Advances in Civil Engineering

Unmanned Aerial Vehicles Applications in Geoinformatics

Lead Guest Editor: Kamal Jain
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Review Article

Uncrewed Aerial Systems in Water Resource Management and Monitoring: A Review of Sensors, Applications, Software, and Issues

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Uncrewed aerial systems (UASs) are becoming very popular in the domain of water resource mapping and management (WRMM). Being a cheaper and quicker option capable of providing high temporal and spatial resolution data, UAS has become a much sought-after platform for remote sensing. Still, their application in the field is in its early stage. This paper encompasses basic concepts of UAS, different payloads and sensor technologies available, various methodologies for its application in WRMM, different software available, and challenges associated with them, thus presenting a comprehensive review of multiple applications of UAS in different sub-domains of water resources. From cryosphere, rivers and lakes, and coastal areas to sub-surface water, as well as from water quality to wastewater management, the authors have discussed various applications of uncrewed aerial vehicles. At the end of the paper, the authors have identified the issues posing problems in the wider implementation of UAS in WRMM. Also, the future scope of the UAS in WRMM has been discussed.

1. Introduction

Water is the dispenser of life on this Earth [1], and almost three-quarters of the Earth's surface are covered with water. About 2.5% of the planet's available water is stored in the form of fresh water in the form of rivers, lakes, glaciers, polar ice caps, groundwater, soil moisture, water vapour, and many other forms. The distribution of water resources is heterogeneous both spatially and temporally. Therefore, continuous monitoring of water resources becomes necessary for water resource management as it is vulnerable to adverse consequences of anthropogenic activities. The UAS technology is particularly suitable for qualitative and quantitative analysis such as mapping and monitoring of dynamic components of the water cycle [2] such as soil moisture, runoff, evapotranspiration, snow cover, and so on, along with water structures and water-related disasters.

UASs have emerged as a viable option to fill many gaps between spaceborne and terrestrial in situ observation technologies [3], offering (1) availability of high spatial resolution at lower cost with high temporal resolution; (2) subjective time of sampling by the operator; and (3) payload flexibility [4]. UAS are, therefore, inexpensive [5, 6], versatile, and safer, which can be very helpful in water resource management and monitoring. Many applications in the domain of water resources demand ultra-high-resolution data that satellites cannot provide, and that can be met by UAS [7]. The majority of water problems lie in developing countries with poor access and a lack of data. In such cases, UAS can be of maximum use in monitoring and managing water resources. The UAS data can also help us to broaden our understanding of how global challenges such as climate change and population growth affect our water resources at the local level. Water resources are running out, and real-time water resource management requires increasingly accurate data on water, soil, and vegetation conditions compared to other monitoring applications. Many applications require ultra-high-resolution data that satellites cannot provide and that UAS can fulfil [3, 4]. The WRMM sector is evolving day by day, adding new applications of UAS. From detecting sea-level changes over time [8], lake level changes [9], estimating water storage [10], monitoring riparian systems [11, 12], flood assessment [13–17] to mapping glaciers [18], drones have been used. Recent developments have made it possible to identify the location and spatiotemporal changes in groundwater storage [19]. Thus, there are a plethora of applications and methods based on UAS data that are being studied. New drone-based solutions (e.g., DOWSE [19]) are being developed in sub-domains of WRMM to increase the data collection efficiency and render services much faster. There have been many reviews on the application of UAVs in water resources [2, 18, 20–25]. Some of these reviews are old or mainly focused on only a component of water resource monitoring. These were very focused and lacked an overall synopsis of the WRMM domain.

1.1. Objective. The main focus of this study is to assess the present state of research, opportunities, and challenges to achieve greater application of UASs in water resource monitoring and their use in their management. This is addressed with the following questions:

(i) What are the different UAS sensors that currently exist?

(ii) How can various UAS observations be used in WRMM?

(iii) Which new WRMM applications have been innovated that can be put into practice?

(iv) What are the challenges of UAS technology and the prospects for their implementation?

Section 1 introduces the objective of this paper. Section 2 highlights the historical progression of UAS and a brief account of sensors that are used in WRMM. Section 3 discusses the different applications of UAS in WRMM. We have divided the applications of UAS in WRMM into two broad categories: surface water resources and sub-surface water resources. Section 4 deals with the issues in the application of UAS in different sectors of water resources. In Section 5, we have tried to give a synopsis of software available for structure from motion (SfM)-based processing of UAS-based images. Section 6 discusses the challenges and Section 7 delves into the prospects of this technology. Section 8 summarizes the paper and is titled as conclusion.

Given the rapid proliferation of UAS applications in WRMM, a full investigation of the current state of the art is required to provide a clearer view and encourage further advances. A detailed analysis of existing work is essential for the continuous improvement of UAS application in WRMM, especially for researchers who want to enter the field. For this reason, this article provides a detailed overview of recent breakthroughs in UAS technologies and applications, focusing on UAS photogrammetry and UAS remote sensing. The area of water resources is itself very vast. Nevertheless, the authors have tried to provide an overview of sensors, applications, software, problems, and the future scope of UAS from the water resource point of view. Future research opportunities are also discussed.

2. UAS: Origin, Types, and Sensors

2.1. UAS: Definition and Characteristics. Uncrewed aerial systems consist of crewless aircraft and the equipment to control them remotely. The aircraft or vehicle is also referred to as an uncrewed aerial vehicle or drone or remotely piloted aircraft or uncrewed autonomous vehicle.

A UAS is a system of systems, i.e., a collection of complementary technologies brought together to achieve a specific goal, and therefore there are many different types of UAS in the market today: it can be said that there is one for each technical combination [26]. At the highest level of UAS technology, three key UAS components are typically identified: the uncrewed aerial vehicle, the ground control station, and the communication data link. A communication data link is a connection between the UAV and the ground control station. The ground control station can be explained as the controlling element responsible for the safe and automated flight of the UAV. These are immobile or mobile hardware/software devices used to monitor and control the uncrewed aerial vehicle [26]. Table 1 shows the advantages and disadvantages of UAS.

The development of UAS was initially driven purely by military applications; as with many other areas of technology, civilian use tends to take control once it has proven itself in the military field. If we consider the basic characteristics of UAVs that they are vehicles that generate aerodynamic lift and/or have some degree of control, it can be said that the kite is the first UAV.

Different platforms for remote sensing or acquiring geodata have many advantages and disadvantages. UAV supersedes in terms of resolution, flexibility, and, to a certain extent, cost-effectiveness. These are listed in Table 1. Based on the review, simplified taxonomy (see Table 2) has been provided on the UAS-based studies applied to the WRMM.

2.2. Classification of UAVs. The classification of UAVs differs from place to place and depends on various parameters. UAVs are divided into three main classes by UVS International [28]. These are

(i) Strategic UAVs.

(ii) Tactical UAVs.

(iii) Special task UAVs.

Tactical UAVs have low endurance and operate from a few meters to five kilometers from the Earth's surface. Strategic ones have a two to 1-day lifespan and operate above 20,000 m altitude. Special-duty UAVs include lethal systems and deception systems.

According to the DGCA (Government of India) [29], UAVs are classified into four classes according to their maximum take-off weight (MTOW), as indicated in Table 3. UAVs can also be classified based on wings and rotors, as shown in Figure 1. Table 4 provides the pros and cons of different types of UAVs.

2.3. Payloads and Sensors. Being a remote platform system, UAS can be loaded with various sensors and instruments based on application requirements. Based on the literature, these UAV payloads used for WRMM can be classified in three classes, i.e., active sensors, passive sensors, and samplers (Figure 2). These can also be classified into imaging sensors, non-imaging sensors, and samplers as shown in Table 5. Remote sensing data can be very instrumental in developing hydrological models. The remote sensors and their data provide the capability to estimate many governing variables of the hydrological cycle, compatible with many hydrological applications. There are also many limitations and issues in fitting these remote sensing payloads into a predefined aircraft system, but development continues to adapt in-house payload systems for different sensors. Different types of UAS-based sensors have been discussed in the subsequent sections.

2.3.1. RGB, NIR, and Multi-Spectral Cameras/Optical Sensors. UAS equipped with inexpensive and lightweight RGB cameras have become standard for remote sensing and photogrammetric research. The simplest and least expensive sensors to deploy are optical ones, and when used appropriately, they can produce high-quality data for WRM [31]. Commercially available lightweight multi-spectral cameras (sensors) for tiny UAVs are now available. High-end multi-spectral sensors are helpful for surveillance because they provide high-quality measurements regardless of lighting (Table 5). These multi-spectral sensors are ideal for a wide range of applications due to their high ground sensing distance down to the centimeter range and their affordable cost. The disadvantage of current sensors of this type is that they are not properly tuned to aquatic applications [32]. When categorizing UAV images, the presence of an additional NIR band with RGB data is beneficial [33]. These sensors have been used in the majority of the UAV-based WRMM studies. This includes water body mapping, river bathymetry determination [34], flood mapping, riparian vegetation mapping [12], water quality mapping, and estimating soil water content [35]. Computer vision techniques find much utilization in deriving information from UAV-acquired RGB data. Even video captured from cameras has been utilized in WRM applications [34].

2.3.2. Hyperspectral Cameras. Many aspects of water resource management have benefited from hyperspectral imagery. Many such hyperspectral sensors have been developed that are compatible with UAVs [27, 36–38]. The application of UAS-based hyperspectral sensors has increased due to their high degree of automation and rapid manoeuvrability. These UAV-compatible spectral sensors are classified as point, push broom, multi-camera, sequential snapshot (multi-point, filter-on-chip, and labelled RGB), and spatial-spectral sensors [39]. The common disadvantages of these sensors are (1) exorbitant prices, (2) sensor dimensions, (3) requirement for specialized software, and (4) low signal-to-noise ratio. Vibration and flight motion also affect the push broom sensors [40]. The UAV-based hyperspectral sensors found application in water quality [41, 42] and mapping of water infiltration rate [43].

2.3.3. Thermal Cameras. Thermal infrared (TIR) sensors can be used to assess soil surface moisture parameters, estimate spatial and temporal scale energy exchange and vegetation cover, and estimate an area's evapotranspiration. TIR data can be used to determine the water content of vegetation and is therefore very resourceful in adjusting local (precision farming) and global (sustainable management of water resources) irrigation water levels. These are very helpful in identifying flow features [52]. Thermal imagers equipped with microbolometer sensors mounted on UAS can provide thermal imaging. The advantages of these sensors are that no validation is required to measure relative temperatures and their lower cost. TIR cameras provide only a single band with very low image resolution [53]. The low sensor resolution, together with a narrower field of view (FOV), complicates the applicability of structure from motion algorithms with TIR images and potentially limits the scale at which UAS-based TIR imaging is suitable [52]. The disadvantage of these sensors is that they require radiometric corrections and are plagued by temperature drift problems. Another issue is the need for expertise in interpreting data products. Thermal radiation from the emitters at the water-land boundary can cause errors. UAS-based TIR remote sensing can be used to map and detect discrete cold or warm water inputs into river channels. These sensors are useful for irrigation monitoring when (i) pairing them with simultaneous capture of visible and near-infrared imagery; (ii) a geometric correction is made to overlay with other images; and (iii) a radiometric correction is applied to account for the drift of the thermal sensors as well as the influence of the atmosphere on the observed temperature [54]. UAV-based thermal images have been used for estimating the soil water content [35, 44]as well as for monitoring water pollution [49–51]. Another application is estimating land surface temperature (LST), which can then be used to estimate evaporation, which is important for water resource management [45, 46]. Table 6 presents the different thermal sensors used in literature and their applications in WRMM.

Table 1: Pros and cons of the existing remote sensing technologies [27].

Platforms	Advantage	Disadvantage
Satellite	(i) Wider coverage (ii) Broad spectral capability	(i) Low resolution (ii) Image acquisition timing (iii) Weak coverage in some regions (iv) Sensitive to clouds
Manned aircraft	(i) Large coverage with a single flight (ii) High resolution (iii) Wide spectral capability	(i) Expensive (for small projects) (ii) Image acquisition timing (i) Weather-dependent (ii) Sensitive to clouds (iii) Not available in remote regions
UAV	(i) Cost-effective for small projects (ii) Very high resolution (fixed-wing up to 2 cm/pixel; rotary: sub-millimeter) (iii) Because of the lower flight height, clouds do not affect the flight (iv) Positional accuracy	(i) Small coverage (ii) Regulations may restrict operations (iii) Sensitive to bad weather (iv) Difficult to reconstruct homogeneous areas (few tie points)
Terrestrial	(i) Excellent positional accuracy (ii) Few data (only required) (iii) Very high resolution (iv) In situ data classification	(i) Labour intensive (ii) Only line-of-sight (iii) Accessibility (some sites)

Table 2: Taxonomy for operating UAV-based remote sensing systems in water resource applications.

Category	Sub-category
(A) Water resource	Surface sub-surface water structures
(B) Application	Reactive proactive passive
(C) Processing	Preprocessing segmentation regression classification 3D reconstruction
(D) Payload	Active passive samplers
(E) Platform	Fixed-wing single rotors multi-rotors lighter than air UAS

Table 3: Classification of UAVs based on their maximum take-off weight.

Category	Specification
Nano	Weight ≤ 250 g
Micro	250 g < weight ≤ 2 kg
Mini	2 kg < weight ≤ 25 kg
Small	25 kg < weight ≤ 150 kg
Large	Weight > 150 kg

2.3.4. Radar and Synthetic Aperture Radar. Many UAS-based radars are being developed [55] but suffer from bottlenecks at both hardware and software levels [56]. Bandini et al. [57] found in their study that radar is the most reliable sensor for measuring water levels compared to sonar and camera laser sensors. Synthetic aperture radar (SAR) interferometry is a powerful tool for terrain mapping [58]. In the literature, most UAV-based SAR systems operate in the X or Ka-band. The NASA-JPL (National Aeronautics and Space Administration-Jet Propulsion Laboratory) has designed and developed a L-band UAV-based SAR (UAVSAR) and developed UAVs for topographic mapping over the decade [58]. The UAVSAR data have been used to assess changes in water levels in wetlands due to tides [42], monitor the land subsidence and aquifer depletion [59–61], etc. [62]. Table 7 summarizes the characteristics of SAR sensors in relation to platforms. Ouchi [63] presented a nice overview of UAV SAR sensors up to 2013. Ludeno et al. [55] described an experiment with a mounted micro-UAV radar system. Wu [64] demonstrated the development of UAV-based ground-penetrating radar for soil moisture mapping. UAV-based radars have also been used to estimate snow depth and density [65]. These sensors are also needed to be explored for WRMM studies.

2.3.5. Radiometer. UAV-based radiometers are suitable for regional or local applications for remote measurement of geophysical parameters, such as soil moisture (SM) or sea surface salinity (SSS) [66], and can be used to detect salt-water infiltration. These are less sensitive to atmospheric influences than satellite-based radiometers.

2.3.6. Gravimeters. Gravimeters are useful in modelling and estimating changes in water storage. Conventional gravimeters are expensive and have a high mass, making them unsuitable for UAV assembly. But lately, some UAV gravimeters are being developed [67–69]. UAV-based gravimetry can complement satellite-based gravity observations and can be beneficial in remote and transitional regions (coastal waters) where terrestrial gravity measurements are difficult and impractical. One such gravimeter is the gravimeter of a microelectromechanical system (MEMS). MEMS gravimeters can be mounted on UAVs [68]. They

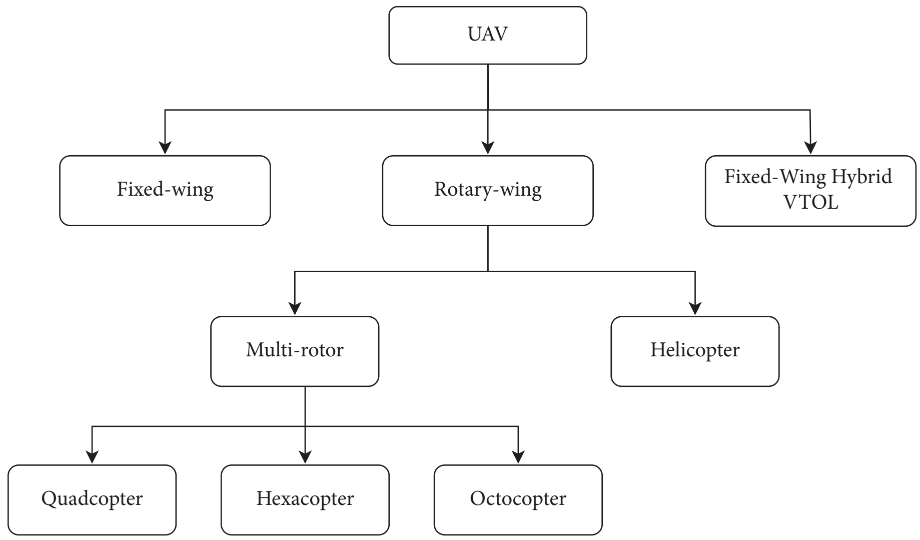

FIGURE 1: UAV types.

TABLE 4: Classification of UAVs.

	Pros	Cons	Uses
Multi-rotor (quad and hexacopters)	(i) Accessibility (ii) Ease of application (iii) VTOL and hover flight (iv) Good camera (v) Can operate in a confined area	(i) Short flight times (ii) Low payload capacity	Photography, simple photogrammetric applications, and video inspection
Fixed-wing	(i) High endurance (ii) Coverage of large area (iii) Fast flight speed	(i) No VTOL/hover (ii) More challenging to fly, skilled training required (iii) Costly (iv) Launch and recovery need a lot of space	Aerial mapping, road, pipeline, and power line inspection
Single-rotor	(i) VTOL and hover flight (ii) Long endurance (iii) Higher payload-carrying capacity	(i) More dangerous (ii) Harder to fly, more training needed (iii) Expensive	Aerial laser scanning (ALS)

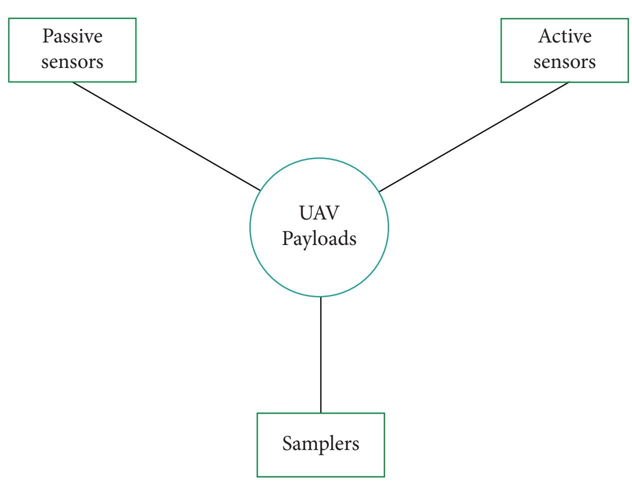

FIGURE 2: Classification of UAV payloads for water resource management and monitoring.

Table 5: Potential UAS payloads/sensors for water resource monitoring and management.

Imaging sensors	Non-imaging sensors	Samplers
Multi-spectral camera	Gravimetric sensors	Water samplers
Infrared sensors	Electromagnetic induction sensors	
Thermal sensors	Thermal profiler	
Hyperspectral sensors	Radiometers	
Microwave sensors		
Light detection and ranging		
Laser fluorosensors		
Magnetometers [30]		

Table 6: Different thermal sensors used for different WRMM applications.

Reference/ study	Sensor used	Range of sensor used	Application of thermal sensor/camera
[12]	ICI mirage 640	3.4 μm–5.1 μm	Computing river discharge
[35]	Zenmuse XT2-uncooled vox microbolometer	7.5 μm–13.5 μm	Predicting soil water content
[44]	ZENMUSE XT	7.5 μm–13.5 μm	Soil moisture retrieval
[45]	Optris PI 450 light weight infrared	7.5 μm–13 μm	Estimating evaporation
[46]	Optris Pi 400	7.5 μm–13 μm	Estimating spatially distributed turbulent heat fluxes
[47]	FLIR A65	7.5 μm–13 μm	Measuring surface flow velocity
[48]	FLIR Tau2 324	7.5 μm–13.5 μm	Monitoring water flux
[49]	Workswell Wiris 640 as	7 μm–14 μm	Oil spill monitoring
[50]	FLIR thermal sensor	8 μm–14 μm	*E. coli* pollution monitoring
[51]	FLIR Vue Pro R 640	7.5 μm–13.5 μm	Monitoring floating marine plastic litter

Table 7: UAV SAR sensor characteristics as compared with airborne and satellite platforms (the sign "ü" means that the requirement is fully attended, "—" means partially attended, and "û" means that the requirement is not attended [62]).

Requirements	UAV	Satellite	Airborne
Resolution (high)	ü	—	ü
Precision (high)	ü	—	ü
Coverage	û	ü	—
Endurance	ü	û	—
Flexibility	ü	û	ü
Rapid deployment	ü	—	û
Low-complexity operation	ü	—	û
Low-complexity logistics	ü	—	û

have the advantage of being mass-producible, lightweight, and cheap. Robust field implementation of these UAV sensors is still pending.

2.3.7. LiDAR. UAS-based LiDAR (light detection and ranging) can be important in capturing high-resolution terrain information, which can help improve visualization and analysis. LiDAR has a distinctive advantage over traditional topographic survey techniques, namely, its ability to derive a more realistic, high-resolution digital elevation model (DEM). LiDAR point density (the number of points/m^2) varies with flight speed [70]. Benefits of this payload include reduced susceptibility to environmental factors and direct geometry measurement. The disadvantages are that it is costly [71] and that the accuracy of the measurements can be affected if the vehicle is not properly stable. Another essential aspect that cannot be ignored is that water absorbs wavelengths commonly used for LiDAR [72]. The phenomena of water volume scattering, water surface reflection and refraction, and turbidity also complicate data modelling. UAV-based LiDAR bathymetry can be useful for underwater object detection, 3D mapping of underwater topography, turbidity estimation, and river and coastal geomorphology and applications [73].

2.3.8. Laser Fluorosensors. Instruments that measure fluorescence with laser beams are called fluorescence LiDAR or laser fluorescence sensors or laser-induced fluorosensors. They are used to analyze physical (e.g., oil spill monitoring) and biological parameters of water bodies, such as turbidity and algae content. Laser fluorine sensors take advantage of the fact that certain substances, such as aromatic compounds in petroleum, absorb ultraviolet light and become electronically excited. This excitation initiates fluorescence emission. These have also been developed for UAVs [74, 75]. This fluorosensor application should not be confused with the UAV application for measuring fluorescent tracers [76], which uses only RGB cameras. The application in WRMM is still in the development phase.

3. UAS Data Reduction Workflows for UAV Images/Sensors

Before discussing how UAS-based data are used for WRMM, it is essential to understand how data are derived from UAV imagery. Just like other remote sensing applications, UAV-based imagery can be used to derive mainly two categories of information: metric and thematic. Hence, the corresponding processes based on the output of images captured by UAV can be called UAV photogrammetry (a term coined by Eisenbeiss [77]) and UAV remote sensing, respectively.

The essential part of optical data acquisition is flight planning, regardless of the technology used. One major challenge is determining how to plan the flight path to ensure a complete and accurate survey of the study area with the least flight time. The camera is typically positioned in a fixed orientation, such as vertical or oblique, and the UAV-RS collects data either manually or using preprogrammed flight paths. Therefore, full and dense coverage is difficult to achieve, especially in urban areas. Using the initial scene reconstruction from nadir acquisition as a baseline to continually optimize the view and location is an interesting technique.

UAV photogrammetry is essentially a hybrid of aerial photogrammetry and close-range photogrammetry (CRP). Here the platform is in the air, but the data reduction follows the principles of CRP. UAV photogrammetry generally applies algorithms called structure from motion (SfM) data reduction algorithms. They involve the simultaneous determination of the (internal and external) geometry features as well as the 3D structure of the scene [79, 80]. This algorithm uses images captured by optical sensors and the positions of their exposure stations as their input, and their outputs are 3D point clouds and digital elevation models, and after ortho-rectification, they result in ortho-mosaics. Al-Kaff et al. [81] presented a comprehensive overview of structure from motion algorithms along with their applications and limitations. Conventional photogrammetric processing of UAS data is presented in Figure 3. The UAV-based 3D models are rich in detail and can therefore be used to obtain knowledge about the hydraulic parameters of waterways [82]. But UAV photogrammetry has its bottlenecks. Insufficient lighting and shadows are the sources of error with SfM products. In snowy areas, the SfM algorithm has difficulty processing due to a lack of contrast and very high reflectivity [18]. For bathymetric mapping applications, UAV-borne multi-media photogrammetry is applied as it involves light diffraction at the air-water interface [73].

UAV remote sensing is the branch of remote sensing that uses UAV as a platform to acquire various parameters about the objects or phenomena to be observed. UAV-based remote sensing uses the application of digital image processing, which exploits the physics associated with the interaction of radiation belonging to a specific range of the electromagnetic spectrum, including the optical range. Using the basic principles of remote sensing, the application of UAS-based data for mapping and characterizing water bodies can be made. Optical remote sensing has some limitations when it comes to mapping water. These include obstacles from other features, shadows on the water surface, changing water surface appearance due to sun-target-sensor geometry, and the dynamic morphology of water bodies [83, 84]. The near-infrared (NIR) and mid-infrared (MIR) regions of the electromagnetic spectrum, with wavelengths between 740 and 2500 nm, are best suited to distinguishing pure water from land [85].

4. UAS in Water Resource Monitoring and Management

There are many different methods for using UASs in WRMM. A standard methodology is to assess the feasibility of UAV surveillance after considering spatiotemporal coverage, acquisition parameters, data quality, legal issues, etc. A decision is taken on how UAS monitoring will be carried out after considering factors like cost and detection parameters, weather conditions, and accessibility of the study area. The firsthand acquisition is an image or a point cloud, or a sample. Then, this image, point cloud, or sample is further processed/analyzed to obtain the primary data, which in turn undergoes secondary processing to provide results. The results are interpreted and displayed in the form of maps, charts, graphs, etc. online or offline. Figure 4 describes the general sequential process of decision making from problem definition to the operational aspect of the application.

Before starting the review, we will summarize the review papers (Table 8) directly or indirectly related to UAVs and their application for mapping and monitoring water resources in the table below. In this overview, we have tried to summarize all the developments that have been made in the mapping and monitoring of water resources. Some of these reviews are old or mainly focused on only a component of water resource monitoring. For our review purpose, we have divided the WRMM applications into three categories, namely, (I) surface water resources, (II) sub-surface water resources, and (III) irrigation and other water structures.

4.1. UAS for Surface Water Resources.

There are different areas of WRMM where UASs are being used. Table 9 summarizes different applications as per different water bodies.

4.1.1. Mapping and Characterizing Water Bodies.

The mapping of (inland) water bodies is essential for the mapping and monitoring of water resources. Sub-meter imagery captured by drones allows for more accurate delineation of water features, which is always desirable for scientists and policymakers. Another aspect is the improved detection of small bodies of water. These include flow tracing, channel bathymetry, and thermal characterization of aquatic ecosystems [155]. Using a thermal imaging camera can help to monitor the seasonal geothermal influence on the rivers [156]. UAV datasets, in synergy with other datasets, can be used to map bodies of water.

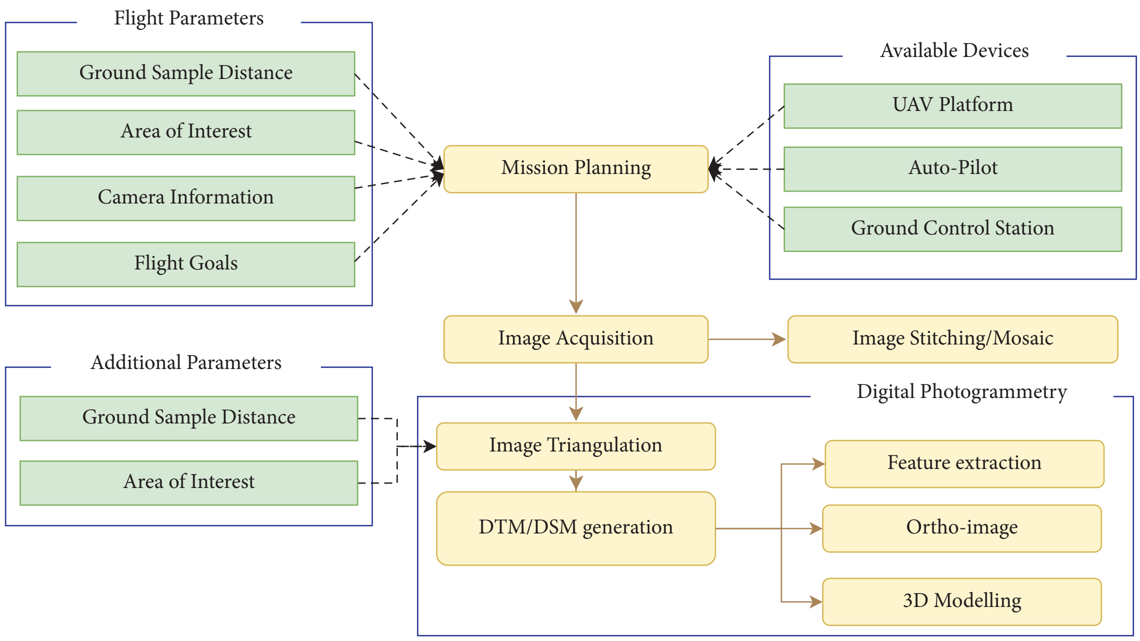

Figure 3: Conventional photogrammetric processing pipeline for UAS data [78].

D'Andrimont et al. [84] used hyperspatial and multi-source data for mapping bodies of water over a large area. The framework proposed in the study successfully handled the heterogeneity of different remote sensing platforms and detected 83% of the water bodies in the area. Fu et al. [104] used UAVs to map land use/land cover, particularly ponds, to assess ecosystem services provided by ponds in hilly areas. Harvey et al. [157] used calibrated thermal images obtained from UAS to study thermal lakes and streams. The study used these images and the Monte Carlo analysis to estimate a mean total heat loss at the surface. Another study [45] showed that UAVs could be used to estimate evaporation. In this study, the surface energy balance components were calculated using land surface temperature from UAS-based thermal imagery and used as input to the physically based two-source energy balance models. Kuhn et al. [158] attempted again to assess thermal heterogeneity via UAV-based imaging. UAS-based thermography has been used to monitor surface water contamination [159, 160]. UAVs have been used to study the shoreline and shoreline erosion of inland lakes and rivers [161–163].

4.1.2. Watershed Mapping and Monitoring. UAV photogrammetry using overlapping stereo images provides very detailed information about terrain, catchment areas, and networks. By providing a thorough understanding of the watershed status and changes over time, UAVs can be used to validate products from various existing and upcoming satellite missions. UAVs can be used to address the need for cross-watershed monitoring and assessment of the large geographic diversity in underground hydrological connections [31].

Templeton et al. [164] characterized the terrain attributes (elevation, slope, orientation, and upstream area) and plant species distribution in a catchment using UAV products supported by an environmental sensor network. The study analyzed the dynamics of energy and water fluxes in the watershed on different timescales (i.e., seasonal, monthly, and storm events) and provided insights into their spatial variations and their interconnection. Spence and Mengistu [165] applied UAS imagery to identify narrow intermittent streams. Pineux et al. [166] presented a UAS-based technique for quantifying the spatiotemporal distribution of erosion/deposition due to precipitation events. This technique can be used to study erosion in the watershed where other methods are too expensive, destructive, or time-consuming. Argüello et al. [167] described a methodology for automatic river basin monitoring using a UAV-mounted multi-spectral sensor.

(1) River Mapping and Velocimetry. UAS remote sensing and photogrammetry products have many applications for studying river systems. These include bathymetric survey, topographic survey, grain size mapping, sediment transport path length, geomorphological change detection, habitat classification, restoration monitoring, vegetation mapping, etc. [168]. Monitoring river discharge is an essential task for water resource management. The study of river morphology is a crucial task in river management. River management facilities such as dikes and river walls play a vital role in flood control. UAVs can help map and monitor all of this. Due to the higher spatial resolution, unmanned aerial vehicles are very well suited for exploring small rivers and streams [169].

Although the major rivers can be mapped from satellite data, smaller rivers flowing through dense vegetation are obscured, making UAVs suitable for mapping small rivers [170]. UAV data are useful in deriving channel parameters, identifying hydromorphological features [171], and studying river dynamics [124] such as geomorphological changes due

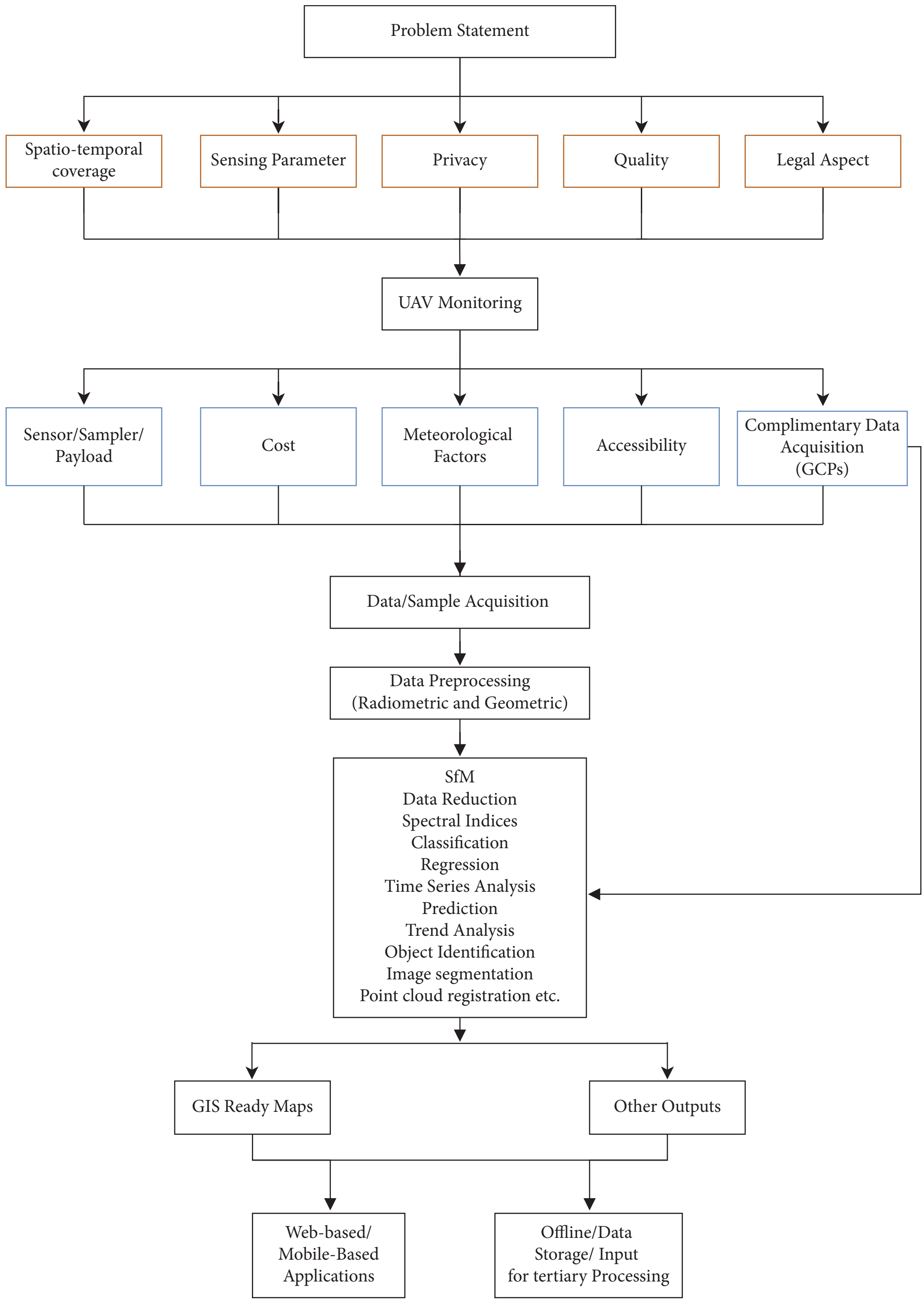

Figure 4: The general sequential process of decision making from problem definition to the operational aspect of the application.

to flooding [125, 171, 172]. Casado et al. [171] used ANN to automatically identify different flow characteristics. Kubota et al. [173] proposed a river asset maintenance management system using UAS-derived three-dimensional point cloud data to solve river management asset problems and improve operational and maintenance efficiency. Zhao et al. [174] used UAV-derived data to collect channel parameters for rapid environmental flow assessment. The DEM derived from the UAV can, in turn, be used to create a flood depth model and other parameters (roughness indices) [26, 117] and thus used in bank erosion studies [112] and flood modelling [70, 109]. The method of precise aerial

Table 8: Topics discussed in the previous articles.

Year	Review topic	Reference
2011	UAV application for environmental remote sensing	[86]
2014	UAVs for 3D mapping application	[78]
2016, 2017	UAV for hazards and disasters	[87, 88]
2016, 2018, 2020, 2021	UAVs for glaciology	[18, 22, 88, 89]
2019	UAV applications in urban storm water management	[90]
2017	Deep learning application for UAV	[91]
2018, 2019	UAV application for monitoring algal bloom	[24, 92]
2017	UAV hyperspectral sensors	[27]
2018	UAV-based spectroscopy	[39]
2020	Structure from motion algorithms for UAV mapping	[93]
2018	UAV for fluvial remote sensing	[94]
2019	UAV for water sampling	[20]
2021	UAV and satellite data synergy	[3]
2021	Accuracy of UAV mapping	[80]
2021	The role of UAS technology in natural resource management	[95]

Table 9: The application of UAVs in WRMM.

Water body type	References
Lakes and reservoirs	[96–103]
Ponds	[104]
Alpine glacial lakes	[105]
Rivers and river basins	[52, 94, 106–125],
Wetlands	[33, 47, 101, 126–138]
Glaciers	[139–141]
Delta, ocean, and coastal regions	[8, 9, 59, 142–153]
Ice caps	[154]

photogrammetry [82, 175] can be applied to UAS imagery to derive geomatic products that can be used as input for flood modelling. UAS-based thermal imaging cameras have been used to monitor seasonal geothermal influence on the rivers [52]. Calle et al. [172] applied UAV photogrammetry to monitor short-lived river changes due to flooding. Langhammer and Vacková [112] used UAS to map the geomorphological effects of flooding with the object-based image analysis. Gebrehiwot et al. [14] applied a deep convolutional neural network to UAS imagery for flood extent mapping. This study achieved an accuracy of 95%. Hashemi-Beni and Gebrehiwot [17] integrated CNN and region-growing (RG) method for mapping existing floods using UAS imagery.

The relevant parameter of UAV surveys for rivers is the area coverage (longitude and latitude). From this source come the associated challenges. On narrow rivers, it is conceivable to fly just one line of flight over the middle of the river while the camera's field of view covers the entire width. However, when the river is too great for a single airline to span, round-trip back-and-forth flights are required, significantly reducing travel time. The line-of-sight restriction mentioned above limits the ability to fly along the river. Larger rivers need multiple flights [176].

Another challenging aspect of river mapping is the vegetation along the river. Mapping is complicated in fast-flowing water, blocked waterways, or dense tree canopies. These trees can block GPS signals. Unfortunately, river conditions severely degrade any GPS signal, resulting in intermittent global position data. The UAS can help overcome these difficulties. Scherer et al. [177] developed a UAV for river exploration and mapping that can estimate position and recognize the river and obstacles. Some of these studies [170, 177] showed that GPS waypoints and previous maps were hardly or not at all required for the autonomous exploration of riverine environments.

Water level and water surface height can be derived from various UAV-based sensors. UAS-based photogrammetry represents a dynamic and non-intrusive approach to studying free-surface topography. Bandini et al. [57] determined levels with an accuracy of better than 57 cm using an integrated payload consisting of a camera-based laser distance sensor (CLDS), radar, and sonar. Water surface elevation data can significantly improve flood forecast models, advance our knowledge of how river geometry and hydraulic roughness affect WSE, and contribute in constructing assessment curves. The currently captured description of the high-resolution surface morphology can answer fundamental questions related to the nature of the free surface [178]. Ridolfi and Manciola [98] performed drone-based measurements of a lake and reported that the total mean error between estimated and actual water level measurements is about 0.05 m. Eltner et al. [179] used deep learning techniques (SegNet and FCNN) in combination with UAV photogrammetry for automatic water level measurement.

UAVs have been used to measure flow velocity. UAS-acquired images have been used in many studies to derive surface velocity [47, 47, 126, 127, 132, 133, 137, 180]. The studies mainly focused on evaluating the technique. Tauro et al. [127] compared results of UAS-based large-scale particle image velocimetry (LSPIV) with in situ measurements and attempted to estimate the impact of platform stability on the results. Koutalakis et al. [181] demonstrated flow velocity measurement by three image-based methods. Strelnikova et al. [133] analyzed photos of the area around the fishway entrance of a dam using UAS-based imagery under seed flow conditions. Pearce et al. [126] performed a sensitivity analysis for five different image velocimetry algorithms, namely, large-scale particle image velocimetry, Kanade–Lucas–Tomasi image velocimetry, large-scale particle tracking velocimetry, surface structure image velocimetry, and optical tracking velocimetry.

4.1.3. Riparian Vegetation Monitoring. The study and management of riparian vegetation is a part of water resource management as it influences various hydrological processes [182]. UAVs are generally used to survey riparian systems on a local scale [12]. A trend was noted in the studies that UAVs are used to study the features associated with the diverse species composition of the riparian ecosystem. Dunford et al. [120] performed one of the first studies on applying UAS to monitor riparian vegetation by implementing pixel-based and object-oriented classification. One of the reviews [21] summarized that the number of studies using UAS to investigate the bank system increased after 2010. Husson et al. [11] concluded in their research that the sub-decimeter resolution of UAV products can be beneficial in mapping river and lake vegetation at the species level. Michez et al. [183] used hyperspectral imagery derived from UAS to classify different riparian plant species.

4.1.4. Bathymetry, Water Surface Elevation Survey. Bathymetry of bodies of water is required to characterize river morphology and monitor river restoration. Shallow rivers can be surveyed using methods such as total stations or RTK-GNSS, which offer high accuracy, but they are limited on a point basis, and surveying becomes difficult as the survey area or river depth increases. UAS can provide much broader and more homogeneous and contiguous spatial coverage. UAS-based bathymetry surveys are more likely to be conducted in river areas since the survey vessel with sonar equipment is very difficult to operate in the river current [184]. In addition, a bathymetric survey using an echo sounder is very difficult to apply in shallow coastal waters.

The Beer–Lambert rule, which defines the absorption effect when light flows through a transparent medium, is used to derive the flow depth from brightness values in images using remote sensing. Multi-spectral, panchromatic, and colour images can be used for this purpose. Shore shading and surface turbulence cause problems in bathymetry estimation [185]. Incorrect georeferencing, poor lighting conditions, and undesirable atmospheric conditions can adversely affect bathymetry derivation from optical data. The refraction effects that should be taken into account make it difficult to determine the bathymetric river area. There are multi-media photogrammetry techniques that consider compensation factors on every image perspective to reduce this inaccuracy [34]. Lejot et al. [116] used image processing techniques such as median filtering, histogram matching, and sub-grouping of the images to remove these inaccuracies. Flener et al. [176] combined UAS-based imagery (for optical bathymetric mapping) and mobile laser scanning data to create a bathymetric model of the river channel along with a digital terrain model of point bars of a meandering river. Structure from motion workflows and optical bathymetric mapping can also be coupled to create fluvial terrain models [186]. However, many problems still affect unmanned image-based bathymetry [155]. Fixed-wing UAVs are less used for bathymetry studies than quadcopters and other UAVs. Woodget et al. [106] used UAS-based hyperspectral sensors for bathymetric mapping. Pan et al. [187] used LiDAR for this. LiDAR-based bathymetry has many challenges. Phenomena such as water volume scattering, water surface reflection and refraction, and turbidity reduce the signal-to-noise ratio (SNR), making processing more difficult. There are also spectral depth approaches for bathymetric mapping. Shintani and Fonstad [188] compared the spectral depth approach to the SfM photogrammetric approach. One of the experiments [189] concluded that the difference between blue and green bands is an optimal band combination for water colour inversion-based bathymetry. Bathymetric survey methods with aerial photos are more likely to be carried out in river areas since the survey ship with echo sounders is very difficult to operate due to the river current. But Woodget et al. [106] suggested that DEM derived from SfM photogrammetry should be used cautiously as in-process models are sensitive to slope.

4.1.5. Wetlands. Wetlands are at the heart of some of the most controversial and pressing issues of sustainable water management because of their complex interrelationships with the hydrological cycle and their critical dependence on water supplies [190]. Chabot and Bird [128] used UAVs for precise, fine-scale mapping of the water-vegetation interface. Multi-temporal water level changes can be detected using UAVs [33, 129]. Chabot et al. [191] applied object-based image analysis to UAS imagery for invasive species monitoring in a wetland. UAV-based LiDAR and hyperspectral sensors are yet to be deployed for various studies. Kalacska et al. [134] applied UAS photogrammetry to study tidal wetlands. Xia et al. [136] presented a novel method for sub-pixel-scale mapping of wetland flooding for satellite imagery using UAS imagery.

4.1.6. Soil Moisture. Although soil moisture contributes quantitatively to the overall global water balance [192], it is of considerable importance for water resource management [193]. According to Chabot and Bird [128], surface soil moisture (SSM) is a critical component of soil water balance that manages water and energy exchange at the surface/atmosphere interface. In addition, soil moisture is a proxy for sub-surface water in the unsaturated zone above the water table.

Hassan-Esfahani et al. [194] used high-resolution UAS images (RGB, NIR, and thermal) and other derived images (normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), vegetation condition index (VCI), and vegetation health index (VHI)) and stored capacity as inputs to an artificial neural network (ANN) model for estimating SSM. Such a modelling process is inherently subjective, and it is location-dependent and time-dependent. Further investigations under different conditions are needed to strengthen such models. Irrigation water management can be linked to the created soil moisture maps for planning and application rates.

Ge et al. [195] used a machine learning algorithm for spectral indices derived from UAV-based hyperspectral data estimation of soil moisture content. Acevo-Herrera et al. [196] described a radiometer system that performed soil moisture mapping from a small, low-altitude UAV platform. They obtained soil moisture with estimated absolute errors between 1% and 6% for the homogeneous agricultural plots. Another application of UAVs was the estimation of water infiltration rates using hyperspectral sensors [43].

4.1.7. Water Quality Monitoring. Water quality can be modelled from inputs of UAS-RS. These models can be roughly divided into three general classes, (a) radiative transfer models, (b) analytical models, and (c) empirical models [197]. Using remote sensing in conjunction with other water quality monitoring methods has four advantages:

(1) Enables more efficient monitoring of spatial and temporal variations by providing a synoptic view of the entire body of water.
(2) Provides a synchronized image of water quality across a range of lakes over a large area.
(3) Provides a detailed historical record of water quality in a specific area and trends over time.
(4) Helps prioritize sampling locations and survey times in the field.

When conducting water quality studies or attempting to predict water productivity using remote sensing, the subsurface volumetric radiance is the parameter used. This irradiance combines incident solar radiation and radiation reflected from the sky, which passes through the air-water interface, interacts with the water and organic and inorganic elements, and then exits the water column without reaching the ground. Water bodies can be surveyed at multiple locations, elevations, and viewpoints with a UAS-based spectrum reflectance measurement system, making repeated measurements over the same site to limit the effects of spectral variations. Another benefit of UAS is that all of its sensors can be calibrated for water surfaces, allowing users to capture high-quality, low-SNR photos, which is not possible with satellite imagery, which is calibrated to measure land surface reflectance. Zeng et al. [198] discussed the testing and development of a low-cost UAS-based reflectance survey tool for retrieving water quality information. However, there are many challenges that UAS technology has to face in this area. This includes the development of appropriate atmospheric correction methods, developing better sensors, and developing new and existing algorithms to derive water quality information from raw sensor data. When mapping the trophic status of small reservoirs, UAS offers better value for money [97]. Freshwater water quality is highly dependent on the condition of aquatic vegetation. Therefore, when assessing water quality, many researchers look to ecological ratings. Flynn and Chapra [122] provided a passive method for remote sensing of submerged aquatic vegetation in a shallow river using UAVs. Su et al. [97] applied a UAV-mounted multi-spectral sensor to monitor water quality in small reservoirs. In this context, the pixel-by-pixel matching algorithm (MPP) has to be mentioned and has been used in many UAV-based water quality monitoring studies [97, 197, 199]. Hyperspectral sensors were used to retrieve suspended matter concentration (SSC) [41]. The study used the least squares support vector machine model. Hyperspectral data have also been used to derive water quality parameters [41, 42, 135]. Initially, these studies use ML algorithms such as SVM and ANN. Zhang et al. [135] applied the deep learning model to retrieve water quality parameters.

Water sampling has become a key activity in the management of freshwater resources. UASs are used not only for remote sensing purposes but also for sampling purposes to monitor water quality. A study [200] showed that the UAS mechanism could collect samples similar to manually collected samples. These UAS significantly reduces the effort and time required for sampling. Ore et al. [201] developed an autonomous UAS-based water sampler. Doi et al. [99] used UAVs to extract environmental DNA (eDNA) from a reservoir. Similarly, Terada [102] sampled a crater lake in Japan. UAVs have been developed that can overcome the speed limitations of flowing waters [202]. The UAVs used for water sampling should be able to support the additional weight of the sampling mechanism, the water collected, and additional provisions for an emergency landing on the water surface. From the literature, many examples of such UAVs, capable of navigating in both air and water, can be used for water sampling [203, 204]. Song et al. [100] discussed the advantages and limitations of UAV-based sampling along with the manual and sensor-based methods in limnology. Ore and Detweiler [205] presented a UAS-based system that includes a submersible sensor probe that can be used to measure water properties that can keep the target submerged. Benson et al. [206] developed a sampling system called DOWSE, DrOne Water Sampling SystEm. Their goal was to study the spatial distribution of microorganisms in freshwater lakes. There is now a need for future drone-based water sampling studies to adapt more robust statistical experimental designs to examine the variability and precision of the collected data [20].

Chung et al. [96] extended the concept of water sampling by UAS to the temperature measurement of the water column (Figure 5). They proposed and tested an automated temperature sensing system based on using an unmanned air system to quickly obtain 3D thermal maps of bodies of water by lowering a temperature probe into the water at controlled depths with an unmanned air system. Demario et al. [207] also developed another UAS-based water temperature measurement system consisting of an IR camera and an immersible temperature probe. Table 10 gives the insight into different water quality parameters derived from different UAS-based sensors.

Figure 5: Image of UAS-based temperature sampler [96].

Table 10: Water quality parameters as derived from UASs.

Water property	Response parameter	Remote sensing indicator	Sensor used	Remark
Hydrology	Water level	Bathymetry	Multi-spectral	Brightness levels in imagery correspond to the depth
Temperature	Temperature	Surface temperature	Thermal	Spatial patterns can predict algae blooms
Transparency	Turbidity and Secchi depth	Secchi disc depth	Multi-spectral	
	Algal growth	Chlorophyll-a	Multi-spectral	NDVI can be used. Spectral mixing could be a troublemaker.
Biota	Phenology	Time series analysis	Multi-spectral	
	Species analysis		Multi-spectral	
Temperature anomaly	Temperature	Surface temperature	Thermal	Locate groundwater discharge to surface water
Thermal pollution from industrial sources	Temperature	Surface temperature	Thermal	

4.1.8. Water Pollution and Wastewater. In recent years, UAV remote sensing is gradually being used to monitor and assess pollution of the aquatic environment. The main application of UAVs for water pollution is the monitoring and mapping of the algal bloom population. Recently, many studies have used UAS-based optical sensors to monitor algal blooms in surface waters, demonstrating their ability to quantify algal species using a variety of indices such as the Normalized Difference Vegetation Index (NDVI), Algal Bloom Detection Index (ABDI), and Green Leaf Index (GLI). However, there are two main problems.

(i) The sub-grid heterogeneity can complicate imagery data assimilation.

(ii) The mismatch between model and measurement scales in the vertical direction represents another problem that needs to be investigated for the assimilation of the remotely sensed data into water quality models.

Another aspect of dealing with water pollution is water spillage. UAVs have been deployed to inspect spills of contaminants and to estimate spill volume and area to quantify pollution [152, 208, 209, 209]. UAS has been mainly used for oil spill mapping and monitoring [49, 152, 210–213]. Coal ash spills have also been assessed and monitored using UAS [208]. Most approaches applied computer vision approaches to oil spill detection. Oil spill monitoring application has seen the application of UAS-Swarm. Kaviri et al. [213] designed a multi-UAS control framework for oil spill mitigation. A novel spray adjustment strategy was also proposed in this study to combat oil spills.

So far, there have only been a few applications of drones, especially in wastewater treatment. Sancho Martínez et al. [214] developed a UAS-based image-based methodology for autonomous inspection of trickling filters and activated sludge systems. Wong et al. [215] used UAVs to inspect the foam in the covered anaerobic lagoon of a sewage treatment plant. Burgués et al. [216] used UAS-based gas sensors for real-time monitoring of emissions from wastewater treatment plants.

UAS-based infrared thermography, together with modern data processing and visualization tools, can aid in the study of numerous environmental issues, including pinpointing pollution point sources and determining the best path between sources and targets. Compared to conventional pollution-source detection methods, UAS-thermography makes finding unlawful sanitary sewers and storm-drain connections, illicit discharges, and other reasons for the surface water contaminationvery easy [159]. For studying such contamination, night flights have been recommended in the literature [217].

Tracer studies can also be performed using UAV data, which can help study water pollution [76]. UAV-based remote sensing can compensate for other platforms' low spatial and temporal resolution for such river investigations. Geraeds et al. [218] showed that UAVs can be used to monitor the spatiotemporal distribution of plastic waste in rivers. Plastic pollution of the marine environment has increased dramatically in recent decades and poses a severe environmental threat to numerous settings worldwide. UAS remote sensing can be used for (i) detection, (ii) identification and categorization, (iii) quantification, and (iv) mapping and estimating the accumulation rate of marine debris. The process with UAVs is faster [219] and more reliable. Ferrara et al. [220] demonstrated the use of remote sensing-based surveillance of coastal waters using thermal imaging to study the extent of pollution. This study hierarchically used satellite, helicopter, and drone data to monitor water quality in pollution scenarios. Consumer-grade UAVs can be used to detect these pollutants [221], particularly when used in conjunction with machine learning [222] and deep learning techniques [144, 223–226]. However, these automated approaches still need to be improved [222]. Gonçalves et al. [222] suggested that manual image screening of the orthophoto should be preferred when more careful characterization of marine litter is required.

4.1.9. Coastal Water Management and Oceans. Drones find tremendous utility in monitoring and mapping oceans and coastal areas [153, 227, 228]. Regular monitoring in coastal areas to assess topographic changes requires very detailed and fast mapping technologies that UAS can provide. Another advantage of UAS technology is its flexibility, which allows UAV surveys to be timed to avoid flooding, insufficient light conditions, etc. [134]. Since light is refracted on the water surface, the most difficult problem of UAV-assisted coastal photogrammetry is to incorporate and exploit surface and underwater imagery records from overhead images [229]. Another difficulty is calibrating UAS-derived elevation information to local sea levels [230]. One of the problems for UAS surveys in coastal environments is the extensive area of salt marshes, tidal flats, etc., where it is challenging to establish ground control points [23]. Jaud et al. [231] suggested that artificial georeferenced targets can be used, which should be easily visible in different beach lighting conditions.

UAS can be used for coastal zone mapping [232], coastal flooding monitoring [142, 149], river deltas [151], tidal reefs [148], dynamic tidal inlets [8, 233], sea-level rise [230], surveying of coastal structures [234], sea-level rise scenario simulation [142], analysis of shoreline changes [9], and beach sediment changes [151]. The drone survey was used to validate satellite monitoring of the Yellow Sea green tide disaster [235]. Similarly, a study [150] to estimate the algal biomass in the Yellow Sea was conducted using UAV data and satellite imagery.

4.1.10. Urban Storm Water. McDonald [90] reviewed the application of urban stormwater drones. UAVs can be used to assess damage from urban flooding [13]. Many studies have shown this applicability of UAS [236]. The study of stormwater contamination is where UAV-based thermal imaging can be used [217].

4.1.11. Cryosphere. The cryosphere is a critical water resource, and snow cover extent and depth are important parameters affecting energy and water balance. Frozen water occurs in remote areas that are difficult to access, especially mountainous areas, and there are limited resources for ground measurements. Unmanned aerial systems can prove to be a boon. The main applications in the cryosphere include DSM generation [154], change detection, snow depth estimation [65, 237, 238], tundra vegetation mapping [239, 240], ice-wedge polygon mapping [241], and so on.

Gaffey and Bhardwaj and Bhardwaj et al. [18, 89] gave a detailed report on the applications of UAVs as a remote sensing platform in cryospheric studies. These reviews showed that modern UAVs have all the necessary equipment and features that can make them useful for glaciological research. But what is needed is an improvement. Since the cryospheric application of UAVs has already been covered in detail, the details will not be covered in this review.

In their study, Ramsankaran et al. [140] summarized various challenges for surveying glaciers and found that the choice of UAV launch/landing sites affects the survey and recommended selection criteria for the most suitable launch/landing sites. Snow-covered surfaces pose photogrammetric challenges as there is a lack of contrast and the surface reflectance is very high. Therefore, weathered old snow under cryospheric conditions is better suited for SfM processing but still not reliable for repeated surveys [18].

4.2. Sub-Surface Water Resources. Groundwater is difficult to map from UAVs because the target of interest is not directly observable from the air. A gravity survey using an unmanned aerial vehicle (UAV) can help determine alluvial groundwater storage and specific yield, which is an important parameter for the long-term management of groundwater resources. Dedicated UAV-based gravimeters are being developed [67–69] that can measure the spatial and temporal variation of sub-surface density with a resolution and accuracy which is almost comparable to terrestrial gravimetry. Advances in gravimetry combined with the development of UAV-based gravimeters will make it possible to analyze changes in groundwater over time. In the future, UAV gravity surveys can be successfully used to determine the specific yield and groundwater storage of alluvium, as has been the case with ground-based time-lapse gravity surveys [242]. This area of UAV-based gravimetric analysis of groundwater needs to be explored.

Under certain conditions, UAS remote sensing can also infer groundwater by quantifying temperature or electrical conductivity anomalies [243]. One such study [19] used the availability of visible surface water as an indication of groundwater and used UAS surveying to model the water table.

UAS data inputs are instrumental in groundwater modelling. Groundwater models have become the most sophisticated tool for decision makers in groundwater management. There are two main ways in which UAS-based remote sensing data can be applied: (1) using UAS-acquired data to construct distributed sets of input parameters for a model and (2) providing constraints to models during the calibration of models by acquired data FH. UAV-based geophysical surveys allow the identification of faults and dykes and mapping of lithology and its alterations and depth of magnetic features (e.g., [244–246]). These data help to develop more realistic aquifer models. The upper limit of an aquifer is also the surface of the topography that restricts the water table. Surface elevations can be determined with sub-decimeter accuracy using UAV imagery processed with structure from motion algorithms. This UAS technology produces DEMs that rival LiDAR in terms of accuracy but is much cheaper.

4.3. Irrigation and Water Structure Monitoring. Irrigation control is related to sustainable water management. UAV-based remote sensing can be used for real-time (daily or weekly) monitoring of various parameters from the field. These may include the following, which can help with irrigation planning and water management:

(i) Water-related information: this includes its quantity and quality-related aspects with spatiotemporal dimensions.

(ii) Soil-moisture related information.

(iii) Vegetation-related information: vegetation index includes its quantity and quality-related aspect with temporal and spatial dimensions, such as crop phenology.

Monitoring of structures related to irrigation or revetments is necessary to ensure their longevity and thus contributes to sustainable water management.

Rathinam et al. [119] proposed a real-time image-based detection algorithm for autonomous inspection of various linear features (canals, rivers, and pipelines) using a UAV. But that was a preliminary concept. Chao et al. [247] provided an overview of UAV-based irrigation control and water management system (hardware and software).

Perea-Moreno et al. [248] used object-based image analysis for the automated classification of UAV videos. This strategy used the hierarchical temporal memory (HTM) learning algorithm. Multi-spectral information from UAS was used to develop a decision support system to regulate irrigation rates [7]. UAVs can also be effective in weed assessment and hydraulic efficiency [249].

Rathinam et al. [119] presented a study demonstrating a structure recognition algorithm that can identify and localize a channel. This type of monitoring is critical to ensure the reliability and life expectancy of canals and other irrigation structures. Irrigation channels were reconstructed virtually with UAS by Brinkhoff and Hornbuckle [250] and monitored for the presence of aquatic weeds. Kadapala et al. [251] implemented UAV photogrammetry to estimate the capacity of an irrigation tank. The UAV data were used to generate an EAC (elevation-area-capacity) curve for the irrigation tank. The use of drones is only successful for small tanks and reservoirs.

Miller et al. [60] used NASA's UAVSAR L-band data for successfully monitoring the California Aqueduct and showed the advantage of UAVSAR over satellite SAR data. Leaks in river levees can be detected with UAS-based thermal levees [252]. Kubota et al. [173] proposed a river facility maintenance management system based on 3D point clouds derived from UAS photogrammetry. Chen et al. [253] used UAS-derived dense point clouds to inspect revetments along urban rivers.

Monitoring complex-shaped dams by UAV surveys is a complex process that has been reinforced by other survey techniques (TLS, GPS, and total station). Several studies on the use of drones for dam inspections have been conducted over the last decades [254–256]. These surveys can be performed reliably and efficiently when the impact of the number and location of GCPs on model accuracy is known a priori [254]. The markers' position affects the survey's accuracy and needs further research [255]. UAVs have found their application in the design of terrace drainage networks. Pijl et al. [257] used the topographical data derived from the UAV survey to analyze and design the drainage networks in terraces in Italy.

Tile drainage systems remove excess water from fields, benefiting both the environment and the economy. Farmers and natural resource managers can better mitigate any adverse environmental and economic impacts by monitoring tile operations. UAS thermal data can provide additional insight into field tile mapping by assessing temperature changes within a field.

5. Software

There are a lot of commercial and a few open-source software programs that allow photogrammetric processing of UAV images. Some of these are summarized in Table 11.

6. Issues

UAVs in water resource management and monitoring open new avenues for research and development. This versatile platform has enormous potential. However, it still faces many problems and bottlenecks in its application in this field. In our literature review, we found the following challenges:

(1) The size of the problem and the mode of application: most water resource problems are extensive in space and time but can be severely limited in the time of their occurrence, especially in the case of catastrophic events and disasters. Given UAVs' intrinsic flight time limitation, their use in large-scale transport challenges should be planned and implemented rigorously. A performance like this would require either UAVs with advanced technology or a swarm of UAVs to increase their capabilities. The biggest shortcomings of unmanned aerial systems are the limited flight duration, the weather, and the regulatory challenges. UAVs must be used responsibly. The result of a UAV survey often reflects human error. The forward and side overlap is one of the user-controlled properties that affect the quality of the orthomosaic. For mapping surveys that require high precision, the recommended forward and side overlap value is at least 80% [258]. Researchers and practitioners in the field of WRMM need to interact with professionals in the field of UAS technology to discover appropriate existing solutions or to develop new technologies to solve specific WRMM problems. UASs face particular problems when inspecting the natural and man-made aquatic environment. Therefore, knowing the strengths and limitations of UAV technology is crucial for selection, development, and mission planning.

(2) Flight time: the flight time of UAVs significantly impacts their application. It limits the area to be captured at once. So, if a larger waterbody or study area has to be monitored, multiple flights or multiple UAS are required. The flight time of UAVs varies from platform to platform.

(3) Payload capacity: commercially viable UAVs are generally smaller in size and therefore cannot carry much larger payloads. The payload capacity dictates the type of sensors that can be utilized. Their payload mainly constrains UAVs. Their payload capacity mainly constrains UAVs. Thus, this also limits the research applications.

(4) Reliability: weather conditions again limit the use of UAS. The UASs are vulnerable to wind and rain. Many terrain conditions also require specially designed UASs for their surveillance. UAV platforms are prone to instability when wind speeds increase. Because lighting conditions vary between images and flights, cloudy skies can cause image quality issues. Another factor is the availability of GPS for UAS operations [2].

(5) Data interoperability with other Earth observation platforms is also an issue. There is heterogeneity in data collection from different platforms and sensors. The synergistic use of UAVs, unmanned surface vehicles, and unmanned submerged vehicles has to be explored and researched from the WRMM perspective. The UAV/satellite synergy potential is still underexploited [3].

(6) Legal issues and drone security: in many ways, operating unmanned aerial vehicles (UAVs) safely and efficiently over water resources and infrastructure is daunting. When surveillance needs to be done on a large scale or in challenging terrain, drone security becomes an issue.

(7) Different data acquisition conditions for different applications: in the field of mapping and monitoring water resources, UAVs need to make some considerations specific to working over water. In the production of remote sensing data from visible band airborne sensors, distortions resulting from the reflection of light from water-based surfaces have long been a problem. The UAS operator must be aware of such difficulties in any data collecting situation over water surfaces because they can appear in complex ways in good-looking data [259]. Different WRMM problems have different requirements, such as requirements for spatial resolution, temporal frequency, flight path, and hardware (payload) requirements.

(8) Lack of geospatial standards and protocols: there is a lack of standards and best practices regarding UAS data collection, planning, data processing, accuracy assessment, feature extraction, etc., especially with regard to application in WRMM [172]. The variation in these methods introduces uncertainties that represent a bottleneck in the widespread use of UAS data. There is a need to establish a standardized procedure for data collection, processing, and output [260]. Few researchers have attempted to recommend practices [261] and develop protocols [262], but this has been limited to the marine environment. Much needs to be done.

(9) Software and hardware challenges: the data collected by the UAV and its secondary products can be large and require huge digital storage. Photogrammetric processing and AI-based processes are

Table 11: UAV photogrammetry data processing software.

Software name	Developer/proprietor	Link/license type	Capability
Agisoft photoscan	Agisoft	Commercial	Newly upgraded version is called agisoft metashape
MATLAB	Mathworks	Commercial (student license available)	Performs geodetic calculations. In a single profile, combines vector and raster datasets Terrain and elevation analysis
OpenDroneMap	OpenDroneMap	Open-source	Transforms 2D pictures into: Point clouds that have been classified. Textured 3D models Imagery that has been georeferenced and orthorectified. Digital elevation models with georeferencing
Pix4D mapper	Pix4D	Commercial	Classification of the point cloud automatically Identification of digital surfaces that are flat and smooth Measures surface, distance, and volume
QGIS	QGIS community	Open-source	Vector analysis, raster analysis, sampling, geoprocessing, geometry, database management. Composes maps Analyzes data
OpenCV	OpenCV	Open-source	Reads and writes pictures. Records and saves videos. Processes images. Performs feature detection. Detects specific objects in videos or images. Estimates movement and track objects.
Drone2Map	ArcGIS	Commercial (organizational license if available)	ArcGIS Drone2Map is a desktop application that converts drone still images into useful information products in ArcGIS Rapid processing
Menci software	Menci software Srl	Commercial	Used for mapping out areas using drones Creation of 3D aerial cartographic inspection and plotting DEM editor toolsets for volume, profile, and advanced DSM/DTM analysis
Autodesk ReCap	Autodesk	Commercial (student license is available)	Viewing projects in 3D, annotating and sharing data to other software Physical-world detail transformation into digital assets
Maps made easy	Automotive Data Research (ADR)	Commercial (free for small executions)	Orthophoto map and 3D model generation, 3D model-based stitching, stockpile volume measurement
3DF zephyr	3D flow	Open-source	3D reconstruction and scanning, reconstructing 3D models from pictures Generates realistic orthophotos, DTM and DSM models, statistics, and project reports
PrecisionHawk 3D map software	PrecisionHawk	Open-source (mobile application)	Rates the image quality. Adds ground control points to ensure data accuracy. Compresses data for cloud upload.
Correlator3D™	SimActive	Commercial	Aerial triangulation (AT) produces DSM, DTM, ortho-mosaics, 3D models, and vectorized 3D features
Drone deploy 3D	Drone deploy	Commercial (free 14-day trial for mobile phone application)	In-field insights, data analysis, and virtual walkthroughs. Provides reports.
Drone photogrammetry software	Propeller	Commercial	Aerial images to 3D models, accurate measurements
Bentley context capture	Bentley	Commercial	Generating multi-resolution 3D models at any scale, producing reality meshes, orthophotos, DSM, and point clouds
ESRI sitescan	ESRI	Commercial	Drone flight planning, fleet management, image processing, image analysis, 3D textured meshes

Table 11: Continued.

Software name	Developer/proprietor	Link/license type	Capability
Agisoft metashape	Agisoft	Commercial	Photogrammetric triangulation, dense point cloud, DSM/DTM generation Georeferenced ortho-mosaic generation
Regard3D		Open-source	Reconstructing 3D models from pictures
COLMAP	Johannes L. Schönberger, jan-michael frahm, and marc pollefeys	Permissive free software	Reconstructing 3D models from pictures
MicMac	IGN (French national geographic institute) and ENSG (French national school for geographic sciences)	Open-source	Reconstructing 3D models from pictures
SOCET GXP	BAE systems	Commercial	Orthomosaic, surface terrain model, bare Earth terrain model, 3D point cloud
Trimble inpho UASMaster	Trimble inc	Commercial	Detailed 3D models and point clouds
ELCOVISION 10	PMS AG Switzerland	Commercial	Detailed 3D models and point clouds

computationally intensive. They require systems with high processing power. Methods of data processing and analysis that effectively exploit these data's high spatial and temporal frequency need to be further explored. Apart from that, there are also many challenges at the data level. Image alignment and radiometric accuracy of thermal images captured by UAS and inexpensive TIR cameras face several challenges.

7. Future

7.1. Diversity in UAVs as a Platform. New platforms are being developed that are more compact, lighter, cheaper, safer, and more reliable. Sensors are also being miniaturized. In the future, the focus will be on increasing the energy-saving capabilities of UAS. With the development of a wide variety of sensors in future studies, it must be emphasized whether the uncalibrated UAV cameras and sensors can be robust measurement tools for applications in WRMM.

7.2. Development of New Methods. UASs face particular problems when inspecting the natural and man-made aquatic environment; therefore, knowing the strengths and limitations of UAV technology is crucial for selection, development, and mission planning. New analysis methods for decision making in water resource systems need to be developed that consider data collection as a goal in the decision-making process. Such methods would explicitly consider the cost and value of data collection, allowing more data to be collected to reduce uncertainty at the expense of decision speed or the economic cost of data collection. Traditional data processing is maturing. Recent developments in the field of artificial intelligence are used in other disciplines. The field of water resource management and mapping can benefit from the application of artificial intelligence. UAS-collected data have a high resolution, so the data volume is large in many cases, which poses a challenge for the analyst. The AI algorithms offer a solution to this problem. We encourage the water resources community to implement the developments for WRMM. UAS applications in the field of WRMM will require new modelling, computational, and mathematical approaches to assimilate data collected by traditional remote sensing and UAS to help identify optimal and timely decisions. The future of using UAS for WRMM will be dominated by advanced algorithms and predictive tools with a focus on analytics-based data mining of crucial information. Ongoing developments in AI, ML, and DL are likely to improve the efficiency and scalability of UAV analysis approaches in WRMM. Virtual and augmented reality can also be helpful in cooperation with UAS exits. Due to its immersive nature, the combination of deep learning with virtual and augmented reality environments represents an important research topic for the effective study of complex environmental phenomena that are difficult to organize in reality.

7.3. The Cost Will Come Down. With advances in electronics and materials science, the cost of UAS is predicted to decrease. This will increase both the popularity and range of drones. In combination with open-source initiatives, this will also promote citizen science. Citizen science is already gaining popularity in the field of mapping and monitoring water resources [263]. Citizens can support the mapping and monitoring of water resources at a low cost and contribute to the data pool in data-poor and understudied areas [264]. Crowdsourced data could be an important complementary data source for monitoring water resources.

7.4. Real-Time Usage. With the demand for a higher degree of automation and a reduction in the time between collection and output, real-time onboard data processing is increasing daily.

7.5. Cost-Benefit Analysis of UAV samplers. When it comes to the cost-benefit analysis of water samples, the cost-benefit analysis is still unclear [20]. These cost-benefit analysis studies may also include health and safety and biosecurity risks. UAV-based water sampling should be compared to other sampling methods helpful in making informed decisions about sampling methods (based on careful cost estimates).

7.6. Synergies with Other (Satellite) Datasets. The UAV/satellite synergy potential is still underexploited. Data fusion can be studied for different sensors for different applications, similar to those in other fields [234]. In the future, there is a lot of scope for developing the integration of satellite intelligence pipelines with drone-based knowledge [265]. The realm of UAV/satellite synergy potential remains untapped for many areas, particularly water resource mapping and monitoring [3]. UAVs can bridge the gap between in situ observations and satellite data [153]. There is cause for optimism that UAS and data collected by different payloads can be used at different scales in monitoring and mapping water resources. However, this optimism must be balanced with a dose of reality regarding technological and legal challenges. Many new techniques for UAV-derived data such as sensor data fusion need to be explored. Addressing these challenges to extend proof-of-concept studies to inflection points and realize the hidden potential of UAS technology requires broader, collaborative methodologies supported by strong funding initiatives. New analytical methods for mapping and monitoring water resource systems need to be developed. Inexpensive UAV sensors may pose problems in synergizing with satellite data [3, 266]. Another aspect to study is the combination of UAVs with aquatic drones (USVs) and unmanned surface boats [10]. Data input from a combined use will improve mapping compared to UAV alone [267]. Few studies have attempted to investigate this in the past [268]. But this aspect has not yet been fully explored.

7.7. Development of Swarm Intelligence. Another area that is increasingly being researched is swarm intelligence and swarm intelligence. The swarm can be applied in many innovative and diverse ways in the field of water resource mapping and monitoring. There have been few studies [211, 247, 269] that attempted to explore the applicability of swarming to different aspects of WRMM. Nevertheless, swarm development itself faces many challenges [267]. Long-term WRMM swarm systems have challenges in terms of scalability, maintainability, safety, and flight endurance. Studies have been limited to testing algorithms or data processing. This swarm system needs to be explored more closely for WRMM.

7.8. Deregulation. Various studies continuously demonstrate that UAS technology can be safely used in mapping and monitoring water resources. This also leads to cautious deregulation of the technology and the removal of legal hurdles by the administrative authorities [270]. All this will lead to increased use of UAS systems in the field of WRMM.

8. Conclusion

The authors attempted to provide an overview of various sensors and the application of unmanned aerial systems in water resource management and monitoring. A wide range of sensors available can cater to WRM practitioners' needs. There are several helpful recommendations in the literature that have been compiled to offer direction for using drones for water resource applications. The information examined was primarily practical and applicable to a variety of subsectors, including river mapping, bathymetric mapping, water quality, wastewater, and coastal mapping. The field of water resources is vast; with each coming day, researchers are inventing new ways to use UAS for this cause. To support WRM applications, UAS should be applied in a multi-disciplinary manner, including different approaches and topics. The UAS technology has many advantages such as low cost, high spatial resolution, operator-subjective temporal resolution, and non-intrusive methodology in many WRMM applications. The field of UAS application in WRMM is yet to be matured and still faces many challenges such as battery life, data interoperability, legal hurdles, and so on. These challenges and issues have been compiled in this research. The authors have identified the areas in which future research can take place. The use of these unmanned aerial systems for water resource mapping, monitoring, and hydrological research remains experimental in many places. This study is very important, especially for new researchers. The information is easily adaptable to different areas of WRMM.

Data Availability

No data were used to support this study.

Disclosure

The sponsors had no role in the design of the study or in the collection, analysis, or interpretation of data when writing the manuscript or when deciding to publish the results.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Rainfall & Seismological Dump Slope Stability Analysis on Active Mine Waste Dump Slope with UAV

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Mine waste dump material has no economic value to the industry. Therefore, the mine waste is dumped, forming slopes. Mine waste dump slopes obtain 30% to 50% of the mining area. To reduce the land occupancy of these slopes, they are created with high altitudes. Hence, they are susceptible to failure. Slope stability analysis is a major aspect of geotechnical engineering. Slope stability analyses are mostly done with assumptions on the geometry. This is avoided in this paper with the usage of UAVs. The 3D model is created from UAV imagery of a coal mine in Raniganj coalfield, India. The model is fine-tuned with the DGPS survey. Geotechnical data were collected and tested in the laboratory for various numerical analyses. An active mine waste dump slope is analyzed for slope failure. Earthquakes and rainfall cannot be controlled, and their effects on the stability of the mine waste dump slope were examined. The study extracted various factor of safety (FOS) analyses on static, seismic, and rainfall conditions. The seismic condition simulates a condition of the slope to be failed with low (0.948) FOS. However, rainfall condition predicts the slope to be more stable. The deformation pattern and magnitude of the slope failure are also discussed.

1. Introduction

Open-pit mining operation excavates the top portion of the soil to extract minerals or coals. During this process, the excavated soil had no economic value to the mining industry. These materials are known as waste [1, 2]. The limitation of the mining area makes it tedious to manage this waste. Therefore, the mine waste is dumped, forming a slope [3, 4]. These dump slopes are enormous. Mine waste dump is made very rapidly, therefore less time for consolidation of waste materials. This hasty approach is making the slopes susceptible to form disasters. From 1921, there were 23 accidents due to mine overburden slope failures only in India. These accidents cost 143 causalities [5, 6]. In 2016, a catastrophic slope failure in Rajmahal opencast mine caused the death of 23 people. Talcher, Bokaro, and Bharatpur recently faced similar accidents [7–9]. Mine dump slope stability analysis is a major subject in geotechnical engineering. The safety study is based on these slopes with SSR (Shear Strength Reduction). In this technique, soil material's strength characteristics are reduced till the failure is obtained in the geometry [10]. This method provides a numeric value that represents the factor of safety [11]. If the value is greater than one, then the stability of the slope is high and vice-versa [12–15]. For traditional numerical simulation, an assumption on geometry is considered [16]. With the usage of UAV, two significant problems in numerical simulations can be solved, the first reduction in geometry assumption, and the second, the GIS tools can be used for mapping, monitoring, and targeting the risk-prone areas for numerical simulation resulting in accurate analysis and less computational time. This approach is possible with UAV's RGB (red, green, and blue) imagery. Overlapped images of UAVs can create a 3D point cloud of an area [17–19]. Furthermore, DTM for slope targeting for

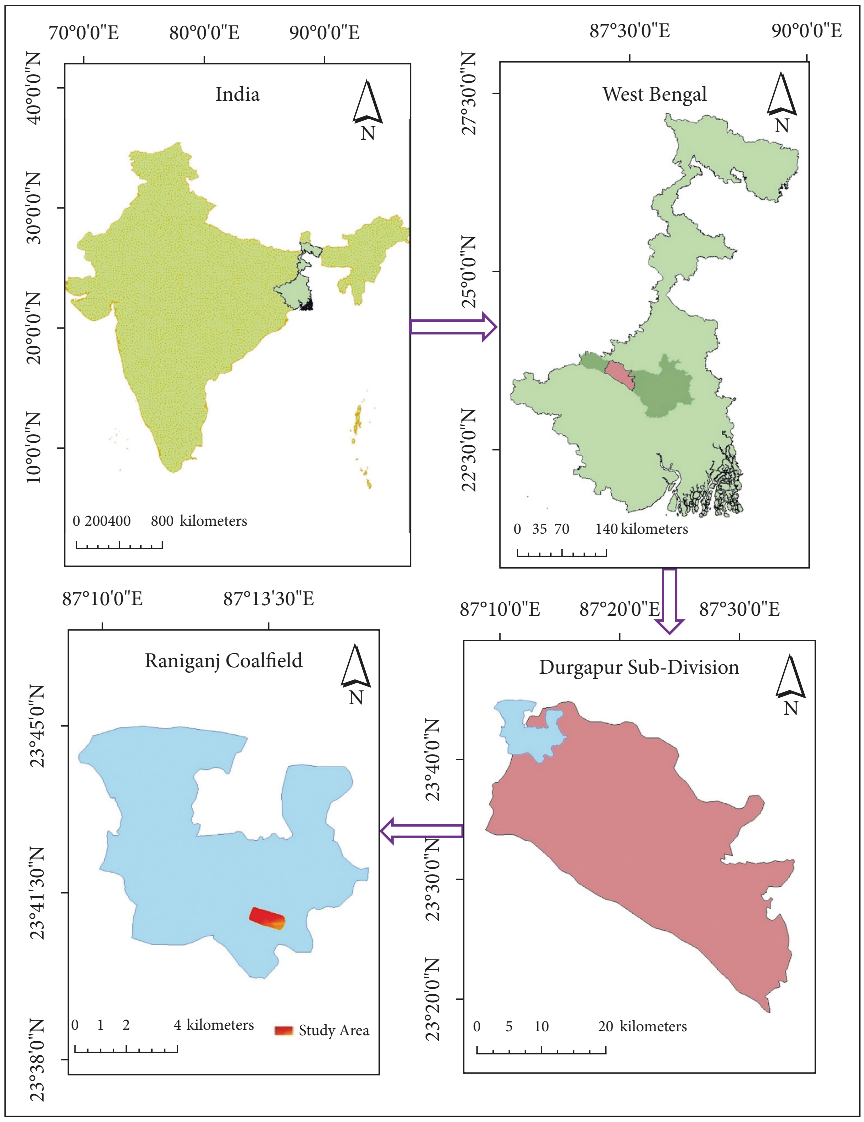


Figure 1: Map showing the study area, located in India's eastern part.

numerical simulation and geometry for numerical simulation can be developed. For testing this approach, Raniganj coalfield, India, has been selected (Figure 1 represents the study area). Raniganj is situated in the eastern part of India. This coalfield region is about 1130 km^2 from 23°25′N to 23°50′N latitude and 86°38′E to 87°20′E longitude [20].

Raniganj coal mines have most of the open cast projects of Eastern Coalfield Ltd., India. In Raniganj coalfield, the biggest open cast mine is situated in Sonepure Bazari [2]. The production of the coalfield is 33.90 million tonnes; thus, high mining activity occurs consistently. The mine we selected has an in-pit waste dumping system, i.e., waste is dumped within the mining area due to the limited range of available land. In-pit waste dump of the study area is shown in Figure 2.

An active mine dumping area was taken for testing for stability analysis, as the chances of failure will be high due to less time for waste to consolidate [12]. Hence, traditional numerical simulation is insufficient in this scenario as rainfall plays a vital role in slope failures and earthquakes [21]. As Raniganj is a subtropical place, heavy rain occurs, and precipitation of 200 to 400 mm every monsoon has been reported yearly. Also, regular cyclones have been impeding [22]. Therefore, an increase in rain directly affects the safety factor of the overburden slope [23].

Figure 2: In-pit mining waste dump at the study area.

2. Materials and Methods

This study focuses on the stability analysis of the active in-pit mine waste dump. Therefore, in data acquisition, UAV imagery, DGPS survey, and geotechnical samples were collected from the study area. With the help of UAV imagery,

3D modeling and proper geometry are extracted from the active waste dump slope. The area was cross-checked with GIS to ensure the proneness to failure. Finally, three geometry of the section was extracted, and numerical simulations were done with the help of geotechnical data. In Figure 3, the steps can be followed. There are four steps to achieving the desired goal; data collection, geotechnical analysis, image processing, and numerical simulation. The numerical simulation focuses on rainfall effects on the stability of the slope and the simulation of seismological impact on the slope. These parts are discussed in this section.

2.1. UAV Data Acquisition. In the field, DJI Phantom 4 Pro UAV has been used (Figure 4 shows the UAV). The UAV can fly for up to 19 minutes on a single charge and capture 20-megapixel resolution worth of imagery. Acquisition of images is made with overlapping of 75% in horizontal and 65% in vertical. DGPS (differential global positioning system) was also used for the accuracy of the generated model [24–26].

The average GSD of the constructed orthoimagery was 5.022 cm per pixel. A total of 561 images were captured with two flights. And the flight plan was grid in nature. The area captured by the UAV is 4716900 m^2. DGPS can extract coordinates of an unknown area without reference. Prominent "+" symbols were drawn in the field with whitewash for this study, as shown in Figure 5. Seven GCPs were used to process the images in Pix4DMapper. As per the software Pix4DMapper with seven GCPs, the RMS should be less than 0.10, making the model highly accurate.

The overlapping helps in recovering lost 3D information of the camera with the same feature extraction in multiple images, and triangulation is done to retrieve the position of the camera in x, y, and z coordinates by reversing the approach after extracting camera location, x, y, and z coordinates of features are extracted. This approach is made by structure from motion pipeline for generating 3D point cloud and other forms of data [27, 28].

2.2. Geotechnical Analysis. Accurate shear strength parameters, i.e., cohesion and internal frictional angle of the waste materials, are necessary for numerical simulation accuracy [29, 30], along with those compaction characteristics that are also needed. For shear strength parameters, triaxial tests were performed [31], and compaction tests were carried out according to Indian Standard (IS:2720) part-6 (1965). Hence, a geotechnical investigation was necessary. The materials were initially tested with grain size distribution. According to Indian Standard Soil Classification System (ISSCS) with various tests, the material showed coarse materials between 80% and 98%, and sand between 2 mm and 0.425 mm was ranging from 22% to 92% and, sand and clay ranging from 3.8% to 46% (particles are less than 0.75 mm) thus making the material poorly graded sand or SP. The samples were collected during UAV data acquisition and have been processed in the institute's laboratory facilities, and the extracted geotechnical parameters can be seen in Table 1.

2.3. 3D Model of UAV Imagery. 3D modeling from UAV imagery is based on epipolar geometry of photogrammetry [28, 32]. Therefore, feature extraction and matching of multiple images are done. Matched features of image pairs are used to create pose estimation (3D location of the camera of the same feature found in various images) with triangulation hence, spatial 3D point cloud data [33, 34]. To minimize errors, bundle adjustment is applied. Bundle adjustment is used on the accumulated 3D model to refine and prevent noise in triangulation [35]. This model is created from a UAV. This 3D model, along with an orthomosaicked image, was used to create a digital elevation model (DEM) for inspection of AOI.

Furthermore, to be accurate, the geometry DGPS surveyed data were integrated before processing the 3D point cloud as ground control points in Pix4DMapper. Figure 6 shows the 3D model of the study area, which is generated from UAV imagery.

2.4. Geometry Extraction for Numerical Analysis. The surveyed area from the UAV mainly covered the mining dump, but most of the area was not visible from the ground survey or observation. So, removing fewer risk-prone zones from the surveyed area helps reduce computational time. The authors targeted an active waste dump slope to be examined. A newly made dump has less time to settle down, and having loose materials causes low shear strength. Therefore, failure can occur.

In Figure 7, the active dumping zone is shown. This area initially needs to be examined with GIS. The GIS technology can cross-check whether the active dumping slope is prone to failure. This is done by developing a slope map of the study area from UAV data. Slope angles represent the relative angle displacements. In Figure 8, the slope map is shown.

From Figure 8, it can be seen that the angular value of the targeted zone exceeds 36 degrees. Thus, this site makes it ideal for examining numerical simulation for slope stability.

Three sections from the active dumping zone have been extracted. These geometries can be seen in Figures 9(b)–9(d). The geometries from the same dumping slope have different angles and heights. Examining only one will derive less in-depth analysis. These sections have a length of 207, 210, and 198 meters horizontally and 66, 83, and 101 meters in altitude displacement (the projection in the figure is in 3D; hence, the perspective of displacement on different axis differs).

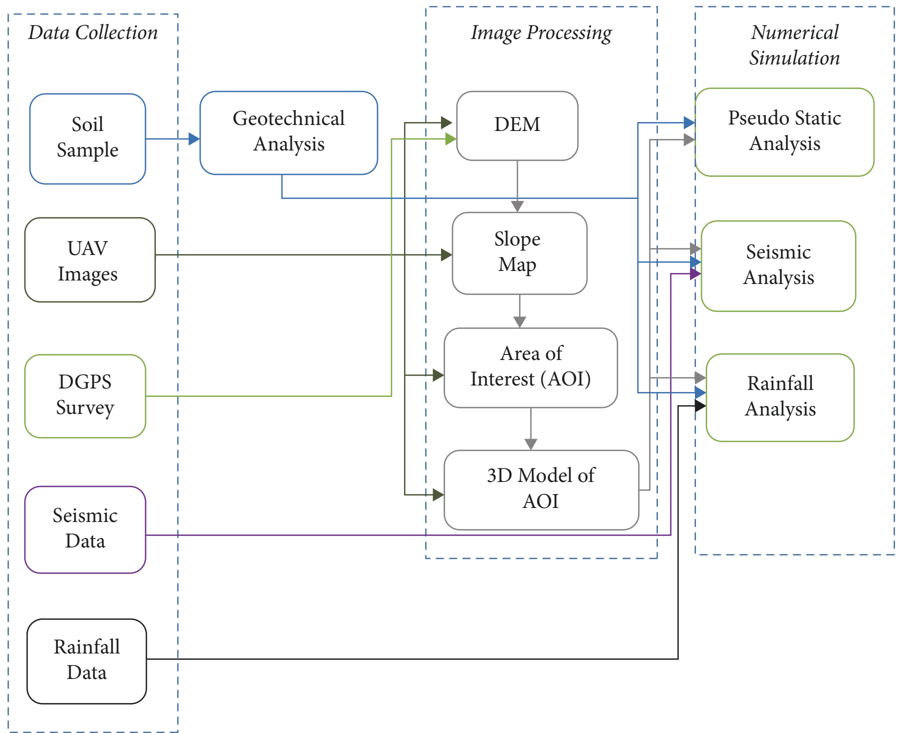


Figure 3: Slope stability analysis method in static, seismic, and rainfall conditions with the UAV.

Figure 4: UAV data acquisition in the study area.

3. Results and Discussion

Flac comes with computing packages for numerical simulation applications. This is widely accepted and recognized. In Flac3D, numerical analysis is done with the shear strength reduction technique or SSR. Constraint boundaries restrict developed geometries. This approach improves accuracy, efficiency, and modeling time, ensuring accuracy and legitimacy [36, 37]. Three geometries were extracted from the targeted waste dump slope. These geometries range between 66 meters and 101 meters in height and 197 meters to 210 meters horizontally. Mohr-Coulomb's failure criteria were adopted in the first iteration of stability analysis. The failure occurs with the critical combination of the shear strength of loose mine waste dump materials with normal stress. The loose, broken waste dump materials contain low shear strength [38, 39]. The dump slope was numerically analyzed with finite element method codes, and the FOS was calculated with displacement values, as shown in Table 2.

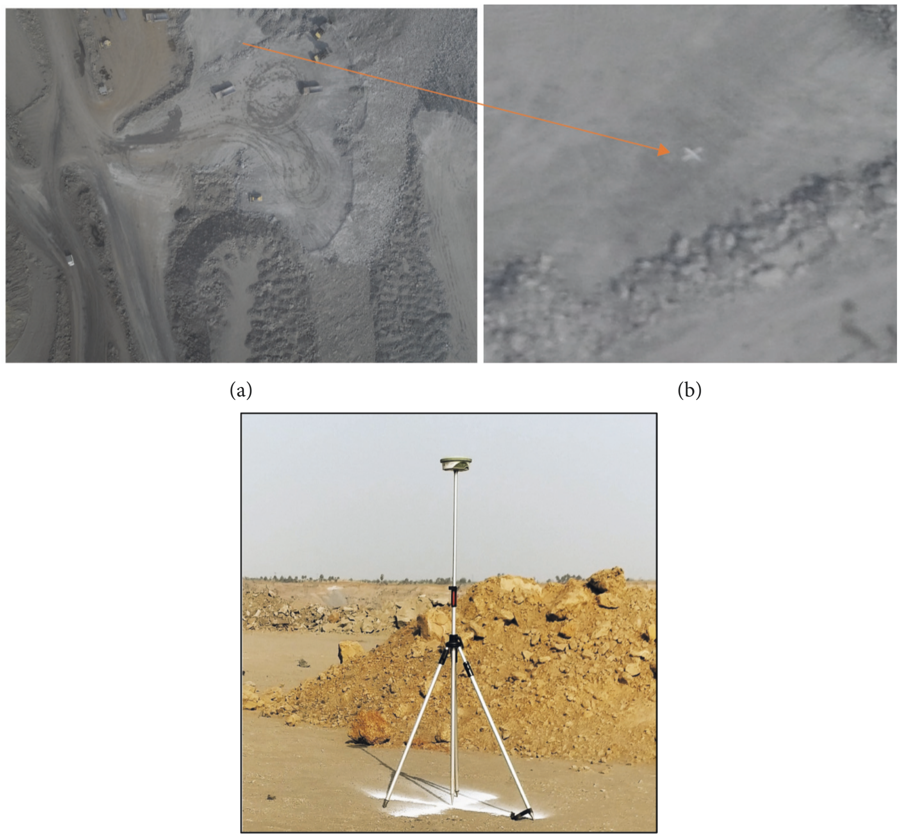
The slope seems to be stable with low displacement values in all the scenarios [38]. Furthermore, the sliding portion of the geometries can be seen in Figure 10. All the failures are circular. The FOS of the sections ranged from 1.26 to 1.53 of the slope under static conditions.

As discussed earlier, static slope stability analysis is insufficient as two significant reasons slope failures occur due to heavy rainfall and seismological effects. These two factors cannot be dealt with human intervention. Therefore, examining these two factors will ensure a more nuanced analysis on analysis.

3.1. Pseudostatic Condition for Seismic Effect. India is divided into four zones for an earthquake. The study area of this paper has zone III in terms of earthquake hazards. According to Figure 11, the study area lies in the moderate damage risk zone, and the factor is 0.16.

A seismic load is given in the numerical simulation of the seismological effect, i.e., 0.16. Therefore, the integrity of the analysis of the limit equilibrium method [41] with seismic conditions on the geometries is ensured. The extracted FOS from the simulation validated a lower stability factor than the static condition. In Table 3 no. 3 FOS of three sections can be seen.

The seismological effect also extracted similar failure patterns as a static condition. The LEM method provides only a stability factor. Therefore, stress and strain information is not achievable, resulting in nondeformation analysis in pseudostatic conditions. The sections after numerical simulation can be seen in Figure 12.



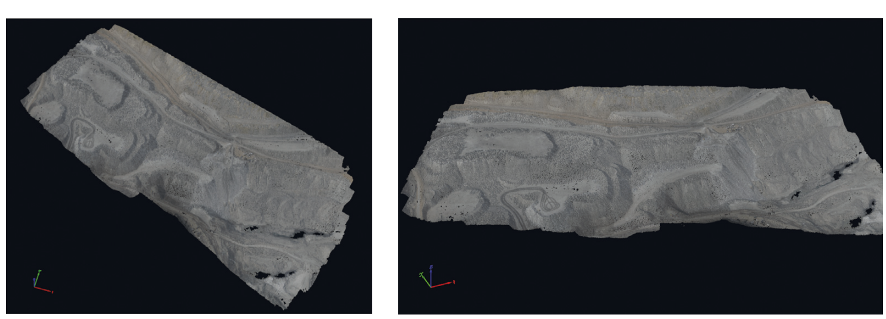
(a) (b)

(c)

Figure 5: (a, b) represent temporary ground control point and (c) DGPS data acquisition for improving the accuracy of the UAV dataset.

Table 1: Waste dump material properties extracted from laboratory tests.

Parameters	Tested result
Soil unit weight (kN/m^3)	17.59914
Friction angle (degree)	25.556
Cohesion (Pa)	50000
Bulk modulus (GPa)	0.32
Shear (GPa)	3.1



(a) (b)

Figure 6: (a, b) 3D models of the study area created from UAV imagery from different views.

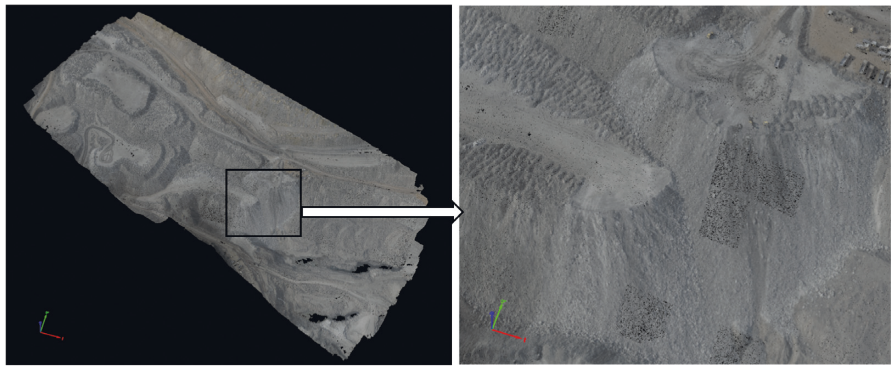


Figure 7: Active waste dumping zone in the study area.

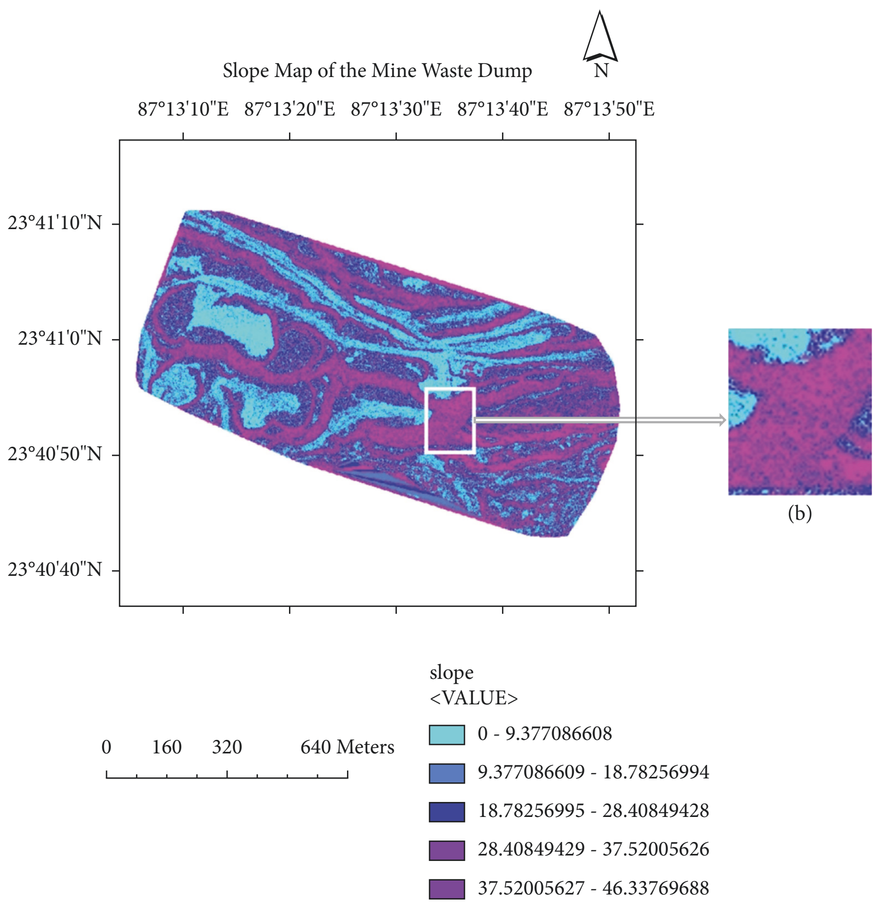
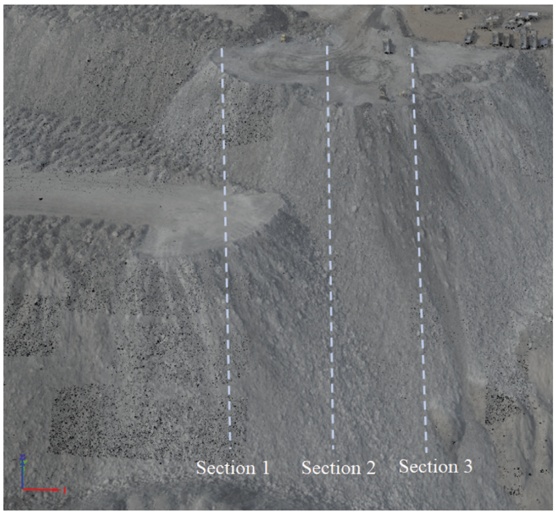


Figure 8: Slope map of the area and (b) cropped area represents the active waste dump slope.

This section validates the analysis methodology as to its capability to calculate the slope failure surface with seismic acceleration. The simulated result is documented with zone III seismic acceleration (Figure 11), which has been analyzed through widely recognized conventional Bishop's limit equilibrium methods [42]. The sections were further analyzed with a 2, 4, 6, and 8 seconds dynamic seismic load.

The el Centro dataset is adopted for input load. The given input data can be seen in Figure 13. This data propagates in the N-S direction. The pick of the acceleration is 0.3 g recorded around 2 seconds, and after 5 seconds, the acceleration gradually decreases with a low spike at 8 seconds and in around 25 seconds with 0.138 g. The displacement of the sections with dynamic load can be seen in Figure 14. In section 3 (Figure 13(e)), the displacement initially started with negative and then moved towards positive, which strongly proposes crack generation in the upper part of section 3 [43].



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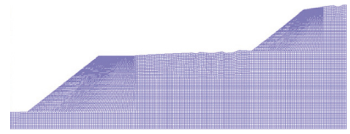

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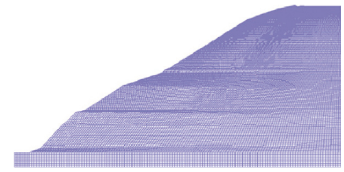

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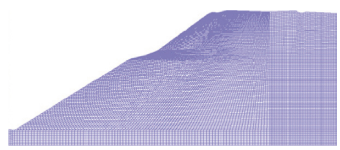
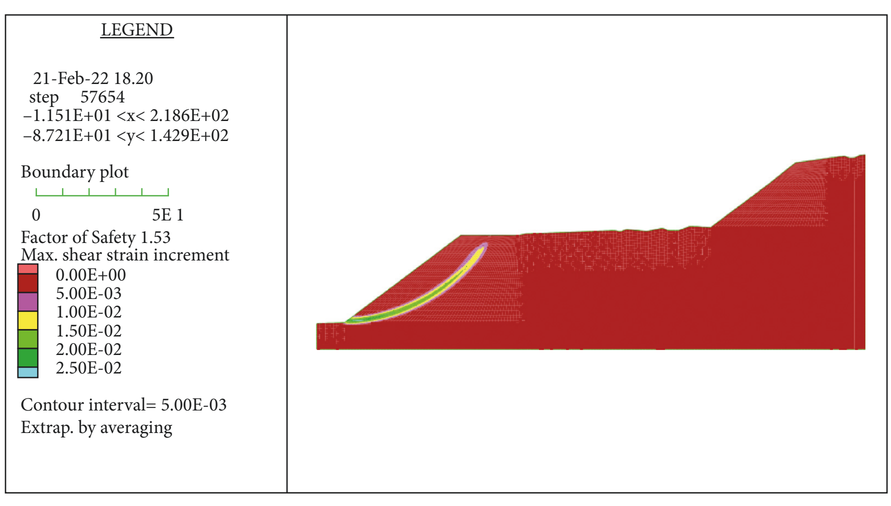


(d)

Figure 9: (a) Three sections marked with dotted lines on the active dumping slope. (b–d) Geometry of section 1, section 2, and section 3, respectively.

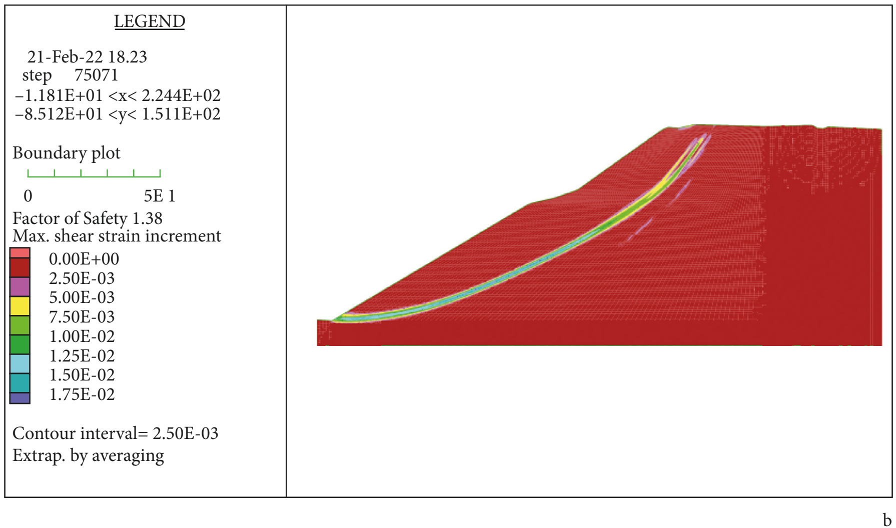
Table 2: FOS of 3 sections in static numerical simulation condition with deformation.

	FOS	Deformation (meters)
Section 1	1.53	$1.059E-01$
Section 2	1.38	$8.084E-02$
Section 3	1.26	$2.226E-01$



(a)

Figure 10: Continued.



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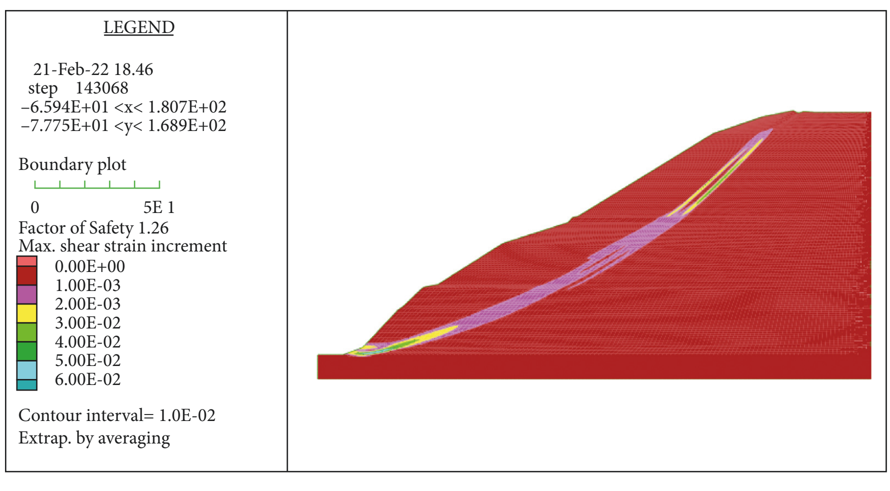


(c)

Figure 10: (a–c) circular failure profiles of sections 1, 2, and 3.

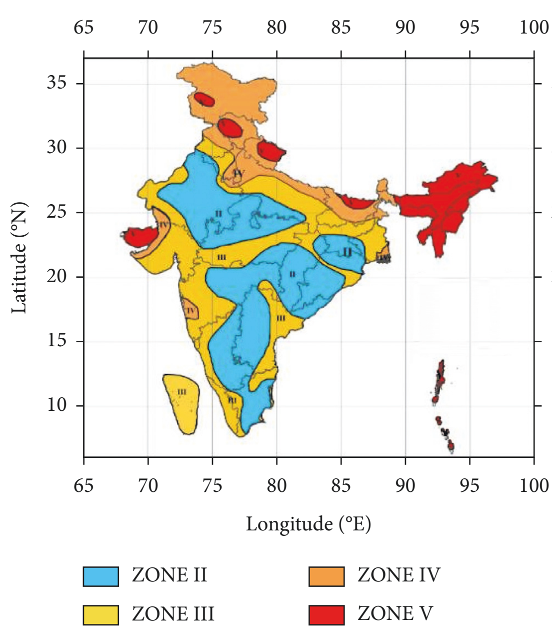


Figure 11: Seismological map of India [40].

Table 3: FOS after applying seismic conditions in LEM.

	FOS
Section 1	1.219
Section 2	1.048
Section 3	0.953

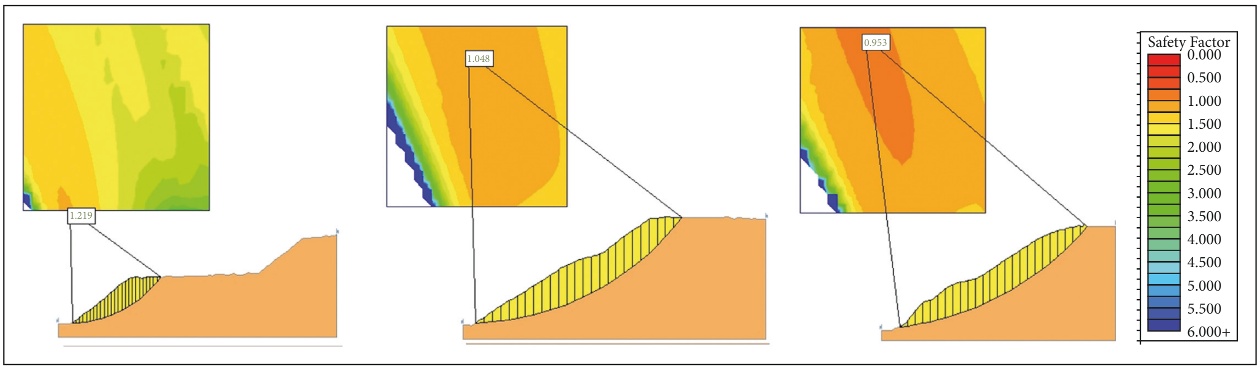


Figure 12: Pseudostatic analysis of three sections.

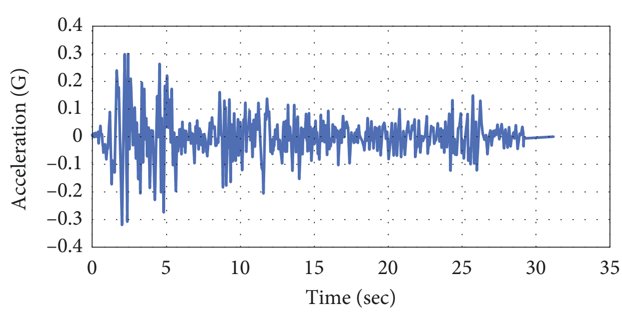


Figure 13: El centro accelerogram.

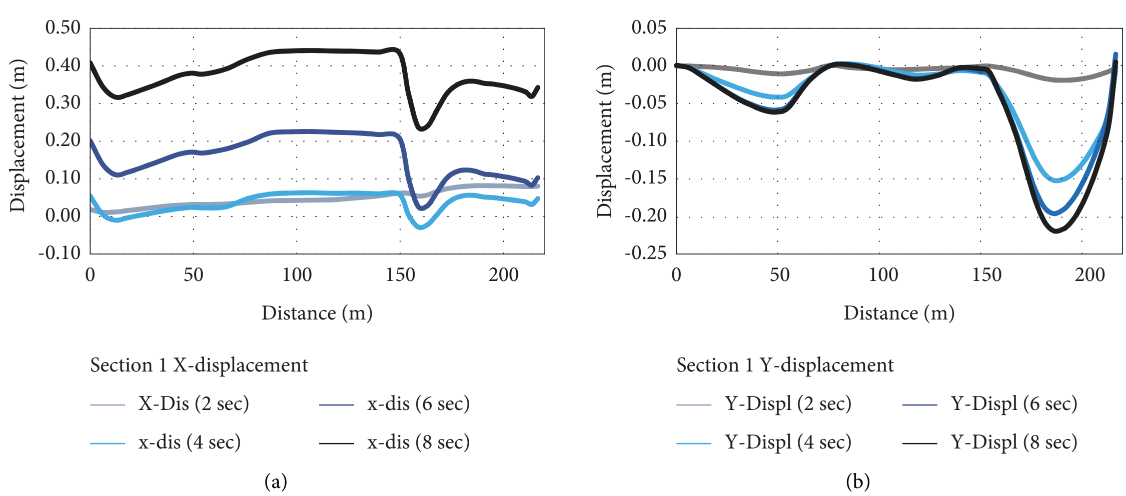


Figure 14: Continued.

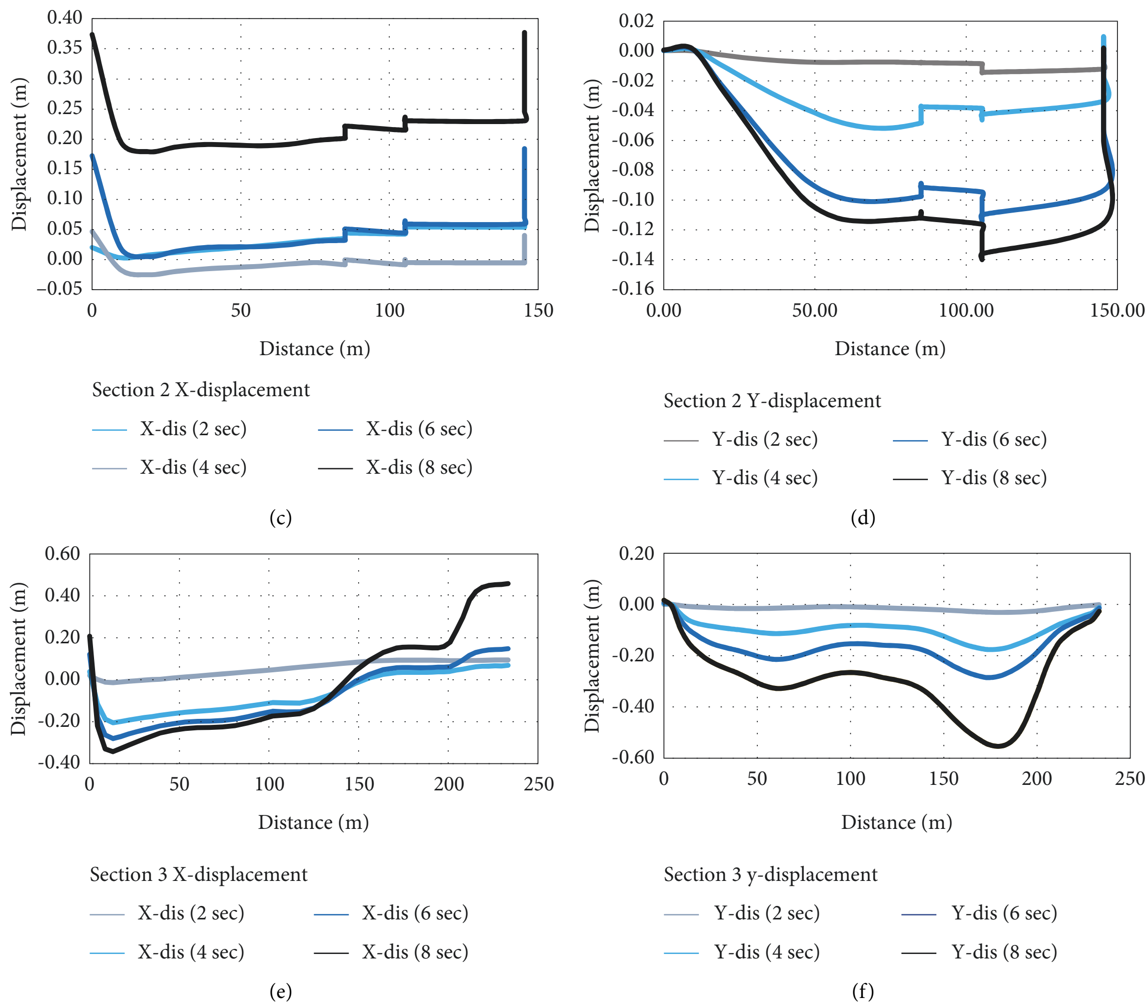


Figure 14: Dynamic load of seismic data with 2, 4, 6, and 8 seconds of sections 1, 2, and 3.

The simulation shows that the FOS of section 3 has a value of 0.953. This makes the section prone to failure. As for sections 1 and 2, they are shown a dip in FOS compared to numerical simulation in static conditions with 1.219 and 1.048.

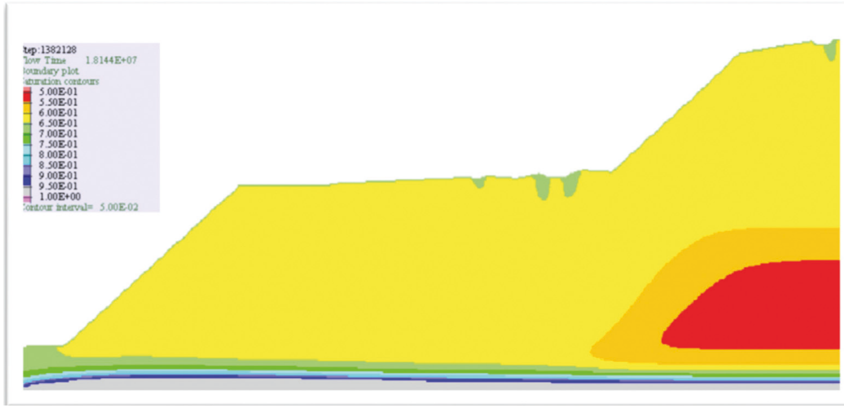
Table 4: FOS with average rainfall during monsoon.

	FOS	Deformation (centimeters)
Section 1	1.60	7.474
Section 2	1.40	14.4
Section 3	1.25	109.8

3.2. Dump Slope Stability Analysis with Average Rainfall. The study area is subtropical in climatic nature. Hence, the rainfall occurs heavily after summer, i.e., from June to September [44–46]. Mine waste dump failures occur primarily in this period due to heavy precipitation. The precipitation in the study area was highest in August. In August, the minimum rainfall was 207.3 millimeters recorded in 2017, and the highest was in 2016 with 601.3 millimeters. In other monsoon months, precipitation varies from 28 millimeters to 515 millimeters. The average rainfall in the monsoon of the study area has been recorded as 264.266 mm in the last ten years. The numerical analysis of the study area with precipitation data was simulated for seven months. Extracted FOS can be seen in Table 4. The FOS in this scenario improved [47].

The improvement in FOS is explainable by two factors. First, seven months for settlement of the slope which is after the monsoon. The second cause is related to the waste dump material characteristic. The material contains clay that has high adhesiveness when mixed with water, which vastly improves the cohesion that benefits the bonding and stability [48]. The saturation profile of the simulation can be seen in Figure 15. This phenomenon was derived from the theory of consolidation, in which precipitation decreases the pour spaces of sand and clay-type materials and improves the consolidation with time.

Deformation of the sections stayed almost the same with low movements of the slope materials, which maxed at 1.098 meters at section 3. The displacement profile of the sections can be seen in Figure 16. The displacement on the slopes with rainfall causes less than 1 meter of negative deformation. In sections 1 and 2, the displacement goes up to 0.05 meters and



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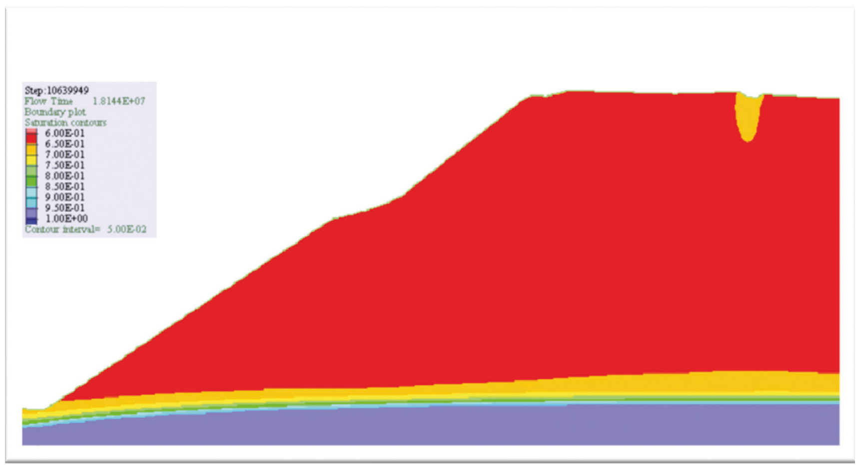

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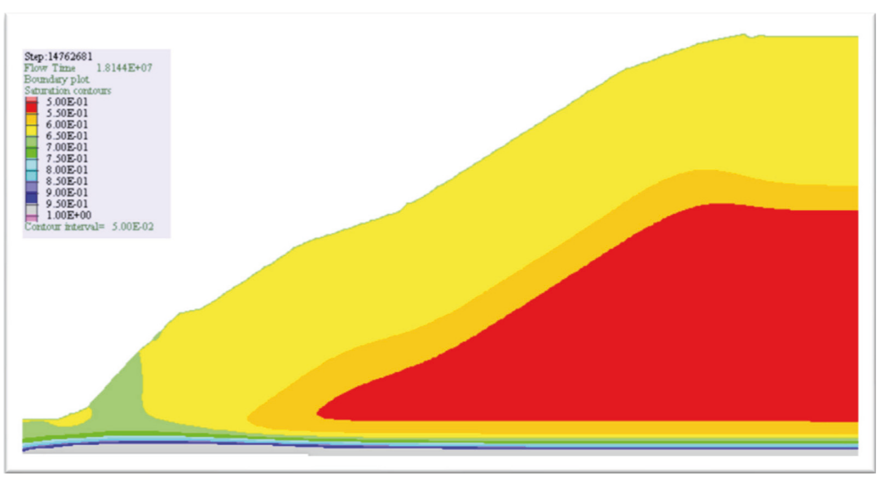

(c)

FIGURE 15: (a–c) represent the saturation profiles of section 1, section 2, and section 3, respectively, with a flow time of 7 months.

0.16 meters, although insection 3 geometry, the deformation goes up to 1 meter.

As a future study, rigorous analyses can be done with various FORM algorithms, and these algorithms were derived from HLRF algorithms. HLRF and FORM algorithms are known for their reliability [49, 50]. Therefore, a basic comparison of the stability of waste dump slopes can be compared with various material properties [51].

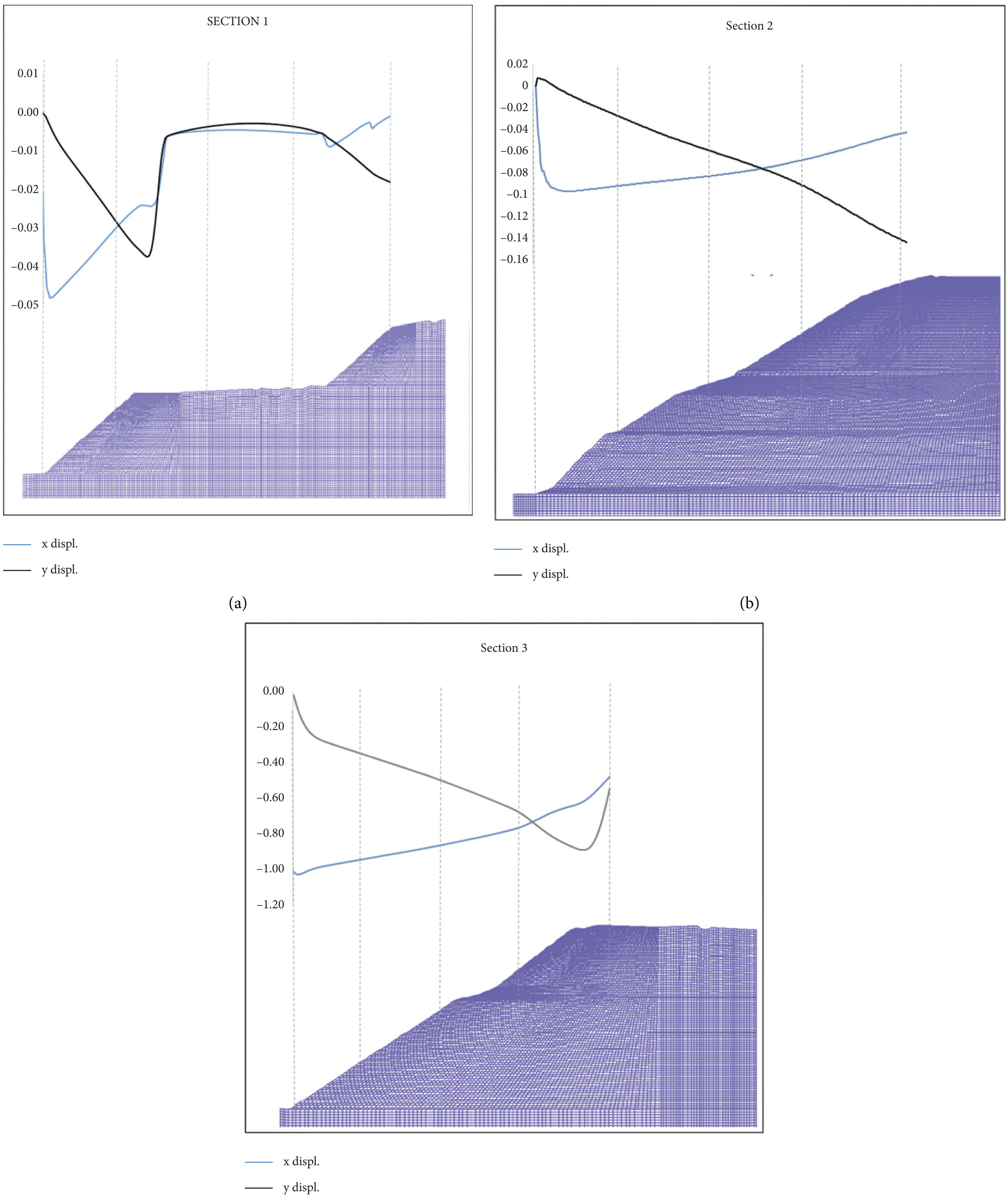

Figure 16: (a–c) represent the displacement profile in meters. The plotted displacement of the X and Y axes along the surface of the geometries of sections 1, 2, and 3 from toe to the pick of the sections.

4. Conclusions

The availability of the UAV and improvement on the image sensor is useful for creating 3D maps and models of the mining area. Proper scale and dimensions are extracted with the help of UAV imagery, DGPS, and photogrammetry. The geometries extracted from the UAV's 3D model represent an active in-pit mine dump slope, which is examined based on less time for the slope to settle waste materials. A geotechnical investigation was carried out on the dump waste materials. The geotechnical properties are instrumental in numerical analysis reliability. Numerical simulations on these geometries are carried out in three different approaches, making the study cohesive. The environments for the numerical simulation consisted of static, seismic, and rainfall conditions. These simulations show the FOS value initially at a stable state, and rainfall with seven months of simulation time increased the stability. However, the seismic condition in Bishop's limit equilibrium method shows significantly lower FOS of the sections. The least FOS was 0.948 achieved in section 3 geometry after seismic load. This outcome illustrates the failure in section 3.

Nevertheless, regular precipitation and time (or settlement of the loose materials) suggest a higher FOS, so the waste dump slope will be stable if no significant seismic acceleration occurs. The displacement analysis also indicates a maximum of 1-meter deformation. Although with seismic activity, cracks will be formed in section 3.

Data Availability

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

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