environmental and earth sciences proceedings

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Proceeding Paper

Assessing Visual Connectivity at Property Crime Hotspots in Nashik City †

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† Presented at the 1st International Online Conference on Urban Sciences (IOCUS 2026), 20–22 May 2026; Available online: https://sciforum.net/event/IOCUS2026.

Abstract

This study assessed visual connectivity at property crime hotspots (PCHs) in Nashik City, India, using Visibility Graph Analysis (VGA). Robbery, burglary, and theft locations were analyzed within 50 m buffers using a 10 × 10 m VGA grid. Descriptive and non-parametric inferential analyses were conducted to examine visual-connectivity patterns across three PCHs. Burglary and theft locations generally exhibited lower mean visual connectivity than corresponding neighborhood means, while robbery showed a less consistent pattern. Kruskal–Wallis tests and Holm-corrected pairwise comparisons revealed no statistically significant differences among crime categories. The findings represent descriptive spatial associations, and visual connectivity should not be interpreted as a direct measure of natural surveillance or crime-prevention effects.

Keywords: Visibility Graph Analysis; CPTED; space syntax; urban planning and design

1. Introduction

Property crime, including robbery, burglary, and theft, continues to be one of the most prevalent forms of urban crime, posing significant challenges to public safety, economic stability, and sustainable urban development [1]. Beyond the direct financial losses suffered by victims, property crimes reduce residents' sense of safety, discourage the use of public spaces, and undermine the overall quality of urban life [2]. Contemporary research in environmental criminology has demonstrated that crime is not randomly distributed across cities but tends to concentrate in specific locations where environmental conditions create opportunities for offending [3]. Consequently, increasing attention has been directed toward understanding how characteristics of the built environment influence criminal opportunities and shape spatial crime patterns [4]. Urban planning and urban design have therefore emerged as important disciplines in crime prevention by promoting environments that enhance surveillance, improve visibility, and discourage criminal activity through informed spatial design [5]. Understanding these relationships provides an important foundation for examining how visual connectivity influences property crime in urban neighborhoods.

The spatial configuration of the built environment plays a fundamental role in shaping human movement, social interaction, and opportunities for natural surveillance, thereby influencing the occurrence of crime [6]. Within the framework of environmental criminology and Crime Prevention Through Environmental Design (CPTED), natural surveillance

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Academic Editor: Jianming Cai

Published: 8 October 2026

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is regarded as one of the most effective strategies for discouraging criminal behavior by increasing the likelihood that offenders will be observed while committing a crime [7]. Among the analytical techniques developed within space syntax, Visibility Graph Analysis (VGA) provides a quantitative framework for examining how the spatial configuration of urban environments influences visual connectivity and accessibility [8]. In particular, VGA evaluates intervisibility between locations by measuring visual connectivity across an environment, enabling the identification of spaces that are visually exposed or secluded [9]. Such analyses enable researchers and urban planners to understand how spatial layouts may either facilitate informal surveillance or create concealed environments conducive to criminal activity [10]. Building upon this theoretical foundation, assessing visual connectivity at locations where property crimes concentrate offers an opportunity to better understand the spatial characteristics associated with crime occurrence and to inform evidence-based urban planning interventions.

Numerous studies have investigated the relationship between the built environment and crime, demonstrating that street networks, land-use characteristics, accessibility, and urban morphology significantly influence the spatial distribution of criminal activities [11]. Research has shown that environments with limited visibility, poor surveillance, and fragmented spatial configurations can create opportunities for offenders by reducing the likelihood of detection, whereas well-connected street environments and visually permeable urban layouts are generally associated with enhanced informal surveillance and lower crime risk [12]. Recent advances in the Geographic Information System (GIS), space syntax, and geospatial analysis have enabled researchers to integrate crime data with spatial configuration measures, thereby improving the understanding of how urban form contributes to crime patterns [13,14]. Although previous studies have demonstrated the potential of space syntax and CPTED for crime analysis, investigations specifically employing VGA to assess visual connectivity at Property Crime Hotspots (PCHs) remain limited [15]. Furthermore, evidence from rapidly urbanizing Indian cities is scarce, despite the need to understand how neighborhood spatial configurations influence opportunities for property crime across diverse urban contexts [16]. Addressing these research gaps is essential for developing context-specific planning strategies that strengthen natural surveillance and contribute to safer urban neighborhoods.

Although previous studies have demonstrated the value of space syntax, natural surveillance, and CPTED in understanding crime patterns, the assessment of visual connectivity at property crime hotspots using VGA remains relatively unexplored, particularly in the context of Indian cities [17]. Therefore, this study aims to assess visual connectivity at identified property-crime hotspots in Nashik City by integrating police-recorded property-crime data with building footprint data and space syntax analysis. The findings are expected to provide empirical evidence on the spatial association between neighborhood visual connectivity and recorded property crime locations while demonstrating the applicability of VGA as a diagnostic tool for crime-sensitive urban planning and urban design [18]. By integrating crime mapping with quantitative spatial analysis, this study provides a practical methodological framework for identifying visually vulnerable urban environments and supporting evidence-based interventions to create safer neighborhoods.

2. Materials and Methods

The methodological framework adopted in this study is illustrated in Figure 1. The workflow comprises four sequential stages: study area and dataset preparation; identification of PCHs; VGA at the identified PCHs; and assessment of visual connectivity to examine the relationship between neighborhood spatial configuration and property crime occurrence.

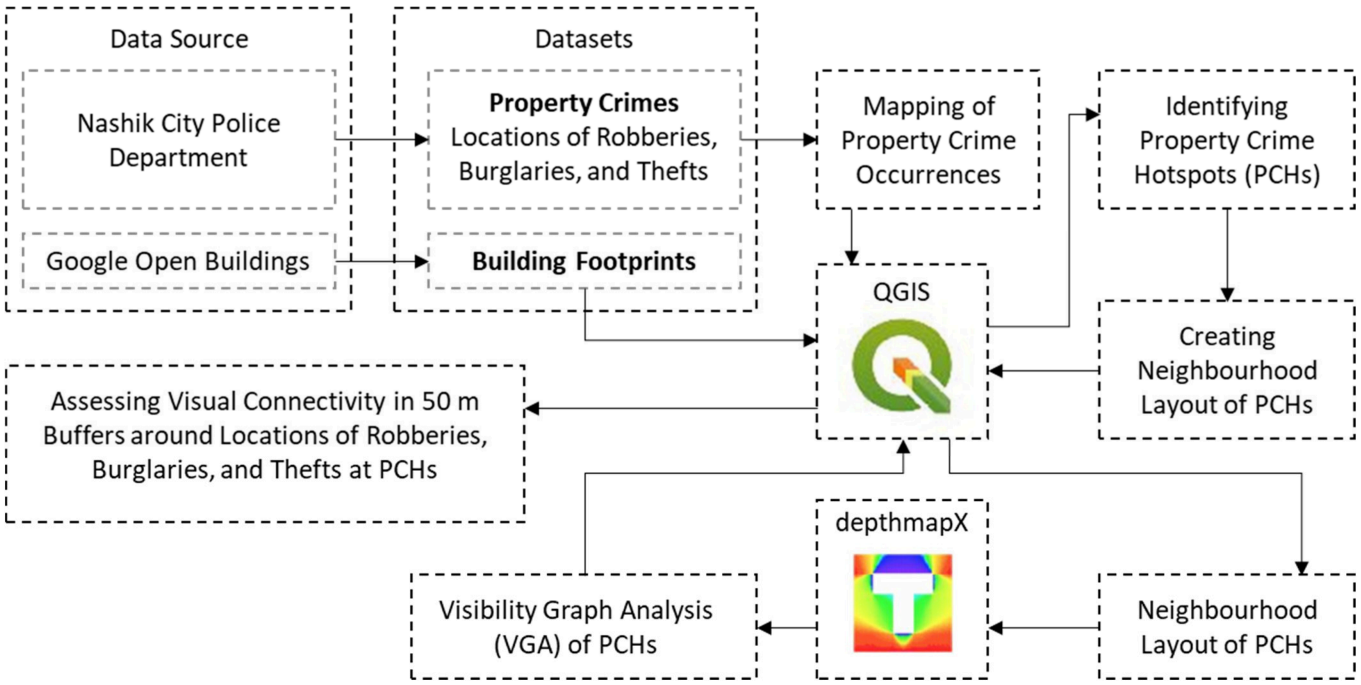


Figure 1. Workflow of the research methodology.

2.1. Study Area and Datasets

Nashik City, located in India (Figure 2), was selected as the study area due to its rapid urban expansion and growing concerns about property crime. The city is a diverse urban environment characterized by residential, commercial, and mixed-use developments. Property crime data, including robbery, burglary, and theft incidents, were obtained from the Nashik City Police Department. Building footprint data required for the visibility analysis was acquired from Google Open Buildings. These datasets served as the basis for identifying property crime hotspots and assessing neighborhood visual connectivity using space syntax-based VGA.

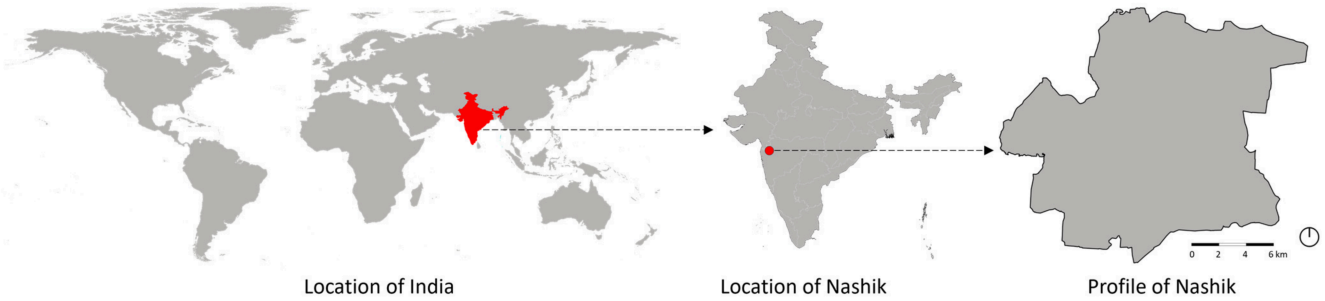


Figure 2. Location of the study area: Nashik City, India.

2.2. Identification of Property Crime Hotspots (PCHs)

Property crime incidents, including robbery, burglary, and theft, were geocoded and mapped in QGIS (version 3.28.3) using their geographic coordinates. Kernel Density Estimation (KDE) was performed for the aggregated property-crime dataset using a quartic (biweight) kernel, a bandwidth of 1000 m, and a 10 m raster resolution. The bandwidth was selected to delineate neighborhood-scale spatial subzones with relatively homogeneous property-crime intensity while maintaining sufficient spatial observations for subsequent analysis, rather than to identify individual street-segment hotspots. The resulting density surface was examined to identify the three PCHs. No fixed numerical density threshold was applied; instead, the three PCHs were delineated using the major roads surrounding each

PCH as practical spatial boundaries. Building footprint data from Google Open Buildings were subsequently used to construct the spatial layout of the identified PCHs, which served as the spatial framework for the subsequent VGA.

2.3. Visibility Graph Analysis (VGA) at PCHs

The spatial layouts of the identified PCHs were imported into depthmapX (version 0.8.0) to perform VGA. A 10 × 10 m analysis grid was used, corresponding to the default grid setting in depthmapX, and intervisibility between grid points was computed to evaluate visual relationships across each PCH. Visual connectivity was evaluated within 50 m buffers around robbery, burglary, and theft locations, providing a compact spatial unit for assessing the immediate built-environment context of individual locations [19]. The analysis generated a visual connectivity value for each grid point, representing the number of other locations directly visible from that point. Higher visual connectivity values indicate greater intervisibility, whereas lower values indicate more visually restricted spaces. These measures represent spatial visibility conditions rather than direct measures of natural surveillance or crime occurrence. The VGA boundaries corresponded to the external edges of the major roads used to delineate the respective PCHs; no explicit edge-effect correction or extension of the surrounding urban fabric beyond these boundaries was applied. The resulting visual-connectivity maps were subsequently exported to QGIS for further analysis.

2.4. Statistical Analysis

The visual-connectivity values extracted from the 50 m buffers around individual property crime locations were summarized using the mean, median, standard deviation (SD), and 95% bootstrap confidence intervals (CIs). Given the relatively small sample sizes for several crime-category and hotspot combinations and the observed variability in visual-connectivity values, non-parametric tests were used. The Kruskal–Wallis test was applied separately within each PCH to assess differences in visual connectivity among robbery, burglary, and theft locations. Where pairwise comparisons were conducted, Mann–Whitney U tests with Holm correction for multiple comparisons were used, and the rank–biserial correlation was reported as the effect size. In addition, a Wilcoxon signed-rank test was used as a supplementary reference-based analysis to compare the distribution of visual-connectivity values at individual crime locations with the corresponding neighborhood-level mean. These analyses were used to assess statistical differences and spatial associations rather than to establish causal relationships between visual connectivity and property crime.

3. Results and Discussion

3.1. Property Crime Hotspots

The spatial distribution of property crime incidents in Nashik City revealed distinct clusters of robbery, burglary, and theft. Using KDE in QGIS, three PCHs with the highest concentrations of property crime incidents were identified (Figure 3). These hotspots provided a focused spatial framework for examining visual-connectivity conditions around recorded crime locations. The concentration of property crimes within specific areas is consistent with environmental criminology, which recognizes that crime tends to cluster spatially rather than being uniformly distributed across cities [3]. Such clustering may reflect the spatial configuration of streets, buildings, and land-use activities that shape movement and visibility [17]. Accordingly, the three identified PCHs were selected for subsequent VGA to assess spatial patterns of visual connectivity around robbery, burglary, and theft locations.

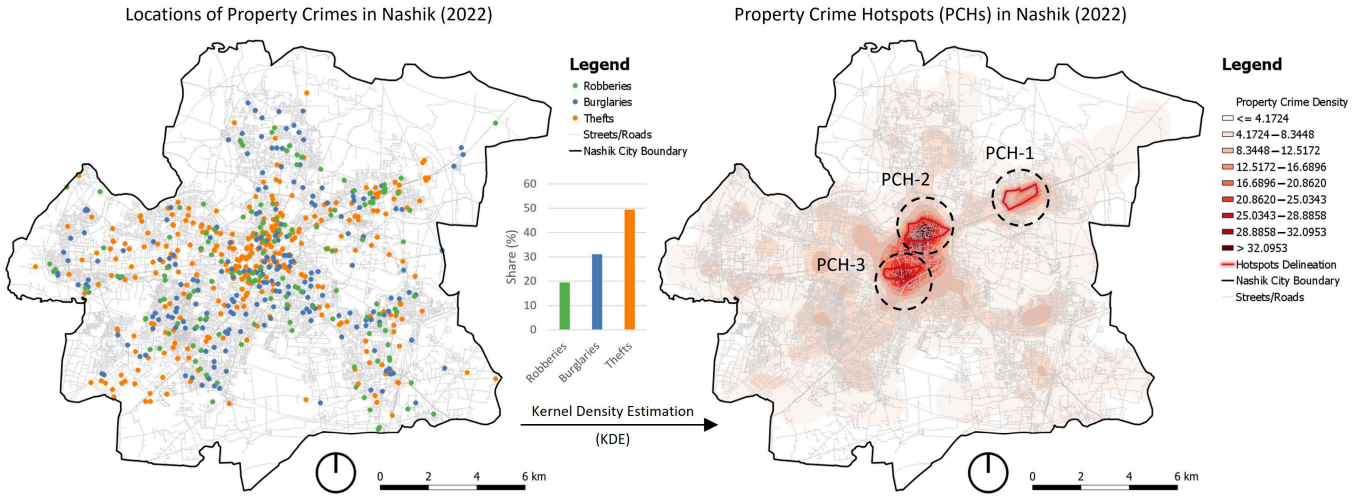


Figure 3. Property crime hotspots identified in Nashik City.

3.2. Spatial Patterns of Visual Connectivity at PCHs

The spatial distribution of visual connectivity varied across the three PCHs, reflecting differences in neighborhood spatial configuration and visibility conditions. As shown in Figure 4, higher visual connectivity was generally observed along major streets and relatively open spaces, whereas lower values occurred within compact residential blocks and visually enclosed areas. Robbery, burglary, and theft locations occurred across varying levels of visual connectivity, with burglary incidents more frequently observed in visually restricted residential areas, while theft locations showed greater spatial variability. Such spatial concentration of crime is consistent with environmental criminology [3]. Differences in environmental characteristics and surveillance opportunities may further contribute to variations in crime locations [17]. The relationship between spatial configuration and crime has also been examined through space syntax-based approaches [10]. However, these patterns represent spatial associations and should not be interpreted as evidence that visual connectivity alone explains the distribution of property crime. The visual-connectivity values were therefore examined statistically across the three crime categories in the subsequent analysis.

3.3. Interpretation of Visual Connectivity at PCHs

The visual-connectivity characteristics of property crime locations across the three PCHs are summarized in Table 1. The results indicate considerable variation in visual connectivity among crime locations and across hotspots. Burglary locations exhibited lower mean visual connectivity than their corresponding neighborhood averages in all three PCHs, whereas theft locations showed the same pattern across PCH-1, PCH-2, and PCH-3. In contrast, robbery locations showed a less consistent pattern, with mean visual connectivity exceeding the neighborhood average in PCH-1 but falling below it in PCH-2 and PCH-3. The differences between mean and median values, particularly for robbery in PCH-2, together with the relatively small number of observations for several crime categories, indicate substantial variability in the data. Therefore, the descriptive statistics are interpreted alongside confidence intervals and non-parametric inferential tests to account for uncertainty in the observed patterns.

The inferential analysis was conducted to assess whether the observed differences in visual connectivity among robbery, burglary, and theft locations were statistically meaningful. As shown in Table 2, the Kruskal–Wallis tests indicated no statistically significant differences among the three crime categories in PCH-1 ($H = 1.435$, $p = 0.488$), PCH-2 ($H = 1.433$, $p = 0.488$), or PCH-3 ($H = 1.123$, $p = 0.570$). Consistently, none of the pairwise

Mann–Whitney U comparisons remained statistically significant after Holm correction, with the observed rank–biserial correlations indicating relatively small-to-moderate differences. The supplementary reference-based analysis showed that burglary and theft locations in PCH-2 and theft locations in PCH-3 had significantly lower visual-connectivity values than their corresponding neighborhood means ($p = 0.031$, $p < 0.001$, and $p = 0.013$, respectively). These findings indicate spatial associations rather than causal relationships between visual connectivity and property crime. Moreover, visual connectivity represents a potential spatial condition for visibility. It should not be equated directly with natural surveillance, which also depends on human activity, land use, pedestrian presence, and other forms of guardianship.

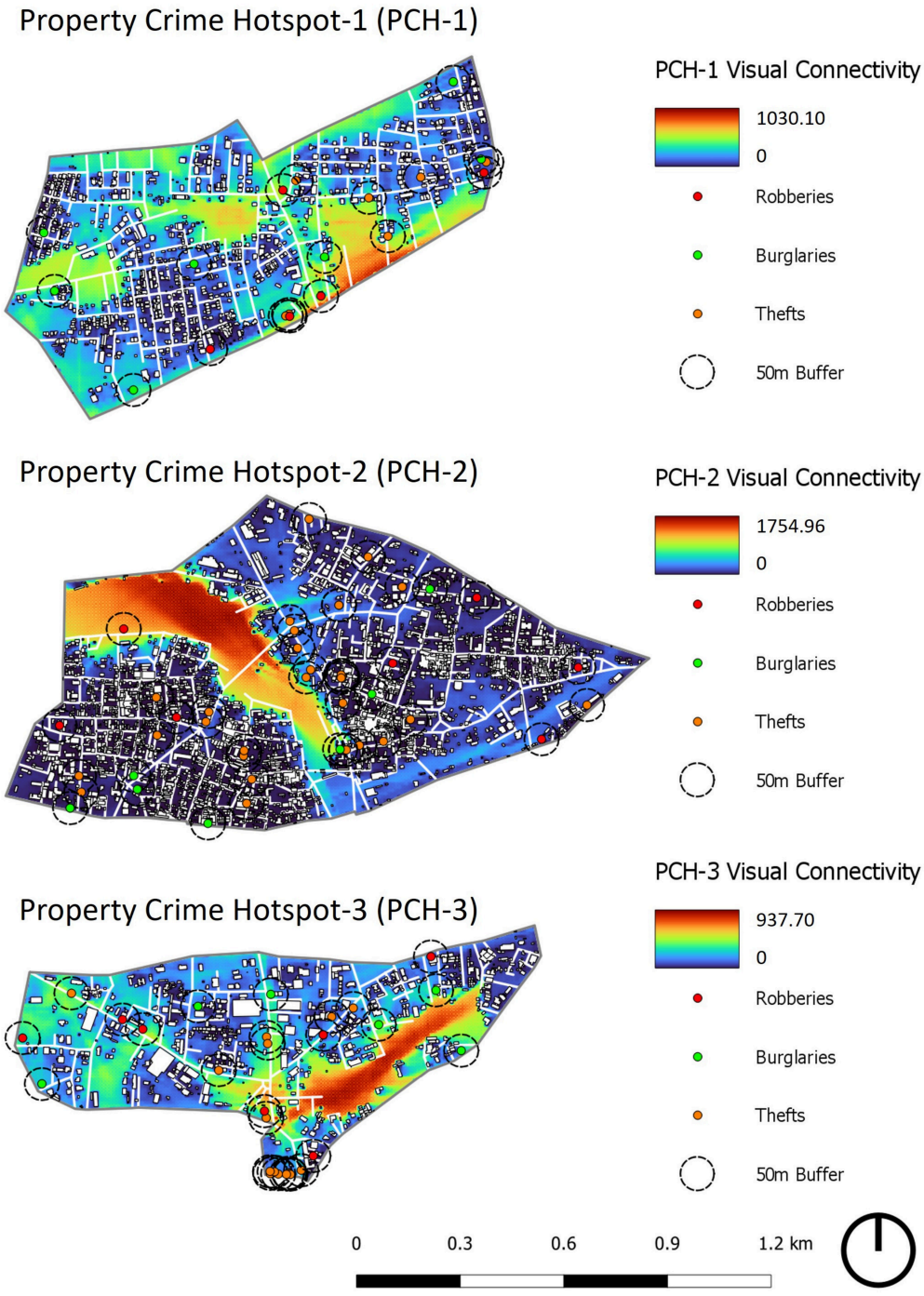


Figure 4. Spatial distribution of property crimes and visual connectivity at the identified property crime hotspots in Nashik City.

Table 1. Descriptive statistics and reference-based comparisons.

PCH	Property Crime	n	Mean	Median	SD	95% Bootstrap CI	Neighborhood Mean	Wilcoxon *p*-Value
PCH-1	Robbery	5	307.12	394.89	187.24	165.91–448.34	279.39	1
	Burglary	7	199.97	140.5	132.41	111.19–290.12	279.39	0.219
	Theft	7	275.92	272.41	138.38	180.75–364.64	279.39	0.813
PCH-2	Robbery	7	216.87	36.91	403.67	40.97–528.38	321.46	0.297
	Burglary	7	84.89	37.99	155.32	18.50–204.66	321.46	**0.031**
	Theft	30	118.47	66.53	123.78	77.68–164.60	321.46	**<0.001**
PCH-3	Robbery	7	221.14	155.2	131.8	137.94–318.02	273.97	0.578
	Burglary	6	231.63	224.14	71.97	179.35–283.22	273.97	0.219
	Theft	16	211.31	187.83	88.14	173.43–255.81	273.97	**0.013**

Note: n denotes the number of recorded crime locations. Mean and median represent the visual-connectivity values extracted from the 50 m buffers around individual crime locations. SD denotes the standard deviation. CI denotes the percentile 95% bootstrap confidence interval based on 10,000 resamples. The neighborhood mean represents the mean visual-connectivity value of all VGA points within the corresponding PCH. The Wilcoxon signed-rank test compares the distribution of individual crime-location buffer values against the corresponding neighborhood mean as the reference; it is used for benchmark analysis and does not treat neighborhood VGA points as an independent comparison sample. Bold *p*-values indicate $p < 0.05$.

Table 2. Inferential analysis of visual connectivity among crime categories.

PCH	Overall Test/Pairwise Comparison	U/H Statistic	*p*-Value	Holm-Adjusted *p*-Value	Rank–Biserial Correlation
PCH-1	Kruskal–Wallis	H = 1.435	0.488	-	-
	Robbery vs. Burglary	U = 24.0	0.343	1	−0.371
	Robbery vs. Theft	U = 21.0	0.639	1	−0.2
	Burglary vs. Theft	U = 18.0	0.456	1	0.265
PCH-2	Kruskal–Wallis	H = 1.433	0.488	-	-
	Robbery vs. Burglary	U = 31.0	0.456	0.911	−0.265
	Robbery vs. Theft	U = 113.0	0.776	0.911	−0.076
	Burglary vs. Theft	U = 75.0	0.259	0.777	0.286
PCH-3	Kruskal–Wallis	H = 1.123	0.57	-	-
	Robbery vs. Burglary	U = 17.0	0.628	1	0.19
	Robbery vs. Theft	U = 49.0	0.671	1	0.125
	Burglary vs. Theft	U = 63.0	0.294	0.882	−0.313

Note: H denotes the Kruskal–Wallis test statistic, and U denotes the Mann–Whitney U statistic. Holm-adjusted *p*-values were calculated separately within each PCH for the three pairwise comparisons. Rank–biserial correlation represents the magnitude and direction of the pairwise difference. Positive values indicate higher ranks for the first-listed crime category, whereas negative values indicate higher ranks for the second-listed category. No pairwise comparison remained statistically significant after Holm adjustment.

4. Conclusions

This study assessed visual connectivity at identified property crime hotspots in Nashik City using VGA. The results showed considerable spatial variation, with burglary and theft locations generally exhibiting lower visual-connectivity values than their corresponding neighborhood means. However, the inferential analysis found no statistically significant differences among robbery, burglary, and theft locations within individual hotspots, indicating that the observed patterns represent descriptive spatial associations rather than causal relationships. Visual connectivity should therefore be understood as a potential spatial condition for visibility rather than a direct measure of natural surveillance or crime-prevention effects, as functional surveillance also depends on human activity, pedestrian presence,

land use, and guardianship. The findings are constrained by the modest number of crime locations in some category–hotspot combinations, coverage of only three PCHs, and the absence of environmental covariates such as commercial density, street hierarchy, and land-use mix, which may introduce omitted-variable bias. In addition, potential edge effects from the PCH boundaries may influence visual-connectivity values near their peripheries.

Author Contributions: A.K.: Conceptualization; methodology; data curation; analysis; writing—original draft preparation. S.B.: Supervision, conceptualization; validation; writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data will be made available on request.

Acknowledgments: We sincerely thank the Nashik City Police Department for granting us access to the 2022 property crime datasets that were used to conduct this research work.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

CPTED	Crime Prevention Through Environmental Design
VGA	Visibility Graph Analysis
GIS	Geographic Information System
PCH	Property Crime Hotspot
KDE	Kernel Density Estimation

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