# Assessing the Impact of Spatial Resolution on Morphological Spatial Pattern Analysis of Urban Green Infrastructure Connectivity: A Case Study of Miami-Dade County, USA

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**Abstract**

Urban green infrastructure plays a crucial role in supporting ecological connectivity, enhancing climate resilience, and promoting human well-being. As cities densify, maintaining functional green networks increasingly depends on understanding the structural continuity of vegetation within complex urban fabrics. Morphological Spatial Pattern Analysis (MSPA) provides a practical framework for quantifying green infrastructure structure; however, its sensitivity to spatial resolution remains insufficiently examined, particularly at metropolitan scales, where high-resolution data are becoming increasingly available. This study examines the impact of spatial resolution on MSPA outputs for mapping and interpreting urban green connectivity in Miami-Dade County, USA. Two scenarios were compared using 10-m canopy data and 2-m high-resolution canopy data processed across 23 tiles. The workflow integrated vegetation preprocessing, MSPA classification, and quantitative and visual comparisons of structural classes to assess scale effects. Results demonstrate that fine-resolution MSPA (2 m) preserves continuous canopy structures and narrow vegetated corridors that the 10-m analysis tends to fragment or omit. High-resolution outputs provide a more realistic representation of neighborhood-scale connectivity, especially in tree-dense areas such as Coral Gables, while also revealing the computational demands of metropolitan-scale MSPA processing. The findings confirm that MSPA results are inherently scale-dependent and that the choice of resolution critically shapes the interpretation of connectivity. This research provides an operational foundation for incorporating high-resolution morphological analyses into urban resilience planning, nature-based solutions, and socio-ecological equity assessments.

## 1. Introduction

Green Infrastructure (GI) has become a central framework for sustainable and resilient urban development, emphasizing the creation of a strategically planned network of natural and semi-natural areas designed to deliver multiple ecosystem services (Monteiro et al., 2020; Shi and Qin, 2018). Rooted in earlier concepts such as ecological networks and greenways, GI is founded on two core principles: multifunctionality and connectivity, supporting ecological processes, human well-being, and climate adaptation (Pozoukidou, 2020; Li & Carter, 2025). Within this paradigm, Green Infrastructure Networks (GINs) consist of hubs-core ecological patches-and corridors, which include linear linkages such as green streets and riparian buffers, as well as stepping-stone features such as private gardens and green roofs (Zhang et al., 2019; Liu et al., 2022a).

### 1.1 Importance of GI Connectivity in Urban Systems

Connectivity is a critical determinant of ecological performance in cities, supporting species movement, biodiversity, microclimate regulation, stormwater management, and social benefits such as recreation and equitable access to nature (Jeong et al., 2021; Badiu et al., 2019). In rapidly urbanizing regions, however, land-use intensification increases fragmentation, reduces ecological core areas, and disrupts habitat continuity-patterns observed in metropolitan regions such as the Ruhr and other European cities (Wang et al., 2022; Rusche et al., 2019). Ensuring connectivity is therefore essential for enhancing climate resilience, particularly in coastal urban areas where GI supports flood mitigation and emergency response capacity (Jeong et al., 2021; Staccione et al., 2022).

### 1.2 Methods for GI Connectivity Assessment

Assessing green infrastructure connectivity relies on spatial analysis methods grounded in landscape ecology and GIS. Contemporary approaches typically integrate structural and functional perspectives to identify key ecological areas and evaluate movement potential across urban landscapes.

Morphological Spatial Pattern Analysis (MSPA) is commonly applied as an initial step to classify binary vegetation maps into structural elements such as Core, Bridge, Loop, Branch, Edge, Perforation, and Islet, providing an objective foundation for identifying source patches within the network (Vogt et al., 2007; Liu et al., 2022b). Structural outputs are often complemented with graph-based metrics such as the Probability of Connectivity and Integral Index of Connectivity to quantify the importance of individual landscape components in maintaining network cohesion (Bolliger and Silbernagel, 2020; Wang et al., 2022).

To capture functional connectivity, resistance-based models simulate ecological movement across heterogeneous urban environments. Least-cost path analysis is widely adopted to identify optimal corridors by assigning impedance values to land-cover classes (Shi and Qin, 2018). In contrast, circuit theory-based models conceptualize movement as random walks, highlighting pinch points and high-flow corridors that are critical for ensuring continuity (Staccione et al., 2022; Wang et al., 2022).

Together, these methods form a multi-stage analytical process that includes identifying ecological hubs, modeling potential corridors, and prioritizing strategic nodes and pathways for conservation or restoration. This integrative approach supports evidence-based planning for resilient and multifunctional green infrastructure networks (Zhang et al., 2019; Liu et al., 2022a).

### 1.3 Gaps in Current Knowledge

Recent assessments of urban resilience and planning support tools highlight that many existing analytical frameworks remain limited in their integration of ecological and spatial data, particularly when applied to dynamic urban contexts (Praharaj, 2026). Despite methodological progress, several limitations persist in GI connectivity research. Structural and functional connectivity are often assessed independently, limiting holistic understanding of ecological flows in complex urban contexts (Liu et al., 2022a). Research has also tended to emphasize large urban parks, with comparatively less attention to small and dispersed green elements—such as private gardens and street trees—that play essential roles in dense urban neighborhoods (Pozoukidou, 2020; Badiu et al., 2019; Das and Praharaj, 2022).

Furthermore, resistance values used in functional connectivity models are often assumed rather than empirically derived, reducing interpretability (Staccione et al., 2022). A critical limitation concerns spatial resolution: many studies rely on medium-resolution datasets that fail to capture fine vegetation structures and narrow canopy linkages essential for urban ecological continuity (Liu et al., 2022b; Rusche et al., 2019). This limitation is closely linked to the well-documented sensitivity of landscape metrics and morphological analyses to spatial resolution. Reviews of landscape indices demonstrate that variations in grain size and extent can significantly alter calculated metrics, affecting estimates of patch size, edge complexity, and connectivity patterns (Šímová & Gdulová, 2012). More specifically, resolution effects on MSPA outputs have been explicitly demonstrated by Hernando et al. (2017), who showed that fragmentation patterns and connectivity assessments varied substantially when using 2 m, 10 m, and 50 m forest cover maps, with coarser resolutions underestimating structural detail and connectivity. Studies using medium-resolution datasets (e.g., 10–30 m) often generalize spatial heterogeneity, leading to the omission or fragmentation of small or linear ecological features, whereas very high-resolution data (≤ 2–5 m) allow for the detection of fine-scale elements essential for ecological functioning (Hu et al., 2024; Lin et al., 2021). In urban environments, where vegetation is frequently distributed in narrow corridors and small patches, such as street trees, private gardens, and riparian buffers, these differences are particularly critical, as many features fall below the effective mapping unit of coarser datasets. Consequently, assessing the impact of 2 m versus 10 m spatial resolution provides a meaningful basis for understanding how key structural components of urban green infrastructure networks are captured or overlooked.

As high-resolution urban vegetation data become more widely available, there is a growing need to evaluate how spatial resolution influences connectivity outcomes, particularly when applying MSPA at the metropolitan scale.

### 1.4 Objective and Contribution of This Study

This study addresses this gap by examining the influence of spatial resolution on MSPA-based GI connectivity analysis in Miami-Dade County, USA. We compare MSPA results generated from 10-m resolution canopy data and 2-m high-resolution canopy data processed across 23 tiles to cover the County area.

This paper contributes by: (a) Demonstrating the effects of spatial resolution on MSPA outputs in a complex urban environment; (b) Highlighting how coarse data may overestimate fragmentation and underestimate canopy connectivity; (c) Documenting a scalable metropolitan-level MSPA workflow using high-resolution canopy input; and by (d) Providing insights on the implications of resolution choice for urban ecological planning and resilience strategies.

By situating morphological connectivity analysis within a high-resolution urban remote sensing context, this research advances methodological understanding and supports improved decision-making for green infrastructure planning in rapidly urbanizing coastal regions.

## 2. Methodology

### 2.1 Study area

Miami-Dade County is located in the southeastern part of Florida, USA, along the Atlantic coast (centered approximately at 25.6° N, 80.4° W). Covering an area of approximately 4,920.7 km², it is the most populous county in Florida, with over 2.68 million inhabitants, according to Census Reporter (2023). The region features a highly diverse landscape structure, comprising dense urban fabric, coastal wetlands, agricultural zones, and extensive suburban developments. See Figure 1.

The county lies within a subtropical coastal environment characterized by a humid climate with pronounced wet and dry seasons. Average annual precipitation exceeds 1,200 mm, with an average annual temperature of 25.5°C, according to the NOAA Climate Series for September 2024 – August 2025 (NCEI, 2025). The terrain is generally flat, bounded by Everglades National Park to the west and Biscayne Bay to the east.

Urban development in Miami-Dade County has accelerated in recent decades, resulting in increased fragmentation of green infrastructure and a decline in tree canopy coverage. According to the 2021 Miami-Dade Urban Tree Canopy Assessment, tree canopy covers approximately 20 % of the county’s urbanized areas (Miami-Dade County, 2021). Since 2006, the county has aimed to achieve a minimum of 30 % canopy cover; however, this objective remains challenging due to factors such as disease and storm-related losses, continued rapid urbanization, and the limited jurisdiction of the county over land available for canopy expansion (Miami-Dade County, 2025).


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While the county's efforts to expand its urban forest face considerable challenges, its diverse land-use composition provides valuable opportunities for spatial analysis. This spatial heterogeneity makes Miami-Dade County (MDC) an ideal case for evaluating the influence of spatial resolution on morphological landscape metrics. The region encompasses dense urban cores (such as Miami, Coral Gables, and Hialeah), transitional peri-urban areas, and extensive natural zones, providing a rich context for examining scale effects in green–non-green pattern detection.

In this study, the entire county extent was analyzed under two spatial resolution scenarios for MSPA: one based on a 10 m resolution raster mosaic and another constructed from 23 tiles processed at 2 m resolution and subsequently merged to represent the whole study area. This multi-scale approach enables a direct comparison of how pixel resolution influences morphological pattern classifications—specifically, the delineation of core, edge, bridge, branch, and islet structures—derived from the binary canopy mask.

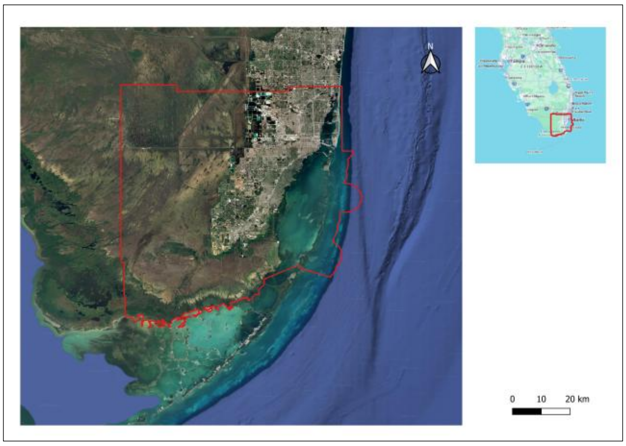


Figure 1. Case study area: Miami-Dade County

## 2.2 Dataset and Preprocessing

The analysis was based on the 1 m resolution Meta Canopy Height Model, retrieved from Google Earth Engine as 23 adjacent tiles covering the entire MDC. Each tile consists of a single-band raster representing canopy height values (in meters) referenced to the geographic coordinate system (EPSG: 4326 – WGS84).

Since the Morphological Spatial Pattern Analysis (MSPA) tool in GuidosToolbox (GTB) requires input data in a specific binary and projection format (8-bit unsigned raster, with foreground = 2, background = 1, and optional missing data = 0, and defined in a projected coordinate reference system), a set of preprocessing steps was applied. These were automated through a Model Designer workflow in QGIS (Figure 2).

Step 1 involved reclassifying the original canopy height raster into a binary format, where all pixels with canopy height values greater than 0 m were assigned as canopy, and all others were assigned as non-canopy. Step 2 converted the output into the required byte data type. Step 3 consisted of reprojection and resampling operations. The coordinate system was first converted from the geographic reference system (EPSG: 4326) to the projected coordinate system (EPSG: 32617 – WGS 84 / UTM Zone 17N). Subsequently, spatial resampling was performed to obtain the two target resolutions. For the first scenario, the preprocessing model was applied separately to each of the 23 tiles, including the reprojection and a final resampling to 2 m resolution. For the second scenario, the 23 original 1 m tiles were first merged into a single mosaic, which was then processed through the same model, with the final resampling step set to 10 m.

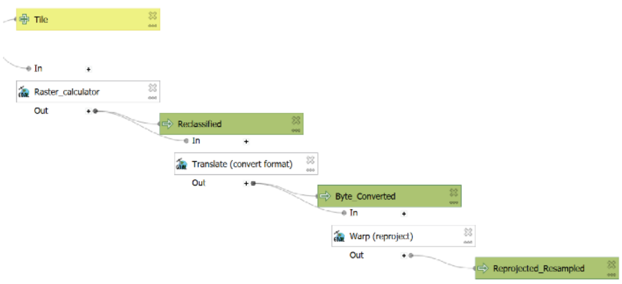


Figure 2. QGIS Model Designer workflow for preprocessing canopy height data prior to MSPA analysis.

## 2.3 Morphological Spatial Pattern Analysis (MSPA)

Building on the preprocessing procedures described in Section 2.2, Morphological Spatial Pattern Analysis (MSPA) was applied to characterize the spatial configuration of green infrastructure across Miami-Dade County (MDC) for both resolution scenarios. MSPA is a binary-based morphological approach that distinguishes the structural components of vegetation patterns (Vogt et al., 2007a, 2007b, 2009; Vogt and Riitters, 2017; Wang et al., 2022). To ensure a robust comparison between the two scales, identical MSPA parameters and workflow steps were implemented in both cases.

MSPA requires raster data consisting of foreground and background pixels and classifies the foreground into a set of structural pattern categories. These categories are briefly summarized in Table 1, with conceptual descriptions adapted from Wang et al. (2022) and binary definitions following Soille and Vogt (2009).

| Class | Definition | |
|---|---|---|
| | Conceptual | Binary |
| Core | Primary green infrastructure (GI) areas surrounded by other GI (8-connected). | Pixels farther than threshold $s$ from non-GI pixels (distance $> s$). |


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| | | |
|---|---|---|
| Islet | Small, isolated GI patch not connected to any core. | GI pixels forming components with no core pixels. |
| Loop | GI path that reconnects to the same core area, forming a loop. | Connector pixels linking within the same core component. |
| Bridge | GI segments linking two or more separate GI core areas. | Connector pixels linking two or more separate core components. |
| Perforation | Inner transition zone within GI, formed by small built-up openings (like holes inside a larger GI patch). | Boundary pixels located inside GI, adjacent to internal holes (at distance ≤ $s$). |
| Edge | Outer boundary between GI and adjacent built-up areas. | Boundary pixels on the outer side of GI, next to external non-GI (distance ≤ $s$, not perforation). |
| Branch | GI extension that emerges from a core but does not connect to another core. | Remaining GI pixels not in core, islet, bridge, loop, edge, or perforation (extensions from those classes). |

Table 1. Conceptual and binary MSPA definitions ($s$ = edge width). Adapted from Wang et al. (2022) and Soille and Vogt (2009).

The analysis was conducted using the GuidosToolbox (GTB) software, version 3.3. The Foreground connectivity (FGConn) was set to 8/4, meaning foreground pixels were treated as 8-connected and background pixels as 4-connected (or vice versa), consistent with Soille and Vogt (2009). An edge width parameter of one pixel was adopted. Following each run, GTB exported the classified MSPA raster as a GeoTIFF and produced a corresponding text file containing the statistical distribution of the structural classes (see example in Figure 3).

For Scenario 1 (2-m resolution), MSPA was executed independently on each of the 23 pre-processed tiles. For Scenario 2 (10-m resolution), the analysis was performed once on the unified MDC raster. The resulting outputs were then visualized in QGIS; the 23 tiles from Scenario 1 were mosaicked to create a seamless 2-m MSPA map of MDC. This resulted in two final MSPA products for the study area: one with a 2 m resolution and one with a 10 m resolution. For consistency in interpretation, both maps were symbolized according to the standard MSPA color scheme recommended by Vogt and Riitters (2017).

```
MSPA results using:
Processing_Tiles_0 (MSPA: 8_1_1_1, FG_area: 17310438, iFG_area:
20985597)

   MSPA-class [color]:  FG/data pixels [%]  #/BGarea
============================================================
      CORE(s) [green]:           --/--      0
      CORE(m) [green]:     86.52/20.62      32056
      CORE(l) [green]:           --/--      0
        ISLET [brown]:      1.13/ 0.27      40299
   PERFORATION [blue]:      1.58/ 0.38      6888
         EDGE [black]:      9.25/ 2.20      25454
        LOOP [yellow]:      0.06/ 0.01      3349
         BRIDGE [red]:      0.13/ 0.03      6839
      BRANCH [orange]:      1.33/ 0.32      81140
    Background [gray]:        --/76.17      16817/55336214
      Missing [white]:           0.33       4/237970
       Opening [gray]:   14.79 Porosity     16806/3675159
Core-Opening [darkgray]:        --/ 4.03      9791/2924977
Border-Opening [gray]:        --/ 1.03      7015/750182
```

Figure 3. Example of MSPA statistical summary generated from GTB software.

## 3. Results

### 3.1 MSPA Outputs Overview

The Morphological Spatial Pattern Analysis of Miami-Dade County highlights clear differences between the two spatial resolution scenarios (10 m vs. 2 m). Figure 4 presents the full-county MSPA maps colored according to standard MSPA classes (Vogt and Riitters, 2017).

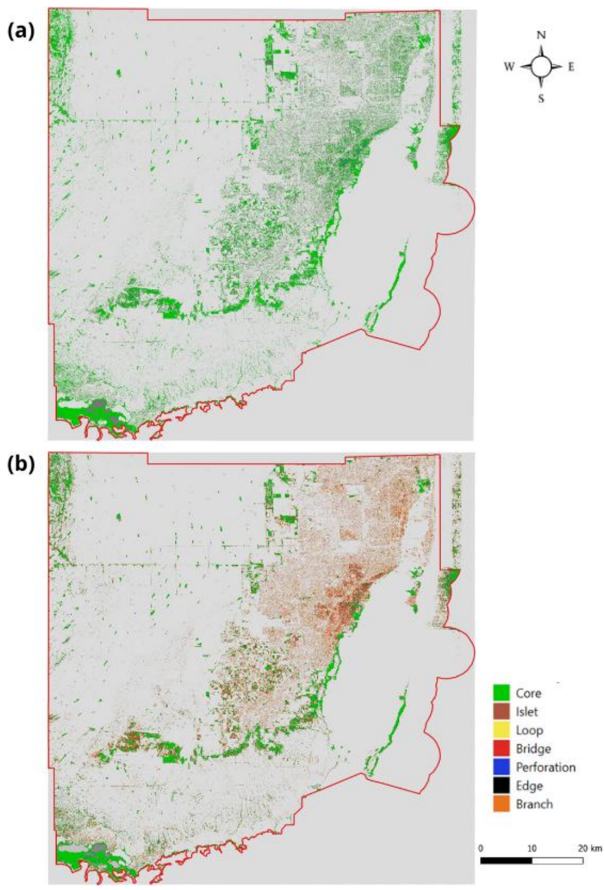


Figure 4. MSPA classification maps of Miami-Dade County at two spatial resolutions: (a) 2 m and (b) 10 m.

At 10 m resolution, the MSPA output identifies large, contiguous green areas as Core pixels; however, a substantial proportion of vegetated areas are classified as Islets or small fragmentary patches. This reflects the tendency of coarser datasets to aggregate vegetation into broader homogeneous units while overlooking thin vegetated corridors and fine-scale structures typical of urban environments. Consequently, the 10 m MSPA output presents a more generalized landscape structure, where small green patches and linear elements are absorbed into larger Core regions or remain fragmented as isolated Islets.

In contrast, the 2 m MSPA output reveals a much richer and more continuous vegetation network. The higher spatial resolution captures narrow corridors, tree-lined streets, canal-side vegetation, and small park features that are otherwise simplified at coarser resolutions. The finer-scale classification results in a more prominent representation of Core pixels within urban blocks, aligning with visual inspection of the input high-resolution imagery, where dense tree canopies and residential greenery form cohesive clusters. At the same time, the enhanced detection of thin vegetated structures results in a substantial increase in Branch and Bridge classes, highlighting the importance of high-resolution data for mapping functional ecological connectivity in heterogeneous urban landscapes.

### 3.2 Quantitative Comparison

Table 2 presents a quantitative comparison of MSPA class areas for the two resolution scenarios. Percentages are calculated relative to the total number of foreground pixels only, excluding background and missing data, to avoid bias from incomplete coverage. To quantify differences between the two resolutions, we computed the percentage change in each MSPA class as:

$$\Delta\% = Pct2m - Pct10m \quad (1)$$

where $Pctr$ represents the proportional share of each class at resolution $r$ (2 m or 10 m) relative to the total foreground pixels.

| Class | Pixels 10 m | Pixels 2 m | Pct (%) 10 m | Pct (%) 2 m | Δ (%) |
|---|---|---|---|---|---|
| Core | 52346 | 775169 | 6.96 | 20.53 | +13.56 |
| Islet | 398613 | 495149 | 53.04 | 13.11 | -39.92 |
| Loop | 17509 | 54885 | 2.33 | 1.45 | -0.88 |
| Bridge | 32536 | 134916 | 4.33 | 3.57 | -0.76 |
| Perforation | 4235 | 97950 | 0.56 | 2.59 | +2.03 |
| Edge | 40856 | 668936 | 5.44 | 17.72 | +12.28 |
| Branch | 205471 | 1549080 | 27.34 | 41.02 | +13.68 |

Table 2. Comparison of MSPA class distribution between 2 m and 10 m resolution for Miami-Dade County, showing total pixels, percentage share (Pct%), and relative difference (Δ%).

At 10 m resolution, Islets constitute the dominant class (53.04%), reflecting substantial landscape fragmentation under coarse spatial representation. However, when analyzed at 2 m resolution, the proportion of Islets decreases sharply to 13.11%, demonstrating that many areas previously interpreted as isolated patches form part of larger structures when observed at a finer scale. Similarly, Edge and Perforation classes increase notably at 2 m (from 5.44% to 17.72% and from 0.56% to 2.59%, respectively), suggesting improved detection of transitional zones and internal voids within vegetated areas.

The Core class exhibits a notable increase in relative share, from 6.96% (10 m) to 20.53% (2 m), demonstrating the finer dataset's enhanced ability to capture dense vegetation clusters and continuous canopies more accurately. This aligns with visual inspection, where Core pixels appear more prominently in the 2 m map, particularly in residential neighborhoods with extensive tree cover. The most notable increase is observed for the Branch class, rising from 27.34% to 41.02%, highlighting the extensive prevalence of narrow vegetated corridors and connectivity structures that are otherwise aggregated or lost at coarser resolution.

Overall, the quantitative analysis confirms that higher spatial resolution substantially improves the representation of urban green connectivity, reduces artificial fragmentation, and enhances the detection of corridor-like structures fundamental to ecosystem continuity in dense urban fabrics. These findings underscore the sensitivity of MSPA outcomes to input resolution, supporting the use of high-resolution data for urban ecological network assessment and planning.

### 3.3 Visual Comparison

To qualitatively illustrate the effect of spatial resolution on green infrastructure pattern detection, a representative residential area in Coral Gables was selected for visual inspection. This area is characterized by mature tree canopies, well-vegetated private yards, and continuous street tree cover, features typical of high-canopy suburban neighborhoods in the MDC.

Figure 5 shows the MSPA classification for the selected neighborhood at 2 m and 10 m resolution. At 2 m resolution, the vegetation network appears largely continuous, with extensive Core (green) regions representing dense canopy blocks across residential parcels. The fine pixel size preserves connectivity between adjacent trees and shrubs, and only thin lines of Edge and sparse Bridge pixels appear along the margins of canopy clusters or narrow connections. This representation aligns closely with the actual vegetation structure observed in aerial imagery, where street trees and backyard vegetation form continuous corridors across the neighborhood.

In contrast, the 10 m MSPA output yields a visibly more fragmented pattern. Many areas that appear as a continuous canopy at 2 m are decomposed into smaller units or converted into Branch and Bridge structures due to pixel aggregation and


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the loss of fine-scale canopy continuity. Narrow connections between trees are frequently disrupted at this coarser resolution, resulting in artificial breaks in the green network and a patchier connectivity structure. Although the overall neighborhood remains largely vegetated, the coarser model underestimates internal continuity and exaggerates fragmentation patterns.

This local comparison reinforces the quantitative findings by demonstrating that high-resolution data preserve critical fine-scale vegetation connectivity features in suburban urban environments. At the same time, coarse resolution may obscure important ecological linkages. Even in a highly vegetated area such as Coral Gables, where canopy connectivity is visually dominant, the 10 m resolution fails to fully capture the continuous nature of the tree canopy network, highlighting the importance of using high-resolution datasets for urban ecological structure and connectivity analyses.

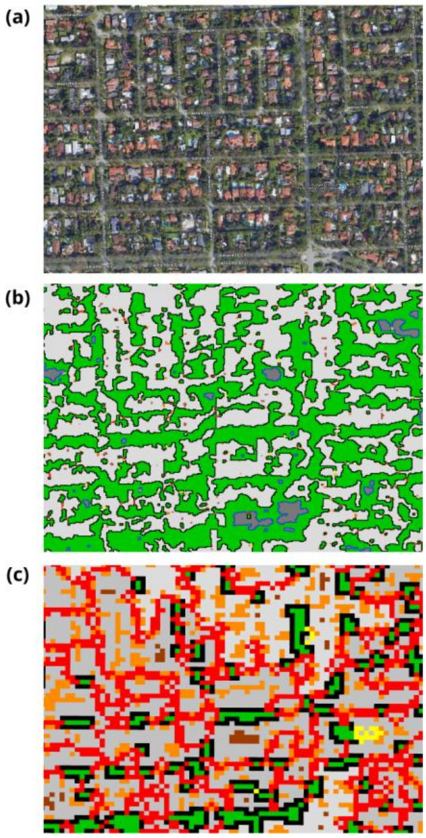


Figure 5. Visual comparison of MSPA outputs in Coral Gables, MDC: (a) reference aerial imagery, (b) 2-m resolution MSPA classification, and (c) 10-m resolution MSPA classification.

## 4. Discussion and Future Research

This study demonstrates that MSPA outputs for urban green infrastructure are strongly influenced by spatial resolution. The 2-m analysis captured more the fine-grained, continuous structure of the urban canopy in Miami-Dade County, particularly in residential areas such as Coral Gables, where tree canopies and private vegetation form connected green networks. In contrast, the 10-m resolution tended to generalize vegetative forms, artificially increasing fragmentation and reducing the visibility of narrow canopy linkages. These results underscore the importance of utilizing sufficiently fine spatial data when analyzing urban vegetation patterns, as coarse datasets can misrepresent connectivity and lead to incomplete or biased assessments in ecological planning and resilience strategies.

These findings align with previous applications of MSPA and green infrastructure connectivity assessments, demonstrating that finer spatial detail substantially improves the identification of ecological linkages in urban and peri-urban systems. High-resolution MSPA outputs more effectively capture narrow corridors, stepping-stone elements, and edge structures that are critical for maintaining functional connectivity, particularly in densely built environments (Staccione et al., 2022; Lin et al., 2023). Importantly, this pattern is consistent with Hernando et al. (2017), who demonstrated that MSPA-derived fragmentation and connectivity metrics vary significantly with spatial resolution, with finer inputs (e.g., 2 m) revealing more detailed structural connectivity compared to coarser datasets (e.g., 10 m and 50 m). Similarly, studies mapping green infrastructure networks across European city regions indicate that coarser resolutions tend to generalize or omit small and linear features, potentially underestimating connectivity and oversimplifying network structures (Rusche et al., 2019). This has direct implications for green infrastructure strategies, as the identification of priority areas for conservation, restoration, or corridor enhancement depends on an accurate representation of spatial continuity. In this context, the improved delineation of canopy linkages observed in the 2 m analysis highlights the importance of aligning data resolution with the spatial scale of planning and design interventions.

While the comparison highlights clear structural differences between resolutions, it is important to note that this study does not rely on independent reference or ground-truth data to quantitatively validate connectivity accuracy. In fact, the higher proportion of Core areas observed in the 2 m results may partly reflect the increased detection of continuous canopy surfaces at finer resolution, rather than a direct increase in functional connectivity, and should therefore be interpreted with caution. The evaluation is therefore based on relative comparison and visual interpretation using high-resolution imagery, which suggests that the 2 m dataset more effectively captures fine-scale vegetation structures such as narrow corridors and small canopy patches. However, further work incorporating reference datasets or field-based validation would be necessary to formally assess the ecological accuracy of MSPA outputs across scales.

From a methodological perspective, the work confirms that MSPA is not scale-neutral. When applying MSPA to large metropolitan areas, resolution choices have both analytical and practical consequences. Running the 2-m MSPA across Miami-Dade required splitting the area into 23 processing tiles, illustrating the computational constraints associated with fine-resolution ecological mapping at the city scale. Future implementations should therefore consider scalable computation approaches, cloud processing environments, or optimized MSPA workflows for large datasets.

In addition to these methodological considerations, some sources of uncertainty should be acknowledged. The binary classification of canopy from the canopy height model (height > 0 m) may introduce minor misclassification, particularly in heterogeneous urban environments. In addition, resampling from the original 1 m data to 2 m and 10 m resolutions may lead to generalization effects, potentially smoothing or omitting fine-scale vegetation features, especially at coarser resolution. Reprojection from a geographic to a projected coordinate system may also introduce small geometric distortions, although these are expected to be limited at the study scale. Finally, the tile-based processing adopted for the 2 m analysis may introduce slight edge inconsistencies, despite mosaicking efforts. Overall, these factors are not expected to significantly affect the comparative interpretation but should be considered when evaluating resolution-related differences in MSPA outputs.

Building on these insights, several promising research directions emerge. First, advancing long-term monitoring frameworks using very-high-resolution imagery and standardized datasets (e.g., Copernicus Urban Atlas, LiDAR) will be key to transferring MSPA methodologies across cities and evaluating canopy change over time. Second, integrating MSPA with AI-driven spatial analysis and predictive modelling, building on previous applications of AI and other digital technologies in urban planning contexts (Moufid et al., 2025a, 2025b), could enhance interpretation and support decision-making by automating connectivity detection, evaluating intervention scenarios, and translating complex landscape patterns into actionable planning tools. Third, combining MSPA with integrated design approaches can inform urban regeneration and nature-based solutions by jointly optimizing the form, connectivity, and ecosystem service delivery of green infrastructure. Finally, embedding MSPA within broader socio-ecological frameworks offers opportunities to study equity, exposure, and ecosystem service access, particularly by examining the role of small green elements and informal vegetation patches in supporting community resilience.

## 5. Conclusions

In this work, we evaluated the role of spatial resolution in Morphological Spatial Pattern Analysis for mapping and interpreting the connectivity of urban green infrastructure. By comparing MSPA outputs at 2-m and 10-m resolution across Miami-Dade County, we assessed how scale influences the delineation of structural vegetation classes and the perception of ecological continuity in urban landscapes. The workflow integrated county-wide vegetation datasets, MSPA computation, and quantitative and visual comparison to systematically examine scale effects.

We have shown that:

1. Spatial resolution has a decisive impact on MSPA outputs: High-resolution (2 m) data reveal continuous canopy structures and preserve thin vegetated corridors. In contrast, coarser 10-m data oversimplify canopy form and artificially elevate fragmentation patterns.
2. Fine-scale MSPA better captures neighborhood-level ecological connectivity: In dense residential tree networks such as Coral Gables, 2-m resolution retains connected canopy cores aligned with physical landscape patterns, whereas 10-m resolution breaks them into multiple branches and isolated patches.
3. MSPA results are scale-dependent and must be interpreted cautiously: Cross-study comparisons require attention to spatial resolution, and ecological or planning conclusions drawn from coarse datasets may misrepresent real connectivity conditions. In addition, the absence of reference data limits the direct validation of connectivity accuracy across scales.
4. High-resolution MSPA can support urban planning and resilience objectives: The finer resolution captures features critical to nature-based solutions, equity-focused canopy strategies, heat-mitigation planning, and biodiversity corridors within the built environment.
5. Resolution constraints impose computational and methodological considerations: Performing MSPA at 2-m resolution across the full Miami-Dade County extent required tiling the study area into 23 independent mosaics, highlighting scalability challenges and the need for efficient processing strategies for metropolitan-scale high-resolution analysis.

This study provides an operational foundation for advancing high-resolution MSPA in the context of urban resilience, climate adaptation, and socio-ecological equity. The results confirm that fine-scale canopy structure is crucial for understanding urban green connectivity, highlighting the importance of selecting an appropriate resolution and integrating reference datasets in ecological analysis and planning. The approach presented here provides a robust foundation for future studies that link green infrastructure connectivity to resilience outcomes and community well-being.

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