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Review

Synergies Between Land Use/Land Cover Mapping and Urban Morphology: A Review of Advances and Methodologies

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Abstract: This study aims to bridge the fields of urban morphology and land use/land cover (LULC) mapping through a systematic analysis of their integration in recent research. The research employs systematic literature review (SLR) methodology combining quantitative and qualitative methods through four methodological steps: data search, data selection, data analysis, and data clustering. The analysis performed three distinct clustering patterns: (1) methods and tools, (2) data types, and (3) urban morphology aspects. The results reveal five distinct methodological approaches—Data-Driven Typological Decoding Approach, Quantitative Structural Metrics Approach, Predictive Spatiotemporal Transition Approach, Temporal Change Detection and Performance Approach, and Spatial Configuration and Density Analysis Approach—each contributing unique insights to urban form analysis. The findings demonstrate the multidimensional nature of urban form analysis, incorporating both social and temporal dimensions, while highlighting the essential role of change detection in understanding urban pattern evolution. This systematic review establishes a comprehensive framework for understanding the relationship between urban morphology and LULC mapping, providing valuable insights for future research integration.

Keywords: urban morphology; LULC mapping; spatial analysis; systematic literature review; clustering analysis

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1. Introduction

1.1. Urban Morphology–LULC Nexus

In the increasingly complex context of the development and transformation of urban settings, there is a necessity for the allied action of different academic and professional fields, and the need for the implementation of multidisciplinary approaches in the study and planning of cities [1]. In such a challenging context, the field of urban morphology tends to adapt to the dynamics of its observatory framework, which on a general level constitutes the study of the physical form of cities [2]. Urban morphology as a field of research was consolidated in the last quarter of the 20th century through the paradigmatic implementation of several schools of thought including (1) historical and evolutionary processes in shaping urban form [3], (2) "typological process" for patterns decoding [4,5], (3) prospectus of social dimensions of urban forms including relationship between urban forms and social, economic, and political dynamics [6], and (4) perceptual and humanistic dimensions of urban form [7]. Also, studies of urban morphology took on comprehensive geographic coverage with the development and enhancement of regional networks that brought and built locally specific and contextually resonant approaches [8,9].

In the contemporary moment of transferring technological advances and methodologies, urban morphology is in the era of a spatial analytical paradigm that tends to "integrate innovative approaches to describe and explain new dynamics and patterns

of urban form—often including revolutionary technologies for data collection, analysis, modeling and simulation" [10] (p. xi). This demanded a comprehensive exploration of four key dimensions (as listed in report of the 30th jubilee International Seminar on Urban Form) [11]: (1) development and application of value-based approaches that enhance normative framework shaping urban development and transformation, (2) cultural influences on urban form through multiscale lens (from the level of the neighborhood to the region), (3) critical interpretation of historical roots that have influenced theory and practice of urban morphology, and (4) advances in the methodological strategies with the special reference on integration of qualitative and quantitative approaches in the study of urban form.

The mentioned key dimensions of the study of urban morphology indicate the necessity of strengthening studies of morphogenesis and temporal dimension of urban form, as well as an even greater affirmation of a multiscale approach [12] that tends to integrate knowledge on more spatial levels from the scale of a spatial unit of building or plot towards a regional or geographical perspective of observation. This further highlights the necessity for methodological advancements in the field of urban morphology by strengthening the current spatial analytical paradigm with insights from other domains with shared focus on observation and analysis of urban settings. The nexus between urban morphology and land use and land cover (LULC) studies offers a framework for building complementary methodologies that could enable a holistic perspective of studying urban form. LULC studies inherently contain an indicator of change, that is, a temporal prism of the study of space, especially from the perspective of observation and monitoring of urban expansion and transformation [13], as well as change detection [14] and land classification [15].

1.2. Challenges and Opportunities in Bridging the Two Fields

While urban morphology basically deals with the study of urban form [16], LULC studies examine the interaction between human socioeconomic activities and the natural environment [17], offering the possibility of combining approaches during the identification, analysis, and classification of patterns of urban growth and transformation. Ongoing research indicates that the basic potential for the synergy of urban morphology and LULC studies is primarily recognized at the methodological level. This synergy is underscored by the importance of four key research groups, which address both challenges and opportunities essential for advancing this field: (1) integration of 2D and 3D features of space, (2) potential of a multiscale oriented analysis, (3) challenge of quantifying urban morphological patterns, and (4) observation of a multidimensional nature of urban form.

The first research group targets the integration of 2D and 3D features of space, demonstrating that the introduction of 3D metric analysis—through the parallel observation of 2D features (e.g., building footprint) and 3D features (e.g., height and volume) of urban form—complements traditional LULC measures, which further enables a more comprehensive assessment of land use intensity [18]. Additionally, approaches based on semantic segmentation align overarching objectives of LULC mapping and urban morphology analysis, facilitating the creation of morphogenetic maps that capture both horizontal and vertical dimensions of urban form over time [19].

The second research group emphasizes the potential of a multiscale-oriented analysis that is developed through combining research techniques such as satellite imagery analysis with on-the-ground surveys [20]. This approach holds a connecting potential when it comes to relating urban phenomena at different spatial levels, from individual plots to block groups and entire urban regions [21], as well as linking pixel-level information with land-use classification [22]. In this analytical domain, operational possibilities are recognized in Geographic Information System (GIS) research strategies that bridge top-down and bottom-up approaches [23] and have integrative potential through the integration of GIS techniques with quantitative analysis [24], fieldwork surveys [25–27], remote sensing data [28], point pattern analysis [29], image classification techniques [23,30], predictive modeling [20], and space syntax [31].

The third research group highlights the challenge of quantifying urban morphological patterns and combining qualitative and quantitative approaches [25], showcasing research opportunities of automated classifications supported by machine learning [29] and deep learning techniques, including moving window approaches [32], to enhance classification and mapping protocols. This group also addresses the limitations of broad LULC categories, which limit insights into specific urban typologies and detailed morphological characteristics. The potential to overcome this challenge was demonstrated through (1) the application of advanced machine learning techniques which could improve classification accuracy [30], (2) engagement of more accurate remote sensing techniques [20], (3) use of high- resolution data and advanced analytical techniques [33], and (4) application of texture analysis [34].

The fourth research group emphasizes the multidimensional nature of urban form through a dual perspective—social and temporal dimension of urban form. The social dimension of urban form is recognized in the context of the development of new methods to analyze the relationships between physical spaces and human activities [31], while the temporal dimension is addressed in studies focusing on year-by-year changes [26], predictions of future urban form [35], and spatiotemporal analysis for decoding of urban expansion patterns and transformation patterns [30].

1.3. Paper Outline

This paper aims to address the initially recognized challenges and opportunities in bridging the fields of urban morphology and LULC mapping, proposing a systematic review through the framework of triple research prism. This framework is designed to provide a multidimensional perspective by examining the integration of these fields from three interrelated angles: (1) the methodological basis, which focuses on identifying tools, techniques, and frameworks that enable the synthesis of urban morphology and LULC studies; (2) the main data types, emphasizing the collection, processing, and analysis methods applied to the literature sample to highlight trends and gaps in data utilization; and (3) the key aspects of urban morphology, encompassing fundamental concepts and notions that shape the theoretical and practical underpinnings of urban form analysis. Together, these three components form a comprehensive lens to systematically investigate the intersection of urban morphology and LULC mapping.

In line with this approach, three research questions (RQs) are defined:

RQ1: What types of analysis are conducted according to leading methods and tools?

RQ2: Which groups of data are collected and/or processed during analytical procedures?

RQ3: Which aspects of urban morphology stand out as leading and in what way are they related to each other?

In accordance with the research questions, the foundational and integrative framework of this study is established, based on the premise that, understanding the relationship and cross-interpretation of the leading (1) methods and tools, (2) types of data, and (3) aspects of urban morphology, specific approaches and thematic trajectories represented in relevant literature documents could be derived.

This manuscript is structured in four sections. The Introduction Section, which provided the general background and motivation for the study, is followed by a comprehensive presentation of the methodological procedure. Methods and Materials (Section 2) gives an insight into the general research flow followed by a more precise elaboration of each research step: data search (Section 2.1), data selection (Section 2.2), data analysis and keywords dataset creation (Section 2.3), and data clustering and co-occurrence (Section 2.4). The third section of the manuscript provides an insight into the results followed by a discussion (Section 3) with a sub-structure that presents three thematic clustering analyses—clustering analysis 1: methods and tools (Section 3.1), clustering analysis 2: data types (Section 3.2), and clustering analysis 3: urban morphology aspects (Section 3.3); as well as the presentation of synthesis clustering (Section 3.4). Finally, the manuscript provides concluding remarks (Section 4), wherein the key findings of this study are synthesized.

2. Materials and Methods

This study engages in a systematic literature review (SLR) through establishing a comprehensive insight into the intersection of LULC mapping and urban morphology. The systematic approach combines quantitative methods to analyze indicators of literature documents and qualitative methods for synthesizing trends or thematic trajectories (interpretation of thematic clusters) and their graphical representation. Overall SLR strategy was performed through 4 methodological phases: (1) data search—definition of initial sample of literature documents, (2) data selection—screening of initial sample, focusing the sample, (3) data analysis and keywords dataset creation—content analysis of focused sample followed by dataset definition, and (4) data clustering and co-occurrence—constructing and visualizing keywords networks (Figure 1).

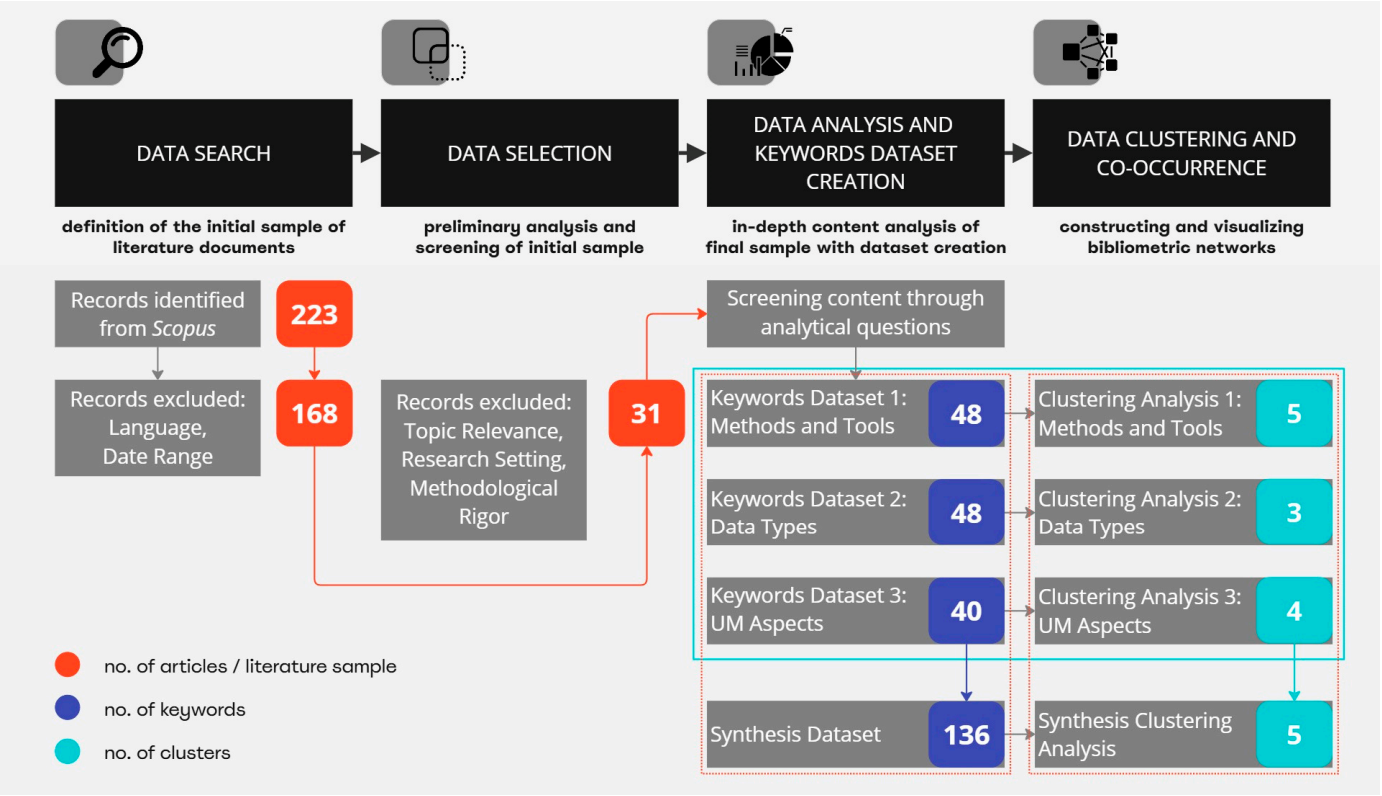

Figure 1. Research flow diagram. Source: Authors.

2.1. Data Search

The data search phase starts with the keyword research strategy, which is formulated in relation to research questions and the intention to establish a relationship between two academic fields—urban morphology and urban form studies on the one hand, and LULC studies on the other. In this sense, the search string is defined using Boolean operators to tackle both fields from a mapping or monitoring perspective: ("Land Use" OR "Land Cover") AND ("Mapping" OR "Monitoring") AND ("Urban Morphology " OR "Urban Form"). The defined string is entered in the search field within the Web of Science and Scopus databases within an article title, abstract, and keywords scope. After a control search and an insight into the search sample, the Scopus database was selected as a reference for the target sample since it included a larger number of literature documents for the defined string, as well as the fact that it was recognized that a sample of documents from the Web of Science database is contained in the Scopus database. In this order, the initial sample number of literature documents based on the search is 223 (processed on 20 October 2024), while two-fold excluded criteria were then applied as follows: (1) year range—by defining the time frame of publication in the last 10 years

(2014–today) which resulted in 174 literature documents, and (2) language limitation—the choice of manuscripts in English resulted in 168 literature documents. A sample of 168 literature documents was exported in CSV (comma-separated values) format as input for the next methodological phase. The exported dataset included a spectrum of bibliographic metadata such as authors information, manuscript titles, source titles, year of publication, number of citations, abstract, author and indexed keywords, document type, and digital object identifiers (DOIs).

2.2. Data Selection

The data selection phase was carried out with the aim of narrowing down the initial sample and is based on its screening by looking at the title of the literature document, abstract and, if necessary, the full paper. Bearing in mind the research questions and objectives of this study, three basic criteria were applied during the selection: (1) relevance to the topic—documents that clearly address aspects of urban morphology and urban form analysis and overlap it with the domain of LULC mapping or monitoring, (2) methodological clarity—studies with clearly defined research questions, research methods, and conclusions, and (3) site specific studies—case studies or observatory studies that include a specific geographical location where the methodological procedure is demonstrated. After the screening, the sample was focused on 31 literature documents which belong to the following subject areas: Social Sciences (20), Environmental Science (14), Earth and Planetary Sciences (10), Computer Science (4), Agricultural and Biological Sciences (3), Engineering (3), Arts and Humanities (2), Business, Management and Accounting (2), Energy (2), and Economics, Econometrics, and Finance (1). Also, the final sample consisted exclusively of manuscripts published in 25 journals (although these were not the initial excluding criteria during data search) (Table 1).

Table 1. List of referenced journals that include literature documents from the final sample.

Journal Name	First Published *	Subject Areas *	CiteScore 2023 *	No. of Selected Manuscripts
Computers, environment, and urban systems	1980	Social Sciences: Urban Studies, Geography, Planning, and Development Environmental Science: Ecological Modeling General Environmental Science	13.3	2
Remote Sensing of Environment	1969	Earth and Planetary Sciences: Geology Computers in Earth Sciences Agricultural and Biological Sciences: Soil Science	25.1	2
Landscape and Urban Planning	1986	Social Sciences: Urban Studies Environmental Science: Nature and Landscape Conservation, Management, Monitoring, Policy, and Law Ecology	15.2	2
Cities	1983	Social Sciences: Sociology and Political Science Urban Studies Development Business, Management, and Accounting: Tourism, Leisure, and Hospitality Management	11.2	2

Table 1. *Cont.*

Journal Name	First Published *	Subject Areas *	CiteScore 2023 *	No. of Selected Manuscripts
Remote Sensing Applications: Society and Environment	2015	Social Sciences: Geography, Planning, and Development Earth and Planetary Sciences: Computers in Earth Sciences	8.0	2
Land	2012	Environmental Science: Nature and Landscape Conservation Ecology Global and Planetary Change	4.9	2
Land use policy	1984	Social Sciences: Geography, Planning, and Development Agricultural and Biological Sciences: Forestry Environmental Science: Nature and Landscape Conservation Management, Monitoring, Policy, and Law	13.7	1
International Journal of Applied Earth Observation and Geoinformation	1998	Earth and Planetary Sciences: Earth-Surface Processes Computers in Earth Sciences Environmental Science: Management, Monitoring, Policy, and Law Global and Planetary Change	12.00	1
GIScience and Remote Sensing	2004	Earth and Planetary Sciences: General Earth and Planetary Sciences	11.2	1
International Journal of Geographical Information Science	1997	Social Sciences: Library and Information Sciences Geography, Planning, and Development Computer Science: Information Systems	11.0	1
Annals of GIS	2009	Earth and Planetary Sciences: General Earth and Planetary Sciences Computer Science: Computer Science Applications	8.3	1
ISPRS International Journal of Geo-Information	2012	Social Sciences: Geography, Planning, and Development Earth and Planetary Sciences: Earth and Planetary Sciences (miscellaneous) Computers in Earth Sciences	6.9	1
Sustainability (Switzerland)	2009	Social Sciences: Geography, Planning, and Development Computer Science: Computer Science (miscellaneous) Hardware and Architecture Computer Networks and Communications Environmental Science: Environmental Science (miscellaneous) Management, Monitoring, Policy, and Law Energy: Energy Engineering and Power Technology Renewable Energy, Sustainability, and the Environment	6.8	1

Table 1. *Cont.*

Journal Name	First Published *	Subject Areas *	CiteScore 2023 *	No. of Selected Manuscripts
International Journal of Digital Earth	2008	Earth and Planetary Sciences: General Earth and Planetary Sciences Computer Science: Computer Science Applications Software	6.5	1
Environment and Planning B: Urban Analytics and City Science	2017	Engineering: Architecture Social Sciences: Urban Studies Geography, Planning, and Development Environmental Science: Nature and Landscape Conservation Management, Monitoring, Policy, and Law	6.1	1
Urban Ecosystems	2001	Social Sciences: Urban Studies Environmental Science: Ecology	5.7	1
Buildings and Cities	2020	Engineering: Architecture Building and Construction Social Sciences: Urban Studies Geography, Planning, and Development Environmental Science: Environmental Science (miscellaneous) Management, Monitoring, Policy, and Law	5.4	1
Environmental Monitoring and Assessment	1981	Environmental Science: General Environmental Science Management, Monitoring, Policy, and Law Pollution	4.7	1
Urban Planning	2016	Social Sciences: Urban Studies	3.6	1
GeoScape	2019	Social Sciences: Urban Studies Geography, Planning, and Development Environmental Science: Nature and Landscape Conservation Ecology	2.7	1
Quaestiones Geographicae	1979	Earth and Planetary Sciences: General Earth and Planetary Sciences	2.0	1
Urban Morphology	1997	Arts and Humanities: Archeology (arts and humanities) Social Sciences: Archeology Urban Studies	1.5	1
International Journal of Oil, Gas and Coal Technology	2008	Energy: General Energy	1.3	1

Table 1. *Cont.*

Journal Name	First Published *	Subject Areas *	CiteScore 2023 *	No. of Selected Manuscripts
Agua y Territorio	2019	Arts and Humanities: History Arts and Humanities (miscellaneous) Economics, Econometrics, and Finance: Economics, Econometrics, and Finance (miscellaneous) Social Sciences: Geography, Planning, and Development	0.5	1
European Journal of Creative Practices in Cities and Landscapes	2018	Social Sciences: Cultural Studies Urban Studies Social Sciences (miscellaneous) Engineering: Architecture	0.4	1

* According to Scopus database.

2.3. Data Analysis and Keywords Dataset Creation

The third research phase starts with the content analysis of a focused sample of literature documents. In order to create a systematic and comparative framework between the documents being analyzed, a set of analytical questions was defined, distributed in 3 groups, which were answered for each of the 31 manuscripts: (1) Questions related to manuscript outline (with special reference on aspects of urban morphology): What is the main objective the literature document is addressing, What is the research problem, Which aspects of urban morphology and urban form analysis are addressed within the study; (2) Questions related to methodological framework: What are the main methods, tools, techniques, or software used in the research, What analyses were conducted in the study; and (3) Questions related to mapping procedure: What mapping methods were applied in the study, What mapping scales are used in the study, What is the subject of mapping.

The selection of the keywords is performed and defined following the results and review of the content analysis (answers to 3 groups of questions), as well as through insight into the indexed keywords as well as keywords defined by authors. Three thematic groups of datasets were created in relation to key aspects for further analysis as follows: (1) Dataset 1: methods and tools—includes keywords that refer to methodological procedures engaged in studies presented in literature documents (derived from questions related to methodological framework), (2) Dataset 2: data types—includes keywords related to key features and inputs for conducting the study and/or mapping (derived from questions related to mapping procedure), and (3) Dataset 3: urban morphology aspects (derived from questions related to manuscript outline)—includes leading concepts and notions from the domain of urban morphology and urban form studies that are addressed in the study.

The creation of datasets was performed through several steps starting with the preliminary formulation of keywords and their distribution into one of three thematic datasets. In the next step, preliminarily defined keywords were screened by removing duplicates (mainly keywords that appear in various formats including synonyms or abbreviations). Finally, the standardization of keywords in all three datasets was carried out by establishing a consistent terminology in order to avoid the clustering of the same notion under different keywords.

2.4. Data Clustering and Co-Occurrence

The data clustering and co-occurrence phase engages in the strategy of constructing and visualizing bibliometric networks. VOSviewer text-mining software tool (version 1.6.20) was used to carry out clustering analysis and creation of co-occurrence networks based on 3 created thematic keyword datasets. The datasets were arranged in 3 separate CSV formats by replacing the author and indexed keywords in the source dataset

exported from the Scopus database: (1) Dataset 1: methods and tools—48 keywords in total, (2) Dataset 2: data types—48 keywords in total, and (3) Dataset 3: urban morphology aspects—40 keywords in total.

Clustering analysis was performed in three iterations for all three datasets in the same way. First, the datasets were imported into the VOSviewer software tool, and the creation of a map (keyword network visualization) was started by defining the co-occurrence type of analysis, selecting all keywords as unit of analysis (in accordance with the updated source dataset), and defining the counting method as full counting. The minimum number of occurrences of keywords is set to 1, keeping in mind the creation of unique keyword datasets and the intention to include all identified keywords. The cluster analysis was performed using a random start value with 10 iterations, and the resolution of the cluster was set at a value 1. Moreover, the definition of clusters was carried out by setting the minimum cluster size (minimum number of keywords per cluster) and accordingly monitoring network visualization, in order to achieve a clear interpretation of clusters in accordance with the defined research questions: (1) minimum cluster size for the Dataset 1 is 7, (2) minimum cluster size for the Dataset 2 is 8, and (3) minimum cluster size for the Dataset 3 is 10. For the created clusters, an analysis was carried out based on established links in the visualized network (primarily through indicators of occurrences (OCCs) and total link strength (TLS)), as well as by monitoring central keywords (keywords are illustrated as nodes, and the co-occurrence relationships between them are illustrated as links).

In the final step, a unique dataset was created that includes all keywords from three created datasets (136 keywords in total). This dataset was created with a control and synthesis role in order to observe potential cross-relations between clusters (or specifically their central keywords) from different thematic domains through the visualization of a comprehensive network. Synthesis clustering analysis was carried out in 5 steps: (1) definition of synthesis clusters—minimum cluster size for the synthesis dataset is 20, (2) affiliation of keywords within synthesis clusters to original clusters from three clustering analyses, (3) quantitative analysis of keywords from the original clusters and their representation in the synthesis clusters, (4) mapping of the influence of the original clusters on the formation of the synthesis clusters (x—irrelevant; ○—neutral; +—relevant; ●—core impact), and (5) interpretation of the synthesis clusters in relation to the research objectives identified in the content analysis.

3. Results and Discussion

In this section of the manuscript, a parallel in-depth discussion and presentation of the results of three conducted clustering analyses will be provided: (1) clustering analysis 1: methods and tools, (2) clustering analysis 2: data types, and (3) clustering analysis 3: urban morphology aspects. While the first clustering analysis identified groups of analyses in relation to the applied methods and tools, the second identified the types of data that are collected, processed, and/or mapped during the analysis process, while the third identified urban morphology aspects (concepts and notions) addressed within the final sample of literature documents. The discussion has two-fold orientation: (1) towards the observation of visualized cluster maps and the interpretation of elements (nodes, chains, and comprehensive networks), as well as the hierarchy between clusters (identification of the leading and core cluster, complementary and supporting clusters, and/or specialized and localized clusters), and (2) reflection on the content analysis of the final sample of literature documents in relation to the keywords affiliated with the identified clusters. Finally, synthesis discussion will be performed in order to understand connections and dependencies in-between all three conducted clustering analyses.

3.1. Clustering Analysis 1: Methods and Tools

The subject of the first clustering analysis is the identification of leading methods and tools in the context of LULC mapping with applications in urban morphology. Special reference is dedicated to the understanding of analyses that are performed through the

application or integration of specific methods and tools—having it as main criteria for the clusters interpretation. Content analysis indicates 48 unique methodology-rooted keywords relevant for clustering scope. During the initial definition of clusters and the co-occurrence analysis of keywords, a larger number of clusters with a smaller number of associated keywords were recognized, indicating several narrowly specialized fields of application, such as a focus on mathematical models like cellular automata and fractal analysis [35], or metrics-based methods focused solely on land use mix measurement [28]. By further defining the minimum number of keywords per cluster (minimum cluster size is set to 7) with the aim to refine perspective on the cluster interpretation and the relationship between the associated methodologies, five thematic clusters are formed as a framework for in-depth discussion (Table 2): (1) statistical and survey-driven analysis (represented by red color, includes 12 keywords)—emphasizes methods for collecting, processing, and analyzing data directly from fieldwork and survey-based approaches, (2) temporal and change detection analysis (represented by green color, includes 11 keywords)—concentrates on computational and machine learning techniques used for detecting changes over time, (3) spatial configuration and connectivity analysis (represented by blue color, includes nine keywords)—includes analytical techniques for understanding spatial relationships and configurations, (4) predictive and transition analysis (represented by yellow color, includes eight keywords)—encompasses simulation and predictive models for understanding and forecasting land use changes and urban transformation, and (5) quantitative metrics-based analysis (represented by purple color, includes eight keywords)—involves quantitative metrics and machine learning approaches/algorithms for analyzing spatial patterns.

Table 2. Review of clusters with the list of keywords within methods and tools analysis.

Cluster Label (Color)/ Topic	Keywords
Statistical and Survey-Driven Analysis (red cluster)	agreement–disagreement maps, analogical (visual) classification, expert interviews, fieldwork, image processing, land use mix measurement, multicriteria decision analysis, proximity analysis, simulation models, spatiotemporal analysis, standardized questionnaire survey, statistical analysis
Temporal and Change Detection Analysis (green cluster)	3D modeling, change detection analysis, decision trees, deep learning, geospatial analysis, moving window method, multi-temporal classification, random forest model, semantic segmentation, spatial analysis of building properties, surface measurement
Spatial Configuration and Connectivity Analysis (blue cluster)	axial maps, CAD file conversion, diachronic analysis, dilatation technique, image texture analysis, lacunarity analysis, space syntax analysis, streetscape analysis, virtual field surveys
Predictive and Transition Analysis (yellow cluster)	cellular automata models, computer modeling, fractal analysis, GIS, land use change analysis, LCLU transition analysis, predictive modeling, Shannon entropy
Quantitative Metrics-Based Analysis (purple cluster)	calculation of spatial metrics, data integration, machine learning, performance evaluation metrics, point pattern analysis, random point sampling method, social sensing/crowdsourcing, TF-IDF algorithm

At the first level of analysis of the visualized cluster map (Figure 2), foundational clusters are identified and interpreted in relation to the type of analysis that is carried out using methodologies that belong to a certain cluster. First, the centralized and leading role of keywords such as “GIS”, “statistical analysis”, and “image processing” is recognized. “GIS” forms a central chain linking “statistical analysis” and “image processing”, which then extend outwards to other specialized keywords including “deep learning” (within green cluster), “space syntax” (within blue cluster), and “machine learning” (within purple cluster), acting as pivotal terms of peripheral clusters. Moreover, the connective keywords are recognized: (1) “random forest model” provides predictive and classification capabilities, thus supporting the integration of machine learning (green and purple clusters) and statistical approaches (red cluster), and (2) “spatiotemporal analysis” represents a core

technique for understanding urban patterns dynamic and land-use changes (connecting red, yellow, and green clusters). A specific but unobtrusive role is played by the term "change detection analysis" (affiliated with green cluster), which represents the only direct link between temporal and change detection analysis (green cluster) and predictive and transition analysis (yellow cluster) acting as a bridge between data-driven machine learning methods and spatiotemporal models. Finally, "space syntax" represents the core node of spatial configuration and connectivity analysis (blue cluster).

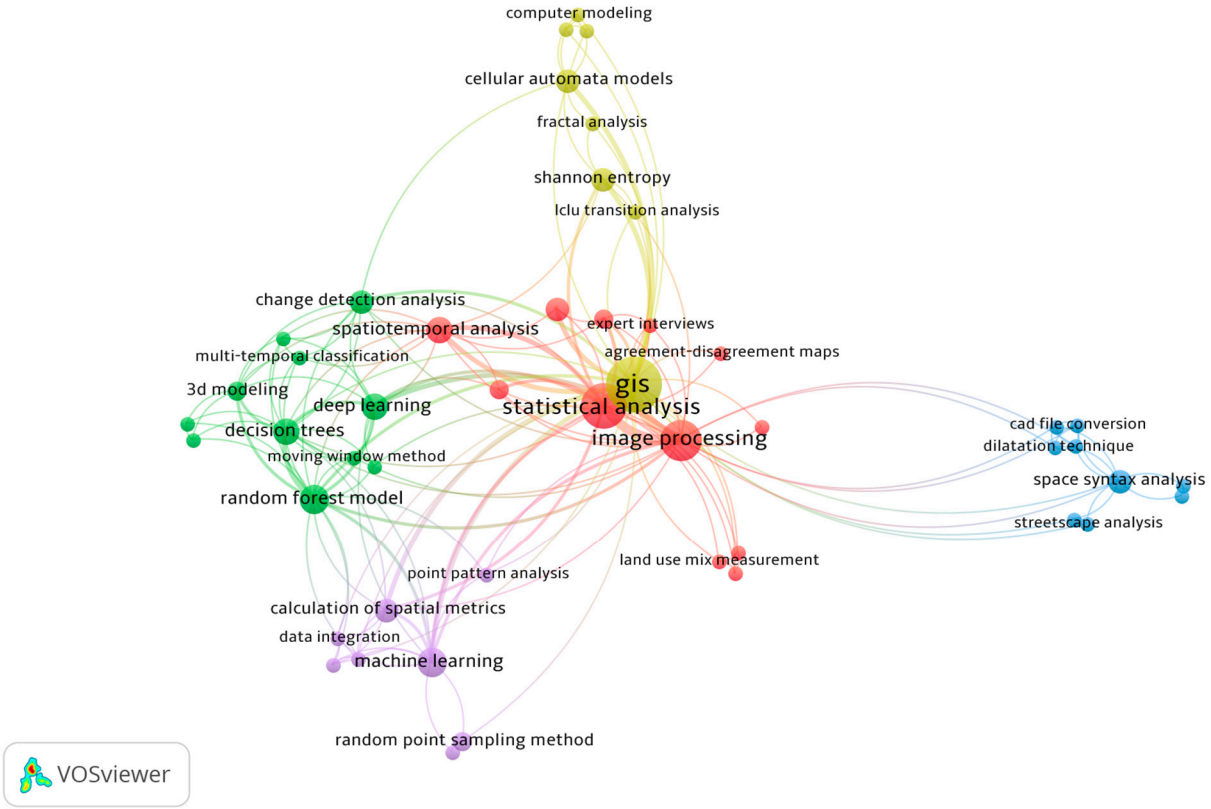

Figure 2. Clusters according to methods and tools (minimum cluster size = 7).

At the second level of analysis of the visualized cluster map (Figure 3), a higher indicator is defined for the minimum cluster size (set to 9), in order to understand the integration and order of connection for foundational clusters. Consequently, the discussion of the cluster hierarchy is based on the comparison of Figure 2 (foundational clusters) and Figure 3 (integrative clusters). The statistical and survey-driven analysis cluster (red) is recognized as a central cluster that connects all other foundational clusters and is aimed at generating raw data and providing analytical frameworks further performed by other clusters. The temporal and change detection analysis cluster (green) is positioned as a primary analytical cluster providing advanced tools for temporal analysis, while the predictive and transition analysis cluster (yellow) plays a supportive role by feeding results back to the core data in the red cluster. The quantitative and metrics-based analysis cluster (purple) is situated to support both the green cluster and the central one—it enhances data integration through quantitative metrics and machine learning. Finally, the spatial configuration and connectivity analysis cluster (blue) has a specialized and peripheral position by operating with a distinct set of spatial configuration tools. Looking at the cluster's synergistic composition (Figure 3), the integration of the red and yellow clusters is recognized, indicating the importance of combining survey-based data with predictive modeling. Also, integration is recognized in-between green and purple clusters under the umbrella of machine learning techniques.

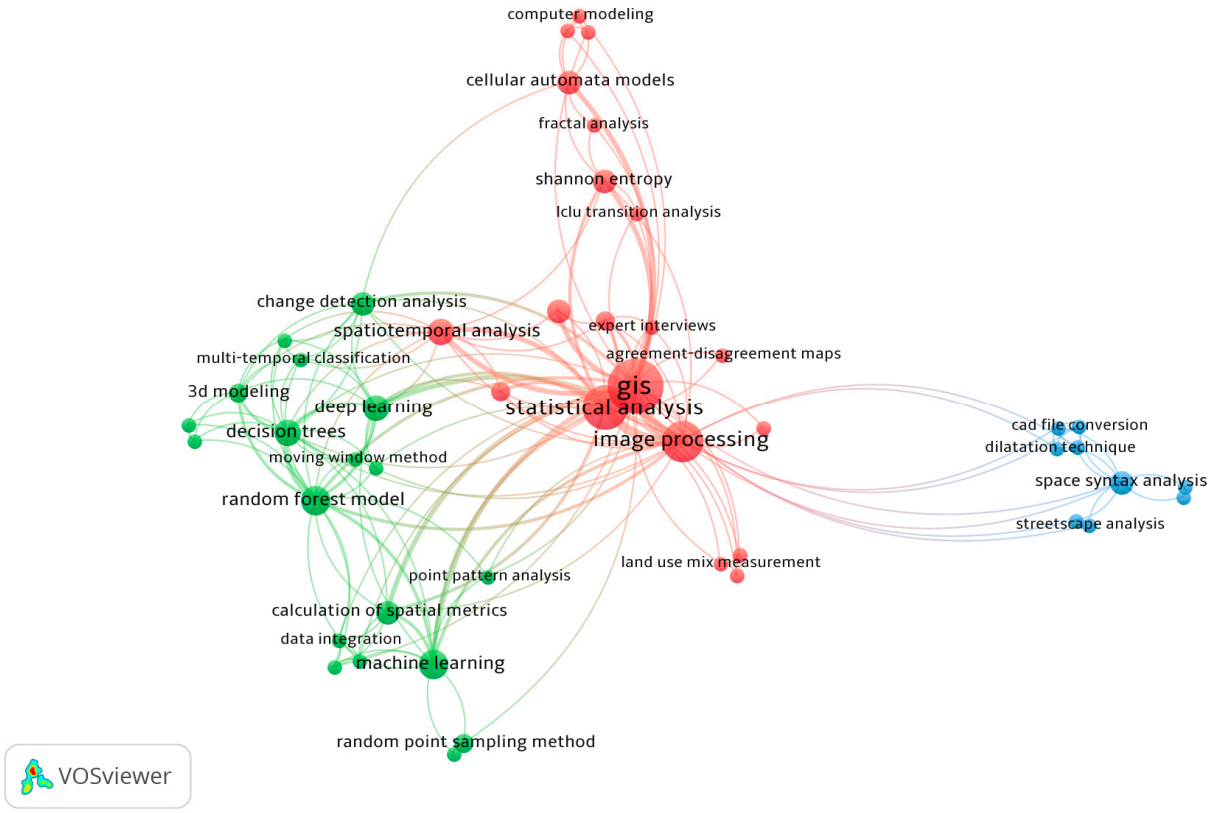

Figure 3. Clusters according to methods and tools (minimum cluster size = 9).

3.1.1. Cluster 1: Statistical and Survey-Driven Analysis

The leading terms of the first cluster are "statistical analysis" (OCC = 14, TLS = 41), and "image processing" (OCC = 11, TLS = 37), followed by "spatiotemporal analysis" (OCC = 4, TLS = 18). The statistical and survey-driven analysis cluster plays an integrative role towards other clusters, because leading terms are pivotal in integrating qualitative and quantitative approaches in the comprehensive framework of urban morphology on three levels: (1) data collection methods (expert interviews, fieldwork, standardized questionnaire surveys), (2) analytical techniques (statistical analysis, multicriteria decision analysis, proximity analysis, land use mix measurement), and (3) visual/spatial analysis (image processing, spatiotemporal analysis, analogical classification, agreement–disagreement maps). The specificity is represented by the term "simulation models" which bridges temporal and change detection analysis (green cluster) and predictive and transition analysis (yellow cluster) as a connecting node from the statistical and survey-driven analysis cluster. The content analysis reveals that simulation models are engaged in the service of creating different urban growth scenarios [36] and to understand the spatial patterns of uncertainty [22].

In the context of data collection methods, fieldwork plays a central role as a traditional method for on-site data collection and direct observation on three levels of integration: (1) integration of fieldwork with GIS analysis [25,26], (2) integration of fieldwork with standardized questionnaire surveys such as socioeconomic surveys [25] and expert interviews [23], and (3) integration of fieldwork with remote sensing imagery analysis to validate and cross-reference observations [27].

In the context of analytical techniques, statistical analysis is recognized as the most represented within the analyzed scope of literature documents (a third of the studies employ some statistical method) through a wide range of applications that include (1) regression and predictive modeling: regression modeling [21,22,33], discriminant analysis [36], Bayesian stochastic approach [22]; (2) clustering: k-Means clustering [21,36], hierarchical clustering [37], Gaussian mixture modeling [38]; (3) dimension reduction: principal

component analysis (PCA) [37], (4) density estimation: kernel density estimation (KDE) method [39]; and (5) statistical tests: correlation analysis [37,40], analysis of variance (ANOVA) [33], chi-square test [24], Kolmogorov–Smirnov (KS) statistical test [25]. The analyzed literature indicates the presence of specific methodological approaches for comprehensive evaluation of urban compactness using statistics-based methods beyond traditional entropy-based methods such as integration of multicriteria decision analysis, proximity analysis, and land use mix measurement [28].

In the context of visual/spatial analysis, image processing and classification are engaged as a drivers for connection with (1) spatial configuration and connectivity analysis cluster (blue) to enable texture analysis [34], (2) predictive and transition analysis cluster (yellow) to achieve high-accuracy land-use classification based on analogical (visual) classification [41], (3) temporal and change detection analysis cluster (green) to ensure accuracy in urban feature identification over time [42], and (4) quantitative metrics-based analysis cluster (purple) to improve accuracy of point-based geometric data [29].

A special domain of integration is reflected in combining statistical methods with visual/spatial analysis such as (1) employment of agreement–disagreement maps [33] in order to understand how morphological characteristics of built-up areas correspond to dataset congruency and influence change detection accuracy, and (2) performance of spatiotemporal analysis in order to establish relationships between growth patterns and their environmental, social, and economic impacts through statistical models [24,36].

3.1.2. Cluster 2: Temporal and Change Detection Analysis

The leading term of the second cluster is "random forest model" (OCC = 5, TLS = 26), followed by "decision trees" (OCC = 4, TLS = 20), and "deep learning" (OCC = 4, TLS = 18). The temporal and change detection analysis cluster plays an analytical role by providing advanced tools for temporal analysis with a three-fold scope: (1) machine learning and classification methods (decision trees, deep learning, random forest model, semantic segmentation), (2) change detection methods (change detection analysis, multi-temporal classification, moving window method), and (3) 3D modeling (3D modeling, spatial analysis of building properties, geospatial analysis).

In the scope of machine learning and classification methods, the central position is occupied by methodological approaches based on the application of random forest models (including random forest (RF) classifier) with the aim to (1) estimate building footprint, height, and volume [18], (2) process and classify morphological dimensions, particularly horizontal density and vertical density [19], (3) classify residential areas using multi-scale signatures of features [29], (4) classify LULC patterns using the local climate zone (LCZ) classification scheme [32], and (5) improve the accuracy of urban land use classification [43]. In addition to the application of random forest models which combine multiple decision trees built on different combinations of explanatory variables, content analysis reveals the application of simpler operations such as decision trees to achieve class-specific classification accuracies at city block level [44]. Certain studies [32] specifically employ random forest models as a benchmark classification method against which other approaches like moving window and deep learning techniques are compared. In this sense, the content analysis indicates the multiple application of deep learning techniques in the service of image processing (convolutional neural networks (CNNs), fully convolutional networks (FCNs)) [19,32], spatial feature extraction (autoencoder neural network) [39], and data classification (multi-layer perceptron neural network classifier) [22]. Furthermore, it has been demonstrated that the integration of semantic segmentation with deep learning techniques and random forest models significantly improves accuracies in urban form mapping [19].

In the context of change detection methods, change detection analysis occupies a specific position in integrating and transferring operational knowledge across clusters. This is achieved through (1) integration with cellular automata models [45] (affiliated with the predictive and transition analysis cluster (yellow)) to understand both the historical

patterns of urbanization and predict future urban growth scenarios, and (2) integration with image processing and statistical analysis (both affiliated with the statistical and survey-driven analysis cluster (red)) to perform mapping at a finer scale that are relevant for detailed urban and neighborhood-level applications [42]. Moreover, change detection analysis in synergy with multi-temporal classification [19] was recognized, as it has been shown to facilitate urban dynamics analysis, with deep learning models demonstrating greater temporal transferability compared to traditional methods. Furthermore, the moving window method, supported by surface measurement, is used to overcome the limitations of traditional spectral-based classification approaches in heterogeneous urban areas [32].

Finally, examining the links within the subject cluster reveals that 3D modeling, combined with spatial analysis of building properties and geospatial analysis, forms a specific sub-cluster. Substantially, 3D modeling is applied for the purpose of capturing both horizontal and vertical configuration of urban form, while procedurally, it leverages insight from random forest models to estimate dimensions and variables essential for modeling [18,19].

3.1.3. Cluster 3: Spatial Configuration and Connectivity Analysis

The spatial configuration and connectivity analysis cluster plays a specialized role by operating with a distinct set of spatial configuration tools having "space syntax analysis" (OCC = 3, TLS = 10) as a nucleus of the cluster. This position is recognized primarily because of the hybridized methodological framework within which space syntax analysis is applied. This type of analysis is integrated or blended with other techniques to operationalize the research insights arising from space syntax analysis.

The first multi-method approach [31] addresses the challenge that analyzing urban districts requires examining multiple elements in their interrelations, rather than individual features of urban form. To enhance analysis accuracy, this approach integrates space syntax analysis with streetscape analysis and virtual field surveys, incorporating multiple data types like building entrances, key attractors, and population densities.

The second novel approach [34] expands space syntax analysis by combining traditional syntactic mapping with image texture analysis to understand spatial patterns. This process begins with CAD file conversion to binary images, followed by applying a dilatation technique crucial for emphasizing various scales in pattern analysis. The interface maps are treated as pixel-based images: lacunarity analysis examines the spatial distribution of pixel gaps across different scales, while image texture analysis identifies spatial patterns through pixel distribution observation.

The third identified approach [46] uses axial maps across temporal phases to analyze the evolution of urban structures. This diachronic analysis examines how integration values and centrality patterns shift over time, revealing the transformation from a centralized to an interconnected urban system. Such a diachronic approach enables the examination of how urban form transforms over time from the lens of space syntax metrics.

3.1.4. Cluster 4: Predictive and Transition Analysis

The predictive and transition analysis cluster (yellow) involves the most influential node in a comprehensive network of keywords—the notion of geographic information system (GIS) (OCC = 22, TLS = 63). The counterweight to the term "GIS" in this cluster is represented by specialized terms "Shannon entropy" (OCC = 3, TLS = 10) and "cellular automata models" (OCC = 3, TLS = 9). GIS represents the methodological pivot in 22/31 literature documents, where it is integrated to the greatest extent with methods from the predictive and transition analysis cluster. In this sense, the understanding of this cluster will be discussed on two levels: (1) the internal level—the level of the GIS relationship with the leading notions of the cluster to which it belongs, and (2) the external level—the level of the GIS relationship with the other four clusters.

The internal level indicates that the relations within the cluster are arranged through flow from GIS as a central node towards simulation and modeling techniques (cellular

automata models, computer modeling) and then to analytical techniques (fractal analysis, Shannon entropy) used to interpret the results. Content analysis indicates that the integration of GIS and cellular automata models is primarily performed to analyze and predict urban growth patterns [45], incorporating multiple types of growth validated through ground surveys and remote sensing analysis towards land use change analysis [20]. In the analytical direction of integration, GIS intersects with Shannon entropy, indicating three specific predictive-oriented approaches: (1) combining GIS-based spatial analysis with Shannon entropy to measure urban sprawl and compactness complemented with fractal analysis to examine the complexity and spatial organization of built-up areas through the box-counting method [35], (2) utilizing GIS to aggregate and process parcel-level data within block groups, then calculate Shannon entropy to measure the concentration or dispersion of built-up areas, and finally analyze LULC transitions over time to determine changes in land use patterns and urban development [21], and (3) integration of Shannon entropy with GIS techniques to quantitatively measure urban growth patterns, ranging entropy values from compact to dispersed [24].

On the external level, GIS is perceived as a driver for connection with (1) statistical and survey-driven analysis cluster (red) to provide a comprehensive spatial framework for accurately mapping, quantifying, and validating urban morphological features [42], (2) temporal and change detection analysis cluster (green) to establish comparative analysis of urban patterns over time [45], (3) spatial configuration and connectivity analysis cluster (blue) to interpret multiple layers of spatial data including street networks, building footprints, and LULC patterns [31], and (4) quantitative metrics-based analysis cluster (purple) to develop an automated, objective approaches for typological classification [29] and for the identification of urban land use functions [43].

3.1.5. Cluster 5: Quantitative Metrics-Based Analysis

The leading term of the fifth cluster is "machine learning" (OCC = 5, TLS = 19), followed by "calculation of spatial metrics" (OCC = 3, TLS = 13). Machine learning represents a central notion that establishes specific approaches for quantitative metrics-based analysis (1) in relation to other methods that belong to this cluster including spatial metrics and pattern analysis [29], data integration and social sensing [47], and performance evaluation and validation [44] or (2) through intertwining multiple machine learning techniques [39,43].

The first approach is concentrated on geometric features [29], extracting them from settlement point patterns (including density, distance, angles, and spacing measurements), calculated across multiple spatial scales. These point pattern metrics serve as input features for a random forest machine learning classifier that predicts settlement types. The specificity of this approach relies on the fact that it is a multiscale perspective by analyzing point patterns through moving windows of various sizes to calculate contextual features.

The second approach combines traditional spatial analysis methods like KDE with advanced machine learning techniques, using an autoencoder for feature dimension reduction and Adaboost for classification [39]. Multiple machine learning approaches are integrated, including RF, support vector machine (SVM), and CNNs, to enhance urban functional zone mapping accuracy.

The third approach represents an integrated analytical framework [43] where the TF-IDF algorithm processes POI data to generate weighted attributes, which are then combined with calculated spatial metrics (including building heights, base areas, and plot ratios). The methodology improves urban function classification accuracy by establishing spatial relationships between POI data and urban form through GIS spatial connection methods.

The fourth approach integrates machine learning with spatial metrics [47] through a two-stage approach: (1) using the random point sampling method to process building heights and morphological data [48], and (2) adopting multi-layer stacking learning, combining remote sensing and social sensing data to automatically analyze various spatial metrics like floor area ratios and building patterns.

The fifth approach is concentrated on the calculation of spatial metrics [44], employing decision trees to analyze multiple types of spatial metrics for the typological classification of urban form. This machine learning approach systematically evaluates metric effectiveness through frequency analysis in classification trees, resulting in improved accuracy and reduced complexity when combining different types of spatial measurements.

3.2. Clustering Analysis 2: Data Types

The subject of the second clustering analysis is the identification of leading features (input data) collected, observed, or processed during analytical procedures presented within clustering analysis 1. Content analysis indicates 48 unique keywords distributed within the three prominent clusters as a framework for in-depth discussion (Table 3): (1) urban density and structural indicators (represented by red color, includes 19 keywords)—data that support understanding of intensity and distribution of built-up areas, as well as insight into the elements related to the physical structure and connectivity of urban areas; (2) land classification and satellite-based data (represented by green color, includes 15 keywords)—data centered on LULC classification, along with associated satellite data sources; (3) high-resolution and specialized imagery data (represented by blue color, includes 14 keywords)—fine-grained spatial information valuable for urban form detection.

Table 3. Review of clusters with the list of keywords within data types analysis.

Cluster Label (Color)/ Topic	Keywords
Urban Density and Structural Indicators (red cluster)	block sizes, building area ratio (BAR), building height, coverage ratio (CR), floor area ratio (FAR), gross floor area (GFA), horizontal morphology variance index (HI), land ownership, number of buildings, number of floors, open space ratios, plot sizes, points of interest (POI) data, public open spaces data, public–private interface maps, street widths, surface area-to-volume ratio (SAVR), vertical morphology dissimilarity index (VI), year of building construction
Land Classification and Satellite-Based Data (green cluster)	administrative boundaries, block boundaries, building size metrics, demographic data, GPS field observation data, historical LULC data, land cover classifications, land use classifications, local climate zone (LCZ) scheme, remote sensing imagery, street networks, time series data, topographic data, urban structure data, vegetation data
High-Resolution and Specialized Imagery Data (blue cluster)	building boundaries, building footprint, building volume, climate change initiative land cover (CCI-LC) data, geometric features, global human settlement layer (GHSL) data, global urban footprint (GUF) data, land use polygon features, LandScan settlement layer (LandScan SL), Modis land cover data, open street map data, settlement area, settlement point data, VHR imagery

The clustering visualization (Figure 4) showcases the presence of many nodes that influence the relationships between clusters and individual features. Notable main nodes are distributed within the land classification and satellite-based data cluster (green) starting with “remote sensing imagery” followed by feature of “street networks”, and classification-based data “land use classifications” and “ land cover classifications”. This node’s prominence suggests a reliance on imagery data as a foundational source for acquiring the required spatial information. In the remaining two clusters, core nodes are represented by quantitative indicators expressed in terms of “building footprint” (affiliated with the high-resolution and specialized imagery data cluster (blue)) and “floor area ratio (FAR)” (affiliated with the urban density and structural indicators cluster (red)).

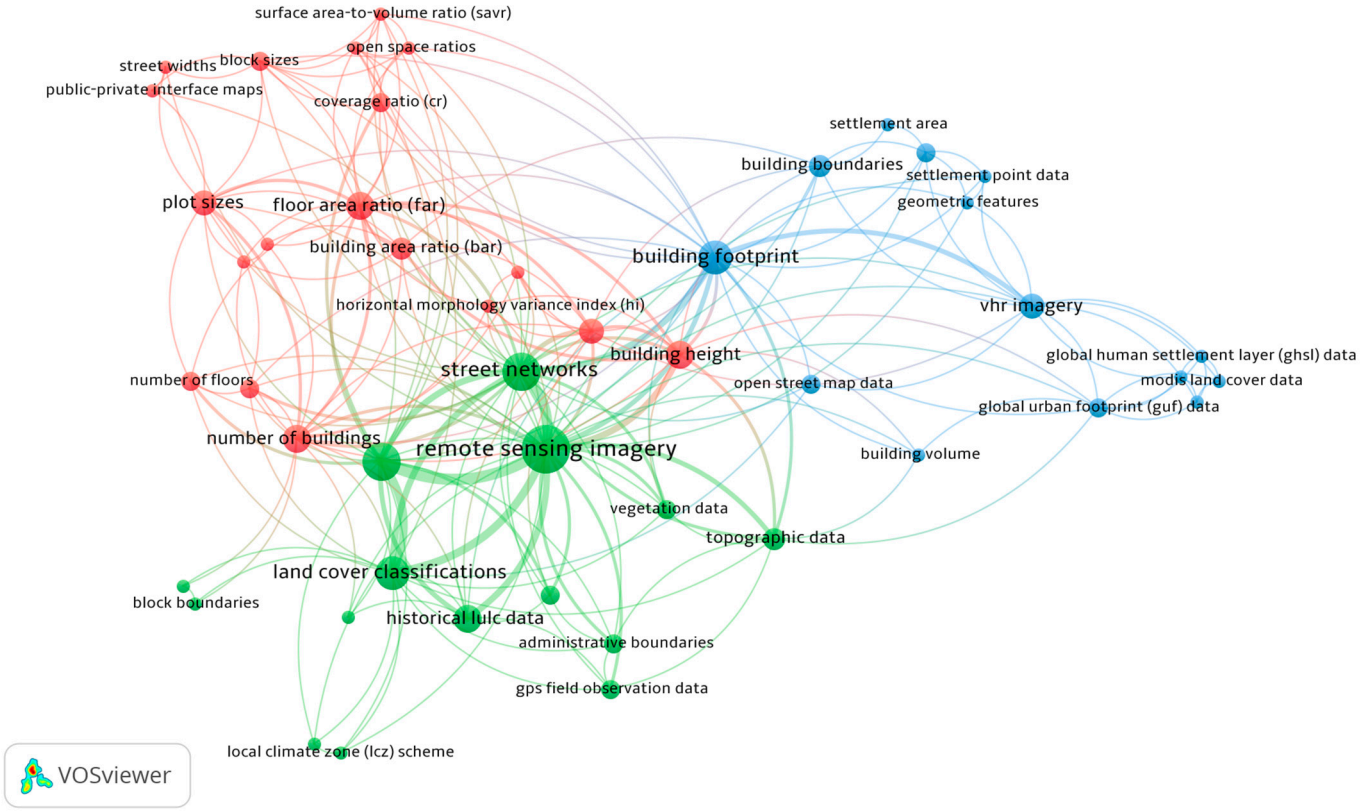

Figure 4. Clusters according to data types.

In terms of hierarchy, the land classification and satellite-based data cluster (green) led by "remote sensing imagery" serves as the primary cluster, suggesting it is the most critical data feature for this study. The urban density and structural indicators cluster (red) and high-resolution and specialized imagery data cluster (blue) appear as supporting clusters, contributing specialized spatial data that enhance the precision of LULC mapping and particularly morphological assessments.

3.2.1. Cluster 1: Urban Density and Structural Indicators

The urban density and structural indicators cluster (red) mainly addresses variables that define the physical and spatial organization of a built environment dominantly including metric data and quantitative measures, dimensions, and indicators. The leading terms of this cluster are "FAR" (OCC = 5, TLS = 26), "building height" (OCC = 5, TLS = 23), and "number of buildings" (OCC = 5, TLS = 23). A specific position is occupied by the terms "plot sizes" (OCC = 4, TLS = 16) and "points of interest (POI) data" (OCC = 4, TLS = 19) as connectors and support elements—"plot sizes" is positioned as a core metric essential for understanding morphological structure, while "POI data" enhances this structure by linking it to social functionality and LULC patterns. Keywords affiliated with the subject cluster could be classified into four groups: (1) building and plot attributes (building area ratio (BAR), FAR, gross floor area (GFA), number of buildings, number of floors, building height, plot sizes, year of building construction), (2) morphometric indices and ratios (horizontal morphology variance index (HI), vertical morphology dissimilarity index (VI), surface area-to-volume ratio (SAVR), coverage ratio (CR), open space ratios), (3) functional and social interface data (public open spaces data, public–private interface maps, POI data), and (4) street and land ownership data (block sizes, street widths, land ownership).

In the context of building and plot attributes, the most common combination of this type of information is recognized in order to achieve specific analytical procedures including both classification of urban patterns [19], and comparation of urban tissues [26]. The BAR is recognized as metric for horizontal density classification, while for vertical density

classification, BAR is combined with building height measurements [19]. Furthermore, content analysis reveals that BAR is represented as one of the key morphological indicators on plot level [43], alongside building height (average and maximum), and FAR. Complementary to BAR, FAR is applied in terms of (1) analyzing density patterns and urban development intensity [26], and (2) distinguishing different land use types [47], using GFA as a key component for FAR calculation [25].

Correlatively, building-level indicators that include number of buildings, number of floors, building height, and year of building construction are utilized for the calculation of morphometric indices and ratios. HI and VI are calculated to improve land use identification accuracy by capturing distinctive vertical and horizontal morphological characteristics of different urban areas [47]. On the other hand, SAVR, CR, and open space ratios are calculated to quantify the urban fabric, and to understand densification process over time [25]. On the other spatial level, plot-level indicators are dominantly based on the feature of plot sizes in order to understand (1) how morphological attributes influence district functionality [31], (2) how different urban tissues transform through processes of subdivision and amalgamation [26], and (3) how urban form and land use interact to create distinct spatial patterns [34].

Furthermore, it is recognized that functional and social interface data are used in combination to perform specific morphological analysis. First, public open spaces data combined with the vector-based spatial data from OpenStreetMap data to perform space syntax analysis [31] and street network analysis [27]. Second, public–private interface maps combined with satellite imagery to perform texture analysis [34]. Finally, POI data combined with (1) VHR imagery to perform texture analysis [39], (2) OpenStreetMap data and satellite imagery to analyze functional density [47], and (3) population data to perform proximity analysis [28].

Unlike the first two groups of features belonging to this cluster, street and land ownership data include indicators related to the spatial level of block and street. Content analysis demonstrates the utilization of block size and block-level data combined with the street configurations (street widths) to understand urban compactness [34] and with field interviews and physical surveys to assess infrastructural quality [25]. Finally, the feature of land ownership is observed in order to decode changes in land use patterns and morphological characteristics conditioned by the policy shift [26].

3.2.2. Cluster 2: Land Classification and Satellite-Based Data

The land classification and satellite-based data cluster (green) contains an integrated dataset represented by “remote sensing imagery” (OCC = 17, TLS = 64), as a leading term of both this cluster and comprehensive network. A specific position is occupied by terms “land use classifications” (OCC = 10, TLS = 41) and “land cover classifications” (OCC = 8, TLS = 28) as reciprocal connections towards other clusters. Moreover, the notion of “street networks” (OCC = 10, TLS = 49) is positioned centrally and strongly linked with the previously mentioned leading terms to serve as a critical dataset that connects both the structural and functional aspects of urban morphology. According to their nature and role, data types belonging to this cluster could be divided into five groups: (1) large-scale spatial data (remote sensing imagery, street networks, GPS field observation data, demographic data), (2) classification data (land cover classifications, land use classifications, local climate zone (LCZ) classification scheme), (3) spatial boundaries and structural data (administrative boundaries, block boundaries, building size metrics, urban structure data), (4) environmental data (vegetation data, topographic data), and (5) historical and temporal data (historical LULC data, time series data).

Content analysis of literature documents indicates that remote sensing imagery (which encompasses Landsat satellite imagery and Nighttime satellite imagery data) is observed within 17/31 studies, indicating the critical importance of this type of data. Also, by looking at the methodological framework of individual studies, different approaches to using this data are recognized, including (1) framework for deriving indices as input

data for random forest models [18,35], (2) harmonization of images to ensure consistent time-series analysis [19,40], (3) combining with vector data analysis to achieve remote sensing-based image classification of settlement areas [29], (4) combining with GIS to quantify and characterize the temporal patterns of urbanization [24,30], (5) application of texture analysis to describe the spatial arrangement of surfaces and built materials [34], and (6) application of visual interpretation techniques to analyze the elements of remote sensing images, relating them to specific LULC classes [22,41].

Within the scope of large-scale spatial data, street networks are primarily engaged through space syntax methodology to understand movement patterns [31] and connectivity patterns [25] or are combined with other geospatial information including administrative boundaries and physical features to analyze urban accessibility [30]. In addition to their role in syntax-based analyses, where they are used in their original form, street networks data are also transferred to spatial boundaries and structural data to provide boundary features [39]. The GPS field observation data are primarily used for validation and accuracy assessment purposes in the context of land cover classification [30] and urban growth analysis [24], while demographic data (mainly population density data) are used to quantify relationships between population dynamics and physical urban growth patterns [40].

In the context of LULC classification data, a number of studies are recognized that process land cover classifications data [30,37,44], land use classifications data [20,25,28,40,48], or both types of data [21,27,32,35,42], implying already established classes, most often through the framework of local government zoning. The content analysis also recognized the adoption of the LCZ classification scheme [32] as it provides a standardized framework for LULC classification.

In contrast to the previously presented types of data that refer to the observation of spatial systems of a wider scope, spatial boundaries and structural data mainly refer to individual geometric entities. In this sense, boundaries serve as a framework for analyzing differences in urbanization patterns between spatial units defined by administrative boundaries [40] or block boundaries [44]. These boundary data are combined with multiple other data types, including building size metrics and urban structure data.

In the context of environmental data, their multiple roles are recognized primarily in understanding urban ecosystem functionality, and characterizing the urban environment through urban morphology types based on vegetation data [42,45]. Topographic data are dominantly recognized as an input for the development of the digital elevation model (DEM) [18], topographic maps [30], and 3D urban configuration model [45].

Finally, historical and temporal data demonstrate a specific application within the predictive-oriented approach of urban form analysis. Historical LULC data and time series data are most often applied combined with LULC classification data to provide a comparative basis for monitoring changes over time. These type of data are created by processing insights from anthropological studies [20], utilizing remote sensing imagery from different time periods [20,24,35], using cartography maps corresponding to different historical periods [46], or by processing historical land use maps provided by local authorities [28].

3.2.3. Cluster 3: High-Resolution and Specialized Imagery Data

The third cluster of high-resolution and specialized imagery data (blue) provides a macro-scale view and high-resolution data for localized urban mapping. The leading term of this cluster is the feature of "building footprint" (OCC = 8, TLS = 34), which, unlike other building and plot attributes affiliated with the urban density and structural indicators cluster (red), differs in the way in which it is extracted and processed. Simultaneously, notions belong to this cluster encompass "VHR (Very High Resolution) imagery" (OCC = 4, TLS = 16) and OpenStreetMap data, both relevant for extracting and decoding high-precise building-level features (building boundaries, building footprint, building volume, geometric features). Accordingly, this cluster connects specialized sources valuable for mapping fine-scale features that cannot be extracted and precisely identified from satellite-based data with lower resolution. This cluster also contains specialized data derived from global

sources including (1) global urban and settlement layers (global human settlement layer (GHSL) data, global urban footprint (GUF) data, LandScan settlement layer (LandScan SL), settlement area, settlement point data) and (2) LULC data (climate change initiative land cover (CCI-LC) data, MODIS land cover data, land use polygon features).

In essence, this cluster demonstrates a methodological shift from pixel-based analysis towards object-oriented feature extraction (including building footprints and geometric features) [29,38], thus providing more accurate detection and quantification of complex local-scale urban patterns [33,39]. Content analysis also indicates a specific approach based on the observation of multiple datasets [33] affiliated with global urban and settlement layers, and LULC data ranging from very high resolution ($\leq$0.5 m) to coarse resolution (500 m) imagery to analyze how different spatial resolutions capture urban morphology and built-up areas. Moreover, the extraction process of building boundaries indicated that VHR imagery is also engaged as validation data to verify completeness and accuracy [39].

3.3. Clustering Analysis 3: Urban Morphology Aspects

The subject of the third clustering analysis is the identification of thematic groups related to the aspects of urban morphology represented in the final sample of literature documents. Content analysis indicated 40 unique keywords that were further distributed into four unique clusters with 10 keywords each (Table 4) as follows: (1) metrics and structural-based aspects (red cluster)—includes keywords that encompass structural and functional features of urban spaces, (2) spatiotemporal aspects (green cluster)—includes keywords that refer to the observation of the temporal dimension of the urban form, (3) typological classification (blue cluster)—gathers keywords related to the classification of urban patterns and elements, and (4) prediction-oriented aspects (yellow cluster)—compiles keywords that address the future perspective of growth and transformation of urban form. The clusters were interpreted in relation to the domains of observation, analysis, and classification of urban form (approaches), as well as based on connections between keywords within the cluster.

Table 4. Review of clusters with the list of keywords within urban morphology aspects analysis.

Cluster Label (Color)/ Topic	Keywords
Metrics and Structural-based Aspects (red cluster)	3D building structure, 3D urban structure, building metrics, building shape characteristics, plot metrics, spatial distribution of functions, urban form dynamics, urban land use intensity, urban structure mapping, urban structure metrics
Spatiotemporal Aspects (green cluster)	block typology, centrality patterns, contiguity of built-up areas, LCLU transitions, morphogenesis, sprawl patterns, urban compactness, urban expansion patterns, urban network structure, urban spaces accessibility
Typological Classification (blue cluster)	building typology, land use patterns, open space typology, settlement typology, street metrics, street network connectivity, street typology, urban density, urban development intensity, urban grid layout
Prediction-oriented Aspects (yellow cluster)	aggregation of built-up areas, block metrics, land cover metrics, urban form prediction, urban growth dynamics, urban growth patterns, urban infill, urban patterns complexity, urban tissues, urban transformation patterns

By looking at the key nodes (keywords) in the visualized cluster map (Figure 5), as well as by interpreting the graphic representation and quantitative indicators defined through OCC and TLS, several indicators could be recognized at a general level. First, the presence of highly influential or commonly connected keywords such as “urban density”, “land use patterns”, “street network connectivity”, “urban compactness”, “morphogenesis”, “urban expansion patterns”, “sprawl patterns”, and “urban growth patterns” is recognized, which indicate the necessity of implementing multiple analysis and simultaneous interpretation of aspects affiliated to several clusters in order to clearly interpret their meaning and role in studies of urban morphology. This group of keywords stands out as the focal chain of

the visualized map, indicating a high level of connectivity between clusters, especially around main nodes. For example, "urban compactness" and "sprawl patterns" connect the spatiotemporal analysis cluster (green) with typological classification cluster (blue), indicating a close relationship between spatial expansion and urban density.

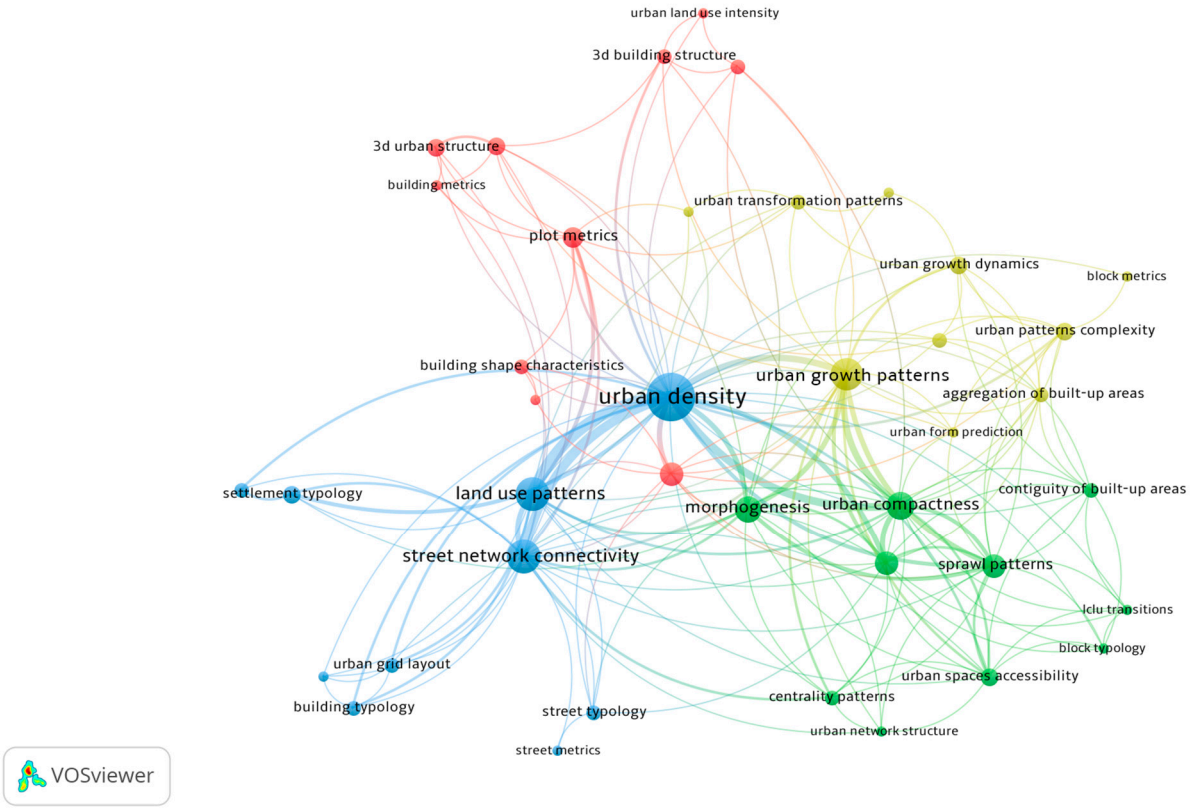

Figure 5. Clusters according to urban morphology aspects.

Looking at the hierarchy of clusters and their centrality, dominance of the typological classification cluster (blue) is recognized, suggesting that typologies (e.g., building, street, and settlement typologies) and the connectivity of urban networks are foundational elements in understanding urban form. The spatiotemporal analysis cluster (green) and prediction analysis cluster (yellow) perform supportive dominance, reflecting that change detection is essential for understanding the evolution of urban patterns over time. Finally, the metrics and structural analysis cluster (red) reflects its specialized focus with localized influence having "urban structure mapping" as a pivotal term in focal chain.

3.3.1. Cluster 1: Metrics and Structural Approach

The metrics and structural approach cluster represents a specialized group within the comprehensive network of analyzed concepts. The leading terms of this cluster are "urban structure mapping" (OCC = 5, TLS = 16) and "plot metrics" (OCC = 4, TLS = 14).

Substantially, this cluster problematizes the integration of horizontal and vertical configuration of urban form by studying 3D building structure (building footprint, height, and volume) and 3D urban structure thus contributing to the characterization of urban land use intensity [18]. Also, this cluster affirms the quantitative analysis of urban form through the introduction of building-level and plot-level metrics [43], which systematize physical–spatial information through various indicators that reflect building layout forms, as well as plot feature attributes. Cross-viewing aspects of 3D urban structure and land use intensity introduces the notion of urban structure metrics through a dual perspective: (1) applied to analyze urban growth patterns at different time steps [40] and (2) applied to decode different settlement types and patterns across regions [18]. While previous aspects

provide framework for urban form quantification, building shape characteristics and spatial distribution of functions advance qualitative features through consideration of geometric measures [39] and hierarchical classification systems [48].

The notion of urban form dynamics can be understood as a focal point within the sub-cluster that introduces the temporal dimension into the context of metrics-based analysis through (1) combining horizontal and vertical dimensions of urban development [19], (2) comparing changes in urban form indices with shifting land use functions [43], and (3) conceptualizing multidimensional urban form by integral consideration of physical elements, configuration, and time [45]. Finally, the nucleus of this cluster is built around the concept of urban structure mapping both as an integral part of LULC classification framework through overlapping urban form (land cover) and function (land use) [22,32,39,42], and as a synergetic method for measuring and monitoring changes in built-up areas [35].

3.3.2. Cluster 2: Spatiotemporal Approach

The spatiotemporal approach cluster has a growth-centric focus highlighting the temporal dimension and changeability of the urban form. The leading term of this cluster is "urban compactness" (OCC = 7, TLS = 34), followed by "morphogenesis" (OCC = 6, TLS = 28), "sprawl patterns" (OCC = 5, TLS = 28), and "urban expansion patterns" (OCC = 5, TLS = 26).

The backbone of this cluster is the notion of morphogenesis manifested as the dynamic process of urban form transformation [20] occurring in both horizontal and vertical dimensions across time [19] analyzed through the prism of (1) urban expansion patterns [21,24,36,40,42] and (2) sprawl patterns [20,21,24,35,46]. From the perspective of the temporality, morphogenetic processes are analyzed through multiple lenses including settlement evolution [25], tracking transformation of urban environment [42], monitoring of densification dynamics [19], and identification of developmental phases [20]. While morphogenesis is basically expressed through the lens of physical transformations, analysis of LULC transitions complementary addresses the question of LULC structural change with urban expansion, and correlation with sprawl patterns [46]. Moreover, contiguity of built-up areas [21,33] is introduced as a multi-factor indicator for decoding both sprawl and centrality patterns [36,46].

Corresponding to the notion of morphogenesis, urban compactness emerges as a central, integrative concept embodied in relation to mixed land use [28,34] and contrasting to development patterns [24]. Like morphogenesis, this concept is analyzed through a time-related perspective on three comparative levels: (1) current analysis and future predictions [35], (2) process (LULC transitions over time) and current form (existing built form conditions) [21], and (3) temporal variations in different growth phases [40]. Furthermore, urban compactness is a connecting concept with prediction analysis cluster through correlation with the notion of urban growth pattern [36].

The specificity of this cluster is the presence of the term block typology, which, unlike other typological entities (building, street, settlement, open spaces), is not affiliated with the typological classification cluster. Within the spatiotemporal approach cluster, block typology is treated as fundamental spatial unit, enabling comparative assessment of sprawl patterns [21]. At last, urban network structure [46] and urban spaces accessibility [21,28] are recognized as specific sub-domains within this cluster referring to integration and connectivity patterns in the urban network.

3.3.3. Cluster 3: Typological Classification

The typological classification cluster interacts significantly with other clusters, serving as a bridge between various thematic areas and suggesting the foundational role of typological-oriented analysis in urban morphology. The leading term of this cluster, as well as comprehensive network of keywords, is "urban density" (OCC = 21, TLS = 77), followed by "street network connectivity" (OCC = 10, TLS = 37) and "land use patterns"

(OCC = 10, TLS = 35). These three keywords also establish the axis of the focal chain within the visualized network.

The wider structure of this cluster is built by typology-based terms positioned as intermediaries which act as specialized, linking elements that provide specific attributes or configurations on different spatial levels including building typology [27,41], open space typology [27], settlement typology [25,29,38], and street typology [37,42]. Content analysis reveals that the observation of building typology is represented in terms of (1) hierarchical classification system based on the criteria of building structures and their uses [41] and (2) systematic approach based on the development of a typo-morphological matrix [27]. In contrast, it is recognized that open space typology is addressed in terms of classification system based on space privacy criteria (private, semi-private, flex spaces, etc.) [27]. Furthermore, the notion of settlement typology [25,29,38] is addressed in relation to the question of urban development intensity with a dual analytical perspective: (1) by analyzing the concentration of residential neighborhoods locations [29] and (2) by analyzing patterns of building density, size, and shape within settlements [38]. Finally, the notion of street typology [37,42] manifests itself as a special research niche that contributes to the formulation of street metrics [37] and decodes the way in which urban grid layout is developed [27,34]. The concept of street network connectivity is derived as the common denominator of the notions that have street as the spatial object of observation focusing on pedestrian accessibility and movement patterns [31], network integration over time [46], accessibility in terms of public facilities' locations [43], informal settlements transformation [25], street blocks definition [22], and terrain and land cover influence on street network patterns [37].

The subject cluster has the strongest link strength, which is established between the core concepts of urban density and land use patterns, indicating that a wider system of concepts (not only those from the typological classification cluster) affects the critical understanding and definition of these concepts. The content of the literature documents that have land use patterns as the object of analysis indicate that this conceptual framework is addressed (1) through the development of classification systems [23,27,41,48], or (2) in relation to a wide span of morphological aspects including plot metrics [26], visual character on street level [31], public–private interfaces [34], land use diversity (LUD) indicator [25], residential development and its expansion [42], and spatial arrangement and proximity [28].

On the other side, the concept of urban density is perceived in relation to a wide range of indicators that are thematically related to the remaining three identified clusters: (1) metrics-based indicators such as 3D building structure metrics [18,19], building grain size [31], BAR and/or FAR measurements [21,25,26,47], building footprint patterns [38], settlement point patterns [29], population-based metrics [23,28], and proportion of built-up area within urban blocks [44], (2) spatiotemporal-based indicators such as spatial distribution and concentration of different urban functions and activities over time [39], changes in concentration degree of urban growth and variations in densification processes [36], spatial distribution of built-up areas across different districts over time periods [24,42], and (3) predictive-oriented indicators such as urbanization intensity index (UII) [35].

3.3.4. Cluster 4: Prediction Approach

The prediction approach cluster functions as a supporting cluster within the comprehensive network, focusing on the prospective development of urban form over time. The leading term of this cluster is "urban growth patterns" (OCC = 9, TLS = 40), followed by "urban patterns complexity" (OCC = 3, TLS = 12) and "urban growth dynamics" (OCC = 3, TLS = 10).

Substantially, urban growth patterns are examined in strong connection with morphological aspects related to LULC changes including (1) consideration of the dynamic interplay between planned development and actual growth patterns [19], (2) analysis of spatiotemporal patterns of urban expansion through LULC changes [30], (3) analysis of growth patterns through projected mapping of mixed land use development [28], (4) analysis of fluctuations in urbanization rates over multiple time periods [40], (5) track-

ing land use transformation over time [20], and (6) deriving spatiotemporal metrics from LULC maps [36]. Some studies specifically address the construct of urban growth dynamics [20,33] in order to note variations in growth intensity and to understand urban patterns complexity emerging from new growth and urban infill [23] of existing areas. Distinctly, urban patterns complexity is tackled through the adoption of spatial metrics [33], fractal dimensions [35], and profile-based metrics [44]. Moreover, content analysis indicates that the aggregation of built-up areas is examined as one of three essential morphological characteristics alongside complexity and contiguity of built-up areas [33], demonstrating that an aggregation approach could enable spatiotemporal and quantitative analysis to evaluate urban growth patterns effectively [24].

In addition to consideration of urban growth patterns, within the predictive framework, urban transformation patterns are also considered predominantly through the notion of urban tissues [26], but also by utilizing landscape metrics to quantify transformation patterns [30]. Specifically, this cluster gathers metric-based concepts (which are not associated with the specialized cluster of metrics and structural analysis), indicating that block metrics [44] and land cover metrics [30] play a significant role in urban form prediction [35].

3.4. Synthesis Clustering Analysis

The subject of the synthesis clustering analysis is oriented towards understanding relations and conditionality in-between clusters affiliated with each of three performed clustering analyses (foundational clusters). By identifying the core impact and relevance of each cluster within synthesis analysis, this study further interprets leading approaches based on LULC mapping and urban form analysis (Table 5). Synthesis analysis engages 136 keywords from all three datasets (methods and tools, data type, and urban morphology aspects) distributed in five synthesis clusters.

Table 5. Synthesis clusters characterization: mapping influence of foundational clusters.

Synthesis Clusters	Clustering Analysis 1: Methods and Tools (CA1)					Clustering Analysis 2: Data types (CA2)			Clustering Analysis 3: Urban Morphology Aspects (CA3)			
	Statistical and Survey-Driven Analysis	Temporal and Change Detection Analysis	Spatial Configuration and Connectivity Analysis	Predictive and Transition Analysis	Quantitative Metrics-Based Analysis	Urban Density and Structural Indicators	Land Classification and Satellite-Based Observation	High-Resolution and Specialized Imagery Data	Metrics and Structural-Based Approach	Spatiotemporal Approach	Typological Classification	Prediction-Oriented Approach
Cluster 1 33 keywords	+	x	x	x	○	○	○	●	x	○	+	○
Cluster 2 32 keywords	○	x	x	○	●	+	○	x	+	x	x	○
Cluster 3 30 keywords	○	x	○	●	x	○	+	x	x	●	x	○
Cluster 4 21 keywords	x	●	x	x	x	x	+	○	+	x	x	x
Cluster 5 20 keywords	○	x	●	x	x	+	○	x	x	x	+	○

Index: x—irrelevant; ○—neutral; +—relevant; ●—core impact.

Cluster 1 (data-driven typological decoding approach) is data-driven and manifests core impact within the high-resolution and specialized imagery data cluster (derived from the CA2) followed by the relevance of typological classification cluster (derived from the CA3) and statistical and survey-driven analysis (derived from the CA1). This cluster indicates the necessity of decoding high-precise building-level features from VHR imagery and specialized data that represent the basis for the effective implementation of typological classifications of urban form and understanding of urban development intensity. By its methodological nature, the approach is focused on the application of analytical techniques (mainly statistical analysis).

Cluster 2 (quantitative structural metrics approach) is analytical-based with core impact within the quantitative metrics-based analysis cluster (derived from the CA1) followed by the relevance of urban density and structural indicators cluster (derived from the CA2) and metrics and structural-based aspect cluster (derived from the CA3). Methodologically, this cluster affirms the application of machine learning in the context of quantitatively oriented analyses that process metric data and quantitative measures, dimensions, and indicators. The application of this approach is situated in the domain of understanding the structure of urban form (both in terms of horizontal and vertical configurations), as well as urban form dynamics.

Cluster 3 (predictive spatiotemporal transition approach) has a twin nature—analytical-based and aspect-focused—with core impact within the predictive and transition analysis cluster (derived from the CA1) and spatiotemporal approach cluster (derived from the CA3) followed by the relevance of land classification and satellite-based observation cluster (derived from the CA2). This cluster indicates a conditioned relationship between predictive-oriented analysis and understanding of the morphogenetic processes and LULC transitions, highlighting the importance of time series data.

Cluster 4 (temporal change detection and performance approach) is analytical-based with core impact within the temporal and change detection analysis cluster (derived from the CA1) followed by the relevance of the land classification and satellite-based observation cluster (derived from the CA2) and metrics and structural-based approach cluster (derived from the CA3). In a methodological sense, this cluster encompasses all keywords affiliated with the temporal and change detection analysis cluster, indicating its role in studying urban land use intensity and performance of urban structure mapping. In the context of the data involved in the analytical process, remote sensing imagery and urban structure data play a leading role.

Cluster 5 (spatial configuration and density analysis approach) is analytical-based with core impact within the spatial configuration and connectivity analysis cluster (derived from the CA1) followed by the relevance of urban density and structural indicators cluster (derived from the CA2) and typological classification cluster (derived from the CA3). By its nature, this cluster is specialized operating with a distinct set of spatial configuration tools. Causally, this approach dominantly contributes to the demystification of the notion of urban density.

4. Concluding Remarks

This study successfully established crucial connections between urban morphology and LULC mapping through a detailed examination of methodological approaches, data types, and morphological aspects. The research establishes a comprehensive framework for understanding the intersection between these two domains, demonstrating how they complement and enhance each other in the study of urban form. Through content analysis of 31 literature documents spanning multiple subject areas, this research reveals the evolving landscape of urban form analysis and its intersection with advanced mapping techniques, as well as the potential for synergy between these fields, particularly at the methodological level.

The first clustering analysis revealed five distinct methodological approaches: statistical and survey-driven analysis, temporal and change detection analysis, spatial con-

figuration and connectivity analysis, predictive and transition analysis, and quantitative metrics-based analysis. This analysis demonstrated the importance of integrating various analytical methods, from traditional statistical approaches to advanced machine learning techniques with strength in combining GIS-based research strategies that bridge top-down and bottom-up approaches.

The second clustering analysis identified three prominent clusters focused on data types: urban density and structural indicators, land classification and satellite-based data, and high-resolution and specialized imagery data. These data types support various aspects of urban analysis, from understanding intensity and distribution of built-up areas to detailed morphological assessments. Comprehensively, this study highlights the complex nature of data requirements in urban morphology studies, emphasizing the need for multiscale and multisource approaches to effectively analyze urban form characteristics or perform typological classification. The findings suggest that comprehensive urban morphology analysis benefits from the integration of both broad-scale satellite data and detailed structural indicators

The third clustering analysis revealed four distinct clusters related to urban morphology: metrics and structural-based aspects, spatiotemporal aspects, typological classification, and prediction-oriented aspects. The analysis revealed significant interconnections between clusters, particularly evident in the relationship between notions related to spatial expansion and urban density patterns. This interconnectedness suggests that comprehensive urban morphological analysis requires simultaneous consideration of multiple aspects rather than isolated examination of individual elements or typological entities.

Finally, this study demonstrated the foundational and integrative framework, based on the premise that understanding the relationship and cross-interpretation of the leading (1) methods and tools, (2) types of data, and (3) aspects of urban morphology, could derive specific methodological approaches. By combining a qualitative analysis of the distribution of concepts from all three analyzed datasets, as well as a quantitative analysis of their representation in relation to foundational clusters, this study identified five specific methodological approaches. In relation to the core impact of foundational clusters, it was demonstrated that methodological approaches are built in three ways—analytical-based, data-driven, or aspect-focused. Also, it was observed that methodological approaches could be built by manifesting dual core impact. Nevertheless, the largest number of analytical-based approaches was identified, confirming the current spatial analytical paradigm of urban morphology.

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