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ORIGINAL ARTICLE

Sat4BIM4D — the concept of using satellite remote sensing to monitor construction progress in conjunction with BIM

Szymon Glinka [1*]

[1]Faculty of Geo-Data Science, Geodesy, and Environmental Engineering, AGH University of Krakow, Al. Adama Mickiewicza 30, 30-059 Kraków, Poland

[*]szym.glinka@gmail.com

Abstract

Monitoring the progress of construction work and adhering to the schedule is crucial for the timely completion of projects. Integrating data from various sensors (e.g., cameras, laser scanners) mounted on diverse platforms (rovers, drones, satellites) with BIM 4D (Building Information Modelling) enables effective construction control solutions. By leveraging 3D models enriched with temporal information, project management can be significantly enhanced. This paper focuses on a comprehensive review of current literature and state-of-the-art practices to design a framework for integrating satellite remote sensing data with BIM 4D, termed the Sat4BIM4D method. Proposals for this method are developed alongside algorithms for processing satellite-derived data to monitor construction progress, particularly for infrastructure projects. The study emphasizes the compatibility and synergy between satellite data and BIM 4D, providing a structured direction for future research. Advantages, limitations, and potential challenges of the proposed approach are also critically analyzed to pave the way for further development in this domain.

Key words: BIM, satellite, remote sensing, progress monitoring, BIM 4D

1 Introduction

The development of data acquisition methods facilitates the enhancement of processes within the construction industry. When combined with the digitalization of these processes, a notable improvement in their efficiency is observed (Elghaish et al., 2020). Presently, digitalization is achieved through the implementation and integration of building information modeling (BIM) technology, alongside modern methods of data acquisition (from a technical perspective) and contemporary approaches to the management of construction investment projects (from a managerial perspective). Based on the BIM methodology, a model consisting of geometric information and alphanumeric data is created throughout the life cycle of an object. When supplemented with the appropriate information, this model can evolve into a digital twin (DT) of the object (Deng et al., 2021). The term digital twin refers to a digital representation of the actual state of a real object, an idea originally widely utilized in the manufacturing industry (Grieves, 2014).

Data that can support the concept of digital twin (DT) include various types of Internet of Things (IoT) sensors, regularly acquired data (e.g., using cameras mounted on UAVs — unmanned aerial vehicles), and geographic information system (GIS) data. During the construction phase, the use of DT enables access to up-to-date information about the construction site and the condition of individual components, facilitating analyses, simulations, and the support of related processes such as logistics. Among the diverse sets of data sources, satellite data are particularly noteworthy, as they enable the rapid acquisition of data or imagery over large areas. Despite their limitations, such as susceptibility to weather conditions in the case of optical sensors, and resolution constraints, their applications are expanding. Advances in sensor technology are continually improving the reliability and accuracy of the acquired data (Zhu et al., 2018).

On the other hand, the need to advance applied technology in the construction industry fosters the development of novel approaches to support decision-making processes. The evolution of BIM towards time-based analysis (BIM 4D), cost analysis (BIM 5D), environmental impact analysis (BIM 6D), and operational phase management (BIM 7D) enhances control over an object or set of objects during individual phases or throughout the entire life cycle of a project (Charef et al., 2018). The concept of digital twin (DT) is primarily realized through BIM 4D, which focuses on scheduling construction activities, conducting simulations, and monitoring the current state of work. This is achieved by collecting data from various sensors and automatically identifying the progress of construction activities.

Why is progress monitoring important and what is the business impact of progress monitoring on the construction industry? Why should there be an aim to automate construction progress monitoring (ACPM)? The traditional approach, where progress data is captured manually, is time-consuming, inaccurate, and expensive (Navon and Sacks, 2007). Furthermore, research shows that the construction industry often struggles to complete projects on time and within budget (Barbosa et al., 2017), partly due to insufficient schedule control (Durdyev and Hosseini, 2019). Hence, there is need for automation and greater attention to progress monitoring. With more accurate project schedule control, it is possible to implement more elaborate management systems linked to, for example, the supply chain (Babič et al., 2010).

This publication focuses on schedule maintenance and control using BIM. By integrating various datasets, it becomes feasible to stage a project, control the progress of work, coordinate and optimize the planning of a construction site, and coordinate the parties conducting the work. This research has focused primarily on the possibility of monitoring the progress of work using remotely sensed satellite data. This approach shows promise, particularly with advancements in satellite-mounted measurement sensors. Linking BIM with remotely sensed geospatial satellite data has also been identified as an opportunity for developing BIM and GIS integration (Glinka, 2022). Despite extensive literature analysis, no solutions combining BIM with satellite-derived data for progress monitoring have been identified, indicating a significant research gap. The only related publications found are Behnam et al. (2016) and Tian et al. (2020), and they do not integrate their findings with BIM 4D capabilities.

This publication aims to analyze solutions described in the literature and based on these analyses, determine the feasibility of using remotely sensed satellite data for monitoring the progress of construction work, primarily in infrastructure projects. Additionally, it seeks to identify the limitations of this technology for such tasks and describe methods to integrate this data with building information modeling (BIM) technology. The work comprises several stages:

- Identification of the current state-of-the-art in construction progress monitoring. This includes describing the technologies and systems used, as well as identifying methods for extracting and communicating progress information in relation to BIM.
- Analysis of solutions for extracting information on objects and change detection from satellite-derived data. This stage involves assessing existing methods and technologies for extracting relevant information from satellite data, with a focus on their limitations.
- Integration of the above analyses and exploration of the feasibility of using satellite data in conjunction with BIM to monitor construction progress. This section attempts to answer whether satellite data can effectively complement BIM in monitoring construction progress. It proposes a method for monitoring construction progress based on BIM and satellite remote sensing, termed Sat4BIM4D.

This study aims to analyze the current state-of-the-art in BIM-based construction progress monitoring and satellite-based change detection and to propose a framework — Sat4BIM4D — that integrates satellite data with BIM to enhance construction progress tracking.

The structure of the article is as follows: Section 2 provides a detailed overview of the background and context, establishing the foundation for the research problem and highlighting relevant literature. Section 3 outlines the research methodology. In Section 4, the findings are presented, with a comprehensive analysis and interpretation of the results. Finally, Section 5 concludes the article, summarizing key insights, addressing the study's limitations, and offering practical recommendations and directions for future research to build on the findings.

2 Background

2.1 BIM 4D and construction progress monitoring

Currently, various project management approaches such as critical path method, s-curve, linear schedule methods, and earned value management are used in the architecture, engineering, and construction (AEC) industry as a basis for scheduling and monitoring progress (Patel et al., 2021). Until the introduction of BIM technology, time-based analysis activities were carried out using CAD 4D (Heesom and Mahdjoubi, 2004), among others. BIM 4D as an extension of CAD (computer-aided design) and the standard BIM approach allows for giving a time aspect to the model and developing a digital work schedule with a 3D model rather than flat CAD documentation (Gledson and Greenwood, 2016) (based on the approaches mentioned above). This allows simulations that facilitate, for example, optimization of the construction site and improving safety (Sulankivi and Kiviniemi, 2014), ordering components on time and improving logistic operations, or minimizing material storage time (Bortolini et al., 2019; Jupp, 2017; Mirarchi et al., 2018). However, effective tools for monitoring work progress are crucial, as research indicates that inadequate progress monitoring is a significant challenge in construction projects (Navon and Sacks, 2007). The schedule in itself is important, but the lack of tools to control it can cause problems during the execution phase.

In the literature, the predominant methods for data acquisition in construction progress monitoring include the use of RFID (radio-frequency identification) sensors or ultra-wideband technology, image acquisition cameras, and laser scanning (ElQasaby et al., 2022). Sensors, depending on their type, are mounted inside or on components (mainly RFID sensors) (Akanmu and Anumba, 2015), and attached to devices that allow the acquisition of large amounts of data in a short time (in particular UAVs (Jacob-Loyola et al., 2021) and ground rovers (Ibrahim et al., 2021)). Additionally, sensors are used on machines performing construction work (e.g., crane (Masood et al., 2020)) or measurements are performed manually by a human (e.g., using a smartphone, professional camera (Golparvar-Fard et al., 2011b) or a laser scanner (Bosché et al., 2015)). There are also systems where human operators manually input the current construction status for various components (Park et al., 2017). As shown in (Duarte-Vidal et al., 2021), it is not unusual for sensors to be combined to provide better quality information, but at this point achieving full interoperability is still limited. The methods used are most often not autonomous. A drone or camera operator is needed to acquire data. The further step of data processing and combining the information with BIM 4D is already increasingly being automated (Patel et al., 2021), which will be described in Section 4.

The integration of BIM 4D with construction progress monitoring facilitates the application of Lean principles (primarily maximizing value while minimizing waste with continuous improvement and efficiency enhancement) across various aspects of construction. This includes addressing logistical challenges through just-in-time implementation and employing visual management techniques such as kanban boards (Demirdöğen et al., 2021). Equally important is the development of the idea of digital twins and linked data, among other things, which makes it possible to build digital versions of real objects with key information for decision-making (Boje et al., 2020).

From an open approach (primarily openBIM approach) perspective, the Industry Foundation Classes (IFC) format plays a crucial role in building information modeling (BIM) (ISO 16739-1:2018, 2018). The schema itself is used globally to unify the exchange of information between stakeholders in the construction process. Examining the schema structure reveals its capability to incorporate scheduling and cost data into individual tasks, linking them to components for detailed time analysis and cost estimation. This functionality is facilitated by the IFC schema extension IfcProcessExtension, which includes subclasses like IfcTask for modeling work and scheduling activities (Sheik et al., 2023). Moreover, the unification achieved through standardized naming conventions within BIM is essential. This consistency enables the automated generation of schedules and other outputs based on the constructed model (Jung et al., 2024). These elements collectively enhance interoperability, facilitate comprehensive data exchange, and support efficient project management within the construction industry.

2.2 Satellite remote sensing

The advancement of sensors capable of acquiring precise, very high-resolution (VHR) data from satellites positioned hundreds of kilometers above the Earth offers significant potential for monitoring both large-scale (macro analyses) and small-scale (micro analyses) areas. Remote sensing technology, primarily applied in environmental sciences, plays a pivotal role in various domains such as vegetation analysis (Xie et al., 2008), hydrology (Engman, 1999), and land cover analyses (Karra et al., 2021; Phiri et al., 2020). These data also find extensive use in disaster management applications (Joyce et al., 2009). One of the biggest advantages of remote sensing data from satellites is that apart from imaging in standard electromagnetic wavelengths — RGB (red, green, and blue), they also provide others. This facilitates the creation of different normalized indicators to extract specific information. The most used are NDVI or NDMI, which help extract environmental information concerning the amount of biomass and moisture. However, other indicators are also used that allow, for example, the extraction of roads (Shahi et al., 2015) or soil (Deng et al., 2015).

In addition to a different number of spectral channels, remote sensing devices are also characterized by a different spatial resolution. Publicly available (free) remote sensing data, e.g., from the Sentinel mission, have a spatial resolution that is far from suitable for the extraction of precise information. On the other hand, commercial sensors allow imaging of the Earth's surface with greater accuracy, but their drawback is associated costs. A balance must therefore be kept between the value of the data for a given application and its economic value.

In order to extract information from satellite remote sensing data, data processing is essential. Various techniques can be applied to the spectral channels to perform feature extraction, thereby supporting algorithms in identifying specific patterns. Presently, machine learning methods such as random forest (RF), support vector machine (SVM) (Saini and Ghosh, 2018), as well as deep learning techniques including convolutional neural networks (CNNs) (Längkvist et al., 2016) and transformers (Xu et al., 2021), are commonly employed for this purpose.

In addition to passive remote sensing devices, active sensors are also utilized, offering reduced dependence on weather conditions. Radar sensors, notably synthetic aperture radar (SAR), are particularly significant in this context as they enable analysis of vertical movements. From SAR data, various products can be derived, including digital elevation models (DEMs) and analyses related to glacier monitoring through InSAR (Interferometric SAR). InSAR is instrumental in monitoring phenomena such as landslide movements, assessing slope stability, observing glacier dynamics, and analyzing 3D ground motions using differential interferometry (D-InSAR) (Zhu et al., 2018). The application of SAR data, especially in infrastructure assessment, is further detailed by Gagliardi et al. (2023).

Taking a broader perspective, there has been a notable increase in the deployment of satellite constellations in recent years, presenting significant opportunities for leveraging satellite remote sensing within the Architecture, Engineering, and Construction (AEC) industry. Satellites such as WorldView-3, WorldView-4, Pleiades Neo, or ICEYE offer resolutions starting from several centimeters. This capability facilitates precise recognition of small objects and accurate detection of changes over time.

Looking from the perspective of infrastructure object analysis, satellite remote sensing is primarily used for ongoing analysis (maintenance) to support the detection of various types of defacements (e.g., detect structural displacements of bridges (Gagliardi et al., 2020), also in conjunction with BIM (D'Amico et al., 2022)), object condition assessment, traffic monitoring or observation of the terrain around infrastructure to support operations and decision-making (Gagliardi et al., 2023). However, a notable research gap exists in utilizing satellite remote sensing during the earlier phases of an object's life cycle.

When it comes to utilizing satellite remote sensing data for construction purposes, there has been limited research conducted in this area, as briefly outlined in this section. This topic will be further elaborated upon in subsequent sections of the article.

3 Methodology

The whole work starts with analyzing what data and information are most often needed during the construction progress monitoring process, what algorithms are currently used to extract information for progress tracking, and how the extracted information is combined with the BIM model to assess the progress of work. Then, it examines what information can be extracted from satellite imagery, particularly in relation to the construction industry and progress monitoring, and explores algorithms for automatic change detection. The conclusion includes combining the previously described steps and assessing whether satellite data can be used as a source for construction work progress monitoring by linking with BIM technology. A scheme is also proposed that may allow the extraction of information on the progress of work and the combination with BIM data, culminating with a discussion of the strengths and limitations of this solution.

As a first step, construction progress monitoring publications were analyzed. Table 1 presents the queries executed in the Scopus database along with the number of records obtained. In addition, publications from the author's own sources library that were missing in the key and are related to the research topic were included in the work in progress. The publications were then classified according to their relevance to the research topic. A three-point scale was adopted, where:

- 0 – Publications that were not completely related to the topic (e.g., those about analyses related to agriculture), retracted or unavailable.
- 1 – Publications that were not related to progress monitoring but related to BIM 4D or presented methods of data acquisition and processing relevant to the analyzed subject.
- 2 – Publications strictly related to the issue under study.

The publications were then analyzed in order to classify them according to the type of publication, the type of sensor used and its medium, the type of algorithm for data processing, as well as the research object. In the next step, publications in which image-based algorithms were used were analyzed in detail.

Table 1. Used queries in the Scopus database

Name	Query	Count
Query 1	TITLE-ABS-KEY (progress AND monitoring AND bim) AND PUBYEAR > 2006 AND (LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "ar"))	258
Query 2	TITLE-ABS-KEY ("remote sensing*" AND (4D OR ("progress monitoring*")) AND construction*) AND PUBYEAR > 2006 AND (LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "ar"))	30

The second step involved an analysis of what information may be extracted from satellite imagery in terms of the construction industry. An attempt was made to create a key that would identify publications in this field, but the queries were ineffective. Therefore, it was decided to manually browse the Scopus database and, based on keywords and abstracts, identify publications that might fit the requirements. Then it was analyzed what input data were selected, what information was extracted (including the accuracy level), and what the opportunities and limitations of satellite imaging were (especially optical).

In the third step, the link between the above-described steps was made. A workflow showing the work performed is presented in Figure 1.

4 Results

4.1 Stage 1: BIM and construction progress monitoring methods

Sensors, objects and methods overview

An analysis of the publications reveals considerable diversity in the sensors utilized for acquiring data on work progress (Figure 2). A significant number of studies focus on processing images or videos obtained from digital cameras mounted on drones (Tuttas et al., 2017), cranes (Masood et al., 2020; Tuttas et al., 2014), erected structures (Arif and Khan, 2021), or carried by a human (Han and Golparvar-Fard, 2014b). The second most frequently used sensor is the laser scanner, which was employed using traditional methods (Maalek et al., 2015), as well as innovative approaches that involve portable devices for faster data acquisition (Prieto et al., 2020). The output of the laser scanner is a point cloud (PC), and similarly, photogrammetry, structure from motion (SfM), and multi-view stereo (MVS) techniques also produce PCs from images captured with digital cameras. Consequently, some algorithms for data processing and integration are based on similar principles. Moreover, several publications report the use of cameras or laser scanners in combination with augmented or virtual reality technologies (Lee et al., 2018; Pour Rahimian et al., 2020). Another category of studies involves the use of IoT sensors, primarily RFID tags or the combination of digital cameras with QR codes (Choi and Seo, 2020). Additionally, the use of total station instruments was proposed, with automated connections to web services for real-time display of measurement results (Arif and Khan, 2020). Furthermore, some publications describe the application of web-based platforms where workers manually input the status or state changes of components (Juan et al., 2019).

Analyzing the subject of the study, it is evident that the majority of use cases described in the articles pertain to buildings, with fewer focusing on infrastructure (Figure 3). Additionally, a small number of publications were categorized as "other" because they examined work progress more from a management perspective or were review articles. Figure 3 illustrates the distribution of publications based on their research focus. The notable disproportion between publications concerning the progress of work on buildings versus infrastructure can be attributed to several factors:

- Restricted implementation of IFC for infrastructure: IFC standard for infrastructure, with the official version IFC4x3 includ-

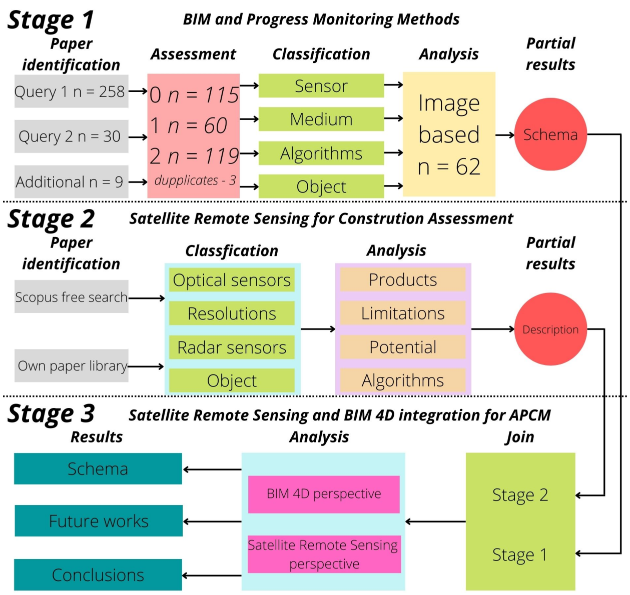

Figure 1. Scheme of methodology

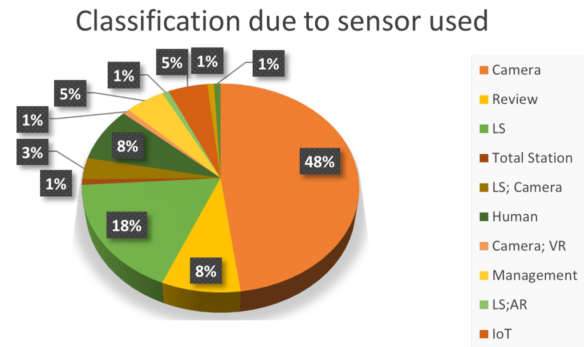

Figure 2. Identified publications classified by the sensor used

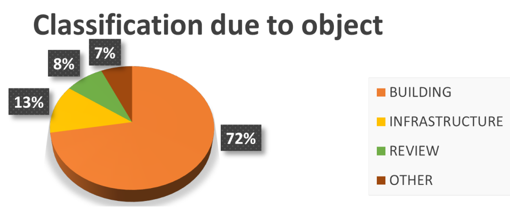

Figure 3. Identified publications classified by research object

ing infrastructure extensions (proper classes and entities) only published in September 2023 has imposed constraints on the ability to write data in open format.
- Development of BIM for buildings versus infrastructure: BIM is more developed for buildings than for infrastructure, as evidenced by the greater number of available publications in the building sector.
- Prototypical nature of progress monitoring solutions: Most proposed progress monitoring solutions are in the prototypical stage. It is generally easier to test these solutions on building projects rather than infrastructure projects due to the more contained and controlled environment of building sites.
- Difficulty in accessing infrastructure: The large scale and limited accessibility of infrastructure projects pose significant challenges for research and data collection. These difficulties make it harder to implement and test progress monitoring solutions in infrastructure settings compared to building projects.

The above results are also confirmed by Patel et al. (2021), where the recommendations state that future work should focus on creating APCM solutions for infrastructure. Thus, the need to create and provide tools to control the progress of work for infrastructure projects is undeniable. Therefore, it is necessary to consider whether the transfer of algorithms from building to infrastructure is possible. To this end, remote sensing satellite imagery is proposed as a primary information source, given its continuous and automatic data acquisition capabilities.

An analysis of the literature identified three publications that utilize remote sensing satellite data to monitor the progress of work. Two of these studies employed passive data acquisition methods (Behnam et al., 2016; Tian et al., 2020), while one utilized an active method (Yang et al., 2017).

Both publications used optical sensors and data from the Pleiades satellite, which has a spatial resolution of 0.5 meters. Additionally, Tian et al. (2020) incorporated data from the Beijing-2 satellite, which captures data with a spatial resolution of 0.8 meters. Both articles focused on infrastructure projects: transmission lines and a bridge over a railway. However, the studies primarily concentrated on point objects, such as poles, pillars, or piles, rather than elongated objects. Behnam et al. (2016) described a case study consisting of four stages: site clearing and bored pile platform activities; pile cap construction; pier work and pier head construction; segmental box girder (SBG) launching and post-tensioning activities. The current state measured with satellite remote sensing was then combined with a timetable to establish correctness, while information extraction was supported by CAD data. The second paper also focused mainly on the extraction of point information about the realization of the poles through which the transmission network passed (Tian et al., 2020). A noteworthy limitation of these studies is the frequency of data acquisition, which was at least one month between images. This infrequent data collection reduces the ability to monitor progress without delay, which is crucial for effective project management and control.

The publication that dealt with active sensors used radar imaging of the surface, TerraSAR-X (Yang et al., 2017). Using different types of change indicators, areas where demolition or construction of a building had occurred were extracted, with measurements applied at a higher frequency than in the publications described in the previous paragraph. The focus was on parts of a business district rather than individual objects, suggesting that this method is primarily suited for urban planning purposes. Further research could explore the potential application of this method for monitoring the progress of infrastructure projects.

Image-based approach

Since satellite remote sensing methods primarily provide images, the subsequent analysis of publications and algorithms for data processing focused mainly on image-based approaches. Publications involving laser scanning were excluded due to the insufficient resolution and accuracy of current satellite laser scanners (Fouladinejad et al., 2019). A total of 62 publications utilizing image-based methods were identified.

Analysis of the publications showed that the processing methods currently used are usually photogrammetric, aimed at creating a point cloud via SfM and MVS or depth and perspective analysis of the image (edge or boundary detection of objects) to combine it with a 3D model and obtain information on the progress of work. The connection is made by using one of three approaches: BIM2Image, Image2BIM, or multi-temporal linking. In the BIM2Image and Image2BIM approaches, similar processing algorithms are employed, focusing on co-registering images with models to facilitate comparison. The multi-temporal linking approach, on the other hand, involves comparing successive products such as digital surface models (DSMs) over time series. Images are most commonly acquired from ground level or various altitudes using UAVs (unmanned aerial vehicles) and satellites. The identified applications concerned both indoor and outdoor measurements.

One of the first publications addressing the problem of automatic progress concerning BIM was Golparvar-Fard et al. (2010), proposing a solution based on D4AR – a 4D model for augmented reality (Golparvar-Fard et al., 2009). The method consisted in acquiring unstructured data – daily photographs and then through SfM obtaining a sparse 3D model along with computing camera pose and performing Euclidean registration to unify (transform) the as-planned and as-built coordinate system, e.g., using ICP (iterative closest point) algorithm. The next step is to apply MVS and create voxels for classification purposes using SVM (support vector machine). The end result is an as-built model that is compared with an as-planned model in IFC format using probabilistic methods. In the following years, the algorithm developed by Golpavard-Fard et al. was improved. In the works Golparvar-Fard et al. (2011a,b), the authors presented the following: the idea of D4AR and the decision support capabilities for different tasks on a construction site and the results obtained for different datasets are compared. A description of image matching via RANSAC (random sample consensus) and SIFT (scale-invariant feature transform) algorithm was also introduced and a method for progress evaluation based on probabilistic progress detection and discriminative learning was improved. Omar et al. (2018) described a method for combining a 3D point cloud with a model for monitoring the progress of columns using a fully automatic method in which cameras are always set on the site (during the construction phase). Progress is calculated through volumetric analyses by relating the photogrammetric point cloud to the model. Wang et al. (2023) also proposed using daily photos to measure the progress of construction work by utilizing a deep learning network to estimate the position and orientation of the photos taken and extract information about the progress of work. In addition to geometry and for progress analyses, Han et al. (2016) and Han and Golparvar-Fard (2014a, 2015) also focus on materials (a library of materials described in Dimitrov and Golparvar-Fard (2014) was also created) and their classification using SVMs based on histograms and clustering. Further proposals are to create a back-projection of the BIM model on-site images and to evaluate the progress of work based on the combined model and image. In contrast, Golparvar-Fard et al. (2015) focus on the analysis of voxels and their comparison with the model. Lin et al. (2015) propose the use of UAVs to acquire additional aerial images and discuss the issues of the advantages of UAVs over close-up images, especially considering the possibility of occlusions.

A very similar approach to that outlined above is used by Braun (2015) and Tuttas et al. (2014, 2015). Slightly different as-planned vs as-built comparison methods are used, which are based on the comparison of octree cells and raster cells derived from PCs from SfM or triangulation. Braun et al. (2015), additionally propose to use the graph notation of the relationship between as-built vs as-planned to improve the evaluation of the object state. Braun et al. (2016) propose HSV (hue saturation value) color analysis to extract the layers of a built wall (steel, concrete, wool). In Braun et al. (2018), an image rendering algorithm is presented by combining a 4D as-planned BIM model and a photogrammetric point cloud created from the images taken of the object under study. It is also possible to use neural networks (e.g., Mask R-CNN) to detect individual components of the object, e.g., columns, and assess their current state (Braun et al., 2020) or wall (Wei et al., 2022). Also, other comprehensive approaches were presented, with a rough registration of components used for condition assessment (Xue and Hou, 2022; Xue et al., 2022). An advanced solution was also presented by Pal et al. (2024), where the authors proposed an activity-level progress monitoring system (ALPMS). It is based on analyzing images from the construction site to build a photogrammetric point cloud (SfM-MVS), and then using the Mask R-CNN architecture to semantically segment the images and point clouds. This is followed by co-registration of the point cloud and the model. Synthetic orthographic views are then generated based on projective transformation and NeRF (neural radiance field). Analysis of the progress of the work is done by comparing the surface for ground truth (model-based image) and real work (point cloud-based image) semantically segmented.

Kropp et al. (2013) proposed progress monitoring using indoor video, through a perspective analysis activity and SVM classification and detection of heating devices based on HOG (histogram of oriented gradients). The as-built result was then compared with the schedule based on the BIM model. In addition, the algorithms using video were extended to analyze the type of material (Kropp et al., 2015). Yang et al. (2023) proposed a vision method based on architecture DeepLabV3+ for video frame image segmentation and concrete pouring stage identification based on floor plans from BIM. A holistic system proposal for in-build progress monitoring was described by Kropp et al. (2018). Asadi et al. (2019) proposed a system to combine measured data with a real-time model. The data is acquired using UGV (unmanned ground vehicle) with Nvidia Jetson and the algorithm is based on SLAM (simultaneous localization and mapping) with trajectory improvement and vanishing point/line detection, through which the BIM model is combined with the acquired images. A slightly different approach for internal progress monitoring is presented in another paper where edge or boundary detection is used as an additional feature to the SVM algorithm to calculate the tiling area (Deng et al., 2020).

Among the identified publications, some capture images not only in standard RGB colors but other spectra are also recorded. Previously described images acquired from belong to this group satellites (Behnam et al., 2016; Tian et al., 2020; Yang et al., 2017). Additionally, Pazhoohesh and Zhang (2015) proposed to use a thermal camera as a data source for progress evaluation. The biggest advantage of such a solution is the possibility to analyze additional component attributes such as temperature or humidity. On the other hand, these cameras offer a slightly lower resolution than traditional cameras.

A considerable number of publications using the image analysis approach are those that use a drone as a sensor medium. The data acquisition algorithm by drone for progress monitoring purposes is described by Qu et al. (2017). There, a method for comparing as-built vs as-planned was also proposed by relating a photogrammetric point cloud and a model on the example of a chimney. Jacob-Loyola et al. (2021) used a similar approach for a building. Kielhauser et al. (2020) highlighted the economic benefits of using drones to track the progress of work and to assess the quality of the completed work. It is also possible to estimate the progress of the work by analyzing the DTMs (digital terrain models) obtained in successive measurement sessions and comparing the volume of cross sections of the road under construction (Lo et al., 2022). A similar approach for infrastructure projects (dams, roads) was presented in several papers where BIM data was also used to verify the progress of work in relation to the obtained DSMs (digital surface models), e.g., through cross-section analysis or volume increment

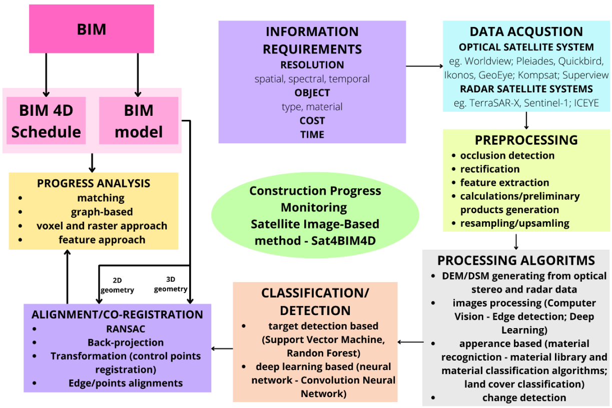

Figure 4. BIM and image-based construction progress monitoring methods and algorithms

analysis (Arbad et al., 2023; De Winter et al., 2022; Sentosa et al., 2023). A solution using UAVs was also presented by Wei et al. (2023), where a methodology for analyzing the progress of work for soil foundations based on a deep learning solution was proposed. The SOLOv2 architecture was used for detection on soil, strut, shuttering, baseplate-on, and baseplate-completed images to evaluate the phase of work and the progress of work in subsequent timelines and mapping to BIM. Somewhat less conventional medium included a crane (Masood et al., 2020). The images were then combined to obtain a point cloud and compared with the model. The case study described here concerned the recognition of the condition of beams using SVMs. Rover is also suggested as a sensor-transferring medium. For example, Liao et al. (2023) propose a solution based on Azure Kinect camera and YOLOv5 architecture to verify the installation of components such as fire hydrant and switch. Solutions combining data from multiple mediums are also proposed with a robotic manipulator, a small drone (Tello), a four-legged robot, and a mobile robot used and compared for monitoring the progress of installation work inside a facility (Zhao et al., 2023b). Barbosa and Costa (2022) propose a concept based on UAVs for measuring the progress of work outside the facility, while 360-degree cameras are suggested for analyzing the interior.

Braun et al. (2017) presented an important issue, including a study on the assessment of the progress state based on images and errors that can occur in the progress assessment by algorithms. It also outlined the potential causes of interference with the algorithms. In particular, occlusions or insufficient acquisition capabilities were singled out. The developed classification can be used for proper visualization and progress assessment. Han and Golparvar-Fard (2017) pointed out the potential of solutions based on visual data for progress monitoring, as well as the need for large disk and computational space and the problems associated with these data. Data acquisition procedures are also important for obtaining photogrammetric products of sufficient quality (Tuttas et al., 2017). Therefore, it is important to properly operate metrics to evaluate the acquired data and confirm its reliability (Ibrahim et al., 2021).

Based on the above analyses, a schema was created to describe what actions are taken to analyze the progress of construction work based on image analysis (Figure 4).

4.2 Stage 2: Satellite remote sensing for construction — assessment

Clearly, the quality of input data significantly influences the performance of data processing algorithms. Therefore, in this stage, research focuses on the possibility of extracting information from remotely sensed images of the Earth's surface characterized by remarkably high spatial resolution. Articles in this field were analyzed to identify data sources, processing methods, and accuracy of final products so that in the next stage a data fusion scheme could be developed. The limitations of this technology were also outlined.

As presented in the description of the methodology, it was not possible to create a key allowing the identification of publications with the above-defined characteristics. Therefore, it was decided to search for them by analyzing bibliographies of publications in this field and based on keywords and free searches of the Scopus database.

At present, commercially available satellites with optical sensors enable imaging of the Earth with a spatial resolution of about 0.3 meters for the panchromatic channel and about 1.2 meters for the other channels on a single satellite (Panagiotakis et al., 2018). In many research centers, work is underway to improve spectral imaging to the pixel size of panchromatic images by means of so-called pansharpening and super-resolution (Rahmani et al., 2010). In addition, systems are being developed to have the ability to revisit spots over the same location 15 times a day, as 6 Worldview-Legion satellites are planned to be launched in 2024 as part of the Maxar Worldview Legion system (Maxar, 2022). From the perspective of active sensors, commercial solutions also offer products with submeter resolution, e.g., TerrasSAR-X or ICEYE, allowing precise analysis of changes occurring in various types of areas including, for example, the detection and classification of vessels in quasi-real time (Zhao et al., 2023a). The penetration capabilities of SAR technology should also be kept in mind here, including the penetration of vegetation when using longer electromagnetic wavelengths.

In the analysis of detection or segmentation possibilities based on very high-resolution optical satellite imagery, a diverse range of research topics emerges. Identified publications primarily focus on extracting smaller objects such as cars and conducting land cover analysis. Behnam et al. (2016) used Pleiades imaging with a spatial resolution of 0.5, with detection accuracies amounting to 72.7 for pile cap and 76.9 for pier construction, respectively. A significant challenge lies in preparing suitable training datasets and employing effective detection algorithms. Researchers explore various approaches including the use of generative adversarial networks (GANs), edge-enhancement techniques, and other methods for generating super-resolution images. Thus, it is possible to increase the image detection accuracy of, e.g., cars to more than 90% (Rabbi et al., 2020). Similar results were obtained for the above task by Mansour et al. (2019).

From the perspective of land cover analysis, very high resolution (VHR) satellites with spatial resolutions below 1 meter typically record reflection in a smaller number of spectral channels (4 – 8). This limitation restricts the range of standardized indices that can be used as additional features in the land cover segmentation process. The four most popular datasets for land cover purposes derived from VHR satellites were identified: LoveDA (Wang et al., 2021), DeepGlobe (Demir et al., 2018), ZurichSummer (Li et al., 2018), and SpaceNet (Van Etten et al., 2018). The problem with the above datasets is the small number of classes (from 2 to 8) representing only the main land cover elements without, e.g., the detection of detailed type of development.

The approach (James et al., 2020) using Pleiades imagery focuses on a slightly more detailed detection using RF and SVM for the detection of 9 classes (including sand, soil, mud, grass, or trees, among others). The accuracy ranges from 80% to 100% for each class. It is also possible to identify tree species using the satellite VHR (Jombo et al., 2021). Also, the detection of construction sites and elevated objects is proposed by researchers for the WorldView satellite, and the accuracy achieved for this one approach reaches 90% (Juergens and Meyer-Heß, 2021).

Progress monitoring can also be seen as analyzing changes in the time series. Deep learning methods for this purpose are currently proposed, with a modified version of the UNET architecture used for the segmentation of change detection and the accuracy obtained exceeding 96% (Peng et al., 2019). Algorithms combining image processing (SLIC method), CNN (convolutional neural network), SVM, and Bayesian optimization are also proposed (Jing et al., 2020). A detailed description of algorithms and methods for change detection is presented by Shafique et al. (2022).

Another area of research involves the identification of publications focused on creating 3D models of terrain surfaces using remotely sensed imagery. The application of multi-view stereo (MVS) and structure from motion (SfM) at satellite levels faces limitations due to challenges in obtaining suitable imagery with adequate illumination and satellite azimuth or elevation angles. Additionally, there is the issue of the small depth-to-distance ratio from the camera to the scene for accurate image alignment, precise information about satellite orientation and rational polynomial coefficients (RPC) calculation is crucial. Ongoing research aims to enhance algorithms to improve the quality of digital surface models (DSM). Currently, the accuracy of such products may not be sufficient for monitoring progress effectively. A comprehensive approach described by Zhang and Gruen (2006) outlines the generation of DSM and digital terrain model (DTM) directly from IKONOS satellite imagery using multi-image matching. The DSM achieved an accuracy of less than a meter with a 5-meter grid for bare soils, although the average accuracy across the analyzed area was 2-3 meters. Slightly better results were obtained using WorldView-2 imagery with a 0.5-meter pixel resolution, producing a DSM and DTM with a 1-meter grid and slightly improved accuracy (Nemmaoui et al., 2019). Other techniques for three-dimensional analysis of optical imaging include shadow analysis in images to assess the height of an object (Glinka et al., 2023).

The main limitation of passive remote sensing data is dependence on atmospheric conditions, in particular clouds, which reduces the analysis possibilities. With the average annual global cloud cover estimated at 66% (Jeppesen et al., 2019; Zhang et al., 2004), this poses a significant problem for tracking the daily progress of construction work.

The different resolutions describing remote sensing data: spatial, radiometric, and spectral are dependent on each other (Al-Wassai and Kalyankar, 2013). There is a noticeable trend toward creating increasingly accurate images, coupled with the development of algorithms aimed at mitigating imaging imperfections and enhancing georeferencing accuracy. However, achieving usable products from these images requires computationally intensive and costly data processing.

Considering the challenges associated with optical satellite imagery outlined above, radar (SAR) data emerges as a valuable complement. SAR applications include monitoring deformations around construction projects (Gheorghe et al., 2019), detecting and classifying ship-type objects (Zhao et al., 2023a), and identifying structural changes (Gagliardi et al., 2023). SAR data are mostly independent of weather conditions but are susceptible to significant noise, necessitating robust processing methods and additional contextual data to generate meaningful products.

4.3 Stage 3: Results — analysis conjunction and Sat4BIM4D method description

The aforementioned analyses highlight the existence of algorithms for integrating imagery with building information modeling (BIM) models to evaluate construction progress. However, it is important to note that much of the research focuses on assessing individual components rather than the entire construction site. Satellite-derived data can be especially advantageous for infrastructure projects, where many structures are exposed. Nonetheless, it is crucial to consider the limitations associated with these technologies, as outlined in Section 4.2.

Given the practical side and the existing algorithms described in 4.1 and 4.2, methods that recognize land cover and larger elements (several meters), as well as the use of edge detection for the purpose of linking to a model of, e.g., a road, can be particularly useful when utilizing satellite remote sensing imagery. However, a significant limitation lies in the creation of 3D models from satellite data. While workflows incorporating SfM and MVS are proposed, current satellite data often restrict the effective application of these algorithms or result in products with insufficient accuracy.

Detection of objects several meters in size remains feasible. Therefore, the current approach to monitoring progress using satellite imagery predominantly relies on 2D analysis with limited terrain detail. It seems that the only way to create 3D images is to combine optical and radar imaging, but the currently used sensors and algorithms also require further development. An additional benefit lies in the potential to enhance monitoring accuracy and reliability by increasing the frequency of satellite image acquisition. SAR data offer advantages including reduced dependence on weather conditions. Conversely, optical sensors capable of registering across various spectral channels provide richer data compared to standard RGB imaging. These attributes highlight the diverse strengths and ongoing development needs within satellite remote sensing technologies.

Therefore, it seems that monitoring the progress of work from the satellite level should be based on the recognition of materials or surface coverage and analysis of its changes. Radar data could be complementary when large embankments or excavations are created. A geometry-based approach, primarily using a 2D analysis, is feasible. In summary, optical data can provide qualitative information, e.g., describe the type of land cover or material type, while SAR data can provide quantitative information – what altitude change occurred over a defined period through, e.g., InSAR analysis.

For the coverage classification, efficient algorithms based on traditional machine learning approaches (e.g., SVM or RF) as well as deep machine learning are implemented. For segmentation or material/cover detection, such algorithms should be considered. However, it should be kept in mind that the machine learning algorithms used require appropriate input data sets for training. Hence, there are increasing proposals to create learning datasets using labeling based on 3D models (Braun and Borrmann, 2019) or open spatial data (Glinka et al., 2022). Apparently, the creation of appropriate datasets is the key element necessary for accurate identification of land cover and building automated solutions for the monitoring of construction progress using satellite imagery.

Limitations arising from, e.g., atmospheric conditions and possible occlusions in the form of clouds or objects reduce the possibility of creating a fully reliable system capable of tracking the progress of construction work in quasi-real time, despite the establishment of new systems that can revisit a spot even several times a day. In addition, at the moment acquiring high-resolution images is expensive, so it is necessary to maintain the economic balance. Consequently, at this moment monitoring progress should be limited to weekly or even monthly intervals, e.g., based on the foreseen milestones of the project.

The perspective of using satellite data to track progress was described above. However, the BIM perspective should also be kept in mind. The use of an IFC file to verify the progress of work on an ongoing basis requires the inclusion of relevant information, which should be agreed upon at the information requirements building stage. First, compared to the methods described in 4.1, where, in most cases, the data had a local coordinate system or was coregistered for the use of satellite data, a very accurate georeferencing is required, which is not always a common practice today. By indicating the appropriate coordinate systems and precise spatial referencing (horizontal and elevation), it is possible to realize this concept. Another element is to record information on the schedule and assign it to the appropriate elements. However, the specific information to be included should be agreed upon in the requirements for information exchange. Another prominent issue is the appropriate modeling of information. In September 2023, the official 4x3 version of the IFC schema was published, including classes relevant to infrastructure. However, at this point, it is not yet fully supported and probably requires time for software providers to fully adapt their software.

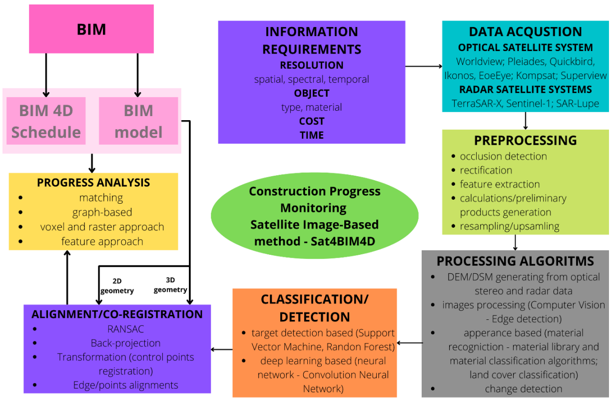

Figure 5. Scheme of the Sat4BIM4D workflow with proposed algorithms

Based on the above analyses, a scheme of combining satellite data with BIM — Sat4BIM4D — together with proposed algorithms is suggested (Figure 5).

5 Discussion

During the research, publications in the field of construction progress tracking in conjunction with BIM, and satellite remote sensing were analyzed to identify the cases currently used in the AEC industry. Then, based on the implications, the capabilities and concept of the Sat4BIM4D system were analyzed.

The following recommendations should be considered to facilitate the implementation of the Sat4BIM4D concept proposed above:

- The development of algorithms to process both optical and radar satellite data and extract specific information about, for example, land cover (instance segmentation, semantic segmentation, change detection) or objects (object detection) on the construction site for progress analyses. The current development of artificial intelligence algorithms points precisely to the use of deep machine learning algorithms.
- Relatedly, to extract specific information and be able to apply machine learning, appropriate datasets must be built. Some of the reviewed publications also emphasized this area. However, they focused mainly on material-type detection for objects like buildings. Detection of land cover or varied materials from satellite images could undoubtedly support the assessment of construction progress and the construction of automatic algorithms used for this purpose. Looking from the perspective of satellite imagery, one should also keep in mind the possibility of using multiple spectral channels to record waves in a wide spectrum.
- As indicated, solutions for automatic tracking of construction progress based on satellite imagery should be based on synergy between passive and active acquisition methods. Complementarity of vision and radar techniques allows us to obtain more information and independence from weather conditions. Hence a need to develop algorithms that combine these data.
- Another area that requires work is algorithms that combine information from the model with post-processing information from satellite data. In the case of infrastructure facilities, analyses show that work progress is primarily assessed using volume increment analyses and as-built (data mostly from UAVs) vs. as-planned (data from BIM) comparisons. For satellite data, this could be one of the selected approaches. Another would be

to consider algorithms to generate synthetic images based on the model and then compare them with the real one. However, these images should have the characteristics of orthoimages.

- Another important aspect, in the case of infrastructure data, is the spread of the use of the 4x3 version of the IFC schema, which has implemented classes that allow the modeling of infrastructure information.
- Determining the frequency of reporting and performing a progress review is also a critical issue. In the identified publications using satellite remote sensing, work progress was assessed at monthly intervals approximately. It would be necessary to consider whether it is possible to create daily work progress and whether such an approach makes economic sense.
- As related to the above-mentioned, higher data frequency leads to increased costs. Thus, a study on the financial aspect of using the aforementioned concept should be conducted, taking into account profit ratios.

Analyzing the concept above, it is currently not possible to fully use satellite-recorded remote sensing data to track daily progress. Optical satellite data can be considered as a support to the UAV-based system as it is strongly dependent on weather conditions (in particular cloud cover).

The proposed workflow is primarily applicable to infrastructure facilities; however, it can also be used for cubic objects, with restrictions on the ability to extract precise information for resolution and component coverage.

The limitations of this article include the lack of a practical case study, which is planned for future work. Before starting the practical work, it was decided to verify the current solutions and assess the feasibility of using satellite data for progress monitoring. The conclusion: partial use of these data is possible, but accuracy requirements are crucial.

Holistically, most proposed algorithms are prototypical and focus on monitoring individual model components. In the image-based approach used so far, a huge portion of work focuses on geometry analysis. For satellite imagery, it is proposed to base the monitoring system mainly on appearance-based (qualitative) supported by single quantitative examples from MVS or SAR data.

6 Conclusions

The purpose of the article was to assess the possibility of combining satellite remote sensing with BIM data, in particular with BIM 4D to build automatic solutions to track the progress of construction work.

The developed scheme of the Sat4BIM4D concept based on the identified publications and recommendations can be treated as a roadmap for the construction of a solution enabling automatic tracking of the progress of construction work, especially infrastructure work. The creation of such a solution can be an element that increases the profitability of the investment and greater control over the schedule or resources.

The obtained results suggest that developing solutions enabling the implementation of the above concept is recommended, as it may offer several benefits including shorter execution times, trimmed costs, and indirectly reduced impact on the environment.

Looking from the perspective of integrating BIM and GIS technologies, the concept described in this publication can be considered as another case of use.

Considering the application, especially in terms of infrastructure projects, the potential of using these data is undeniable, but it requires further development both on the side of BIM and satellite remote sensing. The recording of the information in the model should be easy and computer-readable for effective comparison with the created as-built study (e.g., by recording in ontological form - IfcOWL for BIM and the use of data-linked solutions). With reference to infrastructure projects, one should keep in mind the deficiencies in the ability to effectively write infrastructure data in IFC format and the general state of maturity of BIM implementation in these types of projects. However, this issue is still developing (adoption of the IFC format and BIM implementation).

The potential of the solution described in this article is unquestionable and, along with the development of sensors and algorithms, it can be a fully complementary solution to measurements made with traditional measurement methods. One of the biggest advantages of the proposed system is its automation. Data acquisition and processing for the final report can be done without human intervention.

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