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Editorial

Special Issue "Remote-Sensing-Based Urban Planning Indicators"

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1. The Challenges of Urban Planning

We are living in an urban age. The UN predicts that by 2050 around 68% of the global population will live in urban areas [1]. Global urbanisation rates have distinct geographic patterns. In general, Global North regions have already high urbanisation rates, while Global South regions show high urbanisation dynamics (increasing rates) [2]. Many megacities are very rapidly growing in population numbers and built-up areas [3]. For example, the urban agglomeration of Delhi (India) might reach a population size of 39 million inhabitants by 2030 [1], similar to the present population of the entire continent of Oceania. However, many of the fastest-growing urban areas (in terms of growth rates) are not the primary but secondary cities, as well as urbanising areas (e.g., rural–urban transition zones) [4]. Living conditions and planning questions are very different, depending on the context. Rapidly growing cities (e.g., secondary and primary in the Global South) are facing extreme challenges in terms of matching infrastructure and service provision with increasing demands. In contrast, stagnant and ageing Global North cities face challenges in changing demands (e.g., adapting infrastructure to changes in lifestyle patterns) [5].

2. Data Gaps and Evidence-Based Urban Planning

Urban planning combines different sectors and domains, e.g., housing, infrastructure, services, environment, socio-economic development, and governance. Emerging challenges relate to sustainable, inclusive, compact, resilient, and smart urban development [6–8]. For effectively preparing cities to respond to these challenges, short- and long-term strategies are essential. These require inputs from knowledgeable stakeholders as well as knowledge derived from Findable, Accessible, Interoperable, and Reusable (FAIR) data [9], both embedded into a well-functioning governance and planning framework. Evidence-based planning and policy-making depend on reliable data that support the different stages of planning processes [10,11], e.g., to explore and analyse a certain situation, design possible solutions, and implement and iteratively assess these. In all steps of a planning process, key indicators are required to support these steps as well as to assess how well proposed and implemented solutions meet normative urban development goals [12]. Such policy goals, e.g., linked to the Sustainable Development Goals (SDGs) or the New Urban Agenda (NUA) [2,13], include, for example, the reduction of land consumption, reducing inequality, providing adequate housing, and implementing sustainable transport infrastructure, as well as making progress on gender equality and climate targets [14]. Many cities experience considerable pressure to cope with the multitude of issues. However, both in Global South and North cities, municipal resources are often limited [15]. This also presents challenges in keeping data up-to-date. However, supporting planning and decision making with dated or incomplete evidence might lead to serious economic losses, social inequalities

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and harms, and environmental disasters. Thus, while adequate indicators and reliable, up-to-date data, to measure and monitor indicators, are key to sustainable urban planning and decision making and effective communication within a multi-stakeholder environment, regular in situ data collection is often not feasible due to local conditions [12,16]. Earth observation (EO) data can, for many planning and decision-making questions, supply relevant base data and proxies, in particular to support the development, measuring, and monitoring of urban indicators at different scales [17]. Within this special issue, we aim to understand and learn about the potential of EO data in support of urban planning indicators for various fields of applications.

3. The Role of EO to Develop Urban Planning Indicators

EO data offer manifold opportunities for mapping and monitoring urban areas [18–22]. They serve to derive various physical, climatic, and socio-economic indicators in support of urban planning, emergency response, and decision making [23]. EO data provide quantitative data that are temporally and spatially more consistent than traditional ground surveys and census data and often have finer spatial and temporal resolutions. This allows for analysing and comparing conditions among different urban settlements, cities, and countries, and for different years. For this reason, EO is also a fundamental data source for tracking the progress towards the SDGs and monitoring target indicators, as well as providing actionable information for local, regional, and state governments [19,24–26]. Once translated into regularly updated geospatial information and knowledge, these data can support strategic planning and interventions responding to the multiple challenges related to rapid population growth, scarcity of resources, and increasing frequency and intensity of natural hazards caused by a changing climate.

Multiple data sources have been investigated in the literature, including satellite data of various resolutions (from very high to moderate resolution), aerial and unmanned aerial vehicle (UAV) image acquisitions [27,28]. Several research questions are spurring the scientific community: How can we take full advantage of EO data's large volumes? How can we optimally fuse the data from different sensors and sources? Moreover, how can we automatically extract geospatial information that is reliable and trusted by citizens and decision makers? To address some of these challenges, researchers often resort to statistical modelling and machine learning algorithms [29–31]. Such advanced quantitative and computational methods allow us to process large data volumes effectively and infer maps and other products. The latest wave of deep learning algorithms, including convolutional neural networks, recurrent networks, and generative adversarial networks, offer new strategies for addressing complex geospatial data analysis tasks [29,32]. The ability to learn sophisticated hierarchical features from multiple data sources allows deep learning methods to extract meaningful spatial and temporal patterns and infer information about the physical domain of urban areas and more abstract variables related to their dwellers' socio-economic conditions and quality of life [33].

4. The Contribution of Papers of the Special Issue

In this special issue, we have invited contributions to remote-sensing-based planning indicators across the world. The received contributions show a mix between Global North and South studies, approximately $^1/_3$ to $^2/_3$, respectively. A large share of the papers focus on the rapidly growing urban areas in Asia (Figure 1), while other global regions have relatively equal attention.

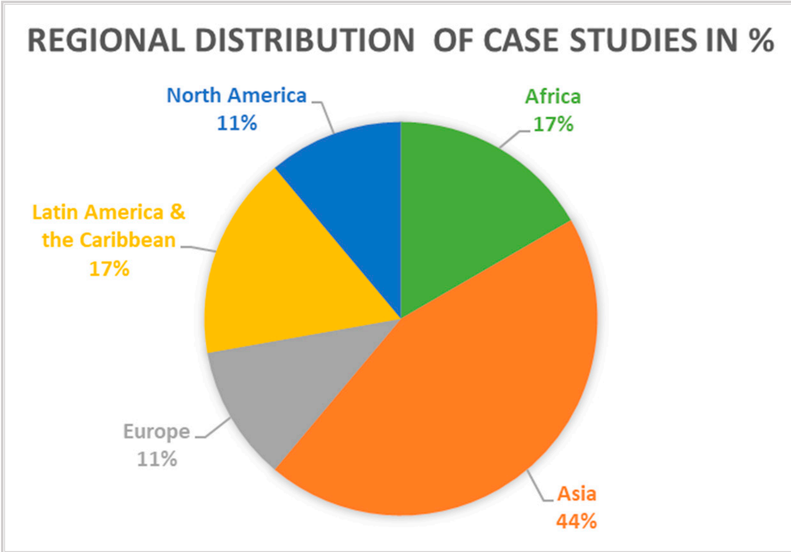

Figure 1. Regional percentages of case studies used in the special issue papers (N = 13).

The contributions and their EO-based indicators cover different planning-related sectors and domains (Table 1). The majority of indicators relate to land and environmental issues (e.g., [34,35]), while only a few indicators provide information that is more complex to derive from EO data, e.g., information on urban services or socio-economic conditions (e.g., [36,37]). In these sectors, there is still much scope for EO data to fill information gaps, e.g., with the recent advances in machine learning to provide data on complex urban classification problems. However, this would require the solution of a large bottleneck for urban EO applications, namely the availability of large sets of training data shared for cities. Presently there are no easily accessible repositories for in situ data for a large number of urban areas (for some recent developments see, e.g., [38]), for example, the around 13,000 urban centres as defined by the Global Human Settlement Layer (GHSL) database [3]. In the absence of such in situ data, researchers have to produce their own training data, often without sufficient ground validation due to high data collection costs. These practices also limit the usability of data for planning questions as uncertainties cannot sufficiently be quantified.

The contributions also show that other urban planning sectors and domains that could further benefit from EO data are urban governance and participation (e.g., interaction with stakeholders), urban hazards, and climate actions. Very-high-resolution (VHR) imagery can support the development of 3D models that can improve communications with multiple stakeholders [39,40]. Climate action could largely benefit from the integration of EO data with local planning models to simulate impacts of changing climate conditions and their interaction with the urban morphology in 2D as well as in 3D [41,42]. Thus we can conclude that there is huge potential for EO to provide routine, accurate, and cost-efficient data in support of urban planning indicators. However, data and methodological questions need further development and better responding to local user needs [43]. This calls for action within the EO community to better engage with local to global (potential) users of EO data and provide data for purpose.

Table 1. Urban planning indicators supported by Earth observation (EO) data within publications of the special issue (* based on EO data).

Urban Sectors	Indicators/Planning Instruments	Type of EO Data	References
Housing	■ Built-up indices ■ Normalised difference concrete condition index (NDCCI) ■ % change in temporal housing (slums) ■ Built-up density	■ WorldView ■ Landsat	[34,37,44]
Infrastructure/Services	■ Street density ■ Distance to roads/accessibility ■ Access to services ■ Night lights/streets	■ Orthophotos ■ WorldView ■ PlanetScope ■ DMSP-OLS/VIIRS	[36,45,46]
Environment/Hazard	■ Land susceptibility ■ Surface temperature ■ Green infrastructure indicators ■ % of open/green spaces	■ WorldView ■ Aster (DEM) ■ RapidEye ■ Urban Atlas * ■ Orthophotos ■ Landsat ■ Google Earth ■ DMSP-OLS/VIIRS	[19,47–49]
Socio-economic conditions	■ Multiple deprivation index ■ % of slums ■ Quality-of-life indicators	■ WorldView ■ PlanetScope ■ Pleiades ■ Urban Atlas *	[36,37,44,49]
Urban governance/Participation	■ 3D models	■ Video/camera	[40]
Land use—territorial planning	■ Land use/cover change (drivers) ■ Urban growth ■ Urban form indicators (e.g., compactness)	■ Orthophotos ■ Landsat ■ Rapideye	[19,34,35,50]

5. Conclusions and Directions for Further Research

EO data and data products are increasingly available but are often not easily accessible to key stakeholders in urban planning and decision making. This friction relates to technological challenges and communication challenges. For example, neither are ready-to-use data available (i.e., easy to be combined with municipal databases) nor are they documented for non-EO experts. This calls for strengthening the collaboration between urban planners and EO experts to conceptualise actionable information and overcome implementation gaps of utilising RS-based products. Well-documented EO data repositories are required that provide guidance to non-EO experts in the use of EO data and products (a recent example of such an initiative is the EO Toolkit for Sustainable Cities and Communities: [14]). Ease of access and well-documented datasets need to be combined with rich quantitative and qualitative data that can add contextual information and support urban information needs, e.g., building on citizen science approaches, to understand how to contextualise numeric data. Such solutions will improve our understanding of complex urban sector relations and support evidence-based urban planning.

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