*remote sensing*

*Editorial*

# Editorial: Geospatial Understanding of Sustainable Urban Analytics Using Remote Sensing

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**Citation:** Sabri, S.; Rajabifard, A.; Chen, Y.; Chen, N.; Sheng, H. Editorial: Geospatial Understanding of Sustainable Urban Analytics Using Remote Sensing. *Remote Sens.* **2022**, *14*, 2748. https://doi.org/10.3390/rs14122748

Received: 3 May 2022
Accepted: 7 June 2022
Published: 8 June 2022

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The increasing trend of urbanization has challenged the traditional ways of urban planning, design, and management. Cities are growing horizontally and vertically, which added to the level of complexity and vulnerability of populations to natural, economic, and social changes. Recently, several cities worldwide are impacted by climate change effects including flood disasters, urban heat, and hurricanes. In Australia, the total losses from disasters were $171.1 billion from 1967 to 2013 [1]. Among the Australian states, more urbanized regions, including New South Wales, Queensland, and Victoria, account for about 83% of total losses nationally. Among the natural disasters, flood causes more loss of life than any other disaster in Australia [2], which is due to the increasing amount of impervious ground cover in cities. As a result, urban design and planning practices need a more advanced type of data and technologies for regulating city development and creating ecologically sustainable guidelines and policies.

However, it is believed that current practices of data collection, data analytics, response, and urban planning approaches in addressing environmental challenges are not sufficient and effective. Urban planners and designers need to change the traditional way of policymaking and utilize new data and technologies for developing strategies to achieve smarter, more resilient, and sustainable future cities [3].

Historically, spatial data, analytics, and infrastructures have significantly supported the planning processes and decision-making [4]. Planning support systems [5], urban analytics data infrastructures [6], and multi-dimensional analytics [7] always supported the planning and design processes toward achieving livability, sustainability, and prosperity in cities. One of the essential requirements for these technologies is remote sensing data and analysis. The recent advancements in the precision, resolution, and frequency of satellite data and other sensors provide an opportunity for changing urban planning and design practices and outcomes.

As such, the new digital technologies, particularly remote sensing data and analytics, spatial data infrastructures, and cloud computing offer immense potential for bringing together multi-source and heterogeneous datasets for spatially enabled analysis, evaluation, and ongoing management in implementing urban policies [8]. In this regard, this Special Issue aimed to understand the crucial role of remote sensing and real-time data capturing and analysis in improving the urban analytics processes. The special issue looked at four different aspects of urban land use/land cover, urban economy, urban ecological adaptation, and urban situational awareness.

The remote sensing data and analytic methods have long been applied in land use/land cover dynamics and urbanization studies. However, given that the traditional remote sensing data was limited in time and accuracy, monitoring and benchmarking of the progress of urbanization dynamics was lacking. To address this challenge, Li et al. (2021) [9] proposed using continuous time-series data such as night-time light (NTL) images combined with land-use data from 2008 to 2018 to investigate the spatiotemporal patterns of urbanization in China. The proposed methodology could support the strategic planners to examine the impact of long-, medium-, and short-term urban development directions.

Furthermore, recent advancements in spatial data processing improved the way urban planners can investigate the spatial and temporal dynamics of urban land use/land cover changes. Cheng et al. (2021) [10] argued that the spatial pattern of land cover characteristics is not linear in nature, therefore, they suggested using fractals and fractal dimension properties to understand the structure, types, and trend of changes in urban land covers. Their methodological framework integrated the information entropy index and fractal dimension to enable urban planners in interpreting the pattern and type of urban growth, the balance of built-up area over the natural land cover, and the impact of urban planning rules and zoning regulations on the structure and diversity of the land cover in urban areas.

Furthermore, understanding the urban land use/land covers can improve the planning for urban ecological adaptation. While this will be explained in the next couple of paragraphs, it is important to mention the role of remote sensing data and analytics in mitigation measures. For instance, this special issue provides an example for exploring the role of urban green spaces and their spatial configuration and extent in mitigating the urban heat island effects [11]. Comparing the land surface temperature and urban green space patterns in Adis Ababa, Ethiopia, Terfa et al. (2020) [11] demonstrated the significant role of this methodology to enable urban planners and urban designers to consider the green spaces' spatial configuration to better address the urban heat island effects of urban development.

Given the vertical growth of urban areas, a three-dimensional (3D) land use/land cover mapping improves our understanding of the urban structures and implications. In this special issue, two research studies communicated the role of 3D data and analytics to improve the previous urban analytics. He et al. (2021) [12], demonstrated how using 3D urban structure parameters can improve our understanding of seasonal urban land surface temperature. Sanlang et al. (2021) [13] introduced an innovative methodology for urban form and functional zoning using light detection and ranging (LiDAR) point clouds and very high-resolution (VHR) images to extract the 3D urban structure parameters and combined them with the spatial patterns of land covers and 2D urban land cover information. This allowed the researchers to couple the developed 3D datasets with multi-machine learning algorithms, called multi-classifiers (MLCs) to create urban functional zone (UFZ) mapping. Evaluating the proposed method in Brooklyn, New York City, USA, Sanlang et al. (2021) [13] demonstrated an increase in the accuracy of land cover classification. Their findings can improve the planning process to understand the distribution patterns of urban land use zones, including commercial, residential, industrial, and vegetation areas. The improved 3D datasets developed in their study could support several urban design and planning activities including urban flood modelling, microclimate analysis, and compact city development. Specifically, methodological improvements in measuring sky view factor (SVF), building height (BH), street aspect ratio (SAR), and floor area ratio (FAR) contribute to the advancement of urban spatial modelling and analysis.

From an urban economy perspective, Li et al.'s (2021) [9] methodological framework using NTL data contributes to the urban agglomeration studies. Their methodology enables urban economists to better understand the dynamics of different urban clusters in a shorter time frame. This innovation can be examined by integrating with periodical labor, job distribution as well as travel-to-work data to uncover further detail about the urban economy landscape changes. The other potential application of night-time light data in connection to the urban economy is demonstrated by Zhou et al. (2021) [14]. Collecting the night-time economic activities and combining them with the points of interest (POIs), Zhou et al. (2021) [14] proposed a methodology to extract the hierarchy of the spatial agglomeration of business circles in cities. Their methodological framework was tested in Yiwu City, China. Leveraging the NTL, Zhou et al. (2021) [14] provided a capability for city planning appraisal on success in developing night-economy. This methodology improves the urban strategic development as well as urban design for offering new models of economic development in the cities.

Besides the physical and economic aspects, one of the major applications of remote sensing data and analytics has been urban ecological adaptation. Forecasting, nowcasting, and postcasting of natural disasters including floods, bushfires, and urban heat islands are very popular in the contribution of remote sensing in urban analytics and urban planning processes. In this special issue, the remote sensing data and analytics are used to develop a flood risk assessment for subway areas [15] and to determine the nearest evacuation place for people and equipment from a disaster area [16]. The case of subway flood risk assessment contributes to the resiliency and socio-environmental costs of underground space developments in highly urbanized areas [17]. Furthermore, Korolov et al., (2021) [16] highlighted the significant role of accurate and timely remote sensing data for situational awareness and determining the drylands for emergency management and evacuation process in urban areas. Given that during the flood events the road networks, the topography of the land, and other built-up and urban infrastructures might disappear, the role of timely data injected in the analytical process is crucial. This opens the new agenda for future studies using emerging technologies such as the internet of things (IoT), machine learning (ML), artificial intelligence (AI), and urban digital twins (UDT) in the fields of remote sensing, spatial analysis, and urban analytics.

This special issue also provides an example of using a spatially enabled UDT for managing large-scale individual mobility data [18]. The methodological framework proposed by Lee et al. (2022) [18] contributes to the theoretical and practical areas of urban management by leveraging the sensors combined with remote sensing data in the spatially enabled UDT, which is a digital representation of urban systems including the city objects, processes, and their interactions. Lee et al.'s (2022) [18] focus on individual urban entities (e.g., cars, pedestrians) is innovative and improves the urban digital twin's maturity level.

This special issue addressed several urban phenomena by leveraging remote sensing data, technologies, and analytics. In response to the challenges of rapid and vast urbanization and the traditional ways of urban planning and design, this special issue communicates the opportunities provided by the advancements in remote sensing and spatial technologies. Future studies can focus more on emerging digital technologies and understanding the role of more frequent and accurate remote sensing data and technologies in sustainable urban analytics.

**Author Contributions:** Conceptualization, S.S. and Y.C.; investigation, A.R. and N.C. and H.S.; writing—original draft preparation, S.S.; writing—review and editing, A.R. and Y.C. and N.C. and H.S.; All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

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

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