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Systematic Literature Review of Drone Utility in Railway Condition Monitoring

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Abstract

Drones have recently become a new tool in railway inspection and monitoring (RIM) worldwide, but there is still a lack of information about the specific benefits and costs. This study conducts a systematic literature review (SLR) of the applications, opportunities, and challenges of using drones for RIM. The SLR technique yielded 47 articles filtered from 7,900 publications from 2014 to 2022. The SLR found that key motivations for using drones in RIM are to reduce costs, improve safety, save time, improve mobility, increase flexibility, and enhance reliability. Nearly all the applications fit into the categories of defect identification, situation assessment, rail network mapping, infrastructure asset monitoring, track condition monitoring, and obstruction detection. The authors assessed the open technical, safety, and regulatory challenges. The authors also contributed a cost analysis framework, identified factors that affect drone performance in RIM, and offered implications for new theories, management, and impacts to society.

Keywords: Railway defect identification; Railway track geometry, Railroad track obstructions; Remote Sensing; Unmanned aerial vehicles; Urban air mobility

Introduction

The railroad industry invests in infrastructure, maintenance activities, and inspections to meet the increasing demands of freight and passenger transport. Maintaining railroad safety and efficiency requires regular track inspections. Railroad companies do so by employing trained personnel to visually inspect the tracks while walking along them or by driving specially instrumented vehicles along the tracks. Shortcomings of those methods include risks to human safety, the expense of specially instrumented vehicles, and the need to close tracks or disrupt train schedules. Therefore, railroad companies have been evaluating inspection methods that use uncrewed aerial vehicles (UAVs) or drones that can fly autonomously at a programmed altitude above railroad tracks (Lebedev, Vasilev, Novgorodov, & Paulish, 2020). Drones also can reduce inspection time because of their flight agility and reduce costs by eliminating the need for additional safety training and human resources. Electrified drones also reduce the carbon footprint by reducing emissions relative to traditional types of inspection vehicles such as helicopters and hi-rail wagons. Drones also increase safety by removing humans from potentially dangerous situations (Frederiksen, Vrincianu, Mette, & Knudsen, 2019).

Transportation organizations and researchers have been exploring the benefits of using drones to monitor other large-scale infrastructure assets such as pipelines (Jabbar, Al-Battbootti, Marin, Goga, & Popa, 2021), canals (Yaacoub, Noura, Salman, & Chehab, 2020), bridges (Chen, et al., 2019), and waterway utilities (Kulkarni & Nagarajan, 2021). Meanwhile, drone technology has been advancing rapidly (Maghazei & Steinmann, 2020) and their applications span cargo delivery (Kellermann, Biehle, & Fischer, 2020), agriculture (Ahirwar, Swarnkar, Bhukya, & Namwade, 2019), photogrammetry (Dering, Micklethwaite, Thiele, Vollgger, & Cruden, 2019), surveying (Montanari, Kringberg, Valentini, Mascolo, & Prorok, 2018), and military surveillance

(Verdiesen, Tubella, & Dignum, 2021). Consequently, the worldwide market for drones has grown tremendously over the last decade (Flammini, Naddei, Pragliola, & Smarra, 2016). Analysts expect that the total economic effect of commercial drone-enabled services will reach $30.9 billion by 2028 and increase at a compound annual growth rate of 50.2% (Mind Commerce, 2022). In 2019 the railway applications market reached $4 billion with an annual growth rate of 40% (Jung, Lee, & Kim, 2018). This study focuses on the worldwide utility of drones in railway inspection and monitoring (RIM).

There is a lack of studies that identified and quantified the specific benefits and costs. Therefore, the goal of this systemic literature review (SLR) is to fill those knowledge gaps by providing a comprehensive view of the benefits and costs of using drones for RIM. The objectives are to identify applications of drones in RIM, classify the benefits, examine factors that affect drone performance, summarize open challenges, and assess implications for new theories, management, and impacts to society.

The organization of the remainder of this paper is as follows: Section 2 explains the SLR methodology. Section 3 provides a descriptive analysis of the publications analyzed. Section 4 summarizes the classification of applications, discusses factors affecting drone performance, and outlines the challenges and open issues. Section 5 identifies the research gaps and discusses the limitations of this study.

Method

To avoid the limitations of narrative reviews, the SLR method was selected among four methods of reviewing the literature - Narrative, Systemic, Critical, and Theoretical. (Tranfield, Denyer, & Smart, 2013). The SLR methodology has become a de facto standard because researchers recognize it as a systematic, transparent, and repeatable approach for recognizing, analyzing, and synthesizing the current body of documented work by researchers, academics, and professionals (Fernández del Amo, Erkoyuncu, Roy, Palmarini, & Onoufriou, 2018). Researchers can use the methodology to collect documents and publications that meet a pre-defined inclusion criterion that addresses the aims and goals of the research project (Mengist, Soromessa, & Legese, 2020).

Prior to the search, the authors reviewed various reports, websites, and webinars by transportation agencies and railroad organizations to gain a broad perspective of the benefits sought by the railroad industry. The authors then formulated the aims and goals of the research. Data collection was carried out through Google Scholar and Scopus databases. Google Scholar has become an important tool to locate highly relevant scholarly material across a large spectrum of sources, and Scopus is one of the most complete databases of peer-reviewed scholarly literature. The search rule was ("drone" OR UAV OR “unmanned aerial vehicle” OR “remote sensing”) AND (track OR rail OR railroad OR railway) AND (monitoring OR inspection) in the title, abstract, and keyword fields of scholarly academic publications. The search filter selected publications in English that included journal papers, theses, and books. The search focused on the fields of business, logistics, transportation, and management. The authors also considered conference papers because in some areas there was a lack of peer-reviewed journal articles.

The initial analysis identified 7,900 articles published since 2014. The first stage of filtering reduced the number of relevant publications to 38 after eliminating unrelated and duplicate articles by reviewing the publication titles and abstracts. Applying the snowball technique to the citations resulted in adding 9 more relevant articles for a total of 47 articles for final careful review.

This paper's workflow is as follows: Railroad applications are divided into safety and maintenance categories. The benefits of using drones are categorized into reducing costs, improving safety, saving time, improving mobility and flexibility, and improving reliability. Factors affecting drone performance are divided into drone characteristics and payload characteristics. Figure 1 shows the workflow of this paper.

Analysis and Results

The subsections that follow present a descriptive analysis of the body of literature reviewed.

Distribution by Publisher and Year

Figure 2 illustrates the distribution of articles by publisher and year. Multidisciplinary Digital Publishing Institute (MDPI) and Elsevier published 7 and 4 of the selected papers, respectively. Given the scarcity of journal papers on the topic, the authors added relevant conference proceedings, which accounted for 30% of the selected articles. IEEE published all the conference proceedings reviewed and 23 other publishers published one each of the remaining articles. In summary, 26 different publishers covering the disciplines of science and technology, engineering, transportation systems, and aeronautics published the 47 articles selected.

Distribution by Year and Country

Figure 3a shows the distribution of selected papers by year and by country of origin. Most of the sampled articles were published within the last three years. At the time of this SLR, three articles appeared in 2022, 15 in 2021, 8 in 2020, 7 in 2019, 4 in 2018, and 5 in 2017. The remaining articles of the sample appeared in 2016 or prior years. DJI released the first series of camera-equipped drones in 2013 (Daly, 2022). The capabilities and applications of drones have expanded rapidly since 2014, which is consistent with the temporal trend of the selected publications. Analysts expect the drone market to be worth $92 billion by 2030 (Cision, 2020), and the trend in publications will reflect that growth as more industries begin to explore how drones can benefit their business and society. Figure 3b suggests that, with China accounting for eight of the sampled publications from 2017 to 2021, the country has led global drone-related research on applications in the railroad industry.

Publications from China accounted for almost 19% of 47 reviewed papers, and most of them appeared in 2020. This finding is consistent with the fact that China currently has the majority market share of drone sales (Daly, 2022). With continued technology advancements, China is well positioned to influence developing industry standards.

India is second with six publications from 2017 to 2021. Using drones for commercial purposes in India became legal after the Directorate General of Civil Aviation (DGCA) published its Civil Aviation Requirements in December 2018 (Dubey, 2020). Half of all the Indian publications originated in 2021. This coincides with new Indian government rules in August 2021 to simplify drone operations for delivery and civil projects and to encourage investments in drone technology (Greyb, 2021).

Five publications originated in Russia. Over the past decade, Russia has developed different types of drones, focusing on tactical unmanned aerial reconnaissance systems (Palavenis, D., 2022). The United States and Poland contributed equally to the selected literature with three publications each. U.S. military experts have accumulated enormous experience in the design, engineering, and use of drone technology during the last ten years (Farley, 2015). In 2021, the Polish government invested €164 million in advancing drone technology and applications. Consequently, analysts forecast that the drone economy in Poland will grow to €128 billion within five years (Dronewatch, 2021).

Turkey, Germany, Canada, Spain, and Switzerland each contributed two papers to the selected literature, and the remaining countries contributed just one publication each. Overall, the country distribution of the sampled publications suggests that the railway industry in China, India, and Russia are leading drone-based research. The trend also suggests that the railroad companies have only recently begin to evaluate the use of drones for inspections and will likely expand their utility across the global railroad industry.

Distribution by Research Methods and Year

Figure 4 shows the distribution of the selected articles by the research method category and publication year. Table 1 lists the publications within each research method category. Fourteen of the publications used algorithms to analyze ground filtering, rail position and direction, and defect formation, with most appearing in 2021. Fourteen of the publications used theoretical models to conduct case studies, test new sensors, and assess remote sensing strategies, with half of them appearing in 2021. Seven studies used simulations to study accident scenarios and method performance in a high-speed operational environment. One study evaluated a prototype system to automatically identify and localize critical structural components such as columns to determine appropriate inspection viewpoints. Two papers used statistical methods to verify gauge measurements and their locations. The review and survey categories included six and three papers, respectively, that examined the challenges and opportunities of using drones to monitor railways worldwide between 2018 and 2021.

Classification of Applications

The SLR classified RIM application of drones into five different areas. Figure 5 shows that railway infrastructure asset monitoring was the most frequent application. Those 19 publications discussed monitoring the railway infrastructure, tunnels, culverts, bridges, stations, and high-speed railway contact wire. Nine studies proposed using drones to identify railway defects by recognizing the rails, detecting rail splits and other surface flaws, detecting irregular track geometry by measuring track gauge, and assessing the condition of rail sleepers, also called railroad ties. Five publications proposed techniques for situational assessment in emergencies and crisis management during a natural catastrophe. This includes a simulation of accident scenarios, monitoring of susceptibility areas, managing risks and assisting with rescue operations during natural disasters. Five papers reviewed track condition-monitoring applications which included monitoring switch point heating, track geometry, track structure such as sinking and depleted ballasts, and the condition of other railway assets such as switches and signals. Five studies used drones to detect track obstructions such as vegetation, rockfalls, accumulation of water, and storage of materials and equipment near the railroad right-of-way or in the ballast. Four publications reviewed rail network mapping.

Figure 6 shows the distribution of the papers by country and application. Most of the papers from China focused on railway infrastructure asset monitoring and track obstruction detection. Papers from Indian focused on defect identification whereas papers from Russia focused on risk assessment and management. Papers from the United States focused on defect identification, risk assessment and management, and identifying track obstructions. The Polish, Spanish, and German studies focused on railway infrastructure asset monitoring. There was only one publication from each of the other countries and they focused on different applications. Almost 70% of the publications discussed maintenance benefits whereas the remaining papers discussed safety or security benefits.

Discussion

Figures 7 and 8 illustrate the proposed classification of drone applications in railroad safety and maintenance, respectively. The first two subsections that follow discuss each application area and describe the specific research conducted in each area.

Safety and Security Applications

Table 2 list the safety applications in RIM and shows the type of drone, sensor, and algorithm or software discussed in each paper.

Defect Identification

Track defect identification: Mammeri et al. (2021) evaluated the effectiveness of a method to segment tracks from drone images by using a fully convolutional encoder-decoder type segmentation network called U-Net from ING Robotic Aviation (Mammeri, Jabbar Siddiqui, & Zhao, 2021). Sushant et al. (2017) proposed a localization method known as Monte Carlo or particle filter localization algorithm to identify fractures along the railway (Sushant, Anand, James, Aravind, & Narayanan, 2017).

Rail defect identification: Wu et al. (2018) proposed an image enhancement algorithm named Local Weber-like Contrast (LWLC) to improve rail images from a DJI Matrice 600 six-rotor drone equipped with a Zenmuse Z30 camera (Wu, Qin, Wang, & Jia, 2018). Bojarczak and Lesiak (2021) utilized a deep-learning network to detect hazardous split defects in railways (Bojarczak & Lesiak, 2021). Mathe et al. (2016) discussed using a lightweight drone to detect problems such as missing indicators or cabling (Mathe, et al., 2016). Singh et al. (2021) described how they recognized concrete sleepers on train tracks by taking low-altitude aerial photos using a DJI Phantom 3 drone. Their sleeper identification model was based on the YOLO v4 algorithm, which provided optimum speed and accuracy in the object recognition models compared to existing techniques (Singh, Swarup, Agarwal, & Singh, 2019). Autonomous rail-based vehicles may be combined with drones to focus inspections on internal track issues (Banh Lau, et al., 2018).

Irregular track geometry identification: Singh et al. (2019) found that using a DJI Phantom 3 drone equipped with a 4K camera and Sony sensors could provide high levels of reliability and accuracy (Singh, Swarup, Agarwal, & Singh, 2019). Shcherbakov et al. (2021) used rail track geometry-measuring trolleys to georeference the images from drones (Shcherbakov, Altyntsev, & Altyntseva, 2021).

Risk Assessment and Management

Evaluate accident scenarios: Using a drone can provide valuable information on natural disasters, such as mudflows, avalanches, and significant snowfalls. Nie et al. (2017) created a 3D simulation to study emergency railway rescues (Nie, et al., 2017). They recreated a railway accident scene from images and displayed a realistic dynamic rescue plan, supported by a real-world physics engine and a self-developed global terrain module. They used the simulator to program and evaluate rescue plans, model physical rescue procedures, train staff, and analyze accidents. Lyovin, et al. (2019) created a method to rapidly respond to threats posed by high-speed rail systems (Lyovin, Shvetsov, Setola, Shvetsova, & Tesei, 2019). Their method relies on automated drone stations to ensure the arrival of a drone at the site of an incident within 13 minutes of the alarm signal, thus allowing the dispatcher to make a rapid decision regarding actions to be taken.

Evaluate vulnerabilities: Gantimurova et al. (2021) proposed an algorithm to detect potentially hazardous landslide areas by utilizing data acquired by drone inspections (Gantimurova, Parshin, & Erofeev, 2021). They also illustrated the results of an indirect heuristic assessment of landslide susceptibility by using an analytical hierarchy process (AHP) within a GIS environment.

Evaluate risks from natural hazards: The risk of fatalities while neutralizing explosives or hazardous/toxic materials can be reduced by using drones equipped with appropriate technology

(Kiss Leizer, 2018). Narazaki et al. (2022) visualized an autonomous system that simulates the logic followed by inspectors during the post-earthquake evaluation of reinforced concrete railway viaducts (Narazaki, Hoskere, Chowdhary, & Spencer, 2022). Flammini et al. (2016) evaluated drone capabilities as part of a railway monitoring framework, including detecting structural faults and security threats, and predicting the consequences of natural disasters and intentional attacks (Flammini, Naddei, Pragliola, & Smarra, 2016). They demonstrated that drone-based sensors can be integrated into existing security surveillance systems by using appropriate sensor integration platforms, middleware, and frameworks.

Trespassing Detection

The United States Federal Railroad Administration (FRA) commissioned an investigation of using drones piloted by trained police officers to identify trespassers on railroad property (FRA, 2020). They evaluated the reliability of the hardware and assessed the degree to which police officers could be trained to effectively use the equipment. They selected an Amtrak endpoint location in Brunswick, Maine, for the test site and used a DJ Matrice 200 drone equipped with a Zenmuse X4s daylight camera and a Zenmuse FLIR XT night vision camera.

Monitoring Grade Crossings

The FRA collaborated with Michigan Technological University to develop a drone-based method to inspect rail-grade crossings (FRA, 2019). Their objectives were to determine whether the method poses safety risks, to evaluate the vertical profile at a crossing relative to vehicle clearances, identify visual sight lines, and detect gate, light, and signage locations. They used a Bergen Hexacopter equipped with a Nikon DSLR camera to gather images with a ground sample distance of 0.1 inches (2.5 mm) over the rail-grade crossing. The group also investigated photogrammetry and LiDAR approaches to model grade crossing. They demonstrated that drones could be used to assess various crossing characteristics such as vertical profile adequacy, visual sightline triangles, and road signs (Stuart & Doran, 2020). They also found that although the LiDAR approach required more expensive equipment and more labor-intensive data processing, the method could create highly accurate 3D models of high-profile crossings.

Theft Monitoring

The French National Railway Company (SNCF) manages the rail traffic in France and the Principality of Monaco. The SNCF tested drones over its network since 2013 to identify copper-cabling thieves that disrupted railroad service and caused significant financial losses. SNCF also used drones to inspect electrical equipment, and the condition of railway ballast (rock), encroaching vegetation, and the condition of other structures like bridges, tunnels, and station roofing (SNCF, 2022). They also used drones to conduct topographical surveys, rail network mapping, and safety and security inspections to advise decision-makers. Prorail is using drones to maintain its 7,000 km of tracks in the Netherlands by inspecting overhead lines while keeping the trains in service (Karpowicz, 2022).

Maintenance Applications

Table 3 summarizes the classification of maintenance applications within RIM, and the types of drones, sensors, and software employed in each publication.

Rail Network Mapping

High-quality railway maps and terrain information informs planning and future construction. Land surveying techniques used on the ground to map railroads are time-consuming and problematic in difficult terrain. Drones offer a lower cost and higher resolution alternative via aerial photogrammetry. In this context, Manatunga et al. (2017) used a DJI Phantom 4 drone to map land use and railroad line network geometry based on textural information from orthophoto and elevation data (Manatunga, Munasinghe, & Premasiri, 2017). Sahebdivani et al. (2020) used the height jump of points to detect and create 3D models of rail tracks from images and then used the RANSAC algorithm to identify the rails (Sahebdivani, Arefi, & Maboudi, 2020). For the same purpose, Huang et al. (2020) utilized a drone equipped with a bandpass filter of about 660 nm and a CMOS camera to propose a mathematical model for eliminating the influence of the drone's self-disturbance on the acquired data (Huang, Jia, & Guo, 2020).

Infrastructure Asset Monitoring

To detect flaws early and ensure safety, it is necessary to conduct a continuous evaluation of railroad infrastructure assets such as bridges, culverts, tunnels, and stations.

Railway tunnel monitoring: In a tunnel, mechanical deformations may pose a serious safety risk, especially during construction and operating activities (Schotte, Nuttens, De Wulf, & Van Bogaert, 2016). In this context, Meng et al. (2021) examined the surface deformation features of the Beijing–Shijiazhuang high-speed railway tunnel in Ledu, China (Meng, et al., 2021). Using a drone equipped with visual and thermal sensors, Bendris et al. (2022) proposed an inspection-driven planning algorithm to increase the quality of data while optimizing the coverage area and the traversal distance (Bendris & Becerra, 2022).

Rail bridge monitoring: Drones can securely access the upper parts of bridges without interrupting traffic flows. Cano et al. (2022) used drones to collect images of two railway bridges in Spain and structural engineers identified defects from those images (Cano, Pastor, Tomás, Riquelme, & Asensio, 2022). Narazaki et al. (2022) used drones for a post-earthquake inspection of reinforced concrete railway bridges and localized critical structural elements (Narazaki, Hoskere, Chowdhary, & Spencer, 2022). The FRA recommended drone use to augment structural inspections but not as a replacement for the required routine annual inspections (MassDOT, 2019).

Railway infrastructure monitoring: Using drones to monitor the railway infrastructure to improve security and safety would increase the efficiency of monitoring operations while freeing up workers to do more valuable tasks (ESCAP, 2019). In this context, Masat & Kaya (2019) combined a line control crew and a DJI Phantom drone to achieve greater cost-effectiveness, efficiency, and safety (Masat & Kaya, 2019). Jarrett et al. (2015) developed a vision-based feedback system that allowed path-following controllers to receive position feedback from railway lines (Jarrett, Perry, & Stol, 2015). They used a Bixler 2 fixed-wing model aircraft with an onboard Raspberry Pi microcomputer to gather and process images. Ghassoun, et al. (2021) used a multicopter to collect rail geometry data and calibrated the measurements by using the rail shoe as a reference (Ghassoun, et al., 2021). Ivashov et al. (2019) found that combining images from satellites and drones in the visible and microwave frequency ranges has advantages in railroad security applications (Ivashov, Tataraidze, Razevig, & Smirnova, 2019). Craven (2017) demonstrated that drone-based photogrammetry can be effective at a height of 25 meters to avoid disrupting normal operations (Craven, 2017). In related work, Zheng et al. (2020) applied the MUSIC algorithm based on fourth order cumulant matrix to track drones operating in high-speed railway environments (Zheng, Xiao, & Shi, 2020).

Equipment monitoring: Kochan, et al. (2018) demonstrated that drones can be used to monitor railroad equipment such as crossings, power units, traffic control devices, signaling devices, and switches (Kochan, Rutkowska, & Mateusz, 2018). The case study demonstrated that the system could recognize the condition of a signaling device by determining the presence of flashes, frequency of blinking lights, and the reliability of displayed signals.

Railway contact wire monitoring: The condition of contact wires is critically important to the safety of high-speed railways. Geng et al. (2021) demonstrated that drone-based LiDAR sensing can be effective in measuring the spatial distribution of geometric characteristics such as contact wire height and stagger (Geng, et al., 2021).

Track Condition Monitoring

Railway embankment monitoring: For decades, visual inspections has been the primary method used to detect surface cracks, shallow and deep cavities, and irregularities in embankments. However, inspectors cannot observe hidden effects, and assessments are subjective. Infrequent evaluations can also miss defects that appear between inspection cycles. Kovacevic et al. (2016) investigated drone use to identify features that can affect track performance (Kovacevic, Gavin, Oslakovic, & Bacic, 2016). Features include ballast fouling, irregular track geometry, embankments forming, boundaries forming between roadbed layers, substructure issues, slope geometry, and conditions hampering water drainage.

Track structure monitoring: Mittal et al. (2017) demonstrated that deep learning models could detect track defects such as sinking and loose ballasts and problems with railway assets such as switches and signals (Mittal & Rao, 2017). Pali et al. (2014) developed a machine vision and control system that enabled a drone to follow the railway track by following lines in the images and keeping the vanishing point in the image center (Pali, Mathe, Tamas, & Busoniu, 2014). Lebedev et al. (2020) developed a control algorithm to enable autonomous drone flights along a railway by using satellite navigation systems (Lebedev, Vasilev, Novgorodov, & Paulish, 2020). The system correctly detected the rail orientation in 93% of the images. One study used a Canny edge detector to identify railway tracks in images (Banić, Miltenović, Pavlović, & Ćirić, 2019).

Track Obstruction Detection

Vegetation: Vegetation growing on or near railway tracks may cause obstructions, increase braking distance due to increased slickness, and lead to poor drainage which can eventually cause the embankment to collapse (Nyberg & Gupta, 2013). Vegetation on tracks may also interfere with visual inspections. In this context, Rahman & Mammeri (2021) explored the effectiveness of DCNNs in automating vegetation recognition from drone imagery (Rahman & Mammeri, 2021). Štroner et al. (2021) combined two types of vegetation filtering algorithms and achieved a total error rate of 0.9% (Štroner, et al., 2021).

Rockfall: The downhill movement of loose or disintegrating rock formations caused by various sources contributes to potentially hazardous conditions near railways due to the instability of the slopes. Therefore, transportation agencies have strict safety standards for maintaining safe clearance zones around rail lines (Congress & Puppala, 2021). To assess slope stability, Congress & Puppala (2021) evaluated a highly weathered rock-cut slope by using drones to ensure safe clearance zones in the event of rockfall. They used the 3D model of the rock slope to carry out a combined 2D and 3D slope stability analyses to determine an efficient re-sloping angle for the rock cut (Congress & Puppala, 2021).

Storage of materials along the ROW: Girshick et al. (2014) found that deep learning methods based on R-CNN, YOLO, and SSD algorithms can effectively detect abnormal objects on railways (Girshick, Donahue, Darrell, & Malik, 2014). SDD provided higher speed and recognition precision but was less effective in detecting small items. Therefore, Li et al (2020) proposed a multi-block SSD method that enhanced the recognition rate of small items by 23.2% (Li, et al., 2020). Guan et al. (2020) proposed a method that identified the railway track position in the images before extracting the salient region to apply morphological processing and filtering for obstruction detection (Guan, Li, Yang, & Jia, 2020).

Graffiti Removal

In 2021, Deutsche Bahn, Europe's leading railway and rail infrastructure provider, began employing drones to combat graffiti-spraying gangs by deterrence or detection and follow-up enforcement (Upton, 2022). They used drones with a one-meter wingspan capable of 80 minutes of flight time and a speed of 33 miles per hour. The drones cost €60,000 each and can be controlled remotely or independently. Although graffiti removal costs Deutsche Bahn €7.6 million annually, those drones are expected to help reduce the expense. Deutsche Bahn is also incorporating drones into the supervision of construction projects to monitor work progress, areas with landslide risk, and the environment. Drone images can be processed and analyzed using Pix4D products such as PIX4Dcloud, PIX4Dmapper, and PIX4Dmatic (French, 2022).

Benefits of Drones in RIM

Table 4 summarizes potential benefits of using drones in RIM and the next subsections expand on the description of findings from the SLR.

Reduce Costs

Using drones instead of traditional methods could reduce inspection costs by saving time and reducing expenses to assure personnel safety. The average cost per hour per vehicle in traditional railroad inspection methods is approximately $300 (Prakesch, 2020). In 2015, Swiss Federal Railway (SBB) spent approximately $90 million on safeguards to assure personnel safety. However, Maghazei and Steinmann (2020) found that using drones could reduce the number of safeguards along with the cost associated with them plus reduce monitoring time (Maghazei & Steinmann, 2020). According to Shift2Rail, using drones reduced energy costs by 20%, reduced driver cost by 50%, increased overall efficiency by 10%, and prevented a 10-50% decrease in line capacity due to closures during inspections (Banić, Miltenović, Pavlović, & Ćirić, 2019). Railroads can calculate their return on investment for using drone-based inspections by quantifying the financial losses from accidents potentially prevented and savings relative to the current method. The savings calculation should include the worker wage eliminated and the cost of human errors prevented.

Drones powered by fuel-cells cost more than twice as much as those that are battery-powered. Fuel cells are still a niche technology and currently account for 49% of the total drone system cost (Belmonte, et al., 2018). Table 5 shows the types of costs that would be incurred when deploying drones that require a remote pilot. Autonomous systems and manufacturing economies of scale in the future will likely reduce the cost much further, particularly when one operator can oversee the operation of drone fleets of various sizes.

Improve Safety

Drones can help to obtain information that can be dangerous, expensive, or inefficient to obtain regularly with traditional monitoring methods. Drones can access areas that are difficult for human inspectors to reach. Railroads can conduct more frequent inspections to identify issues more quickly, without exposing humans to safety risks while working on the right-of-way (Equinox's Drones, 2021). In emergency situations, personnel can remain in a safe area while using drones to efficiently observe the disaster area, which may be inaccessible.

Table 6 summarizes the FRA reported financial losses from accidents in 2021. Drones can produce high-resolution imagery from frequent inspections to identify a large proportion of the accident causes such as switches left in the wrong position, visible track and roadbed problems, signal malfunctions, and track obstructions (Alawad & Kaewunruen, 2021).

Save Time

The ability of drones to fly over railroads saves both time and effort because they can collect images of multiple rail lines at once and operate autonomously without human involvement (Schwab, 2020). Railroad companies can use drones to monitor inaccessible portions of the network to save inspection time. It is possible to cover 50 kilometers of railway track per day by using experienced pilots, GIS experts, and high-end survey drones (Equinox's Drones, 2021). Quickly covering a large area reduces the inspection time and planning cycle and obtaining good quality images by flying closer to the tracks enables more accurate maintenance forecasting.

Improve Mobility and Flexibility

Unlike trucks and trains that require road infrastructure, drones can travel swiftly from one location to another. In addition, aerial platforms and their relatively small size provide access to places that are difficult to reach by roads or by walking. Drones can provide an aerial overview of a large area for quick reconnaissance. Regular train service and other operations can continue while using drones to inspect railway tracks, bridges, and, in some cases, tunnels.

Improve Reliability

The high-resolution images from drones can enable inspectors to detect problems that they may have overlooked during a visual inspection. Drones equipped with LiDAR, thermal, hyperspectral, and other sensors provide multiple views of an inspected area by using different parts of the light spectrum. Images captured by drones can be stitched together with photogrammetry to create high-quality 2D images, 3D models, and point cloud assessments with a 360-degree view (Banić, Miltenović, Pavlović, & Ćirić, 2019).

Factors Affecting Drone Performance

Drone architecture and their payload characteristics are key factors that influence their performance.

Drone Characteristics

Drone selection and attachments are influenced by the inspection goals. For example, drones with a top-mount gimbal are required to reach and inspect the underside of structures such as bridges (Congress & Puppala, 2021). The payload capacity and battery capacity affect the range and flight endurance during inspections. The two main drone architectures are unwinged (multicopters) and winged (fixed-wing aircraft). There are five types of winged designs: transitioning thrust (TT), tilt rotor (TR), tilt wing (TW), folding wing (FW), and fixed rotor (FR). Multicopters can be classified into four types of designs: tricopters (3 rotors), quadcopters (4 rotors), hexacopters (6 rotors) and octocopters (8 rotors). Quadcopters are by far the most popular multirotor drones, and they generally cost less than other types of architectures (AUAV, 2016). In general, winged structures provide superior performance during cruise mode (Bridgelall, Askarzadeh, & Tolliver, 2022). Multicopters provide greater control over position and framing than winged designs. As illustrated in Figure 9, nearly half the papers reviewed mentioned the type of aircraft used. Most of them used multicopters for railway inspection, one used a fixed wing drone, and another used the ING Robotic Aviation's Responder helicopter. The majority of multicopters were quadcopters, and the remaining 40% were hexacopters.

The studies suggested that multicopters are the most appropriate aircraft type for use in RIM applications because they can hover for extended periods of time and their increased maneuverability allows multiple views of a location. Multicopters can fly much more closely to railway tracks to capture higher resolution images. Drones capable of carrying multiple payloads on a single flight improve the inspection efficiency while reducing inspection time. Multiple independent rotors decrease the risk of an accident if one or more propeller malfunctions. Table 7 compares the advantages and disadvantages of multicopters and winged drones in RIM.

Payload Characteristics

There is a tradeoff between payload capacity and flying time. Drone payloads include a wide range of sensors such as LiDAR and different types of cameras such as visible, infrared, multispectral, and hyperspectral. Creating accurate 3D models from drone images requires precise georeferencing, hence, drones may need to carry additional global navigation satellite system (GNSS) equipment to increase positioning accuracy.

Cameras: High-quality data is crucial when informing decisions about the development, maintenance, repair, and renewal of railways (Jung, Lee, & Kim, 2018). Drones are often equipped with high-resolution digital cameras for taking pictures and videos. Sensors include cameras with an ultra 4K resolution of 100MP and video recording equipment with a 4096 × 2160 resolution that can be viewed either vertically or horizontally (Lesiak, 2020). Camera resolution, focus, aperture, and shutter speed all impact video and picture quality. Qualitative inspections may require a zoom lens to prevent the rolling shutter effect, whereas quantitative inspections may require a camera equipped with a global shutter (Congress & Puppala, 2021).

Thermal cameras: They can record wavelengths in the infrared spectrum and display them in the visible spectrum. For instance, they can be used when checking buildings during firefighting or rescue operations. Thermal cameras can also be used to evaluate overheating in railroad equipment and to search for bodies when assessing accident scenes.

Multispectral and hyperspectral cameras: They detect reflected light at wavelengths within and beyond the range of human vision. Multispectral sensors typically capture three to ten wavelength bands, while hyperspectral sensors collect hundreds of wavelength bands within considerably smaller bandwidths. More frequency bands increase the accuracy and range of objects that can be identified. However, hyperspectral data is more voluminous than multispectral data, which increases the difficulty of real-time processing (Adão, et al., 2017).

Light Detection and Ranging (LiDAR): LiDAR sensors can collect accurate point cloud data of surroundings and objects for further processing to display structures in 3D. The point density of airborne LiDAR data depends on the flight speed and altitude of the drone. Flights at low speeds and low altitude produce more points than higher-altitude flights at higher speeds (Lemmens, M., 2017). The demand for LiDAR sensors in machine vision applications has led to continuous size and price reductions (Higgins, 2017).

Mechanical devices: It is possible for drones to carry operational payloads that may involve physical contact or interaction with objects (ProDrone, 2022). Such devices can grasp and transport various shaped items using mechanical arms. Operations include joining items, cutting wires, flipping dials, throwing switches, dropping life-saving floats, and recovering dangerous items.

Figure 10 shows the distribution of payload types from the articles reviewed. There were only 28 studies that mentioned the payload type used. Discussions of camera types occurred in 82% of the reviewed articles. One study used the following four visual cameras to monitor tunnel conditions: three IDS UI-3251LEs, one Basler acA4112-20um, and a thermal camera (Bendris & Becerra, 2022). Two studies used LiDAR to monitor railway contact wire and rockfall. One study used RFID to monitor accident scenarios. Another study used ODROID XU4 and NVIDIA TX1 sensors for early warning, situation assessment, and decision support (Flammini, Naddei, Pragliola, & Smarra, 2016).

Challenges and Open Issues

Despite extensive advances and the continuing development of drones, this technology is still considered to be in its early stages of development. There are still unlimited opportunities for the application of autonomous drone systems. The next subsections provide an overview of the current challenges associated with using drones in RIM applications. Table 8 summarizes those challenges along with the supporting literature.

Technical Challenges

Flying a drone over a railway can pose significant safety and technical challenges. Currently, the requirement to maintain a visual line-of-sight between the operator and the drone is a primary technical limitation (Congress & Puppala, 2021; Banić, et al., 2019). Dense forest areas and long railway tunnels may cause signal propagation issues that could disrupt communications between the pilot and the drone, which may result in loss of control (Rampriya & Suganya, 2021). Some manufacturers implement a fail-safe mode that sends the drone to a predetermined location in the event of a system failure (DeGarmo, 2004) (Falamarzi, Moridpour, & Nazem, 2019) (Flammini, Naddei, Pragliola, & Smarra, 2016).

Some manufacturers are implementing a terrain-following feature in the flight planning and flight control software to enable beyond visual line-of-sight (BVLOS) operations. However, that solution requires sufficiently accurate terrain data and a reliable onboard position tracking system (Sherrock & Neubecker, 2018). A geofencing system is also needed to assure that the drone remains within designated areas. Drones also need laser ranging and optical sensors to detect and avoid hazards while flying (Jordan, et al., 2018), but the additional equipment increases weight and reduces flight time (Bobbe, et al., 2020). Drones commonly used for inspections have a flight time of approximately 20 minutes after an hour of charging (Li & Liu, 2019).

Weather presents another challenge for drone-based RIM (Cano, Pastor, Tomás, Riquelme, & Asensio, 2022). Drones are sensitive to windy and icing conditions (Jarrett, Perry, & Stol, 2015). Flight restrictions and environmental conditions may disrupt the GPS-signal and cause control to change from automatic to manual (Morgenthal & Hallermann, 2014) (Jung, Lee, & Kim, 2018). Consequently, the flight path will be adversely affected (Fernández del Amo, Erkoyuncu, Roy, Palmarini, & Onoufriou, 2018).

The large volume of data collected presents a variety of challenges such as the need for high-speed processing, rectification, referencing, and ground sampling (Singh, Swarup, Agarwal, & Singh, 2019). Some of the processing requires sophisticated deep learning methods and skills to analyze and interpret the results to inform decision making (Gantimurova, Parshin, & Erofeev, 2021) (Geng, et al., 2021) (Ivashov, Tataraidze, Razevig, & Smirnova, 2019). The appropriate lighting condition must be available for good quality image to automate measurements (Ghassoun, et al., 2021). Direct lighting, strong shadows, and cloudy weather reduces image quality and depth of field (Ghassoun, et al., 2021). Overhead structures such as overhead catenary may block visibility of the railway tracks, and some reflectance properties of the tracks may degrade the image quality (Wu, Qin, Wang, & Jia, 2018).

Safety Challenges

Environmental conditions that cause communications failure or errors in the machine vision system can lead to collisions with another vehicle or other obstacles such as overhead lines, track-side equipment, buildings, and rolling stock (Bertrand, Raballand, Viguier, & Muller, 2017) (Mathe, et al., 2016). Strong air gusts such as those sometimes encountered in long tunnels can challenge aircraft control. Flying in BVLOS conditions increases collision risk (Lesiak, 2020) (Bendris & Becerra, 2022). Flying in inhabited locations increase the risk of a collision with humans or animals on the ground (Bertrand, Raballand, Viguier, & Muller, 2017). Other safety concerns include defending against spying or attacks by terrorists and other perpetrators (Sah, Gupta, & Bani-Hani, 2021).

Regulatory Challenges

Irrespective of consumer demand and commercial supply, drones cannot legally operate in the national airspace without government regulations and standards that allow them (Alawad & Kaewunruen, 2021). The lack of regulatory certifications for BVLOS and autonomous operations are two key components currently limiting the adoption of drones for long-distance infrastructure inspection applications (Sherrock & Neubecker, 2018). Current regulations limit operations to three statute miles of visibility, speed under 100 mph, altitude below 400 feet, and 500 feet below or 2,000 feet away from clouds (Schwab, 2020) (Lesiak, 2020). Regulatory bodies worldwide are working to enable BVLOS and autonomous drone operations that can safely integrate into the national airspace (Gantimurova, Parshin, & Erofeev, 2021).

Organizational Challenges

Several organizational barriers prevent the rail industry from widely utilizing drones. Changing from conventional to drone-based inspections requires a sophisticated infrastructure for remote pilots. The process of training and licensing staff for drone flights and operations could be time consuming and costly. Also, companies need to ensure the availability of secure ground facilities with authorized personnel having access to drones and related equipment (Jordan, et al., 2018) (Wu, Qin, Wang, & Jia, 2018). In most countries, organizations must obtain insurance for their drones and pilots before flying (Jordan, et al., 2018).

Conclusions

Most of the reviewed publications focused on discussing the challenges and opportunities of this technology. There were no discussions to qualify or quantify the specific benefit areas in RIM. This SLR is the first attempt to classify and evaluate the benefits of using drones for RIM.

Implications for New Theories

The transition to drone-based inspection and monitoring systems may be delayed by high costs, inadequate support infrastructure, the lack of a skilled workforce, and appropriate regulations for their safe integration into the national airspace. Nevertheless, the technology is evolving at a rapid pace and organizations have been investigating ways that drones can help to improve their operational efficiencies. With the enormous potential for using the new tool in many applications, organizations must conduct benefit-cost analyses to evaluate their return on investment in each application. The utility of drones can be far-reaching and lead to new models of business resilience, agility, and sustainability.

Implications for Management

The goal of deploying a drone-based inspection system is to enable a faster, safer, and more cost-effective method of identifying defects. Therefore, management must be able to interpret the data and make decisions about where to focus validation and remediation resources. An automated system that can collect data more rapidly and frequently also means that managers will need to potentially spend more time in evaluation and decision making. Organizations can use the data collected to create virtual 3D models of the infrastructure to evaluate safety and operational procedures or to plan a response to an accident. As argued earlier, adoption of the technology will also present new issues and challenges that include updating resources, training staff, updating facilities, and enacting new policies.

Implications for Impacts to Society

The potential to improve inspection accuracy and frequency may lead to improved maintenance practices, which could reduce certain types of accidents. Less frequent disruptions from accidents can increase the reliability and resilience of supply chains that depend on rail transport, and thus directly benefit society. The reduction of risks will also reduce the rate of injuries and fatalities from accidents.

Limitations

The number of studies retrieved for this SLR is relatively small because drone-based railway inspections are still a relatively new. Hence, it is possible that the classification of sensor payload, drone technologies, applications, benefits, factors affecting performance, and challenges may have missed a few elements. The technology is still rapidly evolving towards fully autonomous systems that can fly in BVLOS conditions, and therefore require less human involvement. As adoption accelerates, equipment costs will decline with economies of scale. Therefore, the costs discussed will change over time, including savings from a reduction in the human capital needed to operate the system.

Knowledge Gaps and Future Research

The literature discussed broad benefits but did not provide specifics on the costs to adopt the technology for RIM. Research on attitudes towards adopting drones into the railway industry is also lacking. Therefore, it is difficult to quantify a nominal benefit-cost ratio or return on investment (ROI) based on this SLR alone. The ROI calculation requires evaluating the direct benefits, indirect benefits, and costs of the traditional methods relative to the drone-based method. The benefit and cost quantifications will be unique to each organization and application. As the technology and regulatory certification evolves towards more automation, fewer trained staff per drone will be required, and the ROI will increase. As economies of scale in manufacturing drive cost reduction, the ROI will further increase. However, organizations should calculate the ROI with each step in the technology evolution because early adoption can bring a competitive advantage. Future work will conduct a scenario analysis of the ROI based on projections of the technology adoption timeline.

Data Availability Statements

No data, models, or code were generated or used during the study.

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Tables

Table 1. Classification of Publications According to Research Methods.

Research method	Publications
Algorithmic	Sushant et al. (2017); Wu et al. (2018); Bojarczak & Lesiak (2021); Mathe, et al. (2016); Singh et al. (2021); Singh et al. (2019); Saini et al. (2021); Yang et al. (2018); Geng et al. (2021); Lebedev, et al. (2020); Mittal & Rao (2017); Štroner et al. (2021); Li et al. (2020); Rahman & Mammeri (2021)
Theorical	Guan et al. (2020); Congress & Puppala (2021); Banić et al. (2019); Cano et al. (2022); Meng et al. (2021); Kochan et al. (2018); Ghassoun et al. (2021); Masat & Kaya (2019); Manatunga et al. (2017); Mammeri et al. (2021); Flammini et al. (2016); Gantimurova et al. (2021); Lyovin et al. (2019); Guclu et al. (2021)
Statistical	Shcherbakov et al. (2021); Huang et al. (2020);
Simulation	Nie et al. (2017); Jarrett et al. (2015); Zheng et al. (2020); Bobbe et al. (2020); Bendris (2022); Pall et al. (2014); Sahebdivani et al. (2020)
Review	Falamarzi et al. (2019); Jung et al. (2019); Maghazei et al. (2020); Leisak (2020); Rampriya et al. (2021); Leizer (2018)
Survey	Kovacevic, et al. (2016); Ivashov, et al. (2019); Alawad et al. (2021)
Prototype	Narazaki et al. (2022)

Table 2. Safety and Security Benefit Areas of Using the Drones for RIM.

Benefit Area	Categories	Study	Year	Drone	Sensor type	Algorithm/Software
Defect Identification	Track defect identification	Sushant et al	2017	-	8 MP digital cameras	Monte Carlo or particle/Matlab
		Sahebdivani et al	2020	-	-	SfM
	Rail defect identification	Wu et al	2018	DJI Matrice 600	Zenmuse Z30 camera	LWLC+GSME
		Guclu et al	2021	DJI Tello	Camera	Gabor filters
		Bojarczak & Lesiak	2021	-	Ultra 4K cameras with UHD video recording	FCN-8
		Mathe, et al	2016	Parrot AR Drone 2.0	Camera	Features from accelerated segment test (FAST)
		Singh et al	2021	DJI Phantom 3	4K camera	YOLO v4
	Irregular track geometry identification	Singh et al	2019	DJI Phantom 3	4k camera with Sony sensors	Canny/MATLAB
		Shcherbakov et al	2021	DJI Phantom 4 PRO	standard camera + sensor	-
Risk Assessment and Management	Evaluate accident scenarios	Nie et al	2017	-	-	UNIGINE
		Lyovin et al	2019	-	-	-
		Leizer	2018	-	RFID	-
	Evaluate vulnerabilities	Gantimurova et al	2021	SibGIS UAS	2 cameras	LS mapping technology
	Evaluate risks from Natural hazards	Flammini et al	2016	DJI S900/ DJI A2	ODROID XU4 based and NVIDIA TX1 based	CUDA
Monitoring Grade Crossings	Monitoring Grade Crossings	Baron & daSilva	2019	DJI Mavic 2 Pro	20-megapixel Hasselblad camera	Pix4D
		Stuart & Doran	2020	Bergen Hexacopter	Nikon DSLR	DEMs/3D photogrammetry
Trespassing Detection	Trespassing detection	Baron & daSilva	2020	DJ Matrice 200	Zenmuse X4s daylight /Zenmuse FLIR XT night	Pix4D
	Theft monitoring	SNCF	2022	-	-	-

Table 3. Maintenance Benefit Areas of using the Drones for RIM.

Benefit Area	Categories	Study	Year	Drone	Sensor type	Algorithm/Software
Rail Network Mapping	Network Mapping	Huang et al	2020	-	Band pass filter of about 660nm/ CMOS camera	MATLAB
		Mammeri et al	2021	ING Robotic Aviation Responder	Nikon D800	DCNN/ U-Net
		Saini et al	2021	DJI phantom	Camera	ACSM
		Manatunga et al	2017	DJI Phantom 4	Camera	Pix4D/DSM
Infrastructue Asset Monitoring	Infrastructure monitoring	Masat & Kaya	2019	DJ Phantom	Camcorder	-
		Jarrett et al	2015	Bixler 2	Camera	Raspberry Pi
		Ghassoun et al	2021	Multicopter	-	-
		Alawad et al	2021	-	-	-
		Rampriya et al	2021			RSNet
		Leisak	2020			
		Maghazei et al	2020	-	-	-
		Yang et al	2018			CNN/ GMM
		Ivashov, et al	2019	-	Canon EOS 5D Mark II	RANSAC
		Zheng et al	2020	-	-	MUSIC-like
		Bobbe et al	2020	DJI Matrice M600	100MP Phase One iXM-100 camera	
		Jung et al	2019	-	-	-
		Falamarzi et al	2019			
	Equipment monitoring	Kochan et al	2018	-	-	-
	Railway tunnel monitoring	Meng et al	2021	-	-	D-InSAR
		Bendris	2022	DJI Matrice100	Orbbec Astra depth camera/ IDS UI-3251LE / Basler acA4112-20um/ FLIR Tau 640 thermal camera	RRT
	Railway bridge monitoring	Narazaki et al	2022	-	GPS	SLAM or SfM/UNET3+/FCN58
		Cano et al	2022	DJI Matrice 600	Camera	-
	Railway contact wire monitoring	Geng et al	2021	DJI Matrice 600	LIDAR	self-adaptive

Track Condition Monitoring	Railway enbankment monitoring	Kovacevic, et al	2016	-	-	-
	Track structure monitoring	Mittal & Rao	2017	-	-	ResNet and Inception
		Lebedev, et al	2020	DJI's Phantom 4	Logitech C270 camera	PHT
		Pall et al	2014	Parrot AR.Drone	Camera	Canny, Sobel, and Laplace algorithms
		Banić et al	2019	DJI Phantom 3	Camera	Canny
Track Obstruction Detection	Vegetation	Rahman&Mammeri	2021	-	-	DCNN architecture/ DeepLabv3+
		Štroner et al	2021	-	-	CANUPO+SMRF/CANUPO+CSF
	Rockfall	Congress & Puppala	2021	Hexacopter	LIDAR	-
	Storage of materials along the ROW	Li et al	2020	-	-	Multi-block Single Shot/MultiBox
		Guan et al	2020	DJI F550	HERO Camera	Hypercomplex Fourier Transform
Graffiti Removal	Graffiti Removal	Upton	2022	-	-	Pix4D

Table 4. Potentials of Using Drones for RIM.

Potentials	Areas	Description
Reduce Costs	Return the current cost of inspecting railways using old methods	Increase capacity Increase in efficiency by 10% Energy saving of 20% Up to four tracks can be monitored simultaneously Reduce driver's costs Reduce the requirement for traffic shutdown Reduce operation costs by 50%
	Improve safety	Reduce the number of safeguards Reduce the cost of accidents caused by deteriorating railways
	Reduce time	Reduce the number of people employed to support the inspection and monitoring process
Improve Safety	Produce higher-resolution, precise imagery	Reduce the risk of overlooking the defects Improve the quality of monitoring Conduct more frequent inspections and gather more data
	Nondisruptive technology of drones	Inspecting the hard-to-reach places
	Reduce accidents	Reduce the amount of time inspectors need to be on the rails and increase safety Reduce the number of people injured in the train accidents
Save Time	Drones ascend to higher altitudes	Can collect multiple tracks simultaneously
Improve Mobility and Flexibility	Independence from the land-based infrastructure	Travel swiftly from one location to another
	Small size	Inspection of hard-to-access areas
	Fly remotely	Provide a bird's eye view
Improve Reliability	More reliable data	High-resolution views Comprehensive 360-degree view of the structures

Table 5. Cost Areas of Deploying Drones for RIM.

Cost Area	Description	Recurring	Location	Details
Equipment	**Drone component**			
	Airframe	Once	Drone	-
	Battery	Once	Drone	-
	Auxiliary components			
	Regulators	Once	Drone	-
	Parachute	Once	Drone	-
	Cables	Once	Drone	-
	Power management electronics	Once	Drone	-
	Memory chips	Once	Drone	-
	RC receiver	Once	Ground	-
	Radios	Once	Ground	-
	Flight Ops management software	Once	Ground	-
	Drone control and image acquisition			
	Sensor	Once	Drone	-
	Camera	Once	Drone	-
	Telemetry kit	Once	Drone	-
	TX radio control	Once	Ground	-
	Flight terminator	Once	Drone	-
	Data modem	Once	Ground	-
	Ground control Station			
	Monitors	Once	Ground	-
	Network hub	Once	Ground	-
	Image process	Once	Ground	-
	Streaming server	Once	Ground	-
	RC transmitter	Once	Ground	-
	Telemetry kit	Once	Ground	-
	HDMI splitter	Once	Ground	-
	UAV landing pad			
	Wi-Fi router	Once	Ground	-
	Telemetry radio	Once	Ground	-
	Control board	Once	Ground	-
	NEMA box	Once	Ground	-
	Installation service	Once	Ground	-
Staffing	UAS pilot	Monthly	Ground	Recommended at least an FAA instrument-rated pilot.
	Co-pilot or observer	Monthly	Ground	Must have class 2 FAA medical certificates
	Maintenance team	Monthly	Ground	
	Data analyst	Monthly	Ground	Will manage the data acquired by drone.
Resources	Cost of training and staff turnover	Monthly	-	-
	Cost of aviation insurance and safety management	Monthly	-	-
	Registering the drone with the Federal Aviation Administration (FAA)	Once	-	-
	Liability insurance	Monthly	-	-

Table 6. FRA reported financial losses from railway accidents in 2021.

Accident Cause	Financial Loss	Accident Proportion
Human Error	$90 million	37.2%
Track & Roadbed Problems	$84 million	22.6%
Equipment & Signal Problems	$59 million	11.3%
Highway-Rail Grade Crossing	$14 million	9.7%
Miscellaneous	$1.8 million	17.7%

Source: Data from Federal Railroad Administration (2022).

Table 7. Advantages and Disadvantages of Multicopters in RIM.

Type	Advantages	Disadvantages
Multicopters	The capability of carrying multiple payloads on a single flight such as a camera and a flashlight simultaneously improves the efficiency of the aircraft and reduces inspection time.	Limited endurance and speed make them less suited for long-distance inspections.
	Good control of the aircraft during flights along the tracks.	When carrying a lightweight camera payload, they are limited to about 20-30 minutes with current battery technology.
	Increased maneuverability allows it to move up and down on the same vertical axis, backward and forwards, and sideways and rotate for better defect detection and measurement.	-
	The ability to fly closely to assets and provide physical contact with the tracks and assets cutting wires, switching, etc..	-
Winged Drones	The ability to fly further on a single charge while carrying heavier payloads for long linear infrastructure monitoring.	More difficult to land than multicopters.
	Ability to fly at a high altitude.	Some may have limited hovering capabilities.

Table 8. Challenges of Drones in RIM.

Challenges	Description	Supportive literature
Technical challenges	Maintain visual line of sight Payload capacity and flight endurance are limited Limited weather resistance Collisions and interference Rapid battery discharge Lighting conditions Non-uniform illumination and noise corruption Small objects are difficult to detect	Banic et al. (2019); Congress & Puppala (2021); Singh et al. (2019); Rampriya & Suganya (2021); Falamarzi et al. (2019); Flammini et al. (2016); Bobbe et al. (2020); Cano et al. (2022); Jarrett et al. (2015); Jung et al. (2018); Gantimurova et al. (2021); Geng et al. (2021); Ivashov et al. (2019); Ghassoun et al. (2021); Wu et al. (2018); Lebedev et al (2020); Narazaki et al (2020)
Safety challenges	Loss of control of the UAV Non-controlled ground impact Collision with someone Fatal injury to someone The threat of espionage and terrorism	Mathe et al. (2016); Lesiak (2020); Bendris & Becerra (2022); Kochan et al. (2018); Maghazei et al. (2020); Falamarzi et al. (2019);
Regulatory challenges	Inadequate regulatory support and industry standards Regulatory uncertainty and barriers Absence of regulations applicable to small drones	Alawad & Kaewunruen (2021); Lesiak (2020); Gantimurova et al. (2021); Geng et al. (2021); Kochan et al. (2018); Maghazei et al. (2020); Jung et al. (2018);
Organizational challenges	Investing in supporting infrastructure takes time and money Inadequate capabilities, skills, and experience with drones Insurance obligations Certification and training of pilots	Wu et al. (2018); Falamarzi et al. (2019); Cano et al. (2022); Bobbe et al. (2020); Kochan et al. (2018); Rampriya & Suganya (2021);

Figures

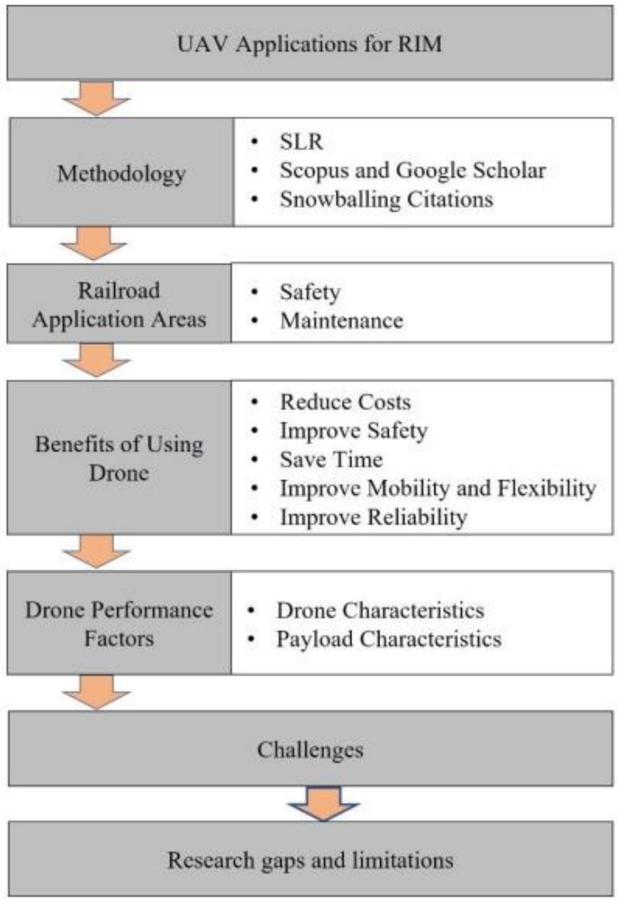

Figure 1: Flow diagram of the review on UAV application in RIM.

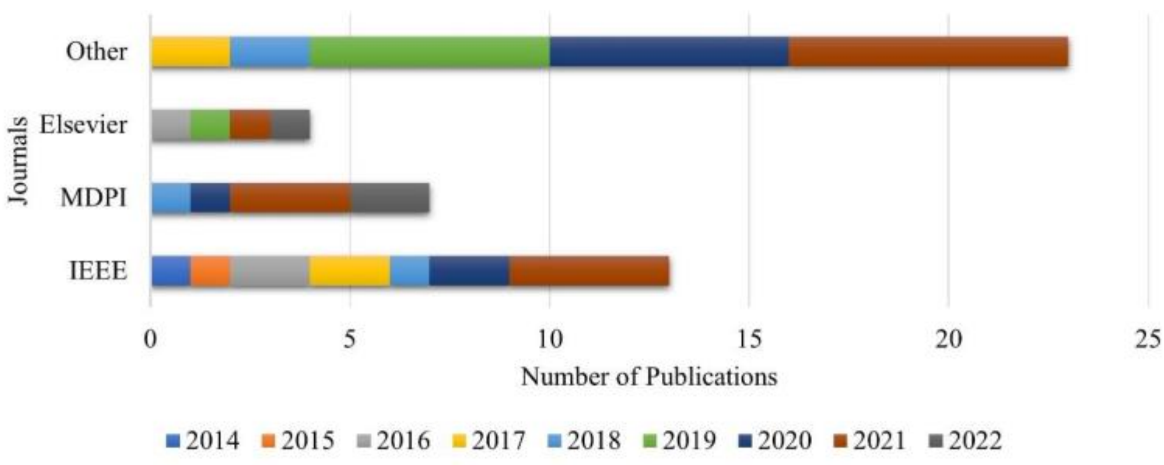

Figure 2: Distribution of publications by journal.

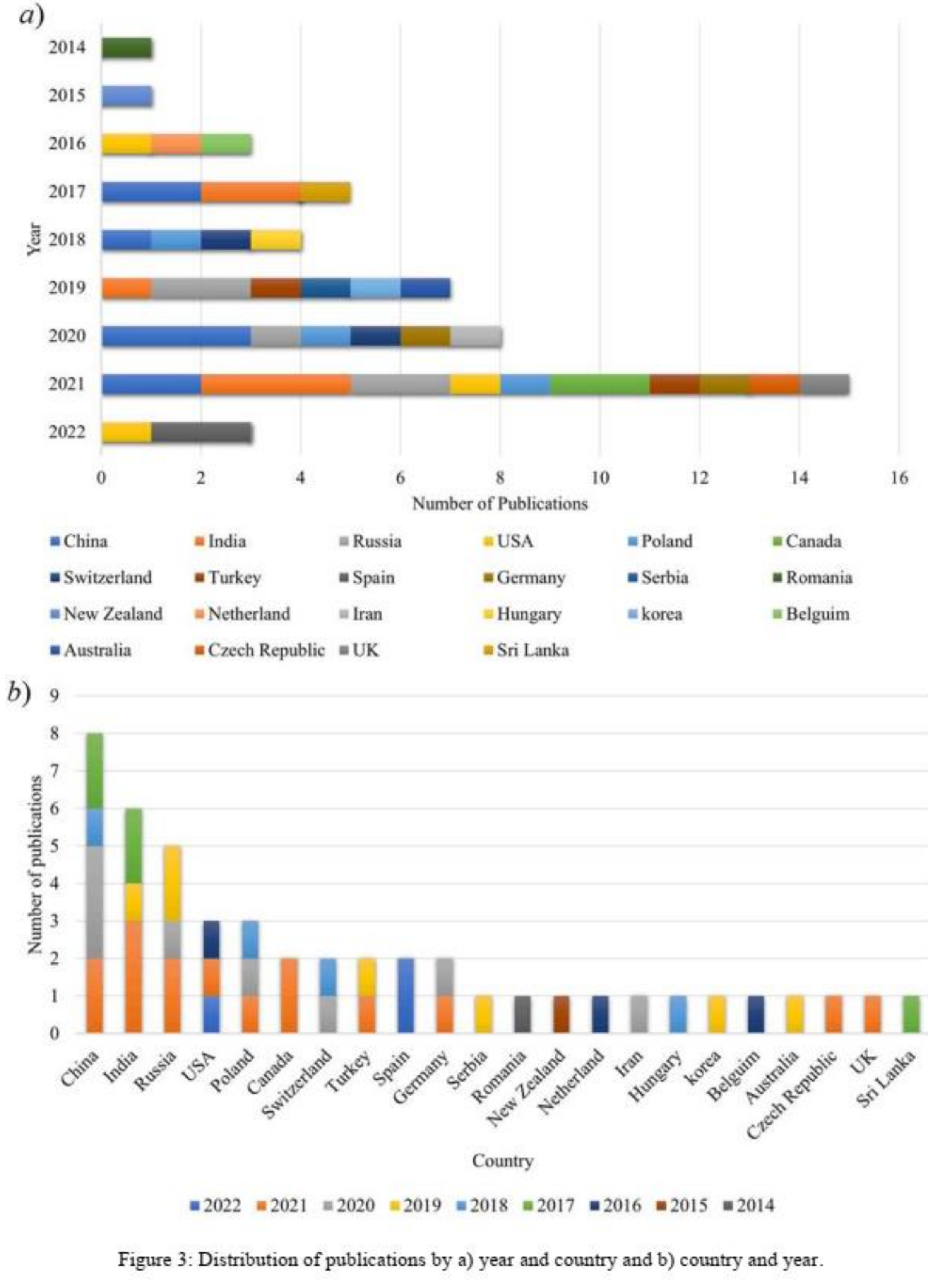

Figure 3: Distribution of publications by a) year and country and b) country and year.

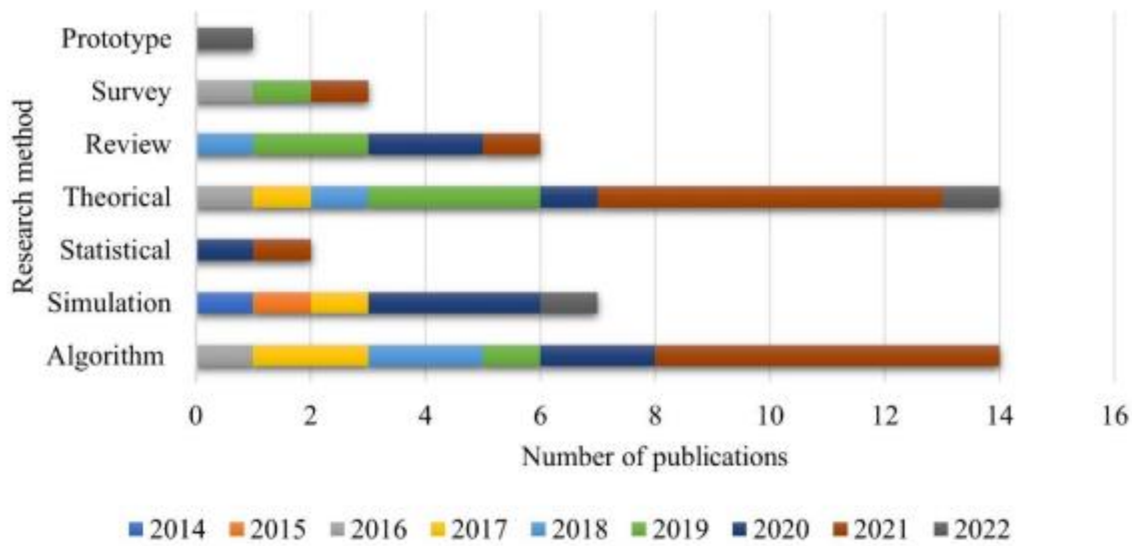

Figure 4: Distribution of publications by year and research methods.

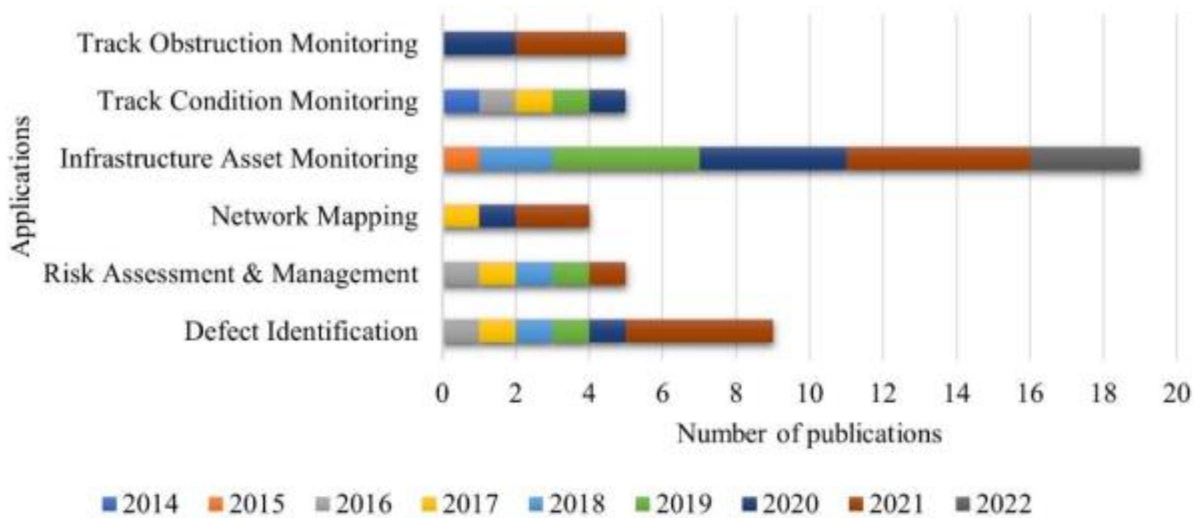

Figure 5: Distribution of publications by application and year.

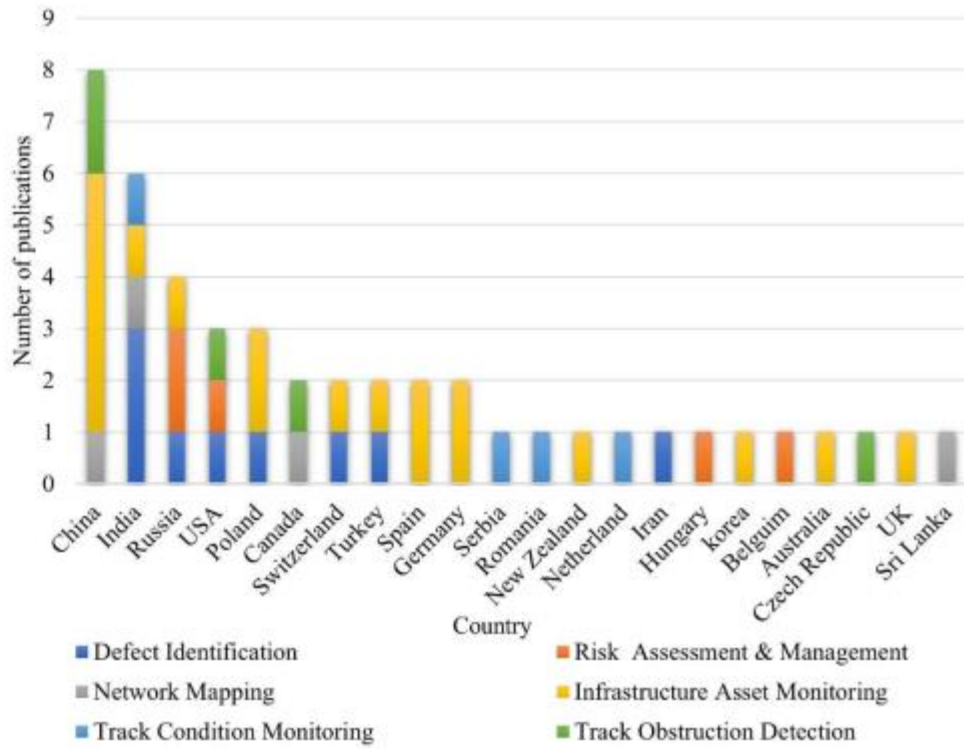

Figure 6: Distribution of publications by location and application.

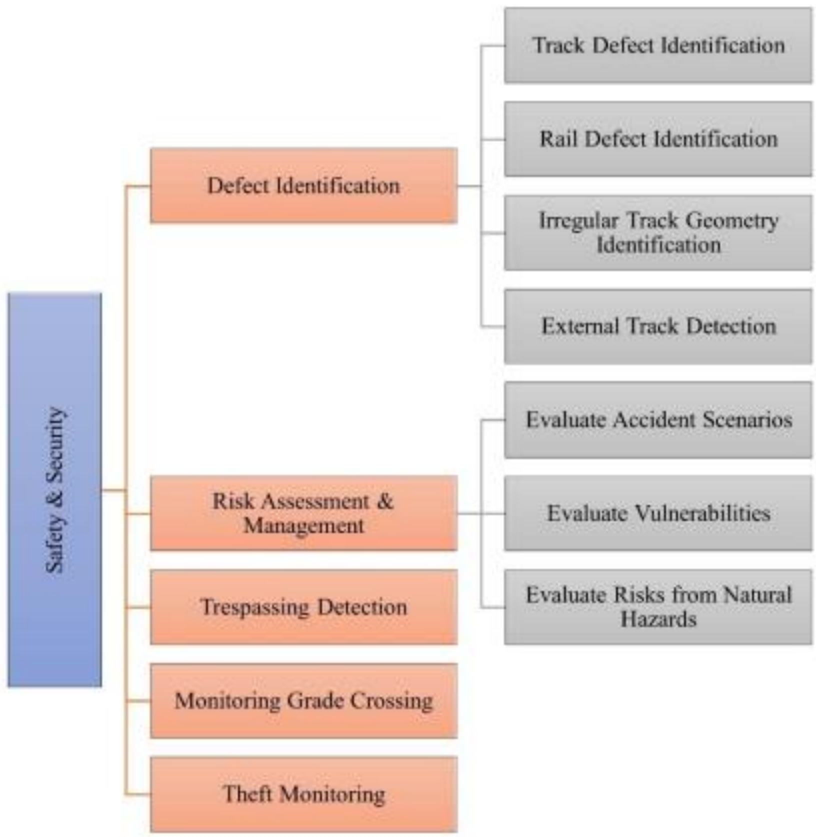

Figure 7: Classification of safety and security applications of drones in RIM.

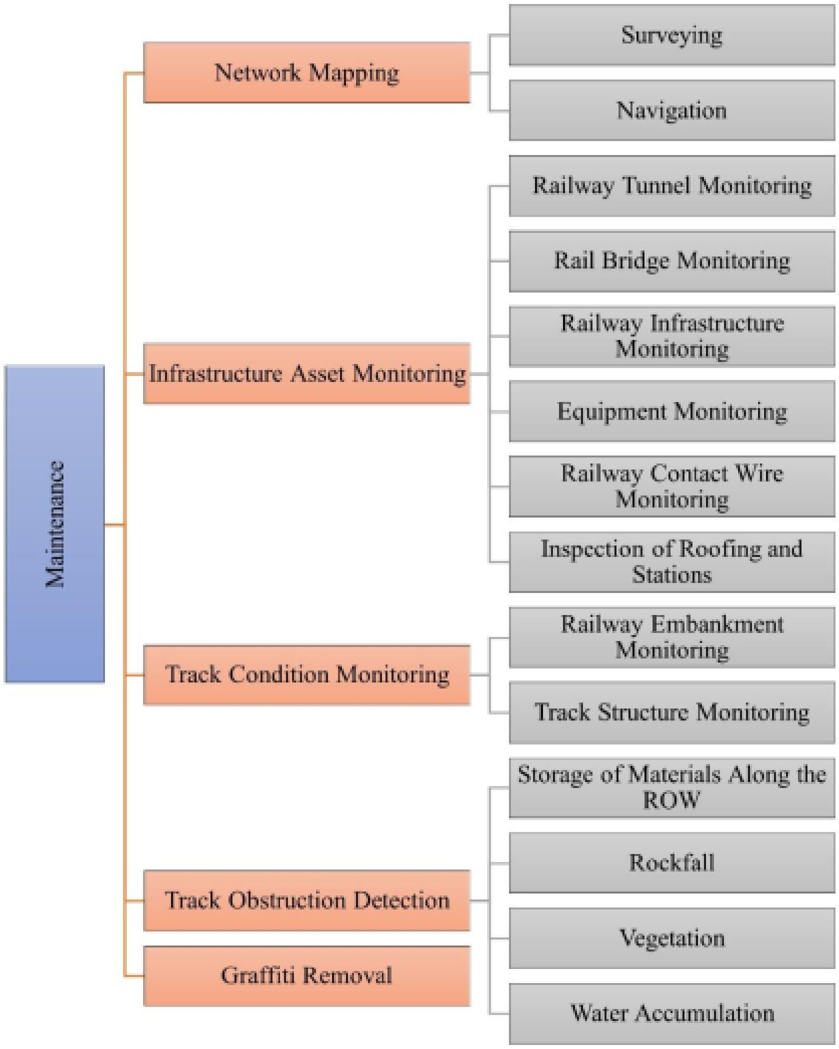

Figure 8: Classification of maintenance applications of drones in RIM.

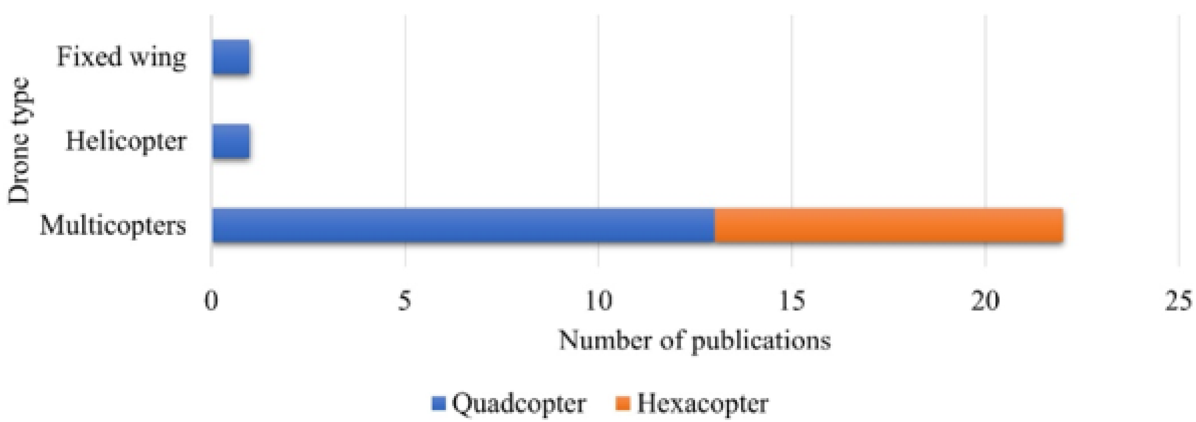

Figure 9: The type of used drones in the reviewed studies.

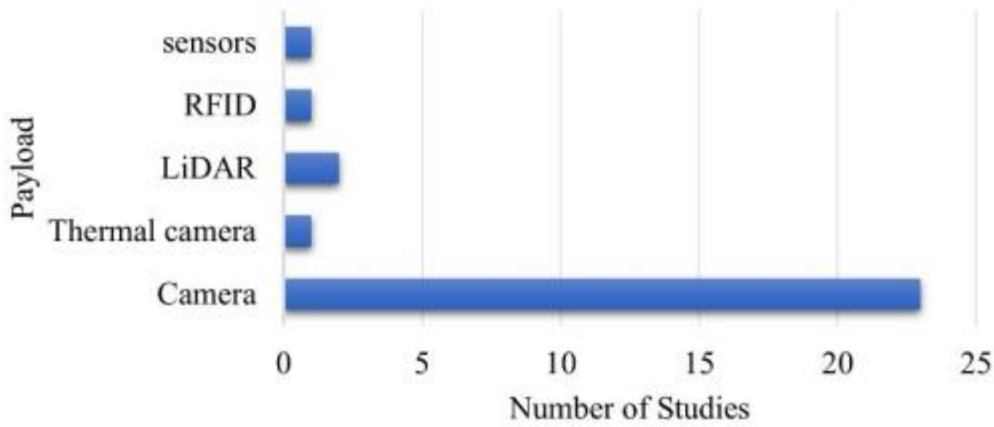

Figure 10: Type of payloads used in the reviewed studies.