be because residents in areas with lower incomes are more likely to be short of basic resources that are essential for normal life (Liu et al., 2022). Fourth, the proportion of the population who are: married, White, and female was negatively associated with the crime rates, which is consistent with previous findings (Ogletree et al., 2022; Venter et al., 2022). Existing evidence suggests that places with lower crime rates may be more attractive to married families, White populations and females, which may partly explain the finding (Sanciangco et al., 2022). Fifth, the proportion of the population who are with low qualifications, long-term unemployed, aged below 18 years, and 18–30 years were negatively associated with the crime rates, which is inconsistent with previous findings (Ogletree et al., 2022; Venter et al., 2022). A possible explanation is that places with the above characteristics may be less economically active and thus offer fewer opportunities for crimes (Duranton and Monastiriotis, 2002). Also, people do not necessarily commit crimes near their residential locations (Jones and Pridemore, 2019), so the above findings can not infer any causalities. Finally, crime rates were lower in places with higher population densities. This may be because crimes in dense areas are more likely to be witnessed and reported, so criminals may try to avoid dense areas (Harries, 2006; Liu et al., 2022).

5.4. Policy implications

Our findings have important implications for crime prevention through green space intervention. First, the proportion of woodland and grassland is generally associated with lower rates of crime, so there may be real benefits to improving the provision and maintenance of such green spaces. Second, our findings suggest that associations between green space and crime are conditional on the rates of crime and types of green space in the local area. This indicates that governments should monitor rates of crime before selecting interventions. For example, improvements to grassland could be prioritised in areas with relatively low crime rates, while improvements to woodland could be prioritised in areas with higher crime rates. Finally, we found evidence that green space-crime associations vary by type of crime. Policymakers therefore need to consider the dominant crime type and rate of crime for a specific region when deciding which type of vegetation may be the most effective for crime prevention in that area.

5.5. Limitations

This study has several limitations, including the potential influence of self-selection bias (Boone-Heinonen et al., 2011). For example, we were unable to adjust for individual characteristics such as personality, which may be associated with both green space preference and crime (Teixeira et al., 2022). Given the cross-sectional study design, we could not infer a causal link between green space and crimes. Therefore, future research should aim to investigate the causality between green space and crime using longitudinal data and include more detailed determinants (e.g., the number of and distance to the nearest police station), especially in developing countries. Also, due to limitations of the model, were not able to specify the detailed thresholds that crime rates have statistically significant associations with grassland and woodland. Through our analysis, we only assessed the availability of green space rather than the actual use of green space, so the mechanisms linking green space, and crimes are still unclear in this study. Also, we only focused on green space quantity in this study and did not consider green space quality due to data availability. Hence, we mainly shed light on the type of vegetation rather than the scale of green space or the function of green space (e.g., public green space vs. private green space), but a small square, a large urban park or the meadows are not the same, which cannot be understood in the same way. Our analysis was based on aggregated data (SOA units) and ecological study design, which may lead to ecological fallacy (Schwartz, 1994). This means the findings from this study may not be valid at the individual level and have an influence on the applicability of our policy implications. The ecological study design based on aggregated data has some limitations which we have highlighted. However, it is the most appropriate study design based on current data availability. There are also some other limitations to the crime data. For example, our data were for 2011/2012–2015/2016 and legislation may have changed during this period, which could lead to bias in our estimation. The green space data are based on LCM 2017, while covariates data are from the 2011 census, so the temporal mismatch among predictor, outcome and covariates may further result in bias in our estimation. Also, the reported crime data may be biased since in areas of low trust or where they have low confidence in action, people may be less likely to report crimes to the police. Another issue is that crime rates are based on the number of incidents of crime that are reported in an area over the number of people resident in that area, but crimes may have been experienced by people living outside the area who were visiting or just passing through. Although we have distinguished between different types of crime, we did not have information on the age, ethnic and sex differences in crimes, which prevents us from further understanding how green space - crime associations vary across socio-economic groups (e.g., we were not able to distinguish between types of sexual and other violence). Finally, our analysis was based on administration boundary which may result in a modifiable areal unit problem (Fotheringham and Wong, 1991). Hence, some variables may suffer from boundary effects (e.g., there could be a police station very nearby but in a different SOA).

6. Conclusion

This study indicates that the proportion of grassland was negatively associated with rates of crime only for areas with relatively low crime rates. Whilst, the proportion of woodland was negatively associated with rates of crime for areas with relatively high crime rates. We also found that the green space-crime association varies across different types of crime. Consequently, policymakers and practitioners may need to consider green space as an intervention for the reduction of crime, but the heterogeneous effects of vegetation type, crime type, and rates of crime across regions should be taken into consideration.

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CRediT authorship contribution statement

Ruoyu Wang: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Ruth Weir:** Writing – review & editing. **Claire L. Cleland:** Writing – review & editing. **Sally McManus:** Writing – review & editing. **George Grekousis:** Writing – review & editing. **Agustina Martire:** Writing – review & editing. **Ruth F. Hunter:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Dominic Bryan:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ufug.2024.128523.

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