A Survey on UAV Applications in Smart City Management: Challenges, Advances, and Opportunities

Haoran Xu, Lizhe Wang, *Fellow, IEEE*, Wei Han, *Member, IEEE*, Yixin Yang, Jiabao Li, Yue Lu, and Jun Li, *Fellow, IEEE*

(Review Paper)

***Abstract*—Smart management of urban space is an important way to achieve the goal of sustainable urban development. Unmanned aerial vehicles (UAVs) have been widely used in urban space management work and have greatly improved the level of it. UAV technology assisting urban space management involves many technical details and has generated a number of problems. Therefore, a systematic review of the applications of UAVs in urban spatial management work is very necessary and can provide a comprehensive reference for relevant researchers. This is conducive to the generation of more new insights, methods, and applications. However, according to our research, there is a lack of relevant systematic investigation. We screened and researched a large number of relevant literature works (about 230) with the help of search tools, such as Web of Science and IEEE Xplore, and combined with our own working experience to review and summarize the field in an all-round way. Taking the definition, needs, and challenges of urban spatial management as an entry point, this article systematically summarizes the task flow, working paradigm, technical system, and application direction of UAV-assisted urban spatial management. It also takes our recently developed UAV urban management system as an example to provide an introduction on how to integrate advanced technologies such as UAV and artificial intelligence. Finally, this article summarizes several concluding findings and proposes several future research directions. The research in this article shows that UAV technology has already played a great role in urban spatial management work, but it is still far from realizing automation and intelligence, and it needs to continue to make efforts in terms of methods, systems, applications, and policies. In order to achieve these goals, UAV technology can be further integrated with advanced technologies such as deep learning, more types of UAV industry applications can be carried out, a more functional unmanned aircraft system can be developed, and better management policies can be formulated.**

***Index Terms*—Sustainable development, unmanned aerial vehicle (UAV), urban management.**

Manuscript received 27 May 2023; revised 27 August 2023; accepted 14 September 2023. Date of publication 20 September 2023; date of current version 4 October 2023. This work was supported by the National Natural Science Foundation of China under Grant 42242105 and Grant 41925007. *(Corresponding author: Lizhe Wang.)*

Haoran Xu, Lizhe Wang, Wei Han, Yixin Yang, Jiabao Li, and Jun Li are with the School of Computer Science, China University of Geosciences, Wuhan 430078, China (e-mail: 1625903738@qq.com; lizhe.wang@gmail.com; weihan@cug.edu.cn; yixin-yang@foxmail.com; wutonglbj@cug.edu.cn; lijuncug@cug.edu.cn).

Yue Lu is with the Key Laboratory of Geological Survey and Evaluation of Ministry of Education, China University of Geosciences, Wuhan 430074, China (e-mail: lu_yue@cug.edu.cn).

Digital Object Identifier 10.1109/JSTARS.2023.3317500

Nomenclature

UAVs	Unmanned aerial vehicles.
SDGs	Sustainable development goals.
ICT	Information and communications technology.
IoT	Internet of Things.
AI	Artificial intelligence.
RGB	Red–green–blue.
LiDAR	Light detection and ranging.
GNSS	Global navigation satellite system.
NDVI	Normalized difference vegetation index.
reNDVI	Red-edge normalized difference vegetation index.
HRS	Hyperspectral remote sensing.
FoV	Field of view.
TIR	Thermal infrared.
FPGA	Field-programmable gate array.
GPU	Graphics processing unit.
ARM	Advanced RISC machine.
DL	Deep learning.
UTM	Unmanned aircraft system traffic management.
RRT	Rapidly-exploring random trees.
PRM	Probabilistic roadmaps.
GA	Genetic algorithm.
PSO	Particle swarm optimization.
ACO	Ant colony optimization.
DRL	Deep reinforcement learning.
RL	Reinforcement learning.
LoRa	Long-range radio.
LWAN	Low-power wide-area network.
NB-IoT	Narrowband IoT.
QoS	Quality of service.
WLANs	Wireless local area networks.
FCS	Flight control system.
SD	Standard definition.
DSM	Digital surface model.
SfM	Structure from motion.
SLAM	Simultaneous localization and mapping.
CNN	Convolutional neural network.
RNN	Recurrent neural network.
YOLO	You only look once.
RCNN	Region CNN.
UI	Urban infrastructure.

DEM	Digital elevation model.
HD	High definition.
BIM	Building information model.
DTM	Digital terrain model.

I. Introduction

GLOBAL urbanization is accelerating [1]. By 2030, the urban population is expected to comprise more than 60% of the global population, and the number of cities with more than one million people worldwide will likely reach 662 [2]. While urbanization brings convenience to people's lives, it also raises many urban space problems, such as urban disasters, environmental pollution, and human–land conflicts. These problems have attracted a great deal of attention all over the world. The United Nations General Assembly held a dialogue on urban issues and included SDGs on cities in the 2030 Agenda, in particular, SDG 11 ("to make cities and human settlements inclusive, safe, resilient, and sustainable") [3].

The continuous advancement of robotics and autonomous systems has had a huge impact on the SDGs and is changing the way the SDGs are achieved [4], [5]. Among them, consumer-grade small light UAVs, the most rapidly developing autonomous systems of the last decade, are increasingly used in urban space management work, such as UI monitoring [6], [7], [8], [9], urban disaster emergency response [10], [11], urban ecological monitoring [12], [13], etc., as shown in Fig. 1. To sum up, the main advantages of UAVs lie in the following points.

1) In terms of data acquisition, UAVs equipped with sensors can reach areas that are inaccessible to humans and can capture large-scale remote sensing image data, detailed gas concentration data, etc.
2) In terms of operation, consumer-grade UAVs are very simple to operate and support functions such as automatic spotting cruise, which greatly reduces operational difficulties.
3) In terms of cost and work efficiency, consumer-grade UAVs are cheaper and more efficient, which can help save a great deal of manpower and financial resources.

However, there are also technical challenges when UAVs are used for the intelligent management of urban space. For example, there are many obstacles such as buildings in a city, and the flight path of a UAV needs to be reasonably planned; the use of UAVs for the inspection of designated targets relies too much on manual visual inspection, and there is an urgent need for automated and intelligent extraction.

How to use UAV technology scientifically and effectively to manage urban space is an issue of great significance and has attracted the attention of many researchers. However, to the best of our knowledge, there is a lack of systematic summaries on this topic. Although several review papers on UAV applications have been published, they mainly focus on specific application areas (e.g., urban flood management [14], urban building management [15], [16], urban traffic management disaster [17], urban ecological environment monitoring [18], etc.) without focusing on the entire business process and technical system.

In order to systematically explain how UAV technology can play a role in urban spatial management work, this article starts with the entire business chain; divides it into the three aspects of data acquisition, data transmission, and data processing; and then systematically summarizes the hardware equipment, technical system, and methodological process of the relevant aspects. It also describes the application direction of UAV technology in urban management work from three aspects: UI monitoring, urban disaster emergency response, and urban ecological environment monitoring. Finally, the architecture, functions, and features of the UAV urban management system are briefly introduced, using our recent development work as an example. In addition, future research directions for UAV-assisted urban spatial management are summarized. The main contributions of this article are as follows.

1) This article summarizes the definitions, needs, and challenges of smart management of urban space and highlights the advantages and the role that UAVs can play.
2) This article summarizes and outlines the general process of UAV-assisted urban spatial management work, i.e., data acquisition, data transmission, and data processing. It also comprehensively organizes and introduces the technical details, hardware equipment, and methodological processes of the above three aspects. To the best of our knowledge, this is the first time to summarize the working paradigm of UAV-assisted urban spatial management work.
3) This article summarizes the direction and current status of UAV applications from three aspects: UI monitoring, urban disaster emergency response, and urban ecological environment monitoring. In addition, this article summarizes several UAV application systems that have been matured in the industry and introduces the UAV intelligent city management system that we have recently developed. We hope that these contents can provide new ideas and insights for related researchers.
4) Finally, this article analyzes and summarizes several future development directions of UAV-assisted urban spatial management work, providing references for relevant researchers.

The overall structure of this article is shown in Fig. 2. A systematic and comprehensive survey article on UAV-assisted urban spatial management is very important. However, according to our research, there is a lack of systematic survey on related aspects. This is not conducive to the further development of the field. Therefore, taking the definition, needs, and challenges of urban spatial management as an entry point, this article systematically summarizes the task flows, technical systems, and application directions of UAV-assisted urban spatial management and introduces the UAV urban management system we have recently developed as an example. A number of concluding findings are then set out, and some important research questions are discussed. In addition, this article also summarizes several future research directions for UAV-assisted urban spatial management. In this article, we have conducted a comprehensive review and summary, rather than focusing

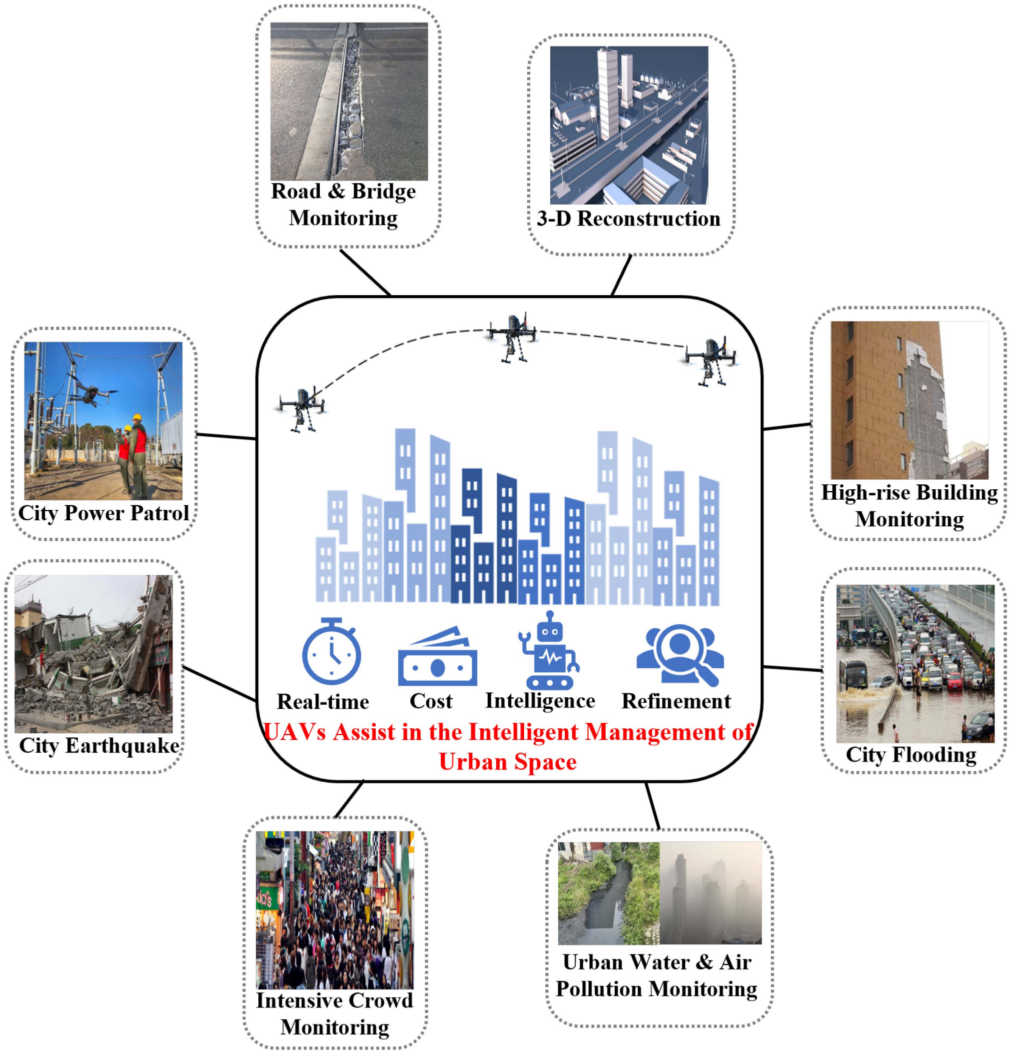


Fig. 1. UAVs assist in the intelligent management of urban space.

only on a specific application area. To the best of our knowledge, this is the first time to summarize the working paradigm of UAV-assisted urban spatial management (data acquisition, data transmission, and data processing). We believe that this article can provide a comprehensive reference for related researchers. We hope that this article will provide comprehensive information and new insights to our readers and lead to the further application and development of UAV technology in urban management.

The rest of this article is organized as follows. Section II describes the definition, needs, and challenges of smart management of urban space and briefly explains the advantages and usage scenarios of UAV technology. Section III introduces data collection, data transmission, and data processing in a holistic manner. Sections IV–VI systematically summarize the technical approaches in UAV urban spatial management work. Section VII summarizes and describes the directions of UAV applications in urban spatial management work. Section VIII introduces some UAV application systems and describes our recent development work. Section IX states several conclusive findings. Section X summarizes several directions in the development of UAV-assisted urban spatial management. Finally, Section XI concludes this article.

II. Intelligent Management of Urban Space

A. Definition, Needs, and Challenges

Urban space is the result of continuous human activities. Urban space consists of a series of elements, mainly UI, topography and landscape, population activities, the ecological environment, and other elements [19]. A large number of activities of people in cities are constantly influencing urban space and its structure. With the increasing population in cities, urban problems such as environmental pollution and traffic congestion arise frequently, which seriously damage urban space and people's quality of life [20]. These conditions demand higher requirements regarding urban space management. In recent years, ICT, including the IoT, "Big Data" applications, AI, and others, has developed rapidly, providing new methods for urban space management [21], [22], [23], [24]. The intelligent management

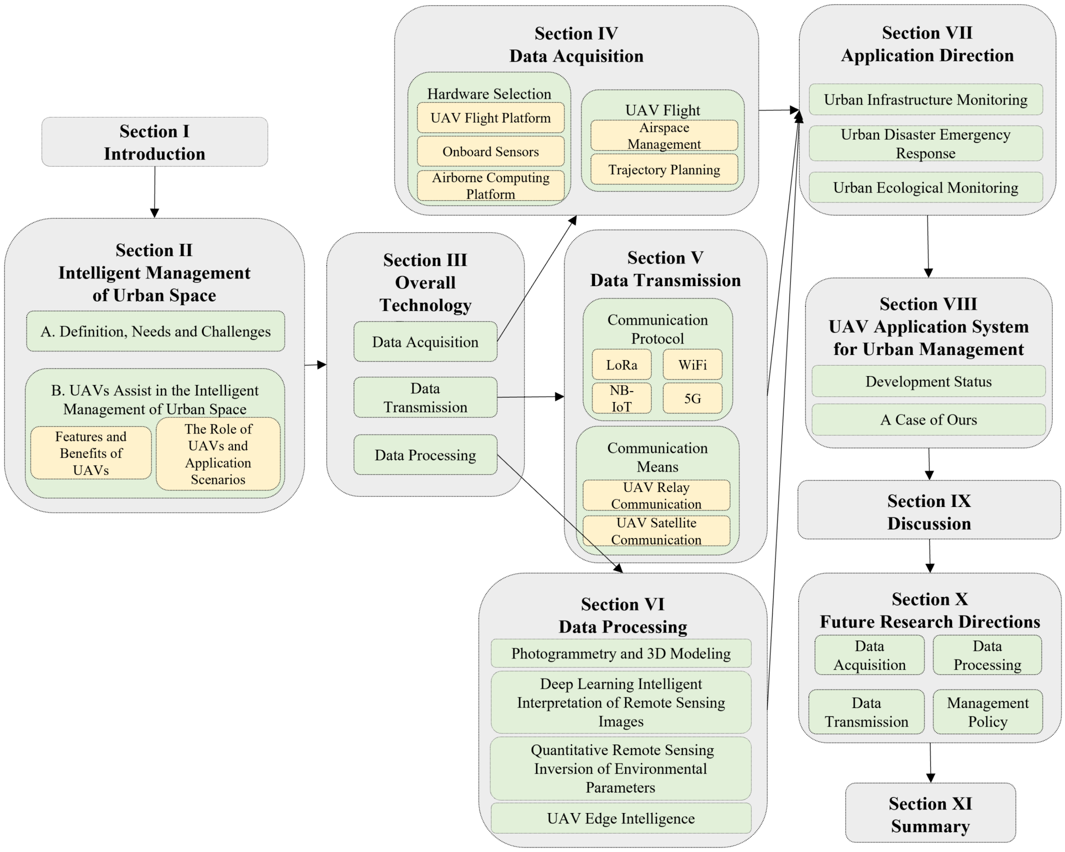


Fig. 2. Structure of this article.

of urban space involves the collection and analysis of a large amount of multimodal heterogeneous sensory data based on the abovementioned advanced technical means to provide decision support for relevant managers, thus improving urban governance and people's quality of life [22], [23], [25]. UI monitoring, urban disaster emergency response, and urban ecological environment monitoring are the three main and common components of urban spatial governance [26], [27]. It is worth noting that urban spatial governance is far from being limited to the above three elements.

In addition, the continuous expansion and high speed of the modern city has placed higher demands and challenges on management. This is reflected in the following four areas.

1) *Real time:* High-speed operation causes people, objects, and their status in the city to change all the time, so there is an urgent need to obtain their status data quickly for analysis and rapid decision making.
2) *Cost efficiency:* Urban areas are often large and involve many monitoring objects, traditional management methods are no longer applicable, and low-cost high-efficiency technical means are urgently needed.
3) *Intelligence:* Big data and AI technology are used to replace traditional manual methods and enhance the automation and intelligence of management.
4) *Refinement:* The high-quality development of cities depends on the refined management of urban space, and more rudimentary management cannot meet these development requirements.

B. UAVs Assist in the Intelligent Management of Urban Space

1) Features and Benefits of UAVs: Recent years have seen considerable development in UAV technology, providing new technical means for urban space management. In brief, UAVs have three main characteristics, namely high spatial and temporal resolution, flexibility, and low cost [28]. High spatial and temporal resolution is accomplished by UAVs carrying sensors, which can quickly acquire high-resolution spatial data while flying close to the ground whenever they need to be deployed [29]. In contrast, traditional satellite remote sensing means can only acquire low-spatial-resolution ground images according to a fixed revisit cycle. This feature of UAVs can meet the highly dynamic and changing scenarios in urban spatial management work. Flexibility includes two main aspects [28]. The first is flexibility in assembling sensors; in other words, different types of sensors or even hybrid sensors can be assembled according to specific mission requirements. The second is flexibility of UAV flight operations; the industry applications of UAVs are now highly automated and intelligent, and the operation method is very simple, allowing for more flexibility. This flexibility offers a wide range of possibilities for urban space management, allowing UAVs to be used in multiple applications. Low cost is

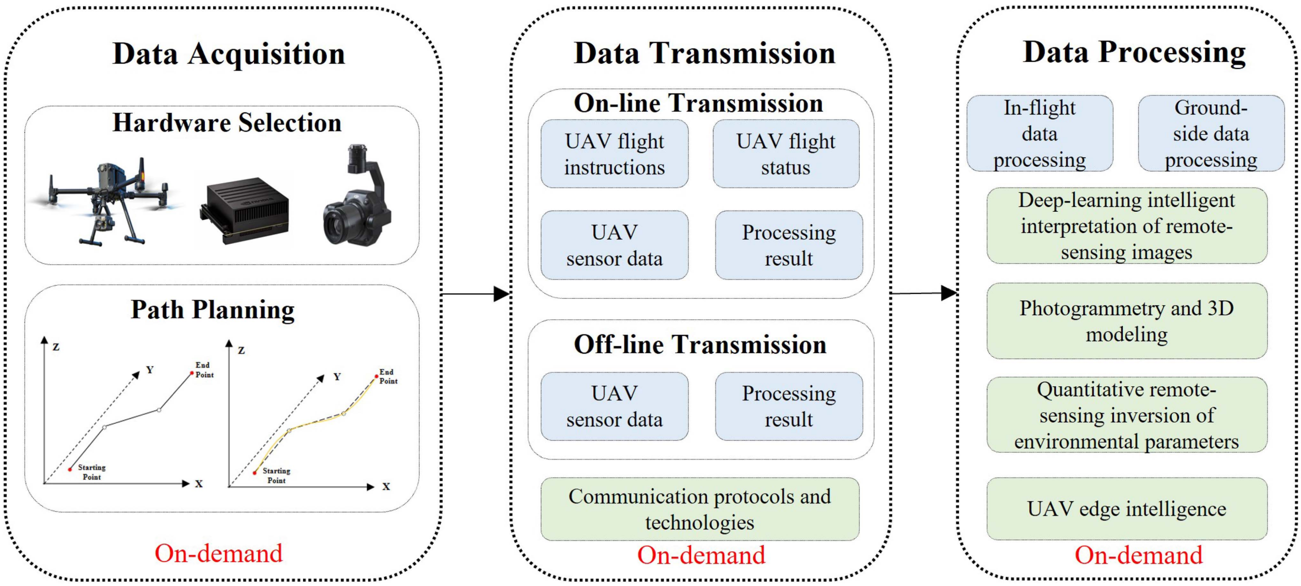


Fig. 3. Overall technical route.

another major feature of UAVs [30]. Compared to aerospace remote sensing means, the operation and maintenance costs of UAVs are extremely low. Highly automated UAVs also provide managers with more freedom regarding their use and the data gathered.

2) Role of UAVs and Application Scenarios: Researchers are committed to defining a highly condensed urban management framework to facilitate the development of smart urban management [25]. However, urban spatial management work involves many different business scenarios and has different characteristics and needs. To be able to better illustrate the role of UAVs in urban spatial management work, we draw on the framework defined by Silva et al. [25] and elaborate on it. They divided the urban management framework into a perception layer, a transmission layer, a data management layer, and an application layer. Correspondingly, in the perception layer, UAVs can carry different kinds of sensors to acquire multisource high-spatial and high-temporal resolution data on the surface, providing a database for intelligent urban spatial management. In addition, UAVs are able to access some areas that are inaccessible to humans (e.g., disaster areas, remote areas, etc.) to obtain sensing data, enhancing its accessibility [31]. In terms of the transmission layer, UAVs are capable of supporting existing sensing networks for data dissemination or enhancing the connectivity of the network, in addition to transmitting data acquired by themselves back to the ground [32]. For example, UAV relay communication technology can enable the transmission of environmental monitoring data in remote areas where there is no public network [33]. On the data management side, UAV edge intelligence technology provides a new means for data processing. It enables near real-time data processing and can make intelligent decisions based on the processing results, guiding the UAV to complete its work intelligently and automatically [34]. At the application level, with many advantages, UAVs can be used for many urban spatial management tasks, such as UI monitoring [6], [7], [8], [9], urban disaster emergency response [10], [11], and urban ecological environment monitoring [12], [13], as shown in Fig. 1.

III. Overall Technology Process

This section first introduces the basic technical process of UAV urban space management work as a whole, including the three aspects of data acquisition, data transmission, and data processing. It is worth noting that UAV technology can be used for many different purposes in urban spatial management, resulting in a variety of technical approaches. However, the basic process mostly follows the "acquisition-transmission-processing" vein.

The use of UAV technology for urban space management work involves the following steps (as shown in Fig. 3).

1) *Data acquisition:* Data acquisition work mainly includes two tasks: the selection of hardware equipment (UAV flight platform, sensors, and onboard computing platform) and UAV trajectory planning (offline and online) [28]. Data acquisition is the key to the subsequent work, and its completion determines the level of management work. The selection of hardware equipment and the development of UAV flight paths should be carried out according to specific work needs.
2) *Data transmission:* There are two primary methods of data transmission: online and offline. The transmitted data include two types. One type includes the flight command, flight status, and other information of the UAV. The other type is the business data of the UAV, in other words, the data acquired by the sensors, the data that results from the processing of the onboard computing platform, etc. Good and stable data transmission is the "artery" of the entire UAV application system [35].
3) *Data processing:* Data processing includes two forms: onboard and ground-side. These two different forms need

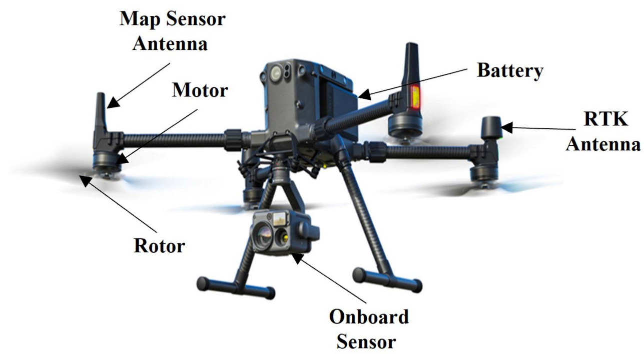


Fig. 4. Composition structure of a multirotor UAV.

Fig. 5. UAV classification. From left to right are a fixed-wing UAV, multirotor UAV, and hybrid fixed-wing multirotor UAV.

to be selected according to specific business needs. In addition, there are many specific processing means involved in data processing, which need to be selected as needed.

IV. Data Acquisition

Data collection is the first step of the smart management of an urban space. Traditional means of sensing and observation have limitations. For example, satellite remote sensing technology can acquire large-scale urban image data, but the spatial resolution and temporal resolution are low [29], [36]. It is very difficult to deploy sensors in areas that are dangerous, remote, hard to reach, etc. [37]. A UAV can mount different types of sensors according to specific needs, which effectively complements the existing means of sensing observation and further enhances the level of sensing. Comprehensively describing the technical details of UAV urban data collection work begins with hardware selection and trajectory planning.

A. Hardware Selection

There are various types of small light civilian UAVs and countless sensors that can be carried. It is crucial to select a UAV flight platform and sensors according to the specific urban management needs. Therefore, this section focuses specifically on UAV flight platforms, sensors, and onboard computing platforms and systematically summarizes the characteristics and application scenarios of these different hardware devices.

1) UAV Flight Platform: A UAV platform is mainly composed of a navigation and control system, energy and power system, onboard sensors, and ground station, as shown in Fig. 4. The navigation control system of the UAV is composed of the following two subsystems. The navigation subsystem provides real-time geographic coordinates, speed, and flight attitude to the UAV and guides the UAV to fly safely, punctually, and accurately along a designated route. The flight control subsystem realizes full control and management of the UAV and controls the UAV to complete the entire flight process, such as takeoff, air flight, mission execution, and return to the user for recovery. The energy and power system mainly includes batteries (or engines) and multiple rotor blades (or fixed wings) to provide power for the UAV flight. Onboard sensors need to be selected according to specific tasks, and options include RGB cameras, hyperspectral cameras, airborne LiDAR, TIR cameras, etc. [38]. They are responsible for acquiring specific information about the observed area (object) and providing raw data for the next step of analysis. The ground station mainly consists of the remote control for sending control commands to the UAV and GNSS ground station for enhancing the positioning accuracy of the UAV. It is responsible for receiving various status information of the UAV in real time and can send user commands to the UAV [35]. The abovementioned components work together to guarantee the normal flight and data acquisition of the UAV.

Currently, fixed-wing and multirotor UAVs are the two common types used for aerial exploration [39]. Fixed-wing UAVs rely on the air pressure difference created by the wing's airfoil surface during flight to gain lift [40]. Compared to multirotor UAVs, fixed-wing UAVs tend to be able to fly for longer periods of time and, thus, cover a larger operational area [41]. However, fixed-wing UAVs are more demanding during takeoff and landing, requiring a larger site [40]. Multirotor UAVs can be classified according to the number of rotors used, for example, quad-rotor, six-rotor, and eight-rotor UAVs are common configurations. Multirotor UAVs rely on the air pressure difference generated by several subrotors to obtain lift and have the advantage of vertical takeoff and landing [42]. However, the flight time and load capacity of multirotor UAVs are often inferior to those of fixed-wing UAVs. In contrast, hybrid UAVs integrate the advantages of the first two and can use multirotors to complete vertical takeoff and landing operations, as well as its fixed wing to complete long-distance operations [40]. In actual operations, a suitable UAV flight platform should be selected according to specific requirements. The technical parameters of several commonly used UAVs are listed in Table I. Fig. 5 shows several commonly used UAVs.

Urban space management work involves many aspects, and different work contexts have different characteristics and needs. Fixed-wing, multirotor, or hybrid-wing UAV flight platforms should be reasonably selected according to specific needs. For example, most small-scale urban 3-D modeling tasks use multirotor UAVs as data collection platforms, while large-scale tasks require the use of fixed-wing UAVs with longer endurance.

2) Onboard Sensors: Airborne earth observation sensors are tools to obtain information related to the ground surface. According to the needs of different work in urban spatial management, specific sensors should be selected to obtain the corresponding information. This is a prerequisite for the subsequent work. For example, an RGB camera is often chosen for urban fine 3-D modeling work [43], and a multispectral camera is usually chosen for urban black fetid water monitoring [44]. Therefore,

TABLE I
DETAILED INFORMATION ON RECENT UAV PLATFORMS

Model	Type	Producer	Year of made	Power	Maximum range (Min)	Maximum takeoff weight (Kg)
DJI M350 RTK	Multirotor	DJI	2023	Battery	55	9.2
DJI Mavic 3E	Multirotor	DJI	2022	Battery	45	1.05
DJI M300 RTK	Multirotor	DJI	2020	Battery	55	9
DJI Phantom 4 Pro V2.0	Multirotor	DJI	2018	Battery	30	1.375
DJI Matrice 600 Pro	Multirotor	DJI	2016	Battery	18	15.5
eBee X	Fixed-wing	SenseFly	2018	Battery	90	1.1–1.4
Feima P300	Fixed-wing	Feima	2018	Battery	90	3.75
Feima V500	Hybrid	Feima	2022	Battery	150, 180	6.8, 7.5
Feima V10	Hybrid	Feima	2020	Battery	150, 240	25
KC3400	Hybrid	AiBird	2016	Oil	240–360	25

TABLE II
MODELS AND PARAMETERS OF SOME COMMONLY USED EARTH OBSERVATION SENSORS

Sensor Type	Model	Spectral Range	Resolution	Weight	Usage
RGB Camera	Sony Alpha 9	∼400–700 nm	∼24.2 MP	∼673 g	Photogrammetry and 3-D modeling, target detection, etc.
	Nikon D850	∼400–700 nm	∼45.75 MP	∼1,005 g	
	DJI Zenmuse X7 [78]	∼400–700 nm	24 MP	449 g	
	Share 100 M Pro	∼400–700nm	102 MP	-	
Hyperspectral Camera	ATH9500	400–1000 nm	2048 2048	<4 kg	Water body detection, target recognition, etc.
	Nano HP	400–1000 nm	-	<1.8 kg	
	Rainbow VN	420–1000 nm	1024×1024, 800×600, 640×512	<500 g	
Airborne LiDAR	HDL-32E	905 nm	32 beam Approximately 700 000 points/s	<2 kg	3-D modeling, power inspection, etc.
	YellowScan Mapper+	905 nm	Emissions per second up to 240k	1.3 kg	
TIR Camera	FLIR Vue Pro R	7.5–13.5 μm	336×256	92.14–113.40 g	Personnel search and rescue, surface temperature monitoring, etc.
	Workswell WIRIS Pro	7.5–13.5 μm	640×512, 1280×1024	<450 g	
Hybrid Sensor	DJI L1 [79]	rgb, 905 nm	RGB Camera: 20 MP LiDAR: –	930±10 g	Pedestrian detection, vegetation monitoring, 3-D modeling, etc.
	DJI Zenmuse H20N [80]	rgb, 8–14 μm, 905 nm	RGB Camera: 2 MP, 4 MP TIR infrared camera: 640×512 LiDAR: –	878±5 g	

this subsection briefly introduces several commonly used unmanned airborne earth observation sensors and describes their characteristics and applicable scenarios. Table II lists several sensors commonly used in each category. The categories are as follows.

1) *RGB camera:* Due to its lightweight, low cost, and wide range of use, an RGB camera is one of the most commonly used sensors for earth observation by UAVs [38]. Using UAVs with RGB cameras can acquire detailed color and texture information of the observed area (object) and can be used in many fields, including photogrammetry 3-D mapping [28], urban pipeline safety inspection [45], river inspection [46], etc. RGB cameras need to be selected according to different task requirements. Common parameters for selecting RGB cameras include focal length, resolution, weight, etc. [38]. Taking photogrammetry as an example, the *Technical Regulations for Tilt Digital Aerial Photography* promulgated by the People's Republic of China makes specific provisions for the RGB aerial camera used, such as the pixels of each subcamera should not be less than 20 million, etc. [47]. Obviously, the better the quality of the RGB camera used, the higher the quality of the data obtained, and the more beneficial this will be for the subsequent analysis. However, the load capacity of the UAV flight platform, power supply capacity, external interface situation, etc., should also be taken into consideration.
2) *Multispectral camera:* Although RGB cameras are most commonly used, they only provide spectral information in the visible range for the surface of the observed area (object). In contrast, multispectral cameras can capture information in multiple bands from the visible to the near-infrared range, especially in the red-edge and near-infrared bands that are sensitive to vegetation monitoring [48]. With a limited cost increase, this type of camera can provide more useful information for remote sensing information extraction. Based on the waveband information captured by a multispectral camera, some commonly used remote sensing indices can be accurately inverted, such as the NDVI, reNDVI, and Nemerow comprehensive pollution index [44], [48], [49]. Therefore, multispectral cameras can be used in more fields, such as urban water quality monitoring [44], urban vegetation monitoring [50], etc.
3) *Hyperspectral camera:* Hyperspectral technology is a passive remote sensing technique that allows quantitative characterization of the earth system [51], [52]. It is capable of acquiring rich spectral information about the earth's

surface and provides a data basis for feature identification and quantitative inversion [53]. Hyperspectral images have a high spectral resolution and usually include hundreds of bands of feature information. In recent years, with the improvement of UAV load capacity and the miniaturization of hyperspectral cameras, UAVs equipped with light hyperspectral cameras have been widely used, such as in water quality parameter inversion and vegetation index extraction [54], [55]. Compared with satellite HRS technology, mini-UAV-borne HRS systems have the advantages of high spatial resolution, high temporal resolution, and low cost, which makes the observation more flexible [56]. The hyperspectral instruments that can be carried by UAVs can be divided into four categories. In [53], four types of sensors are discussed in detail. Although mini-UAV-borne HRS systems have been widely used, there are still some shortcomings: 1) limited range and width, making them impossible to use for large-scale observation missions; and 2) reduced spatial resolution, so the observation needs may require lowering the flight altitude of the UAV at times.

4) *Airborne LiDAR:* LiDAR measures the distance from the object to the sensor by transmitting and receiving laser beams; in turn, a 3-D point cloud is generated with the information of the scanned area (object) [54], [57]. It is an active remote sensing technology and, thus, has the advantage of being independent of weather and light factors. UAVs with LiDAR are widely used in forestry management [58], [59], coastal zone terrain monitoring [60], [61], the construction industry [62], etc. The main parameters of LiDAR include detection range, point cloud density, FoV, scan rate, weight, size, etc. In the detection of forest areas, the laser beam emitted by airborne LiDAR has a certain penetration ability with vegetation, which can reduce the adverse effects caused by vegetation occlusion in obtaining real 3-D terrain data. In addition, airborne LiDAR can acquire not only distance information, but also the reflection intensity, echo count, and other information of surface objects. Different objects generally have different surface properties. Therefore, this additional information can be used in areas such as surface object detection.

5) *TIR camera:* A TIR camera is a passive remote sensing technology that can be used to measure the temperature and thermal emission from the surface of objects, such as large-scale land surface temperature, ocean surface temperature [63], small-scale pedestrians [64], etc. TIR cameras can capture radiation information in the TIR band (3.5–20 μm) and generate radiation images. There are two main types of TIR cameras: cooled and uncooled [65]. Compared with traditional remote sensing platforms, UAV platforms equipped with TIR cameras have the advantages of high spatial and temporal resolution, flexible operation, and low maintenance cost and have been used for urban vegetation monitoring [66], [67], urban surface temperature monitoring [68], [69], personnel and vehicle detection [70], etc. However, compared with RGB images, the radiometric images captured by a TIR camera lack detailed information, such as color and texture.

6) *Hybrid sensor:* A hybrid sensor is a combination of several of the abovementioned different types of sensors that can acquire information about different attributes of the observation area (object) at the same time. Many manufacturers have developed lightweight and small hybrid sensors for UAV flight platforms, such as RGB-TIR hybrid sensors, RGB-LiDAR-TIR hybrid sensors [71], LiDAR-TIR-hyperspectral hybrid sensors [72], etc. To sum up, the main reasons for the emergence of hybrid sensors are as follows. First, the continuous development of sensor technology makes the weight and size of the sensors increasingly smaller. Second, the load capacity of UAV flight platforms has improved, but it is still difficult to mount several different types of sensors at the same time. Third, the information acquired by a single sensor has limitations, and some specific remote sensing observation tasks have raised the demand for the simultaneous acquisition of multimodal data. UAVs carrying hybrid sensors have been applied to many urban management fields, including all-weather pedestrian detection [64], crowd detection [73], and urban tree classification [74].

7) *Gas sensor:* Timely and effective atmospheric monitoring and the detection of toxic gases in hazardous situations place new demands on the measurement means. Typical gas sensors can distinguish between gas species based on the surface interaction between the gas molecules and the sensor [75]. UAVs with gas sensors are a new technological means to measure the concentration and distribution of specified gases (e.g., nitrogen dioxide, flammable gases, etc.) easily, safely, and in three dimensions [76], [77].

3) Airborne Computing Platform: In response to the real-time needs of certain tasks in the intelligent management of urban space, UAVs equipped with an airborne computing platform can immediately analyze the data acquired by the sensors and make the next decision in real time based on the analysis results. As the "brain" of the UAV, the airborne computing platform has the following functions. First, intelligent processing algorithms can be embedded to collect and process the sensory data from various sensors in real time. Second, the computing platform can work closely with flight control to assist the UAV in automatic decision making and control the specific flight movements of the UAV. UAV airborne computing platforms can be broadly classified into five major categories according to the basis of their architecture: FPGA, GPU, ARM, Atmel, and Intel [35]. With the development and application of DL technology, GPU-based airborne computing platforms have been widely used [81], [82], [83]. Table III lists several GPU-based computing platforms that have been in common use recently. Users can deploy corresponding DL algorithms on such platforms to realize the real-time processing of data acquired by airborne sensors and make corresponding decisions in real time based on the processing results to make UAVs perform tasks more intelligently and automatically. This mode of work has been widely used, such as in the automatic inspection of urban power lines [34], wide-area real-time target search [84],

TABLE III
MODELS AND PARAMETERS OF SOME AIRBORNE COMPUTING PLATFORMS

Model	Key Specifications
Nvidia Jetson Nano [81] Developer Kit	GPU: 128-core Nvidia Maxwell architecture GPU CPU: Quad-core ARM Cortex-A57 MPCore processor Memory: 4GB
Nvidia Jetson TX2 Module [82]	GPU: Nvidia Pascal architecture with 256 Nvidia CUDA cores CPU: Dual-core Nvidia Denver 2 64-bit CPU with quad-core Arm Cortex-A57 MPCore composite processor Storage: 8 GB
Nvidia Jetson AGX Orin 64GB [83]	GPU: 2048-core NVIDIA Ampere architecture GPU with 64 Tensor Cores CPU: 12-core Arm Cortex-A78AE v8.2 64-bit CPU 3MB L2 + 6MB L3 Storage: -

traffic management [85], etc. However, this hardware device is not necessary. While it provides the function of real-time data processing and assisted decision making, it also consumes a great deal of energy from UAVs, reducing their endurance. Therefore, it should be reasonably chosen whether to assemble it on the UAV according to the specific context needs.

B. UAV Flight

Urban airspace UAV flight mainly involves two functions: airspace management and trajectory planning. The former serves as the basis of the latter. The purpose of airspace management is to enable UAVs to perform their tasks in an orderly manner under supervision to avoid major safety accidents, such as adversely affecting other aircraft flights. Trajectory planning is the technology in airspace management to help UAVs find a more suitable flight path so that they can safely and successfully complete their guided missions.

1) Airspace Management: Their low price and wide application have led to the emergence of an increasing number of light and small UAVs in urban areas. While bringing convenience to people's lives, the rapid growth of their numbers has also posed a serious challenge to urban low-altitude safety. This issue has attracted great attention from countries around the world. Many national and regional governments have developed a series of measures to restrict the activities of urban UAVs. Xu et al. [86] systematically summarize the technical means and current policies for UAV management in urban areas, which include three main approaches: urban airspace restrictions, active supervision, and UAV public routes. The first is urban airspace restrictions, which include maximum flight altitude, geofencing, and flight separation airspace. For safety reasons, many countries and regions restrict the maximum flight altitude (expressed as the above ground level) of UAVs, with slight variations. Geofencing is the use of virtual "fences" to enclose a geographic area and prohibit UAVs from flying into it; this approach is usually applied in sensitive areas, such as airports, military zones, and government sites. In recent years, many countries and regions have made great efforts to promote the construction of geofencing [87], [88], [89]. Exclusive flight areas for UAVs refer to airspace that is set aside and exclusive, allowing UAVs to fly to meet various needs. In 2015, Amazon proposed the idea of dividing airspace to be used for drone urban logistics services [90]. Xu et al. [91] proposed building a public route network for low-altitude UAVs and conducted field experiments in a local area of Tianjin, China. Inspired by the urban metro system, Wu et al. [92] proposed building an "AirMetro" system to provide a new concept for future 3-D public air transportation. The second main approach for UAV management in urban areas is active supervision. This is primarily accomplished by building an unmanned aircraft system traffic management (UTM) system to realize the functions of UAV registration and management, mission scheduling, and planning. At present, the related more mature systems are UTM in the United States, UOM in China, U-space in Europe, and uTM-UAS in Singapore [86]. Finally, the third approach is the concept of "UAV public routes," which was pioneered by researchers in China and Singapore and has been widely studied. Among them, Xu et al. [91] have established a complete route construction process, which has been applied in several regions of China.

2) Trajectory Planning: It is important to plan the trajectory of UAVs in the context of urban airspace management. This is mainly reflected in two respects. First, there are many obstacles of different heights and shapes (e.g., high-rise buildings, various antennas, elevated roadways, etc.) in urban areas and a large number of UAVs, so there is an urgent need for reasonable and orderly planning of their routes. Second, the energy supply of UAVs is very limited, and a reasonable flight path can enable them to accomplish their intended missions while using their energy capability efficiently. Modeling the urban environment is the first step of UAV trajectory planning, including environment modeling and risk modeling [93], [94]. The purpose of environment modeling is to map the realistic urban 3-D environment into a mathematical space, which typically involves the use of the cell decomposition and roadmap methods [95]. Fig. 6(a) shows an example of the cell decomposition method. Fig. 6(b) shows an example of the roadmap method. In an urban context, UAVs face many potential risks, such as those related to people and vehicles on the ground, invasions of privacy, power limitations, extreme weather, navigation signal strength, etc. A risk map is an enabling tool to reflect the level of risk in different areas. It divides the urban 3-D space into 2-D or 3-D grids and then calculates the risk values of the different grid cells through mathematical models. Fig. 7 shows a 2-D risk map. The darker the color of the grid, the higher the flight risk. The planning of UAV flight trajectories based on urban environment modeling has received a great deal of attention from researchers. Trajectory planning generally consists of two parts: path discovery and trajectory optimization [96]. Path discovery is the first stage and is responsible for finding a collision-free

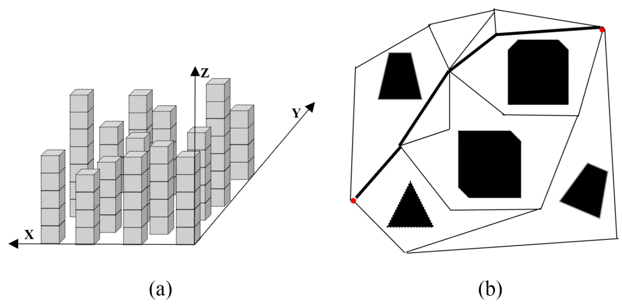


Fig. 6. Two methods of environment modeling. (a) Cell decomposition method. (b) Roadmap method.

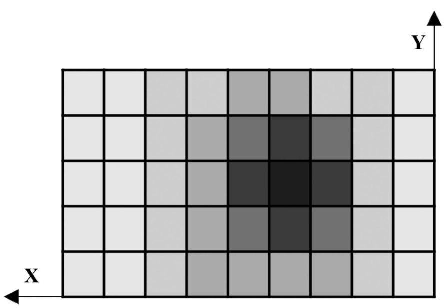


Fig. 7. Two-dimensional risk map.

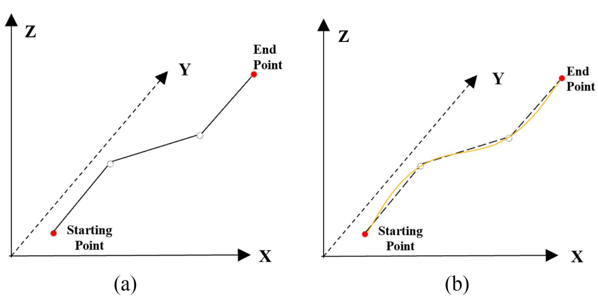


Fig. 8. Two processes of UAV path planning. (a) Path discovery. (b) Trajectory optimization.

continuous low-cost flight path for UAVs in the 3-D space, as shown in Fig. 8(a). Trajectory optimization is based on path discovery to develop the best initial flight path on a higher-order continuous trajectory that conforms to the UAV dynamics, as shown in Fig. 8(b).

Path discovery methods can be classified according to their characteristics; for example, there are node-based, sampling-based, and AI-based path discovery algorithms to name just a few. The Dijkstra [97] and A*[98] algorithms are representative node-based path discovery methods. As the name implies, this class of methods searches for an optimal path in an already constructed graph based on a cost function defined in advance. Among them, the A* algorithm is a modification of Dijkstra's algorithm. It enables a search to approach its endpoint as quickly as possible by adding a heuristic function. The RRT [99] and PRM [100] algorithms are two representative sampling-based path discovery methods. The RRT algorithm was proposed by LaValle in 1998. The basic idea of the algorithm is that an extended tree is generated from the initial point by random sampling, and a path from the starting point to the end point is found when the extended tree reaches or is close to the end point. RRT* [101] and informed RRT* [102] are improvements of the original RRT algorithm. The former ensures that the best possible path is found by improving the way the nodes of the extended tree are connected. The latter speeds up the convergence of the algorithm by iteratively limiting the sampling space. Strictly speaking, the PRM algorithm is a two-stage trajectory discovery method. It first constructs a PRM by sampling and then searches for the optimal path in the graph using the node-based method described above. Inspired by the behavioral activities of humans or animals, researchers have proposed many AI methods for UAV path planning. These mainly include heuristic and neural network methods. Heuristic methods include GAs [103], PSO algorithms [104], ACO algorithms [105], etc. These algorithms are evolutionary algorithms; in other words, the new generation is made closer to the optimal path based on the old generation through continuous iteration. Neural-network-based methods, especially DRL-based methods, have become a research hotspot in the field of UAV local path planning [106], [107], [108]. DRL techniques combine DL techniques with RL techniques, making full use of the powerful understanding and characterization capabilities of DL and the environmental interaction capabilities of RL. The UAV flight environment is highly dynamic, so methods combining global and local trajectory planning have been proposed [109]. For example, an initial collision-free path is planned using global trajectory planning methods, and local path planning is implemented during flight, using methods such as DRL.

V. Data Transmission

After hardware selection and trajectory planning, the UAV is ready to perform aerial missions as designed. During the flight, a UAV needs to maintain necessary communication with the ground control station and transmit the data acquired by the onboard sensors back to the ground station on demand. In addition, in some special cases, a UAV can also serve as a relay system to transmit data back to the data center. One example is collecting environmental monitoring data in remote areas. This section introduces several wireless communication protocols and means for UAV data transmission and their characteristics and applicability, so that users can make an informed decision on how to choose a communication module in assembling a UAV.

A. *Communication Protocol*

Different communication protocols are suitable for different functional requirements, and when deploying UAV communication modules, communication protocols and technologies should be selected according to specific needs. For example, long-range low-power LoRa can be used to wake up ground equipment, and a short-range high-power protocol (Wi-Fi, 5G, etc,) can then be used to quickly transmit the ground data. Some of the communication protocols used are described in the following subsections (specific parameters are presented in Table IV).

TABLE IV
SPECIFIC INFORMATION ON SEVERAL COMMUNICATION PROTOCOLS

Communication Technology	Communication Distance	Maximum Transmission Rate	Frequency Band	Power Consumption	Standard
Wi-Fi	10–100 m	65 Mb/s	ISM Bands 2.4–5 GHz	Low to medium (32–200 mW)	IEEE 802.11
5G	–	10–50 Gb/s	1.8 GHz, 2.6 GHz and 30–300 GHz	-	-
LoRaWAN	5–20 km	50 kb/s	Unlicensed ISM bands 868 MHz in Europe, 915 MHz in North America, 433 MHz in Asia	Low (10.5–28 mA)	LoRa Alliance
NB-IoT	1–10 km	204.7–234.8 kb/s, 200 kb/s	Licensed LTE frequency bands	Low (46 mA)	3GPP

1) LoRa: LoRa is one of the LWAN technologies developed by Semtech [35], [110]. The maximum coverage range of LoRa is about 5–20 km, and the maximum data transmission rate is 50 kb/s. The lower transmission rate limits its application on UAVs, although it can be used to send some command messages with smaller data volume. For example, Zhang and Li [33] used LoRa communication signals to wake up a 5G communication module in the ground station.

2) Narrow Band IoT: NB-IoT, like LoRa, is a LWAN technology. It is a new network protocol of 3GPP LTE Release 13, which has the advantages of wide coverage and low power consumption. LoRa and NB-IoT have similar characteristics. Compared with LoRa, NB-IoT performs better in terms of latency and can provide better QoS; however, its coverage area is slightly smaller than LoRa [111].

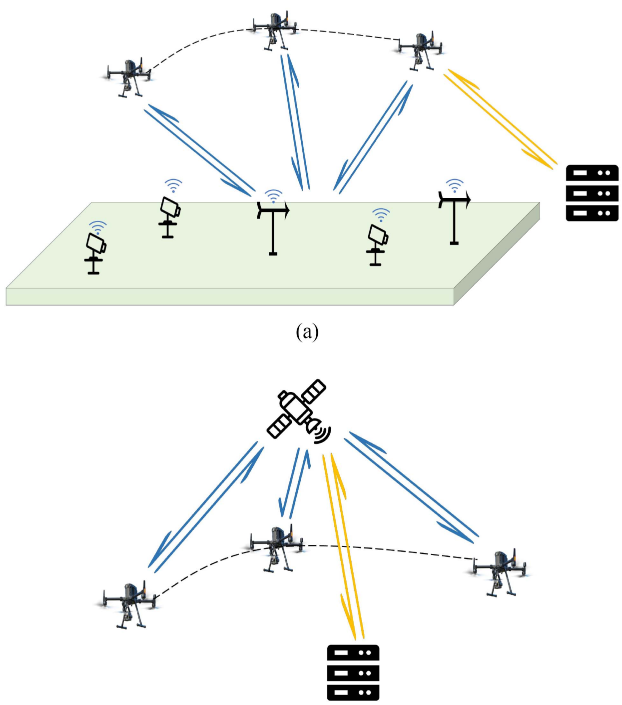
3) Wi-Fi: Wi-Fi is a widely used short-range communication protocol for building WLANs mainly by the use of two frequency bands: 2.4 and 5 GHz. It has the advantages of a high data transmission rate and strong anti-interference capability, but has a high power consumption and small coverage area. In [112], a single UAV was converted into an airborne Wi-Fi node to improve the ground network connectivity.

4) 5G: 5G is the next generation of cellular network after 4G, with the advantages of low latency, high bandwidth, and wide coverage. 5G communication technology and UAV technology have been used by many researchers in combination to improve the shortcomings of existing technologies. There are two main research and application paradigms [113]. One is the use of 5G technology by UAVs as airborne users. Specifically, 5G technology can be used to realize net-connected UAVs, supporting the rapid transmission of flight commands and rapid upload of flight information, further extending the working radius of UAVs. Koumaras et al. [114] addressed the characteristics of UAVs such as low power consumption and small load, offloaded the UAV FCS to a computing device at the edge of the network, and utilized 5G communication technology to achieve real-time transmission of UAV control commands and flight data. Damigos et al. [115] also hosted the UAV FCS on an edge server and used 5G communication technology to transmit UAV flight data and control commands, and carefully evaluated the performance. Verma et al. [116] utilized 5G communication technology to assist UAVs (swarms of UAVs) to communicate, thereby speeding up the delivery process of vaccine delivery using UAVs. The other is that UAVs can carry lightweight and small base stations as airborne relay communication platforms, which are complemented by space-based and ground-based communication technologies to expand the communication range, thus aiding communication [117]. This technology has been widely used in urban space management [118], for example, to provide the necessary communication services in urban areas after a disaster, to improve the network communication capacity in dense urban areas, and so on. In addition, 5G technology can further improve the security of communication [119].

B. Communication Means

1) UAV Relay Communication: UAVs can act as communication relay nodes to establish links with sensor networks deployed on the ground, collect their stored sensing data, and then carry or forward them to data centers [33]. In addition, UAVs can also serve as aerial base stations to enhance network service performance. UAVs carrying communication base stations have been used to deploy temporary networks over areas where network services have been suspended due to disasters, thus aiding communication and rescue efforts [120]. In addition, UAV aerial base stations can enhance network capacity and coverage in localized areas, such as sports stadiums, large outdoor events, etc. [121]. In all three usage scenarios above, the transmission of sensory data are assisted in designated areas and first-hand data are provided for urban spatial management. Fig. 9(a) illustrates the UAV as a relay node in acquiring field monitoring data.

2) UAV Satellite Communication: UAV satellite communications provide technical support for UAV operations over long distances. UAVs usually need to receive control commands from ground stations in order to react quickly. At the same time, UAVs also need to transmit flight status (altitude, speed, direction, etc.) and sensor data (real-time images, etc.) back to the ground station in real time. However, the maximum communication distance between the UAV and the ground station is often limited. For example, the DJI M300 RTK UAV is an industry-grade UAV recently launched by DJI with a maximum effective signal distance (assuming no interference or obstruction) of 15 km [122]. This can severely limit the operational radius of the UAV when performing some large-scale urban management work. With the development of satellite communication technology, UAVs can be freed from the restrictions of ground stations and instead obtain control commands from satellites transmitting UAV-related data. However, the bandwidth of satellite communication is often



(a)

(b)

Fig. 9. (a) UAV relay communication. (b) Satellite communication.

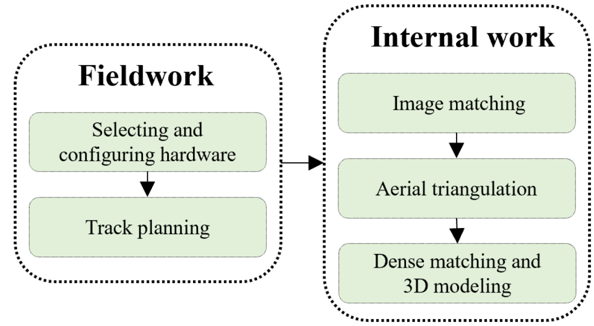


Fig. 10. Flowchart of UAV photogrammetry and 3-D modeling.

very low. Take China Tiantong Satellite One for example; its narrowband data channel can only accommodate the transmission of control commands, and its broadband data channel can only allow the transmission of SD video [123]. Fig. 9(b) shows the UAV satellite communication.

VI. Data Processing

After data acquisition and transmission, processing the data acquired by the UAV is the next critical step. There are many aspects involved in urban spatial management, and different tasks have different data processing methods. This section briefly introduces the data processing methods commonly used in urban spatial management. First, we introduce remote sensing data processing methods in three different areas: photogrammetry and 3-D modeling, DL remote sensing image intelligent interpretation, and remote sensing quantitative inversion of environmental parameters. We then introduce the recently emerging UAV edge intelligence technology. It is very important that in the actual data processing work, the appropriate data processing methods are selected according to the specific task requirements.

A. Photogrammetry and 3-D Modeling

Urban 3-D reconstruction is increasingly important for building smart cities and improving urban spatial management [29]. UAVs equipped with HD digital cameras and photogrammetry processing technology provide a convenient means to generate accurate DSMs for the 3-D modeling of urban areas. The main workflow of UAV photogrammetry and 3-D modeling can be divided into two parts: external data acquisition and internal data processing. Among them, the degree of completion of the external data acquisition directly determines the later results. The external data acquisition work mainly includes the selection of a flight platform and the route planning (which will not be elaborated here). The internal data processing includes image matching, aerial triangulation, intensive matching and modeling, etc., as shown in Fig. 10. The purpose of image matching is to find the correspondence between two or more images, and the current mainstream method is the point-based local feature-matching method [124]. UAV aerial triangulation mainly includes the offline SfM method and online SLAM method; the purpose is to recover the position and pose when the camera is shooting. The purpose of dense matching, in contrast, is to generate a large number of dense point clouds from the matched oriented images to construct fine 3-D models.

B. DL Intelligent Interpretation of UAV Remote Sensing Images

UAVs equipped with earth observation sensors are capable of capturing a large number of ground images. The automated and intelligent analysis of these images to extract useful information relevant to urban spatial management has become a hot topic of interest for researchers. Among them, DL has been widely used in remote sensing image analysis and has become a common technical tool [125]. Among them, CNNs have been more used in the field of UAV remote sensing [126]. A CNN model is constructed by stacking convolutional layers, pooling layers, activation layers, and fully connected layers to achieve the extraction of specific information, as shown in Fig. 11. In addition, an RNN is also a supervised learning model and is mostly used for sequence data analysis [125]. In the field of remote sensing, RNN models have been used to handle time-series tasks.

Target detection, semantic/instance segmentation, and scene classification are the three main tasks in the intelligent interpretation of remote sensing images for DL [126]. The purpose of scene classification is to predict a label category for each sliced image [127]. CNN-based classification models have been the subject of a great deal of research. A CNN model automatically extract more useful discriminative features and, thus, improve the accuracy of remote sensing image scene classification [128]. The commonly used CNN architectures include VGGNet [129],

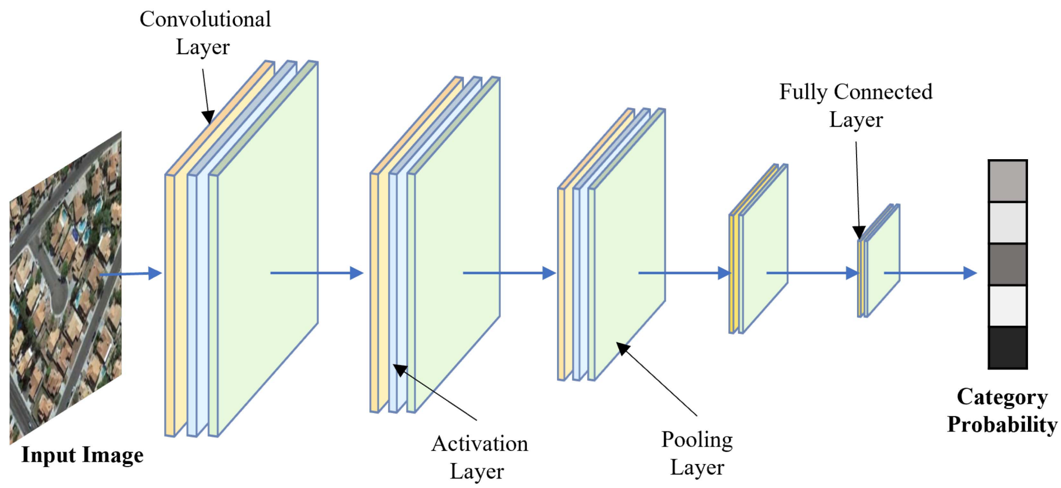


Fig. 11. Specific structure of CNN.

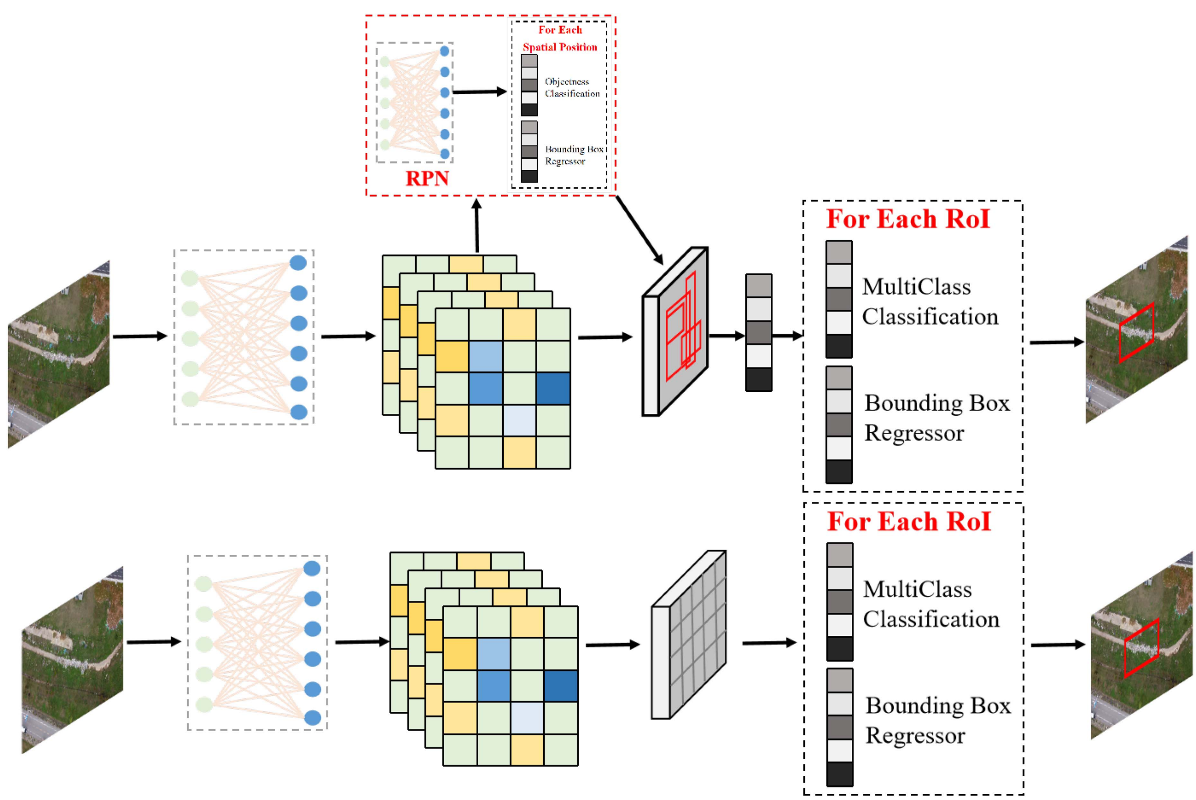


Fig. 12. Basic process of a target detection model.

GoogleNet [130], ResNet [131], etc. UAV high-resolution remote sensing images contain rich contextual, spatial, and spectral information and have been used to classify urban scenes, thus assisting in urban spatial management [132]. Target detection approaches can be mainly classified into one-stage and two-stage methods, as shown in Fig. 12. A one-stage method directly performs target localization and classification simultaneously, which greatly simplifies the network complexity. A two-stage approach first generates suggestions of regions that may contain targets and then classifies and regresses the suggested regions to determine categories to which the targets belong and refine the target bounding boxes. The commonly used one-stage methods mainly include the YOLO series [133], and the commonly used two-stage methods include the fast RCNN series [134]. Target detection has been widely used to automatically extract specified targets from images acquired by UAVs in applications, such as bike sharing, garbage dumping, sewage outfalls, and others involving sensitive targets related to urban space management,

Fig. 13. Some examples of detection targets. The first row shows outfalls taken at different times from different angles; the second row is from the VisDrone dataset.

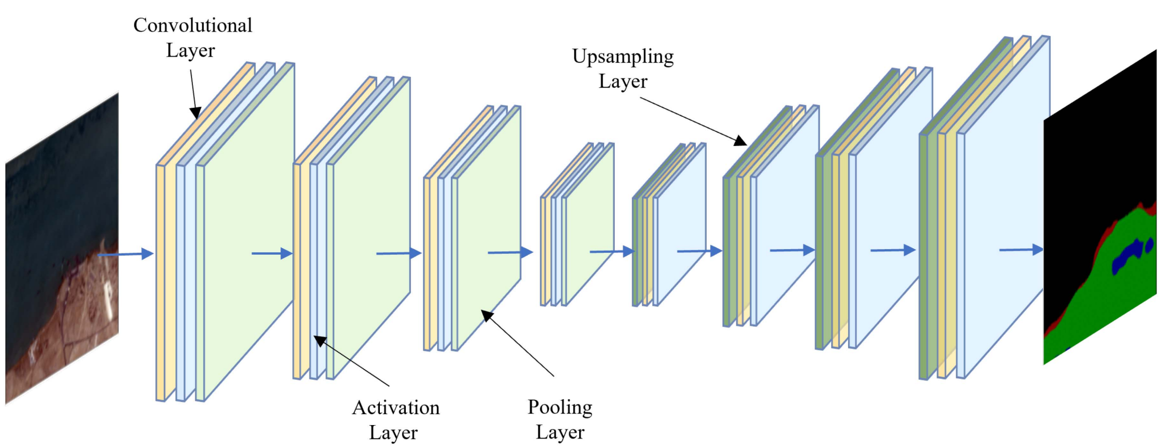


Fig. 14. Image semantic segmentation based on deep neural networks.

thus reducing the investment in urban management costs [46], [135]. CNN-based target detection methods have achieved satisfactory detection results on natural images [136]. However, due to the uncertainty of the flight altitude and shooting angle of UAVs, the images they acquire contain a large amount of surface information. Specific targets to be detected also vary greatly in scale, distribution, color, texture, etc. [137]. Some examples are shown in Fig. 13. This poses a great challenge to target detection. Techniques such as data augmentation, multi-scale learning, contextual learning, and adversarial generative learning have been used to improve the accuracy of weak target detection [138], [139], [140], [141]. Various types of segmentation can also be performed. However, the concepts of semantic, instance, and panoramic segmentation can be very easily confused. The purpose of semantic segmentation is to assign a label class to each pixel in an image (i.e., pixel-level classification). The effect of semantic segmentation is shown in Fig. 14. Semantic segmentation faces two main problems in the field of remote sensing image analysis: pixel-level accuracy requirements and a lack of training instances. Improving pixel-level accuracy relies on overcoming the detail loss problem caused by convolution, which is currently addressed by three mainstream means: multiscale strategies, multimodal fusion, and postprocessing techniques [142], [143], [144], [145]. A large number of training examples are difficult to obtain in practice. To overcome the problem of scarce training examples, researchers have proposed corrective measures, such as synthetic images, migration learning, and semisupervised learning, starting from both training sets and training methods [146], [147], [148]. Instance segmentation is a combination of target detection and semantic segmentation and requires predicting the location and pixel mask of each target instance in the image, which is a very challenging task [149]. Panoramic segmentation, in contrast, is a combination of semantic segmentation and instance segmentation and requires generating pixel masks with category information for all targets in the image. CNN-based segmentation techniques have been used to obtain specified information from UAV remote sensing images, such as in urban building extraction, urban road extraction, urban change detection, etc., thus assisting management work such as urban pattern analysis and urban expansion analysis [150], [151], [152].

C. Quantitative Remote Sensing Inversion of Environmental Parameters

Compared with satellite remote sensing technology, UAVs carrying observation sensors (e.g., multispectral and hyperspectral cameras) can obtain more fine-grained ground sensing data. Therefore, the quantitative inversion of environmental parameters using the data acquired by UAVs will yield more accurate inversion results with higher spatial resolution. The quantitative inversion of environmental remote sensing involves many aspects, such as surface temperature inversion [153], water color and quality inversion [154], vegetation index inversion [155], and so on. Focusing on urban spatial management, the main inversion tasks include water environment inversion, surface temperature inversion, etc. to provide ecological and environmental management of an urban space [44], [156]. The inversion requires a combination of objective mechanisms and experimental observations. Inversion methods can be broadly classified into empirical models, theoretical models, and semitheoretical/semiempirical models according to the degree of involvement of both. In recent years, machine learning methods, including DL, have been widely used for the quantitative inversion of environmental parameters due to a good fitting effect [154].

D. UAV Edge Intelligence

Edge computing places computing tasks, such as data storage and processing, closer to the end user at the edge of the network and is an extension of cloud computing technology with fast processing response times [157]. UAVs equipped with small computing platforms can be used as edge nodes to assist in urban data collection and processing, as shown in Fig. 15. McEnroe et al. [158] have classified the application classes of UAV edge intelligence based on the 6G white paper on edge intelligence, which specifically includes seven categories. Currently, most research work uses three approaches in this method: 1) the UAV acquires visual information and transmits it back to the cloud (ground-side) server for data processing; 2) the UAV processes the acquired visual information directly on the airborne edge device; and 3) the first step of processing is performed on the airborne edge device, and the data are then transmitted back to the cloud (ground-side) server for the second step of fine processing. The second of these is most commonly used, where the AI model is trained on the server and then deployed to the UAV side. For example, Xu et al. [34] ported the power line autonomous sensing and path planning algorithm, which was developed on the ground-side server, into an embedded computer on the UAV to achieve automatic tracking and inspection of high-altitude power lines. Meng et al. [45] developed an UAV edge intelligence system for pipeline safety exclusion, deploying target detection models on airborne edge devices and processing UAV video streams in real time. However, UAV edge intelligence also faces many challenges. For example, small light UAVs have very limited load capacity and cruise capability to carry large computing devices, which, in turn, limits the scale of AI models that can be processed on board. Several possible approaches to solve the above problems include: 1) developing conceptually simpler AI models; 2) AI model compression and pruning; 3) software and hardware codesign; and 4) federated learning [158].

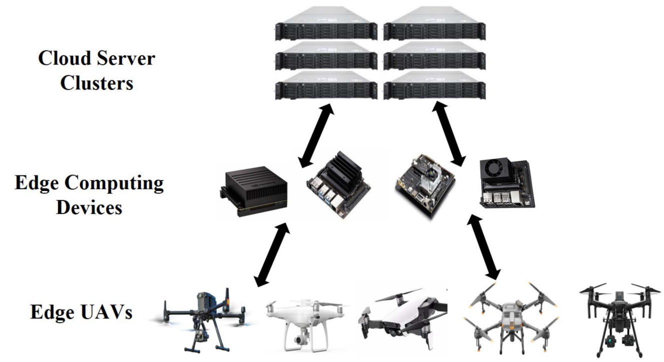


Fig. 15. UAV edge intelligence.

VII. Application Direction

Urban spatial management involves all aspects of cities. This section briefly describes the application directions, progress, and challenges of UAVs from three aspects: UI monitoring, urban disaster emergency response, and urban ecological environment monitoring, as shown in Fig. 16. This helps provide a more comprehensive reference for researchers in related fields.

A. UI Monitoring

While urbanization is increasing, it also brings many challenges [159]. Infrastructure is an important necessity for sustainable urban development. From an engineering point of view, UI mainly includes engineering systems that provide water, energy, transportation, electricity, information, and so on [160]. It is very important to operate and maintain the UI, which is related to the normal operation of a city. The rapid development of UAV and sensor technology provides a powerful technical tool for UI

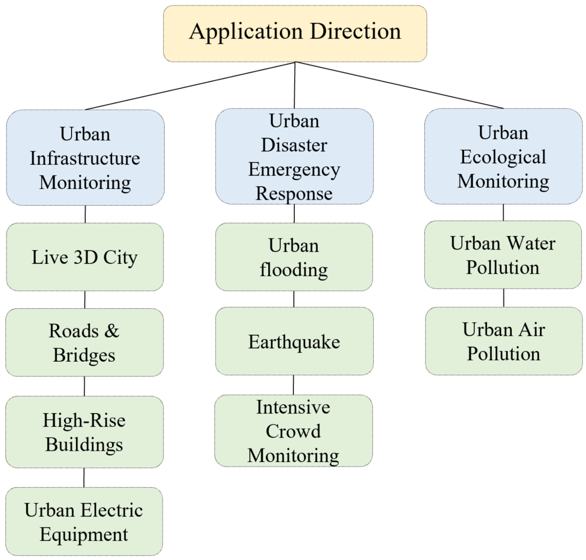


Fig. 16. Direction of applications of UAV in urban space management.

management, which can greatly improve management efficiency in certain work scenarios.

Recently, China's Ministry of Natural Resources has comprehensively promoted the construction of 3-D real scene as a new type of infrastructure [161]. One of the main tasks is to construct DEMs, DSMs, and digital orthophotos covering the entire country's land surface, including major islands. Because of the advantages of high timeliness, high flexibility, and high spatial resolution of UAVs, they have become important platforms for 3-D mapping [28]. UAVs equipped with HD RGB cameras are used to acquire image data of urban areas, and then image matching, offline/online aerial triangulation, dense matching, and 3-D reconstruction steps are taken to obtain 3-D models of urban buildings [162], [163]. In addition, UAVs equipped with LiDAR can acquire detailed and dense 3-D point cloud information of urban areas, which can also be used to produce 3-D models of urban buildings [164]. Researchers from different countries around the world have also conducted a lot of research on UAV photogrammetry and its applications, thus advancing the field. Erenoglu et al. [165] performed 3-D modeling of urban areas in Turkey based on UAV photogrammetry and analyzed the results. The results of the analysis proved that this technique can replace the traditional GNSS surveying technique. He [166] pointed out the problems exposed when using UAVs for fine-grained data acquisition, such as the fixed altitude of the flight path leading to large differences in image resolution, the low efficiency of manually controlling the UAV to get close to the target, and the expensive cost of professional UAVs. In order to make better use of UAVs for data acquisition and modeling of artificial object surfaces in cities (tall building surfaces, tall ancient buildings, etc.), the author proposes a new UAV photogrammetry mode, namely, nap-of-the-object photogrammetry. This technique takes the surface of the object as the photographic object, uses a small UAV to get close to the surface of the object to obtain ultra-high-resolution images, and then finally processes them to obtain the fine structure of the surface of the object. Li et al. [29] proposed the Optimized Views photogrammetry technique. This is an evolutionary extension of the nap-of-the-object photogrammetry technique. Optimized Views photogrammetry utilizes a generalized model of the work area as the planning basis, selects good viewpoints for UAV photography, and generates UAV flight paths to ensure that the UAV can complete the collection of urban building surface data at a lower flight altitude and a closer flight distance. They conducted a field validation of the technology in Qingdao, China. Compared with the traditional oblique photogrammetry, Optimized Views photogrammetry can significantly improve the modeling quality. Especially in urban areas with dense buildings, the modeling accuracy can be improved by three to five times.

Bridges and roads are the most important infrastructures with regard to managing urban traffic, and they need regular inspection and maintenance. Traditional manual inspection methods are labor intensive and cannot sustain a schedule of highly frequent inspections. UAVs offer a new approach to bridge and road inspections by acquiring their surface data with low-altitude overhead observations and then extracting damaged areas from the images in an automated or semiautomated manner. This approach has the advantages of a large scale, high degree of automation, and low cost of inspection. Cracks on the bridge surface can be very harmful to the safety and life of the bridge. They allow water and other materials on the bridge deck to penetrate into the internal structure of the bridge, causing corrosion and damage, which in turn affects the structural performance of the bridge [167]. Therefore, regular inspection of bridge cracks is needed. Lei et al. [6] proposed the crack central point method for problems such as blurred UAV images. Their method can quickly and accurately identify and extract the cracks on a bridge surface. Ayele et al. [168] proposed a workflow for UAV-assisted bridge crack detection, using UAVs with RGB cameras to collect images of bridge surfaces and then extracting surface cracks based on a DL semantic segmentation method. They conducted an experimental validation on a 140 m-long concrete bridge in eastern Norway. The experimental results show that the proposed UAV-assisted bridge crack detection method can achieve up to 90% identification accuracy while reducing sample labeling costs. In addition, a smooth road surface is the basis for stable and steady vehicle operation, so damaged areas on the road surface also need to be identified. Leonardi et al. [7] used a UAV equipped with an RGB camera to acquire DEM data of the road surface to measure and obtain the dimensions of road surface defects. They performed a field test of the proposed method in the Reggio Calabria area, Italy. The measurement error of their proposed method is less than 0.03 m compared to the field measurements. Similarly, Biçici and Zeybek [169] used a UAV with an RGB camera to obtain point cloud information of the road area and used an algorithm to automatically extract the damaged road area. The results of the field experiments conducted in the city of Artvin, Turkey, showed that the root-mean-square error values of the measurements of the proposed method ranged from 2.09 to 6.72 cm. Fan et al. [170] designed a real-time embedded UAV stereo vision system to acquire stereo image pairs of the road surface and process them in real time to obtain a disparity map, making the damaged areas more visible. They tested the proposed method on NVIDIA Jetson TX2 development board and achieved good real-time results. In addition, road markings are important reference information in the field of autonomous driving, and researchers have conducted related research [171]. Bu et al. [171] proposed a UAV-based road marking defect detection method and tested it on three types of roads (highways, ordinary urban roads, and urban roads lacking maintenance) in Nanjing, China. The experimental results show that the detection method is able to achieve more than 93% accuracy and recall in the highway and ordinary urban road scenarios, and more than 76% in the lack of maintenance urban road scenario; the recognition accuracy of road marking defects is greater than 90% in all cases.

Over time, the exterior surfaces of high-rise buildings may deteriorate, crack, and peel off, seriously affecting public safety. Therefore, the regular inspection and maintenance of the exterior surfaces of high-rise buildings are important. Since high-rise buildings are often tens to hundreds of meters high, manual visual inspection is highly subjective, inefficient, and risky. UAVs equipped with RGB cameras can acquire images of the exteriors of high-rise buildings at close range, providing new technical means for inspection work. Carrio et al. [172] proposed the UBRISTES (UAV-based Building Rehabilitation with vISible and ThErmal infrared remote Sensing) system for the detection of anomalies on the external surfaces of buildings. They validated the designed system at the Technical University of Madrid, Spain. The validation results show that the system can assist in identifying anomalies on building surfaces. Grosso et al. [173] addressed the current state of building inspections in Italy, aiming to encourage those involved to use UAVs to carry out regular inspections. The authors also used a case study from Piedmont, Italy, to compare the difference in cost between manual methods and the use of UAVs. Liu et al. [174] retrieved useful information from the BIM of buildings to provide decision support for UAV inspections and developed an AR prototype system for building exterior inspections. The authors conducted field tests using a DJI Phantom 4 UAV at the University of Tennessee, Knoxville, TN, USA, to validate that the developed AR system is effective in improving efficiency. Tan et al. [8], [9] worked on two aspects of building exterior data collection: defect detection and integration. First, they obtained detailed 3-D structural information of the building from the BIM, which was used to guide the UAV flight path planning. Specifically, the viewpoints for UAV image acquisition are first generated based on the 3-D structural information of the building; then, the optimal flight path of the UAV is solved using a GA, and finally the flight parameters of the UAV are calculated. To test the effectiveness of the proposed method, the authors conducted a case study using a DJI Phantom 4 UAV on the campus of Shenzhen University, China. The proposed method takes nearly 50% less time than manual operation and provides 16% higher coverage than manual collection. Second, they used DL techniques to process the acquired image data to automatically identify the exterior damage areas and mapped and integrated the damage information into the BIM of the building to support the dynamic management of the building health status. The authors also validated the proposed new method at Shenzhen University, China. The validation results show that the proposed method is able to complete the data acquisition of one facade of a building in about 60 s and accurately identify centimeter-level defects using a DL approach and finally store the defect information in BIM. Chen et al. [175] proposed a simplified GIS-based management process for acquiring images by UAVs to support the detection of abnormalities in building exterior damage. The authors conducted a case study of the proposed methodology at Virginia Polytechnic Institute and State University, USA, to evaluate the execution efficiency and alignment accuracy. Vasquez et al. [176] addressed the problem of trajectory planning for UAVs in large building inspection work and proposed a method to compute smooth trajectories for quadcopter UAVs based on a 2.5-D model of the building. The authors performed simulation experiments and did not carry out tests on real cases.

Electricity is an important necessity of life in modern society. Therefore, it is necessary to conduct regular inspection and maintenance of power lines to ensure an uninterrupted power supply [177], [178]. The power line inspection consists of two elements: the inspection of power line components and of objects that may be around the power lines [178]. A UAV equipped with an HD digital camera is a very convenient tool for power line inspections, offering advantages such as high flexibility and low cost. Fixed-wing UAVs have a long endurance and are typically used for extensive rough inspections of power lines and obstacle detection next to power lines; multirotor UAVs can get close to power lines for inspection and can acquire more detailed images of power lines by hovering and adjusting camera shooting angles [179], [180]. Zhang et al. [179] used the images acquired by a UAV to achieve automatic measurement of the power line and the area below the line and automatically identified obstacles by calculating the distance between them. The authors conducted on-site measurements on a 220 kV high-voltage line with a length of 3.9 km in Guizhou Province, China. Their proposed method was able to effectively extract the power line with an automatic extraction success rate of 93.2% and effectively identified eight obstacle locations in the experimental area, with a measurement error of less than 0.5 m in the distance from the obstacle to the power line. Chen et al. [181], in contrast, proposed an automatic distance anomaly detection algorithm using LiDAR point cloud data collected by UAVs, which can detect distance anomalies with decimeter-level accuracy. In recent years, with the continuous development of computer vision technology and robotics, researchers have begun to use emerging technologies for power line inspection work, such as image recognition based on DL, automatic control of UAVs, and so on. Shuang et al. [182] constructed a specialized dataset called RSIn-Dataset to address the lack of power line inspection datasets. This dataset contains four different sizes of insulator targets, totaling 3286. The authors tested several commonly used target detection models on this dataset, including SSD [183], Faster R-CNN [184], YOLO V3 [185], YOLO V4, etc., to provide a benchmark for subsequent research work. Souza et al. [186] proposed a method for power line insulator identification called Hybrid-YOLO. The method combines the best model for insulator detection with the best model for insulator classification and is able to achieve 99.262% mAP and 96.216% F1_score on the test dataset. Autonomous UAV control is the key to automated inspection technology. Pussente et al. [187] designed a novel PID controller to solve the power line tracking problem and conducted simulation experiments using the Gazebo simulator, but no real-world testing was performed. In addition to developing high-precision detection algorithms, some researchers have developed a number of UAV applications. Xu et al. [34] developed a UAV power line inspection system based on a UAV, binocular camera, and airborne computing platform; it can automatically detect power lines in the FoV in real time and generate control information based on the location of power lines to guide the UAV to complete line inspection automatically. The unmanned aircraft system (UAS) they developed is capable of tracking transmission lines at a safe distance of 15 m and processing current key frames in about 3 s. Li et al. [188] developed a UAV system integrating core functions such as UAV path planning, mission management, data collection and management, and intelligent fault troubleshooting, in conjunction with the actual needs of power line inspection projects. The authors conducted an actual test at a high-voltage line in Xuzhou City, Jiangsu Province, China. It is worth mentioning that they not only tested the operation of a single UAV but also tested the operation of multiple UAVs at the same time.

B. Urban Disaster Emergency Response

Urban disasters can be divided into two types: 1) natural disasters, such as earthquakes, landslides, ground collapses, floods, extreme weather, etc., and 2) man-made disasters, such as stampede accidents, etc. [189]. When urban disasters occur, UAVs, with their unique advantages, can reach areas that are inaccessible to humans to investigate and assist in rescue missions [190], [191]. Lyu et al. [191] provided a comprehensive overview of the role of UAVs in search and rescue efforts and highlighted the advantages and contributions of UAVs.

Cities are often densely populated with many buildings. Once a natural disaster occurs, the consequences can be unimaginable and first-hand information about the disaster site needs to be obtained in a timely manner. For example, flooding caused by heavy rainfall has become the largest catastrophic natural disaster, posing a serious threat to urban areas [192]. The monitoring and assessment of urban floods using UAVs has become a hot research topic. This consists of two main areas of work. One type is the use of UAVs with sensors onboard to model urban areas in three dimensions and then use flood models to simulate urban inundation to achieve prior assessment of urban flood risk. Li et al. [10] used UAV-mounted LiDAR to obtain high-precision DEM data of urban areas, combined with a hydrodynamic model to simulate the urban waterlogging process; they could then extract and identify areas vulnerable to flooding. The authors validated the measurements in two different environments: a small mountainous area and a large urban area. Five hours and two days were required to complete the work, respectively. Similarly, Trepekli et al. [193] demonstrated that a fine DTM obtained using airborne LiDAR technology can significantly improve the accuracy of urban waterlogging simulation. The authors acquired high-resolution (0.3 m) DTMs for three urban areas in the city of Accra, Ghana, Africa. These data were used to compensate for the 10-m-resolution satellite DTM data, thereby greatly improving the level of refinement in the simulation of urban waterlogging. At the same time, the authors pointed out that the results are somewhat unrealistic when simulations are performed using only low-resolution DTM data. Another category is the intelligent and fast extraction of inundated areas after urban flooding to assist in planning rescue operations or assessing damage. Feng et al. [194] used the Random Forest algorithm to extract flooded areas from digital images acquired by UAVs and confirmed the gain of texture information. The authors conducted a case study in Yuyao City, Zhejiang Province, China. The random forest algorithm was able to accurately extract the flooded areas with an overall accuracy of 87.3% and a Kappa coefficient of 0.746; the classification accuracy was improved by 11.2% after adding texture features. The results show that the proposed method can automatically and accurately extract urban flooded areas. Gebrehiwot et al. [195], in contrast, evaluated the performance of CNNs in urban flooded area extraction. The authors selected three flood-prone areas in North Carolina, USA as the study areas. The UAV image data were taken after the hurricane. The authors tested the algorithms FCN-16s, FCN-8s, FCN-32s, and SVM. The classification accuracies were 97.52%, 97.8%, 94.2%, and 89%, respectively. Rivas Casado et al. [196] proposed a framework for damage assessment based on UAV remote sensing for the accurate estimation of tangible residential property damage caused by flooding. The authors collected data and evaluated the proposed methodology over Cockermouth, U.K. This area had been affected by Storm Desmond. The results of the evaluation show that the accuracy of the damage assessment of the proposed methodology is 84% (compared to the field assessment methodology). Earthquakes are another natural disaster that severely disrupts the normal functioning of cities [197]. UAV flight platforms are able to reach areas that are inaccessible to rescuers in the aftermath of a disaster with limited access. As a result, many research efforts have been conducted using UAVs, mainly for damage assessment, rescue, and post-disaster reconstruction. Of these, disaster assessment is the basis for the latter two efforts. Verykokou et al. [198] used UAV 3-D reconstruction technology to model collapsed buildings after a disaster, thus helping relief workers to grasp the damage situation in time. They evaluated PhotoScan and MicMac-MeshLab and established proven workflows. From the perspective of computational efficiency, Duarte et al. [199] proposed an efficient façade damage detection method that can be effectively used for image data acquired by UAVs. The proposed method first filters out irrelevant images and processes images that are likely to contain damage. It was tested on a set of UAV images acquired after the 2009 L'Aquiladi earthquake in Italy. The results show that the proposed method is able to reduce the area of processed images by a factor of 6, which greatly improves the efficiency of damage detection. Wang et al. [200] proposed a DL segmentation method based on geometric information for segmenting building structural components after an earthquake. The authors evaluated the proposed method on a synthetic urban dataset. The evaluation results show that the proposed method can achieve 97.97% mIoU, which is 1.29% better than the original UNet model. In addition to damage assessment, timely post-earthquake relief is crucial. Strong earthquakes can severely damage urban traffic infrastructure and lead to a paralysis of logistics and transportation. UAVs (swarms) have emerged as an effective alternative for post-disaster material transportation [11]. Nedjati et al. [11] designed a cluster system of UAVs for the timely distribution of urban post-earthquake relief supplies, which can distribute large quantities of supplies to various nodes of need in just a few hours. A case study conducted by the authors shows that 460 UAVs could deliver 100 000 kg of supplies to 44 distribution points in 2.5 h. This result is encouraging for post-earthquake relief efforts. In addition, UAVs are being used to guide urban post-earthquake reconstruction [201].

The monitoring, modeling, and management of dense crowds have been recognized as an important area of research [202]. If a high level of crowd gathering is not properly managed, it may lead to serious stampede accidents. In addition, if a sudden crowd gathering phenomenon occurs, it may mean that there will be a conflict event. The recent global spread of COVID-19 has also placed new requirements on crowd management. UAVs carrying HD cameras, shouters, lights, and other equipment provide a new means of dense crowd management. Researchers have also conducted related studies. In response to the high concentration of crowds, such as the Hajj, which is prone to accidents, Felemban et al. [203] developed a priority-based routing framework for fast transmission of crowd image data from a flying ad hoc network back to the control center. Husman et al. [204] detailed the current state of research on the use of UAVs for intensive crowd monitoring. In addition, urban crime management becomes increasingly challenging as an urban population increases. To address this problem, Miyano et al. [205] proposed a collaborative multidrone framework for predictive crime deterrence and data acquisition based on UAV technology and machine learning techniques to collect training data while improving apprehension success rates, and validated it on a real urban crime dataset.

C. Urban Environmental Pollution Monitoring

As urbanization continues to accelerate, urban environmental pollution problems have become particularly prominent and can be roughly classified as water pollution, air pollution, waste dumping, etc.

Cities are typically closely located to natural and artificial water bodies, such as rivers and lakes. The pollution of urban water bodies will seriously affect the health and quality of life of citizens [206]. In addition, nearby water bodies also play an important role in flood control, maintaining ecological balance, and beautifying the urban landscape [44]. Traditional manual field surveys and satellite remote sensing survey methods have some drawbacks, such as low survey frequency and low survey accuracy. A UAV platform can carry multispectral and hyperspectral sensors to obtain high-spatial-resolution image data of urban water bodies and also has high temporal resolution, flexible operation, and low cost. The obtained image data can be used to invert the water quality parameters and, thus, indicate the specific status of a water body. Wei et al. [12] inferred the integrated pollution index of urban water bodies based on UAV hyperspectral imagery and monitored pollution sources. The authors selected two rivers in Wuhan City, Hubei Province, China, as the study areas and evaluated six regression models, including GBDTR, MLPR, RFR, SVR, OLSR, and KRR. The experimental results show that GBDTR performs better in terms of inversion accuracy and computation time and is able to complete the inversion of the study area within a few minutes. Compared with the traditional field measurements, the UAV-based method is able to obtain large-scale and high-precision survey results in a short period of time. Similarly, Wei et al. [207] used UAV hyperspectral imagery to accurately invert the water transparency of narrow urban rivers. The authors still chose two intraurban rivers in Wuhan, Hubei Province, China, as the study areas. The XGBoost algorithm they used performed well in both study areas with R^2 greater than 0.97. Chen et al. [154] then used machine learning techniques and UAV hyperspectral data to perform quantitative inversions of five water quality parameters of urban rivers. The authors tested the accuracy of six algorithms, including GA-XGBoost, for inversion of water quality parameters (chlorophyll a, total phosphorus, total nitrogen, ammonia nitrogen, and turbidity) on the Nanfang River in Hefei City, Anhui Province, China. The test results shows that the GA-XGBoot algorithm had the highest accuracy with a coefficient of determination of 0.855. Matsui et al. [208] also pointed out the drawbacks of both satellite remote sensing and UAV remote sensing methods used for water quality monitoring and proposed a method to improve the resolution of satellite remote sensing data based on high-spatial-resolution UAV remote sensing data. The method is based on DL technology, which can significantly improve the quality of remote sensing data and thus the accuracy of water quality estimation. In addition, the sources of discharge (e.g., outfalls) can also be investigated, and thus, urban water pollution can be monitored and controlled indirectly. Huang et al. [46] used UAVs to investigate the distribution of urban outfalls on a large scale, which improved the efficiency of urban water pollution source identification. The authors proposed an improved geographic information-based Faster RCNN (GDCNN-outfalls) and conducted experiments in a typical area in Wuhu City, Anhui Province, China. The experimental results show that the proposed method has a recall of 79.3%, a precision of 48.4%, and is ten times faster than manual visual interpretation. In one of our previous works [209], we designed and tested a UAV inspection system based on UAV remote sensing and edge computing technologies for automated outfall inspection work. We installed an outfall inspection model developed based on YOLO V5s in an embedded computer (NVIDIA Jetson AGX Xavier), which is capable of processing images acquired by sensors in real time.

The continuous increase of an urban population and its vehicles will lead to significant air pollution, which will cause serious health hazards for people [210]. Therefore, it is necessary to study the air quality and its distribution in urban areas. The survey methods mainly include dynamic and static measurements. Static measurements are conducted through static monitoring stations to obtain air quality parameters at specified locations,

TABLE V
SOME UAV APPLICATION SYSTEMS FOR URBAN MANAGEMENT

System Name	Functional features of the system	Application Scenarios	Developer
MANAGE STREAM FLY [224]	Based on three software packages, it supports orderly drone management, drone path planning, real-time audio and video transmission, and safe remote operation.	Urban logistics and distribution, public safety enforcement, patrol and inspection, etc.	VOTIX
gNext SaaS [225]	Supports 3-D modeling, point cloud modeling, and other functions.	Infrastructure inspection, construction measurement, etc.	gNext Labs
Sky-Drones Cloud [226]	Supports UAV formation management, mission planning and execution, AI analysis, etc.	Urban logistics and distribution, public safety enforcement, inspection, etc.	Sky-Drones
DroneRoofer [227]	Supports automatic drone operation, real-time data transmission, generation of work reports, etc.	Intelligent outdoor surveys, etc.	Clue
Auterion Suite [228]	Supports UAV device management, real-time data transmission, secondary development, third-party device integration, and other functions.	Surveying and mapping, city inspections, public safety enforcement, etc.	Auterion
DroneHarmony [229]	Supports UAV mission planning, automatic data collection and storage, modeling, etc.	Topographic mapping, power patrol, etc.	DroneHarmony
DroneDeploy [230]	Supports UAV mission planning, automatic data collection and processing, visualization, etc.	UI inspection, etc.	DroneDeploy
DJI Flighthub-2 [231]	Supports UAV mission planning, cloud-based data processing, automatic airport recovery, etc.	Urban law enforcement, engineering surveying and mapping, etc.	DJI
UAV platform [232]	Supports UAV mission planning and remote control, data intelligence analysis, etc.	City inspection, smart city management, etc.	Jdyair
UAV spatial data platform [233]	Supports UAV mission planning, multi-UAV network operation, intelligent data processing and analysis, etc.	City inspection, smart city management, etc.	Renwofei

but they do not cover larger areas. Dynamic measurement methods based on ground mobile platforms such as vehicles can only obtain the ground pollutant distribution and cannot obtain the vertical distribution. Multirotor UAVs support vertical takeoff and landing and fixed-point cruising, and they can meet the demand for 3-D monitoring of urban air pollution. For example, Li et al. [13] designed a multirotor UAV atmospheric monitoring system that can effectively monitor vehicle exhaust with high spatial and high temporal resolution. The system is highly maneuverable and flexible and supports functions such as fixed-point hovering, which greatly improves the spatial and temporal monitoring capability of traffic emissions. The authors tested the system in Fengxian District, Shanghai, China. The test results show that the system is able to monitor the changes of air pollutants in both horizontal and vertical directions, overcoming the drawbacks of fixed-point measurements. Zheng et al. [211] used an UAV platform to monitor and summarize the general spatial distribution of air pollutants next to urban roads. They used a hexacopter UAV for spatial and temporal monitoring of air pollutants (including particulate matter and carbon monoxide) next to one of the main roads in Shanghai. The general pattern summarized by the authors can be found in [211]. Similarly, Samad et al. [212] conducted a similar study with field measurements at two locations, including next to roads. The authors developed a 14 kg hexacopter UAS capable of measuring particulate matter, ultrafine particles, black carbon and meteorological parameters. They conducted field tests, monitored in both vertical and horizontal dimensions, and summarized general patterns in the 3-D distribution of air pollutants. In addition, the authors of [213] and [214] also used UAVs with gas sensors to monitor air quality in urban areas in a 3-D manner. Xin et al. [213] used a UAV to monitor the vertical distribution of PM2.5 near the ground in Xi'an, Shaanxi Province, China. The monitoring sites included water bodies, green areas, and urban built-up areas. The monitoring results demonstrate the general pattern of PM2.5 distribution, which can help urban planners optimize urban spatial planning. Li et al. [214] monitored eight sites in Shenyang City, Liaoning Province, China, for four days using a sensor-carrying UAV. Atmospheric pollutants monitored included SO2, NO2, PM1, PM2.5, and PM10. The monitoring altitude was 120 m. The monitoring results reveal the distribution pattern of atmospheric pollutants in Shenyang city.

VIII. UAV Application System for Urban Management

A. Development Status

Numerous researchers have developed a number of UAV application systems for specific scenarios and have achieved good results [190], [215], [216], [217], [218], [219], [220], [221], [222], [223]. However, mature industry application systems represent the current accepted state of the art in terms of algorithms and technologies. This section introduces several UAV application systems that are already more mature in the industry. They have different functions and mainly involve the management and planning of UAVs (UAV swarms), their inspection, use for photogrammetry, etc. Specific information on UAV application systems is shown in Table V.

B. Case Study

This section introduces in detail our recently designed and developed UAV smart city management system. This system is an application platform for urban governance. It helps to improve the efficiency of urban inspection and governance work through the integrated use of advanced technologies, such as Big Data, AI, and IoT.

1) Architecture and Functionality: The overall architecture of the system is shown in Fig. 17. Among the layers, the bottom is the hardware facility layer, consisting of multiple server nodes, network switches, and so on. The system is based on an HDFS distributed file system and Elasticsearch distributed full-text retrieval engine to complete the storage of the data, as well as to realize the functions of the UAV data input and feedback,

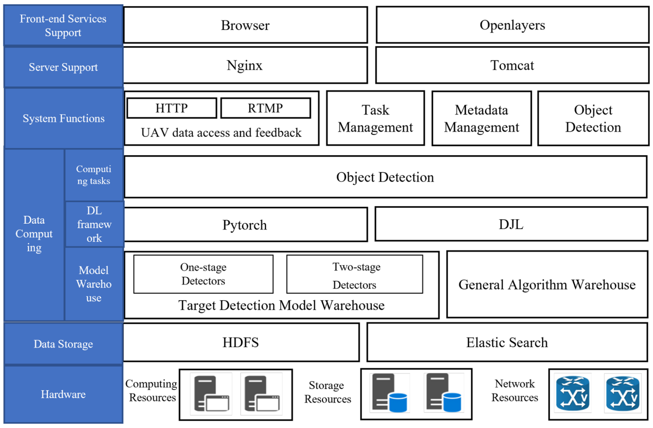


Fig. 17. Systems architecture.

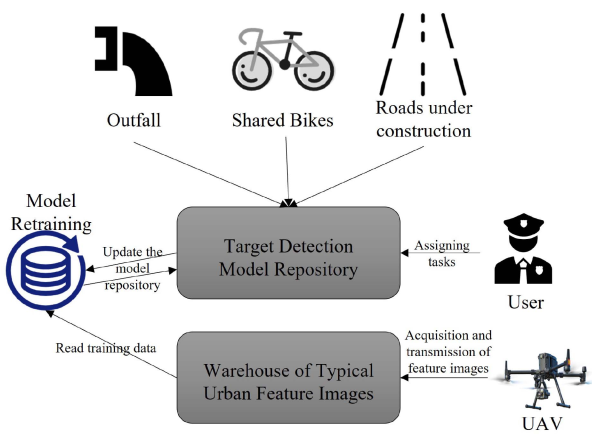


Fig. 18. Iterative update process of the target detection model repository.

management of flight tasks, and metadata management. The main functions of the system include seven major components:

1) comprehensive management of law enforcement officers and UAV equipment, mapping out the "family background" and achieving orderly management;
2) construction of a multiclass feature target detection algorithm library with embedded target detection models for roads under construction, sewage outfalls, etc., while supporting users to upload customized target detection models;
3) support for mission planning and dispatching and for users to interactively specify UAV routes;
4) live multiway video streaming from UAVs;
5) UAV multichannel video stream near-real-time concurrent detection to achieve intelligent detection of typical features;
6) support for the generation and download of work reports, so that law enforcement work is based on evidence;
7) support for online distributed training of target detection models to achieve model updates and upgrades.

It is worth mentioning that the system has a prebuilt internal library of target detection algorithms, as shown in Fig. 18. The system can flexibly call these algorithms to achieve the target

Fig. 19. Interface of the system at work.

detection functions. At the same time, the target detection model can read the feature samples in the sample library for distributed iterative training to update and upgrade the target detection model and improve the detection accuracy.

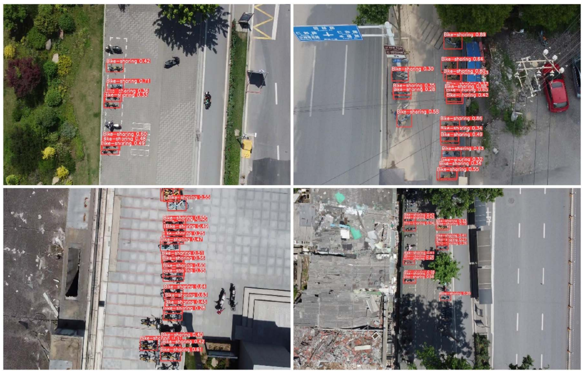
2) Practical Application Cases: With the advanced technical architecture, the system has been successfully used in the practical work of city management. Urban ecology is closely related to natural or artificial water bodies such as rivers and lakes. Real-time and intelligent investigation of sewage sources (e.g., outfalls), and thus indirectly monitoring and treating urban water pollution, is a key issue that needs to be solved. In one of our previous works [209], the system was used to detect outfalls on the banks of urban waters with good results in both real time and accuracy. To the best of our knowledge, this is the first real-time UAS for detecting outfalls in urban waters. The interface of the system at work is shown in Fig. 19. The main page on the left side shows the result video of outfall detection. The function column on the right side includes functions such as detection parameter setting, video playback and download of detection results, display of detection statistics, and display of detection target list. The system better supports the detection work in terms of uploading and management of detection models, real-time video detection, historical video detection, and analysis of detection results.

The system has also been used to detect other geotargets in the city, such as shared bicycles, roads under construction, garbage piles, and so on. The models used for detecting the abovementioned targets have been embedded in the system and support the user to retrain and upload them as per the requirement. The detection results of the models in the system are shown in Fig. 20.

IX. Discussion

Based on the extensive research and summaries mentioned above, this section will summarize the current characteristics, shortcomings, and opportunities of UAV-assisted urban spatial management work from the following aspects and provide some conclusive findings. We hope that the section will inspire relevant researchers.

1) *New technologies, represented by DL, empower UAV technology:* Manually maneuvering a UAV to perform an



(a)

(b)

Fig. 20. (a) and (b) Detection effects of some system-embedded detection models (shared bicycles and garbage piles).

operation, or manually processing data acquired by a UAV, is becoming less and less practical. This mode of working, which relies heavily on manual labor, is being phased out. With the continuous development of UAV technology, more and different types of sensors and computing devices can be carried on the body of the UAV, which provides an opportunity to realize automated UAV operations. Based on the above research and summary of existing works, researchers from different countries and regions of the world are using new technologies to empower UAV technology, such as robotic swarm control, image interpretation based on DL techniques, automatic UAV navigation and control based on multimodal sensors, and so on. Although much progress has been made, there is still a long way to go before UAVs can operate fully autonomously.

2) *Civilian UAVs have become the main driving force behind the development of the UAV industry:* UAV manufacturing companies, represented by the Chinese company DJI, are continuously developing new civilian UAV products. From the above research and analysis, it can be found that by virtue of their affordable price, simple operation, and rich development interfaces, these civil UAVs have been widely used by researchers, which has greatly contributed to the good development of urban spatial management work. However, with the continuous development of urbanization in the world, urban spatial management will face more difficulties. For example, the continuous expansion of urban area leads to the fact that the range of the existing UAVs cannot meet the operational requirements; the high buildings in the city pose a challenge to the existing UAV obstacle avoidance technology. Therefore, UAV manufacturers should continue to make efforts in developing UAVs with richer functions and better performance.

3) *UAV-related applications are becoming more and more diverse:* As can be seen from the above summary, the industry applications of UAVs are becoming more and more diverse. In addition to the three applications mentioned in Section VII, UAVs have great potential to be applied in other fields. Therefore, it is of great significance to explore new industry applications of UAVs in urban spatial management.

4) *Advanced UAV technology needs to be carried by mature UASs:* The development of mature UAS and embedding the proposed methodology into the system is a major trend in current research efforts. Advanced UAV-related technologies must need to be carried by mature UASs. Researchers have developed many mature UASs for urban space management work. This is a strong impetus for the practical implementation of UAV-related technologies in urban management. With the increasing difficulty of urban space management, UAS should be more robust and applicable.

5) *The management of UAV applications is relatively imperfect:* As can be seen from Section IV, the current management of UAV applications in cities is still very insufficient, even at the stage of conceptual design and pilot studies. In recent years, there have been numerous incidents of unauthorized flights of UAVs over cities, which have caused great disturbances to urban management and threatened urban safety. Therefore, mature management policies and management systems are urgently needed.

X. Future Research Directions

Although UAVs have played an important role in urban management, there are still some difficulties and challenges. Based on the above summary and analysis, we have listed directions worthy of in-depth research in the future organized by four aspects for reference.

A. Data Acquisition

It is sometimes impossible to cover the entire urban area using a single UAV. Cooperative observation of multiple UAVs (UAV swarms) provides the technical means to address the above problems. Among them, the task scheduling and path planning problems of multiple UAVs should be focused on [94]. In addition, it has become a trend to use UAVs to acquire data of multiple modalities in the same area at one time. The integration of different types of sensors on demand according to specific mission requirements is a technical issue that needs to be an area of research focus.

B. Data Transmission

Reliable data transmission is the key to everything that follows. In large-scale urban space management work, the radius of activity of existing UAVs severely limits their efficiency. Therefore, it is important to use advanced IoT satellite communication technology to assist UAV communication and, thus, expand the working radius of individual UAVs. In addition, UAV relay communication technology can be a good aid to urban management work and should be a research focus.

C. Data Processing

The data processing can be considered in several aspects. First, the use of multisource data fusion processing may improve the processing accuracy. However, in practical applications, the focus should be on how to adequately and effectively fuse data from different modalities and how to interpret the gain that each modal data can play [234]. In addition, for some applications, fast real-time processing of UAV data and assisted decision making are critical. UAV edge intelligence technology, in contrast, is an effective technical tool that can address these issues to some extent [158].

D. Management Policy

There are two main aspects of management policy: standardization and integration/demonstration. Regarding a standardization example, different sensor manufacturers follow their own standards in production, which creates difficulties for subsequent data processing. In addition, corresponding standards should be established for the data products created. The second aspect is integration and demonstration. From the current status of research in the application direction, it can be seen that most of the applications are focused on a single type of work in a local area, which can lead to very scattered results overall. Reasonable work integration should be carried out according to different management areas. For example, in urban ecological environment monitoring, a highly integrated work system should be established to avoid wasting resources due to scattered work. In addition, relevant departments can set up some typical working demonstration cases to guide the orderly development of related industries.

XI. Conclusion

With the accelerated urbanization process, urban space management is facing unprecedented pressure and challenges. It urgently needs to develop in the direction of intelligence and automation. UAV technology is playing an important role in urban spatial management work. UAV technology has been used in all aspects of urban spatial management and involves numerous technical details. Therefore, a systematic and comprehensive review of UAV applications in urban spatial management is necessary to provide a comprehensive reference for relevant researchers and facilitate the generation of new insights, methods and applications. However, according to our research, there is a lack of systematic investigations on related aspects. Therefore, we provide a comprehensive review and summary of UAV-assisted urban spatial management through this article. First, this article takes the definition, needs, and challenges of urban space management as an entry point, clarifies the relevant concepts of intelligent management work in urban space, and summarizes the advantages and application scenarios of UAVs. Then, based on a large number of references and previous work experience, this article divides the workflow of UAV-assisted urban spatial management into three aspects, i.e., data acquisition, data transmission, and data processing. To the best of our knowledge, this is the first time to summarize the work paradigm of UAV-assisted urban spatial management. Among them, data collection provides a database for urban spatial management. Data transmission provides the data "artery" for the city, realizing efficient and robust data transmission. Data processing focuses on improving automation and intelligence to enhance the efficiency of management. This article summarizes the technical details of these three aspects to help researchers understand the basics of the field and start working quickly. Second, this article summarizes and describes the current status of the applications of UAVs in urban spatial management from three aspects: UI monitoring, urban disaster emergency response, and urban ecological environment monitoring. We hope that this part can provide references for related researchers and help them generate new ideas. This article also describes several different types of UAV application systems and presents our recently developed UAV smart city management system. The purpose of presenting our recent development work is to elaborate on how UAV technology can be highly coupled with DL technology, IoT technology, and big data technology to serve urban spatial management. Finally, this article summarizes and analyzes the existing problems in terms of data collection, data transmission, data processing, and management policies and looks forward to future research directions. We hope that this part of the article can provide references for related researchers, thus prompting research in these areas. We believe that future research will inevitably be carried out in terms of methods, systems, applications, and policies to contribute to the building of livable cities. In order to realize the above goals, research can continue in the following aspects. In terms of methodology, UAV technology should be further combined with advanced technology represented by DL to enhance the automation, intelligence, and clustering level of UAV technology; in terms of application, the application potential of UAVs should be explored to continue to carry out a wide variety of UAV industry applications; in terms of system, research and development of high-reliability and high-performance UAV systems should be continued; and in terms of policy, the management department should take the initiative in planning and formulate reasonable and effective management policies to ensure the orderly operation of UAVs in cities.

References

[1] M. Keith et al., "A new urban narrative for sustainable development," *Nature Sustain.*, vol. 6, no. 2, pp. 115–117, 2023, doi: 10.1038/s41893-022-00979-5.

[2] T. Elmqvist et al., "Sustainability and resilience for transformation in the urban century," *Nature Sustain.*, vol. 2, no. 4, pp. 267–273, 2019, doi: 10.1038/s41893-019-0250-1.

[3] SDG 11. Accessed: May 27, 2023. [Online]. Available: https://www.un.org/sustainabledevelopment/zh/cities/

[4] S. Guenat et al., "Meeting sustainable development goals via robotics and autonomous systems," *Natural Commun.*, vol. 13, no. 1, 2022, Art. no. 3559, doi: 10.1038/s41467-022-31150-5.
[5] J. D. Sachs, G. Schmidt-Traub, M. Mazzucato, D. Messner, N. Nakicenovic, and J. Rockström, "Six transformations to achieve the sustainable development goals," *Nature Sustain.*, vol. 2, no. 9, pp. 805–814, 2019, doi: 10.1038/s41893-019-0352-9.
[6] B. Lei, N. Wang, P. Xu, and G. Song, "New crack detection method for bridge inspection using UAV incorporating image processing," *J. Aerosp. Eng.*, vol. 31, no. 5, 2018, Art. no. 04018058, doi: 10.1061/(ASCE)AS.1943-5525.0000879.
[7] G. Leonardi, V. Barrile, R. Palamara, F. Suraci, and G. Candela, "3D mapping of pavement distresses using an unmanned aerial vehicle (UAV) system," in *New Metropolitan Perspectives: Local Knowledge and Innovation Dynamics Towards Territory Attractiveness Through the Implementation of Horizon/E2020/Agenda2030*, vol. 2. Berlin, Germany: Springer, 2019, pp. 164–171.
[8] Y. Tan, S. Li, H. Liu, P. Chen, and Z. Zhou, "Automatic inspection data collection of building surface based on BIM and UAV," *Autom. Construction*, vol. 131, 2021, Art. no. 103881, doi: 10.1016/j.autcon.2021.103881.
[9] Y. Tan, G. Li, R. Cai, J. Ma, and M. Wang, "Mapping and modelling defect data from UAV captured images to BIM for building external wall inspection," *Autom. Construction*, vol. 139, 2022, Art. no. 104284, doi: 10.1016/j.autcon.2022.104284.
[10] B. Li et al., "Application of LiDAR UAV for high-resolution flood modelling," *Water Resour. Manage.*, vol. 35, pp. 1433–1447, 2021, doi: 10.1007/s11269-021-02783-w.
[11] A. Nedjati, B. Vizvari, and G. Izbirak, "Post-earthquake response by small UAV helicopters," *Natural Hazards*, vol. 80, pp. 1669–1688, 2016, doi: 10.1007/s11069-015-2046-6.
[12] L. Wei, C. Huang, Z. Wang, Z. Wang, X. Zhou, and L. Cao, "Monitoring of urban black-odor water based on Nemerow index and gradient boosting decision tree regression using UAV-borne hyperspectral imagery," *Remote Sens.*, vol. 11, no. 20, 2019, Art. no. 2402, doi: 10.3390/rs11202402.
[13] B. Li et al., "Use of multi-rotor unmanned aerial vehicles for fine-grained roadside air pollution monitoring," *Transp. Res. Rec.*, vol. 2673, no. 7, pp. 169–180, 2019, doi: 10.1177/0361198119847991.
[14] W. McDonald, "Drones in urban stormwater management: A review and future perspectives," *Urban Water J.*, vol. 16, no. 7, pp. 505–518, 2019, doi: 10.1080/1573062X.2019.1687745.
[15] M. V. Rodríguez, S. G. Melgar, A. S. Cordero, and J. M. A. Márquez, "A critical review of unmanned aerial vehicles (UAVs) use in architecture and urbanism: Scientometric and bibliometric analysis," *Appl. Sci.*, vol. 11, no. 21, 2021, Art. no. 9966, doi: 10.3390/app11219966.
[16] V. B. Sharma et al., "Recent advancements in AI-enabled smart electronics packaging for structural health monitoring," *Metals*, vol. 11, no. 10, 2021, Art. no. 1537, doi: 10.3390/met11101537.
[17] I. Bisio, C. Garibotto, H. Haleem, F. Lavagetto, and A. Sciarrone, "A systematic review of drone based road traffic monitoring system," *IEEE Access*, vol. 10, pp. 101537–101555, 2022, doi: 10.1109/ACCESS.2022.3207282.
[18] V. Lambey and A. Prasad, "A review on air quality measurement using an unmanned aerial vehicle," *Water, Air, Soil Pollut.*, vol. 232, pp. 1–32, 2021, doi: 10.1007/s11270-020-04973-5.
[19] Z. Yousefi and H. Dadashpoor, "How do ICTs affect urban spatial structure? A systematic literature review," *J. Urban Technol.*, vol. 27, no. 1, pp. 47–65, 2020, doi: 10.1080/10630732.2019.1689593.
[20] R. Volk, M. Rambhia, E. Naber, and F. Schultmann, "Urban resource assessment, management, and planning tools for land, ecosystems, urban climate, water, and materials—A review," *Sustainability*, vol. 14, no. 12, 2022, Art. no. 7203, doi: 10.3390/su14127203.
[21] P. Ajay, B. Nagaraj, B. M. Pillai, J. Suthakorn, and M. Bradha, "Intelligent ecofriendly transport management system based on IoT in urban areas," *Environ., Develop. Sustain.*, pp. 1–8, 2022, doi: 10.1007/s10668-021-02010-x.
[22] W. Tu et al., "Portraying the spatial dynamics of urban vibrancy using multisource urban big data," *Comput., Environ. Urban Syst.*, vol. 80, 2020, Art. no. 101428, doi: 10.1016/j.compenvurbsys.2019.101428.
[23] Y. Zheng, L. Capra, O. Wolfson, and H. Yang, "Urban computing: Concepts, methodologies, and applications," *ACM Trans. Intell. Syst. Technol.*, vol. 5, no. 3, pp. 1–55, 2014, doi: 10.1145/2629592.
[24] L. K. Gharibvand, A. A. Jamali, and F. Amiri, "Changes in NO_2 and O_3 levels due to the pandemic lockdown in the industrial cities of Tehran and Arak, Iran using sentinel 5P images, Google Earth Engine (GEE) and statistical analysis," *Stochastic Environ. Res. Risk Assessment*, vol. 37, no. 5, pp. 2023–2034, 2023.
[25] B. N. Silva, M. Khan, and K. Han, "Towards sustainable smart cities: A review of trends, architectures, components, and open challenges in smart cities," *Sustain. Cities Soc.*, vol. 38, pp. 697–713, 2018, doi: 10.1016/j.scs.2018.01.053.
[26] A. Heidari, N. J. Navimipour, and M. Unal, "Applications of ML/DL in the management of smart cities and societies based on new trends in information technologies: A systematic literature review," *Sustain. Cities Soc.*, 2022, Art. no. 104089, doi: 10.1016/j.scs.2022.104089.
[27] S. P. Mohanty, U. Choppali, and E. Kougianos, "Everything you wanted to know about smart cities: The Internet of Things is the backbone," *IEEE Consum. Electron. Mag.*, vol. 5, no. 3, pp. 60–70, Jul. 2016, doi: 10.1109/MCE.2016.2556879.
[28] S. Jiang, W. Jiang, and L. Wang, "Unmanned aerial vehicle-based photogrammetric 3D mapping: A survey of techniques, applications, and challenges," *IEEE Geosci. Remote Sens. Mag.*, vol. 10, no. 2, pp. 135–171, Jun. 2022, doi: 10.1109/MGRS.2021.3122248.
[29] Q. Li, H. Huang, W. Yu, and S. Jiang, "Optimized views photogrammetry: Precision analysis and a large-scale case study in Qingdao," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 16, pp. 1144–1159, 2023, doi: 10.1109/JSTARS.2022.3233359.
[30] F. Nex et al., "UAV in the advent of the twenties: Where we stand and what is next," *ISPRS J. Photogrammetry Remote Sens.*, vol. 184, pp. 215–242, 2022, doi: 10.1016/j.isprsjprs.2021.12.006.
[31] N. Takhtkeshha, A. Mohammadzadeh, and B. Salehi, "A rapid self-supervised deep-learning-based method for post-earthquake damage detection using UAV data (case study: Sarpol-E Zahab, Iran)," *Remote Sens.*, vol. 15, no. 1, 2022, Art. no. 123, doi: 10.3390/rs15010123.
[32] M. Ghamari, P. Rangel, M. Mehrubeoglu, G. Tewolde, and R. S. Sherratt, "Unmanned aerial vehicle communications for civil applications: A review," *IEEE Access*, vol. 10, pp. 102492–102531, 2022, doi: 10.1109/ACCESS.2022.3208571.
[33] M. Zhang and X. Li, "Drone-enabled internet-of-things relay for environmental monitoring in remote areas without public networks," *IEEE Internet Things J.*, vol. 7, no. 8, pp. 7648–7662, Aug. 2020, doi: 10.1109/JIOT.2020.2988249.
[34] C. Xu, Q. Li, Q. Zhou, S. Zhang, D. Yu, and Y. Ma, "Power line-guided automatic electric transmission line inspection system," *IEEE Trans. Instrum. Meas.*, vol. 71, 2022, Art. no. 3512118, doi: 10.1109/TIM.2022.3169555.
[35] A. Wilson, A. Kumar, A. Jha, and L. R. Cenkeramaddi, "Embedded sensors, communication technologies, computing platforms and machine learning for UAVs: A review," *IEEE Sens. J.*, vol. 22, no. 3, pp. 1807–1826, Feb. 2022, doi: 10.1109/JSEN.2021.3139124.
[36] J. Wang et al., "Developing a method to extract building 3D information from GF-7 data," *Remote Sens.*, vol. 13, no. 22, 2021, Art. no. 4532, doi: 10.3390/rs13224532.
[37] M. Zhang, L. Zhang, C. Zhao, R. Jin, J. Guo, and X. Li, "Fetching ecosystem monitoring data in extreme areas via a drone-enabled Internet of Remote Things," *IEEE Internet Things J.*, vol. 9, no. 24, pp. 25052–25067, Dec. 2022, doi: 10.1109/JIOT.2022.3195302.
[38] H. Yao, R. Qin, and X. Chen, "Unmanned aerial vehicle for remote sensing Applications—A review," *Remote Sens.*, vol. 11, no. 12, 2019, Art. no. 1443, doi: 10.3390/rs11121443.
[39] A. P. Colefax, P. A. Butcher, and B. P. Kelaher, "The potential for unmanned aerial vehicles (UAVs) to conduct marine fauna surveys in place of manned aircraft," *ICES J. Mar. Sci.*, vol. 75, no. 1, pp. 1–8, 2018, doi: 10.1093/icesjms/fsx100.
[40] C. Lee, S. Kim, and B. Chu, "A survey: Flight mechanism and mechanical structure of the UAV," *Int. J. Precis. Eng. Manuf.*, vol. 22, no. 4, pp. 719–743, 2021, doi: 10.1007/s12541-021-00489-y.
[41] J. Kim, S. Kim, C. Ju, and H. I. Son, "Unmanned aerial vehicles in agriculture: A review of perspective of platform, control, and applications," *IEEE Access*, vol. 7, pp. 105100–105115, 2019, doi: 10.1109/ACCESS.2019.2932119.
[42] M. Idrissi, M. Salami, and F. Annaz, "A review of quadrotor unmanned aerial vehicles: Applications, architectural design and control algorithms," *J. Intell. Robot. Syst.*, vol. 104, no. 2, 2022, Art. no. 22, doi: 10.1007/s10846-021-01527-7.
[43] S. Jiang, C. Jiang, and W. Jiang, "Efficient structure from motion for large-scale UAV images: A review and a comparison of SFM tools," *ISPRS J. Photogrammetry Remote Sens.*, vol. 167, pp. 230–251, 2020, doi: 10.1016/j.isprsjprs.2020.04.016.
[44] F. Wang, H. Hu, Y. Luo, X. Lei, D. Wu, and J. Jiang, "Monitoring of urban black-odor water using UAV multispectral data based on extreme gradient boosting," *Water*, vol. 14, no. 21, 2022, Art. no. 3354, doi: 10.3390/w14213354.

[45] L. Meng et al., “Real-time detection of ground objects based on unmanned aerial vehicle remote sensing with deep learning: Application in excavator detection for pipeline safety,” *Remote Sens.*, vol. 12, no. 1, 2020, Art. no. 182, doi: 10.3390/rs12010182.

[46] Y. Huang, C. Wu, H. Yang, H. Zhu, M. Chen, and J. Yang, “An improved deep learning approach for retrieving outfalls into rivers from UAS imagery,” *IEEE Trans. Geosci. Remote Sens.*, vol. 60, 2021, Art. no. 4703814, doi: 10.1109/TGRS.2021.3113901.

[47] Tilt digital aerial photography technical regulations. Accessed: May 27, 2023. [Online]. Available: https://openstd.samr.gov.cn/bzgk/gb/newGbInfo?hcno=521860C4A5292C3B2EA90CA3FCE2D31F

[48] L. Deng, Z. Mao, X. Li, Z. Hu, F. Duan, and Y. Yan, “UAV-based multispectral remote sensing for precision agriculture: A comparison between different cameras,” *ISPRS J. Photogrammetry Remote Sens.*, vol. 146, pp. 124–136, 2018, doi: 10.1016/j.isprsjprs.2018.09.008.

[49] A. Morales et al., “A multispectral camera development: From the prototype assembly until its use in a UAV system,” *Sensors*, vol. 20, no. 21, 2020, Art. no. 6129, doi: 10.3390/s20216129.

[50] G. Lee, J. Hwang, and S. Cho, “A novel index to detect vegetation in urban areas using UAV-based multispectral images,” *Appl. Sci.*, vol. 11, no. 8, 2021, Art. no. 3472, doi: 10.3390/app11083472.

[51] M. E. Schaepman, S. L. Ustin, A. J. Plaza, T. H. Painter, J. Verrelst, and S. Liang, “Earth system science related imaging Spectroscopy—An assessment,” *Remote Sens. Environ.*, vol. 113, pp. S123–S137, 2009, doi: 10.1016/j.rse.2009.03.001.

[52] J. Suomalainen et al., “A lightweight hyperspectral mapping system and photogrammetric processing chain for unmanned aerial vehicles,” *Remote Sens.*, vol. 6, no. 11, pp. 11013–11030, 2014, doi: 10.3390/rs61111013.

[53] Y. Zhong et al., “Mini-UAV-borne hyperspectral remote sensing: From observation and processing to applications,” *IEEE Geosci. Remote Sens. Mag.*, vol. 6, no. 4, pp. 46–62, Dec. 2018, doi: 10.1109/MGRS.2018.2867592.

[54] O. Nevalainen et al., “Individual tree detection and classification with UAV-based photogrammetric point clouds and hyperspectral imaging,” *Remote Sens.*, vol. 9, no. 3, 2017, Art. no. 185, doi: 10.3390/rs9030185.

[55] M. Cui, Y. Sun, C. Huang, and M. Li, “Water turbidity retrieval based on UAV hyperspectral remote sensing,” *Water*, vol. 14, no. 1, 2022, Art. no. 128, doi: 10.3390/w14010128.

[56] L. W. Kuswidiyanto, H.-H. Noh, and X. Han, “Plant disease diagnosis using deep learning based on aerial hyperspectral images: A review,” *Remote Sens.*, vol. 14, no. 23, 2022, Art. no. 6031, doi: 10.3390/rs14236031.

[57] T. Hu et al., “Development and performance evaluation of a very low-cost UAV-LiDAR system for forestry applications,” *Remote Sens.*, vol. 13, no. 1, 2020, Art. no. 77, doi: 10.3390/rs13010077.

[58] X. Chen, K. Jiang, Y. Zhu, X. Wang, and T. Yun, “Individual tree crown segmentation directly from UAV-borne LiDAR data using the PointNet of deep learning,” *Forests*, vol. 12, no. 2, 2021, Art. no. 131, doi: 10.3390/f12020131.

[59] R. Neuville, J. S. Bates, and F. Jonard, “Estimating forest structure from UAV-mounted LiDAR point cloud using machine learning,” *Remote Sens.*, vol. 13, no. 3, 2021, Art. no. 352, doi: 10.3390/rs13030352.

[60] J. Gonçalves and R. Henriques, “UAV photogrammetry for topographic monitoring of coastal areas,” *ISPRS J. Photogrammetry Remote Sens.*, vol. 104, pp. 101–111, 2015, doi: 10.1016/j.isprsjprs.2015.02.009.

[61] F. Mancini, M. Dubbini, M. Gattelli, F. Stecchi, S. Fabbri, and G. Gabbianelli, “Using unmanned aerial vehicles (UAV) for high-resolution reconstruction of topography: The structure from motion approach on coastal environments,” *Remote Sens.*, vol. 5, no. 12, pp. 6880–6898, 2013, doi: 10.3390/rs5126880.

[62] X. Chen et al., “Implementation of technologies in the construction industry: A systematic review,” *Eng., Construction Archit. Manage.*, vol. 29, no. 8, pp. 3181–3209, 2022, doi: 10.1108/ECAM-02-2021-0172.

[63] M. T. Melis et al., “Thermal remote sensing from UAVs: A review on methods in coastal cliffs prone to landslides,” *Remote Sens.*, vol. 12, no. 12, 2020, Art. no. 1971, doi: 10.3390/rs12121971.

[64] L. Meng, J. Zhou, J. Ma, and Z. Wang, “MPDFF: Multi-source pedestrian detection based on feature fusion,” in *Proc. IEEE Int. Geosci. Remote Sens. Symp.*, 2022, pp. 7906–7909, doi: 10.1109/IGARSS46834.2022.9884864.

[65] H. Sheng, H. Chao, C. Coopmans, J. Han, M. McKee, and Y. Chen, “Low-cost UAV-based thermal infrared remote sensing: Platform, calibration and applications,” in *Proc. IEEE/ASME Int. Conf. Mechatronic Embedded Syst. Appl.*, 2010, pp. 38–43, doi: 10.1109/MESA.2010.5552031.

[66] G. Lee et al., “Vegetation classification in urban areas by combining UAV-based NDVI and thermal infrared image,” *Appl. Sci.*, vol. 13, no. 1, 2022, Art. no. 515, doi: 10.3390/app13010515.

[67] L. Feng, Y. Liu, Y. Zhou, and S. Yang, “A UAV-derived thermal infrared remote sensing three-temperature model and estimation of various vegetation evapotranspiration in urban micro-environments,” *Urban Forestry Urban Greening*, vol. 69, 2022, Art. no. 127495, doi: 10.1016/j.ufug.2022.127495.

[68] N. Gaitani, I. Burud, T. Thiis, and M. Santamouris, “High-resolution spectral mapping of urban thermal properties with unmanned aerial vehicles,” *Building Environ.*, vol. 121, pp. 215–224, 2017, doi: 10.1016/j.buildenv.2017.05.027.

[69] B. Song and K. Park, “Verification of accuracy of unmanned aerial vehicle (UAV) land surface temperature images using in-situ data,” *Remote Sens.*, vol. 12, no. 2, 2020, Art. no. 288, doi: 10.3390/rs12020288.

[70] A. Gaszczak, T. P. Breckon, and J. Han, “Real-time people and vehicle detection from UAV imagery,” *Proc. SPIE*, vol. 7878, 2011, Art. no. 78780B, doi: 10.1117/12.876663.

[71] RGB-LiDAR-TIR hybrid sensors. Accessed: May 27, 2023. [Online]. Available: https://www.dji.com/cn/zenmuse-h20-series

[72] LiDAR-TIR-Hyperspectral hybrid sensors. Accessed: May 27, 2023. [Online]. Available: https://www.azup.com.cn/

[73] S. Schulte, F. Hillen, and T. Prinz, “Analysis of combined UAV-based RGB and thermal remote sensing data: A new approach to crowd monitoring,” *Int. Arch. Photogrammetry, Remote Sens. Spatial Inf. Sci.*, vol. 42, pp. 347–354, 2017, doi: 10.5194/isprs-archives-XLII-2-W6-347-2017.

[74] S. Hartling, V. Sagan, and M. Maimaitijiang, “Urban tree species classification using UAV-based multi-sensor data fusion and machine learning,” *GISci. Remote Sens.*, vol. 58, no. 8, pp. 1250–1275, 2021, doi: 10.1080/15481603.2021.1974275.

[75] H. Yuan et al., “Target detection, positioning and tracking using new UAV gas sensor systems: Simulation and analysis,” *J. Intell. Robot. Syst.*, vol. 94, pp. 871–882, 2019, doi: 10.1007/s10846-018-0909-2.

[76] R. Mawrence, S. Munniks, and J. Valente, “Calibration of electrochemical sensors for nitrogen dioxide gas detection using unmanned aerial vehicles,” *Sensors*, vol. 20, no. 24, 2020, Art. no. 7332, doi: 10.3390/s20247332.

[77] X. He et al., “Autonomous chemical-sensing aerial robot for urban/suburban environmental monitoring,” *IEEE Syst. J.*, vol. 13, no. 3, pp. 3524–3535, Sep. 2019, doi: 10.1109/JSYST.2019.2905807.

[78] DJI ZENMUSE X7. Accessed: May 27, 2023. [Online]. Available: https://www.dji.com/cn/zenmuse-x7

[79] DJI L1. [Online]. Available: https://www.dji.com/cn/zenmuse-l1

[80] DJI ZENMUSE H20N. [Online]. Available: https://www.dji.com/cn/zenmuse-h20-series

[81] Nvidia Jetson Nano. [Online]. Available: https://www.nvidia.cn/autonomous-machines/embedded-systems/jetson-nano/

[82] Nvidia Jetson TX2 Module. [Online]. Available: https://www.nvidia.cn/autonomous-machines/embedded-systems/jetson-tx2/

[83] Nvidia Jetson AGX Orin 64GB. [Online]. Available: https://www.nvidia.cn/autonomous-machines/embedded-systems/jetson-orin/

[84] X. Li, B. He, K. Ding, W. Guo, B. Huang, and L. Wu, “Wide-area and real-time object search system of UAV,” *Remote Sens.*, vol. 14, no. 5, 2022, Art. no. 1234, doi: 10.3390/rs14051234.

[85] N. Balamuralidhar, S. Tilon, and F. Nex, “MultEYE: Monitoring system for real-time vehicle detection, tracking and speed estimation from UAV imagery on edge-computing platforms,” *Remote Sens.*, vol. 13, no. 4, p. 573, 2021, doi: 10.3390/rs13040573.

[86] C. Xu, X. Liao, J. Tan, H. Ye, and H. Lu, “Recent research progress of unmanned aerial vehicle regulation policies and technologies in urban low altitude,” *IEEE Access*, vol. 8, pp. 74175–74194, 2020, doi: 10.1109/ACCESS.2020.2987622.

[87] Industry standard for UAV fencing. Accessed: May 27, 2023. [Online]. Available: https://std.samr.gov.cn/hb/search/stdHBDetailed?id=8B1827F25A56BB19E05397BE0A0AB44A

[88] Data technical specification for geo-fence of civil unmanned aircraft system. Accessed: May 27, 2023. [Online]. Available: https://std.samr.gov.cn/gb/search/gbDetailed?id=E116673EC616A3B7E053 97BE0A0AC6BF

[89] GEOSAFE. Accessed: May 27, 2023. [Online]. Available: https://www.sesarju.eu/projects/geosafe

[90] S. R. R. Singireddy and T. U. Daim, “Technology roadmap: Drone delivery—Amazon prime air,” in *Infrastructure and Technology Management. Innovation, Technology, and Knowledge Management*. Cham, Switzerland: Springer, 2018, pp. 387–412.

[91] C. Xu, X. Liao, H. Ye, and H. Yue, “Iterative construction of low-altitude UAV air route network in urban areas: Case planning and assessment,” *J. Geographical Sci.*, vol. 30, pp. 1534–1552, 2020, doi: 10.1007/s11442-020-1798-4.

[92] Y. Wu, K. H. Low, and X. Hu, “Trajectory-based flight scheduling for airmetro in urban environments by conflict resolution,” *Transp. Res. C, Emerg. Technol.*, vol. 131, 2021, Art. no. 103355, doi: 10.1016/j.trc.2021.103355.

[93] R. Clothier, R. Walker, N. Fulton, and D. Campbell, “A casualty risk analysis for unmanned aerial system (UAS) operations over inhabited areas,” in *Proc. 2nd Australas. Unmanned Air Veh. Conf.*, 2007, pp. 1–16.

[94] Y. Wu, K. H. Low, B. Pang, and Q. Tan, “Swarm-based 4D path planning for drone operations in urban environments,” *IEEE Trans. Veh. Technol.*, vol. 70, no. 8, pp. 7464–7479, Aug. 2021, doi: 10.1109/TVT.2021.3093318.

[95] S. Aggarwal and N. Kumar, “Path planning techniques for unmanned aerial vehicles: A review, solutions, and challenges,” *Comput. Commun.*, vol. 149, pp. 270–299, 2020, doi: 10.1016/j.comcom.2019.10.014.

[96] X. Lin, C. Wang, K. Wang, M. Li, and X. Yu, “Trajectory planning for unmanned aerial vehicles in complicated urban environments: A control network approach,” *Transp. Res. C, Emerg. Technol.*, vol. 128, 2021, Art. no. 103120, doi: 10.1016/j.trc.2021.103120.

[97] Z. He and L. Zhao, “The comparison of four UAV path planning algorithms based on geometry search algorithm,” in *Proc. 9th Int. Conf. Intell. Human–Mach. Syst. Cybern.*, 2017, vol. 2, pp. 33–36, doi: 10.1109/IHMSC.2017.123.

[98] T. Chen, G. Zhang, X. Hu, and J. Xiao, “Unmanned aerial vehicle route planning method based on a star algorithm,” in *Proc. 13th IEEE Conf. Ind. Electron. Appl.*, 2018, pp. 1510–1514, doi: 10.1109/ICIEA.2018.8397948.

[99] S. M. LaValle, “Rapidly-exploring random trees: A new tool for path planning,” *Res. Rep. 9811*, 1998. [Online]. Available: https://msl.cs.illinois.edu/∼lavalle/papers/Lav98c.pdf

[100] L. E. Kavraki, P. Svestka, J.-C. Latombe, and M. H. Overmars, “Probabilistic roadmaps for path planning in high-dimensional configuration spaces,” *IEEE Trans. Robot. Autom.*, vol. 12, no. 4, pp. 566–580, Aug. 1996, doi: 10.1109/70.508439.

[101] X. Li, L. Qiu, S. Aziz, J. Pan, J. Yuan, and B. Zhang, “Control method of UAV based on RRT* for target tracking in cluttered environment,” in *Proc. IEEE 7th Int. Conf. Power Electron. Syst. Appl.-Smart Mobility, Power Transfer Secur.*, 2017, pp. 1–4, doi: 10.1109/PESA.2017.8277732.

[102] J. D. Gammell, S.S. Srinivasa, and T. D. Barfoot, “Informed RRT*: Optimal sampling-based path planning focused via direct sampling of an admissible ellipsoidal heuristic,” in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, 2014, pp. 2997–3004, doi: 10.1109/IROS.2014.6942976.

[103] V. Roberge, M. Tarbouchi, and G. Labonté, “Comparison of parallel genetic algorithm and particle swarm optimization for real-time UAV path planning,” *IEEE Trans. Ind. Informat.*, vol. 9, no. 1, pp. 132–141, Feb. 2013, doi: 10.1109/TII.2012.2198665.

[104] G. Liu, C. Shu, Z. Liang, B. Peng, and L. Cheng, “A modified sparrow search algorithm with application in 3D route planning for UAV,” *Sensors*, vol. 21, no. 4, 2021, Art. no. 1224, doi: 10.3390/s21041224.

[105] J. Chen, F. Ling, Y. Zhang, T. You, Y. Liu, and X. Du, “Coverage path planning of heterogeneous unmanned aerial vehicles based on ant colony system,” *Swarm Evol. Comput.*, vol. 69, 2022, Art. no. 101005, doi: 10.1016/j.swevo.2021.101005.

[106] C. Yan, X. Xiang, and C. Wang, “Towards real-time path planning through deep reinforcement learning for a UAV in dynamic environments,” *J. Intell. Robot. Syst.*, vol. 98, pp. 297–309, 2020, doi: 10.1007/s10846-019-01073-3.

[107] Q. Liu, L. Shi, L. Sun, J. Li, M. Ding, and F. Shu, “Path planning for UAV-mounted mobile edge computing with deep reinforcement learning,” *IEEE Trans. Veh. Technol.*, vol. 69, no. 5, pp. 5723–5728, May 2020, doi: 10.1109/TVT.2020.2982508.

[108] B. Li and Y. Wu, “Path planning for UAV ground target tracking via deep reinforcement learning,” *IEEE Access*, vol. 8, pp. 29064–29074, 2020, doi: 10.1109/ACCESS.2020.2971780.

[109] A. A. Maw, M. Tyan, T. A. Nguyen, and J.-W. Lee, “IADA*-RL: Anytime graph-based path planning with deep reinforcement learning for an autonomous UAV,” *Appl. Sci.*, vol. 11, no. 9, 2021, Art. no. 3948, doi: 10.3390/app11093948.

[110] M. H. M. Ghazali, K. Teoh, and W. Rahiman, “A systematic review of real-time deployments of UAV-based LORA communication network,” *IEEE Access*, vol. 9, pp. 124817–124830, 2021, doi: 10.1109/ACCESS.2021.3110872.

[111] G. Castellanos, M. Deruyck, L. Martens, and W. Joseph, “System assessment of WUSN using NB-IoT UAV-aided networks in potato crops,” *IEEE Access*, vol. 8, pp. 56823–56836, 2020, doi: 10.1109/ACCESS.2020.2982086.

[112] A. Guillen-Perez, R. Sanchez-Iborra, M.-D. Cano, J. C. Sanchez-Aarnoutse, and J. Garcia-Haro, “Wifi networks on drones,” in *Proc. ITU Kaleidoscope: ICTs Sustain. World*, 2016, pp. 1–8, doi: 10.1109/ITU-WT.2016.7805730.

[113] Q. Wu et al., “A comprehensive overview on 5G-and-beyond networks with UAVs: From communications to sensing and intelligence,” *IEEE J. Sel. Areas Commun.*, vol. 39, no. 10, pp. 2912–2945, Oct. 2021.

[114] H. Koumaras et al., “5G-enabled UAVs with command and control software component at the edge for supporting energy efficient opportunistic networks,” *Energies*, vol. 14, no. 5, 2021, Art. no. 1480.

[115] G. Damigos, T. Lindgren, and G. Nikolakopoulos, “Toward 5G edge computing for enabling autonomous aerial vehicles,” *IEEE Access*, vol. 11, pp. 3926–3941, 2023.

[116] A. Verma, P. Bhattacharya, M. Zuhair, S. Tanwar, and N. Kumar, “VaCoChain: Blockchain-based 5G-assisted UAV vaccine distribution scheme for future pandemics,” *IEEE J. Biomed. Health Inform.*, vol. 26, no. 5, pp. 1997–2007, May 2022.

[117] B. Li, Z. Fei, and Y. Zhang, “UAV communications for 5G and beyond: Recent advances and future trends,” *IEEE Internet Things J.*, vol. 6, no. 2, pp. 2241–2263, Apr. 2019.

[118] S. K. Khan, M. Farasat, U. Naseem, and F. Ali, “Performance evaluation of next-generation wireless (5G) UAV relay,” *Wireless Pers. Commun.*, vol. 113, pp. 945–960, 2020.

[119] P. Mehta, R. Gupta, and S. Tanwar, “Blockchain envisioned UAV networks: Challenges, solutions, and comparisons,” *Comput. Commun.*, vol. 151, pp. 518–538, 2020, doi: 10.1016/j.comcom.2020.01.023.

[120] G. Castellanos, M. Deruyck, L. Martens, and W. Joseph, “Performance evaluation of direct-link backhaul for UAV-aided emergency networks,” *Sensors*, vol. 19, no. 15, 2019, Art. no. 3342, doi: 10.3390/s19153342.

[121] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, “Unmanned aerial vehicle with underlaid device-to-device communications: Performance and tradeoffs,” *IEEE Trans. Wireless Commun.*, vol. 15, no. 6, pp. 3949–3963, Jun. 2016, doi: 10.1109/TWC.2016.2531652.

[122] DJI M300 RTK. Accessed: May 27, 2023. [Online]. Available: https://www.dji.com/cn/matrice-300/specs

[123] Tiantong One. Accessed: May 27, 2023. [Online]. Available: http://m.spacechina.com/n2018089/n2018131/c3113978/content.html

[124] C. Schmid, R. Mohr, and C. Bauckhage, “Evaluation of interest point detectors,” *Int. J. Comput. Vis.*, vol. 37, no. 2, pp. 151–172, 2000, doi: 10.1023/A:1008199403446.

[125] L. Ma, Y. Liu, X. Zhang, Y. Ye, G. Yin, and B. A. Johnson, “Deep learning in remote sensing applications: A meta-analysis and review,” *ISPRS J. Photogrammetry Remote Sens.*, vol. 152, pp. 166–177, 2019, doi: 10.1016/j.isprsjprs.2019.04.015.

[126] L. P. Osco et al., “A review on deep learning in UAV remote sensing,” *Int. J. Appl. Earth Observ. Geoinf.*, vol. 102, 2021, Art. no. 102456, doi: 10.1016/j.jag.2021.102456.

[127] F. Li, R. Feng, W. Han, and L. Wang, “High-resolution remote sensing image scene classification via key filter bank based on convolutional neural network,” *IEEE Trans. Geosci. Remote Sens.*, vol. 58, no. 11, pp. 8077–8092, Nov. 2020, doi: 10.1109/TGRS.2020.2987060.

[128] F. Li, R. Feng, W. Han, and L. Wang, “An augmentation attention mechanism for high-spatial-resolution remote sensing image scene classification,” *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 13, pp. 3862–3878, 2020, doi: 10.1109/JSTARS.2020.3006241.

[129] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” in *Proc. 3rd Int. Conf. Learn. Representations*, 2015.

[130] C. Szegedy et al., “Going deeper with convolutions,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2015, pp. 1–9, doi: 10.1109/CVPR.2015.7298594.

[131] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2016, pp. 770–778, doi: 10.1109/CVPR.2016.90.

[132] H. Pourazar, F. Samadzadegan, and F. Dadrass Javan, “A deep 2D/3D feature-level fusion for classification of UAV multispectral imagery in urban areas,” *Geocarto Int.*, vol. 37, no. 23, pp. 6695–6712, 2022, doi: 10.1080/10106049.2021.1959655.

[133] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, “You only look once: Unified, real-time object detection,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2016, pp. 779–788, doi: 10.1109/CVPR.2016.91.

[134] R. Girshick, "Fast R-CNN," in *Proc. IEEE Int. Conf. Comput. Vis.*, 2015, pp. 1440–1448, doi: 10.1109/ICCV.2015.169.

[135] W. Chen, H. Wang, H. Li, Q. Li, Y. Yang, and K. Yang, "Real-time garbage object detection with data augmentation and feature fusion using SUAV low-altitude remote sensing images," *IEEE Geosci. Remote Sens. Lett.*, vol. 19, 2022, Art. no. 6003005, doi: 10.1109/LGRS.2021.3074415.

[136] X. Zhu, S. Lyu, X. Wang, and Q. Zhao, "TPH-YOLOv5: Improved YOLOv5 based on transformer prediction head for object detection on drone-captured scenarios," in *Proc. IEEE/CVF Int. Conf. Comput. Vis.*, 2021, pp. 2778–2788, doi: 10.1109/ICCVW54120.2021.00312.

[137] W. Han et al., "A context-scale-aware detector and a new benchmark for remote sensing small weak object detection in unmanned aerial vehicle images," *Int. J. Appl. Earth Observ. Geoinf.*, vol. 112, 2022, Art. no. 102966, doi: 10.1016/j.jag.2022.102966.

[138] M. Kisantal, Z. Wojna, J. Murawski, J. Naruniec, and K. Cho, "Augmentation for small object detection," in *Proc. CS IT Conf.*, 2019, vol. 9, no. 17.

[139] T.-Y. Lin, P. Dollár, R. Girshick, K. He, B. Hariharan, and S. Belongie, "Feature pyramid networks for object detection," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2017, pp. 2117–2125, doi: 10.1109/CVPR.2017.106.

[140] J.-S. Lim, M. Astrid, H.-J. Yoon, and S.-I. Lee, "Small object detection using context and attention," in *Proc. IEEE Int. Conf. Artif. Intell. Inf. Commun.*, 2021, pp. 181–186, doi: 10.1109/ICAIIC51459.2021.9415217.

[141] J. Li, X. Liang, Y. Wei, T. Xu, J. Feng, and S. Yan, "Perceptual generative adversarial networks for small object detection," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2017, pp. 1222–1230, doi: 10.1109/CVPR.2017.211.

[142] X. Yuan, J. Shi, and L. Gu, "A review of deep learning methods for semantic segmentation of remote sensing imagery," *Expert Syst. Appl.*, vol. 169, 2021, Art. no. 114417, doi: 10.1016/j.eswa.2020.114417.

[143] L. Wang, R. Li, C. Duan, C. Zhang, X. Meng, and S. Fang, "A novel transformer based semantic segmentation scheme for fine-resolution remote sensing images," *IEEE Geosci. Remote Sens. Lett.*, vol. 19, 2022, Art. no. 6506105, doi: 10.1109/LGRS.2022.3143368.

[144] H. Hosseinpour, F. Samadzadegan, and F. D. Javan, "CMGFNet: A deep cross-modal gated fusion network for building extraction from very high-resolution remote sensing images," *ISPRS J. Photogrammetry Remote Sens.*, vol. 184, pp. 96–115, 2022, doi: 10.1016/j.isprsjprs.2021.12.007.

[145] Y. Jiang, "Research on road extraction of remote sensing image based on convolutional neural network," *EURASIP J. Image Video Process.*, vol. 2019, no. 1, 2019, Art. no. 31, doi: 10.1186/s13640-019-0426-7.

[146] R. Kemker, R. Luu, and C. Kanan, "Low-shot learning for the semantic segmentation of remote sensing imagery," *IEEE Trans. Geosci. Remote Sens.*, vol. 56, no. 10, pp. 6214–6223, Oct. 2018, doi: 10.1109/TGRS.2018.2833808.

[147] B. Cui, X. Chen, and Y. Lu, "Semantic segmentation of remote sensing images using transfer learning and deep convolutional neural network with dense connection," *IEEE Access*, vol. 8, pp. 116744–116755, 2020, doi: 10.1109/ACCESS.2020.3003914.

[148] Y. Zheng et al., "Semi-supervised adversarial semantic segmentation network using transformer and multiscale convolution for high-resolution remote sensing imagery," *Remote Sens.*, vol. 14, no. 8, 2022, Art. no. 1786, doi: 10.3390/rs14081786.

[149] H. Su et al., "HQ-ISNet: High-quality instance segmentation for remote sensing imagery," *Remote Sens.*, vol. 12, no. 6, 2020, Art. no. 989, doi: 10.3390/rs12060989.

[150] Y. Sun, X. Zhang, J. Huang, H. Wang, and Q. Xin, "Fine-grained building change detection from very high-spatial-resolution remote sensing images based on deep multitask learning," *IEEE Geosci. Remote Sens. Lett.*, vol. 19, 2020, Art. no. 8000605, doi: 10.1109/LGRS.2020.3018858.

[151] S. Daranagama and A. Witayangkurn, "Automatic building detection with polygonizing and attribute extraction from high-resolution images," *ISPRS Int. J. Geo-Inf.*, vol. 10, no. 9, 2021, Art. no. 606, doi: 10.3390/ijgi10090606.

[152] W. Liu et al., "Accurate building extraction from fused DSM and UAV images using a chain fully convolutional neural network," *Remote Sens.*, vol. 11, no. 24, 2019, Art. no. 2912, doi: 10.3390/rs11242912.

[153] Y. Gao, X. Lian, and L. Ge, "Inversion model of surface bare soil temperature and water content based on UAV thermal infrared remote sensing," *Infrared Phys. Technol.*, vol. 125, 2022, Art. no. 104289, doi: 10.1016/j.infrared.2022.104289.

[154] B. Chen et al., "Machine learning-based inversion of water quality parameters in typical reach of the urban river by UAV multispectral data," *Ecol. Indicators*, vol. 133, 2021, Art. no. 108434, doi: 10.1016/j.ecolind.2021.108434.

[155] Z. Sha et al., "Comparison of leaf area index inversion for grassland vegetation through remotely sensed spectra by unmanned aerial vehicle and field-based spectroradiometer," *J. Plant Ecol.*, vol. 12, no. 3, pp. 395–408, 2019, doi: 10.1093/jpe/rty036.

[156] S. Stagakis et al., "Spatiotemporal monitoring of surface temperature in an urban area using UAV imaging and tower-mounted radiometer measurements," in *Proc. IEEE Joint Urban Remote Sens. Event*, 2019, pp. 1–4, doi: 10.1109/JURSE.2019.8808958.

[157] W. Z. Khan, E. Ahmed, S. Hakak, I. Yaqoob, and A. Ahmed, "Edge computing: A survey," *Future Gener. Comput. Syst.*, vol. 97, pp. 219–235, 2019, doi: 10.1016/j.future.2019.02.050.

[158] P. McEnroe, S. Wang, and M. Liyanage, "A survey on the convergence of edge computing and AI for UAVs: Opportunities and challenges," *IEEE Internet Things J.*, vol. 9, no. 17, pp. 15435–15459, Sep. 2022, doi: 10.1109/JIOT.2022.3176400.

[159] A. P. P. Kasznar et al., "Multiple dimensions of smart cities' infrastructure: A review," *Buildings*, vol. 11, no. 2, 2021, Art. no. 73, doi: 10.3390/buildings11020073.

[160] A. L. C. Ferrer, A. M. T. Thomé, and A. J. Scavarda, "Sustainable urban infrastructure: A review," *Resour., Conservation Recycling*, vol. 128, pp. 360–372, 2018, doi: 10.1016/j.resconrec.2016.07.017.

[161] "The ministry of natural resources comprehensively promotes the construction of a realistic 3D China." Accessed: May 27, 2023. [Online]. Available: http://www.gov.cn/xinwen/2022-03/01/content_5676226.htm

[162] A. Gruen et al., "Joint processing of UAV imagery and terrestrial mobile mapping system data for very high resolution city modeling," *Int. Arch. Photogrammetry Remote Sens. Spatial Inf. Sci.*, vol. 40, pp. 175–182, 2013, doi: 10.5194/isprsarchives-XL-1-W2-175-2013.

[163] S. Espositoa, P. Fallavollitaa, W. Wahbehb, C. Nardinocchic, and M. Balsia, "Performance evaluation of UAV photogrammetric 3D reconstruction," in *Proc. IEEE Geosci. Remote Sens. Symp.*, 2014, pp. 4788–4791, doi: 10.1109/IGARSS.2014.6947565.

[164] K. W. Lee and J. K. Park, "Comparison of UAV image and UAV LiDAR for construction of 3D geospatial information," *Sens. Mater.*, vol. 31, no. 10, pp. 3327–3334, 2019, doi: 10.18494/SAM.2019.2466.

[165] R. C. Erenoglu, O. Erenoglu, and N. Arslan, "Accuracy assessment of low cost UAV based city modelling for urban planning," *Tehnički vjesnik*, vol. 25, no. 6, pp. 1708–1714, 2018.

[166] J. He, "Map-of-the-object photogrammetry and its key techniques," Ph.D. dissertation, School Remote Sens. Inf. Eng., Wuhan Univ., Wuhan, China, 2019.

[167] R. Adhikari, O. Moselhi, and A. Bagchi, "Image-based retrieval of concrete crack properties for bridge inspection," *Autom. Construction*, vol. 39, pp. 180–194, 2014, doi: 10.1016/j.autcon.2013.06.011.

[168] Y. Z. Ayele, M. Aliyari, D. Griffiths, and E. L. Droguett, "Automatic crack segmentation for UAV-assisted bridge inspection," *Energies*, vol. 13, no. 23, 2020, Art. no. 6250, doi: 10.3390/en13236250.

[169] S. Biçici and M. Zeybek, "An approach for the automated extraction of road surface distress from a UAV-derived point cloud," *Autom. Construction*, vol. 122, 2021, Art. no. 103475, doi: 10.1016/j.autcon.2020.103475.

[170] R. Fan, J. Jiao, J. Pan, H. Huang, S. Shen, and M. Liu, "Real-time dense stereo embedded in a UAV for road inspection," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops*, 2019, pp. 535–543, doi: 10.1109/CVPRW.2019.00079.

[171] T. Bu, J. Zhu, and T. Ma, "A UAV photography-based detection method for defective road marking," *J. Perform. Constructed Facilities*, vol. 36, no. 5, 2022, Art. no. 04022035, doi: 10.1061/(ASCE)CF.1943-5509.0001748.

[172] A. Carrio et al., "Ubristes: UAV-based building rehabilitation with visible and thermal infrared remote sensing," in *Proc. 2nd Iberian Robot. Conf.: Adv. Robot.*, 2016, pp. 245–256.

[173] R. Grosso, U. Mecca, G. Moglia, F. Prizzon, and M. Rebaudengo, "Collecting built environment information using UAVs: Time and applicability in building inspection activities," *Sustainability*, vol. 12, no. 11, 2020, Art. no. 4731.

[174] D. Liu, X. Xia, J. Chen, and S. Li, "Integrating building information model and augmented reality for drone-based building inspection," *J. Comput. Civil Eng.*, vol. 35, no. 2, 2021, Art. no. 04020073, doi: 10.1061/(ASCE)CP.1943-5487.0000958.

[175] K. Chen, G. Reichard, A. Akanmu, and X. Xu, "Geo-registering UAV-captured close-range images to GIS-based spatial model for building façade inspections," *Autom. Construction*, vol. 122, 2021, Art. no. 103503, doi: 10.1016/j.autcon.2020.103503.

[176] J. I. Vasquez-Gomez, D. E. T. Romero, M. Antonio-Cruz, and E. Zamora, "Spiral trajectories for building inspection with quadrotors," in *Proc. IEEE Int. Conf. Unmanned Aircr. Syst.*, 2022, pp. 891–896.

[177] V. N. Nguyen, R. Jenssen, and D. Roverso, "Automatic autonomous vision-based power line inspection: A review of current status and the potential role of deep learning," *Int. J. Elect. Power Energy Syst.*, vol. 99, pp. 107–120, 2018, doi: 10.1016/j.ijepes.2017.12.016.

[178] L. Matikainen et al., "Remote sensing methods for power line corridor surveys," *ISPRS J. Photogrammetry Remote Sens.*, vol. 119, pp. 10–31, 2016, doi: 10.1016/j.isprsjprs.2016.04.011.

[179] Y. Zhang, X. Yuan, W. Li, and S. Chen, "Automatic power line inspection using UAV images," *Remote Sens.*, vol. 9, no. 8, 2017, Art. no. 824, doi: 10.3390/rs9080824.

[180] C. Deng, S. Wang, Z. Huang, Z. Tan, and J. Liu, "Unmanned aerial vehicles for power line inspection: A cooperative way in platforms and communications," *J. Commun.*, vol. 9, no. 9, pp. 687–692, 2014.

[181] C. Chen, B. Yang, S. Song, X. Peng, and R. Huang, "Automatic clearance anomaly detection for transmission line corridors utilizing UAV-borne LiDAR data," *Remote Sens.*, vol. 10, no. 4, 2018, Art. no. 613, doi: 10.3390/rs10040613.

[182] F. Shuang, S. Han, Y. Li, and T. Lu, "RSIn-dataset: An UAV-based insulator detection aerial images dataset and benchmark," *Drones*, vol. 7, no. 2, 2023, Art. no. 125.

[183] W. Liu et al., "SSD: Single shot multibox detector," in *Proc. 14th Eur. Conf. Comput. Vis.*, 2016, pp. 21–37.

[184] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," in *Proc. Int. Conf. Neural Inf. Process. Syst.*, 2015, pp. 91–99.

[185] J. Redmon and A. Farhadi, "YOLOv3: An incremental improvement," 2018, *arXiv:1804.02767*.

[186] B. J. Souza, S. F. Stefenon, G. Singh, and R. Z. Freire, "Hybrid-YOLO for classification of insulators defects in transmission lines based on UAV," *Int. J. Elect. Power Energy Syst.*, vol. 148, 2023, Art. no. 108982.

[187] G. A. Pussente, E. P. de Aguiar, A. L. Marcato, and M. F. Pinto, "UAV power line tracking control based on a type-2 fuzzy-PID approach," *Robotics*, vol. 12, no. 2, 2023, Art. no. 60.

[188] Z. Li, Y. Zhang, H. Wu, S. Suzuki, A. Namiki, and W. Wang, "Design and application of a UAV autonomous inspection system for high-voltage power transmission lines," *Remote Sens.*, vol. 15, no. 3, 2023, Art. no. 865.

[189] H. Xu, Y. Li, Y. Tan, and N. Deng, "A scientometric review of urban disaster resilience research," *Int. J. Environ. Res. Public Health*, vol. 18, no. 7, 2021, Art. no. 3677, doi: 10.3390/ijerph18073677.

[190] F. Mohammed, A. Idries, N. Mohamed, J. Al-Jaroodi, and I. Jawhar, "UAVs for smart cities: Opportunities and challenges," in *Proc. Int. Conf. Unmanned Aircr. Syst.*, 2014, pp. 267–273, doi: 10.1109/ICUAS.2014.6842265.

[191] M. Lyu, Y. Zhao, C. Huang, and H. Huang, "Unmanned aerial vehicles for search and rescue: A survey," *Remote Sens.*, vol. 15, no. 13, 2023, Art. no. 3266.

[192] D. T. Bulti and B. G. Abebe, "A review of flood modeling methods for urban pluvial flood application," *Model. Earth Syst. Environ.*, vol. 6, pp. 1293–1302, 2020, doi: 10.1007/s40808-020-00803-z.

[193] K. Trepekli et al., "UAV-borne, LiDAR-based elevation modelling: A method for improving local-scale urban flood risk assessment," *Natural Hazards*, vol. 113, no. 1, pp. 423–451, 2022, doi: 10.1007/s11069-022-05308-9.

[194] Q. Feng, J. Liu, and J. Gong, "Urban flood mapping based on unmanned aerial vehicle remote sensing and random forest classifier—A case of Yuyao, China," *Water*, vol. 7, no. 4, pp. 1437–1455, 2015, doi: 10.3390/w7041437.

[195] A. Gebrehiwot, L. Hashemi-Beni, G. Thompson, P. Kordjamshidi, and T. E. Langan, "Deep convolutional neural network for flood extent mapping using unmanned aerial vehicles data," *Sensors*, vol. 19, no. 7, 2019, Art. no. 1486, doi: 10.3390/s19071486.

[196] M. Rivas Casado, T. Irvine, S. Johnson, M. Palma, and P. Leinster, "The use of unmanned aerial vehicles to estimate direct tangible losses to residential properties from flood events: A case study of cockermouth following the Desmond storm," *Remote Sens.*, vol. 10, no. 10, 2018, Art. no. 1548, doi: 10.3390/rs10101548.

[197] K. Rus, V. Kilar, and D. Koren, "Resilience assessment of complex urban systems to natural disasters: A new literature review," *Int. J. Disaster Risk Reduction*, vol. 31, pp. 311–330, 2018, doi: 10.1016/j.ijdrr.2018.05.015.

[198] S. Verykokou, C. Ioannidis, G. Athanasiou, N. Doulamis, and A. Amditis, "3D reconstruction of disaster scenes for urban search and rescue," *Multimedia Tools Appl.*, vol. 77, pp. 9691–9717, 2018, doi: 10.1007/s11042-017-5450-y.

[199] D. Duarte, F. Nex, N. Kerle, and G. Vosselman, "Towards a more efficient detection of earthquake induced facade damages using oblique UAV imagery," *Int. Arch. Photogrammetry, Remote Sens. Spatial Inf. Sci.*, vol. 42, 2017, Art. no. 93, doi: 10.5194/isprs-archives-XLII-2-W6-93-2017.

[200] Y. Wang, X. Jing, W. Chen, H. Li, Y. Xu, and Q. Zhang, "Geometry-informed deep learning-based structural component segmentation of post-earthquake buildings," *Mech. Syst. Signal Process.*, vol. 188, 2023, Art. no. 110028.

[201] M. Alicandro and M. Rotilio, "UAV photogrammetry for resilience management in reconstruction plan of urban historical centres after seismic events. A case study," *Int. Arch. Photogrammetry, Remote Sens. Spatial Inf. Sci.*, vol. 42, pp. 55–61, 2019, doi: 10.5194/isprs-archives-XLII-2-W11-55-2019.

[202] M. Haghani and M. Sarvi, "Crowd behaviour and motion: Empirical methods," *Transp. Res. B, Methodol.*, vol. 107, pp. 253–294, 2018, doi: 10.1016/j.trb.2017.06.017.

[203] E. Felemban, A. A. Sheikh, and A. Naseer, "Improving response time for crowd management in Hajj," *Computers*, vol. 10, no. 4, 2021, Art. no. 46, doi: 10.3390/computers10040046.

[204] M. A. Husman et al., "Unmanned aerial vehicles for crowd monitoring and analysis," *Electronics*, vol. 10, no. 23, 2021, Art. no. 2974, doi: 10.3390/electronics10232974.

[205] K. Miyano, R. Shinkuma, N. Shiode, S. Shiode, T. Sato, and E. Oki, "Multi-UAV allocation framework for predictive crime deterrence and data acquisition," *Internet Things*, vol. 11, 2020, Art. no. 100205, doi: 10.1016/j.iot.2020.100205.

[206] P. Gong et al., "Urbanisation and health in China," *Lancet*, vol. 379, no. 9818, pp. 843–852, 2012, doi: 10.1016/S0140-6736(11)61878-3.

[207] L. Wei et al., "Transparency estimation of narrow rivers by UAV-borne hyperspectral remote sensing imagery," *IEEE Access*, vol. 8, pp. 168137–168153, 2020, doi: 10.1109/ACCESS.2020.3023690.

[208] K. Matsui, H. Shirai, Y. Kageyama, and H. Yokoyama, "Improving the resolution of UAV-based remote sensing data of water quality of Lake Hachiroko, Japan by neural networks," *Ecol. Informat.*, vol. 62, 2021, Art. no. 101276.

[209] H. Xu et al., "UAV-ODS: A real-time outfall detection system based on UAV remote sensing and edge computing," in *Proc. IEEE Int. Conf. Unmanned Syst.*, 2022, pp. 1–9.

[210] P. Kumar et al., "The rise of low-cost sensing for managing air pollution in cities," *Environ. Int.*, vol. 75, pp. 199–205, 2015, doi: 10.1016/j.envint.2014.11.019.

[211] T. Zheng, B. Li, X.-B. Li, Z. Wang, S.-Y. Li, and Z.-R. Peng, "Vertical and horizontal distributions of traffic-related pollutants beside an urban arterial road based on unmanned aerial vehicle observations," *Building Environ.*, vol. 187, 2021, Art. no. 107401, doi: 10.1016/j.buildenv.2020.107401.

[212] A. Samad, D. A. Florez, I. Chourdakis, and U. Vogt, "Concept of using an unmanned aerial vehicle (UAV) for 3D investigation of air quality in the atmosphere–example of measurements near a roadside," *Atmosphere*, vol. 13, no. 5, 2022, Art. no. 663, doi: 10.3390/atmos13050663.

[213] K. Xin et al., "Effect of urban underlying surface on PM2. 5 vertical distribution based on UAV in Xi'an, China," *Environ. Monit. Assessment*, vol. 193, no. 5, 2021, Art. no. 312, doi: 10.1007/s10661-021-09044-8.

[214] C. Li et al., "Investigating the vertical distribution patterns of urban air pollution based on unmanned aerial vehicle gradient monitoring," *Sustain. Cities Soc.*, vol. 86, 2022, Art. no. 104144, doi: 10.1016/j.scs.2022.104144.

[215] J. Scherer et al., "An autonomous multi-UAV system for search and rescue," in *Proc. 1st Workshop Micro Aerial Veh. Netw., Syst., Appl. Civilian Use*, 2015, pp. 33–38, doi: 10.1145/2750675.2750683.

[216] W. Qu, Q. Sun, and T. Wang, "Design and implementation of UAV intelligent delivery system for special people serving special areas and periods," in *Proc. 2nd Int. Conf. Comput. Data Sci.*, 2021, pp. 1–5, doi: 10.1145/3448734.3450475.

[217] J. Shao, J. Cheng, B. Xia, K. Yang, and H. Wei, "A novel service system for long-distance drone delivery using the 'ant colony+a*' algorithm," *IEEE Syst. J.*, vol. 15, no. 3, pp. 3348–3359, Sep. 2021, doi: 10.1109/JSYST.2020.2994553.

[218] J. Yi, B. Guan, and P. Li, "Intelligent highway speed monitoring UAV system based on deep learning," in *Proc. 4th Int. Conf. Image Graph. Process.*, 2021, pp. 73–79, doi: 10.1145/3447587.3447598.

[219] A. Farahdel, S. S. Vedaei, and K. Wahid, "An IoT based traffic management system using drone and AI," in *Proc. IEEE 14th Int. Conf. Comput. Intell. Commun. Netw.*, 2022, pp. 297–301, doi: 10.1109/CICN56167.2022.10008357.

[220] L. Wenguang and Z. Zhiming, “Intelligent surveillance and reconnaissance mode of police UAV based on grid,” in *Proc. 7th Int. Symp. Mechatronics Ind. Informat.*, 2021, pp. 292–295, doi: 10.1109/ISMII52409.2021.00069.

[221] A. Beg, A. R. Qureshi, T. Sheltami, and A. Yasar, “UAV-enabled intelligent traffic policing and emergency response handling system for the smart city,” *Pers. Ubiquitous Comput.*, vol. 25, pp. 33–50, 2021, doi: 10.1007/s00779-019-01297-y.

[222] A. Giyenko and Y. I. Cho, “Intelligent unmanned aerial vehicle platform for smart cities,” in *Proc. IEEE Joint 8th Int. Conf. Soft Comput. Intell. Syst./17th Int. Symp. Adv. Intell. Syst.*, 2016, pp. 729–733, doi: 10.1109/SCIS-ISIS.2016.0159.

[223] R. K. Rangel, J. L. Freitas, and T. M. De Souza, “Smart & integrated management system-smart cities, epidemiological control tool using drones,” in *Proc. IEEE Aerosp. Conf.*, 2020, pp. 1–12, doi: 10.1109/AERO47225.2020.9172439.

[224] VOTIX. Accessed: May 27, 2023. [Online]. Available: https://www.unmannedsystemstechnology.com/company/votix/

[225] gNext Labs. Accessed: May 27, 2023. [Online]. Available: https://www.unmannedsystemstechnology.com/company/gnext-labs/

[226] Sky-Drones. Accessed: May 27, 2023. [Online]. Available: https://www.unmannedsystemstechnology.com/company/sky-drones/sky-drones-cloud/

[227] Clue. Accessed: May 27, 2023. [Online]. Available: https://lp.droneroofer.com/

[228] Auterion. Accessed: May 27, 2023. [Online]. Available: https://auterion.com/enterprise/suite/

[229] DroneHarmony. Accessed: May 27, 2023. [Online]. Available: https://droneharmony.com/

[230] DroneDeploy. Accessed: May 27, 2023. [Online]. Available: https://www.dronedeploy.com/

[231] Flighthub-2. Accessed: May 27, 2023. [Online]. Available: https://www.dji.com/cn/flighthub-2

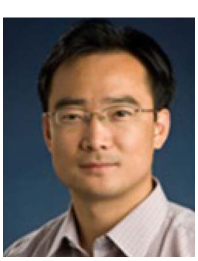
[232] Jdyair. Accessed: May 27, 2023. [Online]. Available: https://jdyair.com/

[233] Renwofei.u-care. Accessed: May 27, 2023. [Online]. Available: http://renwofei.u-care.net.cn/

[234] W. Han et al., “A survey on methods of small weak object detection in optical high-resolution remote sensing images,” *IEEE Geosci. Remote. Sens. Mag.*, vol. 9, pp. 8–34, Dec. 2021, doi: 10.1109/MGRS.2020.3041450.

Haoran Xu received the B.E. degree in surveying and mapping engineering in 2021 from the China University of Geosciences, Wuhan, China, where he is currently working toward the Ph.D. degree in geoscience information engineering.

His research interests include unmanned aerial vehicle remote sensing, unmanned systems, and remote sensing data analysis.



Lizhe Wang (Fellow, IEEE) received the B.E. and M.E. degrees in electrical engineering and automation from Tsinghua University, Beijing, China, in 1998 and 2001, respectively, and the D.E. degree in applied computer science from the University of Karlsruhe, Karlsruhe, Germany, in 2007.

He is currently with the School of Computer Science, China University of Geosciences, Wuhan, China. His research interests include remote sensing information engineering, digital earth, and geocomputing.

Dr. Wang was the recipient of the Distinguished Young Scholars of the National Natural Science Foundation of China, the National Leading Talents of Science and Technology Innovation, and the 100-Talents Program of the Chinese Academy of Sciences. He is the Member of Academia Europaea and a Fellow of the International Society for Optical Engineers, the Institution of Engineering and Technology, and the British Computer Society.

Wei Han (Member, IEEE) received the B.S. degree in network engineering and Ph.D. degree in geoscience information engineering from the China University of Geosciences, Wuhan, China, in 2015 and 2021, respectively.

He is currently an Associate Professor with the School of Computer Science, China University of Geosciences. His research interests include high-resolution remote sensing image processing, geological remote sensing, and high-performance computing.

Yixin Yang received the B.S. degree in information security from the Hangzhou University of Electronic Technology, Hangzhou, China, in 2021. He is currently working toward the M.S. degree in computer technology with the China University of Geosciences, Wuhan, China.

His research interests include unmanned aerial vehicle remote sensing, big data, and unmanned systems.

Jiabao Li received the Master of Engineering degree in computer technology in 2021 from the China University of Geosciences, Wuhan, China, where he is currently working toward the Ph.D. degree in geoscience information engineering.

His research interests include spatiotemporal data management, geoscience big data processing, cloud computing in remote sensing, and remote sensing application systems.

Yue Lu received the B.E. degree in chemical engineering and technology from Nanjing Forestry University, Nanjing, China, in 2020. He is currently working toward the M.E. degree in computer technology with the China University of Geosciences, Wuhan, China.

His research interests include deep learning, remote sensing geological interpretation, and multimodal fusion.

Jun Li (Fellow, IEEE) received the Ph.D. degree in electrical engineering from the Instituto de Telecomunicaçoes, Instituto Superior Técnico, Universidade Técnica de Lisboa, Lisbon, Portugal, in 2011.

From 2013 to 2021, she was a Full Professor with Sun Yat-sen University, Guangzhou, China. Since 2022, she has been a Full Professor with the China University of Geosciences, Wuhan, China. Her main research interests include remotely sensed hyperspectral image analysis, signal processing, supervised/semisupervised learning, and active learning.