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Drones for Road Condition Monitoring: Applications and Benefits

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Drones for Road Condition Monitoring: Applications and Benefits

Abstract

This systematic literature review (SLR) explores the increasing use of drones in road condition monitoring (D-RCM), a development poised to enhance inspection efficiency and reduce costs. Surveying 60 articles from a pool of 619 publications between 2014 and 2022, the study unveils cost and time savings, safety enhancements, improved mobility, and reliability as the primary drivers behind D-RCM adoption. D-RCM applications, categorized into areas like condition monitoring, situation assessment, network mapping, asset monitoring, and construction inspection, face challenges such as visual line-of-sight maintenance, limited flight time, payload capacity, and engineering errors. However, potential solutions emerge, including terrain-following features, optimizing battery capacity-weight balance, and employing trained personnel. Importantly, the study reveals considerable cost benefits and impressive ROI up to 980%, positioning drones as a promising, cost-effective tool for infrastructure management, with profound implications for theory, management, and societal impacts of D-RCM applications.

Keywords: Road monitoring; bridge inspection, pavement monitoring; remote sensing; unmanned aerial vehicles; urban air mobility

1 Introduction

Uncrewed Aerial Vehicles (UAVs), also known as drones, are becoming increasingly prevalent across all sectors of industry. The term civilian applications refer to the deployment of drones in non-military, non-law enforcement contexts (Merkert & Bushell, 2020). Civilian applications use commercial drones because they are simple to deploy, affordable to maintain, and can access locations that are difficult for humans to reach. In 2019, the market value of civilian drones was approximately $7.4 billion. Forecasters expect the industry will generate approximately $22 billion in revenue by 2030, with a projected compound annual growth rate (CAGR) of 14.3% between 2022 and 2030 (Hohnholz, 2022). A wide range of applications are becoming possible as drone technology advances. Civilian applications currently include medical supply delivery (Nyaaba & Ayamga, 2021), insurance risk assessment (Muhamat, et al., 2022), agricultural improvements (Deon, Burchfirld, Witt, Price, & Sharda, 2020), cargo delivery (Mühlhausen & Peinecke, 2021), and surveying. However, several challenges and limitations remain, including ensuring the safety of humans in the event of flight failure, payload capacity limitations, battery life, and the lack of clear government regulations.

The transportation industry utilizes drone technology in many ways, and agencies are continuously exploring potential benefits. Most of those efforts focus on monitoring and inspection, detecting traffic violations, optimizing signal timing, delivery, and network mapping. Highway infrastructure is a crucial component of a nation's economy, with road investments having both economic benefits and excessive costs (Feroz & Dabous, 2021). Budget constraints often lead to the postponement of road maintenance. Delays in maintenance, combined with an increase in traffic loading and unpredictable climatic and environmental conditions, lead to significant structural degradation. This degradation often occurs well before the pavement systems reach their intended design lifespan. Hence, delays can significantly increase the cost of eventual maintenance. Additionally, neglecting maintenance within the design service life can result in the need for major rehabilitation (Peraka & Biligiri, 2020). Approximately 68% of major roads and highways in the United States in 2019 required immediate maintenance. Consequently, commuters spent an estimated $61 billion each year on increased vehicle operating costs, traffic delays, and incidents (ASCE, 2019). ASCE also estimated that agencies will need to spend $130 billion to restore pavements to a good state (ASCE, 2019).

Using drones for roadway condition monitoring (D-RCM) has gained popularity in recent years. Integrating drones with relevant digital technologies can significantly enhance the efficiency of the entire roadway condition monitoring (RCM) process, from data collection to analysis and decision-making. Moreover, the real-time kinematic global positioning system (RTK-GPS) has emerged as a powerful tool to enhance drone localization (Kim, Ham, & Lee, 2020). Additionally, technologists have developed artificial intelligence (AI) techniques such as deep learning and computer vision to identify and extract damage information from data collected by drones.

A few papers published in recent years reviewed the applications of drone technology in transportation asset monitoring. However, most of those studies focused solely on the different applications or machine learning methods. For instance, Dorafshan et al. (2018) reviewed U.S. bridge inspection programs (Dorafshan & Maguire, Bridge inspection: human performance, unmanned aerial systems and automation, 2018), and other studies reviewed pavement monitoring (Peraka & Biligiri, 2020) (Chen & Zheng, 2021). Only one study reviewed the application of drones in three domains of transportation: road safety, traffic monitoring, and highway infrastructure management (Outay, Mengash, & Adnan, 2020). Those studies hinted at the different benefits of D-RCM applications and its challenges, limitations, and implications. To the authors' best knowledge, there is a lack of studies that have identified and quantified the specific benefits and costs.

To fill the gaps in existing knowledge, this systemic literature review (SLR) aims to provide a comprehensive overview of the benefits and costs associated with D-RCM. The primary objectives of this SLR are to identify the various applications within D-RCM, quantify and classify the benefits associated with those applications, address any open challenges, and suggest potential solutions. Additionally, the review aims to evaluate the implications for new theories, management, and impacts to society that arise from D-RCM.

The organization of the rest of this paper is as follows: Section 2 presents the review method, and Section 3 describes the bibliometric analysis of the reviewed publications. Section 4 provides a summary of the classification of applications and benefits of D-RCM, quantifies cost and time benefits, and outlines associated challenges and proposed solutions. Section 5 identifies research gaps and discusses the limitations of the study.

2 Research Methodology

This study followed a systematic review approach based on the seven-step process suggested by Cooper (Cooper, 2015). Figure 1 shows the flowchart of the methodology applied in this review. The first step involved defining the purpose of the review, which was to analyze the various applications within D-RCM and the costs and benefits. The second step involved determining the literature search method, including database and keyword selection. The authors selected the Scopus database for the initial search because it is the most comprehensive database of peer-reviewed scholarly literature. Next, the authors transferred the search results to the Web of Science (WOS) database to utilize its integration with CiteSpace , a software for visualizing patterns of links between the literature. The search terms used were ("drone" OR UAV OR "unmanned aerial vehicle" OR "remote sensing") AND (road OR highway OR pavement OR bridge) AND (monitoring OR inspection) AND (application OR cost OR benefit) in the title, abstract, and keyword fields of scholarly academic publications in Scopus. The procedure considered conference papers only if a few peer-reviewed journal articles were available. The third and fourth steps involved data collection and quality inspection. A preliminary analysis identified 619 articles published since 2000. The first stage of filtering eliminated unrelated and duplicate articles by reviewing the publication titles and abstracts, which reduced the number of relevant publications to 119. Further filtering resulted in 52 studies related to the topic. The snowball method applied to Google Scholar identified eight additional articles, bringing the final review count to 60 articles from 2014 to 2022. The fifth and sixth steps involved data analysis and literature interpretation, with content analysis used as a method of literary analysis.

Version 6.1.R3 of the CiteSpace application helped to visualize patterns and trends in the literature database. Visualizations included journal and keyword co-occurrence, co-citation networks, and country co-authorship networks. The SLR also explored the potential benefits and limitations of D-RCM. Finally, the seventh step involved displaying the results.

3 Analysis and Results

The following sections entail the distribution of papers by year, journal co-citation analysis, keyword co-occurrence network, and country co-authorship network analysis.

3.1 Distribution by year and application

Figure 2 displays the distribution of publications from 2014 (with at least one publication in the first year) to 2022. Studies on monitoring and safety applications using drones received little attention until 2016 and 2017, respectively. However, monitoring studies entered a period of increased attention and growth, reaching a peak in 2020.

3.2 Keywords Co-occurrence Analysis

The goal of keyword co-occurrence analysis is to extract meaningful information about emerging trends, core content, research focus, and promising directions in the field. We selected a time span from 2014 to 2022 with a time slice of 1 to analyze the top 50 cited or commonly occurring items in each slice. The keywords co-occurrence modularity Q was 0.4628, which is greater than 0.3, indicating a reasonable network structure (Newman, 2004). The Silhouette score was 0.7973, which is greater than 0.4 and shows a reasonable result. Figure 3 shows the timeline of the clustered keywords co-occurring network (8 clusters). The visualization not only highlighted the importance of each cluster but also revealed their interactions over time. The nodes in the network represent the keywords, and links show their connections. The rings around the nodes represent the frequency of each keyword in each time slice. The font size of the words indicates relative frequency of occurrence. This approach provides a clear and intuitive representation of the evolution of the research domain by visualizing key trends and patterns over time.

The size and color of nodes revealed that “artificial intelligence” and “aerial photography” have been popular research topics since 2014, while “photogrammetry” and “unmanned aerial vehicle” gained popularity in 2015. Research topics related to “bridge inspection,” “inspection,” and “antenna” emerged in 2017. The hot topics of 2018 were “drones,” “cost” and “UAV,” while topics related to “cost effectiveness,” “machine learning,” and “image enhancement” gained prominence in 2020. The color of clusters and their nodes show that clusters such as “concrete surface crack” (#3), and “service life preservation” (#7) have recently emerged. However, some other clusters such as “collecting decision support system data" (#4) and "crack detection classification" (#5) were of interest to researchers in the past and declined in research interest over time. Table 1 summarizes the clusters by listing their ID, size, silhouette value, year, and log-likelihood ratio (LLR) label. The clusters' LLR labels represent the research frontiers in this knowledge domain. Among the clusters, the first two research areas identified in this knowledge domain are the use of "multirotor unmanned aerial vehicles" and the "streamlined bridge inspection system."

The term "burst keyword" refers to frequently cited keywords over time, where burst detection measures the rate of new keyword adoption (Chen, Dubin, & Kim, 2014). Table 2 presents the top 18 burst keywords with the most significant citation bursts. During the early years of D-RCM research, the field focused on emerging technologies, with "aerial photography" and "image processing" emerging as the most robust keywords. Between 2017 and 2019, research shifted toward discussing and resolving challenges, with "Federal Aviation Administration" and "aircraft detection" as key terms. Recent research concentrated on technology development and benefits, with "machine learning," "cost-effectiveness," "computer vision," and "convolutional neural network" as core keywords. As the top burst keywords (UAV, artificial intelligence, aerial photography, and aircraft detection) closely overlap with other keywords in the table, they should continue to be associated with bursts of publications.

3.3 Journal Co-citation Analysis

A journal co-citation analysis can reveal the structure of a research field, where scholarly journals serve as essential means of communication. Co-citation between two journals occurs when at least one article from each journal appears in a cited article (Chen, Dubin, & Kim, 2014). Figure 4 shows a simplified merged journal co-citation network generated using the minimum spanning tree algorithm. The network illustrates a collection of co-cited journals, with each journal represented as a node and links between them representing co-citation relationships. The size of a node reflects a journal's citation count. The node's size is directly proportional to the journal's cardinality, while the distance between the nodes is a direct measure of the frequency with which the journal is cited. The network indicates a strong correlation between co-citations for journals such as *Automation in Construction, Sensors*, and *Transportation Research Record*, with an extensive network for closely related journals. The network further illustrates that most journals cover topics in remote sensing, automation, and infrastructure.

Table 3 presents a ranking of journals with the strongest citation bursts based on the intensity of the burst. These citation bursts indicate that publications in these journals have received a substantial number of citations in a brief period. While the initial stages of D-RCM research primarily focused on sensors, journals covering infrastructure and engineering aspects have more recently increased in citation rates. The journal *Automation in Construction* stands out as one with bursting citations in the field of using drones for condition monitoring.

3.4 Country Co-authorship Analysis

Figure 5 displays the network of country co-authorship analysis of D-RCM research, illustrating the authorship collaboration among countries. The node type in CiteSpace was "country," and the network pruning algorithm was the minimum spanning tree algorithm. The size of each node reflects the number of papers published by authors in the country. Connections between nodes represent co-authorship between those countries, with the number of connections indicating the span of collaboration. The authors of the 60 papers analyzed in this study are in 22 countries, demonstrating the span of research interest in D-RCM. Table 4 lists the top 11 countries by publication volume in the field of D-RCM. The centrality of a node is based on its position in the network and its connections to other nodes (Chen, Laefer, Mangina, Zolanvari, & Byrne, 2019).

An increase in citation frequency indicates a significant impact, and countries with higher centrality are more influential. Three countries exhibited high centrality: United States (22 publications), United Kingdom (four publications), and Iran (two publications). Further analysis reveals that the quantity of U.S. D-RCM publications (22, 36%) is greater than that from any other country, followed by China and Italy, each with a frequency of eight. Although there are frequent links between countries and regions, their intensities are weak, indicating a lack of cross-country and cross-regional collaborations. The dark purple circles indicate that the United States was the only country to initiate D-RCM research in 2014.

4 Discussion

The first two subsections below discuss the specific research conducted in each application area.

4.1 Safety and Security Applications

Table 5 lists the safety applications in D-RCM, detailing the year, types of drones, sensors, and algorithms or software discussed in each paper.

4.1.1 Risk Assessment

Evaluating Risks after Natural Hazards: An aerial view of roads after natural disasters can be invaluable in assessing damage and formulating an appropriate response. For example, drones are ideal for monitoring the flow of vehicles and changes in routing parameters after a flood, based on information acquired in real-time. Management can use this information to redefine the problem and reroute the flow of vehicles under new parameters (Kashyap, Ghose, Menon, Sujit, & Das, 2019). Kashyap et al. (2019) also discussed a drone-ground vehicle combination system that can deliver critical resources from relief centers to flood-affected areas, providing real-time data on road conditions, flood flow features, and enabling effective rerouting of vehicles based on changes to the road network, vehicle speed, or flood-induced damage. In addition, drones can inspect roads after a hurricane to assess the condition of pavement and identify several types of pavement distress, such as cracking and deformation (Kashyap, Ghose, Menon, Sujit, & Das, 2019). Congress et al. (2019) demonstrated that drones can inspect low-volume roads after a hurricane and identify debris generated by the storm (Congress, Puppala, & Banerjete, Use of Unmanned Aerial Photogrammetry for Monitoring, 2019).

Evaluating Risks on Harsh Roads: Drones can follow the path of operators along roads. However, in dangerous areas such as jungles and mountains, Wang et al. (2021) proposed a new method for path following. If the drone loses contact with its operator, the drone can analyze its past path to simulate the operator's judgment and enable the drone to continue flying (Wang, OuYang, & XianglingShao, 2021).

4.1.2 Landslide Monitoring

Road landslides can cause significant problems, such as retaining wall collapse and road obstruction. Drones provide an effective and efficient means of inspecting remote and difficult-to-reach landforms, with significant cost benefits over traditional methods of manual tracking. Sugianto (2018) showed that drones can be of great benefit in large-scale monitoring to determine landslide hazards, affected areas, and the presence of saturated debris material (Sugianto, 2018). Migliazza et al. (2021) developed a detailed analysis method to evaluate landslide hazard and slope stability conditions. Using this technique, organizations can obtain geometrical data on discontinuities along the entire road, enabling the definition of potential kinematic mechanisms and volumes of potentially detachable blocks by obtaining statistically representative geometrical data corresponding to the rock mass (Migliazza, Carriero, Lingua, Pontoglio, & Scavia, 2021).

4.1.3 Construction Inspection

Monitoring Road Construction Sites: Cost overruns and delays affect most road construction projects. Supervision, monitoring, and inspection are essential elements of project management because they provide insight into a project's progress and potential roadblocks. Using drones to monitor highway projects could save time and increase quality control (Subramanya, Kermanshachi, & Patel, 2022). Lee et al. (2020) examined the possibility of change monitoring using drones at expressway construction sites in Korea (Lee, Song, Kim, & Won, 2020). Jeelani et al. (2021) examined the safety challenges of drone integration in construction sites (Jeelani & Gheisari, 2021). Lo et al. (2022) used drones to provide a progress monitoring framework for a road construction site (Lo, Zhang, Ye, & Cui, 2022).

Monitoring the Construction of Forest Roads: Bugday (2018) aimed to reveal the capabilities of using drones and geographic information systems (GIS) to plan the construction of forest roads. Specifically, the study aimed to assess the feasibility and economic benefits of using drones to monitor forest road construction with the aims of reducing planning time, minimizing construction cost, and increasing productivity (Bugday, 2018).

4.1.4 Environmental Monitoring

Duan et al. (2019) quantified the influential factors in aerial photography route design in highway green belts monitoring to better understand how each drone flight parameter affects image acquisition. The study determined the optimal route planning to monitor different grades of roads based on road surface width (Duan, Hu, & Sang, 2019).

4.1.5 Intersection Monitoring

Removing obstructions at intersections will increase road user safety. However, common approaches, such as changing geometric designs, providing additional traffic control devices, and quickly identifying obstructions within an intersection area, are cost prohibitive to implement at every intersection. Using drones coupled with close-range photogrammetry (UAV-CRP) technology enables fast, safe, and efficient identification of obstructions within intersection sight triangles (Congress, Puppala, Banerjee, & Patil, 2021).

4.2 Maintenance Applications

Most of the research in D-RCM pertains to maintenance applications. Table 6 summarizes the classification of maintenance applications within D-RCM and the types of drones, sensors, and software employed in each publication.

4.2.1 Monitoring Parking Lots

Monitoring vehicle facilities such as parking lots is crucial for informing maintenance to prevent damage. However, the unique characteristics of parking lots can make this task challenging because direct inspection may require blocking access to the facility, leading to delays. To address these issues, Kim et al. (2020) proposed a real-time drone mapping approach that utilizes reference images to significantly improve processing time and accuracy. This method enabled quick and safe inspections without disrupting the facility’s operations (Kim, Ham, & Lee, 2020).

4.2.2 Retaining Walls Defect Identification

Masonry retaining walls made of dry stones are prone to leaning and bulging, primarily due to a lack of cohesion between the stones. The current assessment techniques are inadequate, and the limited knowledge of the behavior of such wall systems poses a significant maintenance challenge for highway authorities, especially in the face of limited funding. In this context, Hain et al. (2019) conducted a notable research effort demonstrating that photogrammetry can produce precise 3D models of masonry retaining walls. These models can identify local areas subject to failure, supplement inspection reports, and aid maintenance efforts. The use of photogrammetry to monitor retaining walls is a practical solution that can improve the accuracy of inspections and lead to timely maintenance, ensuring public safety while minimizing costs (Hain & Zaghi, 2020).

4.2.3 Bridge Inspection and Monitoring

Bridge condition assessment: Recent research has shown the potential benefits of using drones to inspect and monitor bridges. These efforts propose systems that enable bridge managers to leverage drone technology for more efficient and accurate inspections and to monitor the health of the bridge by quantifying and visualizing damage progression (Perry, Guo, Atadero, & Van De Lindt, 2020) (Mandirola, et al., 2022) (Abdallah, Atadero, & Ozbek., 2022). Hubbard et al. (2020) examined in detail the potential for drones to improve bridge inspection safety and the methodology for quantifying the safety benefits of drones using worker compensation rates; they demonstrated the method using survey results from a department of transportation (DOT) case study (Hubbard & Hubbard, 2020). Azari et al. (2022) aimed to improve stakeholders' knowledge of bridge inspection using drones by presenting a prototype and sensors to assist inspection, collect the necessary data, and implement data management methods (Azari, O'Shea, & Campbell, 2022). Song et al. (2022) developed a prototype for an interactive web-based tool, iBIRD, to manage drone-assisted bridge inspections, including the inspection process and a web platform for 3D modeling and inspection reports (Song, Yoo, & Zatar, 2022). Dorafshan et al. (2018) revealed how drones with self-navigation and image processing algorithms can provide accurate, multipurpose, autonomous 3D models and identify damages, which has revolutionized the bridge inspection industry (Dorafshan & Maguire, 2018). Chen et al. (2019) proposed a method that uses imagery-based point clouds and several evaluation mechanisms to check data coverage, analyze point distribution, evaluate outlier noise, and measure geometric accuracy. However, image matching can be challenging in areas with slim features (Chen, Laefer, Mangina, Zolanvari, & Byrne, 2019). Gaspari et al. (2022) compared traditional topographic and global navigation satellite system (GNSS) techniques with transport layer security (TLS) and photogrammetry, utilizing cameras and a LiDAR sensor mounted on a drone. They found that the resulting point cloud's georeferencing accuracy from the drone-mounted LiDAR was less accurate than when manually flying the drone under a bridge (Gaspari, Ioli, Barbieri, Belcore, & Pinto, 2022). Whitley et al. (2020) presented some solutions to the current challenges in implementing all types of drones (Whitley, et al., 2020).

Bridge inspection in harsh environments: Aliyari et al. (2021) conducted a preliminary hazard analysis (PHA) to evaluate the risks associated with using drones for bridge inspections in cold environments. PHA examined technical and environmental hazards, paying particular attention to the impact of cold and harsh conditions on human performance, including that of drone pilots (Aliyari, Ashrafi, & Ayele, 2021).

Concrete bridge crack detection: Lei et al. (2020) addressed the challenge of implementing most vision-based inspection methods on low-cost drones for real-time crack inspection by developing a computationally efficient vision-based crack inspection method. They also developed a new algorithm called the "crack central point method" to extract the most useful information from preprocessed images (Lei, Ren, Wang, Huo, & Song, 2020).

Bridge crack inspection: Ayele et al. (2020) proposed a method for assessing bridge damages using a crack segmentation mask region-based convolutional neural network (RCNN), which detected, located, and quantified cracks and fractures with greater accuracy than a human inspector (Ayele, Aliyari, Griffths, & Droguett, 2020). Humpe (2020) developed a prototype drone with a 360° camera above its airframe to survey critical parts of a bridge. Comparing the results to those obtained with the conventional approach that used a camera underneath the drone, the 360° camera was more appropriate for inspecting corners or the ceiling of an arch bridge (Humpe, 2020).

4.2.4 Unpaved Roads Condition Monitoring

In the United States, approximately two-thirds of all roads are unpaved and receive less funding than their paved counterparts due to lower traffic volume (Dobson, Brooks, Roussi, & Colling, 2013). These unpaved roads are vulnerable to deterioration and require frequent maintenance, leading to higher costs and longer road closures. To address these challenges, researchers have proposed using drone-based remote sensing and predictive road condition modeling to monitor and assess unpaved road conditions. In a 2022 study, Mansourmoghaddam et al. utilized drone imagery to prioritize paving unpaved roads, thus offering a practical solution to the challenges of unpaved road maintenance (Mansourmoghaddam, et al., 2022). Using drones to monitor unpaved roads can provide transportation agencies with accurate and timely information, allowing them to prioritize maintenance and repair activities more effectively, ultimately reducing costs and minimizing the impact of road closures on the public (Dobson, Brooks, Roussi, & Colling, 2013).

Stone and gravel condition monitoring: Monitoring the quality of gravel roads requires measuring various parameters, such as drainage, dust, distress, erosion, potholes, cross-sections, and loose gravel. However, traditional manual inspection is a complex and time-consuming task for inspectors and can also be expensive. Saeed et al. (2020) compared different monitoring methods and found that a combination of drone and machine learning (ML) was the most cost-effective approach (Saeed, Dougherty, Nyberg, Rebreyend, & Jomaa, 2020). Similarly, Garilli et al. (2021) proposed a low-cost method using a DJI Phantom 4 Pro quadcopter drone to inspect stone pavement made from 6/8 class stone cubes (Garilli, Bruno, Autelitano, Roncella, & Giuliani, 2021).

4.2.5 Pavement Condition Monitoring

Pavement distress monitoring: Improving pavement function and ensuring user safety require early detection and measurement of distress (Coenen & Golroo, 2017). In recent years, researchers have used drones to record pavement images and identify surface distresses. Pietersen et al. (2022) developed a condition index by processing pavement images using a convolutional neural network (Pietersen, Beauregard, & Einstein, 2022). Tan et al. (2019) used drone-oblique photogrammetry to reconstruct road 3D models, which allowed automatic pavement distress detection with a high degree of precision compared with field surveys (Tan & Li, 2019). Barrile et al. (2020) evaluated road gradation using a DJI Mavic 2 Pro connected to the cloud for data processing and GIS updating (Barrile, Bernardo, Fotia, Candela, & Bilotta, 2020). Roberts et al. (2020) assessed the level of road degradation using 3D models and flexible segmentation strategies (Roberts, Inzerillo, & Di Mino, 2020). Shaghil et al. (2018) reviewed the capabilities of drones for collecting data for road maintenance assessments. They also evaluated the reliability of using object recognition software to automate pavement distress identification, and the viability of using drones as a replacement for traditional methods for RCM. Chen and Zheng (2021) investigated the application of multi-objective optimization for pavement maintenance and rehabilitation decision-making (Chen & Zheng, 2021). Additionally, Peraka and Biligiri (2020) reviewed drone-based pavement asset management systems (Peraka & Biligiri, 2020).

Surface defect detection: Surface defect detection has undergone significant developments in recent years to identify and analyze crack and pothole propagation. In road surface images, a crack appears as a structure consisting of straight lines, curves, or composite patterns that algorithms can detect. Automatic crack detection involves a critical pre-processing step that plays an essential role in eliminating extraneous elements and reducing processing time and cost (Zakeri, Moghadas Nejad, & Fahimifar, 2017). Miao et al. (2021) developed a semi-automated approach that used a CNN model to detect cracks in drone-captured images (Miao & Srimahachota, 2021). Imaging, vibration, and sensing applications can collect data on potholes. Image processing algorithms can easily detect potholes because of their circular structure (Becker, Siqueira, Matsubara, Gonçalves, & Marcato, 2019). Several studies examined how agencies can detect potholes in a cost-effective way and repair them immediately. Becker et al. (2019) applied a set of parameters for CNNs to detect potholes from drone-collected images, while Saad et al. (2019) used photogrammetric software that utilized structure-from-motion to process data of ruts and potholes. Their study evaluated accuracy based on the comparison of actual and measured data, which found that images captured from low altitudes can provide better results than from high altitudes (Saad & Tahar, 2019).

4.2.6 Road Network Mapping

The use of drones to map linear features like roads has brought about a technological revolution in surveying, and deep learning has enabled the automation of road segmentation. However, most of the current models are computationally intensive, making them unsuitable for remote sensing tasks with limited computing resources. To address this challenge, Sultonov et al. (2022) proposed two lightweight approaches based on depth-wise separable convolutions and ConvMixer inception blocks (Sultonov, Park, Yun, Lim, & Kang, 2022). In both models, depth-wise separable convolutions and multi-scale processing from the inception module are combined and incorporated into the encoder-decoder architecture of the U-Net to achieve high computational efficiency (Sultonov, Park, Yun, Lim, & Kang, 2022). Ruzgienė et al. (2015) utilized a Trimble UX5 to develop a robust and highly user-friendly mapping system with geodetic control measurements for road point positioning accuracy (Ruzgienė, et al., 2015). Hatta Antah et al. (2021) compared road design and networking using different methods such as total station (TS), airborne LiDAR, and drones, and found that drone monitoring is the most accurate and low-cost method (Hatta Antah, Khoiry, Abdul Maulud, & Abdullah, 2021).

4.3 Benefits of D-RCM

4.3.1 Reduce Costs

State departments of transportation are recognizing the advantages of using drones in their work, because drones can significantly reduce risk, manpower requirements, equipment needs, and field time while improving the quality of deliverables. DOT reports estimate that drones can save between 60% to 70% on labor and hardware expenses for most projects (Grazioso, 2022).

A few studies highlighted the cost and time savings associated with D-RCM. According to Wells et al. (2017), using drones resulted in a 66% cost reduction compared with traditional methods. In that study, the drone-based method required only $20,000 and five days on site, whereas the traditional method cost approximately $59,000 and took eight days on site (Wells, Lovelace, & Kalar, 2017). Rashidi and Samali (2020) reported that drone-based inspections were 46% faster and 61% more cost-effective compared with traditional methods (Rashidi & Samali, 2020). Drones can also significantly reduce the time and costs associated with under bridge inspection. A single under bridge inspection vehicle (UBIV) can cost between $500,000 and $1 million, with a per-day operating cost ranging from $2,000 to $3,500, as well as additional costs associated with lane or shoulder closures. In contrast, drone-assisted inspections have been found to save an average of 40% over traditional methods and provide superior data and reporting, including 3D modeling, which can inform decisions about bridge maintenance, repair, and rehabilitation (Wells & Lovelace, 2018). Dorafshan et al. (2019) found that drone-assisted inspections were also significantly more cost-effective than UBIV inspections, with the cost of inspecting the entire bridge being $3,600 (Dorafshan, Thomas, Coopmans, & Maguire, 2019). For inspections conducted by consultants with rented equipment, drone rental costs may lead to additional cost savings over UBIV rental costs. Typical daily rates for drone inspections were around $2,000, while UBIV rental costs ranged from $2,500 to $3,250 (Bridge, Ifju, Whitley, & Tomiczek, 2018). Additionally, the Oregon Department of Transportation (ODOT) estimated that using drones for bridge inspections would cost $45 per inspection, with approximately eight hours of labor required per inspection, with crews often completing two or three inspections per day (Gillins, Parrish, Gillins, & Simpson, 2018). While there is an increase in office time required for flight planning, data processing, and analysis, this technology still offers significant benefits in terms of cost and time savings.

To survey stockpiles, the West Virginia Department of Transportation (WVDOT) reported cost savings of more than $343,000 by using drones in just one month. Manual surveying involved 42 employees working for 15 days, whereas drone surveying involved only seven pilots working for nine days (Aviationtoday, 2022). In road mapping, drone-based surveys are as accurate as conventional surveying but require significantly less time to complete. The superior quality of this technology, as the camera is closer to the subject and less affected by atmospheric haze and vibration, makes it an attractive option. Drone-based surveying may reduce the need for on-the-ground surveying and outsourced aerial imaging (Kemmesat & Stephenson, 2023). To summarize the findings from DOT reports and studies, Table 7 presents detailed cost and time data from traditional and drone-based methods for various applications of RCM.

Cost Saving Percentages: Figure 6 shows the cost savings percentage for each application. It is evident that the percentage of cost savings varies across different applications, with the highest being 90% for stockpile surveys conducted by WVDOT.

Benefit Cost Ratio: The Benefit-Cost Ratio (BCR) is a crucial metric to assess the effectiveness of D-RCM applications. The benefit-cost analysis in this study evaluated the initial costs for road inspections without the use of drones by using cost data obtained from DOTs and previous studies. The potential reductions or increases in cost categories included personnel time, equipment rental and usage, traffic control, travel, drone procurement, and maintenance. Most of the applications have a benefit-cost ratio greater than 1, indicating that using drones is more cost-effective than traditional methods. The stockpiles survey shows a remarkably high benefit-cost ratio of 9.8. However, the intersection inspection by the Texas Department of Transportation (TxDOT) and bridge inspection by Dorafshan et al. (2018) have negative BCRs. The reason for the negative BCR in the application reported by Dorafshan et al. (2018) was due to the extrapolated drone inspection time being longer than the actual UBIV-assisted manual inspection time. This additional time resulted in drone-assisted inspections being 130% more expensive than traditional inspections. Overall, this analysis demonstrated that drones are a promising and cost-effective alternative to traditional methods in various RCM applications, however, achieving consistent cost savings will require time and standardization of approaches.

Return on Investment (ROI): ROI measures investment efficiency and profitability. The ROI formula can quantify the cost reduction of drone-based monitoring relative to traditional monitoring methods. This involves several steps. First, it is important to determine the costs of using drones, including equipment, payload, software, services, pilot, insurance, and other costs (Askarzadeh, Bridgelall, & Tolliver, 2023). Second, quantify the benefits, such as reductions in expenses for labor, travel, equipment, and road closure, and the cost for using traditional methods. Once these factors have been determined, it is possible to calculate the net present value (NPV) of the system by forecasting future discounted cash flows. This study calculated the ROI for a single inspection period because of insufficient data available for several years. The ROI can then be calculated as follows:

NPV = Total benefits – Total costs

ROI = [(Gain from Investment – Cost of Investment) / Cost of Investment] x 100%

The ROI analysis in Table 7 revealed that most of the D-RCM applications show a positive ROI. The highest ROI was for the stockpiles survey application (980%) followed by the crash scenes data application (258%). The bridge inspection procedures by the Michigan Department of Transportation (MDOT), Minnesota Department of Transportation (MnDOT), and Montgomery County Department of Transportation (McDOT) show relatively high ROIs of 283%, 195%, and 105%, respectively. On the other hand, the under-bridge inspection and intersection inspection applications show negative ROIs of -13% and -60%, respectively, based on the previous explanation about the extended inspection time using drones.

4.3.2 Save Time

Studies found that drones are highly efficient with just a 15-minute flight producing more data than a half-day walk by a construction worker (Yıldız, Kıvrak, & Arslan, 2021). The time saving percentage is a critical factor for the benefit cost analysis and ROI evaluations illustrated in Figure 7. Table 7 summarizes the considerable time savings, ranging from 37% to 94%, across various D-RCM applications. For instance, drone-based bridge inspections conducted by MnDOT saved 75% of the time required for the traditional method, which translated into a 283% ROI and a BCR of 1.47. Similarly, the time saving percentage for the WVDOT stockpiles survey was 75%, which led to a 980% ROI and a BCR of 9.8. These results demonstrate the importance of D-RCM applications and the ability to provide efficient and accurate inspections while reducing the time and the number of crew required.

4.3.3 Improve Safety

Road and bridge inspections using traditional methods pose significant safety risks to inspectors because they often work in areas with limited accessibility and require specialized equipment that may cause traffic disruptions (Aliyari, Ashrafi, & Ayele, 2021). During a road or bridge inspection, inspectors, equipment operators, drivers, construction workers, and others are subject to numerous hazards and risks. The US Occupational Safety and Health Administration identified several common hazards associated with conventional RCM. Those hazards include falls from height or through openings, structural instability, contact with downed lines, live electrical equipment, and other utilities (such as water and gas), working on, over, or near water, and inappropriate ladder and scaffolding use (Occupational Safety & Health Administration, 2019). However, one of D-RCM's main benefits is providing a mechanism to keep the inspectors and public out of high-risk situations (Dobson, Brooks, Roussi, & Colling, 2013). Agencies can conduct drone-based inspections of bridges, roads, and pavements without the need for person lifts or road closures, enhancing the safety of inspectors and the public. Furthermore, drone data are comparable to visual inspections while involving fewer personnel and less time, all resulting in reduced costs and safety risks. Currently, the Federal Aviation Administration (FAA) requires the presence of a certified pilot and a spotter for drone operations, and visual inspections that typically involve one to four people (FAA, 2019). Drones also provide a bird's eye view, allowing workers to anticipate and prevent dangerous situations before they occur, resulting in fewer accidents, liabilities, and lower insurance premiums. The use of drones can reduce the risks associated with physical demands and large equipment operations, allowing surveyors to spend less time near highways, construction sites, or under unfavorable weather conditions.

4.3.4 Improve Mobility

Drones have the potential to reduce traffic congestion through efficient inspections, making them particularly beneficial for monitoring roads and bridges during high traffic volumes. In addition, they offer a fast, safe, effective, and potentially superior approach to inspecting large-scale, remote, and difficult-to-access landforms (Dorafshan & Maguire, Bridge inspection: human performance, unmanned aerial systems and automation, 2018). It also facilitates access to certain locations, such as traffic signs mounted on portals, tunnels, and bridges, and to collect data on both horizontal and vertical signalization simultaneously (Trpkovic, Cokorilo, Jevremovic, & Marina, 2020).

4.3.5 Improve Reliability

By using drones, an accurate 3D model of in-situ conditions can be obtained to provide valuable information for repairs, replacements, or increased monitoring of structures. With comprehensive, objective data, prioritization of projects and allocation of funds become easier (Hain & Zaghi, 2020). Moreover, drones can capture every end and vertex of the road, while the conventional method uses a theodolite to measure from vertex to vertex (Basri, Azhar, Tajudin, & Kaamin, 2022). Drones are also eco-friendly since they do not emit greenhouse gases (GHG), and they can transmit high-definition video data of asset components in real time. Those characteristics make them a valuable tool for inspecting and surveying assets (NCHRP, 2022).

Finally, the use of drones provides rapid image acquisition, high resolution images due to the sensors used, and the capability of georeferencing via GPS sensors, which makes ground surveys less efficient in comparison (Gillins, Parrish, Gillins, & Simpson, 2018). Data processing is also performed internally, so there is no delay in obtaining information. Table 8 summarizes the potential benefits of D-RCM.

4.4 Challenges and Proposed Solutions

The D-RCM field encounters challenges like emerging technology implementation and regulatory compliance. Despite this, the technology's vast potential remains. The subsequent subsections outline these challenges and solutions, summarized in Table 9.

4.4.1 Technical Challenges

Technical challenges in D-RCM involve drone properties and operational capabilities. A key limitation is the visual line-of-sight (VLOS) requirement between the operator and the drone, restricting operations (Congress, Puppala, Banerjee, & Patil, 2021). To enable Beyond VLOS or BVLOS operations, commercial drones can incorporate a terrain-following feature in their flight planning and control software or apply for an FCC Part 107 waiver. However, BVLOS operations require accurate terrain data and a reliable onboard position tracking system. Limited flight time and payload capacity are additional challenges for commercial drone operations. While heavier batteries with higher capacity can increase flight time, their weight also increases the thrust required for operation, thus decreasing flight time. Finding the optimal balance between battery capacity and weight is ongoing research (Bridgelall, Askarzadeh, & Tolliver, 2023).

While bright sunshine enhances imaging quality, shadows cast by trees can significantly reduce this quality, thereby making overcast conditions more favorable for effective ground mapping (Sugianto, 2018) (Saeed, Dougherty, Nyberg, Rebreyend, & Jomaa, 2020). Despite the threat that high wind speeds pose to mechanical equipment and structures, it is worth mentioning that drones are still capable of operating effectively in such conditions, provided the wind speed does not exceed two-thirds of the drone's speed. In addition, quadcopters, particularly those with a higher thrust-to-weight ratio, demonstrate an enhanced ability to navigate through intense wind conditions (Posea, 2023) (Saeed, Dougherty, Nyberg, Rebreyend, & Jomaa, 2020). While live streaming offers the advantage of real-time defect detection, researchers must also consider the potential need for post-processing due to challenges such as distance, interference, and adverse weather conditions (Dorafshan, Thomas, Coopmans, & Maguire, 2019). It is also crucial to strike a balance between flight speed and image clarity; slow flight may increase project costs, whereas fast flight risks producing blurred images. This underscores the importance of selecting an optimal image resolution at the planning stage to ensure accurate crack size estimation and minimize data redundancy. Additionally, careful consideration of flight timing can prevent the issue of large shadows obscuring important areas (Dadrasjavan, Zarrinpanjeh, & Ameri, 2019). Finally, the vast amount of data generated through monitoring necessitates the use of high-speed processing, rectification, referencing, and ground sampling. To effectively analyze and interpret these data, the application of sophisticated deep learning techniques is indispensable (Boucetta, Fazziki, & Adnani, 2021). Leveraging cloud-based processing and GIS tools for data analytics can significantly aid in addressing these challenges.

4.4.2 Safety Challenges

Safety challenges in D-RCM include risks to humans and equipment due to engineering errors, causing drones to behave unpredictably (Jeelani & Gheisari, 2021). Communication failures in machine vision systems caused by environmental conditions or obstacles such as bridges can also result in collisions with obstacles, assets, or vehicles (Azari, O'Shea, & Campbell, 2022). Human errors during navigation, planning, and preparation of drones can result in unintentional physical contact, causing drones to move unintentionally or fall (Jeelani & Gheisari, 2021). Although newer drones have obstacle avoidance systems, pilot caution is essential, especially near structures (Dorafshan & Maguire, 2018). Technical failures could result in drones or parts falling, posing risks to inspectors. However, maintaining VLOS and using experienced and trained workers can mitigate such risks. The moving rotors of drones in road construction sites can cause dust emissions and noise that may distract workers and affect their health and safety (Jeelani & Gheisari, 2021). Training workers is a critical step to educate them about drones and familiarize them with using drones. Drone training in virtual reality has multiple benefits and can help reduce negative perceptions among workers. Ensuring that worksite conditions are conducive for drone operations and considering factors such as drone size and shape, flight path, and weather conditions is crucial (CPWR, 2022). Cybersecurity is also a concern, with the potential for nefarious hacking of drones. Several types of cyberattacks, such as GPS spoofing, have led to the loss of drone control to malicious attackers (Kerns, Shepard, Bhatti, & Humphreys, 2014). However, AI solutions and ML-based cyber-attack detection can help shield drones from cybersecurity attacks (Tsao, Girdler, & Vassilakis, 2022).

4.4.3 Regulatory Challenges

The FAA and the European Aviation Safety Agency (EASA) have set regulations for drone operations, including significant restrictions. A key rule is the visual line-of-sight (VLOS) requirement, confining operations to within three statute miles visibility, under 100 mph speed, below 400 feet altitude, and at least 500 feet below or 2,000 feet from clouds. However, regulatory bodies are working to enable BVLOS and autonomous drone operations that can safely integrate into the national airspace. Additional restrictions include daytime operation, altitude, professional training and certification, registration of drones, and prior permissions for use of the airspace (FAA, 2016). The FAA's waiver process offers some leniency in these regulations, evolving to encompass flights over people, moving vehicles, and nighttime operations (FAA, 2019). For inspections involving traffic such as bridge decks, pavement, retaining walls, or even high mast luminaries, traffic adjustments are necessary(Dorafshan & Maguire, 2018).

4.4.4 Organizational Challenges

Organizational challenges impact the deployment of drone technology in road and bridge monitoring. These include the need for skilled pilots for GPS-limited environments and the associated costs, which can vary significantly(Whitley, et al., 2020). The cost of drone pilots may range from $1,200/day to $650/day, plus travel expenses (Dorafshan & Maguire, 2018). Additionally, organizations must employ personnel to manage and analyze the data collected by drones and develop effective protocols for data management and integration into existing systems. Infrastructure that supports drone operations is also necessary; this involves developing policies and procedures for safety and airspace management, as well as protocols for managing drone batteries to ensure availability when needed. Overcoming these challenges requires strategic planning, resource allocation for drone procurement and maintenance, and investment in data processing tools.

5 Research Gaps and Limitations

The reviewed publications discussed the challenges, opportunities, and successful outcomes of D-RCM applications, but none of them provided a quantified analysis of benefits. This study filled that gap by providing the first comprehensive analysis of the benefits of D-RCM, including the quantification of time and cost savings and the classification of other benefits.

5.1 Implications for New Theories

Drone-based inspection and monitoring systems have the potential to improve operational efficiencies, but their widespread adoption may face several obstacles such as prohibitive costs, regulatory challenges, and a shortage of skilled workers. However, organizations are exploring ways to overcome these challenges as drone technology rapidly evolves, realizing the benefits of drone-based applications. Conducting a benefit-cost analysis and evaluating the potential ROI are crucial to forecasting the continued use of drones in road infrastructure maintenance. This SLR suggests that leveraging drone technology can lead to new models of business resilience, agility, and sustainability, enabling businesses to improve their operations, respond quickly to changing market conditions and customer needs, and reduce their environmental impact. This SLR projects that as drone technology continues to evolve, businesses will increasingly adopt the technology to enhance their capabilities and gain a competitive edge.

5.2 Implications for Management

The utilization of drones in RCM can have various management implications for organizations, ranging from data management to workforce organization, regulatory compliance, cost management, and strategic planning. Agencies need to carefully consider these implications to ensure the effective implementation and utilization of D-RCM applications. To manage the significant amount of data gathered by drones, agencies require cloud computing and analysis systems, which may entail additional investments. It is also essential to provide adequate training programs to ensure that employees have the necessary skills to operate and analyze drone data. Agencies need to manage workflow changes resulting from deploying a drone-based inspection system effectively. Furthermore, drone technology can have strategic implications for organizations in terms of long-term maintenance plans, which necessitates considering how it can help them achieve their goals effectively. Finally, the adoption of drone technology presents new issues and challenges, including updating facilities and enacting new policies to ensure regulatory compliance.

5.3 Implications for Impacts to Society

The potential to improve efficiency, data collection quality, and accuracy of RCM may improve safety by reducing the number of accidents caused by inaccuracies. The reduction in inspection time results in a decrease in worker accidents during inspections. Drones can reduce the carbon footprint associated with RCM relative to traditional methods. However, raising concerns about privacy violations could lead to negative consequences.

5.4 Limitations

The present study encountered a limited number of relevant papers, indicating the emerging nature of this technology. As a result, there exists a scarcity of research available on the cost-saving benefits of this technology. Consequently, it is possible that the classification of applications, benefits, challenges, time, and cost saving analysis may have overlooked some elements. Additionally, the time data reported in the literature varied in units, including days and hours, which may complicate direct comparison. Furthermore, over time and depending on the scale of the project, cost elements such as equipment costs, road closure costs, and employee expenses may fluctuate. The data limitations pertaining to the cost and time data for several inspection and monitoring periods may lead to reduced accuracy of the ROI analysis results. There was insufficient data about cost details, such as equipment rental or purchase costs, road closure costs, pilot and crew expenses, and other factors which may affect the accuracy of the cost-benefit analysis.

5.5 Knowledge Gaps and Future Research

Despite the potential benefits of drone-based road condition monitoring, there is a lack of comprehensive benefit cost analysis and case studies that demonstrate their effectiveness and ROI across varying contexts. While some studies have addressed the technical and operational challenges of drone-based monitoring, they paid less attention to the organizational and regulatory implications of adopting this technology. Future work will conduct a scenario analysis of the ROI based on projections of the technology adoption timeline and provide practical guidance to road infrastructure managers and decision-makers on the optimal use of drones for RCM, including the development of strategies for data management, workforce training, regulatory compliance, and risk mitigation.

6 Conclusion

This paper presents a systematic review of drone-based methods for roadway infrastructure monitoring, utilizing the SLR method to analyze 60 articles from a pool of 619 published between 2014 and 2022. It highlights D-RCM's benefits, such as cost and time efficiency, safety, mobility, and reliability. Using Citespace, the study conducted journal co-citation, keyword co-occurrence, and country co-authorship analyses, identifying "Automation in Construction" and "Sensors" as significant journals. Four research themes emerged from co-occurring keyword analysis: UAV, pavement management, image processing, and aerial photography. Artificial intelligence and aircraft detection were identified as emerging research areas within the RCM industry. The country co-authorship analysis emphasized the influence of USA universities and researchers in drone-based RCM research, with a robust collaboration network between the US and China. This study classified D-RCM applications into several domains, such as unpaved and paved road condition monitoring, situational assessment, road network mapping, infrastructure asset monitoring, and construction inspection. A comparative analysis between traditional road inspection methods and D-RCM, including cost-benefit and return on investment evaluations, demonstrated the economic viability of D-RCM. This study's findings carry significant implications for developing new theories, informing management practices, and shaping societal impacts within the D-RCM industry. In summary, this paper offers valuable guidance for the future exploration and implementation of D-RCM.

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Table 1: Clusters by Keyword in the Study of D-RCM.

Cluster-ID	Size	Silhouette	Year	LLR Label
0	40	0.694	2019	Using multirotor unmanned aerial vehicle
1	28	0.763	2018	Streamlined bridge inspection system
2	26	0.729	2019	Dry-stone masonry
3	24	0.785	2019	Concrete surface crack
4	22	0.978	2014	Collecting decision support system data
5	18	0.9	2017	Crack detection classification
6	16	0.833	2019	Safety challenge
7	12	0.862	2019	Service life prediction

Table 2: Top 18 Keywords with the Most Robust Citation Burst from 2014 to 2022.

Keywords	Year	Strength	Begin	End	2014 – 2022
Aerial photography	2014	1.17	**2014**	2019	
Image processing	2014	1.19	**2015**	2017	
Pavement management	2014	1.49	**2017**	2018	
Federal Aviation Administration	2014	0.99	**2017**	2018	
Aircraft detection	2014	1.3	**2018**	2019	
Highway administration	2014	1.14	**2018**	2018	
Three-dimensional computer graphics	2014	1.14	**2018**	2018	
UAV	2014	1.84	**2019**	2020	
Machine learning	2014	1.28	**2020**	2020	
Computer vision	2014	1	**2020**	2020	
Cost-effectiveness	2014	1	**2020**	2022	
Pavement	2014	1.76	**2021**	2022	
Deterioration	2014	1.5	**2021**	2022	
Convolutional neural network	2014	1.23	**2021**	2022	
Photogrammetry	2014	1.06	**2021**	2022	
Deep learning	2014	1.04	**2021**	2022	
Slope stability	2014	1.04	**2021**	2022	
Monitoring	2014	1.04	**2021**	2022	

Table 3: Top 8 Cited Journals with the Strongest Citation Bursts.

Cited Journals	Year	Strength	Begin	End	2014 - 2022
Sensors	2014	**2.5**	2020	2020	
Automation in Construction (AUTOM CONSTR)	2014	**1.97**	2020	2022	
Engineering geology	2014	**1.87**	2021	2022	
Transportation Research Record (TRANSP RES REC)	2014	**1.67**	2020	2022	
IEEE transportations on intelligent transportation systems	2014	**1.43**	2020	2022	
Journal of transportation engineering (J TRANSP ENG)	2014	**1.43**	2020	2022	
Infrastructures (IN)	2014	**1.4**	2021	2022	
Journal of Management in Engineering (J MANAG ENG)	2014	**1.4**	2021	2022	

Table 4: Top 11 Dominant Countries of D-RCM Articles.

Sr. No.	Country	Freq	Centrality	Year
1	United States	22	0.04	2014
2	China	8	0	2018
3	Italy	8	0	2019
4	United Kingdom	4	0.04	2016
5	South Korea	3	0	2020
6	Iran	2	0.03	2017
7	United Arab Emirates	2	0	2020
8	Turkey	2	0	2018
9	Malaysia	2	0	2019
10	Japan	2	0	2020
11	India	2	0	2019

Table 5: Safety Benefit Areas of D-RCM.

Benefit Area	Categories	Study	Year	Drone	Sensor type	Algorithm/Software
Risk Assessment	Evaluating risks natural hazards	Kashyap et al.	2019	Fixed wing and multi rotor	-	MATLAB
		Congress et al.	2019	-	-	UAV-CRP
	Evaluating risks on harsh roads	Wang et al.	2021	Fixed-wing drone	-	Agent operator mode simulation
Landslide Monitoring	Landslide hazards monitoring	Sugianto	2018	-	4K camera	-
	Slope stability monitoring	Migliazza et al.	2021	-	NIKON D800E, CMOS Full-Frame sensor	AMS software
Construction Inspection	Monitoring road construction sites	Lee et al.	2020	DJI Phantom 4 RTK	-	Pix4DMapper
		Jeelani et al.	2021	DJI Phantom 4 Pro	V2.0 High-resolution camera and thermal sensors	-
		Lo et al.	2022	DJI Phantom 4 RTK	RTK GNSS	AutoCAD
		Subramanya et al.	2022	-	-	-
	Monitoring the construction of forest roads	Bugday	2018	DJI Phantom 4	-	Pix4D Capture
Environmental Monitoring	Monitoring green belts	Duan et al.	2019	-	ZENMUSE X5 camera	-
Intersections Monitoring	Intersections monitoring	Congress et al.	2021	DJI Matrice 200	-	DJIGO 4 app

Table 6: Maintenance Benefit Areas of D-RCM (Part I).

Benefit Area	Categories	Study	Year	Drone	Sensor type	Algorithm/Software
Parking Monitoring	Parking lot monitoring	Kim et al.	2020	DJI Mavic PRO	Camera	RMSE/refAT
Retaining Walls Monitoring	**8.1 Pile retaining walls monitoring**	Ekinci et al.	2021	DJI PHANTOM 3 Pro	12-megapixel camera	I-Site Studio, 3D Reshaper/ LAZ
Bridge Inspection	Bridge condition assessment	Feroz et al.	2021	-	-	-
		Rashidi et al.	2020	DJI Matrice 600 Pro	-	Pix4Dmapper
		Hubbard et al.	2020	DJI Mavic 2	Camera	-
		Perry	2020	DJI Mavic 2	-	-
		Chun et al.	2020		LiDAR SLAM	R-CNN
		Chen et al.	2019	DJI phantom 4	Camera	NNS algorithm/SfM
		Khaloo et al.	2018	DJI S800	Sony NEX-7	SGM/ FANN
		Dorafshan et al.	2018	-	-	-
		Dorafshan et al.	2019	DJI Mavic	Gimbaled	-
		Azari et al.	2022	-	-	-
		Zhong et al.	2020	-	-	-
		Whitley et al.	2020	COTS airframe	24 megapixel A6000 digital SLR camera	-
		Song et al.	2022	-	-	PHP/MySQL/iBIRD
		Mandirola et al.	2022	-	-	3D point clouds/GNSS
		Gaspari et al.	2022	DJI Matrice 300	LiDAR DJI Zenmuse	GNSS signal obstruction
		Abdallah et al.	2022	-	-	-
		Li et al.	2022	-		
	Bridge inspection in harsh operating environment	Aliyari et al.	2021	DJI Matrice 100/ DJI Phantom 4 Pro V2.0	Zenmuse Z3 camera/DJI remote controllers	-
	Concrete bridge crack detection	Lei et al.	2020	low-cost quadrotor		SVM/ Raspberry Pi 3 Model B
	Bridge crack inspection	Humpe	2020	DJI Phantom 4 Pro	Ricoh/Theta V 360	-
		Ayele et al.	2020	-	-	-

Table 6: Maintenance Benefit Areas of D-RCM (Part II).

Benefit Area	Categories	Study	Year	Drone	Sensor type	Algorithm/Software
Unpaved Road Condition Monitoring	Unpaved roads monitoring and prioritizing	Dobson et al.	2014	Fixed wing	Nikon D800	SfM/Blender/Patch-Based Multi-View Stereo
		Mansourmoghaddam et al.	2022	-	-	KNN
	Stone and gravel pavement condition monitoring	Garilli et al.	2021	DJI Phantom 4 pro	Camera	CNN
		Saeed et al.	2020	-	-	-
Pavement Condition Monitoring	Pavement distress monitoring	Barrile et al.	2020	DJI Mavic 2 Pro	-	Canny algorithm
		Pieterse et al.	2022	-	-	CNN
		Roberts et al.	2020	DJI Mavic 2 Pro	-	-
		Tan et al.	2019	-	-	Pix4Dmapper
		Ragnoli et al.	2018	-	-	-
		Radopoulou et al.	2016	-	-	-
		Peraka et al.	2020	-	-	-
		Chen et al.	2021	-	-	-
		Coenen et al.	2017	-	-	-
		Inzerillo et al.	2018	Quadcopter	Nikon D5200 camera/ GoPro	Agisoft PhotoScan, Pix4D Pix4Dmapper Pro
		Shaghlil et al.	2018	DJI Mavic Pro	12-megapixel	-
	Surface defect detection	Saad et al.	2019	DJI Phantom 3	Phantom camera	DEM
		Becker et al.	2019	DJI Phantom 4	-	LabelImg/Faster-RCNN
		Miao et al.	2021	-	-	CNN
		Zakeri et al.	2017	-	-	-
Network Mapping	Network mapping	Sultonov et al.	2022	-	-	U-Net
		Ruzgienė	2015	Fixed wing UX5 Trimble	Sony NEX-5R	DTM generation algorithms
		Hatta Antah et al.	2021	-	-	-
Design and Infrastructure Management	Design and infrastructure management	Outay et al.	2020	-	-	-
		McGuire et al.	2017	-	-	-

Table 7: Costs of Traditional and Drone-based Methods of RCM (Part I).

Application	Agency or Reference	Traditional Method				Drone-Based Method			NPV	Cost Saving	Time Saving	ROI	BCR
		Road Closure	Equipment Cost	Total Cost	Time and Crew	Equipment Cost	Total Cost	Time and Crew					
Bridge Inspection	MDOT (AASHTO, 2019)	-	-	$4,600	2 Crews 8 hours	-	$1,200	2 crews 1 hour	$3,400	74%	75%	283%	1.47
	MnDOT (Wells, Lovelace, & Kalar, 2017)	-	-	$59,000	8 days	-	$20,000	5 days	$39,000	66%	37.5%	195%	1.59
	McDOT (Grazioso, 2022)	-	-	$40,800	-	-	$19,900	-	$20,900	40%	-	105%	1.95
	ODOT (Gillins, Parrish, Gillins, & Simpson, 2018)	$3,500	$2,800	$73,800	-	-	$63,600	-	$10,200	13%	-	16%	-0.3
	FDOT (Bridge, Ifju, Whitley, & Tomiczek, 2018)	-	$2,500	$ 4,810	-	$2,000	$ 4,410	-	400	83%	-	9%	2.21
Under Bridge Inspection	(Dorafshan & Maguire, Bridge inspection: human performance, unmanned aerial systems and automation, 2018)	-	-	$1,564	2 crews 1 day	-	$1,800	2 crews 1 day	$-236	-13%	0%	-13%	-9
	MnDOT (Wells & Lovelace, 2018)	$2,500 /day	-	$6,080	2 crews 4 hours		$4,340	2 crews 4.5 hours	1740	40%	-12.5%	40%	1.87
Intersection Inspection	TxDOT (Puppala & Congress, 2021)	-	-	$8,000-$10.000	-	-	$5.000-$7.500	-	3000	37%	-	60%	-3.33
Stockpiles Survey	WVDOT (Aviationtoday, 2022)	-	-	$378,000	2-3 crews Collection: 3 days Processing: 2days	-	$35,000	2 crews Collection: 2-3 hours Processing: 10-12hours	$343,000	90%	75%	980%	9.8
Crash Scene Data	NCDOT (Dorsey, 2018)	$8,600 /hr	-	$12,900	42 crews 15 days	-	$3,600	7 crews 9 days	$9,300	73%	90%	258%	0.91
Road Monitoring	Frontier Precision (Kemmesat & Stephenson, 2023)			50,000	2 hours		21,000	½ hour	$29,000	58%	75%	138%	1.14

Table 7: Costs of Traditional and Drone-based Methods of RCM (Part II).

Application	**Agency or Reference**	**Traditional Method**				**Drone-Based Method**			**NPV**	**Cost Saving**	**Time Saving**	**ROI**	**BCR**
		Road Closure	Equipment Cost	Total Cost	Time and Crew	Equipment Cost	Total Cost	Time and Crew					
Survey	(AASHTO, 2016)	2 Lanes= $3,000		$4,600	Collection: 10 days Processing: 4 days	$50/hr	$250	Collection: 2 days Processing: 2days	$4,350	94%	71.5%	1740 %	1.45

Table 8: Potential Benefits of D-RCM.

Potentials	Areas	Description
Reduce Cost and Time	• Reduce data collection time • Return the current cost of inspecting roads using old methods • Improve safety • Reduce number of crew members	– Eliminate the use of expensive vehicles and hardware – Reduce the number of crew members – Eliminate the road or shoulder closure necessity – Reduce the personnel time required onsite and to optimize data collection from 5 to 2 – Eliminate the cost of driver and inspector – Increase the efficiency – Reduce the number of safeguards – Increase scalability and inspection coverage – Eliminate hazards and risks to improve productivity by 94% – Reduce data collection time by 70% – Obtain more detailed overview necessary to obtain more data of the entire asset
Improve Safety	• Reduce accidents • Produce more reliable information	– Eliminate inspectors' exposure to hazards and risks – Reduce the time of inspection for high traffic roads – Conduct more frequent inspection of hard-to-reach areas like forest roads, under bridges, and pathways – Provide more accurate details by 71% and reduce the risk of collapsing bridges or signs – Reduce the number of accidents related to lane closure – Eliminate the subjectivity involved in human inspections – Reduce the risks associated with physical demands and large equipment operations – Reduce the time spent by surveyors near highways, construction sites, or under unfavorable weather conditions.
Other Benefits	• Reduce Traffic congestion • Improve reliability	– Provide real time, 360-degree, birds-eye and 3D views – Eliminate traffic congestion – Provide the possibility of the simultaneous collection of data on both horizontal and vertical signalization. – Provide high-resolution views

Table 9: Challenges and Solutions of D-RCM

Challenges	Description	Solutions
Technical challenges	– Maintaining a visual line of sight – Limited payload capacity and flight endurance – Lighting conditions – Limited weather resistance – Real-time problems due to severe weather conditions, and distance from the receiver – Drone speed can affect the image resolution – Huge amount of collected data, and sophisticated analyzing methods	– Add a terrain-following feature to flight planning and flight control software or apply for a Part 107 waiver to enable BVLOS operations – Balance the battery capacity and weight to find the best spot – Choose bright sunshine for mapping and overcast day for tree-covered areas – Adjust the drone speed more than the wind speed. Or use a quadcopter with a high thrust-to-weight ratio – Use post-processing – Choose the ideal speed – Process and analyze the data in the cloud and perform data analytics using GIS
Safety challenges	– Hardware engineering errors like loose connections, faulty electronics – Software engineering errors like programming errors, flawed algorithms, and signal interference – Accidents or falls due to human errors. – Collision with a structure while monitoring near it to obtain the best resolution – The drone collides with a worker. – Drone noise distracts workers, which can have secondary safety implications – The fast-moving rotors of drones can cause dust emissions, which can affect the health and safety of workers – Cyberattacks	– An engineer's existence can be helpful in this situation – A trained crew can reduce the human errors – Use autopilot to avoid obstacles – Maintain a visual line of sight and avoid inexperienced drone operators – Train workers – Prepare worksites to ensure drones work efficiently and safely around workers – Using AI solutions and cyber-attack detection through ML
Regulatory challenges	– Limited speed (under 100 mph) – Limited altitude (below 400 ft) – Inadequate regulatory support and industry standards – Absence of regulations applicable to small drones – Prior permission of flying drone – Restriction of fly drones over people	– Regulatory bodies worldwide are working to enable BVLOS and provide more flexible regulations. – Apply a waiver to relax a few strict requirements – Modification of traffic if exposed to traffic – Provide permission before flying drone
Organizational challenges	– Drone registration – Inadequate capabilities, skills, and experience with drones – Insurance obligations for pilot and drone – Certification and training of pilots	– Provide for drone registration and insurance – Use a certified pilot – Provide pilot insurance

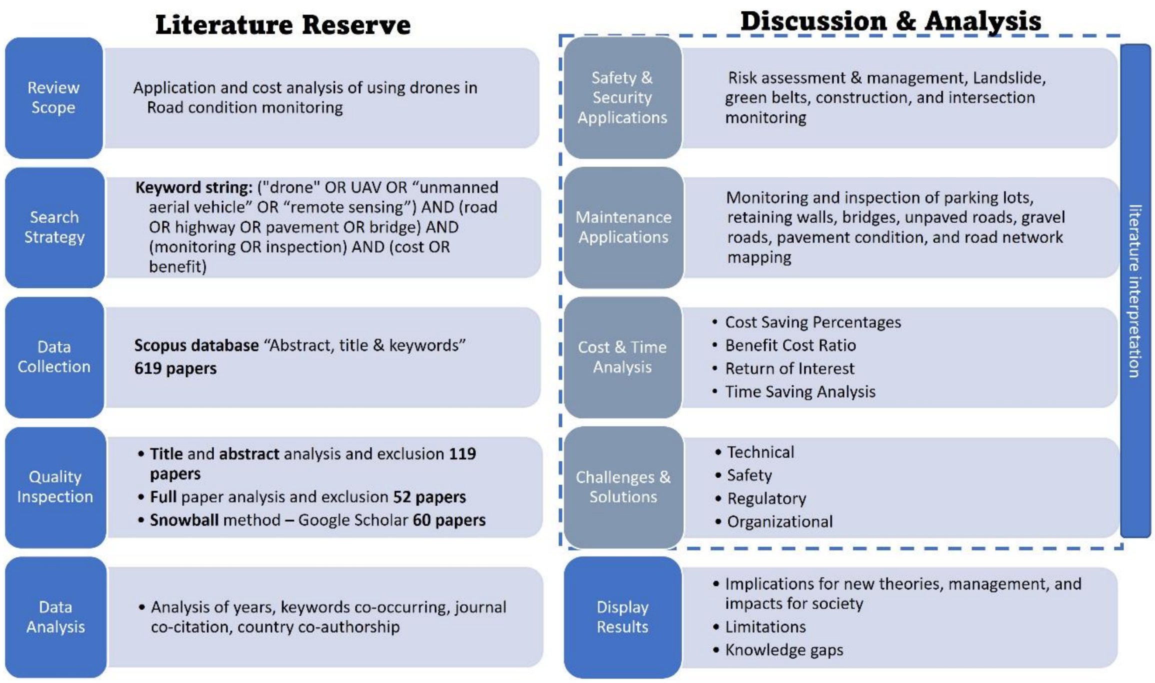

Figure 1: Flow diagram of the methodology applied in this review.

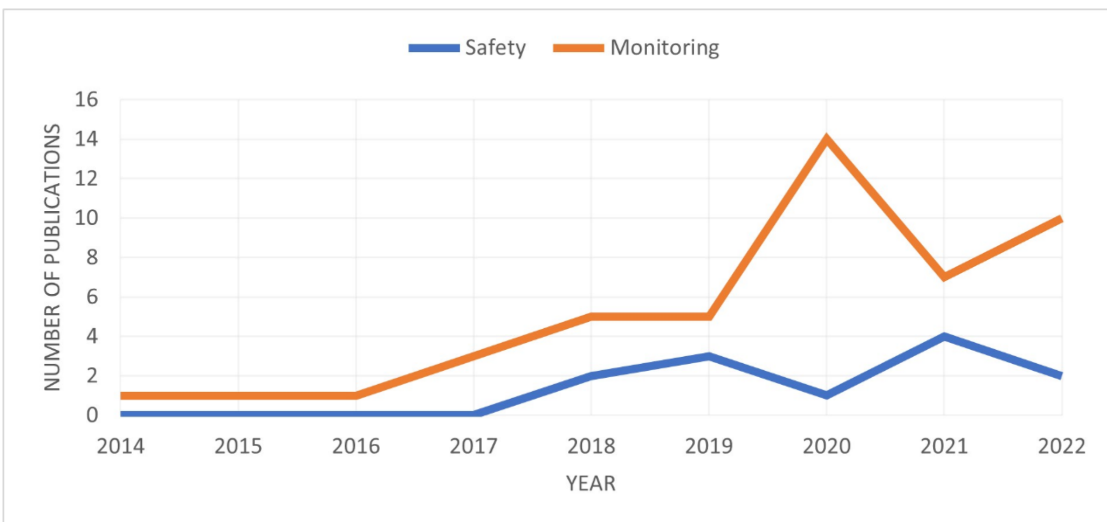

Figure 2: The distribution of retrieved publications based on the applications by year.

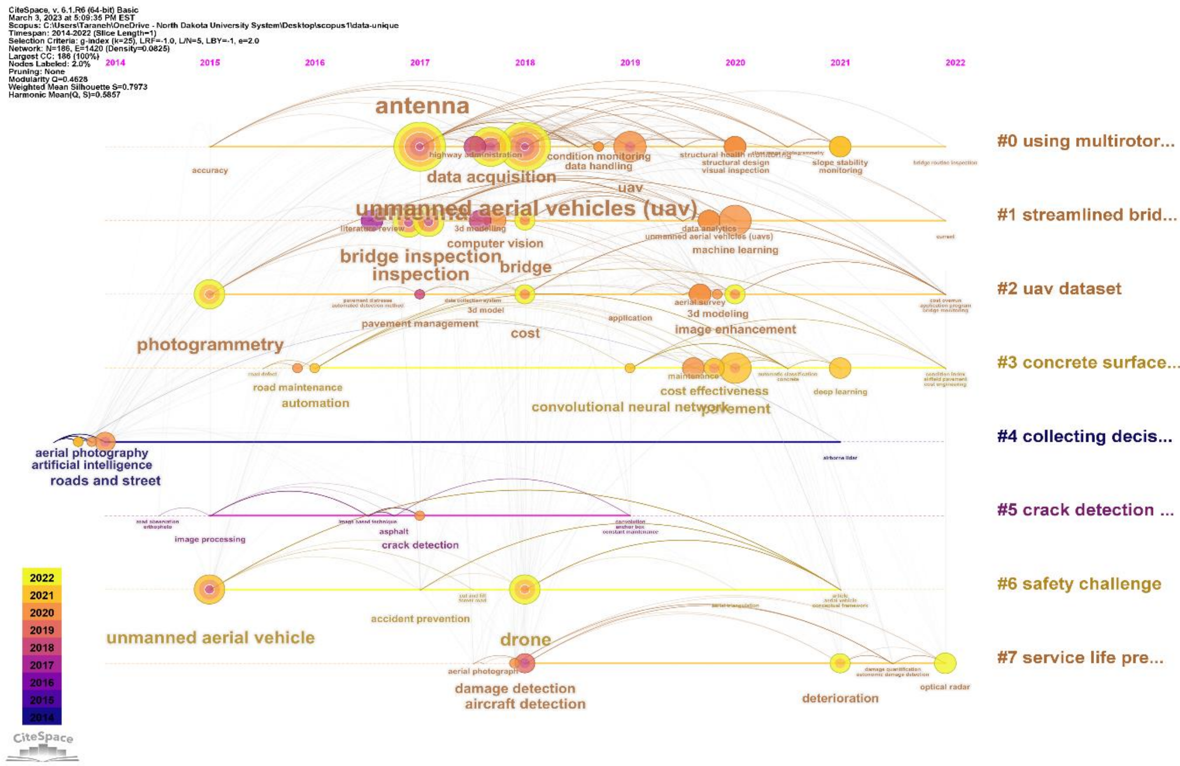

Figure 3: Keyword co-occurrence network of D-RCM.

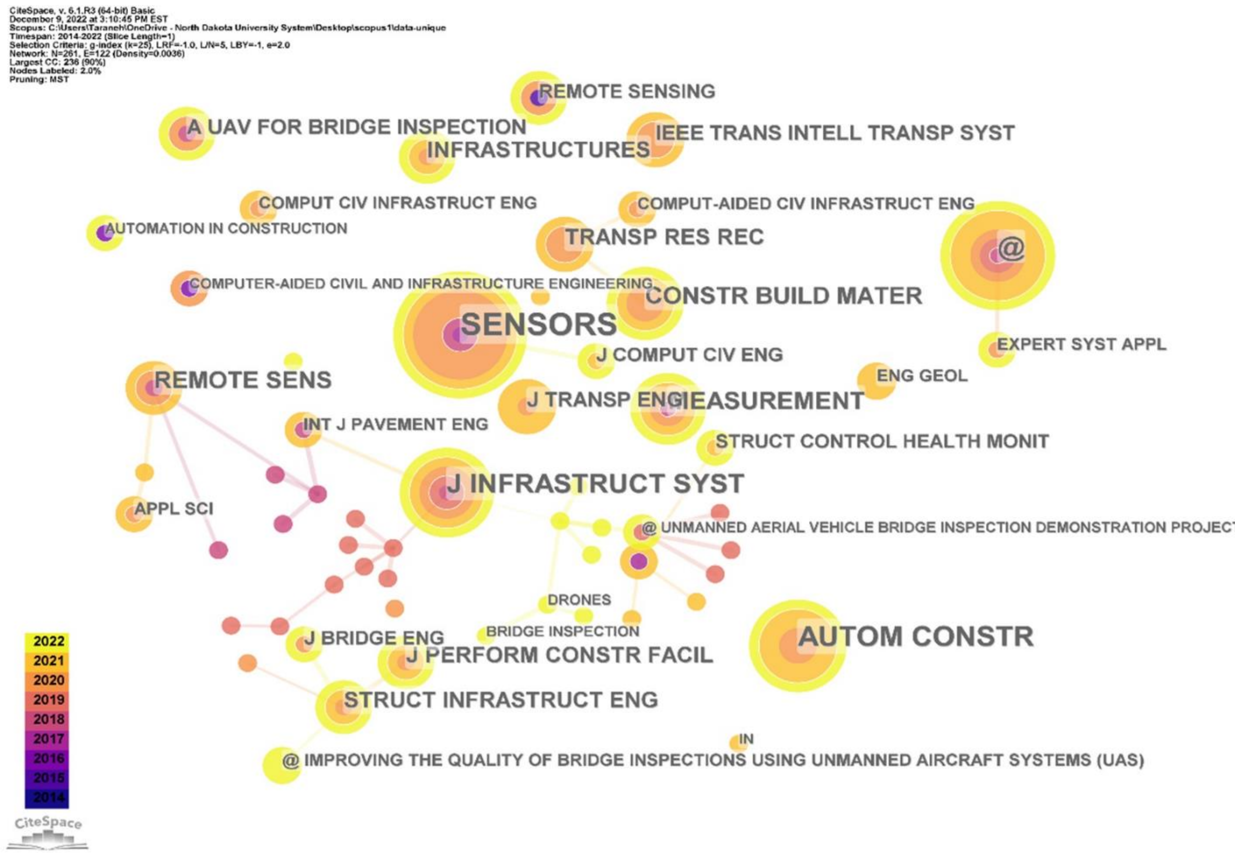

Figure 4: Map of cited journals co-citation network in D-RCM.

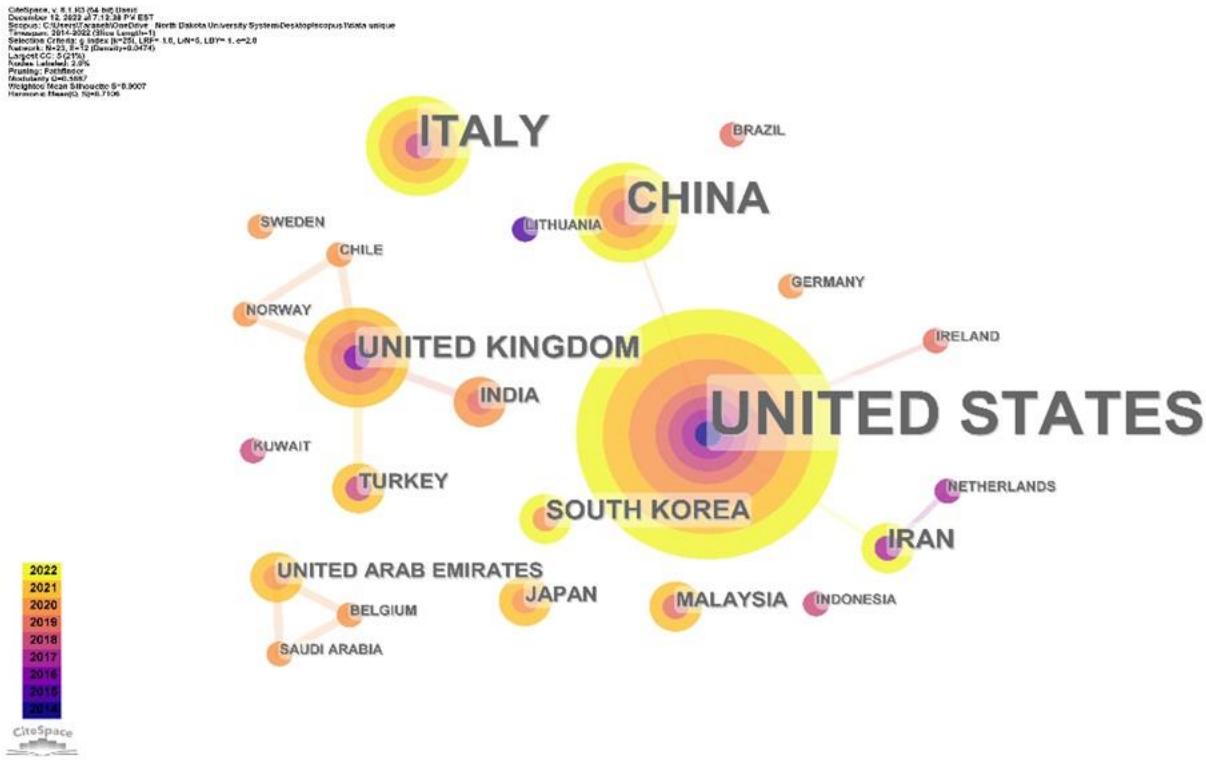

Figure 5: Visualization network map of the country co-authorship analysis.

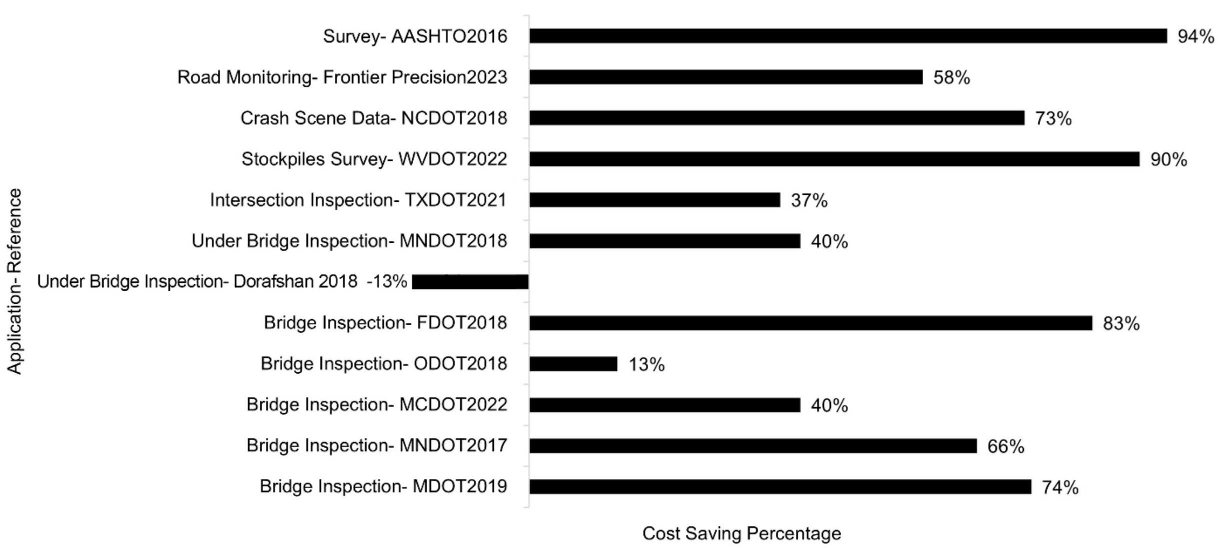

Figure 6: Cost saving percentages of D-RCM.

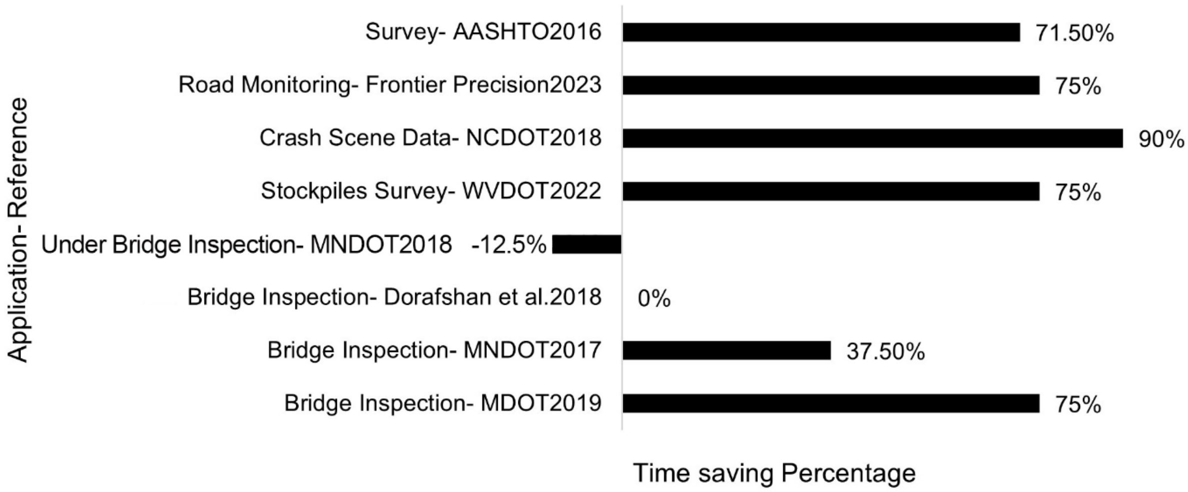

Figure 7: Time saving percentages of D-RCM.