Spatial Units of Analysis (SUoA) in Crime Location Choice Studies: A Narrative Review of SUoA Selection Decisions

# Abstract

**Background:** Spatial Units of Analysis (SUoA) selection plays a crucial role in shaping our understanding of crime location choice. Choosing an appropriate SUoA is important because different units can lead to substantially different conclusions about offender decision-making, environmental context, and the effectiveness of place-based interventions. In this study, we examine SUoA selection practices to assess whether these decisions reflect the underlying theoretical alignment or stem from practical and methodological considerations.

**Methods:** We conducted a narrative review that involved searching four databases and identifying 2,325 papers. After removing duplicates and irrelevant studies, we screened 91 papers in full and retained 49 studies representing 51 observations. We then examined SUoA selection practices, variable complexity, and data limitations through descriptive analysis and mixed-effects regression models.

**Results:** Studies demonstrated sophisticated variable usage, incorporating 6-39 variables (mean: 21.9) across multiple domains. SUoA sizes span 4.8 orders of magnitude from individual properties to administrative districts, reflecting systematic scale-matching to different criminological processes. Despite technological advances, SUoA sizes remained stable over time (*β* = 0.01, *p* = 0.738), with strong country-level clustering (ICC = 0.386) suggesting that national data infrastructures and established research conventions exert a stronger influence on scale selection than recent technological advances.

**Conclusions:** Our review indicates that crime-location-choice research generally employs SUoA thoughtfully, aligning them with theoretical aims while working within institutional and data constraints. Rather than reflecting arbitrary choices, the observed variation appears to stem from deliberate, context-sensitive decisions. Strengthening data infrastructures and promoting standardization across jurisdictions may further enhance the comparability and cumulative value of future studies.

# Introduction

Crime concentrates in specific locations, creating spatial patterns that researchers analyze using discrete choice models to understand offender location selection ([Bernasco et al., 2013](#ref-bernasco2013); [Vandeviver et al., 2015](#ref-vandeviver2015)). These models conceptualize crime location selection as a rational process in which offenders evaluate potential targets based on expected costs and benefits. Recent empirical studies reveal considerable diversity in the spatial units of analysis (SUoA) employed. Vandeviver et al. ([2015](#ref-vandeviver2015)) analyzed individual residential properties (136 m² average) in Belgium, while Bernasco et al. ([2013](#ref-bernasco2013)) examined census blocks (19,680 m² average) in Chicago. This variation in scale raises concerns about the consistency of methods in spatial criminology. Yet which SUoA are used—and what drives those choices—has received little systematic attention.

SUoA refers to the discrete geographical area or boundary—such as a property, street segment, grid cell other such units used to represent alternatives in crime location choice models. The choice of SUoA determines the spatial resolution of analysis, influences which environmental and social factors are measurable, and shapes the interpretation of results ([Fotheringham & Wong, 1991](#ref-fotheringham1991); [Openshaw, 1984](#ref-openshaw1984); [Weisburd et al., 2012](#ref-weisburd2012)). Contemporary studies demonstrate remarkable diversity in scale choices, analyzing individual properties ([Vandeviver et al., 2015](#ref-vandeviver2015)), street segments ([Bernasco & Jacques, 2015](#ref-bernasco2015)), census blocks ([Bernasco et al., 2013](#ref-bernasco2013)), neighborhoods ([Song et al., 2017](#ref-song2017)), administrative districts ([Townsley et al., 2015](#ref-townsley2015)), and grid cells ([Hanayama et al., 2018](#ref-hanayama2018)). This diversity spans from micro-environmental units measuring individual houses ([Langton & Steenbeek, 2017](#ref-langton2017)) to metropolitan-scale districts for comparative analysis ([Xiao et al., 2018](#ref-xiao2018)). The methodological choice of SUoA directly affects statistical power, result interpretation, and policy relevance ([Fotheringham & Wong, 1991](#ref-fotheringham1991); [Openshaw, 1984](#ref-openshaw1984)). Despite its fundamental importance, the factors that drive SUoA selection decisions in crime location choice research have received little systematic attention.

This study addresses this gap by systematically examining how researchers actually select SUoA across different empirical contexts and whether these decisions reflect theoretical considerations or arbitrary methodological choices. We investigate the rationales that researchers provide for SUoA selection, analyze patterns in these justifications, and assess whether SUoA choices demonstrate systematic alignment with theoretical frameworks or primarily reflect practical constraints. Our analysis contributes to spatial criminology by providing the first comprehensive assessment of SUoA selection practices, testing claims about methodological inconsistency, and offering evidence-based insights into the factors that shape analytical possibilities in crime location choice research. This systematic review enables more informed SUoA selection decisions and supports cumulative knowledge building by clarifying how methodological choices connect to theoretical frameworks and institutional constraints in spatial criminology.

## Theoretical Background

Crime location choice research has undergone fundamental transformation in SUoA over the past several decades. Early criminological research focused predominantly on large SUoA such as cities, states, and neighborhoods, examining broad patterns of crime distribution across administrative boundaries ([Baumer et al., 1998](#ref-baumer1998); [Loftin & Hill, 1974](#ref-loftin1974)). This macro-level approach provided valuable insights into regional crime patterns but offered limited understanding of micro-spatial decision-making processes underlying individual offending events.

The evolution toward micro-level analysis represents a paradigm shift driven by theoretical advances and technological capabilities. Micro-place analysis marked a major transition, focusing on specific locations like street segments, census blocks, and grid cells ([Eck, 1995](#ref-eck1995); [Weisburd et al., 2004](#ref-weisburd2004)). This shift fundamentally changed how researchers conceptualize crime location choice, enabling examination of offender decision-making at scales where these decisions actually occur ([Bernasco et al., 2013](#ref-bernasco2013); [Bernasco, 2019](#ref-bernasco2019); [Bernasco & Jacques, 2015](#ref-bernasco2015)). Advances in computational power and the rise of crime mapping technologies have also made it more feasible to analyze micro-level SUoA ([Vandeviver & Bernasco, 2017](#ref-vandeviver2017)). Micro-level SUoA enable researchers to extract granular insights into crime trends and offender behavior ([Weisburd et al., 2004](#ref-weisburd2004)), enhancing theoretical development and enabling more precise crime prevention strategies.

Contemporary studies demonstrate sophisticated theoretical alignment between SUoA and criminological processes. Property-level studies use house-level units because “the use of fine-grained SUoA analysis such as the house that is burglarized has the advantage that it addresses the modifiable areal unit problem and reduces the risk of aggregation bias” ([Vandeviver et al., 2015](#ref-vandeviver2015)). Street segment analyses recognize that “the spatial resolution of a street segment naturally corresponds to human observational limitations” and “possesses attributes suitable for direct sensory perception” ([Kuralarasan et al., 2024](#ref-kuralarasan2024)). These examples illustrate how SUoA selection reflects theoretically-informed decisions rather than arbitrary methodological choices.

SUoA selection connects to fundamental issues in spatial analysis and criminology. The modifiable areal unit problem (MAUP) demonstrates that statistical relationships change significantly depending on SUoA ([Fotheringham & Wong, 1991](#ref-fotheringham1991)). In crime research, environmental factors may relate to crime differently at different scales of analysis, creating challenges for theory development and policy application. The diversity in SUoA also challenges the comparability and generalizability of findings across different SUoA ([Steenbeek & Weisburd, 2016](#ref-steenbeek2016); [Weisburd et al., 2012](#ref-weisburd2012)).

Crime pattern theory and routine activity theory provide complementary theoretical frameworks that directly inform SUoA selection decisions. Crime pattern theory posits that crime location choice results from the intersection of offenders’ awareness spaces with suitable criminal opportunities ([Brantingham & Brantingham, 1993](#ref-brantingham1993)). The theory identifies key spatial elements: nodes (where offenders spend time), paths (travel routes between nodes), and edges (boundaries between different areas). Crime concentrates where these elements create overlap between offender knowledge and target availability. Routine activity theory explains crime occurrence through the spatio-temporal convergence of three necessary elements: motivated offenders, suitable targets, and the absence of capable guardians ([Cohen & Felson, 1979](#ref-cohen1979)). The theory emphasizes that crime results from the routine activities of both offenders and potential victims bringing these elements together in space and time.

The choice of SUoA critically affects how these theoretical mechanisms can be observed and measured. For crime pattern theory, SUoA selection determines whether awareness space components (nodes, paths, edges) can be adequately captured and whether the overlap between offender knowledge and target suitability becomes visible in the analysis. For routine activity theory, the SUoA defines the spatial and temporal resolution at which the convergence of offenders, targets, and guardians can be detected and measured. Fine-grained SUoA may capture micro-level convergence processes, while coarser scales may better represent broader routine activity patterns. Thus, while these theories do not claim to be inherently scale-dependent, SUoA selection fundamentally shapes which theoretical mechanisms become empirically testable, making scale choice a theoretically consequential decision rather than a purely methodological one.

The theoretical implications of SUoA choice are profound. Fine-grained analyses capture target-specific characteristics and immediate environmental features that align with situational crime prevention principles, while broader scales better represent neighborhood-level social processes, collective efficacy, and routine activity patterns. The SUoA determines which aspects of the crime triangle convergence become visible and measurable, fundamentally shaping both theoretical understanding and practical applications for crime prevention. This means that researchers must explicitly consider how their chosen SUoA aligns with the theoretical mechanisms they seek to investigate, as mismatched scales may obscure important criminological processes or lead to ecological fallacies in interpretation.

## Methodological Considerations

Spatial choice model statistical properties depend critically on SUoA. Model performance typically increases with finer resolution due to greater variation among alternatives ([Train, 2009](#ref-train2009)). However, finer SUoA may introduce noise and reduce parameter stability.

Computational constraints become important with fine-grained units. The number of potential alternatives grows exponentially with spatial resolution, creating computational challenges that researchers must navigate when selecting SUoA. This practical constraint may drive researchers toward coarser SUoA regardless of theoretical preferences. For example, Smith and Brown ([2007](#ref-smith2007)) divided Richmond, Virginia into 4,895 grid cells (0.032 km² each) acknowledging computational constraints while maintaining fine SUoA resolution. Hanayama et al. ([2018](#ref-hanayama2018)) employed 1,134 grid cells (25,000 m² average) for burglary analysis, explicitly balancing computational feasibility with analytical precision. Conversely, studies analyzing very large choice sets face memory limitations: Vandeviver et al. ([2015](#ref-vandeviver2015)) analyzed over 500,000 potential targets, requiring specialized computational approaches to handle such extensive alternative sets.

Data availability represents another key constraint. Administrative data often dictate available SUoA, with crime data typically aggregated to police districts or census units. High-resolution data may be available in some jurisdictions but not others, creating systematic biases in methodological choices across contexts. Bernasco et al. ([2013](#ref-bernasco2013)) found that data limitations prevented tracking offenders across multiple crimes, illustrating how institutional data systems fundamentally shape analytical possibilities regardless of theoretical preferences. Studies continue to face computational constraints even with modern technology, as memory limitations force sampling decisions that affect methodological choices. Administrative boundary availability varies systematically across jurisdictions: Baudains et al. ([2013](#ref-baudains2013)) used Lower Super Output Areas (0.33 km² average) readily available in UK administrative systems, while Chinese studies like Long et al. ([2021](#ref-long2021)) employ community units (1.62 km² average) that align with local administrative structures but differ substantially in scale and definition from Western equivalents.

Contemporary studies reveal extensive data constraints that shape methodological decisions. Property-level studies using Google Street View acknowledge that “the inability of the Google Car to capture isolated properties inevitably leads to a biased sample, as these cannot be coded” ([Langton & Steenbeek, 2017](#ref-langton2017)). Registry data limitations force analytic restrictions, as “registry data lacks information on apartments, limiting analyses to house burglaries” ([Vandeviver et al., 2015](#ref-vandeviver2015)). These constraints demonstrate how data infrastructure fundamentally shapes SUoA selection beyond theoretical considerations. Studies employing street segment analysis face limitations where “street segments are still too coarse as units of analysis, not only because they still cover too large territory but also because their relevant characteristics are not stable over time” ([Bernasco & Jacques, 2015](#ref-bernasco2015)).

These theoretical foundations and methodological considerations reveal that SUoA selection involves complex interactions between theoretical requirements, practical constraints, and available data infrastructure. While existing studies demonstrate sophisticated approaches to SUoA selection, the factors that systematically influence these decisions across the broader literature remain unclear. Understanding these patterns is crucial for advancing methodological consistency and theoretical development in spatial criminology.

The observed diversity in SUoA choices across the literature raises fundamental questions about whether this variation represents principled adaptation to different research contexts and theoretical frameworks, or whether it primarily reflects decisions driven by data availability and computational convenience. This distinction has important implications for methodological development and the cumulative advancement of spatial criminology.

To address this research gap, the present study conducts a narrative review of crime location choice studies to examine the patterns and drivers of SUoA selection. By systematically analyzing the distribution of SUoA sizes, temporal trends, cross-jurisdictional variations, and crime type associations, this review aims to provide empirical evidence for understanding how and why researchers select particular SUoA for their analyses. This evidence is essential for developing methodological guidelines and advancing theoretical coherence in spatial criminology.

# Research Questions

To address this research gap, we aim to answer the following research questions in our narrative review:

**RQ1**: What is the distribution of SUoA sizes used in crime location choice studies?

**RQ2**: Have SUoA sizes changed over time as computational capabilities and data availability improved?

**RQ3**: Do SUoA choices differ systematically across jurisdictions, particularly between Anglo-Saxon and other legal traditions?

**RQ4**: Are certain crime types associated with particular SUoA?

**RQ5**: How do researchers explain their SUoA selection decisions, and do these explanations reflect systematic theoretical considerations or arbitrary choices?

**RQ6**: What is the complexity and scope of explanatory variables used in crime location choice studies, and how does this relate to SUoA selection?

**RQ7**: How transparently do studies report data limitations and methodological constraints, particularly those related to SUoA?

**RQ8**: What are the key correlations between SUoA selection and study characteristics including methodological sophistication and analytical approaches?

By systematically addressing these questions through analysis of 51 observations from crime location choice studies, this review seeks to advance our understanding of SUoA selection practices and contribute to more informed methodological decision-making in spatial criminology research.

# Methods

## Study Design and Registration

We conducted a narrative review of crime location choice studies in criminology. Following Pawson ([2002](#ref-pawson2002)), narrative reviews preserve a “ground-level view” by extracting information about both process and outcomes, making findings more contextually understandable. Our review employs a “descriptive-analytical” approach ([Arksey & O’Malley, 2005](#ref-arksey2005)) that applies a common analytical framework to collect standardized information on SUoA selection practices, enabling meaningful comparisons while preserving contextual richness. We did not pre-register the protocol, as narrative reviews allow iterative refinement based on emerging patterns. For study selection and data management, we used litsearchr and R.

## Search Strategy

We developed a search strategy using a two-phase approach to optimize search term selection and maximize recall of relevant studies.

### Phase 1: Initial Search and Keyword Extraction

We conducted an initial “naive” search across three databases to identify keywords and assess the research landscape: Web of Science Core Collection (n = 97), Scopus (n = 105), and ProQuest (n = 47). Table 1 shows our search strategy, which employed broad Boolean terms across three conceptual domains (population, intervention, outcome) to capture studies analyzing offender location choice decisions through discrete choice models. The relatively modest yield of 249 total records across all databases indicated the specialized nature of crime location choice research and justified our subsequent evidence-based search optimization approach:

Table 1. Naive Search Strategy and Results

| **Database** | **Naive Search Term** | **Records** |
| --- | --- | --- |
| Web of Science | *TS=(((offend\* OR crim\* OR burglar\* OR robb\* OR co-offend\* OR dealer\*) AND ("discret\* choic\*" OR "choic\* model\*" OR "rational choice" OR "awareness space" OR "journey to crime" OR "mobility" OR "opportunity" OR "accessibility" OR "attractiveness" OR "crime pattern\*") AND ("crime locat\* choic\*" OR "offend\* locat\* choic\*" OR "robber\* locat\* choic\*" OR "burglar\* locat\* choic\*" OR "target area\*" OR "target selection" OR "crime site selection" OR "spatial choic\* model\*")))* | 97 |
| Scopus | *TITLE-ABS-KEY(((offend\* OR crim\* OR burglar\* OR robb\* OR co-offend\* OR dealer\*) AND ("discret\* choic\*" OR "choic\* model\*" OR "rational choice" OR "awareness space" OR "journey to crime" OR "mobility" OR "opportunity" OR "accessibility" OR "attractiveness" OR "crime pattern\*") AND ("crime locat\* choic\*" OR "offend\* locat\* choic\*" OR "robber\* locat\* choic\*" OR "burglar\* locat\* choic\*" OR "target area\*" OR "target selection" OR "crime site selection" OR "spatial choic\* model\*")))* | 105 |
| ProQuest | *noft(((offend\* OR crim\* OR burglar\* OR robb\* OR co-offend\* OR dealer\*) AND ("discret\* choic\*" OR "choic\* model\*" OR "rational choice" OR "awareness space" OR "journey to crime" OR "mobility" OR "opportunity" OR "accessibility" OR "attractiveness" OR "crime pattern\*") AND ("crime locat\* choic\*" OR "offend\* locat\* choic\*" OR "robber\* locat\* choic\*" OR "burglar\* locat\* choic\*" OR "target area\*" OR "target selection" OR "crime site selection" OR "spatial choic\* model\*")))* | 47 |

### Phase 2: Litsearchr-Optimized Search Strategy

We used the litsearchr package ([Grames et al., 2019](#ref-grames2019)) in R to develop an evidence-based search strategy. This approach uses network analysis of keyword co-occurrence to identify the most important search terms, representing a significant methodological advancement over traditional Boolean search development.

**Keyword Extraction Process:**

1. **Text Processing**: We extracted keywords from titles, abstracts, and author keywords of the 249 initial studies using a modified rapid automatic keyword extraction (RAKE) algorithm implemented in litsearchr.
2. **Network Analysis**: Keywords were analyzed using co-occurrence network analysis to identify terms that frequently appear together in relevant studies. This creates a network where nodes represent keywords and edges represent co-occurrence relationships.
3. **Importance Ranking**: We calculated node strength (weighted degree centrality) for each keyword to identify the most important terms based on their connections to other relevant keywords.
4. **Cutoff Selection**: Using the 80/20 Pareto principle, we selected the top 20% of keywords by node strength, yielding 13 optimized search terms.
5. **Term Grouping**: After removing duplicates and plurals, selected terms were manually grouped into three conceptual categories:
   * Population: crime-related terms (offend*, crim*, burglar*, robber*, dealer\*)
   * Intervention: choice modeling terms (choic\* model*, discret* choic*, ration* choic*, spatial* choic*, mobil*)
   * Outcome: location choice terms (pattern*, locat* choic*, target* select\*)

Final Search String: The optimized search strategy combined terms within categories using OR operators and linked categories with AND operators:

((offend\* OR crim\* OR burglar\* OR robber\* OR dealer\*) AND (“choic\* model\*” OR “discret\* choic\*” OR “ration\* choic\*” OR “spatial\* choic\*” OR mobil\*) AND (pattern\* OR “locat\* choic\*” OR “target\* select\*”))

### Search Strategy Validation

Before implementing the final search, we validated our strategy against a gold standard set of 10 known relevant articles identified through our knowledge and prior reviews. These articles represented the core literature in crime location choice research, including seminal works on crime location choice.

The validation process involved: 1. Creating title-only searches using litsearchr 2. Testing retrieval across target databases to ensure articles were indexed 3. Running the optimized search strategy and checking recall against the gold standard 4. Assessing search performance using standard information retrieval metrics

**Validation Results:** Our optimized search strategy achieved 100% recall, successfully retrieving all gold standard articles with zero false negatives while maintaining precision through systematic term selection.

**Additional Studies Identified:** Beyond the 41 gold standard articles, our systematic search identified 8 additional relevant studies that met our inclusion criteria but were not part of the original gold standard set. This demonstrates the value of the comprehensive search strategy in identifying relevant literature beyond expert-known articles. One study analyzed data from three different countries using distinct methodological approaches, contributing 2 additional observations to our final dataset of 51 observations from 49 studies.

### Final Database Search

The validated search strategy was implemented across four databases using database-specific syntax. Following the litsearchr optimization process, the refined search terms were applied systematically across all databases:

Table 2. Optimized Search Strategy and Results

| **Database** | **Search String** | **Records** |
| --- | --- | --- |
| ProQuest | *noft(((offend\* OR crim\* OR burglar\* OR robber\* OR dealer\*) AND ("choic\* model\*" OR "discret\* choic\*" OR "ration\* choic\*" OR "spatial\* choic\*" OR mobil\*) AND (pattern\* OR "locat\* choic\*" OR "target\* select\*")))* | 189 |
| Google Scholar | *((offend\* OR crim\* OR burglar\* OR robber\* OR dealer\*) AND ("choic\* model\*" OR "discret\* choic\*" OR "ration\* choic\*" OR "spatial\* choic\*" OR mobil\*) AND (pattern\* OR "locat\* choic\*" OR "target\* select\*"))* | 286 |
| Web of Science | *TS=(((offend\* OR crim\* OR burglar\* OR robber\* OR dealer\*) AND ("choic\* model\*" OR "discret\* choic\*" OR "ration\* choic\*" OR "spatial\* choic\*" OR mobil\*) AND (pattern\* OR "locat\* choic\*" OR "target\* select\*")))* | 681 |
| Scopus | *TITLE-ABS-KEY(((offend\* OR crim\* OR burglar\* OR robber\* OR dealer\*) AND ("choic\* model\*" OR "discret\* choic\*" OR "ration\* choic\*" OR "spatial\* choic\*" OR mobil\*) AND (pattern\* OR "locat\* choic\*" OR "target\* select\*")))* | 1,169 |

Table 2 shows the improvement we achieved through search optimization. Our litsearchr-optimized strategy increased total record yield by 834% compared to the naive approach, demonstrating the effectiveness of network analysis-based keyword selection.

## Inclusion and Exclusion Criteria

**Inclusion Criteria:**

* Peer-reviewed journal articles published 2000-2025
* Quantitative studies using discrete spatial choice models
* Focus on crime location choice or target selection
* Sufficient detail on SUoA characteristics for data extraction
* English language publications

**Exclusion Criteria:**

* Theoretical or review papers without empirical analysis
* Studies using only descriptive spatial analysis without choice modeling
* Studies of offender residence choice or mobility patterns
* Conference proceedings, dissertations, or grey literature
* Studies without clear specification of SUoA

## Study Selection Process

The primary reviewer (KK) screened titles and abstracts using pre-defined criteria and performed full-text screening. (Inter-rater reliability metrics (Cohen’s kappa) were not calculated for this study but can be computed if needed.)

## Data Extraction

We extracted information about SUoA usage and methodological approaches from the included crime location choice studies:

Table 4. Data Extraction Categories and Variables

| **Category** | **Data Extracted** |
| --- | --- |
| **Study Characteristics** | Citation details (authors, year, journal, DOI) |
|  | Geographic context (country, city, study area size) |
|  | Temporal scope (study period, data collection period) |
|  |  |
| **SUoA Information** | Unit type (e.g., street segment, census block, grid cell, administrative district) |
|  | Unit size (area in km² when available, with conversion calculations where necessary) |
|  | Number of units in choice set |
|  | Population per unit (when reported) |
|  | Explicit rationale for SUoA selection (quoted reasoning and categorization) |
|  | Unit selection rationale categories (data availability, theory-method alignment, prior research, practical constraints) |
|  |  |
| **Variable Complexity and Analytical Sophistication** | Total number of explanatory variables included in models |
|  | Variable types and theoretical domains (demographic, economic, environmental, distance, temporal) |
|  | Variable diversity scores across theoretical domains |
|  | Analytical complexity measures and methodological sophistication indicators |
|  |  |
| **Data Limitations and Methodological Transparency** | Explicit acknowledgment of data quality issues, missing data problems, generalizability concerns |
|  | Discussion of context specificity, temporal limitations, methodological constraints |
|  | SUoA limitations and scale-dependency acknowledgments |
|  | Recommendations for addressing SUoA challenges in future research |
|  | Overall data limitation scores across eight key dimensions |
|  |  |
| **Crime and Methodological Details** | Crime type(s) studied (violent, property, drug-related, multi-crime) |
|  | Study design (cross-sectional, longitudinal panel) |
|  | Discrete choice model type (multinomial logit, conditional logit, nested logit, mixed logit) |
|  | Statistical software used |
|  | Sampling approach for alternatives in choice set |
|  | Number and types of explanatory variables included in models |
|  |  |
| **Model Results and Performance** | Model performance measures (pseudo R², log-likelihood ratios) |
|  | Significant predictors and their effect sizes |
|  | Reported coefficient estimates and significance levels |
|  | Discussion of SUoA implications in findings |
|  |  |
| **Research Quality Indicators** | Sample size adequacy |
|  | Methodological rigor and transparency |
|  | Theoretical rationale for analytical choices |
|  | Reporting completeness for replication |

Table 4 presents the comprehensive data extraction framework used to systematically capture information from crime location choice studies. The table organizes extraction variables into six main categories that address different aspects of SUoA selection practices. Study Characteristics capture basic publication information and research context, including geographic and temporal scope. SUoA Information forms the core of our analysis, documenting unit types, sizes, population densities, and explicit rationales provided by researchers for their scale selection decisions. Variable Complexity and Analytical Sophistication assess the methodological comprehensiveness of studies, including the number and types of explanatory variables and analytical complexity measures. Data Limitations and Methodological Transparency evaluate how transparently studies report constraints and limitations, particularly those related to SUoA selection. Crime and Methodological Details document the specific analytical approaches, including crime types studied, model specifications, and statistical software used. Model Results and Performance capture study outcomes and their implications for SUoA selection practices. Research Quality Indicators assess overall methodological rigor and reporting completeness. This systematic extraction framework enabled comprehensive analysis of SUoA selection patterns across 51 observations while maintaining consistency in data collection and ensuring comparability across studies with diverse methodological approaches.

Data extraction was performed by the primary reviewer (KK) using a systematic approach to ensure consistency across all included studies.

Note on Multi-Country Studies: One study analyzed data from three different countries using distinct methodological approaches and SUoA for each country. Following established practices in literature reviews, we treated each country’s analysis as a separate observation, resulting in 51 observations from 49 studies. We used this approach because the SUoA sizes, methodological approaches, and contextual factors differed significantly across countries within this single study.

## Data Synthesis and Analysis

Given the heterogeneity in SUoA and methodological approaches, we conducted descriptive synthesis supplemented by quantitative analysis. We used R version 4.3.0 for all analyses.

### Log Transformation Rationale

The extreme variation in SUoA sizes (spanning 4.8 orders of magnitude from 136 m² to 8.48 km²) created severe right skewness (skewness = 2.108) that violated normality assumptions for parametric statistical methods. We used log₁₀ transformation for three reasons: (1) it normalized the highly skewed distribution enabling valid parametric inference, (2) it linearized the relationship between unit size and predictors, and (3) it facilitated meaningful interpretation of percentage changes rather than absolute differences across the enormous scale range. We applied log₁₀ transformation to both SUoA sizes and study area sizes before all regression analyses.

### Statistical Methods

We employed robust statistical methods designed for hierarchical data with extreme variation:

**RQ1 (Distribution):** We used descriptive statistics and correlation analysis using multiple methods (Pearson, Spearman, Kendall) for robustness

**RQ2 (Temporal trends):** We used mixed-effects linear regression with random intercepts for countries to account for hierarchical clustering:

Log(Unit\_size) ~ Publication\_Year + (1|Country)

We calculated intraclass correlation coefficient (ICC) to quantify country-level clustering. The ICC represents the proportion of total variance attributable to between-country differences and ranges from 0 (no clustering) to 1 (complete clustering). ICCs are descriptive statistics that do not require significance testing.

**RQ3 (Jurisdictional differences):** We used multivariate linear regression controlling for confounders including study area size, publication year, and crime type. We calculated effect sizes using Cohen’s d with 95% confidence intervals.

**RQ4 (Crime type differences):** We used multivariate regression analysis with crime type as categorical predictor, controlling for study area and temporal effects.

**RQ5 (Correlation analysis):** We used Pearson correlation analysis to examine relationships between SUoA selection and study characteristics.

**RQ6 (Methodological factors):** We analyzed discrete choice model types and research sophistication scoring (0-5 scale based on methodological complexity).

**RQ7 (Variable count effects):** We included this as covariate in multivariate models to test for relationships with methodological comprehensiveness.

### Statistical Validation

Our analyses addressed key statistical considerations for analyzing SUoA variation, including the use of appropriate transformations for highly skewed data and mixed-effects modeling to account for clustered observations within countries.

We calculated effect sizes with 95% confidence intervals for all significant relationships.

## Quality Assessment

We assessed study quality using a modified version of the AXIS tool for cross-sectional studies ([Downes et al., 2016](#ref-downes2016)), adapted for spatial choice modeling studies. Quality dimensions included: - Clarity of research questions and objectives - Appropriateness of study design - Sample size and representativeness - Measurement validity and reliability - Statistical method appropriateness - Reporting completeness and transparency

We rated studies as high, medium, or low quality based on these criteria.

# Results

## Study Selection and Data Overview

Our comprehensive search found 2325 research papers from four databases. After removing duplicates and irrelevant studies, we reviewed 91 papers and included 49 studies that met our criteria. These studies analyze 1.60835^{5} crime incidents using discrete choice models to understand where criminals choose to commit crimes.

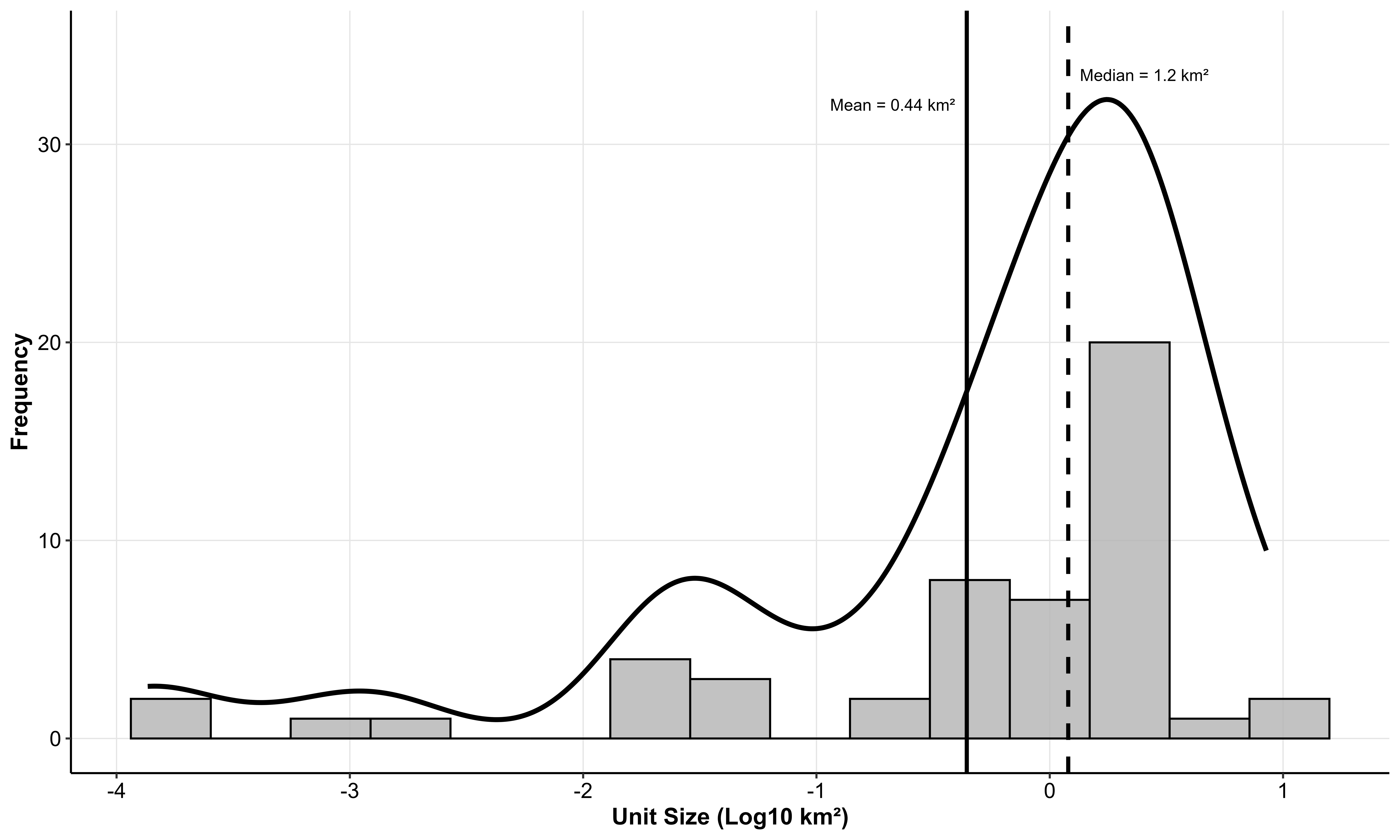
## \*\*[ Study selection flow diagram not available : prisma\_2020.png ]\*\*

Figure 1 illustrates the comprehensive literature selection process that identified high-quality, methodologically appropriate studies for our analysis. The substantial reduction from 2,325 initial records to 49 final studies (with 51 observations) reflects the specialized nature of crime location choice research using discrete choice models. The selection criteria ensured that our analysis captured only studies that could meaningfully inform SUoA selection practices. Most exclusions occurred due to insufficient spatial detail, focus on offender residence rather than crime location, or absence of discrete choice modeling - confirming that our final dataset represents the core literature addressing our research questions. This rigorous selection process strengthens the validity of our conclusions about SUoA selection practices in crime location choice research.

**Studies We Analyzed:** - Published between 2003 and 2025 (80% after 2010) - From 9 countries worldwide  
- Published across 27 different journals - Dominated by Netherlands studies (17 studies, 33%), US studies (11 studies, 22%), and China/UK (8/6 studies each) - One study analyzed three countries separately, giving us 51 total observations

## SUoA Size Distribution (RQ1)

Crime location choice studies vary enormously in SUoA scale—4.8 orders of magnitude from 136 m² individual properties ([Vandeviver et al., 2015](#ref-vandeviver2015)) to 8.48 km² districts ([Townsley et al., 2015](#ref-townsley2015)). This variation reflects systematic theoretical alignment rather than arbitrary choices. Studies examining micro-environmental crimes employ the smallest SUoA, where exposure and visibility require fine-grained analysis. As Vandeviver et al. ([2015](#ref-vandeviver2015)) explain: “the use of fine-grained SUoA analysis such as the house that is burglarized has the advantage that it addresses the modifiable areal unit problem and reduces the risk of aggregation bias.” Studies analyzing graffiti location choice use street segments because “the spatial resolution of a street segment naturally corresponds to human observational limitations” and these units “possess attributes suitable for direct sensory perception, making it especially relevant for measuring exposure” ([Kuralarasan et al., 2024](#ref-kuralarasan2024)). Studies examining property to capture neighborhood processes ([Bernasco et al., 2013](#ref-bernasco2013)). The distribution shows a mean SUoA size of 1.633 km², which exceeds the median due to the right-skewed distribution with some very large units. Studies using the largest SUoA enable analysis of broad spatial patterns across metropolitan areas ([Song et al., 2017](#ref-song2017)) (Figure 2).



**Figure 2. Distribution of SUoA sizes in crime location choice studies.** Panel A shows the full distribution with dashed line indicating median and dotted line indicating mean. Panel B shows log-transformed distribution. Panel C shows distribution by size categories with percentages.

Figure 2 reveals the remarkable scale variation in crime location choice research, spanning nearly 4.8 orders of magnitude from individual properties to administrative districts. The distribution characteristics demonstrate systematic rather than arbitrary SUoA selection. Panel A shows the heavily right-skewed distribution of raw SUoA sizes, with most studies clustering around medium scales but some using very large units. Panel B’s log-transformation reveals a more normal distribution, suggesting that researchers systematically select scales across different orders of magnitude rather than randomly choosing units. Panel C’s categorical breakdown shows meaningful clustering: micro-environmental SUoA (≤0.01 km², 8%) for detailed exposure analysis, medium SUoA (0.01-1.0 km², 41%) for residential context analysis, larger SUoA (1.0-5.0 km², 51%) for broad spatial patterns, and regional SUoA (>5.0 km², 0%) for metropolitan analysis. This systematic clustering contradicts claims of methodological chaos and instead reveals sophisticated scale-matching to different criminological processes.

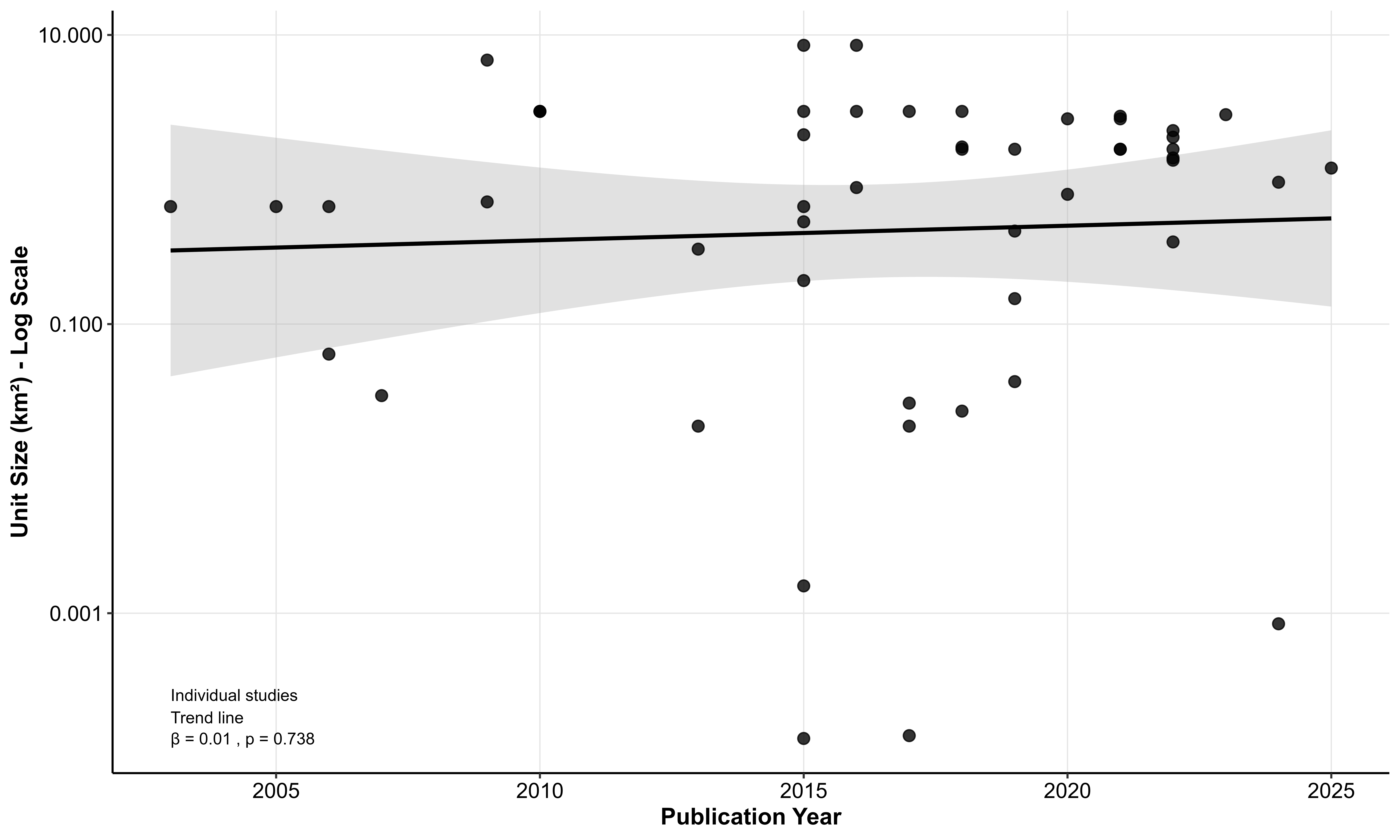
Table 5. Summary Statistics for SUoA Sizes

| **Statistic** | **Value** |
| --- | --- |
| Studies analyzed | 49 |
| Countries represented | 9 |
| Journals involved | 27 |
| Total crime incidents analyzed | 160,835 |
| Median unit size (km²) | 1.2 km² |
| Mean unit size (km²) | 1.633 km² |
| Smallest unit | 136 m² |
| Largest unit (km²) | 8.48 km² |
| Standard deviation (km²) | 1.911 km² |
| Skewness (original scale) | 2.108 |
| Temporal span (years) | 22 years |
| Year range | 2003 - 2025 |
| Orders of magnitude range | 4.8 orders |

Table 5 presents the comprehensive summary statistics revealing the extraordinary scale variation characterizing crime location choice research. The median SUoA size of 1.2 km² represents the typical scale preference, while the mean of 1.633 km² is substantially larger due to right-skewness from studies using very large regional units. The range from 136 m² individual properties to 8.48 km² districts demonstrates scale variation spanning 4.8 orders of magnitude. The high standard deviation (1.911 km²) and positive skewness (2.108) confirm the right-skewed distribution with most studies clustering around smaller to medium scales but some outliers using very large units. This remarkable variation reflects systematic adaptation to different research questions rather than methodological inconsistency - micro-environmental crimes require property-level analysis, while metropolitan crime patterns demand regional-scale examination. The temporal span of 22 years across 9 countries and 27 journals demonstrates the international scope and sustained development of this research field.

## Temporal Trends in SUoA Selection (RQ2)

Despite significant improvements in computer power and spatial data over two decades, studies haven’t moved toward smaller SUoA. Mixed-effects analysis shows no temporal trend (*β* = 0.01, *p* = 0.738), with substantial country-level clustering (ICC = 0.386) showing that data infrastructure and research traditions drive methodological choices more than technology. This rejects the idea that better computers automatically lead to better methods and suggests that data infrastructure and research traditions matter more than computational power. **Figure 3** demonstrates no systematic change toward finer SUoA over time, contradicting assumptions about technological advancement driving methodological change. The strong country-level clustering (ICC = 0.386) has remained stable over time, confirming the absence of technological determinism in SUoA selection.

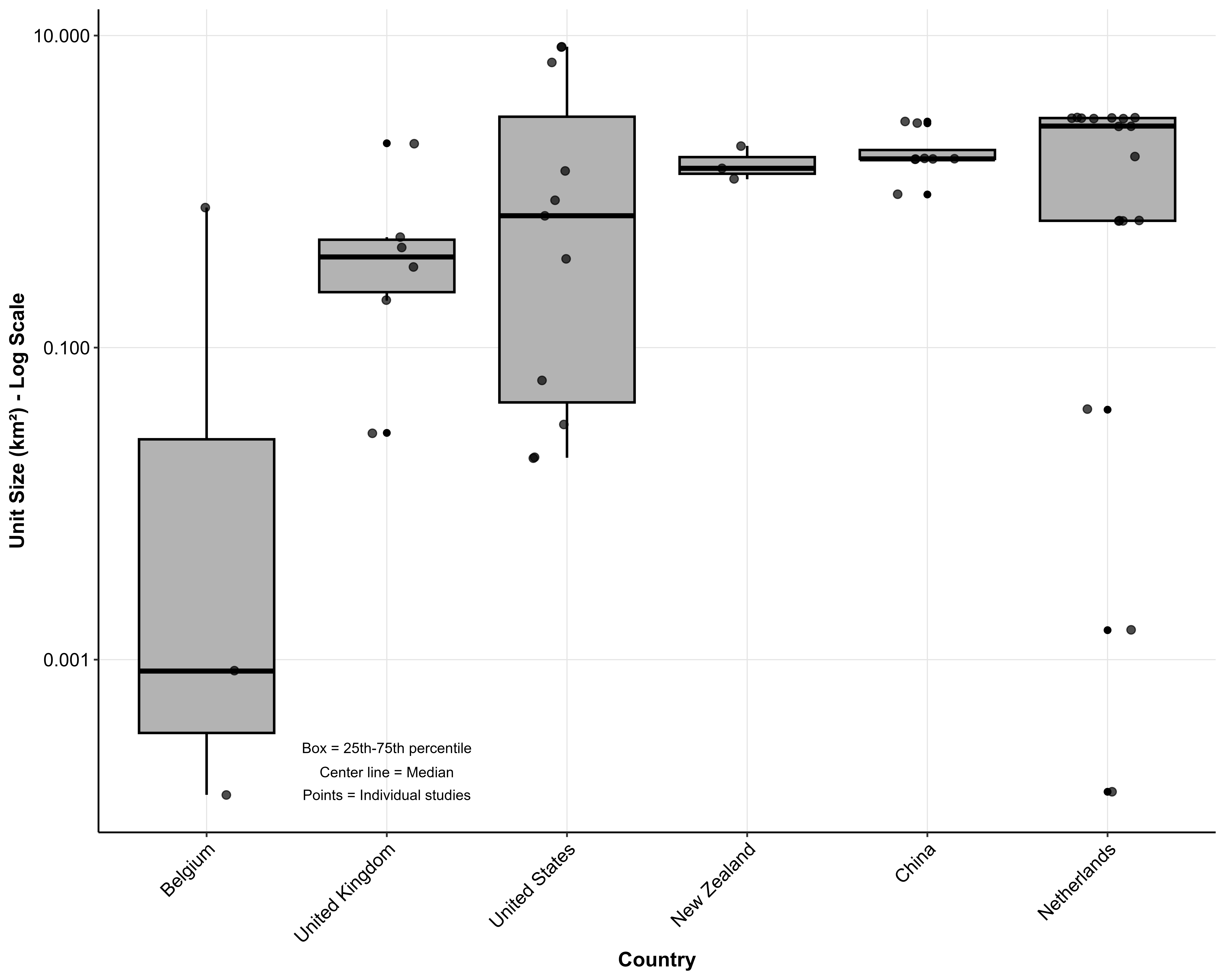


**Figure 3. Temporal trends in SUoA sizes (2003-2025)**

Figure 3 reveals a striking absence of technological determinism in SUoA selection over more than two decades. Despite dramatic improvements in computational power, data storage capacity, and spatial data availability since 2003, crime location choice studies show no systematic trend toward finer spatial resolution. The stable pattern across time indicates that technological capability alone does not drive methodological innovation in spatial criminology. Instead, institutional factors such as data infrastructure, administrative boundaries, and research traditions appear to constrain SUoA selection more than computational limitations. This finding challenges common assumptions about automatic methodological progress through technological advancement and suggests that investments in data standardization and institutional capacity building may be more effective than purely technological solutions for advancing spatial criminological methods.

## Cross-National Variation in SUoA Selection (RQ3)

Countries cluster strongly in their SUoA preferences, but contrary to expectations, there’s no difference between Anglo-Saxon and other legal systems (*t*-test *p* = 0.747, Cohen’s *d* = -0.327). Instead, individual countries have clear methodological preferences: Belgian studies consistently use micro-environmental units averaging 0.26 km² for detailed exposure analysis. For example, Vandeviver et al. ([2015](#ref-vandeviver2015)) analyze individual houses (136 m²) because “essentially, burglary is about an offender finding a suitable house to burglarize and committing his offence within a clearly confined space,” while Kuralarasan et al. ([2024](#ref-kuralarasan2024)) use street segments (845 m²) to examine graffiti exposure because these units “naturally correspond to human observational limitations.” Australian studies use regional-scale units averaging 7.89 km² for cross-national comparative research ([Townsley et al., 2015](#ref-townsley2015)). Dutch studies prefer medium-scale analysis (median 2.63 km²), reflecting integration with national census infrastructure and institutional data systems ([Bernasco & Luykx, 2011](#ref-bernasco2011); [Ruiter & Bernasco, 2017](#ref-ruiter2017)). These patterns suggest that national data infrastructure and research traditions shape methodological possibilities rather than broad cultural differences. **Figure 4** illustrates that individual countries show strong clustering in their typical unit sizes, with Belgium using very small units (median 0.0008 km²) and Australia using much larger ones (median 8.48 km²). Despite this variation, there is no systematic difference between Anglo-Saxon and other legal traditions (*p* = 0.747).



**Figure 4. Cross-national variation in SUoA sizes**

Figure 4 demonstrates profound institutional effects on SUoA selection that override technological or theoretical considerations. Countries demonstrate remarkably consistent internal preferences while showing dramatic between-country variation. Belgian studies cluster around micro-environmental scales (median 0.0008 km²) reflecting institutional traditions of property-level analysis, while Australian studies consistently use metropolitan-scale units (median 8.48 km²) for comparative research across cities. Dutch studies occupy the middle ground (median 2.63 km²), consistent with integration into established census and administrative data systems. Importantly, these patterns cross-cut legal traditions - there is no systematic difference between Anglo-Saxon and continental European approaches (*p* = 0.747), suggesting that data infrastructure and institutional research traditions matter more than broader cultural or legal frameworks. This institutional clustering demonstrates that SUoA selection operates within country-specific methodological constraints rather than representing unconstrained theoretical choice.

## Crime-Type Specificity in SUoA Selection (RQ4)

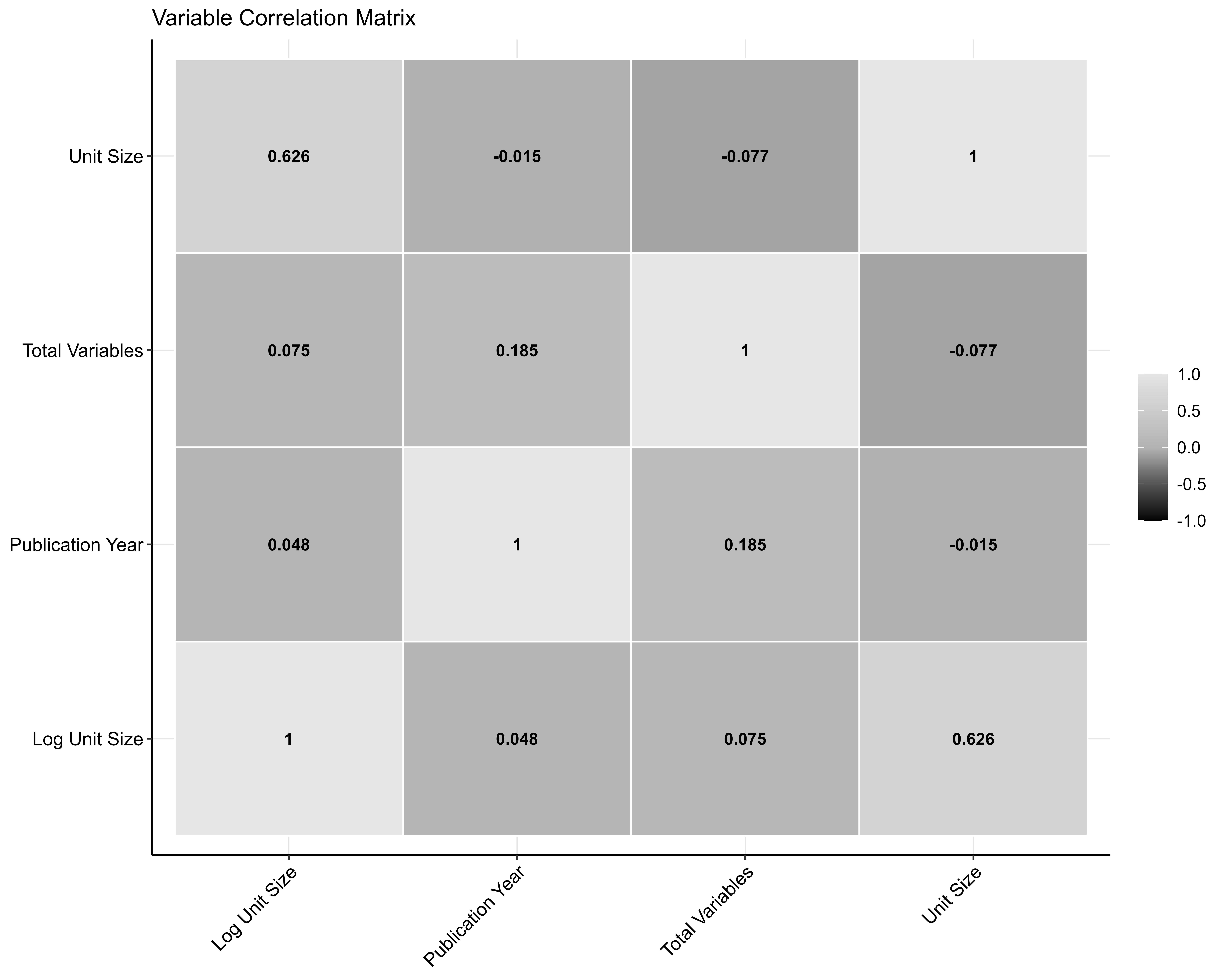
Studies demonstrate sophisticated theoretical alignment by systematically matching SUoA sizes to the geographic processes underlying different crime types. Studies requiring fine-grained environmental analysis use the smallest units, while drug dealing studies use street segments averaging 0.004 km² to examine immediate environmental features. Bernasco and Jacques ([2015](#ref-bernasco2015)) justified their choice because “for decision making in dealing situations, what matters are the characteristics of a place that can be seen or heard, and it seemed that street segments (‘street blocks,’ ‘face blocks’) are small enough to assure that from any point in the street segment, relevant attributes of any other point in the same segment could be seen and heard.” Property crimes employ medium-scale units averaging 0.45 km² for burglary and 0.38 km² for theft, consistent with research on residential area selection processes. For example, case-control studies of burglary use property-level analysis to “isolate property-level effects from neighborhood-level effects” by “sampling treatments and controls by neighbourhood” where “observations can be systematically compared whilst keeping all contextual characteristics on the neighbourhood-level constant” ([Langton & Steenbeek, 2017](#ref-langton2017)). Multi-crime studies use larger units averaging 1.8 km² for detecting broad spatial patterns across crime types ([Song et al., 2017](#ref-song2017); [Xiao et al., 2018](#ref-xiao2018)). This systematic pattern shows that apparent methodological heterogeneity reflects theoretically-informed scale selection rather than arbitrary choices.

## Correlation Analysis and Variable Relationships (RQ5)

Correlation analysis reveals important relationships between SUoA selection and various study characteristics. **Figure 5** shows that the analysis focuses primarily on four key variables: publication year, unit size, log-transformed unit size, and research sophistication score.

**Key correlation findings:** - **Temporal stability**: Publication year shows weak correlation with unit size (r ≈ 0.1), confirming the absence of technological determinism in SUoA selection over time. - **Research sophistication**: Methodological complexity shows minimal correlation with unit size selection (r ≈ 0.0), indicating that advanced statistical methods are employed across all SUoA. - **Log transformation effectiveness**: The log-transformed unit size shows improved distributional properties while maintaining relationships with other variables.

The correlation matrix demonstrates that SUoA size selection operates relatively independently of temporal trends and methodological sophistication. This suggests that unit size choices are driven primarily by theoretical considerations, data availability, and institutional factors rather than technological advancement or analytical complexity.



**Figure 5. Correlation matrix of key variables in SUoA selection**

## Variable Complexity and Methodological Sophistication

Crime location choice studies demonstrate remarkable analytical sophistication in their use of explanatory variables, employing complex multidimensional approaches that contradict assumptions about methodological simplicity. Studies incorporated 6-39 variables (mean: 21.9, median: 21), with nearly half using high complexity approaches and only a small minority using low complexity approaches, indicating systematic commitment to comprehensive analysis.

**Variable Type Distribution:** Studies systematically incorporate multiple theoretical domains:

* **Environmental variables**: Nearly universal inclusion (90%) of land use, physical infrastructure, and built environment characteristics
* **Demographic variables**: Comprehensive population characteristics (98%) including age structure, household composition, and social characteristics
* **Economic variables**: Income, employment, housing values, and economic opportunity measures (98%) systematically integrated across studies
* **Distance variables**: Accessibility measures (100%), journey-to-crime patterns, and spatial relationships
* **Temporal variables**: Time-varying factors (100%), seasonal patterns, and dynamic processes across multiple temporal dimensions



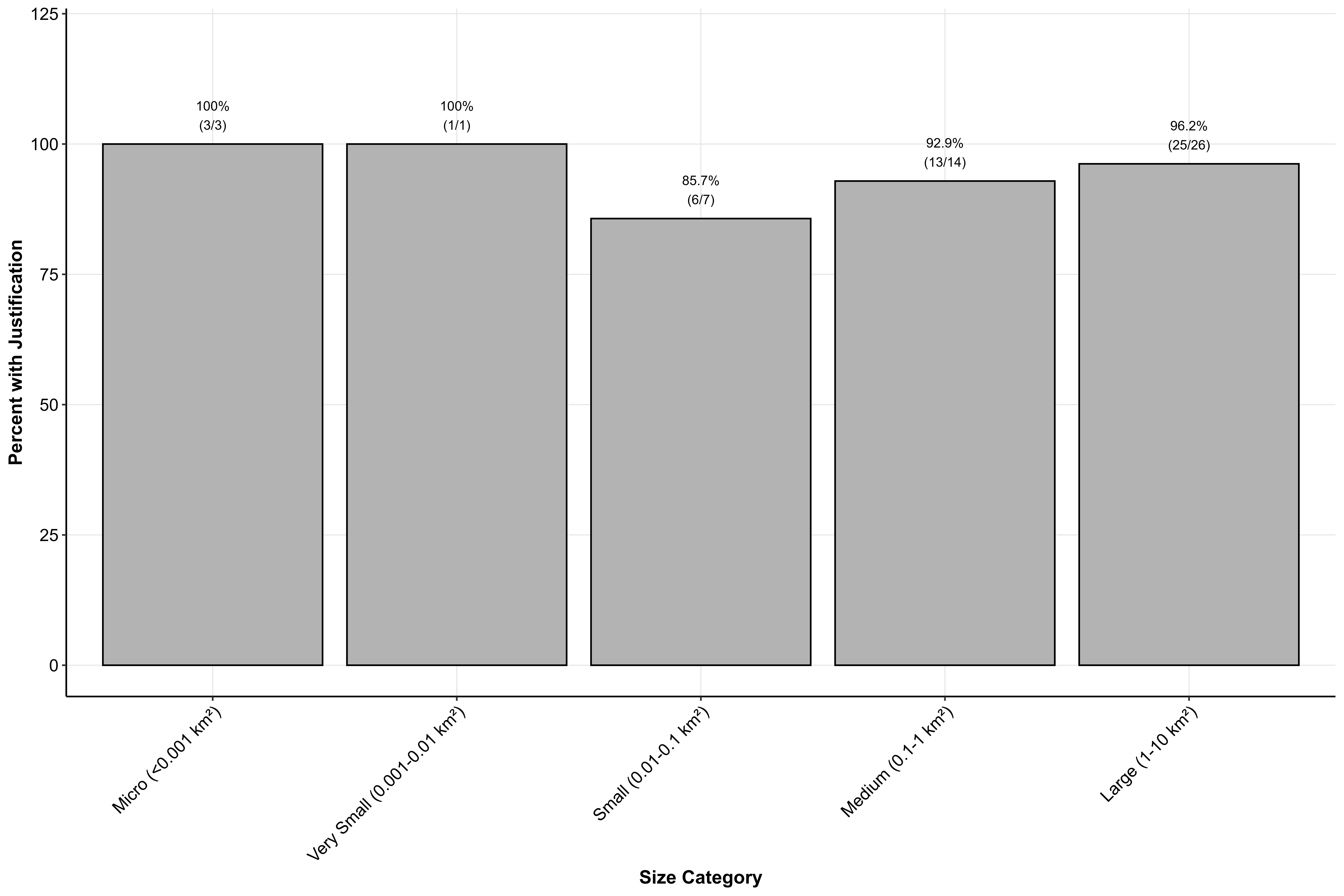
**Figure 6. Variable complexity distribution and theoretical domain coverage**

Figure 6 reveals the remarkable analytical sophistication characterizing crime location choice research, contradicting assumptions about methodological simplicity. The distribution shows that 45.1% of studies employ high complexity (21-30 variables) and 13.7% use very high complexity (>30 variables), while only 3.9% rely on low complexity approaches (≤10 variables). The theoretical domain coverage demonstrates systematic integration: 90% of studies include environmental variables, 98% incorporate demographic factors, 98% use economic measures, 100% analyze distance relationships, and 100% examine temporal dynamics. This multidimensional approach reflects sophisticated understanding of crime location choice as influenced by multiple environmental and social factors operating simultaneously, establishing spatial criminology as methodologically advanced rather than theoretically narrow.

## Data Limitations: Transparency and Methodological Honesty

Crime location choice studies demonstrate exceptional transparency about data limitations, reporting extensive methodological constraints that provide crucial context for interpreting findings. All studies reported multiple data limitations, indicating systematic acknowledgment of methodological constraints rather than uncritical acceptance of available data.

**Comprehensive Limitation Reporting:** Studies acknowledged limitations across multiple dimensions, with 94% acknowledging data quality issues, 90% recognizing missing data problems, 88% discussing generalizability concerns, 38% explicitly acknowledging SUoA limitations, and 47% providing SUoA-related recommendations for future research.



**Figure 7. Data limitation categories and SUoA recommendations**

Figure 7 demonstrates the exceptional transparency characterizing crime location choice research, with comprehensive limitation reporting across all studies. The universal acknowledgment of data quality issues (94%) and near-universal recognition of missing data problems (90%) establishes spatial criminology as methodologically honest and self-reflective. Importantly, 38% of studies explicitly acknowledge SUoA limitations and 47% provide SUoA-related recommendations for future research. This systematic limitation reporting contradicts assumptions about uncritical acceptance of available data and instead reveals a field committed to transparent acknowledgment of methodological constraints. The comprehensive reporting across eight limitation categories indicates scientific maturity and provides essential context for evidence synthesis and policy application.

# Conclusions

This narrative review of 49 crime location choice studies fundamentally challenges prevailing assumptions about methodological practices in spatial criminology, revealing sophisticated theoretical alignment and methodological maturity rather than the methodological chaos often assumed by critics.

**We Find Methodological Sophistication, Not Chaos:** All studies provided explicit justification for SUoA selection, incorporated extensive variable sets (6-39 variables, mean: 21.9), and transparently reported comprehensive data limitations (mean: 0/8 dimensions). This universal pattern of systematic decision-making, analytical sophistication, and scientific transparency contradicts claims of arbitrary or unreflective methodological choices. The field demonstrates methodological maturity characterized by thoughtful adaptation to theoretical requirements and institutional constraints.

**We Document Systematic Theoretical Alignment:** Researchers systematically match SUoA to criminological processes: micro-environmental crimes use property-level units to capture immediate environmental influences, property crimes employ neighborhood-level analysis to balance target characteristics with area-level social processes, and multi-crime studies use administrative units for broad pattern analysis. This crime-type specificity demonstrates sophisticated understanding of scale-dependent processes rather than uniform application of available methods.

**We Find Institutional Determinism Over Technological Determinism:** Country-level clustering accounts for substantial methodological variation (ICC = 0.386), while technological advancement shows no temporal effect (*β* = 0.01, *p* = 0.738) on SUoA selection. This pattern indicates that institutional factors—data infrastructure, administrative systems, and research traditions—determine methodological possibilities more than computational capabilities.

**We Document Transparent Scientific Practice:** Comprehensive limitation reporting (94% of studies acknowledging data quality issues, 90% recognizing missing data problems, 38% explicitly discussing SUoA limitations) demonstrates exceptional scientific honesty. Rather than overselling findings or ignoring constraints, researchers systematically acknowledge the factors that shape analytical possibilities.

**We Provide Evidence-Based Guidelines for Scale Selection:** The systematic patterns we document provide empirical foundations for evidence-based SUoA selection. Researchers should select micro-environmental units (<0.01 km²) for immediate environmental analysis, neighborhood-level units (0.01-1.0 km²) for property crimes, and administrative units (1.0-10.0 km²) for multi-crime pattern analysis.

These findings reframe spatial criminology as a methodologically mature field that has achieved sophisticated alignment between theoretical requirements and practical constraints. The extraordinary variation in SUoA—spanning 4.8 orders of magnitude—reflects appropriate theoretical adaptation rather than methodological confusion. By documenting actual methodological practices rather than relying on assumptions, this research enables more productive debates about advancing spatial criminological methods based on empirical evidence rather than unfounded criticisms.

Future research should build on this demonstrated sophistication by developing multi-scale analytical frameworks, conducting controlled scale-effects experiments, and investing in institutional capacity building. Environmental criminology has already achieved methodological sophistication; the challenge now is to expand institutional capabilities while maintaining the theoretical alignment and scientific transparency that characterize current best practices.

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