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Use of Remote Sensing in Quality Assessment and Distress Identification in Flexible Pavements: A Systematic Review

Uso do Sensoriamento Remoto na Análise de Qualidade e Identificação de Defeitos em Pavimentos Flexíveis: Uma Revisão Sistemática

Ezequiel Silva Rocha [1], Cláudia Maria de Almeida [2], Milton Kampel [3] e Paulo Roberto da Silva Ruiz [4]

1 National Institute for Space Research, São José dos Campos, Brazil. sr.ezequiel2@gmail.com.
ORCID: https://orcid.org/0009-0002-3816-3908
2 National Institute for Space Research, São José dos Campos, Brazil. claudia.almeida@inpe.br.
ORCID: https://orcid.org/0000-0002-6523-3169
3 National Institute for Space Research, São José dos Campos, Brazil. milton.kampel@inpe.br.
ORCID: https://orcid.org/0000-0002-0011-2083
4 São Paulo State Technological Colleges, Adamantina, Brazil. paulo.ruiz2@fatec.sp.gov.br.
ORCID: https://orcid.org/0000-0001-7885-5015

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Abstract: Remote sensing has emerged as a promising tool for flexible pavement evaluation, complementing traditional inspection methods. This systematic review examines techniques such as LiDAR and multispectral imaging, highlighting their effectiveness in detecting surface deformations, cracks, and other distress types. Aerial platforms (UAVs) show superior performance for localized inspections, while vehicle-mounted LiDAR systems are better suited for continuous assessment of extensive road networks. Despite progress, challenges remain including the need for higher spatial resolution to identify micro-cracks, environmental interference, and high computational demands. Emerging solutions involving multi-sensor data fusion and artificial intelligence demonstrate potential to overcome these limitations, though methodological standardization and validation against technical standards remain critical for large-scale adoption. The study concludes that remote sensing already provides tangible benefits for road infrastructure management, with potential to transform pavement monitoring and maintenance practices.
Keywords: Remote sensing. Pavement. LiDAR. Pavement Distress.

Resumo: O sensoriamento remoto tem se mostrado como ferramenta promissora para avaliação de pavimentos flexíveis, complementando métodos tradicionais de inspeção. Esta revisão sistemática analisa técnicas como LiDAR e imageamento multiespectral, destacando sua eficácia na detecção de deformações, trincas e outros defeitos superficiais. Plataformas aéreas (VANTs) apresentam bom desempenho para inspeções pontuais, enquanto sistemas veiculares com LiDAR são mais adequados para avaliação contínua de redes extensas. Apesar dos avanços, persistem desafios, como necessidade de maior resolução espacial para microfissuras, influência de condições ambientais e altos requisitos computacionais. Soluções emergentes envolvendo fusão de dados multissensores e inteligência artificial mostram potencial para superar essas limitações, embora a padronização metodológica e validação conforme normas técnicas permaneçam como aspectos a serem melhorados para adoção em larga escala. O estudo conclui que o sensoriamento remoto já oferece benefícios concretos para gestão de infraestrutura rodoviária, com perspectivas de transformar os processos de monitoramento e manutenção viária.
Palavras-chave: Sensoriamento remoto. Pavimento flexível. LiDAR. Defeitos.

1 INTRODUCTION

Highways play a significant role in fostering Brazil's economic and social growth. According to the National Transport Confederation - CNT (2022), road transport is currently the most widely used mode in the country. Given their social and economic relevance, quality monitoring methodologies for road infrastructure must evolve, ensuring high standards of safety and comfort. However, flexible pavements, which, according to CNT (2017), constitute approximately 99% of the length of the national paved road network, face a series of challenges, including cracks, deformations, and premature wear.

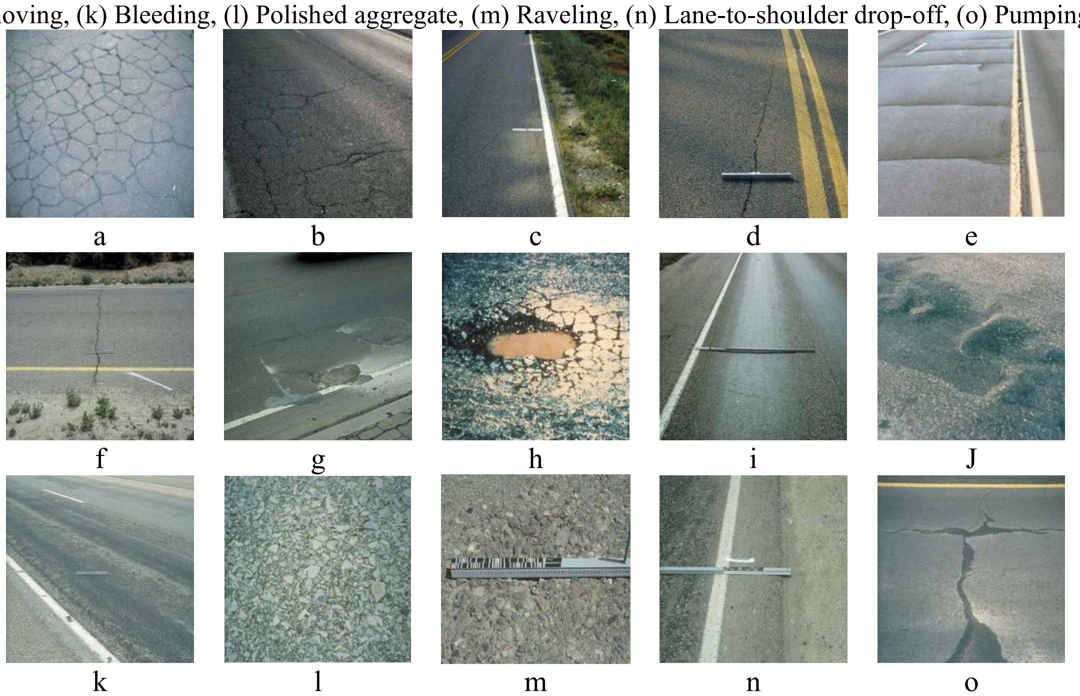
In Brazil, a design period of 10 years is used, which represents the pavement's service life (Bernucci et al., 2022). However, this period is significantly shorter than that adopted in projects in developed countries, which often consider service lives of 30 years or more (UK National Highways, 2021). Even so, due to flaws in execution and design, many pavements show distress before the end of this period, which can cause losses concerning the safety and comfort of users. Factors such as rainfall, temperature variations, and increased traffic contribute to the evolution of these distresses over time (Llopis-Castelló et al., 2020). Therefore, continuous monitoring of pavement quality is essential to avoid high costs associated with correcting premature distress, which can worsen quickly. As the deterioration of the wearing course begins soon after the highway is opened to traffic, monitoring must be initiated concurrently with this opening (Al-Arkawazi, 2017).

Traditional pavement evaluation methods require intensive labor for manual *in situ* data collection, which, besides being inefficient, increases maintenance costs (Liu et al., 2021). Remote sensing is considered a new way to collect data regarding the quality of roads, where different types of sensors, including satellite images, drones, and Light Detection and Ranging (LiDAR) systems, can be employed for this purpose. The use of these sensors facilitates data acquisition and leads to faster and more efficient evaluations (Brewer et al., 2021). A systematic review was prepared on the potential of using remote sensing techniques for monitoring the quality of highways surfaced with flexible pavements.

2 DISTRESSES IN FLEXIBLE PAVEMENTS

Distresses in flexible pavements can arise for various reasons and are, in general, very recurrent on Brazilian highways. Figure 1 presents the 15 types of distresses in flexible pavements, listed in the distress identification manual of the United States Federal Highway Administration (FHWA, 2014). In Brazil, the DNIT 005/2003-TER standard (DNIT, 2003a) lists the types of distresses in flexible pavements; however, even while citing the American standard referencing SHRP 1993 (SHRP, 1993), the Brazilian standard has not been updated since its publication in 2003, being outdated compared to the FHWA identification manual, which, besides being updated in 2014, presents the distresses and lists them in degrees ranging from low severity to high severity. They are discussed below.

Figure 1 – Main distresses in flexible pavements. (a) Alligator cracking, (b) Block cracking, (c) Edge cracking, (d) Longitudinal cracking, (e) Reflection cracking, (f) Transverse cracking, (g) Patching, (h) Pothole, (i) Rutting, (j) Shoving, (k) Bleeding, (l) Polished aggregate, (m) Raveling, (n) Lane-to-shoulder drop-off, (o) Pumping.



Source: Adapted from Federal Highway Administration (2014).

In literature, different types of cracks are presented. Figure 1a shows an example of alligator cracking, which is listed as one of the types of fatigue cracking, according to the FHWA distress identification manual (2014). This distress consists of the interconnection of small cracks that form mosaics on the pavement surface, generally associated with the fatigue of the material covering the road (Bernucci et al., 2022). Figure 1b shows block cracking. This distress is characterized by the junction of cracks that form almost rectangular blocks ranging from 0.1 to 10 m² (FHWA, 2014). This crack configuration may indicate a lack of tensile strength in the asphalt mixture and/or contraction due to temperature change (CNT, 2018). Edge cracking occurs only on roads without paved shoulders, as can be observed in Figure 1c, where they intercept the pavement edge (FHWA, 2014). Transverse and longitudinal cracks, shown in Figure 1d and Figure 1f, are very recurrent. They appear in both the longitudinal and transverse directions of the road and are generally associated with execution flaws or shrinkage of the asphalt mixture (CNT, 2018). Reflection cracks (Figure 1e) occur transversely to the road's central axis and cross the entire pavement surfacing layer (FHWA, 2014), reflecting a pre-existing crack in lower layers, such as the base or sub-base.

Figure 1g shows a patching distress, which arises from repairs of potholes (Figure 1h) and other distresses on the road, where the original material is removed only in a given portion of the road and replaced with new surfacing (FHWA, 2014). Pothole distress is a cavity that forms in the pavement for many reasons, such as lack of adhesion between pavement layers, errors in mix design, among others (CNT, 2018).

Plastic deformations are very common in flexible pavements. Figure 1i shows a distress known as rutting. This problem can be caused by the consolidation of the pavement's base layers and by vehicle wheel loads over time, occurring more frequently at the edges of the roads (CNT, 2018). In turn, Figure 1j shows a permanent deformation (shoving) generally caused by vehicle braking forces, very common in curves (FHWA, 2014).

Bleeding (Figure 1k) is a type of distress that can originate from excess asphalt binder, generally being more visible in the wheel paths. It is characterized by a shiny, almost "wet" appearance. Just as excess binder causes problems, its scarcity also leads to issues, such as polished aggregate (Figure 1l), which shows the coarse aggregate exposed by the wear of the superficial binder layer. The wear of these aggregates can lead to a decrease in surface friction, compromising safety (FHWA, 2014). Along the same lines, Figure 1m shows a case of raveling, caused by the dislodging of aggregate particles and the loss of binder (FHWA, 2014).

The difference in height between the lane and the shoulder (Figure 1n) is also considered a distress according to the FHWA distress manual, generally occurring due to the consolidation of the shoulder material because of the difference in composition between these two parts. Figure 1o shows a case of pumping, where fine aggregates from the underlying layers are pushed through cracks towards the surface. This distress is caused by the flow of water in the pavement structure and is characterized by infiltration stains with fine-grained material (sand).

3 REMOTE SENSING APPLIED TO ROAD MANAGEMENT

The identification and quantification of pavement distresses constitute the essential database for Pavement Management Systems (PMS), which encompass road planning, design, and maintenance (DNIT, 2011). These systems help optimize the use of resources, directing maintenance and rehabilitation strategically. The simple detection of a distress's occurrence is just the starting point. For the data to be useful, it is imperative to quantify the extent and severity with which each type of distress manifests throughout the road network (Haas et al., 1994). Quantifying the extent allows for sizing the problem in terms of affected area or length, providing essential information for logistical planning and repair cost calculation. Concurrently, the severity assessment classifies the level of degradation, differentiating superficial damage from structural compromise.

The set of information on the type, extent, and severity of distresses feeds the pavement performance indices. These indices constitute metrics that transform the complexity of the data into a single score or value, making comparison and decision-making easier. The quantification of distresses is fundamental for generating these indices objectively and systematically. In Brazil, the Global Severity Index (IGG), defined by the DNIT 006/2003-PRO standard (DNIT, 2003b), combines the frequency and severity of distresses to classify the pavement condition into categories such as "excellent," "fair," or "very poor," thus guiding maintenance actions.

Although the Brazilian IGG is functional, it is not as complete when compared to indices used internationally, such as the Pavement Condition Index (PCI), developed by the U.S. Army Corps of Engineers and adopted by agencies like the FHWA in the United States (Vieira et al., 2016). The PCI is differentiated by its more detailed methodology, covering a wider range of distresses and their severities, resulting in an index from 0 to 100. This allows for a more precise assessment of the actual pavement condition, facilitating the identification of specific problems and more assertive decision-making.

While Brazilian standards provide a solid basis for evaluation, they can be considered outdated compared to more modern international methods. The DNIT standards that serve as the basis for evaluating flexible pavements in Brazil, specifically DNIT 006/2003-PRO, which deals with objective evaluation, responsible for quantifying distresses (DNIT, 2003b), and DNIT 007/2003-PRO, for surveying the pavement condition, carried out using specific equipment (DNIT, 2003c), were published in 2003 and have not been updated since their publication.

While in Brazil the standards for visual assessment and performance indices have remained the same for over 20 years, methodologies in countries with cutting-edge infrastructure evolve more frequently. Bodies such as the FHWA in the USA and the American Society for Testing and Materials (ASTM) constantly update their manuals and standards to incorporate new technologies and knowledge about pavement behavior. The ASTM D6433 standard, which describes the procedure for calculating the PCI, undergoes periodic revisions. Its latest version was published in 2024 (ASTM, 2024). This means that, in 20 years, this standard has been revised and updated multiple times with online versions released in 2003, 2007, 2009, 2011, 2016, 2018, 2020, 2023, and 2024, available on this Society's website (ASTM, 2025). These revisions are important to correct possible methodological errors and to add more modern data collection methods, such as remote sensing techniques.

The use of remote sensing products applied to road management has shown promising results in monitoring and analyzing the quality of road structures. Research using digital image processing techniques has already highlighted the applicability of these methodologies in detecting distresses and analyzing pavements (Amhaz et al., 2014; Matarneh et al., 2023; Oliveira & Correia, 2009). However, identifying specific distresses, such as rutting, optical sensors face limitations due to the absence of information about the depth of the deformations. In these cases, LiDAR sensors have been employed to overcome these limitations, allowing detailed analyses of plastic deformations and other distresses, such as potholes (Dong et al., 2023;

Faisal and Gargoum, 2023; Ravi et al., 2020a).

In the context of remote sensing with active sensors, LiDAR stands out for its high precision in measuring distances, working by calculating the return speed of laser beams. This technology is widely used on orbital and non-orbital platforms, including satellites, unmanned (UAVs) and manned aerial vehicles, as well as terrestrial platforms. The main advantage of LiDAR is the ability to generate detailed elevation models, with resolution defined by the density of the generated points (Dong and Chen, 2018). When installed on mobile platforms, LiDAR provides high-precision data without interrupting activities at the analyzed site, making it an essential tool for road management. Studies such as those by Chen & Li (2016), del Río-Barral et al. (2022), and Ravi et al. (2020b) demonstrated the effectiveness of this approach by using vehicle-mounted laser scanning sensors for pavement analysis.

Another example of remote sensing related to road management is the work of Vaaja et al. (2018), who conducted mobile mapping of night-time lighting conditions in road environments. The research used mobile mapping systems to capture data on the distribution and intensity of lighting, providing essential information for the management and maintenance of road infrastructure. This type of application highlights how remote sensing can be used not only for the structural analysis of pavements but also for monitoring environmental variables that directly influence the safety and comfort of users. Other sensors, such as deflection sensors, are equally important for road management. These sensors, like the Falling Weight Deflectometer (FWD), operate by applying a point load on the pavement. They use geophones or accelerometers to measure the vertical settlement of the surface at specific points. In high-speed systems, such as Traffic Speed Deflectometers (TSD), deflection is measured by Doppler laser sensors while the vehicle is moving. The deflection readings are then transmitted to a computer, where they are processed and used to evaluate the structural capacity of the pavement. Zhang et al. (2023) apply TSD sensors to measure structural characteristics of the pavement without traffic interruption, in a system capable of collecting varied information about the wearing course.

In this work, the focus is on the review of articles related to quality analysis and the identification of distresses in the pavement layers. This scope was established because the road structure is composed of various components that can be analyzed by remote sensing, such as infiltration in tunnels, deformations in bridge structures, viaducts, and other engineering structures, which could make the review excessively broad.

4 RELATED WORKS

This topic discusses the works used in this systematic review, which covers 45 scientific studies published between 2009 and 2025 that investigate applications of remote sensing for flexible pavement analysis. This literature review was based on the PRISMA method (Moher et al., 2009), using keywords containing all the previously mentioned terms (synonyms) referring to the use of remote sensing products in the detection of pavement distresses as a filter for searching scientific works. To this end, a broad search of works published and available for consultation in online scientific literature databases – specifically in Scopus, Web of Science, and Google Scholar – was conducted, within a time frame of just over 15 years, extending from August 2009 to February 2025. The selected works had as their main focus the detection of pavement distresses by means of remote sensing (RS).

Table 1 presents the complete list of these works, organized alphabetically by author, containing the references with title and respective publication years. The selection includes research representative of the diverse methodological approaches developed during the period, from conventional image processing techniques (Andreou et al., 2011; Chambon et al., 2011; Oliveira & Correia, 2009) to more modern solutions based on artificial intelligence (Feng et al., 2023; Ma & Li, 2022; Tan et al., 2024).

The analyzed works reflect the technological evolution that occurred in the last decade and a half, with contributions from 20 countries distributed across four continents (Lázaro et al. 2022; Mukti e Tahar 2021; Ravi et al. 2020a). The diversity of approaches includes systems embedded in terrestrial vehicles (Chen & Li, 2016; Díaz-Vilariño et al., 2016) as well as aerial (Flores et al. 2025; Pan et al. 2018) and orbital platforms (Brewer et al., 2021), employing optical, LiDAR, and radar sensors. This methodological variety will be examined in detail in the subsequent sections.

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Table 1 – Reviewed works.

Reference	Title	Year
Amhaz et al.	A New Minimal Path Selection Algorithm for Automatic Crack Detection on Pavement Images	2014
Andreou et al.	Investigation of Hyperspectral Remote Sensing for Mapping Asphalt Road Conditions	2011
Avila et al.	2d Image Based Road Pavement Crack Detection by Calculating Minimal Paths and Dynamic Programming	2014
Brewer et al.	Predicting Road Quality Using High Resolution Satellite Imagery: A Transfer Learning Approach	2021
Chambon et al.	Road Crack Extraction with Adapted Filtering and Markov Model-Based Segmentation: Introduction and Validation	2011
Chen & Li	A Feasibility Study on the Use of Generic Mobile Laser Scanning System for Detecting Asphalt Pavement Cracks	2016
Cord & Chambon	Automatic Road Defect Detection by Textural Pattern Recognition Based on Adaboost	2011
del Río-Barral et al.	Pavement Crack Detection and Clustering Via Region-Growing Algorithm from 3D MLS point Clouds	2022
Díaz-Vilariño et al.	Automatic Classification of Urban Pavements Using Mobile Lidar Data and Roughness Descriptors	2016
Dong et al.	Pavement Crack Detection Based on Point Cloud Data and Data Fusion	2023
Elamin e e El-Rabbany	UAV-Based Image and LiDAR Fusion for Pavement Crack Segmentation	2023
Faisal e e Gargoum	Automated Assessment of Pavement Rutting Using Mobile Lidar Data	2023
Feng et al.	GCN-Based Pavement Crack Detection Using Mobile Lidar Point Clouds	2021
Feng et al.	Pavement Distress Detection Using Terrestrial Laser Scanning Point Clouds Accuracy Evaluation and Algorithm Comparison	2022
Feng et al.	SCL-GCN:Stratified Contrastive Learning Graph Convolution Network for Pavement Crack Detection from Mobile LiDAR Point Clouds	2023
Freitas e e Nobre	Identificação de Patologias em Pavimentos Rodoviários Utilizando Inteligência Artificial	2020
Flores et al.	Aplicação da Aerofotogrametria Com VANT para Análise de Pavimentação Asfáltica	2025
Grandsaert	Integrating Pavement Crack Detection and Analysis Using Autonomous Unmanned Aerial Vehicle Imagery	2015
Hoang & Nguyen	Automatic Recognition of Asphalt Pavement Cracks Based on Image Processing and Machine Learning Approaches: A Comparative Study on Classifier Performance	2018
Huang et al.	A Pavement Crack Detection Method Combining 2D with 3D Information Based on Dempster-Shafer Theory	2013
Kang & Choi	Pothole Detection System Using 2D Lidar and Camera	2017
Khan & Kumar	Terrestrial Lidar Derived 3D Point Cloud Model, Digital Elevation Model (DEM) and Hillshade Map for Identification and Evaluation of Pavement Distresses	2024
Lázaro et al.	Avaliação das Condições de Superfície de Pavimentos Urbanos com o Auxílio de Ferramentas de Análise Espacial	2022
Liu et al.	Application of Combining YOLO Models and 3D GPR Images in Road Detection and Maintenance	2021
Ma & Li	SD-GCN: Saliency-Based Dilated Graph Convolution Network for Pavement Crack Extraction from 3D Point Clouds	2022
Matarneh et al.	An Automatic Image Processing Based on Hough Transform Algorithm for Pavement Crack Detection and Classification	2023
Mettas et al.	Detection of Asphalt Pavement Cracks Using Remote Sensing Techniques	2016
Mukti e e Tahar	Low Altitude Multispectral Mapping for Road Defect Detection	2021
Nunes-Ramos et al.	Distress Manifestation in Asphalt Pavements: Comparison between Local and Unmanned Aerial Vehicle (UAV) Measurements	2024
Oliveira & Correia	Automatic Road Crack Segmentation Using Entropy and Image Dynamic Thresholding	2009
Pan et al.	Object-based and Supervised Detection of Potholes and Cracks from the Pavement Images Acquired by UAV	2017
Pan et al.	Detection of Asphalt Pavement Potholes and Cracks Based on the Unmanned Aerial Vehicle Multispectral Imagery	2018
Ravi et al.	Highway and Airport Runway Pavement Inspection Using Mobile LiDAR	2020a
Ravi et al.	Pothole Mapping and Patching Quantity Estimates Using Lidar-Based Mobile Mapping Systems	2020b
Resende et al.	Classificação Híbrida, Pixel a Pixel e Baseada em Objetos para o Monitoramento da Condição da Superfície dos Pavimentos Rodoviários	2012

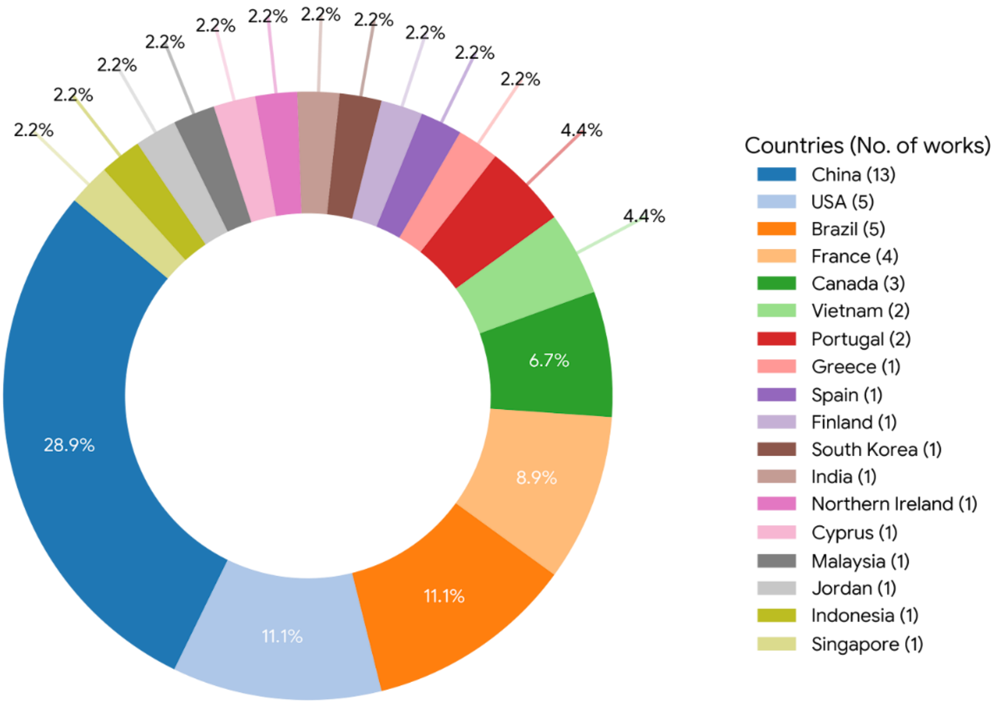
Reference	Title	Year
Safaei et al.	An Automatic Image Processing Algorithm Based on Crack Pixel Density for Pavement Crack Detection and Classification	2022
Shatnawi et al.	Road Pavement Rut Detection Using Mobile and Static Terrestrial Laser Scanning	2021
Tan et al.	Lidar-Based Automatic Pavement Distress Detection and Management Using Deep Learning and BIM	2024
Tran et al.	Detection of Asphalt Pavement Cracks Using Mobile 2D Laser Scanning System: A Case Study of UTM 30LX Laser Scanner	2021
Ukhwah et al.	Asphalt Pavement Pothole Detection Using Deep Learning Method Based on YOLO Neural Network	2019
Zhang et al.	Automatic Pavement Defect Detection Using 3D Laser Profiling Technology	2018
Zhang et al.	Optimizing Pavement Distress Detection With UAV: A Comparative Study of Vision Transformer and Convolutional Neural Networks	2024
Zhang et al.	Automatic Settlement Assessment of Urban Road From 3D Terrestrial Laser Scan Data	2025
Zhong et al.	Pavement Crack Detection from Mobile Laser Scanning Point Clouds Using a Time Grid	2020
Zhu et al.	Measuring Surface Deformation of Asphalt Pavement Via Airborne Lidar: A Pilot Study	2023

Source: Authors (2025)

5 STUDY AREAS

This topic explores the regional distribution characteristics of the analyzed works, with the intent of developing an analysis of the countries and regions that have developed more works in the focus area of this review. Figure 2 presents a distribution chart with the number of works per country.

Figure 2 – Chart of work distribution by country.



Source: Authors (2025).

Based on the reviewed works, it is possible to note a diversified geographical distribution, with concentrations in specific countries. China stands out as the location with the highest number of studies, covering research that uses different sensors, such as LiDAR (Feng et al., 2021; Zhang et al., 2024), multispectral imaging (Pan et al. 2018), and advanced artificial intelligence techniques (Ma & Li, 2022). The large number of works developed in the country may indicate a trend towards modernization of road monitoring systems, with a focus on remote sensing techniques combined with deep learning for automated analysis.

North American countries also stand out, with the United States and Canada together being the second region with the highest number of works on the topic. These countries present significant contributions, especially in the use of mobile LiDAR (Ravi et al., 2020a) and satellite remote sensing (Brewer et al., 2021), with approaches that integrate Building Information Modeling (BIM) systems for infrastructure management. In Europe, countries like France (Cord & Chambon, 2011), Portugal (del Río-Barral et al., 2022), and Spain (Díaz-Vilariño et al., 2016) are developing research focused on image and point cloud processing algorithms, often in collaboration between universities and technology companies, with an emphasis on segmentation methods based on region growing (Chen & Li, 2016; del Río-Barral et al., 2022) and texture analysis (Cord & Chambon, 2011; Matarneh et al., 2023). Other regions, such as Southeast Asia (Vietnam, Malaysia, Indonesia) and the Middle East (Jordan), contribute with research often focused on low-cost adaptations, such as 2D LiDAR sensors (Tran et al., 2021) or drones with affordable cameras (Ukhwah et al., 2019), demonstrating viable solutions for developing countries.

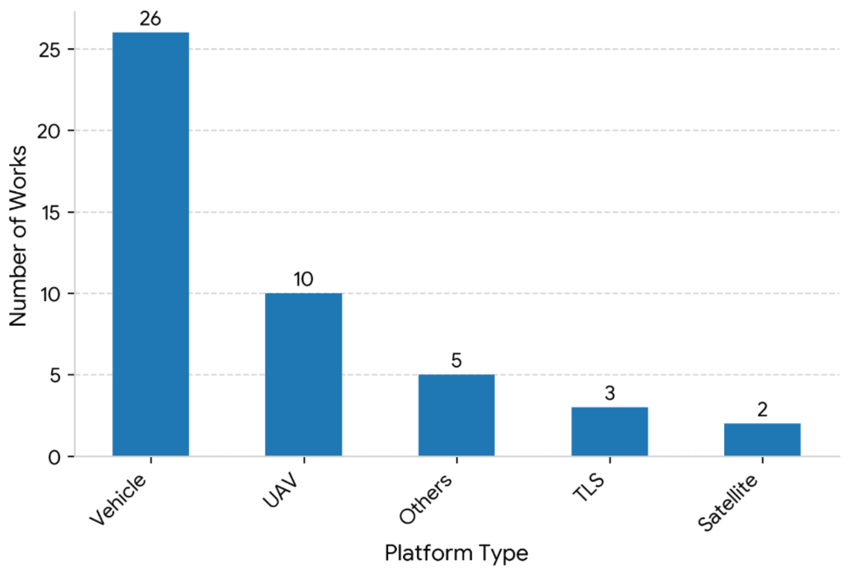
In Brazil, studies are still emerging but already show growth, mainly with the use of UAVs (Flores et al., 2025) and multispectral imaging (Resende et al., 2012). Works like that of Freitas & Nobre (2020) show the application of artificial intelligence in identifying pavement distresses, while Lázaro et al. (2022) explore satellite remote sensing for pavement assessment in an urban environment. In the national context, two works in particular adopt less automated approaches; Nunes-Ramos et al. (2024) use UAV images for manual analysis in AutoCAD, comparing with traditional field inspections, while Lázaro et al. (2022) use Google Earth (QuickBird) images for manual counting of distresses, both without using automatic classification algorithms.

These approaches reflect an initial stage of technological adoption, where remote sensing is used mainly to replace visual in situ inspection, without yet exploring the full potential of automated processing. The use of more advanced techniques already occurs in Brazil, as in the case of the Government of Paraná's project, which used vehicle-mounted sensors for the restoration of PR-170/PRC-466 (Governo do Estado do Paraná, 2024). This case demonstrates that the technology has practical adoption, indicating the need for new works to improve existing techniques and develop more accurate automatic classification algorithms, especially adapted to the conditions of Brazilian highways.

6 PLATFORMS AND SENSORS USED IN THE BIBLIOGRAPHY

Within the context of this review, the platform where the sensor is attached to perform data acquisitions in the field is one of the most important points for the development of methodologies. Figure 3 presents a summary of the number of times a given platform was used in the works reviewed in this study.

Figure 3 – Number of times a given platform was used in the reviewed bibliography.



Source: Authors (2025).

The selection of data acquisition platforms profoundly conditions the applicability of the proposed methods, as evidenced in Figure 3. Vehicular platforms predominate with 26 occurrences, representing more than 50% of the sample, being particularly recurrent in studies with medium and high-precision mobile LiDAR systems. This preference is justified by the ability to cover significant highway lengths, as demonstrated by Ravi et al. (2020a) with an average coverage of 60 km/day under ideal operational conditions. However, only 11 of the 26 studies using a vehicle as the sensor platform explicitly addressed the practical challenges of vibration and dynamic positioning, with Feng et al. (2022) highlighting the need for compensation algorithms that can increase data processing time.

UAVs appear as the second most frequent alternative, present in ten works, with applications concentrated in high-resolution localized inspections. Flores et al. (2025) obtained promising results with 1 cm resolutions in flights at 25 m altitude, however, the study admits operational limitations in urban areas due to airspace restrictions. This problem is corroborated by Pan et al. (2018), who cite potential risks of low-altitude flights in urban environments, in addition to noting that the larger volume of data increases the volume of data collected. It is important to emphasize that the reviewed studies with UAVs did not include economic analyses of the method, a significant gap for assessing feasibility in large-scale projects.

The three studies using Terrestrial Laser Scanning (TLS) share common characteristics regarding superior metric precision and some operational limitations. Khan & Kumar (2024) demonstrate that even state-of-the-art TLS systems cannot provide rapid scans for roads, making them economically unviable for monitoring extensive networks. This limitation can be very relevant in countries like Brazil, with continental road networks, where daily productivity becomes a very relevant factor. Feng et al. (2022) propose an intermediate solution by coupling a TLS sensor to a vehicular base, but with logistical complexities that restrict the application of the methodology, such as, for example, the need for constant vehicle stops to take readings, causing interruption of traffic flow on the road and the need for an escort during field prospecting, representing a clear disadvantage when compared to fully mobile systems for this specific application.

The two studies based on orbital satellite imaging face intrinsic physical barriers related to the available spatial resolution. Brewer et al. (2021) used 30 cm images, suitable for general assessment of the road network, but insufficient for detecting finer structural distresses, showing a high rate of false negatives for smaller cracks. Lázaro et al. (2022) confirm this limitation by comparing QuickBird data with manual field inspections, identifying that only distresses larger than 10 cm were consistently detected. Other well-known problems in satellite imaging can also be mentioned, such as the influence of cloud cover and vegetation cover over the roads, which can influence, or make impossible, the analysis of highways in some locations.

Other works apply unconventional platforms or take readings manually. Among the alternative platform configurations, the study by Tran et al. (2021), which uses a kind of motorized frame, must be analyzed particularly. Although it represents an advance by using a low-cost 2D LiDAR sensor, the system has a low maximum acquisition speed, due to the need for multiple transverse passes. This method can lead the work to have good results related to precision, however, these results are acquired under very restricted conditions with a very small distance from the sensor to the road and a reading focused on a specific location, with a distress already identified previously. This operational limitation restricts the application to larger stretches of a highway. However, the work still represents significant results, by demonstrating that low-cost solutions can achieve satisfactory metric precision when properly configured.

The vast majority of the analyzed studies did not address important operational aspects, such as comparative implementation costs, real productivity in field conditions, and technical team qualification requirements. This methodological gap is evident in research that used pre-existing databases without characterizing the original acquisition conditions. Avila et al. (2014) and Safaei et al. (2022), for example, relied exclusively on sets of processed images, making it difficult to assess applicability in real operational contexts. As a counterpoint, the work of (Liu et al., 2021) stands out for presenting a more comprehensive analysis, which integrates economic, technical, and environmental parameters. The authors describe the precision of the developed vehicular system and detail the difference in maintenance costs using RS versus traditional techniques, indicating savings of $49.4/km, in addition to analyzing energy consumption and carbon emission for both cases. This level of methodological transparency proves to be of great importance and should serve as a reference for future publications in the area.

7 REMOTE SENSING IN PAVEMENT QUALITY ANALYSIS

The evaluation of pavement condition in Brazil is governed by standards DNIT 006/2003 - PRO (DNIT, 2003b) and DNIT 008/2003 – PRO (DNIT, 2003d), which establish the procedure for generating the Global Severity Index (IGG), which is an indicator of the pavement surface condition, in addition to guiding the methodology for the systematic survey of distresses in asphalt. With the calculation of the IGG value, it is possible to assign a class to the asphalt pavement, which can be: excellent, good, fair, poor, and very poor. The DNIT 008/2003-PRO standard establishes the procedure for calculating another index, the Flexible Pavement Condition Index (ICPF), by means of the Continuous Visual Survey (LVC), and at the same time also provides the methodology for calculating the Expedited Global Severity Index (IGGE).

To calculate these indices, it is necessary to perform manual in situ counting and classification of distresses, which results in labor mobilization and operational difficulties. With the advancement of remote sensing and image processing techniques, it was possible to develop the potential for application in the calculation of these indices, improving and systematizing the traditional manual method. Since the 1980s, the Department of Civil Engineering at the University of Waterloo, in the United States, has proposed the use of image and video to form a pavement classification model (Ritchie, 1987), using cameras installed in terrestrial vehicles. In addition to the use of imaging sensors, the pursuit of using 3D laser systems indicated good results, enhancing the use of remote sensing applied to pavement (Ravi et al. 2020a; Tan et al. 2024; Zhu et al. 2023).

Multispectral and hyperspectral sensors are capable of recording radiance values in different spectral bands of the electromagnetic spectrum, enabling the identification of distinct materials. Furthermore, these sensors are directly linked to atmospheric correction (Sanches et al., 2025). Resende et al. (2012) proposed the use of pixel-by-pixel classification in sub-metric spatial resolution hyperspectral images, obtained by the CASI-1500 sensor aboard the Low-Cost Aerial Monitoring System (SMABC), to monitor the surface condition of road pavements. Methodologically, one must first identify the road segment in the images. Next, pavement distresses can be identified through object-based classification (OBIA) techniques. Once these steps are completed, it is possible to calculate the IGI and IGG indices. As asphalt is an element with a generally uniform spectral behavior, the authors use techniques like SAM to select the road area using a spectral library.

The authors perform validation with data measured manually in the field. The work's methodology does not show results with high accuracy in the distress identification step. The authors point out that distresses, such as patches, present great shape variability, which may have negatively influenced the algorithm's training. However, as it is a relatively old work, new techniques and object-based algorithms can be explored, having the potential to show good results. More recent studies show significant advances in this direction, particularly with the combined use of multispectral sensors and deep learning techniques.

Pan et al. (2018) developed a methodology using a UAV equipped with a multispectral sensor, in the 490-950 nm range, to capture high spatial resolution images. The study, conducted in Shihezi (China), applied four supervised classifiers (SVM, ANN, and RF) for pothole and crack detection, with the classifiers showing different results according to parameter changes; overall, RF showed high accuracy in distress detection (>90%) presenting a low processing time. However, the authors state that the identification of distresses is limited by the spatial resolution of the images, limiting application in initial stages of degradation. Complementarily, Mettas et al. (2016) investigated the spectral signature of damaged asphalt in Cyprus, using hyperspectral data from the SVC HR1024 radiometer (400-2,500 nm). The results indicated that the SWIR bands (1,750 nm and 2,250 nm) showed greater potential to differentiate intact from deteriorated areas when compared to the visible (450-550 nm), with a Mahalanobis distance greater than 1.5 between classes. This purely spectral approach, although accurate in the laboratory, faced challenges in the field due to illumination variability.

In the Brazilian context, Nunes-Ramos et al. (2024) compared the traditional IGG calculation with data obtained by UAV (DJI Mavic Air 2), but without automating the process. Despite the high spatial resolution, the analysis remained manual via AutoCAD, resulting in exhaustive manual processing. This work shows that even with modern equipment, many national studies still do not fully integrate a more automated analysis workflow.

More automated solutions emerge with Ukhwah et al. (2019), who applied YOLO architectures

(YOLOv3, YOLOv3-Tiny, and YOLOv3-SPP) for pothole detection in images from a sensor attached to a vehicle in Indonesia. The YOLOv3-SPP achieved a mAP (mean Average Precision) index of 88.93%; this metric combines precision and recall to evaluate the quality of detection, where values closer to 100% indicate better algorithm performance. However, the study presented some limitations; false positives were detected due to shadows and braking marks being classified as distresses. Similar problems were reported by Matarneh et al. (2023), with the Hough transform, where irregular textures of new asphalt generated some erroneous detections. The aspect of calibration was a topic not clearly addressed in most of the reviewed studies. These technical limitations are reflected in the calculated indices. Although approaches based on deep learning, as in the work of Zhang et al. (2024) and multispectral processing (Pan et al., 2018), have shown improvements in automated detection, the reviewed literature still does not report full agreement with the normative standards of DNIT and other norms.

8 LIDAR SENSORS IN PAVEMENT DISTRESS DETECTION

The application of LiDAR systems in pavement evaluation has evolved significantly since the first experiments with laser profilers in the 1990s. Laurent et al. (1997) used static systems with millimetric precision, serving as a basis for the development of current dynamic LiDAR systems, consolidating itself as a good alternative to conventional visual inspection methods. The technology stands out in the three-dimensional detection of plastic deformations and surface cracks, with precision that varies according to the acquisition platform used.

In Mobile Mapping Systems (MMS), as demonstrated by Feng et al. (2021), the combination of LiDAR sensors with vehicular platforms and the integration of different sensors, such as RGB cameras, integrated with positioning sensors with GNSS and INS technologies, allow for the continuous scanning of road extensions. To conduct the study, the authors used the RIEGL VMX-450 sensor system, which integrates two laser scanners and four digital cameras, in addition to the inertial positioning system. However, these systems face non-trivial practical challenges, as demonstrated by the study of Chen & Li (2016), which indicates the presence of noise in the point cloud, bringing the need to apply noise correction algorithms. Ravi et al. (2020b) use a set composed of two LiDAR sensors (Riegl VUX-1HA and Z+F Profiler 9012) and two RGB cameras, in addition to GNSS and INS systems. The authors use an automatic distress detection algorithm that includes noise correction, achieving millimetric accuracy under real operational conditions. This category of systems shows better performance in identifying macroscopic distresses such as depressions and undulations, with higher accuracy for deeper irregularities (Zhu et al., 2023), while narrow cracks (<2 mm) still represent a considerable technical challenge.

The adaptation of LiDAR sensors for aerial platforms brought new possibilities, especially for localized inspection of critical sections. Zhu et al. (2023) demonstrated that flights at 30 m altitude allow detecting rutting deformations with good accuracy (>80%). The fusion of LiDAR data with images proposed by Elamin & El-Rabbany (2023) showed good results by integrating point clouds with RGB images, improving the detection of finer cracks, also demonstrating that lower flight altitudes indeed bring greater density to the point cloud. This hybrid approach proved effective on aged pavements, where the combination of geometric and spectral information allowed differentiating active cracks from sealed cracks, a recurring challenge in purely image-based methods.

del Río-Barral et al. (2022) developed processing algorithms adapted for sparse point clouds, achieving up to 89% accuracy in detecting longitudinal cracks without the aid of imaging data. This solution can be very useful for inspections in large road networks, where point density is often sacrificed in favor of spatial coverage. The work introduces roughness metrics derived from LiDAR, which can serve as complementary information for classification algorithms and identification of potential distress areas. At the opposite end of the technological scale, Khan & Kumar (2024) demonstrated that TLS solutions can identify pavement distresses, using Hillshade in localized inspection, although with inherent limitation in spatial coverage.

9 LIMITATIONS

The implementation of remote sensing technologies for pavement quality assessment faces multidimensional challenges that span technical, operational, and economic aspects. Although advances in the last two decades have been significant, current limitations restrict the large-scale adoption of these methods. Concerning data processing, the reviewed studies reveal some challenges related to the management of large volumes of information. Resende et al. (2012) found that hyperspectral images from the CASI-1500 sensor, with 50 cm spatial resolution, can demand high storage capacity to cover a significant extent of the highway, as also demonstrated by Pan et al. (2018). The limitation regarding processing time has been overcome when deep learning techniques are employed, as evidenced by Ukhwah et al. (2019), where training YOLOv3 neural networks for pothole detection required a fraction of a second of processing for each image, done on Tesla T4 GPUs, showing good accuracy and reduced processing time, highlighting the advances of object detection algorithms based on neural networks.

The complexity of urban environments represents another substantial obstacle. Nunes-Ramos et al. (2024) quantified that the presence of parked vehicles, architectural shadows, and adjacent vegetation reduced the accuracy in automatic pavement segmentation in high-resolution aerial images. Similar problems were documented by Zhang et al. (2024) when selecting images with interferences from shadows, leaves fallen on the road, and other problems, to analyze the impact of this on classification algorithms.

In the specific scope of LiDAR systems, the review identified some limitations. The first refers to spatial resolution: conventional mobile systems rarely achieve point densities with sufficient value to detect microcracks less than 1 mm wide (Dong et al. 2023). Feng et al. (2022) demonstrated that even high-precision TLS systems suffer a reduction in detection effectiveness when applied to cracks with a width of less than 1 mm. Another limitation involves operational stability. Zhu et al. (2023) measured that altitude variations in UAVs can introduce vertical errors of up to 6 mm in higher altitude flight conditions (30 m), while Elamin & El-Rabbany (2023) identified noise in the point cloud that required post-processing filtering in most of the studied cases. These challenges are particularly relevant, considering that most of the reviewed studies with LiDAR did not include standardized protocols for dynamic motion compensation.

Environmental factors constitute another barrier. The study by Kim et al. (2021) demonstrated that the accuracy of mobile LiDAR decreases significantly under heavy rain, with precipitations above 30 mm/h, with a return point rate (NPC) that decreased depending on the target distance and material type, potentially making readings unfeasible in given seasons. Concurrently, Pan et al. (2018) observed that variations in asphalt reflectance caused by differences in solar incidence angle significantly affect the performance of classifiers, directly influencing the algorithm training step. It is worth noting that most of the reviewed works do not address environmental issues as an influence on sensor accuracy, and this could be a space for future research testing different climatic conditions in pavement distress detection.

Operational and economic challenges are no less significant. Feng et al. (2022) documented that TLS inspection requires traffic interruptions, with logistical costs that can represent a large portion of the total budget, which is why the work is focused on testing a low-cost sensor. In contrast, vehicular systems present distinct trade-offs, with mobile sensors representing high-cost acquisition products, something little addressed in the reviewed works, but which is an essential factor for the viability of a methodology.

The lack of methodological standardization can be a problem. Only 11 of the 45 reviewed works (24.4%) used validation metrics consistent with local standards. This heterogeneity makes direct comparisons between studies and the transfer of technology to managing bodies difficult. For example, while Khan & Kumar (2024) used hillshade maps as a primary reference, Díaz-Vilariño et al. (2016) relied exclusively on digital elevation models.

The reviewed Brazilian works, such as Resende et al. (2012), presented metrics present in standards, in an attempt to integrate new inspection methods with the calculation of already known indices. However, the transition of these technologies to operational application at scale will require technical advances and institutional adaptations with the need for updates to national standards and modernization of control metrics.

The comparative analysis of the studies reveals that current limitations are concentrated in extensive road networks (>500 km), where logistical costs become prohibitive, dense urban areas, with multifactorial interferences, and monitoring of smaller distresses, which demand sub-millimetric resolutions. These challenges suggest that, although remote sensing has the potential to complement traditional visual inspection methods, its adoption as an autonomous tool still requires significant developments on several fronts, such as methodological standardization, operationality, computational efficiency, and normative validation.

10 FINAL CONSIDERATIONS

The systematic review of the works demonstrates that remote sensing applied to the analysis of flexible pavements has reached a considerable stage of technological maturity, but with persistent challenges that demand new approaches. Recent advances in acquisition platforms and processing techniques, as evidenced by Tan et al. (2024) with vehicular LiDAR systems integrated with BIM and Zhang et al. (2024) with Vision Transformers on UAV data, indicate promising paths to overcome current limitations. However, the transition of these technologies to large-scale operational application faces some barriers that require careful consideration.

In the domain of imaging sensors, the reviewed studies reveal a clear dichotomy between orbital and non-orbital platforms. While satellite-embedded systems, such as those used by Brewer et al. (2021), offer advantages for monitoring extensive networks (average coverage of 5,000 km²/day), their limited spatial resolution (30 cm in the best scenario) restricts detection to macroscopic distresses (>10 cm), as quantified by Lázaro et al. (2022). In contrast, proximity platforms, particularly UAVs equipped with multispectral sensors, achieved superior performance in studies like Pan et al. (2018), with 98.7% accuracy in identifying potholes when using 1 cm images. This advantage, however, comes with significant operational limitations as a trade-off. Flores et al. (2025) documented that flights below 25 m altitude, necessary for sub-centimetric resolutions, reduce the daily coverage area under ideal conditions, which can make inspection of larger areas on extensive highways difficult.

Environmental heterogeneity remains a central challenge for imaging-based techniques. Nunes-Ramos et al. (2024) demonstrated that, even though visual inspection of images is a less sophisticated methodology, it shows good results compared to classification techniques that face problems with the heterogeneity of urban environments, as seen in the work of Resende et al. (2012). This limitation is relevant, considering that more than half of the reviewed studies with optical sensors were conducted under controlled conditions or in simplified environments, potentially overestimating real performance. Solutions such as the fusion of optical data with short-wave infrared (SWIR) proposed by Mettas et al. (2016) show potential to mitigate these problems, but still lack validation at an operational scale.

In the field of LiDAR systems, the review identified notable progress in the last decade. The evolution from the first systems, such as those used by Laurent et al. (1997), to the current high-density mobile platforms documented by Dong et al. (2023) allowed the detection of distresses with metric precision. Works like that of Ravi et al. (2020a) proved the effectiveness of LiDAR for large-scale distress assessment, while hybrid approaches, such as the one developed by Elamin & El-Rabbany (2023), achieved significant advances in identifying cracks through LiDAR-RGB image fusion. However, as warned by Feng et al. (2021) and Zhu et al. (2023), these systems still face challenges related to point density in motion, meteorological sensitivity, and high computational costs.

Some points for improvement can be explored in future research, such as the integration of multiple technologies, exemplified by the pioneering work of Liu et al. (2021) combining Ground-Penetrating Radar (GPR) with digital image processing techniques to identify distresses in asphalt. Added to this is the development of standardized protocols for validation against normative methods and cost reduction. Finally, as demonstrated by the evolution from the first works with basic imaging (Ritchie, 1987) to the current integrated systems (Zhang et al., 2024), the field continues to develop rapidly.

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Author Contributions

Conceptualization, E.S.R., C.M.A. and P.R.S.R.; Methodology, E.S.R.; Investigation, E.S.R.; Formal Analysis, E.S.R.; Visualization, E.S.R.; Writing - Original Draft, E.S.R.; Writing - Review and Editing, E.S.R., C.M.A., M.K. and P.R.S.R.; Supervision, C.M.A., P.R.S.R. and M.K..

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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Biography of the main author

Ezequiel Silva Rocha was born in the municipality of Barra do Corda, Maranhão, in 2000. He holds a degree in Civil Engineering from the State University of Maranhão (UEMA - 2023) and is a Master's student in Remote Sensing at the National Institute for Space Research (INPE), where he is currently a scholarship holder. He also has a technical degree in Building Construction from the Federal Institute of Maranhão (IFMA - 2017). He develops his research at INPE, in São José dos Campos, focusing on the use of laser sensors (LiDAR) for building documentation. He has professional experience in paving and sanitation projects.