Urban Water Journal

ISSN: 1573-062X (Print) 1744-9006 (Online) Journal homepage: https://www.tandfonline.com/loi/nurw20

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URBAN WATER JOURNAL
2019, VOL. 16, NO. 7, 505–518
https://doi.org/10.1080/1573062X.2019.1687745

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REVIEW ARTICLE

Drones in urban stormwater management: a review and future perspectives

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ABSTRACT
Cities across the world are struggling to address flooding and water quality pollution from stormwater runoff, in part because of a lack of technologies that can effectively support management actions. Drones, or Unmanned Aerial Vehicles, are a technology that have the potential to address this challenge through rapid, on-demand, high-resolution data. Drones have seen an emergence among water resources and environmental researchers and practitioners; however, less attention has been given to their potential for stormwater management. Therefore, this paper presents a review of drone studies that have applications for urban stormwater management and provides future perspectives on their role as an emerging technology. A case is made for drones as a tool that can support asset management, conduct flow and water quality monitoring, collect high spatial resolution data for improved model parameterization, and support the smart and connected cities of the future.

ARTICLE HISTORY
Received 8 March 2019
Accepted 15 October 2019

KEYWORDS
Drones; unmanned aerial vehicles; stormwater; urban stormwater management

1. Background

Urban stormwater runoff is a significant threat to human and ecological health across the world. To address this threat, many governments have put forth regulations that require municipalities or industries to obtain a permit for their stormwater discharge by demonstrating how they are reducing pollution from stormwater runoff. However, with continued urbanization, a changing climate, and uncertain performance of stormwater best management practices, urban stormwater runoff remains a significant environmental challenge. For example, despite three decades of regulatory action in the U.S., many of the nation's waters are still impaired from urban non-point source runoff (U.S. EPA 2019). These impairments highlight the significant challenge of responsibly managing urban stormwater, as well as the knowledge gap between management actions and their impact on pollution processes in stormwater systems (Wagner 2005; Liu et al. 2017). Much of this is due to a lack of engineering tools and resources that can support stormwater management programs in meeting their pollution reduction goals. As cities continue to address stormwater runoff, it is imperative that we consider new and innovative approaches to stormwater management.

Implementing an effective stormwater management plan can be a challenge, as many cities are constrained by a lack of capital for stormwater management actions and may not have the resources to address all that is required by a regulatory agency (McDonald and Naughton 2019). Because municipalities often work under financial constraints, they must make decisions as to what actions produces the best results in terms of improved water quality – a task that is significantly difficult to accomplish. Part of what makes determining which actions are most appropriate difficult is a gap in scientific understanding between stormwater management actions and their water quality outcomes. The treatment efficiency of stormwater control measures – including both emerging green stormwater infrastructure practices (Aguilar and Dymond 2019), as well as those that have been around for half a century such as detention ponds (Clary et al. 2017) – is highly uncertain. Therefore, the practice of build it, leave it, and assume that it works according to design is one that is increasingly under scrutiny.

As such, there is an awareness and movement towards data-informed 'smart regulations'. For example, in the U.S. current compliance is demonstrated by a modeling approach; however, the EPA has set forth a movement towards smart regulations where stormwater compliance is demonstrated not through models but observations and monitoring (Markell and Glicksman 2013). In fact, a recent committee formed to identify improvements in industrial stormwater permits produced a report that highlighted improvements to monitoring as the best way to ensure compliance (NASEM 2019). While this movement towards demonstrating compliance through monitoring would be a big step towards showing actual water quality improvements, it will require economical technologies that can accurately and reliably measure water quality in a stormwater system. This is a challenge as traditional monitoring of stormwater flows, water quality, and infrastructure requires on ground in-situ techniques that can be time and resource intensive to implement (McDonald, Dymond, and Lohani 2018). Therefore, a gap currently exists between the recognized need for monitoring to demonstrate compliance, inform stormwater management efforts, and protect human and ecological health, and the resource and technological capacity to do so.

Drones, or Unmanned Aerial Vehicles (UAVs), represent one such technology that has the potential to help address many of these urban stormwater management challenges. Drones can collect rapid, on-demand, high-resolution remote sensing data

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at a fraction of the cost of aerial surveys and at resolutions and timescales that are unmatched by satellite imagery. In addition to remote sensing, drones can carry payloads, such as water samplers, that make them a versatile tool in supporting stormwater management efforts. Given these advantages, the potential applications of drones for supporting stormwater management are numerous and could include aerial imagery for asset management and illicit discharge detection, monitoring of stream flowrate or water quality for regulatory compliance, or in providing high-resolution watershed data for model parameterization. These potential applications demonstrate that drones could play a large role in filling existing management and monitoring gaps in stormwater programs that seek to protect water quality and safeguard human and ecological health.

To date, drones have seen an emergence within the water and environmental fields, including as a tool for coastal and environmental sensing (Klemas 2015), river hydro morphology (Rhee et al. 2018; Woodget et al. 2017), ecological restoration (Buters et al. 2019), and water resources (DeBell et al. 2016) and environmental (Smith 2015) management; however, their application in stormwater systems has only recently been explored and there is a lack of information on the current state of the practice of drones in urban stormwater management. It's not unreasonable to think that drones could play a large role in managing urban water, as the applications of drones in cities continue to grow, such as in the delivery of packages (Murray and Chu 2015), infrastructure inspections (Máthé and Buşoniu 2015), and public security (West and Bowman 2016). Therefore, given the emergence of drones in water and environmental studies and their growing role within the urban environment, it's important to explore their potential for supporting urban stormwater management. This paper seeks to fill this gap by presenting a review of drone studies that have applications for urban stormwater management, as well as propose unexplored ways in which drones can be used to support stormwater management efforts.

To this end, this paper will (i) summarize the state of the technology in drones, (ii) review drones in water resources and environmental studies with applications for urban stormwater management, (iii) propose new applications of drones in urban stormwater management, and (iv) discuss both barriers to drone adoption and their potential to advance stormwater management in the coming decades. The applications reviewed in this paper point to a future stormwater management paradigm where drones are used to advance stormwater management actions within the context of smart cities, regulations, and management actions.

2. State of the technology

As drone technologies mature, there has been a rapid increase in the number of drone manufacturers, camera systems, and flight and data processing software programs. While the complete extent of drone companies, cameras, and software that may be pertinent to stormwater management efforts is too large to address in full, the basic drone types, camera models, and software systems are summarized in this section. In addition, this section addresses many of the limitations of drone technologies in the context urban stormwater.

Drone types can largely be broken down into two broad categories: fixed-wing and multi-rotor. Fixed wing drones can cover the most ground of the two, with flight ranges between 32–64 km; however, most flight regulations require drones to be flown within line of sight (e.g. U.S. FAA Regulations Part 107), so in practicality this does not necessarily translate into straight line flight distances. Fixed wing drones can also hold relatively larger payloads (typically up to 9 kg) than multi-rotor drones. Disadvantages of fixed-wing drones within the context of stormwater management are that (i) they cannot hover in place, which precludes its use in tasks such as infrastructure inspection, and (ii) they need a large clear area to take off and land, which may not be available within an urban setting. Multi-rotor drones overcome these limitations through propeller systems that allow them to takeoff perpendicular to the ground and hover in place. Disadvantages of multi-rotor drones are that they cover less ground than fixed-wing drones and usually have a shorter battery life in flight, between 30–60 minutes. However, because of their ease of use within the urban environment, many applications of drones in stormwater management or other urban environmental settings have been with multi-rotor drones (e.g. Máthé and Buşoniu 2015; Zhu et al. 2017; Gadi et al. 2018; Naughton and McDonald 2019).

Not unlike the cameras in our phones, camera technologies for drones have seen a rapid increase in capability over the past half-decade. It is common for standard drone packages to come with 4K pictures and video, while keeping the camera price point below $1,000 USD. Other cameras such as multispectral, hyperspectral, and radiometric thermal have begun to be available in formats for plug and play drone use, and have seen extended use in various environmental monitoring applications. Tables A1–A3 in the appendix list a range of commercially available multispectral, hyperspectral, and thermal cameras. Multispectral cameras capture the visual spectrum, as well as a small number of addition bands beyond the visible light range, typically in the infrared spectrum. The differences between multispectral cameras are usually in their spectral range (395–1000 nm), band width, and number of bands (4–12). Hyperspectral cameras on the other hand can capture hundreds of bands and depending upon the cameras can cover a much wider spectral range (350–13,400 nm); however, the cost of these are much higher (Manfreda et al. 2018). There are also numerous radiometric thermal cameras available that can estimate surface temperatures with and accuracy of $\pm$ 0.5–5°C. These cameras typically differ in their resolution (80 $\times$ 60 to 1920 $\times$ 1080 pixels) and thermal sensitivity (30–75 mK). In addition to cameras systems, many drones can be configured to fly with other types of payloads and several drone manufacturers sell developer or research platforms that can be custom built to meet the needs of different sensors or purposes.

Along with the proliferation of drones are several flight software applications that can be used to pilot drone missions. These include applications that enable pilot-controlled flight missions in which the pilot controls takeoff, flight, camera functionality, and landing, as well as those for pre-planned flight missions, in which routes, elevation, speed, camera angle, and picture frequency are preprogrammed into a software that can control the flight mission from takeoff to landing. These types of programs are particularly useful for collecting visual imagery over a wide area, where multiple photos are stitched together to make an orthomosaic. In such cases, there are several computer software programs that are available for stitching together remotely sensed data from drones. While there are free software programs that allow photo stitching, such as OpenDroneMap, there are many more commercial options including Pix4Dmapper, ESRI Drone2Map, and Agisoft PhotoScan. This photogrammetry software also have capabilities beyond producing orthomosaics, including developing index maps and using structure-from-motion (SfM) to derive elevation data.

Many drones are also beginning to become equipped with advanced features such as full airspace awareness, obstacle detection, standard regulatory and safety-based designs, intelligent pilot and automated flying modes, and platform and payload interchangeability. These features can enhance the pilot experience, making flying drones a safe activity for trained pilots, even in an urban environment. They also lower the entrance barrier and expand the potential applications of drones by reducing risks associated with flying. In the context of urban stormwater management, these advanced features may help to translate methodologies and findings from non-urban drone studies – where risks associated with drone failure are lower – to the urban environment.

Despite a proliferation in UAV technologies for remote sensing, there are several limitations surrounding operations, data collection, and data processing. While UAVs offer unprecedented spatiotemporal remote sensing data, they are limited to smaller coverage areas due to limited battery life. This is dependent upon variables such flight altitude, wind, power demands of onboard sensors, and payload weight. Coverage can be extended using higher flight speeds or limited image overlap, but higher flight speeds can contribute to image blur (Sieberth, Wackrow, and Chandler 2016) and inadequate overlap can lead to orthorectification errors (Colomina and Molina 2014). Data quality can also be impacted from light variations due to cloud coverage that impact the reflectance of land surfaces and changes to image resolution from elevation instability (Hakala et al. 2013). Drones are also limited by the weight of their payload typically between 3–9 kg (Hardin et al. 2019). In the past this has limited the use of hyperspectral cameras that exceed these payloads on drones, and while recent hyperspectral cameras built for drones now weigh as little as 180 g (Table A2), there is generally a trade-off between sensor size and data quality (Reulke and Eckardt 2018). Additionally, drones are constrained by the type of environmental conditions that they can fly in, such as wind speeds that are typically recommended to be less than 10–20 m/s.

In addition, using drones for remote sensing can result in a large amount of data. Data storage is not a problem due to large capacity microSD cards, hard drives, and cloud storage, but there are practical complexities involved in transferring, organizing, and analyzing a large set of data. To analyze remote sensing data from drones there are several photogrammetry software to automate most processes (e.g. Pix4D, Agisoft PhotoScan). While this software can be relatively expensive, open source packages, such as OpenDroneMap (http://opendronemap.org/) are beginning to emerge. Depending upon the study, there may be some form of manual digitizing and interpreting beyond the capabilities of these automation software that can take a significant amount of time and is subject to operator error (Vasuki et al. 2014).

3. Drones in water resources and environmental applications

Over the past half-decade, drones have emerged as a valuable technology in water resources and environmental management. The ability to collect on-demand imagery and video in real-time, access difficult to reach terrain, and carry a water sampling payload, have made drones a tool that overcomes the shortcomings of traditional data collection techniques. As such, researchers and practitioners have begun to harness drones as a tool to advance water resources and ecohydrological studies. To date, several water and environmental studies have demonstrated the utility of drones, with many of them having applications for urban stormwater management.

One such application of drones is the remote sensing of water quality. Drones can remotely collect imagery data that can serve as a surrogate measurement of water quality constituents. For example, drone visual, multispectral, and hyperspectral data have been shown to be good indicators of surface water quality parameters such as turbidity, suspended solids, and chlorophyll, as illustrated in Table 1. This table summarizes studies where spectral bands or their indices have been successfully applied to predict in-situ water quality measurements. While these studies demonstrated good model fits, they noted numerous limitations including the influence of ambient lighting and meteorological conditions on spectral signatures, inability to generalize models due to unique characteristics of each water body, and difficulty developing orthmosaics across large water bodies (Flynn and Chapra 2014; Guimarães et al. 2019). Despite these constraints, these measurements produce valuable predictions of surface water body pollutants at a high-spatial resolution, at an on-demand timescale, and with a short time lag between data collection and availability of results. These advantages make drone remote sensing an attractive approach to water quality measurement, especially for phenomena such as eutrophication that may be heterogeneous and happen over short timescales (Kislik, Dronova, and Kelly 2018).

With a proliferation of lightweight thermal cameras, drones can now easily provide real-time temperature data of water bodies (Fitch et al. 2018) and recently several studies have used drone thermal data for water resources applications. These include quantifying the size of stormwater plumes in creeks (Caldwell et al. 2019), identifying thermal inputs into rivers (Dugdale et al. 2019), capturing the thermal structure of lakes (Chung et al. 2015), and surveying groundwater discharge in wetlands (Harvey et al. 2019). However, while there are numerous applications, these methods have limitations including the accuracy of the thermal data, as 66% of the variance has been shown to be explained by environmental conditions and flight characteristics (Dugdale et al. 2019). In addition, it is difficult to stitch together the thermal orthomosaics over low-contrast

Table 1. Details of UAV water quality monitoring studies using remote sensing.

Camera	Waterbody type	Type of drone	Parameter	Bands and Indices Used	Model results	Reference
GoPro Hero3	Rivers	*Multirotor*: DJI Phantom	Nuisance green algae *Cladophora glomerata*	Red, green, blue[5]	τ 0.82–0.84[1]	Flynn and Chapra 2014
Rikola Fabry-Perot Interferometer CMV4000 4.2 Megapixel CMOS camera	Shallow lake	*Fixed wing*: Custom built	Chlorophyll-a	400–500 nm[5]	R^2 0–0.2	Pölönen et al. 2014
			Turbidity	400–500 nm[5]	R^2 0–0.2	
Canon Powershot S110 RGB and NIR sensors	Reservoir	*Fixed wing*: SenseFly eBee	Chlorophyll-a	660 nm; 850 nm	R^2 0.59–1.0	Su and Chou 2015
			Total Phosphorous	660 nm; 850 nm	R^2 0.49–0.99	
			Secci disk depth	660 nm; 850 nm	R^2 0–0.96	
Canon Powershot S100 NDVI	Lake	*Fixed wing*: Zephyr sUAS *Multi rotor*: DJI F550	Cyanobacterial biomass densities[2]	BNDVI[4]; 400–580 nm; 680–780 nm	R^2 0.77–0.87	Van Der Merwe and Price 2015
Canon Powershot S110 RGB and NIR camera	River	*Fixed wing*: SenseFly eBee	Phytoplankton concentration	AI[3]; 850nm; 660nm; 625nm	R^2 0.72	Kim et al. 2016
Canon Powershot S110 RGB and NIR sensors	Reservoirs	*Fixed wing*: SenseFly eBee	Chlorophyll-a	450 nm; 520 nm; 660 nm; 850 nm	R^2 0.69-1	Su 2017
			Secchi disk depth	450 nm; 520 nm; 660 nm; 850 nm	R^2 0-1	
			Turbididty	450 nm; 520 nm; 660 nm; 850 nm	R^2 0.87-1	
Canon ELPH 110HS with	Lake	*Fixed wing*: SenseFly Swinglet CAM	Chlorophyll-a	NDVI, NIR, Green, Blue[5]	R^2 0.51–0.86	Guimarães et al. 2017
Canon RGB	Lake	*Multirotor*: Custom hexcopter	TSS	NDVI[6], NDWI[5,7]	R^2 0.63–0.77	Veronez et al. 2018
			Dissolved organic matter	NDVI[6], NDWI[5,7]	R^2 0.52–0.60	
Parrot Sequoia multispectral	River	*Fixed wing*: SenseFly eBee	Suspended sediment concentration	550 nm; 660 nm; 735 nm; 790 nm	R^2 0.56–0.91	Larson et al. 2018
Parrot Sequoia multispectral	River	*Fixed wing*: SenseFly eBee *Multirotor*: DJI Inspire	Turbidity	NDWI; 550 nm; 660 nm; 735 nm;790 nm	R^2 0.1–0.91	Ehmann, Kelleher, and Condon 2019
Canon ELPH 110HS	Lake	*Fixed wing*: SenseFly Swinglet CAM	TSS	NIR, Green, Blue[5]	R^2 0.75	Guimarães et al. 2019

1 Kendalls tau; 2 Computed as Buoyant Packed Cell Volume; 3 Algal Index; 4 Blue Normalized Difference Vegetation Index; 5 Exact band or band width not specified; 6 Normalized Difference Vegetation Index; 7 Normalized Difference Water Index.

water bodies such as lakes, and may require higher overlapping (95%) to achieve suitable results (Rahaghi et al. 2019).

Drones have also been used to quickly and efficiently collect direct water quality measurements or samples across surface water bodies. For example, multiple studies have equipped multi-rotor drones with grab sampling apparatus to take physical samples of a water body (Ribeiro et al. 2016; Koparan and Koc 2016; Koparan et al. 2018b), water quality multiprobes to measure water quality constituents directly (Esakki et al. 2018; Koparan et al. 2018a), or some combination of both (Alam and Manoharan 2017). In these applications, one advantage to using a drone for water quality sampling is the ability to take quick, repeatable measurements at exact locations through GPS-supported pre-programmed waypoints. This allows a user to repeat sampling at the exact same locations in a water body without having to physically reach them, which may be especially helpful in large or remote water bodies where sampling locations are difficult to pinpoint or accessibility is an issue.

Another emerging area for the use of drones in water resources and environmental studies is in the estimation of flow rates in streams. Visual images captured by drones have been used to estimate tracer concentrations of Rhodamine WT with an R^2 of 0.9 and above, which are then applied to estimate flow rates in streams (Baek et al. 2019). Particle tracking velocimetry methods have been used on drone videos of streamflow with natural and artificial tracers to track the velocity of water in a stream with 85–90% accuracy (Tauro, Porfiri, and Grimaldi 2016; Thumser et al. 2017; Koutalakis, Tzoraki, and Zaimes 2019). In addition, imagery from drones have also been used to derive stream widths for use as input data into hydraulic models for estimating streamflow (King, Neilson, and Rasmussen 2018). These approaches could transform extreme streamflow measurement through non-contact methods that eliminate the risk of contacting the stream for velocity measurements, such as in the case of using acoustic doppler current profilers. In addition, it could allow for flow measurements in stream locations that may be difficult to access due to their remote location, difficult terrain, or urban setting.

Drones have also been used extensively for flood and emergency response management. Drones can collect on-demand visual imagery, which is valuable for responses during floods or other emergencies that require fast and reliable aerial images. (Boccardo et al. 2015; Griffin 2014; Erdelj et al. 2017). Drones have been used to capture imagery during floods for use in flood mapping and verification of flood inundation models (Murphy et al. 2016; Sumalan, Popescu, and Ichim 2017; Feng, Liu, and Gong 2015), and video captured by drones during floods has been applied to estimate surface velocities (Perks, Russell, and Large 2016). Additionally, drones have been used to capture imagery after flood events for the rapid identification of property damage (Casado et al. 2018).

Many other applications of drones are based upon digital elevation models that are derived from drone imagery and structure-from-motion (SfM), which uses overlapping images to calculate a three dimensional position for every pixel (Snavely, Seitz, and Szeliski 2008). Studies include using SfM to assess the volume of coal ash and contaminated water lost during a rupture of a coal ash pond (Messinger and Silman 2016), map complex ice formations (Alfredsen et al. 2018), evaluate the influence of down sampling on the development of digital elevation models (Leitão and de Sousa 2018), develop flood risk maps (Hashemi-Beni et al. 2018; Coveney and Roberts 2017), and detect the water level in dams (Ridolfi and Manciola 2018; Gao et al. 2019) and ponds (Kohv, Sepp, and Vammus 2017). Others have used SfM elevation products for river analyses such as evaluating streambank erosion, finding it to within 4% of terrestrial laser scanning (TLS) and real time kinematic (RTK) GPS methods (Hamshaw et al. 2019), as well as for mapping channel bathymetry and topography (Rusnák et al. 2018; Kim et al. 2019; Lejot et al. 2007; Zinke and Flener 2013). While these methods have been shown to be accurate in estimating elevation, other studies have used UAV-mounted LiDAR sensors where penetration of plant canopies or water is required (Resop, Lehmann, and Hession 2019).

With the ability to collect on-demand high-resolution spatial data such as elevation, drones also present a new tool to better parameterize water resources and environmental models. For example, drone measurements of water level have been applied to model ground water – surface water interactions of a river and its catchment, decreasing RMSE by 75% compared to models that used river discharge only (Bandini et al. 2017a, 2017b). UAV thermal cameras can capture land surface temperature in high spatial and temporal resolutions (Naughton and McDonald 2019) and have been shown to provide sufficient data quality for use in parameterizing land surface heat flux models (Hoffmann et al. 2016). Drone imagery has also been used to collect surface information for more accurate parameterization of terrain for distributed hydrological models (Vivoni et al. 2014) and surface impervious for urban runoff modeling (Tokarczyk et al. 2015).

In addition to these, there are several ecohydrological applications of drones. Images from drone flights have been used to quantify vegetation density in urban green spaces (Gadi et al. 2018), visually inspect eutrophication and track ragweed in a small lake (Fráter et al. 2015), and classify the heterogeneity of river habitat (Woodget et al. 2017). Drones have also been used to study substrate in riverine systems, including the classification of substrate based upon imagery with an accuracy of 61–97% (Arif et al. 2017) and prediction of grain size based upon drone imagery and SfM (Woodget and Austrums 2017). As a whole, these applications of drones for water resources and environmental studies could have several applications for stormwater management.

4. Drones for urban stormwater management

The previous applications demonstrate the advantages of drone data – rapid, on-demand, at high spatial resolutions – for water and environmental applications. These advantages also make drones an appealing tool to advance urban stormwater management efforts. In the urban environment, stormwater challenges are prevalent and require technological solutions that can provide a better understanding of the environmental conditions of the urban waterscape. To this end, this section offers perspectives on several applications of drones for urban stormwater management.

4.1. Drones as an asset management tool

Two advantage of drones for stormwater management are the ability to (i) quickly assess infrastructure or water bodies that may be difficult to observe otherwise and (ii) collect data from a variety of unique aerial perspectives as opposed to only the ground-level. For example, drones have been shown to be an effective asset management tool for identifying the location of storm sewer inlets using visual imagery (Moy de Vitry et al. 2018). Drones provide visual imagery at resolutions much higher than satellite images, which when combined with computer vision algorithms can successfully identify and locate infrastructure. Using a similar approach, drone imagery could be applied to identify stormwater outfalls, which in many cases are poorly catalogued and difficult to find (Bender, Dymond, and Aguilar 2017). Additionally, aerial thermal imagery has been shown to be effective in identifying possible illicit stormwater discharges through thermal anomalies in streams, which help to prioritize outfall visits for illicit discharge detection and elimination efforts (Derrick and Moore 2015). While stitching together a thermal orthomosaic over a large river or stream may require significant overlap and processing time (Rahaghi et al. 2019), the ability to view thermal data during flights could allow an operator to evaluate water surface temperatures from outfalls in real-time. In addition, stormwater outfalls can be difficult to access due to their locations along stream or pond embankments with significant overgrowth, steep slopes, and wet and slippery terrain. Drones could overcome these challenges by accessing stormwater outfalls remotely and evaluating their conditions through aerial visual or thermal imagery from a variety of perspectives as opposed to physical site inspections at the ground-level. To this end, drones hold significant promise for improving the asset management of stormwater infrastructure.

Drones are also a valuable tool for inspection and enforcement of erosion and sediment control practices at construction sites. Sediment runoff from construction sites can be significant (Shen et al. 2018), and it is imperative for cities to properly enforce sediment and erosion control practices; however, doing so remains a challenge. Drones have a unique potential to fill this gap and to this end have been found to be an effective tool for accurate and reliable monitoring of construction site erosion when deployed on a weekly basis or after an accumulation of 1.9 cm of rainfall in 24 hours (Perez, Zech, and Donald 2015). This approach holds great promise, as many construction sites use drones for construction management (Ham et al. 2016) and so applying drones for erosion and sediment control would synergize with those efforts. Beyond erosion and sediment control, drones could be applied to track the progress of other water-related construction projects, such as tracking changes in vegetation and canopy cover during urban watershed restorations (Lu and Hughes 2017).

Furthermore, as green stormwater infrastructure continues to grow as a stormwater management practice, significant challenges emerge for operations and maintenance of distributed infiltrative systems. For example, access for inspection of green stormwater infrastructure is often an issue for municipalities, diagnosing operational health and efficiency of practices such as bioswales from site visits is opaque, and despite a number of resources (Erickson, Taguchi, and Gulliver 2018) there is not a clear consensus on how to diagnose the operational health of green infrastructure practices, of which plant health is a major component (Hunt et al. 2015; Houdeshel et al. 2015). Drones could help to overcome these challenges through valid and repeatable processes that can evaluate the health of plants within green stormwater infrastructure for targeting maintenance and operations efforts. Such an approach is already applied in evaluating the health of agricultural and urban plants using visual and multispectral imagery or imagery derived products such as NDVI (Primicerio et al. 2012; Gago et al. 2015). Because infiltrative stormwater practices, such as bioswales and rain gardens, contain a variety of plant species, these same principles may be able to evaluate the health of plants within green stormwater infrastructure.

4.2. Drones as a water measurement tool

With an emerging recognition towards stormwater regulations that are driven by monitoring (Markell and Glicksman 2013; NASEM 2019), drones are uniquely positioned to help to support these efforts. For example, when demonstrating improvements in stormwater quality as a result of stormwater management actions, often municipalities are constrained by the resources needed to monitor receiving water bodies. Installing and maintaining water quality sampling equipment is an expensive task, and even one station could exceed a municipalities annual stormwater budget (McDonald and Naughton 2019). In addition, these stations are spatially constrained to point locations that may fail to capture an accurate representation of the spatial distribution of pollutants in a water body. While drones are unable to capture data at the continuous temporal resolution of a permanent monitoring station, they can complement these stations with either grab samples across numerous locations or high-resolution remote sensing of water quality.

To this end, drones have been used as to measure water quality by capturing data with probes or through physical collection of water samples (e.g. Ribeiro et al. 2016; Alam and Manoharan 2017; Koparan et al. 2018a). In the urban environment, the ability to directly monitor multiple locations quickly and efficiently would provide stormwater managers with actionable data that they can use to improve stormwater quality management efforts and could help to overcome resource limitations of water sampling programs. Perhaps an even greater advantage of drone remote sensing would be the ability to evaluate water quality on a city-wide scale. For example, urban runoff is a primary driver of eutrophication in many urban water bodies, and multiple studies have demonstrated the use of drone multispectral and hyperspectral imagery for monitoring eutrophication processes in surface waters (Kislik, Dronova, and Kelly 2018). To that end, multispectral data has been shown to be a good predictor of Chlorphyll-a (Su and Chou 2015; Guimarães et al. 2017; Pölönen et al. 2014), algae (Flynn and Chapra 2014; Van Der Merwe and Price 2015), turbidity (Ehmann, Kelleher, and Condon 2019; Su 2017), and TSS (Veronez et al. 2018; Guimarães et al. 2019; Larson et al. 2018), all of which are important parameters for evaluating water quality in stormwater systems.

However, large scale deployment of drones for remote sensing of water quality faces numerous limitations including the influence of unique water body characteristics, ambient lighting, and environmental conditions on spectral signatures (Flynn and Chapra 2014; Guimarães et al. 2019). If these constraints could be addressed, the ability to capture the spatial distribution of pollutants within urban lakes and streams across a city would be helpful to stormwater managers in understanding where pollutants are coming from in the watershed and for developing pollution mitigation strategies. Drone water quality measurements as a mature remote sensing technology could help to augment traditional stormwater monitoring, such as permanent monitoring stations and citizen volunteer monitoring efforts, to provide a holistic picture of stormwater quality within the urban environment.

A better understanding of pollutant sources would further help stormwater managers in complying with other water quality regulations. For example, in the U.S. some municipalities have resisted water quality improvements enforced on them by regulators due in part to a mistrust in their monitoring and assessment methods. These municipalities have therefore implemented continuous monitoring throughout their watersheds to develop a holistic understanding of the impact of their jurisdiction on pollutants through more complete water quality data (Gauron et al. 2014; Dymond, Brendel, and Woodson 2018). What these cases demonstrate is the need for monitoring data that can accurately attribute pollutant runoff to municipalities and other entities within a watershed. Drone-derived water quality information could further advance this understanding and help to develop accurate pollutant load reduction allocations.

Beyond water quality, drones have significant potential to transform the way that stream flowrate is measured in an urban environment. Several studies have applied drone video and particle image velocimetry algorithms to estimate stream velocities (e.g. Tauro, Petroselli, and Arcangeletti 2016; Thumser et al. 2017). While these applications to date have been limited by a need for artificial tracers and ground control points, the methods are transferrable to streams in the urban environment. This technology could complement an existing stormwater monitoring program by allowing stormwater managers to indirectly measure streamflow quickly and efficiently during flood events at critical locations that lack a permanent or semi-permanent monitoring station. This would provide stormwater managers with critical data needed to make decisions regarding infrastructure investments, stream restoration, and emergency flood plain management. In addition to measuring flow rates during a flood, drones have been shown to be valuable in rapid, local risk assessment though post-flood analysis that quantifies the spatial extent of flooding and water ponding conditions in an urban city using aerial imagery (Zhu et al. 2017). Because floods happen quickly and restrict movement on land, the ability to rapidly collect remote sensing data for flood monitoring and risk assessment would be of significant value.

4.3. Drones for better model parameterization

Drones reveal a breadth of environmental data that have the potential to usher in new ways of parameterizing urban stormwater models. Drones can be applied to capture spatial data on-demand, which could allow a modeler to parameterize model components with higher spatial accuracy than typical lumped estimations. For example, high-resolution spatial data in ecohydrological modeling applications in undeveloped ecosystems and has been found it to be valuable in reducing model error (Vivoni et al. 2014; Hoffmann et al. 2016). In addition, thermal infrared imagery has been successfully used to provide calibration targets for a deterministic stream temperature model (Caldwell et al. 2019). This could be even more valuable in an urban environment where the spatial heterogeneity of land use and land cover and their associated impacts on the water cycle (e.g. temperature, infiltration, abstraction, evapotranspiration, etc.) are significant. To this end, researchers have begun to explore the value of high-resolution spatial data in the urban environment by using drone imagery develop fine resolution estimates of land surface temperatures (Naughton and McDonald 2019) and surface imperviousness (Tokarczyk et al. 2015) for use as parameters in stormwater models. Information such as this could support a wide range of rainfall-runoff models from distributed and lumped deterministic models to other black-box models such as artificial neural networks.

4.4. Drones to support smart and connected stormwater systems

With the emerging paradigm of smart and connected cities, researchers are beginning to explore the roles that stormwater infrastructure can play within an integrated smart cities system (Kerkez et al. 2016). Projected visions include networks of sensors that provide real time data, data-informed active controls that dynamically control the flow of stormwater, and flood risk systems that integrate these data to inform traffic operators, food risk managers, and other city-wide infrastructure services.

Within this context, it's important to consider the role drones might play. Beyond stormwater, the applications of drones in smart and connected cities are numerous. This includes drones for use in law enforcement as observational support (West and Bowman 2016), in transportation as a traffic operation diagnostic (Kanistras et al. 2015), for delivery of commercial products (Murray and Chu 2015), and as part of asset management for infrastructure inspections such as bridges (Máthé and Buşoniu 2015). Given the numerous applications, there may be opportunities for data assimilation that could synergize drone flights. For example, imagery data taken during law enforcement operations, could be used to define impervious surfaces and their temporal changes at a high-resolution for use in stormwater runoff models (Tokarczyk et al. 2015), or in developing accurate stormwater fees that are based upon impervious area (Kea, Dymond, and Campbell 2016). Conversely, data collected from drones for stormwater management purposes could be used to inform other connected smart cities systems.

The future of smart and connected cities will require an integration of data, hardware, and communication in which information is integrated within broad decision-making frameworks (Albino, Berardi, and Dangelico 2015). Drone data could provide on-demand imagery and sensing at a high spatial resolution, which could inform processes and decisions that are built upon data from smart and connected cities. For example, drone imagery could be used to collect data on flooding conditions that is used to make control decisions downstream in combined sewer systems or actively-controlled lakes and wetlands. Flooding information from drones could also be integrated with real-time traffic operations to manage traffic lane closures and warnings during floods. Additionally, illicit discharge inspection information could be used by public works officials to identify maintenance needs or opportunities.

Ultimately, the use of drone-related data from stormwater management efforts may have significant applications beyond it's intended use in the smart and connected cities of the future. Questions will arise as to how this information can be stored, accessed, and integrated in a way that is efficient and supports public services, as well as how this information can be used in a manner that does not compromise the privacy and business interests of citizens and industries. As the paradigm of smart and connected cities takes shape, the integration of stormwater technologies – including drones – will be critical for advancing stormwater management to meet ambitious flooding and water quality goals.

5. Barriers to implementation

While drones have significant potential to advance urban stormwater management efforts, there are barriers to implementation that need to be overcome before we see widespread adoption. The first, and perhaps most significant barrier, is the uncertainty around the regulatory usage of drones. Across the globe, governments have enacted legislation to address this new and transformative technology. There are a number of resources to access these laws and policies, including the *Master List of Drone Laws* (UAVCoach 2019) and *Global Drone Regulations Database* (OZYRPAS 2019). Behind the regulations is a desire to protect safety and privacy of its citizens and uphold national security, with most countries requiring some sort of regulatory approval (Ravich 2016). As of October 2016, 65 countries had regulations in place, 15 had regulations pending, 99 had no regulations, and 3 had official bans of UAVs (Stöcker et al. 2017).

As an example, in the United States airspace is regulated solely by the Federal Aviation Administration (FAA) who provides concrete guidelines on how commercial drones can operate (FAA Regulations Part 107). This include when and where you can operate drones, in what airspace, and requirements for pilot operational procedures. However, the U.S. federal government has recently relaxed these rules, including operating at night and flying over crowds, to support the growth of commercial drone usage (FAA Reauthorization Act of 2018, HR 302, 115). While FAA rules are straightforward and govern the airspace you fly in, drone rules at the local and state level are inconsistent. Some states and municipalities have laws regulating the legality of capturing images of private property and where a drone operator can take off and land from (for some of the strictest laws see Texas Government Code, Chapter 423 – Use of Unmanned Aircraft); however, some have no regulations at all (Donohue 2018). This example of uncertainty around drone laws in the U.S. may be reflective of other countries where laws are fragmented from the federal to local levels. This uncertainty may therefore prevent stormwater managers from investing time and resources into a technology whose operational legality is unsettled.

Another barrier is the accepted use of drones for stormwater management by stormwater regulators. While this paper highlights several emerging areas for the use of drones for stormwater management, large-scale adoption among municipalities will only happen when they know that they will get regulatory credits for such actions. For example, in the U.S. current illicit discharge detection and elimination guidelines usually require municipalities to physically inspect stormwater outfalls in-person (e.g. Brown, Caraco, and Pitt 2004; Wisconsin Administrative Code NR216). While the use of drones could provide a more efficient method for outfall inspection, unless it is accepted by the state-level agency enforcing the regulation, a municipality will not take the risk of performing outfall inspections using drones. Therefore, the advancement of this technology may need to take a top-down approach where regulatory agencies provide flexibility to municipalities willing to take alternative approaches to stormwater management.

In addition, stormwater management professionals are traditionally risk averse (Olorunkiya, Fassman, and Wilkinson 2012) and therefore may question the quality and reliability of data from drones for their own decision making. A hesitation to adopt drone methodologies may be due to the relative novelty of drones within stormwater management contexts and a lack of consistency in methodologies from data collection to data processing. In addition, stormwater managers may lack the expertise to conduct drone missions and process and interpret the data. Therefore, we may need to see the technologies and methodologies in stormwater management mature alongside drone competencies in stormwater professionals before widespread adoption takes place.

Another significant barrier to widespread adoption of drones in stormwater is the technological readiness and scientific robustness of many of these applications. Applications that simply rely on visual imagery to infer data, such as the identification of water level, flood damage areas, or sewer inlet locations, are largely reliable and can be applied across a wide range of geographic and environmental conditions. However, other applications, such as the use of multispectral data to infer water quality or video data to estimate stream flow, are subject to greater methodological limitations. Therefore, it may be years or decades until some of these applications are refined enough to be accepted within the stormwater community.

To that end, for these barriers to be overcome there will need to be more research and applications that demonstrate the utility of drones for stormwater management applications. This includes research on the use of drones for water sampling, remote sensing, and asset management efforts. Once these barriers are overcome, we may begin to see drones as a tool that can usher stormwater management into the future. If such an environment exists, this could produce a new workforce centered around environmental drone pilots, thereby contributing to the development of a skilled workforce.

Even though the drone technologies exist, are commercially available, and have many applications that are scientifically defensible, because of these barriers the timeline of implementation may be years off. Once these barriers are overcome, it will require scaled adoptions, workforce training, and community acceptance before drones become ubiquitous in stormwater monitoring and management. However, once in motion, drones have the potential to advance stormwater efforts through rapid on-demand data.

6. Conclusion

Drones have shown great promise as a water and environmental management tool, with many applications for urban stormwater management. These include their use in asset management, water measurement, model parameterization, and as a component of the smart and connected stormwater systems of the future. Despite the proliferation of drone technologies that have considerably lowered the technological barriers to adoption, we have seen limited applications in urban stormwater management to date. This lack of stormwater applications is primarily due to the uncertainty around a new technology, limited amount of stormwater drone research, and constantly changing regulatory environment around drones. However, as drone technologies, regulations, and applications mature, we may see drones playing a leading role in a new frontier of urban water management.

This is important, as our world faces significant water quality and flooding challenges that are difficult to address. This can be seen in the history of stormwater management in the United States where despite three decades of stormwater regulations, many of the nations' water bodies are still plagued by non-point source runoff. These impairments point less to failed efforts to manage stormwater, but to the inherent difficulty in managing and monitoring non-point source runoff. Therefore, as we move into the coming decades of stormwater management, it is imperative that we improve both management and monitoring of non-point source runoff in the urban environment, which drones are uniquely positioned to support.

Acknowledgements

The author would like to acknowledge the generous support of the Marquette University Opus College of Engineering Earl. B. and Charlotte Nelson Award for funding this work. The author would also like to acknowledge Veronika Folvarska for her contribution to the development of Tables A1-A3.

Disclosure statement

No potential conflict of interest was reported by the author.

Funding

This work was funded through the Marquette Univeristy Opus Colllege of Engineering Earl B. and Charlotte Nelson Award.

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Appendix

Table A1. Multispectral cameras applicable to UAVs and their specifications.

Manufacturer	Sensor Model	Size (mm)	Resolution (megapixels)	Pixel Size (μm)	Number of Bands	Spectral Range (nm)	Weight (kg)
Bay Spec	OCI-M+	85 x 60 x 60	-	3956 x Scan Length	12	450 to 1000	0.46
Mapir	Survey 3	59 x 41.5 x 36	12	1.55 x 1.55	6 Filter Options	395 to 945	0.05
	Kernel	34 x 34 x 40	14.4	1.4 x 1.4	21 Filter Options	395 to 945	0.045
Micasense	RedEdge-MX	0.87 x 0.59 × 0.454	1.2	-	5	475 to 840	0.2319
	Altum	82 x 67 × 64.5	3.2	-	5	475 to 840	0.049
Parrot	Parrot Sequoia +	59 x 41 x 28	1.2	3.75 x 3.75	4	550 to 790	0.072
Quest Innovations	The Condor 5 UAV-CMV2000	150 x 130 x 177	-	5.5 x 5.5	5	400–1000	1.45
Sentera	Sentera Quad	76 x 62 x 48	1.2	3.75 x 3.75	4	400 to 825	0.17
	Double 4K (NDVI and NDRE)	59 x 41 x 44.5	12.3	-	4	525 to 890	0.08
	Multispectral Double 4K Agriculture Sensor	59 x 41 x 44.5	12.3	-	5	386 to 860	0.08
	AGX710 Performance	89 x 88 x 98	12.3	-	5	446 to 840	0.27
	AGX840	110 x 102 x 113	1.2	3.75 x 3.75	4	400 to 825	0.37
SlantRange	4P and 4P+	146 x 69 x 57	-	4.8 x 4.8	6	410 to 950	0.35
Tetracam	MCAW6 (Global Shutter)	131.4 x 78.3 x 87.6	1.3	4.8 x 4.8	6	~450 to ~1000	0.6
	MCAW12 (Global Shutter)	154.4 x 78.3 x 87.6	1.3	4.8 x 4.8	12	~450 to ~1000	1.1
	Micro-MCA 4 (Global Shutter)	115.6 x 80.3 x 68.1	1.3	4.8 x 4.8	4	~450 to ~1000	0.497
	Micro-MCA 6 (Global Shutter)	115.6 x 80.3 x 68.1	1.3	4.8 x 4.8	6	~450 to ~1000	0.53
	Micro-MCA 12 (Global Shutter)	115.6 x 155 x 68.1	1.3	4.8 x 4.8	12	~450 to ~1000	1
	Micro-MCA 4 (Rolling Shutter)	115.6 x 80.3 x 68.1	1.3	5.2 x 5.2	4	~450 to ~1000	0.497
	Micro-MCA 6 (Rolling Shutter)	115.6 x 80.3 x 68.1	1.3	5.2 x 5.2	6	~450 to ~1000	0.53
	Micro-MCA 12 (Rolling Shutter)	115.6 x 155 x 68.1	1.3	5.2 x 5.2	12	~450 to ~1000	1
	ADC Micro	75 x 59 x 33	3.2	3.2 x 3.2	3	520 to 920	0.09
	ADC Lite	114 x 77 60.5	3.2	-	3	520 to 920	0.2

Table A2. Hyperspectral cameras applicable to UAVs and their specifications.

Manufacturer	Sensor Model	Size (mm)	Spectral Range (nm)	Number of Bands	Spectral Resolution (pixels)	Weight (kg)
BaySpec	OCI-UAV-1000	80 x 60 x 60	600–1000	~100	2048*	0.18
	OCI-UAV-2000	80 x 60 x 60	600–1000	~20-25	400 x 200	0.18
	OCI-D Airborne VIS-NIR	-	475–975	40	500 x 250	0.54
Brandywine Photonics	CHAI S-640	152 x 127 x 76	825–2125	260	640 x 512	5
Cubert GmbH	FireflEYE S185 SE	-	450–950	125	50 x 50	0.47
Headwall Photonics	Nano-Hyperspec	-	400–1000	270	640*	0.5
	Micro-Hyperspec VNIR A-Series	-	400–1000	324	1004*	0.7
	Micro-Hyperspec VNIR E-Series	-	400–1000	369	1600*	1.1
HySpex	VNIR-1024	305 x 99 x 150	400–1000	108	1024*	4.2
	Mjolnir V-1240	250 x 175 x 170	400–1000	200	1240*	4
	SWIR-384	380 x 120 x 175	1000–2500	288	384*	5.7
Corning	vis-NIR micro HSI-A	-	400–800	120	1360*	0.45
	vis-NIR micro HSI-B	-	400–1000	180	1360*	0.45
	vis-NIR micro HSI-C	-	380–880	150	1360*	0.45
	Alpha-vis micro HSI-A	-	400–800	40	2560*	2.1
	Alpha-vis micro HSI-B	-	350–1000	60	2560*	2.1
	SWIR microHSI 640-A	-	850–1700	170	640*	3.5
	SWIR microHSI 640-B	-	600–1700	200	640*	3.5
	alpha-SWIR microHSI	-	900–1700	160	640*	1.2
Resonon	Pika L	193 x 145 x 134	400–1000	281	900*	1.5
	Pika XC2	326 138 x 134	400–1000	447	1600*	3.1
	Pika NIR-320	299 x 149 x 134	900–1700	164	320*	4
	Pika NIR-640	299 x 149 x 134	900–1700	328	640*	4
	Pika NUV	100 x 264 x 73	350–800	196	1600*	2.1
SENOP	HSC-2	199 x 131 x 97	500–900	up to 1000	1024 x 1024	0.99
SPECIM	FX10	150 x 71 x 85	400–1000	224	1024*	1.26
	FX17	150 x 75 x 85	900–1700	224	640*	1.56
XIMEA	MQ022HG-IM-LS100-NIR	26 x 26 x 31	600–900	100+	2048 x 8	0.032
	MQ022HG-IM-LS150-VISNIR	26 x 26 x 31	470–900	150+	2048 x 5	0.032
	MQ022HG-IM-SM4X4-VIS	26 x 26 x 31	470–630	16	512 x 272	0.032
	MQ022HG-IM-SM5X5-NIR	26 x 26 x 31	665–975	25	409 x 217	0.032
Quest Innovations	Hyperea 660 C3	80 x 100 x 300	400–1000	660	1024*	1.65

*The other dimension varies based upon sensors sweep distance.

Table A3. Thermal cameras applicable to UAVs and their specifications.

Manufacturer	Model	Dimensions (mm)	Resolution (Px)	Pixel Pitch (μm)	Weight (kg)	Spectral Range (μm)	Thermal Sensitivity (mK)	Measurement Accuracy
FLIR	Duo Pro R 640	85 x 86 x 68	640 x 512	2.8	0.325	7.5–13.5	< 50	± 5°C
	Duo Pro R 336	85 x 81 x 68	336 x 256	2.8	0.325	7.5–13.5	<50	± 5°C
	Tau 2 640	44.4 x 44 x 44	640 x 512	17	0.072	7.5–13.5	<30	-
	Tau 2 336	44 x 44 x 44	336 x 256	17	-	7.5–13.5	<50	-
	Tau 2 324	44 x 44 x 44	324 x 256	25	-	7.5–13.5	<50	-
	DJI Zenmuse XT2	123 x 112 x 127	640 x 512 or 336 x 256	17	0.629	7.5–13.5	<50	-
	Vue Pro	57 x 44 x 44	640 x 512 or 336 x 225	-	0.092–0.113	7.5–13.5	-	-
	Vue Pro R	57 x 44 x 44	640 x 512 or 336 x 225	-	-	7.5–13.5	-	± 5°C
Flytron	V3 Micro Thermal	20 x 20 x 15	80 x 60	-	0.003	-	-	-
ICI	Mirage	111 x 96 x 131	640 x 512	15	< 0.765	1.5–5.1	12	± 1°C
	Mirage 640 P-Series	111 x 96 x 131	640 x 512	15	< 0.765	3.0–5.0	12	± 1°C
	Boson 320	21 x 21 x 11	320 x 256	12	0.0075	7.5–13.5	50	-
	9320 P-Series	34 x 30 34	320 x 240	17	0.037	7.0–14.0	-	± 1°C
	8640 Broadband	45 x 45 x 39	640 x 512	17	0.037	3.0–14.0	20	± 1°C
	9160 P-Series	41 x 40 x 39	120 x 90	25	< 0.113	7.0–14.0	-	± 2°C
	SWIR 640 P-Series	46 x 46 x 29	640 x 512	15	< 0.13	0.9–1.7	-	± 1°C
Optris	PI 400i	45 x 45 x 60-75	382 x 288	17	0.195	8.0–14.0	75	± 2°C
	PI 450i	46 x 56 x 76-100	382 x 288	25	0.32	8.0–14.0	40	±2°C
	PI 640	46 x 56 x 90	640 x 480	17	0.32	7.5-13	75	±2°C
Thermoteknix	MicroCAM irGO	40 x 67	384 x 288 or 640 x 480	17	0.107	-	-	-
	MicroCAM2	42.5 x 50 x 25	384 x 288 or 640 x 480	25 or 17	0.043	-	-	-
	MicroCAM 3	-	384 x 288 or 640 x 480	17	0.03	-	-	-
Workswell	WIRIS Pro	83 x 85 x 68	640 x 512	-	0.43	7.5-13	50	± 2°C
	WIRIS Pro SC	83 x 85 x 68	640 x 512	-	< 0.45	7.5–13.5	50	± 2°C
	WIRIS 2nd	135 x 77 x 69	640 x 512 or 336 × 256	-	< 0.39	7.5-13	50	± 0.05°C
	WIRIS Security	111 x 80 x 103	800 x 600	-	< 0.78	7.5–13.5	40	-
YUNEEC	CGOET	81 x 108 x 138	1920 x 1080	-	0.278	8.0–14.0	50	-
	E10T/E10TV	123 × 81 × 140	320 × 256	-	0.37	8.0–14.0	50	-