European Journal of Geography

The publication of the European Journal of Geography (EJG) is based on the European Association of Geographers' goal to make European Geography a worldwide reference and standard. Thus, the scope of the EJG is to publish original and innovative papers that will substantially improve, in a theoretical, conceptual, or empirical way the quality of research, learning, teaching, and applying geography, as well as in promoting the significance of geography as a discipline. Submissions are encouraged to have a European dimension. The European Journal of Geography is a peer-reviewed open access journal and is published quarterly.

Received: 13/06/2024

Revised: 18/08/2024

Accepted: 06/09/2024

Published: 07/09/2024

Academic Editor:
Dr. Alexandros Bartzokas-Tsiompras

DOI: 10.48088/ejg.m.pra.15.3.190.203

ISSN: 1792-1341

Research Article

Tracking Urban Sprawl: A Systematic Review and Bibliometric Analysis of Spatio-Temporal Patterns Using Remote Sensing and GIS

Mohammad Raditia Pradana [1]✉ & Muhammad Dimyati [1]

[1] Department of Geography, Faculty of Mathematics and Natural Sciences, Universitas Indonesia, Depok, Indonesia

✉ Correspondence: raditytapradana20@gmail.com

Abstract: The urban sprawl phenomenon refers to the expansion of urban areas driven by high population growth and migration. A spatio-temporal approach is indispensable in urban sprawl research. Monitoring and evaluating urban sprawl in a region is crucial for controlling drastic environmental changes. Integrated Remote Sensing (RS) and Geographic Information System (GIS) technologies can serve as essential tools for this purpose. The aim of this systematic literature review paper is to gather information on the latest data, methods, and findings to be considered in future urban sprawl research. The PRISMA method was employed, involving filtering from the Scopus database, resulting in 30 papers selected for an in-depth review to address the objectives of this paper. Landsat data remains the preferred choice for monitoring changes due to its extensive historical archive compared to other data sources. Landscape metrics represent a more advanced method compared to conventional change detection in quantifying urban sprawl. Other indices and quantifiers are also used to support the quantification of urban sprawl. Two perspectives exist in selecting the study's temporal intervals: consistent and inconsistent, which are adjusted based on the natural characteristics of "change," namely "abrupt" and "gradual." Suggestions for future research include using data with detailed spatial resolution and narrow study intervals while considering the patterns of urban sprawl formation.

Keywords: bibliometric; geographic information system; landsat; remote sensing; urban sprawl; systematic literature review

Highlights:

- Spatio-temporal approach: Vital for understanding urban sprawl dynamics.
- Remote Sensing and GIS integration: Key for monitoring and controlling sprawl.
- Indices and landscape metrics: Crucial tools for quantifying sprawl change.

1.Introduction

Urbanization is a powerful driver of dynamic changes in both time and space, as it continues to reshape the global landscape (Rahman et al., 2024). As noted by the UN Department of Economic and Social Affairs (2018), 56% of the world's population resided in urban areas in 2020, with projections suggesting an increase to 68% by 2050. The rapid urbanization process often leads to the phenomenon of uncontrolled urban sprawl, which has already impacted many major cities and megacities around the world (Mun et al., 2024; UN Department of Economic and Social Affairs, 2018)

Urban sprawl, characterized by the expansion of urban areas into surrounding rural lands, is a critical consequence of urbanization. This phenomenon results in landscape fragmentation, increased automobile dependence, and the depletion of natural resources, significantly altering the socio-economic and environmental fabric of cities (Bhatta, 2010; Cramer-Greenbaum, 2023; Yan et al., 2024). As urbanization continues at an unprecedented rate, it becomes crucial for city planners, policymakers, and environmental observers to understand the underlying dynamics of urban sprawl (D'Agata et al., 2024; Hysa et al., 2024)

The impacts of urban sprawl are not limited to physical expansion alone. Social and economic disparities often become exacerbated within urban areas, leading to unequal access to resources, services, and opportunities (D'Agata et al., 2024; Taubenböck et al., 2009). Furthermore, the environmental consequences of sprawl, such as increased air and water pollution, loss of biodiversity, and higher carbon emissions, present significant challenges to sustainability and public health (Anand & Deb, 2024; Hysa et al., 2024; Raza et al., 2024). Understanding these multifaceted dynamics is essential for devising effective urban planning strategies that promote equitable development while mitigating environmental degradation (Hamidi et al., 2015; Raza et al., 2024).

The role of Remote Sensing (RS) and Geographic Information Systems (GIS) in monitoring, analyzing, and visualizing urban growth cannot be overstated. These technologies have revolutionized the field by enabling the collection and interpretation of vast amounts of spatial and temporal data, providing deep insights into the patterns and processes driving urban expansion (Alzahrani et al., 2024; Miller et al., 2024; Nolè et al., 2014; Torrens, 2008). RS and GIS facilitate the detection of land-use changes, quantification of urban sprawl, and uncovering of underlying drivers with unprecedented precision (Frenkel & Ashkenazi, 2008; Rana et al., 2024; Sudhira et al., 2004).

However, measuring urban sprawl remains a contentious issue among scholars. Various methods have been developed, each with its strengths and limitations. The complexity of these methods often renders them impractical for underfunded or data-deficient regions (Fuladlu et al., 2021). In response, some studies have developed more accessible and adaptable methodologies for monitoring urban sprawl in developing regions (Frenkel & Ashkenazi, 2008). These advancements are critical as they enable a broader application of sprawl metrics across different geographic and socio-economic contexts.

This paper systematically reviews previous studies on the application of change detection using RS and GIS for quantifying urban sprawl. The review focuses on the data, methods, and findings from these studies, assessing the prominence of specific countries in urban sprawl research, the types of data used, the change detection techniques employed, and the indices used to quantify urban sprawl (Bhatta, 2010; Page et al., 2021). Additionally, a bibliometric analysis will be conducted to identify research trends, influential studies, and emerging themes within the literature, offering a comprehensive overview of the current state of urban sprawl research (van Eck & Waltman, 2010). This research offers a comprehensive assessment of global trends and methodological advancements using some research for sampling. By combining both bibliometric analysis and systematic review, we not only map the evolution of urban sprawl research but also identify emerging techniques and regional disparities that have been overlooked in the existing literature.

2. Literature Review

2.1. Factors contributing to urban sprawl

The phenomenon of urban sprawl, or urban expansion, refers to the extensive urbanization, which is a global phenomenon primarily triggered by large-scale population growth and migration (Deng et al., 2009; Habibi & Asadi, 2011; Smith, 2020). Referring to the term "expansion" indicates that the phenomenon of urban sprawl is associated with the spatial dimension, which is an effect of urbanization (Brueckner, 2000). Besides urbanization, various other factors contribute to the phenomenon of urban sprawl, rendering it a global occurrence (Sudhira et al., 2004). Factors such as social, economic, and environmental elements contribute to urban sprawl, rendering it a global phenomenon (Galster et al., 2001; Glaeser & Kahn, 2003; Gordon & Richardson, 2000). These factors serve as "units" in quantifying urban sprawl phenomena, including physical patterns, extent developments, leapfrog development, and density change (Downs, 1999; European Environment Agency, 2008; Fulton et al., 2001).

The continuous progression of urban sprawl shapes the dynamics and spatial distribution of urban expansion fragments or urban sprawl (Irwin & Bockstael, 2007; Taubenböck et al., 2009). Uncontrolled urban sprawl emerges and proliferates due to population pressure resulting from the urbanization process, leading to unplanned urban sprawl (Wu et al., 2016). Monitoring the phenomenon of urban sprawl is crucial to safeguarding quality of life, the environment, social well-being, and even economic stability, ensuring sustainable urban management and preventing environmental degradation and the loss of valuable land (Kumar et al., 2007).

2.2. Indicators and approaches for monitoring urban sprawl

Indicators that refer to the "units" used in monitoring urban sprawl typically include: growth rate (population and urban area), density (residential and population) (L. Liu et al., 2018; Sultana & Weber, 2014)., human footprint (Gilbert & Shi, 2023), accessibility (Sohn et al., 2012), landscape patterns (Triantakonstantis & Stathakis, 2015), and even economic indicators such as the GDP of a region (Salvati et al., 2012). The spatial-temporal approach employed in monitoring urban sprawl research facilitates a thorough analysis of urban expansion patterns over time (Kar et al., 2018). The integration of spatial and temporal dimensions offers a comprehensive understanding of the dynamics and distribution of urban sprawl within the framework of environmental changes and urban development (Jain et al., 2016; Kumar et al., 2007; Sun et al., 2013). Conversely, employing landscape metrics offers a detailed analysis of spatial patterns and their changes over time, providing valuable insights into the drivers and impacts of urban sprawl too (Berila & Isufi, 2021; Jain et al., 2016; Triantakonstantis & Stathakis, 2015).

Urban sprawl manifests through specific spatial patterns such as leapfrog development, edge expansion, and infill development, each influencing landscape structure in measurable ways (Jiao et al., 2015, 2018; X. Liu et al., 2010; C. Xu et al., 2007). These patterns are often analyzed using landscape metrics or indices, such as fragmentation, patch density, and edge contrast, which quantify the effects of sprawl on land use and urban form. Leapfrog development leads to high fragmentation and increased patchiness, disrupting ecological connectivity, while edge expansion results in elongated urban fringes that can be measured by edge density and shape complexity. Infill development, though sometimes intended to optimize land use, can intensify core area metrics, contributing to congestion and infrastructure strain (G. Xu et al., 2020). Landscape metrics to better understand and compare these spatial patterns, particularly in rapidly urbanizing regions where traditional sprawl dynamics may differ significantly from those observed in developed countries (Balandi et al., 2023; Behnisch et al., 2022).

2.3. Advantages of Remote Sensing and GIS in Quantifying Urban Sprawl

Remote sensing (RS) and Geographic Information System (GIS) offer advantages that can be implemented in quantifying urban sprawl (Berila & Isufi, 2021; Yulianto et al., 2020). Starting from consistent data availability, comprehensive spatial analysis, and the ability to formulate a prediction model, RS and GIS can accommodate spatio-temporal approaches in urban sprawl research (Al-shalabi et al., 2013; Baqa et al., 2021). RS technologies, including satellite imagery and aerial photography, provide valuable spatial data with improved spatial resolution and temporal coverage, enabling more accurate and detailed assessments of urban land cover changes over time (Taubenböck et al., 2009). GIS complements RS by offering powerful tools for spatial analysis and modeling, facilitating the integration of diverse datasets related to urban development, such as land cover, land use, population density, infrastructure, and environmental factors (Berila & Isufi, 2021; Yulianto et al., 2020).

Furthermore, the emergence of advanced RS and GIS techniques, such as object-based image analysis (OBIA) and machine learning algorithms, has enhanced the capability to extract relevant information from remotely sensed data and automate the process of urban sprawl detection and monitoring (Pokhariya et al., 2021; Rana et al., 2024). These advancements have greatly contributed to the refinement of methodologies for quantifying urban sprawl, providing urban planners, policymakers, and researchers with valuable insights for sustainable urban development and land management strategies.

https://doi.org/10.48088/ejg.m.pra.15.3.190.203

3. Materials and Methods

The systematic literature review (SLR) was conducted using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology, which facilitates the various stages of filtering numerous research studies (Page et al., 2021). Apart from PRISMA, there is bibliometric analysis to enrich information related to the review carried out. Bibliometric analysis helps to understand how a specific field evolves over time and highlights the new areas of focus within it (Donthu et al., 2021).

3.1. Data source

The Scopus database is the sole data source in this SLR paper. Scopus is a comprehensive abstract and citation database covering a wide range of academic disciplines, offering tools for citation analysis and tracking research impact (Pranckutė, 2021). Data extraction was conducted on February 27, 2024, using the TITLE-ABS-KEY feature. Articles were searched using the following query: **TITLE-ABS-KEY ("GIS" "Remote Sensing" "Urban Sprawl")**, which was then exported in BibTeX and CSV formats for all required information.

3.2. Screening

The screening stage aims to limit the number of studies from the search results obtained through the query. In this paper, the screening was conducted by limiting papers to the time frame of 2000-2024, written in English, and restricting the document types to only include Articles and Conference papers (Figure 1). The final query format for this screening was as follows: **TITLE-ABS-KEY ("GIS" "Remote Sensing" "Urban Sprawl") AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (PUBSTAGE , "final")).**

3.3. Eligibility

Eligible papers are those that meet the following criteria: (1) relevance to the topic, (2) inclusion of GIS and RS elements, and (3) incorporation of change detection within the article. A total of 30 articles were reviewed to represent a broad overview of the data, methods, and findings of RS and GIS applications in the urban sprawl phenomenon (Figure 1). The deep review criteria for inclusion were centered around the articles' citation counts, with a minimum of 20 citations to ensure the consideration of well-regarded and impactful research. Furthermore, the relevance of each article to the core topics of change detection, remote sensing methodologies, and the application of landscape metrics and indices was a key factor in their selection.

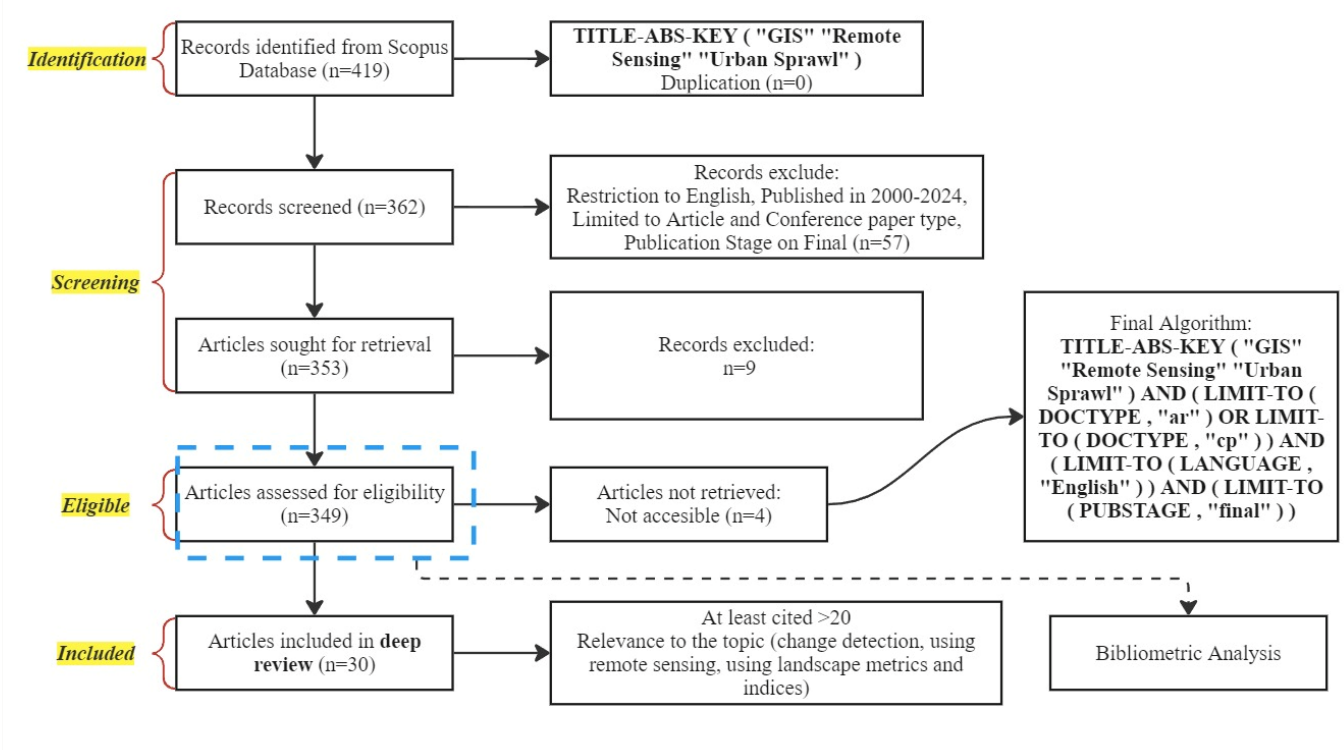

Figure 1. PRISMA flow diagram for SLR and bibliometric analysis.

4. Results

4.1. Findings

All papers that are included in the included stage are tabulated to obtain the acquired information. This information includes the data of the hospitals used, the temporal interval of the study period, the use of landscape metrics/index, other indices and quantifiers used, and the countries examined in the research. This tabulation is depicted in Table 1.

Table 1. Tabulation of reviewed literature.

Ref.	Remote Sensing and GIS Data	Interval Temporal	Landscape metric/index		Indices and other quantifier	Country
			Usability	Metric/index		
(Al-shalabi et al., 2013)	Quick bird, Aerial Photogrpahy,	1994-2003	No			Yemen
(Sun et al., 2013)	Landsat 3 MSS, 5 TM, 7 ETM+	1979-1990-1995-2000-2008	Yes	Patch Density (PD) Landscape Shape Index (LSI) Euclidean Nearest-Neighbour Distance (ENN) Mean Patch Size (MPS) Landscape Expansion Index (LEI)	NDWI[8]	China
(Alsharif & Pradhan, 2014)	Landsat, SPOT 5	1984-2002-2010	No			Libya
(Boori et al., 2015)	Landsat 5 TM dan Landsat 7 ETM+	1989-2001-2014	No		Urban density, Urban growth rate	Malaysia
(Zeng et al., 2015)	Landsat 5 TM, 7 ETM+, ALOS/AVNIR-2, Landsat 8 OLI/TIRS	1990-1995-2000-2005-2010-2013	No		Spatial autocorrelation index (Moran's I) Shannon's entropy (SE) Gravity center migration (GCM)	China
(Jain et al., 2016)	Landsat 3 MSS, 8 OLI/TIRS. IRS	1977-1993-2006-2014	Yes	No. of patches Patch density Total edge Edge density AWMSI AWM-PFD CI		India
(El Garouani et al., 2017)	Landsat 8 OLI/TIRS	1984-2013	No		VSW[3] Urban Sprawl Index	Morocco
(Ahmed, 2018)	Landsat 5 TM, 7 ETM+, 8 OLI/TIRS, ASTER	1988-2008-2011-2014	No		NDVI[1], NDBI[4], UTFVI[5]	Egypt
(E. Dai et al., 2018)	Landsat 5 TM dan Landsat 7 ETM+	1985-1990-2000	Yes	Largest patch index (LPI) Mean patch area (AREA_MN) Contagion index (CONTAG) Interspersion and juxtaposition index (IJI) Shannon's diversity index (SHDI) Shannon's evenness index (SHEI)		China
(Kar et al., 2018)	Landsat 5 TM	1991-2010	No			India
(Patra et al., 2018)	Landsat 7 ETM+ and 5 TM, Indian Remote Sensing (IRS)	1975-1989-2000-2009-2015	No		NDBI[4]	India
(Shaw & Das, 2018)	Landsat 5 TM dan Landsat 7 ETM+	1987-2003-2015	No		The Urbanization intensity index (UII) Shannon's entropy (SE)	India
(Akubia & Bruns, 2019)	Worldview 2 imagery, 2017Quickbird +Worldview 2 imagery, 2008/2009	2008-2017	No		AUERi (Annual Urban Expansion Rate) UGC (Urban Growth Coefficient) UEII (Urban Expansion Intensity Index) UEDi (Urban Expansion Differentiation Index)	Ghana
(Dutta & Das, 2019)		1991-2001-2011-2016	Yes	Landscape Expansion Index (LEI) Landscape Shape Index (LSI)		India

	Landsat 5 TM dan Landsat 8 OLI/TIRS			Euclidean Nearest-Neighbour distance (ENN) Aggregation Index (AI) Ratio of open space (ROS)		
(Yulianto et al., 2020)	Landsat	1990-1996-2000-2003-2009-2016	No		Shannon's entropy (SE)	Indonesia
(Baqa et al., 2021)	Landsat 5 TM, Landsat 8 OLI/TIRS	1990-2000-2010-2020	No			Pakistan
(Berila & Isufi, 2021)	Landsat 7 ETM+ and 8 OLI/TIRS	2000-2020	Yes	Class area (CA) Mean Patch Edge (MPE) Total Edge (TE) Number of Patches (NUMP) Edge Density (ED) mean patch size (MPS) Patch Size Coefficient of Variation (PSCOV) Patch Size Standard Deviation (PSSD) Mean shape index (MSI), Area Weighted Mean Patch Fractal Dimension (AWMPFD) Mean Perimeter–Area Ratio (MPAR)		Kosovo
(X. Dai et al., 2022)	GlobeLand30 remote sensing image data, NPP/VIIRS nighttime light data	2000-2010-2020	Yes	Richardson index (RI) Cole index (CI)	ACx (Accessibility of a certain urban settlement) Nighttime light intensity (NLI) Point Density (PD) POIs mixed index (PMI)	China
(Al-Dousari et al., 2023)	Sentinel 2 Level 1C	2016-2021	No			Iraq
(Aslam et al., 2023)	Landsat 5 TM and Landsat 8 OLI/TIRS	1990-2000-2010-2020	No			Pakistan
(Aurora & Furuya, 2023)	Landsat 5 TM and 8 OLI/TIRS	1990-2021	Yes	Total Edge (TE) Perimeter–Area Fractal Dimension (PAFRAC) Mean Fractal Dimension Index (FRAC_MN) Mean Shape Index (SHAPE_MN) Mean of Euclidean Nearest-Neighbour Distance (ENN_MN) Number of Patch (NP) Landscape Shape Index (LSI) Landscape Division Index (DIVISION	Shannon's entropy (SE)	Japan
(Gogoi et al., 2023)	Landsat 4-5 TM dan Landsat 8 OLI/TIRS	1990-2020	No		NDVI[1], UI[2]	India
(Medayese et al., 2023)	Landsat	1999-2019	Yes	Landscape Expansion Index (LEI) Euclidean Nearest-Neighbour distance (ENN) Aggregation Index (AI) MGRATE	SAVI[9], UI[2], MNDWI[6] Urban Expansion Intensity Index (UEII) Urban Expansion Differentiation Index (UEDI)	Nigeria
(Rana et al., 2024)	Landsat 5 TM, Landsat 8 OLI/TIRS	1991-1996-2001-2006-2011-2016-2021	No		NDVI[1], NDBI[4], NDWI[8], UTFVI[5]	India

(Selmy et al., 2023)	Landsat 5 TM, Landsat 7 ETM+, Landsat 8 and 9 OLI/TIRS, ASTER	1984-2002-2013-2022	No		MNDWI[6], NDVI[1], NDBI[4], DBSI[7]	Egypt
(Wang et al., 2023)	Landsat 5 TM, 7 ETM+, 8 OLI/TIRS	1990-2000-2010-2020	Yes	Fractal Dimension (St) Compactness index (Ct) Shannon's diversity index (SHDI) Shannon's evenness index (SHEI) Aggregation Index (AI)	NDBI[4] Urban expansion rate Urban expansion intensity index Contribution of urban expansion	China
(Gilbert & Shi, 2023)	Landsat 7 ETM+ and Landsat 8 OLI/TIRS, MODIS, DMSP-OLS dataset covers	2000-2010-2020	No		NDVI[1]	Nigeria
(L. Zhang et al., 2023)	DMSP- OLS and NPP-DNB	2000-2020 (for each year)	No		Urban Sprawl Index, Vertical Sprawl Index, NDVI[1]	China
(Bozkurt & Basaraner, 2024)	CORINE (Land Cover dataset)	1990-2018	Yes	Mean shape index (MSI) Area weighted mean shape index (AWMSI) Mean perimeter-area ratio (MPAR) Mean patch fractal dimension (MPFD) Total edge (TE) Edge density (ED) Mean patch edge (MPE) Mean patch size (MPS) Number of patches (NumP) Class Area (CA) Shannon's diversity index (SHDI) Shannon's evenness index (SHEI)	Shannon's entropy (SE)	Turkey
(Waleed et al., 2024)	Landsat 5 TM, 8 OLI/TIRS	1990-200-2010-2020	No			Pakistan

[1] NDVI: Normalized Difference Vegetation Index.
[2] UI: Urban Index.
[3] VSW: Visible and Shortwave Infrared.
[4] NDBI: Normalized Difference Built-up Index.
[5] UTFVI: Urban Thermal Field Variance Index.
[6] MNDWI: Modified Normalized Difference Water Index.
[7] DBSI: Dry Bare Soil Index.
[8] NDWI: Normalized Difference Water Index.
[9] SAVI: Soil Adjusted Vegetation Index.

4.2. The distribution of research based on countries and its population size

Research on urban sprawl typically focuses on countries undergoing significant urbanization and experiencing high population growth, as these conditions are strongly linked to the emergence and intensification of urban sprawl (Deng et al., 2011; Mdari et al., 2022; Waleed et al., 2024). In Table 1, research examining areas in China amounts to 6 (E. Dai et al., 2018; X. Dai et al., 2022; Sun et al., 2013; Wang et al., 2023; Zeng et al., 2015; L. Zhang et al., 2023) and India amounts to 7 (Dutta & Das, 2019; Gogoi et al., 2023; Jain et al., 2016; Kar et al., 2018; Patra et al., 2018; Pokhariya et al., 2021; Shaw & Das, 2018). This distribution suggests a correlation between population size and the prevalence of urban sprawl research. However, high population alone does not directly correlate with the highest levels of urbanization. In 2023, China has an urban population of 65% with an urban growth rate of 1.5%, whereas India has 36% of its population urbanized with an urban growth rate of 2.2% (World Bank, 2024). Thus, a comparative analysis, considering global urbanization trends, could provide a deeper understanding of the interplay between population size, urbanization, and urban sprawl. However, the relationship between urbanization and urban sprawl is complex and can be influenced by various factors, including economic conditions, government policies, and historical contexts (Fuladlu et al., 2021; Hall & Jones, 1999).

Figure 2 represents the bibliometric results of 349 eligible papers, showcasing the amount of research produced by a country and its collaborations. This supports the idea that countries with high populations, such as India, China, and the United States, which are the top three in terms of population, are producing a significant amount of research. Urban sprawl develops as a result of uncontrolled and unplanned expansion of urban areas into surrounding rural or undeveloped land. Initially, cities expand outward in a fragmented fashion due to factors such as rapid population growth and insufficient urban planning. This results in scattered low-density developments that eventually merge into larger interconnected urban sprawl. As these areas coalesce, researchers focus on urban sprawl to address its environmental, social, and economic impacts. Methods such as remote sensing, GIS, and landscape metrics are used to analyze and quantify these changes, providing critical insights into the challenges of managing sprawling urban growth (Al-Dousari et al., 2023; Aslam et al., 2023; Dutta & Das, 2019; Jain et al., 2016). The dynamics of this phenomenon can be interpreted from various perspectives, such as growth (urban growth), expansion/spread (urban sprawl), development (urban development), and planning (urban planning) (Aurora & Furuya, 2023; Baqa et al., 2021; Shaw & Das, 2018; L. Zhang et al., 2023). These perspectives are reflected in the bibliometric results (Figure 3), which illustrate the emergence of relevant terms related to the topic of urban sprawl.

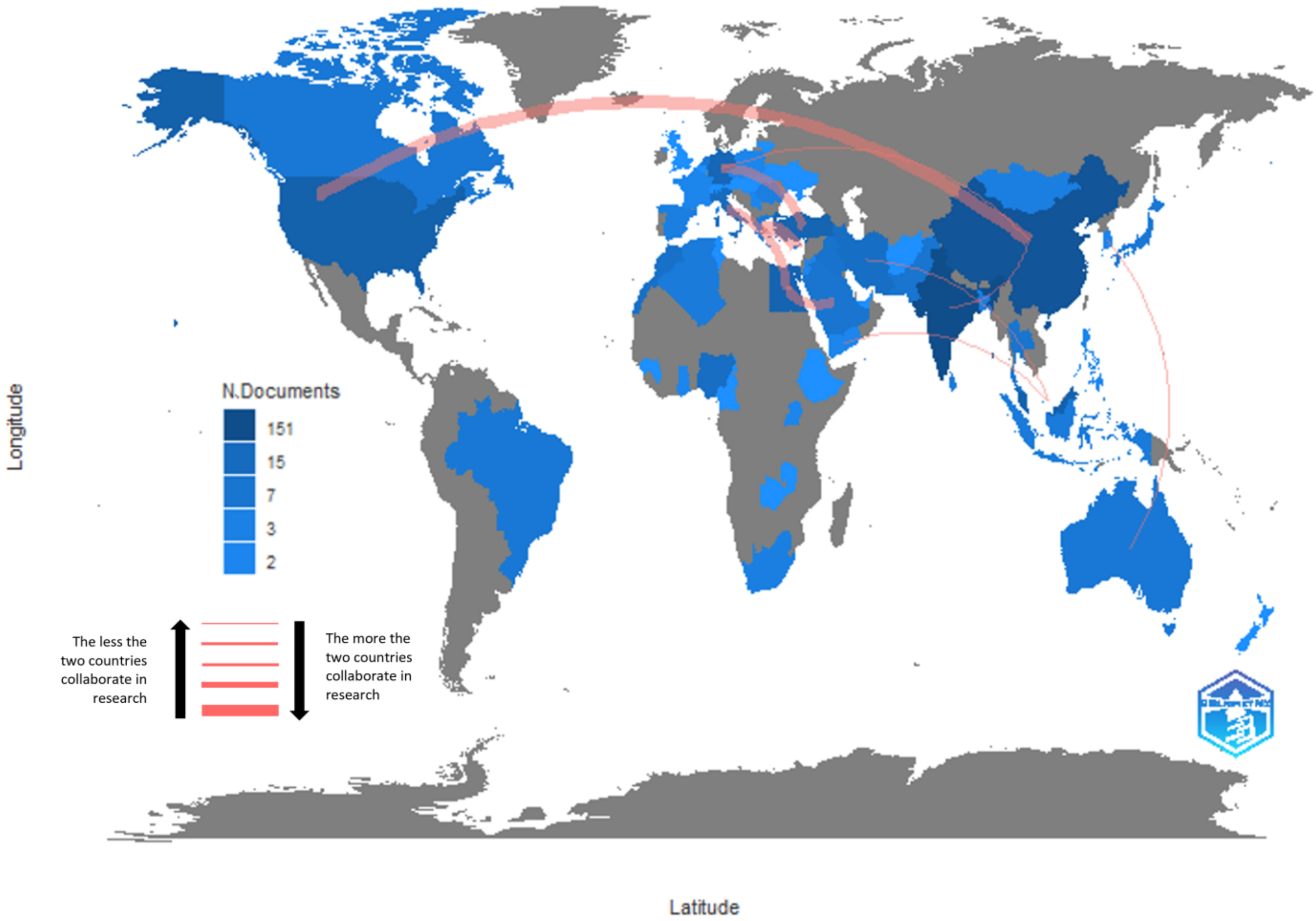

Figure 2. Bibliometric result for country scientific production and collaboration.

4.3. The utilization of Remote Sensing and GIS data in urban sprawl research

Based on Table 1, which indicates the publication range of research spanning from 2000 to 2024, various types of remote sensing (RS) data are used. Landsat 4-9 (TM, ETM+, OLI/TIRS) data (Gogoi et al., 2023; Selmy et al., 2023), SPOT 5 (Jain et al., 2016), Sentinel 2 (Al-Dousari et al., 2023), IRS (Patra et al., 2018), WorldView 2 (Akubia & Bruns, 2019), Quickbird (Akubia & Bruns, 2019), DMP-OLS (nighttime lights) (L. Zhang et al., 2023), NPP/VIIRS (nighttime lights) (X. Dai et al., 2022), dan aerial photography (Al-shalabi et al., 2013) are examples of multispectral RS data, most of which include at least visible bands. The dominance of Landsat (4-9) is evident, with 24 out of 30 reviewed studies choosing Landsat (4-9) data as the primary RS data for monitoring urban sprawl dynamics or change detection (Aurora & Furuya, 2023). The availability of long-term Landsat data is considered advantageous compared to other RS data, such as Sentinel 2, which was launched in 2015, despite having higher spatial resolution (10 m) compared to Landsat (30 m). Landsat has been available since 1982 for Landsat 4 TM (Gogoi et al., 2023). The dominance of Landsat data usage is also reflected in Figure 4, which indicates the relevance of keywords in the 349 studies analyzed bibliometrically.

Multispectral data other than Landsat, such as SPOT 5, Sentinel 2, WorldView 2, Quickbird, and aerial photography, indeed have a disadvantage in terms of long-term availability. However, they offer the advantage of higher spatial resolution (Akubia & Bruns, 2019). Data with detailed spatial resolution but low temporal availability are often used as training data for classifying lower spatial resolution RS data, in addition to ground truth data or field surveys.

Other thematic data such as MODIS, DMP-OLS (nighttime lights), NPP/VIIRS (nighttime lights) (Gilbert & Shi, 2023), and ASTER (Selmy et al., 2023) play a role as parameters for climate, topography, and human footprint to investigate the relationship between these parameters and the phenomenon of urban sprawl. Additionally, data such as CORINE (Bozkurt & Basaraner, 2024) and GlobeLand 30 (X. Dai et al., 2022) are datasets derived from RS data and are widely used as reference data for classifying other RS data. CORINE Land Cover (CLC) provides land cover data for

https://doi.org/10.48088/ejg.m.pra.15.3.190.203

Europe with updates in 2000, 2006, 2012, and 2018. It includes 44 land cover classes, with a spatial resolution of 25 hectares for areal features and 100 meters for linear features. The dataset also features change layers at a higher resolution of 5 hectares (Copernicus, 2020). GlobeLand 30 offers global land cover data for the years 2000 and 2010, with a spatial resolution of 30 meters and 10 land cover classes (Chen et al., 2015). This finer resolution allows for detailed monitoring of land cover changes.

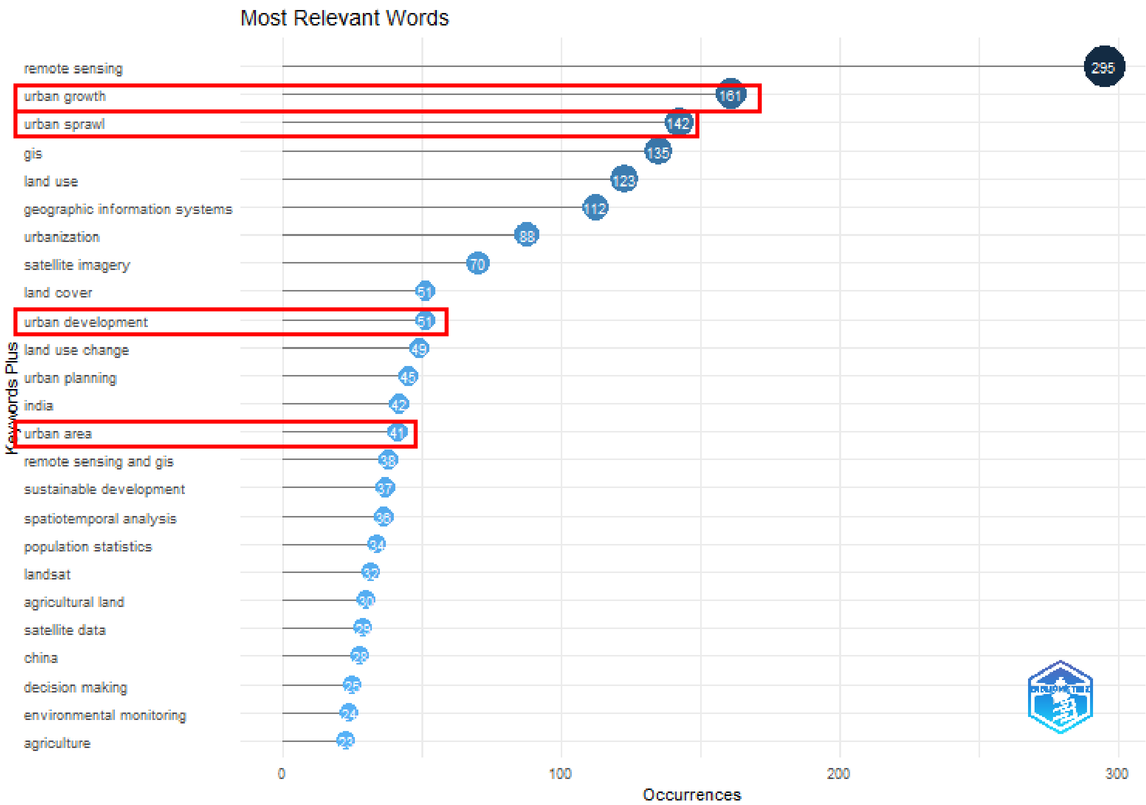

Figure 3. Bibliometric result for most relevance word.

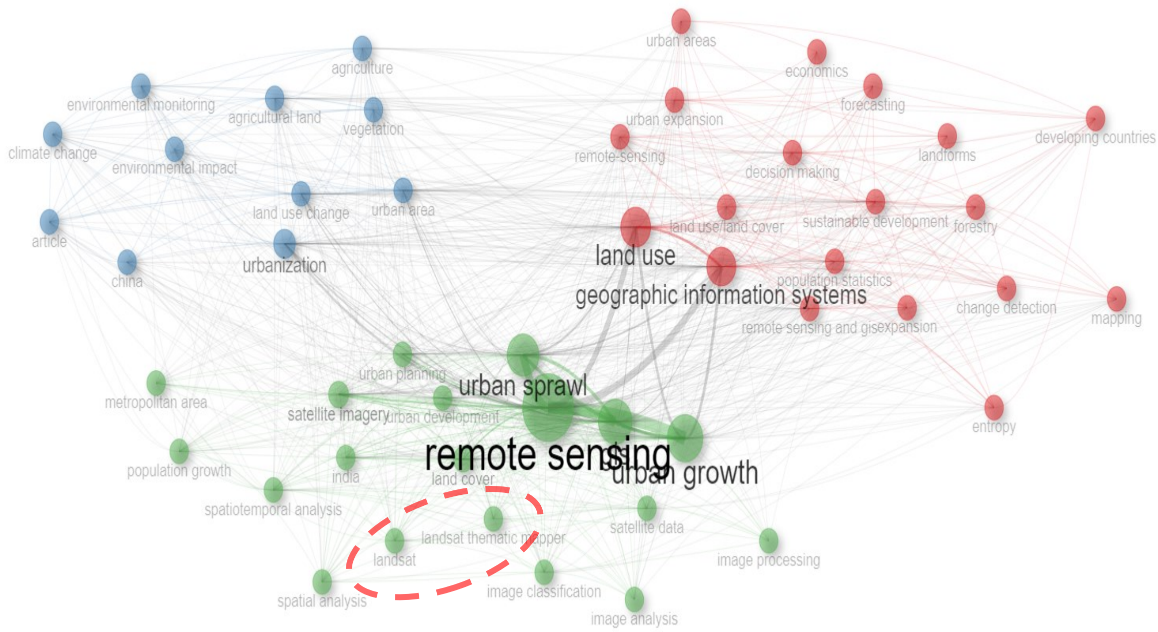

Figure 4. Bibliometric result for collaboration word network.

https://doi.org/10.48088/ejg.m.pra.15.3.190.203

4.4. Method for quantifying urban sprawl

The methods used in quantifying urban sprawl range from simple to complex methods. The variety of these methods can be seen from the temporal data intervals used, analysis of change patterns, and indices as well as quantifiers to provide urban sprawl quantification results. From these 30 studies, there are at least two types of temporal data interval usage, as referred to in Table 1: consistent and inconsistent temporal intervals. Consistent temporal intervals mean that each remote sensing data used has the same temporal distance, such as the studies by Aslam et al. (2023) and Wang et al. (2023) which have intervals of 10 years (1990, 2000, 2010, and 2020). In contrast to these two studies, Sun et al. (2013) used inconsistent intervals (1979, 1990, 1995, 2000, and 2008), and the same is done by Jain et al. (2016), also inconsistent in determining the interval of data used (1977, 1993, 2006, and 2014). If observed, there are two views of "change" used, namely "abrupt" and "gradual" as proposed by Woodcock et al. (2020) dan Coppin et al. (2004).

The landscape metrics method in investigating urban sprawl is the next step from “conventional” change detection, which only calculates the area of land use land cover (LULC) changes. Research from Aurora & Furuya (2023); Berila & Isufi (2021); Bozkurt & Basaraner (2024); E. Dai et al. (2018); X. Dai et al. (2022); Dutta & Das (2019); Jain et al. (20160; Medayese et al. (2023); Sun et al. (2013); dan Wang et al. (2023) used landscape metrics to monitor changes resulting from urban sprawl, or at least a third of the reviewed studies utilize landscape metrics for quantifying change detection due to urban sprawl.

According to Table 1, the indices discussed serve as critical tools from the spectral aspect of remote sensing, enabling a comprehensive analysis of urban sprawl. These indices provide vital insights into various dimensions of urban expansion and its environmental impact. The Normalized Difference Vegetation Index (NDVI) (Rouse, J. W. et al., 1974) and Soil Adjusted Vegetation Index (SAVI) (Huete, 1988) are fundamental for assessing vegetation cover, allowing for monitoring the reduction of green spaces as urban areas spread. The Urban Index (UI) (Kawamura et al., 1997) and Normalized Difference Built-up Index (NDBI) (Y. Zha & Ni, 2003) are essential for measuring the extent and intensity of urbanization, enabling the mapping of built-up areas and their encroachment into natural landscapes. Visible and Shortwave Infrared (VSW) (N. Zhang et al., 2013) analysis further enriches this understanding by offering detailed information on land cover changes. The Modified Normalized Difference Water Index (MNDWI) (H. Xu, 2005) and Normalized Difference Water Index (NDWI) (Gao, 1996) provide crucial insights into the effects of urban sprawl on water bodies, often impacted by increased runoff and pollution as cities grow. The Urban Thermal Field Variance Index (UTFVI) (L. Liu & Zhang, 2011) is indispensable for evaluating the urban heat island effect, a frequent consequence of sprawl, while the Dry Bare Soil Index (DBSI) (Rasul et al., 2018) aids in identifying exposed soils, which often indicate areas transitioning from natural or agricultural land to urban uses. Collectively, these indices form a comprehensive toolkit from the spectral remote sensing perspective, offering both classification capabilities and detailed information on urbanization degrees, vegetation loss, water body changes, and thermal variations across sprawling urban landscapes.

Other indices and quantifiers in those 30 studies are divided into two, namely indices implemented in remote sensing such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-Up Index (NDBI), Normalized Difference Water Index (NDWI), Modified Normalized Difference Water Index (MNDWI), Urban Index (UI), Dry Bare Soil Index (DBSI), and Soil Adjusted Vegetation Index (SAVI) (Ahmed, 2018; Gilbert & Shi, 2023; Gogoi et al., 2023; Medayese et al., 2023; Patra et al., 2018; Rana et al., 2024; Selmy et al., 2023; Wu et al., 2016; L. Zhang et al., 2023) Another index or quantifier is an index designed to evaluate the extent of new urban area expansion, such as the Urban Sprawl Index (USI), Urbanisation Intensity Index (UII), Urban density, Urban growth rate, Nighttime light intensity (NLI), Point Density (PD), POIs mixed index (PMI), Annual Urban Expansion Rate (AUERi), Urban Growth Coefficient (UGC), Urban Expansion Intensity Index (UEII), and Urban Expansion Differentiation Index (UEDI) (Akubia & Bruns, 2019; Boori et al., 2015; X. Dai et al., 2022; Dutta & Das, 2019; El Garouani et al., 2017; Medayese et al., 2023; Wang et al., 2023; L. Zhang et al., 2023).

5. Discussion

Among the 30 papers on urban sprawl that meet the criteria, the research output is notably high in countries with significant urbanization, such as China, India, the United States, and several European nations. This suggests that these countries are not only active in urban sprawl research but may also serve as major research hubs in the field. The substantial urban growth in these regions highlights the urgency for comprehensive studies on the consequences and management of urban sprawl. Further investigation could reveal whether these countries are indeed central research centers for urban sprawl or if their research output is a result of their extensive urbanization challenges. This disparity highlights a varied geographic focus within urban sprawl research. For instance, while research in China and India frequently targets rapidly urbanizing metropolitan areas, studies in the U.S. may address urban sprawl in different contexts or regions, reflecting unique local challenges. Furthermore, research from African countries and Kosovo presents additional perspectives on urban sprawl, emphasizing the global nature of the issue and the diverse scenarios in which urban expansion occurs. The global distribution of research underscores the complexity of urban sprawl and the need for localized solutions that account for regional differences (Deng et al., 2009; Taubenböck et al., 2009; Waleed et al., 2024). This study comprehensively reviews previous research, focusing on data, methodologies, and findings related to urban sprawl. Although the discussion of data and methodologies is robust, this paper enhances the exploration of findings to better align with the research objectives. By further exploring the spatial patterns observed and their implications, the study strengthens its contributions to the understanding of urban sprawl dynamics and their monitoring.

Landsat data, despite its moderate spatial resolution, has become a cornerstone in urban sprawl studies because of its extensive historical coverage (Selmy et al., 2023). he ability to perform long-term change detection is crucial for identifying trends and shifts in land cover patterns. However, the limitations of Landsat's resolution necessitate the use of higher-resolution remote sensing data to enhance the accuracy of classification and interpretation. By integrating higher-resolution data, researchers can overcome the spatial limitations of Landsat imagery, allowing for more detailed examinations of urban sprawl's spatial characteristics.

Remote sensing data with higher spatial resolution plays an important role in classifying satellite imagery with lower or moderate spatial resolution. This detailed remote sensing data is often used as reference or training data (Roelfsema, 2010), aiding in improving classification accuracy and interpretation of satellite imagery with lower resolution. This provides an opportunity to examine changes in land cover patterns in more detail. The discussion also highlights the importance of using various types of thematic data, such as climate data, human footprint indices, and topographic information, to complement satellite imagery. These additional data sources provide a more nuanced understanding of the factors influencing urban sprawl, enabling a holistic analysis of its causes and effects. The integration of such data is essential for developing comprehensive management strategies that address the multifaceted nature of urban sprawl.

https://doi.org/10.48088/ejg.m.pra.15.3.190.203

In selecting temporal data intervals, two common approaches are used: "abrupt" and "gradual." The "abrupt" approach emphasizes sudden changes that occur over a short period, while the "gradual" approach focuses more on changes that occur gradually over a longer period. For example, the expansion of an urban region does not occur suddenly, yet neither does it proceed in a uniformly gradual manner. Instead, it often manifests as a series of numerous minor abrupt alterations. Although the exact delineation of "abrupt" and "gradual" may pose challenges in terms of precise definition, they are undeniably valuable as comparative descriptors. It is evident that remote sensing has proven highly effective in examining abrupt transformations, while also facilitating the surveillance of more gradual shifts (Vogelmann et al., 2016; Woodcock et al., 2020). The use of landscape metrics is the next step in quantifying urban sprawl to gain a deeper understanding of the emerging patterns of urban sprawl over time. Landscape metrics have proven invaluable in quantifying the spatial patterns of urban sprawl. These metrics allow for the assessment of urban sprawl's structural characteristics, providing insights into how urban areas evolve over time. The use of indices and quantifiers in conjunction with these metrics enables a more comprehensive analysis, facilitating the identification of specific patterns and trends that might otherwise go unnoticed.

The role of GIS and RS in understanding urban sprawl cannot be overstated. From the data availability perspective (Kadhim et al., 2016), this technology provides access to various spatial and non-spatial data sources needed to analyze urbanization phenomena holistically (He et al., 2023). By combining data from various sources, including satellite imagery, climate data, and socio-economic data, GIS and RS analysis can provide a comprehensive picture of the patterns (E. Dai et al., 2018; Jain et al., 2016), causes (Taubenböck et al., 2009), and relationships of urban sprawl with other spatial-temporal factors.

Furthermore, the spatial-temporal approach supported by GIS and RS enables researchers to analyze urban sprawl changes dynamically over time. By leveraging spatial-temporal analysis tools, such as change detection analysis, spatial modeling, and space-time interpolation, we can map and understand the evolution of urbanization better. Additionally, by integrating advanced computational techniques such as machine learning (Rana et al., 2024), deep learning (Miller et al., 2024), and artificial intelligence (AI) (Kulwant & Patel, 2024), we can identify complex patterns, analyze deeper cause-and-effect relationships, and explore the relationships between urban sprawl and other spatial-temporal phenomena in more detail. Thus, GIS and RS not only provide tools to understand urban sprawl but also open opportunities to gain new insights into the complexity of urban development and their interactions with the environment and society.

The integration of GIS and RS technologies has significantly enhanced our ability to analyze urban sprawl. By combining spatial and non-spatial data, these technologies offer a powerful toolset for understanding the complex relationships between urban sprawl and other environmental and socio-economic factors. The use of advanced computational techniques, such as machine learning, deep learning, and artificial intelligence, further enhances our capacity to model, predict, and manage urban sprawl, offering new avenues for research and innovation.

5.1. Limitation

This review study has several limitations. Firstly, the number of papers reviewed may be constrained by the availability of relevant literature on the same topic. This could affect the overall representation of the studied spatio-temporal patterns. Secondly, although this study provides comprehensive bibliometric analysis, it has not yet reached the stage of conducting in-depth evaluations of the results from the reviewed papers. This could be a starting point for further research that is more critical.

5.2. Future research recommendation

Regarding future research, there are several areas that can be further explored. Firstly, the use of artificial intelligence (AI), machine learning (ML), and deep learning (DL) in spatio-temporal analysis could enhance the ability to detect and understand urban sprawl patterns more accurately and efficiently. Secondly, research could focus on the use of increasingly dense temporal data, such as shorter time intervals or even daily data, to gain a more detailed understanding of changes over shorter periods. Furthermore, the use of data other than Landsat with higher detail and resolution could provide deeper insights into urban sprawl dynamics. Finally, exploration of hyperspectral remote sensing could provide additional information about urban environmental composition and quality that is not available through conventional remote sensing.

6. Conclusions

The systematic literature review on spatio-temporal analysis of urban sprawl using remote sensing (RS) and GIS applications indicates that research is predominantly focused on countries with high levels of urbanization, such as China, India, the United States, and several European nations. This concentration suggests that these nations play a significant role in advancing research on urban sprawl. However, it would be beneficial to explore whether these countries are leading the research due to their urbanization challenges or if they serve as principal research centers more broadly. This deeper exploration could provide insights into the factors driving research productivity in the field of urban sprawl. This pattern highlights the critical need for focused research in areas experiencing rapid urban expansion, where effective sprawl management is essential. Landsat data, valued for its extensive historical record, remains a cornerstone in sprawl studies, offering valuable insights despite its moderate spatial resolution. To complement Landsat data, high-resolution thematic datasets—such as climate variables, anthropogenic impact measures, and topographical data—are increasingly pivotal in enhancing analytical accuracy and providing a comprehensive understanding of sprawl dynamics.

The integration of diverse data sources and advanced analytical techniques is fundamental for elucidating the complex patterns of urban sprawl. By using different temporal data intervals and advanced landscape metrics to quantify urban sprawl, we gain a detailed understanding of how sprawl patterns evolve over time. Temporal data intervals allow us to track and compare changes in land use across different periods, revealing trends and rates of expansion. Advanced landscape metrics, such as fragmentation indices and patch connectivity measures, provide insights into the spatial distribution and organization of urban areas. These metrics help in assessing the degree of sprawl, identifying patterns of fragmentation, and evaluating the impacts on ecological and social systems. Future research should leverage advanced computational methods, including artificial intelligence (AI), machine learning (ML), and sophisticated image processing algorithms, to refine sprawl detection and analysis. Expanding research to include regions with varying levels of urbanization could reveal unique sprawl characteristics and patterns not evident in highly urbanized areas. Furthermore, employing high-resolution spatial data and shorter temporal intervals will improve the detection of fine-scale sprawl changes. Exploration of hyperspectral remote sensing may also offer enhanced insights into urban environmental quality. Overall, this review underscores the importance of methodological innovation and comprehensive data integration in advancing the field of urban sprawl research and informing sustainable urban management strategies.

Funding: This research received no external funding

Acknowledgments: Acknowledgments to the Department of Geography, Faculty of Mathematics and Natural Sciences, Universitas Indonesia, for their invaluable support throughout this research.

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

References

Ahmed, S. (2018). Assessment of urban heat islands and impact of climate change on socioeconomic over Suez Governorate using remote sensing and GIS techniques. *Egyptian Journal of Remote Sensing and Space Science*, *21*(1), 15–25. https://doi.org/10.1016/j.ejrs.2017.08.001

Akubia, J. E. K., & Bruns, A. (2019). Unravelling the frontiers of urban growth: Spatio-Temporal dynamics of land-use change and urban expansion in greater Accra metropolitan area, Ghana. *Land*, *8*(9), 1–23. https://doi.org/10.3390/land8090131

Al-Dousari, A. E., Mishra, A., & Singh, S. (2023). Land use land cover change detection and urban sprawl prediction for Kuwait metropolitan region, using multi-layer perceptron neural networks (MLPNN). *Egyptian Journal of Remote Sensing and Space Science*, *26*(2), 381–392. https://doi.org/10.1016/j.ejrs.2023.05.003

Al-shalabi, M., Billa, L., Pradhan, B., Mansor, S., & Al-Sharif, A. A. A. (2013). Modelling urban growth evolution and land-use changes using GIS based cellular automata and SLEUTH models: the case of Sana'a metropolitan city, Yemen. *Environmental Earth Sciences*, *70*(1), 425–437. https://doi.org/10.1007/s12665-012-2137-6

Alsharif, A. A. A., & Pradhan, B. (2014). Urban Sprawl Analysis of Tripoli Metropolitan City (Libya) Using Remote Sensing Data and Multivariate Logistic Regression Model. *Journal of the Indian Society of Remote Sensing*, *42*(1), 149–163. https://doi.org/10.1007/s12524-013-0299-7

Alzahrani, A., Aldossary, N., & Alghamdi, J. (2024). Observing the dynamics of urban growth of Al-Baha City using GIS (2006–2021). *Alexandria Engineering Journal*, *95*, 114–131. https://doi.org/10.1016/j.aej.2024.03.096

Anand, A., & Deb, C. (2024). The potential of remote sensing and GIS in urban building energy modelling. *Energy and Built Environment*, *5*(6), 957–969. https://doi.org/10.1016/j.enbenv.2023.07.008

Aslam, R. W., Shu, H., & Yaseen, A. (2023). Monitoring the population change and urban growth of four major Pakistan cities through spatial analysis of open source data. *Annals of GIS*, *29*(3), 355–367. https://doi.org/10.1080/19475683.2023.2166989

Aurora, R. M., & Furuya, K. (2023). Spatiotemporal Analysis of Urban Sprawl and Ecological Quality Study Case: Chiba Prefecture, Japan. *Land*, *12*(11). https://doi.org/10.3390/land12112013

Balandi, J. B., To Hulu, J. P. P. M., Sambieni, K. R., Sikuzani, Y. U., Bastin, J. F., Musavandalo, C. M., Nguba, T. B., Molo, J. E. L., Selemani, T. M., Mweru, J. P. M., & Bogaert, J. (2023). Urban Sprawl and Changes in Landscape Patterns: The Case of Kisangani City and Its Periphery (DR Congo). *Land*, *12*(11), 1–14. https://doi.org/10.3390/land12112066

Baqa, M. F., Chen, F., Lu, L., Qureshi, S., Tariq, A., Wang, S., Jing, L., Hamza, S., & Li, Q. (2021). Monitoring and modeling the patterns and trends of urban growth using urban sprawl matrix and CA-Markov model: A case study of Karachi, Pakistan. *Land*, *10*(7). https://doi.org/10.3390/land10070700

Behnisch, M., Krüger, T., & Jaeger, J. A. G. (2022). Rapid rise in urban sprawl: Global hotspots and trends since 1990. *PLOS Sustainability and Transformation*, *1*(11), e0000034. https://doi.org/10.1371/journal.pstr.0000034

Berila, A., & Isufi, F. (2021). Two Decades (2000–2020) Measuring Urban Sprawl Using GIS, RS and Landscape Metrics: a Case Study of Municipality of Prishtina (Kosovo). *Journal of Ecological Engineering*, *22*(6), 114–125. https://doi.org/10.12911/22998993/137078

Bhatta, B. (2010). *Mapping and Monitoring Urban Growth BT - Analysis of Urban Growth and Sprawl from Remote Sensing Data* (B. Bhatta, Ed.; pp. 65–83). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-05299-6_5

Boori, M. S., Netzband, M., Choudhary, K., & Voženílek, V. (2015). Monitoring and modeling of urban sprawl through remote sensing and GIS in Kuala Lumpur, Malaysia. *Ecological Processes*, *4*(1), 1–10. https://doi.org/10.1186/s13717-015-0040-2

Bozkurt, S. G., & Basaraner, M. (2024). Spatio-temporal investigation of urbanization and its impact on habitat fragmentation in natural ecosystems of Istanbul using Shannon's entropy and landscape metrics in GIS. *Environment, Development and Sustainability*, *0123456789*. https://doi.org/10.1007/s10668-023-04410-7

Brueckner, J. K. (2000). Urban Sprawl: Diagnosis and Remedies. *International Regional Science Review*, *23*(2), 160–171. https://doi.org/10.1177/016001700761012710

Chen, J., Chen, J., Liao, A., Cao, X., Chen, L., Chen, X., He, C., Han, G., Peng, S., Lu, M., Zhang, W., Tong, X., & Mills, J. (2015). Global land cover mapping at 30 m resolution: A POK-based operational approach. *ISPRS Journal of Photogrammetry and Remote Sensing*, *103*, 7–27. https://doi.org/10.1016/j.isprsjprs.2014.09.002

Copernicus. (2020). *CORINE Land Cover*. https://land.copernicus.eu/en/products/corine-land-cover?tab=main

Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B., & Lambin, E. (2004). Digital change detection methods in ecosystem monitoring: A review. *International Journal of Remote Sensing*, *25*(9), 1565–1596. https://doi.org/10.1080/0143116031000101675

Cramer-Greenbaum, S. (2023). Quantifying displacement: Using turnover data to measure physical and psychological neighborhood change. *European Journal of Geography*, *14*(1), 35–46. https://doi.org/10.48088/ejg.s.cra.14.1.35.46

D'Agata, A., Nosova, B., Vardopoulos, I., Rontos, K., Clemente, M., Colombo, M. C., Sateriano, A., & Salvati, L. (2024). Urban decline, economic crisis and fringe landscapes: The mediterranean experience. In *Urban Crisis: Social and Economic Implications for Southern Europe*.

Dai, E., Wu, Z., & Du, X. (2018). A gradient analysis on urban sprawl and urban landscape pattern between 1985 and 2000 in the Pearl River Delta, China. *Frontiers of Earth Science*, *12*(4), 791–807. https://doi.org/10.1007/s11707-017-0637-0

Dai, X., Jin, J., Chen, Q., & Fang, X. (2022). On Physical Urban Boundaries, Urban Sprawl, and Compactness Measurement: A Case Study of the Wen-Tai Region, China. *Land*, *11*(10). https://doi.org/10.3390/land11101637

Deng, J. S., Qiu, L. F., Wang, K., Yang, H., & Shi, Y. Y. (2011). An integrated analysis of urbanization-triggered cropland loss trajectory and implications for sustainable land management. *Cities*, *28*(2), 127–137. https://doi.org/10.1016/j.cities.2010.09.005

Deng, J. S., Wang, K., Hong, Y., & Qi, J. G. (2009). Spatio-temporal dynamics and evolution of land use change and landscape pattern in response to rapid urbanization. *Landscape and Urban Planning*, *92*(3–4), 187–198. https://doi.org/10.1016/j.landurbplan.2009.05.001
Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research*, *133*, 285–296. https://doi.org/10.1016/j.jbusres.2021.04.070
Downs, A. (1999). Some realities about sprawl and urban decline. *Housing Policy Debate*, *10*(4), 955–974. https://doi.org/10.1080/10511482.1999.9521356
Dutta, I., & Das, A. (2019). Application of geo-spatial indices for detection of growth dynamics and forms of expansion in English Bazar Urban Agglomeration, West Bengal. *Journal of Urban Management*, *8*(2), 288–302. https://doi.org/10.1016/j.jum.2019.03.007
El Garouani, A., Mulla, D. J., El Garouani, S., & Knight, J. (2017). Analysis of urban growth and sprawl from remote sensing data: Case of Fez, Morocco. *International Journal of Sustainable Built Environment*, *6*(1), 160–169. https://doi.org/10.1016/j.ijsbe.2017.02.003
European Environment Agency. (2008). Urban Sprawl in Europe, the Ignored Challenge. In *Urban Sprawl in Europe: Landscapes, Land-Use Change & Policy* (Issue 10). https://doi.org/10.1002/9780470692066
Frenkel, A., & Ashkenazi, M. (2008). *Measuring urban sprawl : how can we deal with it ? 35*, 56–80. https://doi.org/10.1068/b32155
Fuladlu, K., Riza, M., & Ilkan, M. (2021). Monitoring Urban Sprawl Using Time-Series Data: Famagusta Region of Northern Cyprus. *SAGE Open*, *11*(2). https://doi.org/10.1177/21582440211007465
Fulton, W., Pendall, R., Nguyen, M., & Harrison, A. (2001). *Who Sprawls Most? How Growth Patterns Differ Across the U.S. July*, 1–24.
Galster, G., Hanson, R., Ratcliffe, M. R., Wolman, H., Coleman, S., & Freihage, J. (2001). Wrestling sprawl to the ground: Defining and measuring an elusive concept. *Housing Policy Debate*, *12*(4), 681–717. https://doi.org/10.1080/10511482.2001.9521426
Gao, B.-C. (1996). NDWI?A Normalized Difference Water Index for Remote Sensing of Vegetation Liquid Water from Space. *Remote Sensing of Environment*, *58*, 257–266. https://doi.org/10.1016/S0034-4257(96)00067-3
Gilbert, K. M., & Shi, Y. (2023). Nighttime Lights and Urban Expansion: Illuminating the Correlation between Built-Up Areas of Lagos City and Changes in Climate Parameters. *Buildings*, *13*(12). https://doi.org/10.3390/buildings13122999
Glaeser, E. L., & Kahn, M. E. (2003). Sprawl and Urban Growth, Discussion paper nº 2004. *Handbook of Urban and Regional Economics*, *IV*. http://www.econ.brown.edu/Faculty/henderson/sprawl.pdf
Gogoi, D., Bhaskaran, G., & Gogoi, A. (2023). An analysis of land dynamics in relation to urban sprawl in the Guwahati city of Assam, India. *Ecocycles*, *9*(1), 49–60. https://doi.org/10.19040/ecocycles.v9i1.258
Gordon, P., & Richardson, H. W. (2000). Critiquing Sprawl' s Critics. *Policy Analysis*, *368*(365), 1–18.
Habibi, S., & Asadi, N. (2011). Causes, results and methods of controlling urban sprawl. *Procedia Engineering*, *21*, 133–141. https://doi.org/10.1016/j.proeng.2011.11.1996
Hall, R. E., & Jones, C. I. (1999). Why Do Some Countries Produce So Much More Output Per Worker Than Others? *The Quarterly Journal of Economics*, *114*(1), 83–116. http://www.jstor.org/stable/2586948
Hamidi, S., Ewing, R., Preuss, I., & Dodds, A. (2015). *Measuring Sprawl and Its Impacts: An Update*. https://doi.org/10.1177/0739456X14565247
He, T., Zhou, R., Ma, Q., Li, C., Liu, D., Fang, X., Hu, Y., & Gao, J. (2023). Quantifying the effects of urban development intensity on the surface urban heat island across building climate zones. *Applied Geography*, *158*(June), 103052. https://doi.org/10.1016/j.apgeog.2023.103052
Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment*, *25*(3), 295–309. https://doi.org/10.1016/0034-4257(88)90106-X
Hysa, A., Löwe, R., & Geist, J. (2024). Ecosystem services potential is declining across European capital metropolitan areas. *Scientific Reports*, *14*(1), 1–19. https://doi.org/10.1038/s41598-024-59333-8
Irwin, E. G., & Bockstael, N. E. (2007). The evolution of urban sprawl: Evidence of spatial heterogeneity and increasing land fragmentation. *Proceedings of the National Academy of Sciences of the United States of America*, *104*(52), 20672–20677. https://doi.org/10.1073/pnas.0705527105
Jain, M., Dimri, A. P., & Niyogi, D. (2016). Urban sprawl patterns and processes in delhi from 1977 to 2014 based on remote sensing and spatial metrics approaches. *Earth Interactions*, *20*(14), 1–29. https://doi.org/10.1175/EI-D-15-0040.1
Jiao, L., Liu, J., Xu, G., Dong, T., Gu, Y., Zhang, B., Liu, Y., & Liu, X. (2018). Proximity Expansion Index: An improved approach to characterize evolution process of urban expansion. *Computers, Environment and Urban Systems*, *70*, 102–112. https://doi.org/10.1016/j.compenvurbsys.2018.02.005
Jiao, L., Mao, L., & Liu, Y. (2015). Multi-order Landscape Expansion Index: Characterizing urban expansion dynamics. *Landscape and Urban Planning*, *137*, 30–39. https://doi.org/10.1016/j.landurbplan.2014.10.023
Kadhim, N., Mourshed, M., & Bray, M. (2016). Advances in remote sensing applications for urban sustainability. *Euro-Mediterranean Journal for Environmental Integration*, *1*(1), 1–22. https://doi.org/10.1007/s41207-016-0007-4
Kar, R., Obi Reddy, G. P., Kumar, N., & Singh, S. K. (2018). Monitoring spatio-temporal dynamics of urban and peri-urban landscape using remote sensing and GIS – A case study from Central India. *Egyptian Journal of Remote Sensing and Space Science*, *21*(3), 401–411. https://doi.org/10.1016/j.ejrs.2017.12.006
Kawamura, M., Jayamanna, S., & Tsujiko, Y. (1997). Quantitative Evaluation of Urbanization in Developing Countries Using Satellite Data. *Doboku Gakkai Ronbunshu*, *1997*(580), 45–54. https://doi.org/10.2208/jscej.1997.580_45
Kulwant, M., & Patel, D. (2024). Application of remote sensing, GIS, and AI techniques in the agricultural sector. In *Agri-Tech Approaches for Nutrients and Irrigation Water Management*. https://doi.org/10.1201/9781003441175-15
Kumar, J. A. V, Pathan, S. K., & Bhanderi, R. J. (2007). Spatio-temporal analysis for monitoring urban growth - a case study of Indore City. *Journal of the Indian Society of Remote Sensing*, *35*(1), 11–20. https://doi.org/10.1007/BF02991829
Liu, L., Peng, Z., Wu, H., Jiao, H., Yu, Y., & Zhao, J. (2018). Fast identification of urban sprawl based on K-means clustering with population density and local spatial entropy. *Sustainability (Switzerland)*, *10*(8). https://doi.org/10.3390/su10082683
Liu, L., & Zhang, Y. (2011). Urban heat island analysis using the landsat TM data and ASTER Data: A case study in Hong Kong. *Remote Sensing*, *3*(7), 1535–1552. https://doi.org/10.3390/rs3071535
Liu, X., Li, X., Chen, Y., Tan, Z., Li, S., & Ai, B. (2010). A new landscape index for quantifying urban expansion using multi-temporal remotely sensed data. *Landscape Ecology*, *25*(5), 671–682. https://doi.org/10.1007/s10980-010-9454-5

Mdari, Y. E., Daoud, M. A., Namir, A., & Hakdaoui, M. (2022). Casablanca Smart City Project: Urbanization, Urban Growth, and Sprawl Challenges Using Remote Sensing and Spatial Analysis. *Lecture Notes in Networks and Systems*, *216*, 209–217. https://doi.org/10.1007/978-981-16-1781-2_20

Medayese, S., Magidimisha-Chipungu, H. H., & Chipungu, L. (2023). Spatial Matrices of Urban Expansion in Lafia, North-Central Nigeria. *Forum Geografi*, *37*(1), 66–79. https://doi.org/10.23917/forgeo.v37i1.18068

Miller, L., Pelletier, C., & Webb, G. I. (2024). Deep Learning for Satellite Image Time-Series Analysis: A review. *IEEE Geoscience and Remote Sensing Magazine*, 2–45. https://doi.org/10.1109/MGRS.2024.3393010

Mun, J., Lee, J. S., & Kim, S. (2024). Effects of urban sprawl on regional disparity and quality of life: A case of South Korea. *Cities*, *151*, 105125. https://doi.org/10.1016/j.cities.2024.105125

Nolè, G., Lasaponara, R., Lanorte, A., & Murgante, B. (2014). Quantifying urban sprawl with spatial autocorrelation techniques using multi-temporal satellite data. *International Journal of Agricultural and Environmental Information Systems*, *5*(2), 20–38. https://doi.org/10.4018/IJAEIS.2014040102

Page, M. J., McKenzie, J. E., Bossuyt, P., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The prisma 2020 statement: An updated guideline for reporting systematic reviews. *Medicina Fluminensis*, *57*(4), 444–465. https://doi.org/10.21860/medflum2021_264903

Patra, S., Sahoo, S., Mishra, P., & Mahapatra, S. C. (2018). Impacts of urbanization on land use /cover changes and its probable implications on local climate and groundwater level. *Journal of Urban Management*, *7*(2), 70–84. https://doi.org/10.1016/j.jum.2018.04.006

Pokhariya, H. S., Singh, D. P., & Prakash, R. (2021). Investigating the impacts of urbanization on different land cover classes and land surface temperature using GIS and RS techniques. *International Journal of Systems Assurance Engineering and Management*. https://doi.org/10.1007/s13198-021-01512-1

Pranckutė, R. (2021). Web of Science (WoS) and Scopus: the titans of bibliographic information in today's academic world. *Publications*, *9*(1). https://doi.org/10.3390/publications9010012

Rahman, M. N., Akter, K. S., & Faridatul, M. I. (2024). Assessing the impact of urban expansion on carbon emission. *Environmental and Sustainability Indicators*, *23*, 100416. https://doi.org/10.1016/j.indic.2024.100416

Rana, B., Bandyopadhyay, J., & Halder, B. (2024). Investigating the relationship between urban sprawl and urban heat island using remote sensing and machine learning approaches. *Theoretical and Applied Climatology*, *0123456789*. https://doi.org/10.1007/s00704-024-04874-1

Rasul, A., Balzter, H., Ibrahim, G. R. F., Hameed, H. M., Wheeler, J., Adamu, B., Ibrahim, S., & Najmaddin, P. M. (2018). Applying built-up and bare-soil indices from Landsat 8 to cities in dry climates. *Land*, *7*(3). https://doi.org/10.3390/land7030081

Raza, A., Syed, N. R., Fahmeed, R., Acharki, S., Aljohani, T. H., Hussain, S., Zubair, M., Zahra, S. M., Islam, A. R. M. T., Almohamad, H., & Abdo, H. G. (2024). Investigation of changes in land use/land cover using principal component analysis and supervised classification from operational land imager satellite data: a case study of under developed regions, Pakistan. *Discover Sustainability*, *5*(1). https://doi.org/10.1007/s43621-024-00263-w

Roelfsema, C. (2010). Integrating field data with high spatial resolution multispectral satellite imagery for calibration and validation of coral reef benthic community maps. *Journal of Applied Remote Sensing*, *4*(1), 043527. https://doi.org/10.1117/1.3430107

Rouse, J. W., Jr., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). Monitoring vegetation systems in the Great Plains with ERTS. *NASA. Goddard Space Flight Center 3d ERTS-1 Symp.*, *1*. https://doi.org/10.1021/jf60203a024

Salvati, L., Munafo, M., Morelli, V. G., & Sabbi, A. (2012). Low-density settlements and land use changes in a Mediterranean urban region. *Landscape and Urban Planning*, *105*(1–2), 43–52. https://doi.org/10.1016/j.landurbplan.2011.11.020

Selmy, S. A. H., Kucher, D. E., Mozgeris, G., Moursy, A. R. A., Jimenez-Ballesta, R., Kucher, O. D., Fadl, M. E., & Mustafa, A. rahman A. (2023). Detecting, Analyzing, and Predicting Land Use/Land Cover (LULC) Changes in Arid Regions Using Landsat Images, CA-Markov Hybrid Model, and GIS Techniques. *Remote Sensing*, *15*(23). https://doi.org/10.3390/rs15235522

Shaw, R., & Das, A. (2018). Identifying peri-urban growth in small and medium towns using GIS and remote sensing technique: A case study of English Bazar Urban Agglomeration, West Bengal, India. *Egyptian Journal of Remote Sensing and Space Science*, *21*(2), 159–172. https://doi.org/10.1016/j.ejrs.2017.01.002

Smith, D. (2020). Population and Urbanization. *The State of the Middle East*, *1*(1), 120–121. https://doi.org/10.4324/9781315065977-35

Sohn, J., Choi, S., Lewis, R., & Knaap, G. (2012). Characterising urban sprawl on a local scale with accessibility measures. *Geographical Journal*, *178*(3), 230–241. https://doi.org/10.1111/j.1475-4959.2012.00468.x

Sudhira, H. S., Ramachandra, T. V., & Jagadish, K. S. (2004). Urban sprawl: Metrics, dynamics and modelling using GIS. *International Journal of Applied Earth Observation and Geoinformation*, *5*(1), 29–39. https://doi.org/10.1016/j.jag.2003.08.002

Sultana, S., & Weber, J. (2014). The Nature of Urban Growth and the Commuting Transition: Endless Sprawl or a Growth Wave? *Urban Studies*, *51*(3), 544–576. https://doi.org/10.1177/0042098013498284

Sun, C., Wu, Z. F., Lv, Z. Q., Yao, N., & Wei, J. B. (2013). Quantifying different types of urban growth and the change dynamic in Guangzhou using multi-temporal remote sensing data. *International Journal of Applied Earth Observation and Geoinformation*, *21*(1), 409–417. https://doi.org/10.1016/j.jag.2011.12.012

Taubenböck, H., Wegmann, M., Roth, A., Mehl, H., & Dech, S. (2009). Urbanization in India - Spatiotemporal analysis using remote sensing data. *Computers, Environment and Urban Systems*, *33*(3), 179–188. https://doi.org/10.1016/j.compenvurbsys.2008.09.003

Torrens, P. M. (2008). *A Toolkit for Measuring Sprawl*. *May 2007*, 5–36. https://doi.org/10.1007/s12061-008-9000-x

Triantakonstantis, D., & Stathakis, D. (2015). Examining urban sprawl in Europe using spatial metrics. *Geocarto International*, *30*(10), 1092–1112. https://doi.org/10.1080/10106049.2015.1027289

UN Department of Economic and Social Affairs. (2018). World Urbanization Prospects. In *Demographic Research* (Vol. 12). https://population.un.org/wup/Publications/Files/WUP2018-Report.pdf

van Eck, N. J., & Waltman, L. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics*, *84*(2), 523–538. https://doi.org/10.1007/s11192-009-0146-3

Vogelmann, J. E., Gallant, A. L., Shi, H., & Zhu, Z. (2016). Perspectives on monitoring gradual change across the continuity of Landsat sensors using time-series data. *Remote Sensing of Environment*, *185*, 258–270. https://doi.org/10.1016/j.rse.2016.02.060

Waleed, M., Sajjad, M., & Shazil, M. S. (2024). Urbanization-led land cover change impacts terrestrial carbon storage capacity: A high-resolution remote sensing-based nation-wide assessment in Pakistan (1990–2020). *Environmental Impact Assessment Review*, *105*(July 2023), 107396. https://doi.org/10.1016/j.eiar.2023.107396

Wang, G., Peng, W., Zhang, L., Xiang, J., Shi, J., & Wang, L. (2023). Quantifying urban expansion and its driving forces in Chengdu, western China. *Egyptian Journal of Remote Sensing and Space Science*, *26*(4), 1057–1070. https://doi.org/10.1016/j.ejrs.2023.11.010

Woodcock, C. E., Loveland, T. R., Herold, M., & Bauer, M. E. (2020). Transitioning from change detection to monitoring with remote sensing: A paradigm shift. *Remote Sensing of Environment*, *238*, 111558. https://doi.org/10.1016/j.rse.2019.111558

World Bank. (2024). *Urban population growth (annual %)*. https://data.worldbank.org/indicator/SP.URB.GROW?end=2023&locations=CN-IN&most_recent_value_desc=false&start=2023&view=bar

Wu, Y., Li, S., & Yu, S. (2016). Monitoring urban expansion and its effects on land use and land cover changes in Guangzhou city, China. *Environmental Monitoring and Assessment*, *188*(1), 1–15. https://doi.org/10.1007/s10661-015-5069-2

Xu, C., Liu, M., Zhang, C., An, S., Yu, W., & Chen, J. M. (2007). The spatiotemporal dynamics of rapid urban growth in the Nanjing metropolitan region of China. *Landscape Ecology*, *22*(6), 925–937. https://doi.org/10.1007/s10980-007-9079-5

Xu, G., Zhou, Z., Jiao, L., & Zhao, R. (2020). Compact Urban Form and Expansion Pattern Slow Down the Decline in Urban Densities: A Global Perspective. *Land Use Policy*, *94*, 104563. https://doi.org/10.1016/j.landusepol.2020.104563

Xu, H. (2005). Study on extracting water body information using improved normalized difference water index (MNDWI). *National Remote Sensing Bulletin*, *5*, 589–595. https://doi.org/10.11834/jrs.20050586

Y. Zha, J. G., & Ni, S. (2003). Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. *International Journal of Remote Sensing*, *24*(3), 583–594. https://doi.org/10.1080/01431160304987

Yan, Y., Yang, Y., & Yang, M. (2024). Unravelling the non-linear response of ecosystem services to urban-rural transformation in the Beijing-Tianjin-Hebei region, China. *Ecological Informatics*, *81*, 102633. https://doi.org/10.1016/j.ecoinf.2024.102633

Yulianto, F., Fitriana, H. L., & Sukowati, K. A. D. (2020). Integration of remote sensing, GIS, and Shannon's entropy approach to conduct trend analysis of the dynamics change in urban/built-up areas in the Upper Citarum River Basin, West Java, Indonesia. *Modeling Earth Systems and Environment*, *6*(1), 383–395. https://doi.org/10.1007/s40808-019-00686-9

Zeng, C., Liub, Y., Steind, A., & Jiao, L. (2015). Characterization and spatial modeling of urban sprawl in the Wuhan Metropolitan Area, China. *International Journal of Applied Earth Observation and Geoinformation*, *34*(1), 10–24. https://doi.org/10.1016/j.jag.2014.06.012

Zhang, L., Zhang, J., Li, X., Zhou, K., & Ye, J. (2023). The Impact of Urban Sprawl on Carbon Emissions from the Perspective of Nighttime Light Remote Sensing: A Case Study in Eastern China. *Sustainability (Switzerland)*, *15*(15). https://doi.org/10.3390/su151511940

Zhang, N., Hong, Y., Qin, Q., & Zhu, L. (2013). Evaluation of the visible and shortwave infrared drought index in China. *International Journal of Disaster Risk Science*, *4*(2), 68–76. https://doi.org/10.1007/s13753-013-0008-8

European Journal of Geography