Satellite-based fine-grained spatio-temporal monitoring of urban building activities as an indicator of economic development

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2025 Joint Urban Remote Sensing Event (JURSE) | 979-8-3503-7183-3/25/$31.00 ©2025 IEEE | DOI: 10.1109/JURSE60372.2025.11075972

***Abstract*—Urbanization, characterized by physical growth and infrastructure expansion, remains a global phenomenon with profound economic, environmental, and social implications. Traditional methods of monitoring construction activity—key indicators of urban and economic development—often suffer from delays and inconsistencies in reporting. This study introduces a Satellite-based Building Activity Indicator (SBAI) leveraging Sentinel-2 imagery and machine learning to provide highly resolved, spatiotemporal data on urban construction activities. The SBAI identifies new urban developments with high accuracy and highlights the ability to track seasonal and project-specific construction trends. Comparison with official statistics on construction activity validates its reliability, while its granularity offers enhanced insights into intra-year variations and localized urban growth dynamics. The SBAI demonstrates significant potential as a tool for national statistical frameworks, offering timely and detailed data to support responsive and informed decision-making at local and national levels.**

Keywords—land cover, Sentinel-2, machine learning, construction sites, building indicator, economic activity

I. Introduction

The majority of the global population lives in urban areas, with a still ongoing trend of movement towards urban livelihood. Until 2050, more than 68% of the population is expected to live in urban areas [1]. Cities are not only the homes for residents, but also represent economical centers and are locations of industrial production, commerce, services, research and development and education which makes them places of innovation and wealth, and they are usually more productive than smaller communities [2]. Densely populated urban areas as a result of urbanization processes result in a spatial concentration of people and infrastructure and are thus much more efficient in terms of land consumption and the use of infrastructure in comparison to low density areas. At the same time, this densification also results in large impervious areas with increased surface water runoff, increased surface and air temperature leading to (surface) urban heat island effects [3], traffic and congestion and increased ambient air pollution [4]. While the scientific term *urbanization* includes a multitude of facets including population growth and economic growth, the most visible result of urbanization is physical urban growth as buildings and infrastructure are needed to house people, offices, shops and production sites, as well as transportation areas are needed to connect these places and people. The material of urbanization is concrete, which on the one hand has a dramatic balance sheet of CO_2 emissions being responsible for a total share of 8% of global emissions [5], but on the other hand has helped to cut down the rate of extreme poverty since the 1990's in half [6] due to the massive growth of urban areas.

The transformation of natural land into built-up areas marks only the physical act of urbanization, while these processes are often preceded by long planning processes, including administrative and legal processes which makes it difficult to compare the physical urbanization processes at international scale compared to official statistics of building activities in cities. Reasons for this can be found in the various ways of monitoring of urban construction sites as part of official national reporting on building activities, e.g. for national censuses etc. Some statistics may report the beginning of the planning process, some report the date of the building permit and some report only the finalized construction. The time between these formal and practical processes can be long, especially in regions with high bureaucratic efforts, resulting in biased statistics on the timeliness of urban construction sites. The latter, however, is a relevant measure of economic activities and can be used to quantify the impact of such intense transformative processes to our environment and it allows to understand the intensity of man-made construction when we see that e.g. China has used as much cement in three years (2011-2013) than the whole U.S. in the entire 20th century [6].

The need for understanding and monitoring of such processes from official side is high, also because they can be used as reliable early indicators of economic activity to be used in estimations of the gross domestic product (GDP) of a country, especially as a growing need of timely and precise statistical data can be observed. The intensity of construction activity plays an important role for the overall economic performs as it can be directly attributed to about 4% of the GDP (https://www.census.gov/construction/nrs/index.html). For the detection and monitoring of urbanization processes, earth observation satellites are an invaluable data source which deliver images in spatially high resolution over multiple decades to map and quantify urban growth at various scales [7]. Monitoring of land-use and land-cover change (LULCC) are key tasks for global Earth observation missions and can provide rapid, unbiased and reliable, objectively derived data and information on change processes on the Earth's surface. With recent advances in satellite-based Earth Observation, some key issues for monitoring LULCC at high spatial granularity could be resolved. Especially the European satellite missions from Sentinel-2 are capable of providing constant data flows on the current state of urban areas and natural land covers. Through the spatial resolution of 10 m, fine-grained details can be extracted from these satellite images while covering large areas at the same time. The Sentinel-2 mission with its twin satellites (Sentinel-2A+B) offers a high revisting rate of 5 days (at the equator) under cloud-free conditions which results in 2-3 days at the latitudes of central Europe. Thus, a timely fine-grained identification of

LULCC can be accomplished. Recent advances in big data processing capabilities using machine learning techniques helped the development of global data sets on urban areas at various spatial scales, e.g. the Global Human Settlement Layer (GHSL) provides global maps of urban areas over four decades using Landsat data at 30 m resolution [8], or the World Settlement Footprint (WSF) providing yearly composites of urban areas [9]. Detailed Sentinel-2 satellite images in combination with high repetition rate of the satellites provide excellent conditions for a data set-up to monitor anthropogenic change processes in urban environments.

Against the background of these recent developments in terms of data availability and image classification methods using novel machine learning techniques, we present in this study a Satellite-based building activity Indicator (SBAI) which aims to provide early information on the building activity in Germany and which can be used to measure and track activity related to commercial and residential construction using Sentinel-2 data. Specifically, the SBAI provides spatially and temporarily highly resolved data on urban building activities at the full spatial resolution of Sentinel-2 of 10 m and as monthly aggregates of newly constructed urban areas. Moreover, we compare and assess the SBAI with official statistics on construction completion from the Federal Statistical Office of Germany to evaluate the potential of satellite images for timely statistical reporting.

II. TEST AREA AND DATA

A. Test area

We test the developed methods for the administrative area of the city of Munich in Germany, as Munich is the fourth largest city in Germany and ranks second in GDP after Berlin which makes it a good choice as an economical center including pronounced building activity. The administrative area of Munich incorporates 560 km² and ~1.6 million inhabitants (2024). Munich's constant increase of population due to high quality of life, education and prosperous labor market, are drivers for ongoing transformation of natural land into urban land. In this context, Munich is planning and constructing some new neighborhoods, e.g. *Freiham* with an area of about 350 ha and housing for 25,000 inhabitants.

B. Satellite data

For the development of the satellite-based building indicator, we use a monthly time series of 59 Sentinel-2 (S2) images from 2016 until 2023 of ten spectral bands from at a geometric resolution of 10 and 20 m, respectively. The S2 twin constellation of allows for a very high repetition rate of up to 5 days in Central Europe, thus increasing the probability of cloud-free acquisitions and making it possible to detect rapid changes on the Earth's surfaces, e.g. in the case of natural disasters. However, even cloud-free satellite images underly various external factors which impact the image quality, such as the sun angle, atmospheric conditions such as haze, which make it difficult for automated processes or pre-trained image classification models to detect the correct class. To increase the standardization of satellite image data, image pre-processing methods are applied for a more effective data utilization. Here, we use a two-stage data pre-processing: first, the Level-2A pre-processor MAJA which is based on the Multi-Temporal Atmospheric Correction and Cloud Screening software (MACCS) in combination with atmospheric correction (ATCOR) [10].

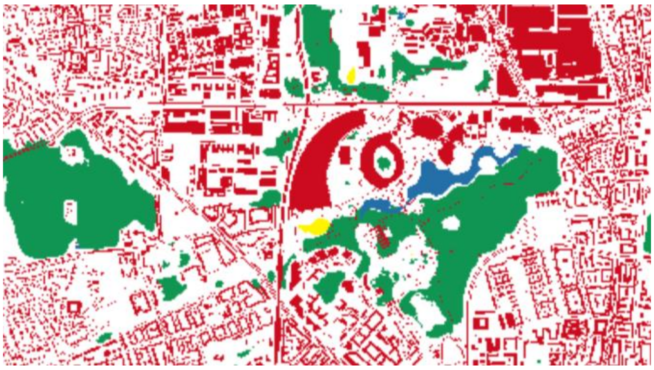

Fig. 1. Subset of Munich visualizing automated reference data for the image classification (green='vegetation', red='urban', yellow='open soil', blue='water', white='NA').

The MAJA processor detects high altitude clouds in the optical images, generates cloud and cloud shadow masks, and corrects cirrus clouds and performs atmospheric correction of the images. In a subsequent step, Level-2A data is used as input for the Weighted Average Synthesis Processor (WASP) [11] which generates monthly aggregates of surface reflectance data. WASP calculates the weighted average of image data over 45 days of cloud-masked images and provides cloud-free Level-3 data with a very low level of artefacts compared to pixel-based methods.

C. Land-cover reference data

To facilitate and automate training data generation for the classification process, we use monthly land-cover reference data on urban areas from freely available data sources such as OpenStreetMap (OSM) (www.openstreetmap.org). Specifically, we use objects representing the urban land-use/land-cover classes 'buildings', 'streets', 'parking lots', 'railway areas', and also 'water surfaces' from OSM as the data quality and timeliness of the data is considered to be of high reliability, at least over large urban areas for countries with an active mapping community. For reference data on natural land, we use land-cover products from Google Dynamic World [12], which is an automatic pixel-based classification of all Sentinel-2 images based on a deep learning method using ca. 24,000 manually labeled image tiles. Empirical testing revealed rather conservative classification for natural land resulting in high user's accuracy and low errors of commission, meaning a high reliability for the vegetated areas. Thus, a random sample taken from pixels classified as 'vegetation' in the Dynamic World product, corresponds very likely to 'vegetation' in reality. Both data sets are combined to a reference land-cover product with the classes 'vegetation', 'urban', 'open soil', 'water', and 'NA' (Figure 1). For independent quantitative evaluation of the performance of the image classification, we use spatial samples from the Land Use and Land Cover Survey (LUCAS) which represents a harmonized in-situ data set over the entire European Union. It is updated every three years and has been already used for large-scale land-cover classifications of Sentinel-2 data [13].

D. Statistical data

For comparison with official data, we use statistics on finished constructions in urban areas from the Federal statistical office in Germany. These data report the number of finished constructions on a monthly basis. The data only reports finished constructions, but cannot temporarily resolve the beginning or the duration of a construction site.

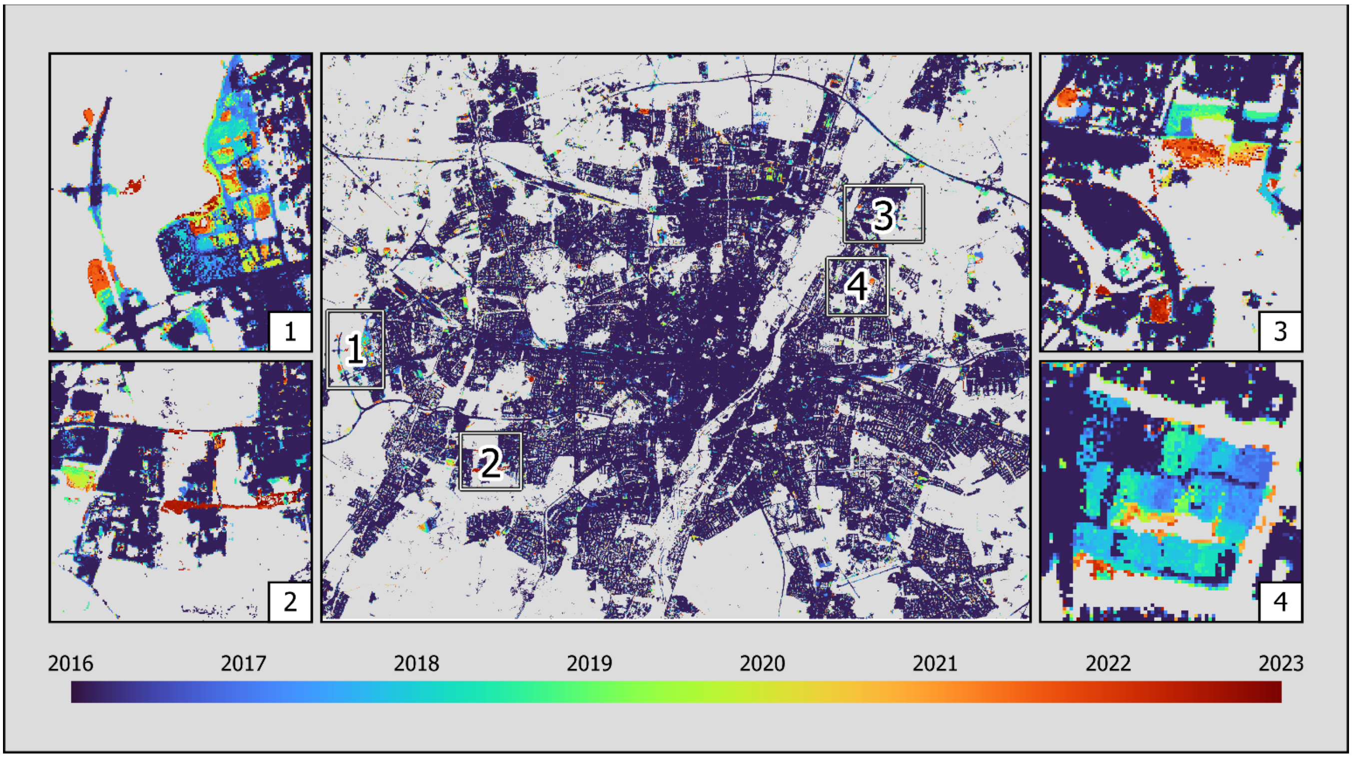

Fig. 2. The satellite-based building activity indicator displaying newly constructed urban areas for the City of Munich over the time period 07/2016-10/2023. Colors indicate the begin of the construction activity (yyyymm).

III. Identification of Newly Constructed Urban Areas

To increase the separability of the target land-cover classes for the image classification, eight spectral features are calculated based on each of the 10 S2-bands. For a detailed description of the 18 indices (10 spectral bands, NDVI, NDWI, NDBI, NDTI, NBAI, NBI, BSI, DBSI), we refer to [14]. For the classification of the monthly-aggregated Sentinel-2 images from 07/2016 until 10/2023, we take random samples of 80% of the automated reference data and train a random forest model [15] for each of the images. The trained models are applied on the entire image tile resulting in a time series of 39 land cover classifications for the four land cover classes. Due to heavily cloudy images and snow cover in winter months, some of the scenes were removed from the classification process. For each classified image, an accuracy assessment is performed based on the remaining 20% reference data and LUCAS data reporting an average overall agreement with the reference data of 95.6% (min.: 93.3%, max.: 96.5%). Class 'vegetation' reports an average accuracy of 97.2% (min.: 96.0%, max.: 97.9%), class 'urban' reports an average accuracy of 94.4% (min.: 91.4%, max.: 95.8%) and 'water' reports 85.3% agreement. Naturally, class 'open soil' reports the lowest agreement with the reference data (49.7%), because of the spectral confusion with urban land and because construction sites are sometimes classified as 'open soil' until the buildings are finished or the roads are paved. For further processing, only the class 'urban' is used, however four land-cover classes are classified because multi-class classifications usually perform better than single-class classifications.

In a next step, the time series of urban land classifications is processed to identify newly constructed areas between two images. Therefore, the land-cover class of each pixel from t_0 is compared with the land-cover class of the same pixel in the subsequent three classifications in $t_{1\text{-}3}$. To account for pixel-based classification errors and to identify only reliable construction sites, we aggregate the second time step over three months ($t_{1\text{-}3}$). If the land cover of a pixel shows a non-urban class in t_0 and for at least two of the three subsequent time steps ($t_{1\text{-}3}$) the class 'urban', the pixel is flagged as identified building activity and the time stamp of the month of the beginning of the construction is stored in the pixel (yyyymm). This step is repeated for all steps of the time series.

Results of the satellite-based building activity indicator are displayed in Fig. 2. The image shows an overview of newly built areas over the time series for the entire city of Munich in the center. Dark blue pixels represent the state of urban land in May 2016. Boxes on each side of the image display magnifications of remarkable areas which have experienced significant building activity in the time period. Box 1 displays the newly constructed urban neighborhood *Freiham* in the West of Munich which is under construction since the year 2016. Box 2 displays the construction of a new metro line since spring 2023, box 3 displays the construction of a large school campus and box 4 displays the transformation of a former area of military barracks into a newly developed housing area with more than 1,800 apartments for about 4,000 residents. For both examples in box 1 and box 4, the beginning of individual parts of the construction sites can be identified based on the color coding.

IV. Comparison with Official Data and Discussion

To assess the applicability of the satellite-based building activity index for timely reporting of national statistics on construction sites, we compare the results of the classified time series for newly constructed urban areas with official data which reports finished constructions at a monthly scale. A visual comparison of both data is displayed in Fig. 3. To allow for a meaningful comparison, both time series were standardized using z-transformation and the timestamps of the SBAI to match the official data on finished constructions.

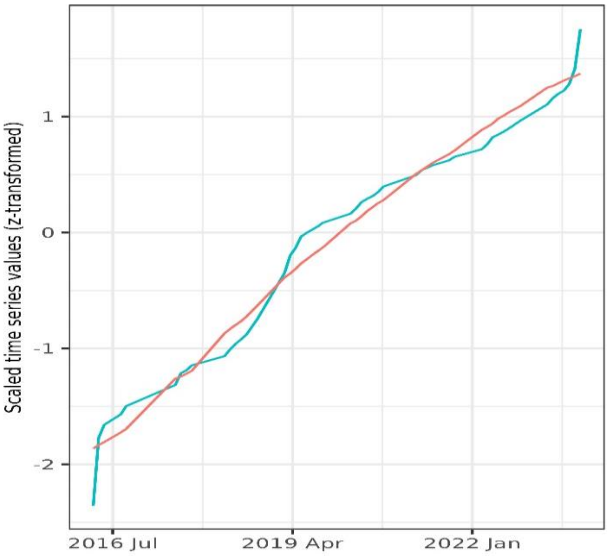

Fig. 3. Comparison of official statistics on finished constructions (red) and the SBAI(cyan) for the administrative area of Munich.

Due to the temporal mismatch of the satellite-based detection of land cover changes versus the reported completion of the construction a detailed assessment of these temporal lags is still pending. While the gradient of the building activity observed in the official data is relatively stable over the analyzed time period, the results derived from the SBAI reveal significant intra-year variations. These variations can be attributed to the finer temporal granularity of satellite data, which enables the identification of seasonal construction trends, temporary pauses in building activity, or variations caused by external factors such as weather or economic disruptions. Moreover, the SBAI provides spatially explicit insights into construction trends. The ability to map and monitor specific urban development projects, as demonstrated in Fig. 2, offers a significant advantage for urban planners, policymakers, and researchers seeking to understand the dynamics of urban growth. The case of Freiham, as well as other highlighted projects, illustrates the potential of remote sensing-based approaches for tracking urban expansion in near real-time. Nevertheless, the comparison shows that the general development of constructions matches very well between the datasets as they have almost the same gradient in the time series, and thus showing a valuable proof-of-concept that building activity can be derived through change detections in Sentinel-2 imagery in fine-grained spatial and temporal detail at large scales.

V. Conclusion

This study demonstrates the value of combining high-resolution S2 satellite data with advanced image classification methods to derive timely, spatially detailed information on construction activity, complementing traditional statistical methods that often depend on aggregated data with significant time lags. The strong correlation between SBAI results and official statistics validates its accuracy, while its finer granularity and ability to detect intra-year variations make it particularly useful for monitoring urban growth processes in greater detail. Beyond urban planning, the SBAI offers significant potential for integration into national statistical systems. By delivering near real-time data, the indicator can assess economic trends, especially in the construction sector, which constitutes a substantial share of GDP. The detailed temporal resolution of the SBAI enables policymakers and analysts to observe dynamic shifts in construction activity that might be obscured in traditional reporting, supporting more responsive and informed decision-making. As urban areas continue to expand and evolve, tools like the SBAI present a promising approach for understanding the interplay between urbanization and economic growth, ultimately contributing to more sustainable and effective policymaking.

Acknowledgements

This study was partly funded by Eurostat within the funding scheme Geospatial Statistics SMP-ESS-2022-GEOS-IBA (project: Satellite-based economic flash-estimation - Sat4Ec), by the Bavarian Ministry of Economic Affairs, Regional Development and Energy (project: EO4CAM) and by DLR (project "HiCLIM").

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