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COMPUTATIONAL METHODS FOR THE IDENTIFICATION AND COMPARATIVE ANALYSIS OF URBAN FORM TYPES: A CASE STUDY OF RUST BELT CITIES

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Presented to
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ABSTRACT

This dissertation presents a novel methodological framework that allows for the comparative analysis of city structures by identifying urban form types, interweaving a data scientific perspective into urban morphology. Proposing a concept of neighboring urban form around individual buildings as a key constituent of the city, a new kind of urban form dataset and method to identify urban form types is introduced. This framework was applied to three Rust Belt cities—Cleveland, Detroit, and Pittsburgh—as a case study. A deep learning model was employed to capture the morphological features from the urban dataset for these cities, clustered them to yield types of urban spaces, and examined the morphological characteristics of each type. These types delineate patterns of urban fabric and reveal urban structures distinctive of Rust Belt cities. Through site surveys and expert interviews, I validated the proposed method's capacity to provide more granular classification of urban forms and lead to more nuanced understanding of city space than conventional urban analysis methods. This dissertation contributes to the field of urban form studies, opening a new perspective to the analysis of urban spaces and redefining urban types and fabric from data science.

COMPUTATIONAL METHODS FOR THE IDENTIFICATION AND COMPARATIVE ANALYSIS OF URBAN FORM TYPES: A CASE STUDY OF RUST BELT CITIES

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LIST OF ACRONYMS

1D one-dimensional

2D two-dimensional

3D three-dimensional

ACADIA the Association for Computer-Aided Design In Architecture

BHAD building area to a grid cell area

CAAD Computer-Aided Architectural Design

CAADRIA the Association for Computer-Aided Architectural Design Research in Asia

CHAD shape complexity of buildings in a grid cell

CP conflict points

DBSCAN Density-Based Spatial Clustering of Applications with Noise

DEM Digital Elevation Model

DF directional fragmentation

DNN deep neural networks

DSM Digital Surface Model

eCAADe Education and research in Computer Aided Architectural Design in Europe

GAN Generative Adversarial Network

GIS Geographic Information Systems

GMM Gaussian Mixture Model

GSV Google Street View

KNN K-Nearest Neighbors

LAS Laser point cloud data

LIDAR Light Detection and Ranging

MBG Minimum Bounding Geometry

MSE Mean Square Error

OSM Open Street Map

PROX proximity to the center of a grid cell

RD relative distance

SSIM Structural Similarity Index

t-SNE T-distributed Stochastic Neighbor Embedding

UMAP Uniform Manifold Approximation and Projection

USGS United States Geological Survey

VAE Variational Auto-Encoder

CHAPTER 1

INTRODUCTION

The field of urban form studies has evolved through a multifaceted relationship with disciplines such as geography, architecture, and urban planning. Within this broad spectrum, a relatively recent sub-discipline—urban morphology—concentrates on identifying types of forms that constitute the urban fabric, followed by an in-depth analysis of urban structures [1, 2]. Urban morphology has developed to offer diverse understandings of the complexities inherent in urban environments, underscoring the importance of interdisciplinary approaches in the examination of urban form and conceptualizing the city in various ways such as landscapes [3], as assemblies of architecture [4], and as networks[5]. In this dissertation, I present how a data-scientific view can add another layer of conceptualizing the city in urban morphology.

The advent and spread of computers in the 1960s significantly influenced the field of urban form studies, particularly in diverse methods of measuring and representing form. This advancement facilitated, for example, the establishment of Space Syntax as a distinct discipline dedicated to analyzing spatial relationships by quantifying space. Space Syntax employs a topological representation of spaces in the form of a graph to describe spatial configurations; spaces and their connectivity are depicted as nodes and edges, respectively. With this representation, Space Syntax introduces the concept of depth instead of physical distance to conduct a quantitative analysis of urban space configuration. Depth refers to the number of directional changes required to move from one space to another. Thus, the determination of a space's depth in urban form analysis does not rely on the physical distance needed to reach it but rather on the number of spaces one must pass through from the starting point. Therefore, a space with greater depth is considered more challenging to access, illustrating a novel approach to understanding spatial accessibility and connectivity

within urban environments.

Moreover, the advent of computers catalyzed the development of urban modeling, a methodological approach that scientifically examines the formation of the diverse elements comprising urban areas. Early research in urban modeling leveraged generative algorithms for reconstructing urban forms, including methods such as cellular automata, which applied geometric principles to emulate city shapes [6]. Notably, this included the exploration of spatial rules in medieval London through interactive systems, which influenced the creation of simulated development plans [7]. Additionally, fractal-based systems were utilized to model street patterns under various constraints, showcasing the adaptability of these algorithms to planning needs [8]. Another example is the generation of virtual cities using shape grammars and procedural modeling, highlighting the potential of these methods in creating detailed urban simulations [9]. These instances collectively illustrate the profound impact of computational tools on urban modeling techniques.

Urban morphology has also become intricately interwoven with computer science, as it seeks to analyze urban form data constructed in various ways using a range of statistical techniques. The majority of these studies in this discipline rely on geometrical guides, such as grids, to segment urban forms. For each segmented urban form, morphological features that can be measured are identified, calculated, and then formulated into morphology indices to classify the segmented urban forms. This classification results in urban form patterns that serve as an informational layer, revealing the structure of the city.

However, this classification approach often leads to a disconnect with actual spaces by randomly segmenting buildings and spaces. This discrepancy becomes especially pronounced when focusing on a micro scale, such as individual buildings and their outside spaces, rather than a macro view of the entire city, resulting in significantly reduced accuracy of classification. In other words, when building forms or urban spaces are segmented, they fail to accurately reflect the characteristics of the real space.

Furthermore, the data used in these analysis is often two-dimensional (2D) shape data

such as building footprints and parcel shapes. However, 2D data has limitations in representing the characteristics of volumetric space into data. 2D data can only represent relationships between shapes projected onto a plane, offering a limited perspective on the complexity of information compared to three-dimensional (3D) data.

The use of geometrical segmentation in 2D data can be seen as a cartographical convention remaining in urban morphology, influenced significantly by urban geography. Urban form analysis based on such convention demonstrates a common methodology: researchers select certain morphological features based on their observations, extract these features from each segmented urban form, formulate these features into morphological indices, and generate patterns that represent the morphological traits of the entire city for analysis.

Contrary to these conventions, there has been a notable increase in studies employing methods that directly extract morphological features from urban form data. These studies utilize statistical models, such as machine or deep learning models, capable of extracting meaningful features from data without formalizing morphology indices. In this context, how information is embedded in the data becomes closely linked to the features extracted, and consequently, how the data is structured becomes crucial.

My research examines how this shifting towards a more data-scientific approach to urban form analysis can alter our perception of the city and reveal different form types and patterns from the conventional methods by leveraging direct feature extraction. This approach seeks to overcome conventional cartographic conventions in urban morphology, proposing a data-driven perspective on urban forms, fabrics, and structures. In this approach, I define urban space and urban form with a broader concept than the typical understanding of urban spaces as public outside or empty spaces in cities, such as plazas or parks. Here, urban space refers to the in-between spaces created by built environments—such as buildings, roads, and terrain— within a specific range. Urban form refers to the forms of the built environment that constitute these urban spaces, including forms of buildings,

streets, terrain, trees, structures, etc.

Building on this perspective, I propose a novel data representation that incorporates the neighboring spaces surrounding the building. I refer to this surrounding as individual urban space, encompassing forms of buildings, roads, terrain, and other elements of the built environment within this surrounding, which I call individual urban form. This representation deviates from conventional segmentation practices, which typically dissect urban spaces, obscuring critical morphological characteristics. By adopting this individual building-centric data point methodology, it becomes possible to depict urban spaces numerous times within the dataset, reflecting their roles as external spaces for a variety of neighboring buildings, with a certain level of repetition and overlap. This technique not only preserves the distinctive connections between buildings and their immediate urban space—thereby conserving essential morphological features—but also encapsulates a wide spectrum of spatial relationships. It achieves this by demonstrating the diverse ways in which identical spaces interact with different buildings and their surroundings. Such repeated representation and the intentional overlapping of urban spaces within the dataset highlight the complex and dynamic interplay between architectural structures and their urban backdrop, facilitating a more nuanced understanding of urban form.

This data representation suggests an alternative way of representing cities that privileges individual urban spaces as their constitutive unit—neither as buildings nor as blocks, but as an aggregation of neighboring urban spaces, a departure from the conventional view of the city as a bounded entity segmented into discrete units. It emphasizes the distinctiveness of each urban space, enabling the precise curation of urban form data tailored to the specific aims of the analysis. This emphasis on individuality allows for the development of a data schema that effectively captures the unique morphology of urban spaces, along with a standardized data format for depicting urban forms. Moving beyond the limitations of one-dimensional (1D) or 2D representations for calculating morphology indices, this approach welcomes the use of 3D data. Such a shift is predicated on the condition that the

chosen schema and format provide a consistent framework for detailing the morphological features of varied urban spaces, thereby enhancing the depth and complexity of information presented.

A statistical model can be employed to extract morphological features from datasets of urban forms and their characteristics. This model utilizes multi-dimensional data to uncover general morphological trends, patterns, and traits within urban spaces.

Therefore, the shift in perspective on urban space can introduce an alternative approach to typo-morphological analysis. This approach is versatile, adapting to a wide range of data subjects, formats, compositions, sizes, and sources, thereby enhancing the extraction of morphological features and the examination of form characteristics. It ensures a consistent representation of urban forms across varied urban contexts, embraces the added complexity of form data through the inclusion of 3D representations, and enables statistical analysis of morphology features in individual urban forms without being constrained by city borders.

Highlighting the limitations of conventional concepts of segmentation, I advocate for the alternative recognition of urban space, form, and data. This concept seeks to capture the uniqueness of each urban space by interpreting its characteristics as phenomena manifesting in urban forms. Every urban space presents a distinct arrangement shaped by its historical, cultural, and social context, reflected through its form. In turn, each urban form embodies the specific characteristics of its respective urban space. Hence, to analyze a city's morphological features is essentially to generalize the unique traits found within each urban form, viewing these as indicative of broader urban spatial characteristics. From this vantage point, urban form is approached through aggregation rather than segmentation, promoting a conceptualization of the city as a cohesive assembly of adjacent urban spaces. This approach is encapsulated in the concept of the city as an aggregation of neighboring urban spaces.

This cognitive shift involves changes in how urban form data are constructed, ana-

lyzed, interpreted, and evaluated, paving the way for a novel framework in computational urban form analysis. At the center of this framework lies the conceptualization and representation of the city as an aggregation of neighboring urban spaces, highlighting the distinctiveness of each space and its representation within data.

With the concept of the city as an aggregation of neighboring urban spaces, I propose a research pipeline comprised of five stages: form data curation, feature processing, characteristics analysis, evaluation, and knowledge. Initially, the curation of form data involves constructing a dataset of urban forms tailored to the research focus, taking into account factors such as the data's subject, source, format, dimension, and composition. The aggregated, composed, and formatted data form a comprehensive urban form dataset. This dataset then advances to the feature processing stage, where morphological features are extracted using deep neural networks, classifying urban forms by their features. Upon training a deep neural network with the urban form dataset, it can identify morphology feature vectors for all urban form samples, providing abstracted representations that retain their unique features. Unsupervised classification algorithms are then applied to these vectors, resulting in the identification of various urban forms, distinguished by their morphological features, and termed 'urban types.'

The characteristics analysis stage involves examining the properties of each urban type through statistical methods, mapping, identification of principal features, representative forms, and qualitative descriptions. This analysis elucidates common urban types and their distinctive structures. The evaluation stage involves validating the clustering results and interpreting the types' characteristics through site surveys and comparisons with findings from traditional methods. Finally, the knowledge stage translates the analyzed and validated morphological characteristics into a spatial understanding of the city, encapsulating the research findings.

I apply this five-stage research pipeline through case studies on Rust Belt cities that share a common urban culture. This approach will demonstrate how the concept of the

city as an aggregation of neighboring urban spaces can lead to methodological changes in analysis of urban forms. Furthermore, it will explore how these changes reveal unseen characteristics of urban forms by identifying different form types and urban structures.

This dissertation is structured into eight chapters, beginning with this introduction as the first chapter. The second chapter addresses the background of the study, briefly covering the research scope of urban form studies, a historical review of urban morphology as it diverged from urban geography, and the recent emergence of a new field that combines statistical and data-scientific methods to analyze urban form. In the third chapter, I collect precedents relevant to this emerging field, meticulously analyzing their methods and perceptions of the city to highlight the limitations of existing approaches.

The fourth chapter, the hypothesis chapter, speculates on the potential changes brought about by viewing the city as an aggregation of neighboring urban spaces from a data-scientific perspective, particularly focusing on how such a viewpoint can alter urban form data. Chapter five, the method chapter, proposes a research pipeline to test this hypothesis, applying it to three Rust Belt cities—Cleveland, Detroit, and Pittsburgh—that share a common urban culture to cluster urban form types.

In chapter six, the results chapter, I examine the characteristics of each type to explore what kinds of spaces emerge and what unique urban structure they yield for Rust Belt cities. Chapter seven, the evaluation chapter, compares and analyzes the differences between urban form types and unique urban structures derived from the conventional approach with those obtained using the proposed method when applied to Rust Belt cities. This chapter also evaluates the potential and suggestions of the proposed method through site surveys, examining how it differs from the actual urban situation.

Finally, the conclusion chapter summarizes the new approaches developed during this research and the findings discovered, highlighting the contributions to urban form studies. It introduces a new concept of urban types, redefining urban fabric through a data science lens by revealing morphological patterns and categorizing urban spaces into unique types.

Additionally, this dissertation pioneers a novel data formatting technique that captures the 3D spatial details of urban forms to offer a more spatially nuanced representation of urban environments. It further demonstrates the effectiveness of employing advanced computational methods, such as deep learning and clustering algorithms, to systematically classify urban forms based on their intricate characteristics. Moreover, this dissertation proposes a new evaluation methodology that contrasts the proposed extracted feature approach with conventional methods, underscoring its advantages and providing a more granular analysis of urban forms. The method includes interviews with a professional who is both an urban planner and a scholar for evaluating the feasibility and applicability of the proposed method in planning practices and research. The concluding chapter also delves into the potential and limitation for broadening the methodology by incorporating non-morphological indicators and discusses future research directions. The discussion includes the significance of this methodology from an urban planning perspective.

CHAPTER 2

BACKGROUND I: EMERGENCE OF COMPUTATIONAL URBAN MORPHOLOGY WITHIN THE LANDSCAPE OF URBAN FORM STUDIES

This chapter traces the emergence of a new field around the use of statistical and data-scientific methods to understand urban form. I propose that this emerging field be identified as computational urban morphology. The necessity of adopting data-focused approaches is increasingly crucial because the design and shape of buildings and urban spaces are deeply connected with a city's complex social and cultural identities, going far beyond mere aesthetic, decorative, or structural design principles. This contention is graphically elucidated in Figure 2.1, which illustrates the influence of computation on the development of architectural and urban form studies and its spread into and intersection with other fields.

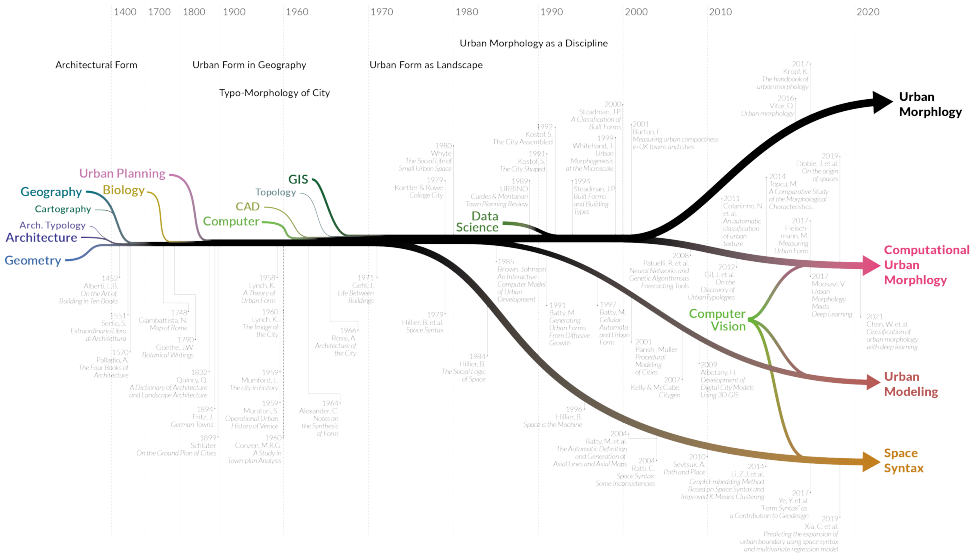


Figure 2.1: The landscape of urban form studies. Please find the larger figure at Appendix A.

To lay the groundwork for this assertion, I introduce form studies in architecture and urbanism and the emergence of early urban morphology from geography and planning,

delineating the primary research focus of urban form studies. By doing so, I highlight the cartographic origins of the conventional approach within urban morphology. I also acknowledge that there have been attempts to consider architectural and urban forms as constituents of urban scenery, social entities, or complex data. Subsequently, I illustrate how the recognition of urban form changes the landscape of urban form studies, describing alterations in the focus and methodologies of research.

Within this landscape, Space Syntax and urban modeling are regarded as distinct fields that have emerged in response to the influx of computation with their own unique research methodologies and objectives. In addition to these two fields, statistical approaches have been employed for quantifying urban forms to analyze changes of urban form in large urban areas during the development process of urban morphology.

Considering the transformative impact of data science technology on research methodologies pertaining to urban form, the chapter delineates the emerging field of computational urban morphology.

2.1 Urban Form Studies

Form has been a controversial concept in architecture and urban design contexts. Certain notable architects have negated form; for instance, Mies van der Rohe, the famous Modernist architect, refused to recognize form as something distinct from design [10, p.106]. Architects who follow the Modernist sentiments commonly point out that form studies focus on the shell and shape of the architecture and city, blurring the structural, functional, and spatial values [11, p.96-97]. The Modernist dictum ”form must follow function” [12, p.403-9] and the Miesian disregard for form, seeing it instead as a byproduct of construction [13, p.242] and functional considerations.

On the other hand, certain others stress form as a design subject that responds and adapts to given circumstances, rather than merely serving as a visible aesthetic or orna-

mental element. For example, Christopher Alexander, the influential British-American architect and design theorist, argued that "the ultimate object of design is form," [14, p.15] highlighting the relationship between form as a design solution and its contexts as a definer of the design problem. The renowned Italian architect and architectural theoretician Aldo Rossi posited architectural and urban form as an attribute of physical artifacts in contexts and derived typology as a precise analytical tool for architecture and urban form, which also provides a rational basis for design [4, p.64-65]. Renowned American architect Peter Eisenman has broadened the concept of form in architecture, transforming it into a platform for both intellectual and experiential engagement. In doing so, he challenges the conventional understanding of architecture as solely a well-composed structure to be admired for its aesthetic qualities [15].

Despite the recent controversy, form has long been central to architecture and to considerations of the city. Predominantly, the focus has been on the principles of proportion and geometric configuration. An example of this geometrical approach is seen in the analysis of the classical Greek order (Figure 2.2). The type of the order is defined with respect to geometrical features of columns through the measurement: scale of fluting, shape of volute, ratio between base, shaft, capital, and abacus. The purpose of the analysis is to discover the principal rules in proportion and configuration for architectural theory and practice. Vitruvius, a Roman architect who is famous for his ten books on *De Architectura*, addressed classical typology based on geometrical features—e.g., proportion, symmetry, location, composition—in architectural planning [16]. In *Book VI*, he provided an idea about type and variations in architecture, analyzing how geometrical principles were applied to architectural planning with different site situations.

The emergence of early cities, expanding from towns, alongside the advancement of cartography, began to cast an understanding of urban forms in close relation to built forms within the city context. On a map, the built forms and their surroundings had been meticulously measured and described as 2D shapes. Therefore, a map could effectively

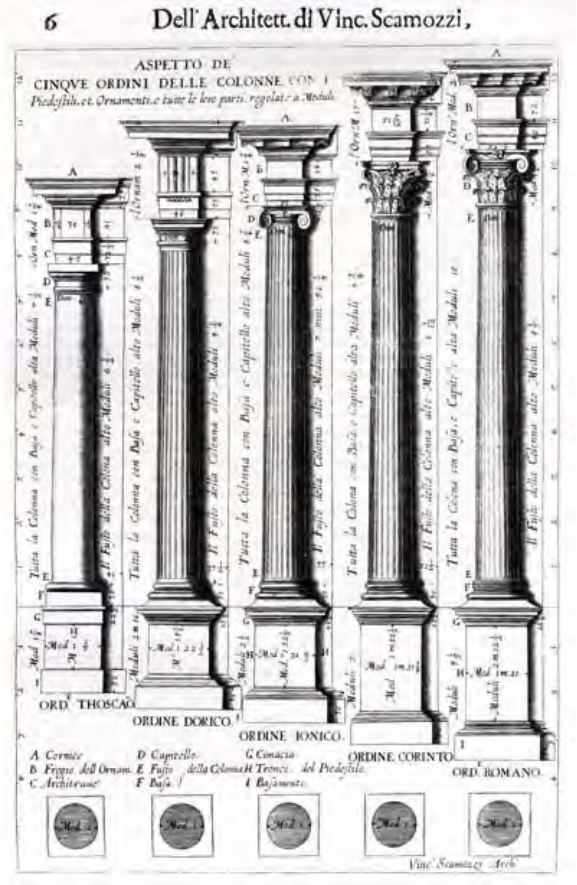


Figure 2.2: Classical Greek orders. Image from Aspetto de' cinque ordini delle colonne. Reprinted from [17].

represent and convey the information of city with more granular hierarchies and symbols, leading to diverse and detailed understandings of urban form and space. An example of urban form analysis on a map can be seen in is Giambattista Nolli's figure-ground map of Rome [18], the renowned historical representation of urban form and aggregation. His map (Figure 2.3) depicts public-private space configurations in sixteenth-century Rome. Unlike typical maps that represent urban elements such as buildings, plots, squares, and streets as individual objects, the map merges the ground-level private spaces and represents them as solid black figures, which foregrounds the ground-level public spaces enclosed by them. This representation is a method to collectively outline 2D shapes of urban forms to visually capture the porosity and connectivity of Rome's public spaces such as squares and plazas.

Nolli's map seems clearly stating the idea of urban form distinguished from the geo-



Figure 2.3: Nolli's map of Rome, 1748. Image from [18].

metrical understanding of architectural form. Within his cartographic depiction, the focus is not on the individual footprints of buildings but rather on portraying the urban space. To this end, the merged outlines of buildings with private space are rendered as black solids. These solids can be regarded as urban forms comprising a city—or occupying 2D map space. The spatial identity of the city is conveyed through the arrangement of its constituent objects, rather than the mere measurement of proportional and configurational features of individual buildings. His representation of urban form pertains not only the physical appearance of buildings, but also encompasses their manner in organizing of urban spaces with location and placement.

As evident in Nolli's map, the examination of urban form as exemplified by urban morphology, entails map and mapping. Maps serve as a medium to document and communicate information pertaining to the configuration of a city. Mapping serves as an analytical instrument that illustrates the correlation between urban forms. Hence, diverse urban form research utilize maps and mappings as their central investigative topic and analytical instruments [19, 3, 4].

The representation of urban forms in maps is subject to changes that reflect the chang-

ing perspectives and modes of expressing such forms. These days, urban form is being understood by composites of the natural environment, human activities, physical products, street systems, plot systems, and building systems including social, cultural, economic aspects of city [20, 21]. Urban form analysis has expanded from interpreting the process of formation and transformation of city shapes [22] to tracing the complex patterns of the physical, environmental, economic, social, cultural, and political interactions of form and its context. For example, [23] explored the Tel Aviv metropolis to understand the complex cultural and political influences on urban form. The study uses the concept of urban clusters—contiguous built-up areas—as the unit of analysis instead of traditional political boundaries. Historical data reveals significant shifts in cluster characteristics, notably in 1964 and 1985, suggesting that this approach can offer insights into broader social and economic phenomena affecting the urban landscape. Further, a team led by James Zhang [24] focused on the complex relationship between urban form and an environmental factor—traffic noise—in high-density areas, using numerical noise mapping technology in 30 Singaporean neighborhoods. The study found that architectural form and urban planning parameters significantly influence traffic noise levels. In this vein, adopting the expanded view, I take the view of urban form as a composite that includes data, insights, and sometimes direct connections concerning the physical arrangement of elements within a city.

As our comprehension of urban forms has broadened, representations of urban forms extend beyond figure-ground maps. One noteworthy contemporary approach is street network analysis, as introduced by [25]. Utilizing statistical and computational methods, street network analysis focuses on identifying patterns of streets from geospatial data, and analyzing their nodes to understand various urban characteristics such as complexity, connectivity, and accessibility. Researchers employing street network analysis posit that street network patterns are crucial factors that both affect and are affected by the formation of cities. Geoff Boeing, an urban form analysist, conducted a study on the centrality of three distinct districts in the United States, where he discovered that different street centrality

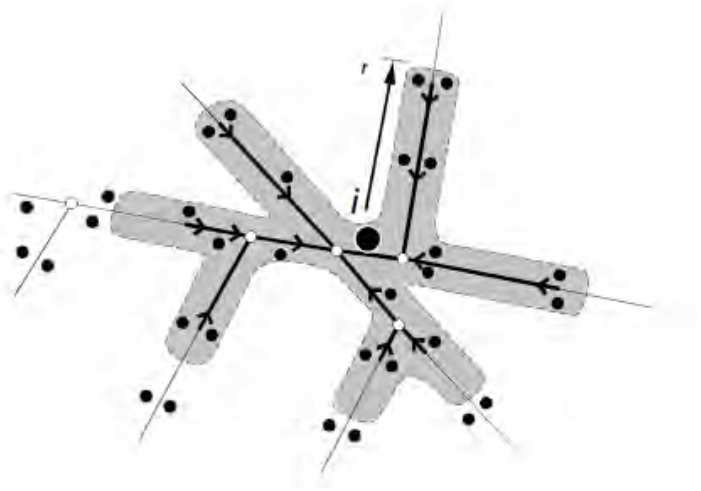


Figure 2.4: Sevtsuk's illustration of the Remote index based on street networks. Image from [25].

patterns reveal the hidden weights of intersections at the neighborhood scale based on the topological features of streets [26].

Such representations on maps allow us to reveal the formal traits of city space in different ways with different urban questions, and in that sense, they serve as distinct modalities for understanding urban form. This then enables us to discover and understand the morphological characteristics of city space. As Nolli developed a new reveal of urban form through drawings of merged private spaces on the figure-ground map, Boeing uses graphs and statistics to produce an alternate and distinctive understanding of street network patterns extracted from a map [26].

In the realm of urban morphology, maps are not merely utilitarian or visualization tools; they signify our recognition of the 3D urban form and space as projected information situated within a 2D grid. A map serves as a systematic and essential medium for conveying a vast amount of morphological information in a coherent manner. However, to understand how urban form has been apprehended through maps and what alternatives to maps have been proposed, it is necessary to re-view the interplay between early urban morphology and cartography.

2.2 Urban Morphology Diverged from Urban Geography

Morphology originated from the classification and evolution in biology and was adopted in urban form studies in the late eighteenth century. Morphology, a compound word of ”morpho-” (shape, form in Greek) and ”-logic” (study in Greek), refers to the ‘form study’ that analyzes, investigates, and reasons the principles of forms. Morphology, originating with Aristotle [27] and later developed by Goethe [28, 29] and Burdach [30], is the study of an organism’s form and structure. It encompasses both external attributes—external morphology or eidonomy—like shape and color and internal components—internal morphology or anatomy—such as bones and organs [1]. Morphology aids in differentiating and understanding relationships among taxa but poses challenges, including cryptic species that appear identical yet are reproductively isolated. However, it has limitations, as DNA analysis can reveal distinct species as one. Techniques like allometric engineering are employed to probe these morphological variations.

In morphology, biological forms such as animals, plants, and organisms are regarded as differentiated variations with certain principles. The focus of morphology is to analyze types and variations according to the principles and their changes. Interpreting a city as an organism that has rules and undergoes creation, differentiation, and extinction led to a morphological understanding of urban form, resulting ‘urban morphogenetics’—the early concept of urban morphology. Morphogenetics refers to the biological process that causes an organism to develop its shape. The focus is on the processes that control the organized spatial distribution of cells during the embryonic development of an organism and the changes in the structure of an organism over time. Morphogenetics is concerned with the processes and mechanisms by which those structures are formed and developed over time, whereas morphology is about the study of the structure and form of organisms.

Applying the concept of morphogenetics to urban study, urban morphogenetics was

[1] When excessively biased towards form study to the extent of allowing leaps in scientific logic, morphology has also been used as a basis to support pseudosciences such as phrenology and physiognomy.

the study of how cities develop and take shape, much like how living organisms form and grow. Just as cells organize themselves to create living beings, cities grow and change through specific processes. Understanding urban morphogenetics helps us comprehend how cities come into being and why they look the way they do. Urban morphogenetics are seen in the classification of city and town shape on maps in nineteenth-century German geography. Fritz, a German geographer, comparatively analyzed about 300 German towns using cartography [31]. He utilized historical maps of the towns to gain insights into the transformations of urban forms. This comparative analysis prompted another German geographer, Otto Schlüter to publish a paper regarding the classification of cities based on their plan types [32]. These German studies of the nineteenth century conceptualized form-related urban phenomena in early cities as the growth or evolution of organisms. They illustrated that urban forms change in response to the rise and fall of cities and can be categorized based on such changes.

In the study of urban form, the mid-twentieth century can be characterized by three distinct perceptions of urban form. The first perception is that of urban form as the culmination of social and historical context, as exemplified by Lewis Mumford—an American historian renowned for his expertise in urban architecture—and Saverio Muratori—an Italian architect. The second perception similar to that of Michael Conzen—a German geographer based in England, views urban form as an object with locally constrained spatial features. Lastly, the perception from Kevin Lynch—an American urban planner—identifies urban form as a constituent element of urban scenery [2]. These perceptions broadened the classification and analysis of the plan of city shapes, which had its roots in the work of German geographers, by introducing diverse ways of recognizing urban forms.

[2]Kevin Lynch's concept of "urban scenery" refers to the visual and sensory elements that constitute a city's unique character and spatial arrangement. Though he did not use the exact term "urban scenery," Lynch is best known for his ideas on how urban environments are perceived, navigated, and understood by their inhabitants, as detailed in his seminal work *The Image of the City* (1960). He identified five key elements—paths, edges, districts, nodes, and landmarks—that help people form a mental map or "image" of their city. This mental map influences how people interact with the urban landscape and contributes to a city's identity or "scenery." Through understanding these elements, city planners and architects can create more livable, navigable, and aesthetically pleasing urban environments.

Mumford viewed the urban form of a contemporary city as the culmination of changes accumulated over time in the past. In his classification, cities are categorized based on their different shapes of occurrence and changes over the course of history [33]. His work can be viewed as an extension of the German geographical studies of cities, in which the city was treated as an organism in history. However, Mumford focused on the spatial dynamics between urban forms and the political, economic, social, and cultural forces in cities, providing a historical example of city space.

Muratori endeavored to construct a theoretical framework to explicate the evolution of urban form by defining various urban types, fabrics, and organisms within a city's history [34]. In the "Operational Urban History of Venice", he recommended the recreation of significant moments of Venice's urban history through detailed and analytical maps of each district. The renowned Italian architect and architectural theoretician Aldo Rossi acknowledged architectural and urban form as a physical artifact in spatiotemporal contexts [4]. He fused architectural typology with urban form studies, using typology as a precise analytical instrument that provides a rational basis for design innovation in traditional settings.

As exemplified by figures ranging from German geographers to Aldo Rossi, a gradual divergence from urban geography and towards a closer coupling with architectural design and urban planning can be observed. This divergence was accompanied by a growing emphasis on the definition and meaning of urban form, particularly in relation to urban spaces. For instance, this shift is visible in the work of Conzen. He focused on systematic analysis of urban forms at the local scale. Prior to Conzen, most analyses of urban form were at city scale so that it was confined to understand how the city was locally formed. Thereby, focusing on elements of urban forms in a certain area of a town, Conzen proposed a method to analyze and categorize types of urban plans that have structured and changed in times [35]. This microscopic approach to analyzing urban form led to the development of Conzenian Urban Morphology.

Scenery of urban space is another noticeable aspect of urban form surfaced in mid



Figure 2.5: Muratori's mapping analysis of urban form changes by times. Image from [36].

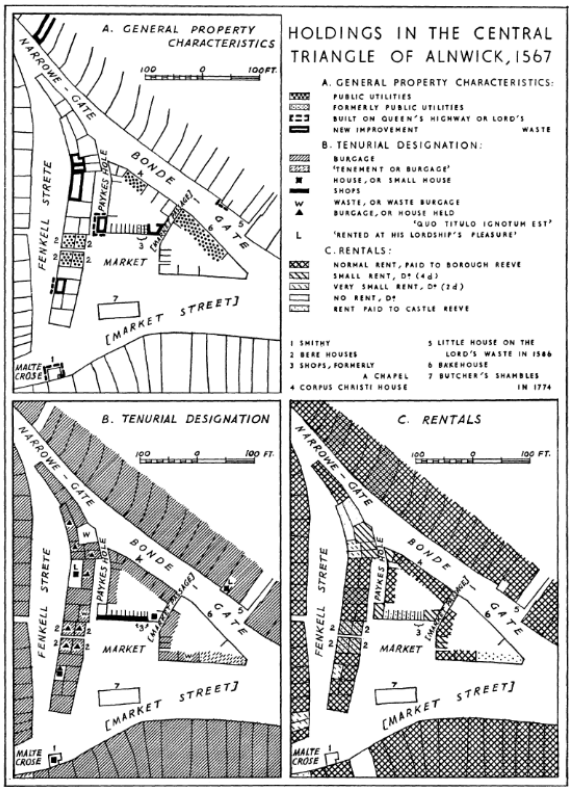


Figure 2.6: Example of Conzen's urban form analysis at local scale. Image from [35].

twentieth century in the United States. In the mid-twentieth century, another noticeable aspect of urban form emerged in the United States, namely the scenery of urban space. Lynch emphasized the importance of urban form as a constituent of urban scenery. He developed the concept of the urban image, which highlights the disparity between the physical layout of a city and its visual appearance [3]. He proposed the classification idea of urban forms through urban images from the path system in a city. This idea laid the groundwork for future efforts to view urban forms as landscapes and to comprehend social aspects of urban



Figure 2.7: Whyte's observation of public space in city at Seagram building. Image from [37].

forms.

As these three perceptions and following methodologies interacted and influenced one another, they stimulated more diverse and nuanced urban form studies. For example, in the "The Social Life of Small Urban Spaces", Whyte, an American urbanist and social critic, examines the social dynamics of small urban spaces in New York City such as plazas, courtyards, and parks, and analyzes how people use and interact with these spaces through extensive mappings along with basic statistical observations and surveys of these spaces, studying factors such as seating arrangements, sun and shade patterns, and pedestrian traffic flow [37]. He found that successful urban spaces were those that provided a variety of seating options, ample sun and shade, and opportunities for people watching and socializing. This study can be regarded as situated at the intersection of Conzen's local analysis of urban form and Lynch's introduction of urban form as an element of scenery.

Another example can be seen in *Collage City* written by John Arthur Koetter—an American architect and urban designer—and Colin Rowe—a British-born American architectural historian and theoretician [1]. In this book, they explore the history and theory of collage in architecture and urban design, and provide examples of collage-based urban design projects from around the world. The authors propose a new set of design principles based on the idea of "thickening" the urban fabric through the layering of different forms

and materials, and the incorporation of existing urban structures and spaces into new designs. The proposed method can be considered to be founded on the recognition of urban form as a culmination of social and historical factors, as well as physical shape, represented through cartographic means.

Furthermore, these perceptions commonly developed the idea of types in urban form from geometrical classification and established the concept of typo-morphology [38]. Typo-morphology is a concept in architecture and urban planning that combines the analysis of urban forms with the classification of urban elements by their physical and spatial characteristics and the understanding of their underlying processes and mechanisms. The concept of typo-morphology significantly contributed to the proliferation of urban morphology that appeared in the 1940s, giving rise to key concepts such as urban fabric, urban blocks, and street networks.

2.3 Urban Morphology as a Discipline

Since the late 1980s, urban morphology has become a discipline through numerous experiments and research in the fields of urban design theory and practice developing their own academic community [3]. Spiro Kostof, an architectural historian, clarified the terminologies and concepts that can be employed for systematic investigation of urban form. In his book *The City Shaped*, Kostof introduced the concept of urban form patterns - regular shapes formed by built structures within a city. He identified unique patterns of urban form in

[3]The academic community of urban morphology owes much to the journal "Urban Morphology," which has been published since the late 1990s. It has provided scholars with a platform to explore the various aspects of urban form and has facilitated the formation of a community of like-minded researchers. The journal has been instrumental in reflecting on the emergence of urban morphology as a discipline and the need for more research on the classification of forms and the clarification of associated concepts. Moreover, it has emphasized the importance of a theoretical and conceptual framework to facilitate links to other studies and enhance the understanding of completed case studies. The challenge of representing the vast geographical scope of the subject matter has also been acknowledged. The journal encourages contributions that address philosophical, methodological, theoretical, and practical issues, as well as studies of specific places and geographical areas that explore more general issues. This journal constitutes a seminal academic community in the field of urban morphology, where attempts to integrate diverse disciplinary perspectives with urban morphology continue to be disseminated.

different cultures throughout history, including organic, grid, symbolic geometric, monarchical, and skyline patterns [22]. In *The City Assembled*, Kostof delved into the constituent elements that make up urban form patterns, including city edges, urban divisions, public spaces, streets, and the urban process. He analyzed how these elements impact and organize urban patterns, and proposed the concept of 'urban process' to describe the forceful and incremental transmutation of cities, which encompasses all other elements [39].

Kostof's concept of patterns laid the foundation for the morphological analysis of urban forms. The patterns illustrate the changes in urban form through the rules of activity in each city, and the changes characterize the urban space in different stages of development. Building upon this foundation, researchers have made rigorous attempts to develop quantitative methods for classifying urban types, identifying urban patterns, and investigating the characteristics of urban spaces based on these types and patterns. The development of form indices has been crucial in advancing the field of quantitative analysis in urban morphology. The form metrics were derived from geometrical features inherent in urban forms, such as compactness, density, orientation, and occupancy, and represented their characteristic values.

An early demonstration of the use of the indices can be observed in *Compactness of Geographic Shape* by an American geographer Maceachren [40]. He examined the different methods suggested for measuring geographic shape compactness. Through the development of his own compactness measurement indices, including perimeter-area measurement, single parameters of related circles, and dispersion of elements of a shape's area, the researcher was able to calculate and compare the compactness of sampled geographic shapes.

In addition to geometric features, non-geometric aspects of urban form, were also translated into attributes of form and expressed as indices. For instance, a study was conducted to explore the connection between the irregularity of land parcels and land use [41]. By constructing form indices and tracing patterns in these indices, alterations in dwelling

types at the town scale were identified [42]. Similarly, an attempt was made to establish solar admittance [43] and population [44] as indices of urban forms.

Since the late 1990s, urban morphology has increasingly become computationally intensive, as the quantification and inclusion of non-geometrical features in the analysis of urban forms have become more complex. Efforts to digitize larger amounts of urban forms using computers and analyze their characteristics have led to a focus on data representation and modeling of urban forms. With the emergence of network theory, topological representation of urban forms and analysis of network configuration has led to the development of a distinct field known as Space Syntax [4]. Furthermore, at the intersection of generative design technologies such as procedural modeling, cellular systems, multi-agent systems, and optimization, with urban form, simulation and virtual cities, urban modeling has emerged as its own field [5].

These fields can be understood as an excursion of the development of Geographic Information Systems (GIS) that emerged in the early 1970s. GIS is a specialized type of information system where the database consists of observations on spatially distributed features, activities, or events, which are definable in space as points, lines, or areas [45, p.106]. GIS data usually consists of two types: shape and properties. Shape is a formal data type which includes coordinates of geometries to be visualized, edited, and manipulated in the system, such shapes as terrains, footprints, parcels, district borders, census tracts, etc.

[4]The concept of "Space Syntax" is most often associated with Bill Hillier and his colleagues at The Bartlett, University College London. The seminal work often cited in discussions of space syntax is Bill Hillier and Julienne Hanson's book *The Social Logic of Space*, first published in 1984. This book lays the theoretical groundwork for the space syntax approach to understanding the spatial organization of buildings, cities, and other environments. The methodology has since been used in a variety of fields including architecture, urban planning, and social sciences.

[5]Michael Batty's seminal work, "Urban Modelling: Algorithms, Calibrations, Predictions," originally published in 1976, has been pivotal in laying the groundwork for urban modeling as a distinct field. The book presents a comprehensive set of mathematical models for urban phenomena, serving both as theories of urban form and as practical algorithms for implementation. Batty organizes the work around the critical tasks of designing and employing these models in real-world contexts. He addresses both the calibration process, which ensures the models' fidelity to real-world conditions, and the challenges involved in defining the spatial systems under study. The book also examines practical implementation issues, such as data organization, and emphasizes the utility of these models in conditional prediction and policy impact assessment. This multi-dimensional approach has contributed to establishing urban modeling as a field with its own distinct theories and implementations, serving as a foundation for researchers and planners alike.

Properties are a non-formal data type which includes statistical and numerical values such as numbers of floors of buildings, education attainment, environmental values, accessibility to transportation facilities, etc.

Unlike digital or computer-aided cartography, GIS focuses on spatial entities and social relationships, together with specific attention to spatial analytical and modelling operations [46, 47, 48]. Nowadays, in urban analysis, GIS is a widely used computational tool to analyze the relationship between urban space and social factors. In analysis, GIS is based on objects referencing property information through shapes and is used to identify meaningful relationships by juxtaposing and overlaying these objects. The identified relationships became logically and mathematically describable and visualizable [49, p.198] through patterns projected onto geographic space.

When GIS is considered as a system that arranges diverse urban information—including both geometrical and non-geometrical—into multiple layers on a digital map, it can be regarded as the initial implementation of computation into the realm of urban form studies. The introduction of GIS facilitated the creation of multi-layered maps that enabled systematic data-ization of urban forms, illustrating physical city space in data spaces with the digitized representation of city elements. The use of GIS can be understood as a foundational framework for the constructing, exchanging, and distributing urban data, specifically pertaining to urban forms. This computational tool has been especially instrumental in niche disciplines such as Space Syntax and computational urban modeling by providing access to urban form data.

The crucial role of maps in the study of urban form, which persisted prior to the advent of GIS, has transitioned to the layered mapping functionality in GIS. As a result, the digital representation and analysis of urban form using GIS has become keys to analysis methods in this field [50, 51]. However, in urban form studies, despite the introduction of GIS, it seems that the cartographic convention continues to be prevalent, whereby urban forms are regarded as objects on a map and their recognition and distinction are dependent on the

cartographic methodology.

2.4 Space Syntax in Urban Form Studies

The advent of computers had an impact on urban form analysis. The active use of computers in urban form studies was delayed compared to the introduction of computers in other disciplines such as geography [52] and physics [53], since "neither the substance of urban physical form nor the source materials was readily amenable to computer applications" [54]. However, there were efforts to computationally comprehend architectural and urban form even though such applications were slower; Christopher Alexander, a British-American architect and design theorist, advocated for the understanding of city structure inspired by computer's data structures. He offered a schematic, abstract, and structural representation of form through nodes and edges—i.e., graph, and analyzed the characteristics of architectural and urban form by such representations. This idea was applied to analyze city form and space, which laid the basis for Space Syntax.

Space Syntax is a set of techniques for the representation, quantification, and interpretation of spatial configuration in buildings and settlements [55, p.363]. For describing spatial configuration, Space Syntax uses topological representation of spaces in the form of a graph; spaces and their connectivity are represented as nodes and edges, respectively. To undertake a quantitative analysis of the configuration of urban space, the notion of depth, which refers to the number of directional changes, is used instead of distance. The determination of the depth of a specific space in urban form analysis is independent of the actual distance required to reach it. Instead, the determination is based on the number of spaces one must traverse from the initial space. Consequently, the greater the depth of a space, the more difficult it is to reach that space.

The construction of graph representations of spaces can be achieved through the axial line analysis, a renowned method in this field. Axial lines, which are maximum line

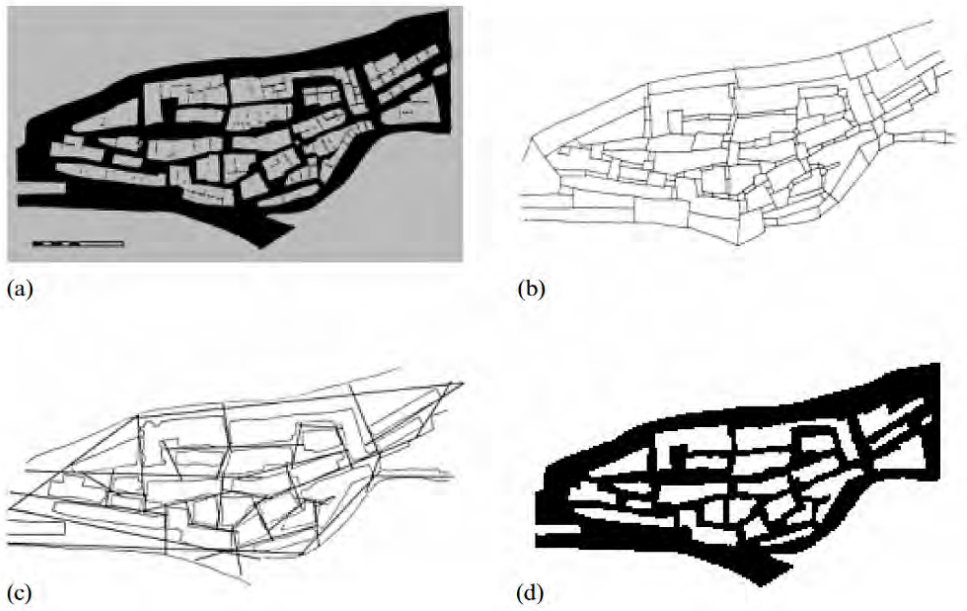


Figure 2.8: Example of process on generating axial maps. Image from [57].

segments based on one's sight across spaces, are treated as units that refer to spaces, while their intersections represent the connectivity of these units. In urban analysis, axial lines typically align with streets, and long and linear spaces are transformed into nodes, with their connectivity represented through edges [56, p.111–28].

The topological representation based on graphs is appropriate for analyzing spatial relationships distributed within a specific area. When the area is extensive, the relationships between spaces become more intricate, and this method of representation can consistently express the relationships among numerous spaces through patterns of their connections. By statistically processing the patterns, the urban space data represented topologically can be elaborated into quantified spatial characteristics, such as which spaces are activated and the types of spatial configurations they exhibit.

Over the past forty years, Space Syntax has developed into a distinct field within urban form studies, characterized by its rigorous application of scientific methodologies, ongoing advancement of analytical techniques, critical discourse, and practical implementation in urban planning. It has been applied across various scales, ranging from individual

properties to entire regions, to analyze morphological characteristics and propose urban simulations based on spatial performance [58, 59, 60, 61]. More recently, Space Syntax has integrated with considerations of environmental [62, 63], social [64], political [65], and economic [66] aspects of urban spaces.

Space Syntax is an endeavor to conceptualize the correlation between urban forms as a network, under the premise that certain principles defining the characteristics of a city are inherent in its forms. Notably, the network representation, which is primarily centered around streets, proves to be highly effective for understanding urban structures within a defined scope. Analyzing these networks allows researchers to identify areas with more intricately connected streets and assess the complexity of the urban form through indicators like the number of intersections and the length of streets. Additionally, when paired with urban socio-economic data, such as traffic patterns and crime rates, Space Syntax offers a multifaceted framework for interpreting the structure of a city. Consequently, this approach this has led to the development of an independent method for representing and analyzing urban forms, which has provided a basis for discerning and exploring the interplay among these forms.

Moreover, Space Syntax can also be considered an efficient analytical tool in terms of data complexity and compatibility. The methodology leverages one-dimensionally represented street networks data to understand the characteristics of a 3D urban space. This not only reduces the size of the dataset but also offers the advantage of lower complexity stemming from its low-dimensionality. Furthermore, the graph-based representation of street networks is efficient for consistently applying the methodology across multiple cities, enabling comparative analyses of urban structures. Given that streets are a universal feature of all cities, converting them into analyzable data points provides a universally applicable analytical methodology, which boasts high compatibility.

However, Space Syntax faces challenges in determining the urban structure arising from the spatial properties of specific urban forms rather than from streets. The graph data

used in Space Syntax does not inherently embed information such as the shapes of individual buildings, spatial relationships between them, or their arrangement at the city scale. This limitation makes it difficult to analyze aspects of urban space that are composed of building shapes, sizes, and lot occupancies. In other words, Space Syntax primarily adopts a perspective that views the city as an object, positing that the characteristics of that object are manifested through its street network, which is then analyzed using various data points. This suggests that Space Syntax serves as a macroscopic analytical tool focused more on the characteristics of the entire city rather than on individual spatial features. Therefore, although methodologically it appears to focus on relational representation through graph analysis, it still incorporates to some extent the geography convention of viewing the city as an object in terms of perception.

2.5 Urban Modeling in Urban Form Studies

Urban modeling is another distinct subfield in urban form studies. This subfield aims at the reconstruction of urban form and space in digital environments, associated with computer graphics, generative algorithms, digital modeling, simulation and virtual space. Early research on urban modeling focused on using generative algorithms for reconstructing urban forms, such as cellular automata [6], fractals [8], shape grammar [9], diffusions [67], among others. These algorithms relied mainly on geometric principles and rules to emulate the actual shape of the city. Examples of the use of generative algorithms in urban modeling include the examination of spatial rules in medieval London through man-machine interactions and their application in imitated development plans [7], the use of fractal-based systems to simulate street patterns under varying levels of field distortion or planning constraint [67] and the creation of a virtual city using the idea of shape grammars, L-systems, and procedural modeling [68].

The proliferation of GIS software and advances in computing hardware have facili-

tated the extension of GIS to 3D modelling of urban space. In recent years, GIS has been developed to accommodate the representation of 3D objects [69]. The digital globe map, such as Google Earth, now includes 3D urban forms such as buildings, streets, and terrains. It appears that GIS is moving towards the visualization of more sophisticated spatial information by integrating both virtual and projected representations with social data in urban analysis.

The distinguishing characteristics of GIS data, which allow for the differentiation of shape and properties, have facilitated the creation of precise 3D virtual city models, obtaining height data from remote sensing. Initially, the modeling process was limited to extracting building footprints from aerial photographs and creating extrusions based on height values. With advancements in remote sensing and data processing technologies, the modeling approach has shifted towards digital reconstruction of real cities [70]. Satellite-based Light Detection and Ranging (LIDAR) systems record detailed forms and materials of cities through numerous laser points, which are then converted into vector information to generate surface geometry in digital space. This digital reconstruction has opened up new avenues for socially and culturally significant urban concepts, such as smart cities, digital twins, and the metaverse.

Contemporary technology has given rise to advanced methods for modeling urban forms using high-resolution satellite imagery, photometry, and deep learning as well as LIDAR surveys [71, 72, 73]. The advancement of modeling urban forms has widened the scope and applications of urban form research, facilitating the comprehension of urban form as data and extending its application to various commercial [74, 75, 76], social [77], and administrative [78] domains. Moreover, this advancement has led to the development of platforms that systematically manage and share data based on joint efforts of the public sector, academia, and the government [79, 80].

Urban modeling, an early method of urban form analysis, was initially developed as a means of simulating the creation of a city. With the advent of various technologies, it has



Figure 2.9: 3D map scene of urban space in Open Street Map (OSM). Screen capture from OSM3D.

emerged as a crucial tool for handling urban forms as data. By conducting research on the generation, processing, and storage of urban forms, this field explicitly regards urban form as data, and as a result, it presently offers diverse data formats and platforms that serve as resources for urban form analysis in conjunction with GIS.

While diversely data-izing urban forms, the issue of the scope and purpose of data collection technologies is becoming more prominent. For instance, in the United States, major cities such as New York, Los Angeles, Boston, and Chicago possess detailed 3D urban models owing to their abundant resources. On the other hand, second-tier cities possess only basic urban maps due to lack of the necessary resources to create even basic 3D urban models for urban planning and research. Cities without a 3D urban model may experience accessibility imbalance, which could limit their ability to explore the intricacies of urban space and gain valuable insights [81]. This example illustrates that social discussions pertaining to data, such as data privacy and collection, are intimately connected to the field of urban modelling.

Urban modeling has played a pivotal role in advancing studies of urban form studies by offering platforms and technologies essential for digitizing a wide range of geometric

information within cities. Initially, urban modeling was employed as simulations to analyze various social, cultural, political, economic, and physical forms manifesting in urban environments. Presently, it is intimately associated with GIS and remote sensing technologies. These integrations are foundational in constructing and restoring urban form data, which, in turn, are being applied to concepts such as smart cities and digital twins, marking a divergence into new areas of study.

2.6 Computational Urban Morphology

In the study of urban form, there is an emerging field that is intertwined with computation spanning from the introduction of computers and the development of GIS to data science. This field distinguishes itself through its methods and purposes, particularly in the analysis and recognition of spatial or form, from other excursions of urban form study such as Space Syntax and urban modeling. This field engages in inquiries into the manifold interrelations between geometrical characteristics and spatial, social, historical and environmental attributes of a city by focusing on quantification of urban form in data. Therefore, I would recognize this field as *computational urban morphology* which encompasses urban form study utilizing various computational techniques, ranging from simple statistics and advanced algorithms to data science.

In the late 1980s, urban morphology began to incorporate quantified urban forms with the influx of data science. Statistical approaches for quantifying urban forms aim to analyze the morphological trends in a vast urban area. Even up to this period, urban morphology maintained a close relationship with geography which also leveraged data science and computation. This development is underscored by the shared reliance on GIS, grounded in cartographic conventions. Notably, Alan M. Maceachern, a geography scholar from the United States, defined geographic shapes in terms of polygons that represent a specific perimeter for generating shape data and conducting statistical investigations into their compactness

[40]. He evaluated different ways to measure geographic shape compactness, relevant to urban morphology and political districting. It sorted these methods into categories focused on perimeter and area, circle-related parameters, comparison to standard shapes, and dispersion within shapes. After testing these indices on U.S. counties, he found intra-category similarities but inter-category differences. It concluded that the most accurate measures of compactness considered the dispersion of elements within the shape, while methods based on comparison to a standard form were also reliable. In contrast, methods focusing on perimeter and area were less accurate.

Urban form studies that utilize statistics, computation, and data science often encounter controversy surrounding the formulated morphological index. For example, Batty and Longley—both British academics in the field of urban geography and planning, made significant contributions to the field of spatial data analysis—examined the relationship between land usage and the shape of land perimeters in a small English town [41]. They defined the irregularity of land parcels and land use by digitizing perimeters and areas. The irregularity was measured by the concept of fractal dimension. Then, Batty and Longley tested three regression approaches, which were found to be inadequate in gauging the range of irregularity over the set of land uses. Methodologically, their study presented a certain consistency in assessing irregularity across different land uses by statistically processing digitized land shapes and their attributes.

This study highlights the importance of carefully defining and formulating morphological indices for computational analysis of urban forms. The study did not use the concept of 'irregularity' to inhibit diversity or to serve any discriminatory purpose. Rather, it seems the study interpreted 'regularities' as a metric for 'shape complexity,' specifically denoting the degree to which the shape changes or remains constant. However, the way in which 'regularity' is defined and measured could inadvertently lead to a preference for urban forms that are homogeneous, or that conform to a particular standard, over those that are diverse or irregular. Such biases could impact the lives of citizens and may be inadver-

tently supported by computational and statistical methods. For example, while Batty and Longley's efforts were unsuccessful in definitively linking higher irregularity in residential urban forms than in commercial, industrial, educational, or transport forms, had they been successful, their findings could have been used to justify problematic claims—such as advocating for making educational spaces similar to residential ones by increasing their 'irregularity.' In this regard, this study provides a cautionary note on the need for meticulous consideration in the employment of statistical and computational analyses within the realm of urban form studies.

Further, computational and data scientific methodologies have been integrated to explore the premise that urban forms are entities influenced by social factors. For instance, [82] employed a sophisticated statistical framework to scrutinize the role of urban form in shaping the spatial characteristics of cities. Focusing on El Paso, Texas, the research illuminated how this city's spatial peculiarities distinguish it from neighboring cities in both the United States and Mexico, particularly as it has developed as a conurbation between the two nations. The study conducted a clustering analysis that integrated urban form data with demographic and census variables, such as educational attainment and economic activity, for El Paso and its adjacent cities. By identifying a unique clustering distribution within El Paso, the author sought to characterize its urban form as a complex conurbation, shaped over extensive time periods by diverse social, physical, cultural, economic, and political influences from multiple countries.

The utilization of statistical approaches has extended beyond the examination of morphological transformations on a city-wide scale and has also been employed in the study of micro-scale morphological changes. Whitehand and his colleagues, British geographers who focus on interpreting urban form and city development over time, conducted a study examining changes to houses and gardens in interwar residential areas of Birmingham and London developed by private enterprise [42]. They distinguished between larger-scale changes subject to development control and smaller-scale changes initiated

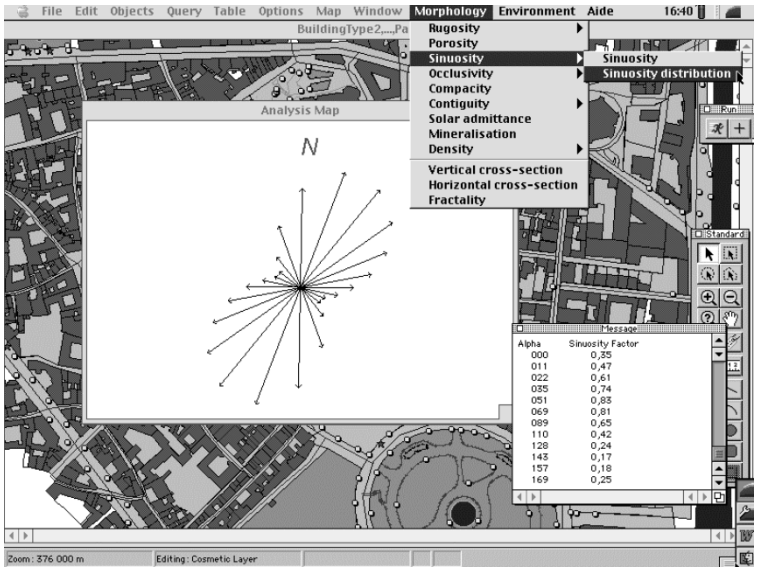


Figure 2.10: Adolphe's simplified representation of urban forms based on geometrical and non-geometrical indices. Image from [43].

by households without permission, such as changes to chimneys, roofs, doors, and windows. The study found that changes subject to development control were negatively correlated with the dwelling density at which the sample areas were originally developed, while smaller-scale changes were positively correlated, possibly due to the greater susceptibility of higher-density areas to the contagious diffusion of minor and cosmetic changes. This study demonstrated the feasibility of employing statistical analysis on digitized geographical information as data, even within the framework of Conzenian urban morphology, which primarily examines regional urban forms.

A data scientific approach to urban morphology has advanced to include statistical analysis of the characteristics of various urban forms and their relationship with spatial features. An exemplary illustration of this advancement is evident in the research of Adolphe, a French scholar in architecture study. He presented a system that extracts urban fabric geometries from geographical information of multiple cities and quantifies geometric indicators of environmental performance, including density, rugosity, porosity, sinuosity, occlusivity, compactness, contiguity, and so on [43]. Adolphe envisaged that the system would facilitate simplified analysis of outdoor microclimate tendencies, sustained environ-

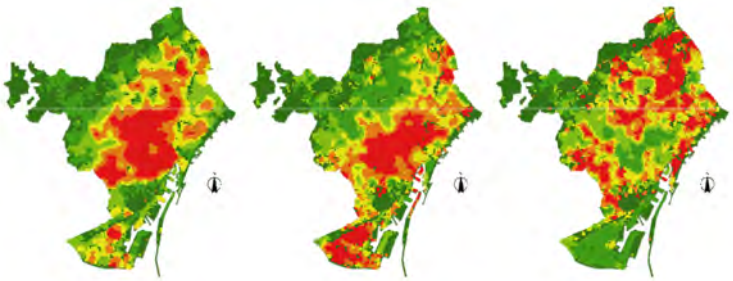


Figure 2.11: Visualization of urban form indices-density, efficiency, and complexity-in Barcelona. Image from [83].

mental evaluation of a neighborhood, inter-district or inter-city comparisons, or modelling of the climate effect on future urban amenities.

In the late 2010s, researchers began to move beyond using the available form data in its raw state. Instead, attempts were made to manipulate and reconfigure this data to align more closely with specific research objectives [84, 85, 83]. Researchers created distinctive form data through the extraction and refinement of intended form information from GIS database. Next, they measured elementary statistical features such as length, area, and density from the data and applied various statistical models to analyze the data. Consequently, the characteristics of cities were exposed and interpreted as their spatial, historical, and social meanings.

The utilization of computation has extended the conventional approaches to urban form analysis, enriching them through larger amounts of study subjects and higher complexity of information. Further, the utilization contributed to the emergence of unique research domains. I have categorized these domains into three fields based on the purpose of the study, the way computation is employed, and the perspectives dealing with the urban form: Space Syntax, urban modeling, and computational urban morphology.

Notably, computational urban morphology, unlike the other two fields, originated from an attempt to view urban form as data and statistically analyze it. This field has emerged from a multidisciplinary nexus that encompasses biology, geography, cartography, urban-

ism, architecture, computer science, and data science. Over the past four decades, it has cultivated its unique methodology, significantly shaped by the transformative impact of data science technology on research methodologies.

As the research on examining, clustering, and classifying urban forms with data-scientific methods increases, urban forms are transforming into subjects of data science. Consequently, curating the information used to construct an urban form dataset has become just as important as selecting which form traits to analyze using pre-defined features in the past deductive method. Additionally, selecting the appropriate statistical model for such a nuanced dataset has a significant impact on the direction of analysis.

The development of data collection, curation, and processing technology has been leading innovative approaches to urban morphology. Equally important is the perspective of dealing with the urban form as the subject of data and how we perceive the city through it. Therefore, reviewing preceding research in computational urban morphology, the next chapter will demonstrate the examination of how geography and cartography conventions remain in the construction and analysis of urban form datasets and how this convention forms a recognition of a city in the datasets.

CHAPTER 3
BACKGROUND II: REVIEW OF PRECEDENTS IN COMPUTATIONAL URBAN MORPHOLOGY

In the preceding chapter, the concept of computational urban morphology was delineated as a discipline within urban form analysis that seeks to unravel relationships between geometric attributes and the spatial, social, and environmental dimensions of a city by quantifying its urban form. The development of computational urban morphology has been intertwined with advancements in computation, leading to the employment of a diverse range of computational techniques. These techniques span from basic statistics to advanced algorithms and data science approaches, all of which have been utilized in this field.

In this chapter, I propose criteria for research to be regarded as precedents of computational urban morphology. Then, I examine the methodological trends in computational urban morphology through various approaches to handling urban form data by establishing a collection of these precedents. From this examination, I address and analyze the current gaps in the recognition and handling of urban forms as data.

3.1 Recent Precedents Computational Urban Morphology

Within the field of computational urban morphology, the primary emphasis remains on analyzing urban form. However, given the field's inclination towards quantifying urban forms and conducting statistical analyses akin to methodologies employed in data science, research in this field necessitates adherence to three critical criteria: measuring, digit-izing, and statistical processing.

Measuring urban form entails not only quantifying its geometric features, including area, density, height, and the like, but also representing its correlation with other forms or

urban factors, such as urban noise and shade. The selection of which urban form features to measure reflects a particular perception of how urban form represents urban space, making it crucial to carefully choose these features in computational urban morphology.

Data-izing the urban form involves the creation of morphological indices suitable for the research's aims by constructing datasets from the measured features and applying these indices to each urban form. These indices may include widely used metrics rooted in geometrical attributes, such as compactness, occupancy, and centrality, as well as researcher-specific indicators such as potential development, accessibility, and development changes. These indices can be defined in various units such as buildings, blocks, neighborhoods, municipalities, and countries. In this way, the indices constitute urban form data in the format of a 1D vector or 2D image or object.

Statistical processing of urban form entails deriving statistically significant results from the urban form data constructed during the data-izing phase. At this phase, "basic statistical operations" such as mean, sum, and variance can be applied, as well as machine learning algorithms such as clustering, classification, and segmentation. The purpose of statistical processing is to investigate the characteristics of the urban form data and extract typo-morphological knowledge from the data.

In accordance with these three criteria, 47 studies that are regarded as precedents of computational urban morphology were selected, as illustrated in Table B.1. Research on urban morphology utilizing computers has been present since the late 1980s, however, studies that encompass all three criteria outlined above only emerged in the 2000s. The primary sources of these precedents are conferences and journals in the fields of urban planning, city science, and urban morphology, including Environmental and Planning B, Landscape and Urban Planning, and the International Seminar on Urban Form. Another main source is Computer-Aided Architectural Design (CAAD) research in the CAAD Futures society, including proceedings from Education and research in Computer Aided Architectural Design in Europe (eCAADe), the Association for Computer-Aided Architectural Design

Research in Asia (CAADRIA), and the Association for Computer-Aided Design In Architecture (ACADIA). Additionally, publications in various fields, such as remote sensing, GIS, and geo-computation, were also reviewed.

The search for precedents was conducted across publications in various fields, but it is important to note that it may not be a comprehensive search in terms of quantity. It is possible that early instances of computational urban morphology exist in non-digitized or undiscovered publication sources. For example, a software named DISCOURSE in William Lyman Porter's 1969 doctoral dissertation can be seen as an early example of computational urban morphology [86]. DISCOURSE employed a matrix to analyze the urban form by expressing it through letters based on the nature of the shape. Boolean and arithmetic operations were then applied to analyze the characteristics of the form. This software can be considered a precedent of computational urban morphology as it was able to quantify urban shapes, define indices expressed through letters, and process them. Nevertheless, there is some disagreement over whether Boolean and arithmetic operations can indeed be considered as statistical processing. Hence, it is also open to discussion whether this research should be merely classified as an early instance of computational geography or GIS. In order to address these limitations, it is necessary to conduct comprehensive historical research and engage in discussions concerning the precedents of computational urban morphology, encompassing the history of software development, computer-aided geography, and the GIS history.

Despite the potential limitations in terms of quantity and comprehensiveness of these precedents, the primary objective of reviewing them is to examine the ways in which urban forms have been treated and processed as data, and how cities and urban spaces have been perceived throughout this process. This allows for an assessment of the limitations of current methodologies, alternative data collection and processing methods, and ultimately, the potential ways to gain new insights into the understanding of cities.

To analyze these precedents, I have established seven attributes for each precedent

study: Form Unit, Data Dim, Data Format, Features, Index, Analysis Model, and Analysis Type. The Form Unit refers to the smallest unit of urban form used in the study, which can be classified at the level of region, municipality, city, grid, block, building, country, or plot. Data Dim refers to the dimensionality of the primary data used in the study, categorizing whether it is 1D, 2D, or 3D. Data Format refers to what type of the data has been processed, closely related to its dimensionality, where a single data point in 1D data is represented as a vector—a numerical representation of organized features. In 2D, data is primarily represented as images which are composed of pixels arranged in a grid-like array, such as satellite imagery and scanned maps. Sometimes 2D data is represented as objects which directly conveys the geometric properties of urban forms, such as polygons or surfaces. The object format is also utilized in 3D data, including meshes or voxels, and may involve unique data objects created by attaching height information to shapes.

The Features attribute pertains to the variables used to create morphology indices, including density, area, adjacency, and perimeter. The Index reveals which morphology indices were constructed, generating new indices from features such as urban centrality, urban entropy, compactness, accessibility, or using features themselves as indices like density. The Analysis Model shows the statistical method used to analyze the form, where Basic Statistics means analyzing urban form data using simple statistics like mean, variance, and extremes. Research using deep learning implies the use of deep neural networks (DNN), where features are extracted from data without specifically selected features. Machine learning refers to studies employing models other than DNN, such as self-organizing maps, Markov models, and regression, which unlike deep learning, involves researcher-selected features. Criteria Mapping involves analyzing the distribution and overlap of indices or features through mapping.

Analysis Type is divided into two categories based on whether a morphology index is constructed: Formularized and Extracted. If features are selected and used to construct a morphology index, it is classified as Formularized. If features are extracted from the

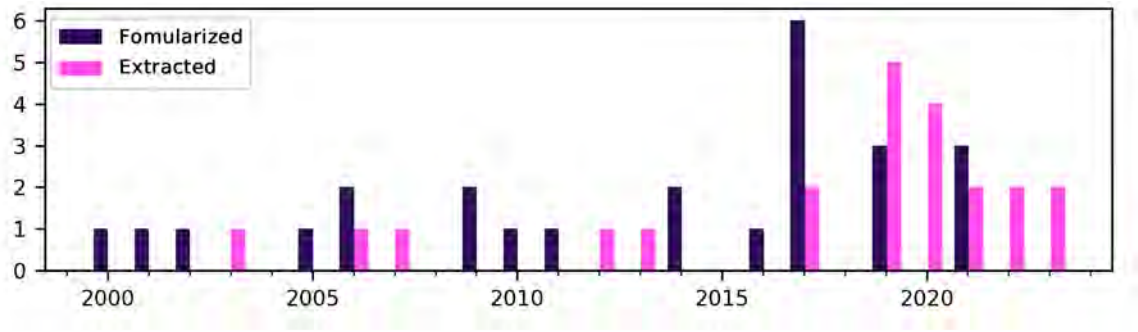


Figure 3.1: Changes of analysis type in computational urban morphology

analysis model using DNN or analyzed without constructing a morphology index, even if the features are selected, it is classified as Extracted.

3.2 Methodological Trend

3.2.1 Increasing Use in Machine Learning for Direct Morphological Feature Extraction

Upon sorting the research methodologies of the precedents chronologically, a noticeable trend becomes evident, highlighting a growing prevalence of methods based on the Extracted analysis type—methods that can directly extract the morphological features using a statistical model. In Figure 3.1, prior to 2017, computational urban morphology was methodologically centered on measuring geometrical features from urban form data, analyzing their relationships based on empirical observations, and formularizing a limited number of form indices representing the relationships. For example, urban space analyst Jorge Gil and his colleague developed a method to analyze various types of urban blocks and streets using a clustering algorithm in machine learning [87]. They created two datasets that extracted 17 and 13 morphological features, including length, width, orientation, perimeter, and connectivity, for urban blocks and streets, respectively. This approach represented each urban block as a 17-dimensional vector and each street as a 13-dimensional vector. By clustering these features using machine learning algorithm, the researchers were able to investigate and visualize different types of blocks and streets. In a

case study, the research presented examples of typo-morphological patterns that described the various types of block and street segments at a district scale.

In [44], an extensive array of urban compactness indices was employed to investigate social sustainability outcomes in twenty-five English towns and cities, encompassing measures of area, field, envelope, radius, and uses of the urban form. The paper presents and examines the values of these indices for various English towns and cities, with the aim of contributing methodological tools to the compact city debate and providing a model for further research, which is essential in this field.

Another exemplary research of formularized indices-based method can be seen in [83]. The authors developed a methodology for identifying and automatically classifying morphologically homogeneous categories and determining the level of compactness of urban texture. The researchers assumed that different urban functions require different forms and focused on measuring various geometric features such as building area, core area, proximity, convex area, and perimeter length, in order to construct form indices for compactness, density, and complexity. These indices are allocated to the grid that divides the city space in a top-down view. They then calibrated a set of indices capable of describing specific formal and functional characteristics, using GIS and statistical analyses to categorize several homogeneous urban structures.

In a recent publication by [88], indices-based methods were employed to perform morphological classification of urban blocks based on compactness and fragmentation of boundary shape. This was carried out using a sample of Adriatic and Ionian coastal cities, considering three historical stages in the 19th century, World War II, and the present day. Geometric features were measured and used to construct indices, including relative distance (RD) and directional fragmentation (DF), leading to a proposed taxonomy based on these indices. Through this taxonomy, the authors discovered universal features of shape compactness and fragmentation in cities that are often associated with smaller blocks, while also observing different patterns of block shape evolution within the sample, amplified by

the configuration of larger blocks.

The methodology of indices-based computational urban morphology has progressed to more sophisticated and complex statistical models beyond the simple statistical models of means and variations. An example can be seen in [89]. The authors of Li and Quan's study proposed a method to identify different types of urban forms based on density, with a case study of Seoul. They divided the Seoul city area into a grid with a cell size of 500 meters, resulting in a total of 2,530 grid cells. They measured eleven diverse geometric features of urban forms in the grid cells, such as building area, height, street length, width, the number of street intersections, plot sizes, and the number of plots. As a result, their urban form dataset was represented as a 2D matrix with a shape of $(2{,}530 \times 11)$. They employed a machine learning model, Gaussian Mixture Model (GMM), to cluster the dataset and found nine different urban form types illustrating varying densities of urban spaces, such as gridded low-rise, apartment complexes, vernacular low-rise, compact low-rise, mixed low-rise, mixed sparsely built, undeveloped, mixed apartment, and sparsely built. By visualizing the map of Seoul with this classification, they were able to illustrate the overall spatial structure of urban spaces in Seoul.

Since approximately 2015, several recent studies in computational urban morphology have started to explore the direct extraction of numerous morphological features and their interrelations from extensive datasets through advanced statistical modeling, diverging from the construction of indices. My master's thesis [90] can be seen as an example of this exploration. In this study, alternative research methods were explored that directly fed custom-generated urban form data to a statistical model adept at feature extraction, rather than selecting specific features and constructing morphological indices. Instead of manually selecting features, I devised a custom scheme of the dataset to include building footprints with their neighboring urban components such as streets, terrains, and lots. The scheme was based on the idea that this specific data framing could include both geometrical features of urban forms and other implicit geometric relationships between urban forms. By

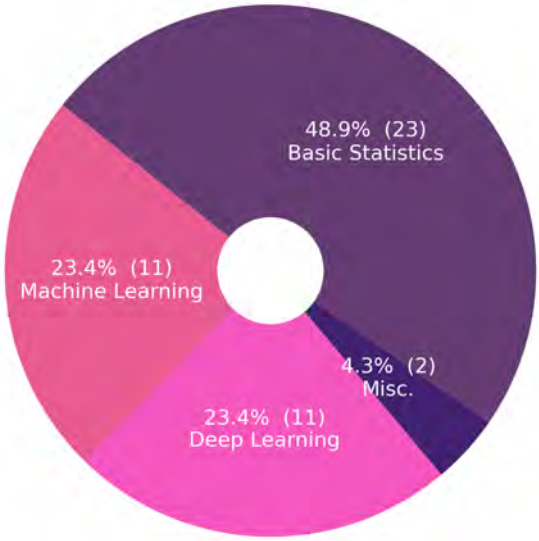


Figure 3.2: Rate of analysis methods in processing features

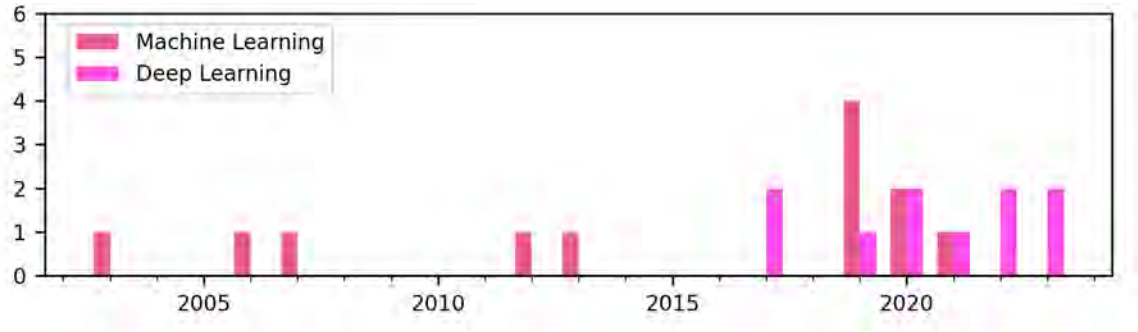


Figure 3.3: Changes of analysis methods that can directly extract the morphological features using a statistical model

subjecting the dataset to analysis using a statistical model, T-distributed Stochastic Neighbor Embedding (t-SNE), I was able to extract and cluster morphology features and identify different types of urban forms.

Further, computational urban morphology has incorporated deep learning as a method to extract numerous form features from data and reveal patterns of the features (Figure 3.2 and Figure 3.3). Deep learning is a machine learning technique that utilizes artificial neural networks to identify trends and patterns based on latent relationships within complex datasets. The majority of machine learning models depend on pre-defined and pre-set features before creating datasets that align with the intended analysis. However, deep learning



Figure 3.4: Urban form data generation combining satellite imagery and customized schemed map images for deep learning. Image from [91].

models necessitate the inclusion of required features into datasets. Deep learning models can extract features from data and identify concealed relationships between these features, whereas machine learning data is constructed by extracting features.

When deep learning is employed in the analysis of urban form data, it omits the steps for measuring, indexing, and feature selection. Instead of manually selecting features and creating indices, researchers frame urban form information pertaining to morphology as data, creating large urban form datasets. Deep learning algorithms are then used to extract numerous and complex features from these datasets, uncover morphological patterns, and derive morphology knowledge.

With this feature extraction functionality of deep learning, research on urban analysis has been increasingly adopting deep learning techniques since 2017 [92]. Specifically, this adoption unlocked a view to urban forms as data entities that have a variety of influences with urban phenomena, constituting the entire urban spaces. Alber and his colleagues developed and utilized a deep learning model with grid units to identify urban forms represented in segmented satellite imagery data and to determine programs such as urban fabrics by different density, forests, water bodies, greens, airports, and leisure facilities in six distinct urban spaces [93]. For another example, Li and Wenbo have introduced an application of deep learning for the morphological analysis of university campuses. This method compresses diagrammatic images of campuses and their urban contexts into integrated feature

vectors (Figure 3.4), facilitating clustering and quantitative analysis of campus morphology [91].

A further example of feature extraction and analysis through deep learning models can be found in the work of [94]. This study delves into the investigation of the relationship between airports and their surrounding urban form to categorize typological relationships within a specific range. The authors framed satellite images as data points with the airport at the center and the surrounding urban spaces included. By segmenting the urban area, greens, and oceans, two datasets were generated: a satellite image dataset and a corresponding labeled masks dataset. A deep neural network model was trained to capture the relationships between these two datasets, enabling the prediction of segmented data for new, unseen satellite images. Through analysis of the predicted segmentation, the authors suggest four different morphological statuses of the airport based on the condition of its surrounding urban spaces: leave, remove, build, and monitor.

Furthermore, while enhancing traditional methods to analyze urban morphology in relation to social phenomena, emerging studies incorporate deep learning to investigate how social factors change in response to variations in urban form [95, 96, 97]. Moreover, by applying deep learning models to street-level perspectives data, relevant features can be extracted and subsequently used to classify urban spaces [98]. This study can be regarded as a quantitatively extended study on Lynch's examination of urban forms as a landscape. Particularly noteworthy is the recent use of deep learning image segmentation techniques to analyze the form and utilization of urban spaces [99], which can be considered as a novel attempt to integrate Whyte's observation-based urban form analysis with data science and computer vision technology.

The adoption of deep learning has enhanced the potential to process data-ized forms for a more nuanced and intricate understanding of the morphology of urban spaces, highlighting two critical aspects of form data: data intensiveness and data curation. Deep learning is a highly data-intensive approach that requires a substantial amount of form data to

capture and infer morphological and spatial relationships. Consequently, there is a growing emphasis on the creation, management, and acquisition of urban form information. In addition, the coordination of various information in data, known as data curation, will also become a critical aspect. The outcomes of deep learning-based morphological analysis are subject to variation depending on the structuring of information in urban form data. Thus, when curating data, careful and deliberate decisions must be made regarding what information is necessary, how different types of information are organized, how the data as a whole can convey the analysis's purpose, and other related inquiries.

3.2.2 Increasing Use of 2D Data and Limited Use of 3D Data

The trends that Extracted feature-based methods appear to be associated with changes in data formats. The primary format for urban form data has been vector-based. However, there has been a noticeable increase in the utilization of image format data, particularly around 2017, coinciding with the rise of deep learning research (Figure 3.5). While the use of vector format data has decreased, the adoption of image format data has been sustained at a certain level. This suggests that the expansion and persistence of image data usage can be correlated to research employing deep learning techniques.

One notable aspect regarding the data type and dimension is the relatively limited utilization of 3D data in computational urban morphology. In contrast to the prevalence of 1D or 2D data processing, the use of 3D data is noticeably less frequent (Figure 3.6). This disparity sets computational urban morphology apart from other fields that have embraced inductive analysis, despite considering recent trends in deep learning and the growing adoption of 3D data in computer-aided architectural design and other fields [92].

Recently, researchers have employed a volumetric representation known as a point to depict forms by employing a discrete collection of data points in 3D space. Each point is associated with its own set of Cartesian coordinates (X, Y, Z), thereby representing a 3D shape or object. Point clouds are a prominent data format within the realm of DNN utilized

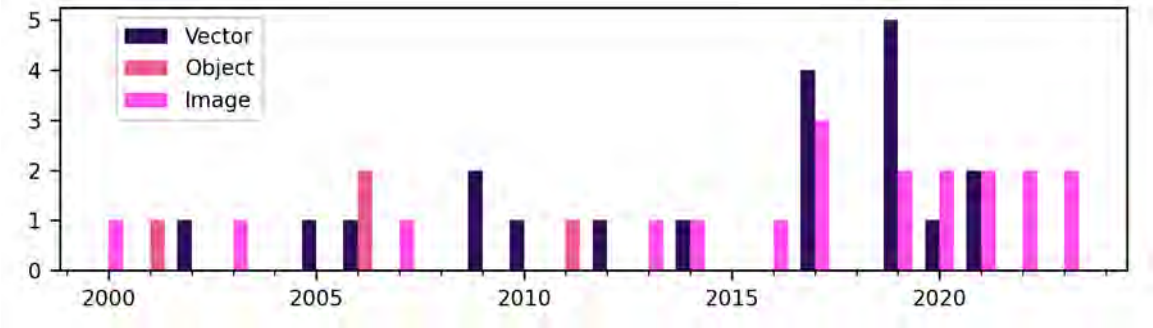


Figure 3.5: Changes of data type in computational urban morphology

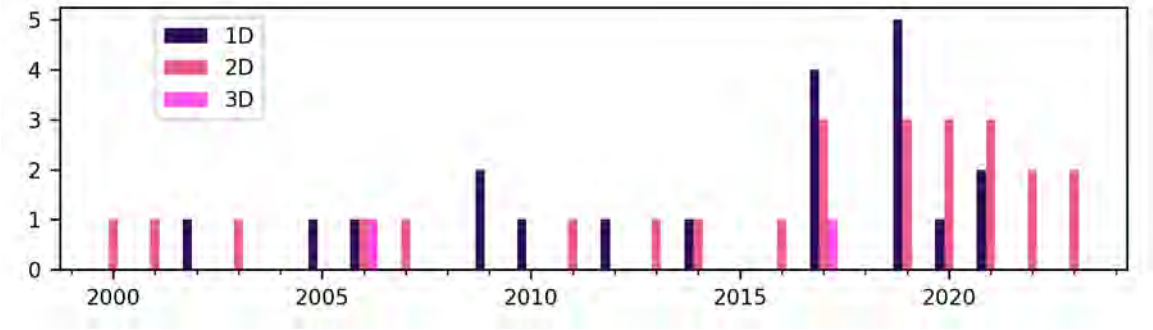


Figure 3.6: Changes of data dimensions used in computational urban morphology

in computer vision research [100, 101, 102]. Further, deep learning techniques for analyzing and generating 3D form data with inductive methods are being developed and widely spread. For example, [100] describes a deep neural network to classify and segment point cloud representation of 3D objects (referred to as a form); [103] demonstrates how a new point cloud can be generated by trained implicit rules derived from the point cloud data; [104] captures morphology features and generated mesh representation of forms using a deep neural network. In design research, point clouds have found application in generating and synthesizing new everyday objects through DNN [105].

Another prominent category of 3D data is voxel grids, commonly referred to as voxels, which serves as a widely recognized volumetric representation technique for capturing forms [106]. Voxels are binary-valued arrays on a regular 3D grid. A voxel has value 1 when it is occupied by the form, and 0 otherwise. Deep neural networks in computer vision research have been employed to capture form features from voxel data [107]. Moreover,

efficiency of the neural networks can be increased by replacing the voxel representation from binary to continuous numbers [108, 109].

The domain in which voxel data has been prominently used is within neuroimaging in medical science. In the context of diagnosing and predicting diseases based on the structural and morphological characteristics of the brain, voxel data derived from MRI (Magnetic Resonance Image) scans of the brain shape is employed to train deep learning models. The trained models can reveal relationships between brain form changes and aging [110], accelerated measurements of brain parts [111], and improved diagnosis of Alzheimer's disease [112].

In the realm of design, there are active endeavors to train deep learning models on voxel-based representations of objects, aiming to generate novel forms or unveil latent meanings of the existing forms. [113] demonstrated a method to synthesize a new form of spire using a deep learning model which is trained by voxelized architectural form data. By adjusting the feature parameters in the model, their model can change the voxelized form according to designer's intention. The study conducted by [114] offers an insightful analysis that expands our comprehension of architectural heritage by employing voxelized architectural form data and deep learning technology. The authors introduce a taxonomy framework that constructs form data utilizing images of Eastern European church architecture, renowned for its distinctive style. This data is subsequently employed to train a deep learning model for the purpose of classifying the church architecture based on its morphological characteristics. Furthermore, the geographical distribution of each church has shed light on the regional prevalence of specific church types.

Technical progress on 3D form data for deep learning [109] along with diverse application of this technology indicate an increasingly improved capability to construct and analyze 3D urban form data and open up the potential for new approaches to urban form analysis. It is instructive to note that height information in 3D urban form data is normally an attribute. When it is embedded in the form data, it is possible to analyze 3D config-

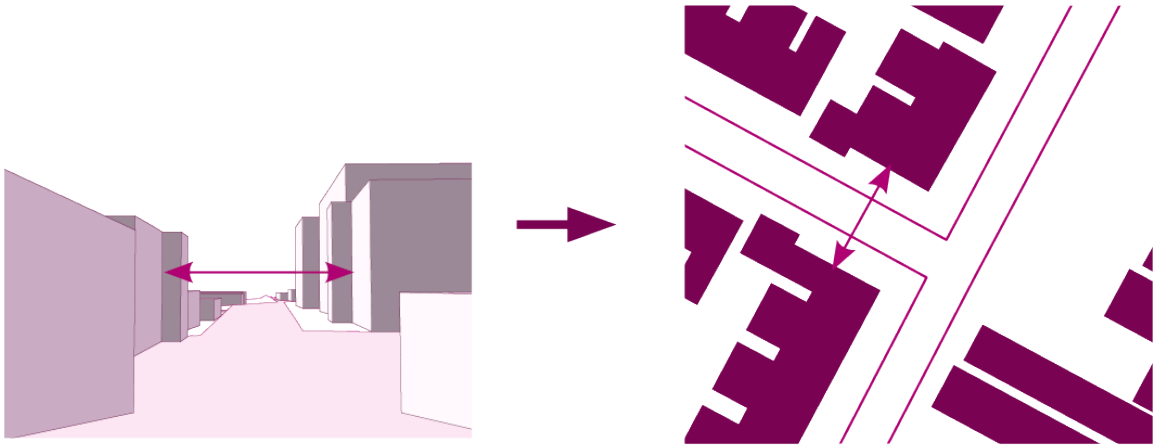


Figure 3.7: Representational difference of urban space through urban form in 3D and 2D data

urational traits of urban spaces—spatial characteristics and relationships that account for height considerations. The conversion of 3D spatial information to a 2D format not only reduces the data dimension but also results in the loss of spatial information derived from urban components such as in-betweenness of buildings (Figure 3.7). Within 2D data, this reduction is manifested as a mere representation of planar vacancies and occupancies. Such a representation may prove inadequate for statistical models designed to extract features from data with a higher degree of complexity in form data.

3.2.3 Segmentation of Urban Form in Data-ization

Segmenting urban form is another notable trait of urban form data in existing computational urban morphology. Urban form data is typically constructed by geometrically segmenting an entire city into numerous parts. For instance, to analyze the compactness of the Barcelona city structure, a regular grid was used to segment the building footprint of the entire city [83]. Block shapes were used to examine the geometrical features of urban forms in historic cities with their own categorized block types. Plot shape has also been used as a unit of the urban form [115]. Subdividing the urban forms into parts using geometrically specified cells—that is, geometrical segmentation—can be efficient when analyzing the

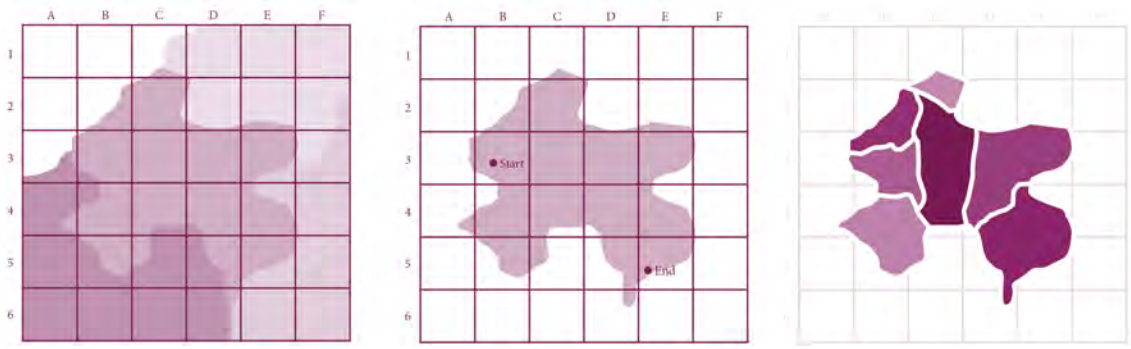


Figure 3.8: Segmenting city boundary shape using a grid

characteristics of an entire structure, assuming each urban form is essentially a composite with boundary and its own appearance.

Geometrical segmentation is predicated on the recognition of the city as an object with a boundary (Figure 3.8), which are segmented into pieces by some sort of geometrical guidance, albeit, a grid structure, cells, parcels, urban blocks, neighborhood boundaries, historical subdivisions, zoning borders, etc. This recognition is based on the hypothesis that the overall characteristics of city space are identified through the analysis of the pieces.

The practice of geometrical segmentation can be viewed as another manifestation of cartographic conventions. In cartography, cities are often represented by coordinates within a grid system. For example, the diagram depicted in the middle of Figure 3.8 demonstrates a coordinate system employed to pinpoint specific locations on a map. The designated starting and ending points are denoted as (B,3) and (E,4) respectively. This discretized spatial framework facilitated by the grid simplifies location identification. Furthermore, segmenting space with unitized geometry, which serves as a jig, facilitates a rapid and intuitive evaluation of the size and scale of the space.

Another method of geometrical segmentation involves utilizing boundaries. These boundaries, such as block or neighborhood boundaries, do not physically exist but represent an invisible geometry that has interconnected politically, socio-culturally, demographically, and historically existed. This approach of segmenting space using boundaries is commonly employed in cartography. Maps typically portray space as a geometric entity with distinct

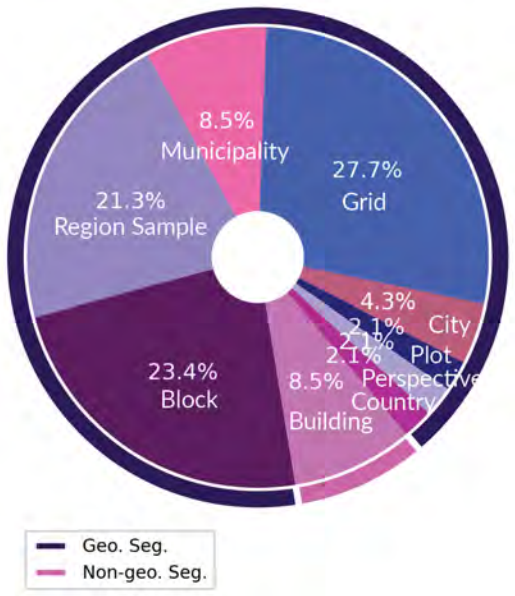


Figure 3.9: Proportion by data unit

color schemes delineating municipal or neighborhood boundaries.

The prevalence of geometrical segmentation becomes evident when examining the unit type of urban form data in the precedents (Figure 3.9). The units can be categorized as follows: ‘grid’ utilizing rectangular cells of a specified size, ‘regional sampling’ that selects a particular area, ‘country’ based on national land perimeter, ‘city’ based on city border, ‘municipality’ based on district or neighborhood boundaries, ‘plot’ based on individual land divisions, ‘block’ defined by street intersections, and ‘building’ represented by their footprints. Among these, the most frequently employed units are grid and block. All these unit types can be regarded as geometrical segmentation except for ’buildings’ which do not inherently segment urban space in data. Notably, more than 90% of the studies utilize geometrical segmentation in their data constructions.

Considering the common methodological steps and frameworks among research using segmentation, the construction of urban form data through geometrical segmentation is intricately related to the development of morphology indices based on measurement. Segmenting a city, perceived as an object with boundaries, into parts within a unit enables the establishment of a consistent data format. Various morphology features, including area,

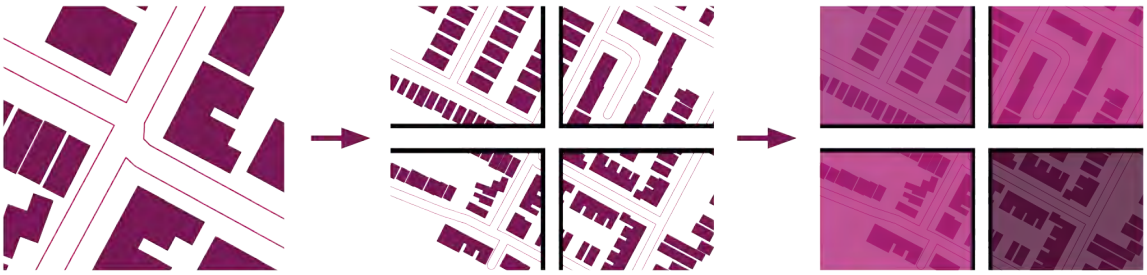


Figure 3.10: The process of segmenting urban form using grid from cartography convention

length, and angle, can be quantitatively measured from the segmented urban form within the unit, facilitating the creation of indices. By statistically comparing and contrasting these indices values derived from the segmented urban form, the overall morphological pattern of the entire city can be drawn. In other words, such indices-based methods that depend on measurement-based morphology features inherently require the use of geometrical segmentation.

However, this top-down geometrical approach may obscure other spatial characteristics. Instead of segmentation reflecting how urban spaces are configured, the use of some sort of geometry jig to subdivide the entire urban form might lead to inconsistent and fragmented representation of urban space in the urban form data. For instance, when an urban form on the border between segmented units falls into several dissected pieces, this will hamper the processing of its initial morphology features. Depending on how the borders of the units are set, morphologically crucial information is either fragmented and hence, scarcely captured, or it is centered on the unit as key features (Figure 3.10).

Regardless of whether grid-based segmentation is more global or boundary-based segmentation is more local, both methods can be interpreted as approaches to segmenting a city as an object. Maps, primarily aimed at storing and communicating spatial information, have relied on such functional segmentation to aid in map creation and utilization. Nonetheless, in the domain of urban morphology, particularly in computational urban morphology which treats urban forms as data, a methodology that more effectively captures form characteristics is necessary, beyond functional segmentation. Essentially, the unit of

the segmentation should be related to the urban spaces—that is, spatial segmentation which changes the viewpoint from an entire city as an object to individual spatial entities in the city.

In this chapter, I presented three critical criteria that computational urban morphology should encompass: measuring urban form, digitizing urban form, and statistically processing urban form. I then selected 47 precedent studies that fulfill these criteria and analyzed their methodological trends. Here is a recap:

- Over the past decade, there has been a notable increase in the use of methods that directly extract morphological features from urban form data without formularizing morphology indices, particularly through machine or deep learning models.
- Over the past decade, there has been a notable increase in the use of 2D image data formats for urban form data, while the use of 3D data remains limited. The reliance on 2D images can lead to information distortion as they cannot fully represent the characteristics of 3D spaces.
- Most precedent studies construct data units by segmenting urban form using geometries such as grids, blocks, and region boundaries as jigs. However, this approach can cause distortion in the information conveyed by the urban form.

In the following chapter, I explore the possibilities observed from these methodological trends and propose new ways of perceiving the city to overcome these limitations and associated changes.

CHAPTER 4

HYPOTHESIS

4.1 City as Aggregation of Neighboring Urban Spaces

Considering the aforementioned relationship between geometrical segmentation and urban form analysis methods in the previous chapter, it is possible to conceive an alternative approach to representing urban form in data based on the characteristics of statistical models adept at feature extraction. The inherent advantage of these models lies in their direct extraction of morphology features from urban form data. This eliminates the need for formulaic or principle-based morphology indices derived through measuring, which have been the core of morphological indices-based methods. By circumventing the construction of morphology indices, the segmentation process for measuring urban form becomes unnecessary.

Before delving into the methodology of the alternative approach, it is crucial to revisit the fundamental question of what urban form data ought to encapsulate; urban form data should encompass not just flat and fragmented geometrical information, but rather an abundance of urban spatial information. An urban space can establish distinct spatial relationships with different buildings. For instance, a building whose main entrance faces south and is adjacent to a plaza may utilize this plaza as its external lobby space. Conversely, for a building that also has a south-facing entrance but is oriented such that its northern façade overlooks the same plaza, this plaza may serve a role akin to a backyard. These multifaceted relationships apply among various urban elements, including between buildings, lands, and streets. When data-izing urban spatial information, it is more effective to represent a specific urban element and its surroundings together, thereby incorporating the multiple relationships of urban spaces.

In this vein, I propose to analyze urban space using a novel data representation that incorporates the neighboring spaces surrounding the building. Unlike conventional segmentation that fragments urban spaces and leads to a loss of morphological features, this building-centered data point approach allows urban spaces to be represented multiple times across the dataset as the external spaces for various surrounding buildings, with some degree of overlap. This method not only preserves the unique relationship each building has with the urban space, thereby minimizing the loss of morphological features, but also embeds a diverse array of relationships within the dataset by illustrating how the same space is differently related to each building and its surroundings (Figure 4.1). This repeated representation and overlap of urban spaces in the data points underscore the multifaceted interactions between buildings and their urban context, offering a more nuanced understanding of urban form.

This data representation suggests an alternative way of representing cities that privileges individual urban spaces as their constitutive unit—neither as buildings nor as blocks. This approach aims to examine urban space not as homogeneously and geometrically segmented parts of the entire city, but rather to analyze the city's overall morphology through the relationships and individual characteristics of each building and its corresponding urban space.

Based on this alternative representation, I refer to the recognition of the city as an aggregation of neighboring urban spaces. This perspective differs from perceiving the city as an object with boundaries, segmented into parts within a unit. The recognition enables a focus on individuality of urban form data and its curation[1] according to intent (of the analysis). Based on individuality, one can devise a data scheme to represent urban space morphology [90] and a consistent data format for urban forms [116, 117]. Data formats are no longer confined to 1D or 2D representations for formularizing morphology indices. As long as the customizable scheme and format work as a consistent representational frame

[1]Data curation is the process of integrating information with constructor's intention using various sources and formatting the information into datasets.



Figure 4.1: The concept of 'aggregation of neighboring space' illustrates how a single urban space is diversely represented in urban form data through overlap and repetition.

to contain morphology features of different individual urban spaces, the utilization of 3D data, which enhances the complexity of information[2], is also viable.

One can then use a statistical model designed to extract morphological features from the form datasets and morphological characteristics of urban spaces. Multi-dimensional features from the form datasets are used to identify generalized morphological trends, patterns, and traits, akin to the identification of high-rise building principles [116] or the typi-

[2]The complexity of information in this context pertains to the magnitude and dimensions of the represented information. Greater complexity arises from the diverse relationships found within larger volumes of information spanning multiple dimensions.

cal urban conditions of a city [90, 91, 94].

Consequently, the change of perspective on city space can lead to an alternative method for typo-morphological analysis of the city space. Adapted to varying data subjects, formats, compositions, sizes, and sources, the method has technically been enriched in extracting morphology features and examining characteristics of form types. The method retains consistency in representing urban forms across diverse urban spaces, accommodates the increased complexity of form data by incorporating 3D representations, and enables statistical analysis of morphology features in individual urban forms without being constrained by city borders.

4.2 Urban Characteristics as Phenomena in Urban Form

By pointing out the limitation of the segmentation, I have proposed the alternative recognition of urban space, form and data. This concept aims to comprehend the distinctiveness of each urban space by considering characteristics of urban space as phenomena appeared in urban forms. Each urban space exhibits its unique configuration influenced by historical, cultural, and social factors through its form. Each urban form encapsulates the characteristics inherent to its corresponding urban space. Therefore, analyzing a city's morphological characteristics can be regarded as analyzing urban spatial characteristics through generalization of the distinctive features embedded in each urban form. From this perspective, the urban form is not subject to segmentation, but rather to aggregation. This recognition of urban space is referred to as "city as aggregation of neighboring urban space".

This cognitive transition encompasses changes of construction of urban form data, comprehensive analysis, interpretation, and evaluation of such data, leading to the emergence of a new framework in computational urban form analysis. Central to this framework is the conceptualization of the city as an aggregation of neighboring urban spaces, emphasizing the individuality of each urban space and its representation in data.

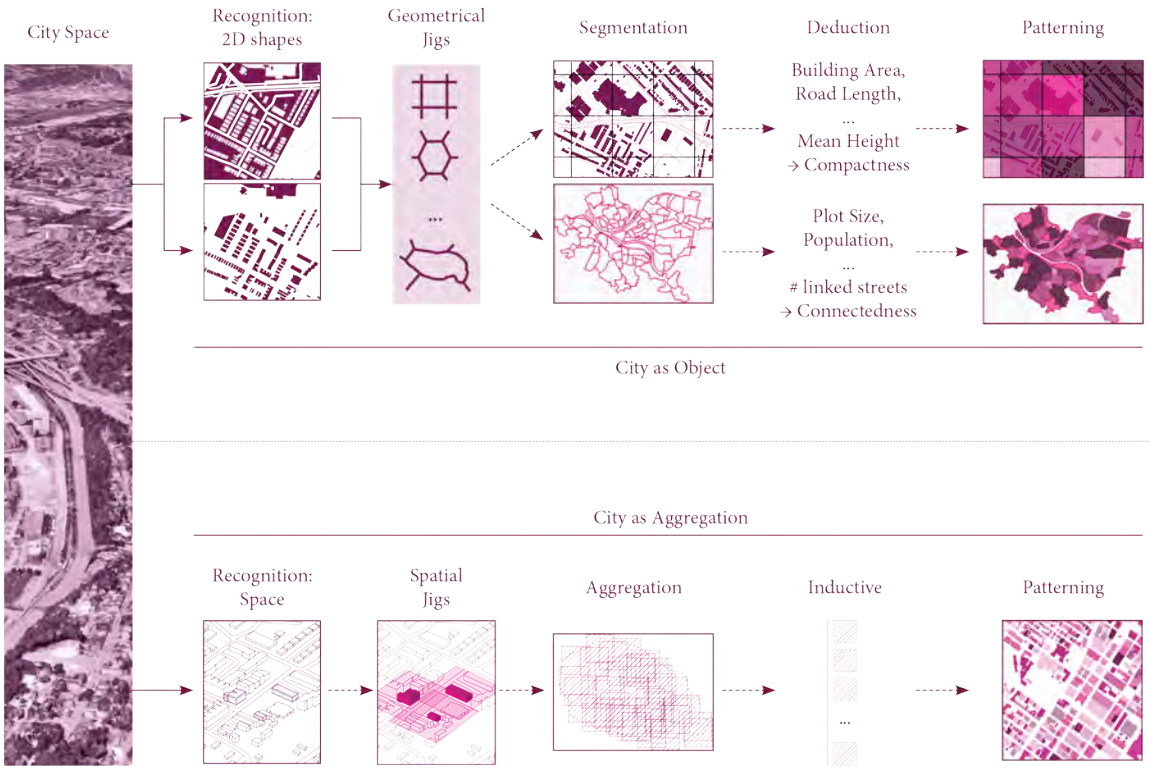


Figure 4.2: The methodological differences in computational urban morphology when viewing the city as an object versus as an aggregation of neighboring urban spaces

Figure 4.2 illustrates two distinct research frameworks within computational urban morphology, predicated upon differing conceptualizations of the city: as an object which is a subject to be segmented (hereafter referred to as "city as object") or as neighboring urban spaces to be aggregated (hereafter referred to as "city as aggregation")[3]. In the context of city as object, t he urban space is perceived as an entity demarcated by boundaries, often delineated through 2D representations such as blocks or building footprints. Employing geometric jigs such as grid cells, block boundaries, or neighborhood borders, the entire urban form can be segmented into discrete fragments. By deriving morphology indices based on measurement within each fragment, the overall morphological tendencies can be discerned (Figure 4.2).

In contrast, city as an aggregation perceives urban space as a collection of individual

[3]The concept of the city as an object refers to a viewpoint that sees the city as an object with boundaries. However, this concept can also be seen as the city as an aggregation of segmented urban spaces. Therefore, I once again refer to the latter as the city as an aggregation of neighboring urban spaces.

urban spaces. A specific scheme is necessitated to define these individual spaces, for instance, a $50m \times 50m \times 50m$ space centered on a single building. Termed spatial jigs, this scheme differentiates itself from geometric jigs in that the former pertains to the division of space represented through 3D forms. Spaces delimited by spatial jigs may exhibit numerous overlaps, signifying diverse spatial relationships. By aggregating these divided spaces, form data can be compiled. Statistical models, such as DNN, can then capture the morphological features of individual urban spaces, leveraging the form data to discern general patterns and reveal the morphological characteristics of urban spaces (Figure 4.2).

The alternative recognition and analytical framework for urban form and space were instigated by the data scientific perspective. Departing from segmentation methods that treat urban forms as mere objects on a map, this framework acknowledges intrinsic 3D nature of urban forms. As a result, it enables an analysis of 3D urban form data, unveiling the manifestation of morphological phenomena within the urban context. It is anticipated that this alternative way of recognizing the city, coupled with its analytical approach to urban form, will engender a renewed and reviewed understanding of urban space, one that centers on neighboring spaces of individual buildings.

Moreover, by abstaining from the use of objects defined by geometric boundaries in the analysis of urban form, the proposed research framework facilitates the examination of morphological characteristics across cities. This framework enables the analysis of morphological phenomena in a city. However, the applicability of this framework's data is not confined solely to the geographical notion of 'a city.' As long as consistent 3D urban form data is generated, each data point can be processed without constraints based on the geographic location. Thereby, the framework allows for the comparison of urban form attributes across multiple cities, standardized in the same format. This facilitates investigations into the occurrence of specific urban forms in various cities and regions, as well as the identification of distinctive urban form typologies associated with particular cities.

In the following chapters, an experiment is conducted to assess the viability of ap-

plying this alternative research framework in urban form study across multiple cities, as a means to uncover novel perspectives on urban spaces and unexplored insights into urban structures. In pursuit of this objective, I establish systematic steps of this framework based on data scientific procedures. These steps include constructing urban form data, extracting and generalizing morphology features from this data using a deep learning model, and evaluating the outcomes. Specifically, through site surveys, I evaluate how valid and reliable the outcomes of the alternative framework are. Additionally, by applying the methodology of a precedent that uses morphology indices to the same case study, I compare how its results differ from those of the alternative research framework, thereby gaining novel insights into the city. Accordingly, the chapters delve into the prospective efficacy of these newfound insights and their potential applications.

CHAPTER 5
METHOD

The next two chapters focus on case studies aimed at testing the feasibility and practicality of the previously proposed alternative framework for analyzing urban form. This case study comprises a total of five steps, with the first two steps discussed in this chapter. The initial step involves experimenting with data curation into an urban form dataset based on the concept of aggregation rather than segmentation. In the second step, the extraction of morphological features from the urban form dataset is described, employing a deep learning model as one of the inductive methods, thereby deriving urban form types based on these features.

The subsequent chapters will include three other steps: characteristic analysis, evaluation, and drawing new knowledge. The characteristic analysis will examine both the quantitative and qualitative aspects of each urban form type, aiming to identify and describe the unique urban types found within each city, along with their distribution and structure. Evaluation involves an investigation into how these characteristics manifest in actual urban spaces for verification of the effectiveness of the proposed framework. Along with site surveys, this is achieved by applying a formularized method from a precedent research to cities used in case studies and comparing the results with those of the alternative framework.

It is important to reiterate that this case study does not utilize morphological indices within geometrical segmentation, such as compactness and density. The rationale behind the proposed approach is that by employing inductive models, specifically deep learning models, more complex morphological features can be extracted from the data compared to what indices can provide. If the urban types derived through this case study exhibit similar configurations of urban form and spaces, it would validate this proposition. Conversely, if the urban types are unclear, it would necessitate an evaluation of whether technical im-

provements are required for this proposition or if a reassessment of the recognition of urban form is necessary. Hence, this case study is viewed as a highly exploratory and experimental endeavor that applies the proposed framework without any guarantee of inferring the urban form types. Even if the identification of urban form types is successful, it is acknowledged that significant novel insights, which can be differentiated from those derived through conventional methods, may not be revealed regarding urban fabrics and structures that rely on these types.

Instead of focusing solely on the analysis results, what deserves attention in this case study is the potential changes that can arise in the analysis of urban form when urban space is approached from a data scientific perspective rather than a cartographic one. Particularly, the emphasis is placed on the unexplored aspect of conducting comparative analyses on the diverse and abundant urban forms observed across multiple cities. Therefore, the possibility and limitations of this novel analysis method, which emerges when urban form is viewed as data, constitute crucial outcomes to be derived from this case study.

5.1 Case Study Design

The aim of this case study is to investigate and examine whether the framework can reveal significant morphological characteristics across multiple cities. An essential criterion for selecting these cities is their shared urban cultures, assuming that cities with similar cultural backgrounds will exhibit comparable urban forms and structures[1]. Accordingly, I have chosen three Rust Belt cities as the cultural context for this specific test case: Cleveland,

[1]The assumption that cities with similar cultural backgrounds will exhibit comparable urban forms and structures is grounded in a body of urban studies and cultural geography literature that suggests urban morphology is significantly influenced by cultural, historical, and socio-economic contexts. For instance, studies by Lynch on *The Image of the City* [3] and by Jacob on *The Life and Death of Great American Cities* [118] have shown that urban form and structure can reflect the cultural practices, historical legacies, and planning ideologies of a society. This theoretical underpinning supports the hypothesis that examining cities with shared cultural backgrounds might reveal morphological similarities[22]. This approach allows for a focused comparison, highlighting how cultural similarities manifest in urban morphology, and offering insights into the interplay between culture and urban form.

Detroit, and Pittsburgh. The selection takes into consideration the availability of publicly accessible urban data sources, geographical proximity to enable on-site surveys for evaluation, similar amount of decreasing rate in population between 1950 and 2000 [119] as well as prior studies conducted by respected scholars in the fields of urban history and policy [120, 121, 122, 123] [2].

Rust Belt cities in the Great Lakes and Midwest region of the United States are metropolitan areas that have experienced industrial decline since around 1980. They share similar urban cultures such as past prosperity from manufacturing growth, chronic population decline, economic downturn that have lasted for over 40 years. They have responded to the decline by restructuring their city space, updating urban facilities, developing green spaces, and instituting policies that are favorable to businesses.

These efforts have been relatively successful in a city such as Pittsburgh [124, 125, 126]; however, in the other Rust Belt cities the decline has not completely halted. There has been strong local support in these cities for strategically reducing the size of the city to kindle future prosperity. This idea responding to the declining focus on restructuring and downsizing the city for recovering lively urban environment in the manageable scale and for potential growth in future [119]. The purpose of this reforming is to stop maintaining huge metropolitan territories and infrastructures demanding large resources but scarcely used, and to adapt them into actively used space in the current urban environment.

There is almost no disagreement on the need for reduction, but how it is done is often the central issue; how to restructure and downsize the large metropolitans; to what extent will the city be reduced? does the newly reduced city need a centralized functional area, such as downtown? will vacant lands simply exclude from the downsized city? Owing to the complex relationships between diverse stakeholders, reducing an existing urban infrastructure under city administration is much more difficult than developing a new city

[2]The primary reason for selecting Rust Belt cities as the subjects for the case study was their proximity. When initially planning and proposing this research, I was physically staying in Pittsburgh, ensuring access to Cleveland and Detroit for site surveys. Beyond this practical reason, it should be noted that the framework can also be applied to other cities, such as those in the Sun Belt

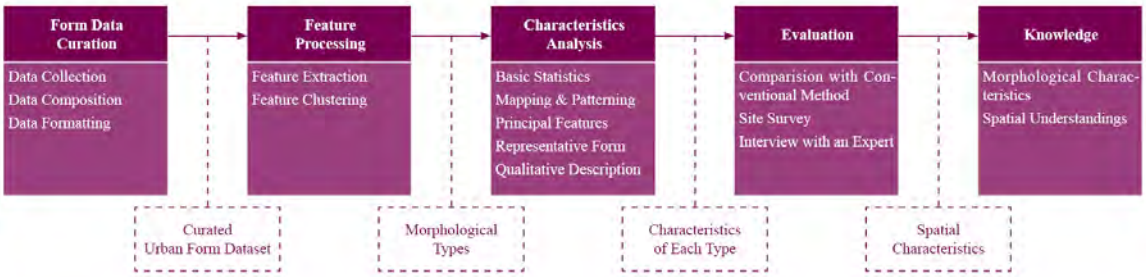


Figure 5.1: Five-step research pipeline for the case study

infrastructure or expanding territory. Hence, any decision for reduction must be carefully addressed not only from the perspective of economy, environment, and policy, but also from the viewpoint of citizen life in the urban space.

For this city reforming, it is important to understand characteristics of urban spaces in granular. In the case study, I expect the framework to reveal common configurations of urban forms and provide a spatially distinguished boundaries of city spaces, demonstrating the spatial influence of the infrastructure. Thereby, the investigation and examination will provide insights into Rust Belt cities' unique characteristics of urban spaces and spatial knowledge pertaining to urban typologies.

This case study will take five steps (Figure 5.1) in a research pipeline: form data, feature processing, characteristics analysis, evaluation, and knowledge. Firstly, form data curation is the step to construct a dataset of urban form according to the research focus and takes into consideration: data subject, source, format, dimension, and composition. I collect raw data for the three Rust Belt cities and Miami which serves as a control group with a different climate, economic growth, industrial conditions, and populations from Rust Belt cities. Although tempting, high-resolution files from commercial GIS services, for example, Maxar, AW3D, Near Map, CyberCity3D, are expensive in time and cost and provide details unnecessary for the purposes of this research. Hence, I will use publicly available data platforms such as airborne LIDAR survey to obtain urban form data.

Once raw 3D data of building forms is collected, I can set the individual unit of an

urban form by sampling a building and its urban contexts. Each unit of a specific 3D range centered on a building to include the immediate urban elements such as terrain and neighboring buildings. The range is determined by measuring the average size of the buildings. Moreover, orientation and height are normalized to the center of the building so that relationships between the building and its contexts are relativized. Thus, each data point includes a relativized representation of the building and its surrounding morphological conditions.

The last task is converting urban form samples into proper representations to capture morphology features using deep learning techniques. There are possible representations that can be explored, for example, polygon mesh, voxels, point cloud, and Digital Surface Model (DSM) [127]. In order to determine an appropriate representation and data format, several factors must be taken into consideration, including data resolution, size, and conversion time. The entire dataset is approximately the same size as the total number of buildings in the selected area [3] of the cities. Based on earlier research [90, 116], I estimate about 60,000 - 70,000 buildings to a city and a total of 240,000-280,000 urban form samples for the four cities. Considering these estimates, a DSM will be employed as the chosen data representation, as it offers a more compact size compared to voxels and point cloud data. Additionally, DSM can be readily converted into both 2D images and 3D models, facilitating the analysis process.

The collected, composited, and formatted data constitutes a large collection of urban form data, henceforth referred to as the urban form dataset. This curated urban form dataset is then passed on to the subsequent stage, namely feature processing. In this step, morphological features are extracted from the dataset using DNN, yielding types of urban forms by their features in data space. I select a proper deep-learning model through an experiment for measuring performance with the dataset. The model includes an encoder capable of

[3] Upon examination, it became apparent that cities encompassing metropolitan and suburban areas incorporate a considerable volume of buildings. Hence, an area was delineated around the urban core, specifically downtown, anticipated to encompass a consistent quantity of buildings, in the range of approximately 60,000 to 70,000.

extracting features from a dataset and a decoder to reconstruct a form using the extracted features. The reconstructed model from the decoder works as a qualitative evaluator for the performance of capturing morphology features.

Once a DNN is trained with the urban form dataset, the network can capture morphology feature vectors of all urban form samples. These vectors work as abstracted representations of the original samples, keeping their distinctive features. Unsupervised classification algorithms can group these morphology feature vectors, thereby yielding various urban forms distinguished by their morphological features. These distinct urban forms are named as 'urban types.'

Characteristics analysis is the step to investigate characteristics of each urban type through basic statistics, mapping, principal features, representative forms, and qualitative descriptions. In this step, the urban types are both quantitatively and qualitatively examined through five different methods: the basic statistic, mapping and patterning, principal features, representative forms, and qualitative description. The basic statistic demonstrates the quantitatively dominant and unique urban types through calculations of occupancy rate, average height, coverage area, and mean density of an urban type in a city. Mapping the information of the types onto the geographical space and deciding the boundaries, patterns of urban fabrics can emerge and visually convey morphological traits of urban space in the cities. Principal axes are a gauge of a morphological characteristics extracted from the abstracted morphology feature vectors. The average composition of principal axes in a type is treated as a quantitative representation of the type. Representative form of each type is defined as the nearest data point of each cluster's arithmetic mean point and the furthest point from the mean point. These forms work as a qualitative descriptor of the morphology characteristics of a type, demonstrating a typical shape and morphological variance of the type.

Using the five methods in analyzing morphology characteristics, I can obtain the common urban types of the Rust Belt cities, which are distinguishable from the urban types in

Miami. Focusing on how variations of urban types appear in Rust Belt cities, I will delve into their spatial characteristics.

Evaluation is the step for validating the results of clustering and interpreting the characteristics of types through site surveys, and a comparison drawn between the findings derived from this case study and the results from extrated feature-based analysis on the same cities. This experiment heavily relies on data and computational methods to examine typo-morphological characteristics of urban forms across multiple cities. Evaluation is the step to verify the results of analyzing typo-morphological traits, supplementing the digital-heavy readings of urban forms with physical attributes.

Site survey is a visually rigorous approach to verifying urban types that are identified by the morphological features. By visiting (and recording) places where common urban types appear in several cities, I can crosscheck whether they have similar spatial compositions and atmosphere. Furthermore, I will sample and observe points across the cities to verify common characteristics of places where specific fabrics conflicts. In case the site survey is restricted, Google Street View (GSV) can be used as an alternative to virtually execute the survey.

After confirming the reliability of the analysis by site visits, I will interpret the relationships between characteristics of the common types and urban development in the Rust Belt cities. The findings and interpretations will be contrasted to the previous morphology index-based analysis of the urban structure of each city.

Knowledge is the final step in the pipeline for translating and discussing the examined and validated morphological characteristics into a spatial understanding of the city. To enrich analysis and interpretation it is important to interact with an expert whose domain knowledge is in the history, planning, and society of Rust Belt cities[4]. Interweaving her expertise and my computationally investigated characteristics of urban types, I expect to address how the unique spatial characteristics of urban types in Rust Belt cities can meet

[4]for this interaction, I invite one urban expert to offer feedback to your dissertation as a reader.

the values demanded by modern cities.

5.2 Form Data Curation

The goal of form data curation is to collect, compose, and format relevant and raw data into urban form data representing neighboring urban space of individual buildings. Figure 5.2 illustrates the overview of the form data curation process from collecting geographic data to final generation of dataset, showing how different urban data is composited and preprocessed to be consistently formatted and capturing individual urban spaces.

5.2.1 Data Collection

To construct the dataset comprising individual urban forms, three primary raw datasets are necessary: neighborhood boundaries, building footprints, and airborne LIDAR surveys. These raw datasets can be obtained from the GIS portal administered by the municipal government. The neighborhood boundaries and building footprints are geometric data stored in the .shp (Shape) format. The shape data for each city is standardized by converting the coordinate system to NAD83 and the distance unit to the metric system. This ensures consistency across all datasets, allowing them to be matched to the same format.

Neighborhoods are strategically chosen with their centers located in downtown areas to ensure that each city comprises approximately 72,000 to 76,000 buildings[5] (step 1 in Figure 5.2). Only the buildings within these chosen neighborhoods are carefully filtered and utilized for data construction (step 2 in Figure 5.2). Specifically, the city of Cleveland comprises 74,181 buildings, Detroit has 73,434 buildings, Pittsburgh has 74,883 buildings, and Miami contains 72,410 buildings. It is widely acknowledged that deep learning algo-

[5]In pursuit of well-distributed dataset sizes across all four cities and to estimate a total data volume that remains computationally manageable, I restricted the number of data points to approximately 72,000 to 76,000. The performance of deep learning models significantly depends on the quantity and quality of data, with more data generally enhancing performance. However, due to the limited computational resources available for this research, it was not feasible to indefinitely increase the dataset size, necessitating the imposition of appropriate constraints.

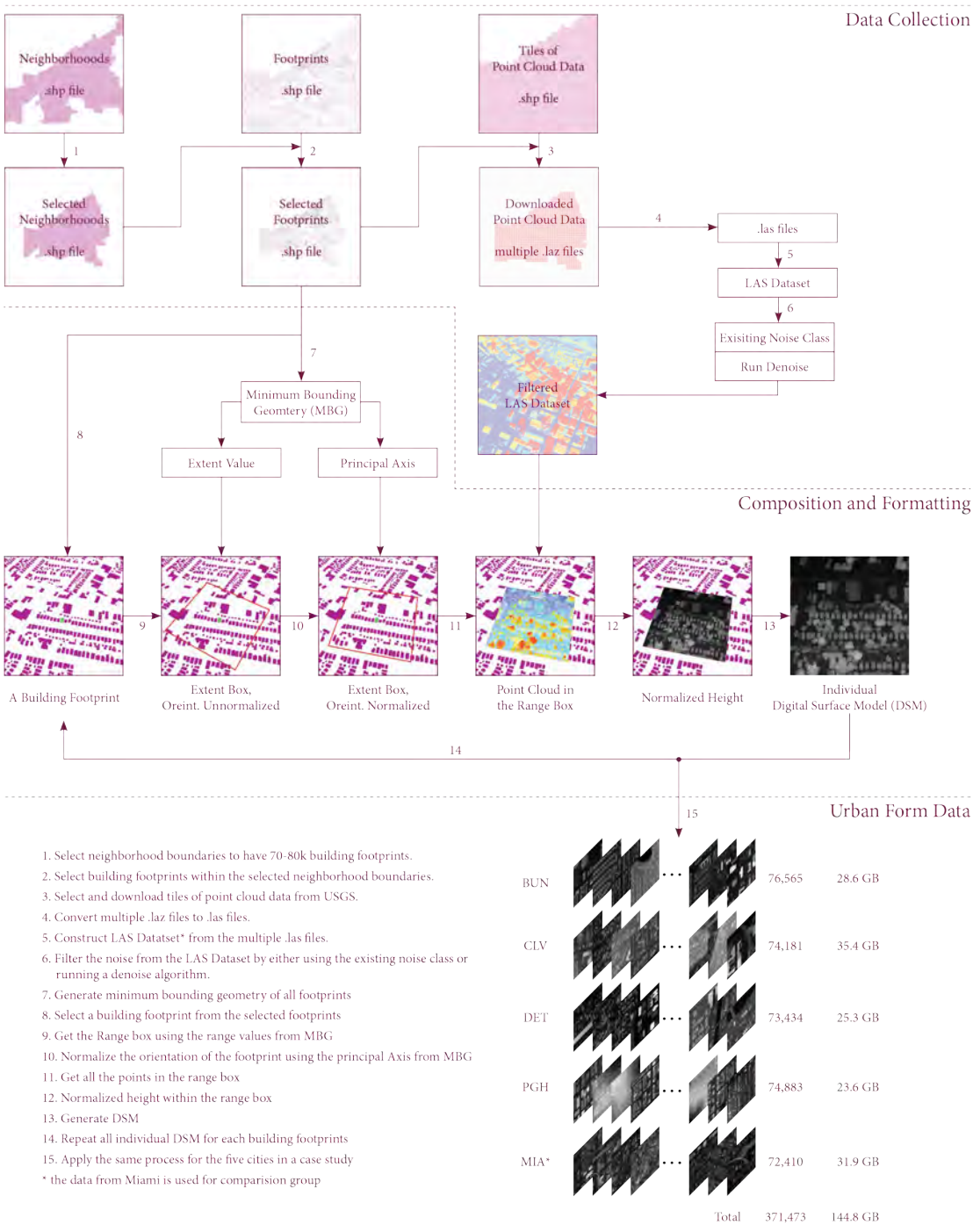


Figure 5.2: Processing workflow and detailed steps in data curation

rithms perform optimally when trained on large and diverse datasets. Therefore, extra data just for training is generated using Buffalo's urban form in a similar manner to the other

cities, resulting in a total of 76,565 buildings.

Once the building footprints are prepared, the next step involves utilizing the airborne LIDAR survey data consists of 3D point information, which provides 3D information of urban space and forms. LIDAR is a technique employed to determine the distances of targeted objects by emitting laser pulses from a scanning source. The scanner emits lasers repeatedly and measures the time it takes for each pulse to return, enabling the calculation of varying distances from the scanner's position. Each measured distance is represented as a 3D point, and the collection of all measured points is aggregated into a point cloud, which is a popular representation for 3D objects or spaces. The resolution of the object in a point cloud is determined by the number of points used to represent it.

LIDAR is widely employed in surveying 3D spaces and cities due to its precise laser-based measurements. The United States Geological Survey (USGS) conducts a comprehensive land survey at a national scale using LIDAR technology mounted on aircraft. The government routinely captures and maps the entire country using LIDAR. The results of these surveys are made publicly available through online repositories in various data formats, such as Laser point cloud data (LAS), Digital Elevation Model (DEM), and DSM.

LIDAR data is generated, managed, and distributed by the USGS and is typically saved with .lasx extension in standardized tiles. To acquire the necessary las file, it is necessary to determine the tiles corresponding to the area that includes the selected building footprints and download them from the USGS portal.

Initially, the individual .lasx files, which represent each tile, are converted into the las format. Then, these LAS files are combined to form a unified LAS dataset, denoted by .lasd extension, thereby establishing a standardized LIDAR file. It is worth noting that this file may contain extraneous noise unrelated to urban information, such as water vapor or clouds present during the survey. To mitigate this issue, the LAS classification function [128] provided by ArcGIS is employed, enabling the removal of various types of noise.

A crucial aspect of noise removal entails making a decision regarding the inclusion of

vegetation, particularly trees, in the LAS data. This decision is closely tied to the consideration of urban vegetation as a component of urban form. In the context of this case study, I deemed trees to be a significant element contributing to the urban form. While the presence and appearance of trees may vary with the seasons, they play a pivotal role in shaping the character of an urban space. For instance, the absence of dense trees in a park would render it as a vast open space, whereas the presence of trees effectively partitions and defines the spatial characteristics of the area. Consequently, I opted to incorporate vegetation information within the urban form data, recognizing its importance in the overall analysis.

5.2.2 Data Composition

With this filtered LAS dataset along with corresponding building footprints, it becomes ready to create new data in the desired format through the process of data composition. The initial task of this data composition process involves determining the extent of the neighboring urban space surrounding a building. If the extent is set too narrow, the data will only capture the intricate details of the building shapes while neglecting the surrounding space. Conversely, if the range is excessively wide, the data will provide a more comprehensive representation of the urban space, but the buildings themselves may appear minuscule and diminish in significance, thereby impeding a clear interplay between buildings and their respective urban spaces[6].

The determination of the extent range is based on an estimation derived from the length of the longest side of each building, obtained through the implementation of rectangular MBG. The rectangular MBG encompasses each building with axes aligned in two directions: the long and short axis. The length of the shorter side is referred to as the width, while the length of the longer side is denoted as the depth (see Figure 5.3).

Figure 5.4 illustrates the depth distribution among the buildings in the five cities[7]. In

[6] I will elaborate on this point in further detail later in this section.

[7] for constructing data composition and training a deep learning model, I have used the dataset including urban form information from Buffalo as extra data for better performance of the model

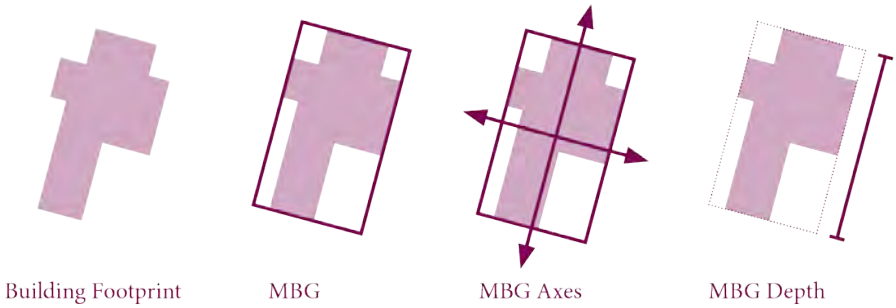


Figure 5.3: Identification of the two principal axes of a building footprint utilizing Minimum Bounding Geometry (MBG): long (depth) and short (width)

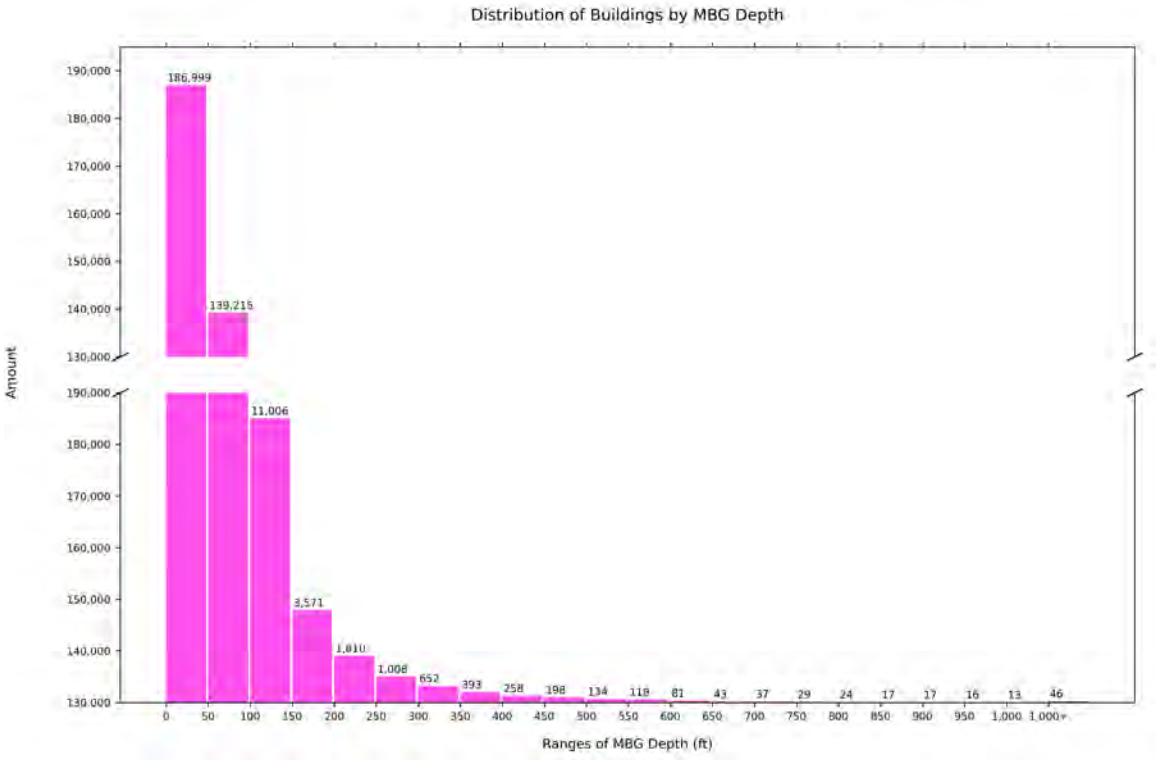


Figure 5.4: The depth distribution among the buildings in the five cities: Cleveland, Detroit, Miami, Pittsburgh, and Buffalo(as extra data)

the majority of instances, the depths of buildings in the five cities span from 0 to 50 feet, with an average depth of 53.19 feet. Notably, buildings with depths falling within the 0-150 ft range account for 90% of the overall dataset. Consequently, a unit of 50 feet is adopted, and the dataset's extent is established within a range encompassing a minimum of 10 buildings (500 ft) and a maximum of 20 buildings (1,000 ft) (Figure 5.5). The precise

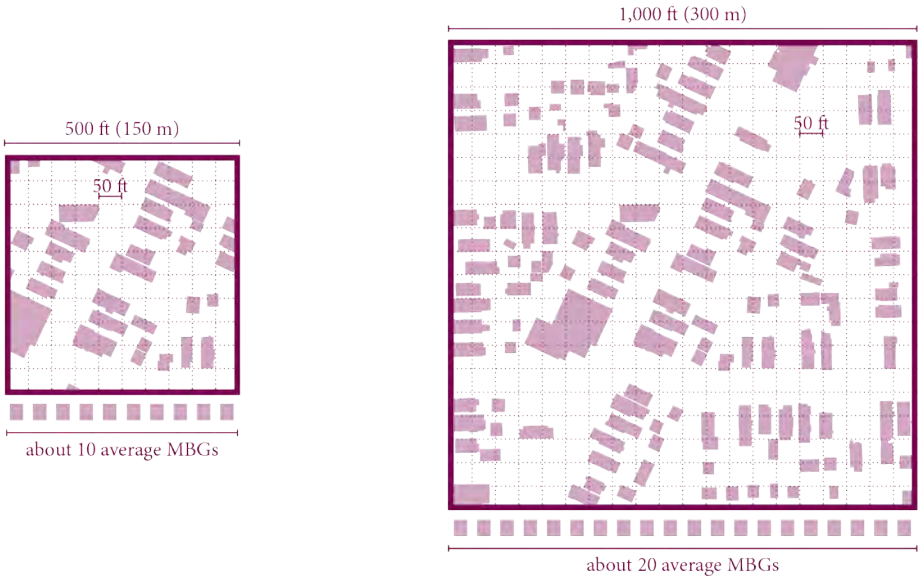


Figure 5.5: Minimum and maximum extent of a dataset using average MBG.

extent value is contingent upon the performance of future deep learning methodologies.

The neighboring urban space of each building is determined based on the maximum extent and each building is positioned at the center of its respective extent. This approach enables the distinction of urban spaces in accordance with their associated buildings in deep learning (see step 7-9 in Figure 5.2).

The subsequent step in the composition process is normalizing the orientation of the extents. This entails rotating the extents to align the depth axes of a building's rectangular MBG with the main orientation. The purpose of this rotation is to standardize the arrangement of urban space, which is influenced by specific orientations in different cities due to natural factors such as topography[8]. Without the orientation alignment, it is possible for the deep learning model to discern disparate forms and capture distinct morphological features, even in cases where urban spaces exhibit similar configurations but differ in orientation due to variations in city topography. Consequently, the process of orientation alignment facilitates the consistent representation of buildings and their neighboring urban spaces across

[8]In the context of deep learning applications for urban or architectural form analysis, orientation can serve as a significant feature. I recommend referring to prior studies [117] that explore the implications of orientation in the study of morphology using deep learning to understand its impact and application in this research area.

different cities.

Once the extent and orientation are determined, the corresponding point clouds within the extent are extracted from the LAS data. The LAS data assigns different colors to the points based on their height, following a rainbow color scheme as depicted at step 11 in Figure 5.2. In this scheme, lower points appear closer to blue, while higher points lean towards red. However, this color scheme is influenced by the range covered by the data. Since LAS data varies across cities due to differences in topography, unaltered color values would inevitably introduce height discrepancies. For instance, Cleveland, with an average elevation of 653 feet, would depict its high-rise buildings as gray or nearly black, while low-rise residential structures in Pittsburgh, with an average elevation of 1,223 feet, would be rendered in very bright white.

Given the capability of deep learning models to recognize color variations as significant indicators of morphological features, it becomes imperative to normalize the height information with respect to individual buildings. This normalization procedure guarantees that height is consistently rendered in relation to each building and its neighboring space. Through this height normalization process, deep learning models can effectively capture and analyze the morphological attributes of the urban environment.

However, the form data should incorporate local topographic changes, at the same time, it should address the influence of height disparities between cities. Thereby, I normalize the height information with the extent of each building. This normalization technique ensures that the lowest region within the extent is visually represented as black, while the highest region is depicted as white. By aligning the height range and black and white color scheme accordingly (see steps 11 and 12 in Figure 5.2), the potential impact of height discrepancies between cities is mitigated, and the distinctive topographic variations within the local space are duly considered during training of deep learning models.

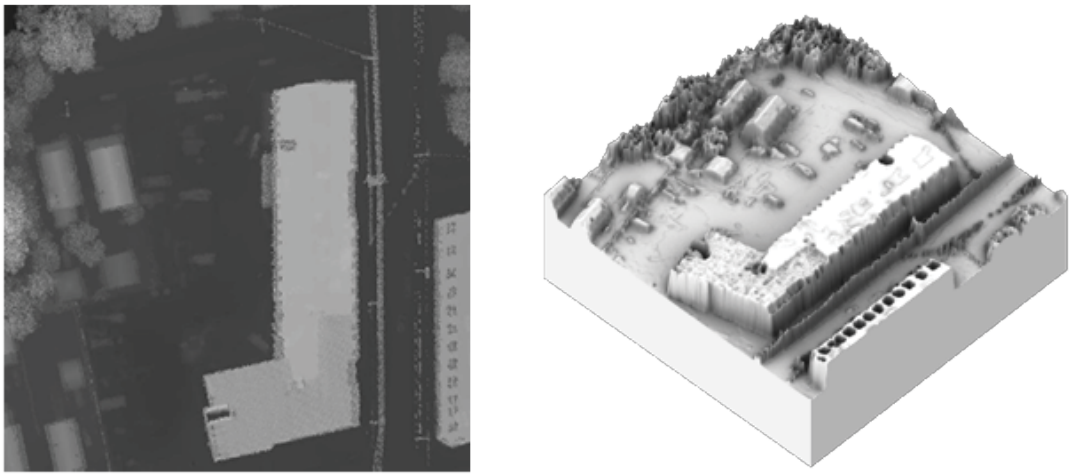


Figure 5.6: 2D images with height information from point clouds (left) and reconstructed 3D (right)

5.2.3 Data Formatting

The normalized point cloud within a designated extent is transformed into a DSM, which is then saved as a .png image file. The resulting image has dimensions of 2000 pixels by 2000 pixels. Although the data format itself is 2D, this data is considered 3D due to the inclusion of height values represented by colors in addition to flat position values. By representing the point cloud as a 2D image, a more consistent and structured representation of point clouds with varying numbers is achieved within an extent. Figure 5.6 illustrated a sample of the generated data and its corresponding 3D reconstruction. It is important to note that the conversion of the point cloud into a mesh may introduce some imperfections and noise; however, this is not indicative of a lack of data information or formatting issues.

The process of composing and formatting the data is iteratively performed for each selected building in every city, resulting in the creation of a curated urban form dataset. Consequently, the number of data samples for each city corresponds to the number of selected buildings in that city. Utilizing a machine equipped with an 'Intel(R) Core (TM) i9-10900x @ 3.70GHz' processor and 256GB of memory, the data generation process required ap-



Figure 5.7: Samples of the generated dataset. See Appendix C for more samples of datasets.

proximately 190 hours (equivalent to approximately 8 days)[9] to complete, resulting in a total of 371,473 urban form data samples. Figure 5.7 showcases a randomly chosen data sample from this dataset.

[9]Based on the electricity consumption, it is estimated that approximately 39,343.3 kg of CO2e has been emitted. Although the assessment of the environmental impacts of this type of work, as well as the suitability of CO2e as a measure of these impacts, lies beyond the scope of this dissertation, it is an issue warranting careful consideration and further study.

5.2.4 Data Transformation

The process of data transformation involves conducting experiments to determine the appropriate sequence of transformations that effectively augment[10] the data during the training of deep learning model for extracting morphological features.

Table 5.1: Estimated Data Sizes by Various Pixel Dimensions

Number of pixels	A Data Size (KB)	Total Data Size (GB)
28	0.78	0.29
36	1.29	0.48
64	4.03	1.50
128	16.38	6.08
256	65.54	24.34
500	250.00	92.87
2000	4,000.00	1485.89

In the previous stages of data composition and formatting, the data was generated with a size of 2000 pixels by 2000 pixels for each building, representing the maximum extent of the data. However, when entering the deep learning model, the data size is typically much smaller, ranging from 28 pixels by 28 pixels to 500 pixels by 500 pixels. This is considerably smaller compared to the curated urban form data. Table 5.1 provides an estimation of the total data size based on the pixel dimensions of grayscale image data with one channel and 8 bits per pixel. Training the data with a size of 2000 pixels would require processing approximately 1.5 TB of data per epoch. This is about 245 times larger than the size of the 128-pixel data and about 16 times larger than the size of the 256-pixel data. It is generally not practical to train deep learning models on super high-resolution images (1000 pixels or higher) unless there is a specific need. Therefore, among the commonly used pixel sizes in

[10]In this context, the term ”augment” refers to the concept of data augmentation, a training technique in deep learning that simulates the effect of possessing multiple datasets by applying various transformations to a single piece of data. This method enhances the model's ability to generalize from the training data by artificially expanding the dataset with transformed instances, thereby improving its performance and robustness.[129, 130]

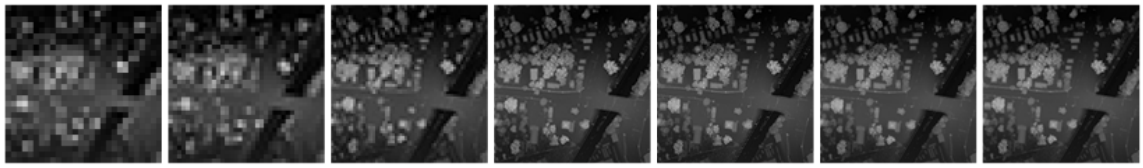


Figure 5.8: Data quality difference by pixel dimensions. From left, 28 px, 36 px, 64 px, 128 px, 256 px, 500 px, 2000 px

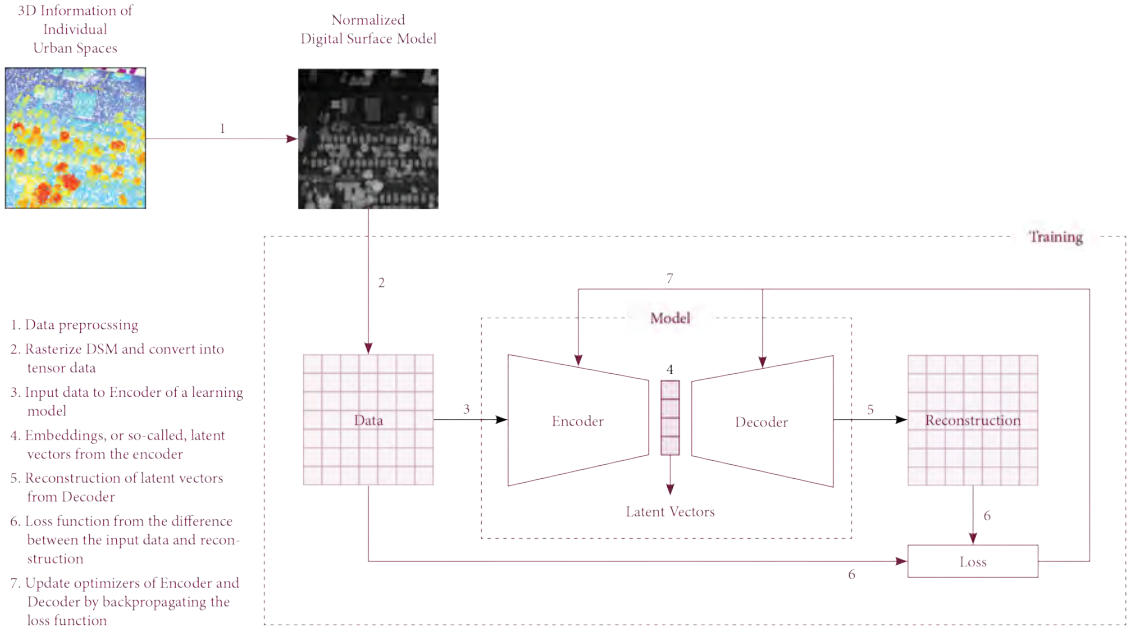


Figure 5.9: Diagram of Variational Auto-Encoder (VAE) training process, featuring encoder and decoder mechanisms

Table 5.1, a pixel size of 256 is chosen, as it allows for the differentiation of various urban elements such as buildings, topography, vegetation, and vehicles (Figure 5.8).

Once the pixel size is determined, various combinations of transformations are applied to the deep learning model to assess its learning performance. In this study, the VAE, a generative deep learning model, is employed (Figure 5.9). A VAE consists of two networks: the encoder and decoder. The encoder extracts data features and compresses the input sample to the reduced dimension of data space, the so-called latent space. The decoder reconstructs the encoded sample to resemble the original sample as closely as possible. Training VAE reduces the error between this reconstruction and the original sample by

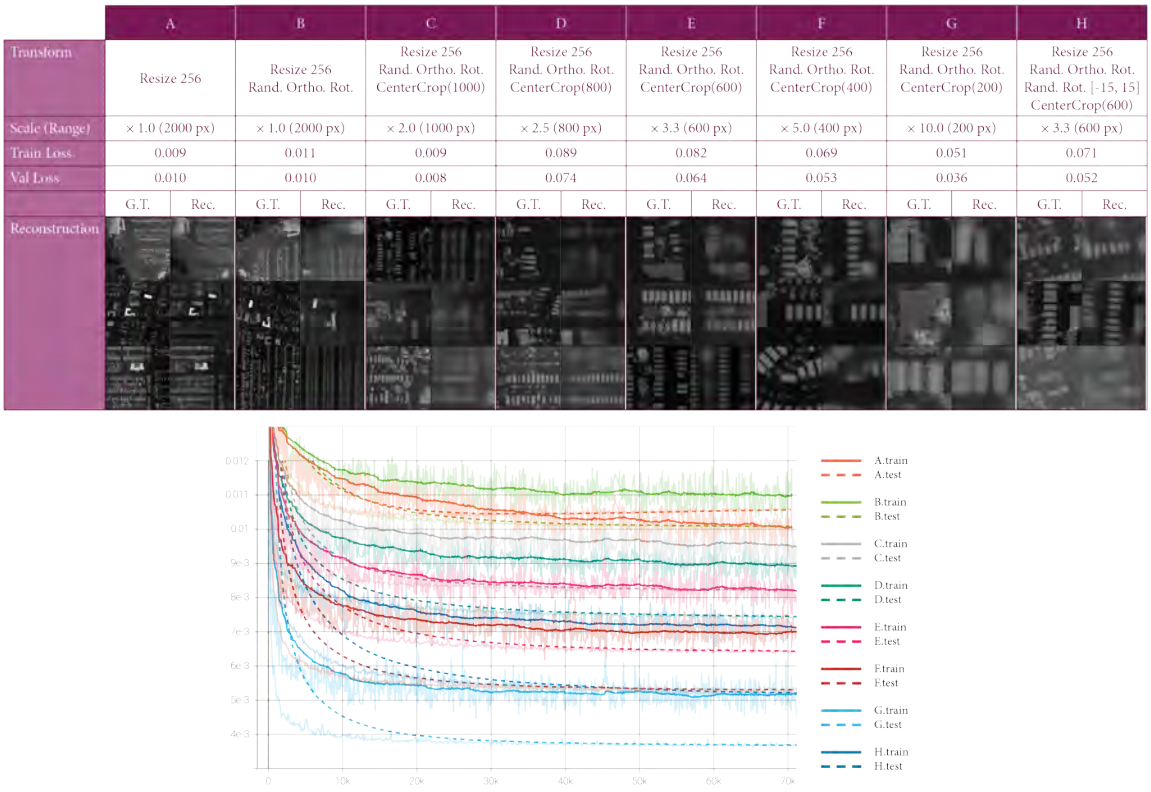


Figure 5.10: Results of training performance by different combinations of data transformation

capturing the data distribution in specific dimensions. The loss metric[11] of the VAE provides a quantitative measure of the learning performance, while the reconstructed image achieved using the VAE decoder serves as a qualitative evaluation.

In the tests for the data transformation, the following transformations were employed. As previously mentioned, the Resize 256 transformation reduces the data size to 256 pixels by 256 pixels. Random Orthogonal Rotation rotates the data by randomly selecting an angle from the options of 0 degrees, 90 degrees, 180 degrees, and 270 degrees. Random Rotation applies a rotation to the data by randomly selecting an angle from a specified range. Center Crop transformation is utilized to crop the image from the center. Since the size remains fixed at 256 pixels, it has a similar effect to scaling the image.

A total of eight transformation combinations, labeled from A to H, were tested in

[11] Mean Square Error (MSE) is used

the study. The results in Figure 5.10 revealed that the best performance, indicated by the lowest loss, was achieved when the original data was magnified approximately tenfold and subjected to random orthogonal rotation, as observed in test G. However, upon examining the image at this enlarged scale, it became apparent that the arrangement of urban space was rarely depicted, with only a limited number of predominant building forms being represented. In other words, the VAE successfully captured the morphological features of the architectural forms and generated a reasonably accurate reconstruction by comparing them with the ground truth data.

Upon analyzing tests D, E, F, and G, it was observed that higher magnification corresponded to better performance, with reduced loss. This suggests that deep learning more effectively captures morphological features as the scale transitions from urban space at the urban unit level to some extent of architectural space. However, this relationship does not hold consistently across all magnifications. Notably, when representing the urban form at a larger scale beyond the city unit, as demonstrated in tests B and C, the performance significantly surpassed that of tests D, E, and F. This implies that the deep learning model recognizes urban forms as granular patterns when the space between buildings is greatly diminished. Furthermore, upon comparing the reconstructed data with the ground data at this wider scale, it becomes evident that the VAE tends to overfit to specific arrangement data, consistently reconstructing urban form arrangements that do not exist in ground truth (see reconstruction of test A, B, C and D in Figure 5.10).

Consequently, the transformation combinations Center Crop 600 px ($3.3\times$ magnification) and Center Crop 400 px ($5\times$ magnification) exhibited satisfactory performance in accurately representing individual urban forms where urban space was appropriately depicted [12]. Between these two options, the $3.3\times$ multiplier with a wider extent was selected to ensure that even larger buildings could be adequately represented within a single data

[12]The blurry representation in reconstruction is due to the technical limitations of the original VAE. To overcome this limitation, another improved VAE will be used in the process of training and extracting features.

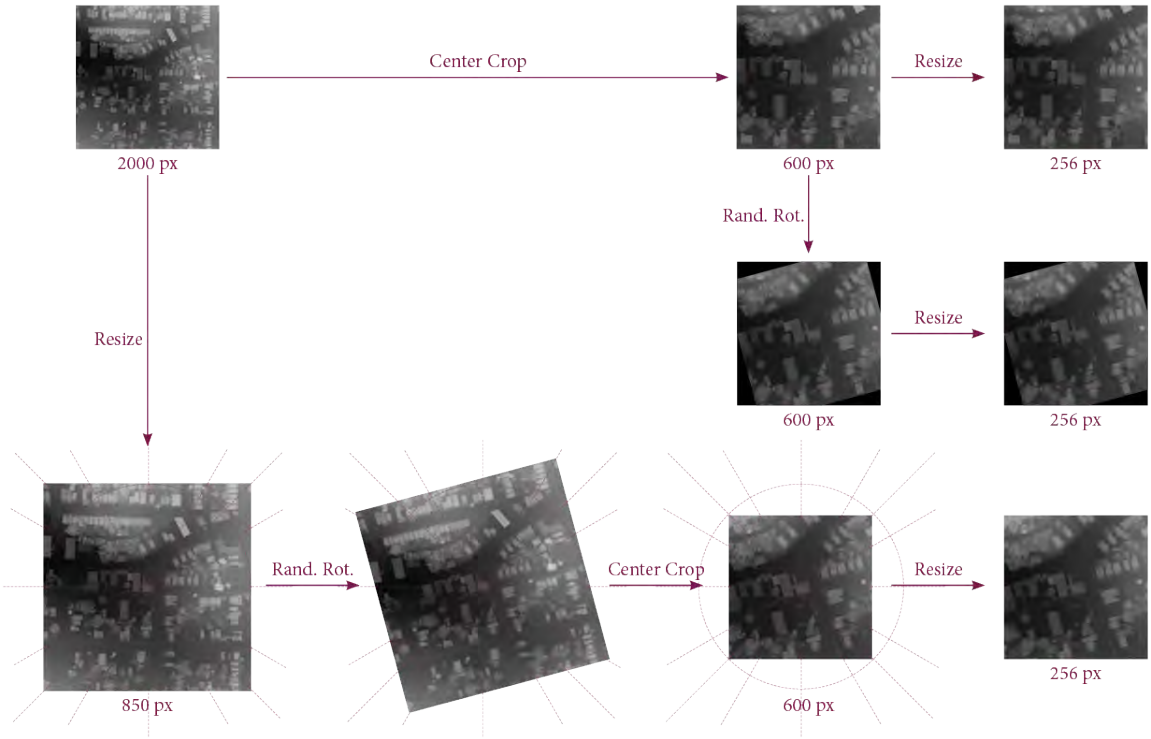


Figure 5.11: Visualization of the determined combination data transformation

sample.

Despite the performance deterioration experienced at magnifications exceeding five times, this issue was mitigated by the inclusion of random rotation. Tests E and H demonstrated improved performance when random rotation was applied, resulting in a reduction in loss by approximately 0.01 (1%). Moreover, this random rotation, which exhibits a bias towards orthogonal arrangements, serves to prevent biased learning and overfitting by encouraging the VAE to learn various configurations of urban patterns.

Building upon these results, a combination of transformations was determined to minimize padding arising from random rotation and to achieve appropriate scaling, as illustrated in Figure 5.11. Initially, the original data of 2000 px is resized to 850 px for scaling. Subsequently, random rotation is applied, wherein an arbitrary angle ranging from -15 degrees to 15 degrees is newly specified each time. As the image rotates according to this angle, it is then cropped to 600 px using Center Crop, and ultimately resized to 256 px, transforming it into the data used for training.

5.3 Clustering

Clustering is creating distinct groups, known as clusters, by extracting morphological features through training a model with the curated dataset and determined transformations, and subsequently classifying these features. To select a suitable model for this task, an initial experiment is conducted. Similar to the data transformation test, a model based on VAE is employed as it allows for qualitative evaluation of the model's performance by examining the reconstruction in conjunction with feature extraction. Based on the loss and reconstruction data, a VAE model is selected and trained for the actual feature extraction process.

Subsequently, the entire dataset is fed into the trained model to extract latent vectors, which are the outputs of the encoder. These vectors are then subjected to clustering, enabling the grouping of urban form data based on their arrangement and configuration. Each group is considered an urban type, representing a distinct categorization of the urban forms present in the dataset.

5.3.1 Model Selection

Six different version of VAE models were tested to select a proper model for this analysis, namely VAE, β-VAE [131], disentangled β-VAE [131], IntroVAE [132], Joint VAE [133], and VQ-VAE2 [134]. β-VAE extends the basic VAE by introducing a hyperparameter called β which controls the trade-off between the reconstruction accuracy and the disentanglement of latent factors. By increasing β, the model is encouraged to learn more disentangled representations. Higher values of βtend to result in more compact and interpretable latent representations, but at the cost of potentially reduced reconstruction quality. β-VAE allows researchers to explore the disentanglement of factors in the learned latent space[13].

[13] A topological space where the latent vectors extracted from the encoder of VAE can be placed. The dimension of a latent space is same as the dimension of the latent vector.

Disentangled β-VAE is an extension of β-VAE that places additional emphasis on learning disentangled representations. It encourages the encoder to map each dimension of the latent space to a specific and independent factor in the data generation process. This disentanglement property can be useful for downstream tasks like data generation, manipulation, and understanding. Disentangled β-VAE achieves disentanglement by adding an additional term to the loss function that encourages independence between the dimensions of the latent space.

IntroVAE is a hybrid model of VAE and Generative Adversarial Network (GAN) [14]. Taking the advantage of both VAE and GAN, we employed a hybrid model—IntroVAE [132]—which consists of an encoder and generator. Capturing data features, the encoder compresses a given data sample and expresses it as a latent vector. Like a decoder, the generator reconstructs the latent vector back to the original data, but it also has a random sampling process as in the GAN generator. The sampling process can diversify training of the encoder, increasing detail in reconstruction. In addition to performing adversarial learning like GANs, the inference and generator models are jointly trained for the given training data to preserve the advantages of VAEs [132], such as not having the need to train a heavy model, the discriminator.

Joint VAE and VQ-VAE2 involve discrete representation. JointVAE assumes that the data can be decomposed into a combination of continuous factors such as pose and lighting and discrete factors like object identity or style. The continuous latent variables capture the continuous variations in the data and are typically modeled as multivariate Gaussian distributions. The discrete latent variables represent the categorical factors and are modeled using a categorical distribution. JointVAE encourages the learned representations to be disentangled and factorized. It achieves this by explicitly maximizing the mutual information

[14]GAN is another generative deep learning model which consists of two networks: the generator and discriminator. The generator maps the captured features of the training data to data space—generating a random data sample—while the discriminator distinguishes whether the input sample is real or fake data by evaluating how similar the sample is to real data. According [135], "the GAN objective is to find the binary classifier that gives the best possible discrimination between true and generated data and simultaneously encouraging the generator to fit the true data distribution."

between the latent variables and the observed data. The mutual information measures the statistical dependence between the latent variables and the data, and maximizing it helps ensure that each latent variable captures an independent factor of variation. It has been used in various domains, such as image generation, style transfer, and data augmentation.

VQ-VAE2 is a model that combines VAE with vector quantization to learn discrete representations of data. Like typical VAE, VQ-VAE2's encoder maps the input data to a continuous latent space representation. Then, the continuous latent space is replaced with a discrete latent space through vector quantization. The discrete latent space is composed of a finite set of learnable embeddings or codebook entries. During training, the encoder maps the input data to the nearest codebook entry, quantizing the continuous latent representation. The decoder then reconstructs the input data based on the quantized latent representation and the codebook entries. VQ-VAE2 has been applied successfully in domains like image synthesis, speech recognition, and video modeling.

Given the scale of the urban form dataset, a representative subset was employed to assess the performance of each model. Specifically, a random selection of 9000 training samples and 1000 validation samples was extracted from the entire dataset and utilized for training. The assessment process involved measuring the loss metric and examining the quality of reconstruction, like the approach employed during the transformation test with the following hardware configuration: an Intel(R) Core(TM) i9-10900x CPU operating at 3.70GHz, 256GB of DDR4 RAM, and an RTX A6000 48GB GPU.

Figure 5.12 illustrates the results of the training different VAEs. Notably, VQ-VAE2 exhibits the smallest loss and achieves crisp reconstruction quality. This exceptional accuracy can be attributed to the distinctive characteristic of VQ-VAE2, whereby the latent codes are represented as arrays through vector quantization rather than vectors as observed in other VAE models. This array-based representation enables the inclusion of more intricate and detailed information within the latent code. Furthermore, it is evident that the reconstructions produced by VAEs without the discretization process appear relatively

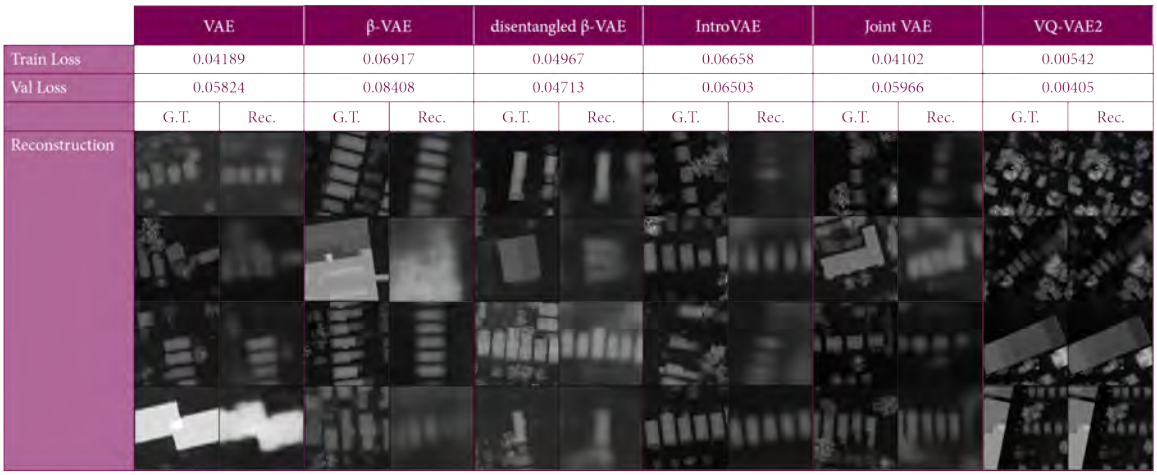


Figure 5.12: Comparative results of data reconstruction from various VAE models

more blurred. Additionally, the reconstructions generated by disentangled β-VAE, Joint VAE, and IntroVAE show instances where a single building is reconstructed as multiple disjointed structures. This suggests that the learning process encountered a prevalence of similar buildings arranged in specific patterns.

Based on these findings, the next step involves extracting latent codes for the entire urban form dataset following the training of VQ-VAE2.

5.3.2 Training

Out of the total dataset comprising 371,473 samples, 5,000 samples were allocated for validation, 1,000 samples for testing, and the remaining 366,473 samples were utilized for training. Considering the consistent emergence of a specific pattern observed in the preceding data transformation and model selection stages, the actual training process incorporates an expanded range of random rotation, spanning from -15 degrees to 15 degrees and further extending to -45 degrees to 45 degrees. Moreover, the dataset is augmented by creating mirror images through vertical and horizontal flipping, effectively providing a fourfold increase in the volume of training data.

The urban form dataset can be effectively processed using a single channel (grayscale) representation. Therefore, a VQ-VAE2 model with the following specifications is em-

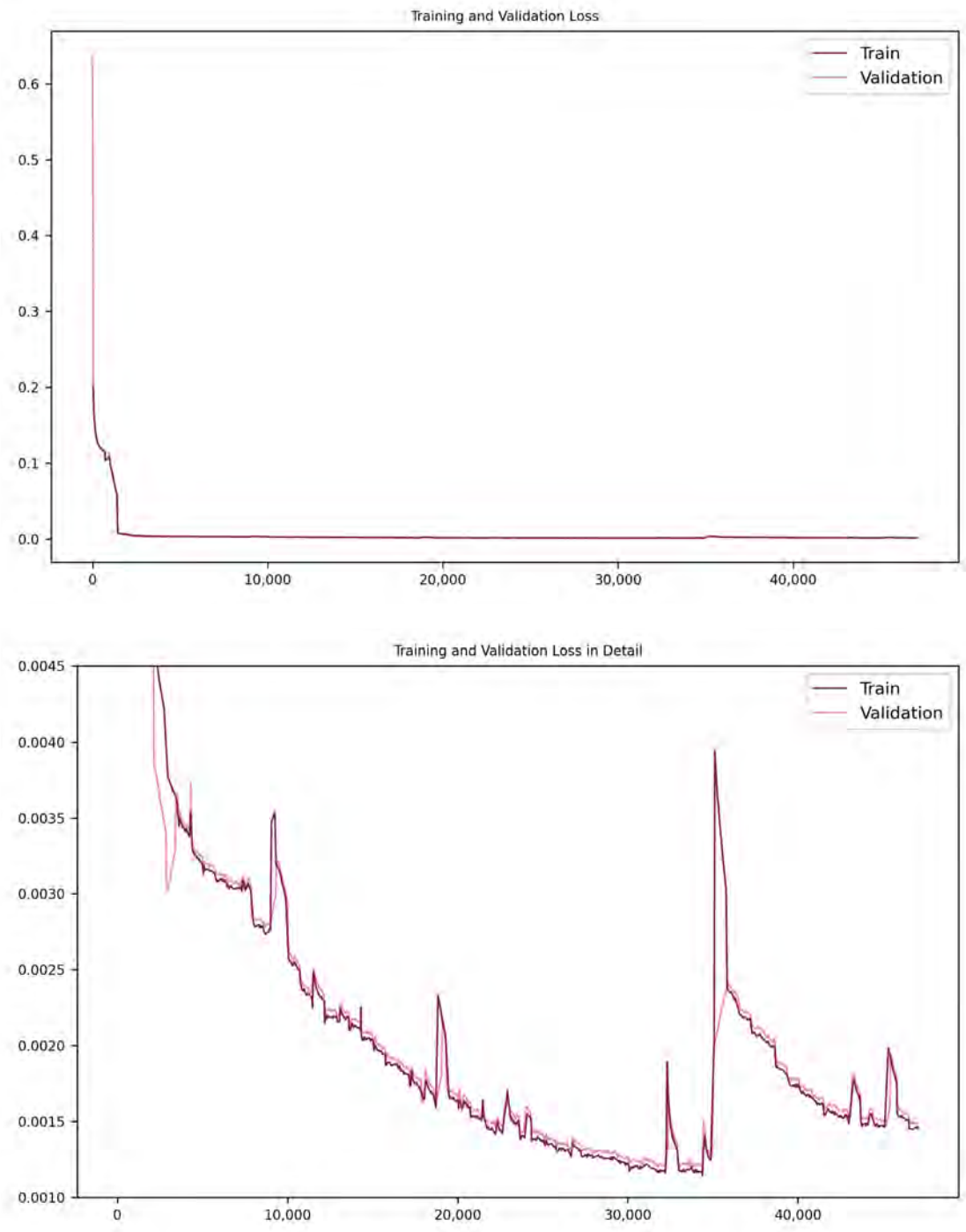


Figure 5.13: Entire (top) and detailed (bottom) graphs of training and validation loss

ployed: the encoder has 1 input channel and 128 output channels, incorporating 2 residual blocks with 32 channels each. The embedded dimension of the latent code is set to 64, and the quantization embedding size is 512. The learning process adopts a learning rate of

3e-4 with a cycle scheduler, a batch size of 512, and a total of 65 epochs. Training on the aforementioned machine, identical to the one utilized in the model selection phase, took approximately 22 hours to complete the training.

Figure 5.13 illustrates the training results, showcasing the progression of train and validation losses. The X-axis represents the iterations, with each iteration encompassing the learning of one batch, where the entire dataset is divided into batches. Approximately 715 iterations correspond to one epoch. The Y-axis represents the loss magnitude. A significant reduction in loss occurs initially, up until around 1450 iterations, indicating early convergence. Subsequently, the loss demonstrates a gradual decline with at the scale of 0.001. However, there is a subsequent notable increase in loss followed by convergence at approximately 0.00145.

This change in convergence is also observed in the quality of reconstruction. Figure 5.14 (see Appendix D for detailed information) displays the reconstructed images of the test data at different iterations. The first and second row of the images in each iteration represents the ground truth and reconstruction respectively. Initially, faint shapes begin to emerge around 850 iterations, and from 950 iterations onwards, the forms in the reconstructions become more distinguishable. Around 1150 iterations, detailed patterns start to manifest alongside the forms, and at approximately 1350 iterations, a blurry yet overall high-quality reconstruction is achieved. Subsequently, the reconstruction details continue to develop with increasing clarity.

Considering the relatively small difference between the train loss and validation loss and the satisfactory reconstruction of images, it can be concluded that the learning process has been successful.

5.3.3 Clustering

The trained model captures latent vectors, which shape is (294908, 64, 64), representing the features of the urban form dataset from the selected four cities. These vectors are

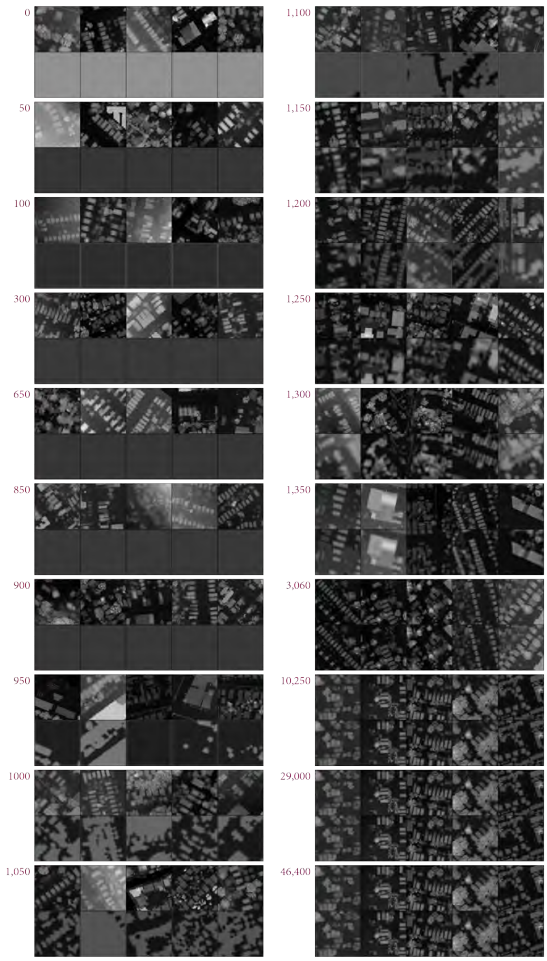


Figure 5.14: Reconstructed images of the validation data at different iterations of training

subsequently flattened into (294908, 4096) vectors for further analysis. K-Means clustering is then applied to this flattened vector space. Previous studies [90, 114] employed density-based clustering [136] after reducing the dimensionality to 2 or 3 dimensions using t-SNE [137]. However, due to the substantial size of the current dataset, which is four to five times larger than those in previous studies, technical limitations arise when using t-SNE. Specifically, inferring a consistent distribution for the data by experimenting with various parameters in t-SNE becomes impractical and technically infeasible for such a vast amount of latent vectors. As a result, in this clustering analysis, I employ K-Means clustering, which is one of the most widely used clustering methods.

K-Means clustering is an unsupervised machine learning algorithm that aims to group

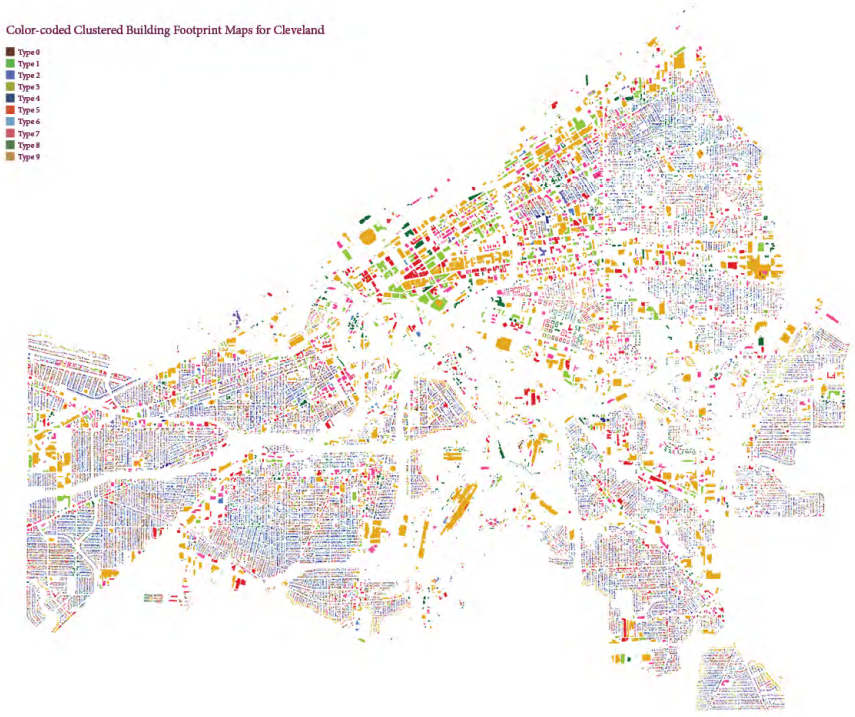
similar data points into K distinct clusters. It starts by randomly initializing K cluster centroids and assigns each data point to the nearest centroid. The centroids are then updated iteratively by calculating the mean of the data points within each cluster. The algorithm converges when the centroids no longer change significantly. K-Means clustering seeks to minimize the within-cluster sum of squares, and the number of clusters, K, needs to be specified. K-Means clustering is widely used in various fields for tasks such as customer segmentation, image compression, document clustering, and anomaly detection.

Within the realm of K-Means clustering, the number of clusters (N) serves as a crucial parameter. By specifying N, K-Means classifies the entire dataset into N groups. Increasing N creates a larger number of distinct groups, while decreasing N reduces the number of groups. Considering that this case study aims to investigate different types of urban spaces, excessively large numbers of clusters complicate the analysis, while a limited number of clusters undermines the meaningfulness of the analysis. Therefore, assuming there are approximately ten urban form types within each city, I set N to 10[15].

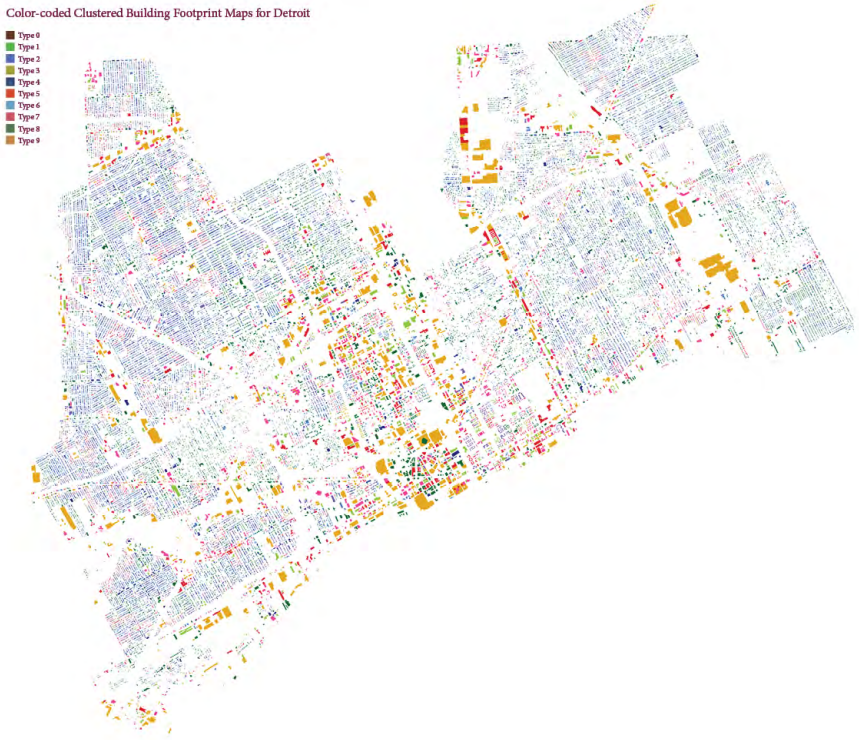
The results of this clustering analysis can be projected onto a map displaying the geographical space, providing insights into the types of urban spaces associated with each building in the city [138]. Figure 5.14 showcases the mapping results for the four cities (see Appendix E for detailed information). These maps not only illustrate the morphological characteristics of individual buildings but also highlight the morphological relationships between building forms and their surrounding urban spaces. Consequently, buildings of the same color may exhibit similarities in terms of their architectural forms, but their primary commonalities lie in the characteristics of the neighboring urban spaces.

This chapter presents a case study that explores the feasibility of applying the proposed alternative research framework, employing an inductive approach, to actual cities. By departing from conventional cartographic conventions, this framework enables compar-

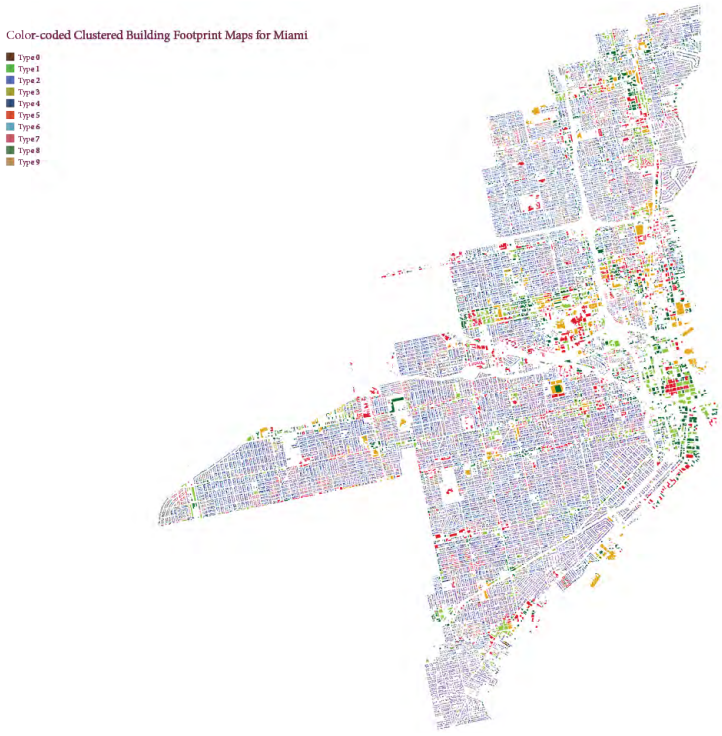
[15] A practical reason exists for determining the number used in K-means clustering, which involves considering the capacity of RAM available. This consideration ensures the clustering process remains feasible within the hardware's limitations.



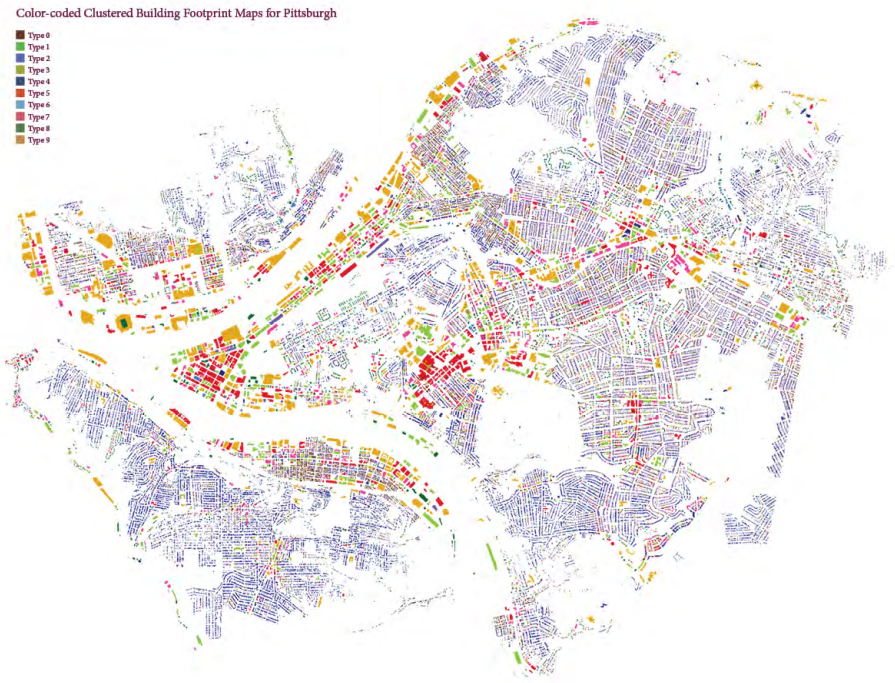
(a) Clustering results projected onto building footprint map: Cleveland



(b) Clustering results projected onto building footprint map: Detroit



(c) Clustering results projected onto building footprint map: Miami



(d) Clustering results projected onto building footprint map: Pittsburgh

Figure 5.14: Color-coded clustered building footprint maps for the four cities. See Appendix E for more details.

ative analysis across geographically and physically distinct cities. Thereby, a case study is proposed to analyze the urban form of four cities, comprising three cities with similar urban cultures and one city anticipated to possess a distinctly different urban culture.

This case study encompasses five steps. The first step, Form Data Curation, involves the collection and preprocessing of data to construct an urban form dataset. The second step, Feature Processing, focuses on extracting morphological features from this dataset and classifying them into different types. The third step, Characteristics Analysis, encompasses an analysis of the characteristics of each type to understand their distribution within a specific city. In the Evaluation step, the effectiveness of this analysis will be assessed. Lastly, the Knowledge step is deriving new insights into urban space through these processes.

In this chapter, the first two steps, Form Data Curation and Feature Processing, are covered. A novel urban form dataset is curated through the collection of standardized raw data and data composition and formatting, focused on the application of an inductive approach. Throughout this process, various transformations necessary for this dataset are experimentally explored. Different combinations of extents and transformation functions are applied to a deep learning model called VAE, which comprises encoders and decoders. The quantitative assessment relies on loss metrics, while the qualitative assessment is based on reconstruction data. Through these experiments, it is revealed that an extent of approximately 750 ft can effectively represent the balanced relationship between buildings and neighboring urban spaces within deep learning. Additionally, it is observed that transformations such as random rotation and flipping are essential for mitigating the bias resulting from overfitting to specific extents and transformations.

Following the transformation selection through the abovementioned experimentation, the performance of six different VAE models is evaluated, ultimately selecting VQ-VAE2 as the final deep learning model due to its exceptional performance. This model is trained using approximately 375,000 data points. The VQ-VAE encoder learns to capture mor-

phological features from input urban form data, while the decoder learns to reconstruct urban form data based on these features. Consequently, by inputting the urban form data of the four cities into the encoder, latent vectors representing morphological features are extracted, and clustering these vectors enables the classification of ten urban form types.

In contrast to previous studies that employed dimensionality reduction and density-based clustering techniques, clustering in this research directly utilizes the latent vectors without dimensionality reduction, employing K-Means clustering. This choice is primarily driven by practical and technical considerations, as reducing the dimensionality of a dataset with over 350,000 samples is technically infeasible. Future research can explore the impact of dimensionality reduction and the sole use of K-Means clustering, provided there are advancements in hardware and software. The resulting clusters represent urban form types, which are subsequently visualized onto map space to illustrate the urban spaces associated with each city. This mapping from the data space to the geographical space allows for an examination of the spatial and morphological characteristics of each urban space. Therefore, in the subsequent chapter, the characteristics and distribution of these urban form types are further analyzed to gain insights into the spatial and morphological attributes of urban spaces.

CHAPTER 6

RESULTS

In the preceding chapter, I employed a deep learning-based approach to derive ten distinct urban form types. Henceforth, I'll refer to these classifications as "Urban Type," emphasizing that urban form transcends mere building forms; it includes neighboring urban spaces of a building, making these types reflect the characteristics of these adjacent urban areas. This chapter delves into an analysis of the characteristics of each urban type. The analysis encompasses quantitative aspects such as average height, average area, and occurrence frequencies for each type. Moreover, the concept of representative form is harnessed to explore the spatial composition and characteristics of these types qualitatively. In a supplementary dimension, the VQ-VAE model is leveraged to extract data features, subsequently subjected to visual analysis to enrich and contrast the outcomes of other analyses. The synthesis of these diverse analyses leads to the articulation of distinctive attributes characterizing each type, ultimately giving rise to an Urban Type taxonomy.

Furthermore, an urban fabric map is constructed, visually elucidating the distribution and configuration of various types within specific locales by incorporating type information embedded in building footprints. Parallelly, the concept of "granularity," which quantifies the diversity of urban types within a designated spatial unit, is introduced, yielding granularity maps. These comprehensive assets, ranging from the Urban Type taxonomy, urban type maps delineated by building footprints, urban fabric maps, to granularity maps, undergo thorough investigation. This multifaceted analysis facilitated an in-depth understanding of fabric distribution and inherent characteristics intrinsic to each city. Drawing from the outcomes of this analysis, a distinct fabric configuration is unveiled across the three Rust Belt cities, in contrast to the urban structure evident in Miami.

6.1 Characteristics of Urban Type

To gain insights into the characteristics of urban form types, a starting point involves examining and analyzing their fundamental statistical attributes. In pursuit of this objective, I investigate the average footprint area and average building heights constituting urban form types, thereby conducting a comparative analysis of the scale relationships between urban form types and their corresponding buildings. Furthermore, I explore the quantity of each type present in each city, enabling an examination of occurrence patterns among types within specific cities.

Firstly, regarding the area, notable points include the following (for more details, please refer to the Appendix F).

- Type 0 and 2 are categorized as medium-sized buildings, with Miami and Pittsburgh showcasing larger average areas compared to Cleveland and Detroit.
- Type 1, 3, and 5 represent smaller structures, with Cleveland showing the highest average areas, indicating uniformity in the scale of these types across the cities.
- Type 4 is distinguished by significantly larger structures, indicating monumental buildings, with Detroit and Miami presenting about 1.45 times larger dimensions than the other cities.
- Types 6 and 7 are noted for medium-sized buildings, with Miami showing a notably larger average area for Type 6.
- Type 8 and 9 denote small to medium-sized and the smallest category of structures, respectively, showcasing modest variances across cities.

The analysis groups the ten urban types into three categories: small buildings (Types 1, 3, 5, 8, and 9), medium-sized buildings (Types 0, 2, 6, and 7), and large buildings (Type 4), highlighting significant differences in average area and urban significance.

Secondly, regarding the height, notable points include the following (for more details, please refer to the Appendix G).

- Buildings in Types 0, 2, 4, and 7 are generally 3 to 5 stories, except in Miami.
- Types 1, 3, 5, and 8 mainly feature 2 to 3-story buildings, with Miami presenting lower heights.
- Miami's buildings often have 1 to 2 stories, diverging from the other cities, except for Type 6, which showcases significant height variations, including high-rises in Miami and Pittsburgh.
- Type 9 is distinct for encompassing one-story buildings across all cities, identifying it as a separate group based on height.

The analysis categorizes urban buildings into distinct groups based on height: Types 0, 2, 4, and 7 as mid-rise (3 to 5 stories) structures excluding Miami, Types 1, 3, 5, and 8 as low-rise (2 to 3 stories) buildings again excluding Miami, and Type 9 as uniformly one-story buildings across all cities. Miami's architecture is notably lower (1 to 2 stories) except for Type 6, which stands out as a group of high-rise buildings (20 to 30 floors) in Miami and Pittsburgh, emphasizing the city's unique urban profile.

Lastly, in terms of the quantity of each type present in each city, notable findings include the following (for more details, please refer to the Appendix H).

- In Cleveland, Type 8 is the most prevalent, followed by Types 1 and 9. Types 4 and 6 are less common, and Type 7 is the least prevalent.
- Detroit's distribution shows Type 6 as the most dominant, with an occurrence of 18,936, followed by Types 3 and 5. Types 8 and 9 are less common, with Type 2 and Type 4 being the least prevalent.
- In Miami, Types 1 and 9 have the highest occurrences, with Type 4 being the least common. Type 6 also shows significantly lower occurrences compared to other cities.

- Pittsburgh exhibits high occurrences of Types 1 and 3, with Types 0, 2, 4, and 7 being relatively less common.
- Detroit has a notably higher occurrence of Type 6 compared to other cities, suggesting a unique architectural emphasis.
- There's a conspicuous scarcity of Type 9 in Detroit, suggesting a lack of smaller one-story structures compared to other cities.
- Miami shows a distinct scarcity of Type 4, indicating a lower number of larger structures (4 to 5 stories) compared to other cities.
- Cleveland has a significant abundance of Type 8, indicating a unique urban spatial composition.
- Cleveland also exhibits relatively higher occurrences of Types 0 and 2, suggesting an abundant distribution of urban spaces surrounding medium-sized buildings.

In summary, a quantitative analysis of the area and height of building types, coupled with their occurrences in each city, sheds light on the prevalence of various urban spaces centered around specific types of buildings. However, it should be noted that such quantitative analysis has its limitations, as qualitative aspects such as the conspicuous occurrences of Type 6 and 8 in specific cities, or relationships between Type 9 and Types 1, 3, and 5, may not be fully understood. Therefore, another investigation into the qualitative attributes of urban spaces in each city will provide a more accurate understanding of the distinctive characteristics of each type.

6.2 Representative Forms

Figure 6.1 depicts random sampling data of urban types across four cities, comprising 25 samples each. As inferred from quantitative analyses, Urban Types 0, 2, 6, and 7 exhibit

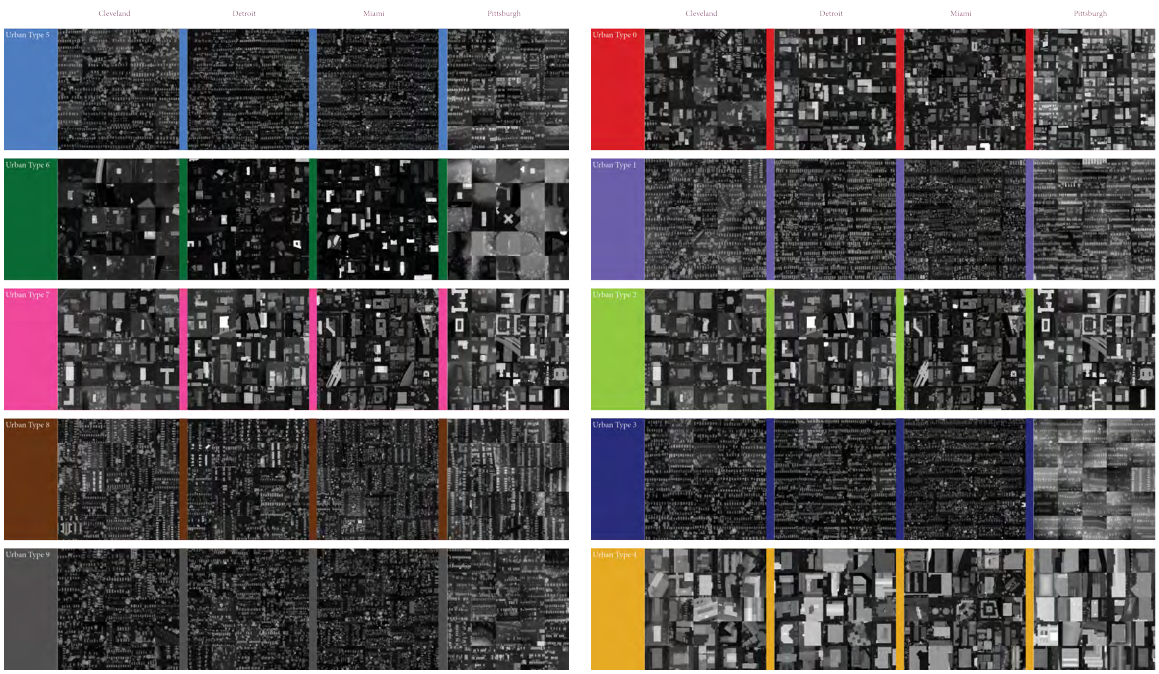


Figure 6.1: Random sampling data of urban types across the four cities. See Appendix I for more detailed figures.

resemblances in terms of mid-sized building dimensions. Within Urban Type 0, there exists a recurring presence of mid-sized buildings that pervade the urban expanse. Conversely, Urban Type 2 manifests as an external domain encompassing solitary medium-sized buildings. In contrast to Urban Types 0, 2, and 7, Urban Type 6 demonstrates a propensity for substantiating a notably expansive encompassing void. In the context of Urban Type 7, small buildings conspicuously adorn the vicinity of substantial edifices with notable frequency.

Types 1, 3, 5, 8, and 9 can similarly be classified on account of their comparable scale. These types coalesce to forge an urban space comprised of small buildings, mostly symmetrically arrayed in linear alignment. Furthermore, it is duly substantiated that Type 4 defines an urban space centered on substantial edifices of considerable magnitude in contrast to Types 0, 2, 6, and 7.

However, it is imperative to acknowledge that the present sampling methodology imposes certain constraints upon the exhaustive appraisal of the qualitative attributes dis-

tinctive to each Urban Type; based on the sampled data, it is challenging to describe the representative qualitative characteristics of each Urban Type due to the stochastic nature of the data selection. Hence, I devise a 'representative form' that can encapsulate the spatial configuration of each Type. To determine representative forms for each type, the latent vectors extracted by the VQ-VAE model's encoder are employed as morphological features. The representative form closely approximates the mean morphological attributes for each type, thus serving as a qualitative descriptor of their morphological traits. A meticulous examination of the representative form alongside sampled instances aids in a more comprehensive analysis of each type's spatial traits.

Urban Type 0 predominantly features mid-sized buildings, often grouped in configurations of 4-5 buildings of similar scale (Figure 6.2). Such clusters may exhibit linear arrangements along thoroughfares or form compact clusters. These spaces primarily comprise the interstices between these clusters and their immediate surroundings. Downtown mid-rise edifices or commercial buildings within retail or office districts exemplify this type.

Urban Type 1 manifests as a composition wherein a prevailing 2-row or 3-row horizontal alignment, predominantly constituted by rectangularly-shaped houses, comes to the fore. The buildings organizations, akin to dwellings, stretch in a contiguous manner along the thoroughfare (Figure 6.3). With these linear arrangements recurring in succession, an long urban space unfolds. Upon casual observation arboreal elements within this area attenuate the coherent linearity of this horizontal assemblage. Nonetheless, amidst the variations in arboreal attributes – their positions and dimensions – a steadfast tripartite horizontal arrangement perseveres unabated. Thereby, one can reasonably surmise that the preeminence of this linear residential configuration substantively distinguishes this typology within the overall urban patterns.

Such urban type could encompass locales of a suburban or habitation-oriented character. Specifically, buildings of this type in Miami tend towards a more elongated form.

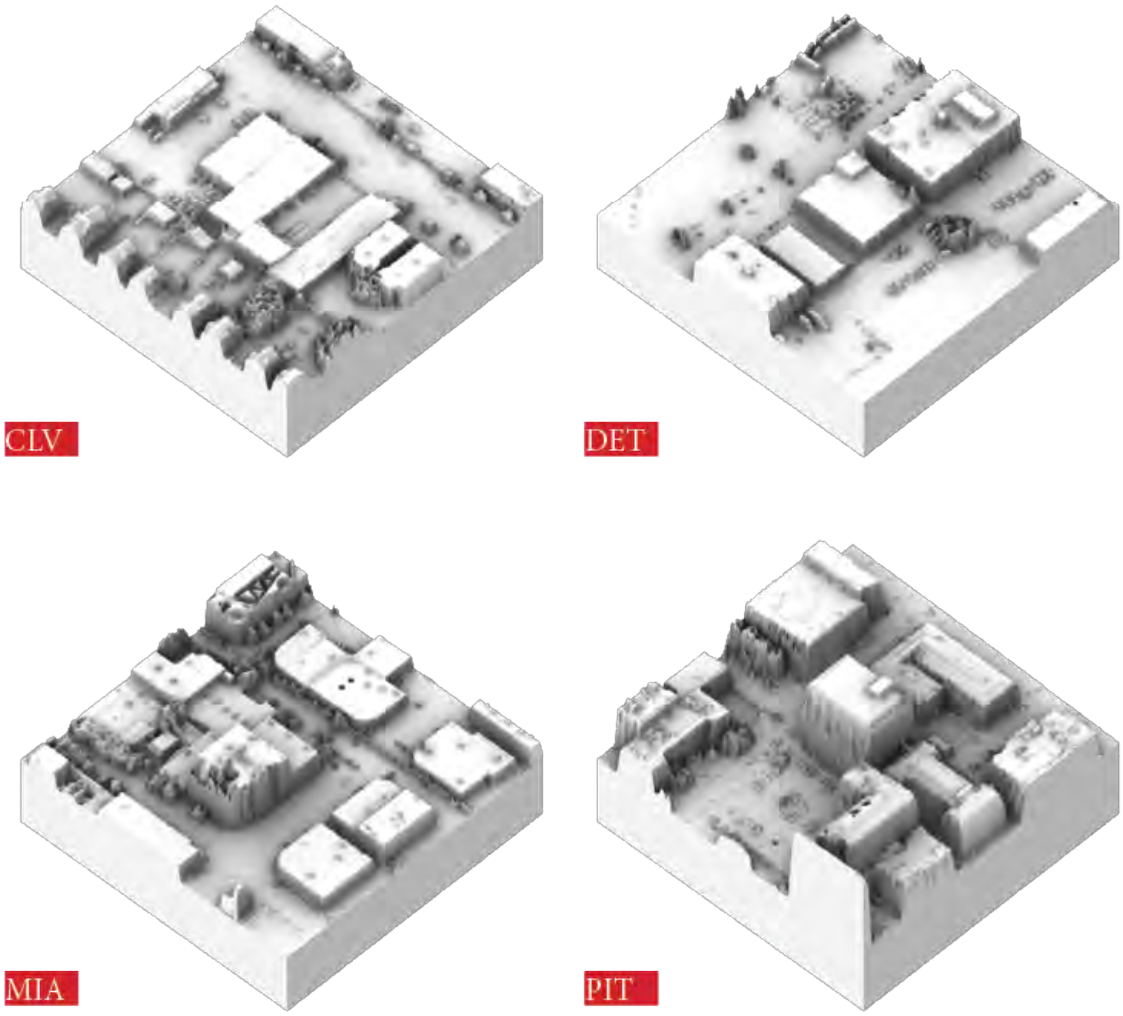


Figure 6.2: Representative forms of Urban Type 0

Further divergence can be observed in this type instances within the Rust Belt cities, characterized by pitched roofs and structures spanning 2 to 3 stories, juxtaposed against their Miami counterparts marked by flat roofs and modest 1 to 2 stories.

Urban Type 2 reveals slightly larger standalone buildings or structures, creating larger independent external spaces compared to Urban Type 0 (Figure 6.4). Whereas buildings in Urban Type 0 are lined up sharing walls or forms clusters with some interstices, Urban Type 2 encompasses standalone medium to large buildings that occupy land with some distance from neighboring buildings. Spaces around monumental buildings such as malls,

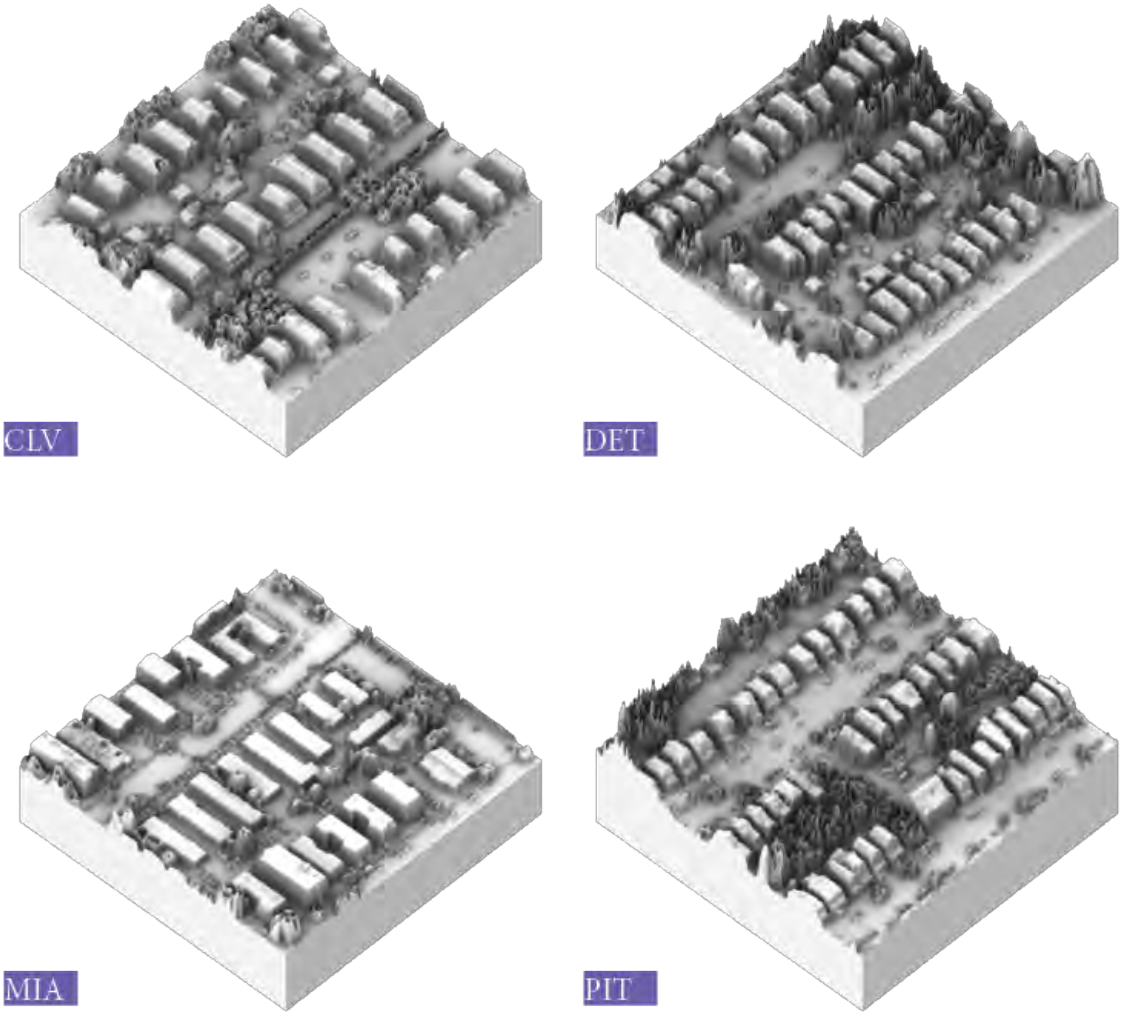


Figure 6.3: Representative forms of Urban Type 1

offices, and institutes align with this type. Notably, the urban form data's outskirts in Miami exhibit linear arrays of small buildings, akin to housing, within Urban Type 2, unlike Rust Belt cities where larger or medium-sized structures dominate.

Parallel to the characteristics of Urban Type 1, Urban Type 3 similarly manifests a configuration typified by a bipartite or tripartite horizontal alignment which predominantly composed of rectangular houses (Figure 6.5). Nonetheless, it is noteworthy that the dimensions of the houses in Urban Type 3, in general, tend to exhibit shallower depths in comparison to their counterparts in Urban Type 1. Furthermore, the interspacing between

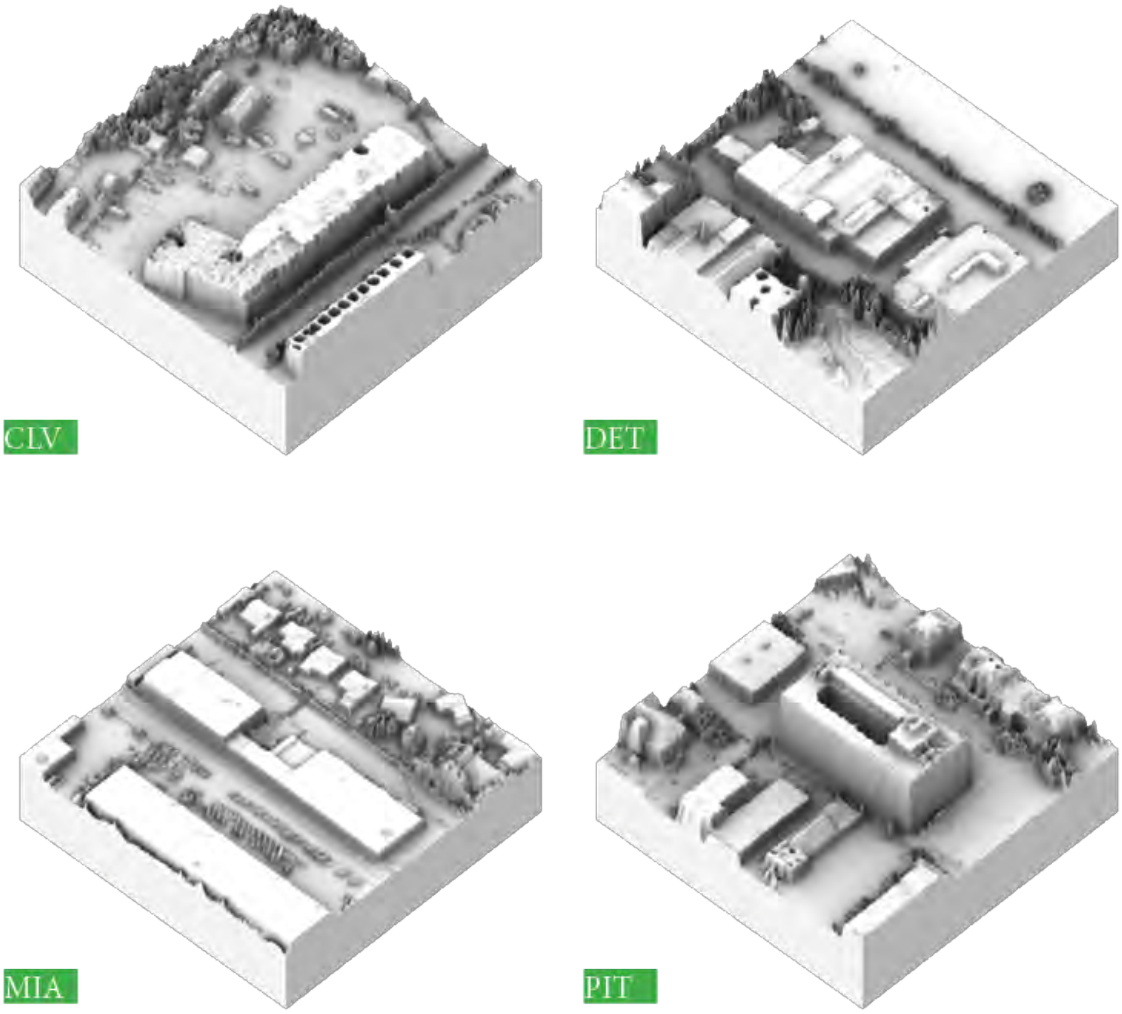


Figure 6.4: Representative forms of Urban Type 2

these residential rows is less uniform. For example, whereas the two interspace amid rows within Urban Type 1 assumed a consistent span of 100 ft, the two inter-row distance for Urban Type 3 would be as 60 ft and 100 ft respectively, leading to the recognition of a cohesive clustering of the two rows. Analogous to the observations concerning Urban Type 1, a dissimilarity is perceptible between height, depth, and roof shape of buildings in Miami and those found within the Rust Belt cities.

Furthermore, a salient aspect deserving attention pertains to the topographical attributes characterizing Urban Type 3 in Pittsburgh. While urban form pattern in the other

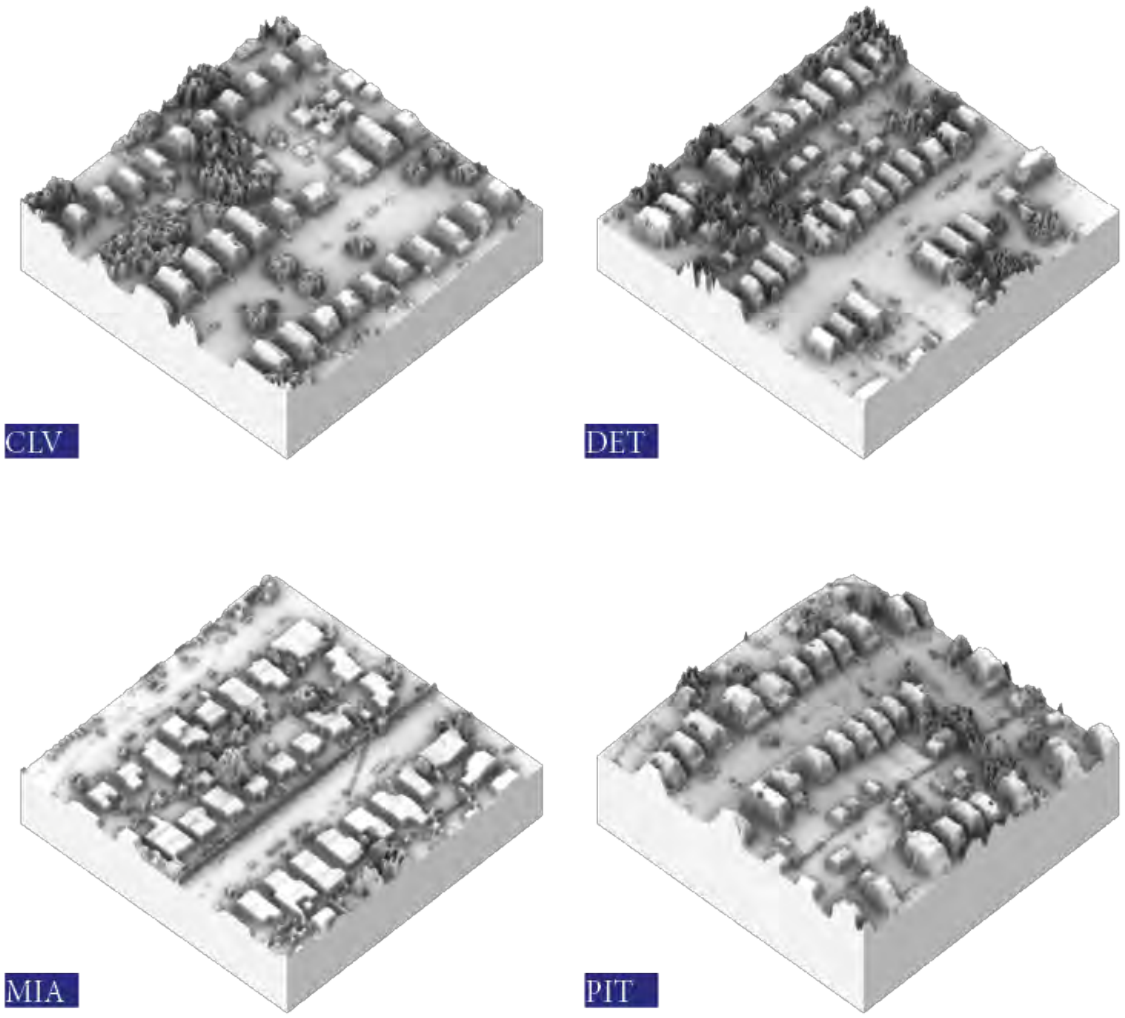


Figure 6.5: Representative forms of Urban Type 3

three cities manifests rows of residences intertwined with an unremarkable undulation of terrain, Urban Type 3 in Pittsburgh distinctly showcases a conspicuously steep alteration in topography. This observation gains reinforcement from the discernment that the set of 25 instances representing Pittsburgh's Urban Type 3 evince a distinctive luminosity of the ground, coupled with a discernible gradient – a phenomenon notably absent in Urban Type 3 instances in the other cities.

This conspicuous alteration in topography, manifesting particularly in Types 1, 5, and 8—all sharing analogous urban configurations—is manifested by a pronounced gradient.

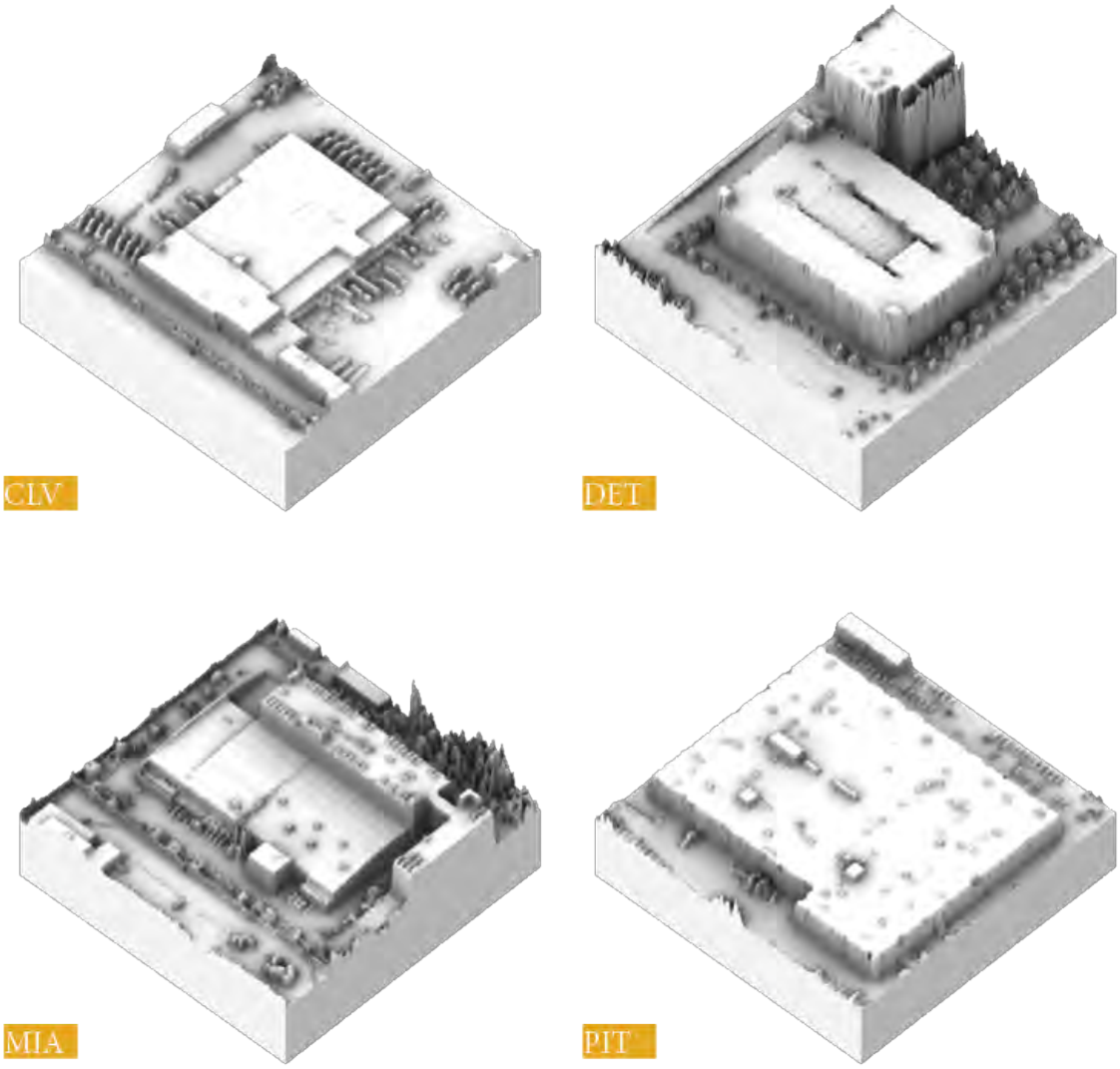


Figure 6.6: Representative forms of Urban Type 4

The term ”gradient” herein denotes the variation in land contour, wherein the color of the gradient shifts rapidly in tandem with substantial changes in slope encompassed within the dataset’s spectrum. While these topographic variations are outwardly observable as distinctive attributes, it is pertinent to acknowledge that their classification, akin to other datasets marked by marginal topographical variations during the processes of feature extraction and clustering, challenges the attribution of a pivotal impact. It is thereby plausible to assert that the arrangement of buildings assumes the morphological features that take precedence over the mutability of the topographical terrain.

Urban Type 4 comprises the surroundings of short and large edifices, with most of the urban form in the data extent occupied by buildings with marginal urban space (Figure 6.6). Upon examining 25 samples, it becomes evident that urban type 4, particularly in the context of Rust Belt cities, adeptly segregates into expansive edifices and their contiguous expanse. Upon examining 25 samples, it becomes evident that the categorization of Urban Type 4 within Rust Belt cities demonstrates a relatively robust proficiency in distinguishing substantial structures and their corresponding peripheries. However, in the Miami context, Urban Type 4 encompasses configurations that could be ascribed to either Urban Type 2—pertaining to the urban space characterized by clustered medium buildings—or Urban Type 4—pertaining to the urban space surrounding the independent medium-sized building.

Quantitatively speaking, the prevalence of expansive structures and their associated external urban space is conspicuous in Rust Belt cities, whereas the corresponding manifestations are notably scarce in Miami. This distinction is indicative of a plausible correlation with the substantial scale characterizing industrial establishments, such as mills and plant facilities, prevalent in Rust Belt cities.

Urban Type 5, akin to its counterparts in the form of Type 1 and 3, exhibits a prevailing disposition marked by a horizontal arrangement of two or three rows, mostly comprising rectangular-shaped houses (Figure 6.7). Nonetheless, it is notable that this type often showcases a less distinct pattern of horizontal arrangement compared to Type 1 and 3. In contrast to the coherent linear arrangement of houses characterizing Type 1 and 3, this type is distinguished by a relatively subdued pattern clarity, attributable to the presence of abundant greenery interspersed between houses. Further, the inclusion of structures beyond residential units, such as offices and retail establishments, further contributes to this type's diminished pattern discernibility. Moreover, this type also encompasses intersections characterized by both vertical and horizontal linear patterns.

Consequently, the nature of this urban typology suggests a spatial composition marked

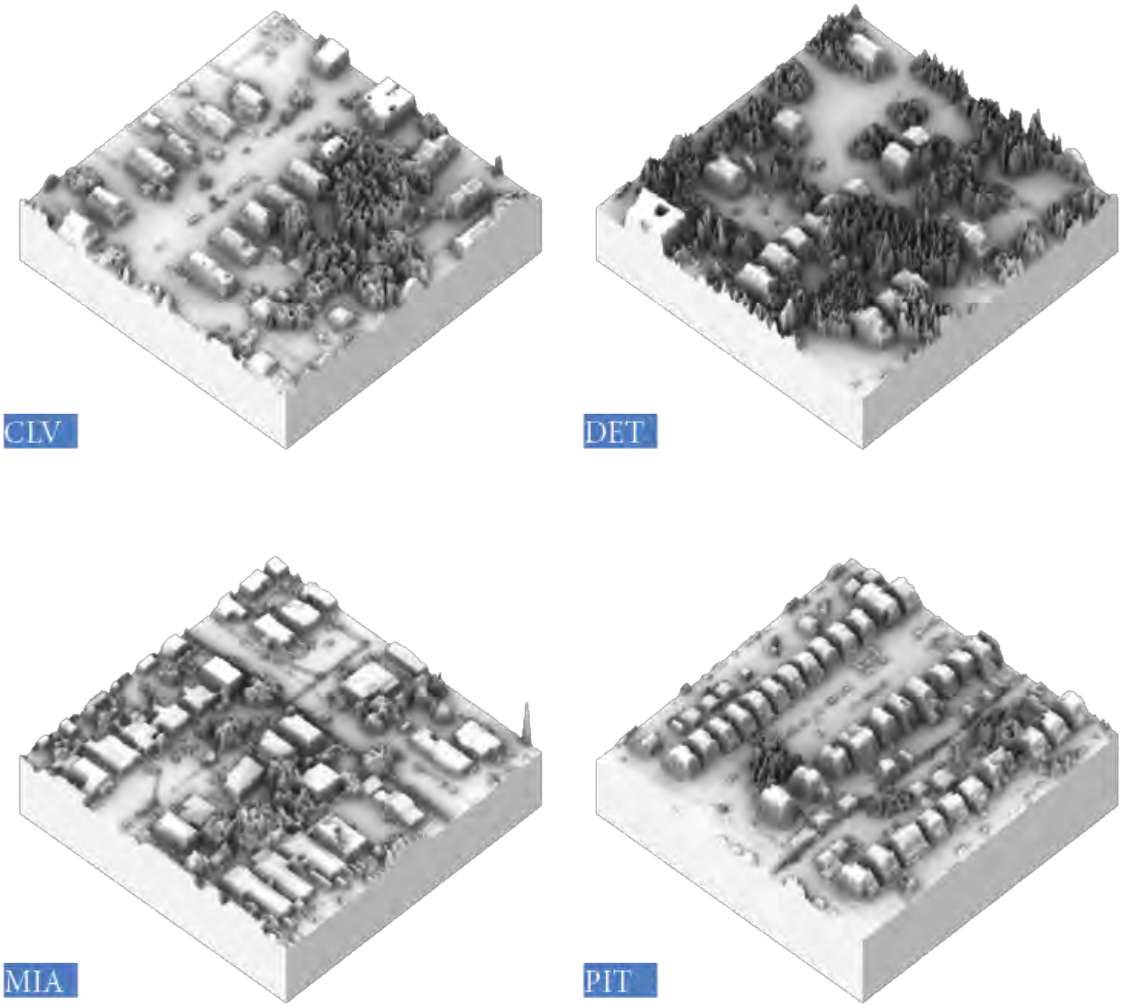


Figure 6.7: Representative forms of Urban Type 5

by subtle deviations within a linear urban configuration. Similar differentials among the four cities parallel those observed for Type 1 and 3. Specifically, Urban Type 5 in Miami predominantly comprises low-rise buildings of 1-2 stories, often featuring flat roofs. Conversely, the counterpart in Rust Belt cities mostly consists of 2-3 story residential buildings typified by sloped roofs, or alternatively, 3-4 story non-residential edifices.

Urban Type 6 is characterized by an expansive independent urban space enveloping a building of smaller scale than those belonging to Urban Type 2 (Figure 6.8). Although the presence of similar scale edifices surrounding these buildings is sparse, this type generally

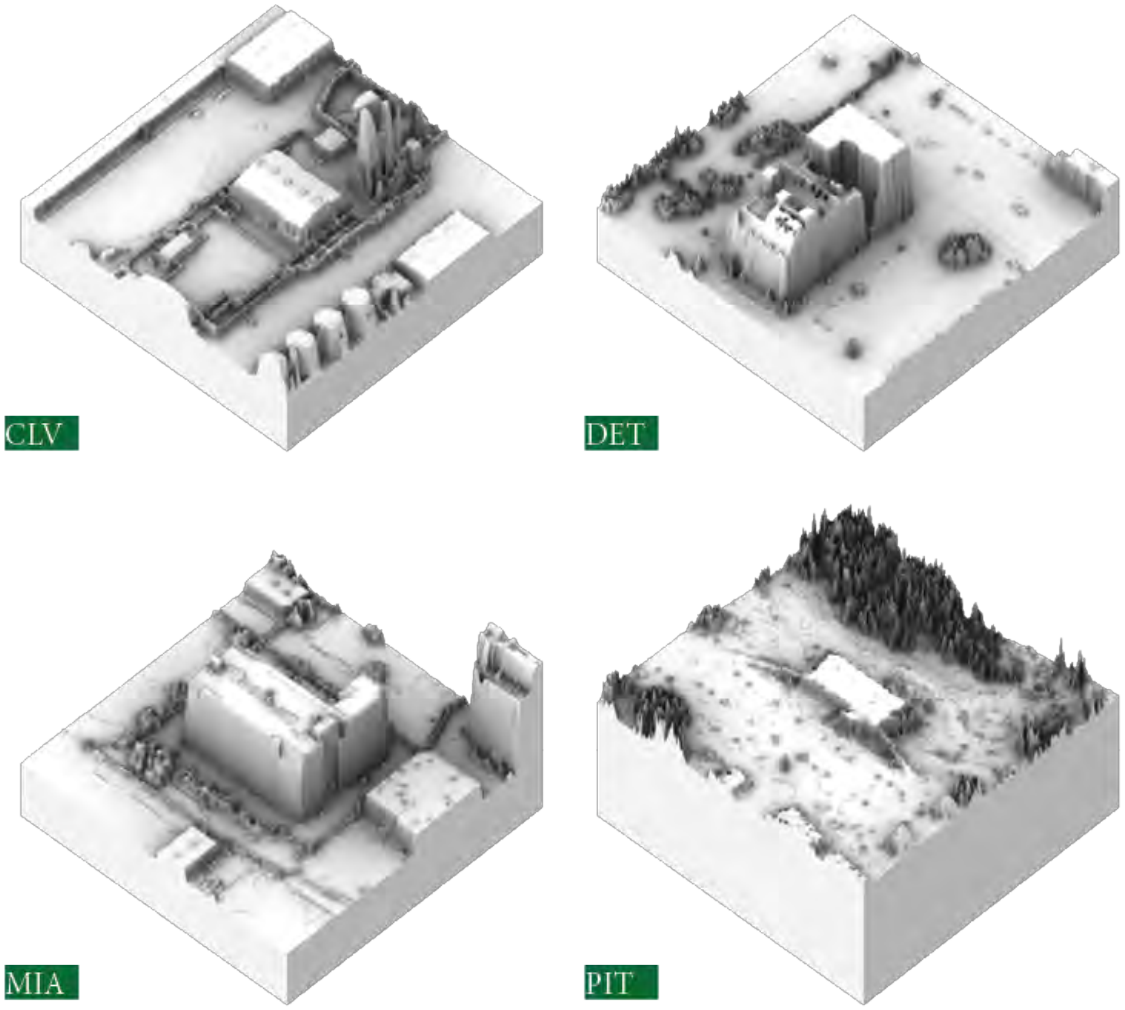


Figure 6.8: Representative forms of Urban Type 6

results in the solitary occupancy of the surrounding space by the focal building. This disposition is especially pronounced in instances where vast plots or urban areas encircle mid- to high-rise establishments, rendering them prime candidates for classification within this type. In Urban Type 6, it is observed that either the focal building is surrounded diminutive buildings cluster, or alternatively, the building itself exhibits markedly reduced scale. This observation substantiates the proposition that instances where the surroundings of Urban Type 0 or 2 buildings become vacant, thus transitioning from a collective configuration, engender the formation of independent external urban spaces qualifying as Urban Type 6.

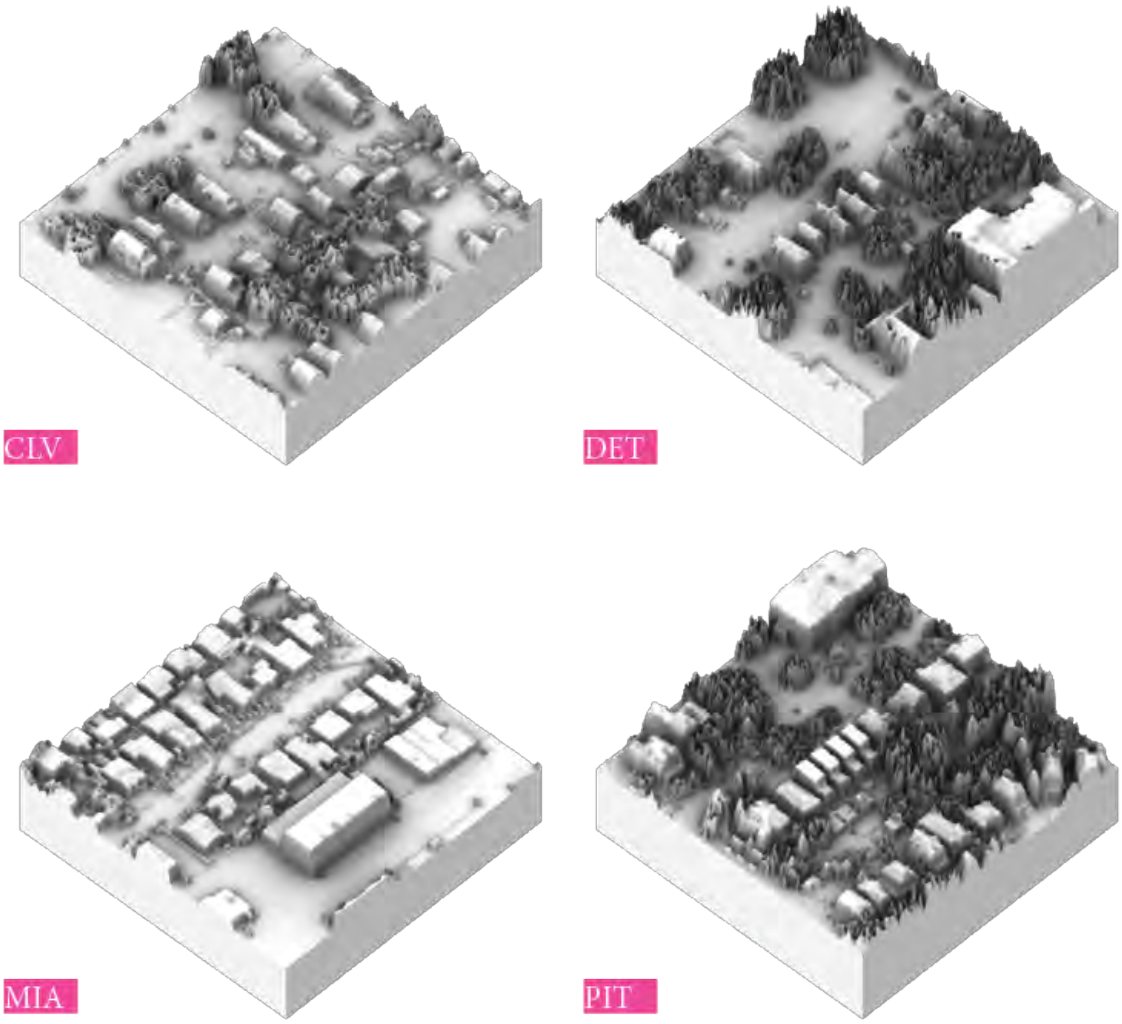


Figure 6.9: Representative forms of Urban Type 7

In line with this proposition and the scale of buildings, the pronounced prevalence of Urban Type 6 in Detroit is reasoned to be attributed to the abundance of buildings accompanied by substantial vacant lots in their proximate surroundings. On the contrary, the conspicuous rarity of Urban Type 6 occurrences in Miami can be ascribed to a significant proportion of these spatial compositions encompassing areas adjacent to independent mid- to high-rise edifices.

Within Urban Type 7, a confluence of medium to large structures and housing rows becomes apparent (Figure 6.9). Specifically, this type encapsulates a composite urban en-

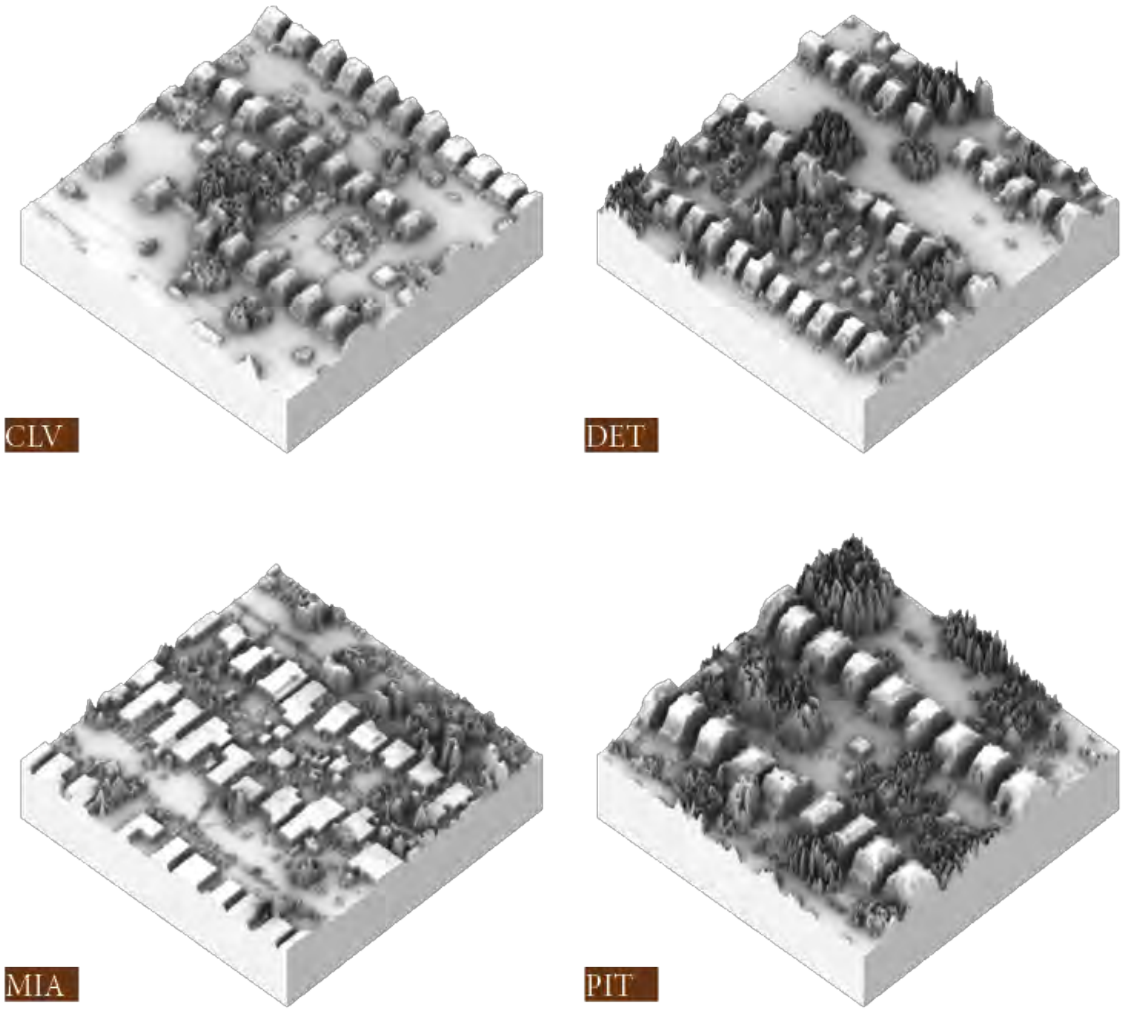


Figure 6.10: Representative forms of Urban Type 8

vironment encompassing traits akin to Types 2 and 6, alongside characteristics of Types 1, 3, and 5. It is noteworthy that within this type, residential amenities like churches, public offices, schools, and low- to mid-rise apartments frequently coexist with row houses. Thus, the urban spaces embraced by Urban Type 7 manifest a blend between linearly arranged urban configuration and spaces surrounding independent structures.

Urban Type 8 is characterized by a vertical arrangement of two or three columns, primarily comprising rectangular-shaped houses (Figure 6.10). While sharing overarching spatial traits with Type 1 and 3, the orientation of this arrangement is defined along the

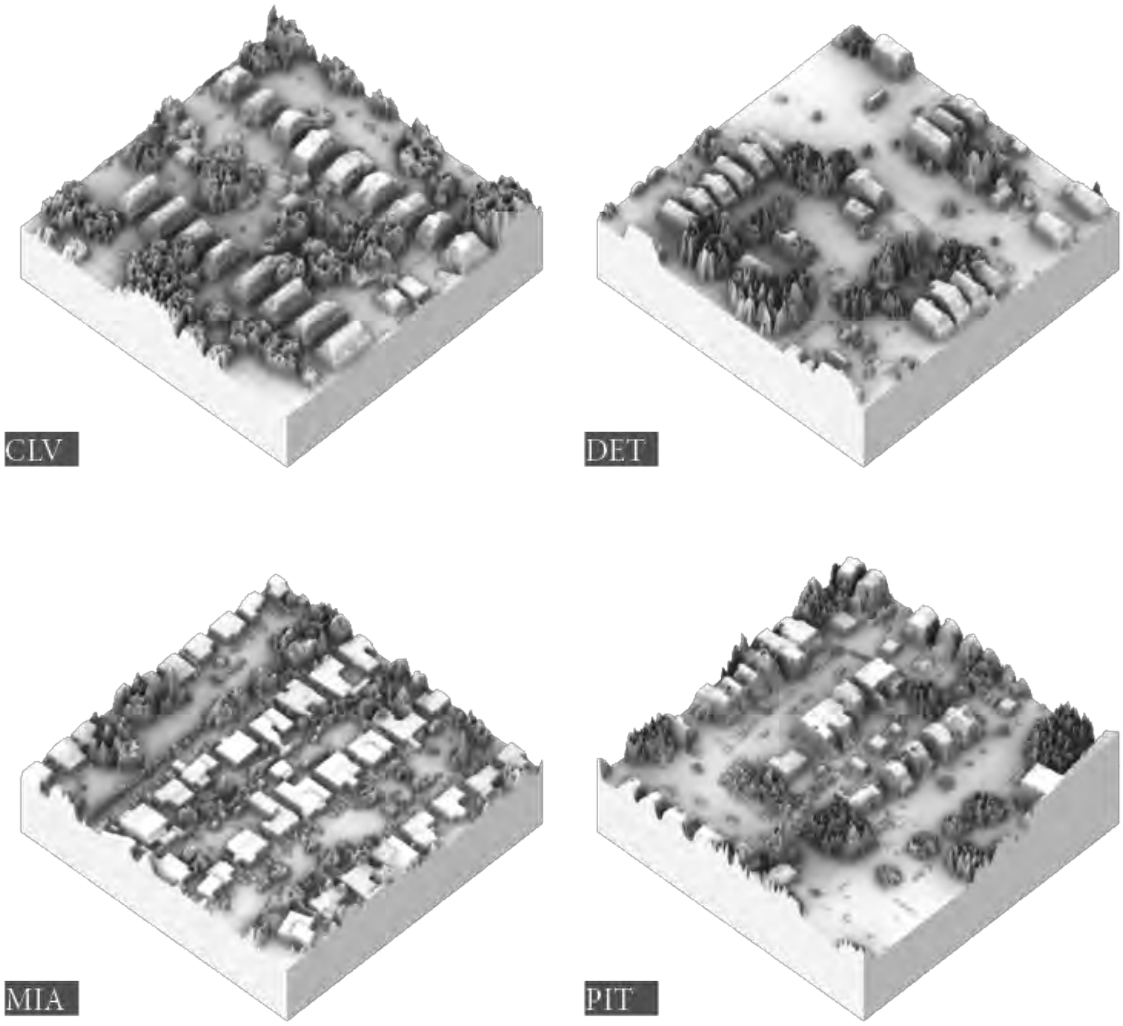


Figure 6.11: Representative forms of Urban Type 9

two axes of the MBG with data normalized based on the elongated axis. Consequently, the structures within this vertical disposition tend to exhibit a shape closer to a square compared to those in Type 1 and 3. Despite these distinctions in orientation and building geometry, the layout of the urban space aligns with the linear patterns observed in Type 1 and 3.

In light of this, the notable prevalence of Type 8 within Cleveland can be attributed to a distinctive building form configuration within this region. The buildings' proportions tend to approximate squares, with negligible disparity between the lengths of the two MBG axes. This inference suggests that the majority of urban forms classifiable under Types 1,

3, and 5 are encompassed by Type 8 due to variations in orientation.

Urban Type 9 mainly characterizes urban spaces enveloping small buildings (Figure 6.11). At first glance, it may appear akin to Type 1, 3, 5, and 8, characterized by linear arrangements. However, a closer inspection reveals a distinctive attribute: the focal building at the center of the data does not conform to the linear arrangement but rather resides amidst the rows. This implies that this spatial configuration is bounded by building rows on two out of all directions, leaving the remaining two directions unobstructed. This intricate spatial pattern suggests that Urban Type 9 likely pertains to external spaces accompanying annexed structures like garages. The prevalence of facilities such as garages and warehouses in this type reasons to the presumed interrelationships between Type 9 and Types 1, 3, and 5 in the quantitative analysis.

6.3 Feature Analysis

For a more intricate analysis of the distinctive attributes across each urban type, an examination of features becomes crucial. Here, "features" refer to the latent vectors extracted by the encoder of the VQ-VAE model. By inputting the data into the encoder, which has been trained on the training dataset, the corresponding latent vectors can be extracted. Within this section of feature analysis, a total of 294,908 urban form data samples corresponding to the four cities—Cleveland, Detroit, Miami, and Pittsburgh—are employed. The input data shape is $294,908 \times 256 \times 256$, which is compressed into latent vectors of $294,908 \times 64 \times 64$ dimensions.

Figure 6.12 depicts the visualization of mean features for each type (top) utilizing the average vector of the extracted latent vectors, accompanied by annotations of corresponding morphological traits (bottom). In this feature visualization, bright areas correspond, as in the data, to relatively elevated and protruding regions, while dark areas represent relatively lower elevations.

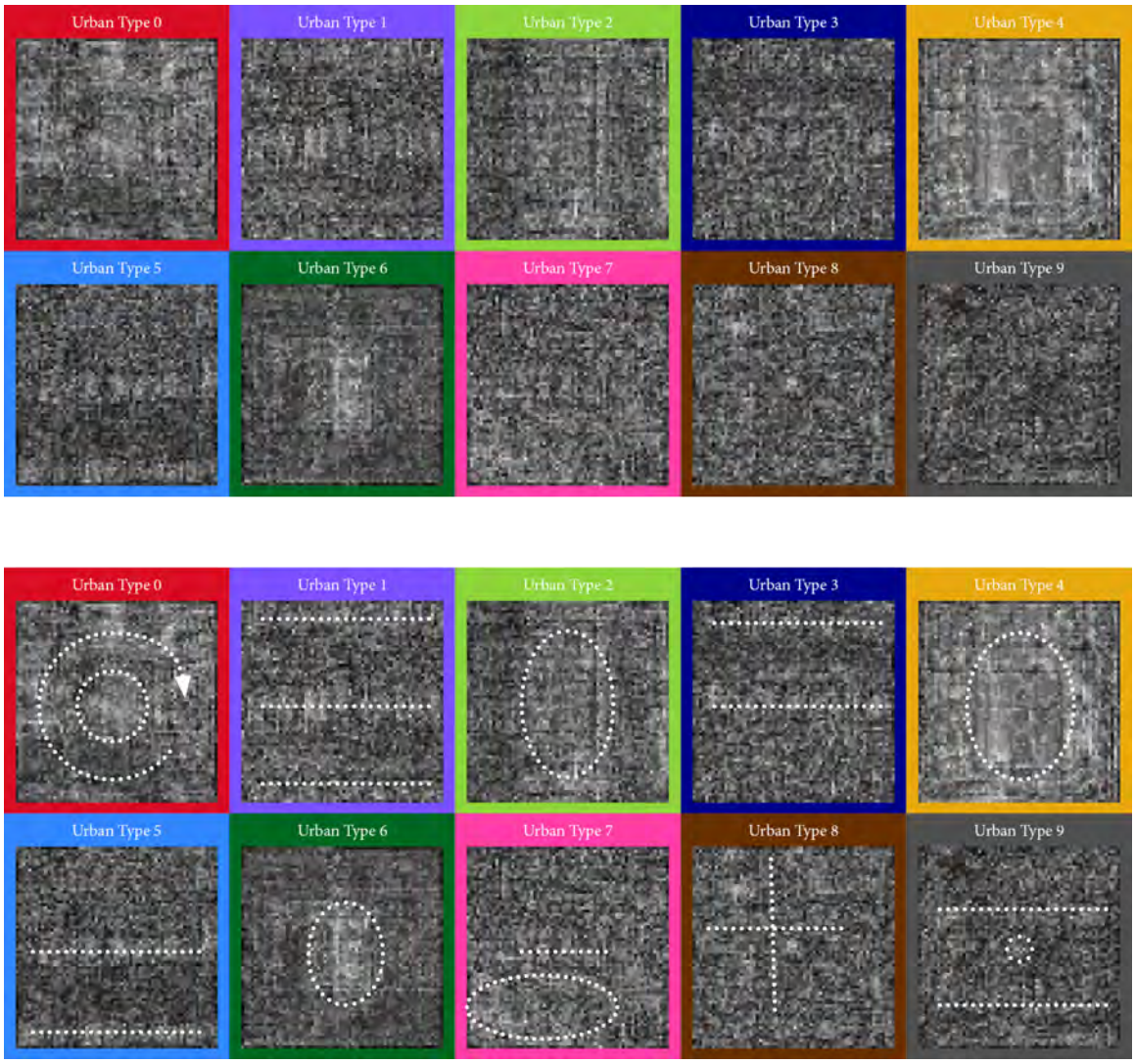


Figure 6.12: Visualization of mean features for each urban form type (top) and annotations of corresponding morphological traits (bottom)

In the Urban Type 0 mean feature, a vivid hue prominently emerges at the center, encircled by a lighter hue interspersed with intermittent darker shades. The mean feature of Urban Type 1 displays strikingly bright patterns, horizontally forming three linear arrangements. Urban Type 2's mean feature assumes a shape resembling a singular elongated mass, vertically oriented. Within the Urban Type 3 mean feature, luminous patterns horizontally form two linear arrangements from the top of the area. In Urban Type 4's mean feature, the majority of the feature area is expressed in a luminous manner. The mean feature of Urban Type 5 displays luminous patterns horizontally form two linear arrangements from

the bottom of the area.

Conspicuously, the mean feature of Urban Type 6 reveals a prominent white cluster at its center, surrounded by darker tones along its periphery. Urban Type 7's mean feature portrays a faint linear pattern at the center, accompanied by a luminous cluster in the lower-left quadrant. Within Urban Type 8's mean features, a darkened motif, creating a slightly skewed cross shape from the center to the upper left corner, is perceptibly discernible albeit in a somewhat indistinct manner. Lastly, the mean feature of Urban Type 9 is characterized by a small pronounced bright cluster at its center, accompanied by faint linear bright patterns above and below the central cluster.

Through this feature visualization and examination, two facts are reinforced. Firstly, the possibility of classification based on the similarity of Types 0, 2, and 6, as well as Types 1, 3, and 5, proposed in quantitative analysis, is also evident through the mean feature. Types 0, 2, and 6 exhibit a bright central region, while Types 1, 3, and 5 display a horizontal linear pattern. The distinct urban forms of the two different configurations are also clearly evident in the mean feature.

Secondly, the inferences drawn from qualitative analysis of Types 4, 7, and 9 are also substantiated in the feature map. For Type 4, the representative forms primarily consisted of low-rise edifices, with minimal exterior urban space apparent in the data. This is confirmed by the predominantly bright regions in the mean feature of Type 4, indicating that most areas represent elevated regions, i.e., buildings. Type 7, characterized by a blend of linear spaces and the surrounds of edifices based on representative forms and sampling analysis, finds visual support in the mean feature visualization. Type 9, characterized as urban space of annexed structures to housing with a linear arrangement through representative forms and sampling analysis, finds validation in the mean feature where a central elevated region bounded by linear arrangements above and below is observed.

However, Type 8 exhibits a discrepancy between the analysis of urban form based on representative forms and sampling, and the examination of mean feature visualization.

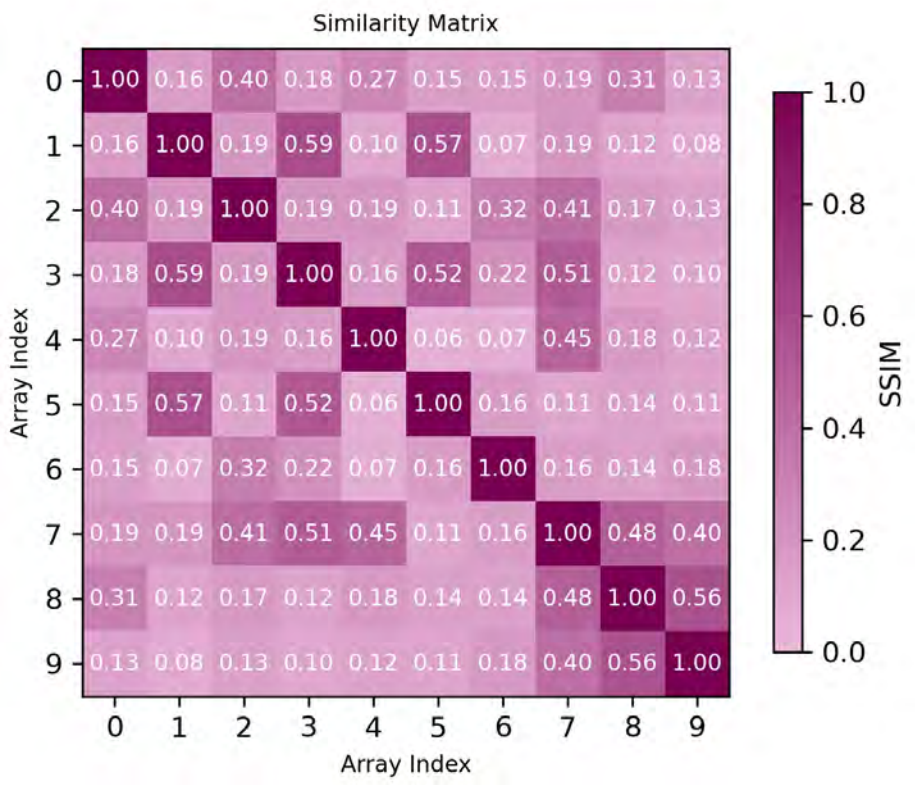


Figure 6.13: Similarity matrix of urban form types

While Type 8 was characterized as having a similar linear arrangement to Types 1, 3, and 5 with distinctiveness only in orientation and building geometry, the mean feature identifies it with a cross-shaped form. This suggests that a more diverse range of Type 8 urban forms may incorporate a mixture of horizontal and vertical linear arrangements.

Given that the representative form, sampling, and mean feature analysis all rely on visual examination, further quantitative examinations are necessary to reveal and validate the similarities among the urban types. To this end, I investigate the inter-type similarities using structural similarity metrics based on the images of mean features. Structural similarity in images refers to quantifying how similar two images are based on their textures, patterns, and details rather than just pixel values. The widely used Structural Similarity Index (SSIM) measures this similarity by considering luminance, contrast, and structure, providing a more nuanced assessment of image likeness than traditional pixel-based metrics. Figure 6.13 presents these similarities in a tabular format, with darker color indicating

	0	1	2	3	4	5	6	7	8	9
Area	C	L	C	L	M	L	C	C	L	M
Height	C	L	C	L	C	L	M	L	L	M
Rep. Form	C	L	C	L	C	L	C	M	L	M
Mean Feat.	C	L	C	L	C	L	C	M	M	M
Feat. Similarity	C	L	C	L	C	L	M	M	M	M
Final Class	C	L	C	L	C	L	C	M	L	M

Table 6.1: The results of grouping by different analyses: building height and footprint area, representative form, mean Features, and feature Similarity

higher degrees of similarity.

In this table, Types 0, 2, and 4 exhibit relatively high similarity among each other, as do Types 1, 3, and 5. Type 6 demonstrates relatively higher similarity with Types 2 and 3. Notably, Types 7, 8, and 9 exhibit notable similarities among each other, particularly with Type 7 displaying high similarity with Types 2, 3, and 4. Based on these findings, the types can be broadly classified into four groups: Types 0, 2, and 4; Types 1, 3, and 5; Types 7, 8, and 9; and Type 6, which does not align distinctly with any of the aforementioned groups.

6.4 Taxonomy of Urban Forms in Rust Belt Cities

Based on the analysis of building height and footprint area, representative form, mean features, and feature similarity, each urban type is classified, culminating in the formulation of a taxonomy. The grouping results are illustrated in Table 6.1. The classifications are denoted by the labels ”C” and ”L,” representing ”Central” and ”Linear” respectively. The label ”M” indicates a distinct class referred to as ”Miscellaneous,” which is independent from both ”Central” and ”Linear.” The final classification for each urban type is determined by the most frequently occurring label in each category.

Urban Types 0 and 2 are distinguished as urban spaces predominantly exhibit central buildings and their surrounding areas across all classification criteria. Conversely, Urban

Types 1, 3, and 5 are characterized by urban spaces predominantly display linear configurations in all aspects. In the case of Urban Type 4, it exhibited distinctive area characteristics from other types, leading to its classification as 'M' based on area analysis. However, it was consistently classified as 'C' in the remaining analyses, resulting in a final 'C' classification. Urban Type 6 mostly falls under central space categorization, yet it deviates in terms of height and feature similarity, leading to its final 'M' classification. Urban Type 7 displayed central area traits in terms of area and linear space characteristics in terms of height, but distinct traits setting it apart from other 'C'-classified types emerged in the other three analyses, thus culminating in an 'M' classification. Urban Type 8 showcased unique traits in the feature analysis, yet due to its linear space attributes in area, height, and representative form akin to Types 1, 3, and 5, it was ultimately classified as a linear space type. Lastly, Urban Type 9, characterized by distinctive traits not aligning with 'C' or 'L' in all analyses, was classified as 'M'.

Consequently, Urban Types 0, 2, 4, and 6 were classified into the "C" class, while Urban Types 1, 3, 5, and 8 were categorized as "L" class. Urban Type 7, although forming a distinct class, possesses attributes that exhibit a hybrid tendency between "C" and "L" classes, warranting its classification as an additional "Hybrid" class. Urban Type 9 represents urban spaces characterized by small, low-rise buildings nestled amidst linear spaces such as garages. As elucidated by mean feature visualization and representative form, this space can also be perceived as a hybrid form, encompassing elements of both central and linear spaces. Hence, Urban Type 9, with its stronger linearity compared to Urban Type 7, is classified as a "Hybrid" class with a more pronounced linear nature.

Figure 6.14 illustrates the four cities' urban form taxonomy derived from the classification. Initially, urban forms are categorized into three main groups: central, linear, and hybrid. Within the Central group, a further division based on the occupancy of the urban space around the target building is apparent, leading to two subgroups: the surrounding type, where the neighboring urban space envelops the target building as independent en-

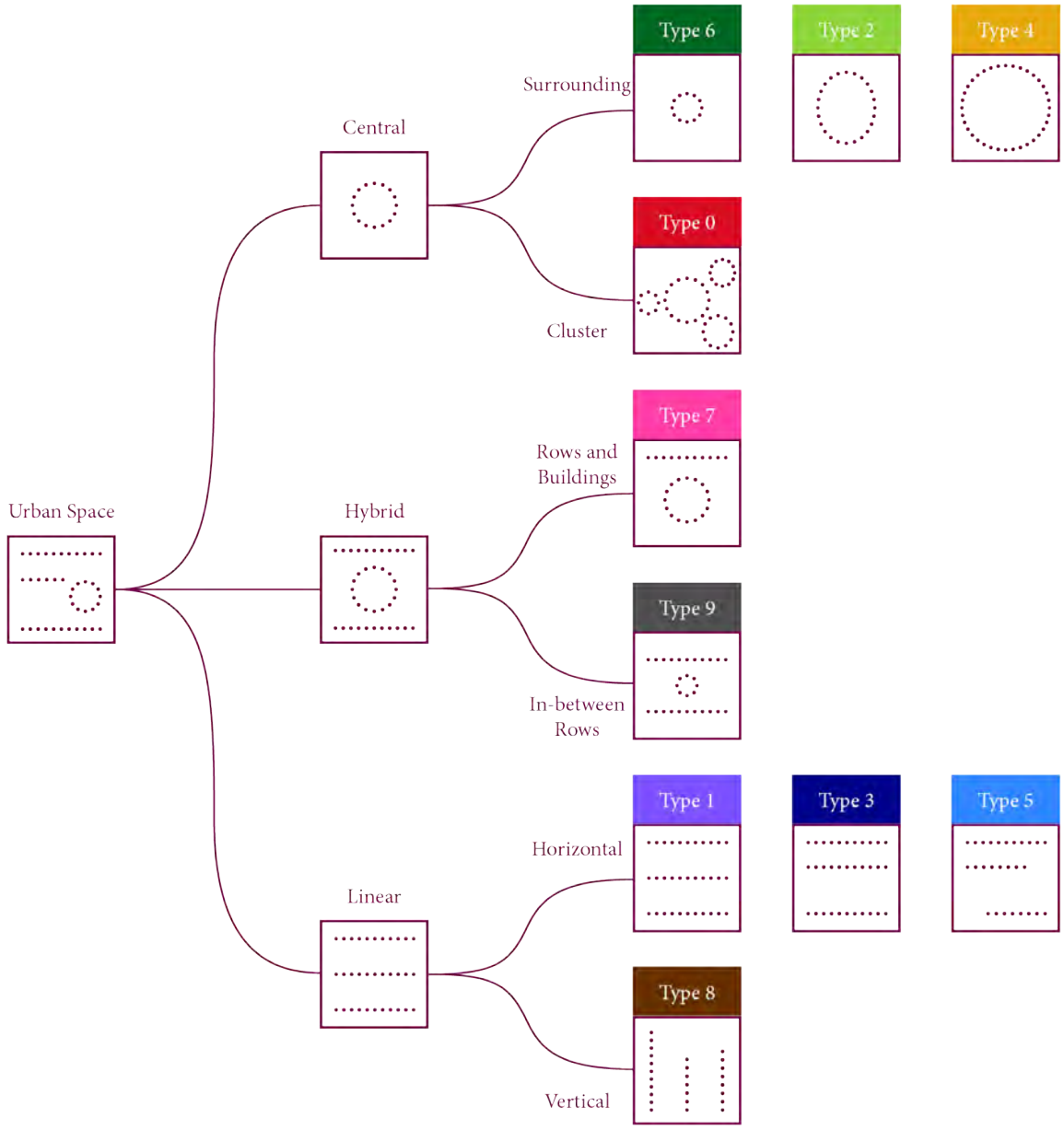


Figure 6.14: Urban form taxonomy of the four cities

tities, and the cluster type, characterized by the aggregation of similarly sized buildings within the adjacent space. The surrounding type is further refined based on size: Urban Type 6, notable for its small area, considerable height, and expansive vacant surroundings; Urban Type 2, housing medium-sized structures of approximately 4-5 stories; and Urban Type 4, distinguished by its remarkably large edifices that nearly occupy the entire data extent. In the cluster type, a notable subtype is Urban Type 0, constituted by an assemblage

of several 3-4 story medium-sized buildings, forming interstices or in-between spaces of buildings as the primary urban space.

The Linear group mainly comprises rows of small structures, such as houses, with the target building situated within one of these rows. This group is further divided into two types based on the orientation of the rows: horizontal and vertical. The horizontal type is subcategorized into three variations based on the arrangement attributes of the rows. If rows manifest with a relatively uniform spacing, forming three linear arrangements, they fall under Urban Type 1. If the constituent buildings have shallower depth and variations in arrangements' spacing occur, it corresponds to Urban Type 3. In cases where there are prominent changes in both length and spacing of arrangements, Urban Type 5 is attributed. When these rows progress in the vertical direction, they are classified as Urban Type 8. The Vertical type, on the other hand, is not differentiated by the spacing or length of rows.

The concept of a "vertical arrangement" occurs when the width axis of the target MBG is longer than the depth axis. In essence, this implies that, typically, houses should have a longer depth than width to form a linear and spatially coherent setting. However, locating houses with a width significantly surpassing their depth, thus conforming to this vertical arrangement, is challenging in Rust Belt cities, or perhaps across many US cities. Thereby, buildings in Urban Type 8 exhibit lengths of width and depth that are quite similar, resembling a square shape.

Due to the prominence of the morphological characteristic of target buildings and their vertical arrangement over variations in the spacing and length of rows, the subdivision of the vertical type did not emerge within the ten clusters. It is inferred that if a greater number of clusters were employed, the possibility of distinct subtypes within the vertical arrangement becomes plausible. The absence of refinement or subgroups within the vertical type can be attributed to the prioritization of morphological and vertical arrangement traits of the target buildings over variations in row spacing and length. However, with an increase in the number of clusters beyond ten, the emergence of subgroups of vertical types becomes

highly plausible.

6.5 Urban Fabric Map

Based on the taxonomy of the analyzed characteristics for each urban type, geospatial analysis can reveal how each type is distributed across the cities. To achieve this, it is necessary to map the information of the types onto the geospatial context. This mapping not only represents the distribution of different types of urban spaces for individual buildings in the geographical space but also allows the investigation of urban fabric based on clustering derived from geolocation. The configurations of these fabrics, in turn, reveal the urban structure. Through such mapping, I aim to reveal the unique urban types, fabrics, and structures present in Rust Belt cities.

6.5.1 Buildings to Fabric

Appendix E represents a map of building footprints indicating the urban types associated with each building in respective cities. At the level of individual buildings on a map, it is possible to discern the surrounding urban spaces they possess. However, understanding how different types of urban spaces are distributed across the entire city and how they form cohesive fabrics is challenging. To extract fabric-related insights, centroids' coordinates of each building footprint are aligned along the X-axis of an input data, while urban type labels are assigned to the Y-axis. Inputting the data to the K-Nearest Neighbors (KNN) classifier, clustering is conducted.

KNN is a supervised machine learning algorithm used for classification and regression tasks. It works by storing labeled data points during training and predicting new data points based on their proximity to the training data. The algorithm calculates the distance between the new data point and existing data points, selects the K nearest neighbors, and assigns a label based on majority voting for classification or average for regression. KNN's

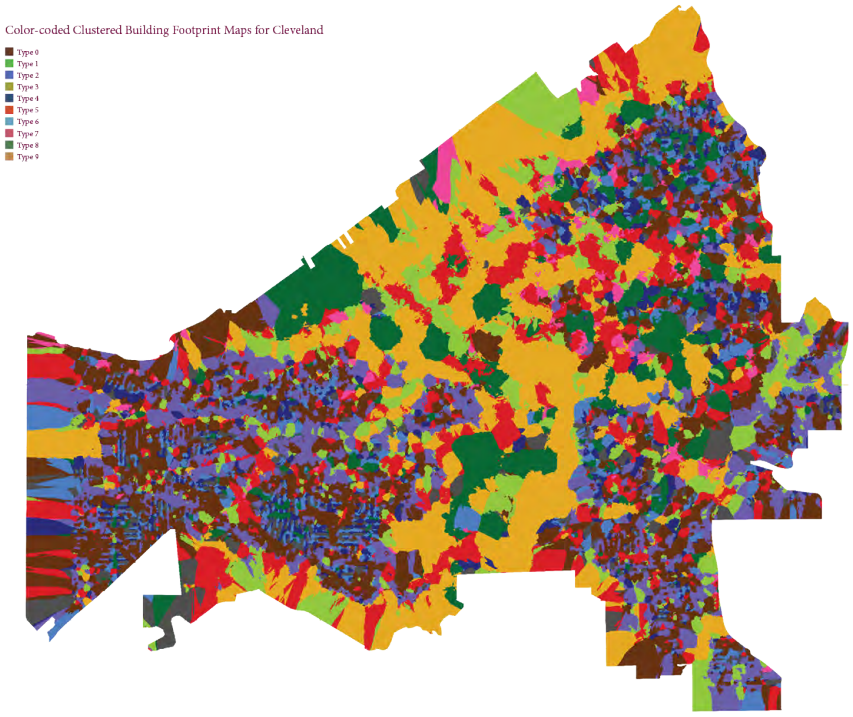
performance can be affected by the choice of K, distance metric, and data scaling. It is best suited for lower-dimensional spaces. Within KNN, the number of neighbor (N) serves as a crucial parameter, used as default values for K-Neighbor queries.

Smaller N values depict more detailed and granular fabric representations, while larger N values depict broader and more abstract fabric delineations. In this section, I analyze the urban fabrics of four distinct cities based on the fabric map established with N=15 (Figure 6.14). See the Appendix J for more detailed figures of the decision boundaries generated by the KNN algorithm for various values of N.

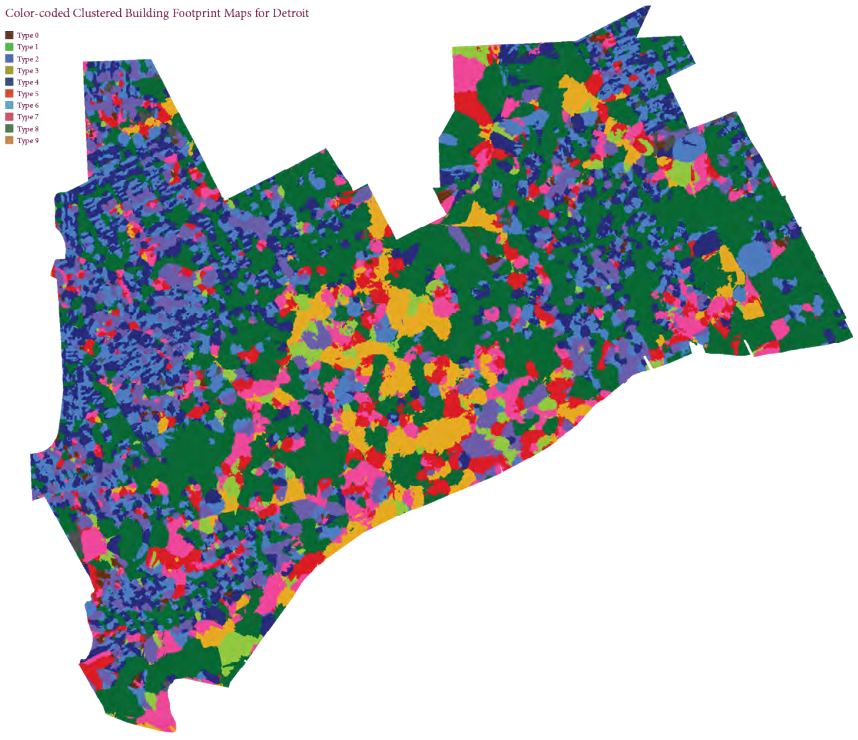
Several noteworthy points arise from this map. Firstly, the colors representing fabric types on this map are entirely unrelated to land use planning, zoning, or functions. For instance, in conventional urban planning, green-colored patches on a map typically symbolize parks or wooded areas. However, in this context, a green-colored patch merely signifies an area corresponding to Urban Type 6 fabric. Moreover, since this map is based on building footprints, it does not account for land programming such as park, water, hills, and so forth. For instance, if there is only one building within a park area classified as Urban Type 6, then a significant portion of the park's area may be represented as Urban Type 6 fabric. Therefore, when interpreting this map, it is essential to consider the granularity that reveals how fabrics of varying sizes are composed and not assume that larger areas are always dominant, referencing the map of building footprints.

6.5.2 Urban Type 4 Distribution and Characteristics

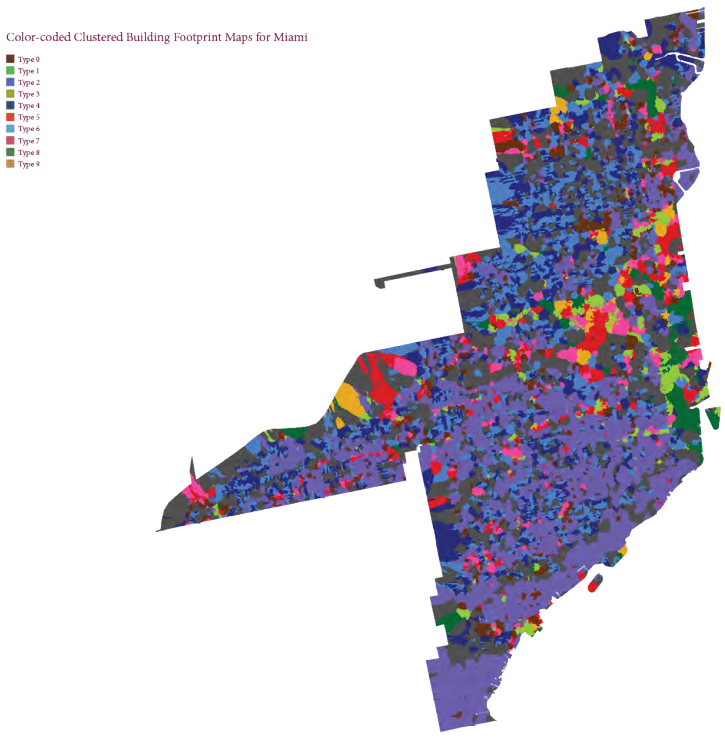
The most noticeable observation is the distribution of Urban Type 4 illustrated in yellow. As observed in Figure 6.15, Cleveland has the highest number of buildings belonging to Urban Type 4. The urban fabric map not only represents the quantity but also the extensive spatial coverage of Urban Type 4 in this city. The size of each fabric is notably larger compared to the other three cities. While it is true that Cleveland has a substantial presence of Urban Type 4, interpreting this as "Urban Type 4 dominance in Cleveland" becomes



(a) Urban fabric map: Cleveland



(b) Urban fabric map: Detroit



(c) Urban fabric map: Miami



(d) Urban fabric map: Pittsburgh

Figure 6.14: Color-coded urban fabric maps. See Appendix K for more details.

more nuanced when observing the footprint map. The significant amount of vacant space between buildings corresponding to Urban Type 4 in Cleveland compared to other cities makes it challenging to simply assert dominance. Instead, it can be argued that the conspicuous expansive area of Urban Type 4 fabric is not merely about its prevalence within Cleveland, but rather its extensive occurrence citywide, playing a significant role in forming the central axis connecting the city's north and south.

Although Detroit has a smaller quantity of Urban Type 4 buildings than Cleveland, its spatial coverage is quite substantial. Compared to Cleveland, the buildings corresponding to Urban Type 4 in Detroit tend to be densely clustered with their surrounding structures. This results in Urban Type 4 fabrics having smaller sizes than Cleveland, and they appear more fragmented with reduced continuity. Consequently, these fabrics exhibit a higher degree of contact with different fabric types within their boundaries.

Pittsburgh, while having about 65% of Urban Type 4 quantity compared to Detroit, exhibits smaller and more fragmented fabrics. Urban Type 4 fabrics in Pittsburgh are characterized by smaller clusters that appear sporadically in the east-west direction from the city center, distinct from the patterns observed in the other two cities. Miami, on the other hand, possesses the fewest Urban Type 4 buildings, and indeed, the Urban Type 4 fabric is scarcely discernible on the map. While sporadic occurrences of buildings classified as Urban Type 4 can be observed to the east of the city center, they mostly exist independently rather than forming clusters like in the other three cities. In contrast to the other cities, Urban Type 2 and 6 fabrics, situated around Urban Type 4, are prominently present in Miami.

Fabrics of Urban Type 4 in Rust Belt cities tend to predominantly emerge near or embracing downtown areas (Figure 6.16). In Miami, the downtown area is primarily characterized by fabrics dominated by Urban Type 2 in light green, representing (vacant) urban spaces around high-rise buildings, and Urban Type 6 in green. The quantities and extents of Urban Type 4 are relatively modest. In contrast, in Rust Belt cities, regions featuring

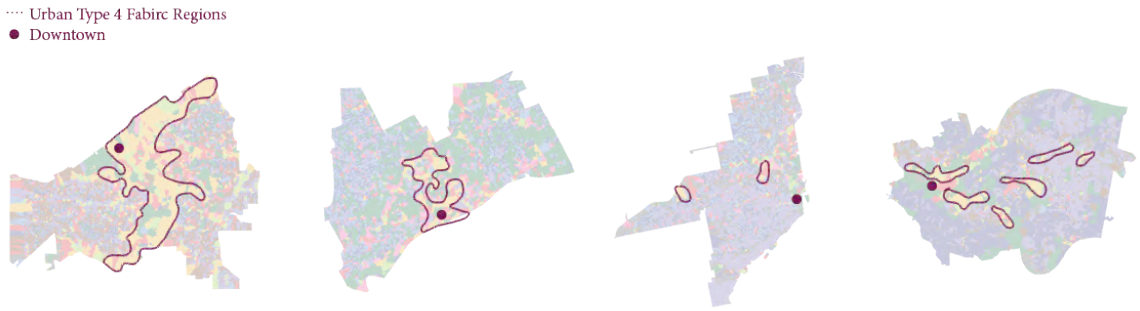


Figure 6.15: Annotated dominant area of urban form type 4 in urban fabric maps.

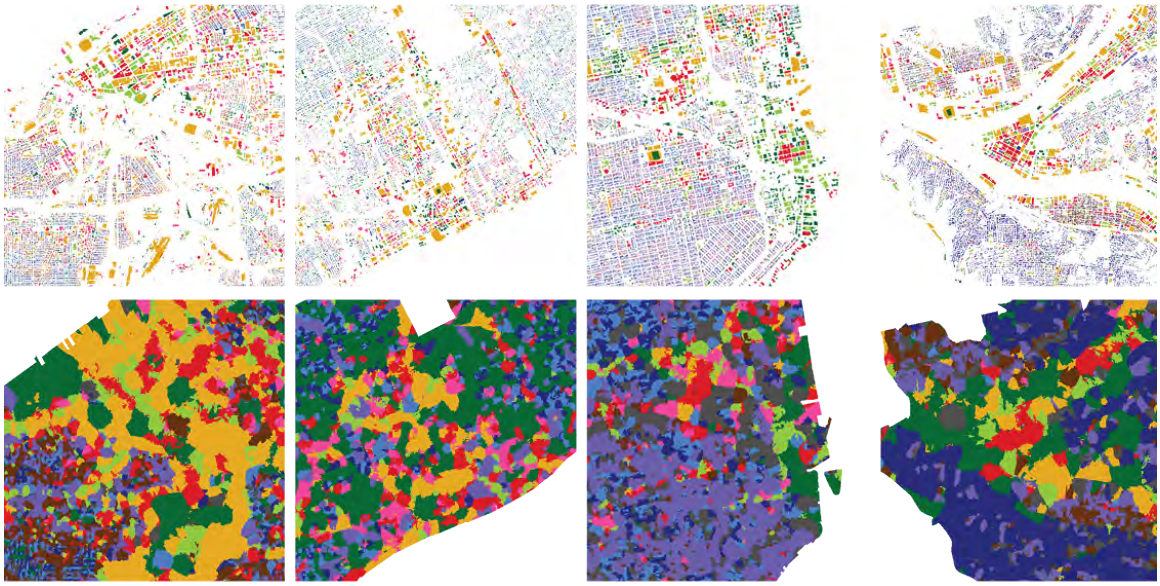


Figure 6.16: Color-coded maps of building footprints (top) and urban fabrics (bottom), zooming in on the downtown area, categorized by urban form types.

Urban Type 4 fabrics near downtown areas are not exclusively composed of a single type. They are collaged with different fabrics such as Urban Type 0 in red, Urban Type 2 in light green, Urban Type 6 in green, and Urban Type 7 in pink.

In particular, substantial areas of Urban Type 0 and 2 fabrics are consistently observed in the downtown areas of Rust Belt cities, accompanied by Urban Type 4 fabrics in their vicinity. Considering that Urban Type 0 comprises mid-sized buildings often grouped in configurations of 4-5 buildings of similar scale, and Urban Type 2 represents urban spaces surrounding mid- or high-rise structures, it can be deduced that downtown cores are characterized by urban spaces formed within the interstices of 4-5 story building clusters, sur-

rounded by larger-scale building environments.

In Rust Belt cities, the periphery of the fabrics collage, predominantly characterized by Urban Types 0, 2, and 4, exhibits smaller, granular fabrics associated with Urban Types 1, 3, 5, and 8. Notably, instances where Urban Type 4 fabrics directly interface with these granular fabrics are limited. Between the Urban Type 4 fabrics and the granular fabrics, there is often the presence of Type 6 or Type 7 fabrics, serving as intermediaries or buffers. A similar pattern emerges in Miami, where fabrics centered around Urban Types 0 and 2, with a limited presence of Urban Type 4, interface with more granular fabrics consisted of Urban Types 1, 3, 5, and 8. However, in contrast to Rust Belt cities, there is less evidence of buffers provided by Urban Type 6 or 7 fabrics, and instead, direct interactions between large buildings or mid-rise clusters and residential fabrics are observed.

In the preceding analysis of type-specific characteristics, it was inferred that the granular fabrics encompassed residential areas organized in rows. Urban Type 6 represented independent buildings within vacant urban spaces, while Urban Type 7 denoted a blend of the surrounding area of a mid-sized building and rows of houses. Reflecting on the urban spatial characteristics of these types, Rust Belt cities exhibit an urban composition where large structures or clusters of mid-rise edifices interface with smaller residential urban spaces in two ways: either leaving open spaces or blending fabrics of different scales and types. These interfacing attributes notably differentiate Miami's urban fabric.

6.5.3 Urban Type 6 Distribution and Characteristics

The subsequent notable aspect is the distribution of Urban Type 6. Detroit had the highest quantity of Urban Type 6, with relatively larger fabric sizes that are widely distributed throughout the city. Pittsburgh follows with the second highest amount of Urban Type 6, showing a distribution that is less broad than Detroit but more extensive than Cleveland or Miami on the fabric map. In Pittsburgh and Cleveland, the Urban Type 6 fabrics exhibit a relatively smaller and more fragmented size compared to Detroit. Miami displays the

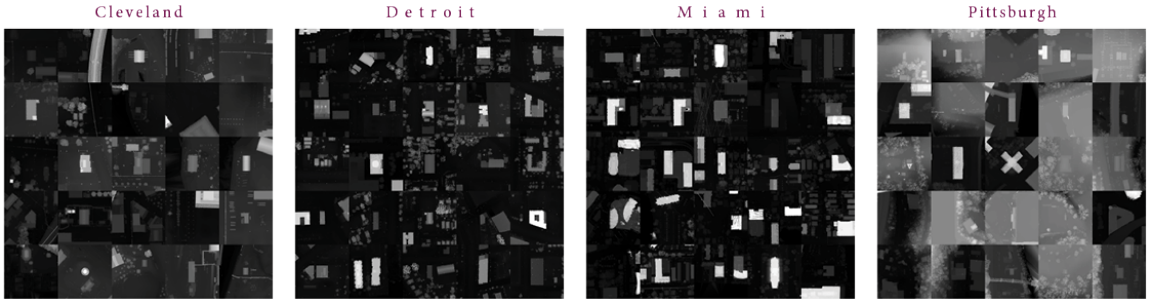


Figure 6.17: Sampled data of urban form type 6



Figure 6.18: Overlaying the location of high-vacant-lot areas on the census map with the urban type 6 fabrics map in Detroit

lowest quantity of Urban Type 6, with its distribution mainly concentrated in the downtown area.

However, scrutinizing Figure 6.17 reveals slight variations in the characteristics of Urban Type 6 across cities. In Detroit, Urban Type 6 often consists of smaller independent structures with sporadic buildings of similar scale appearing within the surrounding vacant spaces. Observing the footprint map, most Urban Type 6 fabrics in Detroit seem originally aligned with rows of houses, but it is inferred that they now represent buildings with independent urban spaces due to the increase in vacant lots. Based on this inference, when overlaying the location of high-vacant-lot areas on the Census map with the Urban Type 6 fabrics map in Detroit, a significant alignment can be noticed (Figure 6.18). This suggests that many Urban Type 6 fabrics in Detroit can be understood as the spatial configuration of buildings with surrounding vacant spaces due to vacant lots.

This characteristic of predominantly vacant spaces forming Urban Type 6 is not exclu-

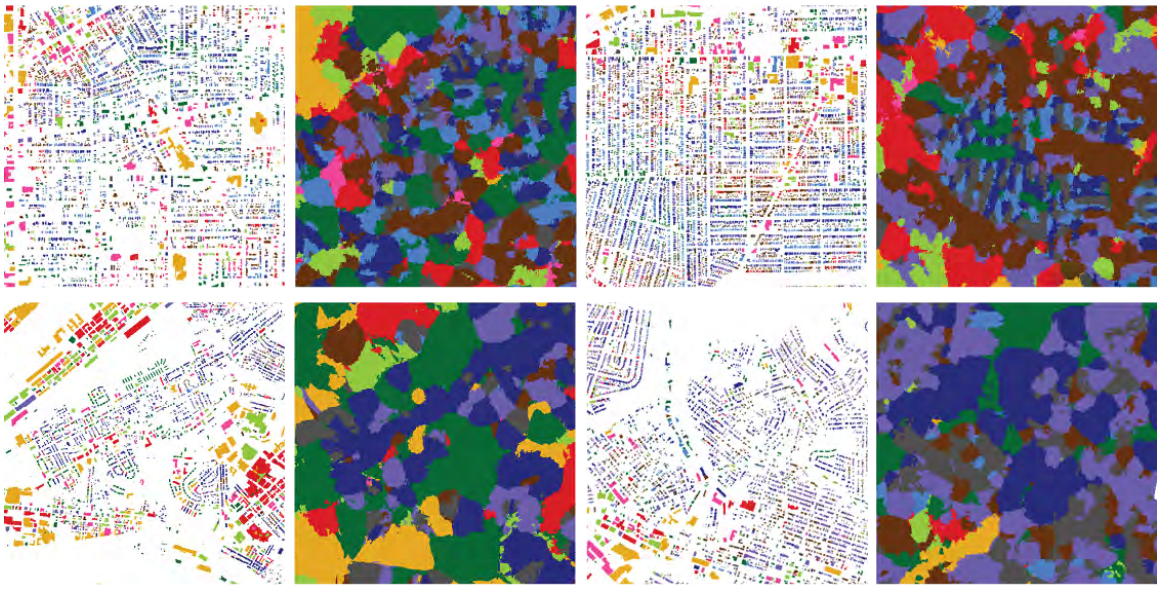


Figure 6.19: Footprint and fabric maps of Cleveland's northeastern (top-left) and southwestern residential areas (top-right), Pittsburgh's downtown vicinity (bottom-left) and northeastern regions (bottom-right)

sive to Detroit. In Cleveland and Pittsburgh, Urban Type 6 primarily features urban spaces centered around medium-sized independent structures. However, in areas with linear arrangements of smaller structures such as Type 1, 3, 5, and 8, similar Urban Type 6 fabrics as observed in Detroit also appear.

Figure 6.19 juxtaposes both footprint and fabric maps of Cleveland's northeastern and southwestern residential areas, as well as Pittsburgh's downtown vicinity and northeastern regions. Buildings classified as Urban Type 6 are not marked by distinct linear arrangements like the surrounding row structures. Instead, they exhibit scattered patterns with relatively wide vacant spaces between rows, reducing the continuity of the arrangement. The classification of Urban Type 6 based on its characteristic of vacant spaces centered around independent structures implies that the increase in vacant spaces within residential arrangements leads to the formation of surrounded vacant spaces of independent buildings. This transformation differentiates these spaces from densely packed collective configurations, gradually transitioning repetitive and homogeneous linear urban spaces into central urban spaces.

In the case of Miami, buildings classified as Urban Type 6 are depicted in a much brighter color, indicating relatively taller structures. These buildings are surrounded by relatively lower structures, often appearing as podiums for surrounding buildings of high-rises. A dark-colored open urban space is represented around this podium. In most cases, the distinction between the surrounding buildings or podiums and the adjacent open space is minimal. This suggests that several high-rise building surroundings in downtown Miami are classified as Urban Type 6 fabrics. This classification is distinct from the vacant lot fabrics around residential structures observed in Detroit and is more similar in spatial configuration to the Urban Type 6 fabrics predominantly found in downtown areas of Cleveland and Pittsburgh.

6.5.4 Granularity Comparison

Granularity can be defined through the size of fabrics and how many different fabrics exist in their surroundings. Higher granularity means more diverse fabrics within a given spatial unit. Based on this concept of granularity, Figure 6.20 illustrates the process of creating a granularity map from an urban fabric map. Firstly, a grid of squares representing unit spaces is overlaid onto the fabric map. The granularity is defined by the number of different urban types within a unit space. The count of urban types present within each unit space is then determined, ranging from a minimum of 0 to a maximum of 10. Converting this count into a grayscale gradient produces the granularity map. This map reveals the extent of diverse urban fabrics in different areas.

Figure 6.21 displays the granularity measured in the fabric map of each city for N=15. The unit spaces are defined using grid cells of approximately 250 m x 250 m. In Cleveland, there is a pronounced area of high granularity extending horizontally from the central part of the city, where cluster-based fabrics centered on Urban Type 4 gather. These areas are predominantly composed of fabrics belonging to Urban Types 1, 3, 5, and 8, with sporadic and fragmented inclusion of other fabrics such as Urban Types 0, 2, 6, 7, and 9. Similarly, in

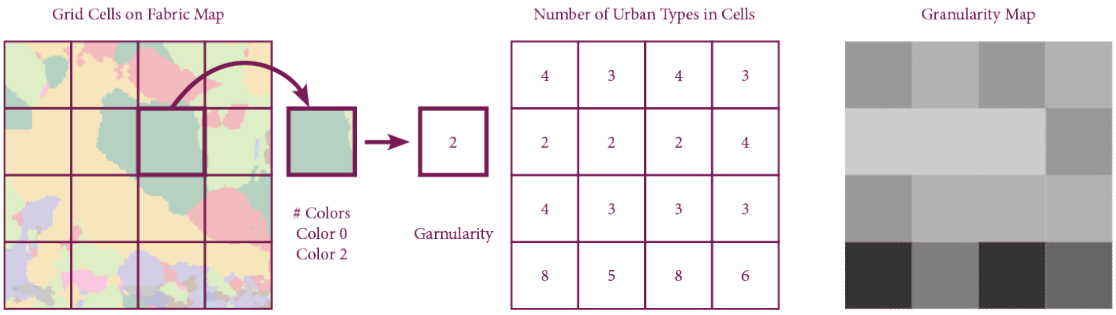


Figure 6.20: Process of creating a granularity map from an urban fabric map

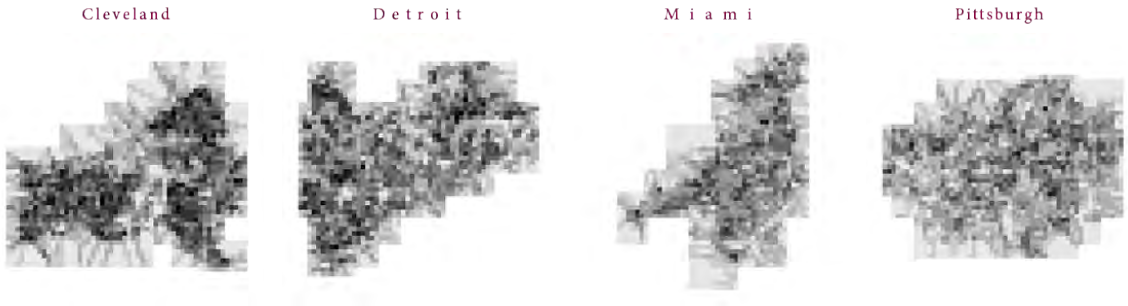


Figure 6.21: Granularity maps of the four cities.

Detroit, the northeastern and western parts of the central region exhibit notable granularity. While the intensity of granularity in these areas is not as extensive as in Cleveland, the presence of strong granularity in areas with residential-focused urban fabrics is evident, akin to Cleveland.

In contrast, both Miami and Pittsburgh have fewer instances of high granularity compared to the other two cities. In Miami, sporadic pockets of strong granularity appear primarily to the north and west of downtown. Pittsburgh, on the other hand, shows relatively lower granularity in areas that seem predominantly residential fabrics. In terms of residential fabric granularity, Pittsburgh exhibits characteristics more similar to Miami than to Cleveland or Detroit.

Based on observation of granularity maps, it can be understood that Cleveland and Detroit exhibit a greater variety of configurations in urban spaces within residential areas compared to Pittsburgh. The higher granularity observed near the boundaries where res-

idential fabrics and central type fabrics—dominated by Urban Type 4—intersect in these cities indicates an increase in fabric types such as Type 7, which serve as buffers. In this context, the granularity maps of Pittsburgh reveal a smoother gradient or weaker distinction between these central fabrics and the residential areas.

However, the diversity of fabrics comprising residential areas does not always carry a positive connotation. The urban fabric is not a rigid fixture, but rather an entity that changes through the interaction of structures and urban environments. Therefore, it is important to always consider the possibility that changes in organization over time could have contributed to the observed diversity. For instance, the occurrence of fabrics corresponding to Urban Type 0 within areas dominated by residential fabrics suggests the presence of clustered spaces with 4-5 story mid-size buildings amidst other residential fabrics. Whether this represents a contraction from previously larger Urban Type 0 fabrics or newly formed fabrics between residential fabrics cannot be discerned without tracking changes of the fabrics over time. Consequently, in the analysis of granularity, reference to the fabrics map is crucial to interpret the intensity of granularity while considering which fabrics predominantly shape it.

Moreover, there is also room for a negative interpretation of this diversity from an urban environmental perspective. As inferred during the analysis of the distribution and characteristics of Urban Type 6, an increase in vacant lots for some reason led to an increase in Urban Type 6 fabrics between residential fabrics. These Type 6 fabrics transform urban spaces with rows arrangements into cluster or central configurations of urban spaces. Further, in cases of substantial proliferation of Urban Type 6 fabrics, linear urban spaces shift to small independent buildings surrounded by empty urban spaces. Even in such scenarios, the granularity increases due to the addition of Urban Type 6 fabrics among the existing linear residential fabrics, thereby altering the composition of the urban space.

Taking these factors into consideration, the lower occurrence of Urban Type 6 within Pittsburgh's residential fabrics, coupled with a lower granularity, suggests that vacant lots

in Pittsburgh's residential areas are not infiltrating the residential fabric as extensively as in the other two Rust Belt cities; rather, they are concentrated in specific regions, contributing to the heightened continuity of the residential fabrics. Conversely, the high granularity and widespread distribution of Urban Types 6 in certain residential areas of Detroit infer that the influence of vacant lots is weakening the residential fabrics, gradually leading them to conflict with central types of urban space.

Although Cleveland possesses a similar quantity of Urban Type 6 fabrics to Pittsburgh, the observation of high granularity in specific areas indicates the coexistence of residential fabrics with different urban fabric types other than Type 6, resulting in blended urban spaces. In the case of Miami, considering the low quantity of Urban Type 6 fabrics and overall low granularity, the presence of central or hybrid types like Urban Types 2, 4, and 7 in areas of high granularity implies the formation of functional sub-centers supporting residential fabrics.

6.6 Unique Urban Structures of Rust Belt Cities

Summarizing the findings gleaned from the cumulative statistical analyses, observations, and examinations conducted thus far, the synthesis can be encapsulated in the following tabular representation, as depicted in Table 6.2 continued on the next page.

Table 6.2: Summary of findings from the statistical analyses, observations, and examinations

Item	Contents
Urban Type 4 Distribution and Characteristics	Cleveland has the highest count and widespread coverage of Urban Type 4 buildings, indicated by a yellow color on the fabric map.
	Buildings corresponding to Urban Type 4 in Detroit are densely clustered with surrounding structures, resulting in smaller and fragmented fabrics.
	Pittsburgh's Urban Type 4 fabrics are smaller and more sporadic, appearing distinct from the patterns in the other cities.
	Miami has the fewest Urban Type 4 buildings, mainly concentrated around the downtown area.
	Fabrics of Urban Type 4 are associated with downtown areas and often coexist with other fabric types such as Urban Type 0, 2, 6, and 7.
Urban Type 6 Distribution and Characteristics	Detroit has the highest quantity and widespread distribution of Urban Type 6 fabrics, which are often associated with vacant spaces.
	Pittsburgh's Urban Type 6 fabrics are smaller and less extensive than Detroit's, appearing sporadically.
	Cleveland's Urban Type 6 fabrics exhibit similar characteristics to Pittsburgh's, mainly around medium-sized independent structures.
	Miami's Urban Type 6 fabrics are concentrated around downtown areas and are fewer in number.
Granularity Comparison	Cleveland and Detroit exhibit higher granularity in residential areas, indicating diverse fabric configurations.
	Pittsburgh and Miami have lower granularity, suggesting less diversity in fabric types within residential spaces.
	Downtown areas of Rust Belt cities often feature fabrics dominated by Urban Types 0 and 2, accompanied by Urban Type 4 fabrics.
	Interfaces between Urban Type 4 fabrics and granular fabrics are often mediated by Urban Type 6 or 7 fabrics.
	Miami displays interactions between large buildings or mid-rise clusters and residential fabrics.
	Diversity in residential fabrics' organization may not always have positive implications, as the urban fabric is a dynamic entity.
	The presence of different fabric types within residential areas can result from changes over time, and reference to fabric maps is crucial for accurate interpretation.
	The presence of Urban Type 6 fabrics in Detroit indicates an influence of vacant lots on spatial configurations, leading to their transformation.
	Pittsburgh's lower occurrence of Urban Type 6 fabrics suggests less infiltration of vacant lots, contributing to continuity in residential fabrics.

Item	Contents (Continued)
	High granularity in Cleveland and Detroit suggests the presence of buffers and interfaces between fabric types.
	Pittsburgh's lower occurrence of Urban Type 6 fabrics and lower granularity indicate a unique spatial continuity.
	Detroit's Urban Type 6 fabrics indicate a potential conflict with central urban spaces due to the influence of vacant lots.
	Cleveland's higher granularity suggests a blend of different fabric types, especially in central areas.
	Miami's low Urban Type 6 count and granularity imply the formation of functional sub-centers supporting residential fabrics.

Based on these findings, Figure 6.22 presents a diagram illustrating three common urban structure features shared among the three Rust Belt cities, distinguishing them from such structure in Miami.

Firstly, in the three Rust Belt cities, urban structure includes an Urban Type 0 fabric, denoting interstices yielded by clusters of 4-5 story medium-sized buildings in proximity to downtown areas. Conspicuously surrounding this is the Urban Type 4 fabric composed of large buildings. Intermittently interspersed between these fabrics is Urban Type 2, signifying the external spaces of mid- or high-rise structures. This combination of types 0, 2, and 4 is termed as central fabrics.

Secondly, Urban Types 1, 3, 5, and 8, constituting residential fabrics encircling the central fabrics, manifest collectively. These residential fabrics exhibit a higher level of granularity compared to the central fabrics, shaping a linear urban space primarily characterized by rows of houses. Vacant lots attributed to Urban Type 6 occasionally can undermine this linearity.

Lastly, when central fabrics interface with residential fabrics, they often utilize fabrics primarily characterized by empty spaces, such as Urban Type 6, or fabrics where linear and central urban spaces blend, like Urban Type 7, as buffers. These are referred to as interfacing fabrics.

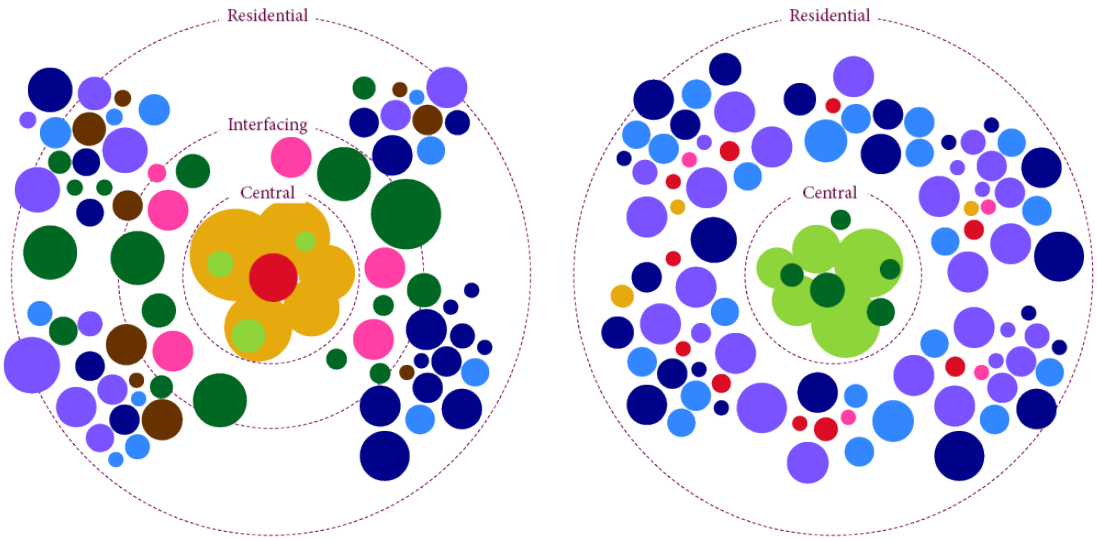


Figure 6.22: Three common urban structure features shared among the three Rust Belt cities (left), distinguished from such structure in Miami (right)

In the case of Miami, it shares similarities with Rust Belt cities in possessing central and residential fabrics. However, in its central fabrics, Urban Type 4 is absent, and Urban Type 2 predominates. Urban Type 6, representing expansive external spaces around independent structures, sporadically intervenes within Urban Type 2 fabrics. Central fabrics directly abut residential fabrics without interfacing fabrics. Within the residential fabrics, fabrics corresponding to Urban Type 0 or 7 form functional sub-centers that support residential fabrics, occasionally even incorporating large buildings corresponding to Urban Type 4.

In this chapter, an investigation was conducted based on a classification of urban form data, comprising ten distinct types. These types were derived from the classification of form data representing buildings and their adjacent spaces. The analysis encompassed average height, average area, and occurrence associated with the quantitative attributes of each type. Additionally, to gain insight into the spatial arrangement and characteristics of these types, the concept of representative form was employed, facilitating the qualitative examination and analysis of each type. As a complementary approach, the VQ-VAE model was utilized to extract data features, which were subsequently subjected to visual analysis

to further enhance and contrast the investigations. Through the synthesis of diverse analyses, distinctive characteristics were revealed for each type, culminating in the proposition of an Urban Type taxonomy.

Furthermore, I created an urban fabric map, illustrating the spatial distribution and configuration of various types within specific areas, leveraging the type information marked on building footprints. Concurrently, a metric termed ”granularity,” signifying the diversity of urban types within a given spatial unit, was formulated and employed across each city, resulting in the creation of granularity maps. These resources, encompassing urban taxonomy, urban type mapping based on building footprints, urban fabric maps, and granularity maps, underwent a comprehensive analysis. This holistic approach enabled an in-depth investigation into the distribution and inherent attributes of fabrics within each city.

Drawing from this analysis, I delineated a specific fabric configuration of three Rust Belt cities, which is distinct from that of Miami regarded as a representative Sun Belt city. In the Rust Belt cities, urban structure features 4-5 story buildings near downtown, surrounded by larger buildings and interspersed with spaces of mid- or high-rise structures, forming central and residential fabrics with occasional vacant lots affecting linearity. Miami, while sharing central and residential fabric characteristics, lacks large building fabrics in its central areas, with mid- or high-rise external spaces more dominant. Unlike Rust Belt cities, Miami’s central and residential fabrics merge directly, creating sub-centers within residential areas, sometimes including large buildings.

To achieve a more definitive grasp of this distinctive structure, future research should encompass a broader scope by analyzing additional Rust Belt cities using similar methodologies, thereby uncovering shared characteristics. Nevertheless, this pursuit is confronted by pragmatic constraints like technical challenges in data capacity and processing capabilities, as well as data resource availability. By surmounting these challenges, a more intricate and nuanced depiction of the unique urban structure can be realized.

The next chapter encompasses an evaluation of these types and their distribution, fab-

rics, and urban structures. I delve into the disparities between urban structures derived through the application of a specific method within the conventional morphology index-based approach and those revealed through the proposed approach spanning chapter 5 and chapter 6. Furthermore, a site survey is conducted to validate the classification reliability of urban form data using the proposed method. This evaluation of both approaches serves as a pivotal foundation for a comprehensive discourse on the potentials and constraints inherent to the proposed approach.

CHAPTER 7

EVALUATION

In the preceding chapter, the application of the proposed extracted feature approach using deep learning resulted in the classification of urban forms in four cities into ten distinct Urban Types. I examined their characteristics and yielded the urban fabrics using the distribution of the types. This examination served as the basis for formulating a taxonomy. Notably, in contrast to Miami, this exploration led to the identification of unique urban structures specific to Cleveland, Detroit, and Pittsburgh.

In this chapter, I evaluate the outcomes derived from the extracted feature approach. I selected one of conventional methods in urban forms analysis and applied to the four cities in order to extract their urban structures. In this application, a dissection of the mechanisms employed by the morphology indices-based approach—hereafter referred to as the ”formularized” feature method.This method involves formulating and computing form indices such as proximity, density, and complexity, which are then used to cluster urban types for classifying urban forms. By comparing the outcomes of this analysis, embodied in the resulting urban structures, to those stemming from the extracted feature method, I could yield their distinctions and concurrences. Based on these comparative insights, a discussion ensues into the potentialities and limitations intrinsic to the extracted feature method.

7.1 Formularized Feature-based Analysis of the Four Cities

Chapter 5 and Chapter 6 introduced an experiment aimed at scrutinizing urban forms, fabrics, and structures by extracting features. In pursuit of this objective, a novel interpretation of urban form was adopted, encompassing both a form of building and its spatial

context within a defined range. This redefined scope prompted the creation of an urban form dataset, wherein the overlaps of surrounding spaces were embedded to incorporate diverse relationships. From this dataset, morphological features were extracted utilizing a probabilistic-based prediction model, e.g., deep learning model. These features were subjected to clustering, resulting in the emergence of distinct urban types. The quantitative and qualitative analysis of these urban types, prevalent in each city, facilitated the discernment of their unique characteristics.

Through the mapping of type information onto the building footprints and subsequent clustering of these types, an urban fabric map was crafted. This map effectively depicted the spatial disposition of various types within the geographical context, thereby encapsulating their inherent characteristics. Leveraging this map, the groundwork was laid for the induction of an exclusive urban structure distinctive to Rust Belt cities. The amalgamation of these multifaceted analyses and mappings culminated in the elucidation of a distinct urban structure that remains exclusive to the Rust Belt context.

Can the conventional formularized feature approach yield comparable outcomes to this extracted feature approach? This question holds not only significant implications for evaluating the results derived from the extracted feature approach but also serves as a crucial means of comprehending the distinctive nature of the proposed methodology. Consequently, this comparative experiment enables the revelation of morphological traits that only the extracted feature approach might unveil. Such traits, which might remain concealed by the formularized feature approach, include unique urban structures found exclusively in Rust Belt cities. It also allows to examine the underlying significance of this revelation and underscores the limitations inherent to both approaches.

To achieve this, I utilized a method of conventional approaches in urban form analysis, referencing [83, Colaninno, Cladera, and Pfeffer 2011] and applied that method here. Initially, I dissected the four cities using a grid, and from each grid cell, three form indices such as proximity, density, and form complexity are extracted from the urban form con-

tained within. These extracted indices are treated as morphology features and are classified using the same clustering method as the extracted feature approach. As in the chapter 6, these clusters are regarded as urban types and projected onto a building footprint map to analyze how each type is distributed. Furthermore, the characteristics of each type are examined both quantitatively and qualitatively, and based on this, the urban structure of Rust Belt cities and Miami is yielded. For a detailed methodological description and analysis of each type, refer to Appendix L.

From this analysis, Cleveland features the most frequent occurrence of small-scale buildings in linear patterns alongside partial footprints of medium and large buildings. It exhibits moderate frequencies of a mixture of linear configurations of small-scale buildings next to medium and large-scale structures and relatively expansive areas not covered by buildings. Additionally, Cleveland has the lowest occurrence of unfragmented medium-sized structures or spaces predominantly occupied by complete or partial footprints of large buildings.

Detroit's distribution primarily features expansive open areas without buildings and areas where small-scale buildings create linear patterns. Conversely, configurations where small-scale buildings are aligned in linear arrangements next to medium and large-scale structures, as well as areas dominated by unfragmented medium-sized buildings or extensively covered by complete or partial footprints of large buildings, are less common.

Miami is characterized by a prominent mix of unique small-scale buildings in linear configurations and partial outlines of medium-sized and large structures as the most common pattern. Additionally, moderately prevalent are unoccupied spaces, small sections of building footprints, and areas largely filled by complete or partial footprints of large buildings. Rarely found in Miami are unfragmented medium-sized buildings or spaces predominantly occupied by either complete or partial outlines of large buildings.

In Pittsburgh, the most common urban patterns include a unique mix of small buildings linearly arranged and partial footprints of larger buildings. This is closely followed by areas

with a blend of small buildings also in linear arrangements and large open spaces without any buildings. The least common are areas with uninterrupted medium-sized buildings or spaces mainly occupied by large buildings, either fully or partially.

Cleveland and Miami exhibit similar patterns, with the most common pattern being a unique blend of small buildings linearly arranged, complemented by partial shapes of medium and large buildings. Following this are areas characterized by small buildings in linear patterns and significant open areas without any buildings. Both cities also feature the rarest presence of continuous medium-sized buildings or spaces predominantly filled with complete or partial shapes of large buildings.

Pittsburgh, though distinct in absolute figures, bears resemblance to Cleveland and Miami, particularly in the commonality of patterns involving unique small buildings in linear formations accompanied by partial footprints of medium and large buildings, small buildings also arranged linearly, and extensive open areas without any buildings.

Detroit stands out with a different distribution pattern, marked by a higher occurrence of extensive open spaces without buildings and areas with small buildings linearly arranged. In contrast, it has fewer instances of unique small buildings in linear formations accompanied by partial footprints of medium and large buildings, and areas where small buildings are aligned next to medium and large structures, compared to the other cities.

7.2 Comparison in Taxonomy and Unique Urban Structure

7.2.1 Taxonomy from Formularized Feature Approach

Like in the extracted feature approach, through the analysis of urban form amounts, representative forms, mean features, and feature similarity, the taxonomy of each urban type is established

This taxonomy progresses from the types of vacant land and diverges towards the types of high building occupancy (Figure 7.1). The initial point of this taxonomy is Type

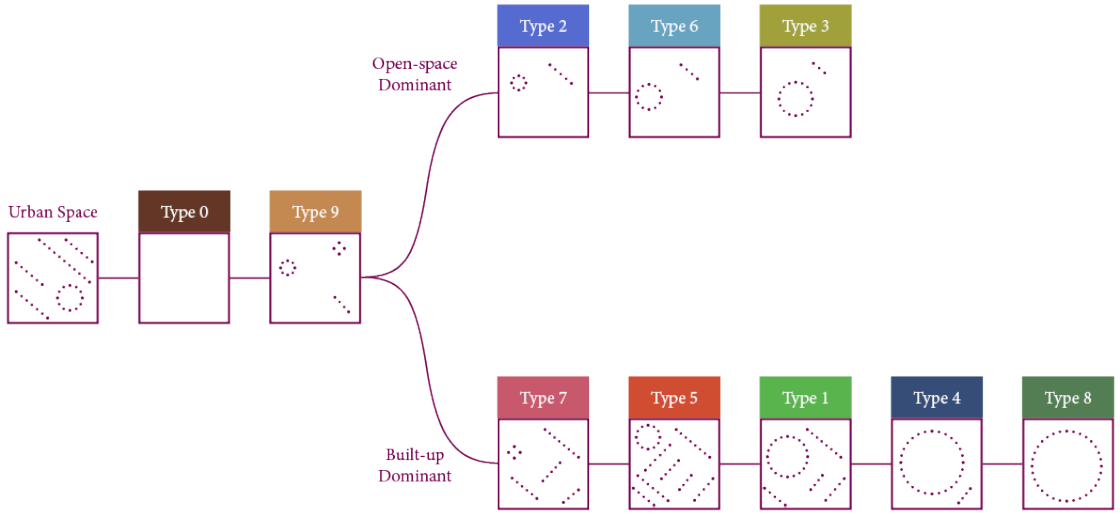


Figure 7.1: Preliminary taxonomy of urban form types from the formularized feature approach

0, representing empty land. As differentiation takes place, it branches into categories dominated by open spaces and those dominated by built-up areas, starting from Type 9 with limited sparse occupancy. In the open-space dominant branch, Types 2, 6, and 3 are discerned by their linear patterns and the frequency of central building occurrences. Type 2 displays small central buildings and a distinct linear pattern, while Type 6 exhibits larger central buildings than Type 2, accompanied by shorter linear patterns. On the other hand, Type 3 features weaker linear patterns and larger central buildings compared to Types 2 and 3. The built-up dominant branch, with Types 7 and 5 that possess prominent linear patterns, gradually shifts to Type 8, characterized by weakened linear patterns and larger central buildings. Eventually, Type 8 encapsulates either whole or substantial portions of large buildings, occupying nearly the entire form extent.

In Figure 7.2, the taxonomy from the formularized feature approach is finalized, maximizing congruence with one from the extracted feature approaches. Notably, it should be recognized that establishing a direct one-to-one correspondence between taxonomies rooted in both extracted and formularized feature approaches may not be attainable. In the extracted feature approach, the arrangement and resulting spatial attributes of buildings

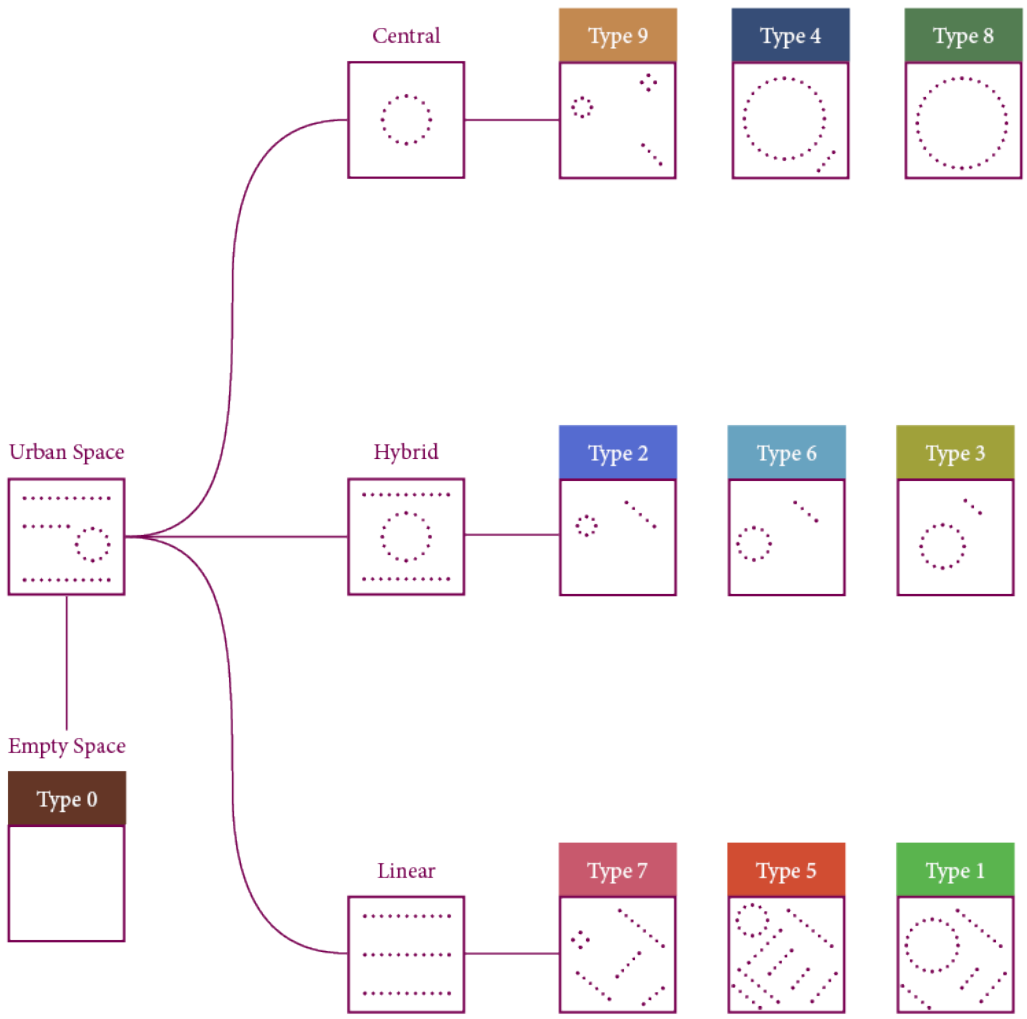


Figure 7.2: Taxonomy of urban form types from the formularized feature approach

directly shape the nodes of the taxonomy. Conversely, the formularized feature approach employs the extent of building occupancy for its nodes, a metric intrinsically associated with their spatial configuration. Consequently, these nodes are categorized based on the dominance of occupancy. Rather than striving for a direct equivalence between these distinct taxonomies, the formularized feature approach's types are harmonized with the three nodes (Central, Hybrid, Linear) of the taxonomy from the extracted feature approach. For

instance, Type 9 in the formularized feature approach reflects the presence of empty land and sparse surroundings akin to Type 6 in the extracted feature approach, while Type 8 in the formularized feature approach can be likened to the external space of a large building akin to Type 4 in the extracted feature approach.

Even with the alignment of the taxonomy from the formularized feature approach into one from the extracted feature approach, it remains difficult to differentiate types based on morphological traits associated with the arrangement of buildings and spatial relationships. For example, in the taxonomy from the extracted feature approach, the spacing and direction of rows enable the differentiation of urban form types with linear patterns. Moreover, in cases of hybrid patterns where linear and central arrangements coexist, the placement of structures constituting the central pattern between rows can determine the classification into different types. However, in the taxonomy from the formularized feature approach, Types like 1, 5, and 7, which share the same linear pattern, lack distinct morphological traits such as orientations, in-betweenness of rows, or length of rows, beyond variations in occupancy stemming from the size of structures constituting the central pattern.

7.2.2 Unique Urban Structures

Analyzing the taxonomy and fabric map derived from the formularized feature approach, a notable urban structure emerges (Figure 7.3). Cleveland, Miami, and Pittsburgh share analogous urban structures, while Detroit stands distinct. In these cities, a common urban fabric consists of large buildings such as Types 4 and 8 in the city center. Surrounding this core, there are urban fabrics characterized by linear patterns formed by residential buildings. Bridging these realms are hybrid types like Types 2, 6, and 3. Notably, Type 1 demonstrates a structural feature of interfacing fabrics, originating from central fabrics, passing through interfacing fabrics, and permeating smaller fabrics within residential fabrics.

In the case of Detroit, the types situated in the city center, including downtown, appear significantly subdued, making central fabrics less distinct. Instead, Types 2, 6, 3, and 1

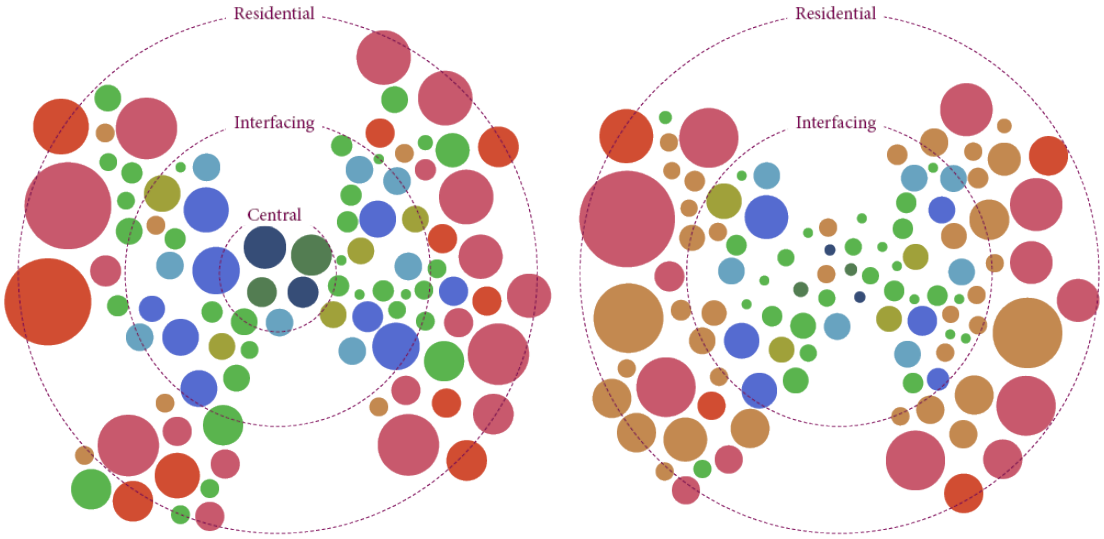


Figure 7.3: Unique urban structures from the formularized feature approach

that constitute interfacing fabrics extend their influence to encompass central fabrics. This results in a partition between interfacing fabrics and residential areas. Furthermore, Type 1, which once permeated residential fabrics, becomes attenuated. In this context, Type 9 emerges prominently within residential fabrics, displaying sparse yet dominant linear patterns interspersed with vacant spaces.

In conclusion, using only small number of formularized features did not unveil the unique urban structures of Rust Belt Cities. This can be attributed decisively to classification discrepancies concerning the city centers, particularly downtown areas. Unlike the extracted feature approach which exhibits the significant presence of large buildings and their surrounding spaces observed in Rust Belt cities, the formularized feature approach did not unveil clear urban fabrics dominated by large buildings in Detroit. However, it is not to say that Detroit lacks large building structures. Figure 7.4 displays the form types classified through the extracted feature approach in downtown Detroit, confirming the presence of substantial-size buildings.

Geometrical segmentation is the reason for the absence of urban fabrics dominated by large buildings in downtown Detroit. Figure 7.4 also illustrates the process of the deductive method's data generation, where grid cells are subdivided into multiple fragments for large



Figure 7.4: Process of data creation where morphological information is distorted through grid-based segmentation

buildings, and each fragment is classified into distinct types. The errors in such classification stem from the construction of form data using the geometrical segmentation and the method of deriving indices from it. This limitation is not merely confined to classifying urban fabrics but can also influence the inference and interpretation of urban structure. This comparison of urban structures from extracted feature and formularized feature approaches underscores this influence.

7.2.3 Findings from Formularized Feature Approach

In the preceding sections, I employed the formularized feature approach to analyze the same four cities that were previously analyzed using the extracted feature approach, focusing on their morphological traits. Viewing a city as a single object, I subdivided it using a rectangular grid, a method of geometrical segmentation. Within this subdivision, I utilized three indices as morphological features for each cell: proximity to the center of a grid cell (PROX), building area to a grid cell area (BHAD), and shape complexity of buildings in a grid cell (CHAD). These features were computed for all cells, and subsequently, cells were

clustered into ten types using these features. The distribution of these types was mapped to create urban fabric maps, similar to the process in the extracted feature approach.

Similar to the analysis using the extracted feature approach, the morphological characteristics of each type were revealed through both quantitative and qualitative analyses. This process led to the formulation of taxonomies for the four cities using the deductive approach. By integrating the spatial distribution and taxonomy, I demonstrated the distinctiveness of Detroit's urban structure compared to the other three cities and identified geometrical segmentation as the underlying cause.

This comparison indicates that the extracted feature approach unveils specific aspects that the formularized feature approach does not. To uncover these differences, a thorough review of the methodological disparities between the two approaches is warranted. Thus, by contrasting the analyses of urban form, fabric, and structure using both approaches, I explore the potentials and limitations inherent in analyses conducted through the extracted feature approach.

Table 7.1 below provides a recap of the characteristics revealed during the formularized feature phase.

Table 7.1: Summary of findings through morphology indexes-based analysis

Item	Contents
Features	Regions with high values of PROX, BHAD, and CHAD align quite well with the areas where the Central type is located in the urban form analysis based on the extracted feature approach.
	While BHAD and CHAD do not distinctly differentiate between suburban areas, they do differentiate the spaces around large buildings, and this differentiation is evident in PROX as well.
	BHAD reveals relatively lower densities in Cleveland and Detroit.
	In CHAD, Miami and Pittsburgh exhibit pockets of high complexity within areas that also have residential fabrics.
Amount	The absolute number of cells varies depending on the city size. Hence, for relative comparisons between cities, focusing on the quantity alone is insufficient; instead, it's necessary to consider the proportion each type occupies within the entire city.
	Cleveland, Miami, and Pittsburgh exhibit a similar distribution, while Detroit stands out with a notably distinct distribution.
	Type 9 in Detroit shows a significantly higher quantity compared to the others.
Rep. Form / Sampling	Building occupancy serves as the key trait in this analysis. However, determining how a certain type corresponds to configurational characteristics such as the arrangement of buildings or urban space remains challenging.
	In the representative form, meaningful shapes are difficult to infer.
	Utilizing 2D shapes as data doesn't offer information about building heights, which in turn means that three-dimensional spatial insights cannot be obtained from the form.
Feature analysis	Due to the use of relatively low-dimensional features, it is possible to visually confirm how types are assigned based on classification reasons like decision boundaries.
	Clear similarities emerge, which is evident in feature visualization. This clarity leads to the derivation of informative content that can be utilized in the taxonomy.

In this formularized feature approach, the revealed characteristics are compared with how they manifest in the extracted feature approach. Firstly, the areas with high PROX, BHAD, and CHAD values in the formularized feature-based urban form analysis align quite well with where Central fabrics are situated in the extracted feature approach. Although PROX, BHAD, and CHAD heatmaps in the formularized feature approach reflect attributes like terrain features or vacant areas based on land use, the corresponding urban fabric maps in the extracted feature approach did not account for such information. Hence,

it should be noted that these vacant areas are represented more extensively in the urban fabric maps compared to the heatmaps. The alignment of these areas suggests that PROX, BHAD, and CHAD are encompassed as morphological features in the extracted feature approach.

The heatmaps of PROX clearly distinguish areas around large buildings in the downtown core that lack distinct differentiation in the heatmaps of BHAD or CHAD. For example, in the case of Cleveland, the radial pattern evident in PROX captures medium and large building fabrics along the roads between residential fabrics, as well as fabrics representing the sub-core of the city. However, in BHAD, these fabrics are represented similarly to residential fabrics, and they lack distinctiveness. This implies that PROX complements features that are not apparent in BHAD or CHAD, and the introduction of more distinctive morphological features could lead to finer and more precise type classifications.

The extracted feature approach employs significantly more morphological features, approximately 1365 times more than the formularized feature approach, for type classification. Furthermore, the extracted feature approach focuses on curating data to embed a broader range of morphological relationships, rather than just form index formulation. Therefore, based on the extracted feature approach, distinctions in the characteristics of suburban areas and spaces around large buildings can be more granularly differentiated in type classification.

Miami and Pittsburgh exhibit relatively high horizontal density. The brightness of the BHAD heatmap in areas with residential fabrics in these two cities is notably higher compared to the other two cities. This implies that these cities occupy land more densely in residential areas than in the other two regions. Given that chapter 6 revealed minimal differences in the building areas of residential fabrics among the cities, the high horizontal density in Miami and Pittsburgh can be attributed to differences in arrangement rather than building area disparities. Contrarily, the extracted feature approach did not explicitly consider city density. However, the prevalence of Type 1 and 3, which are relatively dense

within residential fabrics, in Pittsburgh and Miami indicates that features related to density are already encompassed within the morphological features captured by the extracted feature approach.

Excluding the urban core space extending northwest from downtown, Detroit displays significantly low horizontal density throughout the entire area. The noticeable dimness of the BHAD heatmap in most areas of the city, excluding the city core, indicates that Detroit's horizontal density is conspicuously lower compared to the other three cities. These regions of low density in Detroit align with Urban Type 6 in the extracted feature approach, which represents vacant land around buildings. This observation is further supported by the unusually high occurrence of Urban Type 6 in Detroit. It suggests that the extracted feature approach leverages the arrangement and shape of buildings to implicitly capture features related to horizontal density during the data curation process, without directly relying on explicit density indicators.

In both Miami and Pittsburgh, regions with residential fabrics also exhibit sporadic areas of higher complexity. The CHAD heatmap of Miami and Pittsburgh reveals bright values interspersed within the residential fabrics, and these areas are relatively brighter compared to Cleveland and Detroit. These fabric occurrences align with Type 0, 2, and 7 in the extracted feature approach, which are distinct from the typical residential fabrics. In Miami, these fabrics play a role in supporting residential fabrics by forming the city's subcores characterized by commercial activities. In Pittsburgh, these fabrics consist of large buildings such as mills, hospitals, plants, stations, and universities, along with surrounding commercial establishments. This observation underscores how the extracted feature approach utilizes building arrangements and shapes as features for urban form classification, even without directly relying on explicit complexity indices during the data curation process.

When analyzing the quantity of types occurring in each city, the formularized feature approach presents a challenge due to the variation in the absolute number of cells according

to city size. As the urban area increases, the number of grid cells used for city segmentation also increases. Hence, a meaningful intercity comparison requires to analyze the portion of occurrence in each type relative to the total, rather than focusing solely on the absolute quantity. On the other hand, the extracted feature approach generates data corresponding to the amounts of buildings, enabling a relative quantitative comparison between different cities. In this study, the data for each city has been standardized to around 70,000, allowing for a comparison of both the absolute quantity and the distribution and trends among cities.

When examining the portion of types derived through the formularized feature approach, Cleveland, Miami, and Pittsburgh exhibit a similar distribution, while Detroit showcases a distinct pattern. Firstly, the portion of Type 0, representing vacant spaces, is excluded from distribution analysis due to its association with city topography and size. Among the three cities, Cleveland, Miami, and Pittsburgh, the highest portions are occupied by residential fabrics comprising Type 5, 7, and 9, followed by Type 1, 2, 6, and 8. Type 3 and 4, which represent unfragmented medium-sized buildings or most spaces occupied by either entire or partial footprints of large buildings, constitute the smallest portions. In contrast, Detroit shows notable deviations in its portion distribution. It stands out with an abnormal quantity of a relatively wide area not occupied by buildings (Type 9) within residential fabrics, surpassing the area of small-scale buildings forming linear patterns (Type 7) and showing a significant proportion gap compared to the other cities. Additionally, while the other cities exhibit a higher quantity of a blend of linear arrangements formed by small-scale buildings alongside medium to large-scale buildings (Type 1) compared to unoccupied spaces (Type 2), Detroit shows the opposite trend, with Type 2 surpassing Type 1 by a substantial margin. However, in the extracted feature approach, the distribution of type quantities lacks noticeable similarity among cities. Interestingly, Detroit, Miami, and Pittsburgh share a distinctive trait in their residential fabrics, particularly with Type 1, 3, and 5, showing significant disparities from other types. This contrasts with Cleveland, which displays a smaller differentiation from other types.

7.3 Validation of Two Different Urban Structures through Site Survey

As described in the above, the urban fabric and structure differ between the extracted feature approach and the formalized feature approach. To verify the results from these two, I conducted site surveys.

7.3.1 Validation of Urban Form Characteristics

The initial step in our site survey involves validating the urban form classification derived from an extracted feature approach. This validation does not compare the extracted feature approach and the formularized feature approaches directly. Instead, it assesses the extent to which the extracted feature approach successfully incorporates the characteristics of individual buildings and the surrounding urban spatial context in its classification of forms.

To this end, I initially selected five sites, each representing one of ten types, in four Rust Belt cities. These sites were chosen by overlaying urban fabric maps with footprint maps, ensuring the alignment of organizational and footprint types and, preferably, locating them in the central areas of the urban fabric. While on-site surveys are the primary method for data collection, deficiencies in available data were supplemented with GSV.

In-person field surveys were carried out in Cleveland and Pittsburgh through site visits. Figure 7.5 and Figure 7.6 show approximately five central areas of each urban fabric for the site visit, indicated by black dots.

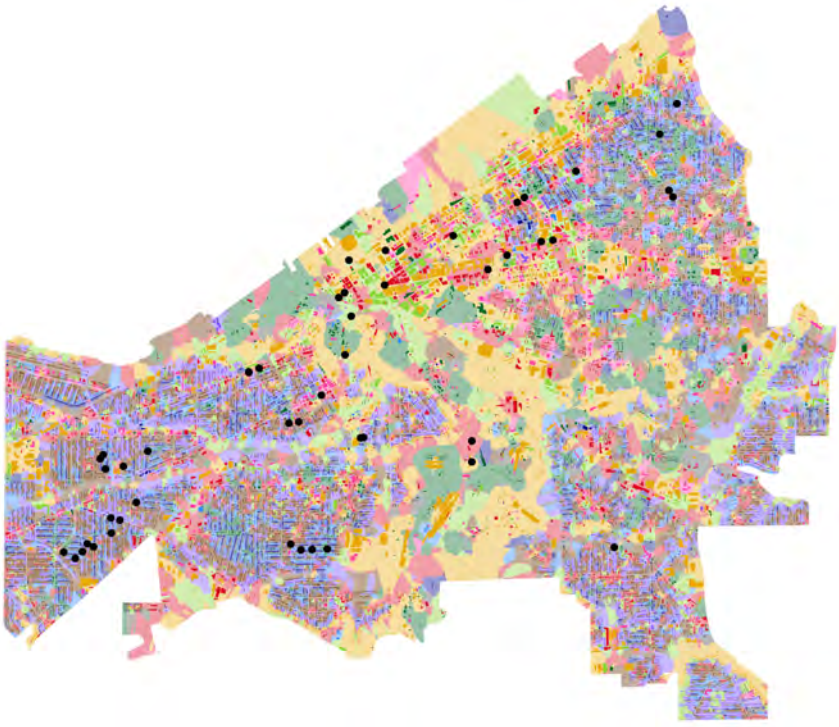


Figure 7.5: Site visit locations in Cleveland



Figure 7.6: Site visit locations in Pittsburgh

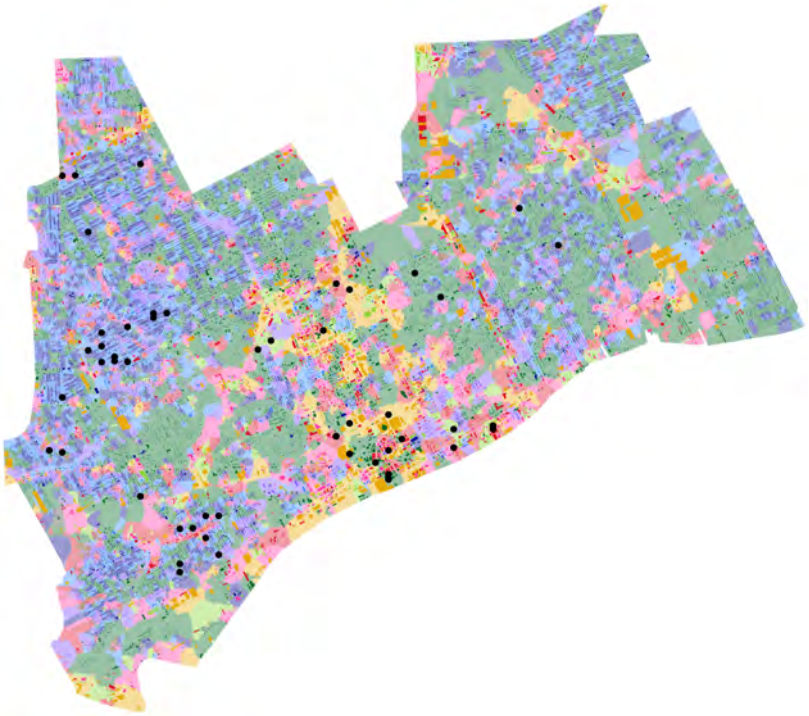


Figure 7.7: Site visit locations in Detroit

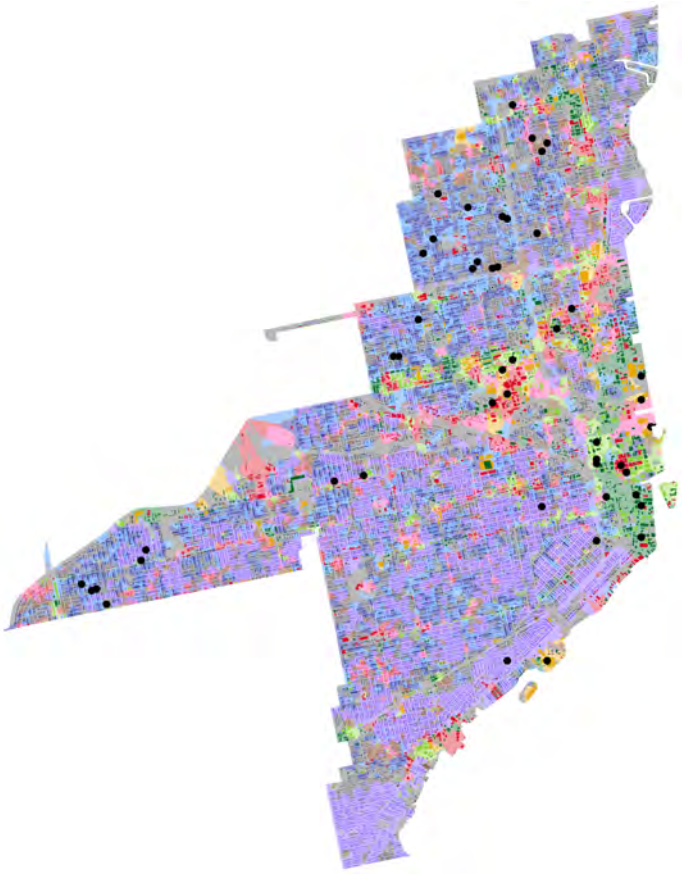


Figure 7.8: Site visit locations in Miami

Constraints prevented site visits in Detroit and Miami, leading to the use of GSV as an alternative. The application of GSV went beyond just substituting for photographs; it enabled active exploration and observation of the actual sites directly through the GSV platform. Figure 7.7 and Figure 7.8 show approximately five central areas of each urban fabric for the virtual visit, indicated by black dots.

Figure 7.9, Figure 7.10, Figure 7.11, and Figure 7.12 are photographic records of the urban spaces formed at the site visit locations selected above.

Type 0 manifested as clusters of large buildings, ranging from 4 to 6 stories, in Pittsburgh, Detroit, and Miami, typically forming approximately two-lane road spaces between midsize buildings. In Cleveland, however, the roads expand to 4-5 lanes, offering a spatially different feel compared to the other cities. This observation aligns well with the previously analyzed characteristics of Type 0, which identified it as predominantly consisting of mid-sized buildings, often grouped in configurations of 4-5 buildings of a similar scale.

Type 1 is characterized by linearly arranged houses across four cities. Pittsburgh maintains a relatively more linear arrangement with less influence from foliage, whereas Cleveland and Detroit see their linearity somewhat diminished by tree coverage. In Miami, the impact of foliage combined with the generally lower height of houses results in a significantly weakened linearity, offering a spatial atmosphere distinct from the other three cities. Previously, Type 1 was analyzed as consisting of 2-3 linear arrangements of rectangularly-shaped houses, with only a single linear space being identifiable from a perspective view from the site survey.

Type 2 is observed in all four cities as having lower heights and larger external spaces between more massive buildings than Type 1. This type predominantly consists of plants, machine shops, logistics warehouses, factories, and large offices. Notably, in Miami, large parking structures—parking garages—of 3-5 stories were frequently identified. Previously, Type 2 was analyzed as comprising larger standalone buildings or structures, creating larger

independent external spaces compared to Urban Type 0. Through this survey, it is distinguishable with a unique spatial characteristic from Type 0 due to its expansive external areas surrounding massive structures.

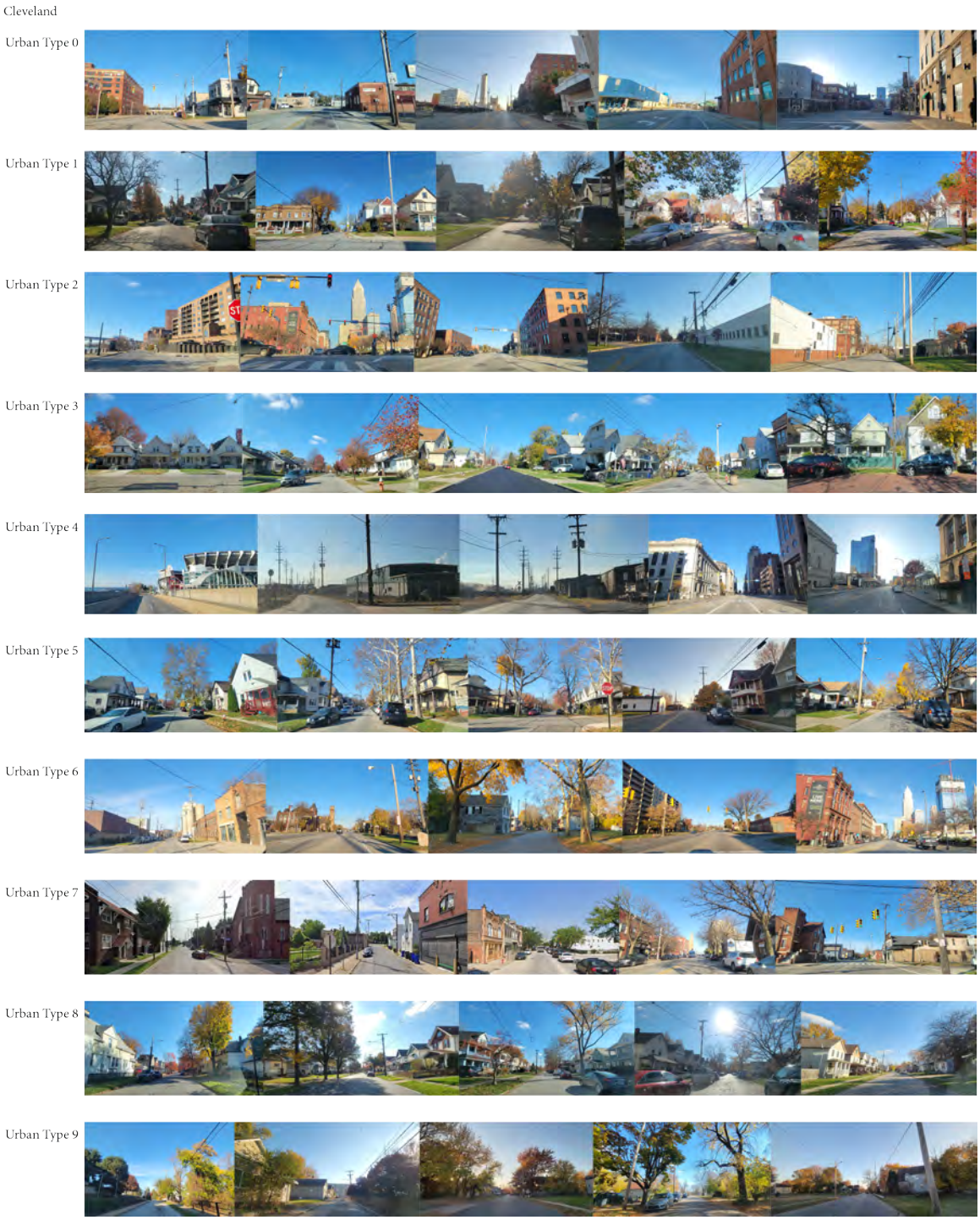


Figure 7.9: Photographic records of spaces at the site visit location in Cleveland

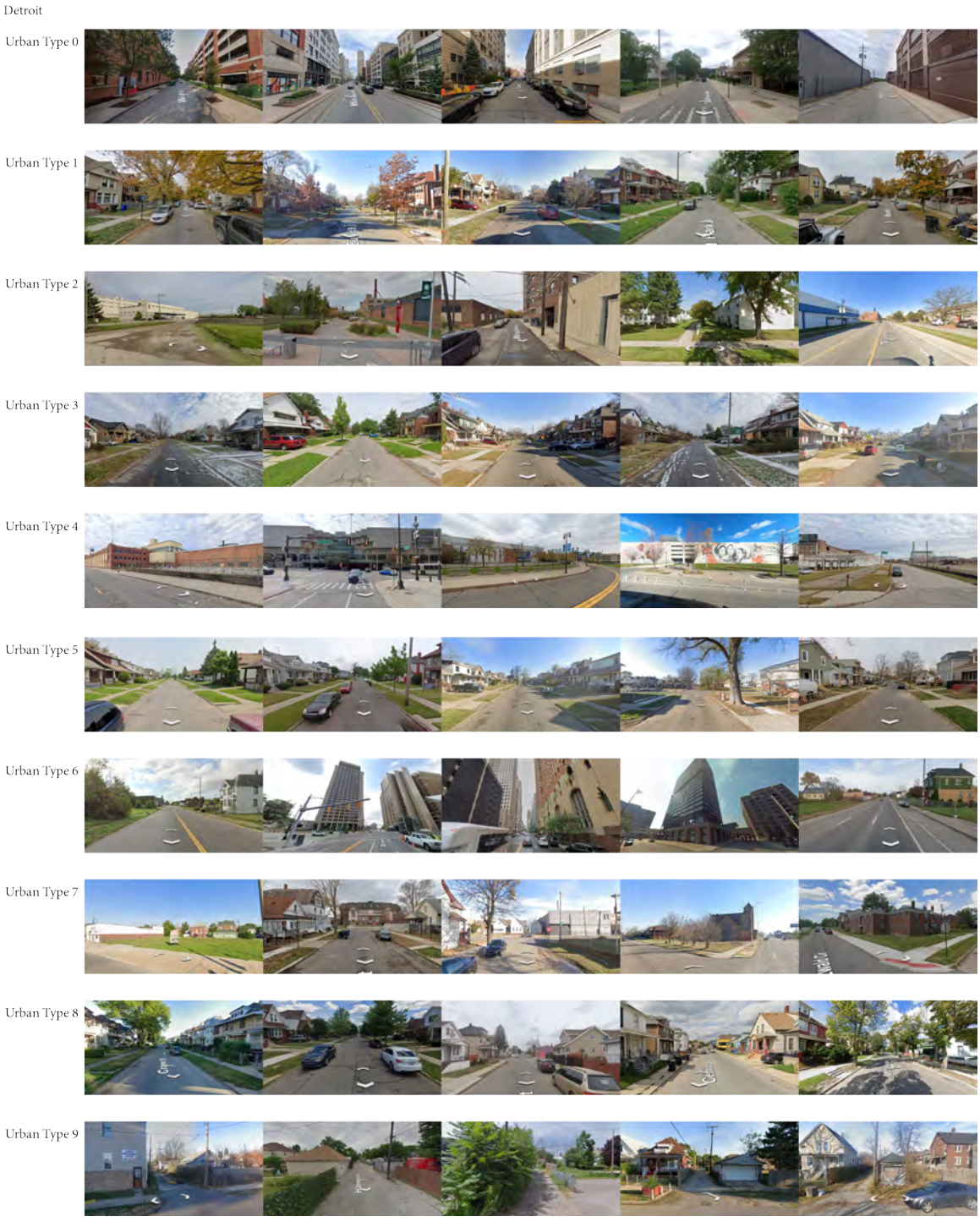


Figure 7.10: Photographic records of spaces at the site visit location in Detroit

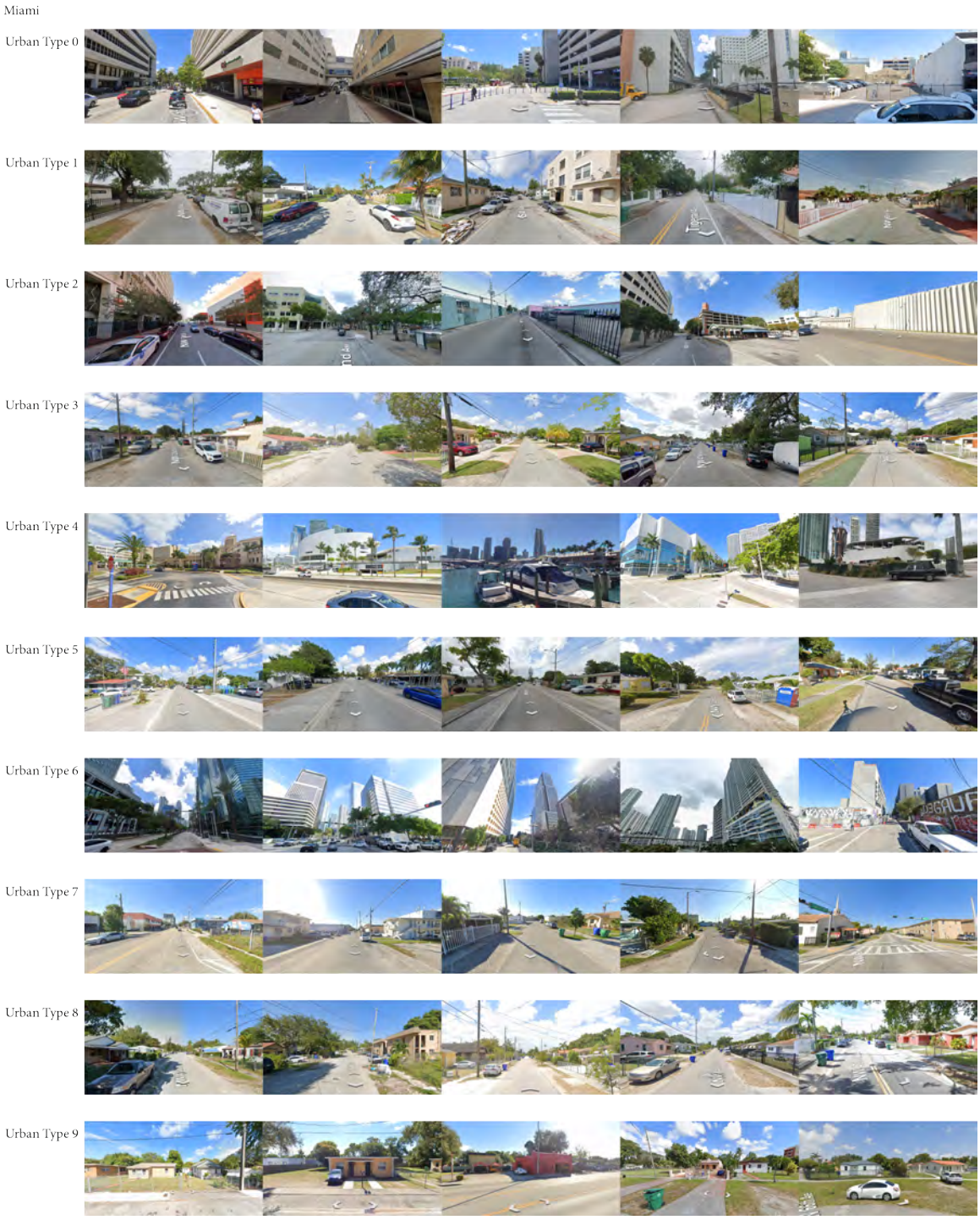


Figure 7.11: Photographic records of spaces at the site visit location in Miami

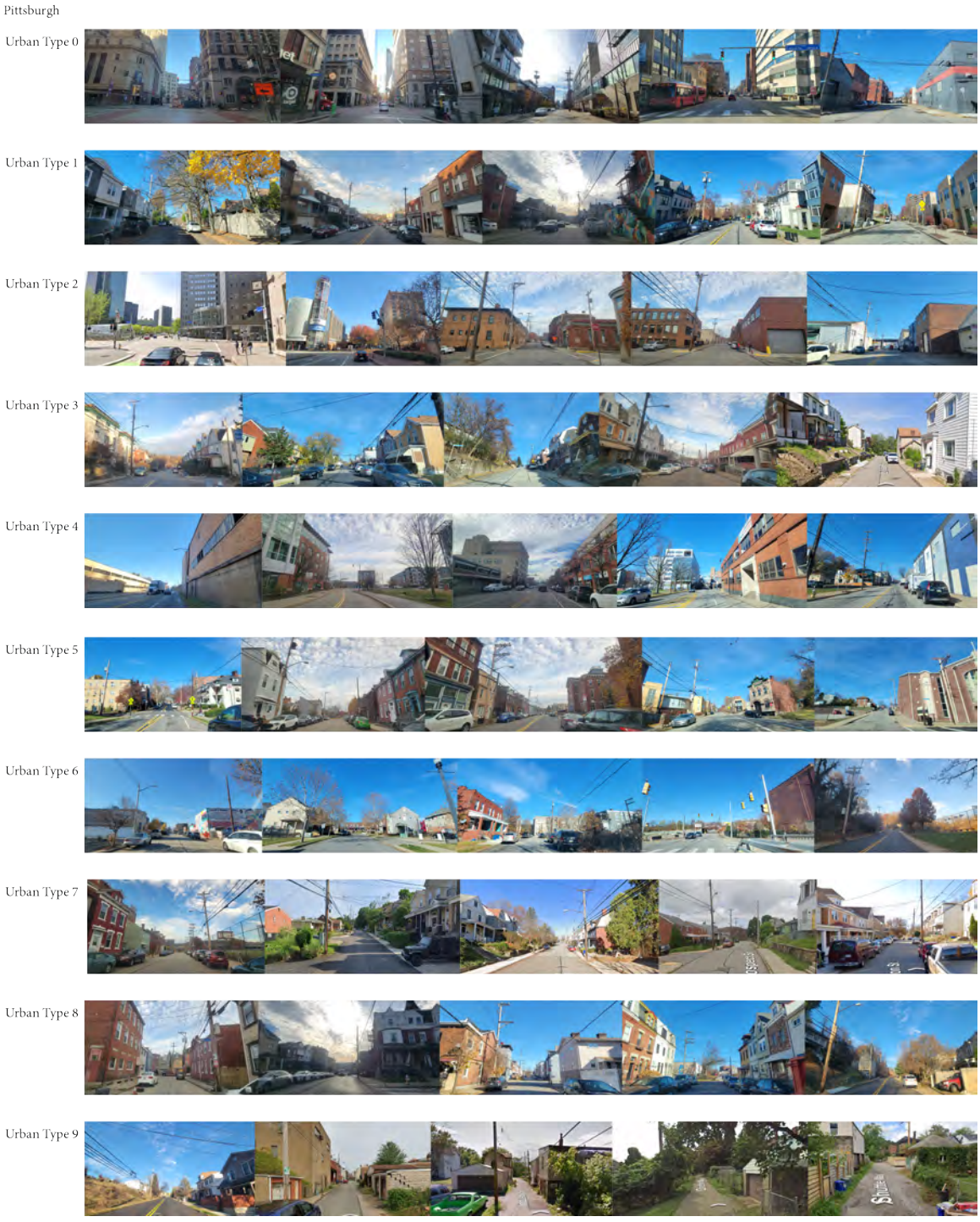


Figure 7.12: Photographic records of spaces at the site visit location in Pittsburgh

Type 3 represents urban spaces where houses are linearly arranged along streets, similar to Type 1. However, in Rust Belt cities, significant differences between Type 1 and Type 3 were observed. Unlike Type 1, Type 3 exhibits varying spatial atmospheres due to the non-uniform width of linear external spaces; some rows present wide, spacious areas, while others show narrow, enclosed linear spaces. This confirms the analysis that Type 3's inter-spacing between residential rows is less uniform than Type 1. Additionally, despite earlier analyses suggesting Type 3 consists of buildings with shorter depths than Type 1, spatial variations due to the depth of residential buildings in a row were not markedly observed.

Type 4, as previously analyzed, encompasses the surrounding spaces of short and large edifices, often revealing expansive open areas characteristic of significant structures. It exhibits programmatic differences between Rust Belt cities and Miami: in Rust Belt cities, Type 4 is associated with urban industrial infrastructure like factories, warehouses, and stations, while in Miami, it relates more to urban cultural infrastructure such as universities, convention centers, markets, and museums. Type 4 spaces in Rust Belt cities are often inaccessible or left as wastelands, whereas in Miami, these spaces are well-maintained with landscaping, actively utilized by people, and feature multiple facilities. These large industrial buildings and their surrounding spaces were identified as key elements in forming a unique urban spatial sense in three Rust Belt Cities—sometimes overwhelming, sometimes desolate, and sometimes weathered.

In the analysis, Type 5 was interpreted as a variation of the linear spaces similar to Types 1 and 3. However, site surveys revealed that Type 5 demonstrates a sparse linear arrangement with empty parcels or lots, indicating streets composed of row houses with a weaker linearity. Consistent with the analysis, it was observed that not only residential buildings but also offices and commercial buildings are intermixed within this linear arrangement, showcasing a blend of uses within these linearly structured spaces.

Type 6 in Rust Belt cities displays a duality of urban spaces: outside spaces surrounding a high-rise building such as apartments or offices, and empty lots surrounding a small

building. Detroit, for instance, exhibits numerous vacant lots within linearly arranged residential areas earlier, leading to isolated residential buildings and frequent occurrences of Type 6, a trend also observed in Cleveland and Pittsburgh. Contrarily, in Miami, Type 6 predominantly manifests as public spaces surrounding downtown skyscrapers, with vacant lots being a rare sight. This aligns with the previous analysis that Type 6 could either cluster around a focal building or present a building of significantly reduced scale.

Type 7 showcases urban spaces where residential areas arranged in a linear pattern coexist with relatively large buildings such as churches or schools. This combination tends to weaken linearity, leading to the observation of converging urban spaces like junctions. This observation aligns with the previous analysis that Type 7 presents a confluence of medium to large structures alongside housing rows, indicating a blend of architectural functions and scales within these spaces.

Type 8 was found to be significantly similar to Type 3, displaying a variety of widths in linear external spaces, which resulted in different spatial feelings across areas. Essentially, Types 3 and 8 did not show considerable differences in a perspective-based site survey. Given the previous analysis that the difference between Types 8 and 3 was the orientation of the linear arrangement, the minimal spatial difference between them could be expected.

Type 9 manifests in all four cities as spaces surrounding detached small garages or storage buildings near residential areas. This observation aligns well with the previous analysis that characterized urban spaces around garages as enveloping small buildings, confirming the initial categorization of these spaces within the urban fabric.

The site survey confirms the classification of each urban type as determined by the extracted feature method. This demonstrates the method's effectiveness, as it reveals distinct urban spaces within all types and consistent urban spaces across the cities for each type.

During this survey, I was quite impressed by how accurately the classification worked. When visiting the sites marked on the map, which classified the form of urban spaces rather than the buildings themselves, it was noticeable how the atmosphere of the space changed



Figure 7.13: A site where the transition between two different urban types occurs. This place was identified by the assistant as a transition point, and it is indeed a location where changes in types are observed on the actual map.

with each different fabric encountered.

This was particularly clear even to the assistant helping with the site survey, who had no background knowledge about the classification or the city at all. Through several visits, this assistant began to understand how urban spaces were classified according to the spaces around buildings and could anticipate the change in the atmosphere of space while he walked through the site, even asking me if they had correctly identified the transition points. It seemed that he roughly understood the classification of the extracted feature approach and used it as a counterpart to develop a sense of the composition of urban spaces and the accompanying changes in the atmosphere. Subsequently, the assistant was able to independently identify the points of change in urban types. This place was predicted by the assistant as a transition point, and it is indeed a location where changes in types are observed on the actual map.

Figure 7.13 shows an example of a space predicted by the assistant and confirmed as a transition point on the actual map. It displays the point where there is a change between an urban type with mid-size buildings and their surrounding large empty spaces, and another



Figure 7.14: The result of confirming different urban types in the building footprint map (bottom left) and the fabric map (bottom right) through a site visit (top) showed that the classification based on building footprints is more accurate.

urban type that features a linear arrangement of small-size residential buildings but interspersed with empty lots. This change is also confirmed in the urban fabric maps located at the top right corner of the figure.

This demonstrates that even non-experts can develop a sense of distinguishing specific urban spaces through interaction with the type and fabric map. It serves as evidence that the urban type and its fabric map, created based on an extracted feature approach, works consistently and corresponds to the actual urban spaces.

However, this method was not always accurate. During the survey, I found several anomalies in the classification. Especially when the fabric map and the building footprint

map indicated different urban types, it was often observed that the actual character of the space matched the classification of the footprint map, but not the fabric map. Figure Figure 7.14 is an example showing this difference. Looking at the footprint map, it was classified that most buildings in this area belong to an urban space signifying Urban Type 0, characterized by clusters of medium to large buildings. However, in the urban fabric map, it was classified as Urban Type 2, representing a large building and its surrounding empty spaces. Through an actual site visit, it was confirmed that the area consisted of clusters of medium to large buildings rather than a single large building, indicating that the map based on footprints was more accurate than the urban fabric map.

This issue is identified as stemming from a technical problem that arises when considering the decision boundary of KNN in terms of urban fabrics. The KNN algorithm projects the results of the classification done by a deep learning model as points onto geographical space. It then creates fabric patches based on the density of these points' types. During this process, some errors can occur. Thereby, it is anticipated that using a more advanced area segmentation algorithm that operates through points could reduce these errors. This issue does not merely show a technical limitation; it also reaffirms that urban form classification using deep learning is quite accurate, even though the accuracy of the fabric map might be lower.

Furthermore, this method includes limitations of its inability to clearly distinguish between spaces around high-rises and residential buildings surrounded by vacant lots in Type 6, despite height differences.

Figure 7.15 illustrates the limitations in Type 6 identification. On the left side of the figure, an urban space classified as Type 6 due to the presence of a significant amount of vacant lots is shown. On the right side, an urban space classified as Type 6 due to the exterior spaces of high-rise buildings is displayed. While these urban spaces might appear similar from a top view, an actual site visit reveals that the atmospheres of these two spaces are markedly different. Despite these differences, both are classified as Type 6, which could



Figure 7.15: These photos show examples of residential areas with vacant lots (left) and areas with empty spaces around high-rise buildings (right), both classified as Urban Type 6.

be attributed to height normalization. When constructing urban form data, I normalized the highest point in a file to a value of 1, represented by white, and the lowest point to a value of 0, represented by black (Figure 7.16). Thereby, it can be inferred that high-rise buildings and their surroundings are depicted in very light colors, while areas with vacant lots in their vicinity exhibit a similar contrast.

Furthermore, Types 8 and 3, despite sharing similar spatial characteristics, are distinguished in analysis by the orientation of their linear arrangements (Figure 7.17. This differentiation stems from a methodological limitation related to how data formatting normalizes orientation, using the building form's MBG. Occasional misclassification of similar spaces as different urban types can also be observed and it suggests a need for further refinement

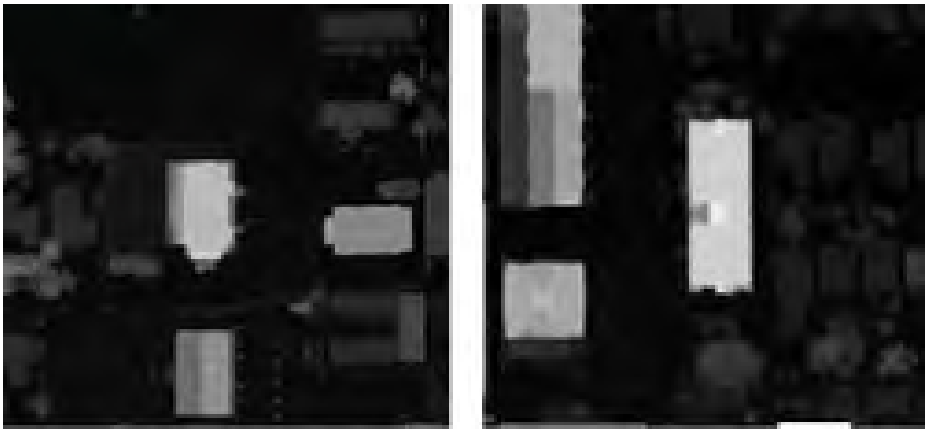


Figure 7.16: In the proposed urban form data, spaces around residential buildings with vacant lots (left) and areas surrounding high-rise buildings (right) are similarly represented.



Figure 7.17: Spaces of Type 3 (left) and Type 8 (right) actually possess very similar spatial characteristics.

and advanced engineering to enhance classification accuracy.

7.3.2 Conflicts among Urban Type

Further to the validation based on surveying sites of each urban type, I examine the potential benefits of the proposed alternative method compared to the formularized feature method by validating how each method classifies urban types at conflict points (CP) where urban types intersect. CP are identified by referencing urban fabric maps (Appendix K) and classified building footprint maps (Appendix E), sampling three locations in each city where two or more urban types collide. For detailed analysis results, refer to the Appendix N.

The proposed method generally showed superior classification performance. For instance, in the case of CP2 in Cleveland, the proposed method classified Type 8, consisting of houses in linear arrangement, and Type 4, denoting the outdoor space of low-rise, large buildings, whereas the formularized feature method classified the linear arrangement of houses as an urban type centered around large buildings, and the large building's outdoor space as an urban type with relatively empty spaces (Figure 7.18). Additionally, in CP2 of Pittsburgh, the proposed method classified various urban types based on residential areas and the outdoor spaces of large buildings, while the formularized feature method classified the entire area as an urban type signifying the spaces between or around medium-sized buildings (Figure 7.19).

A notable case is CP1 in Miami (Figure 7.20), where the proposed method clearly distinguished the space behind residential areas as high-rise apartment spaces. However, with the morphology indexes-based method, these apartment spaces were segmented into various types with different characteristics. This phenomenon was also observed in Detroit's CP2 (Figure 7.21), where urban types incorporating large buildings, such as churches and schools in a linear arrangement, appeared, with the organization of large buildings being segmented into various spaces.

Overall, the proposed method classifies urban types more granularly, regardless of



Figure 7.18: Conflict Point 2 in Cleveland.

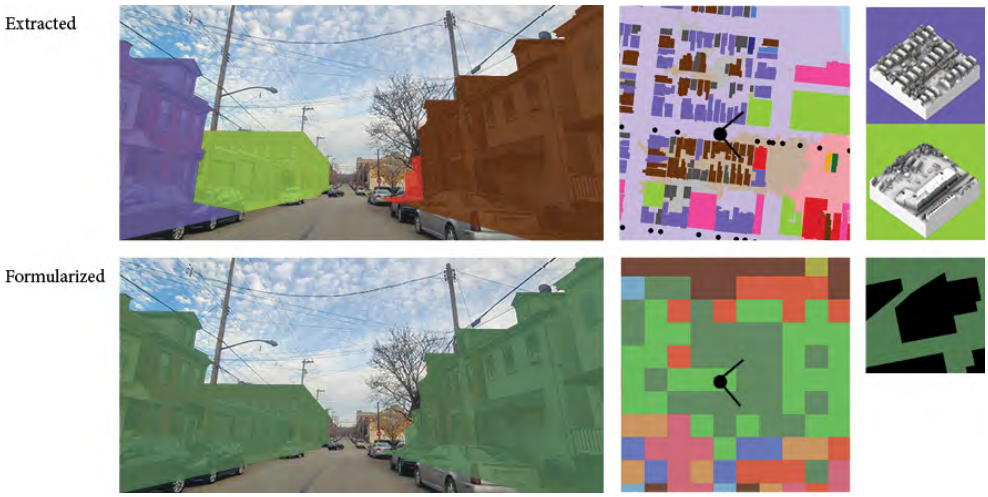


Figure 7.19: Conflict Point 2 in Pittsburgh.

building size, based on the characteristics of the neighboring space of each building, resulting in less discrepancy between the classification results and the actual space upon site visit. The morphology indexes-based method was quite accurate in classifying urban types predominantly featuring linear residential arrangements, but it segmented the outdoor spaces of large buildings into multiple types, resulting in a mix of various urban types and not forming a consistent fabric. This lowers the accuracy of spatial character-based classification in cities with widespread large industrial facilities, such as Rust Belt Cities, distributed throughout the city.

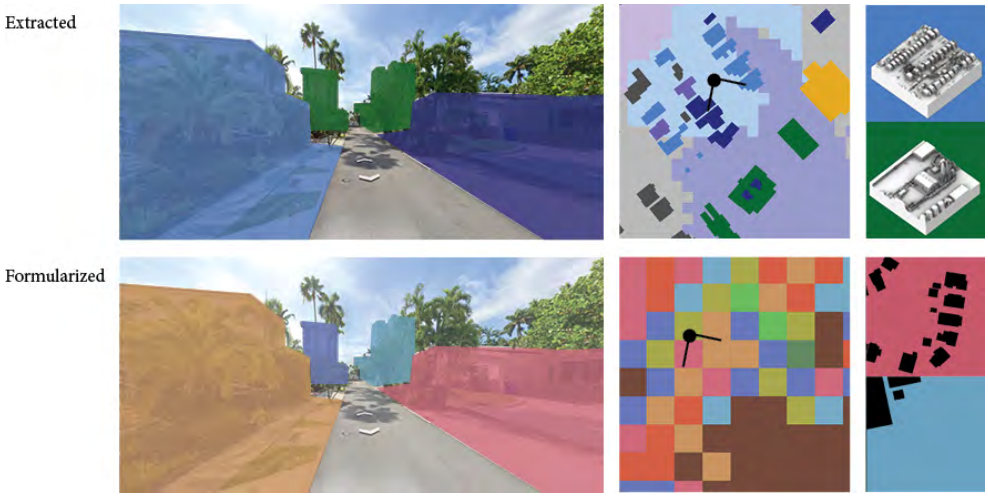


Figure 7.20: Conflict Point 1 in Miami.



Figure 7.21: Conflict Point 2 in Detroit.

7.4 Potentials and Limitations of the Extracted Feature Approach

Site surveys have confirmed that the extracted feature approach allows for a more accurate, detailed, and granular classification of Urban Types based on spatial characteristics. The primary reason for the enhanced performance is the incorporation of more complex information within the data. The proposed extracted-feature approach in this study involves the extraction of morphological features using curated data and a statistical model, without formulating specific form indexes. This approach encompasses a greater number of fea-

tures compared to the formularized feature approach, allowing for the embedding of more complex relationships among features beyond simple metrics like area ratio. By utilizing such relatively intricate data, deep learning models capture morphological features based on urban form configurations rather than mere ratios of occupancy. Unlike the formularized feature approach, this enables the classification and analysis of urban forms according to various spatial arrangements, including the arrangement, orientation, and density of central and surrounding buildings.

Additionally, from a data complexity perspective, the use of 3D information also played a crucial role in enhancing performance. Within the extracted feature approach, harnessing 3D data has afforded a more comprehensive classification of urban morphology, underpinned by a richer set of spatial information. Using 2D forms—so called shapes—as data does not provide information about height, and this lack of height information limits the acquisition of three-dimensional spatial insights from the form. Hence, the representative form remains confined to its 2D shape, complicating interpretation to extract meaningful spatial information. In contrast, the extracted feature approach employs 3D forms as its data basis. This allowed for the construction of data that incorporates the third dimension, facilitating the 3D analysis of configurational traits inherent to each type of space.

Admittedly, the formularized feature approach also has the potential to assimilate 2.5D or 3D information, thereby enabling the extraction of more features from such data and subsequently facilitating the formulation of more form indices. Nonetheless, for this evaluation, I chose to utilize a formularized feature method with 2D data, given that most conventional methods depend on 2D data. This deliberate selection has underscored the limitations inherent in solely relying upon 2D morphological delineations bereft of height data. Using 2D data makes it difficult to accurately identify significant spatial configurations and characteristics and simultaneously increases the chance of introducing inaccuracies in the classification process.

The second factor contributing to the performance of the extracted feature approach

is the method of data configuration. When employing the formularized feature approach to classify urban form, the utilization of geometric segmentation, such as grid cells, leads to the inclusion of building forms and urban spaces in a randomly fragmented manner within the data. While this segmentation minimally affects the overall trends for smaller buildings, its impact becomes critical for larger buildings. Large buildings often span multiple cells, resulting in their representation as subdivided across these cells. This kind of subdivision frequently leads to the classification of a single building into multiple urban types, subsequently altering the interpretation of urban structure.

On the other hand, the extracted feature approach employs a spatial segmentation that defines a consistent extent of the surrounding space with a single building as its focal point. This method allows for the representation of both the individual building and its spatial relationships with the surroundings through its form. Even when a building's size exceeds the designated extent, the segmentation process necessitates a subdivision of the building's shape. However, when the extent of a single building and its immediate neighboring buildings overlap, this overlapping mitigates information loss or distortion by enabling the representation of fragmented forms from various perspectives. As a result, even for larger buildings, it becomes feasible to classify the urban space of an individual building without resorting to subdivision.

These differences were most evident in the analysis of representative forms. The formularized feature approach yields representative forms that do not provide discernible shapes. Employing a grid-based geometrical segmentation, buildings are represented within fragmented cells. This fragmented representative form does not convey how buildings configure space coherently. Since building occupancy serves as a main trait, understanding how certain types contribute to the arrangement of buildings or urban spaces, regarding configurational characteristics, becomes challenging. For instance, distinct configurations are observed in Detroit Type 2 compared to the other three cities. This implies that features based solely on area may not adequately capture the nuances of spatial arrangement. In

contrast, the extracted feature approach within the proposed framework incorporates various morphological traits, including not only building occupancy but also the arrangement, shape, and relationships between buildings. Thereby, its representative form becomes conducive to perceiving and analyzing the emergence of distinct spaces, with less fragmented spaces and buildings.

However, in the extracted feature approach, the abundance of these numerous features introduces a high level of informational complexity, making it challenging to discern relationships among features or relationships between features and urban form. This is because the vast array of features does not necessarily correspond to a one-to-one relationship with form changes. For instance, consider a scenario where 100 morphological features are derived from a deep learning model. Upon increasing Feature 1, one can observe that building width expands, leading to a wider gap between buildings, while decreasing Feature 1 results in narrower width and gaps between buildings. When one increases Feature 57, both building depth and width increase, causing a reduction in the gap between buildings. In such cases, it is speculated that Feature 1 and Feature 57 might have relationships with building width and also other aspects of form. Yet, one cannot conclusively determine whether Feature 1 primarily influences width and gap or interpret the mechanisms by which Features 1 and 57 collectively impact building width. Therefore, it struggles with intuitively understanding morphological features inductively derived from extensive data, making it difficult to identify principal features and their relationship to forms.

7.5 Evaluation of the Proposed Approach's Effectiveness from the Perspective of a Professional Urban Planner

I conducted a comparative analysis of urban form and structure, using Formularized and Extracted approaches on identical cities, to methodologically evaluate their potential and limitations. This analysis extended to incorporate practical urban planning considerations,

assessing how the Extracted approach and its foundational concept—viewing the city as an aggregation of neighboring spaces—might alter our understanding of urban environments, enhance urban planning strategies, and pinpoint critical areas for attention and development. The culmination of this evaluation was an expert interview, centered on this proposed method and a specific case study, to clarify the importance of this methodology within the field of urban planning.

The interview was held with Francisco Alaniz Uribe, a professional urban planner and academic specializing in urban density and regeneration. As an Associate Professor at the University of Calgary, Francisco had been furnished with a document and a concise, approximately 10-minute video brief to familiarize himself with the concept and the case study. This section highlights only the critical and essential points from the conversation. For a more detailed account, please see the interview transcript referenced in Appendix O.

Professor Alaniz initially evaluated the merit of the proposed method that analyzes the entire city's morphological traits through individual urban form/space. He highlighted that this approach facilitates the active integration of data science into urban planning analyses. However, he critically pointed out that the results of such analyses can be significantly influenced by the scale of the area—the extent of the data—represented by individual urban form data. He noted that if this scale ranges between 50-100 meters, the analysis primarily concerns the built environment of individual buildings. Conversely, if the scale extends beyond 500 meters, or even reaches 1000 meters, the analysis shifts to a broader, enabling a more collective understanding of urban dynamics. Such scales can elucidate morphological characteristics of neighborhoods, uncover characteristics of urban spaces in and around low-density areas, and inform issues such as rezoning. He said that this approach would provide insights into the morphological traits of more collective urban entities, representing a shift away from the current focus on granularity. This highlights a limitation of the current study but also indicates that conducting thorough experiments across various scales could provide diverse contributions to urban planning.

He noted that the dataset used in the proposed approach is designed to enrich the analysis by not just capturing the shape of spaces but also their properties. Specifically, he pointed out that this enrichment could be achieved through the integration of parcel information with LIDAR-based 3D form data. This combination provides a detailed representation of how specific private or public lands integrate into the urban fabric, enhancing the process of form identification. By doing so, it augments the dataset with a deeper insight into the urban planning significance of geometrical configurations commonly used in urban form studies. It effectively bridges the gap between theoretical methodological issues and their practical applications in urban planning. This suggests an association between 3D form information and additional morphological data within urban form datasets, highlighting the necessity for a new data format and the potential to develop a novel understanding of urban environments.

He also highlighted the significance and roles of associating urban form data with non-morphological data. He noted that integrating data such as social demographics, income levels, or other socio-economic and educational metrics could provide valuable insights for future research. Although understanding these complex relationships can be challenging, they have substantial potential to influence urban planning and policy-making. For example, analyzing the connections between school enrollments, social demographics, and built form can reveal how urban density affects family dynamics and school populations. This knowledge could guide zoning changes or housing policies tailored to attract young families, thereby shaping the future development of urban landscapes. Using this technology to analyze entire cities, such as Calgary, could uncover critical insights into issues like density, housing, and land values, essential for municipal decision-making. The ability of this tool to merge multiple layers of information—land value, built form, accessibility, and transit—proves invaluable for city planners and real estate developers. By identifying potential areas for redevelopment or investment, this analysis can influence how cities develop, ensuring that infrastructure capacity and investment priorities align with the socio-economic

implications of urban forms.

He offered another example to demonstrate the value of this data association. He suggested examining the interplay between nutrition, urban form, walkability, and socio-economic status to assess accessibility to grocery stores, emphasizing the importance of such access. He noted that people are more likely to walk rather than drive to shop if grocery stores are within walking distance. However, he pointed out a challenge specific to North America, and particularly Canada: the low urban density and the predominance of large-scale grocery stores. These stores generally require a support base of about 10,000 to 12,000 people, yet many communities only number between 2,000 and 3,000 residents, leaving them without nearby grocery options. These residents often have to travel to distant markets or chain stores. While some places subsidize grocery stores to enhance community access, this is not feasible everywhere, especially in areas with varying urban forms. Thus, exploring the relationship between urban form and access to nutritious, everyday food could present a compelling aspect of our project with considerable potential.

Throughout the interview, he emphasized that this approach serves as another method for interpreting cities. He pointed out that the morphological patterns that result from this approach could act as an additional layer of urban information, capable of interweaving with existing layers of information. He suggested that this interweaving could offer an opportunity to refresh our perspectives on the current challenges facing our cities, and guide the direction of future research.

This chapter has illuminated the comparative strengths and challenges of the extracted feature approach in urban form analysis, highlighting its enhanced granularity in classifying urban types through a more nuanced understanding of spatial relationships. Through a discussion with the expert, I evaluated the significance, potentials, and limitations of this approach in urban planning. Transitioning to the conclusion, I will synthesize these insights, reflecting on the broader implications for urban morphology research and the po-

tential pathways for integrating advanced data analysis techniques into urban planning and architectural practices.

CHAPTER 8

CONCLUSION

I have positioned my research in computational urban form analysis, tracing the historical aspects of urban morphology with the intersection of computation. This emerging field, which I referred to computational urban morphology, emphasizes the statistical and data-scientific methods on our understanding of urban form. This field is crucial as it enables a deeper, more nuanced, and granular understanding of cities, emphasizing the new aspects of architectural and urban forms. This approach goes beyond mere aesthetics or compositional principles.

From this perspective, I selected and analyzed existing studies that could be classified under computational urban morphology. The majority of these precedents perceived the city as an object with a shape defined by its boundary. To understand the characteristics of this object, they dissected it using geometries such as grid, parcel, and neighborhood boundaries, creating various segments. Morphology features applied to each segment established morphology indexes through the relationships among these features. Applying these indexes across all city segments visualizes patterns in urban form, yielding insights into the spatial arrangement of cities.

I identified a gap in this approach. While cities are demarcated by boundaries for various geographical, social, and cultural reasons, appearing as bounded objects on maps, actual urban spaces are continuous and boundaries on a map may not reflect true spatial divisions. This applies not only to city outskirts near its boundary but also to administrative borders like neighborhood boundaries, which often emphasize political and social implications over spatial meaning [139]. Moreover, when examining cities not from a macro, top-down planning perspective but at the scale of individual small urban spaces, these boundaries operate differently, suggesting more granular urban spaces beyond con-

ventional borders in a city [37].

Moving beyond the cartographic recognition of city centered on boundary shapes, I explored the configuration of individual urban spaces to discern their collective role in shaping urban spaces. This exploration aims to gain a nuanced understanding of spatial similarities and differences within and across cities, challenging the conventional cartographic recognition and offering a new insight into the spatial and structural characteristics that define urban spaces.

To address this, in chapter 4, I proposed a methodological framework that views the city not as an object composed of dissected spaces, but as an aggregation of the neighboring urban spaces of individual buildings. In chapter 5, I applied this framework to three Rust Belt cities—Cleveland, Detroit, and Pittsburgh—as a case study where a specific scheme of data is used to define individual urban spaces; I created a dataset for urban form data that includes neighboring urban spaces within a cubic area approximately 650ft in width, length, and height, centered on a single building. This urban form data exhibited numerous overlaps of a urban space in the entire dataset, signifying diverse spatial relationships between a building and the urban space. Then, I employed a deep learning model to capture the morphological features of individual urban spaces and clustered the features to yield types of urban spaces, leveraging the form data to reveal the morphological characteristics of urban spaces. These types of urban spaces enabled me to delineate a pattern of urban fabrics. In chapter 6, analyzing these patterns, I investigated urban structures unique to the Rust Belt Cities. Through the evaluation in chapter 7, I confirmed that the proposed method could provide more granular classification of urban forms and lead to more nuanced understanding of city space than conventional methods based on formulaic features that dissect cities into grids.

8.1 Contribution

The framework introduced in this study offers contributions from the following perspective.

Firstly, I introduced a novel concept of urban types along with new definitions for urban fabric derived from the concept. By adopting a data science perspective, I characterized urban forms through the diverse form entities constituting the neighboring spaces of buildings, unveiled common morphological patterns among them, and classified these patterns as urban types. Following this, I mapped the type information onto geographic space, establishing boundaries based on their spatial distribution, a process I proposed as a new method for defining urban fabric. This method, complementing existing approaches to defining urban fabric from cartographic, architectural, landscape, and social viewpoints, broadens the scope of urban morphology research by introducing a data-driven methodology to define urban fabric.

Secondly, the study introduces a novel data formatting approach for urban form analysis, demonstrating its effectiveness. This unique formatting captures three-dimensional spatial information of urban forms within a specific area centered on a single building, including features like neighboring terrains, buildings, streets, trees, and more. While the data's appearance may not significantly differ from traditional grid cells due to the use of rectangular shapes for extracting specific urban forms, the information it aims to embed offers a more spatial-centric representation of urban form, distinctly differentiating it from conventional grid cell approaches.

Thirdly, the study demonstrates the feasibility of analyzing 3D urban forms using universally accessible data sources and processes for dataset construction. Utilizing aerial survey data, a type of public data, I processed it according to the new data format to create a novel urban form dataset. This implies that researchers can conduct similar analyses in any city using publicly available aerial survey data, without needing access to specialized formats like 3D mesh. Metropolitan areas like New York, San Francisco, and LA are de-

veloping or have already developed high-quality urban 3D data and made it available to the public. However, many second-tier cities in the US, such as those in the Rust Belt, face practical challenges in generating such high-quality data, limiting urban analysis research. The method used in this study for constructing urban form datasets can overcome the scarcity of 3D data in these cities, enabling urban space analysis research to progress.

Fourthly, the study presents a method for deriving urban types from large datasets enriched with numerous morphological features, showcasing the ability to process and categorize urban forms based on their complex characteristics efficiently. I utilized the VQ-VAE2, a deep learning model, to extract morphological features from a newly formatted extensive urban form dataset. These features were then classified using the K-means algorithm. This research demonstrates the potential of employing a series of machine learning models to manage and analyze complex and voluminous urban forms, suggesting the feasibility of handling urban morphology with high complexity through advanced computational methods. Technically, future research could improve classification accuracy by testing a various of deep learning models along with advanced clustering algorithms such as t-SNE or Uniform Manifold Approximation and Projection (UMAP). This approach would suggest a path toward refining the analytical precision in categorizing urban forms.

Finally, the framework introduces a new approach in the evaluation process. In the case study, I demonstrated how the extracted feature approach differs from and evaluates against the morphology index-based method. This comparison highlights the distinct methodologies and potential advantages of the extracted feature approach in analyzing urban forms. Moreover, acknowledging the computational intensity of the proposed method, I suggested incorporating site surveys as part of the evaluation to enrich the computationally heavy nature of this approach. This survey aims to complement the computational analysis with empirical insights gained from direct observation, enhancing the overall assessment of urban forms.

The site survey went beyond merely visiting locations to qualitatively validate compu-

tationally classified outcomes. It cross-validated how the results from the extracted feature approach and the formularized feature approach differ by observing the urban configurations presented by the actual sites. This process provided a deeper understanding of the distinct implications the proposed method has on interpreting urban forms. For example, in chapter 6, I claimed that Rust Belt cities, unlike Miami, often feature urban types with large industrial buildings and vast vacant spaces surrounding these buildings., and this contributes to a unique urban structure existing between downtown areas and residential neighborhoods. Through site visits, I not only confirmed this structure, but also found these large industrial buildings and their surrounding spaces to be significant in shaping a unique urban spatial sense in Rust Belt cities.

I believe site surveys are essential to be integrated within the framework as evaluation process, especially when dealing with large data through inductive statistical models like deep learning, which are often black-boxed and lack explicit feature processing. Site surveys enable researchers to verify classification results and provide a practical level of confidence in the outcomes, offering a tangible connection between computational analyses and real-world urban configurations.

Alongside the framework, this study contributes by facilitating a new perspective on how cities are viewed, emphasizing a novel approach to understanding and analyzing urban environments. In this study, the city is not viewed as an object to be analyzed through decomposition but rather as a pool of information formed by overlapping aggregations, where each individual urban space and its relationship with buildings are considered. This perspective shifts the focus from dissecting cities to understanding of individual urban spaces.

Through this process, I proposed that viewing urban spaces differently is possible by capturing information and embedding it into data through careful curation. This perspective posits that, rather than concentrating on the overall form or structure in the analysis of urban spaces or forms, it is possible to comprehend the whole from individual spaces that can be experienced by each person. Thereby, such an approach enables the identification of urban



Figure 8.1: Distribution of large industrial building fabrics, marked in yellow as Urban Type 4, across the four cities. Except for Miami, the other Rust Belt cities display a high frequency of these fabrics.

spaces surrounding a building that resemble other spaces in the city.

The aggregation of individual urban spaces also enabled the comparison of spaces between cities; it allowed for the analysis of how a space in one city resembles or differs from another space in a different city. For instance, as presented in the case study, urban spaces of massive industrial facility buildings corresponding to Type 4 were similarly found in Cleveland, Detroit, and Pittsburgh, showing resembled spatial configurations. Though their programs and occurrences differ, in Miami, large industrial facilities like logistics warehouses were also classified under the same type (Figure 8.1). Through such types

and classification, I introduced a method for comparing the spatial characteristics of cities that are geographically distant, illustrating the potential for spatial analysis across urban environments.

8.2 Discussion

The framework presented in this study emphasizes the increasing importance of data in urban form analysis, which aligns with ”the emergence of new authorial roles related to how data is collected, curated, processed, and visualized”, and suggests that ”the construction of the data, the design of the rules, and the curation of the examples are acts of design.” [140] This study goes beyond merely setting morphology features and constructing novel morphology indexes; it highlights that how urban form data is constructed—data curation—stands as a crucial issue in urban form analysis. This underscores the significance of the methodological aspects of urban form data handling, formatting, and processing. Constructing a dataset with a consistent format that encompasses morphology information, tailored to the analysis objectives, becomes closely related to the outcomes of the analysis. This process is a novelty that can significantly contribute to the methods used in computational urban morphology.

The case study in this research serves as an example of curating urban form data. I hope this study paves the way for more and diverse methods of urban form data curation to emerge. Especially, the method of formatting 3D urban form data requires much more exploration. In this study, rasterized 3D data was used, which is advantageous for ensuring all data inputs a deep learning model in a consistent format. However, this format is not ideal for compromising attributes that significantly impact classification, such as orientation, but do not play a substantial role as morphology features. For instance, if urban form data is formatted as a 3D mesh, it would be represented as a graph composed of nodes and edges. Utilizing loss functions in deep neural networks that are less affected by the ori-

entation in data could minimize the influence of orientation on morphology features. This approach allows for a focus on the intrinsic properties of urban forms without the bias of their orientation.

Another area for exploration in data curation could involve the application of color schemes. For example, applying a gradient color based on the footprint area of buildings in rasterized urban form data could highlight the relationship between a building's area and its neighboring urban spaces. Additionally, while not represented in this case study data, embedding lot boundary information using solid colors for specific lot information is also feasible. In this line, this paper could serve as a foundational step towards experimenting with various novel approaches to data format, representation, and configuration.

Moreover, the curation of an urban form dataset is not just a matter of method. The composition of an urban form dataset reveals how a study approaches, treats, and handles the city, providing clear insights into the research methodology and perspective on urban analysis. In this research, I constructed an urban dataset based on the recognition change of viewing the city as an aggregation of neighboring urban spaces. This approach allowed me to uncover unique urban structures in Rust Belt cities, which conventional methods—viewing the city as an object defined by its boundaries—could not reveal, such as the spaces and their configurations dominated by industrial buildings in three Rust Belt cities. Thus, the way an urban dataset is curated should be a crucial part of computational urban morphology, as it reflects our approach to understanding cities.

This research proposes a methodological framework that interweaves a data scientific perspective into urban morphology, based on the premise that a new perspective on cities enables novel analyses. Contemporary cities are becoming more diverse in their development and planning of space, and the relationships within them increasingly multifaceted and complex. Simply categorizing urban spaces as private/public, inside/outside, or occupied/vacant is insufficient for understanding the complexities of modern urban spaces. To understand contemporary cities, they have been conceptualized in various ways: as land-

scapes [3], as assemblies of architecture [4], and as networks [5]. These perspectives reflect shifts in how cities are perceived and analyzed over time. Within these changes, this study perceives the city as a resource of information where individual spaces aggregate, forming various explicit and implicit relationships. Hence, this perspective posits that characterizing and analyzing the properties of these individual spaces and their interrelations can identify the spatial and structural characteristics of the city as a whole. I recognize this perspective as one that aligns with the widely adopted learning paradigms in data science, framing our understanding of cities through data. Given this adoption, the emergence of new paradigms in data science opens possibilities for developing new perspectives on urban understanding, suggesting that advancements in data science can lead to novel insights into city dynamics and structures.

However, the importance of dataset curation also implies an increased complexity and potential for analysis based on data to mislead, whether intentionally or unintentionally. Subtle alterations in the information included in the data or changes in data formatting can manipulate results to be aligned with predetermined objectives. In my recent study applying a similar framework to architectural form analysis [117], it demonstrated that differences in the orientation normalization of architectural form data can lead to varying results in form classification. This finding highlights the impact of data processing techniques on the outcomes of architectural form analysis, underscoring the importance of methodological considerations in the study of form and structure.

Merely reviewing the rationality of methods would be insufficient to prevent misleading results. The creation of the urban form dataset must develop to be methodologically explored, reviewed, and validated as a critical component of research. This development must maintain a trajectory that is closely aligned with architectural and urban planning disciplines. This methodological rigor is not only theoretical but also has practical implications in the field of urban planning.

From the viewpoint of professional planners, the dataset employed within the pro-

posed framework is posited to facilitate embedding data that encompasses not merely the shape of spaces but also the properties of spaces Appendix O. Specifically, the integration of parcel information alongside LIDAR-based 3D form data significantly enriches the dataset. This combination not only allows for the detailed depiction of how specific private or public lands are integrated within the urban fabric but also enhances the process of form identification. By doing so, it augments the dataset with a deeper understanding of the urban planning significance of geometrical configurations that are conventionally utilized in urban form studies, thereby bridging the gap between theoretical methodological concerns and their practical applications in urban planning.

Further, the presented framework extends its potential beyond conventional morphology features to include non-morphology features, suggesting a wider scope of application and enhanced analytical capabilities. In the case study, urban form data was constructed and processed to analyze urban space characteristics and structures. If this data is associated with indexes of economic, social, or cultural data, the framework could add another layer of understanding these indices. For example, by incorporating a traffic accident occurrence index into an urban form dataset created in the same data format as this case study, it becomes possible to analyze the relationship between specific urban forms and the prevalence of certain types of traffic accidents. However, the correlation between urban form and these indices needs to be very carefully delved into. This could become one direction for the further development of this study. Such future research should not be conducted in isolation but aim to collaborate with various stakeholders of the city to uncover how the proposed framework can be pragmatically utilized and contribute effectively.

The association with non-morphological features is seen as a crucial aspect of this research from the perspective of urban planning scholars Appendix O. This association enables the application of the framework to various real-world urban issues and problems. For example, in some cities, the low walkability and accessibility to grocery stores are becoming major issues in planning efforts. This issue extends beyond simple transportation

problems. A viable grocery store demands a supporting population of around 10 to 12,000, a figure that low-density urban neighborhoods often cannot meet, having populations of merely 2 to 3,000. As a result, grocery stores end up being located significant distances away, making car travel essential for access. This situation reflects broader concerns about how to enhance density in specific areas and strategically locate grocery stores. It calls for an integrated approach that considers urban forms alongside non-morphological attributes such as nutrition, walkability, and socio-economic status. Highlighting the importance of merging these diverse aspects, this approach illustrates the added value of the proposed methodology in enriching our understanding of urban challenges by linking various features.

One key feature demonstrated by this research is the ability to identify similar neighboring urban spaces, made possible by the novel data format. This identification is feasible even across geographically distant cities. This was nearly impossible with the conventional formularized feature method. By comparing the limited number of morphology indexes in different spaces, it was possible to gauge how resembled their forms are. On the other hand, the proposed framework allows for the measurement of resemblance and differences in urban space configurations across geographically distinct areas, due to increased data complexity, a new data format that captures surrounding spatial information without segmenting individual buildings, and the use of inductive statistical models capable of processing these data. This represents an advancement in analyzing urban forms by enabling a detailed comparison of urban spaces as show in chapter 6 and chapter 7.

This concept of resemblance urban space has potential applications, such as in real estate analysis, where a service could enable users to find spaces resembled to their current urban environment. By entering their building's information, the surrounding space could be captured, digitized, and used to suggest resembled urban area. This functionality could be incorporated into real estate applications, offering users valuable insights into comparable spaces.

Additionally, this concept can be utilized in city policy-making to proactively manage urban spaces. For instance, by identifying and preemptively inspecting spaces resembled to those with a specific accident risk, similar incidents can be prevented. For another example, the concept can be used to preemptively manage the occurrence of vacant lots. Monitoring areas with vacant lots and capturing their urban spatial characteristics for data analysis, in conjunction with other indicators, could predict the spread of such vacancies to other areas, aiding in strategic urban planning and prevention measures.

The potential applications highlighted in this research suggest that the identified resembled urban spaces can serve as an additional layer of city management information, in conjunction with indicators of social, cultural, and economic contexts. For instance, in cities like the Rust Belt, where critical decisions about urban reduction are necessary, the active role of information from these resembled spaces can be anticipated. Incorporating the layer of resembled urban space information, decisions about the new scope of city administration can focus on strategies centered on the types of urban spaces needed within new administrative borders and how their structures should transform. The approach facilitates strategic urban planning by promoting detailed discussions on the specific urban spaces needed and their developmental strategies, moving beyond broad, area-based reductions to a more nuanced city reduction that meticulously considers spatial characteristics. This refined strategy enhances targeted urban planning and development, ensuring that interventions are both effective and appropriately scaled.

8.3 Limitation

While this research contributes significant insights into urban form analysis through the proposed framework, it is imperative to acknowledge its limitations. This section aims to critically examine the constraints and challenges encountered during the study. Understanding these limitations is crucial for interpreting the results accurately and for guiding

future research directions.

First of all, to fully grasp Computational Urban Morphology as a discipline, it is essential to conduct a thorough investigation and analysis of a broader archive. I recognized Computational Urban Morphology as an emerging discipline intertwined with various fields such as geography studies, cartography, biology, morphometrics, urban morphology, computer science, data science, and remote sensing, presenting precedents that could be categorized within this interdisciplinary scope. However, it's important to note that the presented precedents are mostly limited to publications after the 2000s, indicating a need for a broader historical perspective to fully understand the scope of this discipline. I acknowledge that significant urban form studies employing computational approaches could have existed during the development of computers in the 1950s and 1960s, and the early computer era of the 1970s. Therefore, it is crucial to explore a wider range of archives and unearth more precedents of computational urban morphology, analyzing and organizing them to create a more concrete reference basis. This endeavor will enrich the historical and methodological understanding of computational contributions to urban morphology.

In terms of methodology, the scope of data units relating to adjacent urban spaces represents a pivotal yet challenging facet requiring in-depth investigation. This aspect has been pinpointed as a significant research gap and a direction for future inquiry, particularly highlighted in interviews with urban planners, as referenced in Appendix O. The task extends beyond the mere technical demarcation of these ranges; it necessitates a nuanced understanding of their urban implications. For example, a 50m range may only capture the area directly surrounding a building, while a 500m range could encompass a whole neighborhood. It is important to conduct comprehensive experiments to discern how varying these ranges influences the accuracy and relevance of type identification outcomes.

Not only the horizontal but also the vertical range included in the data must be thoroughly explored for understanding their impact in urban settings. The method adopted here integrates building heights, applying normalization to each data point to present relative el-

evations. This technique ensures a consistent representation of form heights throughout the dataset. However, it also presents challenges in distinguishing between form types, particularly near unusually tall skyscrapers. This dilemma underscores the importance of addressing scale when curating architectural and urban form datasets. It prompts critical inquiries, such as the strategies for preprocessing buildings of varying dimensions and elevations, while also underscoring the opportunity to reveal the distinct characteristics of architectural and urban forms. As such, addressing this issue requires a blend of data science experimentation and insights from architectural and urban planning, ensuring a comprehensive approach to dataset construction and analysis.

This research also demonstrates several technical and methodological limitations. Primarily, it highlights a lack of experimentation with a crucial parameter for K-Means clustering: the number of clusters (N). Practical challenges, such as limitations in computing resources, prevented exploring clustering variations across different values of N. Future research needs to meticulously investigate how the classification of urban types might vary with different numbers of clusters, such as 9, 11, 12, or 13, instead of just 10.

Additionally, K-Means clustering has limitations in classifying complex morphology features due to its inherent challenges with complex or high-dimensional data [141, 142, 143]. The performance issues of K-Means in handling complex or high-dimensional data stem from the algorithm's reliance on Euclidean distance, which becomes less meaningful as dimensionality increases—a phenomenon known as the "curse of dimensionality." Alternative clustering techniques that address some of these limitations, such as Density-Based Spatial Clustering of Applications with Noise (DBSCAN), hierarchical clustering, or spectral clustering, could also be explored within this framework. These methods can offer insights into overcoming the challenges posed by complex or long vectors.

Feature extraction through VAEs could be further advanced, as seen with models like Stable Diffusion which not only have an encoder for extracting features from data, similar to VAEs, but also include a denoising process to enhance feature extraction performance

[144]. This denoising allows the decoder to generate improved images, and the associated encoder shows enhanced performance in extracting morphology features. Future research should explore using such advanced generative deep learning models for extracting morphology features, leveraging the improved capabilities of these models for more nuanced analysis.

Future research should aim to develop deep learning models that integrate morphology feature extraction and clustering. The current methodological framework utilizes separate models for these tasks, which can independently introduce errors. Even if there are no errors in the deep learning phase, clustering can introduce a different type of error, making it challenging to manage errors in an integrated manner. This separation complicates the reduction and management of errors across the classification process. If a single deep learning model performs both morphology feature extraction and unsupervised clustering, errors occurring during the training process would be integrated across the entire classification, potentially leading to higher classification accuracy. This integrated approach could streamline error management, enhancing the overall effectiveness of urban form analysis.

Form analysis inherently has its constraints; it doesn't always reflect or relate to certain qualities. Overreliance on form studies can lead us towards pseudo-scientific biases and decisions, as seen in historical precedents. Even if the method presented in this study outperforms conventional methods, it remains a part of form studies aiming to understand attributes through form. Insights gained from such studies gain higher reliability and enriched meaning when used alongside various other analyses. Therefore, future research should explore how the presented method interacts with other urban analyses, enhancing or diminishing the outcomes of these analyses.

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Appendices

APPENDIX A

THE LANDSCAPE OF URBAN FORM STUDIES

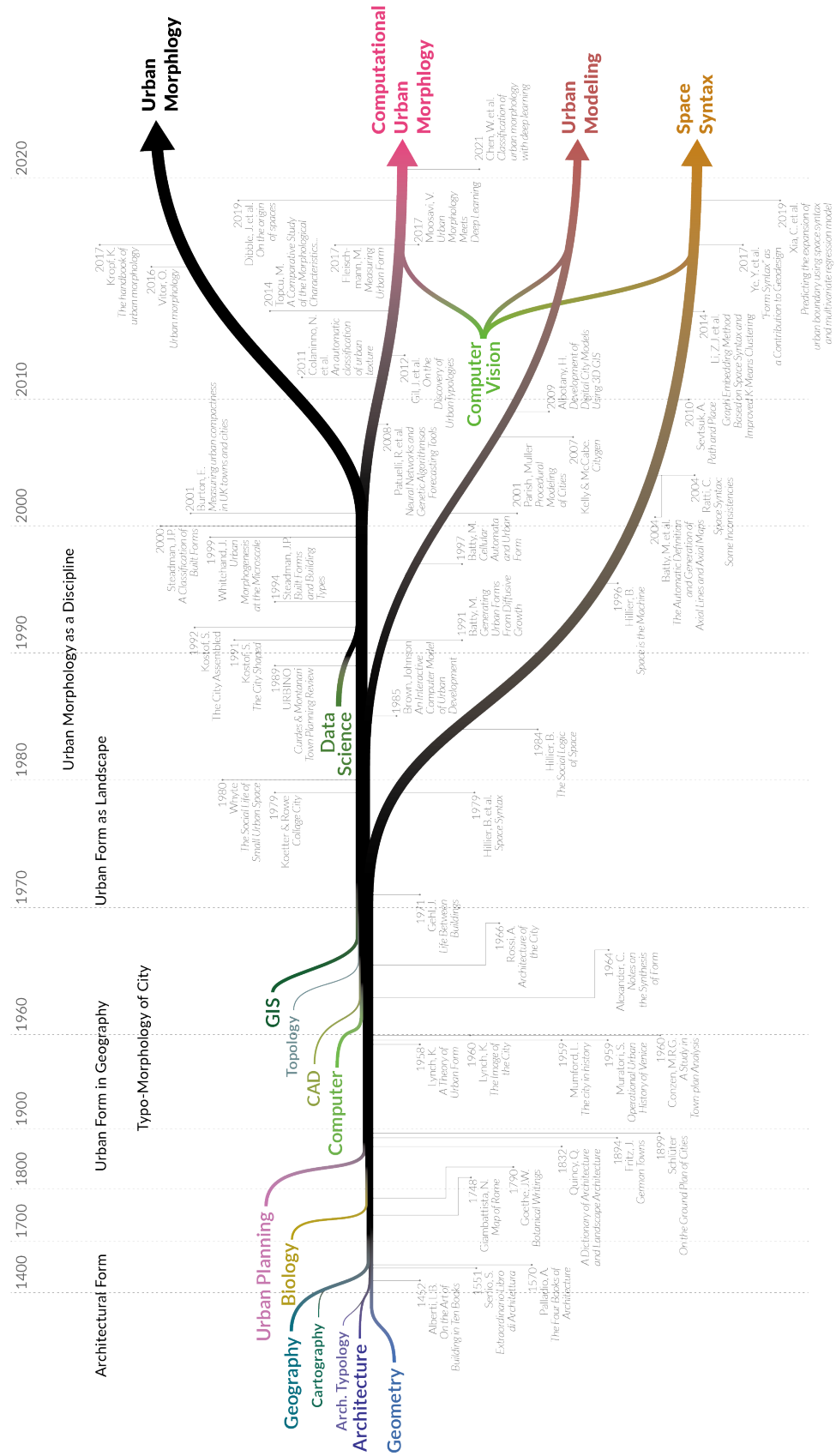


Figure A.1: The landscape of urban form studies

APPENDIX B

PRECEDENTS ANALYSIS

This appendix's table shows how the literature built for the analysis of precedents in Chapter 3 has been classified.

Table B.1: Selected Precedents of Computational Urban Morphology

Title	Author	Year	Form Unit	Data Dim.	Data Format	Features	Index	Analysis Method	Analysis Type
Measuring Urban Morphology Using Remotely-sensed Imagery	Longley	2000	Municipality	2D	Image	Area, Field, Envelope, Radius, Uses	Proportion, Occupancy	Basic Statistics	Formularized
Simplified Model of Urban Morphology: Application to an Analysis of the Environmental Performance of Cities	Adolphe	2001	Region Sample	2D	Object	Density, height/width ratio, mean height of buildings	Rugosity, porosity, sinuosity, etc.	Basic Statistics	Formularized
Measuring Urban Compactness in UK Towns and Cities	Burton	2002	City	1D	Vectors	Density, Uses, Population	Compactness, Mix Uses, Intensification	Basic Statistics	Formularized
Measuring the physical composition of urban morphology using multiple endmember spectral mixture models	Rashed et al.	2003	Grid	2D	Image	Pixel values	Pixel purity index	Machine Learning	Extracted

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Table B.1 continued from previous page

Title	Author	Year	Form Unit	Data Type	Data Format	Features	Index	Analysis Method	Analysis Type
An approach for analysis of urban morphology: methods to derive morphological properties of city blocks by using an urban landscape model and their interpretations	Yoshida Omae	2005	Block	1D	Vectors	Adjacency, area,	Surface and volume per projected area	Basic Statistics	Formularized
Measuring temporal compositions of urban morphology through spectral mixture analysis: toward a soft approach to change analysis in crowded cities	Rashed et al.	2006	Region Sample	3D	Object	Height, Irradiance, Radiance, Urban Horizon Angle, Width, etc.	Sky view factor, irradiation	Basic Statistics	Formularized
The Dynamics of the Tel Aviv Morphology	Benguigui et al.	2006	Grid	2D	Object	Area, Perimeter, Population	Size, Development Changes,	Basic Statistics	Formularized
Classifying urban structures for mapping purposes using discriminant analysis	Steiniger	2006	Building	1D	Vectors	Building Area, Number of Corner Points, Number of Courtyard	Shape Index, Building Wall Squareness, etc.	Machine Learning	Extracted

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Table B.1 continued from previous page

Title	Author	Year	Form Unit	Data Type	Data Format	Features	Index	Analysis Method	Analysis Type
A global comparative analysis of urban form: Applying spatial metrics and remote sensing	Huang et al.	2007	Region Sample	2D	Image	DL-based Extraction from data	N/A	Deep Learning	Extracted
Quantifying intra-urban morphology of the Greater Dublin area with spatial metrics derived from medium resolution remote sensing data	Van de Voorde et al.	2009	Block	1D	Vectors	Area, Coverage	Density	Basic Statistics	Formularized
Detection of Urban Socio-economic Patterns Using Clustering Techniques	Tuia et al.	2009	Municipality	1D	Vectors	54 economic, 20 demographic variables	Poisson Model (LR)	Basic Statistics	Formularized
Urban form revisited—Selecting indicators for characterising European cities	Schwarz	2010	City	1D	Vectors	Area, Resident Population, Density, etc.	Area Discount, Centrality, etc.	Basic Statistics	Formularized
An automatic classification of urban texture: form and compactness of morphological homogeneous structures in Barcelona	Colaninno et al.	2011	Grid	2D	Object	Building Area, Core Area Index, etc.	Compactness, Density, etc.	Criteria Mapping	Formularized

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Table B.1 continued from previous page

Title	Author	Year	Form Unit	Data Type	Data Format	Features	Index	Analysis Method	Analysis Type
Measuring Urban Form: A Systematisation of Attributes for Quantitative Urban Morphology	Fleischmann	2017	Block	1D	Vectors	Width, Length, Perimeter, Area, Height, Volume	Proportion, Squareness, Elongation, etc.	Basic Statistics	Formularized
Urban morphology detection and computation for urban climate research	Xu et al.	2017	Grid	1D	Vectors	Plot Area, Building Area, etc.	Area, Density, Sky View Factor, etc.	Basic Statistics	Formularized
Urban morphology meets deep learning: Exploring urban forms in one million cities, town and villages across the planet	Moosavi	2017	Region Sample	2D	Image	DL-based Extraction from data	N/A	Deep Learning	Extracted
Using Convolutional Networks and Satellite Imagery to Identify Patterns in Urban Environments at a Large Scale	Albert et al.	2017	Grid	2D	Image	DL-based Extraction from data	Agricultural, Airports, etc.	Deep Learning	Extracted
What explains neighborhood type statistically? – Mixing typo-morphological and spatial analytic approaches in urban morphology	Stojanovski	2017	Municipality	1D	Vectors	Area, Distance, Uses, Location, Income	Density, Floor Space Indexes	Basic Statistics	Formularized

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Table B.1 continued from previous page

Title	Author	Year	Form Unit	Data Type	Data Format	Features	Index	Analysis Method	Analysis Type
The spatial distribution and frequency of street, plot and building types across five European cities	Pont et al.	2019	Block	1D	Vectors	Angles, Area, Length, Lot,	Centrality, Accessibility, Compactness	Basic Statistics	Formularized
Emergence of Complexity in Urban Morphology	Goh et al.	2019	Grid	1D	Vectors	Percentage of Apartment, Multi-family House, etc.	Residential, Commercial, Work	Fractal Model	Formularized
Urban form and composition of street canyons: A human-centric big data and deep learning approach	Middel et al.	2019	Perspective	2D	Image	DL-based Extraction from data	N/A	Deep Learning	Extracted
Investigating the Intensive Redevelopment of Urban Central Blocks Using Data Envelopment Analysis and Deep Learning: A Case Study of Nanjing, China	Qu et al.	2019	Block	1D	Vectors	Floor Area Ratio, Building Density, etc.	N/A	Machine Learning	Extracted
An Urban Morphogenesis Model Capturing Interactions Between Networks and Territories	Raimbault	2019	Country	2D	Object	Distance, Density, Uses	Entropy, Hierarchy, Closeness, Performance	Machine Learning	Extracted

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Table B.1 continued from previous page

Title	Author	Year	Form Unit	Data Type	Data Format	Features	Index	Analysis Method	Analysis Type
A Topological Representation for Taking Cities as a Coherent Whole	Jiang	2019	Municipality	1D	Vectors	Sizes and Degree of Wholeness	Power-law Distributions, Differentiation	Basic Statistics	Formularized
A Multiscale Clustering of the Urban Morphology for Use in Quantitative Models	Schirmer Axhausen	2019	Region Sample	1D	Vectors	Area, Perimeter, Orientation, Floor Space, Height, Distance, etc.	Compactness, Influence Zone, Closeness, etc.	Machine Learning	Extracted
Context-rich Urban Analysis Using Machine Learning - A case study in Pittsburgh, PA	Rhee et al.	2019	Building	2D	Image	ML-based Extraction from Data	N/A	Machine Learning	Extracted
Identifying Urban Form Typologies in Seoul with Mixture Model Based Clustering	Li Quan	2020	Grid	1D	Vectors	Building Area, Height, Average, Street Length, etc.	N/A	Machine Learning	Extracted
Machine Learning for Comparative Urban Planning at Scale: An Aviation Case Study	Meeran Joyce	2020	Region Sample	2D	Image	DL-based Extraction from data	N/A	Deep Learning	Extracted

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Table B.1 continued from previous page

Title	Author	Year	Form Unit	Data Type	Data Format	Features	Index	Analysis Method	Analysis Type
Clustering and Morphological Analysis of Campus Context	Li Zhu	2020	Region Sample	2D	Image	DL-based Extraction from data	Subway, Bus Stops, etc.	Deep Learning	Extracted
Spectral Clustering for Urban Networks	Patt	2020	Block	2D	Object	Adjacency	Cohesion, Separation, Silhouette	Machine Learning	Extracted
Sectionmatrix: Mapping Urban Form through Urban Sections	Gu	2021	Block	2D	Image	Length, Coordinates, Angle	Line Connections, Steepness	Basic Statistics	Formularized
Urban spatial structure analysis: quantitative identification of urban social functions using building footprints	Zhao et al.	2021	Block	1D	Vectors	Envelope Area, Orientation	Variable Area Unit, Compactness, etc.	Basic Statistics	Formularized
Towards analytical typologies of plot systems: Quantitative profile of five European cities	Bobkova et al.	2021	Plot	1D	Vectors	Plot Size, Street Frontage Length, etc.	Frontage Index, Compactness	Machine Learning	Extracted
Classification of urban morphology with deep learning: Application on urban vitality	Chen et al.	2021	Grid	2D	Image	DL-based Extraction from data	N/A	Deep Learning	Extracted
Block shape in historic cities: A classification based on compactness and fragmentation	Shpuza	2021	Block	2D	Object	Distance, Convex Hull	Distance, Fragmentation	Basic Statistics	Formularized

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Table B.1 continued from previous page

Title	Author	Year	Form Unit	Data Type	Data Format	Features	Index	Analysis Method	Analysis Type
Morphological Regeneration of the Industrial Waterfront Based on Machine Learning	Huang Zheng	2022	Grid	2D	Image	DL-based Extraction from data	N/A	Deep Learning	Extracted
Where Will Romance Occur, A New Prediction Method of Urban Love Map through Deep Learning	Dong	2022	Grid	2D	Image	DL-based Extraction from data	N/A	Deep Learning	Extracted
EO + Morphometrics: Understanding cities through urban morphology at large scale	Wang et al.	2023	Building	2D	Image	DL-based Extraction from data	N/A	Deep Learning	Extracted
Artificial Intelligence Prediction of Urban Spatial Risk Factors from an Epidemic Perspective	Zhang et al.	2023	Grid	2D	Image	DL-based Extraction from data	N/A	Deep Learning	Extracted

APPENDIX C

SAMPLES OF THE GENERATED URBAN FORM DATASET

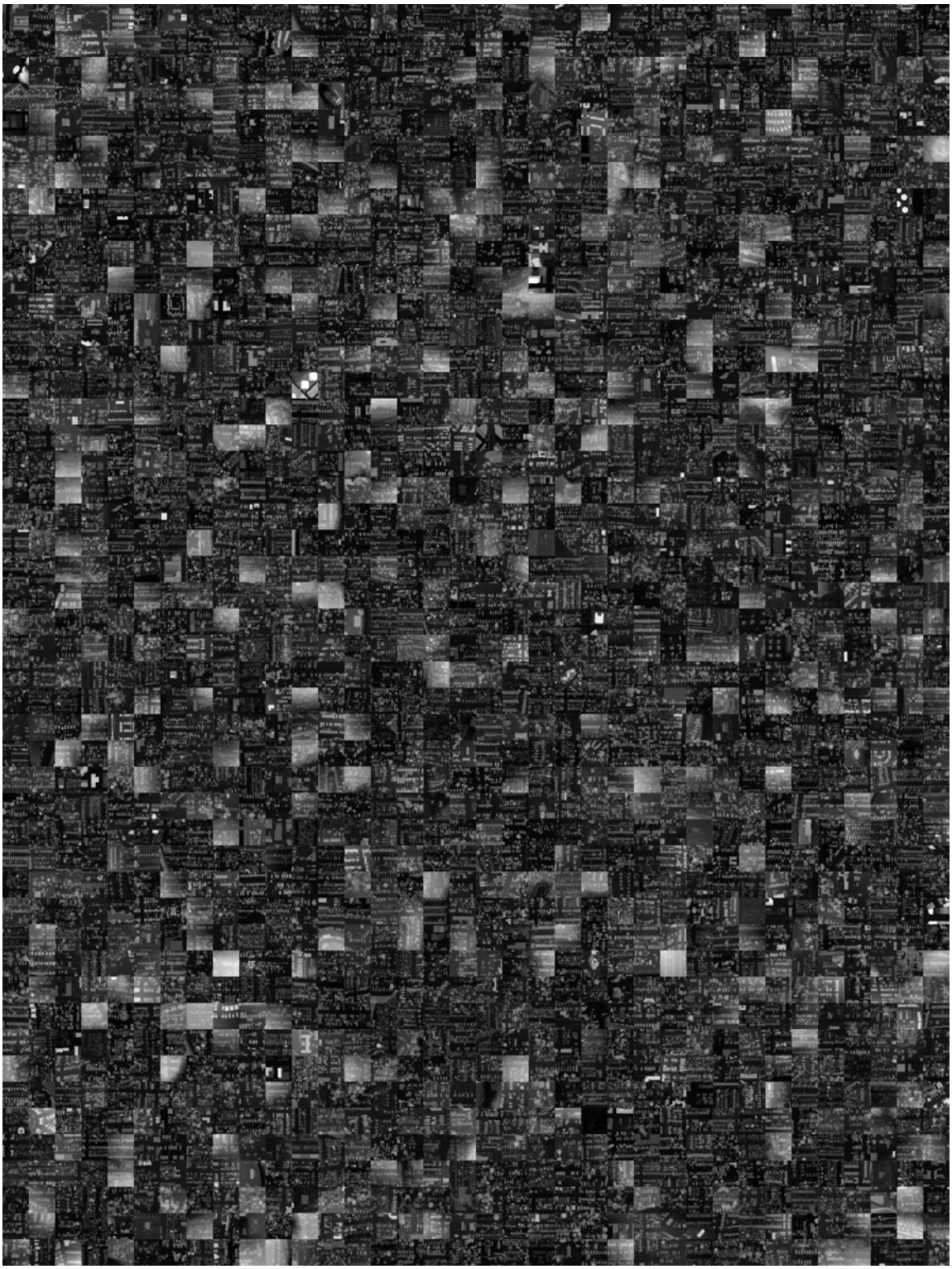


Figure C.1: Randomly selected data 1 from the four Rust Belt cities dataset

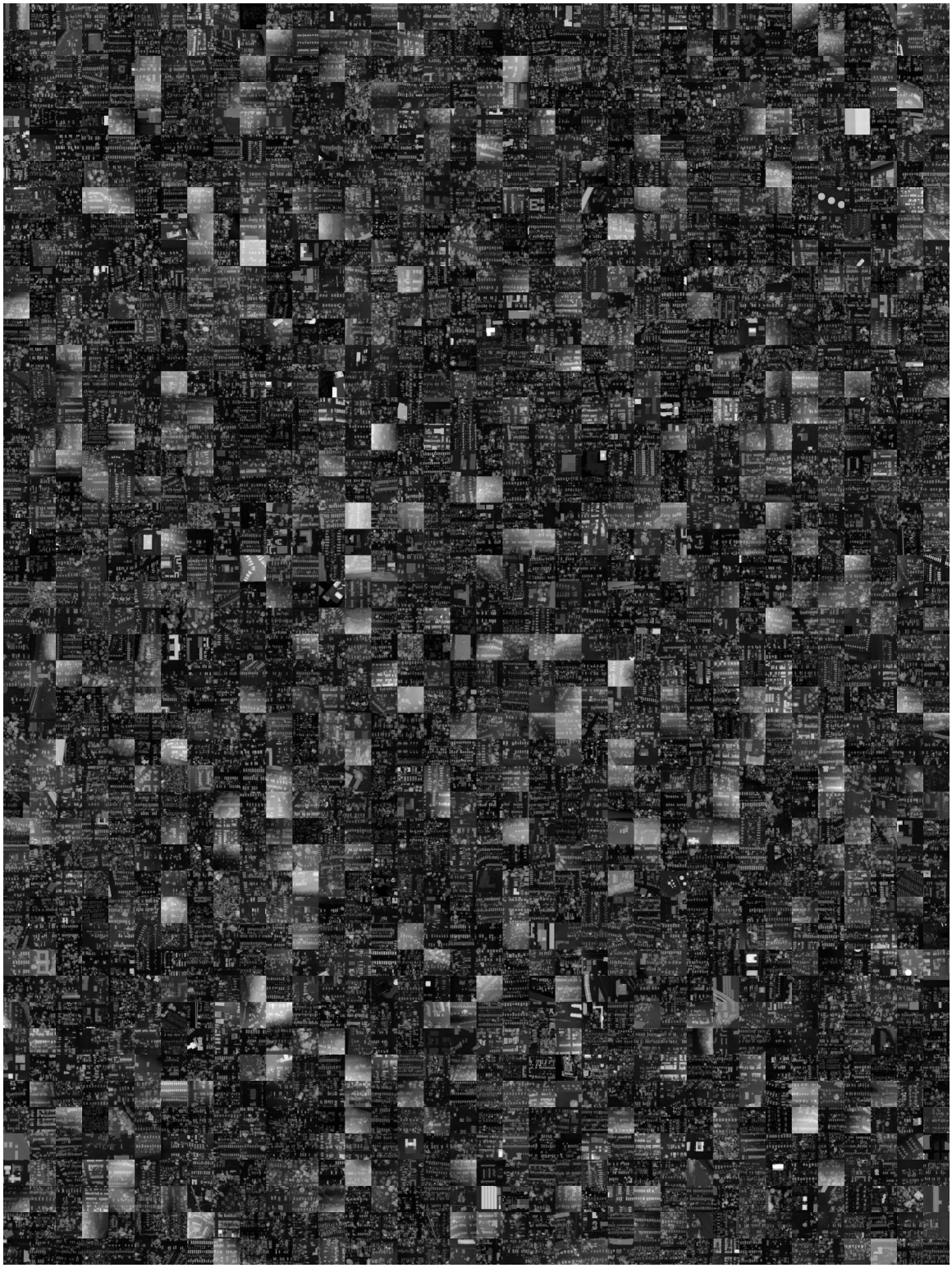


Figure C.2: Randomly selected data 2 from the four Rust Belt cities dataset

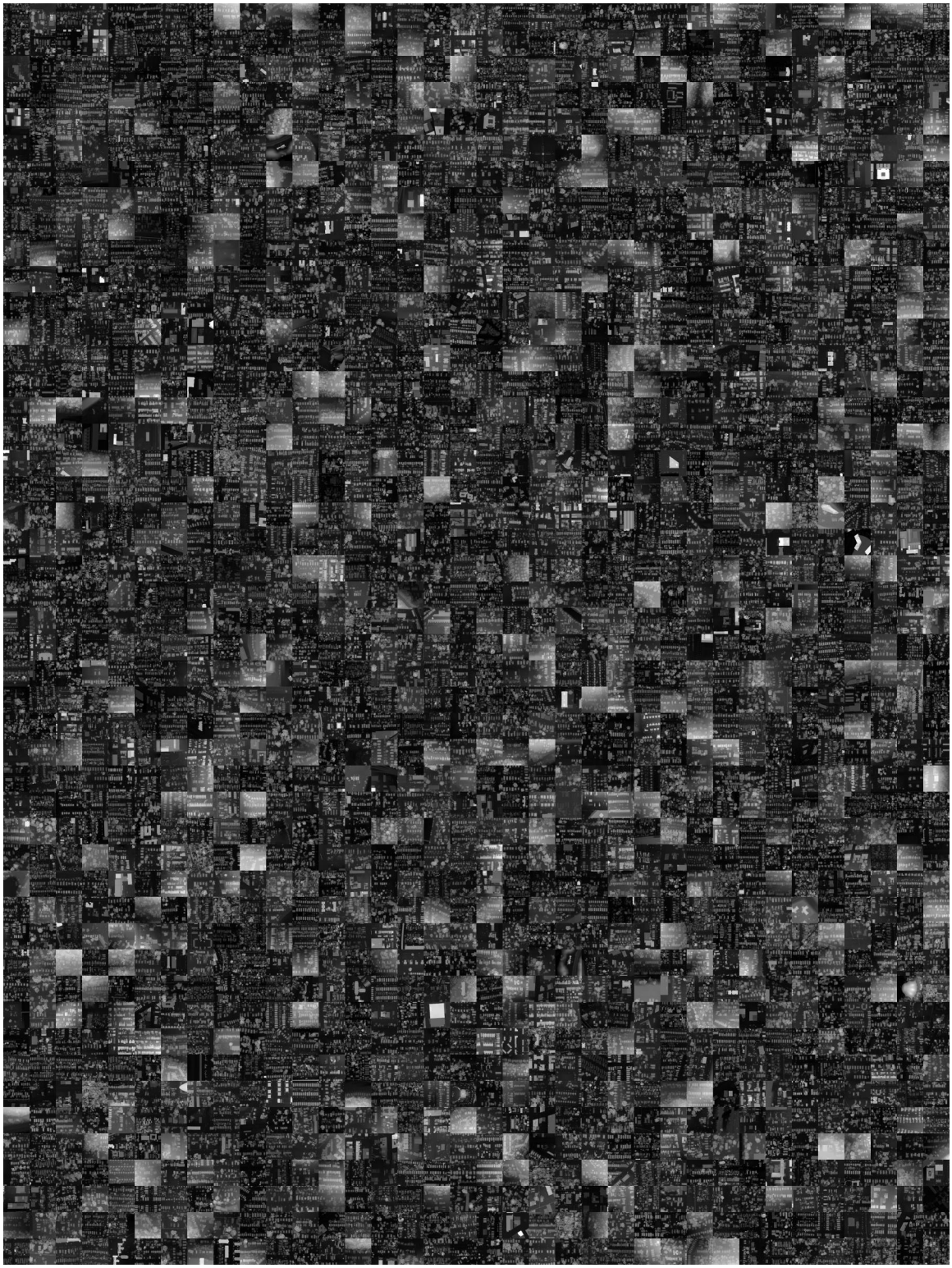


Figure C.3: Randomly selected data 3 from the four Rust Belt cities dataset

APPENDIX D

RECONSTRUCTED IMAGES OF THE VALIDATION DATA

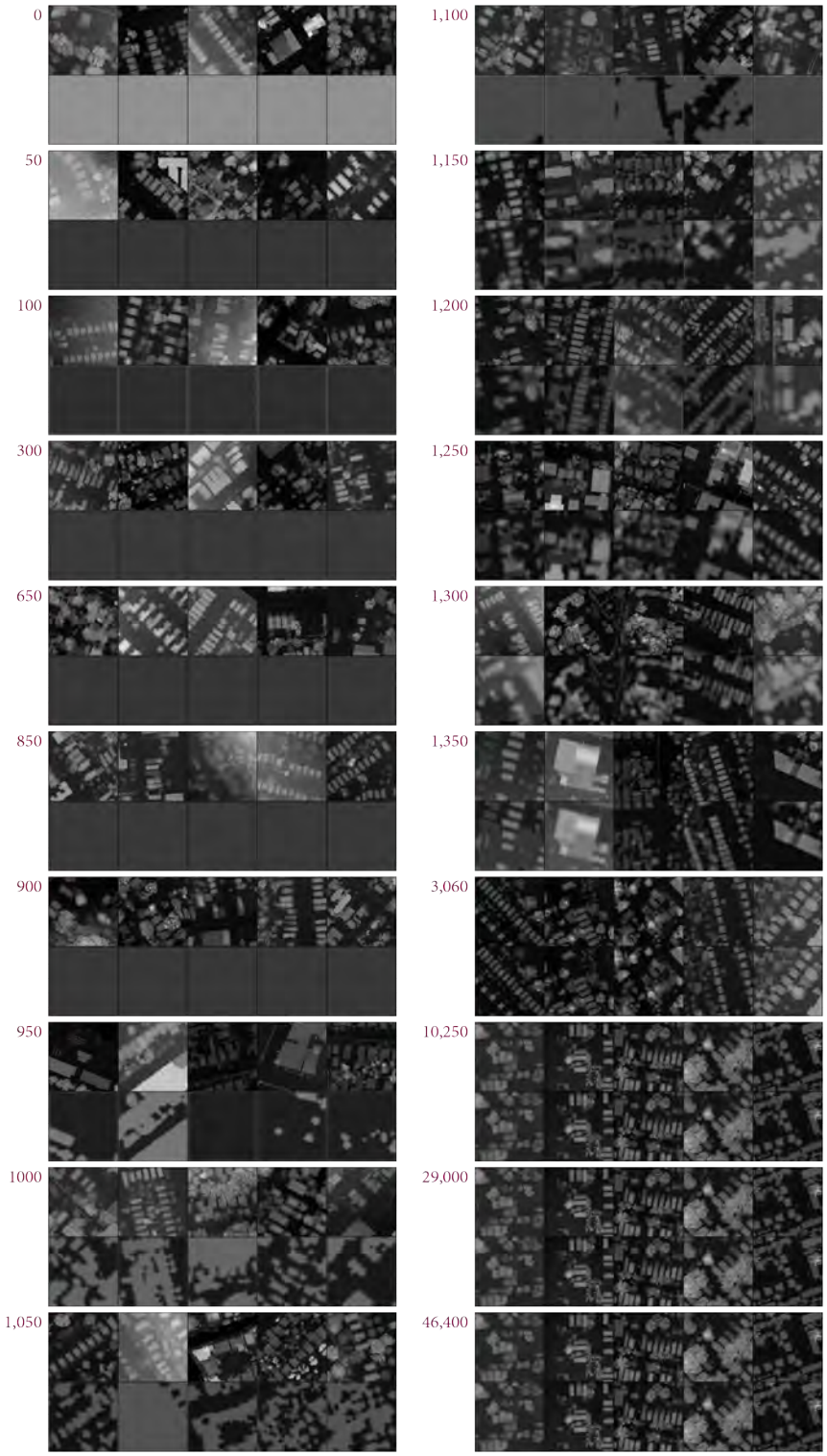


Figure D.1: Accuracy changes by iterations for five sample images

APPENDIX E

CLASSIFIED BUILDING FOOTPRINT MAPS

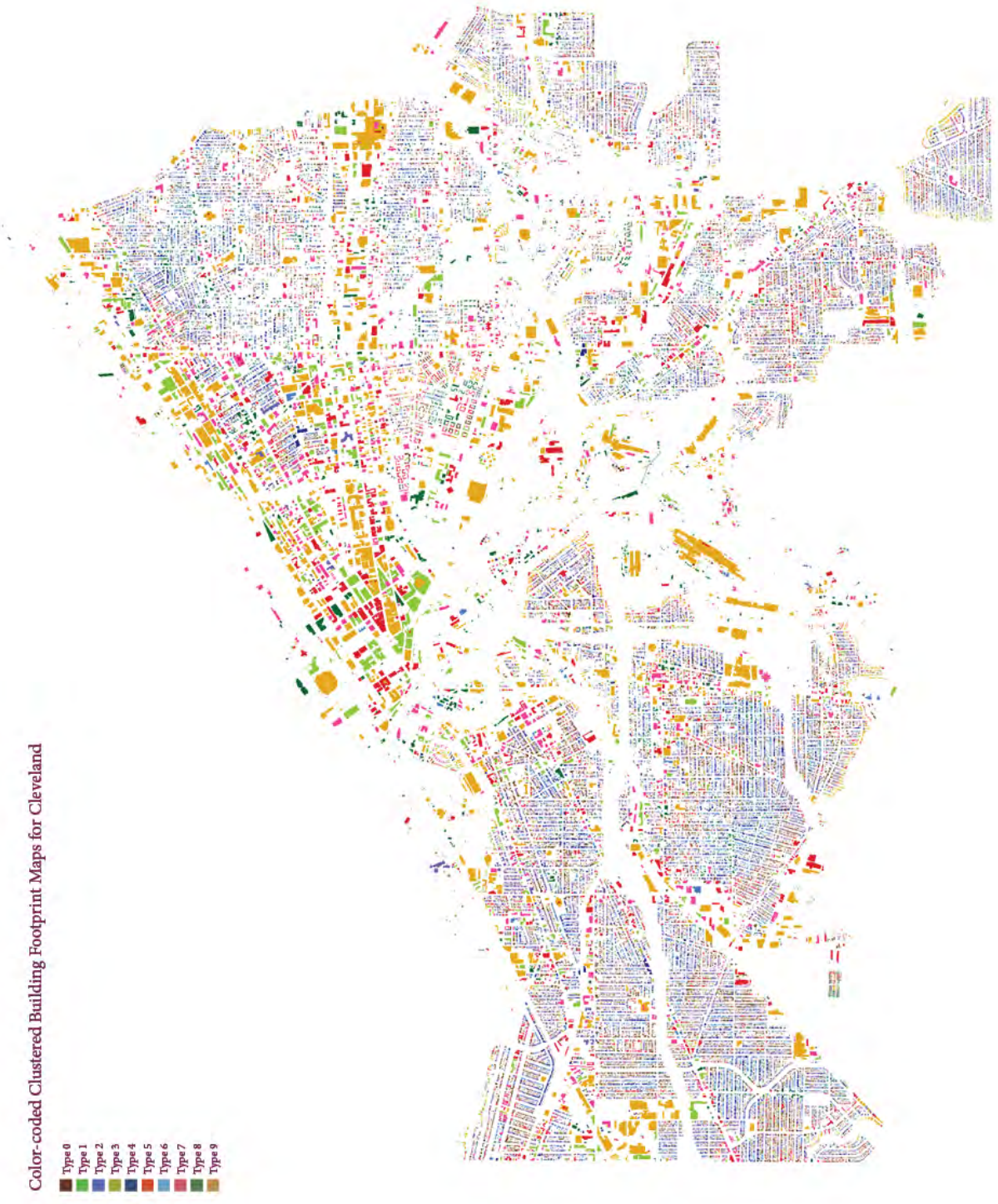


Figure E.1: Clustering results projected onto building footprint map: Cleveland

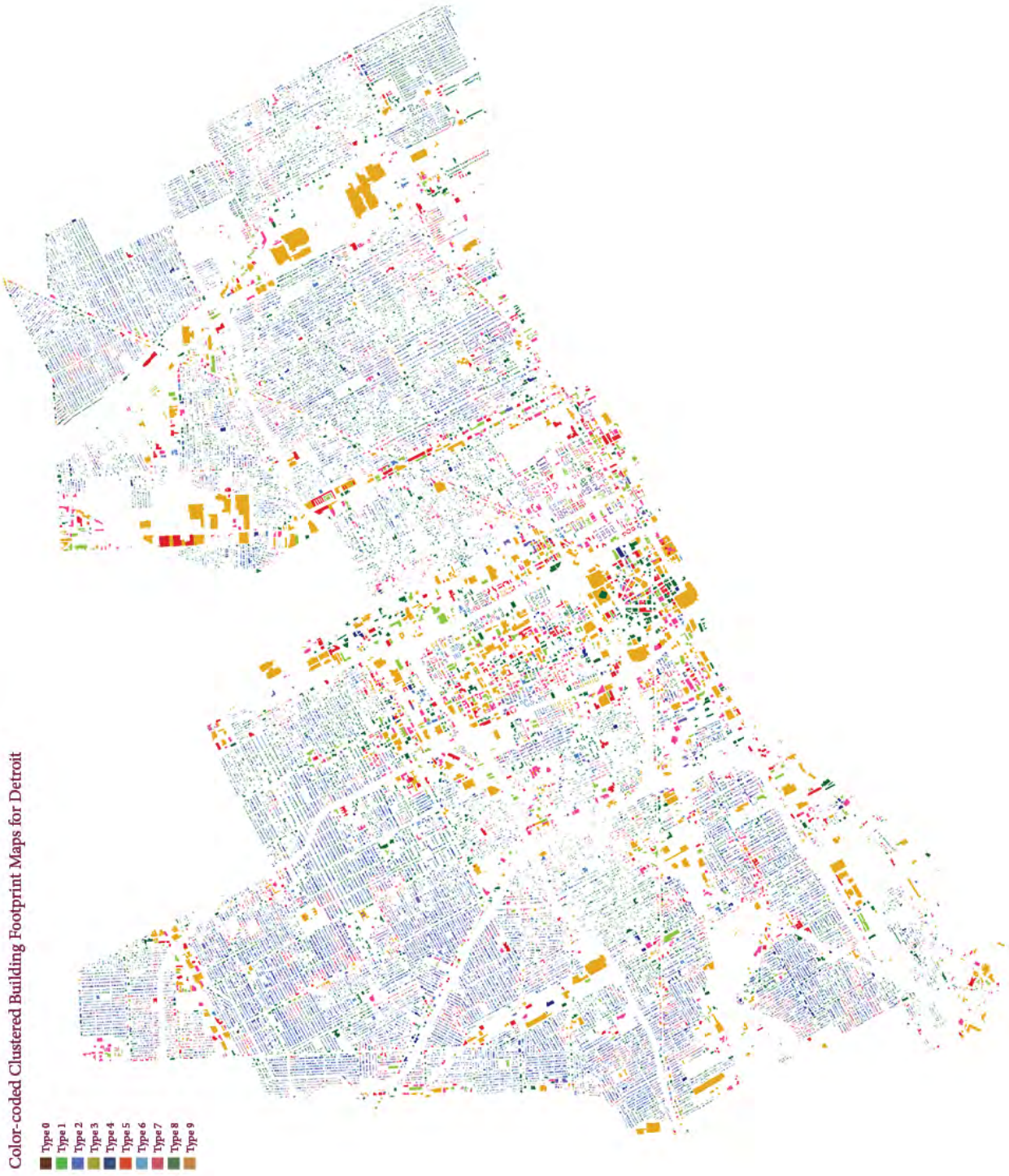


Figure E.2: Clustering results projected onto building footprint map: Detroit

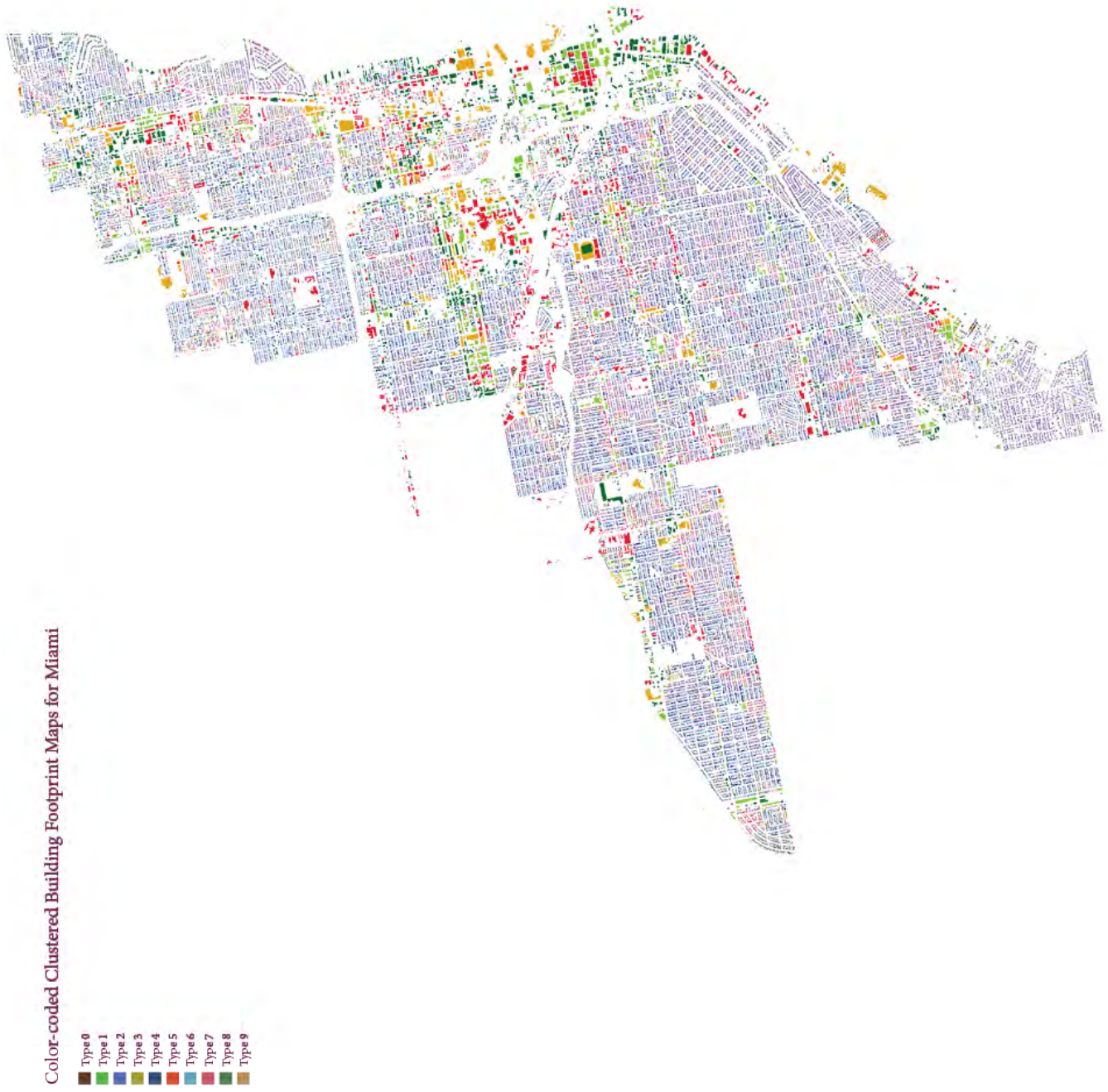


Figure E.3: Clustering results projected onto building footprint map: Miami

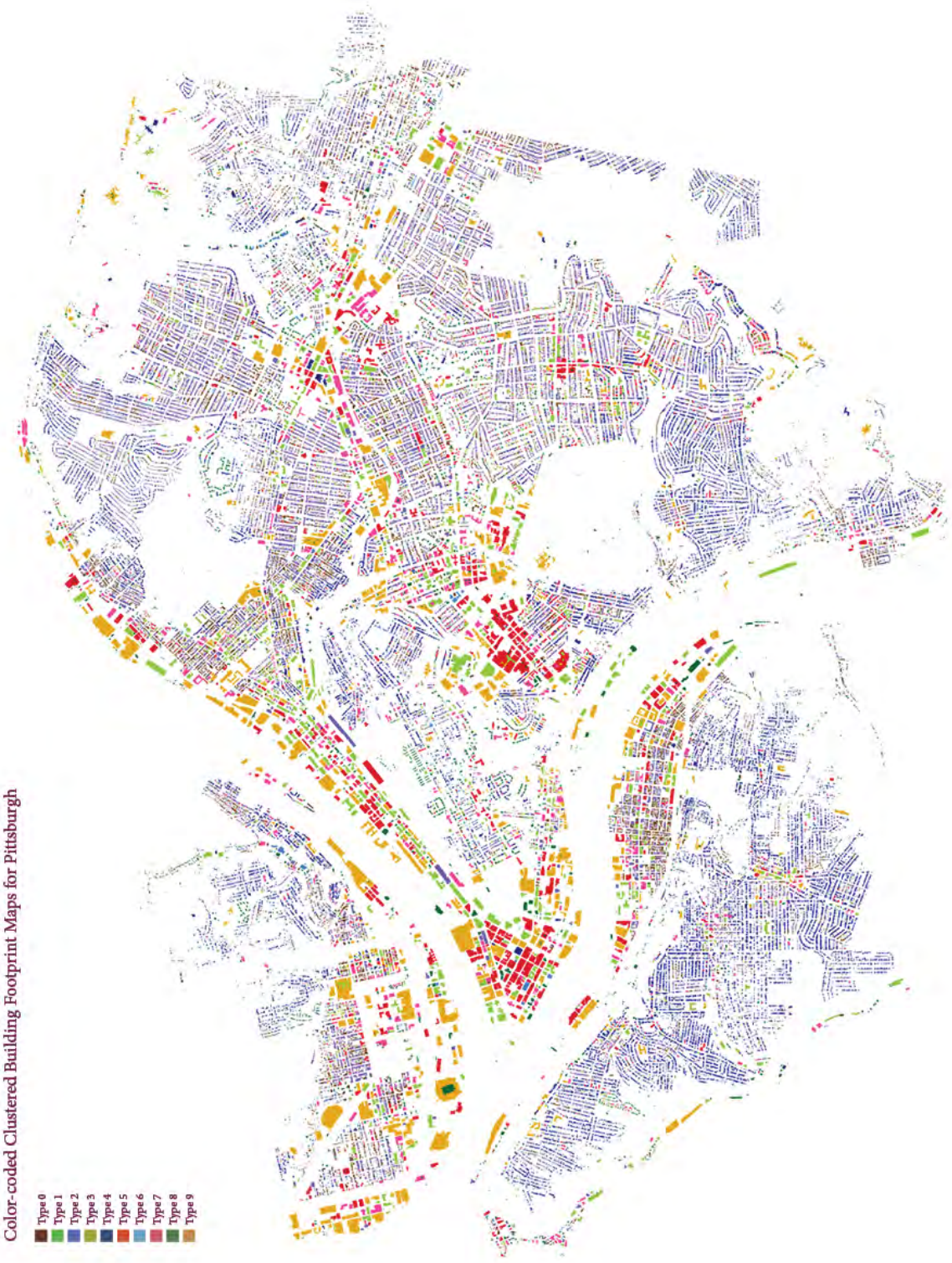


Figure E.4: Clustering results projected onto building footprint map: Pittsburgh

APPENDIX F

AVERAGE AREA OF BUILDINGS BY TYPE

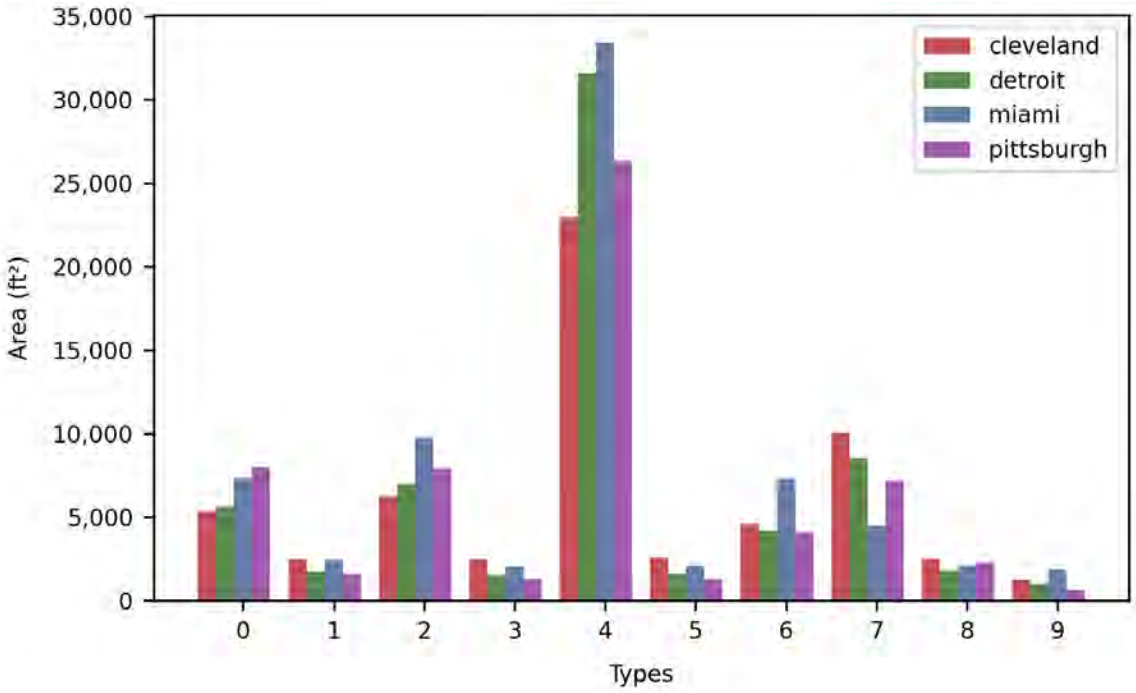


Figure F.1: Average footprint areas of buildings in each type in the four cities

Figure F.1 illustrates the average footprint areas of buildings in each type in the four cities. The average area of buildings in Type 0 spans a range of approximately 5000 ft² to 8000 ft². Pittsburgh boasts the highest average area, quantified at 8009.46 ft², succeeded by Miami with 7309.82 ft², Detroit with 5606.74 ft², and Cleveland with 5345.16 ft². This observation infers that building Type 0 characterizes medium-sized structures, with larger manifestations evident in Miami and Pittsburgh in contrast to Cleveland and Detroit. In the context of buildings in Type 1, Cleveland commands the highest average area at 2445.39 ft², pursued by Miami at 2409.81 ft², Detroit at 1748.27 ft², and Pittsburgh at 1563.57 ft². While Cleveland and Miami share akin average areas, all four cities manifest relatively diminutive dimensions for Type 1, denoting an area less than half of that observed in Type 0. Type

2 pertains to medium-sized edifices, displaying an average area spanning approximately 6200 ft² to 9800 ft². Miami showcases the preeminent average area, registering 9762.32 ft², followed by Pittsburgh with 7928.60 ft², Detroit with 6975.70 ft², and Cleveland with 6239.45 ft². Of note, Miami and Pittsburgh exhibit dimensions roughly 1.3 to 1.5 times larger compared to Cleveland or Detroit.

The configuration of buildings in Type 3, akin to Type 1, typifies smaller structures with dimensions of approximately 1300 ft² to 2000 ft². Cleveland boasts the highest average area at 2434.22 ft², trailed by Miami at 2016.11 ft², Detroit at 1485.37 ft², and Pittsburgh at 1267.89 ft². The distribution of average areas for this classification across the four cities mirrors that of buildings in Type 1. Type 4, identified by its stature as large structures, commands average areas of 22942.63 ft², 31566.49 ft², 33408.49 ft², and 26307.61 ft² in the respective cities. This discerns that buildings in Type 4 exhibits dimensions about 1.45 times larger in Detroit and Miami compared to the remaining two cities, underscoring a substantial distinction. Buildings in Type 5 epitomizes a distribution and scale analogous to that of Types 1 and 3. Cleveland showcases the greatest average area at 2564.99 ft², closely pursued by Miami at 2072.23 ft², Detroit at 1571.98 ft², and Pittsburgh at 1282.44 ft². The divergences remain comparatively modest in relation to other building types.

Buildings in Type 6 demonstrates average areas of 4585.92 ft², 2189.63 ft², 11273.37 ft², and 2063.08 ft², situating it within the classification of medium-sized structures. The distribution of average areas for this type remains notably akin across Cleveland, Detroit, and Pittsburgh, with Miami registering a conspicuously larger average area. Buildings in Type 7 encompasses average sizes spanning about 4500 ft² to 10000 ft², encompassing comparably sized medium-sized structures in Cleveland, Detroit, and Pittsburgh. Miami stands apart with the most modest average area for Type 7. Buildings in Type 8 designates small to medium-sized structures, maintaining relatively uniform average areas of about 1800 ft² to 2400 ft² across the four cities. The deviations remain relatively slight when juxtaposed with other building types. Buildings in Type 9 denotes the most diminutive

category, characterized by average areas of approximately 600 ft² to 1800 ft².

The ten types can be grouped into three categories based on their average area values. Firstly, there is a group consisting of small buildings, encompassing Types 1, 3, 5, 8, and 9. Secondly, there is a group comprising medium-sized buildings, including Types 0, 2, 6, and 7. Additionally, Type 4 can be classified as an independent group representing large buildings. Given the significant difference in area compared to the other types, it can be inferred that Type 4 includes monumental buildings such as convention centers, mills, plants, and stadiums.

APPENDIX G

AVERAGE HEIGHT OF BUILDINGS BY TYPE

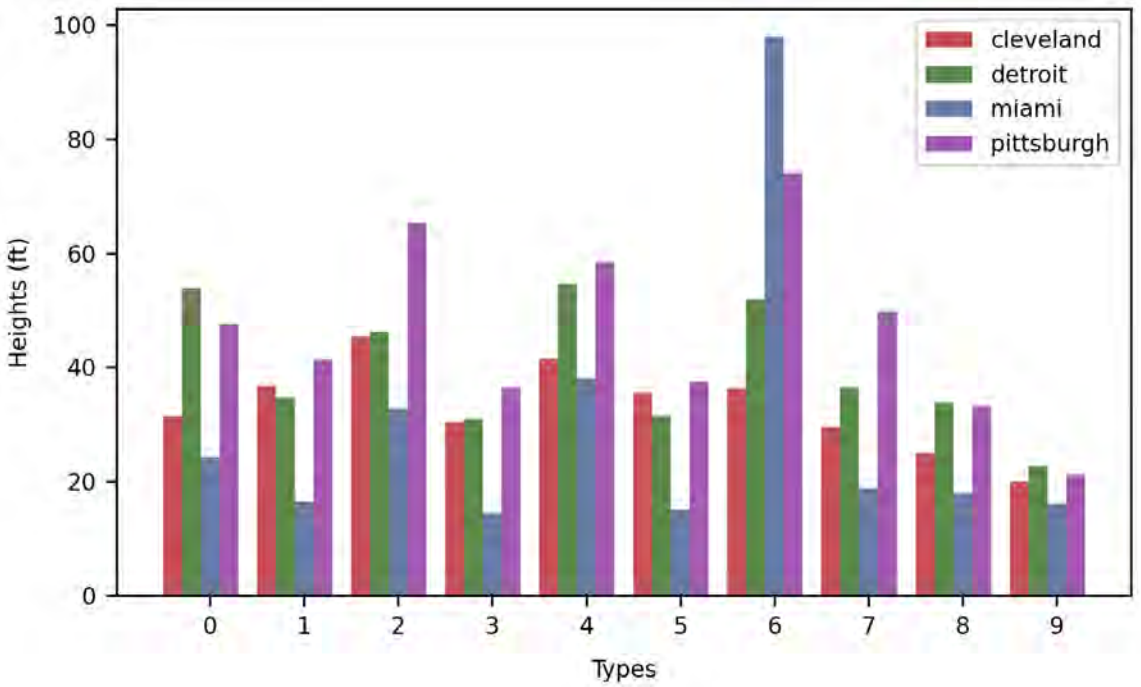


Figure G.1: Average heights of each type of buildings in the four cities

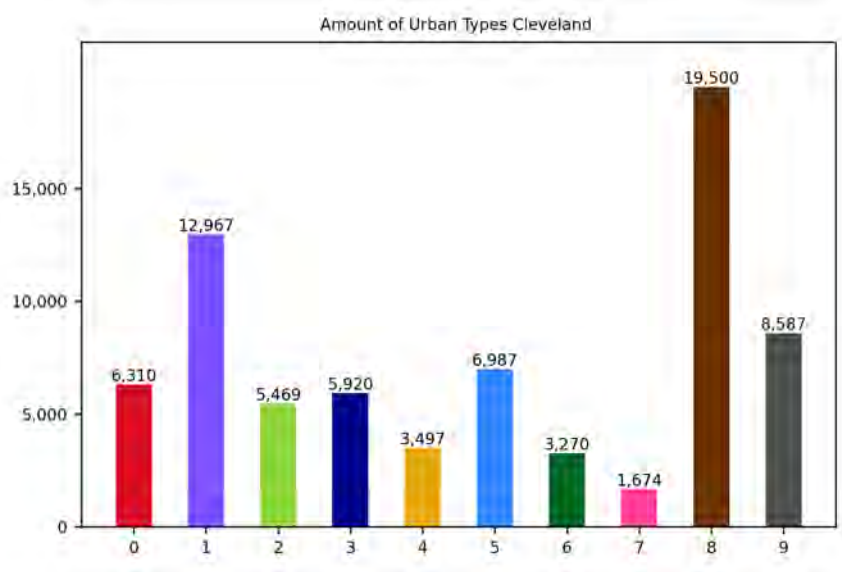
Figure G.1 illustrates the average footprint areas of each type of buildings in the four cities. The average heights of buildings in Type 0 in Cleveland and Miami are approximately 31 ft and 24 ft, respectively, equivalent to about two stories. In contrast, buildings in this type in Detroit and Pittsburgh have average heights of about 53 ft and 47 ft, respectively, corresponding to approximately four stories. For buildings in Type 1, Cleveland, Detroit, and Pittsburgh share similar values, with a three-story height ranging from about 37 ft to 40 ft, while Miami displays a one-story height of 16 ft. Notably, buildings in Type 2 stand out with Pittsburgh exhibiting an average height of about 65 ft, approximately five stories tall, while buildings in the other three cities range from about 2 to 3 stories (33 ft to 46 ft) in height.

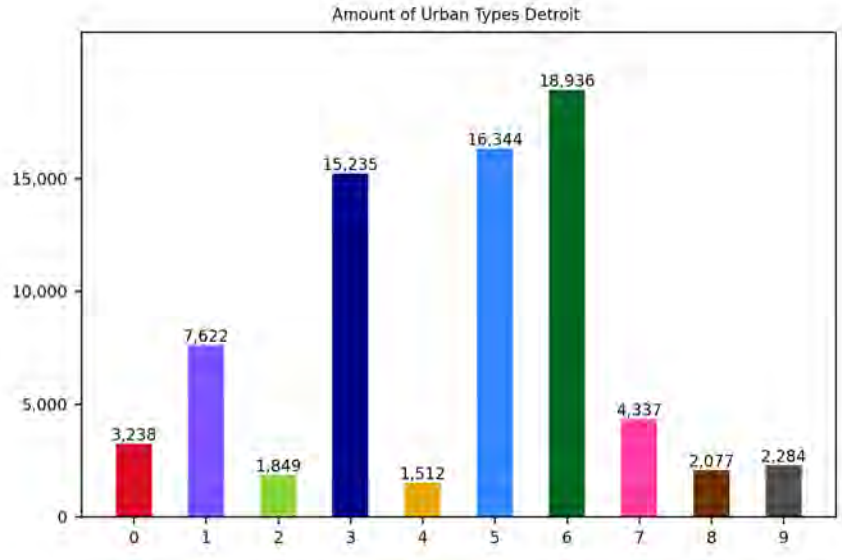
Type 3, similar to Type 1, features one-story buildings in Miami, while Cleveland, Detroit, and Pittsburgh have two or three-story heights. Buildings in Type 4 resemble Type 0, with Detroit and Pittsburgh having approximately four-story buildings at around 54 ft and 58 ft, respectively, while Cleveland and Miami display three-story buildings at 41 ft and 38 ft, respectively. Type 5, similar to Types 1 and 3, includes one-story buildings, except for Miami where the height ranges from 2 to 3 stories. In Type 6, Miami boasts the tallest buildings with an average height of about 96 ft (approximately 7 stories), followed by high-rise buildings in Pittsburgh with an average height of 74 ft (5-6 stories). Detroit has buildings of about 4 stories with a height of 51 ft, similar to Types 0 and 4, while Cleveland features 3-story buildings at 41 ft, akin to Types 2 and 4. Consequently, Type 6 exhibits the highest level of building heights among the four cities, becoming a low-rise structure. Type 7 displays a distribution similar to Type 0, with the exception of Cleveland having 2 to 3-story tall buildings. Type 8 demonstrates a comparable pattern to Types 1 and 3. Miami's buildings stand at around 16 to 18 feet, representing one-story structures, while the other three cities exhibit buildings of approximately two or three stories. Type 9 encompasses one-story buildings in all four cities.

Based on these height values alone, several common types can be identified. Types 0, 2, 4, and 7 form one group consisting of 3 to 5-story buildings, excluding Miami. Meanwhile, Types 1, 3, 5, and 8 comprise another group with 2 to 3-story buildings, again excluding Miami. It is worth noting that buildings in Miami tend to have lower heights, ranging from 1 to 2 stories in most types, except for Type 6. Furthermore, considering that Type 6 buildings in Miami and Pittsburgh exhibit heights of approximately 20 to 30 floors, Type 6 can be inferred as an independent group representing an urban space centered around high-rise structures. Additionally, Type 9, characterized by one-story scales in all cities, can be classified as a distinct group.

APPENDIX H

THE QUANTITY OF EACH URBAN FORM TYPE IN RESPECTIVE CITIES





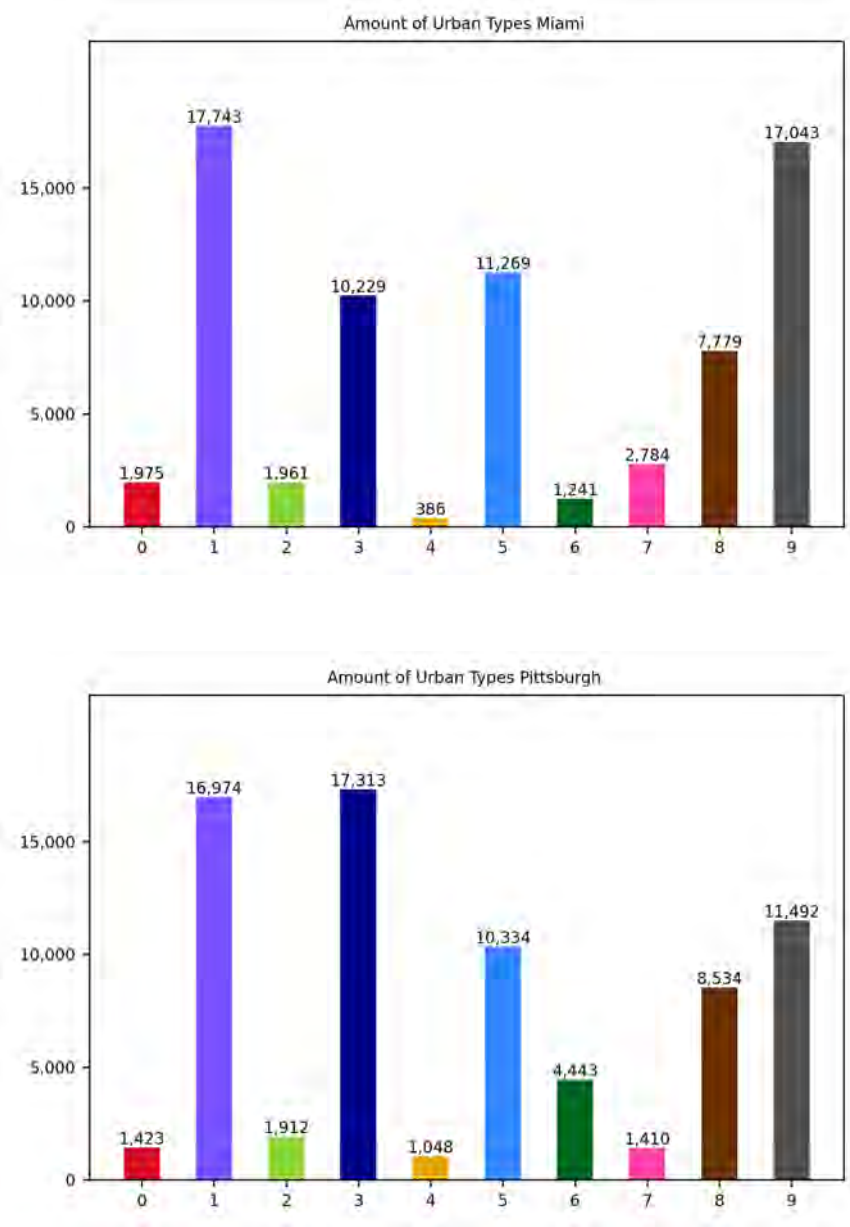


Figure H.1: Amount of each urban form type in the four cities

Figure H.1 presents a visual representation of the distribution of the urban form types across the cities. Upon examining the distribution in Cleveland, it is observed that urban Type 8 is the most prevalent, with an occurrence of 19,500. This is followed by Type 1 and Type 9 as the second most frequent occurrences. Types 0, 2, 3, and 5 exhibit occurrences ranging from approximately 5,000 to 7,000, while Types 4 and 6 show occurrences around 3,200 to 3,500. Type 7 exhibits the least occurrence, approximately 1,600.

Detroit's distribution reveals that Type 6 is the most predominant, with an occurrence of 18,936, followed by Type 3 and Type 5, which show occurrences around 15,000 to 16,000. Type 1 and Type 7 have occurrences of approximately 7,600 and 4,300, respectively, whereas Type 8 and Type 9 have occurrences of around 2,000. Type 2 and Type 4 exhibit the lowest occurrences, around 1,500 to 1,800.

In Miami, Types 1 and 9 have the highest occurrences, with 17,743 and 17,043 respectively. Type 3 and Type 5 follow with occurrences of 10,229 and 11,269. Types 0 and 2 have occurrences around 2,000. Type 4 exhibits the lowest occurrence with 386, while Type 6 is the second lowest with 1,241.

Turning to Pittsburgh, Types 1 and 3 hold the highest occurrences at around 17,000. Types 9 and 5 exhibit the second highest occurrences, approximately 10,000 to 11,000. Type 8 and Type 6 follow with occurrences of around 8,500 and 4,400 respectively. Types 0, 2, 4, and 7 display relatively lower occurrences, ranging from 1,000 to 2,000.

Several noteworthy trends emerge from this distribution. Firstly, Detroit exhibits a significantly higher occurrence of Type 6, while Miami presents a notably lower occurrence. While Type 6 occurrences in Cleveland and Pittsburgh are comparable at around 3,200 and 4,400, respectively, Detroit's Type 6 occurrences surpass those of the former cities by a considerable margin, approximately 4.3 to 6 times higher. Conversely, Miami's Type 6 occurrences at 1,200 are only a fraction of those in the preceding cities. Given the earlier insights into the area and heights of Type 6 in Miami, which were notably larger and taller than in the other cities, it can be inferred that Miami's Type 6 and other three cities represent akin urban domains albeit centered on disparate architectural entities.

Secondly, a conspicuous scarcity of Type 9 occurrences in Detroit is evident. Cleveland, Miami, and Pittsburgh exhibit around 8,500, 17,000, and 11,000 occurrences of Type 9, respectively, suggesting a potential correlation with the occurrences of Types 1, 3, and 5 in each city. In contrast, Detroit's Type 9 occurrences at 2,200 appear unrelated to the relatively larger occurrences of Type 1, 3, and 5, exceeding 7,000. Given the size and height

attributes of Type 9, it can be inferred that Detroit lacks smaller one-story structures in the range of 600 to 800 square feet.

Thirdly, a distinct scarcity of Type 4 occurrences in Miami is notable. The other three cities exhibit occurrences of over 1,000 for Type 4. Specifically, Cleveland's occurrences are around 3,500. However, Miami's occurrences are notably low at around one-third or even one-tenth of those in the other three Rust Belt cities. Considering Type 4's association with relatively larger structures spanning approximately 4 to 5 stories, Miami's lower number of such structures compared to the other three cities is discernible.

Fourthly, the significant abundance of Type 8 occurrences in Cleveland is noteworthy. While Types 8 in the other three cities exhibit occurrences below 10,000, Detroit records around 2,000 occurrences, and Cleveland records an approximate one-tenth of that at 200. Given the similarities in area and height between Type 8 and Types 1, 3, and 5, it is plausible that Type 8 in Cleveland represents building entities similar in scale to Types 1, 3, and 5, albeit with differences in urban spatial composition.

Finally, an observation is made regarding Cleveland's relatively higher occurrences of Types 0 and 2 compared to the other three cities. In Detroit, Miami, and Pittsburgh, Types 0 and 2 exhibit occurrences of approximately 1,500 to 3,000. In contrast, Cleveland's occurrences range from 5,500 to 6,300, surpassing those of the other cities by a factor of two or three. Given the considerations of Type 0 and 2's dimensions and heights, this suggests a relatively abundant distribution of urban spaces surrounding medium-sized buildings characterized by 2 to 3-story structures in Cleveland.

In summary, a quantitative analysis of the area and height of building types, coupled with their occurrences in each city, sheds light on the prevalence of various urban spaces centered around specific types of buildings. However, it should be noted that such quantitative analysis has its limitations, as qualitative aspects such as the conspicuous occurrences of Type 6 and 8 in specific cities, or relationships between Type 9 and Types 1, 3, and 5, may not be fully understood. Therefore, a comprehensive investigation into the qualitative

attributes of urban spaces in each city will provide a more accurate understanding of the distinctive characteristics of each type.

APPENDIX I

RANDOM SAMPLING DATA OF URBAN TYPES

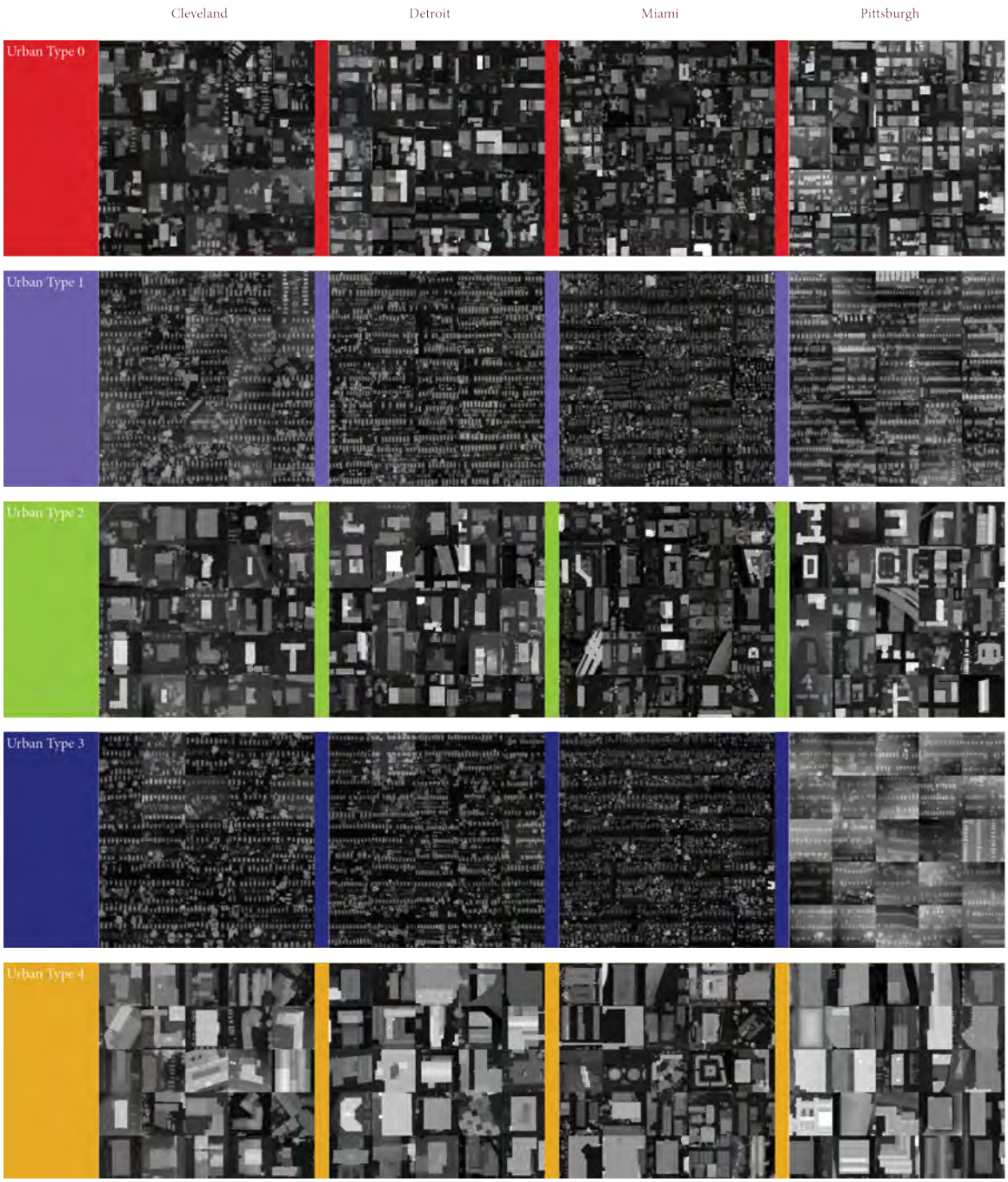


Figure I.1: Random samplings of Urban Types 1-4 in the four cities

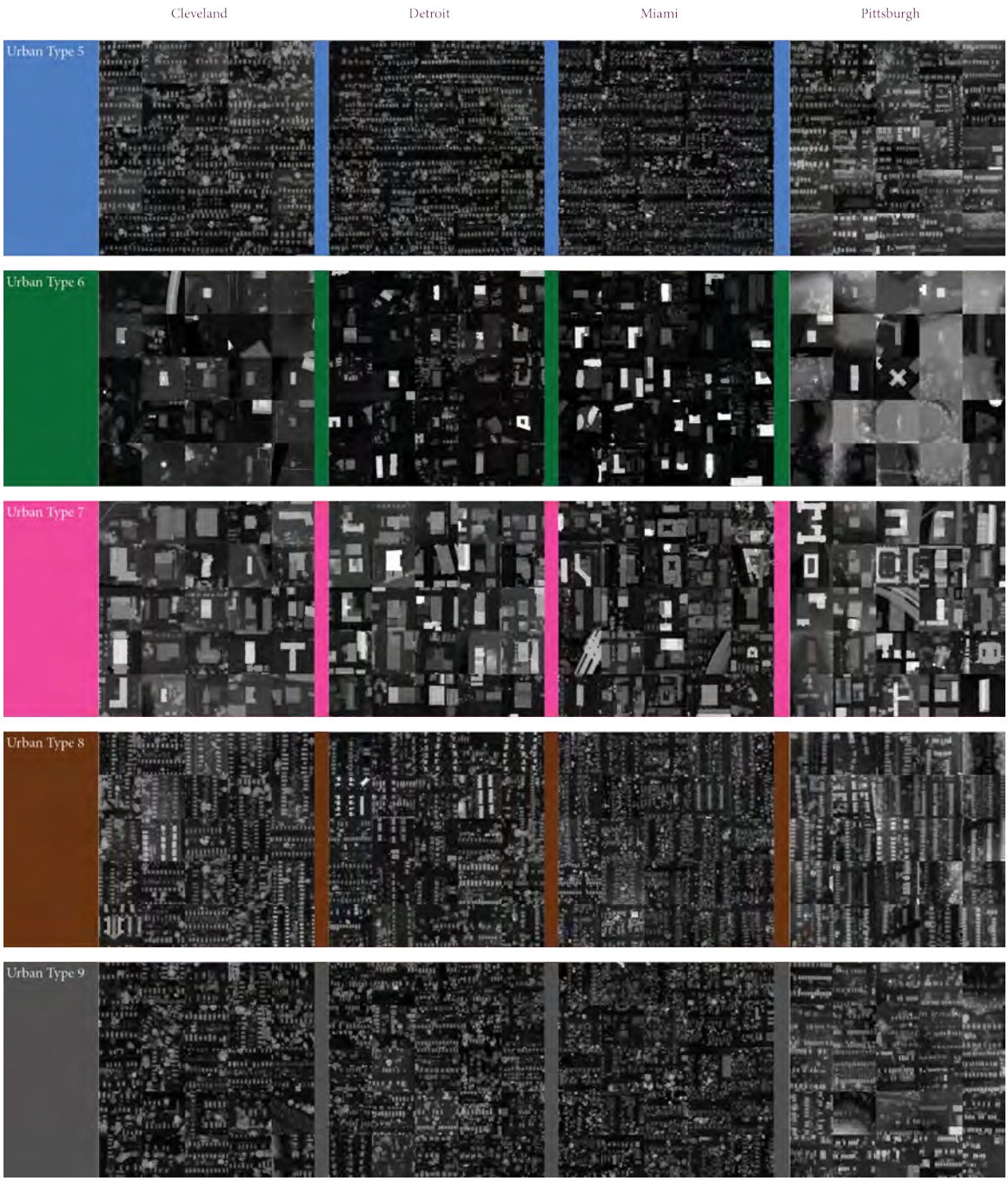


Figure I.2: Random samplings of Urban Types 5-9 in the four cities

APPENDIX J

URBAN FABRIC MAPS BY DIFFERENT N



Figure J.1: Different extent of urban fabrics by a parameter N in the four cities

APPENDIX K

URBAN FABRIC MAPS

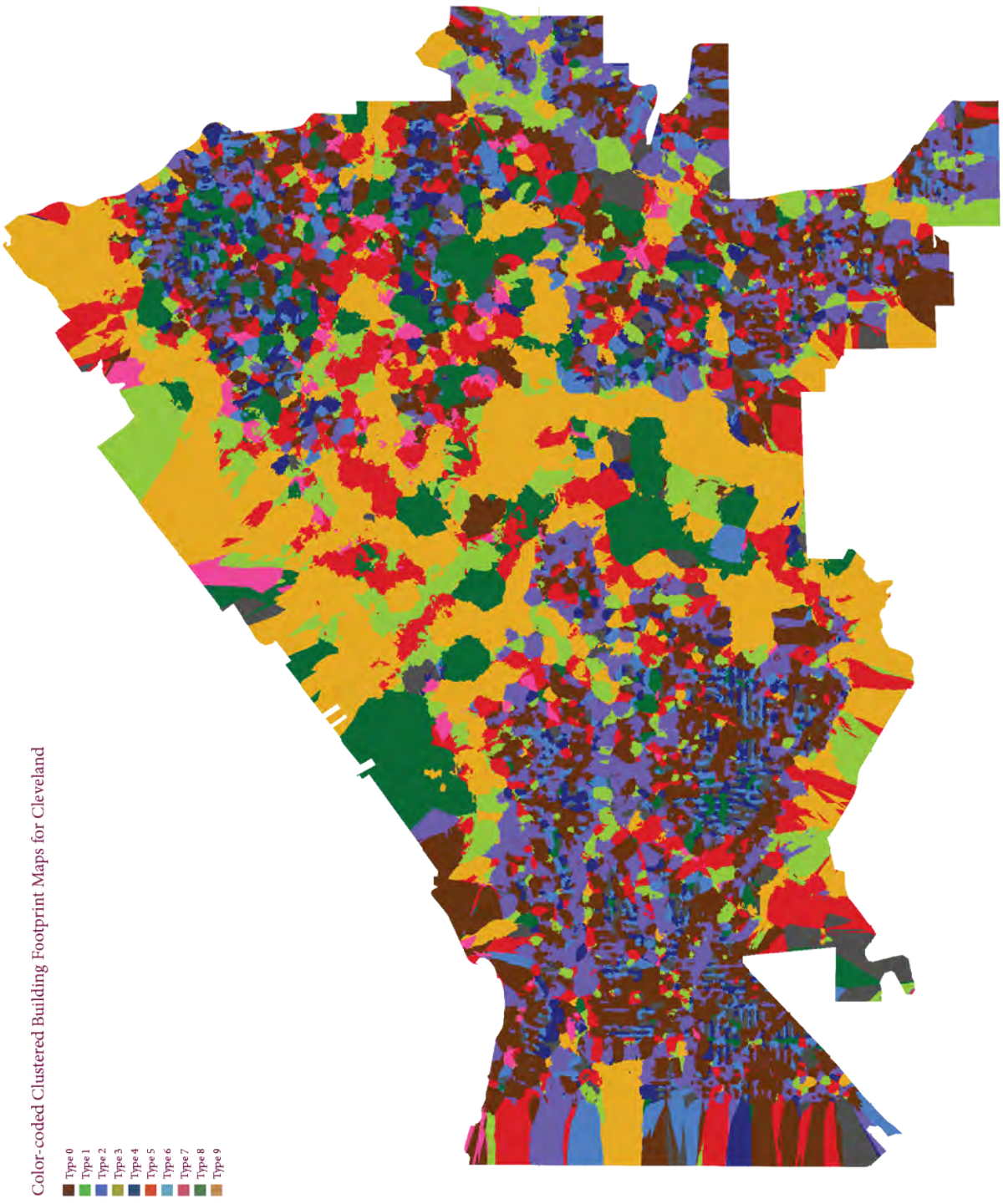


Figure K.1: Urban fabric map: Cleveland

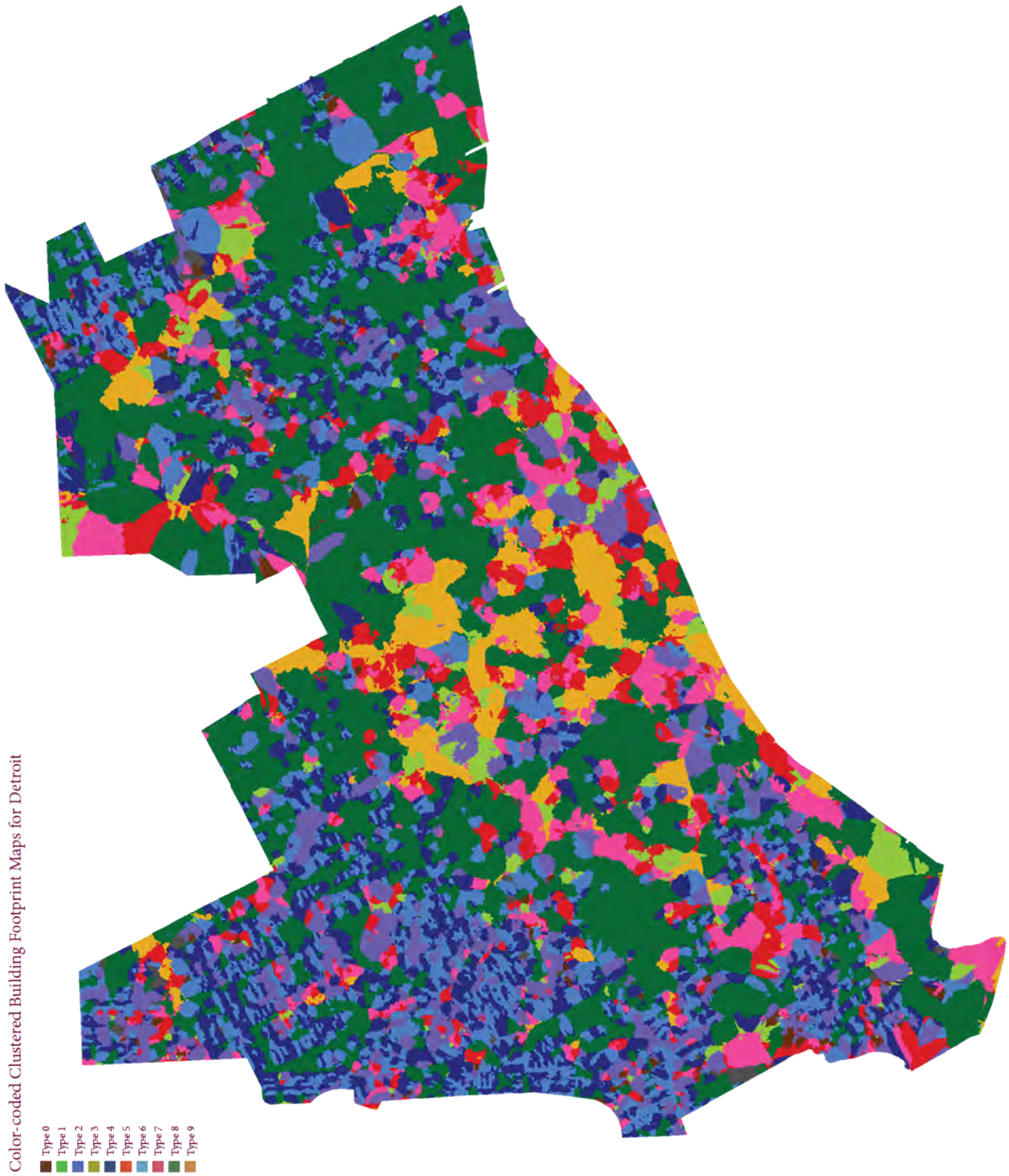


Figure K.2: Urban fabric map: Detroit

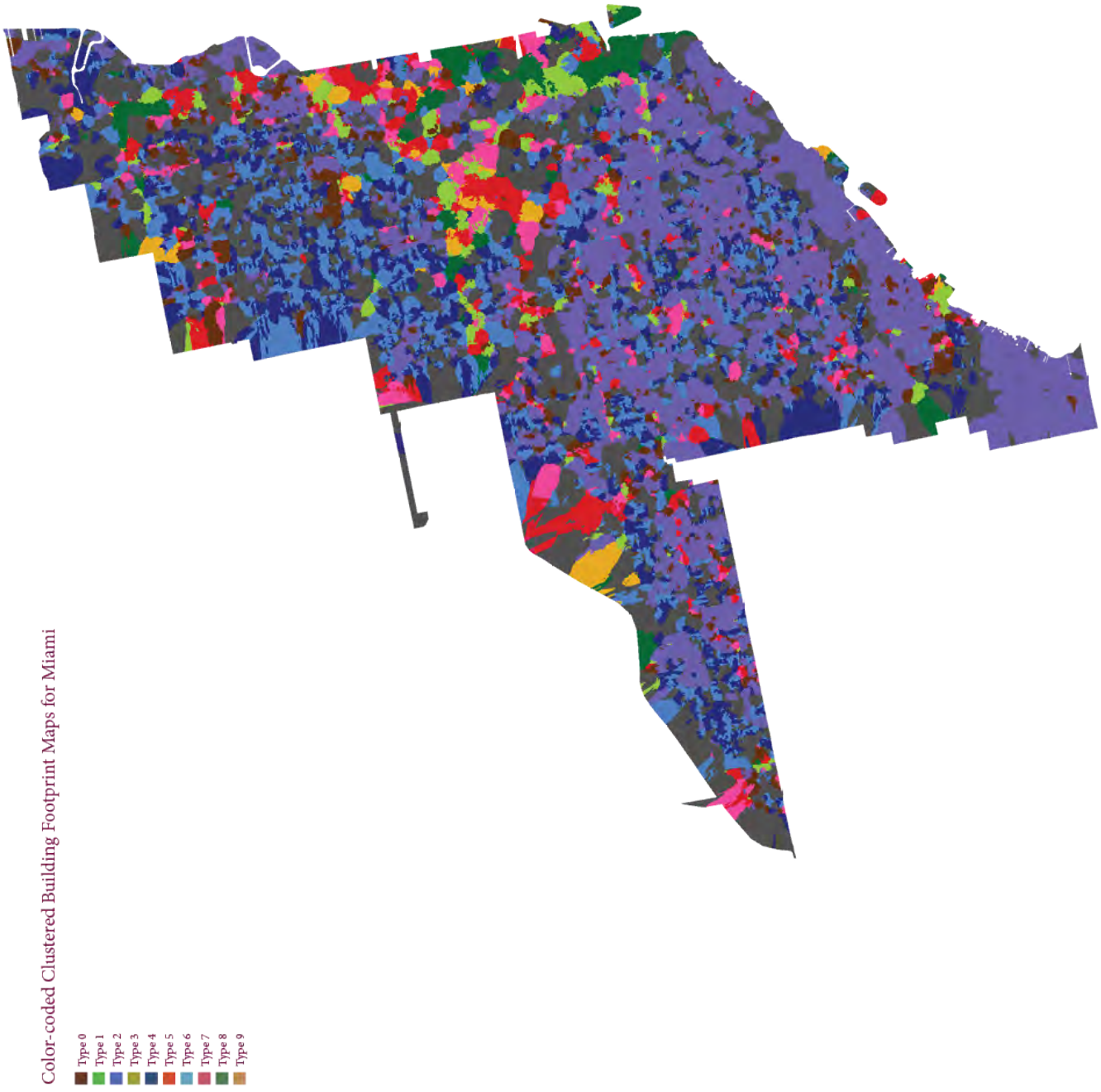


Figure K.3: Urban fabric map: Miami

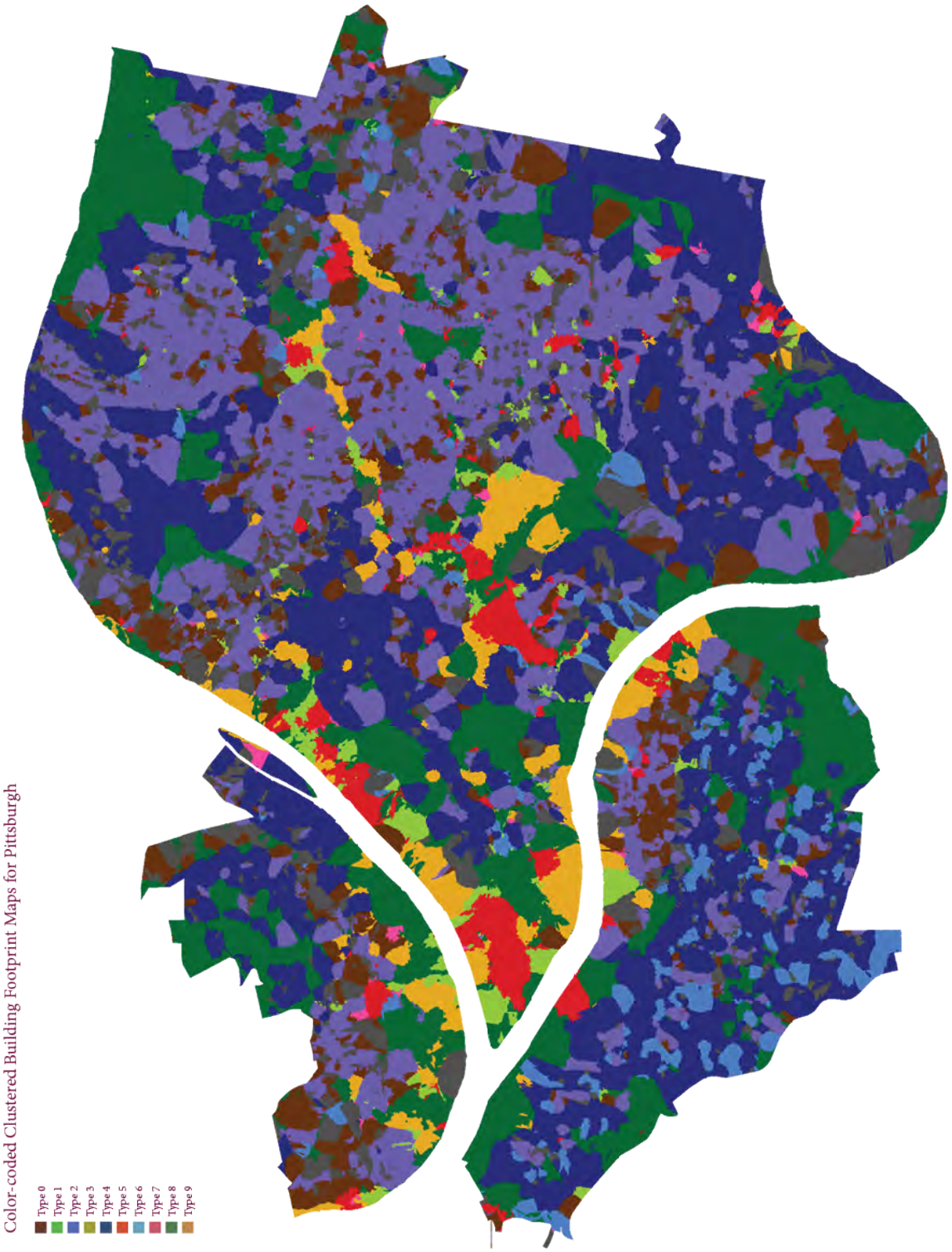


Figure K.4: Urban fabric map: Pittsburgh

APPENDIX L

URBAN FORM ANALYSIS USING FORMULARIZED FEATURE APPROACH

This section presents a detailed account of the process and results of analyzing the urban form of four Rust Belt cities using the formalized feature approach shown in chapter 7. Initially, I dissected the four cities using a grid, and from each grid cell, three form indices such as proximity, density, and form complexity are extracted from the urban form contained within. These extracted indices are treated as morphology features and are classified using a same clustering method as the extracted feature approach. As in the previous chapter 5, these clusters are regarded as urban types and projected onto a building footprint map to analyze how each type is distributed. Furthermore, the characteristics of each type are examined both quantitatively and qualitatively.

L.1 Form Indices

The initial step in the conventional approach involves segmenting the city using geometrical jigs such as grids, blocks, or neighborhoods. In this analysis, the commonly employed grid (as shown in Figure 3.10) is adopted to segment the four cities. The cells of the grid consist of squares with sides measuring 100 m. Typically, the size of this grid falls within the range of 200 to 500 m [83, 145, 89]. However, considering that the extracted feature approach ultimately utilizes data with a scope of around 100 meters, a similar scale of grid cells is applied.

Referencing [83], three form indices are established: PROX, BHAD, and CHAD. PROX serves as an indicator to represent the concentration of urban configurations; a higher PROX value signifies a concentrated urban setup to the center of a grid cell, whereas a lower value indicates a more spread-out arrangement from the center of the cell. PROX is

computed by dividing the cumulative area of buildings within a 200-meter cell radius of a building by the sum of the squares of distances between all buildings in the cell and the central object. This value is then multiplied by the number of buildings in the cell.

BHAD represents the horizontal density of how much area within a cell is occupied by buildings. To calculate BHAD: 1) All buildings intersected by the area are selected. 2) Intersection regions are computed. 3) The ratio of intersection area to cell area is calculated. A higher PROX value indicates a dense occupancy be buildings in a cell, while a lower value suggests a sparse occupancy in the cell.

Lastly, CHAD serves as an index measuring the complexity of building shapes within a cell. It is determined by the ratio of the sum of building areas within a cell to the area of the convex hull formed around these buildings. To compute CHAD: 1) Buildings intersected by the cell are selected. 2) The convex hull around these buildings is calculated. 3) The ratio of building area to convex hull area is determined. A high CHAD value indicates a huge disparity between a building's actual footprint area and its convex hull area. This signifies the prevalence of more concave cases, suggesting that the shapes of buildings within a cell are intricate and complex.

For the purpose of comparative analysis, the indices values of the four cities are normalized to a range between 0 and 1. Figure L.1 illustrates heatmaps of PROX, BHAD, and CHAD values for these cities. Greener colors indicate smaller values, while redder colors indicate larger values. Generally, high values for PROX, BHAD, and CHAD are observed in the vicinity of downtown areas across all cities. Utilizing grid cells to represent urban forms composed of buildings within each cell, distinguishable differences between grid cells containing buildings and those that are empty can be observed. This differentiation highlights the representation of urban voids such as water bodies and parks within the city terrains. In the case of PROX, all four cities exhibit not a gradual gradient, but rather extreme high values, forming the linear and radial pattern predominantly in shades of red, centered around downtown areas. This pattern indicates that buildings located in downtown

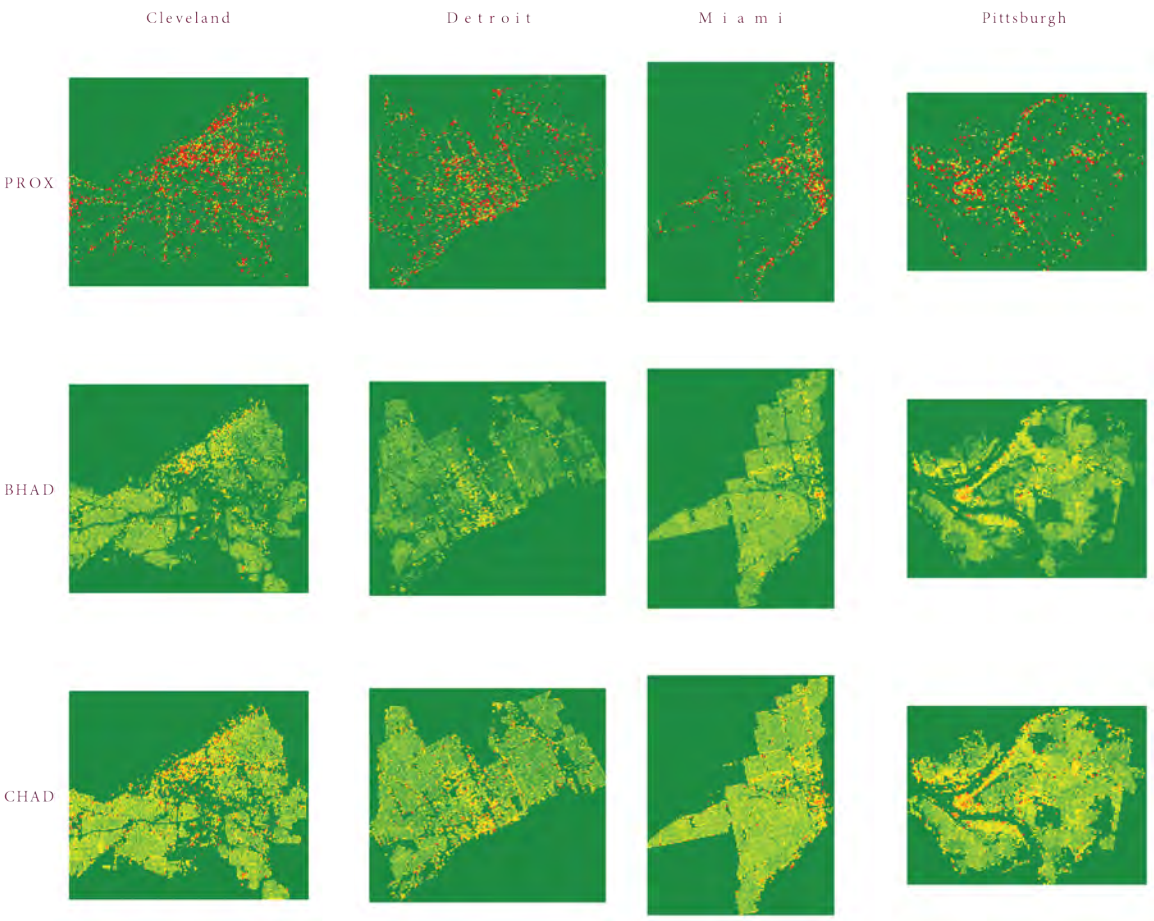


Figure L.1: PROX, BHAD, CHAD for four cities

areas, near boulevards and major roads, or in the vicinity of large buildings are close to each other. Conversely, regions outside these categories exhibit notably low proximity values. This extreme pattern underscores the distinct segregation between urban spaces with high proximity formed by certain urban forms and those with low proximity, emphasizing clear differentiation.

Cleveland forms a radial pattern centered around downtown, while Detroit exhibits a relatively high proximity extending northwest from downtown, displaying a fainter radial pattern. While Cleveland's proximity is highly concentrated around downtown, Detroit's proximity distribution is less dense compared to Cleveland. Miami and Pittsburgh show a similar distribution of proximity, distinct from the other two cities, as areas with high and low proximity are clearly differentiated. Miami and Pittsburgh exhibit a distinct pattern

in proximity distribution, wherein the differentiation between areas with and without high proximity is more pronounced compared to the other two cities. The latter cities display a prevalence of intermediate proximity values, dispersed widely across the urban landscape. Conversely, Miami and Pittsburgh demonstrate concentrated high proximity regions primarily around downtowns and sub-cores of cities. To elaborate, the occurrence frequency of clustered buildings in Cleveland and Detroit is broadly dispersed around boulevards. In contrast, Miami and Pittsburgh display a concentration of such occurrences in downtowns, sub-centers, and areas adjoining large buildings—although the delineation between sub-centers, large buildings, and spatial divisions may not be entirely distinct.

Across all four cities, downtown areas exhibited elevated values of BHAD. Notably, unlike PROX, the distribution of BHAD values displays a discernible gradient rather than extreme divergence. Detroit exhibits the weakest BHAD values, followed by Cleveland. In contrast, Miami and Pittsburgh demonstrate relatively robust BHAD values throughout their urban spaces. The interpretation of BHAD as a representation of the horizontal density within a grid cell suggests that Cleveland and Detroit have relatively lower densities compared to the other cities.

In Cleveland, relatively high-density urban forms are evident in the western region centered around downtown, while the eastern areas, except for the northeast near downtown, exhibit lower-density urban forms. Detroit demonstrates a predominantly low-density urban forms citywide, with an exception of a denser urban core extending northwestward from downtown. Miami displays an overall high density, indicating short-distance and clustered buildings. Pittsburgh shares similarities with Miami in maintaining high urban density throughout the city, yet experiences a significant density reduction in the eastern area just next to downtown and in the city's northeastern region.

CHAD serves as an index to measure the morphological complexity of urban forms within a single grid cell. Similar to PROX and BHAD, it demonstrates relatively high values near downtowns, areas around sub-centers, and large buildings, indicating intricate

shapes of urban forms away from residential areas. Like in the case of PROX and BHAD, high CHAD values in Cleveland and Detroit are broadly distributed around boulevards, while in Miami and Pittsburgh, this distribution is concentrated around downtowns and their immediate surroundings. Particularly noteworthy in Miami and Pittsburgh is the occurrence of sporadic high-complexity spaces even within predominantly residential areas.

L.1.1 Clustering

PROX, BHAD, and CHAD are considered as features representing urban forms within grid cells. The dataset of these features consists of the same number of grid cells that cover the four cities, amounting to 30,481. Consequently, this feature data can be represented as a vector array of dimensions (30481, 3). Similar to the inductive approach, this data is subjected to K-means clustering to form 10 distinct types. Figure L.2, Figure L.3, Figure L.4, and Figure L.5 illustrate the mapping of this clustering information onto a map composed of grids. Within this map, consecutive grid cells of the same type are regarded as constituting an urban fabric.

Within this map, spaces that are generally perceived as vacant stand out conspicuously. Areas designated for water bodies, highways, and parks, among other ground-related programs, manifest as open spaces on the map. Notably, in the cities of Cleveland, Detroit, and Pittsburgh, these vacant spaces appear prominently in contrast to Miami. In Miami, such open spaces are scarcely discernible, except for regions like the eastern coast of the city or areas around the airport in the west.

Furthermore, I could observe a demarcation between downtown and residential zones. Across the four cities, a pattern emerges wherein urban forms predominantly characterized by shades of blue and green primarily denote downtown areas and their peripheries. These forms stand apart from the residential forms depicted in shades of orange and pink. Pittsburgh exhibits a distinctive feature of green urban fabrics extending relatively wider around residential zones. On the other hand, Detroit is characterized by the narrowest expanse of

blue and green fabrics within its relatively limited area.

In addition to visual analysis, other types of analyses are requisite for interpreting

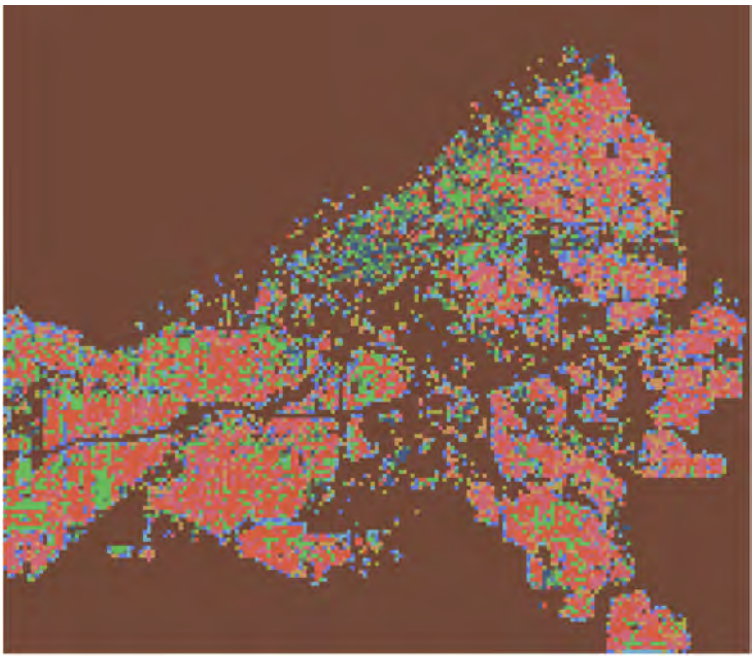


Figure L.2: Mapping of clustering PROX, BHAD, CHAD indexes: Cleveland



Figure L.3: Mapping of clustering PROX, BHAD, CHAD indexes: Detroit

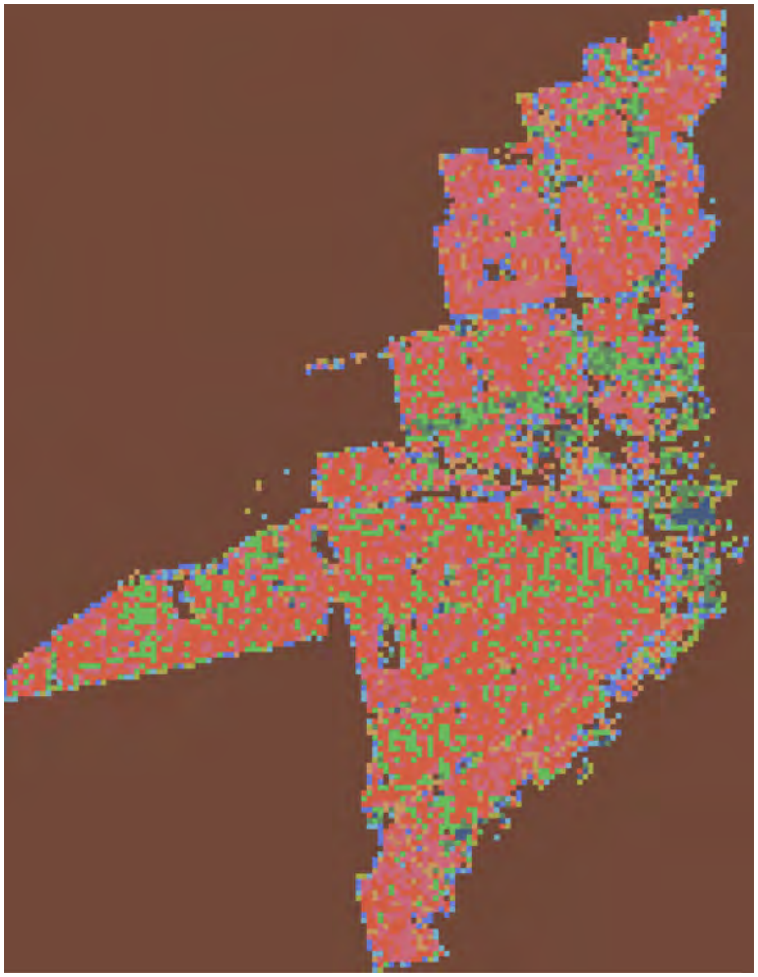


Figure L.4: Mapping of clustering PROX, BHAD, CHAD indexes: Miami

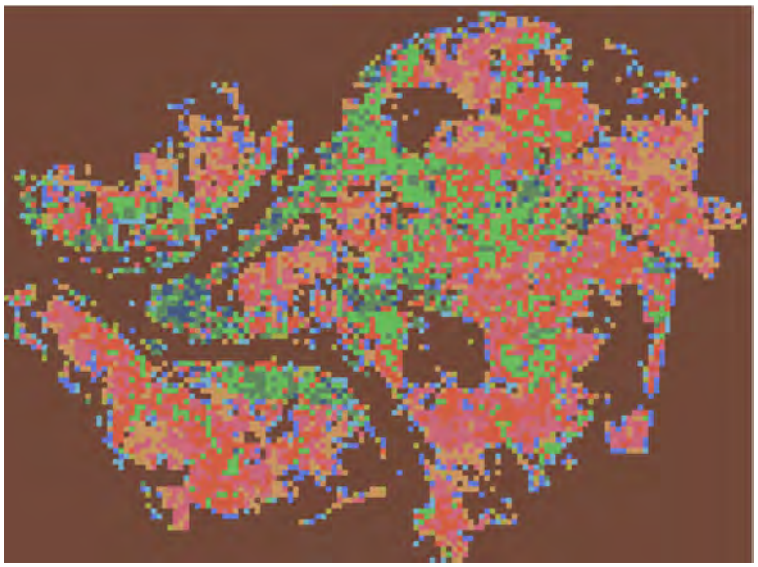


Figure L.5: Mapping of clustering PROX, BHAD, CHAD indexes: Pittsburgh

these types and classifications. Similar to the analysis conducted on the extracted feature approach, these types will also undergo both quantitative and qualitative analyses to reveal their characteristics. However, it is important to note that while the extracted feature approach involved 3D information centered around buildings, allowing for quantitative investigations into building area and height, the formularized feature approach relies on 2D information and segments data into grids. Consequently, these two quantitative investigations are not included within this formularized feature approach.

L.2 Characteristics of Urban Type

L.2.1 The Quantity of Each Type

Figure L.6 illustrates bar graphs providing overviews of the various types and their corresponding occurrence amounts across the four cities. In the context of this quantitative analysis, grid cells located outside the city boundaries were deliberately omitted. Further, it is observed that Type 0—brown color—predominantly encompasses vacant land, visually resembling rivers and parks. Thereby, when examining the frequency of occurrence by type, the description for Type 0 is intentionally minimized.

In the case of Cleveland, it is distinctly apparent that there exists a substantial variation in the distribution of occurrences among these types. Notably, Type 5 stands out with the highest count, totaling 2559, while closely trailing behind is Type 7, accounting for 2049 instances. Types 1, 9, and 2 exhibit relatively similar occurrences, numbering 1448, 1195, and 1033, respectively. Conversely, Types 3 and 4 emerge as the least prevalent in Cleveland, registering quantities of 406 and 389, respectively.

Within Detroit, Type 9 commands the highest count, totaling 4130, closely trailed by Type 7 with 2914 occurrences. Type 2 represents the third most frequent with 1187 instances. Types 5 and 6 manifest within a range of about 600 to 800 occurrences, while Types 1, 3, 4, and 8 exhibit quantities ranging between approximately 170 and 450, indi-

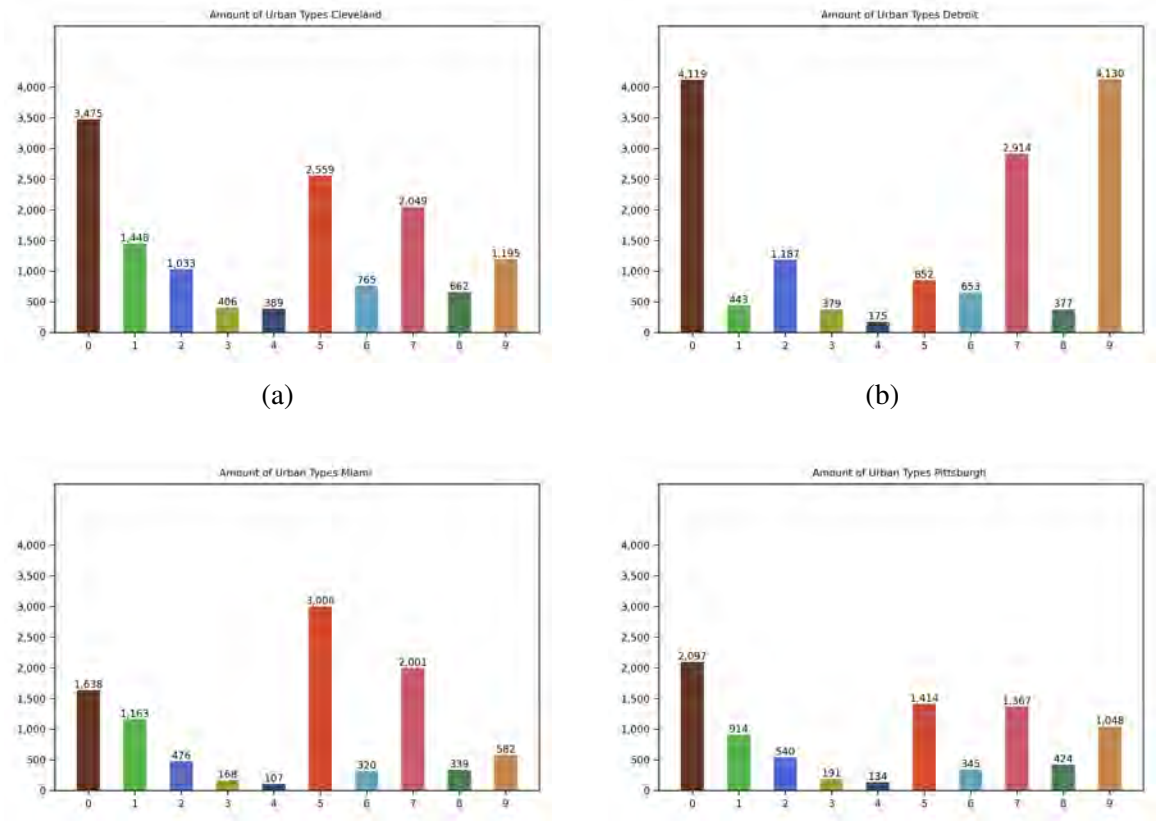


Figure L.6: The Quantity of each urban form type in the four cities from the formularized feature approach.

cating relatively lower instances.

In the context of Miami, Type 5 emerges with the highest count, totaling 3006 occurrences, followed by Type 7 with 2001. Type 1, with a count of 1163, stands as the third most prevalent type, notably differentiated from others. Types 2, 6, 8, and 9 manifest within a range of approximately 320 to 580 instances, while Types 3 and 4 exhibit occurrences between roughly 100 and 170, being the least frequent.

In the case of Pittsburgh, Type 5 also exhibits the highest frequency, totaling 1414 occurrences. However, there is no substantial disparity from Types 7 and 9, which rank as the second and third most prevalent. Type 1 ensues with 914 instances, while Type 3 and 4 have the least occurrences, numbering 191 and 134, respectively.

Cleveland and Miami exhibit a similar distribution pattern in occurrences by type. In both

cities, Type 5 emerges as the most prevalent, followed by Types 7, 1, and 9 in descending order. Additionally, the least occurrence of Types 3 and 4 is a shared characteristic between these two cities. Pittsburgh's distribution of amounts, though differing in absolute values, resembles that of Cleveland or Miami. However, Detroit deviates from the other three cities due to relatively prominent occurrences of Types 9, 7, and 2, juxtaposed with notably minor proportions of Types 5 and 1.

In the context of comparative analysis on the amount of occurrences across these four cities, it can be inferred that Types 5 and 7 are analogous, while Types 1, 2, and 9 share similarities, and Types 3, 4, 6, and 8 exhibit comparable occurrences quantitatively.

Here is the summary of the notable findings in terms of the quantity:

- In Cleveland, Type 5 has the highest occurrence, followed closely by Type 7. Types 1, 9, and 2 have moderate occurrences, while Types 3 and 4 are the least prevalent.
- Detroit's distribution is led by Type 9, with Type 7 also showing significant prevalence. Type 2 is third most frequent, and Types 1, 3, 4, and 8 are among the least common.
- Miami features Type 5 as the most prevalent, followed by Type 7. Type 1 is third, with Types 2, 6, 8, and 9 in the middle range, and Types 3 and 4 as the least frequent.
- In Pittsburgh, Type 5 also ranks highest in occurrences, with Types 7 and 9 closely following. Types 1, 3, and 4 have lower occurrences, with Types 3 and 4 being the least prevalent.
- Cleveland and Miami show a similar pattern of distribution, with Type 5 being the most prevalent, followed by Types 7, 1, and 9. Both cities also share the characteristic of having the least occurrences in Types 3 and 4.
- Pittsburgh's pattern, while different in absolute values, shares similarities with Cleveland and Miami, especially in the prevalence of Types 5, 7, and 9.

- Detroit stands out with a different distribution pattern, having higher occurrences of Types 9 and 7, and lower occurrences of Types 5 and 1, compared to the other cities.

This quantity analysis suggests Types 5 and 7 are generally more prevalent across the cities, whereas Types 3, 4, 6, and 8 have comparable, less frequent occurrences. Detroit's unique pattern compared to the other cities highlights diverse urban planning and architectural preferences.

L.2.2 Representative Forms

In conjunction with the quantitative analysis, a qualitative analysis is conducted by creating representative forms to discern the characteristics of urban spaces represented by each type, similar to the approach undertaken in the extracted feature approach. The term "representative form" denotes an urban form that exhibits the data with the closest Euclidean distance to the mean feature vector of each type, following the classification of feature vectors, each comprising (30481,3) dimensions, into their respective types.

The series of diagrams below sequentially display the representative forms of each type in the four cities: Cleveland, Detroit, Miami, and Pittsburgh. Additionally, a dataset of sampled urban forms was generated, encompassing 25 instances randomly chosen from among the 5000 forms that are in closest proximity to each mean data point. By means of these two methodologies, I conduct an analysis to discern the spatial and morphological attributes inherent to each type.

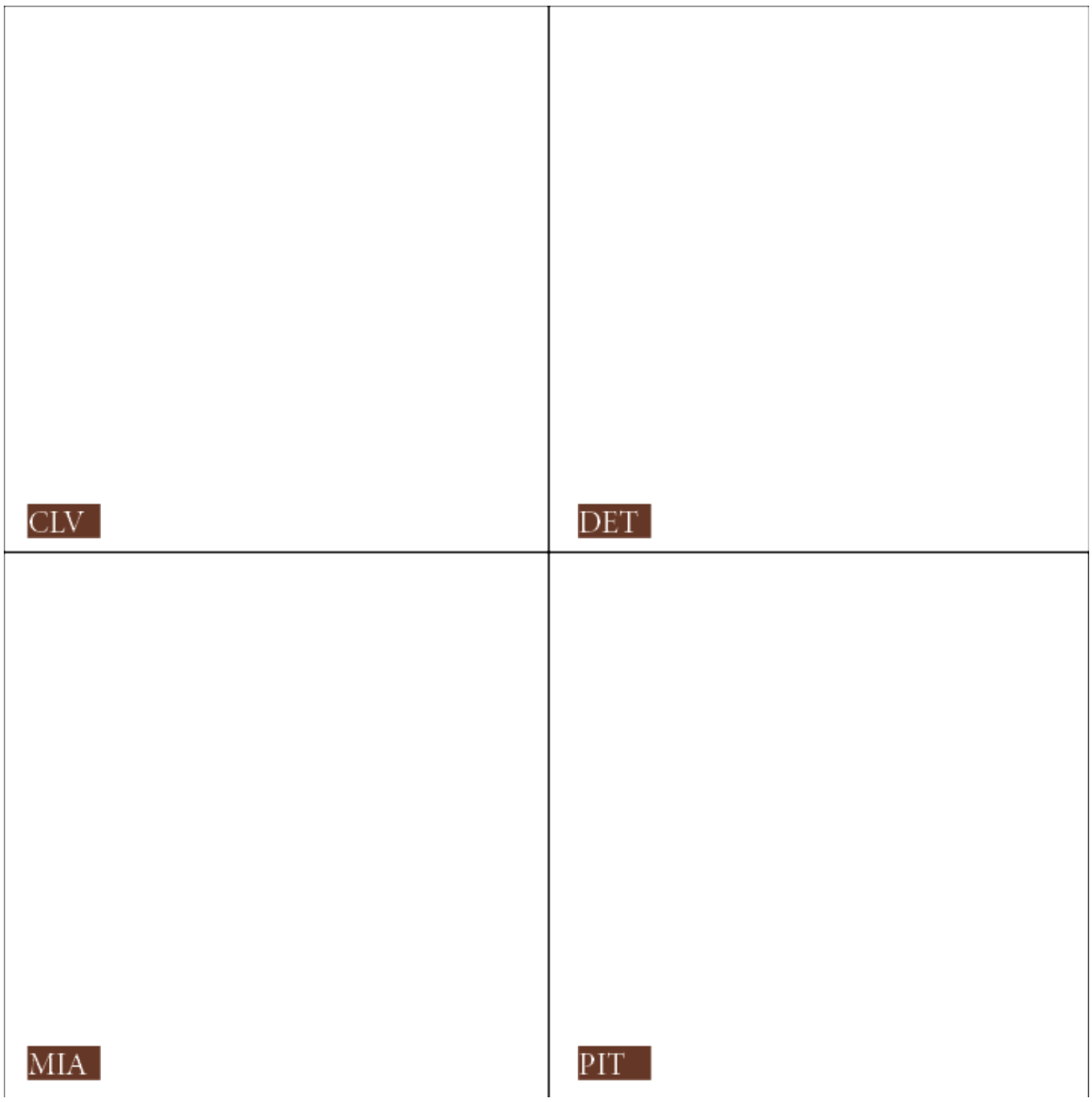


Figure L.7: Representative forms of Urban Type 0

Type 0 represents nearly entirely vacant spaces across the four cities Figure L.7. Upon examining the sampling, it can be deduced that buildings occasionally emerge within these empty areas; however, in essence, these vacant locations are categorized as Type 0.

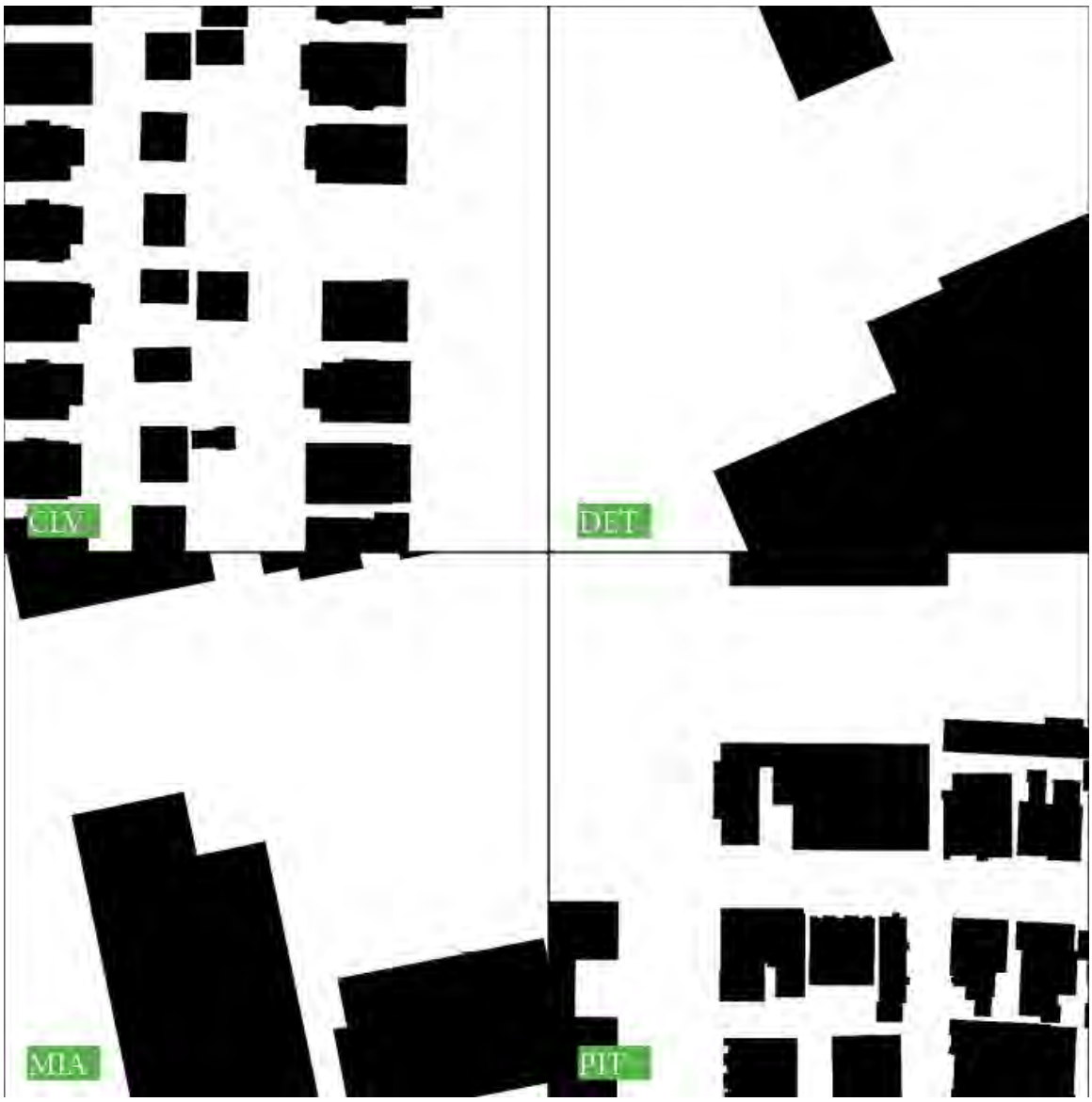


Figure L.8: Representative forms of Urban Type 1

The characteristics of Type 1's representative form is ambivalent Figure L.8. In Cleveland and Pittsburgh, it reveals small-scale buildings forming linear arrangements, while in Detroit and Miami, medium to large-scale buildings partially occupy grid cells. Upon examining the sampling, except for Detroit, the other three cities mostly exhibit a blend of linear arrangements formed by small-scale buildings alongside medium to large-scale buildings. However, in Detroit, small-scale buildings are conspicuously scarce. Hence, the characterization of this type remains ambiguous. It primarily emerges near or on the

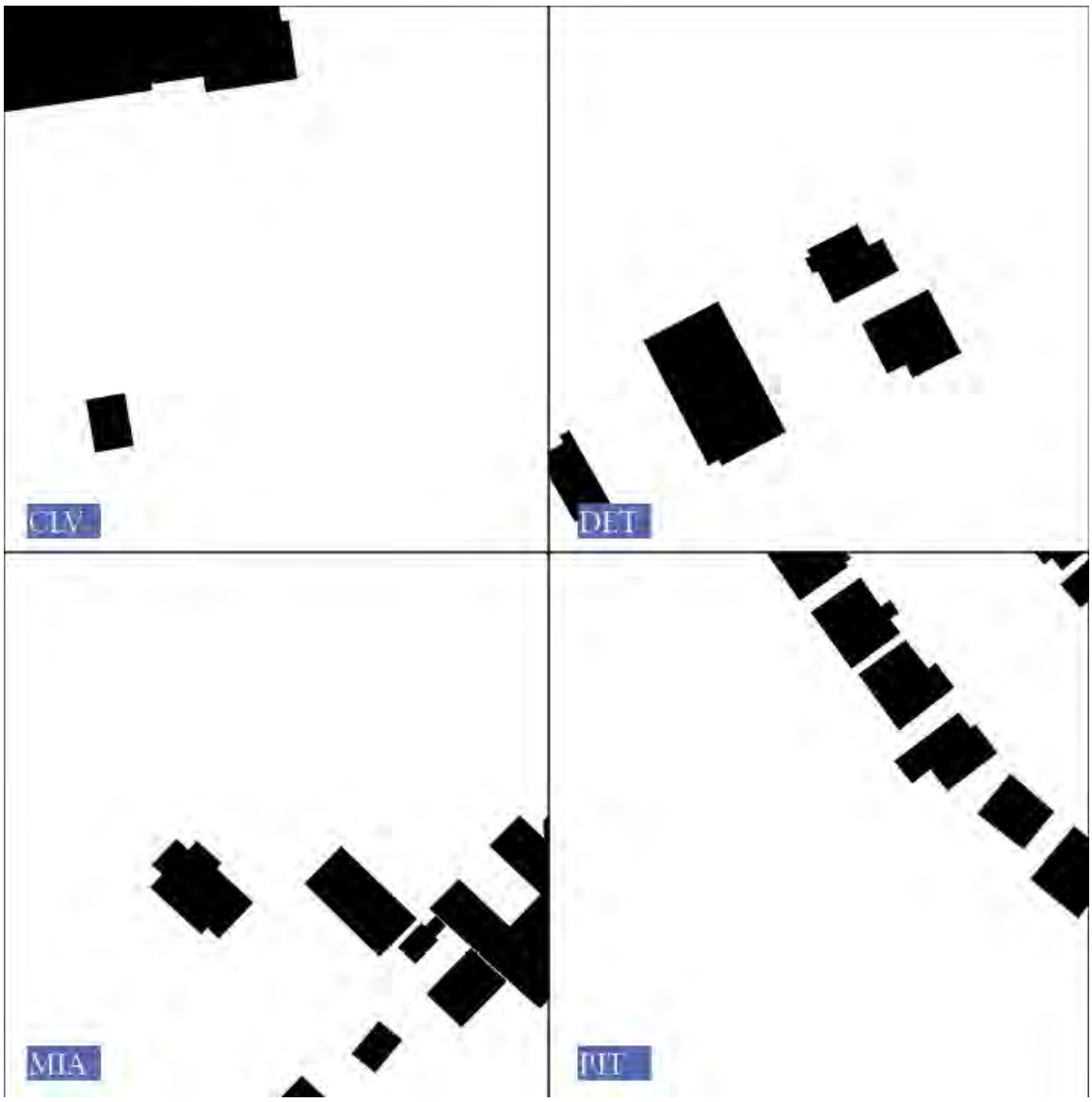


Figure L.9: Representative forms of Urban Type 2

outskirts of Type 5 and 7, which predominantly constitute residential areas.

A notable feature in the representative form of Type 2 is the relatively extensive occurrence of unoccupied spaces Figure L.9. Upon observation of both the representative form and the sampling data, it becomes apparent that this type represents urban forms that encompass portions of large-scale buildings, widely spaced medium to small-sized buildings, or only a portion of linearly arranged houses. This type primarily occurs along roads.

Types 3 and 4 exhibit relatively distinct characteristics of urban forms (Figure L.10

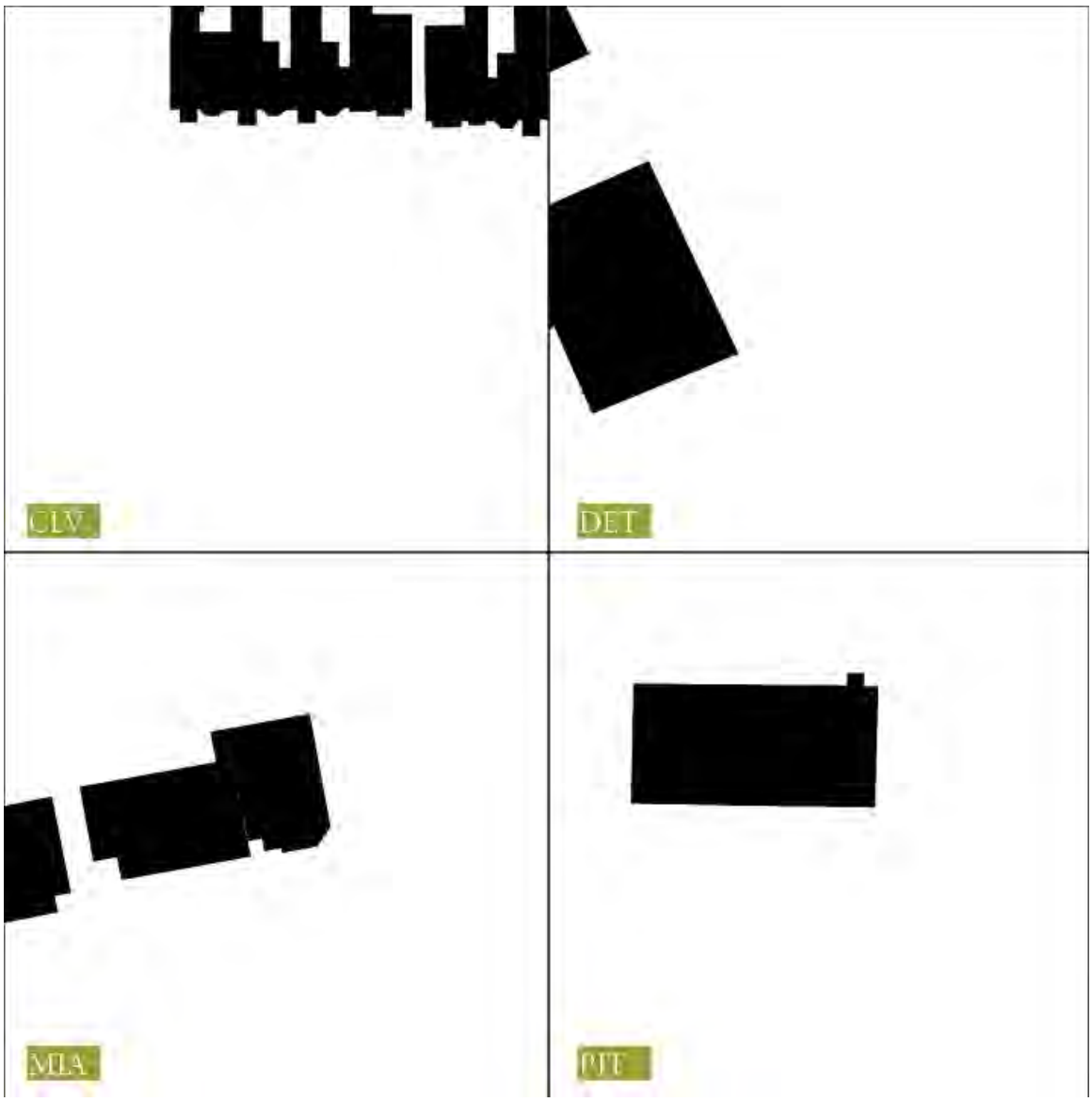


Figure L.10: Representative forms of Urban Type 3

and Figure L.11). In Type 3, unfragmented medium-sized buildings are frequently captured, with fewer prominent linear patterns compared to other types. Type 4 predominantly displays urban forms where most spaces are occupied by either entire or partial footprints of large buildings. This type's distribution is concentrated in downtown areas.

In the representative form, Type 5, similar to Type 1, does exhibit distinctive features: in all four cities, it showcases a mix of distinctive small-scale buildings forming linear arrangements and partial footprints of medium-sized and large buildings Figure L.12.

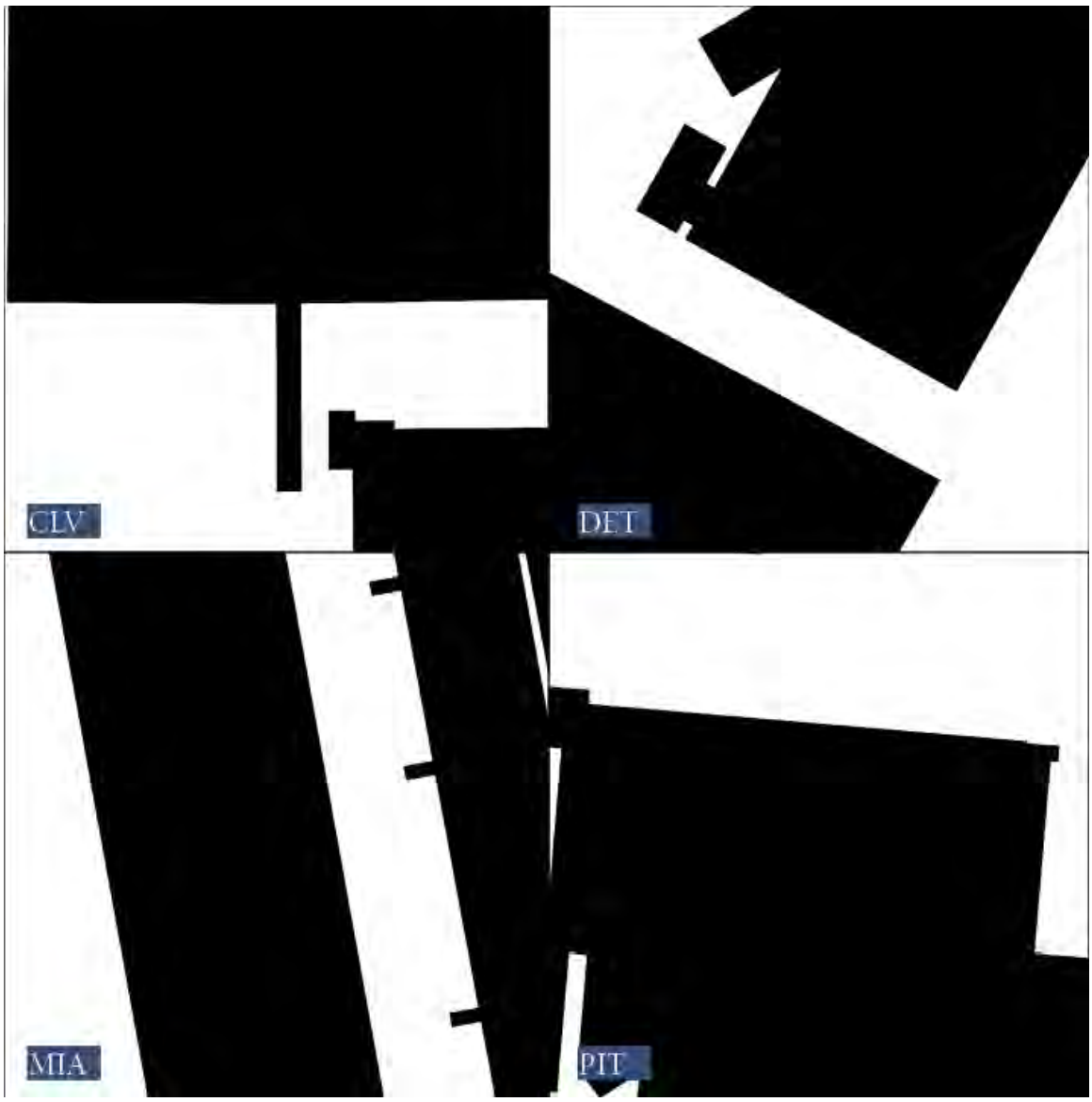


Figure L.11: Representative forms of Urban Type 4

Compared to Type 1, this type has a higher frequency of small-scale building occurrences, which makes the linear pattern relatively prominent. Upon observing the sampling data, these linear patterns become even clearer. However, similar to Type 1, in Detroit, a higher proportion of medium-sized or large-scale buildings is observed rather than a predominant linear pattern.

Type 6, like Type 3, primarily represents only a small part of footprints of buildings Figure L.13, making it difficult to determine their exact scale. Even in the sampling data,

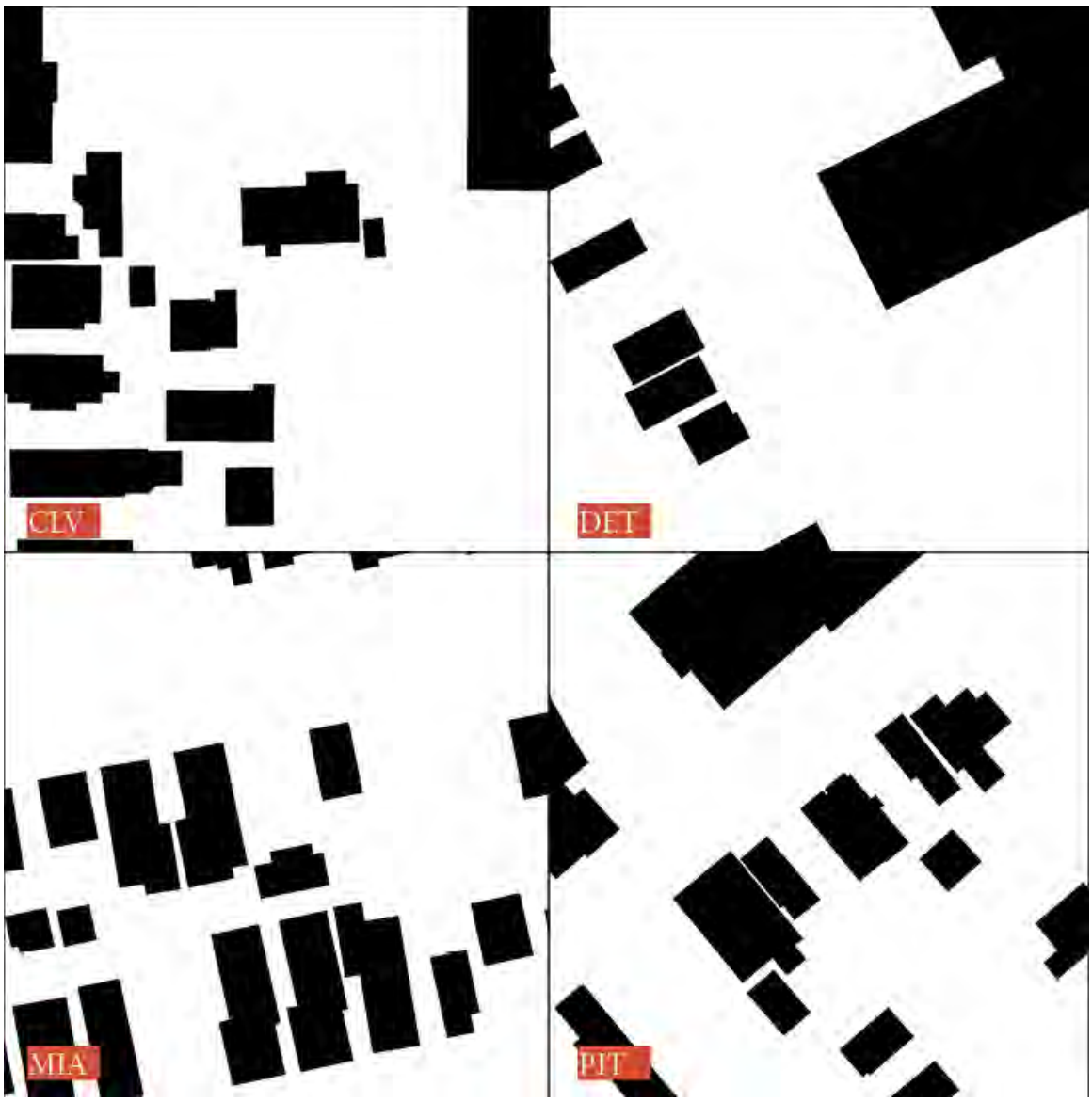


Figure L.12: Representative forms of Urban Type 5

only parts of buildings are depicted, which are generally estimated to be parts of medium-sized and large buildings. Compared to Type 2, this type exhibits larger building footprints, sometimes accompanied by small-scale buildings in linear patterns.

Type 7, like Type 5, predominantly consists of small-scale buildings forming linear patterns Figure L.14. However, the patterns in Type 7 are less dense compared to Type 5, and this type generally exhibits urban forms with lower frequencies of large buildings than Type 5.

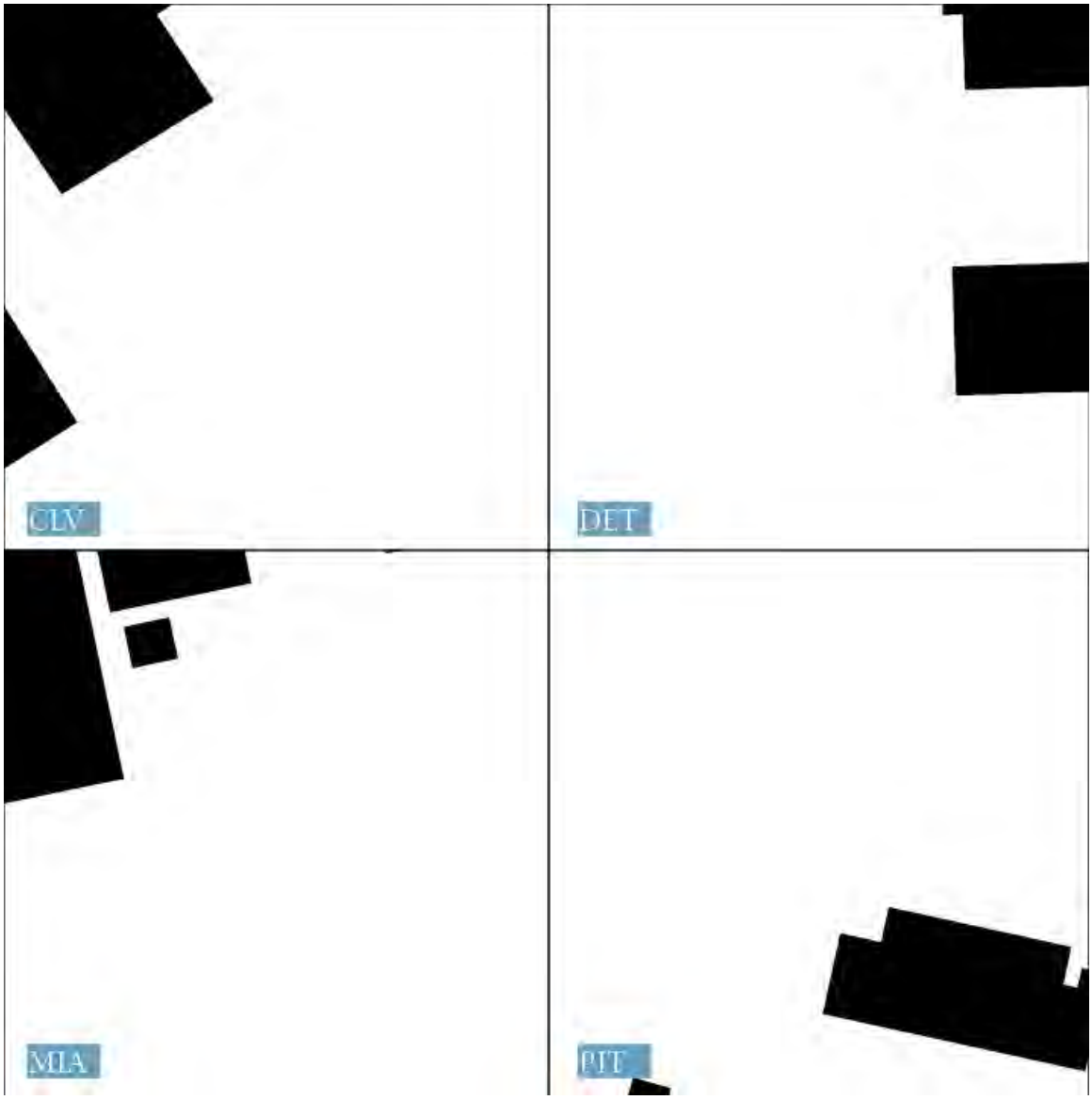


Figure L.13: Representative forms of Urban Type 6

Type 8, like Type 4, primarily consists of spaces mostly occupied by entire or partial large buildings Figure L.15. Upon observing the sampling, it can be inferred that the buildings appearing in Type 8 generally cover a smaller area compared to Type 4, and there is a relatively higher occurrence of fragmented medium and large buildings. This type is mainly found near Type 4 in downtown areas.

Lastly, in Type 9, like Type 2, there is a relatively wide area not occupied by buildings Figure L.16. Upon examination of the sampling data, it is evident that buildings in Type 9

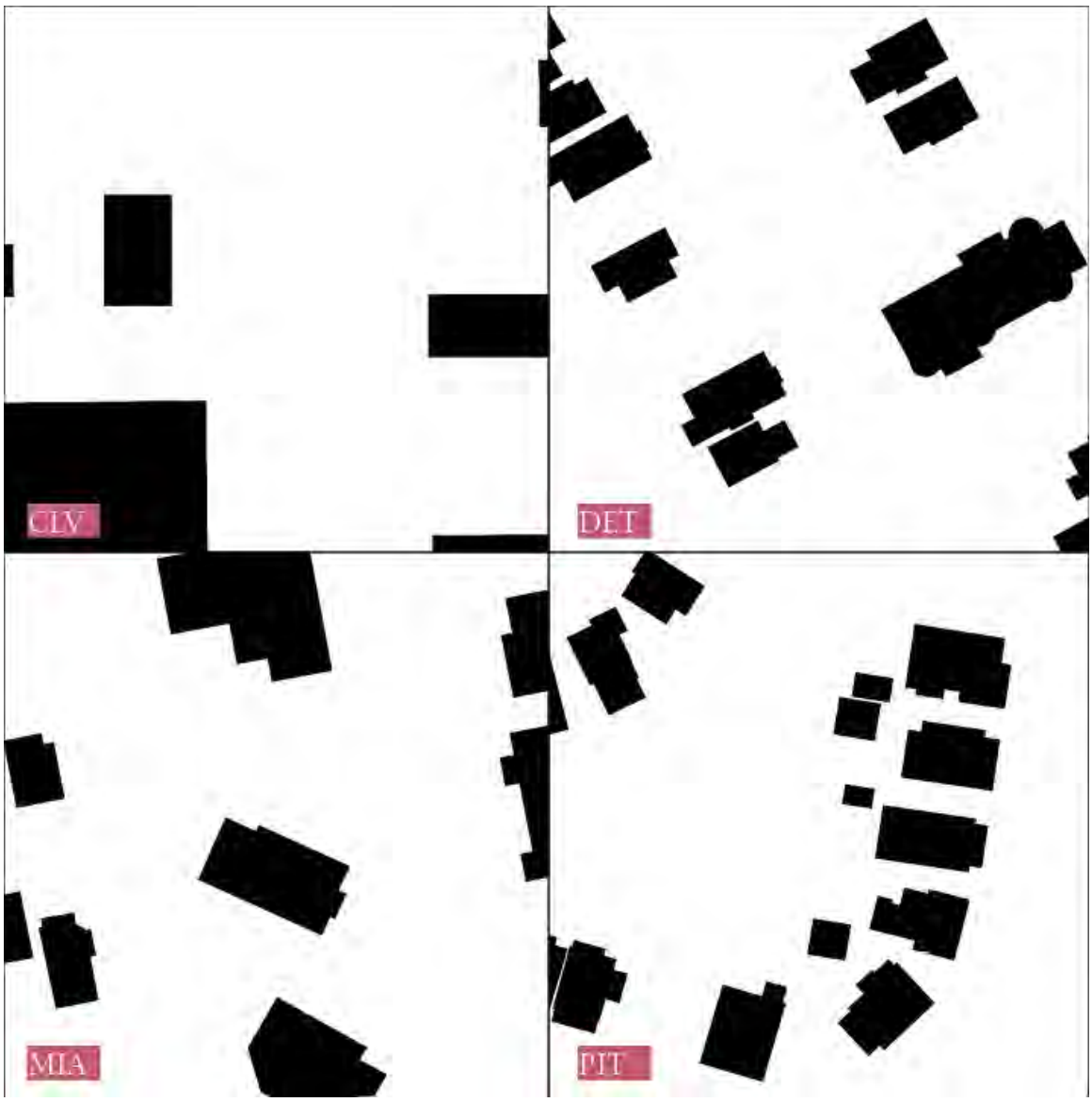


Figure L.14: Representative forms of Urban Type 7

generally exhibit a stronger tendency toward a linear pattern compared to Type 2. Particularly noteworthy is that this type spreads widely in the residential areas to the east, centered around downtown, in Detroit.

Overall, in this analysis, types can be sorted by noticeable differences in area: Type 0 represents urban forms with almost no area occupied by buildings, Types 2 and 9 depict urban forms with clusters of small buildings and significant vacant spaces, Types 3 and 6 show urban forms occupied by medium-sized buildings and some small buildings, Types

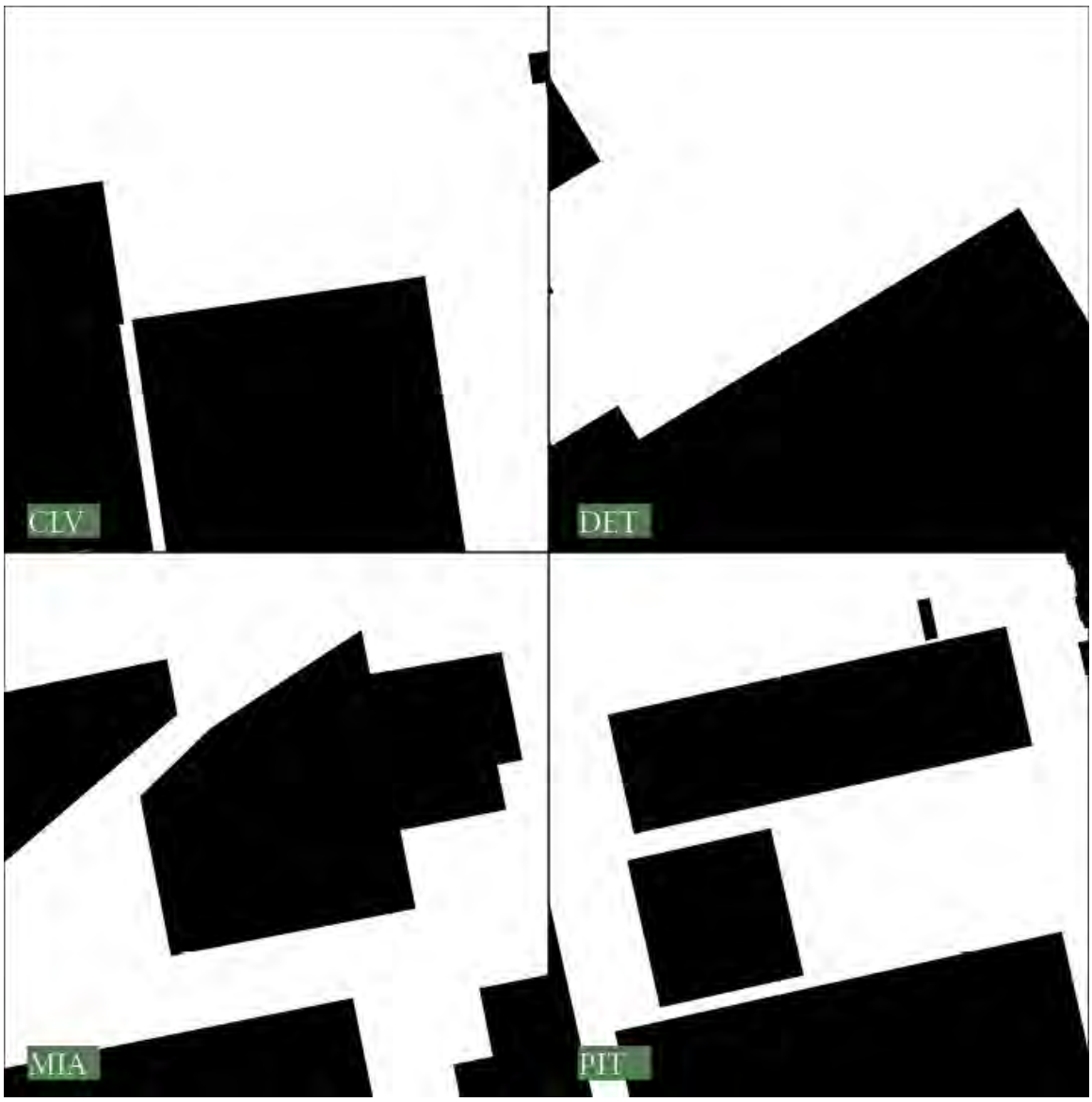


Figure L.15: Representative forms of Urban Type 8

4 and 8 present urban forms dominated by a substantial proportion of large buildings, and Types 5 and 7 are characterized by linear patterns primarily formed by small buildings Figure L.17.

However, as evident in Type 1 where both small and medium-to-large buildings co-exist, the alignment between area and urban form composition is not always consistent. In Detroit's Type 1, for instance, there are only some medium-to-large buildings and a lack of small buildings, whereas the remaining three cities exhibit a clear coexistence of small and

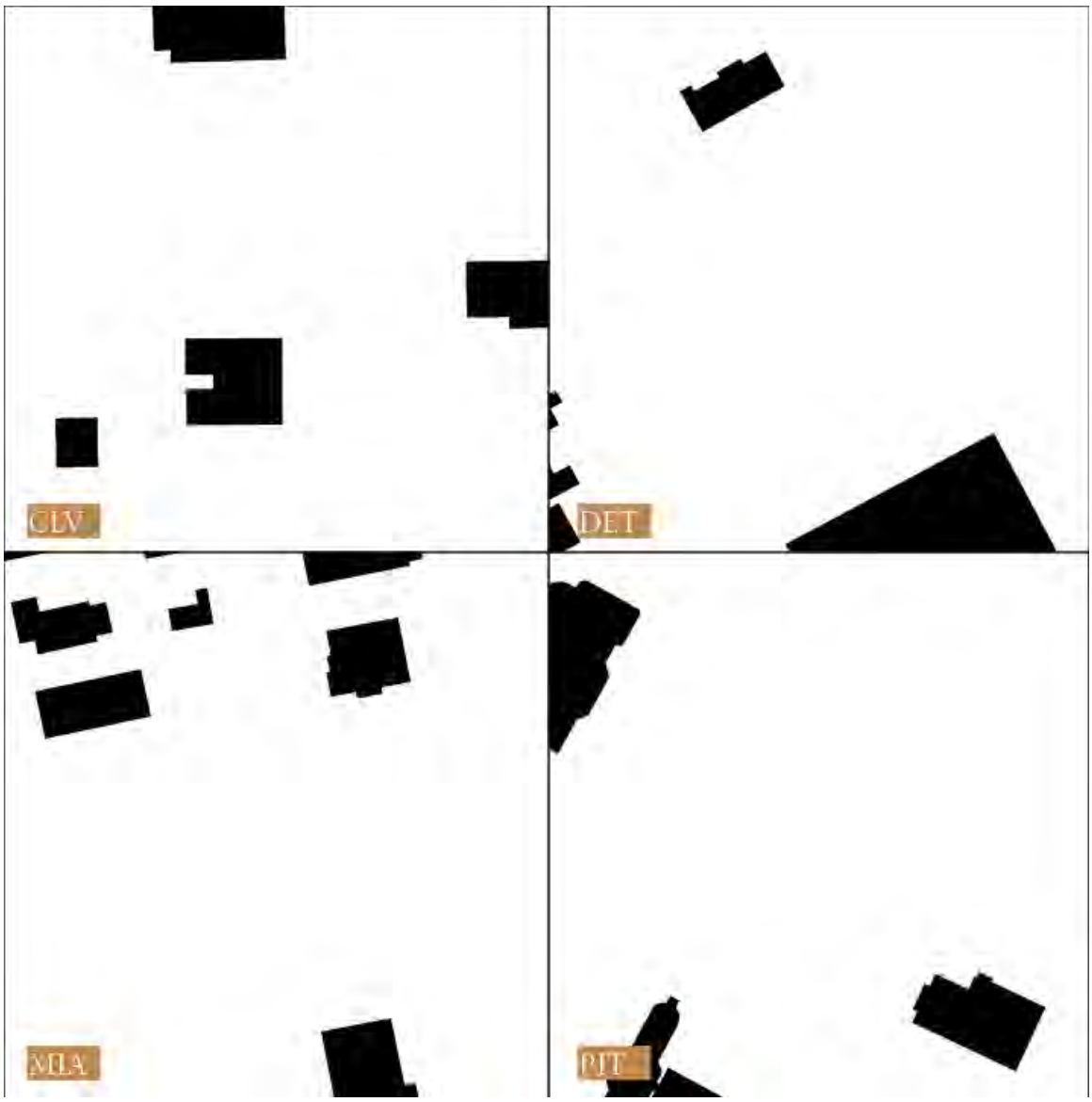


Figure L.16: Representative forms of Urban Type 9

medium-to-large buildings. This suggests that different urban forms could be classified into a same type, based on comparable area occupancy despite having different compositions of urban types.

L.2.3 Feature Analysis

Unlike the extracted feature approach, each type's feature is only one-dimensional with length of three. Thereby, it is possible to visualize the features in a three-dimensional

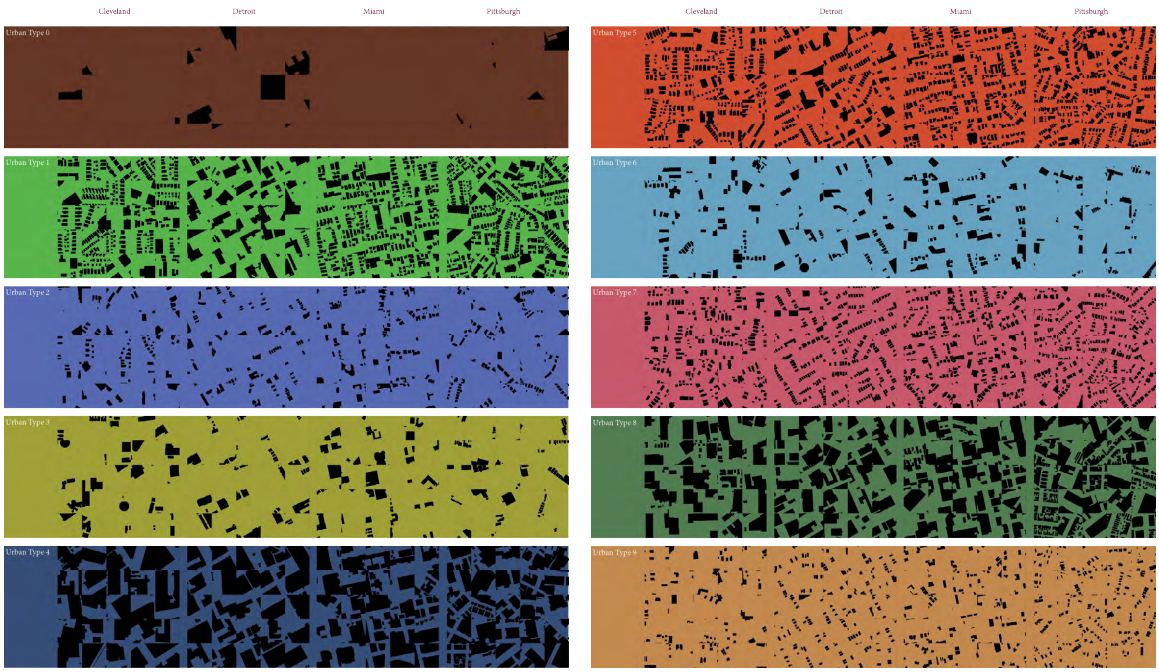


Figure L.17: Random sampling data of Urban Types across the four cities. See Appendix M for more detailed figures.

space using scatter plots without resorting to images. Figure L.18 represents all urban forms in the three-dimensional data space with axes corresponding to PROX, BHAD, and CHAD. Each type is displayed with a distinct color, and the figure also displays the decision boundaries of K-Means for each type. However, clustering continuous data like these form features is not straightforward. Despite the apparent clarity of the decision boundaries in Figure L.18, it is important to interpret the relationships between features bearing in mind that the boundaries are inherently variable based on the algorithm and parameters used. The black-edged points within the decision boundaries represent the means of each type.

Examining the distribution of features, it becomes evident that Type 0 is closest to (0, 0, 0) and the majority of Type 0 data is concentrated around its mean. Type 9 stands as the type closest to Type 0, indicating urban forms with significant vacant spaces around buildings and relatively less complex morphologies than other types. This Type 9 acts as the central node from which two branches emanate: Branch A encompassing Types 2, 6, and 3, and Branch B consisting of Types 7, 5, 1, 4, and 8. This branching becomes clearer

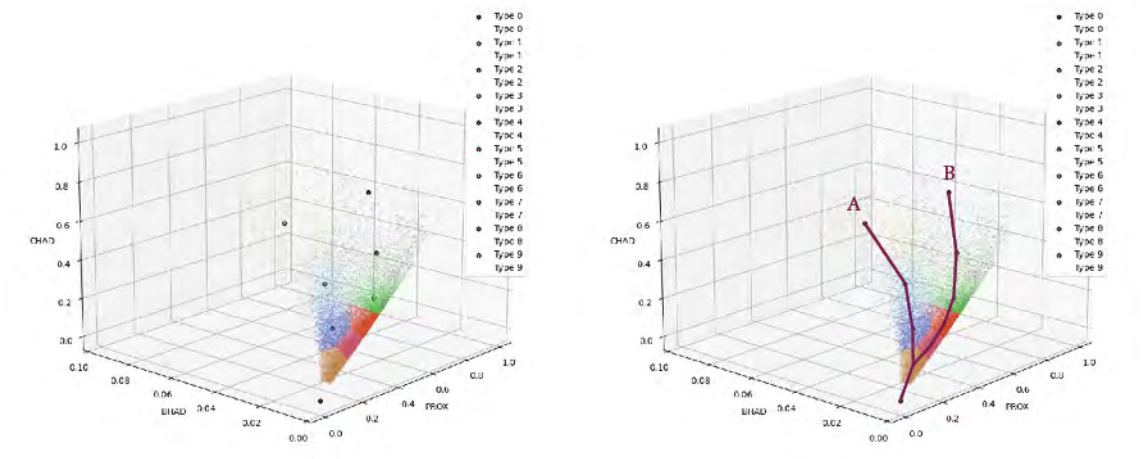


Figure L.18: Distribution of urban form data points in the three-dimensional data space with axes corresponding to PROX, BHAD, and CHAD

when connecting the means of each type.

Branch A has lower PROX values, while Branch B has higher PROX values. In other words, types within Branch A are relatively positioned farther from the center of grid cells, exhibiting buildings that are distanced from the center. On the contrary, types within Branch B are closer to the center of grid cells, suggesting buildings situated more centrally. Referring to the representative forms and sampling, it can be deduced that Branch A includes types with lower building occupancy within grid cells, while Branch B encompasses types with higher building occupancy.

To analyze the relationships between these features, another metric called similarity is considered. Like the extracted feature approach, this similarity is calculated using the squared Euclidean distance between the mean values of the features. Figure L.19 presents a table of these 1 - squared Euclidean distance values, where values closer to 1 indicate higher similarity; this table illustrates the relative distances from each type's mean point to other points, providing insights into the proximity of these points in feature space.

Type 0 exhibited the highest similarity with Type 9. This similarity aligns with the observations from feature visualization, where Type 0 was nearest to Type 9 in the data space. The following highest similar types to Type 0 are Types 7, 2, and 5. For Type

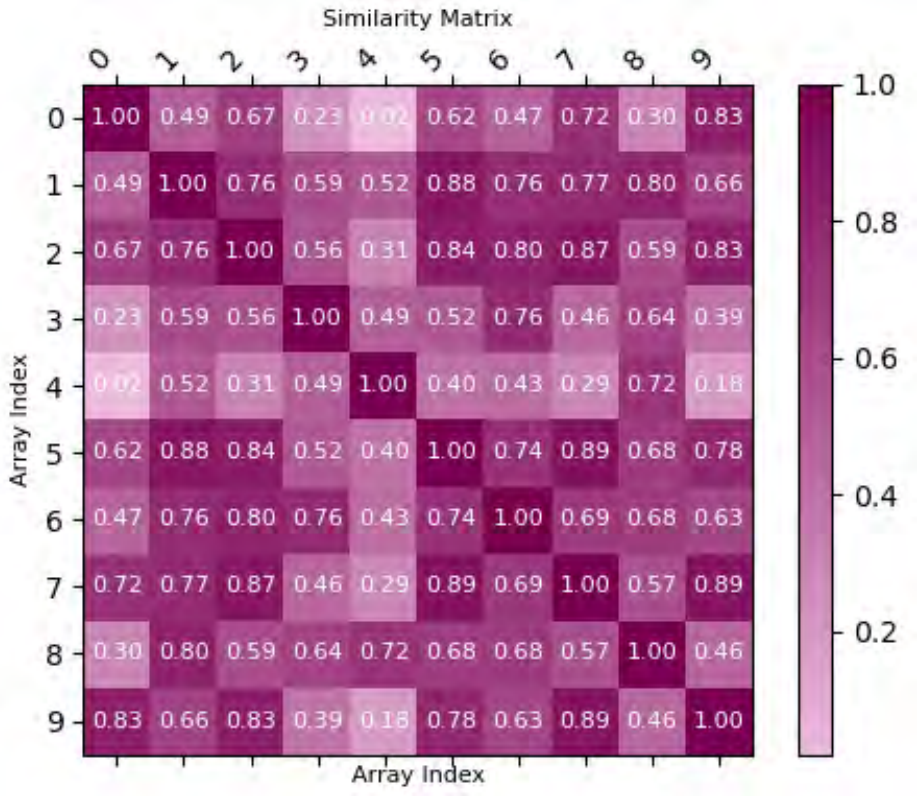
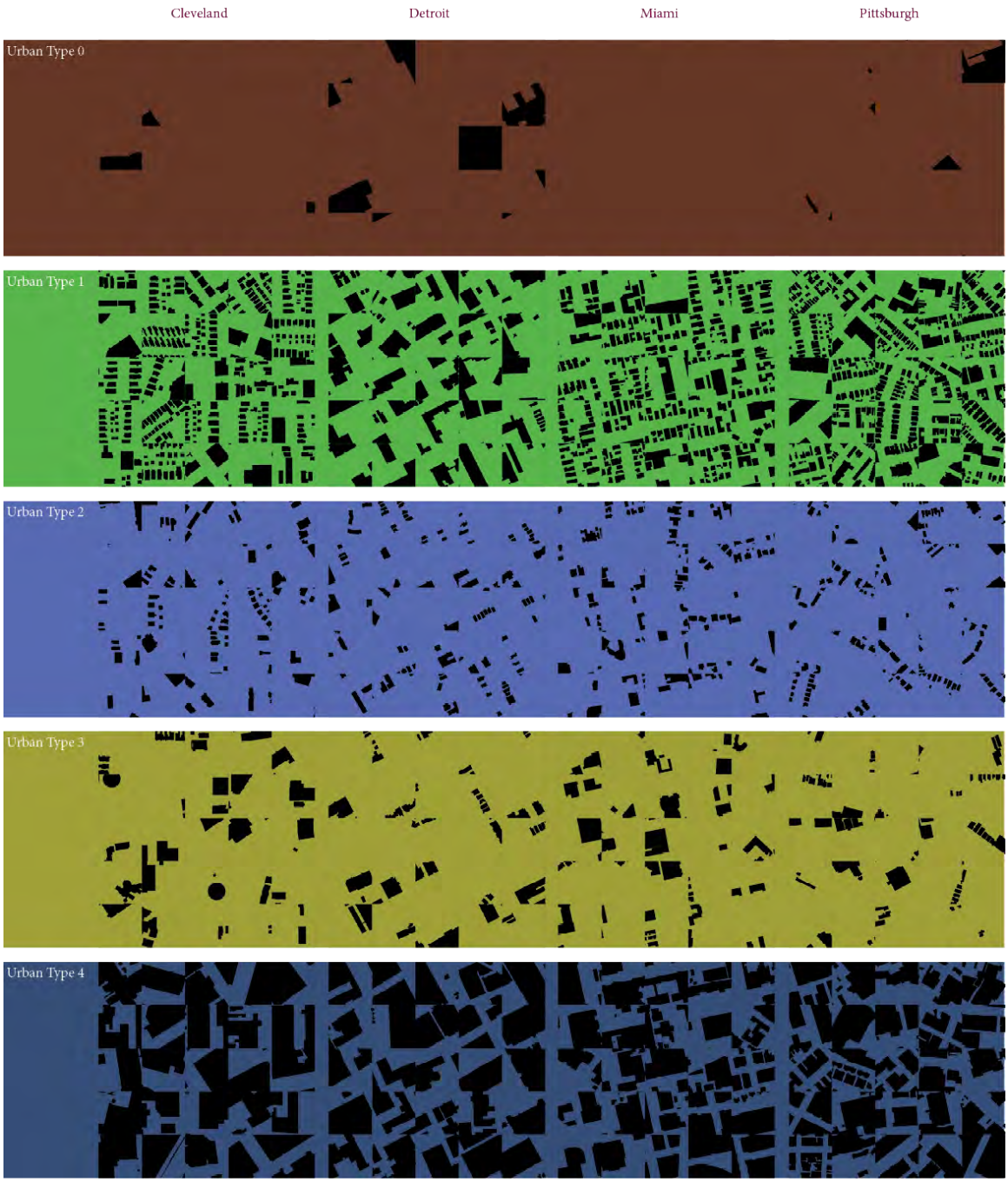


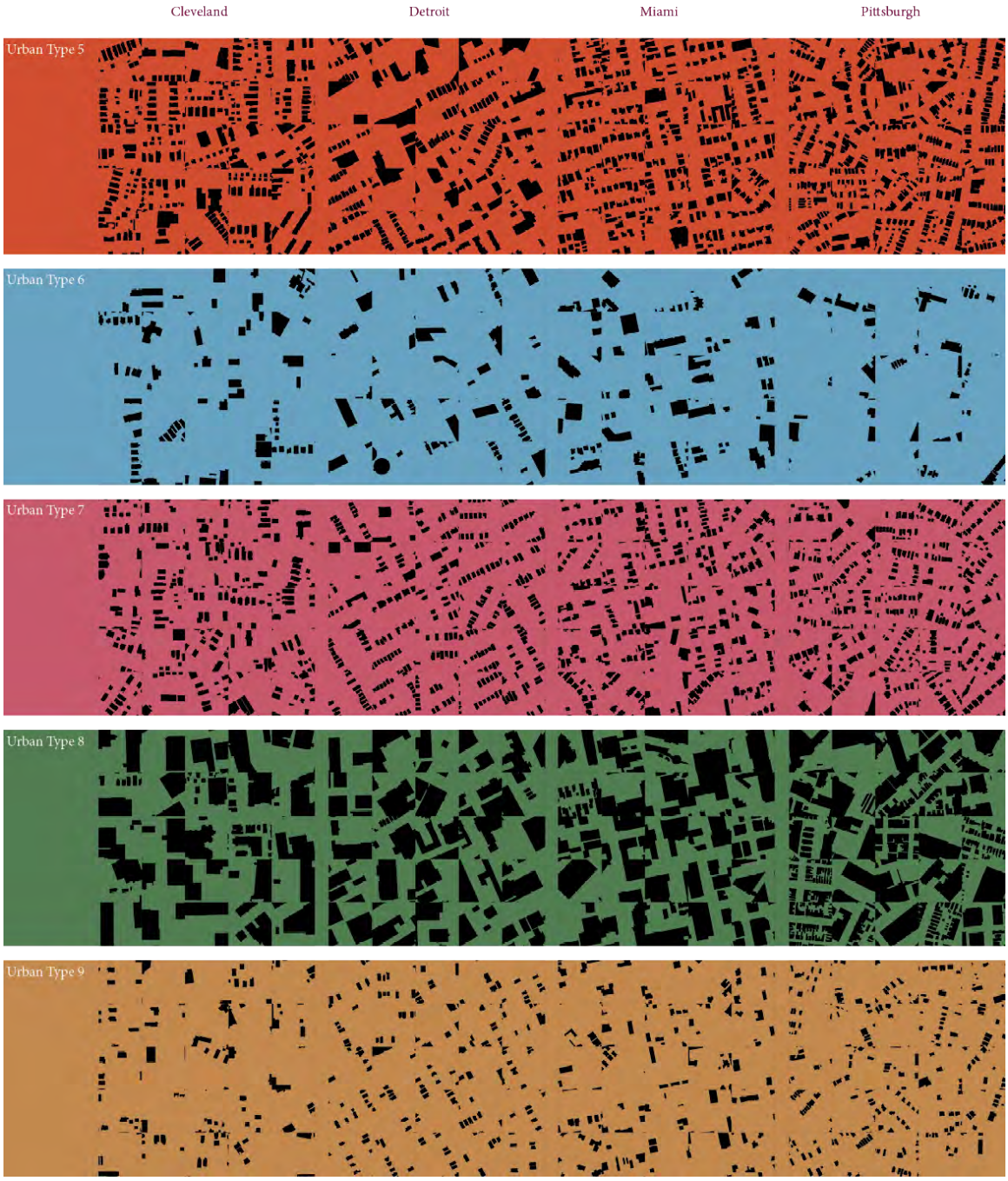
Figure L.19: Similarity matrix of urban form types

1, Types 5 and 8 showed the highest similarity, followed by Types 7 and 2, which are also quite proximate to Type 5. The high similarity between Type 5 and 8 is numerically supported by the observation in their representative forms and sampling included small-scale buildings forming linear arrangements alongside medium and large buildings. Type 2 was most similar to Type 7, Type 3 to Type 6, and Type 4 to Type 8.

APPENDIX M

RANDOM SAMPLING DATA OF URBAN TYPES




Cleveland
Detroit
Miami
Pittsburgh
Urban Type 5
Urban Type 6
Urban Type 7
Urban Type 8
Urban Type 9

APPENDIX N

PHOTOGRAPHS OF CONFLICT POINTS AMONG URBAN TYPE

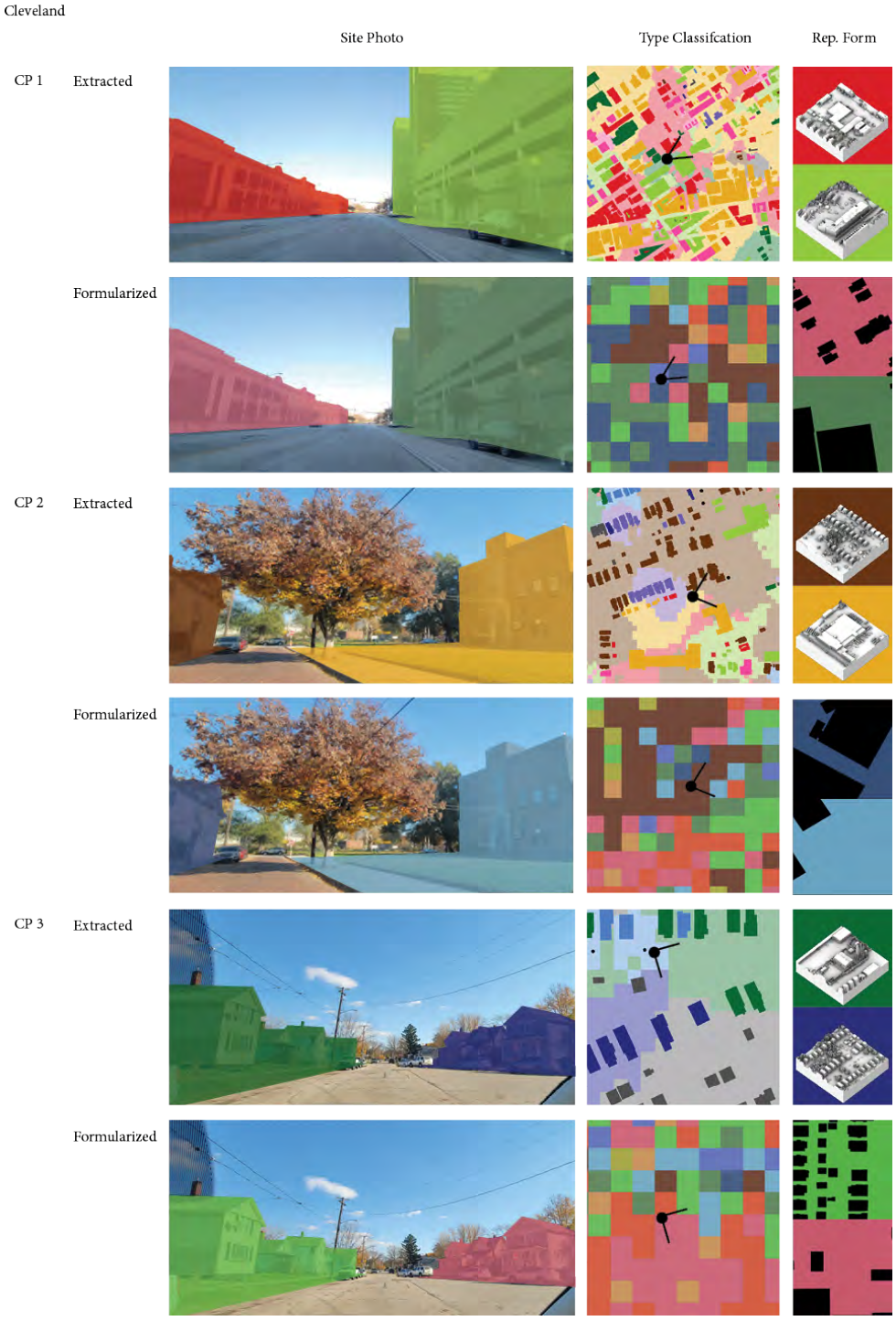


Figure N.1: Overlaying type information from the proposed and conventional methods onto site photos of conflict points: Cleveland

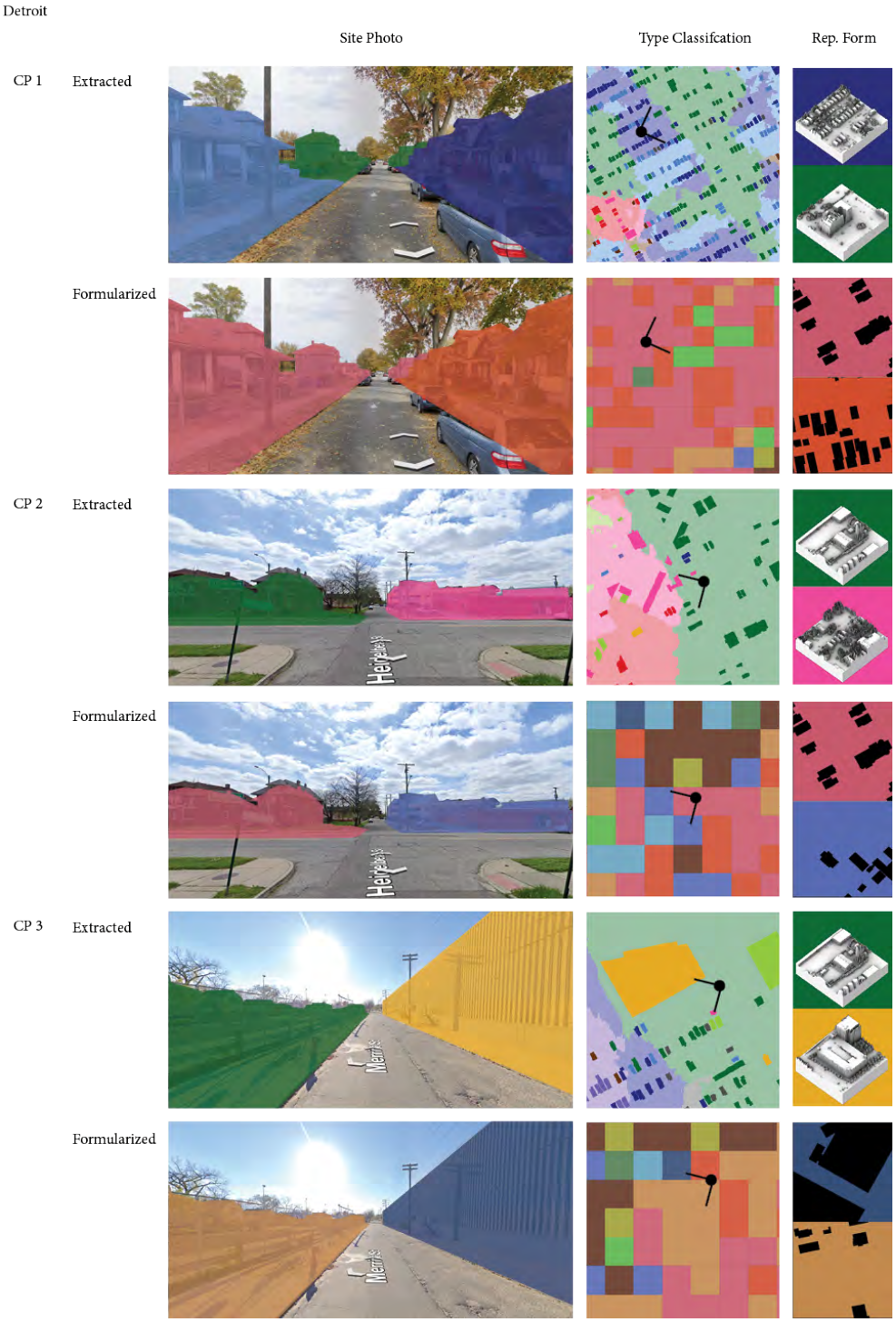


Figure N.2: Overlaying type information from the proposed and conventional methods onto site photos of conflict points: Detroit

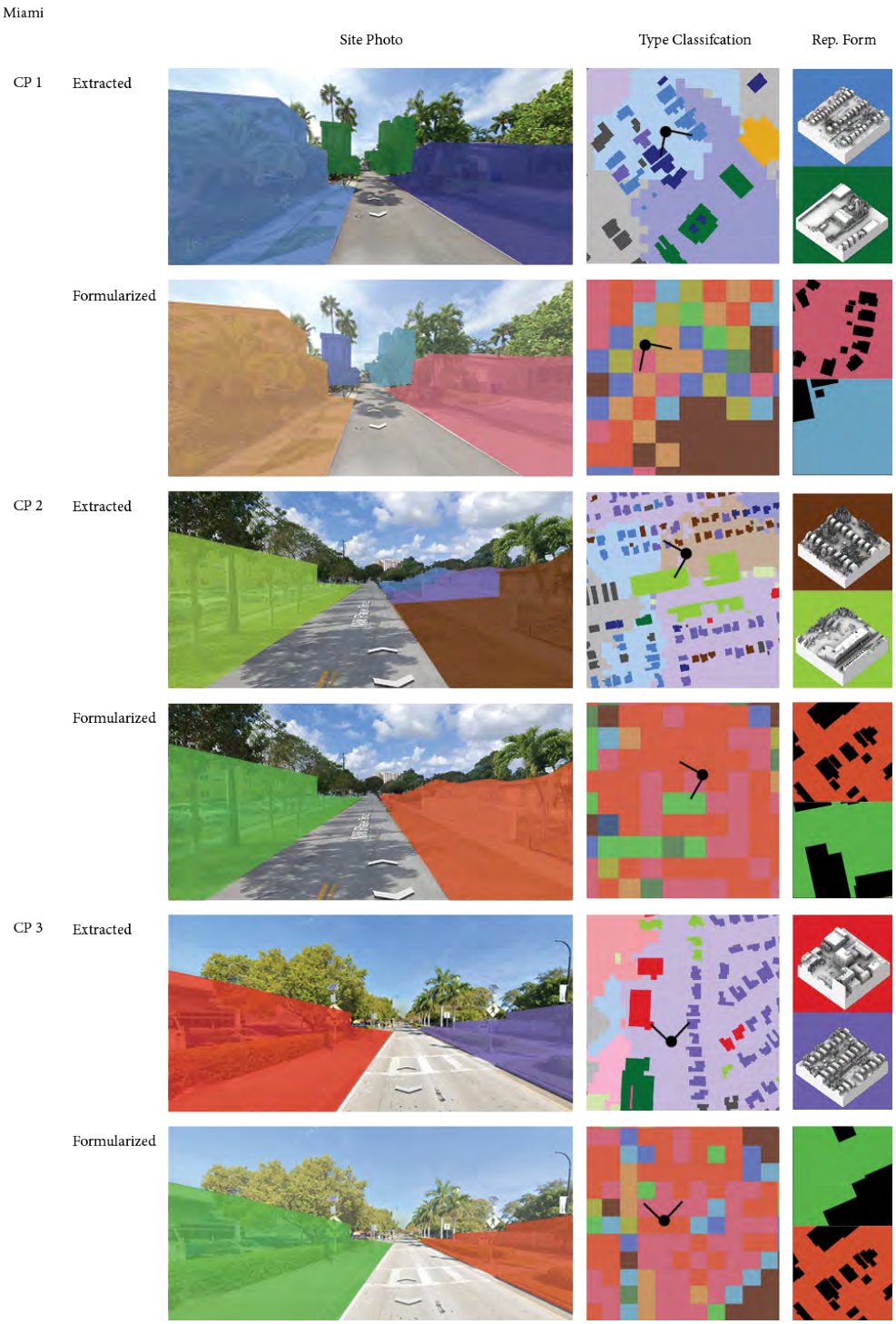


Figure N.3: Overlaying type information from the proposed and conventional methods onto site photos of conflict points: Miami

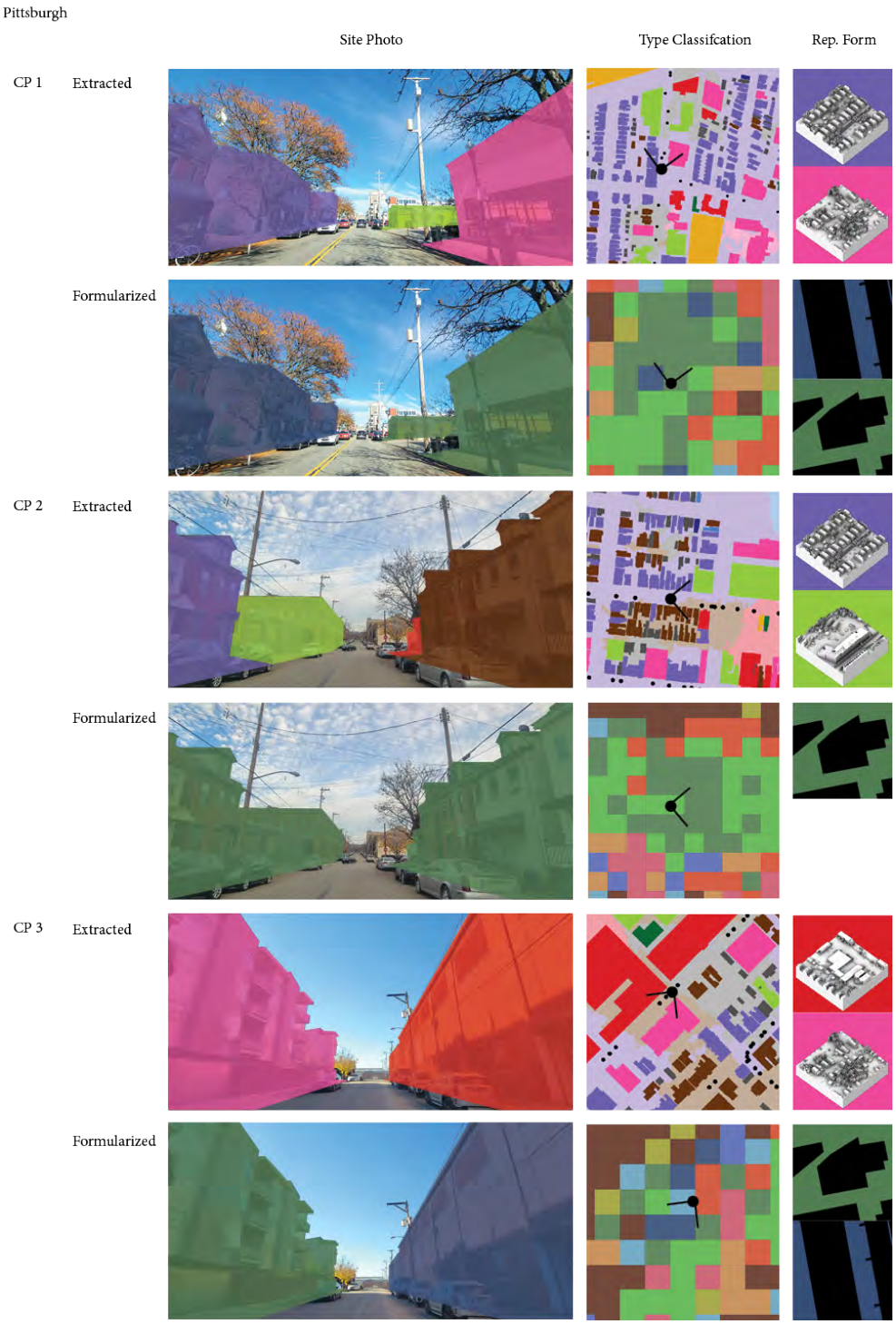


Figure N.4: Overlaying type information from the proposed and conventional methods onto site photos of conflict points: Pittsburgh

APPENDIX O

TRANSCRIPTS OF INTERVIEW

This transcript captures an interview with Francisco Alaniz Uribe, a professional urban planner and urban planning scholar focusing on the study of urban density and regeneration. Francisco, an Associate Professor at the University of Calgary, had previously been provided with a document and a roughly 10-minute video brief to gain a comprehensive understanding of the research in question.

Jinmo: Good afternoon, Professor Franciso. Thank you for joining me today. I've already shared the document and short clips for explaining this research. However, before we go on, do you have any questions?

Francisco: If I understand correctly, I totally get the premise. You're right. It's something that I'm also very much interested in, especially the application of new technology to planning and urban design, which is still very new. We need to explore more to then really develop processes, and that's already of great value for this project.

Jinmo: Thank you, Professor Francisco, for your insightful comments. It's encouraging to hear more about your understanding of this research.

Francisco: What I understand is that you are, rightly so, looking at the complexity of the city and understanding that at a large scale is very hard to analyze and address. You have to break it down into units and then re-aggregate those units again. Based on data scientific aspects of data, you developed your own way to break it down into units and aggregate them. With this way, you used LIDAR as the starting point of data to then break down those units. Then, you used the deep learning to analyze each one of those, identifying characteristics, right? So that they can be regarded as different built or urban form types.

Based on these types, you can make some deductions or conclusions or findings of what's happening in different cities. Okay, so is that correct?

Jinmo: Yes, this is correct in general and larger understanding of this research project.

Francisco: There's been things I did make some notes of what I think is definitely of value. The one thing I didn't fully understand, and I think it's always tricky, is how you break into smaller units. I think there's two approaches there, or at least something to keep an eye on. The first criteria of how to divide that has to do perhaps with the capacity of the machine learning to chewable pieces, let's say. I think that's super important and very valid.

Jinmo: I think you pointed out very important moment in the experiment in this research. Could you elaborate it more?

Francisco: Perhaps there is a reflection there in terms of what does that particular unit mean in terms of urban form and analysis. What if we were to do it traditionally? That unit can give you what it cannot. What I saw in the samples shown in the video, it's a group of buildings usually, and it does also include a very good size, I would say, also for urban form analysis, not at the size of a neighborhood so you wouldn't just put one piece.

Jinmo: Exactly. The key idea of this research is the change the constitutive unit of urban form analysis. In this sense, the range of each data point is important, related to the purpose or aim of the research with questions of what we analyze and examine.

Francisco: Right. You can talk about more relationships or buildings with the public realm and perhaps with their parcel. Now, I think that differentiation of the range or the size of the unit is important. What is the criteria for what the technology can have in terms of size of the subdivision, let's say, or the little piece that you're breaking down? And, you know, Coul you clarify what does that mean?

Jinmo: Yes, that is very important, I agree, that one like I just to set some number based on some statistical analysis and then use the mean data. For example, like a hundred feet, everybody has like a maximum size of a building is like a hundred and then smaller is like 20 feet, so let's use a hundred feet for the range of the possible unit. But I agree that one,

depending on the range, we might have a different identification of urban form types, or we might find different. Like, as you say, it might be neighborhood scale, or it might be just building scale or something like that. So, I think, I appreciate your comment to remind me the process how I set up the range of a urban form unit for each data point; due to technical reasons, I needed to make a decision based on some statistics. Even with that, there might be buildings that are too large to fit within the unit.

Francisco: This might be anomalies, and it might be more industrial-size buildings or shopping malls or stadiums, which are not the majority of the built form in the city to consider in general, but this is important in some cities like your case studies.

Jinmo: Yes, correct. Existence of the large industrial buildings is very crucial components for the unique urban structures and fabrics in Rust Belt cities.

Francisco: The other piece I was thinking about is that in terms of morphology, the kind of the basic layers of morphology that help us quickly understand how a place functions in terms of build form is let's say footprint, the three dimensions, types of buildings, lands of division, so the parcels, and land use. So, LIDAR can give you the buildings, but not so much the lands of division or the land use.

Jinmo: You're right. That wouldn't give me that.

Francisco: But LIDAR in itself has the ability to have some metadata attached to it. The metadata of LIDAR could have potential to be used for solving problems; but not so much on the problems of the parcels, which is very essential and crucial in planning. However, So, I think when you were asking me what you see of some of the limitations of the model will be that.

Jinmo: I see but could you explain in detail?

Francisco: The relationship of parcels with the built form. It can be accommodated by bringing that layer in from, you know, a typical outlook file test for. Land of division is core information actually to identify the characteristics of cities and urban spaces. Let's say three different environments. One being the public realm, which is whatever is not an

individual parcel. The other one is the private parcels, and then also the parcels that are city owned. It gets a bit more complicated because if they can include parks, schools, libraries, or that particular type of parcel can be more complex. To be able to make an analysis on these, you may need to create more detail in your dataset.

Jinmo: I see, that is very important point.

Francisco: In this research, you don't include the parcels, but you can see the potential of the parcel information in your data, illustrating where the building is set, how it relates to the public realm, the presence with the street, or the spaces that it is created, etc. Parcel information can also indicate the role like urban program such as transit, infrastructure, facilities, etc.

Jinmo: I agree that, only adding the layer of parcel data can hugely increase the complexity of the dataset.

Francisco: Right. the important thing is, if you add parcel information indicating whether it's for private use, despite of applying same research method, the results would be very different and interesting.

Jinmo: I think this idea of associating with other form data is very interesting. It might opens a direction to improve the quality of urban form classification through data curation, not just technical improvements. For example, in the results of the classification, most of a house building surrounded by empty lots in Detroit are identified as a same type with urban spaces of high-rise buildings and their surroundings in Miami. Actually, they are different, but when I look at them in data representation, they seem very similar visually.

Francisco: Does the data have height information?

Jinmo: Yes it is. However, it is not actual height; it is more like relative height in a data point since I normalize the height. This is one of the critical issue of constructing and curating architectural and urban form data, which is closely related to issue of scale. It rises questions like "how will we pre-process different size and height of buildings" and, at the same time, it can also shows the potential to bring unique characteristics of architectural

and urban form data. In this sense, associating with other form data to LIDAR data can enhance and compensate the height information.

Francisco: Right, and the association would provide more practicality of this idea. For instance, this tool can help the process of regenerating Detroit, or any other city. What's useful for cities is to have strategies for redevelopment or for areas needing more control. The information definitely involves density, both vertical and horizontal. If the model can't tell if a spot is a skyscraper or has 20 stories, then there's a lot of missing information for privacy. Different strategies are needed for different building types. By analyzing building footprints and heights, you can differentiate between types, like blocks with garages and single-family homes versus multifamily buildings. This differentiation is crucial for developing policies or strategies tailored to each building type, which aids in urban planning and redevelopment efforts. In other words, if your method can provide strong accuracy on this differentiation, it would be developed into a practical tool for city regeneration.

Jinmo: This is a sharp point-out of technical limitations through planner's view and interpretation.

Francisco: Further, incorporating social demographics, income levels, or even associating data with other morphological, socio-economic, or educational data could offer insights into future research directions. Understanding the intricacies of these relationships, though complex, has the potential to significantly impact urban planning and policy-making.

Jinmo: I have been thinking about this too.

Francisco: The associations of these non-morphological layers are indeed helpful not just for understanding what's happening but even more so for making informed decisions. For example, understanding the relationship between school enrollments, social demographics, and built form can provide insights into how urban density influences family dynamics and, consequently, school populations. This analysis can then inform zoning changes or housing policies aimed at attracting young families, thus influencing the urban landscape's future development.

Jinmo: I agree. When this method can be developed to be associated with other non-morphological data, it could reveal unseen urban phenomena in real situations.

Francisco: Yes, applying this technology to analyze entire cities, like Calgary, could reveal insights into density, housing problems, or land values, which are critical for making decisions at a municipal level. This tool's potential to combine layers of information—land value, build form, accessibility, and transit—could be instrumental for city planners and real estate developers alike. Identifying areas for redevelopment or investment could significantly impact how cities evolve, addressing infrastructure capacities and prioritizing investments based on a comprehensive analysis of urban forms and their socio-economic implications.

Jinmo: I appreciate your insight about the future directions of this research.

Francisco: There were other applications for users in methods that I was thinking about. For instance, we could look at nutrition, urban form, walkability, and socio-economic status together to determine how walkable places are to groceries, which is so important. Because if you can walk to get your groceries, you will do it more often than drive. But the problem we have in North America, or specifically in Canada, is our very low density and grocery stores are very big box, meaning the population needed to support a big box grocery store tends to be around 10 to 12,000 people. We have communities that have like 2 to 3,000, so these people have no grocery store nearby them. They have to go to the nearest market or big chain store, which could be far away. And you know, some places are subsidizing that grocery store because they know of the value for the community, but we can't do that everywhere, especially where the urban form is completely different. So thinking about how urban form and access to normal, healthy food is related, that could be another really interesting application for our project. I think it has a lot of potential.

Jinmo: Grocery is another interesting urban phenomenon that this technology can be applied to.

Francisco: I can see also some points that we can collaborate. One of research agenda is to

help identify areas of very low density, in Calgary, and to understand the different factors that prevent or motivate densification. These involve very large and complex databases, and how to pull all of them together with something like your tool in terms of urban and built form, and identify the best locations. Then, with the locations identified, there's a layer of implementation, which involves what strategies and types of investment are needed, what kind of policy changes are necessary, and what would be the final results for consumers. For example, how does an apartment unit in these identified locations compare with something in the green fields of suburbs? And if the trade-offs are not close enough, that density doesn't have an advantage unless we drastically change everything around, which we should, but often don't. So, with that limitation of competing with green field development, how do we then supply the cities?

Jinmo: That is a very interesting research topic and well aligned with my next phase of this research; find the real-world problems and then see if the technology can be updated, modified, and applied to solve these problems. Thank you, Professor Francisco, for sharing your expertise with us today. Your fresh insight on this technology in urban planning and the thoughtful considerations for their application offer valuable guidance for professionals and researchers in the field. Thank you for your time again.