infrastructures

*Review*

# UAV Applications for Monitoring and Management of Civil Infrastructures

**Alberto Villarino [1,*], Hugo Valenzuela [2], Natividad Antón [3], Manuel Domínguez [4] and Ximena Celia Méndez Cubillos [5]**

1 Department of Construction and Agronomy, Construction Engineering Area, High Polytechnic School of Ávila, University of Salamanca, 05003 Ávila, Spain
2 Escuela de Ingeniería Mecánica, Pontificia Universidad Católica de Valparaíso, Quilpué 2430167, Chile; hugo.valenzuela@pucv.cl
3 Department of Construction and Agronomy, Materials Science and Metallurgical Engineering Area, High Polytechnic School of Zamora, University of Salamanca, 49002 Zamora, Spain
4 Department of Mechanical Engineering, High Polytechnic School of Zamora, University of Salamanca, 49002 Zamora, Spain
5 Opencadd Advanced Technology, Av. Brig. Faria Lima, 4055-Jardins, São Paulo 04538-133, Brazil; ximena.cubillos@opencadd.eng.br
* Correspondence: avillarino@usal.es

**Abstract:** Civil engineering is a field of knowledge in direct contact with the citizen, not only in the design and construction of infrastructure but also in its maintenance, conservation, monitoring, and management. The integration of new technologies, such as drones, is revolutionizing work methodologies, offering new possibilities for the execution and management of infrastructure and minimizing human intervention in these jobs, with the increase in occupational safety and cost reduction that this entails. This study presents a comprehensive review of the literature on UAV applications for the monitoring and management of civil infrastructure. The applicability of UAVs and their connection with the main existing sensors and technologies are analyzed, such as visible cameras (RGB), multispectral cameras, and hyperspectral cameras, in the most relevant areas of civil engineering, such as building inspection, bridge inspection, dams, power line inspection, photovoltaic plants, inspection, hydrological studies road inspection, slope supervision, and the maintenance and monitoring of landfill operation. The impact and scope of these technologies are addressed, as well as the benefits in terms of process automation, efficiency, safety, and cost reduction. The incorporation of drones promises to significantly transform the practice of civil engineering, improving the sustainability and resilience of infrastructures.

**Keywords:** UAV applications; civil engineering; infrastructures; monitoring and management structures

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## 1. Introduction

The term drone is popularly used to refer to an unmanned aerial vehicle (UAV), also known as RPAS (remotely piloted aircraft system). These terms refer to a remotely piloted and unmanned aircraft, which can autonomously maintain a controlled and constant level of flight and can be propelled by combustion, electricity, or jet engines [1].

Its origin dates to the beginning of the 20th century, but in recent decades, its use has become widespread and essential for mankind. It was created for military purposes, mainly for aerial surveillance, photography, and as an air-to-ground bomb/missile in armed conflicts. Due to technological advances in radio communications, the use of remotely piloted aircraft has been extended to the civilian sphere.

Their current popularity is because they offer accurate and detailed information at a lower price than other similar technologies, which leads to significant economic, time, and labor savings [2].

Among their advantages are high spatial and temporal resolution, a lower operating cost compared to other data acquisition systems for projects of certain spatial dimensions, and high accuracy, because they generate little atmospheric interference [3,4].

In sectors such as topography, civil engineering, mining, agriculture, security, etc., drones have become an excellent working tool and have transformed how human beings carry out numerous daily activities [5,6]. Drones are mainly classified by the way they are sustained in the air, although there are also terrestrial and aquatic drones. There are three types of drones:

Fixed-wing drones: They need initial flight speed to sustain themselves and must have a launching platform. They are the most like a classic airplane. They have a high flight autonomy and are used in large areas (Figure 1) [7].

**Figure 1.** Fixed-wing drone.

Rotary-wing drones: They are the most popular and best-selling on the market [8]. They have sustained in the air thanks to rotating propellers. They can remain static on a point, which is the main difference from the fixed-wing ones. They are classified according to the number of rotors they have (tricopter, quadcopter, hexacopter, octocopter, and axial) (Figure 2) [9].

**Figure 2.** Rotatory-wing drone.

Fixed-wing hybrids: These combine a multirotor and a fixed-wing; therefore, they have significant autonomy and a vertical takeoff and landing. In the market, there are a wide variety of sensors or cameras that can be installed on drones for data collection. Depending on the work to be performed, the most suitable one can be chosen from the different types.

On the other hand, they can install different sensors and technologies, such as visible cameras (RGB), multispectral cameras, and hyperspectral cameras [10]. The visible cameras (RGB) are sensors that capture information in the visible electromagnetic spectrum and whose images can be perceived by the human eye. They can capture high-resolution images and have an infinite number of applications (visual inspection, terrain elevations, orthophotos, etc.) (Figure 3) [11]. In addition to capturing the visible spectrum, the multispectral cameras can capture the near infrared. They usually have between three and five bands, and they are mainly used in precision agriculture (moisture, stress, pests, etc.). The hyperspectral cameras can divide the electromagnetic spectrum into hundreds of contiguous bands, which provides a higher level of detail and accuracy. Their price is higher, and they are quite powerful.

**Figure 3.** RGB camera DJI Phantom 4.

This work is not limited to listing previous studies but aims to offer a critical and structured review of the state of the art on the use of UAVs in civil engineering. Technological surveillance work has been carried out that synthesizes the main current lines of research, considering not only the type of drones and sensors used but also their specific applicability in different areas (buildings, bridges, dams, power lines, solar plants, etc.).

The review is structured around two key axes:

- The technological evolution of UAVs, including improvements in autonomy, maneuverability, and payload capacity, as well as the integration of more advanced sensors (RGB, thermal, multispectral, LIDAR, etc.) that optimize their use as a diagnostic and maintenance tool.
- The practical application in critical monitoring and inspection tasks, where the benefits in terms of safety, operational efficiency, and accuracy in the detection of structural pathologies through methodologies such as 3D photogrammetry, artificial vision, or artificial intelligence are highlighted.

Regarding the search methodology, in the first phase, the search for information revolves around the concept of a drone, its types, and the sensors used. In the second phase, the search is focused on the different applications of drones in civil engineering. In the third phase, a search for more exhaustive and specific information on these applications is carried out, including the objectives, most used drones, and sensors, the process of obtaining and processing data, as well as the results obtained and future lines of research. Figure 4 presents a diagram of the process.

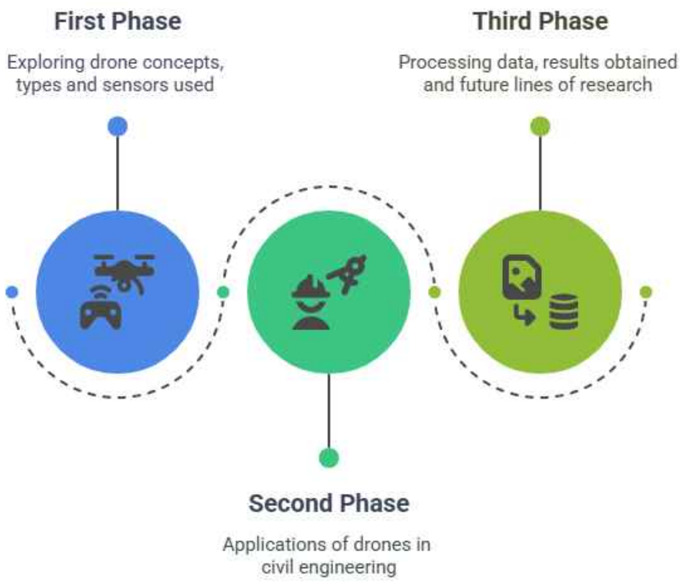



**Figure 4.** Phases of search methodology.

Table 1 shows the different keywords to perform the searches.

**Table 1.** The different keywords to perform the searches.

| Theme | Keywords |
|---|---|
| Drones | "UAV" "RPAS" "Drones" |
| Civil Eng. Applications | "Civil Engineering Applications" |
| Building | "UAV Building Inspection" "UAV Buildings" "Drones AND Building Inspection" |
| Bridges | "UAV Bridge Inspection" "Drones Bridge" |
| Dams | "Dam Inspections UAV" "UAV Dams" "Drones AND Dams AND Engineering" |
| Electrical/solar installations | "UAV Power Lines" "UAV Solar Panels" "Drones AND Photovoltaic" |
| Hydrology | "UAV Water" "UAV River studies" |
| Road | "UAV Road Monitoring/Inspection" "Drones AND Road Inspection" |
| Embankments | "UAV Slope Stability" |

In addition, the number of different types of documents—papers, reviews, and web pages and relevant articles published by year since 2014—is specified in Figure 5.

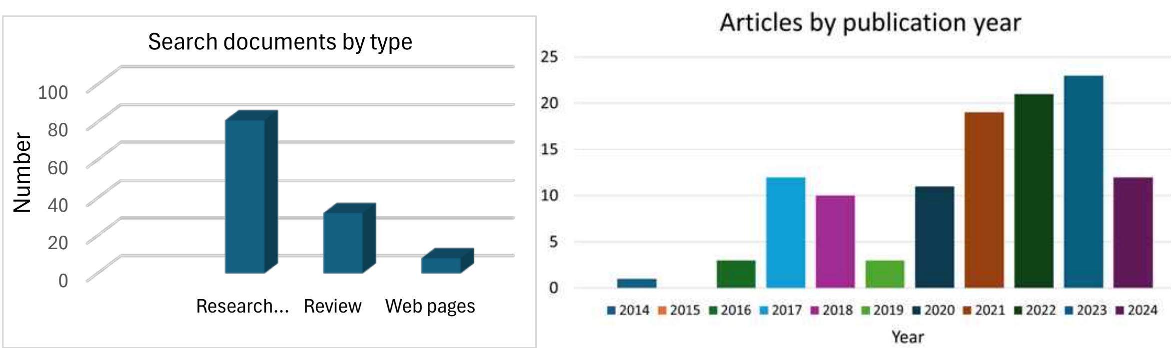



**Figure 5.** Search documents by type and number of articles by publication year. Source: own elaboration.

## 2. Drone Applications in Civil Engineering

Currently, the use of commercial drones in civil engineering is very wide, and their applications are increasing as technology develops [12,13]. This development makes drones increasingly smaller, quieter, more agile, and with more powerful and precise cameras; qualities that make them essential in areas of difficult access and/or maneuverability [14].

Some of the main applications of drones in the field of civil engineering are described below.

### *2.1. Building Inspection*

In these papers, the author refers to the use of UAVs as a tool for the automatic detection of cracks in buildings [15–17]. Traditionally, the inspection of buildings and constructions, to detect cracks or damages in the infrastructure, was performed manually. This process is quite subjective, depending on the experience of the specialist technician, and involves a large amount of time and money, in addition to establishing safety and occupation risk prevention protocols during the execution of the work.

Early detection and the preservation of building structures help to reduce the risks of a possible collapse of the structure. If the building were to collapse, it would cause a significant amount of property damage and, more importantly, many fatalities, as was the case with the Champlain Towers South building in Miami [18].

To solve the problems generated, different studies are being carried out on the use of UAVs for image acquisition, which, using different algorithms, allow the detection of fissures or cracks in the structure automatically, without the need for human intervention [3]. Mainly computer vision algorithms have been used for the detection of cracks or small flaws on the surface of the building [19–21]. These techniques have certain drawbacks, which can be overcome by making use of artificial intelligence (AI) and machine learning [22,23].

On the other hand, the convolutional neural networks (CNNs) have great potential in automatic feature detection on an RGB image [24,25]; they allow the easy detection of cracks or damage, because they are less susceptible to image noise. Neural networks have machine learning capabilities making them the best system for feature extraction. The realization of this project is focused on the creation of a CNN architecture based on 16 different layers and assisted by CycleGAN for the improvement of the results. Its main objective is the localization of cracks in mid-rise buildings (Figure 6) [26] by segmenting images by pixels (Figure 7) [24].

**Figure 6.** Crack location images.

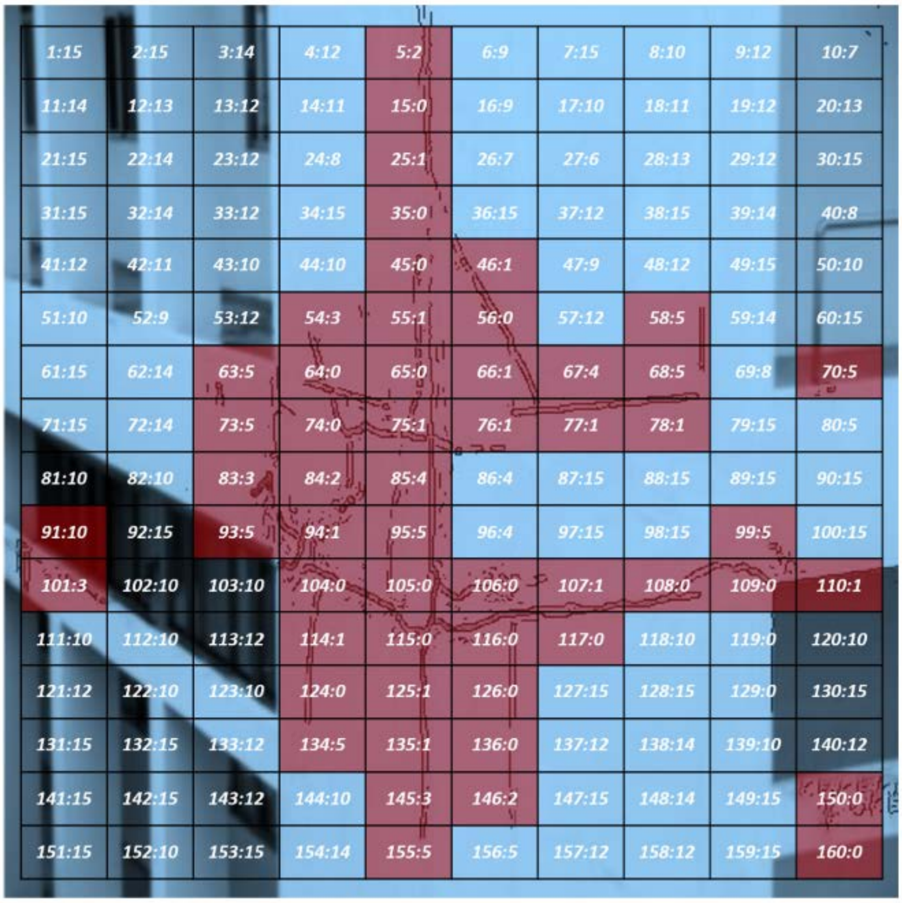



**Figure 7.** Image segmentation by pixels.

The developed algorithm can be implemented on any type of device and is scalable to the realization of different types of buildings depending on their height (low, medium, or high). With the advancement of research on neural networks, the algorithm for automatic crack detection in buildings can become a more powerful tool with significantly improved performance. The author of this paper [27] proposes a joint and complementary work between the BIM models of buildings and the automatic detection of cracks or damage in the walls of buildings carried out by UAV.

Building information modeling (BIM) is a collaborative work methodology for the creation and management of a construction project. Its objective is to centralize all the project information in a digital information model created by all its agents [28].

BIM is the evolution of traditional plan-based design systems, as it incorporates geometric (3D), time (4D), cost (5D), environmental (6D), and maintenance (7D) information [29].

Normally, the data obtained with UAVs are recorded only in reports and is not incorporated into the BIM digital model. The joint implementation of the data obtained with the UAVs to the BIM model allows for the real-time management of buildings.

With this method, first, the data of the images of the building walls are captured to detect the defects automatically using deep learning algorithms. Then, a coordinate transformation is performed between the obtained images and the BIM model. The result is a digital model on which the localized defects are represented (Figure 8) [27].

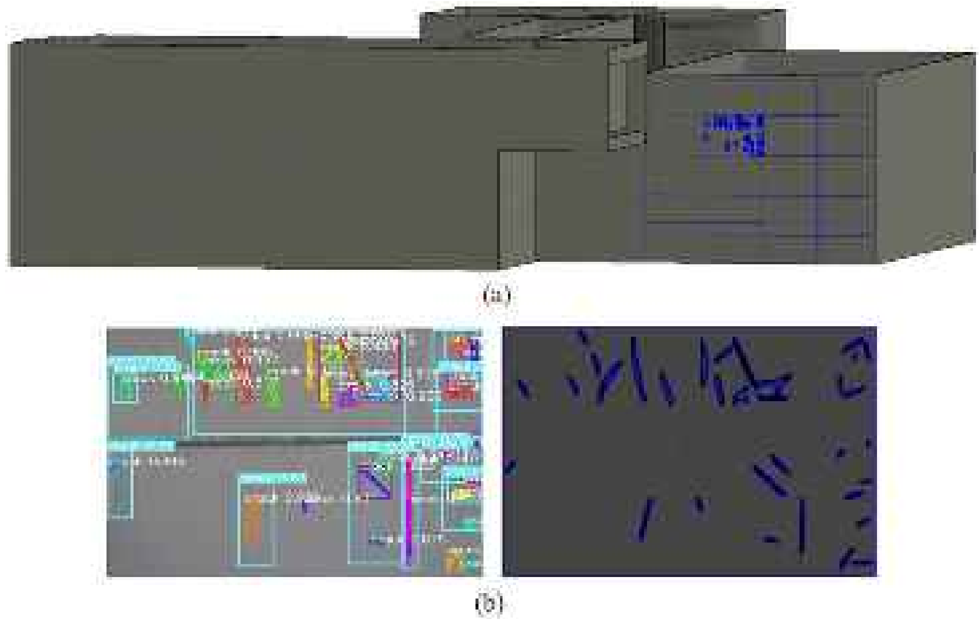


**Figure 8.** (**a**) BIM model and (**b**) the representation of the breaks in the building structure.

*2.2. Bridge Inspection*

Knowing the condition of concrete bridge structures is of vital importance for their maintenance and control. On-site visual inspections are of great help in detecting areas with high degradation, although they do not help us to locate with great precision the areas that are in the worst condition. Some studies have evaluated the possibility of implementing an economical and highly productive solution to evaluate the condition of a bridge structure, which is a fundamental aspect [30–32].

The global road network has many bridges in use today. In the United States, there are said to be more than 614,386 bridges and in Europe a total of 1234 km of bridges over 100 m in length [33,34].

Bridges are considered a critical link in the road infrastructure, and therefore, continuous maintenance of the structure is essential. Any minor structural failure due, for example, to the wear and tear of the structure over the years could cause the bridge to collapse [35,36].

The climatic factor can be a major problem for bridge structures. The materials used in bridge construction can be significantly affected by sudden changes in temperature. In some areas of Europe, such as in Germany, extreme weather events have increased significantly. This generates considerable stress on the surfaces and internal parts of the bridge, subjecting them to a great deal of strain that could cause damage over time. Hence, regular maintenance is of great importance [37].

A rather shocking case that occurred on 14 August 2018 was the collapse of the Morandi Bridge over the Polcevera River (Genoa). The tragedy resulted in the death of 43 people. The total lack of maintenance caused it to collapse [38–40].

Bridges are a rather arduous type of infrastructure and have areas that are difficult to access. Manual maintenance is quite complex and requires the help of certain auxiliary structures (ladders, scaffolding). It is a method with a high operational cost, and where it is necessary to have human resources to perform the tasks, with the added factor of occupational safety in these maintenance and conservation tasks. To address this drawback, the idea of using drones as a mechanism for the visual inspection of bridges was proposed.

UAVs can become a fundamental tool in this field. It is a very cost-effective instrument that minimizes the safety problems associated with manual inspection. There are also several disadvantages to this method. They cannot operate on days with adverse weather, the points where the images are to be taken must be established together with the camera-bridge distance, and photographs must be taken using different camera angles [41].

The conventional UAV has a camera at the front that allows it to take pictures at different angles of inclination, from a 0-degree angle (front view in the direction of flight) to a 90-degree angle (vertical view). It can become inconvenient if you want to take pictures of some areas, such as abutments, decks, and structural arches. Data collection of these areas is essential to know their condition, since it is essential to know the degree of preservation of the bridge.

To achieve the objective, this project presented the use of a 360° camera located on top of the drone. With this camera, the operator will be able to take pictures from all directions. This is a procedure that had never been tried before, and this type of camera allows us to obtain a single-step frontal image of the areas with curved, circular, or oblique geometry of the bridge structure.

The DJI Phantom 4 drone and the RicohTheta V 360 camera were chosen as working instruments. The images obtained with the 360 camera achieved results comparable to those that would have been obtained with the conventional camera of the drone, allowing us to satisfactorily identify the automatic detection of cracks in the structure (Figure 9) [32]. It was necessary to produce algorithms to perform the process and, subsequently, to test their validity. The use of this type of camera is more suitable for the inspection of certain places that cannot be inspected with a conventional camera, from abutments and pillars to the bridge deck.

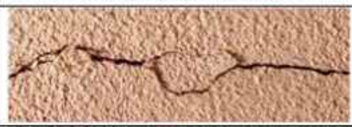
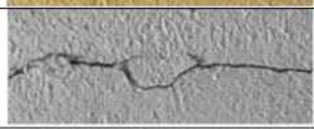
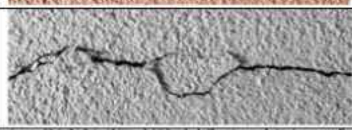
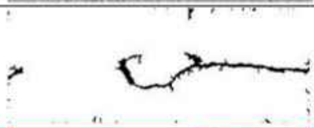
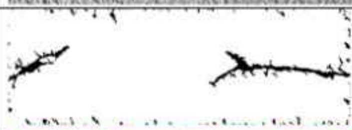
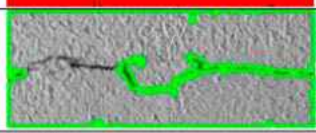
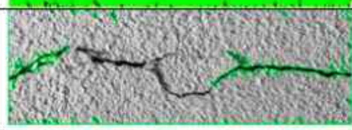
| | 360° camera | Standard HD camera |
|---|---|---|
| Original image |  |  |
| Graystyle image |  |  |
| Binary image |  |  |
| Colored image |  |  |
| Final image |  |  |
| Calculated long slope parameter | 0.8157 | 0.7499 |
| Calculated perpendicular slope | 1.2260 | 1.3334 |

**Figure 9.** Comparison results 360° camera vs. standard HD camera.

This paper compares traditional digital image processing techniques versus deep learning techniques for bridge structure crack detection, listing their advantages and disadvantages [42].

The early detection of cracks in bridge structures is essential to avoid safety problems. The occurrence of cracks in bridges is mainly due to three causes: uneven stress caused by excessive loading, temperature changes, and the quality of materials and construction technology. The work methodology consists of capturing images of the bridge condition using a camera mounted on a UAV. The crack detection process on the images is performed by algorithms in the cloud. The computational load due to a large amount of data makes it necessary to use edge computing technology [43,44].

There are studies in which an inspection procedure integrated with UAV fieldwork and advanced data analysis tools is propounded [45]. The proposed work methodology consists of generating a 3D point cloud obtained from the images taken with the UAV and SfM technology. Then, a segmentation of the bridge parts is performed using machine learning techniques, and an algorithm based on computer vision is applied for the automatic detection of damage [46]. Finally, all the products obtained are implemented together in a digital model (BrIM) [47]. The result will be a 3D model that allows the damage to be visualized and quantified. This study presents the methodologies for the structural diagnosis of the Lucano Bridge in the municipality of Tivoli, Italy [48]. The images obtained with the UAV allow us to obtain a complete 3D representation of the bridge, its chromatic properties, and its size. This information can be used for further architectural restoration studies (Figure 10) [48].

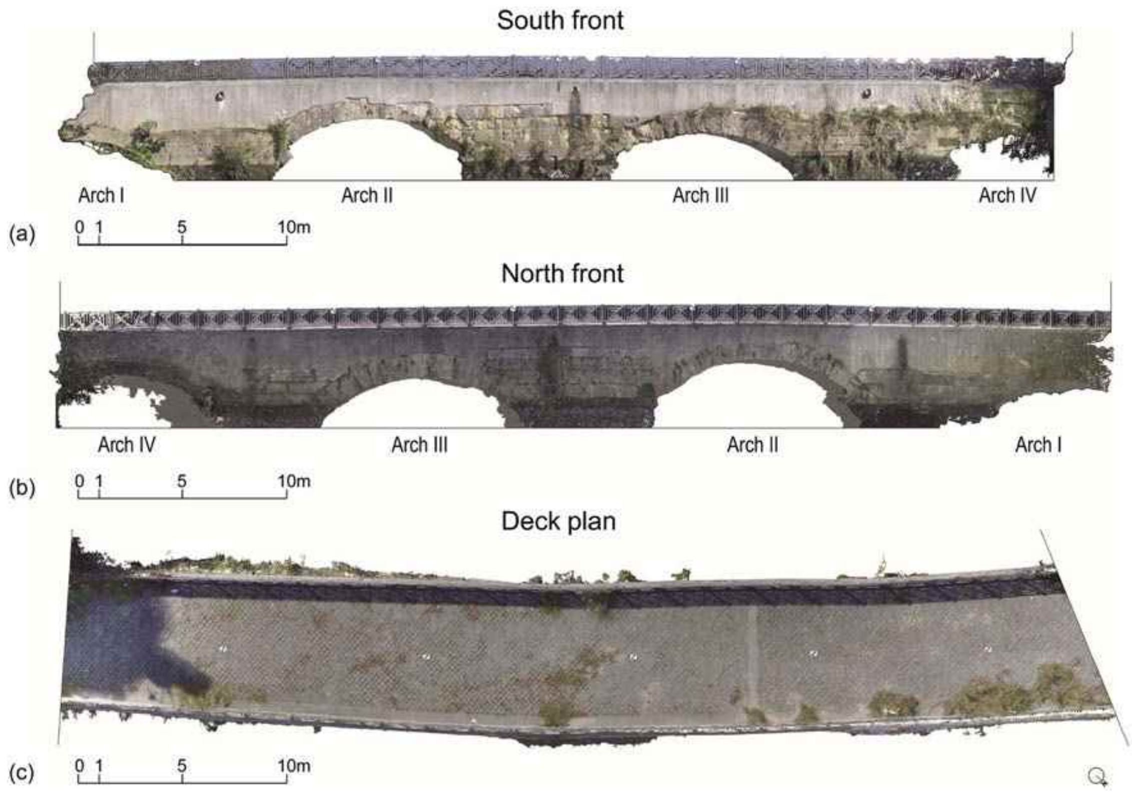



**Figure 10.** 3D model of the Lucano Bridge obtained by photogrammetry (**a**) South front (**b**) North front and (**c**) Deck plan.

The following techniques were used to carry out this work: 3D photogrammetry with UAV, infrared thermography (IRT) [49], and ground penetrating radar (GPR) [50]. The thermal camera can identify surfaces that are affected by water retention. The data collected show that the bridge is subjected to strong temperature changes, which aggravates the risk of cracking (Figure 11) [51].

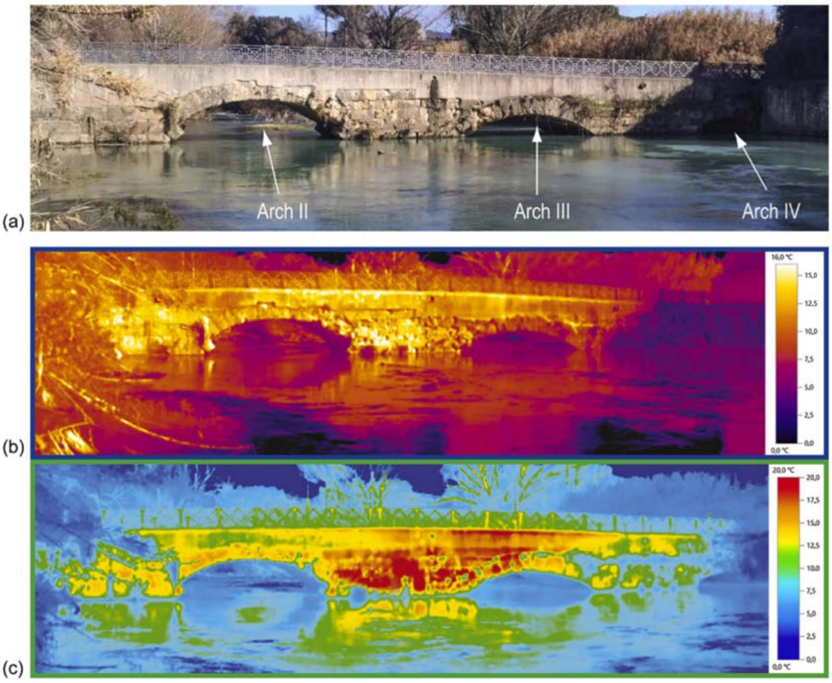



**Figure 11.** Thermographic image of the Lucano Bridge. (**a**) General view (**b**) Low temperature and (**c**) High temperature.

The results obtained with the GPR provided information on the internal structure of the deck and buried objects of the original structure. The goal of using these technologies is the preservation of communication infrastructures and historical heritage.

The use of comprehensive methodology, for the inspection and detection of damage to bridge structures, through UAVs and 3D recreation, is an important aspect for video-based inspections, methodologies for 3D recreation, and data management and exchange.

This paper presents a comprehensive methodology using UAVs for the inspection and detection of damage to bridge structures. The most important aspects covered are video-based inspections, methodologies for 3D recreation, and data management and exchange [52].

A study development by Seo et al. [31] analyzes the effectiveness of the use of drones for bridge inspection. By comparing historical reports with those obtained following the drone inspection methodology, the capability and effectiveness of this equipment were demonstrated.

High-resolution cameras and the use of Photo Scan photogrammetry software provided a detailed and complete view of the damage. A tilt angle of 35° was used to inspect the underside of the platform. Damage such as spalling, corrosion, cracks, and moisture was identified [53–55].

Another type of DIC-based technology can be implemented in drones to determine the load capacity of old or deteriorated bridges, a displacement measurement technique as an alternative to conventional sensor-based measurements by incorporating digital image correlation (DIC) and UAVs [56].

*2.3. Dams*

A dam is an artificial construction whose purpose is to contain the water of a natural channel with the following objectives: to raise the water level so that it can be diverted to conduction, to generate a water reservoir to retain surpluses and supply water in times of scarcity, and to cushion or laminate the peaks of water floods.

Because they are essential infrastructures for the subsistence of the population, their safety is the focus of engineering attention. The absence or lack of vigilance and maintenance of the structure can lead to a failure (rupture) that affects the safety of the population in the surrounding area [57].

With the use of neural networks and computer vision algorithms, the results obtained with the use of UAVs to monitor the structural conditions of dams can be improved. To identify anomalous behaviors and minimize or suppress their effects, the continuous monitoring of dams using different systems is essential to maintain a good state of health of the structure. In addition to the mathematical models that allow a simulation of the behavior of the dam structure and the sensors placed on it, there are other methods based on the artificial vision that allow us to monitor the state of the dam without the need for direct contact with the structure, such as UAVs that can generate high-resolution models representing real structures [58].

The great development of computer vision algorithms [59], the use of convolutional neural networks in terms of their computational scope, and the modernization of sensors have made this type of technology the main tool for monitoring the structural condition of a dam. It allows for the detection of cracks with a resolution based on a pixel. This method is suitable for localized points in the dam structure but not for the dam itself [60].

For the evaluation of the entire dam using two types of drones (Figure 12) [61], images taken from the top face of the dam are used, which are then processed to generate a 3D model to help analyze the weak points of the structure (Figure 13) [58].

**Figure 12.** Drones used for the case of study (DJI Phantom 4 Pro y M210 manufacturer DJI, Jiansanjiang, province of Heilongjiang (Chine)).

To improve the accuracy of the generated 3D model results, ground control points (GCP) can be used (Figure 14) [58] for high forward and lateral overlapping parameters of the images. Due to the complication involved in placing the control points on the terrain (Figure 15) [58], a study is performed that makes use of few GCPs but still allows for an accurate 3D model. This model achieves high accuracy at the crest of the dam for emergency monitoring, it also allows the location of collapses and cracks. This method is efficient and economical, but it does not allow locating millimeter displacements on the dam surface. New algorithms are being developed that help to automatically recognize flaws in the 3D model of the dam.

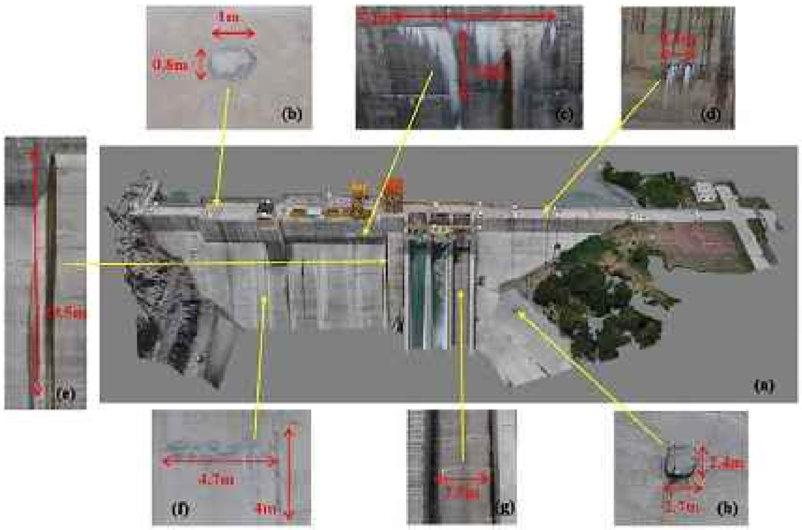



**Figure 13.** 3D model for dam structure damage detection. (**a**) General view and from (**b**–**h**) Damage details.


**Figure 14.** Ground control points (GCP).

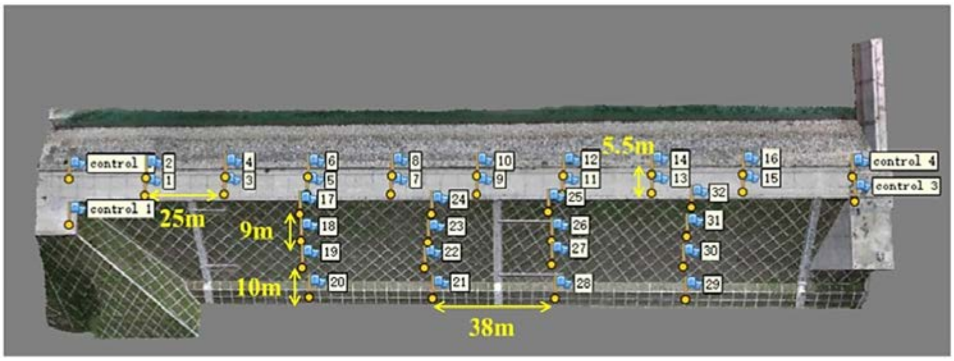



**Figure 15.** Location of ground control points (GCP).

Due to the limitations produced by the difficulty of detecting and growing small fissures, it is possible to take photographs from different angles analyzing the effectiveness of drones for monitoring an arch-gravity-type dam [62]. In contrast to traditional photogrammetry, the structure from motion (SfM) technique [63,64] allows for the use of photographs that have been taken from different angles and distances, without the need to know their position during the shot. Currently, there is different photogrammetry software (version 2014)on the market that allows for the use of the SfM technique (Figure 16) [65] for the creation of point clouds and 3D clouds in a fast way. For this project, different images were taken with a UAV, and a 3D model was generated (Figure 17) [65] as well as a point cloud of the dam. If the model is to be referenced with precise coordinates in a global mapping system, support points or GCPs must be incorporated.

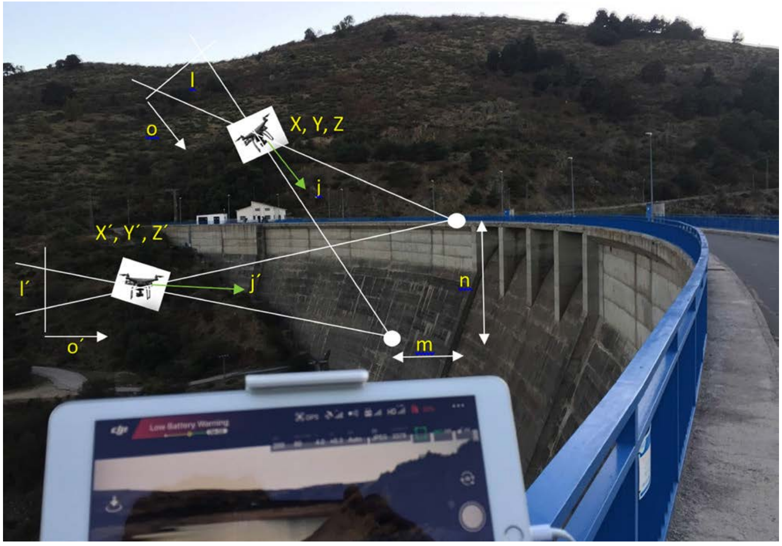



**Figure 16.** Data collection positions following SfM methodology.

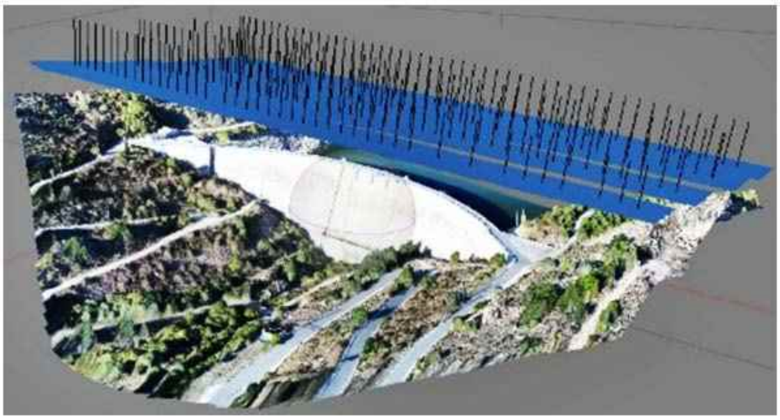


**Figure 17.** 3D model of the arch-gravity dam.

Dam monitoring is based on visual inspection. If a comparison is made of two models at various time intervals and georeferenced in the same coordinate system, displacements and deformations of the dam structure can be identified.

The use of UAVs for monitoring can be applied for the process of dam removal and river restoration [66]. A drone, the SfM photogrammetric technique, and machine learning are used to carry out the process [67]. The main objective is to evaluate the different geomorphological and vegetation changes in the phase before and after dam removal. An algorithm based on support vector machines is used for vegetation classification [68]. Sediment movements after dam removal are also mapped to assess changes in land volume. UAVs provides more accurate information in locations that are difficult to access by conventional ecological assessment methods.

### 2.4. Power Line Inspection

The current society has a strong dependence on electricity and damage to power line components (insulator, tower, conductor, etc.) can trigger a power outage. The main objective of power line inspections is to verify their condition and decide which components should be replaced; to ensure the power supply to the population, the inspection must be conducted dynamically and simply to obtain real-time information that will help in decision making [69,70].

The rugged natural environment, large areas, and the diversification of components pose serious problems for power line inspection. Traditional inspection methods were based on visual inspection in the field or by using aerial vehicles, such as helicopters; their major disadvantage is their high cost, loss of efficiency, and the impossibility of obtaining real-time data (at short time intervals). With the disadvantage of the safety of performing such work with manned vehicles, which, in case of an accident, has a high material and personnel cost.

To solve the above problems, UAV technology, which is booming and widely used in multiple applications, is presented [69,70]. The main advantages over traditional methods are their low cost, high safety, and high efficiency [71]. Data collection is performed remotely, which helps to increase personal safety, because the operator or inspector does not need to go to the study area. Visible spectrum images (RGB) are the most used in this type of work. Sensors that acquire this type of image are available in most drones, and therefore, it is a relatively low-cost product compared to the use of other sensors (multispectral or thermal).

The procedure for the inspection of power lines using drones or UAVs is based on the following two steps: data acquisition in the field and the subsequent analysis of the acquired data. The data acquisition process is quite simple and can be performed by any experienced drone operator; as for the data processing and analysis, it is a somewhat more technical job and must be performed by a specialist technician. The analysis is usually performed by a manual method, which is too time-consuming and often produces inaccurate results. Due to the problems caused by manual analysis, research is being carried out into different fast and highly accurate analysis techniques that allow automatic recognition of the state of the power line using images of the visible spectrum.

Among the different automatic analysis methods, the use of deep learning algorithms is proposed [72]. There are other types of analysis techniques using algorithms, but the use of this type was considered because of its broad advantages for ease of implementation by humans [73,74].

The processes for data acquisition are indicated in two ways: First, images were taken with a visible camera (RGB) and then generating a 3D scene (Figure 18) [75]. The second option proposes the acquisition of LIDAR data using UAVs [76–78]. Drones are an essential tool for power line inspection; however, self-driving UAVs do not guarantee the total reliability of data collection. Finally, the generation of a 3D point cloud from which the power lines and vegetation can be extracted due to measuring their respective distances with high accuracy. Both methods obtain fairly accurate results; the use of visible spectrum (RGB) imaging yields results with lower accuracy compared to LIDAR data (Figure 19) [75], although its cost is much lower. The operator or the company in charge of the work will choose the most cost-effective option to achieve the final objective.

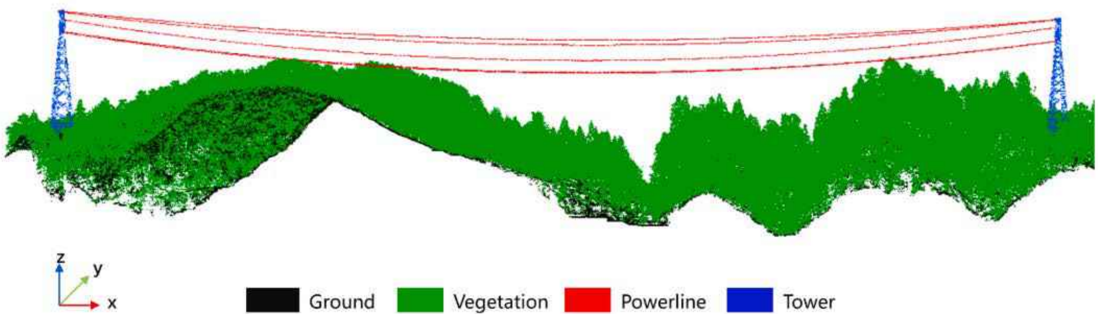



**Figure 18.** Reclassified RGB point cloud.

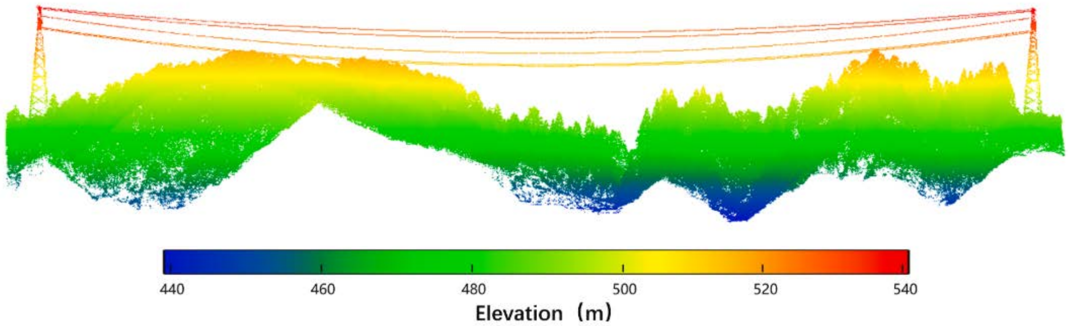



**Figure 19.** LIDAR point cloud.

LIDAR with the help of deep learning algorithms represents a breakthrough for the implementation of autonomous air routes, as it allows the creation of autonomous air routes from a 3D point cloud [79].

For the other hand, the natural environment and advancement of the vegetation surrounding the power lines, large areas, and diversification of components suppose serious problems for power line inspection. The space surrounding the power lines is often referred to as the power line corridor. This space allows a safety distance to be maintained between the power lines and the adjacent elements (buildings or plants). There is a severe problem regarding the invasion of trees into the space represented by this corridor, partly due to their uncontrolled growth. If the growth process of the trees is not monitored, they could break power lines and cause a power outage or fire. Knowing the status of vegetation growth around the corridor's safety zone is of vital importance. Traditionally, field inspectors observed and measured the safety distance between the vegetation and the power line; this method is not very accurate and is very time-consuming. It was proposed to use different complementary techniques that would allow the work to be carried out more efficiently. The technology used was drones or UAVs. With the use of UAVs and its complementary techniques, we know the state of advancement of the vegetation surrounding the power lines to maintain the safety corridor of the power lines in good condition [75].

To determine the growth of the trees, we used Richards' theoretical model [80], which proved to be the one that best adapted to the real representation. This model was used to be able to model a future forecast of the growth of the trees in the area and to be able to carry out the different actions to avoid the invasion of vegetation into the power line corridor.

Although the results obtained from LIDAR processing are quite accurate, they are affected by some errors, such as the non-automated recognition of tree types, error in class extraction, the inaccurate prediction of tree height, and the inaccurate identification of power lines. There is always a need to perform on-site verification of the results obtained and make appropriate decisions.

Therefore, the use of drones or UAVs for the detection of vegetation invasions on power lines does not avoid having to make the respective field visits, although it does improve the efficiency of the work, because there is only the need to go to the areas cataloged with invasive vegetation.

### *2.5. Photovoltaic Plants Inspection*

Due to climate change, other types of cleaner energies have been developed, among which solar energy stands out for being sustainable, clean, and ecological. The construction of photovoltaic projects has proliferated in recent years; for their performance to be adequate, continuous maintenance must be conducted to detect damage or defects. The current trend is to build large areas with solar panels, so the drone is an essential tool, because it allows for the collection of massive data in a relatively brief period.

Inspections are conducted with drones or UAVs [81,82], whose purpose is to detect faults such as:

- Mismatches or imperfections: cells that do not work correctly concerning the others.
- Breakages: these are the most frequent defects, they can occur during the manufacturing, transportation, or assembly process or due to meteorological factors once installed.
- Discolorations: due to internal factors (poor polymer quality) or to a sudden change in temperature and humidity.
- Dirt: caused by accumulated dust, contamination, or bird droppings.
- Lamination: defects in the lamination process or due to external climatic factors.
- Micro-cracks (snail tracks): small breaks in the surface of the plates caused by environmental factors.

Visible spectrum (RGB) and thermal images are used for the inspection process [83,84]. The most important parameters to consider obtaining the GSD (pixel size) are the resolution of the camera and the flight height, as there is a direct relationship between this value and the type of defect being searched for. RGB images should be taken at a maximum tilt angle of 3°, although oblique images are also available. The thermal camera to be used must be sensitive to the bands of the electromagnetic spectrum located between 8–14 μm and with a low thermal sensitivity to be able to detect small temperature variations.

In Figure 20 [82], orthoimages in RGB and thermals are presented [82]. A thermal orthoimage is used for the detection of hot spots. In Figure 21 [82], the detection process of these points was carried out using an algorithm based on different processes for the enhancement or improvement of the images, this being a fully automatic process. A dense RGB point cloud was also generated using structure from motion technology [85], to individually extract each of the solar panels and, subsequently, locate the existing defects. All images obtained were processed using Pix4D Mapper software version 2022 [86].

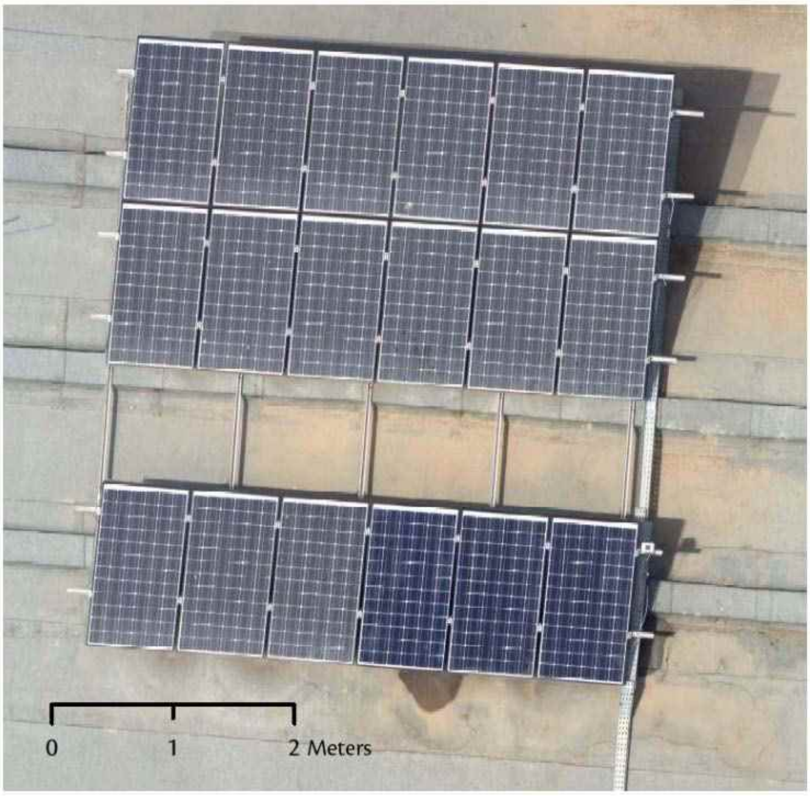



**Figure 20.** Orthomosaic for visual inspection using Pix4D Mapper software.

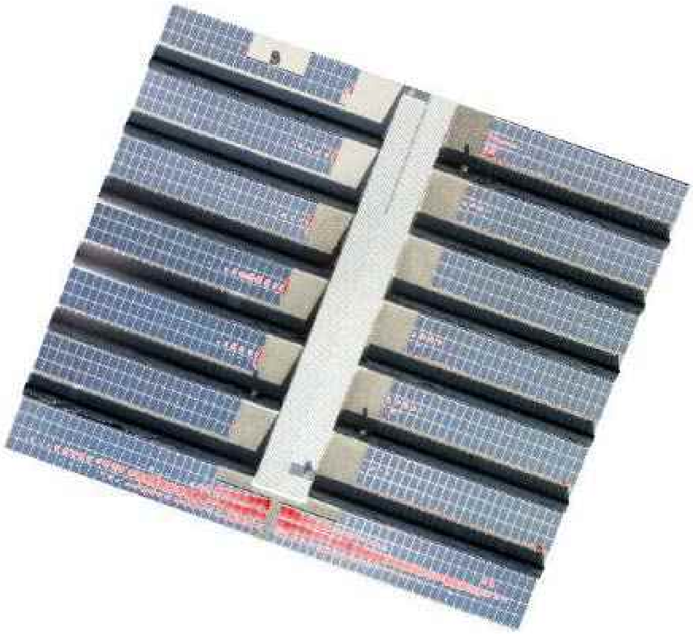


**Figure 21.** Automatic hotspot extraction.

Solar energy is a field that is currently under development, and whose inspection techniques are constantly evolving, with the field of automation of algorithms for detecting defects in the structure of the plates being the one on which most research is being conducted. It can apply the new UAV technology for the maintenance and control of the photovoltaic solar plant system [81]. The images acquired by UAV allow for obtaining the most appropriate location and distribution of the solar power plant. To achieve maximum profitability, UAVs help to detect and classify any factor that diminishes performance, as well as to monitor in real time the status of the solar panels.

### *2.6. Hydrological Studies*

Currently, UAVs are used for environmental monitoring, as they help to decrease the time and field work dedicated to surveying and sampling. The technological development of drone-equipped sensors and improved image processing (SfM) techniques have facilitated environmental research.

Wetlands are particularly important ecosystems, as they provide hydrological regulation, and carbon absorption and support biodiversity. In recent years, they have been highly damaged, and it is essential to carry out conservation and management work, as well as restoration, to prevent their disappearance. The idea of using UAVs as a tool for continuous wetland condition monitoring, mapping, and modeling is promising [87]. Advances in multispectral and hyperspectral sensors have made environmental research easier [88,89], allowing for the analysis and detection of invasive species, making drones essential tools for the monitoring and control of marine and freshwater ecosystems. Due to their limited accessibility and generous size, it is difficult to collect data on the ground, so it is essential to make use of UAVs and sensors or cameras [90,91]. These recent technologies allow for the visual recognition of ecosystem components, the evaluation of indicators, and the condition of wetlands, as well as their mapping, modelling, and change detection for decision making regarding their restoration and conservation.

It is important to monitor the physicochemical parameters of lake water for management and water quality. Water temperature is one of the parameters to be monitored, as any variation in temperature can cause damage to the aquatic system (algae growth, oxygen depletion, and changes in fish distribution) [92]. For temperature monitoring, sensors embedded in buoys are often used; they are useful but require transportation and labor, as well as being in a specific location.

UAVs are more suitable, as they are mobile and deployed from a location close to the lake. These drones have been modified to take in situ measurements using depth (Figure 22) [92] and temperature sensors (Figure 23) [92] on board; in addition, a system for landing and take-off on the surface of the water was developed. These modifications facilitated faster and more efficient data collection, making it possible to cover a larger area of water. Its mobility, high spatial resolution, and low cost also stand out.

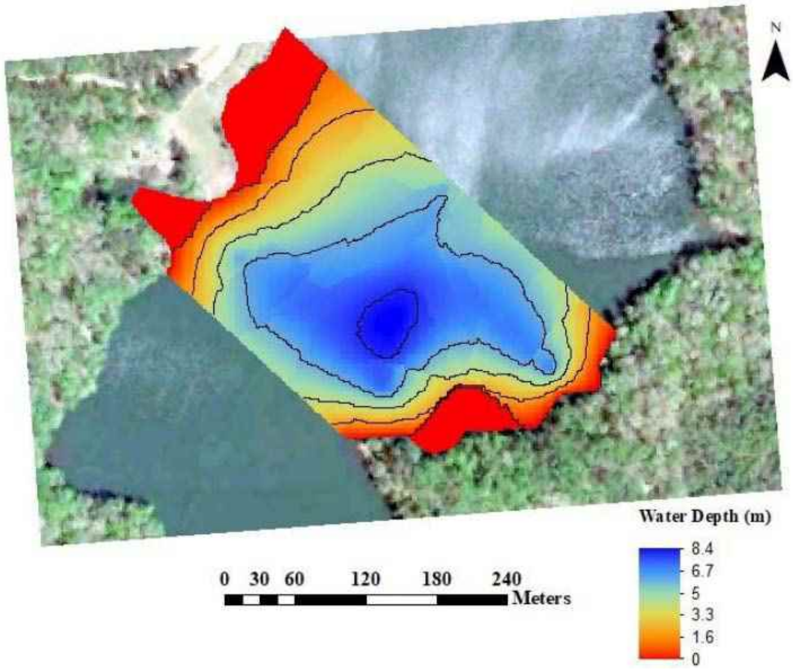



**Figure 22.** Depth map of Lake Issaqueena.

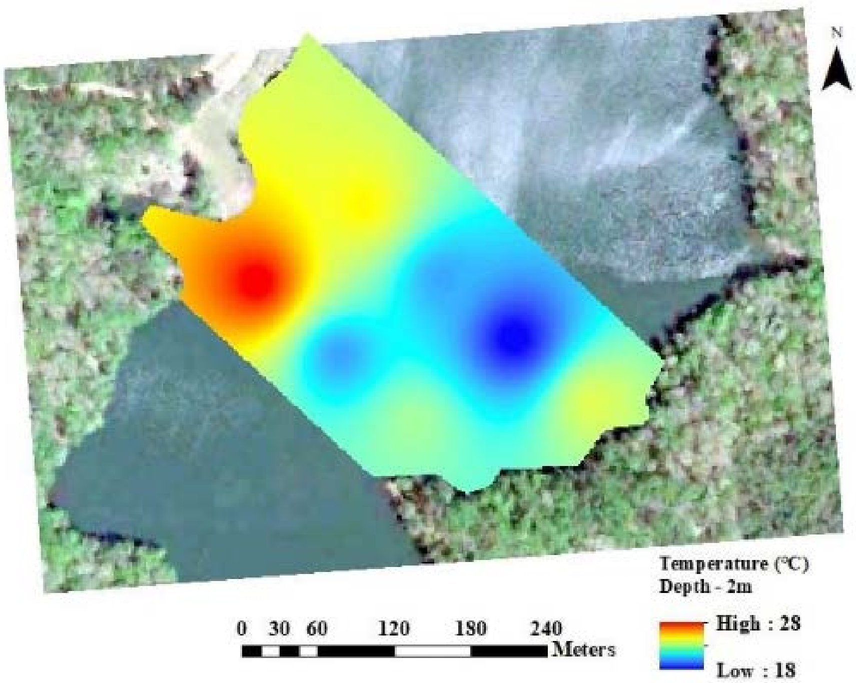



**Figure 23.** Lake Issaqueena temperature map.

In other cases, it is possible to use different sensors on UAVs and topo-bathymetric LIDAR (Figure 24) [93] to predict the variations that the shoreline of the lakes may undergo [93].

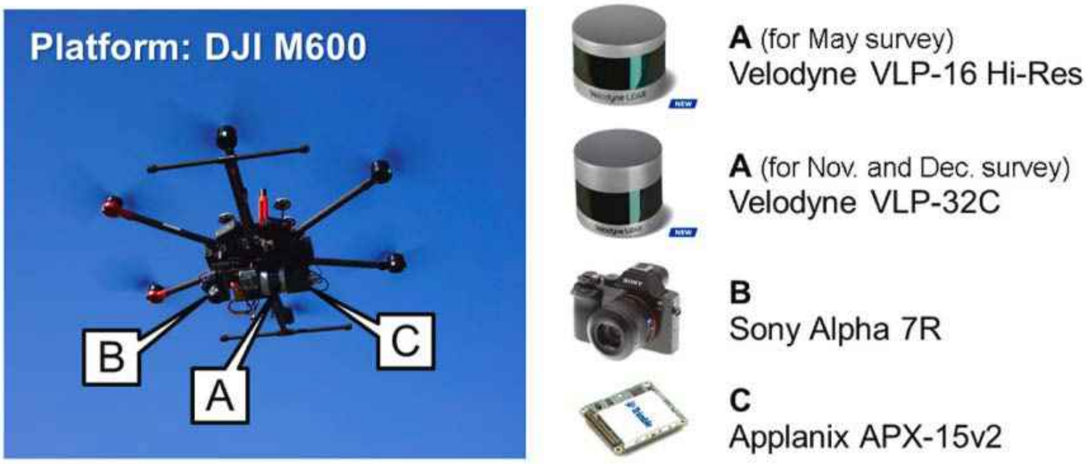



**Figure 24.** Materials used in the study.

Abrupt changes in lake water levels lead to the rapid erosion of lake shorelines, damaging beaches, houses, and infrastructure. Studies of these changes are usually carried out by remote sensing; the most used technology is topo-bathymetric LIDAR [94,95], which maps terrestrial and submarine topography. As the surveys are conducted with airplanes and due to their high cost, the data collection is carried out in large time intervals, so it is not effective to measure the evolution of the coast in short periods. To overcome this obstacle, UAVs are used, because they are more efficient, have high accuracy and high temporal and spatial resolution, and are ideal for taking data in short periods.

The SfM methodology [63], based on visible spectrum imaging, cannot identify elements on homogeneous surfaces and in wooded areas; as an alternative, the LIDAR system is used, which, with its laser ranging unit, can pass through spaces between the branches and collect data below the wooded area, which will be used to develop predictive models of shoreline variations (Figure 25) [92].

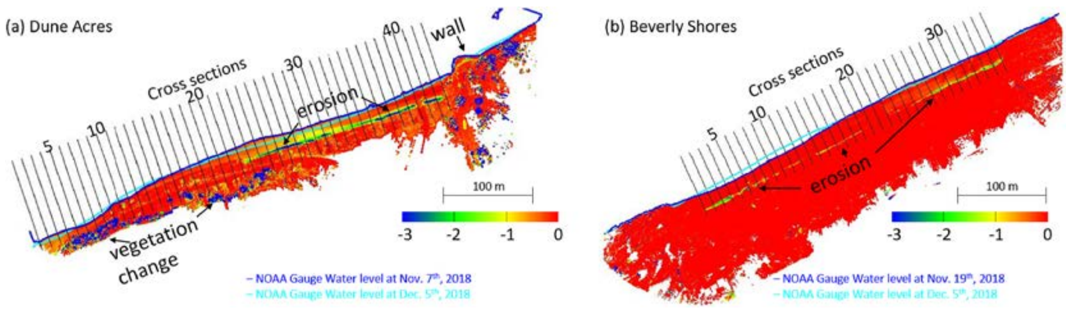



**Figure 25.** Representation of shoreline variations.

The use of UAVs and data acquisition sensors (RGB and infrared cameras) is presented as a simple and efficient method for detecting water leaks in river embankments [96]. Their main application is to detect leaks in embankments in times of floods. It is of vital importance to detect embankment leaks in time to avoid major damage to areas adjacent to the river. If detection work is not carried out in a timely and accurate manner, the consequences can be catastrophic, as was the case in Hunan (China) in 2016 (Figure 26) [97].

**Figure 26.** Dam failure in Hunan (China).

Two types of sensors equipped on UAVs are used to detect water leaks:

- Visible camera. It has a higher resolution that allows obtaining information with greater detail. If the embankment surface is covered by vegetation the accuracy to identify the leak is considerably reduced (Figure 27) [96].
- Thermal or infrared camera. It correctly shows the distribution of the different temperature values for each of the embankment surfaces. Its main disadvantage is that it has a low resolution and provides little information. If the slope of the embankment is complex, the results obtained are not satisfactory (Figure 27) [96].

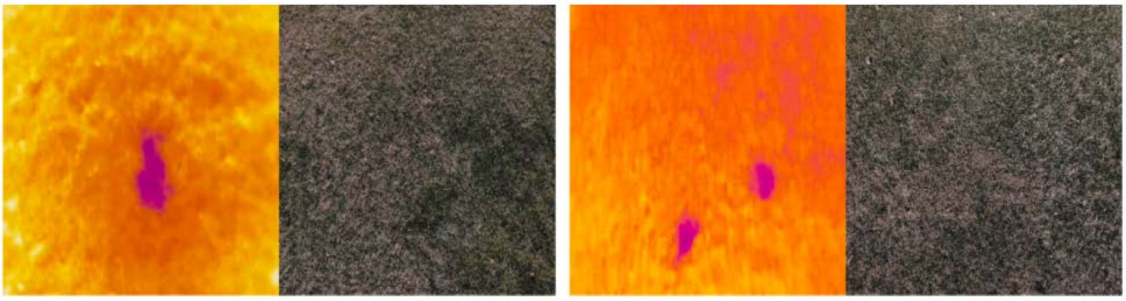


**Figure 27.** Comparison of thermal vs. visible camera results.

The speeded-up robust features (SURF) algorithm is used for the automatic recognition and detection of water leaks [98], which allows for detailed information to be extracted from the images.

To verify that the results obtained by the indicated method are adequate, they are compared with a field test. It is concluded that the method used is feasible and efficient for the identification of water leaks in embankments.

The functions of a water temperature assessment system equipped with a multirotor UAV to evaluate thermal stratification are developed [92]. To achieve in situ measurements, a device was installed that allows for the positioning of the drone on the water surface. In Figure 28 [92], the sensor array consists of a microcontroller unit, a temperature sensor, and a pressure sensor. Seven points on the surface of the lake were chosen for the measurements. Water temperature maps were then created at three different depths at each measurement point. The main advantages of this method are its high spatial resolution, its ease of access to all areas of the lake, its speed of data collection, and its variability in the length of the probe extension cable that allows it to be adjusted according to depth.

**Figure 28.** Technology for UAV positioning over water.

Koutalakis et al. [99] propose the use of UAVs to accurately measure the velocity of a river to subsequently develop water resource management plans. For the measurements, video shots are captured over a specific stretch of Aggie's River in Greece. Three programs were used to calculate the surface water velocity: PIVlab [100], PTVlab [101], and KU-STIV [102] in Figure 29, Figure 30, and Figure 31, respectively [99]. The results of these methodologies were similar. To obtain more reliable results, they were combined with measurements taken with a current meter (Figure 32) [99].

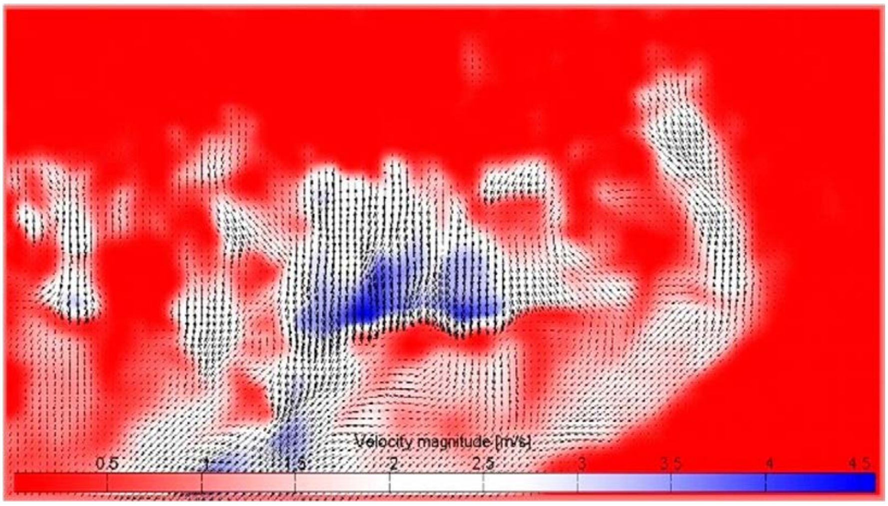



**Figure 29.** Results obtained using PIVlab.

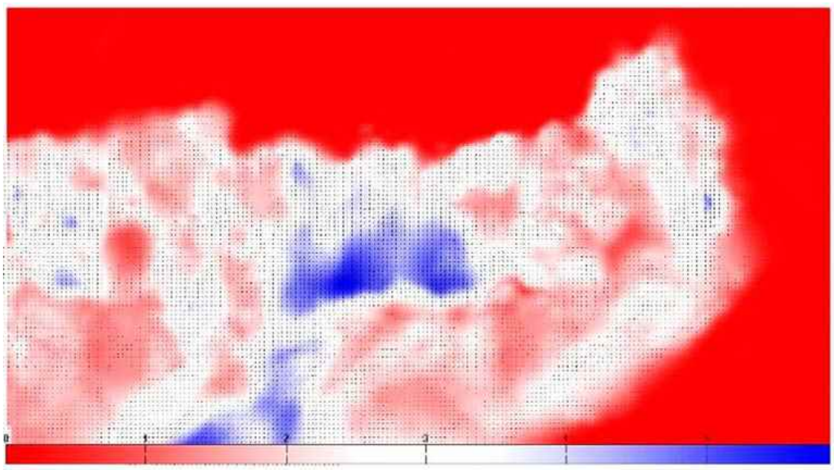


**Figure 30.** Results obtained using PTVlab.

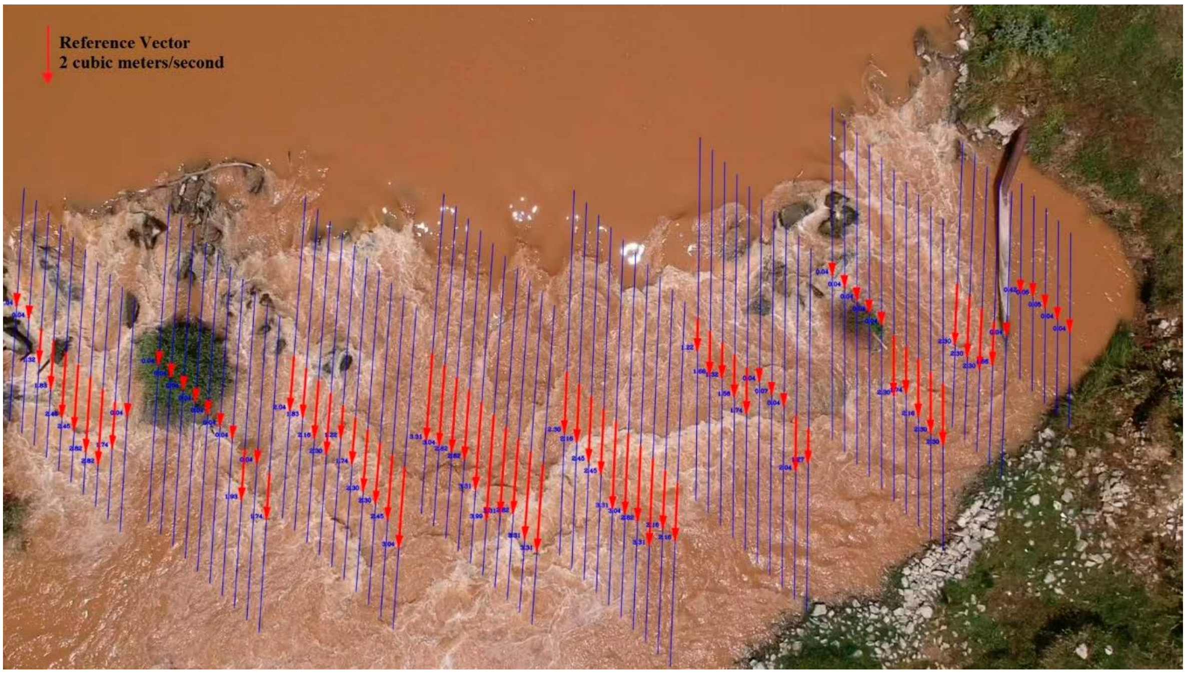



**Figure 31.** Results obtained using KU-STIV.

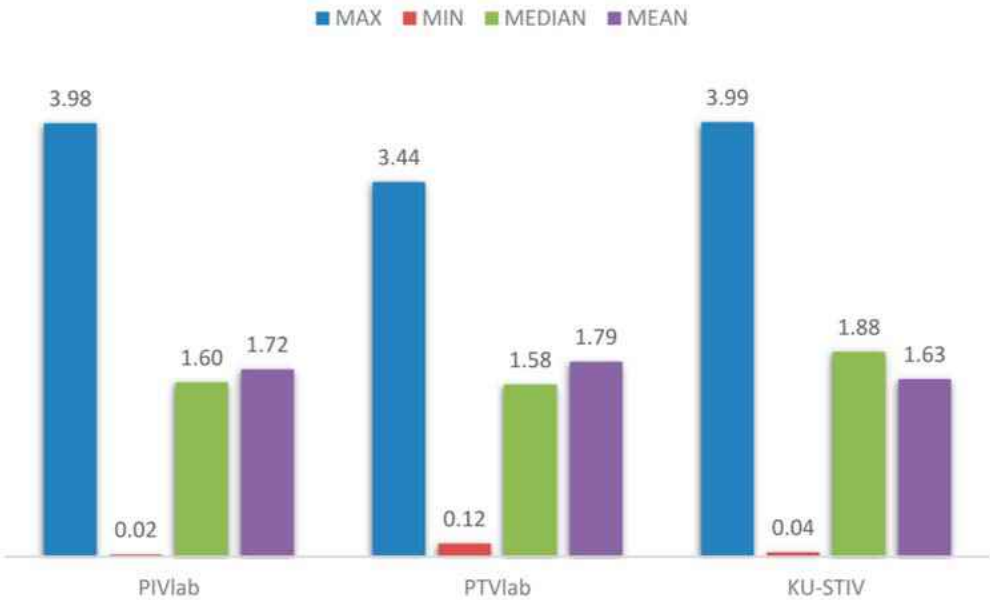



**Figure 32.** Comparative results.

*2.7. Road Inspection*

To maximize safety and increase the service life of roads, maintenance is necessary. This work has been carried out manually and visually, which is time-consuming and labor-intensive, and the results obtained depend on the experience of the worker. Biçici et al. [103] propose to develop a highly accurate automated method for the detection of road surface defects. The images taken by the drones are used to develop 3D point cloud models, using the SfM methodology. To perform the defect detection process, an algorithm is applied to obtain as a result the perimeter, diameter, length, and depth of the defect. The results obtained using the algorithm and the results obtained using the manual identification method were compared, concluding that these results were similar, but the automatic algorithm provides greater time savings and is easier to apply. The problem arises when surfaces are too shiny or shaded by too much or too little light; this can cause failures in the 3D point clouds, and it is more difficult for the algorithm to detect road defects.

Inzerillo et al. [104] evaluated the use of innovative and low-cost technologies (UAV) to analyze and automatically detect road pavement failures. The structure from motion (SfM) technique is used to generate the 3D model (Figure 33) [104], which was compared to the laser-scanned 3D model (Figure 34) [104] to analyze its accuracy and reliability. The results show that it accurately details pavement defects.


**Figure 33.** 3D model generated by the SfM technique.


**Figure 34.** 3D model generated by a laser scanner.

Nappo et al. [105] studied the detection and classification of cracks in the road pavement by using both 3D and 2D photogrammetric techniques. Using the 3D model, a map of hot spots representing pavement damage was obtained to provide an overview of the road condition; a multi-criteria binary classifier that identifies pavement damage; and a roughness-based methodology for the classification of pavement damage (Figure 35) [105] (IRI—international roughness index) [46,106,107] to quantify the damages and to plan the maintenance works.

A 2D orthophoto was used in Figure 36 [105] to locate longitudinal and transverse cracks with a width greater than 1 cm. If you want to quantify the damage to the pavement, you can combine the 3D model with the 2D orthophoto.

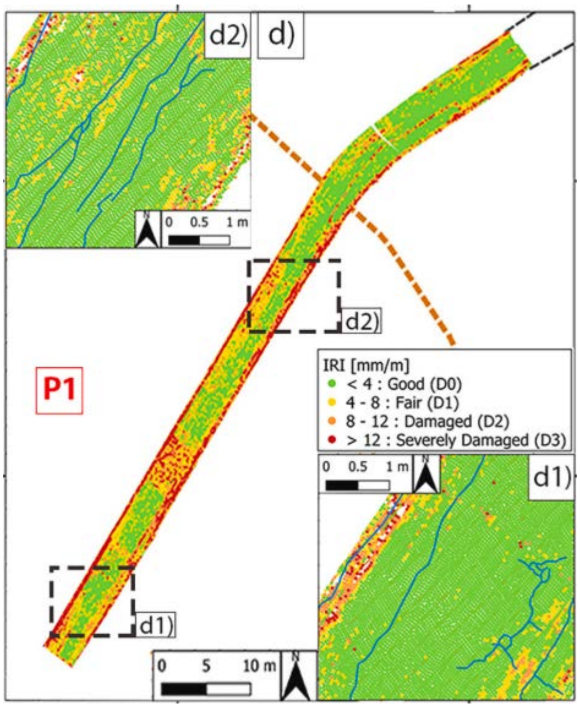



**Figure 35.** Damage classification based on IRI methodology.

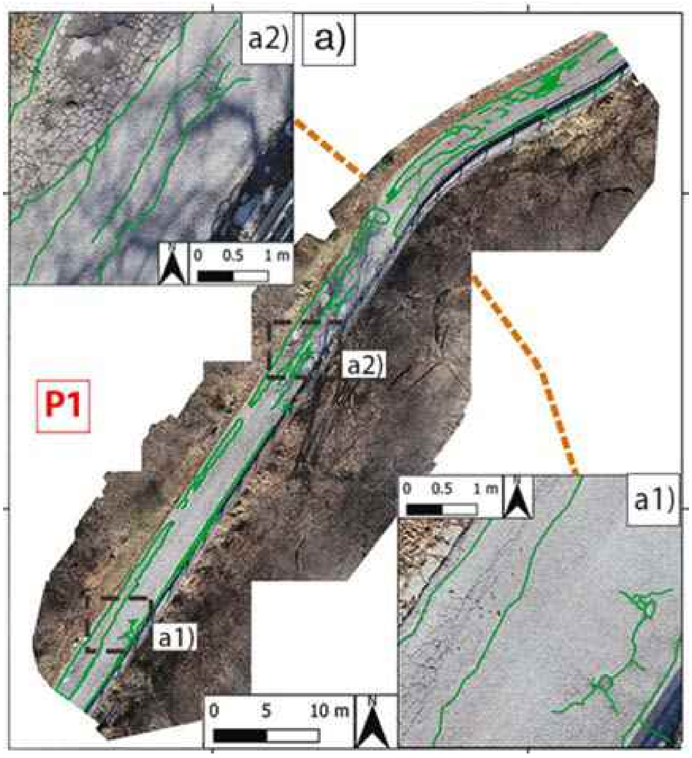



**Figure 36.** 2D orthophoto for the location of grackles.

Although the method used is reliable, it can be refined using complementary information, such as InSAR displacement data [108,109], and field measurements.

*2.8. Slope Supervision and Maintenance*

Many goods are transported by railroads and their tracks are sometimes located between rugged rocks and mountains in inaccessible places. To avoid interruptions or delays on railroad lines caused by rock falls, continuous monitoring and the maintenance of slopes are necessary. It is necessary to develop a rapid and effective assessment methodology for the resolution of the safety problems caused by these landslides, as the traditional methodology is time-consuming, labor-intensive, and involves a danger to the safety of workers.

Puppala [110] presents the efficiency and cost-effectiveness of using UAVs as a tool to monitor the stability of railroad track embankments and improve their safety zones. Drones solves the problems by helping to obtain data remotely, using short-range photogrammetry technology to make qualitative and quantitative estimates of the state of health of infrastructures [111,112]. Images with the topographic characteristics of the slopes are obtained using 3D geometry (Figure 37) [110] to subsequently assess their stability and improve the safety zones (Figure 38) [110].

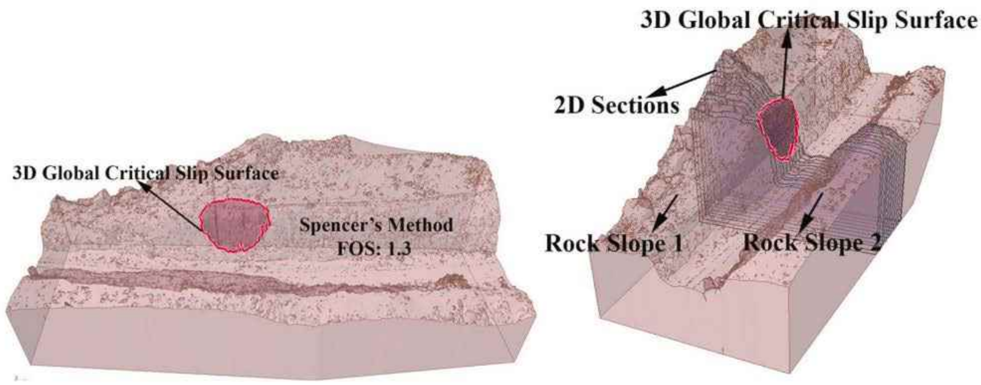



**Figure 37.** Three-dimensional analysis of slope stability.

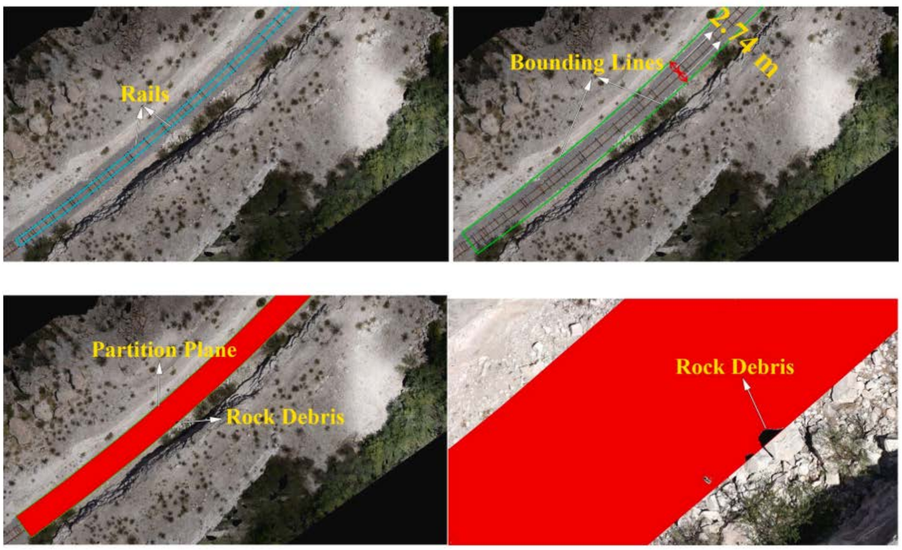



**Figure 38.** Safety zone evaluation.

The methods used for data collection are an optical camera sensor and an airborne LIDAR sensor that allows for the direct generation of the point cloud. By taking data over time, interactive models can be generated, showing the evolution of the slope. These main objectives of this study are to identify the slope angle of the rock-cut, plan the slope stabilization tasks, and specify the type and size of the excavation equipment.

This study demonstrated that 3D models allow for the effective assessment of problem areas and identification of safety zones. The results obtained will be used as a basis for conducting maintenance work to achieve safety in rail traffic.

### 2.9. Monitoring of Landfill Operation

Landfill waste is always moving and settling, which implies a topographic transformation of the soil. A periodic topographic survey is necessary to record the progress of compaction and landfill geometry. To measure its compaction level, a study of its geotechnical stability is conducted.

The geometry of the landfill should be recorded periodically using geographic measurements to assess whether the settlement and placement of the waste are being conducted correctly. Surface settlements and slope profiles should also be measured and compared with predictive models to monitor the geotechnical stability and displacement of the landfill.

Drones or UAVs are a suitable alternative to classical topographic measurements, as the difference between the results is small; due to their low cost, they are an ideal tool for monitoring the geometry of landfills [113]. The measurement gases emitted by the landfill can be measured by thermal infrared sensors equipped with drones, and multispectral sensors allow for determining the humidity and temperature of the terrain.

The study by Mello et al. [114] developed a methodology using UAVs to verify the progress and stability of a landfill. At present, the use of drones for landfill monitoring represents only 5%, but due to their low cost and high accuracy, this percentage will increase considerably in the future. Their main drawback is the need to take control points on the ground, but this can be overcome by using high-precision GNSS systems, although its acquisition cost would be higher [115,116].

To achieve progressive monitoring of the landfill performance, constant studies of the geometry of the landfill surface must be conducted.

Table 2 summarizes the applications, advantages, limitations, and future applications of UAV in civil engineering.

**Table 2.** UAV applications in civil engineering.

| Application | Advantages | Limitations | Future Applications |
|---|---|---|---|
| 1. Building Inspection | Automated crack detection, integration with BIM models, and reduction in costs and occupational risks. | Sensitivity to light and weather conditions and dependence on evolving AI algorithms. | Full UAV-BIM integration for predictive maintenance and early detection with advanced deep learning. |
| 2. Bridge Inspection | Access to hard-to-reach areas, accurate 3D models, safer, and more economical inspections. | Limitations with adverse weather conditions and difficulty in inspection under certain geometries. | Digital Twin models, autonomous inspection with 360° cameras, and real-time AI. |
| 3. Dams | High-resolution 3D models, continuous monitoring, cost reduction, and less human risk. | Difficulty in detecting millimetric displacements and need for control points in the field. | Real-time monitoring and predictive detection of structural failures using AI and deep learning. |
| 4. Power Line Inspection | Efficient fault detection, low cost compared to traditional methods, increased personnel safety. | Limited recognition of component types, errors in automated detection, and on-site verification required. | Fully autonomous inspection with scheduled air routes and predictive fault analysis. |
| 5. Inspection of photovoltaic plants | Fast and massive inspection, identification of thermal and visual defects, and improvement of energy efficiency. | Need for accurate calibration for thermal detection and sensitivity to weather conditions. | Real-time performance monitoring and the use of UAVs for automated preventive maintenance. |

**Table 2.** *Cont.*

| Application | Advantages | Limitations | Future Applications |
| --- | --- | --- | --- |
| 6. Hydrological studies | Rapid environmental monitoring, high spatial resolution, and access to remote or fragile areas. | Cost of advanced sensors, reliance on post-processing techniques, and limited resolution in areas with dense vegetation. | Automated monitoring of physicochemical parameters and predictive modeling of environmental impacts. |
| 7. Road inspection | Damage detection automation, detailed 3D models, and maintenance planning improvement. | Problems with shiny or shaded surfaces and need to supplement with additional data (InSAR, field). | Integration with displacement sensors, dynamic repair planning, and road closures. |
| 8. Slope supervision and maintenance | Accurate stability assessment, safety zone planning, and landslide prevention. | Periodic repetition of flights and difficulty in areas with dense vegetation or unstable rocks. | Continuous monitoring with predictive analysis of geotechnical risk and simulation in digital twins. |
| 9. Monitoring the operation of the landfill | Economic topographic monitoring, monitoring of settlements and emissions, and support in geotechnical decisions. | Need for GNSS or GCP for high accuracy, still low current usage percentage, and limitations in full automation. | Automation of topographic monitoring and analysis and real-time environmental control using AI. |

## 3. Conclusions

Drones have been a great advance in civil engineering projects. Their advantages over traditional methodologies include remote data collection, the ability to access areas that are difficult to reach, and their low cost and time savings.

Unmanned aerial vehicles (UAVs) are rapidly transforming the field of infrastructure inspection, particularly due to their cost-effectiveness when compared to traditional manual methods. Recent studies emphasize that UAV-based inspections significantly reduce both time and labor requirements, offering savings of up to 50% in operational costs for complex structures, such as bridges [117,118], dams, and solar farms [119]. For instance, UAVs eliminate the need for scaffolding, cranes, or road closures, which are commonly associated with manual inspections, thereby minimizing disruptions and indirect costs.

Several works, including those by Zhao et al. (2023) [120] and Mardanshahi et al. (2025) [121], demonstrate that UAVs equipped with RGB and LIDAR sensors can perform detailed structural inspections with comparable or superior accuracy to traditional techniques, while requiring less logistical support and personnel. Additionally, the use of UAVs allows for more frequent inspections at lower marginal costs, which is critical for the maintenance of aging infrastructure. By integrating UAVs into standard inspection workflows, institutions can allocate resources more efficiently and enhance the frequency and coverage of assessments, ultimately improving infrastructure safety and performance. These findings reinforce the economic and operational rationale for adopting UAVs as a viable alternative to traditional inspection methods. Also, artificial intelligence and deep learning algorithms allow the identification of cracks or flaws on the surface of different civil structures (bridges, buildings, dams, roads, etc.) to determine the state of health of the infrastructure.

Although they are a great tool with great versatility for the interpretation and generation of the results, there is the need to make use of different methodologies or techniques (structure from motion) that allow us to obtain different models in 2D or 3D, such as orthophotos or point clouds.

Despite the advantages outlined, the implementation of UAV technology in the monitoring and management of civil infrastructure still faces considerable challenges across multiple dimensions. One of the foremost barriers is the regulatory framework. UAV operations often require strict compliance with national aviation regulations, including flight permissions, altitude restrictions, and pilot certifications. These constraints vary significantly across countries and regions, creating inconsistencies that hinder broader adoption, as discussed by Kerle et al. [19].

Another key limitation lies in technical aspects. UAVs typically have limited flight endurance, especially when carrying heavier sensor payloads, such as LIDAR or GPR. This restricts their usability in large-scale or long-duration inspections. Furthermore, adverse weather conditions (e.g., wind, rain, fog) can disrupt flight stability and data quality, which remains a challenge for their consistent application in real-world construction sites. In addition, the vast amounts of data generated by UAVs—particularly from high-resolution imagery and 3D point clouds—require advanced computational tools for processing, interpretation, and storage. Organizations often lack the in-house expertise or infrastructure to handle these data effectively, which can delay decision making or reduce the actionable value of UAV-derived insights.

Finally, safety and social acceptance concerns also play a role. UAVs may pose risks of collision or injury, especially in congested urban environments or active construction zones. There are also growing concerns around privacy and data security that need to be carefully addressed through robust governance frameworks. To overcome these challenges, future research and industry practices must focus on developing standardized operating procedures, improving autonomous navigation technologies, enhancing real-time data analytics, and fostering collaborations between regulators, engineers, and technology providers. Only through such integrative efforts can the full potential of UAVs be realized in construction and infrastructure monitoring.

As demonstrated in this paper, drones can be used in a wide variety of fields within engineering. The results obtained with this methodology are precise and reliable; but in the case requiring greater precision, it is necessary to rely on complementary techniques, until in the future they reach the necessary development so that their results are comparable to traditional techniques.

As this technology is completely linked to the field of computer science, any progress made in this area will be reflected in improved results and in a reduction in the processing time of the data taken during the flight.

**Author Contributions:** Conceptualization, A.V. and M.D.; methodology, A.V., H.V., and N.A.; experimentation, X.C.M.C.; models iteration numbers, M.D.; validation, A.V. and H.V.; formal analysis, A.V. and N.A.; investigation, A.V., N.A. and X.C.M.C.; resources, A.V.; data curation, M.D. and N.A.; writing—original draft preparation, A.V. and N.A.; writing—review and editing, M.D. and H.V.; project administration, A.V. All authors have read and agreed to the published version of the manuscript.

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