# EARTH OBSERVATION FOR LAND COVER AND HUMAN-ENVIRONMENT INTERACTIONS

Z. Zhang[1*], Y. Song[1], P. Luo[2], P. Wu[1]

[1]School of design and the built environment, Curtin University, Australia – (zehua.zhang, yongze.song, peng.wu)@curtin.edu.au
[2] Chair of cartography and visual analytics, Technical University of Munich, Germany – peng.luo@tum.de

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**ABSTRACT:**

Human-environment interactions (HEI) are dynamic processes involving a wide range of research areas. The complicated interaction processes, with land cover change as an intermediate process, have been investigated for decades. Urban construction, as a type of human activity, is an important part of the HEI. Earth observation (EO) techniques offer disclosure of physical and chemical properties, from spectral information to chemical compositions, on the earth surface. These advanced technologies have been applied from space to the ground, covering smart urban construction, land cover monitoring and other topics under the scope of HEI. The aim of this paper is to review the significance and contribution of earth observation in HEI research. This paper summarised the utility of four types of earth observation regarding topics of urban construction and land cover monitoring under the scope of HEI. Furthermore, this paper reviewed four advanced techniques in earth observation, including Radar, unmanned aerial vehicles (UAVs), machine learning algorithms and advanced computing platforms like Google Earth Engine (GEE), which can lead to future development in smart urban construction and smart city design.

## 1. INTRODUCTION

Human-environment interactions (HEI) are dynamic processes involving a wide range of research areas, and these complex processes have been investigated for decades (Kefalas et al., 2019). Human-environment interactions in this research paper are interpreted by a compound relationship among human activities, land cover and the ecological environment. In this article, the word "environment", refers to the ecological environment, which includes abiotic elements from soil quality, water quality to precipitation and temperature, and biotic components from vegetation cover, agricultural production to biodiversity (Chang et al., 2019). Human activities at a large spatial scale, such as urban constructions, industry development and government-level investment programmes can impose forces leading to land cover change in a short-term to a long-term period (Desjeus et al., 2015; Gellrich and Zimmermann, 2007). In this article, we mainly reviewed urban construction as a kind of human activity and discussed the smart urban construction enabled by earth observation. Land cover has intensive interactions with human activities, and it also works as a key intermediate variable in the HEI dynamic process (Wang et al., 2021). Changes in land cover from urban constructions could convey feedback to cities represented by the urban heat island effect (Song et al., 2014) and other potential landscape ecological changes. Apart from the human forces, land cover can also be influenced by natural features, including wind speed, humidity, precipitation and topography through a chronic geomorphology process (Dai et al., 2014). Furthermore, there are also dense interactions between human activities and the ecological environment. For instance, the aggregation of the construction industry can lead to air pollution and water pollution (Dong et al., 2019), and poor air quality would impose negative effects on an individual's health and finally lead to other social risks. Urban construction levels may vary on various landscapes at different places. Therefore, it is hard to investigate the potential relationships under human-environment dynamics in a systematic way using fixed models. The evolutions of earth observation and remote sensing techniques enable environmental variables and land cover dynamics to be monitored from a more comprehensive global or a more detailed local view (Ustin and Middleton, 2021). Moreover, spatial analysis approaches for earth observation data reveal spatial patterns and make a spatial simulation for landscape management and decision making.

Earth observation techniques offer disclosures of physical and chemical properties, from spectral information to physical compositions, on the earth surface. These advanced technologies have been applied from space to the ground, which include various topics in the human-environment interaction studies. This article aims to summarise and review contributions and significance of earth observation for HEI research from previous studies. Currently, there have been numerous valuable studies revealing humans' impact on the ecological environment (Jin et al., 2019), ecological environment's feedback to humans' society along with influence to humans' decision making (Zhai et al., 2020), and the role of earth observation in the environment monitoring and humans' development monitoring (Phiri et al., 2020). Furthermore, theories and models have been developed to explain the impact and consequence of human activities on the planet. Relevant topics include studies in the carbon cycle, nitrogen cycle (Erisman et al., 2013), climate change (Brody et al., 2018) and other topics relevant to environmental change. Among these topics, numerous issues, covering biology, environmental engineering, spatial engineering, urban planning and social science, are discussed based on datasets generated from earth observation and spatial techniques. Generalised earth observation includes data generated from monitoring stations and mobile technologies, which could represent natural factors (Gellrich and Zimmermann, 2007), social behaviours (Ristea et

[*] Corresponding author

al., 2020) and natural hazards (Bruneau et al., 2021). Apart from academic benefits from the earth surface properties disclosure, the value of earth observation can be added with the help of analytical methods with innovations. In general, these methods could further explore the value of earth observation data by providing valuable information about spatial relationship identification (She et al., 2017), spatial pattern and distribution analysis, spatial estimation to overcome the spatial limitation of field sampling as well as spatial decision making for governance policy. The rest of the article is organised as follows. The second section shows key topics of land cover, urban construction and the environments using earth observation under the scope of HEI. Earth observation data and analysis methods are explained in the third and fourth sections. Smart urban construction plays a key role of sustainable management in HEI research, and earth observation and spatial services make sustainable construction possible. Therefore, the relationship between earth observation development and smart urban construction is explained in the fifth section. The last section is the conclusion.

## 2. IMPLEMENTATION OF EARTH OBSERVATION TO LAND COVER AND URBAN ENVIRONMENT

Land cover is a key component in HEI research, which has already been investigated through earth observation techniques from multiple perspectives (Foley et al., 2005). We summarise earth observation-based land cover studies from three perspectives, including land cover change, land cover mapping, and land cover management and monitoring. Three types of land cover studies represent human's endeavour to identify reasons generating land cover change in the past (Gellrich and Zimmermann, 2007), human development in learning land cover compositions and patterns currently (Milenov et al., 2014), and human's desire to manage land cover for a better life in the future. From a reasoning explanation perspective, investigations have been made to explore natural and social factors relevant to land cover change using earth observation data (Kefalas et al., 2019). From a mapping perspective, the spatial patterns of various land cover types, covering urban area, green space, forest, farming-pastoral ecotones, cropland, terracette, shoreline and other land covers for specific use, are figured out based on earth observation data using spatial approaches. From a land management perspective, soil properties and landscape metrics are intensively investigated. For soil properties, numerous researches have been taken to study soil moisture, above-ground carbon, soil nitrogen, soil organic matters, mineral chemicals and heavy metals. Furthermore, landscape metrics, as indicators revealing land patterns, are also utilised to show landscape design and ecological risk in urban and rural regions (Sahraoui et al., 2021). In HEI studies, earth observation has presented irreplaceable values for the above mentioned indicators. Generally, numerous land cover indicators and relevant spatial metrics are identified with the help of satellites from Landsat, MODIS, and Sentinel-2 to commercial products and airborne-based photos. Soil property information can be collected from field sampling and ground in situ work.

Landscape composition and land cover change are represented by spatial and aspatial patterns of land cover composition and the changes over a time period. Landscape composition and land cover change are critical concepts in earth observation and land cover management (Van et al., 2013). Landscape composition and its changes are considered a key median process when investigating human-environment interactions using earth observation data as summarised in this paper. The change of landscape composition is subjected to short-term or long-term human forces, including urbanisation and population change, governance policy for ecological restoration, economic development, and infrastructure development. Landscape change is also influenced by long-term natural forces caused by precipitation, topography, temperature, humidity and wind speed (Kefalas et al., 2019). The dominance of human force or natural force is determined by the development level of the study area. Human forces can be influential in the HEI processes in highly urbanised regions (Chen et al., 2019). As a process in human-environment interaction, land cover changes caused by urbanisation or vegetation recovery may lead to urban heat island effect or heat mitigation (Song et al., 2014). Typically, land covers are water bodies, urban and built-up, soil, cropland and vegetation, which can be monitored by remote sensing indexes. Normalised difference vegetation index (NDVI), enhanced vegetation index (EVI), normalised difference soil index (NDSI), soil adjusted vegetation index (SAVI) and difference vegetation index (DVI) and impervious surface fraction (ISF) are indicators generated from earth observation to monitor the composition of land covers. Landscape patterns and spatial metrics are other indicators representing morphology and general spatial pattern for urban studies (Herold et al., 2003). Typically, these spatial metrics are originally derived from land composition (types of land cover or land compositions). Landscape pattern and spatial metrics include patch number, total urban area, mean urban patch size, patch density, Shannon's diversity index, interspersion juxtaposition index, landscape aggregation index and eccentricity (McCarty and Kaza, 2015). Land covers are further processed and translated into a new term named "patch", which refers to homogeneous areas for a specific landscape property of research interest such as "industry region", "residential region" and "green space". These patch-based indicators are measurements for modelling forms of urban sprawl and quantifying shape and spatial patterns of vegetation in natural land cover.

The construction industry works for the design and construction for infrastructures supporting our cities. These urban infrastructures include roads, dams, utility supply system, waste service system, green infrastructures and others. These infrastructures support our daily lives and future development. The construction activity, one of the representatives of human activities, is an important process of urbanisation and industrialisation. Therefore, population growth and urbanisation can be supported by the construction industry to some extent. Population change and urbanisation, which are the cause of environmental pollution, ecological risk and land cover change in HEI research, are interpreted as social change and urban development caused by human activities and construction industry aggregations (Dong et al., 2019). Population is usually indicated by population or population density in a certain area, and urbanisation is regarded as a phenomenon of human's aggregation from rural regions to urban areas. Therefore, the urbanisation level can be transformed and measured by the proportion of urban population or other human activities indicators. Population-based data in HEI studies are accessed from census data published by governance authorities, and nighttime light earth observation data can also be utilised as ancillary data when measuring the urbanisation level.

Under the help of earth observation development, ecological risk and environmental pollution can also be measured using remote sensing and spatial techniques. Environmental sensitivity index (ESI), habitat quality (HQ) and ecological risk index (ERI) are three indicators highly relevant to environmental pattern and spatial metrics, demonstrating vulnerability of the ecological environment. As the ecological environment is a complex system composed of various spatial features with dynamic interactions, ESI, HQ and ERI are proposed based on human's needs for evaluating the quality of the physical environment for the purpose of further sustainable development decision making. Currently, spatial studies have already verified strong relationships among landscape ecological risk, urban infrastructure development, governance policy and urbanisation level (Lin et al., 2019).

The ecological and physical environment can also convey feedback to cities or urban areas when environmental degradation, such as environmental pollution or urban heat island effect, happens. In this article, the terminology "environmental pollution" refers to pollutants that are detrimental to an individual's health, covering but not limited to waste water, particulate matters, carbon dioxide, sulfur dioxide, nitrogen dioxide and aerosol optical depth. These environmental pollutants are relevant to governance policy, population and urbanisation, economic development, construction industry development, technology innovation, and landscape design. These pollutants can be measured through air pollution monitoring stations, and hourly updated through open-access platforms in most cases. For broad-area research, air pollutants can be more efficiently monitored by earth observation data using satellite or unmanned aerial vehicle (UAV). Current studies have demonstrated the feasibility of air pollutant monitoring using MODIS products (Zhang et al., 2018), and other forms of air pollutants can be measured via UAV mounted with specific sensors (Lambey and Prasad, 2021).

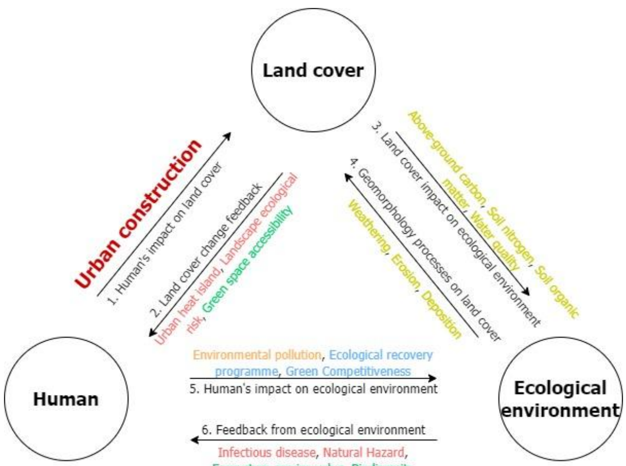


**Figure 1**. Key topics under the scope of HEI

Figure 1 summarises key topics under the scope of HEI. Human activities, land cover and the ecological environment are mutually related through various processes. Urban construction is a kind of human activity under the scope of HEI, which can lead to land cover change and environmental change. The rest of the article will show how earth observation data and analysis methods can be applied in HEI studies, and how earth observation development could lead to smart urban construction.

## 3. EARTH OBSERVATION DATA FOR URBAN CONSTRUCTION, LAND COVER AND THE ENVIRONMENTS

As free open access data, Landsat and MODIS products have been widely and intensively applied in HEI research. Various land information from land cover properties, landscape metrics to land surface temperature and ecological risk indicators can be generated from Landsat and MODIS products. This derived information and indicators are valuable for most of the HEI research relevant to land cover status and construction design. They can be further processed via spatial or aspatial methods. Landsat and MODIS products, generally, can be utilised to identify spatial relationships among variables. These remote sensing products can also be used to explore spatial pattern and distribution, spatial estimation as well as spatial decision making in HEI studies. Advanced requirements in HEI can be fulfilled by commercial satellite or satellite mission for specific purposes. When mapping skinny land features, for instance streams and roads, spatial resolutions for Landsat or Sentinel-2 are too coarse to provide valid information. High-resolution commercial products are able to help with those detailed mapping tasks (Biotto et al., 2009). Further, general commercial satellite image acquisition cost is lower than that of airborne-based or UAV (Lambey and Prasad, 2021). Moreover, Tropical Rainfall Measuring Mission (TRMM) for precipitation (Chen et al., 2018), and Shuttle Radar Topography Mission (SRTM) for topography information enable free access to global natural factors measured from satellites.

Airborne-based earth observation data refers to remote sensing images captured from airborne or unmanned aerial vehicles (UAV). The variability of sensors mounted on airborne or UAVs determines the capability of Airborne-based earth observation data. Typically, airborne-based sensors support spectral detection from visible band to VNIR and SWIR. Active remote sensing, such as Lidar, is also undertaken on airborne. In HEI research, a couple of land cover monitoring, nighttime light collection and species statistics tasks are completed with the help of airborne remote sensing, as aerial images provide higher spatial resolutions compared with satellite images (Kuechly et al., 2012).

Ground-based earth observation data is mainly composed of field sampling and monitoring stations. Field samplings, sometimes known as in situ data; typically refer to samples taken at a specific location, and analysing the physical or chemical properties of those samples in the lab later. This data collection methodology has been intensively utilised for soil property analysis, such as, heavy metal concentration, soil moisture, mineral chemistry, above-ground carbon and nitrogen. Although field sampling has time and budget requirements, as well as spatial limitation, more physical properties and chemical compositions from above ground to soil in-depth, could be comprehensively studied using this type of data. Apart from soil quality sampling, field sampling has been applied for water quality testing (Sun et al., 2016). Ground-based earth observation data also includes data collected from monitoring stations. Ground monitoring stations are established mainly for natural factors monitoring and air quality monitoring. Natural factors from temperature and humidity to precipitation, as well as various air quality indicators can be measured from stations frequently (McCarty and Kaza, 2015). Some other stations are designed for specific monitoring tasks, such as forest soil carbon efflux (Crabbe et al., 2019) and water quality. The drawback of spatial limitation for missing values from the field sampling and monitoring stations can be mitigated by spatial interpolation or remote sensing image complementary (Dang et al., 2018).

Currently, mobile technology generates a new type of earth observation data published from Twitter, online mapping applications or other web-based social media. This type of earth observation data generally contains geographic location, happening event and occurrence time. The superiority of the immediate message sharing function from mobile technology enables real-time monitoring of rapid land cover change (Ristea et al., 2020). Nowadays, this new data type has been applied for hazard monitoring purposes (Bruneau et al., 2021).

## 4. SPATIAL ANALYSIS METHODS FOR EARTH OBSERVATION IN HEI

To identify relationships among spatial variables, spatial statistical methods containing spatial regression models, GWR as well as bi-variable Moran's I can be used. Spatial regressions containing spatial lag, spatial error, or other advanced forms along with GWR are improved forms of analysis methods derived from standard regressions by introducing a spatial matrix. Bi-variable Moran's I enables one-to-one spatial relationship identification, and one response variable can also be tested with a compound explanatory variable representing multiple raw explanatory variables added based on a specific criterion (Balducci and Ferrara, 2018). Relationships among spatial variables can also be identified using aspatial methods covering non-spatial regression, multivariable linear regression and PCA (Chang et al., 2019).

Spatial autocorrelation of spatial variables and topology features of land covers are two issues in EO-HEI. Spatial auto-correlation could be visualised by Moran's I and Gi* (Chen et al., 2020), whereas land topology could be uncovered by digital image processing and spatial metrics. Spatial estimations in HEI mainly refer to spatial interpolation methods to overcome spatial limitation of ground samplings. Numerous Kriging-based methods, as well as deterministic interpolations, are utilised to estimate soil quality and precipitation. Previous studies have shown that Kriging performs the best when estimating soil organic matters (Long et al., 2020). Spatial decision making in HEI includes identifying spatial factors that could influence policymaking, as well as recognizing and assessing influential consequences caused by spatial variables (Jackson, 2003). Spatial decision making can be known as a compound spatial issue at a different level. Spatial decision makings interpret results generated from spatial relationships, spatial patterns as well as spatial estimations, and draw a further conclusion for smart policy making purposes (Cheng et al., 2019).

## 5. DEVELOPMENT IN EARTH OBSERVATION AND FUTURE SMART URBAN CONSTRUCTION

### 5.1 Development in Earth Observation

In the future, changes might happen from data sources to analysis techniques and platforms. From a data source and platform evolution perspective, sentinel series products can be a potentially powerful competitor with MODIS and Landsat series products. UAV and radar images will share a huge proportion of this research area according to their irreplaceable advantages. Furthermore, as a geospatial processing platform that has already been developed and taken into research, the Google Earth Engine will also be a popular tool in HEI studies. From a data processing improvement perspective, image fusion has shown the potentiality in earth observation data pre-processing and machine learning-based methods can be efficient approaches for spatial feature identification.

Radar products and UAV images will also play a non-neglectable role for HEI based on their unique features. Due to the advantage of data acquisition cost and high usability, UAVs mounted with a variety of sensors are utilised to monitor air quality and coastal regions (Adade et al., 2021). Furthermore, the feasibility of UAVs also enables more frequent and higher spatial resolution observations for air pollutants monitoring based on the needs of research (Lambey and Prasad, 2021). As active remote sensing, radar techniques release and receive microwaves, which are not subjected to bad weather or other negative natural risks (Minh et al., 2020) Currently, radar has been applied for plateau and non-residential area mapping (Reinosh et al., 2020). Although low spectral variety and no current open-source platform for data sharing, UAVs and radar products have been applied to some HEI issues including land cover monitoring and air quality monitoring already due to their irreplaceable feasibility and utility.

GEE, existing as a new cloud-based geospatial data platform, will play a key role in the coming HEI studies from a big data handling perspective. Earth observation data can definitely be categorised into big data as the nature of earth observation coincides with the “3V” (volume, velocity and variety) big data definition. The cloud-based GEE platform, as Software as a service (SaaS), is designed to handle spatial big data tasks at the Petabyte level from raw datasets to final valuable products. From a data storage perspective, earth observation big data can be smartly and efficiently stored in such a giant cloud system via distributed networks. Furthermore, GEE, as an integrated and well-managed platform, also increases the accessibility and availability of various earth observation data from multiple sources all over the world. From a processing algorithm perspective, GEE application programming interfaces (APIs) make a better basic earth observation data processing algorithm code sharing and accessing environment possible, which saves time for experts and non-experts. Moreover, GEE computational infrastructure with high-speed parallel processing and distributed computing techniques is an efficient tool for manipulating advanced machine learning or image processing tasks (Tamiminia et al., 2020).

The coming years might witness the prosperity of image fusion and machine learning evolution in future HEI research. Although not involved in current HEI research, image fusion does have the potential to be introduced in the future as the functionality of which is indeed beneficial. Image fusion for hyperspectral images (HSI) and multispectral images (MSI) has been commonly applied in earth observation studies for the purpose of improving HSI spatial resolution and MSI spectral resolution (Dian et al., 2021). The high-quality fused images, created with more detailed and precise geographical features, can be further utilised to monitor land cover change.

### 5.2 Earth Observation and Spatial Tools Support Smart Urban Construction

The construction industry is to serve and change the world by infrastructure development. These infrastructures include roads, bridges, utility supply systems, buildings, green infrastructures


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and other forms of the built system supporting our modern societies physically and spiritually (Bansal, 2011). Understanding and recognizing the reality problem, establishing models and providing feasible solutions are key stages in the construction management. These key stages can be further broken down into multiple tasks from various disciplines including but not limited to spatial engineering, environmental engineering, civil engineering and humanity research (Chiu and Russell, 2011). Each of the tasks needs specific tools to provide a solution. Geographic information system (GIS) is an integrated system, designed to store and analyse spatial information using strategies from statistics and spatial science perspectives. The GIS software includes multiple computational functionalities including database management, spatial data visualisation, spatial data computation, construction scheduling, environmental modelling and safety planning. One of the goals of the GIS application is to provide scientific decision making for stakeholders (Worboys and Duckham, 2021). Therefore, the functionality of GIS software meets the demands of our current construction industry, and GIS has been applied in the construction management from planning, bidding and construction phases. The improvements and innovations in GIS technologies could stimulate the construction management decision making (Cheng and Chen, 2002).

Even though the GIS software has been utilised in the construction management from multiple perspectives, there are three limitations to be bridged (Bansal, 2012). First, the GIS software and relevant strategies are tools for sustainable construction. However, this application has not been fully developed due to the complexity in interactions among multiple influential factors. Furthermore, the concept of sustainability is general and inclusive, and sustainability could be redefined in different scenarios. Second, risk assessment is a critical part of the construction process, and the utility of GIS functionality in construction risk assessment is not fully developed. The risk assessment from a sustainable development perspective can be further analysed using GIS with advanced functions. Third, the popularity of the GIS software and spatial functions in the construction management might be hampered by education background, working experiences and other social issues. Construction management is a field of multiple disciplines, and not all construction professionals are familiar with GIS with up-to-date changes.

Earth observation based on remote sensing techniques can be an effective tool to measure the influential factors relevant to the sustainability issue. The sustainability in construction management includes but is not limited to air pollutant emission, land cover change and urban heat island effect. The implementation of earth observation application could make sustainability measurement feasible. For air pollutant emission evaluation, the Sentinel products and other commercial products can provide global measurement for air pollutant density with high temporal resolution. For land cover change monitoring, satellite-based and UAV-based images can monitor the change of land use and land cover with various images uncovering different physical properties. For the urban heat island effect assessment, remote sensing products with thermal infrared have been utilised in several metropolitans as case studies.

The construction can be categorised into agricultural, residential, commercial, industrial and environmental. The industrial constructions, including infrastructures for mining, manufacturing, waste services and utility supplies, are critical to Australian society. The utility of these infrastructures contributes around 25% of the national GDP, but also contributes around 99% of the human-dominating air pollutant emissions (Department of Environment and Energy, Australian government, 2020). Considering the importance of economic contribution and environmental risk, there is a requirement to investigate and assess the sustainable construction of these three industries. Therefore, the development of earth observation and spatial tools can be a help to assess the sustainable construction for three industries using earth observation data and GIS techniques.

The development of earth observation and spatial tools can help the implementation of smart urban construction by overcoming three gaps. First, in terms of the requirement of various sustainability features for urban areas, different sources of earth observation could provide measures of urban sustainability from socio-economic and environmental perspectives. Second, in terms of the risk assessment in sustainable construction, spatial tools, geography measures and big data analysis approaches could provide reliable sustainable construction analysis and deliver scientific decision makings. Third, in terms of the popularity of GIS and earth observation in the construction and urban design industry, the demand and development of GEE could popularise the application of spatial tools and earth observation. Furthermore, an advanced spatial methodology framework could provide more feasible suggestions, which are acceptable and understandable for experts from non-spatial fields.

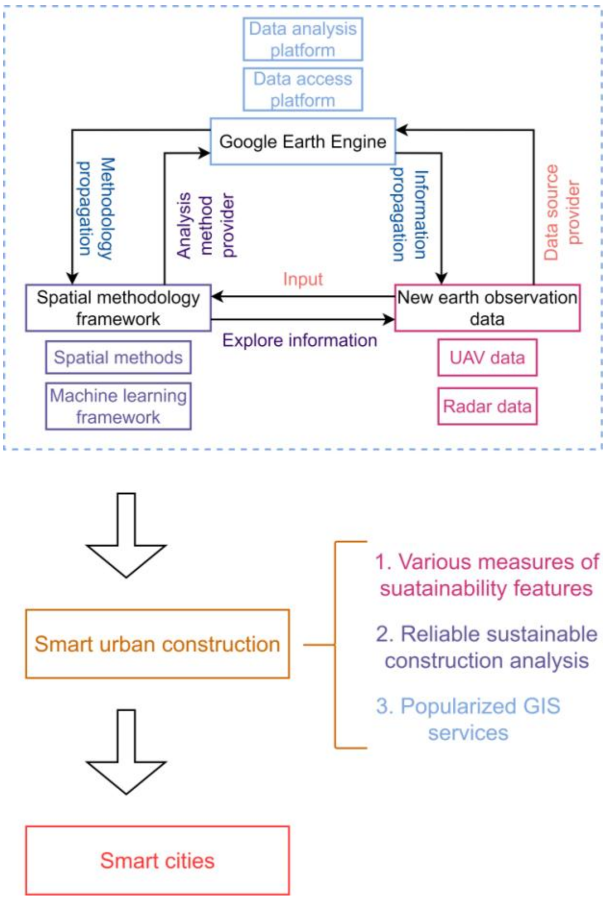


**Figure 2.** The development of earth observation techniques for a better smart urban construction purpose.

Figure 2 summarises how earth observation and GIS services could support smart urban construction and smart city development. New spatial methodology framework, GEE and earth observation data forms a mutually-enhanced system from the view of earth observation application. GEE works as a platform for sharing new remote sensing datasets and advanced spatial methodologies, and GEE could popularise the application of spatial services and remote sensing data from spatial experts to non-spatial experts. New forms of earth observation datasets are input for the innovative spatial methodology framework, and new spatial methods could explore more values of new earth observation data. Under the scope of smart city, the mutually-enhanced earth observation system enables sustainable urban constructions. This system could provide urban construction with measures of sustainability features from socio-economic and environmental perspectives, reliable sustainable construction analysis and popularised spatial services. Under the scope of HEI, the construction industry, as a type of human activity, plays a key role in HEI, and urban construction stimulates the process of urbanisation, industrialization, and population growth. The sustainable urban construction with earth observation as management tools could be beneficial to smart environment design and smart land cover management as well.

## 6. CONCLUSIONS

This article summarises the contribution, potential and significance of earth observation for urban construction and land cover under the scope of HEI. This article shows the application of earth observation in construction management, land cover monitoring and environmental topics. This work also summarises important topics of applying earth observation in land cover monitoring, urban construction and environments. By utilising spatial methods, academic values of earth observation can be explored by numerous analysis methods. In general, earth observation could provide further valuable information regarding spatial relationship identification, spatial pattern and distribution, spatial estimation to overcome the spatial limitation of field sampling as well as spatial decision making for governance policy via spatial or aspatial methods. Finally, potential evolution that might occur in the coming HEI research and this advanced development can be dominated by three mutually enhanced technologies comprising spatial algorithms, the GEE platform and new earth observation data sources. The development of the earth observation and spatial framework system could help us achieve the smart construction and smart city design goals.

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