Can remote sensing data be analysed to detect construction activity?

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Abstract

To support the construction statistics by quality assurance measures, the project 'Earth Observation and AI for Construction Statistics' (EO4ConStat) is set up of a consortium of the German National Statistical Institute (Destatis), the Federal Agency for Cartography and Geodesy (BKG) and the German Aerospace Centre (DLR). The objective of developing a method to quality assure construction activity statistics using remote sensing data and artificial intelligence is relevant for high quality construction statistics.

Due to the German government's ambition to build new, affordable and climate appropriate housing, construction statistics are currently in the political focus. The aim of the project – which is financed by the European Commission – includes developing algorithms to detect buildings and building construction sites and possibly define new construction starts as well as works completions from earth observation data. This is to be achieved by using and adapting a permissive open license segmentation model. Furthermore, a methodology to compare these results of the change detection analysis with the data collected through the traditional statistical channels shall be contrived.

This paper reflects the use of remote sensing data as a rather new data source for official statistics depicting some advantages and disadvantages regarding the data availability and processing for producing statistics. Next, the challenges for construction activity statistics are described. After that, the used segmentation model is presented and the concrete data collected for the projects use case is explained. Finally, the next steps of the project are explained as it is still in its first set-up phase, so far.

Keywords: earth observation data; remote sensing data; construction statistics; artificial intelligence; SAM

1. The use of remote sensing data in official statistics

Remote sensing techniques provide images of large areas of the earth's surface at relatively frequent intervals. During the last decade, technological progress has substantially influenced and improved the availability and analysis of satellite and other remote sensing data on the one hand and the demand for up-to-date data has increased on the other hand. Hence, remotely sensed data is coming into play also in official statistics (Arnold & Kleine, 2017). The information gathered in this way provides valuable insights and facilitates informed decision-making and policy formulation.

1.1 The Characteristics of Remote Sensing Data

Remote sensing has become an indispensable tool in various fields, including environmental and land use monitoring and planning, agriculture, and disaster management. For these purposes, data can be acquired differently: it can be subdivided into three types of remote sensing: spaceborne where the sensor is attached to a satellite or space-missile, airborne where the sensor is attached to an airplane, airship, drone, hot-air balloon or similar and ground remote sensing where the sensor is mounted to a ship, vehicle, measuring station or any other equipment (Luo et al., 2019, p.2). Moreover, it can be differentiated between active remote sensing instruments which operate with their own source of emission or light and passive ones, which rely on recording energy that was emitted by the sun and its reflectance from earth's surface (Kogut, 2020). Based on these principles there is a wide spectrum of remote sensing modalities existing that includes optical, thermal, radar, and LiDAR, each offering unique capabilities and characteristics for earth observation. From radar, LiDAR and laser scans the received response of the actively sent signal can be quantified (e.g. backscatter). The advantage is that these are relatively immune towards weather conditions and hence against a cloud cover. The passive sensors depend on natural energy (e.g. sunrays) that is (partly) reflected by the object of interest. Passive remote sensing uses multispectral or hyperspectral sensors with diverse bands that include spectra within and beyond human vision (visible, IR, NIR, TIR, microwave). These are much easier to interpret and analyse compared to the active sensors.

With these principles remote sensing enables the observation and analysis of Earth's surface and atmosphere at different spatial and temporal scales. The spatial resolution – meaning the pixel dimension of the imagery – varies between a few centimetres (so called digital orthophoto – DOP) up to multiple kilometres for satellite imagery. The temporal resolution depends on the return rate to a certain location and varies from lass than a day (satellite images) up to several years (airplane flyovers for certain areas). An exemplary overview of the spatial and temporal resolution for remote sensing data for Germany is depicted in Table 1.

Table 1: Exemplary availability of remote sensing data for Germany, as of July 2022.

Type of remote sensing data	**Availablity / temporal frequency**	**Spatial resolution**
Satellite imagery	Daily up to every 16 days	0,3m up to 30m
Aerial photo / Digital Orthophoto	Every 2 to 4 years (rolling updates)	0,1m up to 0,4m
3D-Modell of Earth's surface	One-off aerial survey (end of 2025)	40 points per m²

A huge advantage is that remotely sensed data can provide georeferenced information of large areas across administrative boundaries at a small-area level. In addition, different remote sensing data sources can be combined or matched to make the most of spatial and temporal resolution and adapt the data basis for specific tasks or analysis.

1.2 Data Processing and Analysis

Central to remote sensing data analysis is the extraction of meaningful information from raw sensor measurements. This process often involves a series of computational techniques, including image processing, feature extraction, and classification.

Without going into detail, basically the data needs to be radiometrically calibrated, synchronised with the according position e.g. of the aircraft or satellite and then geocorrected (Warren et al., 2013, p.24).

The pre-processed remote sensing images need to be further analysed to extract the information of interest from the data. Within the last years methods of extracting information from optical data have advanced and artificial intelligence (AI) plays a major role in these developments. With segmentation techniques – which is a subfield of digital image processing and computer vision – related regions in an image can be delimited by combining neighbouring pixels according to specific homogeneity criteria. This allows to isolate specific objects or areas and thus to extract thematic raster maps within an image e.g. for navigation, urban planning, environmental monitoring and much more topics or use cases. Bearing this in mind, the question of whether construction activity can be detected through AI techniques used to analyse remote sensing data arises.

2. Construction activity statistics: challenges and the option of remote sensing data analysis

The construction activity statistics are intended to show the structure of construction activity in Germany, which is an important early indicator of economic development in the construction industry. Regular publications contain the monthly statistics on building permits, the annual statistics on works completions, construction progress, construction dismounts and the update of the residential building and housing stock (Schumann et al., 2023, p.28). Several political endeavours as well as a user consultation show that there is a high demand for detailed intra-year statistics of construction starts and works completions.

Optical remote sensing data cannot solve all the demands as they solely provide a view from above. Yet, with an advanced model and additional elevation data and other geo-information the idea is to develop a method that can help to quality assure and enhance construction activity statistics.

3. The Segment Anything Model: An Overview

In 2023 a project was introduced by Meta AI Research to build a foundation model for image segmentation (Kirillov et al., 2023, p.1). A foundation model is an artificial deep learning model which is pretrained on a very large amount of data and can be used to learn new datasets, develop more specific applications and hence perform new tasks. The Segment Anything Model (SAM) provides an approach to semantic segmentation which classifies each pixel of an image so that all objects of a certain class belong together (e.g. 1 – animal, 2 – background one, 3 – background two). The SAM was trained with a large data set of 11 million licensed and privacy-preserving images of a geographically and economically diverse set of countries with which numerous masks (=classifications) were produced (Kirillov et al., 2023, p.2). Hence, SAM segments objects of interest across diverse landscapes and imaging modalities. Its applicability extends to various remote sensing applications, ranging from land cover classification and change detection to object detection and monitoring. An example of how the model basically works is given in Figure 1.

Figure 1: SAM automatically segments everything in an image.
Source: https://segment-anything.com/

Putting a grid on the image | Selecting certain points of interest within the image | Masking the selected points according to the identified class

Traditional segmentation methods need extensive human input and intervention to gain accurate results (Osco et al., 2023, p.1). With more and more advanced AI and deep learning techniques the human input can be reduced and methods further automated. The SAM brings good generalization capabilities and is supposed to deliver accurate predictions with little further training data (ibid.). This makes the model explicitly interesting for remote sensing applications, since the data acquisition and annotating process in this field is highly labour-intensive and requires expert knowledge.

Semantic and instance segmentation, in particular, play a crucial role in identifying and delineating specific objects or land cover classes within remotely sensed imagery. If the SAM performs segmentation with zero domain-specific information this might offer an important advantage for this process (ibid.).

4. The use of SAM to detect construction activity

Construction activity showcases a specific application to analyse. In general, urban areas exhibit a large variety of reflectance patterns in remote sensing data. These areas have large intra-class variations and often also low interclass variation which makes them challenging to accurately analyse (Montoya-Zegarra, 2015, p.127). Within urban areas construction sites could be detected by identifying open soil, because bare soil might not be common. However, if one building replaces another former one, the challenge is to identify the construction start and building phase from the temporally available earth observation data. In rural areas bare soil might be more frequent and therefore the aim is to differentiate between arable land / fields and open soil due to the existence of construction sites. Moreover, the frequency of remote sensing data varies largely as can be seen in Table 1. Therefore, several approaches and diverse input data will be tested within the EO4ConStat project.

To detect buildings and construction sites and possibly define new building starts as well as construction dismounts from earth observation data, the SAM will be adapted and trained accordingly with context specific imagery containing secured label information. The training data will consist mainly of three input data sources: (1) digital orthophotos (DOP) with a spatial resolution of at least 20x20 cm, (2) house perimeter data and (3) Sentinel-2 data from the European Copernicus program. The DOP have a temporal frequency of two to three years, the house perimeter data is a yearly dataset and the Sentinel-2 data are available at least every six to 12 days or as a monthly cloud-free mosaic dataset.

With the more frequent Sentinel-2 data the approach is to perform a time series analysis of building activity to more accurately date the construction stage of houses and find new construction sites which might not be visible in the other datasets which are less frequently available.

5. Conclusions and next steps

The project EO4ConStat is still in the first phase where certain research approaches are yet to be set up and need to be worked out in more detail. For the construction activity statistics all further details to get to know the quality of existing statics better and to narrow down and quantify certain possibly existing gaps or errors in the data will help to quality assure the existing publications. At best, the developed methods will help in the process to further subdivide the current publications of the annual statistics into intra-yearly information.

The SAM, that is used in this research, was just released in 2023 which means there is a huge potential to further adapt it with the current rapid developments in the field of AI and deep learning networks. In particular, the use of the SAM in the field of earth observation data is currently being further developed in various projects, including by other National Statistical Offices (NSI). This will enhance the learning and exchange to improve the use of earth observation data for the statistical process and to quality assure existing statistics in diverse fields.

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